Deep Learning and Masked Language Modelling

Adithya V Ganesan

CSE538 - Spring 2024

Artificial Neural Networks

What is it?

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- Biologically inspired computing model
- Learn patterns from the data
- Can even approximate nonlinear functions in the nature!

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Linear Regression

Linear Regression: $\hat{y} = \beta X$

Objective: *Learn w, such that* $(y - \beta X)^2$ *is minimized*

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$$\beta_{opt} = (X^T X)^{-1} X^T y$$

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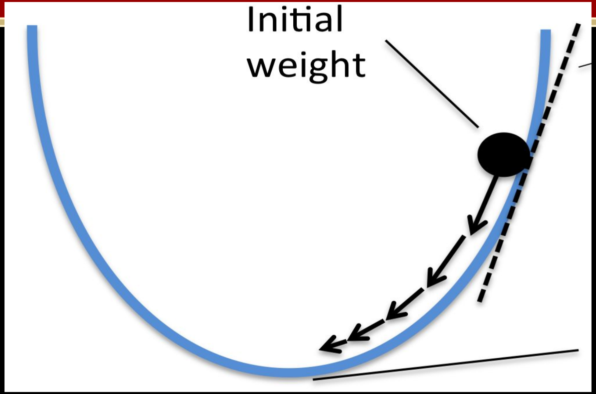

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Numerical Gradient Approach

Linear Regression: Trying to find “betas” that minimize:

$$\beta^* = \text{argmin}_\beta \{\textstyle\sum_i (y_i - \hat{y}_i)^2\}$$

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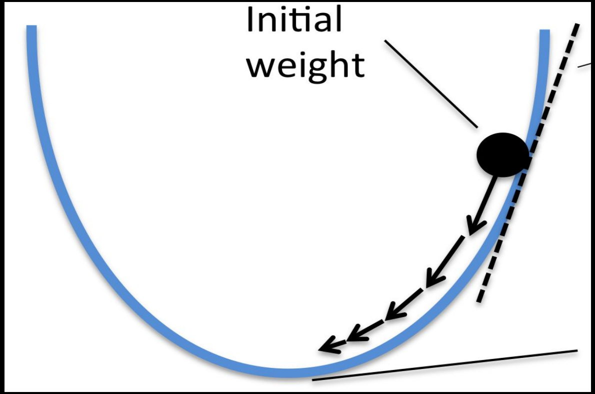

How to update? $\beta_{new} = \beta_{old} - \alpha * \text{grad}$

α: Learning Rate

Numerical Gradient Approach

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Gradient Descent: $\beta_{new} = \beta_{old} - \alpha * grad$

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But there are other gradient descent based optimization methods which are better*

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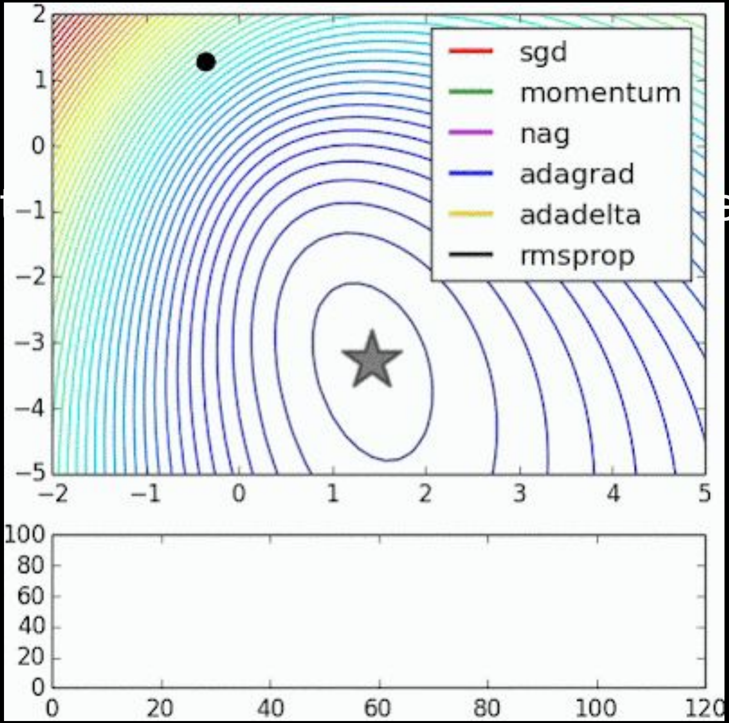

But, how do we model complex systems using these linear systems?

Deep Learning

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Deep Learning

Non-linear functions + Artificial Neural Networks

Activation Functions

$$z = h_{(t)}W$$

Common Activation Functions

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Logistic: $\sigma(z) = 1 / (1 + e^{-z})$

Hyperbolic tangent: $tanh(z) = 2\sigma(2z) - 1 = (e^{2z} - 1) / (e^{2z} + 1)$

Rectified linear unit (ReLU): $ReLU(z) = \max(0, z)$

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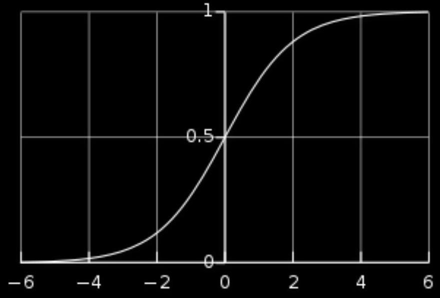

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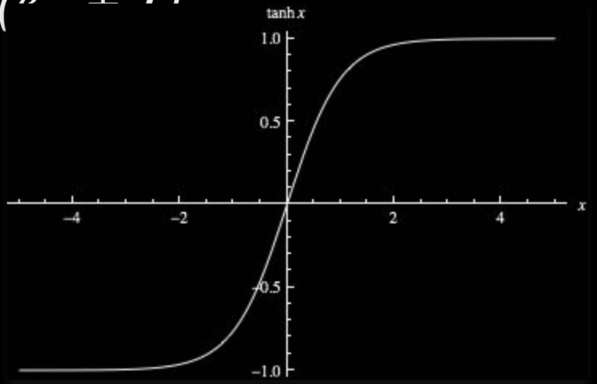

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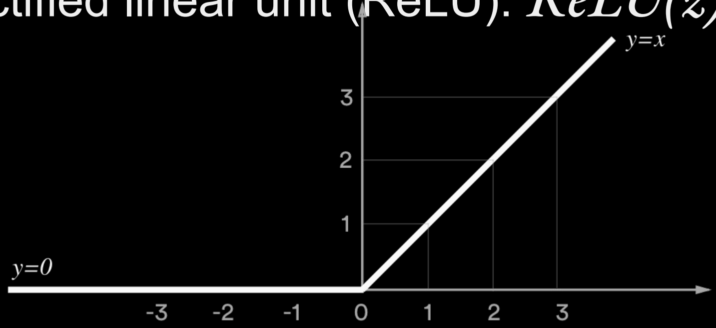

Back Propagation

Linear Regression as DAG

How do Machine learning/ Deep learning frameworks represent these models?

Linear Regression as DAG

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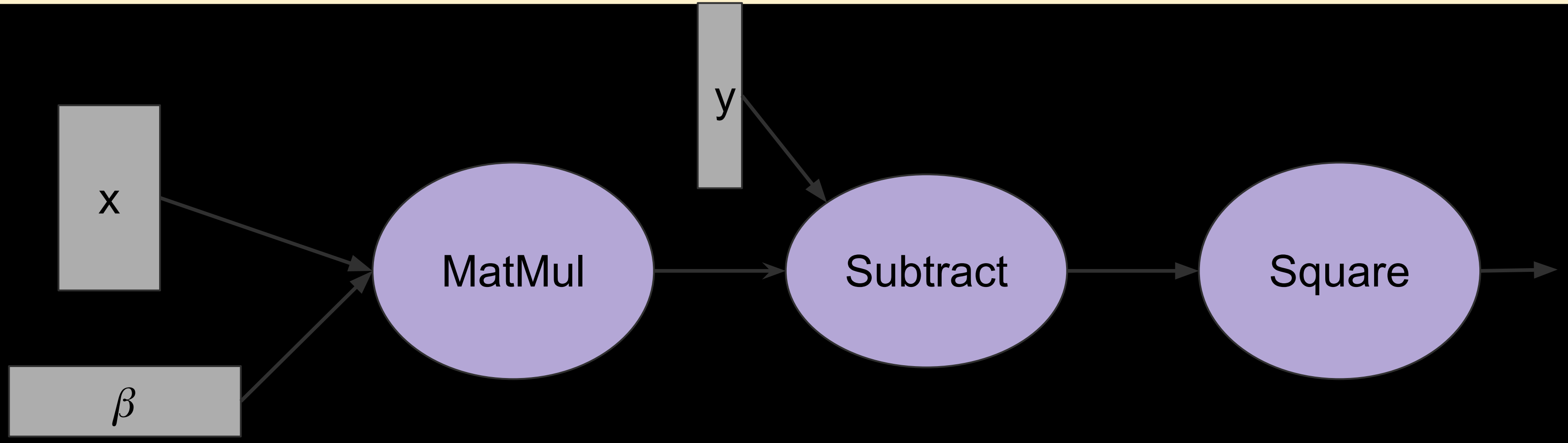
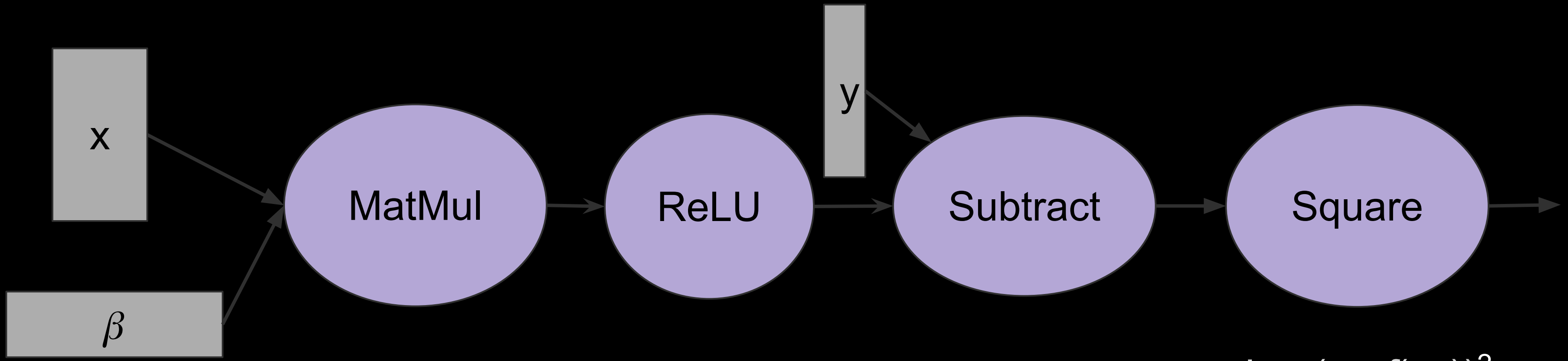
Computational Graph!

