ENGR 102 PROGRAMMING PRACTICE

WEEK 13

Document Filtering

Document Filtering

- Your email address in the wrong hands:

  lots of unnecessary and unsolicited email messages!!!

SPAM SPAM SPAM SPAM SPAM SPAM SPAM SPAM SPAM SPAM SPAM SPAM ...

- A well-known application of document filtering is the elimination of spam.

Classification

- The algorithms are not specific to dealing with spam.
- The general problem of learning to recognize whether a document belongs in one category or another.
- ***App1***: Automatically dividing your inbox into social and work-related email, based on the contents of the messages.
- ***App2***: Identifying email messages that request information and automatically forwarding them to the most competent person to answer them.

Filtering Spam

- Early attempts to filter spam: rule-based classifiers.
  - e.g., overuse of capital letters, ...
- Spammers learned all the rules and stopped exhibiting the obvious behaviors to get around the filters.
- "What is spam"? Subjective!
- How about tailor-fitting?
  You teach me what is spam email and what isn't spam email, and I learn for you to automate the task.

Documents and Words

- The classifier needs features to use for classifying different items.
- Some words are more likely to appear in spam than in not-spam?
- Use words in the document as features.
- Not just individual words, however; word pairs or phrases or anything else that can be classified as absent or present in a particular document.

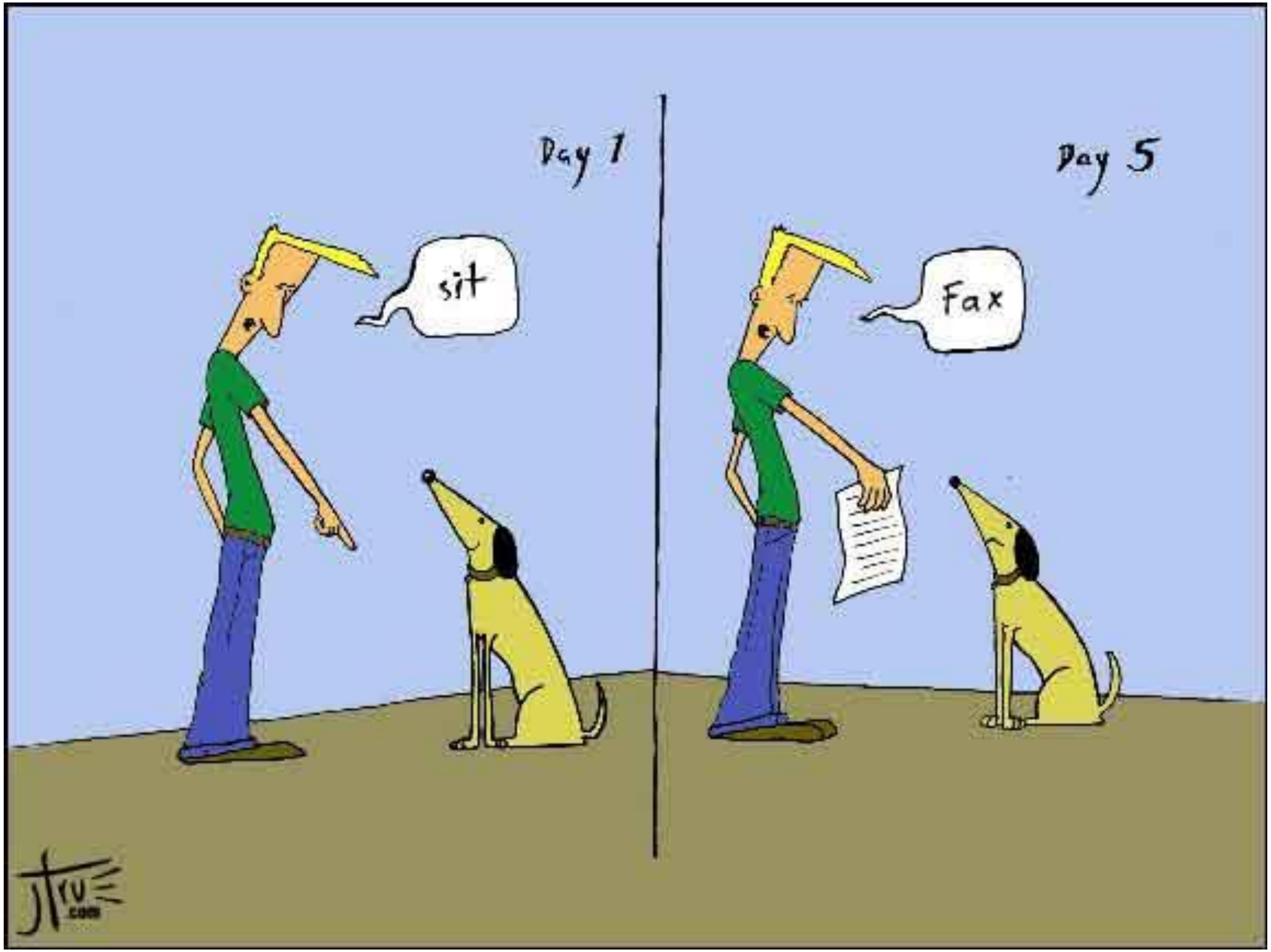
Extracting Features from Text

```
def getwords(doc):
    # equivalent to [^a-zA-Z0-9_]
    splitter = re.compile(r'\W+')

    # Split the words by non-alpha characters
    words = [s.lower() for s in splitter.split(doc)
               if len(s) > 2 and len(s) < 20]

    # Return the unique set of words only
    return dict([(w,1) for w in words])
```

