



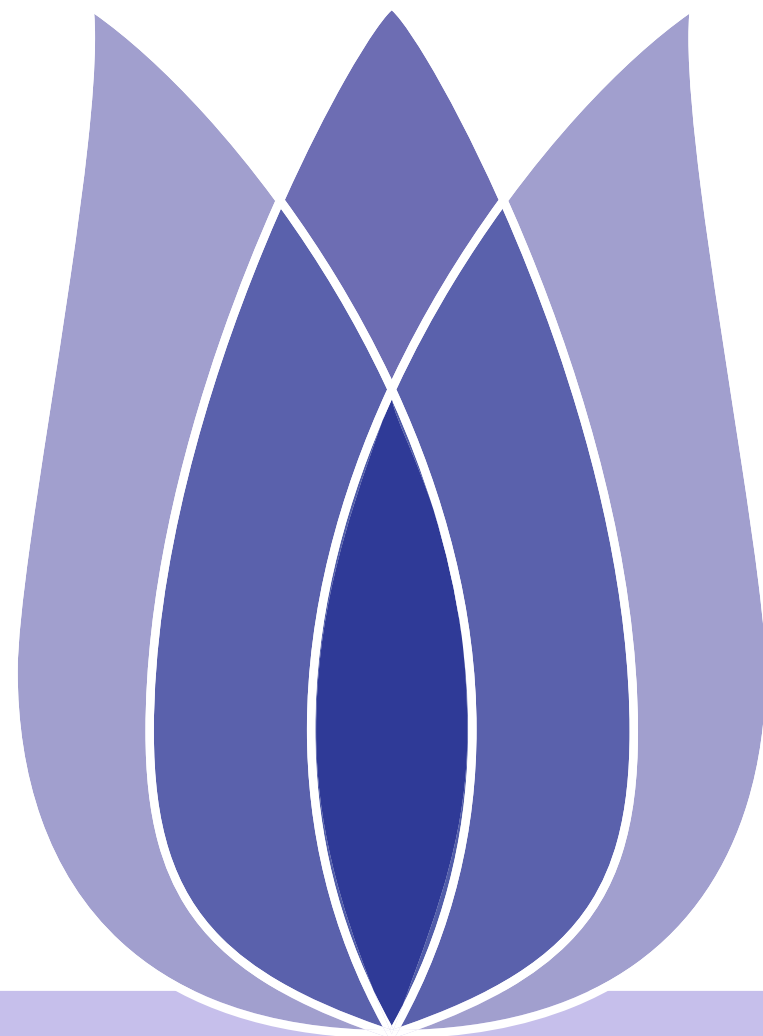
# what's cooking

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# Overview



# Description and Evaluation

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## ■ Description

In this competition, participants are asked to predict the category of a dish's cuisine given a list of its ingredients.

## ■ Evaluation

Submissions are evaluated on the categorization accuracy (the percent of dishes that you correctly classify).



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# Data



# Data Description and Explorer

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## ■ Data Description

In the dataset, it include the recipe id, the type of cuisine, and the list of ingredients of each recipe (of variable length). The data is stored in JSON format.

In the test file test.json, the format of a recipe is the same as train.json, only the cuisine type is removed, as it is the target variable you are going to predict.

## ■ Data Explorer

- ◆ **train.json** – the training set containing recipes id, type of cuisine, and list of ingredients. It contains 39774 entries.
- ◆ **test.json** – the test set containing recipes id, and list of ingredients. It contains 9944 entries.
- ◆ **sampleSubmission.csv** – a sample submission file in the correct format. It just contains 2 columns that is "id" and "cuisine".

# Missing Values Analysis

I statistic missing value in the dataset, Luckily the dataset do not has any missing value.

```
(df.isnull().sum() / len(df)) * 100  
(test_df.isnull().sum() / len(test_df)) * 100
```

Figure 1: Missing values analysis

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There are a total of 20 types of cuisines, and the percentage of each type of cuisine is as follows.

