

Overview of the TAC 2009 Knowledge Base Population Track

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Talk Outline

- Background
- Task Description
- Data
- Target Selection
- Assessment
- Results
- Conclusion



Motivation

- IE & QA technologies have been studied in isolation
 - Not focused on discovery of information for inclusion in an existing knowledge base
 - > No consideration of novelty, contradiction
- Issues when filling in a KB
 - Accurate extraction of facts
 - Global resolution of entities
 - > Maintaining provenance of asserted facts
 - > Avoiding contradiction / detection of novel information
 - > Temporal qualification of assertions
 - > Leveraging existing KB to assist with extraction
 - > Scalability



Comparison to ACE & TREC-QA

• Corpus vs. document focus

- ACE: component tasks (NER, relation extraction) for a set of isolated documents
- KBP: learn facts from a corpus. Repetition not very important. Asserting wrong information is bad.

Context

- In KBP, there is a reference knowledge base, so avoiding redundancy and detecting contradiction are important
- In KBP slots are fixed and targets change. In TREC QA, the targets dictated which questions were asked.

Knowing when you don't know

> TREC QA had a small percentage of NIL questions (4-10%)



Participating Teams

BUAP_1	B. Autonomous University of Puebla		
CSLU.OHSU	Oregon Health and Science University		
DAMSEL	Macquarie University		
HLTCOE	JHU Human Language Technology Center of Excellence		
IBM	TJ Watson IBM Research		
Janya	Janya Inc.		
NLPR_KBP	National Laboratory of Pattern Recognition, China		
PRIS	Beijing University of Posts and Telecommunications		
QUANTA	Tsinghua University		
Siel_09	International Institute of Information Technology		
Stanford_UBC	Stanford University		
TCAR_r6a	National Security Agency		
UC3M	Universidad Carlos III de Madrid		



KBP Snapshot

Track structure

- NIST overall organization, infrastructure, evaluation
- LDC develop and distribute data resources, target selection, human assessments

Datasets

- > LDC produced 1.3M English newswire collection
- Reference KB populated with semi-structured facts obtained from English Wikipedia (Oct '08 dump)
 - 200k people, 200k GPEs, 60k orgs, 300+k misc/non-entities

Two tasks

- Entity Linking Grounding entity mentions in documents to KB entries
- Slot Filling Learning attributes about target entities



Sample KB Entry

```
<entity wiki title="Michael Phelps"</pre>
       tvpe="PER"
       id="E0318992"
       name="Michael Phelps">
<facts class="Infobox Swimmer">
<fact name="swimmername">Michael Phelps</fact>
<fact name="fullname">Michael Fred Phelps</fact>
<fact name="nicknames">The Baltimore Bullet</fact>
<fact name="nationality">United States</fact>
<fact name="strokes">Butterfly, Individual Medley, Freestyle, Backst
<fact name="club">Club Wolverine, University of Michigan</fact>
<fact name="birthdate">June 30, 1985 (1985-06-30) (age 23)</fact>
<fact name="birthplace">Baltimore, Maryland, United States</fact>
<fact name="height">6 ft 4 in (1.93 m)</fact>
<fact name="weight">200 pounds (91 kg)</fact>
</facts>
<wiki text><![CDATA[Michael Phelps
Michael Fred Phelps (born June 30, 1985) is an American swimmer. H
Olympic gold medals, the most by any Olympian. As of August 2008,
world records in swimming. Phelps holds the record for the most gol
```

single Olympics with the eight golds he won at the 2008 Olympic Gan

Michael Phelps Michael Phelps at the 2008 Beiling Olympics

	1 orderia inioniation	
Full name:	Michael Fred Phelps	
Nickname(s)	: The Baltimore Bullet ^[1]	
Nationality:	United States	
Stroke(s):	Butterfly, Individual Medley, Backstroke	Freestyle,
Club:	Club Wolverine, University of Michigan	
Date of birth	: June 30, 1985 (age 23)	
Place of birth:	Baltimore, Maryland, United	States
Height:	6 ft 4 in (1.93 m)	
Weight:	200 pounds (91 kg)	
	Medal record	Ishow

