Intro to Language Processing

ML@B Workshop 9 October 2018

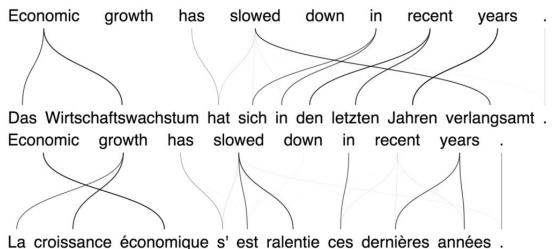
Clone this:

https://tinyurl.com/ydbk6mc7

All Around Us

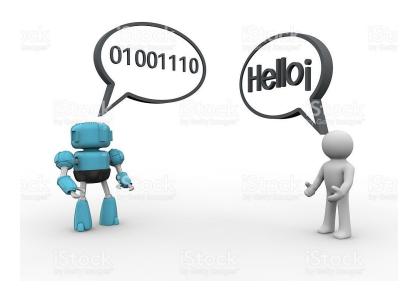






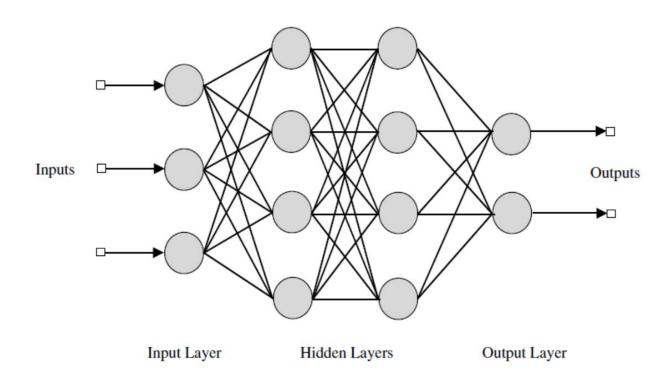
Importance

- Not everyone can code
- Allows broader audience to interact and communicate with machines



Architectures

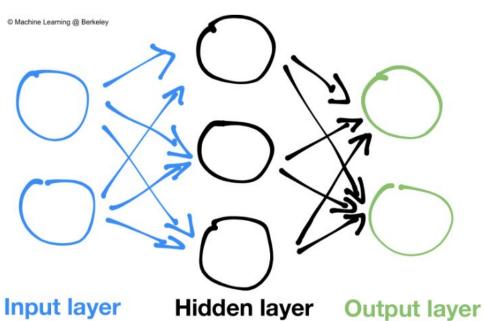
Basic Neural Network



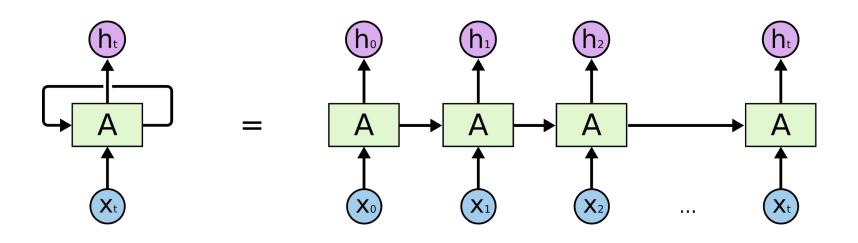
Time

Not able to represent sequential data (No time variable!)

the quick brown fox ...



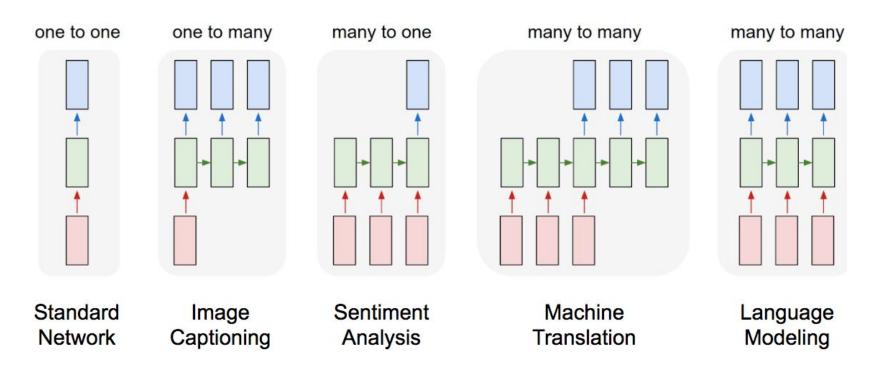
Recurrent Neural Networks (RNNs)



