CS 224n Assignment #3: Dependency Parsing

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Due on Tuesday Jan. 25, 2022 by **3:15pm (before class)**

In this assignment, you will build a neural dependency parser using PyTorch. For a review of the fundamentals of PyTorch, please check out the PyTorch review session on Canvas. In Part 1, you will learn about two general neural network techniques (Adam Optimization and Dropout). In Part 2, you will implement and train a dependency parser using the techniques from Part 1, 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:

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

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

i. (2 points) First, Adam adopts a commonly used technique called *momentum*, which keeps track of $\mathbf{m}$, a rolling average of the gradients:

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

where β_1 is a hyperparameter between 0 and 1 (often set to 0.9). Briefly explain in 2-4 sentences (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.

Solution: The gradient estimated through *momentum* has low variance in comparison with the Vanilla SGD. The reason is that the momentum is effectively an exponential moving average (EMA), which can smooth the noisy series of gradients by exponentially weighting past gradients by right amount of, β_1, and hence stops the parameter updates varying too much.

Without the *momentum*, $\beta_1 = 0$, (gradient has large variance), the learning algorithm might bouncing around (zig-zag steps), leading to slow convergence and hence worse performance. This low variance helps maintain the efficiency of gradient descent, leading to faster convergence.

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

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

[1] Kingma and Ba, 2015, `https://arxiv.org/pdf/1412.6980.pdf`

[2] 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`

where $\odot$ and / denote elementwise multiplication and division (so $\mathbf{z} \odot \mathbf{z}$ is elementwise squaring) and β_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?

Solution: Adam also uses the second moment of the gradient to adaptively update the *learning rates*. The parameters with a scarce history of updates will get larger updates as second moment $\sqrt{v}$ normalises (adapts with EMA of gradient magnitudes) the learning rate. This normalisation of updates steps avoid overshooting or monotonically decreasing the learning rate.

(b) (4 points) Dropout[3] is a regularization technique. During training, dropout randomly sets units in the hidden layer $\mathbf{h}$ to zero with probability p_{drop} (dropping different units each minibatch), and then multiplies $\mathbf{h}$ by a constant γ. 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_{drop} and 1 with probability $(1 - p_{\text{drop}})$. γ 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 γ equal in terms of p_{drop}? Briefly justify your answer or show your math derivation using the equations given above.

Solution:

$$\begin{aligned}
\text{Given, } \mathbb{E}_{p_{\text{drop}}}[\mathbf{h}_{\text{drop}}]_i &= h_i \\
& \boxed{\mathbb{E}[X] = xp(x)} \\
\mathbb{E}_{p_{\text{drop}}}[\mathbf{h}_{\text{drop}}] &= \sum_i (\mathbf{h}_{\text{drop}})_i \;\; p\big((\mathbf{h}_{\text{drop}})_i\big) \\
&= \sum_i \gamma \cdot d_i \cdot h_i \cdot \big[p_{\text{drop}} \; OR \; (1 - p_{\text{drop}})\big] \\
& \text{if } d_i = 0 \text{ the probability is } \big(p_{\text{drop}}\big), \\
& \text{if } d_i = 1 \text{ the probability is } \big(1 - p_{\text{drop}}\big), \\
\text{Hence, } &= \sum_i \gamma \cdot h_i \cdot (1 - p_{\text{drop}}) \\
& \text{for i}^{\text{th}} \text{ index expectation would be:} \\
\mathbb{E}_{p_{\text{drop}}}[\mathbf{h}_{\text{drop}}]_i &= \gamma \cdot h_i \cdot (1 - p_{\text{drop}}) \text{ OR } 0 \\
h_i &= \gamma \cdot h_i \cdot (1 - p_{\text{drop}}) \\
\text{Therefore, } & \boxed{\gamma = \frac{1}{(1 - p_{\text{drop}})}}
\end{aligned}$$

ii. (2 points) Why should dropout be applied during training? Why should dropout **NOT** be applied during evaluation? (Hint: it may help to look at the paper linked above in the write-up.)

Solution: It is observed that training a network with dropout and using this approximate

[3] Srivastava et al., 2014, `https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf`

averaging method at test time leads to significantly lower generalization error on a wide variety of classification problems compared to training with other regularization methods. The reasons are:

1. *During training*, without dropout, model parameters tend to overfit to some features as the neighbouring parameters can have high reliance on each other. These co-adaptations do not generalise to unseen data. Dropout can randomly cut of connections between parameters (weights) during training by zeroing out gradients. Therefore, dropout can reduce the reliance between parameters, making the trained model more robust and better capable of generalization.

