# NLP1 Projects 17/18

#### **Projects**

We offer 6 projects

Teams of 3 will be divided over the projects

Sign up after this lecture (link on Blackboard)

Each project requires implementing a model and writing a report

Implementations in Python & PyTorch

We cannot offer GPUs - but our projects can also be completed on CPU

### List of Projects

- 1. Visual Question Answering
- 2. Image Retrieval from Dialogue
- 3. Neural Graph-based Dependency Parsing
- 4. Neural Language Modeling
- 5. Finding Grammar in Neural Language Models
- 6. What do Neural Machine Translation models encode?

# Visual Question Answering

Who is wearing glasses? man woman





Is the umbrella upside down? yes no





Where is the child sitting? fridge arms





How many children are in the bed?





### Visual Question Answering - Given

Subset of VQA Dataset

Preprocessed Image features

PyTorch Introduction

# Visual Question Answering - Deliverables

- 1. Analyze & Preprocess language data
- 2. Implement the following approaches
  - a. BoW
  - b. Bag of Words + NLP features
  - c. RNN

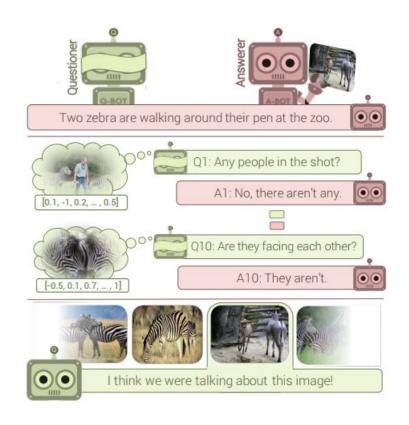
#### **BONUS:**

- d. Implementation of SoA models
- e. Your very own idea
- 3. Error Analysis of Models
- 4. Writer scientific report about your findings

#### Image Retrieval from Dialogue

#### Task Definition:

- Input: The MSCOCO caption of the target image, followed by a dialogue which discusses the image.
- Predict the correct image from a line up of 5/10 images.
- Levels:
  - Easy (One where it should be possible to just guess with the caption)
  - Hard? (Where the images can be chosen from the I2 distance of VGG features or have similar objects(from MSCOCO data)



### Image Retrieval from Dialogue - Given

Subset of VisDial dataset

Preprocessed Image features

**PyTorch Introduction** 

# Image Retrieval from Dialogue - Deliverables

- 1. Analyze & Preprocess language data
- 2. Implement the following approaches
  - a. BoW
  - b. Bag of Words + NLP features
  - c. RNN

#### **BONUS:**

- d. Explore various ways to combine the image and text features
- e. Your very own idea
- 3. Error Analysis of Models
- 4. Writer scientific report about your findings

### Further Reading

**VQA** 

http://visualqa.org/index.html

http://pytorch.org/tutorials/beginner/deep\_learning\_60min\_blitz.html

Image Retrieval from Language

https://visualdialog.org/

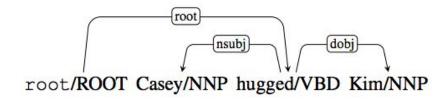
# Neural Graph-based Dependency Parsing



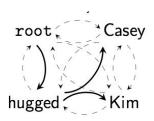
# Neural Graph-based Dependency Parsing

Analyze **grammatical structure** of a sentence; relations between heads & dependants

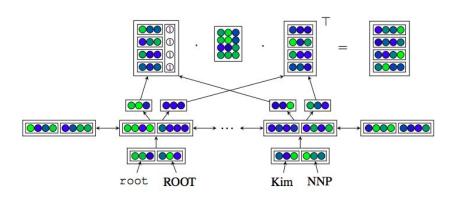
Edges go from heads to dependants:



**Graph-based** approach: calculate a weight for each edge, construct a maximum spanning tree



We will compute the weights using a **Neural Net** 



In this project you will:

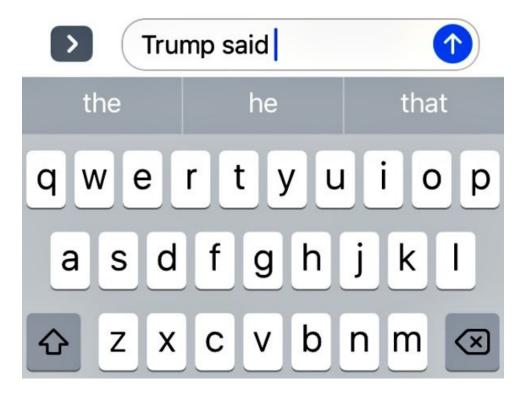
- Run an off-the-shelf parser (baseline)
- Build a state-of-the-art parser in PyTorch
   Ref. <a href="https://arxiv.org/abs/1611.01734">https://arxiv.org/abs/1611.01734</a>
- Learn & implement 2 ways to get an MST

