## Collocation

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## Reference

## - Reference1

- Foundations of Statistical Natural Language Processing, Chapter 3
- Pearce, D. "Synonymy in collocation extraction." In Proceedings of the NAACL'01 Workshop on WordNet and Other Lexical Resources: Applications, Extensions and Customizations. Pittsburgh, PA.


## Outline

- What is collocation
- Why study collocations?
- Approaches to finding collocations
- Summary and Conclusions


## What is collocation

- is an expression of 2 or more words that correspond to a conventional way of saying things.
- broad daylight
- Why not? ?bright daylight or ?narrow darkness
- Big mistake but not ?large mistake
- overlap with the concepts of:
- terms, technical terms \& terminological phrases
- Collocations extracted form technical domains
- Ex: hydraulic oil filter, file transfer protocol


## What is collocation (cont)

## More example :

strong tea

- to check in
- heard it through the grapevine
- he knocked at the door
…


## What is collocation (cont)

## Definition of a collocation

(Choueka, 1988)
[A collocation is defined as] "a sequence of two or more consecutive words, that has characteristics of a syntactic and semantic unit, and whose exact and unambiguous meaning or connotation cannot be derived directly from the meaning or connotation of its components."

## What is collocation (cont)

## Criteria:

- non-compositionality
non-substitutability
- non-modifiability
- non-translatable word for word


## What is collocation (cont)

## Non-Compositionality

- A phrase is compositional if its meaning can be predicted from the meaning of its parts
- Ex : a young man
- Collocations have limited compositionality
- there is usually an element of meaning added to the combination
- Ex: strong tea
- Idioms are the most extreme examples of noncompositionality
- Ex: to hear it through the grapevine


## What is collocation (cont)

Non-Substitutability

- We cannot substitute near-synonyms for the components of a collocation.
- Strong is a near-synonym of powerful
- strong tea ?powerful tea
- yellow is as good a description of the color of white wines
- white wine ?yellow wine


## What is collocation (cont)

Non-modifiability
$\square$ Many collocations cannot be freely modified with additional lexical material or through grammatical transformations

- To get a frog in one's throat ?get an ugly frog in one's throat


## What is collocation (cont)

Non-translatable (word for word)

- English:
- make a decision
- French:
- ?faire une décision
- to test whether a group of words is a collocation:
- translate it into another language
- if we cannot translate it word by word
- then it probably is a collocation


## What is collocation (cont)

## Linguistic Subclasses of Collocations

- Phrases with light verbs:
- Verbs with little semantic content in the collocation
- have, do...
- Proper nouns (proper names)
- John Smith
- Terminological expressions
- concepts and objects in technical domains
- hydraulic oil filter


## Why study collocations?

- In nature language generator (NLG)
- The output should be natural
- make a deci
- Identify collocations to list them in a dictionary
- To distinguish the usage of synonyms or nearsynonyms


## Why study collocations (cont)

- In parsing
- To give preference to most natural attachments
- plastic (can opener) ? (plastic can) opener
- In corpus linguistics and psycholinguists
- Ex: To study social attitudes towards different types of substances
- strong cigarettes/tea/coffee
- powerful drug


## Approaches to finding collocations

- Frequency
- Mean and Variance
- Hypothesis Testing
- t-test
- $\chi^{2}$-test (Chi-Square test)
- Likelihood ratio test
- Mutual Information
- Synonymy in collocation extraction


## Approaches to finding collocations (cont)

## Frequency (cont)

- (Justeson \& Katz, 1995)
- Hypothesis:
- if 2 words occur together very often, they must be interesting candidates for a collocation
- Method:
- Select the most frequently occurring bigrams (sequence of 2 adjacent words)


## Approaches to finding collocations (cont)

## Frequency (cont)

- Not very interesting...
- Except for "New York", all bigrams are pairs of function words

So, let's pass the results through a part-ofspeech filter

| Tag Pattern | Example |
| :---: | :--- |
| A N | linear function |
| N N | regression coefficient |
| A A N | Gaussian random variable |
| A N N | cumulative distribution function |
| N A N | mean squared error |
| N N N | class probability function |
| N P N | degrees of freedom |


| $C\left(w^{1} w^{2}\right)$ | $w^{1}$ | $w^{2}$ |
| ---: | :--- | :--- |
| 80871 | of | the |
| 58841 | in | the |
| 26430 | to | the |
| 21842 | on | the |
| 21839 | for | the |
| 18568 | and | the |
| 16121 | that | the |
| 15630 | at | the |
| 15494 | to | be |
| 13899 | in | a |
| 13689 | of | a |
| 13361 | by | the |
| 13183 | with | the |
| 12622 | from | the |
| 11428 | New | York |
| 10007 | he | said |
| 9775 | as | a |
| 9231 | is | a |
| 8753 | has | been |
| 8573 | for | a |
|  |  | 17 |

