CSC485/2501 A1 Tutorial #2

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Assignment 1

- Due on Oct. 6th, at 11:59 pm.

- Asks you to implement a set of neural dependency parsers.

Assignment 1

- Part 1: Transition-based dependency parser
  - See tutorial #1.

- Part 2: Graph-based dependency parser

Assignment 1

- Part 1: Transition-based dependency parser
  - See tutorial #1.
- Part 2: Graph-based dependency parser
  - We'll focus on this part today!

Outline

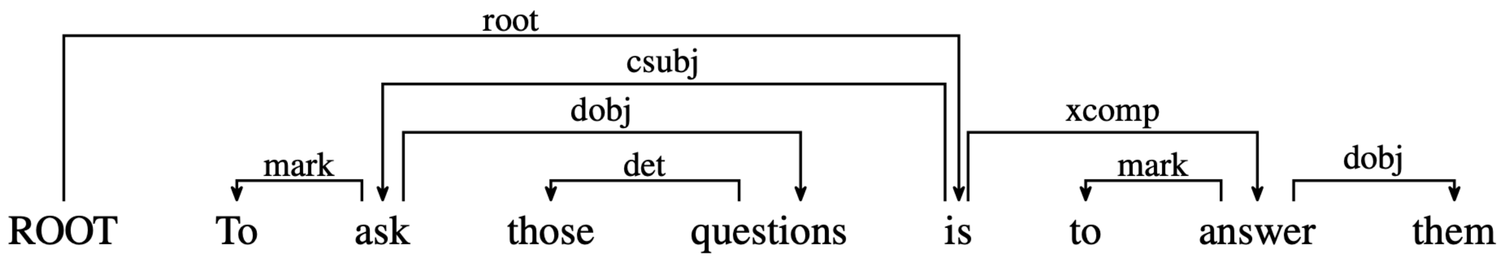
- Edge-factored Parsing Example
- Biaffine-attention Neural Dependency Parser
  - Arc scorer
  - Label scorer
- Tips for Batching

Quiz

- Which of the following *is not* true about BERT?
  a) It contextualizes word2vec vectors.
  b) It uses self-attention.
  c) It assigns a vector to CLS in its output.
  d) It is a decoder LM.

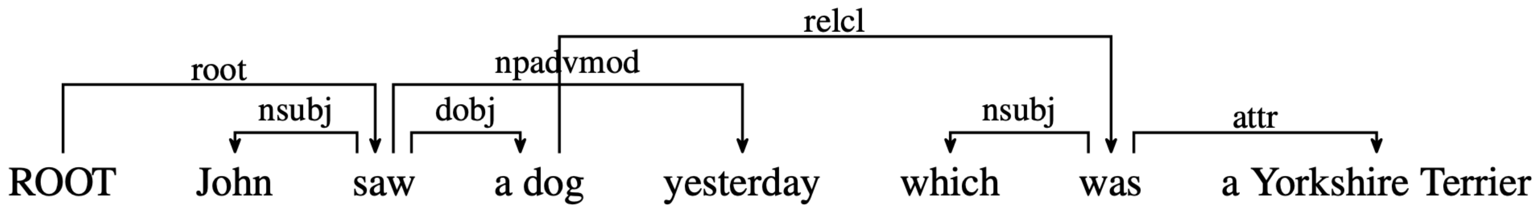
Projective Dependency Trees

- Projectivity: If a dependency arc exist from i $\rightarrow$ j, then there exist a path from i $\rightarrow$ k for every min(i,j) < k < max(i,j).
- A dependency tree is projective if all of its arcs are projective.
- This corresponds to a planar graph:



