

# Numerical Relation Extraction from the Web

## MTP Stage 1 Presentation

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# Outline

1 Motivation

2 Problem Statement

3 Relation Extraction as a Machine Learning Problem

4 Distant Supervision

5 Distant Supervision Techniques

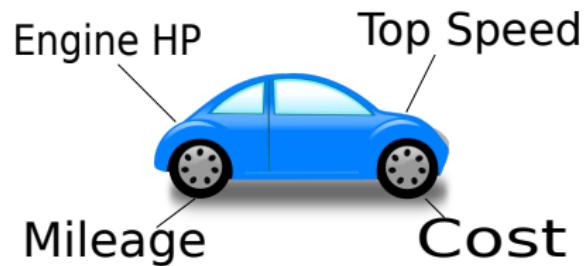
6 TAC Submission

7 Numerical Relation Extraction

8 Units in Numerical Relation Extraction

# Entities and Numerical Attributes





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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.<sup>[9]</sup> 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 km<sup>2</sup>). Alaska, separated from the contiguous United States by Canada, is the largest state at 663,268 square miles (1,717,856 km<sup>2</sup>). Hawaii, occupying an archipelago in the central [Pacific](#), southwest of North America, is 10,931 square miles (28,311 km<sup>2</sup>) in area.<sup>[136]</sup>

- 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

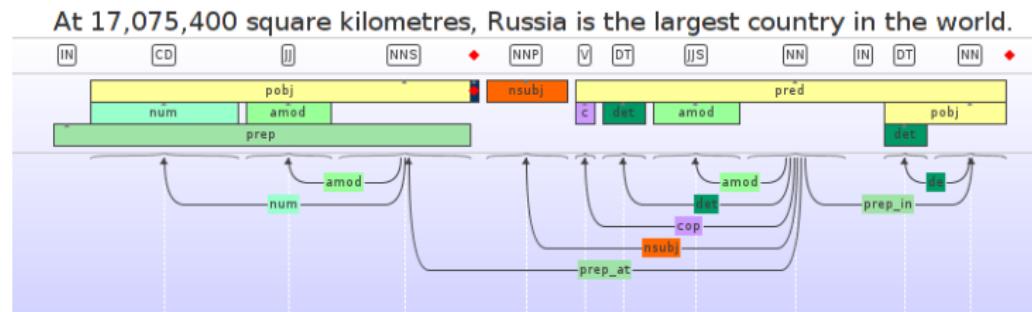
- Structure and content of sentences expressing the same relations can be expected to be similar.
  - At 17,075,400 square kilometres, Russia is the largest country in the world.
  - With an area of 504,030  $km^2$ , Spain is the second largest country in Western Europe.

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

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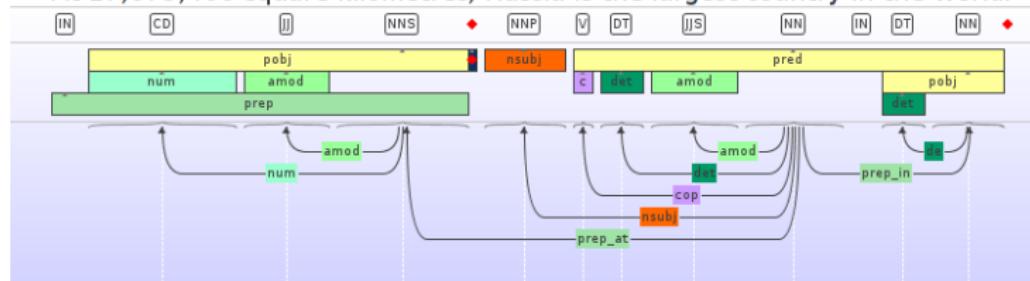
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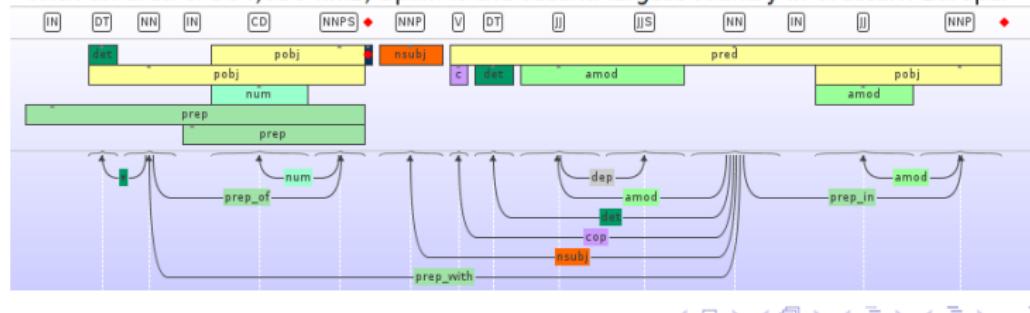
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  - store the fact into database.

