From Strings to Things: KELVIN in TAC KBP and EDL

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Kelvin

- **KELVIN**: Knowledge Extraction, Linking, Validation and Inference
- Developed at the *Human Language Technology Center of Excellence* at JHU and used in TAC KBP (2010-17), EDL (2015-17) and other projects
- Takes English, Chinese & Spanish documents and produce a knowledge graph in several formats
- We’ll review its monolingual processing, look at the multi-lingual use case
NIST TAC
NIST Text Analysis Conference

• Annual evaluation workshops since 2008 on natural language processing & related applications with large test collections and common evaluation procedures

• Knowledge Base Population (KBP) tracks focus on building KBs from information extracted from text
  • Cold Start KBP: construct a KB from text
  • Entity discovery & linking: cluster and link entity mentions
    • Slot filling
    • Slot filler validation
    • Sentiment
  • Events: discover and cluster events in text

http://nist.gov/tac
When Lisa's mother Marge Simpson went to a weekend getaway at Rancho Relaxo, the movie The Happy Little Elves Meet Fuzzy Snuggleduck was one of the R-rated European adult movies available on their cable channels.

After two years in the academic quagmire of Springfield Elementary, Lisa finally has a teacher that she connects with. But she soon learns that the problem with being middle-class is that...
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<table>
<thead>
<tr>
<th>Relation</th>
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<tbody>
<tr>
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<td>per:parents</td>
</tr>
<tr>
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<td>per:parents</td>
</tr>
<tr>
<td>per:parents</td>
<td>per:other_family</td>
</tr>
<tr>
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</tr>
<tr>
<td>per:spouse</td>
<td>per:siblings</td>
</tr>
<tr>
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<td>per:spouse</td>
</tr>
<tr>
<td>per:member_of</td>
<td>{org,gpe}:employees*</td>
</tr>
<tr>
<td>per:schools_attended</td>
<td>org:membership*</td>
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<tr>
<td>per:city_of_birth</td>
<td>org:students*</td>
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<tr>
<td>per:stateorprovince_of_birth</td>
<td>gpe:births_in_city*</td>
</tr>
<tr>
<td>per:country_of_birth</td>
<td>gpe:births_in_stateorprovince*</td>
</tr>
<tr>
<td>per:cities_of_residence</td>
<td>gpe:births_in_country*</td>
</tr>
<tr>
<td>per:statesorprovinces_of_residence</td>
<td>gpe:residents_of_stateorprovince</td>
</tr>
<tr>
<td>per:countries_of_residence</td>
<td>gpe:residents_of_country*</td>
</tr>
<tr>
<td>per:city_of_death</td>
<td>gpe:deaths_in_city*</td>
</tr>
<tr>
<td>per:stateorprovince_of_death</td>
<td>gpe:deaths_in_stateorprovince*</td>
</tr>
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<td>gpe:deaths_in_country*</td>
</tr>
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<td>{per,org,gpe}:holds_shares_in*</td>
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<td>org:founded_by</td>
<td>{per,org,gpe}:organizations_founded*</td>
</tr>
<tr>
<td>org:top_members_employees</td>
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</tr>
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<td>{org,gpe}:member_of</td>
<td>org:members</td>
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<tr>
<td>org:members</td>
<td>{org,gpe}:member_of</td>
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<td>{org,gpe}:subsidiaries</td>
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<td>org:parents</td>
</tr>
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<td>gpe:headquarters_in_city*</td>
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<tr>
<td>org:stateorprovince_of_headquarters</td>
<td>gpe:headquarters_in_stateorprovince*</td>
</tr>
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<td>org:alternate_names</td>
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<td>org:date_founded</td>
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<tr>
<td>per:date_of_death</td>
<td>org:date_dissolved</td>
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<tr>
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<tr>
<td>per:title</td>
<td></td>
</tr>
<tr>
<td>per:religion</td>
<td></td>
</tr>
<tr>
<td>per:charges</td>
<td></td>
</tr>
</tbody>
</table>
Cold Start

Schema

per:children
per:other_family
per:parents
per:siblings
per:spouse
per:employee_of
per:member_of
per:schools_attended
per:city_of_birth
per:stateorprovince_of_birth
per:country_of_birth
per:cities_of_residence
per:statesorprovinces_of_residence
per:countries_of_residence
per:city_of_death
per:stateorprovince_of_death
per:country_of_death
org:shareholders
org:founded_by
You are given:

