

# CS 224n Assignment #3: Dependency Parsing

In this assignment, you will build a neural dependency parser using PyTorch. In Part 1, you will learn about two general neural network techniques (Adam Optimization and Dropout) that you will use to build the dependency parser in Part 2. In Part 2, you will implement and train the dependency parser, before analyzing a few erroneous dependency parses.

## 1. Machine Learning & Neural Networks (8 points)

- (a) (4 points) Adam Optimizer

Recall the standard Stochastic Gradient Descent update rule:

$$\theta \leftarrow \theta - \alpha \nabla_{\theta} J_{\text{minibatch}}(\theta)$$

where  $\theta$  is a vector containing all of the model parameters,  $J$  is the loss function,  $\nabla_{\theta} J_{\text{minibatch}}(\theta)$  is the gradient of the loss function with respect to the parameters on a minibatch of data, and  $\alpha$  is the learning rate. Adam Optimization<sup>1</sup> uses a more sophisticated update rule with two additional steps.<sup>2</sup>

- i. (2 points) First, Adam uses a trick called *momentum* by keeping track of  $\mathbf{m}$ , a rolling average of the gradients:

$$\begin{aligned}\mathbf{m} &\leftarrow \beta_1 \mathbf{m} + (1 - \beta_1) \nabla_{\theta} J_{\text{minibatch}}(\theta) \\ \theta &\leftarrow \theta - \alpha \mathbf{m}\end{aligned}$$

where  $\beta_1$  is a hyperparameter between 0 and 1 (often set to 0.9). Briefly explain (you don't need to prove mathematically, just give an intuition) how using  $\mathbf{m}$  stops the updates from varying as much and why this low variance may be helpful to learning, overall.

Momentum is working as acceleration reflecting the previous gradients tendency.  
High variance is well known to raising overfitting problem.

- ii. (2 points) Adam extends the idea of *momentum* with the trick of *adaptive learning rates* by keeping track of  $\mathbf{v}$ , a rolling average of the magnitudes of the gradients:

$$\begin{aligned}\mathbf{m} &\leftarrow \beta_1 \mathbf{m} + (1 - \beta_1) \nabla_{\theta} J_{\text{minibatch}}(\theta) \\ \mathbf{v} &\leftarrow \beta_2 \mathbf{v} + (1 - \beta_2) (\nabla_{\theta} J_{\text{minibatch}}(\theta) \odot \nabla_{\theta} J_{\text{minibatch}}(\theta)) \\ \theta &\leftarrow \theta - \alpha \odot \mathbf{m} / \sqrt{\mathbf{v}}\end{aligned}$$

where  $\odot$  and  $/$  denote elementwise multiplication and division (so  $\mathbf{z} \odot \mathbf{z}$  is elementwise squaring) and  $\beta_2$  is a hyperparameter between 0 and 1 (often set to 0.99). Since Adam divides the update by  $\sqrt{\mathbf{v}}$ , which of the model parameters will get larger updates? Why might this help with learning?

Parameters that previous gradients are small and not volatile get larger updates.  
This helps model to handle with sparse gradients (merits of AdaGrad) and also non-stationary objectives (merits of RMSProp)

- (b) (4 points) Dropout<sup>3</sup> is a regularization technique. During training, dropout randomly sets units in the hidden layer  $\mathbf{h}$  to zero with probability  $p_{\text{drop}}$  (dropping different units each minibatch), and then multiplies  $\mathbf{h}$  by a constant  $\gamma$ . We can write this as

$$\mathbf{h}_{\text{drop}} = \gamma \mathbf{d} \odot \mathbf{h}$$

where  $\mathbf{d} \in \{0, 1\}^{D_h}$  ( $D_h$  is the size of  $\mathbf{h}$ ) is a mask vector where each entry is 0 with probability  $p_{\text{drop}}$  and 1 with probability  $(1 - p_{\text{drop}})$ .  $\gamma$  is chosen such that the expected value of  $\mathbf{h}_{\text{drop}}$  is  $\mathbf{h}$ :

$$\mathbb{E}_{p_{\text{drop}}}[\mathbf{h}_{\text{drop}}]_i = h_i$$

for all  $i \in \{1, \dots, D_h\}$ .

- i. (2 points) What must  $\gamma$  equal in terms of  $p_{\text{drop}}$ ? Briefly justify your answer.

$$\gamma = \frac{1}{1 - p_{\text{drop}}}$$

- ii. (2 points) Why should we apply dropout during training but not during evaluation?

