Knowledge Representation and Extraction at Scale

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Amazon Research, Cambridge UK

SemDeep-3 @ COLING
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Amazon Alexa

**Entertainment:** Music, Books, Video...

**Household:** Timers, ToDo Lists, Shopping, Calendar...

**Information:** Weather, Traffic, News, Q/A...

**Smart Home:** Lights, Thermostats, Switches...

45,000+ skills: Developed by 3rd Parties
Amazon Alexa

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Alexa Question Answering

“Alexa, what books did Carrie Fisher write?”

“The books that Carrie Fisher is an author of are Delusions of Grandma, Shockaholic, Surrender the Pink, Postcards from the Edge, The Best Awful There Is and Wishful Drinking.”
Alexa Question Answering

Alexa, what books did Carrie Fisher write?
Alexa Question Answering

Alexa, what books did Carrie Fisher write?

Wake Word → user’s utterance → Speech Platform → recognition result → ASR

Speech Platform:
- recognize
- recognition result
- intent
- Q/A
- NLG text
- text
- TTS

Knowledge Base
Alexa Knowledge Base

Named relations between entities

[carrie fisher] [is the author of] [postcards from the edge] [is an instance of] [book]
Alexa Knowledge Base

Named relations between entities

[carrie fisher] [is the author of] [postcards from the edge] [is an instance of] [book]

[donald trump] [is an instance of] [politician] [is an instance of] [republican] [is married to] [melania trump] [timepoint: “1946/6/14”] [is the birthdate of] [donald trump]
Alexa Knowledge Base
KB usage challenges

- Storage/retrieval
  - AWS S3, DynamoDB, Neptune
  - In-memory graphs
  - Backups

- Consistency
  - Ingestion checks
  - Stale facts

- Querying
  - Efficient graph traversal
  - Generated facts
Alexa Knowledge Base

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**Research challenges**

- **Completeness**
  - Demand-weighted
  - Defined w.r.t a given application

- **Extraction**
  - Structured vs unstructured sources
  - Ontology alignment
  - Multiple source languages

- **Verification**
  - Fact correctness assessment
  - Justification in the form of evidence
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Demand-Weighted Completeness Prediction for a Knowledge Base

Hopkinson et al. (2018) – NAACL
Demand-Weighted Completeness

• A KB can be complete for an entity if it contains all possible statements about that entity

• Practically this is not a very useful definition
  • Not all KB applications require all of the data equally
  • For each application, completeness can have a different meaning

• Given an application how can we determine KB completeness?
  • Can come from hand-written archetypes, or KB statistics
  • Can focus on relation existence, or include cardinality of relations
Problem Statement

Given an entity E in a KB, and query usage data of the KB, predict the distribution of relations that E must have in order for 95% of (usage) queries about E to be answered successfully.
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Relation Distributions

query y
x [is the president of] [the united states of america]
x [is married to] y
Relation Distributions

Query $y$

$x$ [is the president of] [the united states of america]

$x$ [is married to] $y$
Relation Distributions

[the united states of america] [is the president of] [donald trump]

[donald trump] [is married to] [melania trump]

query y
[donald trump] [is the president of] [the united states of america]
[donald trump] [is married to] y
Relation Distributions

Query: y
donald trump [is the president of] the united states of america
[donald trump] is married to y

<table>
<thead>
<tr>
<th>[the united states of america]</th>
<th>hasPresident</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>hasCapital</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>hasPopulation</td>
<td>6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>[donald trump]</th>
<th>hasSpouse</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>hasBirthdate</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>hasBirthplace</td>
<td>5</td>
</tr>
</tbody>
</table>
Representing Entities

• We may have little usage information for individual entities
• Some relations may have an incidence lower than 1 per entity
• In order to generalise, we need a representation that allows grouping of similar entities
• Additionally, the representation should be interpretable

• We represent entities by their membership of different classes or class signatures
Representing Entities