## Approaches to finding collocations (cont)

Frequency + POS filter

## Simple method that works very well!

| $C\left(w^{1} w^{2}\right)$ | $w^{1}$ | $w^{2}$ | Tag Pattern |
| :--- | :--- | :--- | :--- |
| 11487 | New | York | A N |
| 7261 | United | States | A N |
| 5412 | Los | Angeles | N N |
| 3301 | last | year | A N |
| 3191 | Saudi | Arabia | N N |
| 2699 | last | week | A N |
| 2514 | vice | president | A N |
| 2378 | Persian | Gulf | A N |
| 2161 | San | Francisco | N N |
| 2106 | President | Bush | N N |
| 2001 | Middle | East | A N |
| 1942 | Saddam | Hussein | N N |
| 1867 | Soviet | Union | A N |
| 1850 | White | House | A N |
| 1633 | United | Nations | A N |
| 1337 | York | City | N N |
| 1328 | oil | prices | N N |
| 1210 | next | year | A N |
| 1074 | chief | executive | A N |
| 1073 | real | estate | A N |

## Approaches to finding collocations (cont)

## Frequency: Conclusion

- Advantages:
- works well for fixed phrases
- Simple method \& accurate result
- Requires small linguistic knowledge
- But: many collocations consist of two words in more flexible relationships
- she knocked on his door
- they knocked at the door
- 100 women knocked on Donaldson's door
- a man knocked on the metal front door


## Approaches to finding collocations (cont)

Mean and Variance

- (Smadja et al., 1993)
- Looks at the distribution of distances between two words in a corpus
- looking for pairs of words with low variance
- A low variance means that the two words usually occur at about the same distance
- A low variance --> good candidate for collocation
- Need a Collocational Window to capture collocations of variable distances

|  | knock |  |  | door |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :---: |
|  | knock |  |  |  |  |  |

## Approaches to finding collocations (cont)

Mean and Variance (cont)

- This is an example of a three word window.
- Sentence : stocks crash as rescue plan teeters
- Bigram :



## Approaches to finding collocations (cont)

## Mean and Variance (cont)

- The mean is the average offset (signed distance) between two words in a corpus
- The variance measures how much the individual offsets deviate from the mean

$$
\operatorname{var}=\frac{\sum_{i=1}^{n}\left(d_{i}-\bar{d}\right)^{2}}{n-1}
$$

- n is the number of times the two words (two candidates) co-occur
- $d_{i}$ is the offset of the $\mathrm{i}^{\mathrm{t}}$ pair of candidates
- is the mean offset of all pairs of candidates


## Approaches to finding collocations (cont)

Mean and Variance (cont)

- If offsets ( $\mathrm{d}_{\mathrm{i}}$ ) are the same in all co-occurrences
- --> variance is zero
- --> definitely a collocation
- If offsets $\left(\mathrm{d}_{\mathrm{i}}\right)$ are randomly distributed
- --> variance is high
- --> not a collocation


## Approaches to finding collocations (cont)

Mean and Variance (cont)

- An Example
- she knocked on his door
- they knocked at the door
- 100 women knocked on Donaldson's door
- a man knocked on the metal front door
- Mean d $=\frac{(3+3+5+5)}{4}=4.0$
$\square$ Std. deviation $s=\sqrt{\frac{(3-4.0)^{2}+(3-4.0)^{2}+(5-4.0)^{2}+(5-4.0)^{2}}{3}} \approx 1.15$


## Approaches to finding collocations (cont)

- "strong...opposition"
- variance is low
- --> interesting collocation
- "strong...support"
- "strong...for"
- variance is high
- --> not interesting collocation





## Approaches to finding collocations (cont)

- Mean and variance versus Frequency
std. dev. $\sim 0$ \& mean offset ~1 --> would be found by frequency method

| would | $\checkmark$ | $\bar{d}$ | Count | Word 1 | Word 2 |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | 0.43 | 0.97 | 11657 | New | York |
|  | 0.48 | 1.83 | 24 | previous | games |
|  | 0.15 | 2.98 | 46 | minus | points |
| std. dev. ~0 \& high mean offset --> very interesting, but would not be found by frequency method | 0.49 | 3.87 | 131 | hundreds | dollars |
|  | 4.03 | 0.44 | 36 | editorial | Atlanta |
|  | 4.03 | 0.00 | 78 | ring | New |
|  | 3.96 | 0.19 | 119 | point | hundredth |
|  | 3.96 | 0.29 | 106 | subscribers | by |

high deviation --> not interesting

## Approaches to finding collocations (cont)

Mean \& Variance: Conclusion

- looser relationship between words
- intervening material and relative position


## Approaches to finding collocations (cont)

## Hypothesis Testing

- If 2 words are frequent... they will frequently occur together...
- Frequent bigrams and low variance can be accidental (two words can co-occur by chance)
- We want to determine whether the co-occurrence is random or whether it occurs more often than chance
- This is a classical problem in statistics called Hypothesis Testing
- When two words co-occur, Hypothesis Testing measures how confident we have that this was due to chance or not


## Approaches to finding collocations (cont)

Hypothesis Testing (cont)

- We formulate a null hypothesis $\mathrm{H}_{0}$
- $\mathrm{H}_{0}$ : no real association (just chance...)
- $\mathrm{H}_{0}$ states what should be true if two words do not form a collocation
- if 2 words $w_{1}$ and $w_{2}$ do not form a collocation, then $w_{1}$ and $w_{2}$ are independently of each other.


