Unpaired Sentiment-to-Sentiment Translation: A Cycled Reinforcement Learning Approach

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Outline

Introduction

Sentiment-to-Sentiment Translation

Examples:

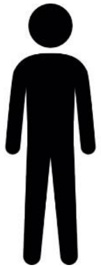
1) **The movie** is **amazing**! — **The movie** is **boring**!

2) I went to this restaurant last weak, **the staff** was **friendly**, and I were **so happy** to have a **great meal**! — I went to this restaurant last weak, **the staff** was **rude**, and I were **so angry** to have a **terrible meal**!

Definition

The goal of sentiment-to-sentiment "translation" is to change the underlying sentiment of a sentence while keeping its content. The parallel data is usually lacked.

Applications: Dialogue Systems



I am sad about the failure of the badminton player A.

The badminton player B defeats A. Congratulations!

sentiment-to-sentiment translation

Refined Answer: I’m sorry to see that the badminton player B defeats A.

Applications: Personalized News Writing

Sentiment-to-sentiment translation can save a lot of human labor!

The visiting team defeated the home team

News for fans of the visiting team: The players of the home team performed badly, and lost this game.

News for fans of the home team: Although the players of the home team have tried their best, they lost this game regretfully.

Challenge: Can a sentiment dictionary handle this task?

- The simple replacement of emotional words causes low-quality sentences.

The food is terrible like rock

The food is delicious like rock

Challenge: Can a sentiment dictionary handle this task?

- For some emotional words, word sense disambiguation is necessary.
  - For example, “good” has three antonyms: “evil”, “bad”, and “ill” in WordNet. Choosing which word needs to be decided by the semantic meaning of “good” based on the given content.

evil

ill

bad

Challenge: Can a sentiment dictionary handle this task?

- Some common emotional words do not have antonyms.
  - For example, we find that WordNet does not annotate the antonym of “delicious”.

Background

Background: State-of-the-Art Methods

Key Idea

1. They first separate the non-emotional information from the emotional information in a hidden vector.
2. They combine the non-emotional context and the inverse sentiment to generate a sentence.

- **Advantage**: The models can automatically generate appropriate emotional antonyms based on the non-emotional context.

- **Drawback**: Due to the lack of supervised data, most existing models only change the underlying sentiment and fail in keeping the semantic content.

The food is delicious  → What a bad movie 

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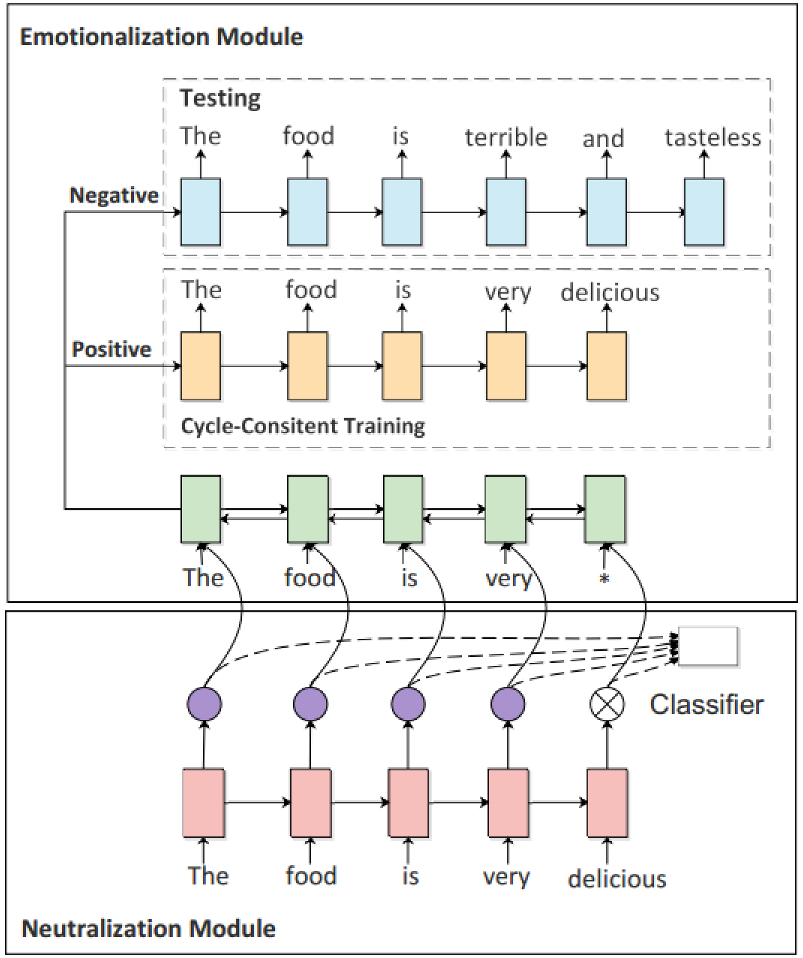
The food is delicious  → What a bad movie 