Personal information



Most Frequent KB Classes

95142 settlement

72992 album

34659 film

32464 musical artist

23138 actor

21195 single

16765 company

15644 book

14567 football biography

14121 person

12646 radio station

12514 nrhp

12324 vq

11813 planet

10818 uk place

10113 television

8353 ort in deutschland

8061 university

7675 airport

7492 military person

7270 road

7185 indian jurisdiction

7123 cityit

6143 australian place

6131 mountain

5957 military conflict

5952 military unit

5937 city

5630 software

5501 mlb retired

5397 writer

5349 scientist

5222 lake

4913 television episode

4636 school

4426 commune de france

4265 aircraft

4229 ice hockey player

3918 german location

3234 nflactive

3168 disease

3070 politician

3036 u.s. county

2956 station

2950 automobile

2933 officeholder

2833 broadcast

2728 swiss town

PER ORG GPE OTHER



Entity Linking Task

John Williams

Richard Kaufman goes a long way back with **John Williams**. Trained as a classical violinist, Californian Kaufman started doing session work in the Hollywood studios in the 1970s. One of his movies was Jaws, with **Williams** conducting his score in recording sessions in 1975...



Debbie Phelps, the mother of swimming star **Michael Phelps**, who won a record eight gold medals in Beijing, is the author of a new memoir, ...

Michael Phelps is the scientist most often identified as the inventor of PET, a technique that permits the imaging of biological processes in the organ systems of living individuals. **Phelps** has ...



John Williams	author	1922-1994
J. Lloyd Williams	botanist	1854-1945
John Williams	politician	1955-
John J. Williams	US Senator	1904-1988
John Williams	Archbishop	1582-1650
John Williams	composer	1932-
Jonathan Williams	poet	1929-

Michael Phelps	swimmer	1985-
Michael Phelps	biophysicist	1939-

Identify matching entry, or determine that entity is missing from KB



Related Work (1)

• Cluster Documents Mentioning Entities

- Mann & Yarowsky (CoNLL 2003)
 - Clustering with TFIDF/BoW+NNPs (F=77%) with the additional use of relation features (F=86%)
- Gooi & Allan (HLT 2004)
 - Agglomerative Clustering (F=80%)
- Studied at Web People Search workshops (WePS-1,2)

Cross-Document Entity Coreference

- Group together mentions of the same named entity across documents in a large corpus
- Studied at ACE 2008 (English and Arabic)



Related Work (2)

- Add missing links between Wikipedia pages
 - > Adafre and de Rijke (2005), Milne & Witten (2008), Fader et al. (2009)
 - Differences with KBP 2009
 - Include non-entities
 - Ignore NIL entities (those not in WP)
 - Cast problem as WSD
- Link entities to matching Wikipedia article
 - Bunescu & Pasca (2006) Personal names (WP text)
 - Cucerzan (2007) All entities (news articles, WP text)
 - Differences with KBP 2009
 - Ignore NIL entities
 - KBP worked with PER/ORG/GPEs; did not focus on popular entities



Slot Filling Task

Target: EPA

(plus 1 document)



Generic Entity Classes Person, Organization, GPE

Missing information to mine from text:

> Date formed: 12/2/1970

Website: http://www.epa.gov/

Headquarters: Washington, DC

Nicknames: EPA, USEPA

> Type: federal agency

> Address: 1200 Pennsylvania Avenue NW

Optional: Also want to link some learned values within the KB:

Headquarters: Washington, DC (kbid: 735)



Entity Attributes

Person	Organization	Geo-Political Entity
alternate names	alternate names	alternate names
age	political/religious affiliation	capital
birth: date, place	top members/employees	subsidiary orgs
death: date, place, cause	number of employees	top employees
national origin	members	political parties
residences	member of	established
spouse	subsidiaries	population
children	parents	currency
parents	founded by	
siblings	founded	
other family	dissolved	
schools attended	headquarters	
job title	shareholders	
employee-of	website	
member-of		
religion		
criminal charges		



Introduction

- Planned resources
 - Source data
 - Knowledge Base
 - Entity Linking and Slot Filling lists
 - System assessment
- Data Distribution
 - 291 copies of 9 unique corpora, to 31 individual organizations
 - Distributed under evaluation license which gives no cost access for purposes of TAC
 - Corpora will be published in LDC catalog





