What a Nasty day: Exploring Mood-Weather Relationship from Twitter

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Oct 26, 2014

Motivation

Sentiment Analysis/ Extraction:

Motivation

Sentiment Analysis/ Extraction:

- Token

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- Token
- Sentence

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- Document

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Feature Based Algorithms

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Feature Based Algorithms

- SVM (Joachims., 1999)
- CRF (Lafferty e al., 2001)
- LDA, sLDA (Blei et al., 2003)
- Neural Network (Socher et al., 2013)

Motivation

Long-term Sentiment Analysis

Sentiment towards an entity over a long period of time.

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- food

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Sentiment towards an entity over a long period of time.

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News Articles,

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News Articles, Diplomatic Relations

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The People's Daily : Governmental Newspaper in People's Republic of China

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More technical, less political ! !

Outline

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- Challenges
- Model
- Experiments
- Conclusion

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Challenge: Multiple entities, multiple sentiments.

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US imperialism set up a puppet regime in Vietnam and sent expeditionary force. People of Vietnam prevailed over the modern-equipped US troops with a vengeance. The result of Johnson Government's intensifying invasion is that... The heroic Army of Vietnam, obtained great victory in the struggle against the US imperialism.

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Positive Entities:
People of Vietnam,
the Workers' party
Ho Chi Minh
Vietnam People's Army

Negative Entities:
US imperialism
US troops
Johnson Government
Ngo Dinh Diem

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Not a coreference problem

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- nicknames

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- Model

Model

Notations:

Sentiment score ranging m (1-7)

- Antagonism
- Tension
- Disharmony
- Neutrality
- Goodness
- Friendliness
- Brotherhood

Model

Notations:

For specific entity e (e.g., USA, Vietnam)

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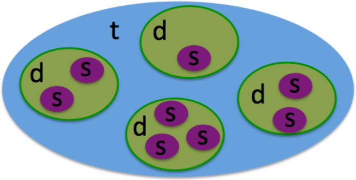
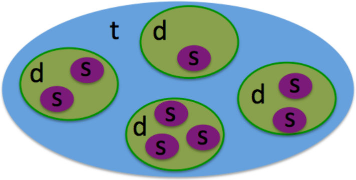
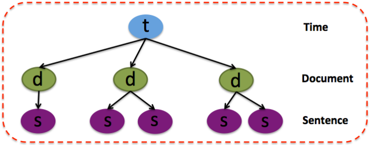
Model

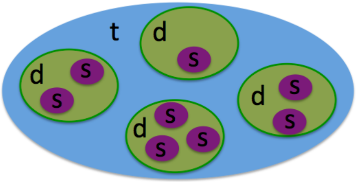


Model





Model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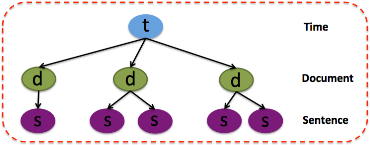
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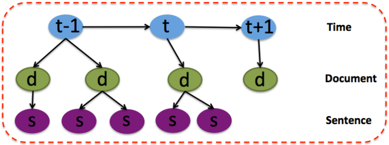
Time
Document
Sentence


t-1
t
t+1
d
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s
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s
s
Time
Document
Sentence

Model

Model

Markov Property at time level:

Model

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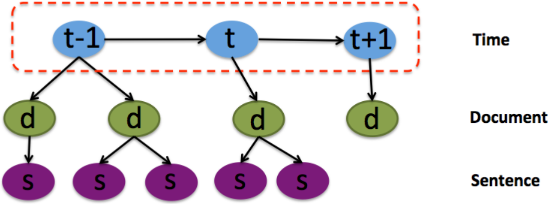
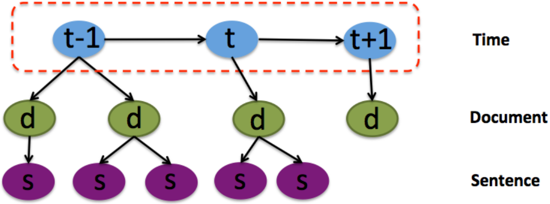


