

Numerical Relation Extraction from the Web

MTP Stage 1 Presentation

Aman Madaan Ashish Mittal

Indian Institute of Technology Bombay, Mumbai

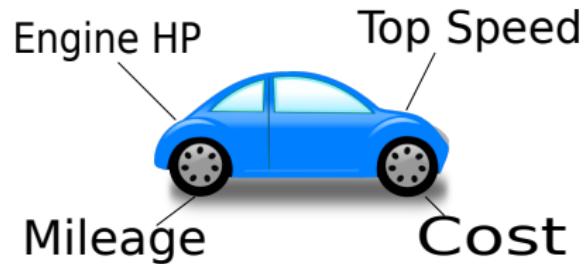
22nd October, 2014

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
- 9 Results

Entities and Numerical Attributes





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 - What is the population of Arbit Apartments, Powai?
 - What is the GDP of Sugarcane Industry of India?
 - Percent of Internet users in Mumbai?

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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)

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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

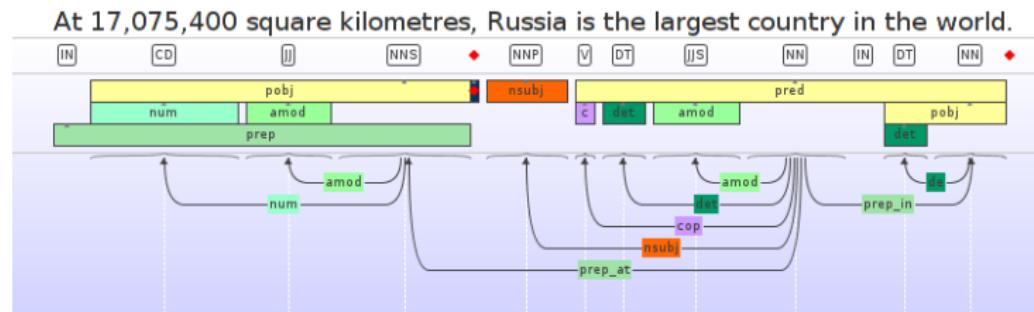
- Structure and content of sentences expressing the same relations can be expected to be similar.
 - At 17,075,400 square kilometres, Russia is the largest country in the world.
 - With an area of 504,030 km^2 , Spain is the second largest country in Western Europe.

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

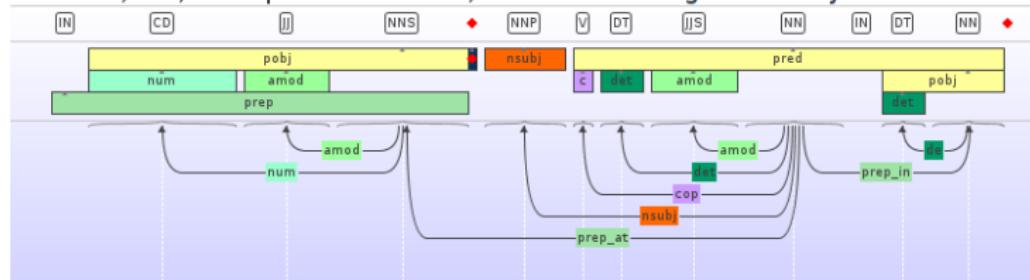
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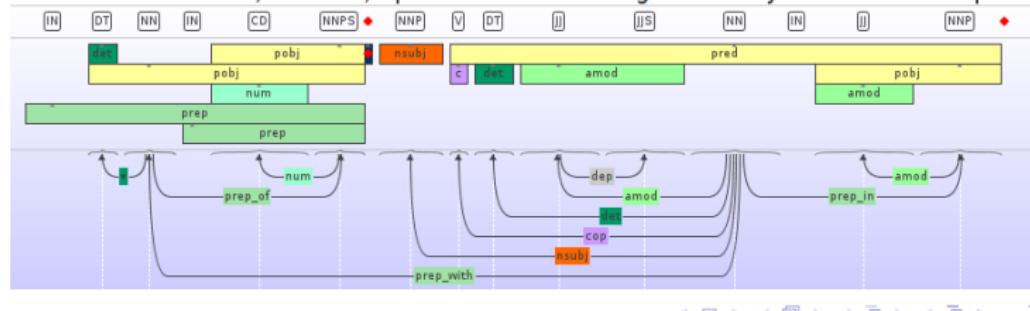
Relation Extraction as a Machine Learning Problem

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 - store the fact into database.

