UMSI

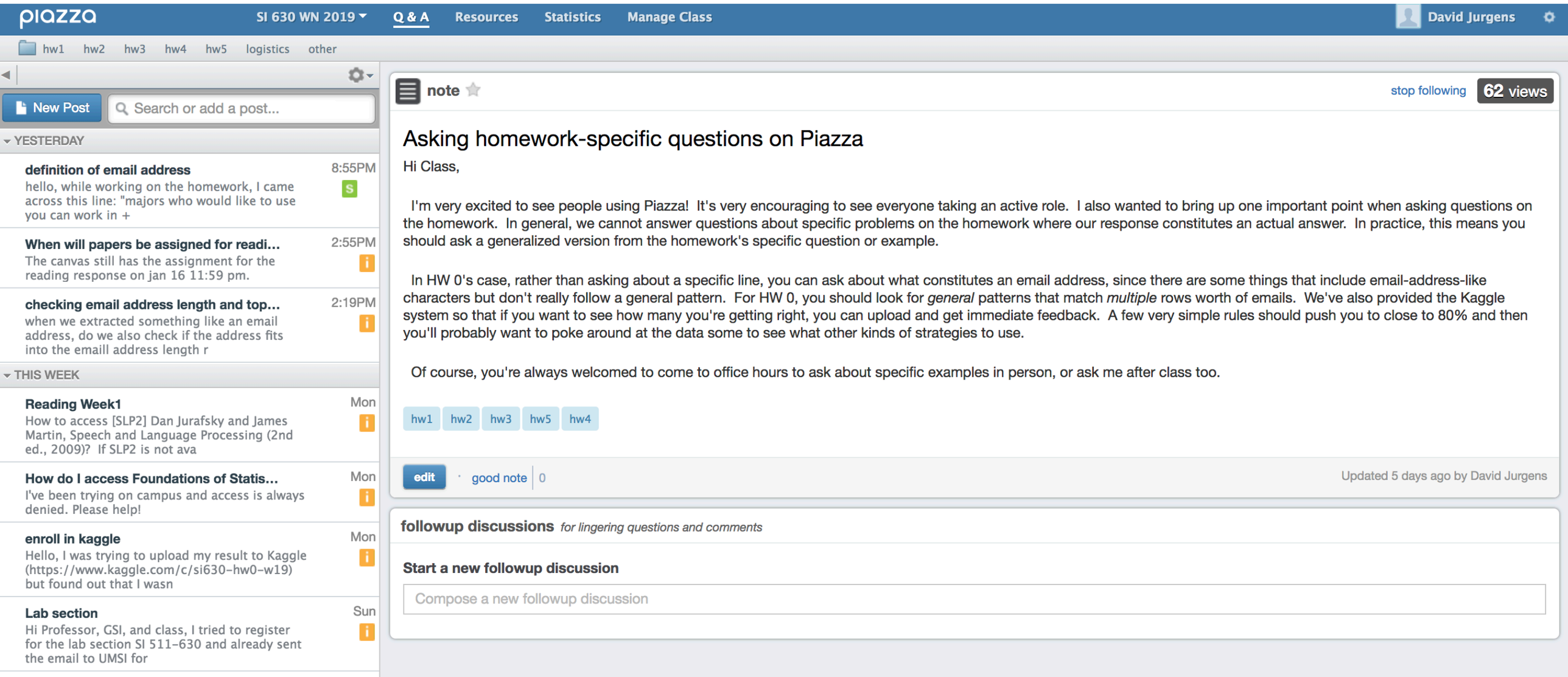
SI 630
Natural Language Processing:
Algorithms and People

Lecture 2: Classification
Jan. 15, 2020

David Jurgens
jurgens@umich.edu

Some slides from David Bamman

Quick Administrative Notes



Unless it's a private matter, all communication is through Piazza. Feel free to answer other's questions too—Wisdom of the crowds in action!

The 511 section is now open for enrollment!

Today's plan

Homework 1

Deep Learning

Linear Regression

Thinking about classifiers

Generative vs. Discriminative models

- Generative models specify a joint distribution over the labels and the data. With this you could generate new data

$$P(x, y) = P(y)\, P(x \mid y)$$

- Discriminative models specify the conditional distribution of the label y given the data x. These models focus on how to discriminate between the classes

$$P(y \mid x)$$

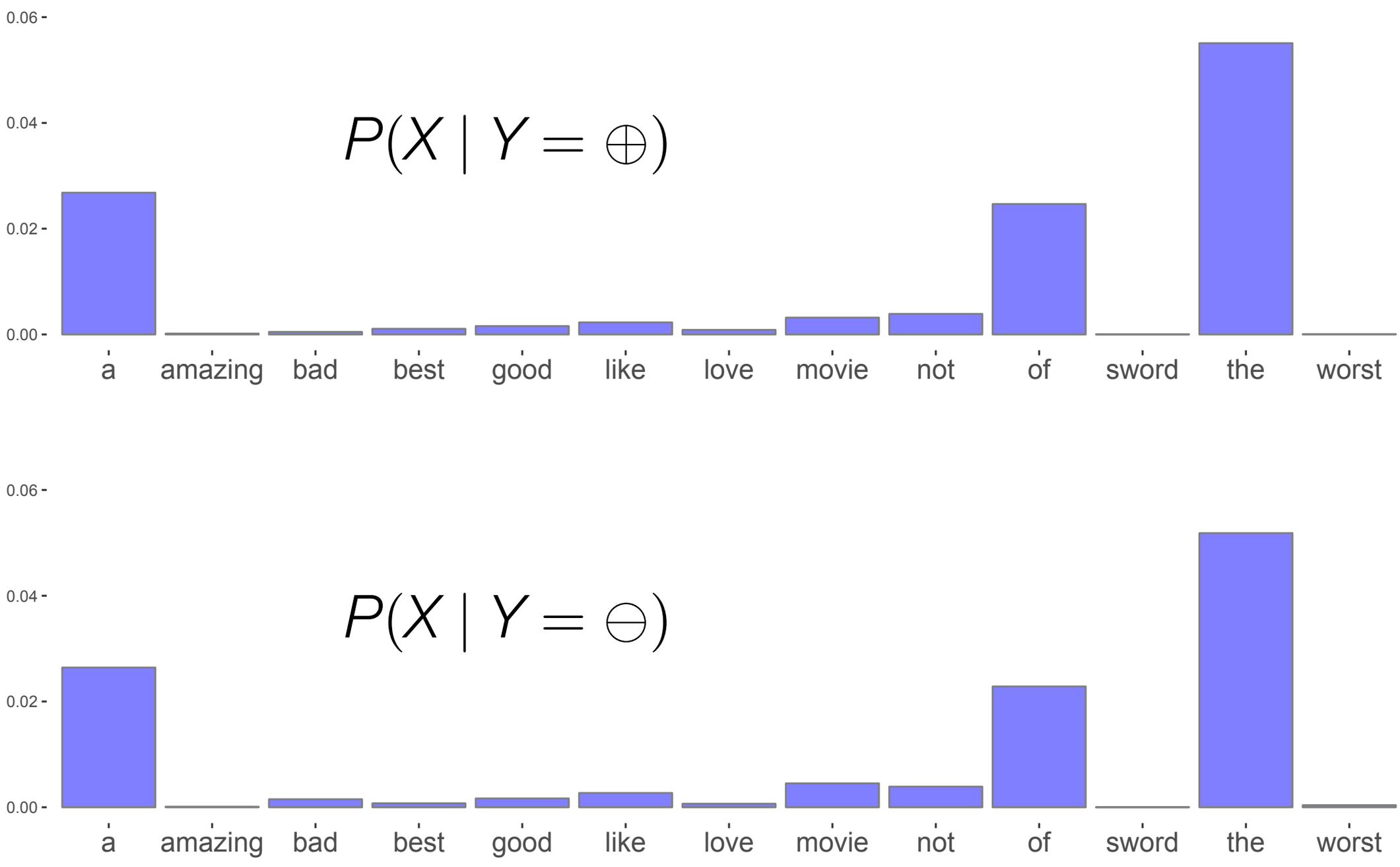
"… is a film which still causes real, not figurative, chills to run along my spine, and it is certainly the bravest and most ambitious fruit of Coppola's genius"

Roger Ebert, Apocalypse Now

"I hated this movie. Hated hated hated hated hated this movie. Hated it. Hated every simpering stupid vacant audience-insulting moment of it. Hated the sensibility that thought anyone would like it."

Roger Ebert, North

Generating


$P(X \mid Y = \oplus)$
0.06
0.04
0.02
0.00
a
amazing
bad
best
good
like
love
movie
not
of
sword
the
worst
$P(X \mid Y = \ominus)$
0.06
0.04
0.02
0.00
a
amazing
bad
best
good
like
love
movie
not
of
sword
the
worst

Generation

taking allen pete visual an lust be infinite corn physical here decidedly 1 for . never it against perfect the possible spanish of supporting this all this this pride turn that sure the a purpose in real . environment there's trek right . scattered wonder dvd three criticism his .

positive

us are i do tense kevin fall shoot to on want in (. minutes not problems unusually his seems enjoy that : vu scenes rest half in outside famous was with lines chance survivors good to . but of modern-day a changed rent that to in attack lot minutes

negative

Generative models

- With generative models (e.g., Naive Bayes), we ultimately also care about P(y | x), but we get there by modeling more.

posterior

prior

likelihood

$$P(Y = y \mid x) = \frac{P(Y = y)P(x \mid Y = y)}{\sum_{y \in \mathcal{Y}} P(Y = y)P(x \mid Y = y)}$$

- Discriminative models focus on modeling P(y | x) — *and only P(y | x)* — directly.

A few math things to remember

$$\sum_{i=1}^{F} x_i \beta_i = x_1 \beta_1 + x_2 \beta_2 + \ldots + x_F \beta_F$$

$$\prod_{i=1}^{F} x_i = x_i \times x_2 \times \ldots \times x_F$$

$$\exp(x) = e^x \approx 2.7^x \qquad \exp(x+y) = \exp(x)\exp(y)$$

$$\log(x) = y \rightarrow e^y = x \qquad \log(xy) = \log(x) + \log(y)$$

A few math things to remember

This equation $3x + 2y + 5z = 7$

can be written as a dot product of two vectors:

$$\begin{bmatrix} 3 & 2 & 5 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix} = 7$$

A few math things to remember

Likewise, these equations

$$3x + 2y + 5z = 7$$

$$-1x + 3y + 9z = 12$$

$$4x + \frac{1}{2}y + 0z = 8$$

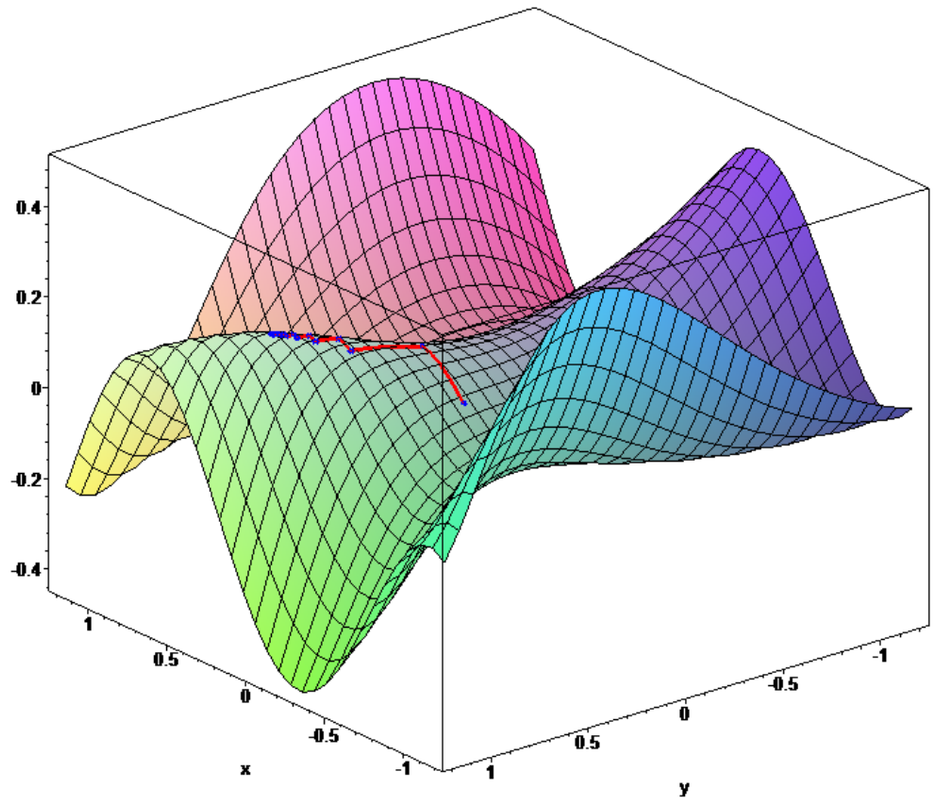
can be written as a dot product of a matrix and a vector:

$$\begin{bmatrix} 3 & 2 & 5 \\ -1 & 3 & 9 \\ 4 & \frac{1}{2} & 0 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 7 \\ 12 \\ 8 \end{bmatrix}$$

Linear Algebra Takeaway:

- You can think of the dot product as applying a set of weights to your vector.
- The dot product of two vectors is a scalar (a normal number, like 7 or 0.34).
- The dot product of a matrix and a vector is a vector.

Quick Math Review: Derivatives



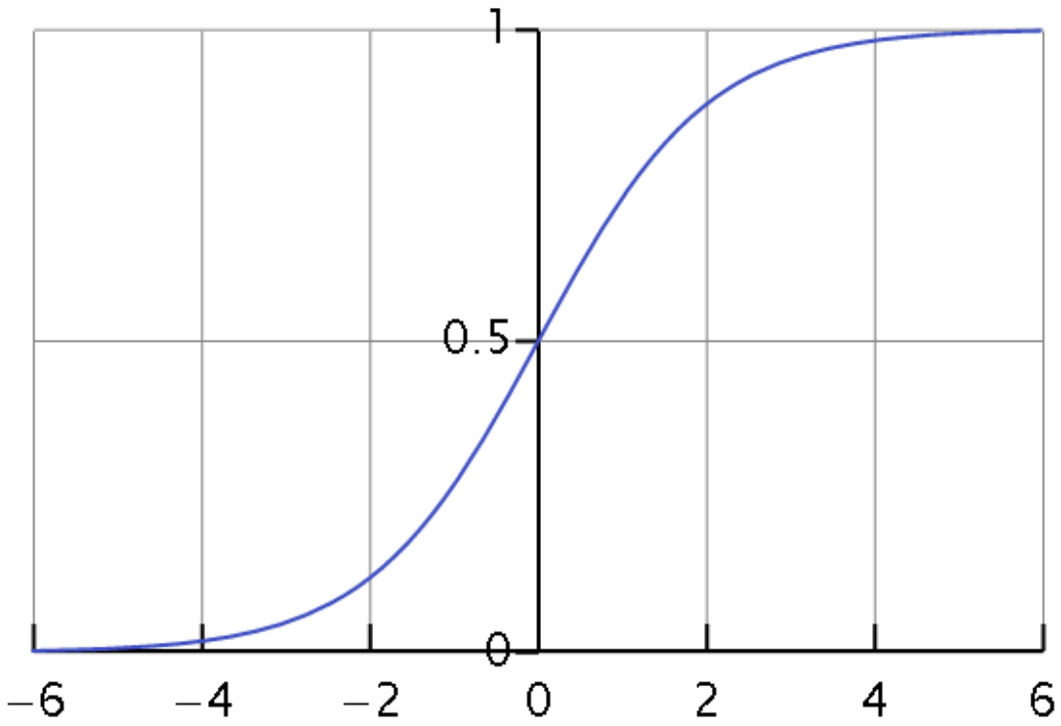
Derivative is a fancy word for slope.

If you are at the point where the green X is, and you want to find the point that minimizes the function, you can use the slope to figure out which way is downhill.

This works in spaces with more than two dimensions, also.

image credit: https://en.wikipedia.org/wiki/Gradient_descent

Quick Math Review: Sigmoid Function



The sigmoid function ranges from 0 to 1. Most of the time, it's much closer to one extreme than the other. This can be nice if you want to classify something as either 0 or 1.

Also called the logistic function, this is a key component of logistic regression.

Classification

Classification defines a mapping *h*

- from input data x (drawn from instance space $\mathcal{X}$)
- to a label (or labels) y from some enumerable output space $\mathcal{Y}$

$\mathcal{X}$ = set of all movie reviews

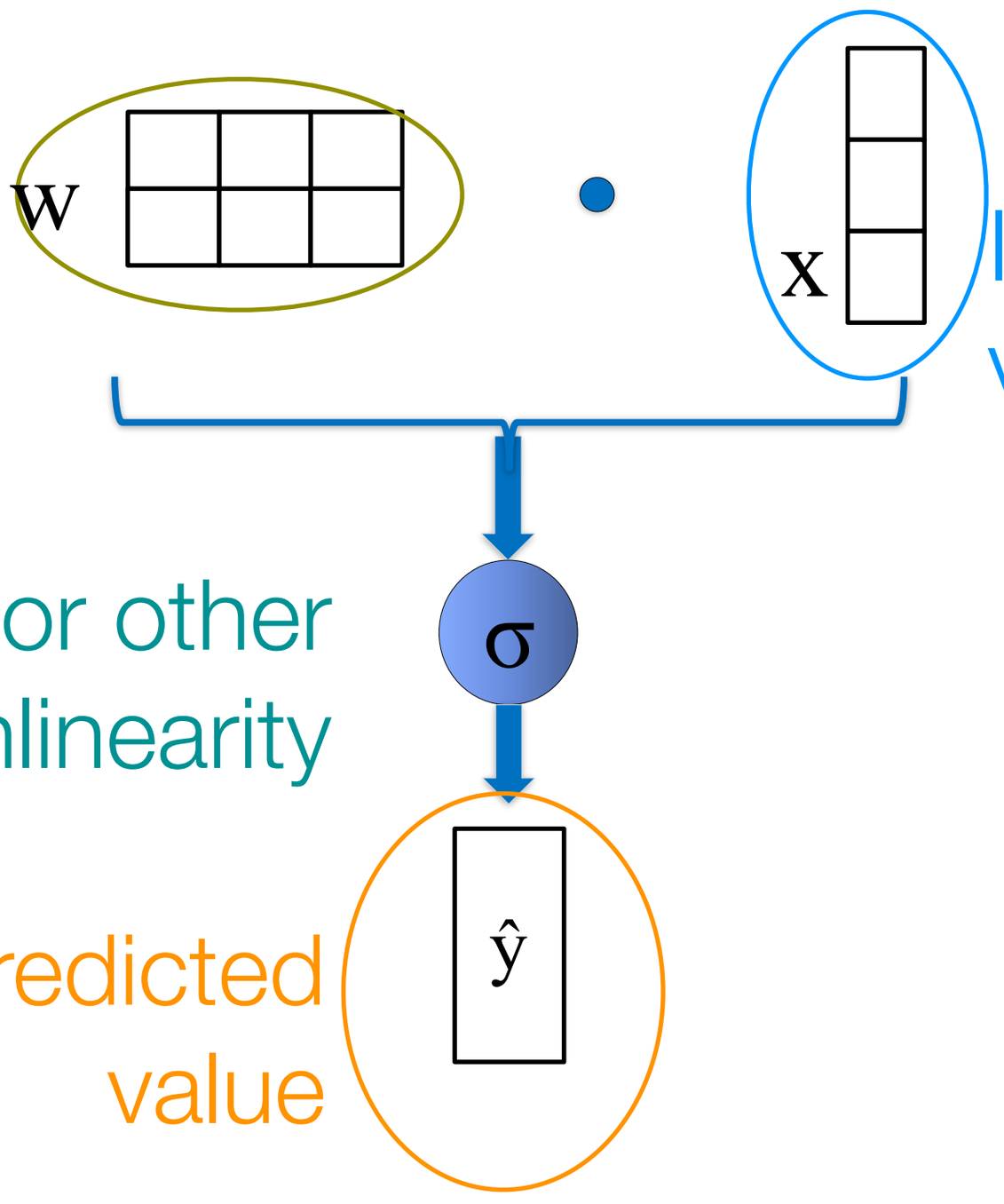
$\mathcal{Y}$ = {good, bad}

x = a single document
y = bad

We will also call this mapping a function

Supervised Machine Learning

Parameters (things we're learning)



Input feature vector

Sigmoid or other nonlinearity

Predicted value

Training data

positive

"… is a film which still causes real, not figurative, chills to run along my spine, and it is certainly the bravest and most ambitious fruit of Coppola's genius"

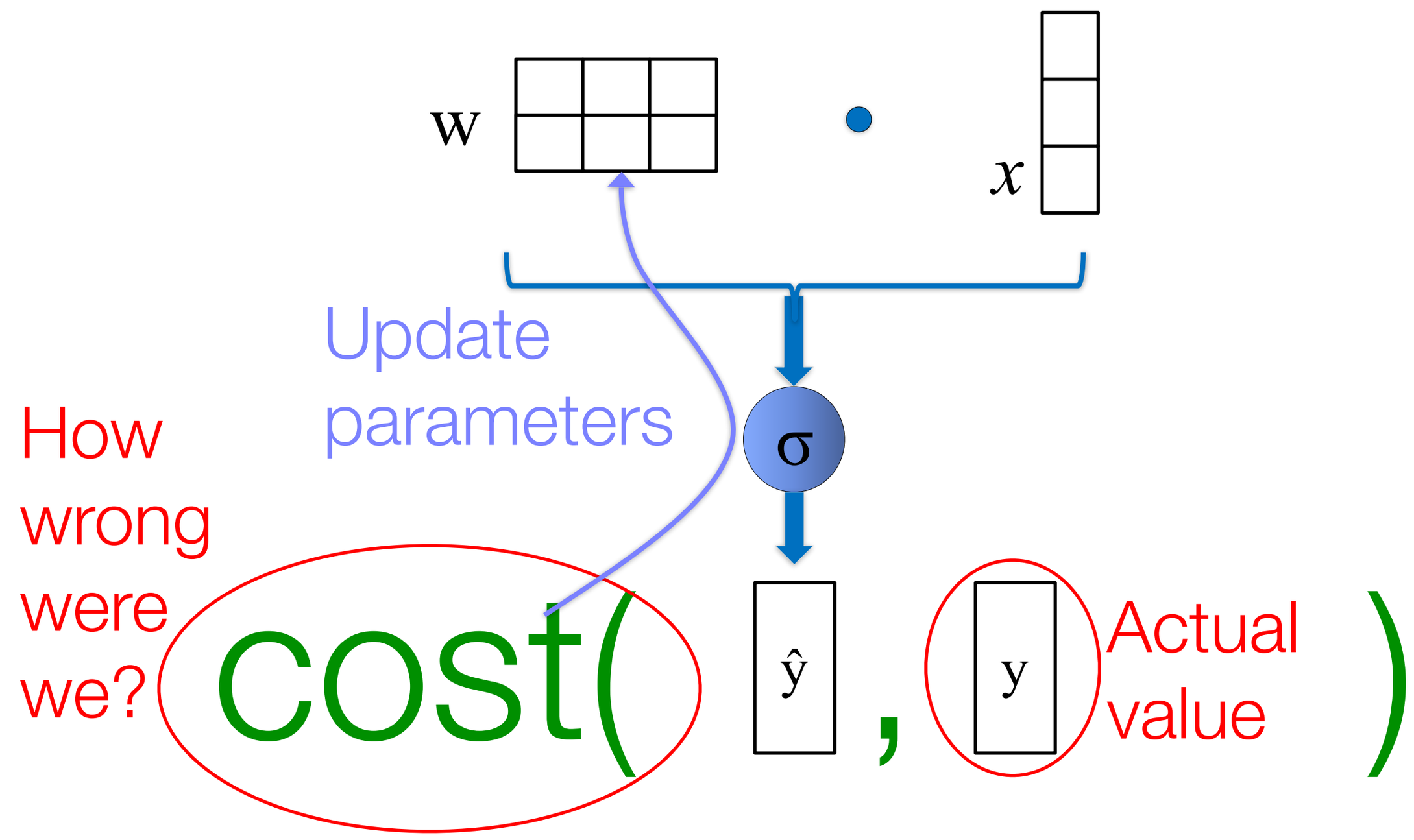
Roger Ebert, Apocalypse Now

- "I hated this movie. Hated hated hated hated hated this movie. Hated it. Hated every simpering stupid vacant audience-insulting moment of it. Hated the sensibility that thought anyone would like it."

Roger Ebert, North

negative

Supervised Machine Learning



What Is the Feature Vector x?

- In document classification, it's often a way of representing the words in the document

- Could which words are in the document: a bag of words

- Or we could use more complex representations of word meaning

- Your eventual job as a practitioner will be to understand what is the best representation

https://wftda.com/wftda-leagues/tucson-roller-derby/

Logistic Regression

Logistic regression

$$P(y = 1 \mid x, \beta) = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

What is the probability that the class is 1, given our parameters β and a vector to be classified x (i.e., a document)

output space $\mathcal{Y} = \{0, 1\}$

x = feature vector

Feature	Value
the	0
and	0
bravest	0
love	0
loved	0
genius	0
not	0
fruit	1
BIAS	1

β = coefficients

Feature	β
the	0.01
and	0.03
bravest	1.4
love	3.1
loved	1.2
genius	0.5
not	-3.0
fruit	-0.8
BIAS	-0.1

	BIAS	love	loved
β	-0.1	3.1	1.2

	BIAS	love	loved	$a=\sum x_i\beta_i$	exp(-a)	1/(1+exp(-a))
x^1	1	1	0	3	0.05	0.952
x^2	1	1	1	4.2	0.015	0.985
x^3	1	0	0	-0.1	1.11	0.474

Features

- As a discriminative classifier, logistic regression doesn't assume features are independent like Naive Bayes does.

- Its power partly comes in the ability to create richly expressive features with out the burden of independence.

- We can represent text through features that are not just the identities of individual words, but any feature that is scoped over the entirety of the input.

features
contains like
has word that shows up in positive sentiment dictionary
review begins with "I like"
at least 5 mentions of positive affectual verbs (like, love, etc.)

Features

feature classes
unigrams (“like”)
bigrams (“not like”), higher order ngrams
prefixes (words that start with “un-”)
has word that shows up in positive sentiment dictionary

Features

Feature	Value
the	0
and	0
bravest	0
love	0
loved	0
genius	0
not	1
fruit	0
BIAS	1

Feature	Value
like	1
not like	1
did not like	1
in_pos_dict_MPQA	1
in_neg_dict_MPQA	0
in_pos_dict_LIWC	1
in_neg_dict_LIWC	0
author=ebert	1
author=siskel	0

How do we get good values for β?

β = coefficients

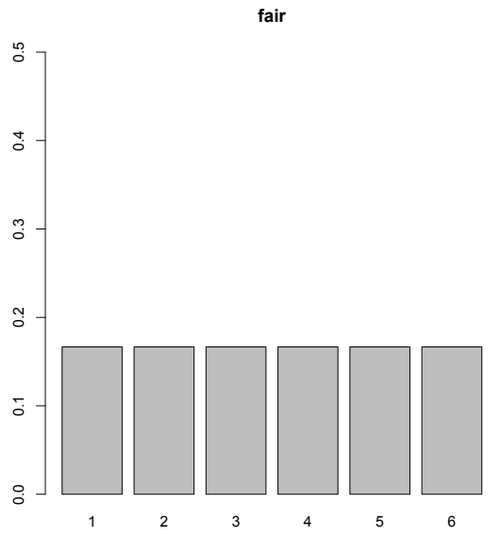
Feature	β
the	0.01
and	0.03
bravest	1.4
love	3.1
loved	1.2
genius	0.5
not	-3.0
fruit	-0.8
BIAS	-0.1

Likelihood

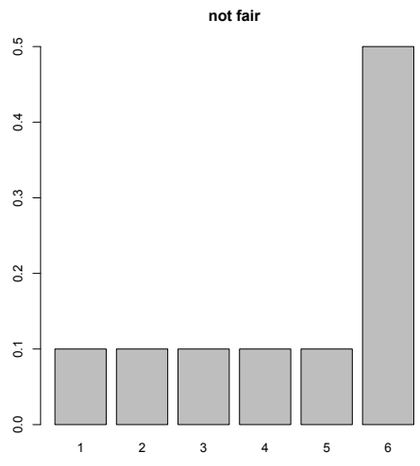
Remember the likelihood of data is its probability under some parameter values

In maximum likelihood estimation, we pick the values of the parameters under which the data is most likely.

Likelihood

P(2 6 6 | 

) =.17 x .17 x .17
= 0.004913

P(2 6 6 | 

) = .1 x .5 x .5
= 0.025

Conditional likelihood

$$\prod_{i}^{N} P(y_i \mid x_i, \beta)$$

For all training data, we want probability of the true label y for each data point x to high

	BIAS	love	loved	$a=\sum x_i\beta_i$	exp(-a)	1/(1+exp(-a))	true y
x^1	1	1	0	3	0.05	0.952	1
x^2	1	1	1	4.2	0.015	0.985	1
x^3	1	0	0	-0.1	1.11	0.475	0

Conditional likelihood

$$\prod_{i}^{N} P(y_i \mid x_i, \beta)$$

For all training data, we want probability of the true label y for each data point x to high

This principle gives us a way to pick the values of the parameters β that maximize the probability of the training data <x, y>

The value of β that maximizes likelihood also maximizes the log likelihood

$$\arg\max_{\beta} \prod_{i=1}^{N} P(y_i \mid x_i, \beta) = \arg\max_{\beta} \log \prod_{i=1}^{N} P(y_i \mid x_i, \beta)$$

The log likelihood is an easier form to work with:

$$\log \prod_{i=1}^{N} P(y_i \mid x_i, \beta) = \sum_{i=1}^{N} \log P(y_i \mid x_i, \beta)$$

- We want to find the value of β that leads to the highest value of the log likelihood:

$$\ell(\beta) = \sum_{i=1}^{N} \log P(y_i \mid x_i, \beta)$$

We want to find the values of β that make the value of this function the greatest

$$\sum_{<x,y=+1>} \log P(1 \mid x, \beta) + \sum_{<x,y=0>} \log P(0 \mid x, \beta)$$

$$\frac{\partial}{\partial \beta_i} \ell(\beta) = \sum_{<x,y>} (y - \hat{p}(x))\, x_i$$

Gradient descent

Algorithm 1 Logistic regression gradient descent

1: Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
2: $\beta = 0^F$
3: **while** not converged **do**
4: $\quad \beta_{t+1} = \beta_t + \alpha \sum_{i=1}^{N} (y_i - \hat{p}(x_i))\, x_i$
5: **end while**

If y is 1 and p(x) = 0, then this still pushes the weights a lot

If y is 1 and p(x) = 0.99, then this still pushes the weights just a little bit

Gradient Descent: An Analogy

We should make our own t-shirts!

Sounds great! How big is a medium t-shirt anyway?

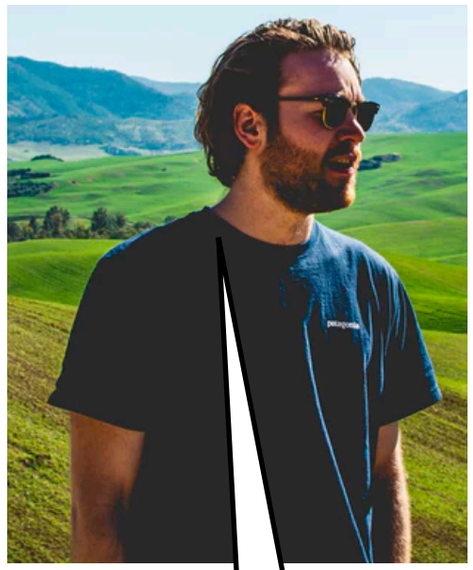
....

