10707
Deep Learning: Spring 2020

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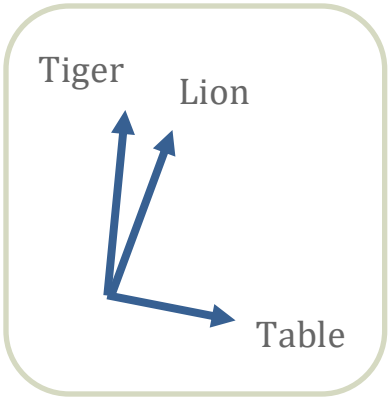
Machine Learning Department

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.

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

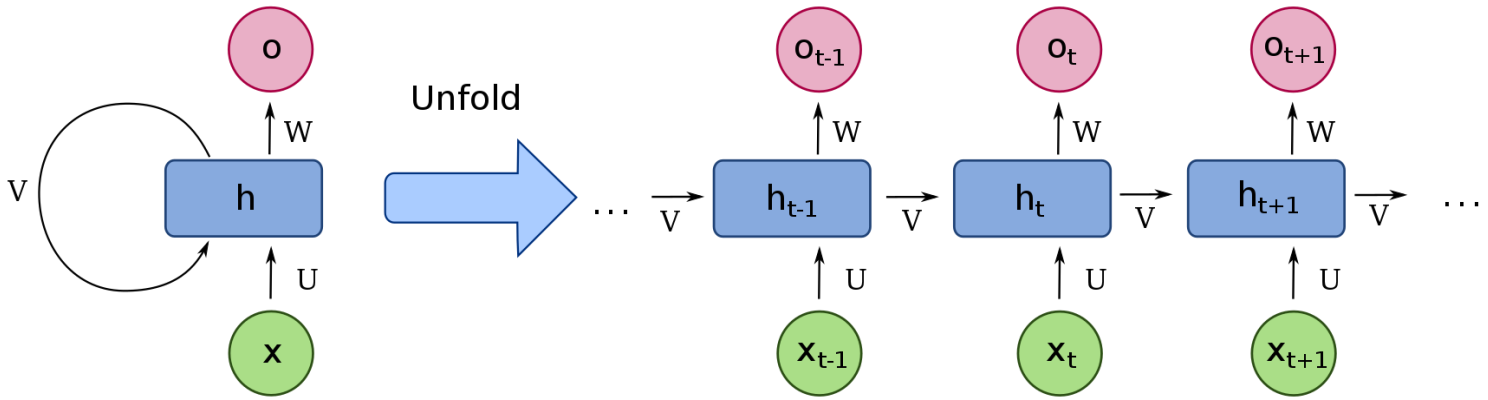
$$o_i = W_{hy} h_i$$

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

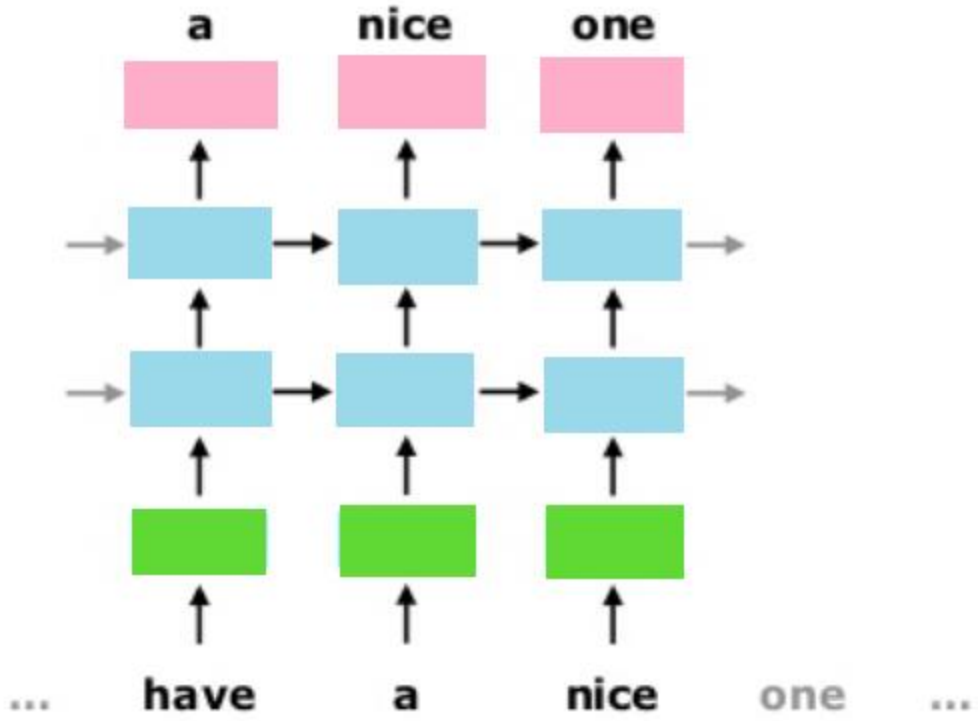
Repurposing RNNs to learn context-dependent embeddings:

