Given a prompt, write an essay

Question: What fundamental economic and political change, if any, is needed for an effective response to climate change?

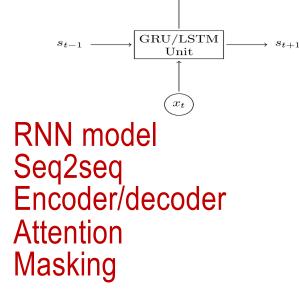
Response: Do we want to go through the same process we have been through for decades with no changes?

Is there a way to build a sustainable energy system that is both affordable and environmentally responsible? The basic premise behind this article is that we need to transform the economics of our energy system by investing in the necessary infrastructure so that it will be affordable for everyone.

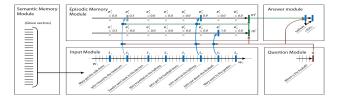
. . .

https://www.economist.com/openfuture/2019/10/01/how-to-respond-toclimate-change-if-you-are-an-algorithm

Recurrent Neural Networks (RNNs)



Lyle Ungar



Recurrent Neural Nets

Needed if you have inputs of varying length

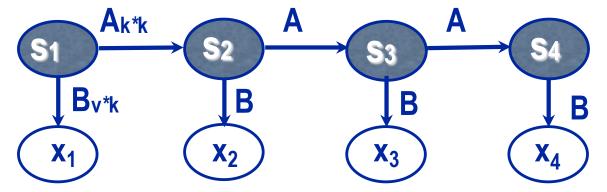
- E.g. sequence of observations
 - speech
 - text
 - robots
 - power plants, chemical plants, data centers

• RNNs are Nonlinear Hidden state dynamical models

• The generalize HMMs or Linear Dynamical Systems

Standard HMM

◆ HMM learning problem: Estimate A and B



A = Markov
transition matrix
B = emission
matrix

Estimation done via EM

• Or spectral methods

History is forgotten with an exponential decay

Why use hidden states?

Markov model on emissions

• p(w_i|w_i) is million x million

Hidden Markov Model

- $p(s_j|s_i)$ is 300 x 300 transition matrix
- p(w_j|s_i) is million * 300 matrix of emeddings

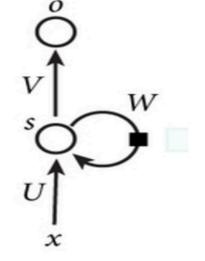
Simple Recurrent Neural Net

$$s_t = \tanh(Ux_t + Ws_{t-1})$$
$$o_t = \operatorname{softmax}(Vs_t)$$

 $x_t = input$ (e.g. a word) $s_t = hidden state$ $o_t = output$ (e.g. probability of the next word) $y_t = true$ value (e.g. x_{t+1})

Softmax $\sigma(\mathbf{z})$ transforms the K-dimensional real valued output \mathbf{z} to a distribution \mathbf{o}

$$\sigma(\mathbf{z})_j = rac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$
 for $j = 1, ..., K$

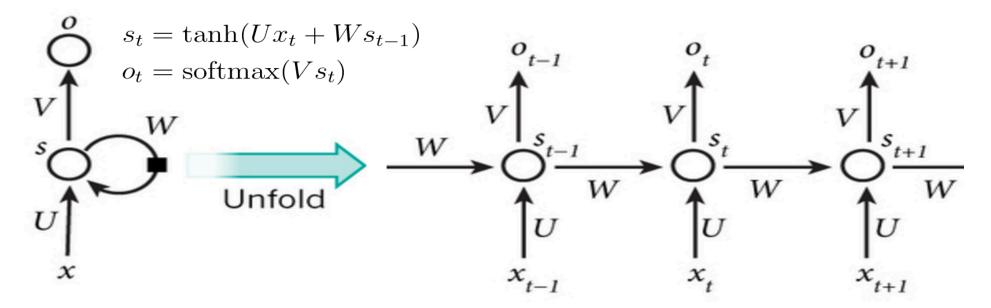


Like HMMs, unroll RNNs in time 0 O_{t-1} O_{t+1} V W W t+1W W W Unfold \boldsymbol{x} x_{t+1} x_{t-1} x,

x_t = input (e.g. a word)
s_t = hidden state
o_t = output (e.g. probability of the next word)

