Microsoft Research

Microsoft

Semantic Parsing via Staged Query Graph Generation: Question Answering with Knowledge Base

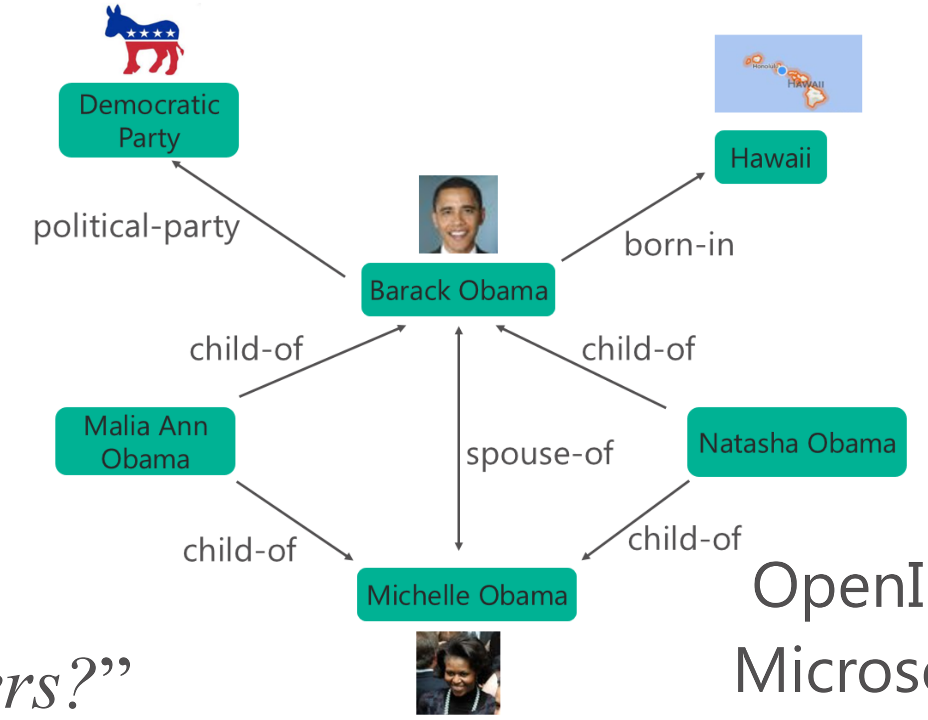
Scott Wen-tau Yih
Ming-Wei Chang, Xiaodong He, Jianfeng Gao

Question Answering with Knowledge Base

- Large-scale Knowledge Base
  - Properties of billions of entities
  - Plus relations among them
- Question Answering

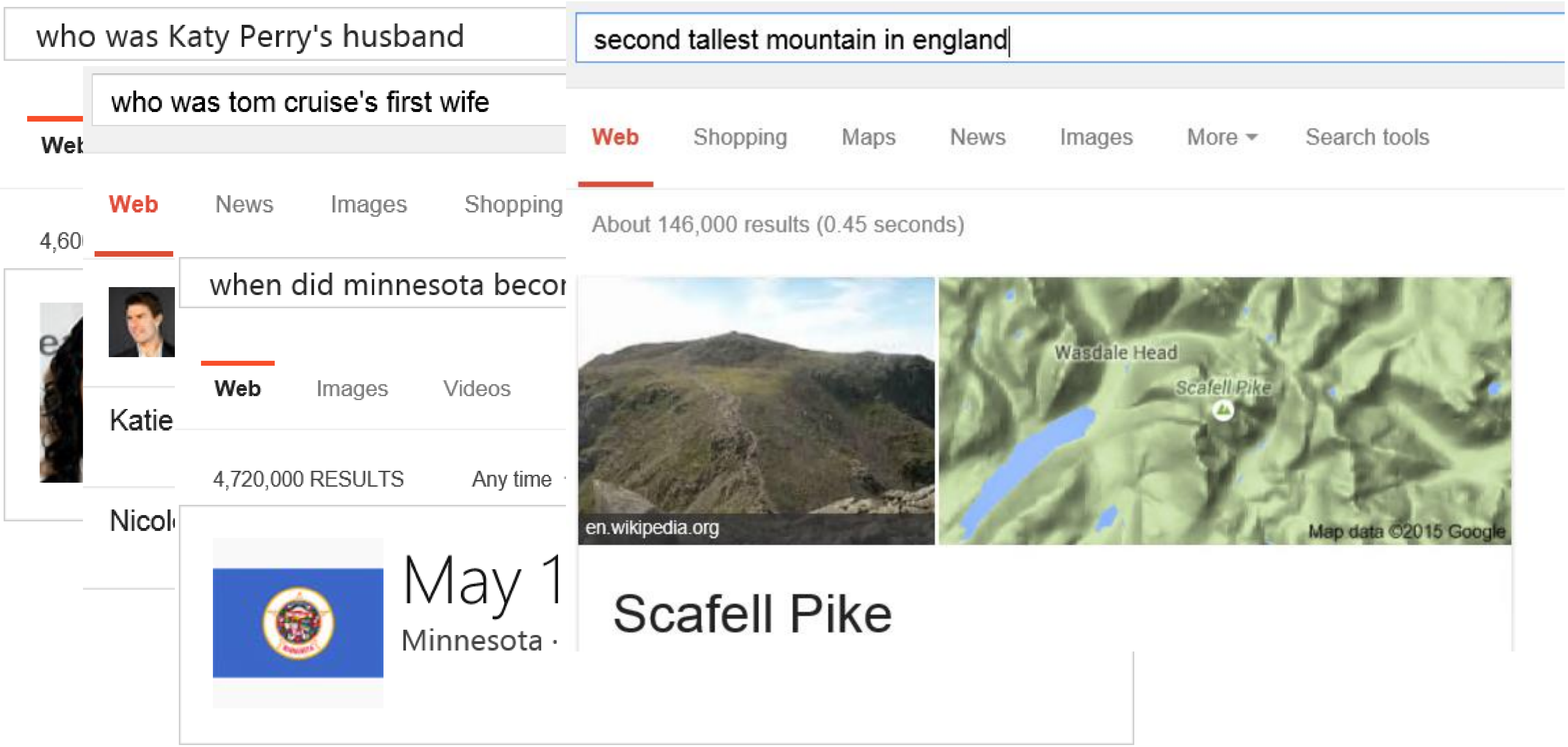
  “*What are the names of Obama’s daughters?*”

  $\lambda x.parent(Obama, x) \wedge gender(x, Female)$



Freebase
DBpedia
YAGO
NELL
OpenIE/ReVerb
Microsoft Satori

Search Engine → QA Engine



Generic Semantic Parsing (e.g., [Kwiatkowski+ 13])

Who is Justin Bieber's sister?

