COMP348 — Document Processing and the Semantic Web

Week 04 Lecture 1: Developing Text Classification Systems

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COMP348 2018H1

Programme

1. Some Text Classification Tasks
2. Multi-label Classification
3. Evaluation

Reading

- NLTK Book Chapter 6 "Learning to Classify Text"

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Programme

1. Some Text Classification Tasks
   - Gender Classification (again)
   - Movie Reviews
   - Sentence Segmentation
2. Multi-label Classification
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Gender Classification - Take 2

- In a past lecture we have used this code to encode the last two characters of a name:

```
def gender_features(word):
    "Return the ASCII value of the last two characters"
    return [ord(word[-2]), ord(word[-1])]
```

- This code is not entirely correct since it is representing characters as numbers.
- In general, non-numerical information is best represented using one-hot encoding.
- sklearn provided the following functions to produce one-hot-encoding vectors:
    - preprocessing.OneHotEncoding: from integers to one-hot vectors.
    - preprocessing.LabelBinarizer: from labels to one-hot vectors.

One-hot Encoding

- Suppose you want to encode five labels: 'a', 'b' ,'c', 'd', 'e'.
- Each label represents one element in the one-hot vector.
- Thus:
  - 'a' is represented as (1, 0, 0, 0, 0).
  - 'b' is represented as (0, 1, 0 ,0 ,0).
  - and so on.
- This is also called binarization.

One-hot Encoding for Gender Classification

```
def one_hot_character(c):
  alphabet = 'abcdefghijklmnopqrstuvwxyz'
  result = [0]*len(alphabet)
  result[alphabet.index(c.lower())] = 1
  return result

def gender_features(word):
    last = one_hot_character(word[-1])
    secondlast = one_hot_character(word[-2])
    return secondlast + last
```

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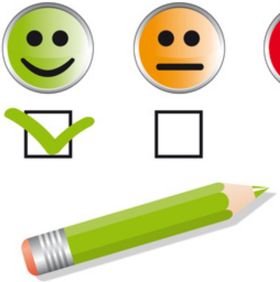
Movie Reviews

- Movie reviews can be positive or negative.
- This can be easily modelled as a text classification task.
- This is also an example of sentiment analysis.



One-Hot Encoding of Words

- A common approach to represent bag of words is the one-hot encoding.
- Basically, each element in the word vector is either 0 or 1.
- The result is a sparse matrix.
- Tf.idf can be seen as an extension of one-hot encoding.

Remember this slide on Vector Space Model?

Each document vector is like an OR operation of the one-hot encoding vectors of each word in the document.

Template:
{computer,software,information,document,retrieval,language,library,filtering}

Initial documents

D1:{computer,software,information,language}
D2:{computer,document,retrieval,library}
D3:{computer,information,filtering,retrieval}

Document vectors

D1: (1,1,1,0,0,1,0,0)
D2: (1,0,0,1,1,0,1,0)
D3: (1,0,1,0,1,0,0,1)

Document matrix

$$D = \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 0 & 1 \end{pmatrix}$$

Finding the 2000 most frequent non-stop words

```
import nltk
import collections
from nltk.corpus import stopwords
stop = stopwords.words('english')
c = collections.Counter([w.lower()
                         for (words,category) in train
                         for w in words
                            if w.lower() not in stop])
top2000words = [w for (w,count) in c.most_common(2000)]
```

Remember

When you compute statistics for machine learning, only use the training set.

Implementing the document features in NLTK

```
def document_features(words):
    "Return the document features for an NLTK classifier"
    words_lower = [w.lower() for w in words]
    result = dict()
    for w in top2000words:
        result['has(%s)' % w] = (w in words_lower)
    return result
```

Training and Evaluating NLTK's Naive Bayes

```
train_features = [(document_features(x),y)
                    for (x,y) in train]
devtest_features = [(document_features(x),y)
                    for (x,y) in devtest]
classifier = nltk.NaiveBayesClassifier.train(train_features)
nltk.classify.accuracy(classifier,devtest_features)
```

Implementing the document features in Scikit-Learn

```
def vector_features(words):
    "Return a vector of features for sklearn"
    words_lower = [w.lower() for w in words]
    result = []
    for w in top2000words:
        if w in words_lower:
            result.append(1)
        else:
            result.append(0)
    return result
```

Training and Evaluating Scikit-Learn's Naive Bayes

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score

train_vectors = [vector_features(x) for (x, y) in train]
train_labels = [y for (x, y) in train]
devtest_vectors = [vector_features(x) for (x, y) in devtest]
devtest_labels = [y for (x, y) in devtest]

sklearn_classifier = MultinomialNB()
sklearn_classifier.fit(train_vectors, train_labels)
MultinomialNB(alpha=1.0, class prior=None, fit prior=True)

predictions = sklearn_classifier.predict(devtest_vectors)
accuracy_score(devtest_labels, predictions)
```

Using tf-idf as document features

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf = TfidfVectorizer()
train_features = tfidf.fit_transform([x for x, y in train_raw

sklearn_classifier2 = MultinomialNB()
sklearn_classifier2.fit(train_features,
                        [y for x, y in train_raw])

devtest_features = tfidf.transform([x for x, y in devtest_raw
predictions = sklearn_classifier2.predict(devtest_features)
accuracy_score([y for x, y in devtest_raw], predictions)
```

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Sentence Segmentation

- Sentence segmentation can be reduced to the process of disambiguating potential punctuation characters.
- So we can apply a classifier to the characters.
- For sentence segmentation we need to look at the context.