<table>
<thead>
<tr>
<th>Schema</th>
</tr>
</thead>
<tbody>
<tr>
<td>per:children</td>
</tr>
<tr>
<td>per:other_family</td>
</tr>
<tr>
<td>per:parents</td>
</tr>
<tr>
<td>per:siblings</td>
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<tr>
<td>per:spouse</td>
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<tr>
<td>per:employee_of</td>
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<tr>
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</tr>
<tr>
<td>per:schools_attended</td>
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<tr>
<td>per:city_of_birth</td>
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<tr>
<td>per:stateorprovince_of_birth</td>
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<tr>
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<td>per:cities_of_residence</td>
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<tr>
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<tr>
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</tr>
<tr>
<td>per:country_of_death</td>
</tr>
</tbody>
</table>

When Lisa’s mother Marge Simpson went to a weekend getaway at Rancho Relaxo, the movie The Happy Little Elves Meet Fuzzy Snuggleduck was one of the R-rated European adult movies available on their cable channels.
When Lisa’s mother Marge Simpson went to a weekend getaway at Rancho Relaxo, the movie The Happy Little Elves Meet Fuzzy Snuggleduck was one of the R-rated European adult movies available on their cable channels.
How do you know that your KB is any good?
How do you know that your KB is any good?

Align it to a ground truth KB
How do you know that your KB is any good? Align it to a ground truth KB

But how are you going to produce ground truth? And wouldn’t the alignment be intractable anyway if the KB were of any reasonable size?
Where did the children of Marge Simpson go to school?
When Lisa's mother Marge Simpson went to a weekend getaway at Rancho Relaxo, the movie *The Happy Little Elves Meet Fuzzy Snuggleduck* was one of the R-rated European adult movies available on their cable channels.

After two years in the academic quagmire of Springfield Elementary, Lisa finally has a teacher that she connects with. But she soon learns that the problem with being middle-class is that...
# Sample Evaluation

## Queries

<table>
<thead>
<tr>
<th>Query Entity</th>
<th>First Relation</th>
<th>Second Relation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adriana Petryna</td>
<td>per:title</td>
<td></td>
</tr>
<tr>
<td>Blackstone Group</td>
<td>org:founded_by</td>
<td></td>
</tr>
<tr>
<td>William Shore</td>
<td>per:organizations_founded</td>
<td>org:date_founded</td>
</tr>
<tr>
<td>Wistar Institute</td>
<td>org:employees</td>
<td>per:title</td>
</tr>
<tr>
<td>Andrew W. Mellon</td>
<td>per:children</td>
<td>per:organizations_founded</td>
</tr>
<tr>
<td>Lycee Alliance Israelite Universelle</td>
<td>org:employees</td>
<td>per:schools_attended</td>
</tr>
<tr>
<td>Tsitsi Jaji</td>
<td>per:schools_attended</td>
<td>org:students</td>
</tr>
</tbody>
</table>
2016 TAC Cold Start KBP

- Read 90K documents: newswire articles & social media posts in English, Chinese and Spanish
- Find entity mentions, types and relations
- Cluster entities within/across documents, link to reference KB when possible (*which George Bush*)
- Remove errors (*Obama born in Illinois*), draw sound inferences (*Malia and Sasha sisters*)
- Create knowledge graph with provenance data for entities, mentions and relations
Dennis Hopper's divorce attorney says in a court filing that the actor is dying and can't undergo chemotherapy as he battles prostate cancer.

Attorney Joseph Mannis described the "Easy Rider" star's grave condition in a declaration filed Wednesday in Los Angeles Superior Court.

Mannis and attorneys for Hopper's wife Victoria are fighting over when and whether to take the actor's deposition.

…

:PER type
:FB:02fn5 link
:WIKI:Dennis_Hopper link
"Hopper" mention
"Dennis Hopper" mention
"Hopper" mention
"丹尼斯·霍珀" mention
:spouse per:spouse
:age per:age
"Victoria" mention
"72" mention

…
• Read 90K documents: newswire articles & social media posts in English, Chinese, and Spanish
• Find entity mentions, types, and relations
• Cluster entities within and across documents and link to a reference KB when appropriate
• Remove errors (Obama born in Illinois), draw sound inferences (Malia and Sasha sisters)
• Create knowledge graph with provenance data

<DOC id="APW_NG_20100325.0021" type="story">
  <HEADLINE>
    Divorce attorney says Dennis Hopper is dying
  </HEADLINE>
  <DATELINE>
    LOS ANGELES 2010-03-25 00:15:51 UTC
  </DATELINE>
  <TEXT>
    <P>
      Dennis Hopper's divorce attorney says in a court filing that the actor is dying and can't undergo chemotherapy as he battles prostate cancer.
    </P>
    <P>
      Attorney Joseph Mannis described the "Easy Rider" star's grave condition in a declaration filed Wednesday in Los Angeles Superior Court.
    </P>
    <P>
      Mannis and attorneys for Hopper's wife Victoria are fighting over when and whether to take the actor's deposition.
    </P>
  </TEXT>
</DOC>
KB Evaluation Methodology

