Deep Learning for IR

- SI650 / EECS549 Information Retrieval
- October 15, 2025

Slides adapted from David Juergen

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Announcements

- HW3 (focused on deep learning) is released
- CRLT results were shared with me last night. I will share insights and our plans next week
- Proposals will be graded soon

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Today's goals

- Exposure to deep learning methods
  - Text-based
  - Their connection to IR

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Query: “natural landscape”

- doc1: “a sandy desert scene with a blue sky”
- doc2: “neural network training loss landscape”

Problem: Our query-document comparison doesn’t recognize similarities between word meanings

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Let's recall Pivoted Normalization…

$$f(q,d) = \sum_{w \in q \cap d} c(w,q) \frac{1 + \ln(1 + \ln(c(w,d)))}{1 - b + b\frac{|d|}{avg\_dl}} \ln \frac{N+1}{df(w)}, b \in [0,1]$$

Why do we only care about terms in both Q and D?

What if we modified Pivoted Normalization so that it took word similarity into account?

$$f(q,d) = \sum_{w_1 \in q} \sum_{w_2 \in d}$$

If similarity(w_1,w_2)=1 only when w_1 and w_2 are the same word (and 0 otherwise) this is the same as Pivoted Normalization

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How might we estimate the similarity of words?

$$f(q,d) = \sum_{w_1 \in q} \sum_{w_2 \in d} similarity(w_1, w_2) \left[c(w_1, q) \frac{1 + \ln(1 + \ln(c(w_2, d)))}{1 - b + b \frac{|d|}{avg\_dl}} \ln \frac{N+1}{df(w_2)}, b \in [0,1] \right]$$

- We could use a thesaurus!
  - Problem: Limited coverage
- Maybe look at word-occurrences, e.g., PMI?
  - Problem: Huge space requirements
- What if learned representations for each word that are comparable?

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Word Vectors

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Word Representations

- Classical representations
  - Bag of Words representation

- Problem: data sparsity

motel [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0] AND
hotel [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0] = 0

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Neural word embeddings

- Neural word embedding (Bengio et al. 2003)
  - All the words are represented in a low-dimensional space
  - Similar words are located closely to each other

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Background: The distributional hypothesis

- "You shall know a word by its company"- J.R. Firth 1957:11

government debt problems turning into	banking	crises as has happened in
saying that Europe needs unified	banking	regulation to replace the hodgepodge

↖ These words will represent *banking* ↗

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word2vec: a library for learning dense word vectors

- Breakthrough in early 2010s
- Fast approach to learn dense vector representations of words where vector similarity ≈ semantic similarity
  - dense in contrast to sparse bag of words
- Many downstream applications used (and still use) these vectors

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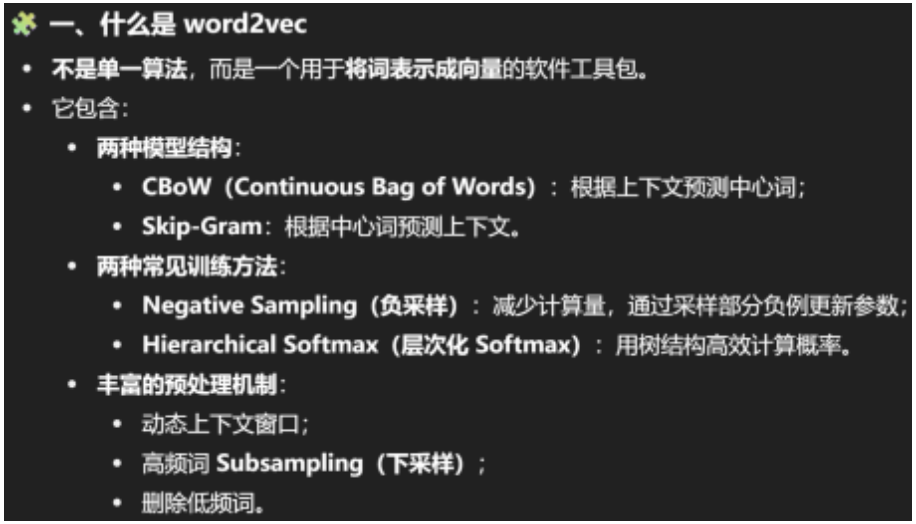
What is word2vec? （一种特征生成工具）

- word2vec is not a single algorithm
- It is a software package for representing words as vectors, containing:
  - Two distinct models
    - CBoW
    - Skip-Gram
  - Various training methods
    - Negative Sampling
    - Hierarchical Softmax
  - A rich preprocessing pipeline
    - Dynamic Context Windows
    - Subsampling
    - Deleting Rare Words



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General idea behind word2vec

- Model this probability (sort of):
  - p(context-word | target-word)
  - what words are more likely to show up nearby any given word?
- Use a simple neural network to do the prediction task
  - Each word has its own weights in the network
  - The weights become the dense vector
- **Intuition**: if words show up in very similar contexts, they'll need similar parameters to predict the same context words

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🧠 二、word2vec 的基本思想

- 它要建模一个概率：

$$p(\text{context word} \mid \text{target word})$$

  即：给定一个词，**它周围哪些词更可能出现?**

- 实现方式：
  - 用一个**简单的神经网络**预测上下文；
  - 每个词在网络中都有自己的一组权重；
  - 这些权重经过训练后就成为**词向量（dense vector）**。

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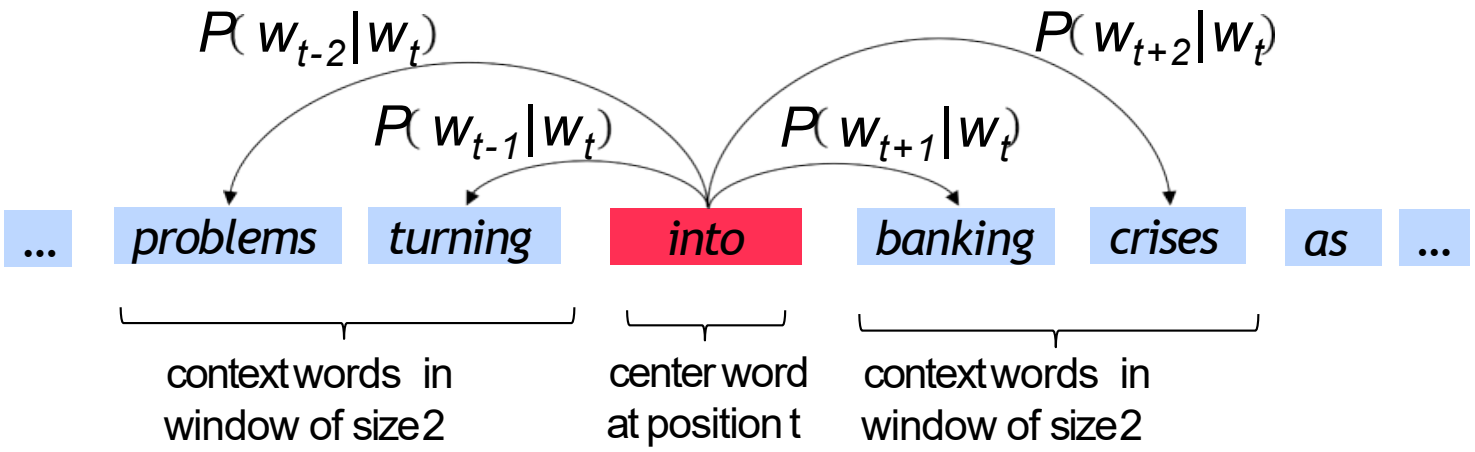
word2vec overview

- Example windows and process for computing $P(w_{t+j}|w_t)$



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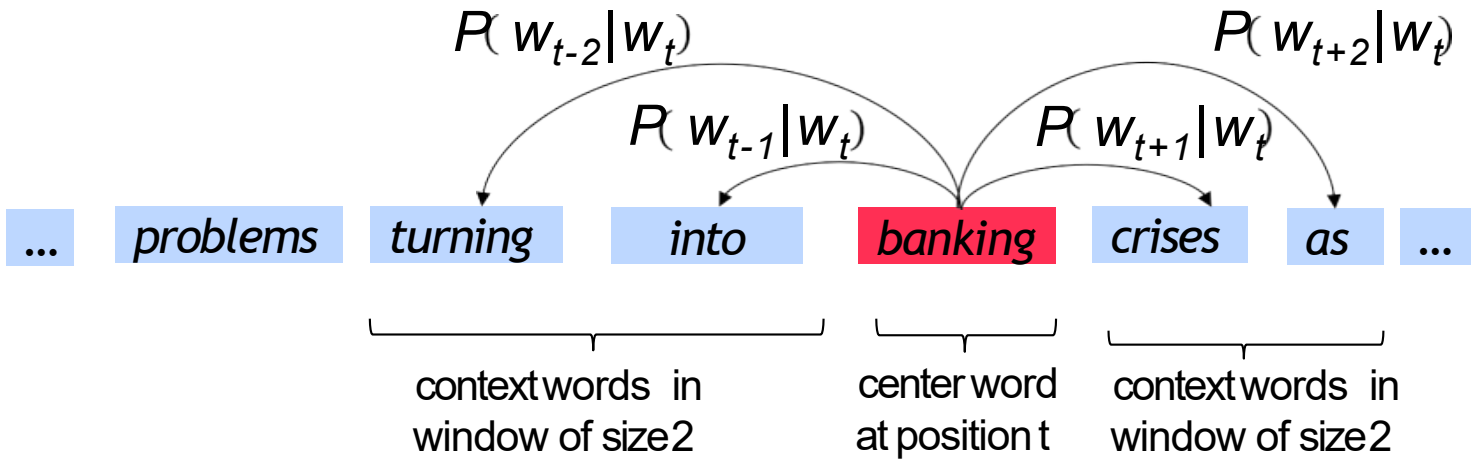
word2vec overview

- Example windows and process for computing $P(w_{t+j}|w_t)$



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Generating positive training examples

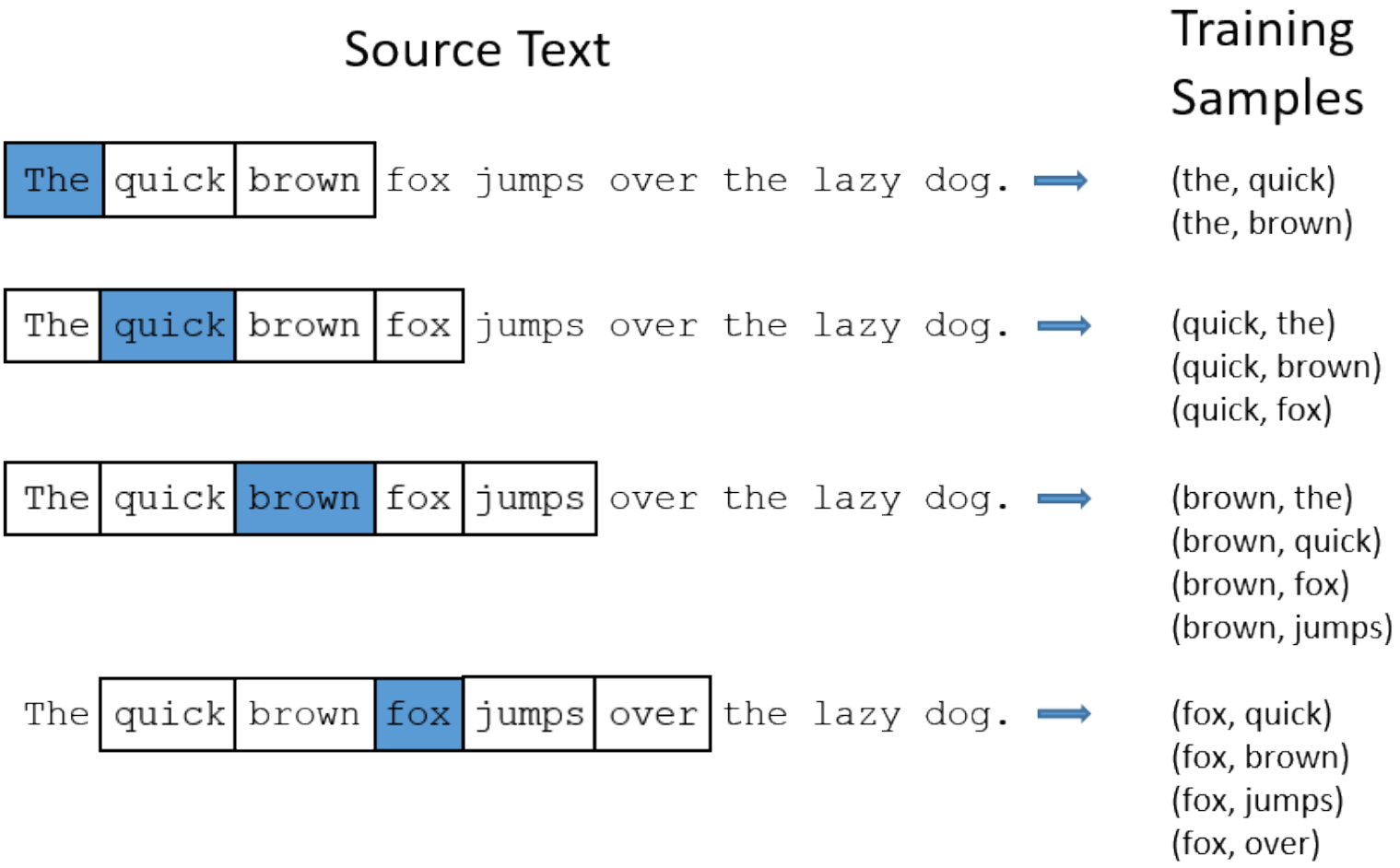

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image credit: http://mccormickml.com/

Learning Word Embeddings

- Word2vec is popular because it is *very efficient* at learning from large amounts of data
- You can learn meaningful vectors from small amounts of text ~1M words—but only for the most common words
- Vector similarities depend on what data you train on. Ideas for what we can use?
  - Wikipedia?
  - News Articles?
  - Social Media?

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Word vectors-nearest neighbors

Word	Neighbors
heart	hart, heart's, iheart, hearth, hearted, art
please	pleased, pleas, pleases, pleaser, plea
plug	plugs, plugged, slug, pug, pluck
chareety	charity, sharee, cheri, tyree, charice, charities

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Simple idea: Bag of Vectors for IR

- Queries and documents are the *average* word vector
- Relevance is cosine similarity of query and document vectors
- Good: Fast, deals with synonyms
- Bad? …
  - Ignores word order
  - Ignores which words are important
- Issue: How to adapt?

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K-NRM:
Using word vectors for IR

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Building dense representations of documents

- The BoW term-document representations may miss potential relevance matches
  - E.g., synonyms, related terminology
- Idea: Use dense vector representations for documents and queries
- Recall our fuzzy Pivoted Normalization… $f(q,d) = \sum_{w_1 \in q} \sum_{w_2 \in d} similarity(w_1, w_2) \left[c(w_1, q) \frac{1+\ln(1+\ln(c(w_2,d)))}{1-b+b\frac{|d|}{avg\_dl}} \ln \frac{N+1}{df(w_2)}, b \in [0,1] \right]$
  - Q: Should we be weighting the similarity somehow?
- Idea: Use a neural network to ***learn*** how to determine relevance from word-pair similarity

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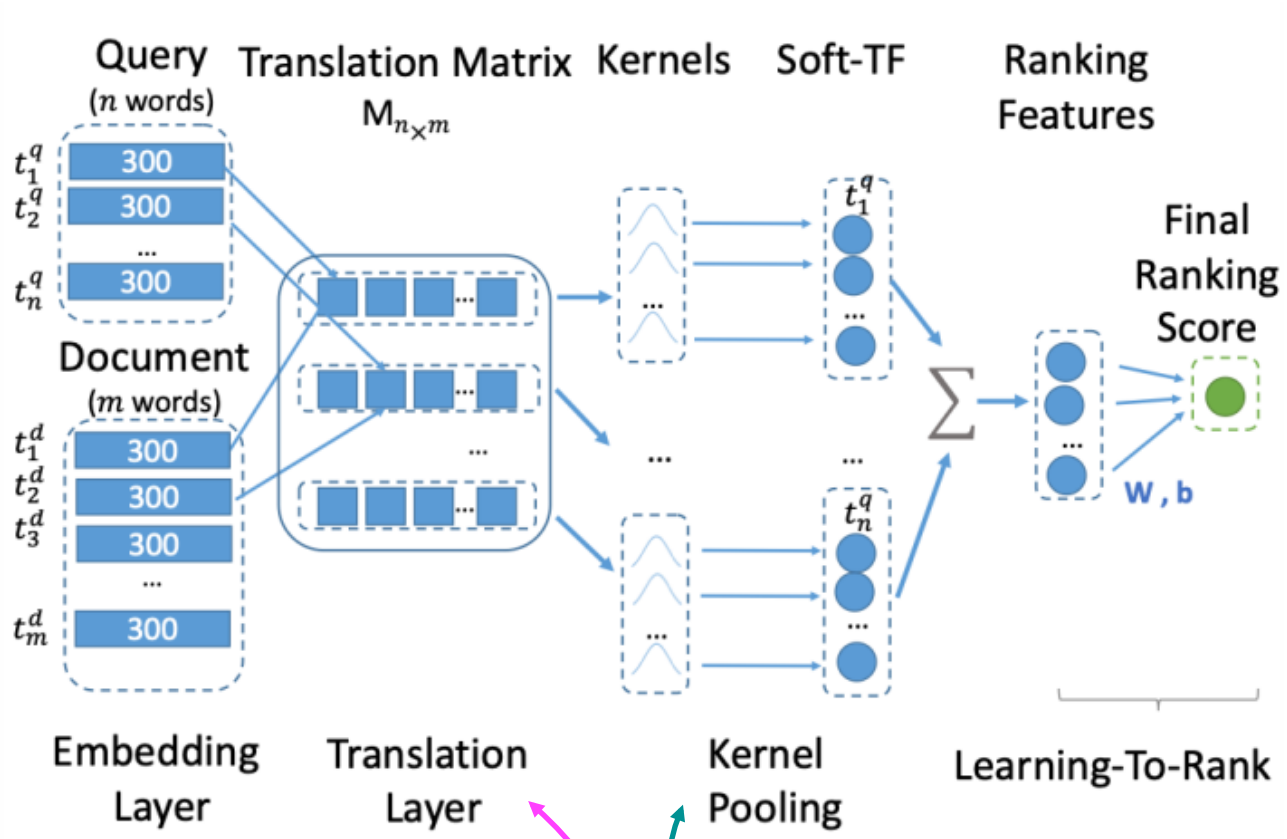
K-NRM: kernel-based neural ranking model