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

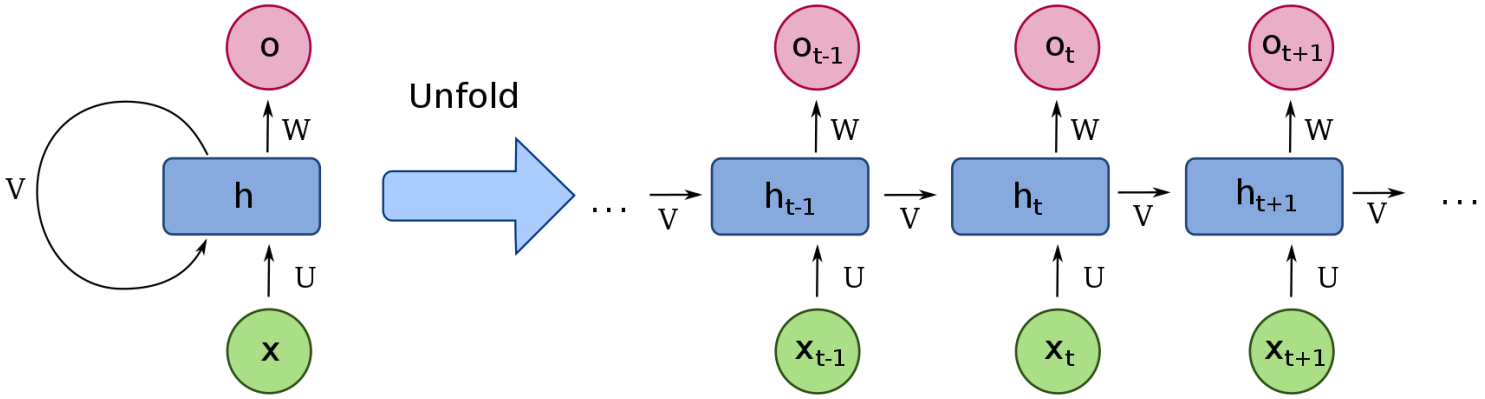


Recurrent neural networks: stacking multiple RNNs



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

Recurrent neural networks



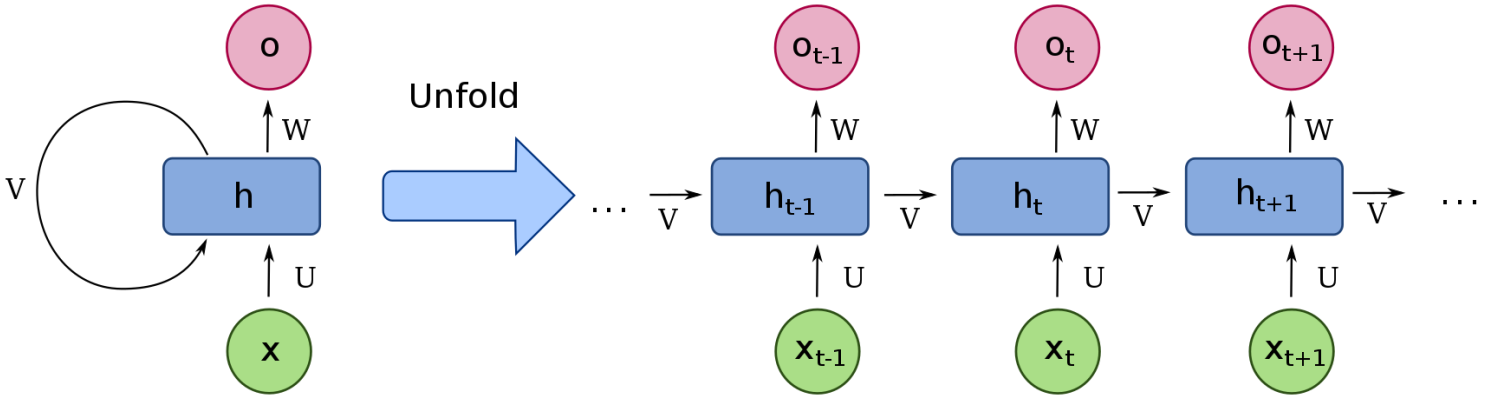
Obvious benefit: copious weight tieing, number of params completely independent of length.

