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Research Article

Machine Learning and Ensemble Learning Based Method Using Online Employee Assessments to Identify and Analyze Job Satisfaction Factors

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Abstract

In this paper it was emphasized that machine learning techniques can achieve high performance in classification and work effectively and scalably with large data sets. The dataset used in this study was obtained from www.kaggle.com. A total of 67529 comments collected from people working at Google, Amazon, Netflix, Facebook, Apple and Microsoft were evaluated. The N-gram model is an important representation scheme in text mining. N-gram models are the unigram model (N = 1), bigram (N = 2), and trigram (N = 3). Three different weighting schemes as TP, TF, and TF-IDF, and three different weighting schemes for traditional machine learning-based analysis as N-gram model (bigram, unigram and trigram) was used. Five supervised learning algorithm was used to train models: Naive Bayes, Support Vector Machines (SVM), Logistic Regression (LR), K-Nearest Neighbor (KNN) and Random Forest (RF).

Keywords: machine learning, text classification, artificial intelligence, ensemble learning.

İş Memnuniyeti Faktörlerini Belirlemek ve Analiz Etmek için Çevrimiçi Çalışan Değerlendirmelerini Kullanan ilgili Makine Öğrenmesi ve Topluluk Öğrenmesi Tabanlı Yöntem

Öz

Bu çalışmada, makine öğrenmesi tekniklerinin sınıflandırmada yüksek performans elde edebileceği ve büyük veri setleri ile etkin ve ölçeklenebilir bir şekilde çalışabileceği vurgulanmıştır. Bu çalışmada kullanılan veri seti www.kaggle.com adresinden elde edilmiştir. Google, Amazon, Netflix, Facebook, Apple ve Microsoft'ta çalışan kişilerden toplanan toplam 67529 yorum değerlendirilmiştir. N-gram modeli, metin madenciliğinde önemli bir temsil şemasıdır. N-gram modelleri, unigram modeli (N = 1), bigram (N = 2) ve trigram (N = 3) şeklindedir. TP, TF ve TF-IDF olmak üzere üç farklı ağırlıklandırma şeması ve N-gram modeli (bigram, unigram ve trigram) olarak geleneksel makine öğrenmesi tabanlı analiz için üç farklı ağırlıklandırma şeması kullanılmıştır. Modelleri eğitmek için beş farklı denetimli öğrenme algoritması kullanılmıştır: Naive Bayes, Destek Vektör Makineleri (SVM), Lojistik Regresyon (LR), K-En Yakın Komşu (KNN) ve Rastgele Orman (RF).

Anahtar Kelimeler: Makine öğrenmesi, metin sınıflandırma, yapay zeka, topluluk öğrenmesi.

1. Introduction

Web is a rich and progressively expanding source of information. Text classification suffers from the high dimensional feature space and feature sparsity problems. The use of conventional representation schemes to represent text documents can be extremely costly especially for the large text collections. In this regard, machine learning techniques are viable tools in representing document collections. The performance of the proposed sample selection method was evaluated on some basic classifiers with machine learning techniques by considering the online assesments of the employees in order to determine and analyze the job satisfaction factors. In addition the effectiveness of different representation structures are evaluated in order to represent the data sets effectively and the main results are obtained regarding the use of classification ensemble in the field of text mining.

2. Material and Method

2.1. Traditional Machine Learning Techniques

The N-gram model is an important representation scheme in text mining. N-gram models are the unigram model (N = 1), bigram (N = 2), and trigram (N = 3). In this part of the study, three different weighting schemes as TP, TF, and TF-IDF, and three different weighting schemes for traditional machine learning-based analysis as N-gram model (bigram , unigram and trigram) was used. Five supervised learning algorithm was used to train models: Naive Bayes, Support Vector Machines (SVM), Logistic Regression (LR), K-Nearest Neighbor (K-NN) and Random Forest (RF).

2.1.1. Naive Bayes (NB)

It is one of the simplest, understandable and easily applicable machine learning algorithms used in text classification. With this method the probability of belonging to the class value of the target attribute of a sample can be found [1].

