Natural Language Processing

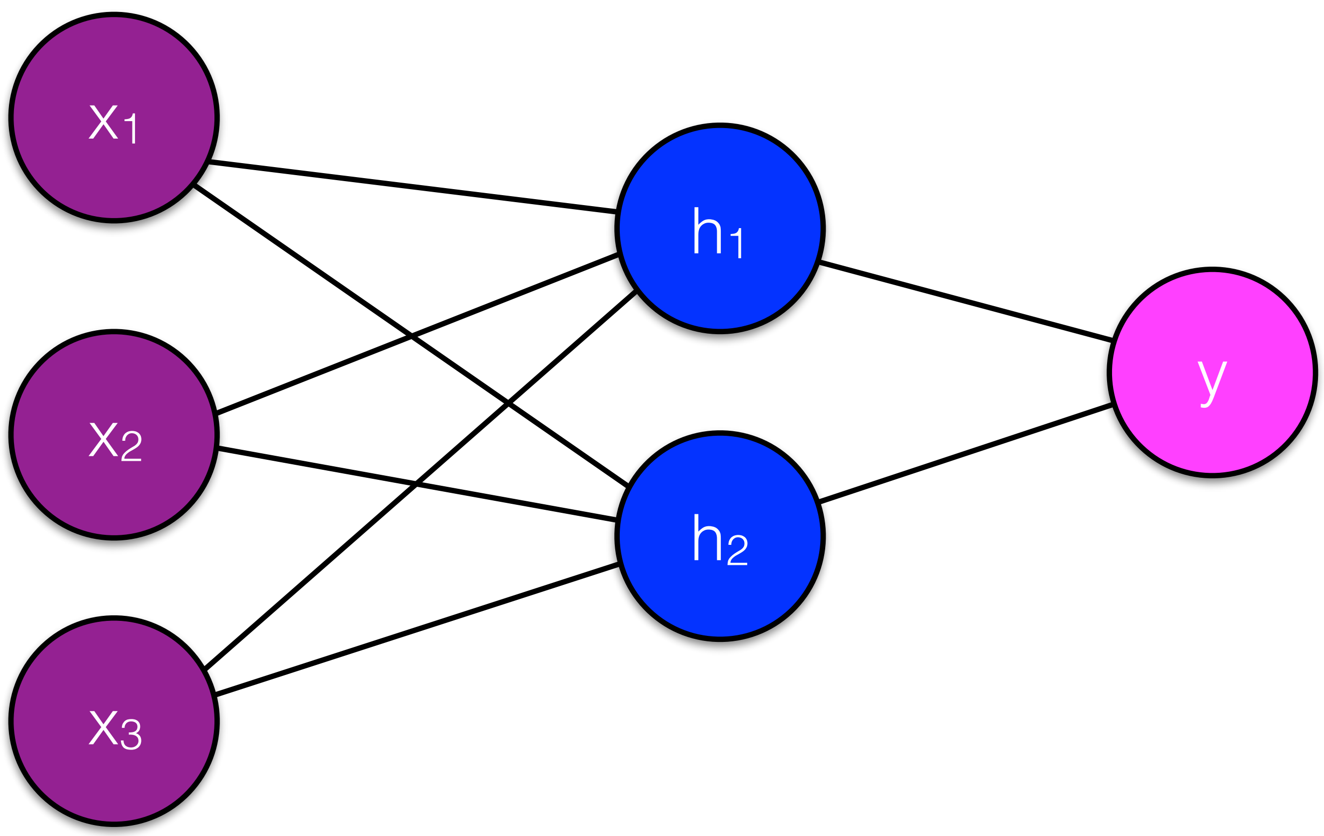
Mehmet Can Yavuz, PhD

Adapted from Info 256 - David Bamman, UC Berkeley

Neural networks

- Tremendous flexibility on design choices (exchange feature engineering for model engineering)
- Articulate model structure and use the chain rule to derive parameter updates.

