10707
Deep Learning: Spring 2021

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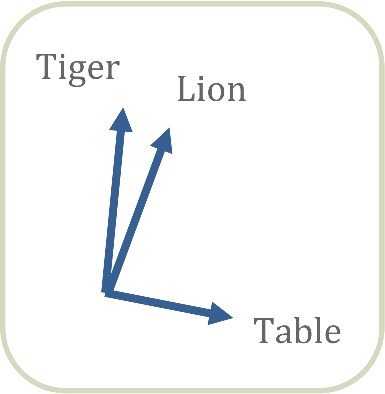
Machine Learning Department

Lecture 21:
The characters of modern NLP – transformers, ELMo and BERT

Word embeddings

Semantically meaningful **vector representations** of words



Example: Inner product (possibly scaled, i.e. cosine similarity) correlates with word similarity.

Word embeddings

Semantically meaningful **vector representations** of words

Example: Can use embeddings to do sentiment classification by training a simple (e.g. linear) classifier

Word embeddings

Semantically meaningful **vector representations** of words

Example: Can train a “simple” network that if fed word embeddings for two languages, can effectively translate.

Word embeddings

The main issue: embeddings are context-independent.

Seems intuitively wrong: determining the meaning of "bank" in

"*Walking along the river bank*" and "*A bank accepts deposits*"

depends on the surrounding context ("river" and "deposits" being the strong indicators of meaning).

One way to handle this? Recurrent neural nets!

Recurrent neural networks

Recurrent neural networks: autoregressive model that can be extended to arbitrary length sequences.

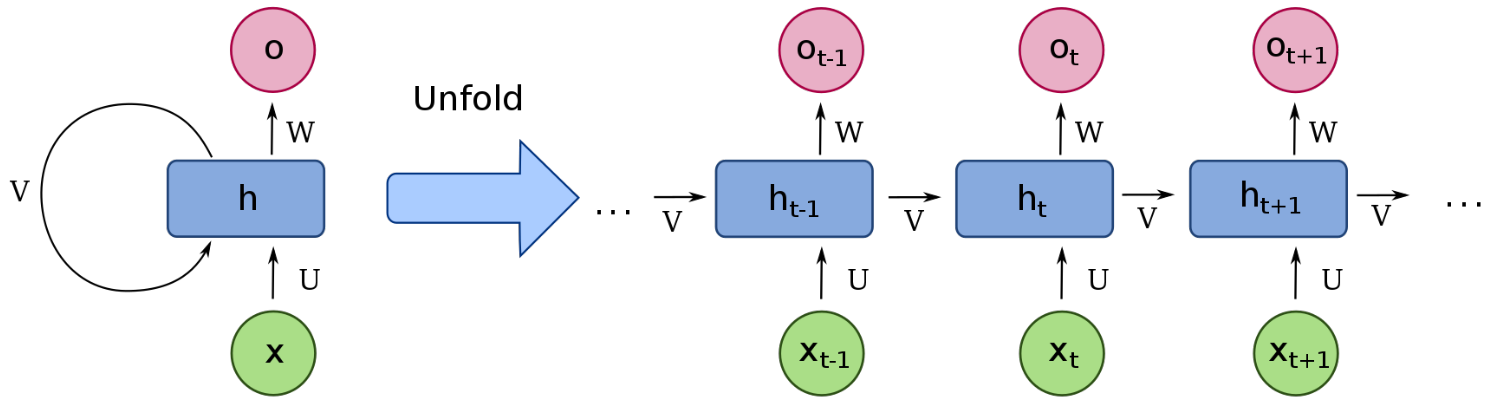
$$h_i = \tanh(W_{hh} h_{i-1} + W_{xh} x_i)$$
$$o_i = W_{hy} h_i$$

o_i specifies parameters for $p(x_i | x_{<i})$, e.g. $\text{softmax}(y_i)$

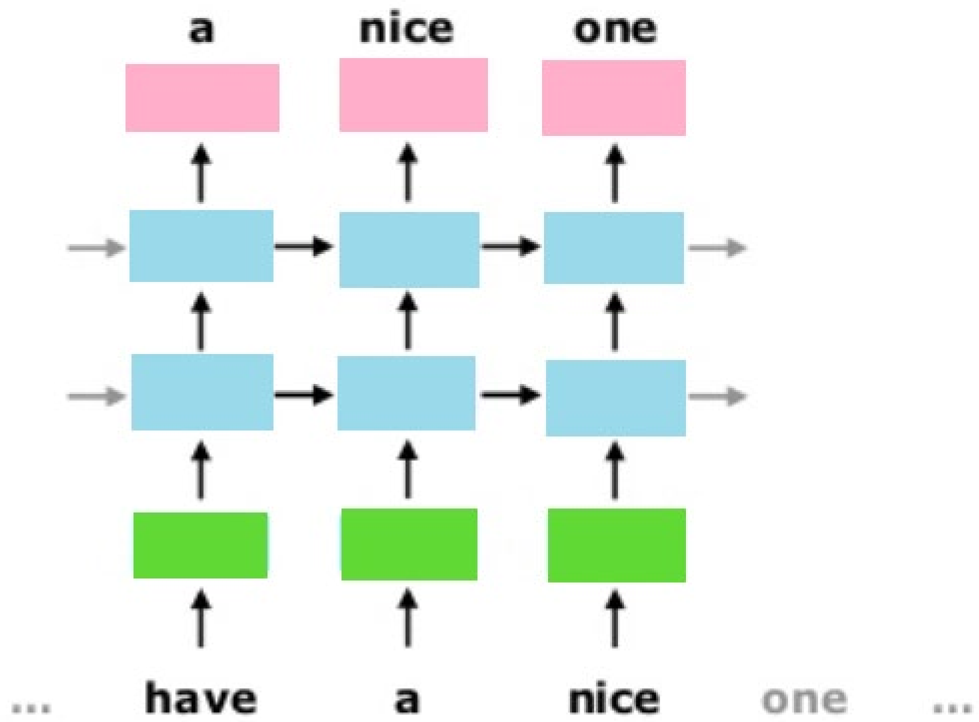
Repurposing RNNs to learn context-dependent embeddings:

think of x_i as one-hot encoding of words, W_{xh} as a $\dim(h)$ word embedding matrix, and h as a context-dependent encoding