Non-projective Dependency Trees

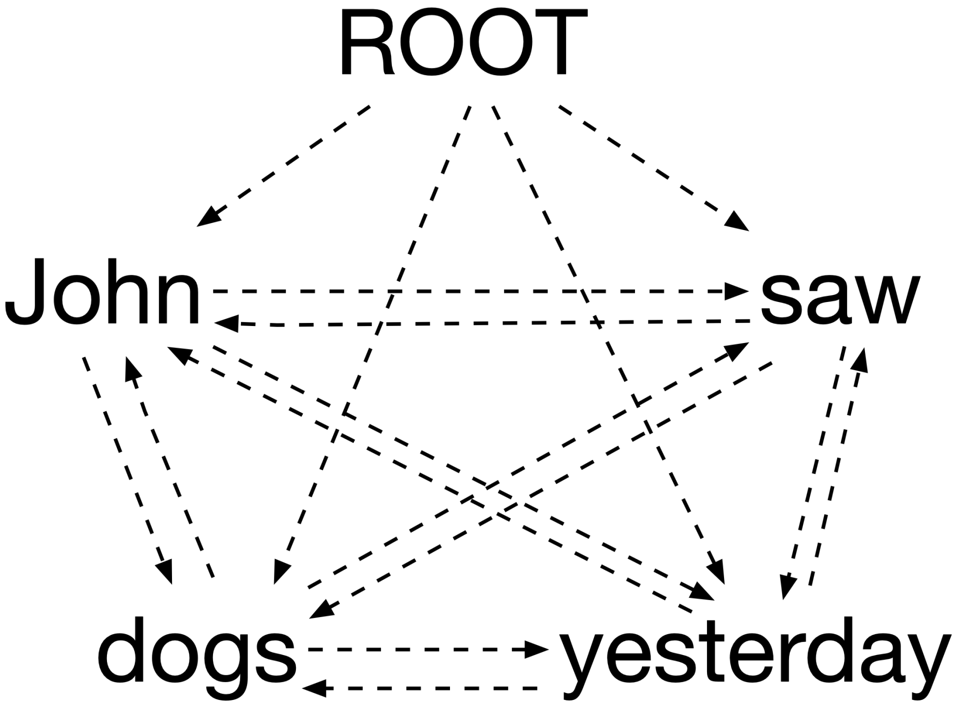
- A non-projective dependency tree has one or more non-projective dependency arc.
- This corresponds to a graph with a cross-over arc:



- Transition-based parsers cannot handle this.

Graph-based Dependency Parsing

- Consider all possible arcs between pairs of words:



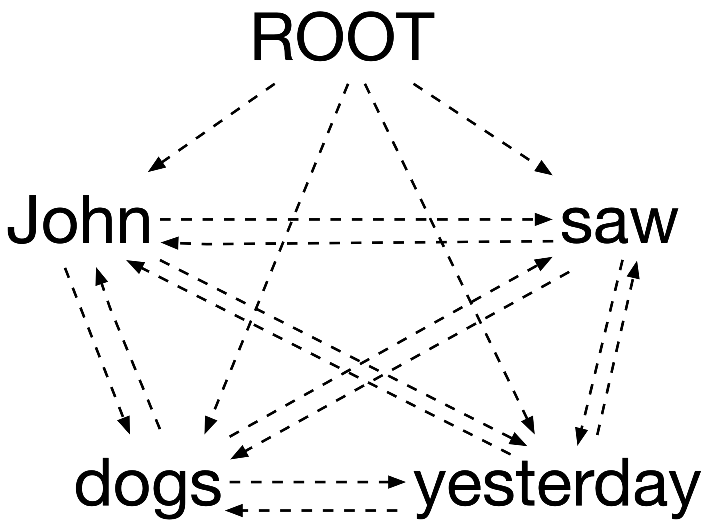
Edge-factored Parsing

- An edge-factored parser involves the following steps:
  1. Create a bidirectional, connected graph that corresponds to the sentence.
  2. Score each arc in the graph.
  3. Finding the maximum spanning tree in the graph and treat the constituent arcs as your dependency arcs.
  4. Tag each arc with an appropriate dependency label.

Edge-factored Parsing

- Step 1: Create a bidirectional, connected graph that corresponds to the sentence.
- Input: Output:

ROOT John saw dogs yesterday

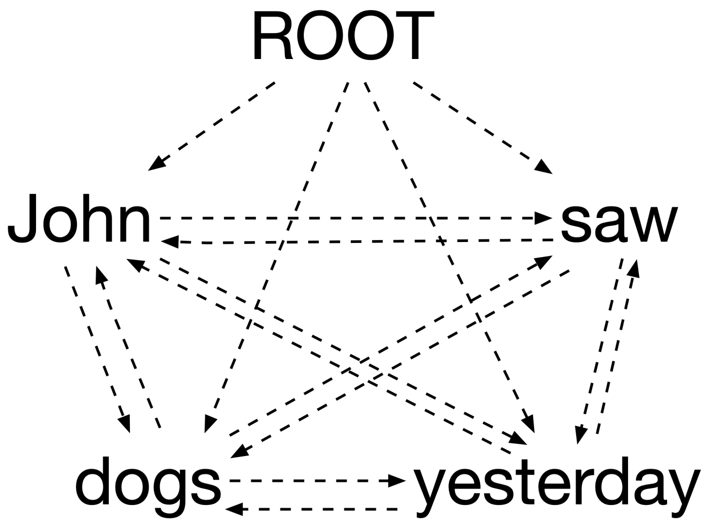


- Add ROOT if necessary.

