COMP3220 — Document Processing and the Semantic Web

Week 03 Lecture 1: Introduction to Text Classification

Diego Mollá

COMP3220 2021H1

Abstract

This lecture will focus on the task of text classification by using statistical classifiers. We will focus on the general workflow for applying statistical classifiers. In this lecture we will view statistical classifiers as black boxes.

Update March 3, 2021

Contents

Reading

- NLTK Book Chapter 6 “Learning to Classify Text”

Some Useful Extra Reading

- Jurafsky & Martin (draft), Chapter 4. ”Naive Bayes and Sentiment Classification”.

1 What is Text Classification

Text Classification

What is Text Classification?
Classify documents into one of a *fixed predetermined* set of categories.

- The number of categories is predetermined.
- The actual categories are predetermined.

Examples

- Spam detection.
- Email filtering.
- Classification of text into genres.
- Classification of names by gender.
- Classification of questions.

Example: Spam Filtering

Distinguish this

Date: Mon, 24 Mar 2008 From: XXX YYY <xxx@yahoo.com> Subj: Re: Fwd: MSc To: Mark Dras <madras@ics.mq.edu.au>

Hi, Thanks for that. It would fit me very well to start 2009, its actually much better for me and I'm planning to finish the project in one year (8 credit points).

from this

Date: Mon, 24 Mar 2008 From: XXX YYY <xxx@yahoo.co.in> Subj: HELLO To: madras@ics.mq.edu.au

HELLO, MY NAME IS STEPHINE IN SEARCH OF A MAN WHO UNDERSTANDS THE MEANING OF LOVE AS TRUST AND FAITH IN EACH OTHER RATHER THAN ONE WHO SEES LOVE AS THE ONLY WAY OF FUN ...

Classification Methods

Manual

- Web portals.
- Wikipedia.

Automatic

Hand coded rules

- e.g. 'Viagra' == SPAM.
- e.g. email filter rules.
- Fragile, breaks on new data.

Supervised learning

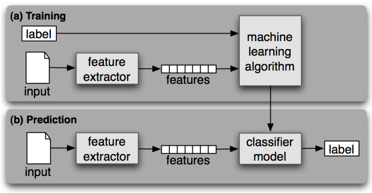
- Use an annotated corpus.
- Apply statistical methods.
- Greater flexibility.

Supervised Learning

Given
Training data annotated with class information.

Goal
Build a *model* which will allow classification of new data.

Method



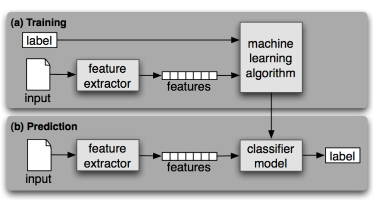
1. Feature extraction: Convert samples into vectors.
2. Training: Automatically learn a model.
3. Classification: Apply the model on new data.

2 Statistical Classification with NLTK and Scikit-Learn

2.1 NLTK

NLTK Features

- Statistical classifiers are not able to make sense of text.
- We need to feed them with our interpretation of the text.
- NLTK classifiers expect a dictionary of features and values.



Example of a Simple Feature Extractor

```
def gender_features(word):
    return {'last_letter': word[-1]}
```

Example: Gender Classification

```
>>> import nltk
>>> from nltk.corpus import names
>>> import random
>>> random.seed(1234) # Fixed random seed to facilitate replicability
>>> names = ([(name, 'male') for name in m] +
             [(name, 'female') for name in f])
>>> random.shuffle(names)
>>> def gender_features(word):
  return {'last_letter': word[-1]}
>>> featuresets = [(gender_features(n), g) for n, g in names]
>>> train_set, devtest_set, test_set =
                featuresets[1000:], featuresets[500:1000], featuresets[:500]
>>> classifier = nltk.NaiveBayesClassifier.train(train_set)
>>> classifier.classify(gender_features('Neo'))
'male'
>>> classifier.classify(gender_features('Trinity'))
'female'
>>> nltk.classify.accuracy(classifier, test_set)
0.776
>>>
```

Note that the classifier is fed with the gender features and not with the actual names.

