# in4080_2020_mandatory_1_a

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## 1 Assignment 1A

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### 1.1 Part 1 - Conditional frequency distributions

```
In [1]: import nltk
        from nltk.corpus import brown
        import matplotlib.pyplot as plt
        import numpy as np
        import pandas as pd
```

```
In [2]: # If installed, seaborn will make a prettier theme for the plots
        try:
            import seaborn as sns
            sns.set()
        except ImportError:
            print("Using default matplotlib theme")
```

#### 1.1.1 a

Conduct a similar experiment as the one mentioned above with the genres: news, religion, government, fiction, romance as conditions, and occurrences of the words: he, she, her, him, as events. Make a table of the conditional frequencies and deliver code and table. (Hint: Have you considered case folding?)

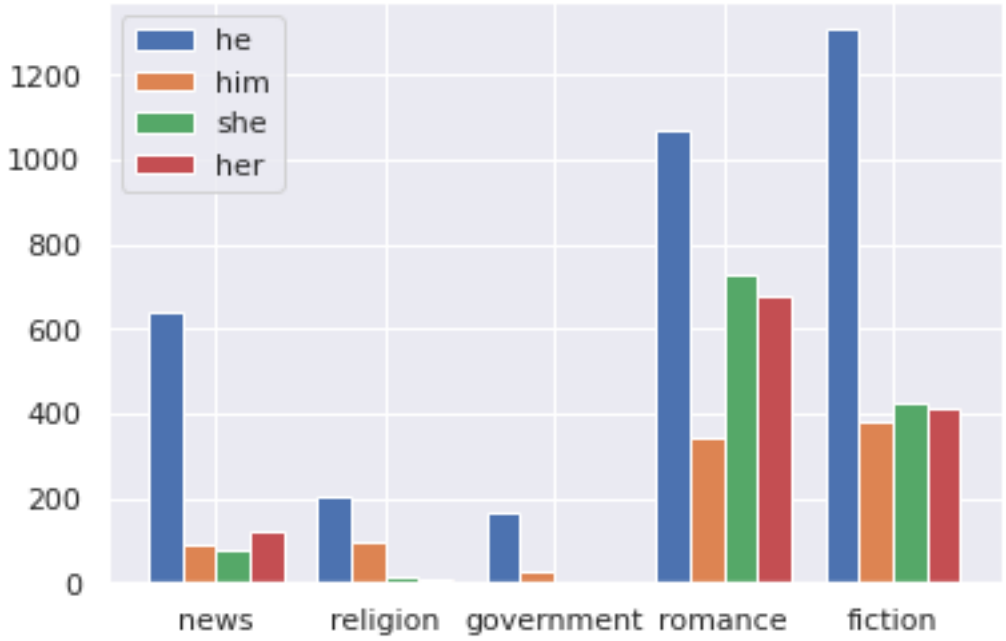
```
In [3]: genres = ["news", "religion", "government", "romance", "fiction"]
        terms = ["he", "him", "she", "her"]
```

```
In [4]: n = len(genres)
        x_pos = np.arange(n)

        tfs = {t : {g : 0 for g in genres} for t in terms}
        for genre in genres:
            text = brown.words(categories=genre)
            fdist = nltk.FreqDist(w.lower() for w in text)
            for t in terms:
```

```
        tfs[t][genre] = fdist[t]
bar_width = 0.20
for i, t in enumerate(terms):
    plt.bar(x_pos + (i-1.5)*bar_width, tfs[t].values(), bar_width, label=t)

plt.legend()
plt.xticks(x_pos, genres)
None
```




```
In [5]: pd.DataFrame.from_dict(tfs)
```

Out[5]:

| | he | him | she | her |
|---|---|---|---|---|
| news | 642 | 93 | 77 | 121 |
| religion | 206 | 94 | 12 | 8 |
| government | 169 | 26 | 1 | 3 |
| romance | 1068 | 340 | 728 | 680 |
| fiction | 1308 | 382 | 425 | 413 |

### 1.2 b

Answer in words what you see. How does gender vary with the genres?

