

Numerical Relation Extraction from the Web

MTP Stage 1 Presentation

Aman Madaan Ashish Mittal

Indian Institute of Technology Bombay, Mumbai

22nd October, 2014

Outline

1 Motivation

2 Problem Statement

3 Relation Extraction as a Machine Learning Problem

4 Distant Supervision

5 Distant Supervision Techniques

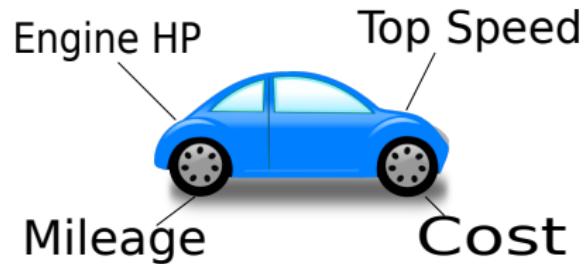
6 TAC Submission

7 Numerical Relation Extraction

8 Units in Numerical Relation Extraction

Entities and Numerical Attributes





Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.

Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.
- Countries are popular and finite, finding complete knowledge bases is possible.

Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.
- Countries are popular and finite, finding complete knowledge bases is possible.
- What about less popular entities?

Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.
- Countries are popular and finite, finding complete knowledge bases is possible.
- What about less popular entities?
 - What is the population of Arbit Apartments, Powai?

Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.
- Countries are popular and finite, finding complete knowledge bases is possible.
- What about less popular entities?
 - What is the population of Arbit Apartments, Powai?
 - What is the GDP of Sugarcane Industry of India?

Entities and Numerical Attributes

- Repositories of facts containing this information can be found at many places, like data.worldbank.org, Wikipedia infoboxes etc.
- Countries are popular and finite, finding complete knowledge bases is possible.
- What about less popular entities?
 - What is the population of Arbit Apartments, Powai?
 - What is the GDP of Sugarcane Industry of India?
 - Percent of Internet users in Mumbai?

Motivation

- Good News!!!

Motivation

- Good News!!!
- Web is huge, probably, there is some page which contains the information we are looking for.

Motivation

- Good News!!!
- Web is huge, probably, there is some page which contains the information we are looking for.
- The way in which you express a fact about an entity depends on the fact, and not the entity.

Motivation

- Good News!!!
- Web is huge, probably, there is some page which contains the information we are looking for.
- The way in which you express a fact about an entity depends on the fact, and not the entity.
- We may expect the sentence structure to be similar.

Motivation

- Good News!!!
- Web is huge, probably, there is some page which contains the information we are looking for.
- The way in which you express a fact about an entity depends on the fact, and not the entity.
- We may expect the sentence structure to be similar.
 - Population of India reached 1.3 billion, making it the second largest country in the world.

Motivation

- Good News!!!
- Web is huge, probably, there is some page which contains the information we are looking for.
- The way in which you express a fact about an entity depends on the fact, and not the entity.
- We may expect the sentence structure to be similar.
 - Population of India reached 1.3 billion, making it the second largest country in the world.
 - Population of Arbit Apartments, Powai reached 1300.

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Problem Statement

- Given that we know a lot about countries, can we train extractors that run over the web and pull similar facts about other entities?

Introduction

- The knowledge is scattered in unstructured text on the web.

According to the [International Monetary Fund](#) (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by [purchasing power parity](#), or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and ready

590.56 million people in China were using
the internet at mid-2013, an increase of
nearly 53 million (or 9.85%) from a year earlier.

The land area of the [contiguous United States](#) is 2,959,064 square miles (7,663,941 km²). Alaska, separated from the contiguous United States by Canada, is the largest state at 663,268 square miles (1,717,856 km²). Hawaii, occupying an archipelago in the central [Pacific](#), southwest of North America, is 10,931 square miles (28,311 km²) in area.^[136]

- Can such facts be extracted automatically?

Relation Extraction: Problem

- Extract 3-tuples which consists of an entity and a numerical value that are bound by some relation.
 - (India, **economy**, 1.842 trillion USD)
 - (China, **internet users**, 590.56 million)
 - (USA, **land area**, 2,959,054 square mile)

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Relation extraction as a Machine Learning Problem

Relation Extraction as a Machine Learning Problem

- Structure and content of sentences expressing the same relations can be expected to be similar.
 - The population of Australia is estimated to be 23,622,400 as of 7 October 2014.
 - According to an official estimate for 1 June 2014, the population of Russia is 143,800,000.

Relation Extraction as a Machine Learning Problem

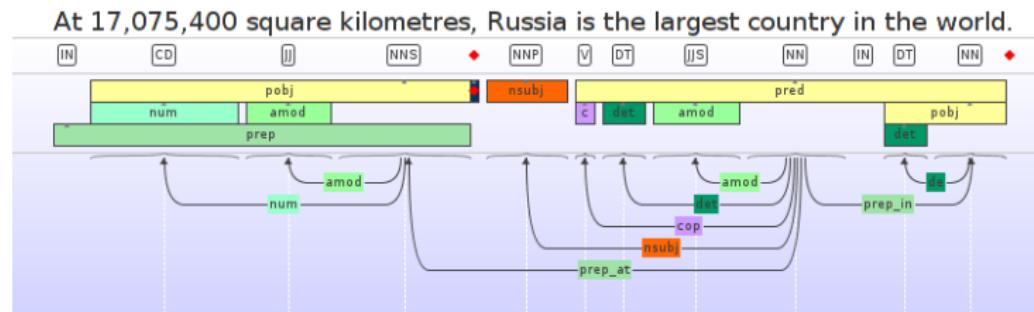
- Structure and content of sentences expressing the same relations can be expected to be similar.
 - At 17,075,400 square kilometres, Russia is the largest country in the world.
 - With an area of 504,030 km^2 , Spain is the second largest country in Western Europe.

Relation Extraction as a Machine Learning Problem

- Redundancy in grammatical features and dependencies of the sentences expressing same relation.

Relation Extraction as a Machine Learning Problem

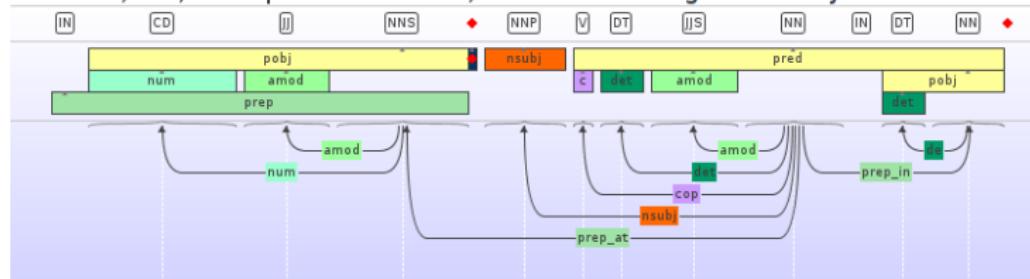
- Redundancy in grammatical features and dependencies of the sentences expressing same relation.