2.1.2. Support Vector Machines (SVM)

It is a training algorithm used to generate learning, classification, clustering, density estimation and regression rules from the data. SVM can be used to solve the two-class and multi-class classification problem. SVM aims to find the closest examples of the classes while classifying the data and also maximize the perpendicular distances of these examples to the separating surface which will separate the two classes. The separator surface can have many different alternatives without changing its success on the dataset. The separating surface is at the same distance to both classes and distance is maximum [2].

2.1.3. Logistic Regression (LR)

It is a statistical method used to predict binary classes. Logistic Regression predicts the probability of an outcome that can only have two values. The prediction is based on the use of one or more predictors as numerical and categorical. Linear Regression is not suitable for values that can be expressed in a binary system such as yes/no. Because it can predict value outside of the range of 0 and 1. Logistic Regression produces a logistic curve limited to values between 0 and 1 [2].

2.1.4. K-Nearest Neighbor (K-NN)

In this method, the classification process is made according to the proximity relations between the objects. It is also known that the k-nn algorithm which has the advantage of ease of development, needs a large amount of memory space, the processing load and cost increase significantly as the data set and size increase. Thus the performance is affected by parameters and features such as the number of k neighbors [3].

2.1.5 Random Forest (RF)

It is a classification algorithm that creates multiple decision trees from the data in the part of the data set reserved for training. Random forest, also called ensemble learning method in the literature, decides the class of the given test input by using the classification results of a large number of decision trees by majority vote. First the algorithm creates a large number of decision trees using the training data. Then it places the test data into each tree to classify the part of the data set reserved for testing. In the final, algorithms evaluates the classification obtained from each tree and chooses the one with the highest value [4].

2.2. Ensemble Learning Algorithms

Ensemble learning algorithms is a machine learning workspace for assigning the class label to the samples to be classified based on the output of multiple learning algorithms rather than a single classification algorithm. Ensemble learning algorithms are expected to have better generalization abilities and lower risk of overfitting compared to base classifier algorithms [5].

Ensemble learning methods, namely AdaBoost algorithm, Bagging, Random space, Voting and Stacking were used in this paper.

2.2.1. AdaBoost Algorithm

It is a meta-algorithm formulated by YoavFreund and Robert Schapire. The Adaboost algorithm is an iterative ensemble classifier that uses weak classifiers within the ensemble structure to improve its performance. In the Adaboost algorithm, the classifiers of the ensemble are added one by one where each subsequent classifier is trained using data that previous ensemble members failed to classify correctly. Selects the training set to train the current learning model based on the last training prediction [6].

2.2.2. Bagging Algorithm

Breiman is based on training different sub-dimensions of the training data set. In this method, different sub-samples are created from the training data set by changing the samples each time. Each sub-training set created is trained with a classifier. At the same time, all classifiers classify different sub-training sets. The bagging method uses the majority vote technique to combine the estimates of the classifiers . In this technique, the majority estimate given by the classifiers among the classification estimates of all the estimators is accepted as the classification estimation of the ensemble method. [7]

2.2.3. Random Space Algorithm (RS)

It is an ensemble learning algorithm in which basic learning algorithms are trained by taking samples from the training set as in the bagging algorithm. However, in obtaining different subsets from the training set, feature space-based partitioning is performed, not instance-based [8].

2.2.4. Voting

Ensemble learning method, the estimation of the majority by combining the estimations of different types of classifiers is accepted as the ensemble estimation. In fact , although the voting method is a combination technique, it has become a very common area of use in combining different types of classifiers. Classification of the same data set by different types of classifiers provides variation in estimations. The variation in estimates is an element that improves accuracy performance in the ensemble method. For this reason, high-performance predictions can be obtained in the case of diversity in voting ensemble methods in general [9].