Drop out is one of the regularizations, which restrict an overfitting. Randomly setting units zero is for make units stronger on abrupt absence of other units.  
And evaluation is made from train, to model being improved. But if we use drop out also at evaluation, it does re-trained with same circumstances, so that can't do well in test.

<sup>1</sup>Kingma and Ba, 2015, <https://arxiv.org/pdf/1412.6980.pdf>

<sup>2</sup>The actual Adam update uses a few additional tricks that are less important, but we won't worry about them here. If you want to learn more about it, you can take a look at: <http://cs231n.github.io/neural-networks-3/#sgd>

<sup>3</sup>Srivastava et al., 2014, <https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf>

## 2. Neural Transition-Based Dependency Parsing (44 points)

In this section, you'll be implementing a neural-network based dependency parser, with the goal of maximizing performance on the UAS (Unlabeled Attachment Score) metric.

Before you begin please install PyTorch 1.4.0 from <https://pytorch.org/get-started/locally/> with the CUDA option set to None. Additionally run `pip install tqdm` to install the tqdm package – which produces progress bar visualizations throughout your training process.

A dependency parser analyzes the grammatical structure of a sentence, establishing relationships between *head* words, and words which modify those heads. Your implementation will be a *transition-based* parser, which incrementally builds up a parse one step at a time. At every step it maintains a *partial parse*, which is represented as follows:

- A *stack* of words that are currently being processed.
- A *buffer* of words yet to be processed.
- A list of *dependencies* predicted by the parser.

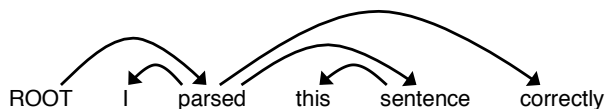
当前处理的单词栈  
剩余单词缓存  
生成的依赖关系列表

Initially, the stack only contains ROOT, the dependencies list is empty, and the buffer contains all words of the sentence in order. At each step, the parser applies a *transition* to the partial parse until its buffer is empty and the stack size is 1. The following transitions can be applied: 三种转移动作:

- SHIFT: removes the first word from the buffer and pushes it onto the stack.
- LEFT-ARC: marks the second (second most recently added) item on the stack as a dependent of the first item and removes the second item from the stack, adding a *first\_word* → *second\_word* dependency to the dependency list.
- RIGHT-ARC: marks the first (most recently added) item on the stack as a dependent of the second item and removes the first item from the stack, adding a *second\_word* → *first\_word* dependency to the dependency list.

On each step, your parser will decide among the three transitions using a neural network classifier.

- (a) (4 points) Go through the sequence of transitions needed for parsing the sentence “*I parsed this sentence correctly*”. The dependency tree for the sentence is shown below. At each step, give the configuration of the stack and buffer, as well as what transition was applied this step and what new dependency was added (if any). The first three steps are provided below as an example.



Stack	Buffer	New dependency	Transition
[ROOT]	[I, parsed, this, sentence, correctly]		Initial Configuration
[ROOT, I]	[parsed, this, sentence, correctly]		SHIFT
[ROOT, I, parsed]	[this, sentence, correctly]		SHIFT
[ROOT, parsed]	[this, sentence, correctly]	parsed→I	LEFT-ARC

- (b) (2 points) A sentence containing  $n$  words will be parsed in how many steps (in terms of  $n$ )? Briefly explain why. 每个单词被移进移出一次:  $2n$
- (c) (6 points) Implement the `__init__` and `parse_step` functions in the `PartialParse` class in `parser_transitions.py`. This implements the transition mechanics your parser will use. You can run basic (non-exhaustive) tests by running `python parser_transitions.py part_c`.

- (d) (8 points) Our network will predict which transition should be applied next to a partial parse. We could use it to parse a single sentence by applying predicted transitions until the parse is complete. However, neural networks run much more efficiently when making predictions about *batches* of data at a time (i.e., predicting the next transition for any different partial parses simultaneously). We can parse sentences in minibatches with the following algorithm.

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**Algorithm 1** Minibatch Dependency Parsing
 

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**Input:** sentences, a list of sentences to be parsed and model, our model that makes parse decisions

Initialize partial\_pares as a list of PartialPares, one for each sentence in sentences

Initialize unfinished\_pares as a shallow copy of partial\_pares

**while** unfinished\_pares is not empty **do**

    Take the first batch\_size parses in unfinished\_pares as a minibatch

    Use the model to predict the next transition for each partial parse in the minibatch

    Perform a parse step on each partial parse in the minibatch with its predicted transition

    Remove the completed (empty buffer and stack of size 1) parses from unfinished\_pares

**end while**

**Return:** The dependencies for each (now completed) parse in partial\_pares.

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Implement this algorithm in the minibatch\_parse function in parser\_transitions.py. You can run basic (non-exhaustive) tests by running `python parser_transitions.py part-d`.

