From Strings to Things:
Populating Knowledge Bases from Text

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Joint work with colleagues and students at the
JHU Human Language Technology Center of Excellence
And University of Maryland, Baltimore County

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TL;DR

I’ll describe the NIST TAC **Knowledge Base Population** tasks and the **Kelvin** system we developed to participate in it

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 KB from text w/o using external KBs
  - **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

2017 TAC Cold Start KBP

- Read 90K documents: newswire articles & social media posts in English, Chinese and Spanish
- Find entity mentions, types & relations (optionally plus events & sentiment) using a shared schema
- Cluster entities & events in/across documents, link to reference KB if possible (*which George Bush*)
- Remove errors (*Obama born in Illinois*), draw sound inferences (*Malia and Sasha sisters*)
- Create graph with provenance (*+ optional confidence score*) in TAC format

Cold Start ?

- Goal: reduce focus on popular entities common in newswire
- Start with empty KB
- All facts must be attested in text
- Can’t use external KBs (e.g., Wikidata) or Web searches

2017 TAC Cold Start KBP

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<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> …
```

2017 TAC Cold Start KBP

<DOC id="APW_ENG_
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Divorce attorney says
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<DATELINE>
LOS ANGELES 2010-0
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<TEXT
<P>
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undergo chemothera
</P>
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</P>
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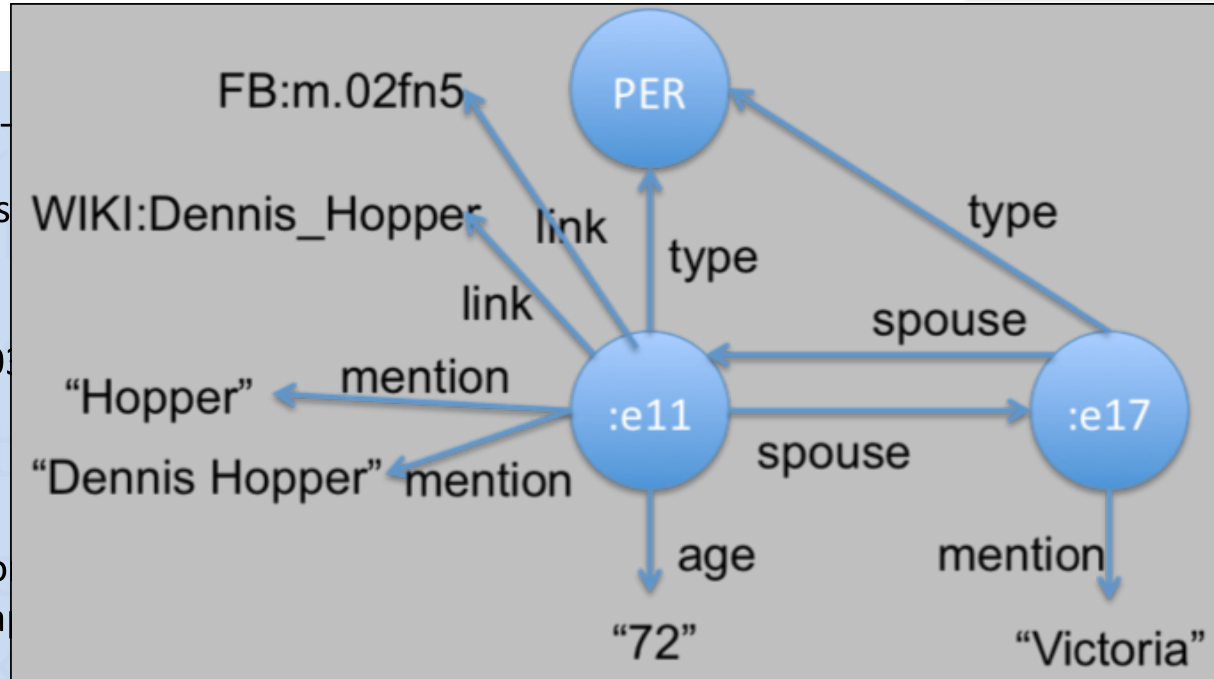
</P> …



2017 TAC Cold Start KBP

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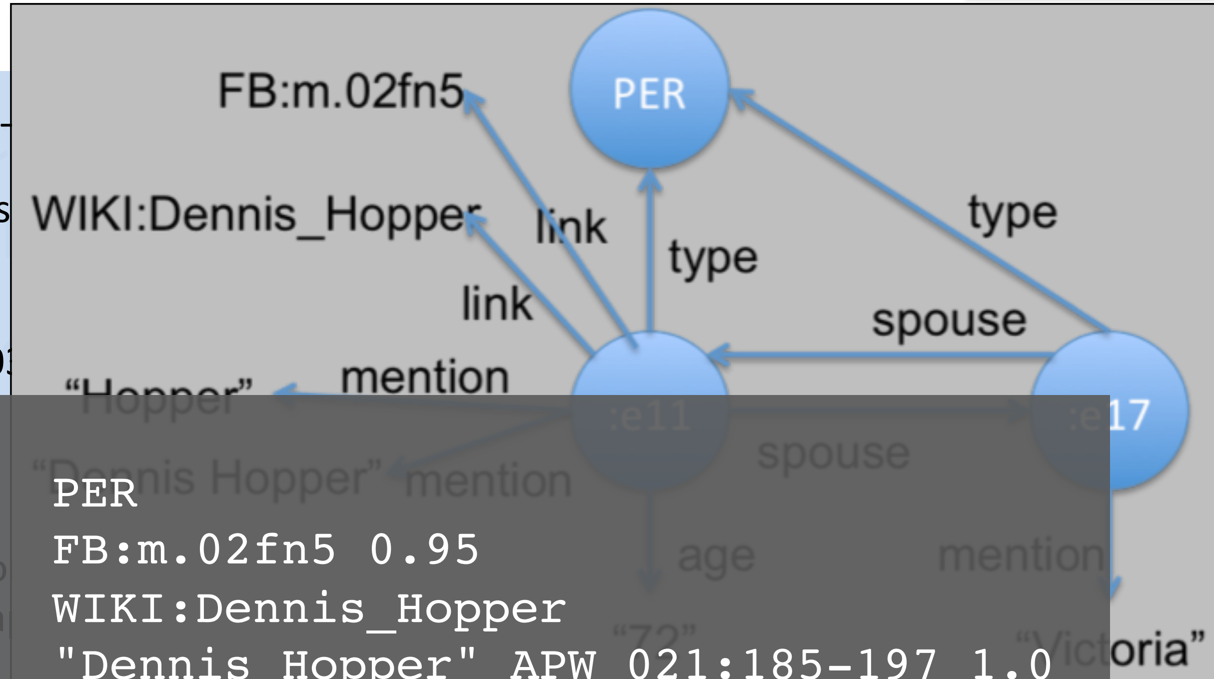


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:e00211 link        FB:m.02fn5 0.95
:e00211 link        WIKI:Dennis_Hopper
:e00211 mention     "Dennis Hopper" APW_021:185-197 1.0
:e00211 mention     "Hopper"     APW_021:507-512  1.0
:e00211 mention     "Hopper"     APW_021:618-623  1.0
:e00211 mention     "丹尼斯·霍珀" CMN_011:930-936  1.0
:e00211 per:spouse :e00217      APW_021:521-528  1.0
:e00217 per:spouse :e00211      APW_021:521-528  1.0
:e00211 per:age     "72"        APW_021:521-528  0.9
…
```

