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Original Article

# HOMONYMY DETECTION USING A NAÏVE BAYES CLASSIFIER

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***ABSTRACT***

***One of the important issues of natural language processing is the semantic differentiation of homonyms. Methods based on machine learning play a special role in solving this problem. Naive Bayes classifier is one of the important machine learning methods. When eliminating homonymy between different and grammatically similar groups of words in the Uzbek language, the naive Bayes classifier differs from other methods in its simplicity and speed. This article describes in detail the processes of using a naive Bayes classifier to identify homonymy between grammatically similar groups of words in the Uzbek language.***

***KEYWORDS: Natural Language Processing, Homonymy, Naive Bayes Classifier, Text Classification, Prior and Posterior Probabilities, Scikit Learning Library.***

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## INTRODUCTION.

Semantic analysis of texts is one of the most important issues in the field of natural language processing, that is, determining the meaning of a sentence by determining the meaning of the words in the text, and determining the meaning of the text through the sentence is one of the topical topics. By determining the meaning of texts, a text (annotation) representing their brief content is created. Semantic analysis of texts is also divided into two parts:

Word sense disambiguation (WSD)

- Synonym
- my name
- Polysemantic
- Polyfunctional
- Antonym
- Paronym
- Hyponym
- Meronym
- Hyperonym

Sentiment analysis

- Determining the feeling in the text
- Determining the purpose of the text

- Determining the area of the text

One of the important issues of word sense disambiguation is the issue of eliminating homonymy. A question arises instead. Why is the identification of homonyms a topical issue? A homonym can have different meanings within one-word group and within different word groups. Determining the exact meaning of this homonym is very important for semantic analysis. World experience shows that the problem of eliminating homonymy can be solved using several methods.

- Rule-based methods
- Methods based on statistical data
- Methods based on machine learning
- Deep learning methods

**Rule-based methods** involve semantic analysis of words using the rules of language grammar. A number of rules have been developed in the Uzbek language. Based on these rules, mathematical considerations have been developed that differentiate some types of homonyms. The essence of this method is that in some cases the context analysis helps to understand the syntactic structure of a part of the sentence and its word forms.

**The method based on statistical** data is used to solve the problem by classifying the grammatical parameters of words. These parameters are chosen differently in different natural languages.

**The method based on machine learning is** based on artificial intelligence. This method is an addition to statistical methods, and is widely used in the world to determine homonymy.

**Deep learning** techniques (also called deep structured learning) are part of a larger family of machine learning techniques based on artificial neural networks.

The Naïve Bayes classifier is a component of machine learning-based methods that helps solve many problems in natural language processing. For example, the famous problem of comment interpretation [1, p. 307-313], detection of fake information [2, p. 900-903], text sentiment analysis [p. 3,176-179, 4,999 -1005-p., 5,6303-6309-p.,6,159-163-p.] are among them. Another important task of natural language processing is to determine the meaning of a word, and the Naïve Bayes classifier plays a special role in solving this problem. Adrian-Gabriel Chifu and Radu-Tudor Ionescular used the Naïve Bayes classifier to eliminate polysemy, and accurate results were also obtained [7, pp. 398-410].4 Machine Learning Methods for Bengali Word Meaning Recognition Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN) by Pal, A. R. et al.) method and Naïve Bayes (NB) methods were used. These basic strategies yielded 63.84%, 76.9%, 76.23%, and 80.23% accurate results, respectively [8, pp. 439-450]. In addition, it can be seen that this classifier was widely used in the preparation of reports on criminal cases, and the accuracy of 87-93.74% was achieved [p. 9,534-541].

It is appropriate to use these methods in the semantic differentiation of homonymous words in the Uzbek language. In the semantic differentiation of homonyms in the Uzbek language, they were divided into two groups according to their occurrence within word groups: homonyms within the same word group and within different word groups.

