Conflict or Cooperation? Predicting Future Tendency of International Relations

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Outline

- **Introduction & GDELT Dataset**
- **Related Work**
- **Problem Statement**
- **Methodology**
- **Experiment**
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Introduction

Motivation

- Predicting future tendency of international relations helps us prepare and make decisions in advance for events that are likely to happen.

- An **early warning system** of conflicts can be further developed.

Introduction

- Generally, recent events between two countries directly reflect the international relation between them.

Idea

- Predicting future tendency of international relations by **predicting future conflict / cooperation events.**

GDELT Dataset

- **GDELT**: Global Data on Events, Location, and Tone [1]
- **GDELT** is available online, providing auto-coded event records from news sources all over the world from 1979 to now.
- Total size: 230.75GB

  (up to 11th Feb. 2020)
- Over $\mathbf{6\times10^8}$ events

[1] Kalev Leetaru and Philip A Schrodt. "Gdelt: Global data on events, location,and tone, 1979–2012". In:ISA annual convention. Vol. 2. 4. Citeseer. 2013,pp. 1–49.

GDELT Dataset

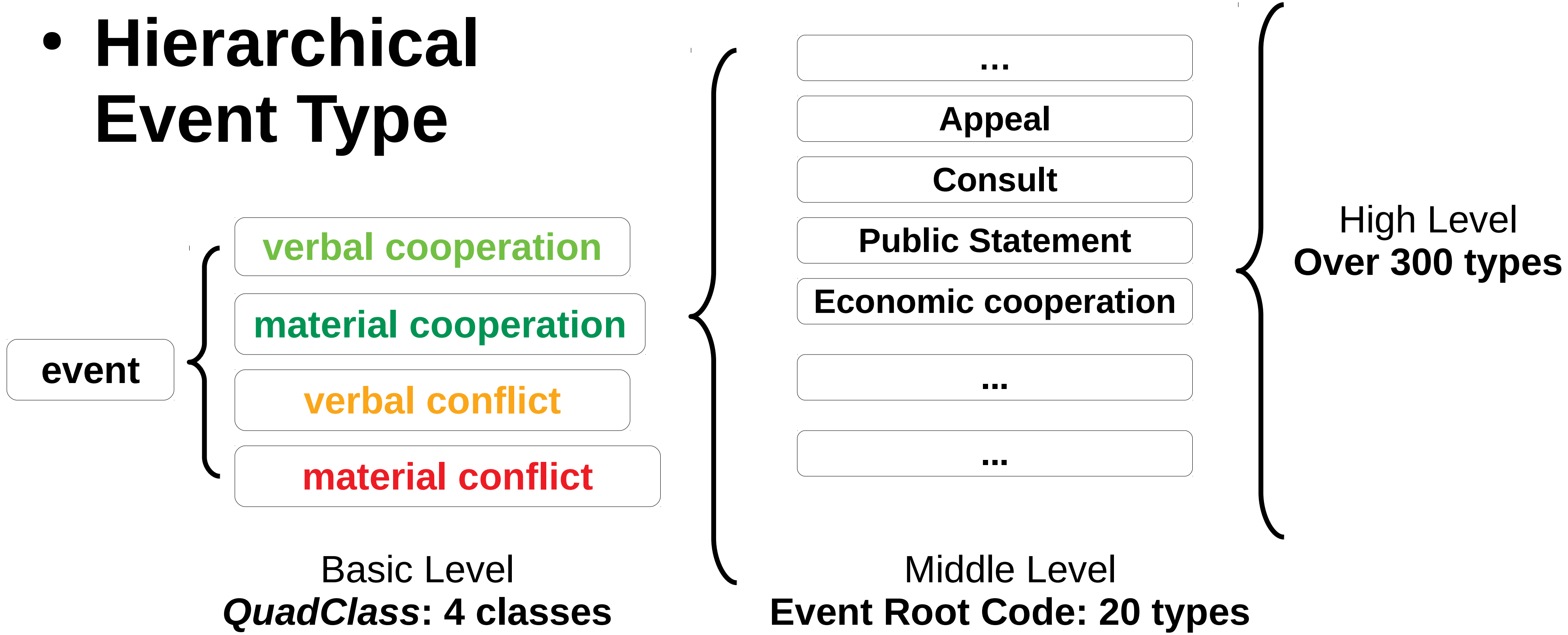
GDELT event database

- One line per event record
- Event Details: Date, Actors, Event Code, NumMentions, ***QuadClass*** ….

SQLDATE	Actor1Code	Actor2Code	EventCode	QuadClass	GoldsteinScale	NumMentions
20150313	USA	JPN	43	1	2.8	4
20160919	USA	JPN	20	1	3	6
20170519	USA	JPN	40	1	1	4
20170519	USAGOV	JPN	61	2	6.4	8
20180517	USA	JPN	20	1	3	1
20181231	USA	JPN	193	4	-10	7
20181231	USA	JPN	80	2	5	2

GDELT Dataset

- **Hierarchical Event Type**



GDELT Dataset

Meterial Conflict

event

- verbal cooperation
- material cooperation
- verbal conflict
- material conflict

