Information Retrieval

WS 2015 / 2016

Lecture 13, Tuesday February 2nd, 2016
(Knowledge Bases, SPARQL, Translation to SQL)

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Overview of this lecture

- Organizational
  - Your experiences with ES12 (Statistical Significance)
- Content
  - Statistical tests again — some clarifications
  - Knowledge bases — motivation + examples
  - SPARQL — standard query language for KBs
  - SQLite — lightweight database software
  - SPARQL to SQL — algorithm + example
  - Performance — making it fast
  - **Exercise Sheet 13:** Implement SPARQL → SQL translation and use to process SPARQL queries with Python+SQLite

Experiences with ES12 1/3

- Summary / excerpts
  - Topic + exercise was interesting and useful
  - Not too much work
  - Technical details behind the T-Test were not clear

    I skipped this part for time reasons and the explanation on the slides were sup-optimal … see slides 6 – 11
  - Why two-sided test and not one-sided test

    Good question … it was discussed on the forum
  - p-value very small for the large test set … see next slide

Experiences with ES12 2/3

- Results
  - Most improvements are by a few percent, for example:

    74% → 80%, 66% → 68%, 69.8% → 73.2%, …
  - Sometimes, the changes even make the results worse

    A common research experience when trying to improve stuff
  - The p-values for 50 or 200 examples are very large

    Understand that this does **not** mean that the variant is not really better … it means that the evaluation does not prove it (the difference might as well be due to random fluctuations)
  - The p-values for 3140 ex. is small, even for small differences

    For example, $p = 0.2\%$ for a 3.4% difference

Experiences with ES12 3/3

- Bottom line
  - With few measurements (for ES12: tens or hundreds), even medium improvements are hardly significant
  - With many measurements (for ES12: thousands), even small improvements can be significant
  - Understand: statistical tests **never** show that the hypothesis (our actual interest) is likely

    For ES12: we have proven nothing about the likeliness that the sophisticated Perceptron is better than the baseline

    They only ever estimate how unlikely the null hypothesis is

    For ES12: that the difference in precision is due to chance

Statistical Tests – Clarifications 1/6

- Mathematics behind the Z-Test and T-Test
  - I decided to skip that in the last lecture

    It's mathematically more demanding than what we did so far, and there was not too much time available

    When preparing the lecture, I tried to take away as much as possible from the complexity … but not very successfully so, it's still relatively hard
  - Bottom line: you do not need to know the mathematical details behind the Z-Test and T-Test for the exam

    The rest of what we did in Lecture 12 is of course relevant for the exam though

Statistical Tests – Clarifications 2/6

- Biased vs. unbiased estimators
  - Let $X_1, \ldots, X_n$ be independent identically distributed random variables with mean μ und variance σ^2
  - Since we don't know the underlying μ and σ^2, we estimate them as follows

    $M = \sum X_i / n$ $\qquad\qquad$ $S^2 = \sum (X_i - M)^2 / n$

  - Mathematically, it seems reasonable to ask that these estimates do the right thing "on average", namely:

    $\mathbf{E}\, M = \mu$ $\qquad\qquad$ $\mathbf{E}\, S^2 = \sigma^2$

  - With the definitions above, this is indeed true for M, but for S^2 as defined above: $\mathbf{E}\, S^2 = (1 - 1/n) \cdot \sigma^2$

Statistical Tests – Clarifications 3/6

- Biased vs. unbiased estimators, continued
  - Alternatively, we can define $S^2 = \sum (X_i - M) / (n - 1)$
  - This estimate is called **unbiased** because $\mathbf{E}\, S^2 = \sigma^2$
  - In practice, the unbiased estimator is used more often

    It's not wrong to used the biased estimator though …
    in the last lecture, I chose it because of simplicity

    Also note that for large values of n, the difference between the two (a factor $1 - 1/n$) is negligible
  - For similar reasons, one often subtracts 1 from the number of measurements (per sequence) for the T-Test

    For our example from Lecture 12: $n - 2$ instead of n

Statistical Tests – Clarifications 4/6

- Mistake on slide 31 of last lecture
  - We correctly computed the estimates σ_1^2 and σ_2^2 of the variances of the two series of measurements

