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CIS 678 – Machine Learning

Project 2

Abstract

We look to further expand our abilities in CIS 678 – Machine Learning, through learning and implementing the Naïve Bayes algorithm for document classification. Using Python, we were able to develop a supervised learning model that uses probabilities from Bayes Theorem. As such, we abstracted our code in a way that allowed for modularity to train and test two different types of datasets: forums and twitter. Using three different validation approaches, we found classification rates over 80% for forum data (guessing would be 1/20 = 5%) and 75% for twitter data (guessing would be ½ = 50%). Our final analyses looked to demonstrate the predictive abilities of our classifier by predicting the sentiment of nearly 30 twitter users' last 3000 tweets, and as such, we obtained a "positivity" rating for each user.

Implementation details

Our program is written in Python 2.7 and bash scripting in Unix. These programs were executed locally on each member's respective Macbook Pro (2012), testing on eos23 and okami.

Summary of Problem

Naïve Bayes is a supervised learning approach that utilizes Bayes Theorem as seen in Equation 1. I should be noted that Naïve Bayes makes the simplifying assumption that features are conditionally independent. In Laymen's terms, Naïve Bayes looks to the prior (proportion of class size to total corpus size) and the likelihood (proportion of word occurrence for particular document type). Additionally, we implement, seen in Equation 2, a log probability transformation to avoid "arithmetic underflow", rather, multiplying decreasingly small probabilities together which trend to zero.

$$p(C_k|\mathbf{x}) = \frac{p(C_k)\ p(\mathbf{x}|C_k)}{p(\mathbf{x})}$$

$$\text{posterior} = \frac{\text{prior} \times \text{likelihood}}{\text{evidence}}$$

Equation 1. Formula of Bayes Theorem

$$\begin{aligned} \log p(C_k|\mathbf{x}) &\propto \log\left(p(C_k)\prod_{i=1}^{n} {p_{ki}}^{x_i}\right) \\ &= \log p(C_k) + \sum_{i=1}^{n} x_i \cdot \log p_{ki} \end{aligned}$$

Equation 2. Naïve Bayes log transformation

Results

Our model correctly classifies over 81% of forum documents stemmed with Porter's Stemmer using a 60/40 training/test holdout validation method, as we note in Figure 1.

```
[terwilla@okami holdout]$ cat holdout-stemmed.txt
Naive bayes classification with holdout method
Learning from training documents:
Classifying test documents:
Classifier Effectiveness:
Correct: 6100, Total: 7528, Effectiveness: 81%
```

Figure 1. Sample validation output using original holdout split

Using the k-fold validation approach, we found 12-fold (92/8) with 86% classification rate offered the most promising results. We find Figure 3, maximizes over the k iterations with the maximum over 2 through 15-fold validation landing around 80%.