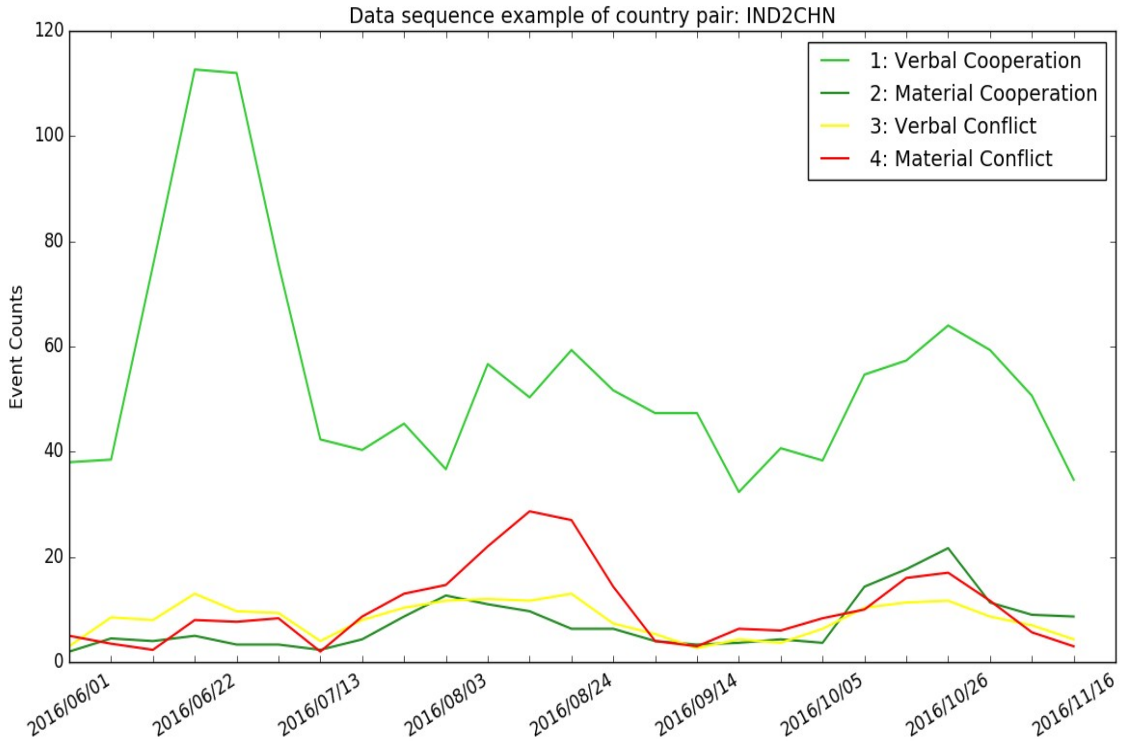
QuadClass: 4 classes

examples

Stop economic assistance
Halt negotiations
Halt mediation
Damage property
Arrest
Use conventional military force
Impose administrative sanctions
…..

GDELT Dataset: Counts of 4 Main Event Classes

- Example of events, where actor1 is India and actor2 is China.
- Counting the weekly number of events.
- **4 classes** of events



Related Work

Predicting future events using GDELT

- Predicting Social Unrest Using GDELT [1]. (models: Random Forest, Ada Boost, LSTM)
- Predicting conflict events in Afghanistan with RNN [2].

Prediction task under different settings

- Stock Price Prediction Using Attention-based Multi-Input LSTM [3].

[1] Divyanshi Galla and James Burke. 2018. Predicting Social Unrest Using GDELT.InInternational Conference on Machine Learning and Data Mining in PatternRecognition. Springer, 103–116.
[2] Smith, Emmanuel M., et al. "Predicting the occurrence ofworld news events using recurrent neural networks and auto-regressive moving average models."
[3] Li, Hao, Yanyan Shen, and Yanmin Zhu. "Stock Price Prediction Using Attention-based Multi-Input LSTM." Asian Conference on Machine Learning. 2018.

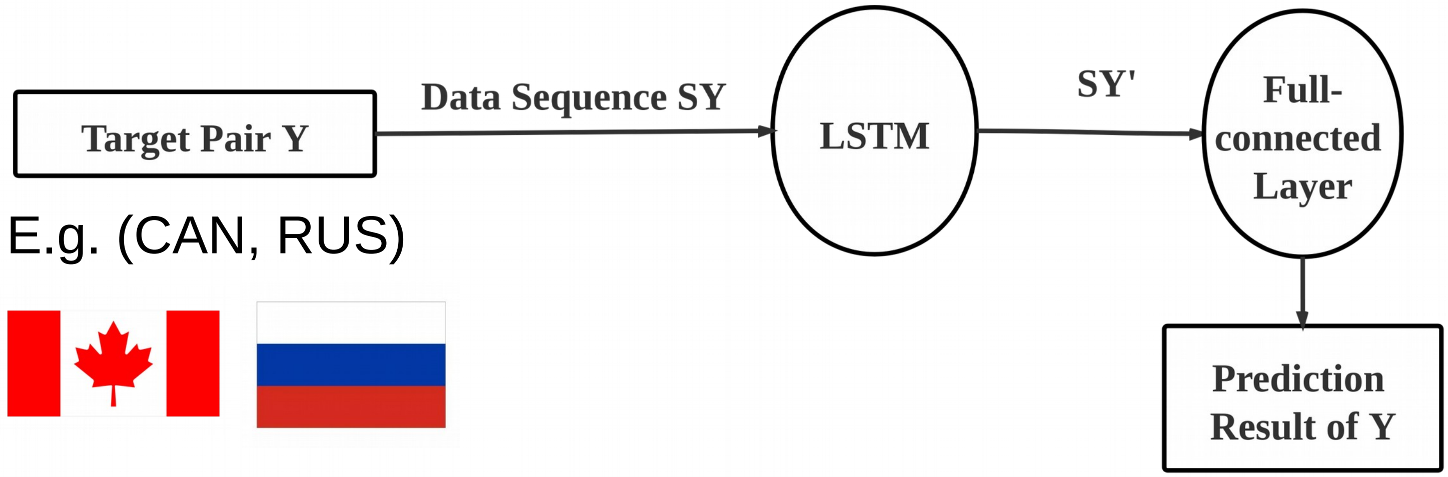
Problem Statement

- Predicting future events between **a pair of countries**.
- Counting the weekly number of each event class (4 classes: ***Verbal/Material Cooperation/Conflict***).
- Given data for consecutive M weeks, predict the event counts in the (M+1)th week.

