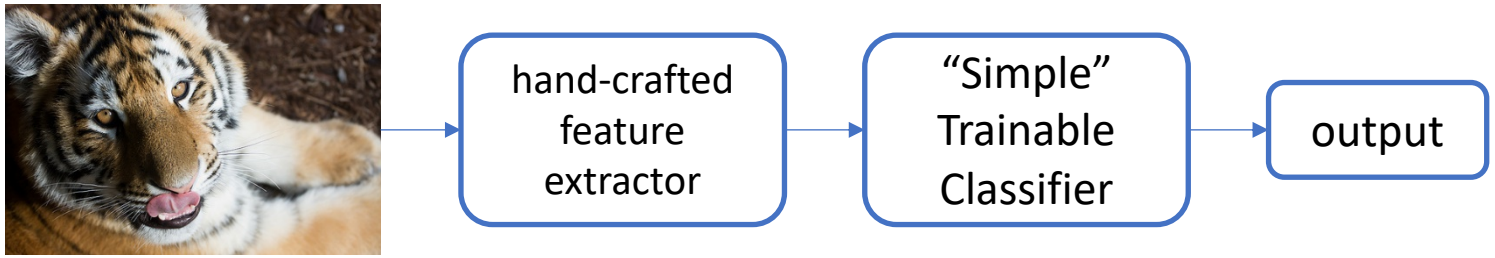
Neural Networks for Information Retrieval and Data Mining

Many slides courtesy Andrew Ng, Stanford

Introduction

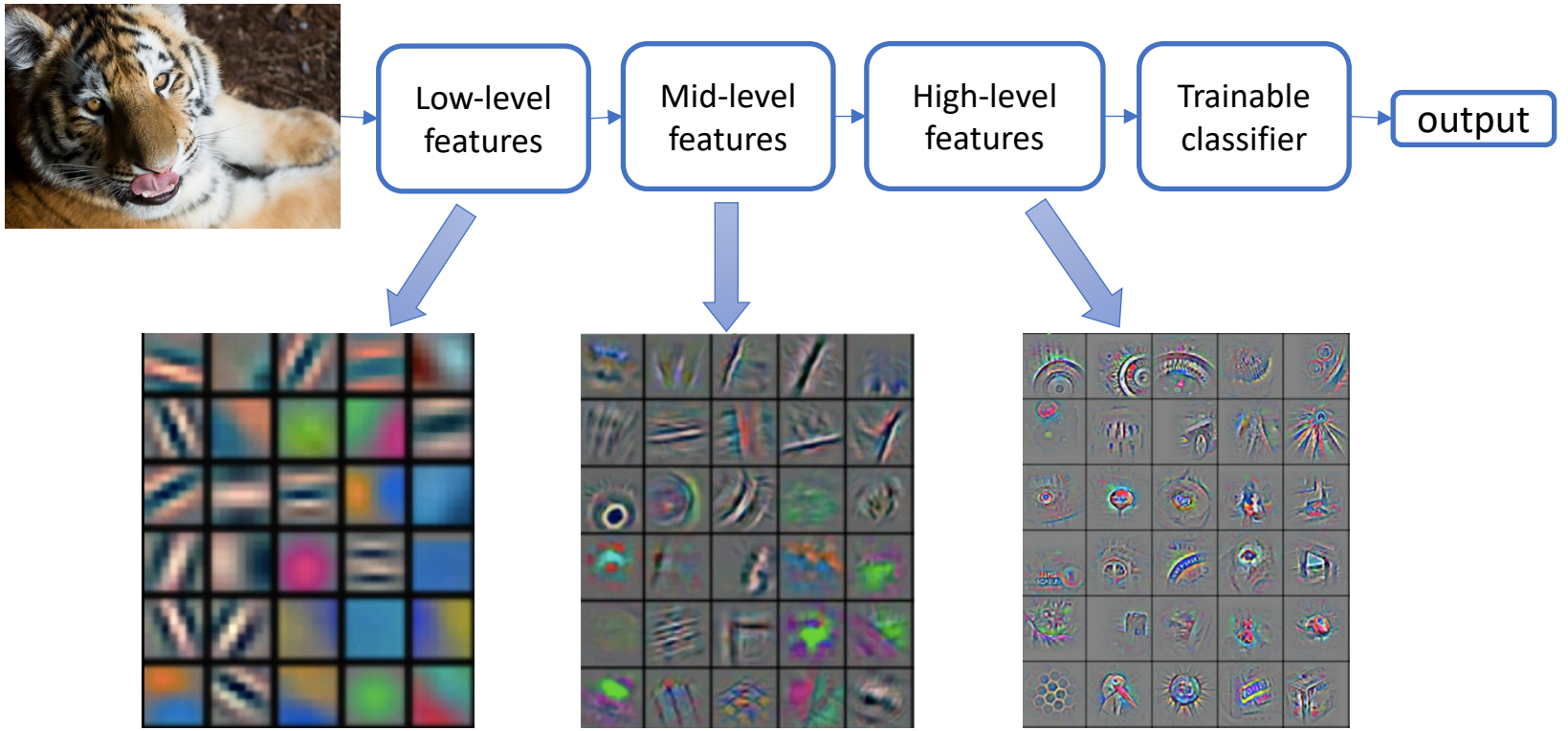
- Traditional machine learning models use hand-crafted features and relatively simple trainable classifier.



- These approaches have the following limitations:
  - It is very tedious and costly to develop hand-crafted features
  - The hand-crafted features are usually highly dependent on one application, and cannot be transferred easily to other applications

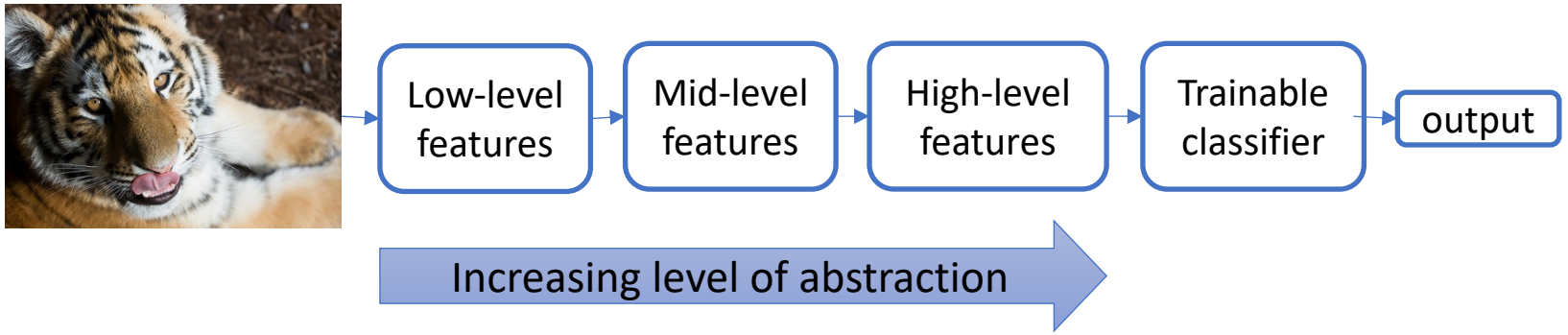
Deep Learning

- Deep learning (a.k.a. representation learning) seeks to learn rich hierarchical representations (i.e. features) automatically through multiple stage of feature learning process.



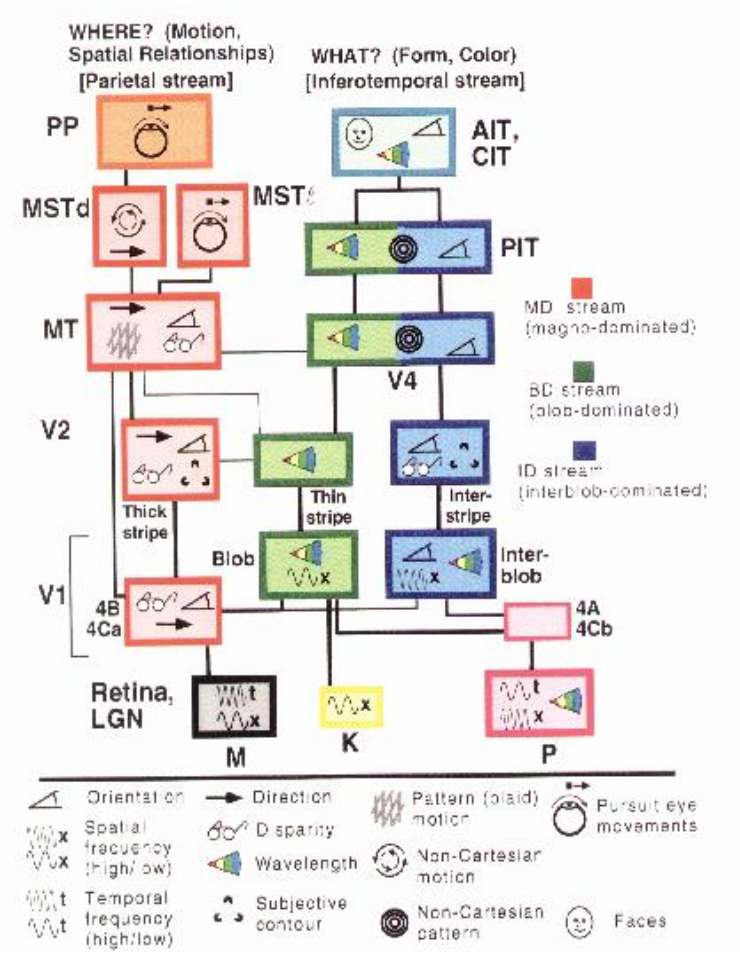
Feature visualization of convolutional net trained on ImageNet (Zeiler and Fergus, 2013)

Learning Hierarchical Representations



- Hierarchy of representations with increasing level of abstraction. Each stage is a kind of trainable nonlinear feature transform
- Image recognition
  - Pixel → edge → texton → motif → part → object
- Text
  - Character → word → word group → clause → sentence → story

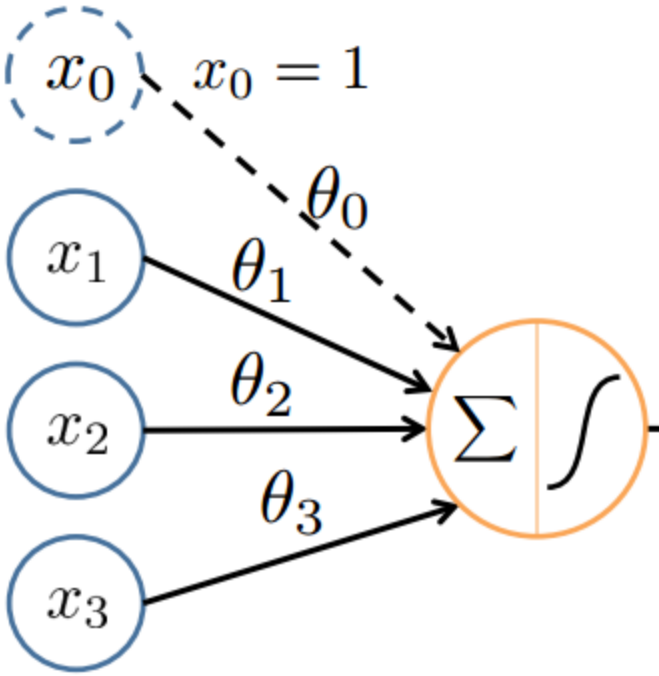
The Mammalian Visual Cortex is Hierarchical



(van Essen and Gallant, 1994)

- Each module in Deep Learning transforms its input representation into a higher-level one, in a way similar to human cortex.
- We need to understand which details are important, and which details are merely the result of evolution.
- It is good to be inspired by nature, but not too much.

Neural Network

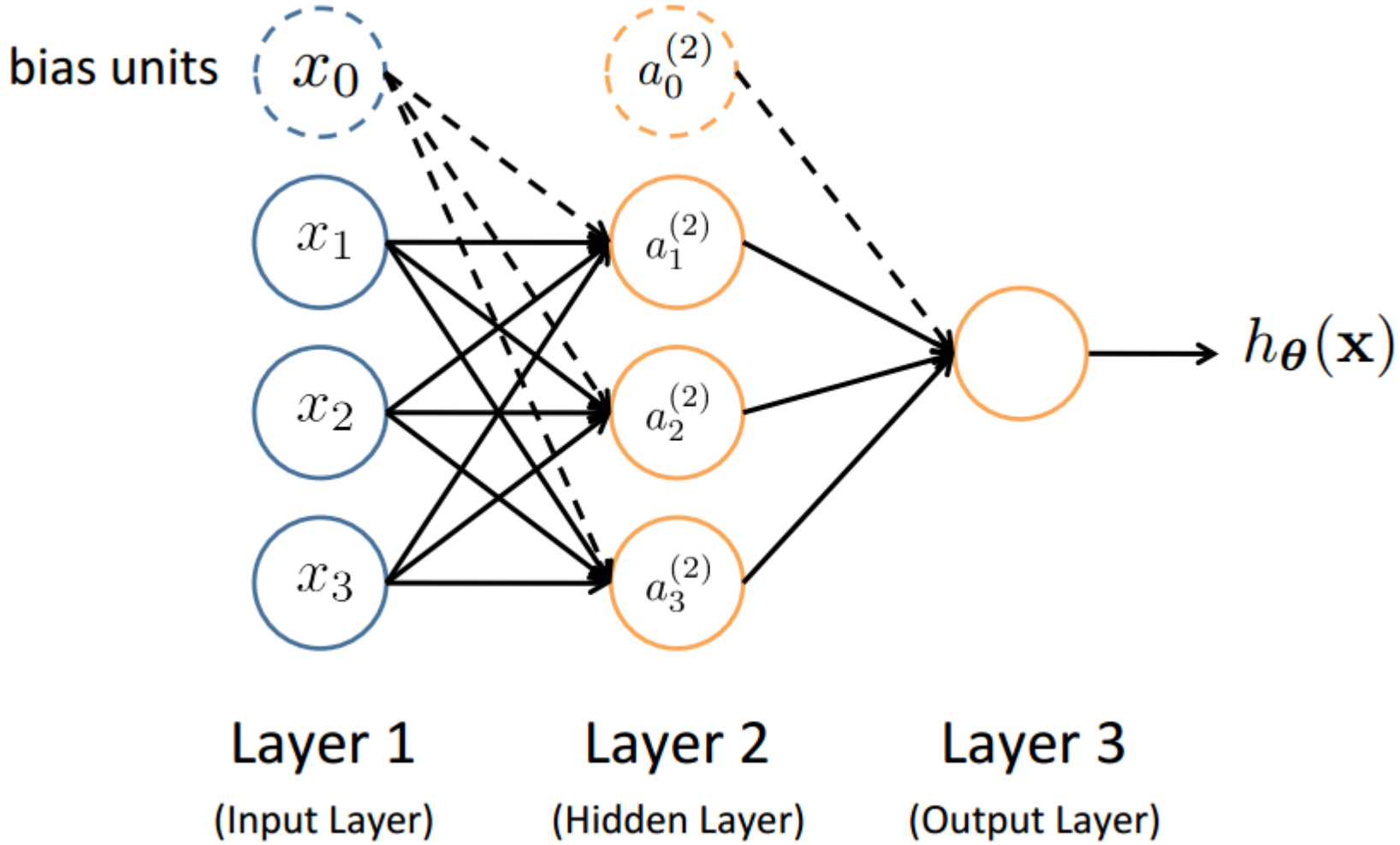


$$\mathbf{x} = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad \boldsymbol{\theta} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix}$$

$$h_{\boldsymbol{\theta}}(\mathbf{x}) = g\left(\boldsymbol{\theta}^{\mathsf{T}}\mathbf{x}\right) = \frac{1}{1 + e^{-\boldsymbol{\theta}^{\mathsf{T}}\mathbf{x}}}$$

Sigmoid (logistic) activation function: $g(z) = \dfrac{1}{1 + e^{-z}}$

Neural Network (Feed forward)

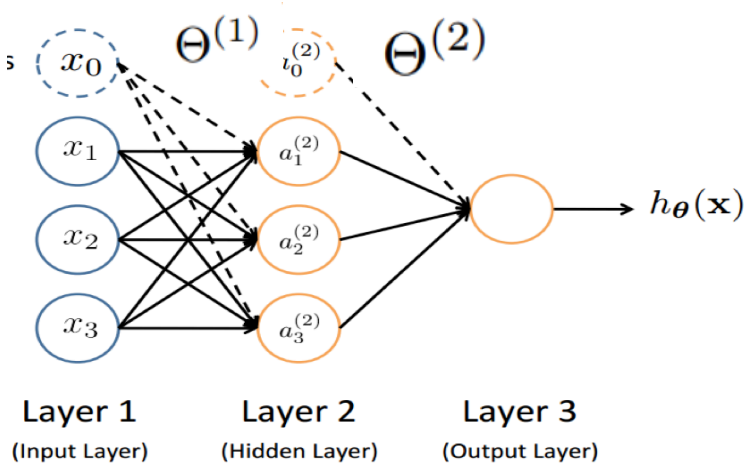


Slide by Andrew Ng

Feed-Forward Process

- Input layer units are features (in NLP/IR, e.g., words)
  - Usually, one-hot vector or word embedding
- Working forward through the network, the **input function** is applied to compute the input value
  - E.g., weighted sum of the input
- The **activation function** transforms this input function into a final value
  - Typically a **nonlinear** function (e.g, **sigmoid**)

Based on slide by T. Finin, M. desJardins, L Getoor, R. Par



$a_i^{(j)}$ = "activation" of unit i in layer j

$\Theta^{(j)}$ = weight matrix controlling function mapping from layer j to layer $j+1$

$$a_1^{(2)} = g(\Theta_{10}^{(1)} x_0 + \Theta_{11}^{(1)} x_1 + \Theta_{12}^{(1)} x_2 + \Theta_{13}^{(1)} x_3)$$
$$a_2^{(2)} = g(\Theta_{20}^{(1)} x_0 + \Theta_{21}^{(1)} x_1 + \Theta_{22}^{(1)} x_2 + \Theta_{23}^{(1)} x_3)$$
$$a_3^{(2)} = g(\Theta_{30}^{(1)} x_0 + \Theta_{31}^{(1)} x_1 + \Theta_{32}^{(1)} x_2 + \Theta_{33}^{(1)} x_3)$$
$$h_\Theta(x) = a_1^{(3)} = g(\Theta_{10}^{(2)} a_0^{(2)} + \Theta_{11}^{(2)} a_1^{(2)} + \Theta_{12}^{(2)} a_2^{(2)} + \Theta_{13}^{(2)} a_3^{(2)})$$

If network has s_j units in layer j *and* s_{j+1} units in layer $j+1$, then $\Theta^{(j)}$ has dimension $s_{j+1} \times (s_j+1)$.

$$\Theta^{(1)} \in \mathbb{R}^{3\times 4} \qquad \Theta^{(2)} \in \mathbb{R}^{1\times 4}$$