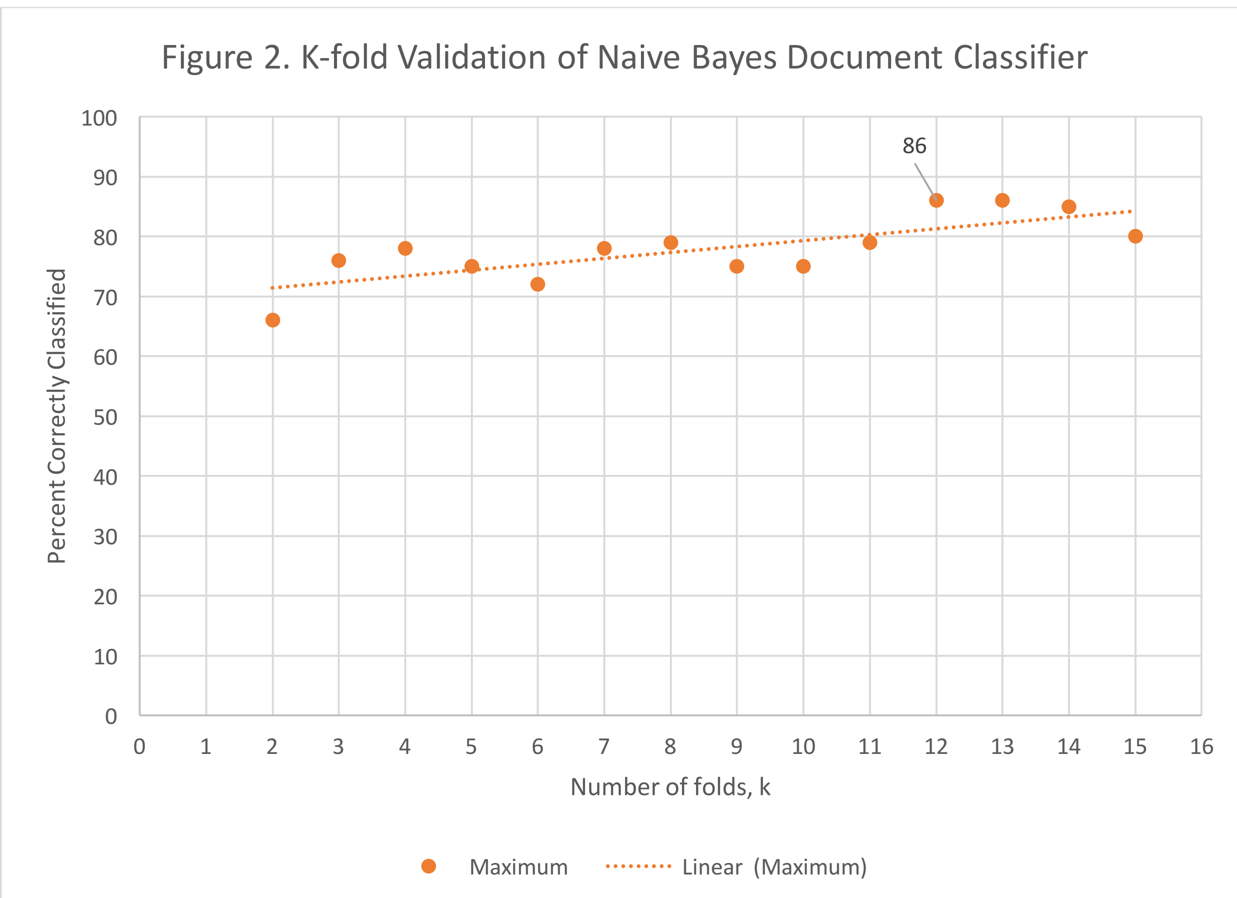