Methodology

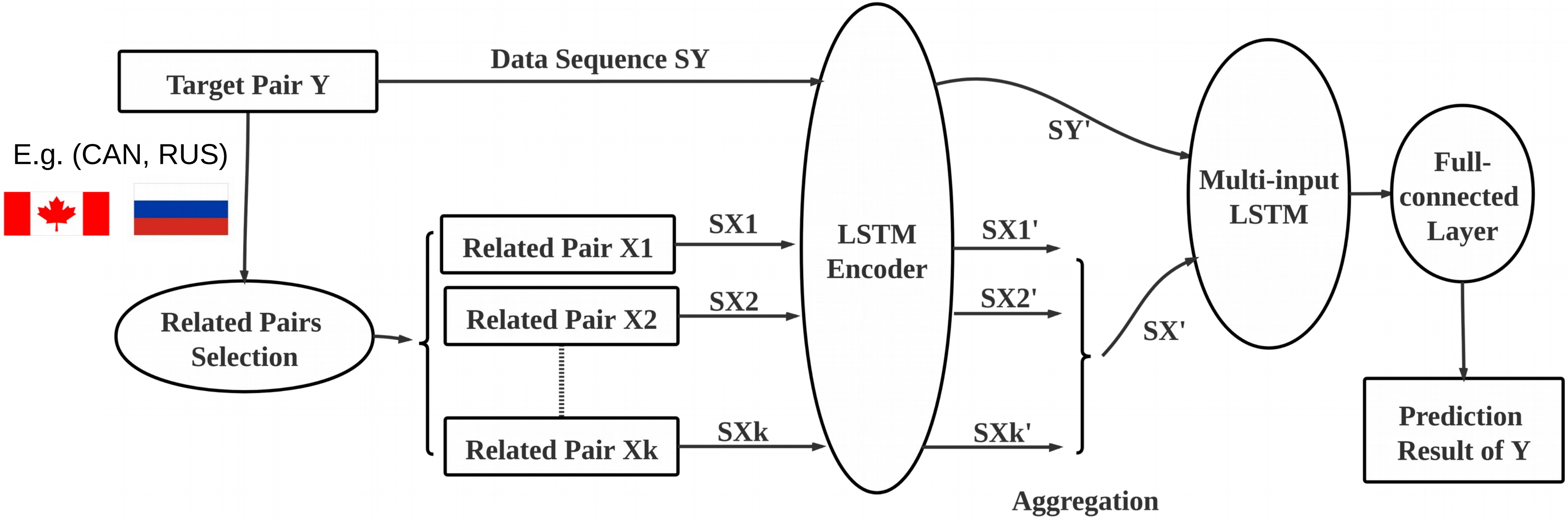
Time Series Learning Models

- Baseline:**Traditional LSTM**



Methodology

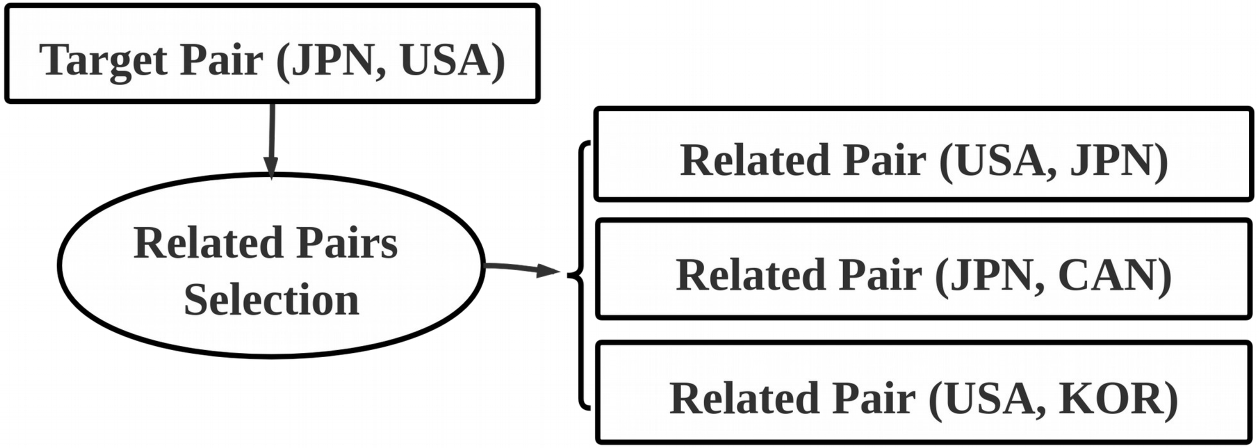
- Proposed: **Related Pairs Selection + Multi-input LSTM**



Methodology

- ***Hypothesis:*** *Relations between a specific pair of countries are likely to be affected by other country pairs.*

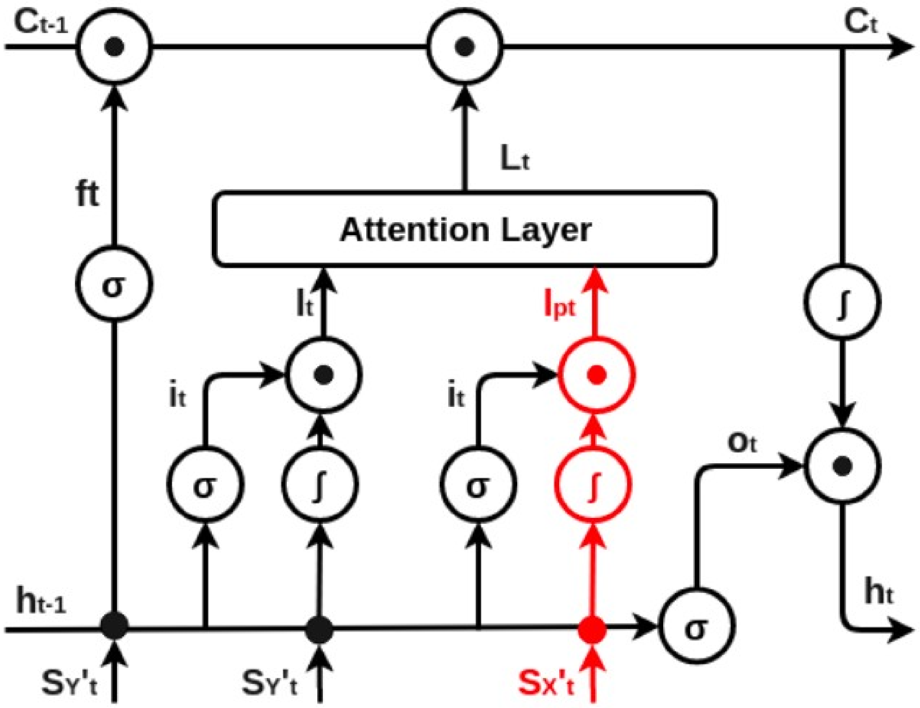
  For example:



Methodology

- A unit of Multi-input LSTM.
- One more input.
- Additional attention layer.
- **Intuition:**

  Use additional information extracted from related pairs to update cell states.