## Approaches to finding collocations (cont)

Hypothesis Testing: t-test

- or Student's t-test
- $\mathrm{H}_{0}$ states that: $\mathrm{P}\left(\mathrm{w}_{1}, \mathrm{w}_{2}\right)=\mathrm{P}\left(\mathrm{w}_{1}\right) \mathrm{P}\left(\mathrm{w}_{2}\right)$
- We calculate the probability p-value that $H_{0}$ was true
- If p-value is too low, we reject $H_{0}$, Otherwise, retain $H_{0}$ as possible
- Typically if under a significant level of $p<0.05,0.01$, or 0.001
- Assume the sample is drawn from a normal distribution


## Approaches to finding collocations (cont)

Hypothesis Testing: t-test (cont)

- t-test compares:
- the sample mean (computed from observed values)
- to a expected mean
$\square$ determines the likelihood ( $p$-value) that the difference between the 2 means occurs by chance.
- a p-value close to 1 --> it is very likely that the expected and sample means are the same
- a small p-value (ex: 0.01) --> it is unlikely (only a 1 in 100 chance) that such a difference would occur by chance


## Approaches to finding collocations (cont)

Hypothesis Testing: t-test (cont)

the higher the value of $t$, the greater the confidence that:
-there is a significant difference

- it's not due to chance
-the 2 words are not independent


## Approaches to finding collocations (cont)

## Hypothesis Testing: t-test (cont)

T-distribution

$$
f_{r}(t)=\frac{\Gamma\left[\frac{1}{2}(r+1)\right]}{\sqrt{r \pi} \Gamma\left(\frac{1}{2} r\right)\left(1+\frac{t^{2}}{r}\right)^{(r+1)} / 2}
$$



## Approaches to finding collocations (cont)

Hypothesis Testing: t-test (cont)

- We think of a corpus of N words as a long sequence of N bigrams
- the samples are seen as random variables that:
- take the value 1 when the bigram of interest occurs
- take the value 0 otherwise


## Approaches to finding collocations (cont)

## t-Test: a simple example :

- Null hypothesis is that the mean height of a population of men is 158 cm
- We are given a sample of 200 men with $x=169$ and $s^{2}=2600$

Confidence level of $\alpha=0.005$, we fine 2.576
$t=\frac{169-158}{\sqrt{\frac{2600}{200}}} \approx 3.05$
Since the $t$ we got is larger than 2.576 , we can reject the null hypothesis with $99.5 \%$ confidence. So we can say that the sample is not drawn from a population with mean 158 cm , and our probability of error is less than $0.5 \%$

## Approaches to finding collocations (cont)

t-Test: Example with collocations

- In a corpus:
- new occurs 15,828 times
- companies occurs 4,675 times
- new companies occurs 8 times
- there are $14,307,668$ tokens overall
- Is new companies a collocation?
- Null hypothesis:
- Independence assumption
- P (new companies) $=\mathrm{P}($ new $) \mathrm{P}($ companies $)$

$$
=\frac{15828}{14307668} \times \frac{4675}{14307668} \approx 3.615 \times 10^{-7}
$$

## Approaches to finding collocations (cont)

t -Test: Example with collocations (cont)

- If the null hypothesis is true, then:
- if we randomly generate bigrams of words
- assign 1 to the outcome new companies
- assign 0 to any other outcome
- ...in effect a Bernoulli trial
- then the probability of having new companies is expected to be $3.615 \times 10^{-7}$
- So the expected mean is $\mu=3.615 \times 10^{-7}$
- The variance $s^{2}=p(1-p) \approx p$ since for most bigrams $p$ is small
- in binomial distribution: $s^{2}=n p(1-p)$... but here, $n=1$


## Approaches to finding collocations (cont)

t-Test: Example with collocations (cont)