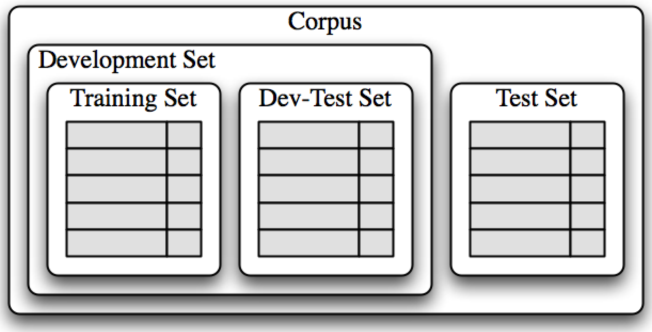
You can see a more complete and working version of this code in the Jupyter notebook associated to this lecture.

The Development Set

Important
Always test your system with data that has not been used for development (Why ...?)

Development and Test Sets

- Put aside a test set and don't even look at its contents.
- Use the remaining data as a development set.
  - Separate the development set into training and dev-test sets.
  - Use the training set to train the statistical classifiers.
  - Use the dev-test set to fine-tune the classifiers and do error analysis.
  - Use the test set for the final system evaluation once all decisions and fine-tuning have been completed.



Error Analysis in our Gender Classifier

```
>>> nltk.classify.accuracy(classifier, devtest_set)
0.756
>>> errors = []
>>> for name, tag in devtest_names:
    guess = classifier.classify(gender_features(name))
    if tag == 'female' and guess == 'male':
        false_males.append(name)
    elif tag == 'male' and guess == 'female':
        false_males.append(name)
>>> len(false_males)
122
>>> len(false_females)
0
>>> for m in false_males[:5]:
        print(m)
```

A Revised Gender Classifier

```
>>> def gender_features2(word):
        return {'suffix1': word[-1:],
                'suffix2': word[-2:]}

>>> train_set2 = [(gender_features2(n), g) for n, g in train_names]
>>> devtest_set2 = [(gender_features2(n),g) for n, g in devtest_names]
>>> classifier = nltk.NaiveBayesClassifier.train(train_set2)
>>> nltk.classify.accuracy(classifier, devtest_set2)
0.77
```

Beware of Over-fitting

If there are many features on a small corpus the system may *over-fit*.

```
>>> def gender_features3(name):
      features = {}
      features['firstletter'] = name[0].lower()
      features['lastletter'] = name[-1]
      for letter in 'abcdefghijklmnopqrstuvwxyz':
```

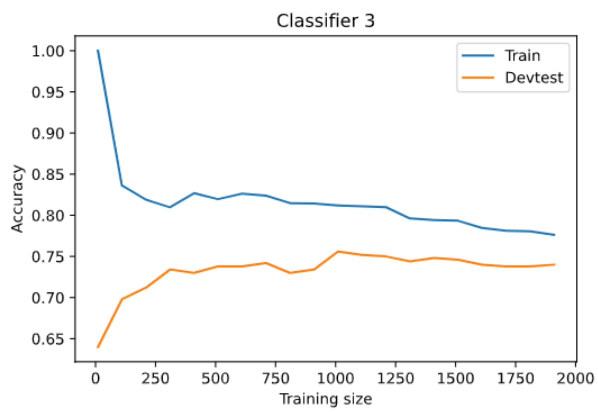
```
        features['count(%s)' % letter] = name.lower().count(letter)
        features['has(%s)' % letter] = (letter in name.lower())
    return features

>>> gender_features3('John')
{'count(u)': 0, 'has(d)': False, 'count(b)': 0, 'count(w)': 0, ...}
>>> train_set3 = [(gender_features3(n), g) for n, g in train_names]
>>> devtest_set3 = [(gender_features3(n), g) for n, g in devtest_names]
>>> classifier = nltk.NaiveBayesClassifier.train(train_set3[:50])
>>> nltk.classify.accuracy(classifier, devtest_set3)
0.698
>>> classifier2b = nltk.NaiveBayesClassifier.train(train_set2[:50])
>>> nltk.classify.accuracy(classifier2b, devtest_set2)
0.7
```

Some types of classifiers are more sensitive to over-fitting than others.

Identifying Over-fitting

(see this week's lecture Jupyter notebook for the code that created this plot)



We can observe over-fitting when the evaluation on the training set is much better than that on the test set. Over-fitting is generally lesser as we increase the size of the training set (X axis). In this example, the system overfits in all cases. Overfitting has reduced as we increase the number of training samples but there is still substantial overfitting even with 2000 training samples.