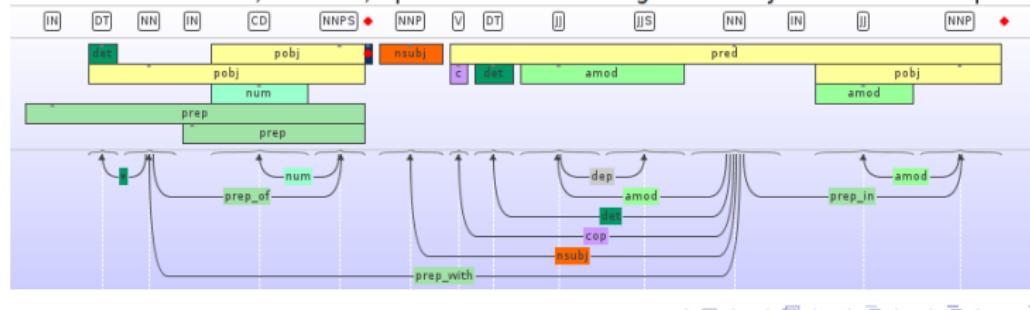
Relation Extraction as a Machine Learning Problem

- Redundancy in grammatical features and dependencies of the sentences expressing same relation.

At 17,075,400 square kilometres, Russia is the largest country in the world.



With an area of 504,030 km², Spain is the second largest country in Western Europe.



Possible Workflow

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.
- Learn a multi-class classifier on this training data (Explained later).

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.
- Learn a multi-class classifier on this training data (Explained later).
- Once the model is learnt, for every sentence

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.
- Learn a multi-class classifier on this training data (Explained later).
- Once the model is learnt, for every sentence
 - Extract features for the sentence

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.
- Learn a multi-class classifier on this training data (Explained later).
- Once the model is learnt, for every sentence
 - Extract features for the sentence
 - Predict the relation using the model for these features

Possible Workflow

- Collect enough examples for each relation so that there are sufficient patterns and enough redundancy to exploit.
- Extract features (important keywords, grammatical structure, parse trees, etc.) for these sentences.
- Learn a multi-class classifier on this training data (Explained later).
- Once the model is learnt, for every sentence
 - Extract features for the sentence
 - Predict the relation using the model for these features
 - store the fact into database.

Challenge

- Large Corpus (16 million sentences), hand labeling is out of questions

Challenge

- Large Corpus (16 million sentences), hand labeling is out of questions
- But we need lots of training data to train high quality extractors!

Challenge

- Large Corpus (16 million sentences), hand labeling is out of questions
- But we need lots of training data to train high quality extractors!
- Is there a middle ground?

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Distant Supervision

Distant Supervision

- Manual labeling of the entire corpus is not possible

Distant Supervision

- Manual labeling of the entire corpus is not possible
- Weak Supervision as a middle ground

Distant Supervision

- Manual labeling of the entire corpus is not possible
- Weak Supervision as a middle ground
- Use Heuristics to align a table of facts with the corpus

Distant Supervision

- Manual labeling of the entire corpus is not possible
- Weak Supervision as a middle ground
- Use Heuristics to align a table of facts with the corpus
- Fuzzy training

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode.
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887.
- Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar.
- Alan Turing biopic The Imitation Game named as London film festival opener.

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode. LABEL : BornIn ✓
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887.
- Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar.
- Alan Turing biopic The Imitation Game named as London film festival opener.

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode. ✓
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887. ✓
- Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar.
- Alan Turing biopic The Imitation Game named as London film festival opener.

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode. ✓
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887. ✓
- **Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar X**
- Alan Turing biopic The Imitation Game named as London film festival opener.

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode. ✓
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887. ✓
- Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar. X
- Alan Turing biopic The Imitation Game named as London film festival opener. ✓

Distant Supervision

Example

- Born - In database

Donald Knuth	Wisconsin
Srinivasa Ramanujan	Erode
Alan Turing	London

- Given Sentences

- Srinivasa Ramanujan was born in his maternal grandmother's home in Erode. ✓
- Srinivasa Ramanujan was born in Erode, Tamilnadu, India, on 22nd December, 1887. ✓
- Turing's father was with the Indian Civil Service (ICS) at Chhatrapur, Bihar. X
- Alan Turing biopic The Imitation Game named as London film festival opener.✓ FALSE POSITIVE

Distant Supervision

Distant Supervision

- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation

Distant Supervision

- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation
- Can quickly label huge corpora

Distant Supervision

- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation
- Can quickly label huge corpora
- Same entity pair can match different relations (Founded(Steve Jobs, Apple) or CEO(Steve Jobs, Apple))

Distant Supervision

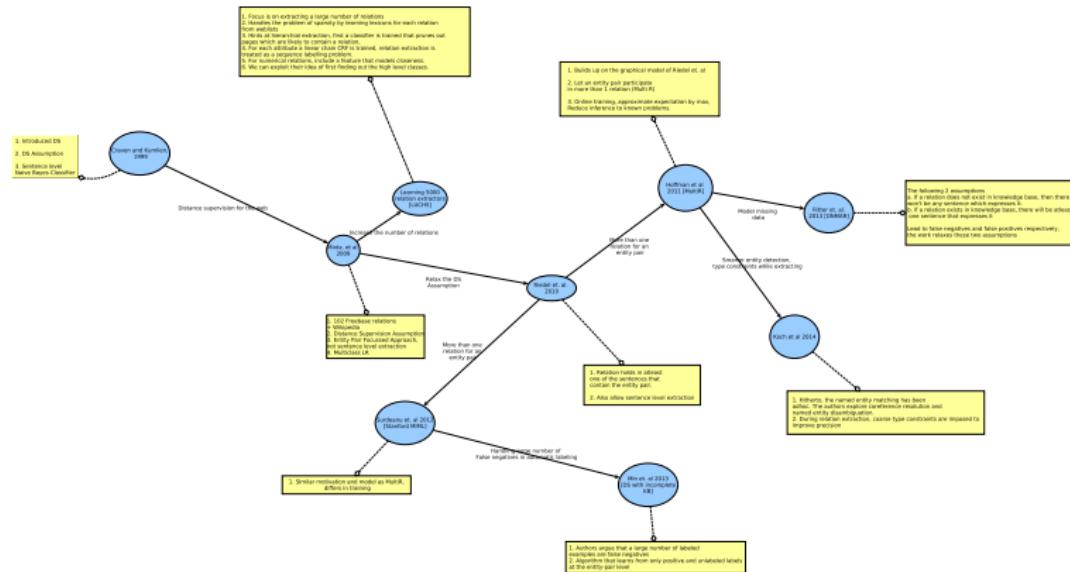
- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation
- Can quickly label huge corpora
- Same entity pair can match different relations (Founded(Steve Jobs, Apple) or CEO(Steve Jobs, Apple))
- False positives, may lead to model learning wrong patterns for relations