Source Data Profile

- Volume
 - 1289649 documents, 6.5 GB
- Epoch
 - >99% from 2007 and 2008, to approximate epoch of the KB (10/2008)
 - 1994-07 through 2008-12 (ACEo8 Evaluation docs)
- Genre
 - newswire
 - broadcast news and conversation
 - weblogs and newsgroups
- Selection
 - 10,000 previously unreleased documents selected for ACE08 Evaluation
 - added NW (2007-2008) from English Gigaword 4 (LDC2009T13)
- Processing
 - source files processed to ACE source document format (SGML)
 - parseable as XML





Knowledge Base Description

- Based on October 2008 snapshot of Wikipedia
- Parsed into XML format from raw wiki markup
 - Only includes pages with (parseable) Infoboxes
 - Infobox fields parsed into <fact> elements
- Infoboxes standardized
 - NIST, LDC, JHU collaborated on Generic Infobox slots for Person, Organization, and GPE entity types
 - LDC created partial mapping from existing infobox types in KB to generic set
- LDC-Base vs. Knowledge Base
 - Knowledge Base the XML data extracted from Wikipedia, distributed to the KBP teams
 - LDC-Base LDC's internal database of entity information developed during annotation; used to produce materials for use in the project (e.g., the entity list, etc.)



Tactity coverage in LDC-base vs. Knowledge Base

LDC-base (KBP Target entities)

Knowledge Base

Entity
Profiles
(NIL
entities)

Entities
matched
to 10/2008
Wikipedia
entries
with
infoboxes
(KB
entities)

10/2008 Wikipedia entries with infoboxes



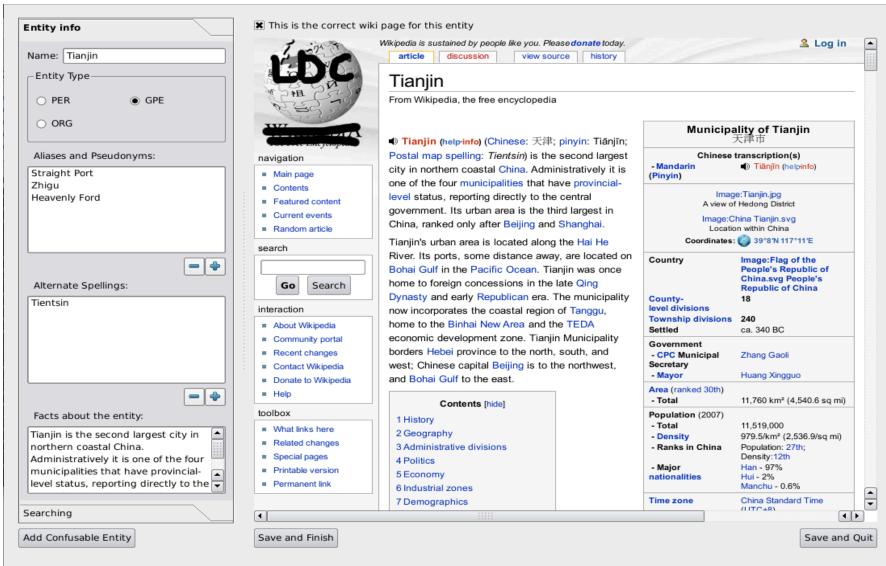
Entity Linking Queries List

- Name mention-document pairs, GS links to Knowledge Base
 - desirable properties variety, confusability, multiple name variants
- Developed via 2 stage process
 - Wikipedia Exploration Stage
 - Started with set of "seed" ACE profiles
 - Searched Wikipedia snapshot:
 - if matching entry found, link to LDC-base and add new facts/variants
 - if confusable, add new node to LDC-base and add facts/variants
 - Corpus Exploration Stage
 - Searched source data for name variants from Wikipedia exploration
 - Matched variants in document context to entity profiles
 - Created new entity profiles for variants not matching existing profiles





Wikipedia Exploration Tool







Corpus Exploration

Stop for now Assigned Variant: PCM

Done with annotation



Falungong asks Canada FM's help to free 15 in China

OTTAWA, April 24, 2007 (AFP)

Canadian relatives of 15 Falungong followers jailed in China asked on Tuesday Foreign Affairs Minister Peter MacKay to bring up their plight during an upcoming official visit to Beijing.

