Lecture 13: Naïve Bayes Classifier Review

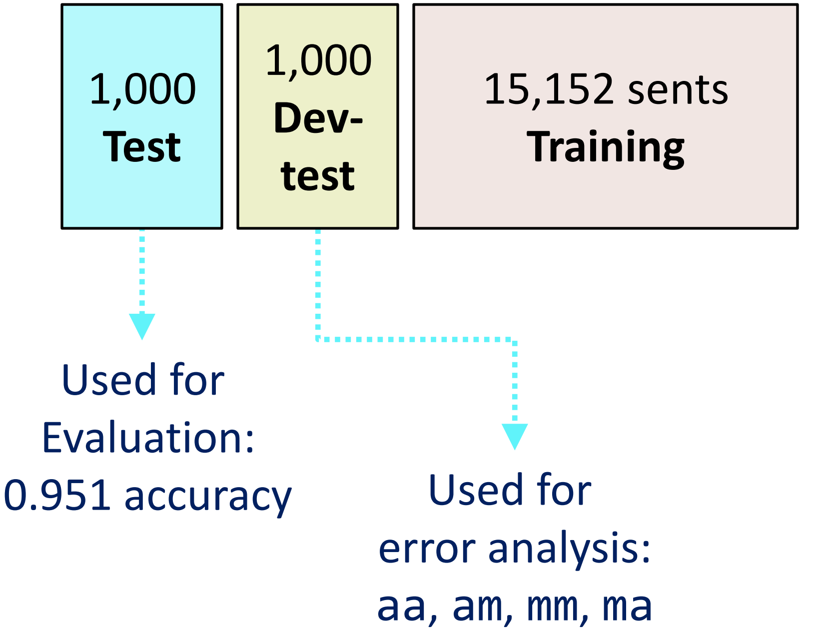
Ling 1330/2330 Intro to Computational Linguistics
Na-Rae Han, 10/10/2023

Outline

- Naïve Bayes and machine learning wrap-up
- Midterm review

whosaid: a Naïve Bayes classifier

- How did the classifier do?
  - 0.951 accuracy on the test data, using a fixed random data split.



- Training set: 15,152 sentences
  - 6,672 are Austen
    - ← P(austen) is 0.44
    - ← **Austen prior**
  - 8,480 are Melville
    - ← P(melville) is 0.56
    - ← **Melville prior**
  - ← Sentences have a higher chance of being Melville out of the gate!

whosaid: error analysis

- ma (really Melville, classified as Austen)

```
0.9947 At first sight , you would not think it so strong as it really is .
0.8933 He feels that his dreadful punishment is just .
0.7817 And here , shipmates , is true and faithful repentance ; not clamorous for
pardon , but grateful for punishment .
0.6192 I knew no one in the place .
0.5713 Indeed , in other respects , you can hardly regard any creatures of the deep
with the same feelings that you do those of the shore .
0.5528 " Oh !
```

'austen' prob shown.

- am (really Austen, classified as Melville)

```
0.9911 It is a sort of prologue to the play , a motto to the chapter ; and will be
soon followed by matter - of - fact prose ."
0.9639 In this age of literature , such collections on a very grand scale are not
uncommon .
0.8823 And at others , what a heap of absurdities it is !
0.7826 shark is only one syllable .
0.7251 said he , offering his hand .
0.6601 " Here is April come !"
```

'melville' prob shown.

Informative features (_all)

```
           ('contains-emma', 1)        austen : melvil ~   1864.5 : 1.0
          ('contains-whale', 1)        melvil : austen ~   1522.5 : 1.0
        ('contains-harriet', 1)        austen : melvil ~   1048.5 : 1.0
         ('contains-weston', 1)        austen : melvil ~    926.5 : 1.0
      ('contains-knightley', 1)        austen : melvil ~    840.1 : 1.0
          ('contains-elton', 1)        austen : melvil ~    771.5 : 1.0
           ('contains-ship', 1)        melvil : austen ~    696.3 : 1.0
           ('contains-ahab', 1)        melvil : austen ~    666.4 : 1.0
      ('contains-woodhouse', 1)        austen : melvil ~    652.0 : 1.0
           ('contains-jane', 1)        austen : melvil ~    613.9 : 1.0
        ('contains-fairfax', 1)        austen : melvil ~    507.1 : 1.0
      ('contains-churchill', 1)        austen : melvil ~    469.0 : 1.0
           ('contains-boat', 1)        melvil : austen ~    424.1 : 1.0
           ('contains-miss', 1)        austen : melvil =    381.7 : 1.0
      ('contains-hartfield', 1)        austen : melvil ~    362.2 : 1.0
         ('contains-whales', 1)        melvil : austen ~    345.4 : 1.0
       ('contains-queequeg', 1)        melvil : austen ~    337.5 : 1.0
          ('contains-stubb', 1)        melvil : austen ~    325.0 : 1.0
          ('contains-sperm', 1)        melvil : austen ~    318.7 : 1.0
          ('contains-bates', 1)        austen : melvil ~    311.4 : 1.0
```