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

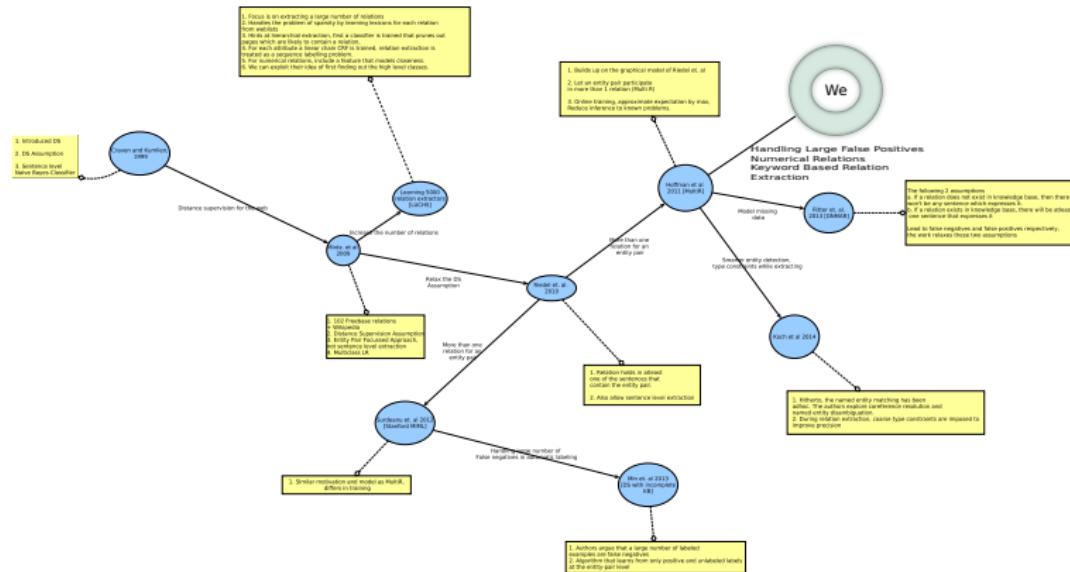
Distant Supervision Techniques

- First paper in 1999, almost every possibility explored



Distant Supervision Techniques

- First paper in 1999, *almost* every possibility explored

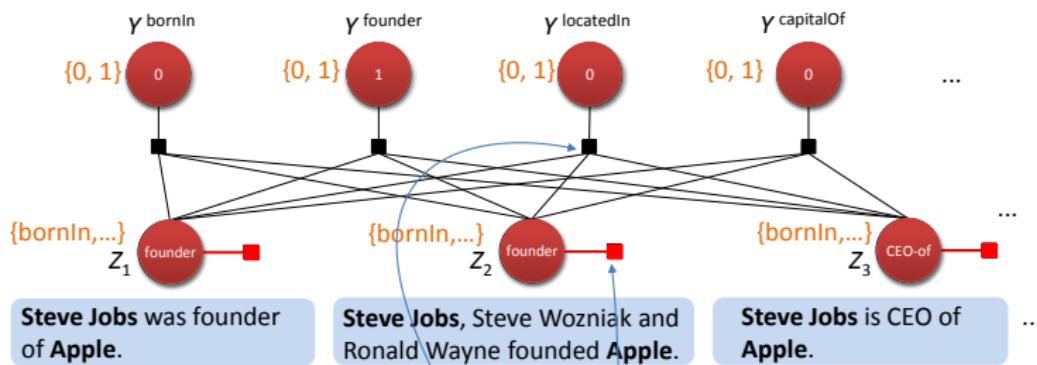


Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Model

Steve Jobs, Apple:



$$p(\mathbf{Y} = \mathbf{y}, \mathbf{Z} = \mathbf{z} | \mathbf{x}; \theta) \stackrel{\text{def}}{=} \frac{1}{Z_x} \prod_r \Phi^{\text{join}}(y^r, z) \prod_i \Phi^{\text{extract}}(z_i, x_i)$$

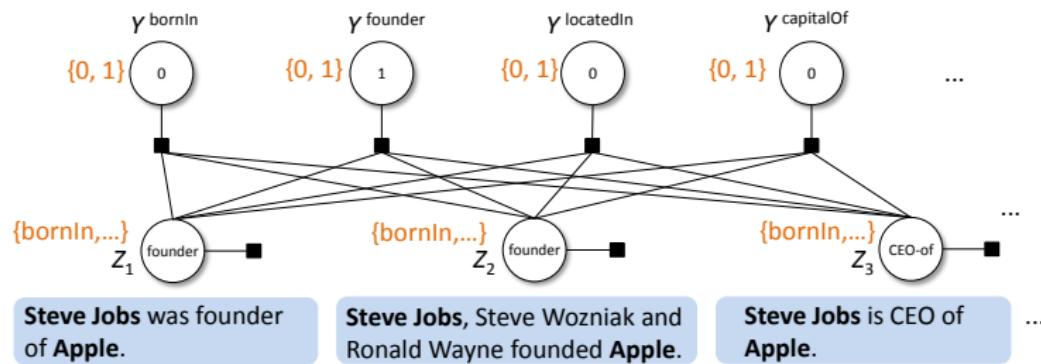
$$\Phi^{\text{join}}(y^r, z) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } y^r = \text{true} \wedge \exists i : z_i = r \\ 0 & \text{otherwise} \end{cases}$$

All features at
sentence-level
(join factors are
deterministic ORs)

Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Model



- Extraction almost entirely driven by sentence-level reasoning
- Tying of facts Y_r and sentence-level extractions Z_i still allows us to model weak supervision for training

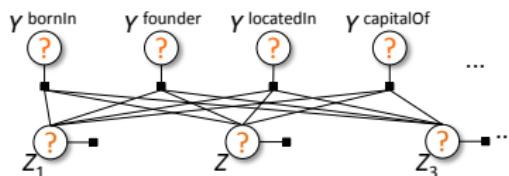
Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Inference

Need:

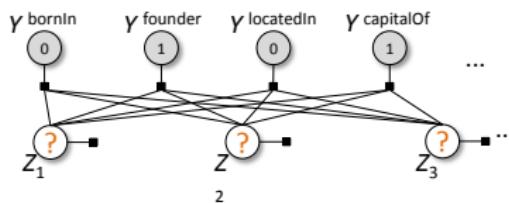
- Most likely sentence labels:



$$\arg \max_{\mathbf{y}, \mathbf{z}} p(\mathbf{y}, \mathbf{z} | \mathbf{x}; \theta)$$