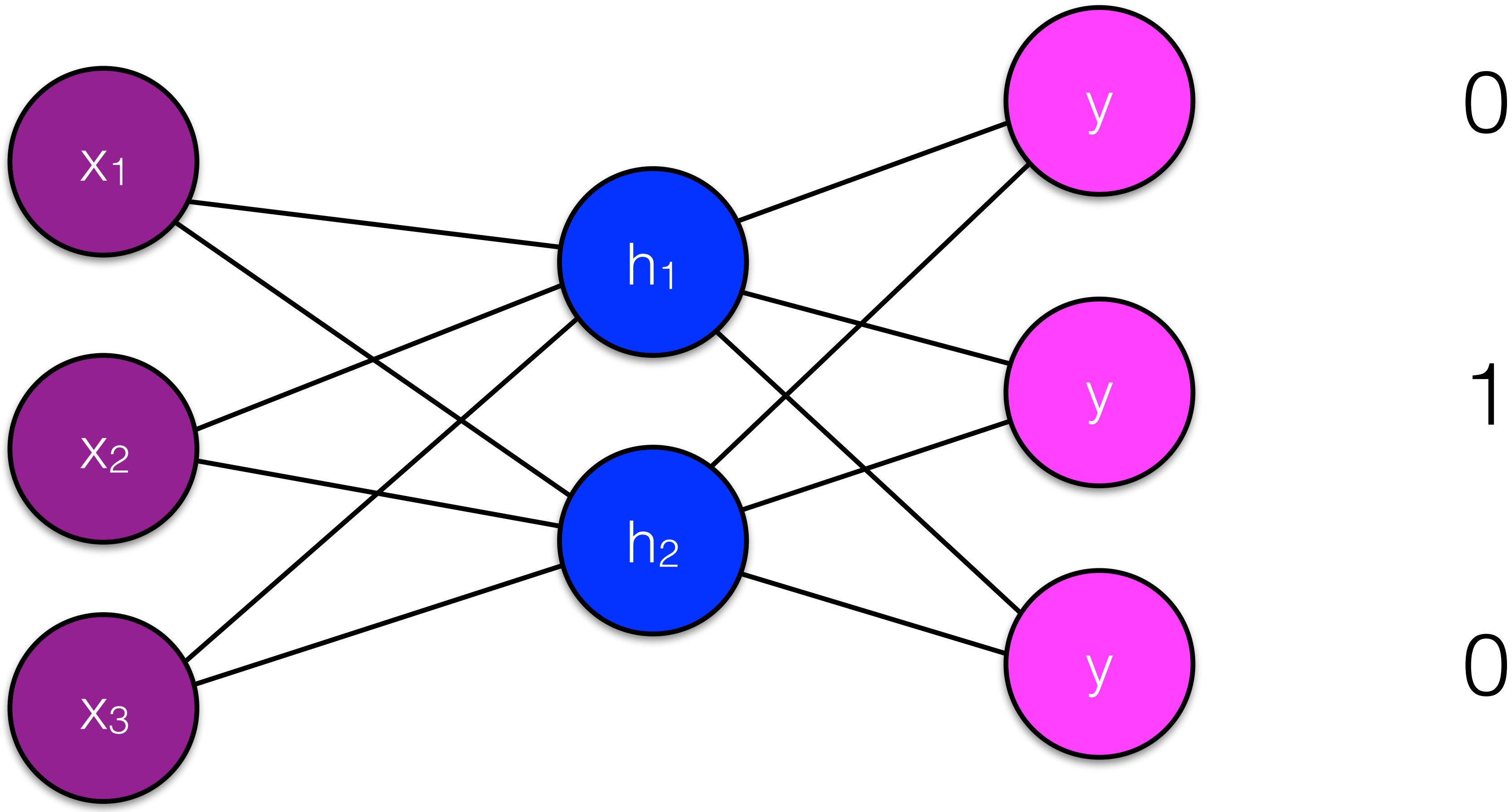
Neural network structures



1

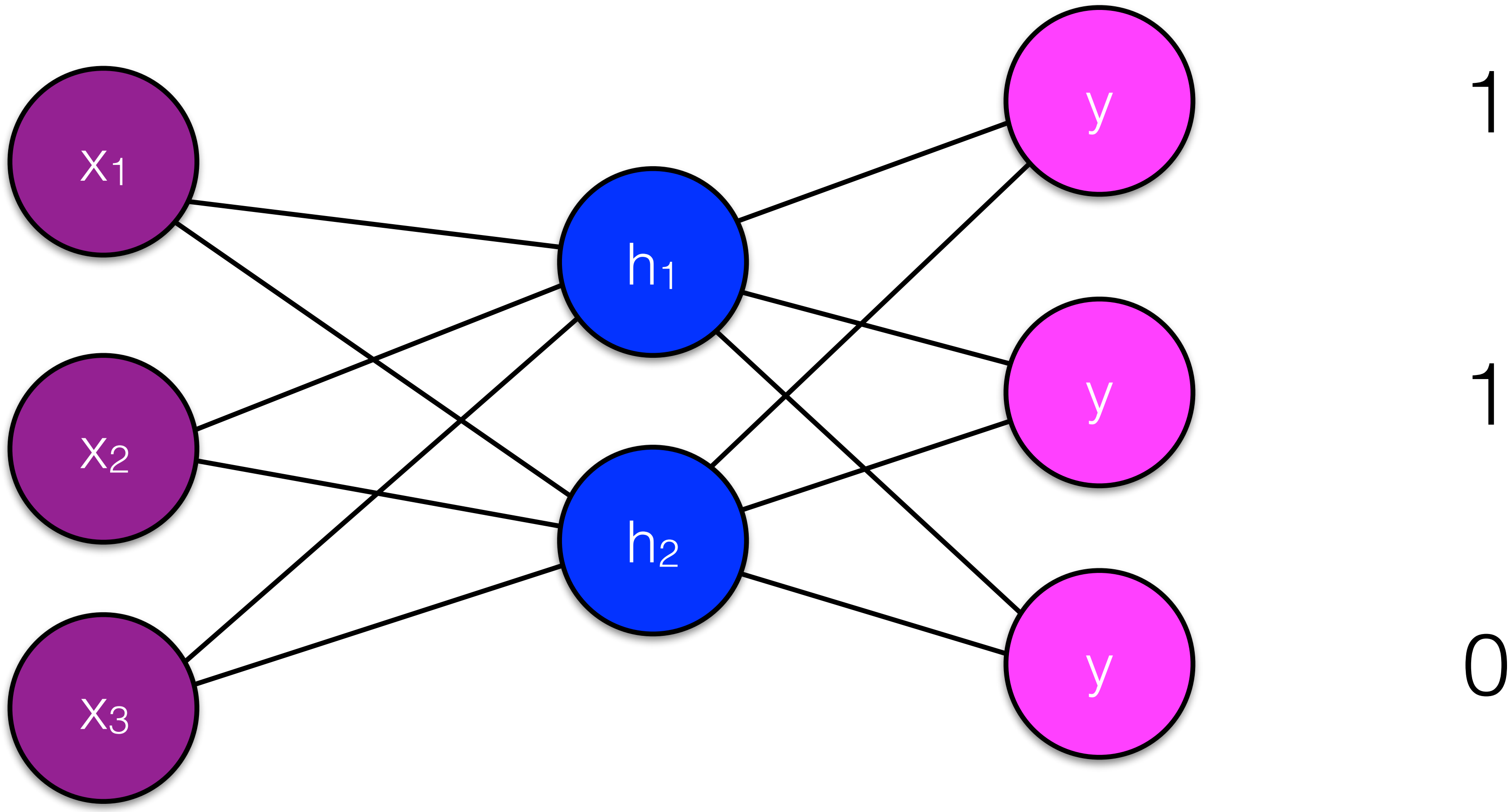
Output one real value

Neural network structures



Multiclass: output 3 values, only one = 1 in training data

Neural network structures



output 3 values, several = 1 in training data

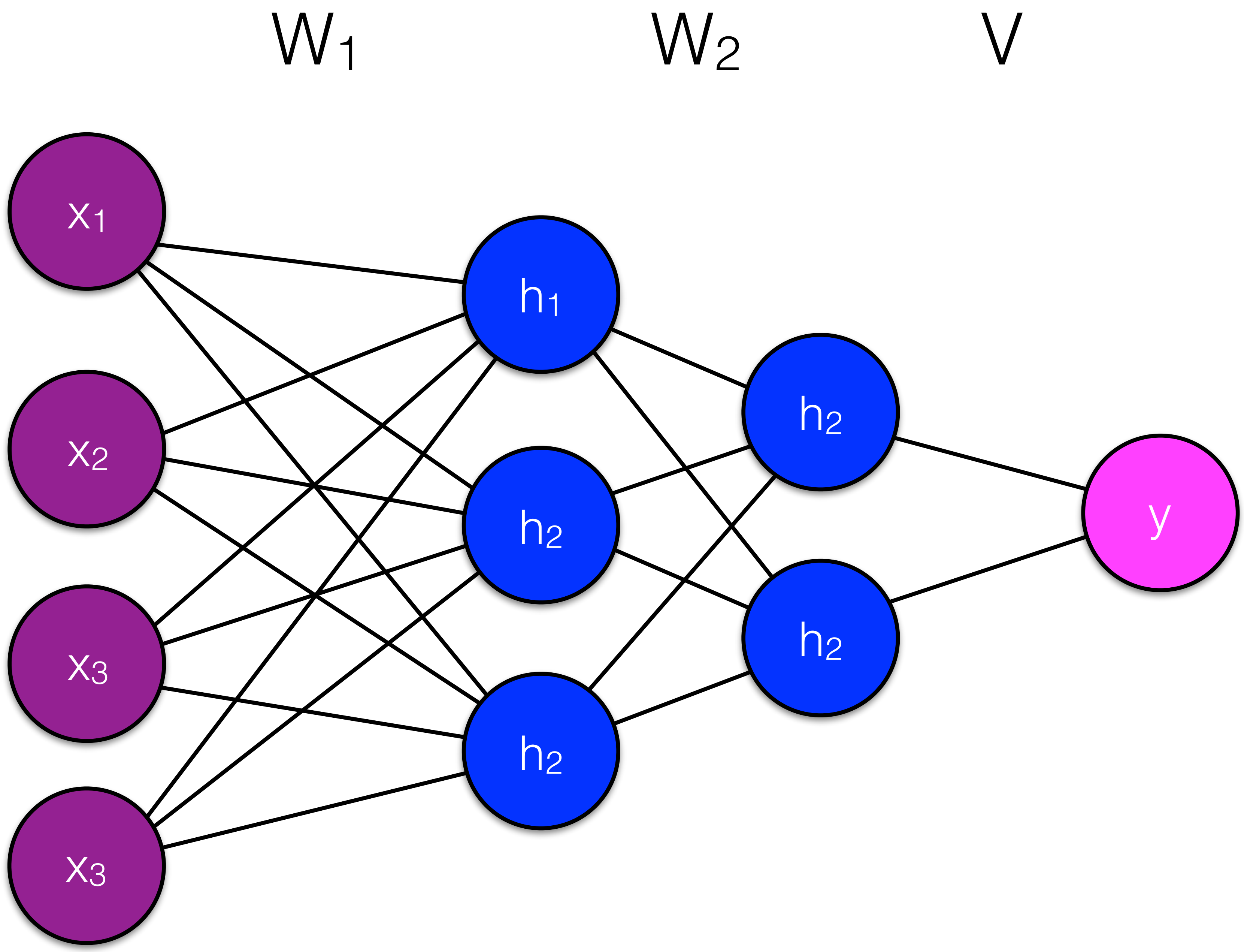
Regularization

- Increasing the number of parameters = increasing the possibility for overfitting to training data