Recurrent neural networks: graphical representation

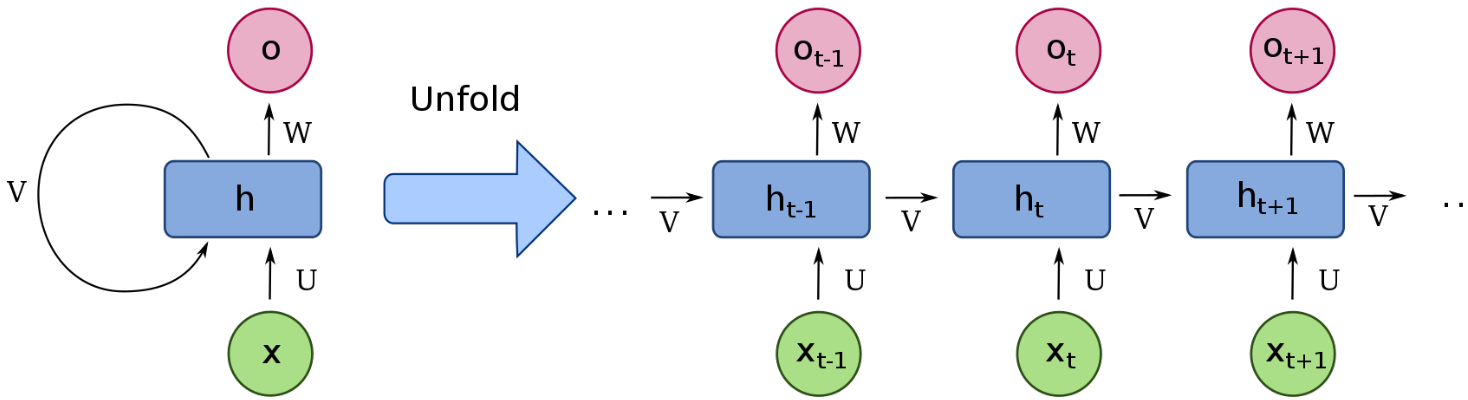


Recurrent neural networks: stacking multiple RNNs



It is quite natural to stack multiple RNNs in the obvious way

Recurrent neural networks



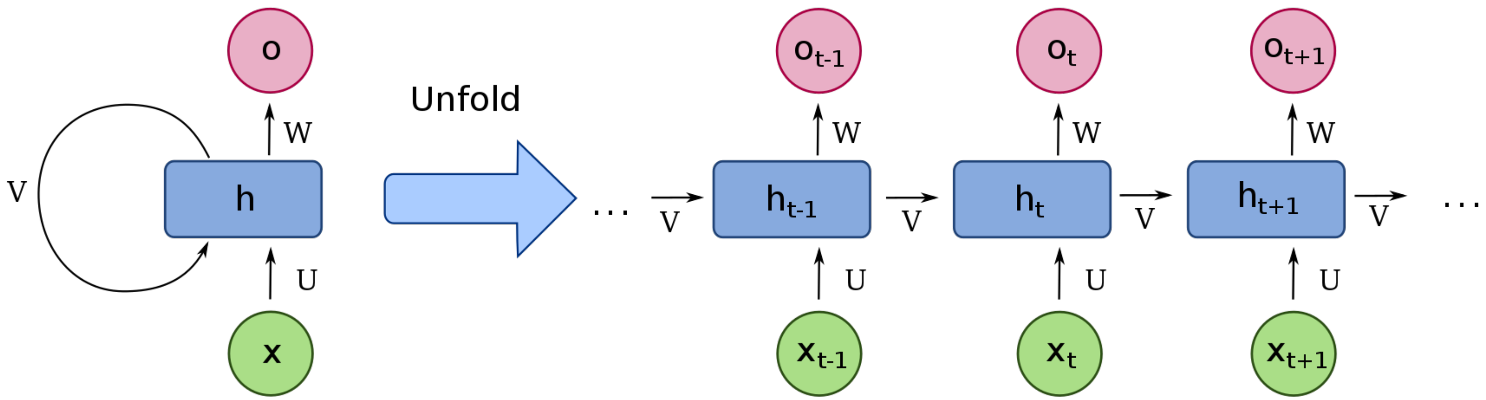
Obvious benefit: copious weight tieing, number of params completely independent of length.

Drawbacks:

<u>Training</u>: backpropagation. Via unfolding equivalence above, same as calculating derivative of a length-t feedforward network.

Same problem as in very deep networks: *gradient explosion/vanishing!*

Recurrent neural networks



Obvious benefit: copious weight tieing, number of params completely independent of length.

Drawbacks:

<u>Training</u>: *gradient explosion/vanishing!*

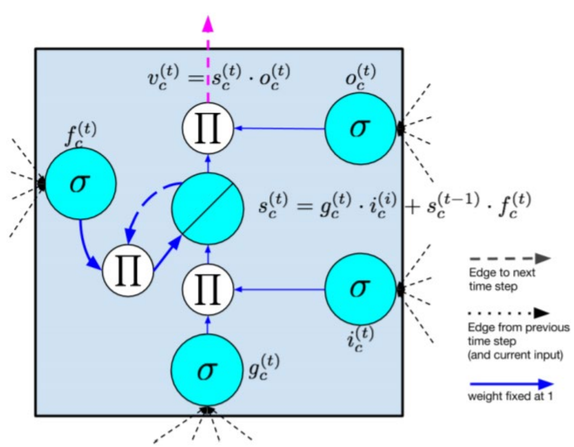
<u>Likelihood evaluation</u>: has to be done **sequentially** (no parallelization, can't really leverage GPUs)

LSTM (Long Short-Term Memory)

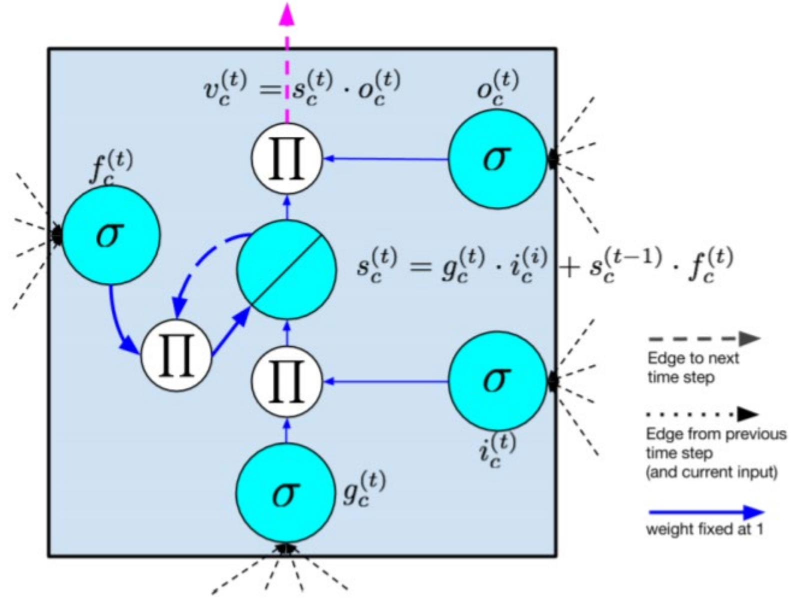
The main issue with training RNN's is long-term dependencies (and correspondingly exploding/vanishing gradients)

The main idea of **LSTM's** (*Hochreiter and Schmidhuber '97*): are gating mechanisms that try to control the flow of information from past.

In practice, they seem to suffer much less from gradient vanishing/explosion. (No good theoretical understanding.)



LSTM (Long Short-Term Memory)



<u>Ingredients</u>:

Input node: $\boldsymbol{g}^{(t)} = \phi(W^{\mathrm{gx}}\boldsymbol{x}^{(t)} + W^{\mathrm{gh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_g)$

Input gate: $\boldsymbol{i}^{(t)} = \sigma(W^{\mathrm{ix}}\boldsymbol{x}^{(t)} + W^{\mathrm{ih}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_i)$

Input node will be "gated" by pointwise multiplication with input gate: how input "flows"

Forget gate: $\boldsymbol{f}^{(t)} = \sigma(W^{\mathrm{fx}}\boldsymbol{x}^{(t)} + W^{\mathrm{fh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_f)$

Will gate the "internal state"

Output gate: $\boldsymbol{o}^{(t)} = \sigma(W^{\mathrm{ox}}\boldsymbol{x}^{(t)} + W^{\mathrm{oh}}\boldsymbol{h}^{(t-1)} + \boldsymbol{b}_o)$

How output "flows"

Internal state: $\boldsymbol{s}^{(t)} = \boldsymbol{g}^{(t)} \odot \boldsymbol{i}^{(i)} + \boldsymbol{s}^{(t-1)} \odot \boldsymbol{f}^{(t)}$

Combine gated version of prev. state w/ forget gate, along with gated input node.

Hidden state: $\boldsymbol{h}^{(t)} = \phi(\boldsymbol{s}^{(t)}) \odot \boldsymbol{o}^{(t)}.$

The parade of Sesame Street: ELMo

Recall our motivating example for the meaning of "bank":

"*Walking along the river bank*" and "*A bank accepts deposits*"

The problem with using an RNN/LSTM is that in the first case, the context for bank is provided by "river" – which comes before it; in the latter by "deposits", which comes after it.

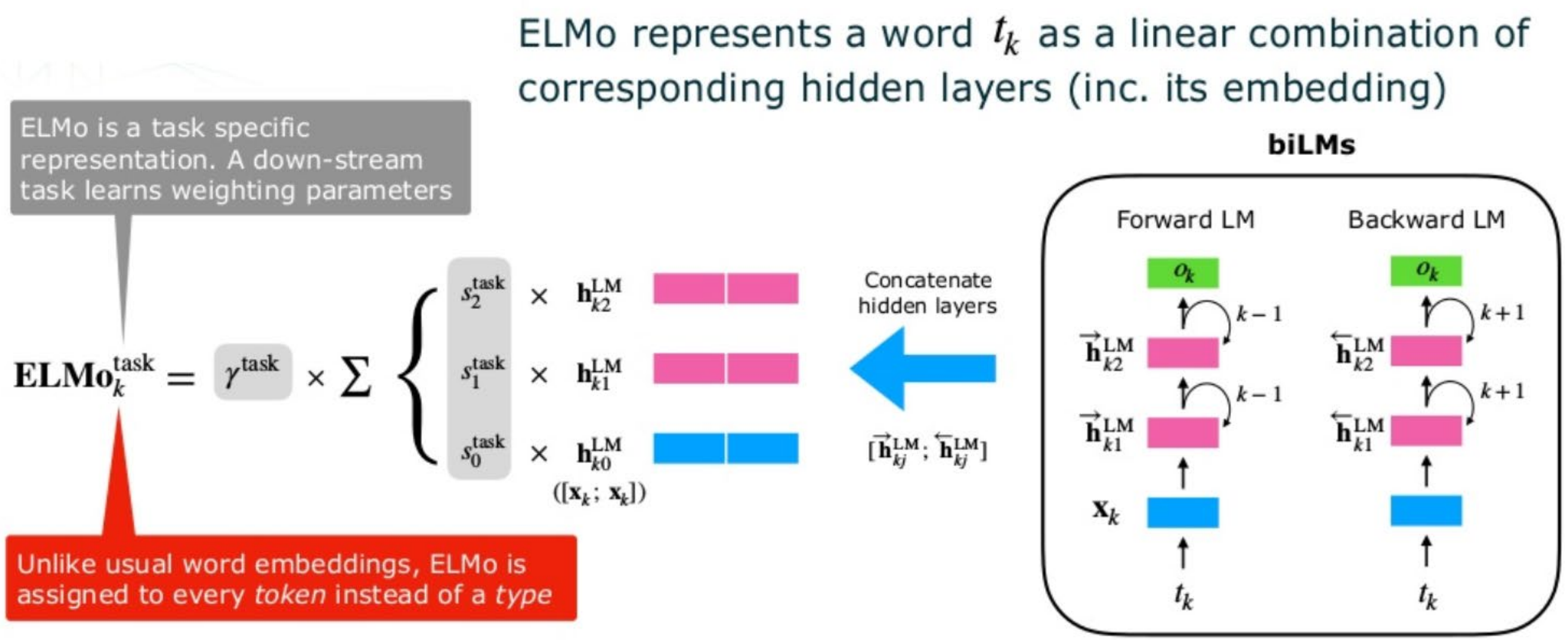
A language model is "unidirectional" – the embedding for a position only depends on previous words.