http://www.nature.com/nature/journal/v521/n7553/full/nature14539.html

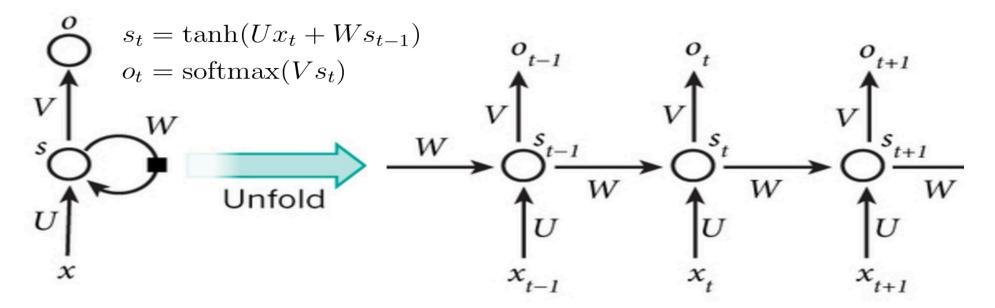
Like HMMs, unroll RNNs in time



What are the dimensions of *U*, *W*, *V*?

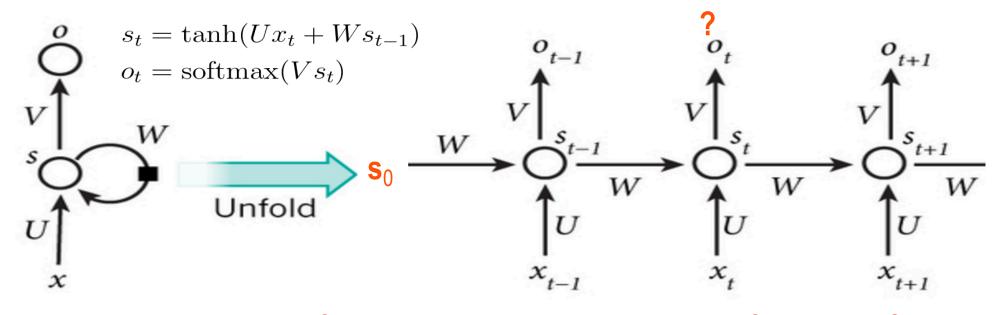
U: k*v **W**: k*k **V**: v*k

Like HMMs, unroll RNNs in time



What is the usual loss function? $-\Sigma_t \log(o_t[y_t]) - est. \text{ prob. of truth}$ where $y_t=i$ gives the true label

Like HMMs, unroll RNNs in time



 $\begin{array}{ll} \mathbf{x}_{t} = \mathbf{input} & \mathbf{v} \\ \mathbf{s}_{t} = \mathbf{hidden \ state} & -\mathbf{v} \\ \mathbf{o}_{t} = \mathbf{output} & -\mathbf{v} \end{array} \begin{array}{ll} \mathbf{f} \ \mathbf{s}_{t-2} = \mathbf{s}_{0} \ \text{, what is } \mathbf{o}_{t} \ \text{in terms of } \mathbf{s}_{0} \ \text{and } \mathbf{x} \\ \mathbf{o}_{t} = softmax(\mathbf{V}\mathbf{s}_{t}) = softmax(\mathbf{V} \ tanh(\mathbf{U}\mathbf{x}_{t} + \mathbf{W}\mathbf{s}_{t-1}) \\ = softmax(\mathbf{V} \ tanh(\mathbf{U}\mathbf{x}_{t} + \mathbf{W} \ tanh(\mathbf{U}\mathbf{x}_{t-1} + \mathbf{W}\mathbf{s}_{t-2})) \end{array}$

RNN gradients 0 o_{t-1} o_{t+1} W S W t+1Sn W W W Unfold x_{t-1} x x_{t+1} $o_t = softmax(V tanh(Ux_t + W tanh(Ux_{t-1} + Ws_{t-2})))$ **Observe** $y_t = i$ What is the stochastic gradient step? $Err = -log(o_t[i])$ Find d Err/dV, d Err/dU, d Err/dW