*Note: You will need minibatch\_parse to be correctly implemented to evaluate the model you will build in part (e). However, you do not need it to train the model, so you should be able to complete most of part (e) even if minibatch\_parse is not implemented yet.*

- (e) (12 points) We are now going to train a neural network to **predict**, given the state of the stack, buffer, and dependencies, which transition should be applied next.

First, the model extracts a feature vector representing the current state. We will be using the feature set presented in the original neural dependency parsing paper: *A Fast and Accurate Dependency Parser using Neural Networks*.<sup>4</sup> The function extracting these features has been implemented for you in `utils/parser_utils.py`. This feature vector consists of a list of tokens (e.g., the last word in the stack, first word in the buffer, dependent of the second-to-last word in the stack if there is one, etc.). They can be represented as a list of integers  $\mathbf{w} = [w_1, w_2, \dots, w_m]$  where  $m$  is the number of features and each  $0 \leq w_i < |V|$  is the index of a token in the vocabulary ( $|V|$  is the vocabulary size). Then our network looks up an embedding for each word and concatenates them into a single input vector:

m个特征，每个特征代表不同的token，例如stack最后一个单词、buffer第一个单词等。然后将每个单词都嵌入成向量，最后拼接起来做为特征

$$\mathbf{x} = [\mathbf{E}_{w_1}, \dots, \mathbf{E}_{w_m}] \in \mathbb{R}^{dm}$$

where  $\mathbf{E} \in \mathbb{R}^{|V| \times d}$  is an embedding matrix with each row  $\mathbf{E}_w$  as the vector for a particular word  $w$ . We then compute our prediction as:

$$\mathbf{h} = \text{ReLU}(\mathbf{x}\mathbf{W} + \mathbf{b}_1)$$

$$\mathbf{l} = \mathbf{h}\mathbf{U} + \mathbf{b}_2$$

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{l})$$

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<sup>4</sup>Chen and Manning, 2014, <http://cs.stanford.edu/people/danqi/papers/emnlp2014.pdf>

where  $\mathbf{h}$  is referred to as the hidden layer,  $\mathbf{l}$  is referred to as the logits,  $\hat{\mathbf{y}}$  is referred to as the predictions, and  $\text{ReLU}(z) = \max(z, 0)$ . We will train the model to minimize cross-entropy loss:

$$J(\theta) = CE(\mathbf{y}, \hat{\mathbf{y}}) = - \sum_{i=1}^3 y_i \log \hat{y}_i$$

最小化交叉熵损失函数

To compute the loss for the training set, we average this  $J(\theta)$  across all training examples.

We will use UAS score as our evaluation metric. UAS refers to Unlabeled Attachment Score, which is computed as the ratio between number of correctly predicted dependencies and the number of total dependencies despite of the relations (our model doesn't predict this).

In `parser_model.py` you will find skeleton code to implement this simple neural network using PyTorch. Complete the `__init__`, `embedding_lookup` and `forward` functions to implement the model. Then complete the `train_for_epoch` and `train` functions within the `run.py` file.

Finally execute `python run.py` to train your model and compute predictions on test data from Penn Treebank (annotated with Universal Dependencies).

#### Note:

- For this assignment, you are asked to implement Linear layer and Embedding layer. Please **DO NOT** use `torch.nn.Linear` or `torch.nn.Embedding` module in your code, otherwise you will receive deductions for this problem.
- Please follow the naming requirements in our TODO if there are any, e.g. if there are explicit requirements about variable names you have to follow them in order to receive full credits. You are free to declare other variable names if not explicitly required.

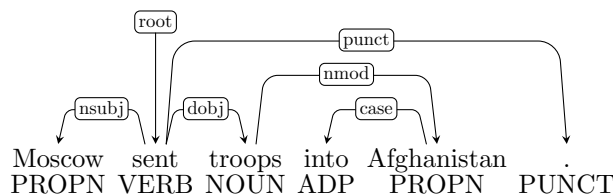
#### Hints:

