NLPCC

A Short Texts Matching Method Using Shallow Features and Deep Features

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Outline

1. Short Text Conversation
2. Retrieval-based Short Text Conversation
3. Matching Short Texts Using Multi-level Features
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1/ Short Text Conversation

Short Text Conversation： a short text-matching task. For a given short text such as a post, this task aims to find a massive suitable response from the candidate set.

P: 深圳 今天 天气 怎么样？ How is the weather like today in Shenzhen?
R+: 深圳 现在 正 大雨磅礴 。 It's pouring down in torrents now in Shenzhen.
R1-: 在 深圳 过的 怎么样 ？ How is everything going in Shenzhen?
R2-:今天 上海 天气 不错哦 。 The weather in Shanghai is very good today.

- Focusing on the research of short text semantic matching
- It’s a simplified task of modeling a complete dialogue session such as Turing test

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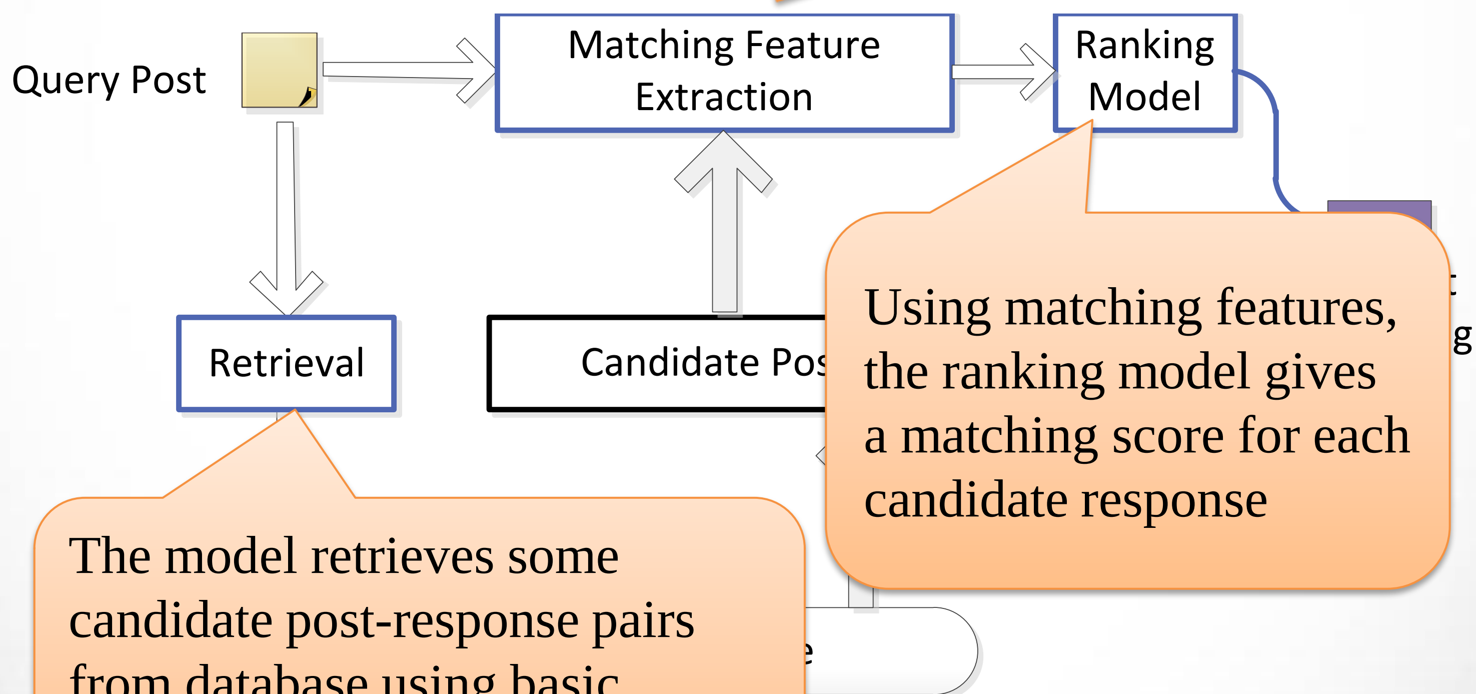
Retrieval-base

Given a query post q, generate matching features $\{\Phi_i(q,(p,r)), i \in \Omega\}$for each candidate post-response pair (p, r)



Using matching features, the ranking model gives a matching score for each candidate response

The model retrieves some candidate post-response pairs from database using basic retrieval models

3/

Matching Short Texts Using Multi-level Features

- **Multi-level Matching Features**
  - Shallow Matching Features
    - Similarity
    - Latent Semantic Similarity
    - BM25 Score (new work)
  - Deep Matching Features
    - Based on word embedding
    - Based on sentence2vec (new work)
  - Rule-based Matching Features

