Common Sense Knowledge in Automatic Knowledge Base Population

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Joint work with
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- Schema
- Facts

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Automatic Knowledge Base Population

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- Hot! Relatively more attention
- Entity and Relation

Here

Populating knowledge facts for existing entity pairs

Theme: Identifying relationship between pairs of entities.

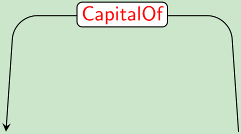
Example

CapitalOf

Paris, capital of France, is the biggest city in Europe.

Theme: Identifying relationship between pairs of entities.

Example



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Relation Extraction

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  - IS-A, event-related, semantic relations , KB predicates
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  - [object] * capital of [subject]
  - relying on fine-gained rules
- Statistical machine learning methods
  - in a supervised manner
  - fancy models, feature engineering, ...

New Assumption: Distant Supervision

Marriage of structured KB and text

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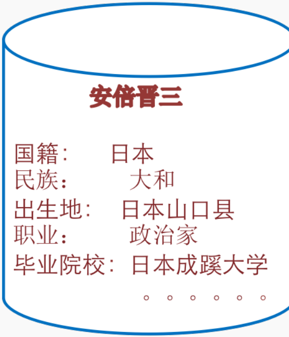

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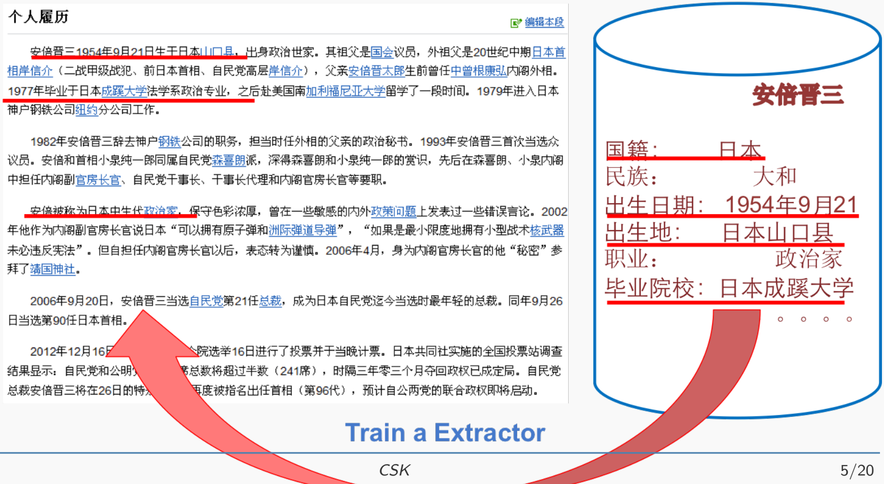

个人履历

编辑本段

安倍晋三1954年9月21日生于日本山口县，出身政治世家。其祖父是国会议员，外祖父是20世纪中期日本首相岸信介（二战甲级战犯、前日本首相、自民党高层岸信介），父亲安倍晋太郎生前曾任中曾根康弘内阁外相。1977年毕业于日本成蹊大学法学系政治专业，之后赴美国南加利福尼亚大学留学了一段时间。1979年进入日本神户钢铁公司纽约分公司工作。

1982年安倍晋三辞去神户钢铁公司的职务，担当时任外相的父亲的政治秘书。1993年安倍晋三首次当选众议员。安倍和首相小泉纯一郎同属自民党森喜朗派，深得森喜朗和小泉纯一郎的赏识，先后在森喜朗、小泉内阁中担任内阁副官房长官、自民党干事长、干事长代理和内阁官房长官等要职。

安倍被称为日本中生代政治家，保守色彩浓厚，曾在一些敏感的内外政策问题上发表过一些错误言论。2002年他作为内阁副官房长官说日本“可以拥有原子弹和洲际弹道导弹”，“如果是最小限度地拥有小型战术核武器未必违反宪法”。但自担任内阁官房长官以后，表态转为谨慎。2006年4月，身为内阁官房长官的他“秘密”参拜了靖国神社。

2006年9月20日，安倍晋三当选自民党第21任总裁，成为日本自民党迄今当选时最年轻的总裁。同年9月26日当选第90任日本首相。

2012年12月16[illegible]院选举16日进行了投票并于当晚计票。日本共同社实施的全国投票站调查结果显示：自民党和公明[illegible]席总数将超过半数（241席），时隔三年零三个月夺回政权已成定局。自民党总裁安倍晋三将在26日的特[illegible]再度被指名出任首相（第96代），预计自公两党的联合政权即将启动。

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- more observations: overlap relations, multiple relations, more noises, ...
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- Fancier models, Harder engineering, ...
- Machine learning drives our research!