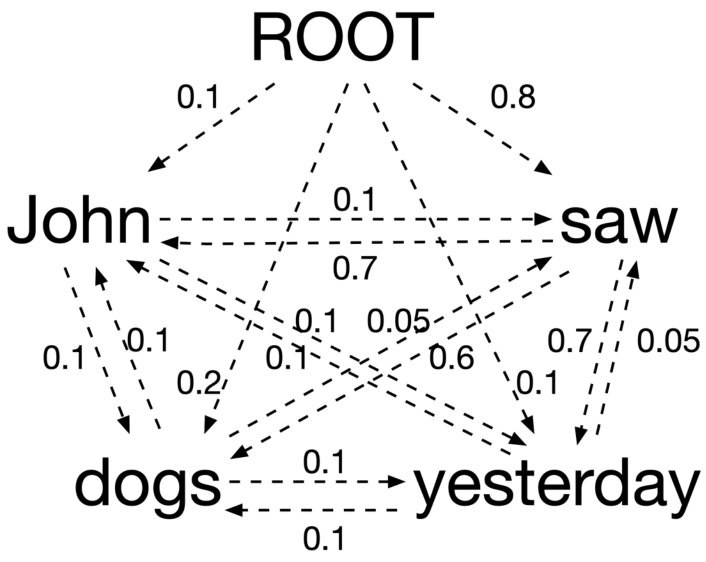
Edge-factored Parsing

- Step 2: Score each edge in the graph.

- Input:



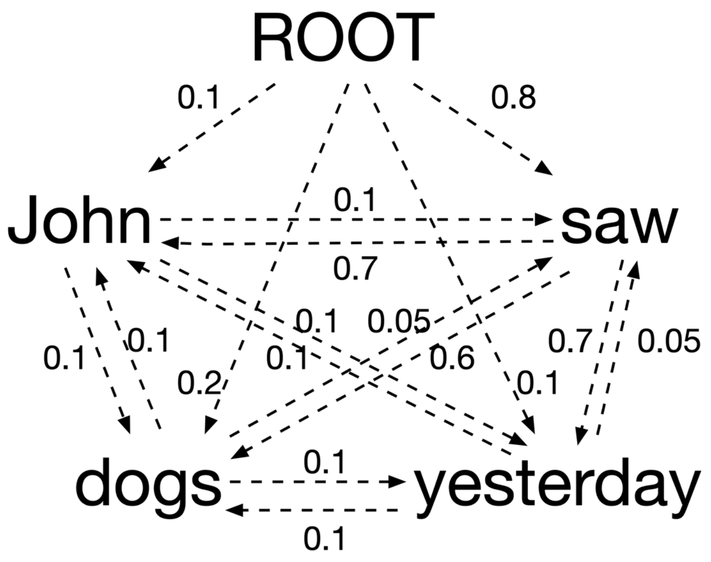
Output:



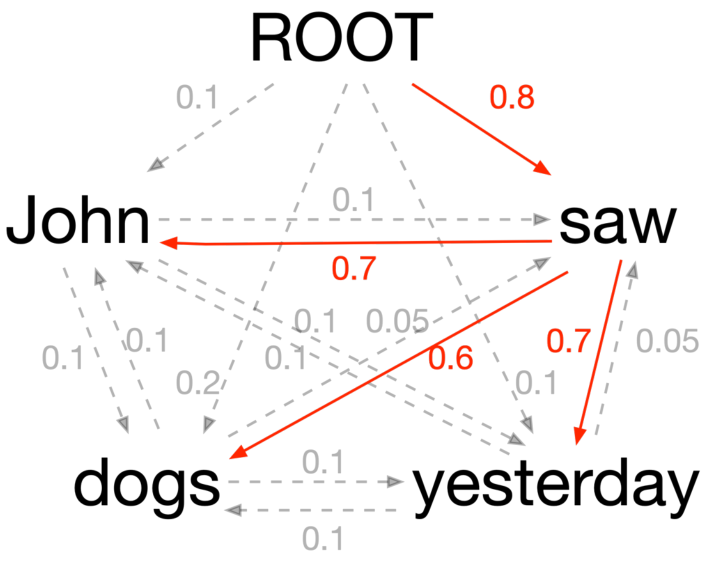
- We will do this using a neural network (see the Arc Scorer).

