Text Analytics

Collocations and Terminologies

Ulf Leser
Content of this Lecture

- Collocations
- Statistical methods for finding collocations
- Case study

Most material from
- [MS99], Chapter 5: “Collocations”
- Schwegge & Broß, FU Berlin, WS 2007/2008
Co-occurrence

• Two terms co-occur if they appear together in a sentence
  – Also possible: Same paragraph, not more than X words apart, …

• Simple method for finding relationships between terms
  – If two terms (genes, people, companies etc.) appear in the same sentence, they very like have a relationship two each other
  – The relationship very likely is the verb of the sentence
  – The more often we find a specific co-occurrence in a corpus, the stronger the evidence that there is a relationship
  – Almost 100% recall (why not 100%?)
  – Precision depends a lot on the task, anything from 10% to 95%
  – Often used as baseline for relationship extraction
Frequent Co-Occurrences

- Some words go together often, some not
  - Best practice, stiff breeze, Big Blue, Big Apple, …
  - Strong breeze? Stiff wind? Big green? Big strawberry?
  - Dark night – white night (OK - Dostojewksi) – yellow night?

- How do we know? Google phrase search
  - “big apple”: 4M hits, “big strawberry”: 120K hits
  - “stiff breeze”: 450K, “stiff wind”: 220K
    - But: “wind”: 1000M; “breeze”: 200M; “stiff”: 145M
    - We would expect many more “stiff wind” than “stiff breeze”
  - “Dark/white/yellow night”: 3.2M / 1.2M / 259K
German Examples

- Starker Tobak – schwacher Tobak?
- Sinn machen – Sinn haben – Sinn ergeben?
- Take a decision – make a decision?
- Red wine, white wine, blue wine?
- Es regnet in Strömen – es regnet in Bächen - es regnet in Flüssen?
- Mittleres Management – vorderes Management?
- Bundesrepublik Deutschland, New York, …
- In der Regel, im allgemeinen, unter anderem, …
Collocations

• “Frequent” co-occurrences are called collocations
• Some definitions from language research
  – A collocation is an expression consisting of two or more words that correspond to some conventional way of saying things [MS99]
  – Collocations of a word are statements of the habitual or customary places of that word [Firth, 1957]
• Towards an operational definition
  – A collocation is a frequently occurring co-occurrence
  – But: “in the”, “to the”, “I am “ … are not collocations
  – A collocation is a co-occurrence that appears significantly more often than expected by chance
Types of Collocations

- Collocations include
  - *Proper names* (New York)
  - *Fixed verb – noun constructions* (take a decision)
  - *Terminological expressions* (data model, text mining)
  - *Associative collocations* (Hospital doctor, university member)

- Legal text is full of *formalized collocations* with mystic meaning
  - “Abschlussarbeiten werden in der Regel von zwei Prüfern begutachtet.” (?)
Characterization

- Collocations …
  - … are accepted combinations of terms
    - “schwacher Tobak” is a semantically correct statement that everybody understands, but it is never used
  - … have a special meaning or co-notation, close to a “Sprichwort”
    - “Ganzer Kerl”
    - “Eine Leiche im Keller haben” – “To have a skeleton in the closet”
    - “To be hands in gloves with somebody” - ?
  - … “represent” a single, fused concept in our mind
  - … are very important for speaking a language properly
    - Very difficult to by acquired by non-native speakers
    - Very important for proper translations
  - … are a constantly changing characteristics of a spoken language
Example

- What is more common – since when?
  - Hat keinen Sinn
  - Ergibt keinen Sinn
  - Macht keinen Sinn
Example

Source: Google's n-gram viewer, many books from 1900-2008: http://ngrams.googlelabs.com/
• Strong co-occurrences of “strong” and of “powerful”

• Lists are disjoint

• Hint to subtle semantic differences

• Listing accepted collocations is one of the best “explanations” for such differences
  – Distributional semantics