Methodology

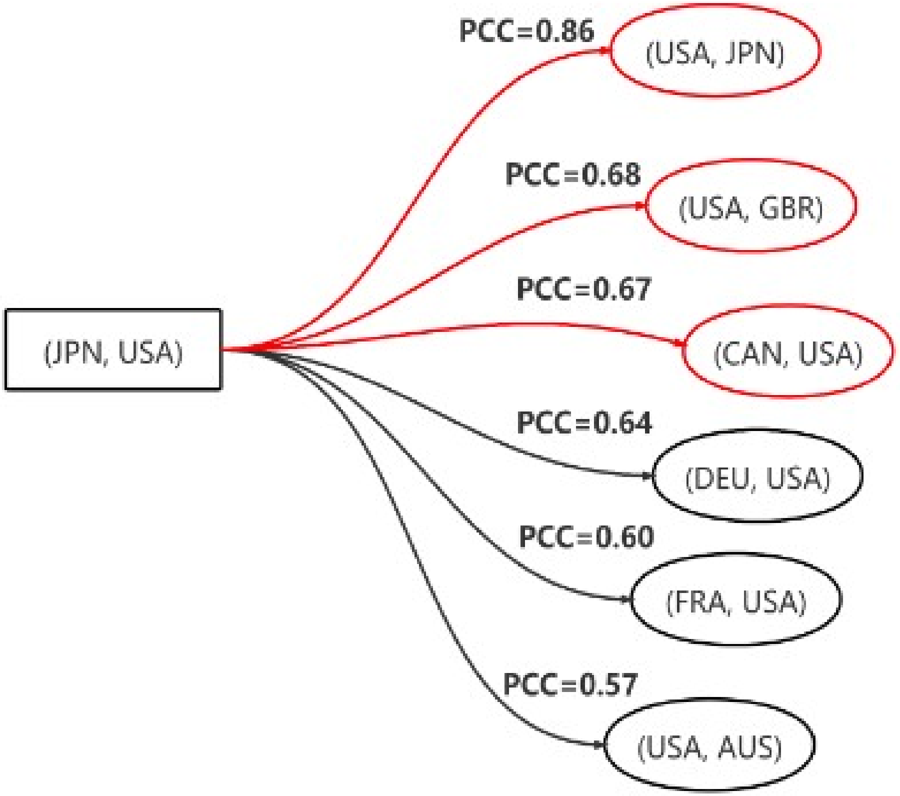
Related Pairs Selection 1

Pearson Correlation Coefficient

Define the data sequence of countries Y and Xi as S_Y and S_{Xi}

$$Cor(S_Y, S_{X_i}) = \frac{Cov(S_Y, S_{X_i})}{\sqrt{Var(S_Y) * Var(S_{X_i})}}$$

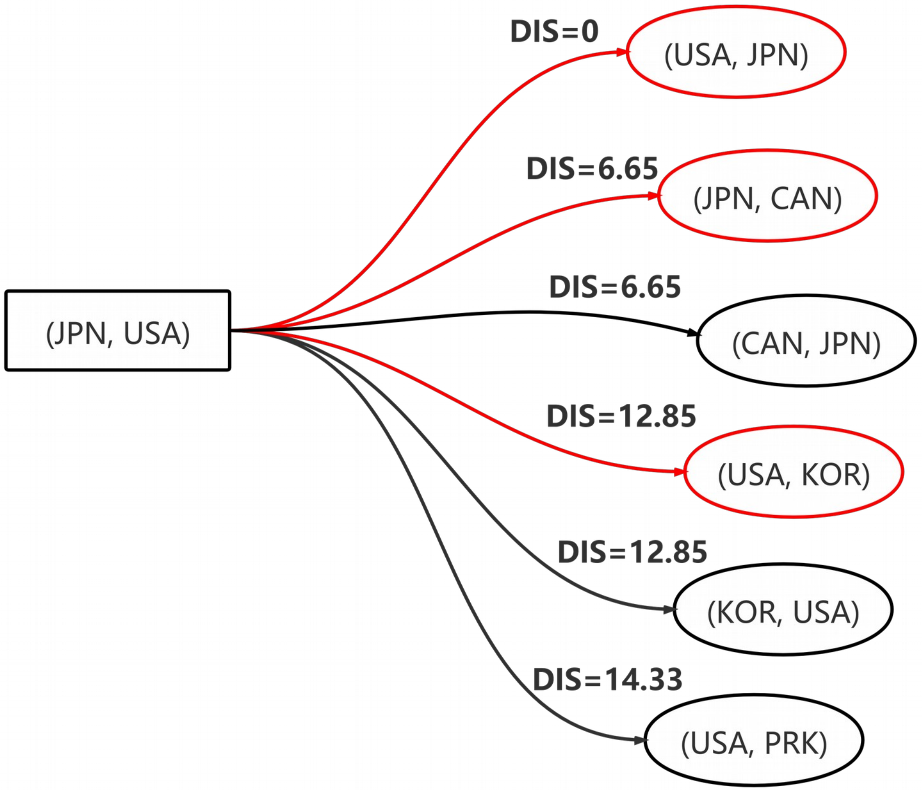
where Cov means covariance, Var means variance.