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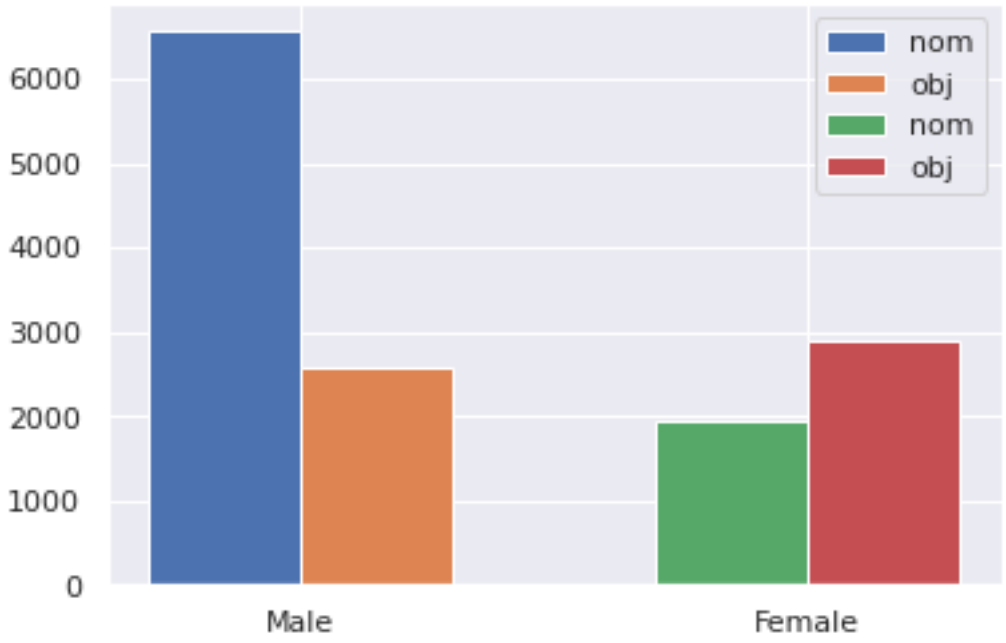
Pronouns are more common in romance and fiction compared to that of government and religion.

"He" seems to be the most frequent term of the four we're looking at. It is interesting to see the contrast between the relationship of "he" and "him" compared to "she" and "her". For instance, in fiction and romance, "he" is by far the most frequent word, though him is the least frequent in the two. This might reflect who appears as subjects and objects in the sentences.

### 1.2.1 C

... First, consider the complete Brown corpus. Construct a conditional frequency distribution, which uses gender as condition, and for each gender counts the occurrences of nominative forms (he, she) and objective forms (him, her). Report the results in a two by two table. Then calculate the relative frequency of her from she or her, and compare to the relative frequency of him from he or him. Report the numbers. Submit table, numbers and code you used.

```
In [6]: conds = {
            "male": ("he", "him"),
            "female": ("she", "her")
        }

        nom = "he", "she"

        cfd_c = nltk.ConditionalFreqDist(
           (gender, "nom" if w in nom else "obj")
           for w in brown.words() for gender, pronouns in conds.items() if w in pronouns
        )

In [7]: cfd_c.tabulate()

        nom  obj
female 1949 2885
  male 6566 2576


In [8]: barwidth = 0.30
        for i, (gender, dist) in enumerate(cfd_c.items()):
            for j, (term, freq) in enumerate(dist.items()):
                plt.bar([barwidth*j + i-0.15], [freq], barwidth, label=term)
        plt.xticks([0, 1], ["Male", "Female"])
        plt.legend()
        None
```




### 1.2.2 d

... What could work is to use a tagged corpus, which separates between the two forms of her, i.e, if the corpus tags her as a personal pronoun differently from her as a possessive pronoun. The tagged Brown corpus with the full tag set does that. Use this to count the occurrences of she, he, her, him as personal pronouns and her, his, hers as possessive pronouns. See NLTK book, Ch. 5, Sec. 2, for the tagged Brown corpus. Report in a two-ways table.

```
In [9]: pronouns = {"him", "his", "her", "hers"}
        cfd_d = nltk.ConditionalFreqDist(t for t in brown.tagged_words() if t[0] in pronouns)
        cfd_d.tabulate()

        NIL    PP$   PP$$ PP$-NC PP$-TL    PPO PPO-NC
 her      0   1775      0      4      0   1106      0
hers      0      0     16      0      0      0      0
 him      0      0      0      0      0   2572      4
 his      2   6418     36      8      2      0      0


In [10]: for i in cfd_d: print(i, "|", *cfd_d[i])

his | PP$ PP$$ NIL PP$-NC PP$-TL
him | PPO PPO-NC
her | PP$ PPO PP$-NC
hers | PP$$
```