How can we introduce bidirectionality?

The parade of Sesame Street: ELMo

Peters et al '18: **ELMo** (Embeddings from Language Models)

Train one (stacked) LSTM model to model $p_\theta(x_t|x_{<t})$ and another LSTM to model $p_\theta(x_t|x_{>t})$. Concatenate two representations. (For downstream tasks, linearly combine tasks with learned weights.)



Slide from Matthew Peters

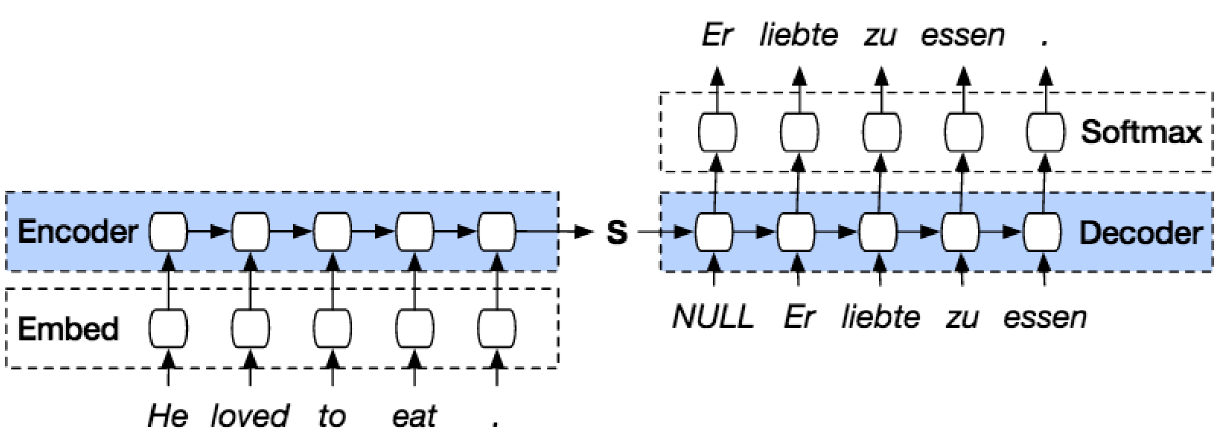
Brief diversion: machine translation

Despite handling gradients better than RNNs, LSTMs are still rather difficult to train, and struggle with long-term dependencies.

A new generation of models that displaced recurrent modern models altogether was initiated by a paper by *Vaswani et al '17*: "Attention is all you need".

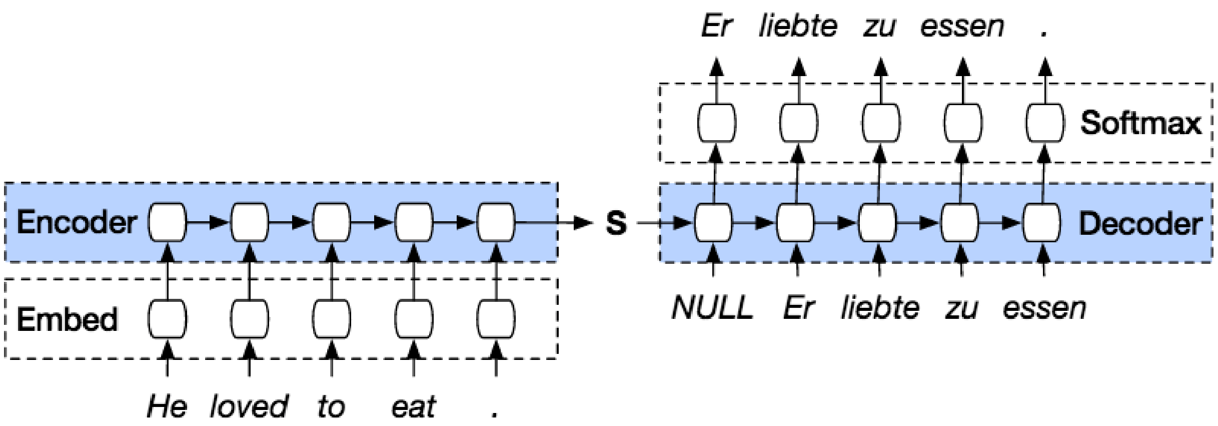
The most natural way to introduce the ideas is through sequence to sequence tasks, in which we try to map sequence in one domain to another.

Most natural instantiation: machine translation.



The encoder/decoder framework

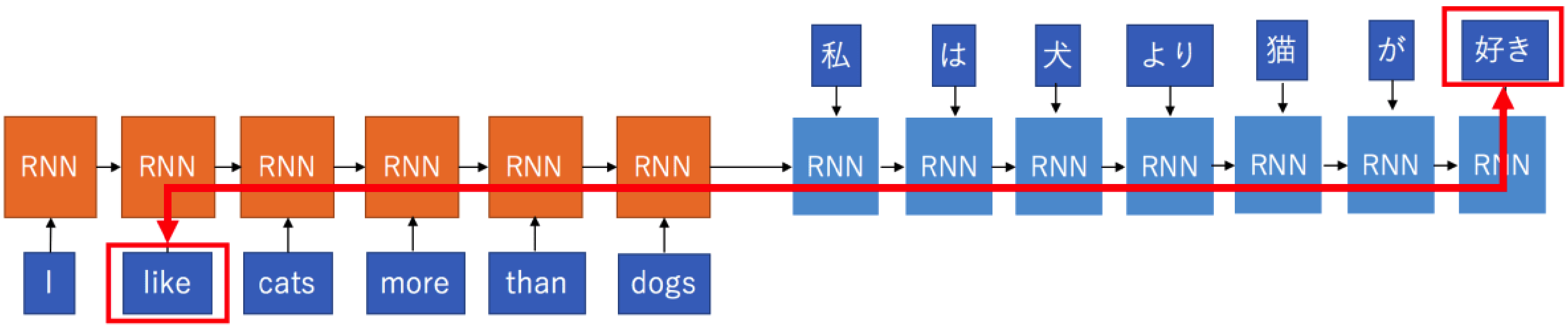
Most natural instantiation: machine translation.



Typical high-level architecture: an **encoder** transforms input to an intermediate representation (i.e. *lingua franca*), and a **decoder** transforms intermediate representation to target sequence.

RNN-based encoder/decoders

Earliest incarnation: Sutskever et al. ’14 – just use RNNs.



As expected, long sentences are a problem. Training is also inherently sequential due to the nature of a recurrent network.

Attention

Attention: when translating a certain word in a sentence, certain words matter more than others. If we can determine which ones matter, that could replace recurrent network.

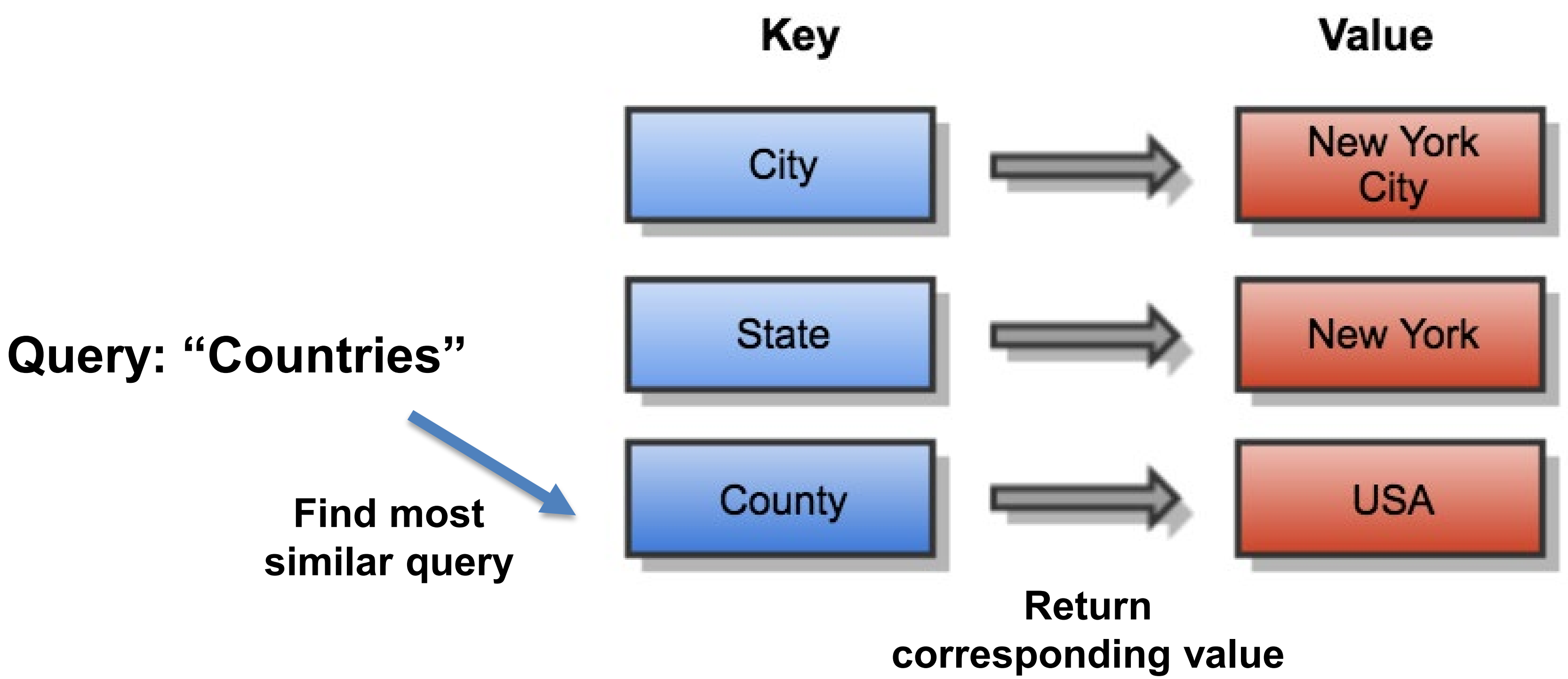
The animal didn't cross the street because it was too tired.
L'animal n'a pas traversé la rue parce qu'il était trop fatigué.

