Learning from Data

Lecture 3: Linear Models, Neural Networks and Word Embeddings

Rik van Noord - 18 September 2023

Previous weeks: Classification

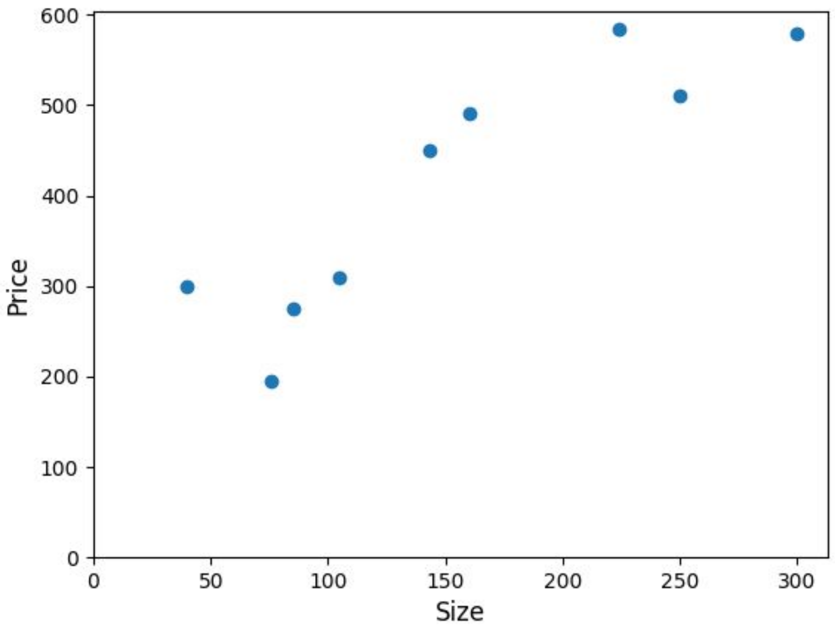
New type of problem: predicting continuous values

Regression

Example data - house prices

Size (m^2)	Price (x1000)
40	300
76	195
85	275
105	310
143	450
160	491
224	585
250	510
300	580

Example data - house prices



Linear model

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How do we use multiple features?

- $Y = b_0 + b_1 * X_1 + b_2 * X_2 + \ldots + X_n * b_n$

Linear model

```
from sklearn import linear_model
```

Setup data set

```
size  = np.array([40, 76, 85, 105, 143, 160, 224, 250, 300]).reshape(-1, 1)
price = np.array([300, 195, 275, 310, 450, 491, 585, 510, 580]).reshape(-1, 1)
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Create model and make predictions on training set

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regr = linear_model.LinearRegression()
regr.fit(size, price)
pred = regr.predict(size)
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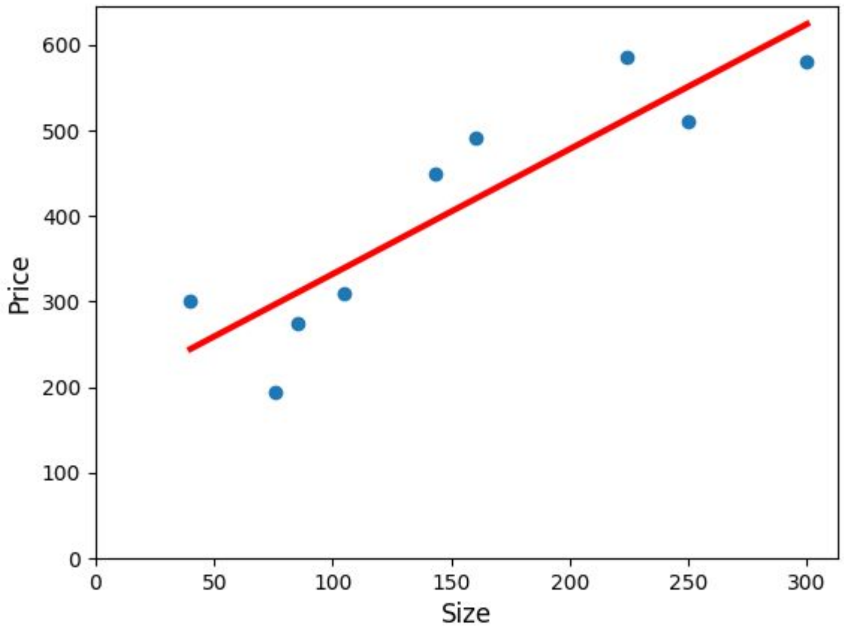
Show in plot