The translation layer computes pair-wise similarities between document words and query words

Learns to score how doc-query relevance from the soft-similarity scores

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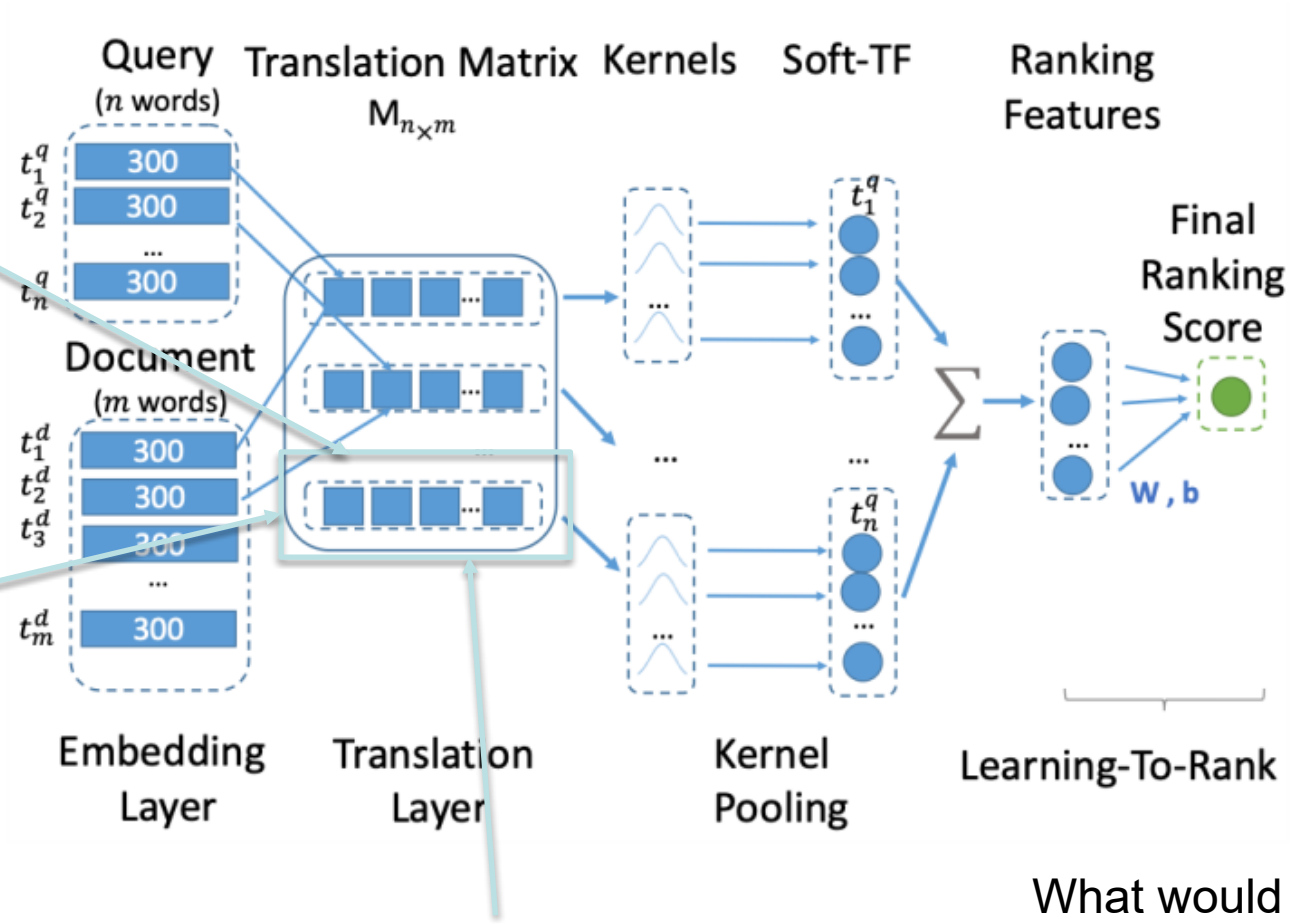
🧩 模型结构分解（从左到右）

1. **Embedding Layer（嵌入层）**
   - 把 query 和 document 的每个词都映射为一个 300 维的词向量（可以用 word2vec、GloVe 等）。
   - 所以每个文档和查询变成一个矩阵。
2. **Translation Layer（翻译层）**
   - 计算每个 query 词和每个 document 词之间的相似度（一般用余弦相似度）。
   - 得到一个“相似度矩阵” $M_{n\times m}$，其中每个元素 $M_{ij} = sim(t_i^q, t_j^d)$。

     👉 图中左侧粉色框解释的就是这一步：“computes pair-wise similarities between document words and query words”。
3. **Kernel Pooling（核池化层）**
   - 不是简单取最大/平均相似度，而是用多个 **Gaussian kernels（高斯核）** 来对不同相似度区间进行软聚合（Soft-TF）。
   - 比如一个核专门统计相似度≈1（完全匹配）的词对，另一个核统计相似度≈0.5（语义相关）的词对。
   - 这样可以捕捉到“软匹配”——不完全相同但语义相近的词。
4. **Learning-to-Rank（学习排序层）**
   - 把每个 query 词的 kernel pooling 结果汇总成一个特征向量；
   - 然后送入一个神经网络，学习输出最终的**相关性分数（Final Ranking Score）**。

     👉 图中绿色框解释的就是：“Learns to score doc-query relevance from the soft-similarity scores”。

K-NRM: kernel-based neural ranking model



Similarity of landscape to each word in doc (a sandy desert scene with a blue sky)

What would happen if the similarity is 1 if identical and zero otherwise?

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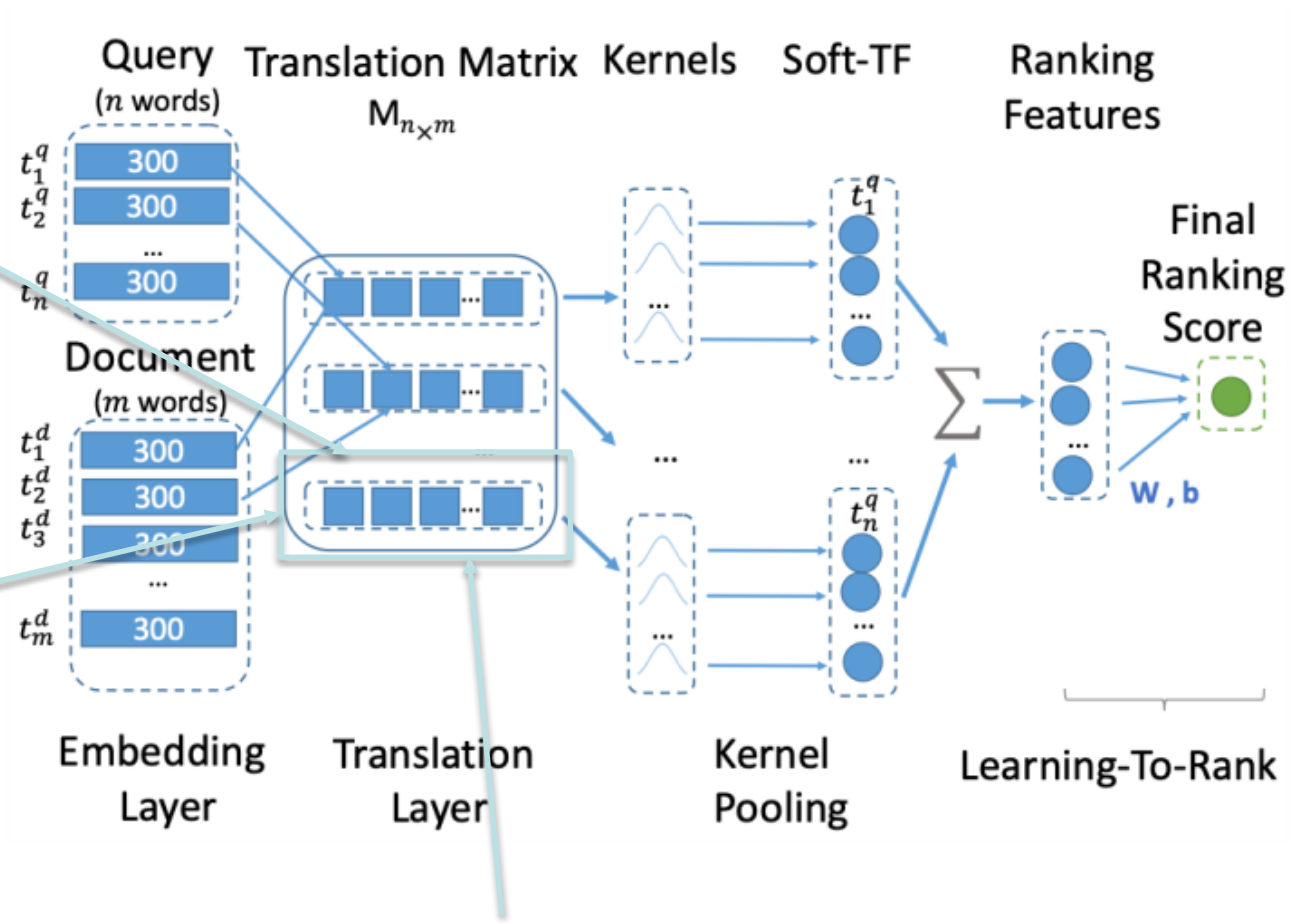
K-NRM: kernel-based neural ranking model



natural landscape

neural network training loss landscape

Similarity of landscape to each word in doc (neural network training loss landscape)

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K-NRM Performance

(a) Testing-SAME. Testing labels are inferred by the same click model (DCTR) as the training labels used by neural models.

Method	NDCG@1		NDCG@3		NDCG@10		W/T/L
Lm	0.1261	−20.89%	0.1648	−26.46%	0.2821	−20.45%	293/116/498
BM25	0.1422	−10.79%	0.1757	−21.60%	0.2868	−10.14%	299/125/483
RankSVM	0.1457	−8.59%	0.1905	−14.99%	0.3087	−12.97%	371/151/385
Coor-Ascent	$0.1594^{\ddagger\S\P}$	–	$0.2241^{\ddagger\S\P}$	–	$0.3547^{\ddagger\S\P}$	–	–/–/–

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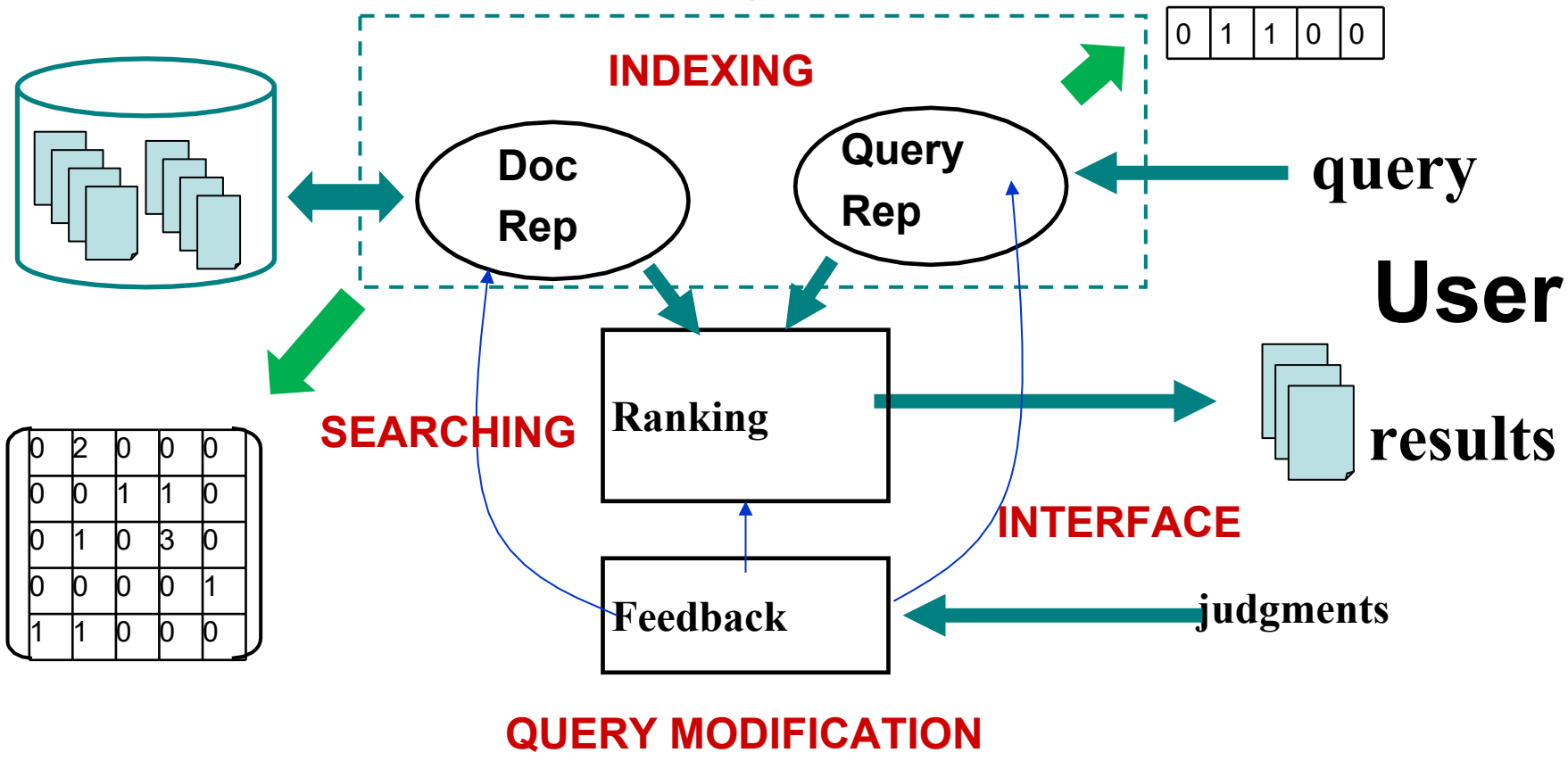
What else can Deep Learning help with?



- can we learn a better document representation?
- … or a model that learns IR-specific representations directly?
- … or how to augment our documents or queries?

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What is Deep Learning in General?