The animal didn't cross the street because it was too wide.
L'animal n'a pas traversé la rue parce qu'elle était trop large.

E.g. "it" refers to "animal" in first sentence, and "street" in second. These have different genders in French ("'il" and "elle"), so system needs to understand which word to "attent" to when translating "it".

Attention

Intuition for attention comes from databases: a key operation is given a **query**, find the relevant **key**, and lookup the corresponding **value**.



Attention

A more "differentiable" variant of this:

$$\text{Attention}(q, K, V) = \sum_i \text{similarity}(q, K_i) V_i$$

Vector

Matrices w/ rows keys/values

Linear combination of "most similar" values

The simplest notion of similarity: inner product.

$$\text{Attention}(q, K, V) = \sum_i \text{softmax}(\langle q, K_i \rangle) V_i$$

Produces distribution over keys

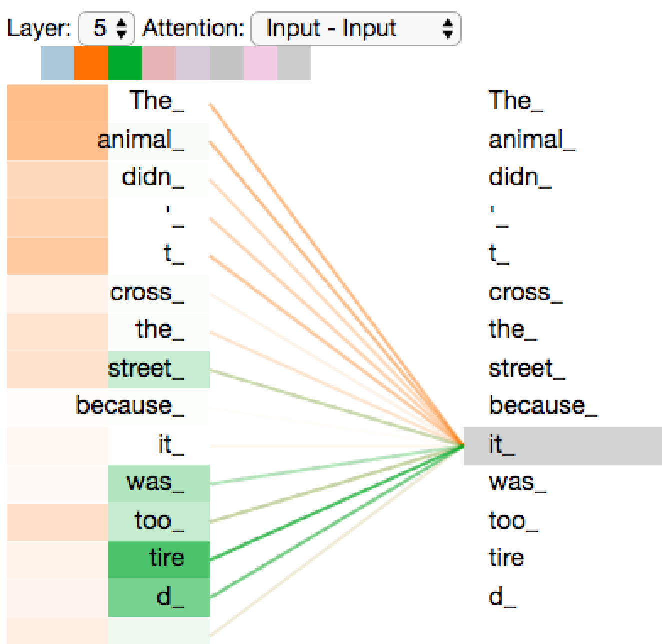
Produces distribution over values

Multiple queries combined in matrix Q: $\text{Attention}(Q, K, V) = \text{softmax}(QK^T)V$

Attention

Multiple queries combined in matrix Q: $\text{Attention}(Q, K, V) = \text{softmax}(QK^T)V$

Example usage (e.g. translation): use each word as query for each other word in the sentence (e.g. what are the "relevant" words to translate it).



(Each color denotes a different learned mechanism – e.g. orange and green "attend" to different things.)

Pro: Unlike RNN, computation can be done in parallel. (Good for GPU-based training.)

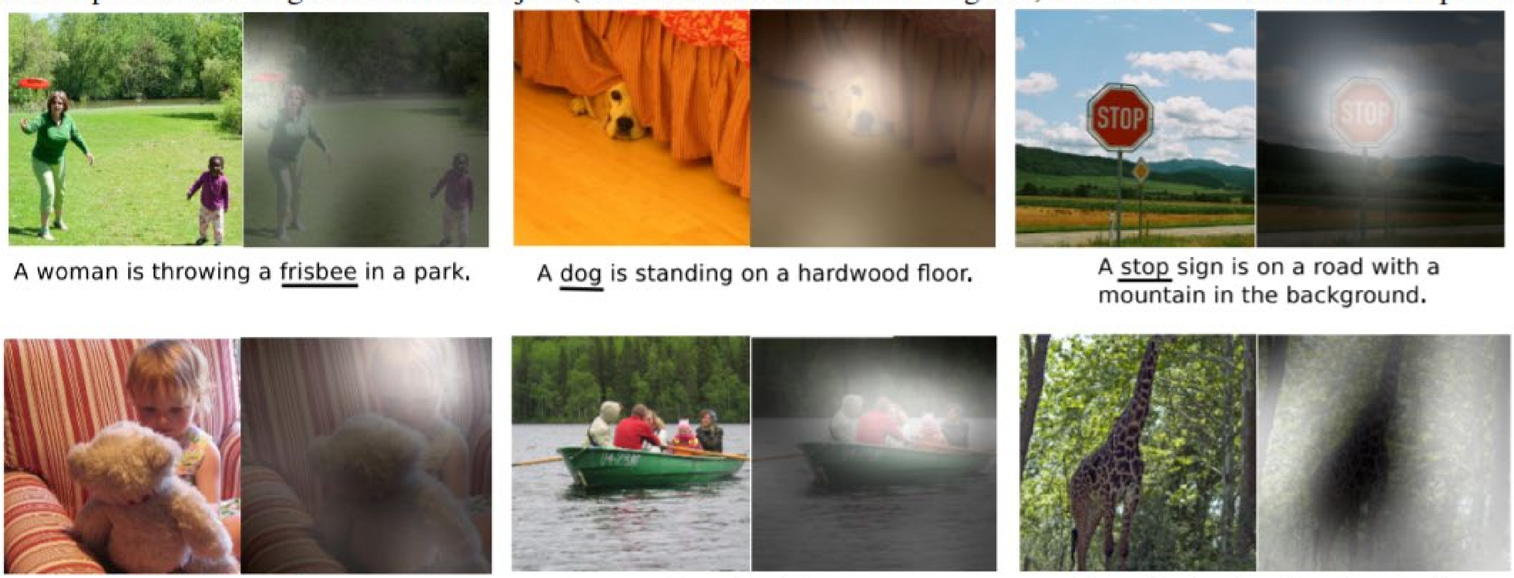
Con: Computation takes $\sim N^2$ on sequences of length N.

http://jalammar.github.io/illustrated-transformer/

Attention

An example using attention-based architectures for captioning.

Figure 3. Examples of attending to the correct object (*white* indicates the attended regions, *underlines* indicated the corresponding word)



A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Figure from “Show, Attend and Tell“ by Xu et al, 2016.