Jazmyn Bieber

semantic parsing

$\lambda x.\, \text{sister\_of}(\text{justin\_bieber}, x)$

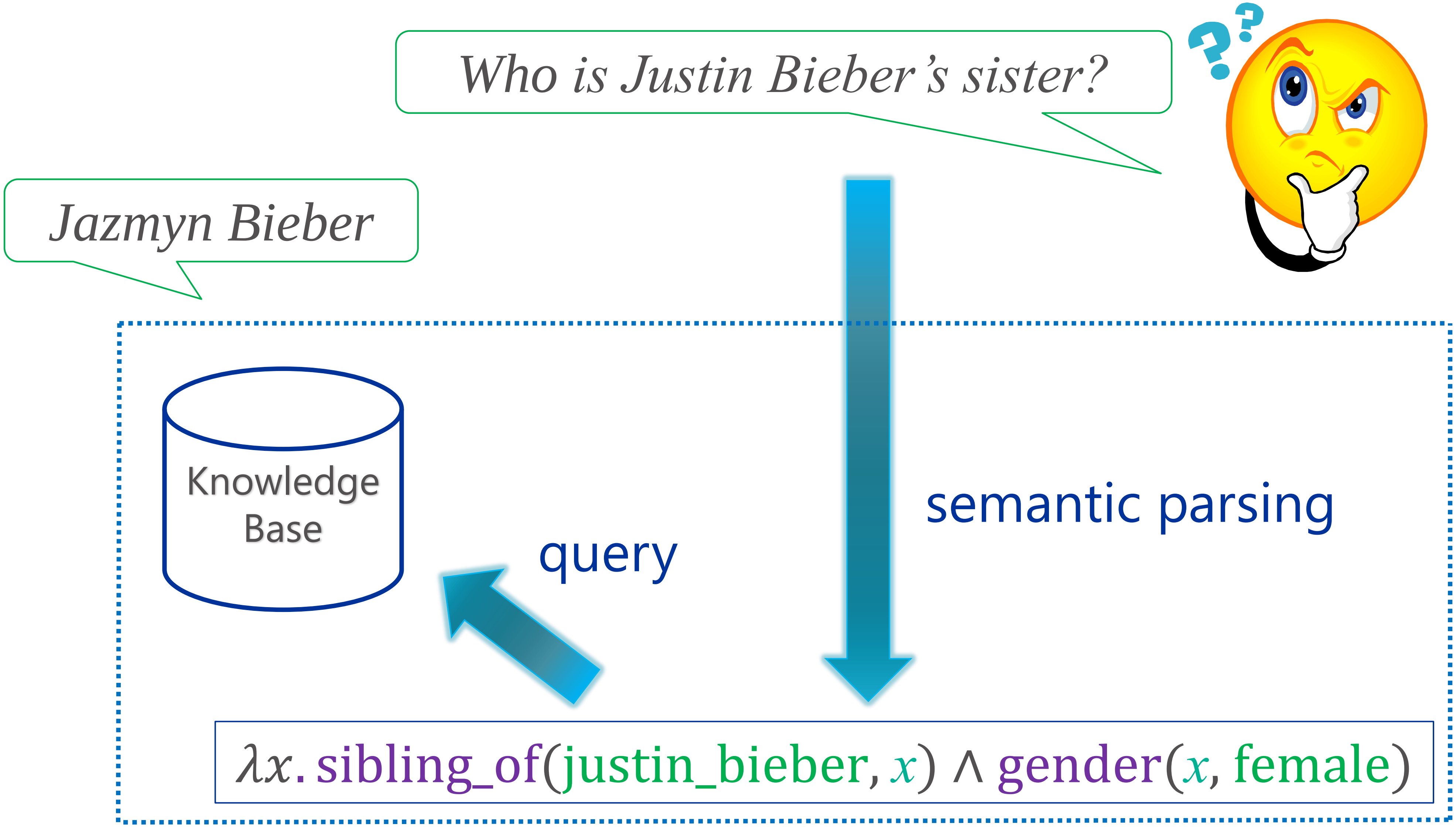
matching

$\lambda x.\, \text{sibling\_of}(\text{justin\_bieber}, x) \wedge \text{gender}(x, \text{female})$

query

Knowledge Base

KB-Specific Semantic Parsing (e.g., [Berant+ 13])



Key Challenges

- Language mismatch
  - Lots of ways to ask the same question

    "What was the date that Minnesota became a state?"

    "When was the state Minnesota created?"

    "Minnesota's date it entered the union?"
  - Need to map them to the predicate defined in KB

    location.dated_location.date_founded
- Large search space
  - Some Freebase entities have >160,000 immediate neighbors
- Compositionality

Staged Query Graph Generation

Basic idea

- Query graph
  - Resembles subgraphs of the knowledge base
  - Can be *directly* mapped to a logical form in λ-calculus
- Semantic parsing
  - A search problem that *grows* the graph through *staged* state-actions

Staged Query Graph Generation
Addresses Key Challenges

- Language mismatch
  - Advanced entity linking
  - Relation matching via deep convolutional NN
- Large search space
  - Representation power of a parse controlled by staged search actions
  - Grounding partially the utterance during search
- Compositionality
  - Possible combinations limited by local subgraphs