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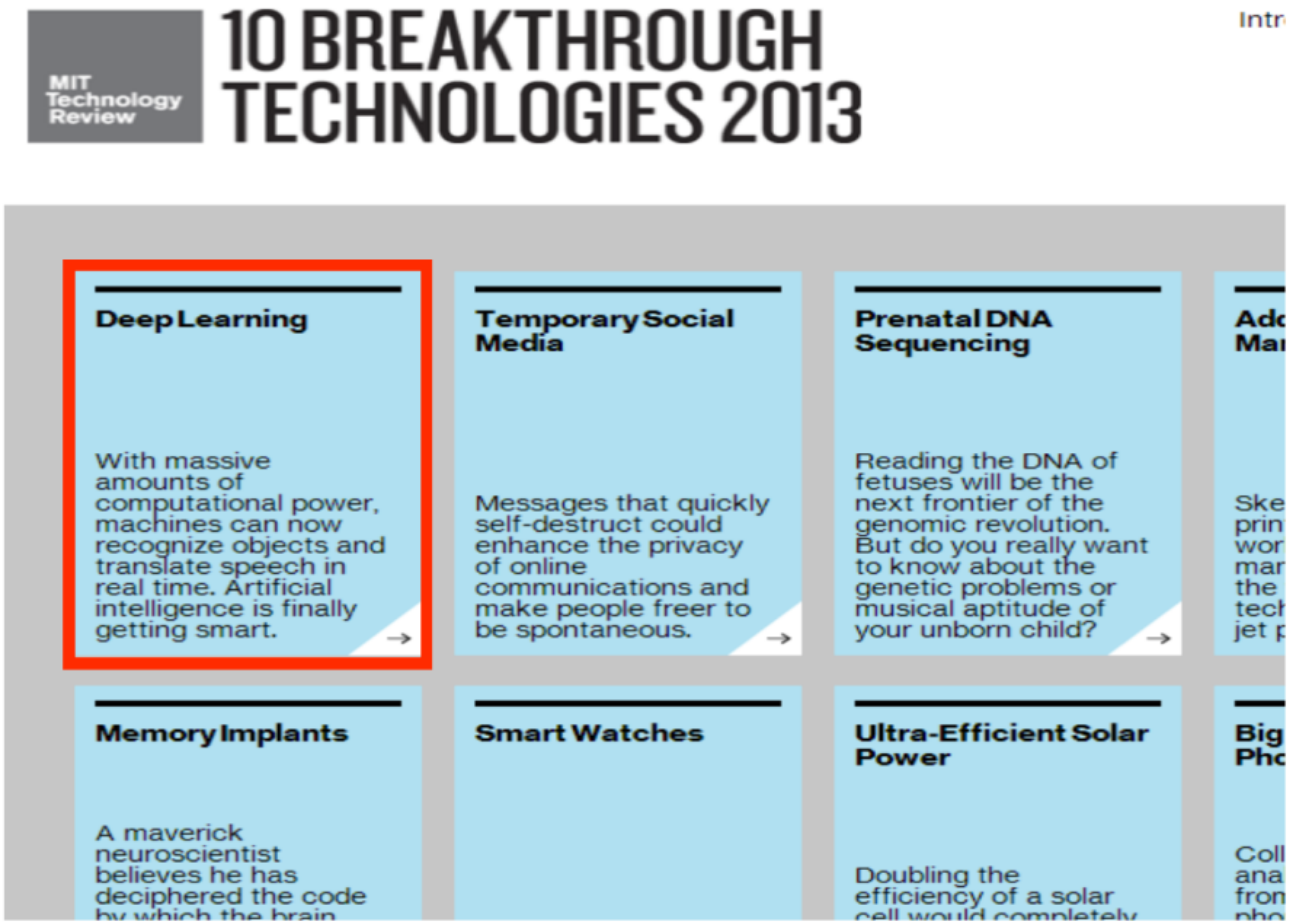

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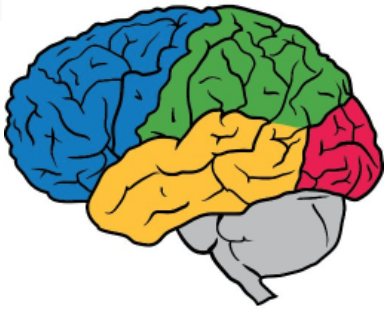
Industry Research Labs of Deep Learning

ANTHROP\C

DeepMind



OpenAI

Facebook AI Research

Baidu Research

Microsoft Research

Tencent AI Lab

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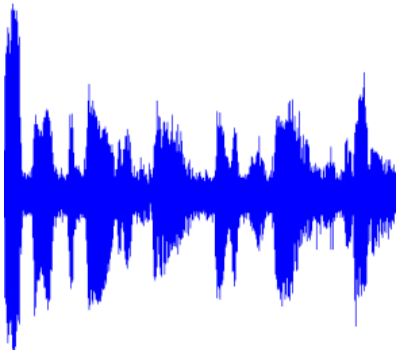
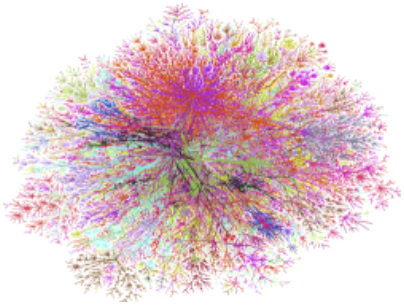
Applications in Multiple Domains



speech

image

text



network

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Speech Recognition Results

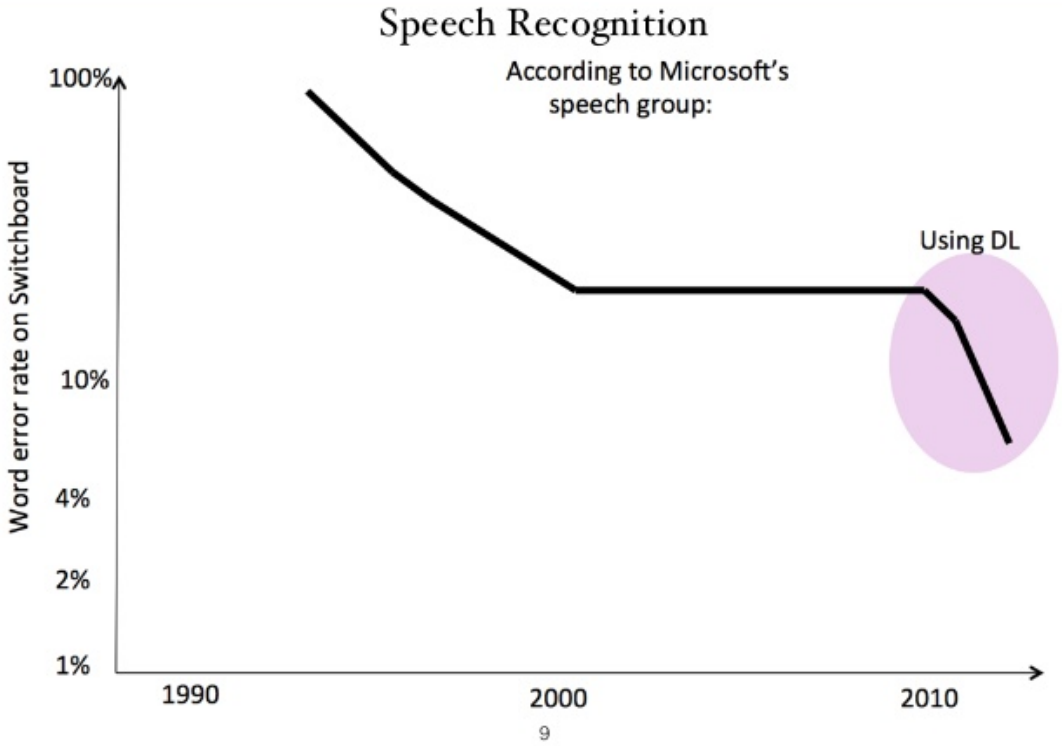

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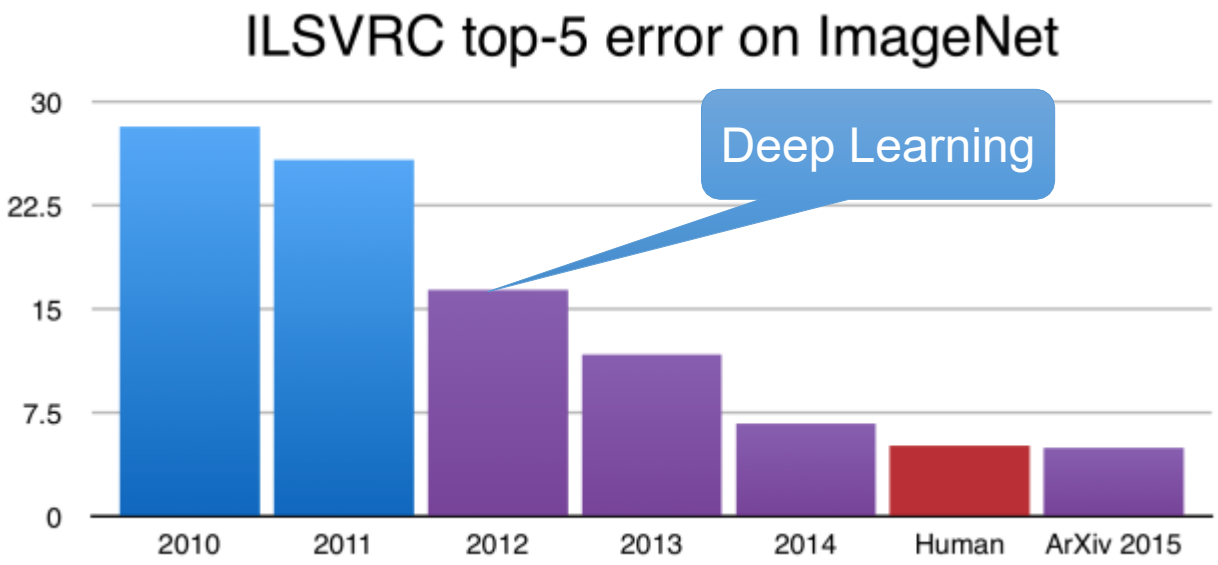
Image Recognition Results



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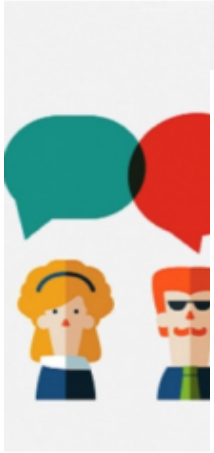
Fast evolvement of Deep Neural Nets

Best NLP Model Ever? Google BERT Sets New Standards in 11 Language Tasks

Synced Follow
Oct 16, 2018 · 3 min read ★

CMU & Google XLNet Tops BERT; Achieves SOTA Results on 18 NLP Tasks

Synced Follow



EDITORIAL ▸ Front Artif Intell. 2024 Jan 12;6:1350306. doi: 10.3389/frai.2023.1350306

Natural language processing in the era of large language models

Arkaitz Zubiaga [1,*]

The new Goog
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▸ Author information ▸ Article notes ▸ Copyright and License information

PMCID: PMC10820986 PMID: 38282904

https://medium.com/syncedreview/best-nlp-model-ever-google-bert-sets-new-standards-in-11-language-tasks-4a2a189bc155

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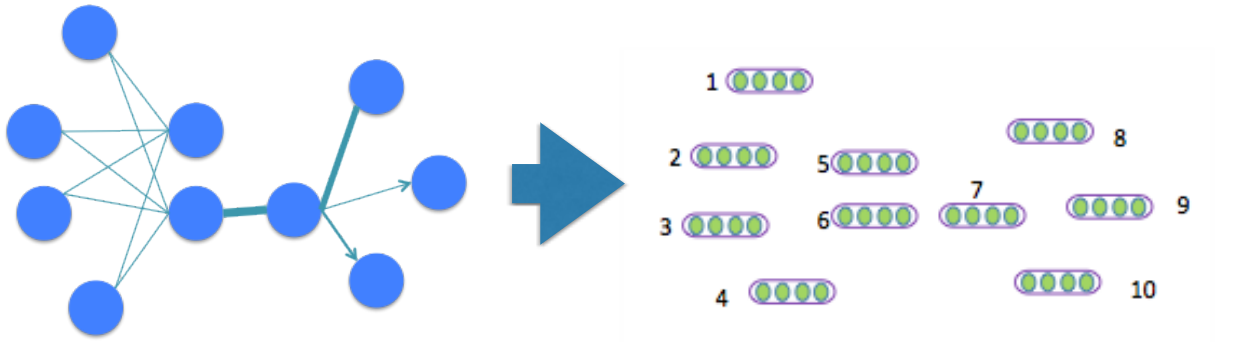
Deep Learning for Networks

- State-of-the-art results on many applications such as node classification, link prediction, cascade prediction
  - DeepWalk, LINE, Node2Vec, GCN, GAT, …



Network **Node representations**

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How Deep is Deep?

- Like “Big” data, “deep” learning is also not well defined.
  - Originally referred to Neural Nets of more than 2 layers (input, output, hidden..), but that dates back to the 80s
  - Other machine learning models can also be “deep” (or non-linear): Random forests, SVM with kernel tricks
- So, what is deep learning?

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Traditional Machine Learning

Hand-crafted
Features

Trainable Classifie
Usually Linear

Domain experts

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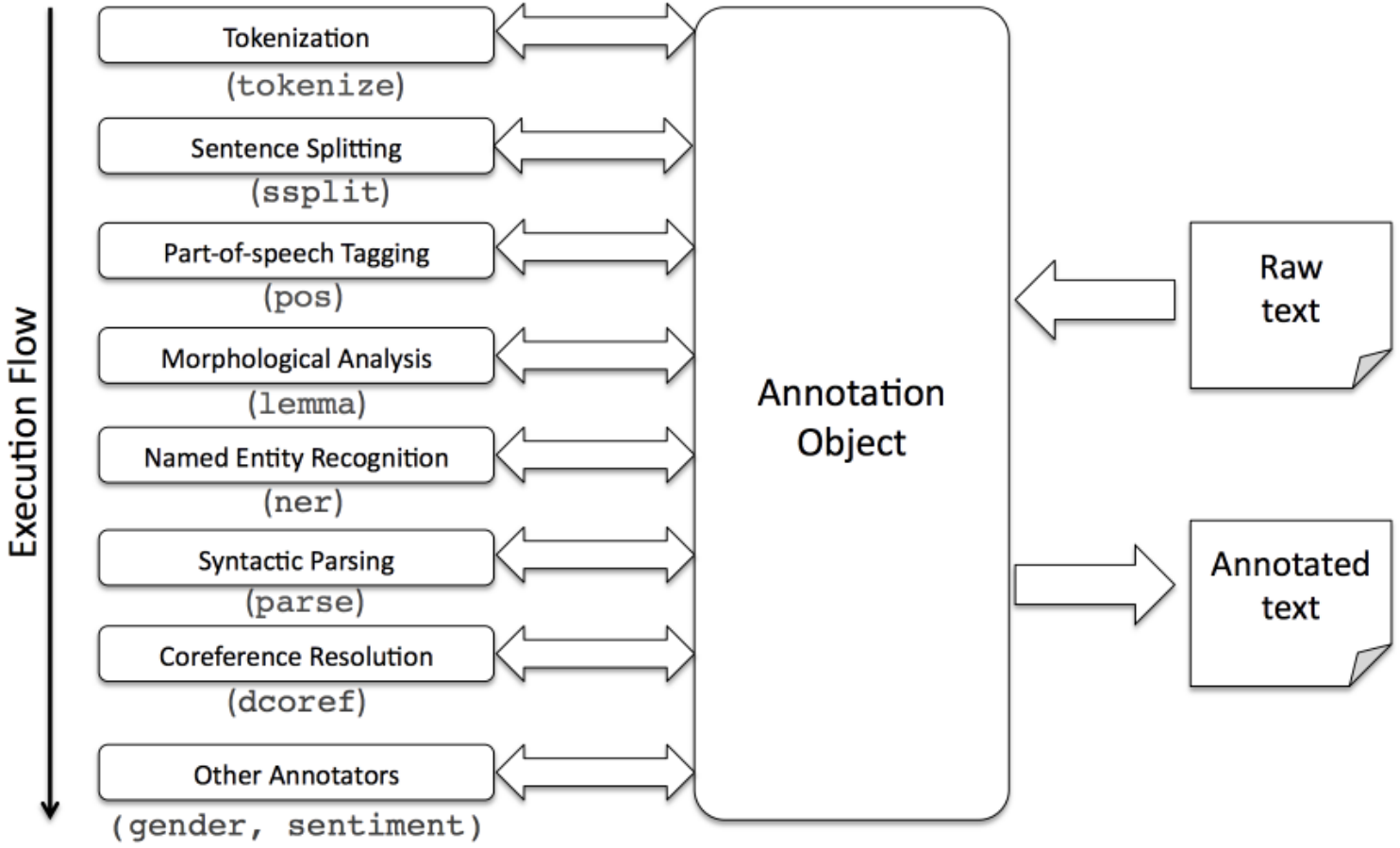
Traditional Approach: NLP Pipelines



https://stanfordnlp.github.io/CoreNLP/pipelines.html

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Problems

- Every level of feature extraction results in a loss of accuracy, and the errors accumulate
- No mechanism to backpropagate the errors made in later stages to improve the previous stages.