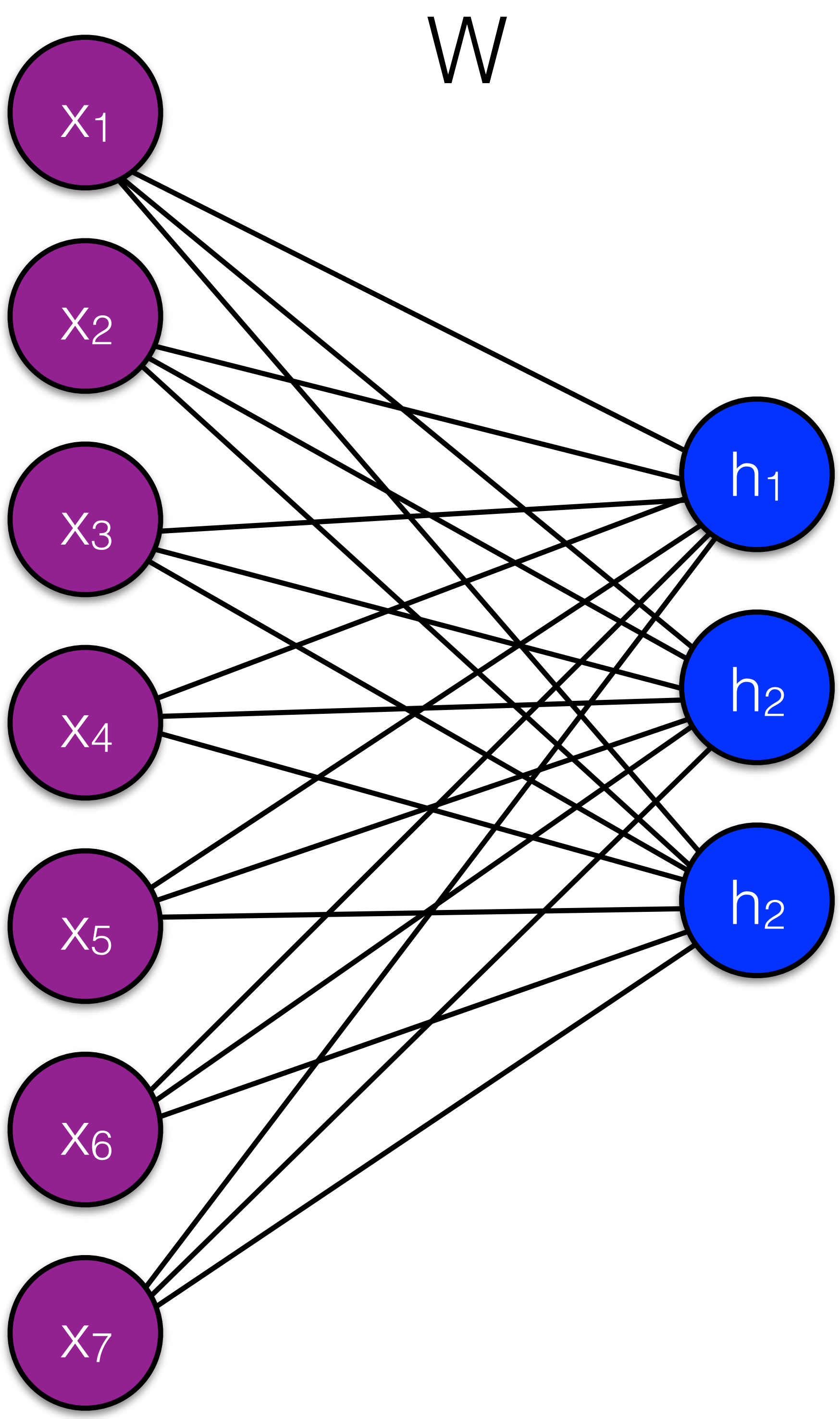
Regularization

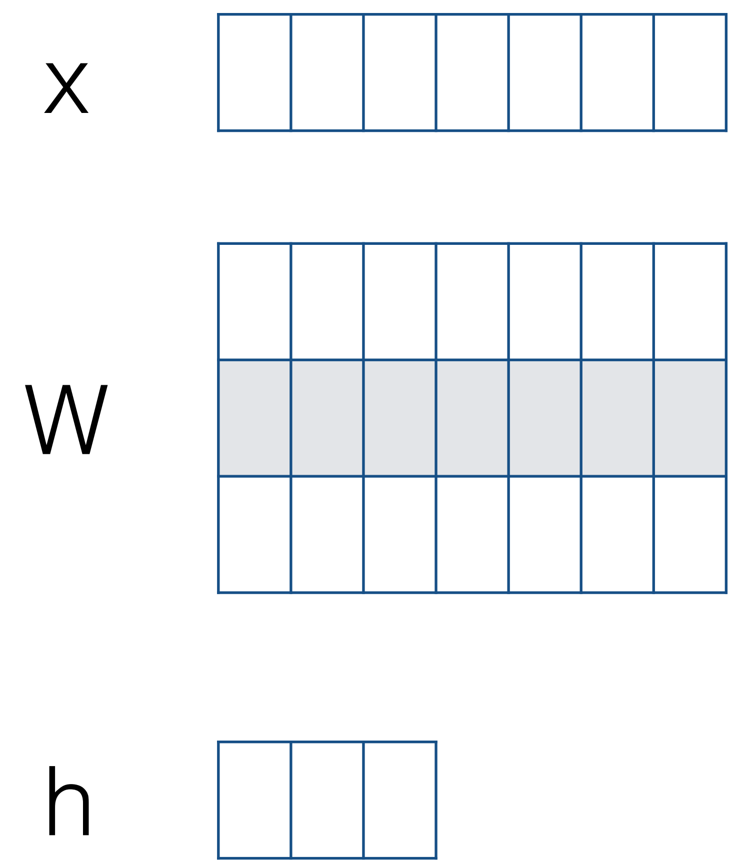
- L2 regularization: penalize W and V for being too large
- Dropout: when training on a <x,y> pair, randomly remove some node and weights.
- Early stopping: Stop backpropagation before the training error is too small.

Deeper networks



Densely connected layer





$$h = \sigma(xW)$$

Convolutional networks

- With convolution networks, the same operation is (i.e., the same set of parameters) is applied to different regions of the input

2D Convolution

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

blurring

http://www.wildml.com/2015/11/understanding-convolutional-neural-networks-for-nlp/
https://docs.gimp.org/en/plug-in-convmatrix.html