- But we counted 8 occurrences of the bigram new companies
- So the observed mean is $\bar{x}=\frac{8}{14307668} \approx 5.591 \times 10^{-7}$
- By applying the t-test, we have: $\quad \dagger=\frac{\bar{x}-\mu}{\sqrt{\frac{s^{2}}{N}}}=\frac{5.591 \times 10^{-7}-3.615 \times 10^{-7}}{\sqrt{\frac{5.591 \times 10^{-7}}{14307668}}} \approx 1$
- With a confidence level $\alpha=0.005$, critical value is 2.576

|  | p | 0.05 | 0.025 | 0.01 | 0.005 | 0.001 | 0.0005 |
| :---: | ---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | C | $90 \%$ | $95 \%$ | $98 \%$ | $99 \%$ | $99.8 \%$ | $99.9 \%$ |
| d.f. | 1 | 6.314 | 12.71 | 31.82 | 63.66 | 318.3 | 636.6 |
|  | 10 | 1.812 | 2.228 | 2.764 | 3.169 | 4.144 | 4.587 |
|  | 20 | 1.725 | 2.086 | 2.528 | 2.845 | 3.552 | 3.850 |
| (Z) | $\infty$ | 1.645 | 1.960 | 2.326 | 2.576 | 3.091 | 3.291 |

- Since $t=1<2.576$
- we cannot reject the $\mathrm{H}_{\text {。 }}$
- so we cannot claim that new and companies form a collocation


## Approaches to finding collocations (cont)

- t test applied to 10 bigrams that occur with frequency $=20$

| pass the t-test | $7$ | $\dagger$ | $C\left(w_{1}\right)$ | $C\left(w_{2}\right)$ | $C\left(w_{1} \mathrm{w}_{2}\right)$ | $\mathrm{w}_{1}$ | W |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $(t>2.756) \mathrm{so}:$ |  | 4.4721 | 42 | 20 | 20 | Ayatollah | Ruhollah |  |
| we can reject |  | 4.4721 | 41 | 27 | 20 | Bette | Midler |  |
| ypothes |  | 1.2176 | 14093 | 14776 | 20 | like | people |  |
| so they form |  | 0.8036 | 15019 | 15629 | 20 | time | last |  |

```
- fail the t-test (t
< 2.756) so:
we cannot reject
the null
hypothesis
so they do not
form a collocation
```

- Notes:
- Frequency-based method could not have seen the difference in these bigrams, because they all have the same frequency
- the $t$ test takes into account the frequency of a bigram relative to the frequencies of its component words
- If a high proportion of the occurrences of both words occurs in the bigram, then its $t$ is high.
- The $t$ test is mostly used to rank collocations


## Approaches to finding collocations (cont)

t -Test: Hypothesis testing of differences
Used to see if 2 words (near-synonyms) are used in the same context or not

- "strong" vs "powerful"
can be useful in lexicography
we want to test:
- if there is a difference in 2 populations
- Ex: height of woman / height of man
- the null hypothesis is that there is no difference
- i.e. the average difference is $0(\mu=0)$


## Approaches to finding collocations (cont)

t -Test: Hypothesis testing of differences (cont)

$$
t=\frac{\bar{x}_{1}-\bar{x}_{2}}{\sqrt{\frac{s_{1}^{2}}{n_{1}}+\frac{s_{2}^{2}}{n_{2}}}} \quad \begin{aligned}
& \bar{x}_{1} \text { is the sample mean of population 1 } \\
& \bar{x}_{2} \text { is the sample mean of population 2 } \\
& s_{1}^{2} \text { is the sample variance of population 1 } \\
& \begin{array}{l}
s_{2}^{2} \text { is the sample variance of population 2 } \\
n_{1} \text { is the sample size of population 1 } \\
n_{2} \text { is the sample size of population 2 }
\end{array}
\end{aligned}
$$

| $\boldsymbol{t}$ | $\boldsymbol{C}(\mathbf{w})$ | $\boldsymbol{C}($ strong $\mathbf{w})$ | $\boldsymbol{C}$ (powerful $\mathbf{w})$ | Word |
| :--- | ---: | :---: | :---: | :--- |
| 3.1622 | 933 | 0 | 10 | computers |
| 2.8284 | 2377 | 0 | 8 | computer |
| 2.4494 | 289 | 0 | 6 | symbol |
| 2.2360 | 2266 | 0 | 5 | Germany |
| 7.0710 | 3685 | 50 | 0 | support |
| 6.3257 | 3616 | 58 | 7 | enough |
| 4.6904 | 986 | 22 | 0 | safety |
| 4.5825 | 3741 | 21 | 0 | sales |

## Approaches to finding collocations (cont)

## $\chi^{2}$-test

- problem with the test is that it assumes that probabilities are approximately normally distributed...
- the $\chi^{2}$-test does not make this assumption
$\square$ The essence of the $\chi^{2}$-test is the same as the t-test
- Compare observed frequencies and expected frequencies for independence
- if the difference is large
- then we can reject the null hypothesis of independence


## Approaches to finding collocations (cont)

## $\chi^{2}$-test (cont)

$$
\begin{aligned}
\chi^{2} & =\frac{\left(O_{1}-E_{1}\right)^{2}}{\sigma_{1}^{2}}+\frac{\left(O_{2}-E_{2}\right)^{2}}{\sigma_{2}{ }^{2}}+\cdots+\frac{\left(O_{k}-E_{k}\right)^{2}}{\sigma_{k}{ }^{2}} \\
& =\sum_{i=1}^{k} \frac{\left(O_{i}-E_{i}\right)^{2}}{\sigma_{i}^{2}} \\
& =\sum_{i=1}^{k} \frac{\left(O_{i}-E_{i}\right)^{2}}{E_{i}} \text { (assumption counts are distributed according to the Poisson distribution) } \\
& =\mathrm{X}^{2}
\end{aligned}
$$