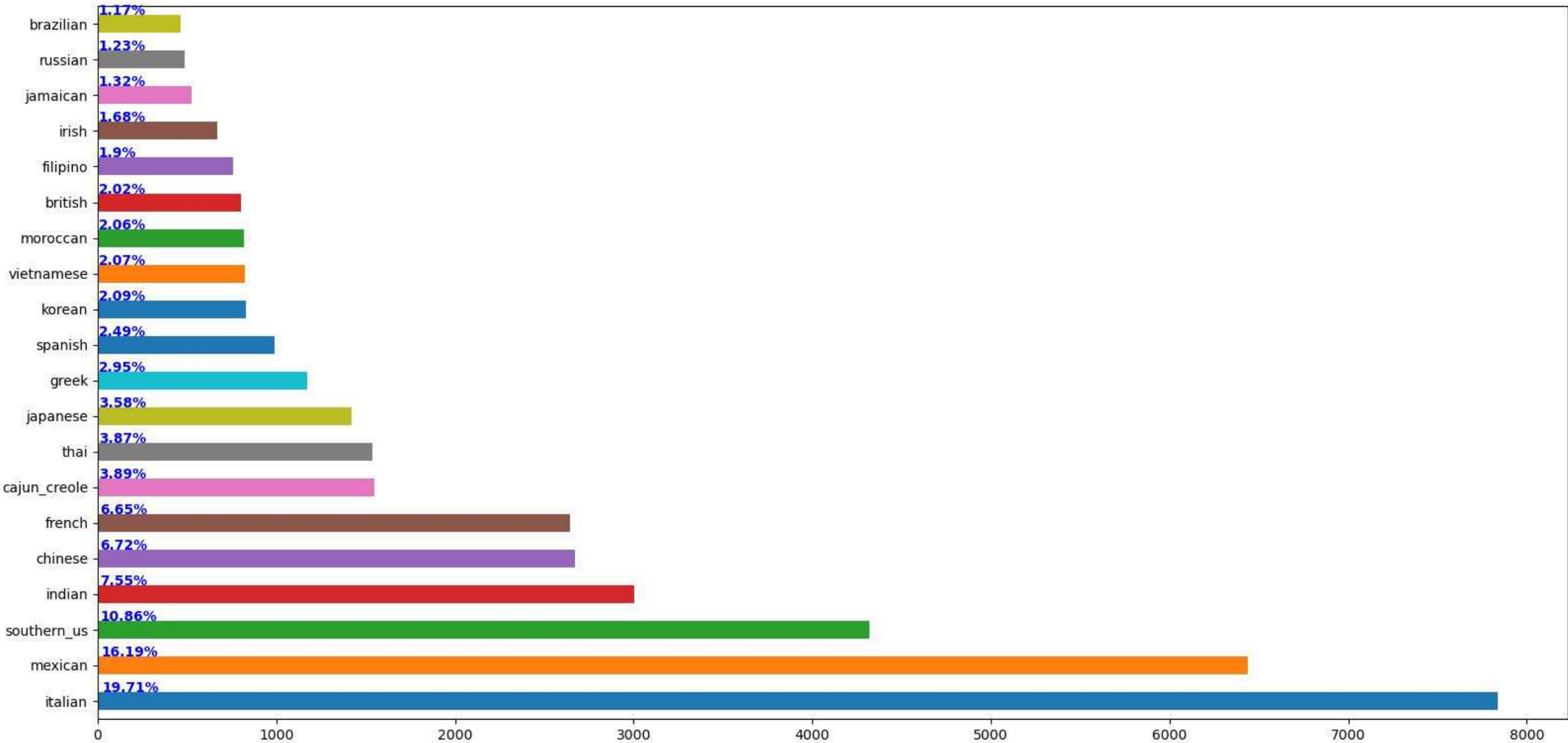


Figure 2: Statistic Cuisine



# Word Frequency Statistics

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Count the number of occurrences of each word in the entire dataset ‘ingredients’, In order to analyze the importance of related vocabulary.