Linear Regression as DAG



$$L = (y - \beta x)^2$$

Linear Regression as DAG



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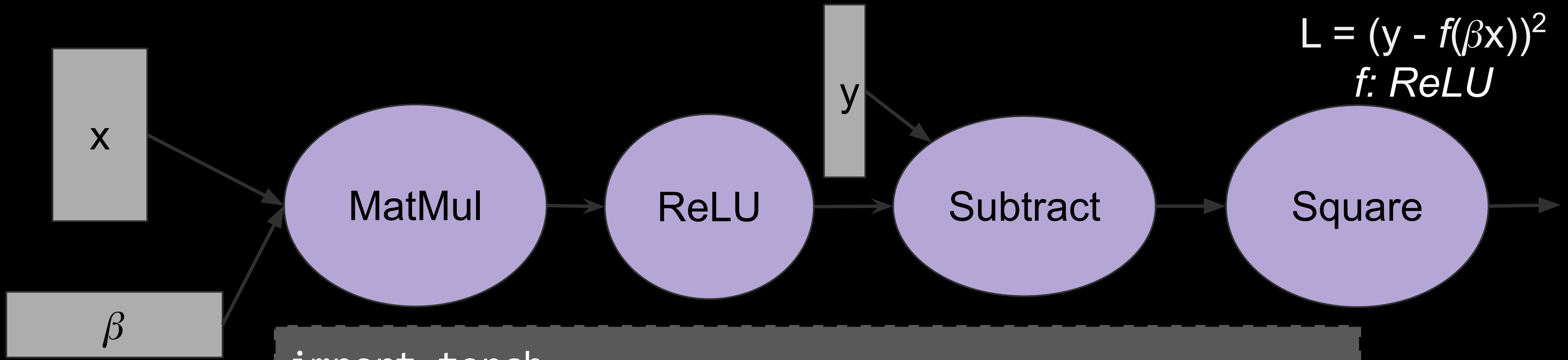



```
import torch
from torch import nn

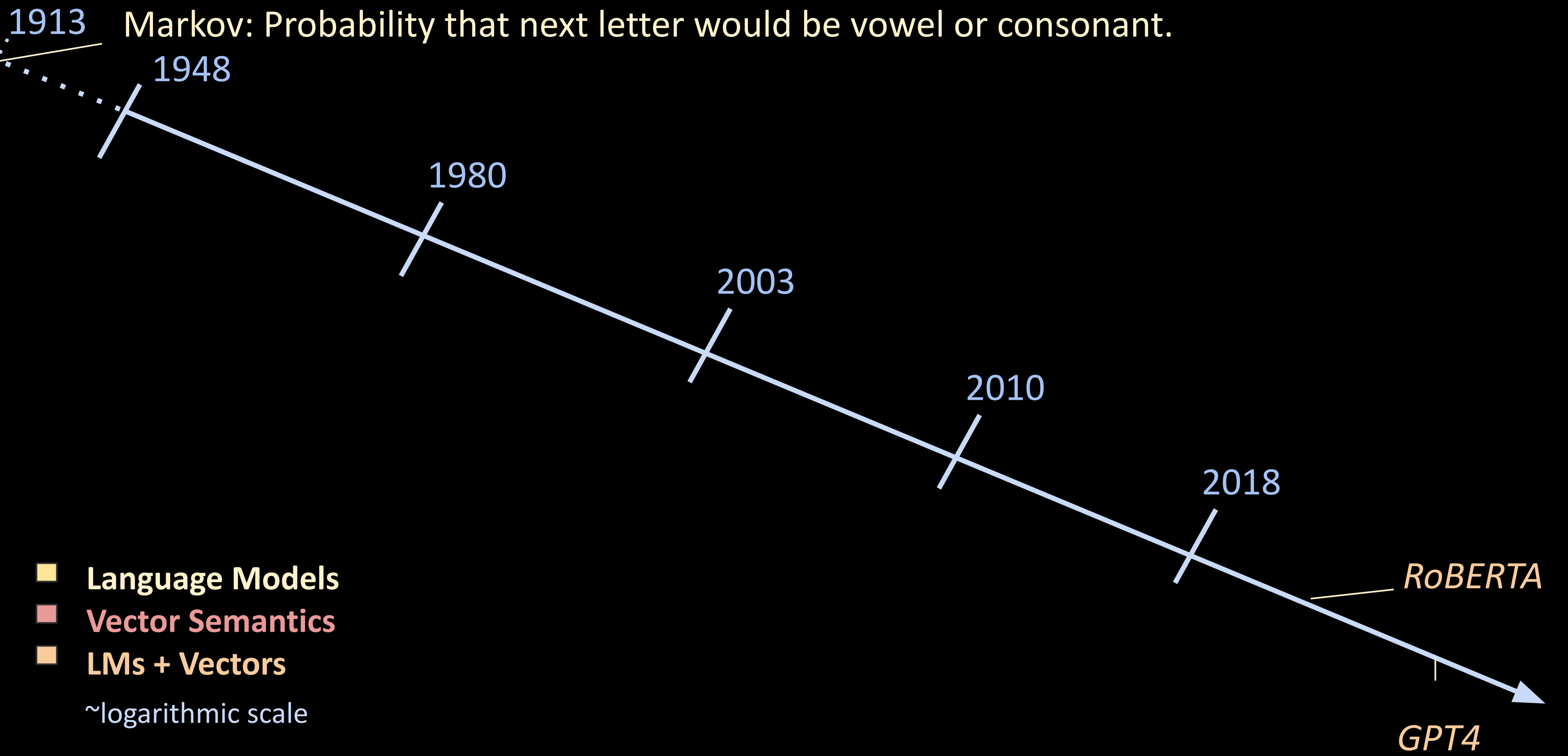
x = torch.Tensor(input)
beta = torch.random.randn(X.shape, 1)
z = torch.matmul(x, beta)
yhat = nn.functional.relu(z)
loss = nn.MSELoss(yhat, torch.Tensor(y))
```

PyTorch Demo

Native Linear Regression Implementation ([Link])

Torch.nn Linear Regression Implementation ([Link])

Timeline: *Language Modeling* and *Vector Semantics*



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1913 Markov: Probability that next letter would be vowel or consonant.

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RoBERTA

GPT4

These (or similar) are behind almost all state-of-the-art modern NLP systems

Language Models

Vector Semantics

LMs + Vectors

~logarithmic scale

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Robustly Optimized BER**Transformers** Pretraining Approch

Generative Pretrained **Transformers**

Bidirectional **Transformers**

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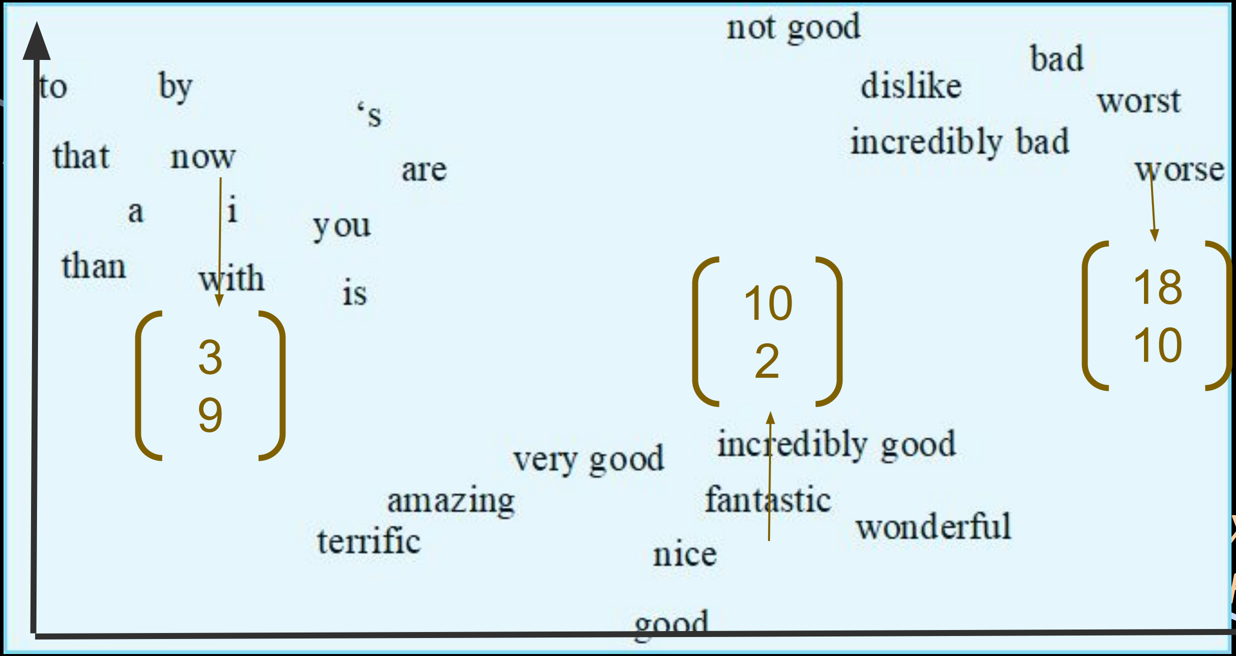

(Li et al. ,2015; Jurafsky et al., 2019)

XLNet

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Word Vectors

To embed: convert a token (or sequence) to a vector that represents **meaning.**

Wittgenstein, 1945: “*The meaning of a word is its use in the language*”

Distributional hypothesis -- A word’s meaning is defined by all the different contexts it appears in (i.e. how it is “distributed” in natural language).

Firth, 1957: “*You shall know a word by the company it keeps*”

The nail hit the beam behind the wall.

Word Vectors

	Person A	**Person B**
How are you?	I feel ***fine*** –even ***great***!	My life is a ***great*** mess! I'm having a very hard time being happy.
What is going on?	Earlier, I ***played*** the ***game*** Yahtzee with my ***partner***. I could not get that ***die*** to roll a 1! Now I'm ***lying*** on my bed for a ***rest***.	My business ***partner*** was ***lying*** to me. He was trying to ***game*** the system and ***played*** me. I think I am going to ***die*** –he left and now I have to pay the ***rest*** of his ***fine***.