RNN Gradients

• $o_t = softmax(V tanh(Ux_t + W tanh(Ux_{t-1} + Ws_{t-2})))$

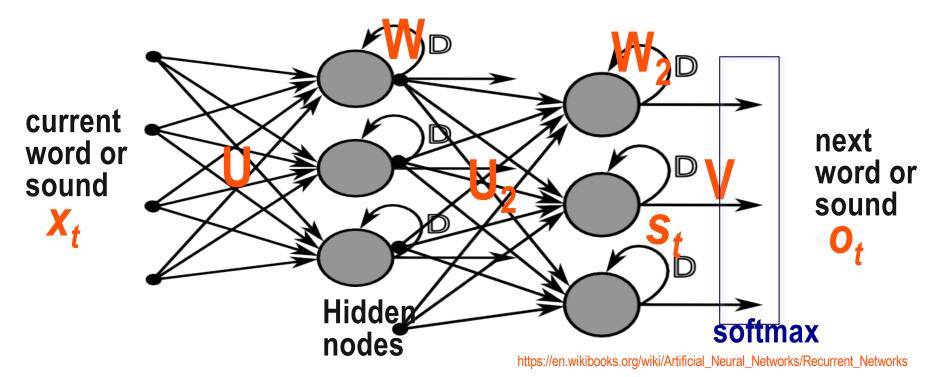
- **Observe** $y_t = i$ What is the stochastic gradient step?
- $Err = -log(o_t[i])$
- $d Err/d\mathbf{V} = -(d \log(\mathbf{o}_t[i]/d\mathbf{o}_t[i]) \quad d\mathbf{o}_t[i]/d\mathbf{V}$ $= -(1/\mathbf{o}_t[i]) \qquad d \operatorname{softmax}(\mathbf{z})/d\mathbf{z} \quad dz/d\mathbf{V}$

 $z = V tanh(Ux_t + W tanh(Ux_{t-1} + Ws_{t-2}))$

 $\frac{d \operatorname{softmax}(\mathbf{z})/dz_j = -1/(\Sigma_k e^{Z_k})^2 e^{Z_j} e^{Z_k} \quad \text{for k not equal to j}}{= -1/(\Sigma_k e^{Z_k})^2 e^{2Z_j} + e^{Z_j}/(\Sigma_k e^{Z_k})} \quad \text{for k=j}$ $\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, ..., K.$

Recurrent Neural Nets (RNNs)

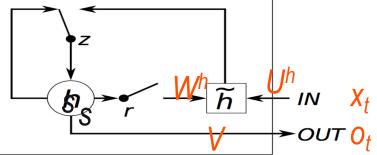
 $s_t = \tanh(Ux_t + Ws_{t-1})$ Can use multiple layers $o_t = \operatorname{softmax}(Vs_t)$



Gated RNNs

 Standard RNNs, like HMMs, tend to forget things exponentially quickly
 Solution: Gated RNN
 You conit need to know this; it's
 You conit need to know this; it's
 Just a punch of weights and xt - input
 Input traps for mations.

 $S_t = (1-z) \circ h + Z \circ S_{t-1}$ s_t : hidden state z=1 keeps state z=0 updates it to h r=1's, z=0's gives simple RNN \circ is pointwise multiplication

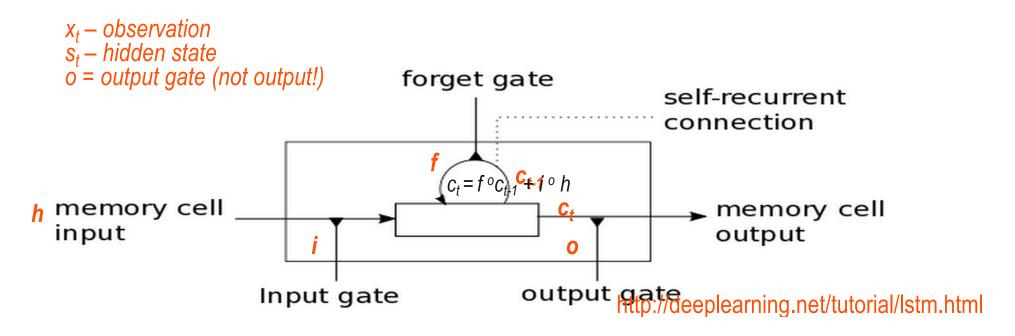


http://deeplearning.net/tutorial/lstm.html

Long Short Term Memory (LSTM)