- sums the differences between observed frequencies
- and expected values for independence
- scaled by the magnitude of the expected values


## Approaches to finding collocations (cont)

## $\chi^{2}$-test (cont)

- In the table :

$$
x^{2}=\sum_{i, j} \frac{\left(O b s_{i j}-E x p_{i j}\right)^{2}}{E x p_{i j}}
$$

- Observed frequencies $O b s_{i j}$

| Observed | $w^{1}=$ new | $w^{1} \neq$ new | TOTAL |
| :--- | ---: | ---: | ---: |
| $w^{2}=$ companies | 8 | 4667 | 4675 |
|  | (new companies) | (ex: old companies) | $c($ companies) |
| $w^{2} \neq$ companies | 15820 | 14287181 | 14303001 |
|  | (ex: new machines) | (ex: old machines) | $c(\sim$ companies) |
| TOTAL | 15828 | 14291848 | 14307676 |
|  | $c($ new $)$ | $c(\sim$ new) | $N=4675+14303001$ |
|  |  |  | $=15828+14291848$ |

## Approaches to finding collocations (cont)

## $\chi^{2}$-test (cont)

- Expected frequencies Exp ${ }_{i j}$
- If independence
- Computed from the marginal probabilities (the totals of the rows and columns converted into proportions)

| Expected | $w^{1}=$ new | $w^{1} \neq$ new |
| :--- | ---: | ---: |
| $w^{2}=$ companies | 5.17 | 4669.83 |
|  | $c($ new $) \times c($ companies $) / N$ | $c($ companies $) \times c\left({ }^{\sim}\right.$ new $) / N$ |
| $w^{2} \neq$ companies | $15828 \times 4675 / 14307676$ | $4675 \times 14291848 / 14307676$ |
|  | 15822.83 | 14287178.17 |
|  | $c($ new $) \times c\left({ }^{\sim}\right.$ companies $) / N$ | $c\left({ }^{\sim}\right.$ new $) \times c\left({ }^{\sim}\right.$ companies) $/ \mathrm{N}$ |
|  | $15828 \times 14303001 / 14307676$ | $14291848 \times 14303001 / 14307676$ |

- Ex: expected frequency for cell $(1,1)$ (new companies)
- marginal probability of new occurring as the first part of a bigram times marginal probability of companies occurring as the second part of bigram:

$$
\frac{8+4667}{N} \times \frac{8+15820}{N} \times N=5.17
$$

- If "new" and "companies" occurred completely independent of each other
- we would expect 5.17 occurrences of "new companies" on average


## Approaches to finding collocations (cont)

## $\chi^{2}$-test (cont)

- But is the difference significant?

$$
x^{2}=\frac{(8-5.17)^{2}}{5.17}+\frac{(46667-46669.83)^{2}}{46669}+\frac{(15820-15822.83)^{2}}{15823}+\frac{(14287181-14287178.17)^{2}}{14287186} \approx 1.55
$$


df in an table $=(n-1)(c-1)=(2-1)(2-1)=1$ (degrees of freedom)

|  | p | 0.99 | 0.95 | 0.10 | 0.05 | 0.01 | 0.005 |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| d.f. | 1 | 0.00016 | 0.0039 | 2.71 | 3.84 | 6.63 | 7.88 |
|  | 2 | 0.020 | 0.10 | 4.60 | 5.99 | 9.21 | 10.60 |
|  | 3 | 0.115 | 0.35 | 6.25 | 7.81 | 11.34 | 12.84 |
|  | 4 | 0.297 | 0.71 | 7.78 | 9.49 | 13.28 | 16.27 |
|  | 100 | 70.06 | 77.93 | 118.5 | 124.3 | 135.8 | 140.2 |

## Approaches to finding collocations (cont)

## $\chi^{2}$-test (cont)

- The probability level of $\alpha=0.05$ the critical value is 3.84
- Since 1.55 < 3.84 :
- So we cannot reject $\mathrm{H}_{0}$ (that new and companies occur independently of each other)
- So new companies is not a good candidate for a collocation


## Approaches to finding collocations (cont)

$\chi^{2}$-test for machine translation

- (Church \& Gale, 1991)
- To identify translation word pairs in aligned corpora
- Ex:

Nb of aligned sentence pairs containing "cow" in English and "vache" in French

| Observed <br> frequency | "cow" | $\sim$ "cow" | IOTAL |
| :--- | ---: | :--- | :--- |
| "vache" | 59 | 6 | 65 |
| $\sim$ "vache" | 8 | 570934 | 570942 |
| TOTAL | 67 | 570940 | 571007 |