Drawbacks:

Training: 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



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Drawbacks:

Training: *gradient explosion/vanishing!*

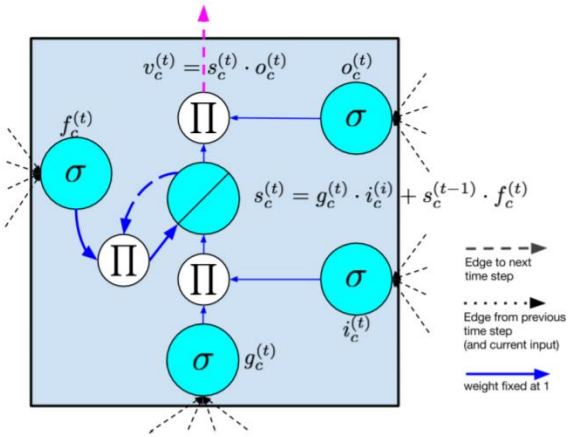
Likelihood evaluation: has to be done **sequentially** (no parallelization)

LSTM (Long Short-Term Memory)

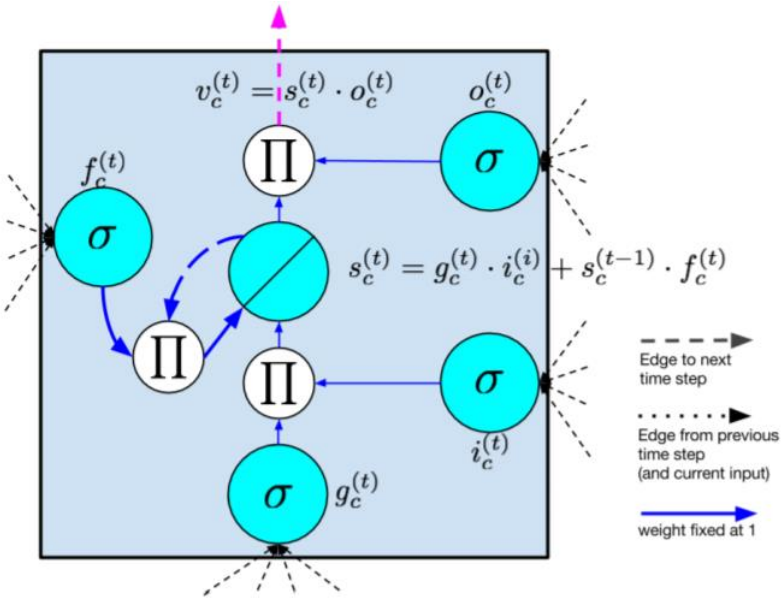
The main issue with training RNN's is long-term dependencies (and correspondingly exploding/vanishing gradients)

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)



Ingredients:

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

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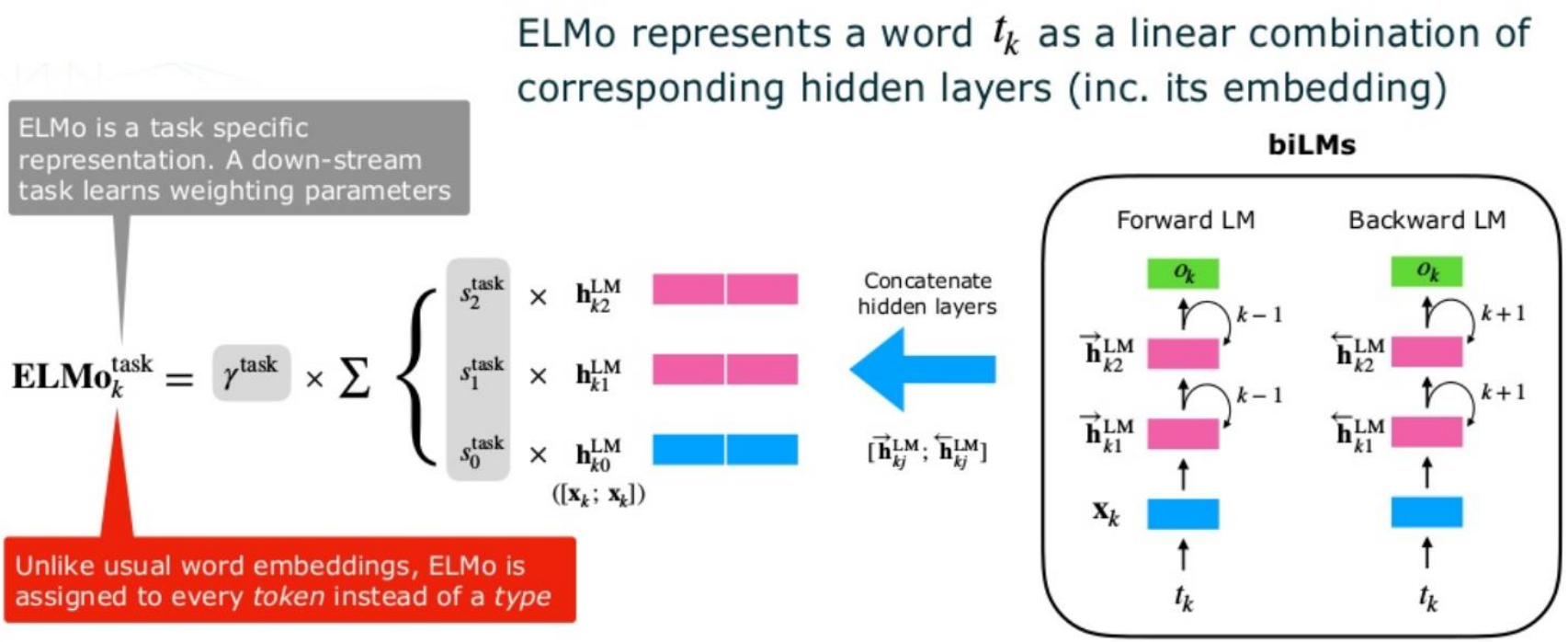
The parade of Sesame Street: ELMo