Model

Markov Property at time level:



$$m_t \sim Poisson(m_{t-1})$$

Model

Sample document sentiment from time sentiment

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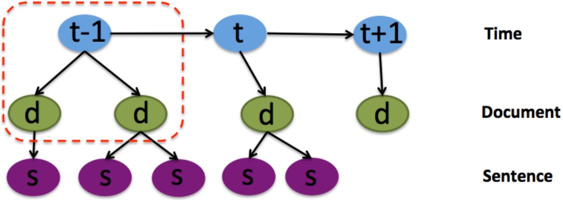

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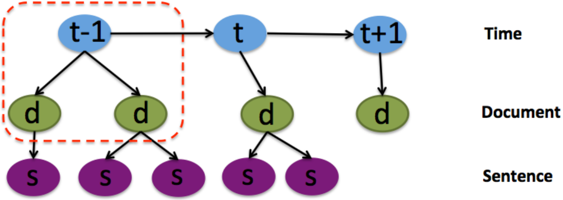

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Sample sentence sentiment from document sentiment

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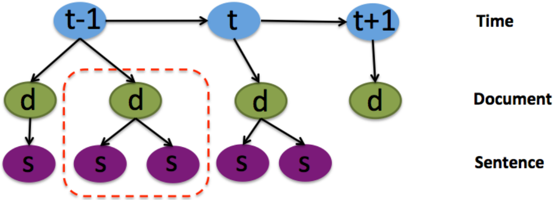

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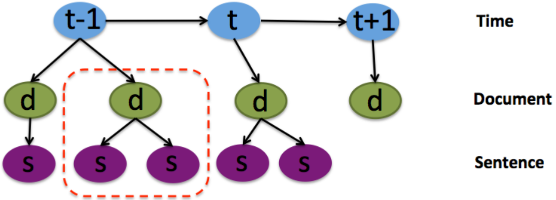

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Model

Bootstrapping

- Gibbs sampling for sentiment score at time- document- level given sentence-level score.

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- Given document-level score, expand entity cluster, subjective lexicon.

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Input:

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- Entity: Vietnam

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- Small collection of subjective lexicon: $\{great, 7\}$, $\{evil, 1\}$

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- Sentiment score at document level m_d
- Small collection of subjective lexicon: $\{great, 7\}$, $\{evil, 1\}$
- $T = \{Vietnam\}$: List of entities.

Model

Model

(1) Vietnam is a great country.

(2) People's Army are great.

(3) People of Army are heroic.

(4) USA is an evil country.

T={Vietnam}

{great,7},{evil,1}

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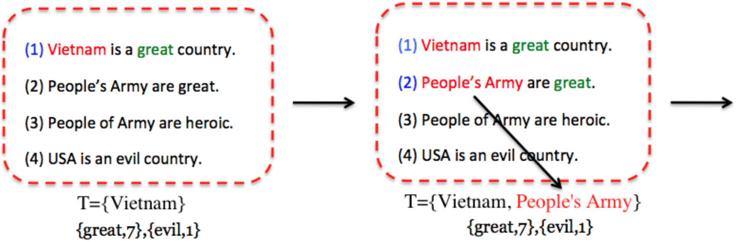
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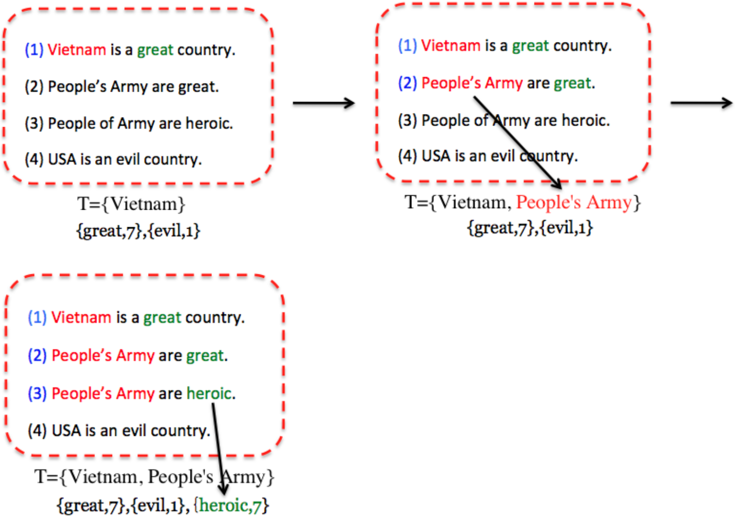
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Model

A is great

Model

A is great
B is heroic

Model

A is great
B is heroic
C is evil.