2. *During evaluation (testing)*, it is not feasible to explicitly average the predictions from exponentially many thinned models. However, a very simple approximate averaging method works well in practice. The idea is to use a single neural net at test time without dropout. The weights of this network are scaled-down versions of the trained weights by probability p_{drop}. By doing this scaling, 2^n networks with shared weights can be combined into a single neural network to be used at test time. Therefore dropout should not be applied during evaluation.

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 follow the README to install all the needed dependencies for the assignment. We will be using PyTorch 1.7.1 from `https://pytorch.org/get-started/locally/` with the `CUDA` option set to `None`, and the tqdm package – which produces progress bar visualizations throughout your training process. The official PyTorch website is a great resource that includes tutorials for understanding PyTorch's Tensor library and neural networks.

A dependency parser analyzes the grammatical structure of a sentence, establishing relationships between *head* words, and words which modify those heads. There are multiple types of dependency parsers, including transition-based parsers, graph-based parsers, and feature-based parsers. 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:

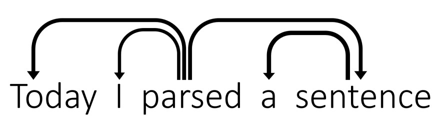
- A *stack* of words that are currently being processed.
- A *buffer* of words yet to be processed.
- A list of *dependencies* predicted by the parser.

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, 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) Complete the sequence of transitions needed for parsing the sentence *"Today I parsed a sentence"*. 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 four steps are provided below as an example.



Stack	Buffer	New dependency	Transition
[ROOT]	[Today, I, parsed, a, sentence]		Initial Configuration
[ROOT, Today]	[I, parsed, a, sentence]		`SHIFT`
[ROOT, Today, I]	[parsed, a, sentence]		`SHIFT`
[ROOT, Today, I, parsed]	[a, sentence]		`SHIFT`
[ROOT, Today, parsed]	[a, sentence]	parsed→I	`LEFT-ARC`

Solution:

[ROOT, parsed]	[a, sentence]	parsed→Today	`LEFT-ARC`
[ROOT, parsed, a]	[sentence]		`SHIFT`
[ROOT, parsed, a, sentence]	[ ]		`SHIFT`
[ROOT, parsed, sentence]	[ ]	sentence→a	`LEFT-ARC`
[ROOT, parsed]	[ ]	parsed→sentence	`RIGHT-ARC`
[ROOT]	[ ]	ROOT→parsed	`RIGHT-ARC`

(b) (2 points) A sentence containing n words will be parsed in how many steps (in terms of n)? Briefly explain in 1-2 sentences why.

Solution: $2n$

Since, each word needs two transitions: 1) `SHIFT`, and 2) one of the `ARCs` (`LEFT` or `RIGHT`) before being removed from the stack. And, parser has to perform only one of these two transition operation in each step. Hence, total $2n$ steps are required to parse complete sentence of length n.

(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 many 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_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.[4] 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 $\mathbf{w} = [w_1, w_2, \ldots, w_m]$ 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). Then our network looks up an embedding for each word and concatenates them into a single input vector:

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

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:

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

$\mathbf{X}$ is a mini-batch of embedded inputs of shape (batch_size, dm). $\mathbf{h}$ is the hidden layer activation of shape (batch_size, hidden_size). $\mathbf{W}$ and $\mathbf{b}_1$ are the weight matrix and bias vector which transform $\mathbf{x}$ into $\mathbf{h}$. And $\mathrm{ReLU}(z) = \max(z, 0)$.
$\mathbf{l}$ is the matrix of output logits in shape (batch_size, num_classes). $\mathbf{U}$ and $\mathbf{b}_2$ are the weight matrix and bias vector which transform $\mathbf{h}$ into $\mathbf{l}$.
Finally, $\hat{\mathbf{y}}$ is the model's final prediction in shape (batch_size, num_classes). Each row is a probability distribution (sums up to 1) over all classes.
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.

We will use UAS score as our evaluation metric. UAS stands for Unlabeled Attachment Score, which is computed as the ratio between the number of correctly predicted dependencies and the number of total dependencies. UAS score is "Unlabeled" because it ignores the types of the dependency relations, which our model does not predict.

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).

Important Notes:

- 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.

More Hints:
Implementation details:

[4] Chen and Manning, 2014, `https://nlp.stanford.edu/pubs/emnlp2014-depparser.pdf`

- Each of the variables you are asked to declare (`self.embed_to_hidden_weight`, `self.embed_to_hidden_bias`, `self.hidden_to_logits_weight`, `self.hidden_to_logits_bias`) corresponds to one of the variables above ($\mathbf{W}$, $\mathbf{b}_1$, $\mathbf{U}$, $\mathbf{b}_2$).
- It may help to work backwards in the algorithm (start from $\hat{\mathbf{y}}$) and keep track of the matrix/vector sizes.

Debugging help:

- 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.

Sanity checks:

- In 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 as there is some randomness when training).
- When debug mode is disabled, it should take about **1 hour** to train the model on the entire the training dataset.
- 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).