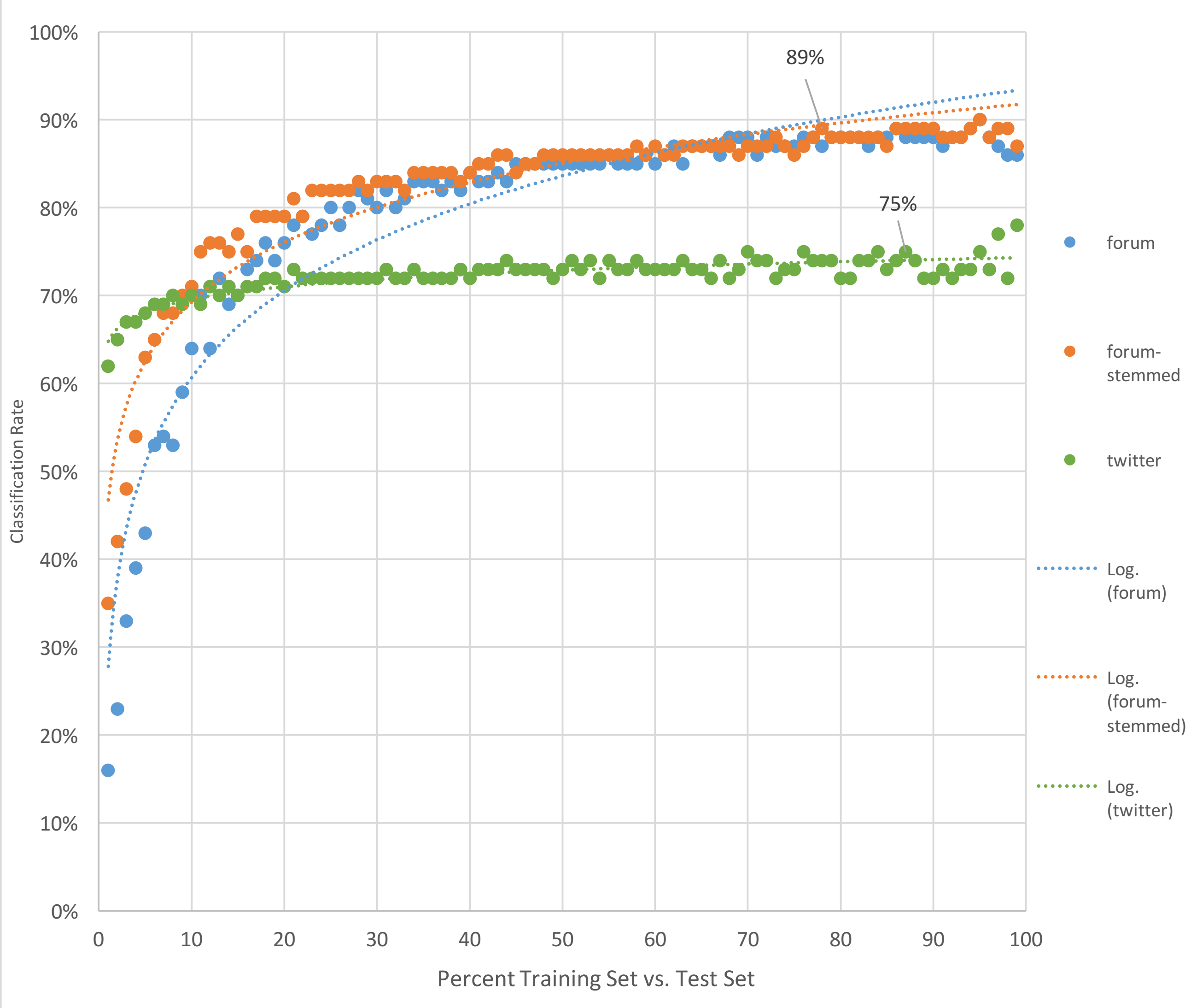


