Identifying Reply-to Relation in Textual Group Chat using Unlabeled Dialogue Scripts and Next Sentence Prediction

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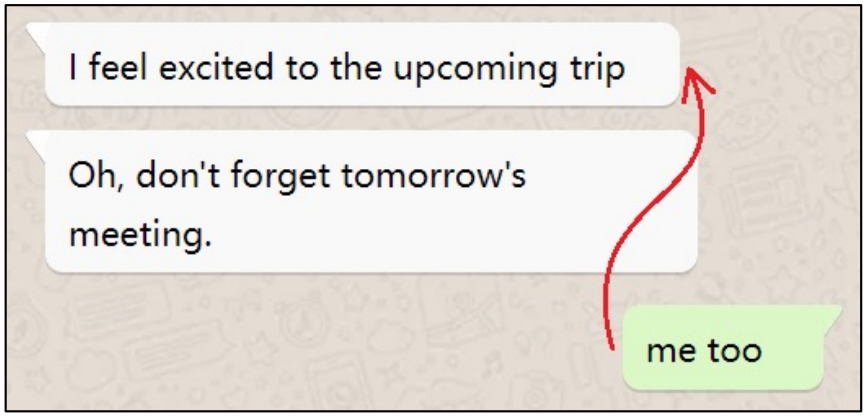
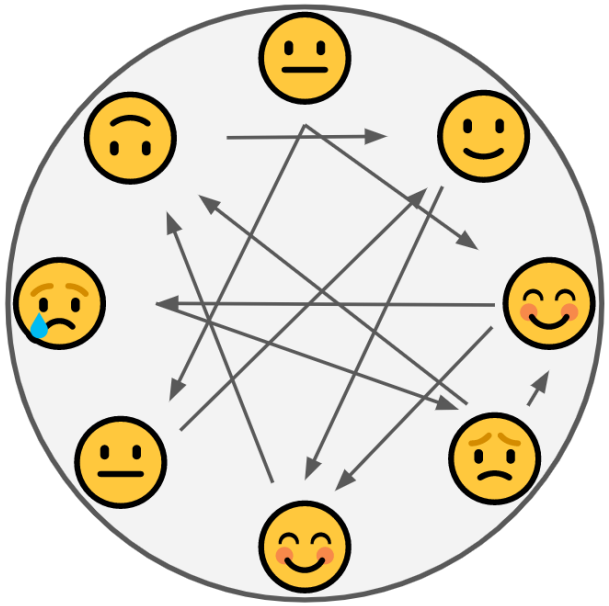
Background

- Instant message (IM) tools have become a part of daily life
- Many researches aim at supporting communications on IMs
  - Relationship analyzation & sustainment
  - Topic recognition & provision
- Need to identify "Reply-to" relation first
  - Especially in the Group Chat





Issues

- Dataset for "Reply-to" relations' identification is hard to collect
  - Need to check "Reply-to" relations manually

- "Reply-to" relations in group chats are more complex
  - "Reply-to" past messages OR start of new topic?
  - Multiple "Reply-to" targets from one message

Message D replies to all of the previous messages A, B and C.

Contributions

1. Collect "Reply-to" messages dataset from dialogue scripts automatically
   Provided a method to sample messages with & without "Reply-to" relations from dialogue scripts

2. Identify "Reply-to" relations with multiple "Reply-to" targets
   Provided & evaluated the method of using Next Sentence Prediction to identify whether each message pair has a "Reply-to" relation.