Edge-factored Parsing

- Step 3: Find the maximum spanning tree in the graph.
- Input:

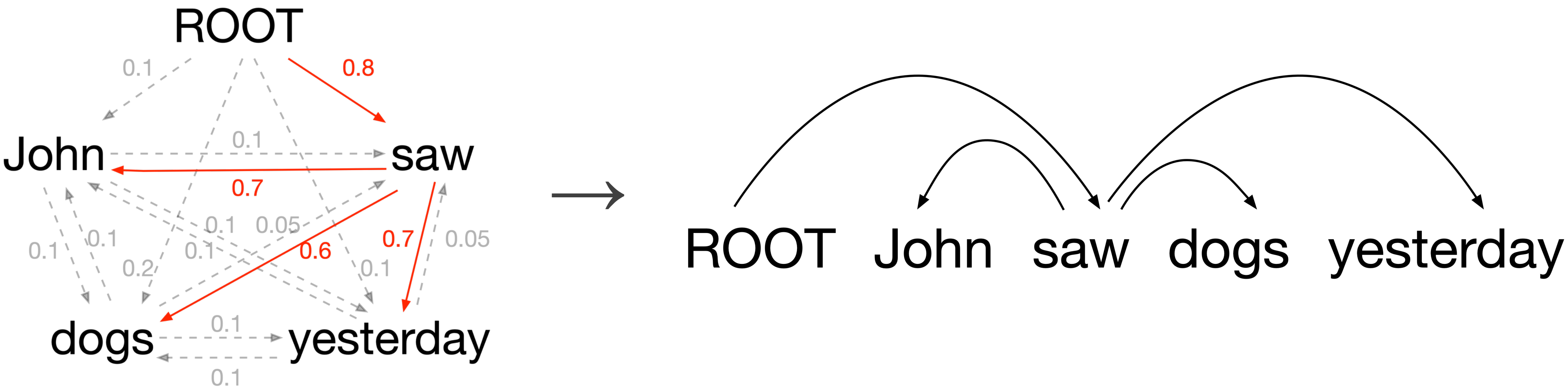


Output:



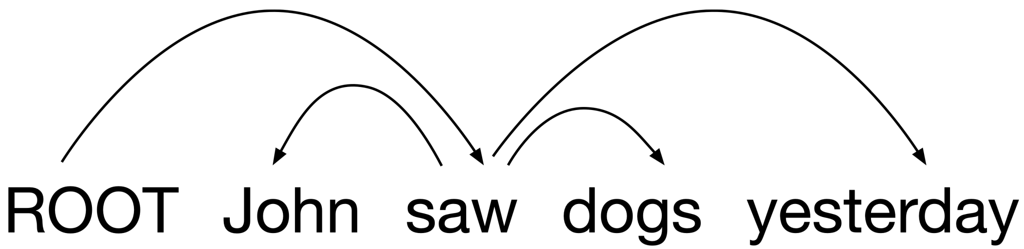
Edge-factored Parsing

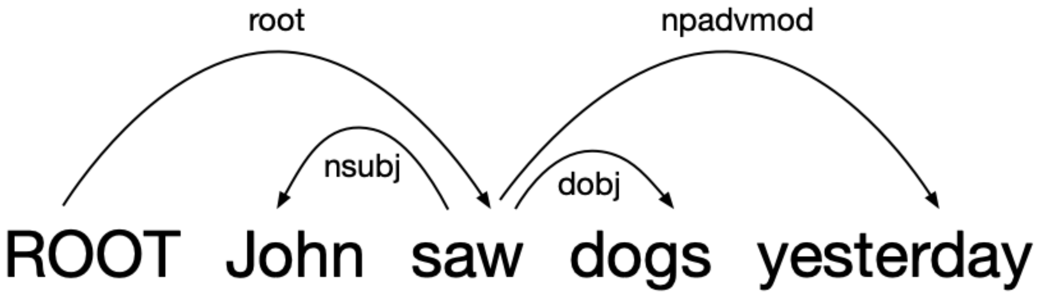
- Find the MST using Chu-Liu Edmonds algorithm.
- Pseudo-code from the textbook and example in the lecture.
- The MST can then be viewed as an unlabeled dependency parse tree:



Edge-factored Parsing

- Step 4: Tag each arc with an appropriate dependency label.
- Input: Output:





- We will also train a neural network to do this (see the Label Scorer).