```
plt.scatter(size, price)
plt.plot(size, pred, color='red', linewidth=3)
plt.show()
```

Example data - house prices



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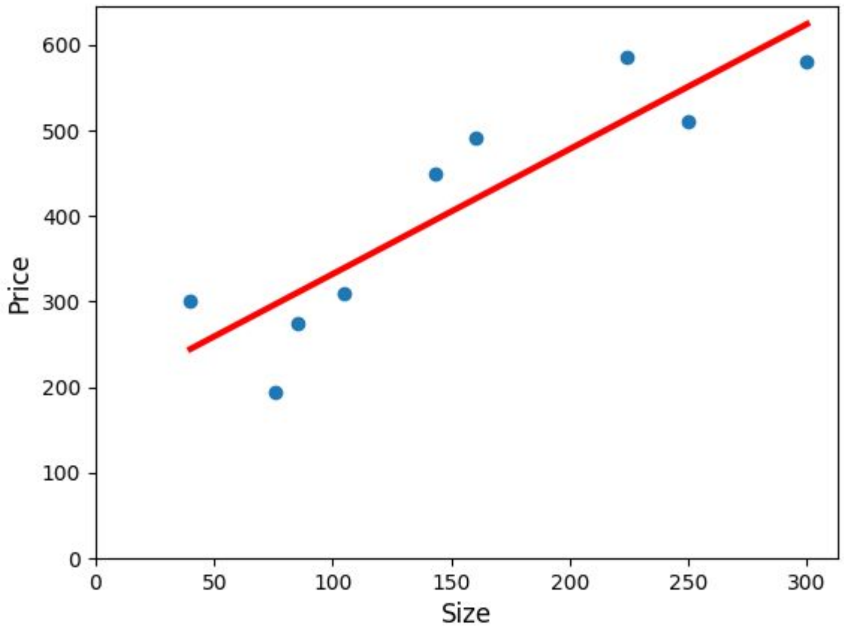

What about a new instance for size = 200?

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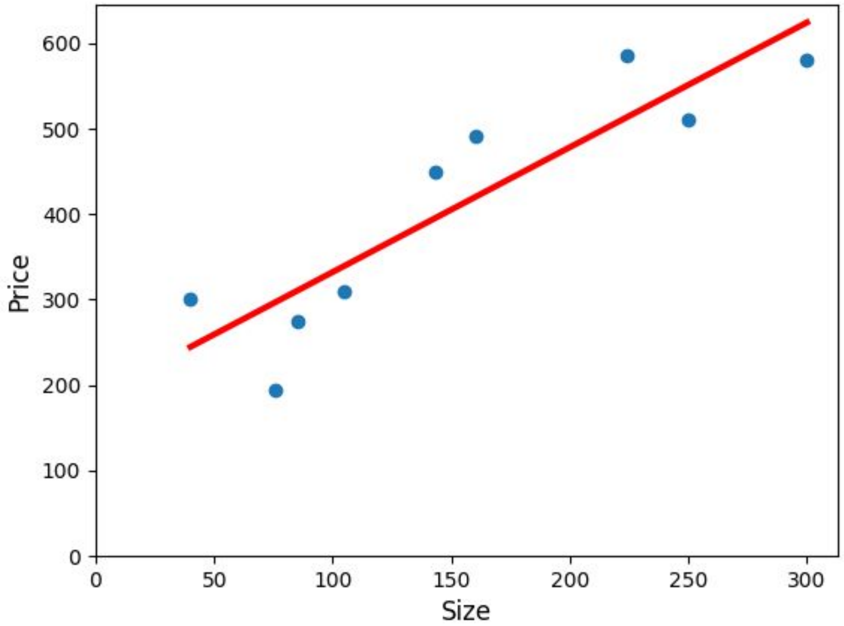


What about a new instance for size = 200?

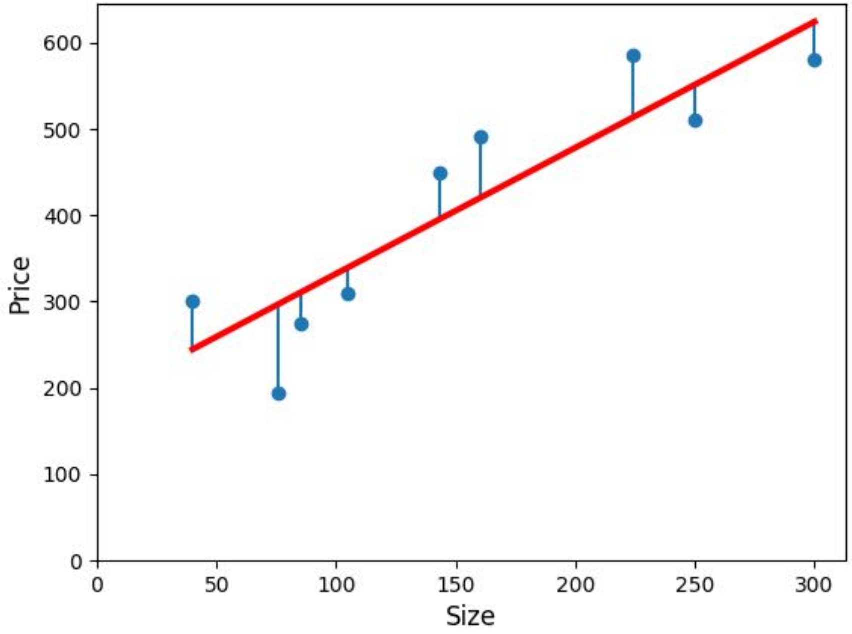
We actually have the exact formula:

$Y = b_0 + b_1 * X_1$

$Y = 186.4 + 1.46 * \text{size}$

$= 186.4 + 1.46 * 200 =$ **478**

Errors as vertical lines



Mean Squared Error (MSE)

How close is a regression line to a set of points?

General idea:

- For each distance, measure distance (=error) to the regression line
- Square the distance
    - Deal with negative numbers, give more weight to large mistakes
- Take average over all errors

The **lower** the number, the better!

Regression models

- Most algorithms will also work with regression
  - KNeighborsRegressor
  - DecisionTreeRegressor
  - RandomForestRegressor
  - svm.SVR (Support Vector Regression)

Sometimes, regression might be a **good fit** even if the data looks categorical

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For example for certain sentiment analysis tasks:

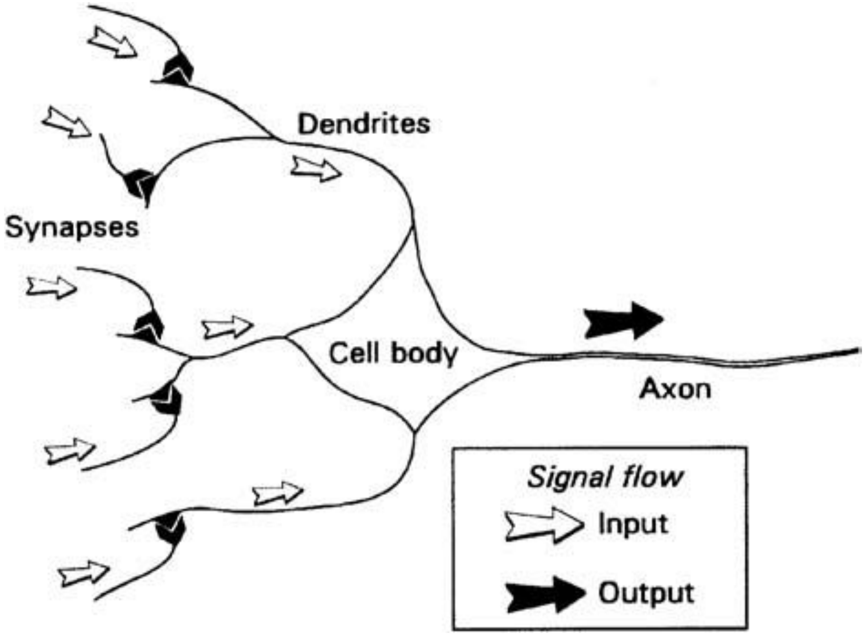
- Positive, neutral and negative can be represented as **1, 0 and -1**
- Classification models don’t know that **neutral** is closer to **positive** than **negative** is!

Neural Networks

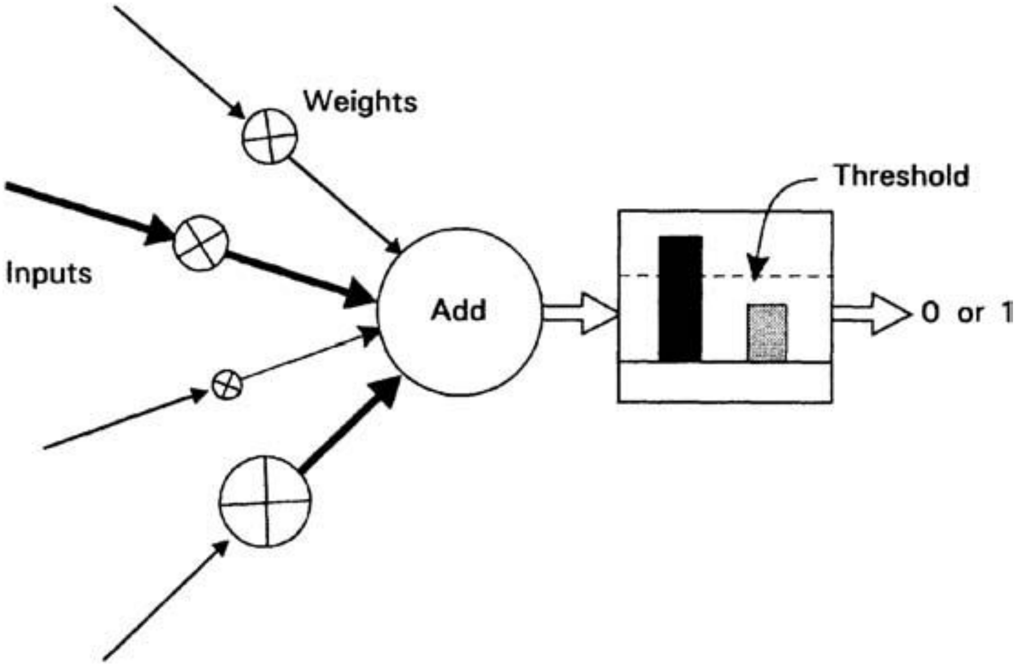
Neural Networks

- For years the dominant method in NLP
- Algorithm that works with vector spaces
- We will start with the most simple variant and gradually work our way up
- Word embeddings: treat words as vector themselves
- Next week: **deep learning**

Human Neuron



Artificial Neuron



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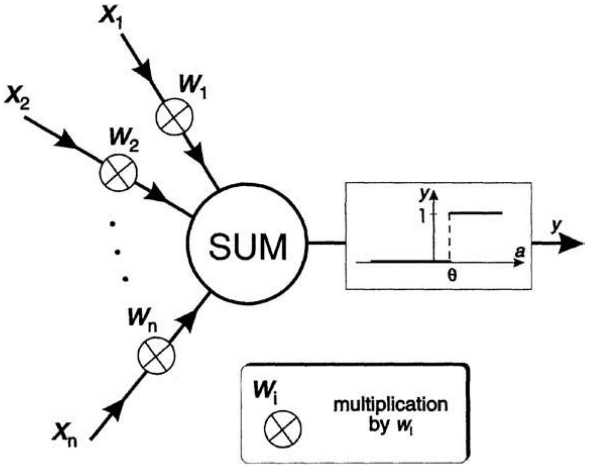
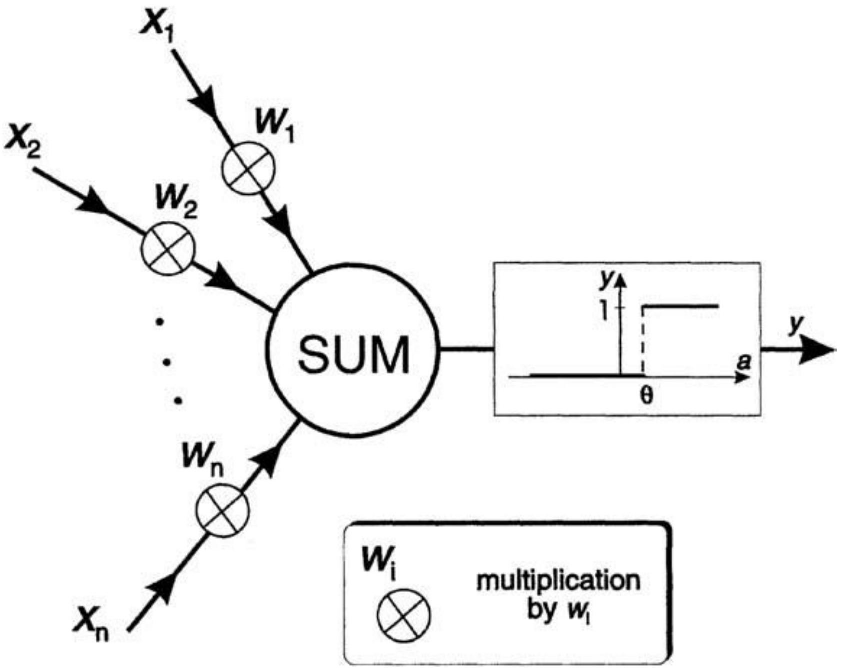


Some definitions

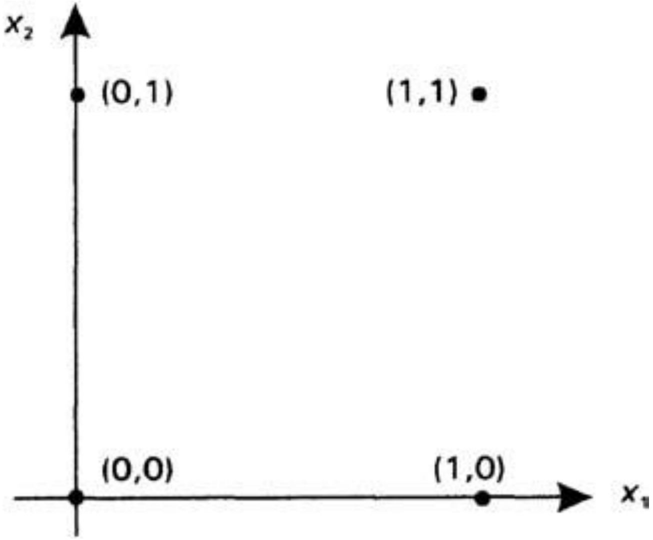
- **Input:** the features x_1, x_2, x_3
- **Weights:** w_1, w_2, w_3
- **Node:** process input (SUM)
- **Activation:** transform input
    - Decision rule

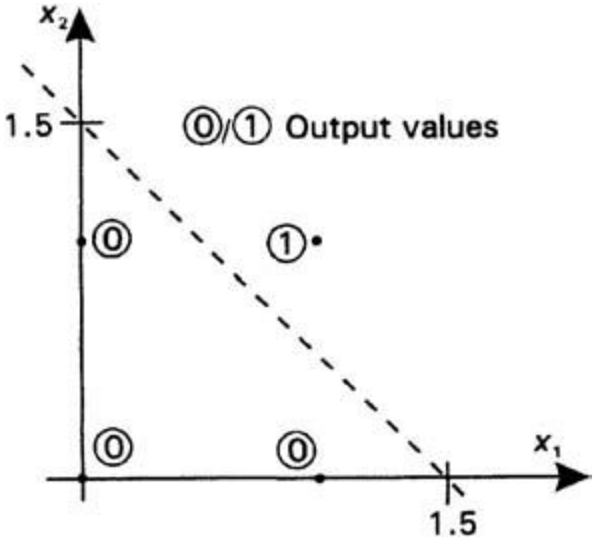
$y(x_1,x_2,x_3)$ = **1 if** $w_0 + w_1 * x_1 + w_2 * x_2 + x_3 * w_3$ **> 0**
else 0

- **Output:** final decision (y)



Classification example





Classification example

Feature 1 (X_1)	**Feature 2 (X_2)**	**Label**
0	0	0
0	1	0
1	0	0
1	1	1

Perceptron example

- **First:** weights are randomly initialized (w_0, w_1, w_2)
  - Say $w_0 = 0.1$, $w_1 = -0.4$ and $w_2 = 0.2$

Let's look at the performance of our model with these weights:

Remember: $a = w_0 + w_1 * x_1 + w_2 * x_2$ and $y = 1$ for $a > 0$ and 0 otherwise

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- **Intuition:** figure out who (what weights) are to blame for mistakes
    - Learning a task == learning the weights