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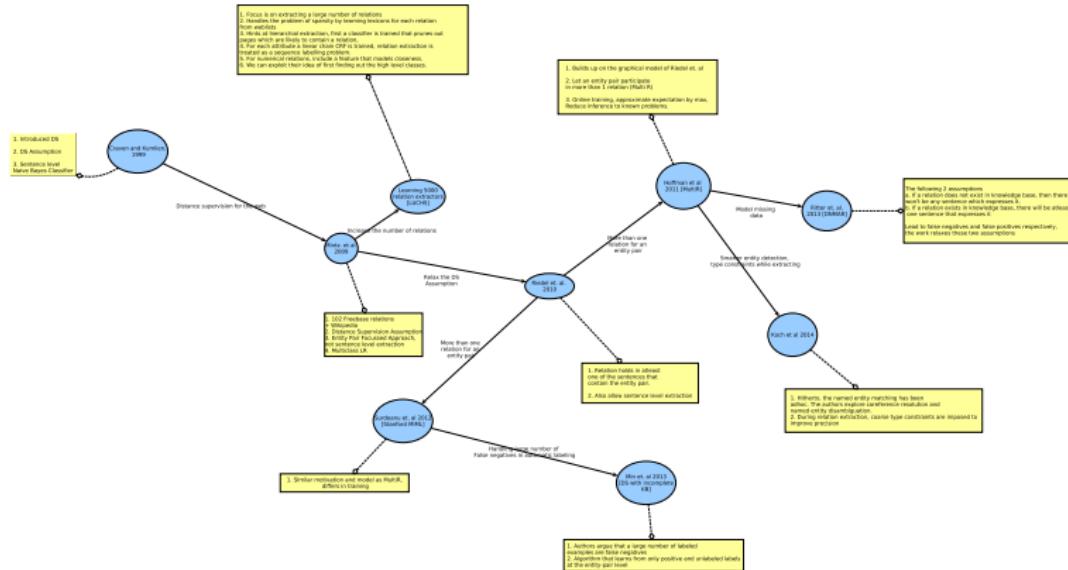
- Distant supervision assumption, any sentence containing the entity pair will express the corresponding relation
- Can quickly label huge corpora
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- False positives, may lead to model learning wrong patterns for relations

