Artificial Intelligence:
Deep Learning for NLP

many slides from: Y. Bengio, A. Ng and Y. LeCun

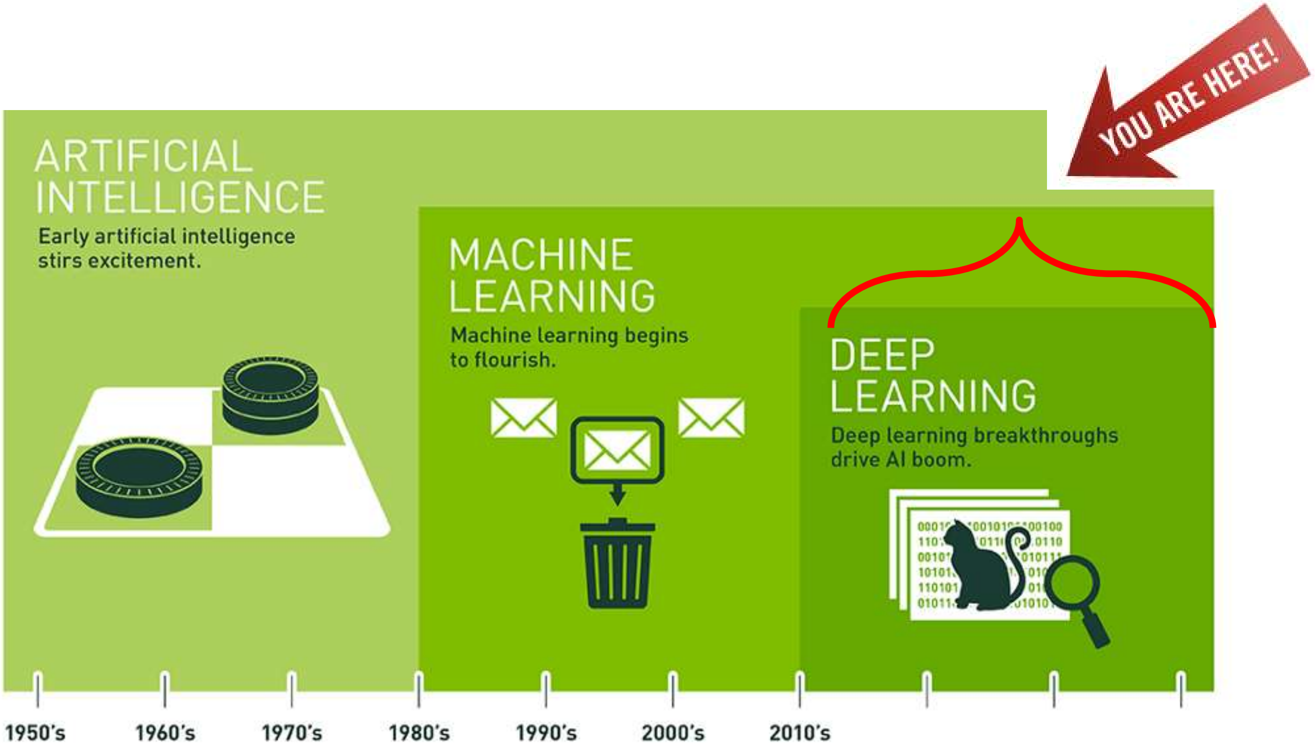
Slides are courtesy of Profs René Witte and Mahdi Hosseini.

Today

1. Introduction

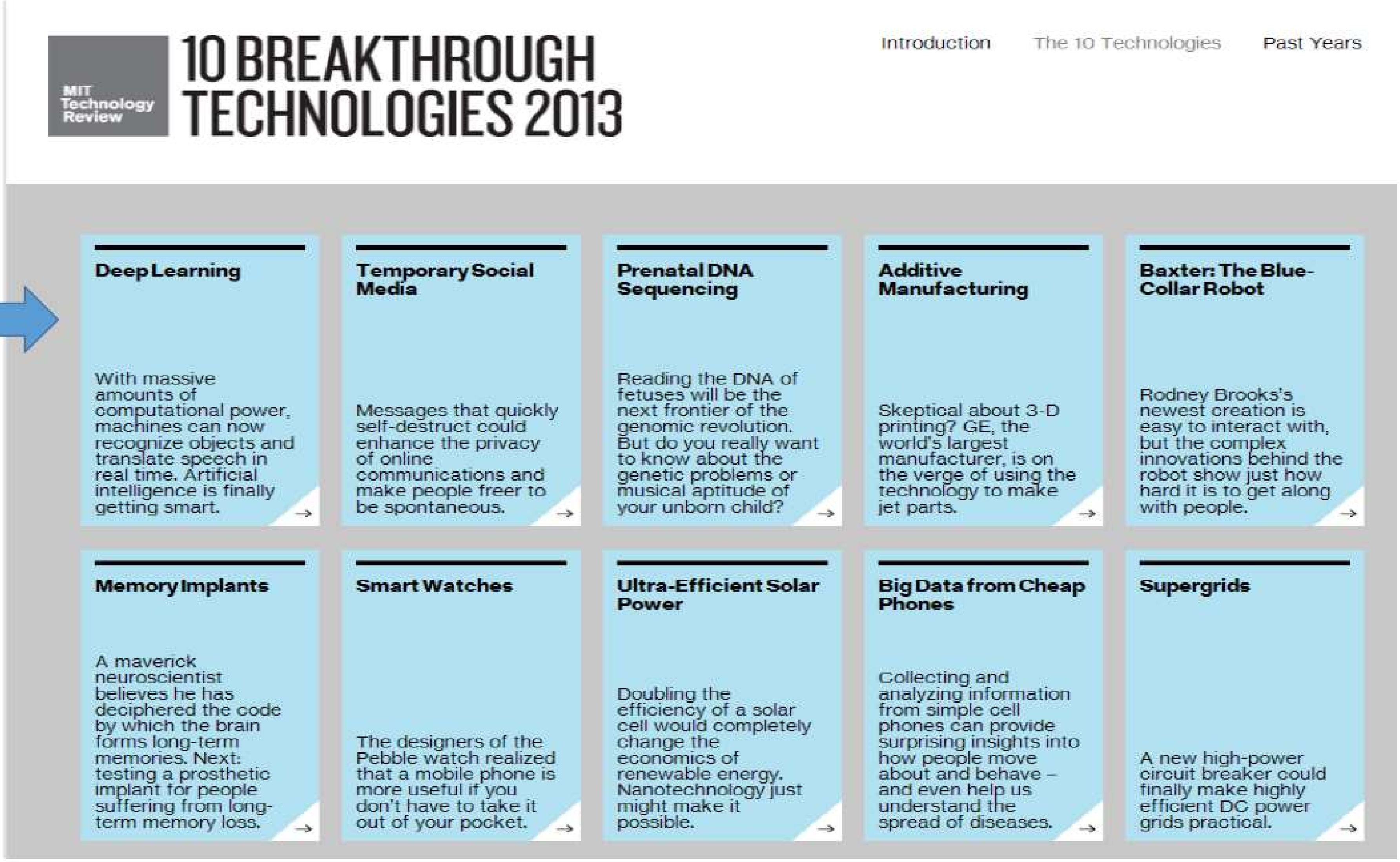
2. Word Embeddings
3. Deep Learning for NLP

History of AI


YOU ARE HERE!
ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.
MACHINE LEARNING
Machine learning begins to flourish.
DEEP LEARNING
Deep learning breakthroughs drive AI boom.
1950's
1960's
1970's
1980's
1990's
2000's
2010's

https://www.linkedin.com/pulse/goedels-incompleteness-theorem-emergence-ai-eberhard-schoeneburg/

Deep Learning in the News (2013)



MIT Technology Review

10 BREAKTHROUGH TECHNOLOGIES 2013

Deep Learning

With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

Temporary Social Media

Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.

Prenatal DNA Sequencing

Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?

Additive Manufacturing

Skeptical about 3-D printing? GE, the world's largest manufacturer, is on the verge of using the technology to make jet parts.

Baxter: The Blue-Collar Robot

Rodney Brooks's newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.

Memory Implants

A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next: testing a prosthetic implant for people suffering from long-term memory loss.

Smart Watches

The designers of the Pebble watch realized that a mobile phone is more useful if you don't have to take it out of your pocket.

Ultra-Efficient Solar Power

Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it possible.

Big Data from Cheap Phones

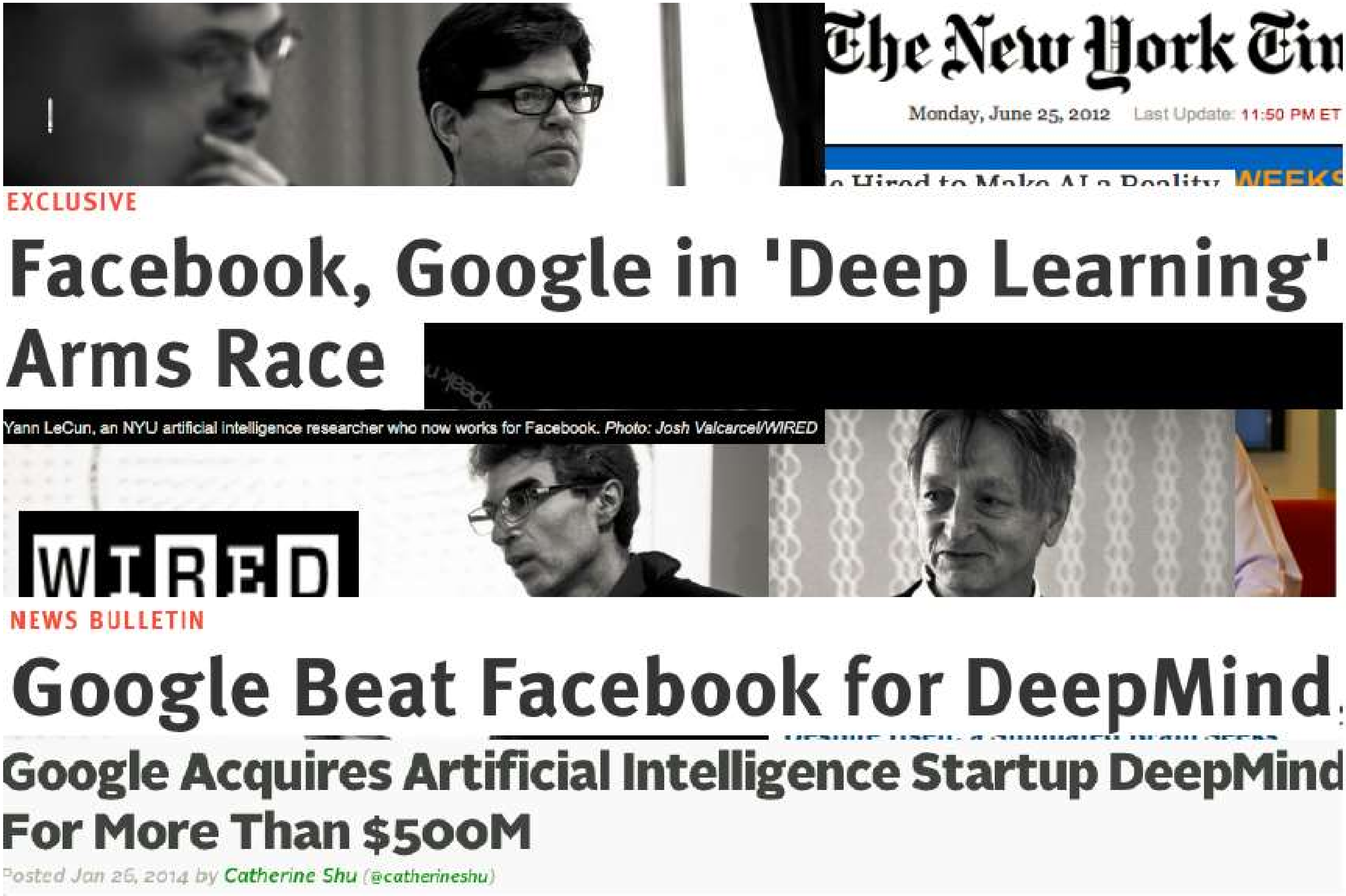
Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave – and even help us understand the spread of diseases.

Supergrids

A new high-power circuit breaker could finally make highly efficient DC power grids practical.

Slide from Yoshua Bengio, 2015

Deep Learning in the News (2012-2014)



The New York Tim

Monday, June 25, 2012 Last Update: 11:50 PM ET

e Hired to Make A.I. a Reality WEEKS

EXCLUSIVE

Facebook, Google in 'Deep Learning' Arms Race

Yann LeCun, an NYU artificial intelligence researcher who now works for Facebook. *Photo: Josh Valcarcel/WIRED*

NEWS BULLETIN

Google Beat Facebook for DeepMind

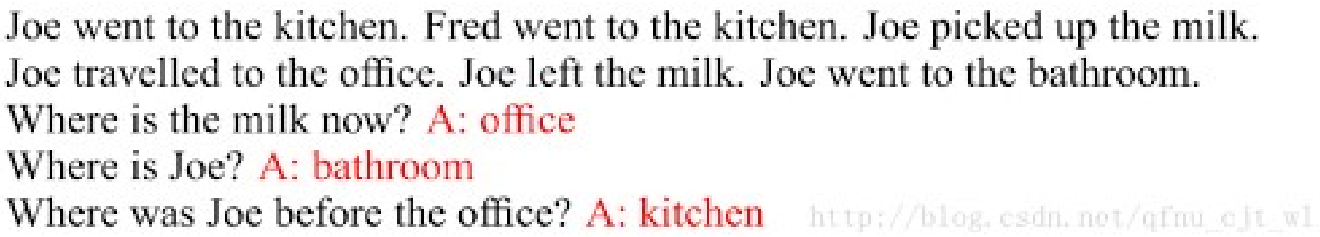
Google Acquires Artificial Intelligence Startup DeepMind For More Than $500M

Posted Jan 26, 2014 by Catherine Shu (@catherineshu)

Slide from Yoshua Bengio, 2015

Major Breakthroughs

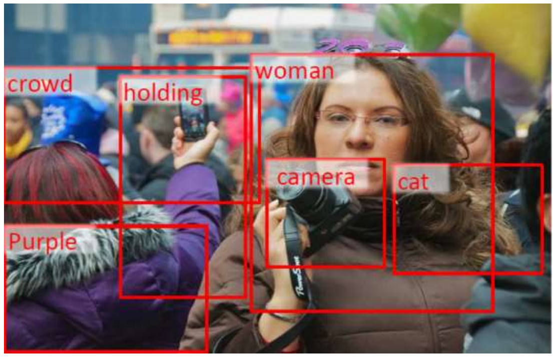
- Speech Recognition & Machine Translation (2010+)
- Image Recognition & Computer Vision (2012+)
- Natural Language Processing (2014+)

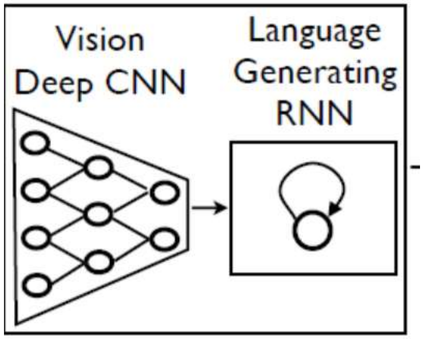


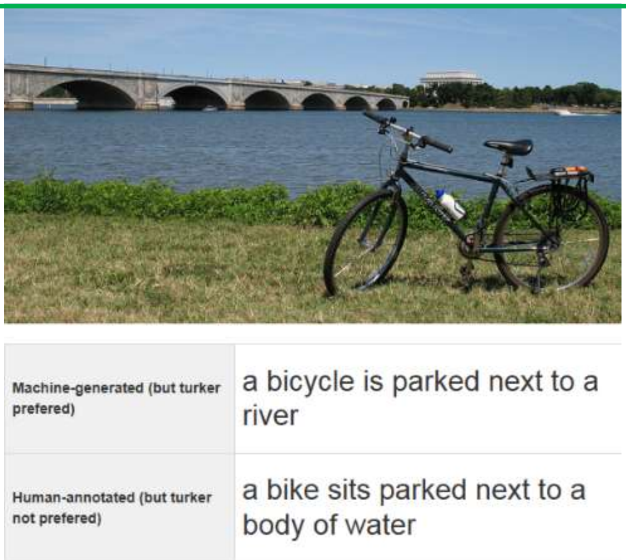
Joe went to the kitchen. Fred went to the kitchen. Joe picked up the milk.
Joe travelled to the office. Joe left the milk. Joe went to the bathroom.
Where is the milk now? A: office
Where is Joe? A: bathroom
Where was Joe before the office? A: kitchen

http://blog.csdn.net/qfnu_cjt_wl

Question Answering



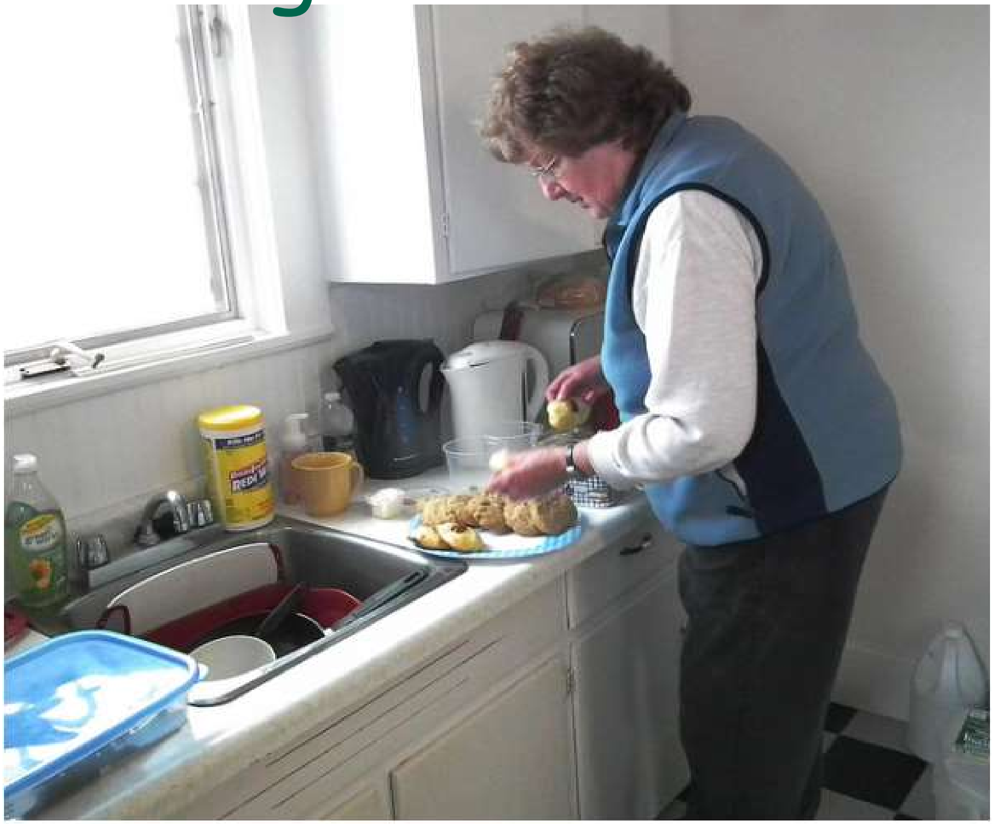




Machine-generated (but turker prefered)	a bicycle is parked next to a river
Human-annotated (but turker not prefered)	a bike sits parked next to a body of water