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Deep Learning = End-to-end Learning/Feature Learning

Trainable
Feature Extractor

Trainable Classifier
Usually DNN

Domain experts

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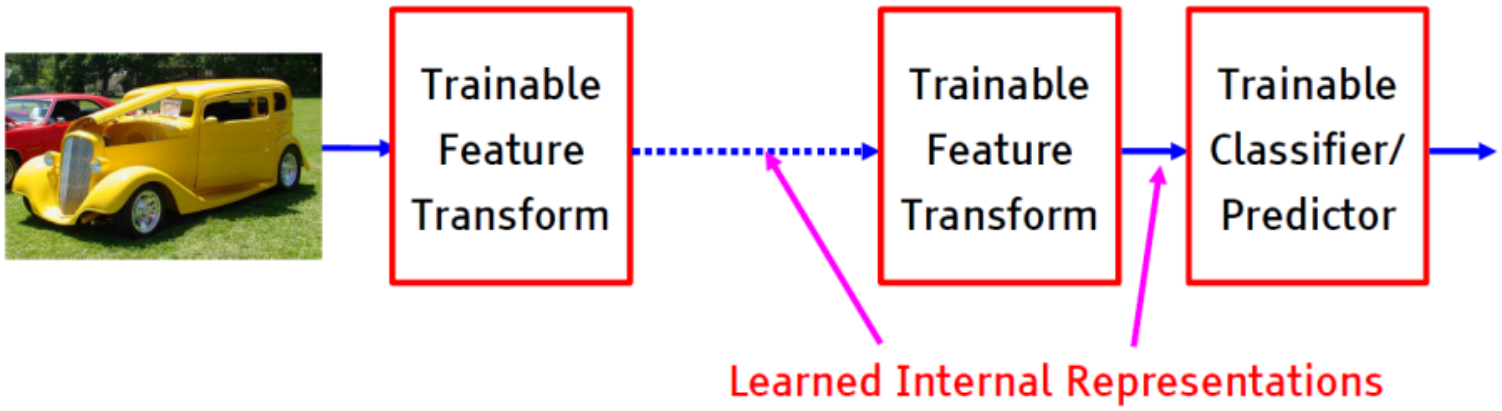
Trainable feature Hierarchies

- A hierarchy of trainable feature transforms
  - Each module transforms its input representations into a higher-level one.
  - High-level features are more global and more invariant
  - Low-level features are shared among categories



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How do neural nets work?

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Neural networks

- Tremendous flexibility on design choices (exchange feature engineering for model engineering)
- Articulate model structure and use the chain rule to derive parameter updates.
- Discrete, high-dimensional representation of inputs (one-hot vectors) -> low-dimensional “distributed” representations.
- Non-linear interactions of input features
- Multiple “layers” to capture hierarchical structure

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Neural network libraries

theano

(Keras)

(Dynet)

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You already know how neural networks* work!

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Logistic regression

- perceptron (one-layer NN)

$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

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SGD

Algorithm 2 Logistic regression stochastic gradient descent

1: Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
2: $\beta = 0^F$
3: **while** not converged **do**
4: **for** $i = 1$ to N **do**
5: $\beta_{t+1} = \beta_t + \alpha \left(y_i - \hat{p}(x_i) \right) x_i$
6: **end for**
7: **end while**

Calculate the derivative of some loss function with respect to parameters we can change, update accordingly to make predictions on training data a little less wrong next time.

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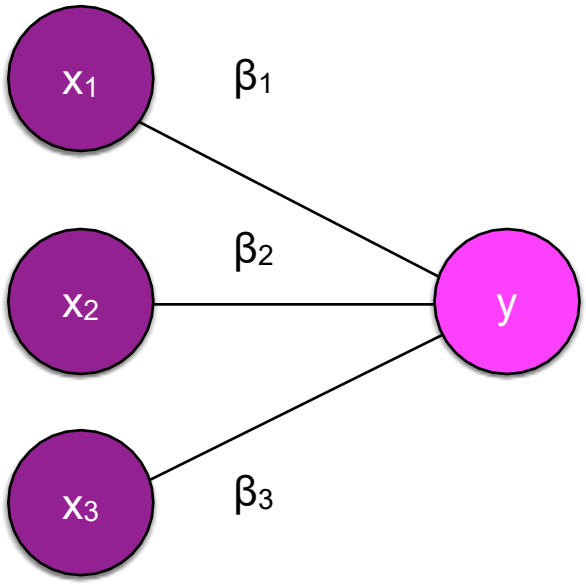
Logistic regression

$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$



	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

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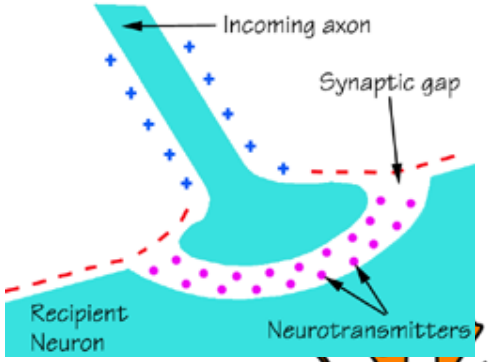
Biological analog of the neuron



How much activation (input) does it take for this neuron to fire (output)?

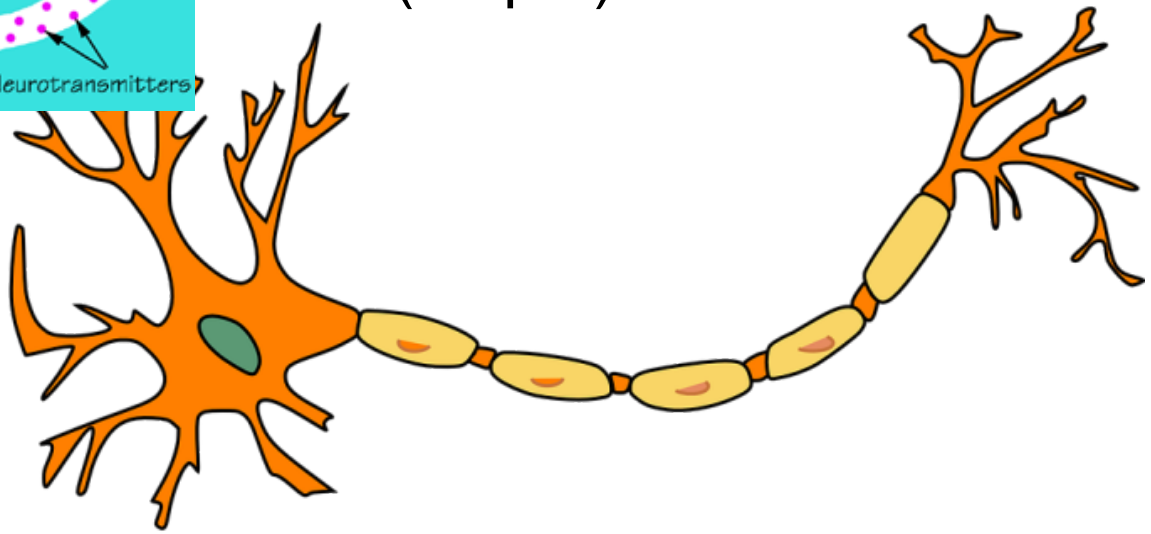


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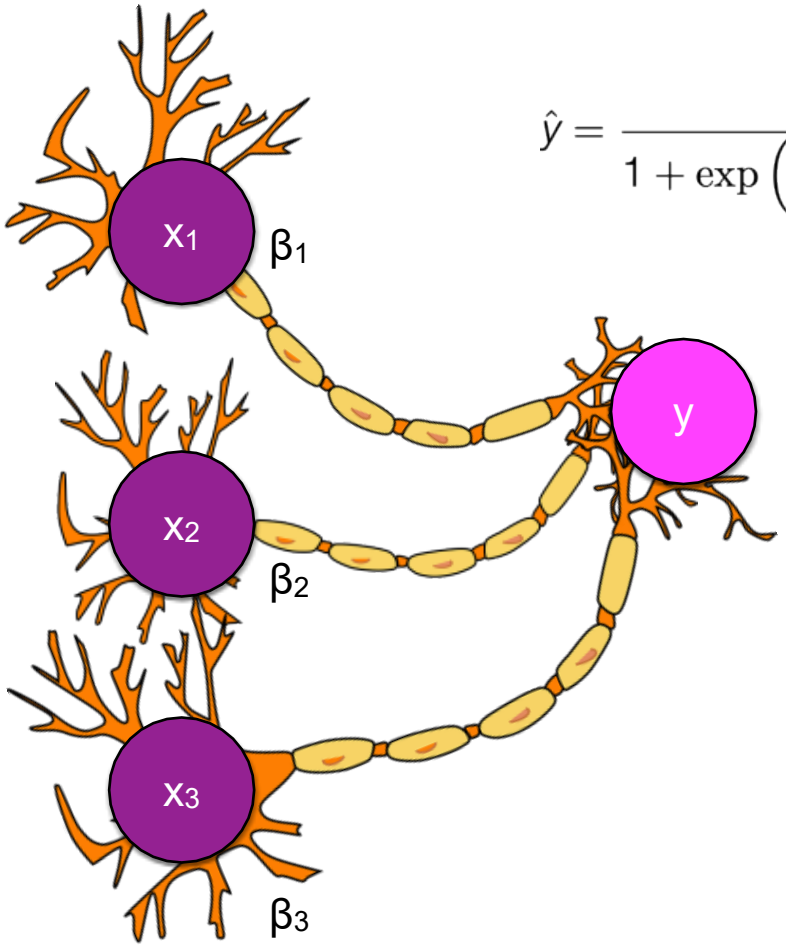
Image credit: https://commons.wikimedia.org/wiki/File:Synapse_diagram.png

Logistic regression



$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

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Deep Neural networks

- Two core ideas:
  - Non-linear activation functions
  - Multiple layers
- These have been around for decades
  - Challenge was how to train them efficiently

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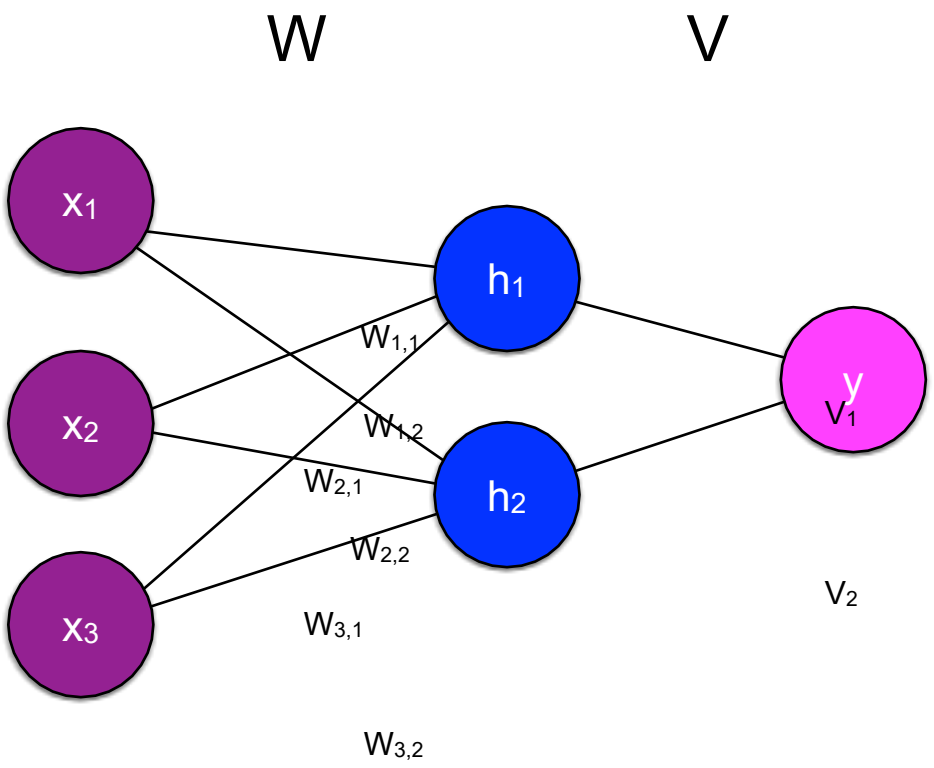
*For simplicity, we're leaving out the bias term, but assume most layers have them as well.



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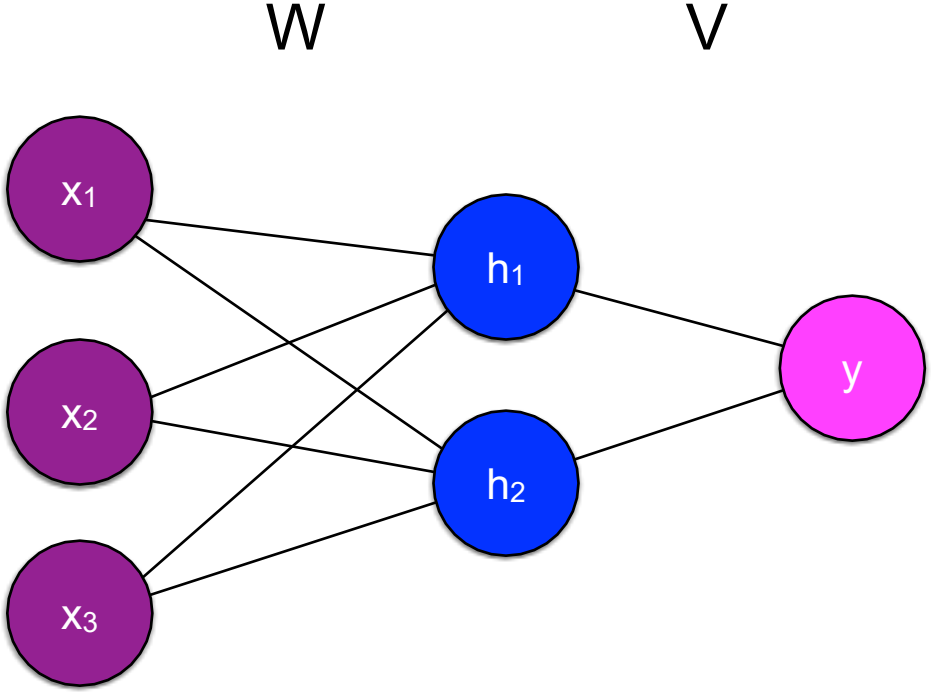

	x	W		V	y
not	1	-0.5	1.3	4.1	1
bad	1	0.4	0.08	-0.9	
movie	0	1.7	3.1		

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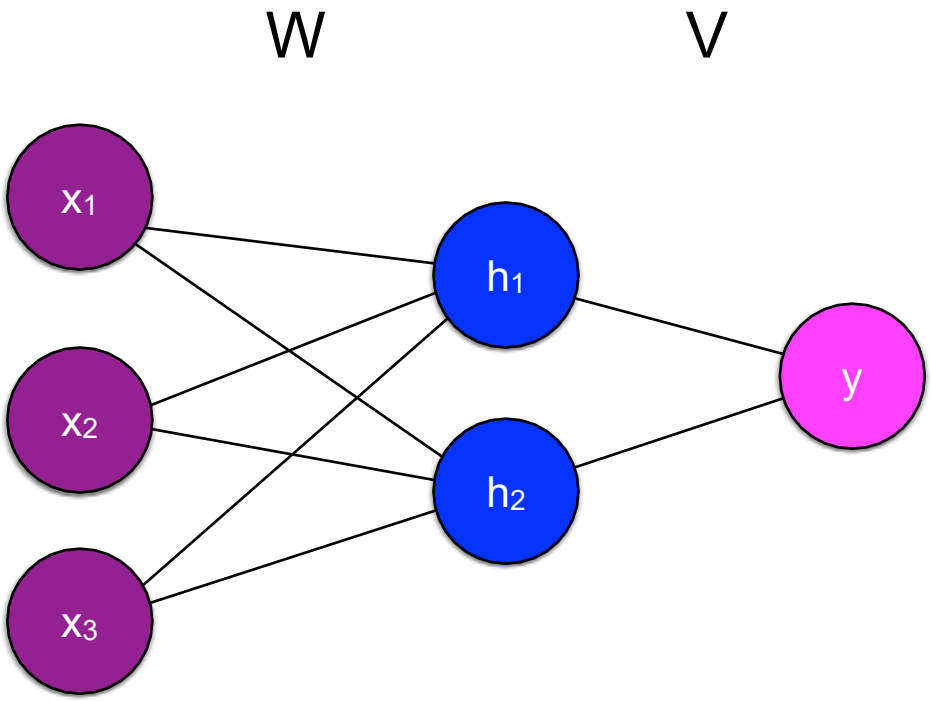

$$h_j = f\left(\sum_{i=1}^{F} x_i W_{i,j}\right)$$

the hidden nodes are completely determined by the input and weights

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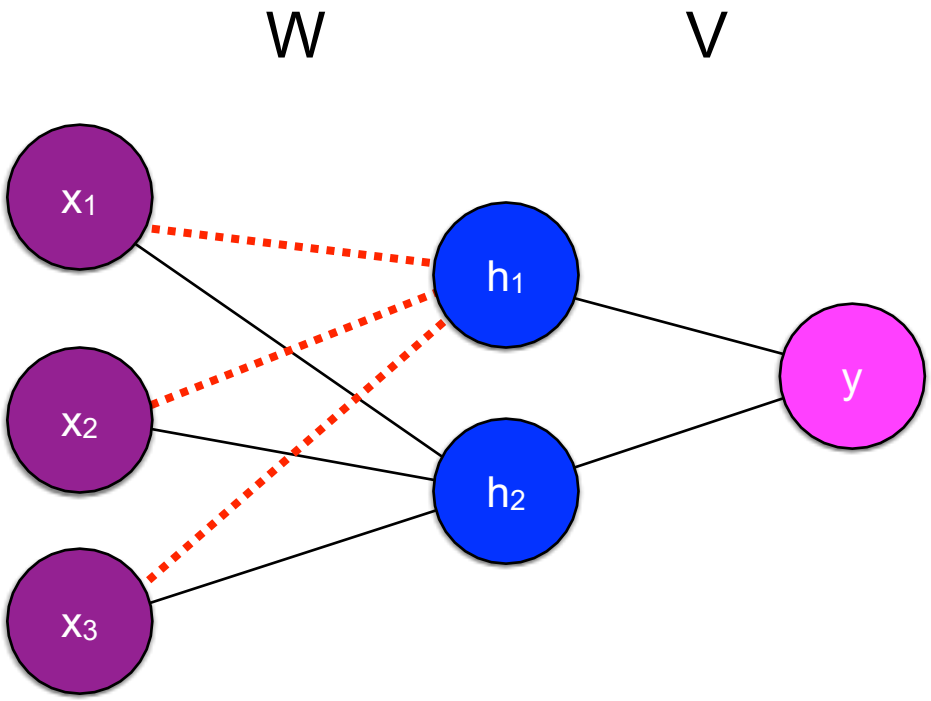

