CS Writing Phrasebook

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[1] https://github.com/WindChimeRan/CS-writing-phrasebook

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Collocations

1.1 Verb

1. We first **decided on** an inventory of semantic relations. [5]

2. We **accept as** relation arguments only noun phrases with common-noun heads. [5]

3. This **distinguishes** our task **from** much work in Information Extraction, which tends to focus on specific classes of named entities and on considerably more fine-grained relations than we do. [5]

4. We also **impose** a syntactic locality requirement on example candidates, **thus excluding** instances where the relation arguments occur in separate sentential clauses. [5]

1.2 Comparison

1. It speaks to the success of the exercise that the participating systems' performance was **generally high, well over an order of magnitude above** random guessing. [5]

2. The best relation (presumably the easiest to classify) is CE, **far ahead of** ED and MC. [5]

3. **As compared to** traditional GNNs, GPGNNs could learn edges' parameters from natural languages, **extending it from performing** inferring on only non-relational graphs or graphs with a limited number of edge types **to** unstructured inputs such as texts. [9]

4. Experiment results show that our model **outperforms** other models **on** relation extraction task **by considering** multi-hop relational reasoning.[9]

1.3 Sentence-init

1. **It speaks to the success of** the exercise that the participating systems' performance was generally high, well over an order of magnitude above random guessing. [5]

1.4 Linker

1. By explicitly reasoning about missing data during learning, our approach enables large-scale training of 1D convolutional neural networks **while mitigating the issue of label noise inherent in distant supervision.** [1]

1.5 Decompose

1. The Star-Transformer **divides the labor of** semantic compositions **between** the radical **and** the ring connections. [3]

1.6 Trade-off

1. The need for compactness and completeness **are plainly at odds with each other** such that existing KG generation techniques **fail to satisfy both objectives properly**. [7]

1.7 Our model

1. **Our model builds on a recent** coreference resolution **model** (Lee et al., 2017), **by making central use of** learned, contextualized span representations. [4]

2. We **use** Transformer (Vaswani et al., 2017) **as the basic building block.** [2]

3. We **cast the task as a** multi-turn question answering **problem**, **i.e., the extraction** of entities and relations **is transformed to the task of** identifying answer spans from the context. [6]

4. **Encoding Layer**. The encoding layer aims to compose the input embeddings of a given instance into its corresponding instance embedding. In this study, we choose two convolutional neural architectures, CNN (Zeng et al., 2014) and PCNN (Zeng et al., 2015) to encode input em beddings into instance embeddings. **Other neural architectures such as recurrent neural networks (Zhang and Wang, 2015) can also be used as sentence encoders. Because**

previous works show that both convolutional and recurrent architectures can achieve comparable state-of-the-art performance, we select convolutional architectures in this study. Note that, our model is independent of the encoder choices, and can, therefore, be easily adapted to fit other encoder architectures. [8]

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Paragraphs

2.1 Introduction

1. GP-GNNs first constructs a fully connected graph with the entities in the sequence of text. After that, it employs three modules to process relational reasoning: (1) an encoding module which enables edges to encode rich information from natural languages, (2) a propagation module which propagates relational information among various nodes, and (3) a classification module which makes predictions with node representations. [9]

2.

2.2 Related Works

1. GNNs were first proposed in 2009... Later the authors in Li et al. (2016) replace... xxx propose to apply GNNs to xx, xx,... There are relatively fewer papers discussing how to adapt GNNs to natural language tasks. For example... Although they also consider applying GNNs to natural language processing tasks, they still perform message-passing on predefined graphs. Johnson (2017) introduces a novel neural architecture to generate a graph based on the textual input and dynamically update the relationship during the learning process. In sharp contrast, this paper focuses on extracting relations from real-world relation datasets. [9]

2.

2.3 Methodology

1. where $f(\cdot)$ could be any model that could encode sequential data, such as LSTMs, GRUs, CNNs, $E(\cdot)$ indicates an embedding function, and

θ denotes the parameters of the encoding module of n-th layer. [9]

2.4 Concept

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