LSTM is a kind of gated RNN

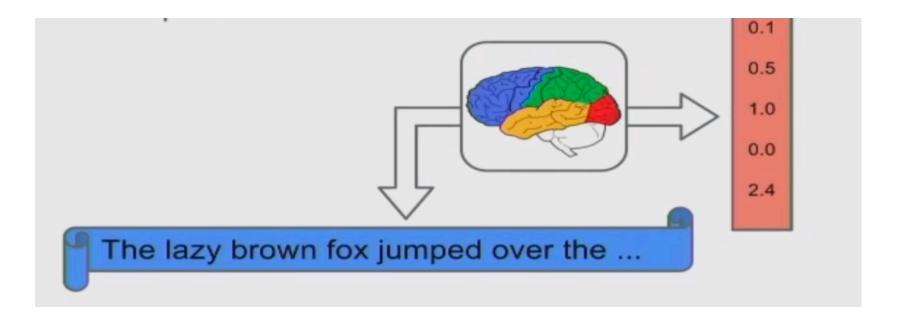
- Just with more, different gates
- Don't worry about what they are!!!



Recurrent Neural Nets

- Predict a label for each observation
 - $y_t = f(x_t, s_t)$
- Predict the next observation given past observations
 - $y_t = x_{t+1} = f(x_t, s_t)$
- Or map one sequence to another sequence
 - An encoder
 - sentence (sequence of words) to vector
 - A decoder
 - vector to sentence (sequence of words)

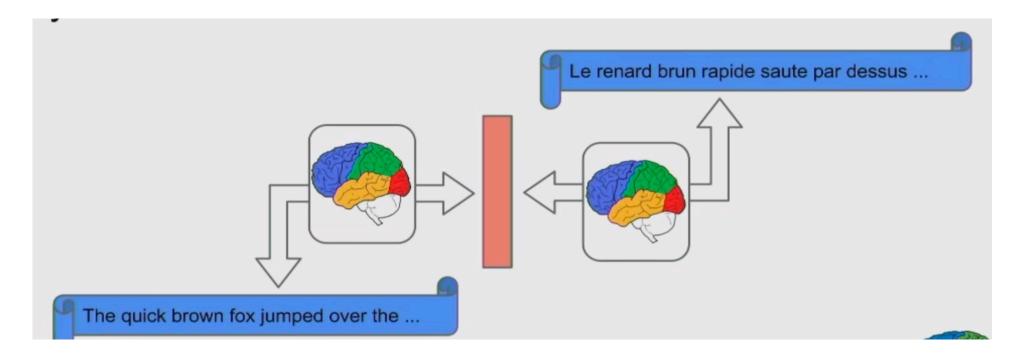
LSTM encodes a sentence



Jeff Dean, google

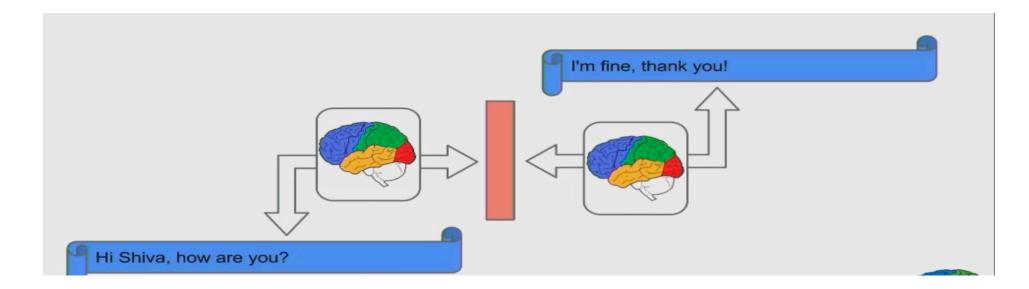
https://www.youtube.com/watch?v=90-S1M7Ny_o&spfreload=1

Sequence to sequence (Seq2seq)



