Natural Language Processing **Tel Aviv University**

Assignment 4: Parsing

Due Date: *January 20, 2021* Lecturer: Jonathan Berant

In this home assignment we will implement and train a neural dependency parser using PyTorch, analyze a few erroneous dependency parses, implement the CKY algorithm and use sequence to sequence (seq2seq) models to train a semantic parser.

0 Preliminaries

Submission Instructions The environment setup and submission tutorial can be found in the following notebook: https://colab.research.google.com/drive/1mc6vS2cNVsZ11yn_eaPZVfL774cKkXF1?usp=sharing

Acknowledgements This assignment was adapted from Stanford's CS224n course. Additional background material was adapted from slides by Joakim Nivre. Their contributions are greatly appreciated.

1 Neural Transition-Based Dependency Parsing

Dependency parsing is the task of analyzing the syntactic dependency structure of a given input sentence $\mathcal{S}$. A dependency parser analyzes the grammatical structure of a sentence, establishing relationships between *head* words, and words which modify those heads. It outputs a dependency tree where the words of the input sentence are connected by typed dependency relations. Formally, the dependency parsing problem asks to create a mapping from the input sentence with words $\mathcal{S} = w_0 w_1 \dots w_n$ (where w_0 is the ROOT) to its dependency tree graph G (see Figure 1 for an example). $G = (\{w_0, w_1, \dots, w_n\}, A)$, where $A \subset \{(w_i, l, w_j) | 0 \leq i, j \leq n, l \text{ is a type of a dependency relation}\}$. It is a well-formed tree if and only if:

- every node has at most one incoming arc (single head)
- the graph is (weakly) connected (no dangling nodes)
- there are no cycles (no word is dependent on itself)

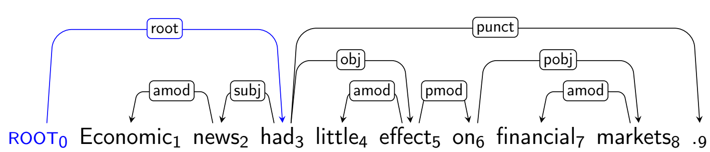


Figure 1: A dependency tree.

Refer to CS224n's lecture notes for more background.

In this section, you'll be implementing a neural-network based dependency parser, with the goal of maximizing performance on the UAS (Unlabeled Attachemnt Score) metric.[1]

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.

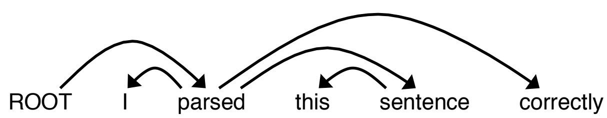
[1] UAS is the percentage of words that get the correct head, without considering the label.

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:

- `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.
- `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.

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

(b) 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`

(c) A sentence containing n words will be parsed in how many steps (in terms of n)? Briefly explain why.

(d) 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_d`.

(e) 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.

Algorithm 1 Minibatch Dependency Parsing

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

Initialize `partial_parses` as a list of PartialParses, one for each sentence in `sentences`
Initialize `unfinished_parses` as a shallow copy of `partial_parses`
while `unfinished_parses` is not empty **do**
  Take the first `batch_size` parses in `unfinished_parses` 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_parses`
end while

Return: The `dependencies` for each (now completed) parse in `partial_parses`.

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_e`. *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.*

(f) 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.*[2] 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 $[w_1, w_2, \ldots, w_m]$ 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). First our network looks up an embedding for each word and concatenates them into a single input vector:

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

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:

$$\begin{aligned}
\mathbf{h} &= \mathrm{ReLU}(\mathbf{x}\mathbf{W} + \mathbf{b}_1) \\
\mathbf{l} &= \mathbf{h}\mathbf{U} + \mathbf{b}_2 \\
\hat{\mathbf{y}} &= \mathrm{softmax}(\mathbf{l})
\end{aligned}$$

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 $\mathrm{ReLU}(z) = \max(z, 0)$. We will train the model to minimize cross-entropy loss:

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

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

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

[2] Chen and Manning, 2014, http://cs.stanford.edu/people/danqi/papers/emnlp2014.pdf

model. Then complete the `train_for_epoch` and `train` functions within the `run.py` file.