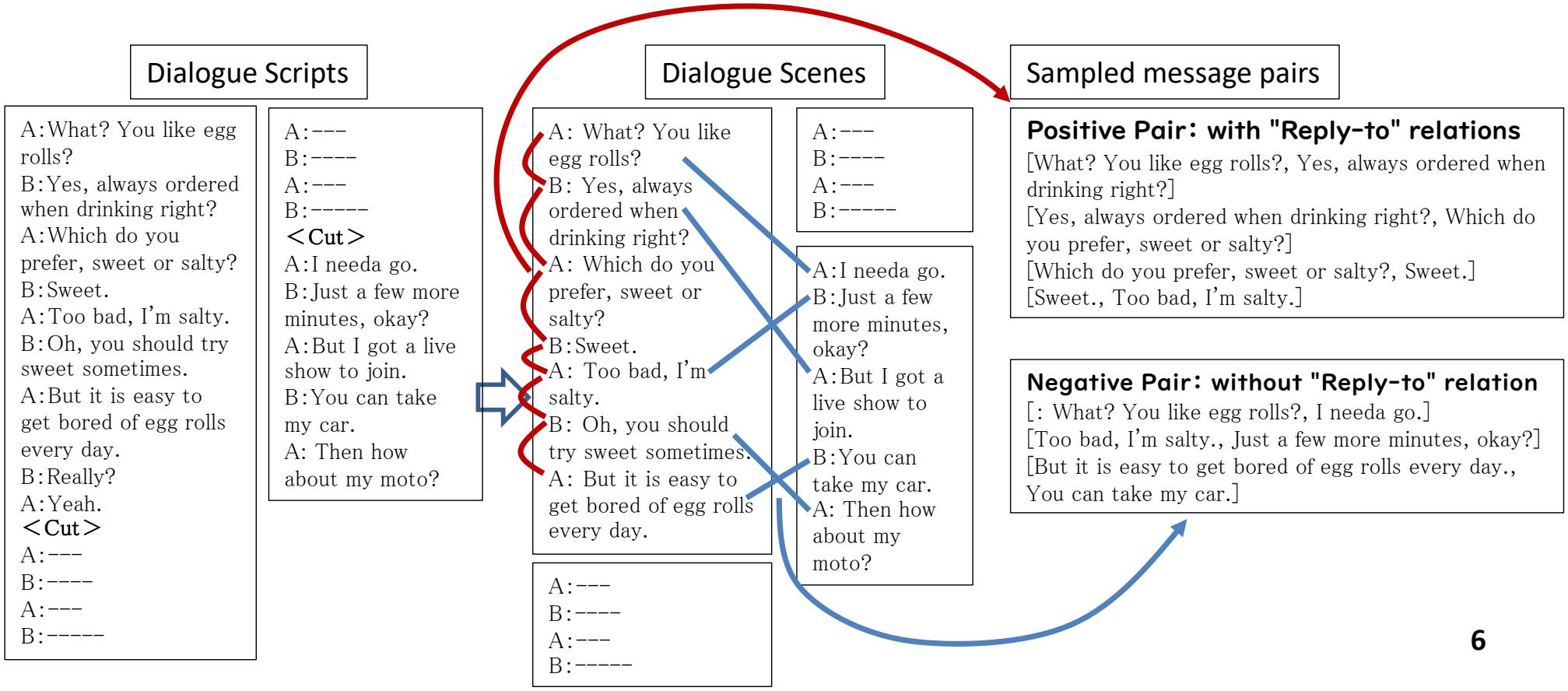
Proposed Method（1）

- Automatic sampling of "Reply-to" messages
  Sampling of messages' "Reply-to" relations from "dialogue scripts" with similar textual features to chat messages.
- Comparison of "dialogue scripts" and "chat messages":

	Chat Messages	**Dialogue Scripts**	Articles or News Reports
Short & Brief	○	○	×
Sequential	×	○	○
Multiple Sending	Many	Less	×
Topic in same time	Distributed	Concentrated	Concentrated
Speaker	Multiple	Multiple	Single
Reply-to relation	Complex	Simple	None

Proposed Method (2)

- Sampling of "Reply-to" relations from dialogue scripts
  - Adjacent two messages (dialogues) → Positive Pair
  - Two messages from different dialogue scenes (scripts) → Negative Pair



Proposed Method (3)

- Identify "Reply-to" relation through Next Sentence Prediction method
- Next Sentence Prediction (NSP) :
  - A supplement of the BERT pre-training process
  - learn to predict whether the 2nd sentence in the pair logically or meaningfully follows the 1st sentence

[I like afternoon tea.], [I usually take some pizza and milk at 4 p.m.]	→ 1
[I like afternoon tea.], [This castle was built 500 years ago.]	→ 0

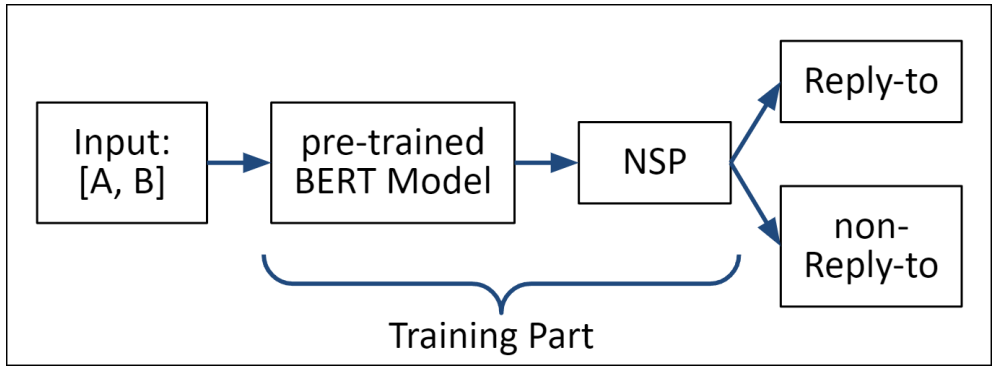
  - NSP task provides a mechanism that could receive sentence pairs directly on the pre-trained BERT model

