Robust Semantic Matching for Question Answering Systems

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Goals

- To provide an overview of the state-of-the-art of semantic matching/approximation techniques.
- Focus on the context of OKBQA.
- Semantic matching is far from being a resolved problem! There is space for new contributions.
- Exciting emerging techniques!
Outline

- Motivation
- Distributional Semantic Models
- Fine-grained Semantic Models
- Compositional Semantics
- Distributional Semantics for Question Answering
Motivation
Vocabulary Problem for Databases

Query: Who is the daughter of Bill Clinton married to?

Semantic Gap

Possible representations

- Abstraction level differences
- Lexical variation
- Structural (compositional) differences
Query: Who is the daughter of Bill Clinton married to?

Possible representations

- Abstraction level differences
- Lexical variation
- Structural (compositional) differences

Semantic approximation

Commonsense Knowledge

Distributional Model

Compositional Model
Robust Semantic Matching: Distributional Semantic Models
Robust Semantic Model

- **Semantic approximation** (matching) is highly dependent on knowledge scale (commonsense, semantic)

Semantics

\[ \text{Semantics} = \text{Formal meaning representation model (lots of data)} + \text{inference model} \]
Robust Semantic Model

- Not scalable!

1st Hard problem: Acquisition

Semantics

= Formal meaning representation model (lots of data) + inference model

Not scalable!
Robust Semantic Model

- Not scalable!

2nd Hard problem: Consistency

Semantics

= Formal meaning representation model (lots of data) + inference model
“Most semantic models have dealt with particular types of constructions, and have been carried out under very simplifying assumptions, in true lab conditions.”

“If these idealizations are removed it is not clear at all that modern semantics can give a full account of all but the simplest models/statements.”
Distributional Semantic Models

- **Semantic Model with low acquisition effort** (automatically built from text)

  Simplification of the representation

- Enables the construction of comprehensive commonsense/semantic KBs

- **What is the cost?**

  Some level of noise
  (semantic best-effort)

  Limited semantic model
Distributional Hypothesis

“Words occurring in similar (linguistic) contexts tend to be semantically similar”

- “He filled the wampimuk with the substance, passed it around and we all drunk some”

References:
- McDonald & Ramscar, 2001
- Baroni & Boleda, 2010
- Harris, 1954
Distributional Semantic Models (DSMs)

“The dog barked in the park. The owner of the dog put him on the leash since he barked.”

contexts = nouns and verbs in the same sentence
Distributional Semantic Models (DSMs)

“The **dog** barked in the **park**. The **owner** of the **dog** put him on the **leash** since he barked.”

contexts = nouns and verbs in the same sentence

- bark : 2
- park : 1
- leash : 1
- owner : 1
Semantic Relatedness

Query: cat

bark

dog

car

run

leash
Semantic Relatedness

Query: cat

bark

dog

cat

leash

car

run

\[ \theta \]
Definition of DSMs

DSMs are tuples $< T, C, R, W, M, d, S >$

$T$ target elements, words for which the DSM provides a contextual representation.
$C$ contexts, with which $T$ co-occur.
$R$ relation, between $T$ and the contexts $C$.
$W$ context weighting scheme.
$M$ distributional matrix, $T \times C$.
$d$ dimensionality reduction function, $d \; M \rightarrow M'$.
$S$ distance measure, between the vectors in $M'$. 
DSMs as Commonsense Reasoning

Dataset predicates, query terms

Semantic Approximation is here

Commonsense is here
Who is the child of Bill Clinton?