Methodology

Related Pairs Selection 2

- **Geographical distance** between **country capitals** is used as distance between different countries.
- For example, distance between (**JPN**, USA) and (**CHN**, USA) equals to ***Dis(Tokyo, Beijing)***.



Methodology

Related Pairs Selection 3

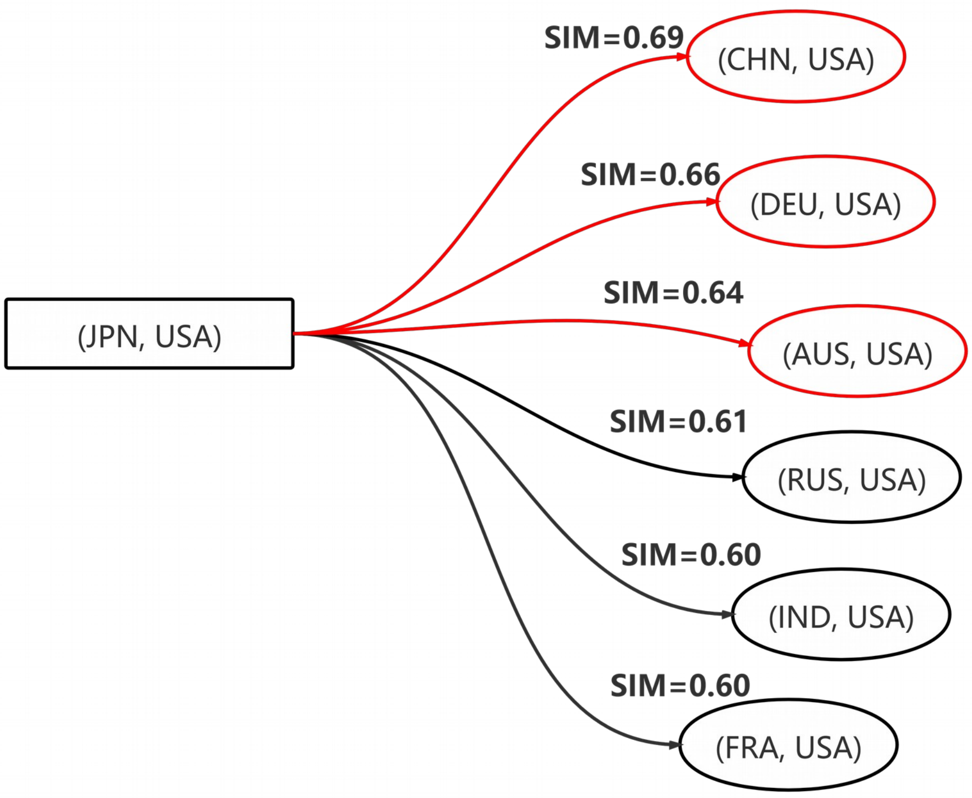
- **Semantic Similarity**

  Use the difference between two semantic vectors (word2vec[1]) of a country pair.

- Difference vector of (JPN, USA) is

$$\overrightarrow{JPN, USA} = \overrightarrow{USA} - \overrightarrow{JPN}$$

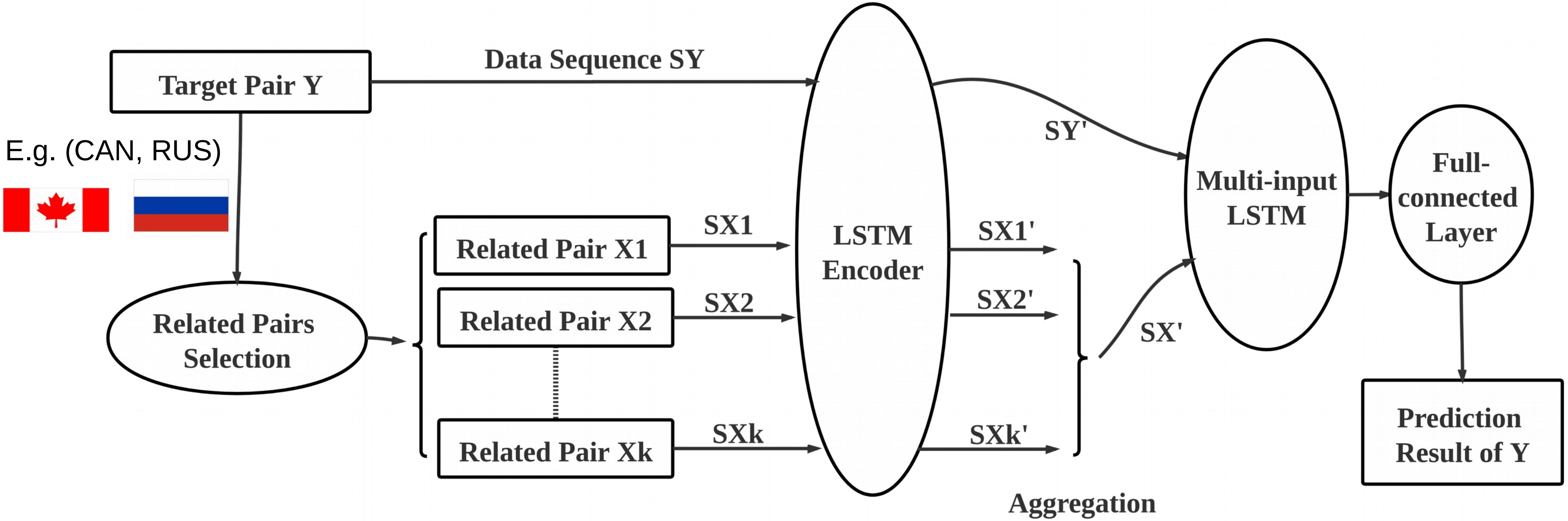
- Correlation: Similarity between difference vectors



[1] Pretrained word2vec on Google News: https://code.google.com/archive/p/word2vec/

Methodology

1. Related Pairs Selection   2. LSTM Encoder   3. Multi-input LSTM



Experiment

Settings:

- Given data of previous **M = 15** weeks, predict event counts in **16^{th}** week.
- **56 target country pairs**