Math Behind the RNN

$$egin{array}{lll} oldsymbol{a}^{(t)} &= oldsymbol{b} + oldsymbol{W} oldsymbol{h}^{(t-1)} + oldsymbol{U} oldsymbol{x}^{(t)} \ oldsymbol{o}^{(t)} &= oldsymbol{c} + oldsymbol{c} oldsymbol{h}^{(t)} \ oldsymbol{o}^{(t)} &= oldsymbol{c} + oldsymbol{V} oldsymbol{h}^{(t)} \ oldsymbol{g}^{(t)} &= oldsymbol{s} &= oldsymbol{c} + oldsymbol{V} oldsymbol{h}^{(t)} \ oldsymbol{o}^{(t)} \ &= oldsymbol{s} &= oldsymbol{c} &= oldsymbol{c} + oldsymbol{V} oldsymbol{h}^{(t)} \ oldsymbol{o}^{(t)} \ &= oldsymbol{s} &= oldsymbol{s} &= oldsymbol{c} &= olds$$

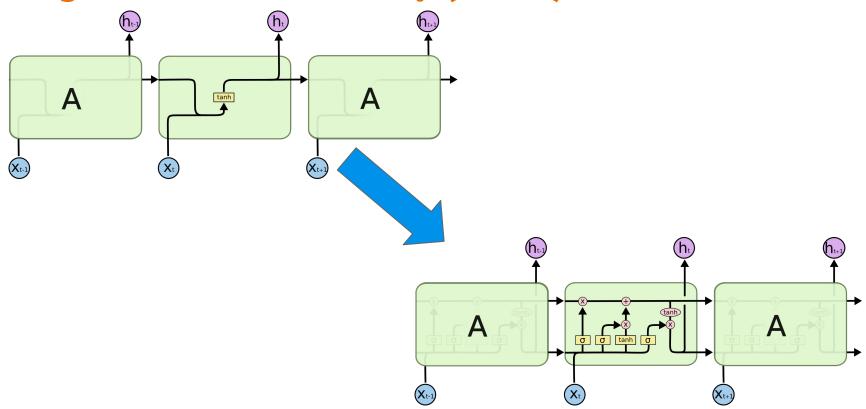
Types of RNN Layers



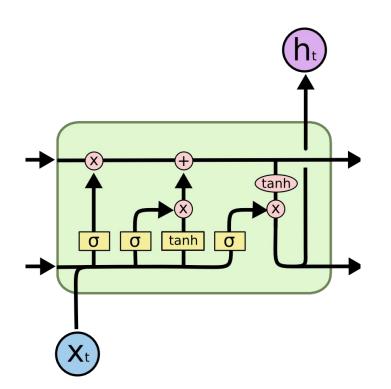
But What's Even Better?

- Math Reason: RNN's suffer greatly from vanishing gradient problem
 - Backpropagation doesn't work very well due to multiplying extremely small numbers by each other over and over again
- Intuitive Reason: RNN's always pass on the information they have
 - No way to forget old information that is no longer necessary

Long Short-Term Memory (LSTM)



LSTM in Detail



$$f_{t} = \sigma (W_{f} \cdot [h_{t-1}, x_{t}] + b_{f})$$

$$i_{t} = \sigma (W_{i} \cdot [h_{t-1}, x_{t}] + b_{i})$$

$$\tilde{C}_{t} = \tanh(W_{C} \cdot [h_{t-1}, x_{t}] + b_{C})$$

$$C_{t} = f_{t} * C_{t-1} + i_{t} * \tilde{C}_{t}$$

$$o_{t} = \sigma (W_{o} [h_{t-1}, x_{t}] + b_{o})$$

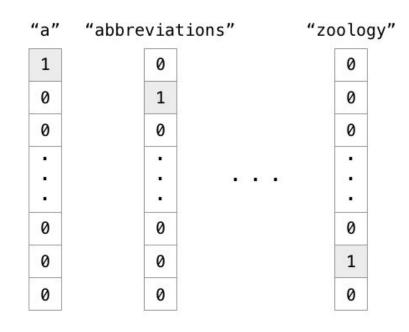
$$h_{t} = o_{t} * \tanh(C_{t})$$

Word Embeddings

How could we represent words to computers?

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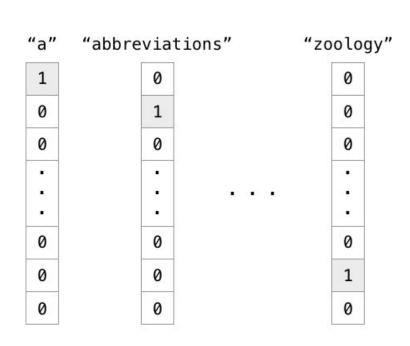
One-Hot Encoding?



