Using RL for Non-Greedy Dependency Parsing

Sidhart Krishnan, Arvind Saligrama
Department of Computer Science, Stanford University

Problem

- **Motivating Problem:** Use reinforcement learning to perform non-greedy decoding for transition-based parsers
- Dependency relationships can improve performance on a variety of NLP tasks and so improving dependency parsing is important
- Supervised methods perform **greedy decoding**
  - RL could be useful because it considers future reward and thus their policies are non-greedy.

Background

Problem Setup: Create an RL Agent that predicts the next move in a transition-based dependency parser and aims to maximize the unlabeled attachment score (UAS)

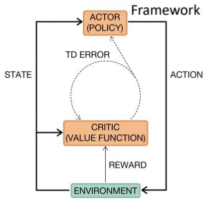
A Fast and Accurate Dependency Parser Using Neural Networks (Chen and Manning [1], 2014): The authors use a neural network to determine the next transition

Dependency Parsing with Deep Reinforcement Learning (Shen et al. [2], 2016): The authors aim to build a reinforcement-based dependency parser to perform non-greedy decoding.

Methods

- Transition-based dependency parsing aims to create a dependency structure for a sentence. We specifically used the arc standard transition system.
- We create a parser environment for our RL setup
  - Is possible because we can frame the shift-reduce parser as a Markov Decision Process (MDP)
  - We must frame the environment as a "game" with a reward function that the agent aims to maximize
- Tested two actor-critic RL algorithms on the parser environment: **A2C** and **PPO**
  - Actor-critic methods have a policy network which decides actions and a value network to determine the expected future reward
  - A2C and PPO differ in how the loss is calculated

Actor Critic Framework

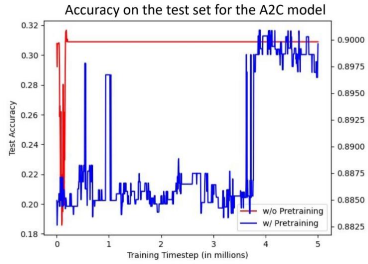


Experimental Setup

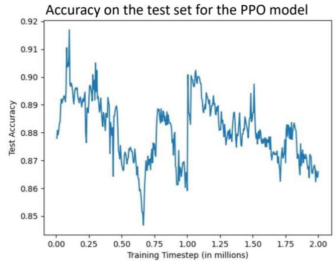
- **Task:** Used the English Penn Treebank (PTB) dataset to load in examples to the environment
  - Agent returns an action based on current parse of sentence
- **Metric:** Unlabeled Attachment Score (UAS) – the percentage of tokens that have the correct head
- The policy network for the A2C and PPO parsers were both initialized to match the parameters of neural dependency parser from Chen and Manning
  - Also trained an A2C model w/o supervised pretraining to determine if better than random policy (UAS = 12.90)

Results

Accuracy on the test set for the A2C model



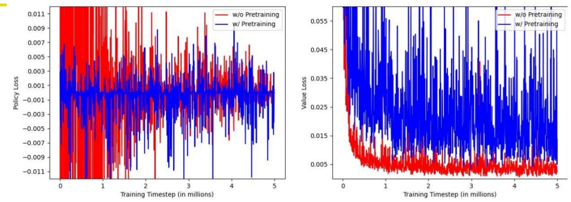
Accuracy on the test set for the PPO model



Model	Avg UAS
Baseline	88.88
A2C	31.20
A2C*	**89.19**
PPO*	89.12

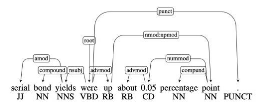
* Indicates that model was pretrained with supervised weights

Loss for Policy and Value Networks during A2C Training

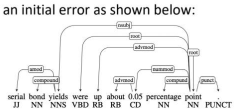


Analysis

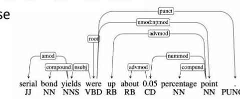
- Policy loss for pretrained A2C much smaller than policy loss of non-pretrained
- Value loss for pretrained A2C initially much higher as critic network must catch up to pretrained policy network
- The RL models often performs better after an initial error as shown below:



Gold Parse



Supervised Parse (UAS = 50)



A2C/PPO Parse (UAS = 80)

Conclusions

- The A2C and PPO models w/ pretraining performed slightly better than the supervised model on the test data
- Initializing the parameters with a pretrained supervised model was critical for the RL model to properly explore the space and learn

Acknowledgements

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References

[1] Chen, Danqi and Manning, Christopher. A Fast and Accurate Dependency Parser using Neural Networks. 2014 Conference on Empirical Methods in Natural Language Processing, 29 Oct. 2014.
[2] Shen, Ying, et al. Dependency Parsing With Deep Reinforcement Learning. 29th Conference on Neural Information Processing Systems, 2016.