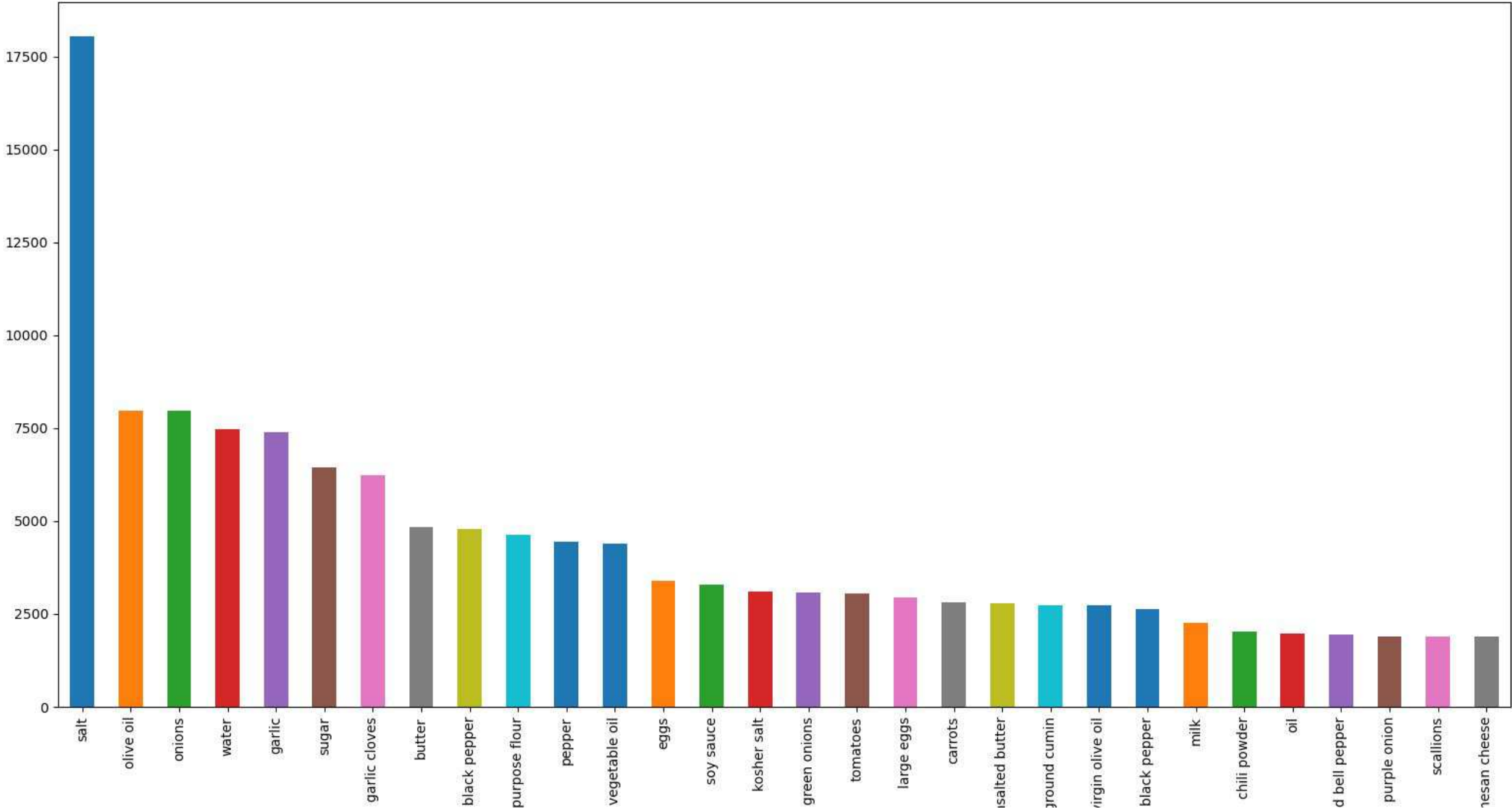


Figure 3: Word frequency statistics of entire dataset



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Count the number of ‘ingredients’ per cuisine. There are twenty cuisine in the train data, just show the ‘Greek’ word frequency statistics. Just Visualize the 25 most commonly used ingredients.