$$h_1 = f\left(\sum_{i=1}^{F} x_i W_{i,1}\right)$$

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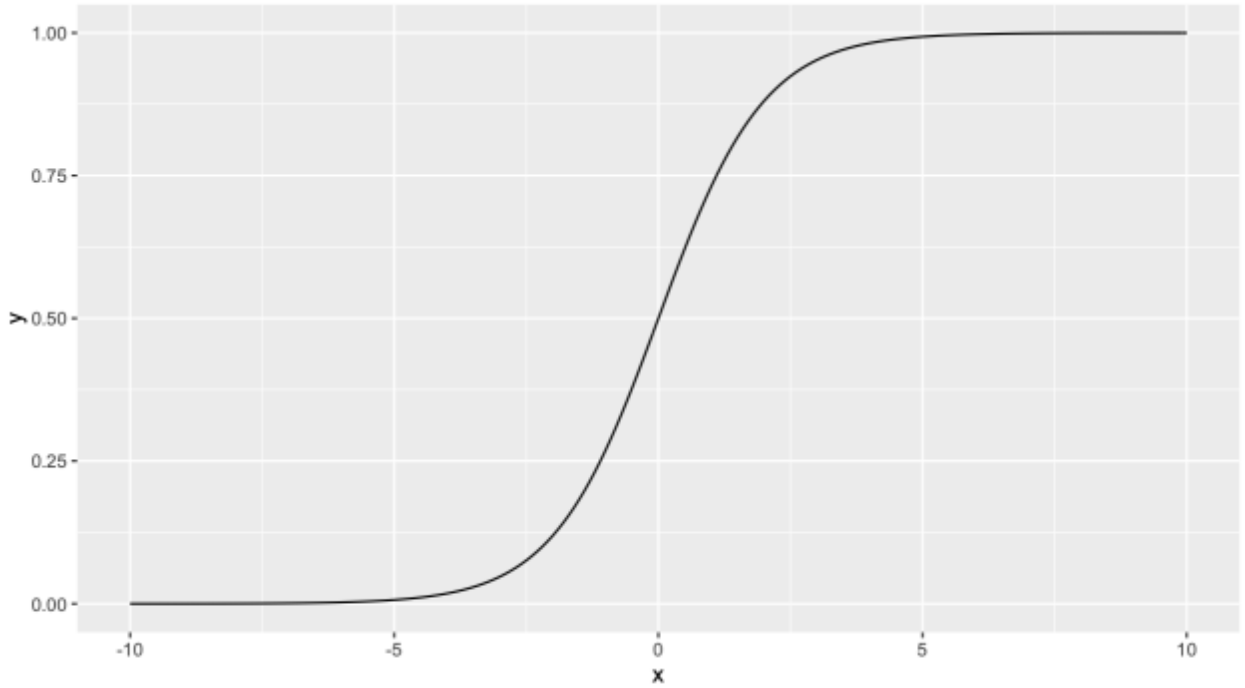
Activation functions

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



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Three Factors to the Success of Deep Learning

- End-to-end learning
- Learning Non-linear functions
  - Theoretically, a neural network with two layers could approximate any function
  - In practice, usually need specialized architecture
- Efficiently learn from large-scale labeled data
  - Through backpropagation
  - GPUs, optimization tricks, distributed computing, etc.

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What do we need for IR?

- Core task: How relevant is a document for a query?
- Needs: some comparable representations for queries and documents
- Bag of Words:
  - good: fast
  - bad: misses synonyms, different kinds of queries…
- Bag of Vectors: (e.g., average word2vec vector)
  - good: fast-ish, capture synonyms
  - bad: ignores word order
- Big Question: Can we get better representations of text for IR?

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Deep Learning for Text

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Deep Learning for Text

- Learn vector representations of words
- Learn representations of sentences/documents
- Natural language generation
- Sequence to sequence modeling

Let's start with how we can learn word vector representations in a new way (other than word2vec)

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Recall what a Language Model is

- A language model computes the probability of a sequence of words $p(x_1, \ldots, x_n)$

- The joint probability can be factorized as follows:

$$p(x_1, \ldots, x_n) = p(x_1) \prod_{i=2}^{n} p(x_i | x_{i-1}, \ldots, x_1)$$

- Previous approaches: unigram, bigram, trigram,….
  - Sparse
  - Ignore the similarity between the words

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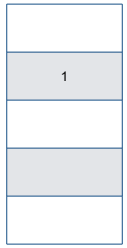
Can we learn a language model with a Feed-Forward Neural Network?

"I forgot the toppings for the pizza so I went to the store to get _____"

Simple feed-forward multilayer perceptron (e.g., one hidden layer)

input x = vector concatenation of a conditioning context of fixed size k



$$x = [v(w_1); \ldots; v(w_k)]$$

Bengio et al. 2003

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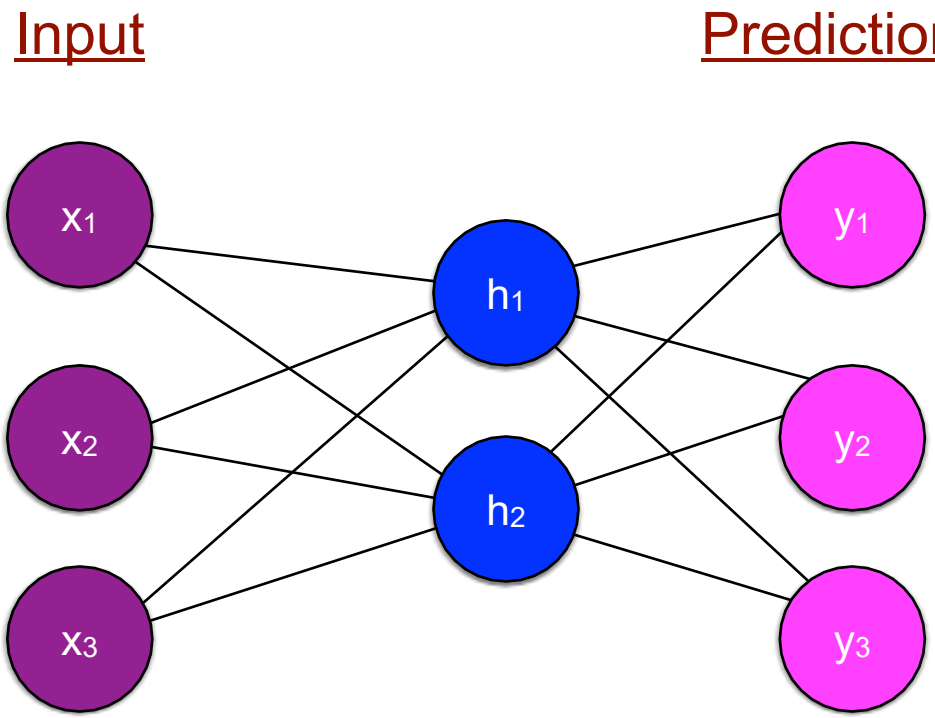
A bigram language model

$\mathcal{V}$ = {dog, my, runs}



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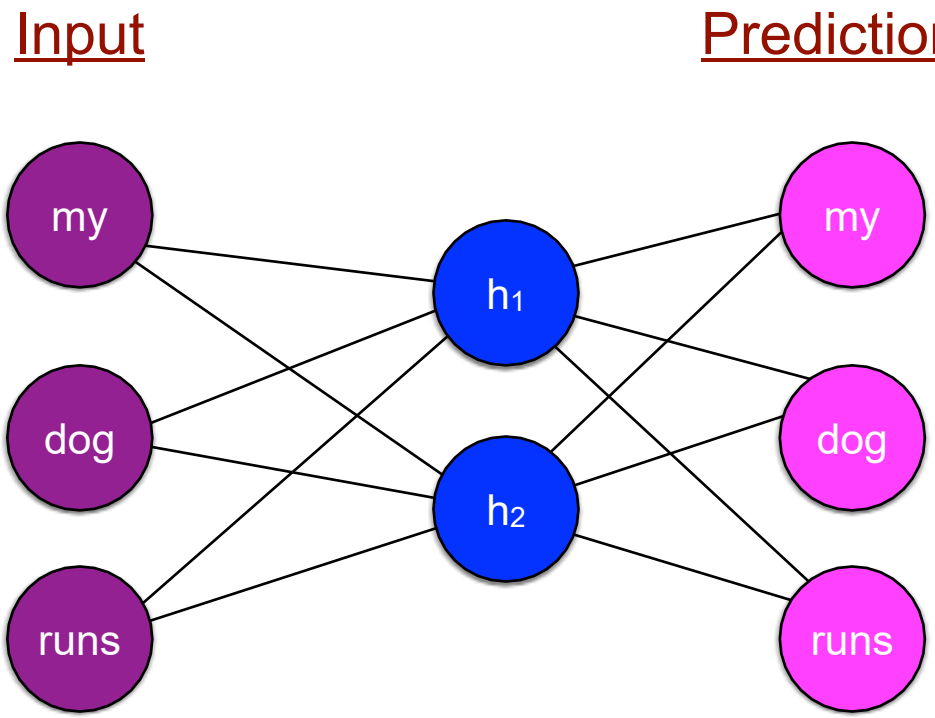
A bigram language model

$\mathcal{V}$ = {dog, my, runs}



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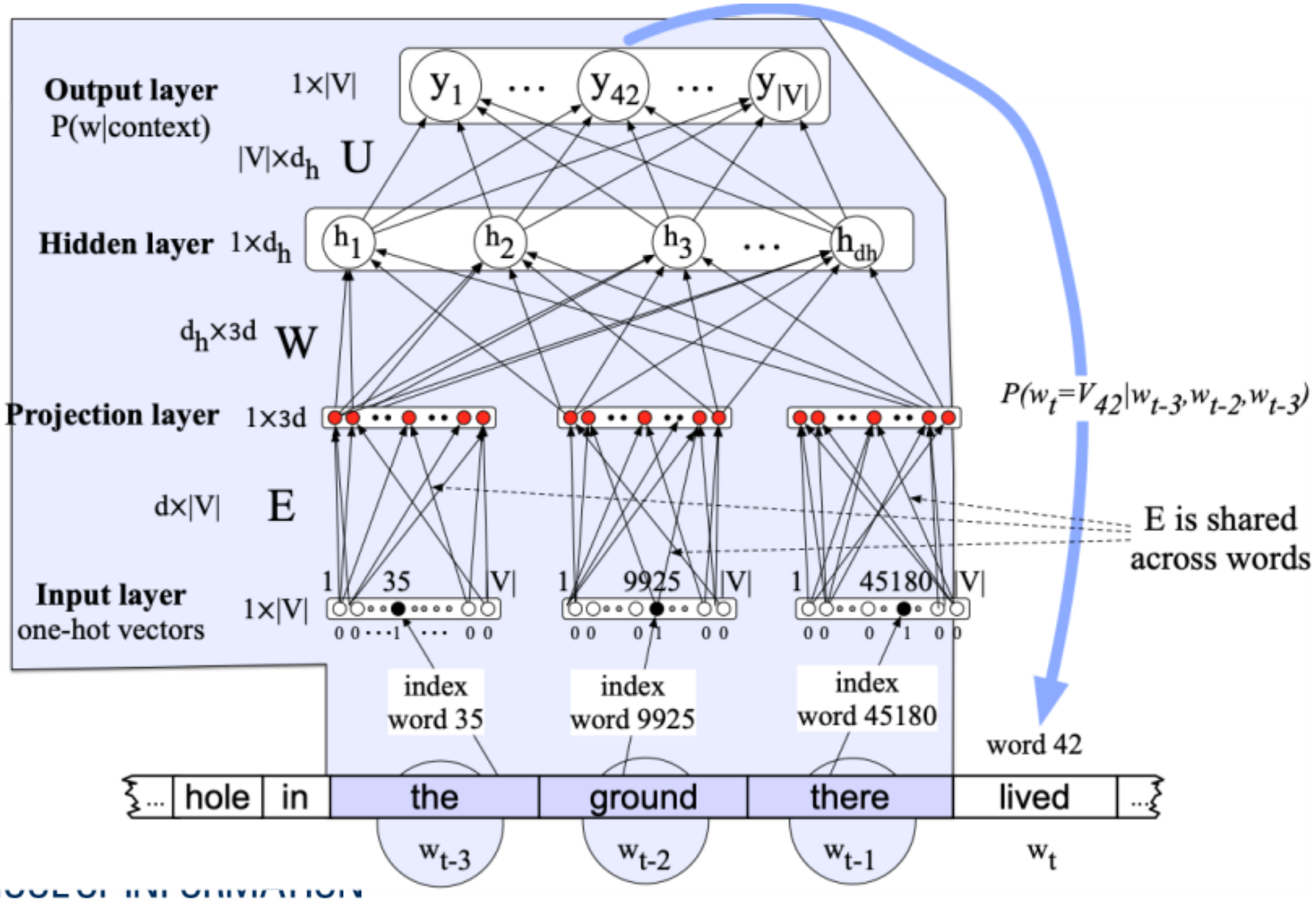
A slightly more complicated neural network language model



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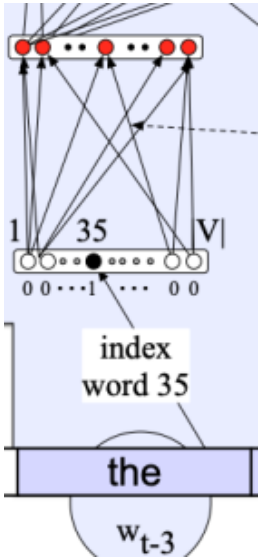
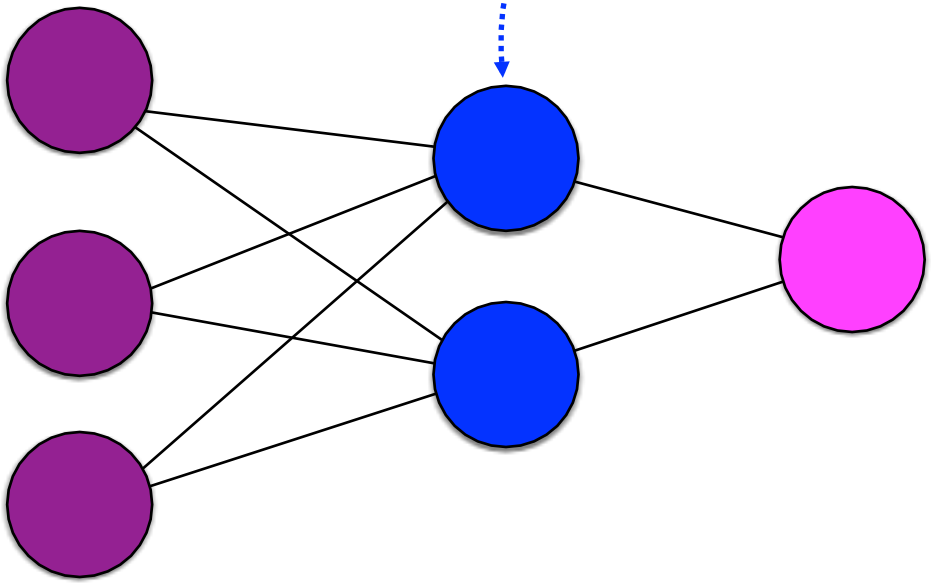
A closer look at that network



$$h = g(xW_1 + b_1)$$



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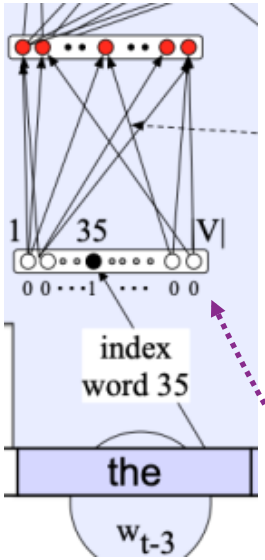
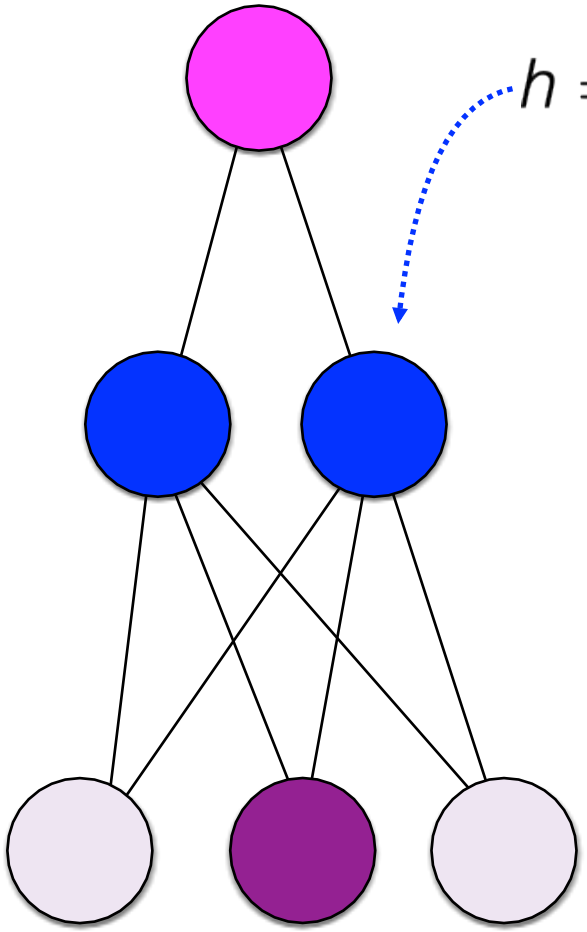
A closer look at that network





$$h = g(xW_1 + b_1)$$

"the"