Figure 2. K-fold Validation of Naive Bayes Document Classifier

The randomized validation approach proved to be the most effective, as we observe in Figure 3. We found nearly 89% classification rate using a 78/22 training/test split for the forum-stemmed data. We explored a sentiment analysis case-study training our Naïve Bayes classifier using over 1.5 million tweets pre-labeled with positive or negative sentiment. Using the randomized validation approach for this twitter data, we observed a classification rate of nearly 76% using an 87/13 training/test split.

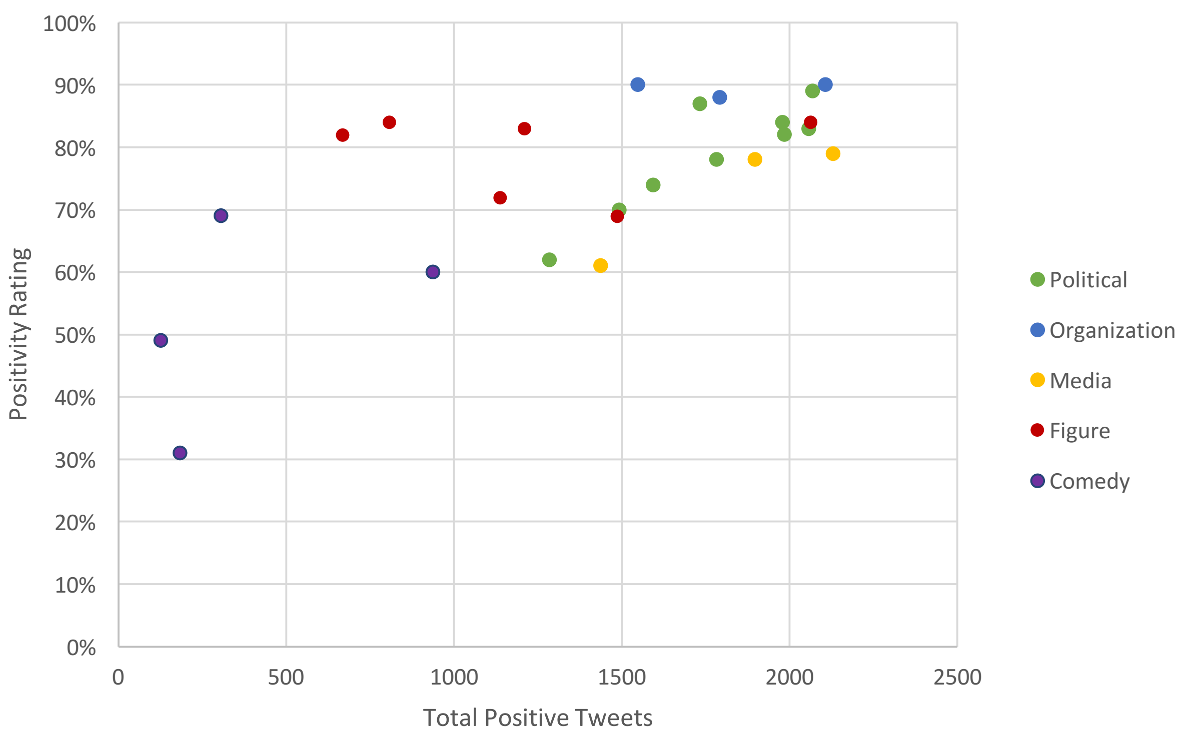
Figure 3. Naive Bayes using Randomized Validation
Correct Classification Rate vs. Size of Training Set



Discussion

In training our Naïve Bayes classifier using over 1.5 million tweets, we looked to use this classifier to make predictions about tweets outside the sample set. As such, we used the Twitter API to pull the last 3000 tweets (if they have that many) for around 30 users. The types of users were grouped into political, organization, media, figure, and comedy, as seen in Figure 4 and Table 1. Due to the unorthodox syntax of most tweets, we utilized libraries that addressed issues like retweets, emoticons, handles, hashtags, and links. Instead of just removing these types of language, we processed them in a way to better train our classifier. For instance, a smiley emoticon ☺, vs. a sad emoticon, ☹ can convey a positive or a negative sentiment.

Figure 4. Positivity Rating of Tweets Classified using Naive Bayes grouped by affiliation



username	Positive	Total	Positivity	Type
tedcruz	2069	2312	89%	Political
RealBenCarson	1732	1989	87%	Political
JohnKasich	1979	2335	84%	Political
marcorubio	2057	2454	83%	Political
BarackObama	1985	2416	82%	Political
JebBush	1782	2258	78%	Political
realDonaldTrump	1593	2141	74%	Political
HillaryClinton	1492	2123	70%	Political
BernieSanders	1284	2064	62%	Political
CERN	1548	1704	90%	Organization
NASA	2107	2326	90%	Organization
SpaceX	1791	2033	88%	Organization
AnaKasparian	2130	2691	79%	Media
cenkuygur	1897	2406	78%	Media
jiadarola	1436	2332	61%	Media
BillNye	806	953	84%	Figure
taylorswift13	2062	2432	84%	Figure
BillGates	1208	1442	83%	Figure
michiokaku	666	805	82%	Figure
neiltyson	1136	1560	72%	Figure
RichardDawkins	1485	2135	69%	Figure
HanSoloFA	306	438	69%	Comedy
StephenAtHome	937	1551	60%	Comedy
KyloR3n	126	254	49%	Comedy
VeryLonelyLuke	183	590	31%	Comedy

Table 1. Positivity results for Twitter validation set

As we note from Table 1, all of the current presidential candidates as of February 16, 2016 are included, as well as, scientific organizations and figures. A handful of media, celebrities, and comedy were pulled to round out the validation set. Some correlations we find from Figure 4 and Table 1 include more conservative politicians are more positive, scientific organizations are leading positivity on Twitter, secular media/scientists are less positive, and comedy/parody accounts are often more negative. We can compare the differences between positive and negative tweets in Figures 5 and 6.

