



STATISTICAL PART OF SPEECH TAGGER FOR URDU

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Dated: August 2007

Dedicated to my Parents

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1 Introduction

Part of speech tagging system can be viewed as consisted of two main phases which are tagset design and implementation of disambiguation technique. This report will discuss each of these phases in detail. Section 2 will discuss the parts of speech proposed by Urdu grammarians. Urdu shares its large vocabulary from Arabic and Persian and shares its morphology and syntactic structure from Hindi. However, there are standard tagging guidelines provided which aims at standardizing the tagsets of all languages of the world. The tagset of English can also be used as guideline for tagset. In section 3, tagset of related languages and earlier work on Urdu tagset will be discussed.

Section 4 will discuss the previous work on major disambiguation technologies. It will discuss the rule based, statistical and transformational based approaches for part of speech disambiguation. Machine learning approach i.e. neural network, and hybrid approaches for disambiguation will also be discussed. Redesigning of tagset on the basis of literature review will be done in section 5. A discussion on ambiguous issues of tagset is also discussed in section 5. Markov Model for disambiguation is chosen in section 6.

Section 7 will discuss the methodology of part of speech tagging process. A manual check was made on the corpus to separate the words by space. Corpus was prepared by applying normalization, and by removing diacritics and non-Urdu words. The process of manual tagging was done on 100,000 words. Various issues related to suffixation, compounding, degree of adjective and adverb, etc. were observed. A statistical part of speech tagger was implemented. It was decided that the tag of a word only depends on its own tag and a tag depends only on its previous tag. Problem of unknown word was solved by making it a candidate for a list of open class words. Disambiguation of tags was left on the tagger. Add Lambda smoothing was applied to calculate the probability of unknown word. Beam search was applied to reduce the search space.

The results of tagger are shown in section 8. Tagger showed an accuracy of 97.2% while testing on the data of 10,000 words. Tagger finds problem in disambiguating between the tags of noun and proper noun. Tagger was unable to detect the features of language based on phrase analysis. Tagger shows low accuracy while disambiguating between demonstratives and pronouns. In the end, it was concluded that the standard disambiguation techniques can be used for Urdu language.

2 Part of Speech Analysis of Urdu

The preparation of tagset may require the computational analysis of parts of speech of the language. Considering the work of Urdu grammarian in this context, their work can be viewed as influenced from two different languages. Many Urdu grammar writers use Arabic language as base line and proposed three main parts of speech for Urdu i.e. noun, verb and particle (Platts 1909, Javed 1981, Haq 1987). However, there are other Urdu grammarians which proposed nearly ten independent parts of speech for Urdu (Schmidt 1999). In this section, parts of speech proposed by Urdu grammarians will be discussed. The list of parts of speech of each grammarian can be found in appendix. However, list of parts of speech in appendix is covering tags up to two levels i.e. starting from the basic part of speech to second level distribution.

In 1909, Platts proposed a part of speech tagset for Urdu. The tagset contains three main parts of speech i.e. noun, verb and particle. Articles were not included under any part of speech. However, it was discussed separately as determiner of noun. Noun was divided into thirteen categories including three categories of adjective and ten categories for pronoun. Nouns and proper nouns were handled under one category of substantive Discussion on noun was based on three features i.e. gender, number and noun. declension. Cardinals, ordinals, collective numerals, distributives and multiplicatives. numeral adverbs, fractional numbers and RAKAM were handled under the category of numerals. In the categories of pronoun, words with marking like "اس نـر" were considered as one word. A separate part of speech of reciprocal pronoun was given to the words like "ايک دوسر". Platts did not propose any subcategory of verb. However, all properties and forms of verb were discussed as its features. Particles were divided into four categories i.e. adverb, postposition, conjunction and interjection (Platts 1909). Α complete list of parts of speech proposed by Platts can be found in appendix.

In 1971, Siddiqi provides an analysis of Urdu grammar and proposed six parts of speech for Urdu. In addition to three categories proposed by Platts, Siddiqui defined a separate category for adjective and pronoun. The adverbs were also kept separate from particles. A new category named distinct was introduced. Adverbs and negative particles were catered inside the category of distinct. Noun was distributed on the basis of its structure and nature. Some semantic distributions of noun were also provided e.g. sound noun. Indefinite pronoun and relative pronoun were also distributed under noun. Numerals were also catered under nouns. On the basis of structure, noun was divided into three sub categories. Common nouns were catered under original noun. Infinitive verbs were categorized under verbal noun. On the basis of the nature of noun, it was divided into three types. Substantive noun were used to cater proper nouns. Adjectives were further divided into comparative and exaggeration. At the first level, particle was divided into construction, conjunction, *it adjusted*. Conjunction was further divided into seven types. The details of parts of speech proposed by Siddiqi can be found in appendix (Siddiqi 1971).

Javed (1981) analyzed parts of speech of Urdu under two categories. The first category contains four parts of speech and second category contains the subtypes of particles. First category was divided into noun, verb, adjective and pronoun. Apparently, the four parts of speech look similar to those proposed by Siddiqi. But the sub types under these categories were quite different. Noun was divided into common noun, proper noun, collective noun, abstract noun and un-count noun. Most of the distributions of noun

were done on semantic grounds. Adjective was divided into personal, numeral, quantitative, emphatic and pronoun. The distribution of adjective was also done on the basis of semantics differences. Verb was divided into seven types. Adverb was taken as sub-category of both verb and pronoun. Words of verbal nature were categorized under verb. Adverbial particles were also considered as sub type of verb. Ker particle (see section 5) was also categorized under verb. Pronoun was divided in ten parts of speech. Pronouns of respect were separately catered under pronoun. Particles were divided into six categories. Particles were consisted of case markers, interjection, conjunction, negative particles and intensifier. Conjunction was further divided into six types. The interjection was semantically divided into the interjection of happiness and sorrow (Javed 1981). List of parts of speech proposed by Javed can be found in appendix.

In 1987, Haq provides an analysis of Urdu grammar and proposes parts of speech based on two features i.e. consistent and non-consistent. The consistent categories were divided into noun, pronoun, adjective, and verb. Non-consistent categories were those categories that alone have no meaning but they add meaning to consistent categories. Non-consistent is divided into noun and proper noun. Pronoun was divided into personal, relative, interrogative, indefinite and demonstratives. Adjective was divided into personal, numeral, quantitative, *interrogative*, is section 5) was also handled under verb as separate part of speech. In comparison with Javed (1981), categories of interjection were merged into one category and no separate category for intensifier was defined (Haq 1987).

In 1999, Schmidt provides an analysis of Urdu grammar. Rather than analyzing the language as consisted of three parts of speech, Schmidt proposed ten basic parts of speech of Urdu. Schmidt analysis was very different from other grammar writers. The tagset includes noun, pronoun, adjective, adverb, postposition, verb, particle, interjection, conjunction and number as main parts of speech of Urdu. Pronouns were divided into seven types which were demonstrative, personal, reflexive, interrogative, indefinite, relative and repeated. Pronouns used as adjective were analyzed under the category of adjective. Adverbs were analyzed as time, place, manner, degree and modal. Postpositions were divided into grammatical, spatial-temporal and compound postpositions. Grammatical postpositions include کو and the inflections of کی , بس , پر , سے .کا were handled under grammatical postpositions. Verb was analyzed as based on their forms. The words with relative nature are handled inside each category. Another difference between Schmidt's tagset and other grammarian's tagset was of particles. Schmidt has included only intensifiers under particles. All other types of particles were defined as separate category. Conjunction was divided into coordinating, correlative, causal, concessive and subordinating conjunctions. The category of number was divided into cardinal, ordinal, fractional, multiplicatives, money and time. A list of parts of speech proposed by Schmidt can be found in appendix (Schmidt 1999).

3 Definition of Tagset

"The computational division of syntactic, morphosyntactic and semantic features of a language into separate categories"

"Computational part of speech categories of a language"

Natural language processing may require building a part of speech tagset which should cover required depth of morphological and derivational categories of the language. There are three types of information that may be considered as guideline for generating a tagset. First type is the tagset of languages that are related in their morphological or morpho-syntactic or syntactic nature with source language. Previous tagsets of Urdu, Persian, Arabic and Hindi may be considered in this context. However, there are morpho-syntactic and syntactic tagsets of English language. Their analysis may also be used for the tagset of Urdu. There are general tagging guidelines provided which aims at standardizing tagsets of all languages of the world (Halteren 2005). In the following section, computational work on Urdu tagset and tagset of related languages will be discussed.

3.1 Earlier Computational Work on Tagset of Urdu

In 2003, Hardie implemented a POS tagger for Urdu. The tagset used by Hardie was based on the analysis of Schmidt and was following EAGLES guidelines of tagset. EAGLES guidelines aims at generalizing the design of the tagset. In EAGLES guidelines, general design of tagset was divided into three parts. First and compulsory part contains thirteen tags which are noun, adjective, pronoun, adverb, verb, article, adposition, numeral, conjunction, interjection, unique, residual and punctuation (Hardie 2003). The recommended attributes include number, gender, case, finiteness and other features. The optional part consists of similar attributes with lesser applicability and depends upon the language under observation. Recommended and optional attributes of EAGLES guidelines increase morpho-syntactic depth of the tagset. That's why; their inclusion in the tagset is optional.

Urdu tagset proposed by Hardie make use of all three levels of EAGLES guidelines. The tagset was based on morpho-syntactic categories of Urdu. A total of 350 tags were provided. In the tagset, noun was divided into 48 tags. Features of noun i.e. gender, number, case were explicitly handled in the tagset. All forms of verb i.e. infinitive, participles, subjunctives, imperatives were handled with separate tags. Verb was divided into 115 tags. The auxiliaries were divided into general and special auxiliaries. Special auxiliary verbs contain [d], μ_{j} , μ_{j} , and μ_{j} . Adjective was categorized as simple, determiner and Y-V-K-J determiners. The determiner adjective was used to define the categories of number, fraction, indefinite determiner. All inflection forms of the tag of Y-V-K-J determiner. Multiplicative marker, adjectival particles and WALA was handled inside adjective. However, all of them and their inflectional forms get separate tag. Pronouns were divided into five categories i.e. personal, personal possessive adjective, Y-V-K-J, reflexive and other pronouns.

According to Hardie, some pronouns take adjective markings. That's why they were named as adjective. The tag Y-V-K-J represents the demonstrative nature of a category. This nature was observed in pronoun, adjective and adverb, and was handled as separate category in each distribution.

Hardie tagset contains 350 tags. All inflectional forms of a word are handled as separate category. The distribution of tags like noun, proper noun and acronym are based on semantic differences. Words with izafat are handled in two separate ways. If izafat is written then it will get a separate tag of zz. However, if izafat is not written then the two words will be handled separately. A complete list of tags can be found in appendix.

In 2007, Ijaz and Hussain proposed a tagset for Urdu. Tagset was divided into eleven parts of speech i.e. verb, adjective, common noun, adverb, numeral, conjunction, auxiliary, postposition, case marker, harf and pronoun. Each tag of the tagset contains a parameters i.e. features of the tag. The properties of each tag i.e. gender, number, case, etc. were handled inside the feature parameter of a tag. (Ijaz et al. 2007).

3.2 Tagset of Related Languages

Urdu is a language of Indo-European family. Major part of Urdu is influenced from Persian and Arabic. The vocabulary of Urdu is also loaned from these languages. The script in which Urdu is written in is based on Arabic alphabets. Urdu and Hindi are closely related languages and share their phonology, morphology, and syntax with each other. In this section, tagsets of Arabic, Hindi and English will be discussed. The detailed tagset can be found in appendix.

The Arabic grammar writers have provided morpho-syntactic tagset for Arabic which consists of 177 tags including 103 tags for noun, 57 tags for verb, 9 tags for particle, 7 tags for residual and 1 tag of punctuation. However, all Arabic grammarian sticks to main three parts of speech i.e. noun, verb, particle. All entities that include in a noun phrase are considered as types of noun i.e. common noun, proper noun, pronoun, adjective and numeral are types of noun. Verb is divided into perfective, imperfective and imperative. All other types are considered under the category of particle (Khoja, et al.).

Urdu shares its morphological and structural information from Hindi. The standard tagset for Hindi is based on the tagset of Penn Treebank. Some categories from Penn Tree are directly taken. The discussion on Penn Treebank can be found later in this chapter. In Hindi tagset, some categories are slightly changed in the tagset. New tags are also proposed according to the nature of language. The basic structure of tagset was based on syntactic categories of the language. The tagset was aimed at less number of tags and was not focusing on finer details of the language. Hindi tagset contains noun, proper noun, pronoun, verb, adjective, adverb, postposition, particles, conjunct, question word, quantifier, negative, interjection and special as main parts of speech¹. The detail tagset can be found in appendix.

The earliest work on tagset was conducted in US and focus was on English language. Major milestone in the history of tagset was proposed by Klein and Simmons (1963).

¹ A part of speech tagger for Indian languages, available at <u>http://shiva.iiit.ac.in/SPSAL2007</u> /iiit_tagset_guidelines.pdf

After that, Greene and Rubin (1971:1) proposed a tagset influenced from the Klein and Simmons tagset. These tagsets were based on the syntactic nature of the text. For example, verbal participles are not described with the verbal elements but with noun, adjectives and determiners.

Ellegård (1978: 96-98) used a tagset to parse text of Brown Corpus. Tagset was defined in decomposable² fashion. There were 25 single character tags for major word classes. However, each tag contains inflectional information about the word. The tagset was based on flat structure such that tags of noun and pronoun were having no relation between them. Penn Treebank tagset contains 48 tags. Out of them, 36 tags consist of main part of speech and rest of the 12 tags is for punctuation marks (Taylor, A., et al.). The tagset was aimed at reducing the number of tags and increasing the accuracy of the system. Tagset neglects those features of language which are recoverable at later stage. The complete list of Penn TreeBank tagset can be found in appendix.

4 Review of Part of Speech Tagging Technologies

This section will discuss different part of speech tagging technologies and the analysis of their results. At the end, technique for the tagging of Urdu will be decided on the basis of the efficiency and available resources.

A part of speech tagging system can be viewed as consisting of three main parts i.e. tokenization, assigning potential tags to each token, disambiguation by choosing most appropriate tag for a word or tagging unknown words (van Halteren and Voutilainen 1999:110). The task of assigning potential tags to a word can be done either by looking from the lexicon or by extracting some morphological information from the word and then tag it accordingly. Next phase is to remove the ambiguity and to assign the most appropriate tag to that word. Several methods are used to remove the ambiguity between the tags.



Figure 1: Methodologies for part of speech tagging (Hardie 2003)

Figure 1 describes generally used methodologies for part of speech tagging (Hardie 2003). However, hybrid approaches can also be used by combining different methodologies. Considering figure 1.1, linguist's knowledge is used to define the rules for disambiguation of tag. Corpus of text provides different types of words with their appropriate tags. Type B takes tagged corpus and on the basis of the frequency of the word with a particular tag, annotates the un-tag text. The most recent approaches to disambiguation are machine learning techniques like neural networks. Neural networks technique uses corpus data to extract linguistic information. Thus lies in category B.

 $^{^{2}}$ According to Hardie (2003: 48), if the string representing a tag having more than one character and its shorter string represent some other tag then that tagset is called decomposable. For example, tag N is used to represent a noun and some other character with N to show some additional properties of the noun.

Type C extracts the contextual information from the corpus of text and defines the rules to disambiguate the tag. Most recent work on this type of technique is done by Eric Brill in 1999. Section 4.3 will describe some work done under type C.

No work has been found under type D (Hardie 2003). This may be due to the reason that different human beings have different level of knowledge about the language. Thus, generating probabilities on the frequency of the occurrence of a word may differ from person to person.

Following section describes different approaches to disambiguation. There are three approaches that are commonly used i.e. rule based, statistical and transformational based. However, there are other approaches like finite state intersection grammar, finite state morphology, hybrid approaches to part of speech tagging, etc. (Torbjőrn Lager and Joakim Nivre, Bryan Jurish). This document will focus on the most commonly used techniques for part of speech tagging.

4.1 Rule Based Approaches to Disambiguation

Rule based approaches to disambiguation consist of a rule containing word and its contextual information. The application of rule on a particular word reduces the number of potential tags attached to that word to single tag. According to Jurafsky et al. (2005: 327), ideally rule based part of speech tagging system consists of two stages. First stage assigns each word a list of potential parts of speech by using a dictionary. Second stage uses hand written disambiguation rules to cut down the list to a single part of speech for each word.

One of the earliest works on rule based part of speech tagging was done by Klein and Simmons (1963). Their program, computational grammar coder (CGC), tags the word using lexicon and the suffix information. Set of rules are defined to remove the ambiguity. Klein and Simmons use a tagset of 30 tags and achieve accuracy rate of 90%. Greene and Rubin also use rule base approach to tag the word (Greene and Rubin, 1971). Their program, TAGGIT, follows same steps, using lexicon and the suffix information, to tag the word. However, TAGGIT was able to handle exceptions like capitalized words, words having apostrophes, etc. Greene and Rubin's disambiguation method was different from CGC. Rules were applied in order i.e. from most specific to least specific. Their first rule was based on instinct. Hardie (2003) explains it by an example that Greene and Rubin write a rule that a verb following modal auxiliary verb is infinitive rather than having present tense. Greene and Rubin then use a program to add rules by manually disambiguating the tags. These rules introduce errors of incorrectly tagging a word. TAGGIT was reported to have a disambiguation rate of 77%. Remaining ambiguity was removed manually. Later work on CG approach was done by Voutilainen (1995) and Karlsson (1995). Voutilainen (1995) made ENGTWOL tagger which was based on early rule based systems of two stage architecture, although both lexicon and rules were much complicated than early once. Hindle (1989) works on disambiguating words in a deterministic parser and analyzes rule based tagger without giving any information of the syntax. Other work on rule based tagger was done by Brodda (1982), Paulussen and Martin (1992) and Brill et al (1990).

4.2 Statistical Approaches to Disambiguation

Statistical approaches are based on the information from the corpus of text. Corpus of text provides the frequency of the sequence of tag which will help in disambiguating the sentence by choosing the sequence of tag with highest frequency. The work on statistical part of speech tagging started in late 1970's. Some initial work was done by Bahl and Mercer (1976) and Debili (1977). However, significant work on probabilistic part of speech tagging started when Garside and Leech (1985), and Beale (1985) provide the probabilistic formulation of disambiguation problem in part of speech tagging. In 1986, Derouault and Merialdo did some significant work for the training of statistical parameters. Derouault and Merialdo (1986) manually tag a small amount of text and then use a bootstrap method to tag large corpus. Church (1988) and Kempe (1993) use second order Markov Models for disambiguation. Training of their system is done by using a large hand tagged corpora. Using this method, Church (1988) and Kempe (1993) are able to tag 96% of words correctly. The problem arises for languages that are not having any training data available. Jelinek (1985) and Cutting et al. (1992) overcome the problem of tag training data and train their taggers on untagged data using Baum-Welch algorithm. The results provided by Jelinek (1985) and Cutting et al. (1992) were comparable with Church (1988) and Kempe (1993).

