2021/12/17 @ WI-IAT'21 Event Causal Relationship Retrieval

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Background | The importance of history

- History does not repeat itself, but rhythms repeat themselves
- Analyzing and knowing history is important
 - Understanding how the present shape
 - Using historical knowledge in the present
 - Many countries have classes for learning history from elementary school
- Practice and research in history learning supporting
 - $\circ \quad \text{Understanding history} \rightarrow \text{Developing Thinking Skills} \rightarrow \\ \text{Utilization of the ability of using historical knowledge [1]}$
 - Research on learning environments that support the ability to use history in school education[2]

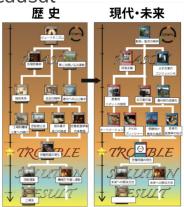
[1]: MEXT (2018): government course (curriculum) guidelines

[2]: P., Lee (2005) : Historical Literacy: Theory and Research, History Education Research Journal 5(1)

Related works | Focusing on Causal Relationships

• We can use the knowledge of the past for the present and future.

- Promoting historical analogies [3]
 - Card-game-based learning material for finding similar causal relationships between past and present
 - Learners manually constructs the causal relationship
 - Theme is fixed by the research



[3]: Ryohei Ikejiri. 2011. Designing and Evaluating the Card Game which Fosters the Ability to Apply the Historical Causal Relation to the Modern Problems. Japan Society for Educational Technology 34, 4 (april 2011), 375–386. (in Japanese).

Related works | Focusing on Causal Relationships

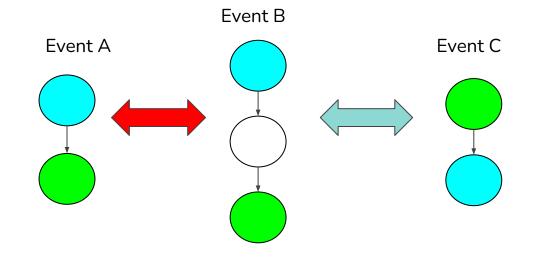
- We can use the knowledge of the past for the present and future.
- Predicting future events [4~5]
 - \circ Learning relationship A \rightarrow B from texts
 - **Predicting** \circ of A' $\rightarrow \circ$ using the learned relationships



Earthquake \rightarrow Tsunami

Objective of this study

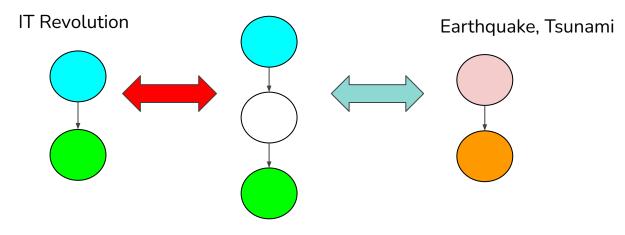
- Measure similarity between causal relationships
 - Assumption: Event graph is given



Usage | Future work

- Searching past/present events with the same/similar cause
 - \circ for history education

Industrial Revolution



Outline

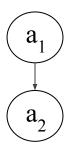
- Definition
- Proposed algorithm (ECM)
 - Event Causal relationship Measurement
- Experimental evaluation
- Conclution

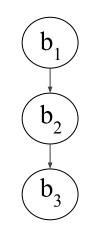
Data representation

A causal relationship is a list of events

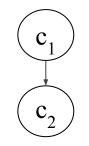
Industrial Revolution

IT Revolution



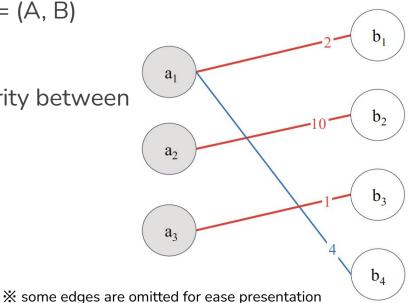


Earthquake, Tsunami



Bipartite graph construction

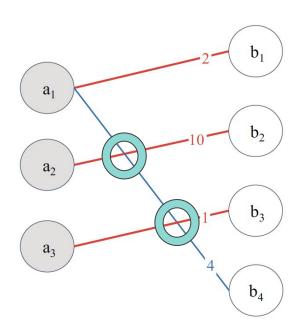
To compare two causal relationships A and B ECM constructs a bipartite graph G = (A, B) A, B: lists of events A weight w of e = (a_i, b_j): similarity between two events a_i and b_j



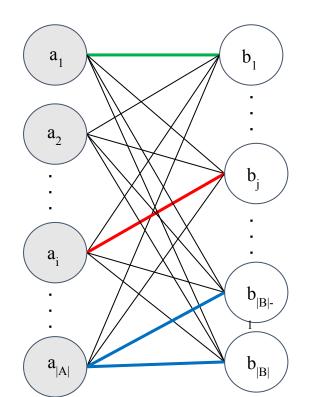
Algorithm | Theory

- Maximum weight matching problem on Bipartite graph
- We extend the general problem by adding
 - no intersection points on the edges that are the solutions to the problem