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

KB Evaluation Methodology

- Evaluating KBs extracted from 90K documents is non-trivial
- TAC's approach is simplified:
  - **Fix the ontology** of entity types and relations
  - Specify **a serialization** as triples + provenance
  - Sample a KB using a set of **queries** grounded in an *entity mention* found in a document
  - Get ground truth for queries and assess results
- Given a KB, we can then evaluate its **precision and recall** for a set of queries

KB Evaluation Methodology

- **A query:** What schools were attended by children of entity mentioned in document #45611 at characters 401-412
  - That mention is *George Bush* which a system under test identifies as :e629 (i.e., G.H.W. Bush)
  - A query finds answer entities in a test system's graph (e.g., Yale, Harvard, Tulane, UT Austin, UVA …) along with the provenance strings for the two relations
- **Assessors** determine good answers in corpus and check the submitted results' **provenance**

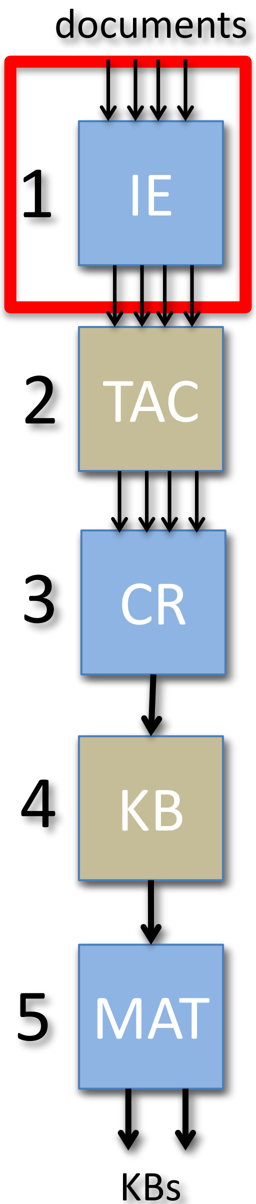
TAC Ontology

- Derived from the Automatic Content Extraction (ACE) ontology
- Entity **types**: PER (people), ORG (organizations), GPE (geopolitical entities), LOC (locations) and FAC (facilities)
- Entity **mentions**: both name & nominal mentions
- 41 **relations** *(plus inverses):* entity to entity/string
- 18 **event types**: plus 85 event argument relations
- 2 **sentiment relations** *(plus inverses):* entity to entity

Kelvin

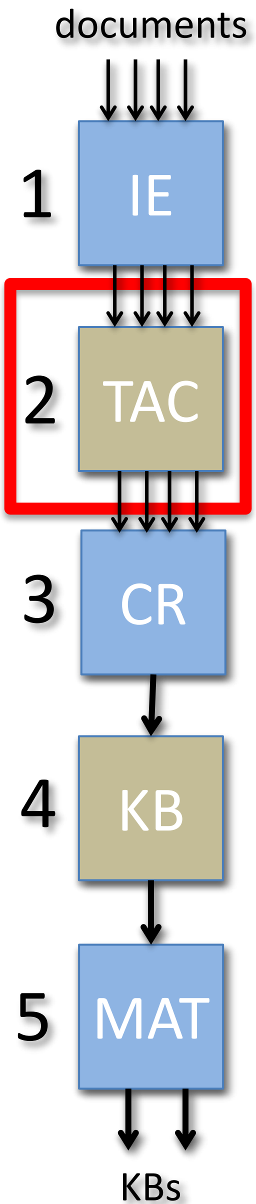
- **KELVIN**: **K**nowledge **E**xtraction, **L**inking, **V**alidation and **In**ference
- Developed at the ***Human Language Technology Center of Excellence*** at JHU and used in TAC KBP (2010-17), EDL (2015-17) and other projects
- Takes English, Chinese & Spanish documents and produce a knowledge graph in several formats
- We'll review its monolingual pipeline, look at the multi-lingual use case

1 Information Extraction



- Process documents in **parallel** on a grid
- Apply an ensemble of NLP tools (e.g., language ID, Serif, CoreNLP, …) to find **document-level** mentions, entities, relations and events
- Produce an **Apache Thrift** object for each document with text and extracted data using **Concrete,** a common NLP schema

2 Integrating NLP data

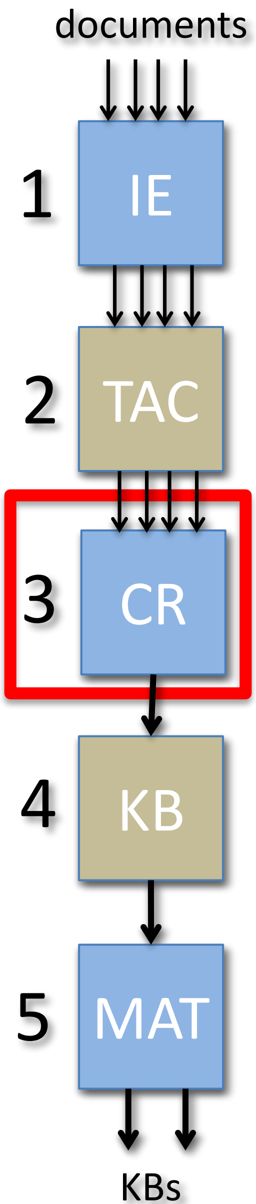


Process Concrete objects in parallel to:

- **Integrate** data from tools (e.g., Serif, CoreNLP, OpenIE)
- **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 our extended **TAC ontology**