Encode and Decode = translate

Seq2seq chatbot



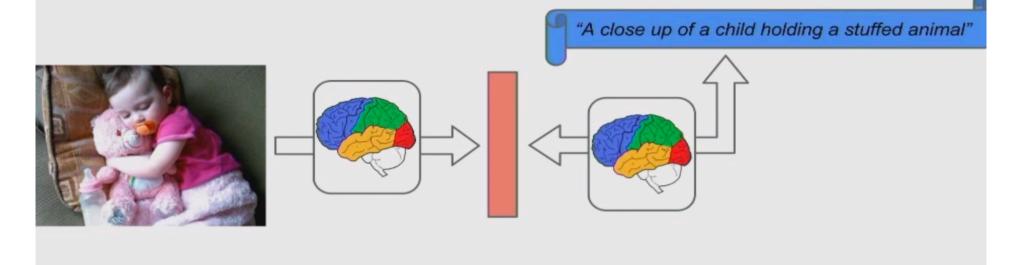
Encode and Decode = chatbot

It works (sort of)

User> hello , i have a problem with my machine BrainStop> hi BrainStop> this is shiva . BrainStop> how are you doing today ? User> hi shiva , how are you ? BrainStop> i ' m fine , thank you ! BrainStop> how may i assist you today ? User> i want to access using vpn BrainStop> currently the computer is connected to corp network ? User> no BrainStop> check this solution : BrainStop> check this solution : BrainStop> https : //INTERNAL_HOSTNAME_REDACTED / articles / connecting - to disconnecting - from - ssl - vpn # heading - 4 User> thanks , bye ! BrainStop> thank you .

Can map images to words

Connect sequence and image models, you get a captioning system



It works (sort of)



A man holding a tennis racquet on a tennis court.



A group of young people playing a game of Frisbee



Two pizzas sitting on top of a stove top oven

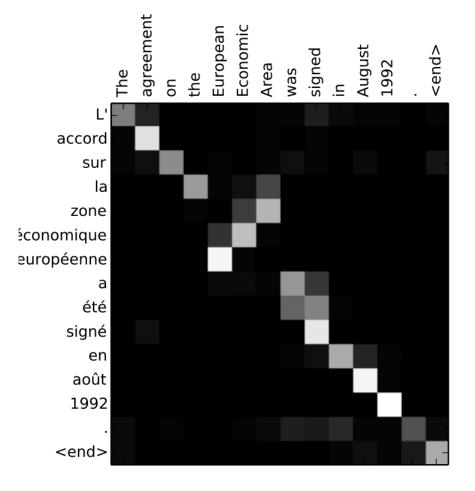


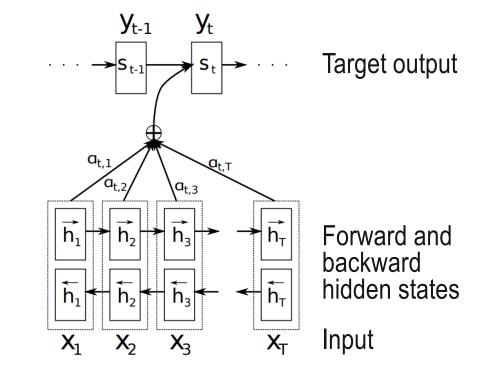
A man flying through the air while riding a snowboard

Language inputs to RNNs

- Words ("one-hot")
- Characters ("one-hot")
- Bytecodes ("one-hot")
- Word embeddings
 - Typically 300 dimensional for context-independent (Word2vec)
 - Much bigger for context-sensitive (BERT)

