# INFO 3350/6350

## Lecture 10: Fightin' words

### Measuring distinctive words between corpora

We often want to know which words are used differently in two corpora. There are a bunch of ways to do this. We can train classifiers and examine their feature weights. We can look at mutual information metrics. We could just count the words and see which ones are used more frequently in one corpus than another.

### Fightin' words

But a simple go-to approach that is robust to different underlying word frequencies and makes Bayesian assumptions about how often we would *expect* to see each word, given its frequency in a reference corpus, is Monroe et al.'s Fightin' words.

Using code originally developed by Jack Hessel (a Cornell PhD grad!), we've provided you with fightinwords.py. We'll walk through that code and then see how it performs on real-world data.

The basic algorithm is to measure the observed frequency of each word in two corpora, (optionally) compare that frequency to an empirical prior, and normalize the result using a z-score. The words that have the largest magnitude z-scores (positive or negative) are the ones that tell us the most about the unique vocabulary of each corpus.

```
import fightinwords as fw
import numpy as np
import os
from sklearn.feature_extraction.text import CountVectorizer
```

```
In [2]:
         # test on two novels with 40 more for informative priors
         vectorizer = CountVectorizer( # set up a vectorizer
             lowercase=True,
             strip_accents='unicode',
             input='filename',
             encoding='utf-8',
         )
         # get file names
         data dir = os.path.join('...', 'data', 'texts')
         files = os.listdir(data dir)
         bambi_file = 'O-Salten-Bambi-1923.txt'
         mme bovary file = 'F-Flaubert-Madame Bovary-1857-M.txt'
         if '.DS_Store' in files: files.remove('.DS_Store')
         files.remove(bambi_file)
         files.remove(mme_bovary_file)
         corpus = [os.path.join(data_dir, file) for file in files] # background corpus
```

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```
Notebooks
samples = [os.path.join(data_dir, file) for file in [bambi_file, mme_bovary_file]
# read target files by line
bambi text = [fw.basic sanitize(line) for line in open(samples[0], 'rt').readline
mme bovary text = [fw.basic sanitize(line) for line in open(samples[1], 'rt').rea
# convenience function to FW display output
def display_fw(data, n=10, name1='corpus one', name2='corpus two'):
    '''Display the indicated number of top terms from fightinwords output.'''
    print("Top terms in", name1)
    for term, score in reversed(data[-n:]):
        print(f"{term:<10} {score:6.3f}")</pre>
    print("")
    print("Top terms in", name2)
    for term, score in data[:n]:
        print(f"{term:<10} {score:6.3f}")</pre>
# results with a flat (noninformative) prior
# note idiom: pass in text, use default vectorizer
```

```
In [3]:
         flat = fw.bayes_compare_language(bambi_text, mme_bovary_text)
         display_fw(flat)
```

```
Vocab size is 1533
Comparing language...
Top terms in corpus one
mother
          15.121
he
          14.397
          13.322
there
          12.155
just
         11.533
can
         11.526
you
         11.388
now
don
          10.211
they
           9.863
          9.290
Top terms in corpus two
          -21.136
her
```

```
the
           -20.736
of
           -18,484
           -17.866
she
           -9.291
on
           -8.932
at
           -8.150
in
for
           -6.817
which
           -6.611
           -6.449
an
```

Meh. Not wrong, but I can't make much of this. Let's try it with an informative prior ...