Easy

- Most likely sentence labels *given* facts:



$$\arg \max_{\mathbf{z}} p(\mathbf{z} | \mathbf{x}, \mathbf{y}; \theta)$$

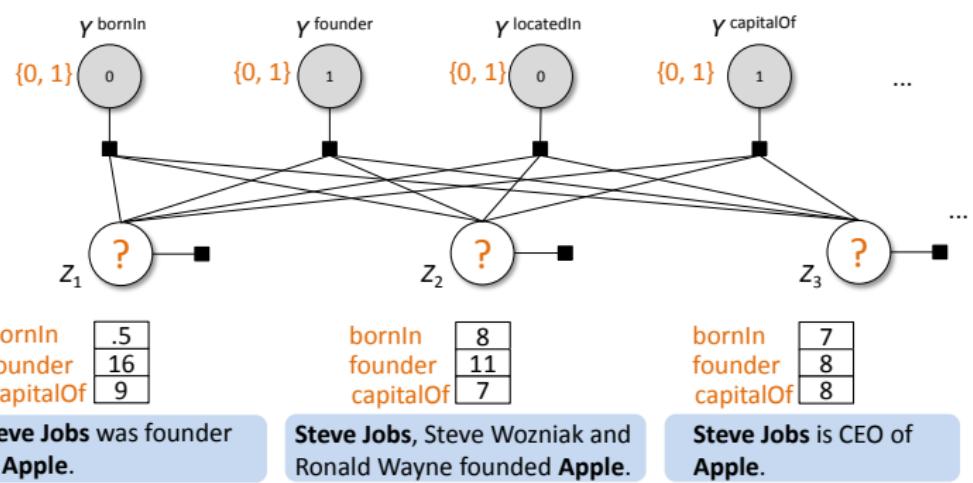
Challenging

Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Inference

- Computing $\arg \max_z p(z|x, y; \theta)$:

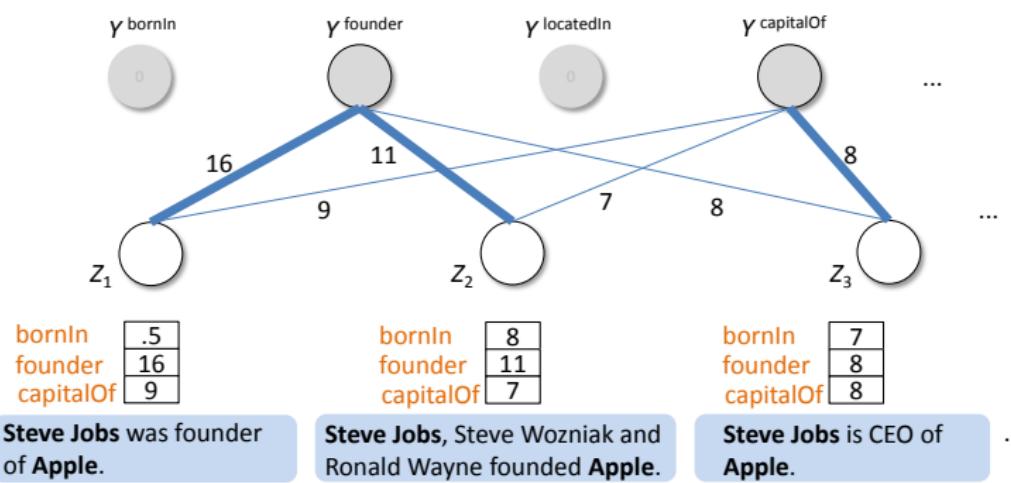


Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Inference

- Variant of the weighted, edge-cover problem:



Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Learning

- Training set $\{(\mathbf{x}_i, \mathbf{y}_i) | i = 1 \dots n\}$, where
 - i corresponds to a particular entity pair
 - \mathbf{x}_i contains all sentences with mentions of pair
 - \mathbf{y}_i bit vector of facts about pair from database
- Maximize Likelihood

$$O(\theta) = \prod_i p(\mathbf{y}_i | \mathbf{x}_i; \theta) = \prod_i \sum_{\mathbf{z}} p(\mathbf{y}_i, \mathbf{z} | \mathbf{x}_i; \theta)$$

Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Learning

- Scalability: Perceptron-style additive updates
- Requires two approximations:
 1. Online learning
For example i (entity pair), define

$$\phi(\mathbf{x}, \mathbf{z}) = \sum_j \phi(x_j, z_j)$$

Use gradient of local log likelihood for example i:

$$\begin{aligned}\frac{\partial \log O_i(\theta)}{\partial \theta_j} &= E_{p(\mathbf{z}|\mathbf{x}_i, \mathbf{y}_i; \theta)} [\phi_j(\mathbf{x}_i, \mathbf{z})] \\ &\quad - E_{p(\mathbf{y}, \mathbf{z}|\mathbf{x}_i; \theta)} [\phi_j(\mathbf{x}_i, \mathbf{z})]\end{aligned}$$

2. Replace expectations with maximizations

Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Learning: Hidden-Variable Perceptron

passes over
dataset

for each
entity pair i

most likely
sentence labels
and inferred facts
(ignoring DB facts)

most likely
sentence labels
given DB facts

```
initialize parameter vector  $\Theta \leftarrow 0$ 
for  $t = 1 \dots T$  do
    for  $i = 1 \dots n$  do
         $(\mathbf{y}', \mathbf{z}') \leftarrow \arg \max_{\mathbf{y}, \mathbf{z}} p(\mathbf{y}, \mathbf{z} | \mathbf{x}_i; \theta)$ 
        if  $\mathbf{y}' \neq \mathbf{y}_i$  then
             $\mathbf{z}^* \leftarrow \arg \max_{\mathbf{z}} p(\mathbf{z} | \mathbf{x}_i, \mathbf{y}_i; \theta)$ 
             $\Theta \leftarrow \Theta + \phi(\mathbf{x}_i, \mathbf{z}^*) - \phi(\mathbf{x}_i, \mathbf{z}')$ 
        end if
    end for
end for
Return  $\Theta$ 
```

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Cold Start Knowledge Base Population, 2014

- Knowledge Base Population (KBP) track of TAC encourages the development of systems that can match entities mentioned in natural texts with those appearing in a knowledge base and extract novel information about entities from a document collection and add it to a new or existing knowledge base.

Cold Start Knowledge Base Population, 2014

- Knowledge Base Population (KBP) track of TAC encourages the development of systems that can match entities mentioned in natural texts with those appearing in a knowledge base and extract novel information about entities from a document collection and add it to a new or existing knowledge base.
- Some example relations:
 - children of
 - city of birth
 - shareholders
 - countries of residence

Cold Start Knowledge Base Population

- Modeled the problem using distant supervision.
- Used Freebase as an existing Knowledge base.
- **Freebase:** Freebase is a large collaborative knowledge base consisting of metadata composed mainly by its community members.
- It is an online collection of structured data harvested from many sources, including individual, user-submitted wiki contributions.

Corpus

- The TAC corpus consisted of three type of documents:

Corpus

- The TAC corpus consisted of three type of documents:
 - **discussion forums** 99,063 English discussion forum documents selected from the BOLT Phase 1 discussion forums source data releases. Each forum includes at least 5 posts.

- The TAC corpus consisted of three type of documents:
 - **discussion forums** 99,063 English discussion forum documents selected from the BOLT Phase 1 discussion forums source data releases. Each forum includes at least 5 posts.
 - **newswire** 1,000,257 documents selected from English Gigaword Fifth Edition.