How could we represent words to computers?

One-Hot Encoding?

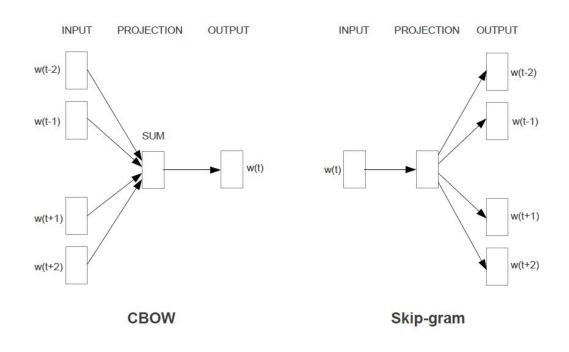
Every vector would need to have the length of our entire vocabulary size. Horribly inefficient



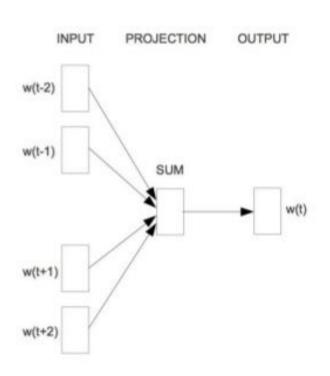
Word Embeddings!

- Every word is a vector, can be around size 200-300 rather than entire vocabulary
- Where do the vectors come from?

Learning Word Embeddings: CBOW and Skip-Gram



CBOW (Continuous Bag-Of-Words) Example



the cat climbed a tree

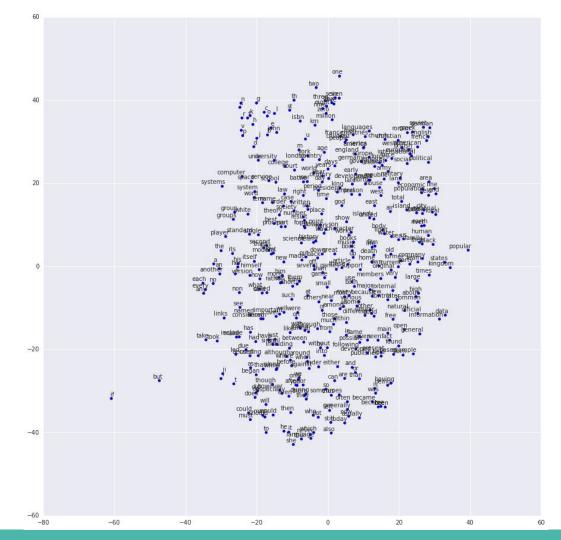
Given context:

a, cat, the, tree

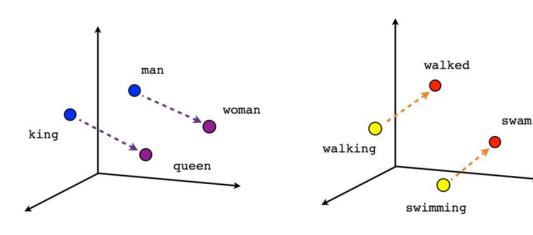
Estimate prob. of

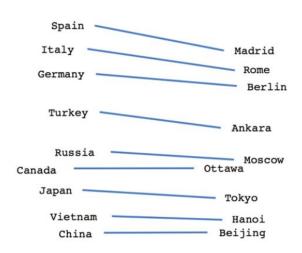
climbed

Word Embedding Demo



Cool Properties





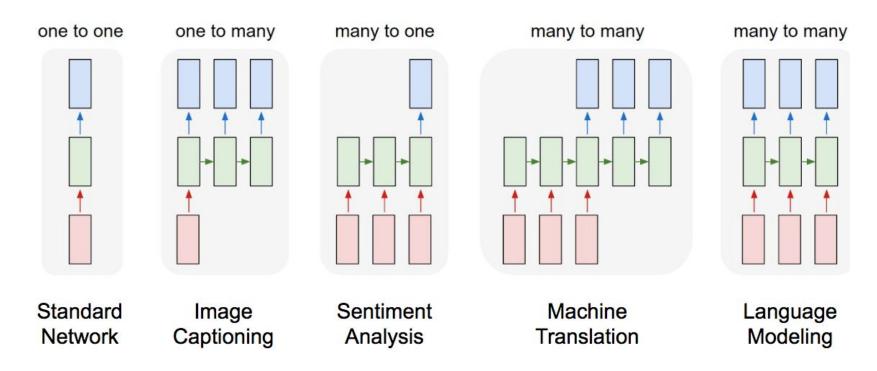
Male-Female

Verb tense

Country-Capital

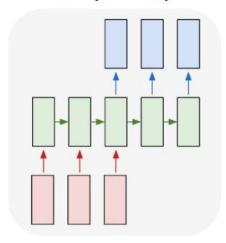
Machine Translation

Translation is a sequence-to-sequence problem.