Slide by Andrew Ng

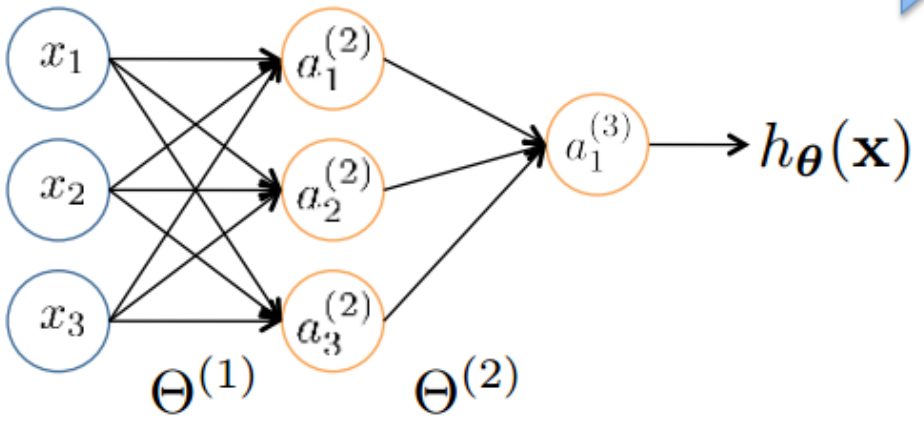
Vector Representation

$$a_1^{(2)} = g\left(\Theta_{10}^{(1)}x_0 + \Theta_{11}^{(1)}x_1 + \Theta_{12}^{(1)}x_2 + \Theta_{13}^{(1)}x_3\right) = g\left(z_1^{(2)}\right)$$

$$a_2^{(2)} = g\left(\Theta_{20}^{(1)}x_0 + \Theta_{21}^{(1)}x_1 + \Theta_{22}^{(1)}x_2 + \Theta_{23}^{(1)}x_3\right) = g\left(z_2^{(2)}\right)$$

$$a_3^{(2)} = g\left(\Theta_{30}^{(1)}x_0 + \Theta_{31}^{(1)}x_1 + \Theta_{32}^{(1)}x_2 + \Theta_{33}^{(1)}x_3\right) = g\left(z_3^{(2)}\right)$$

$$h_\Theta(\mathbf{x}) = g\left(\Theta_{10}^{(2)}a_0^{(2)} + \Theta_{11}^{(2)}a_1^{(2)} + \Theta_{12}^{(2)}a_2^{(2)} + \Theta_{13}^{(2)}a_3^{(2)}\right) = g\left(z_1^{(3)}\right)$$



Feed-Forward Steps:

$$\mathbf{z}^{(2)} = \Theta^{(1)}\mathbf{x}$$

$$\mathbf{a}^{(2)} = g(\mathbf{z}^{(2)})$$

Add $a_0^{(2)} = 1$

$$\mathbf{z}^{(3)} = \Theta^{(2)}\mathbf{a}^{(2)}$$

$$h_\Theta(\mathbf{x}) = \mathbf{a}^{(3)} = g(\mathbf{z}^{(3)})$$

Based on slide by Andrew Ng

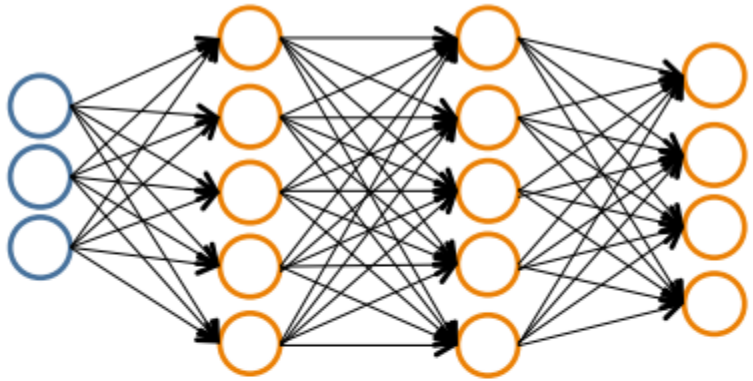
Can extend to multi-class

Pedestrian

Car

Motorcycle

Truck



$$h_\Theta(\mathbf{x}) \in \mathbb{R}^K$$

We want:

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

when pedestrian

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

when car

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

when motorcycle

$$h_\Theta(\mathbf{x}) \approx \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

when truck

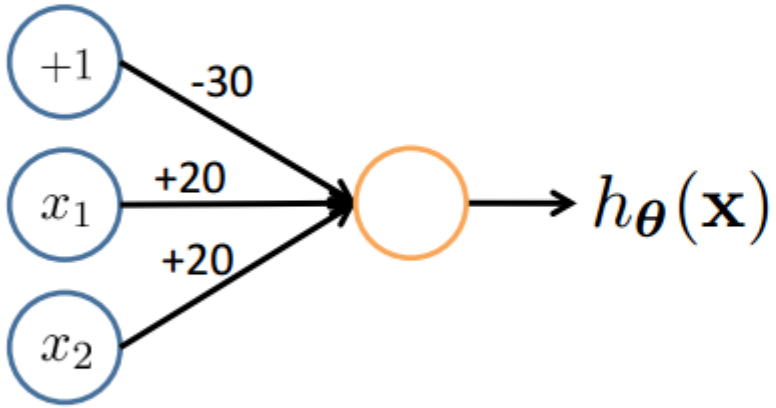
Slide by Andrew Ng

Why staged predictions?

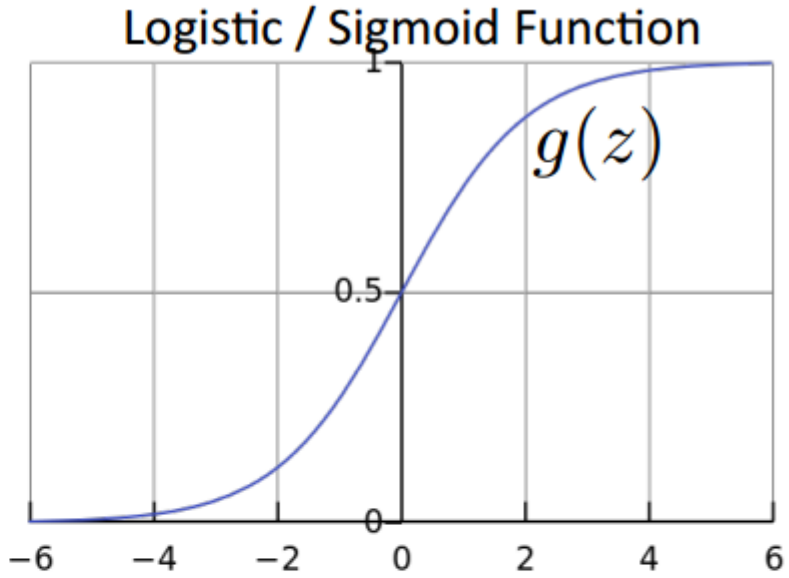
Simple example: AND

$x_1, x_2 \in \{0, 1\}$

$y = x_1 \text{ AND } x_2$



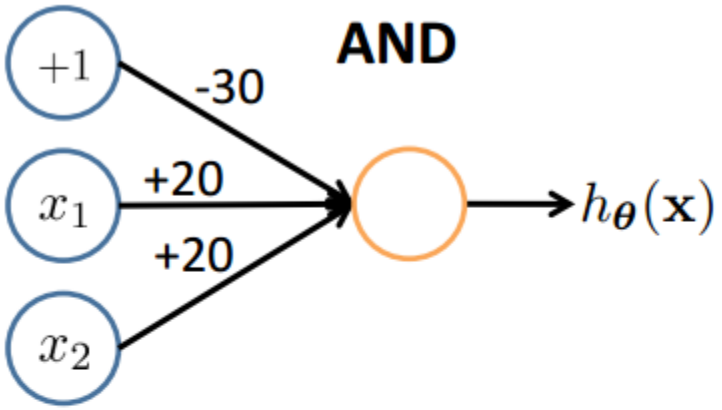
$$h_\Theta(\mathbf{x}) = g(-30 + 20x_1 + 20x_2)$$

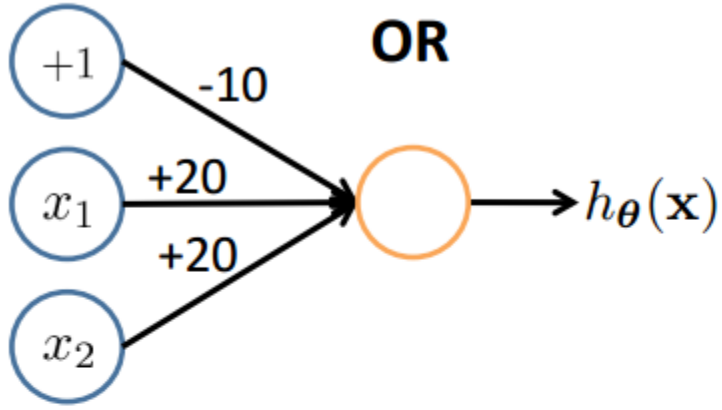


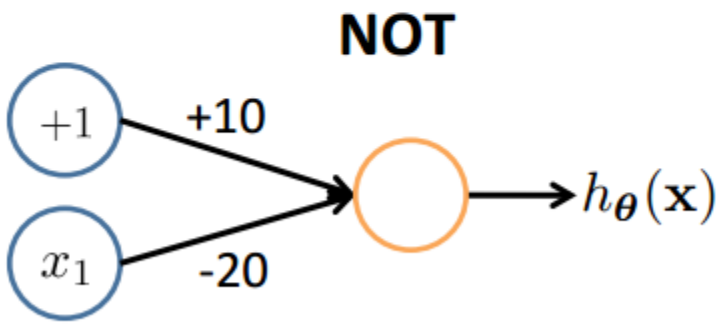
x_1	x_2	$h_\Theta(\mathbf{x})$
0	0	$g(-30) \approx 0$
0	1	$g(-10) \approx 0$
1	0	$g(-10) \approx 0$
1	1	$g(10) \approx 1$

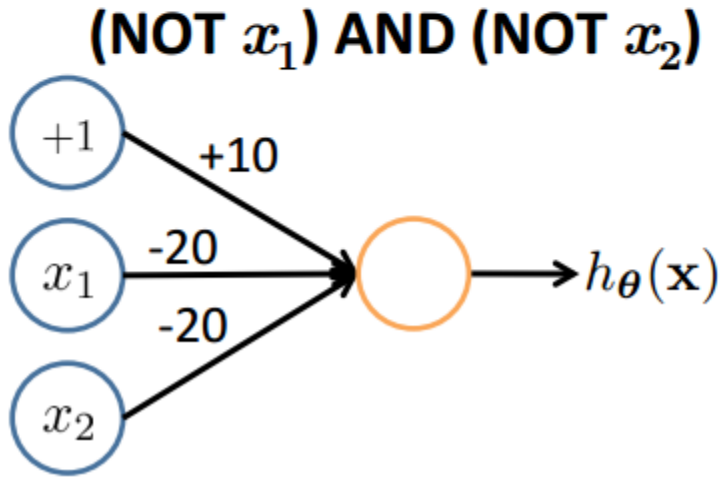
Based on slide and example by Andrew Ng

Representing Boolean Functions

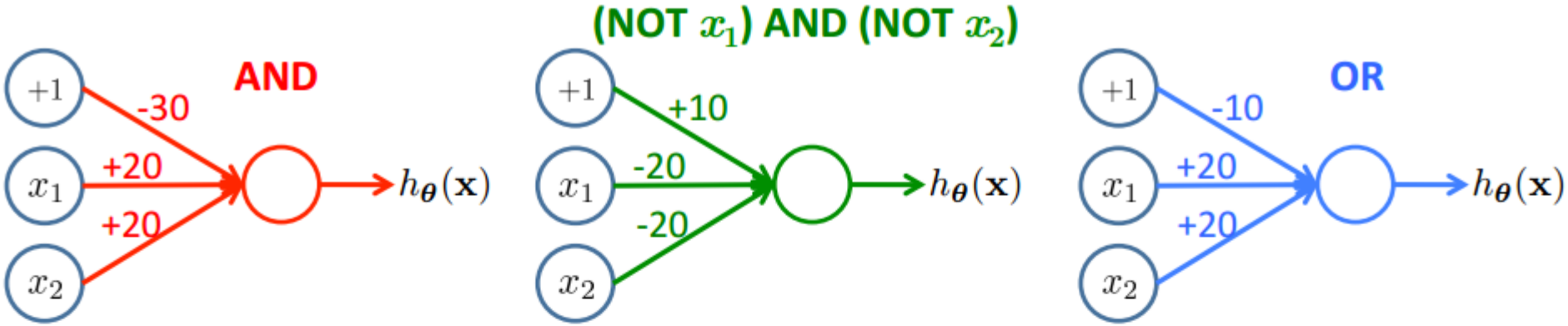


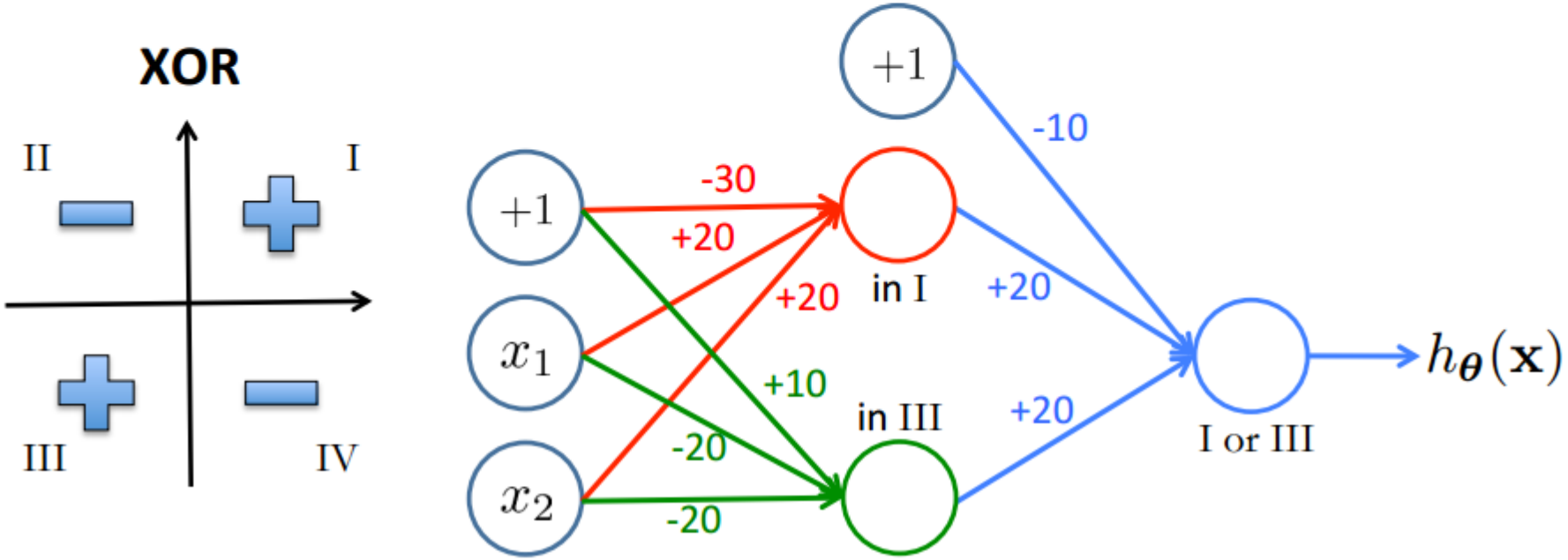






Combining Representations to Create Non-Linear Functions





Based on example by Andrew Ng

Training in Neural Networks: Gradient Descent

Given a training set $\mathcal{D} = \{(\boldsymbol{x}, y)\}$

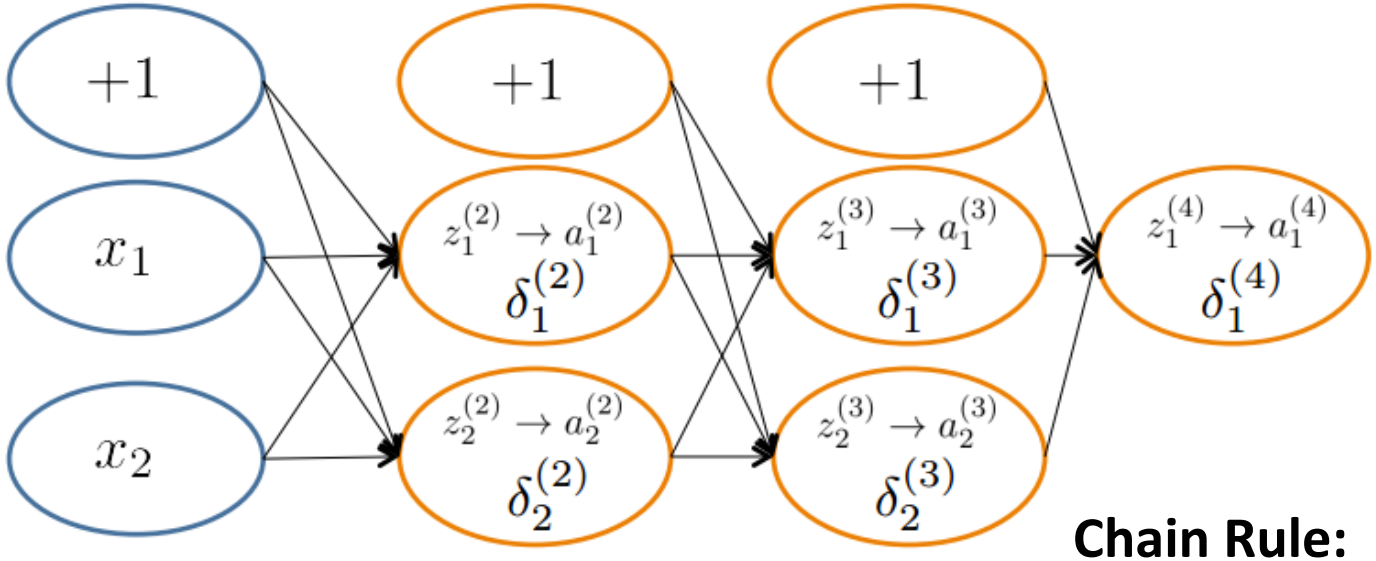
1. Initialize $\boldsymbol{w} \leftarrow \mathbf{0} \in \mathbb{R}^n$
2. For epoch $1 \ldots T$:
3. For $(\boldsymbol{x}, y)$ in $\mathcal{D}$:
4. Update $w \leftarrow w - \eta \nabla f(\theta)$
5. Return θ

Recap: Logistic regression

Let $\mathrm{h}_\theta(x_i) = 1/(1 + e^{-\theta^T x_i})$ (probability $y = 1$ given x_i)

$$\min_{\boldsymbol{\theta}} \frac{1}{n} \sum_i \mathrm{y_i} \log(\, h_\theta(x_i)) + (1 - y_i)\, (\, \log(1 - h_\theta(x_i))$$

Backpropagation: Compute Gradient



Chain Rule:

$$\frac{d}{dt} f(g(t)) = f'(g(t))g'(t) = \frac{df}{dg} \cdot \frac{dg}{dt}$$

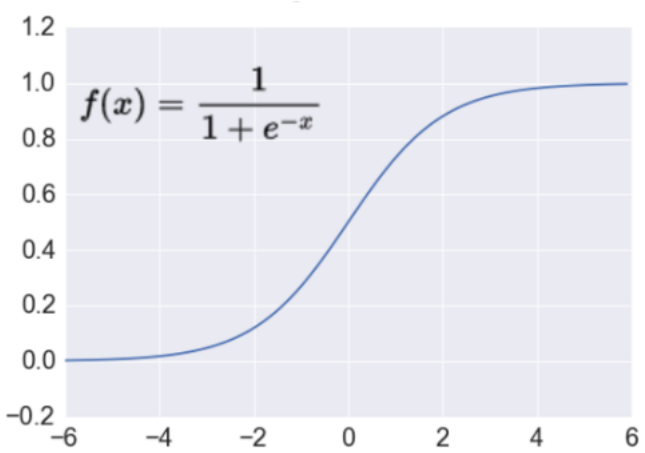
$\delta_j^{(l)}$ = "error" of node j in layer l