Bill Clinton father of Chelsea Clinton

Distributional Commonsense KB
(Terminology-level)

\[ s_{rel}(childOf, fatherOf) = "0.03259" \]
\[ s_{rel}(childOf, sonOf) = "0.01091" \]
\[ s_{rel}(childOf, kidOf) = "0.01046" \]
\[ s_{rel}(childOf, daughterOf) = "0.01059" \]
\[ ... \]
\[ s_{rel}(childOf, occupation) = "0.00356" \]
\[ s_{rel}(childOf, religion) = "0.00120" \]
\[ s_{rel}(childOf, almaMater) = "0.0" \]
\[ ... \]
Terminology-level Search (Video)
Semantic Relatedness Measure as a Ranking Function
Evaluating Terminology-level Semantic Matching

<table>
<thead>
<tr>
<th></th>
<th>Avg. Precision@5</th>
<th>Avg. Precision@10</th>
<th>MRR</th>
<th>% of queries answered</th>
</tr>
</thead>
<tbody>
<tr>
<td>ESA</td>
<td>0.732</td>
<td>0.646</td>
<td>0.646</td>
<td>92.25%</td>
</tr>
</tbody>
</table>

- Distributional semantics provides a more comprehensive semantic matching with medium-high precision.
EasyESA: Semantic approximation made easy

http://easy-esa.org

- Distributional model based on the English Wikipedia
Dinfra: Multilingual distributional semantics

- In 11 languages.

- [http://vmdgsit04.deri.ie/dinfra?lang=en&model=esa&terms=love&targetSet=mother;father](http://vmdgsit04.deri.ie/dinfra?lang=en&model=esa&terms=love&targetSet=mother;father)
Fine-grained Semantic Models
Text Entailment

- Given the fact: Mary gave birth.
- Is the following fact true? Mary is a mother.
Beyond Word Vector Models

Distributional semantics can give us a hint about the concepts’ semantic proximity...

...but it still can’t tell us what exactly the relationship between them is.
Beyond Word Vector Models

give birth

mother

33
Example

Does John Smith have a degree?

:John Smith :occupation :Engineer
Hybrid Lexico-Distributional Models

Step: Resoning context = <John Smith, degree>

Does **John Smith** have a **degree**?
Hybrid Lexico-Distributional Models

Step: Get neighboring relations

Does **John Smith** have a **degree**?
Hybrid Lexico-Distributional Models

Step: Calculate the distributional semantic relatedness between the target term and the neighboring entities.

Does John Smith have a degree?

Distributional Commonsense KB

Structured Commonsense KB

John Smith

engineer

occupation

sem rel (engineer, degree) = 0.07

catholic

religion

sem rel (catholic, degree) = 0.004

...
Hybrid Lexico-Distributional Models

Step: Filter the elements below the threshold

Does John Smith have a degree?

Structured Commonsense KB

Distributional Commonsense KB

John Smith

engineer

occupation

catholic

religion

...
Does John Smith have a degree?

Step: Navigate to the next nodes
Hybrid Lexico-Distributional Models

Step: redefine the reasoning context:
<engineer, degree>

Does John Smith have a degree?
Hybrid Lexico-Distributional Models

Step: Get neighboring relations

Does John Smith have a degree?
Hybrid Lexico-Distributional Models

Step: Calculate distributional semantic relatedness between the target term and the neighboring entities

Does John Smith have a degree?

\[
\begin{align*}
\text{sem rel (dam, degree)} &= 0.002 \\
\text{sem rel (bridge a river, degree)} &= 0.004 \\
\text{sem rel (learn, degree)} &= 0.01
\end{align*}
\]
Step: Filter the elements below the threshold

Does John Smith have a degree?

- \( \text{sem rel (dam, degree)} = 0.002 \)
- \( \text{sem rel (bridge a river, degree)} = 0.004 \)
- \( \text{sem rel (learn, degree)} = 0.01 \)
Hybrid Lexico-Distributional Models

Step: Search highly related entities in the KB not connected (distributional semantics)
Does **John Smith** have a degree?

Reasoning context: ‘learn degree’

- Distributional Commonsense KB
- Structured Commonsense KB

![Diagram showing relationships between 'John Smith', 'engineer', 'learn', and 'occupation']
Hybrid Lexico-Distributional Models

Step: Navigate to the elements above the threshold

Does John Smith have a degree?
Hybrid Lexico-Distributional Models

Step: Repeat the steps

Does **John Smith** have a **degree**?
Hybrid Lexico-Distributional Models

Step: Repeat the steps

Does **John Smith** have a **degree**?