30K ENG: 430K entities; 1.8M relations

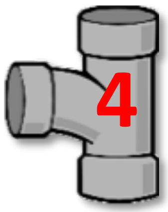
3 Kripke: Cross-Doc Coref

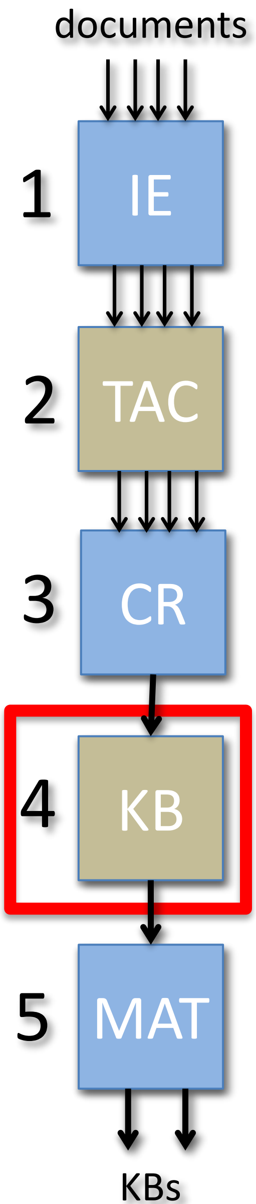


- Cross-document **co-reference** creates initial KB from the document-level data
  - Identify that *Barack Obama* entity in DOC32 is same individual as *Obama* in DOC342, etc.
- **Language agnostic**; works well for ENG, CMN, SPA document collections
- Uses entity **type** and **mention strings** and **context** of co-mentioned entities
- Untrained, agglomerative **clustering**

30K ENG: 210K entities; 1.2M relations

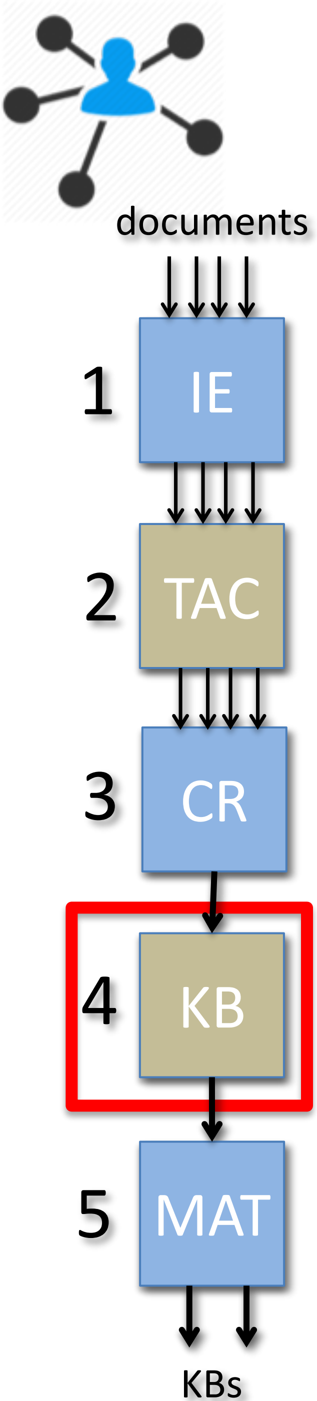
4 Inference & adjudication





Reasoning to

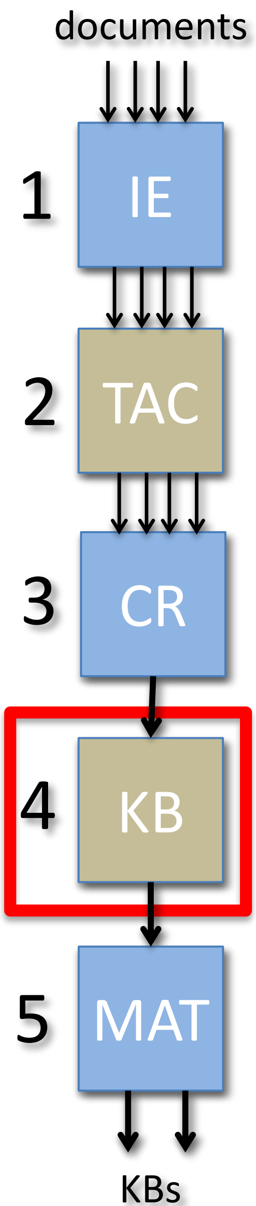
- Delete relations violating ontology constraints
  - *Person can't be born in an organization*
  - *Person can't be her own parent or spouse*
- Infer missing relations
  - *Two people sharing a parent are siblings*
  - *X born in place P_1, P_1 part of P_2 => X born in P_2*
  - *Person probably citizen of their country of birth*
  - *A CFO is a per:top_level_employee*