### 1.2.3 e

We can now correct the numbers from point (b) above. How large percentage of the feminine personal pronoun occurs in nominative form and in objective form? What are the comparable percentages for the masculine personal pronoun?

```
In [11]: total = sum(cfd_d["her"].values())

         get_percent = lambda n: f"{round(n*100, 1)}%"

         her_po = cfd_d["her"]["PP$"]
         her_pe = cfd_d["her"]["PPO"]
         print(f"Her as posessive: {get_percent(her_po/total)}, as personal: {get_percent(her_p
```

```
Her as posessive: 61.5%, as personal: 38.3%
```

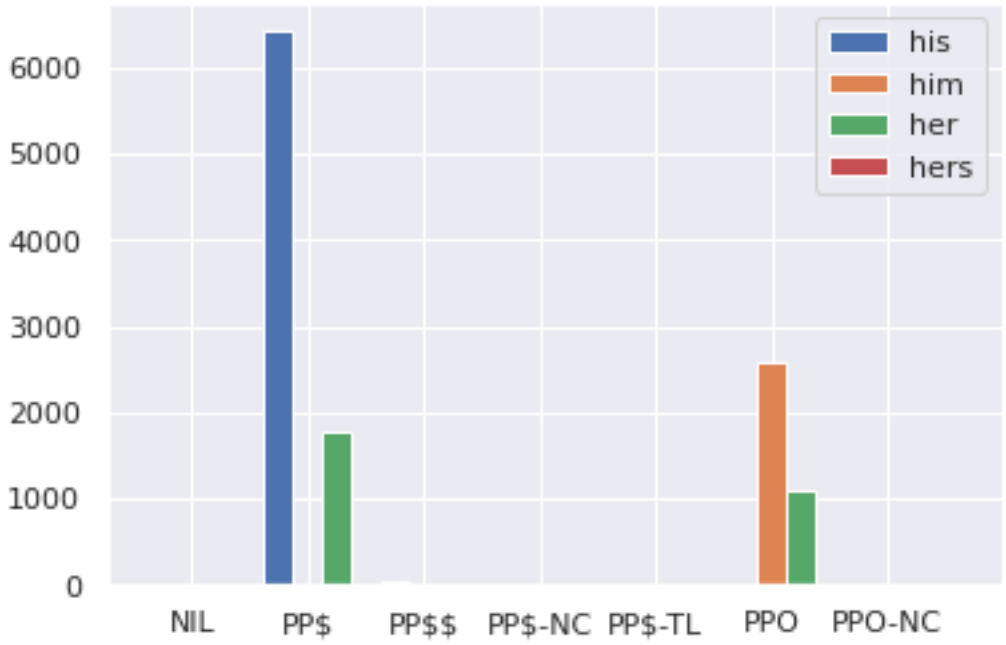
```
In [12]: for pronoun in ["him", "his"]:
             sigma = sum(cfd_d[pronoun].values())
             print(pronoun)
             for tag, count in cfd_d[pronoun].items():
                 print(tag, get_percent(count/sigma))
```

```
him
PPO 99.8%
PPO-NC 0.2%
his
PP$ 99.3%
PP$$ 0.6%
NIL 0.0%
PP$-NC 0.1%
PP$-TL 0.0%
```

```
In [13]: tags = sorted(set(tag for dist in cfd_d.values() for tag in dist.keys()))
         tags
```

```
Out[13]: ['NIL', 'PP$', 'PP$$', 'PP$-NC', 'PP$-TL', 'PPO', 'PPO-NC']
```

```
In [14]: barwidth = 0.25
         xtics = np.linspace(0, 6, len(tags))

         for i, (pronoun, dist) in enumerate(cfd_d.items()):
             widths = np.array([j+(i-1)*barwidth for j in range(len(tags))])
             freqs = [dist.get(t, 0) for t in tags]
             plt.bar(widths, freqs, barwidth, label=pronoun)
         plt.xticks(xtics, [tag.replace("$", r"\$") for tag in tags])
         plt.legend()
         None
```




#### 1.2.4 Looking at the results

What does the data show? The brown corpus was assembled in 1961 and contains various text documents from various categories. In this analysis, we looked at the extent to which the gender pronouns were used and represented in these texts. What have we found? The male pronouns are vastly overrepresented, compared to those of females. That is the case in all of the genres. Why is this? If we consider each category, there might be different reasons. In religion and history, protagonists and antagonists are usually male, as males historically have been dominating all societal positions of power considering that of females. Many of these authors are also male which might be a factor. Historical oppression of women has also had a significant effect in hindering their precesne in literature. If we create semantic ai-agents based on old values and stereotyping, the agent will adopt this way of though. Creating a semantic vector space based on this corpus will also place things associated with men and women closer to pronouns relating to men and women. Conventional methods of creating word embeddings, or mapping vocabularies to euclidean space, is heavily based on words that appear in another word's context. This will place 'carpenter' closer to male pronouns and nurse closer to female pronouns

## 2 Part 2

#### 2.0.1 a)

```
In [15]: with open("tom_sawyer.txt", "r", encoding="UTF8") as f:
             lines = list(f)
         print(*lines[:30])
```

```
The Project Gutenberg EBook of The Adventures of Tom Sawyer, Complete by
Mark Twain (Samuel Clemens)

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no restrictions whatsoever. You may copy it, give it away or re-use
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Title: The Adventures of Tom Sawyer, Complete

Author: Mark Twain (Samuel Clemens)

Release Date: August 20, 2006 [EBook #74]
Last Updated: February 23, 2018

Language: English

Character set encoding: UTF-8

*** START OF THIS PROJECT GUTENBERG EBOOK TOM SAWYER ***

Produced by David Widger




THE ADVENTURES OF TOM SAWYER
```

#### 2.0.2 b)

We turn the text into lowercase as we dont want duplicates of entries in our vocabulary. Both for efficiency, and simplicity.
We remove all punctuation marks using the translate method. The headers are simply sliced off.

```
In [16]: # Task b: remove metadata
         import string
         doc = "".join(lines[27:]).translate(str.maketrans('', '', string.punctuation)).lower()
```

#### 2.0.3 c)

```
In [17]: tokens = nltk.tokenize.word_tokenize(doc)
```

#### 2.0.4 d)

```
In [18]: tokendist = nltk.FreqDist(tokens)

In [35]: # 'the' is the most common word
         max(tokendist, key=lambda x: tokendist[x])

Out[35]: 'the'
```

#### 2.0.5 e)

```
In [19]: countdist = nltk.FreqDist(tokendist.values())
         countdist

Out[19]: FreqDist({1: 4643, 2: 1343, 3: 623, 4: 429, 5: 234, 6: 190, 7: 158, 8: 133, 10: 96, 9

In [20]: d = {}
         for i in range(1, 11):
             print("words that occur ",i, "times:", countdist[i])
             d[str(i)] = countdist[i]

words that occur  1 times: 4643
words that occur  2 times: 1343
words that occur  3 times: 623
words that occur  4 times: 429
words that occur  5 times: 234
words that occur  6 times: 190
words that occur  7 times: 158
words that occur  8 times: 133
words that occur  9 times: 77
words that occur  10 times: 96


In [21]: mid = sum(v for k, v in countdist.items() if 11 < k < 50)
         d["11 < x < 50"] = mid
         f"{mid} terms between 11 and 50 occurences"

Out[21]: '448 terms between 11 and 50 occurences'

In [22]: top = sum(v for k, v in countdist.items() if k > 100)
         d["x > 100"] = top
         f"{top} terms occur more than 100 times"

Out[22]: '101 terms occur more than 100 times'

In [26]: pd.DataFrame(d.items(), columns=["term occurence", "count"])

Out[26]:    term occurence  count
         0               1   4643
         1               2   1343
```

```
2                3    623
3                4    429
4                5    234
5                6    190
6                7    158
7                8    133
8                9     77
9               10     96
10    11 < x < 50    448
11        x > 100    101
```

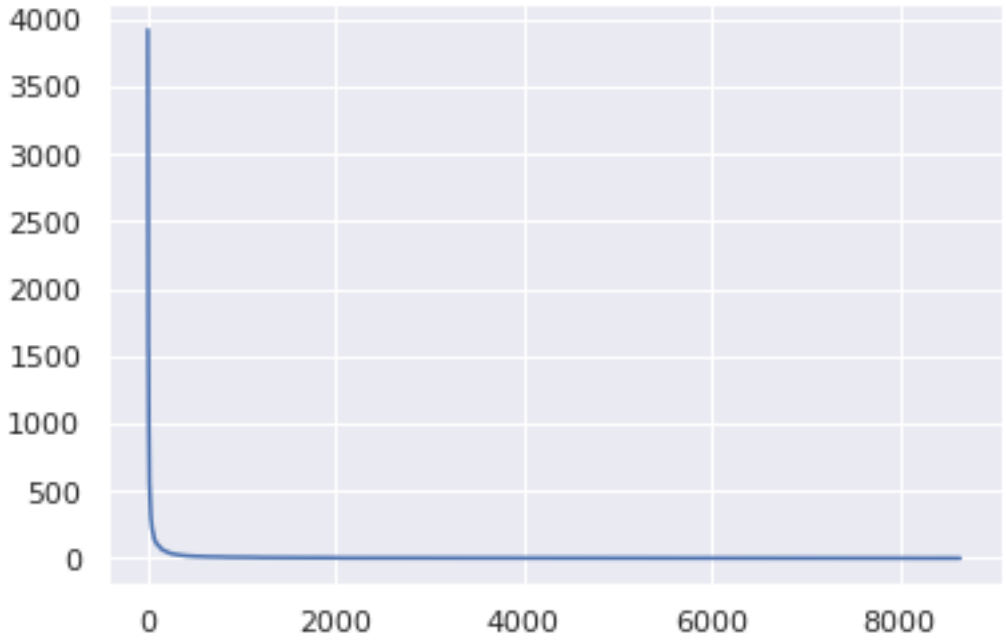
#### 2.0.6 f)

In [36]:
```
counts = sorted(tokendist.values(), key=lambda a: -a)
counts
pd.DataFrame(list(zip(counts[:20], [i * counts[i-1] for i in range(1, 21)])), columns=
```

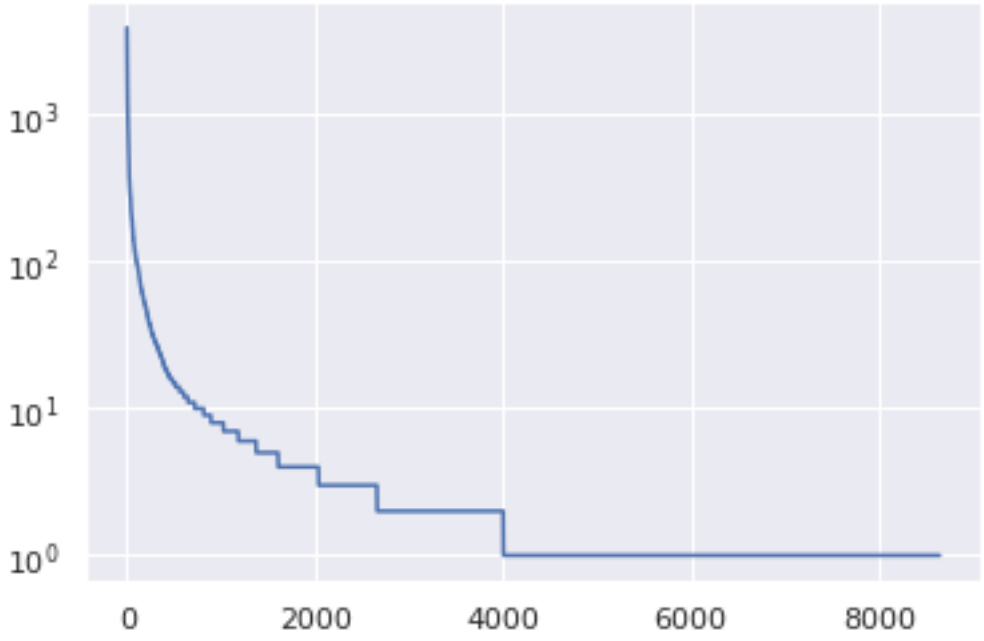
Out[36]:
```
        n  r * n
0    3921   3921
1    3082   6164
2    1876   5628
3    1793   7172
4    1577   7885
5    1545   9270
6    1538  10766
7    1182   9456
8    1169  10521
9    1127  11270
10   1004  11044
11    905  10860
12    827  10751
13    819  11466
14    746  11190
15    702  11232
16    688  11696
17    551   9918
18    546  10374
19    533  10660
```

In [37]:
```
plt.plot(counts)
```

Out[37]:
```
[<matplotlib.lines.Line2D at 0x7f4477e1c350>]
```




In [41]:
```
plt.plot(counts)
plt.yscale("log")
# plt.xscale("log")
```



In [42]:
```
plt.plot(counts)
plt.yscale("log")
plt.xscale("log")
```