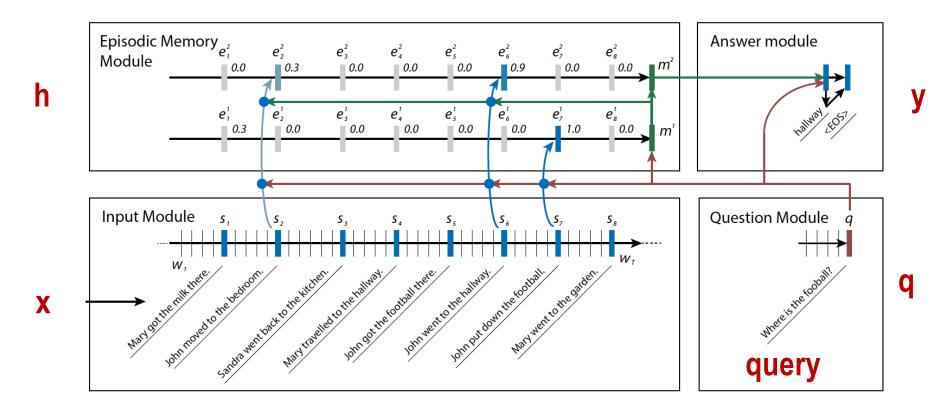
Attention-based Machine Translation





Neural machine translation by jointly learning to align and translate 2015

Attention-based Q&A



Find similarity between query and input, **x**

Ask Me Anything: Dynamic Memory Networks for Natural Language Processing

Attention-based Q&A

by ent423, ent261 correspondent updated 9:49 pm et, thu march 19,2015 (ent261) a ent114 was killed in a parachute accident in ent45, ent85, near ent312, a ent119 official told ent261 on wednesday.he was identified thursday as special warfare operator 3rd class ent23,29, of ent187, ent265." ent23 distinguished himself consistently throughout his career.he was the epitome of the quiet professional in all facets of his life, and he leaves an inspiring legacy of natural tenacity and focused

ent119 identifies deceased sailor as ${\bf X}$, who leaves behind a wife

. . .

by ent270, ent223 updated 9:35 am et, mon march 2, 2015 (ent223) ent63 went familial for fall at its fashion show in ent231 on sunday, dedicating its collection to `` mamma" with nary a pair of `` mom jeans " in sight .ent164 and ent21, who are behind the ent196 brand, sent models down the runway in decidedly feminine dresses and skirts adorned with roses, lace and even embroidered doodles by the designers ' own nieces and nephews .many of the looks featured saccharine needlework phrases like `` i love you,

X dedicated their fall fashion show to moms

Teaching Machines to Read and Comprehend 2015

Attention-based Q&A

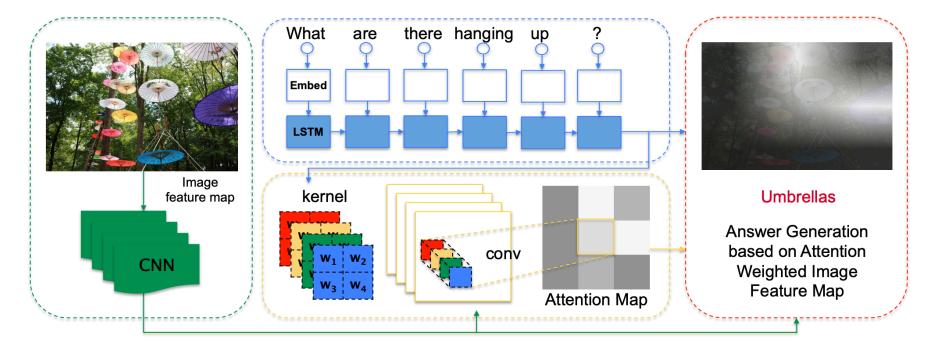
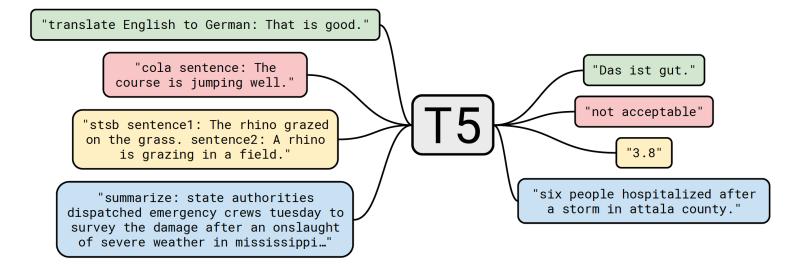


Figure 2. The framework of ABC-CNN. The green box denotes the image feature extraction part using CNN; the blue box is the question understanding part using LSTM; the yellow box illustrates the attention extraction part with configurable convolution; the red box is the answer generation part using multi-class classification based on attention weighted image feature maps. The orange letters are corresponding variables explained in Eq. (1) - (6).