We mentioned the ease of using the method based on machine learning to identify homonymy within a word group in our previous articles [10, pp. 150-162]. Homonymous words within different word groups can be divided into 3 groups depending on the fact that they form homonyms within word groups 2, 3 and 4 [11, pp. 393-400, 12, 164-170- b.]. Homonyms within different lexicons can be distinguished using Rule-Based methods, Statistics-based methods, and Machine Learning-based methods. Among word groups, there are word groups that are grammatically similar, and there are no rules for distinguishing them. If there is, it is not fixed. For example, noun and adjective word groups can be said to be grammatically similar word groups. That is, the adjective word group has the property of accusative, which means that the same suffix can be added to the word belonging to both word groups. Among grammatically similar word groups in the Uzbek language, homonymous words can be divided into groups as shown in Figure 1. This article deals with the use of Naïve Bayes classifier in the semantic differentiation of homonyms in the Uzbek language.

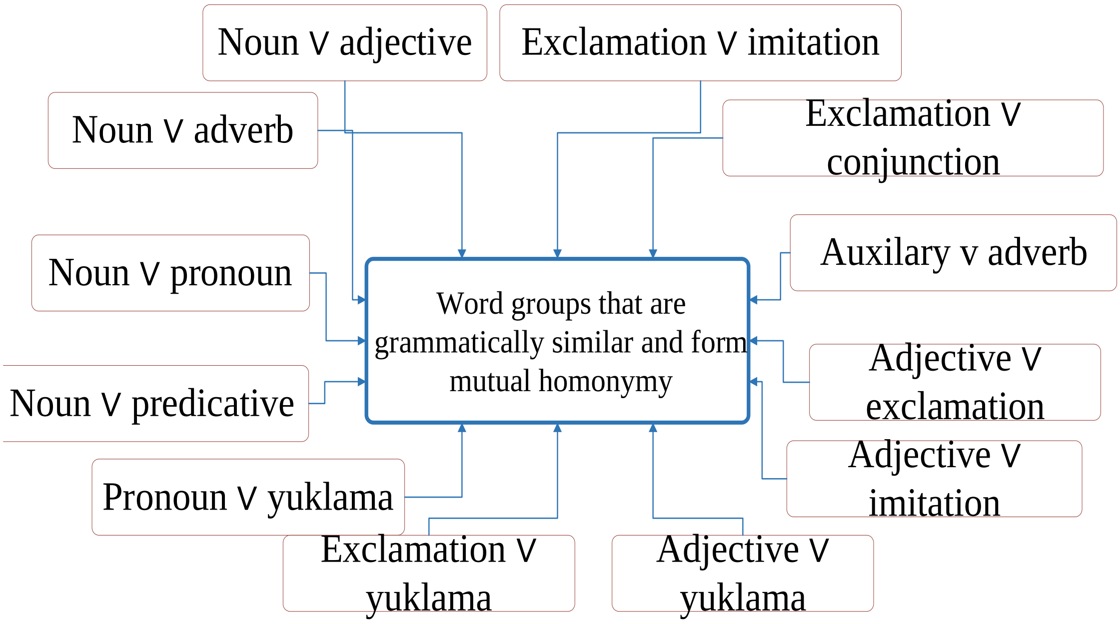


**Figure 1: Word Groups that are Grammatically Similar and Form Mutual Homonymy**

It is known that homonymy between word groups presented in Figure 1 is obtained from statistical data in the semantic differentiation of words. In the article [12, p. 164-170, 13, p. 106], we presented detection using the frequency method. A large amount of data is needed to identify homonymy using the frequency method. Naïve Bayes classifier is one of the methods that provides simple and quick operations on such big data.

## METHOD AND MATERIALS

Naive Bayes algorithm is a statistical classification method based on Bayes theorem [14, p. 1-7]. Statistical classification is the result of observation of classified texts. Here we define the term text classification.