- Compare predicted and gold values and change weights accordingly
    - Bigger contribution to error means bigger change in weight

Learning the weights

Rule: $\Delta w_i = r * (t - y) * x_i$ with: **Δw**: change in weight

r: learning rate (rate of change)

t: target (gold label)

y: output (predicted label)

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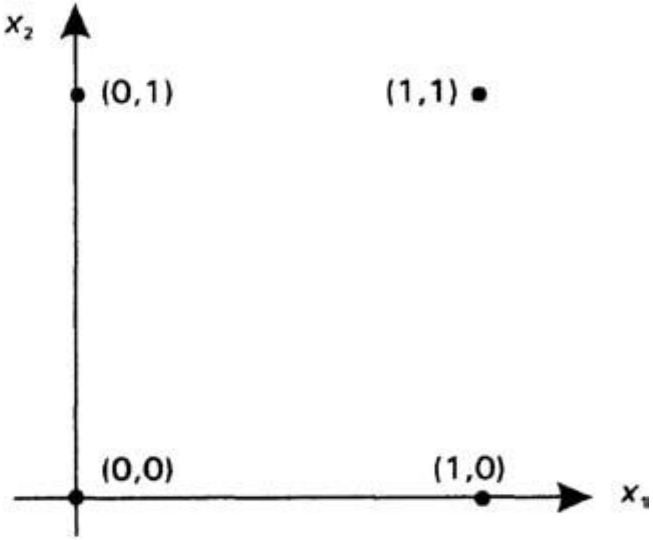
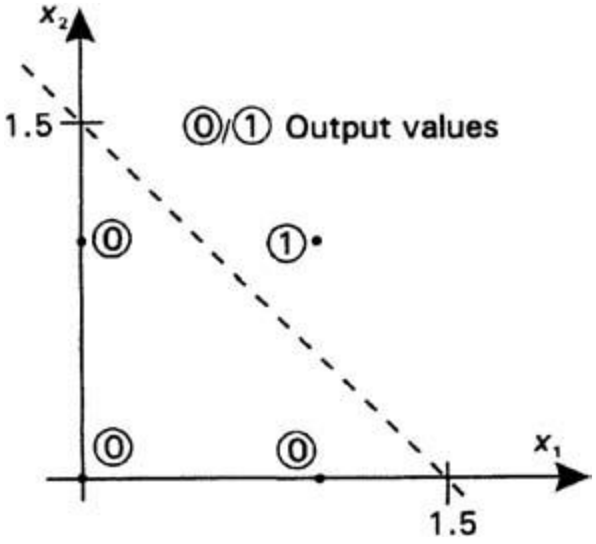
- If the feature value x_i is zero, Δw_i is zero
  - No change for this weight, as it was not to blame for the wrong decision

Classification example





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Perceptron example

w_0	x_1	w_1	x_2	w_2	a	y	t	r * (t - y)	Δw_0	Δw_1	Δw_2
0.1	0	-0.4	0	0.2	0.1	1	0	-0.25	-0.25	0	0
-0.15	0	-0.4	1	0.2	0.05	1	0	-0.25	-0.25	0	-0.25
-0.4	1	-0.4	0	-0.05	-0.8	0	0	0	0	0	0
-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25

The rule: $\Delta w_i = r * (t - y) * x_i$

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-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25

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-0.4	1	-0.4	0	-0.05	-0.8	0	0	0	0	0	0
-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25

We can loop over the data multiple times!

Perceptron example

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-0.4	1	-0.4	0	-0.05	-0.8	0	0	0	0	0	0
-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
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-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
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-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
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-0.4	1	-0.4	0	-0.05	-0.8	0	0	0	0	0	0
-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
-0.15	0	-0.15	0	0.2	-0.15	0	0	0	0	0	0
-0.15	0	-0.15	1	0.2	0.05	1	0	-0.25	-0.25	0	-0.25

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-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
-0.15	0	-0.15	0	0.2	-0.15	0	0	0	0	0	0
-0.15	0	-0.15	1	0.2	0.05	1	0	-0.25	-0.25	0	-0.25
-0.4	1	-0.15	0	-0.05	-0.55	0	0	0	0	0	0

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w_0	x_1	w_1	x_2	w_2	a	y	t	r * (t - y)	Δw_0	Δw_1	Δw_2
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-0.15	0	-0.4	1	0.2	0.05	1	0	-0.25	-0.25	0	-0.25
-0.4	1	-0.4	0	-0.05	-0.8	0	0	0	0	0	0
-0.4	1	-0.4	1	-0.05	-0.85	0	1	0.25	0.25	0.25	0.25
-0.15	0	-0.15	0	0.2	-0.15	0	0	0	0	0	0
-0.15	0	-0.15	1	0.2	0.05	1	0	-0.25	-0.25	0	-0.25
-0.4	1	-0.15	0	-0.05	-0.55	0	0	0	0	0	0
-0.4	1	-0.15	0	-0.05	-0.55	0	1	0.25	0.25	0.25	0.25

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- Sure enough, this converges after 7 loops over the data!
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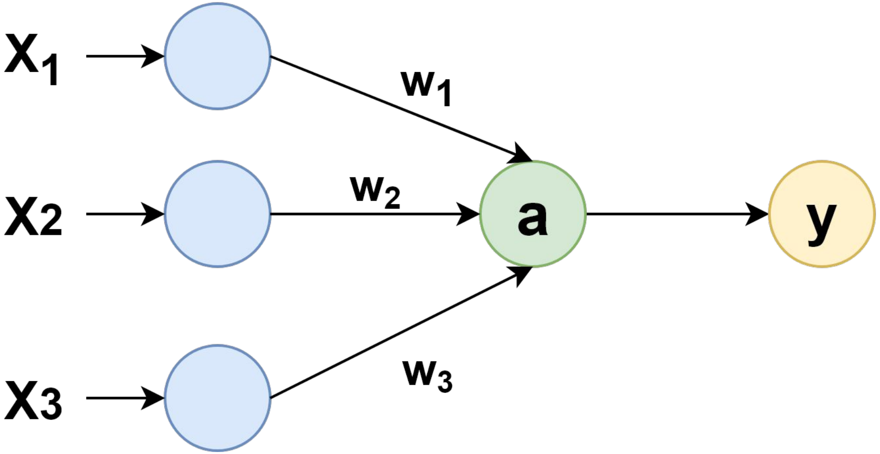
w_0	x_1	w_1	x_2	w_2	a	y	t
-0.65	0	0.6	0	0.2	-0.65	0	0
-0.65	0	0.6	1	0.2	-0.05	0	0
-0.65	1	0.6	0	0.2	-0.45	0	0
-0.65	1	0.6	1	0.2	0.15	1	1

Check for yourself