(Kjell, Kjell, and Schwartz, 2023)

Objective

$$\textit{great} \xrightarrow{\text{embed}} \begin{pmatrix} 0.53 \\ 1.5 \\ 3.21 \\ -2.3 \\ .76 \end{pmatrix}$$

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great.a.2, outstanding (of major significance or importance)

great.a.3 (remarkable or out of the ordinary in degree or magnitude or effect)

bang-up, bully, corking, cracking, dandy, **great.a.4**, groovy, keen, neat, nifty, not bad, peachy, slap-up, swell, smashing, old (very good)

capital, **great.a.5**, majuscule (uppercase)

big, enceinte, expectant, gravid, **great.a.6**, large, heavy, with child (in an advanced stage of pregnancy)

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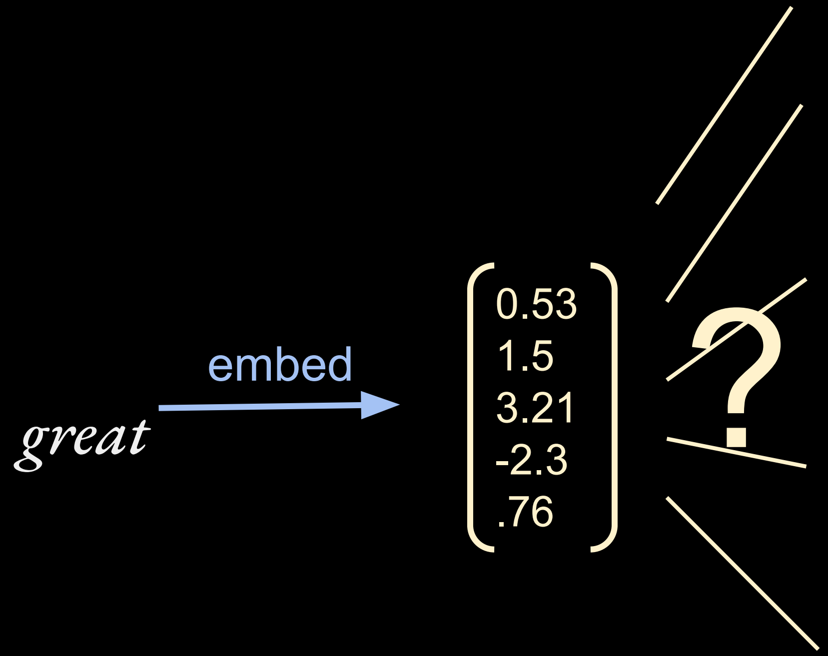

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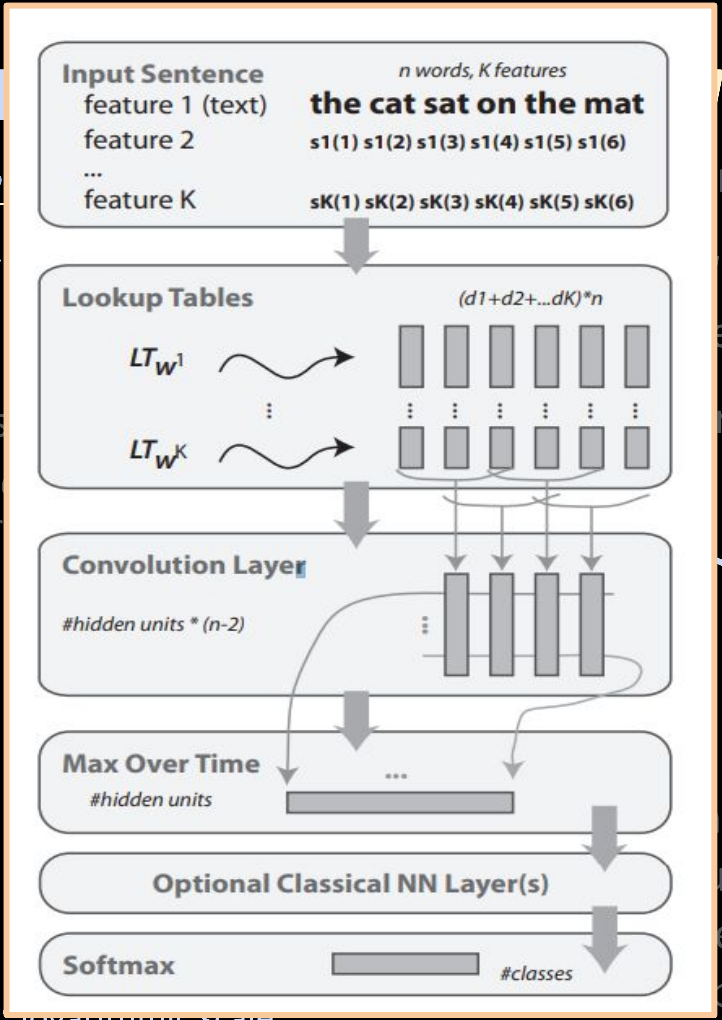

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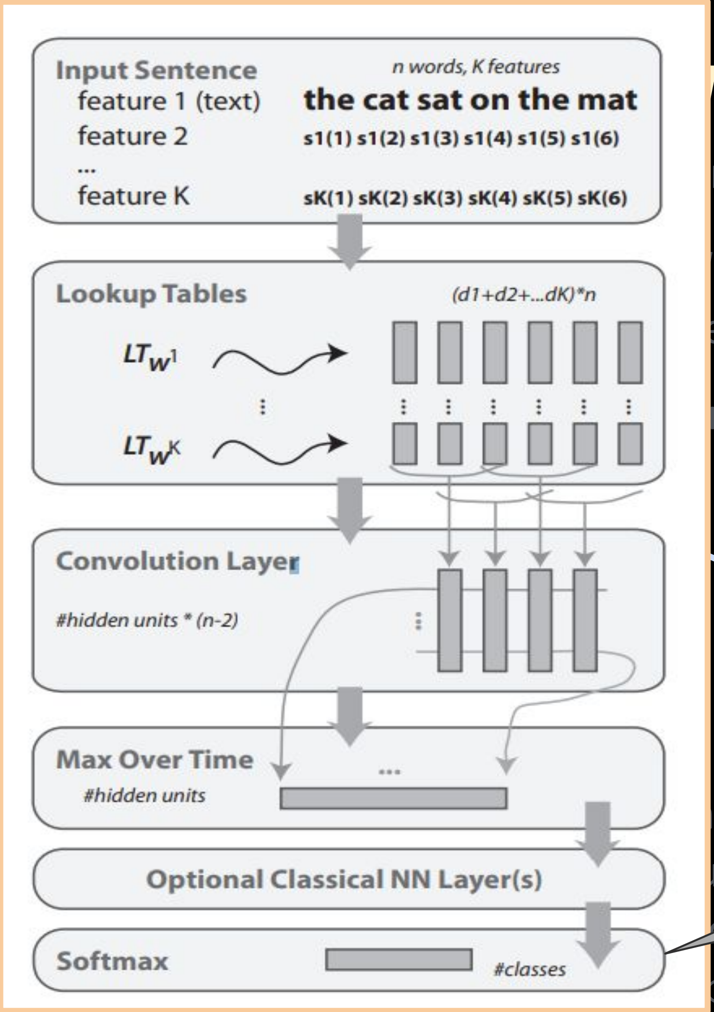

POS, Chunking (Shallow Parsing), NER, SRL, Modified Language Modelling

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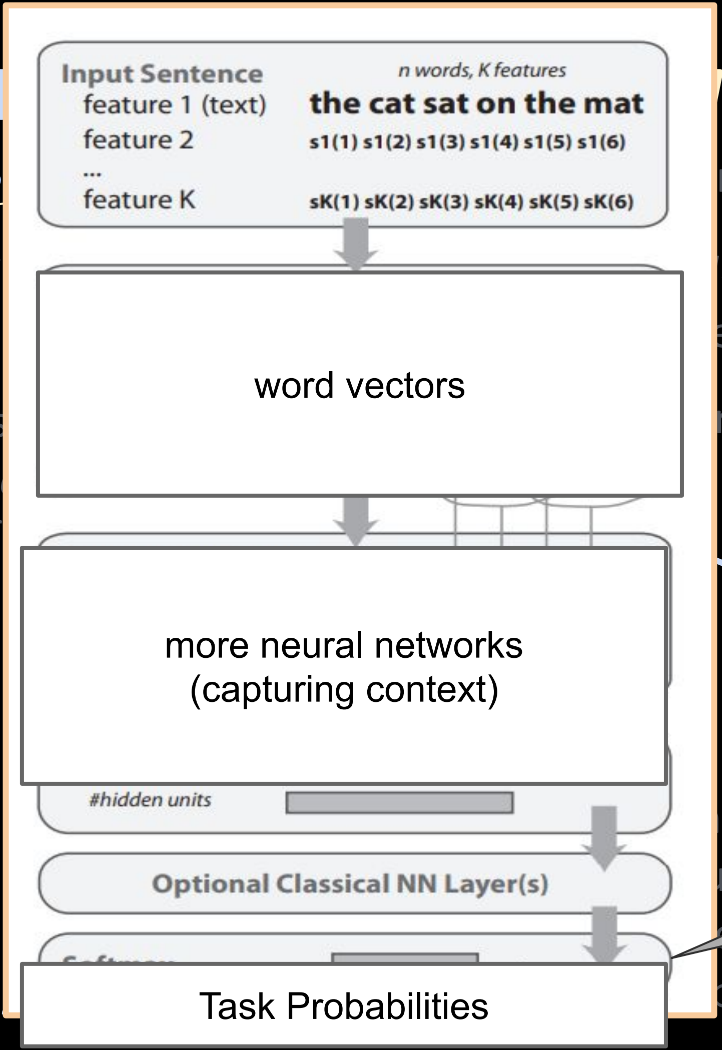

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architecture for natural language processing: Deep neural networks