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A is great
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Albania Workers' party is the glorious party of Marxism and Leninism

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B is heroic
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Albania Workers' party is the glorious party of Marxism and Leninism
We strongly warn Soviet Revisionism.

Target/Expression Extraction

A is Great .

B is evil.

Red: Target

Green: Expression

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A is Great .

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The heroic people of Vietnam obtained great victory

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Segment based Sequence Model:
Semi-CRF (Sarawagi and Cohen, 2004; Yang and Cardie, 2013)

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600 manually labeled sentences

Features

- word, part of speech tag, word length, NER

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- Subjectivity lexicon features
- Syntactic features, e.g., VPcluster, VPpred, VParg (Yang and Cardie, 2013)

model

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- Identify Target/Expression for sentences.

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- Gibbs sampling to estimate document- time- level sentiment score.
- Bootstrapping: expand subjective list and entity cluster.

Some details

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  Example: [People's / Army].
  Chinese encyclopedia (e.g., Baidu encyclopedia and Chinese Wikipedia)

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  Chinese encyclopedia (e.g., Baidu encyclopedia and Chinese Wikipedia)
- Compound sentences are segmented into clauses based on parse trees.

- Experiments

Experiments

Target/Expression Extraction

Single: Sentences with only one target.

Experiments

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Target/Expression Extraction
Single: Sentences with only one target.
Comparing Semi-CRF with CRF

	P	R	F
	Total		
semi-CRF	**0.74**	**0.78**	**0.76**
CRF	0.73	0.66	0.68
	Single		
semi-CRF	**0.87**	**0.92**	**0.90**
CRF	0.80	0.87	0.83

Experiments

Subjective Lexicon

antagonism (m=1)	残暴(extremely cruel), 敌人(enemy)
tension (m=2)	愤慨(indignation), 侵犯(offend)
disharmony (m=3)	失望(disappointed), 遗憾(regret)
neutrality (m=4)	关切, 关注(concern)
goodness (m=5)	发展的(developmental), 尊重(respect)
friendship (m=6)	友谊(friendship), 朋友(friend)
brotherhood (m=7)	伟大(firmly), 兄弟(brother)

Experiments

Foreign Relation Evaluation

Gold Standards: Qualitative Political Analysis

Experiments

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Institute of Modern International Relations, Tsinghua University,

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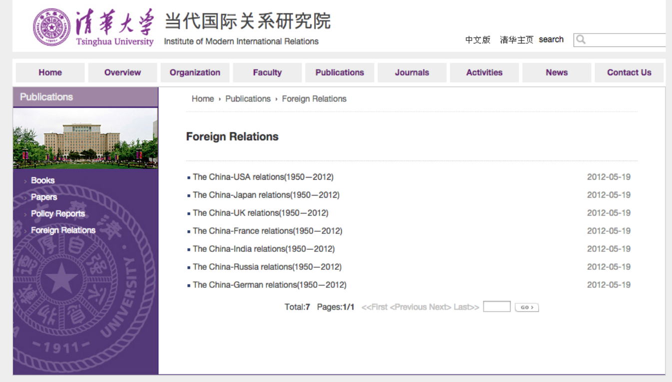

Experiments

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The China-USA relations(1950—2012)

	1	2	3	4	5	6	7
1950	-7.5	-7.5	-7.5	-7.5	-7.5	-7.6	-7.6
1951	-8.2	-8.2	-8.2	-8.2	-8.3	-8.2	-7.8
1952	-7.9	-7.9	-7.9	-7.7	-7.8	-7.8	-7.8
1953	-8.0	-8.0	-7.8	-7.4	-7.3	-7.2	-6.1
1954	-6.1	-6.0	-6.0	-5.9	-5.9	-5.8	-5.8
1955	-6.9	-7.0	-7.0	-6.7	-6.7	-6.7	-6.3
1956	-5.9	-5.9	-5.9	-5.9	-5.9	-5.9	-5.9
1957	-5.8	-5.8	-5.8	-5.8	-5.8	-5.9	-5.9
1958	-5.7	-5.7	-5.7	-5.7	-5.7	-5.7	-5.7
1959	-5.7	-5.7	-5.7	-5.7	-5.7	-5.7	-5.7