- Once you have implemented `embedding_lookup` (e) or `forward` (f) you can call `python parser_model.py` with flag `-e` or `-f` or both to run sanity checks with each function. These sanity checks are fairly basic and passing them doesn't mean your code is bug free.
- When debugging, you can add a debug flag: `python run.py -d`. This will cause the code to run over a small subset of the data, so that training the model won't take as long. Make sure to remove the `-d` flag to run the full model once you are done debugging.
- When running with debug mode, you should be able to get a loss smaller than 0.2 and a UAS larger than 65 on the dev set (although in rare cases your results may be lower, there is some randomness when training).
- It should take about **1 hour** to train the model on the entire the training dataset, i.e., when debug mode is disabled.
- When debug mode is disabled, you should be able to get a loss smaller than 0.08 on the train set and an Unlabeled Attachment Score larger than 87 on the dev set. For comparison, the model in the original neural dependency parsing paper gets 92.5 UAS. If you want, you can tweak the hyperparameters for your model (hidden layer size, hyperparameters for Adam, number of epochs, etc.) to improve the performance (but you are not required to do so).

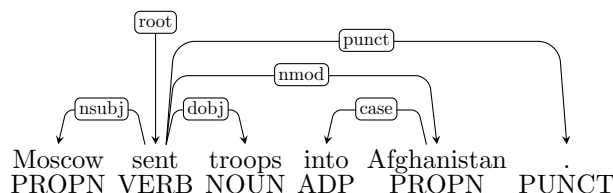
#### Deliverables:

- Working implementation of the neural dependency parser in `parser_model.py`. (We'll look at and run this code for grading).
- Report the best UAS your model achieves on the dev set and the UAS it achieves on the test set.

(f) (12 points) We'd like to look at example dependency parses and understand where parsers like ours might be wrong. For example, in this sentence:



the dependency of the phrase *into Afghanistan* is wrong, because the phrase should modify *sent* (as in *sent into Afghanistan*) not *troops* (because *troops into Afghanistan* doesn't make sense). Here is the correct parse:



More generally, here are four types of parsing error:

- **Prepositional Phrase Attachment Error:** In the example above, the phrase *into Afghanistan* is a prepositional phrase. A Prepositional Phrase Attachment Error is when a prepositional phrase is attached to **the wrong head word** (in this example, *troops* is the wrong head word and *sent* is the correct head word). More examples of prepositional phrases include *with a rock*, *before midnight* and *under the carpet*.
- **Verb Phrase Attachment Error:** In the sentence *Leaving the store unattended, I went outside to watch the parade*, the phrase *leaving the store unattended* is a verb phrase. A Verb Phrase Attachment Error is when a **verb phrase is attached to the wrong head word** (in this example, the correct head word is *went*).
- **Modifier Attachment Error:** In the sentence *I am extremely short*, the adverb *extremely* is a modifier of the adjective *short*. A Modifier Attachment Error is when a **modifier is attached to the wrong head word** (in this example, the correct head word is *short*).
- **Coordination Attachment Error:** In the sentence *Would you like brown rice or garlic naan?*, the phrases *brown rice* and *garlic naan* are both conjuncts and the word *or* is the coordinating conjunction. The second conjunct (here *garlic naan*) should be attached to the first conjunct (here *brown rice*). A **Coordination Attachment Error is when the second conjunct is attached to the wrong head word** (in this example, the correct head word is *rice*). Other coordinating conjunctions include *and*, *but* and *so*.

In this question are four sentences with dependency parses obtained from a parser. Each sentence has one error, and there is one example of each of the four types above. For each sentence, state the type of error, the incorrect dependency, and the correct dependency. To demonstrate: for the example above, you would write:

- **Error type:** Prepositional Phrase Attachment Error
- **Incorrect dependency:** troops → Afghanistan
- **Correct dependency:** sent → Afghanistan

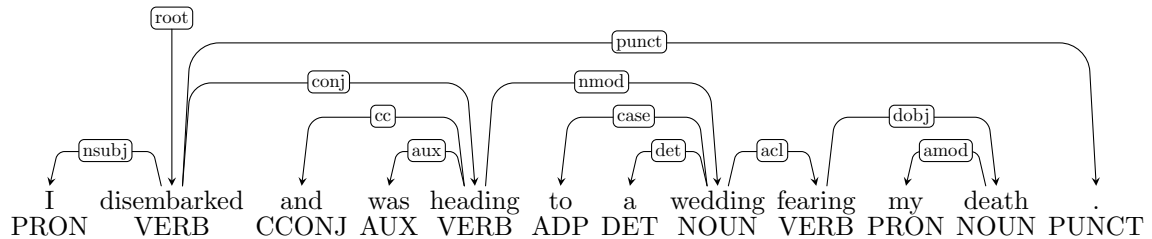
**Note:** There are lots of details and conventions for dependency annotation. If you want to learn more about them, you can look at the UD website: <http://universaldependencies.org><sup>5</sup> or the short introductory slides at: <http://people.cs.georgetown.edu/nschneid/p/UD-for-English.pdf>. However, you **do not** need to know all these details in order to do this question. In each of these cases, we are asking about the attachment of phrases and it should

<sup>5</sup>But note that in the assignment we are actually using UDv1, see: <http://universaldependencies.org/docsv1/>

be sufficient to see if they are modifying the correct head. In particular, you **do not** need to look at the labels on the the dependency edges – it suffices to just look at the edges themselves.

