Paraphrase Generation from Latent-Variable PCFGs for Semantic Parsing

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Semantic Parsing for Question Answering

Semantically parsing questions into Freebase logical forms for the goal of question answering

- task-specific grammars (Berant et al., 2013)
- strongly-typed CCG grammars (Kwiatkowski et al., 2013; Reddy et al., 2014, 2016)
- neural networks without requiring any grammar (Yih et al., 2015)

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Sensitive to words used in a question and their word order

Vulnerable to unseen words and phrases

Semantic Parsing for Question Answering: An Example

What language do people in Czech Republic speak?

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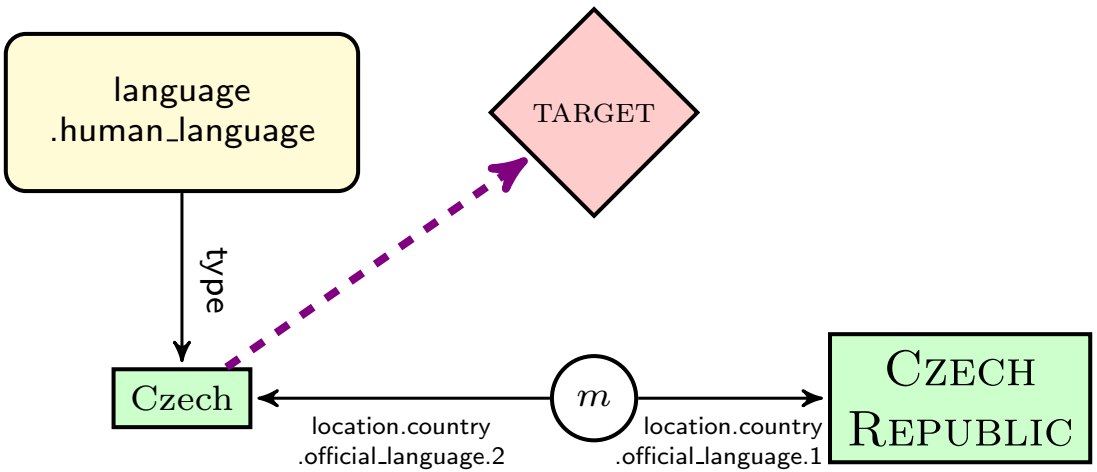
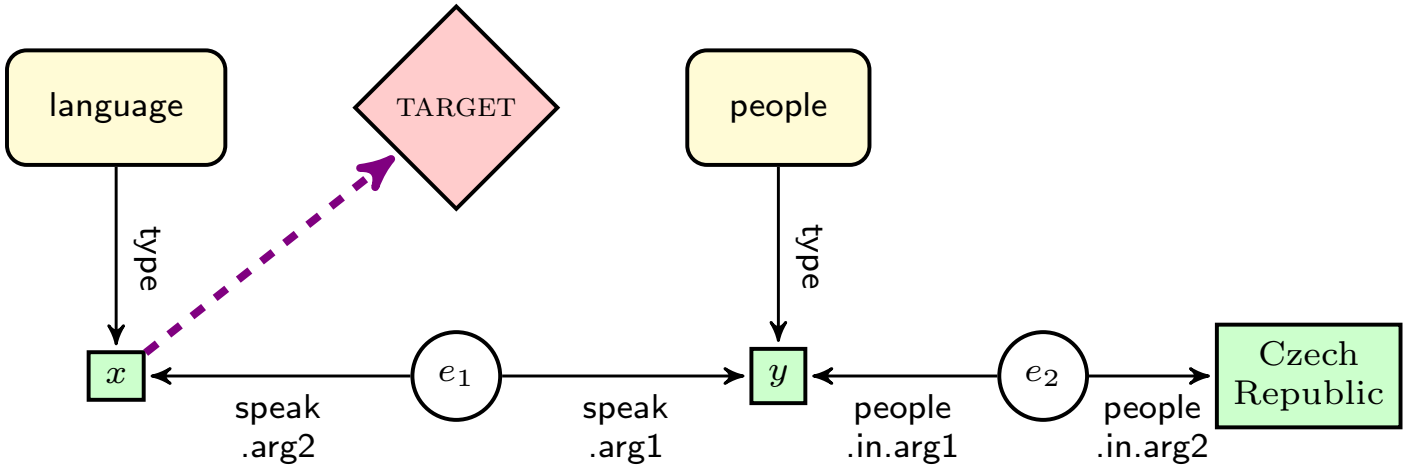
Freebase knowledge graph



Graph Matching Problem

What language do people in Czech Republic speak?



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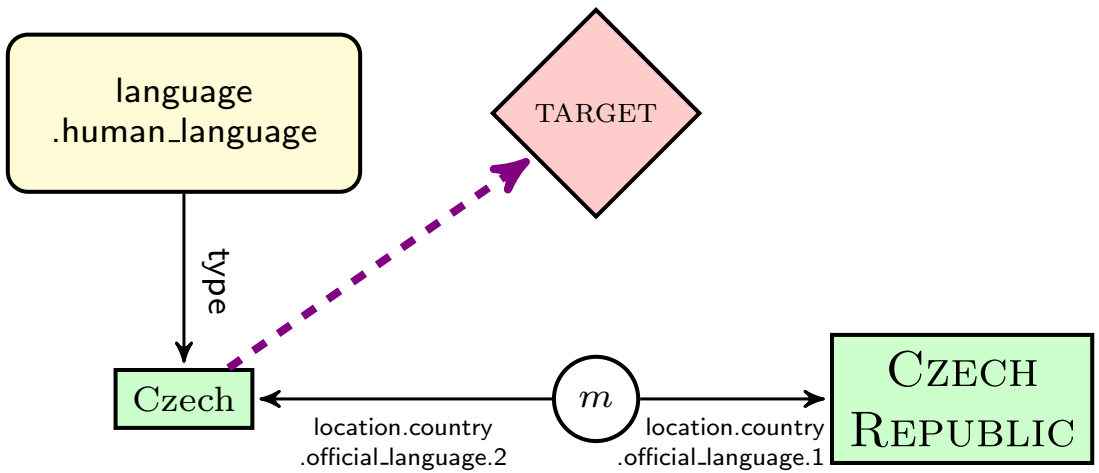

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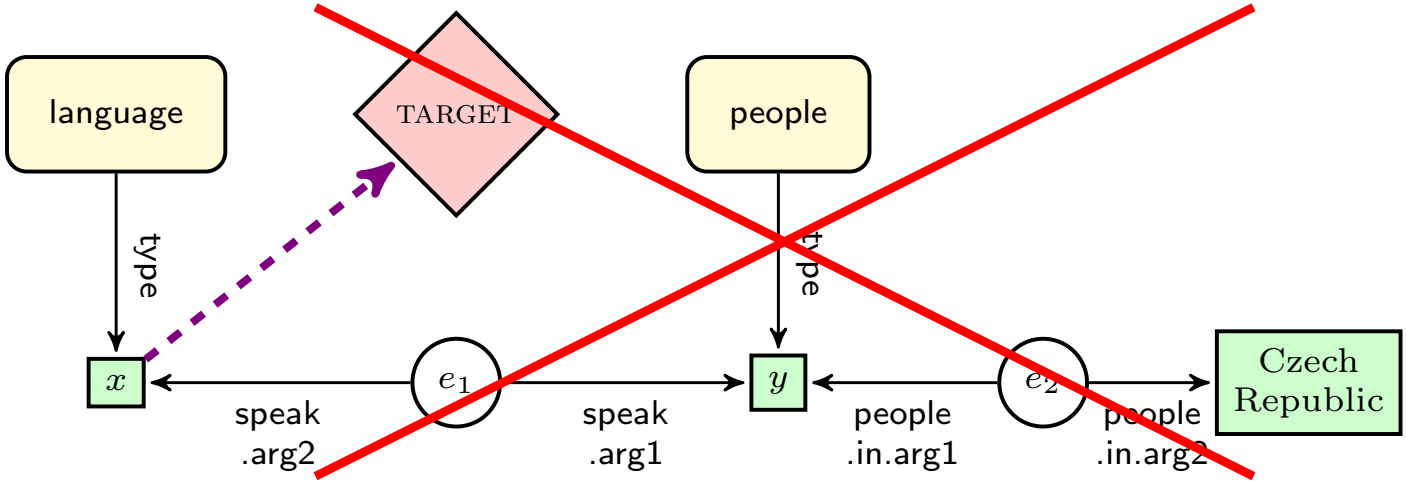