Red: solutions of the extended problem Blue: solutions of the general problem

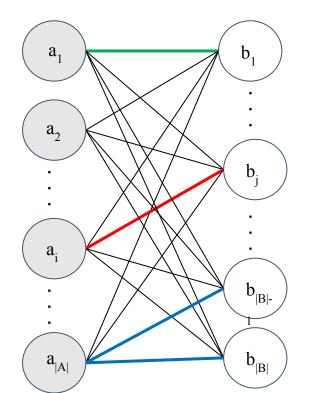


Algorithm | Implementation as a dynamic programming



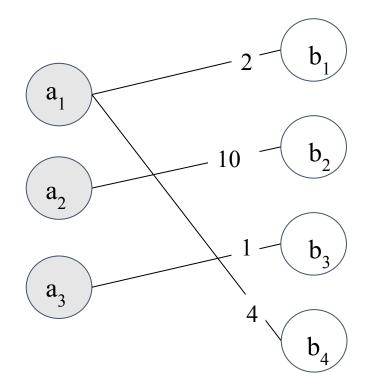
Green: Selected edges as solutions Red: An edge ECM is analyzing Blue: Edges ECM will analyze future

Algorithm | Implementation as a dynamic programming



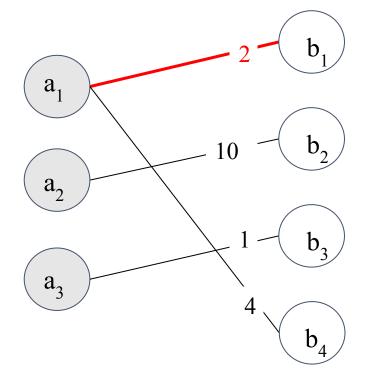
	1	2	3		j		B
1	70	66	99	57	56	76	94
2	2	18	73	10	82	69	3
3	27	26	13	96	79	89	22
	58	85	54	38	46	67	30
i	8	55	14	78			
A							

Green: Selected edges as solutions Red: An edge ECM is analyzing Blue: Edges ECM will analyze future



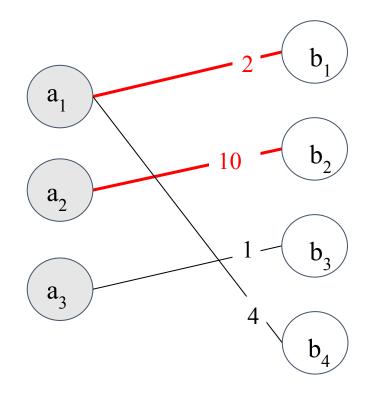
W	b ₁	b ₂	b ₃	b ₄
a ₁	2	0	0	4
a ₂	0	10	0	0
a ₃	0	0	1	0

DP	0	0	0	0
0				
0				
0				



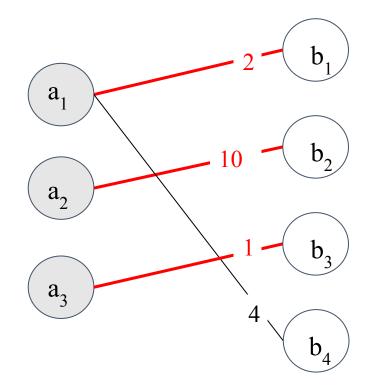
W	b ₁	b ₂	b ₃	b ₄
a ₁	2	0	0	4
a ₂	0	10	0	0
a ₃	0	0	1	0

DP	0	0	0	0
0	2			
0				
0				



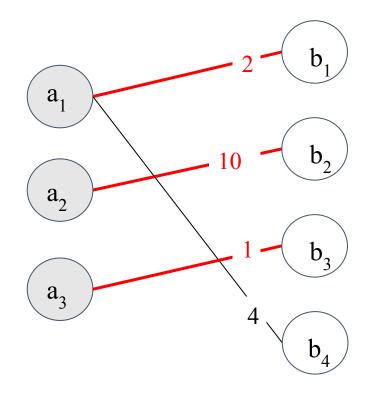
W	b ₁	b ₂	b ₃	b ₄
a ₁	2	0	0	4
a ₂	0	10	0	0
a ₃	0	0	1	0

DP	0	0	0	0
0	2			
0		12		
0				



W	b ₁	b ₂	b ₃	b ₄
a ₁	2	0	0	4
a ₂	0	10	0	0
a ₃	0	0	1	0

DP	0	0	0	0
0	2			
0		12		
0			13	



W	b ₁	b ₂	b ₃	b ₄
a ₁	2	0	0	4
a ₂	0	10	0	0
a ₃	0	0	1	0

DP	0 0		0	0
0	2	2	2	6
0	2	12	12	12
0	2	12	13	13

Experimental evalution | Dataset

- W2E[6]: Wikipedia-based causal relationship dataset
 - a. Every causal relationship has a category
 - b. Num. of causal relationship: 322
 - c. Num. of events: 1,041
 - d. Num. of categories: 10
 - e. Ave. num. of events per causal relationship: 3.23