Approach

Approach: Overview

- ❑ Neutralization module
  - ➢Extract non-emotional semantic information
- ❑ Emotionalization module
  - ➢Add sentiment to the neutralized semantic content
- ❑ Cycled reinforcement learning
  - ➢Combine and train two modules.



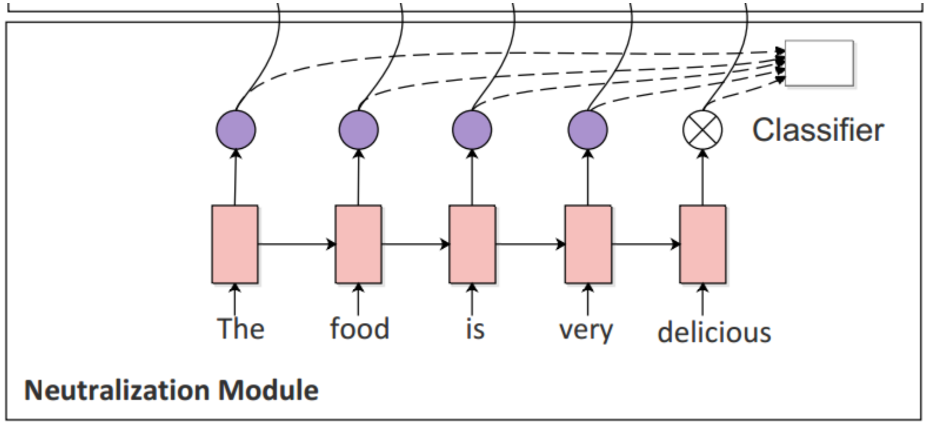
Neutralization Module

Long-Short Term Memory Network

- Generate the probability of being neutral or being polar

Pre-train

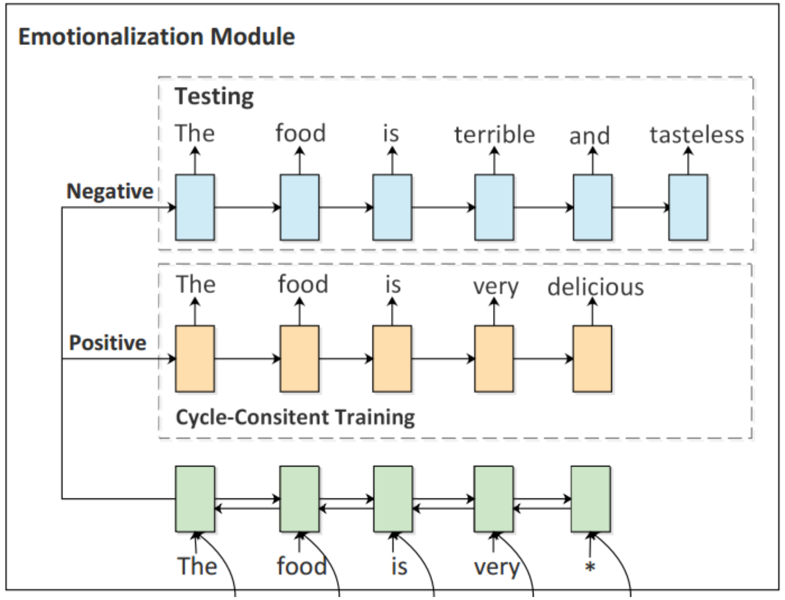
- The learned attention are the supervisory signal.
- The cross entropy loss is computed as