***Text classification methods.*** To perform text classification, the first step is to understand the problem, identify potential features and labels. Attributes are a set of properties or attributes that affect the labeling results. These features are defined as features that help the model classify texts. Text classification consists of two stages: **consists of a learning stage** and **an evaluation stage.** In the learning phase, the classifier trains its model on a given data set. In the evaluation stage, the performance of the classifier is tested. The developed model is evaluated based on various parameters such as accuracy, error and flexibility.

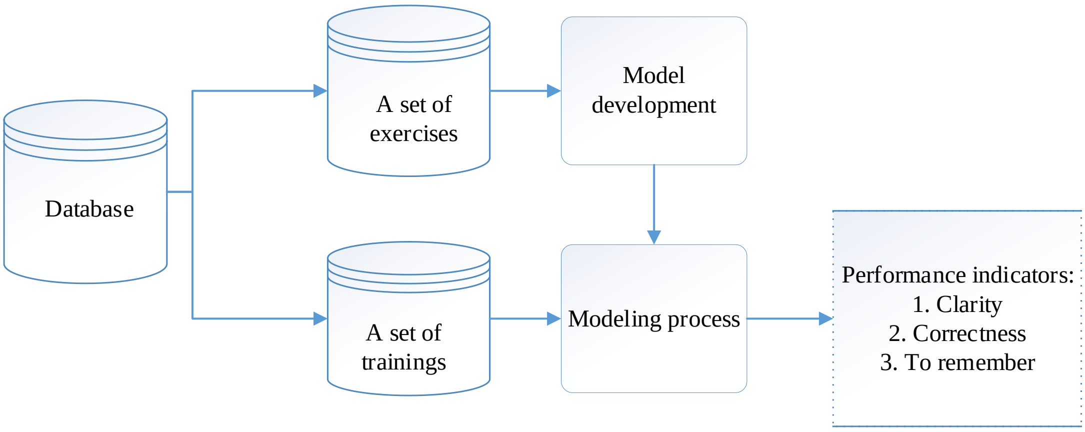


**Figure 2: Stages of Text Classification**

Naïve Bayes classifier can be used based on text classification features. A Naive Bayes classifier assumes that the effect of a particular feature in a class is independent of other features. Although these features are interrelated, they are also considered independently. This assumption simplifies the calculation and is therefore considered simple. This assumption is called conditional independence of the class [p. 15,174-182]. The Naive Bayes classifier calculates probabilities for each feature and selects the result with the highest probability.

$$P(class|data) = \frac{P(data|class) \cdot P(class)}{P(data)} (1)$$

- **P(class):** the probability that the class hypothesis is true (regardless of the data). This is used as the a priori probability of the class.
- **P(data):** probability of data (regardless of hypothesis). This is used as a priori probability.
- **P(class|data):** probability of class hypothesis based on data. This is used as the posterior probability.
- **P(data|class):** probability of data given that the class hypothesis is true. This is used as the posterior probability.

$\boldsymbol{P(A|B)}$is read as "probability of occurrence of event A when event B occurs." The expression on the right side of equation (1) is calculated by dividing the probability of both events occurring together by the probability of occurrence of the data event.

Naive Bayes classifier as we classify text data into discrete labels using a classifier, we have a set of input functions for the Naive Bayes algorithm and a corresponding output class. The Naive Bayes classifier calculates the probability using the following formula:

$$P(y_1|x_1, x_2, x_3) = \frac{P(y_1) \cdot P(x_1|y_1) \cdot P(x_2|y_1) \cdot P(x_3|y_1)}{P(x_1) \cdot P(x_2) \cdot P(x_3)} (2)$$

$P(y_1|x_1, x_2, x_3)$in this equation represents the probability that y1 will be the output based on the received data {$x_1$, $x_2$, $x_3$} [p. 16,24-31, p. 17,692]. The number of these features can be n.