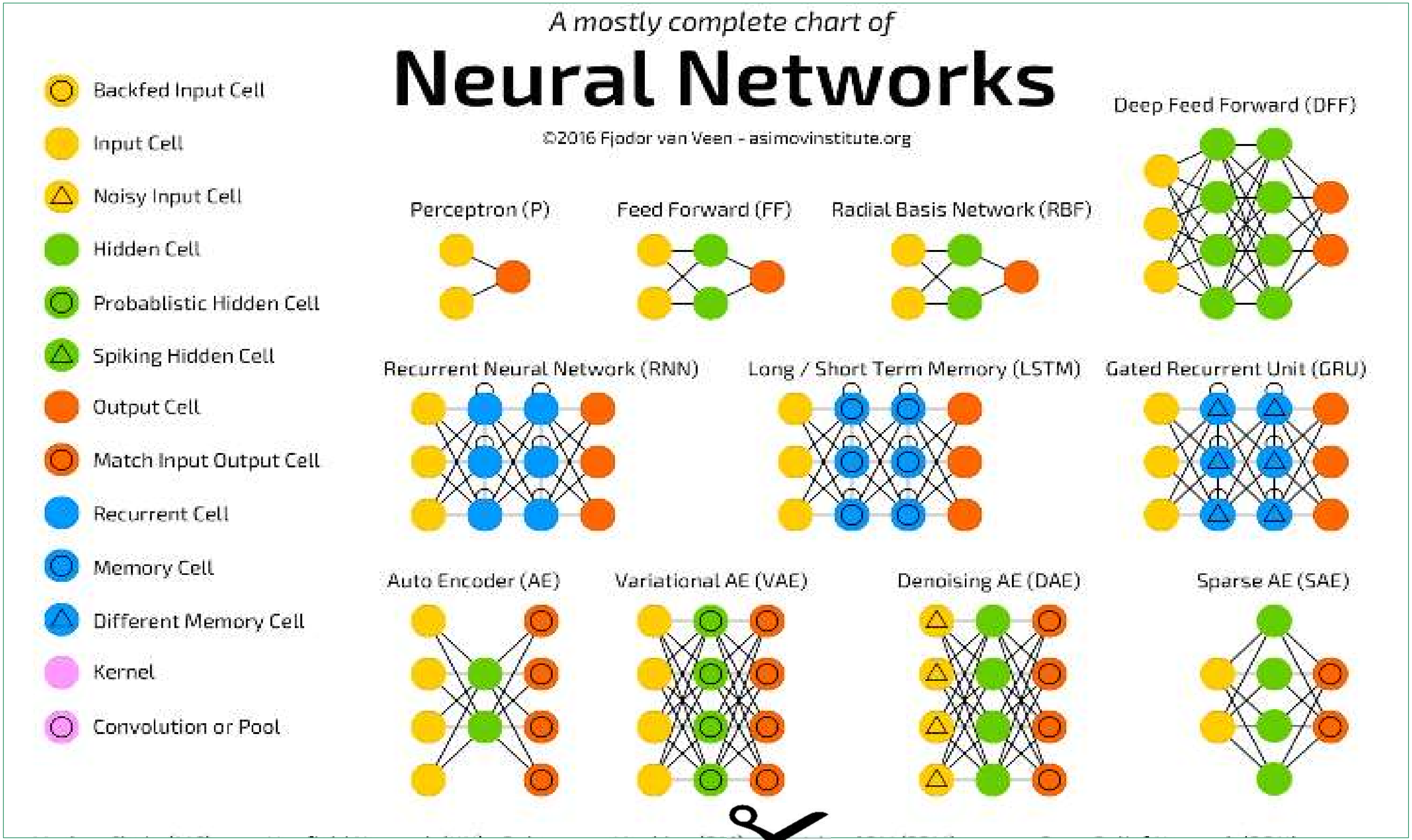
Image Captioning (deep vision + deep NLP)

Image Captioning: Better than humans?



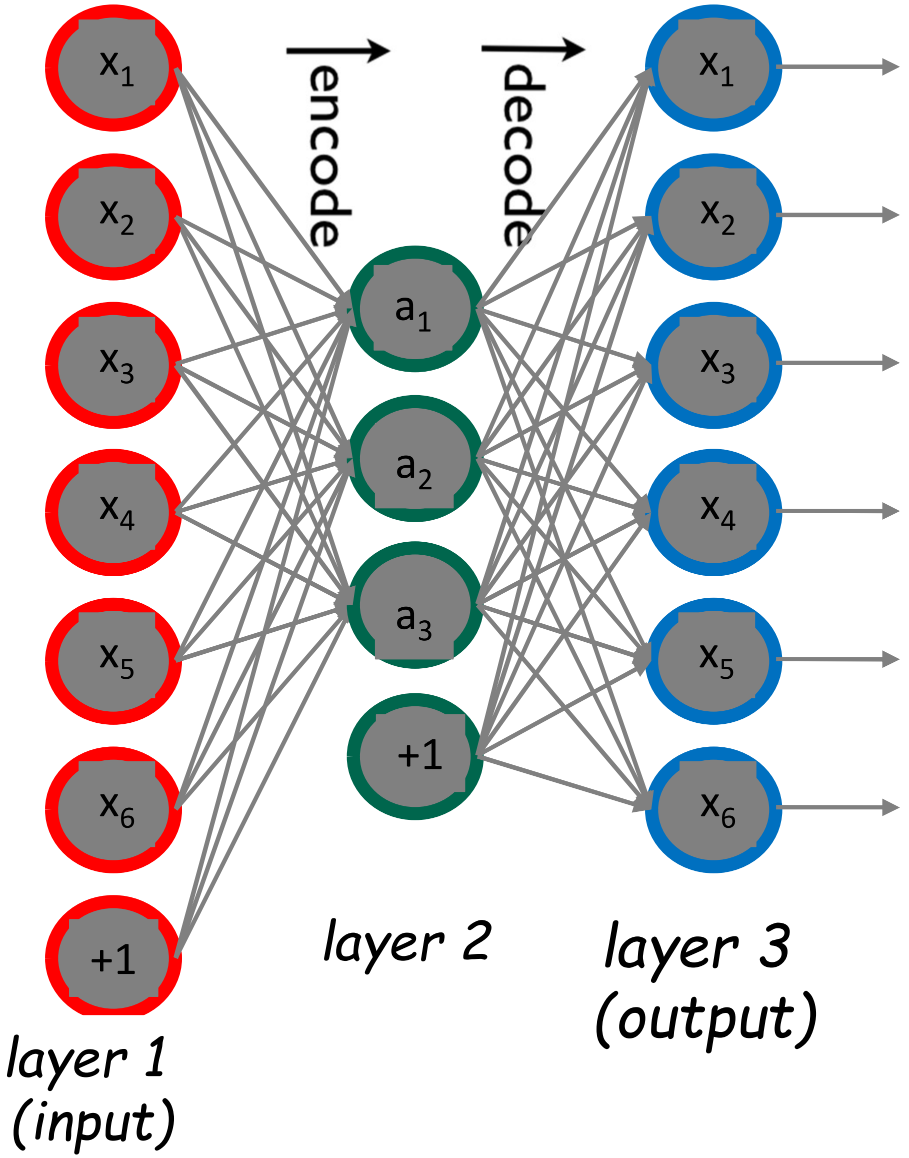
A	a woman in a kitchen preparing food
B	woman working on counter near kitchen sink preparing a meal

Many Types of Neural Networks



https://becominghuman.ai/cheat-sheets-for-ai-neural-networks-machine-learning-deep-learning-big-data-678c51b4b463

Autoencoder

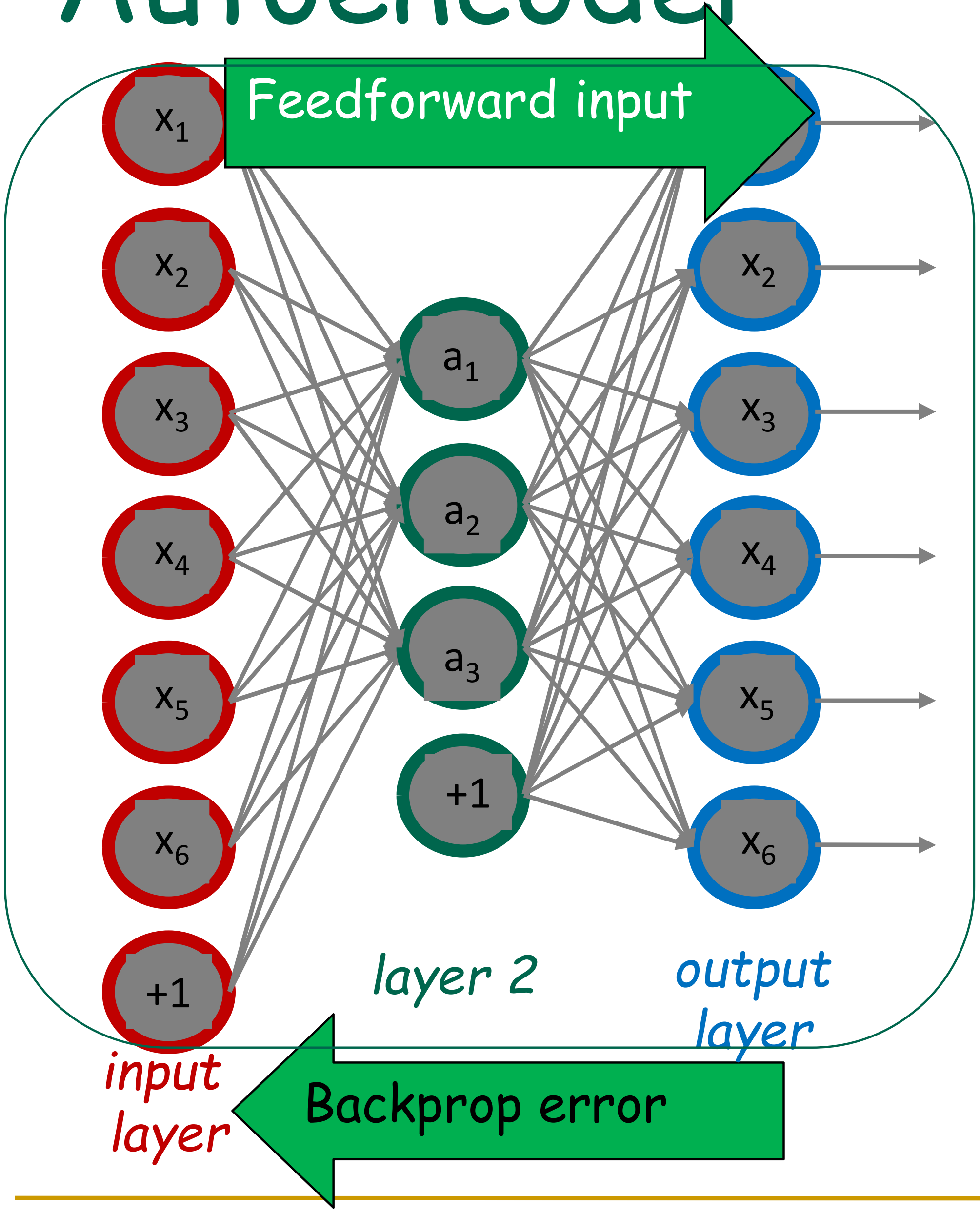


- The network is trained to output the input
- i.e. learn the identity function.

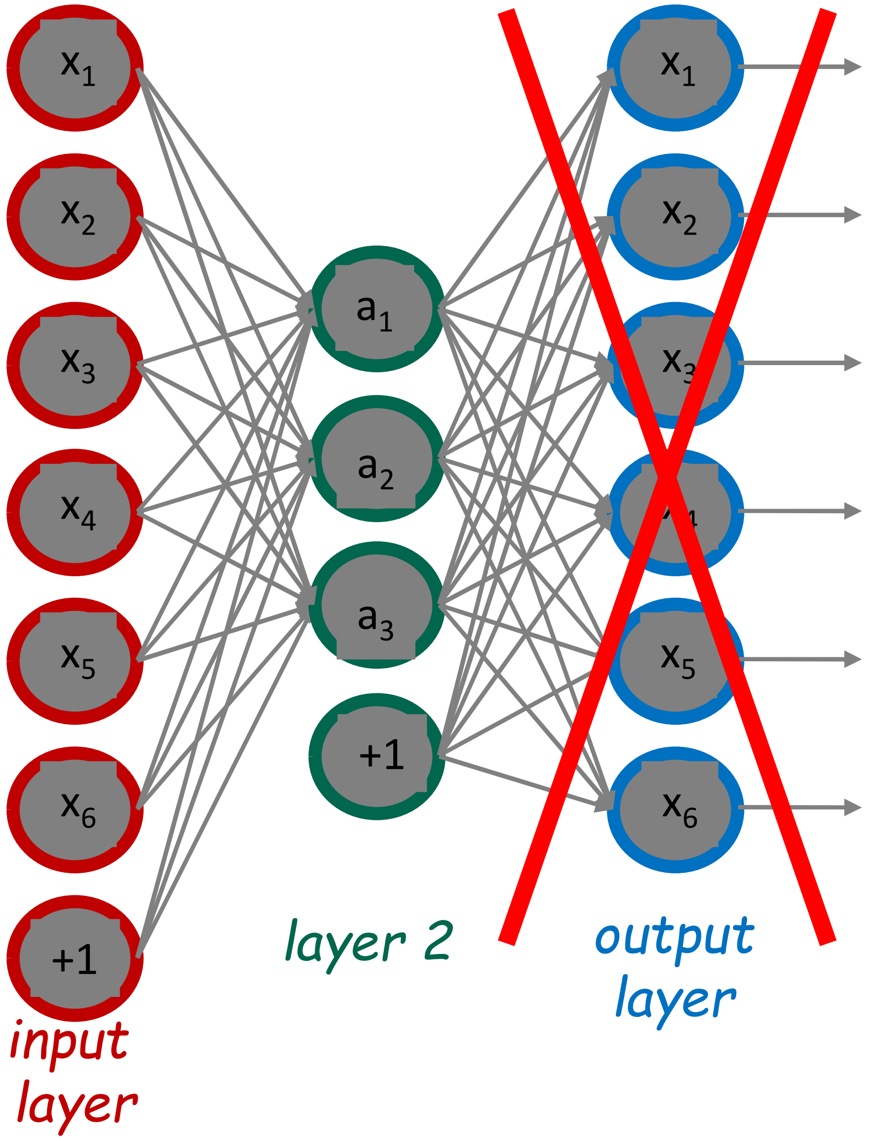
- Trivial… unless, we impose constraints:
  - Nb of units in layer 2 < nb of input units (learn compressed representation)

    OR
  - Constrain layer 2 to be sparse (i.e. many connections are "disabled")

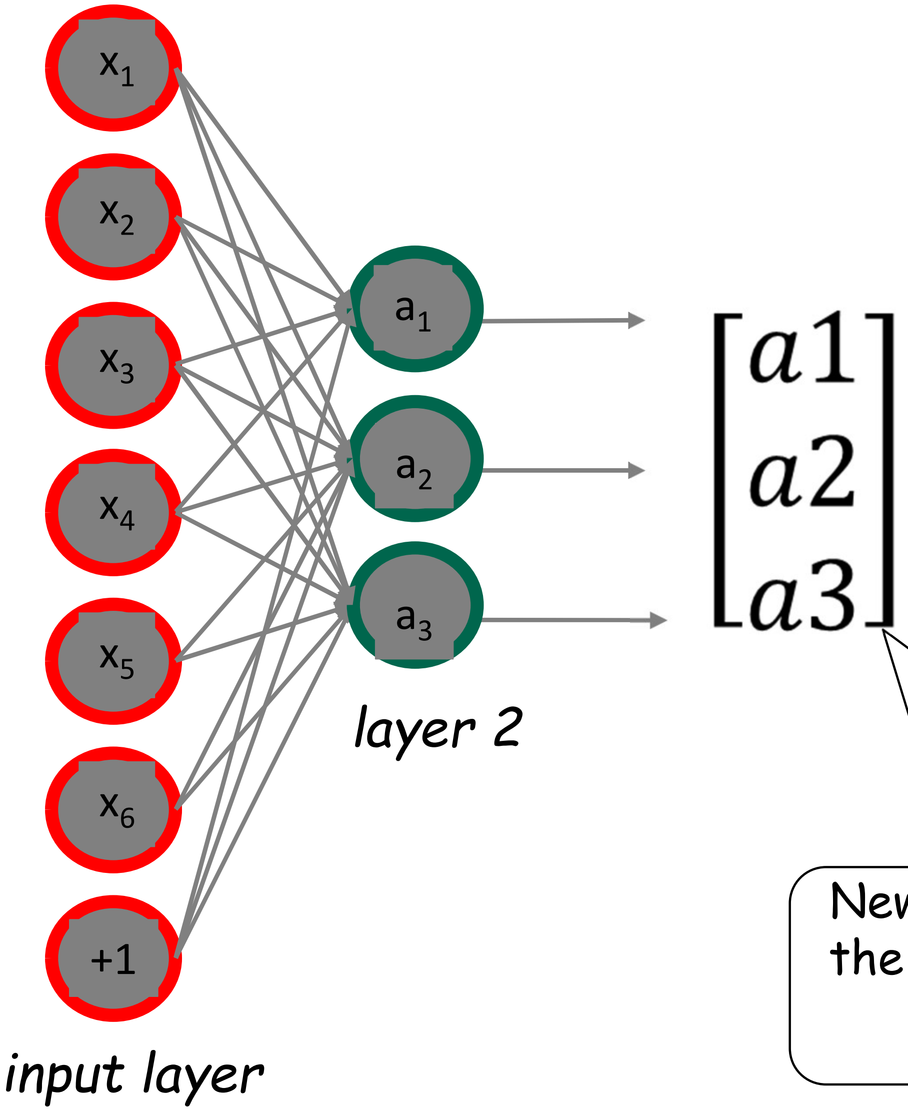
Autoencoder



Autoencoder



Autoencoder



$$\begin{bmatrix} a1 \\ a2 \\ a3 \end{bmatrix}$$

New (compressed) representation of the input to be fed to the next layer i.e. the encoded x

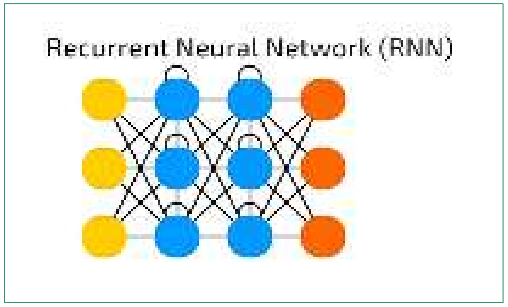
Today

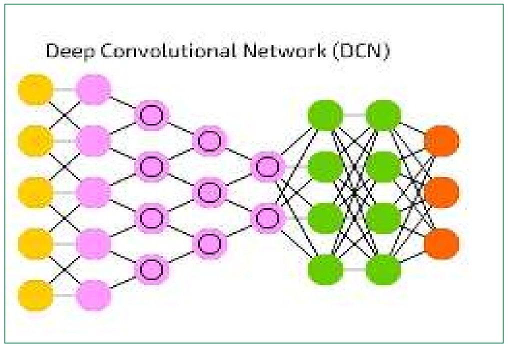
1. Motivation
2. Word Embeddings
3. Deep Learning for NLP

Deep Learning for NLP

Deep learning models for NLP use

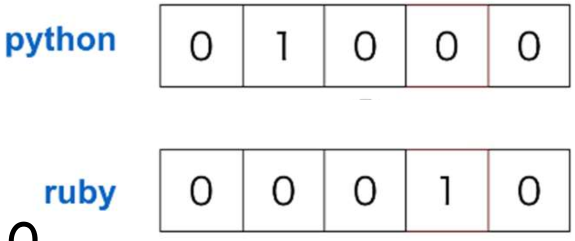
- Vector representation of words
    - i.e., word embeddings
- Neural network structures
    - Recurrent Neural Networks (RNNs)
    - Convolutional Networks (CNNs)
    - Recursive Neural Networks
    - ...