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- 不忘初心！

More to Do

Knowledge are far more than individual <s, p, o> triples,

- not isolated, but connected in nature

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- Mao was born in China
- Mao was born in US

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- Mao was born in US
- Born in two countries?

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- Mao was born in 1990
- Mao graduated from MIT in 1991

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- Mao was born in 1990
- Mao graduated from MIT in 1991
- A one-year-old MIT student?

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Example

- Mao met with Lin in Beijing this morning
- Mao visit MoMA of New York this afternoon

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- Hours to fly 12,000km?

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- **A type of Common Sense Knowledge**

- more general, enduring but dynamic...
- predictive, explanatory, ...
- causal
- ...

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- Hence, hard to utilize by computers

Our Attempt I: RE [Chen et al. (ACL 2014)]

In Relation Extraction,

- Local predictions may not be coherent

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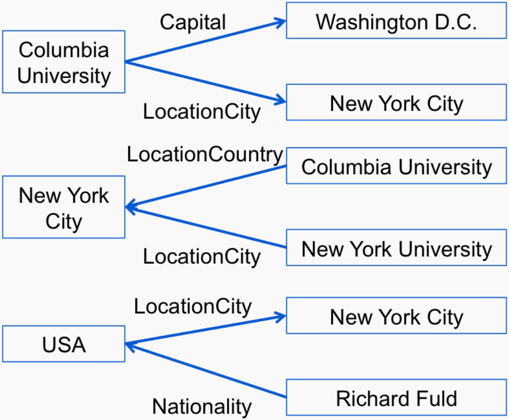

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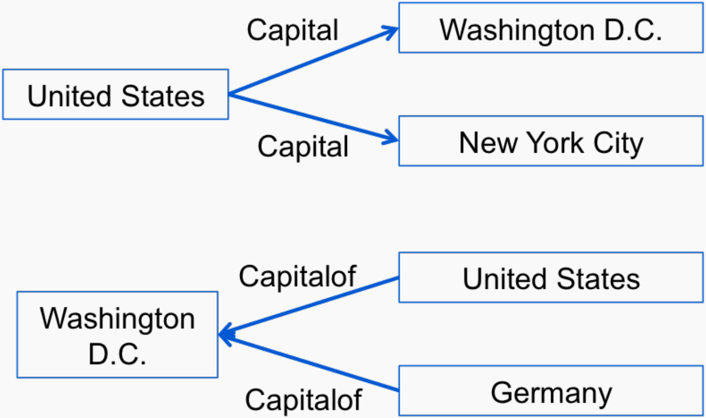

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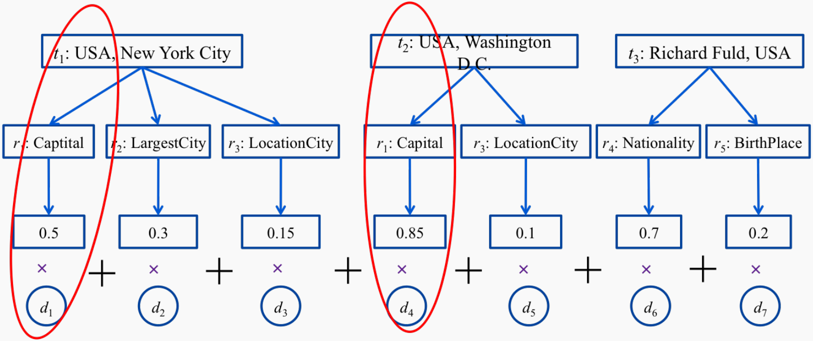
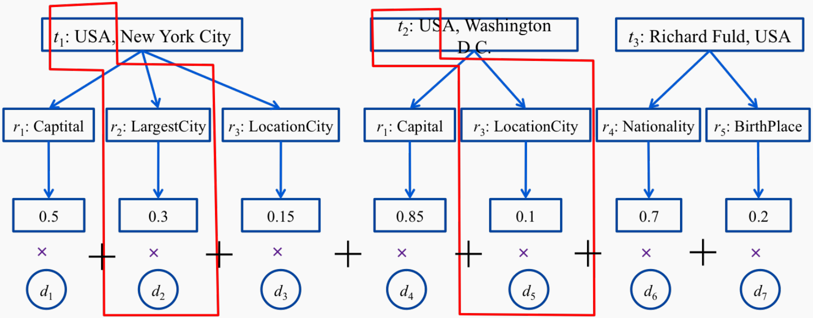
  - cardinality issues
- CSK as constraints
  - type constraint
  - cardinality constraint
- Optimizing local predictions with constraints