Transformers: using attention

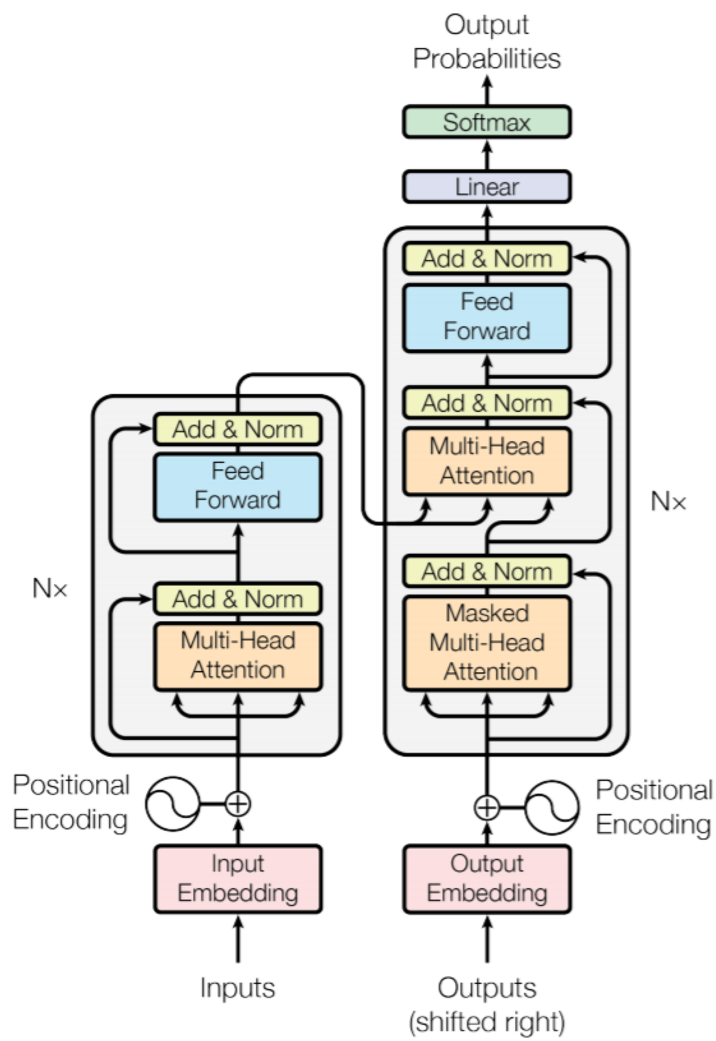
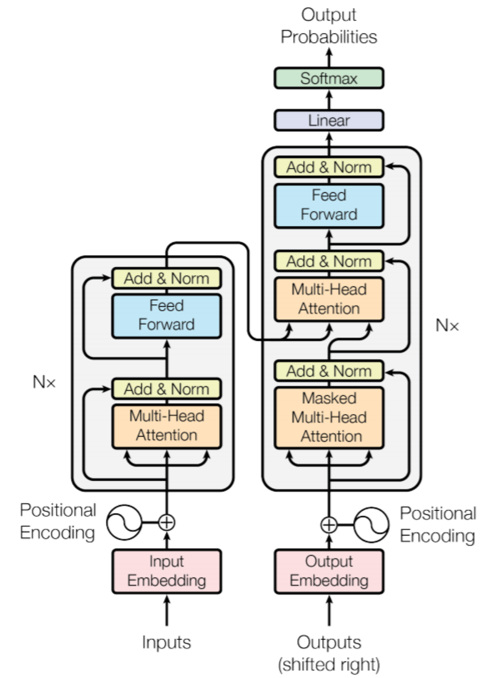


Figure from Vaswani et al ’17: “Attention is all you need”.

Transformers: encoder



Part 1: Multi-head self-attention

Self-attention: Attention(Q, K, V) where:

The queries/keys/values Q_i, K_i, V_i all correspond to vectors for each word i in input sequence.

In other words, decide what the relevant input context is for every input word.

Multi-head: instead of a single attention mechanism, (linearly) project Q, K, V multiple times, and learn self-attention w/ projected vectors.

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

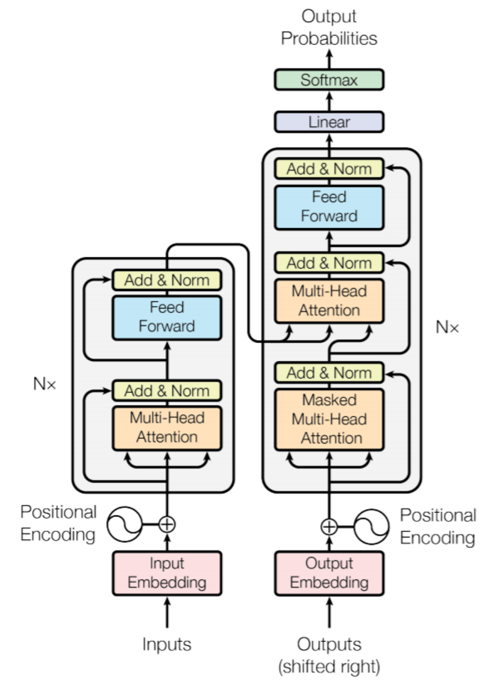
Where the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

Transformers: encoder

Part 2: Positional encoding

We'd like the embedding fed into the stack of attention mechanisms to have some dependence on position. The authors choice: combine position-independent embedding (additively) with (*quite weird* choice!)

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$



Part 3: Non-linearities

The output of each attention block is fed through a non-linearity, represented by a feed-forward network.
The "Add & norm" layers renormalize layers to whiten mean/covariance (similar as batch norm, except per layer rather than per node).

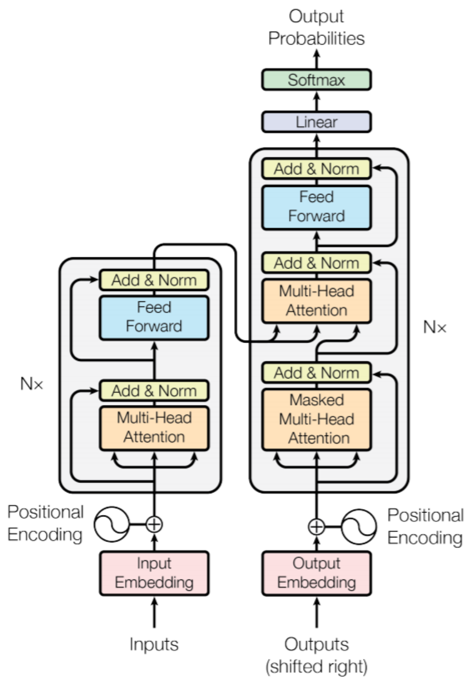
Transformers: decoder

Part 1: Attention b/w encoder and decoder

Queries: outputs of encoder (one per word in sequence)

Values/keys: output sequence (one per word in sequence)

Learn which parts of input to attend to
when building translations for parts of output.

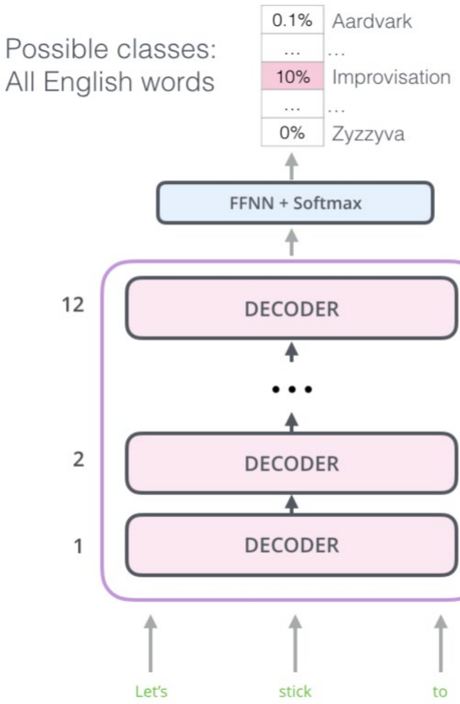


Remaining parts: basically the same as encoder.

Only important difference: multi-head self-attention is *masked* to only allow attending to prior symbols. (This is because the model can't be allowed to look ahead to predict next word in loss.)

Using transformers for feature learning: the obvious way

The obvious way to use this architecture to simply extract features: use a decoder only!