- $\chi^{2}=456400 \gg 3.84$ (with $\alpha=0.05$ )
- So "vache" and "cow" are not independent... and so are translations of each other


## Approaches to finding collocations (cont)

## $\chi^{2}$-test for corpus similarity

(Kilgarriff \& Rose, 1998)

- Ex:

| Observed <br> frequency | Corpus 1 | Corpus 2 | Ratio |
| :--- | ---: | ---: | :--- |
| Word1 | 60 | 9 | $60 / 9$ |
| Word2 | 500 | 76 | 6.6 |
| Word3 | 124 | 20 | 6.2 |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| Word500 | $\ldots$ | $\ldots$ | $\ldots$ |

- Compute $\chi^{2}$ for the 2 populations (corpus1 and corpus2)
- $H_{0}$ : the 2 corpora have the same word distribution


## Approaches to finding collocations (cont)

## $\chi^{2}$-test: Conclusion

Differences between the $t$ statistic and $\chi^{2}$ statistic do not seem to be large

- But:
- the $\chi^{2}$ test is appropriate for large probabilities
- where $t$ test fails because of the normality assumption
- the $\chi^{2}$ is not appropriate with sparse data (if numbers in the 2 by 2 tables are small)
- Against using $\chi^{2}$ if the total sample size is smaller than 20 or if it is between 20 and 40 and the expected value in any of the cells is 5 or less/


## Approaches to finding collocations (cont)

## Likelihood ratios

- It is simply a number that tells us how much more likely one hypothesis is than the other.
- Likelihood ratios are more appropriate for sparse data than the Chi-Square test. In addition, they are easier to interpret than the Chi-Square statistic.


## Approaches to finding collocations (cont)

Likelihood ratios (cont)

- Hypothesis 1. $P\left(w^{2} \mid w^{1}\right)=p=P\left(w^{2} \mid \neg w^{1}\right)$
- Hypothesis 2. $P\left(w^{2} \mid w^{1}\right)=p_{1} \neq p_{2}=P\left(w^{2} \mid \neg w^{1}\right)$
- Hypothesis 1 is a formalization of independence, hypothesis 2 is a formalization of dependence which is good evidence for an interesting collocation
- We use the usual MLE for $p, p_{1}$ and $p_{2}$ and write $c_{1}$, $c_{2}$ and $c_{12}$ for the number of occurrences of $w^{1}, w^{2}$ and $w^{1} w^{2}$ in corpus

$$
p=\frac{c_{2}}{N}, \quad p_{1}=\frac{c_{12}}{c_{1}}, \quad p_{2}=\frac{c_{2}-c_{12}}{N-c_{1}}
$$

## Approaches to finding collocations (cont)

## Likelihood ratios (cont)

Assuming a binomial distribution: $b(k ; n, x)=\binom{n}{k} x^{k}(1-x)^{(n-k)}$

$$
\begin{array}{lll} 
& H_{1} & H_{2} \\
P\left(w^{2} \mid w^{1}\right) & p=\frac{c_{2}}{N} & p_{1}=\frac{c_{12}}{c_{1}} \\
P\left(w^{2} \mid-w^{1}\right) & p=\frac{c_{2}}{N} & p_{2}=\frac{2-c_{12}}{N-c_{1}} \\
c_{12} \text { out of } c_{1} \text { bigrams are } w^{1} w^{2} & \mathrm{~b}\left(c_{12} ; c_{1} P\right) & \mathrm{b}\left(c_{12} ; c_{1}, P_{1}\right) \\
c_{2}-c_{12} \text { out of } N-c_{1} \text { bigrams are } \neg w^{1} w^{2} & \mathrm{~b}\left(c_{2}-c_{12} ; N-c_{1}, p\right) & \mathrm{b}\left(c_{2}-c_{12}-N-c_{1},\right.
\end{array}
$$

Table 5.11 How to compute Dunning's likelihood ratio test. For example, the likelihood of hypothesis $H_{2}$ is the product of the last two lines in the rightmost column.

$$
\begin{aligned}
& L\left(H_{1}\right)=b\left(c_{12} ; c_{1}, p\right) b\left(c_{2}-c_{12} ; N-c_{1}, p\right) \\
& L\left(H_{2}\right)=b\left(c_{12} ; c_{1}, p_{1}\right) b\left(c_{2}-c_{12} ; N-c_{1}, p_{2}\right)
\end{aligned}
$$

## Approaches to finding collocations (cont)

Likelihood ratios (cont)

$$
\begin{aligned}
\log \lambda & =\log \frac{L\left(H_{1}\right)}{L\left(H_{2}\right)} \\
& =\log \frac{b\left(c_{12}, c_{1}, p\right) b\left(c_{2}-c_{12}, N-c_{1}, p\right)}{b\left(c_{12}, c_{1}, p_{1}\right) b\left(c_{2}-c_{12}, N-c_{1}, p_{2}\right)} \\
& =\log L\left(c_{12}, c_{1}, p\right)+\log L\left(c_{2}-c_{12}, N-c_{1}, p\right) \\
& -\log L\left(c_{12}, c_{1}, p_{1}\right)-\log L\left(c_{2}-c_{12}, N-c_{1}, p_{2}\right)
\end{aligned}
$$