$$L_\theta = -\sum_{i=1}^{T} P_{N_\theta(\hat{\alpha}_i | x_i)}$$

Emotionalization Module

- Bi-decoder based encoder-decoder network
  - The encoder compresses the context
  - The decoder generates sentences
- Pre-train
  - The input is the neutralized input sequence
  - The supervisory signal is the original sentence
  - The cross entropy loss is computed as



$$L_{\emptyset} = -\sum_{i=1}^{T} P_{E_{\emptyset}(x_i|\hat{x}_i,s)}$$

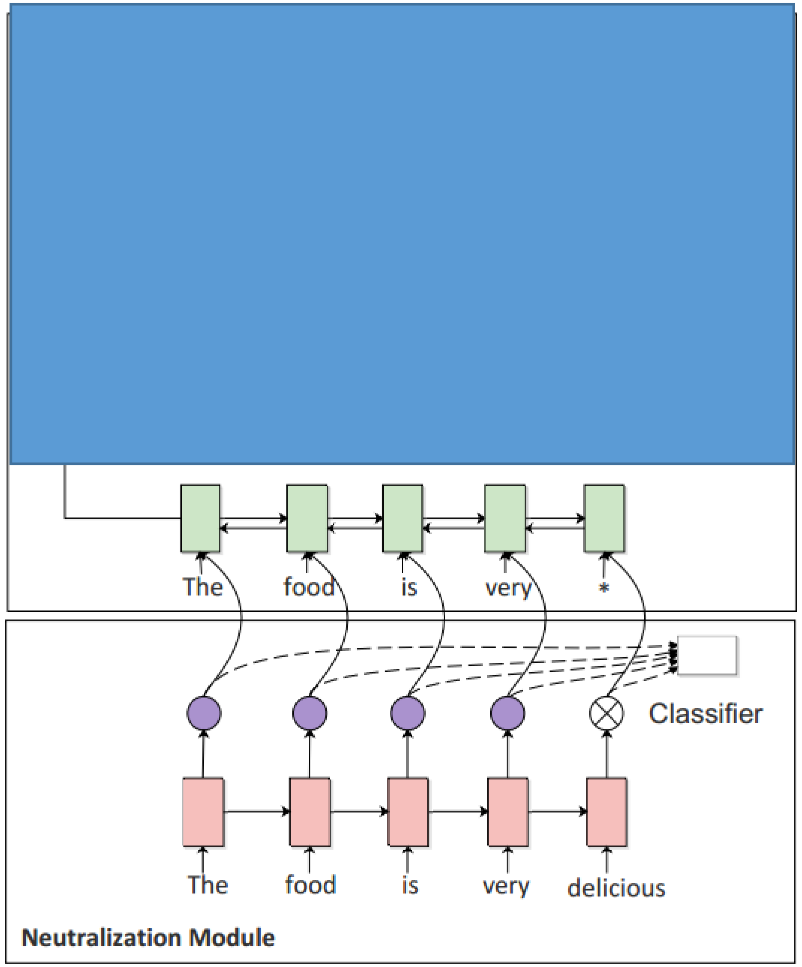
Cycled Reinforcement Learning

1) Neutralize an emotional sentence to non-emotional semantic content.

2) Reconstruct the original sentence by adding the source sentiment.

3) Train the emotionalization module using the reconstruct loss.

4) Train the neutralization module using reinforcement learning.