Biaffine-attention Neural Dependency Parser

- We need to train two neural networks to complete our parser:

1. Arc Scorer: Scores the likelihood for each arc in the graph.
    - The Scores are then passed to an MST algorithm.
    - Why can't we just take the argmax here?

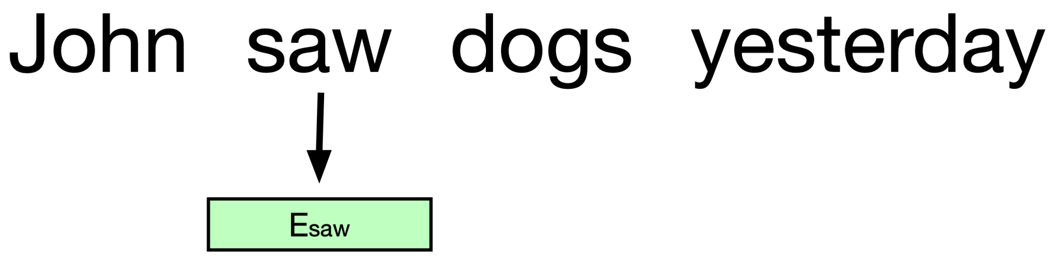
2. Label Scorer: Given an arc in the graph, output a score distribution over all possible tags.
    - In this case, we can simply take the argmax.

- For the original architecture, see Dozat et al. (2017):
    - https://aclanthology.org/K17-3002.pdf

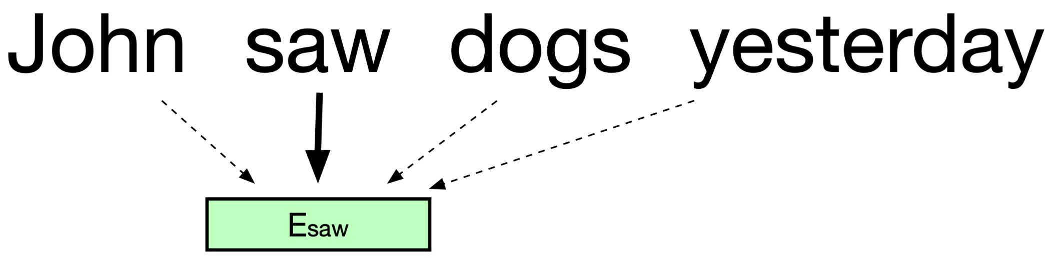
Contextualized Word Embedding

- Quick aside: The graph structure does not encode word order information.
- We can retain this information by using contextualized word embeddings, which is aware of its usage context:

Word2Vec:



BERT:



Arc Scorer

$$D_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ad}}(S)$$
$$H_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ah}}(S)$$
$$a_{ij} = [D_{\mathrm{A}}]_i W_{\mathrm{A}} ([H_{\mathrm{A}}]_j)^{\mathrm{T}} + [H_{\mathrm{A}}]_j \cdot b_{\mathrm{A}}$$

- S – Contextual word embeddings for the sentence.
- D_A – Learned representations for all words in the sentence when considered as dependents.
- H_A – Learned representations for all words in the sentence when considered as heads.
- a_{ij} – Numeric score corresponding to the arc $j \rightarrow i$

Arc Scorer

$$D_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ad}}(S)$$
$$H_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ah}}(S)$$
$$a_{ij} = [D_{\mathrm{A}}]_i W_{\mathrm{A}}([H_{\mathrm{A}}]_j)^{\mathrm{T}} + [H_{\mathrm{A}}]_j \cdot b_{\mathrm{A}}$$

- W_A and b_A are learnable parameters in the model.
- Use *torch.nn.Parameter* to create these weights/biases.
  - E.g. b_A = torch.nn.Parameter(torch.ones((10)), requires_grad=True)
- This tells PyTorch to register the tensor with your neural network module, in which you can find the parameters using *self.parameters*.