```
data = [[0,0], [0,1], [1,0], [1,1]]
gold = [0, 0, 0, 1]
w0, w1, w2 = 0.1, -0.4, 0.2
lr = 0.25
for epoch in range(7):
    for idx, (x1, x2) in enumerate(data):
        a = w0 + (x1 * w1) + (x2 * w2)
        y = 1 if a > 0 else 0
        change = lr * (gold[idx] - y)
        w0 += change
        w1 += (change * x1)
        w2 += (change * x2)
```

Perceptron schematically



Perceptron formula

Features:

Represented as a vector: $x = [x_1, x_2, \ldots, x_n]$

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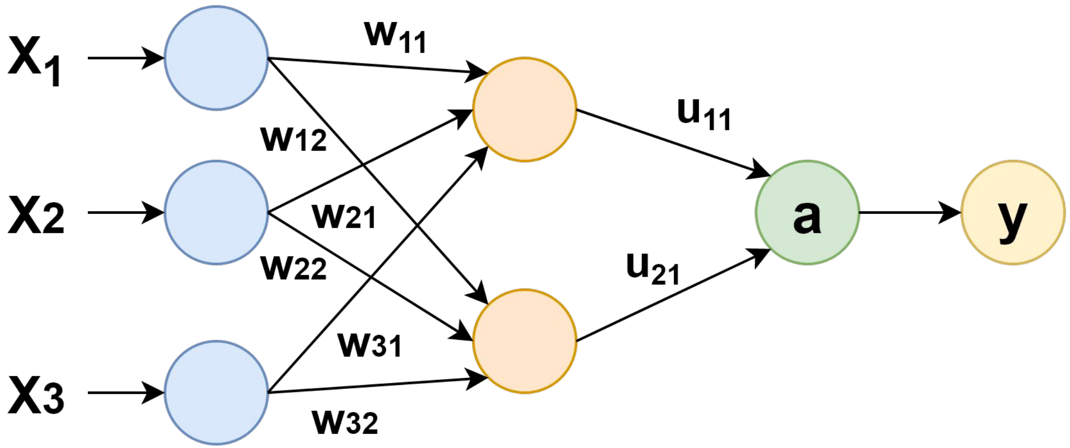
Formula for calculating output a:

$a = w_1x_1 + w_2x_2 + \dots + w_nx_n$

$a = x \cdot v$ = a scalar (single value)

(Actually +b for bias, but we leave this out for simplicity)

Multi-layer perceptron



Formulas

Single-layer perceptron:

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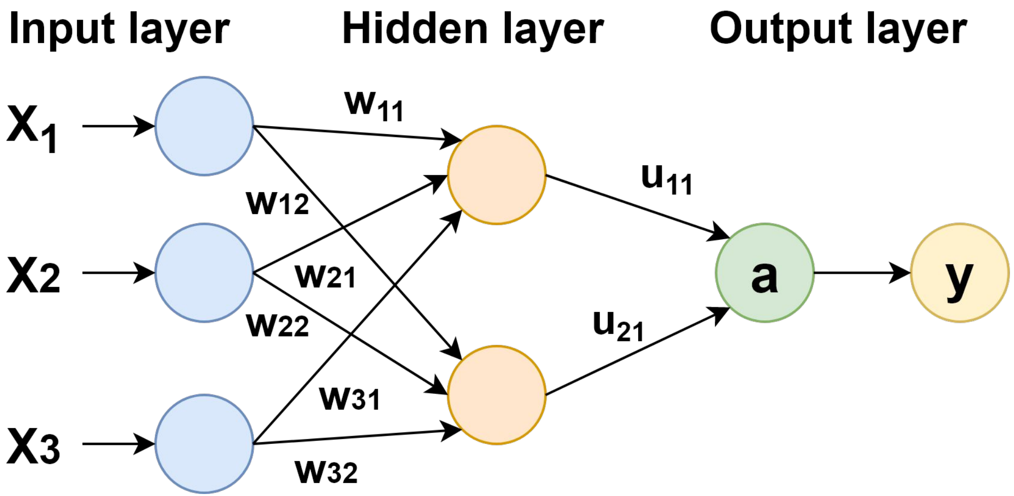
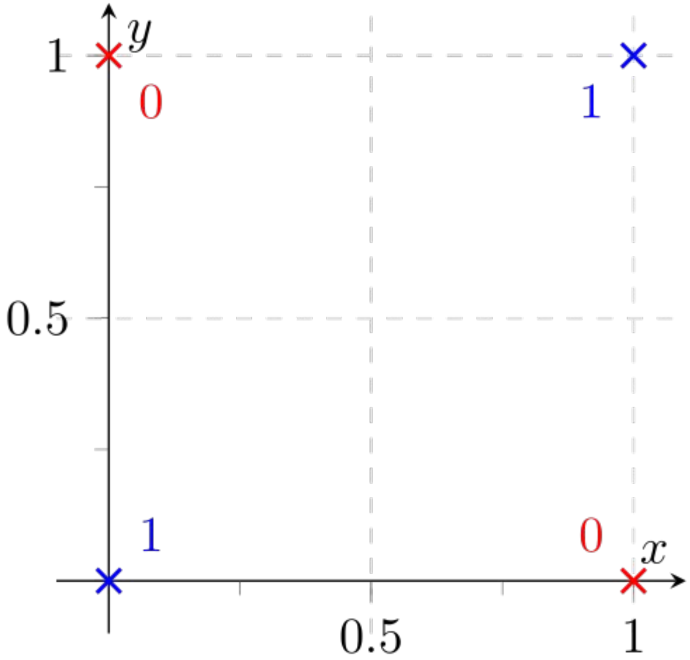
Giving us the formula:

$a = u \cdot (x \cdot W) = u(xW)$, but usually written as: $a = (xW_1)W_2$


Input layer
Hidden layer
Output layer
X1
X2
X3
w11
w12
w21
w22
w31
w32
u11
u21
a
y

But this is still a linear model?

XOR-problem



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- Remember the kernel trick for SVMs

Let’s apply it to our hidden vector and call the function **g:**

$a = g(xW_1)W_2$

Non-linear functions

Let's do an example:

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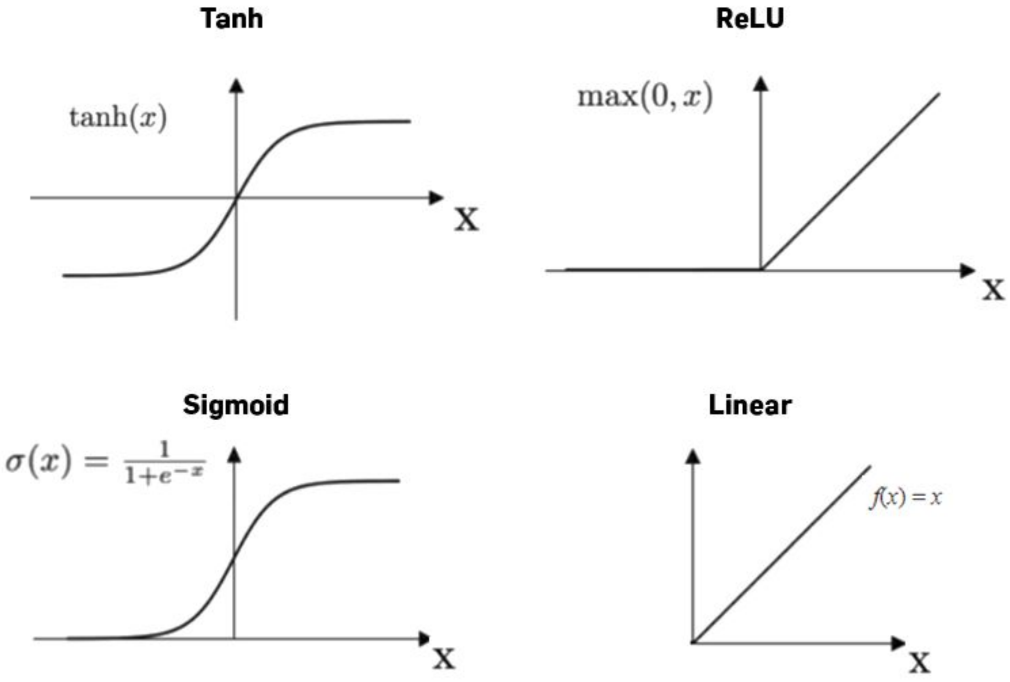


Non-linear functions

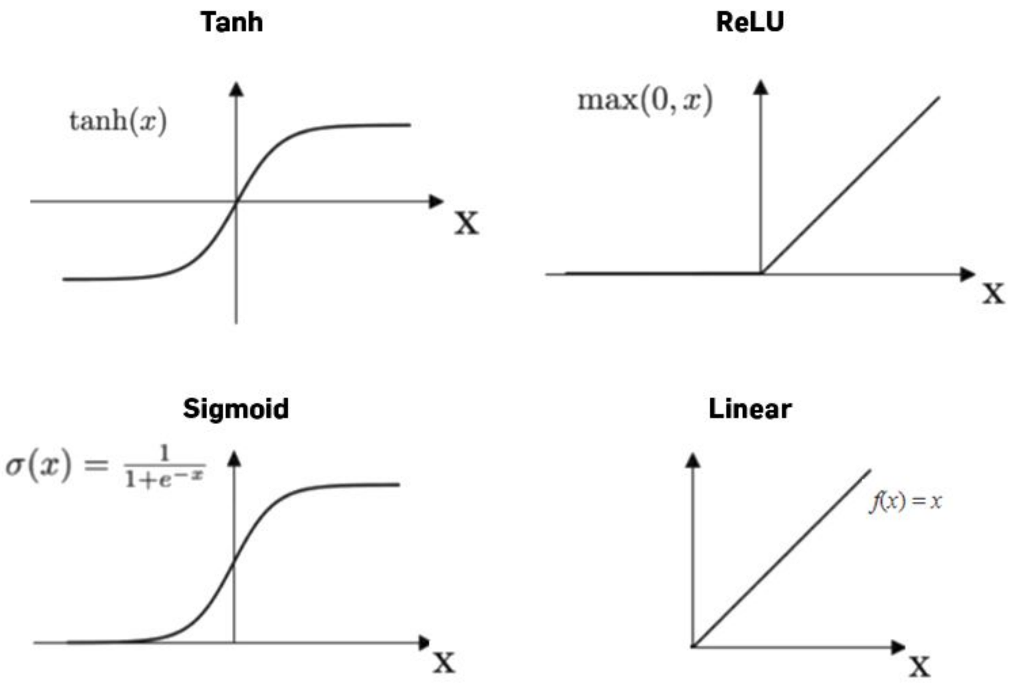
Let's do an example:

x = [-0.4, 0.8, 1.9, -1.1]

tanh(x)   = [-0.38, 0.66, 0.96, -0.80]

σ(x)   = [0.4, 0.69, 0.87, 0.25]

ReLu (x) = [0, 0.8, 1.9, 0]



These functions are called activation functions

Multi-layer perceptrons

1 hidden layer:

$a = g(xW_1)W_2$

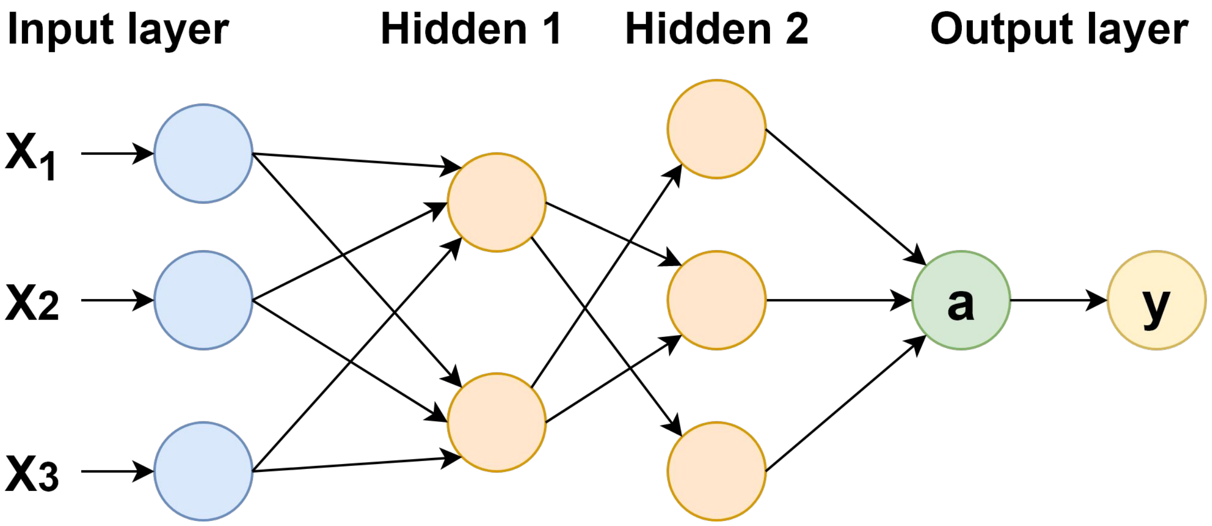
2 hidden layers:

$a = (g_2(g_1(xW_1)W_2)W_3$

2 hidden layers using intermediary variables:

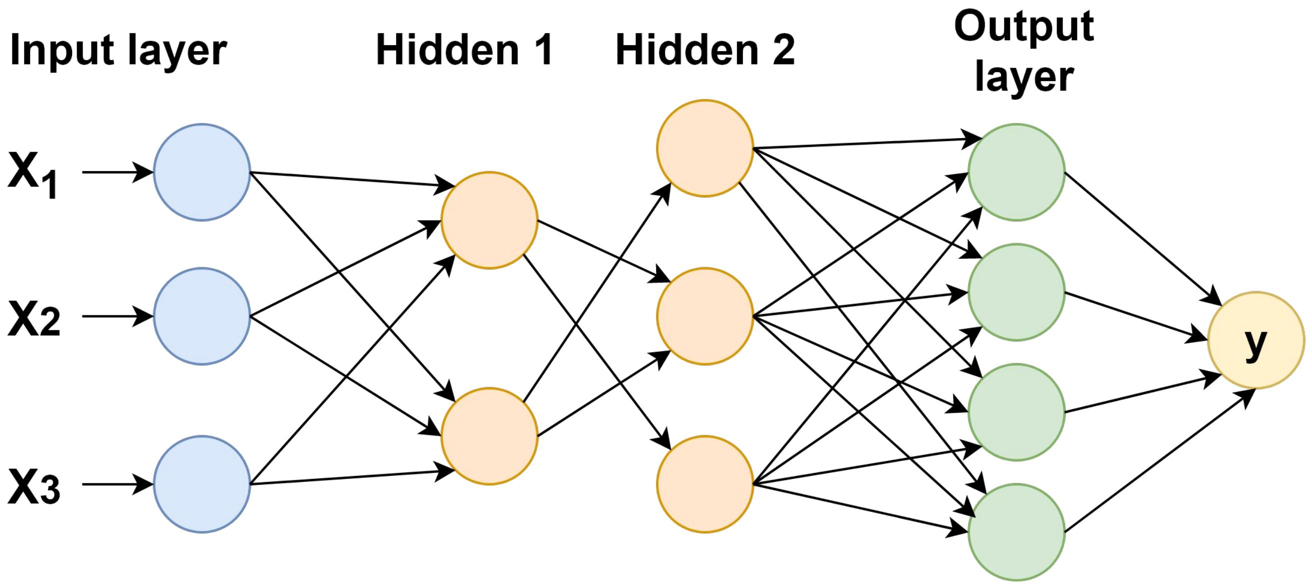
$h_1 = g_1(xW_1)$
$h_2 = g_2(h_1W_2)$
$a = h_2W_3$

2 hidden layers



What about multi-class classification?

Multi-class classification



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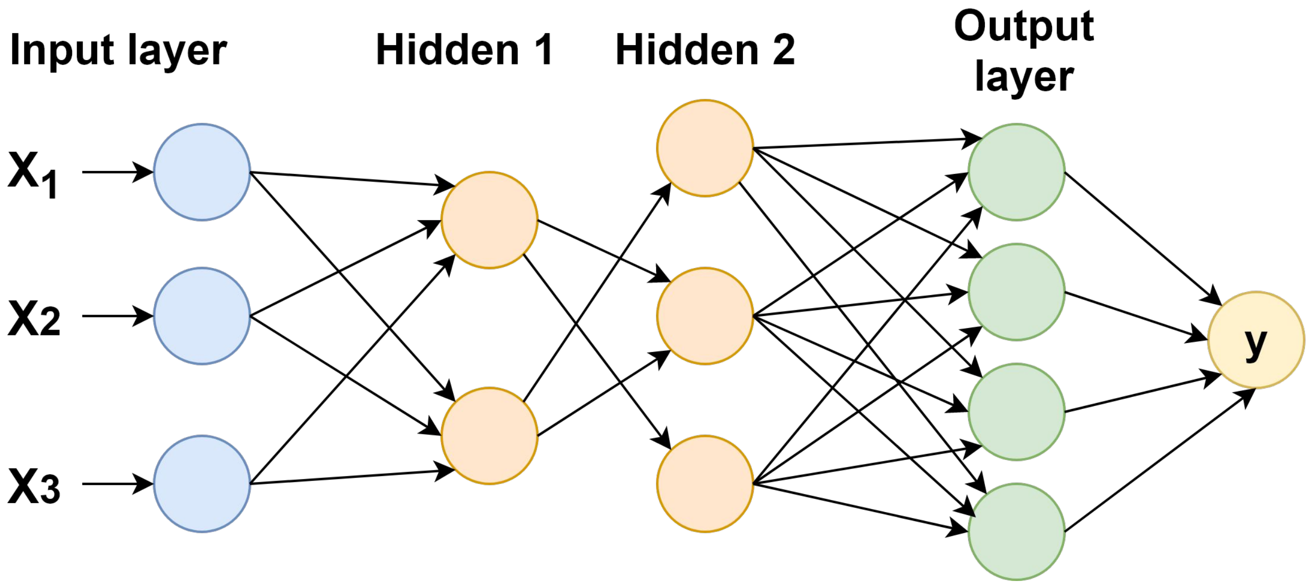
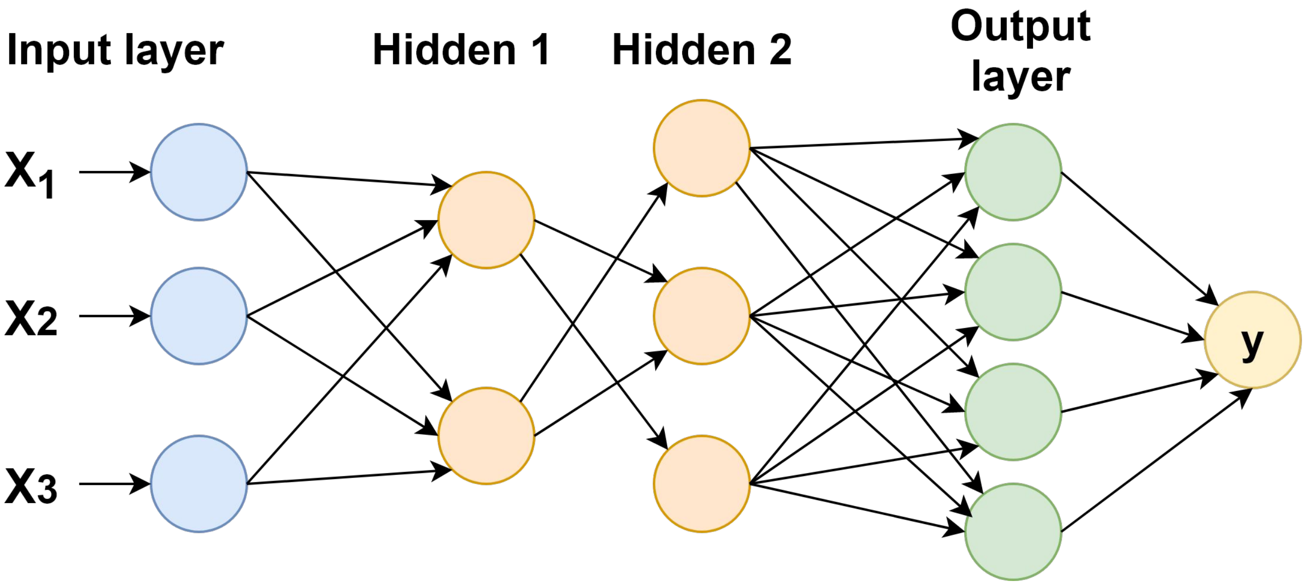


Each output class is represented by a node (green). We then simply take the node with the highest value as our final prediction (y).

Multi-class classification



For probabilities per class, put the output layer values through the **softmax function**

This normalizes the output vector to sum to 1 (i.e. perfect for probabilities)