Possible Context-based Features

The following features could be useful to determine if a punctuation character is an end of sentence:

1. Is the next word capitalised?
2. What is the previous word?
3. What is the current punctuation character?
4. Is the previous word a character?

Feature Extraction with Context

```python
def segmenter_features(tokens, i):
    """Return the features of token[i]"""
    return {'next-word-capitalized':
                tokens[i+1][0].isupper(),
            'prev-word': tokens[i-1].lower(),
            'punct': tokens[i],
            'prev-word-is-one-char':
                len(tokens[i-1]) == 1}
```

ML for Sentence Segmentation

Training and Testing Data

- We only need to look at candidate characters.
- For training and testing we need to keep track of the positions of all sentence endings.

```
candidates = '.?!'
train_features = [(segmenter_features(train_tokens, i),
                   (i in train_boundaries))
                  for i in range(1, len(train_tokens)-1)
                  if train_tokens[i] in candidates]
test_features = [(segmenter_features(test_tokens, i),
                  (i in test_boundaries))
                 for i in range(1, len(test_tokens)-1)
                 if test_tokens[i] in candidates]
```

Running the Classifier

```
segmenter=nltk.NaiveBayesClassifier.train(train_features

test = ["This", "is", "a", "sentence", ".", "This",
       "is", "another", "one"]
for i in range(0,len(test)):
   if test[i] in candidates and \
      classifier.classify(features(test,i)):
      print "Sentence boundary at position", i
```

Evaluation of the Classifier

```
>>> nltk.classify.accuracy(segmenter,
                           test_features)
1.0
```

- Accuracy on the test set is impressive.
- However, sentence segmentation is almost always easy.
- Let's compare against a very simple baseline.

A Majority Baseline

- A majority baseline is a classifier that always returns the majority class.
- In our case, in most cases the punctuation character is an end of sentence.

```
>>> from collections import Counter
>>> train_counter = Counter([f[1] for f in train_features
>>> train_counter
Counter({False: 62, True: 3687})
```

- If our classifier always classify the end of sentence as True, the accuracy is very high:

```
>>> test_counter = Counter([f[1] for f in test_features])
>>> test_counter
Counter({False: 2, True: 405})
>>> 405/407
0.995085995085995
```

- High accuracies are common when there is unbalanced data.

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Multilabel Text Categorisation

The Reuters-21578 Corpus

- http://about.reuters.com/researchandstandards/corpus/
- A collection of Reuters news stories.
- Each news stories has one or more topics.
- Available in NLTK.

Demo on classifying Reuters documents using NLTK:

- See related notebook.

Assigning Multiple Labels to a Document

- You can use independent classifiers, one per label.
- Each classifier is trained independently from the others.
- When you want to label a document, run each independent classifier.
- If classifier X assigns the positive class to the document, then label the document with label X.

Evaluation of Multilabel Text Categorisation

- Recall, Precision, F are designed for binary classification.
- In multilabel classification, we will need to evaluate each separate label and average the results.

Macro-averaged Recall (Precision, F)

- Average the evaluation across all labels.
- All labels have the same weight.
- But what if some labels may have very few samples?

Micro-averaged Recall (Precision, F)

- The evaluation is based on the total number of true positives, false positives, and false negatives.

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Recap on Training and Testing

- Use the training set to train the classifier.
- Use a separate test set to evaluate the classifier.
- Make sure that there is no bias in the training or test sets.
- We often need a dev-test set if we are going to fine-tune our system.

Remember

- Never look at the test set to fine-tune your system.
- Never train the system using the test set.
- Do not evaluate using the training set unless you want to check for over-fitting.

Cross-Validation

If we do not have enough data we can use cross-validation.

N-fold Cross-Validation

1. Divide the data into N partitions called folds.
2. Keep fold 1 for testing and train with the other folds.
3. Repeat with folds 2, 3, . . . , N.
4. Report the average of the results.
5. The standard deviation gives you an indication of the robustness of the system.

Cross-validation in Scikit-learn

http://scikit-learn.org/stable/modules/cross_validation.html

The Easiest Way

Scikit-learn provides several evaluation metrics that can be used for cross-validation, such as accuracy, F1, and many more.

```
>>> cross_val_score(crossval_classifier, train_features, train_labels,
                    cv=10, scoring="accuracy")
array([ 0.79338843,  0.80833333,  0.76666667,  0.79166667,  0.80833333,
        0.79166667,  0.825     ,  0.83333333,  0.79166667,  0.80672269])
```

Iterating over KFolds

If we want to have more flexibility on what to do on each iteration of cross-validation we can use the KFold iterator.
(see notebook for an example of use)

Take-home Messages

1. Create one-hot encoding of words for NLTK and Scikit-learn.
2. Design useful feature extractors in NLTK and Scikit-learn.
3. Design feature extractors that use context.
4. Train and evaluate statistical classifiers.
5. Compare with a baseline.
6. Perform cross-validation.

What's Next

Week 5

- Sequence Labelling.
- Friday: GOOD FRIDAY (Easter)
  No lecture, no workshop session

Reading

- NLTK Chapter 6.