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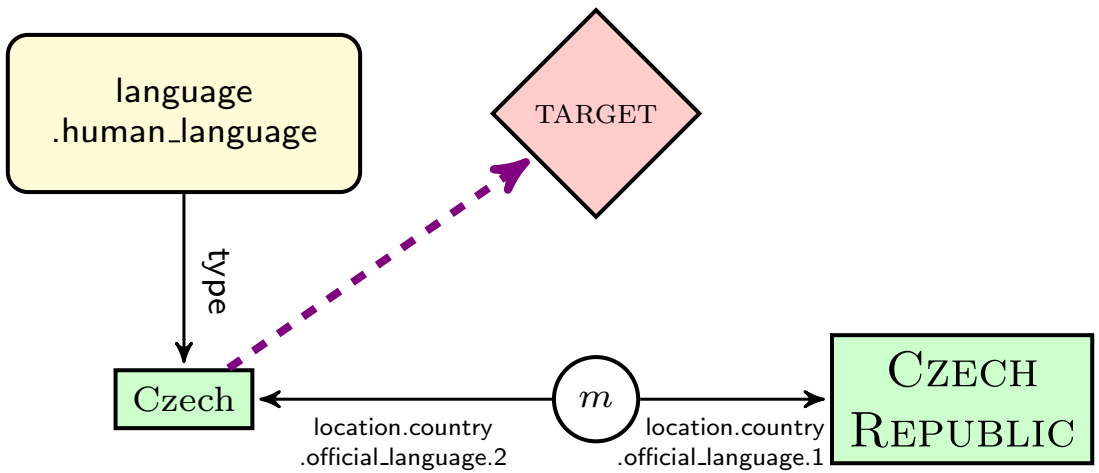
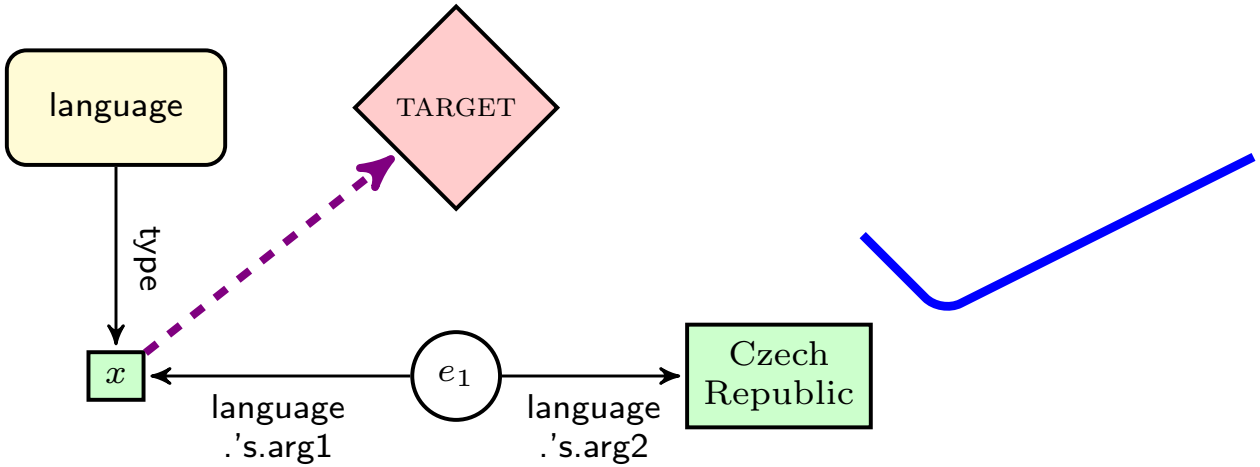


Graph Matching Problem with Paraphrases

What is Czech Republic's language?



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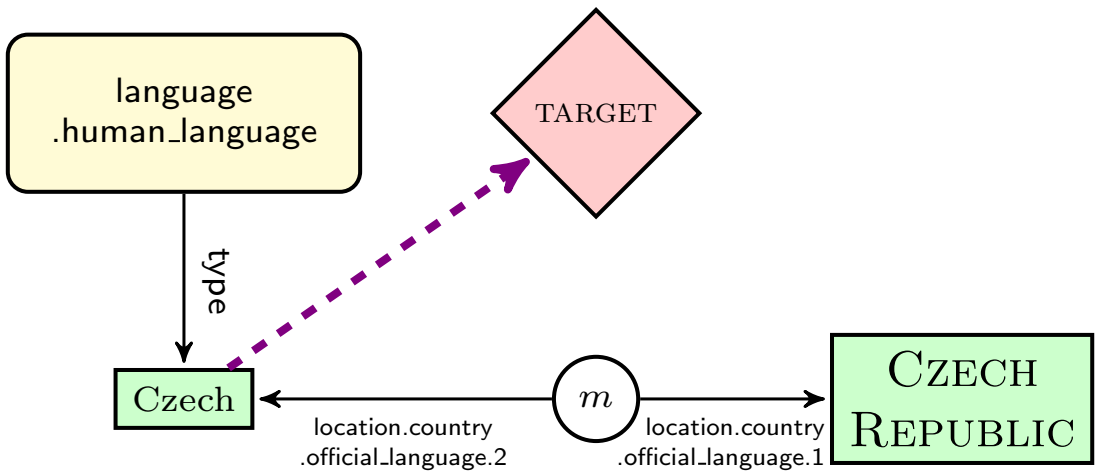

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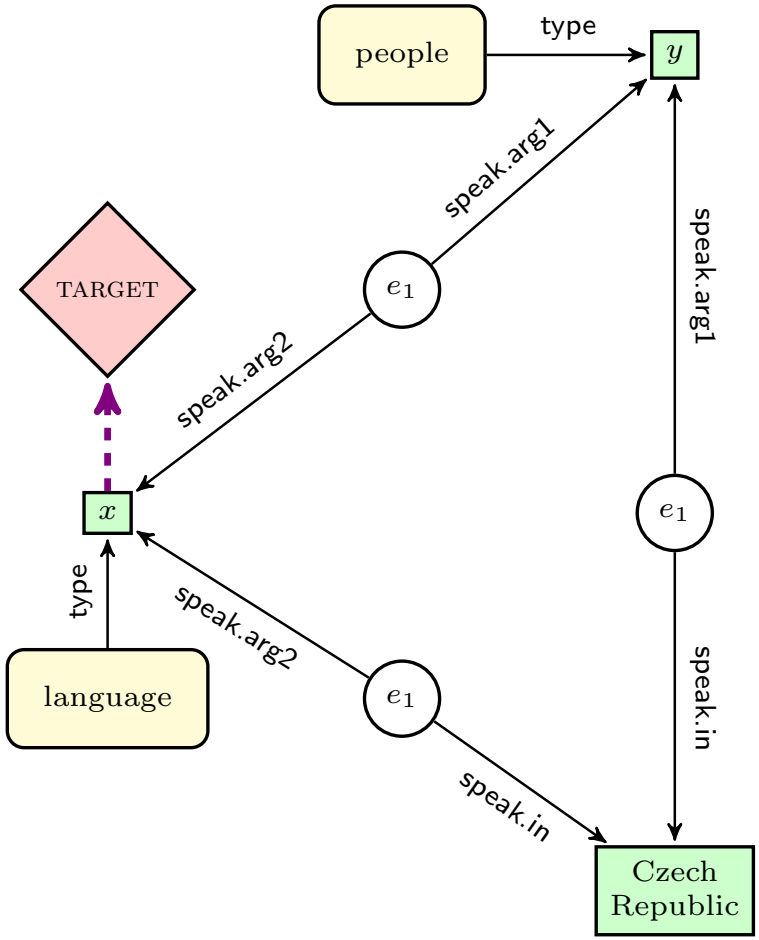

Question Answering with Paraphrases

Paraphrasing with **phrase-based machine translation** for text-based QA (Duboue and Chu-Carroll, 2006; Riezler et al., 2007)

Paraphrasing with **hand annotated grammars** for KB-based QA (Berant and Liang, 2014)

This talk ...

