Information Retrieval

Collocations

Ulf Leser
Content of this Lecture

- **Collocations**
- Statistical methods for finding collocations
- Case study

- Most material from
  - [MS99], Chapter 5: “Collocations”
  - Schweppe & 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 likely have a relationship to each other
  - The type of 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
Special Co-Occurrences

- In human languages, some words go together very well
  - 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
Examples

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

• **Collocations:** Co-occurrences with its own meaning

• **Characteristics:** 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” – “unter einer Decke stecken”
  - … represent a single, fused concept in our mind
  - … are very important for speaking a language properly
    - And difficult to be acquired by non-native speakers
  - … 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/
NLP

• Definitions from NLP 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]
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.” (?)
Application: Understanding Semantic Differences

- Frequent 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
  - Current trend: Word embeddings

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<th>TERM2</th>
<th>Freq</th>
</tr>
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<tbody>
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| 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
- Just appearing together frequently is not a reliable indication for a colocation
  - Beware: Collocations need not be continuous

<table>
<thead>
<tr>
<th>w1</th>
<th>w2</th>
<th>cnt(w1,w2)</th>
</tr>
</thead>
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<tr>
<td>It</td>
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<tr>
<td>Web</td>
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<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 surprising, because both words are rather rare
  - We need to quantify “surprisingness”
POS Tagging

• Simple tag set
  - The/D koala/N put/V the/D keys/N on/P the/D table/N

• Including morphological information
  - The/D koala/N-sing put/V-past-3rd the/D keys/N-p on/P ...

• Using Penn tag set
  - The/DT koala/NN put/VBN the/DT keys/NNS on/P ...

<table>
<thead>
<tr>
<th>The</th>
<th>koala</th>
<th>put</th>
<th>the</th>
<th>keys</th>
<th>on</th>
<th>the</th>
<th>table</th>
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<tbody>
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<td>N</td>
<td>V</td>
<td>D</td>
<td>N</td>
<td>P</td>
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</tr>
<tr>
<td>D</td>
<td>N-sing</td>
<td>V-past-3rd</td>
<td>D</td>
<td>N-plu</td>
<td>P</td>
<td>D</td>
<td>N-sing</td>
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<tr>
<td>DT</td>
<td>NN</td>
<td>VBN</td>
<td>DT</td>
<td>NNS</td>
<td>P</td>
<td>DT</td>
<td>NN</td>
</tr>
</tbody>
</table>
Brown Tag Set

- Has 87 tags in total
  - Table: Most important tags
- Definition of classes is not at all fixed
  - London-Lund Corpus of Spoken English: **197 tags**
  - Lancaster-Oslo/Bergen: **135 tags**
  - U-Penn: **45 tags**

<table>
<thead>
<tr>
<th>Tag</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>DT</td>
<td>Determiner</td>
</tr>
<tr>
<td>IN</td>
<td>Preposition</td>
</tr>
<tr>
<td>JJ</td>
<td>Adjective</td>
</tr>
<tr>
<td>NN</td>
<td>Noun, singular</td>
</tr>
<tr>
<td>NNP</td>
<td>Proper Noun</td>
</tr>
<tr>
<td>NNS</td>
<td>Noun, plural</td>
</tr>
<tr>
<td>PERIOD</td>
<td>„“, „?“, „!“</td>
</tr>
<tr>
<td>PN</td>
<td>Personal pronoun</td>
</tr>
<tr>
<td>RB</td>
<td>Adverb</td>
</tr>
<tr>
<td>TO</td>
<td>„to“</td>
</tr>
<tr>
<td>VB</td>
<td>Verb, base form</td>
</tr>
<tr>
<td>VBZ</td>
<td>Verb, 3d singular present</td>
</tr>
<tr>
<td>VBD</td>
<td>Verb, past tense</td>
</tr>
<tr>
<td>WDT</td>
<td>Wh – determiner</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
</tr>
</tbody>
</table>
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 a door”
  - 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 of both 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”
  - \( \emptyset(\text{knock, door}) = 12/4 = 3; \text{var}(\text{knock, door}) = 3 \)
  - 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>$d$</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>
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<tr>
<td>0.48</td>
<td>1.83</td>
<td>24</td>
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<td>games</td>
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<td>dollars</td>
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<tr>
<td>1.13</td>
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<td>organizations</td>
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<tr>
<td>1.01</td>
<td>2.00</td>
<td>112</td>
<td>Richard</td>
<td>Nixon</td>
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<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 $d$ 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 and/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
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• 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 just by chance
  – Frequently finding pairs of frequent words is not surprising

• How can we measure the “surprisingness” of a bi-gram?
  – Given the frequencies of the words and the size of a corpus?
  – Beware: If the corpus is “large enough”, many words become somewhat frequent

• Solution: Statistical test

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Statistical Tests

• Statistical test: Assess the probability that a certain value has been generated by chance or not
• Approach: Probability of null hypothesis
  - Null hypothesis $H_0$: $w_1$, $w_2$ statistically independent: $c = p(w_1)\cdot p(w_2)$
  - Compute probability $p$ of the observed count assuming $H_0$
  - Refute $H_0$, if $p$ is too small, e.g. $p \leq 0.05$ (=5%)
  - Application: If $w_1, w_2$ are not statistically independent, assume a co-location
Example

• Before looking at co-locations, we test something simpler
• We measure the height of persons and reason about their mean value
• Example
  - 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?
  - Depends on the expected distribution of values given the mean
  - Underdetermined: Need an additional assumption
  - We know that height is not equally distributed (in range $[0;250]$)
  - Height is normally distributed
Naive Approach: Bootstrapping ("Just Try")

- **Generate** normally distributed values according to H0 very often and see how often this yields the observed mean
  - H0: Height is normal distributed with mean $d=158$
  - Underdetermined: We also need variance $s$
  - Trick: Assume that variance in sample and reality is equal

- **Operations**
  - Generate 100 values drawing from normal distr. with $d$, $s$
  - Compute **mean** $d''$ **of sample**
  - Repeat 10,000 times (or more)
  - How **often** was $d''=d'$?

