Question Auto-Completion using a Typed LSTM Language Model

MASTER THESIS BY NATALIE PRANGE

Query Auto-Completion

Source: https://i.imgur.com/eObv3jI.jpg

Query Auto-Completion

Goals of Query Auto-Completion (QAC):

- Reduce typing effort
- Prevent spelling errors
- Assist in phrasing a query

A QAC system must therefore present completion predictions …

- … after a minimal amount of keystrokes
- … in real time
- … properly ranked

Motivation

Most QAC research focuses on QAC using query logs

Problems with query log approaches:

- Not available to search engines with a small user base or recently deployed search engines
- Publicly available query logs are outdated
- Queries that have never been asked before can not be predicted

→ Use a language-model-based approach

Tackling the Data Sparsity Problem

A common problem when working with language models:

Receiving an input that did not occur in the training data

Solution: Use a typed language model (LM)

Concrete entities are replaced by abstract types

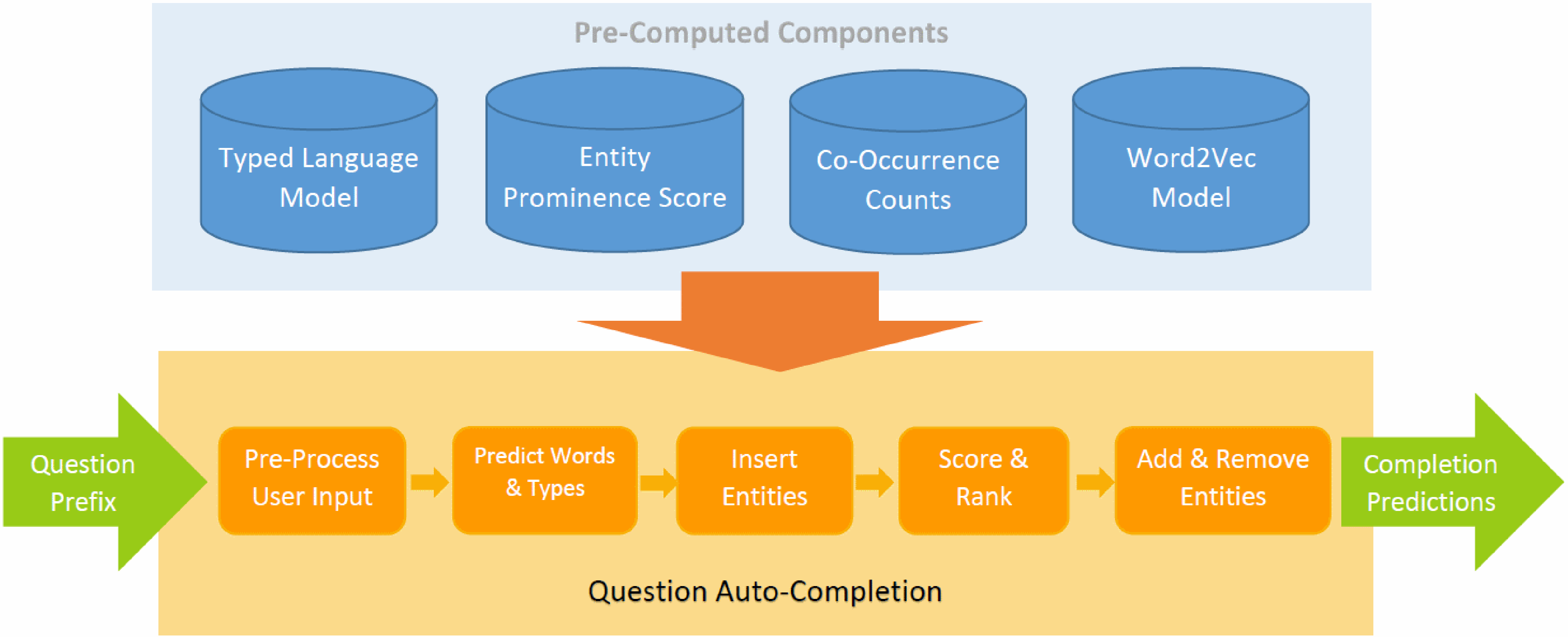
E.g. "*Who played **Gandalf** in **The Lord of the Rings**?*"

