Related Works

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1.ECE(Emotion Cause Extraction) & ECPE(EC Pair Extraction)

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[6]Fan, C., Yuan, C., Du, J., Gui, L., Yang, M., Xu, R., 2020. Transition-based Directed Graph Construction for Emotion-Cause Pair Extraction, in: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Presented at the Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics, Online, pp. 3707–3717. <https://doi.org/10.18653/v1/2020.acl-main.342>

[7]Gui, L., Wu, D., Xu, R., Lu, Q., Zhou, Y., n.d. Event-Driven Emotion Cause Extraction with Corpus Construction 11.

[8]Kim, E., Klinger, R., n.d. Who Feels What and Why? Annotation of a Literature Corpus with Semantic Roles of Emotions 15.

[9]Liu, J., Chen, Y., Liu, K., Bi, W., Liu, X., 2020. Event Extraction as Machine Reading Comprehension, in: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). Presented at the Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), Association for Computational Linguistics, Online, pp. 1641–1651. <https://doi.org/10.18653/v1/2020.emnlp-main.128>

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2.Connectives

(1)Discourse Relation with Connectives

[1]Explict connective prediction & Implicit connective prediction

Kishimoto, Y., Murawaki, Y., Kurohashi, S., n.d. Adapting BERT to Implicit Discourse Relation Classification with a Focus on Discourse Connectives 7.

[2]Adversarial Network for exploiting connectives

Qin, L., Zhang, Z., Zhao, H., Hu, Z., Xing, E., 2017. Adversarial Connective-exploiting Networks for Implicit Discourse Relation Classification, in: Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Presented at the Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Association for Computational Linguistics, Vancouver, Canada, pp. 1006–1017. <https://doi.org/10.18653/v1/P17-1093>

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Xiang, W., Wang, Z., Dai, L., Wang, B., n.d. ConnPrompt: Connective-cloze Prompt Learning for Implicit Discourse Relation Recognition 10.

[4]Multi-task Connectives and Relation

Nguyen, L.T., Ngo, L.V., Than, K., Nguyen, T.H., 2019. Employing the Correspondence of Relations and Connectives to Identify Implicit Discourse Relations via Label Embeddings, in: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. Presented at the Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, Association for Computational Linguistics, Florence, Italy, pp. 4201–4207. <https://doi.org/10.18653/v1/P19-1411>

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[6]Connective-based Word Representation

Braud, C., Denis, P., 2016. Learning Connective-based Word Representations for Implicit Discourse Relation Identification, in: Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. Presented at the Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics, Austin, Texas, pp. 203–213. <https://doi.org/10.18653/v1/D16-1020>

[7]Explicitate Connectives with Seq2Seq Network

Shi, W., Demberg, V., 2019. Learning to Explicitate Connectives with Seq2Seq Network for Implicit Discourse Relation Classification, in: Proceedings of the 13th International Conference on Computational Semantics - Long Papers. Presented at the Proceedings of the 13th International Conference on Computational Semantics - Long Papers, Association for Computational Linguistics, Gothenburg, Sweden, pp. 188–199. <https://doi.org/10.18653/v1/W19-0416>

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[10]Effects of Discourse Connectives Prediction

Zhou, Z.M., Lan, M., Niu, Z.Y., Xu, Y., Su, J., n.d. The Effects of Discourse Connectives Prediction on Implicit Discourse Relation Recognition 8.

(2)Connectives Identification

[1]Explicit discourse connectives identification

Scholman, M., Dong, T., Yung, F., Demberg, V., 2021. Comparison of methods for explicit discourse connective identification across various domains, in: Proceedings of the 2nd Workshop on Computational Approaches to Discourse. Presented at the Proceedings of the 2nd Workshop on Computational Approaches to Discourse, Association for Computational Linguistics, Punta Cana, Dominican Republic and Online, pp. 95–106. <https://doi.org/10.18653/v1/2021.codi-main.9>

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3.Causal Inference

(1)Review

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4.Discourse Relation Analysis

(1)ML

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(2)Supervised

[1]Externally Controllable Multi-level RNN

Yue, X., Fu, L. and Wang, X. (2018) ‘Externally Controllable RNN for Implicit Discourse Relation Classification’, in X. Huang et al. (eds) Natural Language Processing and Chinese Computing. Cham: Springer International Publishing (Lecture Notes in Computer Science), pp. 158–169. Available at: <https://doi.org/10.1007/978-3-319-73618-1_14>.

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Guo, F., He, R. and Dang, J. (2019) ‘Implicit Discourse Relation Recognition via a BiLSTM-CNN Architecture With Dynamic Chunk-Based Max Pooling’, IEEE Access, 7, pp. 169281–169292. Available at: <https://doi.org/10.1109/ACCESS.2019.2954988>.

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5.Probing

(1)Probes' Theory

[1]Control Task & High Linguistic Task Accuracy + Low Control Task Accuracy

Hewitt, J. and Liang, P. (2019) ‘Designing and Interpreting Probes with Control Tasks’, in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Hong Kong, China: Association for Computational Linguistics, pp. 2733–2743. Available at: <https://doi.org/10.18653/v1/D19-1275>.

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Pimentel, T. et al. (2020) ‘Information-Theoretic Probing for Linguistic Structure’. arXiv. Available at: <http://arxiv.org/abs/2004.03061> (Accessed: 8 November 2022).

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