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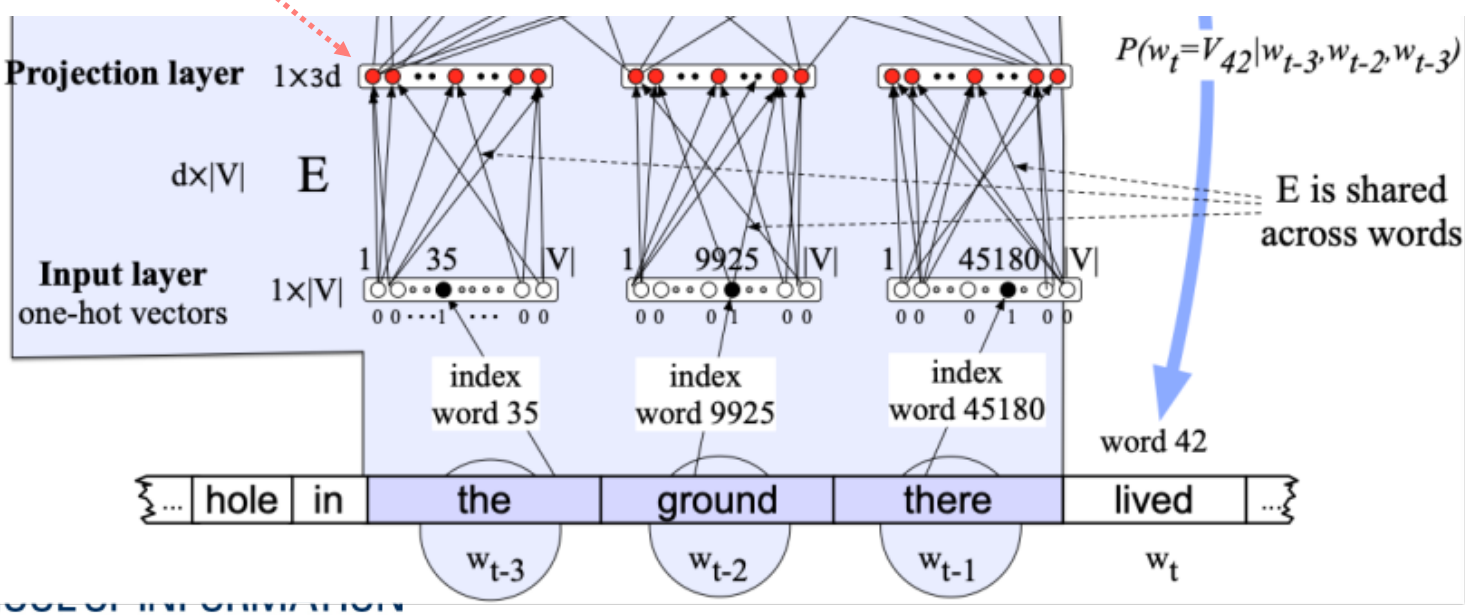
A closer look at that network

The projection layer is also known as an **embedding layer**.
It's a distributed vector representation of the word



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Sidenote: Softmax

$$P(Y = y \mid X = x; \beta) = \frac{\exp(x^\top \beta_y)}{\sum_{y' \in \mathcal{Y}} \exp(x^\top \beta_{y'})}$$

The softmax function is the general case of the sigmoid function for multiple classes.

$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)} = \sigma\left(\sum_{i=1}^{F} x_i \beta_i\right)$$

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Neural LM

conditioning context

tried to prepare residents for the hardships of recovery from the

y

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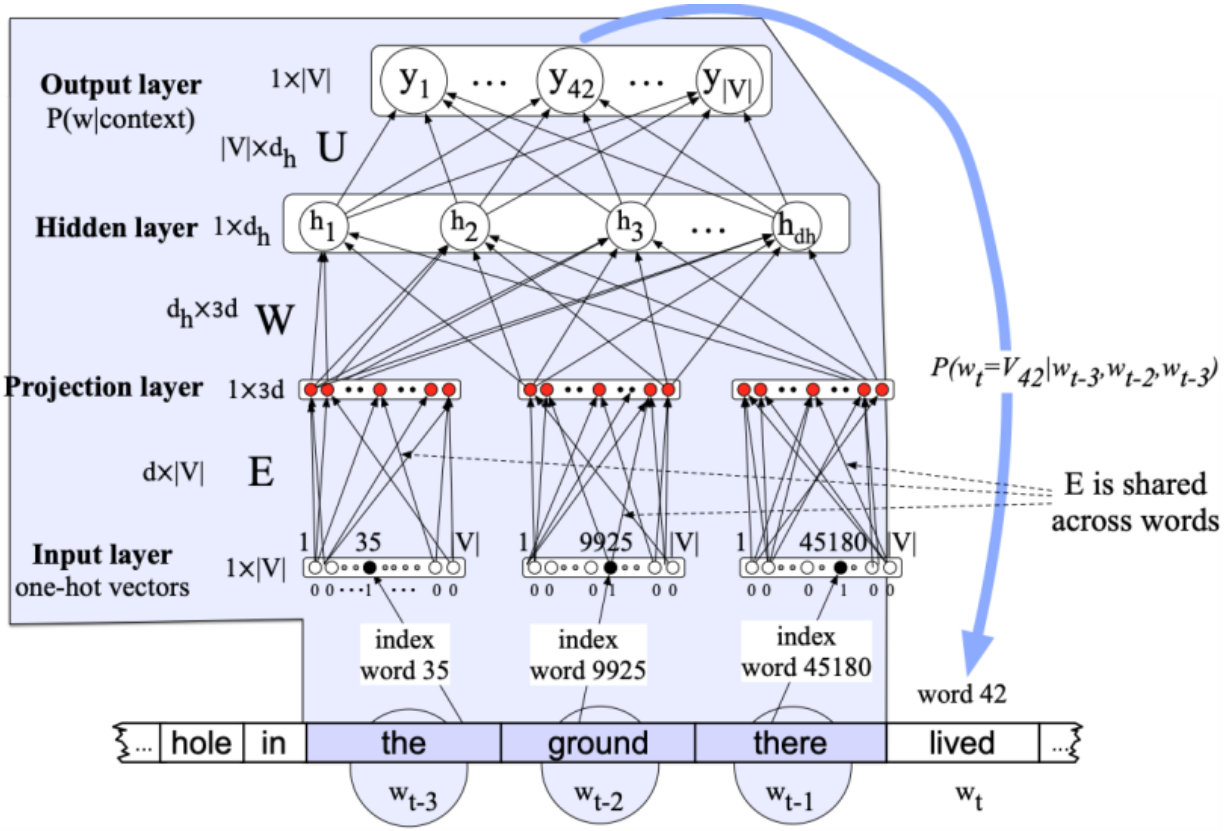
Feed-forward networks can be limited

- No ability to "look back" at distant prior inputs
  - Can only see what's in the current window

Attend discussion sections for more models (eg models that give longer look back)



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More Models – Discussion Section

- RNNs
- LSTMs
- Transformers

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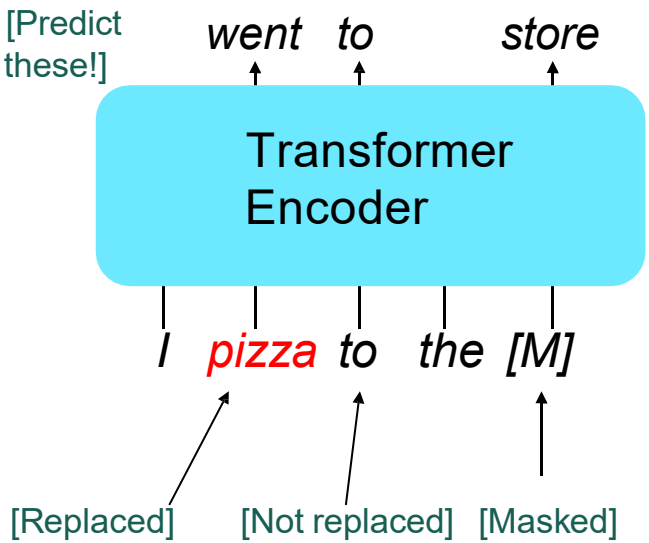
BERT: Bidirectional Encoder Representations from Transformers

- Devlin et al., 2018 proposed the "Masked LM" objective and released the weights of a pretrained Transformer, a model they labeled BERT.
- Masked LM for BERT:
  - Predict a random 15% of (sub)word tokens.
  - Replace input word with [MASK] 80% of the time
  - Replace input word with a random token 10% of the time
  - Leave input word unchanged 10% of the time (but still predict it!)
  - Why? Doesn't let the model get complacent and not build strong representations of non-masked words. (No masks are seen at fine-tuning time!)



[Devlin et al., 2018]

BERT: Bidirectional Encoder Representations from Transformers

- Mask out k% of the input words, and then predict the masked words
  - They always use k = 15%

store gallon

↑ ↑

the man went to the [MASK] to buy a [MASK] of milk

- Too little masking: Too expensive to train
- Too much masking: Not enough context

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🔹 背景

Devlin 等人在 2018 年提出 BERT，它基于 Transformer 编码器（Encoder）结构，并通过 **“Masked LM” 目标函数** 进行预训练。

- “Bidirectional” 表示 BERT 同时从**左右两个方向**理解上下文，而不像传统语言模型那样只看左边或右边的词。

🔹 Masked LM（掩码语言模型）机制

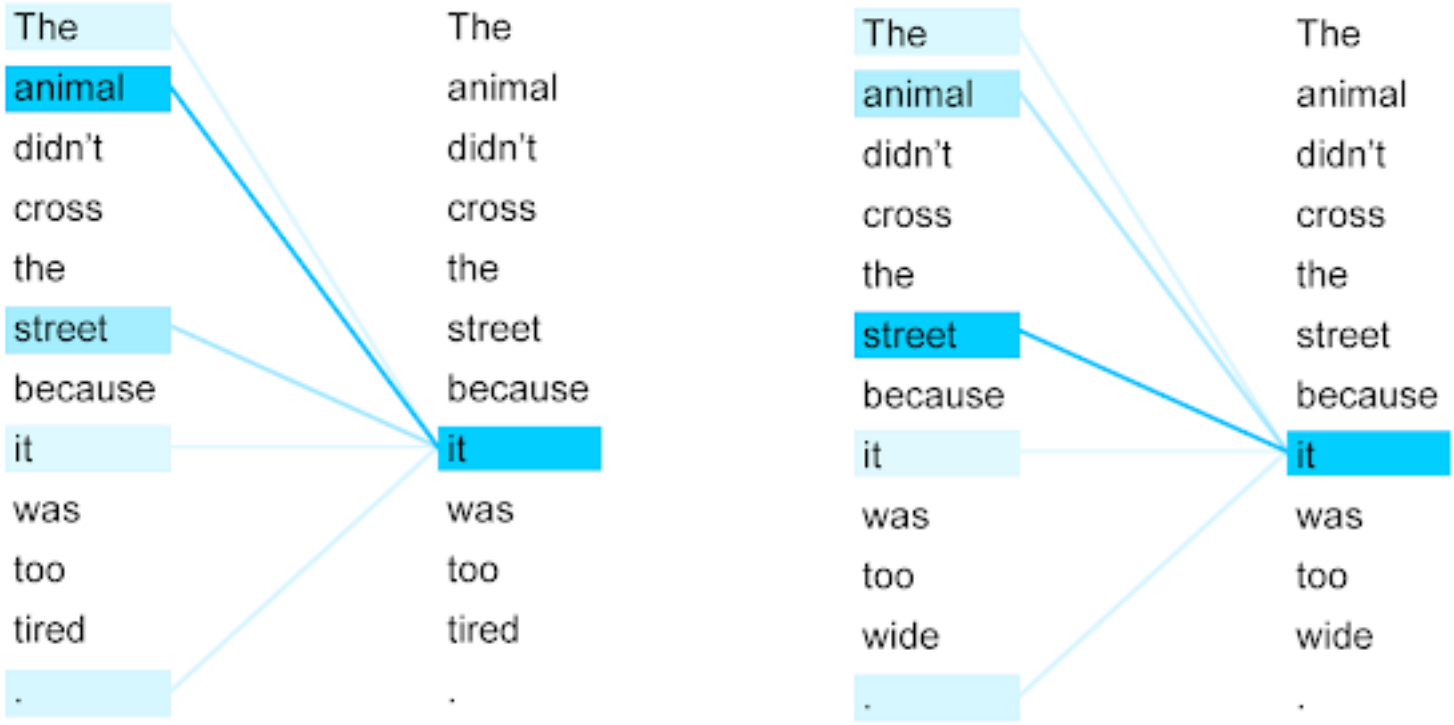
训练时，BERT 随机选择 15% 的词（或子词 token）进行掩码处理，让模型去预测这些被遮盖的词。

BERT 在掩码时采用以下策略：

1. **80% 的概率** → 把词替换成 `[MASK]`
   例如：
   “I went to the store” → “I went to the [MASK]”
2. **10% 的概率** → 把词随机换成别的词
   “I went to the store” → “I went to the pizza”
3. **10% 的概率** → 不替换，保留原词
   “I went to the store” → “I went to the store”
   但模型仍然要预测这个词。

👉 这样设计的原因是：
如果全部用 `[MASK]`，模型会依赖掩码标志；若全保留原词，模型又无法学到遮蔽词预测能力。混合方式让模型既能**学习语义上下文**，又能**泛化到没有 [MASK] 的 实任务**。

BERT's attention can be a way of model interpretation



https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

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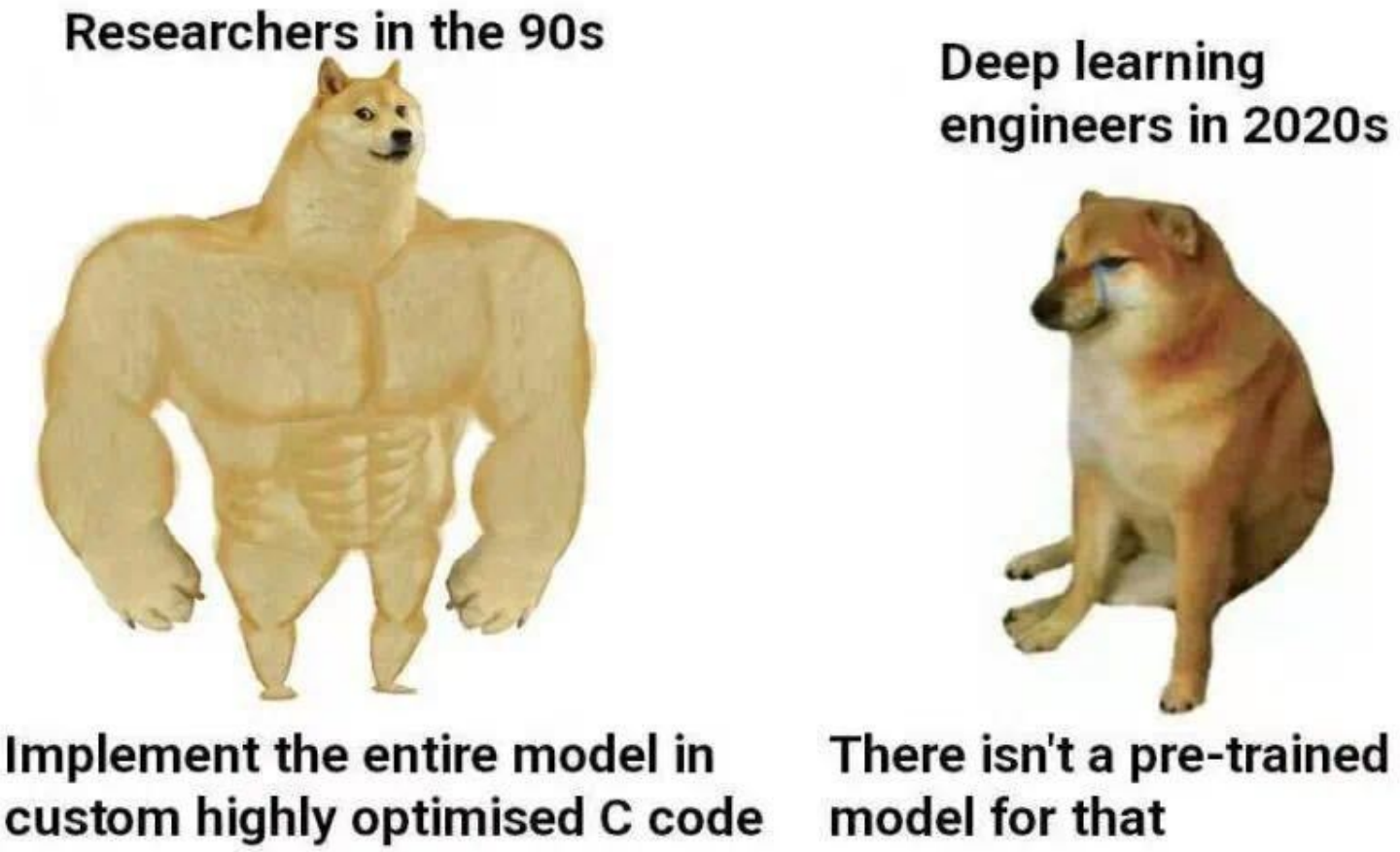
BERT: Bidirectional Encoder Representations from Transformers

- Two models were released:
  - BERT-base: 12 layers, 768-dim hidden states, 12 attention heads, 110 million params.
  - BERT-large: 24 layers, 1024-dim hidden states, 16 attention heads, 340 million params.
- Trained on:
  - BooksCorpus (800 million words)
  - English Wikipedia (2,500 million words)
- Pretraining is expensive and impractical on a single GPU.
  - BERT was pretrained with 64 TPU chips for a total of 4 days.
    - TPUs are special tensor operation acceleration hardware
- Finetuning is practical and common on a single GPU
  - "Pretrain once, finetune many times."