### Term Co-occurrence Table

<table>
<thead>
<tr>
<th>TERM1</th>
<th>TERM2</th>
<th>Freq</th>
</tr>
</thead>
<tbody>
<tr>
<td>strong</td>
<td>US</td>
<td>46123</td>
</tr>
<tr>
<td>strong</td>
<td>I</td>
<td>39807</td>
</tr>
<tr>
<td>strong</td>
<td>Christian</td>
<td>28577</td>
</tr>
<tr>
<td>strong</td>
<td>European</td>
<td>18188</td>
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<tr>
<td>strong</td>
<td>And</td>
<td>15555</td>
</tr>
<tr>
<td>strong</td>
<td>Q4</td>
<td>13300</td>
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<tr>
<td>strong</td>
<td>R</td>
<td>12955</td>
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<tr>
<td>strong</td>
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<td>12283</td>
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<td>12021</td>
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<tr>
<td>strong</td>
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<td>10991</td>
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</table>

| powerful | Speaker  | 48618|
| powerful | Web      | 36161|
| powerful | DVD      | 30215|
| powerful | Windows  | 23368|
| powerful | HRMS     | 21987|
| powerful | Business | 20400|
| powerful | Internet | 20321|
| powerful | PC       | 20233|
| powerful | God      | 19555|
| powerful | FTP      | 19513|
Content of this Lecture

• Collocations

• Statistical methods for finding collocations
  - Bi-Gram frequencies
  - Word distance
  - Hypothesis testing

• Case study
Statistical Approach I: Counting Frequencies

- Obviously, we should find “white wine” much more often in a corpus than “black wine”
- First approach: Count bi-grams
- Google LDC corpus
  - Tokens: 1,024,908,267,229
  - Sentences: 95,119,665,584
  - Unigrams: 13,588,391
  - Bigrams: 314,843,401
- Words “just” appearing together frequently are not interesting
- Beware: Collocations need not be continuous

<table>
<thead>
<tr>
<th>w1</th>
<th>w2</th>
<th>cnt(w1,w2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contact</td>
<td>Us</td>
<td>198887927</td>
</tr>
<tr>
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<td>States</td>
<td>173331792</td>
</tr>
<tr>
<td>Privacy</td>
<td>Policy</td>
<td>161052207</td>
</tr>
<tr>
<td>New</td>
<td>York</td>
<td>153457830</td>
</tr>
<tr>
<td>Site</td>
<td>Map</td>
<td>111486987</td>
</tr>
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<tr>
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<td>Site</td>
<td>32482311</td>
</tr>
<tr>
<td>OF</td>
<td>THE</td>
<td>32013260</td>
</tr>
<tr>
<td>In</td>
<td>Stock</td>
<td>30534425</td>
</tr>
</tbody>
</table>
Three Tricks for Getting Rid of Boring Bi-grams

• Look at **Part-of-Speech tags**
  - In collocations, the combinations of POS tags are fairly restricted
• Look at **distribution of distances**
  - Collocations have preferred distances in sentences
• Consider **frequency of constituent words**
  - “of the” not surprising, because both words are very frequent
  - “Privacy policy” is exciting, because both words are rather rare
  - We need to quantify “surprising’ness” – see later
Using POS Tags

- Allow as collocations only a small set of POS-tag pairs [Justeson, Katz, 1995]
  - ADJ NN (linear function)
  - NN NN (Regression coefficient)
  - ADJ ADJ NN (gaussian random variable)
  - NN ADJ NN (mean squared error)
  - ...

- Result: The combination of (bi-gram) frequency and POS filtering works quite well
Problems with Bi-Grams

- Bi-Gram counting is restricted to *consecutive collocations*
- What about more distant collocations?
  - You knock on a door; you don’t beat a door or hit it
  - Thus, “knock” and “door” are a collocation
  - But they never appear directly after each other
  - “Knock the door, please”
  - “She knocked on his door”
  - “They knocked at the door”
  - “She knocked on Peters door”
  - “She knocked on the black, large and metal door”
Relaxed-Bi-Gram Definition

• Option 1: Relax bi-gram definition
  – Slide a window of size $t$ over the text
  – Within $t$, count all pairs of words (in whatever distance and order)
  – Example ($t=4$)
    • (she knocked), (she on), (she his), (knocked on), (knocked his), (knocked door), (on his), (his door), …
    • Counts: (knock door 3), (she on 3), (on door 2), …
    • But we will not find (hit door)
  – A bit arbitrary; which $t$ should we chose?