Formally, $\delta_j^{(l)} = \dfrac{\partial}{\partial z_j^{(l)}} \text{cost}(\mathbf{x}_i)$

where $\text{cost}(\mathbf{x}_i) = y_i \log h_\Theta(\mathbf{x}_i) + (1 - y_i) \log(1 - h_\Theta(\mathbf{x}_i))$

http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Activation Functions: Sigmoid



http://adilmoujahid.com/images/activation.png

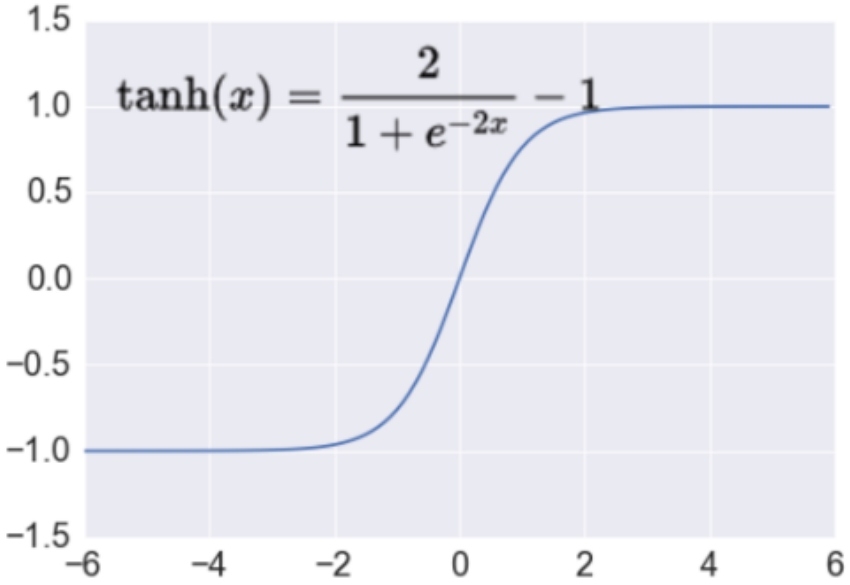
Takes a real-valued number and "squashes" it into range between 0 and 1.

$$R^n \rightarrow [0,1]$$

\+ Nice interpretation as the **firing rate** of a neuron
- 0 = not firing at all
- 1 = fully firing

\- Sigmoid neurons **saturate** and **kill gradients**, thus NN will barely learn
- when the neuron's activation are 0 or 1 (saturate)
  gradient at these regions almost zero
  almost no signal will flow to its weights
  if initial weights are too large then most neurons would saturate

Activation Functions: Tanh



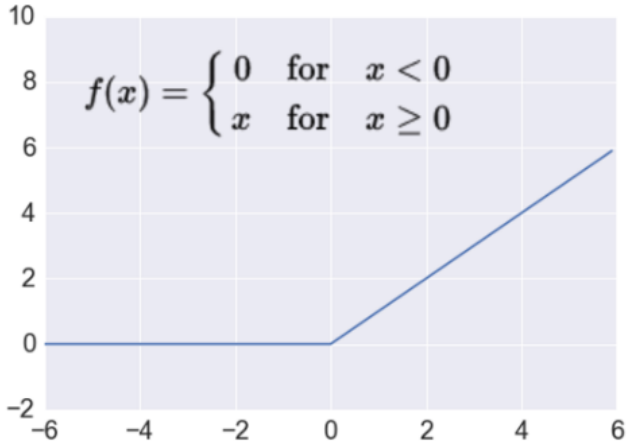
http://adilmoujahid.com/images/activation.png

Takes a real-valued number and "squashes" it into range between -1 and 1.

$$R^n \rightarrow [-1,1]$$

- Like sigmoid, tanh neurons **saturate**
- Unlike sigmoid, output is **zero-centered**
- Tanh is a **scaled sigmoid**: $\tanh(x) = 2sigm(2x) - 1$

Activation Functions: ReLU



http://adilmoujahid.com/images/activation.png

Takes a real-valued number and thresholds it at zero $\mathrm{f}(x) = \max(0, x)$

$$R^n \rightarrow R_+^n$$

Most Networks use ReLU nowadays

Trains much **faster**

- accelerates the convergence of SGD
- due to linear, non-saturating form

Less expensive operations

- compared to sigmoid/tanh (exponentials etc.)
- implemented by simply thresholding a matrix at zero

More **expressive**

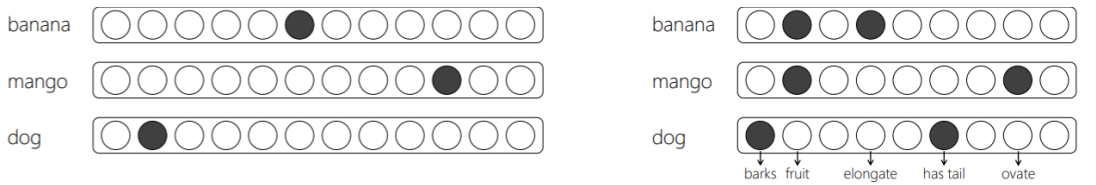
Prevents the **gradient vanishing problem**

Term embeddings

Types of vector representations

Local (or one-hot) representation
Every term in vocabulary T is represented by a binary vector of length |T|, where one position in the vector is set to one and the rest to zero

Distributed representation
Every term in vocabulary T is represented by a real-valued vector of length k. The vector dimensions may be *observed* (e.g., hand-crafted features) or *latent* (e.g., embedding dimensions).



(a) Local representation (b) Distributed representation

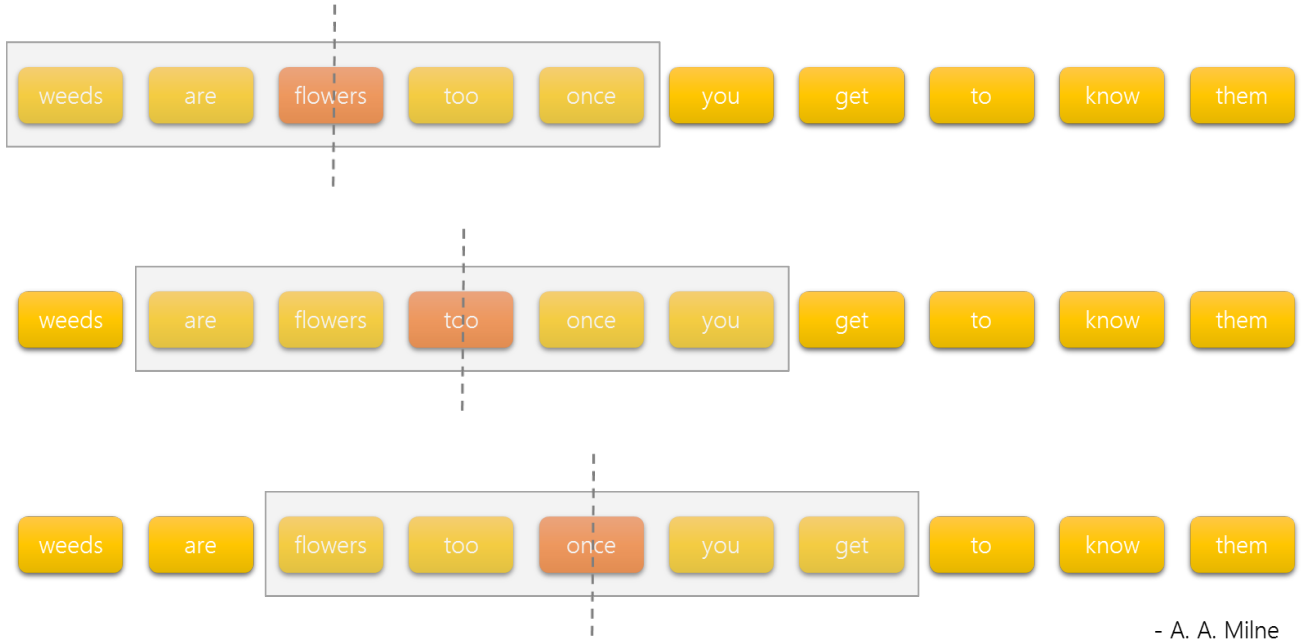
Figure 3.1: Under local representations the terms "banana", "mango", and "dog" are distinct items. But distributed vector representations may recognize that "banana" and "mango" are both fruits, but "dog" is different.

Word2vec

Goal: simple (shallow) neural model learning from billion words scale corpus

Two different architectures:

1. Skip-gram
2. CBOW

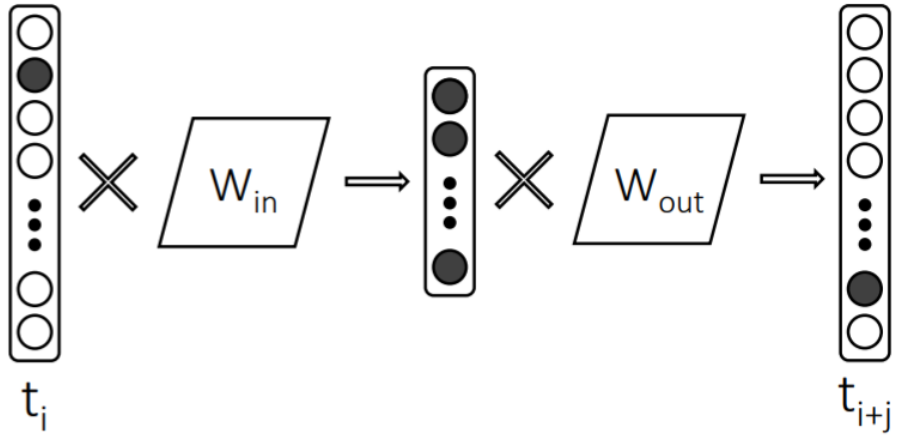


- A. A. Milne

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In NIPS, 2013.

Skip-gram Model

Predict neighbor t_{i+j} given term t_i



(a) Skip-gram

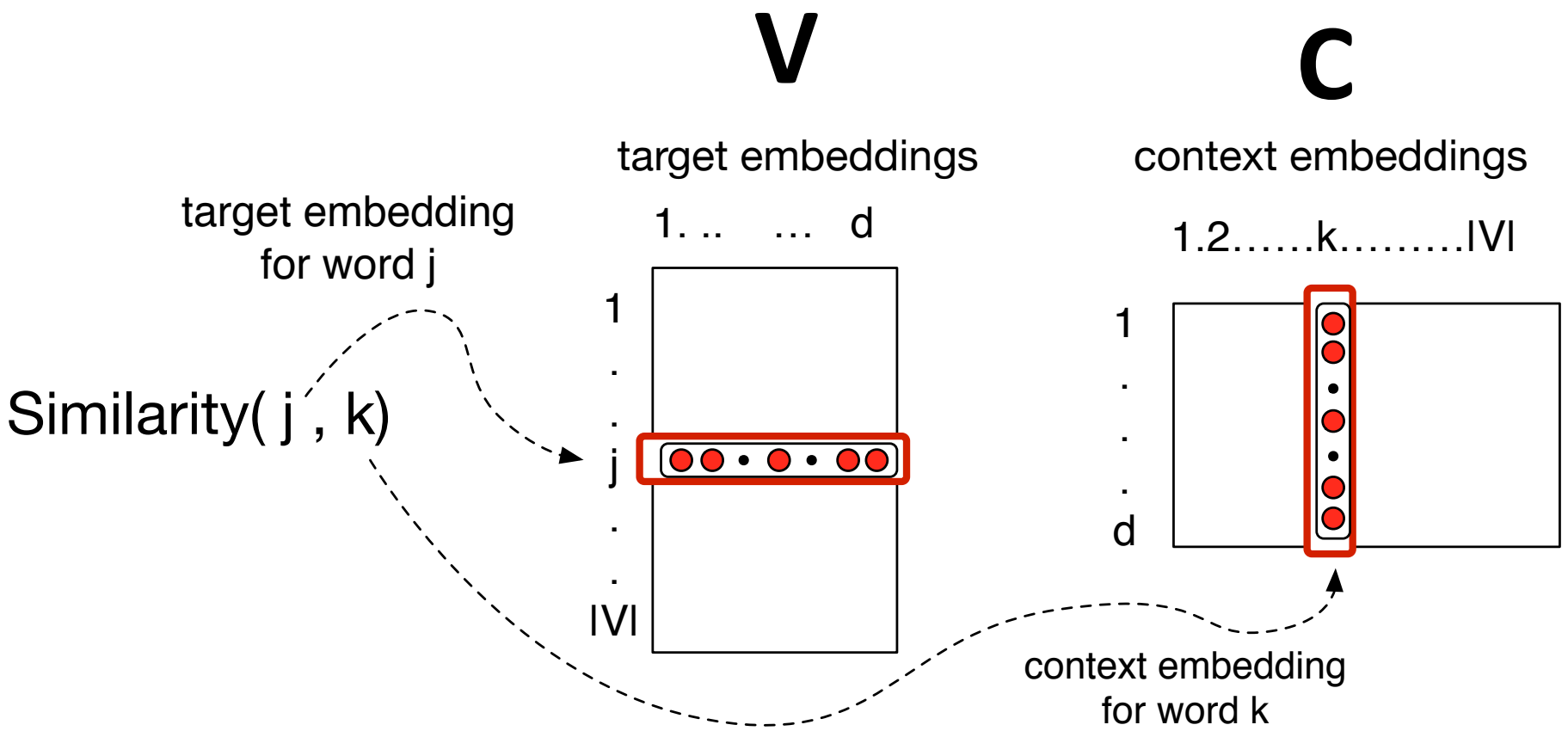
The Skip-gram loss

$$\mathcal{L}_{skip-gram} = -\frac{1}{|S|}\sum_{i=1}^{|S|}\sum_{-c\leq j\leq +c, j\neq 0} log(p(t_{i+j}|t_i))$$

S is the set of all windows over the training text

c is the number of neighbours we need to predict on either side of the term t_i

Word similarity as dot-product between a target vector and context vector



Turning dot products into probabilities

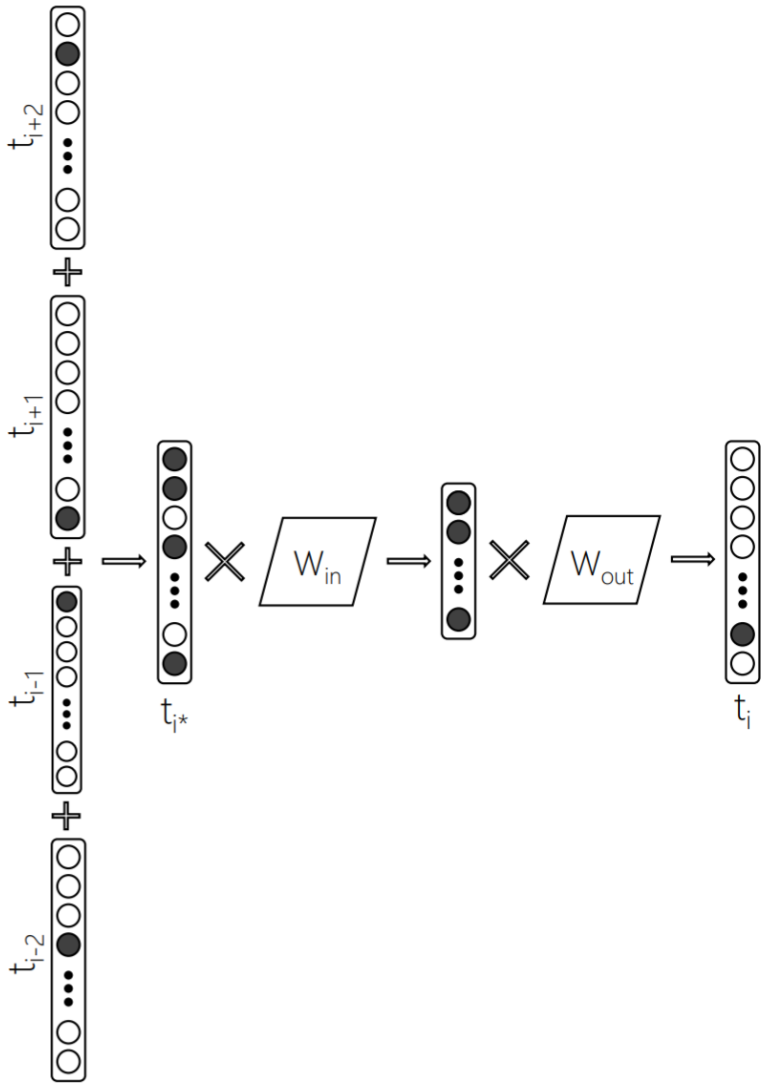
- Similarity(j,k) = $c_k \cdot v_j$

- We use softmax to turn into probabilities

$$p(w_k|w_j) = \frac{exp(c_k \cdot v_j)}{\sum_{i \in \text{C}} exp(c_i \cdot v_j)}$$

Continuous bag-of-words (CBOW)

Predict the middle term t_i given $\{t_{i-c}, \cdots, t_{i-1}, t_{i+1}, \cdots, t_{i+c}\}$



(b) Continuous bag-of-words (CBOW)

The CBOW loss

$$\mathcal{L}_{CBOW} = -\frac{1}{|S|}\sum_{i=1}^{|S|} log(p(t_i| \sum_{-c \leq j \leq +c, j \neq 0} t_{i+j}))$$

Note: from every window of text skip-gram generates 2 x c training samples whereas CBOW generates one – that's why CBOW trains faster than skip-gram

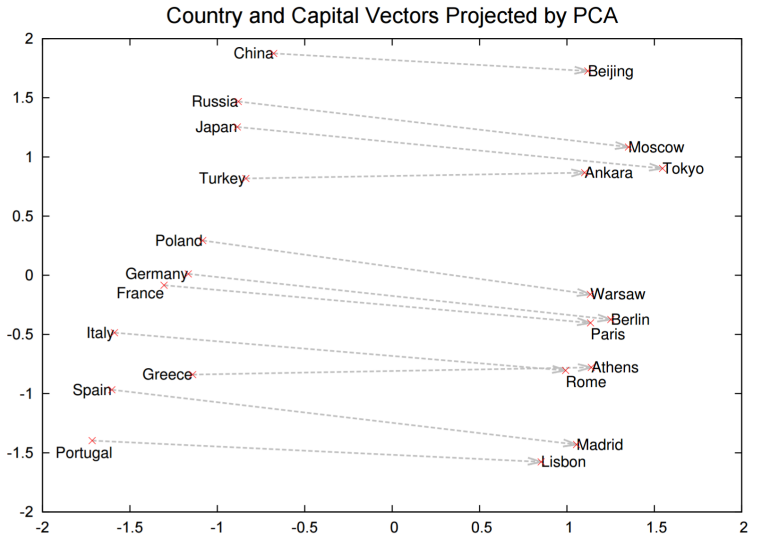
Word analogies with word2vec

W2v is popular for word analogy tasks

$$\vec{v}_{king} - \vec{v}_{man} + \vec{v}_{woman} \approx \vec{v}_{queen}$$

Table 1: *Examples of five types of semantic and nine types of syntactic questions in the Semantic-Syntactic Word Relationship test set.*