Paraphrase Generation with **Latent-Variable PCFGs (L-PCFGs)**

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- Uses **spectral method** of Narayan and Cohen (EMNLP 2015) to learn **sparse and robust** grammar to sample paraphrases, and

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Improving semantic parsing of questions into Freebase logical forms using paraphrases

Outline of this talk

Spectral Learning of Latent-variable PCFGs

Paraphrase Generation using L-PCFGs

Semantic Parsing using Paraphrases

Results and Discussion

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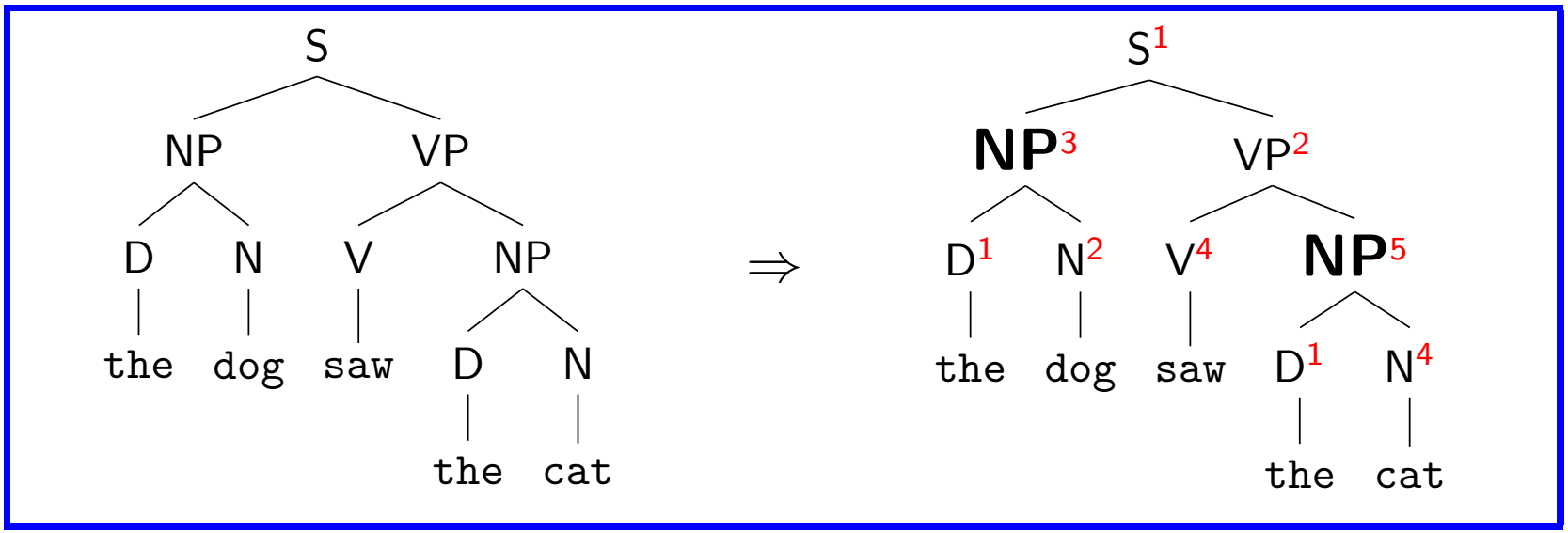
Probabilistic CFGs with Latent States (Matsuzaki et al., 2005; Prescher 2005)



Latent states play the role of nonterminal subcategorization, e.g., $\text{NP} \rightarrow \{\text{NP}^1, \text{NP}^2, \ldots, \text{NP}^{24}\}$

- analogous to syntactic heads as in lexicalization (Charniak 1997) ?

They are not part of the observed data in the treebank

Estimating PCFGs with Latent States (L-PCFGs)

EM Algorithm (Matsuzaki et al., 2005; Petrov et al., 2006)

⇓ **Problems with local maxima**; it fails to provide certain type of theoretical guarantees as it doesn't find global maximum of the log-likelihood

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Spectral Algorithm (Cohen et al., 2012, 2014, Narayan and Cohen, 2015, 2016)

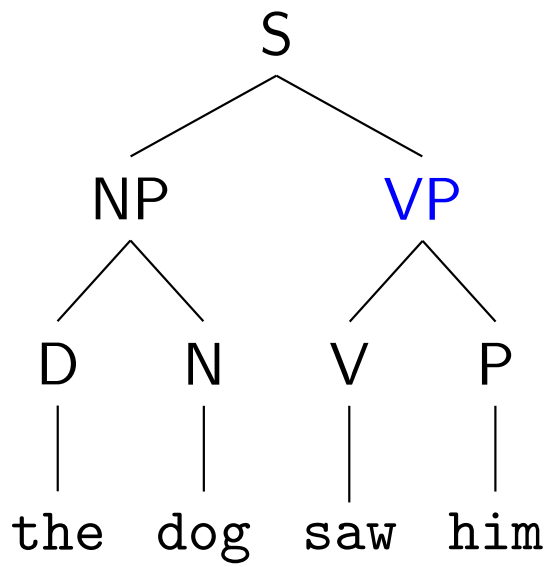
⇑ Statistically consistent algorithms that make use of spectral decomposition

⇑ Much faster training than the EM algorithm

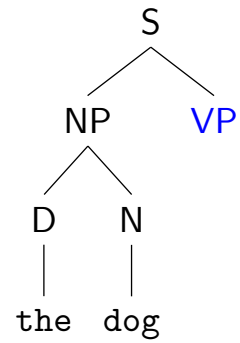
Intuition behind the Spectral Algorithm

Inside and outside trees

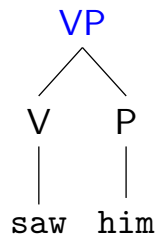
At node VP:



Outside tree $o =$



Inside tree $t =$

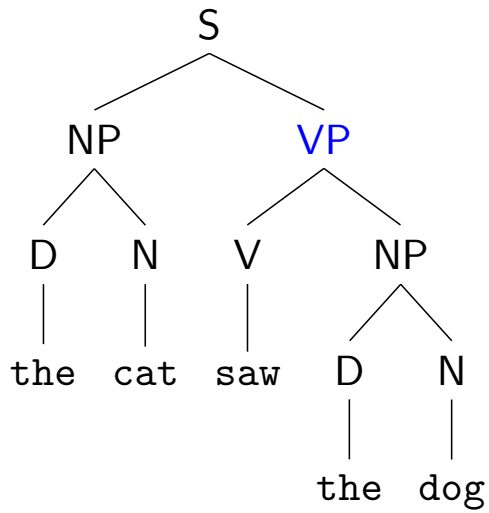


Conditionally independent given the label and the hidden state

$$p(o, t|\text{VP}, h) = p(o|\text{VP}, h) \times p(t|\text{VP}, h)$$

Inside Features used

Consider the VP node in the following tree:

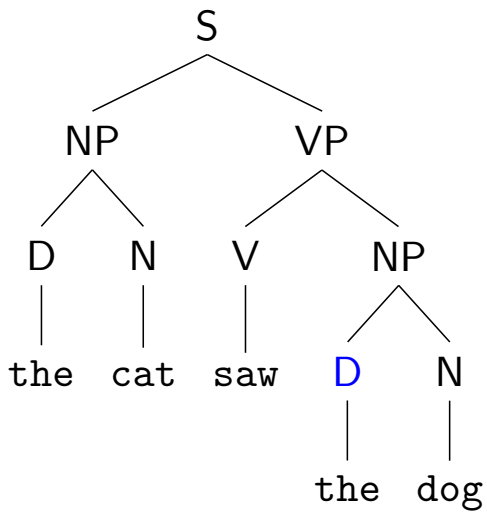


The inside features consist of:

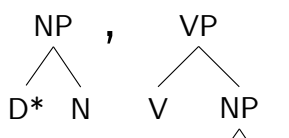
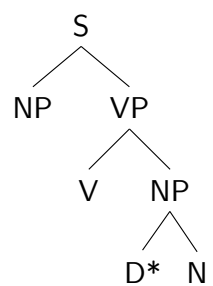
- The pairs `(VP, V)` and `(VP, NP)`
- The rule `VP` $\longrightarrow$ `V NP`
- The tree fragment `(VP (V saw) NP)`
- The tree fragment `(VP V (NP D N))`
- The pair of head part-of-speech tag with `VP`: `(VP, V)`

Outside Features used

Consider the D node in the following tree:



The outside features consist of:

- The pairs `(D, NP)` and `(D, NP, VP)`
- The pair of head part-of-speech tag with `D`: `(D, N)`
- The tree fragments  , and 

Recent Advances in Spectral Estimation

Singular value decomposition (SVD) of cross-covariance matrix for each nonterminal

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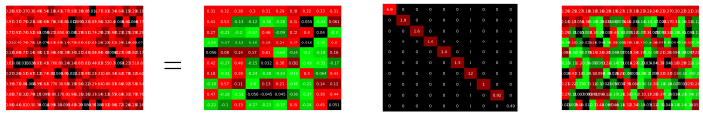

SVD Step

Method of moments (Cohen et al., 2012, 2014)

- Averaging with SVD parameters $\Rightarrow$ Dense estimates

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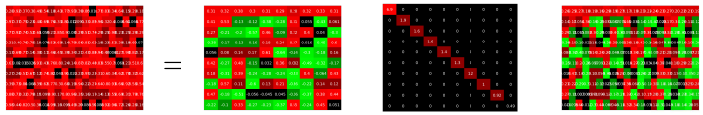

