Deep Learning for NLP

The lecture starts at 13:15

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Relevant Literature

- Jurafsky & Martin, SLP, 3rd Edition: Chapters 6, 7
    - (including slides), references therein
- M. Nielsen, Neural Networks and Deep Learning, 2019

Contents

- Vector Semantics & Embeddings
  - Lexical and Vector Semantics
  - Words as Vectors
  - Measuring similarity & tf-idf
  - Word2Vec
- Neural Networks
  - Perceptron, units, activation functions
  - Feed forward
  - Training
- Neural Language Models

Vector Semantics & Embeddings

Distributional Hypothesis

- First formulated in 1950 (Joos), 1954 (Harris), 1957 (Firth)
- Observation: synonyms tend to occur in the same environment

  oculist and *eye-doctor*

  "An oculist is just an eye-doctor under a fancier name"

  near *eye* or *examined* (but not near *lawyer*)

  "… Burns was an oculist, but since he didn't know the professional titles, he didn't realize that he could go to him to have his eyes examined"

- **"Does a language have a distributional structure?"** (Harris)

  "occurrences of parts … relative to other parts"

  "without intrusion of other features" (meaning)

Distributional Hypothesis

- First formulated in 1950 (Joos), 1954 (Harris), 1957 (Firth)
- **“Does a language have a distributional structure?”** (Harris)

  “occurrences of parts … relative to other parts”

  “without intrusion of other features” (meaning)

- Distribution of an element (of a part): sum of all its environments

  “An oculist is just an eye-doctor under a fancier name”

  “… Burns was an oculist, but since he didn't

Distributional Hypothesis

- First formulated in 1950 (Joos), 1954 (Harris), 1957 (Firth)
- **"Does a language have a distributional structure?"** (Harris)

  "occurrences of parts … relative to other parts"

  "without intrusion of other features" (meaning)

- Words that are synonyms occur in the same environment
- Words occurring in similar contexts (environment) tend to have similar meanings"
- Difference in similarity between those two terms **correlates** with the difference in their environments.

Distributional Hypothesis – Vector Semantics

- First formulated in 1950 (Joos), 1954 (Harris), 1957 (Firth)

- Words that are synonyms occur in the same environment
- Words occurring in similar contexts (environment) tend to have similar meanings”
- Difference in similarity between those two terms **correlates** with the difference in their environments.

- Vector semantics = instantiation of the distributional hypothesis
  - Representation learning (embeddings)

Lexical Semantics

Q: How to represent the meaning of a word?

- N-Gram: string of letters/characters
- Index in a vocabulary list
- …

But:

- *cold* vs. *hot*
- *happy* vs. *sad*

The trophy doesn't fit into the brown suitcase because it's too small.

-> Model of the **meaning**

Lexical Semantics

-> Model of the **meaning**

The trophy doesn't fit into the brown suitcase because it's too small.

Draw useful inferences to help us solve meaning-related tasks:

Q&A

Plagiarism & paraphrasing

Dialogue

Summarization

Last week: Logical semantics, graph based formalism

Lexical Semantics - Lemma and Senses

Lemma == dictionary form == citation form

```
mouse (N)
1.  any of numerous small rodents...
2.  a hand-operated device that controls a cursor...
```

word senses
(polysemous)

mouse is the **lemma** for *mice* (will not be in the dictionary)

mice == **word form**

Lemma is what you find in the dictionary

Lexical Semantics – Synonymy

- Identical meanings:
  - couch/sofa vomit/throw up car/automobile water / H2O

- Two words are synonyms if they are substitutable for each other in any sentence, without changing the truth […] of the sentence (i.e. same propositional meaning).

- Truth preserving !≈ identical in meaning

  "I was hiking and my bottle of *water* was empty."

  Principle of contrast

On average an english word has 1.6 synonyms
But truth preserving is not the same as identical meaning

„You can substitute H20 but the meaning is not the same (but truth is preserved)
This is called the principle of contrast. This is because having H20 brings additional information (like that likely that a chemist used this word)

Lexical Semantics – Antonymity

- Opposite senses:
  - up / down   hot / cold   in / out

- Can define binary opposition
- Can be at the opposite ends of a scala (long / short)
- Can be reversives (rise / fall)

Lexical Semantics – Similarity

Similar meaning, but not synonyms

`car, bicycle`

`cow, horse`

There are many similar words.
car and bicycle and not synonyms but they are both for moving

We're moving from the sense of a word to comparing words.
How do you decide if 2 words are similar:
- ask human (see experiment on RHS)

Sense vs. sense

Word vs. word

vanish	disappear	9.8
behave	obey	7.3
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

Lexical Semantics - Relatedness

Words are related by

- Semantic fields
- …

`car, bicycle`: **similar**

`car, gasoline`: **related**, not similar

Also called word association.

Lexical Semantics - Relatedness

Words are related by

- Semantic fields (surgeon, scalpel, nurse, anaesthetic, hospital)
- ...

`car, bicycle`: **similar**

`car, gasoline`: **related**, not similar

- -> topic models (LDA)

The way that NLP connect these words is through the usage of semantic fields

LDA takes thiese words and try to detect the similarity

Lexical Semantics – Superordinate / Subordinate

One sense is a **subordinate** of the other:
the first is more specific (subclass of the other)

- `car` subordinate of `vehicle`.
- `vehicle` **superordinate** of `car`.

Lexical Semantics – Connotations

Words have affective meanings

- positive connotations (happy)
- negative connotations (sad)

positive evaluation (great, love)

negative evaluation (terrible, hate).

Vector Semantics

Combines the intuition of distribution (looking where the word occurs in relation to how close they are) and some form of

Computational model to deal with these different aspects?

Combines the distributionalist intuition and the vector intuition.

Affective meaning variance along axes:

- Valence (pleasantness)
- Arousal (intensity of emotion)
- Dominance (degree of control)

	Valence	Arousal	Dominance
courageous	8.05	5.5	7.38
music	7.67	5.57	6.5
heartbreak	2.45	5.65	3.58
cub	6.71	3.95	4.24
life	6.68	5.59	5.89

Experiement to rate each word with respect to these axes.
Then words were compared with vector comparison and it was the first encoding of words as vector.
This model was done to try and find some dimensions to the words.

Osgood et al. (1957)

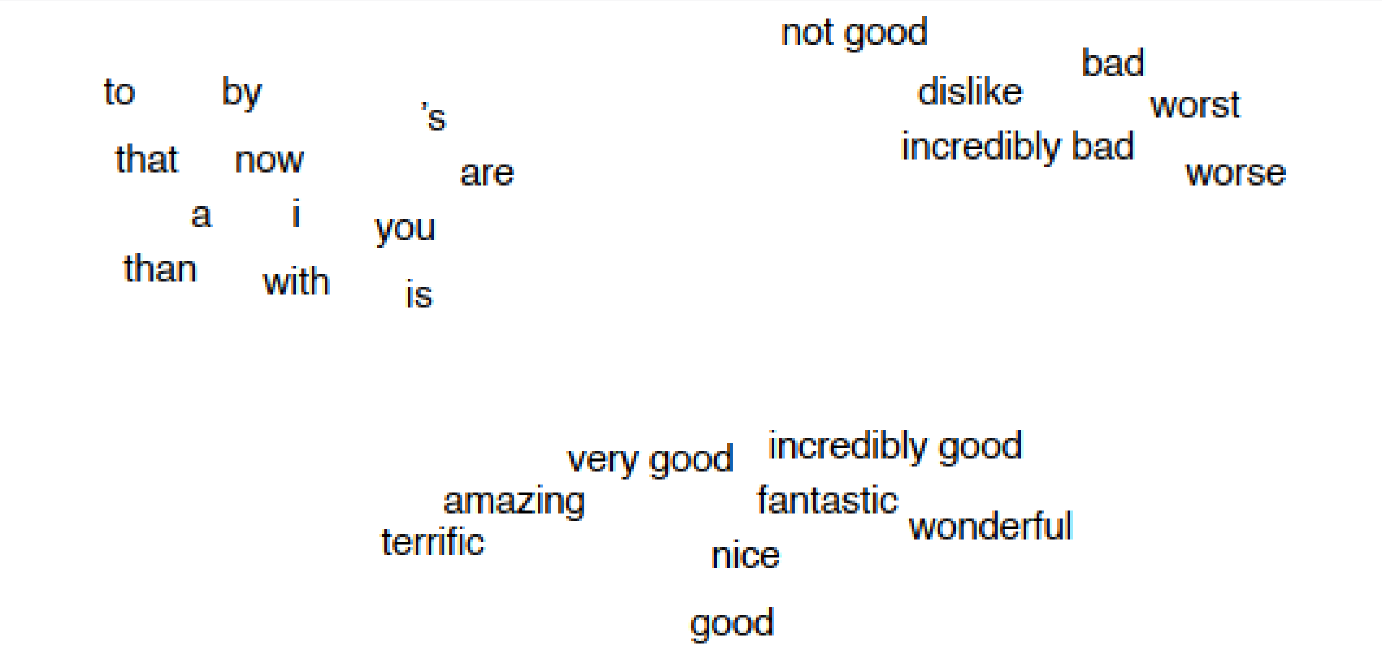
Now we define words as vectors and place them in this numerical space. This is called embedding

Vector Semantics

- Define words as vectors
- "embedding" – embedded into a (multi-dimentional) space

- Standard in NLP

The projection on this 2-dimensional space tends to group the words.



Types of Embeddings

- TF-IDF
  - Common baseline
  - Sparse vectors
  - Words as function of counts

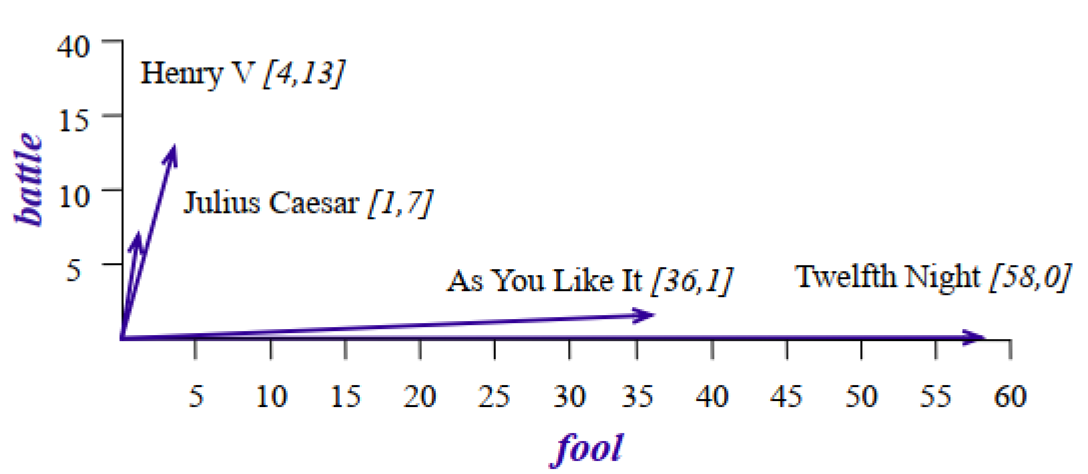
- Word2vec
  - Dense vectors
  - Representations distinguish between near/far words.

From Words to Vectors

Term-document matrix

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

- Vectors similar for the two comedies



From Words to Vectors

Term vector

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
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fool	36	58	1	4
wit	20	15	2	3

Word–word matrix (term–context matrix)

word-document matrix

Term-context – Matrix

Two **words** are similar in meaning if their context vectors are similar

is traditionally followed by	**cherry**	pie, a traditional dessert
often mixed, such as	**strawberry**	rhubarb pie. Apple pie
computer peripherals and personal	**digital**	assistants. These devices usually
a computer. This includes	**information**	available on the internet

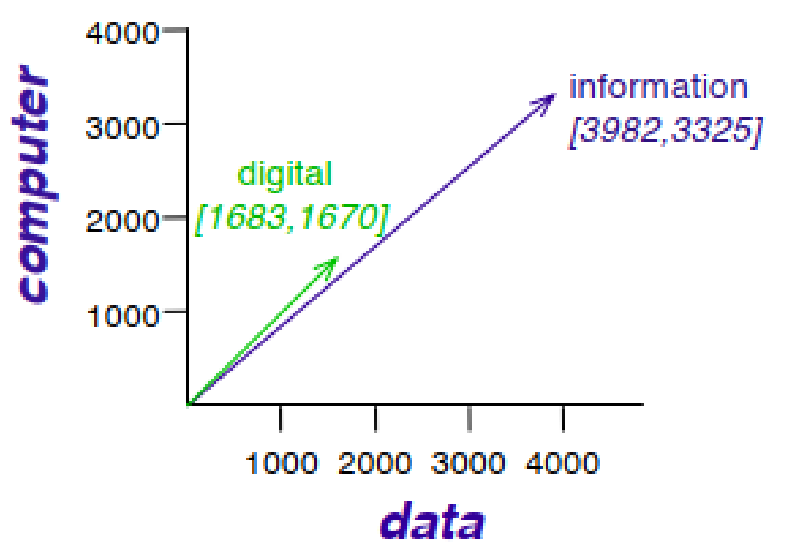
	aardvark	...	**computer**	**data**	**result**	**pie**	**sugar**	...
cherry	0	...	2	8	9	442	25	
strawberry	0	...	0	0	1	60	19	
digital	0	...	1670	1683	85	5	4	
information	0	...	3325	3982	378	5	13	

|V| x |V| (10K – 50K words), sparse vectors!

Cosine for Similarity

Measure the angle between vectors

$$\text{cosine}(\mathbf{v},\mathbf{w}) = \frac{\mathbf{v}\cdot\mathbf{w}}{|\mathbf{v}||\mathbf{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$



Cosine example

However ….

raw-frequencies are

skewed

non-discriminative

	pie	data	computer
cherry	442	8	2
digital	5	1683	1670
information	5	3982	3325

$$\cos(\text{cherry}, \text{information}) = \frac{442 * 5 + 8 * 3982 + 2 * 3325}{\sqrt{442^2 + 8^2 + 2^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .017$$

$$\cos(\text{digital}, \text{information}) = \frac{5 * 5 + 1683 * 3982 + 1670 * 3325}{\sqrt{5^2 + 1683^2 + 1670^2}\sqrt{5^2 + 3982^2 + 3325^2}} = .996$$

TF-IDF

- **TF: term frequency**. frequency count (log-ransformed):

$$\mathrm{tf}_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{count}(t,d) & \text{if } \mathrm{count}(t,d) > 0 \\ 0 & \text{otherwise} \end{cases}$$

log flattens the large numbers

- **IDF: inverse document frequency:**

$$\mathrm{idf}_t = \log_{10}\left(\frac{N}{\mathrm{df}_t}\right)$$

! *df* – document frequency – is not collection frequency

TF-IDF

- **TF: term frequency**. frequency count (log-ransformed):

$$\mathrm{tf}_{t,d} = \begin{cases} 1+\log_{10}\mathrm{count}(t,d) & \text{if } \mathrm{count}(t,d)>0 \\ 0 & \text{otherwise} \end{cases}$$

- IDF: inverse document frequency:

$$\mathrm{idf}_t = \log_{10}\left(\frac{N}{\mathrm{df}_t}\right)$$

- TF-IDF weighted value:

$$w_{t,d} = \mathrm{tf}_{t,d} \times \mathrm{idf}_t$$

TF-IDF vs Raw Frequencies

Raw frequencies

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

TF-IDF frequencies

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

good appears a lot but does not really help with understanding the documents
so we got rid of it.

Recap

- Vector Semantics & Embeddings
  - Lexical and Vector Semantics
  - Words as Vectors
  - Measuring similarity & tf-idf
    - Sparse

  - Word2Vec

Dense Vectors – Word2Vec

TF-IDF vectors are

- long (length |V|= 20,000 to 50,000)
- sparse (most elements are zero)

Main problem with this is that it leads to quite big matrices

Want vectors which are

- short (length 50-1000)
- dense (most elements are non-zero)

Dense Vectors – Word2Vec

Why dense vectors?

Generally better than tf-idf. tf-idf are only based on presence absence and synonyms are hard to detect with cosine distance, so it depends a lot on which dimensions you use and if you have many dimension you have a lot of noise.

- easier to use as features in machine learning (less weights to tune)
- generalize better than storing explicit counts
- They may do better at capturing synonymy, because:
  - `car` and `automobile` are synonyms; but are distinct dimensions in TF-IDF space
  - a word with `car` as a neighbour and a word with `automobile` as a neighbour should be similar, but aren't (in sparse vector/TF-IDF models)
- In practice, they work better

Where to look for Dense Embeddings

Word2vec (Mikolov et al.)

https://code.google.com/archive/p/word2vec/

Fasttext

http://www.fasttext.cc/

Glove (Pennington, Socher, Manning)

http://nlp.stanford.edu/projects/glove/

Word2Vec

Very popular and at the basis of everything embedding method

In word2vec you are computing probabilities instead of counting.

- Popular embedding method
- Very fast to train
- Code available on the web

Idea: **predict** rather than **count**

Word2Vec Intuition

- 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 "*apricot*"?

- We don’t actually care about this task
  - But we'll take the learned classifier weights as the word embeddings

Brilliant Insight!

implicitly supervised because the text written by a human is technically correct

Use running text as implicitly supervised training data!

Take a word *s* near *apricot* see it as the gold ‘correct answer’ to the question :

“Is word *w* likely to show up near apricot?”