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

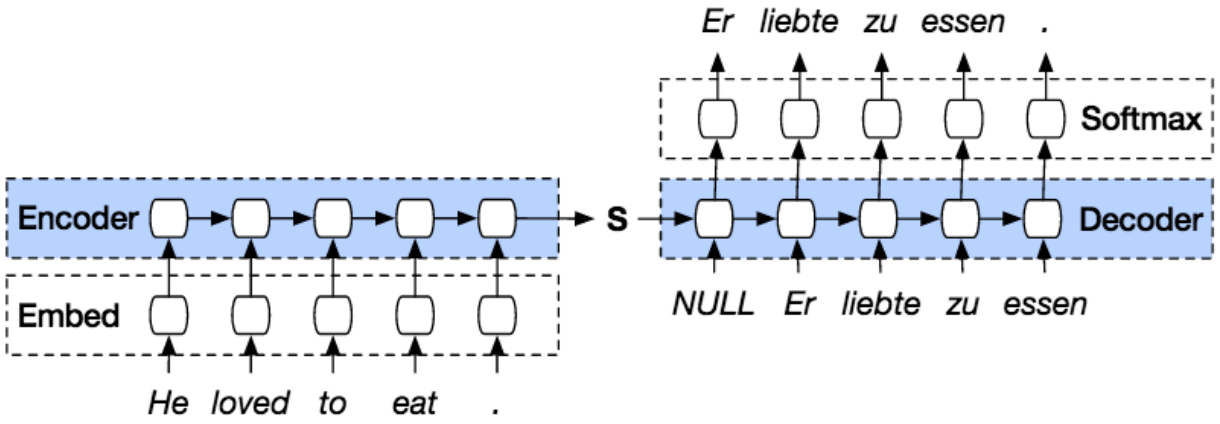
Brief diversion: machine translation

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".

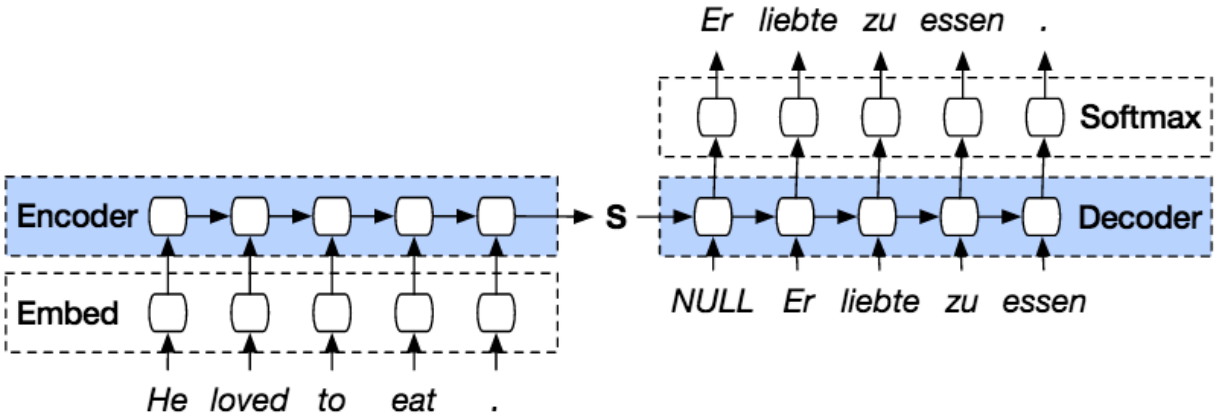
The most natural way to introduce the ideas is through sequence to sequence tasks, in which we try to map sequence in one domain to another.

Most natural instantiation: machine translation.



The encoder/decoder framework

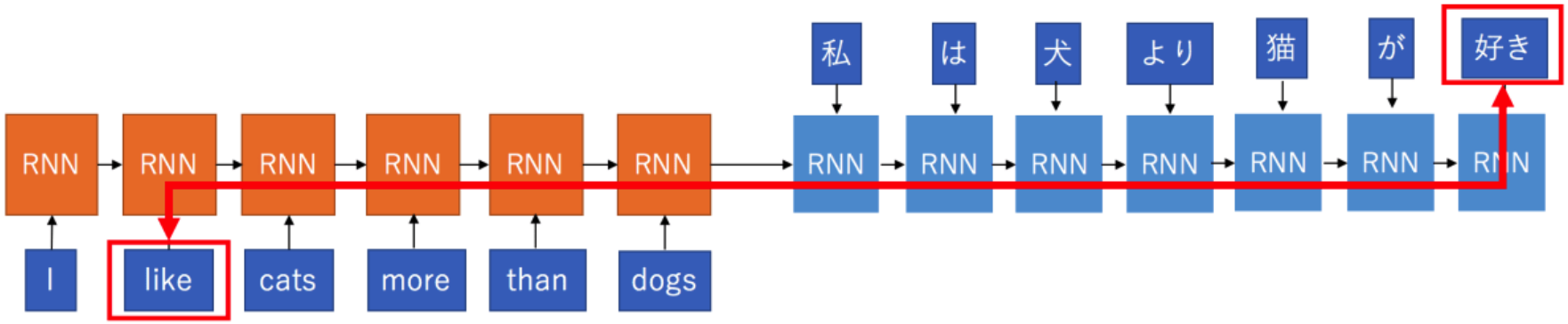
Most natural instantiation: machine translation.