Actual founders of the
Ann Arbor T-shirt Company

Gradient Descent: An Analogy

All potential customers

Too small



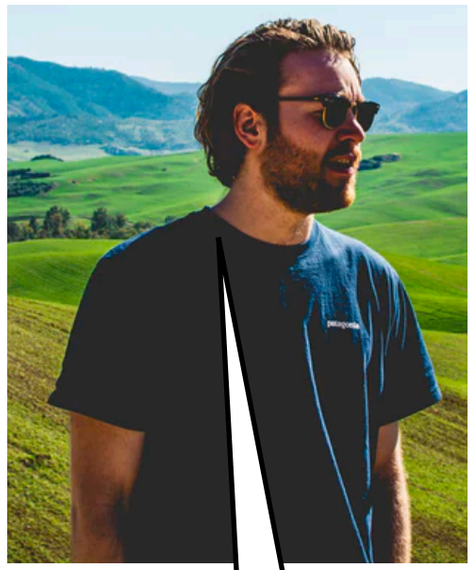
Ok-ish

Way too small

https://sites.psu.edu/siowfa15/2015/12/01/why-do-our-clothes-shrink-after-wash/

Gradient Descent: An Analogy

All potential customers



Somewhat small

Ok

Too small

https://sites.psu.edu/siowfa15/2015/12/01/why-do-our-clothes-shrink-after-wash/

Gradient Descent: An Analogy

These are our parameters β

Somewhat small

How close did we get to getting the right shirt size? This is our loss

$$(y_i - \hat{p}(x_i))\, x_i$$

https://sites.psu.edu/siowfa15/2015/12/01/why-do-our-clothes-shrink-after-wash/

Gradient descent

Algorithm 1 Logistic regression gradient descent

1: Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
2: $\beta = 0^F$
3: **while** not converged **do**
4: $\quad \beta_{t+1} = \beta_t + \alpha \sum_{i=1}^{N} (y_i - \hat{p}(x_i))\, x_i$
5: **end while**

If y is 1 and p(x) = 0, then this still pushes the weights a lot

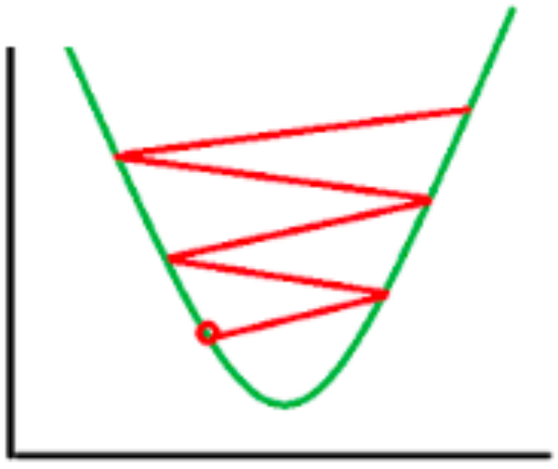
If y is 1 and p(x) = 0.99, then this still pushes the weights just a little bit

Learning rates

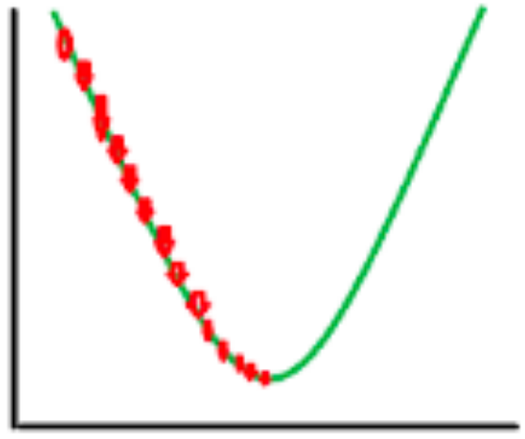
Algorithm 1 Logistic regression gradient descent

1: Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
2: $\beta = 0^F$
3: **while** not converged **do**
4: $\quad \beta_{t+1} = \beta_t + \alpha \sum_{i=1}^{N} (y_i - \hat{p}(x_i))\, x_i$
5: **end while**

The learning rate decides how much we update each iteration.
Usually named α or η



High α



Low α

Stochastic Gradient Descent (SGD)

- Batch gradient descent reasons over every training data point for each update of β. This can be slow to converge.

- Stochastic gradient descent updates β after each data point.

Algorithm 2 Logistic regression stochastic gradient descent

Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
$\beta = 0^F$
while not converged **do**
    for $i = 1$ to N **do**
        $\beta_{t+1} = \beta_t + \alpha \left(y_i - \hat{p}(x_i)\right) x_i$
    end for
end while

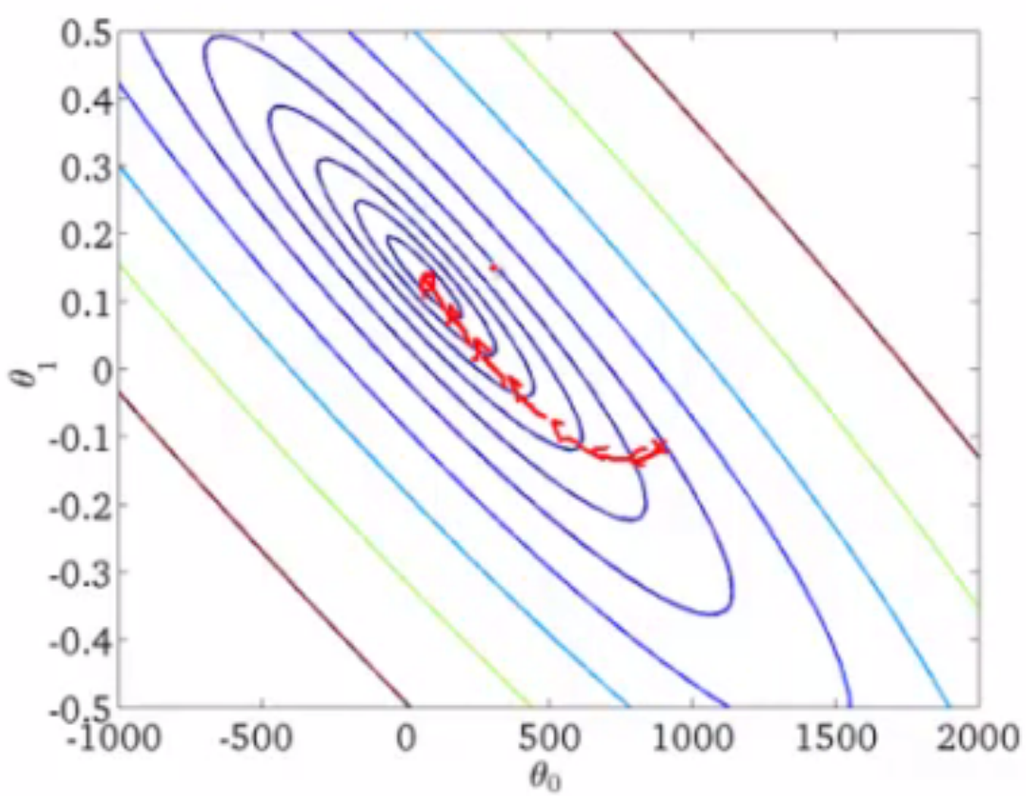
Gradient Descent vs. Stochastic Gradient Descent

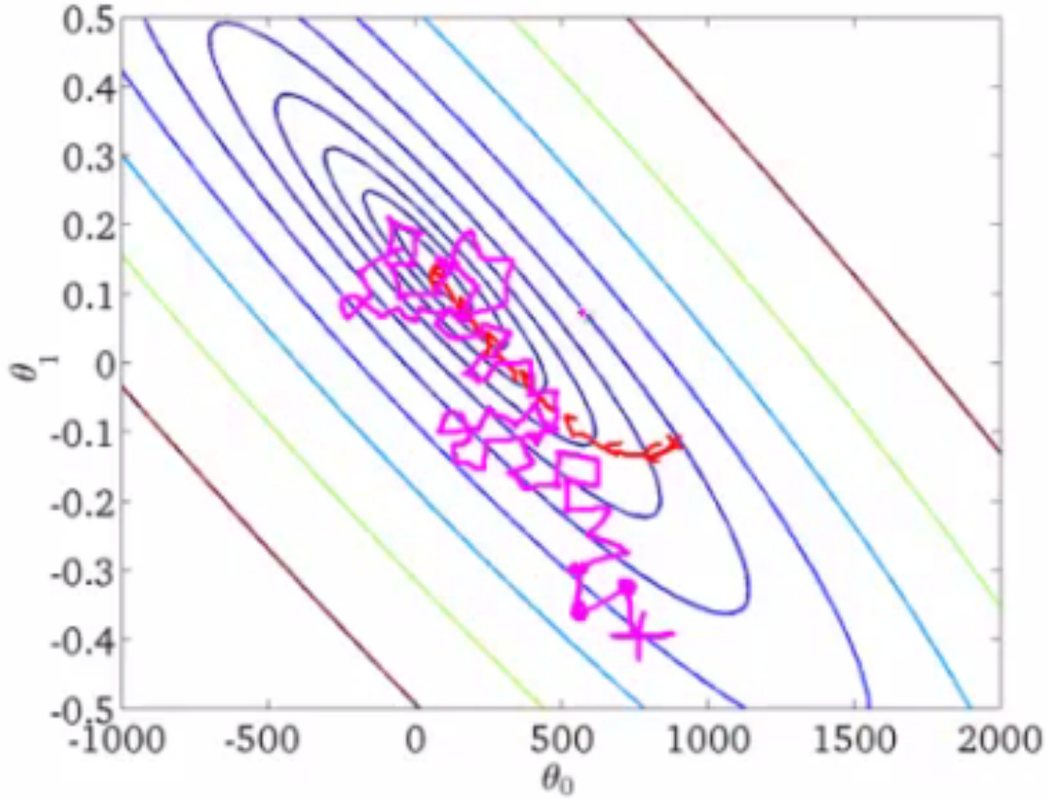
Algorithm 1 Logistic regression gradient descent

Data: training data $x \in \mathbb{R}^F, y \in \{0,1\}$
$\beta = 0^F$
while not converged **do**
    $\beta_{t+1} = \beta_t + \alpha \sum_{i=1}^{N} (y_i - \hat{p}(x_i))\, x_i$
end while

Algorithm 2 Logistic regression stochastic gradient descent

Data: training data $x \in \mathbb{R}^F, y \in \{0,1\}$
$\beta = 0^F$
while not converged **do**
    for $i = 1$ to N **do**
        $\beta_{t+1} = \beta_t + \alpha\, (y_i - \hat{p}(x_i))\, x_i$
    end for
end while





Practicalities

- When calculating the P(y | x) or in calculating the gradient, you don't need to loop through all features — only those with nonzero values
- (Which makes sparse, binary values useful)

$$P(y = 1 \mid x, \beta) = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

$$\frac{\partial}{\partial \beta_i} \ell(\beta) = \sum_{<x,y>} (y - \hat{p}(x))\, x_i$$

Quiz time: Which of the following is true?

- In text classification most words are

  A.rare

  B.not correlated with any class

  C.given low weights in the
  Logistic Regression classifier

  D.unlikely to affect classification

  E.not very interesting

$$\frac{\partial}{\partial \beta_i} \ell(\beta) = \sum_{<x,y>} (y - \hat{p}(x))\, x_i$$

If a feature x_i only shows up with the positive class (e.g., positive sentiment), what are the possible values of its corresponding β_i?

$$\frac{\partial}{\partial \beta_i} \ell(\beta) = \sum_{<x,y>} (1 - 0)1$$

$$\frac{\partial}{\partial \beta_i} \ell(\beta) = \sum_{<x,y>} (1 - 0.9999999)1$$

always positive

Many features that show up rarely may likely only appear (by chance) with one label

More generally, may appear so few times that the noise of randomness dominates

β = coefficients

Feature	β
like	2.1
did not like	1.4
in_pos_dict_MPQA	1.7
in_neg_dict_MPQA	-2.1
in_pos_dict_LIWC	1.4
in_neg_dict_LIWC	-3.1
author=ebert	-1.7
author=ebert ∧ dog ∧ starts with “in”	30.1

Feature selection

- We could threshold features by minimum count but that also throws away information

- We can take a probabilistic approach and encode a prior belief that all β should be 0 unless we have strong evidence otherwise

L2 regularization

$$\ell(\beta) = \underbrace{\sum_{i=1}^{N} \log P(y_i \mid x_i, \beta)}_{\text{we want this to be high}} - \underbrace{\eta \sum_{j=1}^{F} \beta_j^2}_{\text{but we want this to be small}}$$

- We can do this by changing the function we're trying to optimize by adding a penalty for having values of β that are high
- This is equivalent to saying that each β element is drawn from a Normal distribution centered on 0.
- η controls how much of a penalty to pay for coefficients that are far from 0 (optimize on development data)

no L2 regularization		some L2 regularization		high L2 regularization	
33.83	Won Bin	2.17	Eddie Murphy	0.41	Family Film
29.91	Alexander Beyer	1.98	Tom Cruise	0.41	Thriller
24.78	Bloopers	1.70	Tyler Perry	0.36	Fantasy
23.01	Daniel Brühl	1.70	Michael Douglas	0.32	Action
22.11	Ha Jeong-woo	1.66	Robert Redford	0.25	Buddy film
20.49	Supernatural	1.66	Julia Roberts	0.24	Adventure
18.91	Kristine DeBell	1.64	Dance	0.20	Comp Animation
18.61	Eddie Murphy	1.63	Schwarzenegger	0.19	Animation
18.33	Cher	1.63	Lee Tergesen	0.18	Science Fiction
18.18	Michael Douglas	1.62	Cher	0.18	Bruce Willis

L1 regularization

$$\ell(\beta) = \underbrace{\sum_{i=1}^{N} \log P(y_i \mid x_i, \beta)}_{\text{we want this to be high}} - \underbrace{\eta \sum_{j=1}^{F} |\beta_j|}_{\text{but we want this to be small}}$$

- L1 regularization encourages coefficients to be exactly 0.
- η again controls how much of a penalty to pay for coefficients that are far from 0 (optimize on development data)

How to evaluate a classifier

Classification

A mapping *h* from input data x (drawn from instance space $\mathcal{X}$) to a label (or labels) y from some enumerable output space $\mathcal{Y}$

$\mathcal{X}$ = set of all documents

$\mathcal{Y}$ = {english, mandarin, greek, …}

x = a single document

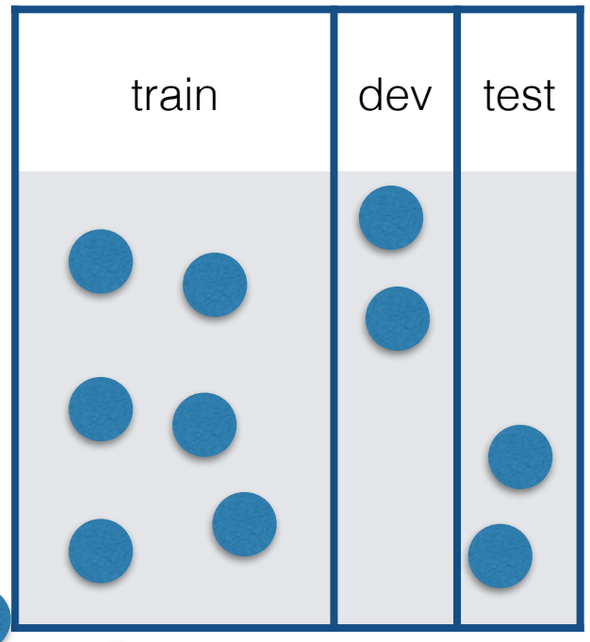
y = ancient greek

Experiment design

	training	development	testing
size	80%	10%	10%
purpose	training models	model selection	evaluation; never look at it until the very end

$\mathcal{X}$

instance space



Metrics

- Evaluations presuppose that you have some metric to evaluate the fitness of a model.
    - Language model: perplexity
    - POS tagging/NER: accuracy, precision, recall, F1
    - Phrase-structure parsing: PARSEVAL (bracketing overlap)
    - Dependency parsing: Labeled/unlabeled attachment score
    - Machine translation: BLEU, METEOR
    - Summarization: ROUGE

Metrics

- Downstream tasks that use NLP to predict the natural world also have metrics:
    - Predicting presidential approval rates from tweets.
    - Predicting the type of job applicants from a job description.
    - Conversational agent

Single-class confusion matrix

True (y) \ Predicted (ŷ)	Offensive	Inoffensive
Offensive	100	2
Inoffensive	0	104

Multiclass confusion matrix

True (y) \ Predicted (ŷ)	NN	VBZ	JJ
NN	100	2	15
VBZ	0	104	30
JJ	30	40	70

Accuracy

$$\frac{1}{N}\sum_{i=1}^{N} I[\hat{y}_i = y_i]$$

$$I[x] \begin{cases} 1 & \text{if } x \text{ is true} \\ 0 & \text{otherwise} \end{cases}$$

Predicted (ŷ)

True (y)	NN	VBZ	JJ
NN	100	2	15
VBZ	0	104	30
JJ	30	40	70

Precision

Precision(NN) =

$$\frac{\sum_{i=1}^{N} I(y_i = \hat{y}_i = \mathrm{NN})}{\sum_{i=1}^{N} I(\hat{y}_i = \mathrm{NN})}$$

Precision: proportion of predicted class that are actually that class.

True (y) \ Predicted (ŷ)	NN	VBZ	JJ
NN	100	2	15
VBZ	0	104	30
JJ	30	40	70

Recall

$$\text{Recall(NN)} = \frac{\sum_{i=1}^{N} I(y_i = \hat{y}_i = \text{NN})}{\sum_{i=1}^{N} I(y_i = \text{NN})}$$

Recall: proportion of true class that are predicted to be that class.

Predicted (ŷ)

True (y)

	NN	VBZ	JJ
NN	100	2	15
VBZ	0	104	30
JJ	30	40	70

F score

$$F = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

Ablation test

- To test how important individual features are (or components of a model), conduct an ablation test
  - Train the full model with all features included, conduct evaluation.
  - Remove feature, train reduced model, conduct evaluation.

Ablation test

	Dev.	Test	
Our tagger, all features	88.67	89.37	
independent ablations:			
−DISTSIM	87.88	88.31	(−1.06)
−TAGDICT	88.28	88.31	(−1.06)
−TWORTH	87.51	88.37	(−1.00)
−METAPH	88.18	88.95	(−0.42)
−NAMES	88.66	89.39	(+0.02)
Our tagger, base features	82.72	83.38	
Stanford tagger	85.56	85.85	
Annotator agreement	92.2		

Table 2: Tagging accuracies on development and test data, including ablation experiments. Features are ordered by importance: test accuracy decrease due to ablation (final column).

Gimpel et al. 2011, “Part-of-Speech Tagging for Twitter”

Significance

Your work	58%
Current state of the art	50%

- If we observe difference in performance, what's the cause? Is it because one system is better than another, or is it a function of randomness in the data? If we had tested it on other data, would we get the same result?

Hypotheses

hypothesis
The average income in two sub-populations is different
Web design A leads to higher CTR than web design B
Self-reported location on Twitter is predictive of political preference
Your system X is better than state-of-the-art system Y

Null hypothesis

- A claim, assumed to be true, that we'd like to test (because we think it's wrong)

hypothesis	H_0
The average income in two sub-populations is different	The incomes are the same
Web design A leads to higher CTR than web design B	The CTR are the same
Self-reported location on Twitter is predictive of political preference	Location has no relationship with political preference
Your system X is better than state-of-the-art system Y	There is no difference in the two systems.

Hypothesis testing

- If the null hypothesis were true, how likely is it that you'd see the data you see?

Hypothesis testing

- Hypothesis testing measures our confidence in what we can say about a null from a sample.

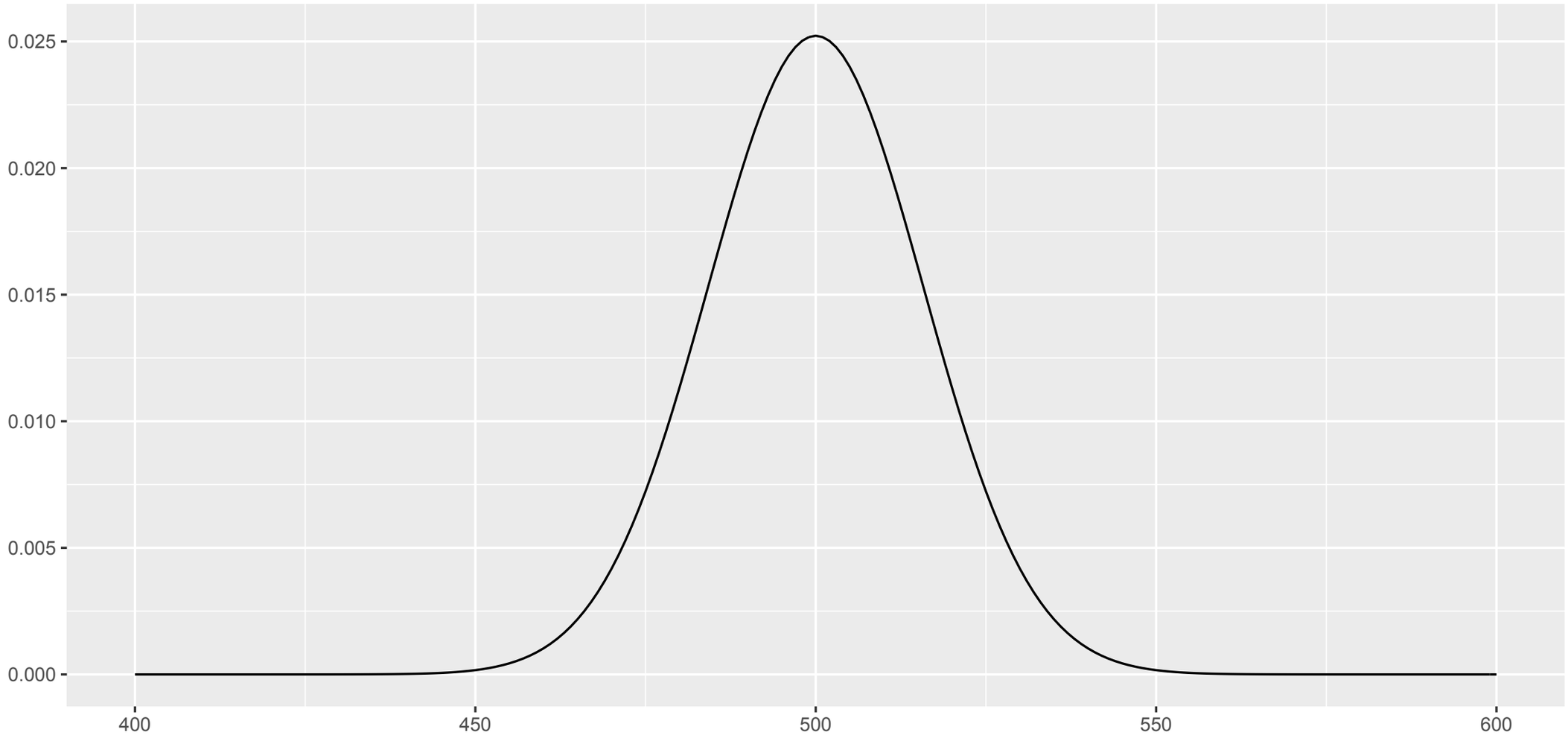
Hypothesis testing

- Current state of the art = 50%; your model = 58%. Both evaluated on the same test set of 1000 data points.

- Null hypothesis = there is no difference, so we would expect your model to get 500 of the 1000 data points right.

- If we make parametric assumptions, we can model this with a Binomial distribution (number of successes in n trials)

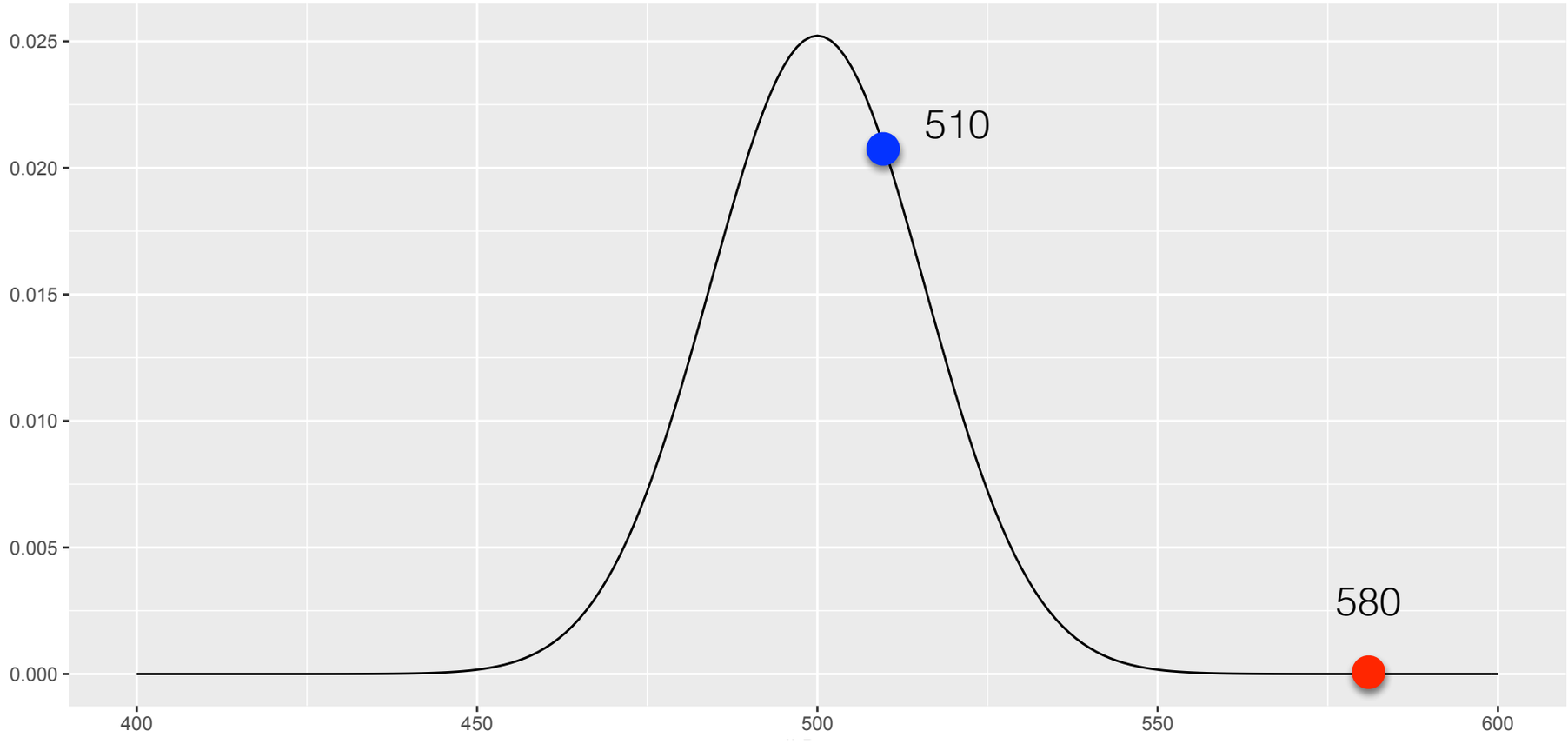
Example



Binomial probability distribution for number of correct predictions in n=1000 with p = 0.5

Example

At what point is a sample statistic unusual enough to reject the null hypothesis?



Example

- The form we assume for the null hypothesis lets us quantify that level of surprise.

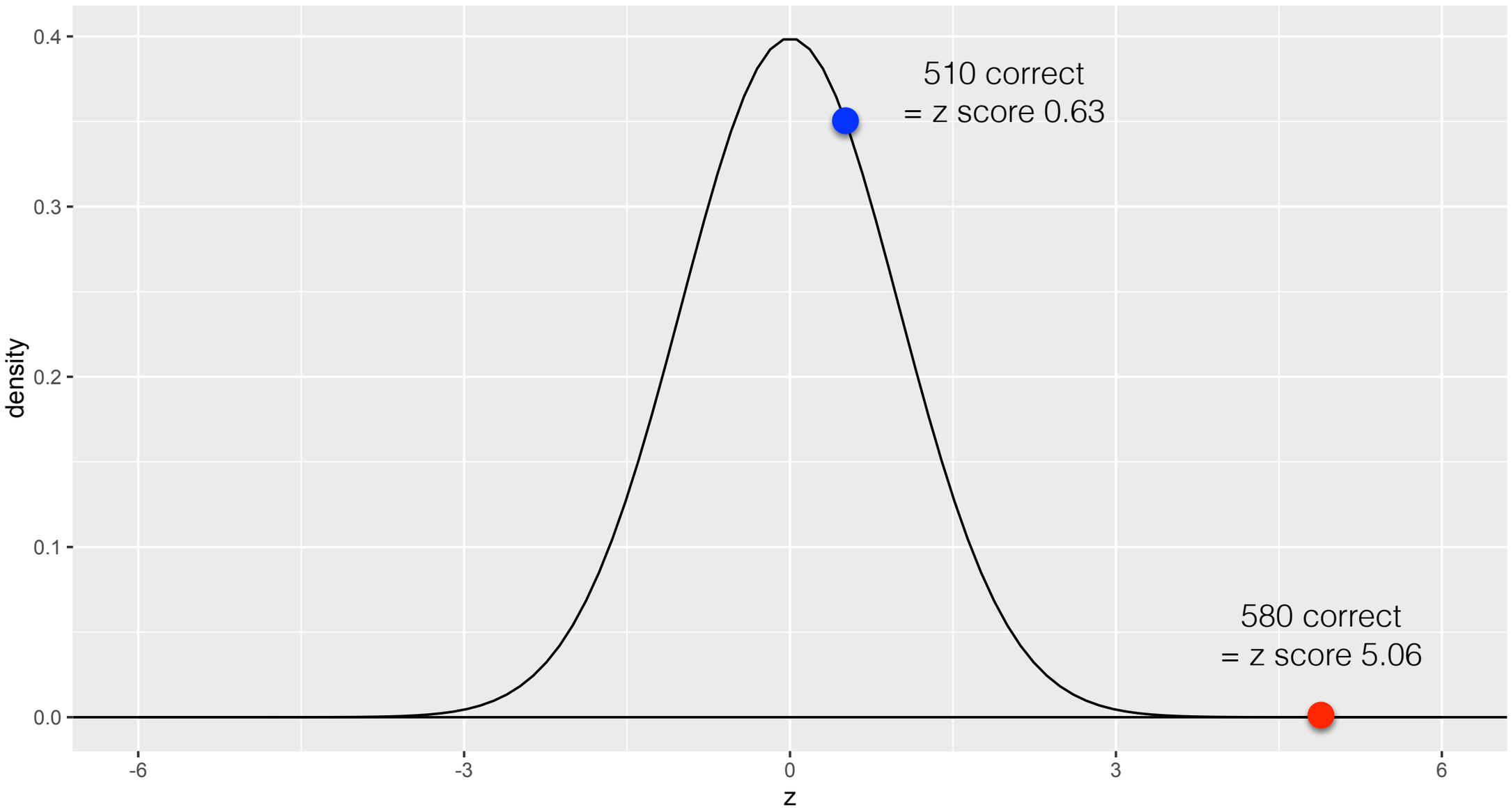
- We can do this for many parametric forms that allows us to measure $P(X \leq x)$ for some sample of size n; for large n, we can often make a normal approximation.