$$d_1 + d_4 \leq 1$$

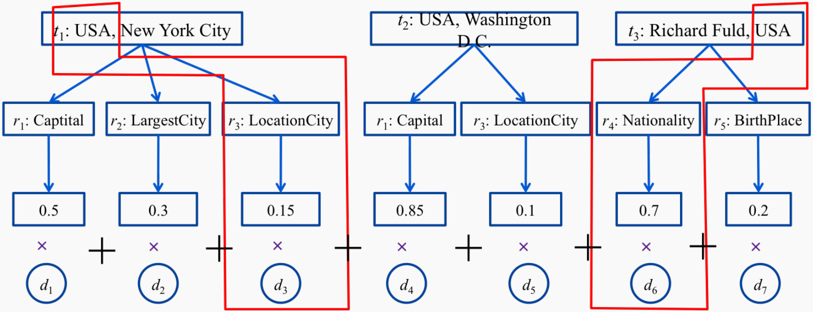
Usually, US has ONLY one capital!



$$d_1 + d_4 \leq 1$$

$$d_2 + d_5 \leq 1$$

US can NOT be State/Country and Organization at the same time!



$$d_1 + d_4 \leq 1$$
$$d_2 + d_5 \leq 1$$
$$d_3 + d_6 \leq 1$$

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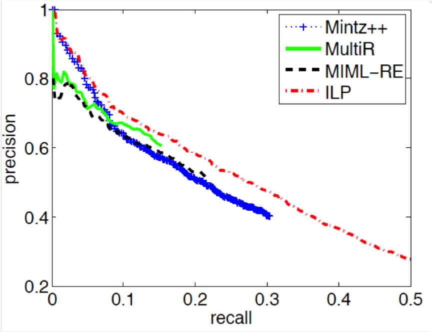
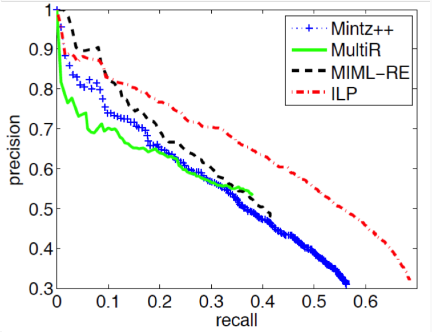


DBpedia dataset



Chinese dataset

Stable performances over English and Chinese datasets

Our Attempt II: KBP [Chen et al. (ACL 2014)]

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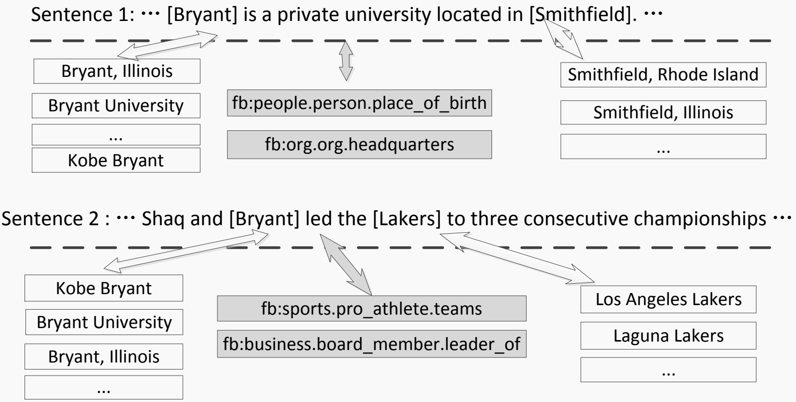