Translation is a sequence-to-sequence problem.

many to many



Machine Translation

Variants of "Languages"

Languages can actually be quite general!

Variants of "Languages": Summarization

"Argentina coach Alejandro Sabella believes Lionel Messi's habit of throwing up during games is because of nerves. The Barcelona star has vomited on the pitch during several games over the last few seasons and appeared to once again during Argentina's last warm-up match against Slovenia on Saturday."



"Argentina coach Sabella believes Messi's habit of being sick during games is down to nerves."

CNN / Daily Mail Dataset.

Variants of "Languages": Chatbots

"Hey Alexa, what is the weather like tomorrow?"



"It's seventy-five degrees and cloudy tomorrow."

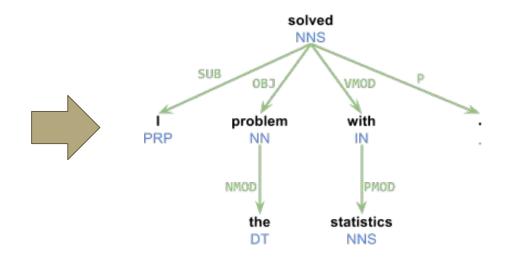
Variants of "Languages": Part-of-Speech Tagging

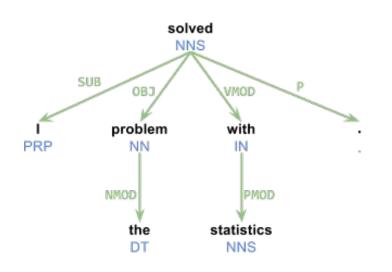
"Machine learning is cool!"



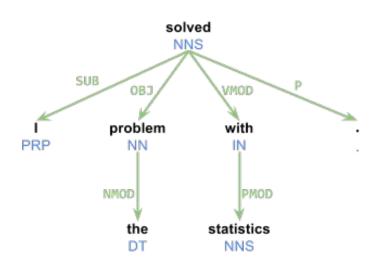
"ADJ NN VBZ JJ"

"I solved the problem with statistics."





```
[ ROOT solved NNS
   [SUBIPRP]
    [ OBJ problem NN
       [ NMOD the DT ]
    [ VMOD with IN
        [ PMOD statistics NNS ]
    [P..]
```



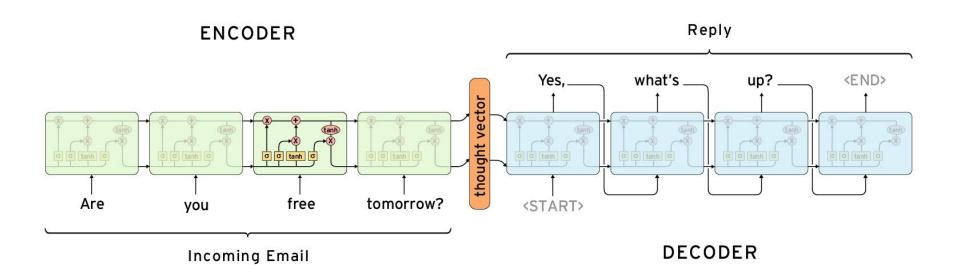
[ROOT solved NNS [SUB | PRP] [OBJ problem NN [NMOD the DT]] [VMOD with IN [PMOD statistics NNS]] [P...]]

"I solved the problem with statistics."