4.3 Transformational Based Approach

Transformation based approach for tagging is a machine learning approach (Brill, 1995). It was inspired from both rule based and stochastic taggers. Like rule based systems, transformational based learning is based on rules. Like probabilistic approach, rules are automatically induced from the data (Jurafsky et al. 2005, 333).

Transformational approach for tagging, called Brill tagging, is not a disambiguation technique. It is a learning or improvement technique. It takes an unambiguously tagged text to learn from it. Pre-tagged corpus is used to evaluate the results of the rules. System starts by running an initial state annotator on an un-tagged corpus. This process assigns a single tag to each word based on the lexicon in which frequency of word with the tag is given. This tagged corpus is compared against pre-tagged corpus and list of rules are learned. These rules are applied on the output taken from state annotator. After applying these rules, success of transformation is measured by comparing it with the reduction in errors. The list of transformations is ordered from most effective to least effective. The process of adding rules ends when no more transformations can be found that improve the tagging (Hardie 2003, 271).

Brill (1992) argues about the advantages of transformational based approach over rule based and stochastic approaches. According to Brill (1992), in rule based approaches, it is difficult to construct rules and in probabilistic approaches much space is required to store the tables of frequencies. Transformational based approach overcomes these issues by providing an automatic extraction of rules. Space required to store these rules is less than storing the probabilistic information. Other advantages describe by Brill (1992) is that it is easy to use Brill's tagger with other tagsets or with different languages.

4.4 Other Approaches to Disambiguation

Neural Networks Approach:

According to Hardie (2003: 280), neural network approach to disambiguation is a machine learning approach. It consists of interconnected layers where each layer works as a processing unit. On activation of a layer, it connects with other layers with weighted

links. Weights given to the links and the activation values of the units are the parameters of the network. Figure 2 provides an overview of 3-layer structure of neural network (Schmid 1994).



Figure 2: A 3-layer structure of neural network

The bottom layer is called the input layer and top layer is called the output layer. Layers between input and output layers are called Hidden layers as only the input and the output layers are visible. The training of neural network can be done by adjusting the weights of the links and the activation values of the layers or units (Hardie, 2003: 281).

Neural network system takes ambiguously tagged word and its contextual information as input. Input layer consists of a set of units equal to the number of tags in the tagset. For each word, all tags with which a word was marked are activated. Network knows about the correct tag due to the training and deactivates other output units. The use of contextual information varies from system to system. Schmid (1994) takes three preceding words and 2 following words as contextual information of a word. According to Schmid (1994), reducing contextual information from three preceding words and one following word to two preceding words and one following word decreases the accuracy only by 0.1%. Increasing the contextual information to three preceding words and two following words showed no improvement in accuracy.

Hardie (2003: 283) finds the performance of neural network taggers comparable with the performances of rule based and probabilistic approaches. Schmid (1994) reported an accuracy rate of 96.22% and found it better than Markov model tagger.

4.5 Hybrid Approaches to Disambiguation

A hybrid tagger can be defined as a combination of disambiguation techniques use to serve the purpose of a single disambiguation technique. Hybrid methods are ideally be used to increase the accuracy of the system.

CLAWS system is a good example of hybrid approach. In CLAWS1, the WORDTAG lexical analysis component has initially assigned potential tags which were altered by rule based component IDIOMTAG. After that a stochastical disambiguator was applied (Hardie 2003).

CLAWS system gives an example of hybrid approach in which both rule based system and stochastic system were developed together. Tapanainen and Voutilanien (1994) do

an experiment to combine rule based system, EngCG, and stochastic disambiguation system, Xerox tagger, initially developed as separate systems. These two taggers were having complementary strength i.e. EngCG is rarely wrong but does not disambiguate fully whereas Xerox tagger is less reliable but disambiguate fully (Hardie 2003: 292). Tapanainen and Voutilanien run both taggers parallel on same text and then combine both outputs by allowing Xerox tagger to resolve the ambiguities left by the EngCG tagger. Results were found to have accuracy rate of 98.5% which were better than any of the tagger.

5 Redesigning of Urdu Tagset

Tagset of a language caters main parts of speech as well as morphological information of the language. There are various issues that need to consider for the efficient design of tagset. First problem is about the level of categorical distribution that the tagset should contain. A tagset may be consisted either of syntactic categories or it may be consisted of morpho-syntactic categories. Considering the efficiency in machine learning process and to reduce lexical and syntactic ambiguity, it was decided to concentrate on the syntactic categories of language. The syntactic categories lead to less number of tags which also improves accuracy of manual tagging³ (Taylor, A., et al.).

Considering the work of Urdu grammar writers, most of the categories were based on semantic differences. The morphological information of the categories was either handled through separate parts of speech or was considered as features of the language. Most of the categories were lacking their computational side. However, the detailed analysis of these grammar writers really helps in covering the depth of the language. The tagset of Hardie was properly covering the features of Urdu. Some of the tags were divided on the basis of semantic differences (see section 3.1). For a syntactic tagset, the features of Urdu language need to be analyzed on the basis of the structure of the language. It was also mentioned in the literature that smaller tagset improves the accuracy of the tagger. Following is the redesigning of tagset on the basis of the work of Urdu grammarians and earlier tagsets of Urdu.

There were three types of corpus available for analysis i.e. literature, news and poetry corpus. For the design of tagset, only literature and news corpus was analyzed. The corpus was based on the most recent available vocabulary used by local people.

Following is the proposed list of POS tags followed by some of their examples. The syntactic analysis on the tags is done in discussion section.

Demonstrative: Demonstratives are divided into four categories. All four categories of demonstratives have ambiguity with four categories of pronoun. Phrase level analysis was done to distinguish between demonstrative and pronoun. The detailed comparison of demonstrative and pronoun can be found in discussion section. Following are some examples of demonstratives.

PersonalThis category includes the elements of demonstrative and
personal demonstratives. Following is an example of it.

³ A part of speech tagger for Indian languages, available at <u>http://shiva.iiit.ac.in/SPSAL2007</u> /iiit_tagset_guidelines.pdf.

ہم، تم، آپ، یہ، وہ، اس	یہ <pd> مسجدیں <nn> ہماری <g> پہچان<nn> ہیں <sm>-<vb></vb></sm></nn></g></nn></pd>
Relative demonstrative (RD) جو، جنہوں	جو <rd> لڑکا<nn> صبح<nn> آیا<vb> تھا<ta> وہ<pp> میرا<g> دوست<nn> ہے<vb>۔<vb< td=""></vb<></vb></nn></g></pp></ta></vb></nn></nn></rd>
Kaf demonstrative (KD) کن، کوئی	کن <kd> لوگوں<nn> کو<p> آم<nn> اچھا<adj> لگتا<vb> ہے<ta>۔ کمر ے<nn> میں<p> کوئی<kd> لڑکا<nn> نہیں<neg> ہے<vb>۔</vb></neg></nn></kd></p></nn></ta></vb></adj></nn></p></nn></kd>
Adverbial demonstrative (AD) اب، نب، ادھر ، یہاں	میں <pp> ایسا <ad> کام <nn> نہیں<neg>کر <vb>سکتا<aa>۔</aa></vb></neg></nn></ad></pp>

Nouns: Nouns are divided into two categories. First category consists of simple nouns which are represented by NN in the tagset. However, there are other nouns that show adverbial nature like time, place, manner, etc. These are also catered under noun. The proper nouns are kept in a separate category. Following are some examples of different types of nouns.

Noun (NN)	ہ <pd> مسجدیں <nn> ہماری <g> پہچان<nn> ہیں <vb>۔</vb></nn></g></nn></pd>	
جہار، زمین، درخت، لڑکا، اوپر، اندر، سمیت، طرح، طرف	چھت <nn> کے <p> اوپر <na> حامد<pn> ہے<vb>۔</vb></pn></na></p></nn>	
Proper noun (PN) لاہور، پشاور، پاکستان	لاہور <pn> باغات <nn> کا <p> شہر <nn> ہے<vb>۔</vb></nn></p></nn></pn>	

Pronouns: Pronouns are divided into six categories based on their syntactic structure. Most of the categories are consistent with the types provided by Urdu grammarians. The analysis and justification of the newly proposed categories can be found in discussion section. Following are some examples of the types of pronouns.

Personal pronoun (PP) میں، ہم، تم، آپ، یہ، وہ، اس	میں <pp> تمهارا <g> دوست <nn> ہوں <vb>۔</vb></nn></g></pp>
Reflexive pronoun (RP) خود، آپ	میں <pp> اپنا <gr> کام<nn> خود<rp> کروں<vb> گا<ta-۔< td=""></ta-۔<></vb></rp></nn></gr></pp>
Relative pronoun (REP) جو، جن، جنہوں	علی <pn> جو <rep> حامد<pn> کا <p> بھائی <nn> ہے<vb> میرا <g>دوست <nn> ہے<vb>۔</vb></nn></g></vb></nn></p></pn></rep></pn>

Adverbial pronoun (AP): The adverbial pronouns occur at the place of nouns with adverbial nature and show the property of time, place, manner, etc. They are represented by AP in the tagset. Consider the following examples:

Example:	<ta> $1/B>$ $1/2<$ <math><nn></nn></math> $1/2<$ $AP>$ $1/2P>$ $1/2P$</ta>
اب، تب، ادهر، يہاں	

Kaf pronoun (KP): Kaf pronouns add interrogative property in the sentence. They are divided into two categories. Kaf pronouns, represented by KP, are used to ask question about a noun. The second category includes adverbial kaf pronouns which are used at the place of nouns with adverbial nature. Following are their examples:

 Kaf pronoun (KP)
 کون < KP> ہے<UB> ہے<UB> ہے<UB> ہے<UB> کون ، کوئی ، ، کن

 Adverbial kaf pro (AKP)
 کون ، کیا <UB> ہے<UB> کدھر ، کب ، کیسا

 علی <NP> کدھر (AKP> گیا <UB> ہے<UB> کدھر (Consider the above example of genitive reflexive.

 Genitives (G)
 Consider the above example of genitive reflexive.

Genitives (G) میرا، تمهارا، ہمارا، تیرا

Verb (VB): At sentence level, any word showing action in any form is considered as verb. No further categorization is done. Consider the following examples of verb:

Example: لکهنا، کهاتا، جاتا، کرنا

وہ <PP> روٹی<NN> کھا <VB> رہا<AA> ہے<TA>۔

Auxiliaries: Based on the syntactic nature of language, auxiliaries are divided into two categories. Aspectual auxiliaries always occur after main verb of the sentence. Tense auxiliaries are used to show the time of the action. They occurred at the end of the verb phrase. Consider the examples of aspectual and tense auxiliaries:

Aspectual auxiliary (AA) Consider the example of verb. ربا، کرنا، چکہ Tense auxiliary (TA) بے، ہیں، ہوں، تھا، تھے، تھیں، گا، گی، گے، ہو، ہوں

Adjective (ADJ): Adjectives are catered as one category. The information related to the degree of adjective is not taken into account. Following are given some examples of adjectives.

ظالم، خوبصورت، کمزور، بیکار، سمجهدار، نفیس

حامد <PN> بہت <ADV> ظالم <ADJ> لڑکا <NN> ہے<VB>۔

Adverb (ADV): Adverbs are handled as one category in the tagset. Consider the following examples of adverbs.

Example:

بېت، نېايت، بر ا

Quantifier (Q): Consider following examples of quantifier:

Example:

سب <Q> لوگ<NN> تھوڑا <Q> انتظار <NN> کرئیں <VB>۔ تھوڑا، تھوڑا، تھوڑے، کئی، بعض، کل **Numerals:** Numerals are divided into four categories based on their syntactic structure. Cardinal (CA), ordinal (OR), fractional (FR) and multiplicative (MUL) are types included in the tagset. Following are the examples of each category.

Cardinal (CA) ایک، دو، تین، چار بیالیس، انسٹه، ننانوے، بزار، دو بزار

Ordinal (OR) Consider the example of cardinal. پېلا، دوسرا، نيسرا، چوتها، پانچواں، چهڻا، ساتواں، آڻهواں، آخری

Fractional (FR) جوتھائی، ڈھائی، اڑھائی

علی <PN>حامد<PN> سے<P> دگنا<MUL> موٹا<ADJ> ہے<VB>۔ گنا، دگنا، دیرا، تہرا

Measuring unit (U): They are frequently used with numerals. However, they have a different syntactic structure than numerals. Consider the example of fractional to see the occurrence of measuring units.

Example: پون، پائو، کلو، سیر

```
ڈھائی <FR> کلو<U> دودھ<NN> دینا<VB>۔
```

ڈھائی <FR> کلو <U> دو دھ<NN> دبنا<VB>۔

يبلے <OR> دو <CA> لڑکوں <NN> کو<P> بلاؤ <VB> ۔

Conjunction: Conjunctions are divided into coordinating and subordinating conjunctions. Following are their examples:

 Coordinating (CC)
 دوست<NN> ہیں<NN> دوست<PN>۔ دوست<PN> اور <PN> علی<PN> یا , اور

 یا , اور
 Subordinating (SC)

 حامد <PN> سے<P> ملے<PN>۔ حاکہ <SC> مجہ<PN> سے<P> ملے<PN>۔ حالے<PN>۔ حالے<PN»۔ حالی <PN»۔ حالی <P

Intensifier (I): There are only three words in this category. Consider their following examples:

Example: ہی، بھی، تو

میں <PP> بھی <I> آؤں <VB>گا.<TA>۔

Adjectival particle (A): This category includes only one word sa with its two inflection forms. This particle is normally used for comparison. Consider the following examples of adjectival particle.

مینڈک<NN> ایک<AD> عجیب<ADJ> سا<A> جانور <NN> ہے<VB>۔ سا، سے، سی

KER particle (KER): These particles normally occur in verb phrase. There are only two entities in this class. Consider the following examples:

Title: Titles are divided into two categories based on their pre and post occurrence around a proper noun. Consider their examples below.

Pre-title (PRT)	میاں <prt> سرمد<pn> صاحب<pot> اچھے<adj> انسان<nn></nn></adj></pot></pn></prt>
حضرت، میاں	ہیں <vb>۔</vb>

Post-title (POT) جي، صاحب

Consider the example of pre-title above.

Semantic Marker (P): Following are the list of particles included into this category. However, the entity سے is kept as separate category due to its ambiguous usage. حامد<PN> کو<P> علی<PN> نے<P> چپڑی<NN> سے <SE> کا، کو، کی، کے ، نے، میں، مارا<VB>۔

SE (SE): Consider the above example

Wala (WALA): This category contains one word wala and its inflections. Consider its examples: Example: ندمی<NN> آدمی<NN> آیا<NN> بیچنے<VB> والا<NN> والا، والی، والے، والے

Negation (NEG): Consider the following examples of negation.

میں <PP> ایسا <AD> کام <NN> نہیں<NEG>کر <PB>کر <PB>۔ کنہ، نہیں

Interjection (INT): Interjections normally occur at the start of the sentence. They are kept as separate category in the tagset. Following are its examples:

Example:

واہ<INT> کی<ADJ> اچھی<ADJ> اچھی<ADJ> بات<NN> کی<TA>۔

Question words (QW): There are some words instead of kaf pronouns that are used for the interrogation in the sentence. However, these words cannot be replaced by a noun or pronoun. A separate category of question words has been formed for these words. Consider their examples below:

Example:

کیا، کیوں

کیا <QW>علی <PN> سکول <NN> جائے <VB> گا.<TA>۔

Punctuation marks: In this tagset, punctuation marks are divided into two categories. Sentence markers mark the boundary of the sentence. Phrase markers are used inside the sentence but never used at the end of sentence. Consider their examples below:

Sentence marker (SM)	'.', '? '
Phrase marker (PM)	· · · · · · · · · · · · · · · · · · ·
DATE	2007, 1999

Expression (Exp): Any word or symbol which is not handled in this tagset will be catered under expression. It can be mathematical symbols, digits, etc.

5.1 Discussion

Considering above tag set, noun is divided into noun and proper noun. However, in the tagset, it is mentioned that nouns with adverbial nature are also kept under noun. These nouns contained information about time and place. Due to this reason, most of the grammar writers categorize them as noun of time and place (Platts 1909, Javed 1981, Haq 1987). However, some grammar writers also consider them under adverbs (Schmidt 1999). Looking at the language syntactically, these elements with adverbial nature occur at the place of noun. To make syntactic structure of language consistent, it was decided to consider them under noun. Following are some examples of it.

صبح<NN> اللهنا<VB> الچهی<ADJ> عادت<NN> ہے<VB>۔ جهت<NN> کے <P> او یر <NN> حامد<PN> ہے <VB>۔

Pronouns are divided into six types based on their syntactic nature in the sentence. The adverbial pronouns are of same nature like nouns with adverbial features. That's why, they are categorized under pronoun.

حامد <PN> نے<P> صبح <NN> کھانا <NN> کھایا<VB>۔ حامد <PN> نے<P> تب <AP> کھانا <NN> کھایا<VB>۔ تب <PN> کھانا of Adverbial pronoun

Most of the categories involved in pronouns are similar with demonstratives. Difference was analyzed on the basis of their phrase boundary. It was observed that pronouns occur as standalone unit in a phrase or occur without having a noun as its neighbor in a phrase whereas demonstratives make phrase boundary with the next noun. The adverbial pronouns are also showing similar behavior. Consider following examples:

یہ <PP> حامد<PN> کا<P> بھائی<NN> ہے<VB>۔ یہ <PP> مسجدیں <NN> ہماری <G> پہچان<NN> ہیں <VB-۔

In case of pro-drop, demonstrator becomes the pronoun. Consider the example below; if word لوگ (people) is dropped here then وه will become the pronoun here.

وہ <PD> لوگ<NN> گانا<NN> گاہیں<VB> کے<TA>۔

وہ<PP> گانا<NN> گاہیں<VB> کے<TA>۔

Kaf pronouns are divided into two categories. Both are actually question words that can be replaced by a noun. However, syntactic structure of adverbial kaf pronoun is different from other kaf pronouns. While observing kaf pronouns in general, the ambiguity was found with the demonstratives. Phrase level analysis as explain above is used to distinguish between kaf pronoun and demonstratives. The demonstrators with interrogative nature are kept inside demonstrative category. Consider following examples of kaf pronouns, adverbial kaf pronouns and kaf demonstratives.

لاaf pronoun کمر ے<NN> میں<P> کون<NP> ہے<UB> ہے<TA> کو ک
اچھے حADJ> لگتے UB> کو SAD> ہیں<TA>۔ کن<AD> لگتے UB> اچھے CAD> اچھے CAD> لگتے UB> ہیں<TA>۔ Adverbial kaf pronoun حامد<PN> کدھر CAS> کیا<UB> ہے CAS> ہو CAS> ہو CAS>۔ تم CAD> سے SE> ملنے CAS> جا UB> رہے CAS> ہو CAS>۔

KER tag contains two elements کے، کر (Javed 1981). These particles occur in verb phrase and semantically show the completion of verb. Following are there examples:

میں<PP> کام<NN> کر<VB> کے<KER> تھک<BN> گیا<AA> بوں<TA>۔ میں<PP> کام<NN> کر<VB> کر<VB> کے<KER> تھک<BD> تھک<AB> گیا<AA> بوں<TA-۔ میں<PP> وہاں<AP> جا<VB> کر<KER> تھک<BD> تھک<AB> گیا<AA> ہوں<TA-۔

Semantic marker is containing particles that show the semantic marking of subject, object and indirect object, etc. (Butt et al. 2001). The marking objects are also called semantically motivated cases as they are used to express semantic motivations (Butt et al. 2001). Due to this reason, they are not separated under more than one category. However, SE is kept separate under unique category due to its ambiguous usage.