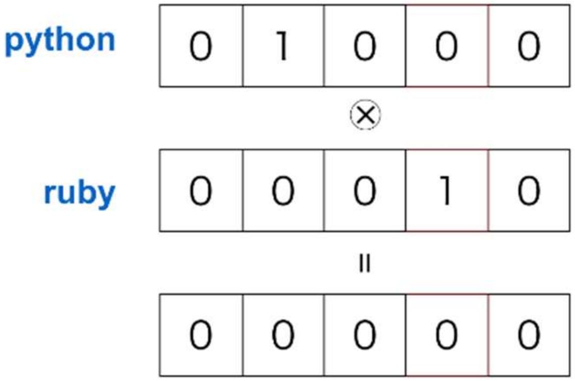


Word Embeddings

- To do NLP with neural networks, words need to be represented as vectors
- Traditional approach: “one hot vector”
  - Binary vector
  - Length = | vocab |
  - 1 in the position of the word id, the rest are 0
  - [0, 0, 0, 1, 0, 0, 0, . . .]



- However, this does not represent word meaning ;-(
- Similar words such as *python* and *ruby* should have similar vector representations
- However, similarity/distance between all “one hot vectors” is the same



http://ahogrammer.com/2017/03/22/why-is-word-embeddings-important-for-natural-language-processing/

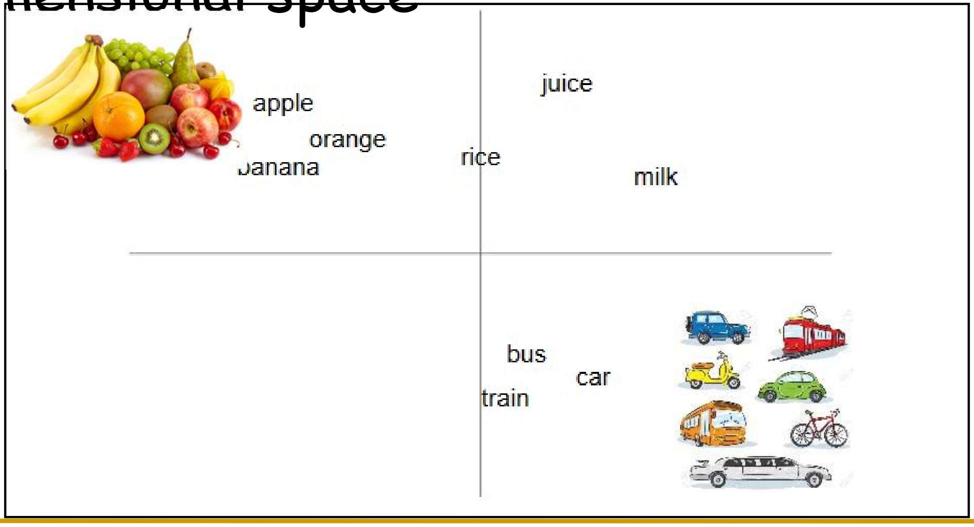
Word Embeddings

- We would like:
    - cat/kitty/dog … to have similar representations
    - cat/orange/train/python… to have dissimilar representations

- Word embeddings:
    - aka. word representations
    - Represent each word by a vector of fixed dimensions (eg, n= 50 to 300)
    - Like a point in n-dimensional space

50～300 *dim*

python	0.52	0.21	0.37	…
ruby	0.48	0.21	0.33	…
word	0.05	0.23	0.06	…



Word2vec

- Popular embedding method
- Very fast to train
- Code available on the web
  - https://code.google.com/archive/p/word2vec
- Idea:
  - **predict** rather than **count**
  - use unsupervised texts from the Web

Word2vec

- Instead of **counting** how often each word *w* occurs near "*apricot*"
- Train a classifier on a binary **prediction** task:
  - Is *w* likely to show up near "*cat*"?
- In the end, we do not actually care about this task

  - But we will take the learned weights as the word embeddings

- Use as training set readily available texts, so no need for hand-labeled supervision !

Word2vec Models

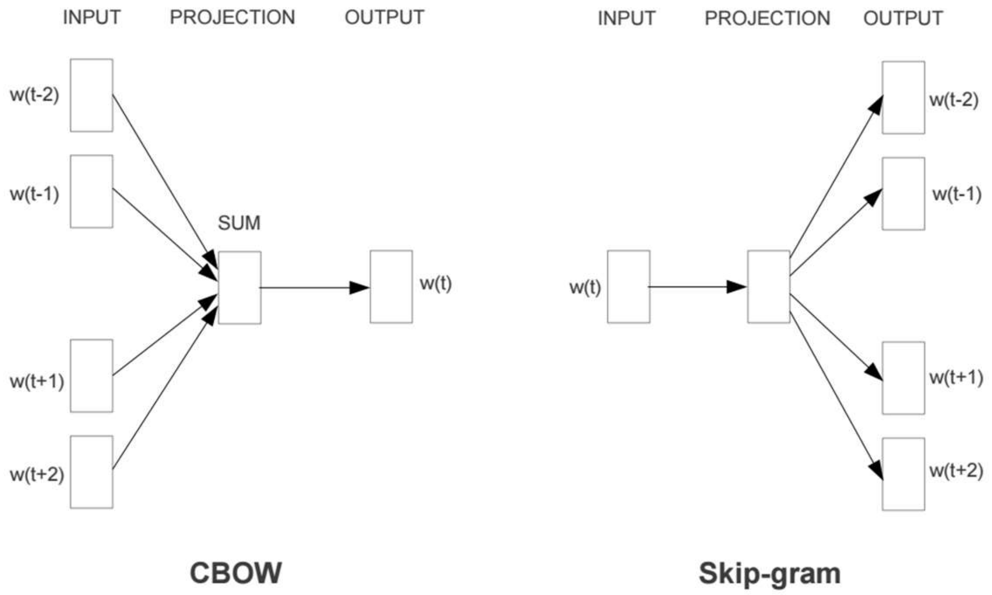
"A word is known by the company it keeps" – J. R. Firth

- Basic Idea:
  1. Similar words should have similar contexts (surrounding words)
  2. So we can use the contexts to guess the word (or vice-versa).
     - The cat/kitty/dog hunts for mice.
     - The brown furry cat/kitty/dog is eating.
     - John's cat/kitty purrs.
  3. Train an ANN to guess a word given its context (or vice-versa)

Word2Vec models

Word2Vec has 2 models:

1. CBOW: given context words, guess the word
2. Skip-gram: given a word, guess one of its surrounding word



http://rohanvarma.me/Word2Vec/

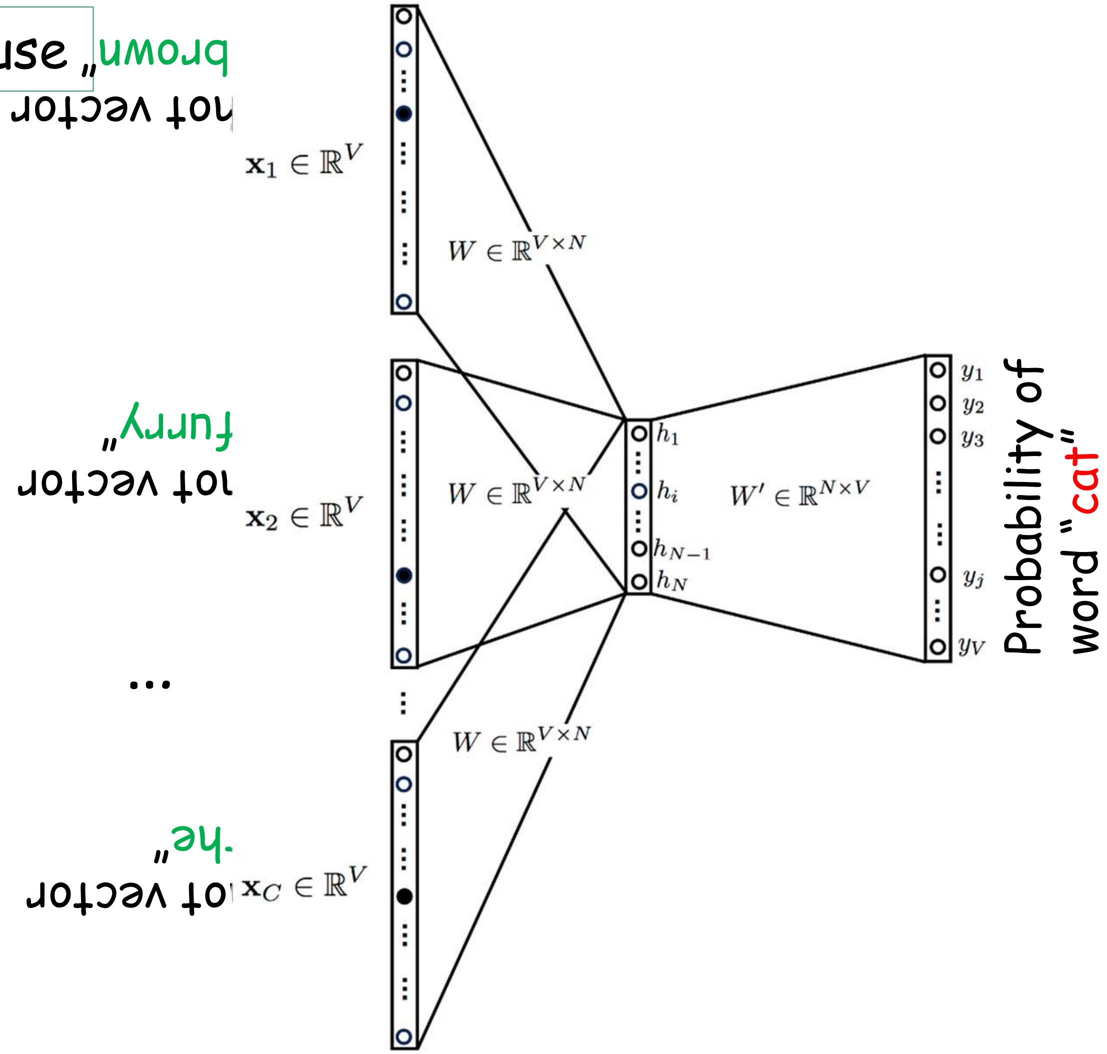
Word2Vec: CBOW Model

The brown furry cat chases the mouse

Uses a shallow neural network with only 3 layers:

1. One input layer
2. One hidden layer and
3. One output layer.

goal: predict the probability of a target word (cat) given a context (brown furry chases the).


„brown"
hot vector
$\mathbf{x}_1 \in \mathbb{R}^V$
„furry"
hot vector
$\mathbf{x}_2 \in \mathbb{R}^V$
...
„the"
hot vector
$\mathbf{x}_C \in \mathbb{R}^V$
$W \in \mathbb{R}^{V \times N}$
$W \in \mathbb{R}^{V \times N}$
$W \in \mathbb{R}^{V \times N}$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N \times V}$
y_1
y_2
y_3
y_j
y_V
Probability of word "cat"

http://www.claudiobellei.com/2018/01/06/backprop-word2vec/

Word2Vec – Creating the Data Set

The brown furry cat chases the mouse inside the house.

…

…

Assume context words are those in +/- 2 word window

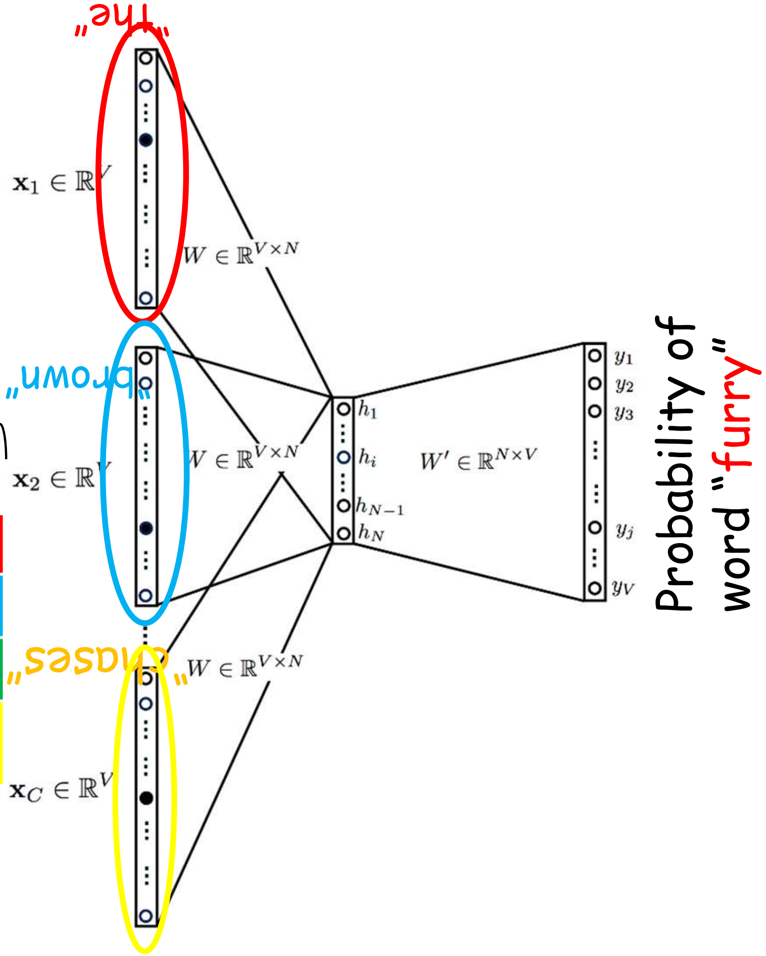
Instance	**Context word -2**	**Context word -1**	**Context word +1**	**Context word +2**	**To Predict**
1	the	brown	cat	chases	furry
2	brown	furry	chases	the	cat
3	furry	cat	the	mouse	chases
4	cat	chases	mouse	inside	the
5	chases	the	inside	the	mouse
6	the	mouse	the	house	inside

Word2Vec - Input to the Network

V = size of vocabulary
N = size of the embedding that we want
(i.e. number of neurons in the hidden layer)
C = size of context (2 words before + 2 after)

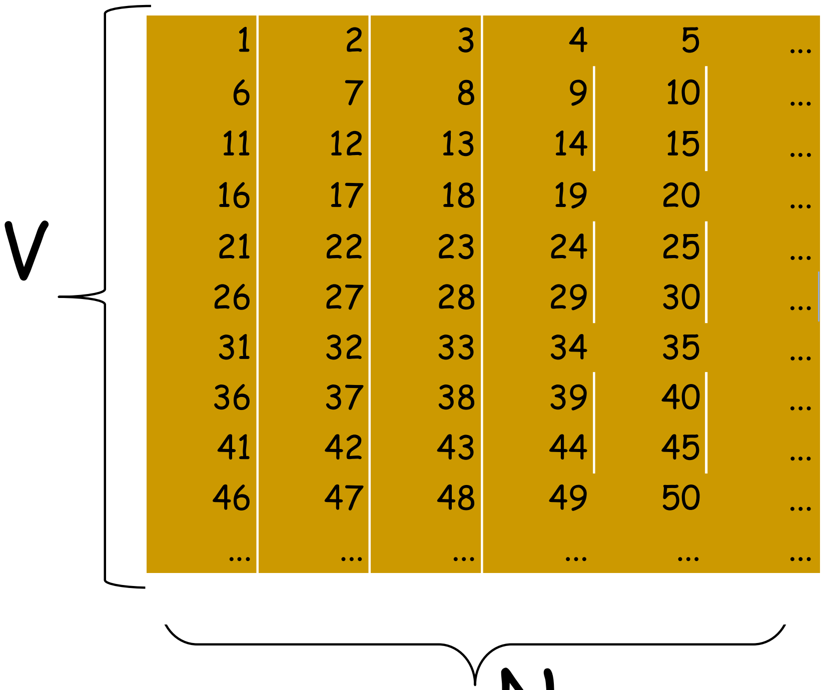
Instance	**Input word**						V				
1	Context -2	the	0	1	0	0	0	0	0	0	0	…
1	Context -1	brown	0	0	0	0	0	1	0	0	0	…
1	Context +1	cat	1	0	0	0	0	0	0	0	0	…
1	Context +2	chases	0	0	0	1	0	0	0	0	0	

Instance	**Input word**										
2	Context -2	brown	0	0	0	0	0	1	0	0	0	…
2	Context -1	furry	0	0	0	0	1	0	0	0	0	…
2	Context +1	chases	0	0	0	0	0	0	0	0	1	…
…	Context +2	the	0	1	0	0	0	0	0	0	0	…


„the"
$\mathbf{x}_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
„brown"
$\mathbf{x}_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
„chases"
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_C \in \mathbb{R}^V$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_3
y_j
y_V
Probability of word "furry"

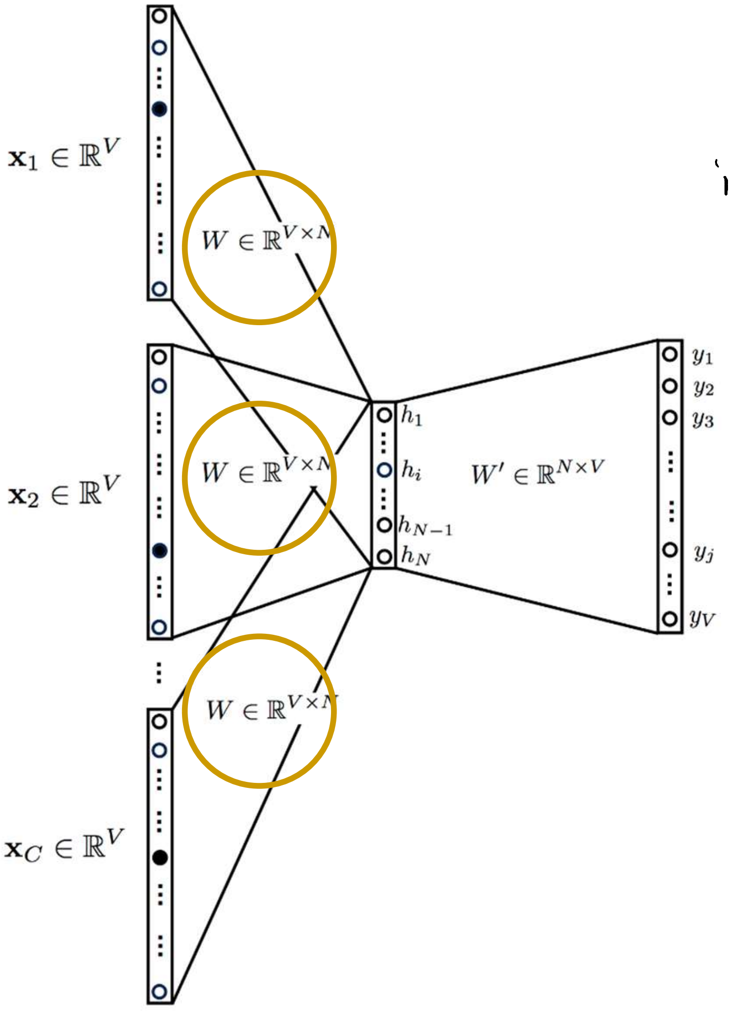
Word2Vec – Weights W

- Weight Matrix W between input & hidden layer
- W is a VxN matrix…
- Initially random but modified via backprop
- No bias!