1D Convolution

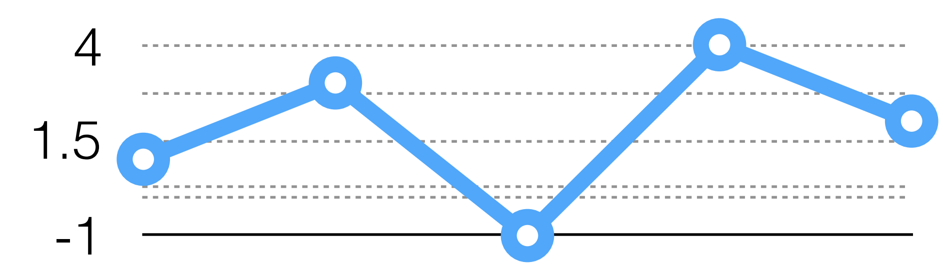
convolution *K*

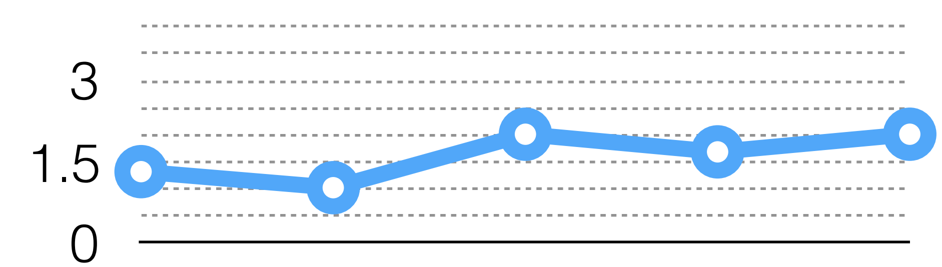
1/3	1/3	1/3

x

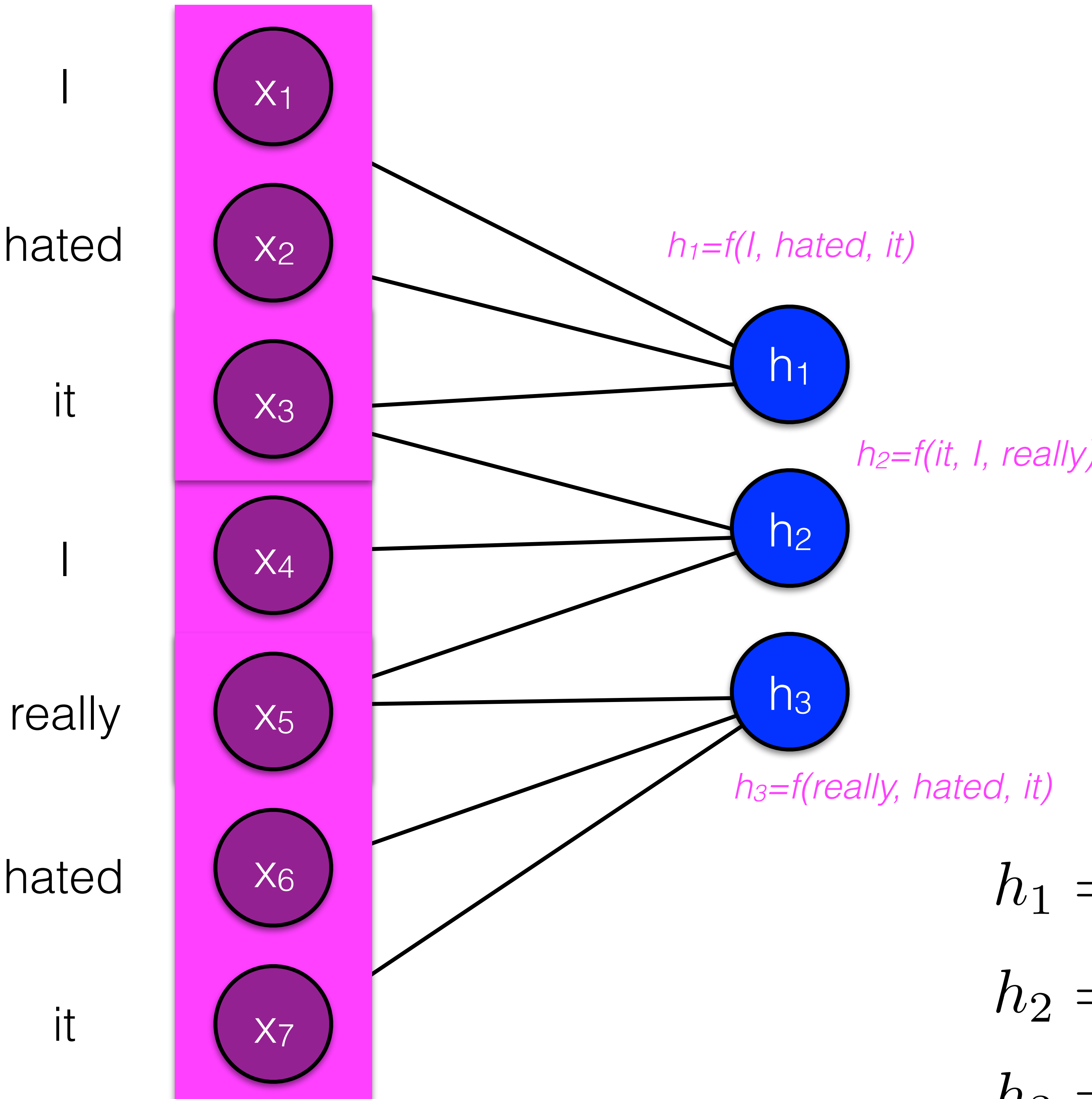
0	1	3	-1	4	2	0

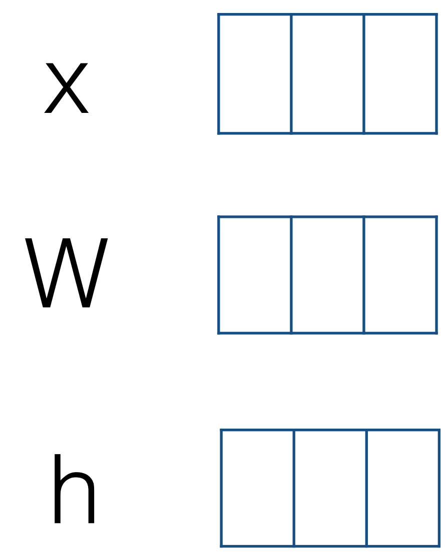
1⅓	1	2	1⅔	2





Convolutional networks





$$h_1 = \sigma(x_1 W_1 + x_2 W_2 + x_3 W_3)$$

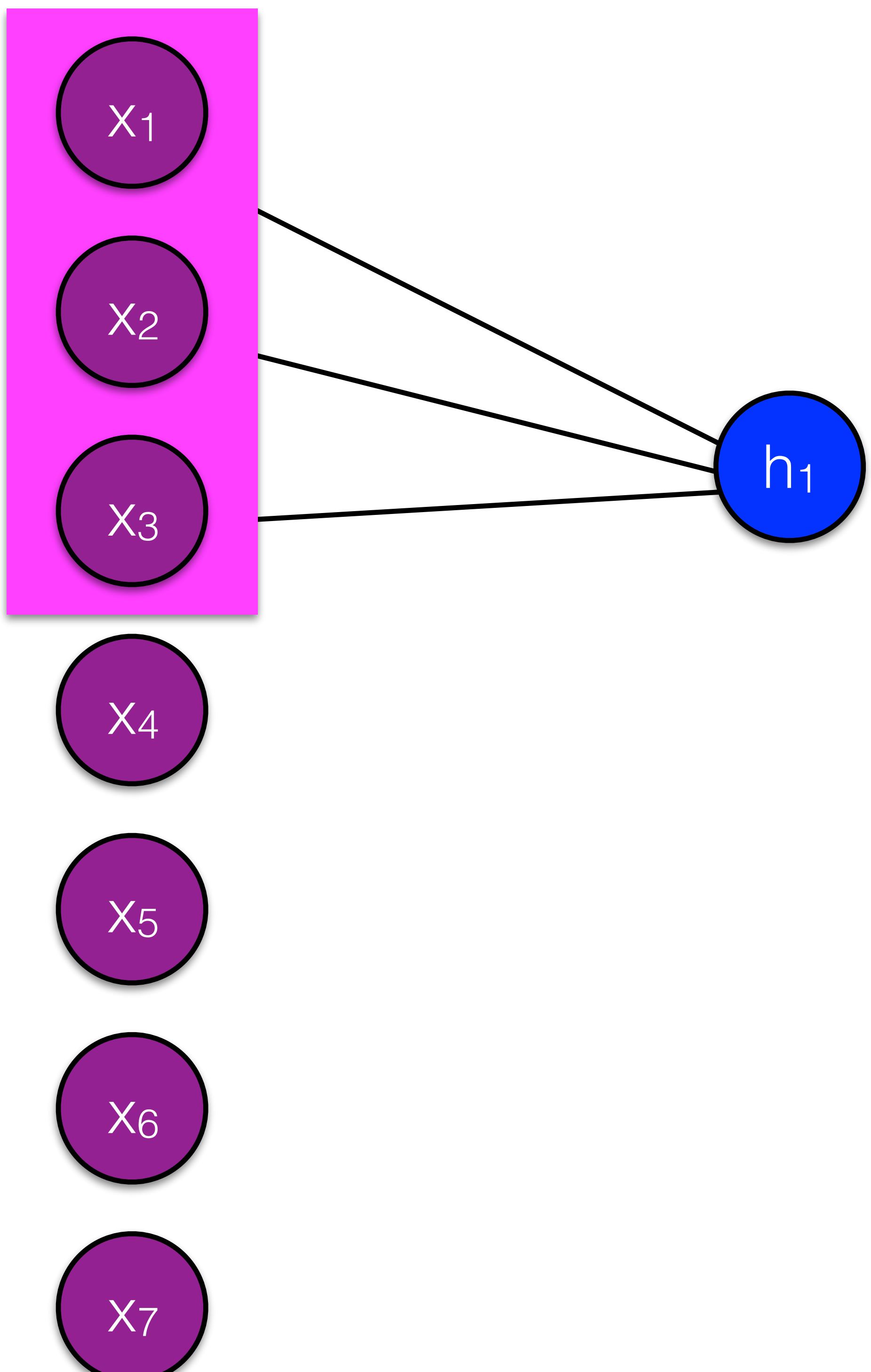
$$h_2 = \sigma(x_3 W_1 + x_4 W_2 + x_5 W_3)$$

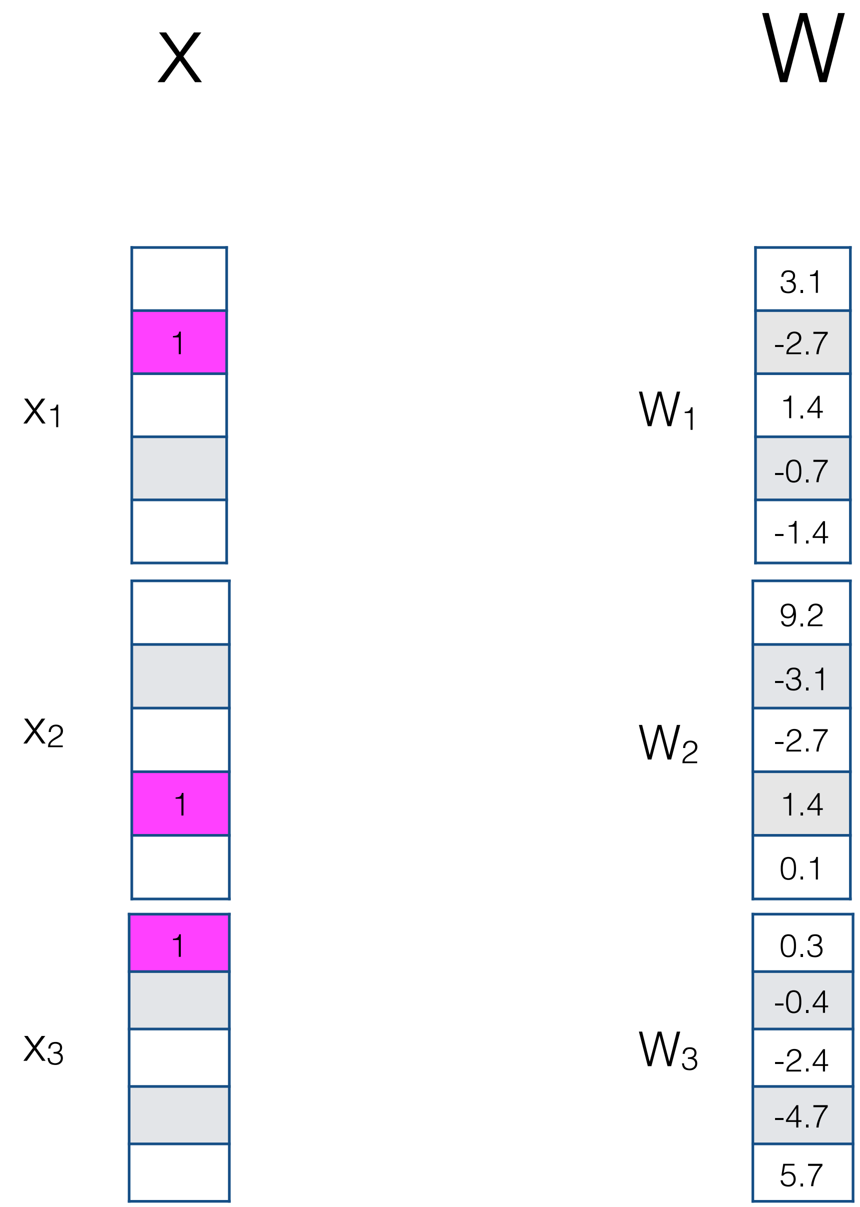
$$h_3 = \sigma(x_5 W_1 + x_6 W_2 + x_7 W_3)$$