- Distributional Commonsense KB
- Structured Commonsense KB

Diagram:
- **John Smith**
  - subjectof **engineer**
  - occupation **learn**
  - have or involve **education**
  - at location **university**
Hybrid Lexico-Distributional Models

Step: Search highly related entities in the KB not connected (distributional semantics)

Does John Smith have a degree?

Reasoning context: ‘university degree’

- university
  - at location
- education
  - have or involve
- engineer
  - subjectof
- learn
  - occupation

Distributional Commonsense KB

Structured Commonsense KB
Hybrid Lexico-Distributional Models

Step: Search highly related entities in the KB not connected (distributional semantics)

Does John Smith have a degree?

Reasoning context: ‘university degree’

- colledge
- university
- education
- engineer
- learn
- John Smith

Distributional Commonsense KB
Structured Commonsense KB
Does **John Smith** have a **degree**?

```
John Smith  engineer  subjectof  learn  occupation
            
John Smith  university  at location

John Smith  college  degree  gives

education  have or involve
```
Distributional semantic relatedness as a selectivity heuristics
Distributional semantic relatedness as a selectivity heuristics
Distributional semantic relatedness as a selectivity heuristics
Examples of Selected Paths

Reasoning context: < battle, war >
Too much complexity? Deep Learning to the Help!

- Relatively recent Machine Learning techniques which support the creation of expressive hierarchical models.

- **Semi-supervised!**
  - Uses unlabeled data to build a substantial part of the model.

- Starting to be heavily used in NLP tasks.
(Deep) Neural Models of Distributional Word Vectors

- Creating specialized versions of distributional models.
- NNLM, HLBL, RNN, ivLBL, Skip-gram/CBOW, (Bengio et al; Collobert & Weston; Huang et al; Mnih & Hinton; Mnih & Kavukcuoglu; Mikolov et al.)
Interesting properties such as analogical reasoning

- Semantic relations appear as linear relationships in the space of learned representations.

- Paris – France + Italy ≈ Rome

Mikolov et al. 2013
However, best word vectors are not “deep”

- LSA (Deerwester et al.), LDA (Bleiet al.), HAL (Lund & Burgess), Hellinger-PCA (Lebret & Collobert) …
- Scale with vocabulary size and efficient usage of statistics.

Socher et al. EMNLP Tutorial
Take-away message

- Distributional semantic models = great tools for comprehensive semantic approximation (automatically built from text).

- Different distributional models serve to address different semantic matching problems.
  - E.g. ESA is good for more comprehensive types of semantic matching

- Deep learning provides a promising approach to build better distributional semantic models.
Compositional Semantics: Beyond Single Word Vectors
I find it rather odd that people are already trying to tie the Commission's hands in relation to the proposal for a directive, while at the same calling on it to present a Green Paper on the current situation with regard to optional and supplementary health insurance schemes.

= ?

I find it a little strange to now obliging the Commission to a motion for a resolution and to ask him at the same time to draw up a Green Paper on the current state of voluntary insurance and supplementary sickness insurance.
Compositional Semantics

- Can we extend DS to account for the meaning of phrases and sentences?

- **Compositionality**: The meaning of a complex expression is a function of the meaning of its constituent parts.
Compositional Semantics

Words in which the meaning is directly determined by their distributional behaviour (e.g., nouns).

Words that act as functions transforming the distributional profile of other words (e.g., verbs, adjectives, ...).
Compositional-Distributitional Semantics
Modeling Compositionality

Socher et al., EMNLP 2012.

the country of my birth
the place where I was born

But how can we represent the meaning of longer phrases?
By mapping them into the same vector space!
How should we map phrases into a vector space?

Use principle of compositionality

The meaning (vector) of a sentence is determined by
(1) the meanings of its words and
(2) the rules that combine them.