  (formed by Australia, Canada, China，France, Japan, Russia, USA, UK)
- Baseline: **Traditional LSTM**
- Training set: [Jan. 1, 2005, Jun. 1, 2016) (**595** weeks)
- Test set: [Jun. 1, 2016, Dec. 1, 2018) (**130** weeks)

  Size(Training) : Size(Test) ≈ 80% : 20%

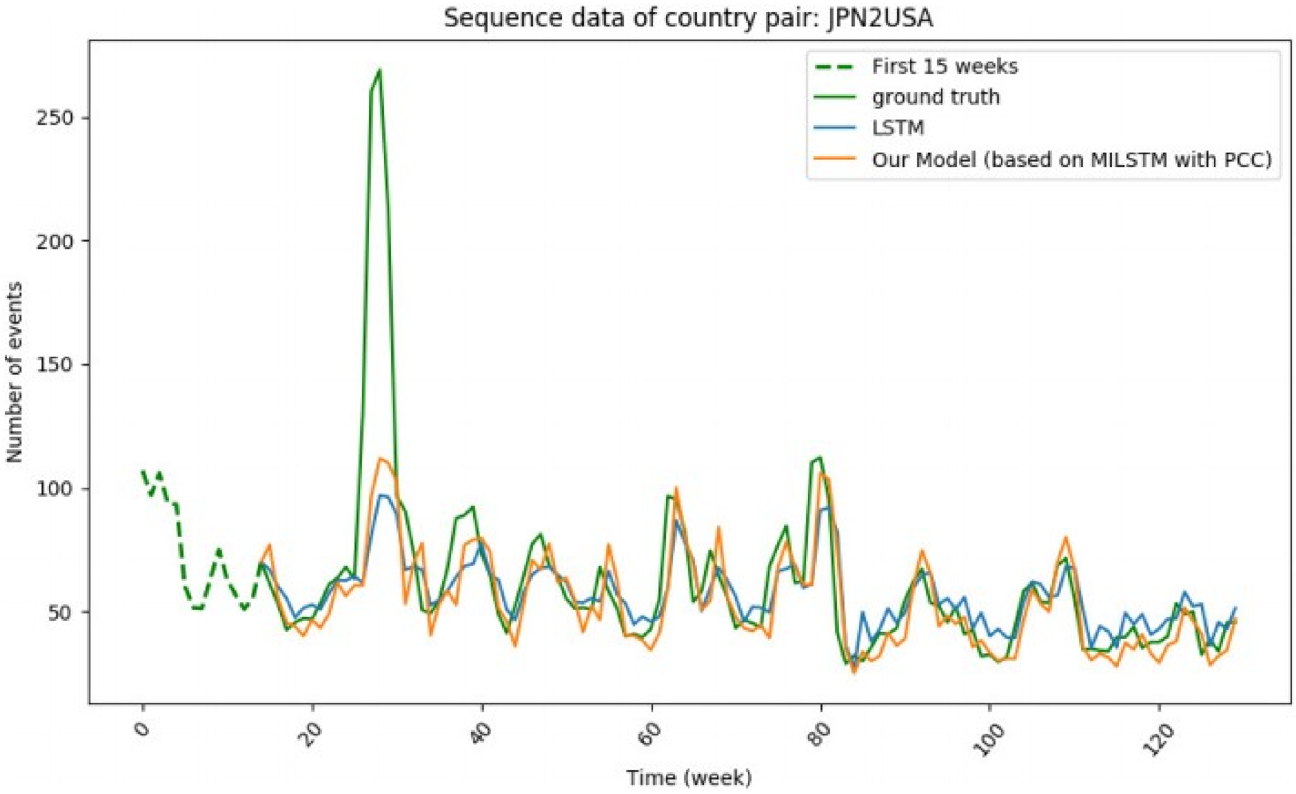
Experiment

- Example of prediction
- Material Conflict
  of (JPN, USA)