WALA Vi is considered a unique entity due to its different morpho-syntactic nature. It is categorized under adjective and noun by Urdu grammar writers (Javed 1981, Schmidt 1999). However, it is still considered as an issue due to varied usage. For this tagset, it is decided to handle it as a separate tag.

Expression includes symbols, mathematical formulae, digits, etc. In general, this tag caters any exceptional word or character that occurs in the text. There might be a case when two exceptional characters or words are occurring consecutive. In that case, only one expression tag will be assigned.

6 Selecting Disambiguation Approach for Urdu

Literature review of disambiguation approaches can be summarized as follows:

- Rule based approach
- Probabilistic approach
 - Markov model
- Transformational based learning
- Other approaches like neural networks
- Hybrid approaches

There are many factors that play an important role while selecting a disambiguation approach. Performance of disambiguation approach, properties of the language, nature of the tagset, available resources, and time limitations, all played an important role in the selection of an approach.

According to Daelemans (1999: 303-304), methods like neural networks have several advantages over statistical methods such as requiring less training data, fewer parameters and fast training procedure. However, Daelemans provides some counter arguments in support of statistical methods such as the effectiveness of new technologies has not been evaluated fully.

Considering the performance of the systems, Markov model taggers generally achieve an accuracy of 97% (Hardie 2003: 295). Brill (1995) reports a similar accuracy rate. Voutilainen (1995: 186-187) reports an accuracy rate of 99.7%-100% using rule based CG methodology. For comparability, these are small performance differences. Thus, choosing the methodology on the basis of performance of the system is difficult.

Consider language; Urdu is written in Perso-Arabic text, the texts in question are coded in Unicode. Brill (1995) and Cutting et al. (1992)'s tagger require ASCII text. So, it is possible to rule out these two taggers.

Urdu is a highly inflected language and having SOV word order. Sánchez León and Nieto Serrano (1997: 163-164) suggest that the potentially free order of language could lead to greater ambiguity i.e. it becomes harder to guess the tag of a word on the basis of its context. This might suggest that for a language like Urdu, probabilistic model would be unsuitable. Dandapat et al. (2006) implemented a Markov model for Bengali which is a free order language and reported an accuracy of 89%. Brill (1995: 544) reports that all disambiguation techniques utilize the same kind of information. Thus probabilistic model can not be ruled out by just arguing that the language is free order.

The nature of the tagset may affect the performance of disambiguation method. Tapanainen and Voutilainen (1994) suggest that Markov model taggers operate better with small tagsets, whereas rule based approaches operate better with larger tagsets. Sánchez León and Nieto Serrano (1997) work on Spanish tagsets ranging from 40 to 475 tags and use them with Markov model and report that larger tagset improves performance if the model has appropriate biases. Thus size of the tagset may not help in deciding the disambiguation technique.

Let's consider the practical benefits and drawbacks of the probabilistic approach, rule based approach and hybrid approach. Hybrid approach uses the best features of several methodologies. Tapanainen and Voutilainen (1994) create a hybrid tagger from two pre-existing taggers. In case of Urdu, one rule based tagger is available (Hardie 2003). Hybrid approach requires at least one more tagger for Urdu. Considering the time limitation of the thesis, only one approach can be implemented and hybrid work can be left for future research. Therefore, hybrid approach can be ruled out.

According to Weischedel et al. (1993), having a corpus of limited vocabulary; the probabilistic models offer a mathematically grounded means of predicting the most likely tag. In case of unknown words, probabilistic models provide the best solution. Weischedel et al. (1993) also mention that for a given vocabulary size, it is difficult to provide full syntactic and semantic features by handcrafted rules. Probabilistic models

overcome this limitation by considering contextual information from the corpus. Another point mentioned by Weischedel et al. (1993) was that rule based approach do not perform well on long sentences on which probabilistic approach can effectively operate.

Now considering Urdu, a corpus of approx eighty million words is available. The number of unique words in the corpus is about 52,000⁴. Thus, shows a good frequency of the words in the corpus. Making the rules of 52,000 words over the corpus of 10,000,000 words seem cumbersome and much time consuming. Here, after considering the resources and the analysis of different writers, rule based approach can be ruled out. Hence, for the current work, statistical approach can be used for part of speech tagging.

7 Methodology

This section will discuss the steps followed in the implementation of part of speech tagger. The availability of training data is the first step towards the automatic annotation of text. A corpus of 110,000 words was selected from two domains. After applying normalization and removing diacritics, data of 100,000 words was manually annotated for training. In the implementation of part of speech tagger, Hidden Markov model was implemented. Add Lambda smoothing was applied to avoid zero probabilities. In order to shorten the search space and to speed up the time, beam search was applied. The detail discussion of each step is as followed.

7.1 Preparation of Corpus

The accuracy of a tagger also depends on the corpus. The inclusion of foreign words, free orderness in the corpus significantly affects the results of the tagger. A corpus of amount eighty million words was taken from Jang (www.jang.com.pk). The available eighty million corpus was based on six domains i.e. games, news, finance, culture entertainment, consumer information and personal information. At start, it was decided to drop the corpus of games, finance and consumer information due to the excess of foreign words in the corpus. At later stage, personal information was also dropped due to the lack of structure of the corpus. Out of the domain of news and cultural entertainment, 110,000 words were selected as corpus. Before actually starting the annotation, corpus was gone through various steps in order to maintain the consistency of the text.

7.1.1 Normalization

Urdu shares its character set with Arabic. There are characters in Urdu that can be represented by more than one Unicode. This problem of inconsistency was frequently seen in the corpus. In order to keep the characters consistent, normalization was applied before doing any processing on the corpus. Following is the list of normalizations applied.

Problem words	Unicode	Normalized words	Unicode	
ö	0629	ö	06C3	
ای	0643	ک	06A9	
٥	0647	٥	06C1	

Table 1: Normalization

⁴ Corpus of Urdu is available with Centre for research in Urdu language processing (CRULP). Further detailed about the corpus can be found in section 7.1

ى	0649	ى	06CC
ي	064A	ى	06CC
ۀ	06C0	ۀ	06C2
,	002C	6	060C
	002E	-	06D4
•	003B	4	061B
?	003F	?	061F
Ĩ	0622	T	0627 + 0653
"	0623		0627 + 0654
ۇ	0624	و	0648 + 0654
ۀ	06C2	4	06C1 + 0654
2	06D3	ئے	0626 + 06D2

7.1.2 Other Issues

In Urdu, most of the diacritics are considered optional. Due to optionality of diacritics, two similar words one with diacritics and other without diacritics do exist in the corpus. Therefore, it was decided to remove the diacritics from the corpus. It was also observed that there occur some non Urdu characters in the corpus. These words were also deleted from the corpus. A List of diacritics and non-Urdu words is given below.

Diacritics	Non-Urdu words			
(0650)	"			
(064B) [*]	*			
(064F) ′	#			
(064D) ₋	\$			
(064C) [*]	%			
(0670)	&			
(0652) [°]	'			
(0656)	*			
(0654) ُ	+			
، (060C) ،	-			
(0651) ័	/\			
(0657)	<>			
(0659)	=			
(0640) -	@			
(0653)	()			
(FDFA)	٨			
(064E) [´]				
	~			
	`			
	"			
	6			
	,			
	"			

Table 2: Diacritics and non-Urdu words

7.2 Manual Tagging

A corpus of 100,000 words was selected for manual tagging. After applying normalization and by removing diacritics, test corpus was divided into 10 equal parts. A word list of the corpus was generated and each word was given its expected tag. This lexicon was further use to speed up the annotation process. Each part of the corpus was first annotated with the generated lexicon. All potential tags of each word were assigned. The errors were manually removed from the corpus. Same procedure was repeated up to 50,000 words. Rest of the 50,000 words was automatically annotated from the tagger and was manually checked for errors. This procedure speeds up the manual tagging process and helps in analyzing the issues of the tagger and the corpus. Following section will discuss some linguistic issues faced while manually annotating the corpus.

7.2.1 Suffixation

The problem of considering suffixes as one word or considering it as part of its root word was faced during annotation. Considering suffix as separate word may create the problem of including a non-word in the lexicon. Some suffixes like ناک do exist as separate word but their usage as suffix makes it an adjective rather than a noun. This way of handling suffixation may also disturb the learning of statistical tagger and increase the ambiguity for the tagger. Consider the following example:

Table 3: Three ways of tagging the word having a suffix

(a)	(b)	(C)
خوفناک <adj> انسان<nn></nn></adj>	خوف <nn> ناک<nn> انسان<nn></nn></nn></nn>	خوف <adj> ناک<adj></adj></adj>
		انسان <nn></nn>

In the above example, the word with suffix can be tagged in three ways. Part b is lexically assigning the tags to the words. This will tag the word independent of its context. Thus, lose the actual feature of the word. Part c is separately tagging the word and suffix but assigning the tag according to the context of the word. This will wrongly guide the machine learning process as in this way noun is followed by two adjectives rather than one. The ambiguity for word will also be increased. For these reasons, it was decided to consider the root and suffix as one word.

7.2.2 Words with Zer-e-izafat

In Urdu, combining words with zer-e-izafat is a very common phenomenon. Sometimes these words cannot be separated as two words or can be replaced by having semantic marker in it. Consider the following example:

(a)	(b)
وزيراعظم <nn></nn>	وزیر <nn> صحت<nn></nn></nn>
* اعظم کا وزیر	صحت کا وزیر

Here, it is clear that part (a) of the example becomes ungrammatical when replaced. That's why, it was decided to consider (a) as on word and consider (b) as two separate words.

7.2.3 Verb Phrases Acting as Adjective

It was observed that the occurrence of verb phrase at the place of adjective is very frequent in corpus. Consider the following example:

(a)	(b)	(C)				
روتے <vb> ہوئے<aa></aa></vb>	روتے <adj> ہوئے<adj></adj></adj>	روتےہوئے <adj> بچے<nn></nn></adj>				
بچے <nn></nn>	بچے <nn></nn>					

Table 5: Verb	phrase acting	as adjective
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There are three possible ways of tagging this problem. However, example (c) is not appropriate as we are considering two words as one word. Example (b) is again causing problem to machine learning process. At the end, it was decided to treat verb and auxiliaries independent of its context.

7.2.4 Complex Predicate

There are some words which are noun and adjective, and occur in a verb phrase. These words are called complex predicates (Butt 2003). When these words were analyzed separately, it becomes very difficult to distinguish them either noun or adjective. For the current work, it was decided to keep word and its tag consistent throughout the training corpus. However, a practical solution to this problem is discussed later.

7.3 Computational Modeling

This section will discuss the techniques used in the implementation of a part of speech tagger. Hidden Markov Model was used as disambiguation technique. In order to reduce the search space of the tagger, beam search was applied. Frequency of unknown words is handled by applying Add-Lambda smoothing. Following is the detailed discussion of each technique.

7.3.1 Design

Design of application was divided into three components. Pre-processor and training database works as standalone unit. Output of pre-processor and training database is used by tagger to annotate the text. Pre-processor takes input in the form of text file. After applying normalization rules, diacritics and symbols were removed from the input. Training database takes annotated text in the form of a text file and calculates the unigram word tag probabilities and the probability of a tag t_i given its previous tag t_{i-1} . The words from the list of word tag probability will be used as lexicon by the tagger. Tagger takes two inputs, one the output of pre-processor and second the output of training database and outputs the annotated text. The detail discussion on the working of each module can be found in next section. Following is the design diagram of the tagger.



Figure 3: Design of the tagger

7.3.2 Pre-processor

In order to control the consistency between training data and input text, a separate module called pre-processor was build. Pre-processor module takes input in the form of a text file and normalize the text. Diacritics were also removed from the text. Following is the algorithm of pre-processor.

- Take input from a text file
- Load normalization rules
- Load a list of diacritics
- Load a list of symbols
- Apply normalization
- Remove diacritics
- Remove symbols from the corpus
- Save the output in a text file

A list of normalization rules, symbols and diacritics can be found in section 7.1.

7.3.3 Training Database

Part of speech tagger takes information from three databases i.e. lexicon, word tag probabilities and tag tag probabilities. These information sources are built by training database by using annotated text or training text as input. In the implementation, a separate module was built for each database. Following is the discussion on each algorithm.

General Algorithm of training database

- Take annotated text from a text file
- Calculate total counts of each word tag pair i.e. total number of occurrences of each word w with tag t
- Calculate total counts of each tag tag pair i.e. total occurrences of each tag t $_{i}$ having previous tag $t_{i\!-\!1}$
- Calculate total counts of each tag i.e. total occurrences of each tag t i.e.
- Apply smoothing (next section)
- Calculate probabilities
- Save the probabilities of word tag pair and tag tag pair in separate files

Probability calculation was done using following formula:

Word tag probability $P(w_i | t_j) = C(w_i t_j) / C(t_j)$ Tag tag probability $P(t_i | t_{i-1}) = C(t_i t_{i-1}) / C(t_{i-1})$

In order to calculate the probability of unknown word, smoothing was applied by introducing an unknown pair in the database. The smoothing algorithm can be found in next section.

7.3.4 Tagger

Application of part of speech tagger takes two inputs i.e. cleaned input text from preprocessor and other is the databases. Input text is observed sentence by sentence by the tagger. Tagger creates the annotated output of each sentence. Following is algorithm of the tagger.

- Read input from text file
- Load databases
- Divide input on the basis of sentence marker
- Continue until input ends
 - o Take a sentence

- Repeat until sentence end
 - Take a word from sentence
 - Assign its potential tags from lexicon or assign potential tags for an unknown word (Make branches if potential tag > 1)
 - Assign word tag probabilities to the pair
 - Assign tag tag bigram probabilities
 - If number of branches are more than Beam size (say 10), sort all branches on the basis of cumulative score up to the current word and take top 10 branches (highest score)
- Save the output sentence by sentence
- Write output in a text file

At sentence level, file containing probabilities of word tag pair was used as lexicon for the tagger. Hidden Markov model was used as disambiguation technique. Problem of unknown word was handled by assigning a list of candidate tags to that word. Zero probability of unknown word was handled by applying Add Lambda smoothing. Following are the details on Hidden Markov model, Add Lambda smoothing and unknown word handling.

7.4 Implementation Techniques

7.4.1 Markov Model for Part of Speech Tagging

Hidden Markov model is used to estimate the best sequence of tags for a sentence. It utilizes a tagged corpus to estimate the frequency of the occurrence of a tag with a word. It is called Hidden as the actual sequence of states i.e. tag generated for a sentence is unknown. According to Rabiner (1989), Hidden Markov model has five parameters (Scott M. Thede et al).

- 1. Total number of states in the model is represented by N. For part of speech tagger, N is the total number of tags used by the system. One tag consists of one state.
- 2. Total number of output symbols and is represented by M. For part of speech tagging, M will be the number of words in the lexicon of the system.
- 3. Probability of moving from state i to state j and is represented by a_{ij}. It is called transition probability of the states. For part of speech tagging, state transition probability will be the probability of moving from tag i to tag j in other words, probability that tag j will follow tag i. This probability is normally estimated from the corpus.
- 4. Observation probability $b_j(k)$ will be the probability of having symbol k on state j. For part of speech tagging, it will be the probability of word having tag j.
- 5. Initial state distribution π_i is the probability that model will start in state i. For part of speech tagging, this is the probability that the sentence will start with tag i.

Choosing HMM for part of speech tagging will determine the most likely tag sequence that generates the words in the sentence. Following formula provides an overview of the basic HMM part of speech tagging (Jurafsky et al. 2005, 329).

Equation 1 represents a tag sequence for the whole sentence. According to 1, the tag of a word depends on the probability of a word tag pair multiply by the probability of the sequence of tags from the start of the sentence. Dependency of a tag on previous n tags is called N-gram model. In order to tag a single word, bigram HMM tagger has to use. The bigram model of tagging a word w_i with a tag t_i is given by the maximum probability of tag t_i with previous tag t_{i-1} and the probability of the word w_i having tag t_i i.e. (Jurafsky et al. 2005, 329).

$$\mathbf{t}_{i} = \operatorname{argmax} P(\mathbf{t}_{i} \mid \mathbf{t}_{i-1}) P(\mathbf{w}_{i} \mid \mathbf{t}_{i})$$
(2)

Consider a sequence of words $W = w_1 w_2 \dots w_n$, and a sequence of tags $T = t_1 t_2 \dots t_n$. The maximum probable solution for a sequence of tags given that the sequence of words can be represented as follows:

Max P(
$$t_1 t_2 ... t_n | w_1 w_2 ... w_n$$
) (3)

Taking T = $t_1 t_2 ... t_n$ and W = $w_1 w_2 ... w_n$, equation 3 becomes;

$$Max P(T | W)$$
(4)

According to Bayes theorem;

$$P(A|B) P(B) = P(B|A) P(A)$$
(5)

$$P(T|W) P(W) = P(W|T) P(T)$$
(6)

Here, P(W|T) can be expressed as the probability of the sequence of words W given that the tag sequence T. P(W) is the probability of the sequence of words which will remain constant for a sentence so neglecting P(W) for further calculations. P(T) is the probability of the tag sequence. P(T|W) can be expressed as the probability of the sequence of tags given that the sequence of observation symbols W. The equation becomes;

$$P(T|W) = \max P(W|T) P(T)$$
(7)

$$P(t_1 t_2 ... t_n | w_1 w_2 ... w_n) = \max_{t_n} P(w_1 w_2 ... w_n | t_1 t_2 ... t_n) P(t_1 t_2 ... (8)$$

Taking the simplifying assumption to reduce the complexity and dependency of the equation (Jurafsky et al. 2005, 332; Charniak et al. 1993);

- 1. Words are independent of each other
- 2. Words identity only depends on its own tag
- 3. A tag depends only on its previous tag

Applying the first assumption will reduce the sequence of words to one word i.e. the word of a tag depends on the maximum probability of the sequence of tags of the previous words plus its own tag.

max
$$P(w_i | t_1 t_2 ... t_n) P(t_1 t_2 ... t_n)$$
 where $i = 1...n$ (9)

Applying the second assumption, that a words depend only on its own tag;

max
$$P(w_i | t_1 t_2 ... t_n) P(t_1 t_2 ... t_n)$$
 where $i = 1...n$ (10)

max
$$P(w_i | t_i) P(t_1 t_2 ... t_n)$$
 where $i = 1...n$ (11)

Third assumption will change the dependency of a tag on the previous tag.

max
$$P(w_i | t_i) P(t_i | t_{i-1})$$
 where $i = 2...n$ (12)

The dependency of a tag only on its previous tag is called the first order Hidden Markov model as shown in equation 11. In second order HMM, the current tag depend on two previous tags can be formulated as:

$$\max P(w_i | t_i) P(t_i | t_{i-1} t_{i-2}) \text{ where } i = 3...n$$
(13)

For the current tagger, it was decided to limit the probability of tag sequence to bigram. Thus following formula will be implemented for part of speech tagger.