Experiments

Evaluation Matrics: Pearson Correlation

Baselines

- Bootstrapping+NoTime

Experiments

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Baselines

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- Document-level SVR (Joachims, 1999; Pang and Lee, 2008), bag of words

Experiments

Evaluation Matrics: Pearson Correlation

Baselines

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- Document-level SVR (Joachims, 1999; Pang and Lee, 2008), bag of words
- Supervised-LDA

Experiments

Model	Pearson Correlation
SVR	0.482
sLDA	0.527
No-Time	0.808
Ours	0.884

Experiments

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SVR	0.482
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Experiments

Analysis

Experiments

Analysis

We have no permanent allies, no permanent friends, but only permanent interests -Lord Palmerston

Experiments

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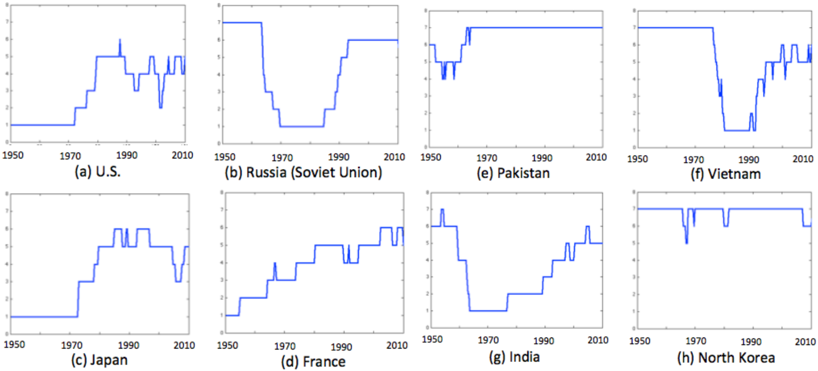
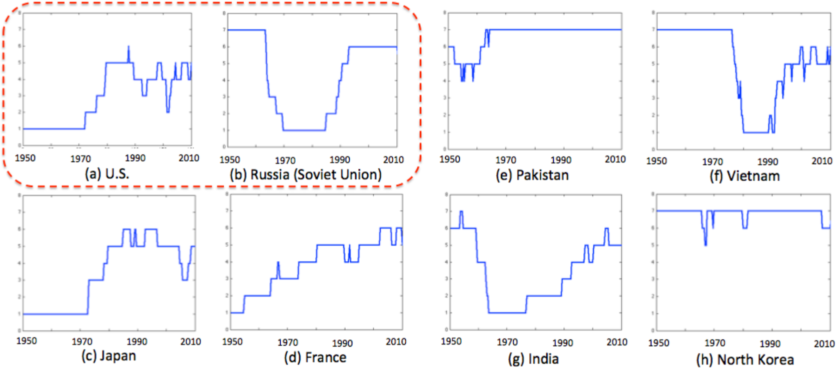
Experiments



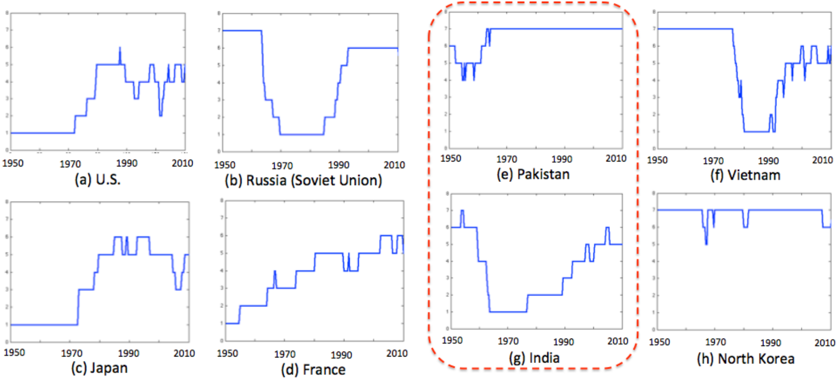
(a) U.S. (b) Russia (Soviet Union) (e) Pakistan (f) Vietnam