GPT 1/2/3: Transformer-based architectures due to OpenAI

Figure from http://jalammar.github.io/illustrated-bert/

Using transformers for feature learning: the obvious way

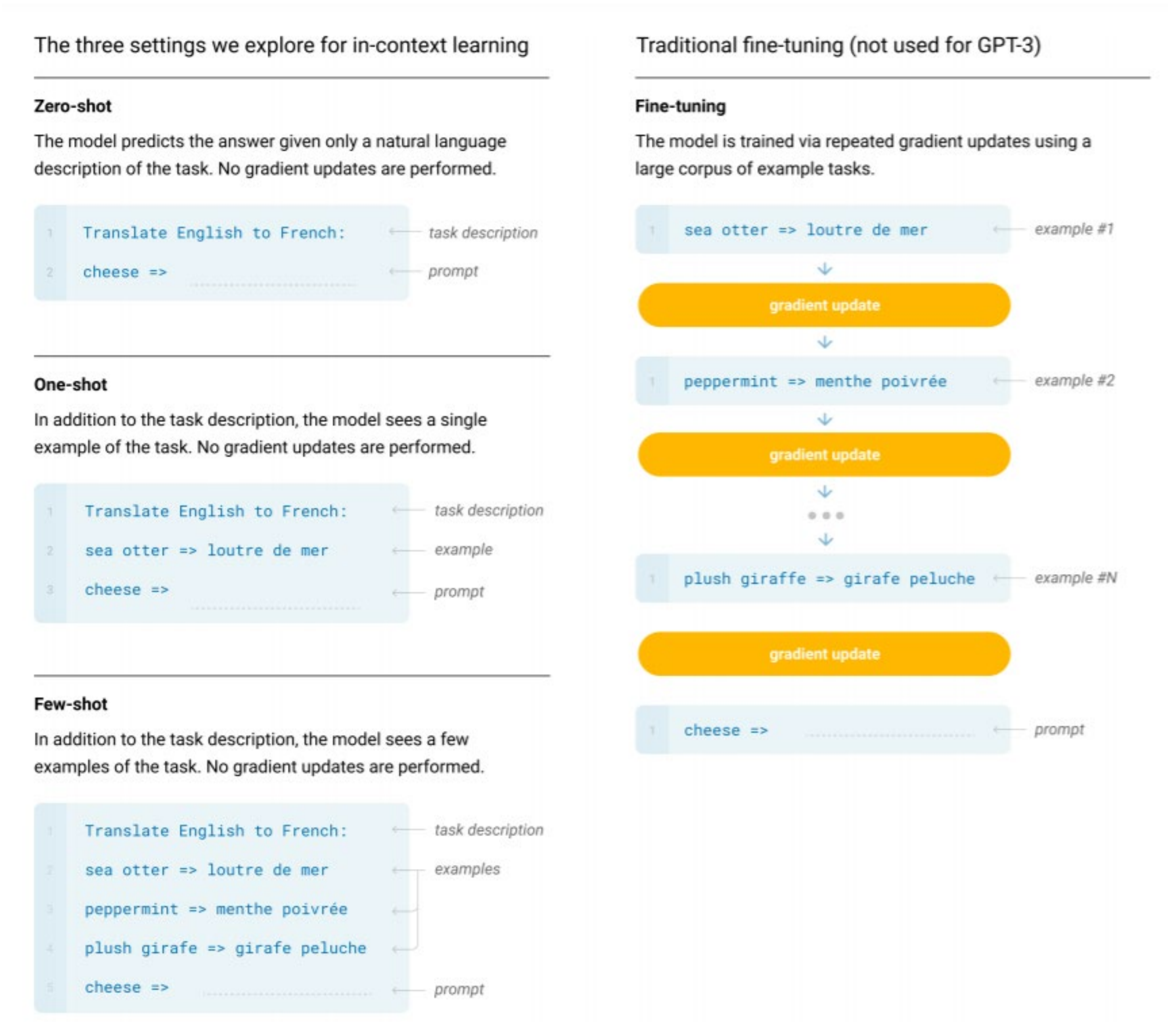


Figure from "Language Models are Few-Shot Learners", Brown et al 2020

Using transformers for feature learning: the obvious way

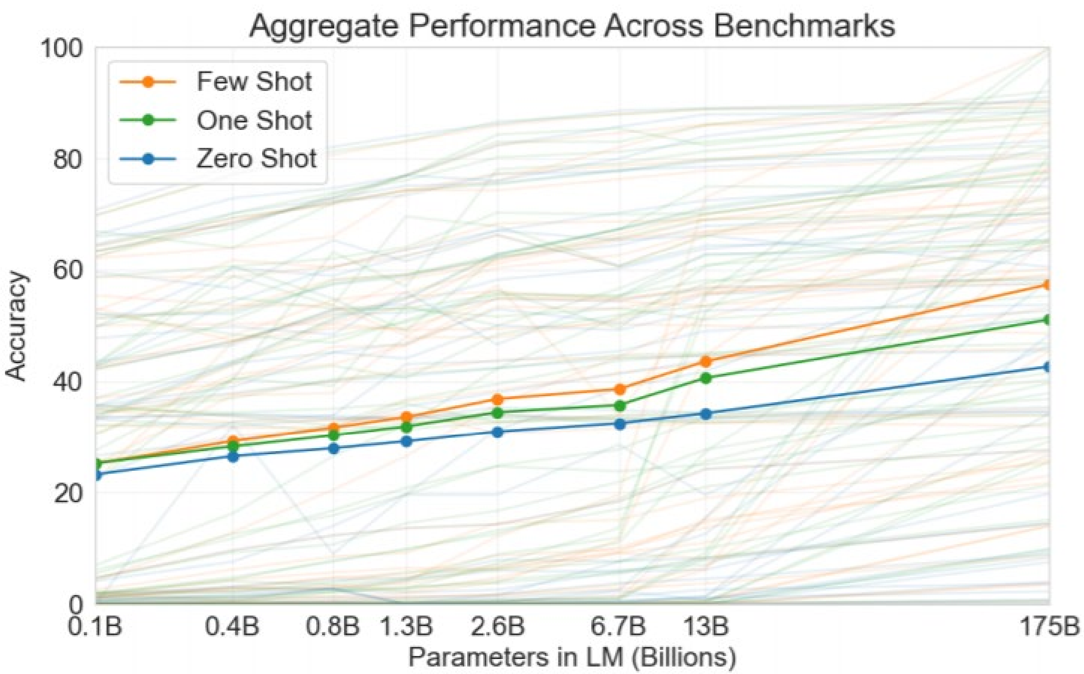


Figure from "Language Models are Few-Shot Learners", Brown et al 2020

The less obvious way: BERT

Something is still amiss: the decoder from transformers still predicts the next word. *Still unidirectional*!

The insight of Devlin et al. ’18: BERT (Bidirectional Encoder Representations from Transformers) – use an **encoder** instead!

But how? What are trying to predict?

Predict random *15%* of the words, given the rest

The parade of Sesame Street: BERT

Masked LM task: Predict random *15%* of the words, given the rest

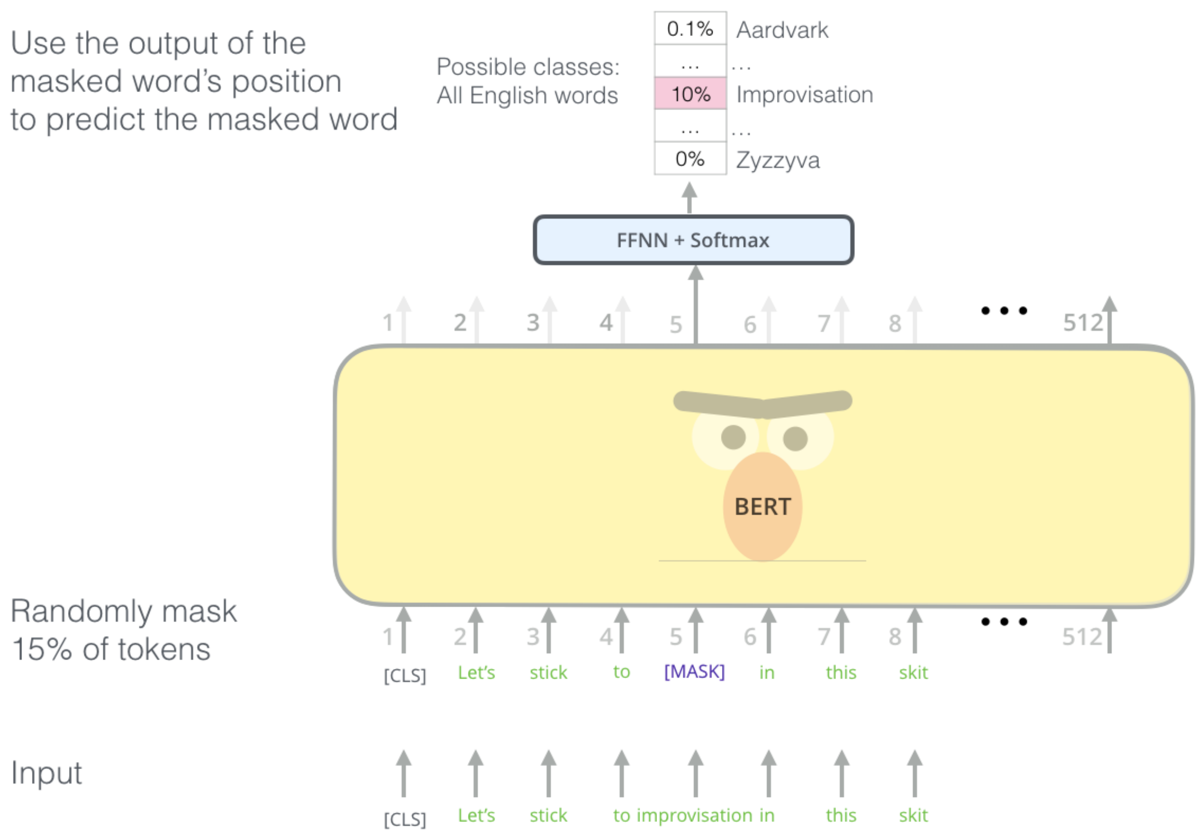


Figure from http://jalammar.github.io/illustrated-bert/

The parade of Sesame Street: BERT

Slight mismatch with downstream tasks: these will never have a token [MASK]. Can this be a bit ameliorated?

Yes, with some probability change word to be masked out to a random word, or leave as is.

Performance

At publication time, improved state of the art, by solid 5% on GLUE tasks.
Today, variants of BERT are pretty much defacto pretraining method.

The General Language Understanding Evaluation (GLUE) benchmark (Wang et al., 2018) is a collection of diverse natural language understanding tasks.

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.9	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	88.1	91.3	45.4	80.0	82.3	56.0	75.2
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.1	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**91.1**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**81.9**

Performance

SQuAD 2.0 Question Answering leaderboard 2019-10-09

Passage

Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi's Stadium in the San Francisco Bay Area at Santa Clara, California.

Question: Which team won Super Bowl 50?