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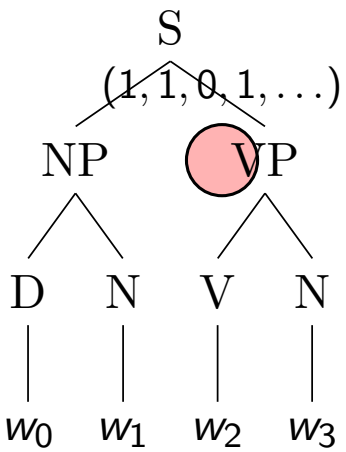
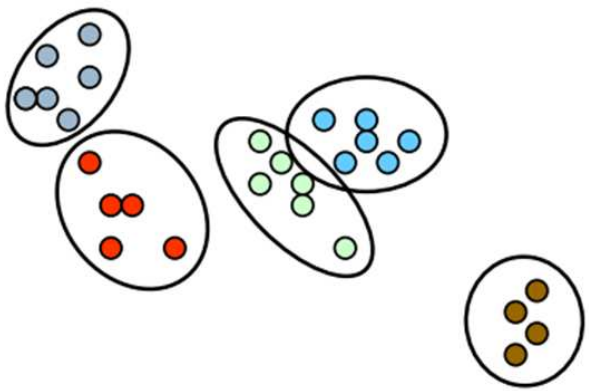
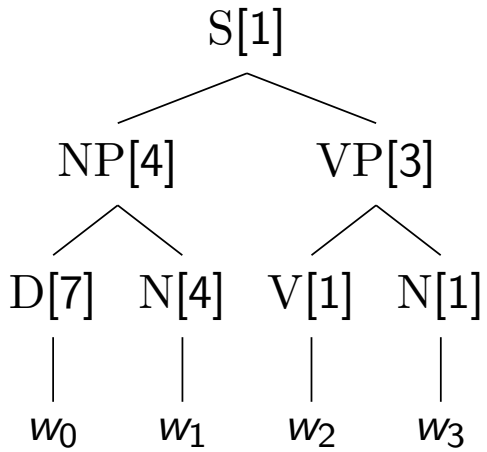
Clustering variants (Narayan and Cohen 2015)







Sparse estimates

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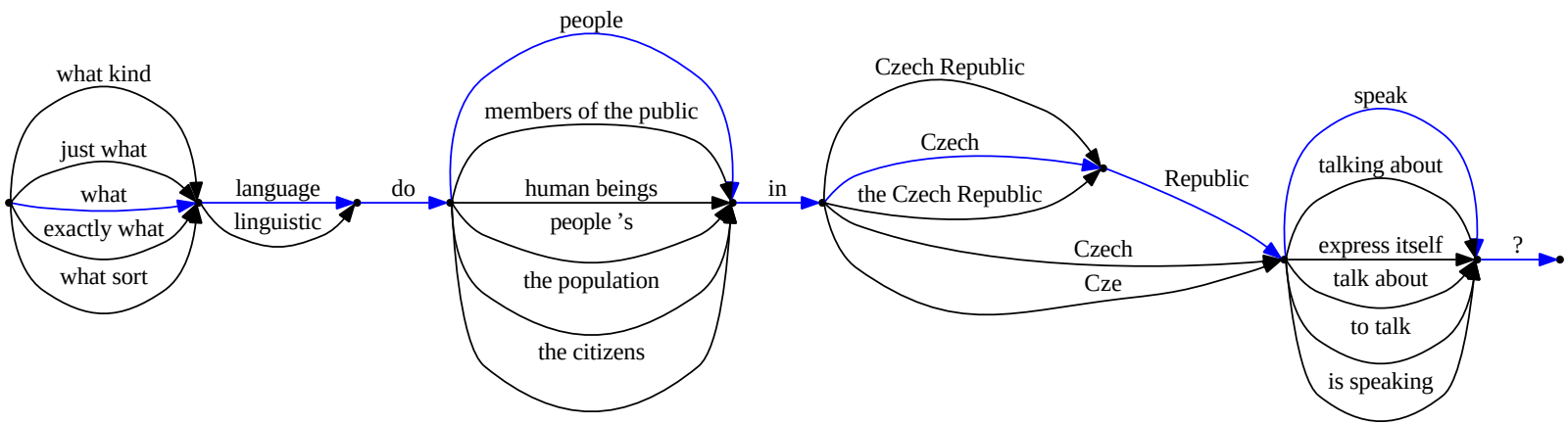
Given an input sentence

- **Word lattice construction** to constrain our paraphrases to a specific choice of words and phrases



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- **Sampling paraphrases** using L-PCFGs, constrained by the word lattice
- **Paraphrase classification** to improve precision

L-PCFG Estimation for Sampling Paraphrases

The PARALEX Corpus, 18m paraphrase pairs with 2.4M distinct questions (Fader et. al. 2013)

Who wrote the Winnie the Pooh books?
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L-PCFG Estimation for Sampling Paraphrases

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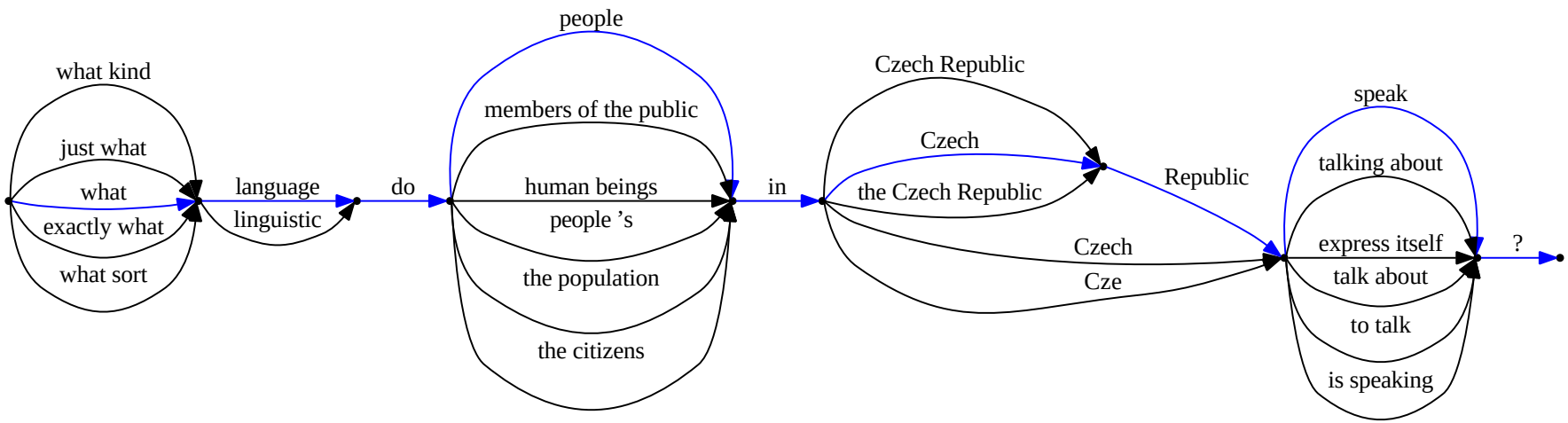
Parse all the questions using the BLLIP Parser (Charniak and Johnson, 2005)

Estimate a **robust** and **sparse** L-PCFG G_{syn} with $m = 24$ (Narayan and Cohen 2015)

Sampling Sentential Paraphrases using L-PCFG G_{syn}

Given an input word lattice and a grammar G_{syn}:

Lexical pruning: Extract a grammar G'_{syn} from G_{syn} which is constrained to the lattice



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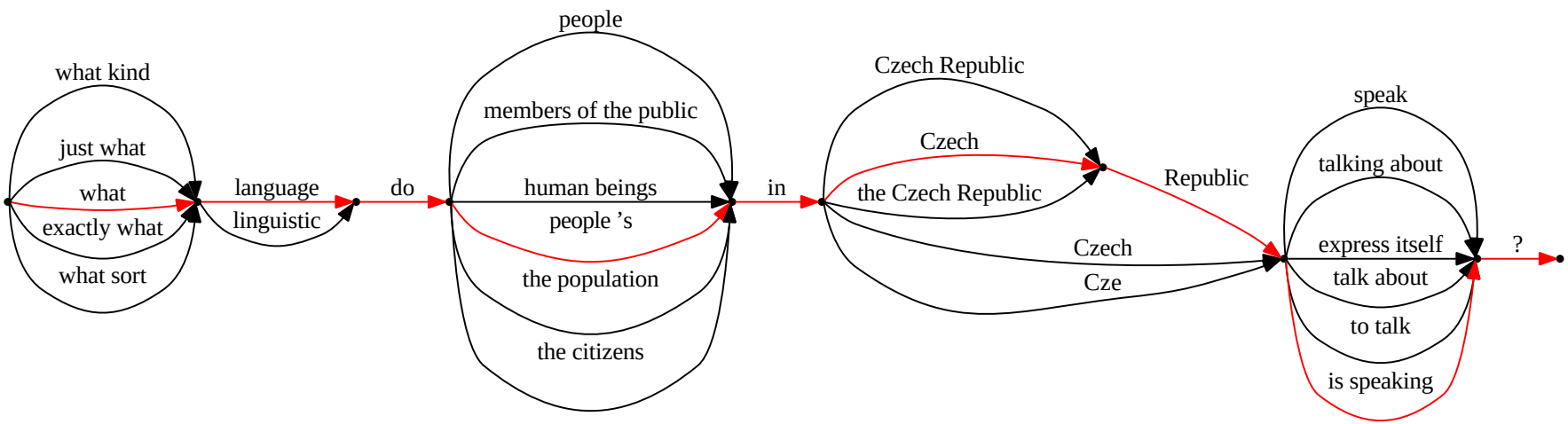
Sampling Sentential Paraphrases using L-PCFG G_{syn}