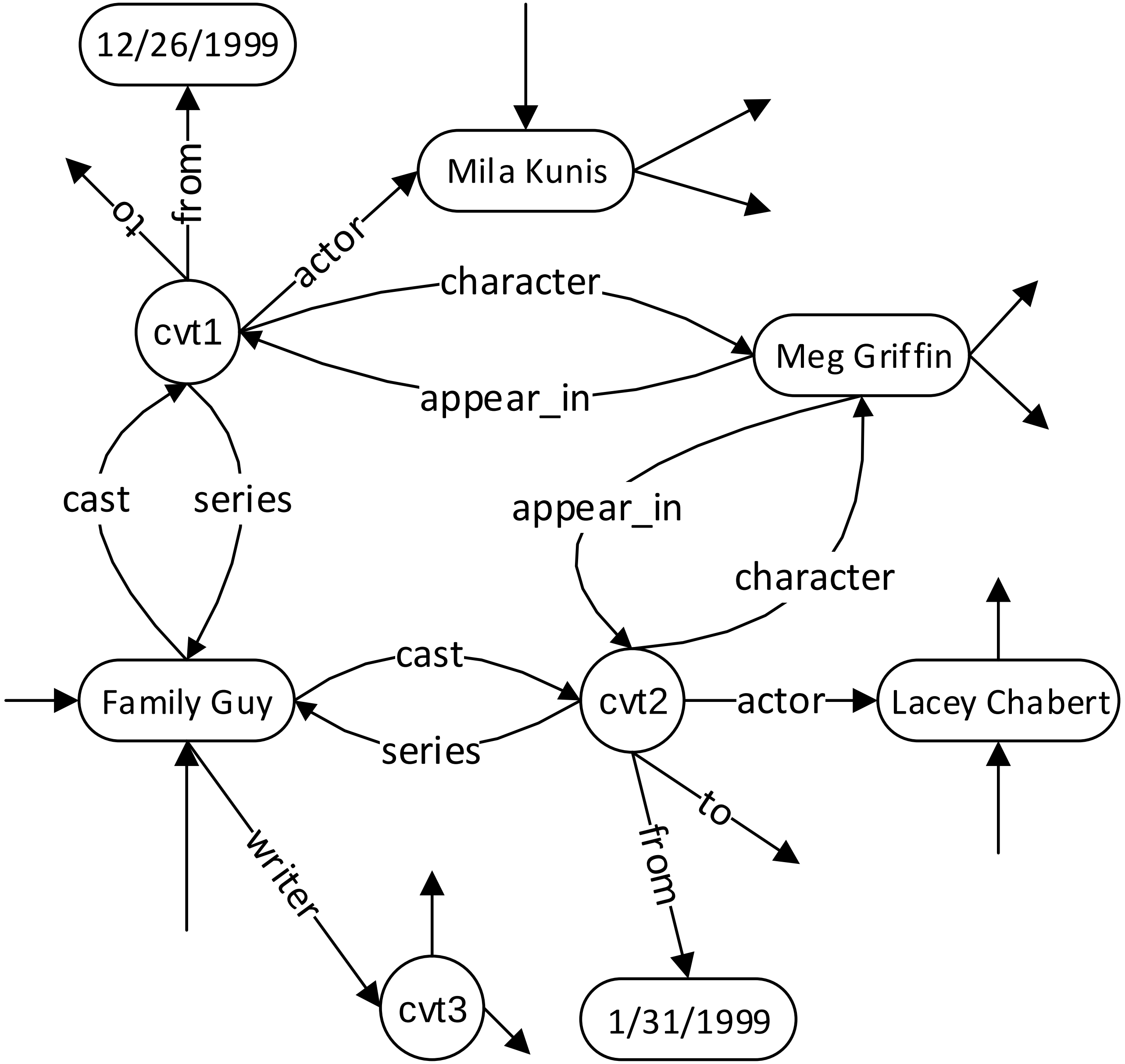
52.5% F_1 (Accuracy) on WebQuestions

Outline

- Introduction
- Background
  - Graph knowledge base
  - Query graph
- Staged Query Graph Generation (Our Approach)
- Experiments
- Conclusion

Knowledge Base

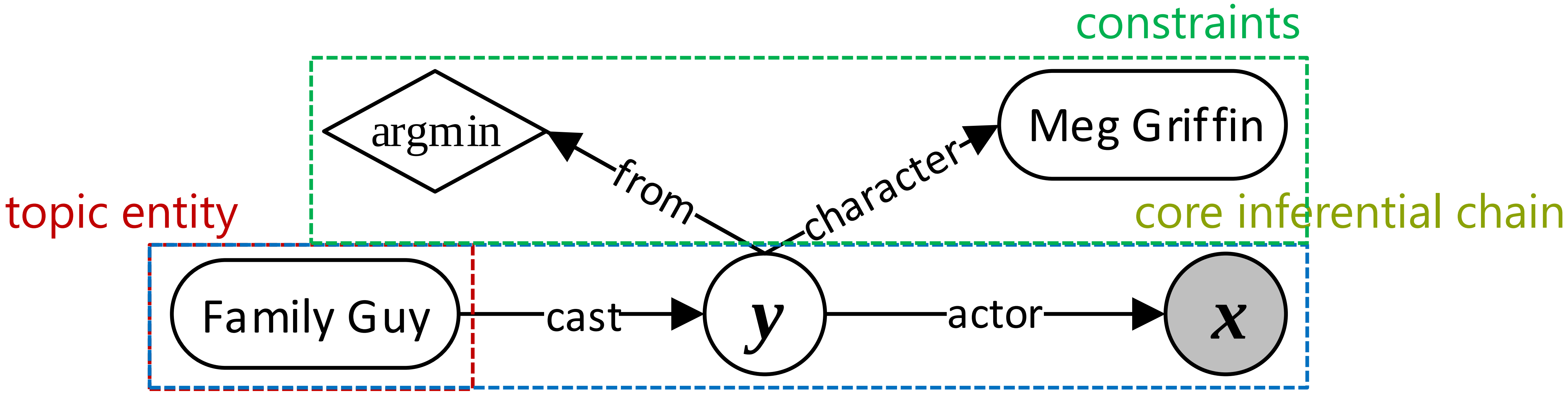
- Triples of **subj-pred-obj** (e_1, p, e_2)
- Knowledge graph
  - Each entity is a node
  - Two related entities linked by a directed edge (predicate)
- CVT node
  - Compound value type
  - Encode n-ary relations



Query Graph

Who first voiced Meg on Family Guy?

$$\lambda x.\, \exists y.\, \mathrm{cast}(\mathrm{FamilyGuy}, y) \wedge \mathrm{actor}(y, x) \wedge \mathrm{character}(y, \mathrm{MegGriffin})$$



Inspired by [Reddy+ 14], but closer to λ-DCS [Liang 13]