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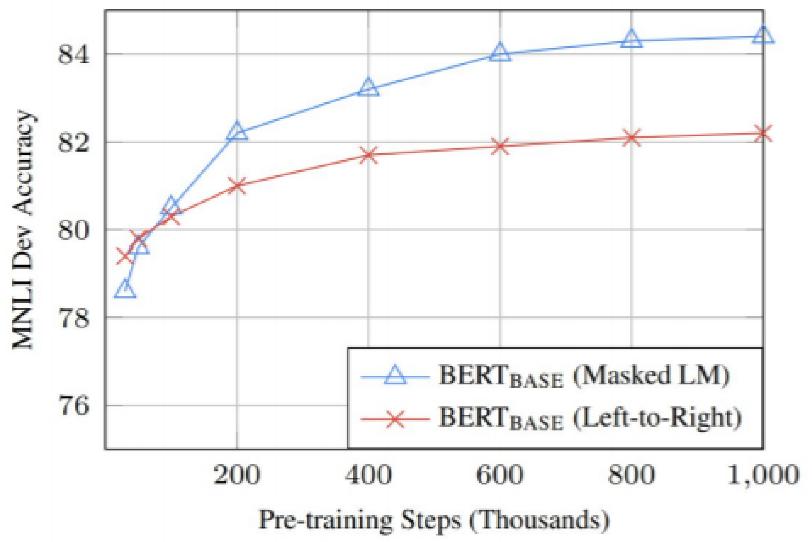
Rank	Model	EM	F1
	Human Performance *Stanford University* (Rajpurkar & Jia et al. '18)	86.831	89.452
1 Sep 18, 2019	ALBERT (ensemble model) *Google Research & TTIC* https://arxiv.org/abs/1909.11942	**89.731**	**92.215**
2 Jul 22, 2019	XLNet + DAAF + Verifier (ensemble) *PINGAN Omni-Sinitic*	88.592	90.859
2 Sep 16, 2019	ALBERT (single model) *Google Research & TTIC* https://arxiv.org/abs/1909.11942	88.107	90.902
2 Jul 26, 2019	UPM (ensemble) *Anonymous*	88.231	90.713
3 Aug 04, 2019	XLNet + SG-Net Verifier (ensemble) *Shanghai Jiao Tong University & CloudWalk* https://arxiv.org/abs/1908.05147	88.174	90.702
4 Aug 04, 2019	XLNet + SG-Net Verifier++ (single model) *Shanghai Jiao Tong University & CloudWalk* https://arxiv.org/abs/1908.05147	87.238	90.071
5 Jul 26, 2019	UPM (single model) *Anonymous*	87.193	89.934
6 Mar 20, 2019	BERT + DAE + AoA (ensemble) *Joint Laboratory of HIT and iFLYTEK Research*	87.147	89.474
6 Jul 20, 2019	RoBERTa (single model) *Facebook AI*	86.820	89.795

Slide by Chris Manning.

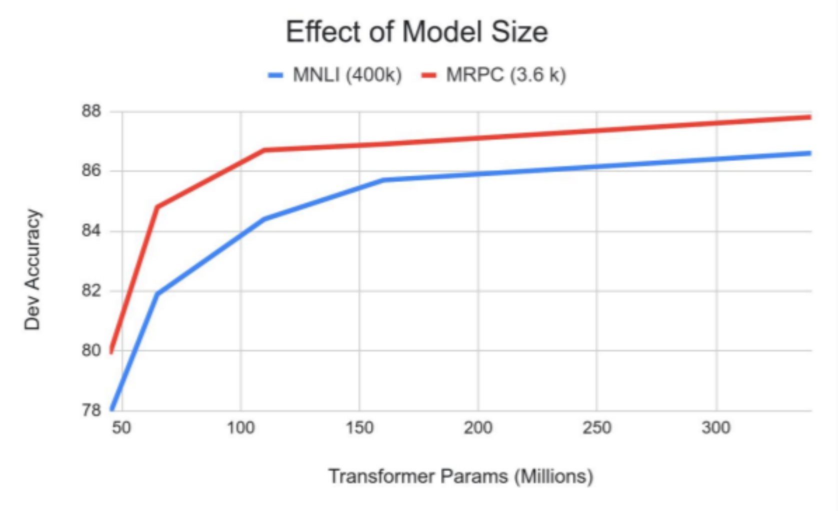
The value of bidirectionality



- Masked LM takes slightly longer to converge because we only predict 15% instead of 100%
- But absolute results are much better almost immediately

Slide from Jacob Devlin

Big models matter, a lot



- Big models help *a lot*
- Going from 110M -> 340M params helps even on datasets with 3,600 labeled examples
- Improvements have *not* asymptoted

Slide from Jacob Devlin

Big models matter, a lot

Transformer models

ELMo	GPT	BERT	GPT-2	XL-Net,
Oct 2017	June 2018	Oct 2018	Feb 2019	ERNIE,
Training:	Training	Training	Training	Grover
800M words	800M words	3.3B words	40B words	RoBERTa, …
42 GPU days	240 GPU days	256 TPU days ~320–560 GPU days	~2048 TPU v3 days according to a reddit thread	July 2019
AI2	OpenAI	Google AI	OpenAI	Facebook AI Research (FAIR) Google AI UW NLP Baidu 百度 Carnegie Mellon University

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Slide from Chris Manning

Why did this not happen earlier?

- Why did no one think of this before?
- Better question: Why wasn't contextual pre-training popular before 2018 with ELMo?
- Good results on pre-training is >1,000x to 100,000 more expensive than supervised training.
  - E.g., 10x-100x bigger model trained for 100x-1,000x as many steps.
  - Imagine it's 2013: Well-tuned 2-layer, 512-dim LSTM sentiment analysis gets 80% accuracy, training for 8 hours.
  - Pre-train LM on same architecture for a week, get 80.5%.
  - Conference reviewers: "Who would do something so expensive for such a small gain?"

Slide from Jacob Devlin

Are we done with modeling in NLP?

Good systems are great, but still basic NLU errors

> The Yuan dynasty is considered both a successor to the Mongol Empire and an imperial Chinese dynasty. It was the khanate ruled by the successors of Möngke Khan after the division of the Mongol Empire. In official Chinese histories, the Yuan dynasty bore the Mandate of Heaven, following the Song dynasty and preceding the Ming dynasty. The dynasty was established by Kublai Khan, yet he placed his grandfather Genghis Khan on the imperial records as the official founder of the

What dynasty came before the Yuan?

Gold Answers: ① Song dynasty ② Mongol Empire ③ the Song dynasty

Prediction: Ming dynasty [BERT (single model) (Google AI)]

Slide from Chris Manning

Are we done with modeling in NLP?

Two problems

BERT and friends are **awesome** as a universal pre-training base for natural language understanding tasks

Nevertheless, we still have work to do:

1. We've built powerful, **neural matching machines**, rather than devices that can **think**
2. We've built devices for one-step classification, QA etc., rather than devices that can **reason** through a series of steps

Slide from Chris Manning

Are we done with modeling in NLP?

Answering Complex Open-Domain Questions: Single-step vs. Multi-step Question Answering

[Qi, Lin, Mehr, Wang, and Manning EMNLP-IJCNLP 2019]

Context: Aquaman is a 2018 American superhero film based on the DC Comics character of the same name. …

Question: When was the movie Aquaman released?

Answer: 2018 ✓

Question: What's the Aquaman actor's next movie?

Answer: Jason Momoa ✗

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Slide from Chris Manning

Are we done with modeling in NLP?