Z score

$$Z = \frac{X - \mu}{\sigma / \sqrt{n}}$$

For Normal distributions, transform into standard normal (mean = 0, standard deviation =1)

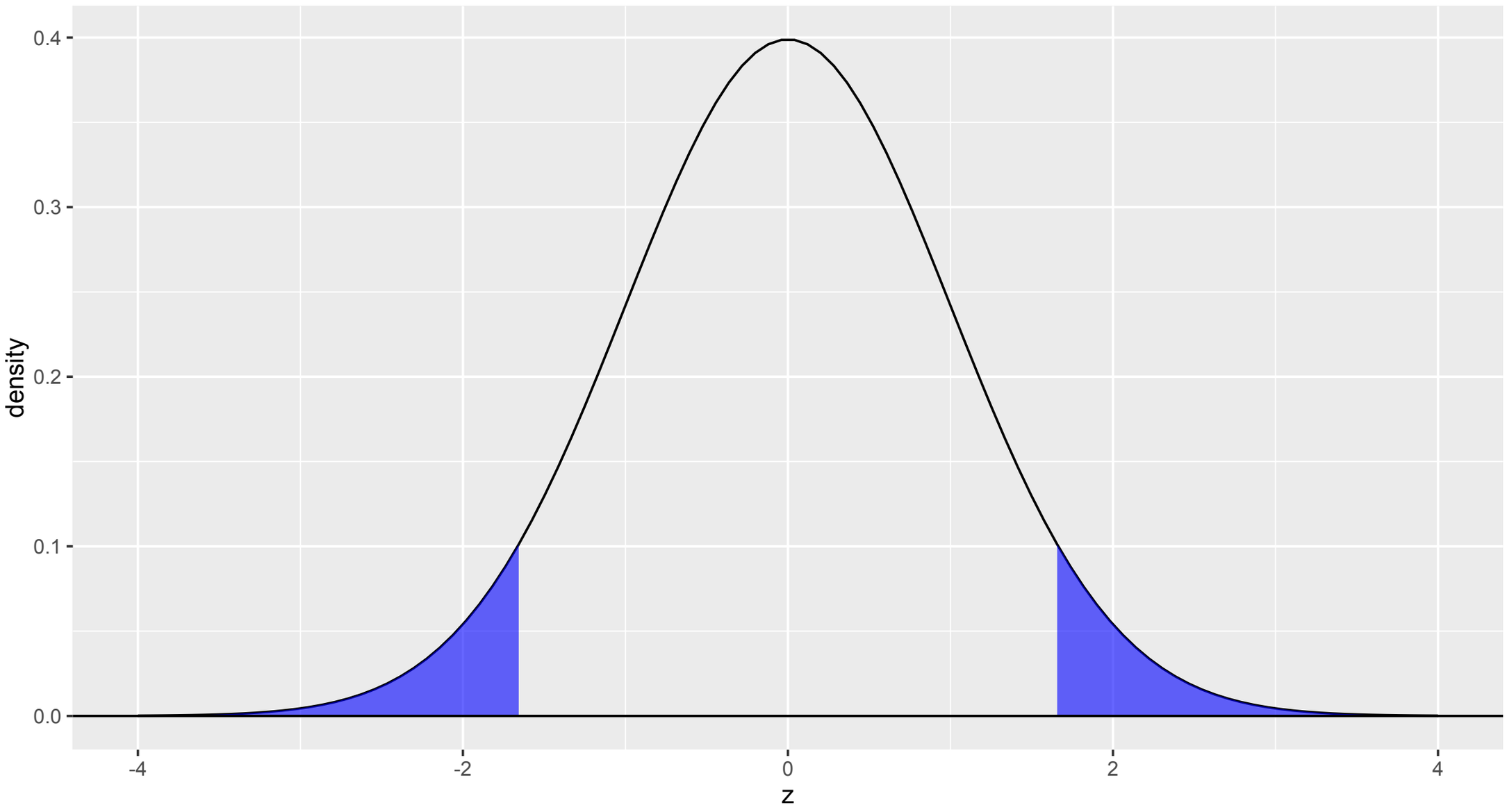
Z score


0.4
0.3
0.2
0.1
0.0
density
510 correct
= z score 0.63
580 correct
= z score 5.06
-6
-3
0
3
6
z

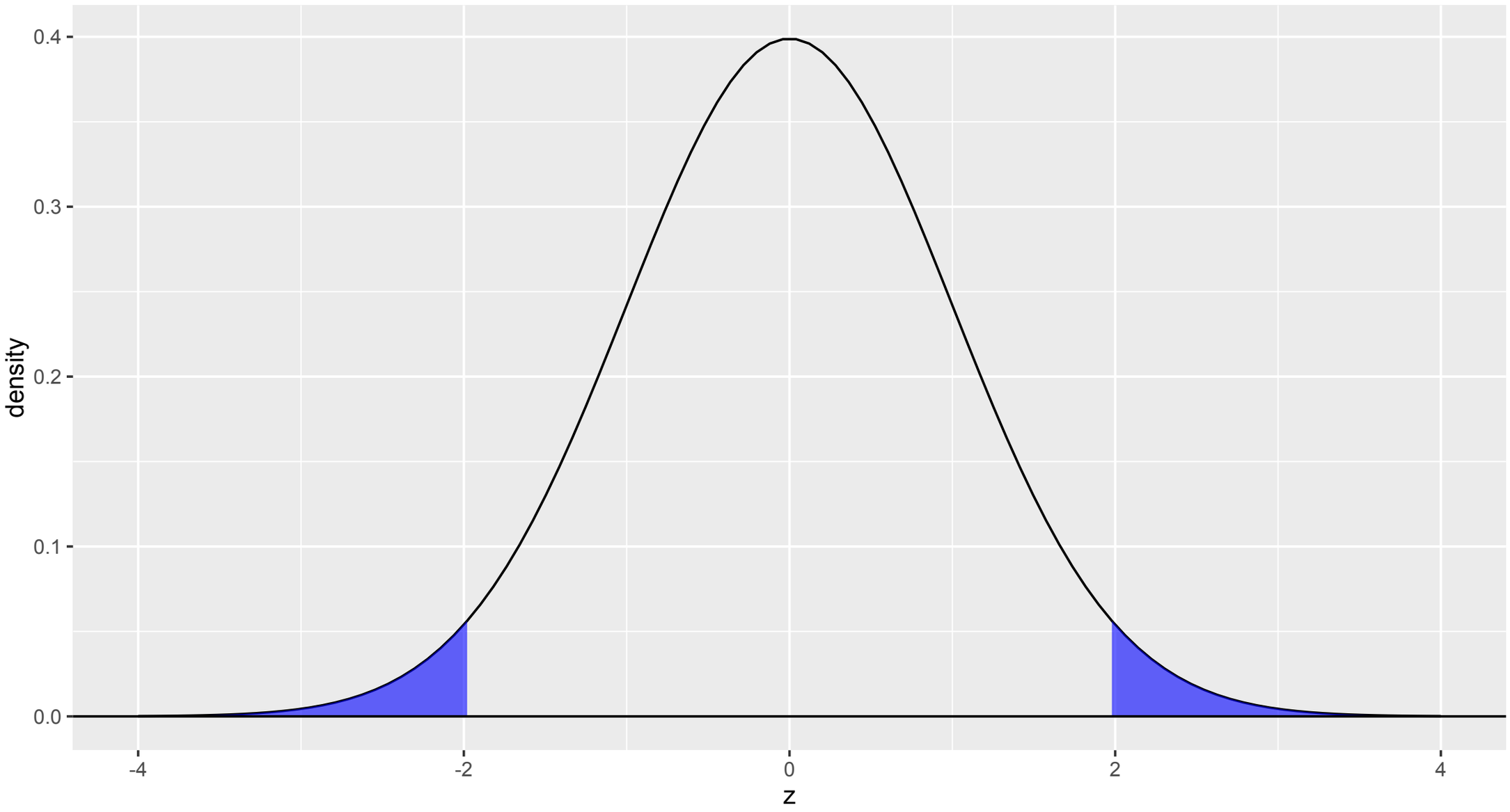
Tests

- We will define “unusual” to equal the most extreme areas in the tails

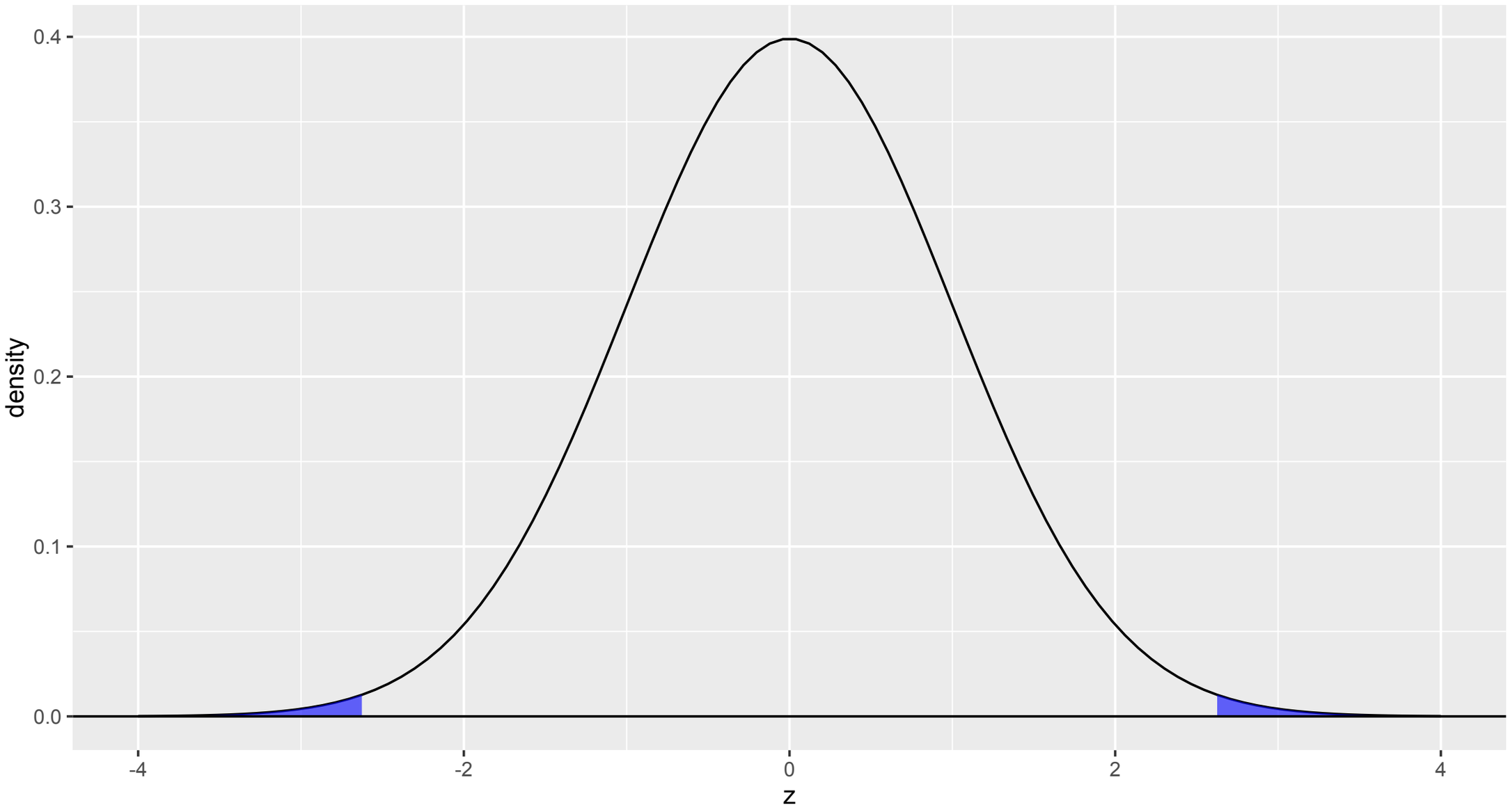
least likely 10%



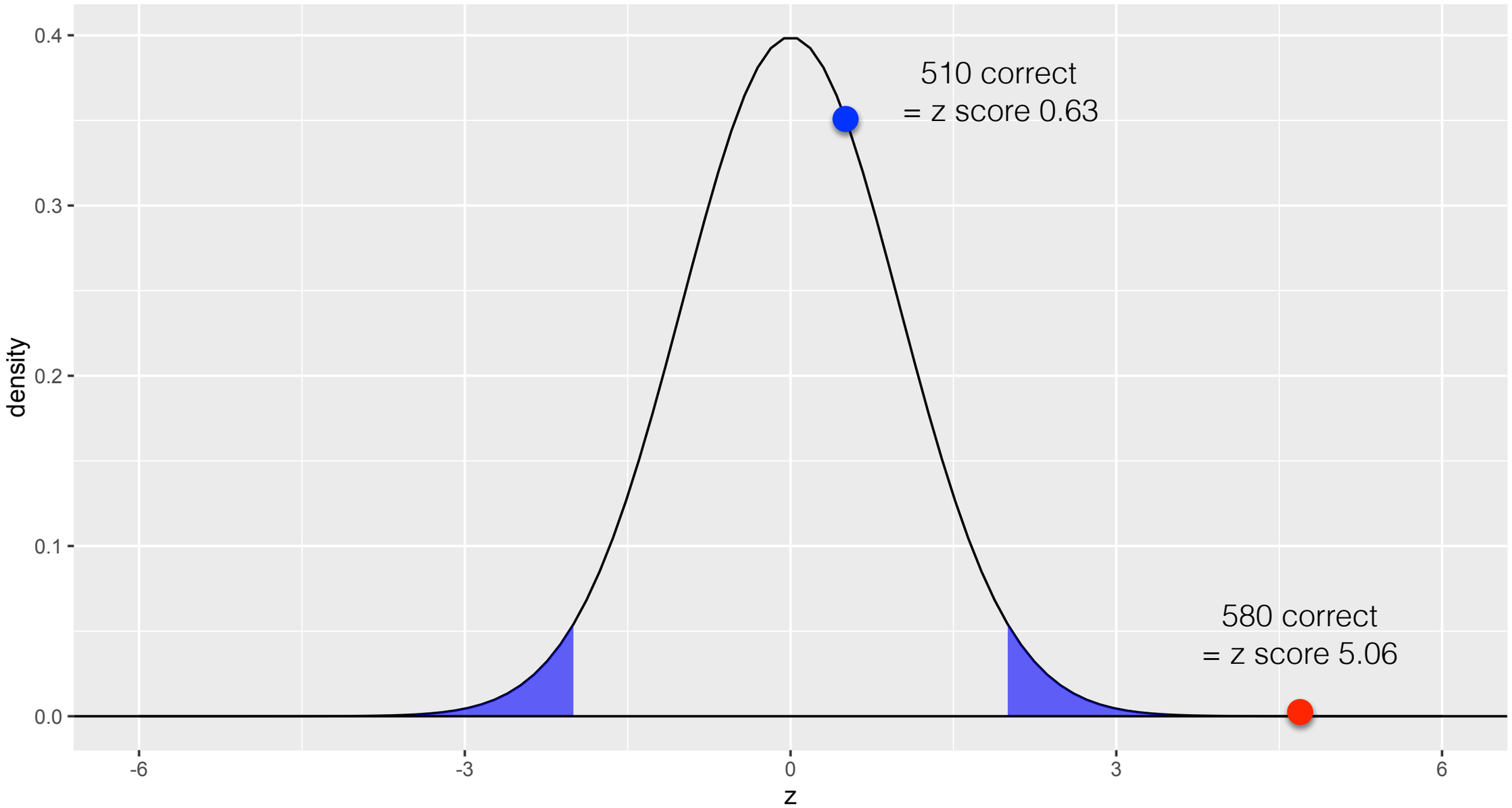
least likely 5%



least likely 1%



Tests


0.4
0.3
0.2
0.1
0.0
density
510 correct
= z score 0.63
580 correct
= z score 5.06
-6
-3
0
3
6
z

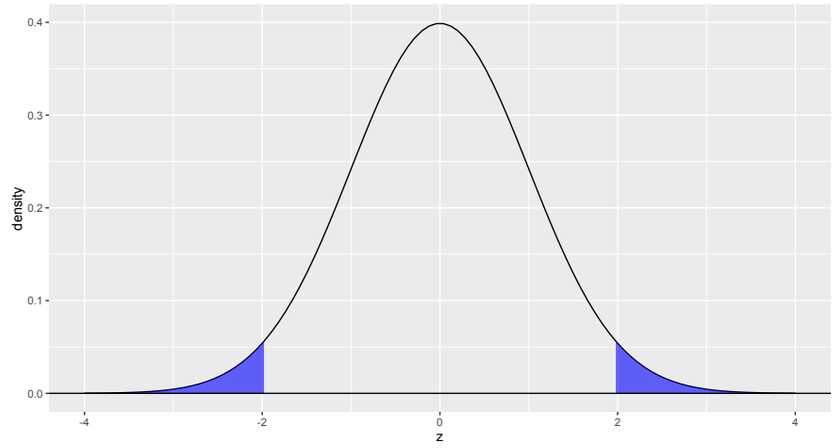
Tests

- Decide on the level of significance α. {0.05, 0.01}

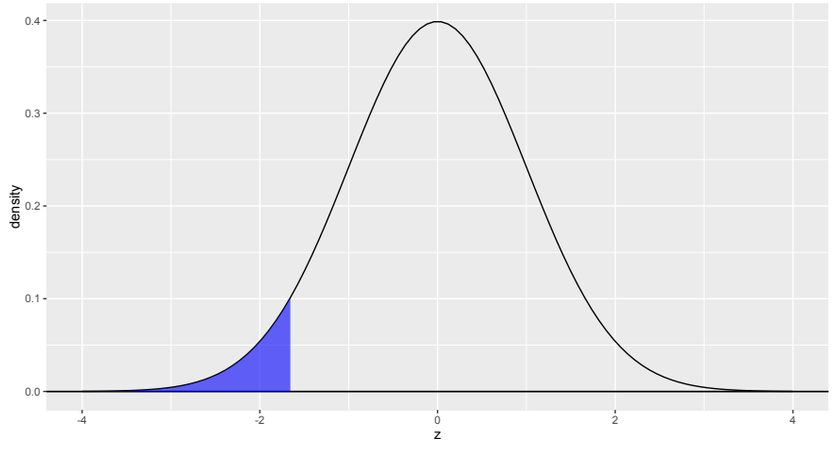
- Testing is evaluating whether the sample statistic falls in the rejection region defined by α

Tails

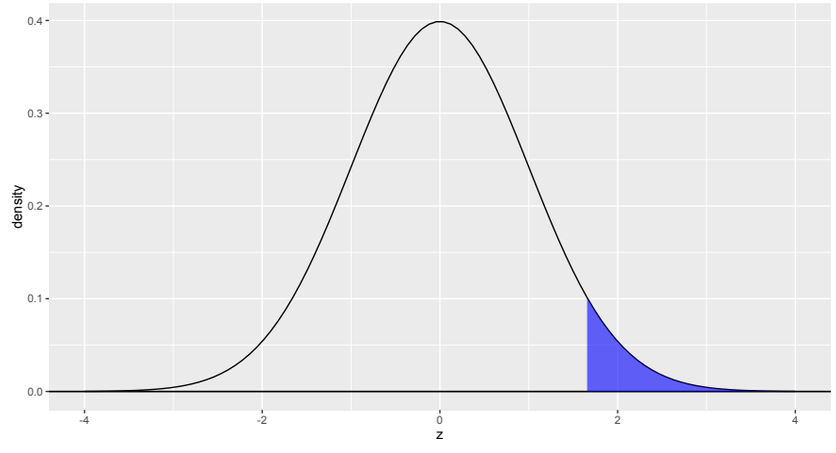
- Two-tailed tests measured whether the observed statistic is different (in either direction)
- One-tailed tests measure difference in a specific direction
- All differ in where the rejection region is located; α = 0.05 for all.



two-tailed test



lower-tailed test



upper-tailed test

p values

A p value is the probability of observing a statistic at least as extreme as the one we did if the null hypothesis were true.

- Two-tailed test $\text{p-value}(z) = 2 \times P(Z \leq -|z|)$
- Lower-tailed test $\text{p-value}(z) = P(Z \leq z)$
- Upper-tailed test $\text{p-value}(z) = 1 - P(Z \leq z)$

Errors

Truth \ Test results	keep null	reject null
keep null		Type I error α
reject null	Type II error β	Power

Errors

- Type I error: we reject the null hypothesis but we shouldn't have.

- Type II error: we don't reject the null, but we should have.

The boy who cried wolf

Type 1 Error

Type 2 Error

The tale concerns a shepherd boy who repeatedly tricks nearby villagers into thinking a wolf is attacking his town's flock. When a wolf actually does appear and the boy again calls for help, the villagers believe that it is another false alarm and the sheep are eaten by the wolf.

1	“jobs” is predictive of presidential approval rating
2	“job” is predictive of presidential approval rating
3	“war” is predictive of presidential approval rating
4	“car” is predictive of presidential approval rating
5	“the” is predictive of presidential approval rating
6	“star” is predictive of presidential approval rating
7	“book” is predictive of presidential approval rating
8	“still” is predictive of presidential approval rating
9	“glass” is predictive of presidential approval rating
…	…
1,000	“bottle” is predictive of presidential approval rating

Errors

- For any significance level α and n hypothesis tests, we can expect αxn type I errors.

- α=0.01, n=1000 = 10 “significant” results simply by chance

Multiple hypothesis corrections

- Bonferroni correction: for family-wise significance level α_0 with n hypothesis tests:

$$\alpha \leftarrow \frac{\alpha_0}{n}$$

- [Very strict; controls the probability of at least one type I error.]

- False discovery rate

Nonparametric tests

- Many hypothesis tests rely on parametric assumptions (e.g., normality)
- Alternatives that don't rely on those assumptions:
    - permutation test
    - the bootstrap

Back to logistic regression

β	change in odds	feature name
2.17	8.76	Eddie Murphy
1.98	7.24	Tom Cruise
1.70	5.47	Tyler Perry
1.70	5.47	Michael Douglas
1.66	5.26	Robert Redford
…	…	…
-0.94	0.39	Kevin Conway
-1.00	0.37	Fisher Stevens
-1.05	0.35	B-movie
-1.14	0.32	Black-and-white
-1.23	0.29	Indie

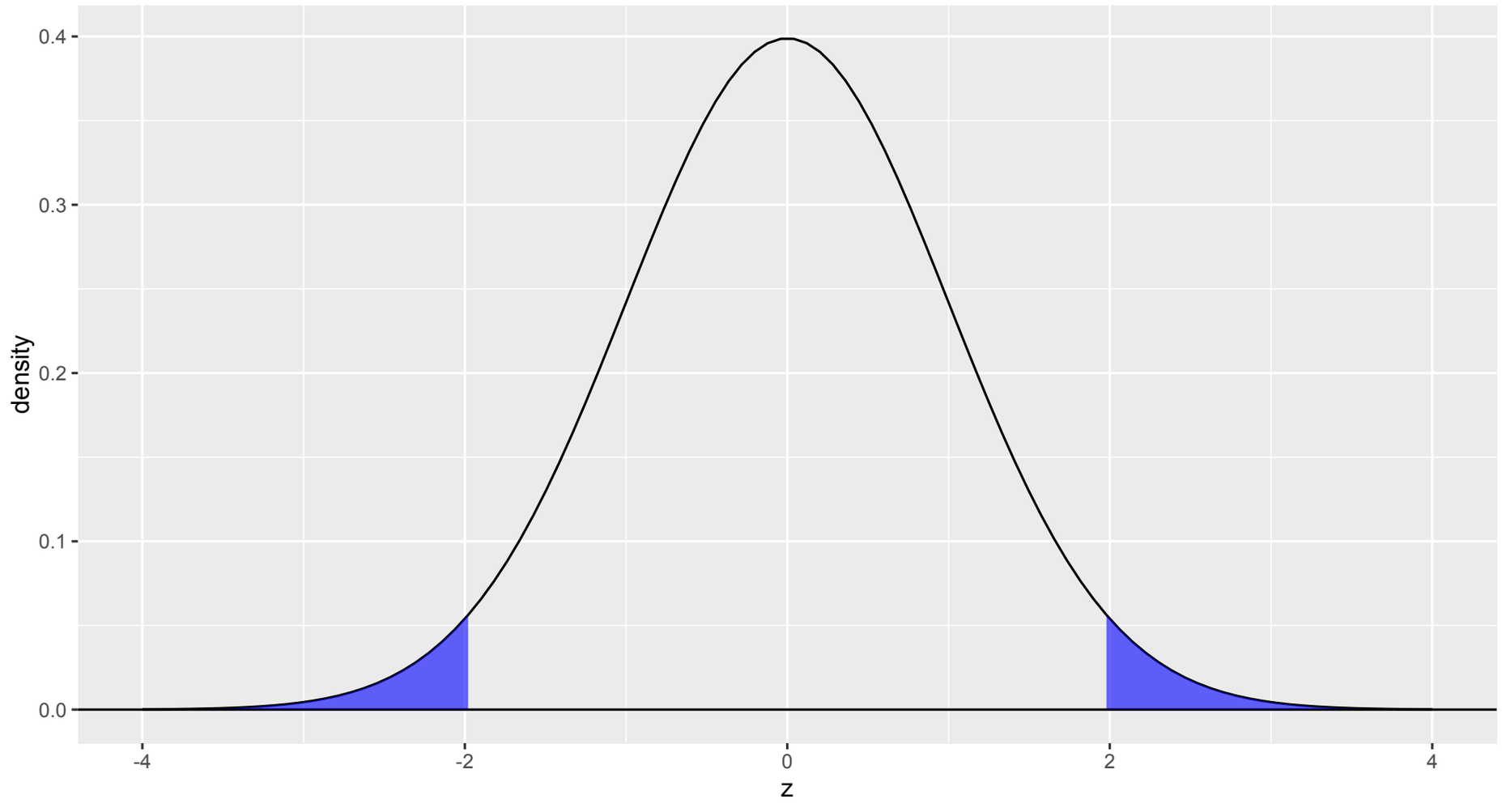
Significance of coefficients

- A β_i value of 0 means that feature x_i has no effect on the prediction of y

- How great does a β_i value have to be for us to say that its effect probably doesn't arise by chance?

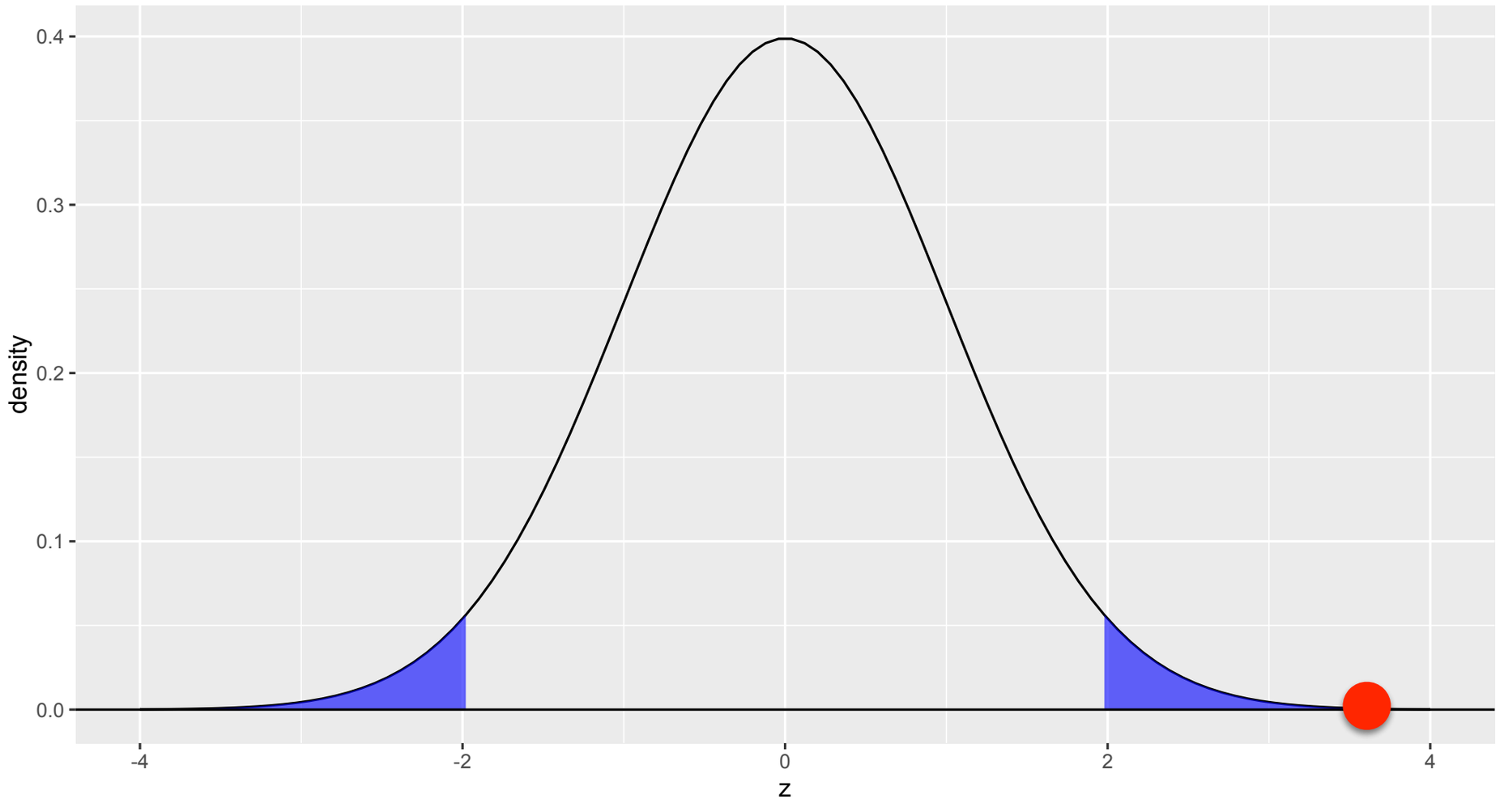
- People often use parametric tests (coefficients are drawn from a normal distribution) to assess this for logistic regression, but we can use it to illustrate another more robust test.

Hypothesis tests



Hypothesis tests measure how (un)likely an observed statistic is under the null hypothesis

Hypothesis tests



Permutation test

- Non-parametric way of creating a null distribution (parametric = normal etc.) for testing the difference in two populations A and B

- For example, the median height of men (=A) and women (=B)

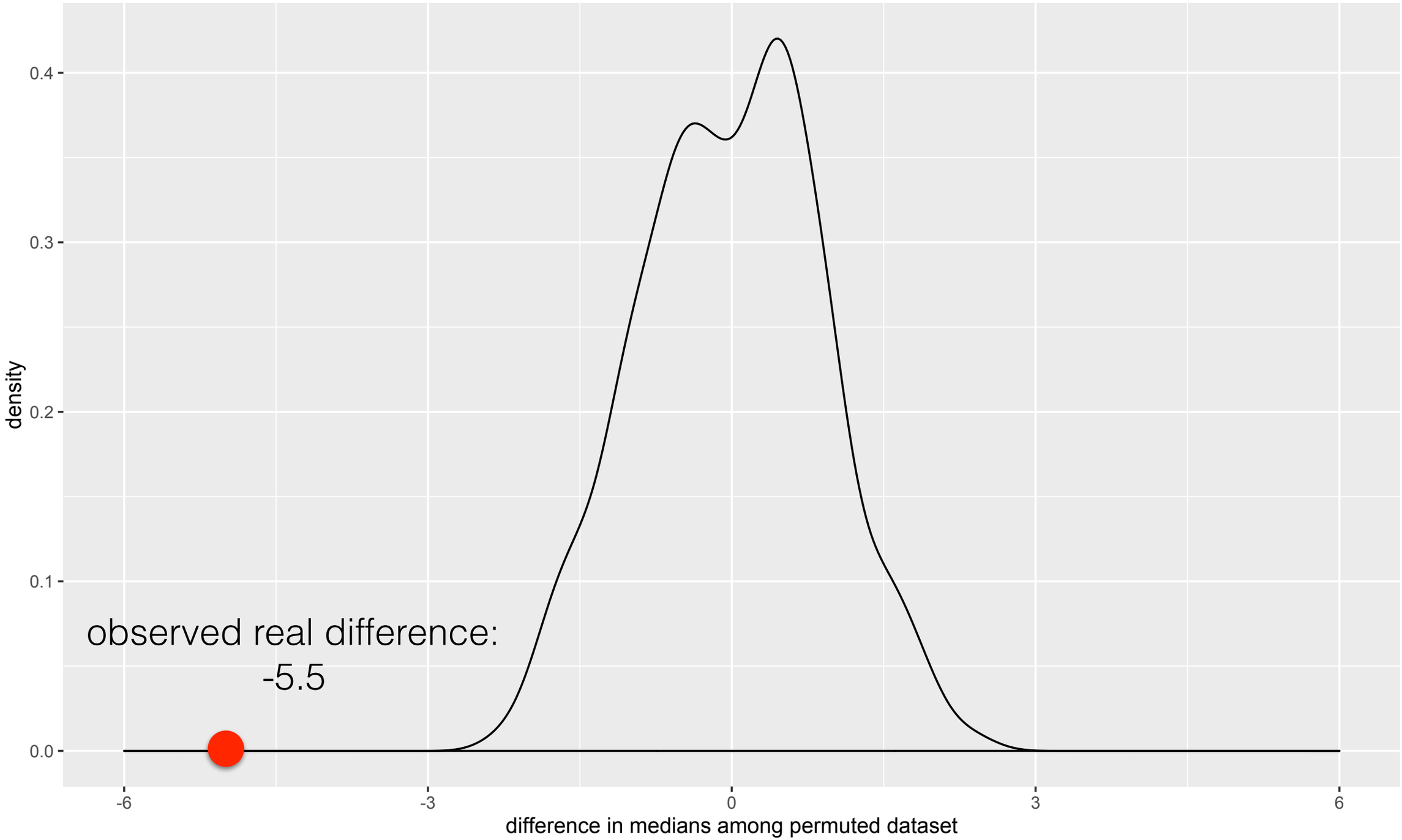
- We shuffle the labels of the data under the null assumption that the labels don’t matter (the null is that A = B)

		true labels	perm 1	perm 2	perm 3	perm 4	perm 5
x1	62.8	woman	man	man	woman	man	man
x2	66.2	woman	man	man	man	woman	woman
x3	65.1	woman	man	man	woman	man	man
x4	68.0	woman	man	woman	man	woman	woman
x5	61.0	woman	woman	man	man	man	man
x6	73.1	man	woman	woman	man	woman	woman
x7	67.0	man	man	woman	man	woman	man
x8	71.2	man	woman	woman	woman	man	man
x9	68.4	man	woman	man	woman	man	woman
x10	70.9	man	woman	woman	woman	woman	woman

observed true difference in medians: -5.5

		true	perm 1	perm 2	perm 3	perm 4	perm 5
x1	62.8	woman	man	man	woman	man	man
x2	66.2	woman	man	man	man	woman	woman
…	…	…	…	…	…	…	…
x9	68.4	man	woman	man	woman	man	woman
x10	70.9	man	woman	woman	woman	woman	woman
difference in medians:		4.7	5.8	1.4	2.9	3.3	

how many times is the difference in medians between the permuted groups greater than the observed difference?