Indicator vector

- Every token is a V-dimensional vector (size of the vocab) with a single 1 identifying the word

vocab item	indicator
a	0
aa	0
aal	0
aalii	0
aam	0
aardvark	1
aardwolf	0
aba	0

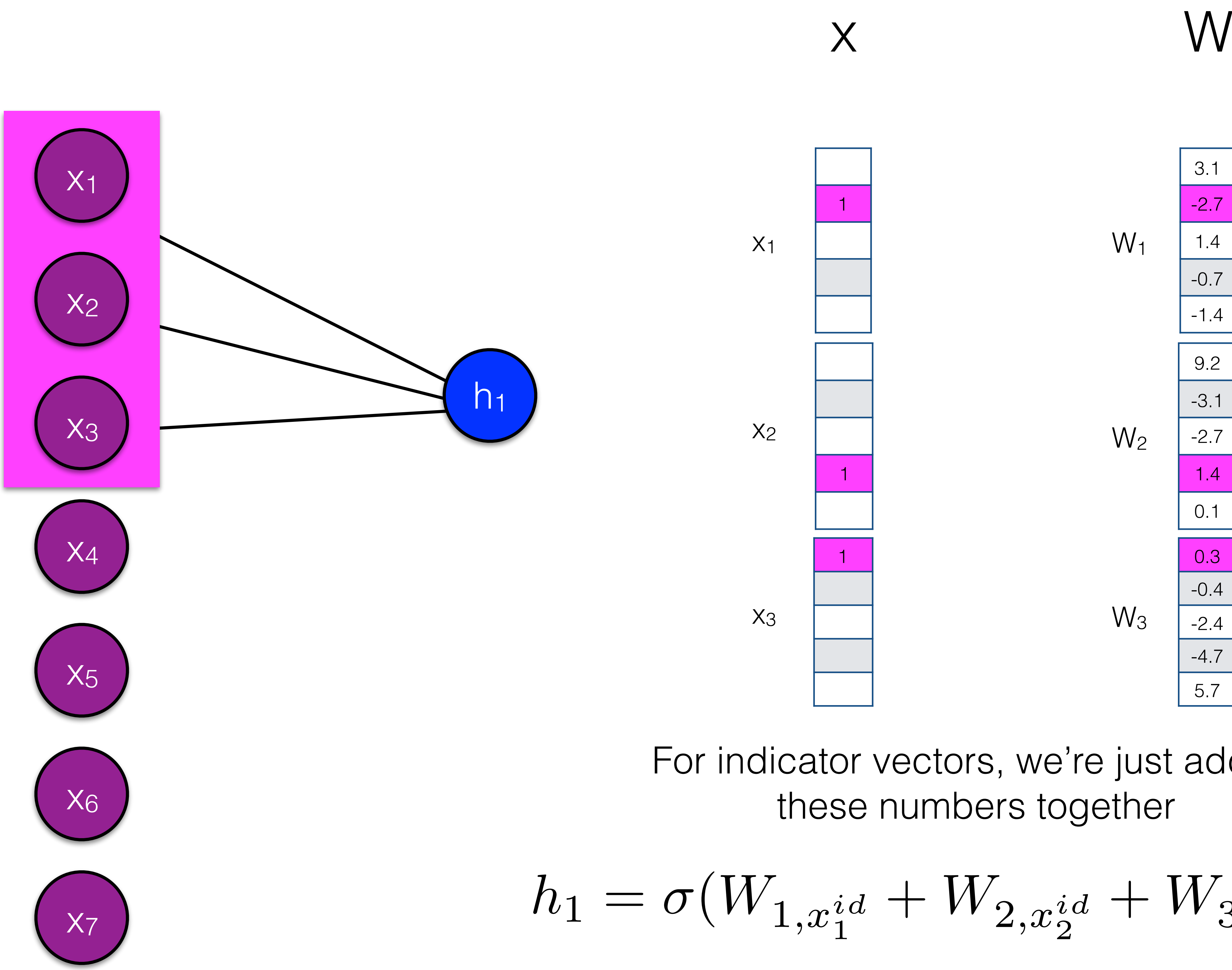




$$h_1 = \sigma(x_1 W_1 + x_2 W_2 + x_3 W_3)$$

$$h_2 = \sigma(x_3 W_1 + x_4 W_2 + x_5 W_3)$$

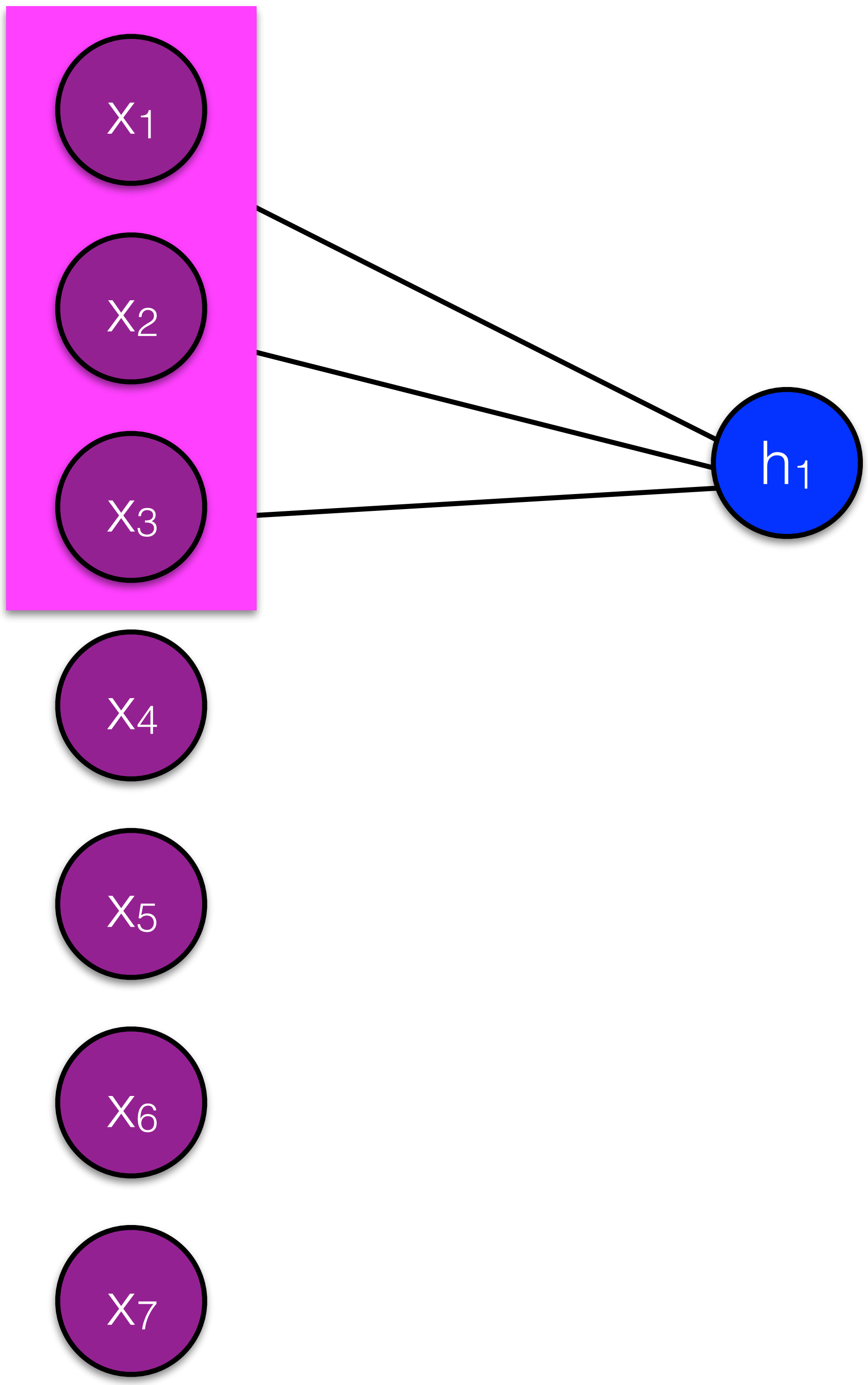
$$h_3 = \sigma(x_5 W_1 + x_6 W_2 + x_7 W_3)$$