Challenge

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- Is there a middle ground?

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- 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.

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- Alan Turing biopic The Imitation Game named as London film festival opener.✓ FALSE POSITIVE

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- Same entity pair can match different relations (Founded(Steve Jobs, Apple) or CEO(Steve Jobs, Apple))

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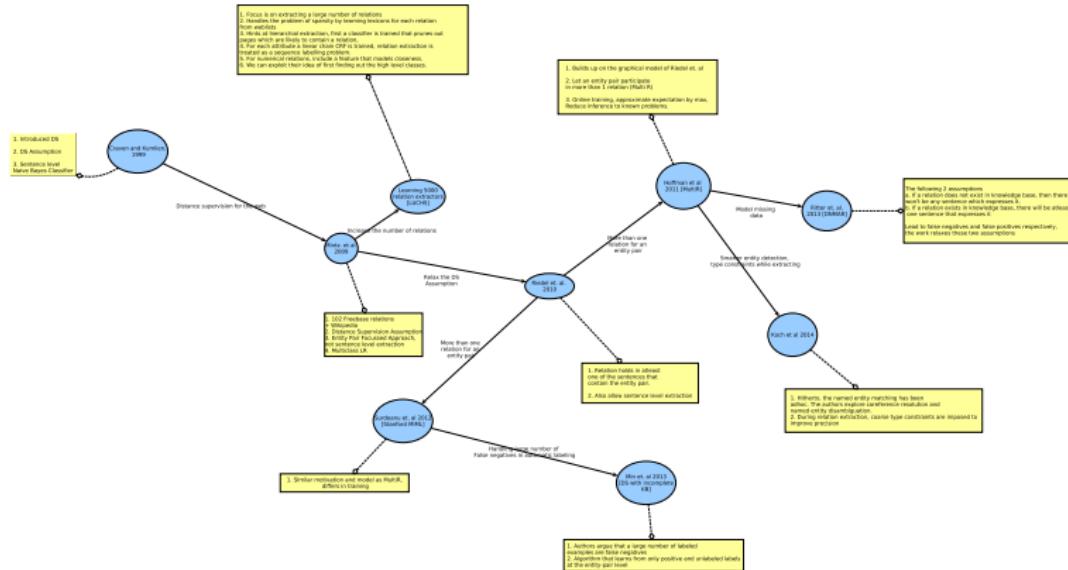
- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation
- Can quickly label huge corpora
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- False positives, may lead to model learning wrong patterns for relations

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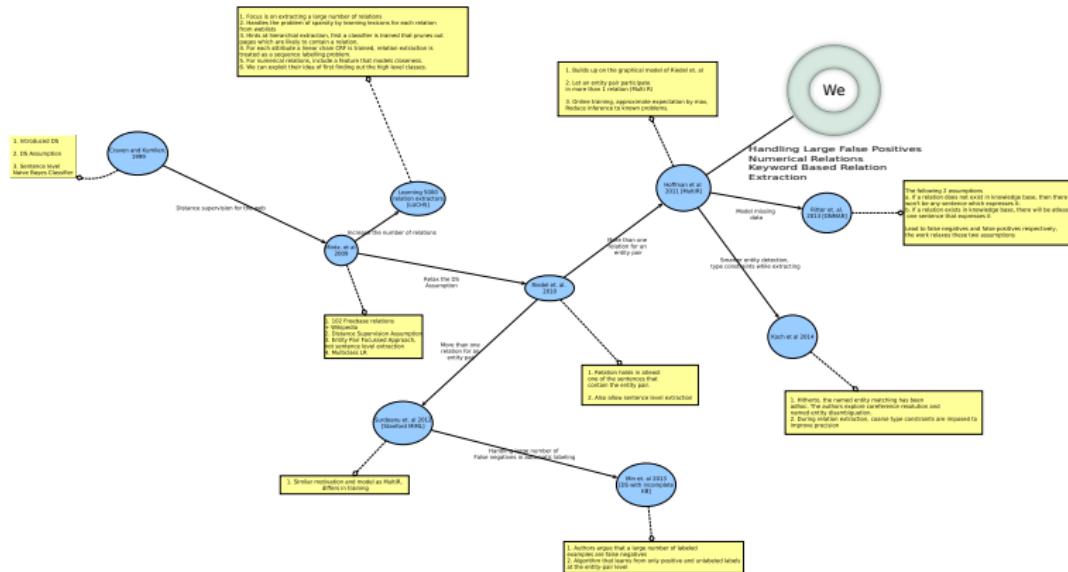
Distant Supervision Techniques