3 Matching Short Texts Using Multi-level Features

Shallow Features

Deep Features

Rule-based Features

Ranking model

given a post q and a candidate post-response pair (p, r)

- Similarity: vector space model with TF-IDF weights
  - ✓ Similarity between q and r: $\Phi_1(q,(p,r)) = S_{cos}(q,r)$
  - ✓ Similarity between q and p: $\Phi_2(q,(p,r)) = S_{cos}(q,p)$
- Latent Semantic Similarity: Latent semantic indexing (LSI) model
  - ✓ Latent Semantic Similarity between q and r:
    $$\Phi_3(q,(p,r)) = S_{cos}(q_{lsi}, r_{lsi})$$
  - ✓ Latent Semantic Similarity between q and p:
    $$\Phi_4(q,(p,r)) = S_{cos}(q_{lsi}, p_{lsi})$$
- New work: BM25 score of (q, r) and (q, p)

3

Matching Short Texts Using Multi-level Features

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A matching model based on neural networks and word embedding

- given a post q and a candidate post-response pair (p, r)

  1. choose the top m words in q by TF-IDF weights

  $$q' = (w_1\ w_2\ w_3\ \dots\ w_m)$$

  2. choose the top n words in r by TF-IDF weights

  $$r' = (w_1\ w_2\ w_3\ \dots\ w_n)$$

  3. convert them into a set of vectors

  $$Q' = (v_1\ v_2\ v_3\ \dots\ v_m)$$
  $$R' = (v_1\ v_2\ v_3\ \dots\ v_n)$$

  4. get a correlation matrix with size $m*n$

  $$M_{cor}' = \{S_{cos}(v_i, v_j) \mid v_i \in Q, v_j \in R\}$$

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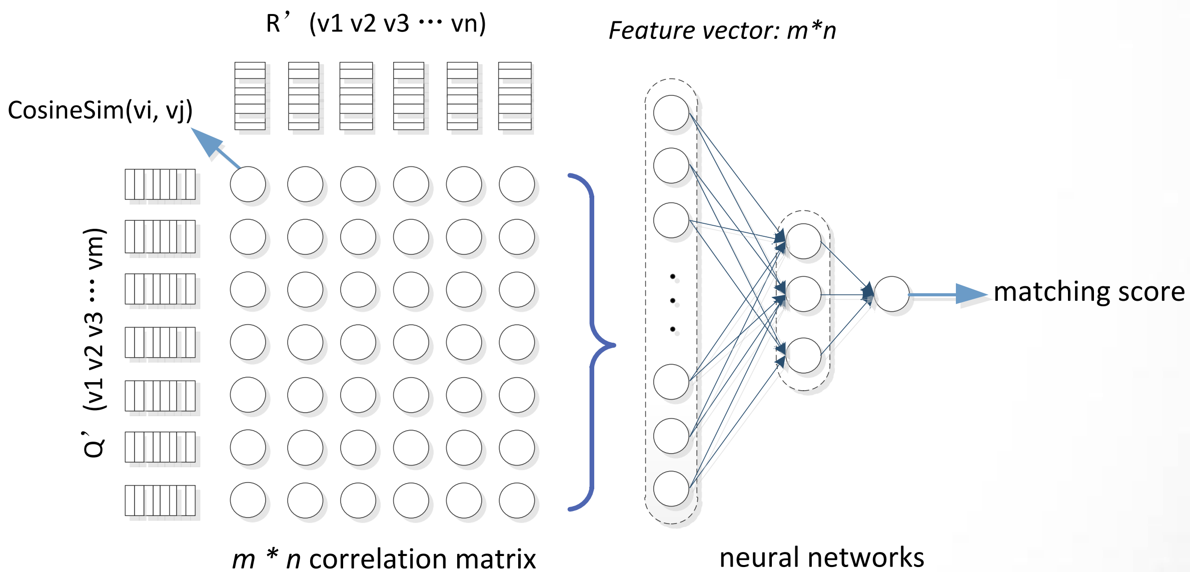

$$\Phi_7(q,(p,r)) = S_{w2v}(q,r)$$

3/ Matching Short Texts Using Multi-level Features

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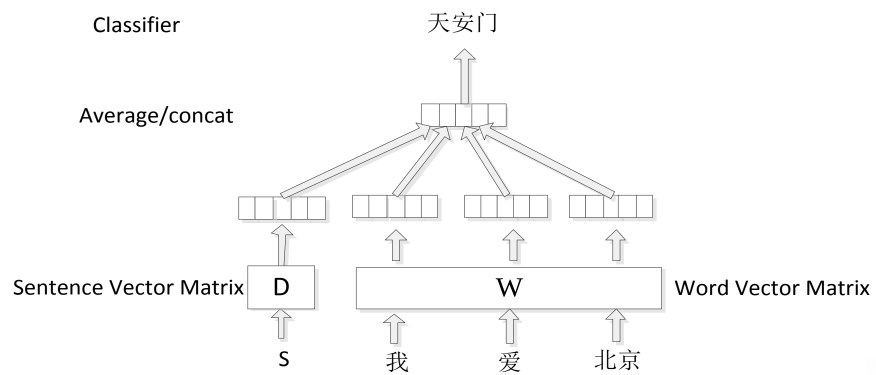
New work: matching feature based on distributed representations of sentences (sentence2vec)