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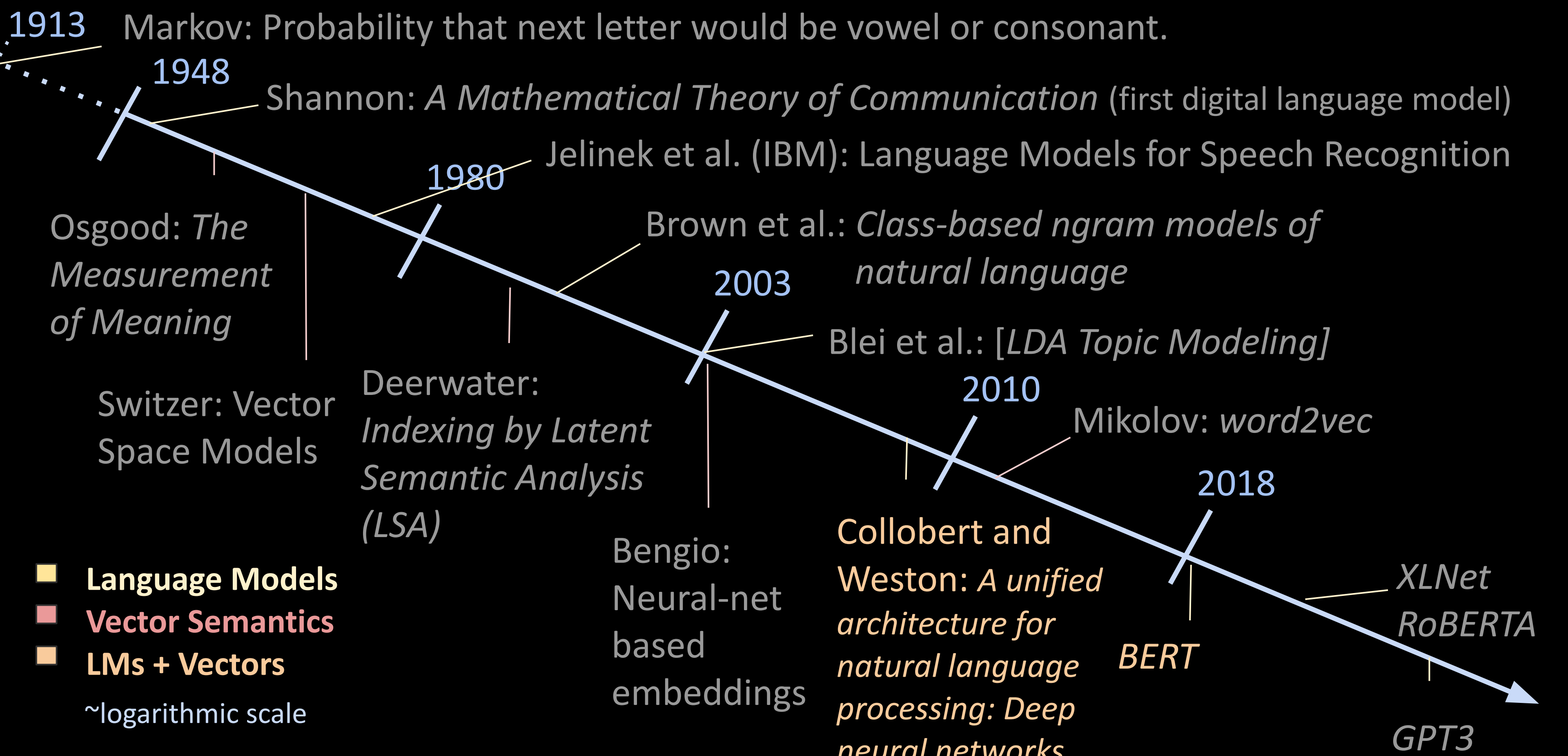

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BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

Jacob Devlin Ming-Wei Chang Kenton Lee Kristina Toutanova
Google AI Language
{jacobdevlin,mingweichang,kentonl,kristout}@google.com

Abstract

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).

1 Introduction

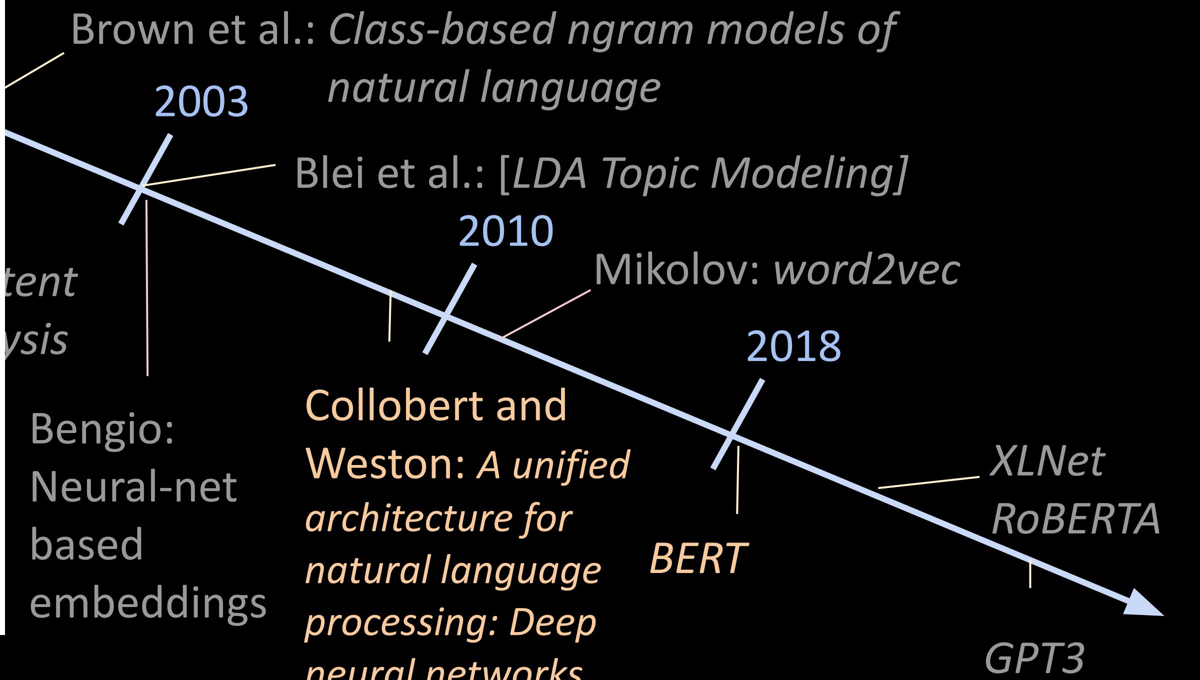
Language model pre-training has been shown to be effective for improving many natural language processing tasks (Dai and Le, 2015; Peters et al., 2018a; Radford et al., 2018; Howard and Ruder, 2018). These include sentence-level tasks such as natural language inference (Bowman et al., 2015; Williams et al., 2018) and paraphrasing (Dolan and Brockett, 2005), which aim to predict the relationships between sentences by analyzing them holistically, as well as token-level tasks such as named entity recognition and question answering, where models are required to produce fine-grained output at the token level (Tjong Kim Sang and De Meulder, 2003; Rajpurkar et al., 2016).

There are two existing strategies for applying pre-trained language representations to downstream tasks: *feature-based* and *fine-tuning*. The feature-based approach, such as ELMo (Peters et al., 2018a), uses task-specific architectures that include the pre-trained representations as additional features. The fine-tuning approach, such as the Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), introduces minimal task-specific parameters, and is trained on the downstream tasks by simply fine-tuning *all* pre-trained parameters. The two approaches share the same objective function during pre-training, where they use unidirectional language models to learn general language representations.

We argue that current techniques restrict the power of the pre-trained representations, especially for the fine-tuning approaches. The major limitation is that standard language models are unidirectional, and this limits the choice of architectures that can be used during pre-training. For example, in OpenAI GPT, the authors use a left-to-right architecture, where every token can only attend to previous tokens in the self-attention layers of the Transformer (Vaswani et al., 2017). Such restrictions are sub-optimal for sentence-level tasks, and could be very harmful when applying fine-tuning based approaches to token-level tasks such as question answering, where it is crucial to incorporate context from both directions.

In this paper, we improve the fine-tuning based approaches by proposing BERT: **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. BERT alleviates the previously mentioned unidirectionality constraint by using a "masked language model" (MLM) pre-training objective, inspired by the Cloze task (Taylor, 1953). The masked language model randomly masks some of the tokens from the input, and the objective is to predict the original vocabulary id of the masked

Proceedings of NAACL-HLT 2019, pages 4171–4186
Minneapolis, Minnesota, June 2 - June 7, 2019. ©2019 Association for Computational Linguistics



BERT: Pre-training of Deep Bidirectional Transformers for

BERT Rediscovers the Classical NLP Pipeline

Ian Tenney[1] Dipanjan Das[1] Ellie Pavlick[1,2]
[1]Google Research [2]Brown University
{iftenney,dipanjand,epavlick}@google.com

Abstract

Pre-trained text encoders have rapidly advanced the state of the art on many NLP tasks. We focus on one such model, BERT, and aim to quantify where linguistic information is captured within the network. We find that the model represents the steps of the traditional NLP pipeline in an interpretable and localizable way, and that the regions responsible for each step appear in the expected sequence: POS tagging, parsing, NER, semantic roles, then coreference. Qualitative analysis reveals that the model can and often does adjust this pipeline dynamically, revising lower-level decisions on the basis of disambiguating information from higher-level representations.

of the network directly, to assess whether there exist localizable regions associated with distinct types of linguistic decisions. Such work has produced evidence that deep language models can encode a range of syntactic and semantic information (e.g. Shi et al., 2016; Belinkov, 2018; Tenney et al., 2019), and that more complex structures are represented hierarchically in the higher layers of the model (Peters et al., 2018b; Blevins et al., 2018).

We build on this latter line of work, focusing on the BERT model (Devlin et al., 2019), and use a suite of probing tasks (Tenney et al., 2019) derived from the traditional NLP pipeline to quantify where specific types of linguistic information are

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anguage Models for Speech Recognition

lass-based ngram models of atural language

i et al.: [*LDA Topic Modeling*]

2010

Mikolov: *word2vec*

2018

Bengio: Neural-net based embeddings

Collobert and Weston: *A unified architecture for natural language processing: Deep neural networks*

BERT

XLNet
RoBERTA

GPT3

BERT: Pre-trair

Jacob Devlin Mi

{jacobdevlin,mi

Abstract

We introduce a new languag tion model called BERT, whi Bidirectional Encoder Represe Transformers. Unlike recent la sentation models (Peters et al., ford et al., 2018), BERT is de train deep bidirectional represe unlabeled text by jointly conditi left and right context in all lay sult, the pre-trained BERT mod tuned with just one additional to create state-of-the-art mode range of tasks, such as question language inference, without su specific architecture modificatio

BERT is conceptually simple a powerful. It obtains new state sults on eleven natural langua tasks, including pushing the G 80.5% (7.7% point absolute i MultiNLI accuracy to 86.7% (improvement), SQuAD v1.1 qu ing Test F1 to 93.2 (1.5 point provement) and SQuAD v2.0 T (5.1 point absolute improvemen

1 Introduction

Language model pre-training ha be effective for improving many processing tasks (Dai and Le, 20 2018a; Radford et al., 2018; Ho 2018). These include sentence-le natural language inference (Bow Williams et al., 2018) and para and Brockett, 2005), which aim lationships between sentences by holistically, as well as token-lev named entity recognition and que where models are required to pro output at the token level (Tjong De Meulder, 2003; Rajpurkar et

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FALL 1953

"Cloze Procedure": A New Tool For Measuring Readability

BY WILSON L. TAYLOR*

Here is the first comprehensive statement of a research method and its theory which were introduced briefly during a workshop at the 1953 AEJ convention. Included are findings from three pilot studies and two experiments in which "cloze procedure" results are compared with those of two readability formulas.

