**IFT3335 TP2 Report**

**1. Experimental design**

To deal with the word meaning disambiguation problem, we aim to classify a word used in a context into the appropriate meaning class. The implementation process mainly includes data preprocessing, analysis of multiple classification algorithms, parameter sensitivity analysis, and draws some experimental conclusions and prospects for future optimization directions.

**2. Data preprocessing**

Data preprocessing mainly includes four parts: data denoising, feature extraction, feature selection and data set division.

**2.2 Feature Extraction**

Feature extraction includes two ways: feature extraction using grammatical part-of-speech granularity (gc) and feature extraction using word granularity (nw). The part-of-speech extraction method is to obtain the part-of-speech of each n adjacent words before and after the predicted word, such as VB VBG NNS IN, and the stem extraction method is to obtain the stems of each n adjacent words before and after the predicted word. Perform stem restoration, such as working->work.

**2.3 Feature Selection**

Since a word can appear several times in the text, and its importance may vary according to its frequency of occurrence. Therefore, consider extracting features from part-of-speech or stemming words by using CountVectorizer and TfidfVectorizer for feature selection, and using "frequency" to measure the importance of a word in the text. Among them, CountVectorizer uses the frequency of each word or part of speech in the entire training corpus as a feature, and TfidfVectorizer uses the word frequency-inverse text frequency of each word or part of speech in the entire corpus as its feature.

**2.4 Dataset division**

This dataset includes 2369 sentences, 6 semantics about "interest" or "interests". Detailed data can be found at: <http://www.d.umn.edu/~tpederse/data.html>, using the training set to train the model.

**3. Performance Analysis and Comparison of Classification Algorithms**

This section first makes a horizontal comparison of the performance of different classifiers under the same feature conditions, and then compares and analyzes different features and parameter settings.

In the process of effect comparison, this paragraph gives the Accuracy of each model.

Conclusion: The prediction accuracy of the mlp model is significantly better than other classification models, and the model works best when using n-words features. Therefore, in order to analyze the impact of model parameters on the effect more deeply, the following paragraphs will conduct parameter analysis based on the mlp model.

The mlp model has stronger scalability (the number of neural network layers, the number of hidden layer nodes, optimization methods, etc.), and stronger fitting capabilities, so its performance is also better.

**3.1 gc\_dataset:**

gc\_dataset.csv\_DecisionTreeClassifier: gc\_dataset.csv\_MLPClassifier

**图表, 折线图

描述已自动生成** 图表, 折线图

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gc\_dataset.csv\_MultinomialNB gc\_dataset.csv\_RandomForestClassifier

图表, 折线图

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gc\_dataset.csv\_SVC

图表, 折线图

描述已自动生成

**3.2 ng\_dataset:**

ng\_dataset.csv\_DecisionTreeClassifier. ng\_dataset.csv\_MLPClassifier

图表, 折线图

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ng\_dataset.csv\_MultinomialNB

图表, 折线图

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ng\_dataset.csv\_RandomForestClassifier ng\_dataset.csv\_SVC

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**3.3 nw\_dataset:**

nw\_dataset.csv\_DecisionTreeClassifier nw\_dataset.csv\_MLPClassifier

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nw\_dataset.csv\_MultinomialNB nw\_dataset.csv\_RandomForestClassifier

图表, 折线图

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nw\_dataset.csv\_SVC

**图表, 折线图

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**4. Parameter sensitivity analysis**

**4.1 Analysis of removing stop words**

Removing stop words includes removing punctuation marks (such as "/", ":", "\n", etc.), parts of speech ('/IN', '/DT', '/CC') and meaningless vocabulary (tool word list(stoplist).txt) has three parts, no stop words are removed, only punctuation marks and parts of speech are removed. Through experiments, if the words contained in stoplist.txt are removed, the effect of all classifiers will be reduced. We think it is because tool word list(stoplist).txt contains a lot of words and names, Words related to the user's emotional color, whether to delete stop words depends largely on the tasks we are performing and the goals we want to achieve, and we are training a model that can recognize the meaning of "interest", and keep stop words make the classification effect better.

The detailed experimental training parameters and the effects of various classifiers are as follows:

**(1) Remove stop words:**

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**(2) Do not remove stop words:**

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**4.2 Analysis of feature extraction method**

Conclusion: The model trained using stemmed word features (nw) outperforms the other two methods.

Stemming is to extract the stem or root form of a word, which can reduce the noise interference caused by tense, singular and plural, deformation, etc., and can obtain more useful information in sentences than other methods. For the effect of using only nw as a feature for model training, you can see the image data in **3.3 nw\_dataset**

**4.3 Window size**

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**4.4 Analysis of Feature Selection Method**

**TfidfVectorizer and CountVectorizer.**

Conclusion: TfidfVectorizer works better than CountVectorizer on most classifiers.

CountVectorizer only considers the frequency of vocabulary in the text, which belongs to the bag of words model feature, while TfidfVectorizer not only considers the frequency of a certain vocabulary in the text, but also pays attention to the number of all texts containing this vocabulary. It can reduce the impact of high-frequency meaningless words and get more meaningful features.

The experimental training parameters and the effects of various classifiers are as follows:

**(1) tf-idf**

**(2)count**

**4.5 Classifier parameters**

**4.5.1 Number of Network Layers**

**4.5.2 Optimizer**

**4.5.3 Activation function**

**5. Conclusions and expectations**

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