"The persecution of Falungong is a key policy of the Chinese regime among its many severe human rights violations," said Li Xun, president of the Falun Dafa Association of Canada.

"It is a serious issue that must be raised during any human rights talks with the regime."

China banned the spiritual group in 1999, accusing Falungong of spreading rumors in a bid to undermine "social stability" and Beijing's international relations, but the group is politically active in Canada.

The Canadian wing is expected to meet with the Foreign Affairs Department's China Desk on Wednesday to outline the plight of the 15, including the brother of a refugee who was himself freed from a Chinese prison with help from Canadian lawmakers, and the Beijing branch manager of Paris-based PCM Pumps.

The group accused Chinese authorities of "beating" and "brainwashing" their brethren, and sending them to forced labor camps.

Asylum seeker Yao Lian said PCM Pumps was "pressured to abandon their inquiries if they wished to continue doing business in China" after her husband Ma Jian was arrested at their Beijing offices.

"His arrest had a huge impact on their operations," she said, noting that French presidential candidate Segolene Royal wrote to Falun Dafa's Paris offices to "express concern" about Ma's fate, but failed to secure his release.

A Canadian government spokesman was not immediately available for comment.

But relations between Beijing and Ottawa have been strained recently over accusations that China is spying on Canadian corporations, the jailing of a Canadian imam in China, Canada's failure to deport a Chinese fugitive, talks between Ottawa and the Dalai Lama as well as stalled trade negotiations.

Last month, the wife of a Chinese diplomat defected to Canada and accused Beijing's embassy in Ottawa of inciting hatred against Falungong practitioners in Canada.

Previous 1 of 7 Next



Add Confusable



Entity Linking List

- Result from Wikipedia Exploration, Corpus Exploration, and Quality Control checks
 - 560 unique entities, 3904 name mention-document pairs (queries)
 - 15% PER, 70% ORG, 15% GPE
 - Original seed entities: 40% PER, 40% ORG, 20% GPE
 - 32.5 % KB, 67.5 % NIL
 - 33.4 % have 10/2008 Wikipedia entry with no infobox
 - 34.1% no 10/2008 Wikipedia entry
- query ID, name string, document ID
- Gold Standard version adds entity ID
 - Entity id = link to a unique entity node in KB or LDC-base (NIL)
 - used to evaluate performance on Entity Linking task





Slot Filling

- Subset of Entity Linking task entities selected for slot filling task
 - Top goal: slot filling info in corpus but not in KB
 - Manual selection by lead annotator
 - Some KB, some NIL, variety of type
 - Entities with Wikipedia entries more newsworthy
 - ◆ 51% NIL entities with Wikipedia entries (33% in superset Entity Linking list)
 - KB entities with common info missing from infoboxes
 - Citibank: missing founded date, number of employees
- ◆ 53 entities, 32% PER, 58% ORG, 9% GPE





Slot Filling Task Assessment

- Sequential assignment of all slots with pooled responses for an entity
- Stage 1: judge filler against doc vs. KB entry/Entity Profile
- Stage 2: for correct fillers, create equivalence classes
 - For entities already in KB, provide pre-existing equivalence class
- Stage 3: for correct fillers w/ proposed link to KB entry, judge the link
- Double- blind assessment, adjudication of disagreement
- NIL Link assessment post-process
 - Searched KB for NIL links in system output for Slot Filler KB linking task
 - 55/233 slot fillers had Wikipedia entries, 17/55 had infoboxes
 - Result: 17/233 assessed slot fillers found to be incorrectly NIL





Conclusions

- Challenges
 - Name strings corresponding to multiple entities in documents
 - Specificity issue with GPE equivalence classes
 - Slot filling entities manual selection
- Suggestions
 - Automatic solution to multiple name strings in documents, or take char offsets for name strings
 - Build in stage to search corpus for slot fillers for subset of Entity Linking entities