  Green: Ground Truth

  Blue: LSTM

  Orange: MILSTM with PCC



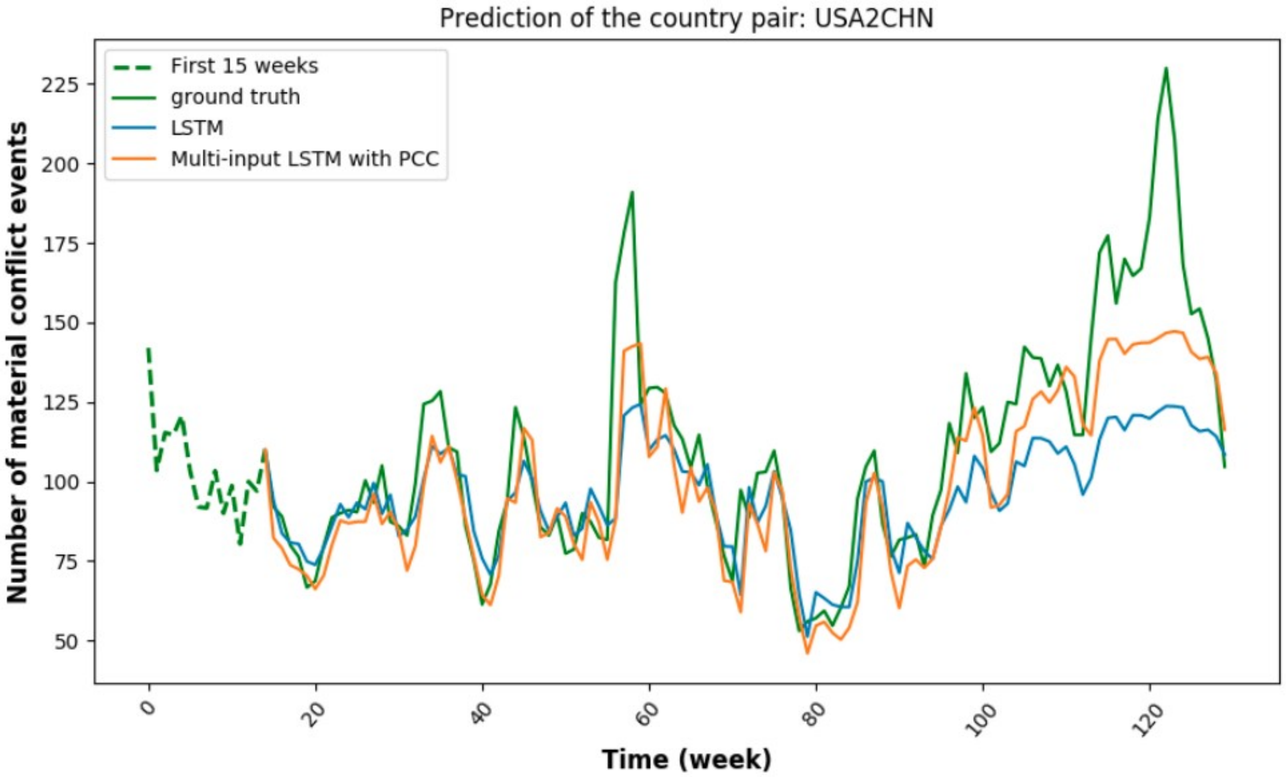
Experiment

- Example of prediction
- Material Conflict of (USA, CHN)

Green: Ground Truth

Blue: LSTM

Orange: MILSTM with PCC



Experiment

- **Evaluation:** Root Mean Square Error **(RMSE)** (Different from **MSE** in the submitted paper)

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m} \left| Y_{i,\ GroundTruth} - Y_{i,\ Predicted} \right|}$$

  where m is the number of test cases.

- **Predicted Events:** Verbal Cooperation, Material Cooperation

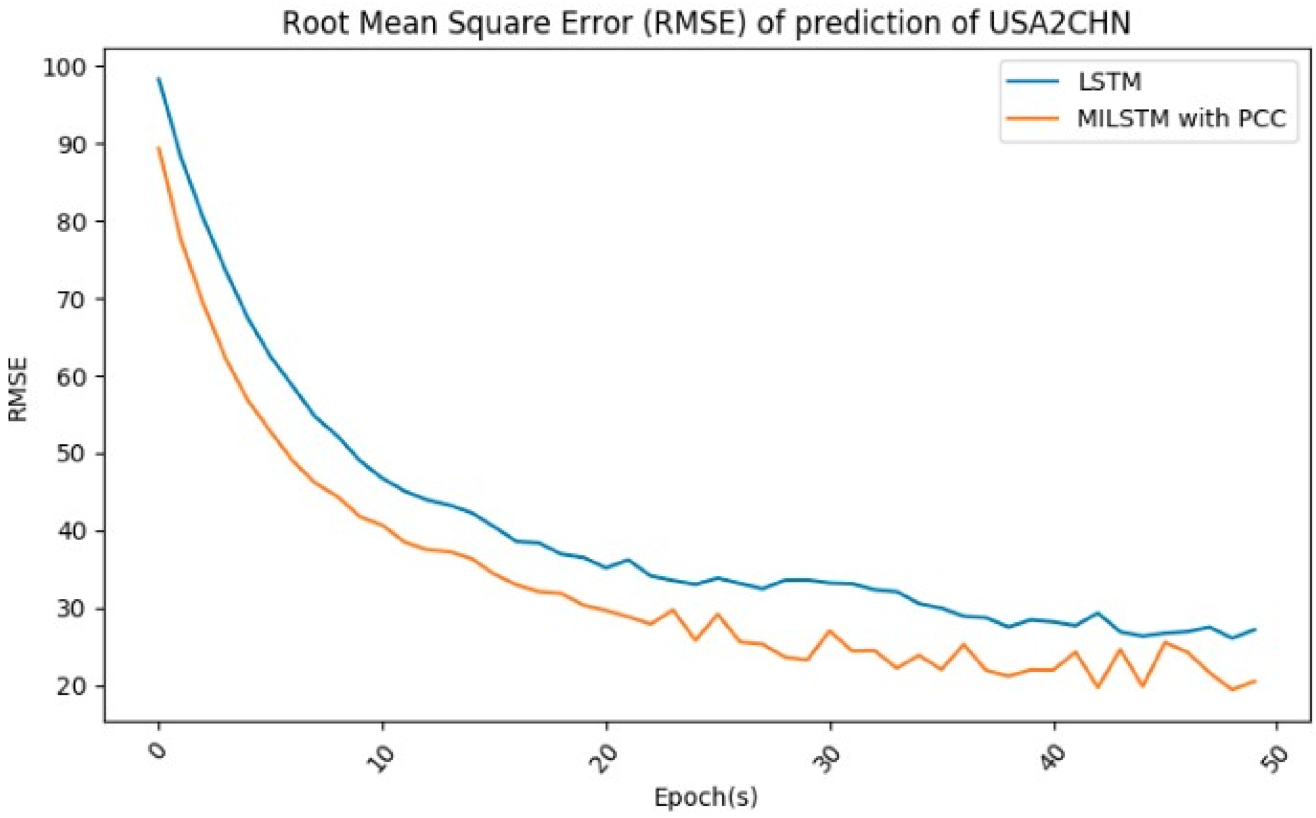
  Verbal Conflict, Material Conflict

Experiment

- Example of **Training Loss**
- Prediction of Material Conflict of (USA, CHN)
- RMSE