Given an input word lattice and a grammar G_{syn}:

Controlled sampling: Sample a question from G'_{syn} by recursively sampling nodes in the derivation tree, together with their latent states, over the lattice



(what, language, do, people 's, in, Czech, Republic, is speaking, ?)

$\Downarrow$

what is Czech Republic 's language?

Paraphrase Classification

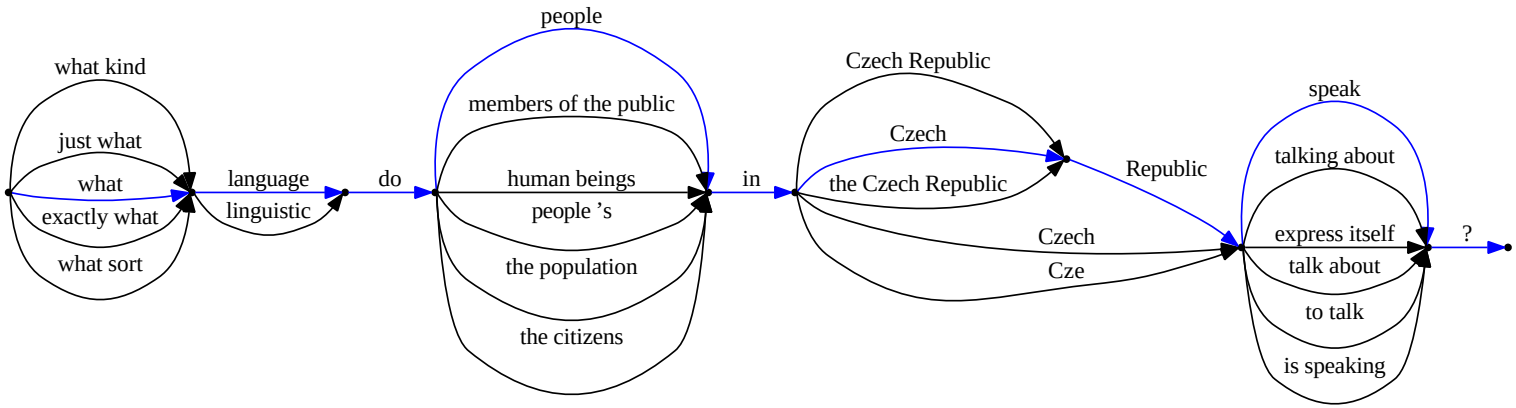
Filter with a classifier to improve the precision of the generated paraphrases

MT metrics for paraphrase identification (Madnani et al. 2012)

Word Lattice Construction

Two approaches:

1. Lexical and phrasal paraphrase rules from the **Paraphrase Database** (Ganitkevitch et al., 2013)



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2. Lexical paraphrases from **Bi-layered L-PCFG**

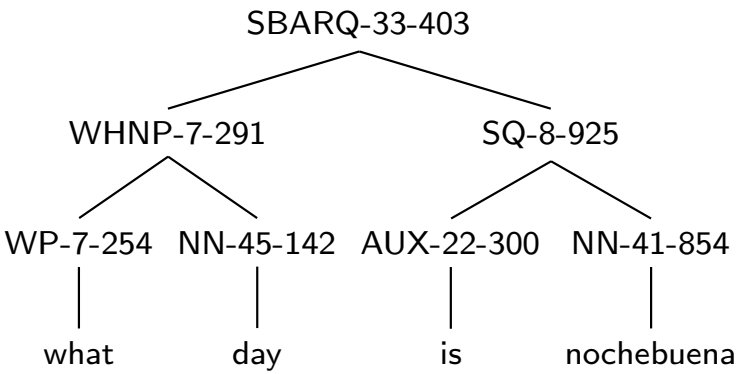
Inducing Paraphrases with a Bi-layered L-PCFG

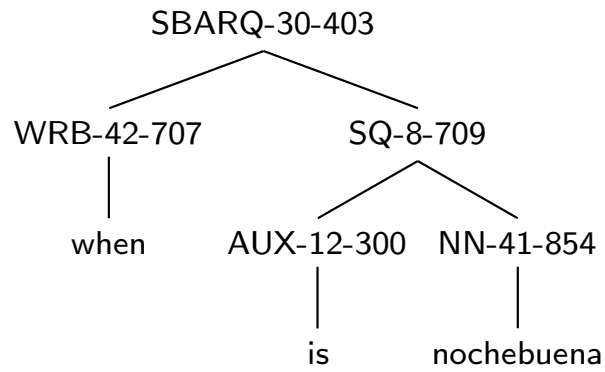
L-PCFG $G_{layered}$ with two layers of latent states:

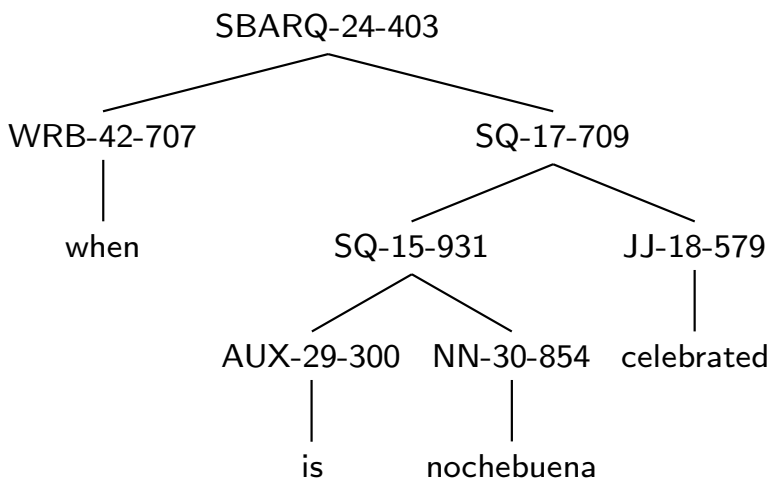
one layer is intended to capture the usual syntactic information (traditional G_{syn} with $m = 24$), and

the other aims to capture semantic and topical information by using a large set of states (G_{par} with $m = 1000$)

Training trees for Bi-layered L-PCFG Training

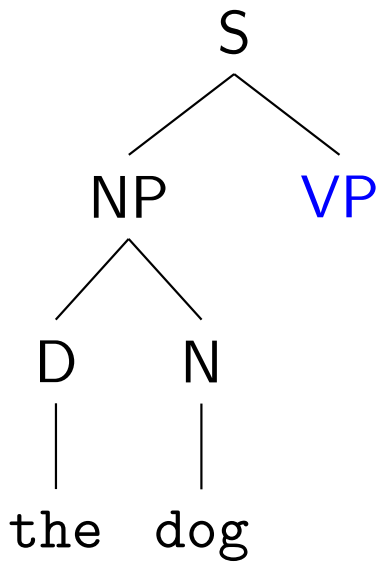


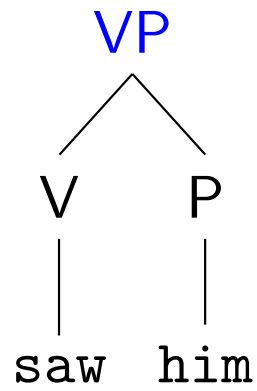




Features for Second Layer

Design feature functions ψ and ϕ:





Outside tree $o \Rightarrow$	Inside tree $t \Rightarrow$
$\psi(o) = [0, 1, 0, 0, \ldots, 0, 1] \in \mathbb{R}^{d'}$	$\phi(t) = [1, 0, 0, 0, \ldots, 1, 0] \in \mathbb{R}^{d}$
Bag of aligned words	Bag of aligned words
(the, dog, pet, . . .)	(saw, him, notice, . . .)