- **Problem**: Very slow
- **We need a test that is independent of** $d$ **and** $s$
Frequently Used: t-Test

• Statistical test for samples of a normal distribution
  - d: distribution mean, s: distribution variance (often unknown)
  - d’: sample mean, s’: sample variance
  - N: sample size
• Without further knowledge, we use s’ as estimate for 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
Meaning of a t-Value

• Assume a normally distributed set $X$ of values
• Compute mean $d$ and variance $s$
• Now do the following very often
  – Sample $N$ values at random from $X$
  – Compute sample mean $d'$ and variance $s'$
  – Compute t-value
• Gives a distribution of t-values: The t-distribution
  – Similar, but not identical to normal distribution
  – Depends on $N$

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

- We can assess the probability of a given t-value by looking at a pre-computed distribution of t-Values
  - Dependent on N: Degree-of-freedom
- Table gives the probability that a given t-Value has emerged by chance (given N)

One Sided, two sided

- **p-Value** of t-value $t$: Probability of a value from the t-distribution being absolutely larger than $\text{abs}(t)$
- **Together**
  - Compute t-value, lookup p-value: The probability of $H_0$ being wrong
  - Refute $H_0$ if $p$ is too large (compared to your favorite threshold)
- **One sided**: Prob. of the mean being greater than expected
- **Two sided**: Prob. of the mean being away from expected
Example

• $H_0$: 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 $t \sim 12.4 > 3.17$
• For $N=100$, 3.17 corresponds to a significance level of $p=0.002$
  - Smallest $p$ for which precomputed $t$ is smaller than observed $t$
• Thus, $H_0$ can be rejected with $>99.8\%$ confidence

\[ t = \sqrt{N} \frac{d'-d}{\sqrt{s}} \]
App for Co-Locations: Preparatory Work

- $H_0$: $w_1$, $w_2$ are statistically independent
- We expect $p_{\text{ind}} = p(w_1, w_2) = p(w_1) \cdot p(w_2)$
- This count $p_{\text{ind}}$ is normally distributed
  - Consider the experiment of drawing very often $N$ bi-grams randomly, where $(w_1, w_2)$ appears with a relative frequency of $p_{\text{ind}}$, and each appearance of $(w_1, w_2)$ is counted as 1, all others are counted as 0
  - This is a Bernoulli trial, creating a normal distribution of counts
  - The mean of this distribution is $p_{\text{ind}} \cdot N$, its variance is $s = p_{\text{ind}} \cdot (1 - p_{\text{ind}})$
  - Since $p_{\text{ind}}$ will be very small, we may assume $s = p_{\text{ind}} \cdot (1 - p_{\text{ind}}) \sim p_{\text{ind}}$
Application

- We apply the t-test to collocations
- Set \( N = \) Number of bi-grams in corpus
- Set \( d = p_{\text{ind}} \), the \textbf{expected relative frequency} (given \( H_0 \))
- Set \( s = p_{\text{ind}} \)
- 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 \( H_0 \)
Example

• Consider the term “new company”
  - Assume it appears 8 times in a corpus of N=14,307,668 bi-grams
  - Assume count(new)=12,828, count(company)=4,675

• Under $H_0$: $d = \frac{\text{count(new)} \times \text{count(company)}}{N^2} \sim 2.93 \times 10^{-7}$

• The observed relative frequency is $d' = \frac{8}{N} \sim 5.59 \times 10^{-7}$

• t-value
  \[ t = \frac{d' - d}{\sqrt{s/N}} = \frac{5.59 \times 10^{-7} - 2.93 \times 10^{-7}}{\sqrt{5.59 \times 10^{-7} / 1.43 \times 10^{-7}}} \sim 1.35 \]

• p-value around 0.1
• $H_0$ should rather not be refuted
  - “new company” is not a collocation but probably occurs in this corpus that often by chance
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
Discussion

- [MS99]: Out of 831 bi-grams which occurred >20 times, H₀ is rejected for 824 (p=0.05)
- Thus, 824 pairs (~all) should 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 H₀
  - This assumption will be refuted too often
- t-test still useful for ranking potential collocations
Multiple Testing

• Given threshold $p=0.05$; 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 $100M \cdot p = 5M$ of the tests went wrong
  - Many collocations are false positives, i.e., stem from bigram frequencies that probably 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
Selbsttest

- What is a colocation? Give examples
- Name three ways to find colocations
- A t-test produces a p-value of 0.12 for a certain result of an experiment. What does this mean?
- What are assumptions of a t-test (which are not tested)
- Why is the independence assumption inherent in our application of t-tests to colocation analysis wrong?
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

**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.
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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

**Phenotype description**

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...
Example - Problem

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