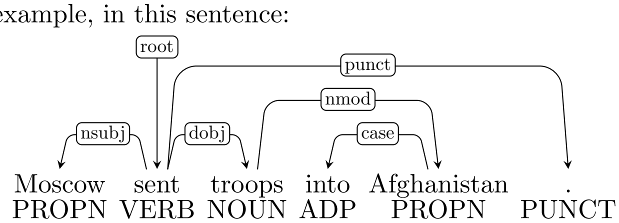
Deliverables:

- Working implementation of the transition mechanics that the neural dependency parser uses in `parser_transitions.py`.
- Working implementation of minibatch dependency parsing in `parser_transitions.py`.
- Working implementation of the neural dependency parser in `parser_model.py`. (We'll look at and run this code for grading).
- Working implementation of the functions for training in `run.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 in your writeup.**

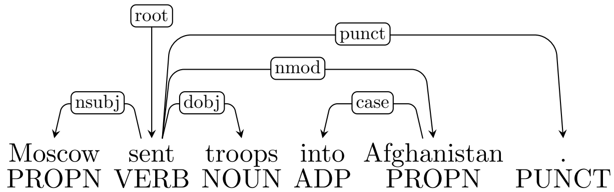
Solution:

- The best UAS on the dev set: 88.92
- The best UAS on the test set: 89.28

(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[5]. It modifies *sent*, specifying the destination of this action. Therefore, the correct dependency is *sent* → *Afghanistan*. A Prepositional Phrase Attachment Error is when a prepositional phrase is attached to the wrong 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[6]. In this example, this verb phrase modifies *went* (*went* → *leaving*). A Verb Phrase Attachment Error is when a verb phrase is attached to the wrong head word.
- **Modifier Attachment Error**: In the sentence *I am extremely short*, the adverb *extremely* is a modifier of the adjective *short*. The correct head word of *extremely* is *short* (*short* → *extremely*). A Modifier Attachment Error is when a modifier is attached to the wrong head word.
- **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*) (*rice* → *naan*). A Coordination Attachment Error is when the second conjunct is attached to the wrong head word. Other commonly seen coordinating conjunctions include *and*, *but* and *so*.

In this question there are four sentences with dependency parses obtained from a parser. Each sentence has one error type, 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. While each sentence should have a unique error type, there may be multiple possible correct dependencies for some of the sentences. To demonstrate: for the example above, you would write:

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

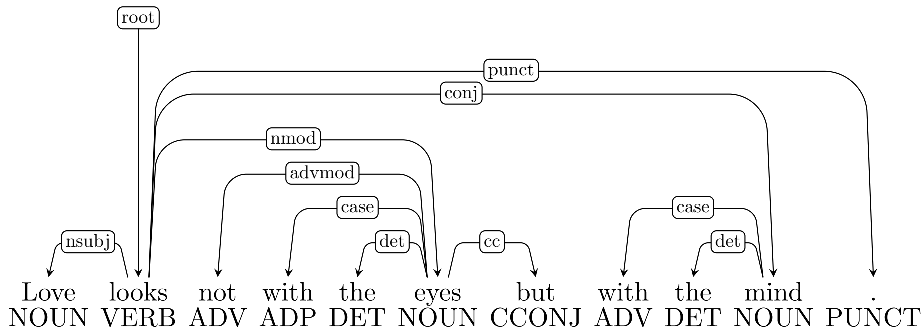
Note: *There are lots of details and conventions for dependency annotation. If you want to learn more about them, you can look at the UD website:* `http://universaldependencies.org`[7] *or the short introductory slides at:* `http://people.cs.georgetown.edu/nschneid/p/UD-for-English.pdf`*. Note that you* ***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.*

[5] For examples of prepositional phrases, see: https://www.grammarly.com/blog/prepositional-phrase/

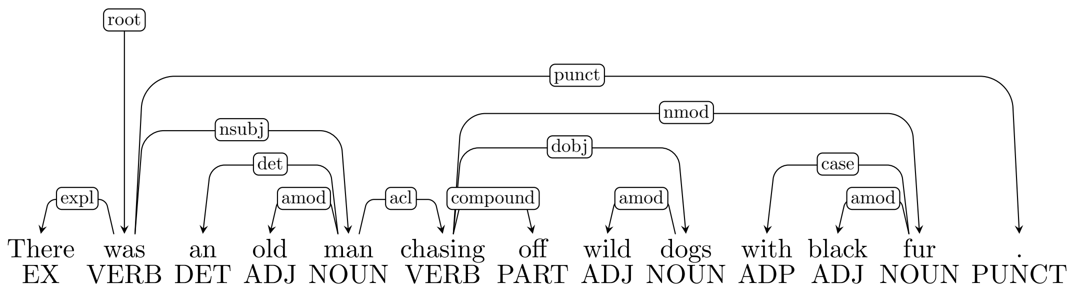
[6] For examples of verb phrases, see: https://examples.yourdictionary.com/verb-phrase-examples.html