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.

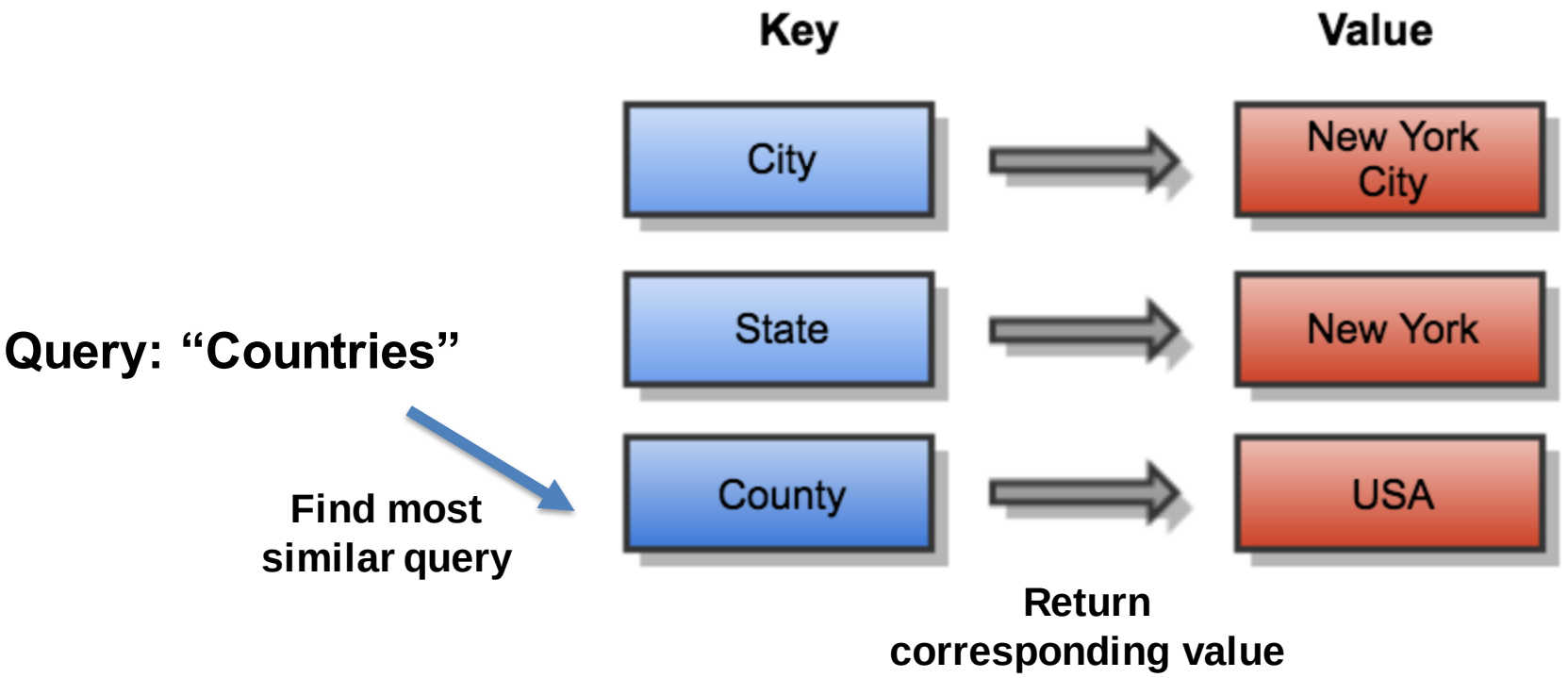
The animal didn't cross the street because it was too tired.
L'animal n'a pas traversé la rue parce qu'il était trop fatigué.

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 of keys/values

Linear combination of "most similar" values

The simplest notion of similarity: inner product.