Entity Linking

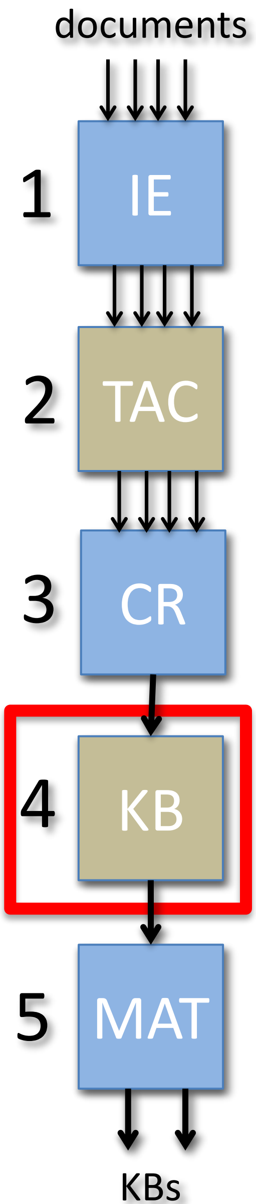
- Try to links entities to reference KB, a subset of Freebase with
  - ~4.5M entities and ~150M triples
  - Names and text in English, Spanish and Chinese
- Don't link if no matches, poor matches or ambiguous matches

KB-level merging rules



- Merge entities linked to same external 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 …

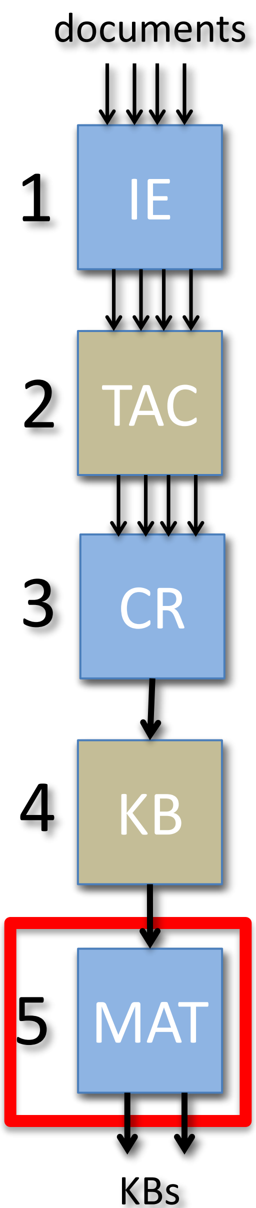
Slot Value Consolidation



- **Problem:** too many values for some slots, especially for ‘popular’ entities, e.g.,
  - An entity with 2 ***per:city_of_birth*** values
  - Obama had ~100 ***per:employee_of*** values
- **Strategy:** rank values and select best
  - Rank values by # of attesting docs and certainty scores
  - Choose best N values depending on relation type and distribution of frequency counts

30K ENG: 183K entities; 2.1M relations

Materialize KB versions



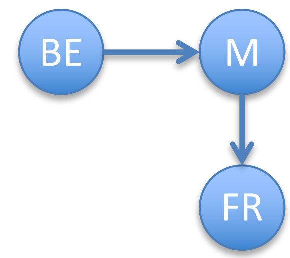
- Generate TAC serialization for scoring
- Also encode KB in a database or graph store, e.g. the RDF/OWL Semantic Web languages or