"CLOZE PROCEDURE" IS A NEW PSYchological tool for measuring the effectiveness of communication. The method is straightforward; the data are easily quantifiable; the findings seem to stand up.

At the outset, this tool was looked on as a new approach to "readability." It was so used in three pilot studies and two experiments, the main findings of which are reported here.

First, the results of the new method were repeatedly shown to conform with the results of the Flesch and Dale-Chall devices for estimating readability. Then the scope broadened, and cloze procedure was pitted against those standard formulas.

If future research substantiates the results so far, this tool seems likely to have a variety of applications, both theoretical and practical, in other fields involving communication functions.

THE "CLOZE UNIT"

At the heart of the procedure is a functional unit of measurement tentatively dubbed a "cloze." It is pronounced like the verb "close" and is derived from "closure." The last term is one gestalt psychology applies to the human tendency to complete a familiar but not-quite-finished pattern—to "see" a broken circle as a whole one, for example, by mentally closing up the gaps.

*The writer is particularly obligated to Prof. Charles E. Osgood, University of Illinois, and Melvin R. Marks, Personnel Research Section, A.G.O., Department of the Army, for instigating and assisting in the series of efforts that yielded the notion of "cloze procedure." Both are experimental psychologists. Among others who have advised, encouraged or otherwise aided are these of the University of Illinois: Prof. Lee J. Cronbach, educational psychologist and statistician; Dean Wilbur Schramm, Division of Communications; Prof. Charles E. Swanson, Institute of Communications Research, and George R. Klare, psychologist, both of whom have authored articles on readability; and several journalism teachers who lent their classes. Kalmer E. Stordahl and Clifford M. Christensen, until recently research associates of the Institute, also contributed.

ng and *Vector Semantics*

e vowel or consonant.

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2010

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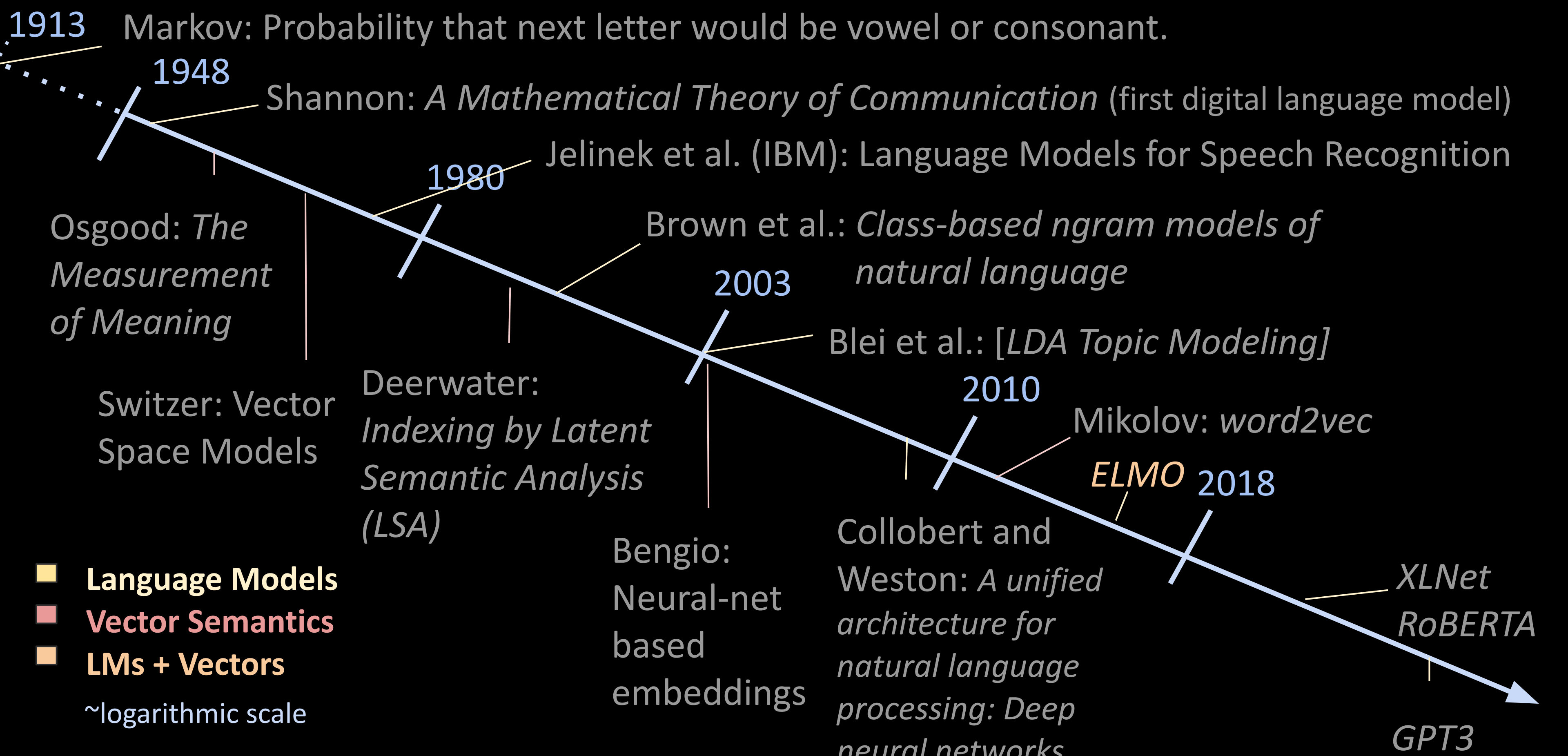
Timeline: *Language Modeling* and *Vector Semantics*



Masked Language Modeling

Task: Estimate $P(w_i | w_1,\ldots w_{i-1}, w_{i+1}\ldots w_n)$

:P(masked word given history)

P(with | He ate the cake <M> the fork) = ?

Masked Language Modeling

Task: Estimate $P(w_i | w_1,...w_{i-1}, w_{i+1}... w_n)$

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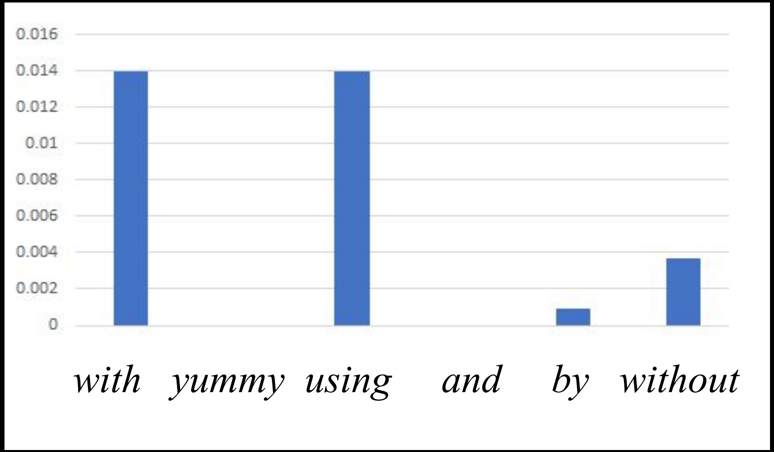
$P(with \mid He\ ate\ the\ cake$ <M> $the\ fork) = ?$



Masked Language Modeling

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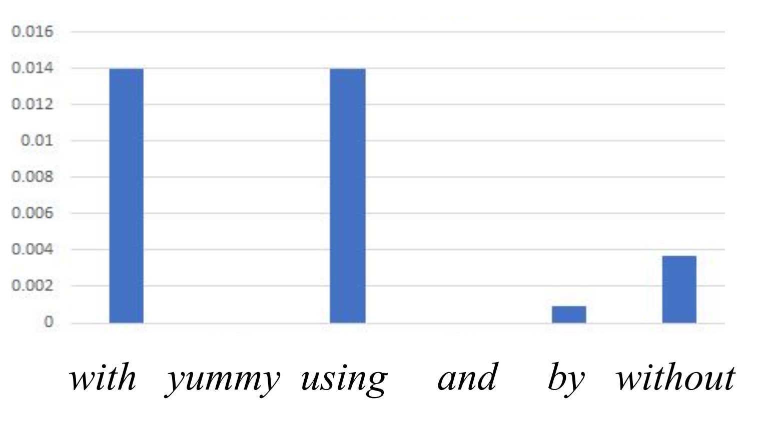


Masked Language Modeling

Task: Estimate $P(w_i | w_1,\ldots w_{i-1}, w_{i+1}\ldots w_n)$

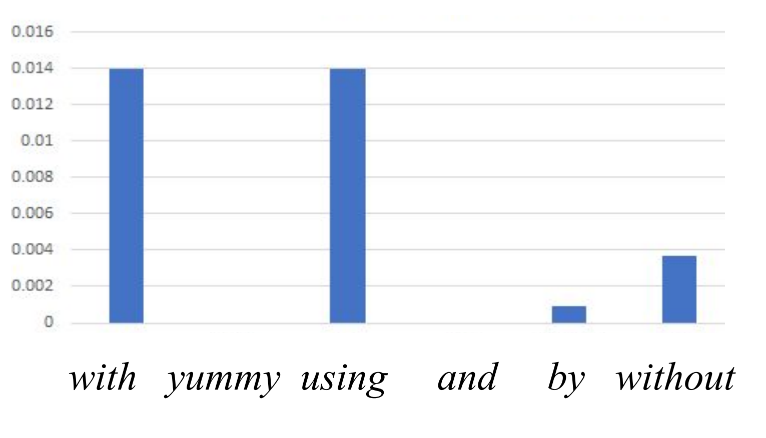
:P(masked word given history)

P(with | He ate the cake <M> the fork) = ?