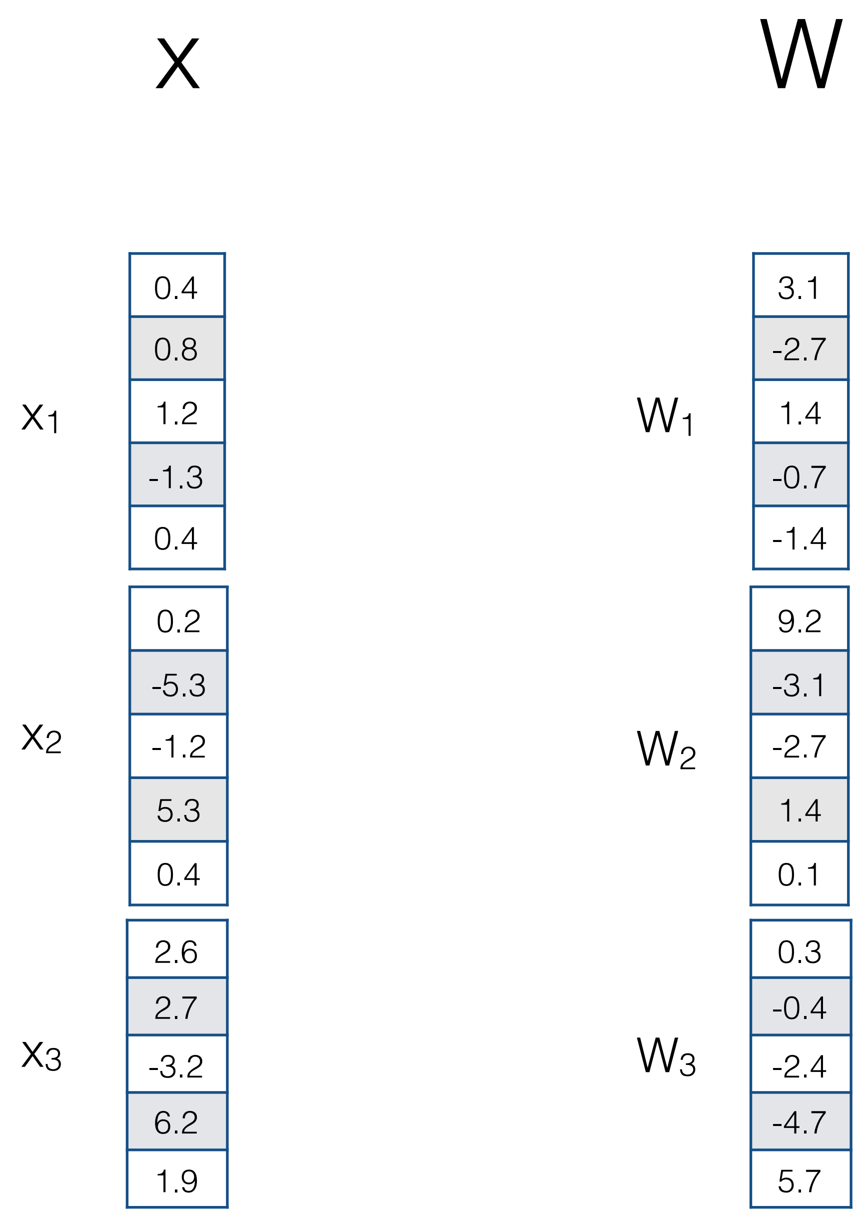


For indicator vectors, we're just adding these numbers together

$$h_1 = \sigma(W_{1,x_1^{id}} + W_{2,x_2^{id}} + W_{3,x_3^{id}})$$

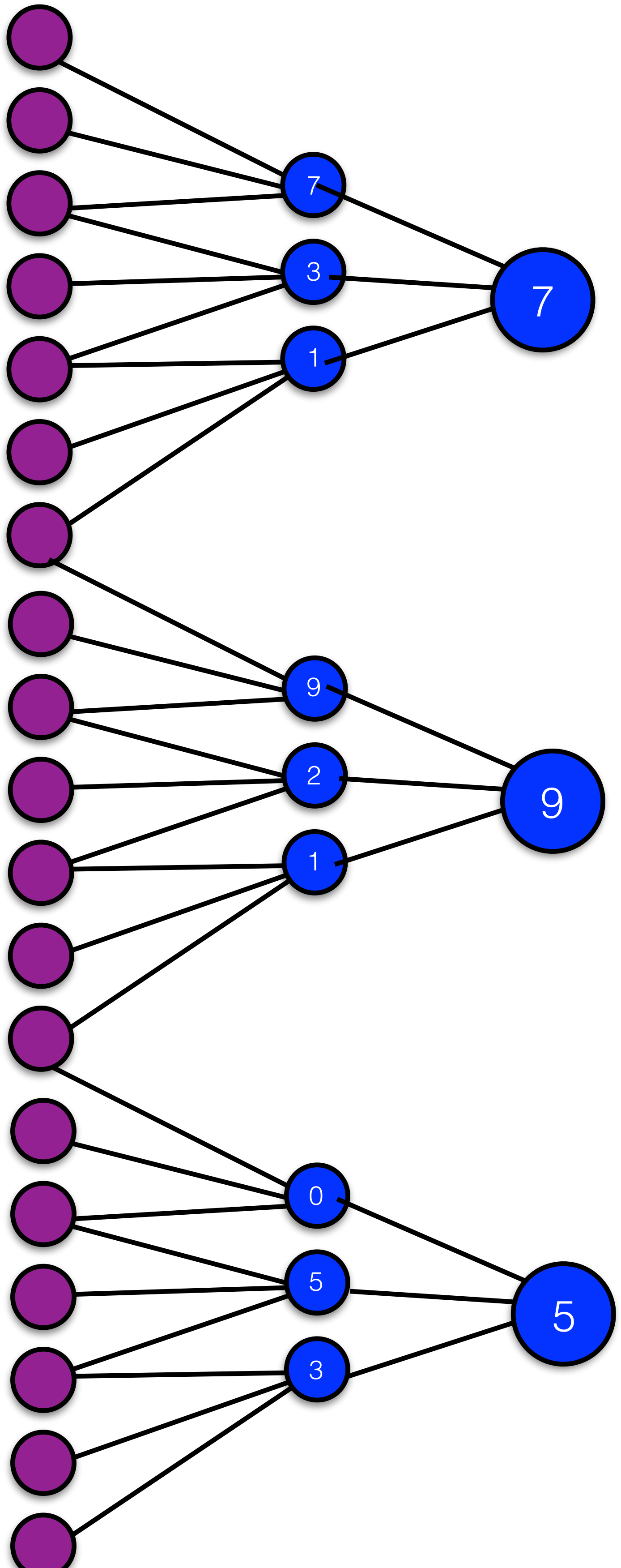
(Where x_n^{id} specifies the location of the 1 in the vector — i.e., the vocabulary id)





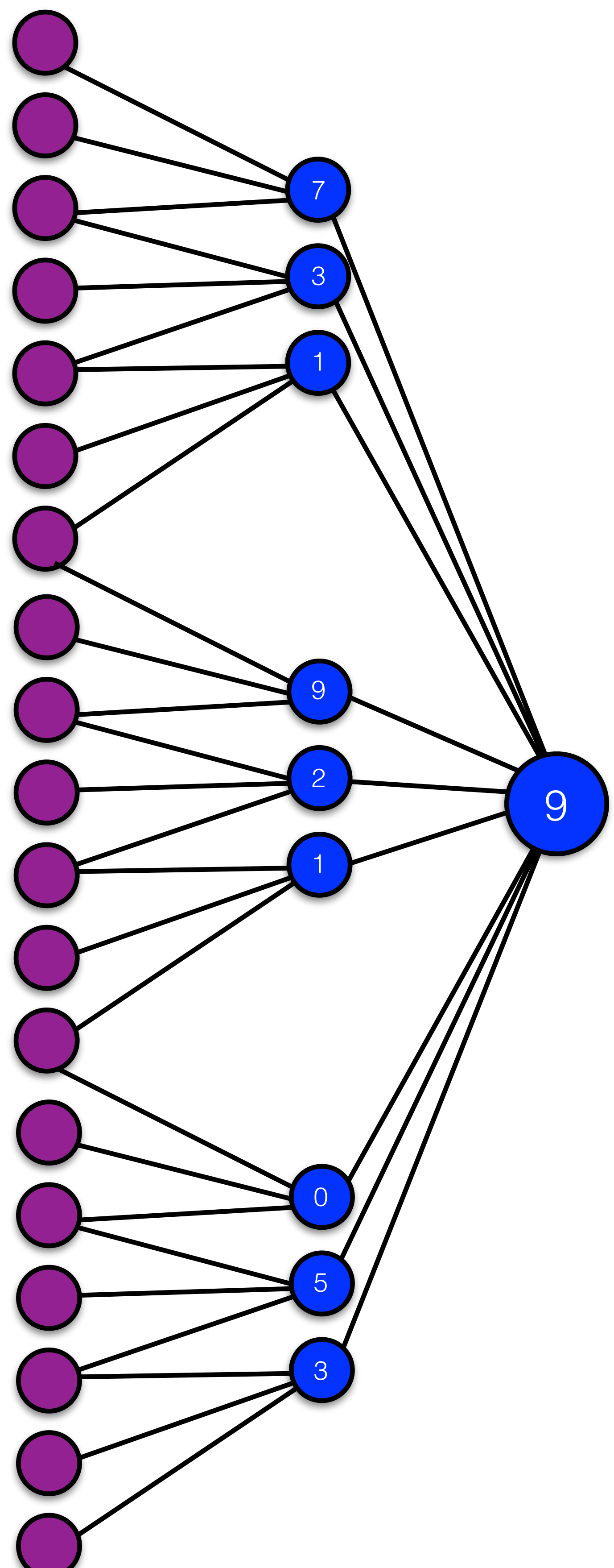
For dense input vectors (e.g., embeddings), full dot product