- The TAC corpus consisted of three type of documents:
 - **discussion forums** 99,063 English discussion forum documents selected from the BOLT Phase 1 discussion forums source data releases. Each forum includes at least 5 posts.
 - **newswire** 1,000,257 documents selected from English Gigaword Fifth Edition.
 - **web** 999,999 English web documents selected from various GALE web collections.

- The TAC corpus consisted of three type of documents:
 - **discussion forums** 99,063 English discussion forum documents selected from the BOLT Phase 1 discussion forums source data releases. Each forum includes at least 5 posts.
 - **newswire** 1,000,257 documents selected from English Gigaword Fifth Edition.
 - **web** 999,999 English web documents selected from various GALE web collections.
- We have submitted the knowledge base populated using our techniques on the above corpus and waiting for results.

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Distant supervision for Numerical Relation Extraction

Knowledge Base

- Derived from data.worldbank.org, 4371979 numerical facts about 249 countries, 1281 attributes

Freebase Entity	Value	Relation
/m/04g5k	3126000130	Electricity Production
/m/02k8k	1969.179	CO_2 Emission
/m/06nnj	332315	Total Population
/m/019rg5	55.020073	Life Expectancy
/m/05sb1	19974.148	CO_2 Emission
/m/05v8c	10000000000	Electricity Production
/m/03spz	7639000100	Electricity Production
/m/06vbd	44249.688	CO_2 Emission
/m/0d060g	51.3	Internet Users(%)
/m/05qkp	62.298927	Life Expectancy

Selected Relations

Relation Name	Relation Code
Land area (sq. km)	AG.LND.TOTL.K2
Foreign direct investment, net (current US\$)	BN.KLT.DINV.CD
Goods exports (current US\$)	BX.GSR.MRCH.CD
Electricity production (kWh)	EG.ELC.PROD.KH
CO2 emissions (kt)	EN.ATM.CO2E.KT
Pump price for diesel fuel (US\$ per liter)	EP.PMP.DESL.CD
Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG
Internet users (per 100 people)	IT.NET.USER.P2
GDP (current US\$)	NY.GDP.MKTP.CD
Life expectancy at birth, total (years)	SP.DYN.LE00.IN
Population (Total)	SP.POP.TOTL

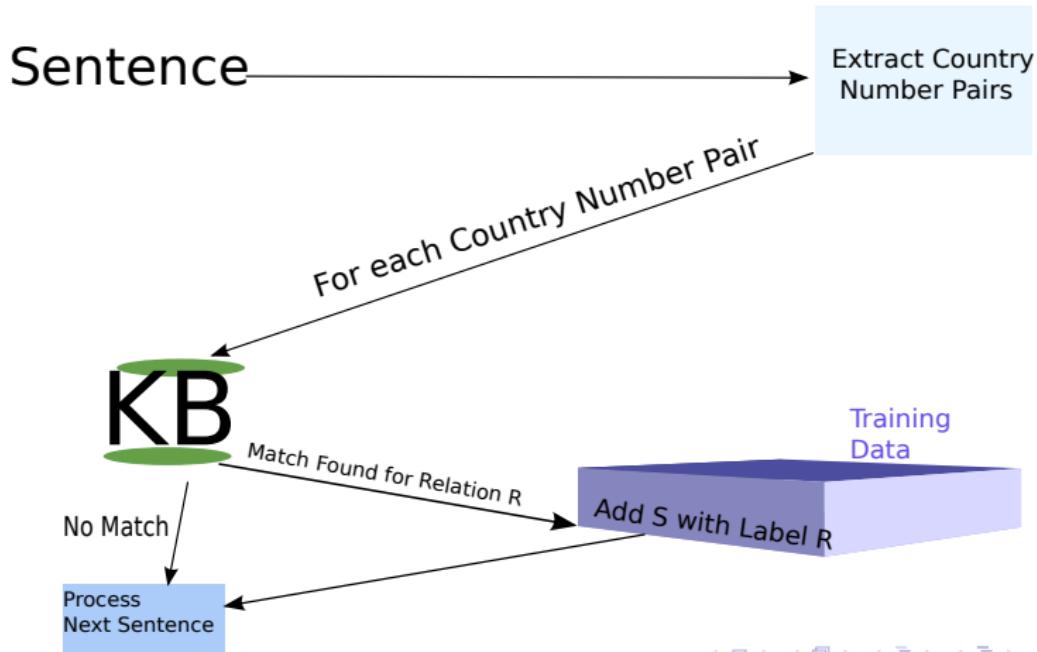
Corpus

- Subset of the tac corpus
- 268, 036 Documents, X sentences having a country and a number
- List of countries augmented manually by adding all possible synonyms (Dutch, Netherlands) and inflections (Ireland, Irish)

Distant supervision process for numerical relation extraction

- Extract a country and number from a sentence, go to kb and check if there is a match.
- Can be creative during matching:
 - Distance based matching
 - Time based matching

First Attempt: Vanilla Matching



Vanilla Matching

- A large number of matches
- Most of them false positives

Vanilla Matching: Results

Relation	Total Matches	Sampled Matches	True Matches	Precision(%)
Land Area	1884	15	1	6.7
Foreign Direct Investment	0	0	0	0
Goods Export	0	0	0	0
Electricity Production	381	10	0	0
CO ₂ Emission	0	0	0	0
Diesel Prices	8491	15	0	0
Inflation(%)	8689	15	0	0
Internet Users(%)	182319	40	0	0
GDP(\$)	0	0	0	0
Life Expectancy	267	10	0	0
Total Population	0	0	0	0

Sample Matches for Vanilla Matching

Country	Relation	Value	Sentence
South Africa	Internet Users(%)	24	Montjane, 24 , was crowned on Sunday evening at the Superbowl at Sun City, in South Africa 's North West province.
Croatia	Inflation	500	Croatian police say more than 500 guns turned in after the country's 1991 war were stolen from a police depot and sold on the black market.
France	Life Expectancy	75	France : Hugo Lloris, Eric Abidal, Patrice Evra, William Gallas, Bacary Sagna, Abou Diaby, Yoann Gourcuff (Florent Malouda, 75), Jeremy Toulalan, Nicolas Anelka (Thierry Henry, 72), Sidney Govou (Andre-Pierre Gignac, 85), Franck Ribery.
France	Diesel prices	1.72	Lotte Friis of Denmark won the women's 800 freestyle in 8:23.27, followed at 0.73 seconds by Ophelie Cyriell Etienne of France and Federica Pellegrini of Italy, 1.72 seconds back.
Bermuda	Land Area(sq. km)	50	Forecasters were also closely tracking the path of Tropical Storm Fiona about 360 miles (580 km) south of Bermuda , with wind speeds of up to 50 miles (85 km) per hour.