2.2.5. Stacking

Stacking ensemble learning method developed by Wolpert is based on the principle of producing a higher performance estimation from these estimations by accepting the estimations of different types of classifiers as input for the meta classifier. Stacking ensemble learning method offers a two-stage learning process in this sense. In the first stage, predictions are obtained from the same training dataset with different types of classifiers. In the second stage, the predictions obtained from the first stage are processed in the meta classifier and the prediction of the ensemble learning model is obtained. This method, which generates ensemble estimation from estimations with meta classifier, has been developed to provide higher performance [10].

3. Results and Discussion

In order to calculate the performance of classification algorithms in the evaluation process, a number of model performance criteria frequently used in the literature were used [11].

The parameters used in the formulation of these criteria are defined as:

TP (True Positive): The number of comments that are positive and also considered positive by the classifier.

TN (True Negative): The number of comments that are negative and also considered negative by the classifier.

FP (False Positive): The number of comments that are negative but considered positive by the classifier.

FN (False Negative): The number of comments that are positive but considered negative by the classifier.

For experimental analysis, the text corpus was modeled using three weight schemes as TF, TP, and TF-IDF and three different N-gram models (bigram , unigram and trigram). In this way nine different configurations were obtained. The results obtained from the analyzes are shown in the tables below according to the Accuracy Values, Precision Values, Recall Values and F-measure Values.

Table 1. Accuracy Values

Algorithms	**Unigram+ TP**	**Unigram+ TF**	**Unigram+ TF-IDF**	**Bigram+ TP**	**Bigram+ TF**	**Bigram+ TF-IDF**	**Trigram+ TF**	**Trigram+ TP**	**Trigram+ TF-IDF**
KNN	80.09	80.7	80.51	79.27	79.82	79.48	76.89	78.78	78.1
SVM	82.33	82.64	82.55	82.35	82.46	82.39	82.14	82.28	82.22
LR	81.69	82.09	81.97	81.5	81.68	81.59	80.88	81.39	81.23
NB	83.34	83.63	83.57	83.44	83.5	83.48	83.31	83.41	83.34
RF	82.87	83.15	83.11	82.88	82.99	82.94	82.71	82.83	82.8
AdaBoost(KNN)	87.06	87.32	87.31	87.17	87.24	87.19	87.09	87.16	87.13
AdaBoost(SVM)	87.57	87.88	87.81	87.71	87.74	87.73	87.58	87.64	87.62
AdaBoost(LR)	87.33	87.57	87.55	87.46	87.5	87.48	87.35	87.42	87.38
AdaBoost(NB)	88.38	88.73	88.63	88.49	88.56	88.53	88.25	88.46	88.35
AdaBoost(RF)	87.92	88.21	88.14	88	88.04	88.02	87.91	87.97	87.93
bagging(KNN)	83.81	84.14	84.09	83.89	83.98	83.95	83.69	83.81	83.77
Bagging(SVM)	84.73	84.99	84.95	84.79	84.85	84.8	84.7	84.77	84.74
bagging(LR)	84.41	84.67	84.62	84.5	84.6	84.54	84.3	84.39	84.36
bagging(NB)	85.38	85.62	85.6	85.47	85.56	85.54	85.4	85.45	85.43
bagging(RF)	85.05	85.37	85.3	85.17	85.21	85.19	85.07	85.14	85.12
RS(KNN)	88.76	89.1	89	88.85	88.94	88.9	88.77	88.81	88.8
RS(SVM)	90.22	90.57	90.49	90.07	90.34	90.14	89.87	90	89.91
RS(LR)	89.53	89.81	89.8	89.61	89.67	89.64	89.42	89.57	89.48
RS(NB)	93.61	94.02	93.91	92.64	93.03	92.87	92.08	92.36	92.21
RS(RF)	91.3	91.93	91.73	91.01	91.3	91.08	90.68	90.92	90.8
Voting(Minimumprobability)	85.6	85.87	85.83	85.75	85.78	85.77	85.65	85.68	85.67
Voting(Maximumprobability)	85.89	86.15	86.12	85.99	86.07	86.06	85.9	85.97	85.95
Voting(Majorityvoting)	86.17	86.41	86.39	86.24	86.29	86.26	86.17	86.22	86.19
Voting(Productofprobability)	86.41	86.73	86.65	86.55	86.57	86.57	86.44	86.49	86.45
Voting(Averageofprobabilities)	86.79	87.05	87.01	86.9	86.98	86.93	86.8	86.85	86.83
Stacking	89.15	89.4	89.37	89.22	89.28	89.25	89.12	89.18	89.14