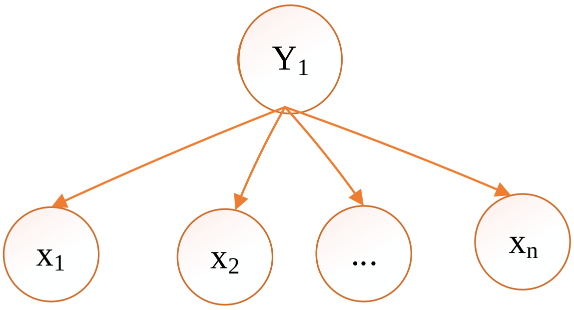


**Figure 3: Dependence of the Output Class on N Feature**

Let our NLP problem have a total of 2 classes, i.e. $\{y_1, y_2\}$. Now it is necessary to calculate the probability of occurrence of y1 from the above formula, and then the probability of occurrence of y2 [p. 18, 247-260, 19, 787-785]. Whichever is more likely is our predicted class. Let's consider the problem of distinguishing homonymous words between grammatically similar word groups using the Naïve Bayes classifier. For this, we need classification features of word groups. This can be determined based on the grammatical features of word groups.

Let's assume that the problem of determining homonymy between nouns or adjectives is set. First, the classification parameters for noun and adjective word groups should be defined. Observations show that noun and adjective word groups can occur mainly in cases where there is a stem and an affix in the structure, i.e. stem and stem +aff (affix). As an example, we give the word hot, which creates homonymy within the noun or adjective word groups.

When we searched for the word "hot" among the data of the Uzbek language corpus, it was observed in 30,782 places. *Issiq*word in the observations

- *Uy* ***issiq*** *bo'lgani uchun tutun yuqoriga ko'tarilmaydi.*
- *Onamning* ***issiqqina*** *bag'rini, mehrini baribir hech narsa bosolmaydi*-*da.*
- *Jazirama* ***issiqda*** *sun'iy suv havzalarida cho'milish bolalarga bir olam zavq berishi shubhasiz.*
- *Charchadim o'qishdanmi, o'ylovlardanmi,* ***issiqdanmi****, sovuqdanmi bilmayman.*
- *Metro tomondan ishxonaga intilayotgan,* ***issiqda*** *biroz toliqqan Ustozga ko'zim tushdi.*

there were cases of meeting in such word forms. As a result of observations, it was found that the parameters for classifying words that create homonyms between noun or adjective word groups are their *root and root+aff*. So $x_1$= *root*, $x_2$= *root+aff*, $y_1$= *adjective and* $y_2$= *noun*. First, the cases of meeting in the form of a core were analyzed. According to the analysis, it was observed that the word "hot" in its root form mainly belongs to the group of adjective words. (Figure 3).

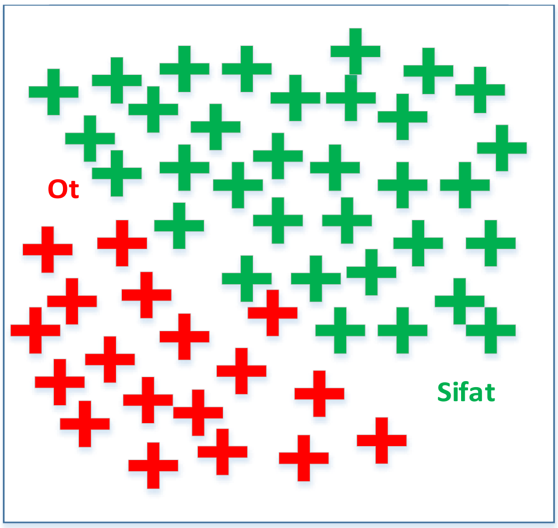


**Figure 4: Cases of Meeting the Word "Hot" in the Root Word Form**

Frequency and probability tables can be used to simplify the process of calculating the a priori and a posteriori probability of the word hot based on the statistical data obtained from the results of observations. Both of these tables help calculate a priori and posterior probabilities [pp. 20,112–114.] A frequency table contains labels for all features. There are also two probability tables, Table 1 shows the a priori probability of labels and Table 2 shows the a posteriori probability.