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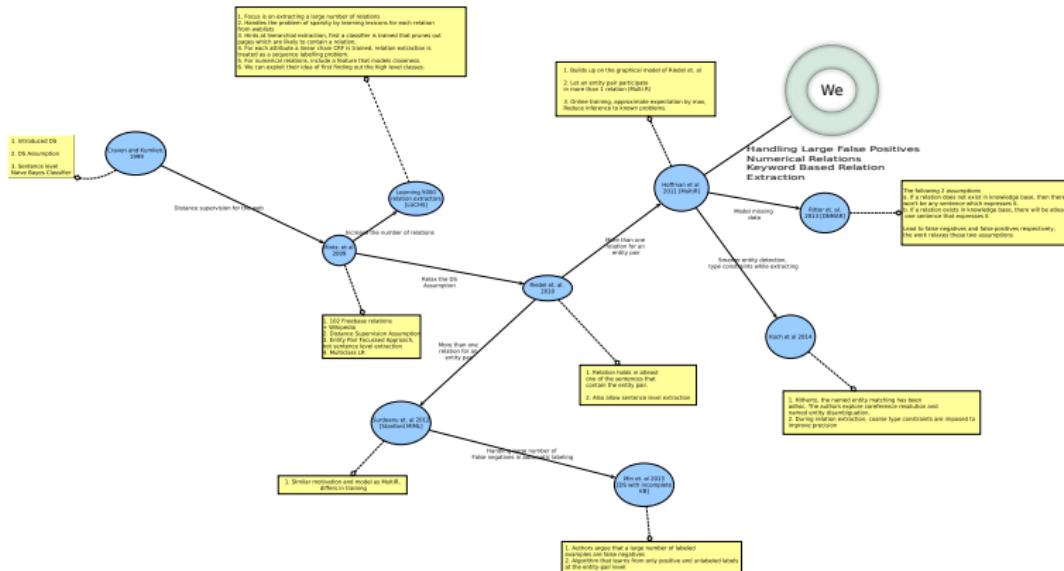
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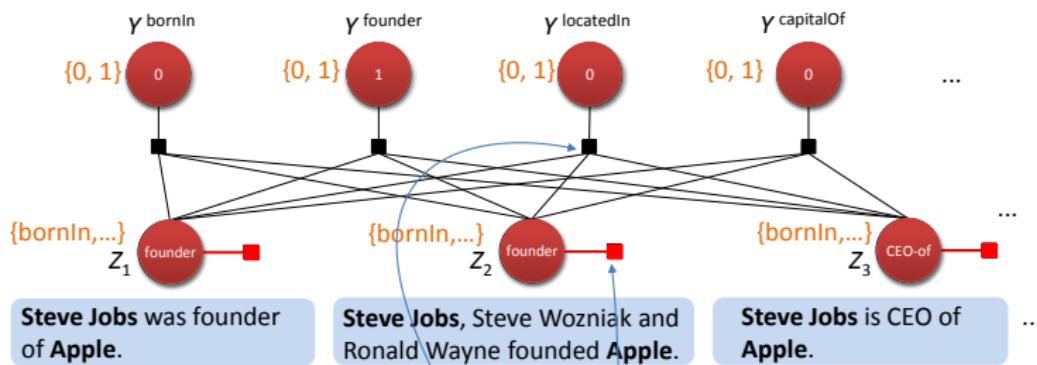


# Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

## Model

Steve Jobs, Apple:



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

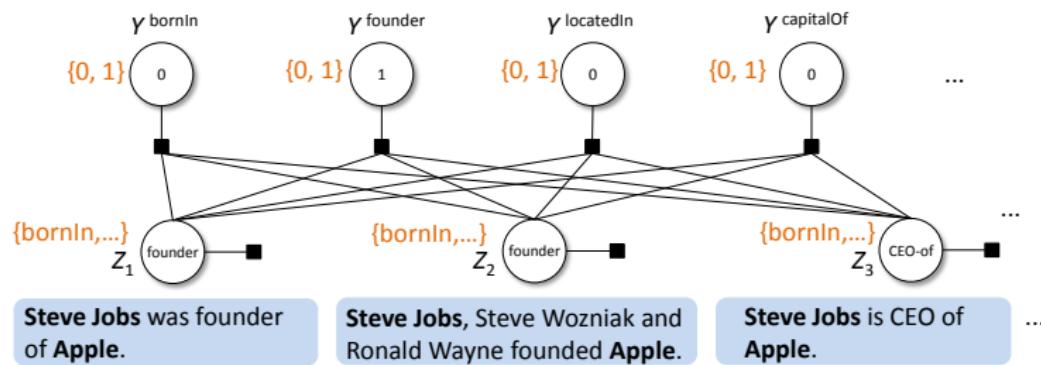
All features at  
sentence-level

(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

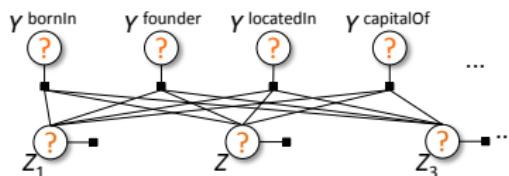
# Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

## Inference

Need:

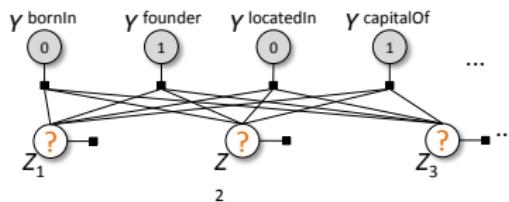
- Most likely sentence labels:



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

Easy

- Most likely sentence labels *given facts*:



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

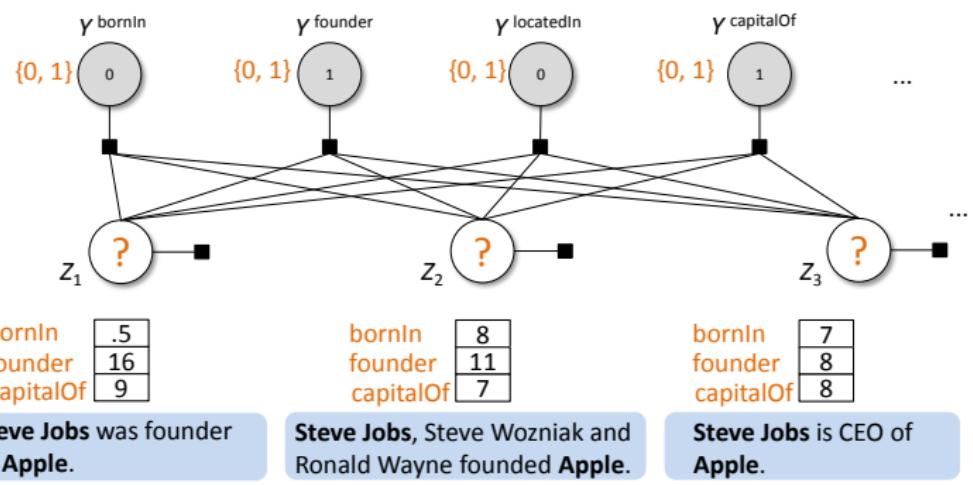
Challenging

# Relation Extraction Using MultiR

From raphaelhoffmann.com/publications

## Inference

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

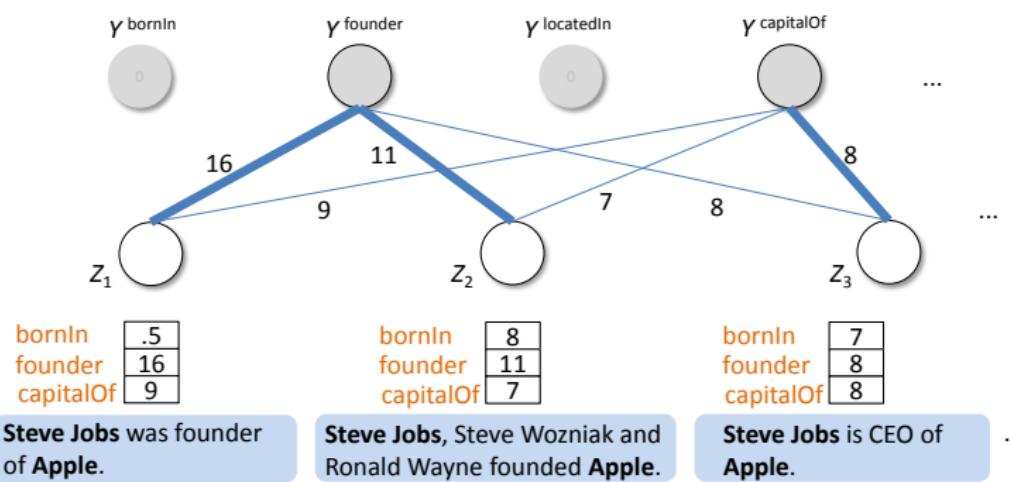


# Relation Extraction Using MultiR

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## 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

- 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.

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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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- 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](http://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

