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.
- It 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.

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

![Graph showing accuracy on the test set for different models](image)

<table>
<thead>
<tr>
<th>Model</th>
<th>Avg UAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>88.88</td>
</tr>
<tr>
<td>A2C*</td>
<td>89.12</td>
</tr>
<tr>
<td>PPO*</td>
<td>89.12</td>
</tr>
</tbody>
</table>

*Indicates that model was pretrained with supervised weights.

![Graph showing accuracy on the test set for different models](image)

- 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:

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.

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References