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

Produces distribution over keys

Produces distribution over values

Multiple queries combined in matrix Q:

$$\text{Attention}(Q, K, V) = \text{softmax}(QK^T)V$$

Transformers: using attention

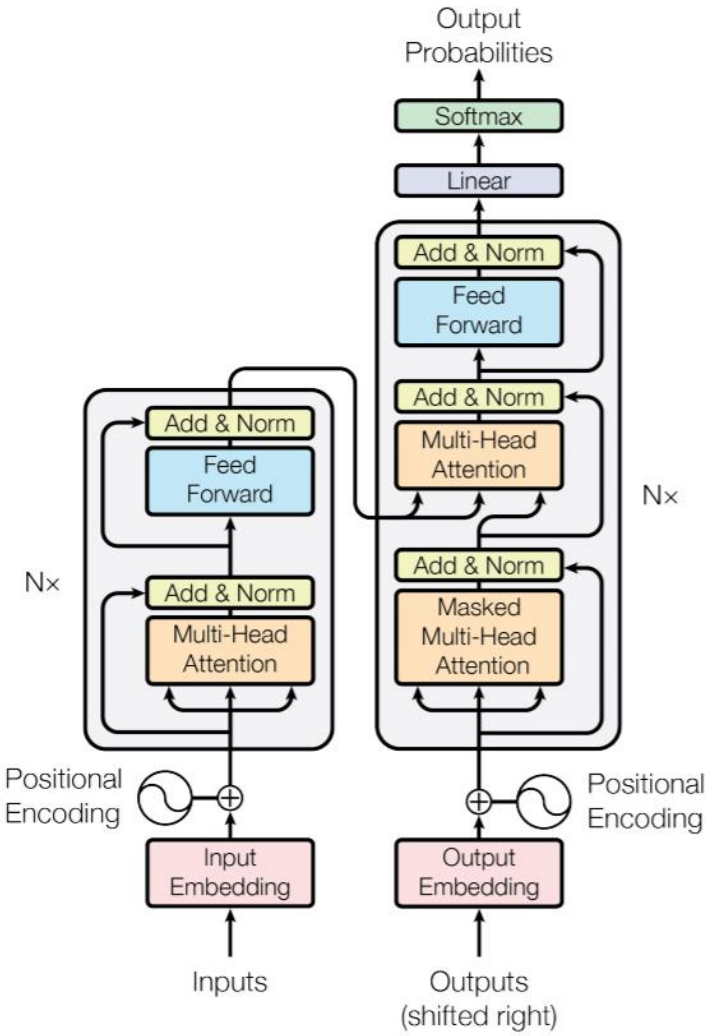


Figure from Vaswani et al ’17: “Attention is all you need”.

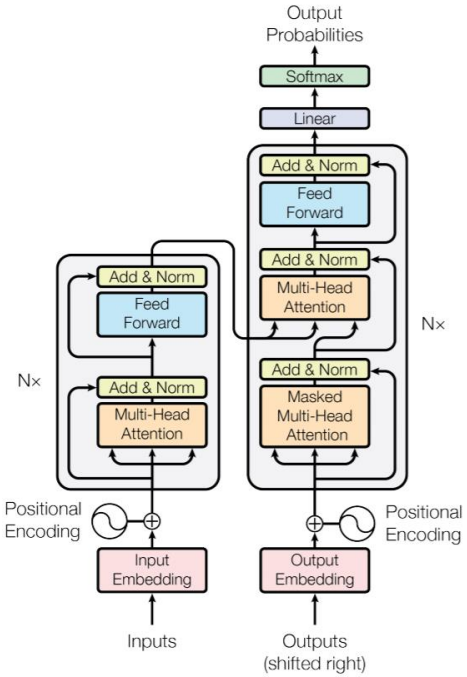
Transformers: encoder

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.

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$
$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

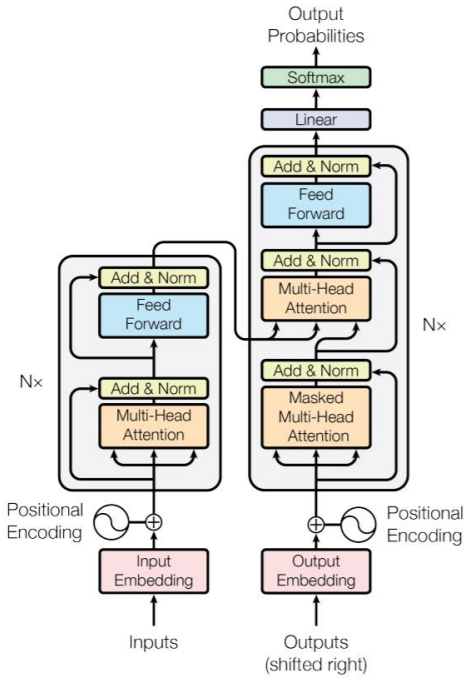
Where the projections are parameter matrices $W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_v \times d_{\text{model}}}$.

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).

