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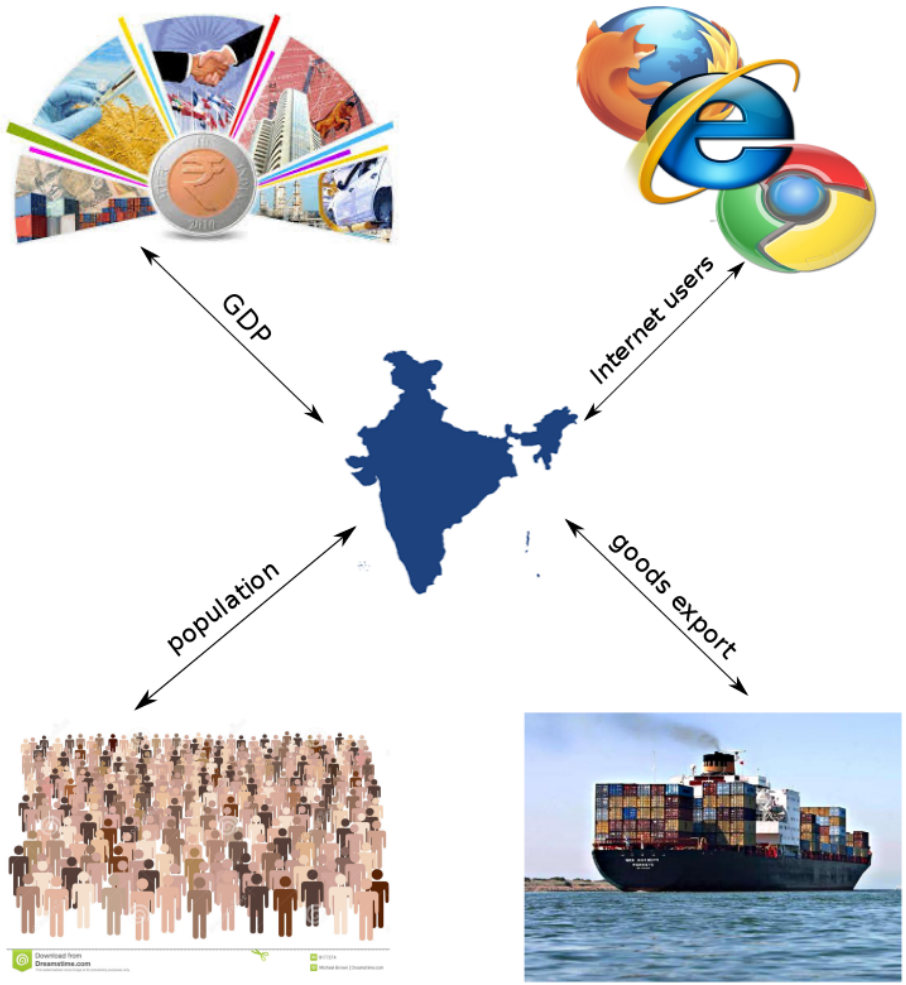

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  - Population of India reached 1.3 billion, making it the second largest country in the world
  - Population of Arbit Apartments, Powai reached 1300

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 reac

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^2). Alaska, separated from the contiguous United States by Canada, is largest state at 663,268 square miles (1,717,856 km^2). Hawaii, occupying an archipelago in the central Pacific, southwest of North America, is 10,931 square m (28,311 km^2) 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)

Relation extraction as a Machine Learning Problem

Machine Learning for Relation Extraction

- 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.