| | Parametrs | Part of speechs |
|---|---|---|
| 1 | Root | Adjective |
| 2 | Root +aff | Noun |
| 3 | Root | Adjective |
| 4 | Root | Adjective |
| 5 | Root | Noun |
| 6 | Root | Adjective |
| 7 | Root +aff | Noun |
| 8 | Root | Adjective |
| 9 | Root +aff | Noun |
| 10 | Root | Adjective |
| 11 | Root +aff | Noun |
| 12 | Root +aff | Noun |
| 13 | Root | Adjective |
| 14 | Root | Noun |
| … | … | |

| Parametrs | Noun | Sifat |
|---|---|---|
| Root | 2 | 7 |
| Root +aff | 4 | 1 |
| General | 6 | 8 |

**1-Probability table**

| Parametrs | Noun | Sifat | | |
|---|---|---|---|---|
| Root | 2 | 7 | =9/14 | 0.64 |
| Root +aff | 4 | 1 | =5/14 | 0.36 |
| General | 6 | 8 | | |
| | =6/14 | =8/14 | | |
| | 0.43 | 0.47 | | |

**2-Probability table**

| Parametrs | Noun | Adjective | To be Probability (noun) | To not be Probability (Adjective) |
|---|---|---|---|---|
| Root | 2 | 7 | 2/9=0.22 | 7/9=078 |
| Root+aff | 4 | 1 | 4/5=0.8 | 1/7=0.14 |
| General | 6 | 8 | | |

**Figure 5: Frequency and Probability Tables.**

We will consider the process of calculating the probability that the nouns or adjectives found in the sentence are related to adjectives. Let's consider these calculations in the example of the following sentence

Uy ***issiq*** bo‘lganligi sababli tutun yuqoriga ko‘tarilmaydi.

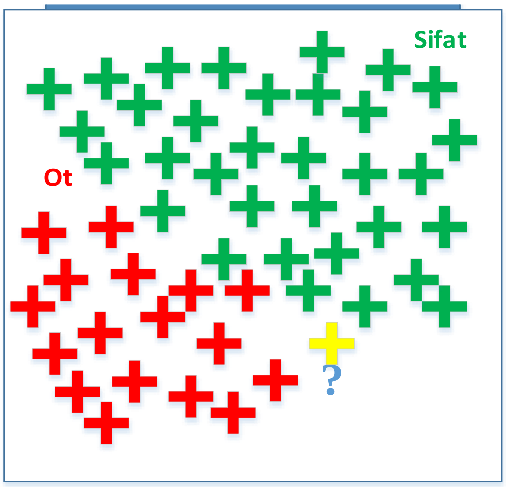


**Figure 6: Tagging a Newly Encountered Hot Word**

So, the hot word in the sentence is a root word, and we calculate the probability of matching the properties $x_1$ and $x_2$ for this word.

- **The probability that the word belongs to the adjective group:**

$$P(Adjective|Root) = \frac{P(Root|Adjective) \cdot P(Adjective)}{P(Root)}$$

(3)

Calculating a priori probabilities:

$$P(Root) = 7/14 = 0.5$$

$P(Adjective) = 8/14 = 0.57$

Calculation of posterior probabilities:

$P(Root|Adjective) = 7/9 = 0.78$

Calculation of the probability that the quality belongs to the part of speech through Aprior and Aposterior probabilities:

$$P(Adjective|Root) = \frac{0.78 \cdot 0.57}{0.5} = 0.89\ (Yuqori)$$

- **Calculating the probability that a noun belongs to a word group**:

$$P(Noun|Root) = \frac{P(Root|Noun) \cdot P(Noun)}{P(Root)}$$

Calculation of a priori probabilities:

$$P(Noun) = 6/14 = 0.43$$

$P(Root) = 9/14 = 0.64$

Calculation of a aposterior probabilities:

$P(Root|Noun) = 2/9 = 0.22$

Calculating the probability of a word not being an adjective (being a noun) using a priori and aposteriori probabilities:

$$P(Noun|Root) = \frac{0.22 \cdot 0.64}{0.43} = 0.33$$

So,

$$P(Adjective|Root) = 0.89$$

$P(Noun|Root)$=0.33

According to the results of calculations, we estimate that the word hot in the sentence "Uy ***issiq*** bo‘lganligi sababli tutun yuqoriga ko‘tarilmaydi" belongs to the adjective group with 88% accuracy. Observations show that the word hot can also be found in the form $x_2$ = root + aff.