No need for hand-labeled supervision

The idea comes from neural language modeling (2003, 2011)

Word2Vec: Skip-Gram

- "skip-gram with negative sampling" (SGNS)

1. Treat the target word and a neighboring context word as positive examples.
2. Randomly sample other words in the lexicon to get negative samples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the weights as the embeddings

Word2Vec Classification Task

Training sentences:

... lemon, a tablespoon of apricot jam a pinch ...

c1 c2 target c3 c4

Classification goal: Given a tuple (t, c) = target, context

- (*apricot*, *jam*)
- (*apricot*, *aardvark*)

- Compute the probability that c is a real context word:

$$P(+|t,c)$$

$$P(-|t,c) = 1 - P(+|t,c)$$

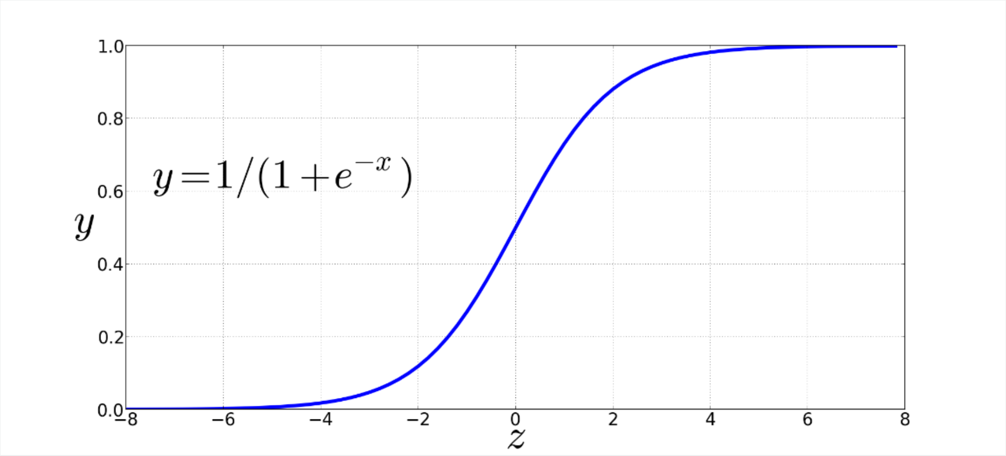
How to compute P(+|t,c)?

- Words are likely to appear near similar words
- Model similarity with dot-product!
- Similarity(t,c) $\propto t \cdot c$ same as cosine similarity but is not a probebility hence why we need logistic regression

Problem:

Dot product is not a probability!

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



Turning dot product into a probability

This assumes that all the words are independent -> very strong simplifying assumption

$$P(+|t,c) = \frac{1}{1+e^{-t\cdot c}}$$

$$P(+|t,c_{1:k}) = \prod_{i=1}^{k} \frac{1}{1+e^{-t\cdot c_i}}$$

$$\log P(+|t,c_{1:k}) = \sum_{i=1}^{k} \log \frac{1}{1+e^{-t\cdot c_i}}$$

$$\begin{aligned} P(-|t,c) &= 1-P(+|t,c) \\ &= \frac{e^{-t\cdot c}}{1+e^{-t\cdot c}} \end{aligned}$$

One word in the context of t

All words in the context of t

Simplifying assumption!

Skip-Gram Training Data

Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...
c1 c2 t c3 c4

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	preserves
apricot	or

negative examples -

t	c	t	c
apricot	aardvark	apricot	twelve
apricot	puddle	apricot	
apricot	where	apricot	
apricot	coaxial	apricot	

$$P_\alpha(w) = \frac{count(w)^\alpha}{\sum_{w'} count(w')^\alpha}$$

Noise words – selection by weighted unigram frequency

Training Phase

You create for your vocabulary 10000 vectors of length 300

Then you want to adjust these to ensure that what you get at the end makes sense.

Given:

- positive & negative training instances
- Initial set of embedding (random vector values) – length 300

Goal: Adjust embeddings such that

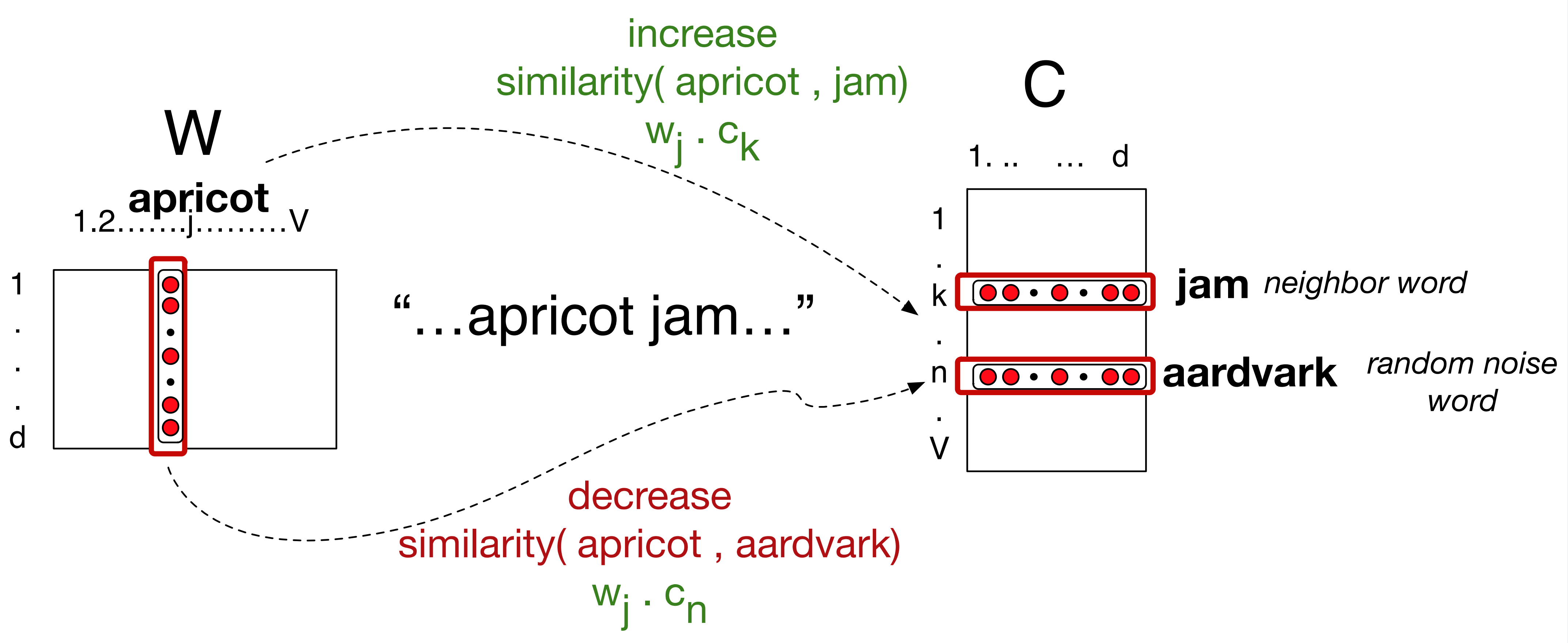
- Positive (target, context) instance similarity is maximised
- Necative (target, context) instance similarity is minimized

Formally:

$$L(\theta) = \sum_{(t,c)\in +} \log P(+|t,c) + \sum_{(t,c)\in -} \log P(-|t,c)$$

Use Gradient Descent

Training Phase



At beginning of algorithm W and C are same but at the end they no longer are. So now at the end we have an extra embedding for words in C, but we generally use the one in W

Summary: **How to** learn word2vec (skip-gram) embeddings

- Start with V random 300-dimensional vectors as initial embeddings
- Select positive / negative training data
- Use logistic regression
- Adjust weights by making positive pairs closer to each other (i.e. positive classification)

- Throw away the classifier code and keep the embeddings (regression weights!)

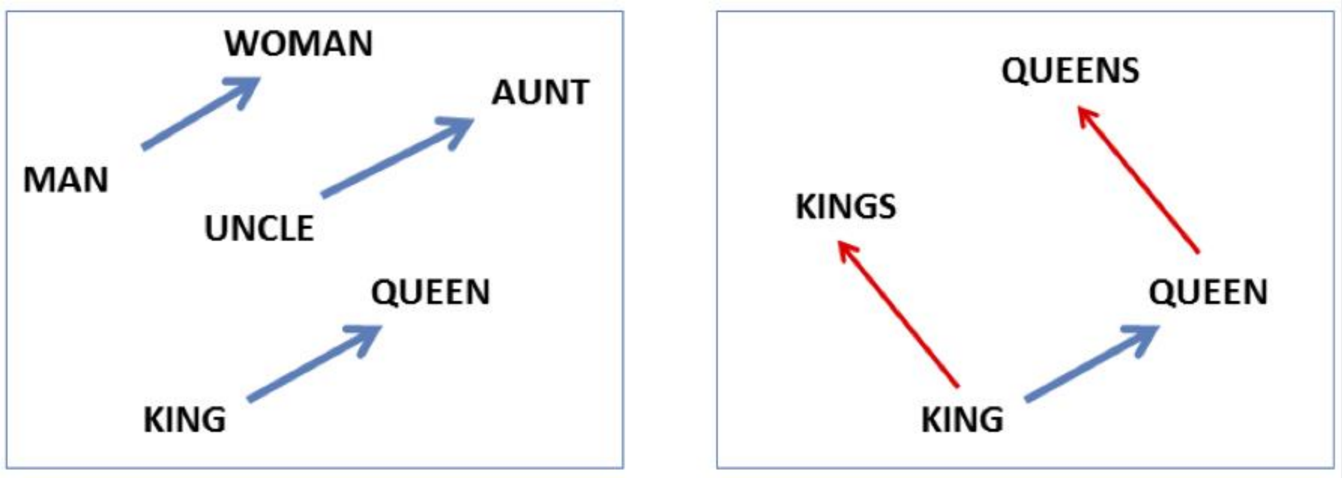
Word2Vec Embeddings: Semantic Properties

Similarity depends on context window size:

- Short context windows – similar words
- Long context windows – similar topics

Analogy: relational meaning appears to be captured

Distance between man and woman very similar to distance between uncle and aunt, which is good.



vector(‘*king*’) - vector(‘*man*’) + vector(‘*woman*’) ≈ vector(‘queen’)
vector(‘*Paris*’) - vector(‘*France*’) + vector(‘*Italy*’) ≈ vector(‘Rome’)

Cultural Bias in Embeddings

Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." In *Advances in Neural Information Processing Systems*, pp. 4349-4357. 2016.

Ask “Paris : France :: Tokyo : x”

x = Japan

Ask “father : doctor :: mother : x”

x = nurse

Ask “man : computer programmer :: woman : x”

x = homemaker

Cultural Bias in Embeddings

Implicit Association test (Greenwald et al 1998): How associated are

- concepts (*flowers*, *insects*) & attributes (*pleasantness*, *unpleasantness*)
- Studied by measuring timing latencies for categorization.

Psychological findings on US participants:

- African-American names are associated with unpleasant words (more than European-American names)
- Male names associated more with math, female names with arts
- Old people's names with unpleasant words, young people with pleasant words.

Embeddings reflect and replicate all sorts of pernicious biases.

Debiasing

Greenwald, A. G., McGhee, D. E., and Schwartz, J. L. K. (1998). Measuring individual differences in implicit cognition: the implicit association test. Journal of personality and social psychology, 74(6), 1464–1480.

Caliskan, Aylin, Joanna J. Bruson and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science 356:6334, 183-186.

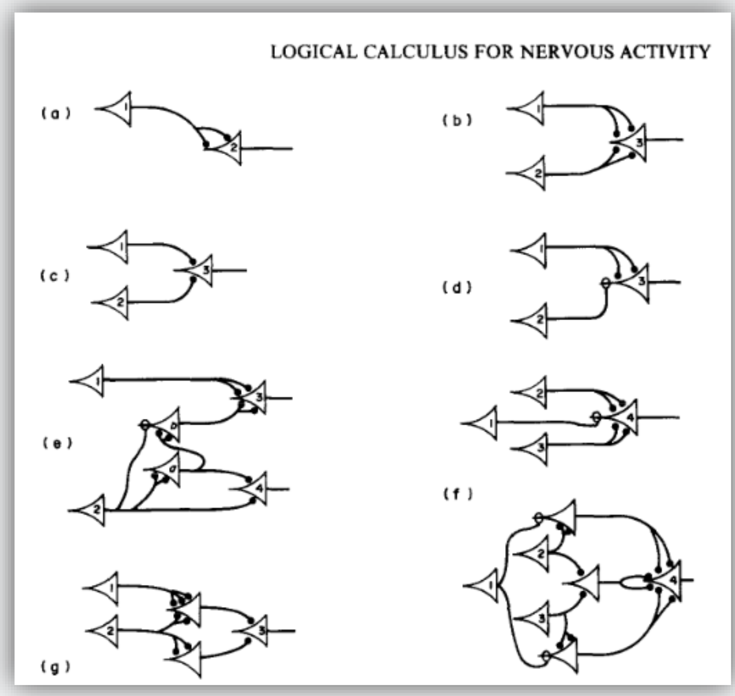
Recap

- Vector Semantics & Embeddings
  - Lexical and Vector Semantics
  - Words as Vectors
  - Measuring similarity & tf-idf
    - Sparse
  - Word2Vec
- Neural Networks

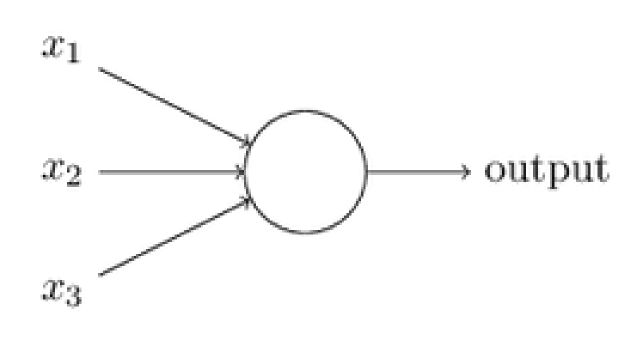
Neural Networks

Neural Networks – the beginnings

- In text processing – NNs are a fundamental computational tool
- 1943 McCulloch-Pitts neuron –> simplified model of a neuron
- Propositional logic &
    temporal propositional expressions



- 1950s and '60s
    perceptron



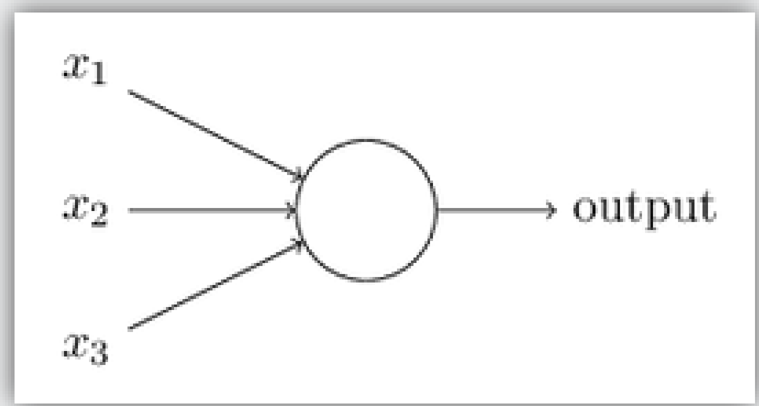
https://www.cs.cmu.edu/~./epxing/Class/10715/reading/McCulloch.and.Pitts.pdf

The Perceptron

- Simple rule to compute the output {0, 1}

- Inputs x_1, x_2, x_3
- Weights *w_i* for importance (*w_i* in $\mathbb{R}$)

- Weighted sum greater than a *threshold* then *output*



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

Perceptron – a Device that Takes a Decision

- A cheese festival coming weekend. You like cheese, and decide whether or not to go to the festival.
- You might make your decision by weighing up three (four) factors:

1. Is the weather good?
2. Does your friend/partner want to accompany you?
3. Is the festival near public transit? (You don't own a car)
4. Is there a Covid-19 curfew?

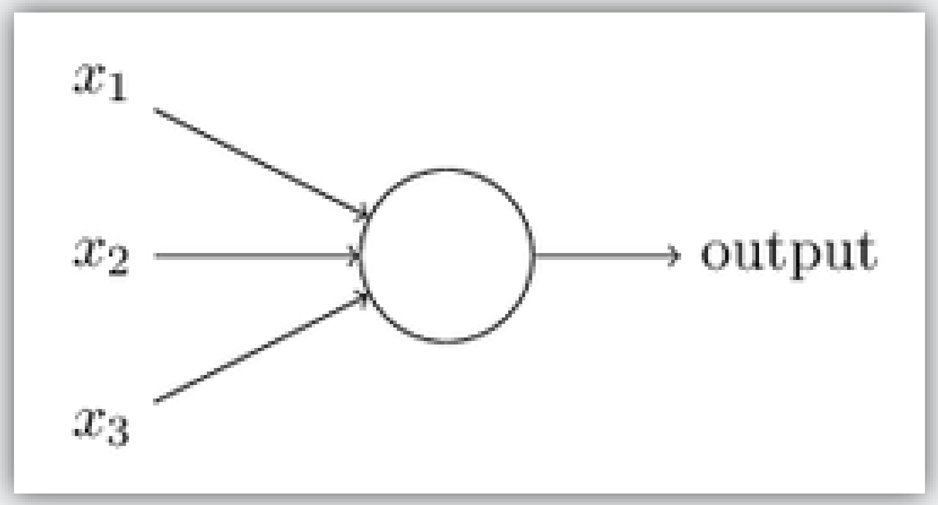
Perceptron – a Device that Takes a Decision