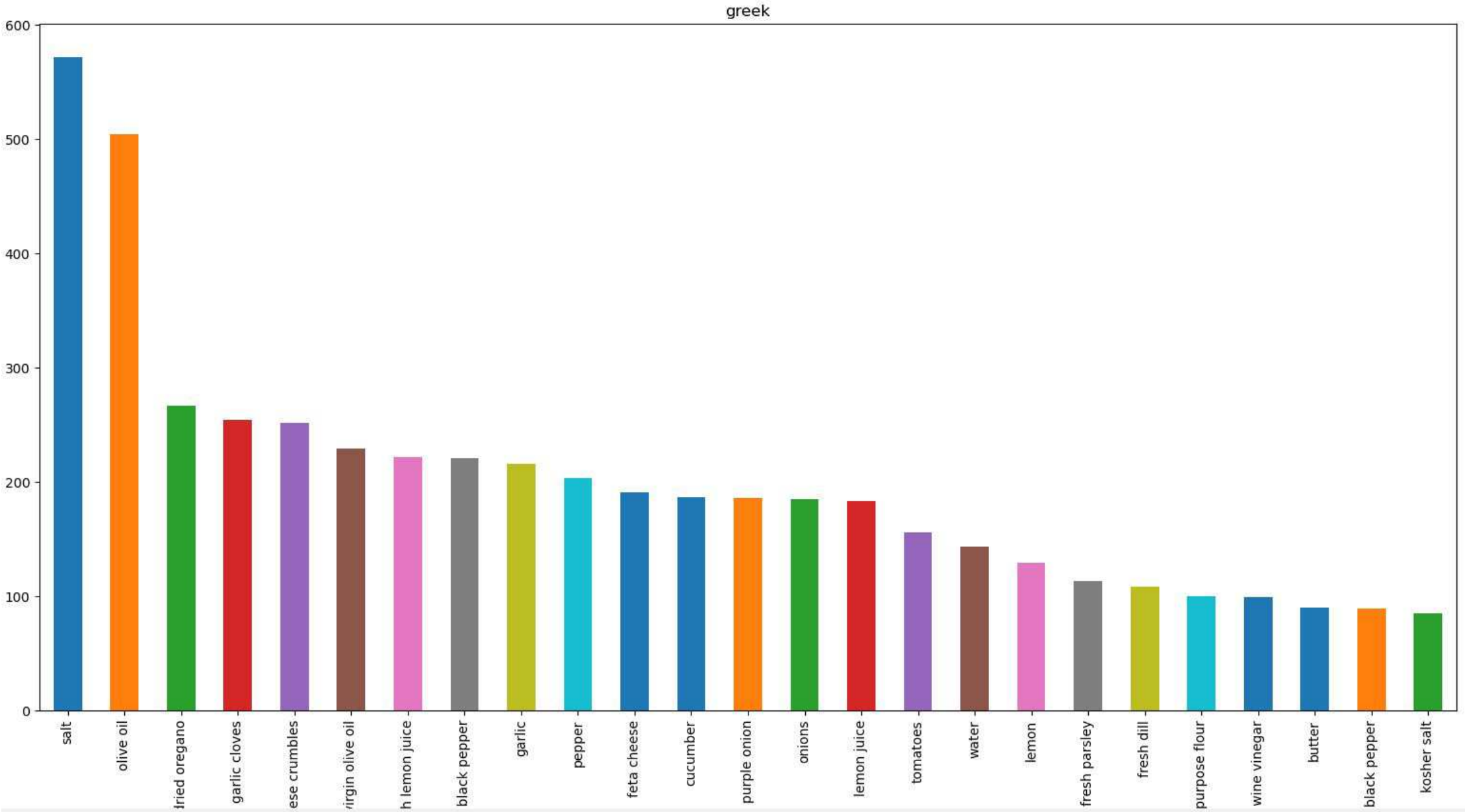


Figure 4: Greek word frequency statistics

# String Preprocess

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- 1: Use the WordNetLemmatizer().lemmatize() method to restore the part of speech
- 2: remove the useless suffix of the word
- 3: remove the non-letter symbols
- 4: change the uppercase letters to lowercase

```
# 处理字符串
def process_string(x):
    x = [" ".join([WordNetLemmatizer().lemmatize(q) for q in p.split()]) for p in x] # Lemmatization
    x = list(map(lambda x: re.sub(r'\(.*oz.\)|crushed|crumbles|ground|minced|powder|chopped|sliced', '', x), x))
    x = list(map(lambda x: re.sub("[^a-zA-Z]", " ", x), x)) # To remove everything except a-z and A-Z
    x = " ".join(x) # To make list element a string element
    x = x.lower() # 所有大写字母转换为小写字母
    return x
```

Figure 5: String preprocess



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# Feature Engineering



# Count Vectorizer

Convert a document into a vector by counting to complete feature extraction, which get a word frequency matrix.

```
# Count Vectorizer
def count_vectorizer(train, test=None):
    cv = CountVectorizer()
    train = cv.fit_transform(train)
    if test is not None:
        test = cv.transform(test)
        return train, test, cv
    else:
        return train, cv
```

Figure 6: code of count vectorizer



# TFiDF Vectorizer

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Input the word frequency matrix to get the TF-IDF weight matrix.

```
# TFiDF Vectorizer
def tfidf_vectorizer(train, test=None):
    tfidf = TfidfVectorizer(stop_words='english', ngram_range=(1, 1), analyzer="word", max_df=.57,
                           binary=False, token_pattern=r'\w+', sublinear_tf=False)

    train = tfidf.fit_transform(train)
    if test is not None:
        test = tfidf.transform(test)
        return train, test, tfidf
    else:
        return train, tfidf
```

Figure 7: code of TFiDF vectorizer



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# Cluster as Parameter

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There are 20 different types of cuisine to classify. Certain groups of cuisine may have much more similarity than others. So we use the clustering information as part of the feature.

The "cuisine\_df" is also used to generate the weight matrix through the TFiDF Vectorizer. Use PCA to reduce dimensionality.

Predict clusters in the test data, encoded as Onehot vectors.

Combine the TFIDF vector and the cluster vector as a feature vector.







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I have choose the SVC as classification model.

```
from sklearn.svm import LinearSVC, SVC

C = 604.5300203551828
gamma = 0.9656489284085462

clf = SVC(C=float(C), gamma=float(gamma), kernel='rbf')
clf.fit(train, target)
y_pred = clf.predict(test)
```

Figure 8: SVC

The percentage of the number of correctly classified cuisines in the total number is used as the accuracy rate.

My accuracy rate is 81.06%



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