• We may have little usage information for individual entities
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• In order to generalise, we need a representation that allows grouping of similar entities
• Additionally, the representation should be interpretable

• We represent entities by their membership of different classes or class signatures

<table>
<thead>
<tr>
<th>[donald trump]</th>
</tr>
</thead>
<tbody>
<tr>
<td>person</td>
</tr>
<tr>
<td>politician</td>
</tr>
<tr>
<td>democrat</td>
</tr>
<tr>
<td>republican</td>
</tr>
<tr>
<td>...</td>
</tr>
</tbody>
</table>
Models

• Baseline – Frequency Based model
  • Statistics for each class
  • Combine and normalize the relation counts for an entity’s classes

• Linear Regression
  • Least squares linear regression

• Neural network
  • Feed-forward network with n-hot input vector for the class signature
  • Single 10 node ReLU hidden layer, softmax output layer
  • Objective function: KL Divergence
Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Classes</th>
<th>Relations</th>
<th>Signatures</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1_{small}</td>
<td>4,400</td>
<td>1,300</td>
<td>12,000</td>
</tr>
<tr>
<td>D2_{medium}</td>
<td>8,000</td>
<td>2,000</td>
<td>25,000</td>
</tr>
<tr>
<td>D3_{large}</td>
<td>9,400</td>
<td>2,100</td>
<td>37,000</td>
</tr>
</tbody>
</table>
## Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Jaccard</th>
<th>False Negative</th>
<th>False Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>D\textsubscript{1 small}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>0.779</td>
<td>0.066</td>
<td>0.123</td>
</tr>
<tr>
<td>Regression</td>
<td>0.667</td>
<td>0.090</td>
<td>0.242</td>
</tr>
<tr>
<td>NN</td>
<td>0.808</td>
<td>0.032</td>
<td>0.159</td>
</tr>
<tr>
<td>D\textsubscript{2 medium}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>0.816</td>
<td>0.059</td>
<td>0.094</td>
</tr>
<tr>
<td>Regression</td>
<td>0.703</td>
<td>0.077</td>
<td>0.220</td>
</tr>
<tr>
<td>NN</td>
<td>0.840</td>
<td>0.037</td>
<td>0.123</td>
</tr>
<tr>
<td>D\textsubscript{3 large}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency</td>
<td>0.819</td>
<td>0.062</td>
<td>0.088</td>
</tr>
<tr>
<td>Regression</td>
<td>0.720</td>
<td>0.069</td>
<td>0.210</td>
</tr>
<tr>
<td>NN</td>
<td>0.850</td>
<td>0.038</td>
<td>0.113</td>
</tr>
</tbody>
</table>
Summary

• For each entity in a KB:
  • Get its class signature
  • Predict the relation distribution the entity ‘should’ have
  • Compare the existing facts for the entity to the predicted distribution
  • Record the missing relations, and their weight

• Do an entity-weighted aggregation over all entities

• This gives a demand-weighted list of missing facts in the KB
Alexa Knowledge Base

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- **Querying**
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**Research challenges**
- **Completeness**
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- **Verification**
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Simple Large-scale Relation Extraction from Unstructured Text

Christodoulopoulos and Mittal (2018) – LREC
Knowledge from Unstructured Text

The Goal:
Carrie Fisher wrote several semi-autobiographical novels, including Postcards from the Edge.
Knowledge from Unstructured Text

The Goal:
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Entity Recognition
Entity Resolution
Relation Extraction
Knowledge from Unstructured Text

The Goal:

Carrie Fisher wrote several semi-autobiographical novels, including *Postcards from the Edge.*

[carrrie fisher] [is the author of] [postcards from the edge]
Relation Extraction Approaches

• Rule-based
• Fully supervised
• Unsupervised
• Distant/weakly supervised
  • Snow, Jurafsky, Ng, 2005
  • Main assumption: if two entities are linked by a relation, any sentence containing both entities is likely to express that relation
    • [steven spielberg] [is the director of] [saving private ryan]
    • “Spielberg’s film Saving Private Ryan is based on…”
Distant supervision label generation