Training the Classifier



Training the Classifier

- The more examples the classifier is fed with, the better the classifier will get at making predictions.
  - example: a document and its classification
- The classifier starts off very uncertain and increase in certainty as it “learns”
  - which features are important for making a distinction.

Creating a classifier

```
class Classifier:

    def __init__(self, getfeatures):

        # Counts of feature/category combinations
        self.fc = {}

        # Counts of documents in each category
        self.cc = {}

        self.getfeatures = getfeatures
```

Training the Classifier

fc:

```
{
        'python': {'bad': 0, 'good': 6},
        'the':    {'bad': 3, 'good': 3}
 }
```

cc:

```
 {
        'good': 4,
        'bad':  5
 }
```

Creating classifier

```
# Increase the count of a feature/category pair
def incf(self,f,cat):
    self.fc.setdefault(f,{})
    self.fc[f].setdefault(cat,0)
    self.fc[f][cat] += 1

# Increase the count of a category
def incc(self,cat):
    self.cc.setdefault(cat,0)
    self.cc[cat] += 1

# The number of times a feature has appeared in a category
def fcount(self,f,cat):
    if f in self.fc and cat in self.fc[f]:
        return self.fc[f][cat]
    return 0
```

Creating classifier

```
# The number of items in a category
def catcount(self,cat):
    if cat in self.cc:
        return self.cc[cat]
    return 0

# The total number of documents
def totalcount(self):
    return sum(self.cc.values())

# The list of all categories
def categories(self):
    return self.cc.keys()
```

Creating a Classifier – Train method

```python
def train(self, doc, cat):
    features = self.getfeatures(doc)

    # Increment the count for every feature with this category
    for f in features:
        self.incf(f, cat)

    # Increment the count for this category
    self.incc(cat)
```

Let’s check if our classifier works correctly so far!

```
import docclass
cl = docclass.Classifier(docclass.getwords)

cl.train('the quick brown fox jumps over the lazy dog','good')
cl.train('make quick money in the online casino','bad')

print(cl.fcount('quick','good'))
print(cl.categories())
```

Creating a Classifier – Sample Train method

```
def sampletrain(cl):
    cl.train('Nobody owns the water.','good')
    cl.train('the quick rabbit jumps fences','good')
    cl.train('buy pharmaceuticals now','bad')
    cl.train('make quick money at the online  casino','bad')
    cl.train('the quick brown fox jumps','good')
```

Calculating probabilities

- We have counts for how often email messages appear in each category (after training).
- The probability that a word is in a particular category C:

$$= \frac{\text{\# of documents that contains “word” in C}}{\text{the total number of documents in C}}$$

Calculating probabilities

```
def fprob(self,f,cat):
    if self.catcount(cat) == 0:
        return 0
    # The total number of times this feature appeared in this
    # category divided by the total number of items in this cat.
    return self.fcount(f,cat)/self.catcount(cat)
```

Conditional probability

- This is called and usually written as Pr(A | B) and read as “the probability of A given B.”
- If the word “quick” appears in 2 out of a total of 3 documents classified as good,

  then:

  there’s a probability of Pr(quick | good)=0.666 that a **good document** will <u>contain that word</u>.

Conditional probability - Example run

```
import docclass
cl = docclass.Classifier(docclass.getwords)

cl.train('the quick brown fox jumps over the lazy dog','good')
cl.train('make quick money in the online casino','bad')

print(cl.fcount('quick','good'))
print(cl.categories())

print(cl.fprob('quick', 'good'))
```

Zero counts

- In the sample training data, the word “online” only appears in one document and is classified as bad.
- Since the word “online” is in one bad document and no good ones, the probability that it will appear in the good category is now 0.
- This is a bit extreme, since “online” might be a perfectly neutral word that just happens to appear first in a bad document.