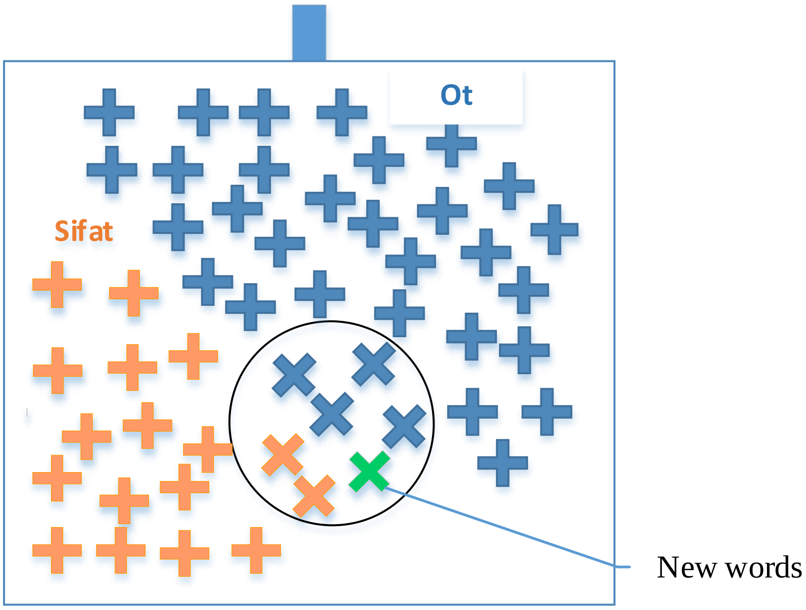


**Figure 7: Cases Where the Word Hot is Found in the Root+Aff word Form**

Example,

***Issiqda*** *terlab-pishib sport bilan shug‘ullanish nafaqat yoqimsiz, balki sog’liq uchun xavflidir.*

Let's consider the process of calculating the probability of which word group the word *issiqda* in the sentence belongs to. *issiqda=Root+aff=*$x_2$.

- *Calculating the probability that an adjective belongs to a word group*:

$$P(Adjective|Root + aff) = \frac{P(Root + aff|Adjective) \cdot P(Adjective)}{P(Root+aff)}$$

(4)

Calculation of a priori probabilities:

$$P(Root + \text{aff}) = 5/14 = 0.36$$

$P(Adjective) = 9/14 = 0.64$

Calculation of posterior probabilities:

$P(Root + aff|Adjective) = 1/5 = 0.2$

Calculation of the probability that the quality belongs to the part of speech through *Aprior* and *Aposterior* probabilities:

$$P(Adjective|Root + \text{aff}) = \frac{0.2 \cdot 0.64}{0.36} = 0.35$$

- **Calculation of the probability that the noun belongs to the word group:**

$$P(Noun|Root + aff) = \frac{P(Root + aff|Noun) \cdot P(Noun)}{P(Root+aff)}$$

(5)

Calculation of a priori probabilities:

$$P(Root + \text{aff}) = 5/14 = 0.36$$

$P(Noun) = 6/14 = 0.42$

Calculation of posterior probabilities:

