Cuisine Classification from Ingredients
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Introduction

The goal of the project is to categorize a dish’s cuisine type (Indian, Italian, Chinese, etc.), by analyzing its ingredient list. The dataset for the project is provided by Yummly. In the dataset, there are 20 types of cuisines. The team need to build a dictionary of ingredients and use several multi-class classification models to predict the type of cuisines given a new dish.

Given the dataset with more than 39000 examples, the total number of ingredients with different names is 6714. There are many ingredients which are basically the same but with slight difference in names. Therefore the ingredients is largely redundant. The team came up with several methods to reduce the number of features and use them in several different classification models to compare their performance.

Since there are 20 classes in the cuisine set. The team used several multiclass classification models including OVA multiclass Naive Bayes, OVA R2-regularized logistic regression, OVA multi-class SVM, Multi-class SVM with crammer method, and K nearest neighbor.

Classification algorithms and performance

- Multi-class text classification problem can be reduced to a series of binary classification problems.
- Error-Correcting Output Coding (ECOC)[1], which trains several numbers of different binary classifiers, and then uses the outputs of these classifiers to predict the label for a new example.
- The code matrix R is the one-verse-all (OVA) code matrix. And it is applied to train a series of Naive Bayes, SVM and logistic regression classifiers.
- Multiclass SVM introduced by Crammer and Singer[2]
- K-nearest-neighbor algorithm [3]
- 80% of the dataset as training set
- 20% of the dataset as test set
- Key words Combination method only search for some key words to combine.
- Combination & Reduction does both Key words Combination and descriptive words reduction.

| Table 1. Overall performance for each classification algorithms |
|------------------|------------------|------------------|------------------|------------------|
|                  | OVA NB | OVA SVM | OVA Logistic | SVM by Crammer | Knn               |
| Original features | 0.623   | 0.751   | 0.772        | 0.746           | 0.661             |
| Reduced accuracy  | 0.670   | 0.742   | 0.757        | 0.732           | 0.683             |
| Mutual Information| 0.713   | 0.757   | 0.771        | 0.743           | 0.697             |
| Key words Combination | 0.653 | 0.750   | 0.768        | 0.740           | 0.690             |
| Combination &Reduction | 0.622 | 0.765   | 0.784        | 0.754           | 0.714             |

Observations and future work

- After feature selection, the reduced feature set didn’t improve the performance much.
- Chart 1 and Chart 2 show that cuisine types that have small training examples have larger error rates.
- Future works:
  - Better natural language processing schematic in the context of recipes
  - Performance may suffer from the lack of training examples of several cuisines: Brazilian, Jamaican and Russian. Additional training examples in these classes would be beneficial.
  - Additional models would be tried like “bags of words”, etc.

References & Acknowledgements

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Pre-processing and feature selection

Figure 1. Feature selection Schematic

Five steps in feature selection
Step 1. remove punctuation, digits, content inside parenthesis
Step 2. remove brands
Step 3. convert to lower case and remove stop words
Step 4. Remove low-content adjectives
Step 5. Porter Stemmer Algorithm

Table of features: 6714 --> 5353
Table of cuisines: 20

Figure 2. Mutual Information of reduced ingredients

Figure 3. Cuisine distribution

Figure 4. Test Error for Logistic Regression with different feature methods

Figure 5. Training error and test error on logistic regression with Combination & Reduction

Chart 1. Error label rate mislabeled into each class
Chart 2. Error label rate of each class mislabeled into other classes