• Option 2: Analyze distances between words
  – Often, words in a collocation have a somewhat constant distance
  – Characteristic distance depends on the specific collocation
Word Distances

• Idea: Count for a given pair of words
  - All distances where both appear in the same sentence
  - Compute mean and variance

• What do we expect?
  - Collocations should have a small mean and a small variance
  - Small mean: Collocations usually are local (<5 words)
  - Small variance: Expression must be fairly stable (by definition)

• Example
  - “She knocked on his door”, “They knocked at the door”, “She knocked on Peters door”, “She knocked on the black, large and metal door”
  - $\emptyset(knock, door) = 16/4 = 4$; $\text{var}(knock, door) \sim 1.9$
  - A counter-example: s4 is “too strange” (and certainly very rare)
Frequency Histograms

Clear collocation

Collocation

No collocation

Source: [MS99]
Variance and Mean

Mean $s$ and variance $d$

<table>
<thead>
<tr>
<th>$s$</th>
<th>$\bar{d}$</th>
<th>Count</th>
<th>Word 1</th>
<th>Word 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.43</td>
<td>0.97</td>
<td>11657</td>
<td>New</td>
<td>York</td>
</tr>
<tr>
<td>0.48</td>
<td>1.83</td>
<td>24</td>
<td>previous</td>
<td>games</td>
</tr>
<tr>
<td>0.15</td>
<td>2.98</td>
<td>46</td>
<td>minus</td>
<td>points</td>
</tr>
<tr>
<td>0.49</td>
<td>3.87</td>
<td>131</td>
<td>hundreds</td>
<td>dollars</td>
</tr>
<tr>
<td>4.03</td>
<td>0.44</td>
<td>36</td>
<td>editorial</td>
<td>Atlanta</td>
</tr>
<tr>
<td>4.03</td>
<td>0.00</td>
<td>78</td>
<td>ring</td>
<td>New</td>
</tr>
<tr>
<td>3.96</td>
<td>0.19</td>
<td>119</td>
<td>point</td>
<td>hundredth</td>
</tr>
<tr>
<td>3.96</td>
<td>0.29</td>
<td>106</td>
<td>subscribers</td>
<td>by</td>
</tr>
<tr>
<td>1.07</td>
<td>1.45</td>
<td>80</td>
<td>strong</td>
<td>support</td>
</tr>
<tr>
<td>1.13</td>
<td>2.57</td>
<td>7</td>
<td>powerful</td>
<td>organizations</td>
</tr>
<tr>
<td>1.01</td>
<td>2.00</td>
<td>112</td>
<td>Richard</td>
<td>Nixon</td>
</tr>
<tr>
<td>1.05</td>
<td>0.00</td>
<td>10</td>
<td>Garrison</td>
<td>said</td>
</tr>
</tbody>
</table>

Table 5.5  Finding collocations based on mean and variance. Sample deviation $s$ and sample mean $\bar{d}$ of the distances between 12 word pairs.

- Small mean, small variance: Collocation
- Small mean, large variance: No collocation
- Large mean, even with small variance: No collocation
- Small mean, medium variance: In between
Comparison

- Counting bi-grams only works for bi-grams
  - Combined with POS-pair filtering, results are acceptable

- Using sliding window or mean/variance vastly increases search space, but also improves accuracy
  - Sliding window: Many more pairs of words
  - Word distance: We either need to know what we are looking for, or we need to test all word pairs in each sentence

- Many variations
  - Count bi-grams with gaps
  - Let gap length vary slightly
Content of this Lecture

- Collocations
- Statistical methods for finding collocations
  - Bi-Gram frequencies
  - Word distance
  - Hypothesis testing
- Case study
Surprising Collocations

• Recall the problem of boring bi-grams
• The core of the problem
  – Pairs of frequent words are frequent by chance
  – Finding pairs of frequent words frequently is not surprising
• How can we measure the “surprising’ness” of a bi-gram?
  – Given the frequencies of the words and the size of a corpus?
  – If the corpus is “large enough”, everything gets frequent
• Solution: Statistical test

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Statistical Tests

• We want to test if a certain value is probable or not
• Statistical test
  - Null hypothesis $H_0$: $w_1$, $w_2$ do not form a collocation
  - Thus, they are independent: We expect $c=p(w_1)\times p(w_2)$
  - Compute probability $p$ of the observed count assuming $H_0$
  - Refute $H_0$, if $p$ is too small, e.g. $p \leq 0.05$
    • In such a setting, $1-p$ is usually called a confidence level
• Example
  - We assume $H_0$: mean height in a given population is $d=158$
  - In a sample $N=100$, we observe $d'=160$, variance $s'=2.6$
  - Given this sample, how likely is it that $H_0$ is true?
  - We may use the fact that height is normally distributed
Frequently Used: t-Test