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*

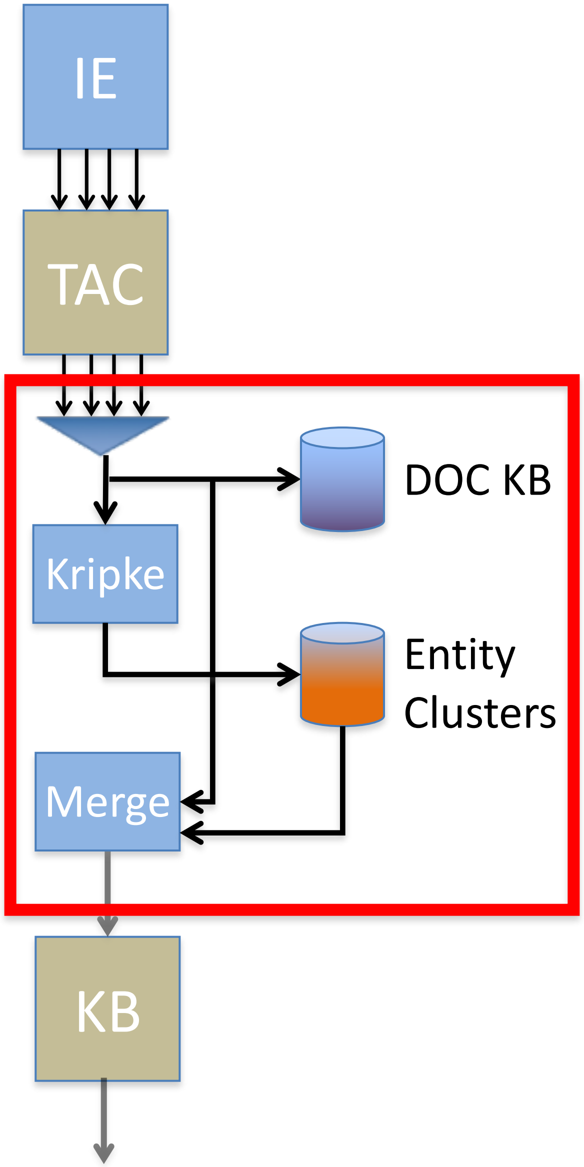


- Why we know both live in Munich:

1. :e8 gpe:residents_of_city :e23 ENG_3:3217-3235
   ...said the younger **Bodo Elleke**, who was born in Schodack in 1930 and is now a retired architect **who lives in Munich**.
2. :e8 gpe:residents_of_city :e25 CMN...0UTJ:292-361
   拉霍伊在接受西班牙国家电台的采访时肯定，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*