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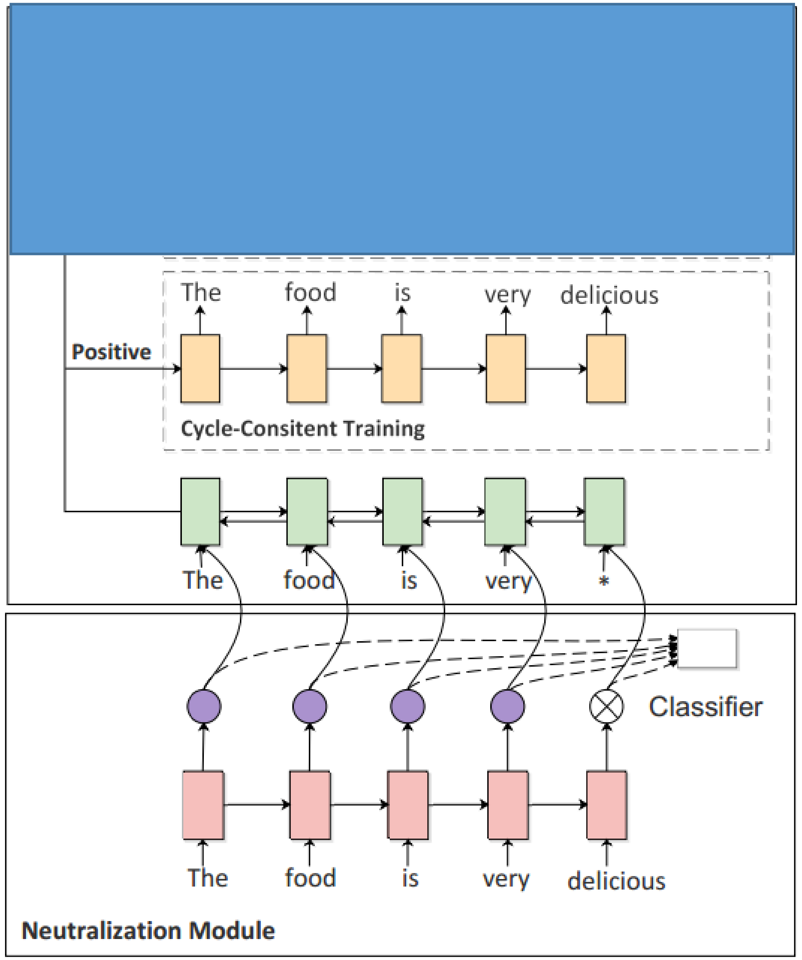

Cycled Reinforcement Learning

1) Neutralize an emotional sentence to non-emotional semantic content.

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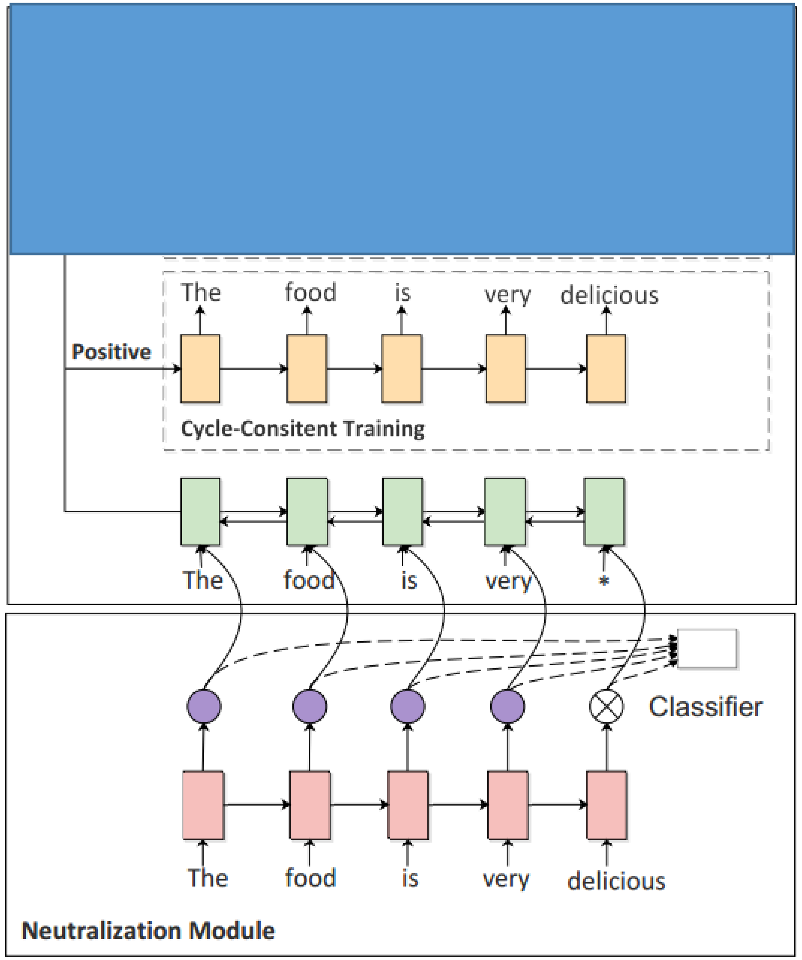