Socher et al., EMNLP 2012.
Compositionality over Natural Language Category Descriptors (NLCDs)

Noun phrases containing a combination one or more components:
- attributive adjectives;
- adjective phrases and participial phrases;
- noun adjuncts;
- prepositional phrases;
- adnominal adverbs and adverbials;
- relative clauses;
- infinitive phrases.

Examples

- Football Players from United States
- French Senators Of The Second Empire
- Churches Destroyed In The Great Fire Of London And Not Rebuilt
- Training Groups Of The United States Air Force.
Distributional Search

execution time: 15.43 seconds

1. fleets of the people's liberation army navy
2. wolves in folklore, religion and mythology
3. prehistoric canines
4. prehistoric hyenas
5. prehistoric thylacines
6. native american composers
7. ugandan composers
8. ancient greek composers
9. ancient music composers
10. sacred music composers

options:
- use wordnet expansion:
- use vsm:
Distributional Search

Execution time: 23.92 seconds

1. italian women's rights activists
   score: 2.4712107
2. political organizations in italy by ideology
   score: 2.2052965
3. italian folk dances
   score: 2.1587896
4. violence against women in italy
   score: 2.1061168
5. political party factions in italy
   score: 2.1026607
6. coalitions of parties in italy
   score: 2.0923867
7. sports governing bodies in italy
   score: 2.0865817
8. political movements in italy
   score: 2.0862813
9. italian dance music groups
   score: 2.0791843
10. italian folk music groups
    score: 2.0791843
Test Collection and Experiments

- **Full dataset:**
  - more than 300,000 Wikipedia categories

- **Test Collection:**
  - sub-set of 75 categories were paraphrased by 10 English speaking volunteers resulting in 125 queries.

- **Examples:**

<table>
<thead>
<tr>
<th>Target category</th>
<th>Paraphrased version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beverage Companies Of Israel</td>
<td>Israeli Drinks Organizations</td>
</tr>
<tr>
<td>Swedish Metallurgists</td>
<td>Nordic Metal Workers</td>
</tr>
<tr>
<td>Rulers Of Austria</td>
<td>Austrian leaders</td>
</tr>
</tbody>
</table>
# Results

<table>
<thead>
<tr>
<th>Approach</th>
<th>AVG Precision</th>
<th>AVG Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Approach Top10</td>
<td>0.0355</td>
<td>0.3555</td>
</tr>
<tr>
<td>Our Approach Top20</td>
<td>0.02</td>
<td>0.4</td>
</tr>
<tr>
<td>Our Approach Top50</td>
<td>0.0089</td>
<td>0.4445</td>
</tr>
<tr>
<td>WordNet QE Top10</td>
<td>0.0205</td>
<td>0.2052</td>
</tr>
<tr>
<td>WordNet QE Top20</td>
<td>0.0118</td>
<td>0.2358</td>
</tr>
<tr>
<td>WordNet QE Top50</td>
<td>0.0061</td>
<td>0.2969</td>
</tr>
<tr>
<td>String Matching Top10</td>
<td>0.0146</td>
<td>0.0989</td>
</tr>
<tr>
<td>String Matching Top20</td>
<td>0.0101</td>
<td>0.1042</td>
</tr>
<tr>
<td>String Matching Top50</td>
<td>0.0073</td>
<td>0.1093</td>
</tr>
</tbody>
</table>
Take-away message

- Addressing compositionality is a fundamental aspect of semantic matching.

- Compositional-distributional models are promising approaches to support approximation of full expression/sentences.
Towards an Information-Theoretical Model for Schema-agnostic Semantic Matching

**Semantic Complexity & Entropy:** *Configuration space* of semantic matchings.

- Query-DB semantic gap.
- Ambiguity, synonymy, indeterminacy, vagueness.
Semantic Entropy

$H_{\text{syntax}}$

$H_{\text{term}}$

$H_{\text{matching}}$

$H_{\text{struct}}$

$H_{\text{term}}$
Minimizing the Semantic Entropy for the Semantic Matching

Definition of a semantic pivot: first query term to be resolved in the database.