Outline

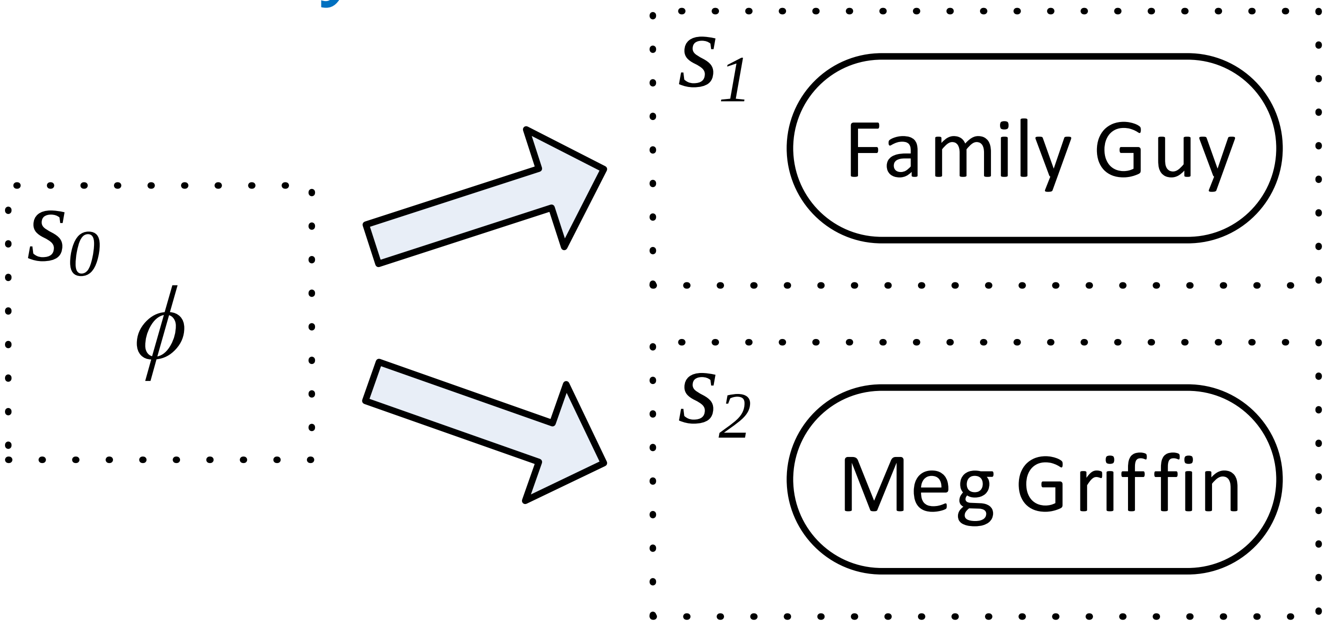
- Introduction
- Background
- Staged Query Graph Generation (Our Approach)
  - Link topic entity
  - Identify core inferential chain
  - Augment constraints
- Experiments
- Conclusion

Staged Query Graph Generation

- A search problem with staged states and actions

Who first voiced Meg on Family Guy?

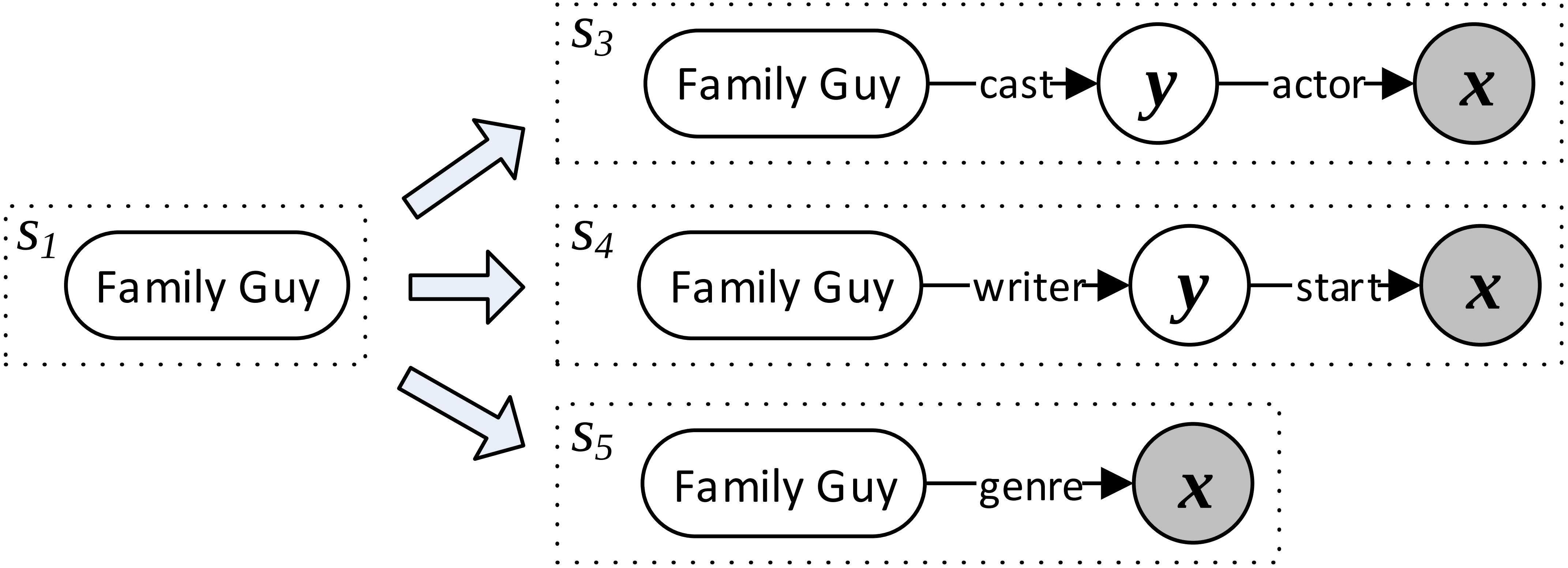
(1) Link Topic Entity



Staged Query Graph Generation

Who first voiced Meg on Family Guy?