#### Further reading

- J&M 3rd edition Ch. 14 Dependency parsing <a href="https://web.stanford.edu/~jurafsky/slp3/14.pdf">https://web.stanford.edu/~jurafsky/slp3/14.pdf</a>
- Kiperwasser & Goldberg (2016)
   Simple and Accurate Dependency Parsing Using Bidirectional LSTM Feature Representations <a href="https://aclweb.org/anthology/Q16-1023">https://aclweb.org/anthology/Q16-1023</a>
   <a href="mailto:Esp. section 5">Esp. section 5</a> (Graph based parsing)
- Dozat & Manning (2017)
   Deep Biaffine Attention for Neural Dependency Parsing https://arxiv.org/abs/1611.01734

You will need to read (1) to understand (2) to understand (3).

# Neural Language Modeling



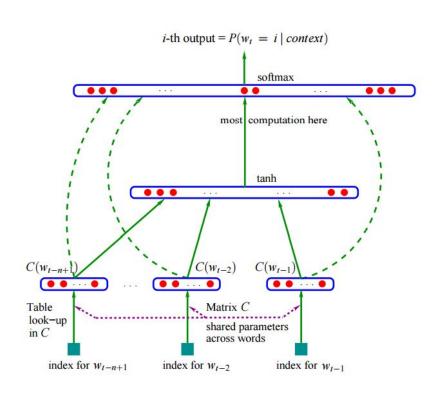
### Neural Language Modeling

A Language Model gives the **probability** of the **next word** given a **history** of previous words

It can assign a probability to a sentence

In this project you will:

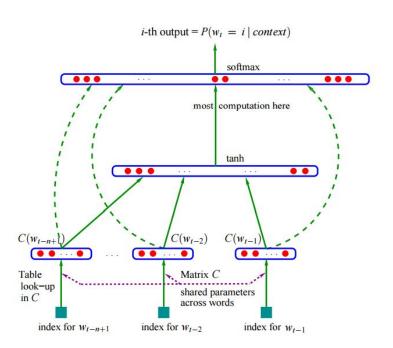
- Run an off-the-shelf LM as a baseline
- Develop your own Neural Language models in PyTorch
  - Feed-forward
  - Simple RNN
  - o RAN <a href="https://arxiv.org/abs/1705.07393">https://arxiv.org/abs/1705.07393</a>
  - ISTM
- Analyze your models, e.g. what word is in focus when generating the next word?



### Further reading

- Bengio NNLM <a href="http://www.jmlr.org/papers/volume3/bengio03a/bengio03a.pdf">http://www.jmlr.org/papers/volume3/bengio03a/bengio03a.pdf</a>
   This is a feed-forward network that predicts the next word given a **fixed** amount of previous words.
- Simple RNN LM
   <a href="http://www.fit.vutbr.cz/research/groups/speech/publi/2010/mikolov\_interspeech2010\_IS100722.pdf">http://www.fit.vutbr.cz/research/groups/speech/publi/2010/mikolov\_interspeech2010\_IS100722.pdf</a>
   A recurrent NN that (in principle) models unlimited history.
- 3. Recurrent Additive Networks <a href="https://arxiv.org/abs/1705.07393">https://arxiv.org/abs/1705.07393</a>
  RANs are a simpler version of LSTMs. This makes them not only faster to train, it also allows us to inspect which previous word was most influential in predicting the current word. Using RANs can be cool for analysis, and you can try to tweak them to get even better performance.
- 4. LSTM / GRUs
  You can also train an LSTM (or GRU) language model. See (3) for details. Note that, of all networks, training this will take the longest, especially on CPU.