• Evaluating KBs extracted from 90K documents is non-trivial

• TAC’s approach is simplified by:
  – Fixing the ontology of entity types and relations
  – Specifying a serialization as triples + provenance
  – Sampling a KB using a set of queries grounded in an entity mention found in a document

• Given a KB, we can evaluate its precision and recall for a set of queries
KB Evaluation Methodology

• **A query:** What are the names of schools attended by the children of the entity mentioned in document #45611 at characters 401-412
  – That mention is *George Bush* and the document context suggests it refers to the 41st U.S. president
  – Query given in structured form using TAC ontology

• **Assessors** determine good answers in corpus and check submitted results using their provenance

• **Answers:** entities for Yale, Harvard, Tulane, UT Austin, Univ. of Virginia, Boston College, ...
TAC Ontology

• Five basic entity types
  – PER: **people** (John Lennon) or groups (Americans)
  – ORG: **organizations** like IBM, MIT or US Senate
  – GPE: **geopolitical** entity like Boston, Belgium or Europe
  – LOC: **locations** like Lake Michigan or the Rockies
  – FAC: **facilities** like BWI or the Empire State Building

• Entity Mentions
  – **Strings** referencing entities by name (Barack Obama), description (the President) or pronoun (his)

• ~65 relations
  – Relations hold between two entities: parent_of, spouse, employer, founded_by, city_of_birth, ...
  – Or between an entity & string: age, website, title, cause_of_death, ...
Our ontology has official TAC types/relations and many more we capture from tools and infer from the data
Monlingual
Kelvin
Kelvin

• **KELVIN**: Knowledge Extraction, Linking, Validation and Inference

• Developed at the *Human Language Technology Center of Excellence* at JHU and used in TAC KBP (2010-17), EDL (2015-17) and other projects

• Takes English, Chinese & Spanish documents and produce a knowledge graph in several formats

• We’ll review its monolingual processing, look at the multi-lingual use case
• Process documents in parallel on a grid, applying information extraction tools to find mentions, entities, relations and events

• Produce an Apache Thrift object for each document with text and relevant data produced by tools using a common Concrete schema for NLP data
2 Integrating NLP data

Process Concrete objects in parallel to:

- **Integrate** data from tools (e.g., Stanford, Serif)
- **Fix problems**, e.g., trim mentions, find missed mentions, deconflict tangled mention chains, ...
- Extract relations from **events** (life.born => date and place of birth)
- Map relations found by open IE systems to TAC ontology ("is engineer at" => per:employee_of)
- Map schema to extended **TAC ontology**

30K ENG: 430K entities; 1.8M relations
3 Kripke: Cross-Doc Coref

- Cross-document **co-reference** creates initial KB from a set of single-document KBs
  - Identify that *Barack Obama* entity in DOC32 is same individual as *Obama* in DOC342, etc.

- **Language agnostic**; works well for ENG, CMN, SPA document collections

- Uses entity **type** and **mention strings** and context of co-mentioned entities

- **Untrained**, agglomerative **clustering**

30K ENG: 210K entities; 1.2M relations
4 Inference and adjudication

Reasoning to

• Delete relations violating ontology constraints
  – Person can’t be born in an organization
  – Person can’t be her own parent or spouse

• Infer missing relations
  – Two people sharing a parent are siblings
  – X born in place $P_1$, $P_1$ part of $P_2$ => X born in $P_2$
  – Person probably citizen of their country of birth
  – A CFO is a per:top_level_employee
**Entity Linking**

- Try to links entities to reference KB, a subset of Freebase with
  - ~4.5M entities and ~150M triples
  - Names and text in English, Spanish and Chinese

- Don’t link if no matches, poor matches or ambiguous matches
KB-level merging rules

- Merge entities of same type linked to same KB entity
- Merge cities in same region with same name
- Highly discriminative relations give evidence of sameness
  - per:spouse is few to few
  - org:top_level_employee is few to few
- Merge PERs with similar names who were
  - Both married to the same person, or
  - Both CEOs of the same company, or ...
Slot Value Consolidation

- **Problem:** too many values for some slots, especially for ‘popular’ entities, e.g.,
  - An entity with four different `per:age` values
  - Obama had ~100 `per:employee_of` values

- **Strategy:** rank values and select best
  - Rank values by # of attesting docs and probability
  - Choose best N value depending on relation type

30K ENG: 183K entities; 2.1M relations
Materialize KB versions

- Encode KB in your favorite database or graph store
- We use the RDF/OWL Semantic Web technology stack
Multi-lingual Kelvin
Multilingual KBP