Training a Bi-layered L-PCFG

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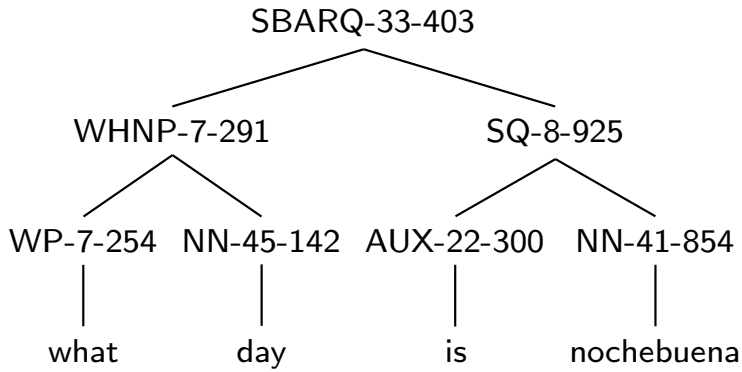

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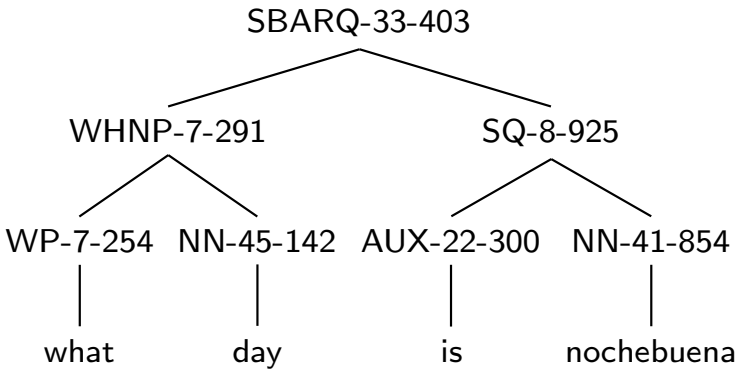

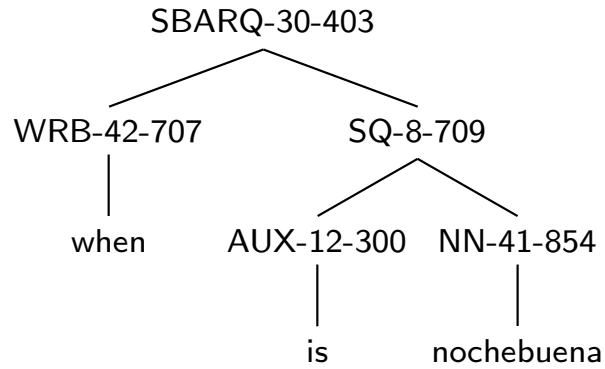

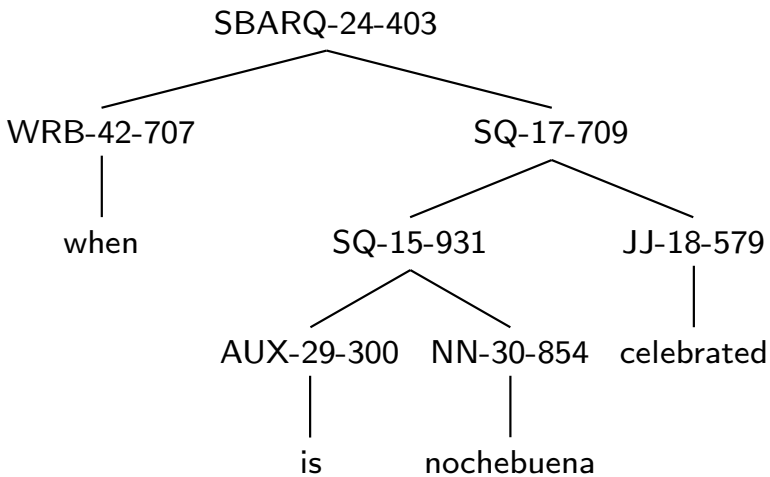

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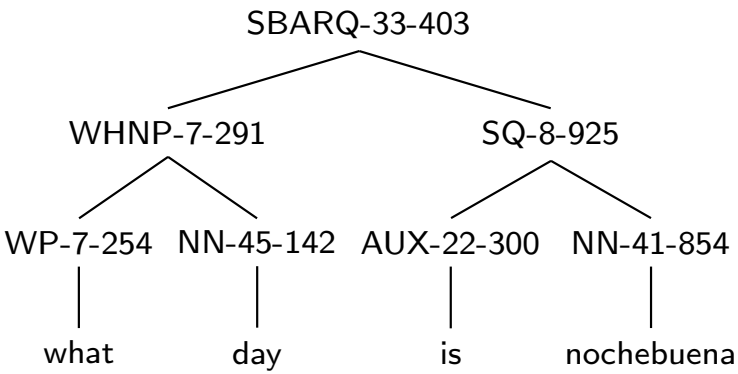
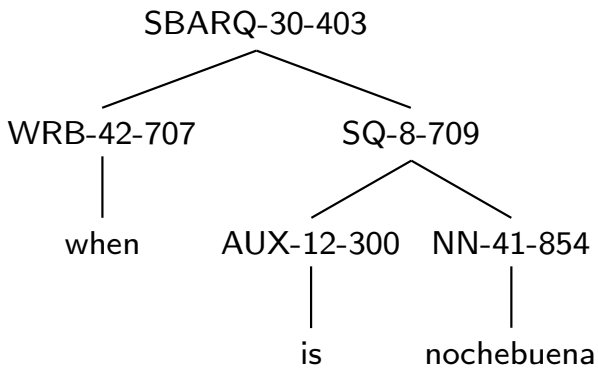
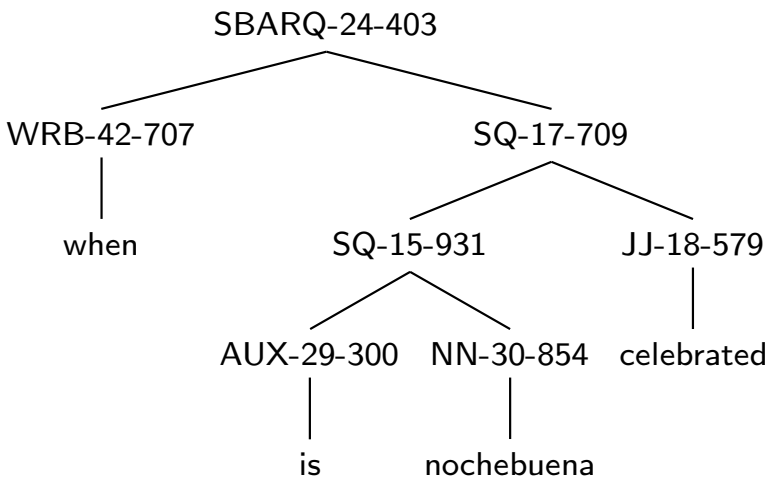
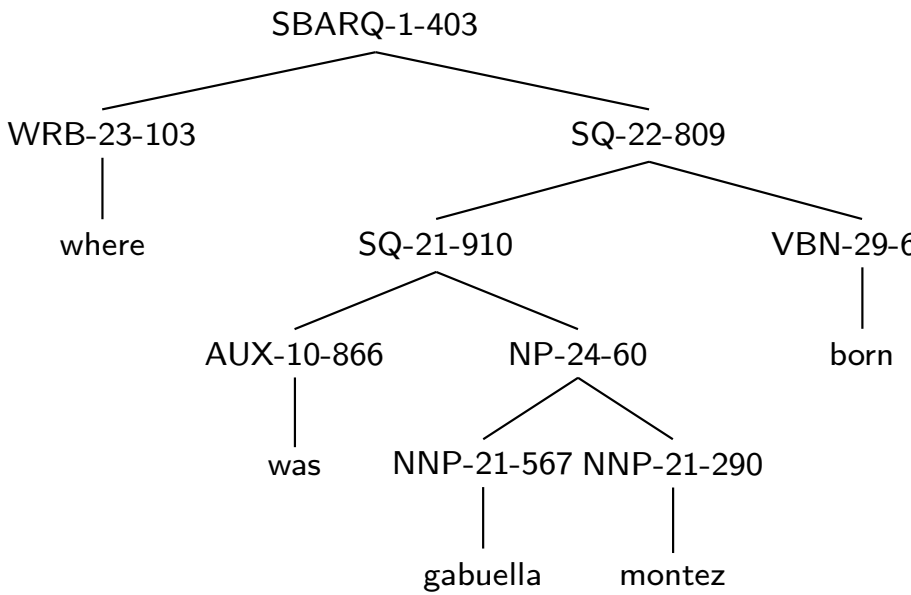
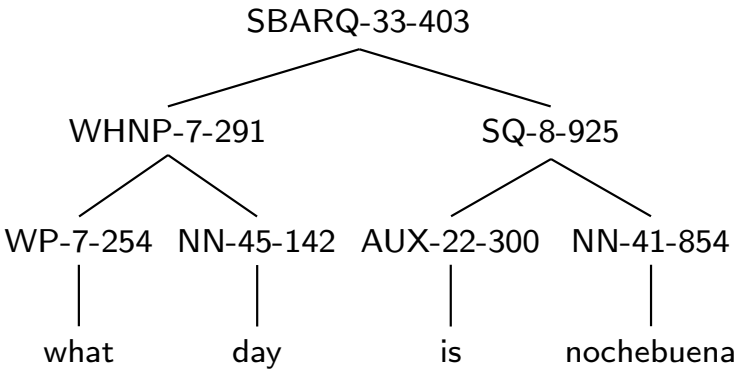