Sequence
(He, at, the, cake,<MASK>, the, fork)

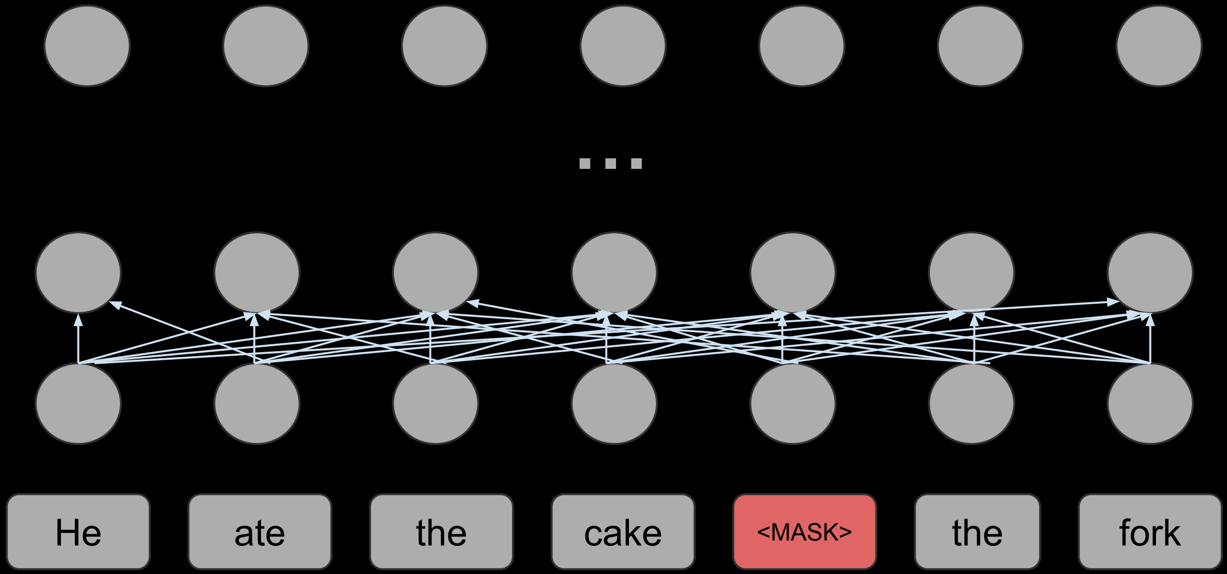
→ Neural Network →

What is the masked word in the sequence?

