Implement a spamfilter based on naive bayes theorem

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- Bayes rule
- ,Bag of words 'and Independence assumptions
- MAP, ML

02.

${\bf Implementation}$

- Naive Bayes Classifier
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Classification Methods: Supervised Machine Learning

- Input:
- A fixed set of classes C = { 'spam', 'ham'}
- A test set of n prelabeled documents (d_i, c_i)
- A training set of m prelabeled documents (d_i, c_i)
- Output:
- A learned classifier $\gamma: d \to c$
- Classifier art:
- Naïve Bayes
- Support-Vector machines
- Logistic regression

Naive Bayes Classifier

Bayes rule for a document d and a class c

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

- Assumptions
- Bag of words Model:
 assume position of words doesn't matter
- Conditional Independence:

 Assume the feature probabilities are independent given the class c

$$P(x_1, \dots, x_n \mid c) = P(x_1 \mid c) \bullet P(x_2 \mid c) \bullet P(x_3 \mid c) \bullet \dots \bullet P(x_n \mid c)$$

Maximum a posteriori

 Most likely class according to the known result

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(c \mid d)$$
$$= \underset{c \in C}{\operatorname{argmax}} \frac{P(d \mid c)P(c)}{P(d)}$$

• In der Implementation is P(d) a fixed value

$$= \underset{c \in C}{\operatorname{argmax}} P(d \mid c) P(c)$$

• Document d is represented as features x1...xn

$$= \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \dots, x_n \mid c) P(c)$$

Applying the assumptions above

$$c_{NB} = \underset{c \in C}{\operatorname{argmax}} P(c_j) \prod_{x \in X} P(x \mid c)$$

Maximum Likelihood estimates

 Just count the frequencies in the labeled data(in the case of binomial distribution)

$$\hat{P}(c_j) = \frac{doccount(C = c_j)}{N_{doc}}$$

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

- Count of word wi among all words in documents of class cj
- Problem arises a new word which is not in the training documents appears

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Laplace smoothing

• Extract the Vocabulary from training corpus

$$\hat{P}(w_i \mid c) = \frac{count(w_i, c) + 1}{\sum_{w \in V} (count(w, c)) + 1}$$

$$= \frac{count(w_i, c) + 1}{\left(\sum_{w \in V} count(w, c)\right) + |V|}$$

Underflow Prevention

- By transforming into the log space,
 multiplying of probabilities becomes sum logs
 of probabilities
- Calculation error because of the limited floating point number could be avoided

$$c_{NB} = \operatorname*{argmax}_{c_j \in C} \log P(c_j) + \sum_{i \in positions} \log P(x_i \mid c_j)$$

Underflow Prevention

• Direct multiply the probabilities using Bayes theorem

```
zhouyuxuan@zhouyuxuan-Lenovo-Y50-70:~/spamfilter$ python spamfilter_test.py trai
n -m /home/zhouyuxuan/spamfilter/spamdata/model -c /home/zhouyuxuan/spamfilter/s
pamdata/train
{'--corpuspath': '/home/zhouyuxuan/spamfilter/spamdata/train',
'--modelpath': '/home/zhouyuxuan/spamfilter/spamdata/model',
'<path>': None,
'classify': False,
'train': True}
Training size is: 9000
Accuracy is 0.7006666666666667
```

```
zhouyuxuan@zhouyuxuan-Lenovo-Y50-70:~/spamfilter$ python spamfilter_test.py clas
sify -m /home/zhouyuxuan/spamfilter/spamdata/model /home/zhouyuxuan/spamfilter/s
pamdata/test
{'--corpuspath': None,
 '--modelpath': '/home/zhouyuxuan/spamfilter/spamdata/model',
 '<path>': '/home/zhouyuxuan/spamfilter/spamdata/test',
 'classify': True,
 'train': False}
Test size is: 3000
Accuracy is 0.736
```

Underflow Prevention

• Direct multiply the probabilities using Bayes theorem

```
zhouyuxuan@zhouyuxuan-Lenovo-Y50-70:~/spamfilter$ python spamfilter.py classify
-m /home/zhouyuxuan/spamfilter/spamdata/model /home/zhouyuxuan/spamfilter/spamda
ta/test
{'--corpuspath': None,
   '--modelpath': '/home/zhouyuxuan/spamfilter/spamdata/model',
   '<path>': '/home/zhouyuxuan/spamfilter/spamdata/test',
   'classify': True,
   'train': False}
Test size is: 3000
Accuracy is 0.855
```

Programm Design

- Naive Bayes Classifier:
- Defined as a class object

self.classified = []

```
class classifier:
    def __init__(self,p_ham,p_spam,p_w_ham,p_w_spam,V):
        self.p_ham= p_ham
        self.p_spam= p_spam
        self.p_w_ham = p_w_ham
        self.p_w_spam = p_w_spam
        self.v = V
```

- Spamfilter:
- Handle the data, and define the Interface for user

Program Design

• Save the Class Object, Classifier ' import _pickle as cPickle # save the classifier if not os.path.exists(opts['--modelpath']): os.makedirs(opts['--modelpath']) with open(opts['--modelpath']+ '/NBclassifier.pkl', 'wb+') as fid: cPickle.dump(clas, fid) Load it by classifying # load it again with open(opts['--modelpath']+ '/NBclassifier.pkl', 'rb') as fid: clas = cPickle.load(fid)

Naive Bayes Classifier

Mehtods:

```
Train
  @classmethod
   def train(cls,train_features,alpha=0.7):
  return cls(p ham,p spam,p w ham,p w spam,V)
Then it can be called and assigned at the same time
  #train a classifier
  clas = classifier.train(train_features)
• Evaluate
  def evaluate(self, test_features):
   , Compare the labels '
   accuracy = cor / (cor + wro)
   print(f'Accuracy is {accuracy}')
```

Spamfilter

• Command line interaction(docopt)

```
def main(opts):
   if opts['train']:
```

• Load Data(Save in suitable form)

```
for File in FileList:
    with open(folder + File.encoding="utf-8". errors="surrogateescape") as f:
```

• Preprocessing Data (Token, Lemmatization, Shuffle)

```
from nltk import word_tokenize, WordNetLemmatizer
```

Extracting the Features (Stopwords, Frequency)

```
from nltk.corpus import stopwords
```

```
def get_features(text):
    return {word: count for word, count in Counter(preprocess(text)).items() \
    if not word in stoplist}
```