Where $L(k, n, x)=x^{k}(1-x)^{n-k}$

## Approaches to finding collocations (cont)

## Likelihood ratios (cont)

| -2 $\log \lambda$ | $C\left(w^{1}\right)$ | $C\left(w^{2}\right)$ | $C\left(w^{1} w^{2}\right)$ | $w^{1}$ | $w^{2}$ |
| ---: | ---: | ---: | ---: | :--- | :--- |
| 1291.42 | 12593 | 932 | 150 | most | powerful |
| 99.31 | 379 | 932 | 10 | politically | powerful |
| 82.96 | 932 | 934 | 10 | powerful | computers |
| 80.39 | 932 | 3424 | 13 | powerful | force |
| 57.27 | 932 | 291 | 6 | powerful | symbol |
| 51.66 | 932 | 40 | 4 | powerful | lobbies |
| 51.52 | 171 | 932 | 5 | economically | powerful |
| 51.05 | 932 | 43 | 4 | powerful | magnet |
| 50.83 | 4458 | 932 | 10 | less | powerful |
| 50.75 | 6252 | 932 | 11 | very | powerful |
| 49.36 | 932 | 2064 | 8 | powerful | position |
| 48.78 | 932 | 591 | 6 | powerful | machines |
| 47.42 | 932 | 2339 | 8 | powerful | computer |
| 43.23 | 932 | 16 | 3 | powerful | magnets |
| 43.10 | 932 | 396 | 5 | powerful | chip |
| 40.45 | 932 | 3694 | 8 | powerful | men |
| 36.36 | 932 | 47 | 3 | powerful | 486 |
| 36.15 | 932 | 268 | 4 | powerful | neighbor |
| 35.24 | 932 | 5245 | 8 | powerful | political |
| 34.15 | 932 | 3 | 2 | powerful | cudgels |

$\mathrm{H}_{1}$ is $e^{0.5 \times 82.96} \approx 1.3 \times 10^{18}$ times more likely than $\mathrm{H}_{2}$

Easier to interpret

Table 5.12 Bigrams of powerful with the highest scores according to Dunning's likelihood ratio test.

## Approaches to finding collocations (cont)

Likelihood ratios (cont)
■ $-2 \log \lambda$ is asymptotically $\chi^{2}$ distributed (Mood et al. 1974:440)

- The approximation is usually good, even for small sample sizes.


## Approaches to finding collocations (cont)

## Pointwise Mutual Information

Uses a measure from information-theory

- Pointwise mutual information between 2 events x and y (in our case the occurrence of 2 words) is roughly:
- a measure of how much one event (word) tells us about the other
- or a measure of the independence of 2 events (or 2 words)
- If 2 events $x$ and $y$ are independent, then $I(x, y)=0$

$$
I(x, y)=\log _{2} \frac{p(x, y)}{p(x) p(y)}
$$

## Approaches to finding collocations (cont)

## Pointwise Mutual Information (cont)

- Assume:
- c(Ayatollah $)=42$
- $c($ Ruhollah $)=20$
- $c($ Ayatollah, Ruhollah $)=20$
- N = 143076668
- Then:

$$
\begin{aligned}
& I(x, y)=\log _{2} \frac{p(x, y)}{p(x) p(y)} \\
& I(\text { Ayatollah, Ruhollah })=\log _{2}\left(\frac{\frac{20}{14307668}}{\frac{42}{14307668} \times \frac{20}{14307668}}\right) \approx 18.38
\end{aligned}
$$

- So? The occurrence of "Ayatollah" at position i increases by 18.38bits if "Ruhollah" occurs at position i+1
- works particularly badly with sparse data(favors low frequency events).


## Approaches to finding collocations (cont)

## Pointwise Mutual Information (cont)

- With pointwise mutual information:

| $\mathrm{I}\left(w_{1}, w_{2}\right)$ | $C\left(w_{1}\right)$ | $C\left(w_{2}\right)$ | $C\left(w_{1} w_{2}\right)$ | $w_{1}$ |
| ---: | ---: | ---: | :--- | :--- |
| 18.38 | 42 | 20 | 20 | Ayatollah |
| 17.98 | 41 | 27 | 20 | Bette |

- With t-test (see p. 37 of slides)

| $\dagger$ | $C\left(w_{1}\right)$ | $C\left(w_{2}\right)$ | $C\left(w_{1} w_{2}\right)$ | $w_{1}$ |
| :---: | ---: | ---: | :---: | :--- |
| $w_{2}$ |  |  |  |  |
| 4.4721 | 42 | 20 | 20 Ayatollah | Ruhollah |
| 4.4721 | 41 | 27 | 20 | Bette |