1	2	3	4	5	…
6	7	8	9	10	…
11	12	13	14	15	…
16	17	18	19	20	…
21	22	23	24	25	…
26	27	28	29	30	…
31	32	33	34	35	…
36	37	38	39	40	…
41	42	43	44	45	…
46	47	48	49	50	…
…	…	…	…	…	…

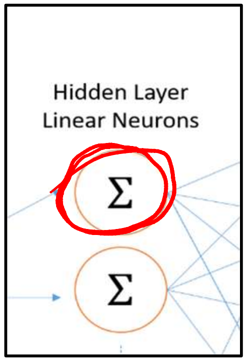
N (nb of nodes in hidden layer, i.e. size of the embedding)

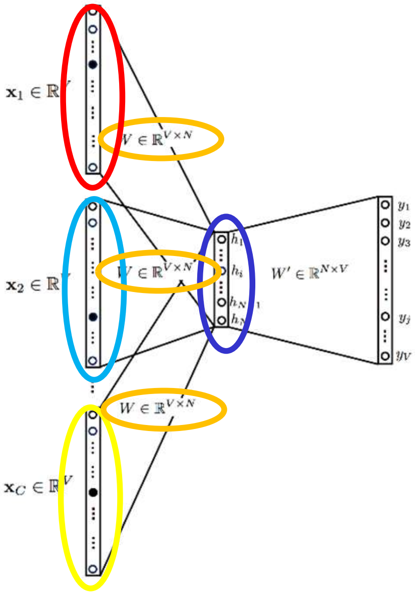

$\mathbf{x}_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_3
y_j
y_V
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_C \in \mathbb{R}^V$

Probability "cat"

Word2Vec - Feedforward

1. Calculate the output of each of the N hidden nodes for each context word
   Note: there is **no activation function.**
   Output of hi is just the dot product
2. Then take the average





$x_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V \times N}$
$x_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V \times N}$
$x_C \in \mathbb{R}^V$
$W \in \mathbb{R}^{V \times N}$
h_1
h_i
h_N
$W' \in \mathbb{R}^{N \times V}$
y_1
y_2
y_3
y_j
y_V

C

instance 1	Context -2	the	0	1	0	0	0	0	0	0	0	…
instance 1	Context -1	brown	0	0	0	0	0	1	0	0	0	…
instance 1	Context +1	cat	0	0	0	0	0	0	0	0	1	…
instance 1	Context +2	chases	0	0	0	0	1	0	0	0	0	…

V

•

V

1	2	3	4	5	…
6	7	8	9	10	…
11	12	13	14	15	…
16	17	18	19	20	…
21	22	23	24	25	…
26	27	28	29	30	…
31	32	33	34	35	…
36	37	38	39	40	…
41	42	43	44	45	…
46	47	48	49	50	…
…	…	…	…	…	…

N

=

h1	h2	h3	h4	h5	…
6	7	8	9	10	…
26	27	28	29	30	…
41	42	43	44	45	…
21	22	23	24	25	…

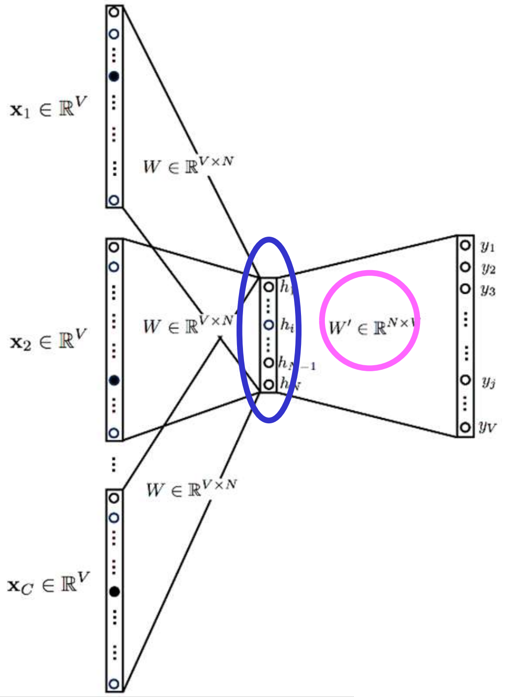
average of dot products

h1	h2	h3	h4	h5	
24	25	26	27	28	…

N

Word2Vec – Weights W’

- Weight Matrix W’ between hidden & output layer
- W’ is a NxV matrix…
- Initially random but modified via backprop
- Feed forward average of hidden neurons and do dot product with matrix W’


$\mathbf{x}_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_C \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_3
y_j
y_V

average of dot products

h1	h2	h3	h4	h5	
24	25	26	27	28	…

N (size of embeddings)

•

Matrix W’

0.70	0.13	0.14	0.60	0.16	0.17	0.60	0.19	0.20	0.21	…
0.12	0.50	0.14	0.15	0.50	0.30	0.18	0.20	0.20	0.21	…
0.17	0.40	0.60	0.25	0.26	0.50	0.35	0.37	0.30	0.55	…
0.32	0.33	0.34	0.38	0.36	0.37	0.25	0.55	0.56	0.41	…
0.42	0.43	0.44	0.45	0.46	0.47	0.48	0.49	0.50	0.30	…
…	…	…	…	…	…	…	…	…	…	…

N

V

= output layer

y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	
43.7550	46.0750	43.1300	46.5950	44.8300	46.8250	47.2600	46.8500	45.8400	43.2200	…

V

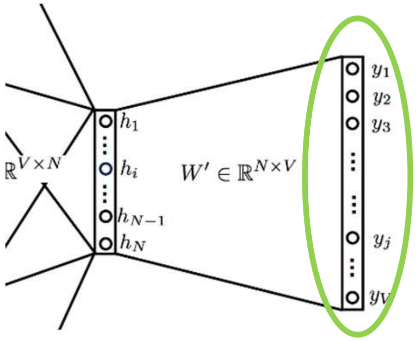
Turn dot product into probabilities

V

	y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	
output layer	43.7550	46.0750	43.1300	46.5950	44.8300	46.8250	47.2600	46.8500	45.8400	43.2200	…

$$S(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

// use softmax function
// to turn the vector above into
// a vector of probabilities
// (that nicely add up to 1)



output layer	43.7550	46.0750	43.1300	46.5950	44.8300	46.8250	47.2600	46.8500	45.8400	43.2200	…	sum
e^y_i	1.01E+19	1.02E+20	5.38E+18	1.72E+20	2.95E+19	2.17E+20	3.35E+20	2.22E+20	8.09E+19	5.89E+18	…	1.180E+21
softmax(y_i)	0.0085	0.0868	0.0046	0.1459	0.0250	0.1837	0.2837	0.1883	0.0686	0.0050	…	1.0000

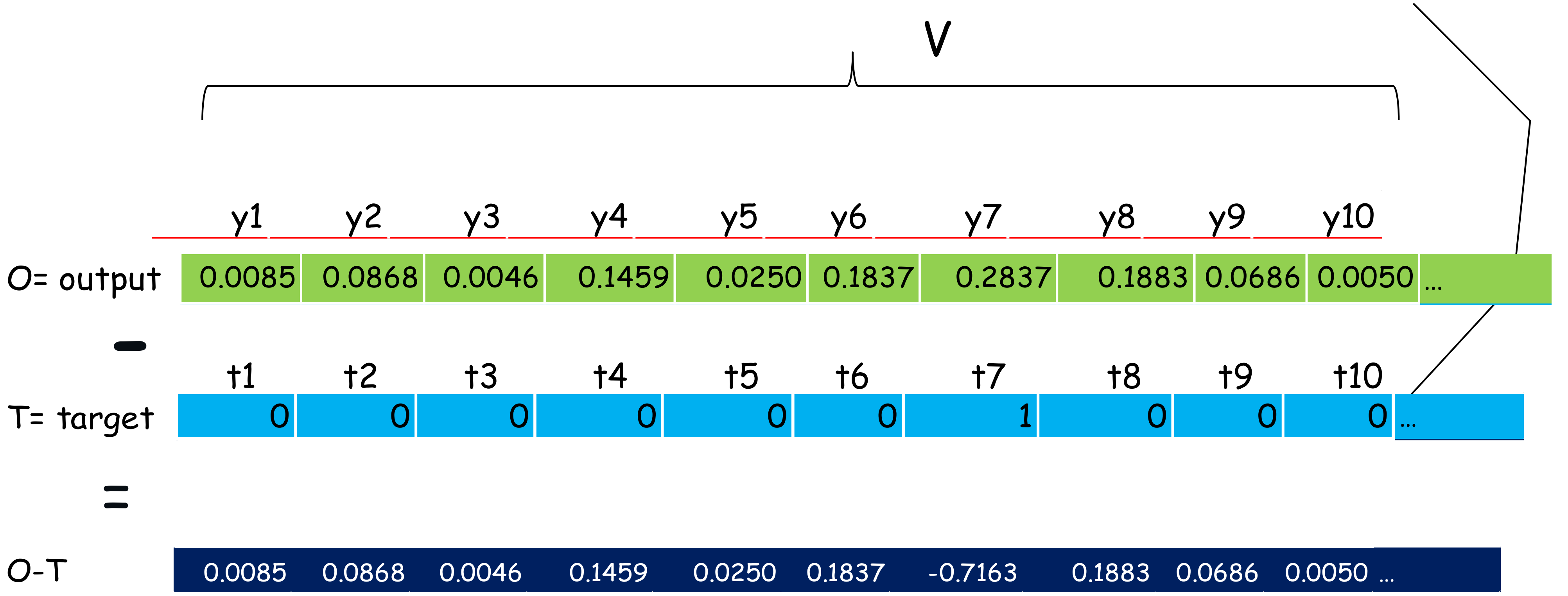
V

Compute Error of output layer

remember the training set:

Instance	Context word -2	Context word -1	Context word +1	Context word +2	To Predict
1	the	brown	cat	chases	furry
2	brown	furry	chases	the	cat
…	…	…	…	…	…

// target = 1 hot representation of the target (furry) in the training set



	y1	y2	y3	y4	y5	y6	y7	y8	y9	y10	
O= output	0.0085	0.0868	0.0046	0.1459	0.0250	0.1837	0.2837	0.1883	0.0686	0.0050	…

−

	t1	t2	t3	t4	t5	t6	t7	t8	t9	t10	
T= target	0	0	0	0	0	0	1	0	0	0	…

=

O-T	0.0085	0.0868	0.0046	0.1459	0.0250	0.1837	-0.7163	0.1883	0.0686	0.0050	…

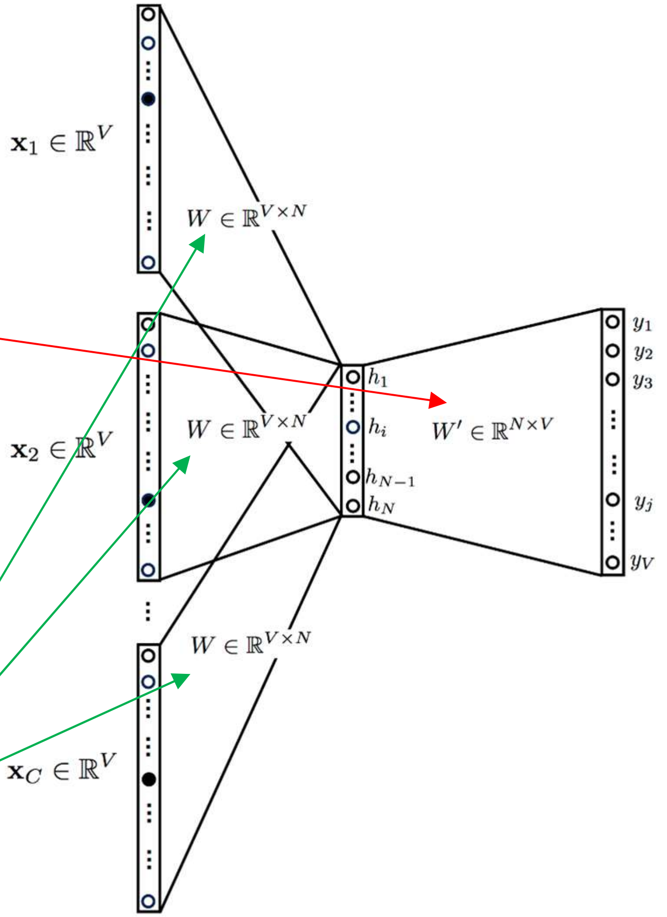
Backpropagate errors to adjust W and W'

- Adjust W' and W using backpropagation
- <after a bit of math>, we get:

$$w'_{jk} = w'_{jk} - \eta(y_k - t_k)h_j$$

update only the w_{ij} for the inputs where x1 =1

$$w_{ij} = w_{ij} - \eta \frac{1}{C}\sum_{k=1}^{V}(y_k - t_k)w'_{jk}$$


$\mathbf{x}_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_C \in \mathbb{R}^V$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_3
y_j
y_V

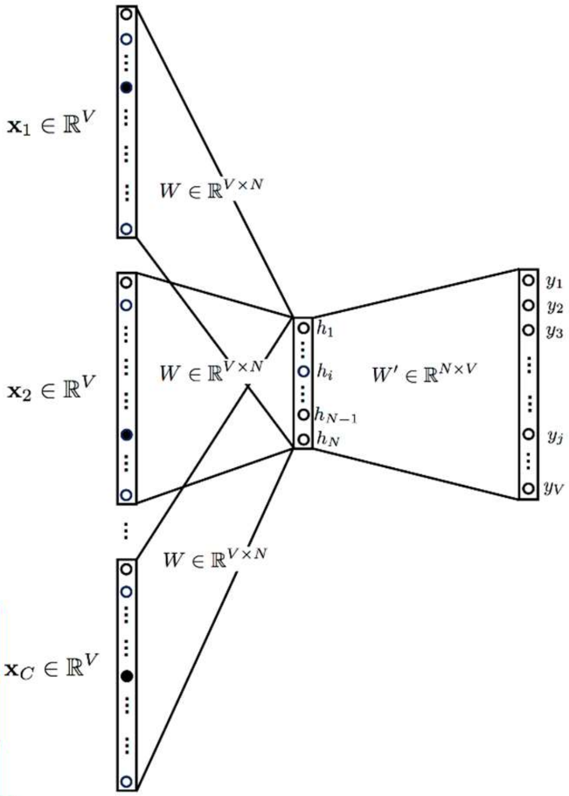
η: learning rate
C: size of context (eg 4)

The weight updates are ONLY done on the "rows" of W that correspond to the input word, not for all elements of W. Remember that the input words are represented as 1-hot vectors, so only the weights of the word that has a "1" are updated. This makes intuitive sense, as we want to update the weight only of the context word since its previous weights lead to an error.

http://www.stokastik.in/understanding-word-vectors-and-word2vec/

Word2Vec - FeedForward next data

Instance	Context word -2	Context word -1	Context word +1	Context word +2	To Predict
~~1~~	~~the~~	~~brown~~	~~cat~~	~~chases~~	~~furry~~
2	brown	furry	chases	the	cat
3	furry	cat	the	mouse	chases
4	cat	chases	mouse	inside	the
5	chases	the	inside	the	mouse
6	the	mouse	the	house	inside


$x_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$x_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$x_C \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_3
y_j
y_V

Instance	Input word											
2	Context -2	brown	0	0	0	0	0	1	0	0	0	…
2	Context -1	furry	0	0	0	0	1	0	0	0	0	…
2	Context +1	chases	0	0	0	0	0	0	0	0	1	…
1	Context +2	the	0	1	0	0	0	0	0	0	0	…

- Iterate feedforward/ backprop until error is minimized
- Trained on Google News dataset (about 100 billion words).
- See: https://code.google.com/archive/p/word2vec/

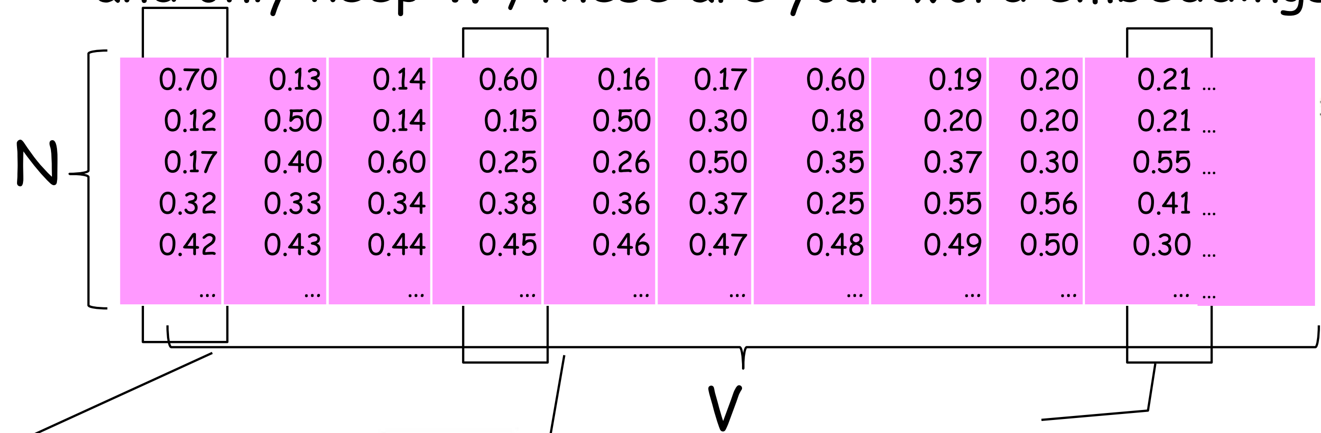
almost...

remember, we did all this to get embeddings...

I'm not leaving 'till I get my embeddings!

Word2Vec- Get the embeddings

- After many iterations of feedforward, backpropagation on the entire training set ...
- The classifier will be built!
- Then, we throw it away ! (yes, we do!)
- and only keep W', these are your word embeddings!

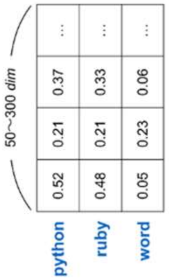


0.70	0.13	0.14	0.60	0.16	0.17	0.60	0.19	0.20	0.21	...
0.12	0.50	0.14	0.15	0.50	0.30	0.18	0.20	0.20	0.21	...
0.17	0.40	0.60	0.25	0.26	0.50	0.35	0.37	0.30	0.55	...
0.32	0.33	0.34	0.38	0.36	0.37	0.25	0.55	0.56	0.41	...
0.42	0.43	0.44	0.45	0.46	0.47	0.48	0.49	0.50	0.30	...
...	...	...	...	...	...	...	...	...	...	...