1. Is the weather good?

2. Friend/partner Joining?

3. Public transportation

4. Is there a Covid-19 curfew?



output = {1/go, 0/no_go}

Perceptron – a Device that Takes a Decision

1. Is the weather good?

    0 – bad, 1 – good

2. Friend/partner Joining?

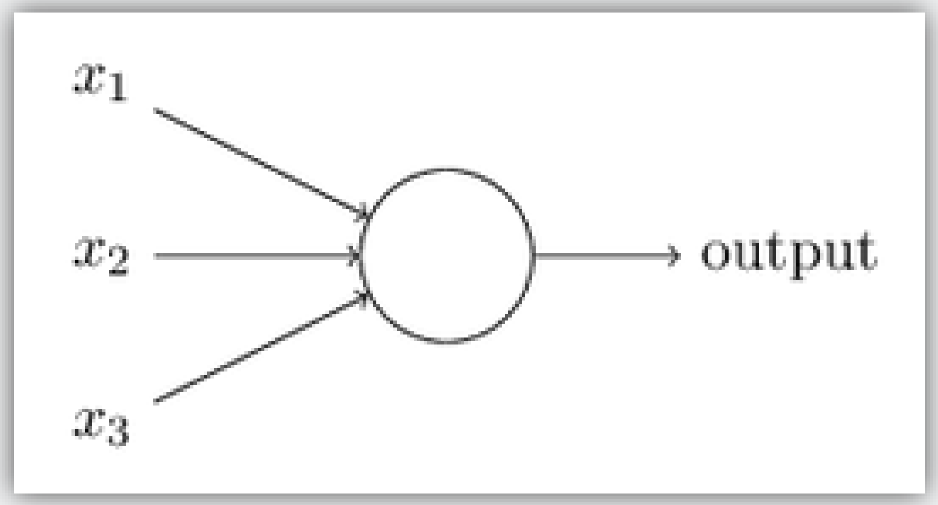
    0 – no, 1 – yes

3. Public transportation

    0 – no, 1 – yes

4. Is there a Covid-19 curfew?

    0 – no, 1 – yes



output = {1/go, 0/no_go}

Perceptron – a Device that Takes a Decision

1. Is the weather good?

   0 – bad, 1 – good, *w_1 = 6*

2. Friend/partner Joining?

   0 – no, 1 – yes *w_2 = 2*

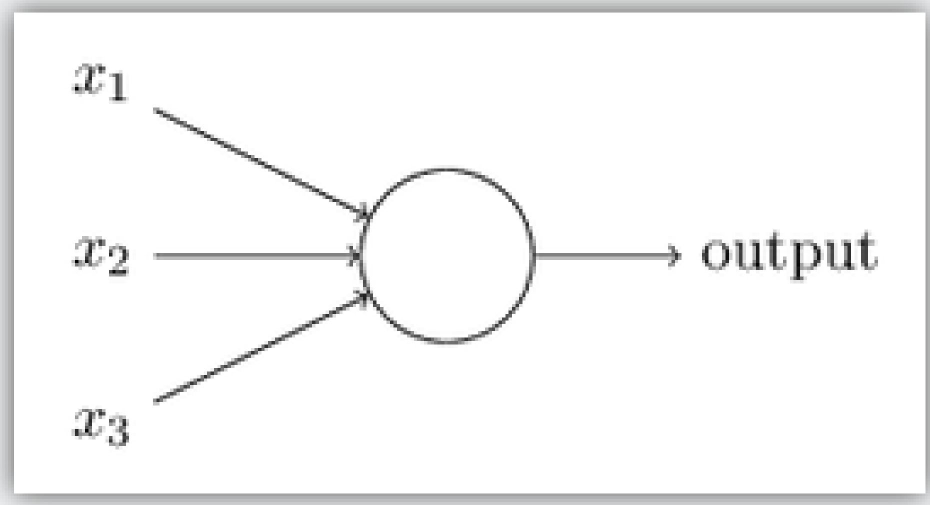
3. Public transportation

   0 – no, 1 – yes *w_3= 2*

4. Is there a Covid-19 curfew?

   0 – no, 1 – yes *w_4 = -5*

compute $\sum_j w_j x_j$



output = {1/go, 0/no_go}

threshold = 7

Perceptron – a Device that Takes a Decision

1. Is the weather good?

   0 – bad, **1 – good**, *w_1 = 6*

2. Friend/partner Joining?

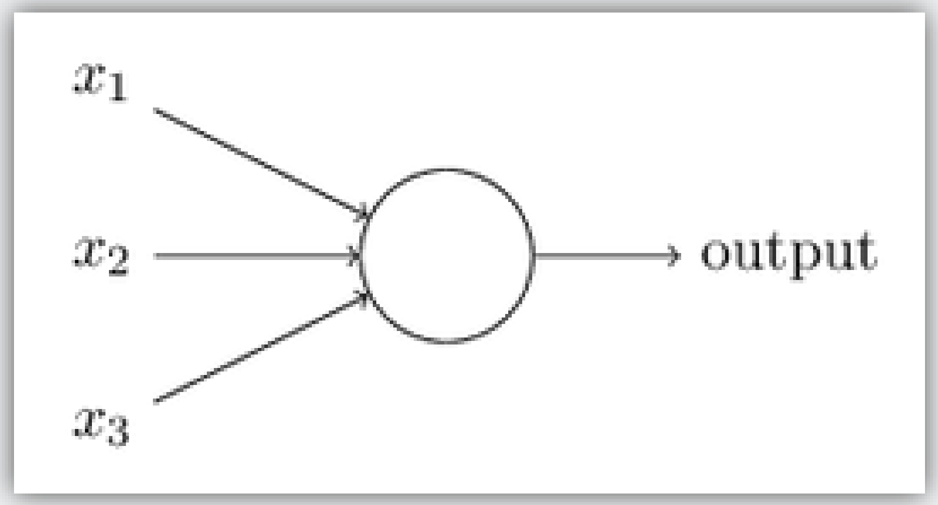
   0 – no, **1 – yes** *w_2 = 2*

3. Public transportation

   0 – no, 1 – yes *w_3= 2*

4. Is there a Covid-19 curfew?

   0 – no, **1 – yes** *w_4 = -5*



output = {1/go, 0/no_go}

threshold = 7

compute $\sum_j w_j x_j$ = 8 (go) = 3 (no_go)

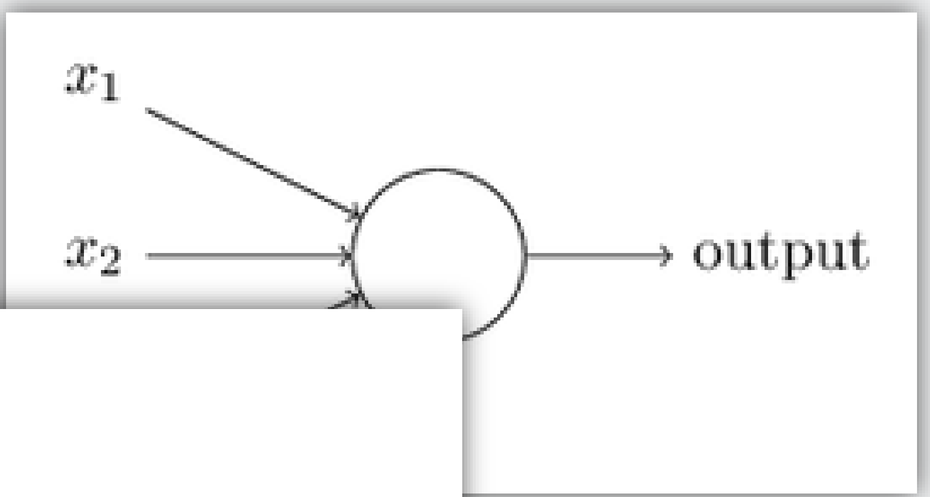
Perceptron – a Device that Takes a Decision

1. Is the weather good?

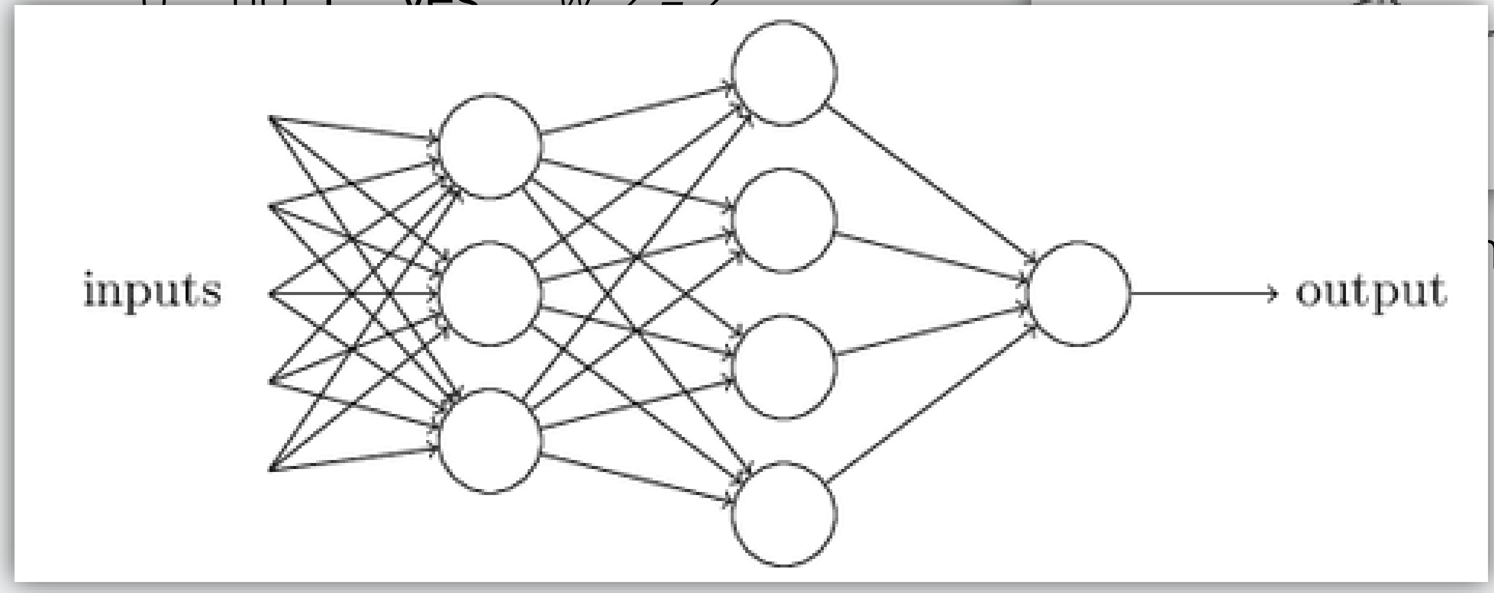
    0 – bad, **1 – good**, *w_1 = 6*

2. Friend/partner Joining?

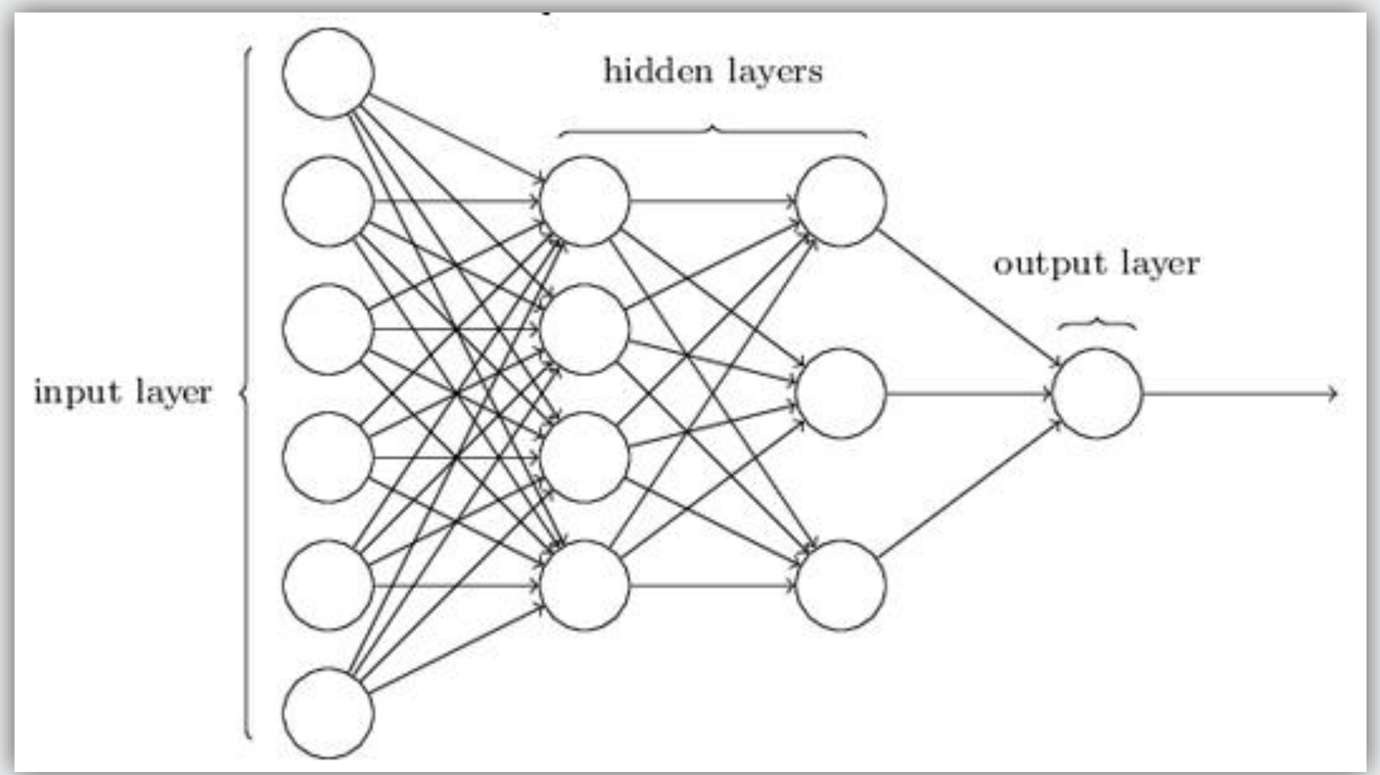
    0 – no, **1 – yes**, *w_2 = 2*



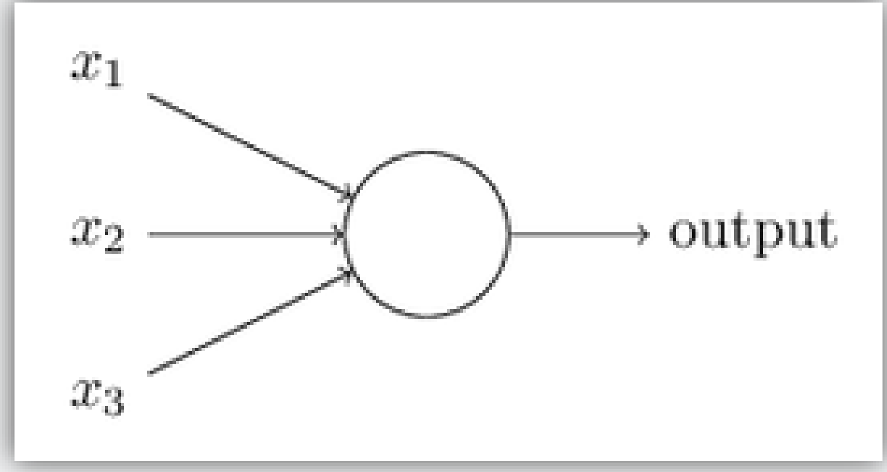
no_go}



Architecture of a (feedforward) Neural Network



Perceptron – some simplifications



$$\text{output} = \begin{cases} 0 & \text{if } \sum_j w_j x_j \leq \text{ threshold} \\ 1 & \text{if } \sum_j w_j x_j > \text{ threshold} \end{cases}$$

$$w \cdot x \equiv \sum_j w_j x_j$$

$$b \equiv -\text{threshold}$$

$$\text{output} = \begin{cases} 0 & \text{if } w \cdot x + b \leq 0 \\ 1 & \text{if } w \cdot x + b > 0 \end{cases}$$

1 ⇔ “firing” an electrical pulse

b – how easy it is to “fire”

Compute anything!

Perceptrons:

weigh evidence to make decisions

compute elementary logic functions

-> simulate an NAND gate (universality)

\+ Powerful tool

\- Just another NAND gate? – actually, no

Learning algorithms

Sigmoid Neuron

Perceptrons: small changes in intput cause large changes in output

Reason: Nodes (neurons) have only two states: 0 or 1

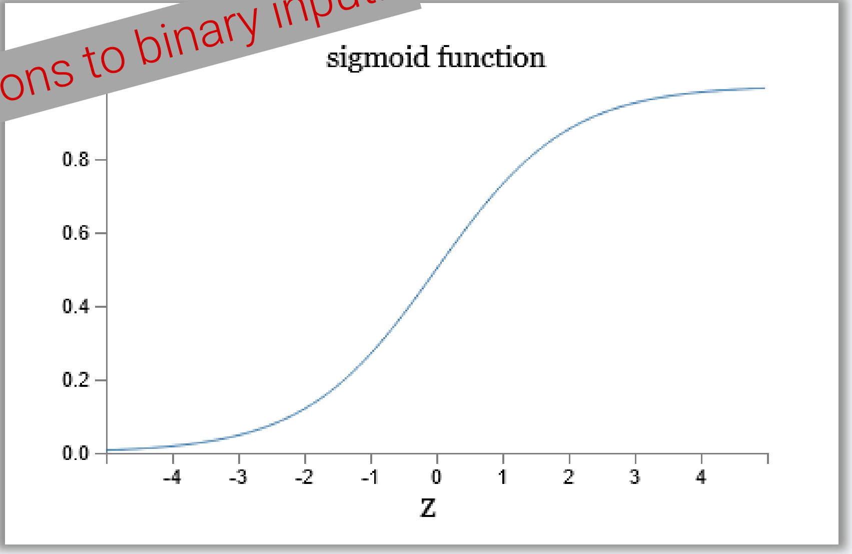
Can we output a continuum of values?