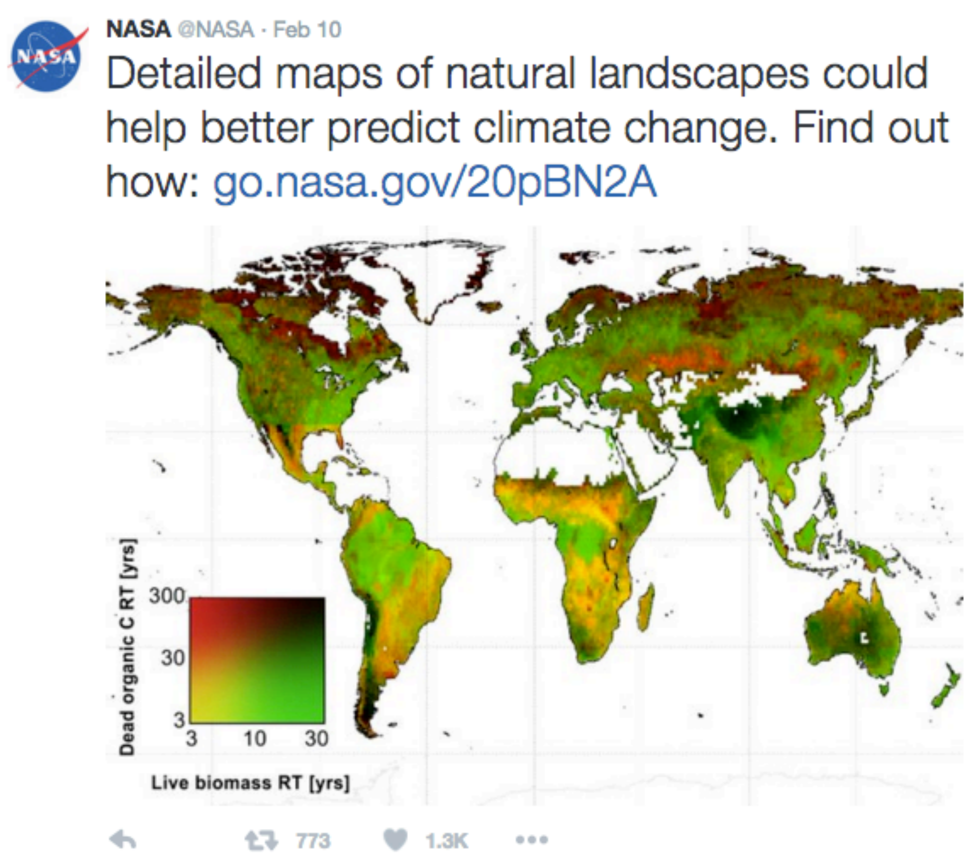


Figure 5. Example of Positive Tweet.

Figure 6. Example of Negative Tweet.

Future Work

We have four main directions we would pursue if time allowed: topic clustering, precision/recall, n-grams, and maximum entropy. We can gain some preliminary intuition from the word clouds in Figures 7 and 8 that topics like “atheism” and “religion” may be quite similar as we note words like “god”, “people”, “belief” and “faith” appear frequently in both classes of documents.

Figure 7. Atheism Word Cloud

Figure 8. Religion Word Cloud

As a complementary analysis to traditional training vs. testing validation, precision/recall offers additional insights into the types of error that the classifier is making, as seen in Figure 9.