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks



Term embeddings for IR

Retrieval using vector representations

Generate vector representation of query

Generate vector representation of document

Estimate relevance from q-d vectors

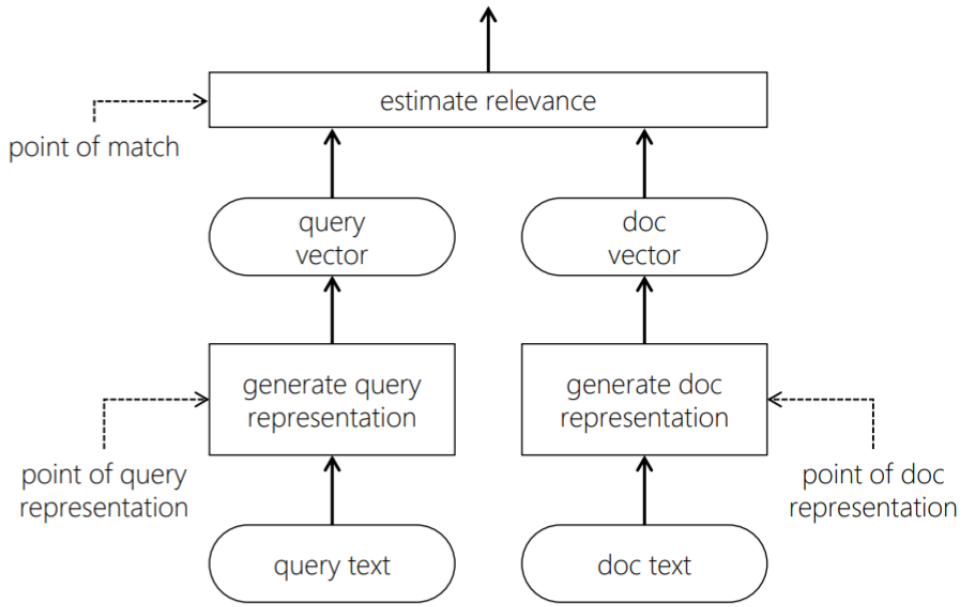
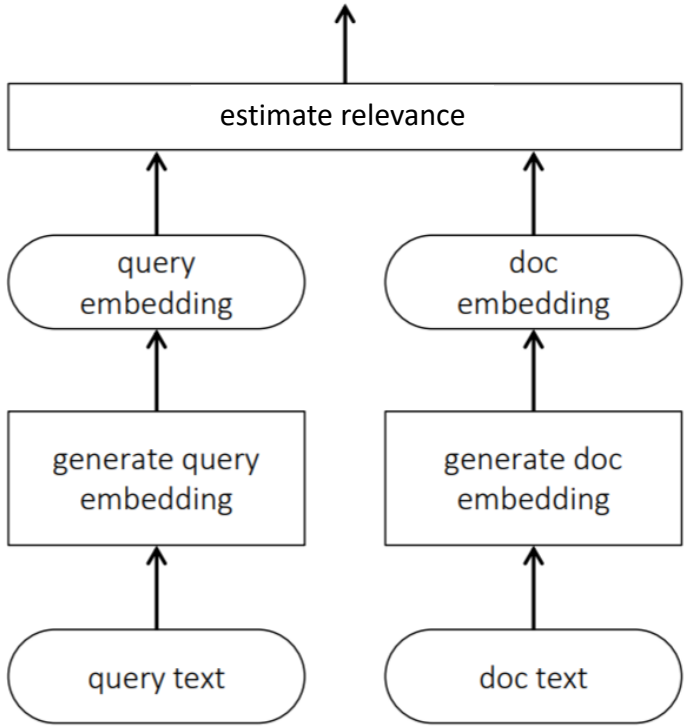
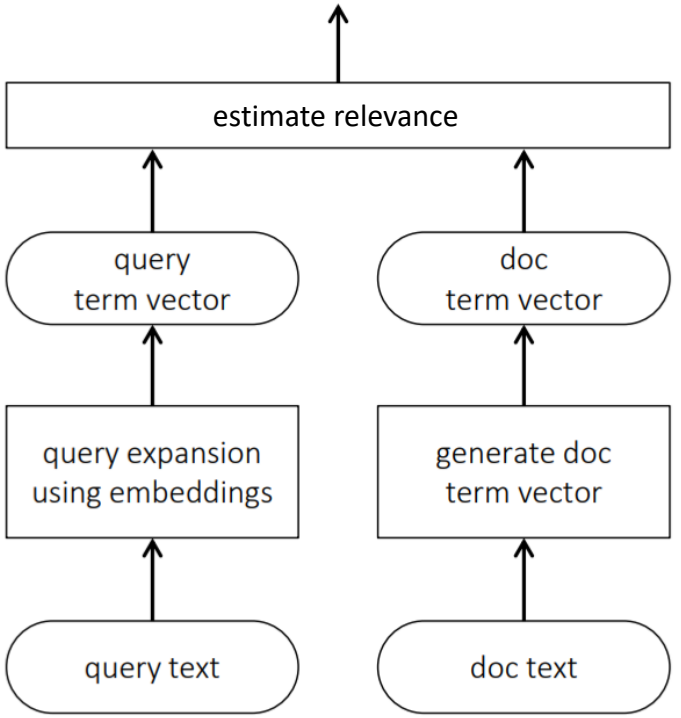


Figure 2.3: Document ranking typically involves a query and a document representation steps, followed by a matching stage. Neural models can be useful either for generating good representations or in estimating relevance, or both.

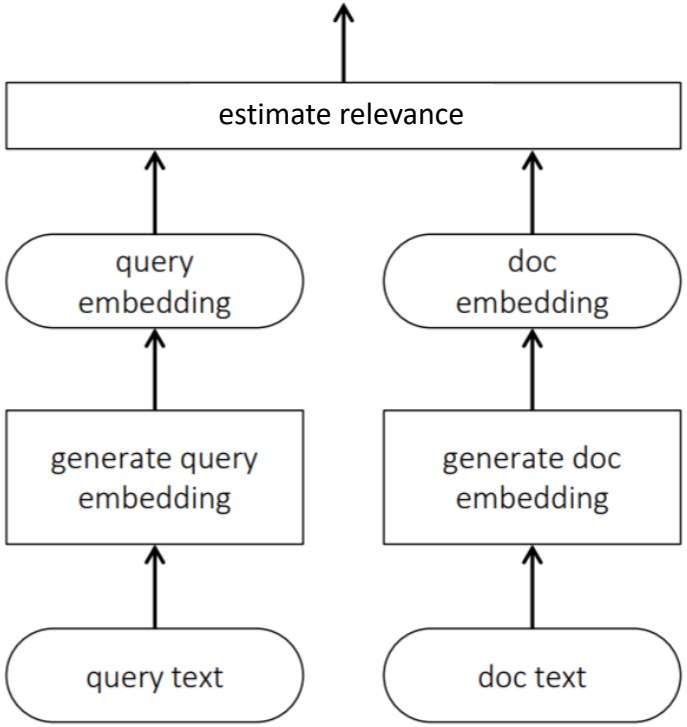
Popular approaches to incorporating term embeddings for matching



Compare query and document directly in the embedding space



Use embeddings to generate suitable query expansions



Compare query and document directly in the embedding space

E.g.,

Generalized Language Model [Ganguly et al., 2015]

Neural Translation Language Model [Zuccon et al., 2015]

Average term embeddings [Le and Mikolov, 2014, Nalisnick et al., 2016, Zamani and Croft, 2016, and others]

Word mover's distance [Kusner et al., 2015, Guo et al., 2016]

Average Term Embeddings

Q-D relevance estimated by computing cosine similarity between centroid of q and d term embeddings

$$sim(q,d) = cos(\vec{v}_q, \vec{v}_d) = \frac{\vec{v}_q^{\intercal}\vec{v}_d}{\|\vec{v}_q\|\|\vec{v}_d\|}$$

$$\text{where,} \quad \vec{v}_q = \frac{1}{|q|}\sum_{t_q \in q}\frac{\vec{v}_{t_q}}{\|\vec{v}_{t_q}\|}$$

$$\vec{v}_d = \frac{1}{|d|}\sum_{t_d \in d}\frac{\vec{v}_{t_d}}{\|\vec{v}_{t_d}\|}$$

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

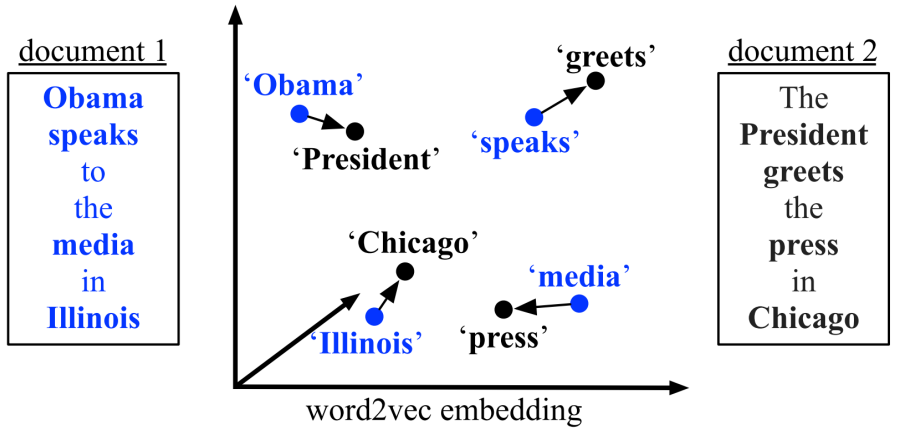
Word mover's distance

Based on the Earth Mover's Distance (EMD)
[Rubner et al., 1998]

Originally proposed by Wan et al. [2005, 2007], but used WordNet and topic categories

Kusner et al. [2015] incorporated term embeddings

Adapted for q-d matching by Guo et al. [2016]

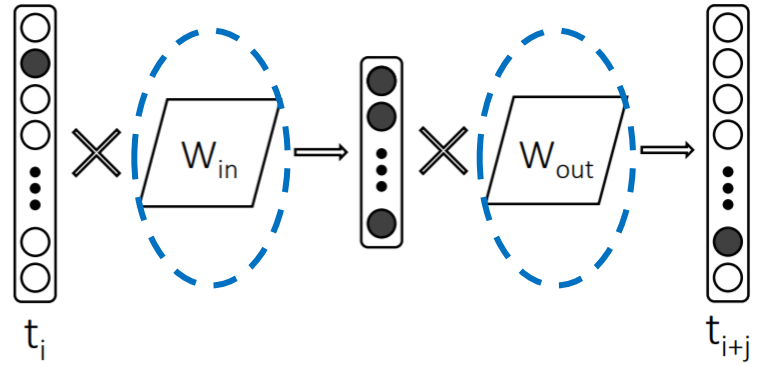


Yossi Rubner, Carlo Tomasi, and Leonidas J Guibas. A metric for distributions with applications to image databases. In CV, 1998.
Xiaojun Wan and Yuxin Peng. The earth mover's distance as a semantic measure for document similarity. In CIKM, 2005.
Xiaojun Wan. A novel document similarity measure based on earth mover's distance. Information Sciences, 2007.
Matt Kusner, Yu Sun, Nicholas Kolkin, and Kilian Weinberger. From word embeddings to document distances. In ICML, 2015.
Jiafeng Guo, Yixing Fan, Qingyao Ai, and W Bruce Croft. Semantic matching by non-linear word transportation for information retrieval. In CIKM, 2016.

But, wait… what term embeddings should we use?

Dual embedding space model

What if I told you that everyone using word2vec is throwing half the model away?



(a) Skip-gram

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Dual embedding space model

IN-OUT captures a more Topical notion of similarity than IN-IN and OUT-OUT, which capture more typical notion of similarity

Effect is exaggerated when embeddings are trained on short text (e.g., queries)

yale		**seahawks**		**eminem**	
IN-IN	IN-OUT	IN-IN	IN-OUT	IN-IN	IN-OUT
yale	yale	seahawks	seahawks	eminem	eminem
harvard	faculty	49ers	highlights	rihanna	rap
nyu	alumni	broncos	jerseys	ludacris	featuring
cornell	orientation	packers	tshirts	kanye	tracklist
tulane	haven	nfl	seattle	beyonce	diss
tufts	graduate	steelers	hats	2pac	performs

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Dual embedding space model

Average term embeddings model, but use IN embeddings for query terms and OUT embeddings for document terms

$$DESM_{in-out}(q,d) = \frac{1}{|q|} \sum_{t_q \in q} \frac{\vec{v}_{t_q,in}^{\intercal} \vec{v}_{d,out}}{\|\vec{v}_{t_q,in}\| \|\vec{v}_{d,out}\|}$$

$$\vec{v}_{d,out} = \frac{1}{|d|} \sum_{t_d \in d} \frac{\vec{v}_{t_d,out}}{\|\vec{v}_{t_d,out}\|}$$

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Dual embedding space model

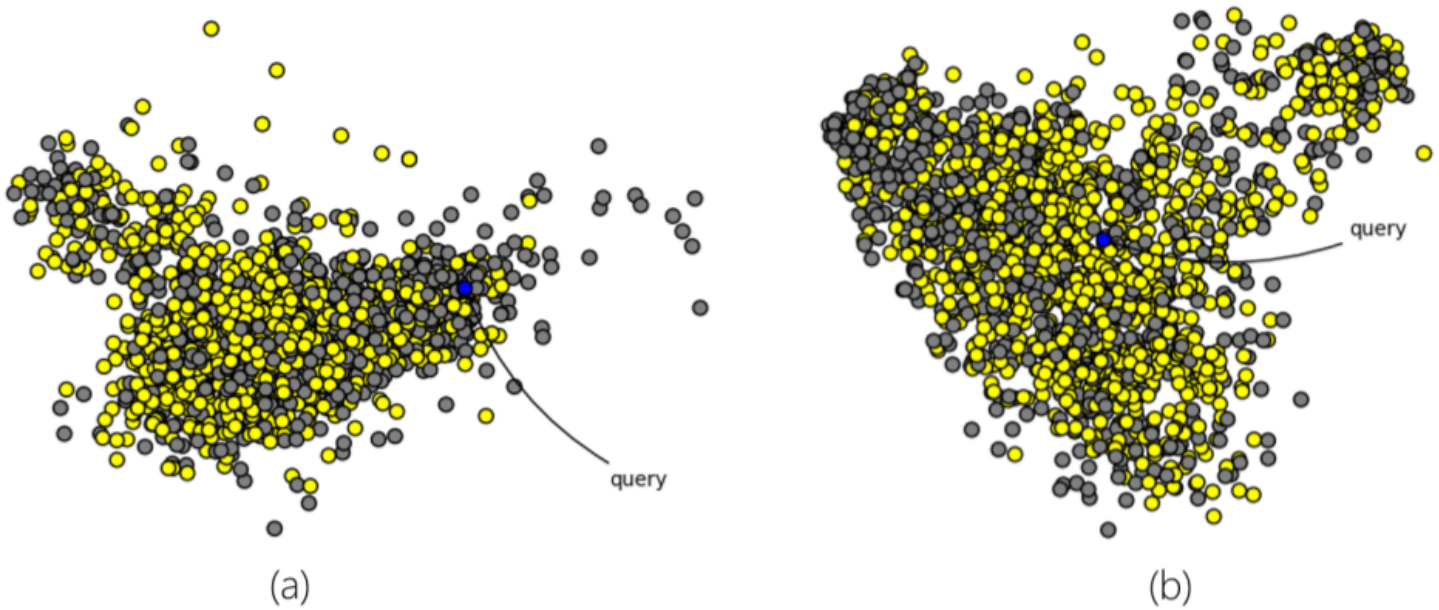


Figure 1: A two dimensional PCA projection of the 200-dimensional embeddings. Relevant documents are yellow, irrelevant documents are grey, and the query is blue. To visualize the results of multiple queries at once, before dimensionality reduction we centre query vectors at the origin and represent documents as the difference between the document vector and its query vector. (a) uses IN word vector centroids to represent both the query and the documents. (b) uses IN for the queries and OUT for the documents, and seems to have a higher density of relevant documents near the query.

Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Challenge

IN+OUT Embeddings for 2.7M words
trained on 600M+ Bing queries

http://bit.ly/DataDESM

Can you come up with interesting t-SNE visualizations that demonstrates the differences between IN-IN and IN-OUT term similarities?

Download

A tale of two queries

"pekarovic land company"

Hard to learn good representation for the rare term *pekarovic*

But easy to estimate relevance based on count of exact term matches of *pekarovic* in the document

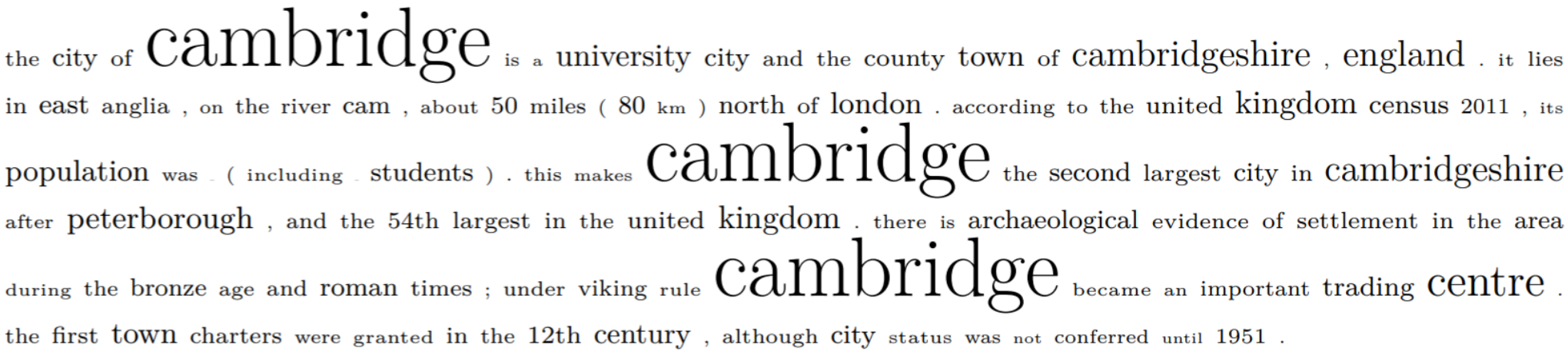
"what channel are the seahawks on today"

Target document likely contains *ESPN* or *sky sports* instead of *channel*

The terms *ESPN* and *channel* can be compared in a term embedding space

Matching in the term space is necessary to handle rare terms. Matching in the latent embedding space can provide additional evidence of relevance. Best performance is often achieved by combining matching in both vector spaces.

Query: Cambridge (Font size is a function of term-term cosine similarity)



(a) Passage about the city of Cambridge

Besides the term “Cambridge”, other related terms (e.g., “university”, “town”, “population”, and “England”) contribute to the relevance of the passage

Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Query: Cambridge (Font size is a function of term-term cosine similarity)

oxford is a city in the south east region of england and the county town of oxfordshire . with a population of _ it is the 52nd largest city in the united kingdom , and one of the fastest growing and most ethnically diverse . oxford has a broad economic base . its industries include motor manufacturing , education , publishing and a large number of information technology and _ businesses , some being academic offshoots . the city is known worldwide as the home of the university of oxford , the oldest university in the _ world . buildings in oxford demonstrate examples of every english architectural period since the arrival of the saxons , including the _ radcliffe camera . oxford is known as the city of dreaming spires , a term coined by poet matthew arnold .

(b) Passage about the city of Oxford

However, the same terms may also make a passage about Oxford look somewhat relevant to the query “Cambridge”

Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

Query: Cambridge (Font size is a function of term-term cosine similarity)

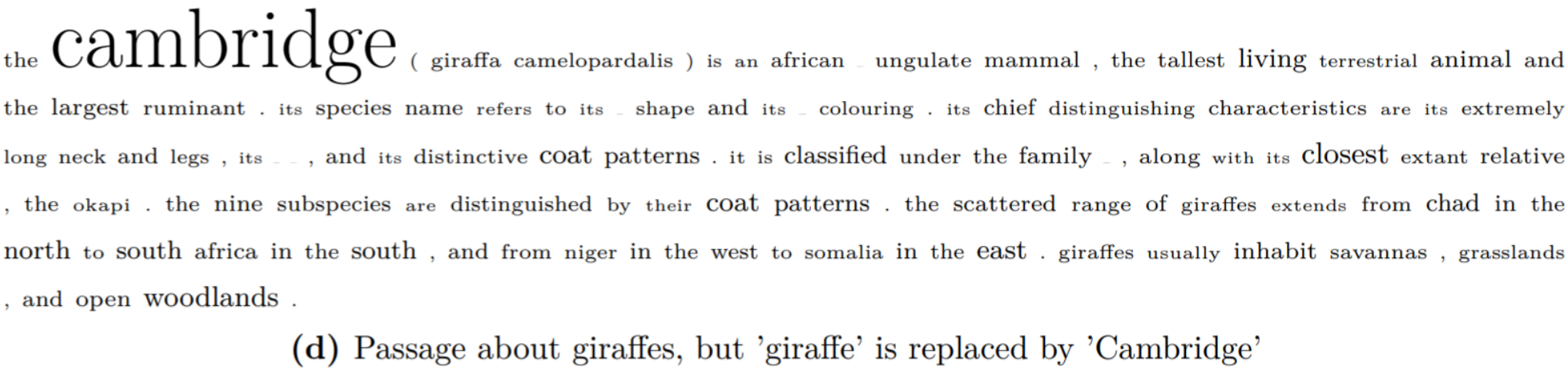
the giraffe (giraffa camelopardalis) is an african _ ungulate mammal , the tallest living terrestrial animal and the largest ruminant . its species name refers to its _ shape and its _ colouring . its chief distinguishing characteristics are its extremely long neck and legs , its _ , and its distinctive coat patterns . it is classified under the family _ , along with its closest extant relative , the okapi . the nine subspecies are distinguished by their coat patterns . the scattered range of giraffes extends from chad in the north to south africa in the south , and from niger in the west to somalia in the east . giraffes usually inhabit savannas , grasslands , and open woodlands .