- Maximizes the reduction of the semantic configuration space.
Semantic Pivots

Who is the daughter of **Bill Clinton** married to?

![DBpedia Logo]

> 4,580,000

<table>
<thead>
<tr>
<th>dbpedia:spouse</th>
<th>dbpedia:children</th>
<th>:Bill_Clinton</th>
</tr>
</thead>
<tbody>
<tr>
<td>100,184</td>
<td>62,781</td>
<td>437</td>
</tr>
</tbody>
</table>
Minimizing the Semantic Entropy for the Semantic Matching

Definition of a **semantic pivot**: first query term to be resolved in the database.

- Maximizes the reduction of the semantic configuration space.
- Less prone to more complex synonymic expressions and abstraction-level differences.
Semantic Pivots

Who is the daughter of Bill Clinton married to?

Bill Clinton
William Jefferson Clinton
William J. Clinton

Thomas Edward Lawrence
T. E. Lawrence
Lawrence of Arabia

Paris
City of light
French capital
Capital of France

Proper nouns tend to have high percentage of string overlap for synonyemic expressions.
Minimizing the Semantic Entropy for the Semantic Matching

Definition of a semantic pivot: first query term to be resolved in the database.

- Maximizes the reduction of the semantic configuration space.
- Less prone to more complex synonymic expressions and abstraction-level differences.
- Semantic pivot serves as interpretation context for the remaining alignments.
- proper nouns >> nouns >> complex nominals >> adjectives, verbs.
Analyzing the Semantic Gap

Schema-agnostic Queries
Semantic Web Challenge

ESWC 2015

The Challenge in a Nutshell

To create a query mechanism that semantically matches schema-agnostic user queries to knowledge base elements.
Example Mappings

languageOf (p) -> spokenIn (p) | related
writtenBy (p) -> author (p) | substring, related
FemaleFirstName (c o) -> gender (p) | substring, related
state (p) -> locatedInArea (p) | related
extinct (p) -> conservationStatus (p) | related
constructionDate (p) -> beginningDate (p) | substring, related
calledAfter (p) -> shipNamesake (p) | related
in (p) -> location (p) | functional_content
in (p) -> isPartOf (p) | functional_content
extinct (p) -> 'EX' (v o) | substring, abbreviation
startAt (p) -> sourceCountry (p) | substring, synonym
U.S._State (c o) -> StatesOfTheUnitedStates (c o) | string_similar
wifeOf (p) -> spouse (p) | substring, similar
Take-away message

- Most works in QA have approached the problem of semantic matching at a systems level.

- Necessary to move the discussion to a more fine-grained understanding of which semantic approximation models work better for different types of semantic gaps.

- Detecting the semantic pivot is fundamental for efficient semantic approximation.
Distributional Semantics for Question Answering
Towards a New Semantic Model for Schema-agnostic databases

- **Strategies:**
  - Distributional semantic model for semantic matching of query terms and database entities.
  - Semantic pivoting.
Approach Overview

Schema-agnostic Query

Query Analysis

Query Planner

Query Features

Query Plan

T-Space

Core semantic approximation & composition operations

Database

Distributional semantics

Commonsense knowledge

Large-scale unstructured data
Core Operations

Query

\[ < q'_0, q'_1, \ldots, q'_n > \]
Core Operations

Query

\[ \langle q'_0, q'_1, \ldots, q'_n \rangle \]

Search & Composition Operations
Search and Composition Operations

- **Instance search**
  - Proper nouns
  - String similarity + node cardinality

- **Class (unary predicate) search**
  - Nouns, adjectives and adverbs
  - String similarity + Distributional semantic relatedness

- **Property (binary predicate) search**
  - Nouns, adjectives, verbs and adverbs
  - Distributional semantic relatedness

\[
\text{sr}(q^t_1, p^t_0) \geq \eta
\]

- **Navigation**

\[
< (q^{t_1} - p^{t_1}), (q^{t_2} - p^{t_2}), \cdots, (q^{t_n} - p^{t_n}) >
\]

- **Extensional expansion**
  - Expands the instances associated with a class.