Between 0 and 1?

$$\sigma(z) \equiv \frac{1}{1+e^{-z}}.$$

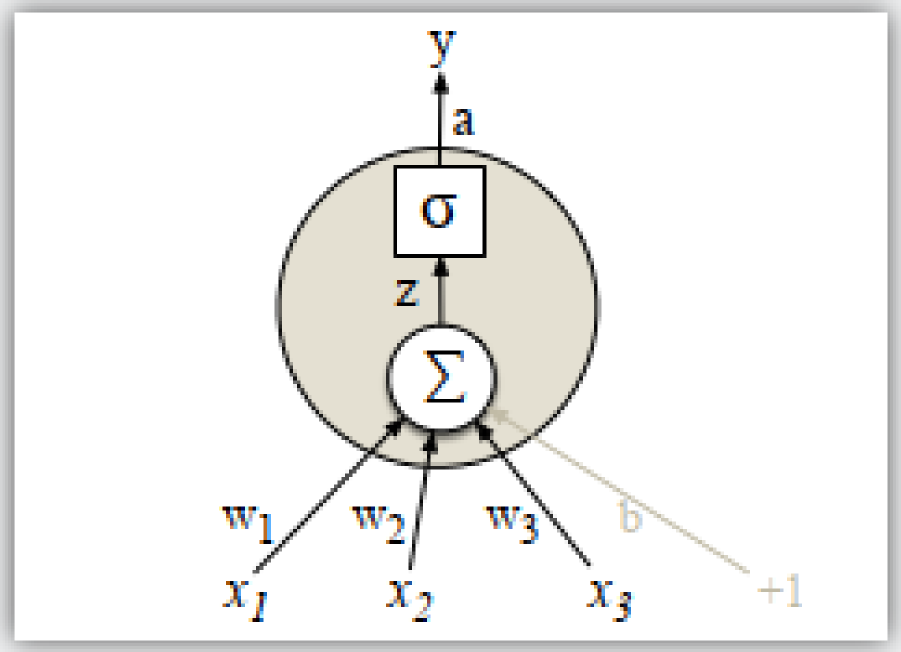
No restrictions to binary input!

$$\frac{1}{1+\exp(-\sum_j w_j x_j - b)}$$



Activation Functions

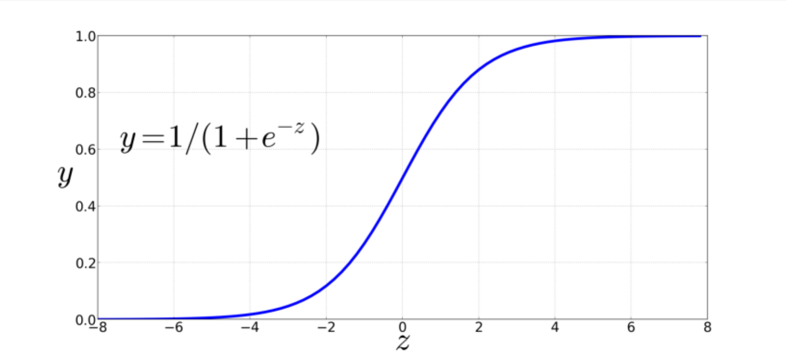
1. Sigmoid function
2. Hyperbolic tan
3. Rectified Linear Unit (ReLU)
4. Leaky Rectified Linear Unit
5. Maxout
6. …



Activation Functions

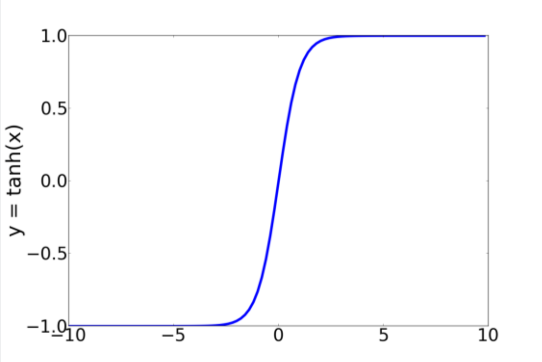
1. Sigmoid function

$$\frac{1}{1+e^{-z}}$$



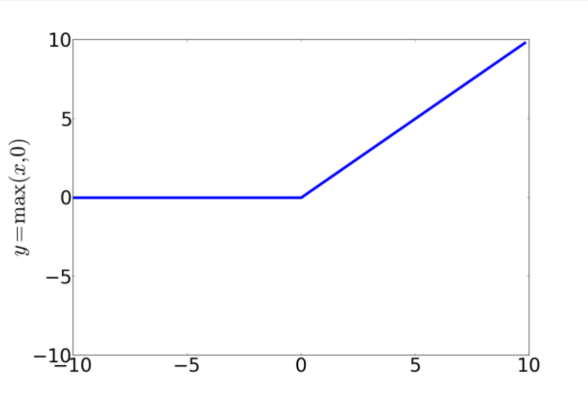
2. Hyperbolic tan

$$\frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$



3. Rectified Linear Unit (ReLU)

$$max(x,0)$$



Feed-Forward Neural Networks

- Multilayer network
- Units connected without cycles

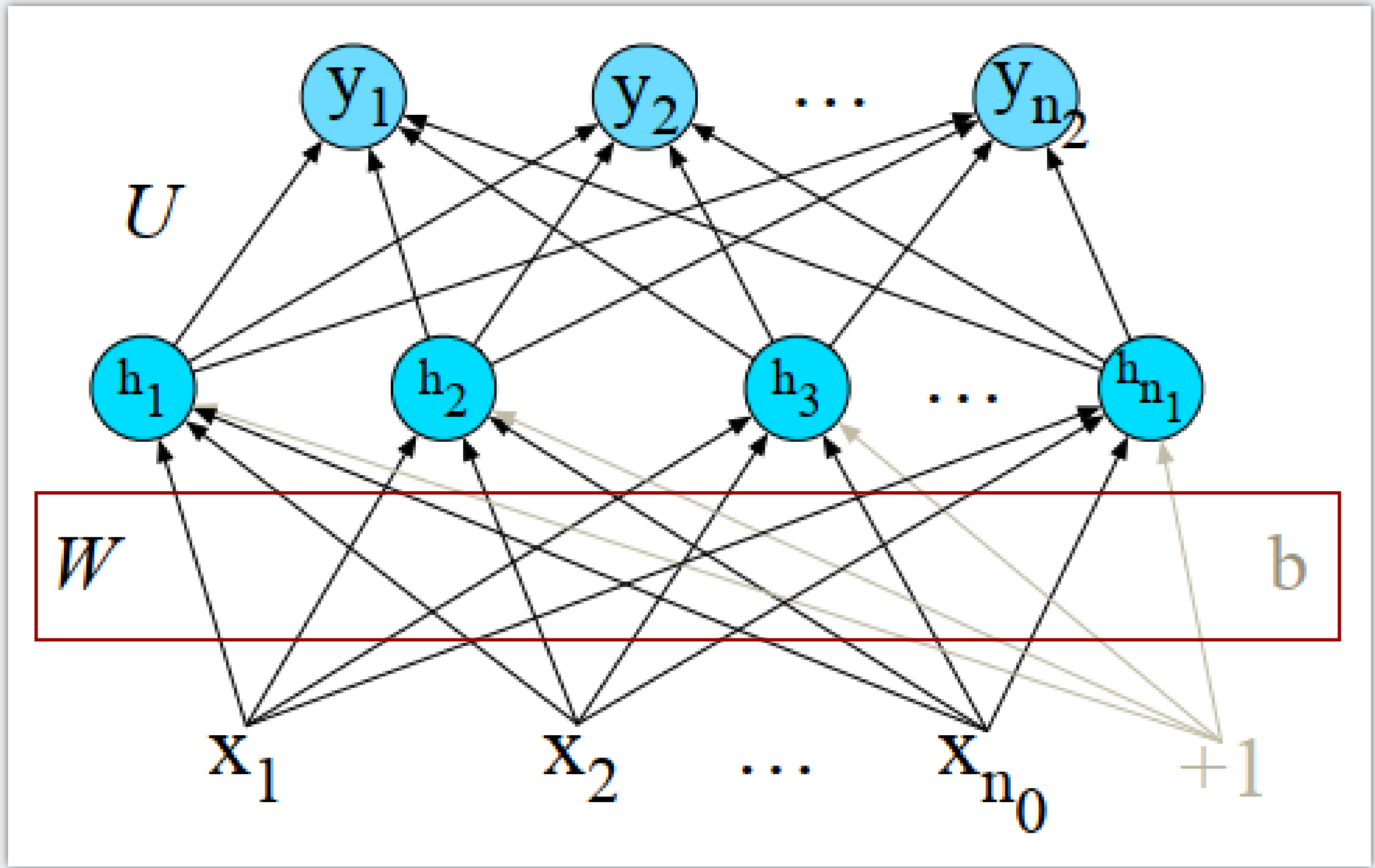
- Node types:
  - Input units
  - Hidden units
  - Output units

Feed-forward Neural Network

- Fully connected
- Hidden units sum over all inputs
- $W_{i,j}$ link between x_i and h_j

$h = \sigma\,(Wx + b)$

(elementwise)

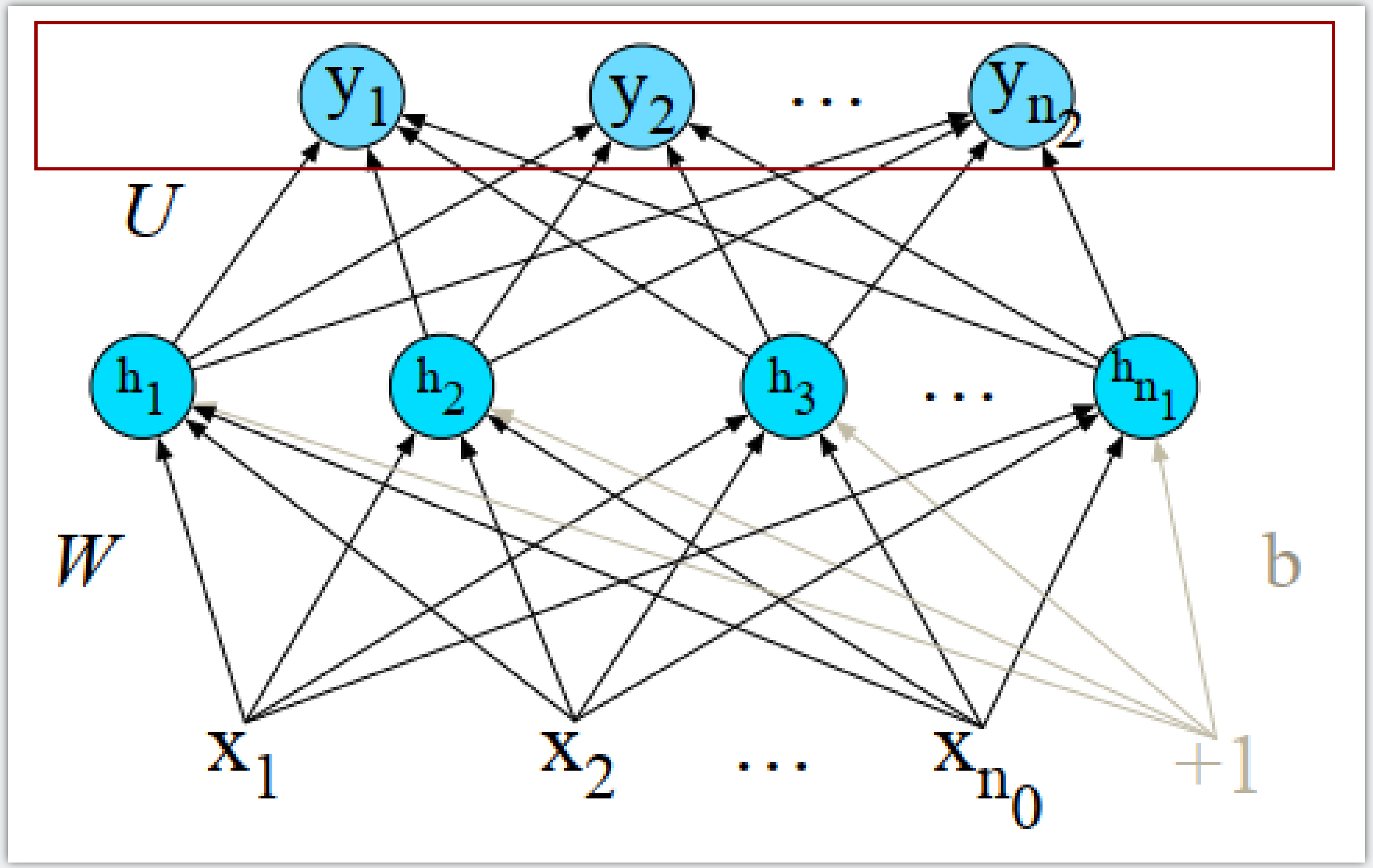


Feed-forward Neural Network

Output layer
probability distribution

Hidden layer (hypothesis)

Input layer



Feed-forward Neural Network

Output layer

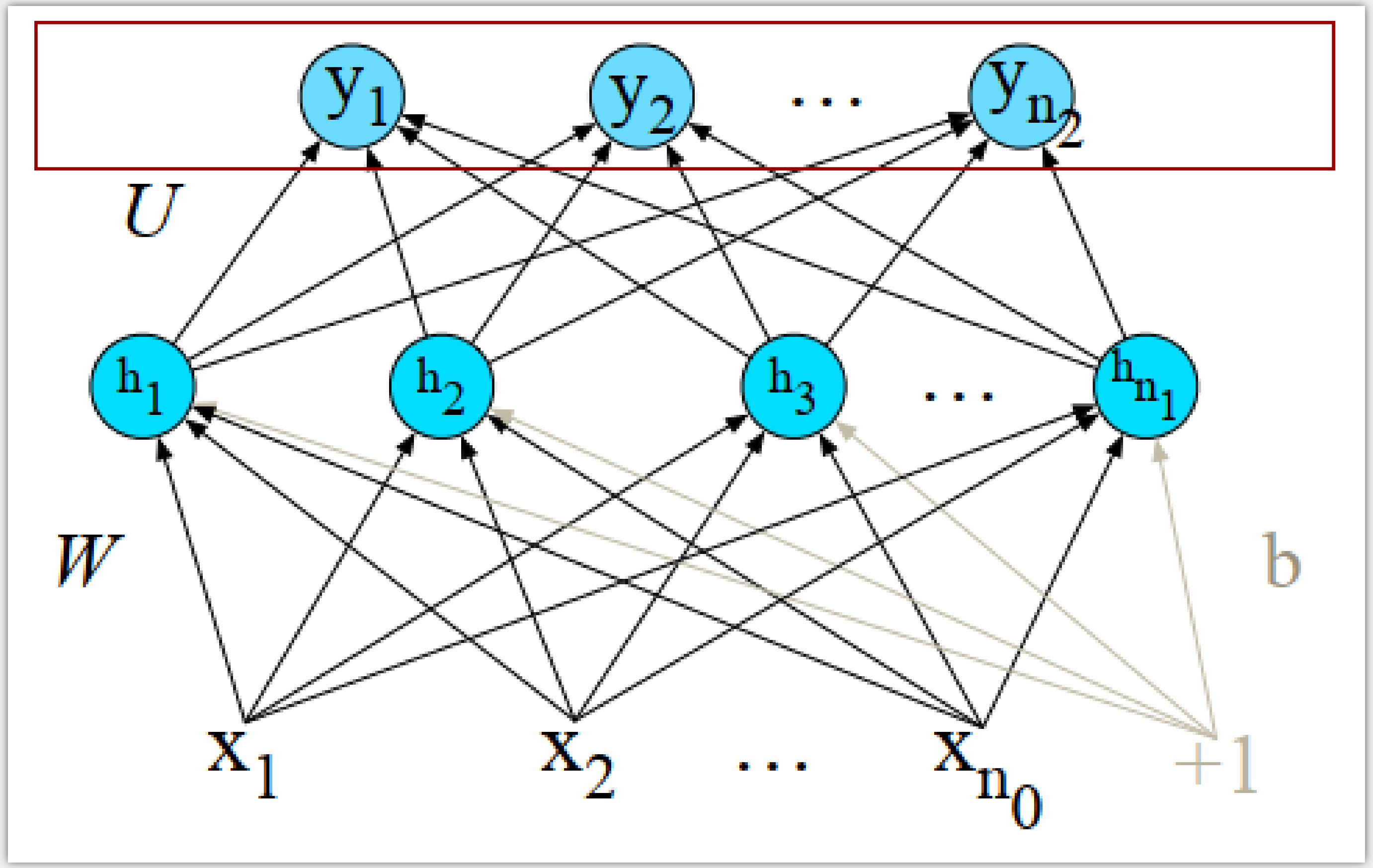
probability distribution

U output layer weight matrix

z = U h – no output

Normalizing

$$\mathrm{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{d} e^{z_j}} \quad 1 \le i \le d$$



Feed-forward Neural Network

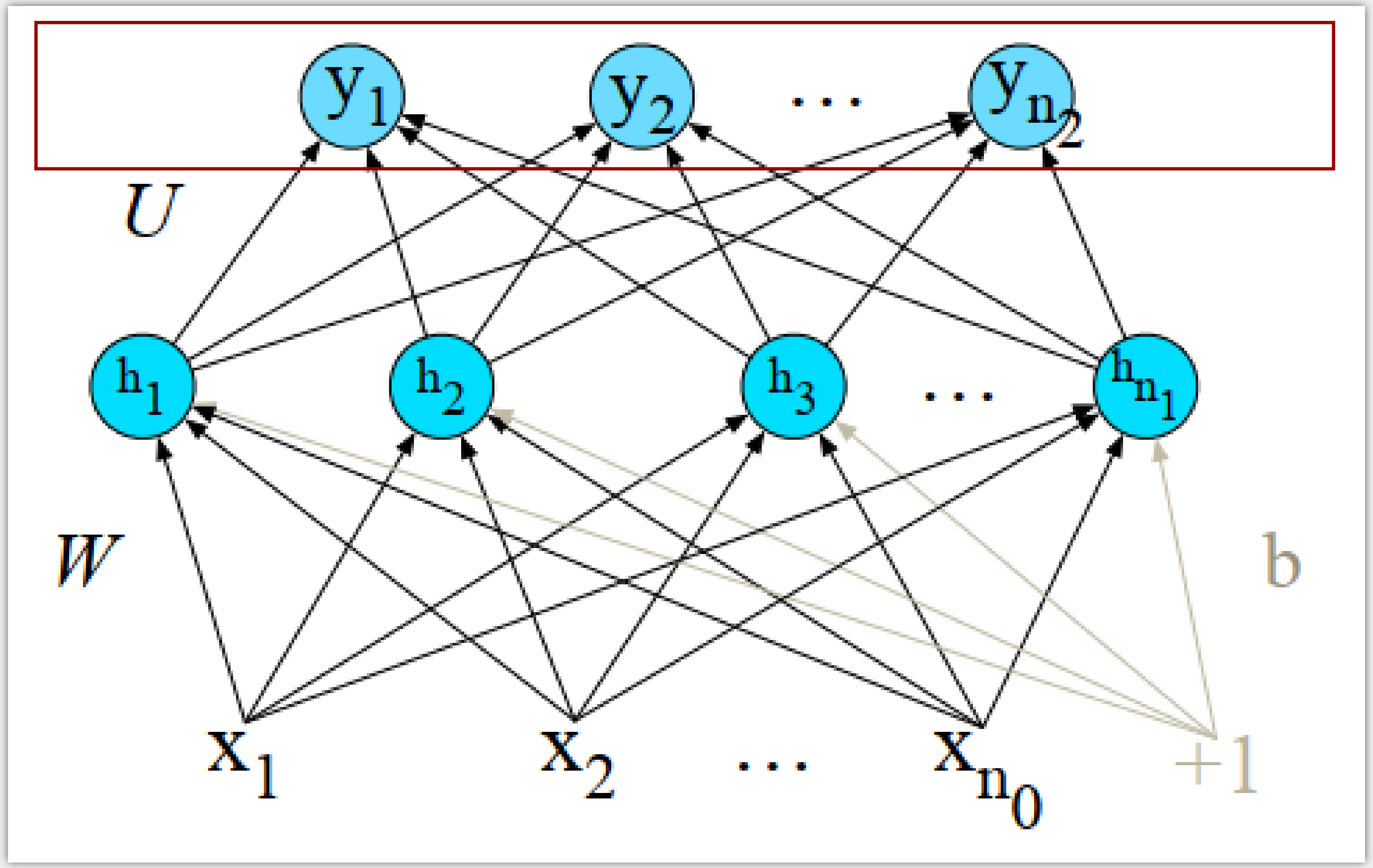
Output layer

probability distribution

Hidden layer (hypothesis)