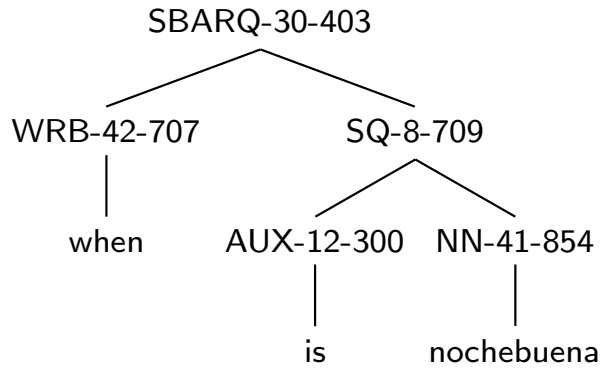


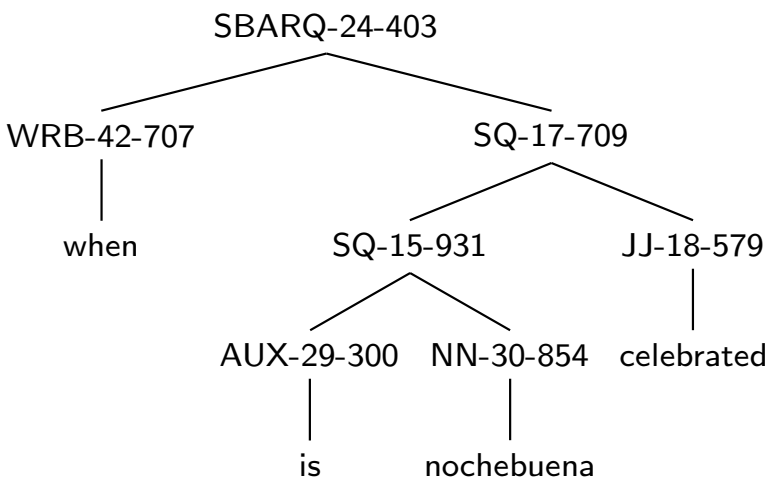


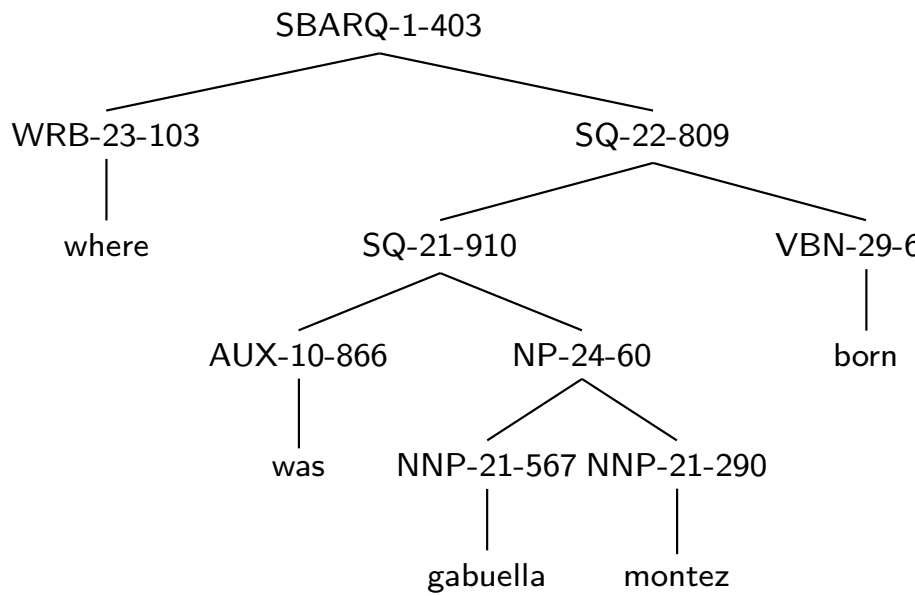


Inducing Paraphrases with a Bi-layered L-PCFG









Inducing lexical paraphrases only

Outline of this talk

Spectral Learning of Latent-variable PCFGs

Paraphrase Generation using L-PCFGs

Semantic Parsing using Paraphrases

Results and Discussion

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Semantic Parsing using Paraphrases (Reddy et. al., 2014)

What language do people in Czech Republic speak?

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What language do people in Czech Republic speak? What is Czech Republic's language? What language do people speak in Czech Republic? ...

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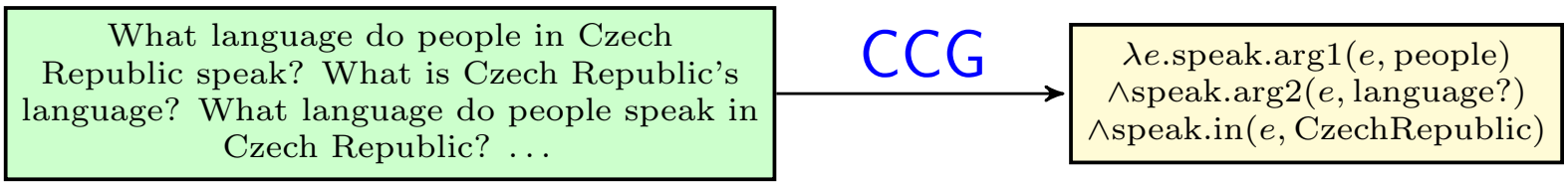

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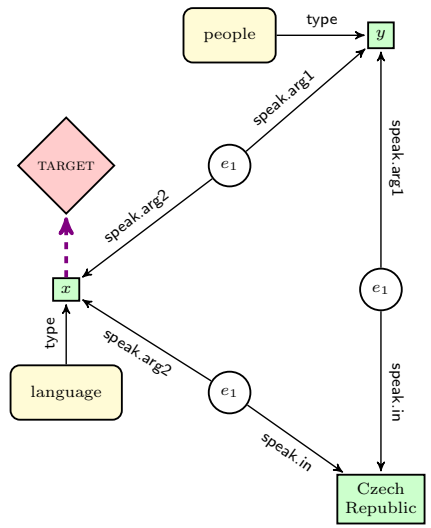
CCG

$\lambda e.\text{speak.arg1}(e, \text{people})$
$\wedge \text{speak.arg2}(e, \text{language?})$
$\wedge \text{speak.in}(e, \text{CzechRepublic})$