We can also see that accuracy of the test set keeps increasing as we increase the training size, up to a training size of about 1000 samples. This means that there is no point in adding more than 1000 samples of tranining data.

This conclusion (that there's no need to add more than 1000 samples of training data) may not apply to other tasks, other methods to extract features, or other machine learning classifiers. In particular, you may obtain better results if you use the deep learning classifiers that we will study in the following weeks.

2.2 Scikit-Learn

Text Classification in Scikit-Learn

- Scikit-learn includes a large number of statistical classifiers.
- All of the classifiers have a common interface.

- The features of a document set are represented as a matrix.
  - Each row represents a document.
  - Each column represents a feature.
- Scikit-learn provides some useful feature extractors for text:
  1. CountVectorizer returns a (sparse) matrix of word counts.
  2. TfidfVectorizer returns a (sparse) matrix of tf.idf values.

Gender Classifier in Scikit-Learn - Take 1

```
>>> from sklearn.naive_bayes import MultinomialNB
>>> def gender_features(word):
        "Return the ASCII value of the last two characters"
        return [ord(word[-2]), ord(word[-1])]
>>> featuresets = [(gender_features(n), g) for n, g in names]
>>> train_set, test_set = featuresets[500:], featuresets[:500]
>>> train_X, train_y = zip(*train_set)
>>> classifier = MultinomialNB()
>>> classifier.fit(train_X, train_y)
>>> test_X, test_y = zip(*test_set)
>>> classifier.predict(test_X[:5])
array(['female', 'female', 'male', 'female', 'female'],
      dtype='|S6')
```

In this code, the function "gender_features" returns a list with the ASCII values of the last two characters of the word. This is so because the matrix can only have numerical values.

We also see Python's way to unpack a list. The variable "train_set" is a list where each element is a pair (vector, outcome). We want to unpack the list into two lists: one containing all the vectors, and the other containing all the outcomes. The instruction:

```
train_X, train_y = zip(*train_set)
```

is equivalent to this sequence of instructions:

```
train_X = [x[0] for x in train_set]
train_y = [x[1] for x in train_set]
```

That is, assign to "train_X" the list of all training vectors, and assign to "train_y" the list of all target outcomes. The "*" in the instruction is important.

The complete code of a working program is:

```
from nltk.corpus import names
from sklearn.naive_bayes import MultinomialNB

def gender_features1(word):
    return [ord(word[-1])]

def gender_features2(word):
    return [ord(word[-1]), ord(word[-2])]

def gender_features3(name):
```

```
    features = []
    features.append(ord(name[0].lower()))
    features.append(ord(name[-1]))
    for letter in 'abcdefghijklmnopqrstuvwxyz':
        features.append(name.lower().count(letter))
        features.append(int(letter in name.lower()))
    return features

def accuracy(classifier, test_X, test_y):
    "Return the classifier accuracy"
    results = classifier.predict(test_X)
    correct = results[results == test_y] # returns the list of results that
                                         # are correctly predicted
    return float(len(correct))/len(test_y)

def demo(data, featurefunction):
    featuresets = [(featurefunction(n),g) for (n,g) in data]
    train_set, test_set = featuresets[500:], featuresets[:500]
    train_X, train_y = zip(*train_set)
    test_X, test_y = zip(*test_set)
    classifier = MultinomialNB()
    classifier.fit(train_X, train_y)
    print "Classification of Neo:", \
        classifier.predict([featurefunction('Neo')])[0]
    print "Classification of Trinity:", \
        classifier.predict([featurefunction('Trinity')])[0]
    print "Classifier accuracy:", accuracy(classifier, test_X, test_y)


if __name__ == "__main__":
   m = names.words('male.txt')
    print "There are", len(m), " samples of male names"

    f = names.words('female.txt')
    print "There are", len(f), " samples of female names"

    import random
    names = ([(name, 'male') for name in m] +
             [(name, 'female') for name in f])
    random.shuffle(names)

    print "Classifier 1:"
    demo(names, gender_features1)
    print

    print "Classifier 2:"
    demo(names, gender_features2)
    print

    print "Classifier 3:"
    demo(names, gender_features3)
```

Gender Classification - Take 2

- In the past slide 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 provides 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 or categorical encoding.