Key Observations on vanilla matching

- Units for precision, not just recall
- Dates and Sports articles lead to a lot of false positives
- Small numbers generate larger false positives; finer numbers generate fewer false positives.
 - Intuitively, it makes sense that we'll see a lot of 2s, 3s, 71s in different contexts than 1,000,232,112. Due to similar reasons, getting an exact match for 23.14152 is more difficult than matching 23.

False Positives

Numbers are weak entities

- Vanilla numerical relation matching is bound to attract humoungous amounts of false positives;

False Positives

Numbers are weak entities

- Vanilla numerical relation matching is bound to attract humoungous amounts of false positives;
- Stems from the fact that numbers don't have an identity of their own.

False Positives

Numbers are weak entities

- Vanilla numerical relation matching is bound to attract humoungous amounts of false positives;
- Stems from the fact that numbers don't have an identity of their own.
- Consider India and Mumbai Vs. India and 19

False Positives

Numbers are weak entities

- Vanilla numerical relation matching is bound to attract humoungous amounts of false positives;
- Stems from the fact that numbers don't have an identity of their own.
- Consider India and Mumbai Vs. India and 19
- Mumbai is a strong entity, 19 is a **weak** entity.

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can appear with India in several contexts:

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can be appear with India in several contexts:
 - Internet user %

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can be appear with India in several contexts:
 - Internet user %
 - Billion dollars invested by a company

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can be appear with India in several contexts:
 - Internet user %
 - Billion dollars invested by a company
 - % of people below the poverty line

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can appear with India in several contexts:
 - Internet user %
 - Billion dollars invested by a company
 - % of people below the poverty line
 - date (if we are not careful)

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can appear with India in several contexts:
 - Internet user %
 - Billion dollars invested by a company
 - % of people below the poverty line
 - date (if we are not careful)
 - number of medals won by Indian athletes...

False Positives

Numbers are weak entities

- Compare the number of sentences in which India and Mumbai appear together, vs the number of sentences in which India and 19 appear together.
- Just 19 can be appear with India in several contexts:
 - Internet user %
 - Billion dollars invested by a company
 - % of people below the poverty line
 - date (if we are not careful)
 - number of medals won by Indian athletes...
- Can we expect the situation to be even worse for certain types of numbers?

Outline

- 1 Motivation
- 2 Problem Statement
- 3 Relation Extraction as a Machine Learning Problem
- 4 Distant Supervision
- 5 Distant Supervision Techniques
- 6 TAC Submission
- 7 Numerical Relation Extraction
- 8 Units in Numerical Relation Extraction

Numbers are incomplete without units

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth [US\\$1.842 trillion](#); it is the eleventh-largest economy by market exchange rates, and is, at [US\\$4.962 trillion](#), the third-largest by [purchasing power parity](#), or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reaching

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth [US\\$1.842 trillion](#); it is the eleventh-largest economy by market exchange rates, and is, at [US\\$4.962 trillion](#), the third-largest by [purchasing power parity](#), or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reac-

- Units help in improving recall.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth [US\\$1.842 trillion](#); it is the eleventh-largest economy by market exchange rates, and is, at [US\\$4.962 trillion](#), the third-largest by [purchasing power parity](#), or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reaching

- Units help in improving recall.

- In above example 1.842 as number alone would not match with the fact regarding economy in knowledge base.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth **US\$1.842 trillion**; it is the eleventh-largest economy by market exchange rates, and is, at **US\$4.962 trillion**, the third-largest by **purchasing power parity**, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reaching

- Units help in improving recall.

- In above example 1.842 as number alone would not match with the fact regarding economy in knowledge base.
- But with the unit trillion USD, we can normalize the value and then it would match existing facts in knowledge base.

Numbers are incomplete without units

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reac-

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reac-

- Units help in improving recall.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reac-

- Units help in improving recall.
 - In above example 1.842 as number alone would not match with the fact regarding economy in knowledge base.

Numbers are incomplete without units

- Apart from being a constant quantity, a number usually makes sense when presented along with units.

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reac-

- Units help in improving recall.

- In above example 1.842 as number alone would not match with the fact regarding economy in knowledge base.
- But with the unit trillion USD, we can normalize the value and then it would match existing facts in knowledge base.

Numbers are incomplete without units

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reaching

- Units help in reducing false positives and hence improving precision.

Numbers are incomplete without units

According to the International Monetary Fund (IMF), as of 2013, the Indian economy is nominally worth US\$1.842 trillion; it is the eleventh-largest economy by market exchange rates, and is, at US\$4.962 trillion, the third-largest by purchasing power parity, or PPP.^[9] With its average annual GDP growth rate of 5.8% over the past two decades, and reaching

- Units help in reducing false positives and hence improving precision.
- If there is a fact, e.g, **inflation(India, 1.842%)** in knowledge base, then ignoring units can cause an incorrect match which leads in learning towards noisy patterns.

Unit Extraction is not easy!

Unit Extraction is not easy!

- Different ways to represent a single unit.

Unit Extraction is not easy!

- Different ways to represent a single unit.
 - Tunisia occupies an area of 163,610 **square kilometres**, of which 8,250 are water.

Unit Extraction is not easy!

- Different ways to represent a single unit.
 - Tunisia occupies an area of 163,610 **square kilometres**, of which 8,250 are water.
 - With an area of about 9.6 **million km²**, the People's Republic of China is the 3rd largest country in total area behind Russia and Canada, and very similar to the United States.

Unit Extraction is not easy!

- Different ways to represent a single unit.
 - Tunisia occupies an area of 163,610 **square kilometres**, of which 8,250 are water.
 - With an area of about 9.6 **million km²**, the People's Republic of China is the 3rd largest country in total area behind Russia and Canada, and very similar to the United States.
- Multiple units to represent a single numerical fact.

Unit Extraction is not easy!

- Different ways to represent a single unit.
 - Tunisia occupies an area of 163,610 **square kilometres**, of which 8,250 are water.
 - With an area of about 9.6 **million km²**, the People's Republic of China is the 3rd largest country in total area behind Russia and Canada, and very similar to the United States.
- Multiple units to represent a single numerical fact.
 - Vatican City, a walled enclave within the city of Rome, with an area of approximately **44 hectares (110 acres)**, and a population of 842, is the smallest internationally recognized independent state in the world by both area and population.

Overview of Unit Extraction System

Overview of Unit Extraction System

- A discriminative context free grammar with scores attached to each possible production in the grammar.

Overview of Unit Extraction System

- A discriminative context free grammar with scores attached to each possible production in the grammar.
- A production P in the grammar is of the form $R ::= R_1 R_2$, scored as

$$score(P) = \mathbf{w} \cdot \mathbf{f}(P, x, i, j, k),$$

where (i, j) and $(j + 1, k)$ are text spans in x that R_1 and R_2 cover.