- The training model of sentence2vec is similar to word embedding



- given a post q and a candidate post-response pair (p, r)
  - ✓ sentence similarity between q and r:
    $$\Phi_8(q,(p,r)) = S_{s2v}(q,r) = S_{cos}(q_v,r_v)$$
  - ✓ sentence similarity between q and p:
    $$\Phi_9(q,(p,r)) = S_{s2v}(q,p) = S_{cos}(q_v,p_v)$$

3 Matching Short Texts Using Multi-level Features

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Matching Features	Definition
$\Phi_{10}(q,(p,r))$	This feature measures whether post q and response r have same entity words.
$\Phi_{11}(q,(p,r))$	This feature measures whether post q and response r have same number such as date and money.
$\Phi_{12}(q,(p,r))$	This feature indicates the length of the longest common string between a post and a response.
$\Phi_{13}(q,(p,r))$	This feature indicates the ratio of the length of post q to the length of response r.

3/ Matching Short Texts Using Multi-level Features

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- The ranking model learned a linear score function by RankSVM.

$$Score(q,(p,r)) = \sum_{i \in \Omega} \omega_i \Phi_i(q,(p,r))$$

- Here $\Phi_i(q,(p,r))$ stands for the acquired matching feature and w_i is the weight of $\Phi_i(q,(p,r))$ to be learned.

4/ Experiment

Dataset

Benchmark

Performance

- The dataset of short-text conversation based on the real-world instances from Sina Weibo, which is published by Wang, et al.

Dataset	Use	Size
Unlabeled post-response pairs	For training matching models	Posts: 38,016 Responses: 618,104 Post-response pairs: 618,104
Labeled post-response pairs	For testing	Posts: 422 Responses: 12,402 Responses for each test post: 30
Origin Weibo dataset	For training word embedding	Posts: 33,405,212 Size: 6 GB Vocabulary Size: 10,214 Dimension: 100

4 Experiment

Dataset

Benchmark

Performance

- **MAP:** Mean Average Precision

$$MAP(Q) = \frac{1}{|Q|}\sum_{j=1}^{|Q|}\frac{1}{m_j}\sum_{k=1}^{m_j} Precision(R_{jk})$$

- **P@1:** the precision of the top response returned by model

$$P@1 = \frac{|matched(top\ 1)|}{|Q|}$$

4 Experiment

Dataset

Benchmark

Performance

➢ There are four competitor methods:

1. Baseline: A retrieval-based model (Wang, et al. EMNLP 2013)
2. DeepMatch: A deep architecture for matching short texts (Lu and Li. NLPS 2013)

Two newly added models by Ji, et al.

3. TransLM: Translation-based Language Model
4. TopicWord: Topic-Word Model

4 Experiment

Dataset

Benchmark

Performance

- Our early work in paper:

Model and Features	P@1
Retrieval-based Response Model	0.574
DeepMatch	0.424
Shallow Features	0.577
Shallow Features + Deep Features	0.612
All Features	**0.637**

- When combined with deep features, the performance significantly outperforms baseline model.
- Deep features can capture the deep semantic relevance information between two text objects.
- Rule-based features are necessary for some special cases.

4 Experiment

Dataset

Benchmark

Performance

➢ New work after adding BM25, Sentence2vec and new competitor methods.

Model and Features	MAP	P@1
Baseline	0.621	0.574
Baseline + DeepMatch	0.628	0.587
Baseline + DeepMatch + TransLM	0.643	0.625
Baseline + DeepMatch + TransLM + TopicWord	0.654	0.637
Shallow Features	0.593	0.602
Deep Features	0.521	0.531
Shallow Features + Deep Features	0.636	0.640
Shallow Features + Rule-based Features	0.619	0.612
Deep Features + Rule-based Features	0.609	0.610
Shallow + Deep + Rule-based Features	**0.658**	**0.651**

5 Summary

- Short Text Conversation is a challenging problem and current main approach is retrieval-based method.
- Deep features cover rich semantic relevance information between post and response, which the shallow features cannot capture.
- More studies are necessary on matching models based on word embedding and sentence2vec.
- More labeled post-response pairs are required for building more powerful matching models.

References

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Lu, Zhengdong, and Hang Li. A Deep Architecture for Matching Short Texts. Advances in Neural Information Processing Systems. 2013.

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Thanks

Q&A