• Statistical test for samples of a normal distribution
  - d: distribution mean
  - d’: sample mean, s’: sample variance
  - N: sample size
  - We assume that sample variance s’ = distribution variance s

• We compute the t-value, a measure for the deviation in the mean (d’-d) given the variance s

\[ t = \sqrt{N} \frac{d' - d}{\sqrt{s}} \]

  - Large s: Differences are less significant
  - Large N: Differences become more and more significant
Experiment: Assessing the Meaning of a T-Value

- Assume any normally distributed set $X$ of values
- Compute mean $\mu$ and variance $\sigma$
- Now do the following very often
  - Sample $N$ values at random from $X$
  - Compute sample mean $\mu'$ and sample variance $\sigma'$
  - Compute t-value
- Gives a distribution of t-values
  The t-distribution
  - Similar, but not identical to normal distribution

Source: http://davidmlane.com/hyperstat/A48339.html
Application

- Note: The T-distribution is independent of the concrete underlying distribution, but only dependent on N
- Now we can assess the probability of a given t-value by looking at a pre-computed distribution of t-Values – Dependent on N (called degree-of-freedom)
- Table gives the probability that the absolute of a given t-Value is created by chance (given N)

Confidence Levels

• **p-Value** of a given t-value t: Probability of a value from the corresponding t-distribution being absolutely larger than abs(t)

• Together
  - Compute t-value, lookup p-value, the probability of $H_0$ being wrong
  - **Refute $H_0$ is p too large** (compared to your favorite threshold)

• **Note**: This is a two-sides, one-sample student t-test
Example

- H₀: mean height of some population is 158
- In a sample of N=100, we observe d′= 160, s=s′=2.6
- We get a value of t ~ 12.42 > 3.17
- 3.17 corresponds to a significance level of p=0.002
- Thus, H₀ can be rejected with >99.8% confidence

\[ t = \sqrt{N} \frac{d' - d}{\sqrt{s}} \]
Some Preparatory Work

- $H_0$: We find as many pairs $(w_1 \ w_2)$ as we expect assuming independence: $p(w_1) \cdot p(w_2) = p$

- Consider the experiment of drawing very often $N$ bi-grams randomly, where $(w_1 \ w_2)$ appears with a probability of $p$, and each appearance of $(w_1 \ w_2)$ is counted as 1, all others are counted 0.

- Which distribution of counts do we expect?
  - This is a Bernoulli trial
  - The mean of this distribution is $p \cdot N$
  - The variance is $s=p \cdot (1-p) \sim p$ (since $p$ will be very, very small)
Application

- We apply the t-test to collocations
- Set $N = |K|^2$
  - We “draw” as often as there are term pairs
- Set $d = \rho$, the expected relative frequency (given $H_0$)
- Set $s = \rho(1-\rho) \sim \rho$
- Set $d' = \text{count}(w_1, w_2)/N$
- Set $s' = s$
  - Again, assuming equal variance in sample and distribution
- Compute t-Value, set your threshold, refute/accept $H_0$
One more Detail

- **Two-sided t-test**: Probability that the absolute of a given t-Value is created by chance (given N)
- **Single-sided t-test**: Probability that any t-value larger than the given t-Value is created by chance (given N)
- We need to apply the single sided test: We are not looking for “negative collocations” ~ words co-occurring must less often than expected by chance
- **Computation**: Simply divide p-value by 2
Example

- Consider the term “new company”
  - Assume it appears 8 times in a corpus of \( N = 14,307,668 \) bi-grams
  - Assume \( \text{count(new)} = 12,828 \), \( \text{count(company)} = 4,675 \)
- Under \( H_0 \): \( d = \frac{\text{count(new)} \times \text{count(company)}}{N^2} \approx 3.65 \times 10^{-7} \)
- The observed count is \( d' = \frac{8}{N} \approx 5.59 \times 10^{-7} \)
- t-test
  \[
  t = \frac{d' - d}{\sqrt{s/N}} = \frac{5.59 \times 10^{-7} - 3.65 \times 10^{-7}}{\sqrt{5.59 \times 10^{-7} / 1.43 \times 10^{-7}}} \approx 0.999
  \]
- p-value around 0.15
- \( H_0 \) should rather not be refuted
- “new company” is no collocation but probably occurs that often by chance
Discussion