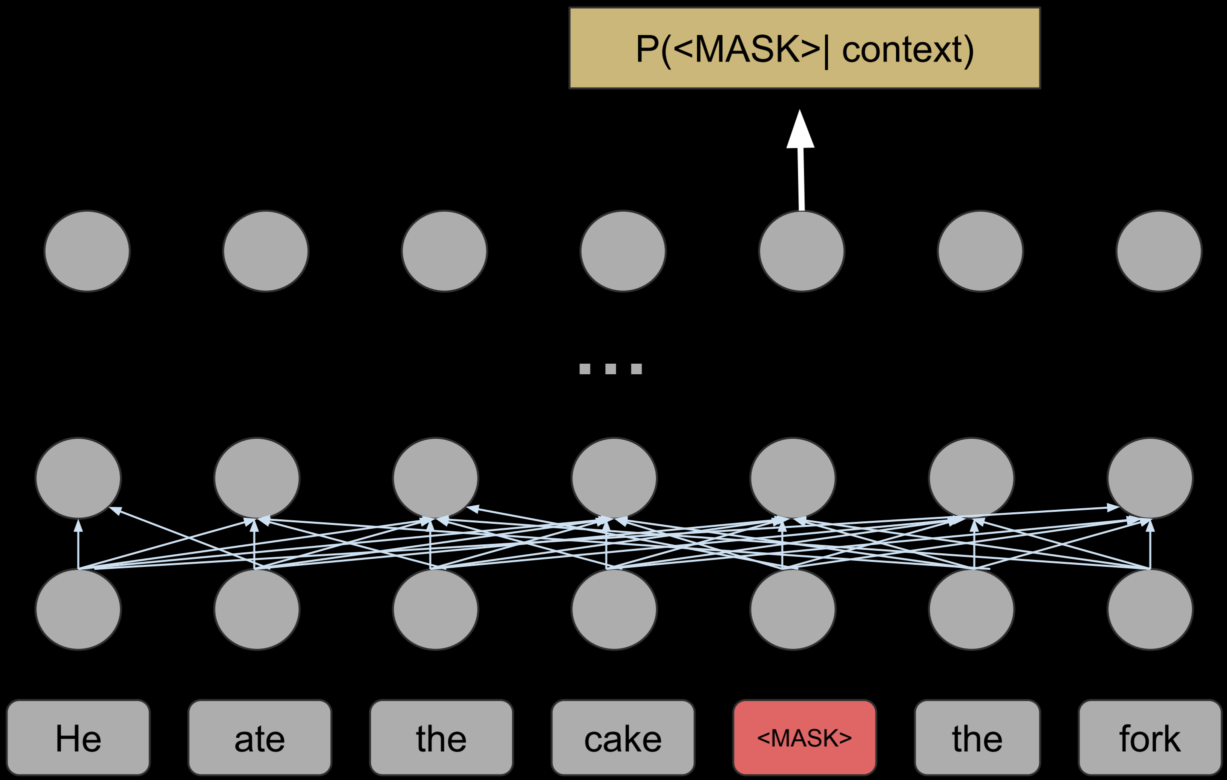


Masked Language Modelling with DNN

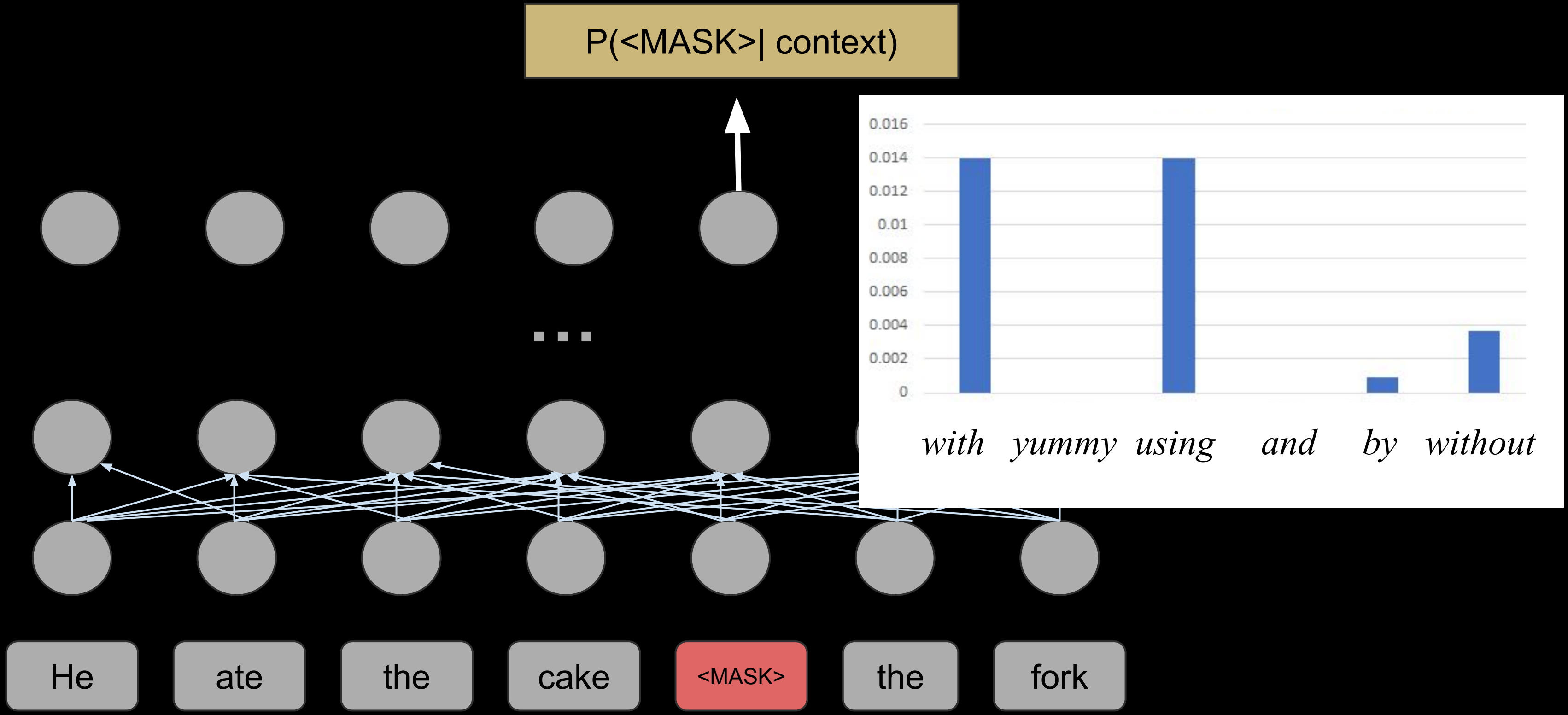
Masked Language Modelling with DNN



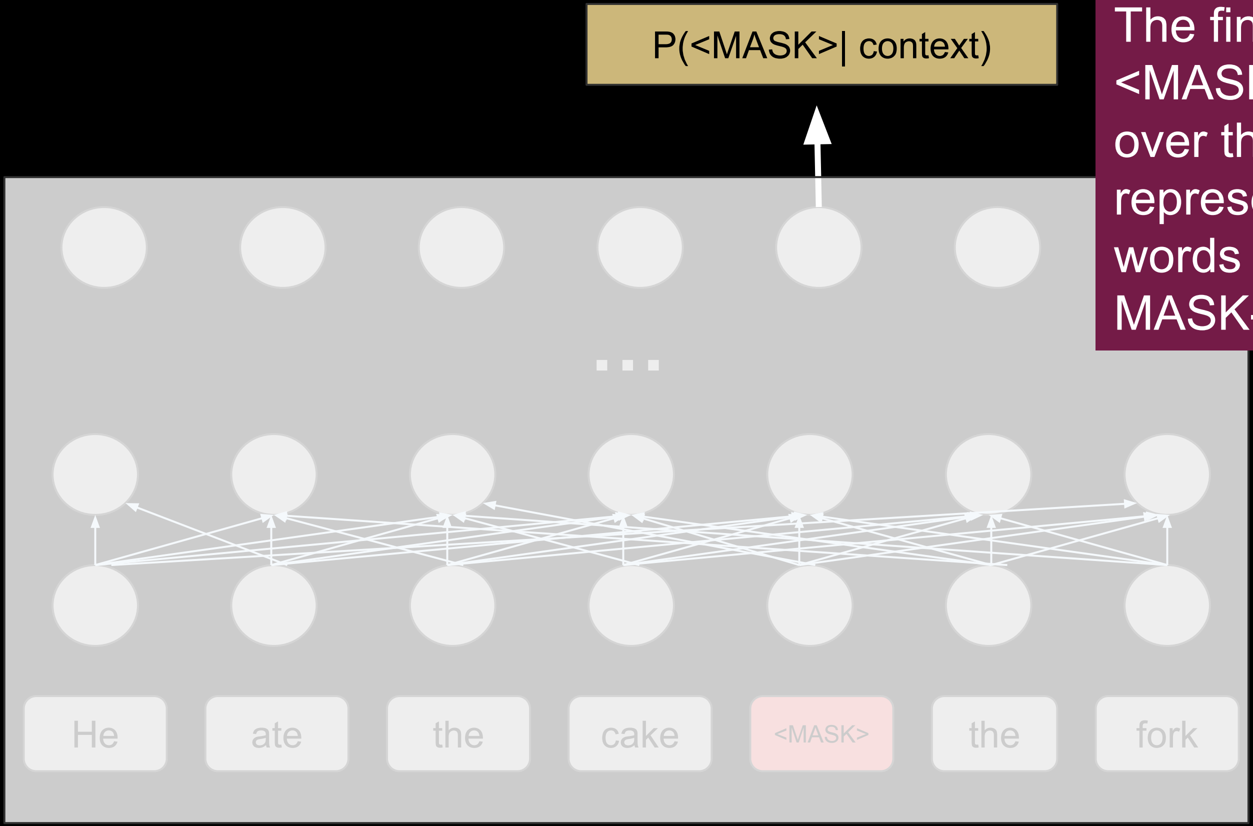
Masked Language Modelling with DNN



Masked Language Modelling with DNN

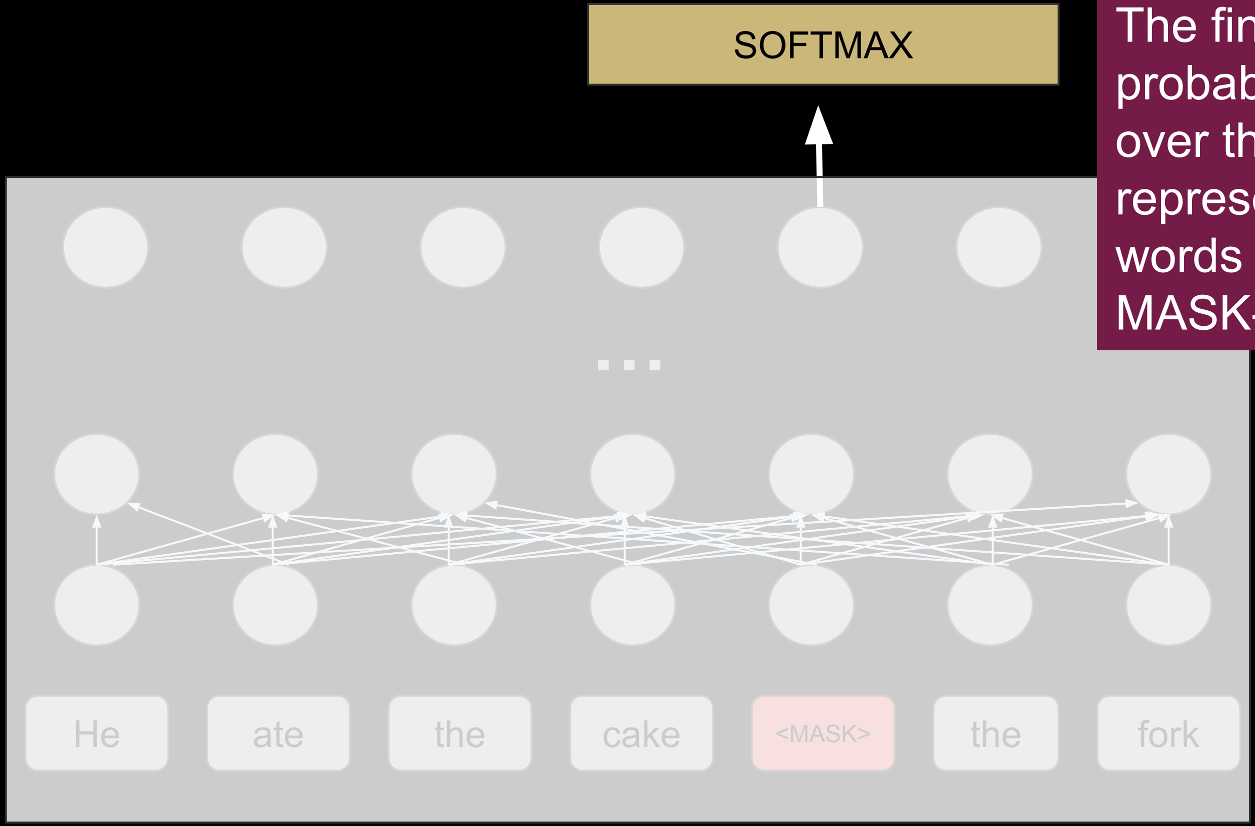


Masked Language Modelling with ANN



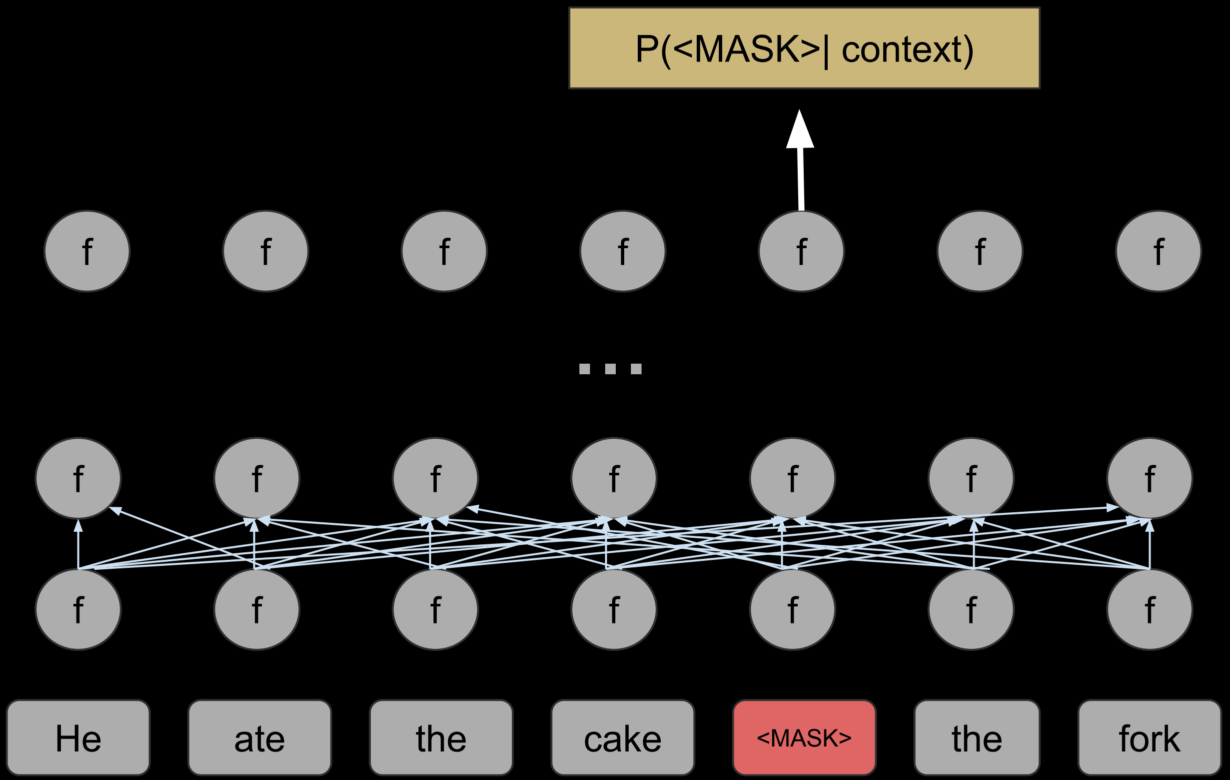
The final layer produces a <MASK> distribution over the vocabulary, representing the likely words to fill in the MASK-ed token

Masked Language Modelling with DNN

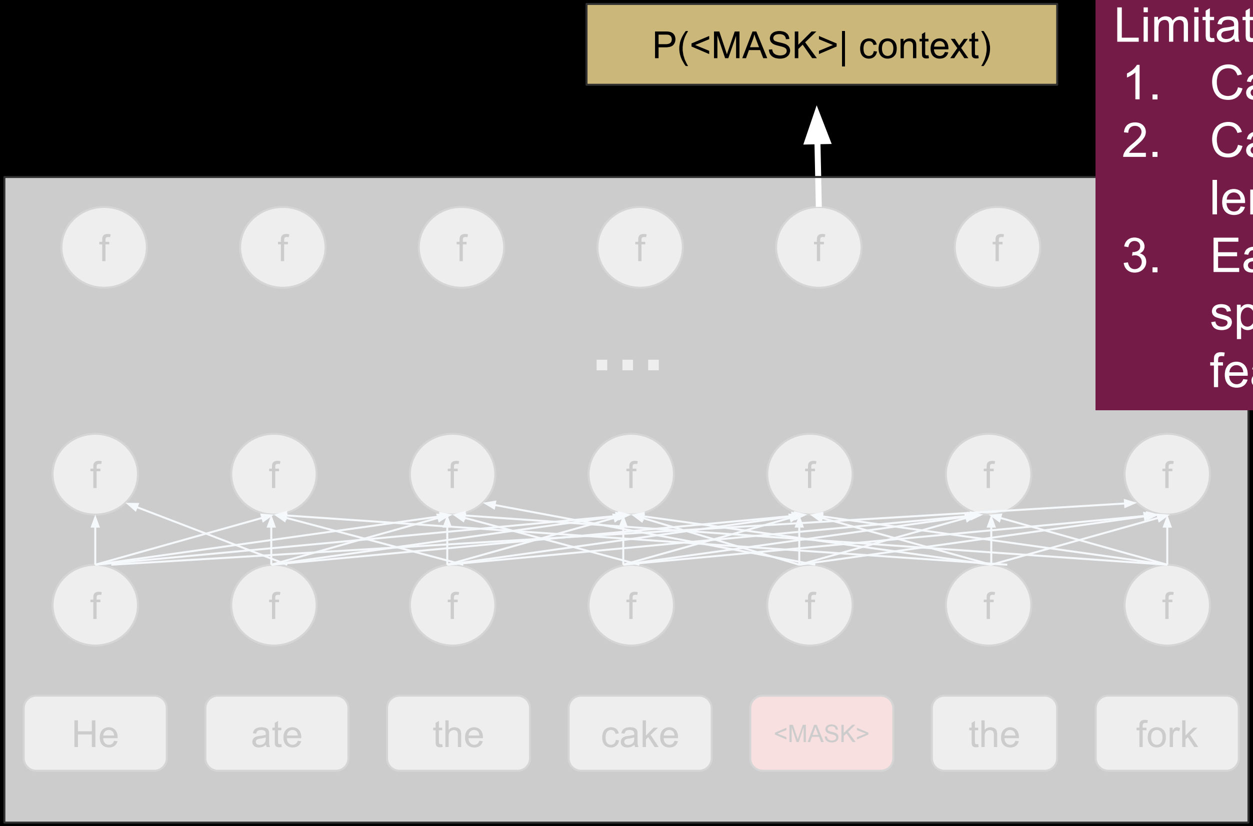


The final layer produces a probability distribution over the vocabulary, representing the likely words to fill in the MASK-ed token