Machine Learning for Relation Extraction

- 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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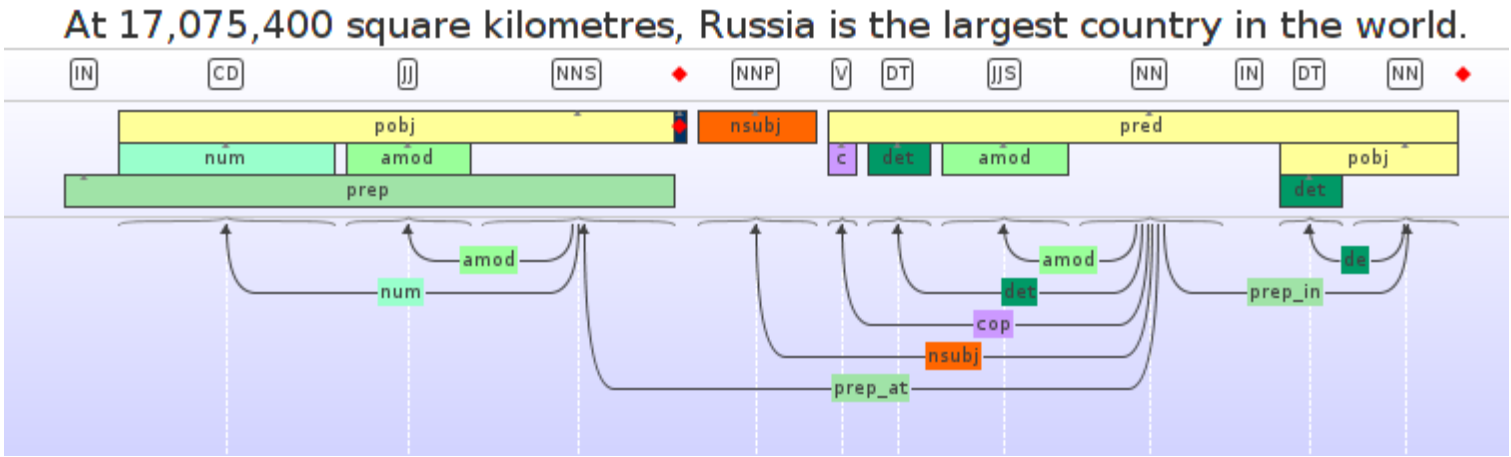

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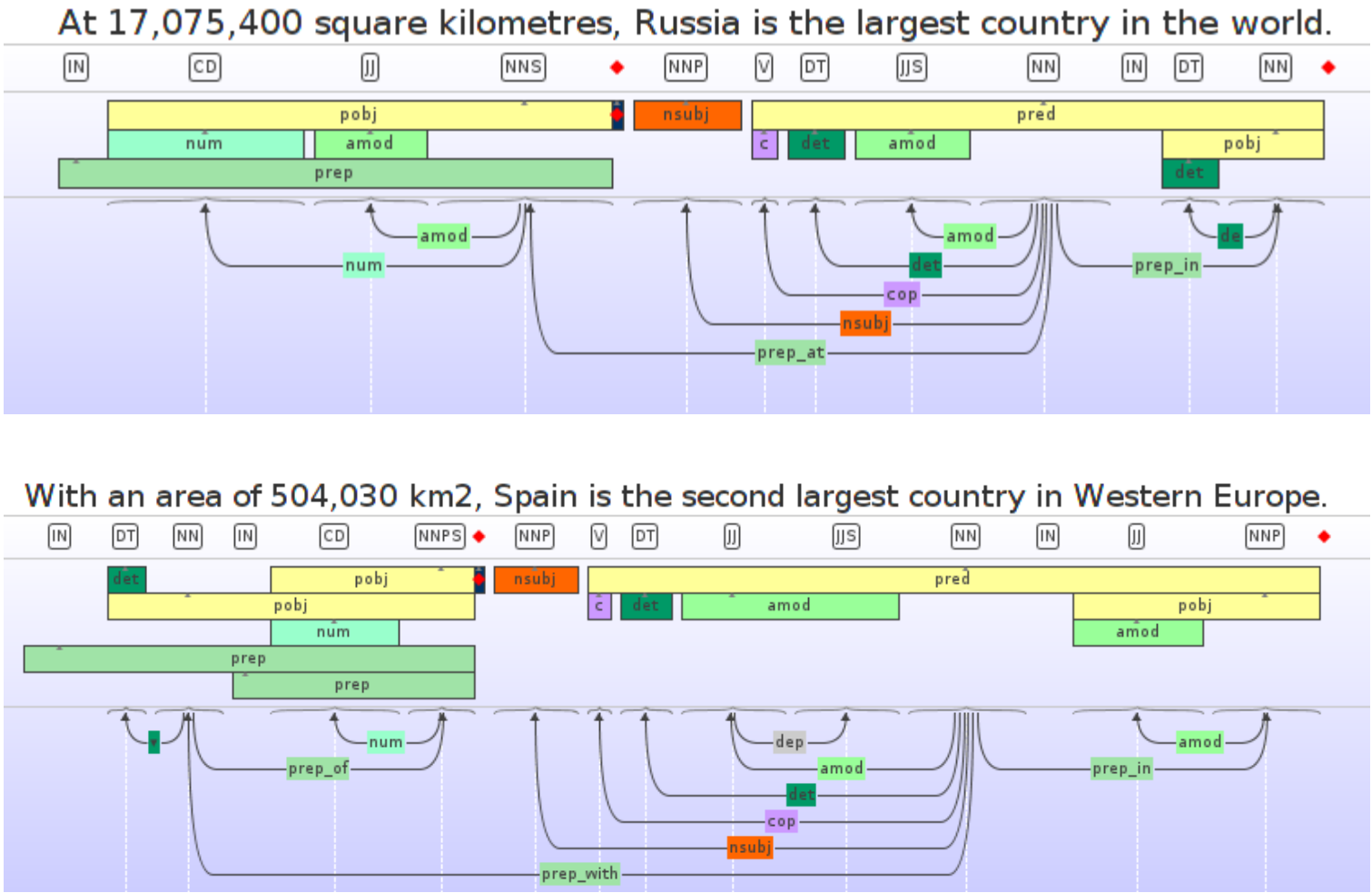