A=100 samples from Norm(70,4)

B=100 samples from Norm(65, 3.5)

Permutation test

The p-value is the number of times the permuted test statistic t_p is more extreme than the observed test statistic t:

$$\hat{p} = \frac{1}{B} \sum_{i=1}^{B} I[abs(t) < abs(t_p)]$$

Permutation test

- The permutation test is a robust test that can be used for many different kinds of test statistics, including coefficients in logistic regression.
- How?
    - A = members of class 1
    - B = members of class 0
    - β are calculated as the (e.g.) the values that maximize the conditional probability of the class labels we observe; its value is determined by the data points that belong to A or B

Permutation test

- To test whether the coefficients have a statistically significant effect (i.e., they're not 0), we can conduct a permutation test where, for B trials, we:

1. shuffle the class labels in the training data

2. train logistic regression on the new permuted dataset

3. tally whether the absolute value of β learned on permuted data is greater than the absolute value of β learned on the true data

Permutation test

The p-value is the number of times the permuted β_p is more extreme than the observed β_t:

$$\hat{p} = \frac{1}{B}\sum_{i=1}^{B} I[abs(\beta_t) < abs(\beta_p)]$$

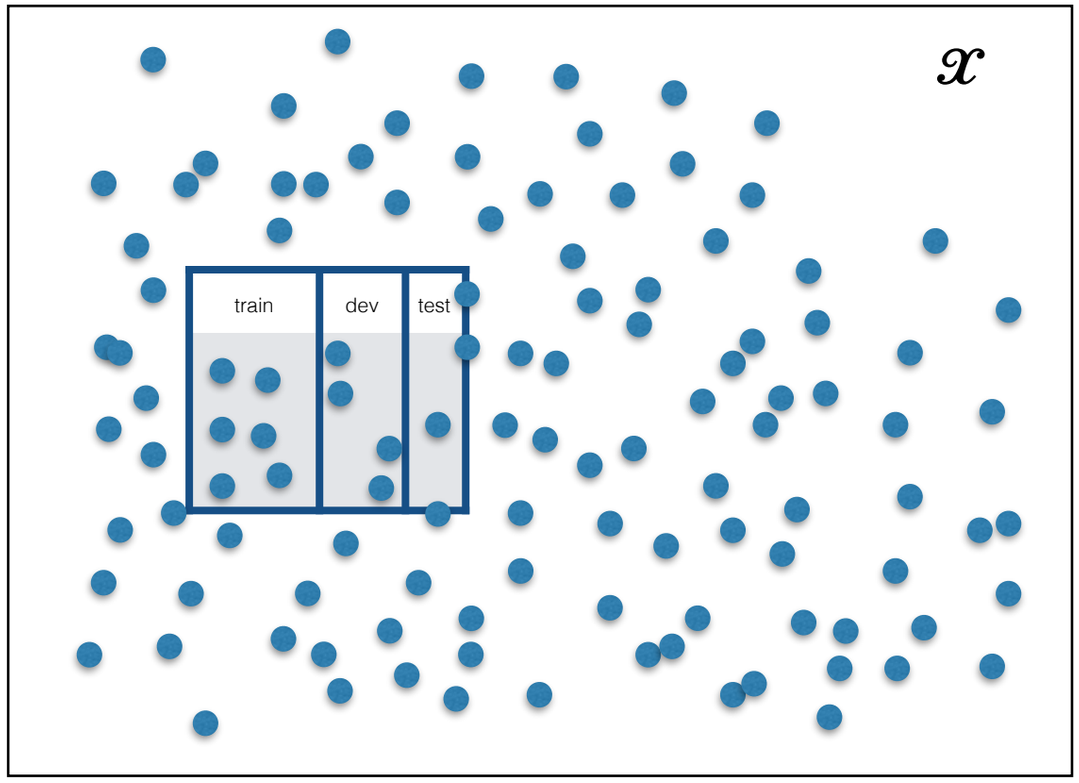
Bootstrap

- The permutation test assesses significance conditioned on the test data you have (we rearrange the labels to form the null distribution, but the data itself doesn't change).

- To also model the variability in the data we have, we can use the statistical bootstrap (Efron 1979).

Bootstrap

- Core idea: the data we happen to have is a sample from from all data that could exist; let's sample from our sample to estimate the variability.



Bootstrap

- Start with test data x of size n
- Draw b bootstrap samples x(i) of size n by sampling with replacement from x
- For each x(i)
    - Let m(i) = the metric of interest calculated from x(i)

Bootstrap

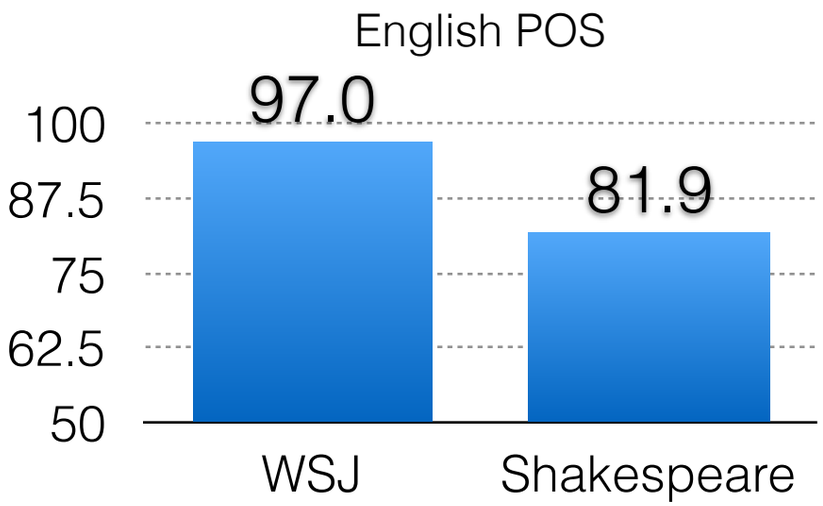
- At the end of the process, you end up with a vector of values m = [m(1), …, m(b)] (for b bootstrap samples)

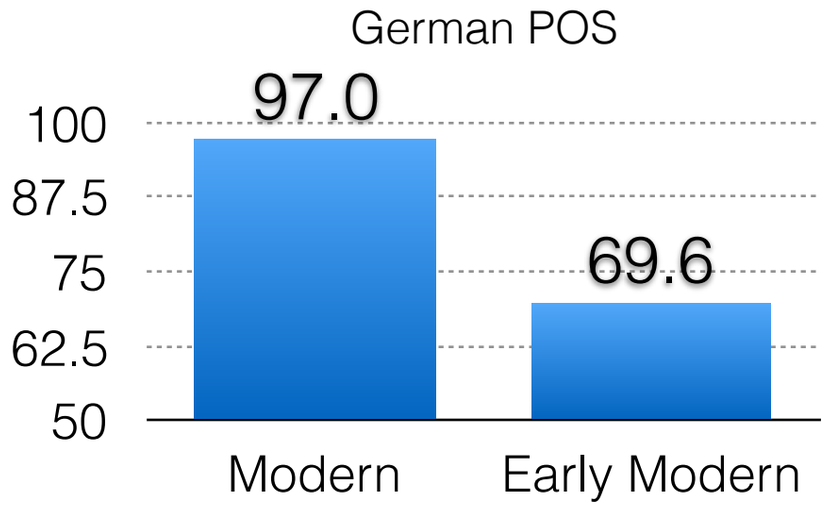
m	Utility
POS accuracy for System A	Estimate confidence intervals
I[System A > System B]	Calculate significance of difference

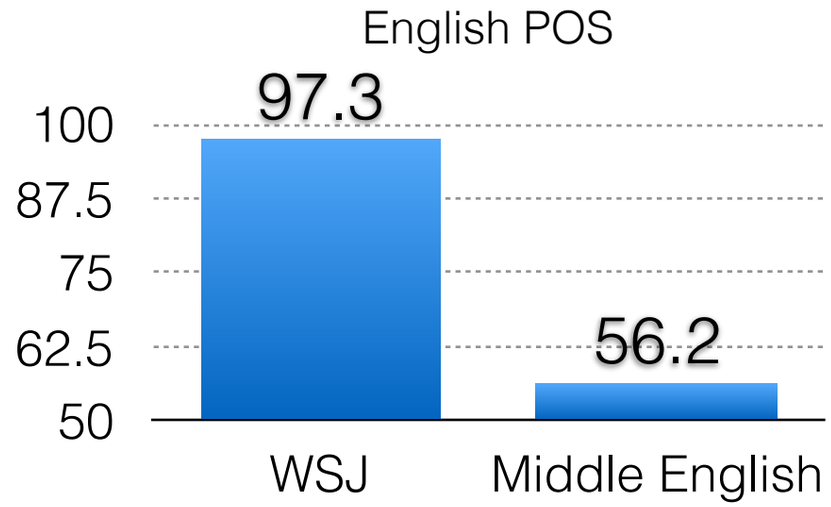
Issues

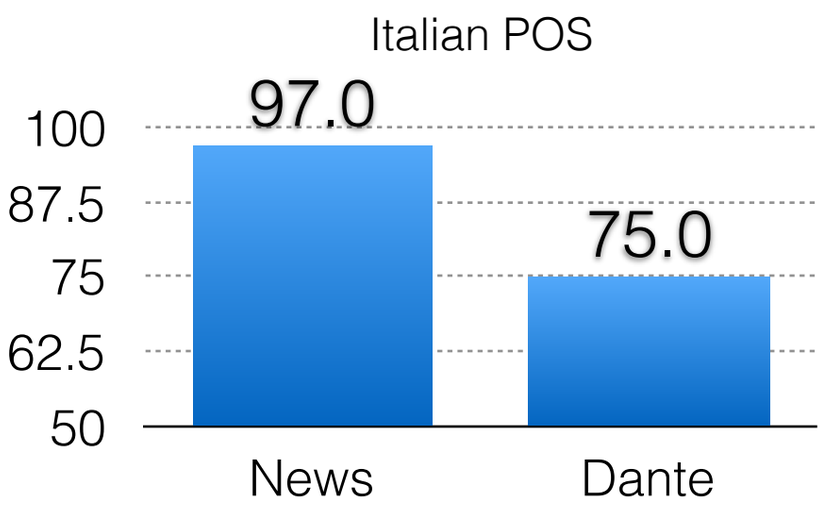
- Evaluation performance may not hold across domains (e.g., WSJ →literary texts)
- Covariates may explain performance (MT/parsing, sentences up to length n)
- Multiple metrics may offer competing results

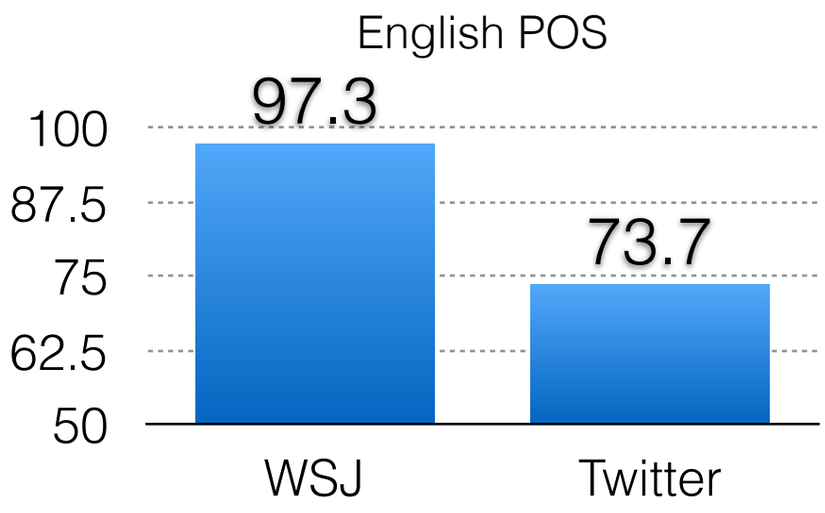
Søgaard et al. 2014

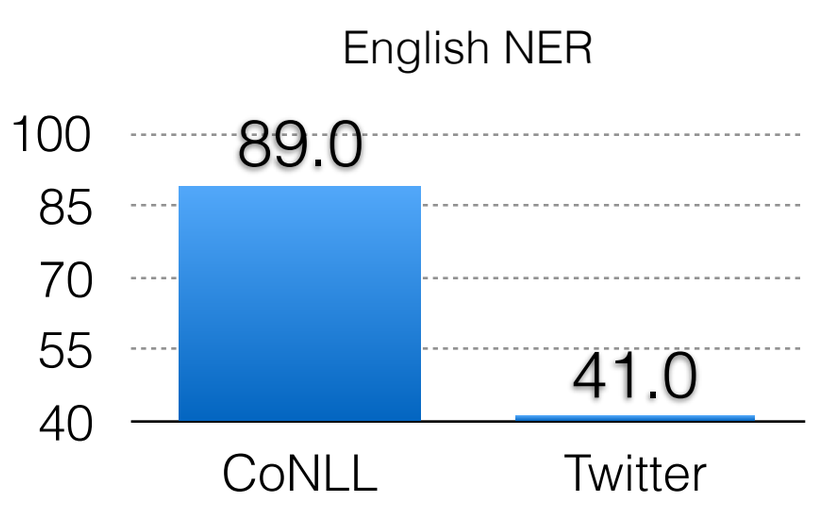

English POS
97.0
81.9
100
87.5
75
62.5
50
WSJ
Shakespeare

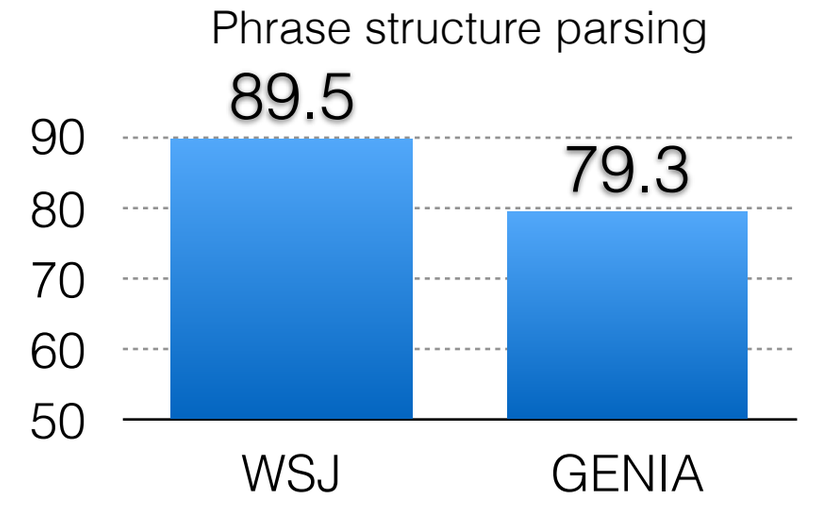

German POS
97.0
69.6
100
87.5
75
62.5
50
Modern
Early Modern

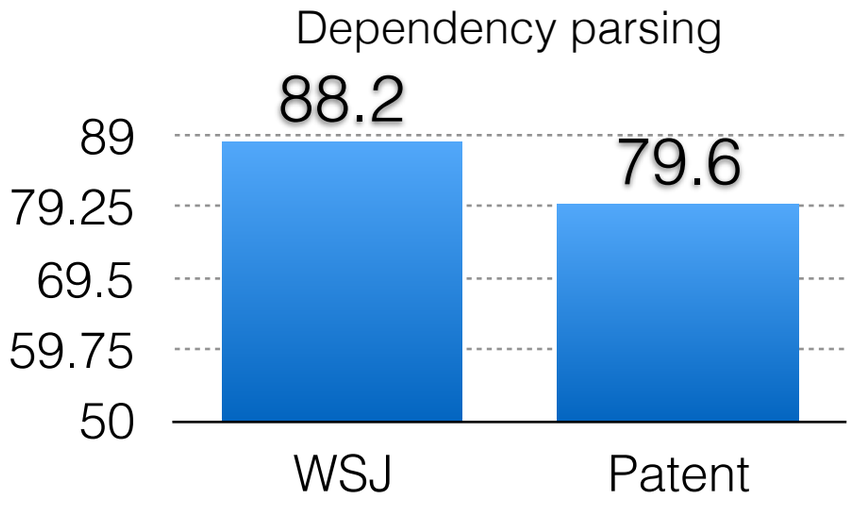

English POS
97.3
56.2
100
87.5
75
62.5
50
WSJ
Middle English

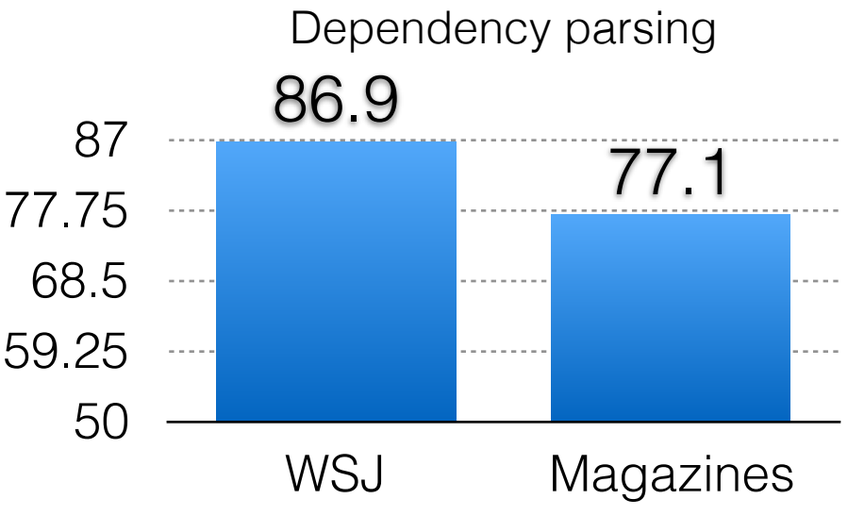

Italian POS
97.0
75.0
100
87.5
75
62.5
50
News
Dante


English POS
97.3
73.7
100
87.5
75
62.5
50
WSJ
Twitter


English NER
89.0
41.0
100
85
70
55
40
CoNLL
Twitter


Phrase structure parsing
89.5
79.3
90
80
70
60
50
WSJ
GENIA


Dependency parsing
88.2
79.6
89
79.25
69.5
59.75
50
WSJ
Patent


Dependency parsing
86.9
77.1
87
77.75
68.5
59.25
50
WSJ
Magazines

Takeaways

- At a minimum, always evaluate a method on the domain you're using it on

- When comparing the performance of models, quantify your uncertainty with significant tests/ confidence bounds

- Use ablation tests to identify the impact that a feature class has on performance.

https://www.guitarworld.com/artists/keith-richards-isolated-guitar-gimme-shelter-rolling-stones

History of NLP

- Foundational insights, 1940s/1950s
- Two camps (symbolic/stochastic), 1957-1970
- Four paradigms (stochastic, logic-based, NLU, discourse modeling), 1970-1983
- Empiricism and FSM (1983-1993)
- Field comes together (1994-1999)
- Machine learning (2000–today)

J&M 2008, ch 1

- Neural networks (~2014–today)

Neural networks in NLP

- Language modeling [Mikolov et al. 2010]
- Text classification [Kim 2014; Iyyer et al. 2015]
- Syntactic parsing [Chen and Manning 2014, Dyer et al. 2015, Andor et al. 2016]
- CCG super tagging [Lewis and Steedman 2014]
- Machine translation [Cho et al. 2014, Sustkever et al. 2014]
- Dialogue agents [Sordoni et al. 2015, Vinyals and Lee 2015, Ji et al. 2016]
- (for overview, see Goldberg 2017, 1.3.1)

Neural networks

- Discrete, high-dimensional representation of inputs (one-hot vectors) -> low-dimensional “distributed” representations.
- Non-linear interactions of input features
- Multiple “layers” to capture hierarchical structure

Neural network libraries

(Keras)

(Dynet)

You already know how neural networks* work!

Logistic regression

$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

SGD

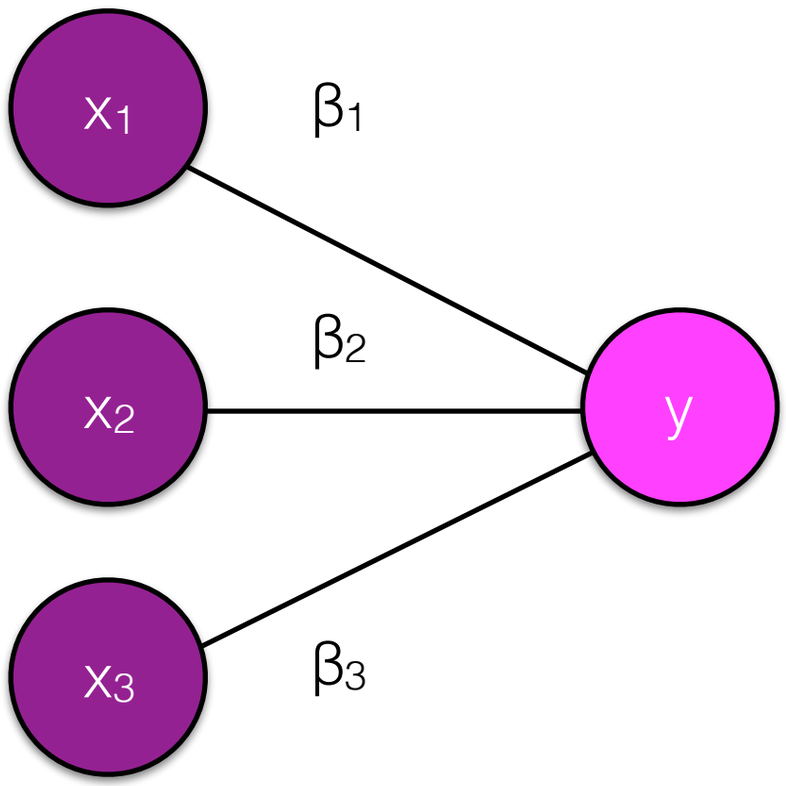
Algorithm 1 Logistic regression gradient descent

1: Data: training data $x \in \mathbb{R}^F, y \in \{0, 1\}$
2: $\beta = 0^F$
3: **while** not converged **do**
4: $\quad \beta_{t+1} = \beta_t + \alpha \sum_{i=1}^{N} (y_i - \hat{p}(x_i))\, x_i$
5: **end while**

Calculate the derivative of some loss function with respect to parameters we can change, update accordingly to make predictions on training data a little less wrong next time.

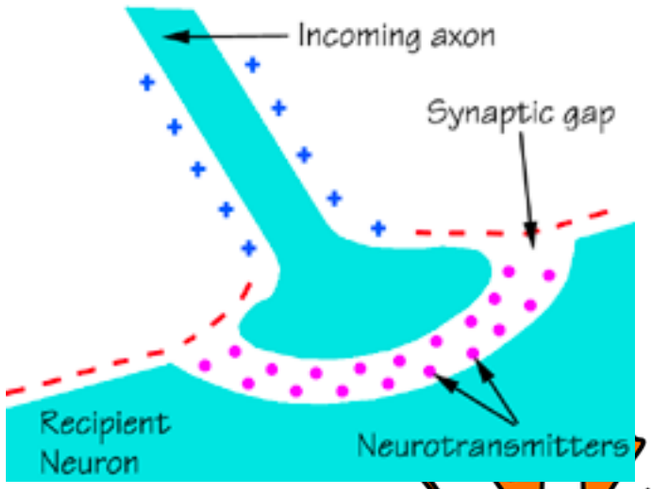
Logistic regression

$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$



	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

Biological analog of the neuron



How much activation (input) does it take for this neuron to fire (output)?

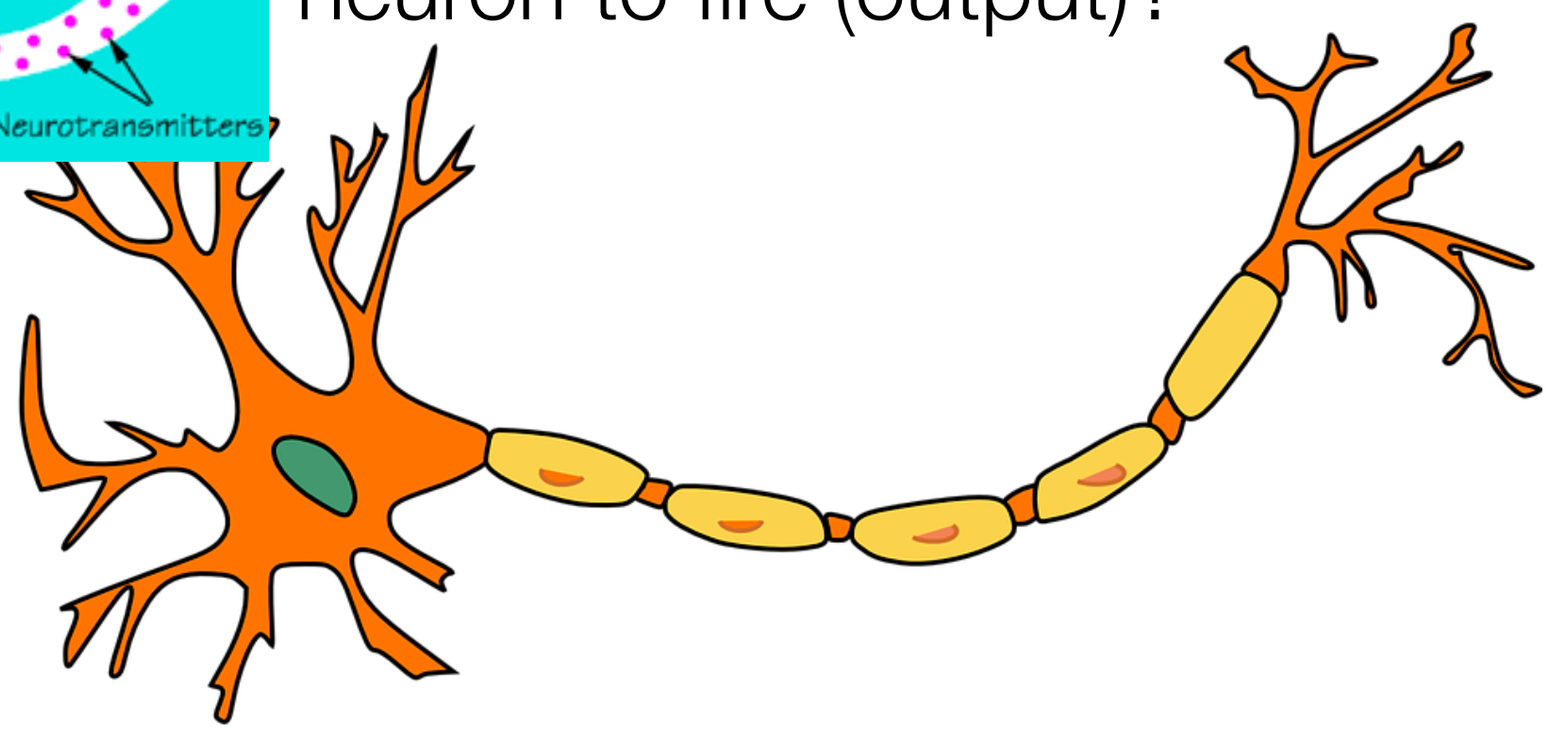
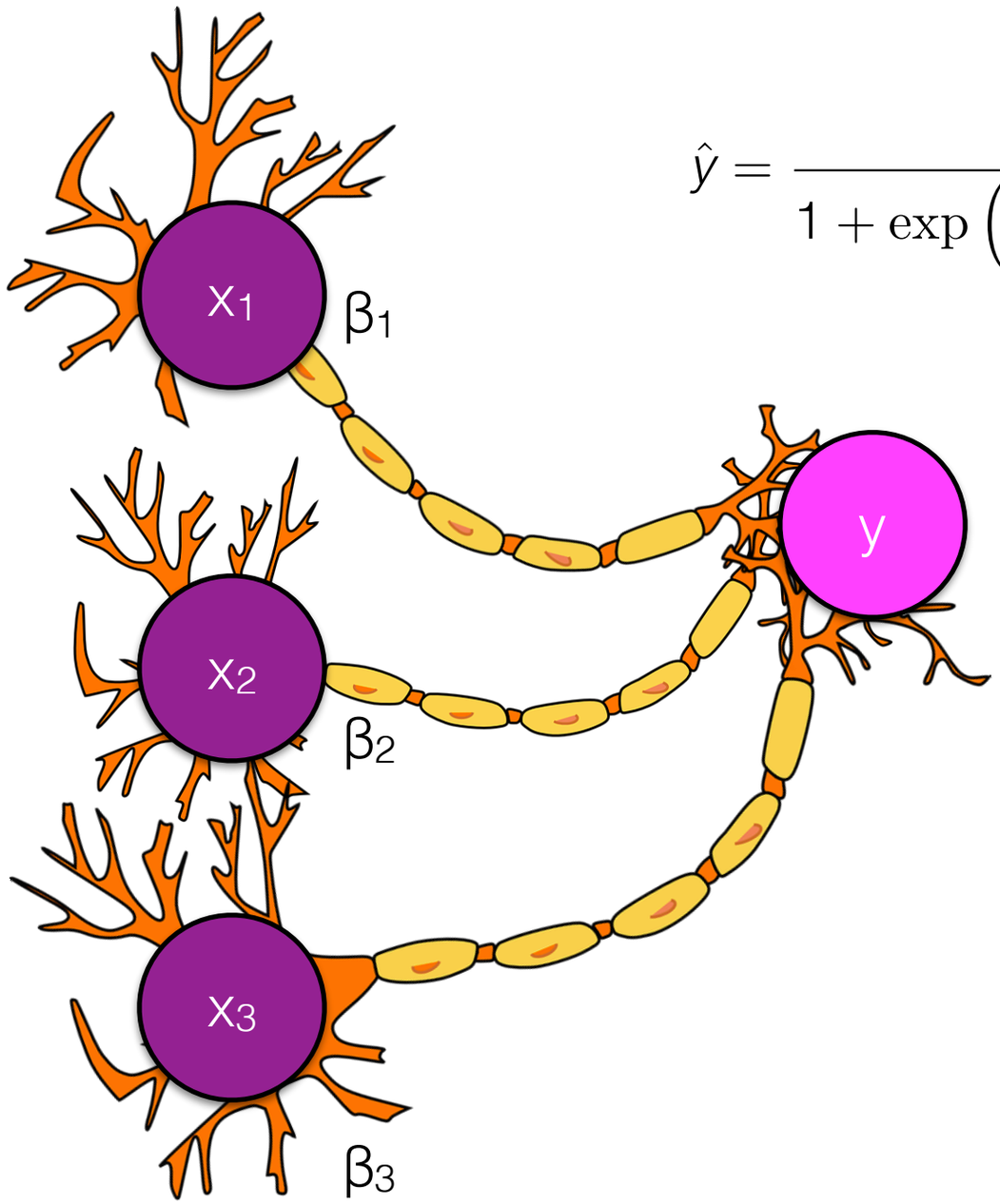