Softmax

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

softmax([0.1, 0.05, 1.2, 0.4]) = [0.16, 0.15, 0.48, 0.21]

softmax([-0.5, -0.1, 0.3, 5]) = [0.004, 0.006, 0.009, 0.98]

softmax([1.5, 1.5, 1.5, 1.5]) = [0.25, 0.25, 0.25, 0.25]

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We will go over these items one by one to see what happens in each step

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In other words, we calculate **y**, given the current input vector **x** (say [0.2, 0.3, -0.1]) and the weight matrices $\mathbf{W_1}$, $\mathbf{W_2}$ and $\mathbf{W_3}$

$$y = (g_2(g_1(xW_1)W_2)W_3$$

Remember that **g** is a non-linear function such as tanh or sigmoid

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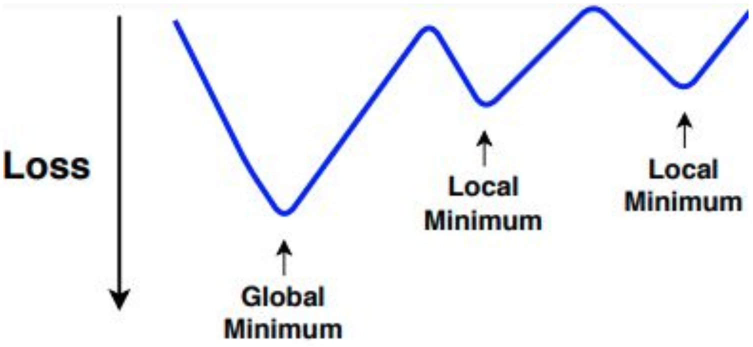
The **lower** the number, the better!

How do we know how to update the weights?

Intuition: since the loss is a function (with parameters/weights), we can minimize it by looking at its **derivative**



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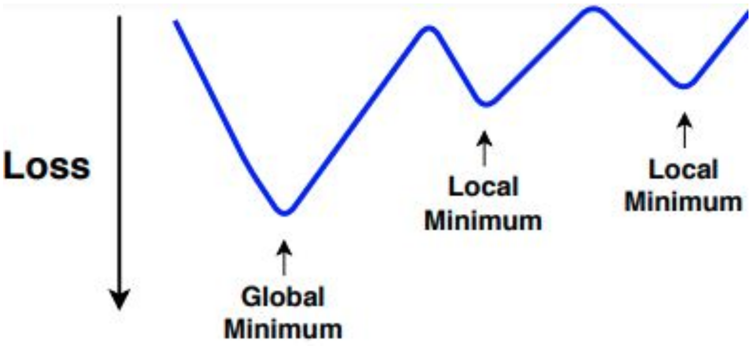

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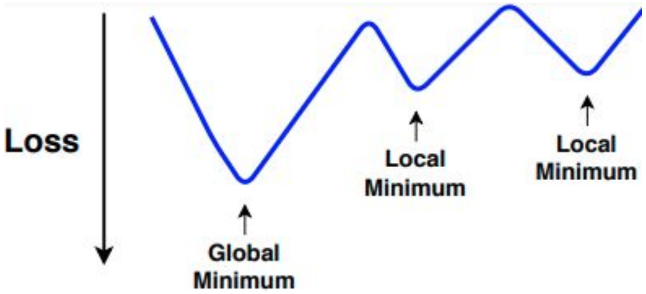

Though this gets complicated: the loss is dependent on the weights, which are dependent on previous weights, etc. How do we calculate the gradient?

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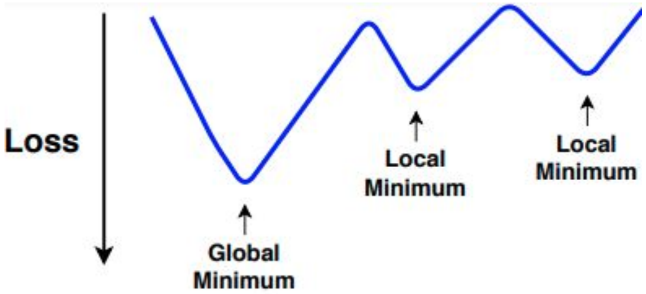

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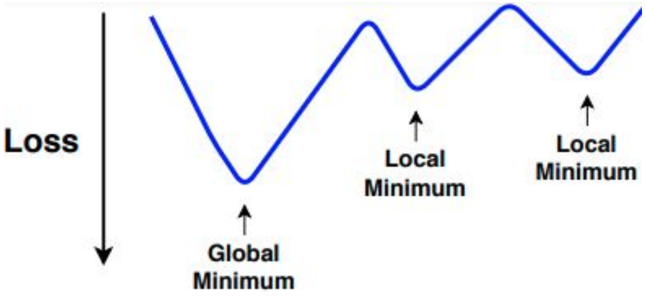
Solution: **backpropagation**. Calculate gradients by recursively calculating partial derivatives by using the chain rule.

Gradient Descent

This method of changing the weights is known as **gradient descent**



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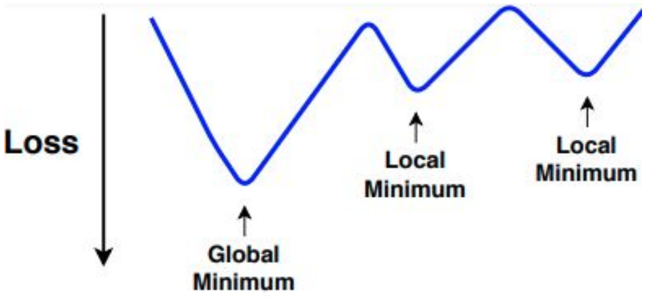
How much we change the weights at each step is known as the **learning rate.**
We usually update the weights based on a number of instances (**batch size**).



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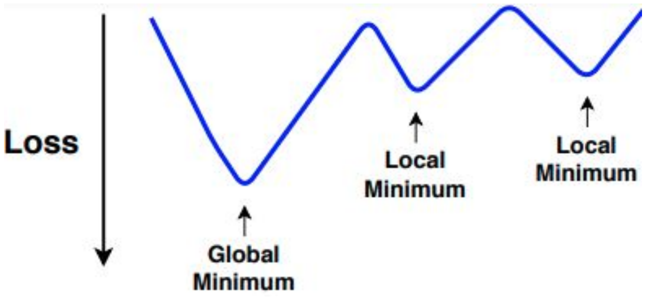
This method of changing the weights is known as **gradient descent**

How much we change the weights at each step is known as the **learning rate.**
We usually update the weights based on a number of instances (**batch size**).

These two settings you have to set yourself and are very important!



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- Stochastic Gradient Descent (**SGD**):
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- **Momentum:** previous updates influence current update