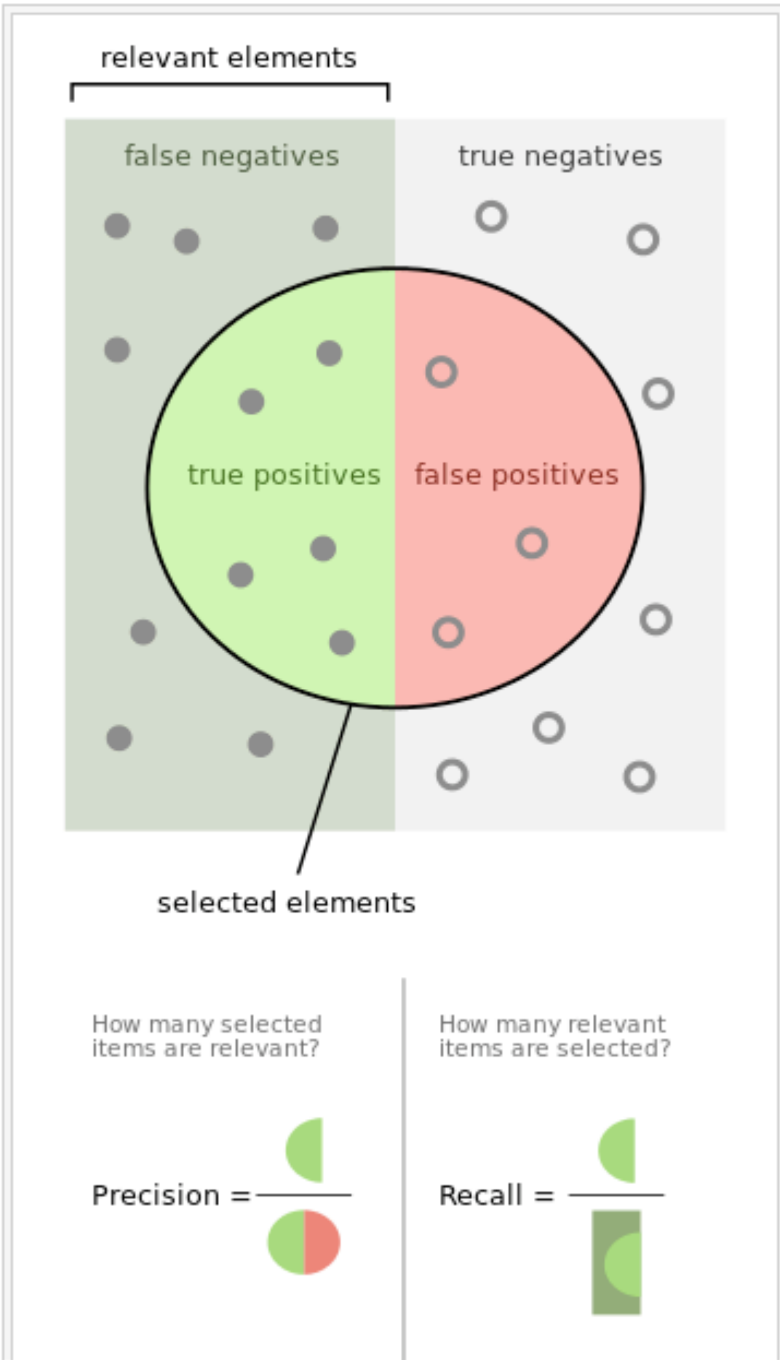


Figure 9. Precision vs. Recall

As mentioned in the summary of the problem, Naïve Bayes makes the underlying assumption that features/observations are independent. Maximum Entropy classification and n-grams look to an alternative, as we may find instances where independence may not be inferred (i.e. “President”, “Obama” / “President”, “Bush” vs. “President Obama” / “President Bush”). We can understand more about maximum entropy and n-grams in Figures 10 and 11.