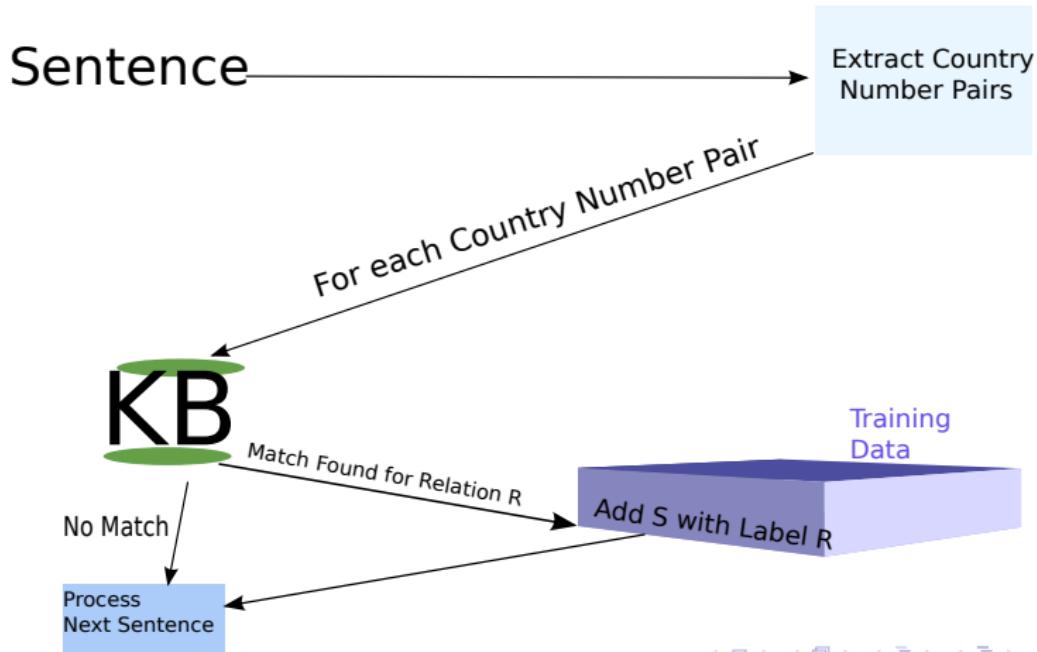
# Corpus

- 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	<b>1</b>	<b>0.067</b>
Foreign Direct Investment	0	0	0	0
Goods Export	0	0	0	0
Electricity Production	381	10	0	0
CO <sub>2</sub> 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, <b>24</b> , was crowned on Sunday evening at the Superbowl at Sun City, in <b>South Africa</b> 's North West province.
Croatia	Inflation	500	<b>Croatian</b> police say more than <b>500</b> 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	<b>France</b> : Hugo Lloris, Eric Abidal, Patrice Evra, William Gallas, Bacary Sagna, Abou Diaby, Yoann Gourcuff ( <b>Florent Malouda, 75</b> ), 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 <b>France</b> and Federica Pellegrini of Italy, <b>1.72</b> 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 <b>Bermuda</b> , with wind speeds of up to <b>50</b> 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.

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- Mumbai is a strong entity, 19 is a **weak** entity.

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  - 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

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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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  - 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
<b>Land Area</b>	98	40	32	0.8
Foreign Direct Investment	791	40	1	0.025
Goods Export	816	40	3	0.075
Electricity Production	19	19	0	0
CO <sub>2</sub> Emission	196	40	2	0.05
Diesel Prices	2	2	2	1
Inflation(%)	27598	40	0	0
Internet Users(%)	24639	40	0	0
GDP(\$)	1790	40	0	0
Life Expectancy	3081	40	0	0
<b>Total Population</b>	5225	40	11	0.275

# Sample Matches for Unit Based Matching

Country	Relation	Value	Sentence
Lebanon	Land Area	$1.02 \times 10^{11}$ sq m	Lebanon lies in the eastern Mediterranean and covers about <b>4,030 square miles</b> (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 <b>US\$10.2 billion</b> to Russia over the next three years to help Russians transform their economy.
Australia	Internet Users(%)	0.6%	South Korea's main index added <b>0.6 percent</b> , China's Shanghai's benchmark climbed 1.5 percent and <b>Australia's</b> index advanced 1.1 percent.
Israel	Internet Users(%)	20.0%	<b>Israel's</b> Arab community numbers 1.3 million, about <b>20 percent</b> of the population.
Pakistan	Life Expectancy(years)	60	Why does a small elite still control vast swaths of land more than <b>60 years</b> after <b>Pakistan</b> 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
<b>Land Area</b>	61	40	<b>30</b>	<b>0.75</b>
Foreign Direct Investment	8	0	0	0
Goods Export	4	4	0	0
Electricity Production	0	0	0	0
CO <sub>2</sub> Emission	16	16	2	0.125
Diesel Prices	2	2	2	1
<b>Inflation(%)</b>	3853	40	25	0.625
Internet Users(%)	308	40	7	0.175
GDP(\$)	0	0	0	0
<b>Life Expectancy</b>	99	40	15	0.375
<b>Total Population</b>	607	40	24	0.6

## 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