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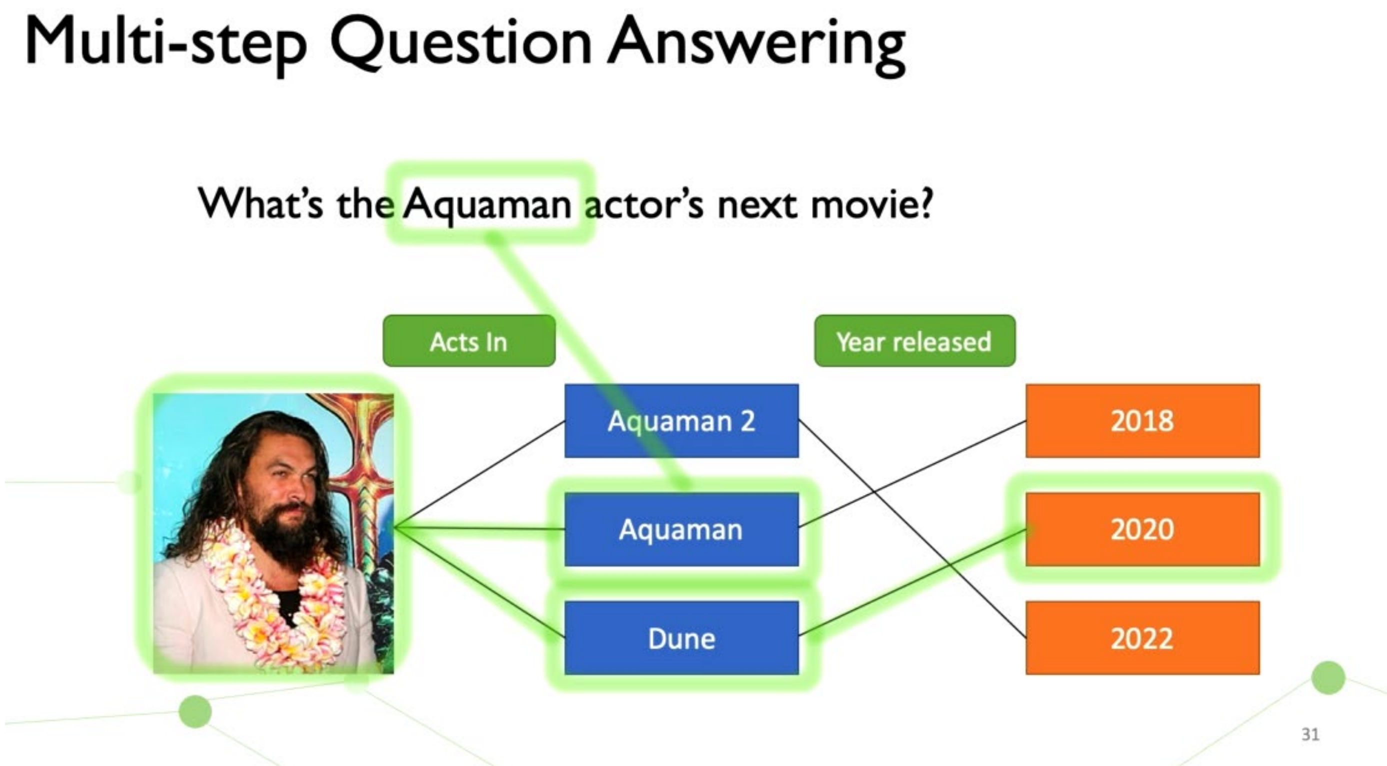
Slide from Chris Manning

More complex datasets



Slide from Chris Manning

More complex datasets

1) What is the giraffe looking at? *person* ✓
2) Is the fence in front of the giraffe made of metal? *no* ✓
3) Is the woman's shirt blue or yellow? *blue* ✓
4) On which side of the image is the person? *right* ✓
5) Is there a child behind the giraffe? *no* ✗

1) What is the fruit to the right of the salad? *strawberries* ✓
2) Is the fork to the right of the salad? *no* ✓
3) Is the plate white and square? *no* ✓
4) Is the cup behind the round plate? *yes* ✓
5) What is the plate made of? *paper* ✗

1) Are there either scarves or hats that are not pink? *no* ✓
2) Do the bear's dress and the person's shirt have the same color? *yes* ✓
3) Is the bear sitting or standing? *sitting* ✓
4) What is the green object that the bear is sitting on? *book* ✓
5) Is the bear wearing white shoes? *yes* ✗

1) Are there either a chair or a clock in the image? *no* ✓
2) Are there any flowers behind the bed on the left of the room? *yes* ✓
3) What color is the appliance on the right? *black* ✓
4) Is the carpet brown or blue? *brown* ✓
5) Is the TV turned on? *yes* ✗

Figure 2: Question examples along with answers predicted by the NSM. The questions involve diverse reasoning skills such as multi-step inference, relational and spatial reasoning, logic and comparisons.

Figure from Hudson & Manning '19,
VQA (visual question-answering) datasets

More complex models

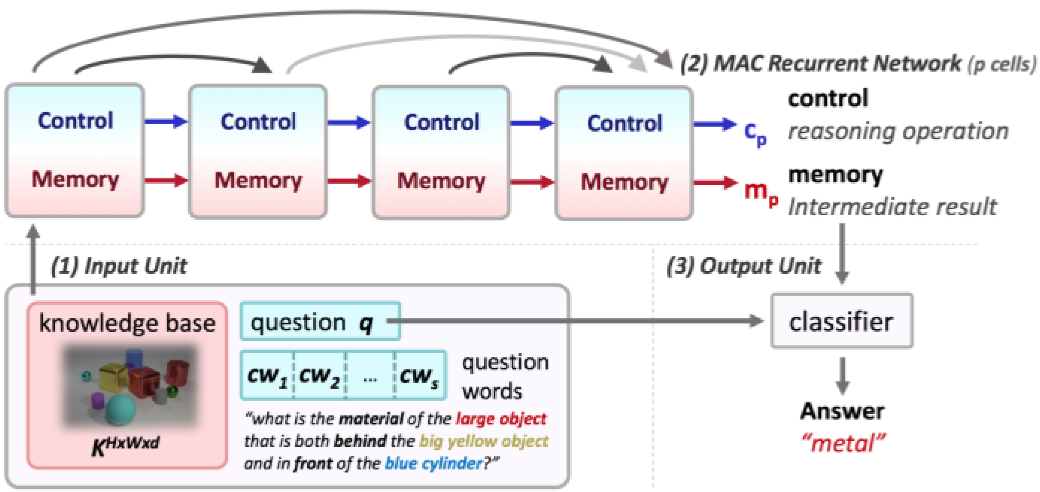


Figure 2: Model Overview. The MAC network consists of an input unit, a core recurrent network and an output unit. (1) The input unit transforms the raw image and question into distributed vector representations. (2) The core recurrent network reasons sequentially over the question by decomposing it into a series of operations (*control*) that retrieve information from the image (knowledge base) and aggregate the results into a recurrent *memory*. (3) The output classifier computes the final answer using the question and the final memory state.

Figure from Hudson & Manning '18

More complex models

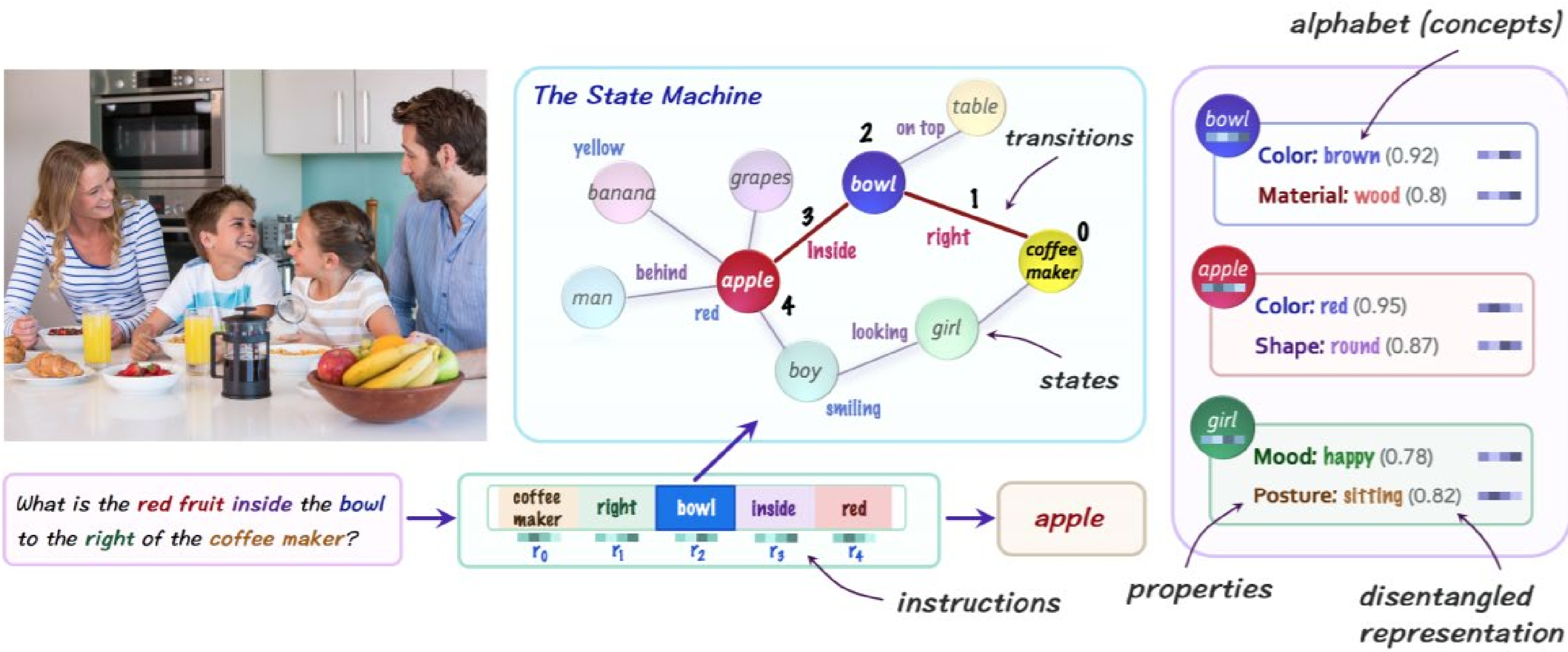


Figure 1: The Neural State Machine is a graph network that simulates the computation of an automaton. For the task of VQA, the model constructs a probabilistic scene graph to capture the semantics of a given image, which it then treats as a state machine, traversing its states as guided by the question to perform sequential reasoning.

Figure from Hudson & Manning ’19