- **Operator application**
  - Aggregations, conditionals, ordering, position

- **Disjunction & Conjunction**

- **Disambiguation** dialog (instance, predicate)
Does it work?
Addressing the Vocabulary Problem for Databases (with Distributional Semantics)

Gaelic: direction
Simple Queries (Video)
More Complex Queries (Video)
Query Pre-Processing (Query Analysis)

- Transform natural language queries into triple patterns.

“Who is the daughter of Bill Clinton married to?”
Query Pre-Processing (Query Analysis)

- Step 1: POS Tagging
  - Who/WP
  - is/VBZ
  - the/DT
  - daughter/NN
  - of/IN
  - Bill/NNP
  - Clinton/NNP
  - married/VBN
  - to/TO
  - ?/.
Query Pre-Processing
(Query Analysis)

- **Step 2: Semantic Pivot Recognition**
  - Rules-based: POS Tags + IDF

Who is the daughter of **Bill Clinton** married to?
(PROBABLY AN INSTANCE)
Query Pre-Processing (Question Analysis)

Step 3: Determine answer type
Rules-based.

Who is the daughter of Bill Clinton married to?
(PERSON)
Query Pre-Processing
(Question Analysis)

- **Step 4: Dependency parsing**
  - dep(married-8, Who-1)
  - auxpass(married-8, is-2)
  - det(daughter-4, the-3)
  - nsubjpass(married-8, daughter-4)
  - prep(daughter-4, of-5)
  - nn(Clinton-7, Bill-6)
  - pobj(of-5, Clinton-7)
  - root(ROOT-0, married-8)
  - xcomp(married-8, to-9)
Query Pre-Processing (Question Analysis)

- **Step 5: Determine Partial Ordered Dependency Structure (PODS)**
  - Rules based.
  - Remove stop words.
  - Merge words into entities.
  - Reorder structure from core entity position.

Diagram:

- **INSTANCE**
  - Bill Clinton
  - daughter
  - married to

- **ANSWER TYPE**
  - Person

**QUESTION FOCUS**
Transform natural language queries into triple patterns

“Who is the daughter of Bill Clinton married to?”

Bill Clinton → daughter → married to

(INSTANCE) → (PREDICATE) → (PREDICATE)
Map *query features* into a *query plan*.

A *query plan* contains a sequence of *core operations*.

- (1) INSTANCE SEARCH (Bill Clinton)
- (2) $p_1 \leftarrow$ SEARCH PREDICATE (Bill Clinton, daughter)
- (3) $e_1 \leftarrow$ NAVIGATE (Bill Clinton, $p_1$)
- (4) $p_2 \leftarrow$ SEARCH PREDICATE ($e_1$, married to)
- (5) $e_2 \leftarrow$ NAVIGATE ($e_1$, $p_2$)
Query Plan Execution
Instance Search

Query:

Bill Clinton → daughter → married to

Linked Data:

:Bill_Clinton
Predicate Search

Query:

Bill Clinton -> daughter -> married to

Linked Data:

:Bill_Clinton

:child

:Chelsea_Clinton

:religion

:Baptists

:almaMater

:Yale_Law_School

(PIVOT ENTITY)

(ASSOCIATED TRIPLES)
Predicate Search

Query: Bill Clinton → daughter → married to

Linked Data:
- :Bill_Clinton
- :Chelsea_Clinton
- :Baptists
- :Yale_Law_School

Which properties are semantically related to ‘daughter’?

- `sem_rel(daughter, child) = 0.054`
- `sem_rel(daughter, child) = 0.004`
- `sem_rel(daughter, alma mater) = 0.001`
Navigate

Query:

Bill Clinton → daughter → married to

Linked Data:

:Bill_Clinton → :child → :Chelsea_Clinton
Navigate

Query:

Linked Data:

Bill Clinton -> daughter -> married to

:Bill_Clinton -> :child -> :Chelsea_Clinton

(PIVOT ENTITY)
Predicate Search

Query:
- Bill Clinton → daughter → married to

Linked Data:
- :Bill_Clinton
  - :child
    - :Chelsea_Clinton
      - :spouse
        - :Mark_Mezvinsky

(PIVOT ENTITY)
Results

"Who is the daughter of Bill Clinton married to?"