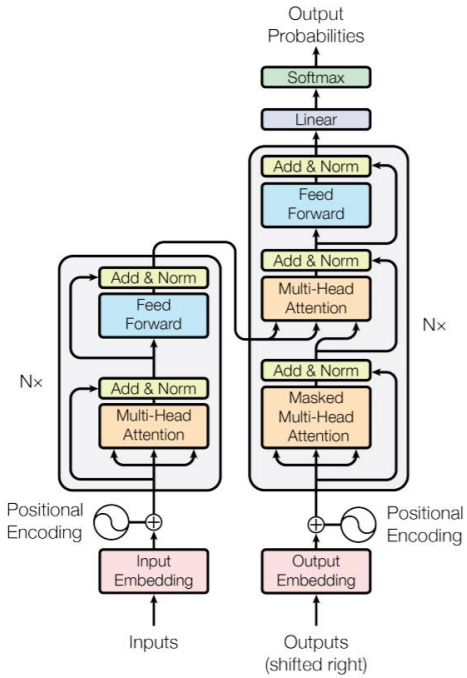
Transformers: decoder

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)

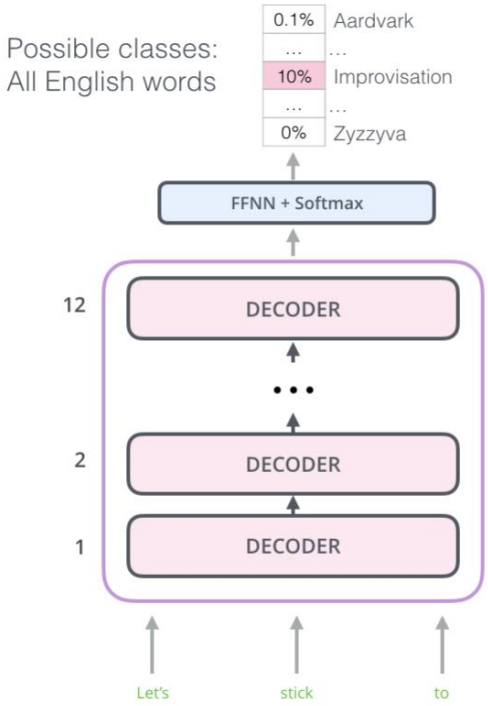
Learn what word to attend to for purposes of translation.



Remaining parts: basically the same as encoder.
Only 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!