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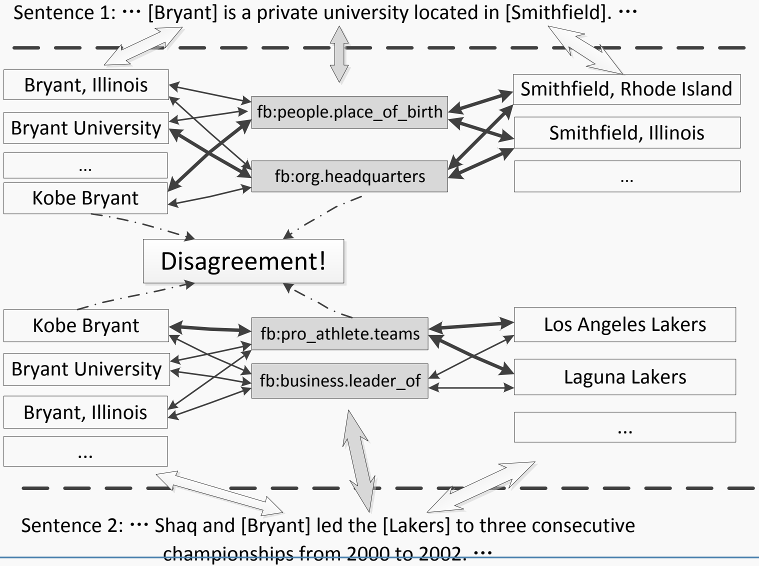
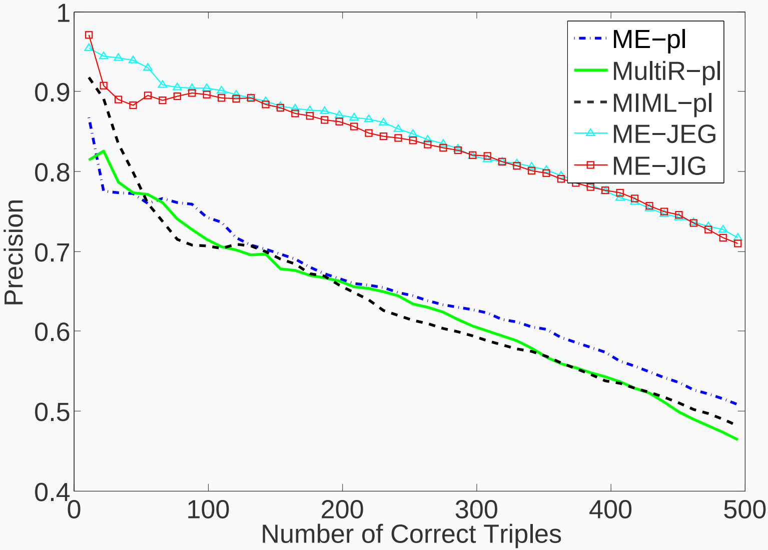
Framework



Sentence 1: ⋯ [Bryant] is a private university located in [Smithfield]. ⋯
Bryant, Illinois
Bryant University
...
Kobe Bryant
fb:people.place_of_birth
fb:org.headquarters
Smithfield, Rhode Island
Smithfield, Illinois
...
Disagreement!
Kobe Bryant
Bryant University
Bryant, Illinois
...
fb:pro_athlete.teams
fb:business.leader_of
Los Angeles Lakers
Laguna Lakers
...
Sentence 2: ⋯ Shaq and [Bryant] led the [Lakers] to three consecutive championships from 2000 to 2002. ⋯

Performance



Our Attempt III: QA [Zhang et al. (ACL 2015)]

Backgrounds required for question understanding,

- *which is the biggest city in China?*
- *which the longest/largest river in Africa?*
- *tell me the highest building?*

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- Analyze superlative expressions using KBs!

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Interpret CSK using structured KB

- Analyze superlative expressions using KBs!
- Learn from coarse-gained training data

- *the longest river* $\rightarrow$ **fb:geography.river.length**
- 90% of precision for commonly seen suplative-predicate pairs
- Correctly answer 40% complex questions with superlatives in WebQ

- *the longest river* $\rightarrow$ **fb:geography.river.length**
- 90% of precision for commonly seen suplative-predicate pairs
- Correctly answer 40% complex questions with superlatives in WebQ
- Still a lot to do: *the Best Actor of the Year* ? or, *the most beautiful town* ?

- definitely promising for various NLU applications
- how to formally represent or model CSK ?
- how to better utilize CSK ?

Thanks!

References

- ACL 2014: *Encoding Relation Requirements for Relation Extraction via Joint Inference*. Liwei Chen, Yansong Feng, Songfang Huang, Yong Qin, Dongyan Zhao, ACL 2014
- EMNLP 2014: *Joint Inference for Knowledge Bases Population*. Liwei Chen, Yansong Feng, Songfang Huang, Dongyan Zhao, EMNLP 2014
- ACL 2015: *Semantic Interpretation of Superlative Expressions via Structured Knowledge Bases*. Sheng Zhang, Yansong Feng, Kun Xu, Songfang Huang and Dongyan Zhao, to appear ACL 2015