关系抽取调研

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目录

1	关系	禁抽取研究资料	1
	1.1	深度学习有监督方法	1
		1.1.1 流水线方法	1
		1.1.2 联合方法	1
	1.2	深度学习远程监督方法	2
2	关系	抽取关键问题	3
3	2019	9 ACL 文献整理	4
参	考文献	· · · · · · · · · · · · · · · · · · ·	5

1 关系抽取研究资料

关系抽取是文本挖掘和信息抽取的核心任务,主要通过对文本信息建模,自动抽取出实体对之间的语义关系。为自动问答、知识图谱等下游 NLP 任务服务。

实体关系抽取有许多经典方法,但是特征提取存在深误差传播问题。度学习端到端和自动特征提取的特性有效的缓解提取特征误差传播的问题。深度学习应用到关系抽取分为有监督和远程监督两类。

1.1 深度学习有监督方法

有监督的关系抽取包括流水线和联合抽取。流水线:把实体识别和关系分类作为两个 完全独立的过程,不会相互影响,关系的识别依赖于实体识别的效果。联合:实体识别和 关系分类的过程共同优化。

1.1.1 流水线方法

基于 RNN 模型进行关系抽取的方法由 Socher [14] 等人于 2012 年首次提出。Zhang 等人 [24] 在 2015 年提出 Bi-LSTM 进行关系分类。随后,基于 Attention 的 Bi-LSTM [25] [18] [7] 被用来实体关系分类。

Zeng 等人 [23] 在 2014 年首次提出使用 CNN 进行关系分类。Wang [16] 等人于 2016 年提出的 CNN 架构依赖于一种新颖的多层次注意力机制来捕获对指定实体的注意力 (首先是输入层级对于目标实体的注意力) 和指定关系的池化注意力 (其次是针对目标关系的注意力)。

Liu [10] 等人提出基于依赖的神经网络模型, Cai [2] 等人于 2016 年提出了一种基于最短依赖路径 (SDP) 的深度学习关系抽取模型: 双向递归卷积神经网络模型 (BRCNN), 通过将卷积神经网络和基于 LSTM 单元的双通道递归神经网络相结合, 进一步探索如何充分利用 SDP 中的依赖关系信息。

Wu 等人 [17] 使用 Google 的 Bert 预训练模型, 在 SemEval-2010 数据集取得了 STOA 的成绩。

1.1.2 联合方法

Miwa [12] 等人在 2016 年首次将神经网络的方法用于联合表示实体和关系。Katiyar 等人 [6] 在 2016 年首次将深度双向 LSTM 序列标注的方法用于联合提取。

1.2 深度学习远程监督方法

Mintz [11] 于 2009 年首次提出将远程监督应用到关系抽取任务中,远程监督方法通过数据自动对齐远程知识库来解决开放域中大量无标签数据自动标注的问题。Zeng 等人指出远程监督关系抽取的两个问题: 错误标签的噪声和提取特征的误差传播,并提出 PCNN [22] (Piecewise Convolutional Neural Networks) 结合多实例学习进行远程监督关系抽取。Lin [9] 在 Zeng 的基础上采用 Attention 机制,充分利用包内的信息,进一步减弱错误打标的示例语句产生的噪声。

Ren 在文献 [39] 中提出了联合抽取模型 COTYPE, COTYPE 模型与 PCNN 等单模型相比不仅可以扩展到不同领域,而且通过把实体抽取和关系抽取两个任务结合,较好地减弱了错误的累积传播。实验结果表示,其明显提升了当时 State-of-the-art 的效果。