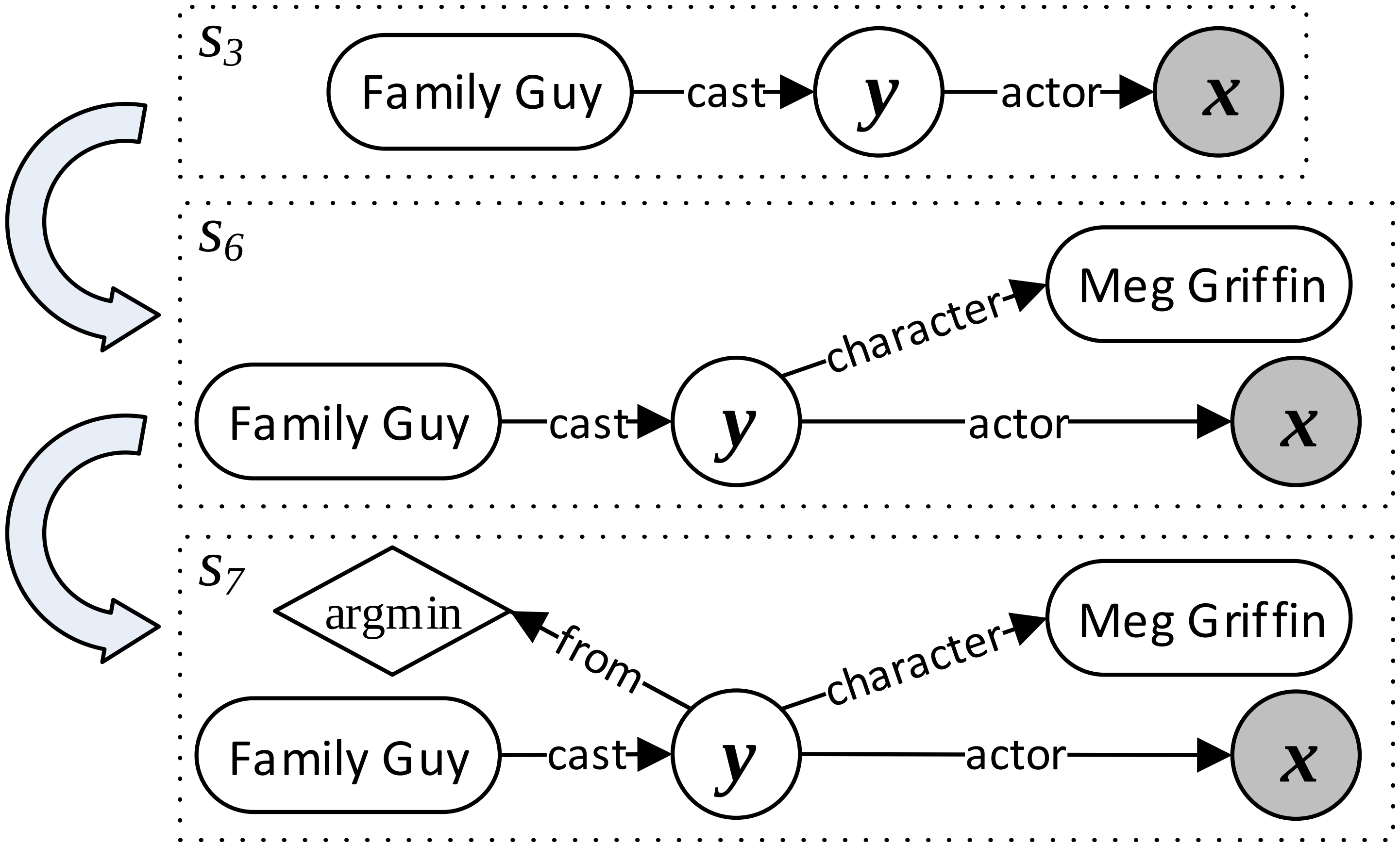
(2) Identify Core Inferential Chain



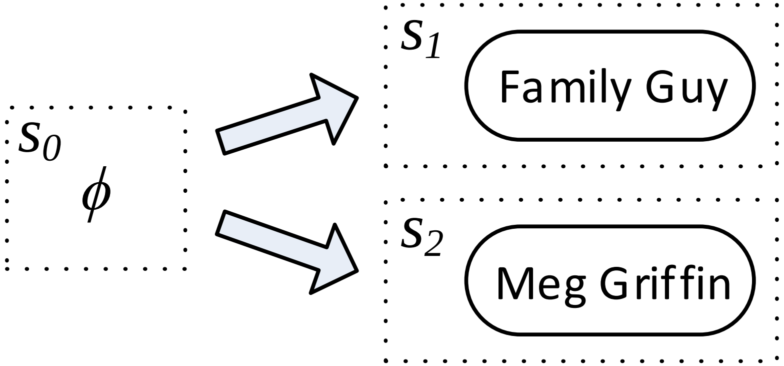
Staged Query Graph Generation

Who first voiced Meg on Family Guy?

(3) Augment Constraints



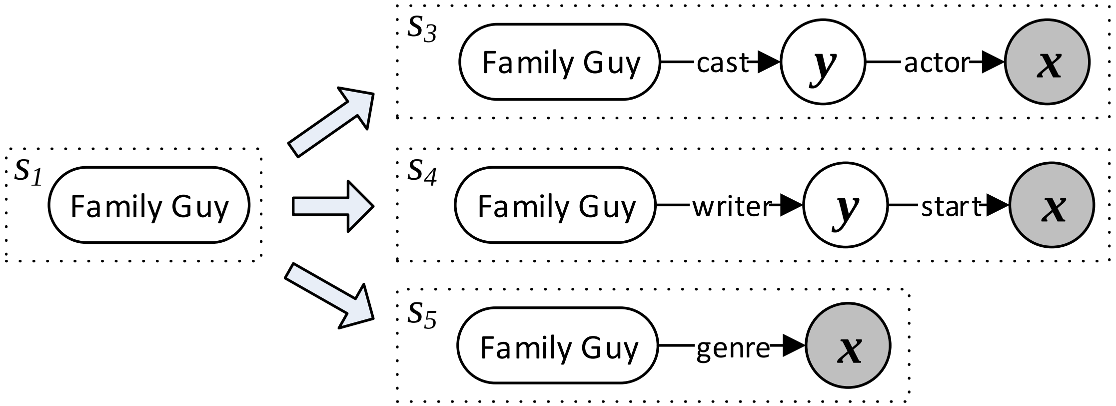
Link Topic Entity



- An advanced entity linking system for short text
  Yang & Chang, "*S-MART: Novel Tree-based Structured Learning Algorithms Applied to Tweet Entity Linking.*" In ACL-15.
- Prepare surface-form lexicon $\mathcal{L}$ for entities in the KB
- Entity mention candidates: all consecutive word sequences in $\mathcal{L}$, scored by the statistical model
- Up to 10 top-ranked entities are considered as topic entity

Identify Core Inferential Chain

- Relationship between topic and answer (x) entities
- Explore two types of paths
  - Length 1 to non-CVT node
  - Length 2 where y can be grounded to CVT