#### Finding Grammar in Neural Language Models

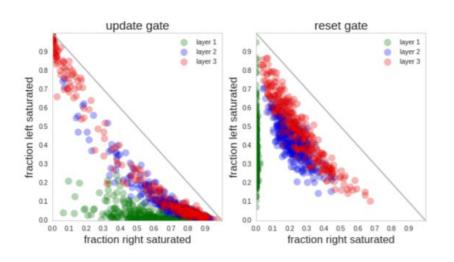


#### Goals

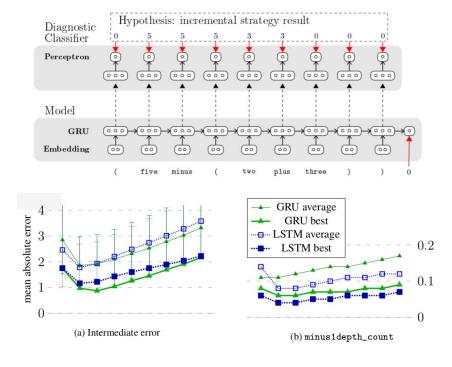
- Getting acquainted with recurrent neural network models
- Gaining a better understanding of what neural language models encode
- Testing their syntactic awareness
- Learning how to inspect and visualise the internal dynamics of recurrent networks
- Proposing methods to make them more syntactically aware

#### Methods

#### Visualising gate saturation values



#### Diagnosing symbolic strategies



#### Further Reading

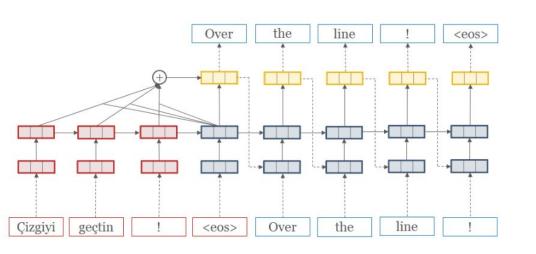
Assessing the Ability of LSTMs to learn Syntax-Sensitive Dependencies: <a href="https://arxiv.org/pdf/1611.01368.pdf">https://arxiv.org/pdf/1611.01368.pdf</a>

Visualisation and diagnostic classifiers reveal how recurrent and recursive neural networks process hierarchical structure <a href="http://dieuwkehupkes.nl/research/JAIR.pdf">http://dieuwkehupkes.nl/research/JAIR.pdf</a>

Exploring the Syntactic Abiities of RNNs with Multi-task Learning <a href="http://tallinzen.net/media/papers/enguehard\_goldberg\_linzen\_2017\_conll.pdf">http://tallinzen.net/media/papers/enguehard\_goldberg\_linzen\_2017\_conll.pdf</a>

Visualizing and Understanding Recurrent Networks <a href="https://arxiv.org/pdf/1506.02078.pdf">https://arxiv.org/pdf/1506.02078.pdf</a>

#### What do Neural Machine Translation Models do?

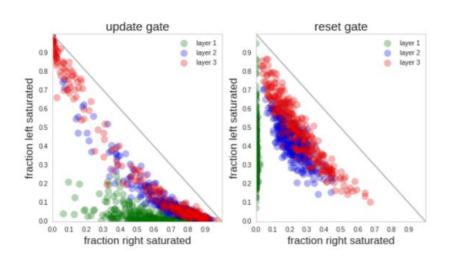


#### Goals

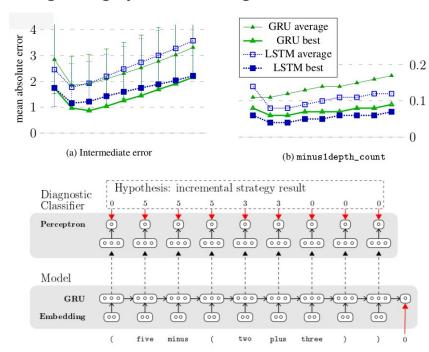
- Learning to use pretrained MT models
- Developing hypotheses about what MT models encode
- Getting an insight in what is important for neural MT models
- Learning how to inspect the dynamics of recurrent neural models

#### Using visualisation and Diagnostic Classifiers

Visualising gate saturation values



#### Diagnosing symbolic strategies



#### Further Reading

Assessing the Ability of LSTMs to learn Syntax-Sensitive Dependencies: <a href="https://arxiv.org/pdf/1611.01368.pdf">https://arxiv.org/pdf/1611.01368.pdf</a>

Visualisation and diagnostic classifiers reveal how recurrent and recursive neural networks process hierarchical structure <a href="http://dieuwkehupkes.nl/research/JAIR.pdf">http://dieuwkehupkes.nl/research/JAIR.pdf</a>

Visualizing and Understanding Recurrent Networks <a href="https://arxiv.org/pdf/1506.02078.pdf">https://arxiv.org/pdf/1506.02078.pdf</a>