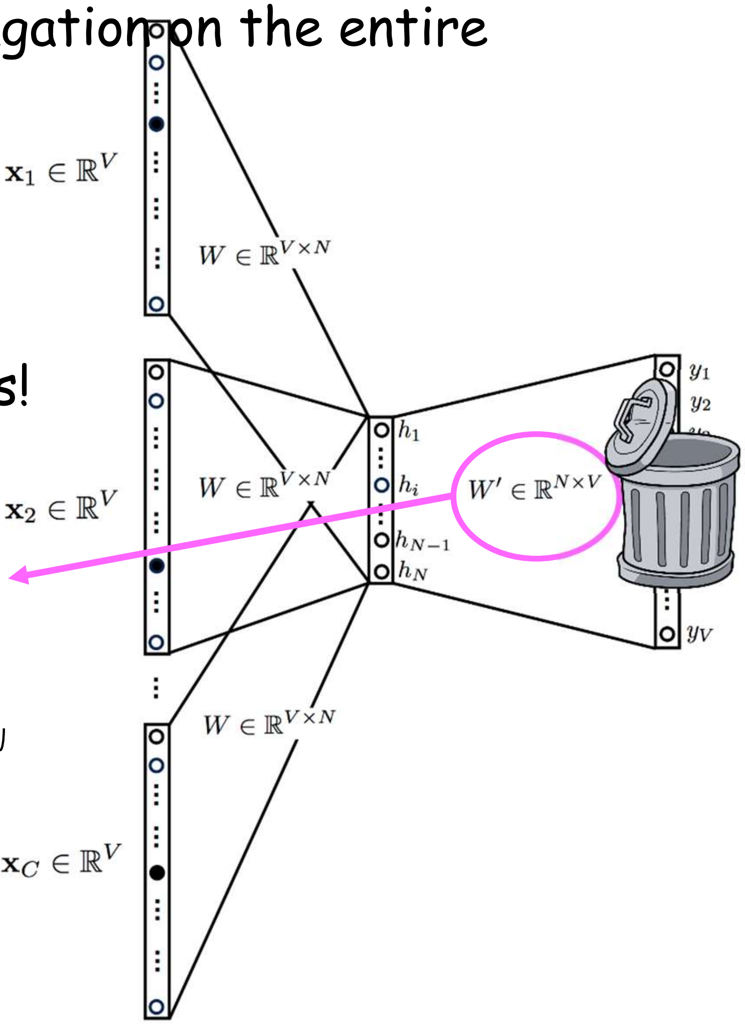
Embedding for airplane

Embedding for banana

Embedding for zoo

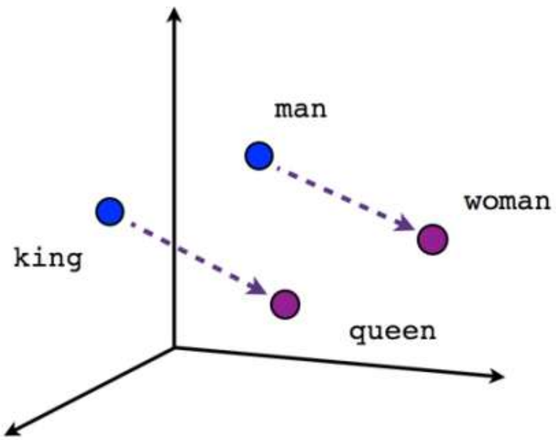


python	0.52	0.21	0.37	...
ruby	0.48	0.21	0.33	...
word	0.05	0.23	0.06	...

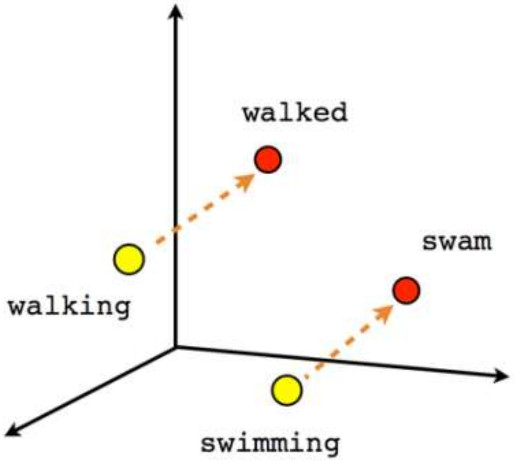


$\mathbf{x}_1 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_2 \in \mathbb{R}^V$
$W \in \mathbb{R}^{V\times N}$
$W \in \mathbb{R}^{V\times N}$
$\mathbf{x}_C \in \mathbb{R}^V$
h_1
h_i
h_{N-1}
h_N
$W' \in \mathbb{R}^{N\times V}$
y_1
y_2
y_V

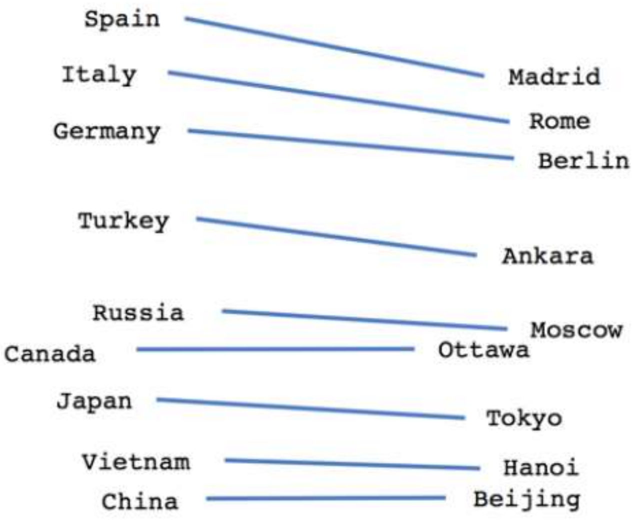
Results



Male-Female



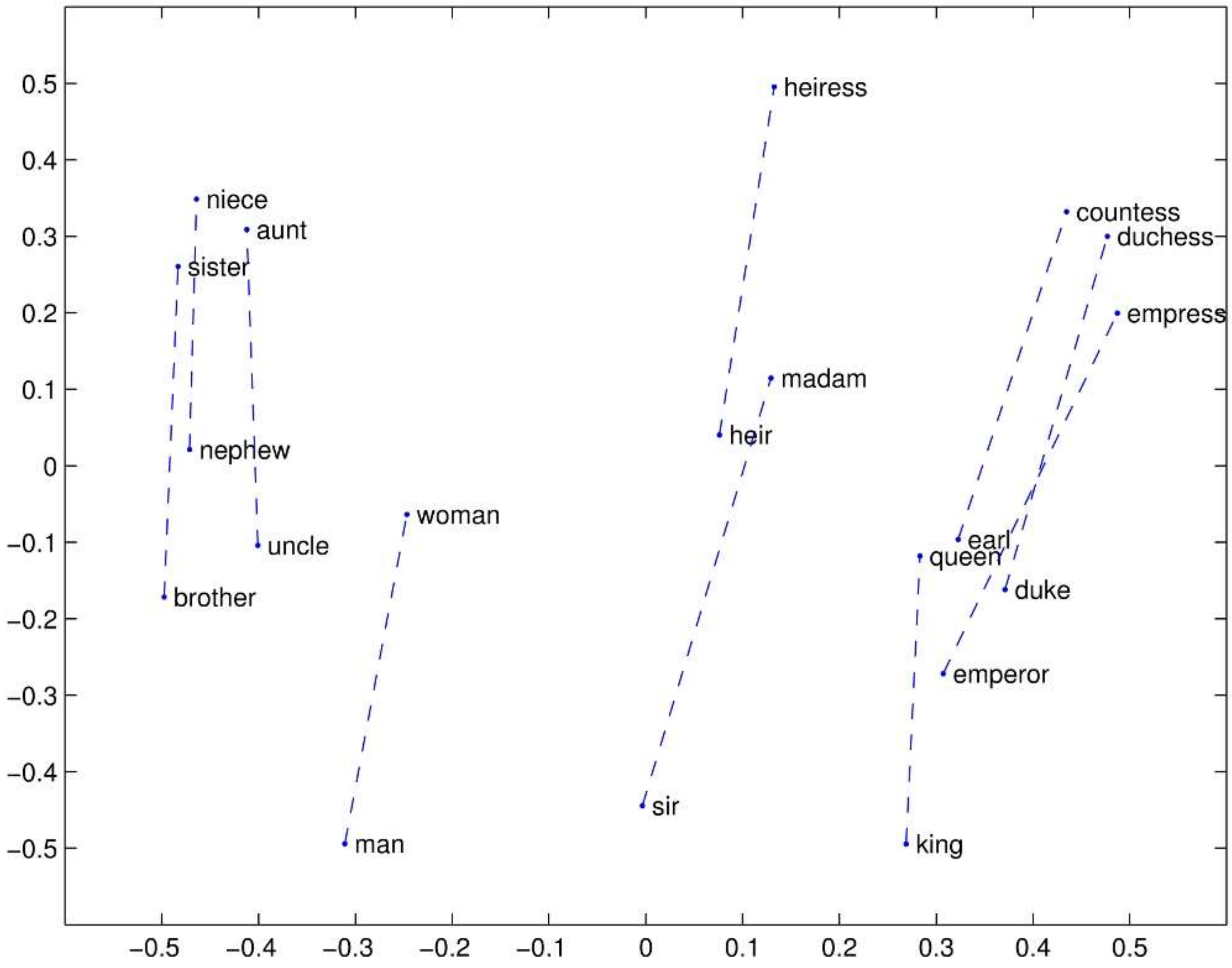
Verb tense



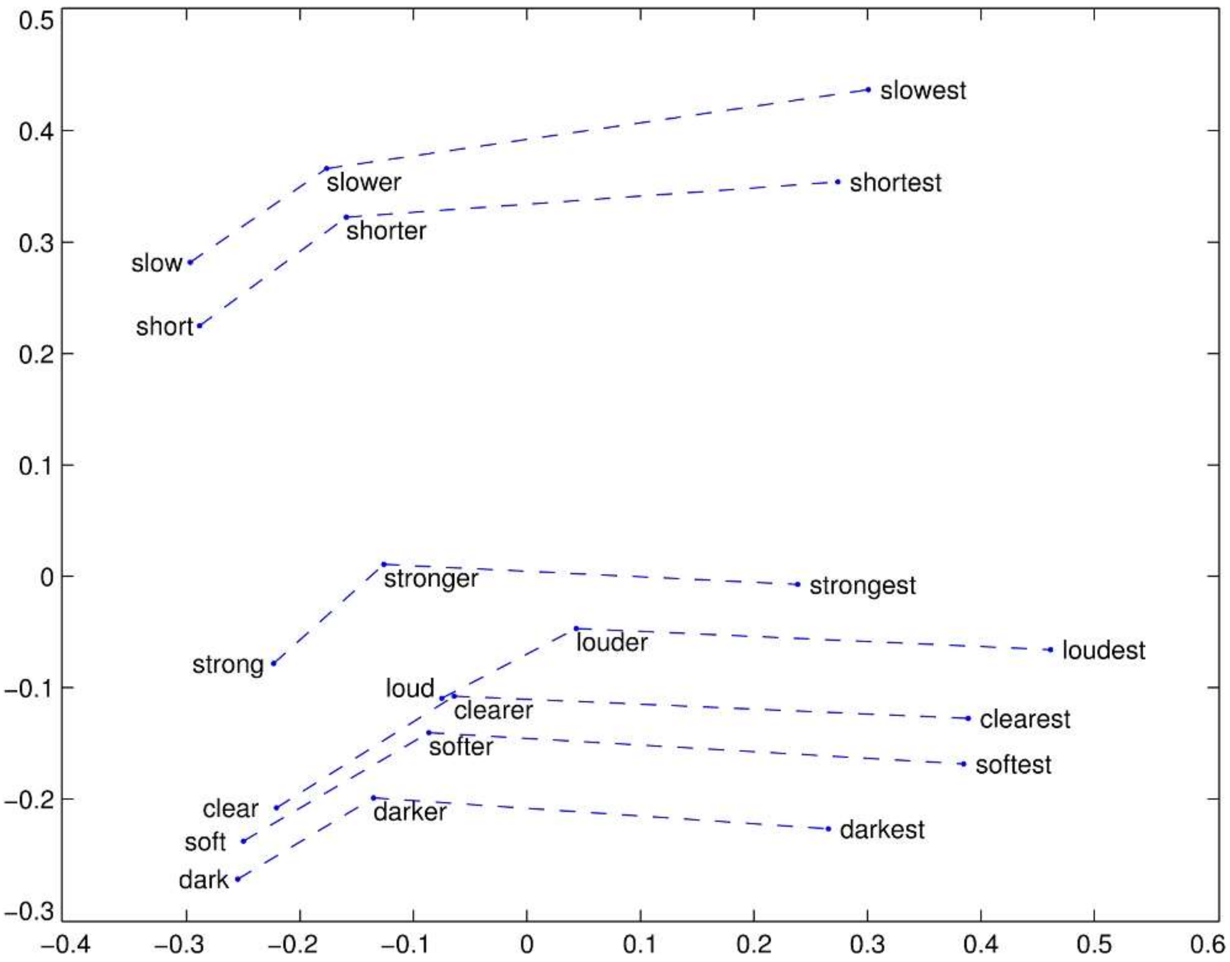
Country-Capital

vector[queen] ~ vector[king] - vector[man] + vector[woman]
vector[swimming] ~ vector[swam] - vector[walked] + vector[walking]
vector[Rome] ~ vector[Madrid] – vector[Spain] + vector[Italy]

Results

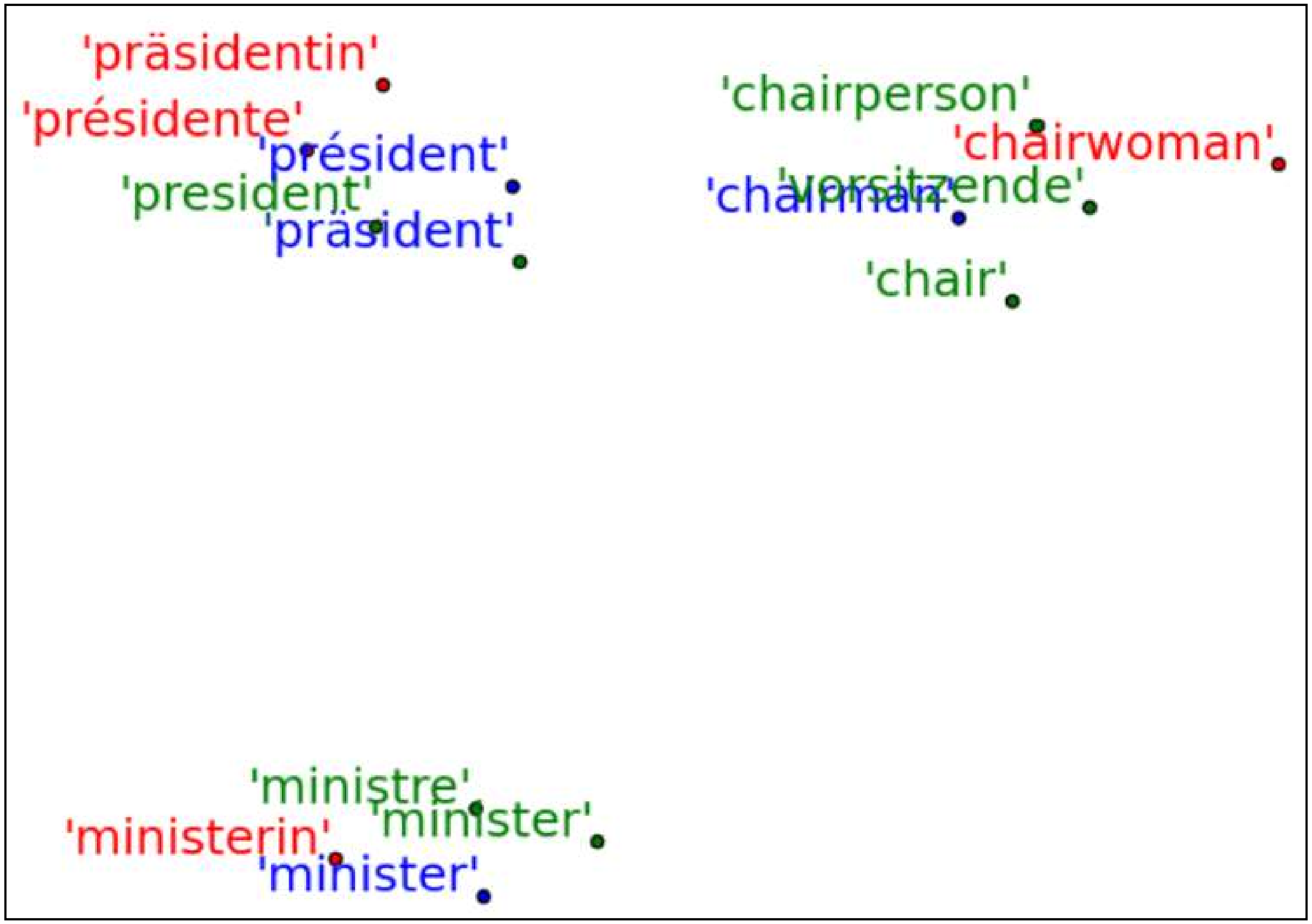

heiress
niece
aunt
sister
countess
duchess
empress
madam
heir
nephew
woman
uncle
brother
earl
queen
duke
emperor
sir
man
king
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.5
−0.5
−0.4
−0.3
−0.2
−0.1
0
0.1
0.2
0.3
0.4
0.5

Results



slowest
slower
shortest
shorter
slow
short
stronger
strongest
strong
louder
loudest
loud
clearer
clearest
softer
softest
clear
soft
dark
darker
darkest
0.5
0.4
0.3
0.2
0.1
0
−0.1
−0.2
−0.3
−0.4
−0.3
−0.2
−0.1
0
0.1
0.2
0.3
0.4
0.5
0.6

Multilingual Word Embeddings

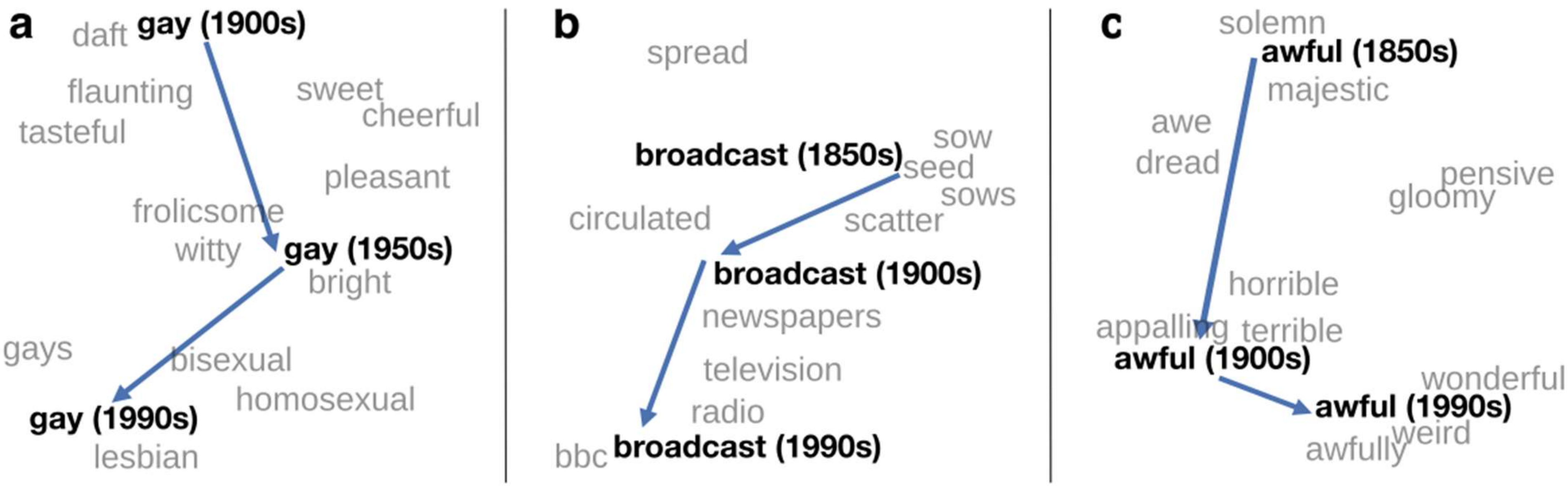


Words in different languages but with similar meanings (i.e. translations) are represented by similar vectors