ABC-CNN: An Attention Based Convolutional Neural Network for Visual Question Answering 2016

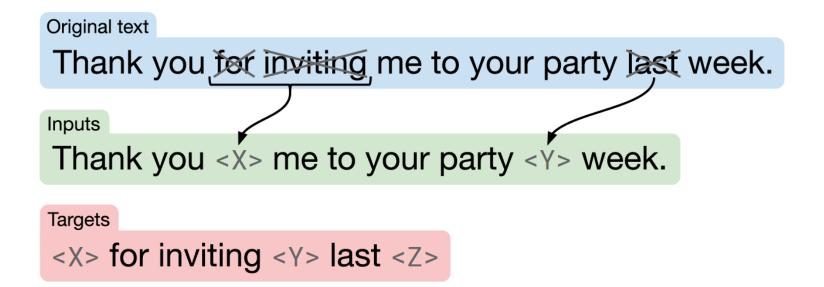
Transformer – seq2seq extension



Uses "self attention"

Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer 2019 – building on Attention is All you Need

Transformer trained using masking



Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer, 2019

GTP-3

Autoregressive Transformer model

- Input: part of a sentence
- Input: ... Time flies like ____
- Input: ... flies like an ____

- Output: the next word Output: an
- Output: arrow

♦ Use it

• Input: part of a story

Output: the rest of the story

GPT-3 is big

175 billion adjustable parameters
Trained on 500 billion words of text

- 410 billion tokens from <u>Common Crawl</u>
- 67 billion tokens from Books
- 19 billion tokens from WebText2
- 3 billion tokens from Wikipedia

Training cost \$4.6M

http://jalammar.github.io/how-gpt3-works-visualizations-animations/

GPT-3 can finish a story

Human: I am feeling bored today. Grandma, tell me a story about the time the Cat stole the sun.

AI: Okay, Let's begin. First, you must know that the sun is actually a cat. Also, you must know that the sun is actually not a cat. But it's also not a piece of cheese, or an orange, or even a gold ring. ...

https://analyticsindiamag.com/openai-gpt-3-model-machine-learning-products/

GPT-3 can finish a poem

Q: Shall I compare thee to a summer's day? Thou art more lovely and more temperate:
Rough winds do shake the darling buds of May,
And summer's lease hath all too short a date;
A: winter's day, when beams of sun are few,
And skies are grey with clouds intemperate,
Is to thy beauty somehow sordid grown.
Her lovely-lovely eye is quite shut up,

https://www.gwern.net/GPT-3

GPT-3 can translate legalese

Legal Clause: Sale of all or substantially all of the assets of the Company or a sale of shares involving a change in control (each, a "Corporate Transaction") will be treated in the same way as a liquidation and the proceeds of sale will be distributed as set out in paragraph 3. If the holders of Series A Shares have received any Special Dividend it shall be set off against their Liquidation Preference.

Plain English: If the company is sold, or a new owner takes control, the proceeds of the sale will be distributed as in the liquidation clause above. Any special dividend paid will be treated as an initial payment towards the Series A investors.

@michaeltefula

GPT-3 makes really dumb mistakes

Q: Who was president of the United States in 1600?A: Queen Elizabeth I was president of the United States in 1600.

It is great at completing patterns based on the 500 billion words it has read, but it isn't able to do reasoning, or to answer questions about things it hasn't seen. It writes great prose, and makes dumb mistakes

https://mindmatters.ai/2020/07/gpt-3-is-mindblowing-if-you-dont-question-it-too-closely/

GPT memorizes a lot

- Q. What do you call a droid that takes the long way around?
 - A. R2 detour.
- ♦ Q. Why was 6 afraid of 7?
 - A. Because 7 8 9!
- ♦ Q. What did the Dalmatian say after lunch?
 - A. That hit the spot!

https://www.gwern.net/GPT-3#dad-jokes

GPT is less impressive otherwise

◆ Q. When does a joke become a "dad" joke?

- A. When it's not funny.
- Q. How do you stop an astronaut's baby from crying?
 - A. You go into space!

◆ Q. How does a vampire start a letter?

• A. Dear blood.

https://www.gwern.net/GPT-3#dad-jokes

What you should know

- Recurrent Neural Nets (LSTMs) generalize HMMs, Kalman filters
- They have replaced HMMs for speech-to-text and machine translation
 - Now used (as "Transformers") for natural language generation
- Lots of black magic "engineering"
 - Number and size of layers, regularization
 - Forms of gating (LSTM ...), attention, masking
 - Gradient descent can be tricky
 - "Fine tune" a model that was trained on an enormous data set