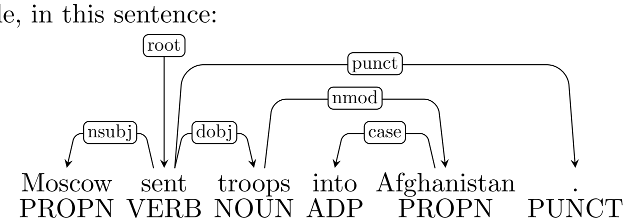
Finally execute `python run.py` to train your model and compute predictions on test data from Penn Treebank (annotated with Universal Dependencies).

Hints:

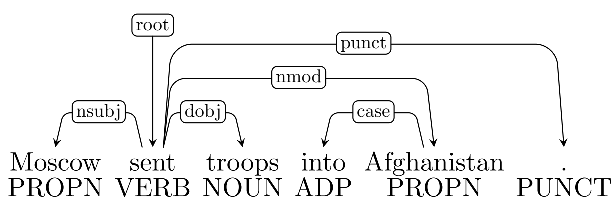
- When debugging, execute `python run.py --debug`. This will cause the code to run over a small subset of the data, so that training the model won't take as long.
- When running with `--debug`, you should be able to get a loss smaller than 0.2 and a UAS larger than 65 on the dev set (although in rare cases your results may be lower, there is some randomness when training).
- When running without `--debug`, 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, **without changing hyperparameters**. 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).

(g) Report the best UAS your model achieves on the dev set and the UAS it achieves on the test set.

(h) 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*).

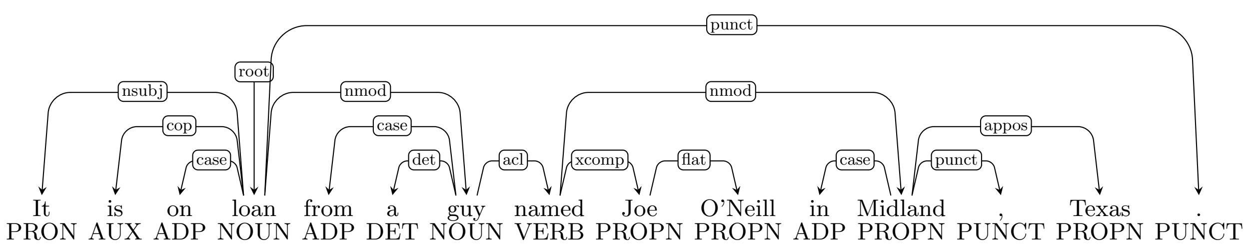
- **Modifier Attachment Error**: In the sentence *I am extremely short*, the adverb *extremely* is a modifier of the adjective *short*. A Modifier Attachment Error is when a modifier is attached to the wrong head word (in this example, the correct head word is *short*).
- **Coordination Attachment Error**: 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
- **Error type**: sent → Afghanistan

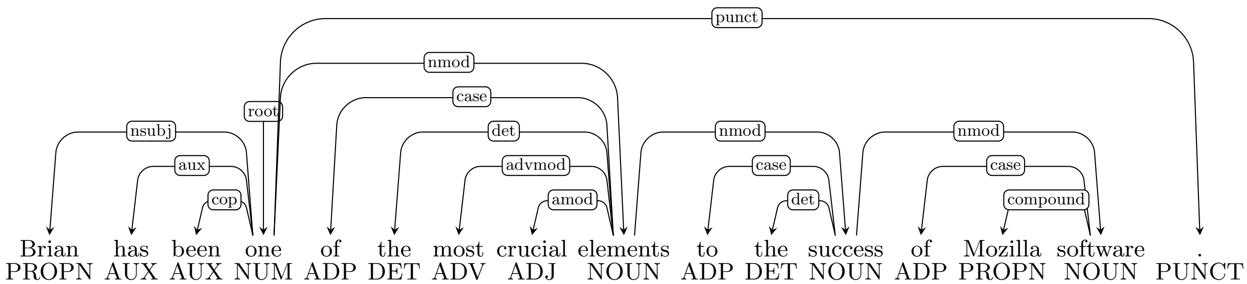
***Note**: There are lots of details and conventions for dependency annotation. If you want to learn more about them, you can look at the UD website: `http://universaldependencies.org`.*[3] *However, you **do not** need to know all these details in order to do this question. In each of these cases, we are asking about the attachment of phrases and it should 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.