GPT2: Transformer-based architecture due to OpenAI

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

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

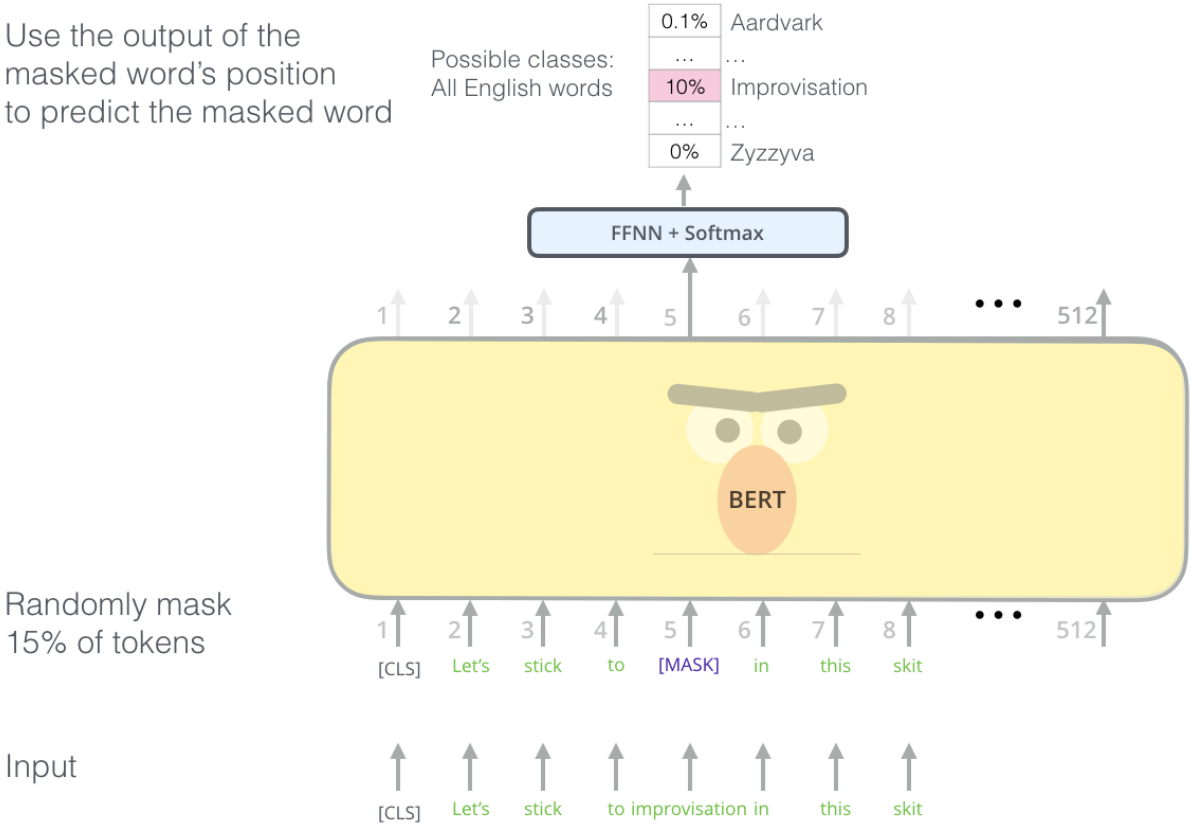
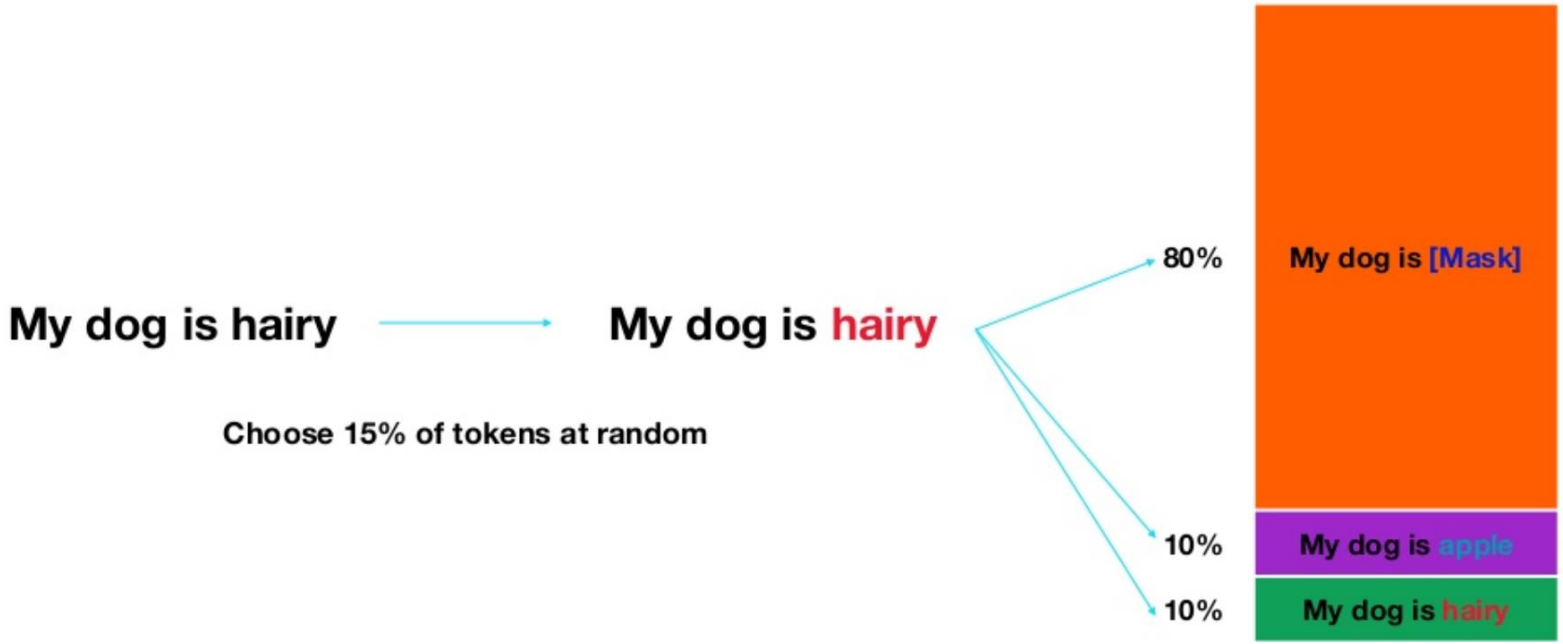


Figure from http://jalammar.github.io/illustrated-bert/

The parade of Sesame Street: BERT

Slight issue with features trained: downstream tasks 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.



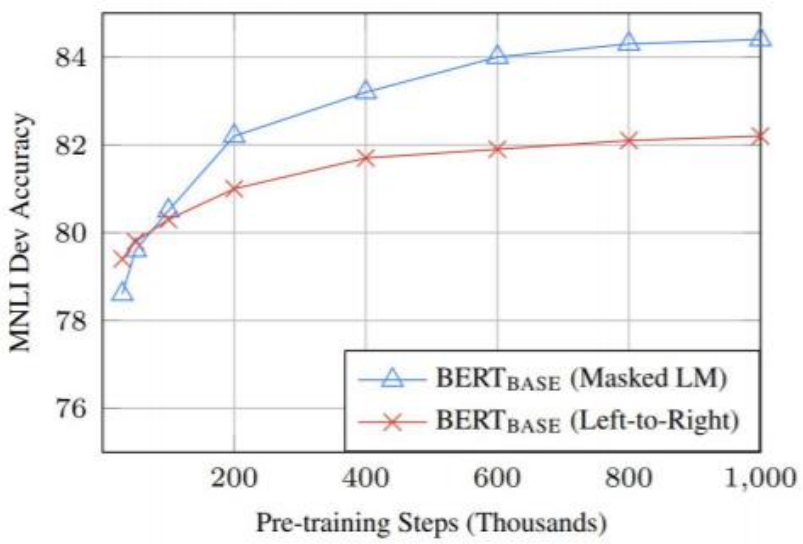
Performance

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) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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**

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

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