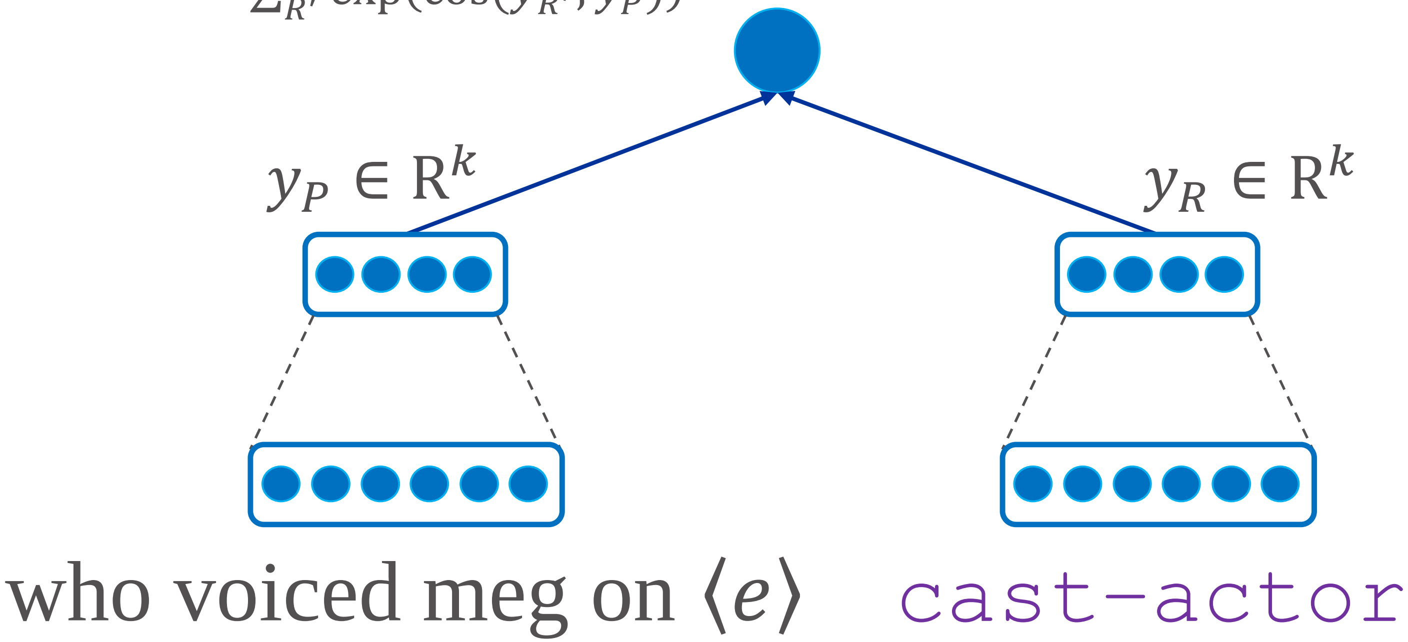
Who first voiced Meg on Family Guy?

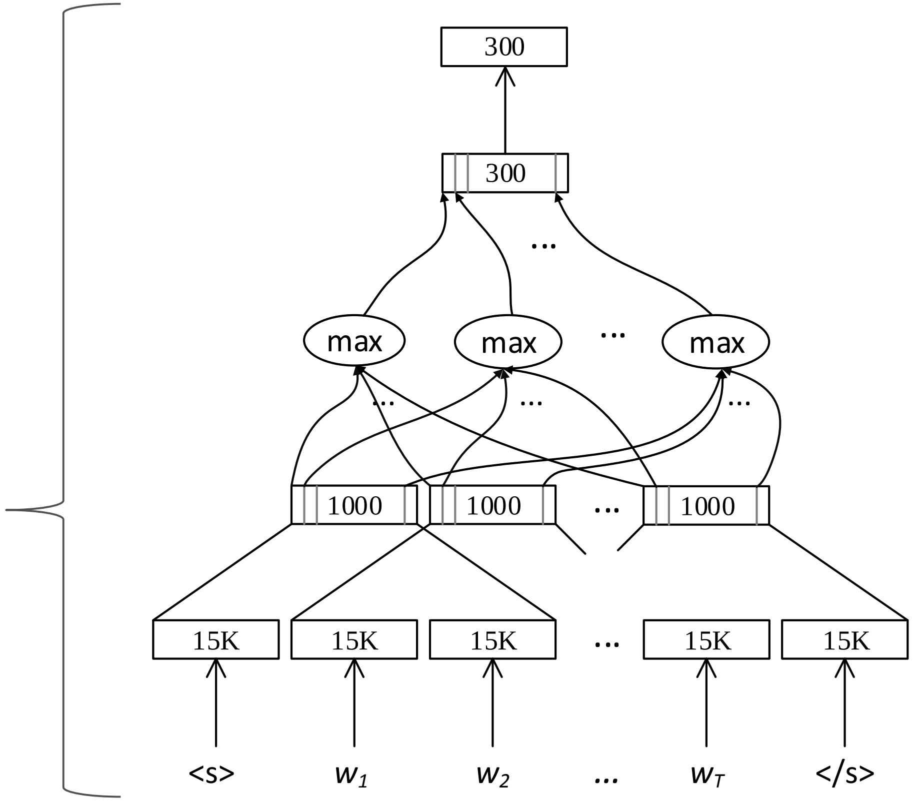
{cast-actor, writer-start, genre}

Relation Matching using Deep Convolutional Neural Networks (DSSM [Shen+ 14])

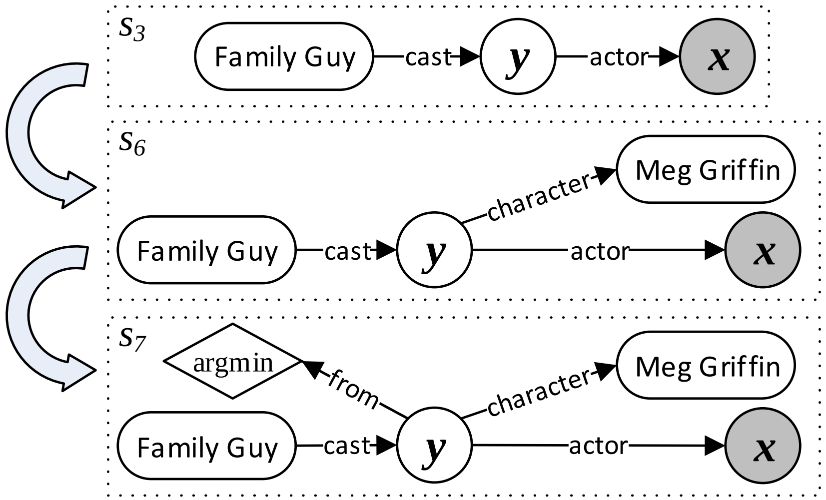
- Input is mapped to two $\boldsymbol{k}$-dimensional vectors
- Probability is determined by softmax of their cosine similarity

$$P(R|P) = \frac{\exp(\cos(y_R, y_P))}{\sum_{R'} \exp(\cos(y_{R'}, y_P))}$$

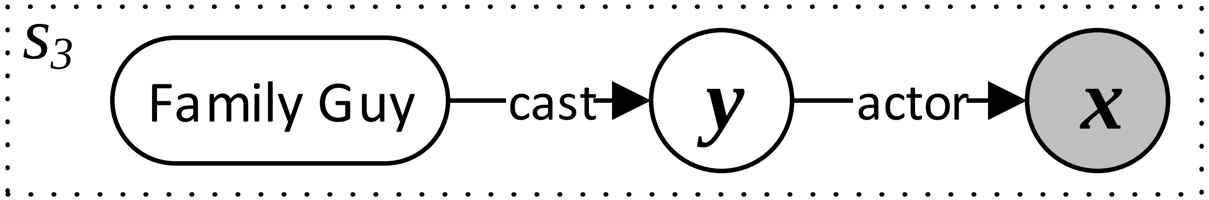




Augment Constraints



- Who first voiced Meg on Family Guy?