$P(Root + aff|Noun) = 4/5 = 0.8$

Calculation of the probability that a noun belongs to a word group using Aprior and Aposterior probabilities:

$$P(Noun|Root + \text{aff}) = \frac{0.8 \cdot 0.42}{0.36} = 0.93$$

So$P(Adjective|Root + \text{aff}) = 0.35\ vaP(Noun|Root + \text{aff}) = 0.93$values were generated. It follows that "***Issiqda*** *terlab-pishib sport bilan shug'ullanish nafaqat yoqimsiz, balki sog'liq uchun xavflidir*" sentence was determined that the homonym word hot in the sentence belongs to the noun group with 93% probability. The conducted observations show that the occurrences of adjectives or homonyms within the noun group are not mutually exclusive. That is, it is impossible to use formula (3) from $x_1$ and $x_2$ properties at the same time.

## RESULTS

Scikit learning library of Python programming language helps to create Naïve Bayes model. There are 3 main types of Naive Bayes algorithms in the Scikit learn library:

Gaussian Naive Bayes

Multinomial Naive Bayes

Bernoulli Naive Bayes

Naive Bayes classifier is one of the most popular multi-class classification algorithms. Depending on the data being considered, any of the 3 types of Naive Bayes algorithms can be used.

**Gaussian:** Used for event classification and assumes that the characteristics of the classification follow a normal distribution.

**Multinomial: U**sed for discrete computation. For example, let's say we have a text classification problem. Here we can consider Bernoulli trials, which go one step further and count "how often a word occurs" rather than "occurrence of an input word in the corpus".

**Bernoulli:** The binomial model is useful if the feature vectors are binary (i.e., zeros and ones). One application could be text classification with a "bag of words" model, where 1 and 0 represent "the word occurs in the document" and "the word does not exist in the document", respectively.

The process of identifying homonymy between adjectives or word groups considered above corresponds to the Gaussian Naïve Bayes model. Because it uses classification features and it follows a normal distribution (classification features are independent). A dataset consisting of the results of searching the Uzbek national corpus for the homonymous word "issiq" within the adjective or noun categories was created

```
importpandasaspd

df = pd.read_csv("d:/data/omonim.csv")

df.head()
```

**Table 1: Statistical Information about The Word 'Issiq'**

| | Parametrlar | SuzTurkumi |
|---|---|---|
| **1** | *Root* | *Adjective* |
| **2** | Root+aff | *Noun* |
| **3** | Root | *Adjective* |
| **4** | Root | *Adjective* |
| **5** | Root | *Noun* |
| **6** | Root | *Adjective* |
| **7** | Root+aff | *Noun* |
| **8** | Root | *Adjective* |
| **9** | Root+aff | *Noun* |
| **10** | Root | *Adjective* |
| **11** | Root+aff | *Noun* |
| **12** | Root+aff | *Noun* |
| **13** | Root | *Adjective* |
| **14** | Root | *Noun* |
| **…** | … | |

```
#inputs.pos= inputs.pos.map({'Adjective':1,'Noun':2})

turkum = pd.get_Pos(inputs.Pos)
```

turkum.head(14)

**Table 2: Separation of Adjective and Noun Categories**

| | Adjective | Noun |
|---|---|---|
| **0** | 1 | 0 |
| **1** | 0 | 1 |
| **2** | 1 | 0 |
| **3** | 1 | 0 |
| **4** | 0 | 1 |
| **5** | 1 | 0 |
| **6** | 0 | 1 |
| **7** | 1 | 0 |
| **8** | 0 | 1 |
| **9** | 1 | 0 |
| **10** | 0 | 1 |
| **11** | 0 | 1 |
| **12** | 1 | 0 |
| **13** | 0 | 1 |

#inputs.Parametr = inputs.Parametr.map({root: 1,'root+aff':2})

param = pd.get_parametr(inputs.Parametr)

param.head(14)