representation of the input

Input layer



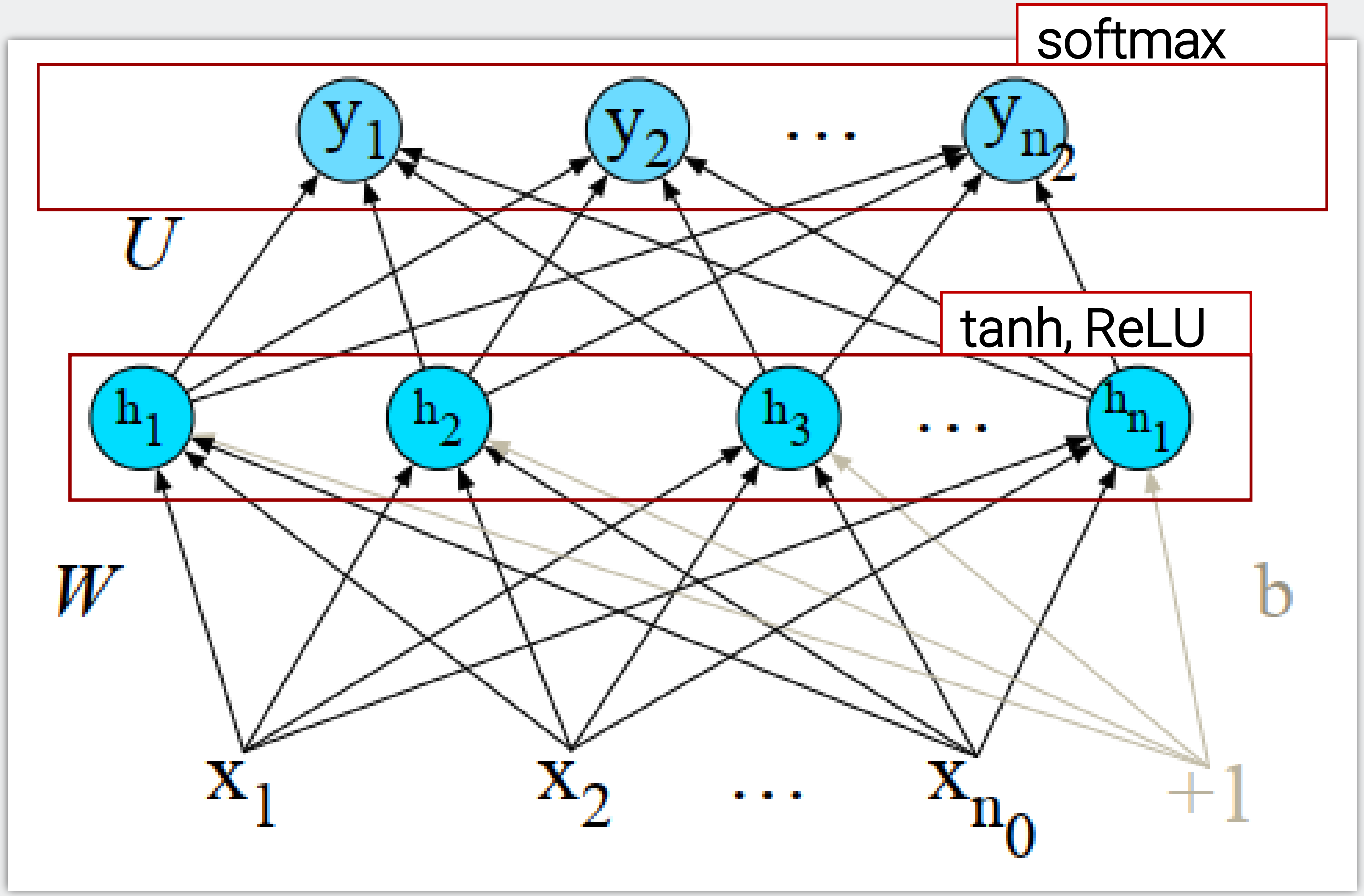
Feed-forward Neural Network

~ logistic regression:

(a) with many layers,

(b) induces the feature representations themselves (not "by hand").

$$
\begin{aligned}
h &= \sigma(Wx+b) \\
z &= Uh \\
y &= \text{softmax}(z)
\end{aligned}
$$

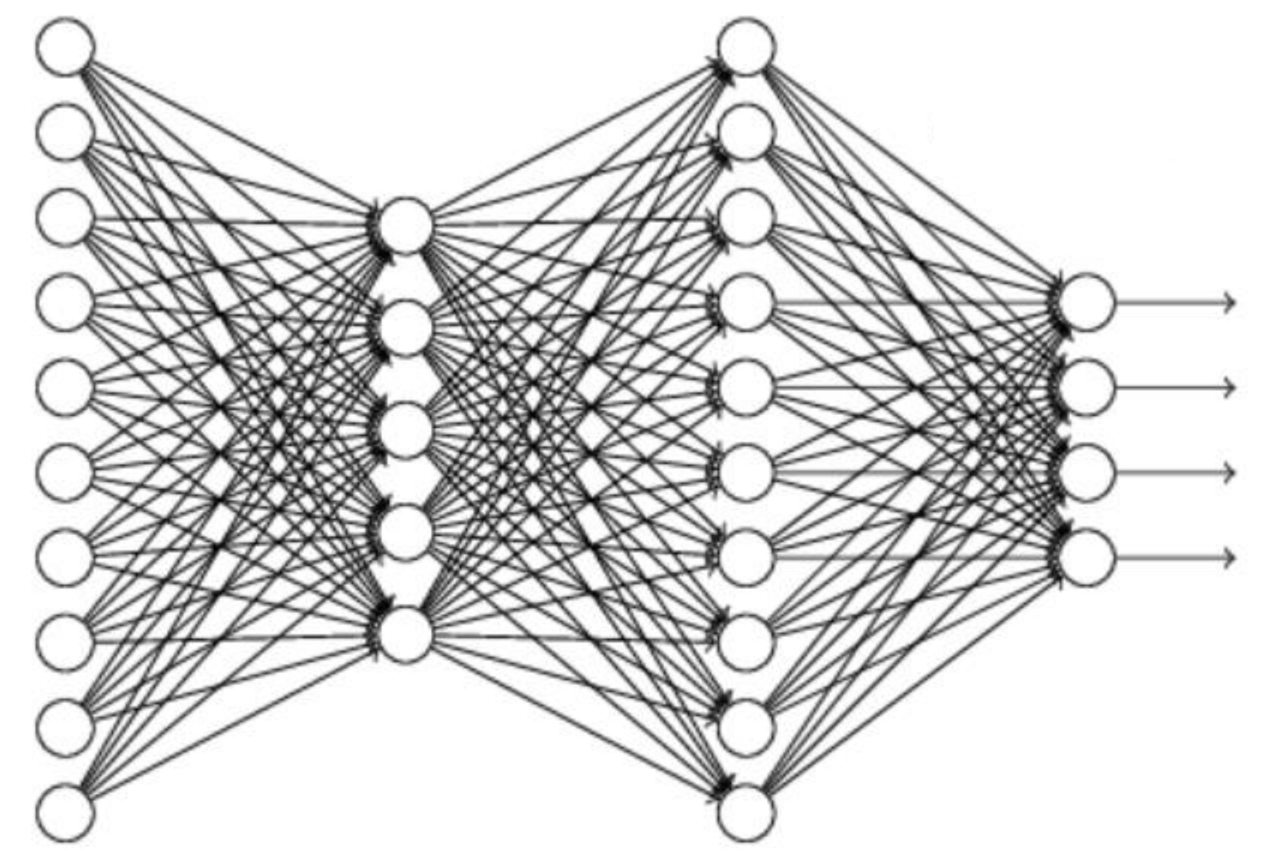


Training (Forward) Neural Networks

- Instance of supervised learning
- (x, y) training pairs
- ŷ system's estimate of y

- Find parameters W_i and b_i for each layer i s.t. ŷ as close to y as possible

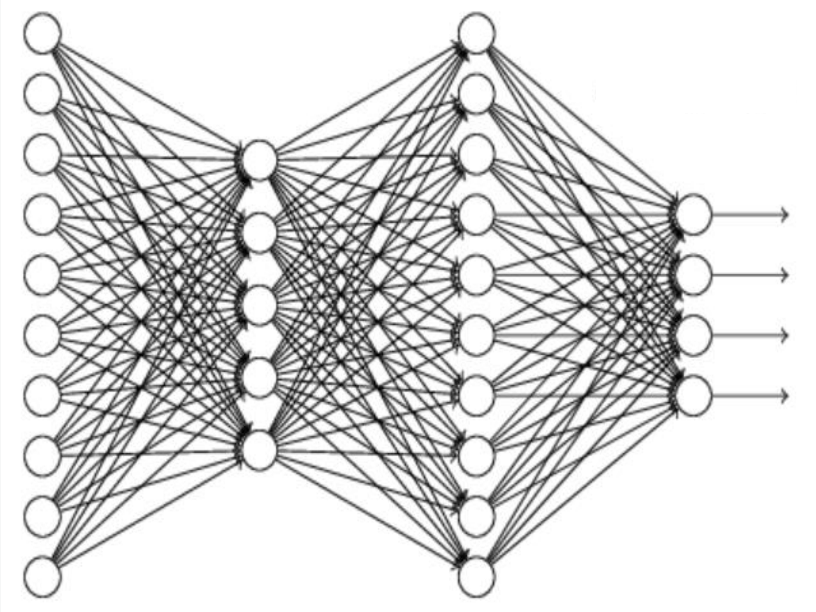
- Logistic regression (Chap 5, SLP3)



Training (Forward) Neural Networks

- Define a **loss function** (for ŷ and y)
  - Cross-entropy loss function
- Choose algorithm to minimize the **loss function**
  - Gradient descent
- Compute partial derivatives wrt. each parameter

- (1986) Error backpropagation
  a.k.a. reverse differentiation

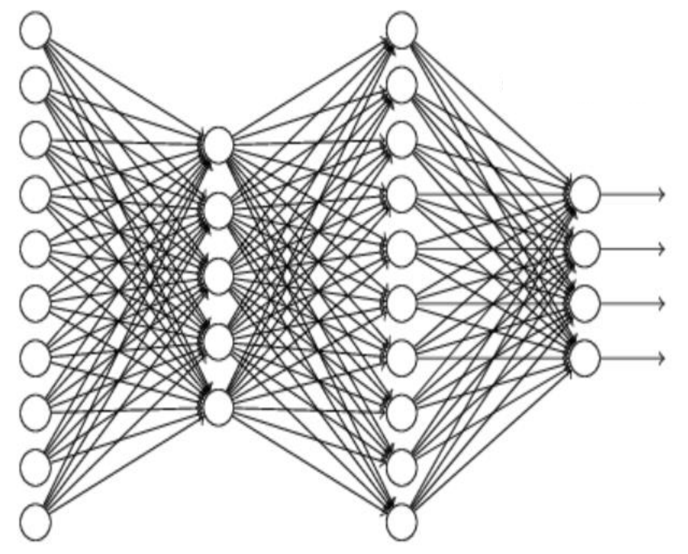


Training (Forward) Neural Networks

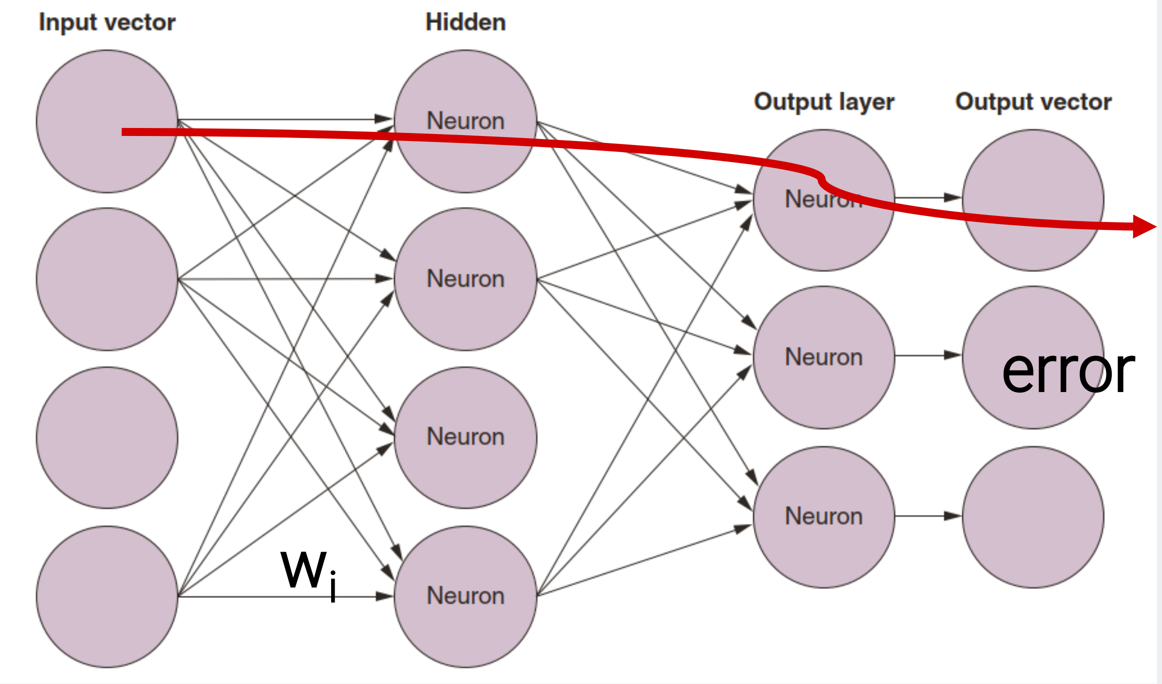
- Define a **loss function** (for ŷ and y)
  - Cross-entropy loss function
- Error backpropagation

- Requires activation functions that are continuously differentiable

- Derivative –> partial derivatives wrt. variables



Training (Forward) Neural Networks



LOSS(ŷ, y)

Composition of functions

(dot products and activation functions)

Chain rule (general form)

(F'(x) =) (f (g(x))' = f'(g(x))g'(x)

Chain rule: Finds you the derivative for the activation functions:

- For each neuron
- Wrt. its input

- Includes learning rate as hyper parameter

http://neuralnetworksanddeeplearning.com/index.html

Weight Changes – when to apply them?

- Be specific about it
- Calculations depend on the network state
- Changes are applied in one go to all the weights of the network
  - For each input
  - Aggregated, and applied after all training data was looked at.
  - Batched
  - …

Training Feed-Forward Neural Networks

1. Pass in all the inputs.
2. Get error for each input.
3. Backpropagate errors to each of the weights.
4. Update each weight with the total change in error

Steps 1.-4. for all training data

- EPOCH
- Can pass the data again -> new refinements

- Overfitting!

Optimizing Learning

- Weight initialization with random, small numbers
- Normalize input values
- Dropout: avoid overfitting
- Tuning hyperparameters
  - learning rate,
  - mini-batch size,
  - number of layers,
  - nodes / layer
  - choice of activation functions
- Gradient decent variants
- Computational graphs (pythorch, tensorflow)

Recap

- Vector Semantics & Embeddings
  - Lexical and Vector Semantics
  - Words as Vectors
  - Measuring similarity & tf-idf
  - Word2Vec
- Neural Networks
  - Perceptron, units, activation functions
  - Feed forward
  - Training
- Neural Language Models

Neural Language Models

Relevant Literature

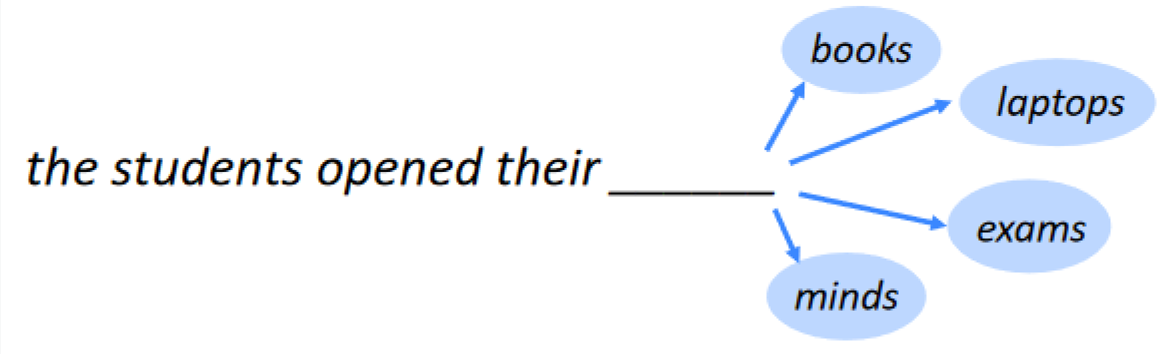
- Jurafsky & Martin, SLP, 3rd Edition: Chapters 7, 9
  - (including slides), references therein
- Cho, 2017, NLU with Distributional Representation, Chapters 4, 5
- Other material listed on individual slides

Content

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

Recall: Language Model

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$
- Probabilistic Language Models
  - Compare probabilities of sequence of words
  - Probability of upcoming word



Recall: Language Model

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$
- Probabilistic Language Models
  - Compare probabilities of sequence of words
  - Probability of upcoming word

- How did you compute P?
  - Count and divide
  - Markov Assumption

$$P(\text{the} \mid \text{its water is so transparent that}) = \frac{Count(\text{its water is so transparent that the})}{Count(\text{its water is so transparent that})}$$

$$P(\text{the} \mid \text{its water is so transparent that}) \text{ » } P(\text{the} \mid \text{that})$$

$$P(\text{the} \mid \text{its water is so transparent that}) \text{ » } P(\text{the} \mid \text{transparent that})$$

Recall: Language Model

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$
- Probabilistic Language Models
  - Compare probabilities of sequence of words
  - Probability of upcoming word

- How did you compute P?
  - Count and divide
  - Markov Assumption

- Unigrams
- Bi-grams
- …
- N-grams

Language Model: A simple example

$$P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

<s> I am Sam </s>

<s> Sam I am </s>

<s> I do not like green eggs and ham </s>

Symbols for the start and end of a sentence

$$P(\texttt{I} \mid \texttt{<s>}) = \tfrac{2}{3} = .67 \qquad P(\texttt{Sam} \mid \texttt{<s>}) = \tfrac{1}{3} = .33 \qquad P(\texttt{am} \mid \texttt{I}) = \tfrac{2}{3} = .67$$

$$P(\texttt{</s>} \mid \texttt{Sam}) = \tfrac{1}{2} = 0.5 \qquad P(\texttt{Sam} \mid \texttt{am}) = \tfrac{1}{2} = .5 \qquad P(\texttt{do} \mid \texttt{I}) = \tfrac{1}{3} = .33$$

Recall: Language Model

- A model that predicts P(W) or $P(w_n \mid w_1, w_2 \ldots w_{n-1})$
- Probabilistic Language Models
  - Compare probabilities of sequence of words
  - Probability of upcoming word

Perplexity

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i \mid w_1 \ldots w_{i-1})}}$$

- How did you compute P?
  - Count and divide
  - Markov Assumption

- Unigrams
- Bi-grams
- …
- N-grams

- Issues: zero probabilities, smoothing, interpolation

Neural Language Model

- No smoothing
- Longer histories (compared to the fixed N in ”N-gram”)
- Generalize over contexts

- Higher predictive accuracy!
- Further models are based on NLMs.