- **Adagrad:** smaller updates for parameters associated with frequent features
- **Adadelta:** less aggressive version of AdaGrad
- **Adam:** combination of advantages of Adadelta and Momentum

Usually, you want to try multiple and see how they perform!

Note this is a highly active research area. For more: https://ruder.io/optimizing-gradient-descent/

How often do we perform these updates?

Training

- There is no clear stopping criterion: we can loop over the data and keep updating the weights as long as we want. Note that a single loop over the data is called an **epoch**

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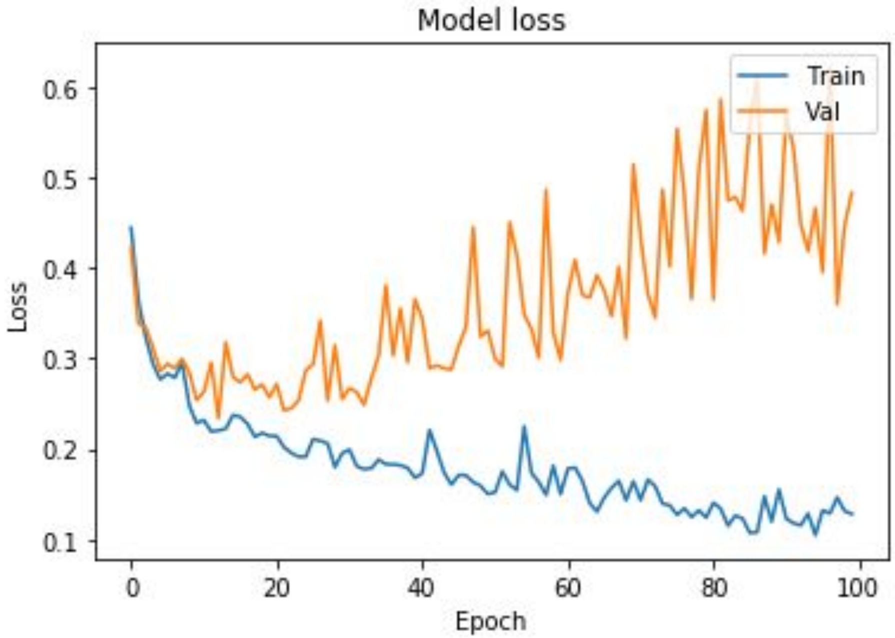
Common solution: check loss or performance on development set after each epoch. If we stop improving, we stop training. Note that no weight updates are performed by looking at the development set (only forward pass).


Model loss
Train
Val
0.6
0.5
0.4
0.3
0.2
0.1
Loss
0
20
40
60
80
100
Epoch

Dropout

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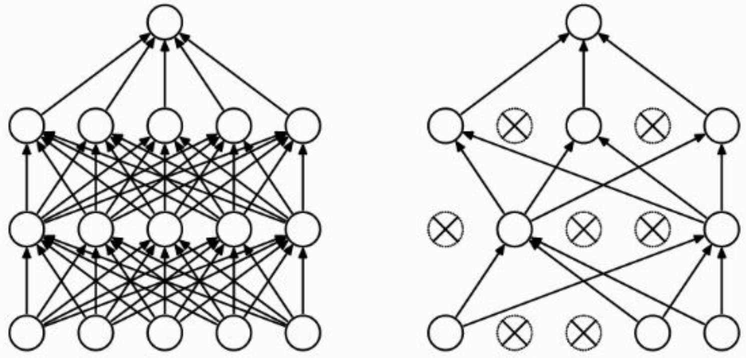
- Teaches the model to not be too reliant on single weights
- Add this after a hidden layer + activation



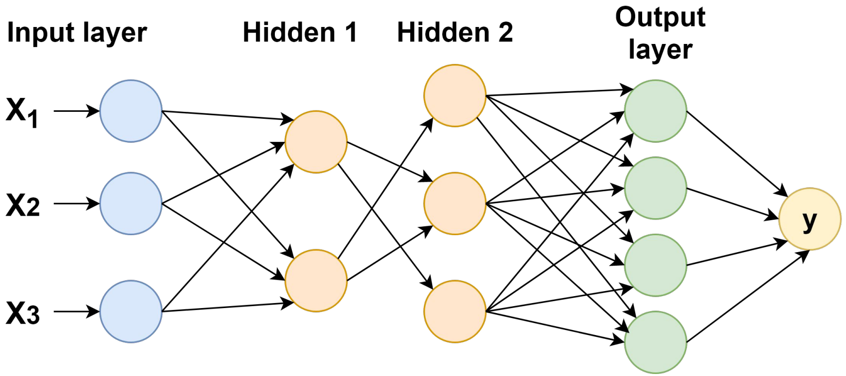
(a) Standard Neural Net

(b) After applying dropout.

Creating a neural network

To create a neural net, you have to specify:

- Input features and output categories



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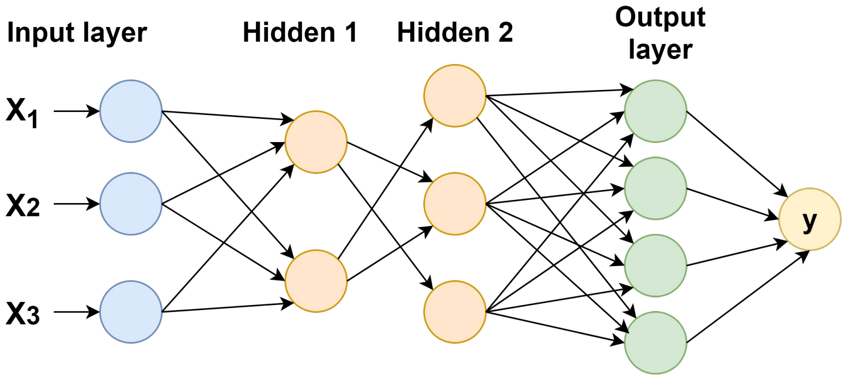

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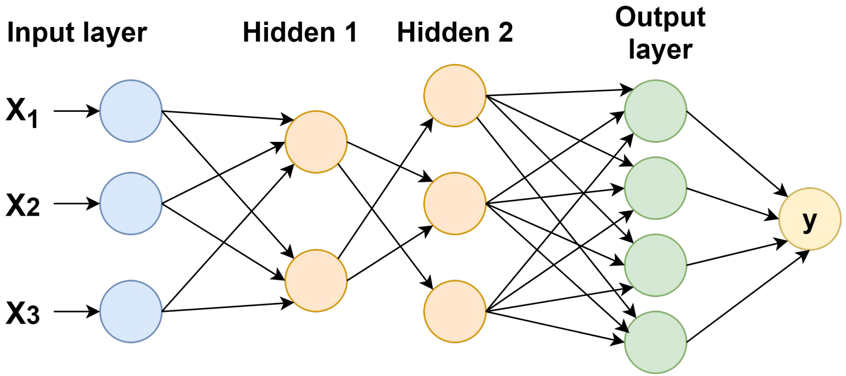

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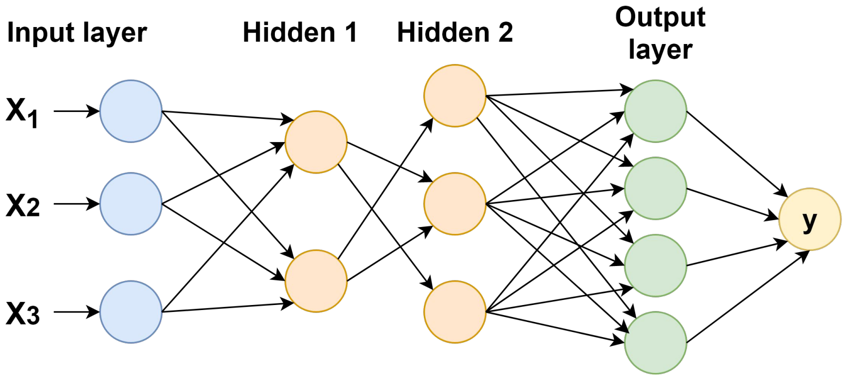

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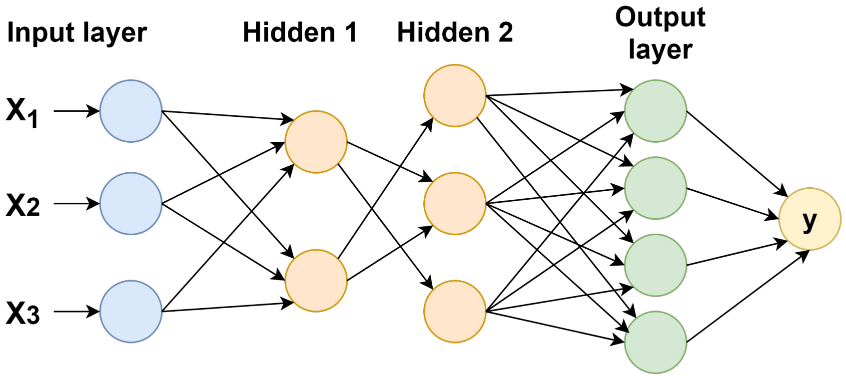

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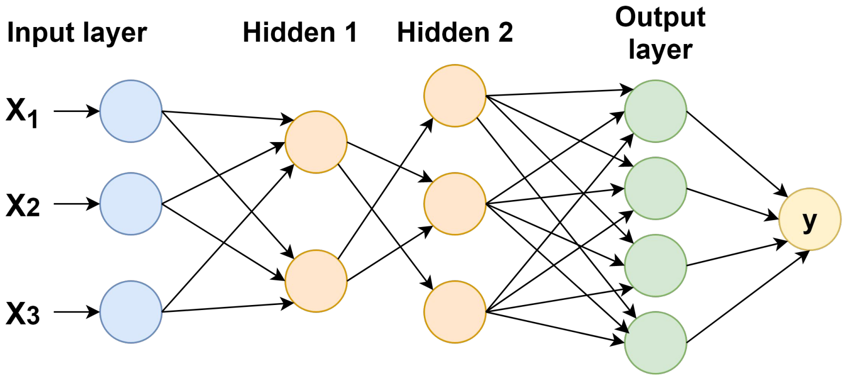

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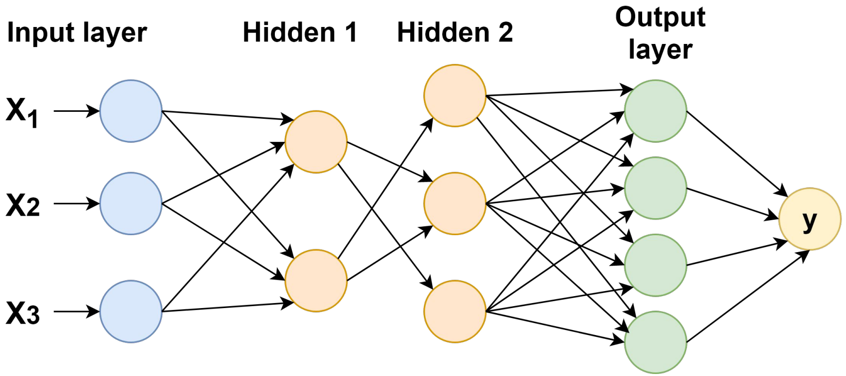

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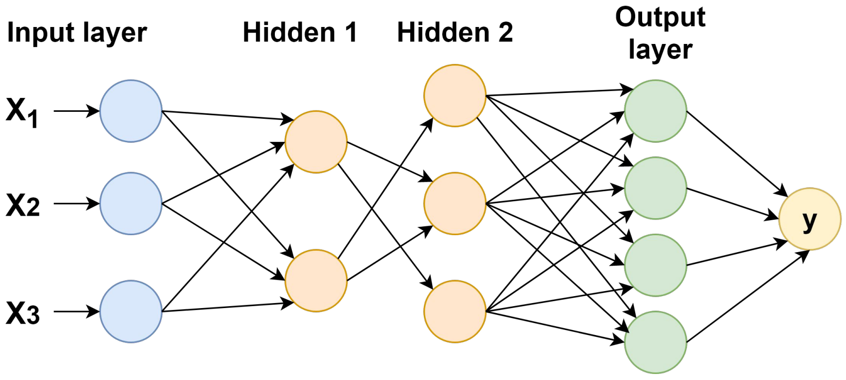

Of course, you don't always know what works in advance. **Experiment!**

Finding the best settings

Once you have neural net set up, you want to push the performance. You can do this by trying to optimize:

- Number of epochs
- Optimizer
- Activation function
- Learning rate
- Number of nodes in hidden layers
- Batch size
- Dropout percentage

(And of course by changing things from the previous slide)

Training a neural net

- Loop over data set in **batches**
- For each batch, update the weights of the network:
  - Calculate what we would have predicted (**forward pass**)
  - Calculate how far off we are (**loss function**)
  - Change the weights given the optimizer and learning rate (**backpropagation**)
- Measure loss throughout the process, stop training if we stop improving
- Save the weights as our final model
- Predict on new data by only doing a **forward pass** (no backpropagation)
  - Remember that a forward pass is nothing more than vector-matrix multiplications
- Given accuracy, perhaps make some changes and start again!

In the lab, we do a small competition!

Wait, how do we get the features?

Features

- Bag-of-words is too sparse and inefficient for neural networks
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We will now look at the concept of **pretrained word embeddings**, or in other words, have an associated **dense vector per word** in the vocabulary.

Word embeddings intuition

“You shall know a word by the company it keeps”

J.R. Firth, 1957

Words as vectors

- **Intuition:** documents have features, but words can also have features!

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Not just adjectives: we want to represent **all words** in this **vector space**

How do we determine these features?
And how do we set them?

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- Words that are similar in meaning should have similar vectors
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Goal:

- Words that occur in similar contexts should have similar vectors
- Words that occur in different context should have different vectors

Don’t count, predict!

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- Train a neural network to predict the next word given the previous word(s)

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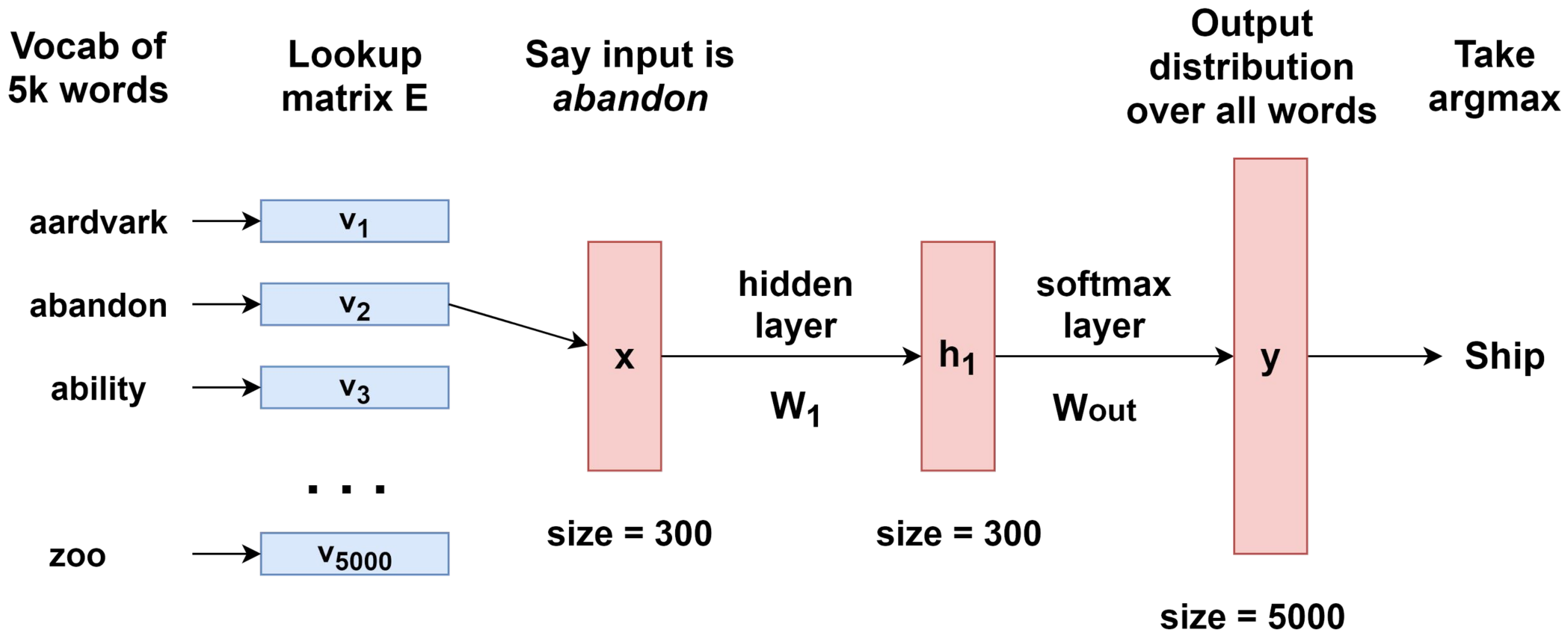
  - Train the system: backpropagate errors through $\mathbf{W}_1$, $\mathbf{W}_2$, $\mathbf{W}_{out}$ and also **E**!

Neural Language Model



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Intuition: we trained word vectors on a task were we have lots of data. Hopefully they learned some general things about language. We can then simply use them on a different task with not as much data!

Training procedures

- The actual best systems use a more complicated procedure
  - Though the intuition remains the same
- Some of the most popular procedures:
  - **CBOW:** use surrounding context to predict a word (**word2vec, FastText**)
  - **Skipgram:** use input word to predict context (**word2vec**)
  - Predicting co-occurrence counts (**GloVe**)