Masked Language Modelling with DNN



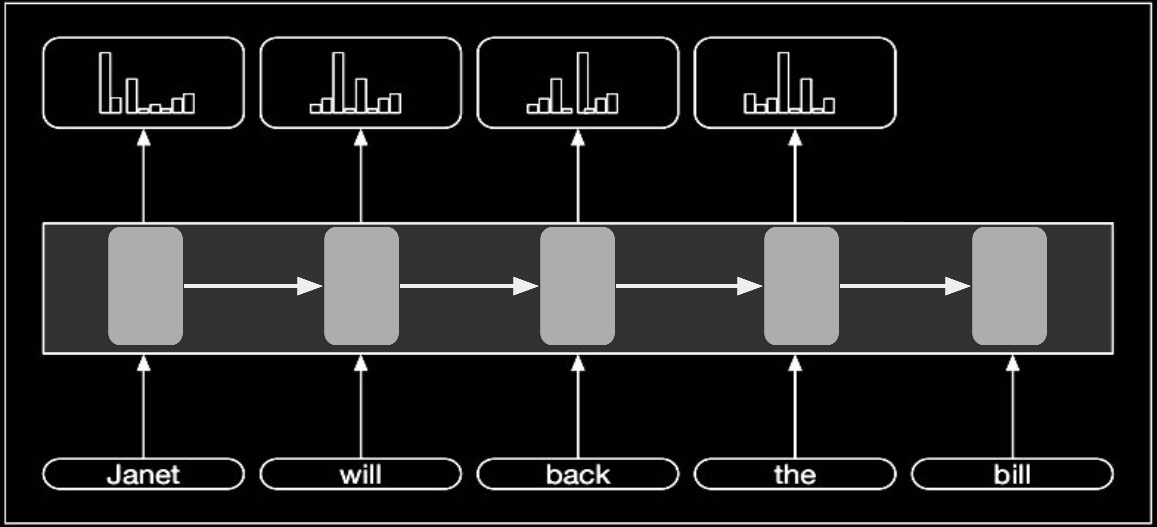
Masked Language Modelling with DNN



Limitations:

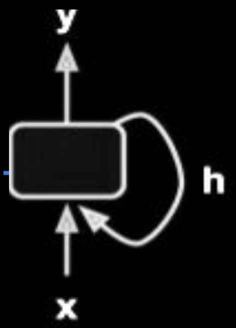
1. Can’t handle order
2. Can’t handle variable length sequences
3. Each parameter to specific to the input feature (token)

Recurrent Neural Network



Masked Language modeling with an RNN

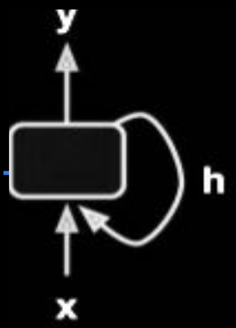
Example: Forward Pass



(Geron, 2017)

```
#define forward pass graph:
h(0) = 0
for i in range(1, len(x)):
    h(i) = g(U h(i-1) + W x(i)) #update hidden state
    y(i) = f(V h(i)) #update output
```

Example: Forward Pass

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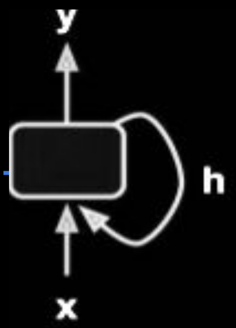
```

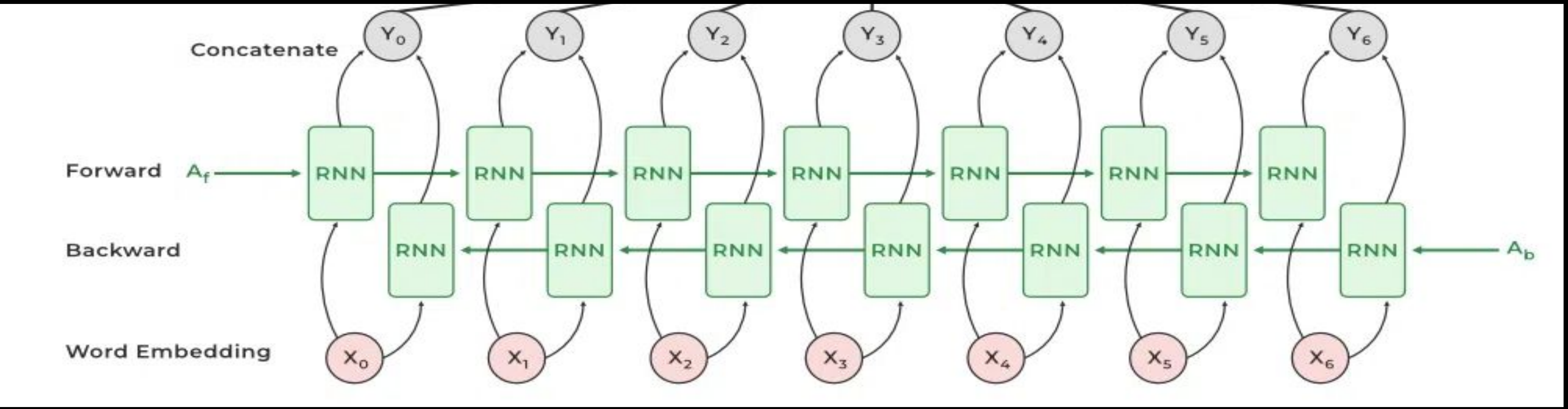
Example: Forward Pass




```
#define forward pass graph:
h_(0) = 0
for i in range(1, len(x)):
    h_(i) = tanh(matmul(U,h_(i-1))+ matmul(W,x_(i))) #update hidden state
    y_(i) = softmax(matmul(V, h_(i))) #update output
```

Masked Language Modelling with Recurrent Network

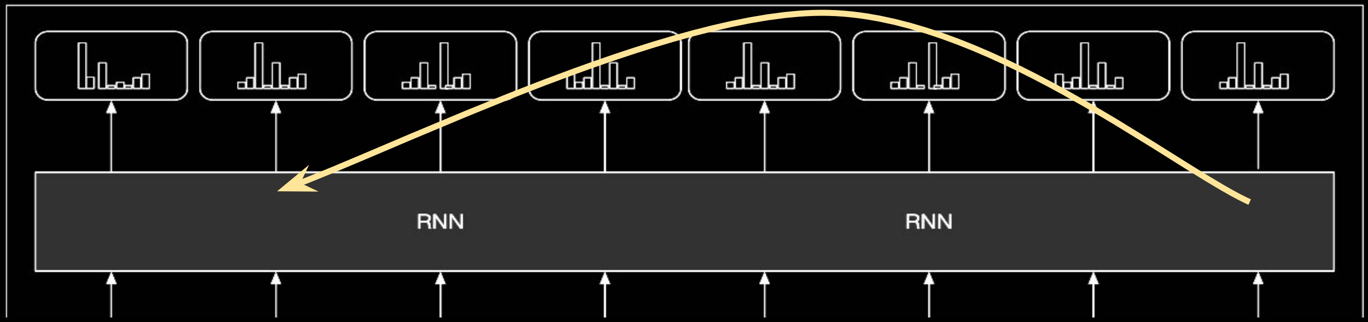
P(<MASK>| context)



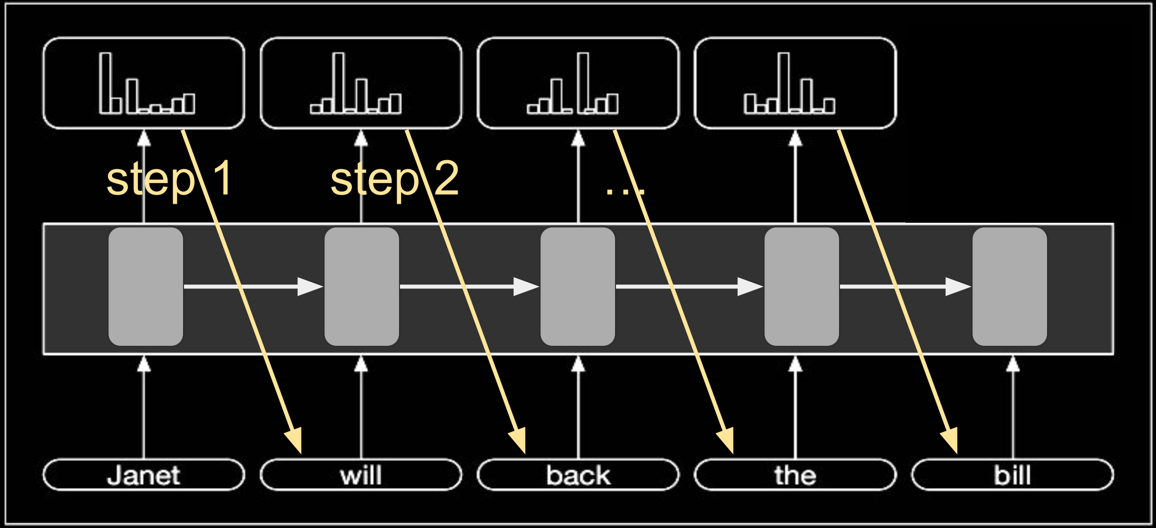
He | ate | the | cake | <MASK> | the | fork

RNN: Limitation:
Losing Track of Long Distance Dependencies

The horse which was raced past the barn tripped .



RNN: Limitation: Not parallelizable



Language modeling with an RNN

Next Lecture

- Deep dive into Self Attention (Vaswani et al., 2017)
- Masked Language Modelling using Transformers (Devlin et al., 2019)