**Table 3: Root and Root +aff character extraction**

| | Root | Root+aff |
|---|---|---|
| **0** | 1 | 0 |
| **1** | 0 | 1 |
| **2** | 1 | 0 |
| **3** | 1 | 0 |
| **4** | 1 | 0 |
| **5** | 1 | 0 |
| **6** | 0 | 1 |
| **7** | 1 | 0 |
| **8** | 0 | 1 |
| **9** | 1 | 0 |
| **10** | 1 | 0 |
| **11** | 0 | 1 |
| **12** | 1 | 0 |
| **13** | 1 | 0 |

inputs.columns[inputs.isna().any()]

**Table 4: The Table Formed by Combining Tables 2 and 3**

| | Root | Root+aff | Adjective | Noun |
|---|---|---|---|---|
| **0** | 1 | 0 | 1 | 0 |
| **1** | 0 | 1 | 0 | 1 |
| **2** | 1 | 0 | 1 | 0 |

| | | | | |
|---|---|---|---|---|
| **3** | 1 | 0 | 1 | 0 |
| **4** | 1 | 0 | 0 | 1 |
| **5** | 1 | 0 | 1 | 0 |
| **6** | 0 | 1 | 0 | 1 |
| **7** | 1 | 0 | 1 | 0 |
| **8** | 0 | 1 | 0 | 1 |
| **9** | 1 | 0 | 1 | 0 |
| **10** | 1 | 0 | 0 | 1 |
| **11** | 0 | 1 | 0 | 1 |
| **12** | 1 | 0 | 1 | 0 |
| **13** | 1 | 0 | 0 | 1 |

class_count**(**inputs.Parametr.map({Root,'Root'=1,'Adjective'=1, 'Noun'=1})**)**

| Training | Root | Adjective | Noun |
|---|---|---|---|
| 14 | 9 | 7 | 2 |

fromsklearn.model_selectionimporttrain_test_split

X_train, X_test, y_train, y_test = train_test_split(inputs,target,test_size=0.3)

fromsklearn.naive_bayesimportGaussianNB

model = GaussianNB()

model.fit(X_train,y_train)

model.score(X_test,y_test)

0. 8873546295522388

model.predict_proba(X_test)

array([0.88735462,0.13021545])

class_count**(**inputs.Parametr.map({Root+aff',Root+aff'=1, Adjective=1, 'Noun'=1})**)**

| **Training** | Root+aff | Adjective | Noun |
|---|---|---|---|
| **14** | 5 | 1 | 4 |

model = GaussianNB()

model.fit(X_train,y_train)

model.score(X_test,y_test)

0.93333333

model.predict_proba(X_test)

array([0.34896122,0.93333333])

Although the above calculations are presented on the example of one word, this classifier allows to determine the homonymy within the total noun or adjective word groups. Because homonyms within noun or adjective word groups are differentiated using root and root+aff parameters. In addition, parameters classifying homonyms within different grammatically similar word groups are determined and statistical data are obtained. Based on the obtained results, the above calculations are performed and evaluated.

In addition, different methods can be used to determine homonymy within different word groups. In the course of the research, the calculations for determining homonymy using the frequency method were determined.

**Table 5: Results from the Naive-Bayes Classifier and the Frequentist Method**

| | Noun | | Adjective | |
|---|---|---|---|---|
| | Root (%) | Root+aff (%) | Root (%) | Root+aff (%) |
| Naïve Bayes | 33 | 93 | 89 | 35 |
| Frequency method | 5 | 95 | 95 | 5 |

It can be seen from Table 5 that the classification parameters must be determined to use the frequency method.

## CONCLUSIONS

In conclusion, it can be said that the issue of determining homonymy in the Uzbek language is a complex process. When determining homonymy, it is appropriate to divide them into different groups and use different methods based on their differentiating factors. Naïve Bayes classifier is one such method. Naïve Bayes classifier was used to eliminate homonymy between grammatically similar word groups in the Uzbek language. In order to use the Naïve Bayes classifier to identify homonymy within different word groups, the parameters for classifying grammatically similar word groups were determined. Statistical data were obtained taking into account the classification parameters. Based on the statistical data, Naïve Bayes calculations were performed and the results were evaluated.

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