The lawsuit contended that the chairman of the [[News Corporation]Et-Company]Es-Founder , [[[Rupert Murdoch]Es-Company]Et-Founder]Es-Nationality , promised certain rights to shareholders , including the vote on the poison pill , in return for their approval of the company 's plan to reincorporate in the United States from [Australia]Et-Nationality .
Both [Steven A. Ballmer]Es-Company , [[[Microsoft]Et-Company]Et-Company]Es-Founder 's chief executive , and [[Bill Gates]Es-Company]Et-Founder , the chairman , have been involved in that debate inside the company , according to that person .

Table 4: Extraction examples by our model. The words in a bracket represents an entity extracted by the model. *Es* stands for source entity and *Et* for target entity. A predicted relation indicator is marked in background color (e.g. "Murdoch" in the first instance). The entities which form a triple are bracketed in the same color.

Model	NYT11			NYT11-plus		
	Prec	Rec	F_1	Prec	Rec	F_1
FCM	.502	.479	.490	.447	.327	.378
MultiR	.465	.439	.451	.423	.336	.375
CoType	.558	.558	.558	.491	.413	.449
SPTree	.650	.614	.631	**.700**	.343	.460
CopyR	.480	**.714**	.574	.626	.426	.507
HRL-Ent	**.676**	.676	**.676**	.577	.321	.413
HRL	.654	.654	.654	.626	**.456**	**.527**

Table 5: Performance comparison on relation detection.

dramatic drops are observed on *NYT11-plus* where we have 327 relations from 149 sentences, implying that our method (HRL) captures the dependency across multiple extraction tasks and the high-level policy benefits from such interactions. Therefore, our hierarchical extraction framework indeed enhances the interaction between relation detection and entity extraction.

Case Study

Table 4 presents some extraction examples by our model to demonstrate the ability to extract overlapping relations. The first sentence shows the case that an entity pair has multiple relations (type II). Two relations (*Rupert Murdoch*, `person-company`, *News Corporation*) and (*News Corporation*, `company-founder`, *Rupert Murdoch*) share the same entity pair but have different relation types. The model first detects the relation type `person-company` at "Murdoch", and then detects the other relation type `company-founder` at the *comma* position, just next to the word "Murdoch". This shows that relation detection is triggered when sufficient evidence has been gathered at a particular position. And the model can classify the same entities into either source or target entities (for instance, *Rupert Murdoch* is a source entity for `person-company` whereas a target entity for `company-founder`), demonstrating the advantage of our hierarchical framework which can assign dynamic tags to words conditioned on different relation types. In addition, *Rupert Murdoch* has a relation with *Australia*, where the two entities locate far from each other. Though this is more difficult to detect, our model can still extract the relation correctly.

The second sentence gives another example where an entity is involved in multiple relations (type I). In this sentence, (*Steven A. Ballmer*, `person-company`, *Microsoft*) and (*Bill Gates*, `person-company`, *Microsoft*) share the same relation type and target entity, but have different source entities. When the agent scans to the word "Microsoft", the model detects the first relation. The agent then detects the second relation when it scans to the word "Gates". This further demonstrates the benefit of our hierarchical framework which has strengths in extracting overlapping relations by firstly detecting relation and then finding the entity arguments. In addition, our model predicts another relation (*Bill Gates*, `founder-of`, *Microsoft*), which is wrong for this sentence because there is no explicit mention of the relation. This may result from the noise produced by distant supervision, where there are many noisy sentences that are aligned to that relation.

Conclusion and Future Work

In this paper, we present a hierarchical extraction paradigm which approaches relation extraction via hierarchical reinforcement learning. The paradigm treats entities as the arguments of a relation, and decomposes the relation extraction task into a hierarchy of two subtasks: high-level relation indicator detection and low-level entity mention extraction. The high-level policy for relation detection identifies multiple relations in a sentence, and the low-level policy for entity extraction launches a subtask to further extract the related entities for each relation. Thanks to the nature of this hierarchical approach, it is good at modeling the interactions between the two subtasks, and particularly excels at extracting overlapping relations. Experiments demonstrate that our approach outperforms state-of-the-art baselines.

As future work, this hierarchical extraction framework can be generalized to many other pairwise or triple-wise extraction tasks such as aspect-opinion mining or ontology induction.

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Voluptate exercitationem autem at, illum sunt dolorum tempore at nostrum necessitatibus quia ratione obcaecati cumque error, voluptate cupiditate sit illo, quia nesciunt dolorem asperiores accusamus laudantium magnam, doloremque totam recusandae?