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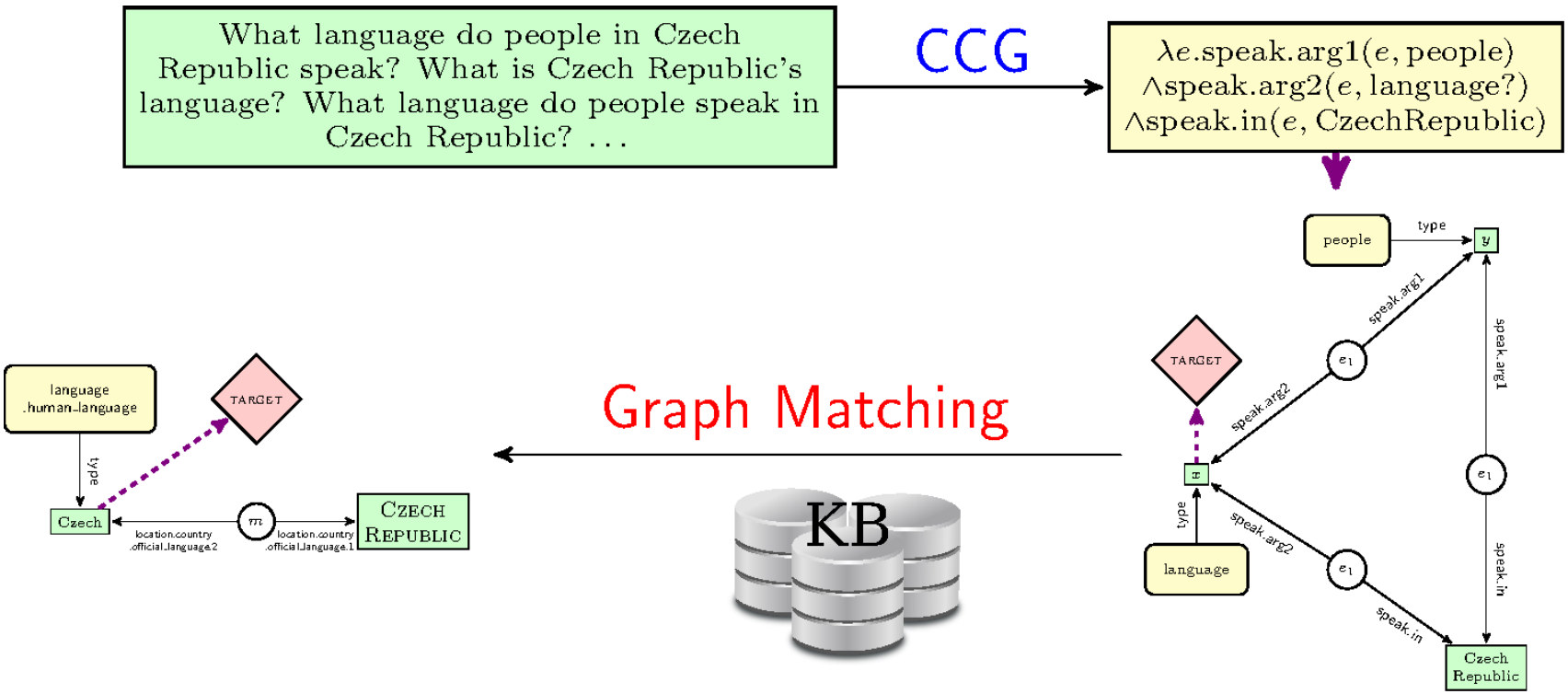

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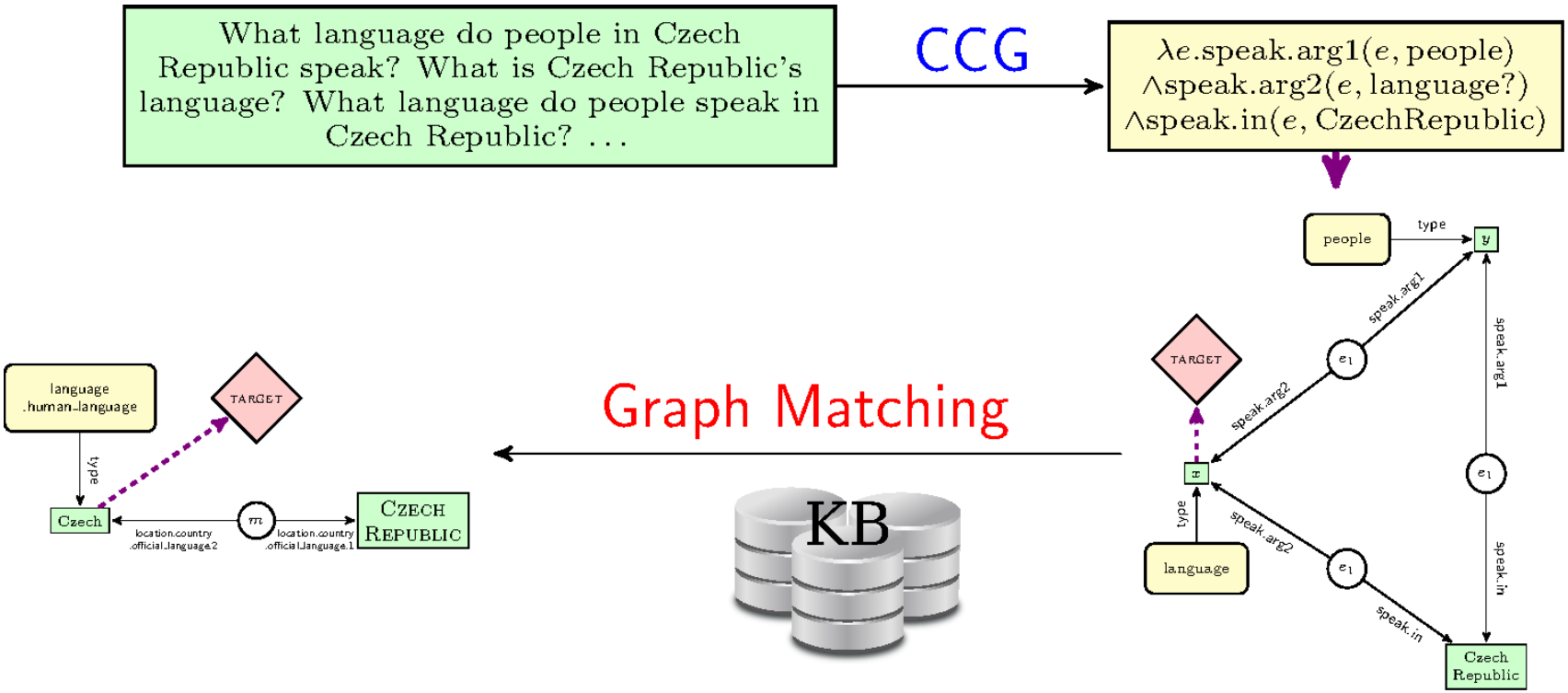

$$(\hat{p}, \hat{u}, \hat{g}) = \underset{(p,u,g)}{\arg\max}\, \theta \cdot \Phi(p, u, g, q, \mathcal{K})$$

where, $\Phi(p, u, g, q, \mathcal{K}) \in \mathbb{R}^n$ denotes the features for the tuple of paraphrase p, ungrounded u and grounded g graphs

Model

Structured Perceptron: Ranks a tuple of paraphrase, grounded and ungrounded graph.

$$(\hat{p}, \hat{u}, \hat{g}) = \arg\max_{(p,u,g)} \theta \cdot \Phi(p, u, g, q, \mathcal{K})$$

Features: Φ is defined over sentence, grounded and ungrounded graph.

Training: Use surrogate gold graph to update weights

$$\theta^{t+1} \leftarrow \theta^t + \Phi(p^+, u^+, g^+, q, \mathcal{K}) - \Phi(\hat{p}, \hat{u}, \hat{g}, q, \mathcal{K}),$$

More details: We use Margin-Sensitive Averaged Peceptron.

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Experimental Setup

WebQuestions (Berant et al., 2013)

- Google search queries starting with wh question words
- 5,810 question-answer pairs (3,778 training and 2,032 test)
- *Development experiments*: held-out data consisting of 30% training questions

Experimental Setup

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Evaluation metric

- Average precision, average recall and average F_1 (Berant et al., 2013)

Experimental Setup

Our systems

- NAIVE: Word lattice representing the input sentence itself
- PPDB: Word lattice constructed using the PPDB rules
- BILAYERED: Word lattice constructed using the bi-layered L-PCFG

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Baselines

- ORIGINAL: Semantic parser (Reddy et. al., 2014) without paraphrases
- MT: Monolingual machine translation based model for paraphrase generation (Quirk et al., 2004; Wubben et al., 2010)

Results on the Development Set

Oracle statistics and Average F_1 Scores

Method	avg oracle F_1	# oracle graphs	avg F_1
ORIGINAL	65.1	11.0	44.7
MT	71.5	77.2	47.0
NAIVE	71.2	53.6	47.5
PPDB	71.8	59.8	47.9
BILAYERED	71.6	55.0	47.1

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Method	avg P.	avg R.	avg F_1
ORIGINAL	53.2	54.2	45.0
MT	48.0	56.9	47.1
NAIVE	48.1	57.7	47.2
PPDB	48.4	58.1	47.7
BILAYERED	47.0	57.6	47.2

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Others			
Berant and Liang '14	40.5	46.6	39.9
Bordes et al. '14	-	-	39.2
Dong et al. '15	-	-	40.8
Yao '15	52.6	54.5	44.3
Bao et al. '15	44.7	52.5	45.3
Bast and Haussmann '15	49.8	60.4	49.4
Berant and Liang '15	50.4	55.7	49.7
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Error Mining

78.4% of the errors are partially correct answers occurring due to incomplete gold answer annotations or partially correct groundings

13.5% are due to bad paraphrases, and

the rest 8.1% are due to wrong entity annotations

Conclusion

Our method is rather generic and can be applied to any question answering system

Bi-layered L-PCFG for semantic similarity tasks