Image credit: https://commons.wikimedia.org/wiki/File:Synapse_diagram.png

Logistic regression



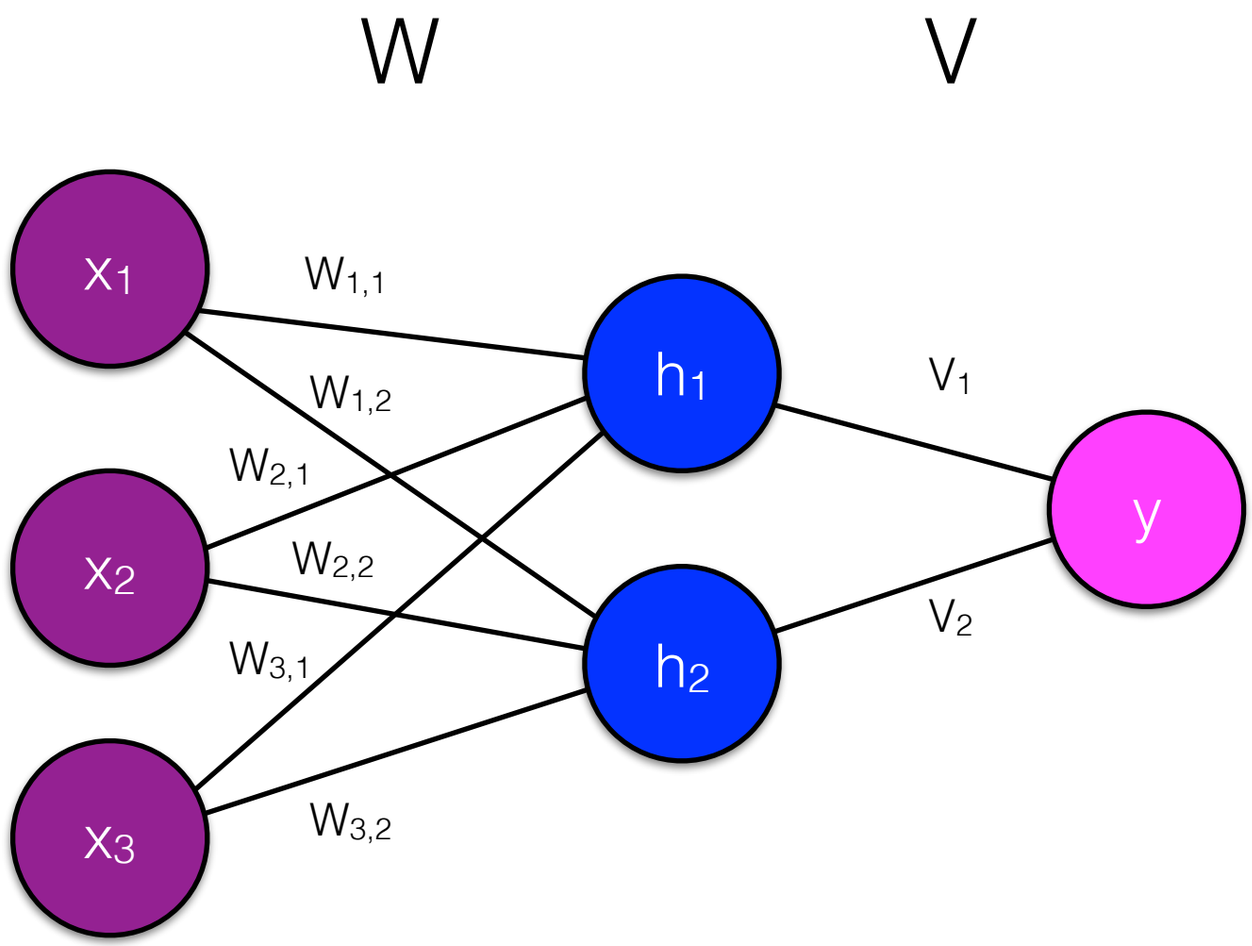
$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

	x	β
not	1	-0.5
bad	1	-1.7
movie	0	0.3

Neural networks

- Two core ideas:
  - Non-linear activation functions
  - Multiple layers

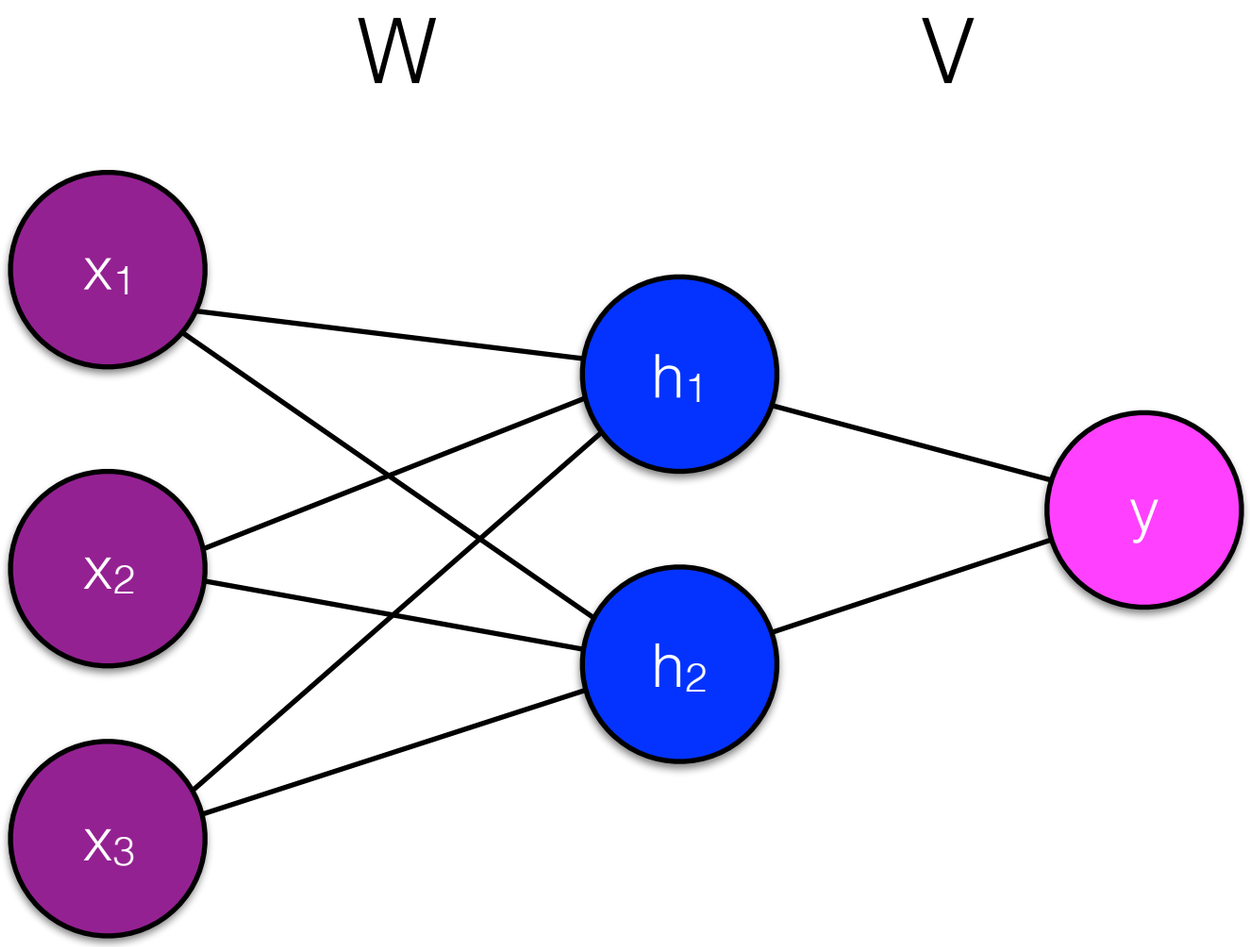
*For simplicity, we're leaving out the bias term, but assume most layers have them as well.



Input

"Hidden" Layer

Output

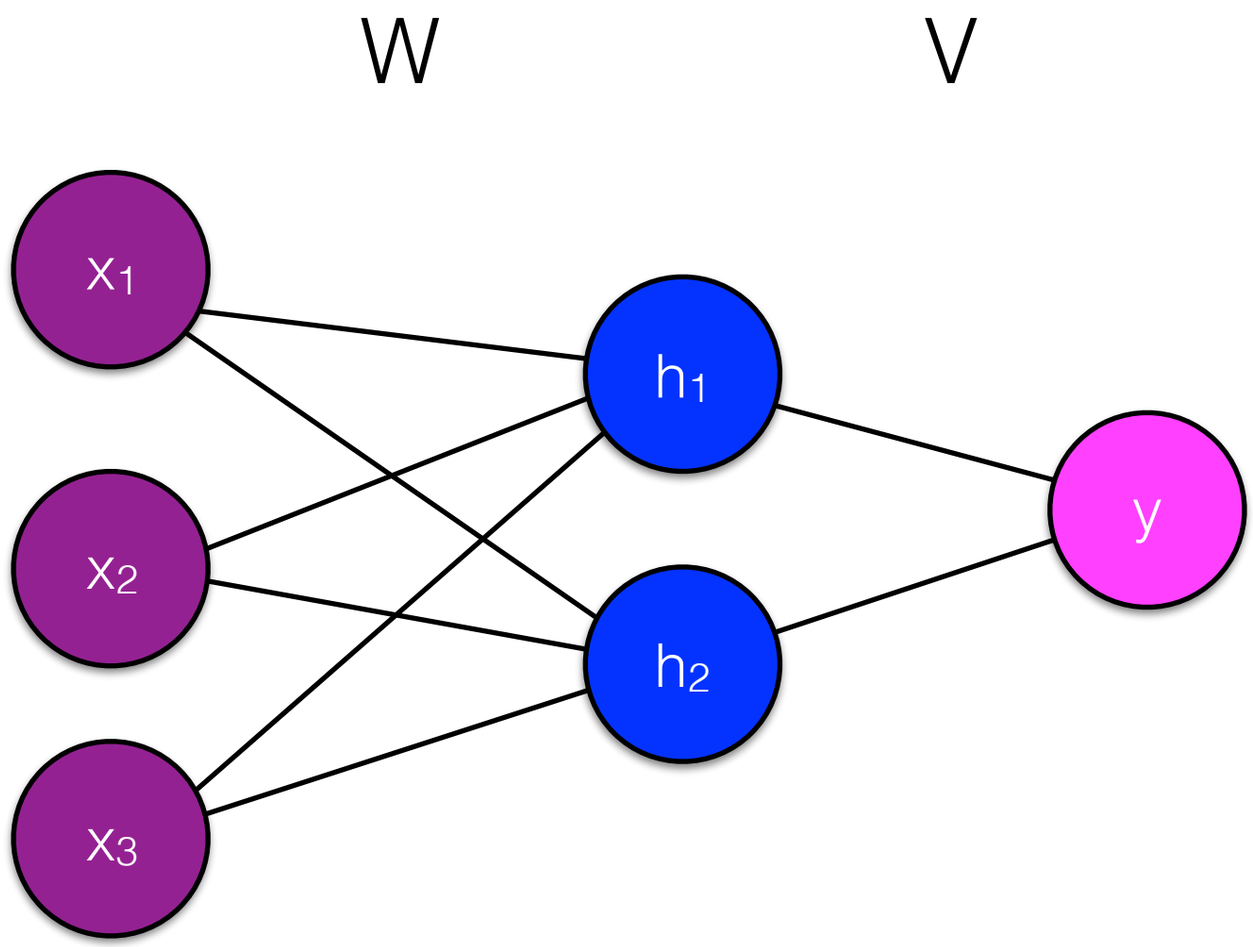


	x
not	1
bad	1
movie	0

W	
-0.5	1.3
0.4	0.08
1.7	3.1

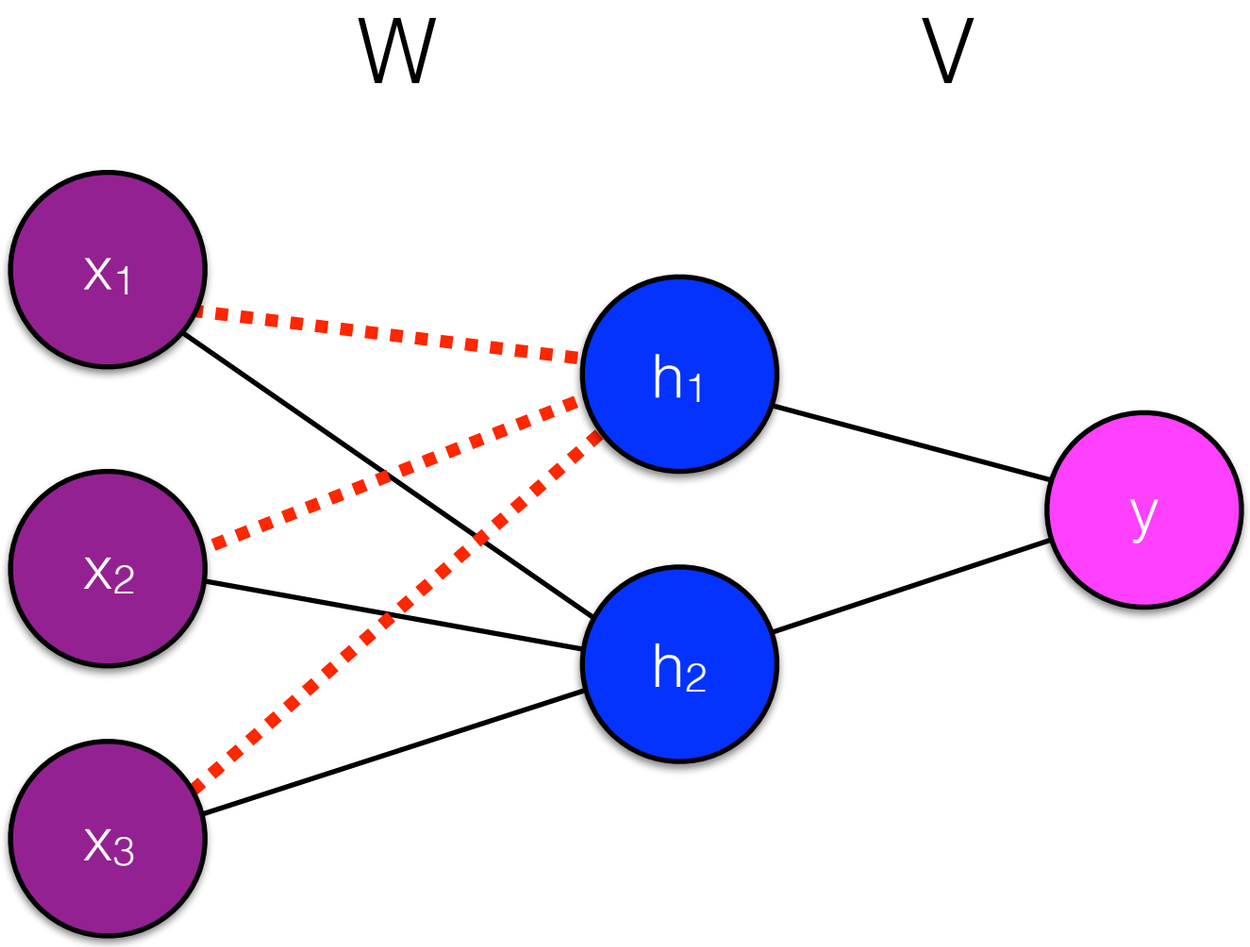
V
4.1
-0.9

y
1



$$h_j = f\left(\sum_{i=1}^{F} x_i W_{i,j}\right)$$

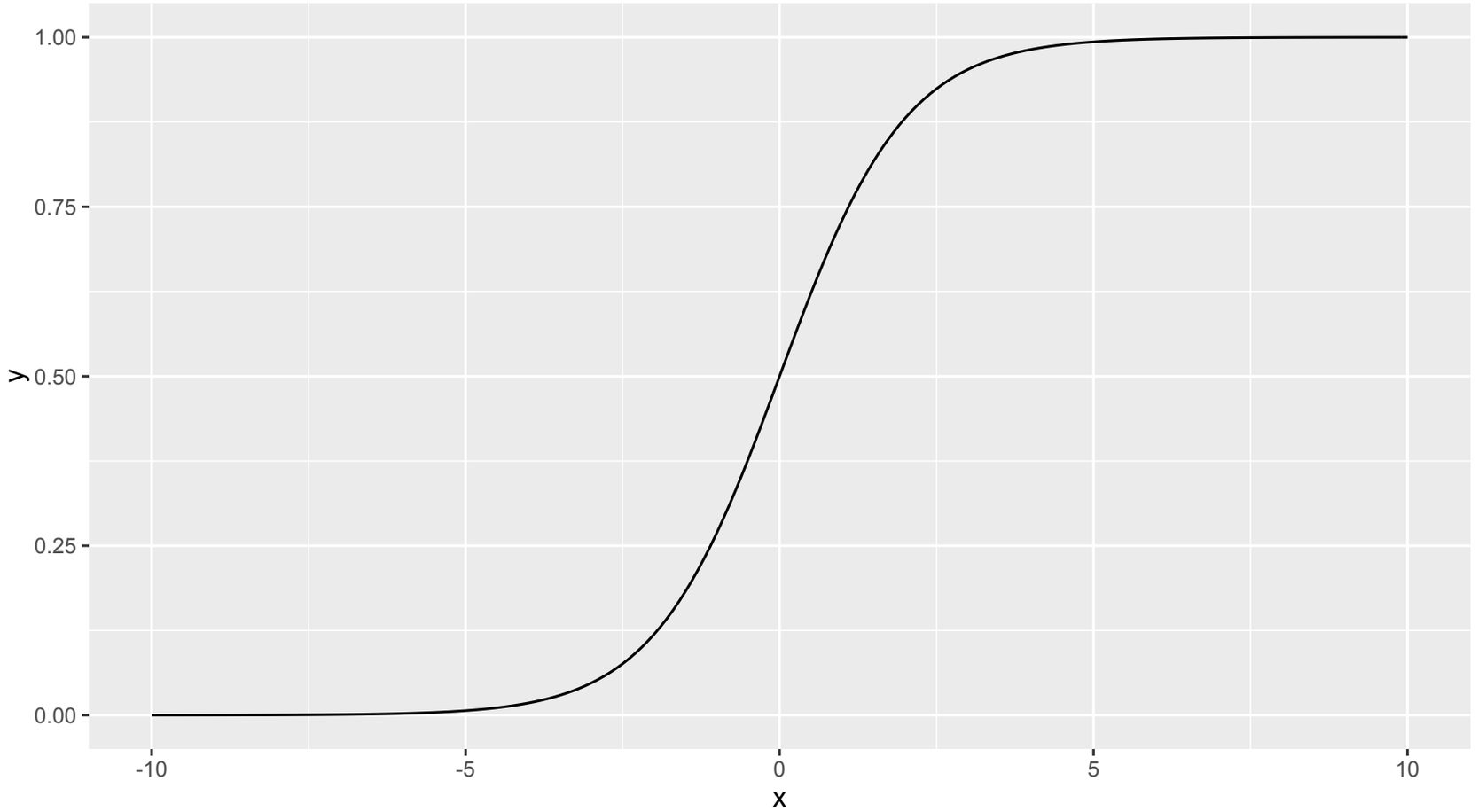
the hidden nodes are completely determined by the input and weights



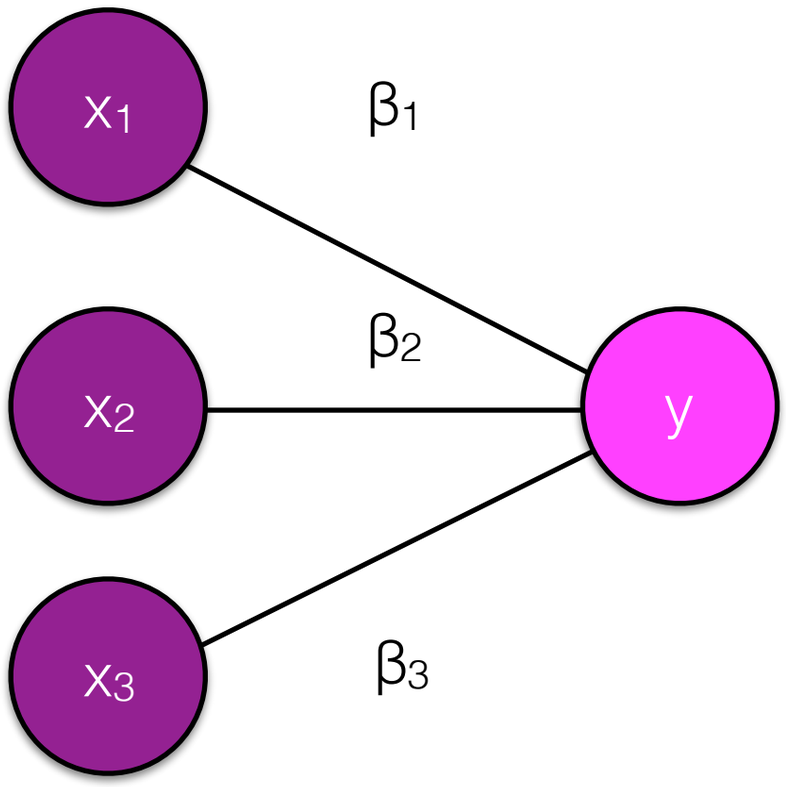
$$h_1 = f\left(\sum_{i=1}^{F} x_i W_{i,1}\right)$$

Activation functions

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$



Logistic regression



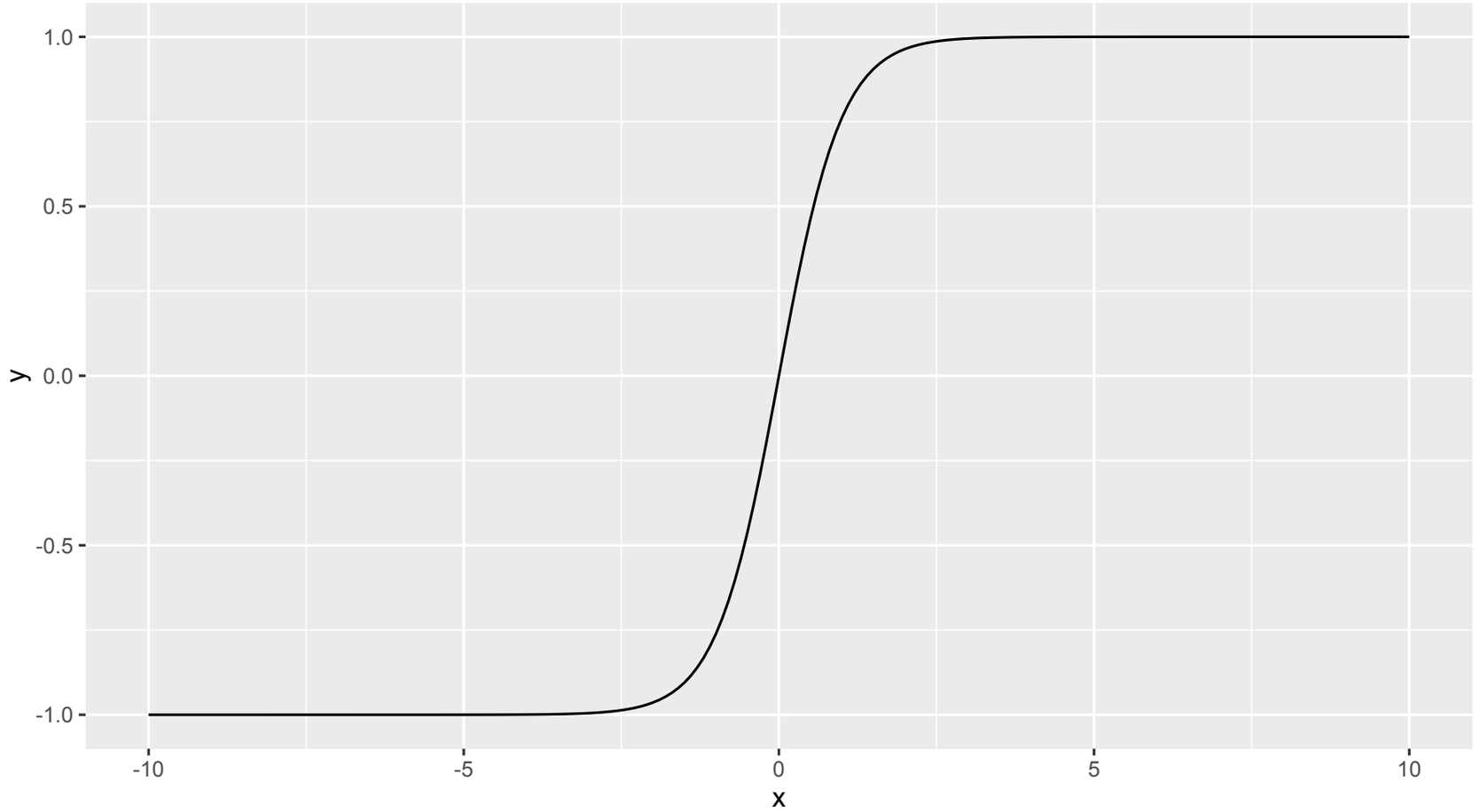
$$\hat{y} = \frac{1}{1 + \exp\left(-\sum_{i=1}^{F} x_i \beta_i\right)}$$

$$\hat{y} = \sigma\left(\sum_{i=1}^{F} x_i \beta_i\right)$$

We can think about logistic regression as a neural network with no hidden layers

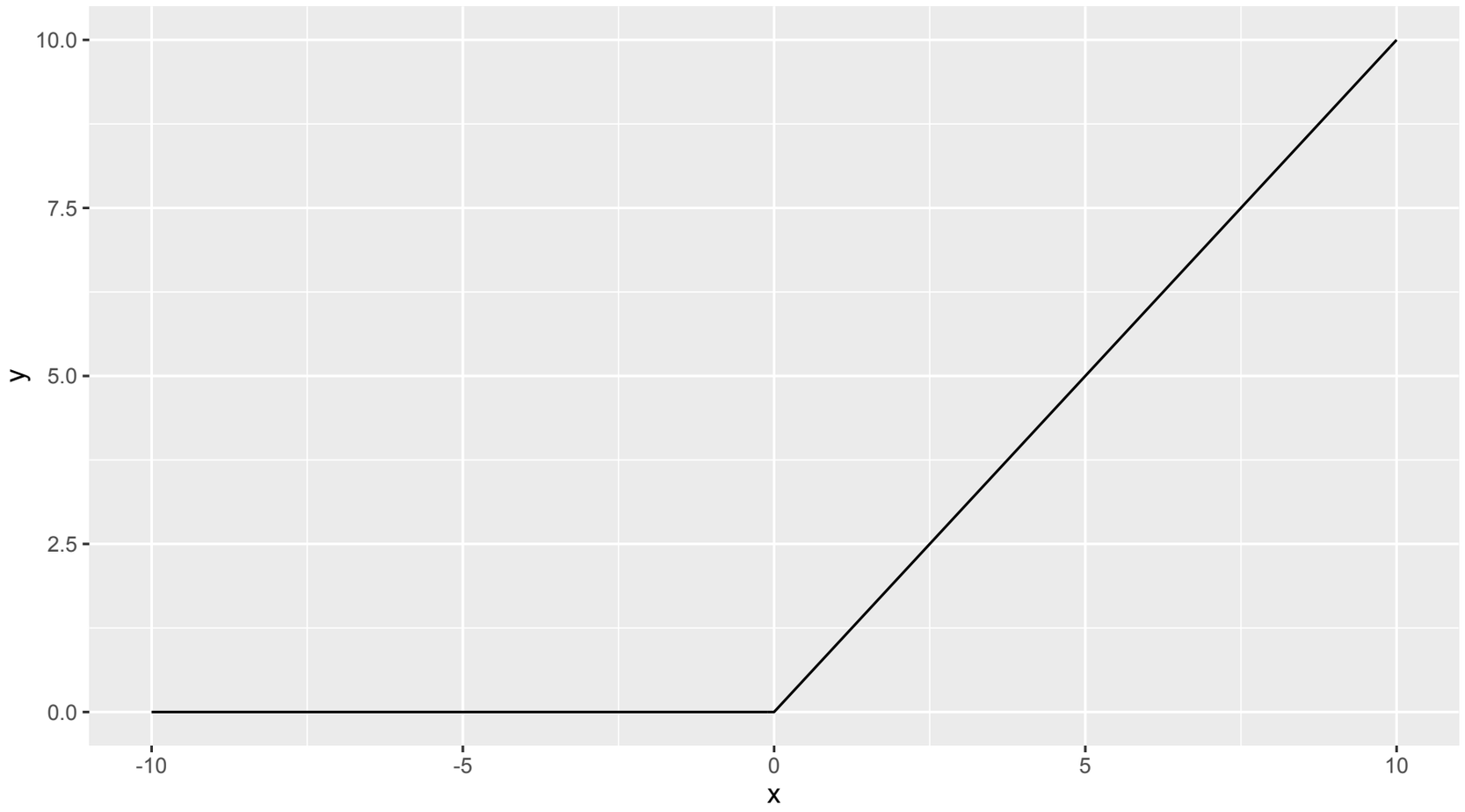
Activation functions

$$\tanh(z) = \frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)}$$

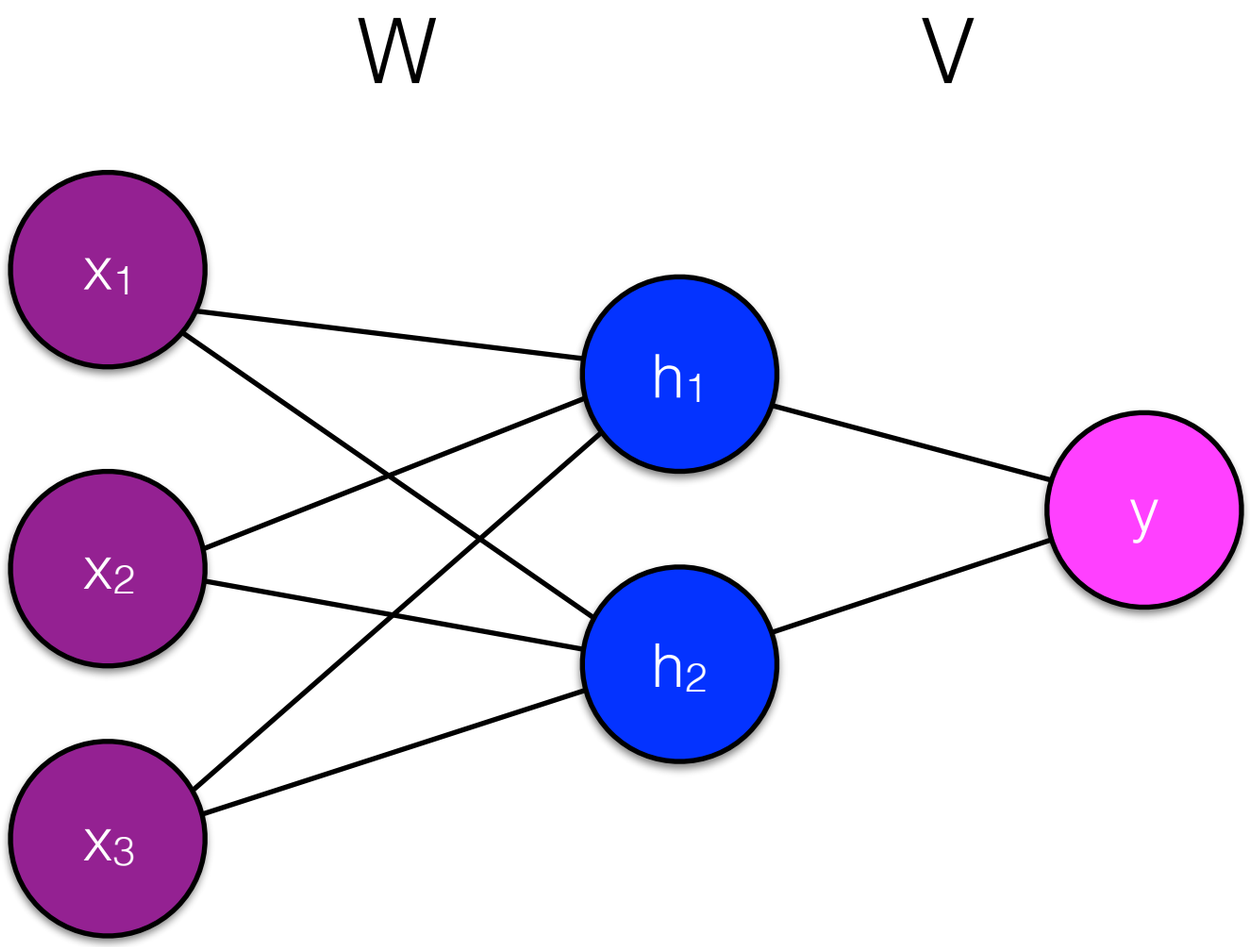


Activation functions

$$\textit{rectifier}(z) = \max(0, z)$$



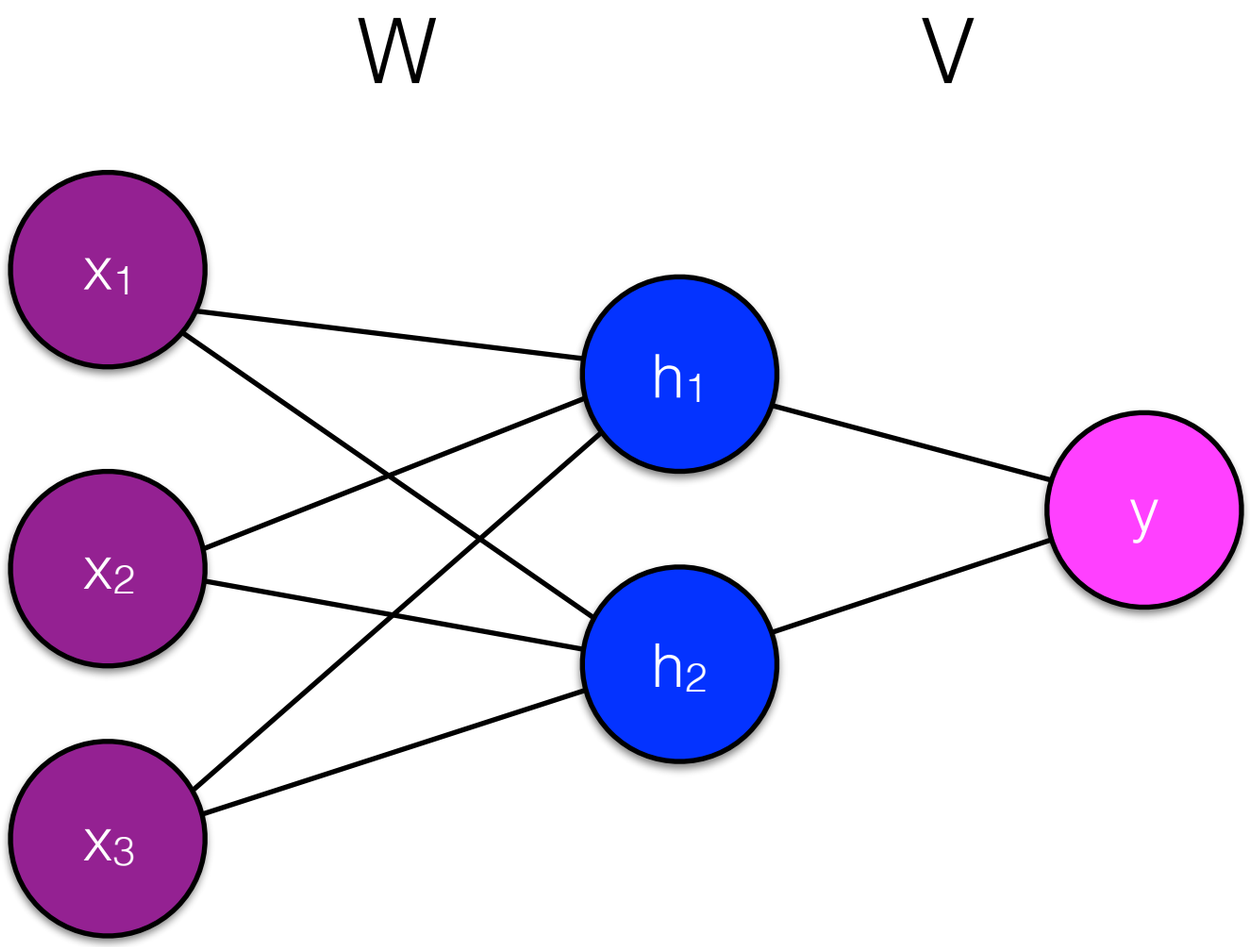
Also known as a Rectified Linear Unit (ReLU)



$$h_1 = \sigma\left(\sum_{i=1}^{F} x_i W_{i,1}\right)$$

$$h_2 = \sigma\left(\sum_{i=1}^{F} x_i W_{i,2}\right)$$

$$\hat{y} = \sigma\left[V_1 h_1 + V_2 h_2\right]$$



$$\hat{y} = \sigma\left[V_1\left(\sigma\left(\sum_i^F x_i W_{i,1}\right)\right) + V_2\left(\sigma\left(\sum_i^F x_i W_{i,2}\right)\right)\right]$$