- [MS99]: Out of 831 bi-grams which occurred >20 times, $H_0$ is rejected for 824 (p=.005)
- 824 pairs (almost all) can be considered as collocations
- Many pairs of words are surprisingly (and significantly) frequent
- This is a property of language, because only very few pairs actually occur (and those rather often)
- Independence assumption is no good candidate for $H_0$
  - This assumption will be refuted too often
- t-test still very useful for ranking potential collocations
Multiple Testing

- Given threshold $k=0.05$; are all word pairs in a corpus of 100M different bigrams with p-value smaller $k$ collocations?
  - Every single test as an error probability of up to 0.05
  - We performed 100M such tests
  - Thus, approximately $100M \times t = 5M$ of the tests went wrong
  - Many collocations are false positives, i.e., stem from bigram frequencies that occurred by chance only

- We need multiple testing correction
  - Whenever many tests are performed, results of statistical tests must be corrected
  - The more urgent, the more liberal the threshold is chosen
  - Simplest method: Divide threshold by $N$
Testing Collocations Empirically

• How can we **empirically test** whether a word pair should be considered as a collocation?

• **Stimulus-Response Test**
  - Give a set of persons one of the words
  - Let them, very quickly, write down words that come into their mind first when they hear the first word

• Good methods for collocations perform surprisingly well
  - Ranking by t-value yields similar top-K collocations as stimulus-response tests

• But: One is usually interested in **finding new (rare) collocations**, i.e., those that do not come to mind first
  - To learn about language use, language evolution, etc.
Co-Occurrence Graphs

• Co-occurrences can be visualized nicely
  – Layout: Bring (Euclidian) distances close to semantic distances

• Clusters in the graph usually form semantically close topics

• Applications
  – Learn about a domain
  – Disambiguation of senses
  – Detection of synonyms

• Properties
  – Small world
  – Distribution of the degrees of the nodes is Zipf

• Also true for “human” assoc-graphs

Source: Luis Rocha, U Indiana
Content of this Lecture

- Definition of collocations
- Statistical methods for finding collocations
- **Case study:** Learning a Terminology and an Ontology
  - Defining a Phenotype Terminology
  - Learning a Phenotype Ontology
From Phenotype to Function
(Groth et al. 2008, Böhm et al. 2009, Groth et al. 2010a, Groth et al. 2010b)
Phenotypes

- **Observable characteristic** of an organism
  - Description of a disease
  - Response to a drug
  - …
- A “phenotype” usually is a **derivation from the norm**
- Small-scale experiments to measure phenotypes since long
- **Systematic experimental approaches** only for some years
  - Systematic perturbation of genotypes or the environment => effect on phenotype
  - Natural mutations, **breeding**, **knock-out**, **RNAi**
Describing Phenotypes

- Many data sources
- Different species, different experiments, different vocabulary, different format, different …
- Technical integration is a challenge
- Semantic integration is much more of a challenge
- Least common denominator: Text
Motivation

• Building ontologies manually is costly
• **Ontology bootstrapping**  
  Automatically building a first draft of an ontology by analyzing a domain-specific corpus

• Four steps
  - Concept discovery  - concepts of the ontology
  - Concept matching - occurrences of concepts
  - Relationship extraction - relationships between concepts
  - Ontology extraction - a “good” subset of all relationships
Z-100 is an arabinomannan extracted from Mycobacterium tuberculosis that has various immunomodulatory activities, such as the induction of interleukin 12, interferon gamma (IFN-gamma) and beta-chemokines. The effects of Z-100 on human immunodeficiency virus type 1 (HIV-1) replication in human monocyte-derived macrophages (MDMs) are investigated in this paper. In MDMs, Z-100 markedly suppressed the replication of not only macrophage-tropic (M-tropic) HIV-1 strain (HIV-1JR-CSF), but also HIV-1 pseudotypes that possessed amphotropic Moloney murine leukemia virus or vesicular stomatitis virus G envelopes. Z-100 was found to inhibit HIV-1 expression, even when added 24 h after infection. In addition, it substantially inhibited the expression of the pNL43lucDeltaenv vector (in which the env gene is defective and the nef gene is replaced with the firefly luciferase gene) when this vector was transfected directly into MDMs. These findings suggest that Z-100 inhibits virus replication, mainly at HIV-1 transcription. However, Z-100 also downregulated expression of the cell surface receptors CD4 and CCR5 in MDMs, suggesting some inhibitory effect on HIV-1 entry. Further experiments revealed that Z-100 induced IFN-beta production in these cells, resulting in induction of the 16-kDa CCAAT/enhancer binding protein (C/EBP) beta transcription factor that represses HIV-1 long terminal repeat transcription. These effects were alleviated by SB 203580, a specific inhibitor of p38 mitogen-activated protein kinases (MAPK), indicating that the p38 MAPK signalling pathway was involved in Z-100-induced repression of HIV-1 replication in MDMs. These findings suggest that Z-100 might be a useful immunomodulator for control of HIV-1 infection.
1. Define Set of Terms