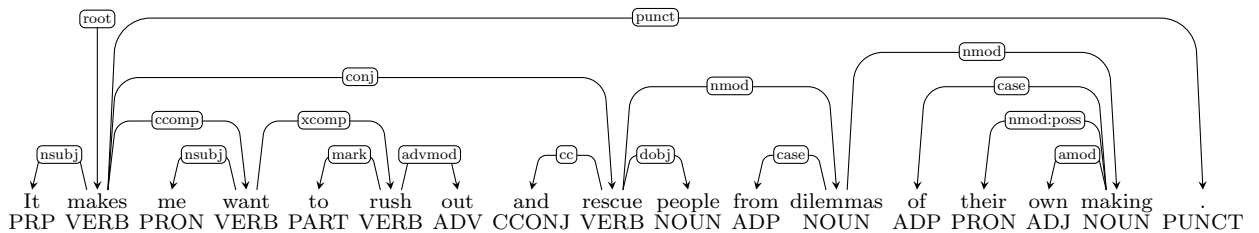
i.

Error type: Verb Phrase Attachment Error  
 Incorrect dependency: wedding → fearing  
 Correct dependency: heading → fearing



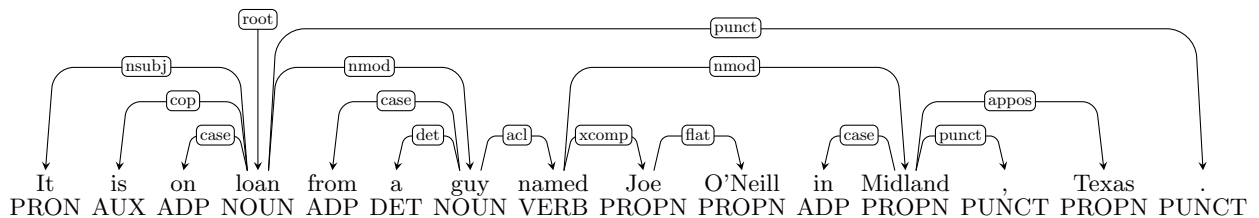
ii.

Error type: Coordination Attachment Error  
 Incorrect dependency: rescue → and  
 Correct dependency: rescue → rush



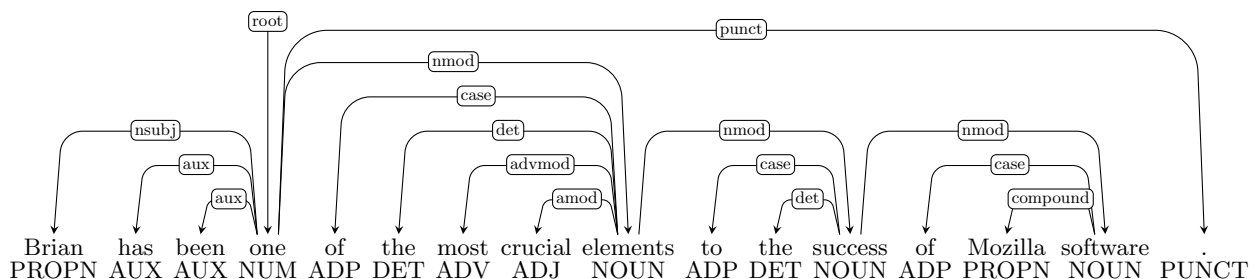
iii.

Error type: Prepositional Phrase Attachment Error  
 Incorrect dependency: named → Midland  
 Correct dependency: guy → Midland



iv.

Error type: Modifier Attachment Error  
 Incorrect dependency: element → most  
 Correct dependency: crucial → most



## Submission Instructions

You shall submit this assignment on GradeScope as two submissions – one for “Assignment 3 [coding]” and another for ‘Assignment 3 [written]’:

1. Run the `collect_submission.sh` script to produce your `assignment3.zip` file.

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2. Upload your `assignment3.zip` file to GradeScope to “Assignment 3 [coding]”.
  3. Upload your written solutions to GradeScope to “Assignment 3 [written]”.