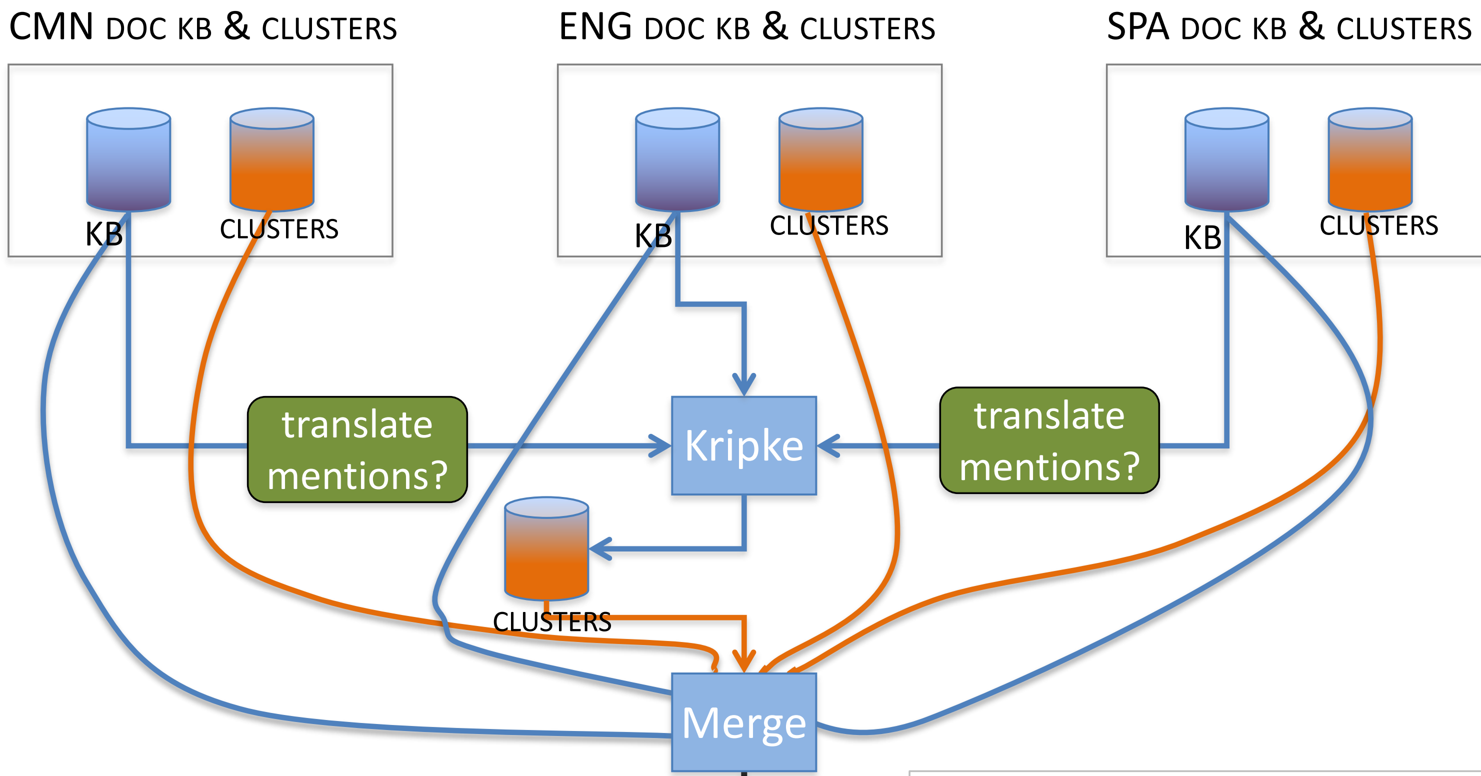
Monolingual to Multilingual Kelvin

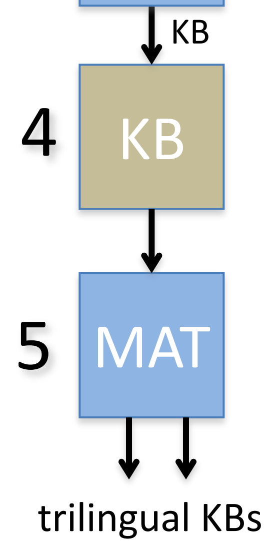


Zoom in on our cross-doc co-ref step

- 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





- **Run Kelvin on monolingual collections**