Table 2. Precision Values

Algorithms	Unigram +TP	Unigram +TF	Unigram +TF-IDF	Bigram +TP	Bigram +TF	Bigram +TF-IDF	Trigram +TF	Trigram +TP	Trigram +TF-IDF
KNN	0.81	0.82	0.81	0.80	0.81	0.80	0.78	0.80	0.79
SVM	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83
LR	0.83	0.83	0.83	0.82	0.83	0.82	0.82	0.82	0.82
NB	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
RF	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
AdaBoost(KNN)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
AdaBoost(SVM)	0.88	0.89	0.89	0.89	0.89	0.89	0.88	0.89	0.89
AdaBoost(LR)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
AdaBoost(NB)	0.89	0.90	0.90	0.89	0.89	0.89	0.89	0.89	0.89
AdaBoost(RF)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
bagging(KNN)	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Bagging(SVM)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
bagging(LR)	0.85	0.86	0.85	0.85	0.85	0.85	0.85	0.85	0.85
bagging(NB)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
bagging(RF)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
RS(KNN)	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
RS(SVM)	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
RS(LR)	0.90	0.91	0.91	0.91	0.91	0.91	0.90	0.90	0.90
RS(NB)	0.95	0.95	0.95	0.94	0.94	0.94	0.93	0.93	0.93
RS(RF)	0.92	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92
Voting(Minimumprobability)	0.86	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Maximumprobability)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Majorityvoting)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Productofprobability)	0.87	0.88	0.88	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Averageofprobabilities)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Stacking	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90

Table 3: Recall Values

Algorithms	Unigram+ TP	Unigram+ TF	Unigram+ TF-IDF	Bigram+ TP	Bigram+ TF	Bigram+ TF-IDF	Trigram+ TF	Trigram+ TP	Trigram+ TF-IDF
KNN	0.82	0.82	0.82	0.81	0.81	0.81	0.78	0.80	0.80
SVM	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
LR	0.83	0.84	0.84	0.83	0.83	0.83	0.83	0.83	0.83
NB	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
RF	0.85	0.85	0.85	0.85	0.85	0.85	0.84	0.85	0.84
AdaBoost(KNN)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
AdaBoost(SVM)	0.89	0.90	0.90	0.90	0.90	0.90	0.89	0.89	0.89
AdaBoost(LR)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
AdaBoost(NB)	0.90	0.91	0.90	0.90	0.90	0.90	0.90	0.90	0.90
AdaBoost(RF)	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
bagging(KNN)	0.86	0.86	0.86	0.86	0.86	0.86	0.85	0.86	0.85
Bagging(SVM)	0.86	0.87	0.87	0.87	0.87	0.87	0.86	0.87	0.86
bagging(LR)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
bagging(NB)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
bagging(RF)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
RS(KNN)	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
RS(SVM)	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
RS(LR)	0.91	0.92	0.92	0.91	0.92	0.91	0.91	0.91	0.91
RS(NB)	0.96	0.96	0.96	0.95	0.95	0.95	0.94	0.94	0.94
RS(RF)	0.93	0.94	0.94	0.93	0.93	0.93	0.93	0.93	0.93
Voting(Minimumprobability)	0.87	0.88	0.88	0.88	0.88	0.88	0.87	0.87	0.87
Voting(Maximumprobability)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Voting(Majorityvoting)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Voting(Productofprobability)	0.88	0.89	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Voting(Averageofprobabilities)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
Stacking	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91