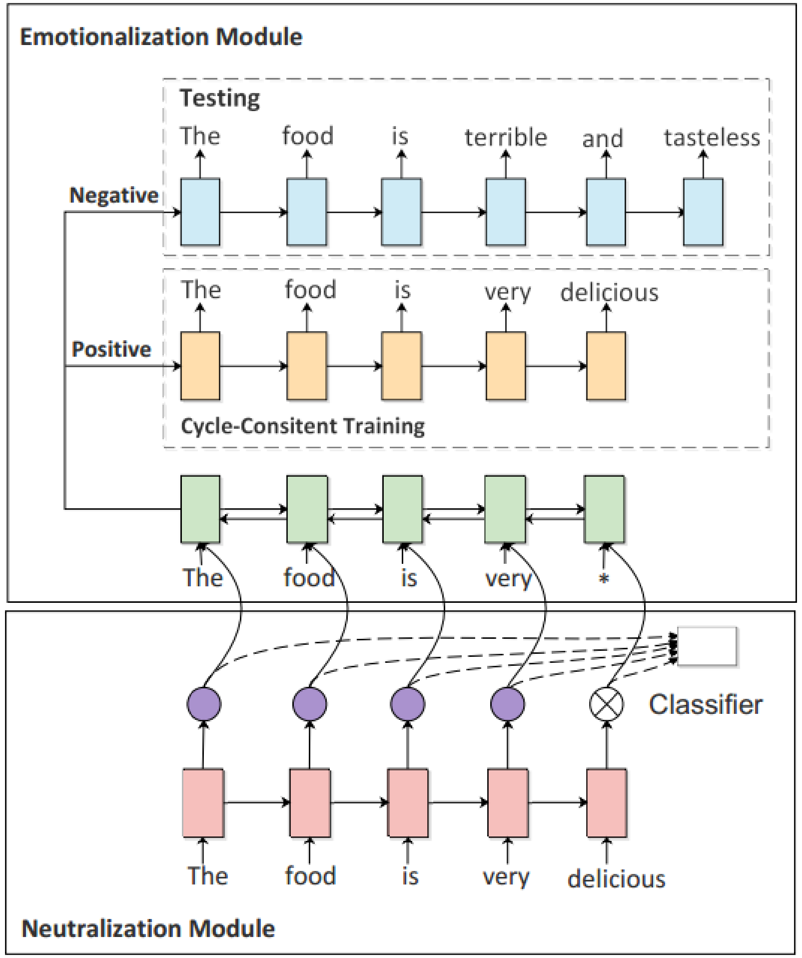
Cycled Reinforcement Learning

1) Neutralize an emotional sentence to non-emotional semantic content.

2) Force the emotionalization module to reconstruct the original sentence by adding the source sentiment.

3) The reconstruct loss is used to train the emotionalization module.

4) Train the neutralization module using reinforcement learning.



Reward

- Add **different sentiment** to the semantic content
  - Positive
  - Negative
- Use the quality of the generated text as reward
  - The confidence score of a sentiment classifier
  - BLEU