Informative features, noCharNames

```
        ('contains-whale', 1)       melvil : austen ~   1522.5 : 1.0
         ('contains-ship', 1)       melvil : austen ~    696.3 : 1.0
         ('contains-boat', 1)       melvil : austen ~    424.1 : 1.0
         ('contains-miss', 1)       austen : melvil =    381.7 : 1.0
       ('contains-whales', 1)       melvil : austen ~    345.4 : 1.0
        ('contains-sperm', 1)       melvil : austen ~    318.7 : 1.0
         ('contains-deck', 1)       melvil : austen ~    271.5 : 1.0
         ('contains-crew', 1)       melvil : austen ~    195.9 : 1.0
        ('contains-boats', 1)       melvil : austen ~    195.9 : 1.0
         ('contains-mast', 1)       melvil : austen ~    175.5 : 1.0
      ('contains-whaling', 1)       melvil : austen ~    175.5 : 1.0
            ('contains-`', 1)       austen : melvil ~    166.5 : 1.0
         ('contains-thee', 1)       melvil : austen ~    162.9 : 1.0
           ('contains-ll', 1)       melvil : austen ~    142.4 : 1.0
         ('contains-sail', 1)       melvil : austen ~    137.7 : 1.0
       ('contains-voyage', 1)       melvil : austen ~    137.7 : 1.0
        ('contains-flask', 1)       melvil : austen ~    134.5 : 1.0
        ('contains-ships', 1)       melvil : austen ~    125.1 : 1.0
    ('contains-leviathan', 1)       melvil : austen ~    125.1 : 1.0
        ('contains-cabin', 1)       melvil : austen ~    118.8 : 1.0
```

He, she, very

```
>>> whosaid.classify(gen_feats('He knows the truth'.split()))
'melville'
>>> whosaid.prob_classify(gen_feats('He knows the truth'.split())).prob('austen')
0.44921141639835876
>>> whosaid.prob_classify(gen_feats('She knows the truth'.split())).prob('austen')
0.9314339848201395
>>> whosaid.feature_weights('contains-he', 1)
{'melville': 0.1554651574106827, 'austen': 0.16881462610520007}
>>> whosaid.feature_weights('contains-she', 1)
{'melville': 0.011496285815351963, 'austen': 0.2079274689045407}
>>> whosaid.feature_weights('contains-very', 1)
{'melville': 0.0321306449711119, 'austen': 0.13899295669114342}
>>>
```

Fun times with Whosaid

5 minutes

- A sentence with **"whale" categorized Austen**?
  - Start with "a whale", then <u>gradually add words</u> to make the sentence more "Austen".
- A **perfectly ambiguous sentence**?
  - Can you come up with a sentence that's at least 5 words long that is as close to 50-50 Austen-Melville?
- Which word feature is **neutral**?
  - You will need to think "**odds ratio**".
  - `whosaid.feature_weights('contains-...', 1)` is the function to use.

When you and your buddy have an answer, paste a screenshot on MS Teams!