\- Slower to train!

Neural Language Model - Definition

- Standard Feed-Forward Network
- Input: a representation of previous words (w_1, w_2, …)
- Output: probability distribution over possible next words.

$$P(w_n \mid w_1, w_2 \ldots w_{n-1}) = f_\theta^{w_n}(w_1, w_2 \ldots w_{n-1})$$

Neural Language Model - Input

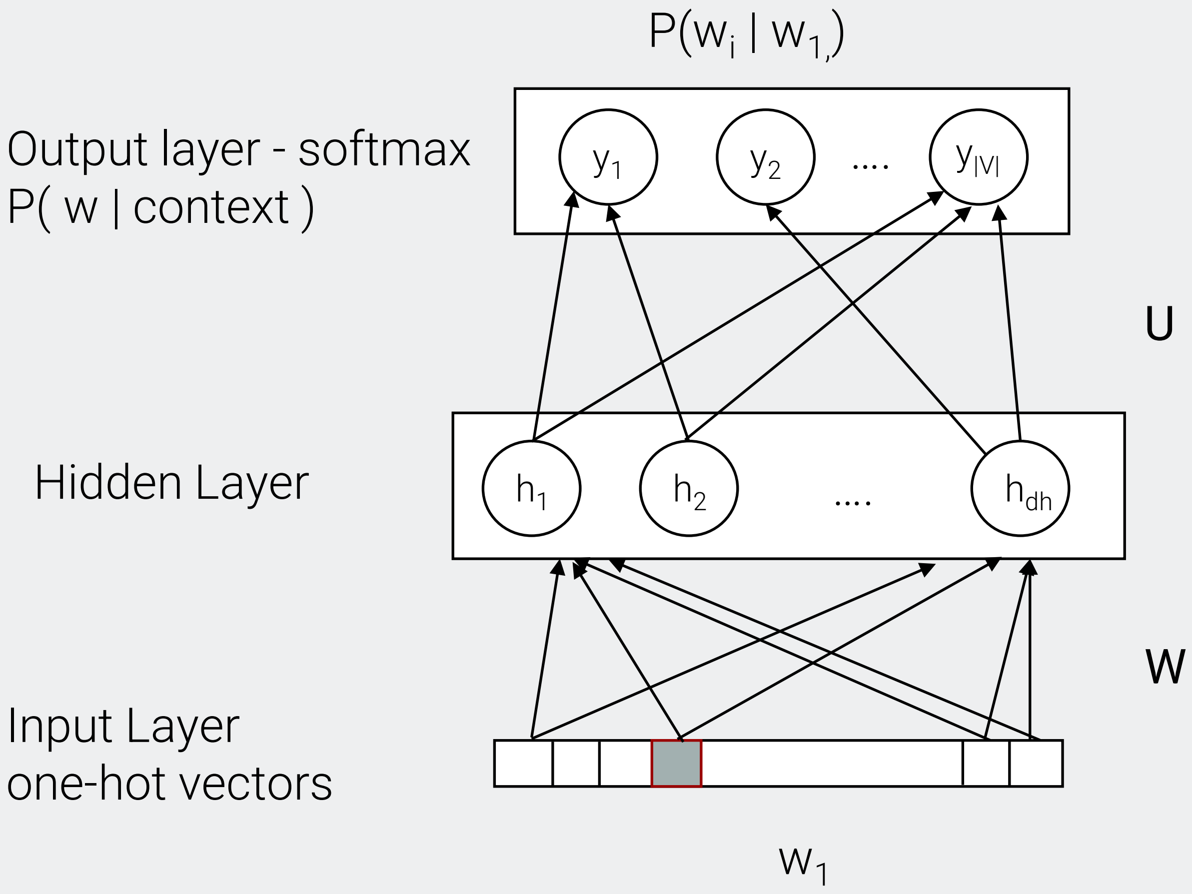
- Standard Feed-Forward Network
- Input: a representation of previous words (w_1, w_2, …)
- Output: probability distribution over possible next words.

- N-grams used exact words! (P(“cat”))

- Equi-distance!
- 1-of-N encoding (aka. one-hot vector)

[1, 2, 3, 4, 5, 6, 7, …., …, | V |]
[0, 0, 0, 0, 0, 1, 0, …., 0, 0 , 0]

Feed Forward Net - execution



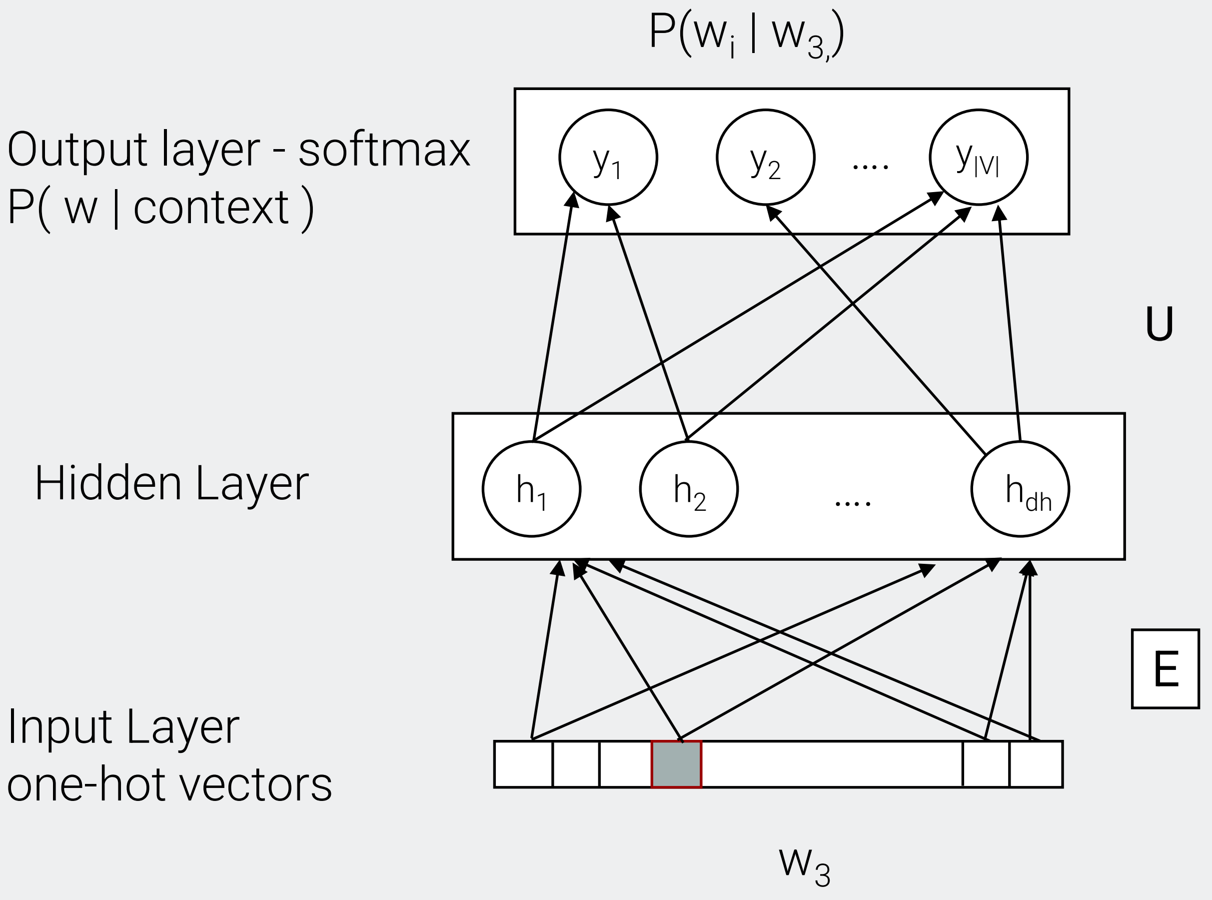
[1, 2, 3, 4, 5, 6, 7, …., …, | V |]
[0, 0, 0, 0, 0, 1, 0, …., 0, 0 , 0]

Feed Forward Net - Training

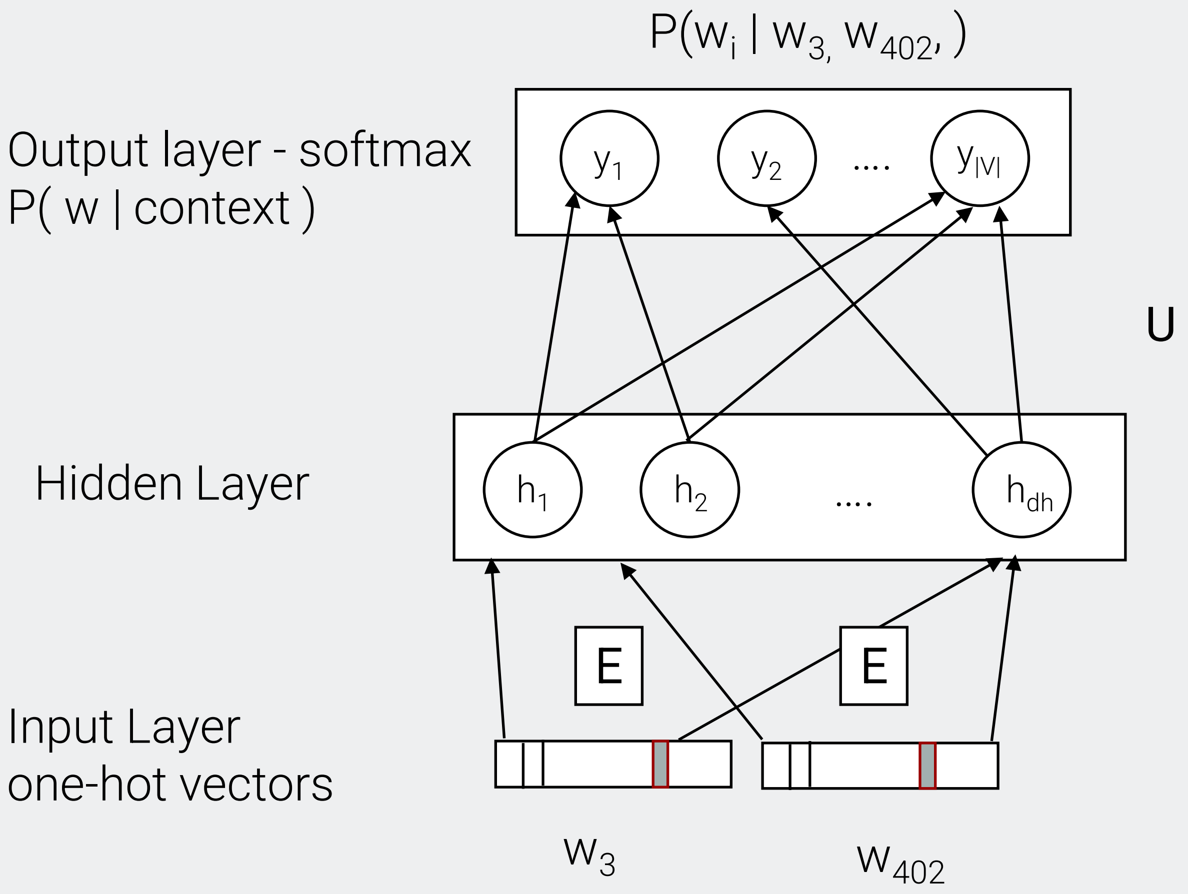
Positive samples ($w_{3,}$ w_{402})
(metal jacket)

Negative samples ($w_{3,}$ w_{xx})
(metal heavy)
(metal towel)

[1, 2, 3, 4, 5, 6, 7, …., …, | V |]
[0, 0, 0, 0, 0, 1, 0, …., 0, 0 , 0]



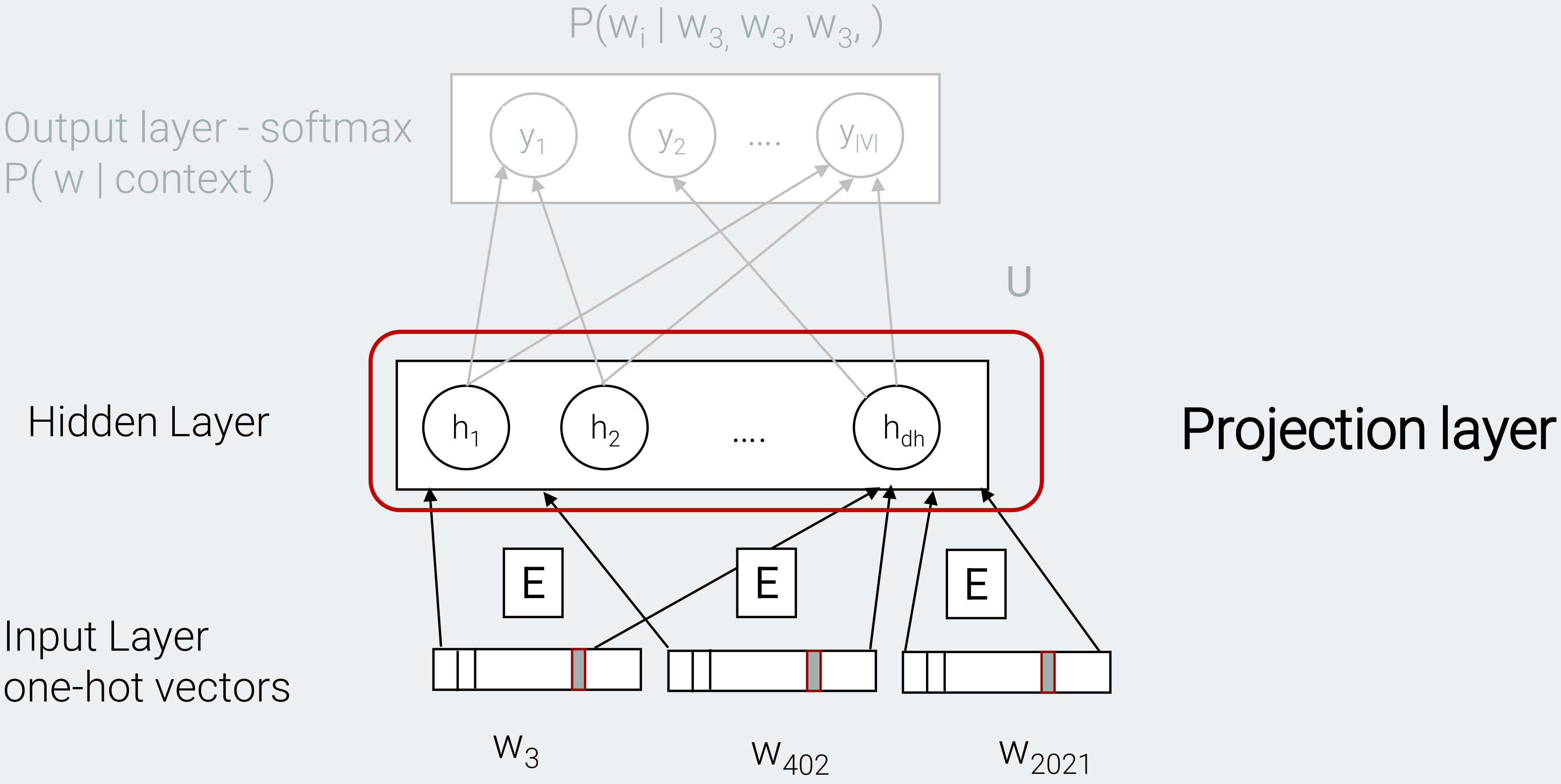
Feed Forward Net - Training

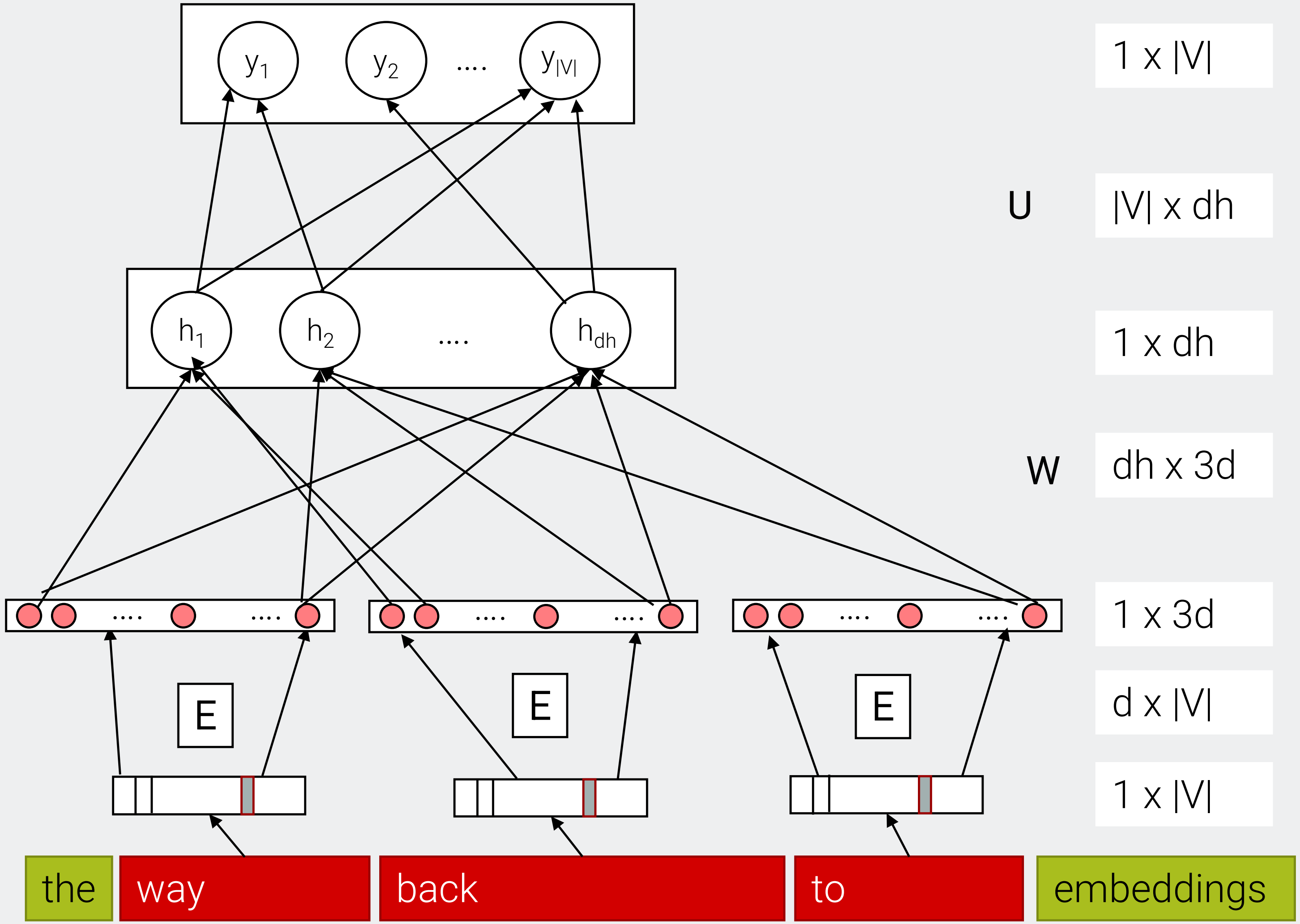


Positive samples $(w_{3,}\, w_{402}, w_{2021})$
(**metal skirt hanger**)