Entity Linking Metrics

$$Accuracy_{micro} = \frac{NumCorrect}{NumQueries}$$

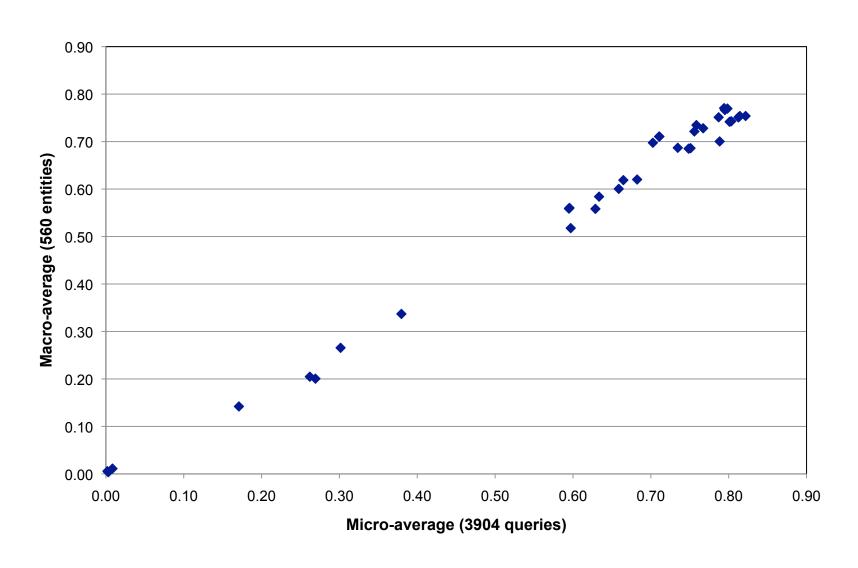
Estimate of performance for a random query. **Official Metric.** 3904 queries in total.

$$Accuracy_{macro} = \frac{\sum_{i}^{NumEntities} \frac{NumCorrect(E_i)}{NumQueries(E_i)}}{NumEntities}$$

Estimate of performance for a random entity. 560 distinct entities.



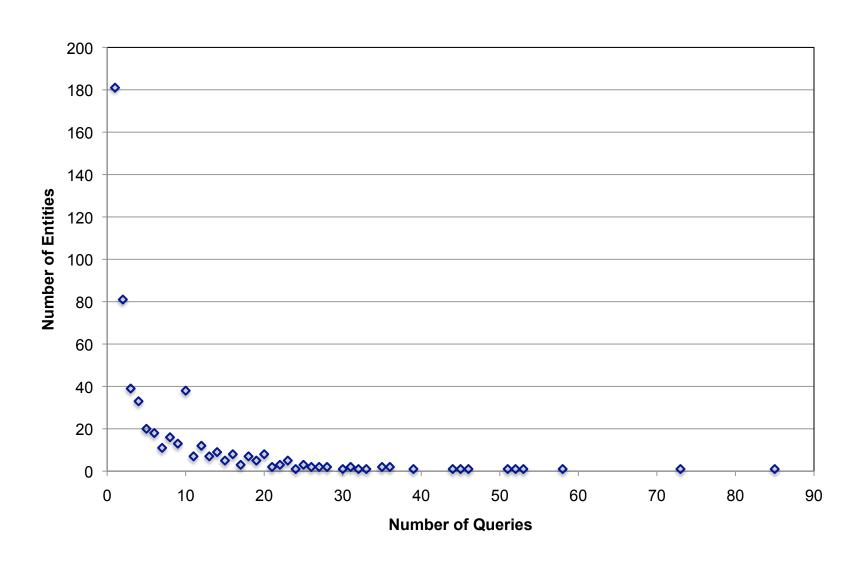
Micro vs. Macro



35 runs. Pearson correlation coefficient: 0.996



Queries per Entity





Top 5 Systems

Team	All	in KB	NIL
Siel_093	0.8217	0.7654	0.8641
QUANTA1	0.8033	0.7725	0.8264
hltcoe1	0.7984	0.7063	0.8677
Stanford_UBC2	0.7884	0.7588	0.8107
NLPR_KBP1	0.7672	0.6925	0.8232
'NIL' Baseline	0.5710	0.0000	1.0000

Micro-averaged accuracy



Performance by Entity Type

	All	in-KB	NIL
All	0.8217 (3904)	0.7654 (1675)	0.8641 (2229)
PER	0.8309 (627)	0.8039 (255)	0.8495 (372)
ORG	0.8151 (2710)	0.7305 (1013)	0.8696 (1697)
GPE	0.8480 (567)	0.8280 (407)	0.8812 (160)

