

HONOURS PROJECT PRESENTATION



Temporal Ordering of Historical Events using Contextual Data

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May 4, 2017

Introduction

Is the use of contextual data useful to the temporal ordering of events?

“Alaska Becomes 49th US state”
1959-01-03

“Manchester Shipping Canal Opens”
1894-01-01

Our dataset has 6224 of these.

Related Work

Chambers & Jurafsky (2009)-

- Unsupervised Learning of Event Relations
- Argument Representation

Abend et. al (2015) -

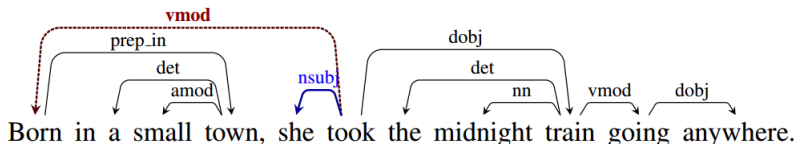
- Edge-factor models
- ILP & Greedy Pathfinding

Mani et. al (2006) -

- Hand Written & Lexical Rules
- Ordering of Temporally Anchored Events

Information Extraction

Using OpenIE data extraction, extract subject, objects and relation



"Manchester Shipping Canal Opens"

Subject: "Manchester" Object: "Shipping Canal" Relation: "Opens"

Article Retrieval

Use Wikipedia API for article retrieval

1. Extraction of only sentences that had a date within them
2. Extraction of only sentences that had the other party in the relation within them
3. Extraction of only sentences that had a date and the other party within them
4. Extraction of paragraphs that referenced the other party
5. Extraction of sentences that contained the object or the subject
6. Extraction of sentences that contained the object or the subject referenced the action between the two

Method	Average # Sentences Retrieved	Relevancy
1	16	-0.875
2	2	-1
3	0.04	0.5
4	20	-0.4
5	27	-0.11
6	32	0.444

Table: Retrieval Methods and their results

Experiments

$$\{(t_i, s_i, t_j, s_j, b_{ij})\} \text{ for } i, j \in [M]$$

where $b_{ij} = [y_i > y_j]$ indicates which event came first. T_* is a title. S_* is the retrieved sentences.

From this we train various different classifiers:

- Decision Tree
- SVM
- Logistic Regression
- Perceptron
- Multilayer Perceptron

Results - Classifiers

Accuracy	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	53%	66%	76%	66%	83%	$\frac{1}{2^{622}}$ %
With Titles	43%	51%	52%	46%	54%	$\frac{1}{2^{622}}$ %

Table: Classification Results for Tuples

Accuracy	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	13%	13%	23%	27%	21%	$\frac{1}{4^{622}}$ %
With Titles	21%	13%	24%	33%	14%	$\frac{1}{4^{622}}$ %

Table: Classification Results for Triples

Graphing

- Integer Linear Programming
 - Find global optimum path
- Greed
 - Find local optimum next step

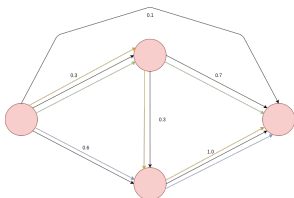


Figure: An Example of beam search pruning
Iteration 1: Blue Iteration 2: Green, Iteration 3: Yellow

Results - Tuples

A* Search	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	0.695	0.419	0.3	0.376	0.7333	0
With Titles	0.06	-0.09	0.048	-0.52	-0.28	0

Table: ILP Pathing Results for Tuples

Beam Search	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	0.42	0.5151	0.3	0.44	0.5454	0
With Titles	0.214	-0.62	0.17	0.09	0.32	0

Table: Greedy Pathing Results for Tuples

Results - Triples

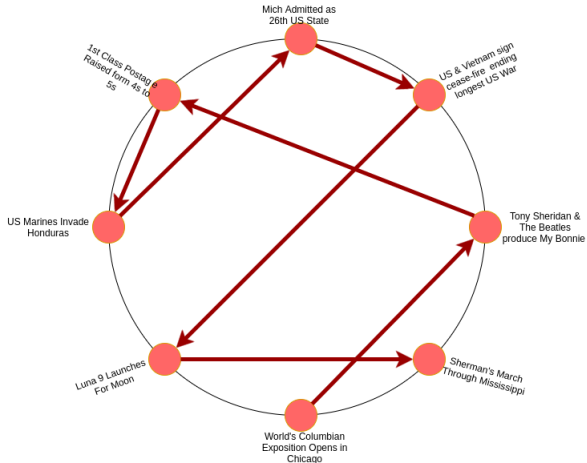
A* Search	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	-0.64	-0.54	-0.92	-0.53	-0.58	0
With Titles	-0.62	-0.68	-0.87	-0.61	-0.59	0

Table: ILP Pathing Results for Triples

A* Search	DT	SVM	LR	Perceptron	MLP	Baseline
With Articles	-0.64	-0.54	-0.92	-0.53	-0.58	0
With Titles	-0.62	-0.68	-0.87	-0.61	-0.59	0

Table: ILP Pathing Results for Triples

Graphs



Conclusion

- Use of external data source provide up to 30% better accuracy
- Multiplayer Perceptron with ILP proved best - 83% Accuracy
- Further improvements can build upon this work