- **Translate entity mentions into English and recluster**
- **Run results thru rest of pipeline**

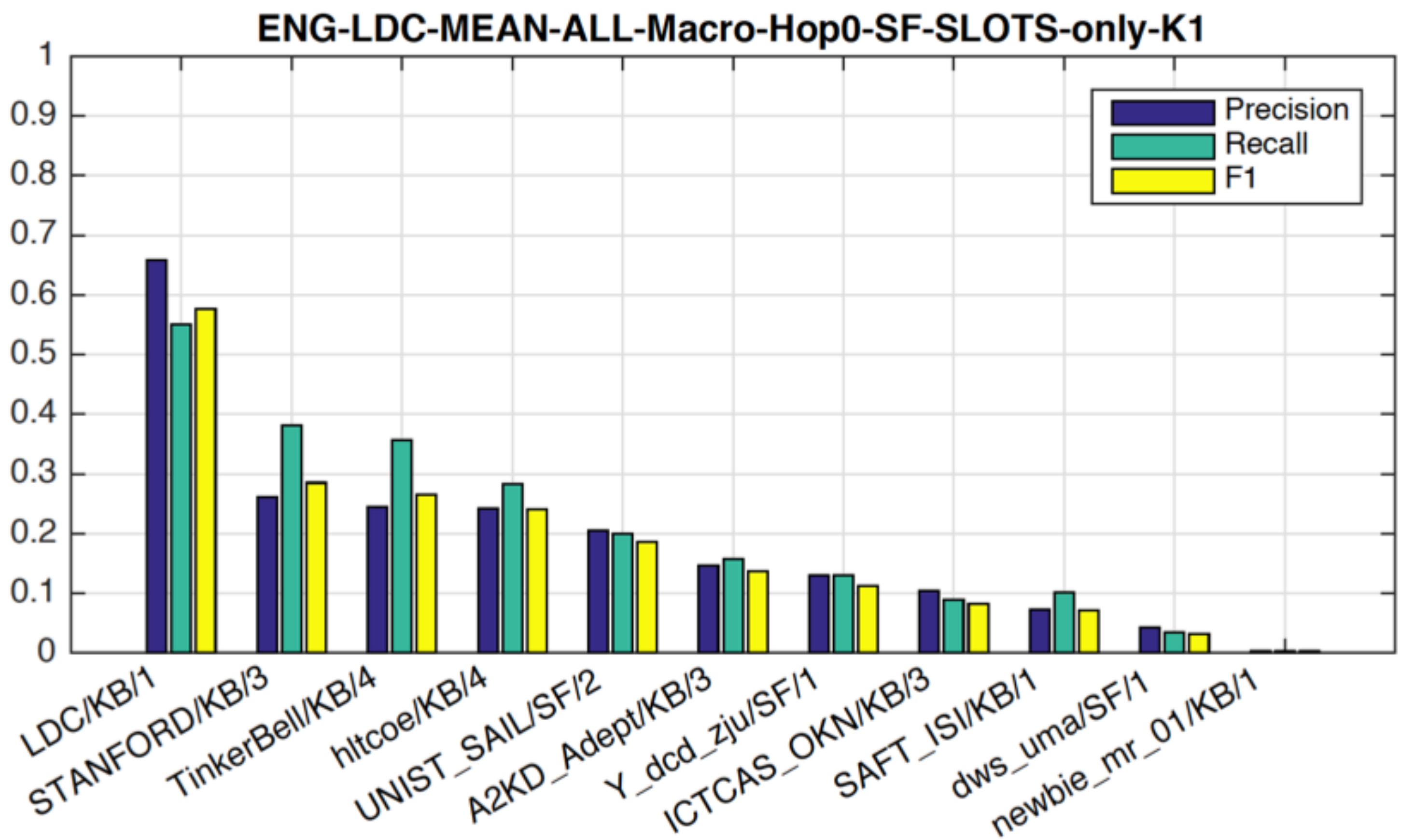
- Kripke computes CLUSTERS for combined monolingual DOC KBs
- Optionally translates non-English mentions
- Use all 4 CLUSTERS to merge entities in 3 DOC KBs