(c) Passage about giraffes

A passage about giraffes, however, obviously looks non-relevant in the embedding space…

Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.

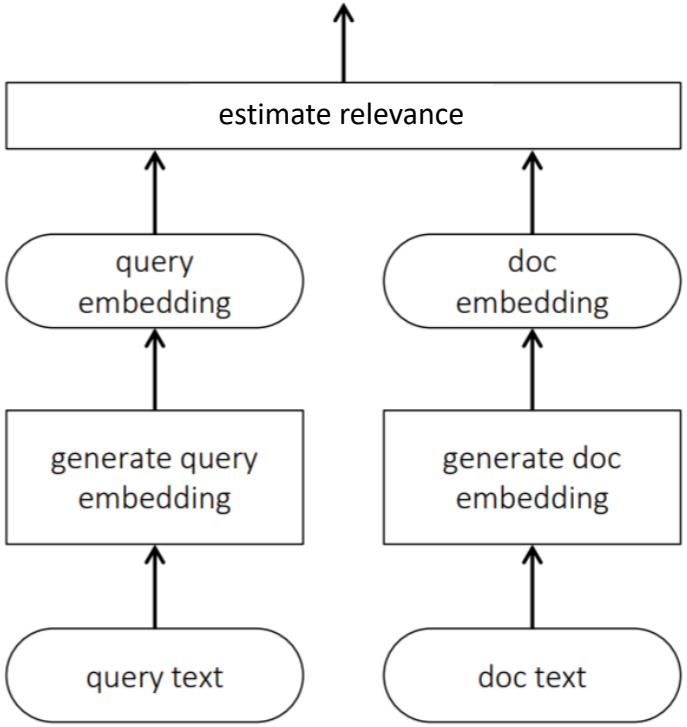
Query: Cambridge (Font size is a function of term-term cosine similarity)



(d) Passage about giraffes, but 'giraffe' is replaced by 'Cambridge'

But the embedding based matching model is more robust to the same passage when "giraffe" is replaced by "Cambridge"—a trick that would fool exact term based IR models. In a sense, the embedding based model ranks this passage low because Cambridge is not "an African even-toed ungulate mammal".

Bhaskar Mitra, Eric Nalisnick, Nick Craswell, and Rich Caruana. A dual embedding space model for document ranking. arXiv preprint arXiv:1602.01137, 2016.



Compare query and document directly in the embedding space

E.g.,

Generalized Language Model [Ganguly et al., 2015]

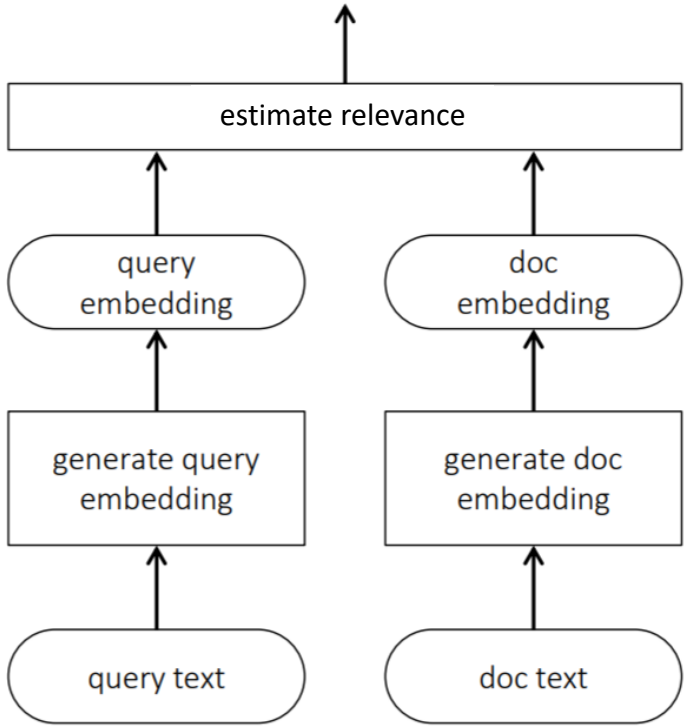
Neural Translation Language Model [Zuccon et al., 2015]

Average term embeddings [Le and Mikolov, 2014, Nalisnick et al., 2016, Zamani and Croft, 2016, and others]

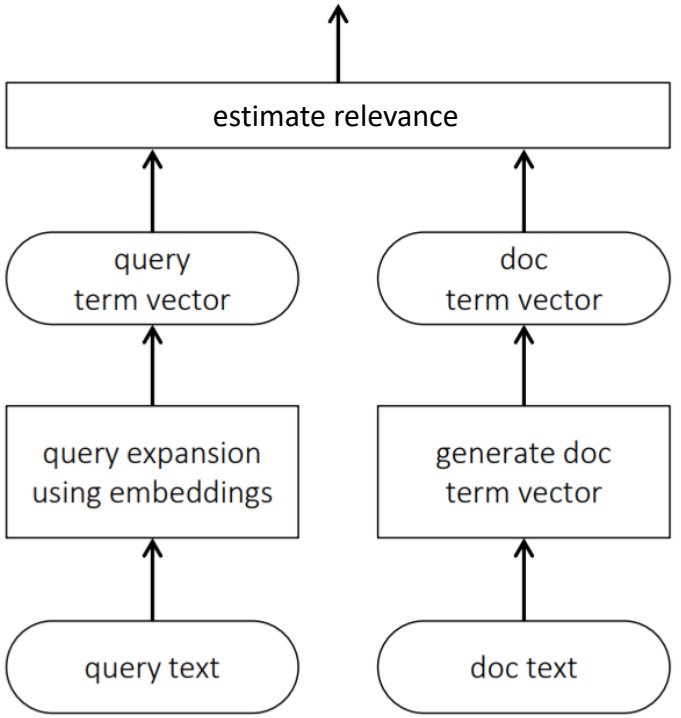
Word mover's distance

Debasis Ganguly, Dwaipayan Roy, Mandar Mitra, and Gareth JF Jones. Word embedding based generalized language model for information retrieval. In SIGIR, 2015.
Guido Zuccon, Bevan Koopman, Peter Bruza, and Leif Azzopardi. Integrating and evaluating neural word embeddings in information retrieval. In ADCS, 2015.
Quoc V Le and Tomas Mikolov. Distributed representations of sentences and documents. In ICML, 2014.
Eric Nalisnick, Bhaskar Mitra, Nick Craswell, and Rich Caruana. Improving document ranking with dual word embeddings. In WWW, 2016.
Hamed Zamani and W Bruce Croft. Estimating embedding vectors for queries. In ICTIR, 2016.

Popular approaches to incorporating term embeddings for matching



Compare query and document directly in the embedding space



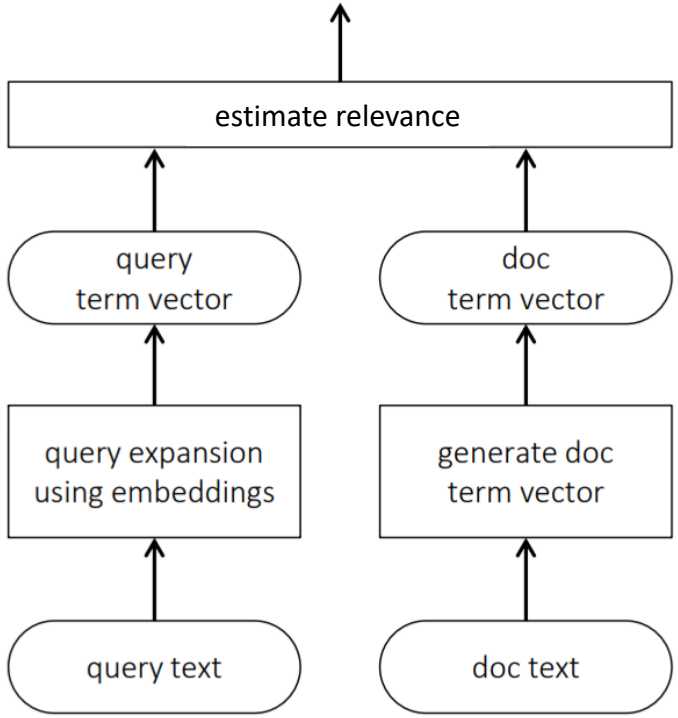
Use embeddings to generate suitable query expansions

Query expansion using term embeddings

Find good expansion terms based on nearness in the embedding space

$$score(t_c, q) = \frac{1}{|q|} \sum_{t_q \in q} cos(\vec{v}_{t_c}, \vec{v}_{t_q})$$

Better retrieval performance when combined with pseudo-relevance feedback (PRF) [Zamani and Croft, 2016] and if we learn query specific term embeddings [Diaz et al., 2016]



Use embeddings to generate suitable query expansions

Fernando Diaz, Bhaskar Mitra, and Nick Craswell. Query expansion with locally-trained word embeddings. In ACL, 2016.
Dwaipayan Roy, Debjyoti Paul, Mandar Mitra, and Utpal Garain. Using word embeddings for automatic query expansion. arXiv preprint arXiv:1606.07608, 2016.
Hamed Zamani and W Bruce Croft. Embedding-based query language models. In ICTIR, 2016.

Learning to Rank

Learning to Rank (LTR)

"... the task to automatically construct a ranking model using training data, such that the model can sort new objects according to their degrees of relevance, preference, or importance."

- Liu [2009]

L2R models represent a rankable item—e.g., a document—given some context—e.g., a user-issued query—as a numerical vector $\vec{x} \in \mathbb{R}^n$

The ranking model $f: \vec{x} \rightarrow \mathbb{R}$ is trained to map the vector to a real-valued score such that relevant items are scored higher.

Tie-Yan Liu. Learning to rank for information retrieval. Foundation and Trends in Information Retrieval, 2009.

Features

Traditional L2R models employ hand-crafted features that encode IR insights

They can often be categorized as:

Query-independent or static features
e.g., incoming link count and document length

Query-dependent or dynamic features
e.g., BM25

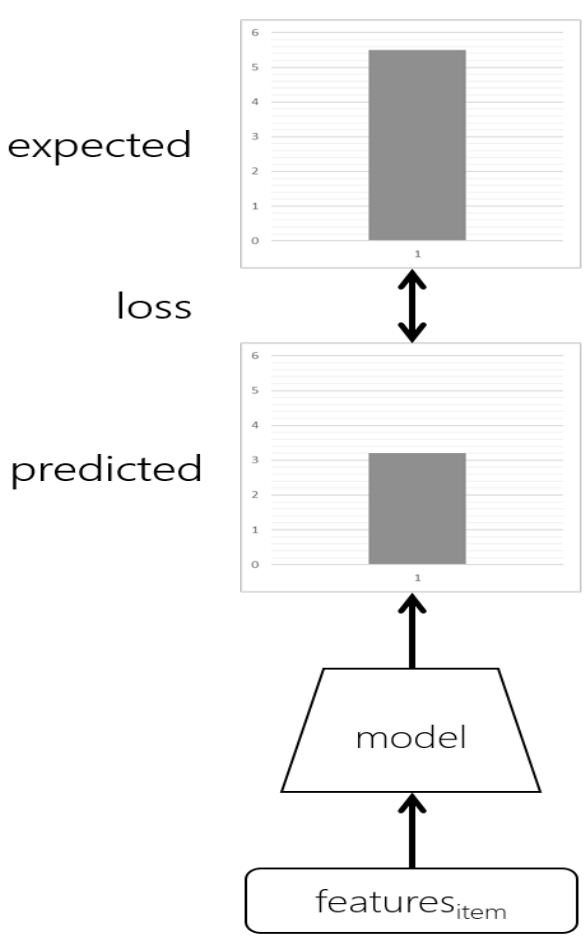
Query-level features
e.g., query length

Features

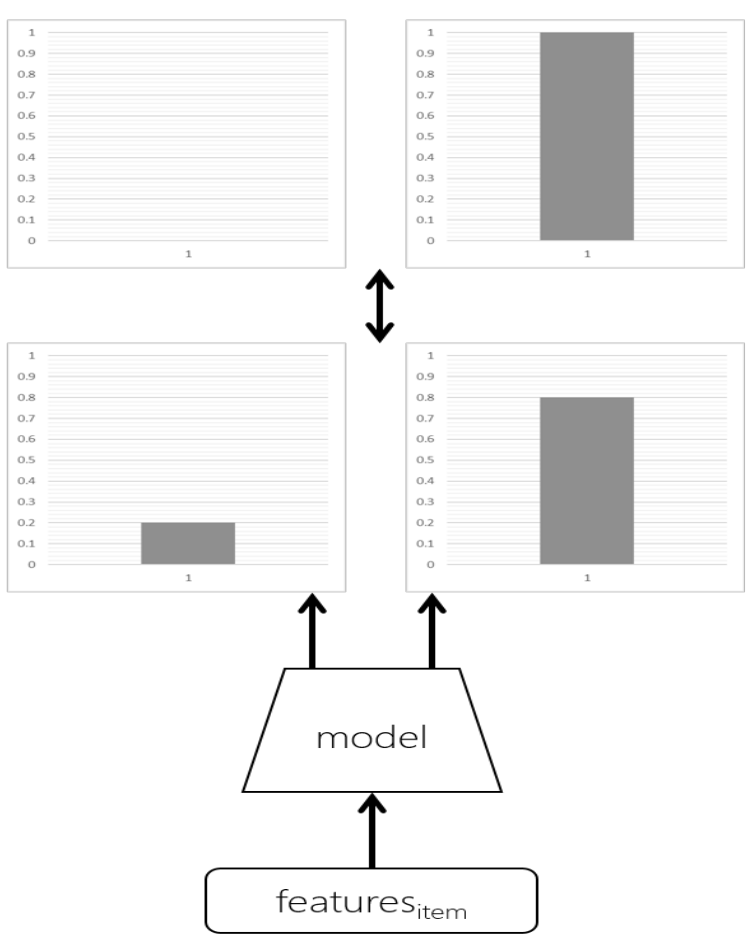
ID	Feature description	Category
1	$\sum_{q_i \in q \cap d} c(q_i, d)$ in body	Q-D
2	$\sum_{q_i \in q \cap d} c(q_i, d)$ in anchor	Q-D
3	$\sum_{q_i \in q \cap d} c(q_i, d)$ in title	Q-D
4	$\sum_{q_i \in q \cap d} c(q_i, d)$ in URL	Q-D
5	$\sum_{q_i \in q \cap d} c(q_i, d)$ in whole document	Q-D
6	$\sum_{q_i \in q} idf(q_i)$ in body	Q
7	$\sum_{q_i \in q} idf(q_i)$ in anchor	Q
8	$\sum_{q_i \in q} idf(q_i)$ in title	Q
9	$\sum_{q_i \in q} idf(q_i)$ in URL	Q
10	$\sum_{q_i \in q} idf(q_i)$ in whole document	Q
11	$\sum_{q_i \in q \cap d} c(q_i, d) \cdot idf(q_i)$ in body	Q-D
12	$\sum_{q_i \in q \cap d} c(q_i, d) \cdot idf(q_i)$ in anchor	Q-D
13	$\sum_{q_i \in q \cap d} c(q_i, d) \cdot idf(q_i)$ in title	Q-D
14	$\sum_{q_i \in q \cap d} c(q_i, d) \cdot idf(q_i)$ in URL	Q-D
15	$\sum_{q_i \in q \cap d} c(q_i, d) \cdot idf(q_i)$ in whole document	Q-D
16	$\|d\|$ of body	D
17	$\|d\|$ of anchor	D
18	$\|d\|$ of title	D
19	$\|d\|$ of URL	D
20	$\|d\|$ of whole document	D
21	BM25 of body	Q-D
22	BM25 of anchor	Q-D
23	BM25 of title	Q-D
24	BM25 of URL	Q-D
25	BM25 of whole document	Q-D
26	LMIR.ABS of body	Q-D
27	LMIR.ABS of anchor	Q-D
28	LMIR.ABS of title	Q-D
29	LMIR.ABS of URL	Q-D
30	LMIR.ABS of whole document	Q-D
31	LMIR.DIR of body	Q-D
32	LMIR.DIR of anchor	Q-D
33	LMIR.DIR of title	Q-D
34	LMIR.DIR of URL	Q-D
35	LMIR.DIR of whole document	Q-D
36	LMIR.JM of body	Q-D
37	LMIR.JM of anchor	Q-D
38	LMIR.JM of title	Q-D
39	LMIR.JM of URL	Q-D
40	LMIR.JM of whole document	Q-D
41	Sitemap based term propagation	Q-D
42	Sitemap based score propagation	Q-D
43	Hyperlink based score propagation: weighted in-link	Q-D
44	Hyperlink based score propagation: weighted out-link	Q-D
45	Hyperlink based score propagation: uniform out-link	Q-D
46	Hyperlink based propagation: weighted in-link	Q-D
47	Hyperlink based feature propagation: weighted out-link	Q-D
48	Hyperlink based feature propagation: uniform out-link	Q-D
49	HITS authority	Q-D
50	HITS hub	Q-D
51	PageRank	D
52	HostRank	D
53	Topical PageRank	Q-D
54	Topical HITS authority	Q-D
55	Topical HITS hub	Q-D
56	Inlink number	D
57	Outlink number	D
58	Number of slash in URL	D
59	Length of URL	D
60	Number of child page	D
61	BM25 of extracted title	Q-D
62	LMIR.ABS of extracted title	Q-D
63	LMIR.DIR of extracted title	Q-D
64	LMIR.JM of extracted title	Q-D

Tao Qin, Tie-Yan Liu, Jun Xu, and Hang Li. LETOR: A Benchmark Collection for Research on Learning to Rank for Information Retrieval, Information Retrieval Journal, 2010

Neural models for other tasks



regression

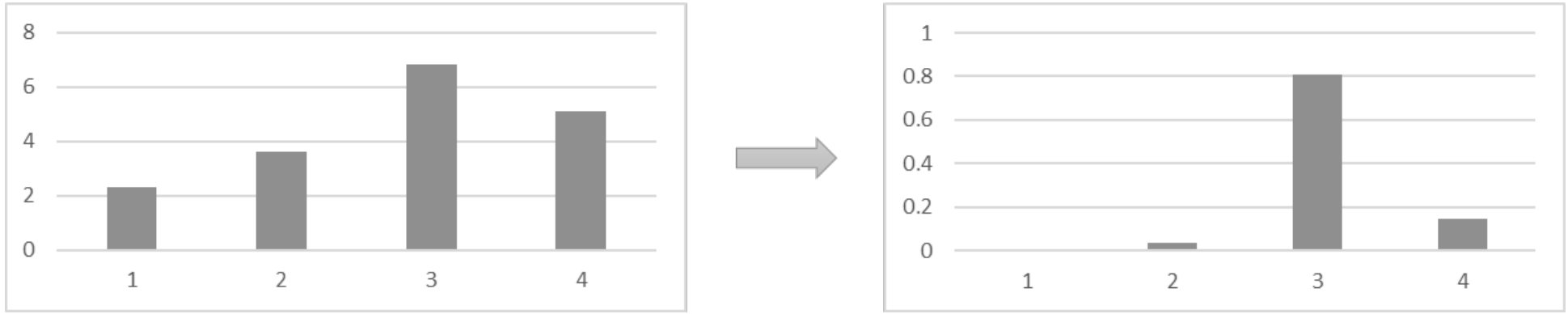


classification

The softmax function

In neural classification models, the softmax function is popularly used to normalize the neural network output scores across all the classes