Performance for top-scoring run: Siel_093



Hardest Queries

- > Subsidiary organization
 - 3871 Xinhua Finance Ltd .vs Xinhua Finance Media Ltd
- > Typographical mistake / ambiguous acronym
 - 1213 DCR for Democratic Republic of Congo
 - 3141 MND (Taiwan Ministry of National Defense) referred to as NDM in text
- Metaphorical 'names'
 - 1717/1718 Iron Lady (several strong female politicians)
- > Unclear referent
 - 2599 New Caledonia (country or soccer team)
- Mistakes in assessments
 - 3333,3334 NYC Dept of Health, not US Dept of Health
 - 3335 NY State Dept of Health, not US Dept of Health



Entity Linking Example

EL1718 – Iron Lady

The furor also brought China's long-running domestic food safety problems to light, just as Beijing prepares to host hundreds of thousands of foreign visitors at the summer Olympics in August.

The seriousness with which the government took the issue was underscored by the appointment of its top problem solver, Vice Premier Wu Yi, to head a Cabinet-level panel overseeing the campaign.

Wu, a stern-looking, 69-year-old woman known as the "Iron Lady," shepherded China's difficult entry into the World Trade Organization, took over as health minister during the SARS epidemic and has been tasked with handling the vociferous U.S. complaints about China's exchange rate policy.

One month into the product safety campaign, Wu herself set out to randomly inspect shops and restaurants in the eastern province of Zhejiang. She had no itinerary and told no one in advance, making the driver stop at her whim.



Entity Linking Example

EL3871 - Xinhua Finance

Chinese business news giant Xinhua Finance Media Ltd. is seeking to raise up to 371 million dollars through an initial public offering (IPO) on the Nasdaq stock market, according to a US regulatory filing.

. . .

"These outlets reach an estimated 210 million potential television viewers, a potential listening audience of 33 million people, and the readers of leading magazines and newspapers," Xinhua Finance Media said.

...

Describing itself as "a leading diversified media company in China," Xinhua Finance said it would use 50 million dollars from its US share listing to repay debts and "an undetermined amount" for future acquisitions.

The firm, which is based in the Cayman Islands, said it would be 36.7 percent owned by parent Xinhua Finance Ltd., 8.0 percent by Patriarch Partners Media Holdings LLC., and 5.8 percent owned by chief executive Fredy Bush, among other shareholders.



Sample SF Target

• SF25: Convocation of Anglicans in North America

- docid: LTW_ENG_20070506.0050.LDC2009T13

- enttype: ORG

- nodeid: NIL0031

Slot	Correct Values in Pools
org:alternate_names	CANA
org:founded	2005
org:founded_by	Peter Akinola
org:headquarters	Nigeria
org:member_of	Anglican Church, Nigerian Anglican Church
org:number_of_employees/members	100,000
org:parents	diocese of the Church of Nigeria, Nigerian Anglican Church
org:political/religious_affiliation	Anglican, Anglican Communion, Episcopal, Episcopal church, Christianity
org:top_members/employees	Peter Akinola, Bishop Martyn Minns, Kelly Oliver
org:website	www.canaconvocation.org



Convocation of Anglicans in North America

founded_by

Akinola, AMIA Bishop Chuck Murphy, Bishop Martyn Minns, Episcopal, Helmandollar, Jim Robb, Martyn Minns, Minns, Peter Akinola, Robinson, Stephen

shareholders

Anglican Church, Bishop Martyn Minns, CANA, Episcopal Church, Martyn Minns, Peter Akinola

headquarters

> America, Nigeria, Quincy, Woodbridge



Slot Filling Scoring

- Responses were marked as one of Correct, Inexact, Redundant, or Wrong
- Responses had to be justified from a single supporting document
 - > Unsupported responses were marked wrong
- 53 target entities (17 PER, 31 ORG, 5 GPE)
 - 255 single-value slots 39 (15%) had correct values in the pooled responses
 - > 499 list slots 129 (26%) had correct values
 - > Thus predicting NIL (no response) is correct ~80% of the time
 - > 48/53 entities had at least one learnable attribute



Easy / Hard Slots

Slot	Filled Entities	Correct Responses	Submitted Responses
per:title	16/17	86	409
per:employee_of	10/17	38	429
per:origin	9/16	16	117
per:member_of	9/17	41	424
org:top_members/ employees	24/31	258	1463
org:alternate_names	23/31	87	710
org:headquarters	11/21	17	131

No values for:

PER: other_family, parents, spouse

• ORG: shareholders

GPE: capital, political_parties, population



Slot Filling Metrics

$$Score_{single} = \frac{NumCorrect}{NumSingleSlots}$$

$$ListSlotValue = \frac{5 \times IP \times IR}{4 \times IR + IP}$$

 F_{β} =2 to weight precision over recall.