    We computed unbiased estimates, but that was ok
  - Then we computed the total variance as $\sigma^2 = \sigma_1^2 + \sigma_2^2$

    That was a mistake, we should have computed the total variance as the average $\sigma^2 = (\sigma_1^2 + \sigma_2^2) / 2$

    Then the value for x becomes larger (by a factor of $\sqrt{2}$) and the (two-sided) p-values becomes smaller:

    Z-Test: $\sigma^2 = 1.5 \rightarrow x = 2.3094 \rightarrow p = 2.1\%$
    T-Test: $\sigma^2 = 1.5 \rightarrow x = 2.3094 \rightarrow p = 5.0\%$

Statistical Tests – Clarifications 5/6

- Intuition of the x-value
  - Recall the values from the previous slide:

    Z-Test: $\sigma^2 = 1.5 \rightarrow x = 2.3094 \rightarrow p = 2.1\%$
    T-Test: $\sigma^2 = 1.5 \rightarrow x = 2.3094 \rightarrow p = 5.0\%$

  - Understand that x and p have the following "meaning":

    p: the probability that what we see happened by chance

    x: what we see is as (un)likely as a random variable from the assumed distribution deviates by x times or more the standard deviation from its mean

    one-sided test: deviation in one direction

    two-sided test: deviation in either direction

Statistical Tests – Clarifications 6/6

- R-Test vs. Z-Test and T-Test
  - For the example in the last lecture, the R-Test had a much larger p-value (18%) than the Z-Test or T-Test
  - Reason: the Z-Test and T-Test make assumptions on the underlying distribution

    These assumptions become more and more reasonable for large n but can be quite unrealistic for small n
  - However, the R-Test requires (extensive) computation

    In the old days, that was simply not feasible

    Nowadays, with ubiquitous access to computers, the R-Test is the method of choice

Knowledge Bases 1/4

- Definition
  - A knowledge base is a database of statements about entities and their relations

    Critical: **unique** identifiers for each entity and relation

  - A common format / schema is to express all statements as subject predicate object triples:

Brad Pitt	acted in	Mr. and Mrs. Smith
Brad Pitt	acted in	Burn After Reading
Angelina Jolie	acted in	Mr. and Mrs. Smith
Joel Cohen	directed	Burn After Reading
Ethan Cohen	directed	Burn After Reading
Brad Pitt	married to	Angelina Jolie

Knowledge Bases 2/4

- Freebase and WikiData
  - Freebase is the largest open general-purpose KB to date

    Started by Metaweb in 2007, acquired by Google in 2010

    Current size: **≈3 billion** triples on **≈50 million** entities

    Freebase has become read-only in March 2015 and most of its data will eventually be merged into WikiData
  - WikiData is the soon-to-become largest open general-purpose knowledge base to data

    WikiData is the "Wikipedia" among the knowledge bases

    Current size: **≈80 million** triples on **≈20 million** entities

Knowledge Bases 3/4

- Reification
  - Restriction to triples is no real restriction: n-ary relationships can also be represented as triples:

m/0jy6xg	film	Finding Nemo
m/0jy6xg	actor	Ellen DeGeneres
m/0jy6xg	character	Dory
m/0jy6xg	type	Voice

m/0jy6xg is an entity name from Freebase

In the example above, it's a so-called mediator, which serves as a link between the entities it connects

Knowledge Bases 4/4

- Relation to the "Semantic Web"
  - The Semantic Web initiative is concerned with making knowledge base data **explicitly** available on the web

    Variant 1: semantic mark-up in normal web pages

    Typical format: Microdata or JSON-LD

    Variant 2: web pages containing only structured data

    Typical format: RDF
  - No rules that enforce consistent entity or relation names

    The hope is that people adhere to standards nevertheless, and that machines can resolve the remaining heterogeneity