Answer

Chelsea Clinton  spouse  Marc Mezvinsky
Bill Clinton  child  Chelsea Clinton
Bill Clinton  children  Chelsea Clinton
William Jefferson Blythe, Jr.  child  Bill Clinton
Virginia Clinton Kelley  child  Bill Clinton
Virginia Clinton Kelley  children  Bill Clinton
Class (Unary Predicate) Search

Query: Mountain \rightarrow highest

Linked Data: :Mountain

(PIVOT ENTITY)
Extensional Expansion

Query:

Mountain -> highest

Linked Data:

:Mountain -> :typeOf -> :Everest
:Mountain -> :typeOf -> :K2

(PIVOT ENTITY)
Distributional Semantic Matching

Query: Mountain highest

Linked Data:
- :Mountain
- :Everest
- :K2
- :typeOf
- :deathPlaceOf
- :typeOf
- :elevation

(PIVOT ENTITY)
Application of the functional definition of the operator

Query:

Linked Data:

(PIVOT ENTITY)
Results

"What is the highest mountain?"

Answer

Mount Everest elevation 8848.0
Test Collection

- Test Collection: QALD 2011.
- DBpedia 3.6.
- Two test sets (76/50) natural language queries.

Dataset (DBpedia 3.6 + YAGO classes):
45,768 properties
288,316 classes
9,434,677 instances
128,071,259 triples
## Relevance

<table>
<thead>
<tr>
<th>Relevant</th>
<th>Accurate semantic matching for a semantic best-effort scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ranking</td>
<td>Ranking in the second position in average</td>
</tr>
<tr>
<td>MRR</td>
<td>Medium-high query expressivity / coverage</td>
</tr>
</tbody>
</table>

### Table: Relevance

<table>
<thead>
<tr>
<th>Relevance</th>
<th>Avg. Precision</th>
<th>Avg. Recall</th>
<th>MRR</th>
<th>% of queries answered</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.62</td>
<td>0.81</td>
<td>0.49</td>
<td>80%</td>
</tr>
</tbody>
</table>
Performance & Adaptability

- Low maintainability/adaptability effort
- Low query execution time
- High scalability

<table>
<thead>
<tr>
<th>Measure</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. query execution time (ms)</td>
<td>8.530</td>
</tr>
<tr>
<td>Avg. entity search time (ms)</td>
<td>3.495</td>
</tr>
<tr>
<td>Avg. predicate search time (ms)</td>
<td>3.223</td>
</tr>
<tr>
<td>Avg. number of search operations per query</td>
<td>2.70</td>
</tr>
<tr>
<td>Avg. index insert time per triple (ms)</td>
<td>5.35</td>
</tr>
<tr>
<td>Avg. index size per triple (bytes)</td>
<td>250</td>
</tr>
<tr>
<td>Dataset adaptation effort (minutes)</td>
<td>0.00</td>
</tr>
<tr>
<td>Dataset specific semantic enrichment effort per query (secs)</td>
<td>0.00</td>
</tr>
<tr>
<td>Dataset specific semantic enrichment effort (minutes)</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Avg. 1.52 s (simple queries)
Avg. 8.53 s (all queries)

- Interactive query execution time
- Indexing size overhead (20% of the dataset size)
- Significant overhead in indexing time.
- Low adaptability effort
Final Remarks

- Semantic approximation is at the center of every QA system.
- This is far from being a resolved problem!
- Distributional semantic models provide a comprehensive and effective method for supporting semantic approximations.
- Vector spaces models are easy to use!
- However these models need to evolve in the direction of more fine-grained semantics and better compositionality.
- Deep learning brings a promising approach to address these problems.
- Great area to be involved with now!