BERT is hugely versatile: Finetuning BERT led to new state-of-the-art results on a broad range of tasks.

- **QQP**: Quora Question Pairs (detect paraphrase questions)
- **QNLI**: natural language inference over question answering data
- **SST-2**: sentiment analysis
- **CoLA**: corpus of linguistic acceptability (detect whether sentences are grammatical.)
- **STS-B**: semantic textual similarity
- **MRPC**: microsoft paraphrase corpus
- **RTE**: small natural language inference corpus

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	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**



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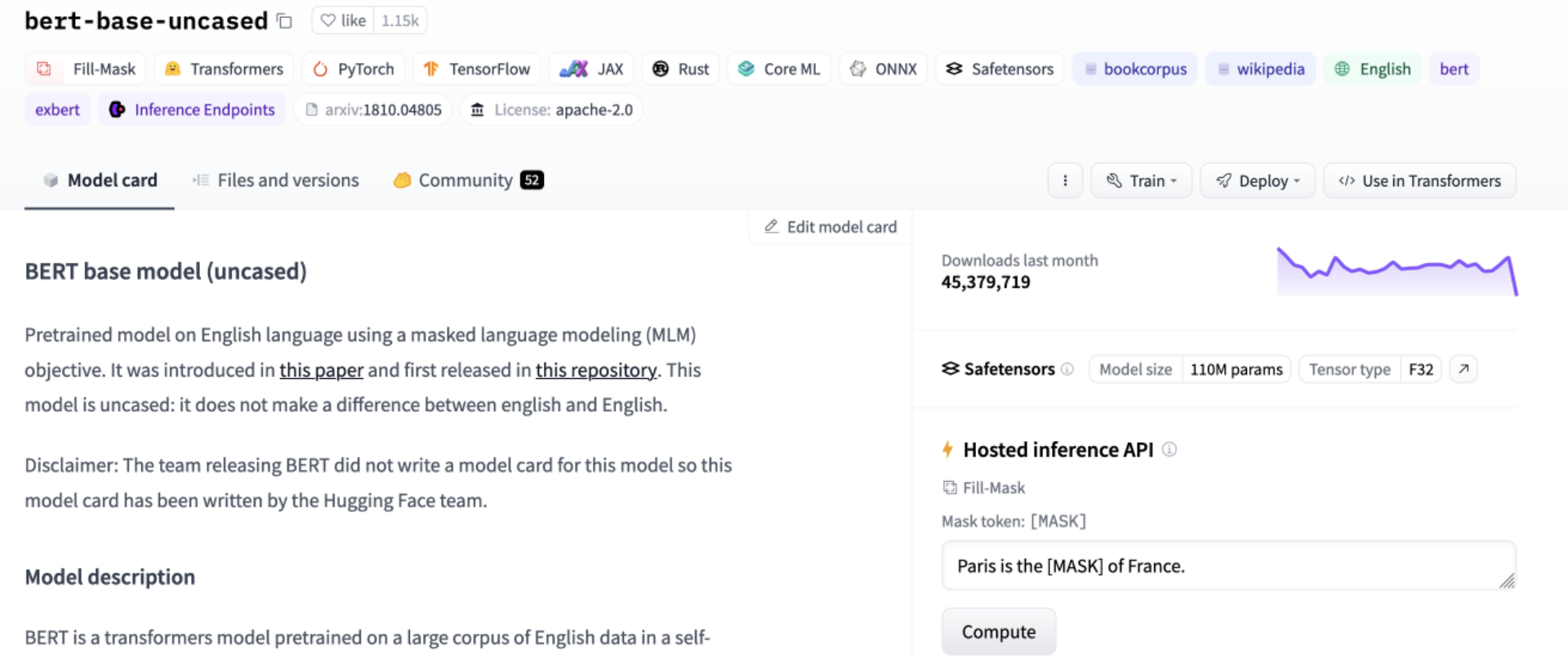
Huggingface makes models easy

- Example: https://huggingface.co/bert-base-



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Encoded inputs become vectors

- Can get the [CLS] token or even the average word embedding

```
from transformers import BertTokenizer, BertModel
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained("bert-base-uncased")
text = "Replace me by any text you'd like."
encoded_input = tokenizer(text, return_tensors='pt')
output = model(**encoded_input)
```


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[CLS] 是 BERT 等 Transformer 编码器里的一种**特殊标记（special token）**：

- **位置**：放在输入序列最开头（句首）。
- **作用**：它对应的隐藏向量作为**整段序列的聚合表示**，常被拿来接一个线性层做**分类/打分**（情感分类、文本匹配、检索重排等）；也常被当作"句向量/段向量"的候选表示（有时会用全序列平均池化替代）。

SI650-Week-08-Deep-Learning-for... SI650-Week-08-Deep-Learning-for...

更多细节

- 训练时，[CLS] 和普通词一样会被编码、更新参数；但它**不代表真实词**，只是"让模型有个专门的槽位来汇聚全局信息"。
- 句对任务通常格式：`[CLS] sent1 [SEP] sent2 [SEP]`，再用 `[CLS]` 向量做分类/相关性判断。
- 抽取式问答一般用起止位置预测，不直接用 `[CLS]`，但有些设置会用它判"无答案"。
- 做句向量时，**[CLS] 还是平均池化谁更好**取决于是否为该目的做过微调；直接拿预训练 BERT 的 [CLS] 做句向量往往不如平均池化或专门的句向量模型。

一句话：**[CLS] 就是序列级表示的"占位符"**，方便模型把整段话的信息集中到一个向量上，再用于下游任务。

SI650-Week-08-Deep-Learning-for...

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Deep Learning Representations for IR

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Contextualized Representations for IR

- Example Query: “nova for sale”
  - Probably searching for the car
- Documents:
  - “A nova (plural novae or novas) is a transient astronomical event that causes the sudden appearance of a bright, apparently "new" star…”
  - “The Chevrolet Chevy II/Nova is a small automobile manufactured by Chevrolet…”
- Idea: vector representations that take contextual meaning into account can give better retrieval

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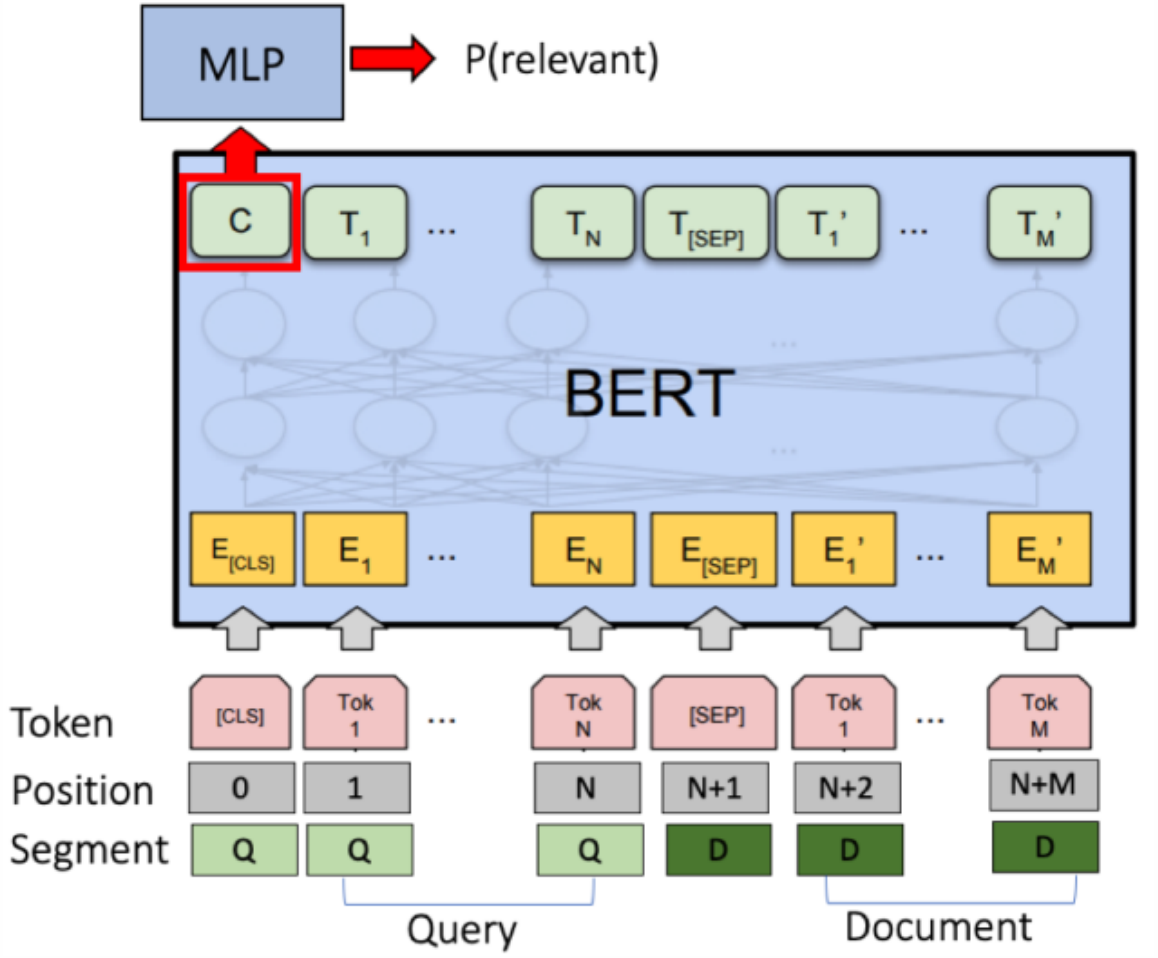
Use BERT to encode document and query jointly



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How to handle long documents?

- Problem: BERT is $O(n^2)$ in the length of the input
  - Most documents are hundreds of tokens
- Idea:
  - Break documents into overlapping passages
  - Score relevance of each pass
  - Aggregate passages' scores somehow…
    - max? mean? sum?

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BERT for IR

Table 2: Search accuracy on Robust04 and ClueWeb09-B. † indicates statistically significant improvements over Coor-Ascent by permutation test with p< 0.05.

	nDCG@20			
	Robust04		ClueWeb09-B	
Model	Title	Description	Title	Description
BOW	0.417	0.409	0.268	0.234
SDM	0.427	0.427	0.279	0.235
RankSVM	0.420	0.435	0.289	0.245
Coor-Ascent	0.427	0.441	**0.295**	0.251

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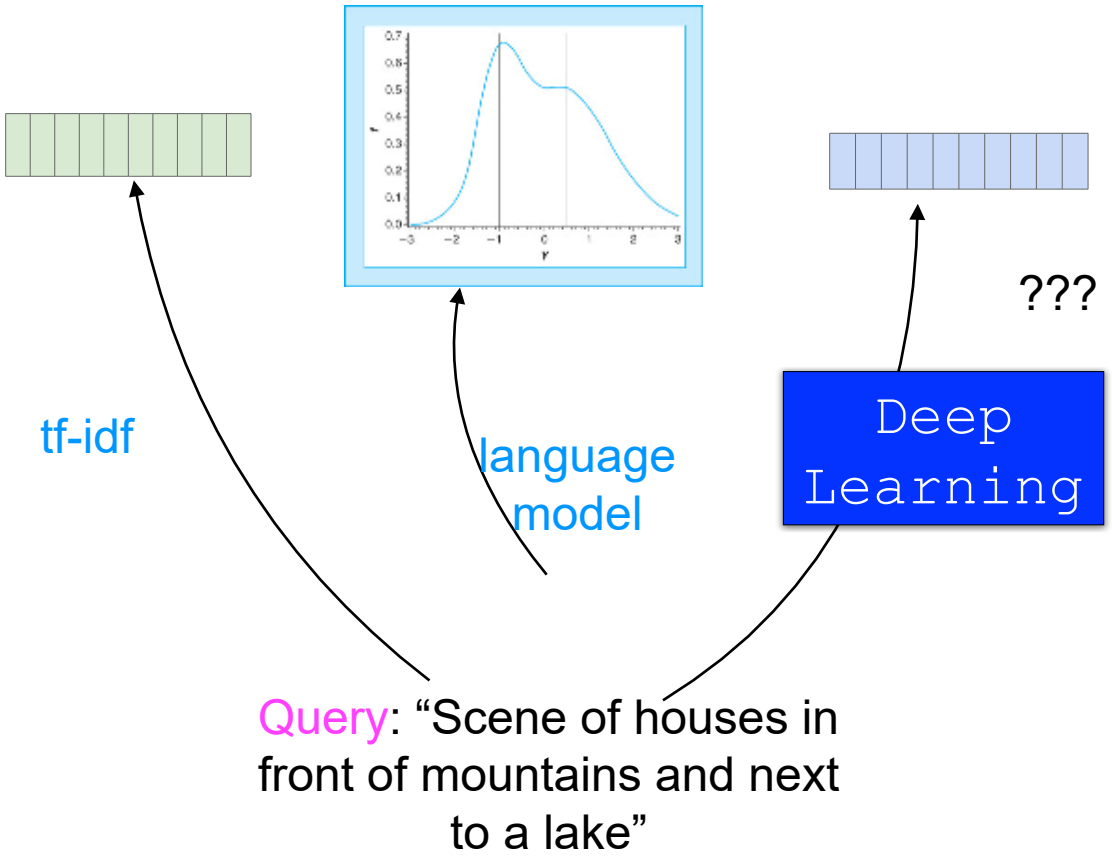
We can think of an encoder as a function of some input to a vector output



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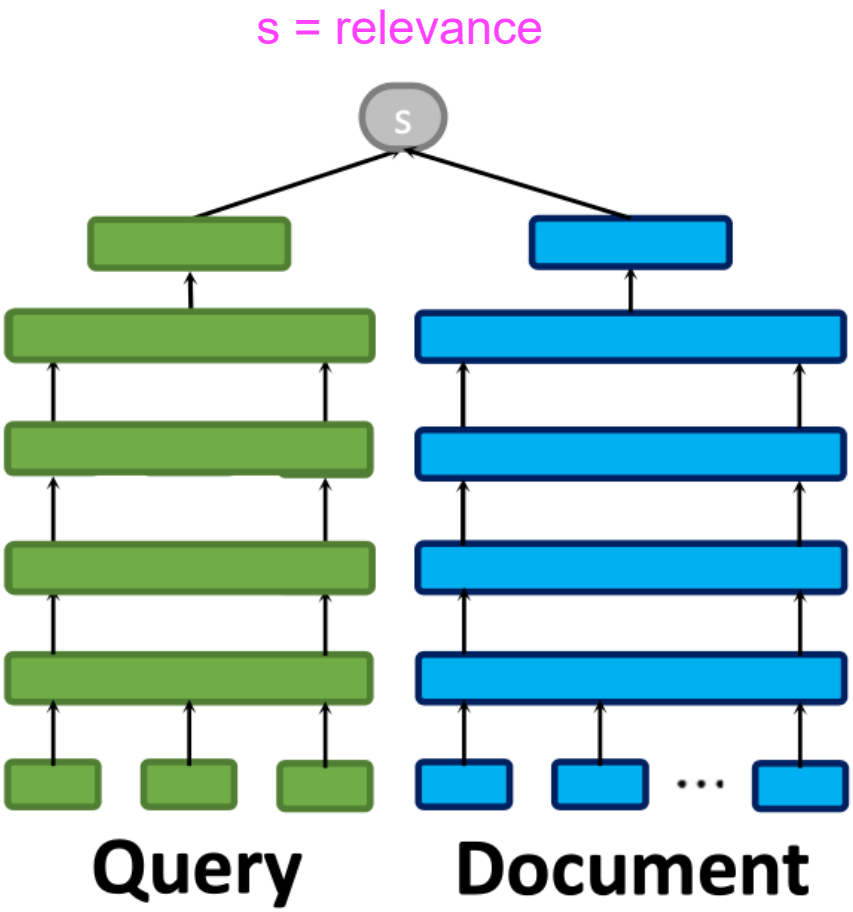
We could try another formulation that *learns* how to encode queries and documents