    Anyway: this is **not** the topic of this lecture / course

SPARQL 1/5

- Definition
  - The standard query language for knowledge bases

    SPARQL = **S**PARQL **P**rotocol **A**nd **R**DF **Q**uery **L**anguage
  - Example query in natural language: actors who are married and starred together in at least one movie
  - The same query expressed in SPARQL

```
SELECT ?person1 ?person2 ?film WHERE {
  ?person1  acted_in  ?film  .
  ?person2  acted_in  ?film  .
  ?person1  married_to  ?person2
}
```

SPARQL 2/5

- Syntax
  - In the lecture today, we use a simplified syntax

    See the example from the last slide
  - The actual SPARQL syntax is slightly more complicated and has many more features

    In particular, it involves namespaces, so that names can be made globally unambiguous

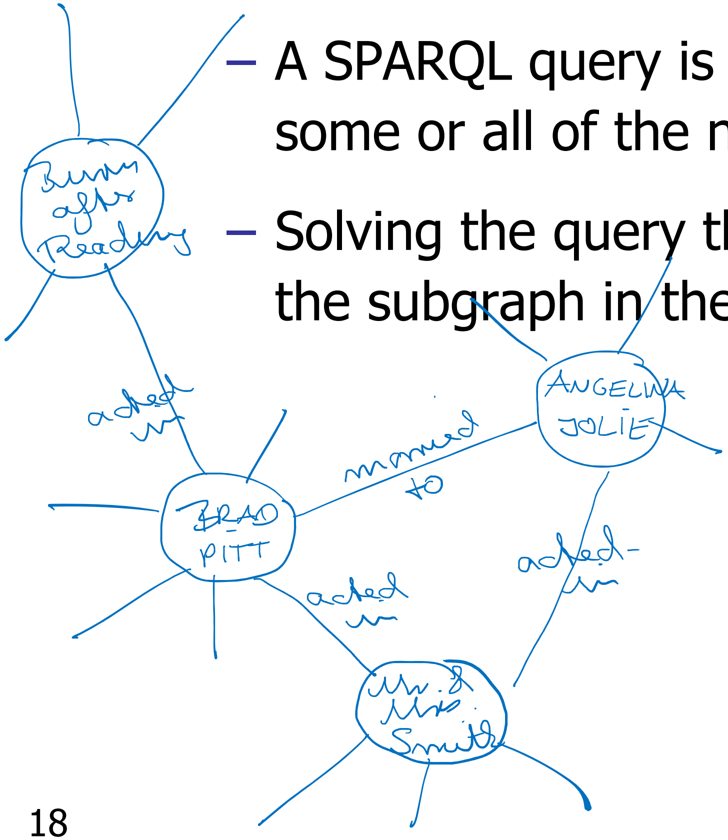
    See the Wikipedia page or the W3C specification if you are interested

    Not relevant for our lecture today

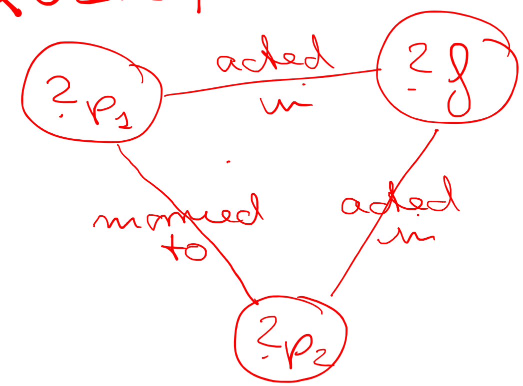
SPARQL 3/5

- SPARQL queries as subgraphs
  - On can view a knowledge base as a **graph**, where the nodes are the entities, and the edges are the relations
  - A SPARQL query is then a sub-graph with variables at some or all of the nodes
  - Solving the query then amounts to finding all matches of the subgraph in the (large) knowledge base graph

KB



QUERY



SPARQL 4/5

- Relation to SQL
  - Data from a KB can be stored in an ordinary database

    This is also what we do in the lecture and for ES13
  - The standard query language for databases is SQL

    SQL = **S**tructured **Q**uery **L**anguage

SPARQL 5/5

FILM

actor	film
Brad Pitt	Burn after...
...	...

SPOUSE

person1	person2
B. Pitt	A. Jolie
...	...