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

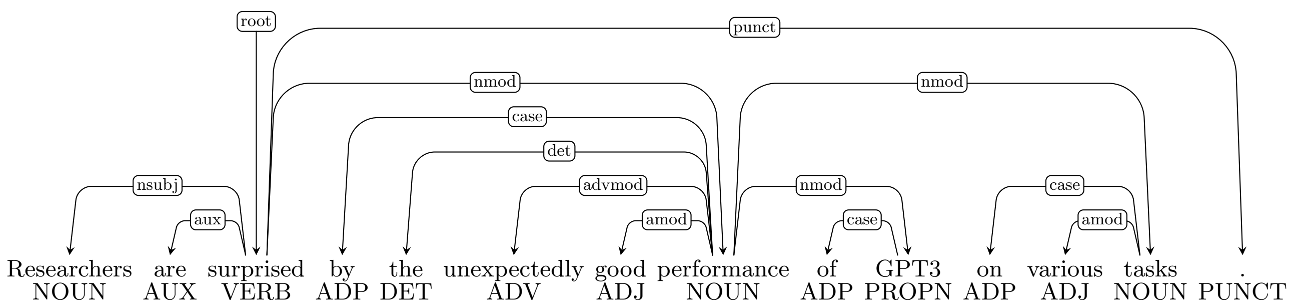
i.


root
punct
conj
nmod
advmod
case
nsubj
det
cc
case
det
Love looks not with the eyes but with the mind .
NOUN VERB ADV ADP DET NOUN CCONJ ADV DET NOUN PUNCT

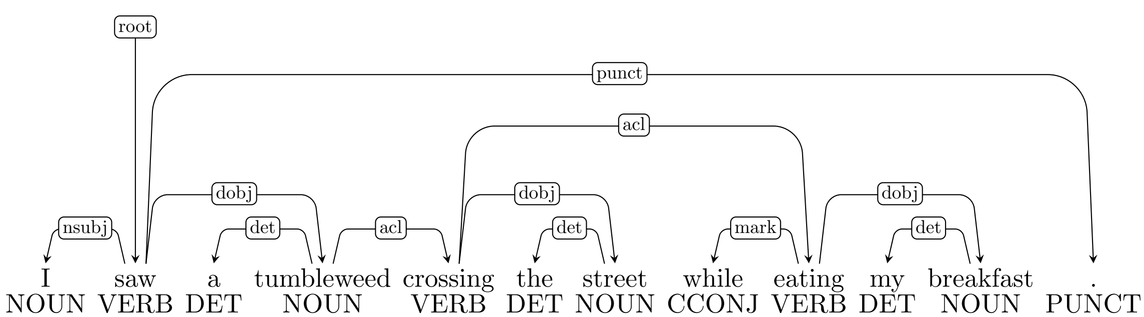
ii.


root
punct
nmod
nsubj
dobj
det
case
expl
amod
acl
compound
amod
amod
There was an old man chasing off wild dogs with black fur .
EX VERB DET ADJ NOUN VERB PART ADJ NOUN ADP ADJ NOUN PUNCT

iii.


root
punct
nmod
nmod
case
det
advmod
nsubj
nmod
case
aux
amod
case
amod
Researchers are surprised by the unexpectedly good performance of GPT3 on various tasks .
NOUN AUX VERB ADP DET ADV ADJ NOUN ADP PROPN ADP ADJ NOUN PUNCT

iv.


root
punct
acl
dobj
dobj
dobj
nsubj
det
acl
det
mark
det
I saw a tumbleweed crossing the street while eating my breakfast .
NOUN VERB DET NOUN VERB DET NOUN CCONJ VERB DET NOUN PUNCT

Solution:

i.

Error type: Coordination Attachment Error

Incorrect dependency: looks $\rightarrow$ mind

Correct dependency: eyes $\rightarrow$ mind

ii.

Error type: Prepositional Phrase Attachment Error

Incorrect dependency: chasing $\rightarrow$ fur

Correct dependency: dogs $\rightarrow$ fur

iii.

Error type: Modifier Attachment Error

Incorrect dependency: performance $\rightarrow$ unexpectedly

Correct dependency: good $\rightarrow$ unexpectedly

iv.

Error type: Verb Phrase Attachment Error

Incorrect dependency: crossing $\rightarrow$ eating

Correct dependency: saw $\rightarrow$ eating

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.
2. Upload your `assignment3.zip` file to GradeScope to "Assignment 3 Coding".
3. Upload your written solutions to GradeScope to "Assignment 3 Written".