Max
$$P(w_i | t_i) P(t_i | t_{i-1})$$
 where $i = 2...n$ (14)

7.4.2 Unknown Word Problem

A training corpus of 100,000 words is used to train Hidden Markov Model. Length of the corpus is always finite. It is not possible to cover all words of the language. Also due to high inclusion of foreign words, new words are entering into the language day by day. These new words and the words which are not part of the corpus are known as Unknown word. Every tag of the word has some probability to be the tag of that word. This means, whenever an unknown word occurs, number of branches will exceed by the total number of tags. And if consecutive unknown words occur then the number of branches will exceed exponentially. The time to calculate these branches will also increased exponentially. The number of candidate tags for new word can be reduced if training corpus is covering all words of closed class. However, currently it was not that case. However, analysis was done on the training corpus and those closed class tags were removed from the list of candidate tags which were completely covered by the training corpus. A list of potential tags for a new word is given in the following table.

Tuble e. Gundidule lage	
NN	ADJ
ADV	CA
VB	OR
AA	U
ТА	DATE
Q	

Table 6: Candidate tags for unknown words

The probability of new words is handled by smoothing and reduction in search space is done by beam search. Next two sections will discuss them.

7.4.3 Smoothing

Due to the high productivity of language, there may occur words that have not seen before by the tagger. These unknown words will be assigned zero probability by the

tagger. Thus makes the probability of whole sentence zero. Smoothing is used to assign these unknown words some probability other than zero. For part of speech tagger, Add Lambda smoothing was applied. A value of 0.5 was taken for lambda⁵. For unknown word, a new word tag pair was added in the list of word tag probabilities. For new tag sequence, a new tag tag pair was introduced in the list. Following algorithm was applied on each case.

- Add all counts to a variable say "All"
- Add unknown word pair with count equal to zero
- Add 0.5 to each count
- Add all counts after adding 0.5 say "All0.5"
- Multiply each count with the result of ("All" / "All0.5")

Smoothing was applied in the training database module. After calculating the frequency of each pair, smoothing was applied on each count. The probability of each pair was calculated with the help of smoothed counts.

7.4.4 Beam Search

Part of speech tagger process the input in the chunks of sentence. While working at sentence level, if an unknown word occurs, there will be 11 candidate tags for it. If a sentence is having five unknown words then the branches for these five words will be 11^{5} i.e. exponential increase in branches. Processing so many branches may cause loss of memory and time. In order to control the number of branches, a threshold of 50, 30, 10 and 1 was selected. The accuracy of the tagger was observed on these thresholds. It was found that tagger shows relatively high accuracy at threshold of 10 i.e. number of branches should not increase 10. Whenever, number of branches exceeds 10, first ten branches with relatively high cumulative score were selected. Following graph is showing the rise and fall of accuracy curve over the change in threshold.



⁵The information about the value of lambda is taken from: http://www-rohan.sdsu.edu/~gawron/stat/discounting.htm

8 Results

Accuracy of tagger was checked over test corpus of 10,000 words. Test data was randomly selected from same domain. After applying normalization and by removing diacritics, test data was automatically tagged through tagger. Same test data was manually tagged in order to compare the accuracy of tagger. An application was build which takes automatically tagged test data and manually tagged data as input. In order to see the percentage of error over test corpus, tag of a word in test corpus was compared against the tag of manually tagged corpus. Tagger showed an accuracy of 97.2% i.e. an error rate of 2.8% over the test corpus of 10,000 words. Error rate over each tag was also calculated and analyzed to further improve the accuracy of tagger.

Results of the tagger are sorted over the accuracy rate of tags. In order to see the effect of each tag over the accuracy of tagger, total occurrences of each tag in test corpus are also calculated. All those tags that have an occurrence of below 10 are neglected from the analysis. Looking at the accuracies, tags can be divided into various clusters. The tags of accuracy 96% to 100% can be considered as satisfactory. The tags of accuracy between 84% and 94% can be considered as second cluster. It is interesting to see that most of the tags of demonstratives and pronouns lie in second cluster. Discussion on low accuracy rate of these categories can be found in next section. Last cluster contains two frequently occurring tags i.e. proper noun and KER tag. The high frequency and low accuracy rate of these tags significantly affect the results of the tagger. Following table is summarizing the results of the tagger.

Тад	Total occurrences in test corpus	Accuracy					
FR	-	-					
MUL	-	-					
POT	-	-					
NEG	-	-					
SM	404	100					
RP	3	100					
GR	56	100					
G	7	100					
Q	82						
CC	171	100					
SE	190	100					
WALA	50	100					
INT	2	100					
SC	188	100					
CA	185	100					
AD	112	100					
AP	63	100					
DATE	20	100					
OR	32	100					

Table 7: Results	of tagger	over test co	orpus of	10.000 words
	or tagger			10,000 00100

KD	14	100
PRT	8	100
U	14	100
Р	1978	99
1	96	99
ТА	293	98
NN	2600	98
AA	379	97
ADV	131	97
REP	43	97
KER	72	97
RD	18	96
ADJ	487	96
VB	1008	96
PP	248	96
PD	112	92
PN	384	83
KP	7	80
QW	9	75
A	7	62
AKP	4	33

9 Analysis of Tagset on the Basis of Results

Manual annotation requires linguist to analyze corpus on the basis of phrase level analysis. Results of the tagger help in analyzing the practicality of tagset. Various points that may need a change in the tagset were observed in the process of manual annotation and in the analysis of the output. However, due to time limitation, only some changes were made in the tagset and other changes were left for future work. Following is the discussion on each issue.

9.1 Noun

While observing language, linguist finds problem in disambiguating the part of speech of a word as adjective or noun. Situation becomes worst when handling the words of complex predicates. It was observed that noun can be analyzed under these parameters:

- Nouns accept an adjective in their noun phrase other does not
- Noun can occur as complex predicates other not
- Nouns accept an adverb behind them other not
- Some nouns are derived from adjectives

These parameters were observed in the corpus and it was found that in the category of noun, there are different syntactic structure exist. However, due to time limitation, these were not properly observed.

9.2 Infinitive Verbs

In manual annotation, verbs acting as noun (infinitive verbs) are treated as verb. Analyzing syntactic structures of these words, it was observed that these words occur at the place of noun. Due to small training data, occurrence of unknown word is very frequent in test corpus. Whenever an unknown word occurs at the place of noun, the most probable tag for that word will be noun which is wrong in our case. The accuracy of KER tag is also affected by considering infinitives as verb. KER tag takes a verb behind it. The tagger needs to disambiguate KER tag with the $\geq \leq$ word of semantic marker. Major distinction between KER tag and semantic marker can be made by considering the tag of one previous word. But infinitive verbs nullify this distinction. Consider following example:

(a)	(b)	(C)		
کام <nn> کرنے<p>> کے<p></p></p></nn>	کام <nn> کر<ker> کے<ker></ker></ker></nn>	کام <nn> کرنے<nn> کے<p></p></nn></nn>		
بعد <nn></nn>		بعد <nn></nn>		
Handling of infinitive in	Syntactic structure of KER	Future work		
manual tagging				

There were 72 words of KER tag in the test corpus. Out of these 72 words, 3% words of kER tag were wrongly detected by the tagger. The accuracy of verb is also due to infinitive verbs. It was observed that accuracy of KER tag can be improved if infinitive verbs are handled separate from verb.

9.3 Noun vs. Other Tags

Tagger confuses the category of pre-title and post-title with nouns. Syntactically, the behavior of pre-title and post-title is same as that of noun. Difference was made on semantic grounds. For an unknown word, it is not possible for the tagger to get a higher probability of pre-title tag.

10 Analysis of Statistical approach on the Basis of Results

Statistical approaches to disambiguation require training data to model the language. The analysis on input data is based on the statistical technique and training data. While observing Urdu language and analyzing the results of the tagger, it was observed that statistical approach is finding problem in disambiguating between some particular pairs of tags. Following is the discussion on these categories.

10.1 Demonstratives vs. Pronouns

Demonstratives are divided into four types. All these types are ambiguous with the four types of pronoun. Difference between pronouns and demonstratives is based on phrase boundary analysis which is discussed in the section of tagset. Looking at tagger practically, it analyses the language in a flat structure. In flat structure, there is an equal probability of getting a noun after pronoun and demonstratives. Consider the following example:

Table 10: Examples of demonstratives and pronoun

گاہیں <vb></vb>	گانا <nn></nn>	لوگ <nn></nn>	<pd> -<ta>2</ta></pd>	وہ گ	وہ <pp> گانا<nn> گاہیں<vb> گے<ta>۔</ta></vb></nn></pp>

In the above example of demonstrative, it is taking a noun inside its phrase and pronoun is not having any noun inside its phrase. But in flat structure, both demonstratives and pronouns are having noun after them thus confusing the tagger. This issue can be quoted as deficiency of statistical approach in handling phrase level ambiguities of Urdu language.

10.2 Noun vs. Proper noun

In the tagset, noun is divided into two categories i.e. noun and proper noun. Most of the distinction between nouns and proper nouns is based on semantics. However, there are structural differences as well. Nouns take pre-nominal elements i.e. adjectives, cardinal, ordinal, etc. behind them whereas proper nouns only take some pre-nominal elements in special cases. Consider the following example:

Table 11: Examples of nouns and proper nouns						
ے <or> دو<ca> حامد<pn> کو<p> کو<ca> دو<ca> دو<ca> دو<ca> کو<ca> کو<ca> دو<ca> دو<ca> دو<ca> کو</ca></ca></ca></ca></ca></ca></ca></ca></ca></p></pn></ca></or>						
بلائو <vb></vb>				بلائو <vb></vb>		

The example of proper noun taking pre-nominal elements is very rare in normal Urdu. However, probability of having Noun and proper noun at the start of a sentence is nearly equal. Due to these structural similarities, tagger confuses while handling unknown words as noun or proper noun.

11 Future Work

Part of speech tagger implemented above gives an accuracy of 97.2%. An obvious extension is to improve the accuracy up to 99%. An analysis of tagset on the basis of results is given in section 9. For future work, further analysis on the tagset can be done and implemented. Analysis of statistical technique is also given in section 11. A good future work is to analyze the implemented statistical technique and add heuristics to help the tagger in disambiguating the tags.

Words from the corpus of 100,000 words were used as lexicon for the tagger. For future work, larger lexicon can also be build which will significantly improve the accuracy of the tagger. Training data of 100,000 words was not sufficient to get a very high accuracy from the tagger. For future work, training data up to 1000,000 words can also be built and statistical technique can also be extended to bigram word probabilities.

12 Conclusion

Thesis was aimed at designing a syntactic tagset of Urdu and implementing a standard statistical approach to compare its results with other languages. In the thesis, Hidden Markov Model was implemented. Over the training corpus of 100,000 words, tagger showed an accuracy of 97.2%. By applying a standard statistical technique and achieving a relatively good accuracy are the answers to these questions. On the basis of the results, it can be concluded that standard statistical approach can be used for Urdu language. It was also observed that free orderness is not very frequent in writing. Thus does not significantly affect the accuracy of the tagger. It was also observed that tagger finds problems while disambiguating at phrase level. High accuracy can be achieved by merging the problematic categories of the tagset or by adding some heuristics which will help the tagger in disambiguating the tags.

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Appendix

Parts of Speech Proposed by Platts

Main	Sub category	Example
Noun	Substantive noun	All common and proper noun e.g. ماں، احسان، لڑکا
	Adjective	اچھا، عمد ہ، بہادر
	Numeral adjective	ایک، ستره، پانچواں، دونوں، سیکڑوں، دوکنا، دو دو، ڈهائ، ایک بار
	Personal pronoun	میں، تو، مجه، تجه، میرا، همارا
	Demonstrative pronoun	یہ، وہ، اس، انھوں، اس سے، ان میں
	Relative pronoun	جو، جس
	Correlative pronoun	جو کرے گا سو بھرے گا۔
	Interrogative pronoun	کون، کس، (who, what, which)
	Indefinite pronoun	كۇ ' ئى، كسى، جو كوئى، كوئى، يور
	Reflexive pronoun	اپنا، اپ سے، اپ کو
	Reciprocal pronoun	ایک دوسر ا
	Possessive pronoun	میرا، اس .Genitive case of personal pronoun e.g
	Pronominal adjective	دونوں، بېت، بعض، سب، فلاں
Verb	Conjunctive participle	Platts dd not propose any type of verb under its subcategory. However, all the properties and forms of verb are discussed as its features.
Particle	Adverb	نېيں، کر تو سېی، میں کہاں تو کہاں
	Postposition	اگے، سااتہ، طرف، نزدیک
	Conjunction	اور، نہ نفع ہو نہ نقصان، یا، کہ، مگر، لیکن،ورنہ، پر، اس لیے، لہزا
	Interjection	واه، کاش

Table 12: Analysis of Platts (Platts 1909)

Parts of Speech Proposed by Siddiqi

Main	Sub category	Example
category		
Noun	With respect to structure	
	With respect to nature	
	Sound	ميائوں، بھن بھن، گڑگڑاہٹ
	Indefinite	فلانا، ایسا، تیسا
	Relative	جو
	Interrogative	کیا، کون، کون سی، کب، کیسا، ادہر ، کتنا، کیسے
	Numerals	ايک، دو، پاؤ، بعض، کچه، بېت
Adjective	Personal	لمبا، خوبصورت، بيمار
	نسبتى	فارسی، مدنی، مردانہ، عیسوی
	Numeral	پېلا، دوسرا
Pronoun	Demonstrative	یہ، وہ
	Personal	میں، ہم، تم، أپ
	Relative	احمد کے پاس ہے وہ میری <u>ہےجو</u> رہ کتاب
	Interrogative	کیا، کون
	Indefinite	كوئي، كچه
	Reflexive	(For emphasis) خود، أپ
Verb	Intransitive	ہ <u>ے بیٹھا</u> رہا ہے، اسلم <u>کھا</u> احمد آم
	Transitive	<u>دی</u> احمد نے اسلم کو کتاب
	Predicative	ہو، ہوں، ہے، تھا
Distinct		اب، تب، ادہر، تو، بلکل، یکایک، ایک بار، دو بار، کتنا، جی
		ہاں، نہیں تو، کبھی نہ کبھی، أگے أگے
Particle	Construction	نے، کو، سے، میں، تک، پر، کا، کے، کی
	Conjunction	
	تخصيص	ہی، تو، بھی، تنہا، تو، صرف، اکیلا، کبھی، کہاں، یوں
	فجاءيه	واہ، کاش، خدا کرے، سبحان اللہ

Table 13: Analysis of Siddigui (Siddigui 1971)

Table 14: Subcategories proposed by Siddiqui (Siddiqui 1971)

Main category	Sub category		Example
Noun with	Original		اونٹ، تلوار ، قلم
respect to	Verbal		الثهنا، بيثهنا، جاگنا، سونا
structure	Morphed		<u>بڑ</u> ھتا تھا، پڑھنا سے <u>سر</u> خیسرخ سے
Noun with	Substantive		قلم، كاغذ، لاہور، پاكستان
respect to	Adjective	Comparative	کم، کم تر، خوب، خوب تر، بہتر، اکبر
nature	-	Exaggeration	بڑا۔ بہت، خوب، نہایت، نہایت ہی
	Pronoun		یہ، وہ
Personal	Courteous		تم، أپ، وه
pronoun	Possessive		میرا، تمهارا
Conjunction	شرط		جب، جو، اگر، جو، جس وقت، جوں جوں، کیوں، ورنہ
particle	استثنا		ليکن، مگر، کبھی، سوا
	استدراک		میں نہیں مانا، بلکہ، البتہ، مگر مگر لیکن،اس نے بہت کہا

	ہاں
ترديد	نہ نہ، خواہ، چاہو، کہ، یا، یا تو
وصل	وقار أيا <u>يهر</u> يا، و، احمد أيا _ب اور
بيانيہ	کہ
علت	اس لیے، اس واسطے، تاکہ، لہزا، کہ

Parts of Speech Proposed by Javaid

	Table 15: An	alysis of Javaid (Javaid 1981)
Main	Sub category	Example
category		
Noun	Common	کتا، بلی، قلم، کاغذ
	Proper	لاہور، پاکستان
	Collective	فوج، جھنڈ، ریوڑ
	Abstract	وقت، فاصلہ، جذبہ
	Un-count	پانی، چاندی
Adjective	Personal	لمبا، خوبصورت، بيمار
-	Numeral	ايک، دو، پاؤ، بعض، کچه، بېت
	Quantitative	پانىتھوڑا دودھ، كَچە
	Emphatic	(To show intensity)کافی، بہت، بڑا شریر
	Pronoun	یہ، وہ
Verb	Predicative	ہو، ہوں، ہے، تھا
	Intransitive	ہے بیٹھا رہا ہے، اسلم کھااحمد آم
	Transitive	احمد نے اسلم کو کتاب دی
	Verbal	جانا، کھانا، شرمانا، مسکرانا
	حاليہ	ڈرتے ڈرتے، آتے آتے، بہتا ہوا پانی
	حاليہ معطوف	اٹھا، میں کام کر کر کے تھک گیا کرسو
	Adverb	یں، آس پاس، ار دگرد، <u>گھر</u> م تر ، زیادہ سے، تیزی سے، غلطی
		<u>ے آگے، پر سوں س</u> کے
Pronoun	Demonstrative	یہ، وہ
	Personal	میں، ہم، تم، أپ
	Relative	احمد کے پاس ہے وہ میری ہےجووہ کتاب
	Interrogative	کیا، کون
	Courteous	تم، أب، وه
	Possessive	میرا، تمهارا، أپ کا، تیرا
	Reflexive	(For emphasis) خود، أپ
	Common	تو کرو، فلا <u>ںکچ</u> ەکوئی، بعض،
	اضافی مشترکہ	کا کام ک <u>ر ۔اس</u> کام کرو، وہ <u>تمہارا</u> تم
	Adverb	کب، ادھر ، یوں، ایسے، کیسے
جار		نے، کو، سے، میں، تک، پر، کا، کے، کی، کے پاس، کے
		پہلے، کی کے سا تہ، کے لیے، کی وجہ سے
عطف		جو، جہاں، حالانکہ، تاوقتیکہ ، بھی، پھربھی، اس لیے، یایا
	وصل	کیا کیا، یا اور
	ترديد	نہ نہ، خواہ
	استثنا	ليكن، مگر
	ترقى	بلکہ، پھر بھی، تا ہم
	علت	اس لیے، اس واسطے، تاکہ، لہزا
فجاءيہ		واہ، کاش، خدا کرے، سبحان اللہ