Arc Scorer

$$D_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ad}}(S)$$
$$H_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ah}}(S)$$
$$a_{ij} = [D_{\mathrm{A}}]_i W_{\mathrm{A}}([H_{\mathrm{A}}]_j)^{\mathrm{T}} + [H_{\mathrm{A}}]_j \cdot b_{\mathrm{A}}$$

- For this assignment, create the multi-layer perceptron (a.k.a. fully connected layers) using *torch.nn.Sequential*:
  - E.g. nn.Sequential(nn.Linear(50, 100), nn.ReLU(), nn.Dropout(0.5))
- This creates an encapsulated layer that is equivalent to passing an input into the three layers sequentially.

Arc Scorer

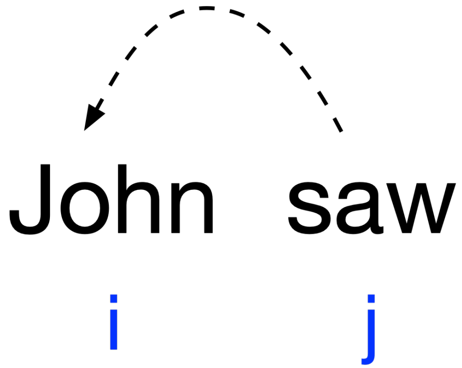
$$D_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ad}}(S)$$
$$H_{\mathrm{A}} = \mathrm{MLP}_{\mathrm{Ah}}(S)$$
$$a_{ij} = [D_{\mathrm{A}}]_i W_{\mathrm{A}} ([H_{\mathrm{A}}]_j)^{\mathrm{T}} + [H_{\mathrm{A}}]_j \cdot b_{\mathrm{A}}$$

- The obtained score is then passed into a softmax layer:

$$\hat{h}_i = \mathrm{softmax}(a_i \ )$$
$$J_{\mathrm{h}} = CE(h, \hat{h}) = -\sum_{i=1}^{n} h_i \log \hat{h}_i$$

Arc Scorer

$$D_{\text{A}} = \text{MLP}_{\text{Ad}}(S)$$
$$H_{\text{A}} = \text{MLP}_{\text{Ah}}(S)$$
$$a_{ij} = [D_{\text{A}}]_i W_{\text{A}}([H_{\text{A}}]_j)^{\text{T}} + [H_{\text{A}}]_j \cdot b_{\text{A}}$$



- Intuitions for the architecture:
  - The MLP layers create a pair of distinct representations for each word in the sentence, one for when the word is viewed as a dependent in an arc, and another for when it is viewed as a head.
  - The biaffine transformation between these representations then checks the appropriateness of having a directed edge between two words.
  - The bias term acts as a prior checking how likely a word is to be used as a head of an arc.

Label Scorer

$$D_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Ld}}(S)$$
$$H_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Lh}}(S)$$
$$l_{ij} = [D_{\mathrm{L}}]_i W_{\mathrm{L}} ([H_{\mathrm{L}}]_j)^{\mathrm{T}} + [H_{\mathrm{L}}]_j W_{\mathrm{Lh}} + [D_{\mathrm{L}}]_i W_{\mathrm{Ld}} + b_{\mathrm{L}}$$

- S – Contextual word embeddings for the sentence.
- D_L – Learned representations for all words in the sentence when considered as dependents.
- H_L – Learned representations for all words in the sentence when considered as heads.
- l_{ij} – Vector of numeric scores where the k'th value correspond to the score of having the k'th dependency relation labeled for the arc $j \rightarrow i$

Label Scorer

$$D_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Ld}}(S)$$
$$H_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Lh}}(S)$$
$$l_{ij} = [D_{\mathrm{L}}]_i W_{\mathrm{L}}([H_{\mathrm{L}}]_j)^{\mathrm{T}} + [H_{\mathrm{L}}]_j W_{\mathrm{Lh}} + [D_{\mathrm{L}}]_i W_{\mathrm{Ld}} + b_{\mathrm{L}}$$

- Since l_{ij} is a vector, W_L and b_L both have one extra dimension.
  - Back in the arc scorer case, W is of shape [X, X], but now it is of shape [X, Y, X], where X and Y are both integers.
  - The bias term is now a vector instead of a number.