Table 4: F-measure Values

Algorithms	Unigram+ TP	Unigram+ TF	Unigram+ TF-IDF	Bigram+ TP	Bigram+ TF	Bigram+ TF-IDF	Trigram+ TF	Trigram+ TP	Trigram+ TF-IDF
KNN	0.81	0.82	0.82	0.80	0.81	0.81	0.78	0.80	0.79
SVM	0.84	0.84	0.84	0.84	0.84	0.84	0.83	0.84	0.83
LR	0.83	0.83	0.83	0.83	0.83	0.83	0.82	0.83	0.82
NB	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
RF	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84	0.84
AdaBoost(KNN)	0.88	0.89	0.89	0.88	0.89	0.89	0.88	0.88	0.88
AdaBoost(SVM)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
AdaBoost(LR)	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89	0.89
AdaBoost(NB)	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
AdaBoost(RF)	0.89	0.90	0.89	0.89	0.89	0.89	0.89	0.89	0.89
bagging(KNN)	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Bagging(SVM)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
bagging(LR)	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86
bagging(NB)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
bagging(RF)	0.86	0.87	0.87	0.86	0.87	0.86	0.86	0.86	0.86
RS(KNN)	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90
RS(SVM)	0.92	0.92	0.92	0.91	0.92	0.92	0.91	0.91	0.91
RS(LR)	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91	0.91
RS(NB)	0.95	0.95	0.95	0.94	0.94	0.94	0.93	0.94	0.94
RS(RF)	0.93	0.93	0.93	0.92	0.93	0.92	0.92	0.92	0.92
Voting(Minimumprobability)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Maximumprobability)	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87
Voting(Majorityvoting)	0.87	0.88	0.88	0.88	0.88	0.88	0.87	0.88	0.88
Voting(Productofprobability)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Voting(Averageofprobabilities)	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88	0.88
Stacking	0.91	0.91	0.91	0.91	0.91	0.91	0.90	0.91	0.90