2016 TAC KBP Results

- 2016 KBP results (2017 KBP results similar)
  - 1st or 2nd on XLING
  - 2nd or 4th on ENG depending on metric
  - 1st or 2nd on CMN depending on metric
  - We did poorly on SPA, finding few relations
- Lots of room for improvement for both *precision* and *recall*

The task is hard

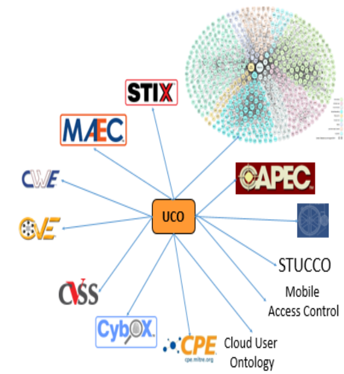
Best 2017 system: F1=0.29 for English hop 0 queries.



Current work 1: improving Kelvin

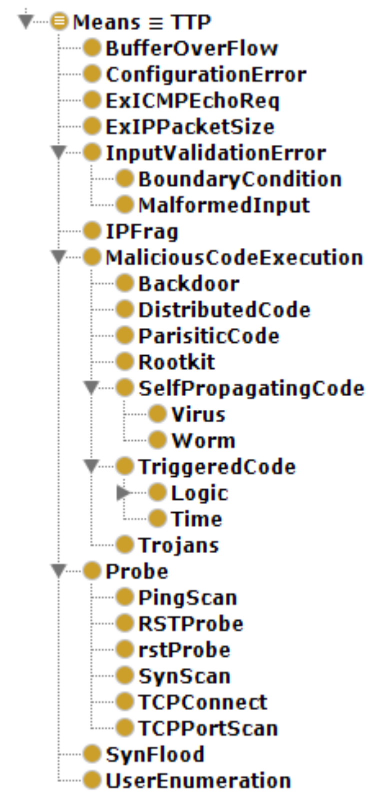
- Upgrade components to use newer machine learning approaches
- Enhance Kripke entity clustering with more data (nominal mentions, embeddings)
- Add tensor-decomposition based learning to identify likely/unlikely relations
- Add other components to detect and fix "dubious facts"

Current work 2: cybersecurity



UMBC is working with IBM on extracting cybersecurity information from text

- Describe entities, relations & events using UCO, the Unified Cybersecurity Ontology
  - Rich schema supports reasoning
  - Better data sharing, interoperability, integration and human understanding
  - Link to background knowledge graphs and common metadata models (CVE, Stix, Cybox…)
- Use graph to enhance analytics and machine learning for intrusion detection systems



http://unifiedCyberOntology.github.io

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 a events is hard
- Modelling the temporal extent of relations is important, but still a challenge

For more information,
contact finin@umbc.edu