Experimental evalution | Dataset

	S	AA	BE	ST	AC
Ave. Num. of events	2.92	3.26	3.85	2.0	2.66
Num. of topics	13	73	7	2	3
Ave. Num. of tokens	29.44	27.15	34.59	23.25	34.37
	LC	PE	IR	DA	HM
Ave. Num. of events	3.06	3.14	3.43	3.11	4.66
Num. of topics	32	84	57	45	6
Ave. Num. of tokens	34.53	31.87	38.20	29.54	28.25

S: Sports

AA: Armed conflict and Attack BE: Business and Economy ST: Science and Technology AC: Arts and Culture LC: Law and Crime PE: Politics and Election IR: International relations DA: Disaster and Accident HM: Health and medicine

Examples of W2E

Category	TOPIC ID Event texts	TOPIC ID Event texts
Politics and elections	 2016-07-13 The new Prime Minister of the United Kingdom Theresa May begins forming her ministry following the end of the Second Cameron ministry. 2016-07-14 Elizabeth Truss is named Secretary of State for Justice and first ever female Lord Chancellor of the United Kingdom as former chancellor Michael Gove is ousted from the cabinet. 	 TOPIC-1780 2016-06-29 The process to elect a new leader of the Conservative Party to replace outgoing Prime Minister David Cameron begins in the United Kingdom. 2016-07-05 Home Secretary Theresa May gets 165 votes after the first ballot of Conservative members of parliament to select a new Leader and the next Prime Minister. 2016-07-11 Prime Minister David Cameron announces he will step down on Wednesday, July 13.

Baselines

1. BM25:

Bag-of-words-based ranking function

2. TF-IDF + dynamic time warping(DTW)

DTW evaluates the similarity between data considering time series

Bipartite graph construction

Each node is constructed by TF-IDF vector

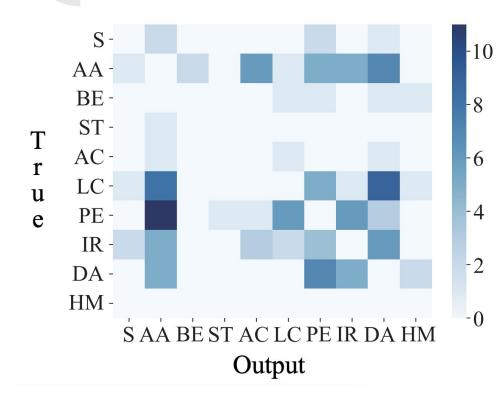
Each weight of an edge is a result of cosine similarity

	TF-IDF	LSA	LDA	Doc2Vec
CosSim	59.8 %	48.8%	26.4%	14.3%
Euclid	17.7%	11.2%	20.2%	15.0%
JS	14.0%	-	17.7%	-



	MAP	Р	R	F_1
BM25	33.1%	25.8%	25.8%	25.8%
DTW	54.4%	49.4%	49.4%	49.4%
ECM	62.5 %	59.8 %	59.8 %	59.8 %

Results | Prediction distribution



S: Sports

AA: Armed conflict and Attack **BE:** Business and Economy ST: Science and Technology AC: Arts and Culture LC: Law and Crime PE: Politics and Election **IR:** International relations DA: Disaster and Accident HM: Health and medicine

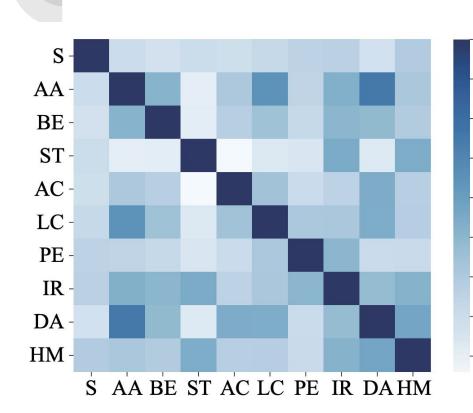
Error Analysis | Correct ratio per category

Sport	Armed conflicts	Business	Science	Arts	Law	Politics	International	Disaster	Health
61.5%	63.0%	42.8%	50.0%	0.0%	21.8%	66.6%	61.4%	57.7%	100.0%
13	73	7	3	3	32	84	57	45	6

Error Analysis | Jaccard coefficient and mutual information

Sport	Armed conflicts	Business	Science	Arts	Law	Politics	International	Disaster	Health
0.11	0.11	0.09	0.19	0.08	0.10	0.12	0.10	0.13	0.13
0.10	0.10	0.11	0.27	0.05	0.09	0.13	0.10	0.13	0.10

Whole average Jaccard: 0.12 Mutual information: 0.12



S: Sports 0.0200 AA: Armed conflict and Attack -0.0175**BE:** Business and Economy -0.0150 ST: Science and Technology -0.0125 AC: Arts and Culture -0.0100 LC: Law and Crime -0.0075 PE: Politics and Election -0.0050 IR: International relations -0.0025DA: Disaster and Accident HM: Health and medicine -0.0000

Error Analysis | Mutual information

Conclusion

We proposed an algorithm to evaluate the similarity of causal relationships.

- Goal: measuring the similarity of events with a focus on causality to facilitate historical analogies
- Proposed algorithm: using DP to calculate similarity between two relationships

Future works

• Using the proposed algorithm in history learning tool to evaluate how the algorithm is useful to enhance historical analogy