Used in Machine Translation

Word History through Embeddings

Train embeddings on old books to study changes in word meaning



Project 300 dimensions down into 2

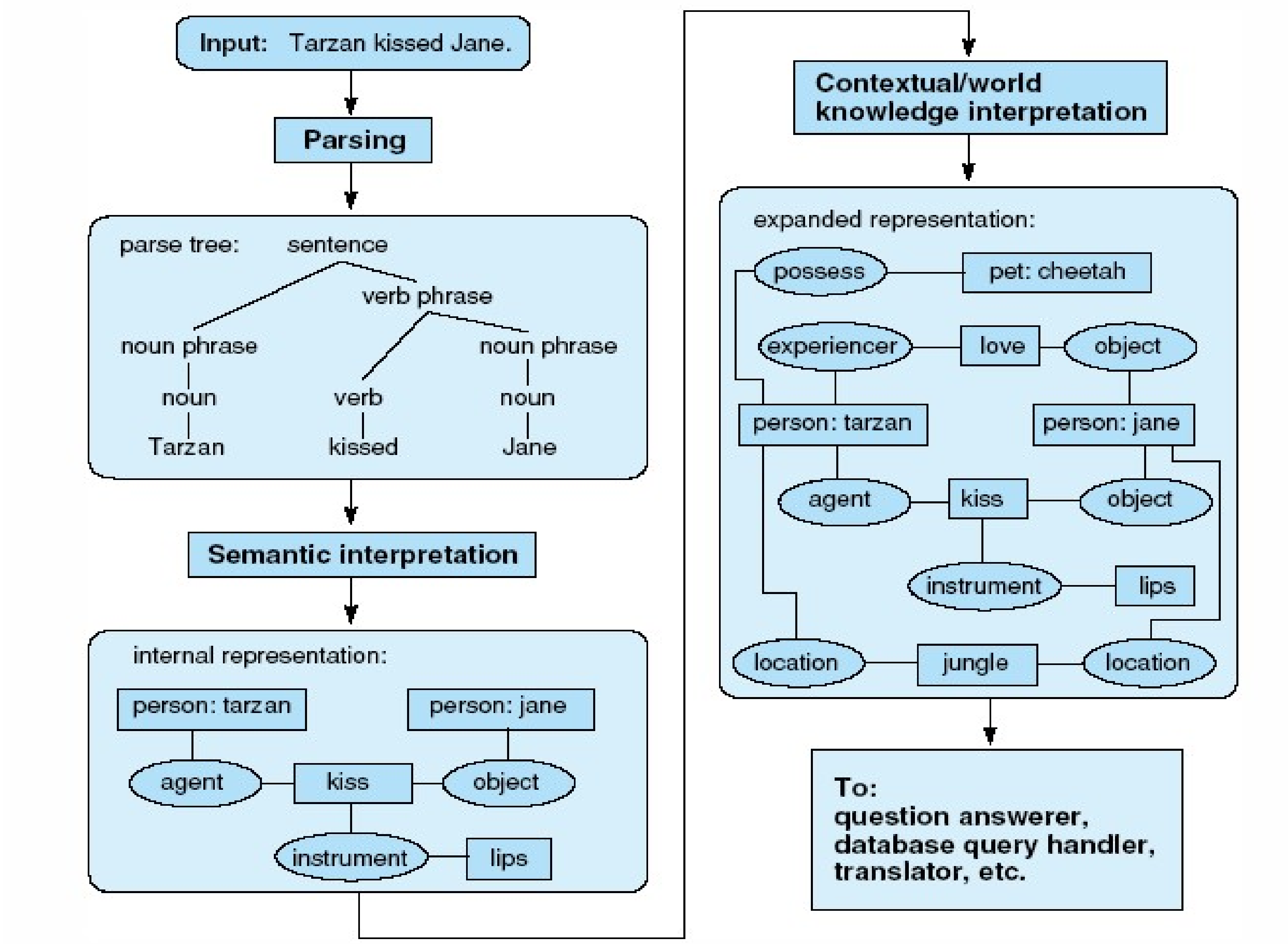
Word2Vec - Parameters

- Choice of model architecture (CBOW or Skip-Gram)
- Size of training dataset (corpus)
- Vector space dimensions
- Window size
- …

Today

1. Motivation
2. Word Embeddings
3. Deep Learning for NLP

Stages of NLU



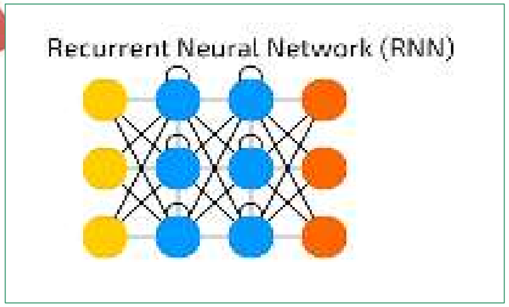
source: Luger (2005)

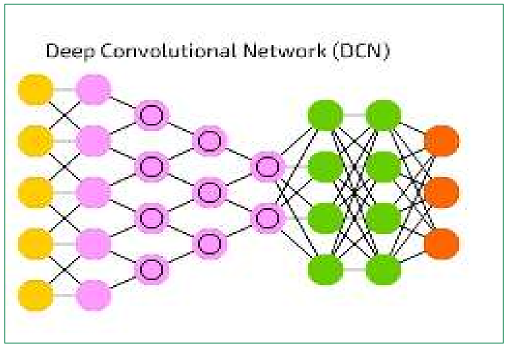
Deep Learning for NLP

Deep learning models for NLP use:

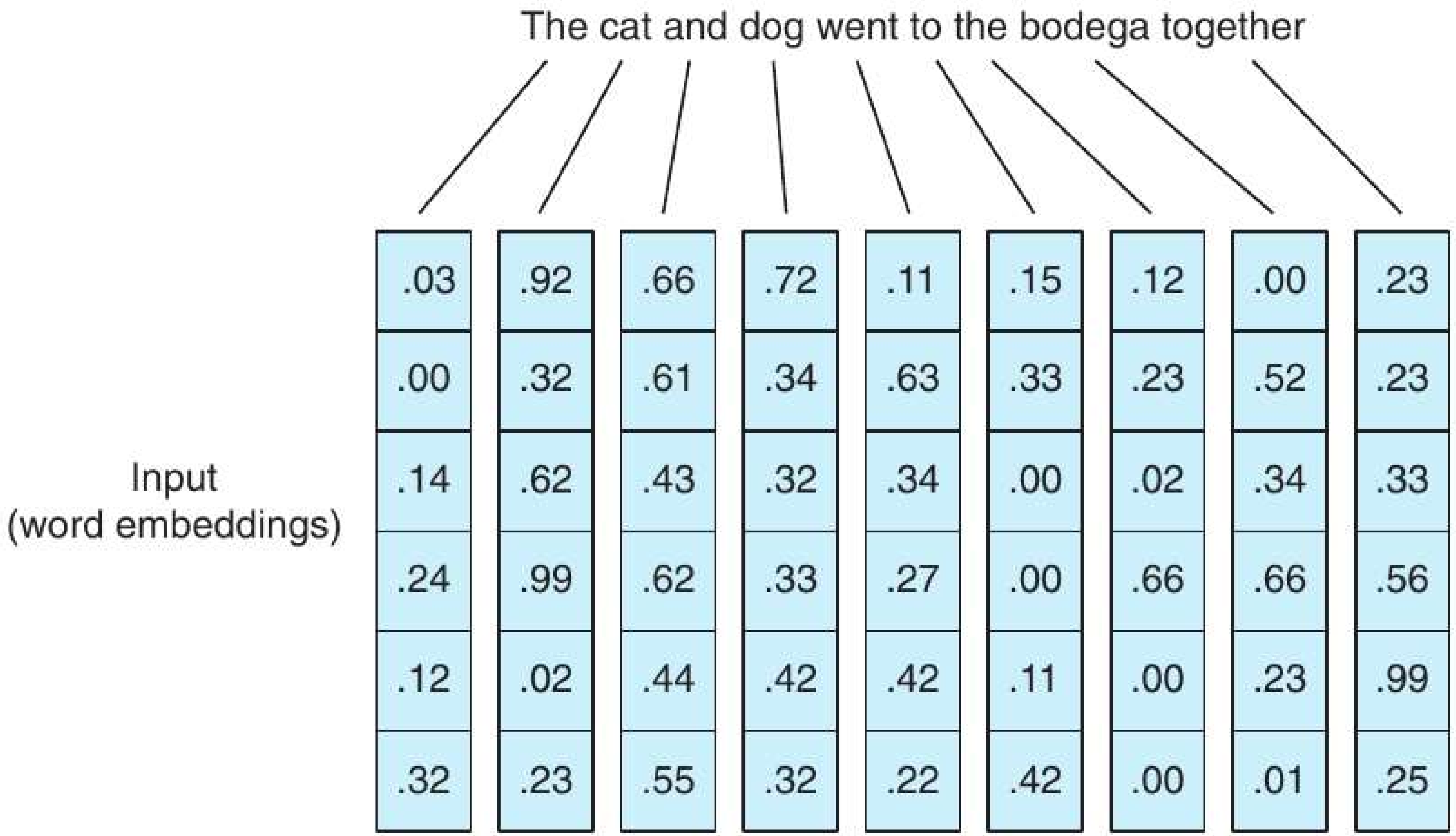
- Vector representation of words
  - i.e., word embeddings

- Neural network structures
  - Recurrent Neural Networks (RNNs)
  - Recursive Neural Networks
  - Convolutional Networks (CNNs)
  - …





CNNs for NLP



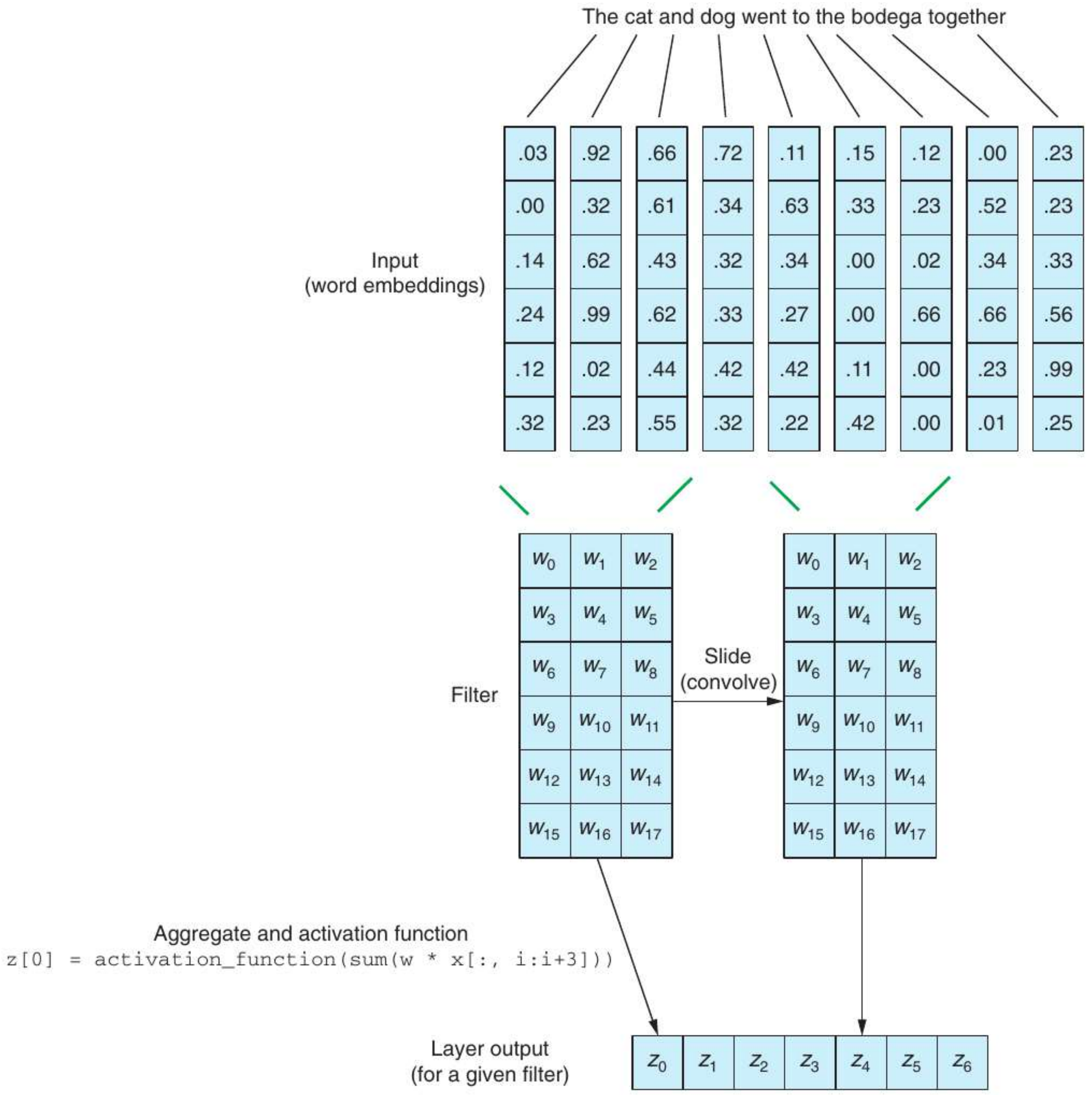
The cat and dog went to the bodega together

Input
(word embeddings)

.03	.92	.66	.72	.11	.15	.12	.00	.23
.00	.32	.61	.34	.63	.33	.23	.52	.23
.14	.62	.43	.32	.34	.00	.02	.34	.33
.24	.99	.62	.33	.27	.00	.66	.66	.56
.12	.02	.44	.42	.42	.11	.00	.23	.99
.32	.23	.55	.32	.22	.42	.00	.01	.25

[Hobson Lane, Cole Howard, and Hannes Max Hapke: *Natural Language Processing in Action*. Manning Publications Co., 2019.
https://concordiauniversity.on.worldcat.org/oclc/1102387045]

CNNs for NLP (II)

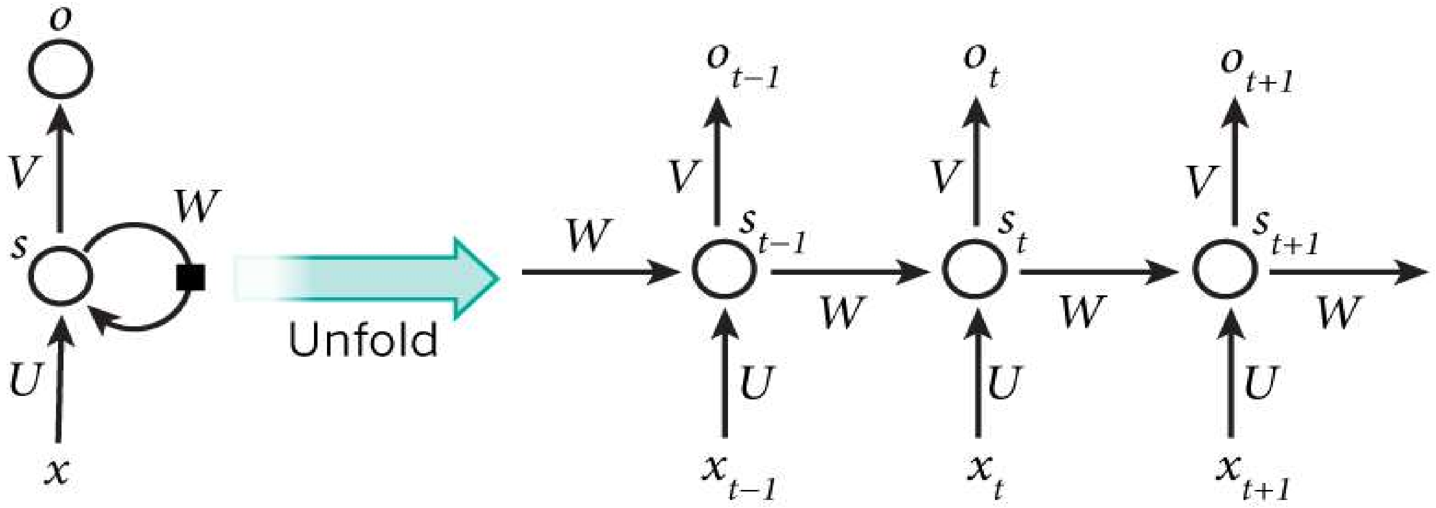


```
z[0] = activation_function(sum(w * x[:, i:i+3]))
```

[Hobson Lane, Cole Howard, and Hannes Max Hapke: *Natural Language Processing in Action*. Manning Publications Co., 2019. https://concordiauniversity.on.worldcat.org/oclc/1102387045]

Recurrent Neural Networks

- To model sequences of decisions, such as machine translation, language modelling, ….
  - e.g., A word at position n can influence a word/decision at position n+t
- decision/output from the past can influence current decision/output
- Networks with loops in them, allowing information to persist.



http://www.wildml.com/2015/09/recurrent-neural-networks-tutorial-part-1-introduction-to-rnns/

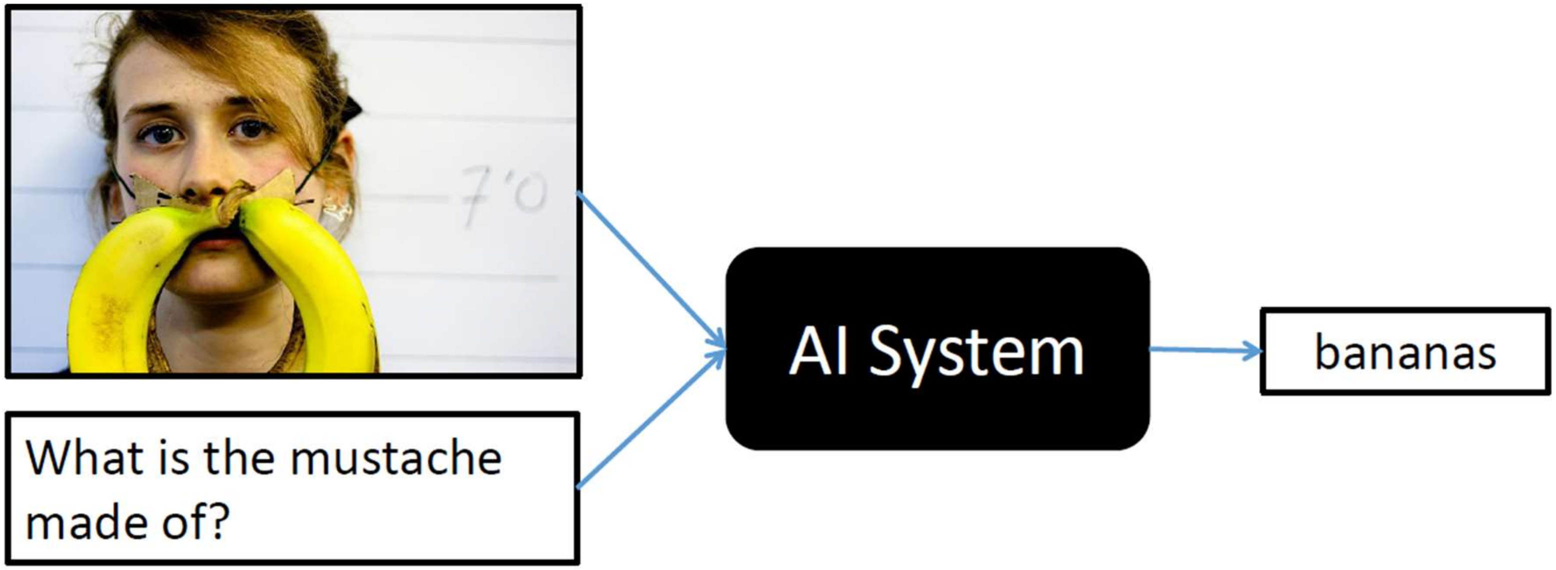
Cool Applications

- RNNs + word embeddings
  - [Google Translate]
    - As of July 2017, uses an RNN + word embeddings (called Neural Machine Translation (NMT))
    - Input sequence: words in a source sentence
    - Output sequence: words in the target language
  - [Dialogue Systems]
- [CNNs + RNNs + word embeddings]
  - [Image Captioning]
  - [Video to Text Descriptions]
  - Visual Question Answering
- …