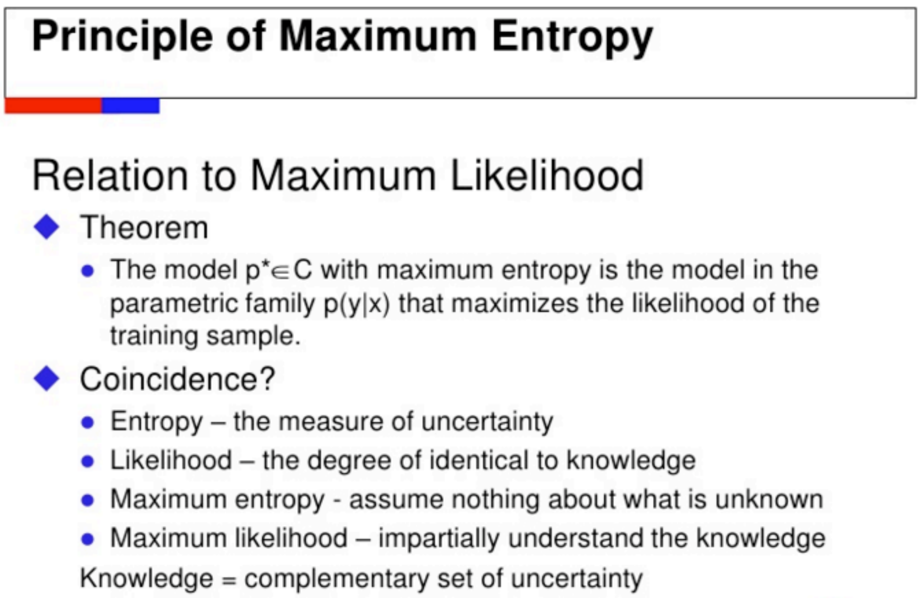


Figure 10. Further exploration of Maximum Entropy Classification

Full sentence	It does not, however, control whether an exaction is within Congress’s power to tax.
Unigrams	“It”; “does”; “not,”; “however,”; “control”; “whether”; “an”; “exaction”; “is”; “within”; “Congress’s”; “power”; “to”; “tax.”
Bigrams	“It does”; “does not,”; “not, however,”; “however, control”; “control whether”; “whether an”; “an exaction”; “exaction is”; “is within”; “within Congress’s”; “Congress’s power”; “power to”; “to tax.”
Trigrams	“It does not”; “does not, however”; “not, however, control”; “however, control whether”; “control whether an”; “whether an exaction”; “an exaction is”; “exaction is within”; “is within Congress’s”; “within Congress’s power”; “Congress’s power to”; “power to tax.”

Figure 11. Example of n-grams

Credits

- [Simple Explanation of Naive Bayes](http://stackoverflow.com/questions/10059594/a-simple-explanation-of-naive-bayes-classification)
- [Where to start with text mining](http://tedunderwood.com/2012/08/14/where-to-start-with-text-mining/)
- [Intro to Topic Modeling](http://journalofdigitalhumanities.org/2-1/topic-modeling-a-basic-introduction-by-megan-r-brett/)
- [Naive Bayes Time Complexity](http://nlp.stanford.edu/IR-book/html/htmledition/naive-bayes-text-classification-1.html)
- [K-fold Cross Validation](https://www.cs.cmu.edu/~schneide/tut5/node42.html)
- [Python - Time Complexity of Operations](https://www.ics.uci.edu/~pattis/ICS-33/lectures/complexitypython.txt)
- [Python Progress Bar](https://github.com/WoLpH/python-progressbar)
- [Python K-fold Cross Validation](http://stackoverflow.com/questions/16379313/how-to-use-the-a-10-fold-cross-validation-with-naive-bayes-classifier-and-nltk)

Important pre-processing code for twitter data was imported with all credit to yogeshg.

- [Twitter-sentiment] (https://github.com/yogeshg/Twitter-Sentiment)

Using the Twitter API, all credit to tweet scraping goes to yanofsky and tweepy.

- [Twitter for Python] (https://gist.github.com/yanofsky/5436496, http://www.tweepy.org/)

All stemming and removing stop words gives credit to mchaput's Porter's stemmer library.

- [Stemming] (https://bitbucket.org/mchaput/stemming)