- Wikipedia
- Chunking, PoS Tagging
- Entity denotations (surface forms)
- Gazetteers
- Entity pairs (KB IDs)
Distant supervision label generation

1. Wikipedia
2. Chunking
   PoS Tagging
3. Entity denotations
   (surface forms)
4. Gazetteers
5. Entity pairs
   (KB IDs)

- Ontological Constraints
- Check against KB

- Positive Label
- Negative Label

YES
NO
His studies were interrupted by army service and at the end of the war he was forced to return. . .
[the second world war] [is an instance of] [cause of death]

In the intro to the song, Fred Durst makes reference to. . .
[intro 15367][is an instance of] [song]

Turner also released one album and several singles under the moniker Repeat.
[the singles the 2011 album] [is an instance of] [album]
Distant supervision label generation

Wikipedia page → URL → KB ID lookup → Main entity (KB ID) → KB → Related entities (x) (KB IDs) → KB ID → Denotations lookup → Entity denotations (x + main strings)

Chunking PoS Tagging → Entity denotations (surface forms) → Gazetteers → Entity pairs (KB IDs)

Ontological Constraints → Check against KB

YES → Positive Label

NO → Negative Label
Distant supervision label generation

- Wikipedia page
- KB Main entity (KB ID)
- URL à KB ID lookup
- Related entities (KB IDs)
- rel \(x_1\), main
- rel (main, \(x_2\))
- KB ID à Denotations lookup
- Entity denotations (\(x + \) main strings)
- Wikipedia Chunking
- PoS Tagging
- Entity denotations (surface forms)
- Gazetteers
- Entity pairs (KB IDs)
- YES
- NO
- Positive Label
- Negative Label
- Check against KB (Bloom filters)
- Ontological Constraints
- "George Springate"
- "judge"
- "Concordia University"
- "football player"
- "McGill University"
- "journalist"
- "Montreal Quebec"
- "human"
- "person"
- "African-American"
- "Law Firm Office"
- "Lawyer"
- "columnist"
- "Masters Degree"
- "Occupation"
- "Politician"
- "Columnist"
- "The Chicago Tribune"
- "Politician"
- "Columnist"
- "Judge"
- "Footballer"
- "Journalist"
- "Montreal"
- "Quebec"
- "Human Being"
- "Lawyer"
- "McGill University"
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- "Montreal"
- "Quebec"
- "Human Being"
- "Lawyer"
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- "Occupation"
- "Politician"
- "Columnist"
- "The Chicago Tribune"
- "Politician"
- "Columnist"
Call Your Girlfriend was written by Robyn, Alexander Kronlund and Klas Åhlund, with the latter producing the song.

[call your girlfriend 3] [is an instance of] [song]

Forget Her is a song by Jeff Buckley.

[forget her] [is an instance of] [song]

The Subei Mongol Autonomous County is an autonomous county within the prefecture-level city of Jiuquan in the northwestern Chinese province of Gansu.

[subei mongol autonomous county] [is an instance of] [chinese county]
Relation extraction

• HypeNET (Shwartz and Goldberg, 2016)
• Hyponyms [is an instance of] only
  • LexNET extends to multiple relations
• Using dependency paths

Dependencies are a grammar formalism

X/NOUN/nsubj/> be/VERB/ROOT/- Y/NOUN/attr/<

Dependencies are defined as a grammar formalism

X/NOUN/dobj/> define/VERB/ROOT/- as/ADP/prep/< Y/NOUN/pobj/<
Relation extraction

- HypeNET (Shwartz and Goldberg, 2016)
- Hyponyms [is an instance of] only
  - LexNET extends to multiple relations
- Using dependency paths
Relation extraction

- fastText (Joulin et al., 2016)
- Linear model
  - One hidden layer
  - Rank constraint
Results

HypeNET equally good as the much simpler fastText with the same input features.