$$h_1 = \sigma(x_1 W_1 + x_2 W_2 + x_3 W_3)$$



Pooling

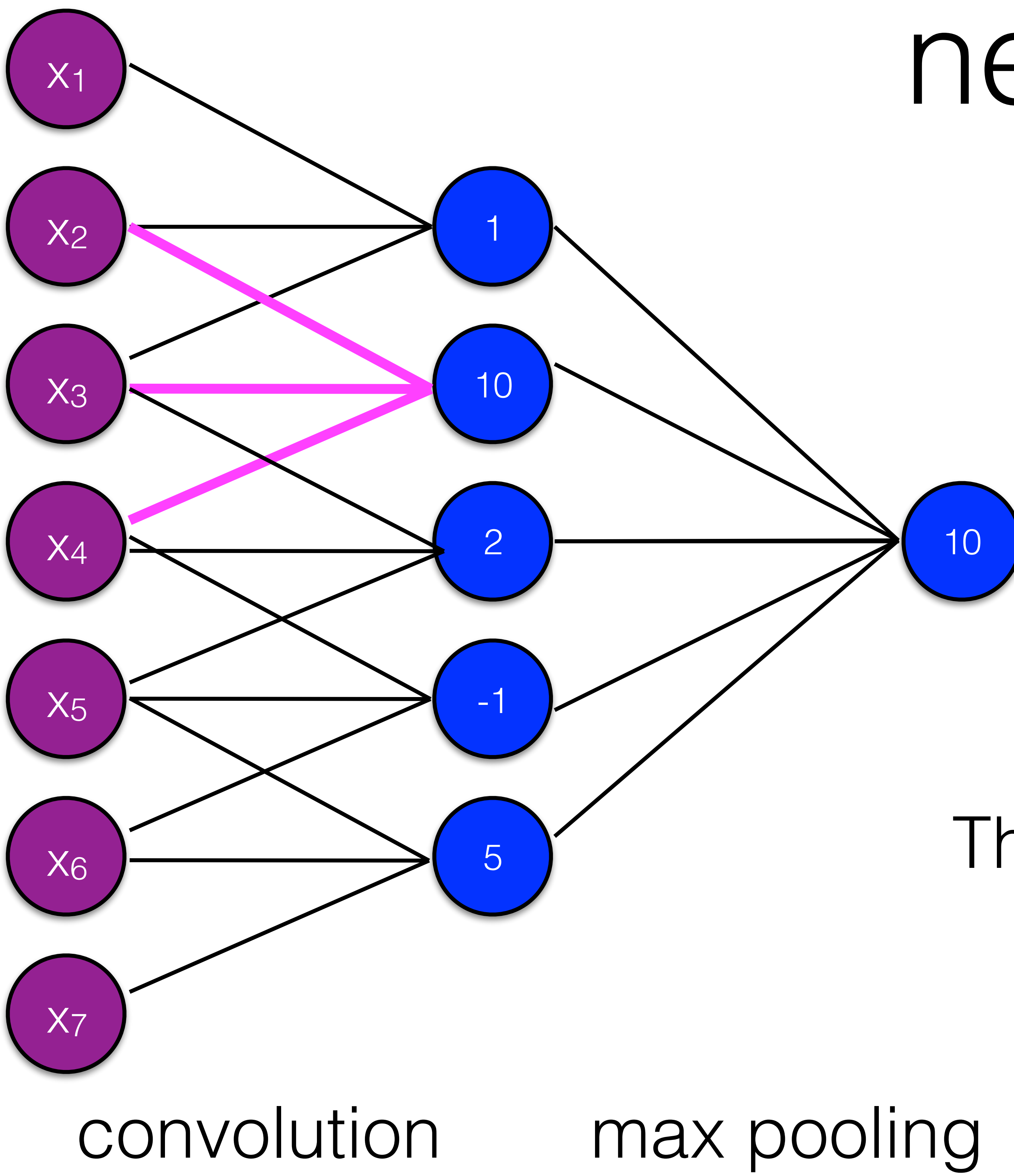
- Down-samples a layer by selecting a single point from some set
- Max-pooling selects the largest value
- Very common for computer vision problems.



Global pooling

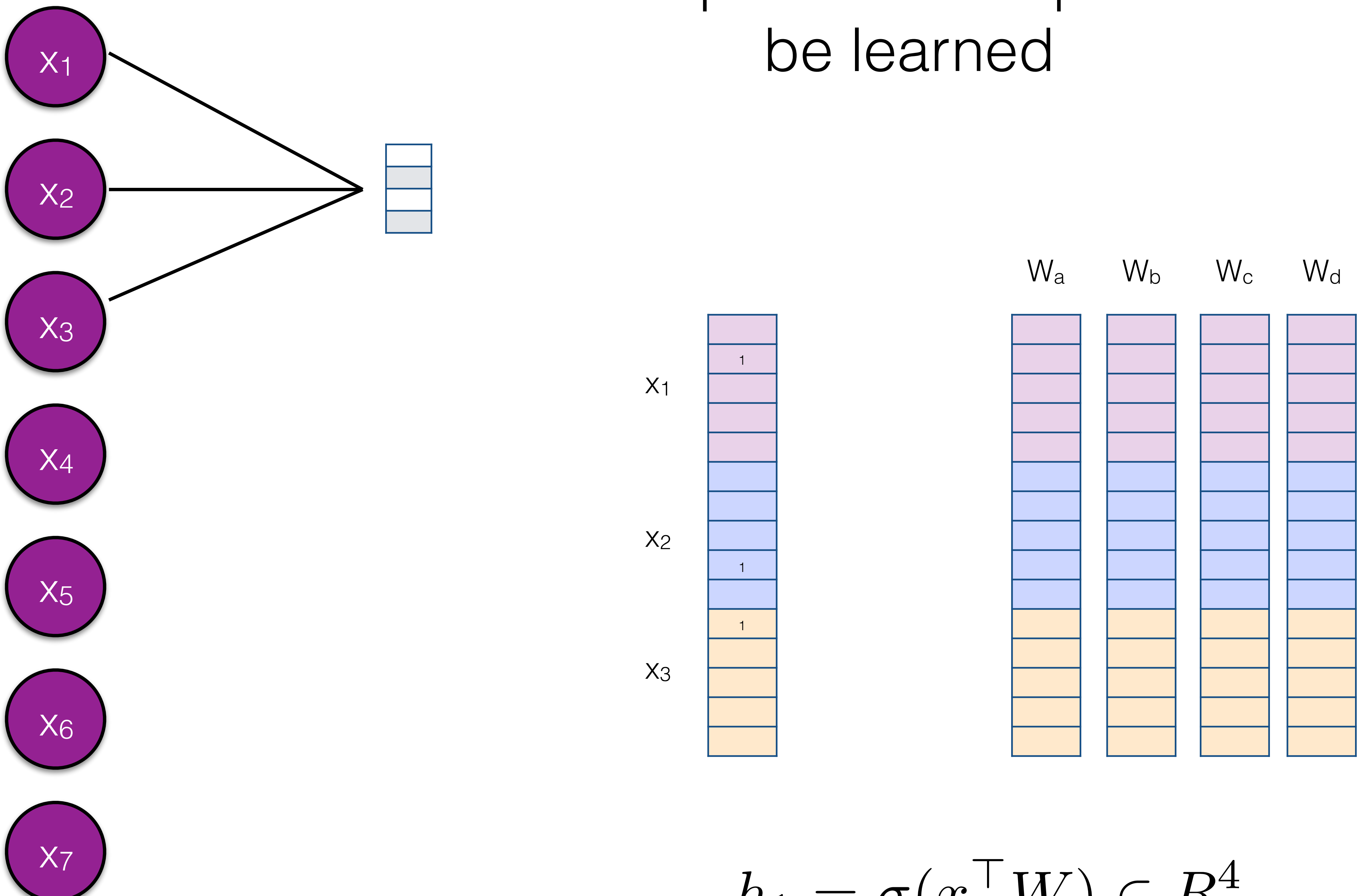
- Down-samples a layer by selecting a single point from some set
- Max-pooling over time (global max pooling) selects the largest value over an entire sequence
- Very common for NLP problems.

Convolutional networks



This defines one filter.