Word ID : [CLS], [word list of 1st sentence], [SEP], [word list of 2nd sentence], [SEP]
Type ID : [0], [0], [0], [0], [0], [1], [1], [1], [1], [1],

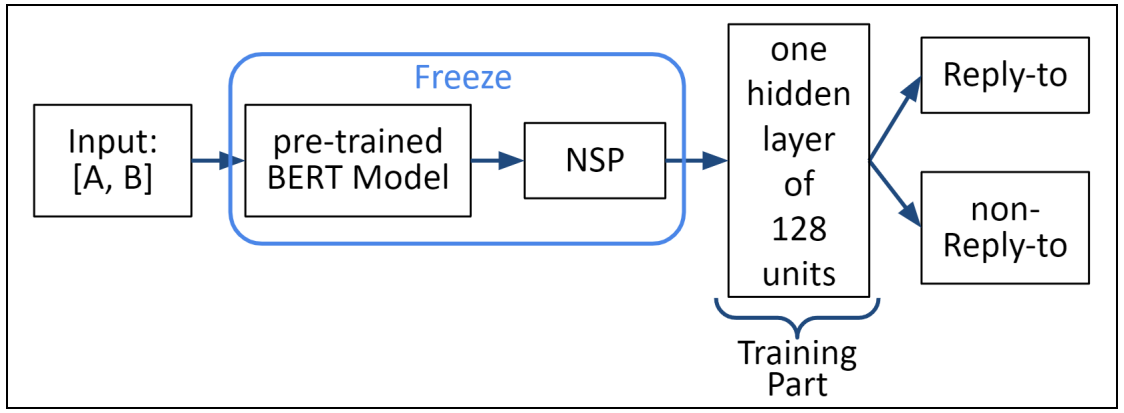
1st sentence　　2nd sentence

Proposed Method (4)

- Built and evaluated three structure settings of the NSP model to verify the effect of "Reply-to" relations' identification
  - 1, Orig-NSP: Original NSP model

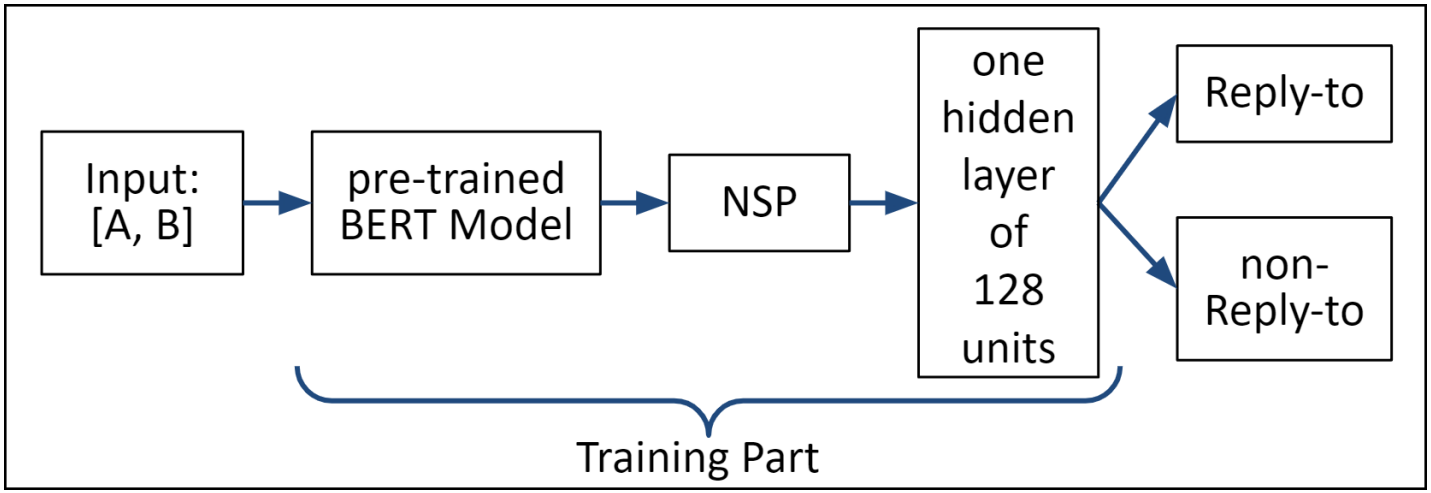


  - 2, NSP-FA-1L: NSP model for embedding sentence pair



提案手法（5）

– NSP-1L: NSP model + one hidden layer of 128 units



All three NSP models were initialized by the pre-trained Japanese BERT model published by Tohoku University:
https://github.com/cl-tohoku/bert-japanese/tree/v2.0