→ "*Who played **[fictional character]** in **[film]**?*"

Entities are later inserted using

- an entity prominence score
- co-occurrence
- word vector similarity

Overview of the System



Building the Typed Language Model

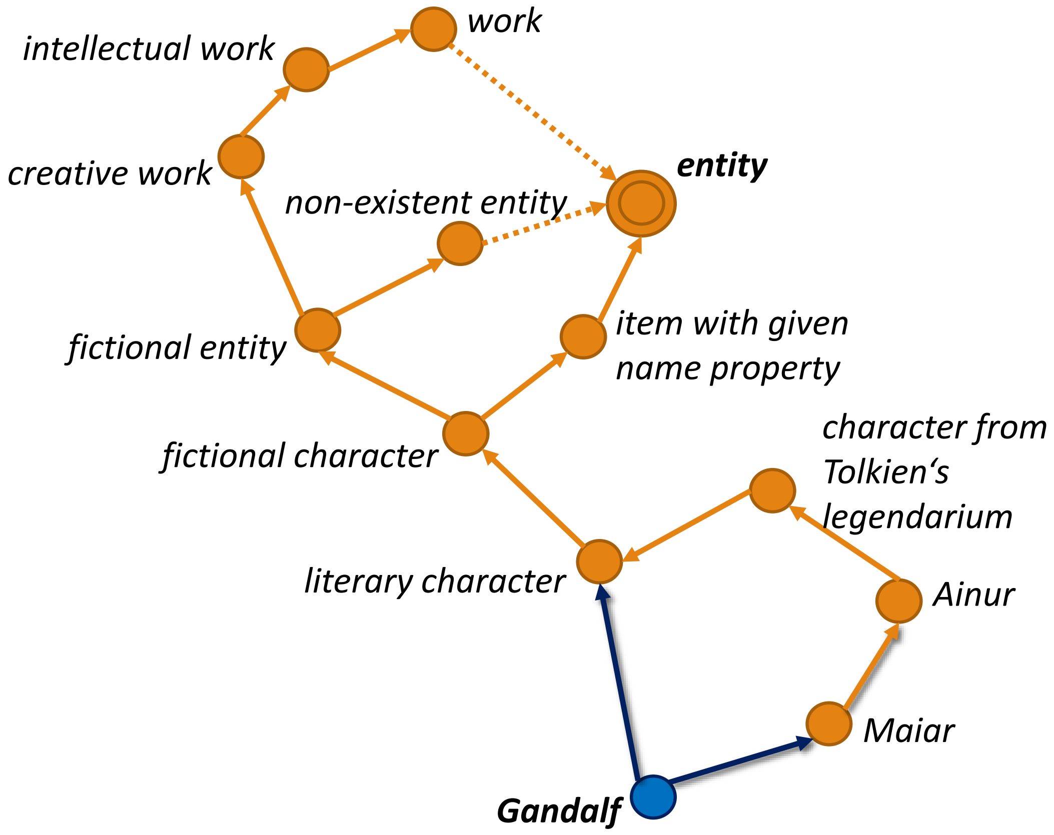
Create an entity-to-type mapping using Wikidata entities and classes

Challenge: Types must neither be too general nor too specific

→ Use two types: a more specific type (*primary type*) and a more general type (*secondary type*)

- E.g. *Gandalf* → *fictional character (primary)*
  → *creative work (secondary)*

→ Use a hand-crafted and sorted list of preferred types



Training Data for the Language Model

- Dataset with 11,290,367 questions
- 97% of questions stem from the WikiQuestions dataset:
  - Wikipedia sentences with entity mentions transformed into questions
- The remaining 3% of questions stem from the ClueWeb12 corpus
  - Questions from English web pages with entity mentions
- Entities are replaced by their types
  - E.g. *"Who is* ***Gandalf****?"* → *"Who is* ***[fictional character/creative work]****?"*