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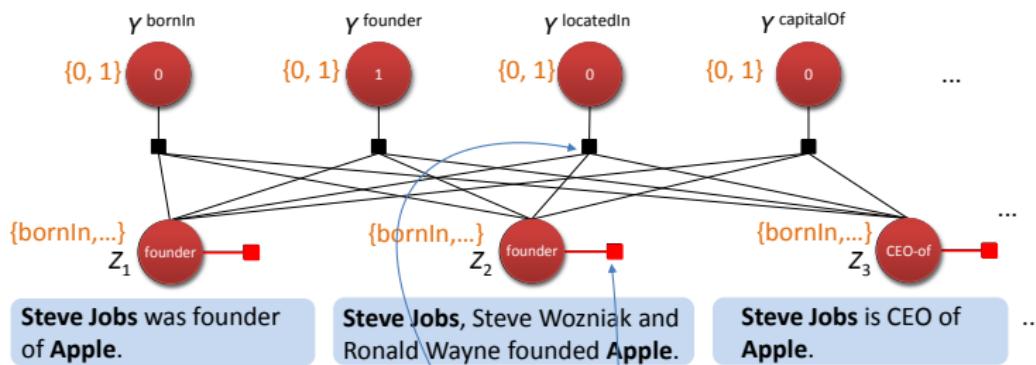


Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Model

Steve Jobs, Apple:



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

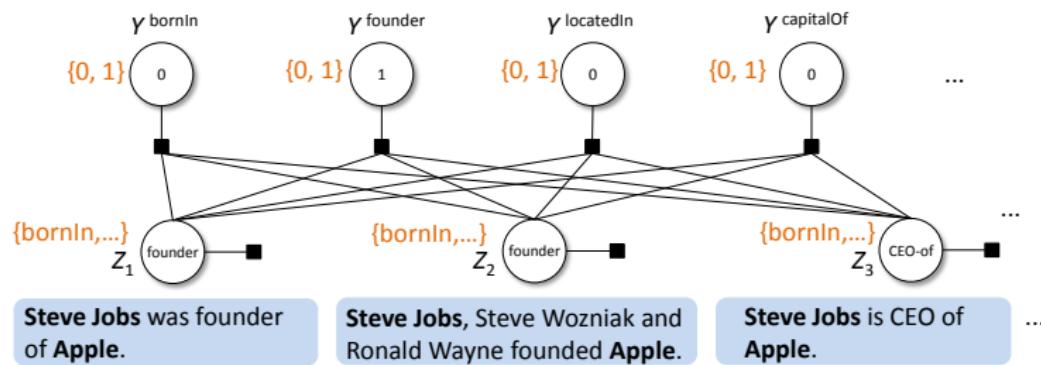
$$\Phi^{\text{join}}(y^r, z) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } y^r = \text{true} \wedge \exists i : z_i = r \\ 0 & \text{otherwise} \end{cases}$$

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

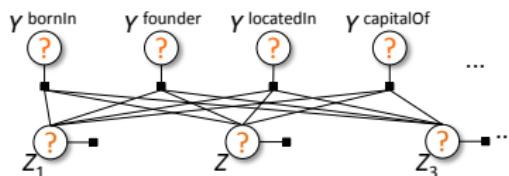
Relation Extraction Using MultiR

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Inference

Need:

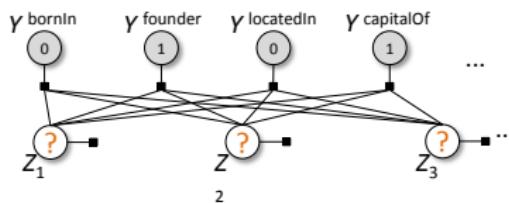
- Most likely sentence labels:



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

Easy

- Most likely sentence labels *given facts*:



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

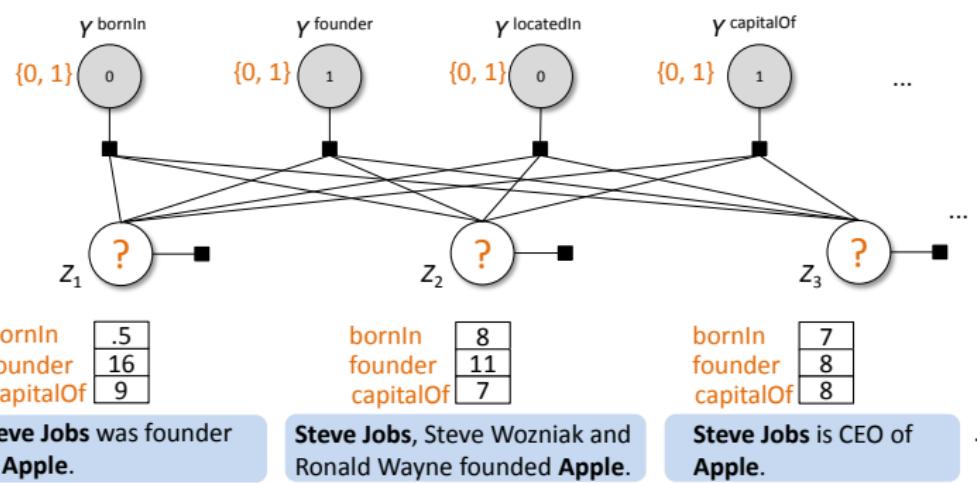
Challenging

Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

Inference

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

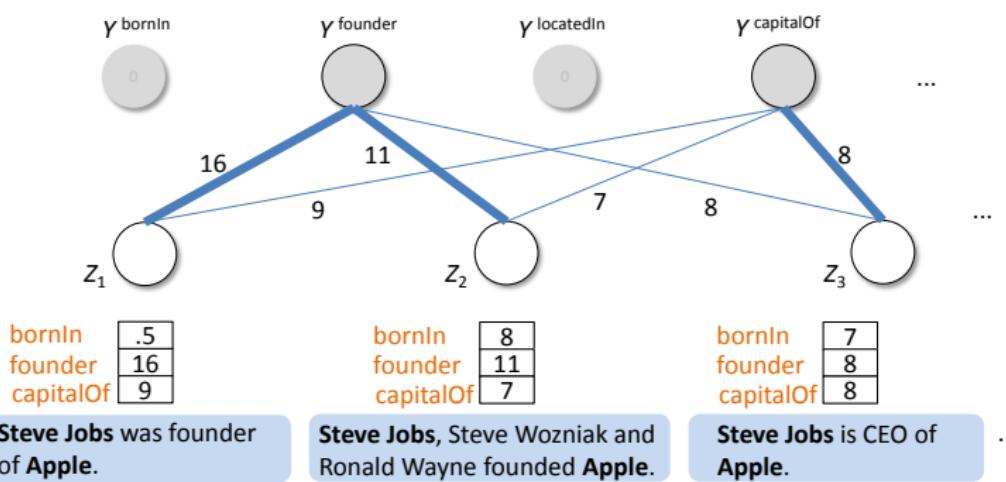


Relation Extraction Using MultiR

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  $\Theta$ 
```

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Cold Start Knowledge Base Population, 2014

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- 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

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 - **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.

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Distant supervision for Numerical Relation Extraction

Knowledge Base

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

/m/04g5k	3126000130	EG.ELC.PROD.KH
/m/02k8k	1969.179	EN.ATM.CO2E.KT
/m/06nnj	332315	SP.POP.TOTL
/m/019rg5	55.020073	SP.DYN.LE00.IN
/m/05sb1	19974.148	EN.ATM.CO2E.KT
/m/05v8c	10000000000	EG.ELC.PROD.KH
/m/03spz	7639000100	EG.ELC.PROD.KH
/m/06vbd	44249.688	EN.ATM.CO2E.KT
/m/0d060g	51.3	IT.NET.USER.P2
/m/05qkp	62.298927	SP.DYN.LE00.IN

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

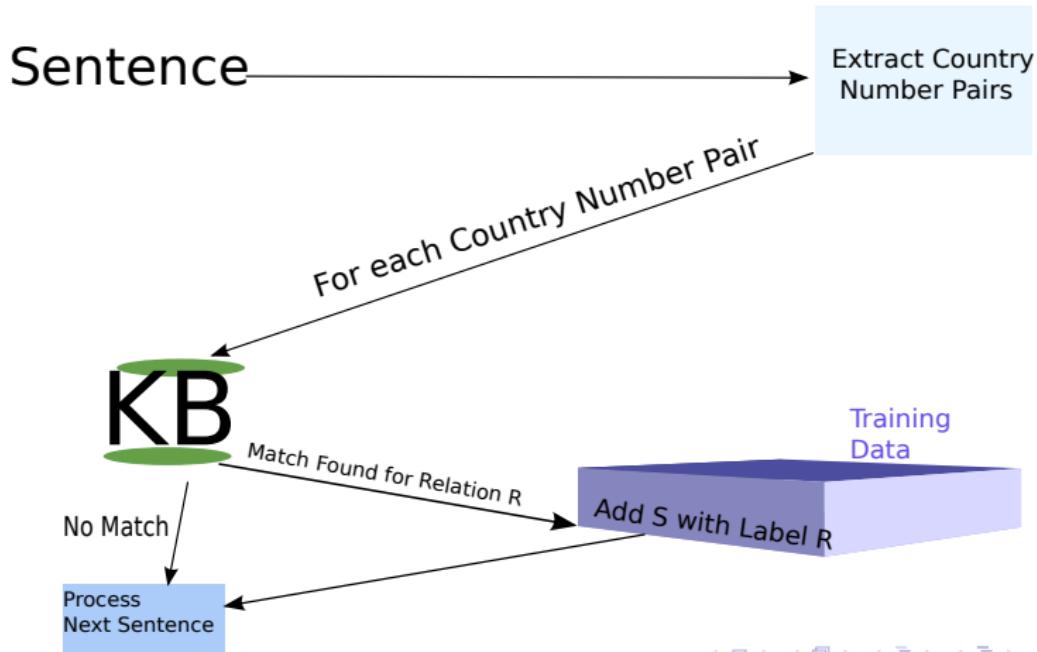
Corpus

- 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
AG.LND.TOTL.K2	1884	15	1	0.066666666667
BN.KLT.DINV.CD	0	0	0	0
BX.GSR.MRCH.CD	0	0	0	0
EG.ELC.PROD.KH	381	10	0	0
EN.ATM.CO2E.KT	0	0	0	0
EP.PMP.DESL.CD	8491	15	0	0
FP.CPI.TOTL.ZG	8689	15	0	0
IT.NET.USER.P2	182319	40	0	0
NY.GDP.MKTP.CD	0	0	0	0
SP.DYN.LE00.IN	267	10	0	0
SP.POP.TOTL	0			

False Positives

Numbers are weak entities

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- Consider India and Mumbai Vs. India and 19

False Positives

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- 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

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- 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

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- Can we expect the situation to be even worse for certain types of numbers?

Outline

- 1 Motivation
- 2 Problem Statement
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- 5 Distant Supervision Techniques
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- 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.

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- 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.

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- 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.

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 - 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

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?

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