```
In [4]:
         # learn vocab from *corpus* (not samples) and calculate priors
         priors = np.sum(vectorizer.fit_transform(corpus), axis=0).reshape(-1,1)
         priors.shape
```

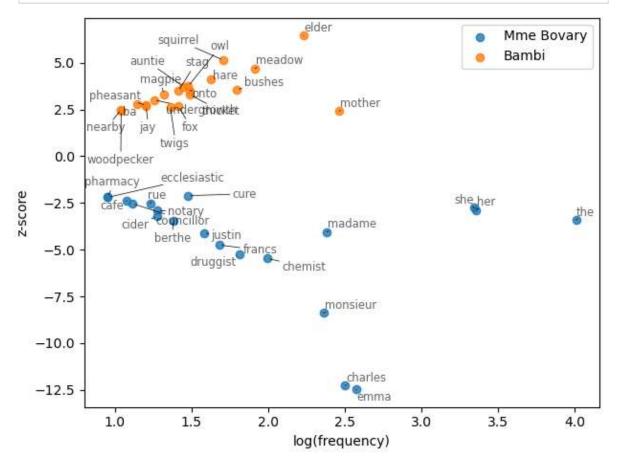
Out[4]: (53861, 1)

Note that we have changed the input features in this case. We have learned word frequencies on a corpus the DOES NOT include either Bambi or Mme Bovary. So we probably won't see "Bambi" as a feature.

```
In [5]:
         # vectorize test books using fitted vectorizer
         test_books = vectorizer.transform(samples) # NOT .fit(); want to keep existing vo
         print(test books.shape)
       (2, 53861)
In [6]:
         # use informative prior
         # different idiom: pass in index positions in pre-computed feature matrix
         informative = fw.bayes_compare_language(
             11=[0],
             12=[1],
             features=test books,
             cv=vectorizer,
             prior=priors,
             #prior weight=10 <- optional normalize and reweight the data
         display_fw(informative)
      Vocab size is 53861
      Comparing language...
       Top terms in corpus one
       elder
                  6.438
       squirrel
                5.134
                 4.699
      meadow
      hare
                  4.088
      owl
                  3.728
       auntie
                 3.726
      bushes
                 3.561
                  3.518
      onto
       stag
                  3.489
                  3.311
      magpie
      Top terms in corpus two
       emma
                 -12.470
       charles
                 -12.265
                -8.382
      monsieur
       chemist
                 -5.474
                 -5.268
       druggist
      francs
                 -4.747
                 -4.117
       justin
                 -4.046
      madame
      berthe
                 -3.478
       the
                 -3.423
```

#### **Plotting results**

```
for word, z_score in informative:
    count = df[word].sum()
    if count > 0:
        zscores.append(z_score)
        words.append(word)
        frequencies.append(count)
# plot result
texts = []
fig, ax = plt.subplots(1,1)
ax.scatter(
    np.log10(frequencies[:num_words_to_plot]),
    zscores[:num_words_to_plot],
    alpha=0.8,
    label="Mme Bovary"
)
ax.scatter(
    np.log10(frequencies[-num_words_to_plot:]),
    zscores[-num_words_to_plot:],
    alpha=0.8,
    label="Bambi"
)
for i in range(-num_words_to_plot, num_words_to_plot):
    texts.append(ax.text(np.log10(frequencies[i]), zscores[i], words[i], size='sm
adjust_text(texts, arrowprops=dict(arrowstyle="-", color='k', lw=0.5))
plt.xlabel('log(frequency)')
plt.ylabel('z-score')
plt.legend()
plt.tight_layout()
plt.show()
```



#### **News data**

```
In [8]:
          # read data from disk and examine
          import re
          news = pd.read_csv(os.path.join('...', 'data', 'news', 'news_text.csv.gz'))
          # a function to get rid of datelines at the start of articles
          # matches one or more hyphens or colons in first 40 chars,
          # drops everything before that match (plus the match itself)
          pattern = '[-:]+ '
          matcher = re.compile(pattern) # compiled regexs are faster
          def remove dateline(text, matcher=matcher):
              Remove source names and datelines from a text string
              If there is a hyphen or colon in the first 40 characters,
                drops everything before the hyphen(s)/colon(s)
              If no hyphen/colon, do nothing
              Return processed string
              result = matcher.search(text, endpos=40)
              if result:
                  return text[result.end():]
              else:
                  return text
          # clean article text
          news['body'] = news['body'].apply(remove_dateline)
In [9]:
          num_holdout_articles = 20000
          vec = CountVectorizer(
              lowercase=True,
              strip_accents='unicode',
              input='content',
              encoding='utf-8',
          )
          # calculate priors on non-holdout volumes
          priors = np.sum(vec.fit_transform(news.body.iloc[num_holdout_articles:]), axis=0)
          priors.shape
Out[9]: (57875, 1)
In [10]:
          sports = news.iloc[:num_holdout_articles].loc[news.label=='Sports', ['body']]
          other = news.iloc[:num holdout articles].loc[~(news.label=='Sports'), ['body']]
          result = fw.bayes compare language(
              l1=[j for i, j in sports.itertuples()],
              12=[j for i, j in other.itertuples()],
              cv=vec,
              prior=priors
          )
       Vocab size is 57875
       Comparing language...
In [11]:
          display fw(result, n=10, name1='sports', name2='other')
        Top terms in sports
                    9.281
```