Training the LSTM Language Model

LSTM network = Long Short Term Memory network

Architecture:

- Embedding layer of size 100
- Two stacked LSTM layers of size 512
- Softmax layer of size of the vocabulary

→ Given a question prefix, the network outputs a probability distribution over the vocabulary

Training:

- Batch size of 512
- 15 epochs

→ training time: ca. 9 days and 21 hours

Predicting Words and Types

The typed LM should predict the next word or type given a question prefix

E.g. "*Who directed the Lord of t*"

Standard LM:

- predict words for the **current word prefix "*t*"** given the context words C = ("*who*", "*directed*", "*the*", "*Lord*", "*of*")

Typed LM:

- predict words for **all possible current word prefixes** i.e. "***t***", "***of t***", "***Lord of t***" …

→ predict "*Who directed **[film]***"

Inserting Entities for Predicted Types

Extract candidate entities that …

- … have the predicted primary type (as primary or secondary type)
- … start with the current word prefix

Define **insertion context words** $\boldsymbol{I(C)}$ as set of **entities** contained in a question prefix and ***<type>*** if question starts with *"Which <type>"*

- E.g. for the context words C = ("*Which*", "*country*", "*did*", "*J.R.R. Tolkien*")

  → I(C) = ("*country*", "*J.R.R. Tolkien*")

Inserting Entities for Predicted Types

If insertion context words $I(C) = \emptyset$:

→ Use an **entity prominence score** to score candidate entities

- Based on an entity's Wikibase sitelink count
- Counts are normalized to a score between 0 and 1

Else:

→ Use the **co-occurrence count** between insertion context words and candidate entity

- Co-occurrence is computed over a Wikipedia dump with entity mentions
- Counts are normalized to a score between 0 and 1

Ranking Completion Predictions

Completion predictions are ranked according to a final score

Components of the final score:

- Language model probability
- Insertion score
- Penalty factors

Language model probability

- Incorporate probability to observe given context words
- For a completion prediction w and context words $C = (w_1, w_2, \ldots, w_i)$

$$p_{lm}(w|C) = \hat{p}(C) * p(w|C)$$

$\hat{p}(C)$: Discounted LM probability to observe the context words C

$p(w|C)$: LM probability of the predicted word or type of w given the context words C

Ranking Completion Predictions

Entity insertion score

- Normalized sitelink count or normalized co-occurrence count for entities

Normal word insertion score

- Balance prediction of normal words vs. entities
- If $I(C) = \emptyset$: Use constant score of 0.01
- Else: compute word vector similarity between non-stopwords in the question prefix and the predicted normal word

Ranking Completion Predictions

Penalty factors

- Penalize prediction of consecutive entities with penalty factor g_{ce}

$$g_{ce} = \begin{cases} 0.04 & if\ completion\ prediction\ is\ an\ entity\ and\ previous\ word\ is\ an\ entity \\ 1 & else \end{cases}$$

- Penalize prediction of the entity type *[human]* with penalty factor g_h

$$g_h = \begin{cases} 0.02 & if\ LM\ predicts\ type\ [human] \\ 1 & else \end{cases}$$

- Penalize alias-based completion predictions with penalty factor g_a

$$g_a = \begin{cases} 0.6 & if\ completion\ prediction\ is\ based\ on\ entity\ alias\ instead\ of\ entity\ label \\ 1 & else \end{cases}$$

Final score:

$$s = p_{lm} * (s_{insert} * g_a)^{0.3} * g_{ce} * g_h$$

Adding and Removing Entities

- Append entities when not enough completion predictions were generated using co-occurrence
  - Use product of word vector similarity and sitelink count to score candidate entities
- Append completely typed entities
- Remove double completion predictions