Odds ratio

```
>>> def getOddsRatio(word):
...     fw = whosaid.feature_weights('contains-'+word, 1)
...     print(fw)
...     aweight = fw['austen']
...     mweight = fw['melville']
...     if aweight > mweight:
...         print('austen-melville odds ratio', round(aweight/mweight, 2))
...     else:
...         print('melville-austen odds ratio', round(mweight/aweight, 2))
...
>>> getOddsRatio('sea')
{'melville': 0.04533663483079826, 'austen': 0.0018732204405814477}
melville-austen odds ratio 24.20
>>> getOddsRatio('unfortunate')
{'melville': 0.0002947765593679903, 'austen': 0.0011239322643488685}
austen-melville odds ratio 3.81
>>> getOddsRatio('must')
{'melville': 0.02835750501120151, 'austen': 0.07095759028922524}
austen-melville odds ratio 2.50
>>> getOddsRatio('!')
{'melville': 0.11348897535667964, 'austen': 0.06601228832609021}
melville-austen odds ratio 1.72
>>> getOddsRatio('why')
{'melville': 0.01232166018158236, 'austen': 0.006518807133223438}
melville-austen odds ratio 1.89
>>> getOddsRatio('the')
{'melville': 0.5981016389576701, 'austen': 0.3763674509216244}
melville-austen odds ratio 1.59
>>> getOddsRatio('at')
{'melville': 0.1218062964273081, 'austen': 0.1184624606623707 5}
melville-austen odds ratio 1.03
>>>
```

Many function words are not neutral, lean towards Melville or Austen

'at' is almost perfectly neutral

Austen vs. *whale*

- Can a sentence with 'whale' ever be classified as 'austen'?

```
>>> whosaid.prob_classify(gen_feats('a whale'.split())).prob('austen')
0.00046963208159057055
>>> whosaid.prob_classify(gen_feats('a beautiful whale'.split())).prob('austen')
0.001629566209242024
>>> whosaid.prob_classify(gen_feats('she married a whale'.split())).prob('austen')
0.10371709682345985
>>> whosaid.prob_classify(gen_feats('she married a beautiful whale'.split()))
.prob('austen')
0.28673216572155275
>>> whosaid.prob_classify(gen_feats('she married a very beautiful whale'.split()))
.prob('austen')
0.6349019382913935
```

Even though 'whale' never occurs in Austen, 'contains-whale', 1 for 'austen' gets assigned a tiny weight through smoothing

More in homework KEY

- We went over the solutions in class.
- Will be posted on Canvas! (Along with HW2 KEY)

whosaid vs. movie review classifier

- `whosaid` on tiny sentences with strong features:

```
>>> whosaid.prob_classify(gen_feats('he was a whale'.split())).prob('austen')
0.0008505667723433306
>>> whosaid.prob_classify(gen_feats('she was delighted'.split())).prob('austen')
0.9967617928216123
```

- The movie review classifier behaves very differently:

```
   contains(outstanding) = True              pos : neg    =     11.0 : 1.0
         contains(mulan) = True              pos : neg    =      7.7 : 1.0
        contains(seagal) = True              neg : pos    =      7.4 : 1.0
         contains(damon) = True              pos : neg    =      5.7 : 1.0
         contains(awful) = True              neg : pos    =      5.6 : 1.0
>>> classifier.prob_classify(document_features('damon was outstanding'.split()))
.prob('neg')
0.9999998931163593
>>> classifier.prob_classify(document_features('seagal was awful'.split()))
.prob('neg')
0.9999999999655637
```

Both strongly neg? How could this be?

whosaid vs. movie review classifier

- `whosaid` on tiny sentences with strong features:

```
>>> whosaid.prob_classify(gen_feats('he was a whale'.split())).prob('austen')
0.0008505667723433306
>>> w                                                      e                        prob('austen')
0.99
```

Whosaid only encodes presence of a word as a feature.

Four features of value 1 for this sentence

- The movie review classifier behaves very differently:

```
   contains(outstanding) = True              pos : neg    =     11.0 : 1.0
         contains(mulan) = True              pos : neg    =      7.7 : 1.0
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.prob('neg')
0.9999998931163593
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.prob('neg')
0.9999999999655637
```

Here, 2000 *most common* words are encoded as 'presence' or 'absence' features.

Becomes a set of 2,000 True/False features!

whosaid vs. movie review classifier

- whosaid on tiny sentences with strong features:

```
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>>> whosaid.prob_classify(gen_feats('she was delighted'.split())).prob('austen')
0.9967617928216123
```

What is NOT in this sentence does not affect labeling decision at all.