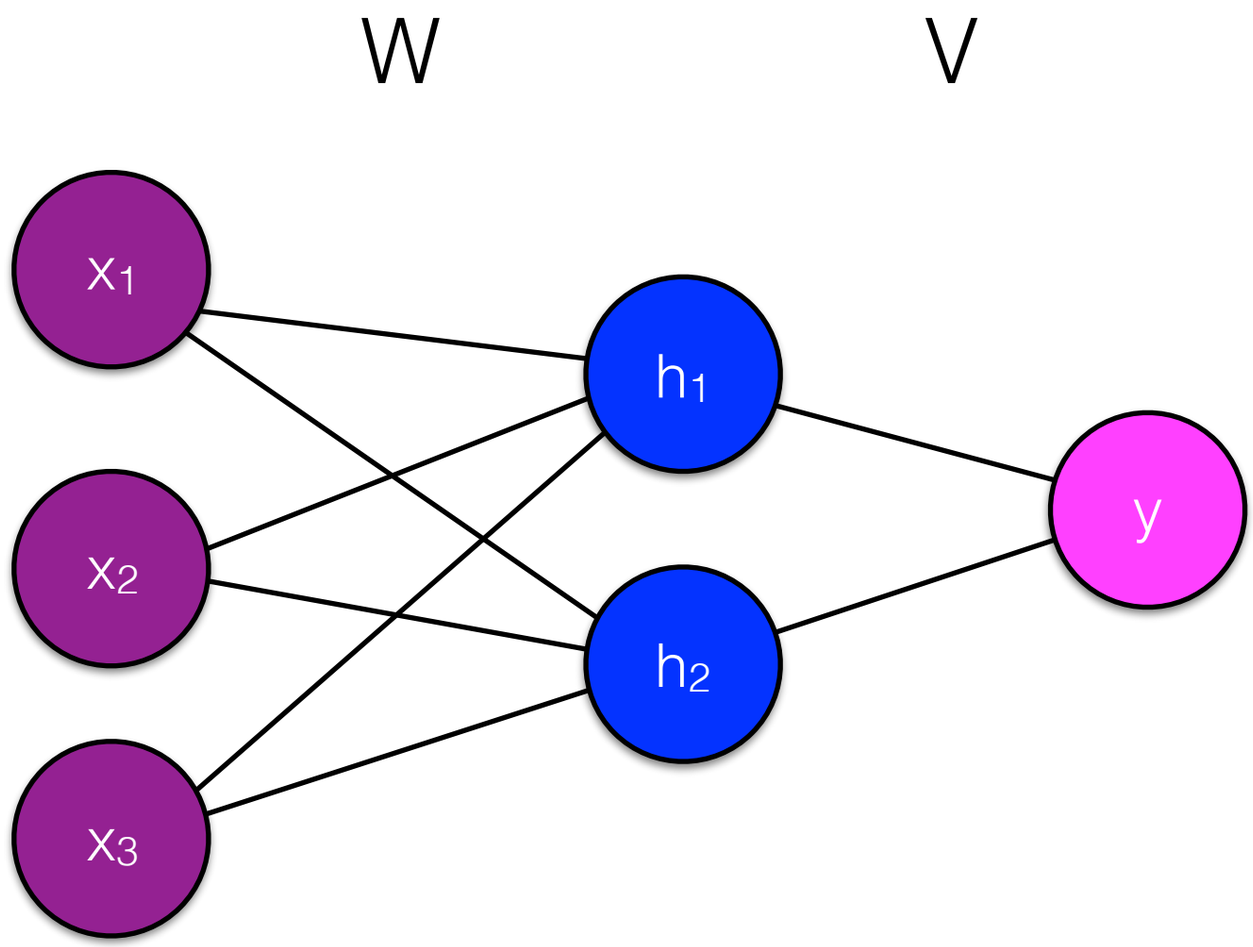
we can express y as a function only of the input x and the weights W and V


What a great sounding neural network!
But how to I get it to sound like?

$$\hat{y} = \sigma\left[V_1 \underbrace{\left(\sigma\left(\sum_i^F x_i W_{i,1}\right)\right)}_{h_1} + V_2 \underbrace{\left(\sigma\left(\sum_i^F x_i W_{i,2}\right)\right)}_{h_2} \right]$$

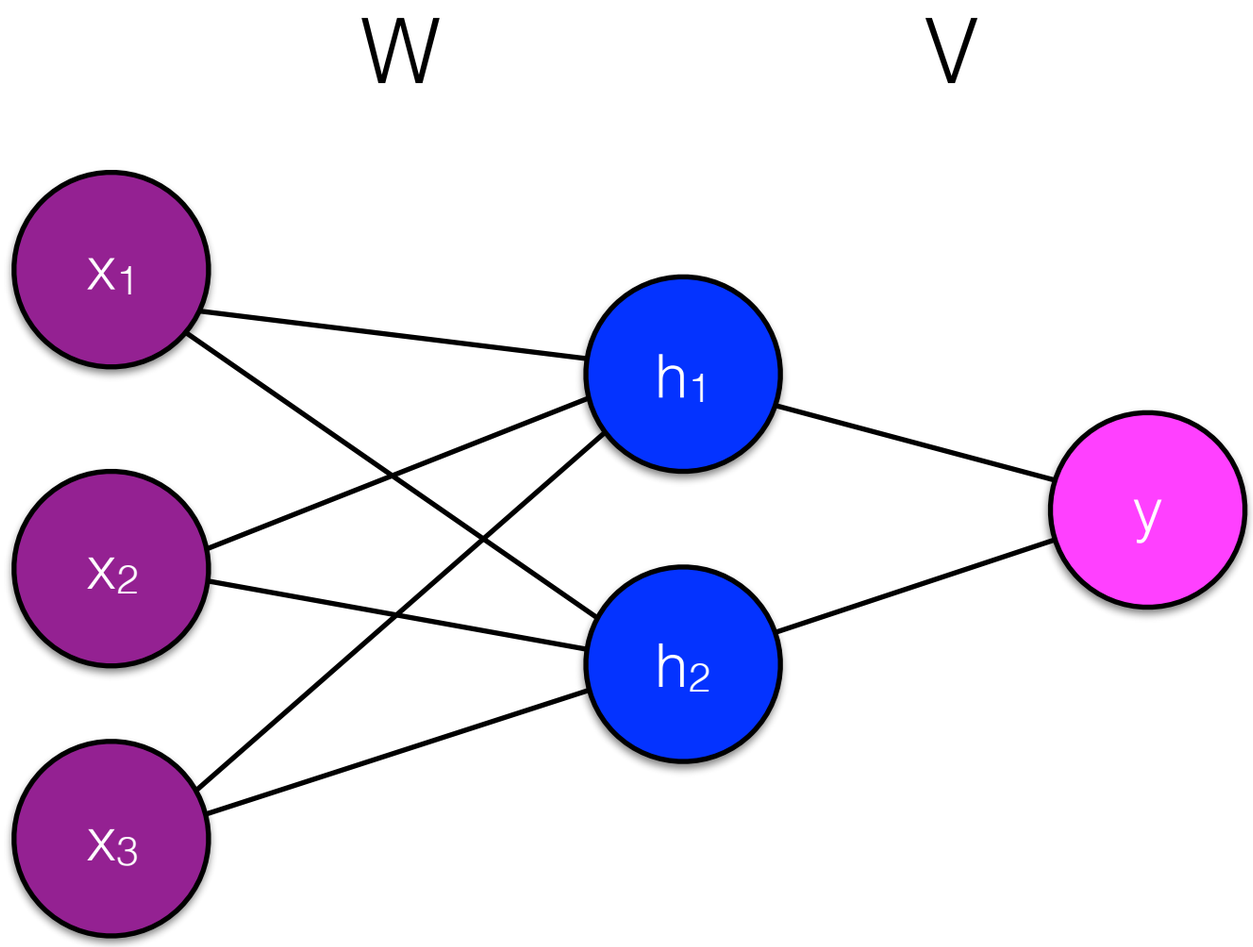
This is hairy, but differentiable

Backpropagation: Given training samples of <x,y> pairs, we can use stochastic gradient descent to find the values of W and V that minimize the loss.



Neural networks are a series of functions chained together

$$xW \rightarrow \sigma(xW) \rightarrow \sigma(xW)V \rightarrow \sigma(\sigma(xW)V)$$



Neural networks are a series of **functions** chained together

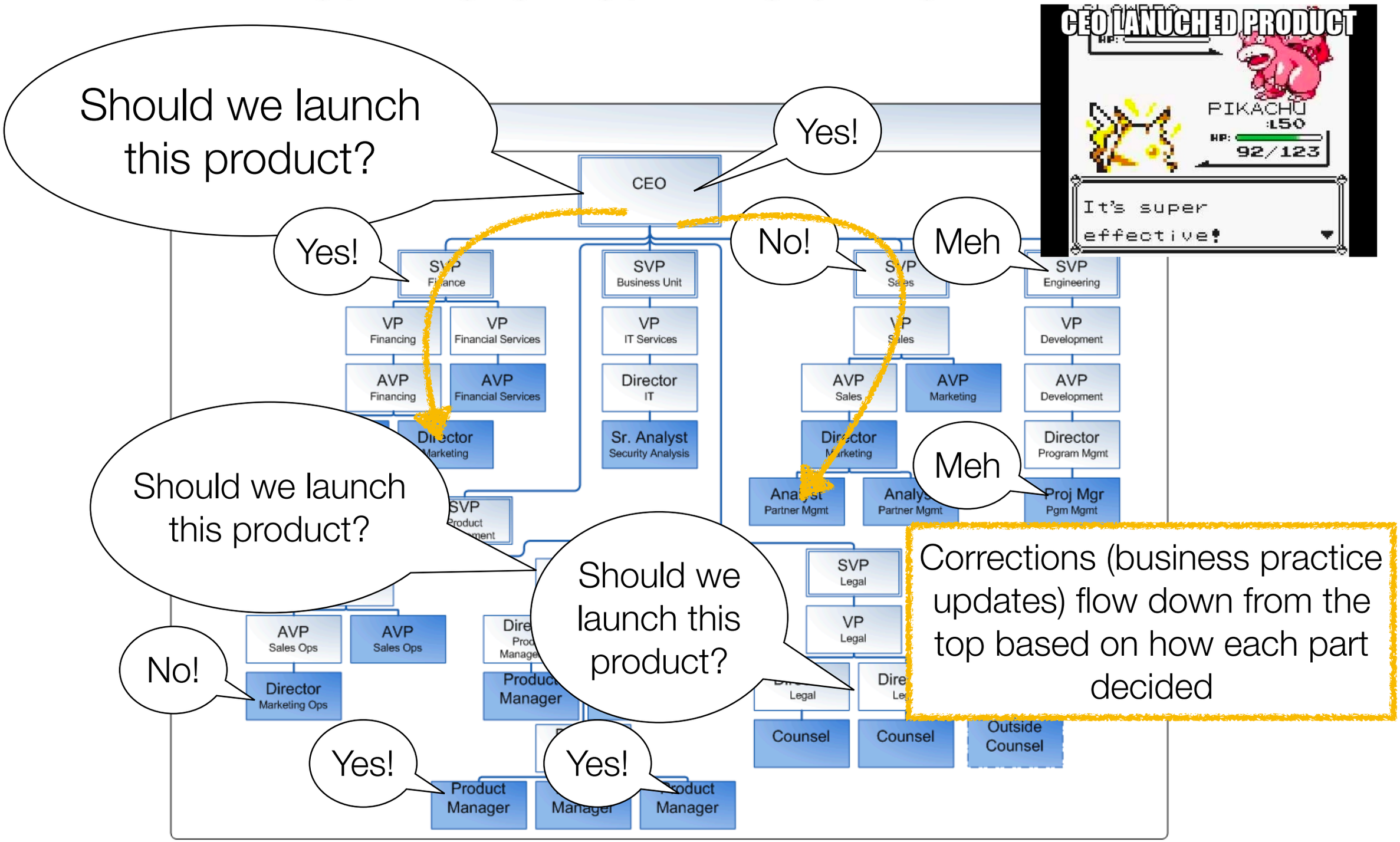
$$xW \rightarrow \sigma(xW) \rightarrow \sigma(xW)V \rightarrow \sigma(\sigma(xW)V)$$

The loss is another function chained on top

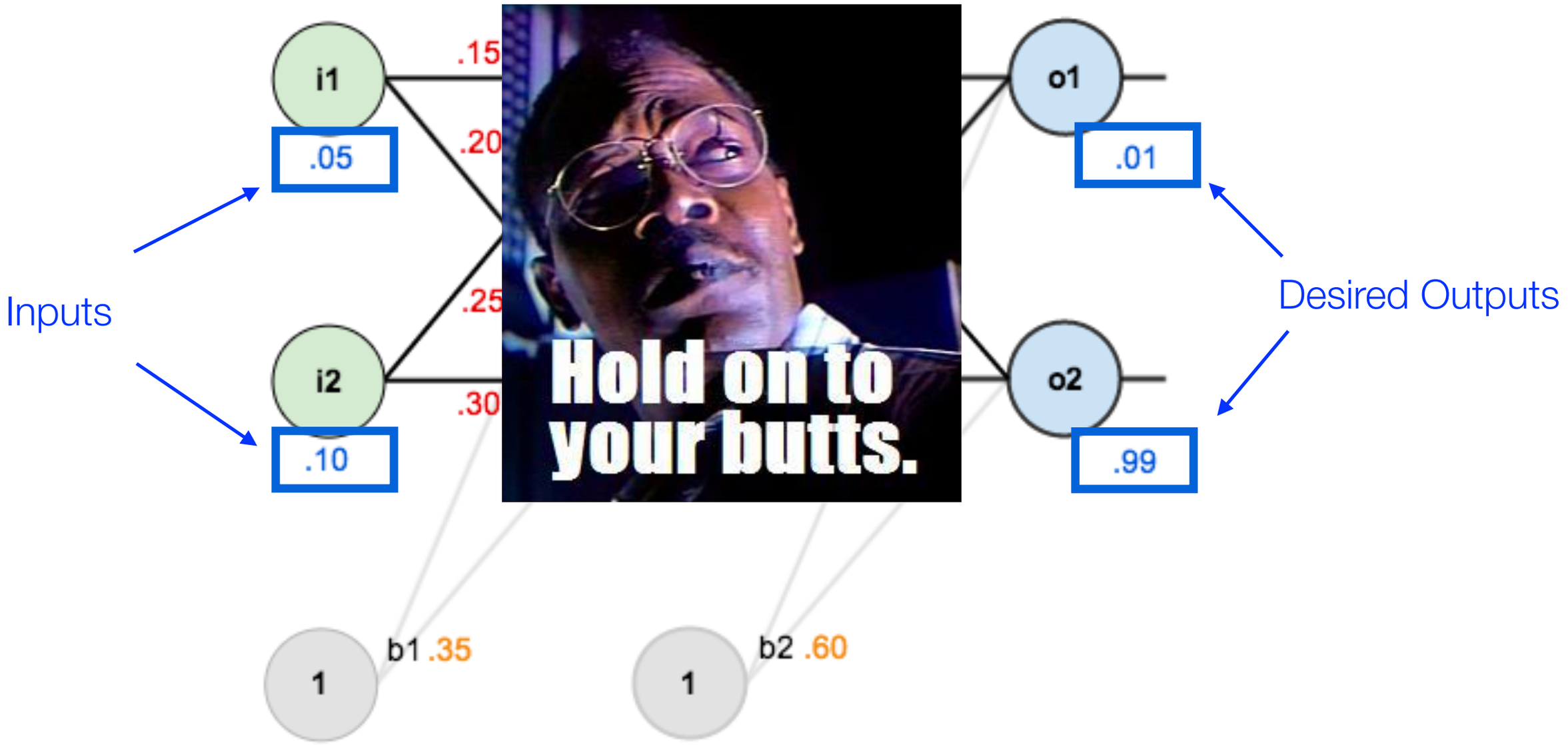
$$\log(\sigma(\sigma(xW)V))$$

The loss tells us how much the prediction was wrong

An analog on how to update a neural network



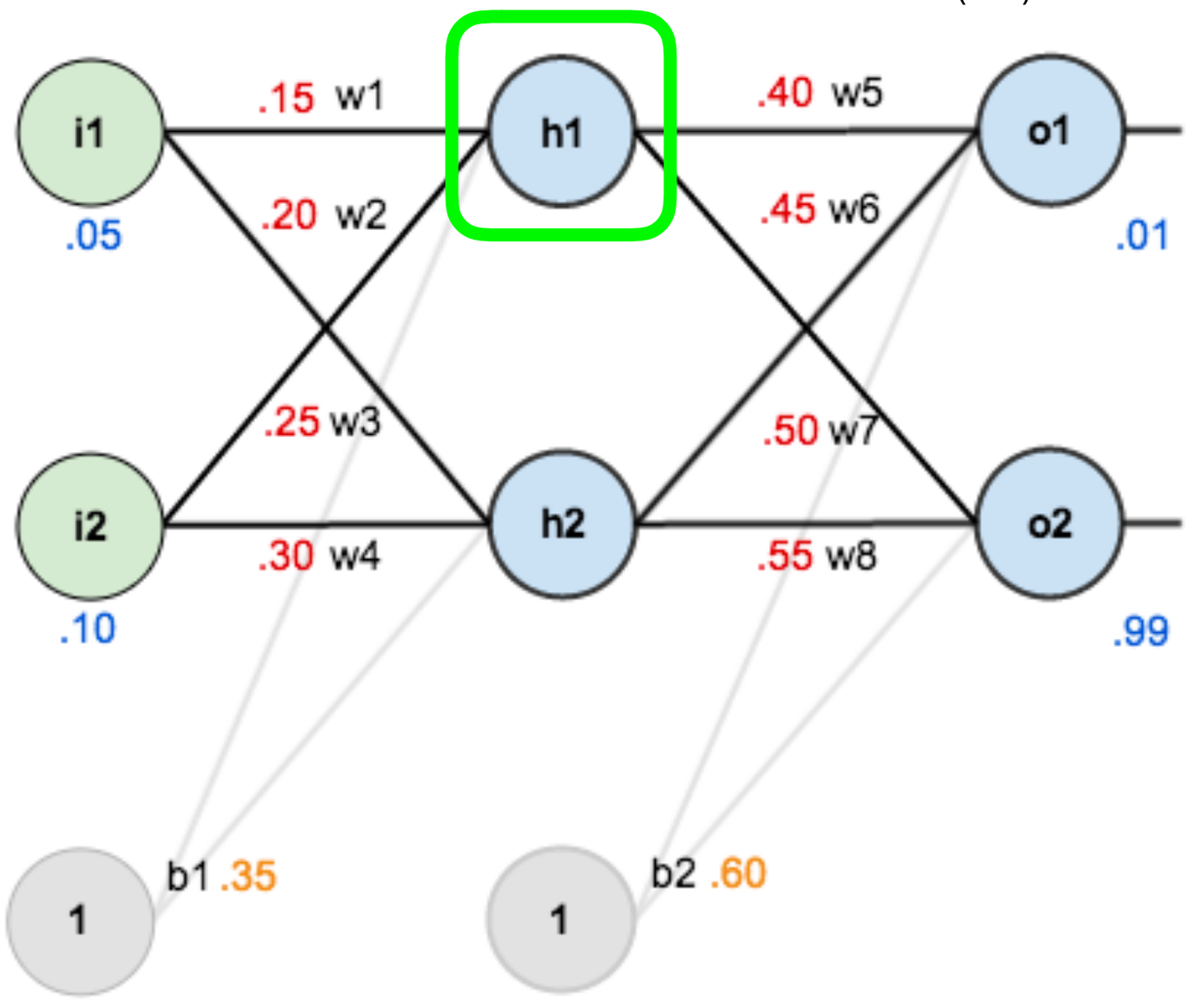
Let's try updating a real network!



Let's try updating a real network!

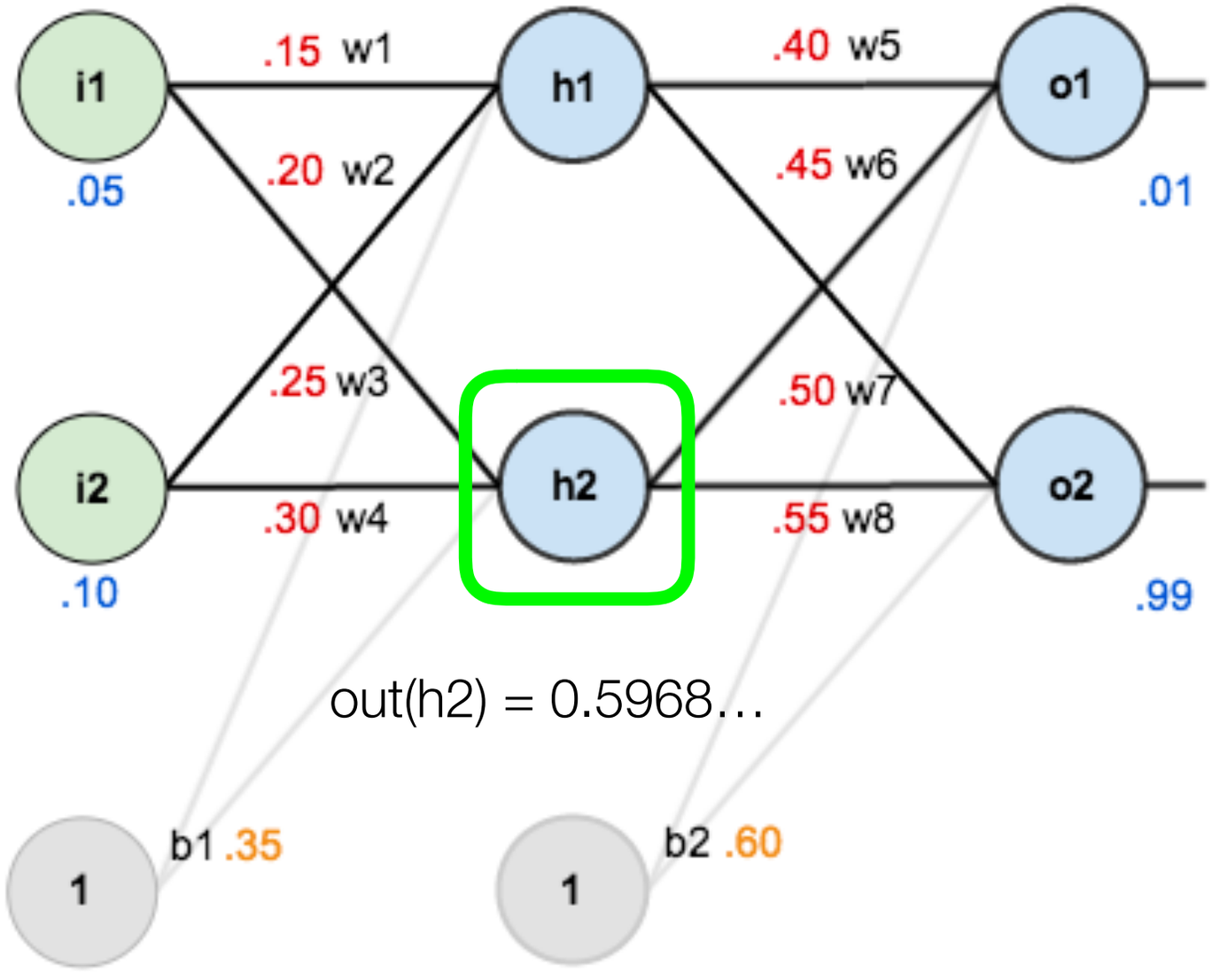
net(h1) = w1*i1 + w2*i2 + b1
= 0.15*0.05 + 0.20*0.10 + 0.35
= 0.3775

out(h1) = sigmoid(net(h1))
out(h1) = 1/ (1 + e^-0.3775)
out(h1) = 0.5932…



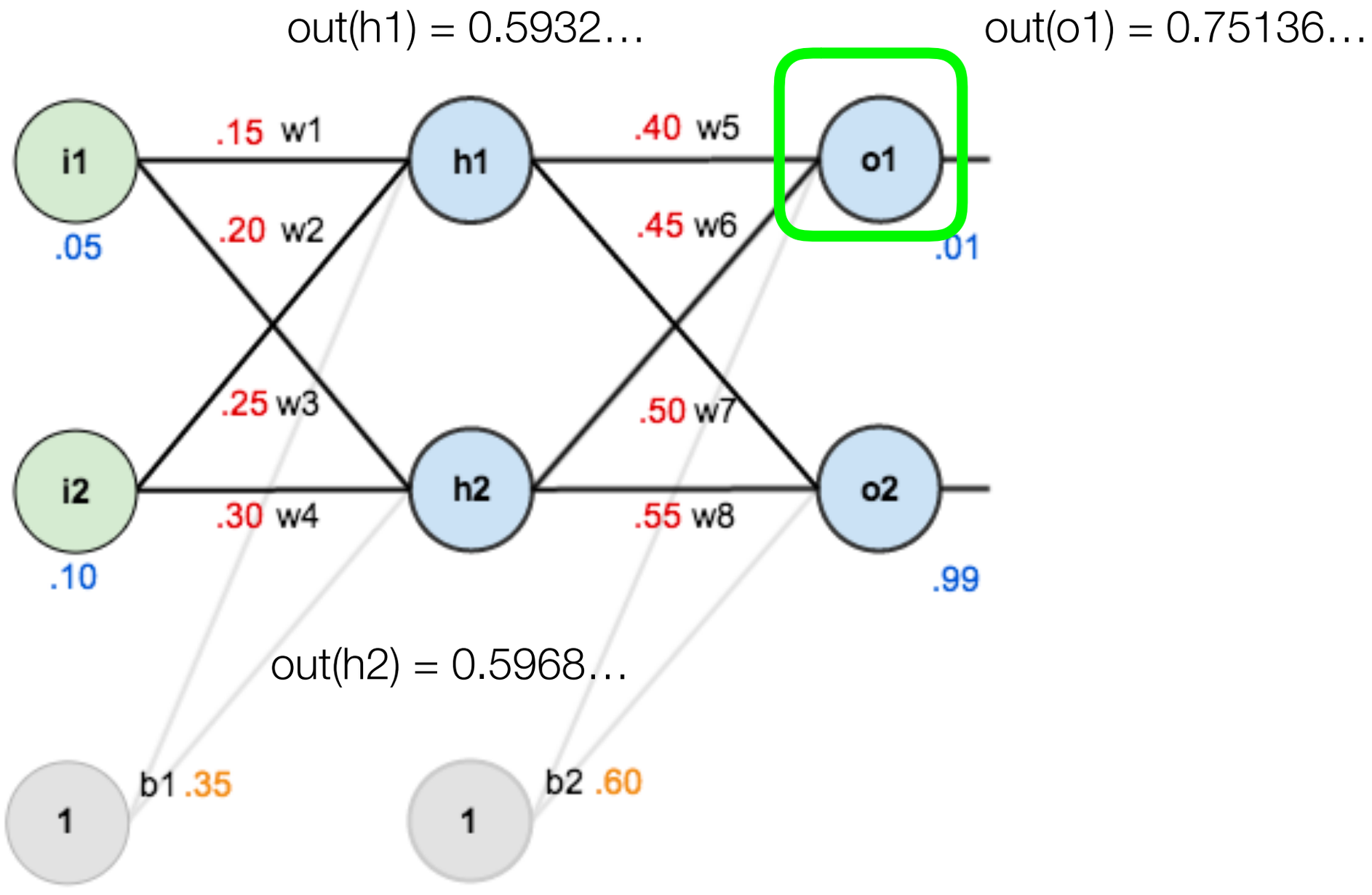
Let's try updating a real network!

out(h1) = 0.5932…

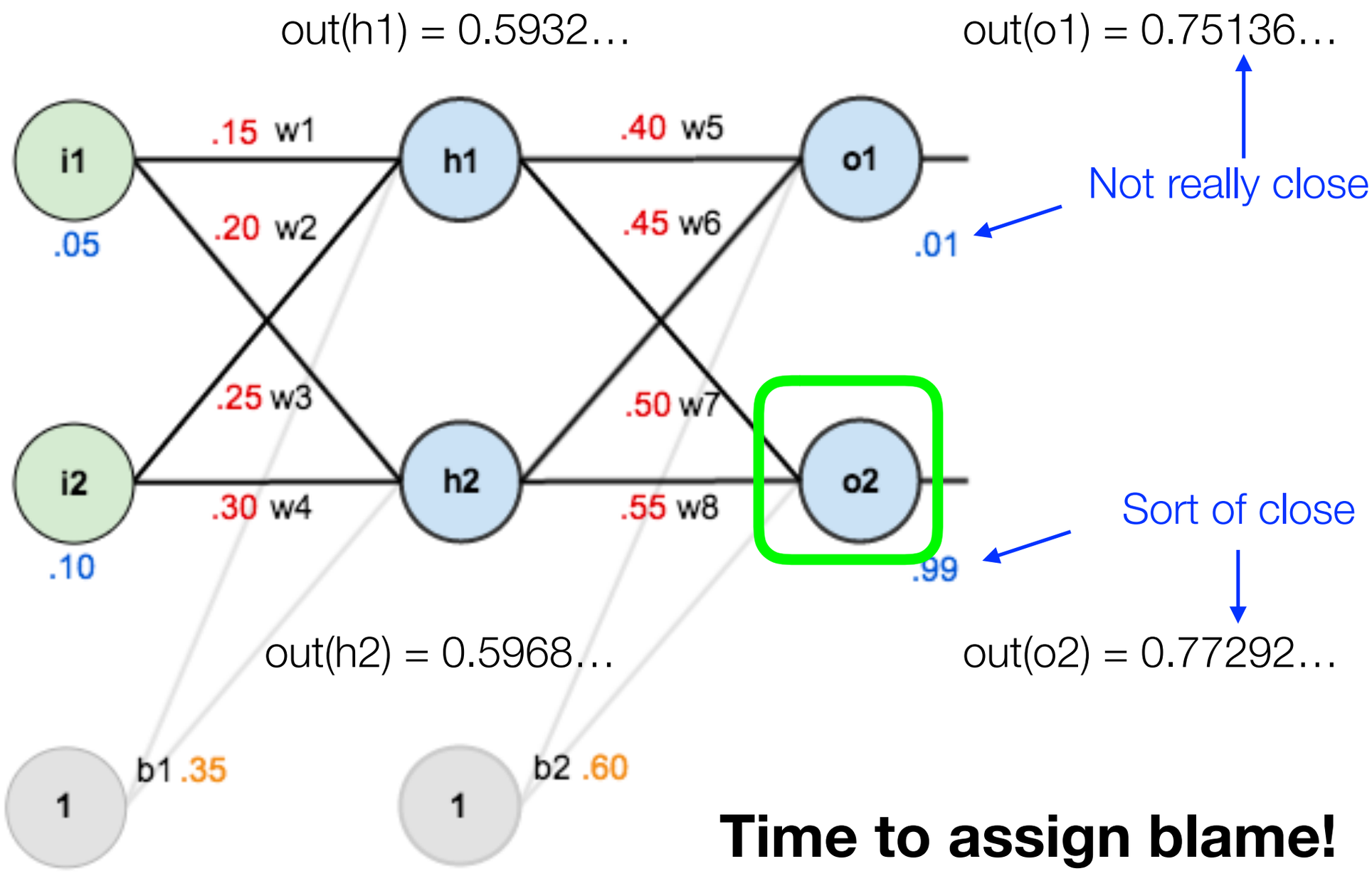


out(h2) = 0.5968…

Let's try updating a real network!