2 关系抽取关键问题

3 2019 ACL 文献整理

基于 attention 使用整颗依赖树进行关系抽取 [5]。

通过在知识图谱中的 Dihedral Group 进行关系 embedding [19]。

类似于词向量,学习预训练的泛化的关系 embedding [3]。

改进的图神经网络,直接对原始文本处理,推理多跳关系[26]。

将关系抽取问题转化为多轮问答问题 [8]。

关系抽取数据不平衡,很多实体之间没有关系,BIO 标注这些实体的正负样本性,通过多任务学习来提升关系抽取质量 [20]。

通过预训练的 Transformer, 一次传入进行多个关系抽取 [15]。

微调预训练的 Transformer (GPT) 来进行远程监督学习 [1]。

通过图卷积神经网络对实体和关系联合抽取[4]。

通过多层匹配和注意力聚合关系抽取[21]。

有别于传统的关系抽取方法和远程监督方法,一种新的方式 [13]。

参考文献

- [1] Christoph Alt, Marc Hübner, and Leonhard Hennig. Fine-tuning pre-trained transformer language models to distantly supervised relation extraction. arXiv preprint arXiv:1906.08646, 2019.
- [2] Rui Cai, Xiaodong Zhang, and Houfeng Wang. Bidirectional recurrent convolutional neural network for relation classification. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 756–765, 2016.
- [3] Zhiyu Chen, Hanwen Zha, Honglei Liu, Wenhu Chen, Xifeng Yan, and Yu Su. Global textual relation embedding for relational understanding. arXiv preprint arXiv:1906.00550, 2019.
- [4] Tsu-Jui Fu, Peng-Hsuan Li, and Wei-Yun Ma. Graphrel: Modeling text as relational graphs for joint entity and relation extraction.
- [5] Zhijiang Guo, Yan Zhang, and Wei Lu. Attention guided graph convolutional networks for relation extraction. arXiv preprint arXiv:1906.07510, 2019.
- [6] Arzoo Katiyar and Claire Cardie. Going out on a limb: Joint extraction of entity mentions and relations without dependency trees. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 917–928, 2017.
- [7] Joohong Lee, Sangwoo Seo, and Yong Suk Choi. Semantic relation classification via bidirectional lstm networks with entity-aware attention using latent entity typing. Symmetry, 11(6):785, 2019.
- [8] Xiaoya Li, Fan Yin, Zijun Sun, Xiayu Li, Arianna Yuan, Duo Chai, Mingxin Zhou, and Jiwei Li. Entity-relation extraction as multi-turn question answering. arXiv preprint arXiv:1905.05529, 2019.
- [9] Yankai Lin, Shiqi Shen, Zhiyuan Liu, Huanbo Luan, and Maosong Sun. Neural relation extraction with selective attention over instances. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2124–2133, 2016.

- [10] Yang Liu, Furu Wei, Sujian Li, Heng Ji, Ming Zhou, and Houfeng Wang. A dependency-based neural network for relation classification. arXiv preprint arXiv:1507.04646, 2015.
- [11] Mike Mintz, Steven Bills, Rion Snow, and Dan Jurafsky. Distant supervision for relation extraction without labeled data. In *Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 2-Volume 2*, pages 1003–1011. Association for Computational Linguistics, 2009.
- [12] Makoto Miwa and Mohit Bansal. End-to-end relation extraction using lstms on sequences and tree structures. arXiv preprint arXiv:1601.00770, 2016.
- [13] Livio Baldini Soares, Nicholas FitzGerald, Jeffrey Ling, and Tom Kwiatkowski. Matching the blanks: Distributional similarity for relation learning. arXiv preprint arXiv:1906.03158, 2019.
- [14] Richard Socher, Brody Huval, Christopher D Manning, and Andrew Y Ng. Semantic compositionality through recursive matrix-vector spaces. In *Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning*, pages 1201–1211. Association for Computational Linguistics, 2012.
- [15] Haoyu Wang, Ming Tan, Mo Yu, Shiyu Chang, Dakuo Wang, Kun Xu, Xiaoxiao Guo, and Saloni Potdar. Extracting multiple-relations in one-pass with pre-trained transformers. arXiv preprint arXiv:1902.01030, 2019.
- [16] Linlin Wang, Zhu Cao, Gerard De Melo, and Zhiyuan Liu. Relation classification via multi-level attention cnns. 2016.
- [17] Shanchan Wu and Yifan He. Enriching pre-trained language model with entity information for relation classification. arXiv preprint arXiv:1905.08284, 2019.
- [18] Minguang Xiao and Cong Liu. Semantic relation classification via hierarchical recurrent neural network with attention. In *Proceedings of COLING 2016*, the 26th International Conference on Computational Linguistics: Technical Papers, pages 1254–1263, 2016.
- [19] Canran Xu and Ruijiang Li. Relation embedding with dihedral group in knowledge graph. arXiv preprint arXiv:1906.00687, 2019.

- [20] Wei Ye, Bo Li, Rui Xie, Zhonghao Sheng, Long Chen, and Shikun Zhang. Exploiting entity bio tag embeddings and multi-task learning for relation extraction with imbalanced data. arXiv preprint arXiv:1906.08931, 2019.
- [21] Zhi-Xiu Ye and Zhen-Hua Ling. Multi-level matching and aggregation network for few-shot relation classification. arXiv preprint arXiv:1906.06678, 2019.
- [22] Daojian Zeng, Kang Liu, Yubo Chen, and Jun Zhao. Distant supervision for relation extraction via piecewise convolutional neural networks. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1753–1762, Lisbon, Portugal, September 2015. Association for Computational Linguistics.
- [23] Daojian Zeng, Kang Liu, Siwei Lai, Guangyou Zhou, Jun Zhao, et al. Relation classification via convolutional deep neural network. 2014.
- [24] Shu Zhang, Dequan Zheng, Xinchen Hu, and Ming Yang. Bidirectional long short-term memory networks for relation classification. In *Proceedings of the 29th Pacific Asia conference on language, information and computation*, pages 73–78, 2015.
- [25] Peng Zhou, Wei Shi, Jun Tian, Zhenyu Qi, Bingchen Li, Hongwei Hao, and Bo Xu. Attention-based bidirectional long short-term memory networks for relation classification. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 207–212, 2016.
- [26] Hao Zhu, Yankai Lin, Zhiyuan Liu, Jie Fu, Tat-seng Chua, and Maosong Sun. Graph neural networks with generated parameters for relation extraction. arXiv preprint arXiv:1902.00756, 2019.