Visual Question Answering

Demo Website

Input: an image + a natural language question
Output: natural language answer



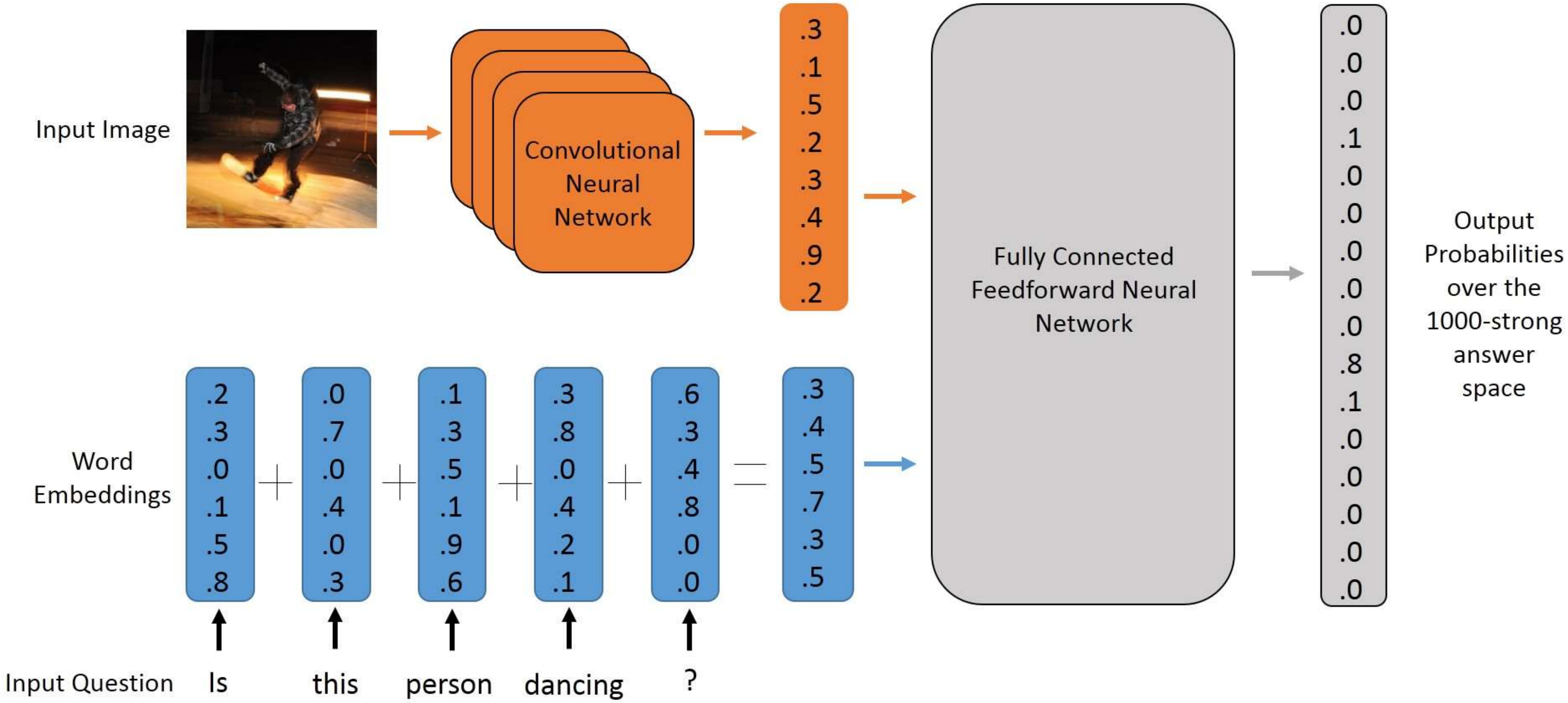
What is the mustache made of?

AI System

bananas

Picture from (Antol et al., 2015)

Visual Question Answering



Input Image

Convolutional Neural Network

.3 .1 .5 .2 .3 .4 .9 .2

Fully Connected Feedforward Neural Network

.0 .0 .0 .1 .0 .0 .0 .0 .0 .8 .1 .0 .0 .0 .0 .0

Output Probabilities over the 1000-strong answer space

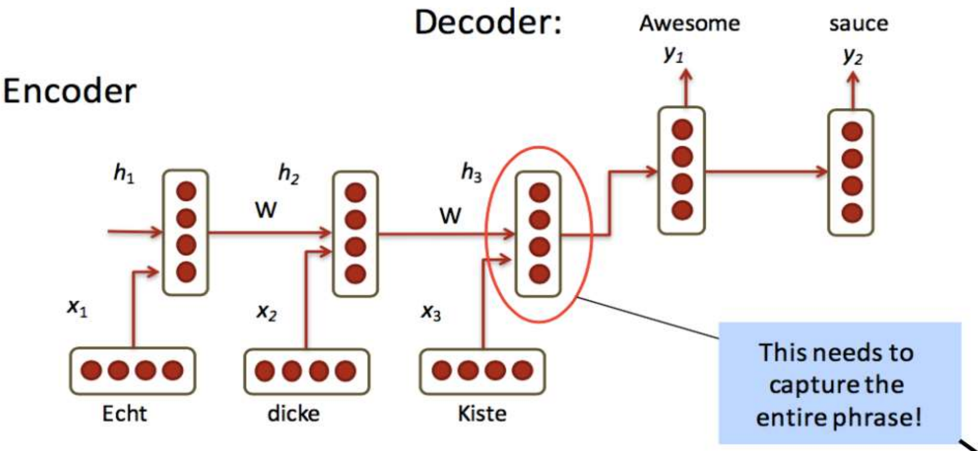
Word Embeddings

.2 .3 .0 .1 .5 .8 + .0 .7 .0 .4 .0 .3 + .1 .3 .5 .1 .9 .6 + .3 .8 .0 .4 .2 .1 + .6 .3 .4 .8 .0 .0 = .3 .4 .5 .7 .3 .5

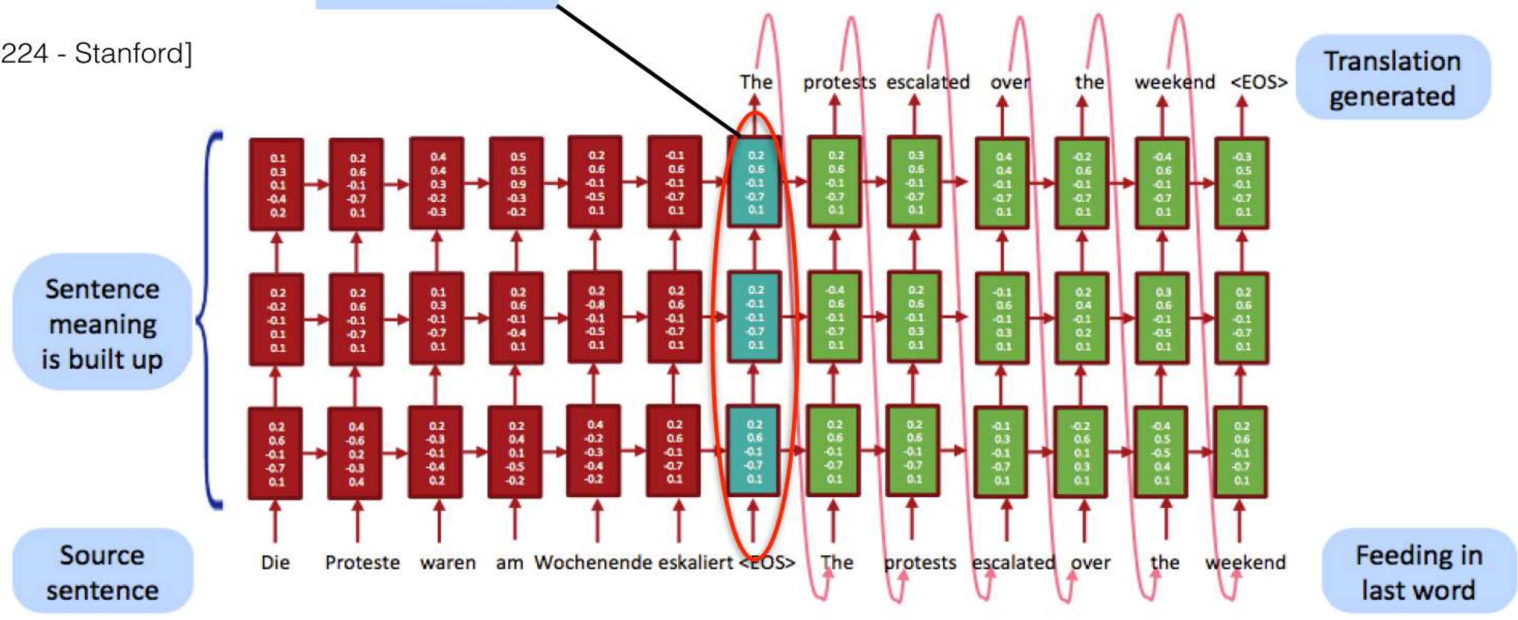
Input Question Is this person dancing ?

- The output is conditioned on both image and textual inputs.
- A CNN is used to encode the image.
- A RNN is used to encode the sentence.

Machine Translation

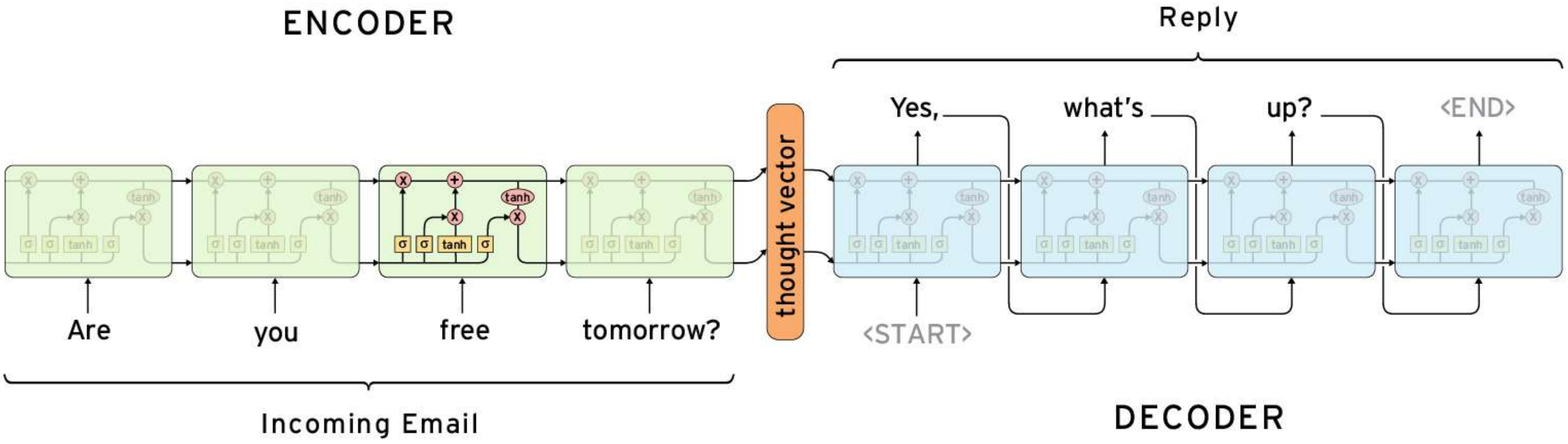


[CS224 - Stanford]



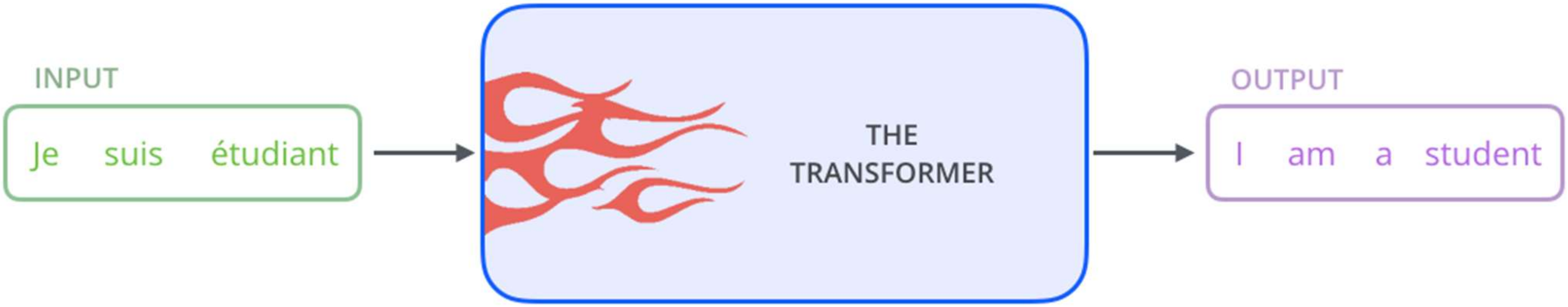
[CS224 - Stanford]

Conversational Agents



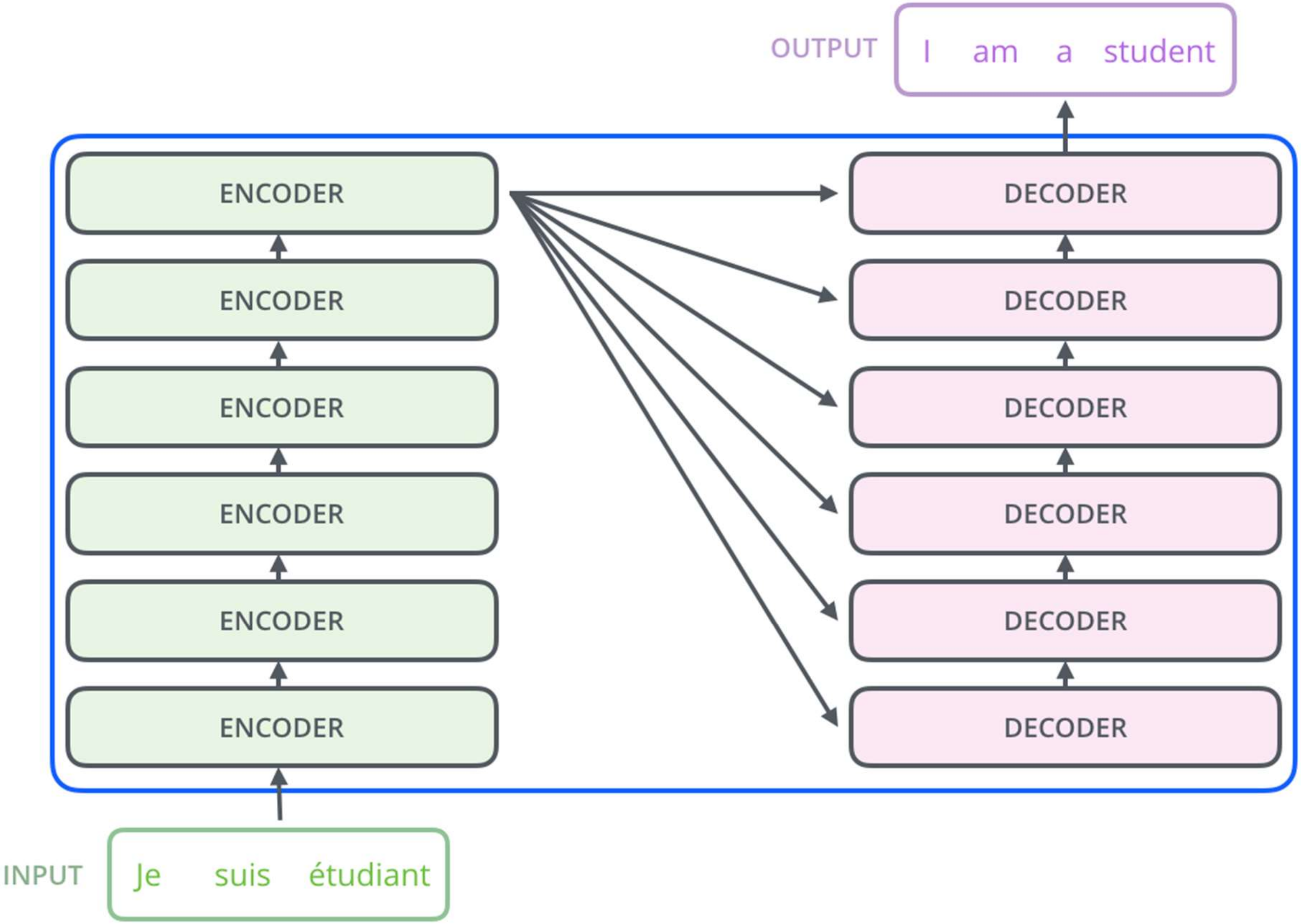
http://www.wildml.com/2016/04/deep-learning-for-chatbots-part-1-introduction/