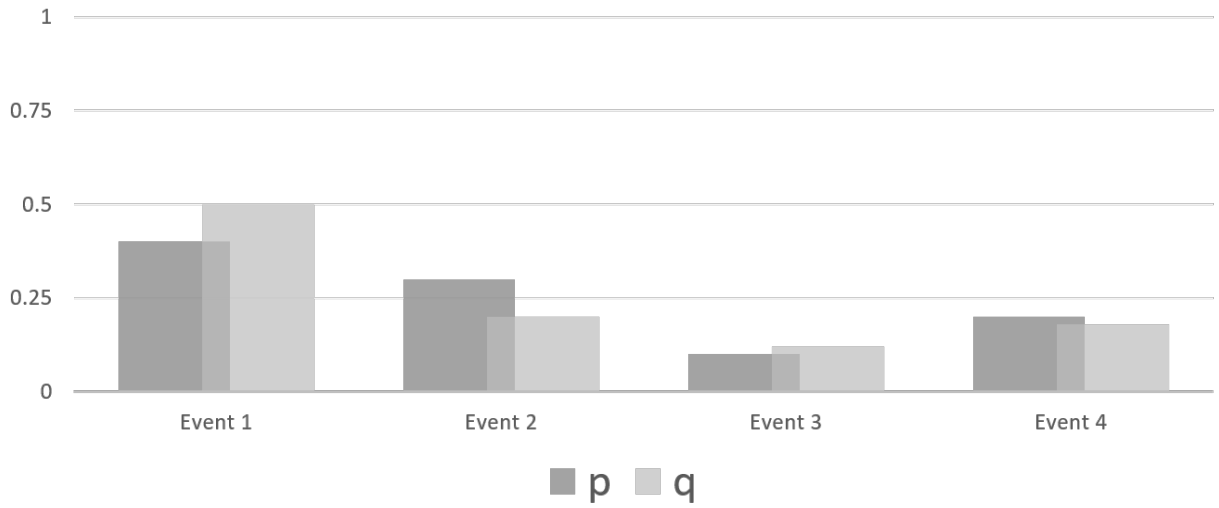
$$p(z_i) = \frac{e^{\gamma z_i}}{\sum_{z \in Z} e^{\gamma z}} \qquad (\gamma \text{ is a constant})$$



Cross entropy

The cross entropy between two probability distributions p and q over a discrete set of events is given by,

$$CE(p,q) = -\sum_i p_i \log(q_i)$$



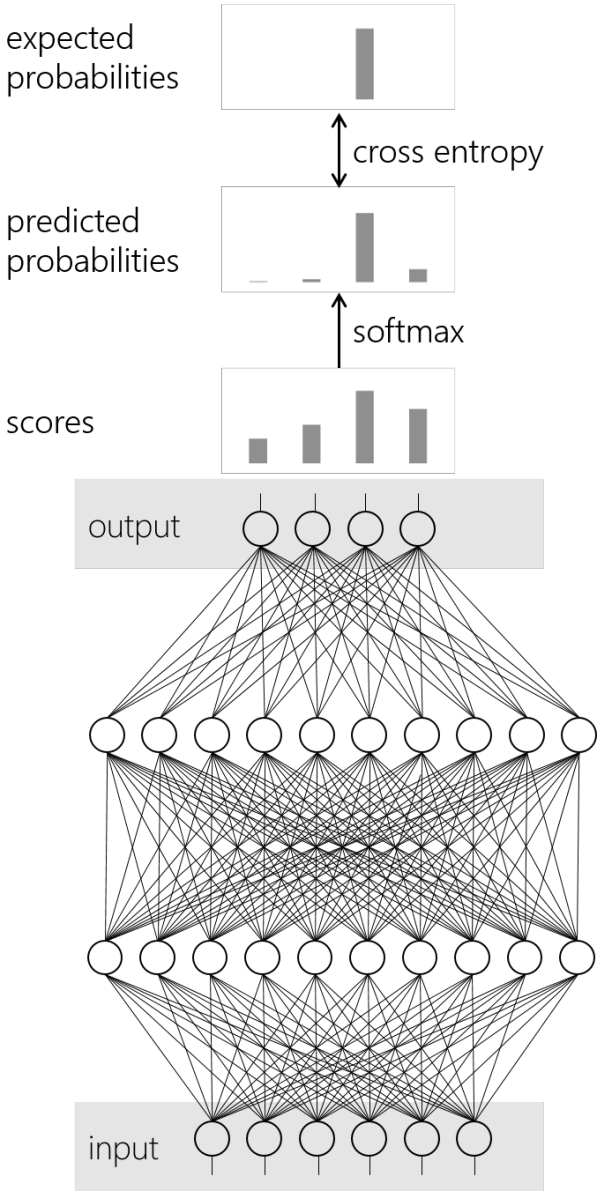
If $p_{correct} = 1$and $p_i = 0$ for all other values of i then,

$$CE(p,q) = -\log(q_{correct})$$

Cross entropy with softmax loss

Cross entropy with softmax is a popular loss function for classification

$$\mathcal{L}_{\text{CE}} = -log\Big(\frac{e^{\gamma z_{correct}}}{\sum_{z \in Z} e^{\gamma z}}\Big)$$



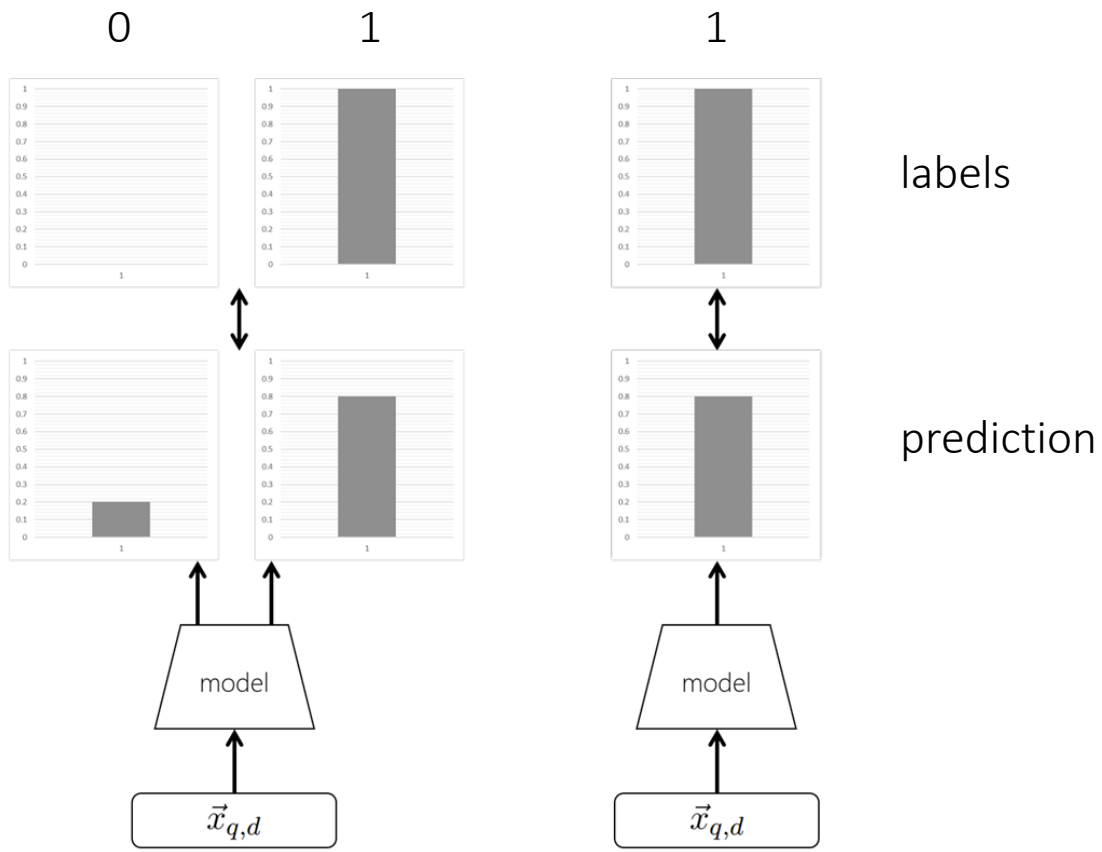
Pointwise objectives

Regression loss

Given $\langle q, d \rangle$ predict the value of $y_{q,d}$

e.g., square loss for binary or categorical labels,

$$\mathcal{L}_{Squared} = \|y_{q,d} - f(\vec{x}_{q,d})\|^2$$



Norbert Fuhr. Optimum polynomial retrieval functions based on the probability ranking principle. ACM TOIS, 1989.

David Cossock and Tong Zhang. Subset ranking using regression. In COLT, 2006.

Pointwise objectives

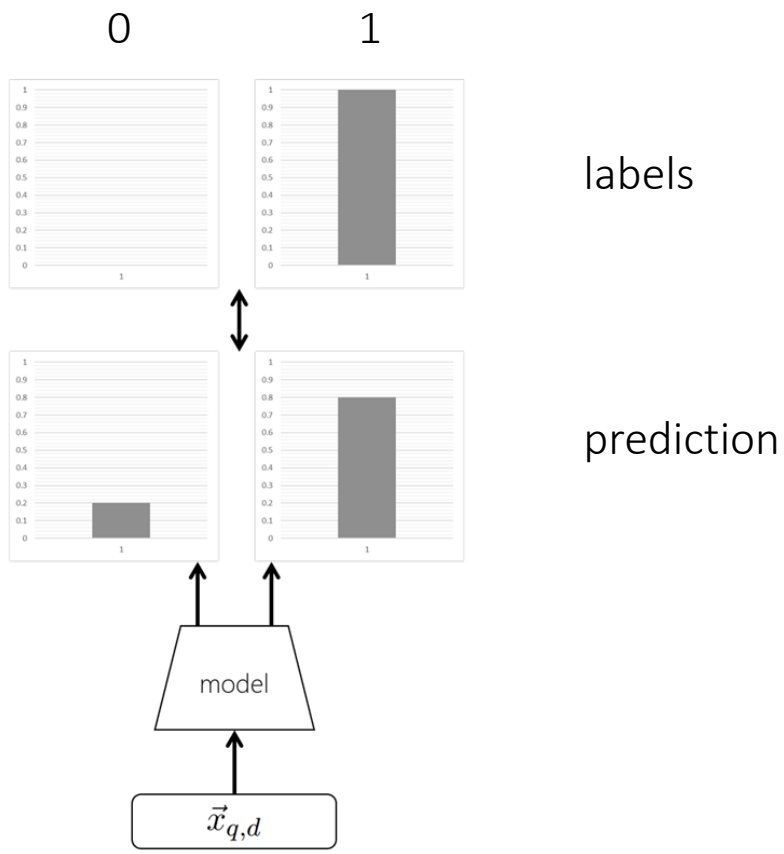
Classification loss

Given $\langle q, d \rangle$ predict the *class* $y_{q,d}$

e.g., cross-entropy with softmax over categorical labels Y [Li et al., 2008],

$$\mathcal{L}_{\text{CE}}(q, d, y_{q,d}) = -log\Big(p(y_{q,d}|q, d)\Big) = -log\Big(\frac{e^{\gamma \cdot s_{y_{q,d}}}}{\sum_{y \in Y} e^{\gamma \cdot s_y}}\Big)$$

where, $s_{y_{q,d}}$ is the model's score for label $y_{q,d}$



Ping Li, Qiang Wu, and Christopher J Burges. Mcrank: Learning to rank using multiple classification and gradient boosting. In NIPS, 2008.

Pairwise objectives

Pairwise loss minimizes the average number of inversions in ranking—i.e., $d_i \succ d_j$ w.r.t. q but d_j is ranked higher than d_i

Given $\langle q, d_i, d_j \rangle$, predict the more relevant document

For $\langle q, d_i \rangle$ and $\langle q, d_j \rangle$,

Feature vectors: $\vec{x}_i$ and $\vec{x}_j$

Model scores: $s_i = f(\vec{x}_i)$ and $s_j = f(\vec{x}_j)$

Pairwise loss generally has the following form [Chen et al., 2009],

$$\mathcal{L}_{pairwise} = \phi(s_i - s_j)$$

where, ϕ can be,

- Hinge function $\phi(z) = max(0, 1 - z)$ [Herbrich et al., 2000]
- Exponential function $\phi(z) = e^{-z}$ [Freund et al., 2003]
- Logistic function $\phi(z) = log(1 + e^{-z})$ [Burges et al., 2005]
- Others…

Wei Chen, Tie-Yan Liu, Yanyan Lan, Zhi-Ming Ma, and Hang Li. Ranking measures and loss functions in learning to rank. In NIPS, 2009.

Ralf Herbrich, Thore Graepel, and Klaus Obermayer. Large margin rank boundaries for ordinal regression. 2000.

Yoav Freund, Raj Iyer, Robert E Schapire, and Yoram Singer. An efficient boosting algorithm for combining preferences. In JMLR, 2003.

Chris Burges, Tal Shaked, Erin Renshaw, Ari Lazier, Matt Deeds, Nicole Hamilton, and Greg Hullender. Learning to rank using gradient descent. In ICML, 2005.

Pairwise objectives

RankNet loss

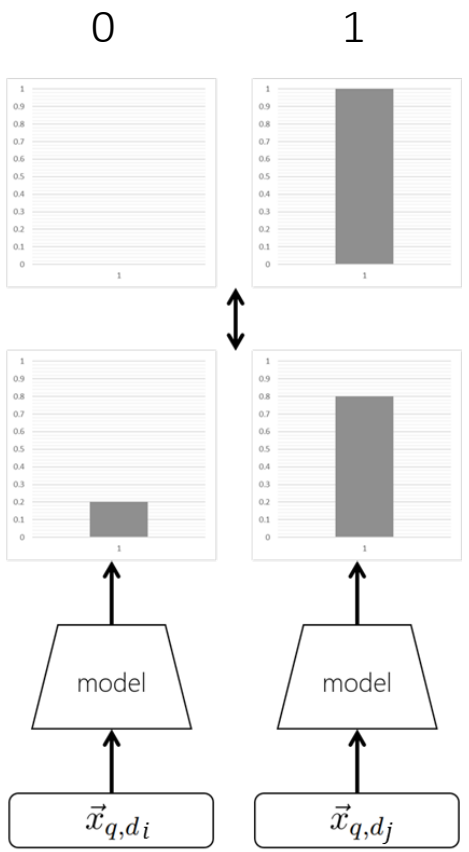
Pairwise loss function proposed by Burges et al. [2005]—an industry favourite [Burges, 2015]

Predicted probabilities: $p_{ij} = p(s_i > s_j) \equiv \frac{e^{\gamma . s_i}}{e^{\gamma . s_i} + e^{\gamma . s_j}} = \frac{1}{1 + e^{-\gamma . (s_i - s_j)}}$

Desired probabilities: $\bar{p}_{ij} = 1$ and $\bar{p}_{ji} = 0$

Computing cross-entropy between p and $\bar{p}$

$$\mathcal{L}_{RankNet} = -\bar{p}_{ij} . log(p_{ij}) - \bar{p}_{ji} . log(p_{ji}) = -log(p_{ij}) = log\left(1 + e^{-\gamma . (s_i - s_j)}\right)$$



Chris Burges, Tal Shaked, Erin Renshaw, Ari Lazier, Matt Deeds, Nicole Hamilton, and Greg Hullender. Learning to rank using gradient descent. In ICML, 2005.

Chris Burges. RankNet: A ranking retrospective. https://www.microsoft.com/en-us/research/blog/ranknet-a-ranking-retrospective/. 2015.

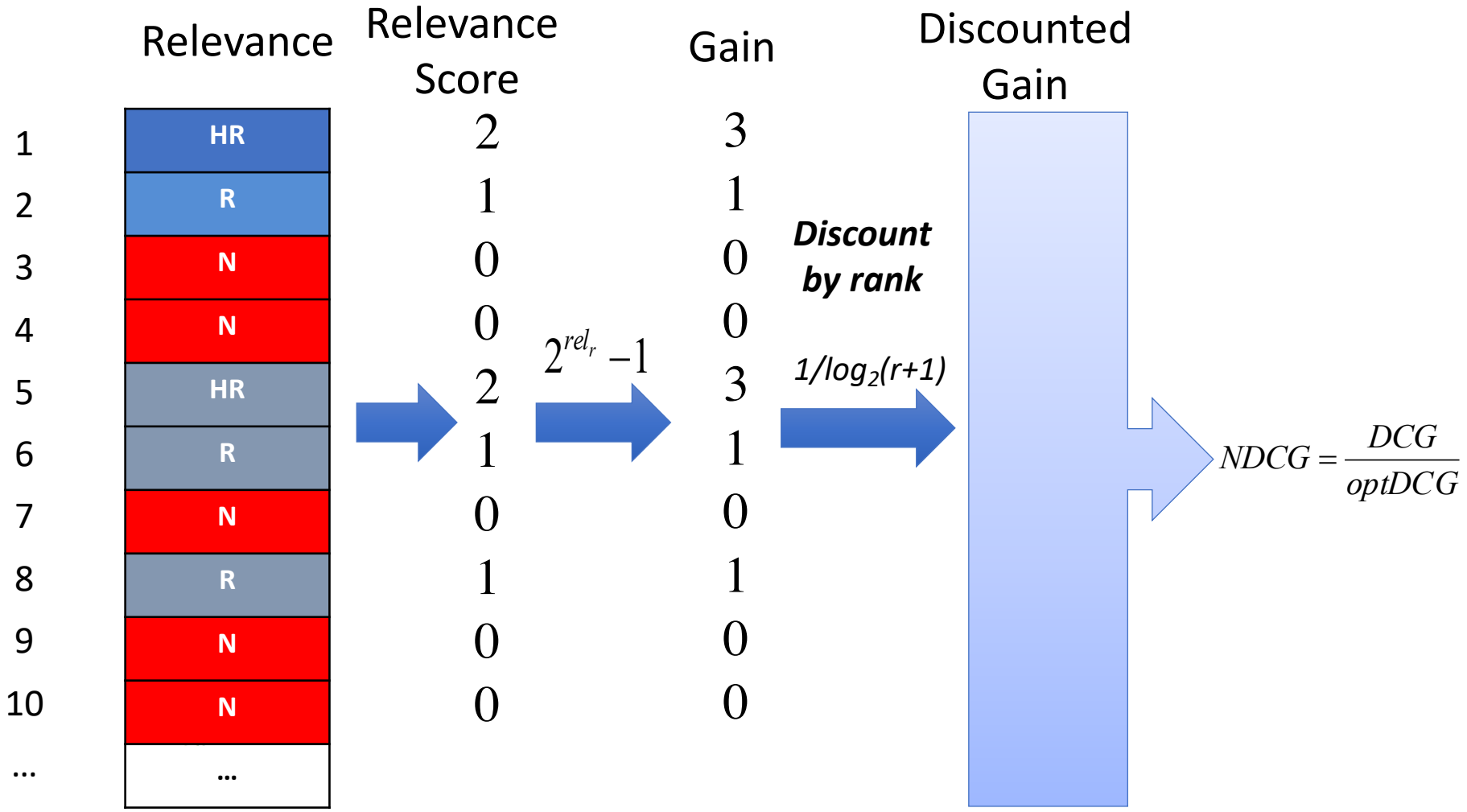
LISTWISE OBJECTIVES

Optimize for a metric that is assumed to be evaluating user satisfaction from the ranking

[Burges, 2010]

Christopher JC Burges. From ranknet to lambdarank to lambdamart: An overview. Learning, 2010.

Evaluating Ranking Quality: Normalized Discounted Cumulative Gain (NDCG)



LISTWISE OBJECTIVES

Blue: relevant Gray: non-relevant

NDCG higher for left but pairwise errors less for right

Due to strong position-based discounting in IR measures, errors at higher ranks are much more problematic than at lower ranks

But listwise metrics are non-continuous and non-differentiable

[Burges, 2010]

Christopher JC Burges. From ranknet to lambdarank to lambdamart: An overview. Learning, 2010.