Evaluation

Multiple-True-Completions Evaluation

- Evaluate over set of 100 question prefixes along with reasonable completion predictions

- Measure **precision at k = 5** (P@5)

$$P@k = \frac{|Q_{true} \cap Q_{results}^{k}|}{k}$$

Q_{true} : set of true completions

$Q_{results}^{k}$: set of top k completions predicted by the system

- Measure **average precision** (AP)

$$AP = \frac{\sum_{i=1}^{n} P@r_i}{n}$$

$r_1, \ldots, r_n$: list of positions at which predictions from Q_{true} appear in $Q_{results}$

Evaluation

- Measure **normalized discounted cumulative gain at k = 5** (nDCG@5)

Discounted cumulative gain at k:

$$\mathrm{DCG@k} = rel_1 + \sum_{i=2}^{k} \frac{rel_i}{log_2(i+1)}$$

rel_i: relevance score for the completion predicted at rank i

Normalized discounted cumulative gain at k:

$$\mathrm{nDCG@k} = \frac{DCG@k}{IDCG@k}$$

$IDCG@k$: ideal discounted cumulative gain

Evaluation

Single-True-Completion Evaluation

- Base test set: 10,000 random questions
- 1ICW test set: 10,000 questions with one insertion context word
- >1ICW test set: 10,000 questions with more than one insertion context word

- Measure **mean reciprocal rank** (MRR)

  $$RR = \frac{1}{r}$$

  r: rank of the correct completion prediction
  Compute RR for each word in each question after its 1st letter has been typed
  Report the mean over all computed RR scores

- Measure **required user interaction** (RUI)

  $$RUI = \frac{\#\,user\ interactions\ needed\ given\ completion\ predictions}{\#\,user\ interactions\ needed\ without\ completion\ predictions}$$

  Typing a letter and selecting a completion prediction each count as one interaction

Evaluated Versions

Three main versions that differ in the entity insertion method for $I(C) \neq \emptyset$

- *sitelinks:* Entity insertion based on sitelink count (Baseline)
- *sitelinks + w2v:* Entity insertion based on product of sitelink count and word vector similarity
- *co-occurrence:* Entity insertion based on co-occurrence

Additional versions:

- *co-occurrence w/o* g_{ce}*:* no penalty for consecutive entities
- *co-occurrence w/o* g_h*:* no penalty for prediction of type *[human]*
- *co-occurrence w/o w2v fill-up:* no filling up of entities using word vector similarity

Multiple-True-Completions Evaluation Results

	P@5	AP	nDCG@5	Time
sitelinks	0.286	0.375	0.422	**0.64 s**
sitelinks + w2v	0.322	0.464	0.524	0.77 s
co-occurrence w/o g_{ce}	0.338	0.481	0.551	0.70 s
co-occurrence w/o g_h	0.316	0.473	0.543	0.70 s
co-occurrence w/o w2v fill-up	0.340	0.489	0.564	0.65 s
co-occurrence	**0.344**	**0.500**	**0.572**	0.69 s

Single-True-Completion Evaluation Results

	Base Test Set		1ICW Test Set		>1ICW Test Set	
	MRR	RUI	MRR	RUI	MRR	RUI
sitelinks	0.532	0.542	0.537	0.538	0.529	0.525
sitelinks + w2v	**0.533**	0.541	**0.540**	0.535	**0.533**	0.523
co-occurrence	0.531	**0.538**	0.537	**0.529**	0.531	**0.510**

Single-True-Completion Evaluation Results

Correctly predicted entities for $I(C) \neq \emptyset$		
	$entity \in I(C)$	$<type> \in I(C)$
sitelinks	468	200
sitelinks + w2v	718	195
co-occurrence	**1062**	**280**

On the >*1ICW* test set after typing the first letter of the entity label

Future Work

- Experiment with different methods for language modeling
- Make system robust against spelling errors
- Create a larger ground truth for the evaluation
- Enhance completion predictions with contextual information