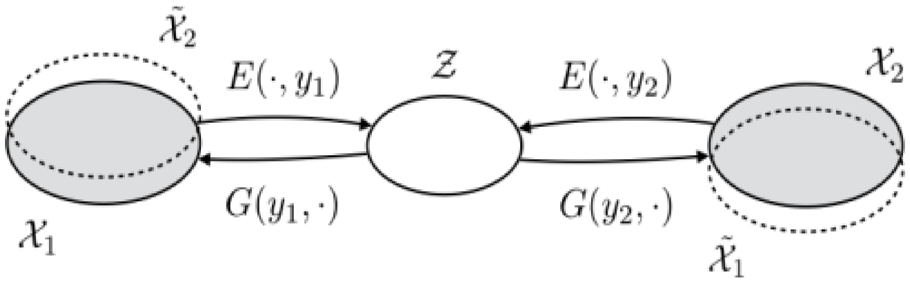
Experiment

Dataset

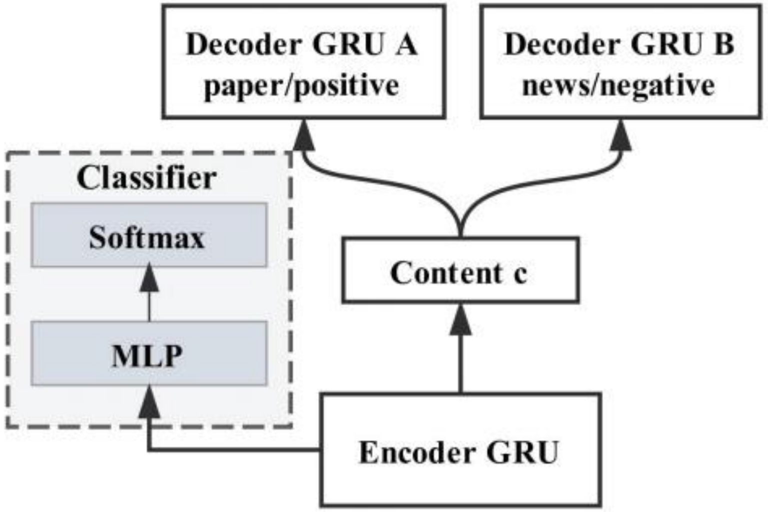
- **Yelp Review Dataset (Yelp)**
  - Yelp Dataset Challenge.
- **Amazon Food Review Dataset (Amazon)**
  - Provided by McAuley and Leskovec (2013). It consists of amounts of food reviews from Amazon.

Baselines

- **Cross-Alignment Auto-Encoder (CAAE)**
  - Refined alignment of latent.



- **Multi-Decoder with Adversarial Learning (MDAL)**
  - A multi-decoder model with adversarial.



Evaluation Metrics

Automatic Evaluation

- Accuracy
- BLEU
- G-score

Human Evaluation

- The annotators are asked to score the transformed text in terms of sentiment and semantic similarity.

Evaluation Metrics

Automatic Evaluation

- Accuracy
- BLEU
- G-score

Human Evaluation

- sentiment and semantic similarity.

Results

Yelp	ACC	BLEU	G-score
CAAE	93.22	1.17	10.44
MDAL	85.65	1.64	11.85
Proposed Method	80.00	22.46	**42.38**
Amazon	ACC	BLEU	G-score
CAAE	84.19	0.56	6.87
MDAL	70.50	0.27	4.36
Proposed Method	70.37	14.06	**31.45**

Automatic evaluations of the proposed method and baselines.

Results

Yelp	Sentiment	Semantic	G-score
CAAE	7.67	3.87	5.45
MDAL	7.12	3.68	5.12
Proposed Method	6.99	5.08	**5.96**
Amazon	**Sentiment**	**Semantic**	**G-score**
CAAE	8.61	3.15	5.21
MDAL	7.93	3.22	5.05
Proposed Method	7.92	4.67	**6.08**

Human evaluations of the proposed method and baselines.

Generated Examples

Input: *I would strongly advise against using this company.*

CAAE: *I love this place for a great experience here.*

MDAL: *I have been a great place was great.*

Proposed Method: *I would love using this company.*

and best.

Input: *Worst cleaning job ever!*

CAAE: *Great food and great service!*

MDAL: *Great food, food!*

Proposed Method: *Excellent outstanding job ever!*

Input: *Most boring show I've ever been.*

CAAE: *Great place is the best place in town.*

MDAL: *Great place I've ever ever had.*

Proposed Method: *Most amazing show I've ever been.*

Analysis

Analysis of the neutralization module

Michael is absolutely wonderful.

I would strongly advise against using this company.

Horrible experience!

Worst cleaning job ever!

Most boring show i ’ve ever been.

Hainan chicken was really good.

I really don’t understand all the negative reviews for this dentist.

Smells so weird in there.

The service was nearly non-existent and extremely rude.

Error Analysis

☐ Sentiment-conflicted sentences

- ➢ Outstanding and bad service

The service here is very good → Outstanding and bad service

☐ Neutral sentences

- ➢ Our first time to the bar

It's our first time to the bar and it is totally amazing → It's our first time to the bar

Conclusion

A. Enable training with unpaired data.

B. Tackle the bottleneck of keeping semantic.

C. State-of-the-art results.

Thank You!

If you have any question, please send an e-mail to jingjingxu@pku.edu.cn