Negative samples $(w_{3,}\, w_{402}, w_{xx})$
(metal skirt mouse)
(metal skirt towel)

Feed Forward Net - Training





Output layer - softmax
P(w | context)

$$\boxed{y = \text{softmax}(z)}$$

$$\boxed{z = Uh}$$

$$\boxed{h = \sigma(We + b)}$$

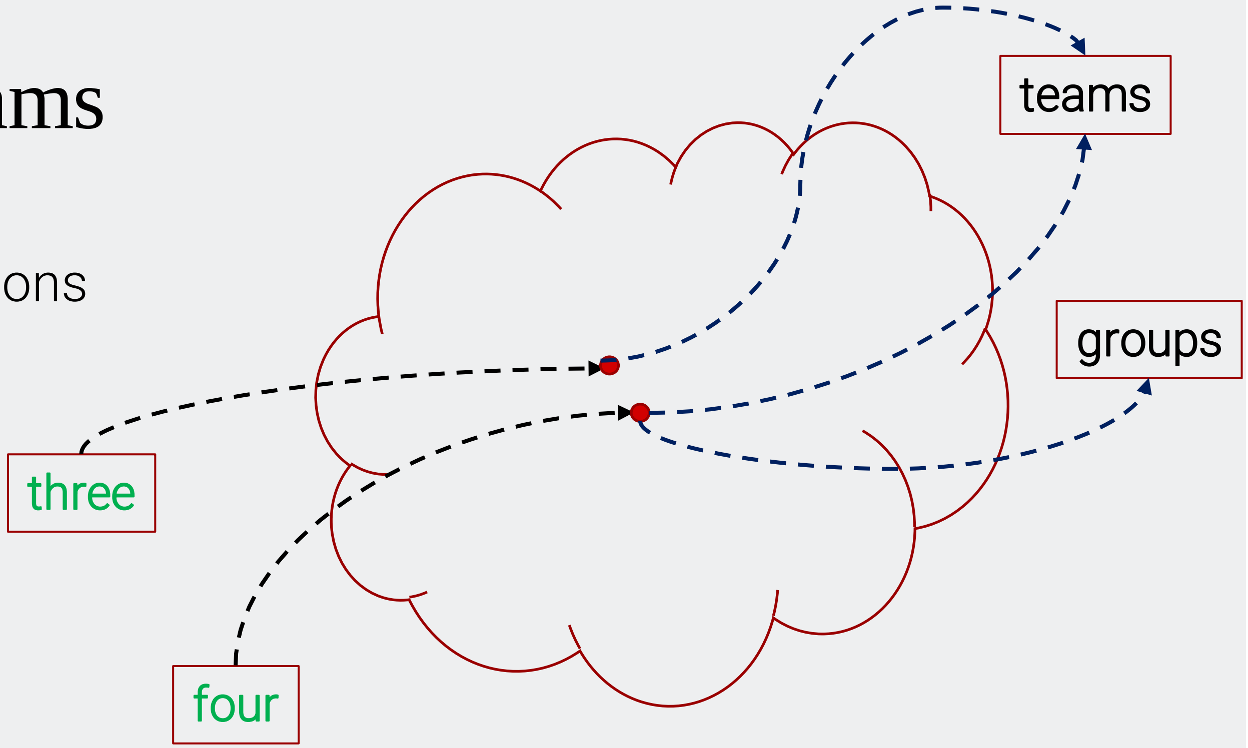
$$\boxed{e = (Ex_1, Ex_2, \ldots, Ex)}$$

Projection layer

Input Layer, one-hot vectors

Generalization to Unseen n-grams

- There are three **teams** left for the qualifications
- four **teams** have passed the first round
- four **groups** are playing in the field

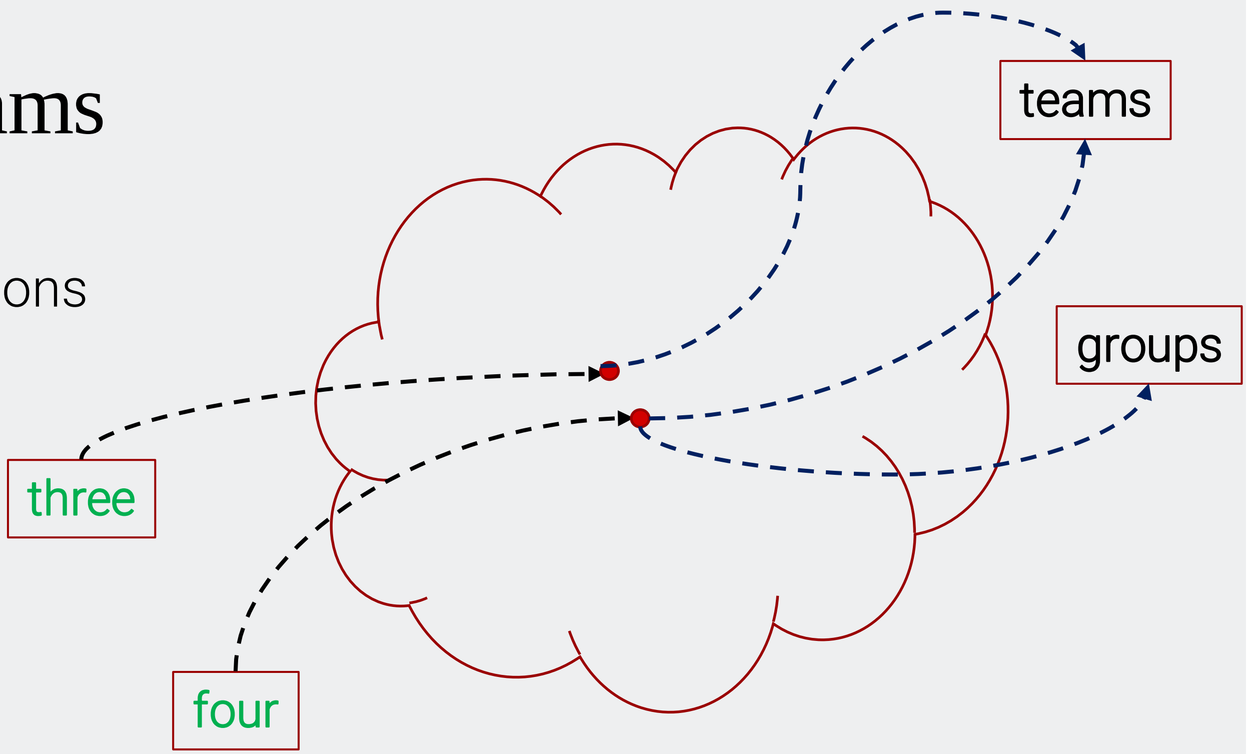


$P(\text{teams} \mid \text{four}) \approx P(\text{groups} \mid \text{four})$

Generalization to Unseen n-grams

- There are three **teams** left for the qualifications
- four **teams** have passed the first round
- four **groups** are playing in the field

- Assign probability to “three groups”



P(**teams** | four) ≈ P(**groups** | four)

Neural Language Models – In a small nutshell

- pattern recognition problems
- Data-driven
- High performance in many problems
- No domain knowledge needed
- Generalization

- Data-hungry (bad for small data sets)
- Cannot handle symbols very well
- Computationally high costs

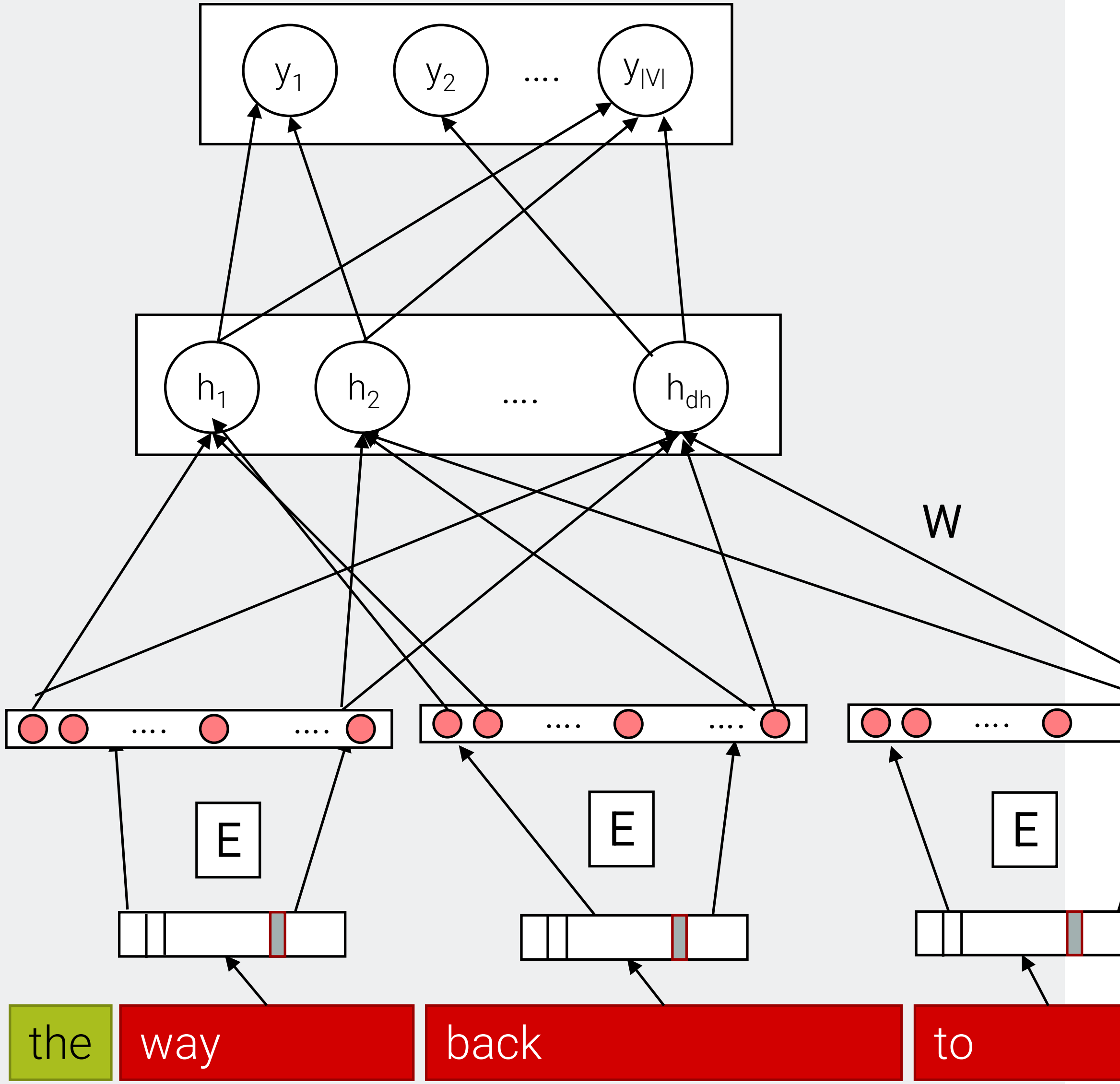
Content

- Neural Language Models
- Recurrent Neural Networks
- LSTMs (Long Short-Term Memory Networks)

(Simple) Neural Language Models

- Improvements over n-gram LM
  - No sparsity problem
  - Don't need to store all observed n-grams
- Remaining problems:
  - Fixed window is too small
  - Enlarging window enlarges W
  - Window can never be large enough!
  - (embedded) words are multiplied by completely different weights in W

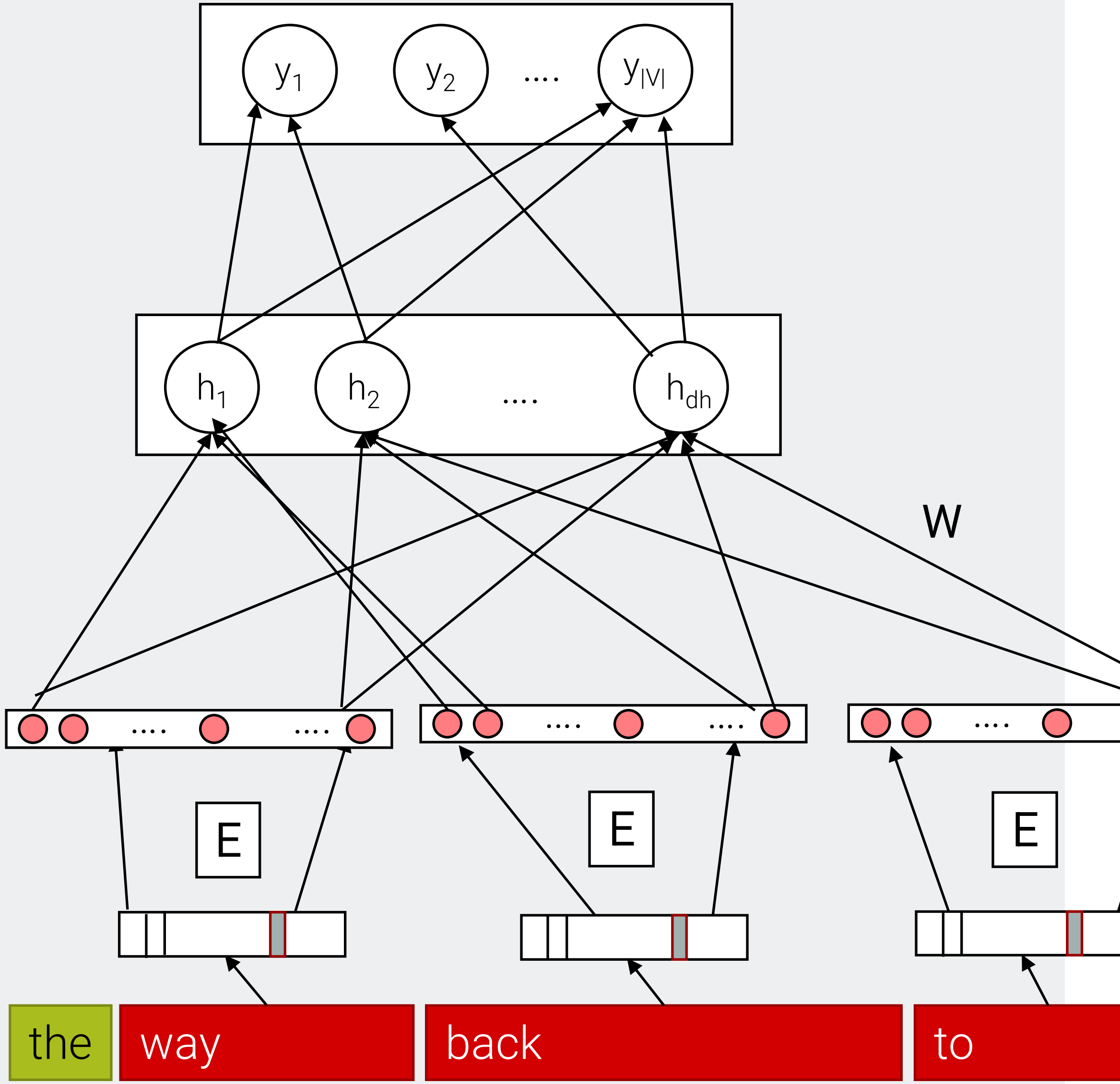
    (No symmetry in input processing)



(Simple) Neural Language Models

- How to deal with inputs of varying lengths (i.e. sequences)?