- SQL example
  - Assume we have two tables film (with columns actor and movie) and spouse (with columns person1 and person2)
  - Our example query can be expressed in SQL as follows:

```
SELECT  spouse.person1, spouse.person2
FROM    spouse, film as film1, film as film2
WHERE   spouse.person1 = film1.actor
AND     spouse.person2 = film2.actor
AND     film1.film = film2.film;
```

SQLite 1/4

- A full-fledged database, easy to install and use
  - On Debian/Ubuntu install with: sudo apt-get install sqlite3
  - Two types of commands … examples on next slides

    SQL commands: must end with a semicolon

    SQLite commands: start with a dot, no semicolon at end
  - Two modes to start SQLite:

    sqlite3 will work on an in-memory database

    sqlite3 <name>.db create database in that file, and if file exists, use database from that file

    Let's read our example tables in SQLite using the commands from the next two slides … it's easy

SQLite 2/4

- Some useful SQLite commands by example
  - Specifies the column separator used for input and output

    .separator "	" use Ctrl+V TAB for TAB !
  - Read table from TSV (tab-separated values) file

    .import film.tsv film
  - Execute commands from script file (typical suffix is .sql)

    .read <file with commands>
  - Show execution time of every command

    .timer on

SQLite 3/4

- Some useful SQL commands by example
  - Create a table with a given schema

    CREATE TABLE film(actor TEXT, movie TEXT);

  - Create an index for a column of a table

    CREATE INDEX file_index ON film(actor);

  - Extract / combine data from tables

    SELECT * FROM film WHERE … LIMIT 100;

  - Delete table / index (without error msg if it's not there)

    DROP TABLE IF EXISTS film;

    DROP INDEX IF EXISTS film_index;

SQLite 4/4

- Python interface to SQLite
  - Executing SQL commands to a SQLite database from within Python is very easy:

```
import sqlite3
db = sqlite3.connect("example.db")
cursor = db.cursor()
cursor.execute("SELECT * FROM table")
for row in cursor.fetchall():
    entries = [str(entry) for entry in row]
    print("\t".join(entries))
```

Beware: the SQLite command (starting with a dot) cannot be executed from within Python, you need SQLite for those

SPARQL to SQL Translation 1/4

- Motivation
  - We want to translate a given SPARQL query to a SQL query that gives the desired results on a given database
  - In the following example, we use one table per relation

    CREATE TABLE film(actor TEXT, film TEXT)
    CREATE TABLE spouse(person1 TEXT, person2 TEXT)

    Note: all elements from one table are from one relation, so we don't need to store the relation name in the table

    For ES13, use **one big table** for all the data, with three columns named **subject**, **predicate**, **object**

SPARQL to SQL Translation 2/4

#rows in spouse table : m
#rows in film table : n
looking at $m \cdot n^2$ combinations of rows

- Example
  - SPARQL query

```
SELECT ?p1 ?p2 ?f
WHERE {
  ?p1  film  ?f .
  ?p2  film  ?f .
  ?p1  spouse  ?p2
}
```

SQL query

f1.film

```
SELECT spouse.partner1, spouse.partner2,
FROM spouse, film AS f1, film AS f2
WHERE spouse.partner1 = f1.actor
AND   spouse.partner2 = f2.actor
AND   f1.film = f2.film
```

SPARQL to SQL Translation 3/4

- Algorithm
  - It is up to you in ES13, to design a generic algorithm that works for arbitrary basic SPARQL queries

    Of the form SELECT <vars> { <triples> }
  - The algorithm is not difficult, but requires understanding of how the data is stored and SPARQL and SQL work

    So perfect exercise to understand the basics !
  - On the next slide we give you valuable advice

SPARQL to SQL Translation 4/4

- Algorithm, advice for ES13
  - If there are k query triples in the SPARQL query, have k entries in the FROM clause of the SQL query

    FROM freebase as f1, freebase as f2, ... , freebase as fk

  - In your code, for each variable from the SPARQL query, build an **array** of all its occurrences in the query, e.g.

    ?x: f1.subject, f2.object, f5.object

  - Then, when building the SQL query, add the corresponding equalities to the WHERE clause, e.g.