<table>
<thead>
<tr>
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<th>HypeNET</th>
<th>fastText</th>
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<tbody>
<tr>
<td>[is an instance of]</td>
<td>94.29 (0.21)</td>
<td>94.31 (0.03)</td>
</tr>
<tr>
<td>[is the birthplace of]</td>
<td>85.57 (0.26)</td>
<td>87.63 (0.01)</td>
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<tr>
<td>[applies to]</td>
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### Alexa KB

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### Wikidata

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<tbody>
<tr>
<td>instance of (P31)</td>
<td>93.90 (0.21)</td>
<td>96.44 (0.01)</td>
</tr>
<tr>
<td>birthplace of (P19)</td>
<td>92.06 (0.90)</td>
<td>93.05 (0.07)</td>
</tr>
<tr>
<td>part of (P527)</td>
<td>48.73 (2.59)</td>
<td>72.87 (0.16)</td>
</tr>
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Results

HypeNET equally good as the much simpler fastText with the same input features.

MaxEnt results show that features alone are not enough. Need to create higher-dimensional representations of discrete features.

### Alexa KB

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<th>MaxEnt</th>
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</thead>
<tbody>
<tr>
<td>[is an instance of]</td>
<td>94.29 (0.21)</td>
<td>94.31 (0.03)</td>
<td>83.93</td>
</tr>
<tr>
<td>[is the birthplace of]</td>
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<td>87.63 (0.01)</td>
<td>80.83</td>
</tr>
<tr>
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<td>86.17 (0.01)</td>
<td>65.27</td>
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</table>

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<tbody>
<tr>
<td>instance of (P31)</td>
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<td>58.45</td>
</tr>
<tr>
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<td>66.72</td>
</tr>
<tr>
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<td>72.87 (0.16)</td>
<td>45.13</td>
</tr>
</tbody>
</table>
Summary

• New method for entity resolution
  • Page-specific gazetteers
• Features are important
  • HypeNET vs fastText
• Feature representation is important
  • fastText vs MaxEnt
Alexa Knowledge Base

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FEVER: a Large-scale Dataset for Fact Extraction and VERification

Thorne et al. (2018) – NAACL
Why automate verification?

• More frequent updates
  • Match the scale/speed of fact extraction
• Increased number of facts checked
• Wider variety of sources
• Provide justification of answers
The FEVER dataset (fever.ai)

- 185,000 true and false claims
  - Written by human annotators
- For each claim
  - Evidence from multiple Wikipedia pages at a sentence level
  - supported/refuted/not enough info label given the evidence
- Both evidence and label must be correct for scoring
Claim:
The Rodney King riots took place in the most populous county in the USA.

Evidence:
[wiki/Los Angeles Riots]: The 1992 Los Angeles riots, also known as the Rodney King riots were a series of riots, lootings, arsons, and civil disturbances that occurred in Los Angeles County, California in April and May 1992.

[wiki/Los Angeles County]: Los Angeles County, officially the County of Los Angeles, is the most populous county in the United States.
Claim:
The Rodney King riots took place in the most populous county in the USA.

Evidence:
[wiki/Los Angeles Riots]: The 1992 Los Angeles riots, also known as the Rodney King riots were a series of riots, lootings, arsons, and civil disturbances that occurred in Los Angeles County, California in April and May 1992.

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Dataset construction

- Sentences
- Factoid Claims
- Mutated Claims
- Verification & Labeling
Dataset construction

• Sentences
• Factoid Claims
• Mutated Claims
• Verification & Labeling

- June 2017 English Wiki Dump
- Sentence-split, tokenized 5.4m pages (CoreNLP)
- Kept only the intro section of articles
- Used 50,000 popular pages for claim generation
Dataset construction

• Sentences

• Factoid Claims
  • Simple sentences from the original sentence
  • One fact (clause) per sentence
  • Context from original Wikipedia article
  • World knowledge introduced using dictionary of Wikipedia first sentences

• Mutated Claims

• Verification & Labeling
Dataset construction

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Simple sentences from the original sentence
- One fact (clause) per sentence
- Context from original Wikipedia article
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Generating Claims About

Source Sentence
This is the sentence that is used to substantiate your claims about Warren Buffett

Dictionary
Click the word for a definition. These definitions can be used to support the claims you write or make the claims more complex by making a deduction using the dictionary definitions
The dictionary comes from the blue links on Wikipedia. This may be empty if the passage from Wikipedia contains no links.