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2. Find all Occurrences of those Terms

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3. Find Relationships between Terms

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4. Extract a Nice and Consistent Ontology

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Step 1: What is a „Phenotypic“ Term?

- Build a “phenotype” corpus and a “normal” corpus
- Look at each term occurring in both corpora
- Compute TF*IDF values of each term in each doc
- Compare the distributions of TF*IDF values across documents of each term in both corpora (A, B)
Comparing Distributions

• When are two distributions significantly different?
  – No t-test: We look at the entire distributions, not just the means

• Alternative: Two sample Wilcoxon Rank Sum Test
  – Non-parametric test – does not assume any value distributions
  – Decides with which probability two distributions are equal
  – To this end, it sorts all values (of both distributions) and computes the sum of the ranks of each corpus
  – If both samples are from the same distribution, these sums follow a pre-computable distribution
  – We can lookup the probability of the computed sum to be generated from this distribution
  – This defines a p-value for $H_0: A=B$
Multi-Token Terms

- The previous method only works for single-token terms
- Finding **multi-token (composed) concepts** (here for n=2)
  - Count frequencies of both terms
  - Count frequency of combined concept
  - (Very debatable) filter: Only consider composed terms consisting only of phenotypic terms
  - Test for **statistical independence**
  - Test **defines a ranking** of composed terms
  - We used the first 3,000 composed terms
Phenotypic Concepts

- “significant defects”
- “spindel elongation”
- “mutant phenotype growth”
- But: Occurrences in text
  - „We observed a significant genomic defect in …“
  - „Elongation of the spindel correlated with …“
  - „Mutant growth was normal compared to …“
- Interspersed token, missing token, re-order, spelling variations, …
- Avg. concept length in MPO is 3.5, ~5% single token
3. Relationship Extraction

- **Goal:** Infer that
  - cancer ISA disease
  - early abort ISA abort

- **Various proposals in the literature**
  - Subsumption, Hearst-Pattern, ...

- **Subsumption**
  - For every pair of concepts $c_1$, $c_2$, compute $p(c_1|c_2)$
    - How often do we see an occurrence of $c_1$ in the neighborhood of an occurrence of $c_2$?
  - $p(c_1|c_2) > t \Rightarrow c_2$ is a specialization of $c_1$
Example

A number sign (#) is used with this entry because it represents a contiguous gene deletion syndrome. See 274000 for another contiguous gene deletion syndrome, thrombocytopenia-absent radius (TAR) syndrome, that maps to a nonoverlapping region of chromosome 1q21.1.

Gene deletion syndromes also play an important role ...
Gene deletion syndromes also play an important role in various genetic diseases, including thrombocytopenia.
Application to 300K Texts and 12K Concepts

- No tree-like backbone structure
- **Cyclic relationships**: A ISA B ISA A
- Semantically suspicious, redundant, “not nice” parts
  - Parents that are brothers
  - Chains of single-child specializations
  - Parents with hundreds of children
  - …
- Incomprehensible
4. Ontology Extraction Problem

- Given a directed, weighted Concept Graph $G=(V,E)$
  - Edge weights: strength of evidence
- Find a subgraph (Ontology Graph) $G'$ that is
  - Consistent (= cycle-free)
  - Maximal confidence (= maximal total edge weight)
  - Nice (= adheres to some topological properties)
Evaluation Compared to MPO

- Mammalian Phenotype Ontology
  - 11700 concepts, 6828 relations, 172134 transitive relations

- Greedy Edge Inclusion (GEI)
  - 4,400 True Positives
  - Precision 0.45

- Hierarchical Greedy Expansion (HGE)
  - 1,200 True Positives
  - Precision 0.51

- Weighted Dominating Set Approach (wDSP)
  - 1,900 True Positives
  - Precision 0.54