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SG01 at the NTCIR-13 STC-2 task

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Introduction

Team Name: SG01

Joint Team from Sogou Inc. and Tsinghua University

Subtask: Chinese subtask

- Retrieval-based method: 3 submissions
- Generation-based method: 5 submissions
- **Top performance** in both methods
- Next ...
 - Retrieval-based Method
 - Generation-based Method
 - Conclusions
 - Q & A

Overview of Retrieval-based Method



- Data-Preprocessing
 - Remove *frequent, advertising* and *short* post-comment pairs
- Put the repository into a light-weighted search engine
 - Treat post-comment pairs as webpages
- Retrieve 500 pairs for a given query (or "new post")
- Keep the calculated features for searching for later usage
 - BM25
 - MRF for term dependency [D. Metzler 2005]
 - Proximity [T. Tao 2007]
 - ...

- Employ features more intuitive in STC task
 - cosine similarity of TF-IDF vector between ...
 - negative Word Mover Distance [M. J. Kusner 2015] between ...
 - query \leftrightarrow post
 - query \leftrightarrow comment
 - ▶ query \leftrightarrow post + comment
 - Translation based language model [Z. Ji 2014] Score_{trans}

Ranking

- Treat each feature as a ranker
- Simply add the sequence numbers to get a final rank
- Keep top 50 pairs

Ranking Stage II: new features | Retrieval-based Method

- Employ more neural network features capturing richer structure in STC
 - Score_{embd}
 - ► Score_{BiLSTM+CNN} [R. Yan 2016]

 $L = \max(0, 1 - s(x, y^{+}) + s(x, y^{-}))$

Trained with ranking based objective, using given repository plus extra 12 million crawled post-comment pairs, noted as Repoertn

- Score_{S2S}-p_{2c}
 Score_{S2S}-c_{2p}

← Defined later in Generation-based Method

Ranking Stage II: learning 2 rank | Retrieval-based Method

- Use all features aforementioned
- Training data: given 11 thous. plus 30 thous. labeled pairs
- LambdaMART
- **Top 10** to be the final result
- Score_{trans} and Score_{BiLSTM+CNN} are a little more important

Experiments | Retrieval-based Method

Submission	Learning to rank respect to which measure on training data	nG@1	P+	nERR@10
SG01-C-R1	nG@1	0.5355	0.6084	0.6579
SG01-C-R2	nERR@10	0.5168	0.5944	0.6461
SG01-C-R3	P+	0.5048	0.6200	0.6663

Overview of Generation-based Method



Generative Models | Generation-based Method

- ▶ S2SAttn
 - seq2seq [I. Sutskever 2014] with attention mechanism
- ▶ S2SAttn−addmem
 - Add dynamic memory to the attention
- ▶ VAEAttn
 - Use Variational Auto-Encoder
- VAEAttn—addmem
- Training data: Repo_{extn} with data-preprocessing
- Decode using segment-beam-search

Candidates Ranking: scores | Generation-based Method

Scoring Features

- likelihood
 - ▶ $\log(P(Y'|X))$, for post X and generated comment Y'
 - We note score from one model as $Score_{s2s-p2c}$
 - For scores from different models (except VAE models) and implementations, we add them up as *Li*

posterior

- $\succ \log(P(X|Y'))$
- \blacktriangleright Score_{s2s-c2p}
- **Po**

Calculated by our well trained models

Candidates Ranking: rank & output | Generation-based Method

Ranking

• score =
$$\frac{\lambda * Li + (1 - \lambda) * Po}{lp(Y')}$$

• Discount factor $lp(Y') = \frac{(c+|Y'|)^{\alpha}}{(c+1)^{\alpha}}$ [Y. Wu 2016]

- Before Final Output: Process candidates by rules
 - Abandon candidates with keywords in blacklist
 - De-duplicate consecutively repeated segments
 - Truncate consecutively repeated punctuations

Submission	Fusion of candidates from*	Scoring By**	nG@1	P+	nERR@10
SG01-C-G5	VAEAttn, VAEAttn—addmem	Li	0.3820	0.5068	0.5596
SG01-C-G4	S2SAttn, S2SAttn–addmem	Li	0.4483	0.5545	0.6129
SG01-C-G3	S2SAttn, S2SAttn–addmem	Li & Po	0.5633	0.6567	0.6947
SG01-C-G2	VAEAttn, VAEAttn—addmem	Li & Po	0.5483	0.6335	0.6783
SG01-C-G1	All 4 kinds of models	Li & Po	0.5867	0.6670	0.7095

*: could be multiple implementations for one model, using different subset of corpus and hyper-parameters **: all scores are discounted by lp

Analysis | Generation-based Method

- The feature Po brings advantage with statistical significance to those without Po, by giving higher rank to more informative candidates
- VAE does worse than traditional seq2seq, but it can bring in interesting candidates
- Using fusion of results from models do better than relying on single model, because the ranking will bring preferable candidates to top 10

Conclusions

Comparison between methods

- Generation-based method does better, however, it still tends to generate "safe" responses
- Retrieval-based method tends to get context-dependent or incoherent comments
- Size of training data maters

References

- **Z. Ji**, Z. Lu, and H. Li. An information retrieval approach to short text conversation. CoRR, abs/1408.6988, **2014**.
- M. J. Kusner, Y. Sun, N. I. Kolkin, and K. Q. Weinberger. From word embeddings to document distances. In Proceedings of the 32Nd International Conference on International Conference on Machine Learning -Volume 37, ICML'15, pages 957–966. JMLR.org, 2015.
- D. Metzler and W. B. Croft. A markov random field model for term dependencies. In Proceedings of the 28th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '05, pages 472–479, New York, NY, USA, 2005. ACM.
- I. Sutskever, O. Vinyals, and Q. V. Le. Sequence to sequence learning with neural networks. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 27, pages 3104–3112. Curran Associates, Inc., 2014.
- T. Tao and C. Zhai. An exploration of proximity measures in information retrieval. In Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR '07, pages 295–302, New York, NY, USA, 2007. ACM.
- Y. Wu, M. Schuster, Z. Chen, Q. V. Le, M. Norouzi, W. Macherey, M. Krikun, Y. Cao, Q. Gao, K. Macherey, J. Klingner, A. Shah, M. Johnson, X. Liu, L. Kaiser, S. Gouws, Y. Kato, T. Kudo, H. Kazawa, K. Stevens, G. Kurian, N. Patil, W. Wang, C. Young, J. Smith, J. Riesa, A. Rudnick, O. Vinyals, G. Corrado, M. Hughes, and J. Dean. Google's neural machine translation system: Bridging the gap between human and machine translation. CoRR, abs/1609.08144, 2016.
- R. Yan, Y. Song, X. Zhou, and H. Wu. "Shall I Be Your Chat Companion?": Towards an Online Human-Computer Conversation System. In Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, CIKM '16, pages 649–658, New York, NY, USA, 2016. ACM.



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