We can specify multiple filters; each filter is a separate set of parameters to be learned



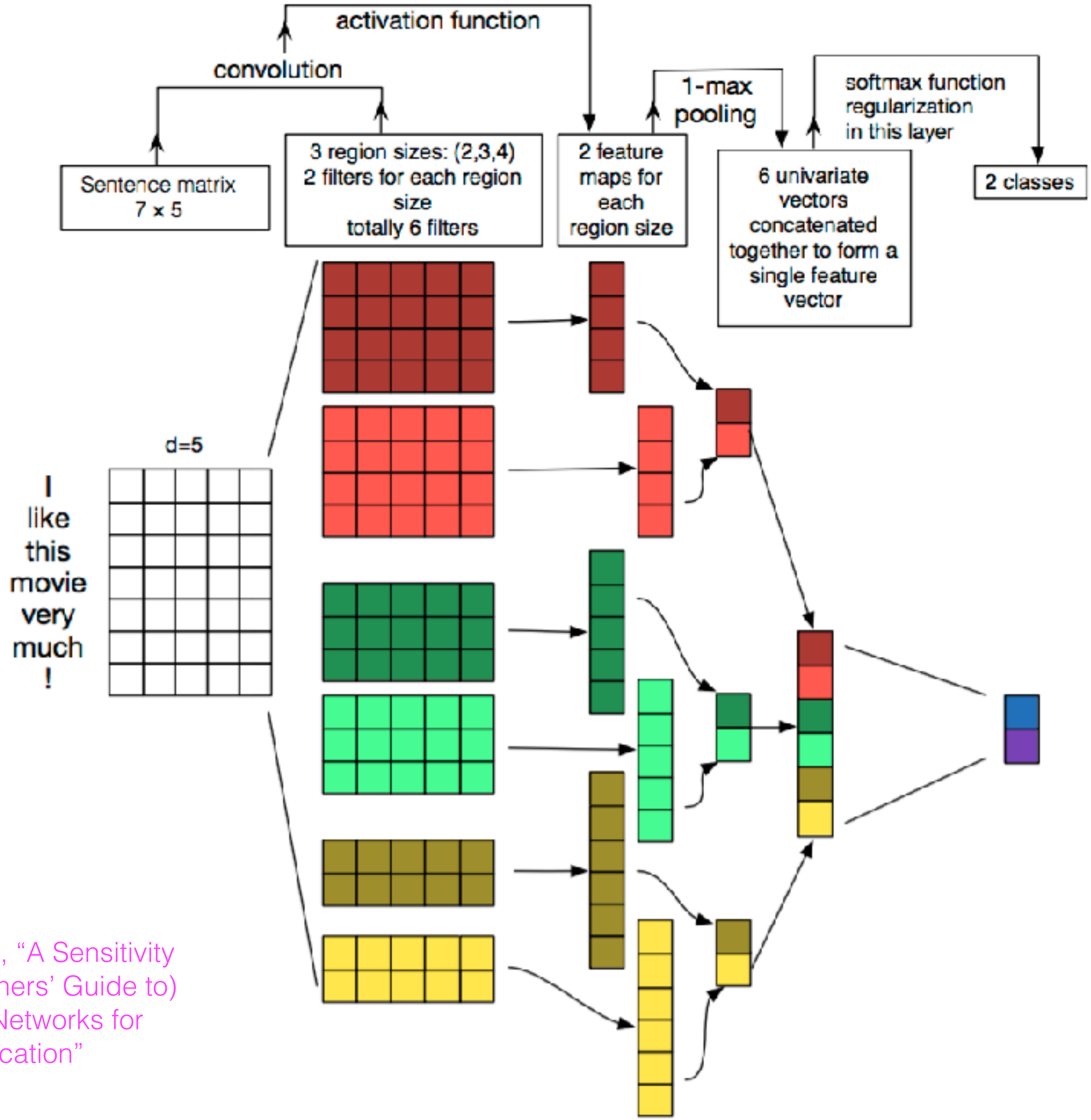
$$h_1 = \sigma(x^\top W) \in R^4$$

Convolutional networks

- With max pooling, we select a single number for each filter over all tokens

- (e.g., with 100 filters, the output of max pooling stage = 100-dimensional vector)

- If we specify multiple filters, we can also scope each filter over different window sizes



Zhang and Wallace 2016, "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification"

CNN as important ngram detector

Higher-order ngrams are much more informative than just unigrams (e.g., “i don’t like this movie” [“I”, “don’t”, “like”, “this”, “movie”])

We can think about a CNN as providing a mechanism for detecting important (sequential) ngrams without having the burden of creating them as unique features

	unique types
unigrams	50921
bigrams	451,220
trigrams	910,694
4-grams	1,074,921

Unique ngrams (1-4) in Cornell movie review dataset

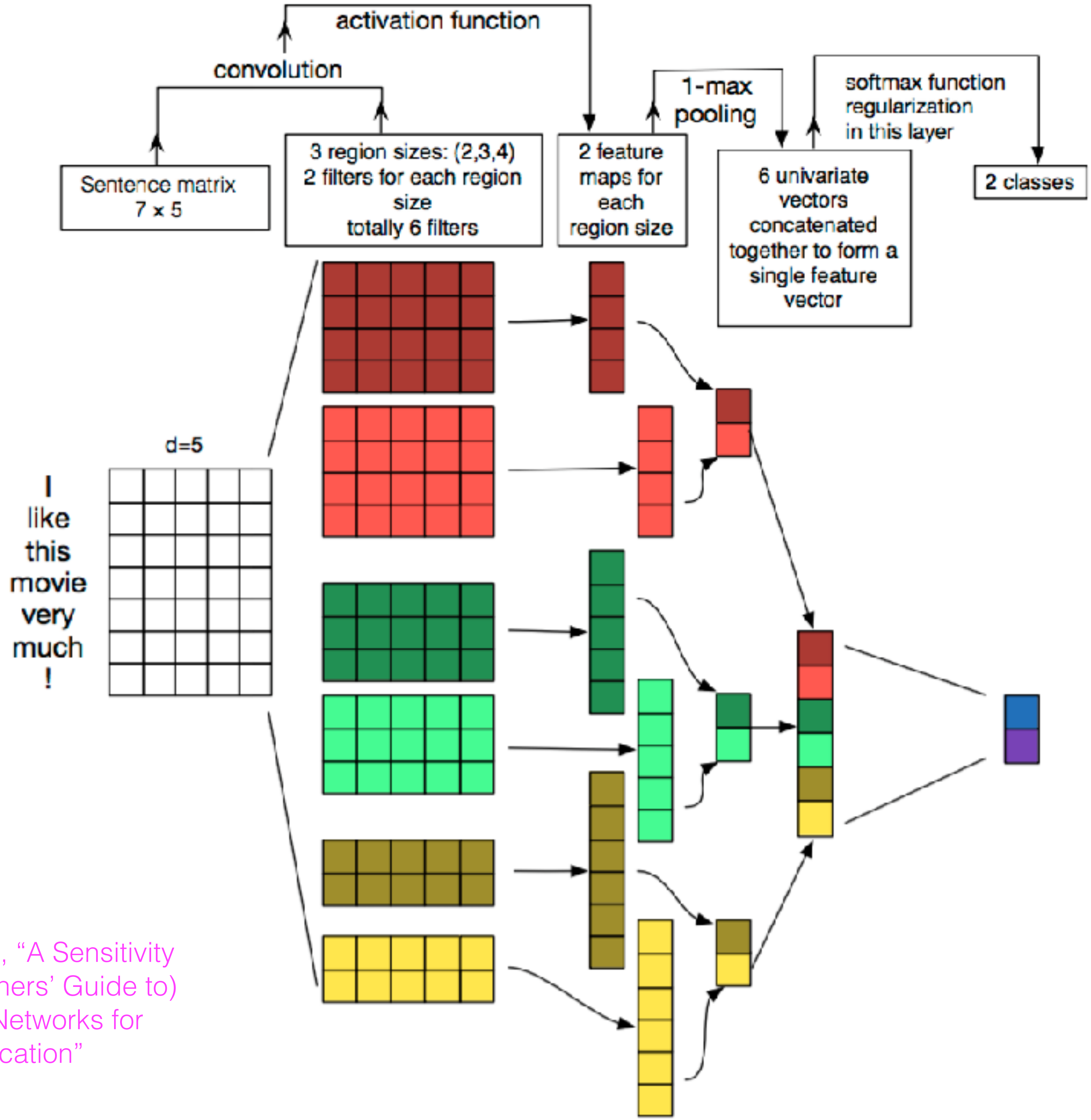
Keras

- We’ll be using keras to implement several neural architectures over the next few weeks
- Today: Functional models

Sequential

- Useful for models of limited complexity where the input to every layer is the output of the previous layer.

```
model = Sequential()

model.add(Embedding(input_dim=vocab_size,
output_dim=word_embedding_dim,
weights=[embeddings], trainable=False))

model.add(Conv1D(filters=50, kernel_size=2,
strides=1, padding="same", activation="tanh"))

model.add(GlobalMaxPooling1D())

model.add(Dropout(0.2))

model.add(Dense(1, activation='sigmoid'))
```



Zhang and Wallace 2016, "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification"

Functional

- Useful for complex models where a single layer can have multiple inputs/output that don’t need to be linearly related to each other
- Layers here are functions that give you more control over the inputs and outputs

Functional

```
word_sequence_input = Input(shape=(None,),
dtype='int32')

word_embedding_layer =
Embedding(vocab_size, word_embedding_dim,
weights=[embeddings], trainable=False)

embedded_sequences =
word_embedding_layer(word_sequence_input)
```