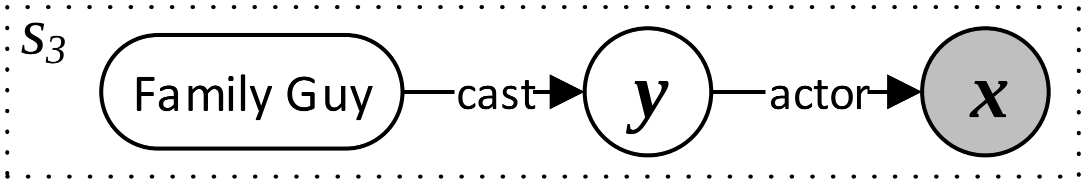
$$\lambda x. \exists y. \mathrm{cast}(\mathrm{FamilyGuy}, y) \wedge \mathrm{actor}(y, x)$$

- One or more constraint nodes can be added to y or x
  - y : Additional property of this event (e.g., $\mathrm{character}(y, \mathrm{MegGriffin})$)
  - x : Additional property of the answer entity (e.g., gender)
- Only subset of constraint nodes are considered
  - e.g., entities detected in the question (more detail in Appendix)

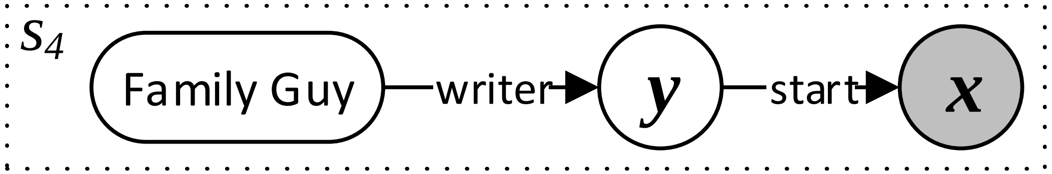
Learning Reward Function γ

- Judge whether a query graph is a correct semantic parse
- Log-linear model with pairwise ranking objective [Burges 10]

Who first voiced Meg on Family Guy?

$\gamma($ 

$)$

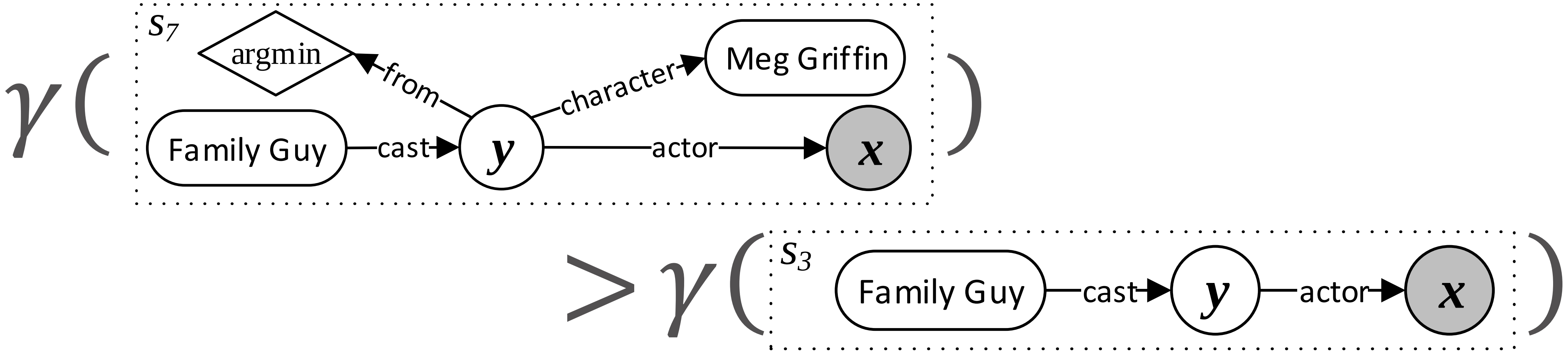
$> \gamma($ 

$)$

Learning Reward Function γ

- Judge whether a query graph is a correct semantic parse
- Log-linear model with pairwise ranking objective [Burges 10]

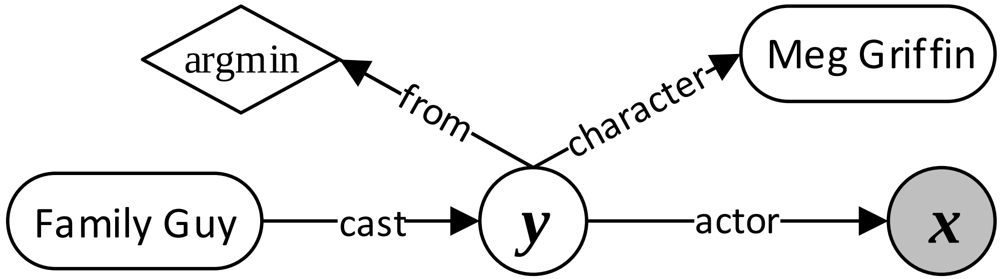
Who first voiced Meg on Family Guy?



Learning Reward Function – Features

q = Who first voiced Meg on Family Guy?

s =



- Topic Entity
  - Entity linking scores
- Core Inferential Chain
  - Relation matching scores (NN models)
- Constraints: Keyword and entity matching
  - ConstraintEntityWord("Meg Griffin", q) = 0.5
  - ConstraintEntityInQuestion("Meg Griffin", q) = 1
- Overall
  - NumNodes(s) = 5
  - NumAnswers(s) = 1

Outline

- Introduction
- Background
- Staged Query Graph Generation (Our Approach)
- Experiments
  - Data & evaluation metric
  - Creating training data from Q/A pairs
  - Results
- Conclusion

WebQuestions Dataset [Berant+ 13]

- *What character did Natalie Portman play in Star Wars?* ⇒ Padme Amidala
- *What currency do you use in Costa Rica?* ⇒ Costa Rican colon
- *What did Obama study in school?* ⇒ political science
- *What do Michelle Obama do for a living?* ⇒ writer, lawyer
- *What killed Sammy Davis Jr?* ⇒ throat cancer

[Examples from Berant]

- 5,810 questions crawled from Google Suggest API and answered using Amazon MTurk
  - 3,778 training, 2,032 testing
  - A question may have multiple answers → using Avg. F1 (~accuracy)

Creating Training Data from Q/A Pairs

Relation Matching (Identifying Core Inferential Chain)