Let's try updating a real network!



Time to assign blame!

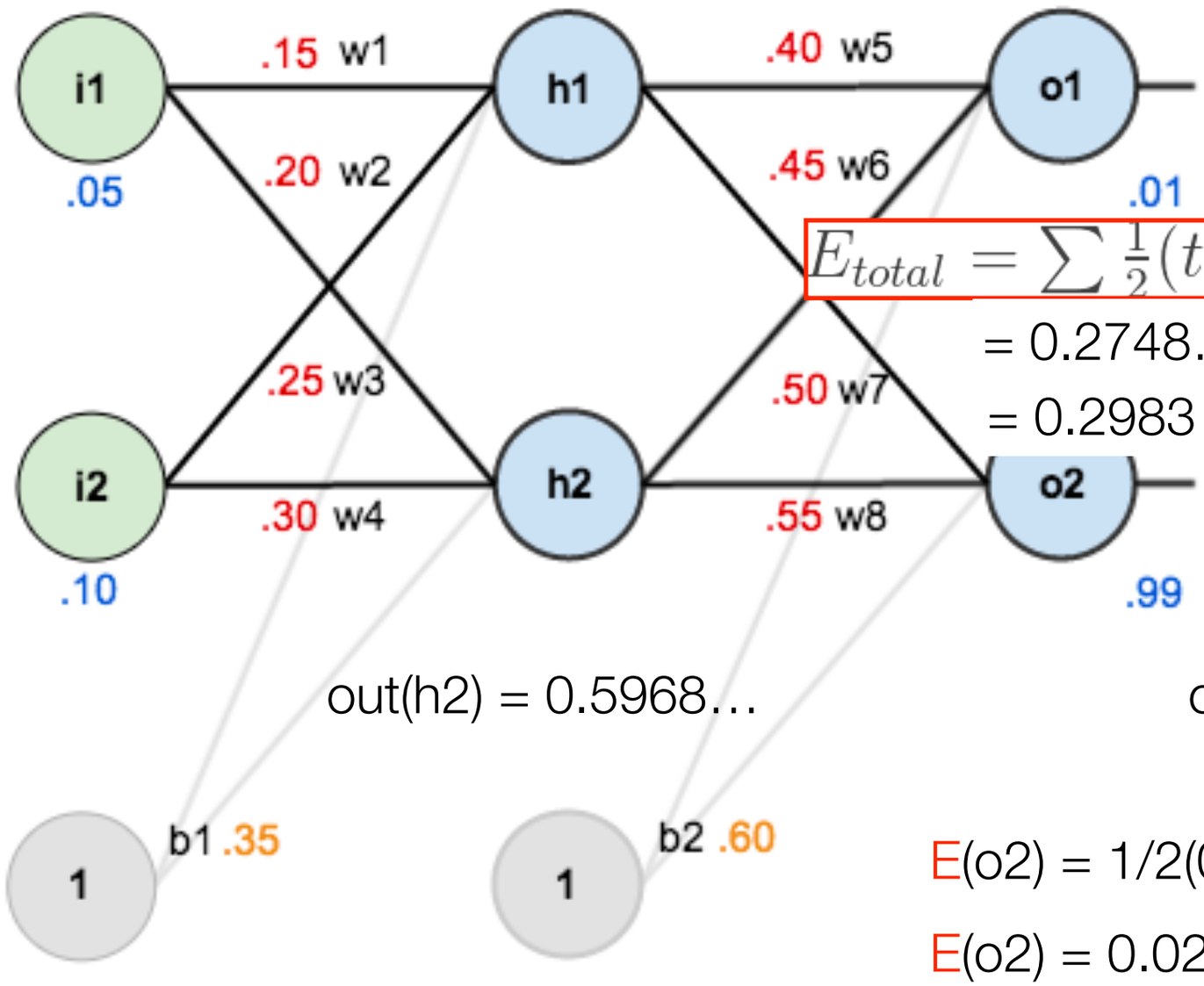
Let's try updating a real network!

E(o1) = 1/2(0.01 - 0.75136…)^2

E(o1) = 0.27481…

out(h1) = 0.5932…

out(o1) = 0.75136…



$$E_{total} = \sum \frac{1}{2}(target - output)^2$$

= 0.2748… + 0.02456…

= 0.2983

out(h2) = 0.5968…

out(o2) = 0.77292…

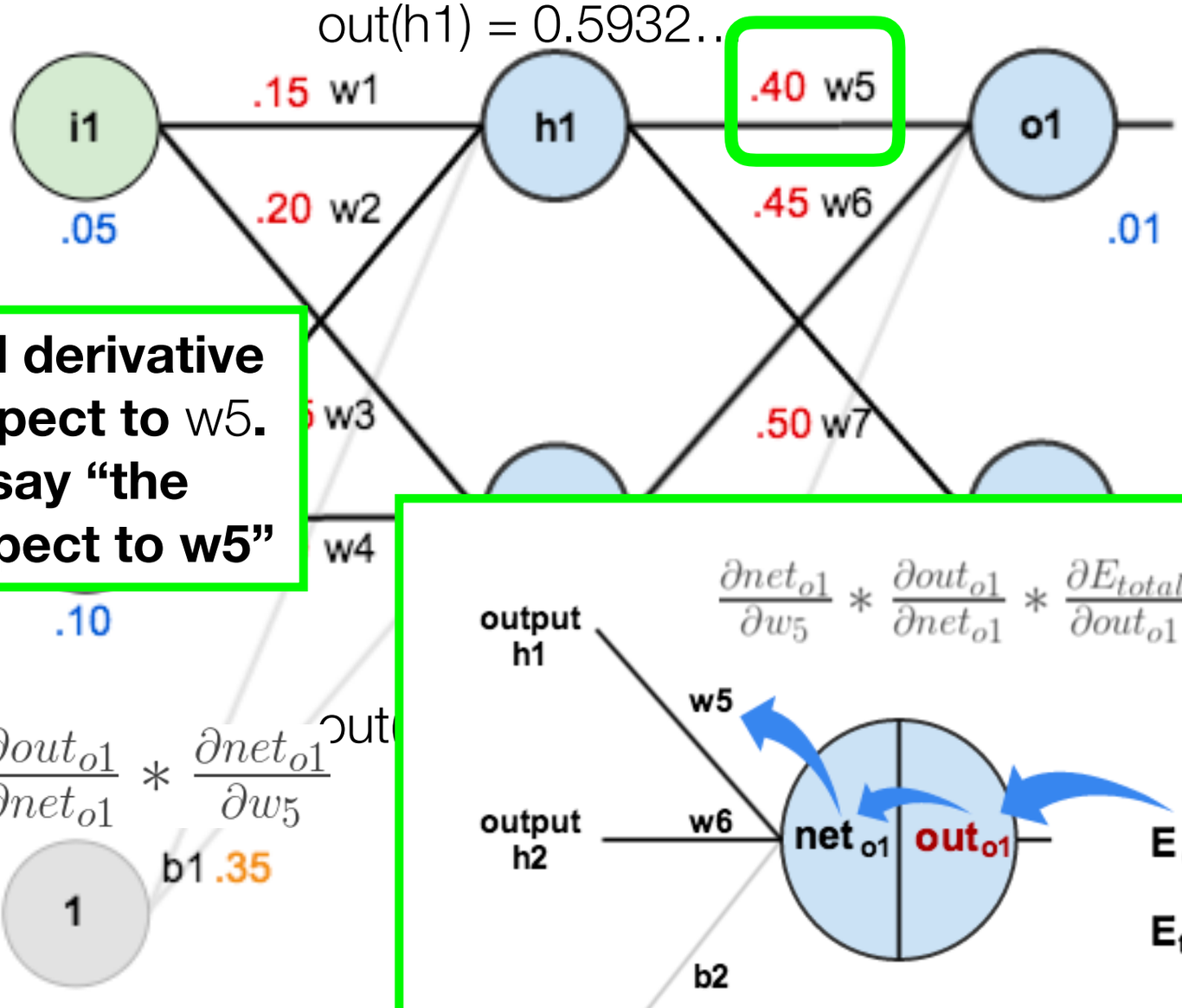
E(o2) = 1/2(0.99 - 0.77292…)^2

E(o2) = 0.02356…

Let's try updating a real network!

How much should we change w5 to reduce the total error?

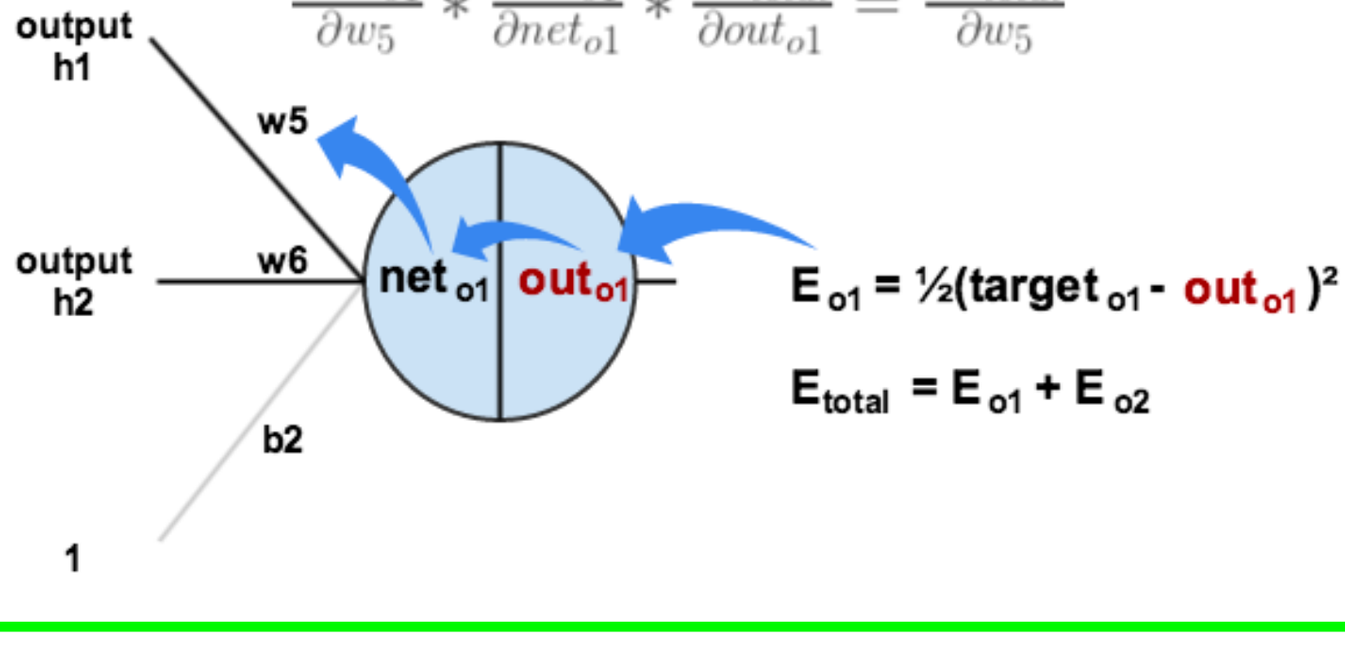
$$\frac{\partial E_{total}}{\partial w_5}$$



This is the partial derivative of E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

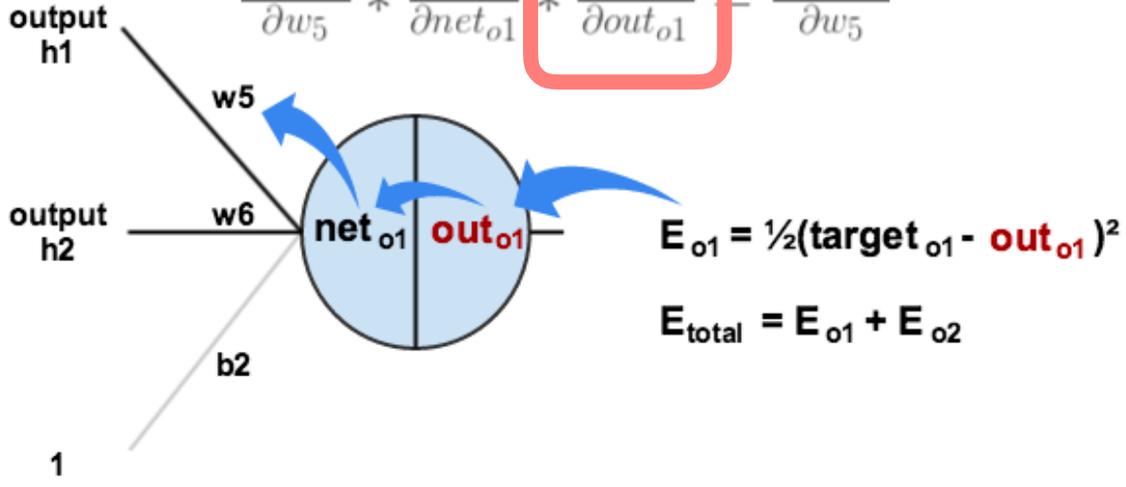
$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

$$\frac{\partial net_{o1}}{\partial w_5} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial E_{total}}{\partial out_{o1}} = \frac{\partial E_{total}}{\partial w_5}$$



Let's try updating a real network!

$$\frac{\partial net_{o1}}{\partial w_5} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial E_{total}}{\partial out_{o1}} = \frac{\partial E_{total}}{\partial w_5}$$



We're asking how much does the total error change with respect to the output

$$E_{total} = \frac{1}{2}(target_{o1} - out_{o1})^2 + \frac{1}{2}(target_{o2} - out_{o2})^2$$

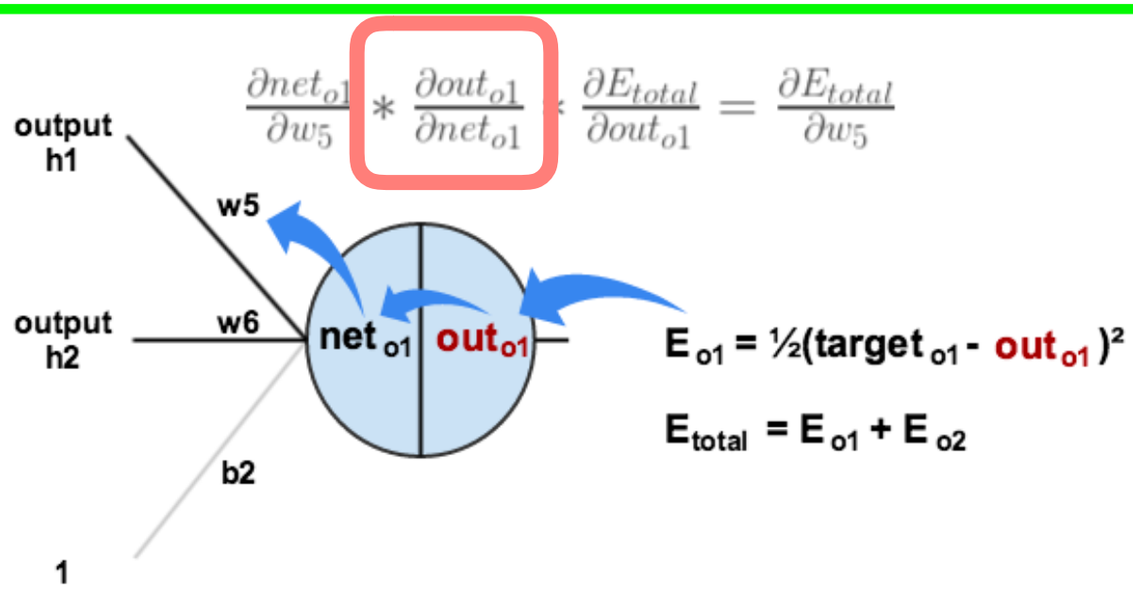
$$\frac{\partial E_{total}}{\partial out_{o1}} = 2 * \frac{1}{2}(target_{o1} - out_{o1})^{2-1} * -1 + 0$$

$$\frac{\partial E_{total}}{\partial out_{o1}} = -(target_{o1} - out_{o1})$$

$$\frac{\partial E_{total}}{\partial out_{o1}} = -(0.01 - 0.75136507) = 0.74136507$$

$\frac{\partial E_{total}}{\partial w_5}$ **is the partial derivative of** E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

Let's try updating a real network!



$$\frac{\partial net_{o1}}{\partial w_5} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial E_{total}}{\partial out_{o1}} = \frac{\partial E_{total}}{\partial w_5}$$

32.

We're asking how much does the output of o1 change with respect to the total net input (i.e., the sum before the sigmoid)

$$out_{o1} = \frac{1}{1+e^{-net_{o1}}}$$

$$\frac{\partial out_{o1}}{\partial net_{o1}} = out_{o1}(1 - out_{o1})$$

$$= 0.75136507(1 - 0.75136507)$$

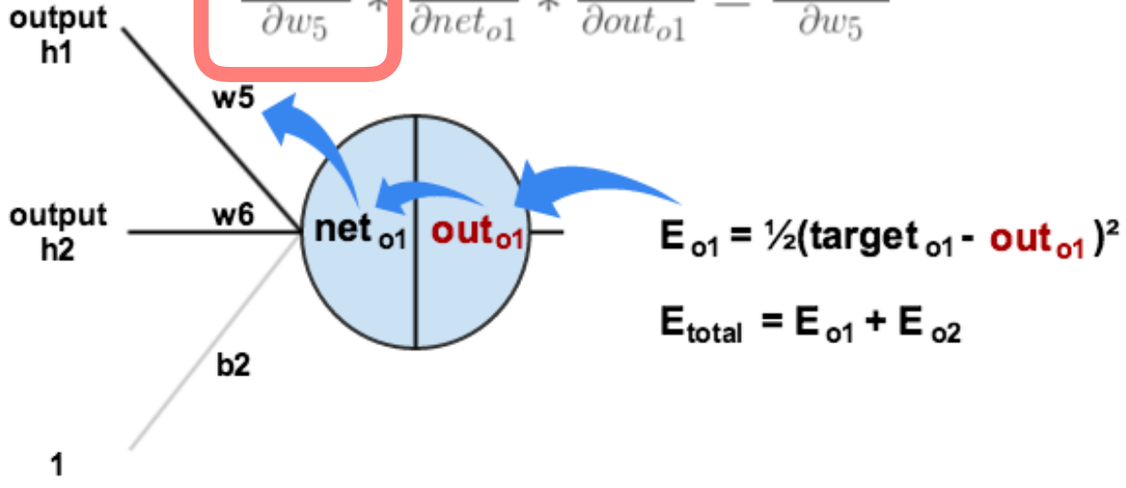
$$= 0.186815602$$

$\frac{\partial E_{total}}{\partial w_5}$ **is the partial derivative of** E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

Let's try updating a

We're asking how much does the total net output of o1 change with respect to w5

$$\frac{\partial net_{o1}}{\partial w_5} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial E_{total}}{\partial out_{o1}} = \frac{\partial E_{total}}{\partial w_5}$$



32…

$$net_{o1} = w_5 * out_{h1} + w_6 * out_{h2} + b_2 * 1$$

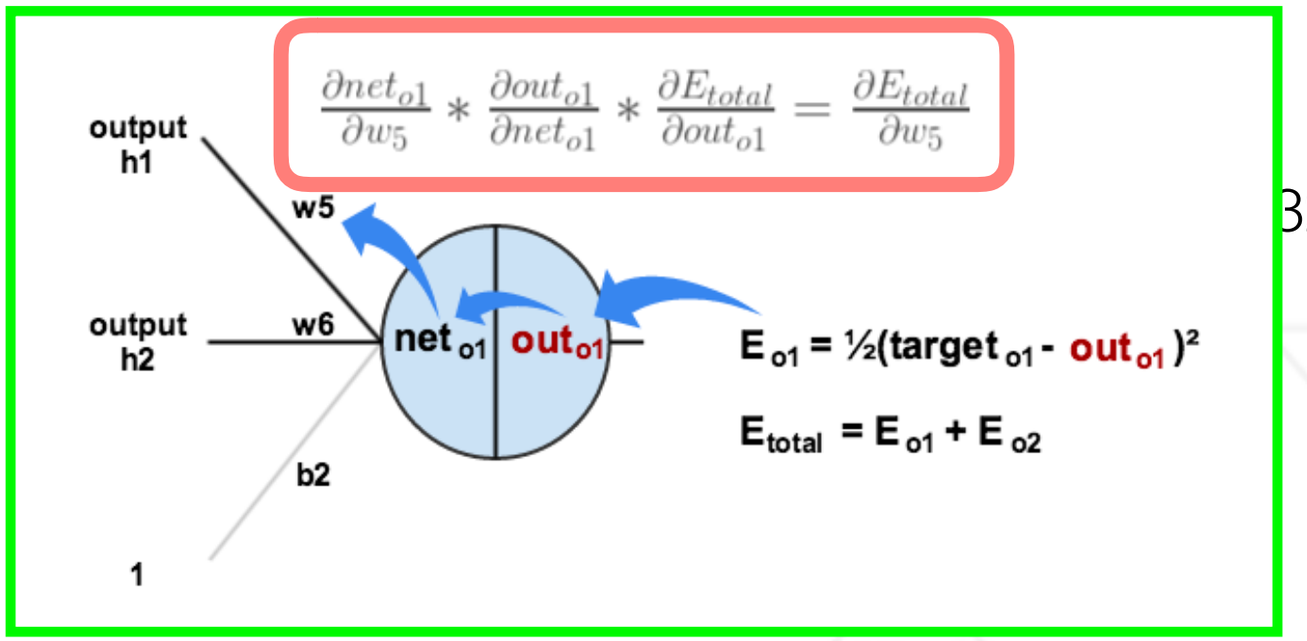
$$\frac{\partial net_{o1}}{\partial w_5} = 1 * out_{h1} * w_5^{(1-1)} + 0 + 0$$

$$\frac{\partial net_{o1}}{\partial w_5} = 1 * out_{h1} * w_5^{(1-1)} + 0 + 0 = out_{h1} = 0.59326999$$

$$= out_{h1} = 0.593269992$$

$\frac{\partial E_{total}}{\partial w_5}$ **is the partial derivative of** E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

Let's try updating a real network!



32…

E(o1) = 0.27481…

out(o1) = 0.75136…

E *total*= 0.2983

$$\frac{\partial E_{total}}{\partial w_5} = \frac{\partial E_{total}}{\partial out_{o1}} * \frac{\partial out_{o1}}{\partial net_{o1}} * \frac{\partial net_{o1}}{\partial w_5}$$

$$\frac{\partial E_{total}}{\partial w_5} = 0.74136507 * 0.186815602 * 0.593269992$$

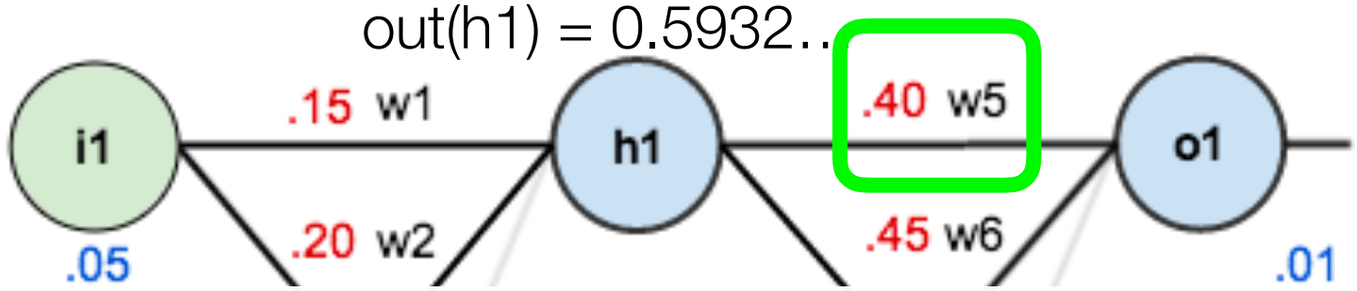
$$\frac{\partial E_{total}}{\partial w_5} = 0.082167041$$

$\frac{\partial E_{total}}{\partial w_5}$ **is the partial derivative of** E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

Let's try updating a real network!

How much should we change w5 to reduce the total error?

$\frac{\partial E_{total}}{\partial w_5}$



E(o1) = 0.27481…

out(o1) = 0.75136…

The new value of w5

$$w_5^+ = w_5 - \eta * \frac{\partial E_{total}}{\partial w_5} :$$

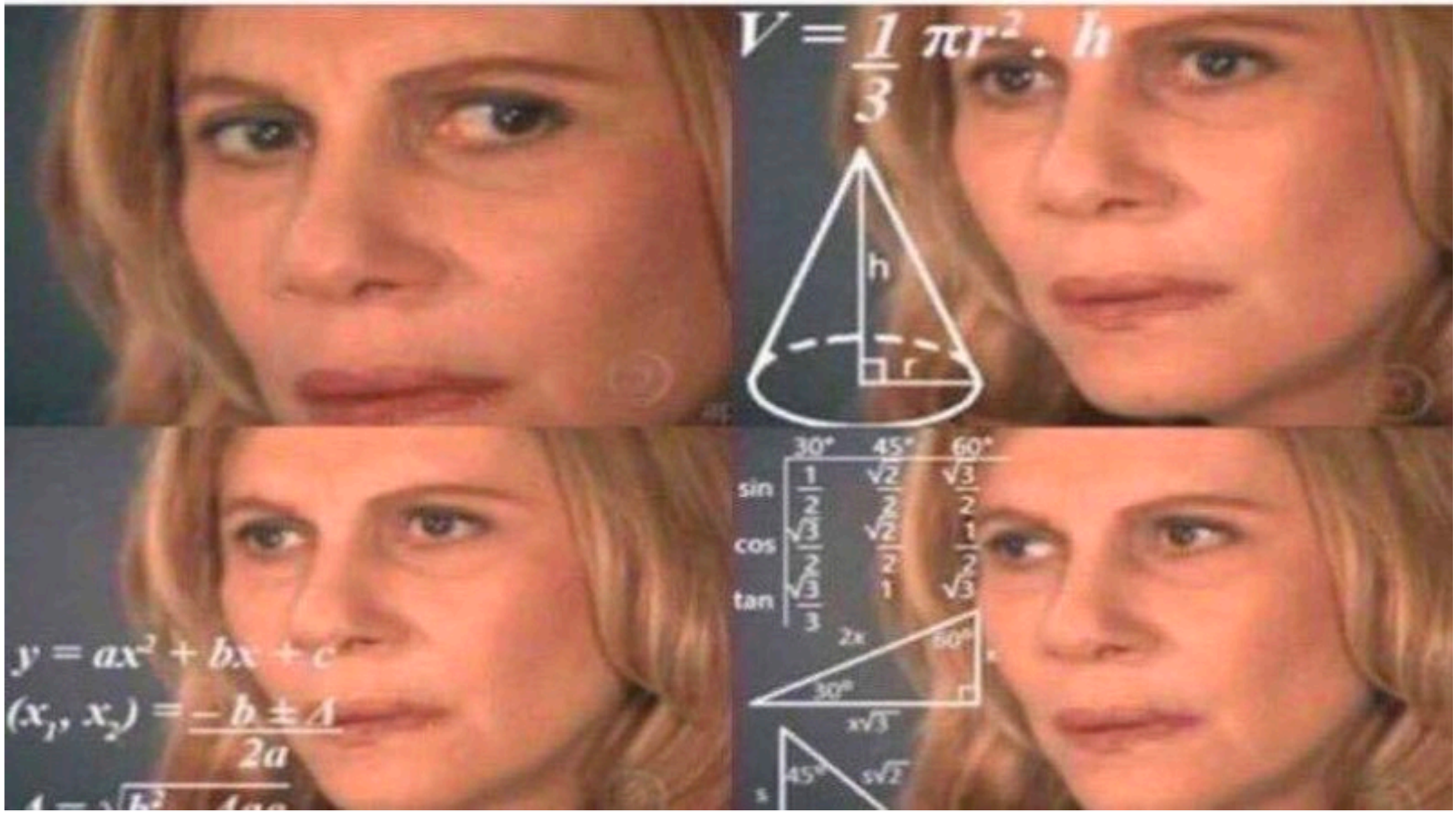
This is the *learning rate* for how much we update the network at each time step

$$w_5^+ = 0.4 - 0.5 * 0.082167041$$

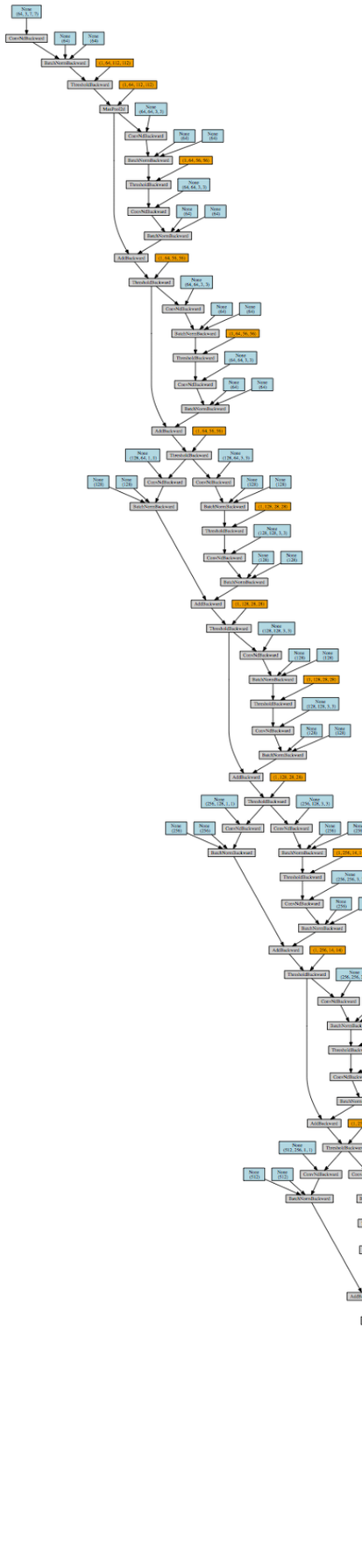
$$= 0.35891648$$

$\frac{\partial E_{total}}{\partial w_5}$ **is the partial derivative of** E *total* **with respect to** w5**. You can also say "the gradient with respect to w5"**

Your turn: solve for all the nodes!