  - Exploiting syntactic structure (dependency triples)
  - And many more!

What they have in common: a release of words with associated vectors

How to use them?

We can assign a pretrained vector to each word in our input, but how do we then deal with a set of input vectors of variable length?

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- Average them, or apply max pooling, or some other method
- Next week we will look at models that can deal with them directly!

This week: input is a single word, so just take the vector as input features

How to evaluate word embeddings?

Extrinsic vs Intrinsic Evaluation

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- Use the embeddings in a downstream application
- Higher performance $\Rightarrow$ high quality embeddings
- **Pro:** useful, realistic, meaningful
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Intrinsic:

- Use embeddings to measure similarity and analogies
- **Pro:** cheap, fewer confounding factors
- **Con:** too specific, human judgments are imperfect, different datasets

Let’s look at the power of word embeddings

Similarities

FRANCE	JESUS	XBOX	REDDISH	SCRATCHED	MEGABITS
AUSTRIA	GOD	AMIGA	GREENISH	NAILED	OCTETS
BELGIUM	SATI	PLAYSTATION	BLUISH	SMASHED	MB/S
GERMANY	CHRIST	MSX	PINKISH	PUNCHED	BIT/S
ITALY	SATAN	IPOD	PURPLISH	POPPED	BAUD
GREECE	KALI	SEGA	BROWNISH	CRIMPED	CARATS
SWEDEN	INDRA	PSNUMBER	GREYISH	SCRAPED	KBIT/S
NORWAY	VISHNU	HD	GRAYISH	SCREWED	MEGAHERTZ
EUROPE	ANANDA	DREAMCAST	WHITISH	SECTIONED	MEGAPIXELS
HUNGARY	PARVATI	GEFORCE	SILVERY	SLASHED	GBIT/S
SWITZERLAND	GRACE	CAPCOM	YELLOWISH	RIPPED	AMPERES

Calculated by using the **cosine similarity** between two vectors.

Similarity

Similarity does not mean the same thing across different settings!

- Example: “good” vs “bad”
  - Sentiment analysis: good and bad are very different
  - Parsing: good and bad are treated the same
- Ambiguity: word meaning differs depending on context
  - He won the first **set**
  - I accidentally **set** myself on fire

Word embeddings only look at co-occurrence in contexts.

Common problem: antonyms get similar vectors

Assignment 2

- Individual. Have to answer questions only (not like research report!)
  - No need to submit code this week
- In the lab: **live competition** to train the best neural net using embeddings!
  - Optimizer hyperparameters, architecture, training time, etc
  - Best performing students get a bonus
  - See assignment for details

Check **Brightspace** for a list of resources/papers that might help

Deadline: Monday September 25th 10:59 AM

Next week: deep learning