```
8.134
         season
                      8.120
         cup
         league
                      8.102
                      7.594
         night
         team
                      7.417
        his
                      7.392
         victory
                      7.276
                      7.262
         game
         coach
                      7.040
         Top terms in other
         us
                     -8.665
         lta
                     -7.274
                     -7.033
         its
         said
                     -6.039
         email
                     -5.784
         companys
                     -5.625
         worlds
                     -5.598
         walmart
                     -5.282
         countrys
                     -5.258
         inc
                     -4.954
In [12]:
            print(f"Words in prior: {np.sum(priors):>10}")
           print(f"Words in samples: {np.sum(vec.transform(news.body.iloc[:num_holdout_artic
        Words in prior:
                              3221236
        Words in samples:
                               597077
In [13]:
            # what's up with '39'?
            sports.loc[sports.body.str.contains('39')]
Out[13]:
                                                              body
                   Miami Dolphins owner Wayne Huizenga and presid...
              15
                         It was a fight that was to receive national ex...
              26
                      Johnny Damon speaks the truth. Quoth the hair...
              36
                        Receiver Eric Moulds is all for team owner Ral...
              41
                       Arsenal #39;s 100 per cent record in the Premi...
           19937
                        Michael Anti of the United States won the silv...
           19967
                        Scotland #39;s prospects of qualifying for the...
           19971
                     Favourite Anja Paerson of Sweden won the seaso...
           19974
                      Oklahoma wide receiver Mark Clayton scores a t...
           19991
                    European soccer #39;s governing body on Tuesda...
          1394 rows × 1 columns
In [14]:
            other.loc[other.body.str.contains('39')]
```

Out[14]: body

12 The Palestinians have taken a double hit this ...

- **20** The hardline Democratic Unionist leader Ian Pa...
- quot; This is completely a part of BT #39;s tr...
- 44 Forstmann Little amp; Company, a New York buy...
- One of Labor #39;s challenges is to come up wi...

•••

- **19970** Shares of food makers were mixed in Monday tra...
- **19980** Joan Marie Gilbert and her 15-year-old daughte...
- **19983** The most satisfied new-home buyers in the Wash...
- **19995** Struggling automotive supplier Visteon Corp. t...
- **19997** RadioShack to take over the operation of cell ...

2752 rows × 1 columns

Oh, well that's dumb. Clearly need more/different preprocessing. This is the sort of thing you want to check when you see odd results. That said, I guess sports articles use more apostrophes than do other articles?

```
In [15]:
          # compare without priors
          no_priors = fw.bayes_compare_language(
              11=[j for i, j in sports.itertuples()],
              12=[j for i, j in other.itertuples()],
              cv=vec,
          display fw(no priors)
       Vocab size is 57875
       Comparing language...
        Top terms in corpus one
       his
                   28.952
                   24.496
        season
       night
                   24.434
                   24.285
        game
        the
                   24.005
```

game 24.285
the 24.005
he 23.236
team 23.035
win 21.673
victory 21.201
points 16.945

```
Top terms in corpus two
           -22.583
its
said
            -21.354
us
           -18.299
            -14.657
that
of
            -12.680
company
           -12.627
           -12.380
president
people
            -10.942
```

government -10.240 million -9.987

In [ ]: