

Handout 6: Collocations

Bigrams and generators

1. Three unigram distributions

a. Consider:

```
1 >>> list(nltk.bigrams(['a', 'b', 'c']))
2 [('a', 'b'), ('b', 'c')]
```

b. Unigrams in corpus: a 1, b 1, c 1.

c. As left member of bigram: a 1, b 1.

d. As right member of bigram: b 1, c 1.

e. The fix: add the wrap-around bigram ('c', 'a').

2. Creating a generator: **yield**

a. Example:

```
1 def lengths (strings):
2     for s in strings:
3         yield len(s)
```

b. Using it:

```
1 >>> lengths(['my', 'name', 'is', 'Ishmael'])
2 <generator object lengths at 0x100676c60>
3 >>> for n in lengths(['my', 'name', 'is', 'Ishmael']):
4     ...     print('n=', n)
5     ...
6     n= 2
7     n= 4
8     n= 2
9     n= 7
10 >>> list(lengths(['my', 'name', 'is', 'Ishmael']))
11 [2, 4, 2, 7]
```

3. Exercise.

Redefine the function **bigrams**. It should take a list or text as input, and it should return a generator containing the bigrams of the text, including the wrap-around bigram.

```
1 >>> list(bigrams(['a', 'b', 'c']))
2 [('c', 'a'), ('a', 'b'), ('b', 'c')]
```

a. What are the unigram distributions now?

Conditional probability

4. Our little corpus: `tokens = list('abbdabdbbd')`

	a	b	d	
a	—	2/10	—	2/10
b	—	2/10	3/10	5/10
d	2/10	1/10	—	3/10
	2/10	5/10	3/10	

5. Consider bigram (b, d)

- a. $p(\mathbf{b}, \mathbf{d}) = 3/10$
- b. In two steps: pick a position in the corpus at random. $p(\mathbf{b}) = 1/2$
- c. **Conditional distribution** over bigram right, for bigrams beginning with b:

a	b	d
—	2/5	3/5

- d. Second step: choose a random right member: $p(\mathbf{d}|\mathbf{b}) = 3/5$
- e. Together: $p(\mathbf{b}, \mathbf{d}) = p(\mathbf{b}) p(\mathbf{d}|\mathbf{b}) = (1/2)(3/5) = 3/10$

6. Another example

- a. In *Moby Dick*, white whale occurs 31 times:

```
1 >>> bd = FreqDist(bigrams(text1))
2 >>> bd['white', 'whale']
3 31
```

- b. Using circular bigrams, same number of unigrams and bigrams:

```
1 >>> fd = FreqDist(text1)
2 >>> fd.N()
3 260819
4 >>> bd.N()
5 260819
```

- c. The word white occurs 191 times. $p(\text{white}) = 191/N$
- d. Of those 191, *whale* comes next 31 times: $p(\text{whale}|\text{white}) = 31/191$
- e. $p(\text{white}, \text{whale}) = p(\text{white}) p(\text{whale}|\text{white}) = \frac{191}{N} \cdot \frac{31}{191} = 31/N$

7. Definition of conditional probability

- a. Counts and probabilities: $p(x) = c(x)/N$
- b. $c(\text{white}) = 191$, $c(\text{white}, \text{whale}) = 31$
- c. Condition probability is $31/191$:

$$p(y|x) = \frac{c(x, y)}{c(x)} = \frac{c(x, y)/N}{c(x)/N} = \frac{p(x, y)}{p(x)}$$

8. Summary

- a. The **chain rule**: $p(x)p(y|x) = p(x,y)$
- b. The **marginal probability**: $p(x)$
- c. The **conditional probability**: $p(y|x) \equiv p(x,y)/p(x)$
- d. The **joint probability**: $p(x,y)$

9. Exercises. What are these probabilities?

- a. When rolling a single die, the probability of an even number given that we roll a high number (≥ 4).
- b. When rolling a pair of dice, the probability of rolling “boxcars” (two sixes).
- c. The probability that we have rolled boxcars, if the number on the first die is a six.

10. Conditional frequency distributions

- a. Our little example:

```
1 >>> from nltk import ConditionalFreqDist
2 >>> cfd = ConditionalFreqDist(bigrams('abbdabdbbd'))
3 >>> cfd.tabulate()
4      a    b    d
5 a     0    2    0
6 b     0    2    3
7 d     2    1    0
```

- b. Row labels are **conditions**.

```
1 >>> cfd.conditions()
2 ['a', 'b', 'd']
```

- c. Rows are FreqDists.

```
1 >>> cfd['b']
2 FreqDist({'d': 3, 'b': 2})
```

- d. Rows represent **conditional probabilities**. $p(d|b) = 3/5$

```
1 >>> cfd['b'].freq('d')
2 0.6
```

- e. Contrast with joint probability $p(b,d)$

```
1 >>> bd = FreqDist(bigrams('abbdabdbbd'))
2 >>> bd.freq(('b', 'd'))
3 0.3
```

11. Exercise. How do we get the most-likely item following *b*?

(In)dependence

12. Conditional dependence

- a. Is **d** more likely following **b**? $p(\mathbf{d}|\mathbf{b}) > p(\mathbf{d})$?

```
1 >>> fd.freq('d')
2 0.3
3 >>> cfd['b'].freq('d')
4 0.6
```

- b. When rolling a single die, is an even number more likely, knowing that you rolled high?
- c. When rolling two dice, is a six more likely on the second die, knowing that you rolled six with the first die?

13. Expected count

- a. If x and y are **independent**, then $p(y|x) = p(y)$

- b. Joint probability

$$p = p(x) p(y|x)$$

- c. Expected joint probability, assuming independence:

$$\hat{p} = p(x) p(y)$$

- d. Expected count, assuming independence:

$$\hat{c}(x, y) = N\hat{p}(x, y)$$

- e. What is the expected count of (**b**, **d**), assuming independence?

```
1 >>> fd.N() * fd.freq('b') * fd.freq('d')
2 1.5
```

- f. Actual count is 3: twice the expected count

14. The **dependence ratio**: ratio of actual count to expected count

- a. Same as ratio of $p(y|x)$ to $p(y)$

$$r = \frac{c(x, y)}{\hat{c}(x, y)} = \frac{Np(x, y)}{N\hat{p}(x, y)} = \frac{p(x) p(y|x)}{p(x) p(y)} = \frac{p(y|x)}{p(y)}$$

- b. Example: $p(\mathbf{d}|\mathbf{b})/p(\mathbf{d}) = \frac{3}{5}/\frac{3}{10} = 2$

15. Exercises.

- a. What is the dependence ratio for (**d**, **a**)? More or less than (**b**, **d**)?
- b. What is the dependence ratio between rolling an even number and rolling a high number?

16. A **collocation** is a word pair with a high degree of dependence.

a. Is white whale a collocation? Expected count:

```
1 >>> fd = FreqDist(text1)
2 >>> fd.N() * fd.freq('white') * fd.freq('whale')
3 0.6634716029123645
```

b. What is the actual count?

```
1 >>> cfd = ConditionalFreqDist(bigrams(text1))
2 >>> cfd['white']['whale']
3 31
```

c. It occurs times as often as we expect

```
1 >>> 31 / 0.6634716029123645
2 46.723928897518576
```

d. Computing from $p(y|x)$ and $p(y)$:

```
1 >>> cfd['white'].freq('whale')
2 0.16230366492146597
3 >>> fd.freq('whale')
4 0.003473673313677301
5 >>> cfd['white'].freq('whale') / fd.freq('whale')
6 46.723928897518576
```

17. Mutual information

a. (Pointwise) mutual information is the log of the degree of dependence

```
1 >>> from math import log10
2 >>> def pmi (x, y, fd, cfd):
3 ...     return log10(cfd[x].freq(y) / fd.freq(y))
4 ...
5 >>> pmi('white', 'whale', fd, cfd)
6 1.6695393543691355
7 >>> 10 ** pmi('white', 'whale', fd, cfd)
8 46.72392889751858
```

b. Pmi = 1 means times as likely

c. Pmi = 2 means times as likely

d. Pmi = means equally likely

e. Pmi = 0.5 means 3.2 ($= \sqrt{10}$) times as likely

f. Pmi = 1.5 means times as likely

g. What does a negative pmi mean?

18. Differing collocation strengths:

```
1 >>> pmi('the', 'whale', fd, cfd)
2 0.8888516296076806
3 >>> pmi('sperm', 'whale', fd, cfd)
4 2.1825403779780537
```

19. Symmetry and assymetry

- a. What is the dependence ratio between rolling a high number and rolling an even number?
- b. Is the dependence ratio symmetric in general?

$$\frac{p(y|x)}{p(y)} = \frac{p(x,y)}{p(x)p(y)} = \frac{p(x|y)}{p(x)}$$

- c. But be careful:

$$\frac{\Pr[R = y|L = x]}{\Pr[R = y]} = \frac{\Pr[L = x|R = y]}{\Pr[L = x]}$$

$$\frac{\Pr[R = y|L = x]}{\Pr[R = y]} \neq \frac{\Pr[L = y|R = x]}{\Pr[L = y]}$$

- d. Example:

```
1 >>> pmi('whale', 'the', fd, cfd)
2 -1.3771447408873985
```