 \overrightarrow{IP} = Instance precision.

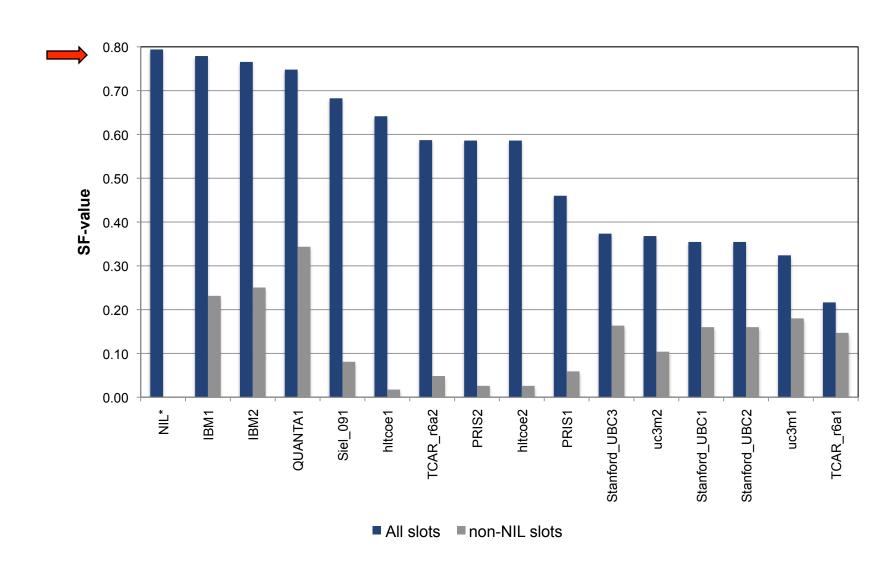
IR = Instance recall.

$$Score_{list} = \frac{\sum ListSlotValue}{NumListSlots}$$

$$SF_{\text{value}} = \frac{1}{2} \left(Score_{\text{single}} + Score_{\text{list}} \right)$$



SF Results





Lessons from Slot Filling

- GPEs have few learnable attributes in news
 - latitude, longitude, elevation not commonly reported
 - > population is, but usually available in KB/Wikipedia
- Difficult to estimate how much information is available (and novel) for a candidate target entity
 - Manual search needed both to facilitate target selection and enrich pools
- Balance scoring between slots with discoverable vs. NIL values
- End-to-end assessment of 'KB improvement' is difficult.
 Component evaluation for KBP is worth considering.
 - Can a passage support a given slot for a given entity? (The IR4QA problem)
 - > Is a particular slot fill justified from a passage? (An RTE task)
 - Is this slot fill redundant with another value?



Evaluation Issues

Imperfect KB

- Wikipedia focuses on presentation, not representation
 - irrelevant slots (colors, image sizes), values are not normalized (e.g., dates)
- > Many non-entities
- Use of external resources
- Generic entities (vs. thousands of classes)
 - > Slot names were inconsistent (birthdate, date-of-birth)
- Response granularity
 - USA, Hawaii, Honolulu which should be considered correct birthplaces for President Obama?
- Dealing with time
 - Key USA leadership: G. Washington or B. Obama
- Query Difficulty (and high NIL percentage)
- Assessing KB Growth
 - Difficult to directly measure benefit from adding to KB



Conclusion

- Pilot evaluation for adding information to a reference knowledge base
- 2 initial tasks
 - > Linking name mentions to KB entries
 - > Augmenting profiles for target entities
- KBP 2010
 - Refine and extend evaluation
 - Ralph Grishman and Heng Ji have volunteered to serve as the track coordinators
 - Please come to the planning meeting!