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- So for every relation learn the patterns that express it.
  - grammatical patterns - POS tags, dependency parse.
  - keywords for the relations.
- This forms the relation extraction as a multi-class classification problem.

Relation Extraction Problem

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

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- For model to generalize well, we need lot of training data.
- What to do then?

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 was born in Paddington, London, while his father was on leave from his position 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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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

- 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

False Positives

Numbers are weak entities

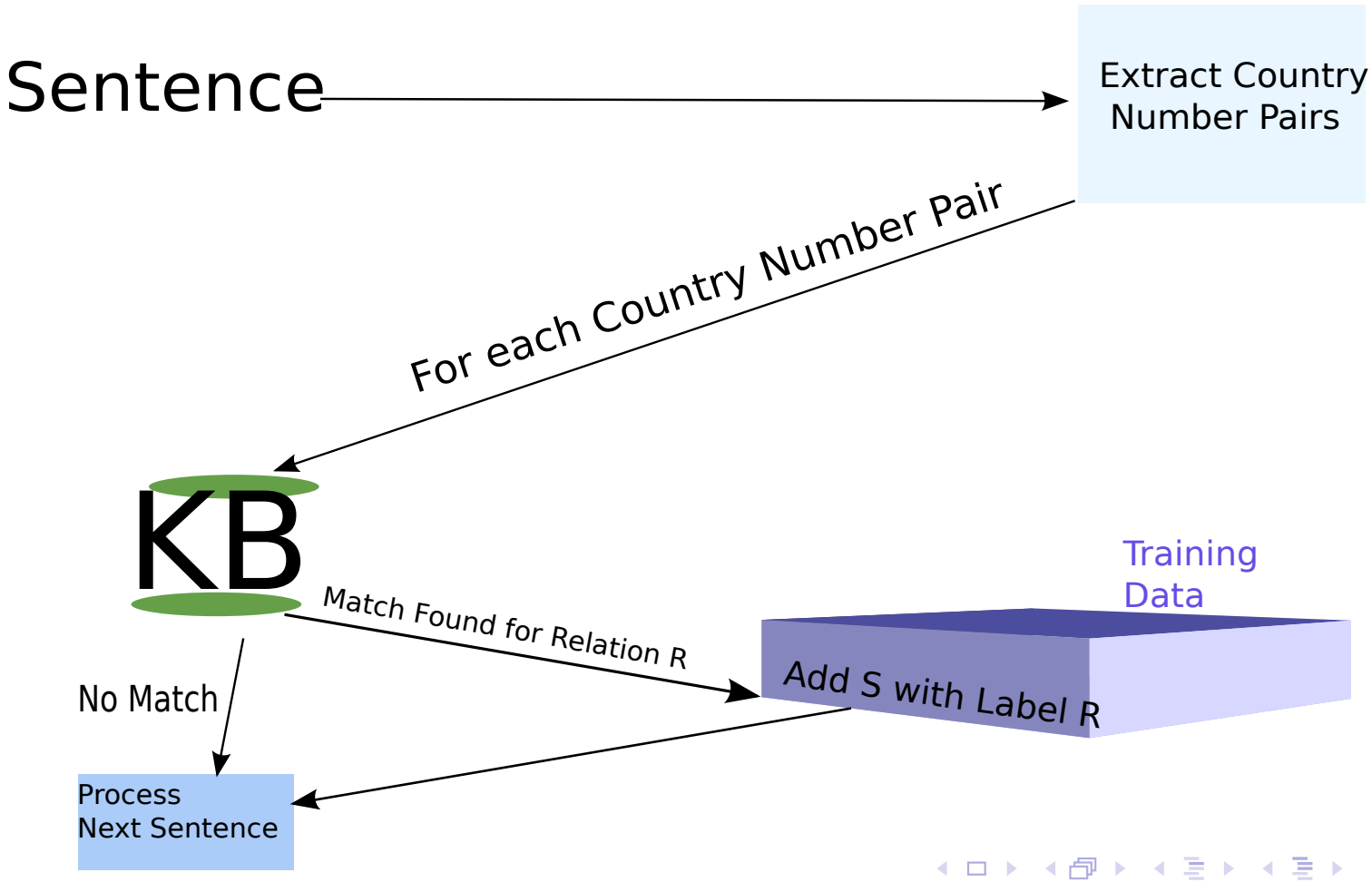
- Vanilla numerical relation matching is bound to attract humoungous amounts of false positives;
- Stems from the fact that numbers don't have an identity of their own.
- Consider India and Mumbai Vs. India and 19
- Mumbai is a strong entity, 19 is a **weak** entity.

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.
- 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?

One Thousand Words



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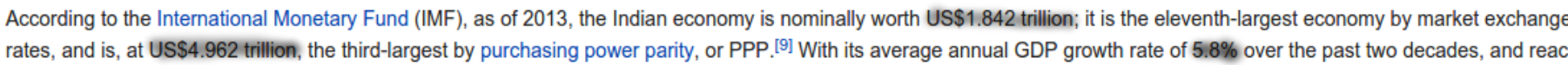
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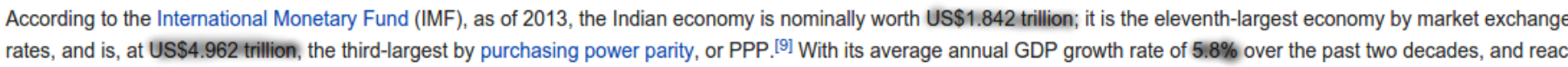
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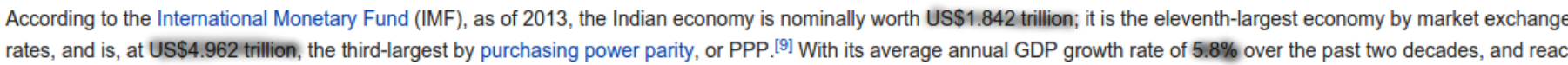
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  - Vatican City, a walled enclave within the city of Rome, with an area of approximately **44 hectares (110 acres)**, and a population of 842, is the smallest internationally recognized independent state in the world by both area and population.

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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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  - Co-occurrence statistics - presence of strongly co-occuring 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 (Relation(Country, 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?