Overview of Unit Extraction System

- Some of the features that grammar uses to assign the best scores to various parses are as belows:

Overview of Unit Extraction System

- Some of the features that grammar uses to assign the best scores to various parses are as belows:
 - Matches with Unit Catalog

Overview of Unit Extraction System

- Some of the features that grammar uses to assign the best scores to various parses are as belows:
 - Matches with Unit Catalog
 - Lexical Clues

Overview of Unit Extraction System

- Some of the features that grammar uses to assign the best scores to various parses are as belows:
 - Matches with Unit Catalog
 - Lexical Clues
 - Relative Frequency - Prior of the word to be present as unit, then as an non-unit word. This is derived from WordNet ontologies.

Overview of Unit Extraction System

- Some of the features that grammar uses to assign the best scores to various parses are as belows:
 - Matches with Unit Catalog
 - Lexical Clues
 - Relative Frequency - Prior of the word to be present as unit, then as an non-unit word. This is derived from WordNet ontologies.
 - Co-occurrence statistics - presence of strongly co-occurring words in the text can help in disambiguating the various candidate units

Units Based Matching: Results

Relation	Total Matches	Sampled Matches	True Matches	Precision(%)
Land Area	98	40	32	80
Foreign Direct Investment	791	40	1	2.5
Goods Export	816	40	3	7.5
Electricity Production	19	19	0	0
CO ₂ Emission	196	40	2	5
Diesel Prices	2	2	2	100
Inflation(%)	27598	40	0	0
Internet Users(%)	24639	40	0	0
GDP(\$)	1790	40	0	0
Life Expectancy	3081	40	0	0
Total Population	5225	40	11	27.5

Sample Matches for Unit Based Matching

Country	Relation	Value	Sentence
Lebanon	Land Area	1.02×10^{11} sq m	Lebanon lies in the eastern Mediterranean and covers about 4,030 square miles (10,450 square kilometers) – smaller than the U.S. state of Connecticut.
Russia	Goods Export	10^{10} USD	The IMF agrees to offer a loan of US\$10.2 billion to Russia over the next three years to help Russians transform their economy.
Australia	Internet Users(%)	0.6%	South Korea's main index added 0.6 percent , China's Shanghai's benchmark climbed 1.5 percent and Australia's index advanced 1.1 percent.
Israel	Internet Users(%)	20.0%	Israel's Arab community numbers 1.3 million, about 20 percent of the population.
Pakistan	Life Expectancy(years)	60	Why does a small elite still control vast swaths of land more than 60 years after Pakistan became a nation?

Key Observations on Unit Based Matching

- When it comes to numbers, distant supervision assumption is weak as can be evident from the examples above. Since second argument of a relation is number, this number can be related to the entity in multiple number of ways, which then gives lot of false positives.
- For the attributes like inflation, percentage of internet user, whose values are in percentage are affected by stock data that is heavily present in news corpus.
- For relations FDI, Goods Export, GDP we have almost similar values for three values. Hence a (entity, number) pair matches all of the three relations. We can improve our matching function for closely related attributes.

A case for Keywords

- A large number of false matches had no reference to the relation involved.
- Eg. No mention of Population in the following matches:
 - The website of China's Ministry of Defense (MOD) has attracted around 1.25 billion visits in the three months since its opening, with the United States topping the source countries for foreign visits, website editor-in-chief Ji Guilin said.
 - Insulza, for his part, said the Organization of American States expects to raise 10 million dollars for Haiti's recovery.
 - Koloini and others brought 10 million euros, probably 15 million, back from Iraq at the time, Falter quoted from the diary.
- No reference to Co2 emission:
 - China's iron ore imports surged 41.6 percent to 627.8 million tonnes in 2009, with the value falling 17.4 percent as prices were hit by the global downturn, customs data shows.

A case for Keywords

Good News

Sentences expressing a numerical relation can be expected to have keywords that denote the relation

- Take all the labeled sentences, prune out sentences that don't have atleast one of the relevant keywords

Internet User %	"Internet"
Land Area	"area", "land", "land area"
Population	"Population"
Diesel	"diesel"
GDP	"Gross domestic", "GDP"
CO2	"Carbon", "Carbon Emission", "CO2"
Inflation	"Inflation", "Price Rise"
FDI	"Foreign", "FDI"
Goods Export	"goods"
Life Expectancy	"life", "life expectancy"
Electricity Production	"Electricity"

A case for Keywords

- Numbers are the second entity in our setup ($\text{Relation}(\text{Country}, \text{Number})$)
- Unlike real world entities, numbers don't have an identity of their own, sentences should have words (keywords!) indicating what the number stands for
- Manual inspection of 400 sentences pruned out after applying keyword based filter backs this conjecture, not even one false negative
- The keywords are created manually, can this process be automated?

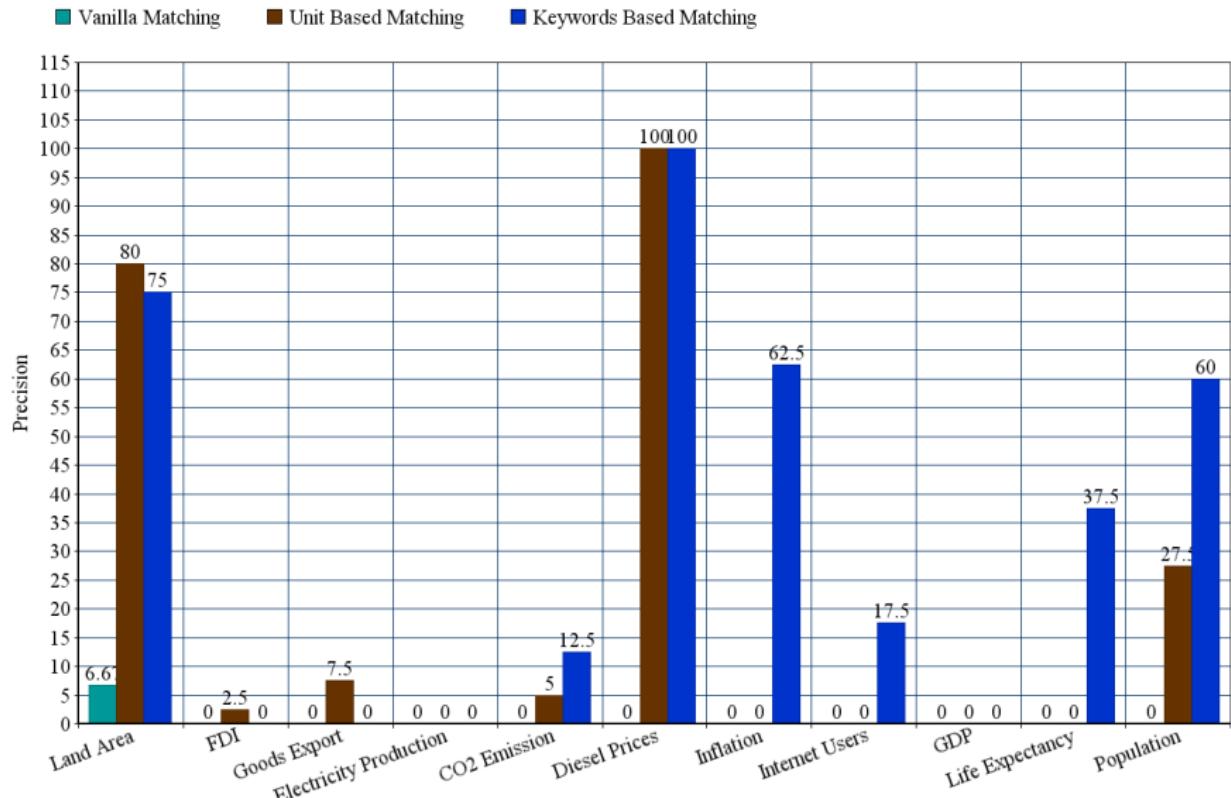
Keywords + Units Based Matching: Results