Creating a Classifier – Sample Train method

```
def sampletrain(cl):
    cl.train('Nobody owns the water.','good')
    cl.train('the quick rabbit jumps fences','good')
    cl.train('buy pharmaceuticals now','bad')
    cl.train('make quick money at the online casino','bad')
    cl.train('the quick brown fox jumps','good')
```

Calculating probabilities Consider zero prob.

```
def fprob(self, f, cat, default_prob=0.01):
    if self.catcount(cat) == 0:
        return 0

    if self.fcount(f, cat) == 0:
        return default_prob
    # The total number of times this feature appeared in this
    # category divided by the total number of items in this cat.
    return self.fcount(f,cat)/self.catcount(cat)
```

Calculating probabilities

```
import docclass
cl = docclass.Classifier(docclass.getwords)
docclass.sampletrain(cl)
print(cl.fprob('online','good',cl.fprob))
```

Combining probabilities

- We know the probability of a document in a category containing a particular word.

- We need a way to combine the individual word probabilities to get the probability that an entire document belongs in a given category.

  Naive classifier: we assume that the probabilities being combined are independent of each other.

Naive Classifier

- **Assumption**: the probability of one word in the document being in a specific category is unrelated to the probability of the other words being in that category.

- This is actually a false assumption!
  - Documents containing the word “casino” are much more likely to contain the word “money” than documents containing “programming”.

Naive Classifier

- You *can't actually use the probability* created by the naïve Bayesian classifier as the actual probability that a document belongs in a category.

- However, you can **compare** the results for different categories and see which one has the highest probability.

Naive Classifier

- Suppose that:
  *the word "Python" appears in 20% of your **bad** documents:* *Pr(Python | Bad) = 0.2*

  *the word "casino" appears in 80% of your **bad** documents: Pr(Casino | Bad) = 0.8*
- The independent probability of "Python" and "casino" appearing together in a ***bad*** document:

  Pr(Python & Casino | Bad) = $0.8 \times 0.2 = 0.16$

Naive Classifier

```
class NaiveBayes(classifier):

    def docprob(self,item,cat):
        features = self.getfeatures(item)
        # Multiply the probabilities of all the features together
        p = 1
        for f in features:
            p *= self.fprob(f,cat)
        return p
```

Naive Classifier

- We know how to calculate Pr(Document | Category).
- In order to classify documents, we need **Pr(Category | Document)**
- In other words, given a specific document, what’s the probability that it fits into this category?
- A British mathematician named Thomas Bayes figured out how to do this about 250 years ago.

Bayes' Theorem

- Pr(A | B) = Pr(B | A) x Pr(A) / Pr(B)

Therefore,

$$\Pr(\text{Cat} \mid \text{Doc}) = \frac{\Pr(\text{Doc} \mid \text{Cat}) \times P(\text{Cat})}{\Pr(\text{Doc})}$$

Bayes' Theorem

- Pr(Cat): the number of documents in the category divided by the total number of documents.

- Pr(Doc| Cat) → docprob(…)

  Pr(Python & Casino | Bad) = $0.8 \times 0.2 = 0.16$

- Pr(Doc) is independent of category. It will only scale the results by the same amount. So we will ignore this term.

  - We are interested in **ranking** class probabilities rather than using their actual numeric values.

Naive Classifier

```
def prob(self,item,cat):
    catprob = self.catcount(cat) / self.totalcount()
    docprob = self.docprob(item, cat)
    return docprob * catprob
```

$$\Pr(\text{Cat} \mid \text{Doc}) = \frac{\Pr(\text{Doc} \mid \text{Cat}) \times P(\text{Cat})}{\Pr(\text{Doc})}$$

Play with prob method!

```
import docclass

cl = docclass.NaiveBayes(docclass.getwords)

docclass.sampletrain(cl)

print(cl.prob('quick rabbit','good'))
print(cl.prob('quick rabbit','bad'))

print(cl.prob('quick money','good'))
print(cl.prob('quick money','bad'))
```

```
def sampletrain(cl):
      cl.train('Nobody owns the water.','good')
      cl.train('the quick rabbit jumps fences','good')
      cl.train('buy pharmaceuticals now','bad')
      cl.train('make quick money at the online  casino','bad')
      cl.train('the quick brown fox jumps','good')
```

Assignment to a class

- How to decide in which category a new item belongs?
  - Calculate the probability for each category, and choose the category with the best probability.

- For some applications, a marginally high probability may be enough to determine the class.

- For other applications, you have to be overly confident for making any assignment.

Classify method

```python
def classify(self, item):
    # Find the category with the highest probability
    max=0.0

    for cat in self.categories():
        cat_prob = self.prob(item,cat)

        if cat_prob > max:
            max = cat_prob
            best = cat

    return best
```

Practice with our classifier!

```
import docclass

cl = docclass.NaiveBayes(docclass.getwords)

docclass.sampletrain(cl)

print(cl.prob('quick rabbit','good'))
print(cl.prob('quick rabbit','bad'))

print(cl.prob('quick money','good'))
print(cl.prob('quick money','bad'))

print(cl.classify('quick rabbit'))
print(cl.classify('quick money'))
```