• Many examples where facts from different languages combine to answer queries or support inference
  
  Q: Who lives in the same city as Bodo Elleke?
  A: Frank Ribery aka Franck Ribéry aka 里贝里

• Why we know both live in Munich:
     ...said the younger Bodo Elleke, who was born in Schodack in 1930 and is now a retired architect who lives in Munich.
     拉霍伊在接受西班牙国家电电台的采访时肯定, 今年的三位金球奖热门候选人中, 梅西“度过了一个出色的赛季”, 而拜仁慕尼黑球员里贝里则“赢得了一切”

• Kripke merged entities with mentions Frank Ribery, Franck Ribéry & 里贝里
Monolingual to Multilingual Kelvin

Zoom in on our cross-doc co-ref step

- Concatenate document-level KBs to form a **DOC KB** as input to Kripke
- Kripke outputs a set of **CLUSTERS** defining an equivalence relation
- Merger uses **CLUSTERS** to combine **DOC KB** entities, yielding the initial KB
- We use the **DOC KB** and **CLUSTERS** from each language to create an initial multilingual KB
Trilingual KBP & EDL

- Kripke computes CLUSTERS for combined multilingual DOC KBs

CMN DOC KB & CLUSTERS

ENG DOC KB & CLUSTERS

SPA DOC KB & CLUSTERS

Kripke

Merge

KB

MAT

trilingual KBs
Translating non-English mentions to English, when possible enhances clustering

**Trilingual KBP & EDL**

- Kripke computes CLUSTERS for combined monolingual DOC KBS
- Optionally translate non-English mentions
Kripke computes CLUSTERS for combined monolingual DOC KBS

- Optionally translate non-English mentions
- Use all four CLUSTERS to merge entities in the three DOC KBS

Combine the four cluster equivalence relations to produce on global one

Trilingual KBP & EDL
Results
2016 TAC KBP Results

• For the 7 KB and 11 SF submissions, depending on metric (macro/micro avg), we placed
  – 1st or 2nd of 5 on XLING and were the only team to do all three languages
  – 2nd or 4th of 18 on ENG depending on metric
  – 1st or 2nd of 4 on CMN depending on metric
  – We did poorly on SPA, finding few relations

• See workshop paper for details

• TAC EDL results are forthcoming
## 2016 TAC KBP Results

<table>
<thead>
<tr>
<th>Run</th>
<th>0-hop</th>
<th>1-hop</th>
<th>All-hop</th>
</tr>
</thead>
<tbody>
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<td>R</td>
<td>W</td>
</tr>
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<td>X4</td>
<td>4094</td>
<td>321</td>
<td>385</td>
</tr>
</tbody>
</table>

Ground-truth, right, wrong & duplicate answers for 2016 KBP KB runs
## 2016 TAC KBP Results

<table>
<thead>
<tr>
<th>Run</th>
<th>0-hop</th>
<th>1-hop</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>R</td>
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<td>E1</td>
<td>0.3458</td>
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<tr>
<td>E3</td>
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<td>0.2322</td>
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<tr>
<td>C1</td>
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<td>0.1877</td>
<td>0.2773</td>
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<tr>
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<tr>
<td>C3</td>
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</tr>
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<td><strong>0.0120</strong></td>
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</tr>
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Micro precision, recall and F1 scores for 2016 KBP KB runs
2016 EDL XLING Results

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<td>F1</td>
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XLING run precision, recall and F1 measures for four key metrics: strong typed mention match (NER), strong all match (Linking), strong nil match (Nil), and mention ceaf plus (Clustering)
2016 Results Observations

• Overall XLING1 was best
• Variations for monolingual runs were similar
  – Using translated mentions for non-English helped
  – Using nominal mentions seemed to improve cross-doc co-ref slightly
• EDL scores (and maybe KBP) lowered by bug in our nominal mention trimming code; the nominal strings correctly identified but offsets were wrong 😞
Kelvin Docker Container

• **Problem:** Kelvin is a large and complex system that’s difficult to port to a new Unix environment, let alone a different OS

• **Solution:** We use Docker to virtualize Kelvin as several containers that can be run on any system that supports Docker—e.g., most Unix systems, Mac OSX and Windows
Conclusion
Lessons Learned

• We always have to mind precision & recall
• Extracting information from text is inherently noisy; reading more text helps both
• Using machine learning at every level is important
• Making more use of probabilities will help
• Extracting information about events is hard
• Recognizing the temporal extent of relations is important, but still a challenge
Conclusion

• KBs help in extracting information from text
• The information extracted can update the KBs
• The KBs provide support for new tasks, such as question answering and speech interfaces
• We’ll see this approach grow and evolve in the future
• New machine learning frameworks will result in better accuracy