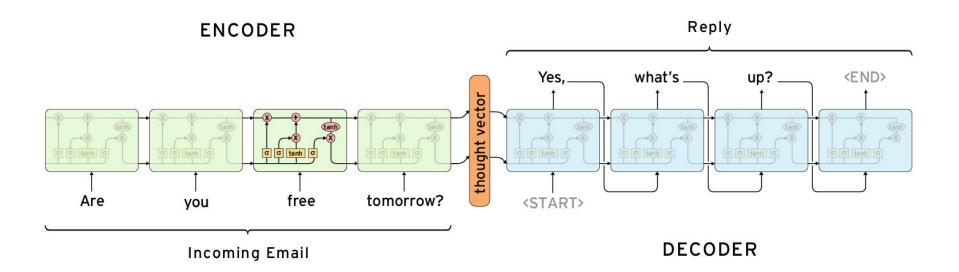
```
[ ROOT solved NNS [ SUB I PRP ] [ OBJ problem NN [ NMOD the DT ] ] [ VMOD with IN [ PMOD statistics NNS ] ] [ P . . ] ]
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Encoder-Decoder Model

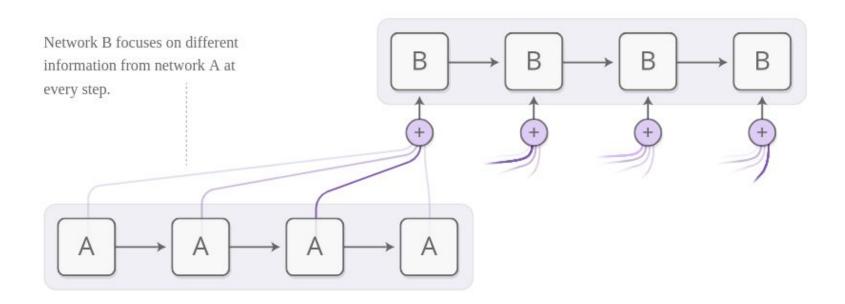


Attention

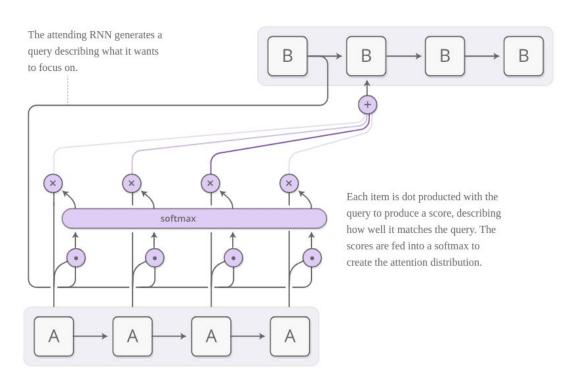
Attention: Motivation



Attention: Focus on the entire input.

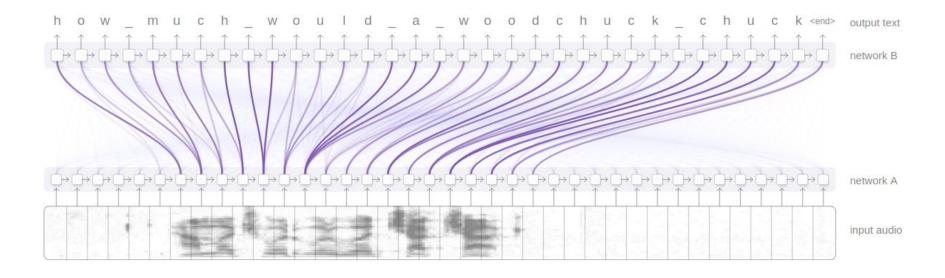


Attention: Architecture



Translation with Attention Demo

Attention: Also used for Audio



Attention: Also used for Image Captioning



a little girl sitting on a bench holding an umbrella.



a herd of sheep grazing on a lush green hillside.



a close up of a fire hydrant on a sidewalk.



a yellow plate topped with meat and broccoli.



a zebra standing next to a zebra in a dirt field.



a <u>stainless</u> steel oven in a kitchen with <u>wood</u> cabinets.



two birds sitting on top of a tree branch.



an elephant standing next to rock wall.



a man riding a bike down a road next to a body of water.

Further Reading

Transformers

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

> Llion Jones* Google Research llion@google.com

Noam Shazeer*
Google Brain
noam@google.com

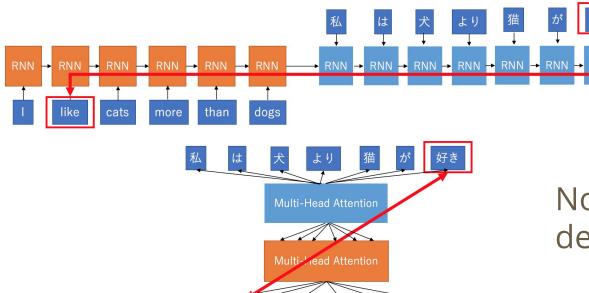
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Transformers



dogs

No more long-term dependencies!