Training settings & results

- NSP model settings:
  - Training Data:
    Automatic sampled
    5094 message pairs
    from dialogue scripts
    - 1,698 Pos
      (with "Reply-to" relation)
    - 3,396 Neg
      (without "Reply-to" relation)

Items	Values
# of training data	5,094 message pairs
Token level	Character
Max length of input	128 (characters)
Batch Size	64
Epoch	10
Validation Rate	0.1
Learning Rate	5e-5 (0.00005)
Optimizer	Adam

- Training results

Model	Train Loss	Train Acc	Val Loss	Val Acc
Orig-NSP	0.0389	95.56%	0.6259	87.06%
NSP-FA-1L	0.4974	76.20%	0.4594	78.24%
NSP-1L	0.0807	97.25%	0.3888	**88.82%**

Evaluation

- Evaluation through actual Japanese group chat records
- Evaluation Procedures
  1. Collect actual messages record from chat group
  2. Manually check "Reply-to" relations between messages
  3. Predict "Reply-to" relations through trained NSP model
  4. Calculate Acc & F1 scores from prediction results and manually checked labels

B : How about the date ?
A : At those 4 places
B : It may take 2 nights to go around these spots.
C : My August is pretty full
A : so am I, maybe in late September I think
C : September is ok for me

B : There will be a mid-term report, late September.

1st Message (A)	2nd Message (B)	Reply-to	Predict
At those 4 places	There will be a mid-term report, Late September.	0	0
It may take 2 nights to go around these spots.	There will be a mid-term report, late September.	0	0
My August is pretty full	There will be a mid-term report, late September.	0	1
so am I, maybe in late September I think	There will be a mid-term report, late September.	1	1
September is ok for me	There will be a mid-term report, late September.	1	1

Evaluation Results

- Evaluation results of Accuracy & F1 score

Model	Accuracy	F1 Score
No-Training	49.8%	0.456
Orig-NSP	56.63%	0.519
NSP-FA-1L	**69.64%**	0.458
NSP-1L	62.77%	**0.558**

  - No-Training: original pre-trained BERT model without fine-tuning by sampled dialogue scripts' message pairs.
  - NSP-FA-1L obtained the highest accuracy of 69.64%
  - NSP-1L model got the highest F1 score of 0.558

Discussion

- Results Summary

Model	Val Acc	Test Acc	F1 Score
No-Training	-	49.8%	0.456
Orig-NSP	87.06%	56.63%	0.519
NSP-FA-1L	78.24%	**69.64%**	0.458
NSP-1L	**88.82%**	62.77%	**0.558**

  - All three trained models outperformed No-Training
    → Dialogue script data is effect for identifying "reply-to" relation
  - For all three trained models, Val Acc > Test Acc
    → Maybe caused by lack of training data (1698 Pos + 3396 Neg)
  - NSP-FA-1L obtained highest test Acc、but F1 score is almost the same as No-Training → Risk of over-fitting (only 1 layer trained)
  - NSP-1L outperformed Orig-NSP in both Acc & F1 score
    → Adding a smaller hidden layer is beneficial to support NSP fine-tuning to focus more on specific tasks

Discussion (2)

- Analysis of correct & incorrect identifications

	Aver. Length of First Msg. (A)	Aver. Length of Second Msg. (B)	Aver. Length of Input Pair
Correct	12.72	14.28	27.0
Incorrect	11.05	9.89	20.95

  - Aver length of 2nd Msg in incorrect < correct results
    → Identify "reply-to" relation between two independent msgs and ignore the contextual information
    →More incorrect identifications at short common response ("Yes", "Okay", "Sure", "Agree"…)

A : Oh, but the plane is in AA?
B : Or in BB?
A : I wonder if the plane is in CC too?
B : If so, I think AA might be a little confused.
B : But for the travel distance, the Zoo is difficult, isn't it?

C : Maybe

1st Msg (A)	2nd Msg (B)	Reply-to	Predict
Oh, but the plane is in AA?	Maybe	0	1
Or in BB?	Maybe	0	1
I wonder if the plane is in CC too?	Maybe	0	1
If so, I think AA might be a little confused.	Maybe	0	1
But for the travel distance, the Zoo is difficult, isn't it?	Maybe	1	1

Conclusion & Future Work

- A method for identifying multiple “Reply-to" targets of messages in group chat.
  - A method for automatically sampling "reply-to" relations between messages from "dialogue scripts" data, which textual features are similar to chat messages.
  - Identify "reply-to" relations from each two-message pair input through Next Sentence Prediction method.
- Built & trained three NSP models via collected 5094 message pairs from dialogue scripts, evaluated with actual group chat records.
  - Greater than 80% accuracy on validation set, higher than 60% accuracy on test set.
- Try to increase the training data, improve the proposed model and explore its effect more clearly.

Thank you very much!