One-hot Encoding for Gender Classification

```
def one_hot_character(c):
  alphabet = 'abcdefghijklmnopqrstuvwxyz'
  result = [0]*(len(alphabet)+1)
  i = alphabet.find(c.lower())
  if i >= 0:
      result[i] = 1
  else:
      result[len(alphabet)] = 1 # out of the alphabet
  return result

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

This code sums the one-hot representations of the last two characters into a unique vector so that it can be used by scikit-learn.

3 Advice on Machine Learning

Possible Problems with Machine Learning

- ML methods are typically seen as black boxes.
- Some methods are better than others for specific tasks but people tend to just try several and choose the one with best results.

Possible problems/mistakes you might face

1. Train and test are the same dataset (don't do this!).
2. The results on the test set are much worse than on the dev-test set.
3. The results of both the test set and the training set are bad.
4. The train/test partition is not random.
5. The results on the test set are good but then the results on your real application problem are bad.

Partition into Training and Testing Set

What's wrong with this partition?

```
from nltk.corpus import names
m = names.words('male.txt')
f = names.words('female.txt')
names = ([(name, 'm') for name in m]+
         [(name, 'f') for name in f])
trainset = names[1000:]
devtest = names[500:1000]
testset = names[:500]
```

Advice

1. Make sure that the train and test sets have no bias.
2. Make sure that the train ant test sets are representative of your problem.

Randomised Partition

A better partition

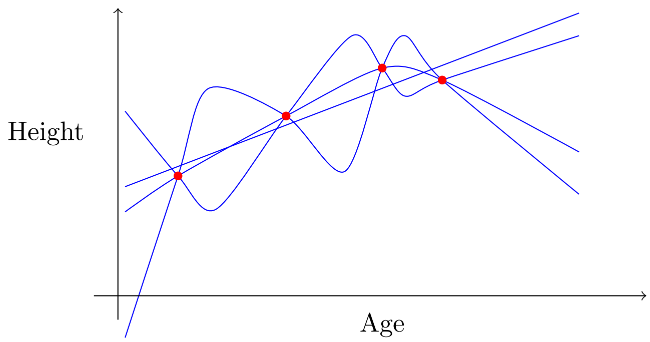
```
from nltk.corpus import names
import random
m = names.words('male.txt')
f = names.words('female.txt')
names = ([(name, 'm') for name in m]+
         [(name, 'f') for name in f])
random.seed(1234)
random.shuffle(names)
trainset = names[1000:]
devtest = names[500:1000]
testset = names[:500]
```

When you create a random partition it is useful that different runs of the same code generates the same partitions. For this reason, we set a fixed random seed. The choice of number does not matter (1234 in our case), as long as it is the same seed number in each run.

Unfortunately the random seeds do not guarantee the same generation of random numbers in different machines because the random generation algorithm is implementation-specific.

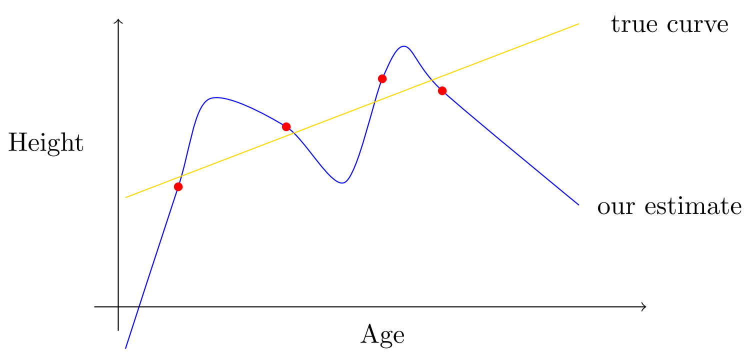
3.1 Over-fitting

Why is machine learning hard?



- There are an infinite number of curves that fit the data
  - even more if we don't require the curves to exactly fit (e.g., if we assume there's noise in our data).
- In general, more data would help us identify the correct curve better.

Over-fitting the Training Data



- Over-fitting occurs when an algorithm learns a function that is fitting noise in the data.
- Diagnostic of over-fitting: performance on training data is much higher than performance on dev or test data.

Take-home Messages

1. Explain and demonstrate the need for separate training and test set.
2. Implement feature extractors for statistical classifiers in NLTK and Scikit-Learn.
3. Use NLTK's and Scikit-Learn's statistical classifiers.
4. Detect over-fitting.

What's Next

Week 4

- Deep Learning.

Reading

- Deep Learning book chapters 2 and 3.