(c) Japan (d) France (g) India (h) North Korea

Experiments



Experiments



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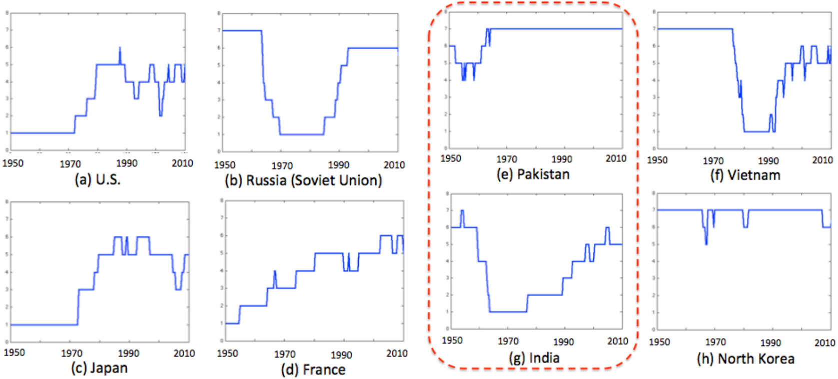
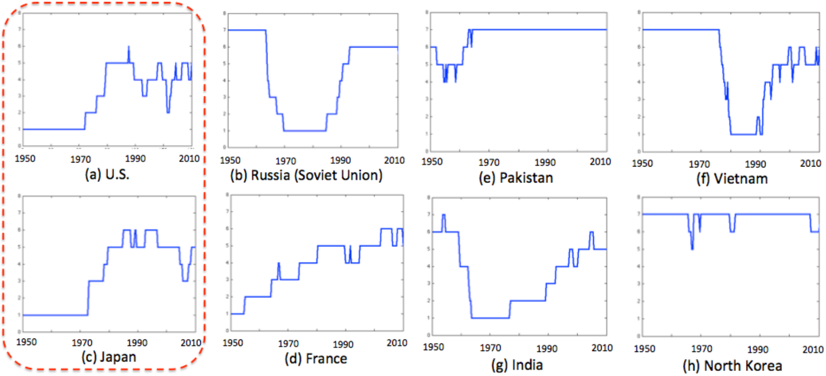


The enemy of my enemy is my friend -Arabic proverb

Experiments



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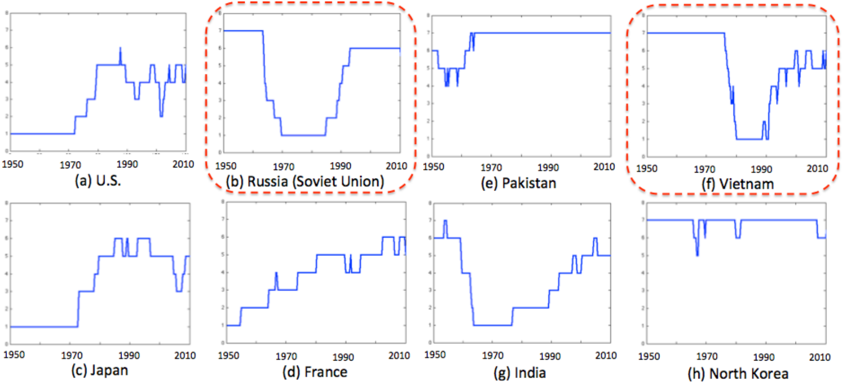

Conclusion

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- We propose a semi-supervised algorithm that harnesses higher level information (i.e., document-level, time-level).

Conclusion

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- We propose a semi-supervised algorithm that harnesses higher level information (i.e., document-level, time-level).
- Quantitative evaluation of diplomatic relations that may facilitate political scientists' work.

Target/ Expression dataset:
`http://web.stanford.edu/~jiweil/dataset`

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Thank you !

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Questions, Suggestions