Relation	Total Matches	Sampled Matches	True Matches	Precision(%)
Land Area	61	40	30	75
Foreign Direct Investment	8	0	0	0
Goods Export	4	4	0	0
Electricity Production	0	0	0	0
CO ₂ Emission	16	16	2	12.5
Diesel Prices	2	2	2	100
Inflation(%)	3853	40	25	62.5
Internet Users(%)	308	40	7	17.5
GDP(\$)	0	0	0	0
Life Expectancy	99	40	15	37.5
Total Population	607	40	24	60

Sample Matches for Keywords Based Matching

Country	Relation	Value	Sentence
India	Land Area	3.00×10^{12} sq m	With an area of 2.98 million square km , India is the largest country in South Asia.
Bulgaria	CO_2 Emission	6×10^7 ton	Depending on the Commission's ruling on the country's challenging of the quotas, Bulgaria would end up with at least 60 million tonnes of CO2 or 60 million EUAs to trade, which are worth several hundred million euros.
Malawi	Life Expectancy(years)	40 years	Malawi , like other southern African countries, has seen its life expectancy drop from about 60 years in the early 1990s to below 40 years presently due to the HIV-AIDS pandemic.
Iceland	Total Population	330000	home to 320,000 people , Iceland officially apply to join the EU at the end of July.
Japan	Inflation(%)	8.2%	Japan 's economy decline by 8.4 percent , after adjustment for inflation , from the first quarter of 2008 to the first quarter of 2009.

Precision Comparison



Relative Recall

- Different Heuristics improved some aspect of matching for distant supervision.
- But we need to be careful, that with aggressive pruning of incorrect sentences, we are not leaving some good sentences.
- So for all the Heuristics, we calculate the percentage of true matches that were extracted by each Heuristics. We call this **Relative Recall**

Total Sentences for evaluation	676
Total True Positives	138
Vanilla Matching	2
Units + Distance Based Matching	79
Keywords + Units + Distance Based Matching	112

Dependency Path Based Relation Extraction

Peculiarity of Numerical Relations

- Analyzing a number of sentences expressing numerical relations lead to several insights as already discussed.
- **Keywords** We can expect presence of certain keywords that might help in identifying relations.
- **Modifiers** A large number of false positives stem out of mentions where a change in the numerical attribute is mentioned.

Dependency Path Based Relation Extraction

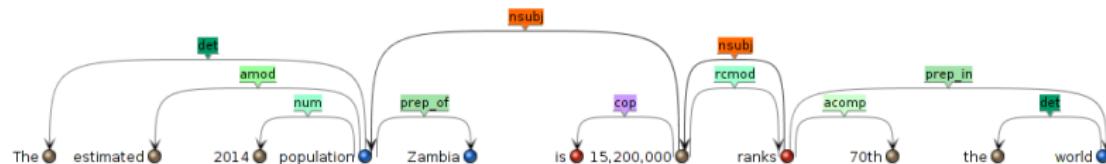
Dependencies

- Dependencies: Grammatical relation between two words, governor and dependent.
- “The red ball was lost”
 - **amod(ball,3,red,2)** “Red” is an adjective for “ball”
 - **det(ball,3,The,1)** “the” is a determiner of “ball”
 - **nsubjpass(lost,5,ball,3)** “ball is the subject of lost”
 - **auxpass(lost,5,was,4)** “was is an auxiliary of lost”



Dependency Path Based Relation Extraction

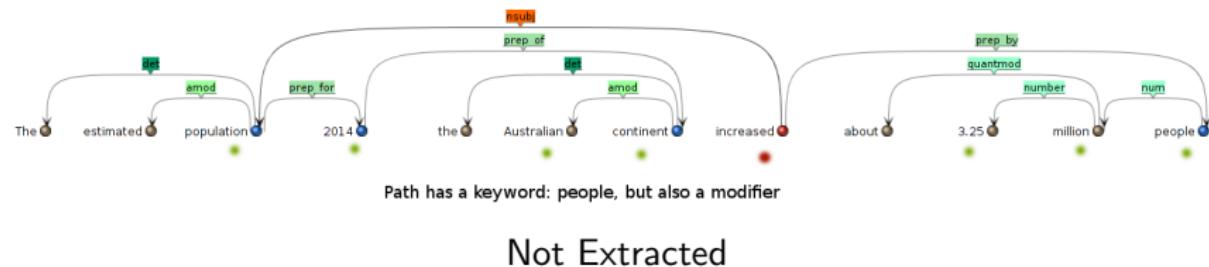
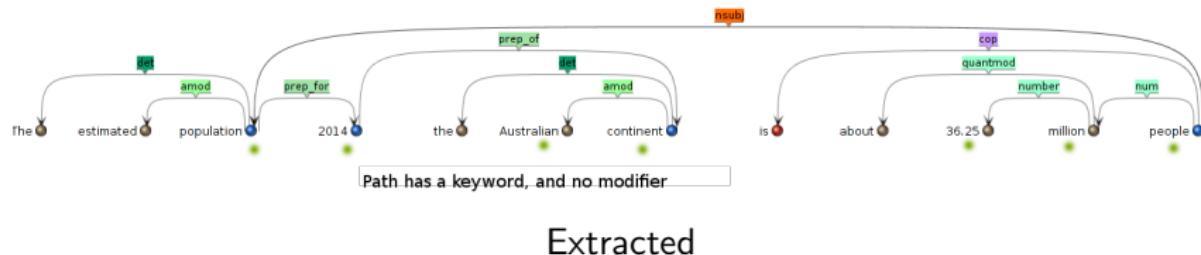
- Given a Country-Number pair, extract the shortest undirected path between them in the dependency graph.



- Path(Zambia - 15,200,000) = {Zambia, population, 15,200,000}
- For a match, the path:
 - Should have one of the keywords
 - Should not have a modifier

Dependency Path Based Relation Extraction

Example



- The extractor was applied to 30 sentences expressing 23 different relations.



	Relations Present	Relations not Present (False positives)
Extracted	16	17
Not Extracted	7	N/A

- Precision: 48.4%
- Recall: 69.6%
- The precision will increase further on applying unit based pruning.