True Claims (one per line)
Aim to spend about 2 minutes generating 2-5 claims from this source sentence
If the source sentence is uninformative, press the skip button
Example

Warren Buffett

Buffett has been the chairman and largest shareholder of Berkshire Hathaway since 1970, and his business exploits have had him referred to as the "Wizard", "Oracle" or "Sage" of Omaha by global media outlets.

Show Context

Berkshire Hathaway
Berkshire Hathaway Inc. is an American multinational conglomerate holding company headquartered in Omaha, Nebraska, United States.

List of assets owned by Berkshire Hathaway
Omaha, Nebraska
Omaha is the largest city in the state of Nebraska and the county seat of Douglas County.

shareholder

Warren Buffett is the chairman of an American multinational company. Warren Buffett's company is based in the largest city in the state of Nebraska.
Dataset construction

• Sentences

• Factoid Claims

• Mutated Claims

• Verification & Labeling

• 6 mutations akin to relations in NLI
  • paraphrasing
  • negation
  • generalization
  • specialization
  • substitution with similar entity/relation
  • substitution with dissimilar entity/relation

• Mutated claims may be true or false or unknown
Dataset construction
• Sentences
• Factoid Claims
• Mutated Claims
• Verification & Labeling

59 mutations akin to relations in NLI
• paraphrasing
• negation
• generalization
• specialization
• substitution with similar entity/relation
• substitution with dissimilar entity/relation

Mutated claims may be true or false or unknown

Substitution for a similar entity and/or relation (Type 3)
Substitute either a relation, property and/or an attribute of Warren Buffett in the claim to something else from the same set of things.

Avoid rephrasing the original claim.
The mutated claim should not imply the original claim.
The mutated claim must be about Warren Buffett.
Examples
Warren Buffett is the chairman of a Canadian multinational corporation.
Warren Buffett is the president of an American multinational company.
Warren Buffett is chairman of McDonalds.

Substitution for a dissimilar entity and/or relation (Type 4)
Substitute either a relation, property and/or an attribute of Warren Buffett in the claim to something plausible from a different set of things.

Avoid rephrasing the original claim.
The mutated claim should not imply the original claim.
The mutated claim must be about Warren Buffett.
Examples
Warren Buffett is the chairman of an American football team.

Original Claim
Warren Buffett is the chairman of an American multinational company.
Generated From: Buffett has been the chairman and largest shareholder of Berkshire Hathaway since 1970, and his business exploits have had him referred to as the "Wizard", "Oracle" or "Sage" of Omaha by global media outlets.

Make the Claim more Specific (So that the new claim implies the original) (Type 5)
Modify the claim by replacing either a relation, property and/or an attribute of Warren Buffett to something more specific that implies the original claim.

Avoid rephrasing the original claim.
The mutated claim should imply the original claim.
The mutated claim must be about Warren Buffett.
Examples
Warren Buffett is chairman of Berkshire Hathaway

Make the Claim more General (So that the new claim is implied by the original) (Type 6)
Modify the claim by replacing either a relation, property and/or an attribute of Warren Buffett to something more general that is implied by the original claim.