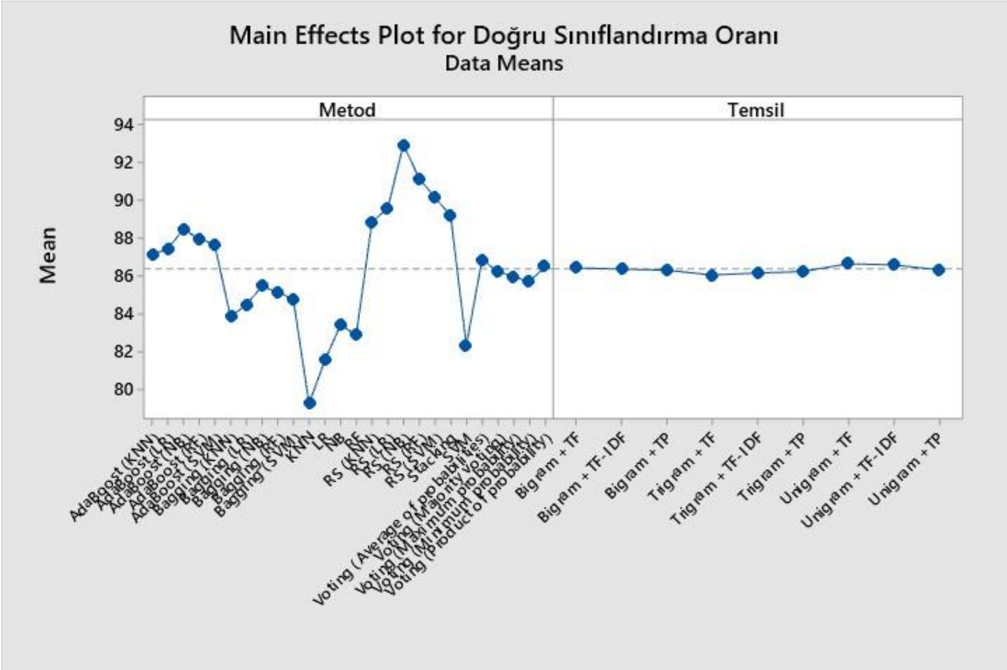

Fig. 1. Main effects plot for accuracy

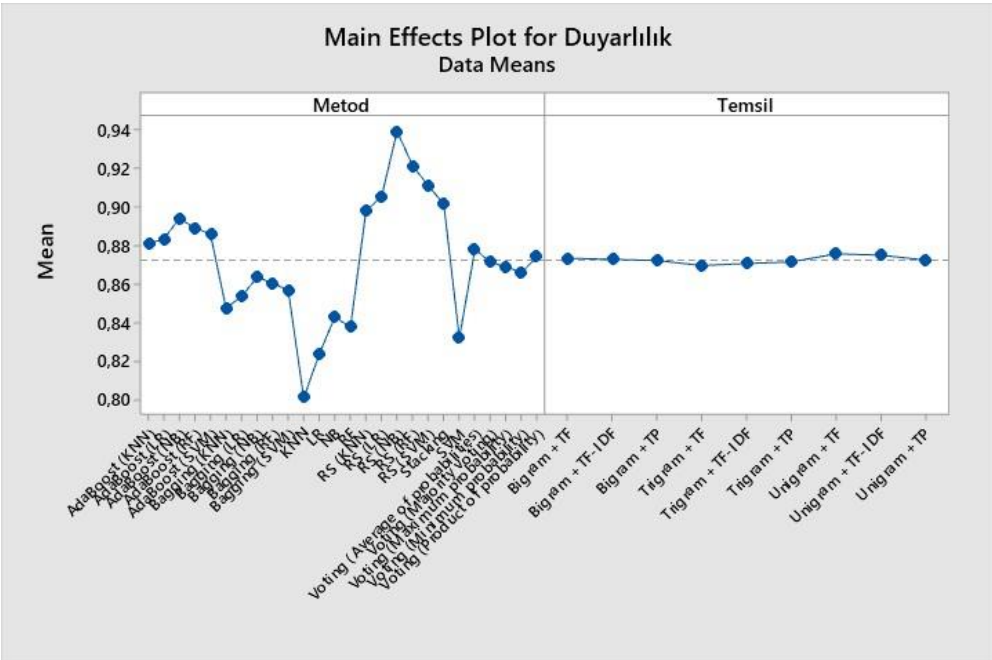

Fig. 2. Main effects plot for precision

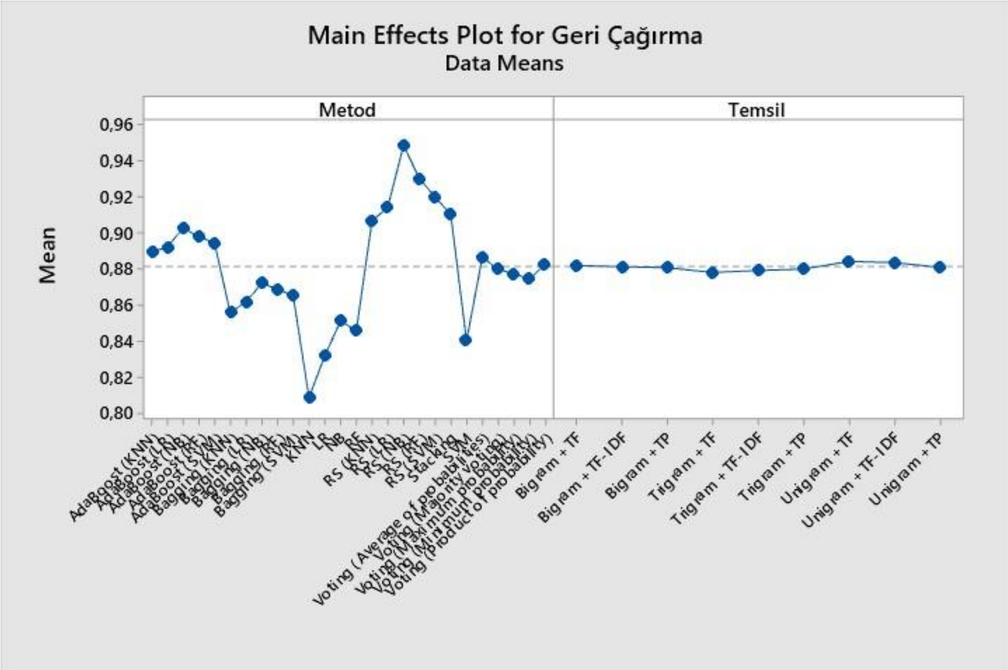

Fig. 3. Main effects plot for recall

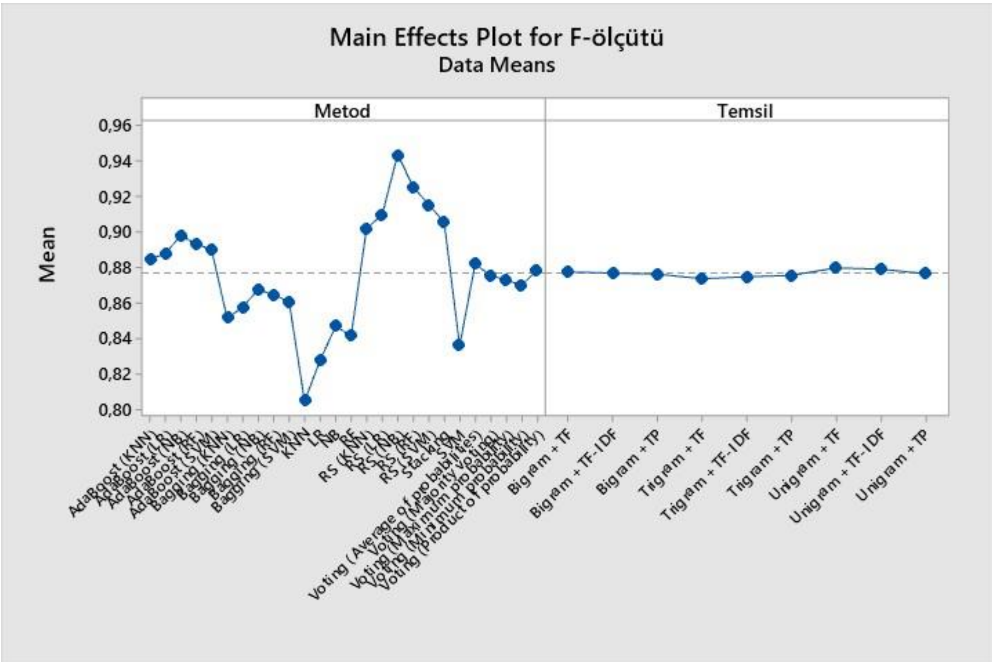

Fig. 4. Main effects plot for F-measure

4. Conclusions and Recommendations

In this paper classification was made with text mining in order to accurately analyze large datasets created with texts containing comments made by employees about the companies they work for. For this purpose K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), Logistic Regression (LR), Naive Bayes (NB) and Random Forest (RF) machine learning algorithms were used. These algorithms are implemented with Python programming language and scikit - learn library. The results which shown the tables and graphics above were analyzed comparatively of by accuracy value, presicion, recall and F-measure. When the results are compared and the performance values are analyzed, Random Space (RS) algorithm has got the highest success rate was obtained from the experiment with Naive Bayesian use. The highest accuracy value obtained from this experiment was 94.02 by using unigram and TF together as seen in Table 1., also precision value was 0.95, TP, TF and TF-IDF methods were used together with unigram as shown in Table 2; recall value was found with 0.96 success rate by using TP, TF and TF - IDF together with unigram and F -measure was found with 0.95 success rate by using TP, TF and TF-IDF methods together with unigram. Experimental results shows that Naive Bayes classification algorithm is more successful algorithm in text mining compared to other methods.

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