[3]But note that in the assignment we are actually using UDv1, see: `http://universaldependencies.org/docsv1/`

ii.



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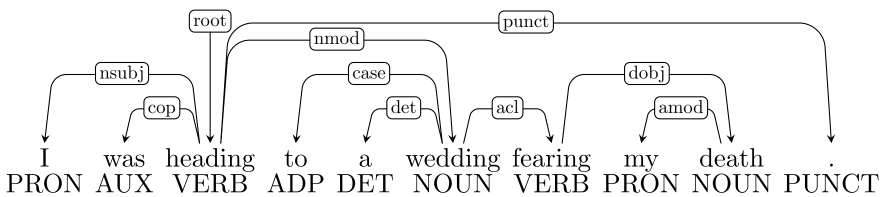

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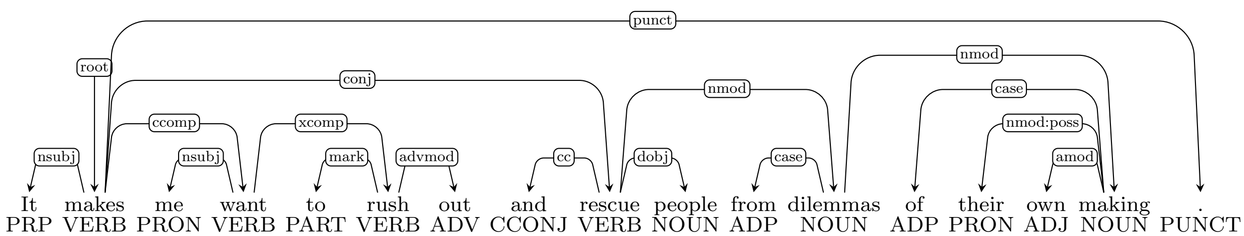

2 Syntactic Parsing

We provide you with a basic grammar. Each line in the grammar file describes a grammar rule:

1. The rule's weight.
2. The rule's left hand side - a non-terminal symbol.
3. The rule's right hand side - a sequence of one or more non-terminal and terminal symbols.

You can generate sentences from the grammar using the `python cky.py --mode gen`

(a) Why does the program generate so many long sentences? Specifically, what grammar rule is responsible and why? What is special about this rule?

(b) The grammar allows multiple adjectives, as in "the fine perplexed pickle". Why do the generated sentences do this so rarely?

(c) The grammar format allows specifying different weights to different rules. Which numbers should you modify to fix the problems in (a) and (b).

(d) Implement the CKY algorithm. The algorithm receives a sentence to parse and a grammar, and returns the derivation of the sentence with the highest probability. Fill your implementation in the function cky in cky.py. The algorithm should assume that the input grammar is in Chomsky Normal Form (CNF).

(e) Use your implementation to find the derivation for the sentence ”the president ate the delicious sandwich“. Run your code using `python cky.py --mode inference --sent <Your sentence here>`

3 Semantic Parsing

In this section you will use sequence to sequence (seq2seq) models to tackle geoqueries880, a semantic parsing dataset, you will implement increasingly complex models and observe their increasingly better performance.

Follow the instructions, complete the code, and answer the questions from this Google Colab notebook[4]: https://colab.research.google.com/drive/1c6Tamefg-ReEEtvt5g8eigs5egz5z0Sx?usp=sharing

[4]Feel free to comment inside the notebook.