- The movie review classifier behaves very

```
   contains(outstanding) = True              pos : neg    =     11.0 : 1.0
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.prob('neg')
0.9999999999655637
```

All top 2,000 words, <u>even those **not** in this review</u>, affect the labeling decision!

Collective power of features

Voting for "positive":
- 'damon' & 'outstanding', strongly positive-leaning, for being IN the review
- All negative-learning words (e.g., 'awful') for NOT BEING IN the review

Voting for "negative": **WINS**
- 'was', which turns out leans slightly negative, for being IN the review
- All the rest (1000+!!) positive-learning words for NOT BEING IN the review

```
   contains(outstanding) = True              pos : neg    =     11.0 : 1.0
         contains(mulan) = True              pos : neg    =      7.7 : 1.0
        contains(seagal) = True              neg : pos    =      7.4 : 1.0
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0.9999999999655637
```

Naïve Bayes classifier: variants

(1) WhoSaid

(2) Movie Review classifier

← In both, features had *discreet*, *categorical* values (1, True/False)

- Can we use actual word *count* (2, 3, 5, …) as numerical feature values, instead of just presence/(absence)?
  - "movie is fantastic … fantastic … fantastic" ← 3 times!
  - Yes it can be done. It's common to convert raw counts into what's known as **TF-IDF** (Term Frequency -- Inverse Document Frequency) with a normalized value between 0 and 1.

Naïve Bayes: strength

- `whosaid` is a fairly simple statistical model.
- Yet it achieves 95.1% accuracy.
- Why is it so successful?
  - Is it just because of a handful of strong, topical features like 'whale', 'ship'...?
- What are the strengths of Naïve Bayes classifier?

Weighting the evidence

- A classification decision involves reconciling multiple features with different levels of predictive power.
  - ←Different types of classifiers use different algorithms for:
    1. Determining the **weights of individual features** in order to maximize its labeling success in the training data
    2. When given an input, using the feature weights to **compute the likelihood of a label**
- Popular machine learning methods:
  - **Naïve Bayes**
  - Hidden Markov model (HMM)
  - Maximum entropy (ME)
  - Decision tree
  - Support vector machine (SVM)
  - Neural network → Deep learning (!!)

With Naïve Bayes, the association between feature weights and the underlying data is fairly straightforward.

Weighting the evidence

- A classification decision involves reconciling multiple features with different levels of predictive power.

  ← Different types of classifiers use different algorithms for:

  1. Determining the **weights of individual features** in order to maximize its labeling success in the training data
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- Popular machine learning methods:
  - **Naïve Bayes**
  - Hidden Markov model (HMM)
  - Maximum entropy (ME)
  - Decision tree
  - Support vector machine (SVM)
  - Neural network → Deep learning (!!)

With more sophisticated ML models, the relationship becomes **more complex** to the point of **almost completely opaque** (Deep Learning).

Machine learning: the vast ocean

- 'Machine Learning is too easy' https://hunch.net/?p=634

  (2009: before Deep Learning's time)

- WEKA: a collection of machine learning algorithms for data mining
- Scikit-Learn (Python library for ML)
- Deep Learning libraries
  - PyTorch (Facebook)
    - https://pytorch.org/
  - Tensorflow (Google)
    - https://ai.googleblog.com/2016/11/celebrating-tensorflows-first-year.html
  - MXNet (Amazon)
    - https://aws.amazon.com/mxnet/

Wrapping up

- Midterm on Thu. ➔ Details next slide

- Regular expressions and FSA
  - *Language and Computers*, Ch.4 Searching
    - 4.4 Searching semi-structured data with regular expressions
    - 4.41 Syntax of regular expressions
  - NLTK 3.4 Regular expressions
    - https://www.nltk.org/book/ch03.html#sec-regular-expressions-word-patterns
  - J&M Regular expressions
    - https://web.stanford.edu/~jurafsky/slp3/2.pdf

Midterm exam: what to expect

- 10/12 (Thursday)
  - 75 minutes.
  - At LMC's PC Lab (G17 CL) ← NOT our usual classroom!
- Exam format:
  - Closed book. All pencil-and-paper.
  - Topical questions: "what is/discuss/analyze/find out/calculate…"
  - Bring your calculator! →

- A letter-sized cheat sheet allowed.
  - Front and back.
  - Hand-written only.