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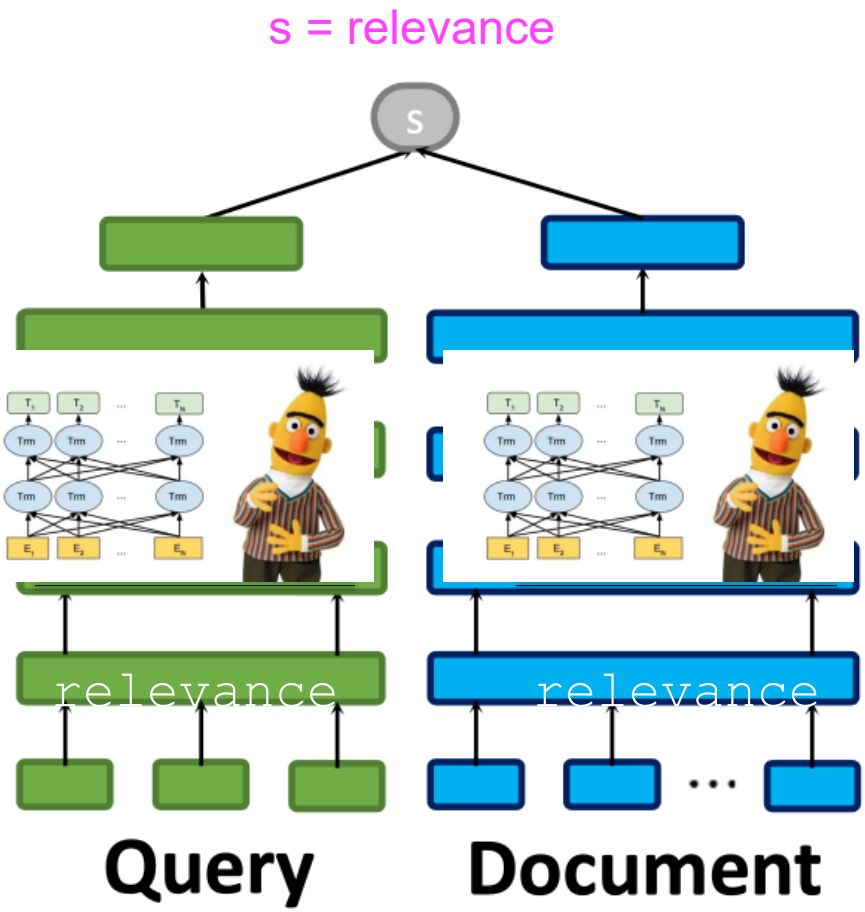
We could try another formulation that *learns* how to encode queries and documents



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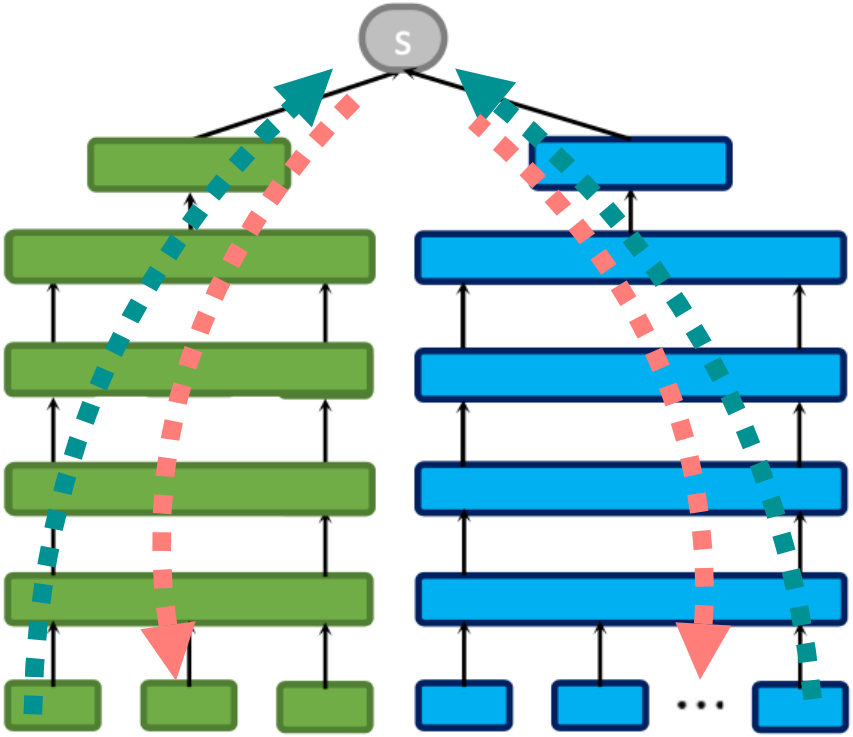
By training to predict relevance, we update how the models learn to represent a query and document

Predict



Update weights with Stochastic Gradient Descent

Query: “How do magnets work?”

Document: “Magnetized metals consist of …”

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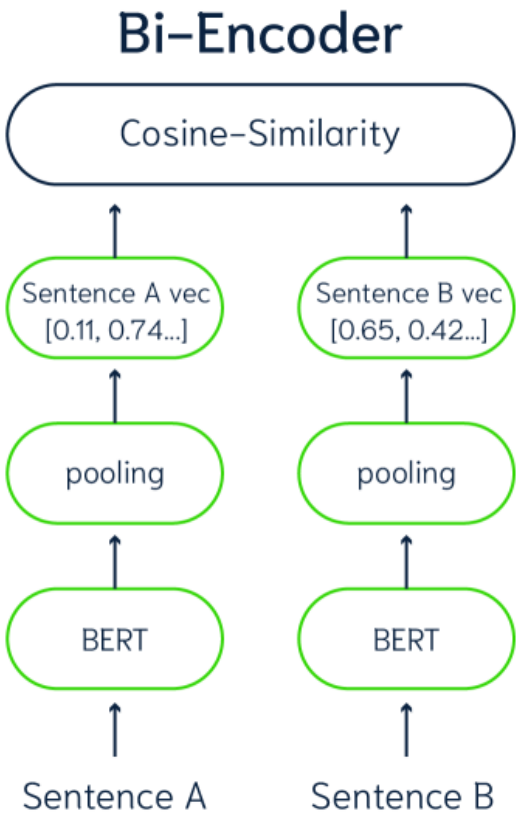
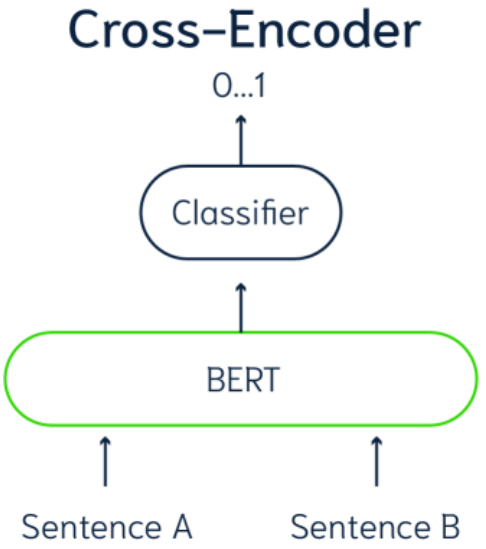
IR Architectures: Bi-Encoder vs. Cross-Encoder





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量/分数汇聚成更短的表示的一步，用于后续打分或分类。它解决"长度不一、

token 表示做池化得到一个固定维度向量
效 token 取平均（最常用、稳健）
最大，突出最强信号
用 [CLS] 的向量作为序列表示（需为此目标微调）
ing-for...
用 [CLS] 接 MLP 得相关性分数，也可在需要时对token分数再做聚合
...。
g：不是对 token 向量做均值/最大，而是
相似度矩阵；
词相似度区间做"软计数"（Soft-TF）；
送入学习排序层输出最终分数 SI650-Week-08-Deep-Learning-for... 。

好！给你三个直观小例子👇

例子1：Mean pooling（最常见）

句子："**red car**"

设两个 token 的向量分别是：

- red → $[1,\ 0]$
- car → $[0,\ 1]$

Mean pooling：对每维取平均

$$h_{\text{mean}} = \frac{[1,0]+[0,1]}{2} = [0.5,\ 0$$

得到一个固定长度的句向量，可拿去跟文档向量做余弦相似度/分类。

例子2：Max pooling（取最强信号）

句子："**not bad**"

向量：

- not → $[0.2,\ 0.1,\ 0.9]$
- bad → $[0.8,\ 0.3,\ 0.2]$

Max pooling：逐维取最大

$$h_{\text{max}} = [\max(0.2, 0.8),\ \max(0.1,$$ ↓ $$),\ \max(0.9, 0$$

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Architecture Trade-offs

- Bi-encoders:
  - Good: Can precompute document vectors
  - Good: Fast similarity comparison: it's just vector similarity!
  - Bad: No query-document word interaction
- Cross-encoder:
  - Good: Can better interpret/compare query and document contents
  - Bad: Requires re-encoding Q+D every time (slow)

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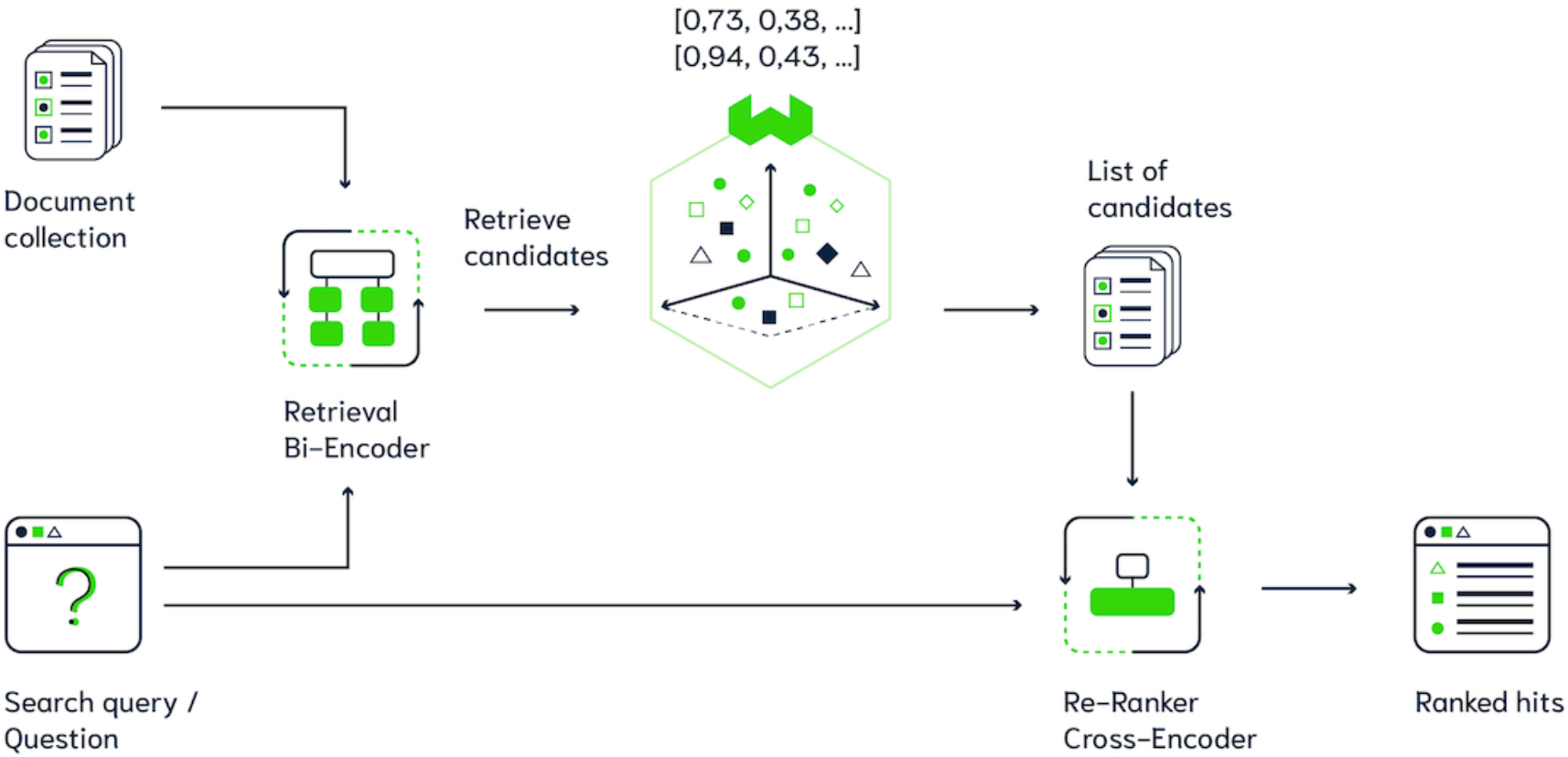
Both setups are are typically used together in practice



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Brief look into how this will work in practice… (optional)

You will look into this in more detail during the discussion sections.

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Beyond BERT

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Doc2Query Idea

- Problem: Deep learning is slow and expensive
- Idea: Could we use deep learning to augment our documents at indexing time, rather than query time
  - Retrieval stays the same (BM25, L2R, …)

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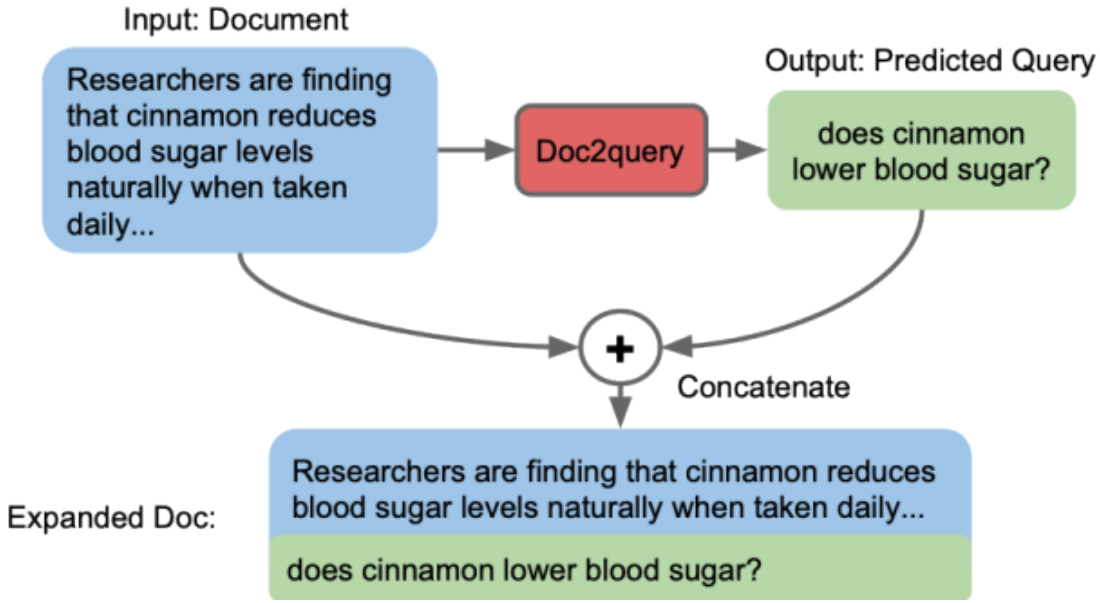
Augmenting Documents with Doc2Query



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How to predict queries for documents??

- Use an encoder-decoder framework similar to translation:
  - encode document, decode queries
- Truncate documents to 400 tokens, queries to 100
- Train on relevant query-document pairs

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Performance when adding machine-generated queries

	TREC-CAR MAP	MS MARCO MRR@10	
	Test	Test	Dev
Single Duet v2 (Mitra and Craswell, 2019b)	-	24.5	24.3
Co-PACRR♠ (MacAvaney et al., 2017)	14.8	-	-

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Things not covered today

- What can go wrong when using pre-trained language models (covered next week!)
- How these models are actually trained
- Many technical details
- Lots of recent advances in neural networks

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What You Should Know

- Know what deep learning is about
- Know the intuitions of why deep learning works
- Know the basic models of deep learning and how they are applied to text
- Know the basic ideas of Word2Vec
- Know how deep/large language models can be applied to IR

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