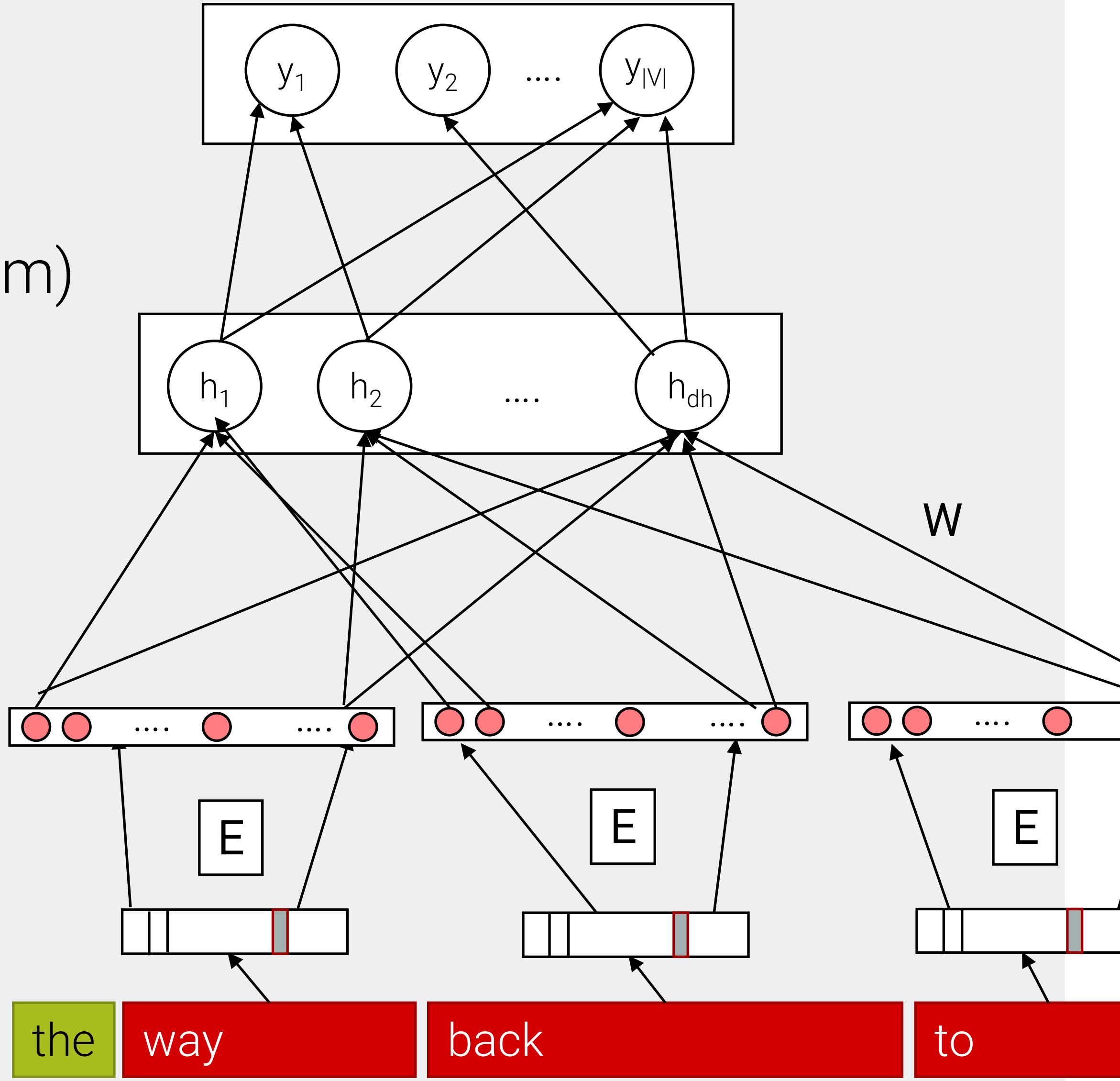
- Slide the input window
- Still, decision on one window does not influence decision on other window.
- Cannot learn systematic patterns (e.g. Constituency)



(Simple) Neural Language Models

- Language is temporal (continuous stream)
  - "Sequence that unfolds in time"
- Algorithms use this
  - Viterbi

- Previous ML approaches have access to all input, simultaneously
- How to deal with sequences of varying lengths?



Sequences – Input of **Variable Lengths**

- Each input has a variable number of elements:

$$x^1 = (x_1^1, x_2^1, \dots, x_{l^1}^1)$$

$$x^n = (x_1^n, x_2^n, \dots, x_{l^n}^n)$$

- Simplification: binary elements (0 or 1 values)
- How many 1s in this sequence? How can we implement that?

Sequences – Input of Variable Lengths

$$x^1 = (x^1_1, x^1_2, \ldots, x^1_{l^1})$$

- Simplification: binary elements (0 or 1 values)
- How many 1s in this sequence? How can we implement that?

- ADD1, Recursive function
- Call it for each element of the input.

Algorithm 1 A function $\textsc{Add1}$

$s \leftarrow 0$
function $\textsc{Add1}(v,s)$
  if $v = 0$ **then return** s
  else return $s+1$
  end if
end function

Algorithm 2 A function $\textsc{Add1}$

$s \leftarrow 0$
for $i \leftarrow 1,2,\ldots,l$ **do** $s \leftarrow \textsc{Add1}(x_i, s)$
end for

Sequences – Input of Variable Lengths

- How many 1s in this sequence? How can we implement that?

$$x^1 = (x^1_1, x^1_2, \ldots, x^1_{l^1})$$

Algorithm 1 A function ADD1

$s \leftarrow 0$
function ADD1(v,s)
    if $v = 0$ **then return** s
    else return $s + 1$
    end if
end function

Algorithm 2 A function ADD1

$s \leftarrow 0$
for $i \leftarrow 1, 2, \ldots, l$ **do** $s \leftarrow$ ADD1(x_i, s)
end for

- Memory ***s*** which counts the 1s.
- ADD1 applied
    1. To *each* symbol
    2. One at a time ! and together with ***s***

Recursive Function for Natural Language Understanding

- ADD1 is hardcoded
- Parametrized recursive function
- Memory: $\mathbf{h} \in \mathbb{R}^{d_h}$
- Input x_1 and memory **h**, returns the new **h**
- Time index!

$$h_t = f(x_t, \mathbf{h}_{t-1})$$

$$f(x_t, \mathbf{h}_{t-1}) = g(\mathbf{W}\phi(x_t) + \mathbf{U}\mathbf{h}_{t-1}).$$

Algorithm 1 A function ADD1

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function ADD1(v,s)
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end function

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Recursive Function for Natural Language Understanding

$$\mathbf{h} \in \mathbb{R}^{d_h}$$

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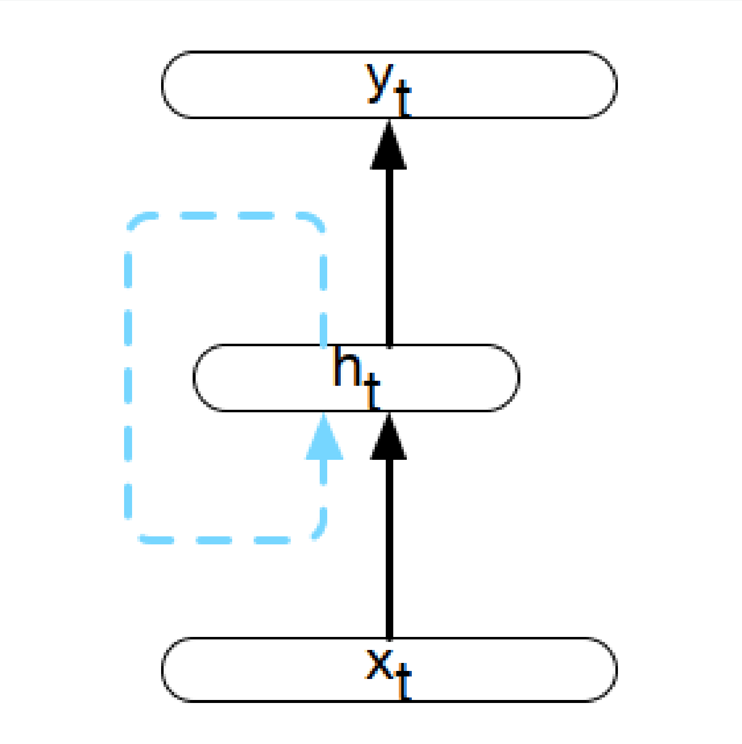
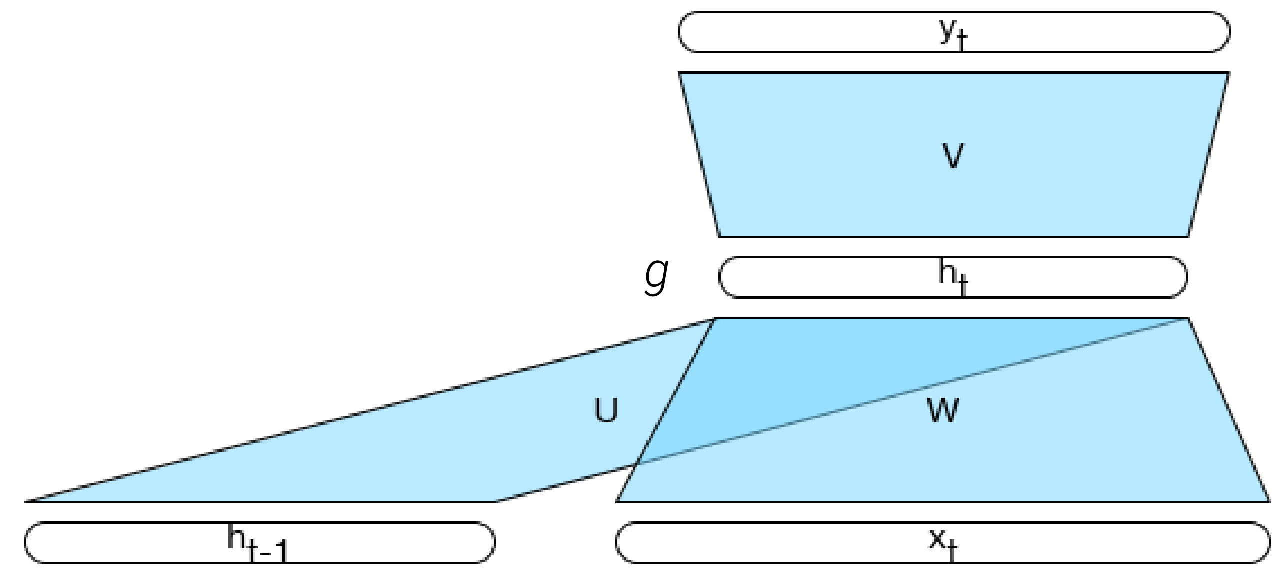


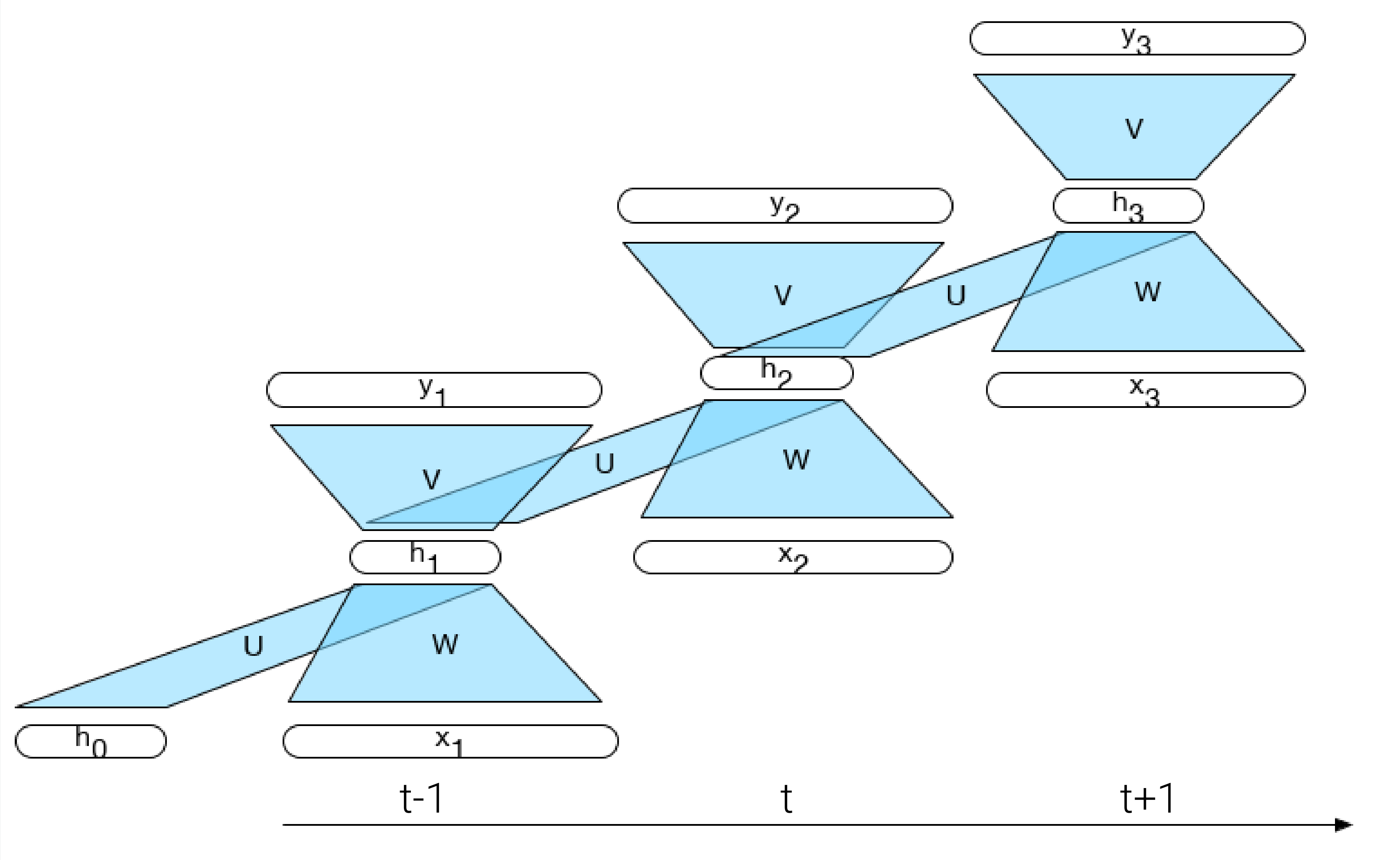
Recursive Neural Network – Unrolled

$$h_t = g(Uh_{t-1} + Wx_t)$$
$$y_t = f(Vh_t)$$

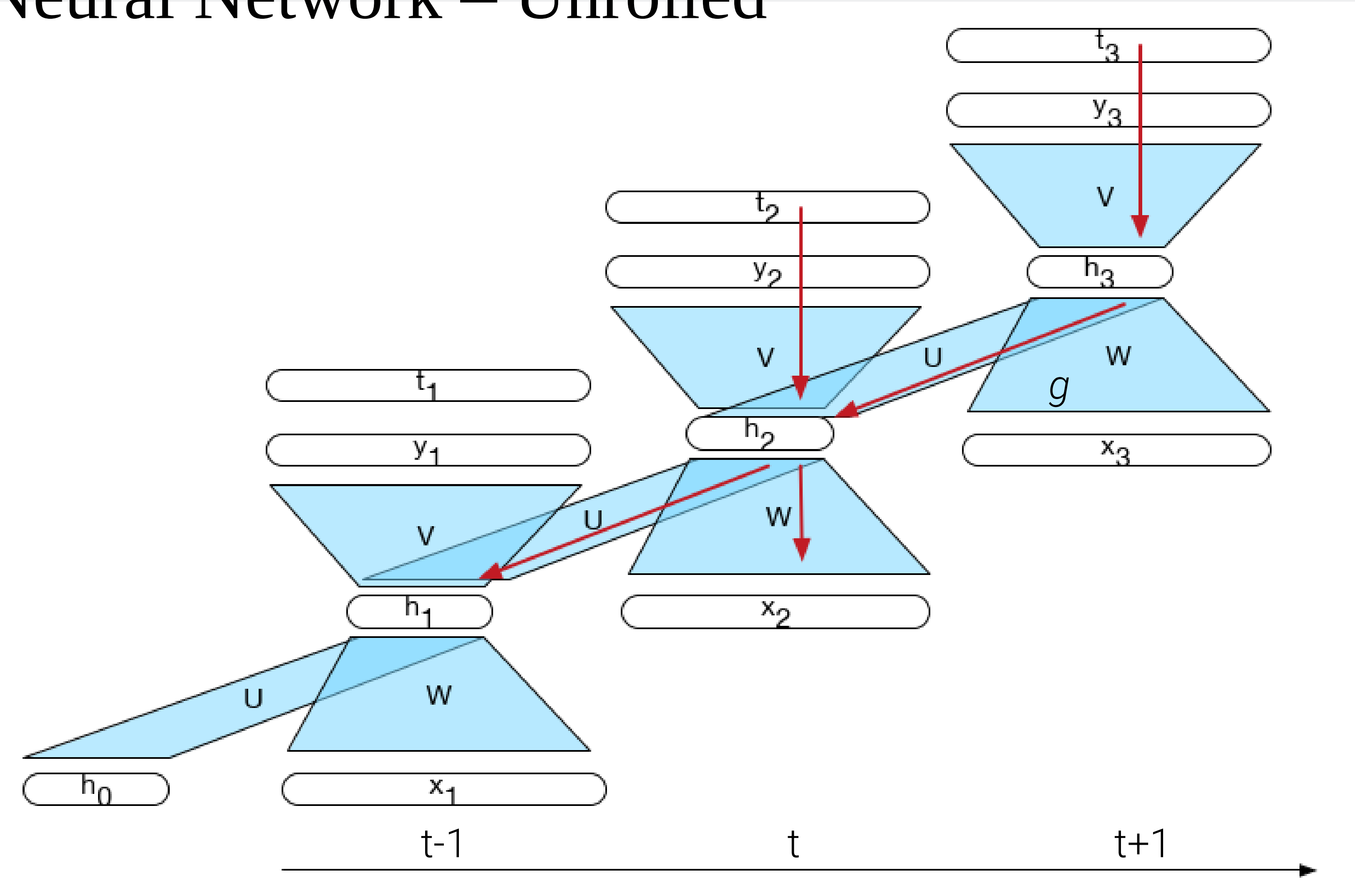
$$y_t = softmax(Vh_t)$$



Recursive Neural Network – Unrolled



Recursive Neural Network – Unrolled



Content

- Neural Language Models
- Recurrent Neural Networks
  - RNN Language Models
    - (Autoregressive) generation
  - Sequence labelling
  - Sequence classification
- LSTMs (Long Short-Term Memory Networks)

RNN – Applications

- RNN Language Models
  - (Autoregressive) generation
- Sequence labelling
- Sequence classification
- …