Transformers



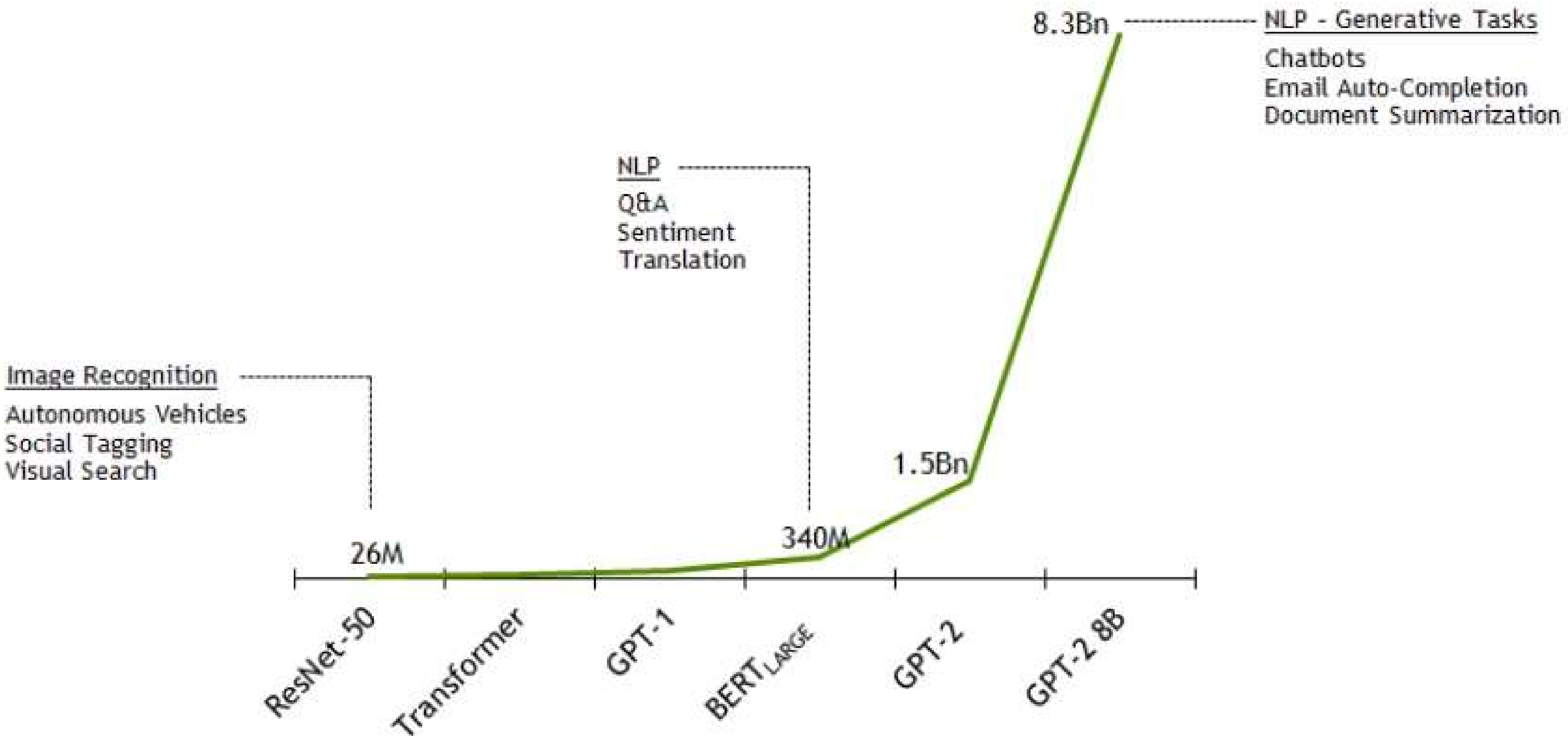
http://jalammar.github.io/illustrated-transformer/

Transformers (II)



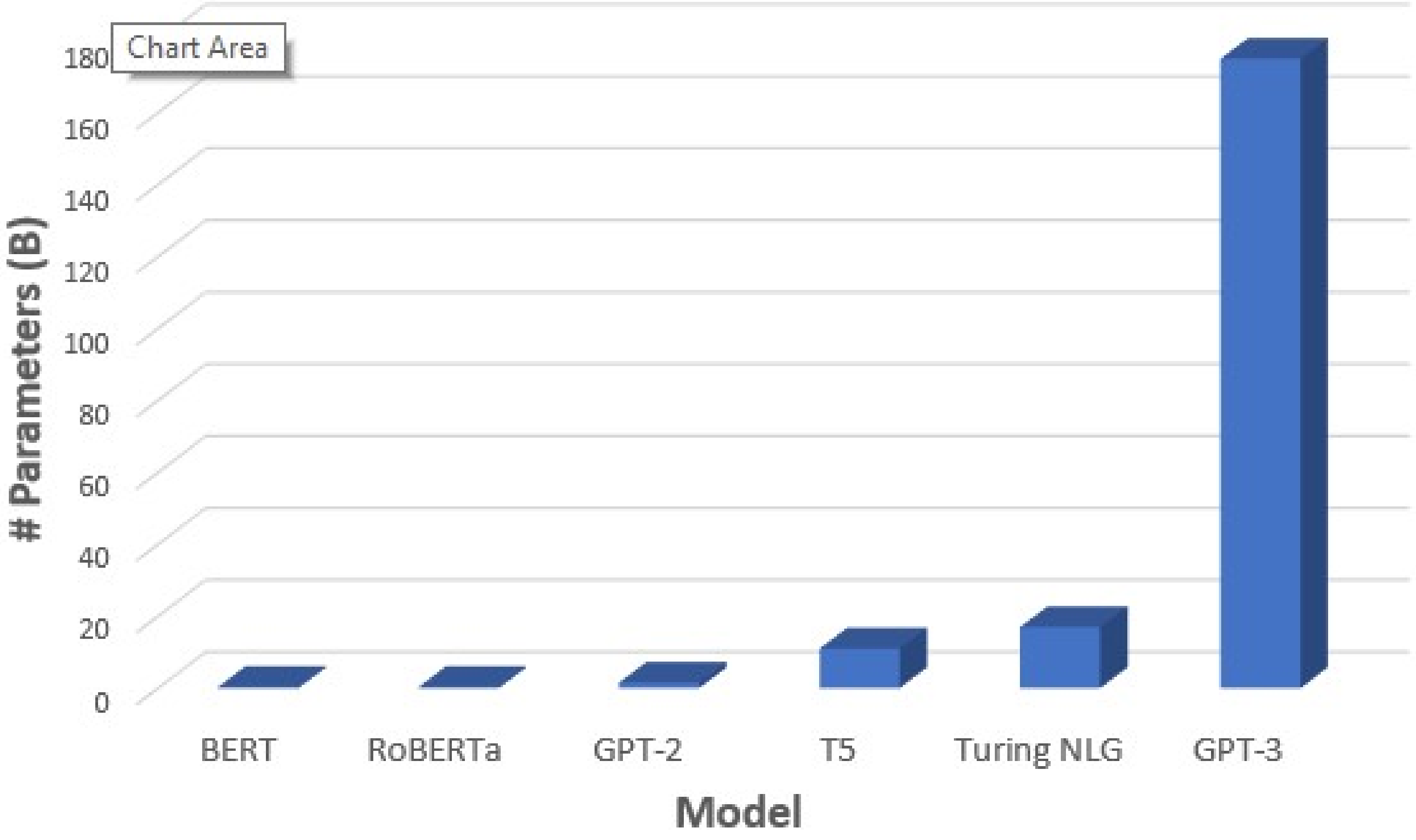
http://jalammar.github.io/illustrated-transformer/

Transformers (II)



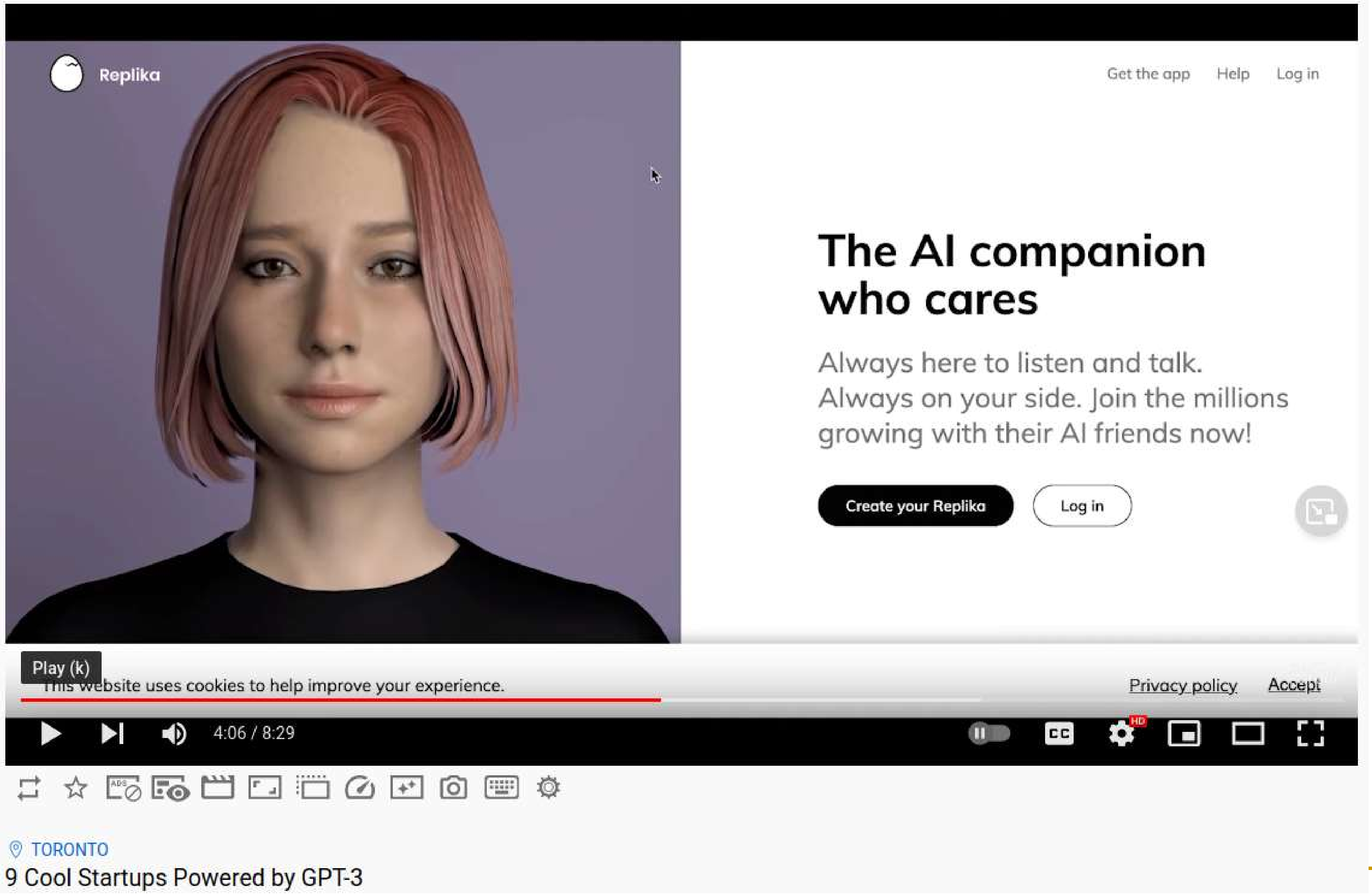
https://devblogs.nvidia.com/training-bert-with-gpus/

GPT-3



https://towardsdatascience.com/gpt-3-the-new-mighty-language-model-from-openai-a74ff35346fc

GPT-3 Applications



The AI companion who cares

Always here to listen and talk. Always on your side. Join the millions growing with their AI friends now!

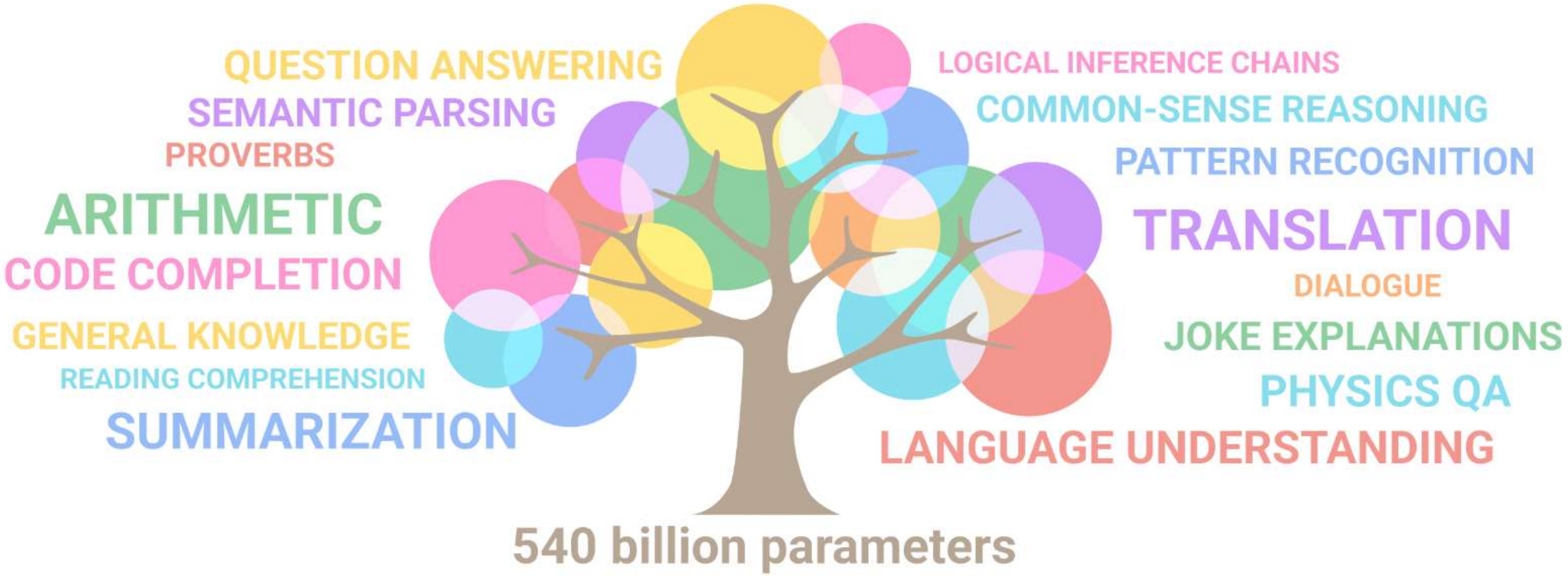
This website uses cookies to help improve your experience.

9 Cool Startups Powered by GPT-3

https://www.youtube.com/watch?v=QYfZJ5jbUWU

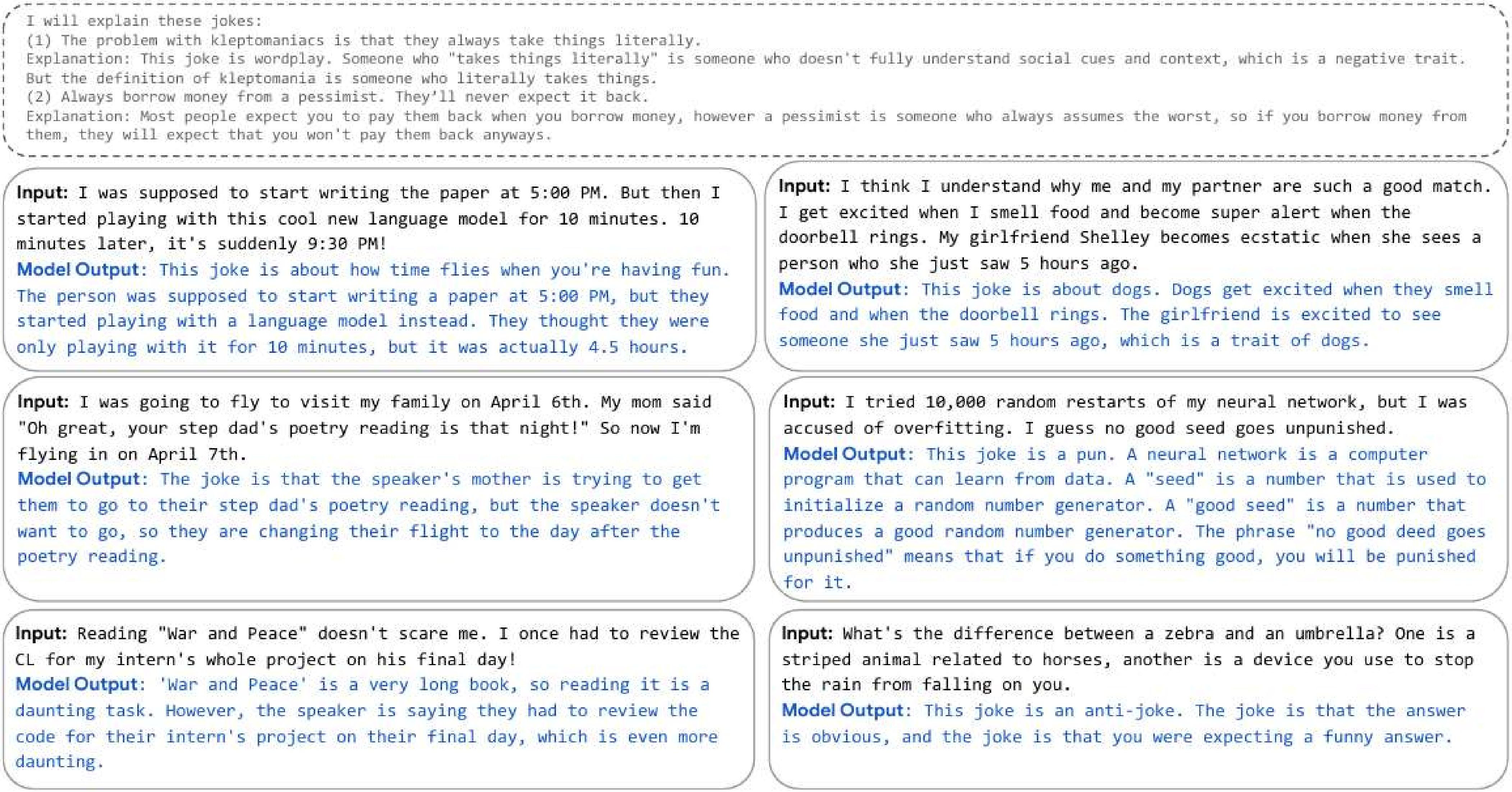
Google PaLM (April 2022)

Pathways Language Model (PaLM):
Scaling to 540 Billion Parameters for Breakthrough Performance



https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html

Google PaLM: Explaining Jokes!



I will explain these jokes:
(1) The problem with kleptomaniacs is that they always take things literally.
Explanation: This joke is wordplay. Someone who "takes things literally" is someone who doesn't fully understand social cues and context, which is a negative trait. But the definition of kleptomania is someone who literally takes things.
(2) Always borrow money from a pessimist. They'll never expect it back.
Explanation: Most people expect you to pay them back when you borrow money, however a pessimist is someone who always assumes the worst, so if you borrow money from them, they will expect that you won't pay them back anyways.

Input: I was supposed to start writing the paper at 5:00 PM. But then I started playing with this cool new language model for 10 minutes. 10 minutes later, it's suddenly 9:30 PM!
Model Output: This joke is about how time flies when you're having fun. The person was supposed to start writing a paper at 5:00 PM, but they started playing with a language model instead. They thought they were only playing with it for 10 minutes, but it was actually 4.5 hours.

Input: I think I understand why me and my partner are such a good match. I get excited when I smell food and become super alert when the doorbell rings. My girlfriend Shelley becomes ecstatic when she sees a person who she just saw 5 hours ago.
Model Output: This joke is about dogs. Dogs get excited when they smell food and when the doorbell rings. The girlfriend is excited to see someone she just saw 5 hours ago, which is a trait of dogs.

Input: I was going to fly to visit my family on April 6th. My mom said "Oh great, your step dad's poetry reading is that night!" So now I'm flying in on April 7th.
Model Output: The joke is that the speaker's mother is trying to get them to go to their step dad's poetry reading, but the speaker doesn't want to go, so they are changing their flight to the day after the poetry reading.

Input: I tried 10,000 random restarts of my neural network, but I was accused of overfitting. I guess no good seed goes unpunished.
Model Output: This joke is a pun. A neural network is a computer program that can learn from data. A "seed" is a number that is used to initialize a random number generator. A "good seed" is a number that produces a good random number generator. The phrase "no good deed goes unpunished" means that if you do something good, you will be punished for it.

Input: Reading "War and Peace" doesn't scare me. I once had to review the CL for my intern's whole project on his final day!
Model Output: 'War and Peace' is a very long book, so reading it is a daunting task. However, the speaker is saying they had to review the code for their intern's project on their final day, which is even more daunting.

Input: What's the difference between a zebra and an umbrella? One is a striped animal related to horses, another is a device you use to stop the rain from falling on you.
Model Output: This joke is an anti-joke. The joke is that the answer is obvious, and the joke is that you were expecting a funny answer.

https://ai.googleblog.com/2022/04/pathways-language-model-palm-scaling-to.html

Today

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