Label Scorer

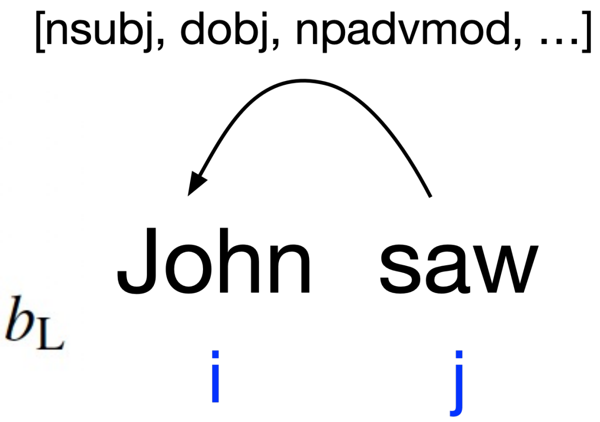
$$D_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Ld}}(S)$$
$$H_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Lh}}(S)$$
$$l_{ij} = [D_{\mathrm{L}}]_i W_{\mathrm{L}} ([H_{\mathrm{L}}]_j)^{\mathrm{T}} + [H_{\mathrm{L}}]_j W_{\mathrm{Lh}} + [D_{\mathrm{L}}]_i W_{\mathrm{Ld}} + b_{\mathrm{L}}$$

- The score vector is then also passed into a softmax layer:

$$\hat{r}_{ij} = \mathrm{softmax}(l_{ij})$$
$$J_{\mathrm{r}} = CE(r, \hat{r}) = -\sum_{i=1}^{n} \sum_{j=0}^{n} r_{ij} \log \hat{r}_{ij}$$

- Taking an argmax over the softmax scores gives the predicted label.

Label Scorer



$$D_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Ld}}(S)$$
$$H_{\mathrm{L}} = \mathrm{MLP}_{\mathrm{Lh}}(S)$$
$$l_{ij} = [D_{\mathrm{L}}]_i W_{\mathrm{L}} ([H_{\mathrm{L}}]_j)^{\mathrm{T}} + [H_{\mathrm{L}}]_j W_{\mathrm{Lh}} + [D_{\mathrm{L}}]_i W_{\mathrm{Ld}} + b_{\mathrm{L}}$$

- Intuitions for the architecture:
  - The MLP layers and the biaffine transformation are very similar, except now that the biaffine transformation checks the appropriateness of having each individual tag on a directed edge between two words.
  - The two subsequent terms in the sum checks the appropriateness of having a certain word as the head/dependent of a given dependency relation.
  - The bias term sets a prior over all possible dependency relations.

Batching

- We apply batched computation to take advantage of powerful parallelism in modern hardware (i.e. GPUs).
- The tensors given to you in the assignment are already in batch format.
- You'll need to maintain the given batch format in all neural network computations.

Batching

S1: Word_0, Word_2, Word_3
S2: Word_3, Word_1, Word_1, Word_0
S3: Word_3, Word_2, Word_1, Word_2, Word_0

- Directly encoding this into an array gives us:

```
[ [0,2,3],
  [3,1,1,0],
  [3,2,1,2,0] ]
```

- Cannot perform parallel computation because the sequence lengths are not matched.

Batching

S1: Word_0, Word_2, Word_3
S2: Word_3, Word_1, Word_1, Word_0
S3: Word_3, Word_2, Word_1, Word_2, Word_0

- Trick: Pad the shorter sequences and keep track of sequence lengths.

[[0,2,3,0,0],
[3,1,1,0,0],
[3,2,1,2,0]]

[3,4,5]

- This results in an extra batch dimension B in your tensor. In the example above, B=3.

Working with Batched Tensors

- To perform efficient computation, you don't want to unpack the batch dimension.
- Let A, B be two batched tensors of shape (b, X, Y) and (b, Y, Z) respectively. Now, to compute a matrix multiplication:

```
for i in range(b):
    result[i] = A[i] * B[i]
```

```
torch.einsum('bij,bjk->bik', A, B)
```

Working with Batched Tensors

- torch.einsum(...) allows efficient batched operations.

```
torch.einsum('bij,bjk->bik', A, B)
```

- Separated by commas, each term to the left of the arrow defines the dimensions of the input tensors.
- The term following the arrow specifies the output, where every missing dimension will be summed over.

Working with Batched Tensors

- torch.einsum(…) allows efficient batched operations.

torch.einsum(‘bij,bjk->bik’, A, B)

- The matrix operation defined above is thus equivalent to computing:

$$\text{result}[b,i,k] = \Sigma_j\, A[b,i,j] * B[b,j,k] \quad \forall\, b, i, k$$

- More examples in the PyTorch documentation:
  - https://pytorch.org/docs/stable/generated/torch.einsum.html

The End

- Good luck on the assignment!
- Please post any questions you have on Piazza.