Listwise objectives

Burges et al. [2006] make two observations:

1. To train a model we don't need the costs themselves, only the gradients (of the costs w.r.t model scores)
2. It is desired that the gradient be bigger for pairs of documents that produces a bigger impact in NDCG by swapping positions

LambdaRank loss

Multiply actual gradients with the change in NDCG by swapping the rank positions of the two documents

$$\lambda_{LambdaRank} = \lambda_{RankNet} \cdot |\Delta NDCG|$$

Christopher JC Burges, Robert Ragno, and Quoc Viet Le. Learning to rank with nonsmooth cost functions. In NIPS, 2006.

Listwise objectives

According to the Luce model [Luce, 2005], given four items $\{d_1, d_2, d_3, d_4\}$ the probability of observing a particular rank-order, say $[d_2, d_1, d_4, d_3]$, is given by:

$$p(\pi|s) = \frac{\phi(s_2)}{\phi(s_1)+\phi(s_2)+\phi(s_3)+\phi(s_4)} \cdot \frac{\phi(s_1)}{\phi(s_1)+\phi(s_3)+\phi(s_4)} \cdot \frac{\phi(s_4)}{\phi(s_3)+\phi(s_4)}$$

where, π is a particular permutation and ϕ is a transformation (e.g., linear, exponential, or sigmoid) over the score s_i corresponding to item d_i

ListNet loss

Cao et al. [2007] propose to compute the probability distribution over all possible permutations based on model score and ground-truth labels. The loss is then given by the K-L divergence between these two distributions.

This is computationally very costly, computing permutations of only the top-K items makes it slightly less prohibitive.

R Duncan Luce. Individual choice behavior. 1959.

Zhe Cao, Tao Qin, Tie-Yan Liu, Ming-Feng Tsai, and Hang Li. Learning to rank: from pairwise approach to listwise approach. In ICML, 2007.

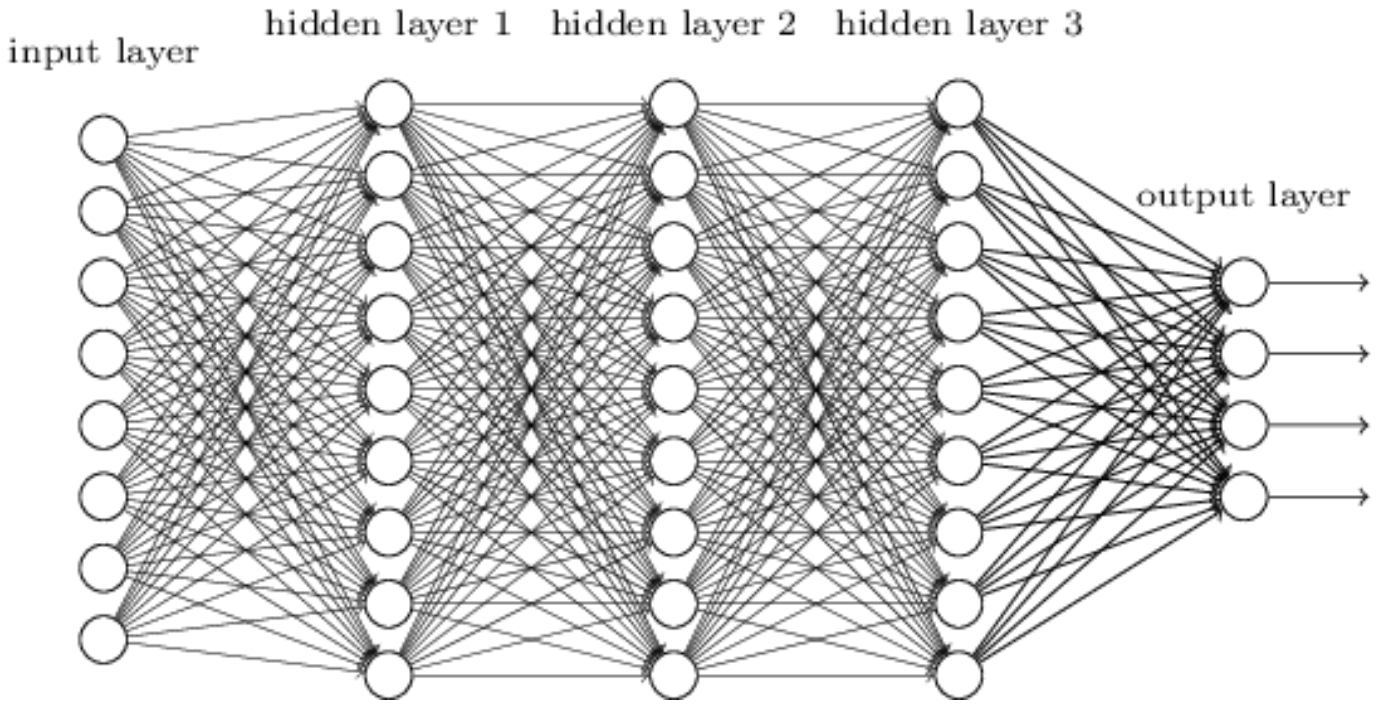
Fen Xia, Tie-Yan Liu, Jue Wang, Wensheng Zhang, and Hang Li. Listwise approach to learning to rank: theory and algorithm. In ICML, 2008.

Deep neural networks

Smaller Network: Convolutional Neural Networks

.

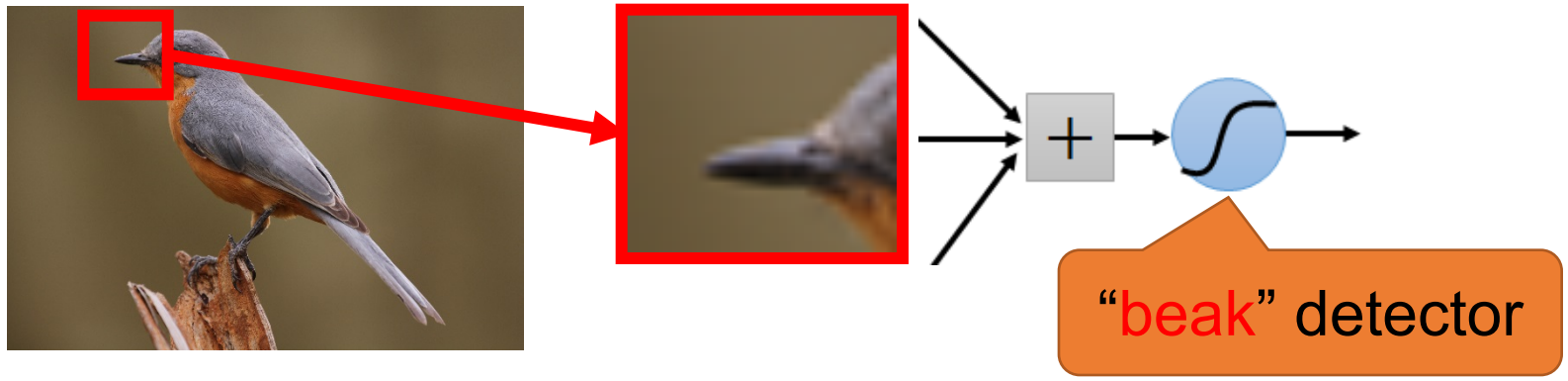
- From this fully connected model, do we really need all the edges?
- Can some of these be shared?



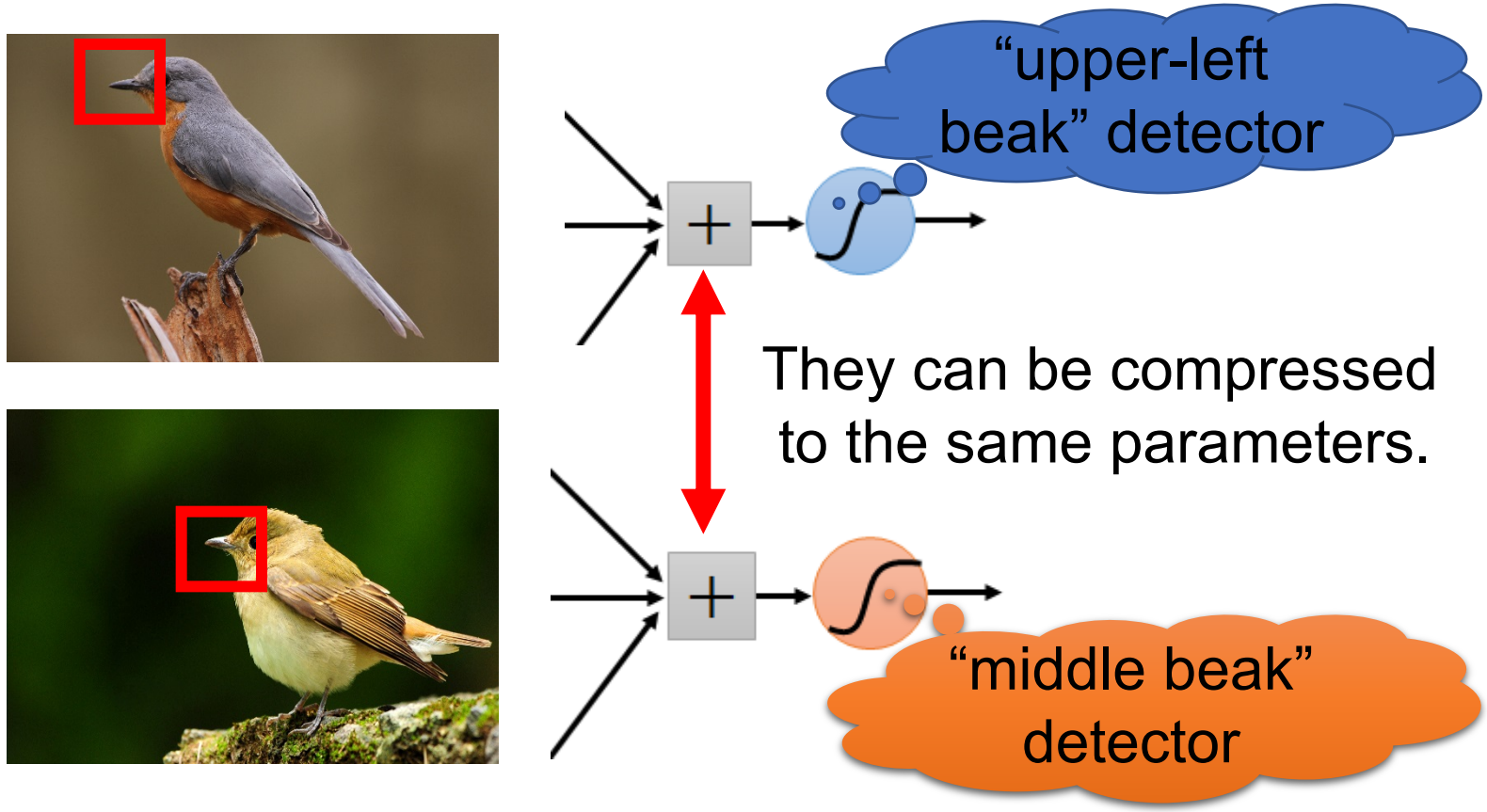
Consider learning an image:

- Some patterns are much smaller than the whole image

Can represent a small region with fewer parameters

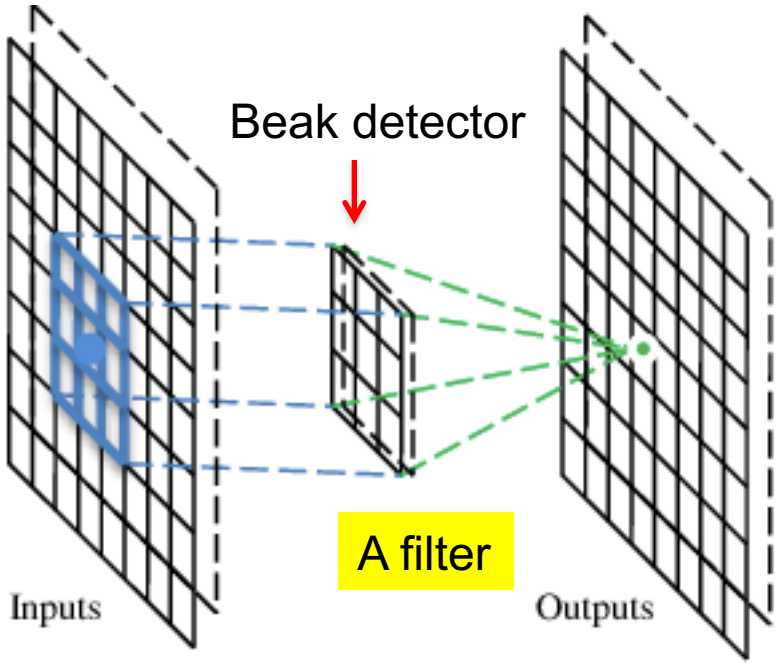


Same pattern appears in different places:
They can be compressed!
What about training a lot of such “small” detectors
and each detector must “move around”.



A convolutional layer

A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has a number of filters that does convolutional operation.



Main CNN idea for text:
Compute vectors for n-grams and group them afterwards

Example: “this takes too long” compute vectors for:
This takes, takes too, too long, this takes too, takes too long, this takes too long

Convolution

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

These are the network parameters to be learned.

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

⋮ ⋮

Each filter detects a small pattern (3 x 3).

Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Dot product → 3 -1

6 x 6 image

Convolution

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

3 -3

Convolution

-1	1	-1
-1	1	-1
-1	1	-1

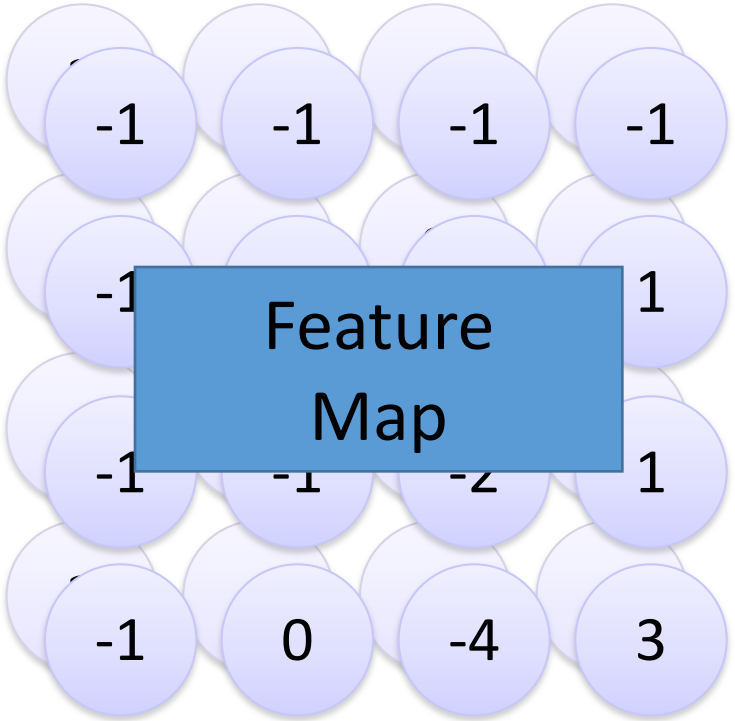
Filter 2

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

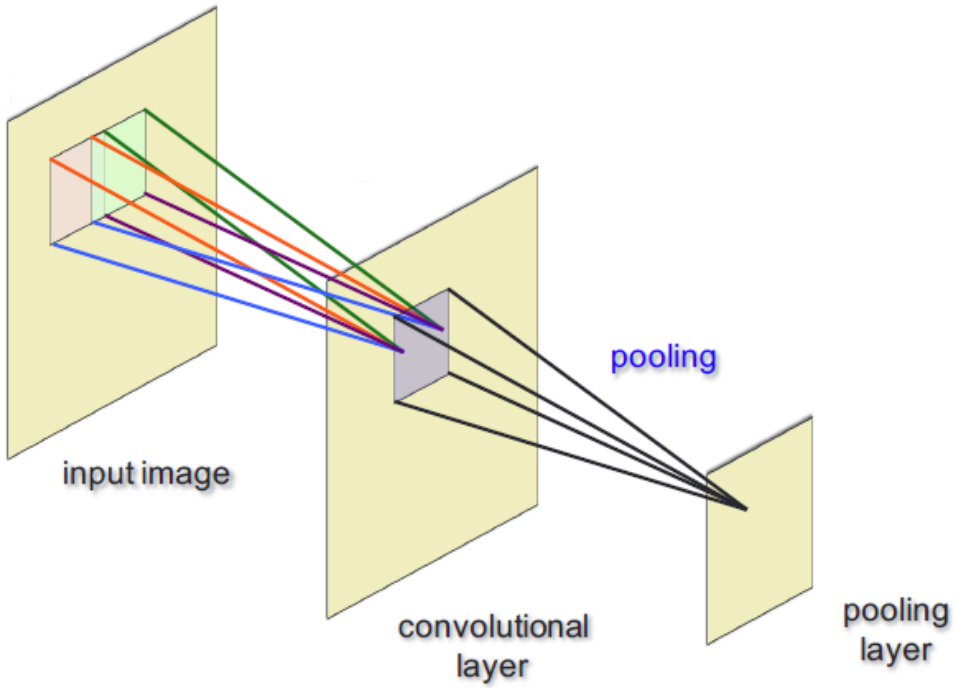
6 x 6 image

Repeat this for each filter



Pooling

- Common pooling operations:
  - Max pooling: reports the maximum output within a rectangular neighborhood.
  - Average pooling: reports the average output of a rectangular neighborhood (possibly weighted by the distance from the central pixel).



Why Pooling?

