Overview of the TAC2013 Knowledge Base Population Evaluation: Temporal Slot Filling

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with a lot of help from: Hoa Dang, Joe Ellis, Heng Ji, Ralph Grishman, and Taylor Cassidy

Introduction

Temporal Slot filling (TSF): grounds fillers
 extracted by SF by finding the start and end
 dates when they were valid.

- This was the 2nd year for a KBP TSF evaluation
 - There was a pilot evaluation in 2011
- A few new things this year

~ New: Seven Slots Considered

- per:spouse
- per:title
- per:employee_or_member_of
- per:cities_of_residence
- per:statesorprovinces_of_residence
- per:countries_of_residence
- org:top_employees/members

New: Input Queries

```
Column 1: TEMP70711
Column 2: per:spouse
Column 3: Barack Obama
Column 4: AFP_ENG_20081208.0592.LDC2009T13
Column 5: Michelle Obama
Column 6: XXX-YYY
Column 7: ZZZ-WWW
Column 8: SSS-TTT
Column 9: 1.0
Column 10: E0566375
Column 11: E0082980
```

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New: Input Queries

New: Provenance of Dates

```
<DOC>
<DOCID> AFP ENG 20081231.0121.LDC2009T13 
<DOCTYPE SOURCE="newswire"> NEWS STORY </DOCTYPE>
<DATETIME> 2008-12-31 </DATETIME>
<BODY>
<HEADLINE>
Thousands protest in Brussels against
Israeli action in Gaza
</HEADLINE>
<TEXT>
<P>
Thousands took the streets in Brussels on Wednesday
calling for an end to Israeli bombing of the
Palestinian Gaza Strip ...
</DOC>
```

New: Provenance of Dates

```
<DOC>
<DOCID> AFP_ENG_20081231.0121.LDC2009T13 
<DOCTYPE SQURCE="nowswire"> NEWS STORY </DOCTYPE>
<DATETIME> | 2008-12-31 | </DATETIME>
<BODY>
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Thousands prot
Israeli
          Provenance of date mentions used
</HEADLI
         for normalization must be reported!
<TEXT>
<P>
Thousands took the streets in Brussels on Wednesday
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Palestinian Gaza Strip ...
</DOC>
```

Scoring Metric

- Same four-tuple used to represent dates: [T1 T2 T3 T4]
 - Relation is true for period beginning
 between T1 and T2 and ending between T3
 and T4
- Has limitations
 - Recurring events

Scoring Metric

- For each query:
 - System output $S = \langle t1, t2, t3, t4 \rangle$
 - Gold tuple $S_g = \langle g1, g2, g3, g4 \rangle$
 - Individual query score: $Q(S) = \frac{1}{4} \sum_{i} \frac{1}{1 + |t_i g_i|}$
- Overall: $Accuracy = \frac{\sum_{S^i \in S} Q(S^i)}{N}$

PARTICIPANTS

Participants

Team Id	Organization(s)	SF?	TSF?
ARPANI	Bhilai Institute of Technology		
CMUML	Carnegie Mellon University	$\sqrt{}$	$\sqrt{}$
PRIS2013	Beijing University of Posts and Telecommunications	$\sqrt{}$	
TALP_UPC	TALP Research Center of Technical University of Catalonia (UPC)	\	
UWashington	Department of Computer Science and Engineering, University of Washington	$\sqrt{}$	
utaustin	University of Texas at Austin – AI Lab	$\sqrt{}$	
SINDI	Korea Institute of Science and Technology Information	$\sqrt{}$	
CohenCMU	Carnegie Mellon University	$\sqrt{}$	
UMass_IESL	University of Massachusetts Amherst, Information Extraction and Synthesis Lab	V	
BIT	Beijing Institute of Technology	√ √	
SAFT_KRes	University of Southern California Information Sciences Institute	V	
UNED	Universidad Nacional de Educación a Distancia	√ √	1
IIRG	University College Dublin	V	•
NYU	New York University	l v∕	
Stanford	Stanford University	\downarrow	
lsv	Saarland University	\downarrow	
Compreno	ABBYY	\downarrow	√
RPI-BLENDER	Rensselaer Polytechnic Institute	\downarrow	\downarrow
MS_MLI	Microsoft Research	•	$$

Participation Summary

	Teams	Submissions
2011	4	7
2013	5	16

RESULTS

Data

- 273 queries
- Only 201 were actually scored
 - 5 dropped because neither LDC nor systems found correct fillers
 - 67 dropped because gold annotations had an invalid temporal interval
 - Valid interval: $T1 \le T2$, $T3 \le T4$, and $T1 \le T4$

Scoring and Baseline

Justification ignored (for now) in scoring

- DCT-WITHIN baseline of Ji et al. (2011)
 - Assumption: the relation is valid at the doc date
 - Tuple: <-∞, doc date, doc date, +∞>

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Baseline	24.70	17.40	15.18	17.83	14.75	21.08	23.20	19.10
MS_MLI	31.94	36.06	32.85	40.12	33.04	31.85	27.35	33.15
RPI-BLENDER	31.19	13.07	14.93	26.71	29.04	17.24	34.68	23.42
UNED	26.20	6.88	8.16	15.24	14.47	14.41	19.34	14.79
CMUML	19.95	7.46	8.47	16.52	13.43	5.65	11.95	11.53
Compreno	0.0	2.42	8.56	0.0	13.50	7.91	0.0	5.14
LDC	69.87	60.22	58.26	72.27	81.10	54.07	91.18	68.84

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Locations of residence tend to perform worse than average

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Employment relations tend to perform better than average

Results:
Identification of Filler Mentions: A Hidden Problem!

	TSF Accuracy	SF F1	SF Precision	SF Recall
LDC	68.8	83.1	97.3	72.5
MS_MLI	33.1	77.3	96.8	64.4
RPI-BLENDER	23.4	51.8	69.2	41.4
UNED	14.8	46.6	69.9	35.0
CMUML	11.5	32.2	38.5	27.6
Compreno	5.1	18.5	53.6	11.2

Results: Identification of Slots: A Hidden Problem

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Identification of correct mentions of fillers is a challenge!

Technology

- Most groups used distant supervision (DS) to assign labels to <entity, filler, date> tuples
 - Training data:
 - Freebase (structured) RPI, UNED
 - Wikipedia infoboxes (semi-structured) Microsoft
 - Labels: Start, End, In, Start-And-End
- Ensemble models for DS (RPI)
 - Explicit features + tree kernels

Technology

- Language model to clean up DS noise (Microsoft)
 - Learns that n-grams such as "FILLER and ENTITY were married" are indicative of per:spouse
 - These n-grams then used in a boosted decision tree classifier, which identifies noisy tuples

Conclusions

- Slight increase in participation
- On average, performance worse than in 2011
 - 2/5 systems outperformed the baseline vs. 3/4
 - New and complex task!
- Notable contributions
 - Noise reduction for TSF
 - Ensemble models for TSF