Blue: LSTM

Orange: MILSTM with PCC



Experiment

Evaluation Results

- RMSE
- Verbal Conflict
- Sort pairs by **average weekly verbal conflict**

	LSTM	MILSTM with PCC	MILSTM with geo-distance	MILSTM with word2vec	Average Weekly Verbal Conflict
(USA, RUS)	153.1	122.9	126.0	**116.4**	118.3
(RUS, USA)	124.9	101.6	**101.5**	121.1	115.9
(USA, CHN)	35.0	**28.1**	32.7	32.5	92.0
(CHN, USA)	49.0	38.9	40.4	**31.3**	89.2
(GBR, USA)	36.9	27.4	**25.3**	32.9	62.2
(USA, GBR)	32.6	26.9	25.3	**25.2**	59.1
(USA, CAN)	21.7	19.9	**19.3**	19.4	43.2
(CAN, USA)	29.5	30.1	**27.4**	29.7	41.1
(CHN, JPN)	10.9	**9.7**	10.7	10.6	36.0
(FRA, USA)	**13.4**	18.7	14.5	14.6	32.4
(GBR, RUS)	146.9	144.3	**142.7**	143.5	30.9
(JPN, CHN)	11.0	12.3	10.7	**9.4**	30.6
(USA, FRA)	21.5	**19.1**	21.3	21.7	30.0
(USA, JPN)	7.6	12.7	9.5	**7.2**	29.1
(JPN, USA)	6.8	**6.5**	6.6	7.4	27.5
...	...	...	...	...	...

RMSE Improvement:

Average Weekly Verbal Conflict	≥ 100	≥ 80	≥ 60	≥ 40	≥ 20	≥ 10	≥ 0
Number of Pairs	2	4	5	8	18	26	56
MILSTM with PCC	19.8%	19.7%	20.9%	16.6%	3.5%	-0.2%	-4.5%
MILSTM with geo-distance	17.8%	15.2%	18.4%	16.0%	7.0%	3.5%	-0.8%
MILSTM with word2vec	24.0%	17.6%	16.2%	14.3%	7.3%	4.2%	-0.9%

Experiment: Improvement

- **Verbal Cooperation**
- **Material Cooperation**
- **Verbal Conflict**
- **Material Conflict**

Average Weekly Verbal Cooperation	≥ 400	≥ 300	≥ 200	≥ 100	≥ 40	≥ 20	≥ 10	≥ 0
Number of Pairs	5	6	12	20	34	48	54	56
MILSTM with PCC	9.3%	9.7%	9.5%	8.5%	5.6%	4.4%	3.6%	2.7%
MILSTM with geo-distance	10.0%	9.3%	8.7%	7.6%	5.5%	3.0%	2.4%	1.5%
MILSTM with word2vec	9.3%	9.6%	8.0%	6.1%	4.6%	3.4%	2.2%	1.3%

Average Weekly Material Cooperation	≥ 80	≥ 60	≥ 40	≥ 20	≥ 10	≥ 0
Number of Pairs	1	6	9	14	26	56
MILSTM with PCC	14.0%	11.1%	-1.8%	-2.6%	-5.7%	-5.7%
MILSTM with geo-distance	23.3%	9.8%	2.5%	-2.0%	-4.9%	-4.6%
MILSTM with word2vec	19.3%	12.4%	2.4%	-0.6%	0.0%	-4.3%

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MILSTM with geo-distance	17.8%	15.2%	18.4%	16.0%	7.0%	3.5%	-0.8%
MILSTM with word2vec	24.0%	17.6%	16.2%	14.3%	7.3%	4.2%	-0.9%

Average Weekly Material Conflict	≥ 80	≥ 60	≥ 40	≥ 20	≥ 10	≥ 0
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MILSTM with PCC	21.2%	10.0%	8.8%	5.5%	1.6%	-2.2%
MILSTM with geo-distance	21.1%	10.2%	7.4%	4.6%	0.4%	-3.7%
MILSTM with word2vec	18.8%	5.7%	8.1%	4.8%	2.1%	-1.1%

Experiment

- When Average Weekly Event Counts >= 20,
- MILSTM outperforms LSTM for most target pairs.

	Verbal Conflict	Material Conflict	Verbal Cooperation	Material Cooperation	Overall
MILSTM with PCC	3.5%	5.5%	4.4%	-2.6%	2.70%
MILSTM with geo-distance	7.9%	4.6%	3.0%	-2.0%	3.38%
MILSTM with word2vec	7.3%	4.8%	3.4%	-0.6%	3.73%

Table 6.15: RMSE improvement of MILSTM compared to LSTM.

	Verbal Conflict	Material Conflict	Verbal Cooperation	Material Cooperation
MILSTM with PCC	77.8%	71.4%	73.5%	64.3%
MILSTM with geo-distance	88.9%	78.6%	73.5%	50.0%
MILSTM with word2vec	72.2%	71.4%	70.6%	57.1%

Table 6.14: Proportion of better prediction of MILSTM compared to LSTM .

Conclusions

- **Related pairs** does indeed help the model achieve **better** performance, especially for predicting pairs with high frequency of interactions (**Large Average Weekly event counts**).
- MILSTM is **not suitable** for some country pairs with **few** international events.
- Overall, the performance of three types of MILSTM is **similar**, but MILSTM with **word2vec(semantic similarity)** is **slightly better**.

Future Work

- 1: **Effectiveness**
  - Training MILSTM is too slow
  - **Combination of basic models (easy to use)**
- 2. **Dynamic** Related Pairs Selection
  - Current: Static, Select pairs before training
  - **Calculate correlation dynamically with Graph Convolutional Network**

References

[1] Qiao, Fengcai, et al. ”Predicting social unrest events withhidden Markov models using GDELT.”

[2] Smith, Emmanuel M., et al. ”Predicting the occurrence ofworld news events using recurrent neural networks and auto-regressive moving average models.”

[3] Li, Hao, Yanyan Shen, and Yanmin Zhu. "Stock Price Prediction Using Attention-based Multi-Input LSTM." Asian Conference on Machine Learning. 2018.

[4] Divyanshi Galla and James Burke. 2018. Predicting Social Unrest Using GDELT.InInternational Conference on Machine Learning and Data Mining in PatternRecognition. Springer, 103–116.

[5] Kalev Leetaru and Philip A Schrodt. “Gdelt: Global data on events, location,and tone, 1979–2012”. In:ISA annual convention. Vol. 2. 4. Citeseer. 2013,pp. 1–49.

Thank you!

Thanks to all staff for their efforts in hosting SAC 2020 in this difficult time!