- Same ranking as t-test


## Approaches to finding collocations (cont)

## Pointwise Mutual Information (cont)

- good measure of independence
- values close to 0 --> independence
- bad measure of dependence
- because score depends on frequency
- all things being equal, bigrams of low frequency words will receive a higher score than bigrams of high frequency words
- so sometimes we take $C\left(w_{1} w_{2}\right) I\left(w_{1}, w_{2}\right)$


## Approaches to finding collocations (cont)

## Pointwise Mutual Information (cont)

| $t_{1000}$ | $w^{1}$ | $w^{2}$ | $w^{1} w^{2}$ | Bigram | Izseno | $w^{\prime}$ | $w^{2}$ | $w^{\text {J }} w^{2}$ | Bigram |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 16.95 | 5 | 1 | 1 | Schwarlz eschews | 14.46 | 106 | 6 | 1 | Schwart\% eschews |
| 15.02 | 1 | 19 | 1 | fewest visits | 13.06 | 76 | 22 | 1 | FIND GARIDEN |
| 13.78 | 5 | 9 | 1 | FIND GARDEN | 11.25 | 22 | 267 | 1 | fewest visits |
| 12.00 | 5 | 31 | 1 | Indonesian pieces | 8.97 | 43 | 663 | 1 | Indonesian pieces |
| 9.82 | 26 | 27 | 1 | Reds survived | 8.04 | 170 | 1917 | 6 | marijuana growing |
| 9.21 | 13 | 82 | 1 | marijuana growing | 5.73 | 15828 | $5]$ | 3 | new converts |
| 7.37 | 24 | 159 | 1 | doubl whether | 5.26 | 680 | 3846 | 7 | doubt whether |
| 6.68 | 687 | 9 | 1 | new converts | 4.76 | 739 | 713 | 1 | Reds survived |
| 6.00 | 661 | 15 | 1 | like offensive | 1.95 | 3549 | 6276 | 6 | must think |
| 3.81 | 159 | 283 | 1 | must think | 0.41 | 14093 | 762 | 1 | like offensive |

These examples illustrate that a large proportion of bigrams are not well characterized and that mutual information is particularly sensitive to estimates that are inaccurate due to sparseness.

## Approaches to finding collocations (cont)

Synonymy in collocation extraction

- Different between baggage and luggage?
- A new definition of collocation : a pair of words is considered a collocation if one of words significantly prefer a particular lexical realization of the concept the other the represents.


## Approaches to finding collocations (cont)

## Synonymy in collocation extraction (cont)

- Formalization :
- A sequence of pairs of words, $p^{1} \cdots p^{N}$
- The occurrence count of a particular pair of words $\left\langle w_{a}, w_{b}\right\rangle$ is defined by $c\left(w_{a}, w_{b}\right)=\sum_{i=1}^{N} \delta\left(p^{i}=\left\langle w_{a}, w_{b}\right\rangle\right)$
- Where $\delta(x)$ is 1 if X is true and 0 if X is false
- WordNet is defined as a set of synsets, W, where

$$
W=\left\{S_{1}, S_{2}, \cdots\right\}
$$

- WordNet : http://wordnet.princeton.edu/


## Approaches to finding collocations (cont)

## Synonymy in collocation extraction (cont)

- Formalization (cont)
- Each synset consists of a set of words which realize the same concept
- The co-occurrence set ,cs ${ }_{w}$ of a word, $w$ is defined as : $c s_{w}=\left\{w_{v}: c\left(w, w_{v}\right)>0\right\}$
- Synsets are filtered with respect to $w$ to obtain its Candidate Collocation SynSets $C C S_{w}$, is defined as : $C C S_{w}=\left\{S \in W:\left|S \cap c s_{w}\right|>1\right\}$
- Thus, each CSS consists of at least two elements whose co-occurrence count with $w$ is non-zero.


## Approaches to finding collocations (cont)

## Synonymy in collocation extraction (cont)

- Formalization (cont)

$$
\begin{aligned}
w^{\prime} & =\underset{w \in S}{\arg \max } c\left(w, w_{v}\right) \\
f^{\prime} & =\max _{w \in S} c\left(w, w_{v}\right) \\
f^{\prime \prime} & =\max _{w \in S^{\prime}} c\left(w, w_{v}\right) \text { where } S^{\prime}=S-w^{\prime} \\
S & =\frac{f^{\prime}-f^{\prime \prime}}{f^{\prime}} \begin{array}{l}
\text { A value of } s \approx 1 \text { indicates high collocation strength } \\
\text { and } s \approx 0 \text { Indicates low }
\end{array}
\end{aligned}
$$

## Approaches to finding collocations (cont)

Synonymy in collocation extraction : conclusion
$\square$ A assumption that any given synset has one and only one element that forms a collocation with a particular target word.

- Using the Non-Substitutability criterion of collocation.