نداءيہ	اے، ارے، او
تاكيد	ېي، تو، بهي، سېي، ېر گز
اثبات و نفي	ہاں، نہیں، جی ہاں

Parts of Speech Proposed by Haq

Main category	Sub category	Example
Noun	Proper	لاہور، پاکستان
	Common	کتا، بلی، قلم، کاغذ
Pronoun	Personal	میں، ہم، تم، أپ، اس کا
	Relative	احمد کے پاس ہے وہ میری ہے، جنہوں نے، جن س <u>ےجو</u> وہ کتاب
	Interrogative	کیا، کون
	Indefinite	کوئی، کچه
	Demonstrative	يہ، وہ
Adjective	Personal	لمبا، خوبصورت، بيمار، ڻھوس، ٻلکا
	Numeral	ایک، دو ، پاؤ ، بعض، کچه، بېت، دوگنا، اتنا، سب، کئی، پون
	Quantitative	چار سیر، پانچ گز
	نسبتى	فارسی، مدنی، مردانہ، عیسوی
	Pronoun	وہ، یہ، کون، جو، کیا
Verb	Predicative	ہونا، دینا، دکھائی دینا
	Intransitive	احمد أيا
	Transitive	احمد نے اسلم کو کتاب دی
	معطوف	اڻھا، وہ خبر سنا کر چلا گيا <u> کر</u> سو
	Adverb	اب، کب، أج، اچانک، یکا یک، ہمیشہ، یہاں، باہر ، یوں، سچ مچ، جتنا، کتنا
ربط		نے، کو، سے، میں، تک، پر، کا، کے، کی، پیچھے، باہر، درمیان،
		طرح
عطف	وصل	اور، و
	ترديد	نہ <u>یںکم</u> یایا، خواہ خواہ، نہ نہ، أتے ہو
	استدراک	میں نہیں مانا، بلکہ <u>مگر</u> لیکن،اس نے بہت کہا
	استثنا	وہ نہیں ایا <u>مگر</u> سب ائے
	شرط	جب، جو ، اگر
	علت	کیونکہ، اس لیے، لہزا
	بيانيہ	کہ
تخصيص		ہی، تو ، بھی
فجاءيه		واہ، کاش، خدا کر ے، سبحان اللہ

Table 16: Analysis of HAQ

Parts of Speech Proposed by Schmidt

Main category	Sub category	Example
Noun		لڑکا، گھر، کنواں، لڑکپن
Pronoun	Demonstrative	کو گھوڑے کہتے <u>ان</u> کا نام کیا ہے،ہم <u>اس</u> گھڑا ہے، <u>یہ</u> ایک لڑکا ہے، <u>وہ</u> تھے
	Personal	میں، تو، وہ پاس رہتا ہے ، یہ علی کے پاس جانا چاہتا ہے، تم، مجہ، اس میں کوئی شک نہیں، ان، ہم
	Reflexive	اپنا، خود، آپس ميں، خود بخود
	Interrogative	کیا، کون، کس، کنہوں نے

Table 17: Analysis of Schmidt (Schmidt1999)

	Indefinite	کرو يار کچهکوئی، کسی،
	Relative	جو، کون کون، کوئي نہ کوئي، کچه کچه، کچه نہ کچه
Adjective		اچھا، دلچسپ، معلوم ہونا، مبتلا ہونا، ایسا، کیسا، ویسا، سا، سے، والا
Adverb	Time	ہمیشہ، کل، اکثر ، اب، تب، کب، کس وقت، جس وقت
	Place	وہاں، ادہر ، اس جگہ، اس طرف، اندر ، باہر ، قریب، دور
	Manner	کرو ایسایوں، اس طرح، کیوں،
	Degree	ذ <u>ېينې</u> رياده،
	Modal	نېيں، نہ، مت، شايد، ضرور ، پھر ، صرف
Postposition	Grammatical	تار بھیہجا <u>کو</u> کا، کے، کی، نے، والدہ
	Spatial-temporal	سے، تک، میں، پر
	Compound	کی وجہ سے، کے ساتہ، کے بعد، کے نیچے
Verb	Root	جا، کر ، دے، سن
	Imperfective participle	آتا، جاتا،
	Perfective participle	آیا، گیا، سنا
	Infinitive	جانا، كرنا، دينا، سننا
Particle	Contrastive emphatic	پڑ ہے گا، نہیں توتووہ اردو
	Exclusive emphatic	بى
	Inclusive emphatic	بھی
	Adjectival	سا، سی، سے
Interjection	Vocative	او ، ار ے
	Free	و اہ، ہائے، اوبو
Conjunction	Coordinating	اور ، یا، مگر ، لیکن، بلکہ، جب سے
	Correlative	(بھی بھی)، یا یا، نہ نہ <u>بھی</u> جاؤں گا اور تم <u>بھی</u> میں
	Causal	کیونکہ، چونکہ
	Concessive	اگرچہ، حالانکہ
	Subordinating	اگر، تاکہ، بشرطیکہ، کہ
Number	Cardinal	ایک، سترہ، لاکہ
	Ordinal	پېلا، دوسرا، اکيسويں
	Fraction	يو ن، سو ا، جو تھائي، بڻا، تين يار ، دو گنا، دفعہ، مر تيہ

Urdu	Tagset	Proposed	d bv	Hardie
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Tag	Example	Description
AL	ال	Arabic definite article
AU	واه	Interjection
СС	مگر	Coordinating conjunction
CCC	يا	Correlative coordinating conjunction
CS	کہ	Subordinating conjunction
FF		Foreign word
FX		Non-Perso-Arabic string
FO		Formula (e.g. mathematical)
FZ		Letter of the alphabet
FS		Other symbol
FA		Acronym
FB		Abbreviation
FU		Other unclassifiable non-Urdu element
IB	از ، فی	Preposition
II	پر، میں	Unmarked postposition
IIC	ے ، یں، ہیں	Clitic postposition ē, ē~, hē~
IIM1N	کا	Marked masculine singular nominative postposition <i>kā</i>
IIM1O	کے	Marked masculine singular oblique postposition $k\bar{e}$
IIM2N	کے	Marked masculine plural nominative postposition $k\bar{a}$
IIM2O	کے	Marked masculine plural oblique
		Marked feminine singular nominative
	_ى	postposition <i>kī</i> Marked feminine singular oblique
IIF10	تى	postposition $k\bar{i}$
IIF2N	کی	postposition $k\bar{i}$

IIF2O	کی	Marked feminine plural oblique postposition $k\bar{i}$
IV	کے	Verbal postposition kē
JJM1N	بڑا	Marked masculine singular nominative adjective
JJM1O	بڑے	Marked masculine singular oblique adjective
JJM2N	بڑے	Marked masculine plural nominative adjective
JJM2O	بڑے	Marked masculine plural oblique adjective
JJF1N	بڑی	Marked feminine singular nominative adjective
JJF10	بڑی	Marked feminine singular oblique adjective
JJF2N	بڑی	Marked feminine plural nominative adjective
JJF2O	بڑی	Marked feminine plural oblique adjective
JJU	خطرناک	Unmarked adjective
JD	زیادہ ، کافی	Indefinite determiner
JDNU	ایک ، اٹھارہ	Cardinal number
JDNUO	دونوں	Oblique cardinal number
JDNUC	چو(گنا)	Pre-multiplicative clitic cardinal number <i>du</i> -, <i>ti</i> -, <i>cau</i> -
JDNM1N	تسبرا	Masculine singular nominative ordinal number
JDNM10	تسرے	Masculine singular oblique ordinal number
JDNM2N	تسرے	Masculine plural nominative ordinal number
JDNM2O	تسرے	Masculine plural oblique ordinal number
JDNF1N	تسرى	Feminine singular nominative ordinal number
JDNF10	تسرى	Feminine singular oblique ordinal number
JDNF2N	تسرى	Feminine plural nominative ordinal number
JDNF2O	تسرى	Feminine plural oblique ordinal number
JDFU	سوا	Unmarked fraction
JDFM1N	پونا	Masculine singular nominative fraction
JDFM10	پونے	Masculine singular oblique fraction

JDFM2N	پونے	Masculine plural nominative fraction
JDFM2O	پونے	Masculine plural oblique fraction
JDFF1N	پونی	Feminine singular nominative fraction
JDFF10	پونی	Feminine singular oblique fraction
JDFF2N	پونی	Feminine plural nominative fraction
JDFF2O	پونی	Feminine plural oblique fraction
JDYM1N	اِتنا ، ایسا	Masculine singular nominative proximal demonstrative adjective (<i>itnā, aisā</i>)
JDYM10	اِتنے ، ایسے	Masculine singular oblique proximal demonstrative adjective (<i>itnē</i> , <i>aisē</i>)
JDYM2N	اِتنے ، ایسے	Masculine plural nominative proximal demonstrative adjective (<i>itnē</i> , <i>aisē</i>)
JDYM2O	اِتنے ، ایسے	Masculine plural oblique proximal demonstrative adjective (<i>itnē</i> , aisē)
JDYF1N	اِتنی ، ایسی	Feminine singular nominative proximal demonstrative adjective (<i>itnī, aisī</i>)
JDYF10	اِتنى ، ايسى	Feminine singular oblique proximal demonstrative adjective (<i>itnī, aisī</i>)
JDYF2N	اِتنی ، ایسی	Feminine plural nominative proximal demonstrative adjective (<i>itnī</i> , <i>aisī</i>)
JDYF2O	اِتنی ، ایسی	Feminine plural oblique proximal demonstrative adjective (<i>itnī, aisī</i>)
JDVM1N	اًتنا ، ويسا	Masculine singular nominative distal demonstrative adjective (<i>utnā</i> , <i>vaisā</i>)
JDVM10	ر اُتنے ، ویسے	Masculine singular oblique distal demonstrative adjective (<i>utnē</i> , <i>vaisē</i>)
JDVM2N	ر – میں – اُتنے ، ویسے	Masculine plural nominative distal demonstrative adjective (<i>utnē</i> , <i>vaisē</i>)
JDVM2O	ر – میں – اُتنے ، ویسے	Masculine plural oblique distal demonstrative adjective (<i>utnē</i> , <i>vaisē</i>)
JDVF1N	ر <u> </u>	Feminine singular nominative distal demonstrative adjective (<i>utnī</i> , <i>vaisī</i>)
JDVF10	۔ اُتنی ، ویسی	Feminine singular oblique distal demonstrative adjective (<i>utnī</i> , <i>vaisī</i>)
JDVF2N	۔ اُتنی ، ویسی	Feminine plural nominative distal demonstrative adjective (<i>utnī, vaisī</i>)
JDVF2O	۔ اُتنی ، ویسی	Feminine plural oblique distal demonstrative adjective (<i>utnī, vaisī</i>)
JDKM1N	کتنا ، کیسا	Masculine singular nominative interrogative adjective (<i>kitnā, kaisā</i>)
JDKM10	کتنے ، کیسے	Masculine singular oblique interrogative adjective (<i>kitnē, kaisē</i>)
JDKM2N	کتنے ، کیسے	Masculine plural nominative interrogative adjective (<i>kitnē</i> , <i>kaisē</i>)

JDKM2O	کتنے ، کیسے	Masculine plural oblique interrogative adjective (<i>kitnē</i> , <i>kaisē</i>)
JDKF1N	كتنى ، كيسى	Feminine singular nominative interrogative adjective (<i>kitnī</i> , <i>kaisī</i>)
JDKF10	كتنى ، كيسى	Feminine singular oblique interrogative adjective (<i>kitnī</i> , <i>kaisī</i>)
JDKF2N	كتنى ، كيسى	Feminine plural nominative interrogative adjective (<i>kitnī, kaisī</i>)
JDKF2O	كتنى ، كيسى	Feminine plural oblique interrogative adjective (<i>kitnī, kaisī</i>)
JDJM1N	جتنا ، جيسا	Masculine singular nominative relative adjective (<i>jitnā</i> , <i>jaisā</i>)
JDJM10	جتنے ، جیسے	Masculine singular oblique relative adjective (<i>jitnē</i> , <i>jaisē</i>)
JDJM2N	جتنے ، جیسے	Masculine plural nominative relative adjective (<i>jitnē</i> , <i>jaisē</i>)
JDJM2O	جتنے ، جیسے	Masculine plural oblique relative adjective (<i>jitnē</i> , <i>jaisē</i>)
JDJF1N	جتنی ، جیسی	Feminine singular nominative relative adjective (<i>jitnī, jaisī</i>)
JDJF10	جتنی ، جیسی	Feminine singular oblique relative adjective (<i>jitnī, jaisī</i>)
JDJF2N	جتنی ، جیسی	Feminine plural nominative relative adjective (<i>jitnī, jaisī</i>)
JDJF2O	جتنی ، جیسی	Feminine plural oblique relative adjective (<i>jitnī</i> , <i>jaisī</i>)
JXGM1N	گنا	Masculine singular nominative multiplicative marker gunā
JXGM10	گنے	Masculine singular oblique multiplicative marker gunē
JXGM2N	گنے	Masculine plural nominative multiplicative marker gunē
JXGM2O	گنے	Masculine plural oblique multiplicative marker gunē
JXGF1N	گنی	Feminine singular nominative multiplicative marker gunī
JXGF10	گنی	Feminine singular oblique multiplicative marker gunī
JXGF2N	گنی	Feminine plural nominative multiplicative marker gunī
JXGF2O	گنی	Feminine plural oblique multiplicative marker gunī
JXSM1N	سا	Masculine singular nominative adjectival particle <i>sā</i>
JXSM10	للبلے	Masculine singular oblique adjectival particle <i>sē</i>
JXSM2N	للبلے	Masculine plural nominative adjectival particle <i>sē</i>

JXSM2O	ببیے	Masculine plural oblique adjectival particle sē
JXSF1N	سىي	Feminine singular nominative adjectival particle <i>sī</i>
JXSF10	ىنىپى	Feminine singular oblique adjectival particle <i>sī</i>
JXSF2N	سىي	Feminine plural nominative adjectival particle <i>sī</i>
JXSF2O	سىي	Feminine plural oblique adjectival particle <i>sī</i>
JXVM1N	والا	Masculine singular nominative adjectival / occupational particle <i>vālā</i>
JXVM1O	والے	Masculine singular oblique adjectival / occupational particle vālē
JXVM2N	والے	Masculine plural nominative adjectival / occupational particle vālē
JXVM2O	والے	Masculine plural oblique adjectival / occupational particle vālē
JXVF1N	والى	Feminine singular nominative adjectival / occupational particle <i>vālī</i>
JXVF10	والى	Feminine singular oblique adjectival / occupational particle <i>vālī</i>
JXVF2N	والى	Feminine plural nominative adjectival / occupational particle <i>vālī</i>
JXVF2O	والى	Feminine plural oblique adjectival / occupational particle <i>vālī</i>
LL	زمہ	Nongrammatical lexical element
NNMM1N	لڑکا	Common marked masculine singular nominative noun
NNMM10	لڑکے	Common marked masculine singular oblique noun
NNMM1V	لڑکے	Common marked masculine singular vocative noun
NNMM2N	لڑکے	Common marked masculine plural nominative noun
NNMM2O	لڑکوں	Common marked masculine plural oblique noun
NNMM2V	لڑکو	Common marked masculine plural vocative noun
NNMF1N	چڑیا	Common marked feminine singular nominative noun
NNMF10	چڑیا	Common marked feminine singular oblique noun
NNMF1V	چڑیا	Common marked feminine singular vocative noun
NNMF2N	چڑیاں	Common marked feminine plural nominative noun
NNMF2O	چڑیوں	Common marked feminine plural oblique

		noun
NNME2V	415	Common marked feminine plural
	<u> </u>	vocative noun
NNUM1N	بھاتے	Common unmarked masculine singular
		Common unmarked masculine singular
NNUM1O	بھاتی	oblique noun
	<u>tla</u> ,	Common unmarked masculine singular
	بھانی	vocative noun
NNUM2N	بھائی	Common unmarked masculine plural nominative noun
		Common unmarked masculine plural
NINUM20	بھانیوں	oblique noun
NNUM2V	بھائيو	Common unmarked masculine plural vocative noun
NNUF1N	بېن	Common unmarked feminine singular nominative noun
NNUF10	بېن	Common unmarked feminine singular oblique noun
NNUF1V	بېن	Common unmarked feminine singular vocative noun
NNUF2N	بہنیں	Common unmarked feminine plural nominative noun
NNUF2O	بہنوں	Common unmarked feminine plural oblique noun
NNUF2V	بېنو	Common unmarked feminine plural vocative noun
NPMM1N		Proper marked masculine singular nominative noun
NPMM10		Proper marked masculine singular oblique noun
NPMM1V		Proper marked masculine singular vocative noun
NPMM2N		Proper marked masculine plural nominative noun
NPMM2O		Proper marked masculine plural oblique noun
NPMM2V		Proper marked masculine plural vocative noun
NPMF1N		Proper marked feminine singular nominative noun
NPMF10		Proper marked feminine singular oblique noun
NPMF1V		Proper marked feminine singular vocative noun
NPMF2N		Proper marked feminine plural nominative noun
NPMF2O		Proper marked feminine plural oblique noun

NPMF2V		Proper marked feminine plural vocative noun
NPUM1N		Proper unmarked masculine singular nominative noun
NPUM10		Proper unmarked masculine singular
NPUM1V		Proper unmarked masculine singular
		Proper unmarked masculine plural
		nominative noun Proper upmarked masculine plural
NPUM2O		oblique noun
NPUM2V		Proper unmarked masculine plural vocative noun
NPUF1N		Proper unmarked feminine singular nominative noun
NPUF10		Proper unmarked feminine singular
NPUF1V		Proper unmarked feminine singular
NPUF2N		Proper unmarked feminine plural
		nominative noun Proper unmarked feminine plural oblique
NPUF2O		noun
NPUF2V		Proper unmarked feminine plural vocative noun
00	و	Persian compound-forming conjunction \bar{o}
PPM1N	میں	First person singular nominative personal pronoun (<i>mai</i> ~)
PPM10	مجھ	First person singular oblique personal pronoun (<i>mujh</i>)
PPM2N	ڊ م	First person plural nominative personal pronoun (<i>ham</i>)
PPM2O	ب م	First person plural oblique personal pronoun (<i>ham</i>)
PPT1N	تو	Second person singular nominative personal pronoun $(t\bar{u})$
PPT10	تجه	Second person singular oblique personal pronoun (<i>tujh</i>)
PPT2N	تم	Second person plural nominative personal pronoun (<i>tum</i>)
PPT2O	تم	Second person plural oblique personal pronoun (<i>tum</i>)
PGM1M1N	ميرا	First person singular masculine singular nominative possessive adjective $(m\bar{e}r\bar{a})$
PGM1M1O	میرے	First person singular masculine singular oblique possessive adjective $(m\bar{e}r\bar{e})$
PGM1M2N	میرے	First person singular masculine plural

		nominative possessive adjective (mērē)
PGM1M2O	میرے	First person singular masculine plural
		oblique possessive adjective (<i>mērē</i>)
PGM1F1N	میری	First person singular feminine singular
	_	nominative possessive adjective (meri)
PGM1F1O	میری	First person singular feminine singular
		First assessive adjective (<i>meri</i>)
PGM1F2N	میری	First person singular feminine plural nominative possessive adjective $(m\bar{e}r\bar{r})$
		First person singular feminine plural
PGM1F2O	میری	oblique possessive adjective $(m\bar{e}r\bar{i})$
		First person plural masculine singular
PGM2M1N	دمار 1	nominative possessive adjective
		(hamārā)
	1	First person singular masculine singular
PGM2M1O	ہمارے	oblique possessive adjective $(ham\bar{a}r\bar{e})$
	1	First person singular masculine plural
PGM2M2N	ہمارے	nominative possessive adjective ($ham\bar{a}r\bar{e}$)
	1	First person singular masculine plural
PGM2M2O	ہمارے	oblique possessive adjective ($ham\bar{a}r\bar{e}$)
	1	First person singular feminine singular
PGM2F1N	ہماری	nominative possessive adjective (hamārī)
	1	First person singular feminine singular
PGM2F1O	ہماری	oblique possessive adjective (hamārī)
50.00500	1	First person singular feminine plural
PGM2F2N	ہماری	nominative possessive adjective (hamārī)
DOMOFOO		First person singular feminine plural
PGM2F2O	ہماری	oblique possessive adjective (hamārī)
		Second person singular masculine
PGT1M1N	تيرا	singular nominative possessive adjective
		(tērā)
		Second person singular masculine
PGT1M1O	تیرے	singular oblique possessive adjective
		$(t\bar{e}r\bar{e})$
	تى ہ	Second person singular masculine plural
FOT IWZN	2,7	nominative possessive adjective (tērē)
	تى ہ	Second person singular masculine plural
10111020	~~~	oblique possessive adjective (tērē)
PGT1F1N	تىرى	Second person singular feminine singular
	0.5.4	nominative possessive adjective (teri)
PGT1F10	تىرى	Second person singular feminine singular
	0.04	oblique possessive adjective (<i>tērī</i>)
PGT1F2N	تیری	Second person singular feminine plural
	0.04	nominative possessive adjective $(t\bar{e}r\bar{i})$
PGT1F2O	تیری	Second person singular feminine plural
		oblique possessive adjective (<i>teri</i>)
PGT2M1N	تمہار ا	Second person plural masculine singular
		formative possessive adjective
		(tumhara)