Avoid rephrasing the original claim.
The mutated claim should be implied by the original claim.
The mutated claim must be about Warren Buffett.
Examples
Warren Buffett is the chairman of a company.
Dataset construction

• Sentences

• Factoid Claims
  • Sentence-level annotation for supporting/refuting information
  • Can combine information from multiple pages
  • Trade-off between time to find evidence vs. recall

• Mutated Claims

• Verification & Labeling

[Image 30x11 to 173x40]
[Image 177x1 to 297x49]
The 1992 Los Angeles riots occurred in the most populous county in the United States.

Wikipedia article for 1992 Los Angeles riots

The 1992 Los Angeles riots, also known as the Rodney King riots, the South Central riots, the 1992 Los Angeles civil disturbance, the 1992 Los Angeles civil unrest, and the Los Angeles uprising, were a series of riots, lootings, arsons, and civil disturbances that occurred in Los Angeles County, California in April and May 1992.

The unrest began in South Central Los Angeles on April 29 after a trial jury acquitted four officers of the Los Angeles Police Department of the use of excessive force in the videotaped arrest and beating of Rodney King.

It then spread throughout the Los Angeles metropolitan area as thousands of people rioted over a six-day period following the announcement of the verdict.

Widespread looting, assault, arson, and killings occurred during the riots, and estimates of property damage were over $1 billion.

Order was only restored after members of the California Army National Guard, the 7th Infantry Division, and the 1st Marine Division were called in to stop the rioting when local police could not control the situation.

In total, 58 people were killed during the riots, more than 2,000 people were injured, and more than 11,000 were arrested.

LAPD chief of police Daryl Gates, who had already announced his resignation by the time of the riots, took much of the institutional blame.

Los Angeles County, California

- Los Angeles County, officially the County of Los Angeles, is the most populous county in the United States.
- Its population is larger than that of 42 individual U.S. states.
- It has 88 incorporated cities and many unincorporated areas and at 4083 sqmi, it is larger than the combined areas of the U.S. states of Delaware and Rhode Island.
- The county is home to more than one-quarter of California residents and is one of the most ethnically diverse counties in the U.S. Its county seat, the City of Los Angeles, is also its most populous city at about four million.

Rodney King

- Rodney Glen King (April 2, 1965 -- June 17, 2012) was a taxi driver who became internationally known after being beaten by Los Angeles Police Department officers following a high-speed car chase on March 3, 1991.
- A witness, George Holliday, videotaped much of the beating from his balcony, and sent the footage to local news station KTLA.
- The footage shows four officers surrounding King, several of them striking him repeatedly, while other officers stood by.
Quality of annotation

• Precision: 95.4%, Recall: 72.4%
  • against super-annotators with no time restrictions
• 5-way IAA $\kappa$ of 0.684 over 4% of claims (n=7506)
• We re-annotated 227 claims, 91.2% annotated correctly

• Lessons Learned:
  • Hard to remove annotator’s world knowledge
  • Hard to come up with ‘universal’ definitions
The FEVER challenge

• 87 submissions from 23 teams
• Preliminary leaderboard – pending further annotation

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team Name</th>
<th>Evidence F1</th>
<th>Label Accuracy</th>
<th>FEVER score</th>
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<td>Baseline</td>
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Summary

• Fact verification is crucial for QA systems
  • Gauge of extracted fact quality
  • Provide justification of answers

• First large-scale dataset for fact verification
  • 185,000 human-generated claims
  • Labelled via evidence annotation

• Shared task results
  • Significant improvements over baselines – plenty of room for more

• FEVER 2?
Overall conclusions

• Knowledge at scale is difficult!

• Presented ideas on
  • **What**: demand-weighted coverage
  • **How**: entity/relation extraction from unstructured text
  • **Why**: verification through evidence

• Challenges
  • Different languages, sources, relations
  • Emerging trends
Overall conclusions

- Knowledge at scale is difficult!
- Presented ideas on
  - **What**: demand-weighted coverage
  - **How**: entity/relation extraction from unstructured text
  - **Why**: verification through evidence
- Challenges
  - Different languages, sources, relations
  - Emerging trends

Get more FEVER at the EMNLP workshop!
Thanks!