    WHERE f1.subject = f2.object AND f2.object = f5.object

    Note: if ?x occurs m times, m – 1 equalities are enough

Performance 1/4

- Cross product of tables
  - Understand that, conceptually, an SQL statement like

    SELECT … FROM T_1, T_2, …, T_k WHERE …

    selects elements from the **cross-product**

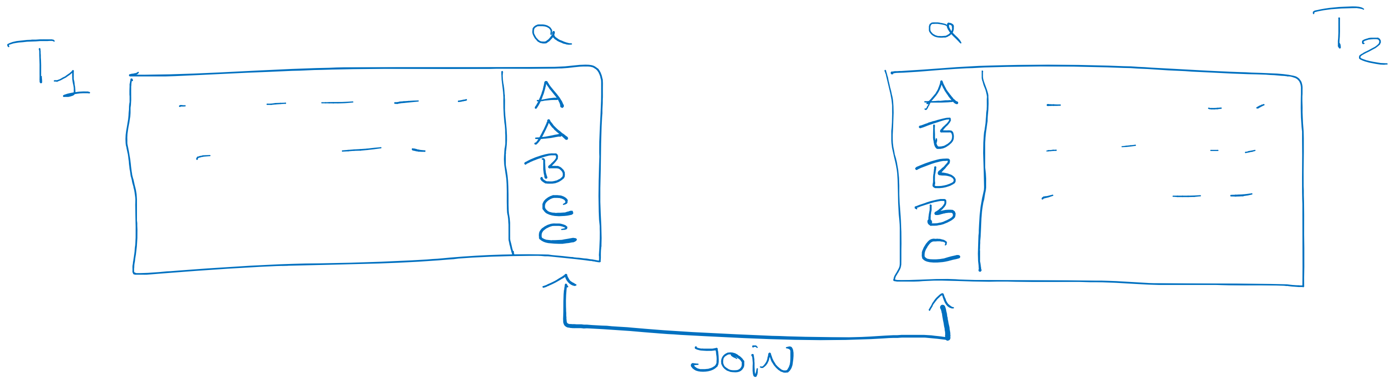
    $T_1 \times \cdots \times T_k$ (which has $|T_1| \cdot \cdots \cdot |T_k|$ elements)

    (where some or all of the T_i can be the same table)

Performance 2/4

- Joining of tables
  - The WHERE … = … effectively ask for a JOIN
  - This JOIN effectively asks for a **list intersection**
  - If we CREATE an index for the respective tables on the respective join attributes, this list intersection gets fast

    E.g., by sorting (a copy of) the table by that attribute



Performance 3/4

- Join ordering
  - Typical SQL-from-SPARQL queries require multiple joins
  - Order of joins can make a **huge** performance difference
  - For our example query, the film table (actors – films) is more than ten times larger than the spouse table
  - Join order 1: look at all married couples and for each get their films and check whether they overlap

    materializes list of films of all married people (small)
  - Join order 2: look at all pairs of actors who played in the same film, and for each check whether they are married

    materialized all pairs of actors from same film (large)

Performance 4/4

- Join ordering, continued
  - Without further ado, SQLite seems to take the order of the tables in the FROM clause as its join order

```
SELECT  spouse.person1, spouse.person2
FROM    film as film1, film as film2, spouse        ≈18 sec
WHERE   spouse.person1 = film1.actor
AND     spouse.person2 = film2.actor
AND     film1.movie = film2.movie;
```

Alternatives: (note that there are 6 possible orderings)

```
FROM    spouse, film as film1, film as film2        ≈8 sec
FROM    spouse, film as film2, film as film1        ≈2.3 sec
```

References

- Textbook
  - Nothing about this topic in the text book by Manning, Raghavan, and Schütze
- Wikipedia
  - http://en.wikipedia.org/wiki/Ontology_(information_science)
  - http://en.wikipedia.org/wiki/SPARQL
  - http://en.wikipedia.org/wiki/SQL
  - http://en.wikipedia.org/wiki/SQLite
  - http://en.wikipedia.org/wiki/Freebase