PGT2M1O	تمہارے	Second person singular masculine singular oblique possessive adjective (<i>tumhārē</i>)
PGT2M2N	تمہارے	Second person singular masculine plural nominative possessive adjective (<i>tumhārē</i>)
PGT2M2O	تمہارے	Second person singular masculine plural oblique possessive adjective (<i>tumhārē</i>)
PGT2F1N	تمہاری	Second person singular feminine singular nominative possessive adjective (<i>tumhārī</i>)
PGT2F1O	تمہاری	Second person singular feminine singular oblique possessive adjective (<i>tumhārī</i>)
PGT2F2N	تمہاری	Second person singular feminine plural nominative possessive adjective (<i>tumhārī</i>)
PGT2F2O	تمہاری	Second person singular feminine plural oblique possessive adjective (<i>tumhārī</i>)
PY1N	يہ	Singular nominative proximal demonstrative pronoun (<i>yah</i>)
PY10	اِس	Singular oblique proximal demonstrative pronoun (<i>is</i>)
PY2N	بر	Plural nominative proximal demonstrative pronoun (<i>yah</i>)
PY2O	ان	Plural oblique proximal demonstrative pronoun (<i>in</i>)
PY2E	إنہوں	Plural oblique proximal demonstrative pronoun before <i>nē</i> (<i>inhō</i> ~)
PV1N	وه	Singular nominative distal demonstrative pronoun (<i>vah</i>)
PV10	اس	Singular oblique distal demonstrative pronoun (<i>us</i>)
PV2N	وه	Plural nominative distal demonstrative pronoun (<i>vah</i>)
PV2O	ر ان	Plural oblique distal demonstrative pronoun (<i>un</i>)
PV2E	ر اُنہوں	Plural oblique distal demonstrative pronoun before <i>nē</i> (<i>unhō</i> ~)
PK1N	کیا، کون	Singular nominative interrogative pronoun (<i>kyā</i> , <i>kaun</i>)
PK1O	کس	Singular oblique interrogative pronoun (<i>kis</i>)
PK2N	کیا، کون	Plural nominative interrogative pronoun (<i>kyā</i> , <i>kaun</i>)
PK2O	کن	Plural oblique interrogative pronoun (kin)
PK2E	کنہوں	Plural oblique interrogative pronoun before <i>nē</i> (<i>kinhō</i> ~)

PJ1N	جو	Singular nominative relative pronoun $(j\bar{o})$
PJ1O	جس	Singular oblique relative pronoun (jis)
PJ2N	جو	Plural nominative relative pronoun $(j\bar{o})$
PJ2O	جن	Plural oblique relative pronoun (jin)
PJ2E	جنہوں	Plural oblique relative pronoun before $n\bar{e}$ (<i>jinh</i> \bar{o} ~)
PRF	خود ِ آپ	Reflexive pronoun (<i>āp</i> , <i>xud</i>)
PRC	آپس	Reciprocal pronoun (āpas)
PGRM1N	اپنا	Masculine singular nominative reflexive possessive adjective (<i>apnā</i>)
PGRM10	اپنے	Masculine singular oblique reflexive possessive adjective $(apn\bar{e})$
PGRM2N	اپنے	Masculine plural nominative reflexive possessive adjective $(apn\bar{e})$
PGRM2O	اپنے	Masculine plural oblique reflexive possessive adjective $(apn\bar{e})$
PGRF1N	اپنی	Feminine singular nominative reflexive possessive adjective $(apn\overline{i})$
PGRF10	اپنی	Feminine singular oblique reflexive possessive adjective $(apn\overline{i})$
PGRF2N	اپنی	Feminine plural nominative reflexive possessive adjective $(apn\bar{i})$
PGRF2O	اپنی	Feminine plural oblique reflexive possessive adjective $(apn\bar{i})$
PNN	کچھ کوئی	Nominative indefinite pronoun (<i>kōī</i> , <i>kuch</i> , <i>sab</i>)
PNO	كسى	Oblique indefinite pronoun (<i>kīsī</i> , <i>kuch</i> , <i>sabhō</i> ~)
PA	آپ	Honorific pronoun (āp)
QQ	کیا	Question marker kyā
RR	ہمیشہ	General adverb
RRJ	بائيں	General adverb derived from adjective
RD	زياده	Degree adverb
RM	ضرور	Modal adverb
RMN	نہیں، نہ، مت	Negative modal adverb (nahī~, nah, mat)
RY	اب	Proximal demonstrative adverb (<i>ab</i> , $yah\bar{a}$ ~, <i>idhar</i> , $y\bar{u}$ ~)
RYXHC	يہيں	Fused proximal demonstrative adverb and exclusive emphatic particle: $yah\bar{a} + h\bar{i} =$

		yahī~
RYJ	ادسہ	Proximal demonstrative adverb derived
	~ 4	from adjective (<i>aisē</i>)
RV	وہاں	Distal demonstrative adverb (<i>tab</i> , <i>vahā</i> ~, <i>udhar</i> , <i>tyū</i> ~)
	-	Fused distal demonstrative adverb and
RVYHC	وبنزر	exclusive emphatic particle: $vah\bar{a}_{\sim} \pm h\bar{i} =$
	0.10	vahī~
		Distal demonstrative adverb derived from
RVJ	ویسے	adjective (<i>vaisē</i>)
DV	6	Interrogative adverb (kab, kahā~, kidhar,
RK	حيوں	kyō~)
DKYLIC		Fused interrogative adverb and exclusive
KKARC	-ہیں	emphatic particle: $kah\bar{a} + h\bar{i} = kah\bar{i} -$
		Interrogative adverb derived from
RKJ	حيسنے	adjective (kaisē)
RI	cea	Relative adverb (<i>iab iabā</i> , <i>iidbar</i> $i\bar{u}_{a}$)
110	J	Kelative adverb (jub, juna*, junar, ju*)
RJXHC	جہیں	Fused relative adverb and exclusive
		emphatic particle: $jah\bar{a} + h\bar{i} = jah\bar{i} -$
R.I.I	جيسے	Relative adverb derived from adjective
1,00	- 4 1	(jaisē)
ТТ	ىىيېى	Sentence tag-word
VV0	سن	Root form lexical verb
	· · ·	Infinitive lexical verb, masculine singular
VVINIVITIN	لتنتقا	nominative
		Infinitive lexical verb, masculine singular
	_	oblique
		Infinitive lexical verb, masculine plural
	<u> </u>	nominative
		Infinitive lexical verb, feminine singular
VVINEI	ى	nominative
		Infinitive lexical verb, feminine plural
VVINFZ	ى	nominative
	1	Masculine singular (nominative)
VVIIVIIN	فتتقا	imperfective participle lexical verb
	3340	Masculine singular oblique imperfective
VVINIO		participle lexical verb
	3140	Masculine plural (nominative)
VVIIVIZIN	<u> </u>	imperfective participle lexical verb
	3140	Masculine plural oblique imperfective
V V T IVIZO	<u> </u>	participle lexical verb
	سىنتى	Feminine singular (nominative)
	6	imperfective participle lexical verb
	سنتى	Feminine singular oblique imperfective
	6	participle lexical verb
\/\/TE2N	سىنتى	Feminine plural (nominative)
	,	imperfective participle lexical verb

	سنتيں	
\/\/TE20	سنتى	Feminine plural oblique imperfective
VVII 20	6	participle lexical verb
VVYM1N	ابينا	Masculine singular (nominative)
••••••••		perfective participle lexical verb
VVYM10	ستنا	Masculine singular oblique perfective
	-	Masculino plural (nominativa) parfactiva
VVYM2N	ستغا	participle lexical verb
	_	Masculine plural oblique perfective
VVYM2O	سىنغ	participle lexical verb
	•	Feminine singular (nominative)
VVYF1N	ىتىتى	perfective participle lexical verb
	• • • •	Feminine singular oblique perfective
VVYF10	سىيى	participle lexical verb
	in sta	Feminine plural (nominative) perfective
VVYFZN	سين سي	participle lexical verb
	:	Feminine plural oblique perfective
VVYF2O	للتكى	participle lexical verb
		First person singular subjunctive lexical
V V SIVI I	سوں	verb
	سىغى ر	First person plural subjunctive lexical
V V 31VIZ	0.	verb
V/VST1	ستنج	Second person singular subjunctive
**011	-	lexical verb
VVST2	ستقور	Second person plural subjunctive lexical
	<u> </u>	verb
VVSV1	سىنے	Third person singular subjunctive lexical
		Third parson plural subjunctive laviced
VVSV2	سنيں	vorb
		Second person singular imperative levical
VVIT1	سىن	verb
		Second person singular imperative lexical
VVIT2	سنو	verb
		Second person honorific imperative
VVIA	تتبيين	lexical verb
VXO	L	Root form general auxiliary verb
VAU	しき	Root form general advinary vero
VXNM1N	یرٹ نا	Infinitive general auxiliary verb,
	24	masculine singular nominative
VXNM1O	یڑنے	minitive general auxiliary verb,
		Infinitive general suviliary years
VXNM2	پڑنے	manuve general auxiliary verb,
		Infinitive general auxiliary verb feminine
VXNF1	پڙني	singular nominative
	• •	Infinitive general auxiliary verb. feminine
VXNF2	پرنی	plural nominative