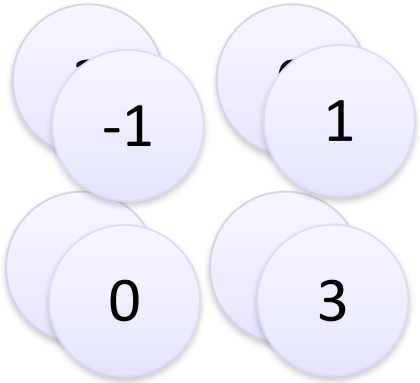
- Subsampling pixels will not change the object

bird

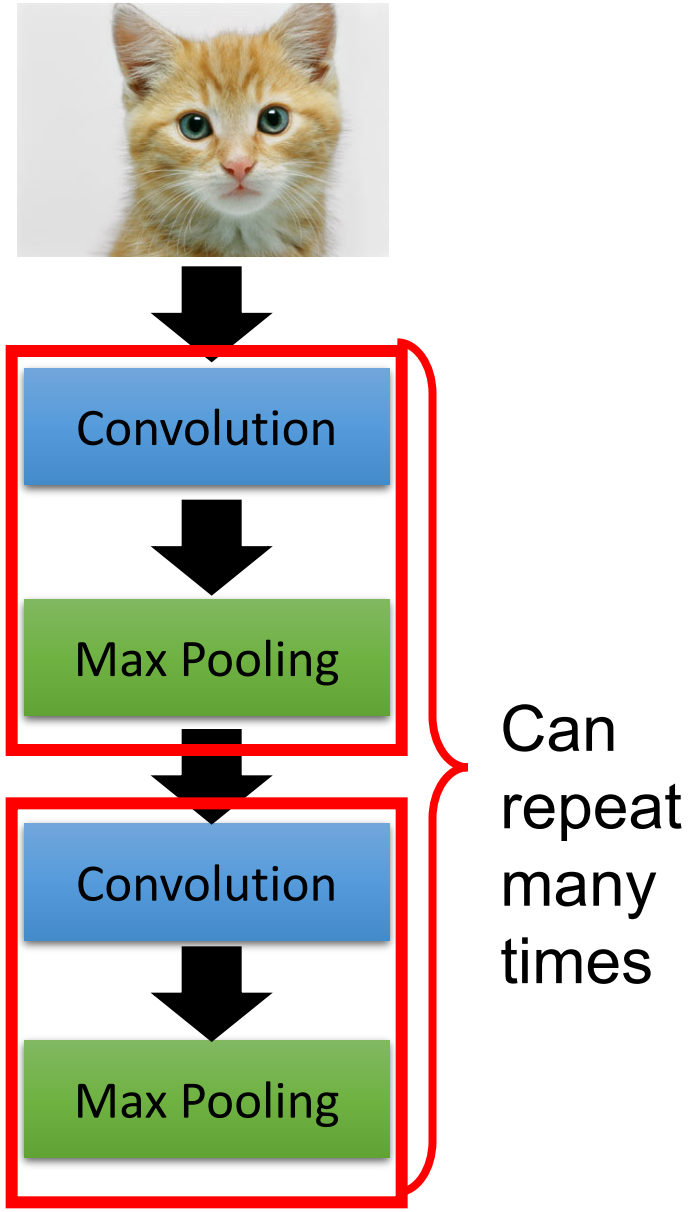
Subsampling

bird

The whole CNN

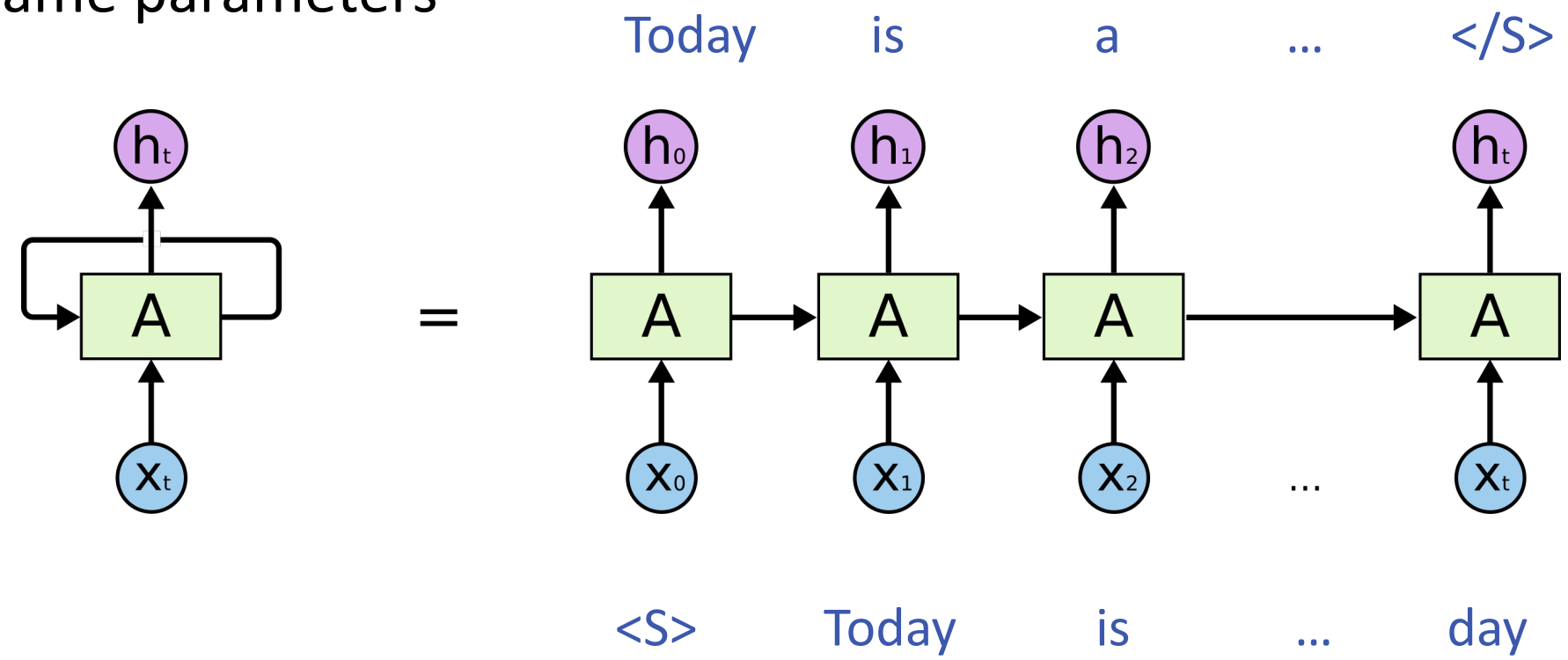


Smaller than the original image



How to deal with input with variant size?

- Use same parameters



Recurrent Neural Networks

Feed-forward NN

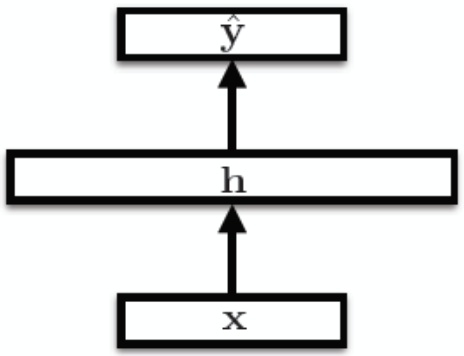
$$\mathbf{h} = g(\mathbf{V}\mathbf{x} + \mathbf{c})$$

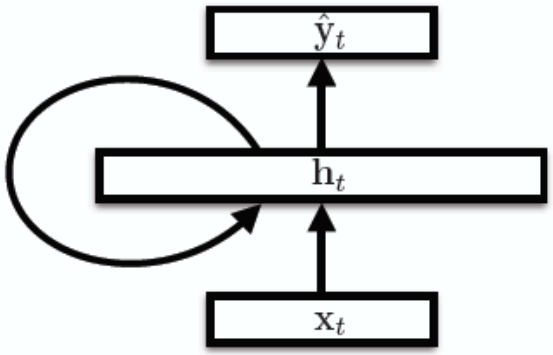
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h} + \mathbf{b}$$

Recurrent NN

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$

$$\hat{\mathbf{y}}_t = \mathbf{W}\mathbf{h}_t + \mathbf{b}$$

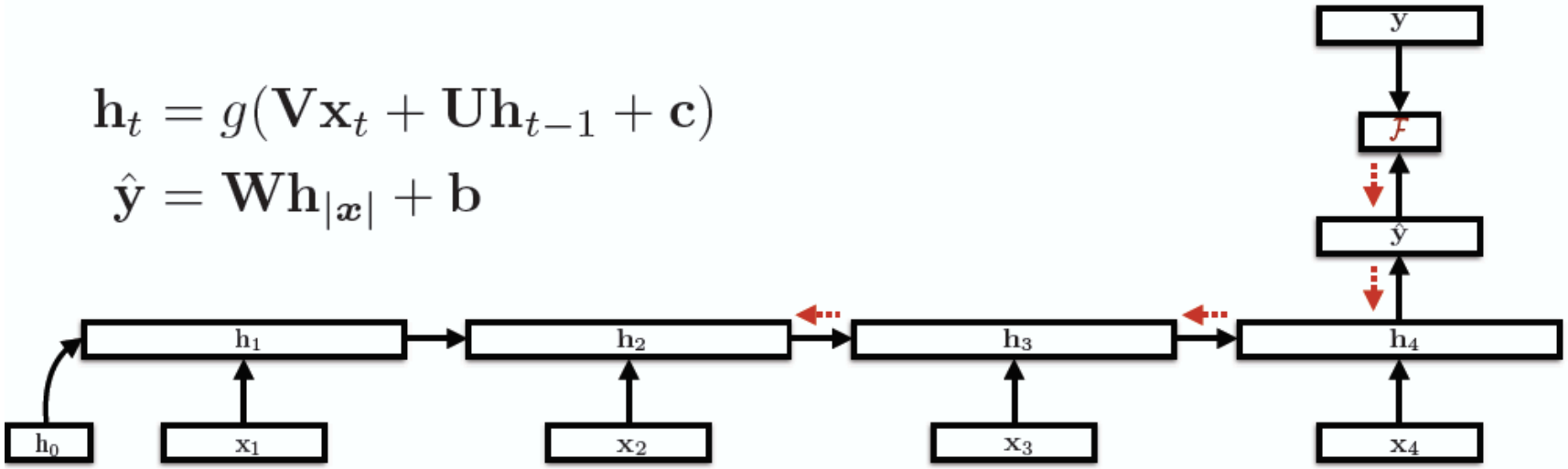




RNN training

- Back-propagation over time

$$\mathbf{h}_t = g(\mathbf{V}\mathbf{x}_t + \mathbf{U}\mathbf{h}_{t-1} + \mathbf{c})$$
$$\hat{\mathbf{y}} = \mathbf{W}\mathbf{h}_{|\boldsymbol{x}|} + \mathbf{b}$$



What happens to gradients as you go back in time?

$$\frac{\partial \mathbf{h}_3}{\partial \mathbf{h}_2}\frac{\partial \mathbf{h}_4}{\partial \mathbf{h}_3}\frac{\partial \hat{\mathbf{y}}}{\partial \mathbf{h}_4}\frac{\partial \mathcal{F}}{\partial \hat{\mathbf{y}}}$$

Vanishing Gradients

- For the traditional activation functions, each gradient term has the value in range (-1, 1).
- Multiplying *n* of these small numbers to compute gradients
- The longer the sequence is, the more severe the problems are.

RNNs characteristics

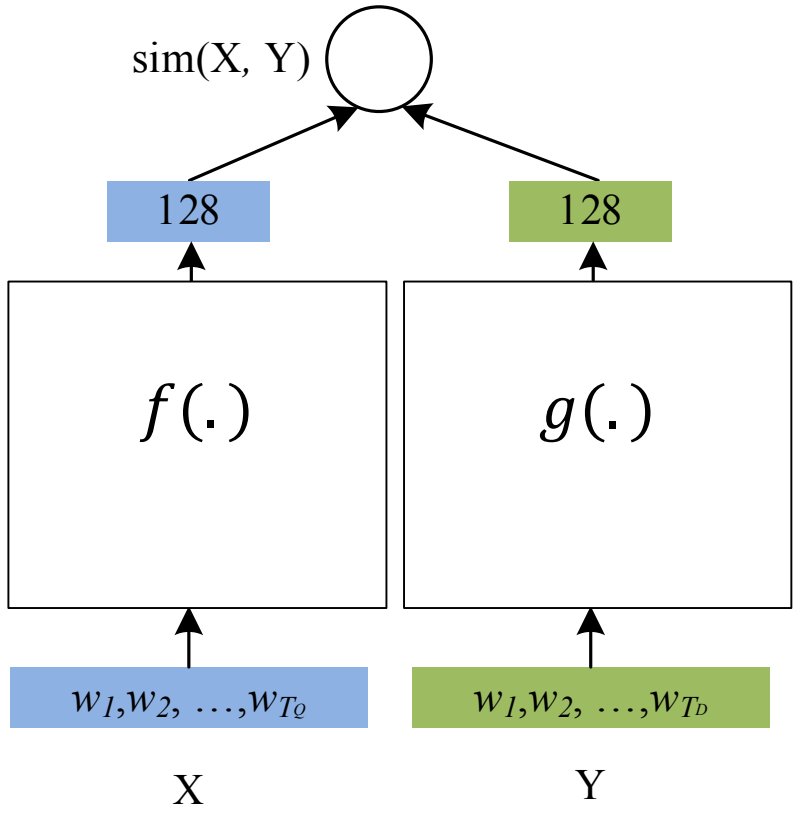
- Model hidden states (input) dependencies
- Errors “back propagation over time”
- Vanishing gradient problem:
  cannot model long-distant dependencies of the hidden states.

How to Solve the Vanishing Gradient Problem?

- Use ReLU instead of tanh or sigmoid activation function
  - *ReLU derivate is a constant of either 0 or 1, so it isn't likely to suffer from vanishing gradients*
- Use Long Short-Term Memory or Gated Recurrent unit architectures

Deep Structured Semantic Models (DSSM)

Relevance measured by cosine similarity



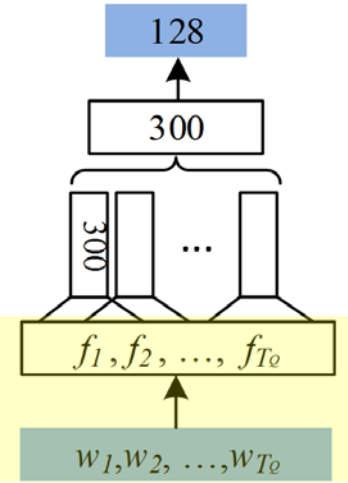
Word sequence x_t

Learning: maximize the similarity between X (source) and Y (target)

Representation: use DNN to extract abstract semantic features, f or g is a

- Multi-Layer Perceptron (MLP) if text is a bag of words [Huang+ 13]
- **Convolutional Neural Network (CNN) if text is a bag of chunks** [Shen+ 14]
- Recurrent Neural Network (RNN) if text is a sequence of words [Palangi+ 16]

Deep Structured Semantic Models (DSSM)

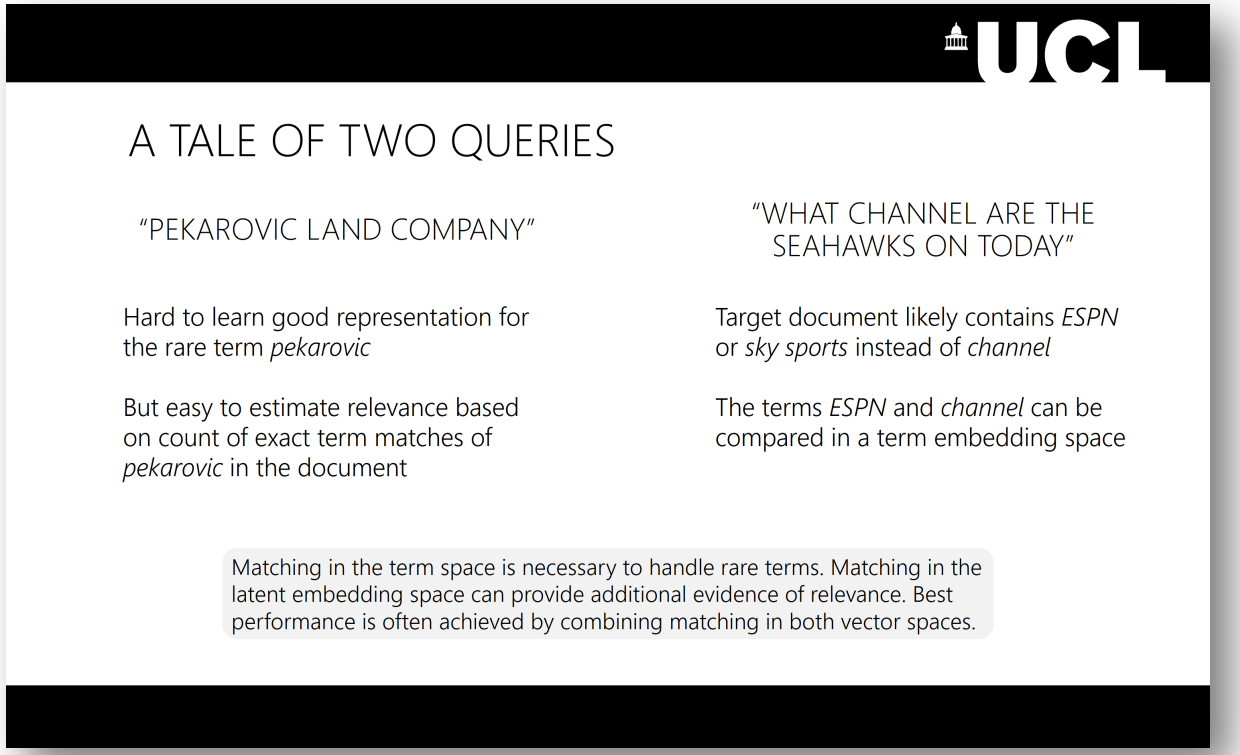


- Letter-trigram Representation
- Control the dimensionality of the input space
  - e.g., cat → #cat# → #-c-a, c-a-t, a-t-#
  - Only ~50K letter-trigrams in English
- Capture sub-word semantics (e.g., prefix & suffix)
- Words with small typos have similar raw representations
- Collision: different words with same letter-trigram representation?

Vocabulary size	# of unique letter-trigrams	# of Collisions	Collision rate
40K	10,306	2	0.0050%
500K	30,621	22	0.0044%
5M	49,292	179	0.0036%

Remember…

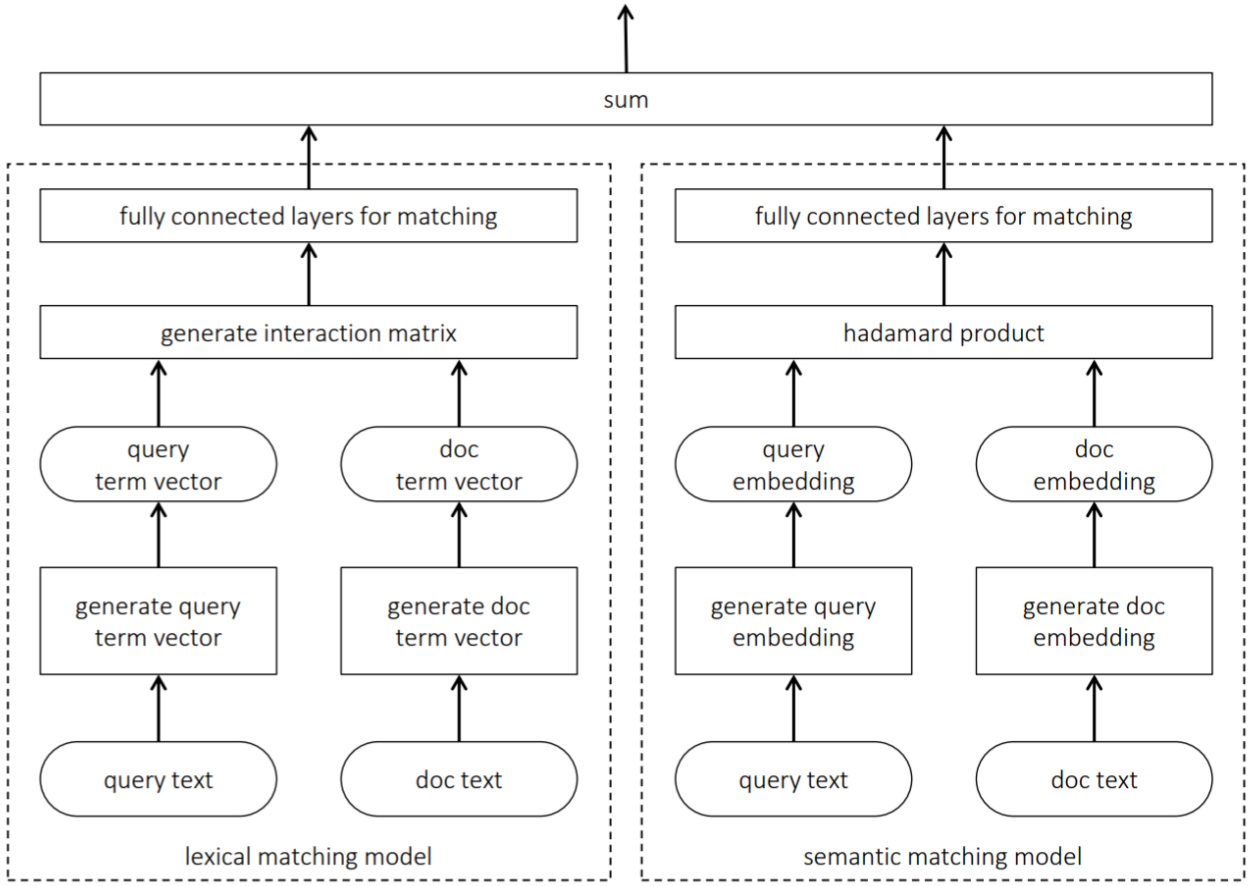
…the importance of incorporating exact term matches as well as matches in the latent space for estimating relevance?



Lexical and semantic matching networks

Mitra et al. [2016] argue that both lexical and semantic matching is important for document ranking

Duet model is a linear combination of two DNNs—focusing on lexical and semantic matching, respectively—jointly trained on labelled data



Bhaskar Mitra, Fernando Diaz, and Nick Craswell. Learning to match using local and distributed representations of text for web search. In WWW, 2017.

Conclusions

- Introduction to Neural Networks
- Term embeddings for IR
- Learning to Rank
- Deep learning
- Deep Structured Semantic Models