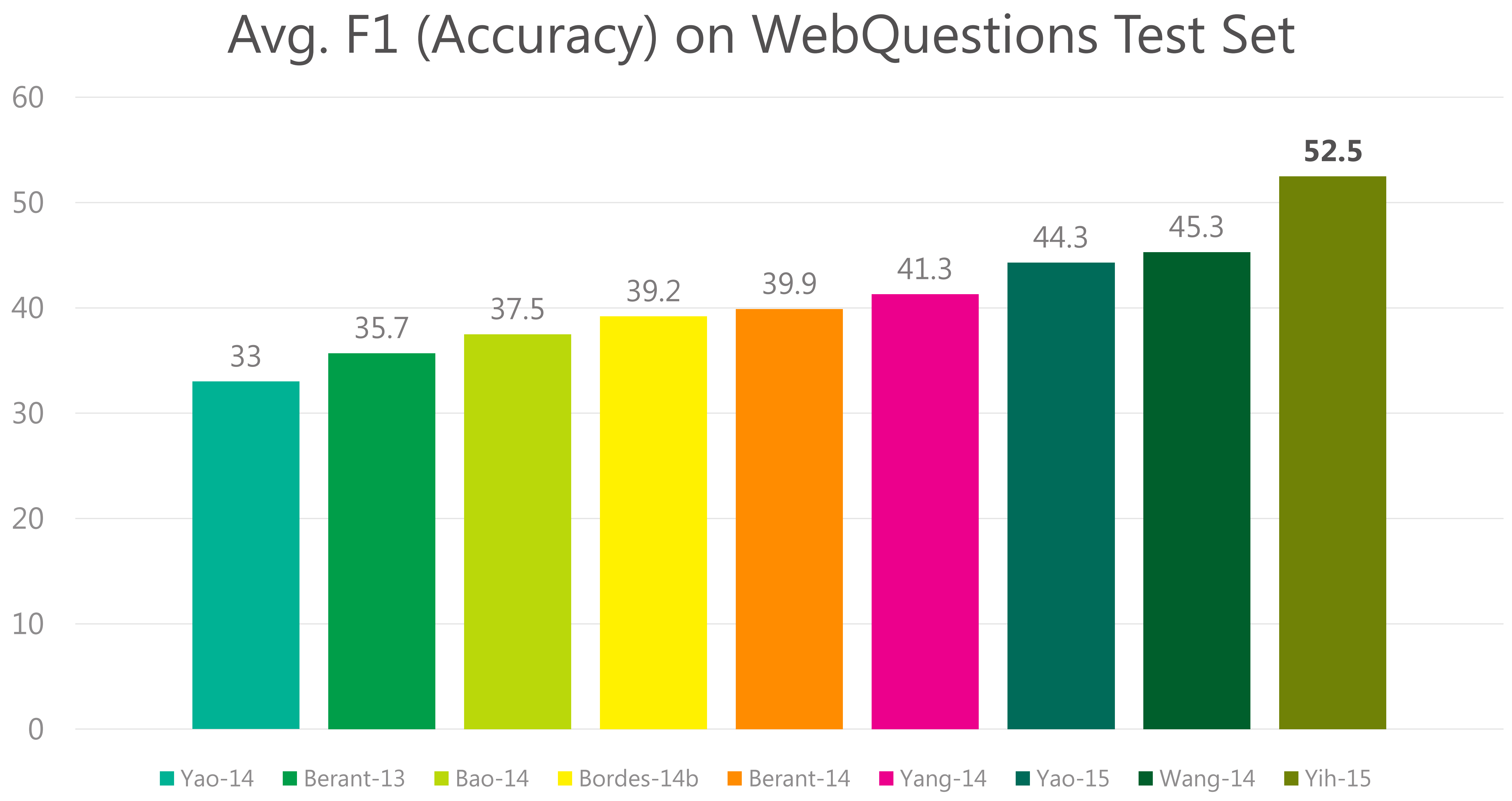
- List all the length 1 & 2 paths from any potential topic entity
- Treat any inferential chain resulting in $F_1 \geq 0.5$ to create positive pairs

Pattern	Inferential Chain
what was <e> known for	people.person.profession
what kind of government does <e> have	location.country.form_of_government
what year were the <e> established	sports.sports_team.founded
what city was <e> born in	people.person.place_of_birth
what did <e> die from	people.deceased_person.cause_of_death
who married <e>	people.person.spouse_s people.marriage.spouse

Creating Training Data from Q/A Pairs

Reward Function γ

- Apply the same best-first search procedure to training data
- Use the F_1 score of the query graph as the reward function
- For each question, create 4,000 candidate query graphs
  - All positive ($F_1 > 0$) examples
  - Randomly selected negative examples


Avg. F1 (Accuracy) on WebQuestions Test Set
60
50
40
30
20
10
0
33
35.7
37.5
39.2
39.9
41.3
44.3
45.3
52.5
Yao-14
Berant-13
Bao-14
Bordes-14b
Berant-14
Yang-14
Yao-15
Wang-14
Yih-15

Contribution from Entity Linking

- Statistics of entity linking results on training set questions

Method	#Entities	Covered Ques.	Labeled Ent.
Freebase API	19,485	98.8%	81.2%
Yang & Chang, ACL-15	9,147	99.8%	87.8%

- F_1 drops from 52.5% to 48.4% when using Freebase API

Contribution from Relation Matching

- F_1 score of query graphs that have only a core inferential chain: 49.6 (vs. 52.5 full system)

- Questions from search engine users are short & simple
  - 1,888 (50%) training questions can be answered exactly ($F_1 = 1$)
- Even if the correct parse requires more constraints, the less constrained graph still gets a partial score

Error Analysis

A random sample of 100 incorrectly answered questions

- Label issues (34%)
  - Label error (2%)
  - Incomplete labels (17%, e.g., “What songs did Bob Dylan write?”)
  - Acceptable answers (15%, e.g., “Time in China” vs. “UTC+8”)
- Incorrect entity linking (8%)
- Incorrect inferential chain (35%)
- Incorrect/Missing constraints (23%)

Conclusions (1/2)

A new framework for semantic parsing of questions

- Query graph
  - Meaning representation that can be *directly* mapped to logical form, using predicates in target KB
- Semantic parsing
  - Query graph generation as staged search problem
- New state-of-the-art on WebQuestions (52.5 F_1)
  - Advanced entity linking
  - Convolutional NN for relation matching

Conclusions (2/2)

- Future Work
  - Improve the current system
    - Matching relations more accurately
    - Handling constraints in a more principled way
    - Joint structured-output prediction model (e.g., SEARN [Daumé III 06])
  - Extend the query graph to represent more complicated questions
- Data & Resource
  - Sent2Vec (DSSM) http://aka.ms/sent2vec
  - System output http://aka.ms/codalab-webq
  - Intermediate files (e.g., entity linking, model files, training data, etc.) will be released soon http://aka.ms/stagg