VXTM1N لار) بالمالي المالي VXTM1O بالمالي المالي VXTM2N بالمالي Masculine singular oblique imperfective participle general auxiliary verb VXTM2N بالمالي المالي VXTM2O بالمالي المالي VXTM2O بالمالي Masculine plural oblique imperfective participle general auxiliary verb VXTF1N بالمالي Feminine singular (nominative) imperfective participle general auxiliary verb VXTF1O بالمالي المالي VXTF2N بالمالي المالي VXTF2N بالمالي المالي VXTF2O بالمالي المالي VXTF2O بالمالي المالي VXYM1N المالي المالي VXYM1N المالي Perfective participle general auxiliary verb VXYM1O باله باله VXYM2N باله المالي VXYM2O باله المالي VXYM2O باله المالي VXYM2D بالله المالي VXYF1D بالي المالي VXYF1N المالي Perefective participle g	VXTM1N	پڑتا	Masculine singular (nominative)
VXTM10بزیVXTM2NبزیVXTM2NبزیWasculine singular oblique imperfective participle general auxiliary verbVXTM2OبزیVXTM2OبزیVXTF1NبزیVXTF10بزیVXTF2NبزیVXTF2NبزیVXTF2NبزیVXTP2OبزیVXTF2NبزیVXTF2NبزیVXTF2NبزیVXTP2OبزیVXTF2NبزیVXTF2OبزیVXYM1NبزیVXYM10بزیVXYM2OبزیVXYM2OبزیVXYF10بزیVXYF10بزیVXYF10بزیVXYF10بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXYF20بزیVXSM1بزیVXSM1بزیVXSM2بزیVXSM1بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2بزیVXSM2			verb
VXTM10 بلون المعادي VXTM2N بورن المعادي VXTM2N بورن المعادي VXTM2O بورن المعادي VXTM2O بورن المعادي VXTM2O بورن المعادي VXTM2O بورن المعادي VXTF1N بورن المعادي VXTF1O بورن المعادي VXTF2N بورن المعادي VXTF2N بورن المعادي VXTF2N بورن المعادي VXTF2O بورن المعادي VXTF2O بورن المعادي VXTF2O بورن المعادي VXTF2O بورن المعادي VXYM1N بورن المعادي VXYM1N بورن المعادي VXYM10 بورن المعادي بورن المعادي بورن المعادي VXYM2O بورن المعادي VXYM2O بورن المعادي VXYM2O بورن المعادي VXYF1N بورن المعادي VXYF10 بورن بورن المعادي VXYF20 بورن بورن المعادي VXYF20 بورن بورن المعادي VXYF20 بورن بورن المعادي VXYF20 بورن بورن المعادي			Masculine singular oblique imperfective
VXTM2NبڑےMasculine plural (nominative) imperfective participle general auxiliary verbVXTM2OبڑےMasculine plural oblique imperfective participle general auxiliary verbVXTF1NبڑےFerninine singular (nominative) imperfective participle general auxiliary verbVXTF1OبڑےFerninine singular oblique imperfective participle general auxiliary verbVXTF2NبڑےFerninine plural (nominative) imperfective participle general auxiliary verbVXTF2OبڑےFerninine plural (nominative) imperfective participle general auxiliary verbVXYM1N1بڑےVXYM10بڑےMasculine singular oblique imperfective participle general auxiliary verbVXYM10بڑےMasculine singular (nominative) perfective participle general auxiliary verbVXYM2NبڑےMasculine singular oblique perfective participle general auxiliary verbVXYM2NبڑےMasculine singular oblique perfective participle general auxiliary verbVXYF1NبڑےMasculine plural (nominative) perfective participle general auxiliary verbVXYF10بڑےFerminine singular oblique perfective participle general auxiliary verbVXYF20بڑےFerminine plural (nominative) perfective participle general auxiliary verbVXSM1بڑےFerminine plural noblique perfective participle general auxiliary verbVXSM2بڑےFerminine plural noblique perfective participle general auxiliary verbVXSM1بڑےSecond person singular subjunctive general auxiliary verbVXSV1جڑےSecond person	VATIVITO	پر بے	participle general auxiliary verb
VXTM2N بڑی پڑتی imperfective participle general auxiliary verb VXTM2O بڑی پڑتی Masculine plural oblique imperfective participle general auxiliary verb VXTF1N پڑتی پڑتی Feminine singular (nominative) VXTF1O پڑتی پڑتی پڑتیں VXTF2N پڑتی پڑتی پڑتیں VXTF2N پڑتی پڑتیں VXTF2O پڑتی پڑتیں VXTF2O پڑتی پڑتیں VXYM1N پڑتی پڑتی پڑتیں VXYM1N پڑتی پڑتی پڑتیں VXYM2N پڑتی پڑتی VXYM10 پڑتی پڑتی پڑی پڑتی Masculine singular oblique perfective participle general auxiliary verb VXYM2N پڑی VXYF10 پڑی VXYF10 پڑی VXYF20 پڑی پڑی VXYF10 پڑی پڑی VXYF10 پڑی پڑی VXYF20 پڑی پڑی پڑی پڑی Feminine plural oblique perfective participle general auxiliary verb VXYF10 پڑی پڑی پڑی VXYF20 پڑی پڑی پڑی پڑی پڑی Feminine plural oblique perfective participle general auxiliary verb VXXYF20 پڑی پڑی پڑی <td></td> <td></td> <td>Masculine plural (nominative)</td>			Masculine plural (nominative)
VXTM2Oنوٹ ہےVXTM2Oنوٹ ہےVXTF1Nنوٹ ہےVXTF1Nنوٹ ہےVXTF1Oنوٹ ہےVXTF2Nنوٹ ہےVXTF2Nنوٹ ہےVXTF2Oنوٹ ہےVXTF2Oنوٹ ہےVXTF2Oنوٹ ہےVXTM1Nنوٹ ہےVXYM1Nنوٹ ہےVXYM1Nنوٹ ہےVXYM2Nنوٹ ہےVXYF1Oنوٹ ہےVXYF1Oنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےVXYF1Nنوٹ ہےنوٹ ہےFeminine plural oblique perfective participle general auxiliary verbVXYM2Nنوٹ ہےنوٹ ہےMasculine singular oblique perfective participle general auxiliary verbVXYF1Nنوٹ ہےVXYF10نوٹ ہےVXYF20نوٹ ہےVXYF20نوٹ ہےVXYF20نوٹ ہےVXSM1نوٹ ہےVXSM1نوٹ ہےVXSM2نوٹ ہےVXSM2نوٹ ہےVXST1نوٹ ہےVXSV1نوٹ ہے <td< td=""><td>VXTM2N</td><td>پڑتے</td><td>imperfective participle general auxiliary</td></td<>	VXTM2N	پڑتے	imperfective participle general auxiliary
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VXTF1Nبرتی پزتیFeminine singular (nominative) imperfective participle general auxiliary verbVXTF1Oپزتی پزتیFeminine singular oblique imperfective participle general auxiliary verbVXTF2Nپزتی پزتیپزتی پزتیVXTF2Oپزتی پزتیFeminine plural (nominative) imperfective participle general auxiliary verbVXTF2Oپزتی پزتیFeminine plural oblique imperfective participle general auxiliary verbVXTF1Nپزتی پزتیFeminine singular (nominative) perfective participle general auxiliary verbVXYM1Nپزتی پزتیMasculine singular oblique perfective participle general auxiliary verbVXYM1Oپزتی پزتیMasculine singular oblique perfective participle general auxiliary verbVXYM2Oپزتی پزتیMasculine plural oblique perfective participle general auxiliary verbVXYF1Nپزتی پزتیVXYF10پزتی پزتیVXYF20پزتی پزتیVXYF20پزتی پزتی پزتیVXSM1پزتی پزتی پزتیVXSM2پزتی پزتی پزتی ¥VXSM1پزتی پزتی پزتی ¥VXST1پزتی پزتی Second person singular subjunctive general auxiliary verbVXSV1پزتی پزتی ¥	VX110120	<i>C-</i> 04	participle general auxiliary verb
VXTF1NپرتیVXTF1OپرتیVXTF1OپرتیVXTF2NپرتیVXTF2OپرتیVXTF2OپرتیVXYM1NپرتیVXYM1OپرتیVXYM2NپرتیVXYM2DپرتیVXYF1OپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF1NپرتیVXYF2NپرتیVXYF2NپرتیVXYF2NپرتیVXYF2NپرتیVXYF2NپرتیVXSM1پرتیVXSM1پرتیVXSM2پرتیVXSM2پرتیVXSM2پرتیVXSM1پرتیVXSM2پرتیVXSV1پرتی </td <td></td> <td></td> <td>Feminine singular (nominative)</td>			Feminine singular (nominative)
VXTF10بیزتیFerminine singular oblique imperfective participle general auxiliary verbVXTF2Nپیزتی, پیزتی, پیزتی, strong participle general auxiliary verbFerminine plural (nominative) imperfective participle general auxiliary verbVXTF2Oپیزتی, پیزتی, پیزتی, verbVXYM1NایزMasculine singular (nominative) perfective participle general auxiliary verbVXYM10پیزMasculine singular (nominative) perfective participle general auxiliary verbVXYM2NپیزMasculine plural oblique perfective participle general auxiliary verbVXYM2OپیزMasculine plural (nominative) perfective participle general auxiliary verbVXYF1NپیزPerminine singular oblique perfective participle general auxiliary verbVXYF10پیزFerminine singular oblique perfective participle general auxiliary verbVXYF20پیزFerminine singular oblique perfective participle general auxiliary verbVXSM1پیز<	VXTF1N	پرتی	imperfective participle general auxiliary
VXTF10برتیFeminine singular oblique imperfective participle general auxiliary verbVXTF2Nبرتی, پرتی, پرتی اس		_	verb
vxrr10نجاریvxrF2Nپزتی پزتی پزتی (nominative)vxrF2Oپزتی پزتی پزتی (nominative)vxrF2Oپزتی پزتی پزتی (nominative)vxrM1Nپزتی (nominative)vxYM1Nپزتی (nominative)vxYM10پزتی (nominative)vxYM2Nپزتی (nominative)vxYM2Nپزتی (nominative)vxYM2Nپزتی (nominative)vxYP1Nپزتی (nominative)vxYM2Nپزتی (nominative)vxYM2Nپزتی (nominative)vxYP10پزتی (nominative)vxYF1Nپزتی (nominative)vxYF1Nپزتی (nominative)vxYF10پزتی (nominative)vxYF20پزتی (nominative)vxYF20پزتی (nominative)vxYF20پزتی (nominative)vxXF2پزی (nominative)vxSM1پزی (nominative)vxSM2پزی (nominative)vxSM2پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxYF20پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)vxSV1پزی (nominative)v	VXTE10		Feminine singular oblique imperfective
VXTF2Nبرتی پڑتی پڑتی (nominative) imperfective participle general auxiliary verbVXTF2Oبرتی پڑتی پڑتی (nominative) participle general auxiliary verbVXYM1NاليVXYM1OبرتیVXYM2NبرتیVXYM2NبرتیVXYM2DبرتیVXYF1NسانیVXYF1NبرتیVXYF1NبرتیVXYF1NبرتیVXYF1NبرتیVXYF1NبرتیVXYF1NبرتیVXYF10برتیVXYF20برتیVXYF20برتیVXYF20برتیVXYF20برتیVXSM1برتیVXSM1برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXSM2برتیVXST2ودما person singular subjunctive general auxiliary verbVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتیVXSV1برتی </td <td>VALLIO</td> <td>چرسی</td> <td>participle general auxiliary verb</td>	VALLIO	چرسی	participle general auxiliary verb
VXTF2Nپرتی, پرتینimperfective participle general auxiliary verbVXTF2OپرتیFeminine plural oblique imperfective participle general auxiliary verbVXYM1NیزیMasculine singular (nominative) perfective participle general auxiliary verbVXYM1OپرتسینVXYM2NپرتMasculine singular oblique perfective participle general auxiliary verbVXYM2NپرتMasculine singular oblique perfective participle general auxiliary verbVXYM2OپرتMasculine plural (nominative) perfective participle general auxiliary verbVXYF1NپرتFeminine singular (nominative) perfective participle general auxiliary verbVXYF2NپرتپرتVXYF2OپرتFeminine singular oblique perfective participle general auxiliary verbVXYF2OپرتFeminine plural (nominative) perfective participle general auxiliary verbVXSM1پرتپرتVXSM2پرتFeminine plural (nominative) perfective participle general auxiliary verbVXSM2پرتFeminine plural oblique perfective participle general auxiliary verbVXSM2پرتFirst person singular subjunctive general auxiliary verbVXST1پرتSecond person singular subjunctive general auxiliary verbVXSV1پرتSecond person plural subjunctive general auxiliary verb			Feminine plural (nominative)
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VXYM10بزیMasculine singular oblique perfective participle general auxiliary verbVXYM2Nبزیسابت المعاليVXYM2OبزیالمعاليVXYM2OبزیالمعاليVXYF1NبزیالمعاليVXYF1NالمعاليالمعاليVXYF1OالمعاليالمعاليVXYF2NالمعاليالمعاليVXYF2NالمعاليالمعاليVXYF2NالمعاليالمعاليVXYF2OالمعاليالمعاليVXSM1المعاليالمعاليVXSM2المعاليالمعاليVXSM2المعاليالمعاليVXST1المعاليالمعاليVXST2المعاليالمعاليVXSV1المعالي			verb
VXYM10بازیVXYM2NبازیVXYM2NبازیVXYM2OبازیVXYM2OبازیVXYF1NبازیVXYF1NبازیVXYF1OبازیVXYF2NبازیVXYF2NبازیVXYF2NبازیVXYF2NبازیVXYF2OبازیVXYF2NبازیبازیFeminine singular oblique perfective participle general auxiliary verbVXYF2NبازیVXYF2OبازیVXSM1بازیVXSM2بازیVXST1بازیپزیSecond person singular subjunctive general auxiliary verbVXST2بازیVXSV1بازیVXSV1بازیThird person singular subjunctive general auxiliary verbVXSV1بازیThird person singular subjunctive general auxiliary verbVXSV1بازیThird person singular subjunctive general auxiliary verbVXSV1بازی۲Third person singular subjunctive general auxiliary verbVXSV1بازی۲Third person singular subjunctive general auxiliary verb۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲۲	1000000	L .	Masculine singular oblique perfective
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VXYM2OپڑےMasculine plural oblique perfective participle general auxiliary verbVXYF1NپڑےFeminine singular (nominative) perfective participle general auxiliary verbVXYF1OپڑےFeminine singular oblique perfective participle general auxiliary verbVXYF2NپڑےFeminine plural (nominative) perfective participle general auxiliary verbVXYF2NپڑےFeminine plural (nominative) perfective participle general auxiliary verbVXYF2OپڑےFeminine plural oblique perfective participle general auxiliary verbVXSM1پڑےFeminine plural oblique perfective general auxiliary verbVXSM2پڑےFirst person singular subjunctive general auxiliary verbVXST1پڑےSecond person singular subjunctive general auxiliary verbVXSV1پڑےThird person singular subjunctive general auxiliary verb	VXYM2N	پرے	participle general auxiliary verb
VXYM2OپرےVXYF1NپرےVXYF1NپرےVXYF1OپرےVXYF1OپرےVXYF2NپرےVXYF2NپرےپرےFeminine singular oblique perfective participle general auxiliary verbVXYF2OپرےVXSM1پرےVXSM2پرےVXST1پرےپرےSecond person singular subjunctive general auxiliary verbVXST1پرےپرےSecond person singular subjunctive general auxiliary verbVXST2پرےVXSV1پرےVXSV1پرےپرےThird person singular subjunctive general auxiliary verbVXSV1پرےپرےThird person singular subjunctive general auxiliary verb	VXYM2O	پڑے	Masculine plural oblique perfective
VXYF1NبیڑیFeminine singular (nominative) perfective participle general auxiliary verbVXYF1OبیڑیFeminine singular oblique perfective participle general auxiliary verbVXYF2Nپیڑی, پڑیںFeminine plural (nominative) perfective participle general auxiliary verbVXYF2Nپیڑی, پڑیںFeminine plural (nominative) perfective participle general auxiliary verbVXYF2OپڑیںFeminine plural oblique perfective participle general auxiliary verbVXSM1پیڑیFirst person singular subjunctive general auxiliary verbVXSM2پڑیںFirst person plural subjunctive general auxiliary verbVXST1پڑیSecond person singular subjunctive general auxiliary verbVXST2پڑیSecond person plural subjunctive general auxiliary verbVXSV1پڑیThird person singular subjunctive general auxiliary verb			participle general auxiliary verb
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VXYF10بوریVXYF10پزیVXYF2NپزیVXYF2NپزیپزیFeminine plural (nominative) perfective participle general auxiliary verbVXYF2OپزیVXSM1پزیVXSM2پزیVXST1پزیپزیSecond person singular subjunctive general auxiliary verbVXST1پزیپزیSecond person singular subjunctive general auxiliary verbVXST1پزیپزیSecond person singular subjunctive general auxiliary verbVXST2پزیپزیThird person singular subjunctive general auxiliary verbVXSV1پزی	VXYF1N		perfective participle general auxiliary
VXYF10پڑیFeminine singular oblique perfective participle general auxiliary verbVXYF2Nپڑی, پڑیFeminine plural (nominative) perfective participle general auxiliary verbVXYF2Oپڑی, پڑیFeminine plural oblique perfective participle general auxiliary verbVXSM1پڑیFirst person singular subjunctive general auxiliary verbVXSM2پڑیFirst person plural subjunctive general auxiliary verbVXST1پڑیSecond person singular subjunctive general auxiliary verbVXST2پڑیSecond person plural subjunctive general auxiliary verbVXSV1پڑیThird person singular subjunctive general auxiliary verb			verb
VXYF10یریپیریparticiple general auxiliary verbVXYF2Nپیری, پیریFeminine plural (nominative) perfective participle general auxiliary verbVXYF2Oپیری, پیریFeminine plural oblique perfective participle general auxiliary verbVXSM1پیریFirst person singular subjunctive general auxiliary verbVXSM2پیریFirst person plural subjunctive general auxiliary verbVXST1پیریSecond person singular subjunctive general auxiliary verbVXST2پیریSecond person plural subjunctive general auxiliary verbVXSV1پیریThird person singular subjunctive general auxiliary verb		پڑی	Feminine singular oblique perfective
VXYF2Nپڑی, پڑیں پڑیںFeminine plural (nominative) perfective participle general auxiliary verbVXYF2Oپڑی, پڑیںFeminine plural oblique perfective participle general auxiliary verbVXSM1پڑیںFirst person singular subjunctive general auxiliary verbVXSM2پڑیںFirst person plural subjunctive general auxiliary verbVXST1پڑیںSecond person singular subjunctive general auxiliary verbVXST2پڑےSecond person plural subjunctive general auxiliary verbVXSV1پڑےThird person singular subjunctive general auxiliary verb	VXYF1O		participle general auxiliary verb
VXYF2Nپری پریپریVXYF2OپیFeminine plural oblique perfective participle general auxiliary verbVXSM1پیFirst person singular subjunctive general auxiliary verbVXSM2پیFirst person plural subjunctive general auxiliary verbVXST1پیSecond person singular subjunctive general auxiliary verbVXST2پیSecond person plural subjunctive general auxiliary verbVXSV1پیThird person singular subjunctive general auxiliary verb		L . L .	Feminine plural (nominative) perfective
VXYF2OپزیVXSM1پزیVXSM2پزیVXST1پزیVXST1پزیپزیSecond person singular subjunctive general auxiliary verbVXST1پزیVXST2پزیVXSV1پزیپزیSecond person plural subjunctive general auxiliary verbVXSV1پزیپزیSecond person singular subjunctive general auxiliary verbVXSV1پزیپزیSecond person singular subjunctive general auxiliary verbVXSV1پزیVX	VXYF2N	پری پریں	participle general auxiliary verb
VXYF2OپرتیVXSM1پیژیVXSM2پیژیںVXST1پیژیںVXST2پیژیVXST2پیژیVXST2پیژیVXSV1پیژیVXSV1پیژیپیژیSecond person singular subjunctive general auxiliary verbVXSV1پیژیVXSV1پیژیپیژیSecond person plural subjunctive general auxiliary verbVXSV1پیژیVXSV1پیژیپیژیThird person singular subjunctive general auxiliary verbVXSV1پیژیV		L	Feminine plural oblique perfective
VXSM1پڑوںVXSM2پڑوںVXST1پڑوںFirst person plural subjunctive general auxiliary verbVXST2پڑوںVXST2پڑوںVXSV1پڑوںVXSV1پڑوںVXSV1پڑوںVXSV1پڑوںVXSV1پڑوںVXSV1پڑوںVXSV1پڑوںپڑوںThird person singular subjunctive general auxiliary verbVXSV1پڑوں	VXYF2O	ږرى	participle general auxiliary verb
VXSM1پڑوںVXSM2پڑوںVXST1پڑےVXST2پڑےVXST2پڑےVXSV1پڑےVXSV1پڑے			First person singular subjunctive general
VXSM2پڑیںVXST1پڑیںVXST2پڑیںVXST2پڑیVXSV1پڑےVXSV1پڑے	VXSM1	<u>پروں</u>	auxiliary verb
VXSM2 پرین Instribution plantal subjunctive general auxiliary verb VXST1 پرئے Second person singular subjunctive general auxiliary verb VXST2 پرئے Second person plural subjunctive general auxiliary verb VXSV1 پرئے Third person singular subjunctive general auxiliary verb	VXSM2	L	First person plural subjunctive general
VXST1پزےVXST2پزےVXSV1پزےVXSV1پزے		پریں	auxiliary verb
VXST1پزےVXST2پزےVXSV1پزےVXSV1پزے		L	Second person singular subjunctive
VXST2 پزو VXSV1 پزو Second person plural subjunctive general auxiliary verb Third person singular subjunctive general auxiliary verb	VXST1	پڑے	general auxiliary verb
VXST2 پرتو VXSV1 پرتو		L	Second person plural subjunctive general
VXSV1 پزے Third person singular subjunctive general auxiliary verb	VXST2	پڙو.	auxiliary verb
VXSV1 پزرے استان کی پرنے		L	Third person singular subjunctive general
	VXSV1	پرے	auxiliary verb

VXSV2	پڑیں	Third person plural subjunctive general auxiliary verb
VXIT1	پڑ	Second person singular imperative general auxiliary verb
VXIT2	پڑو	Second person singular imperative general auxiliary verb
VXIA	پڑئے	Second person honorific imperative general auxiliary verb
VGM1	گا	Masculine singular future auxiliary $g\bar{a}$
VGM2	گ	Masculine plural future auxiliary $g\bar{e}$
VGF1	گی	Feminine singular future auxiliary $g\overline{i}$
VGF2	گی	Feminine plural future auxiliary $g\overline{i}$
VRM1	2	Masculine singular durative auxiliary <i>rahā</i>
VRM2	رہے	Masculine plural durative auxiliary rahē
VRF1	رہی	Feminine singular durative auxiliary rahī
VRF2	رہی	Feminine plural durative auxiliary <i>rahī</i>
VC1	چاہئے	Singular cāhiē-type auxiliary
VC2	چاہتیں	Plural cāhiē-type auxiliary
VH0	ہو	Root form <i>hō</i>
VHNM1N	ہونا	Infinitive <i>hōnā</i> , masculine singular nominative
VHNM10	ہونے	Infinitive <i>hōnē</i> , masculine singular oblique
VHNM2	ہونے	Infinitive <i>hōnē</i> , masculine plural nominative
VHNF1	ہونی	Infinitive <i>hōnī</i> , feminine singular nominative
VHNF2	ہونی	Infinitive <i>hōnī</i> , feminine plural nominative
VHTM1N	ہوتا	Masculine singular (nominative) imperfective participle <i>hōtā</i>
VHTM1O	ہوتے	Masculine singular oblique imperfective participle <i>hōtē</i>
VHTM2N	ہوتے	Masculine plural (nominative) imperfective participle <i>hōtē</i>
VHTM2O	ہوتے	Masculine plural oblique imperfective participle <i>hōtē</i>
VHTF1N	ہوئی	Feminine singular (nominative) imperfective participle <i>hōtī</i>
VHTF10	ہونی	Feminine singular oblique imperfective

		participle <i>hōtī</i>		
بەت. بەتىرى VHTE2NI		Feminine plural (nominative)		
	0-97,6-97	imperfective participle hotī / hotī~		
VHTF2O	یو ئے ر	Feminine plural oblique imperfective		
	607	participle <i>hoti</i>		
VHYM1N	ہوا	perfective participle $h\bar{u}\bar{a}$		
		Masculine singular oblique perfective		
VHYM1O	ہوتے	participle <i>huē</i>		
	•	Masculine plural (nominative) perfective		
VHYM2N	ہوبے	participle hūē		
	1	Masculine plural oblique perfective		
	ہوئے	participle <i>hūē</i>		
	101	Feminine singular (nominative)		
VIIII	6.57	perfective participle <i>hūī</i>		
VHYF10	ہو ئے ر	Feminine singular oblique perfective		
	00.	Femining plural (nominative) perfective		
VHYF2N	ہوتی ہوتیں	participle $h\bar{u}\bar{u} / h\bar{u}\bar{v}_{\sim}$		
		Feminine plural oblique perfective		
VHYF2O	ہوتی	participle $h\bar{u}\bar{i}$		
VHSM1	ہوں	First person singular subjunctive hū~		
VHSM2	<i>ډون</i>	First person plural subjunctive hō~		
VHST1	ہو	Second person singular subjunctive hō		
VHST2	ہو	Second person plural subjunctive hō		
VHSV1	ہو	Third person singular subjunctive hō		
VHSV2	ہوں	Third person plural subjunctive <i>hō</i> ~		
VHIT1	ہو	Second person singular imperative $h\bar{o}$		
VHIT2	ہو	Second person plural imperative $h\bar{o}$		
VHIA		Second person honorific imperative		
VHHM1	ہوں	First person singular indicative present $h\bar{u}$ ~		
VHHM2	ہیں	First person plural indicative present hai~		
VHHT1	<u> </u>	Second person singular indicative present <i>hai</i>		
VHHT2	ہو	Second person plural indicative present		
		Third person singular indicative present		
VHHV1	<i>_</i> ?	hai		
) (I II I) (O		Third person plural indicative present		
VHHV2	ہیں	hai~		

VHPM1	تها	Masculine singular indicative past thā
VHPM2	تھے	Masculine plural indicative past thē
VHPF1	تھی	Feminine singular indicative past $th\bar{t}$
VHPF2	تھیں	Feminine plural indicative past <i>thī</i> ~
XT	تو	Contrastive emphatic particle $t\bar{o}$
ХН	ہی	Exclusive emphatic particle $h\bar{i}$
XHC	ى، يں، ہيں	Clitic exclusive emphatic particle $\bar{\imath}$, $\bar{\imath}$ ~, $h\bar{\imath}$ ~
ZZ	نے	izāfat
•	-	Full stop (U+06D4)
,	4	Comma (U+060C)
?	ę	Question mark (U+061F)
!	!	Exclamation mark (U+0021)
:	:	Colon (U+003A)
;	:	Semi-colon (U+061B)
"	"	Neutral quotation mark (U+0022)
()	Open parenthesis (U+0028)
)	(Close parenthesis (U+0029)
[[Open square bracket (U+005B)
]	[Close square bracket (U+005D)
~	/	Other punctuation

Arabic Tagset

Tag	Description of word category	Example (Arabic)	Transcription	Translation
NCSgMNI	Singular, masculine, nominative, indefinite common noun	كتاب	kitabun	book
NCSgMAI	Singular, masculine, accusative, indefinite common noun	1,12	kitaban	book
NCSgMGI	Singular, masculine, genitive, indefinite common noun	کتاب	kitabin	book
NCSgMND	Singular, masculine, nominative, definite common noun	الكتاب	alkitabu	the book
NCSgMAD	Singular, masculine, accusative, definite common noun	الكتاب	alkitaba	the book
NCSgMGD	Singular, masculine, genitive, definite common noun	الكتاب	alkitabi	the book
NCSgFNI	Singular, feminine, nominative, indefinite common noun	مدرسة	madrasatun	school
NCSgFAI	Singular, feminine, accusative, indefinite common noun	مدرستأ	madrasatan	school
NCSgFGI	Singular, feminine, genitive, indefinite common noun	مدرسةٍ	madrasatin	school
NCSgFND	Singular, feminine, nominative, definite common noun	المدرسة'	almadrasatu	the school

NCSgFAD	Singular, feminine, accusative, definite common noun	المدرسة"	almadrasata	the school
NCSgFGD	Singular, feminine, genitive, definite common noun	المدرسةِ	aladrasati	the school
NCDuMNI	Dual, masculine, nominative, indefinite common noun	كتابان	kitaban	two books
NCDuMAI	Dual, masculine, accusative, indefinite common noun	كتابين	kitabain	two books
NCDuMGI	Dual, masculine, genitive, indefinite common noun	كتابين	kitabain	two books
NCDuMND	Dual, masculine, nominative, definite common noun	الكتابان	alkitaban	the two books
NCDuMAD	Dual, masculine, accusative, definite common noun	الكتابين	alkitabain	the two books
NCDuMGD	Dual, masculine, genitive, definite common noun	الكتابين	alkitabain	the two books
NCDuFNI	Dual, feminine, nominative, indefinite common noun	مدرستان	madrasatan	two books
NCDuFAI	Dual, feminine, accusative, indefinite common noun	مدرستين	madrasatain	two schools
NCDuFGI	Dual, feminine, genitive, indefinite common noun	مدرستين	madrasatain	two schools
NCDuFND	Dual, feminine, nominative, definite common noun	المدرستان	almadrasatan	the two schools
NCDuFAD	Dual, feminine, accusative, definite common noun	المدرستين	almadrasatain	the two schools
NCDuFGD	Dual, feminine, genitive, definite common noun	المدرستين	almadrasatain	the two schools
NCPIMNI	Plural, masculine, nominative, indefinite common noun	کتب - مسلمون	muslimoon – kutubun	Muslims – books
NCPIMAI	Plural, masculine, accusative, indefinite common noun	كتبا - مىلمىن	muslimeen – kutuban	Muslims – books
NCPIMGI	Plural, masculine, genitive, indefinite common noun	کتبٍ ۔ مسلمین	muslimeen – kutubin	Muslims – books
NCPIMND	Plural, masculine, nominative, definite common noun	الكتب - المسلمون	almuslimoon – alkutubu	the Muslims – the books
NCPIMAD	Plural, masculine, accusative, definite common noun	الكتبّ - المسلمين	aluslimeen – alkutuba	the Muslims – the books
NCPIMGD	Plural, masculine, genitive, definite common noun	الكتبر - المسلمين	almuslimeen – alkutubi	the Muslims – the books
NCP1FNI	Plural, feminine, nominative, indefinite common noun	مسلمات مدارس	madarisun – muslimaatun	schools – Muslims
NCP1FAI	Plural, feminine, accusative, indefinite common noun	مسلماتا [*] -مدارسا *	madarisan – muslimaatan	schools – Muslims
NCP1FGI	Plural, feminine, genitive, indefinite, common noun	مىلماتېمدارىس	madarisin – muslimaatin	schools – Muslims
NCPIFND	Plural, feminine, nominative, definite common noun	المسلمات–المدارس	almadarisu – almuslimaatu	the schools – the Muslims
NCPIFAD	Plural, feminine, accusative, definite common noun	المسلمات-المدارس	almadarisa – almuslimaata	the schools – the Muslims
NCPIFGD	Plural, feminine, genitive, definite common noun	المسلمات,-المدارس,	almadarisi – almuslimaati	the schools – the Muslims
NP	Proper noun	سَبِرِين-جده	Jiddah – Shyryn	Jeddah – Shereen
NPrPSg1	First person, singular, neuter, personal pronoun	كتابي - ضريني-أنا	ana- kitaabee – darabanee	Me – my book – he hit me
NPrPSg2M	Second person, singular, masculine, personal pronoun	كتابك أنت	anta – kitaabuka	You – your book
NPrPSg2F	Second person, singular, feminine, personal pronoun	كتابافر-أنتر	anti – kitaabuki	You – your book
NPrPSg3M	Third person, singular, masculine, personal pronoun	هو -كتابه	kitaabahu – huwa	His book – him
NPrPSg3F	Third person, singular, feminine, personal	ھی ۔ کتابھا	kitaabuhaa – hiya	Her book –

	0/00 000			her
NPrPDu2	Second person, dual, neuter, personal pronoun	pronotal Second person, dual, neuter, personal pronoun كتابكما–أنتما		You two – your book
NPrPDu3	Third person, dual, neuter, personal pronoun	كتابهما ــ هما	humaa – kitaabahumaa	Those two – their book
NPrPP11	First person, plural, neuter, personal pronoun	كتابنا-نحن	na <u>h</u> nu – kitaabunaa	Us – our book
NPrPP12M	Second person, plural, masculine, personal pronoun	كتابكم_أنتم	antum – kitaabakum	You – your book
NPrPP12F	Second person, plural, feminine, personal pronoun	كتابكن_أتتن	antunna – kitaabakunna	You – your book
NPrPP13M	Third person, plural, masculine, personal pronoun	کتابهم–هم	hum – kitaabahum	Them – their book
NPrPP13F	Third person, plural, feminine, personal pronoun	هن - کتابهن	kitaabahunna – hunna	Their book – them
NPrRSSgM	Singular, masculine, specific, relative	الذى	allathi	Who
	pronoun Singular feminines specific relative			
NPrRSSgF	pronoun	التي	allati	Who
NPrRSDuM	Dual, masculine, specific, relative pronoun	اللذين ــ اللذان	alla <u>dhai</u> ni – alla <u>dhai</u> ni	Who
NPrRSDuF	Dual, feminine, specific, relative pronoun	اللتين ــ اللتان	allataani – allataini	Who
NPrRSPIM	Plural, masculine, specific, relative pronoun	اللذين - اللائي	allaiy – alla <u>dh</u> eena	Who
NPrRSP1f	Plural, feminine, specific, relative pronoun	التتي - التئي	allaaiy - allatee	Who
NPrRC	Common, relative pronoun	مهما- ما -من	men – maa – mahmaa	Who – what
NPrDSgM	Singular, masculine, demonstrative pronoun	ذلك ــ ذاك ــ ذا ـهذا	ha <u>dh</u> aa – <u>dh</u> aa – <u>dh</u> aaka – <u>dh</u> aalika	This – that
NPrDSgF	Singular, feminine, demonstrative pronoun	ــ نلك ــ ذي ــ ذه ــ هذي ــهذه نبِك ــنلك	haa <u>dh</u> ihi — haa <u>dh</u> ee — <u>dh</u> ih — <u>dh</u> y — tilka — taaka — teeka	This – that
NprDDuM	Dual, masculine, demonstrative pronoun	– هذین – ذانك – ذان –هذان ذینك–ذین	haa <u>dh</u> ani – <u>dh</u> aani – <u>dh</u> aanika – ha <u>dh</u> aini – <u>dh</u> aini	This – that
NprDDuF	Dual, feminine, demonstrative pronoun	ئين – هئين – ئانڭ – ئان –هئان ئينڭ–	haatani – taani- taanika – haataini	This – that
NPrDPl	Plural, neutral, demonstrative pronoun	أو لائك – أو لاء – أو لى –هؤ لاء أو لاك – أو لاك –	haaolaai – olaa- olaaika- olaalika – olaaka	Those
NNuCaSgM	Singular, masculine, cardinal number	أريع	arba'	Four
NNuCaSgF	Singular, feminine, cardinal number	أربعة	arba'a	Four
NNuOrSgM	Singular, masculine, ordinal number	ربع	raabi	Fourth
NNuOrSgF NNuNaSaM	Singular, remaine, ordinal number	ربعه دياء	raabia	Offour
NNuNaSeF	Singular, masculine, numerical adjective	رياعي	rubaa'iya	Offour
	Singular, masculine, nominative,		, ,	
NACSgMNI	indefinite adjective	يتعتز	sa'ydun	happy
NACSgMAI	adjective	مىعيدا	sa'ydan	happy
NACSgMGI	Singular, masculine, genitive, indefinite adjective	مى مىر چ	sa'ydin	happy
NACSgMND	Singular, masculine, nominative, definite adjective	السعيد	alsa'ydu	the happy
NACSgMAD	Singular, masculine, accusative, definite adjective	السعيد	alsa'yda	the happy
NACSgMGD	Singular, masculine, genitive, definite adjective	الممعيد	alsa'ydi	the happy
NACSgFNI	Singular, feminine, nominative, indefinite adjective	سعيدة	sa'ydatun	happy

NACSgFAI	Singular, feminine, accusative, indefinite adjective	سعيدنا	sa'ydatan	happy
NACSgFGI	Singular, feminine, genitive, indefinite adjective	<i>سعيد</i> ةٍ	sa'ydatin	happy
NACSgFND	Singular, feminine, nominative, definite adjective	السعيدة'	alsa'ydatu	the happy
NACSgFAD	Singular, feminine, accusative, definite adjective	السعيدة'	alsa'ydata	the happy
NACSgFGD	Singular, feminine, genitive, definite adjective	السعيدة	alsa'ydati	the happy
NACDuMNI	Dual, masculine, nominative, indefinite	سعيدان	sa'ydan	two happy
NACDuMAI	adjective Dual, masculine, accusative, indefinite adjective	سعيدين	sa'ydain	two happy
NACDuMGI	Dual, masculine, genitive, indefinite adjective	سعيدين	sa'ydain	two happy
NACDuMND	Dual, masculine, nominative, definite adjective	السعيدان	alkitaban	the two happy
NACDuMAD	Dual, masculine, accusative, definite adjective	السجدين	alsa'ydain	the two happy
NACDuMGD	Dual, masculine, genitive, definite adjective	السجدين	alsa'ydain	the two happy
NACDuFNI	Dual, feminine, nominative, indefinite adjective	سعيدتان	sa'ydatan	two happy
NACDuFAI	Dual, feminine, accusative, indefinite adjective	سعيدتين	sa'ydatain	two happy
NACDuFGI	Dual, feminine, genitive, indefinite adjective	سعيدتين	sa'ydatain	two happy
NACDuFND	Dual, feminine, nominative, definite adjective	السعيدتان	alsa'ydatan	the two happy
NACDuFAD	Dual, feminine, accusative, definite adjective	السعيدنتين	alsa'ydatain	the two happy
NACDuFGD	Dual, feminine, genitive, definite adjective	السعيدنين	alsa'ydatain	the two happy
NACPIMNI	Plural, masculine, nominative, indefinite adjective	سعيدون	sa'ydoon	happy
NACPIMAI	Plural, masculine, accusative, indefinite adjective	سعيدين	sa 'ydeen	happy
NACPIMGI	Plural, masculine, genitive, indefinite adjective	سحيدين	sa 'ydeen	happy
NACPIMND	Plural, masculine, nominative, definite adjective	السجدون	alsa'ydoon	the happy
NACPIMAD	Plural, masculine, accusative, definite adjective	السجدين	alsa'ydeen	the happy
NACPIMGD	Plural, masculine, genitive, definite adjective	السجدين	alsa'ydeen	the happy
NACPIFNI	Plural, feminine, nominative, indefinite adjective	سعيدات	sa'ydaatun	happy
NACPIFAI	Plural, feminine, accusative, indefinite adjective	سعيدانا ^ع	sa'ydaatan	happy
NACPIFGI	Plural, feminine, genitive, indefinite, adjective	مىعيدات	sa'ydaatin	happy
NACPIFND	Plural, feminine, nominative, definite adjective	السجيدات	alsa'ydaatu	the happy
NACPIFAD	Plural, feminine, accusative, definite adjective	السجيدات	alsa'ydaata	the happy
NACPIFGD	Plural, feminine, genitive, definite adjective	السعيدات	alsa'ydaati	the happy
VPSg1	First person, singular, neuter, perfect verb	كبرك	kasartu	I broke
VPSg2M	Second person, singular, masculine, perfect verb	كسرت	kasarta	You broke
VPSg2F	Second person, singular, feminine, perfect verb	کسرے	kasarti	You broke
VPSg3M	Third person, singular, masculine, perfect verb	كسر	kasara	He broke
VPSg3F	Third person, singular, feminine, perfect verb	گىرڭ	kasarat	She broke
VPDu2	Second person, dual, neuter, perfect verb	كسرتما	kasartumaa	You (two) broke

VPDu3M	Third person, dual, masculine, perfect verb کسرا kasaraa		kasaraa	They (two) broke
VPDu3F	Third person, dual, feminine, perfect verb	كسركا	kasarataa	They (two) broke
VPP11	First person, plural, neuter, perfect verb	کسرنا	kasarnaa	We broke
VPP12M	Second person, plural, masculine, perfect verb	كسرتم	kasartum	You broke
VPP12F	Second person, plural, feminine, perfect verb	گسرتن	kasartunna	You broke
VPP13M	Third person, plural, masculine, perfect verb	کسروا	kasaroo	They broke
VPP13F	Third person, plural, feminine, perfect verb	كسرن	kasarna	They broke
VISg1I	First person, singular, neuter, indicative, imperfect verb	أكسر	aksiru	I break
VISg1S	First person, singular, neuter, subjunctive, imperfect verb	أكسر	aksira	I break
VISg1J	First person, singular, neuter, jussive, imperfect verb	أكسر	aksir	I break
VISg2MI	Second person, singular, masculine, indicative, imperfect verb	تكسر	taksiru	You break
VISg2MS	Second person, singular, masculine, subjunctive, imperfect verb	ئكسر	taksira	You break
VISg2MJ	Second person, singular, masculine, jussive, imperfect verb	ئكسر	taksir	You break
VISg2FI	Second person, singular, feminine, indicative, imperfect verb	نگسرين	taksiryna	You break
VISg2FS	Second person, singular, feminine, subjunctive, imperfect verb	نكسر ي	taksiry	You break
VISg2FJ	Second person, singular, feminine, jussive, imperfect verb	نگسر ي	taksiry	You break
VISg3MI	Third person, singular, masculine, indicative, imperfect verb	يكسر'	yaksiru	He breaks
VISg3MS	Third person, singular, masculine, subjunctive, imperfect verb	يكسر	yaksira	He breaks
VISg3MJ	Third person, singular, masculine, jussive, imperfect verb	يكسر	yaksir	He breaks
VISg3FI	Third person, singular, feminine, indicative, imperfect verb	تكسر	taksiru	She breaks
VISg3FS	Third person, singular, feminine, subjunctive, imperfect verb	ئكسر	taksira	She breaks
VISg3FJ	Third person, singular, feminine, jussive,	تگسر	taksir	She breaks
VIDu2I	Second person, dual, neuter, indicative, imperfect yerb	نگسران	taksiraani	You break
VIDu2S	Second person, dual, neuter, subjunctive, imperfect verb	تكسرا	taksiraa	You break
VIDu2J	Second person, dual, neuter, jussive, imperfect verb	تكسرا	taksiraa	You break
VIDu3MI	Third person, dual, masculine, indicative, imperfect verb	يكسران	yaksiraani	They break
VIDu3MS	Third person, dual, masculine, subjunctive, imperfect verb	يكسرا	yaksiraa	They break
VIDu3MJ	Third person, dual, masculine, jussive, imperfect verb	يكسرا	yaksiraa	They break
VIDu3FI	Third person, dual, feminine, indicative, imperfect verb	يكسران	yaksiraan	They break
VIDu3FS	Third person, dual, feminine, subjunctive, imperfect verb	يكسرا	yaksiraa	They break
VIDu3FJ	Third person, dual, feminine, jussive, imperfect verb	يكسرا	yaksiraa	They break
VIP111	First person, plural, neuter, indicative,	تكسر'	naksiru	We break
VIP11S	imperfect verb First person, plural, neuter, subjunctive,	نكسر	naksira	We break
VIP11J	imperfect verb First person, plural, neuter, jussive,	نكسر	naksir	We break
VIP12MI	Second person, plural, masculine, indicative, imperfect verb	تگىرون	taksiroon	You break

Hindi Tagset

Table 18: Tagset for Hindi language⁶

Main Category	Sub category	Example
Noun	Noun	Boy, river, thought, hardness
	Location	Up, down, front, back
	Compound	
Proper noun	Compound	RAM, BJP
Pronoun		Who, that, he, the boy who
Verb	Verb finite main	He drinks, the boy is
	Auxiliary	Has
	Nonfinite adjectival	Eating
	Nonfinite adverbial	After eating, drinking
	Nonfinite nominal	Drinking
Adjective		
Adverb.		Slowly, fast
Postposition		By, for
Particle		ہی، بھی، تو
Conjunct		And, or , that
Question words		What, how
Quantifer		More, little, all, much
Number quatifier		Third, three
Intensifier		Too much, much more
Negative		No, not
Interjection		
words		
Special		

⁶ A part of speech tagger for Indian languages, available at <u>http://shiva.iiit.ac.in/SPSAL2007</u> /iiit_tagset_guidelines.pdf

Tagset of Penn Treebank

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Category	Sub category
Coordinating	
conjunction	
Cardinal number	
Determiner	
Existential there	
Foreign word	
Preposition or	
subordinating	
conjunction	
Adjective	Comparative, superlative
List item marker	
Modal	
Noun	Singular, plural, proper singular, proper plural
Pre-determiner	
Pronoun	Personal, possessive
Adverb	Comparative, superlative
Particle	
Symbol	
То	
Interjection	
Verb	Root, past tense, gerund, past participle, non-3 rd person singular
	present, 3 rd person singular present
Question words	Wh-determiner, wh-pronoun, possessive wh-pronoun, wh-adverb
Punctuation marks	

⁷ The information about Penn TreeBank is taken from the following document: http://www.ling.ohiostate.edu/~dm/02/spring/795K/casden-treebank-4up.pdf