You can walk through the whole example with more detail here:
https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/



Deep learning sounds impossible

Recent advancements in neural networks are partly due to better hardware (GPUs), libraries, and algorithms like autograd that compute the gradients (differentials) for you

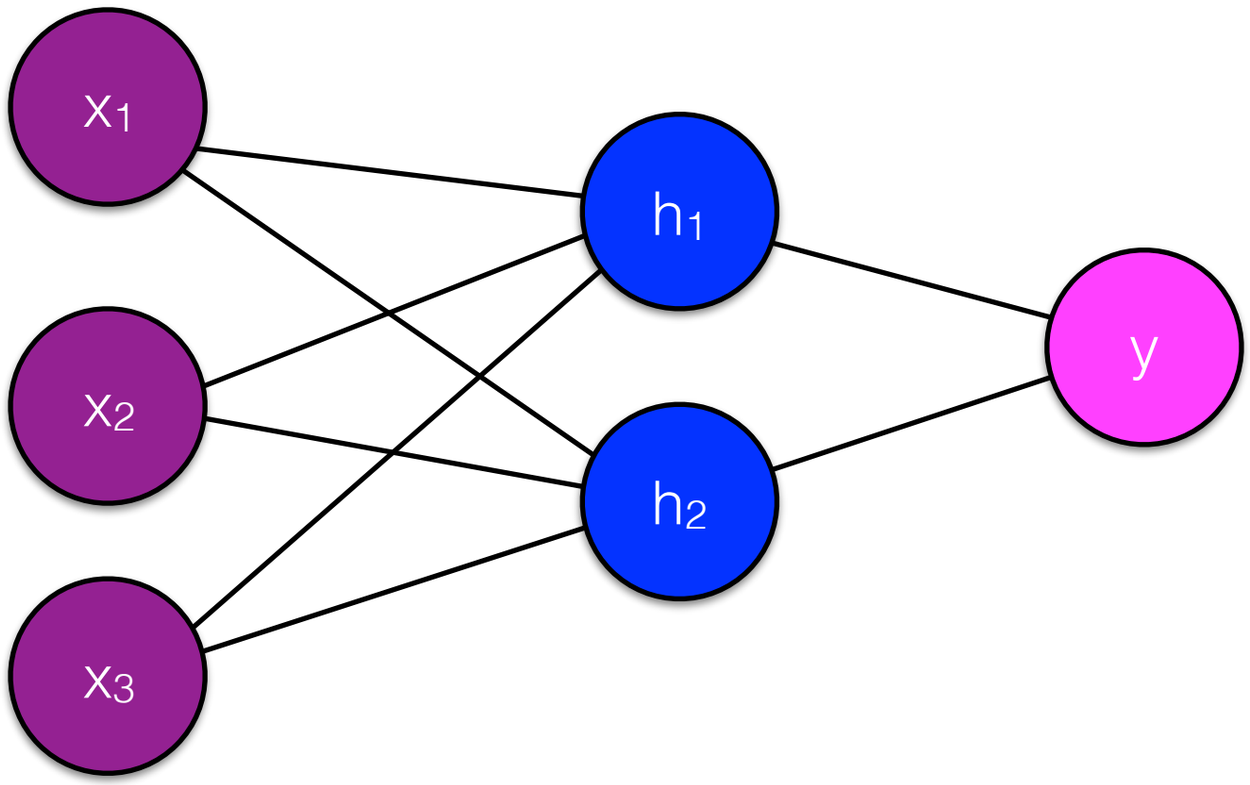
https://www.smithsonianmag.com/science-nature/what-can-rodents-tell-us-about-why-humans-love-180949441/

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.

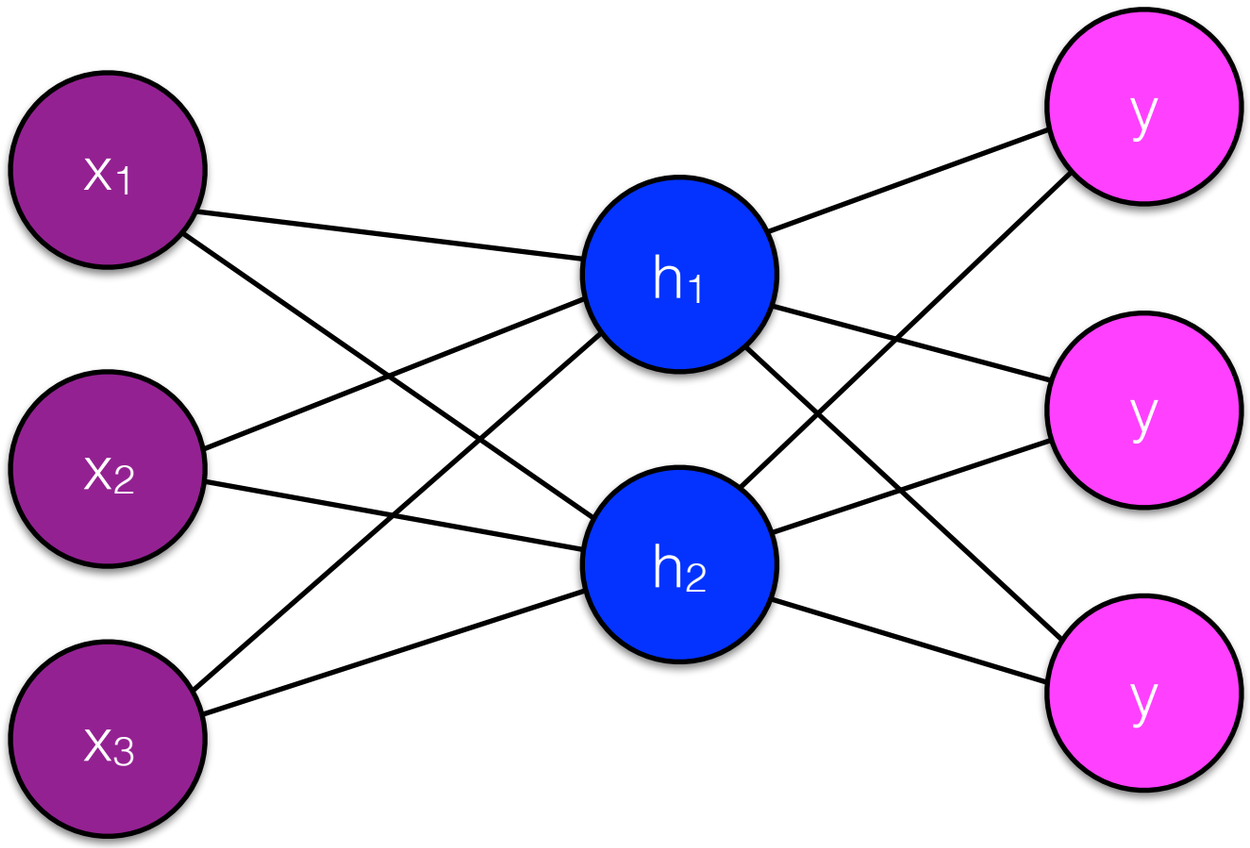
Neural network structures



1

Output one real value

Neural network structures



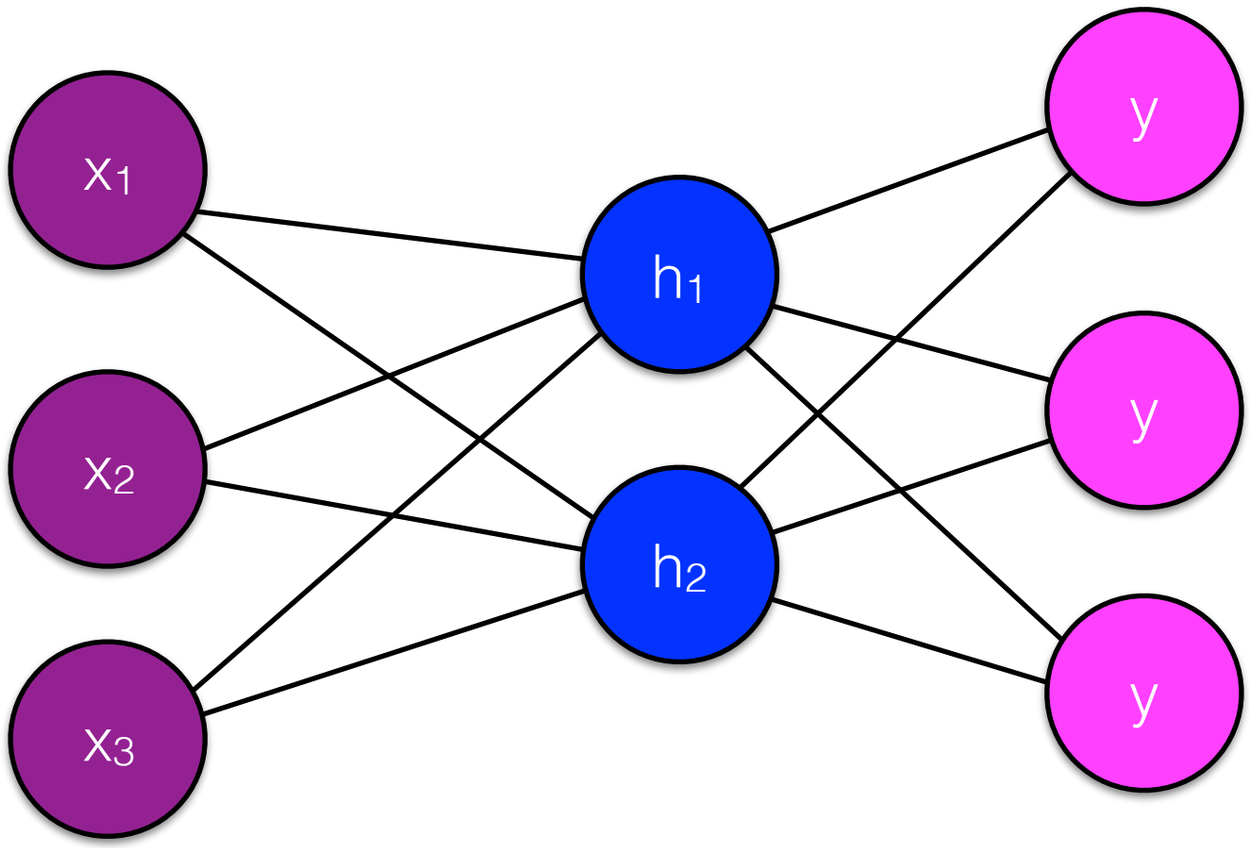
0

1

0

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

Neural network structures



1

1

0

output 3 values, several = 1 in training data

Regularization

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

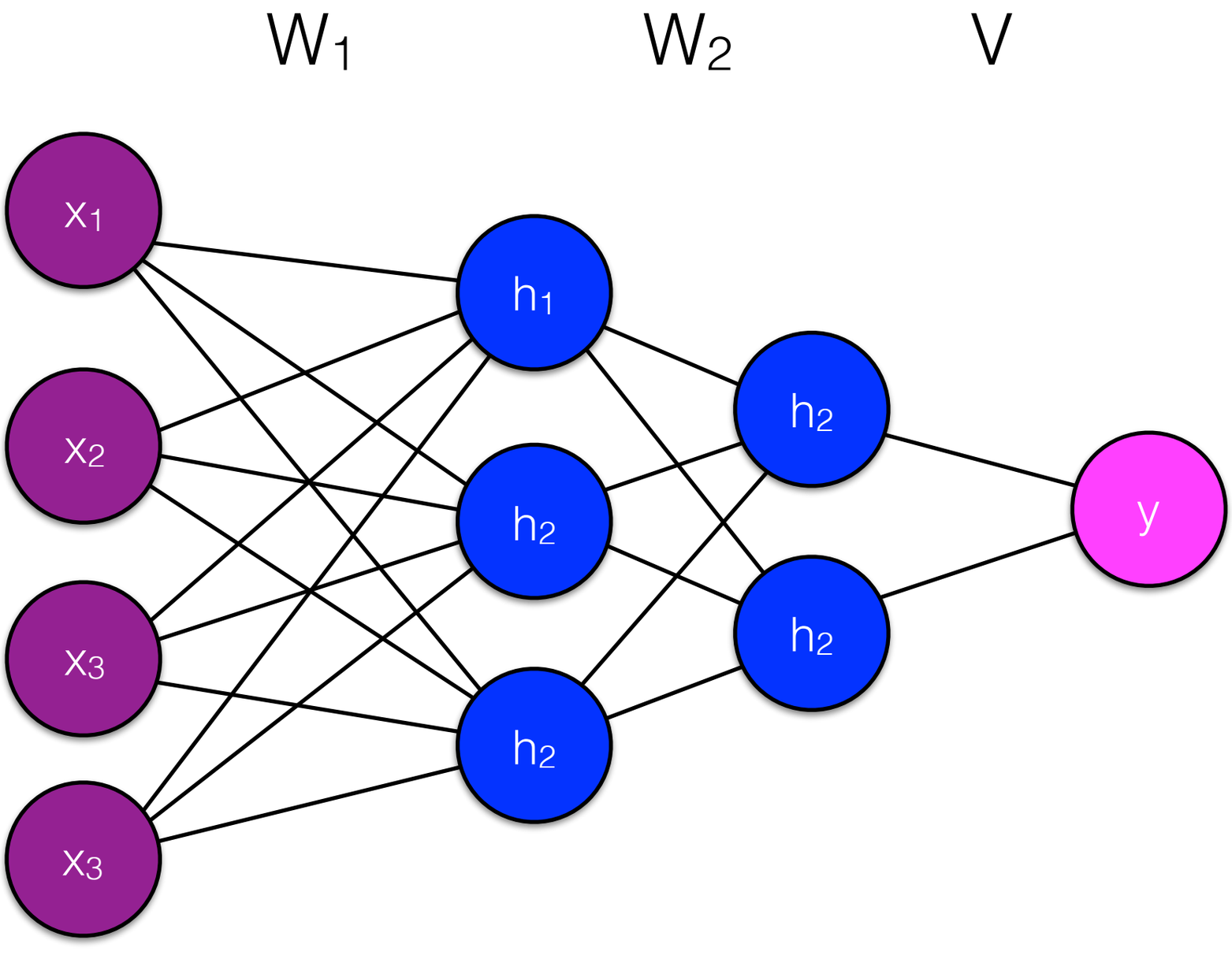
Regularization

- L2 regularization: penalize W and V for being too large

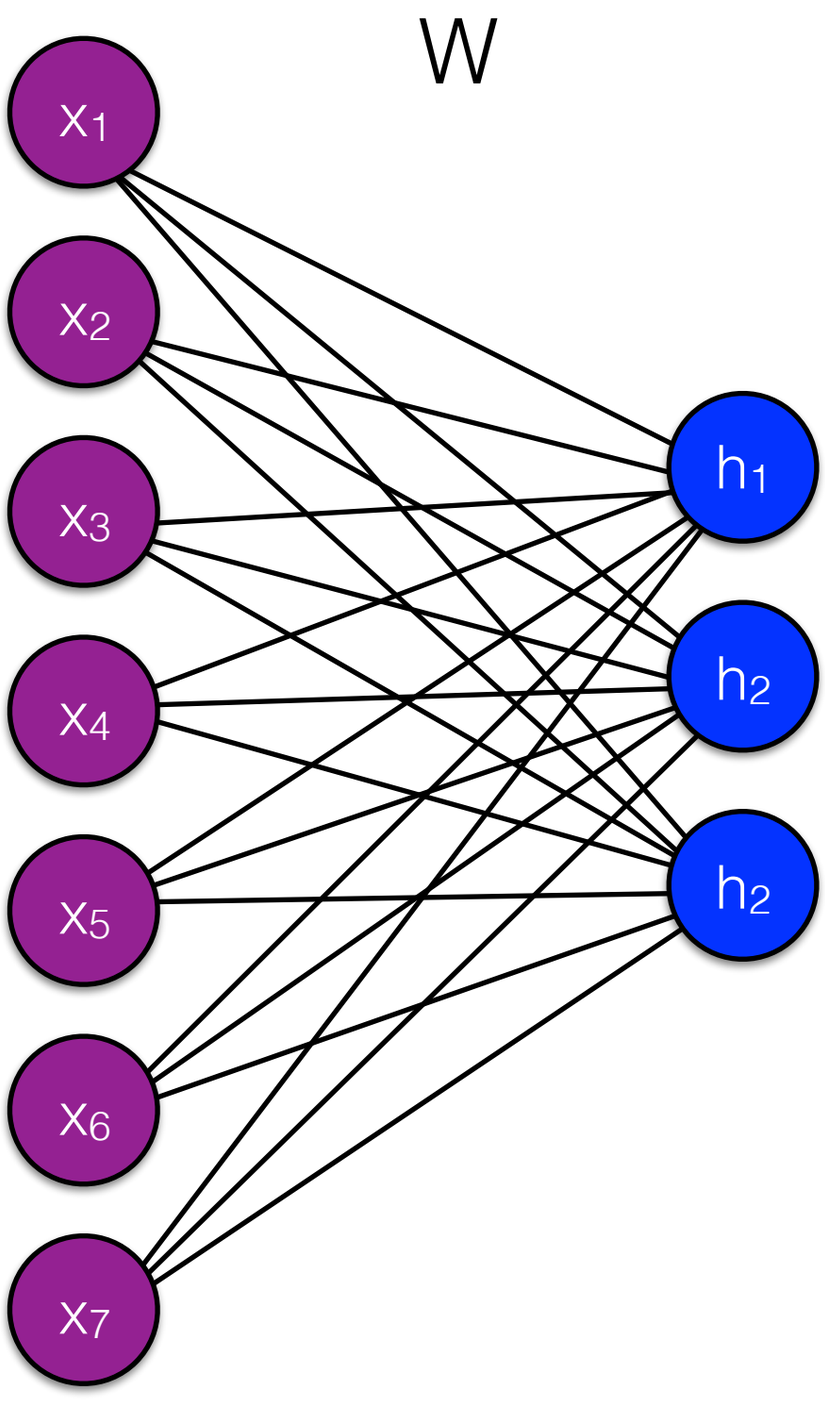
- Dropout: when training on a <x,y> pair, randomly remove some node and weights.

- Early stopping: Stop backpropagation before the training error is too small.

Deeper networks

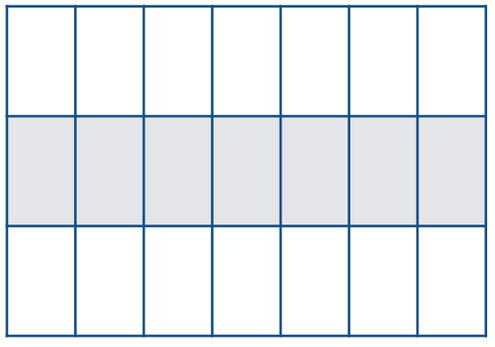


Densely connected layer

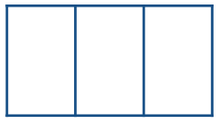


x

W



h



$$h = \sigma(xW)$$

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	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

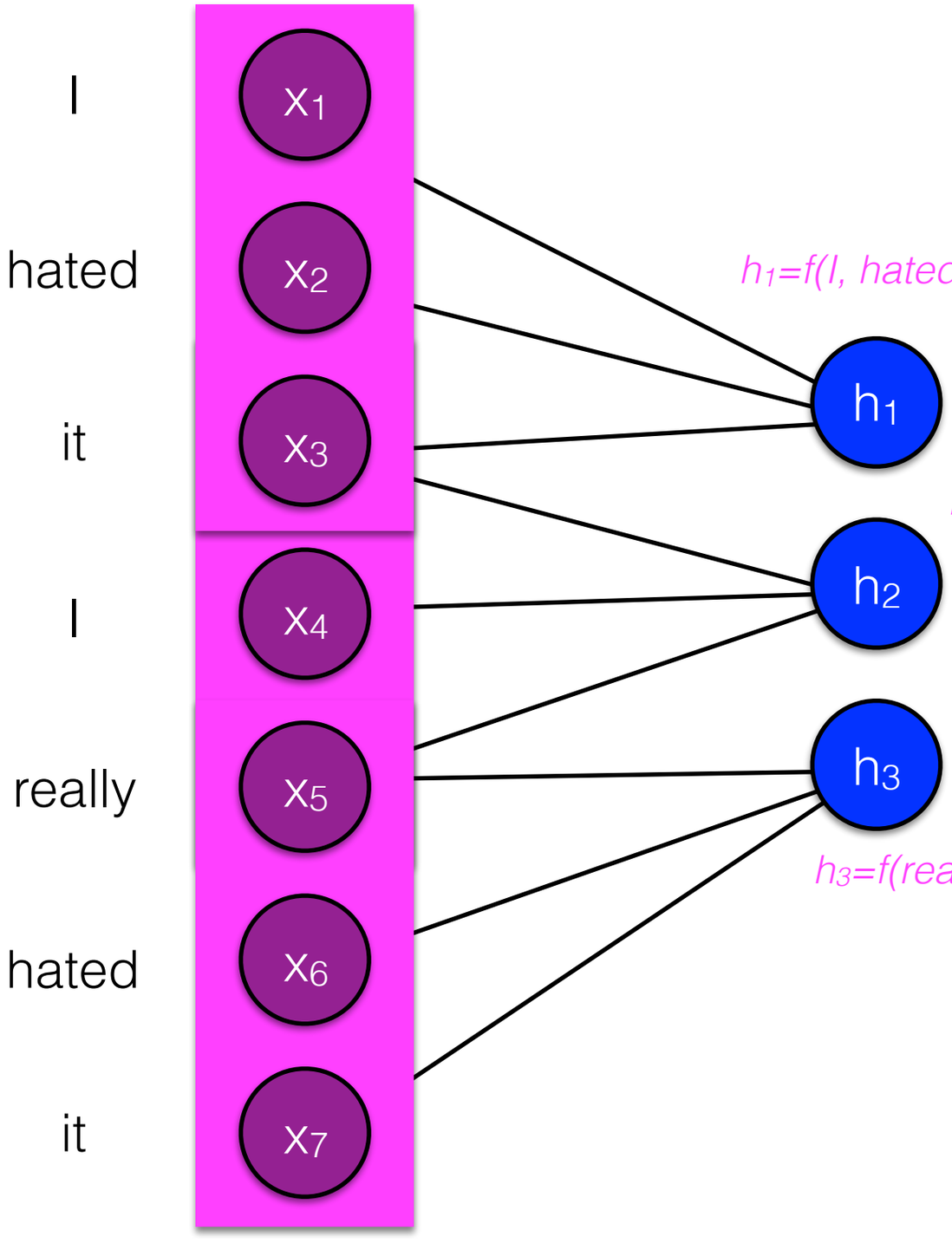
1/3	1/3	1/3

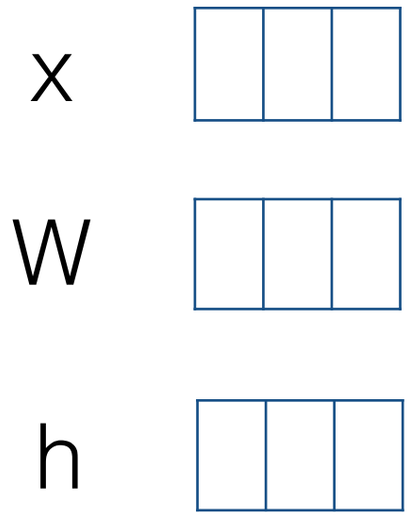
x

1	3	-1	4	0

$x_{1:4}^{\top} K$ = moving average

Convolutional networks



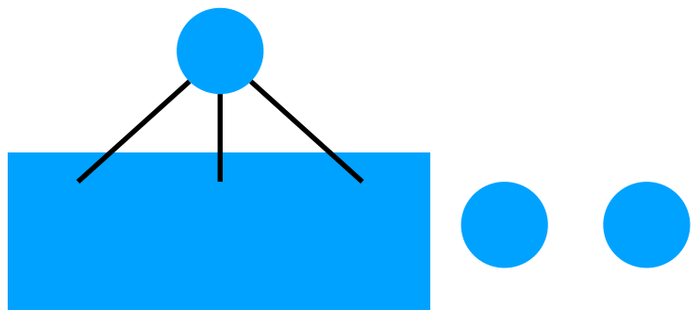


$$h_1 = \sigma(x_1 W_1 + x_2 W_2 + x_3 W_3)$$

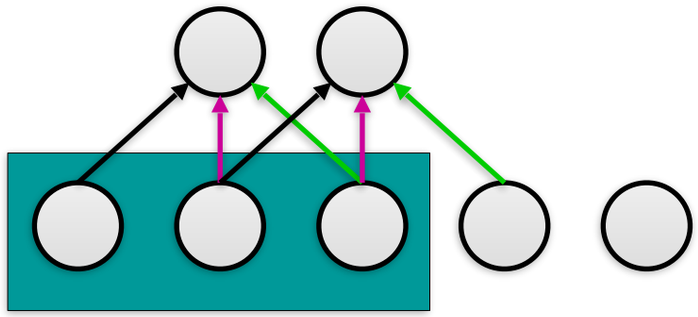
$$h_2 = \sigma(x_3 W_1 + x_4 W_2 + x_5 W_3)$$

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

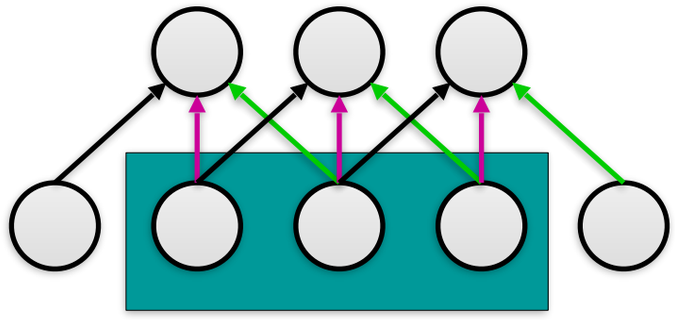
Basic Idea of CNNs



Basic Idea of CNNs



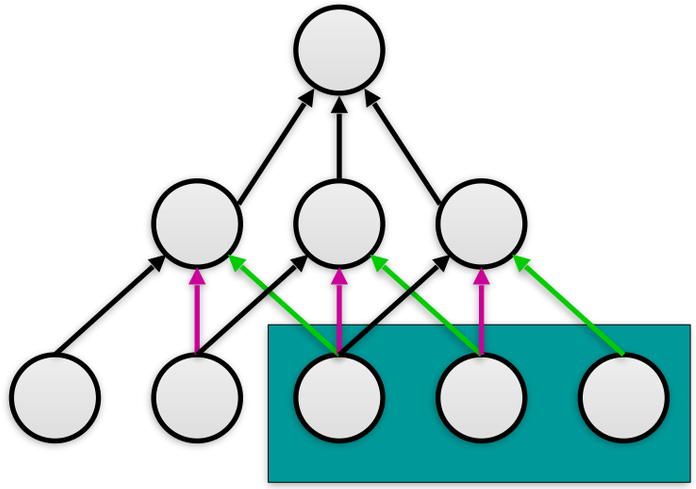
Basic Idea of CNNs



Hidden layer

Input

Basic Idea of CNNs



Hidden layer

Input

Cats' Brains and CNNs

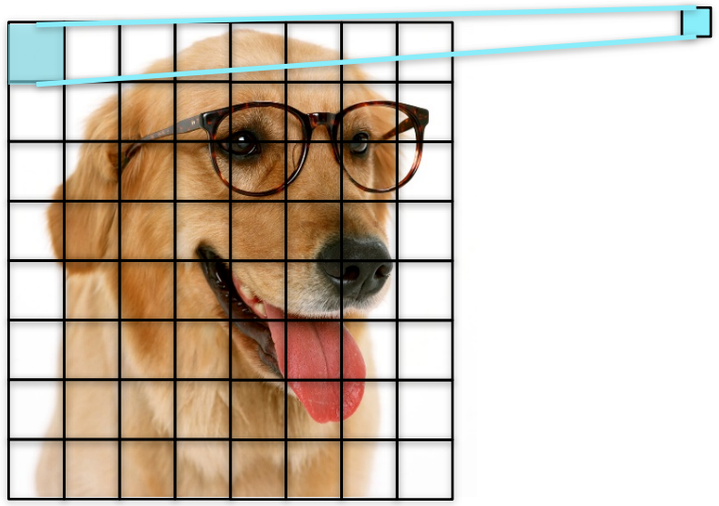
(Be nice to your cats)

With the exception of distinguishing cucumbers from deadly snakes, cats' brains are really good at image classification.

Yann LeCun et al. (1998) found that a neural network that works like a cat's visual cortex was good at digit classification.

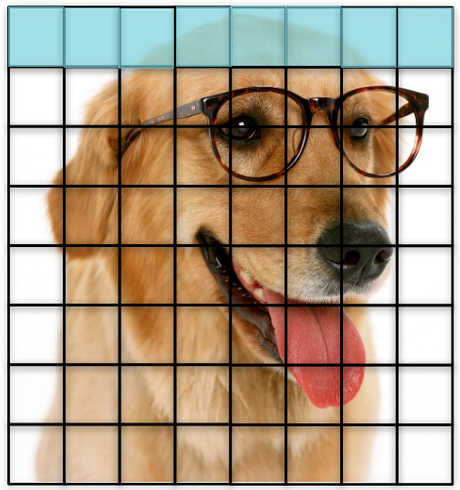
When machines got powerful enough, it also turned out to be great at image classification. (Krizhevsky et al. 2012)

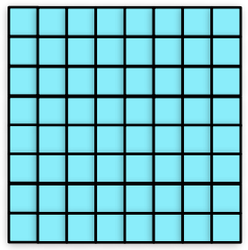
CNN for Image Classification



Convolutional Layer

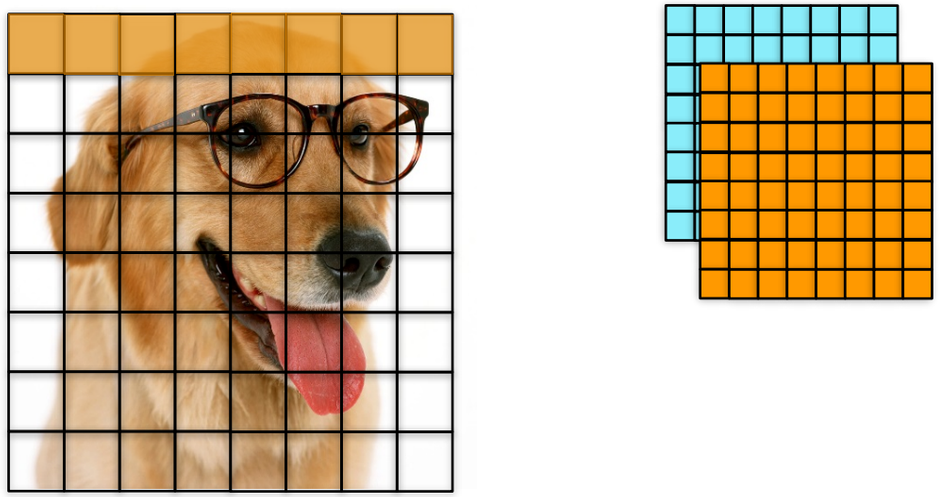
CNN for Image Classification





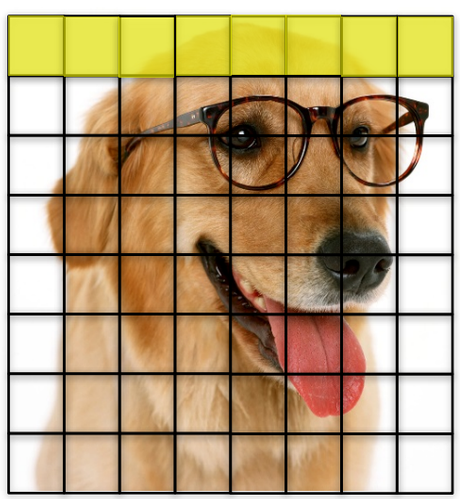
Convolutional Layer

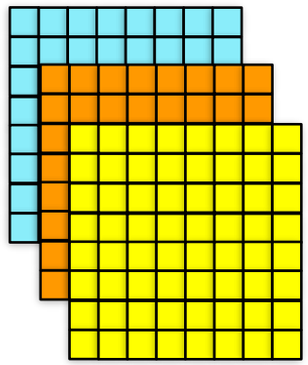
CNN for Image Classification



Convolutional Layer

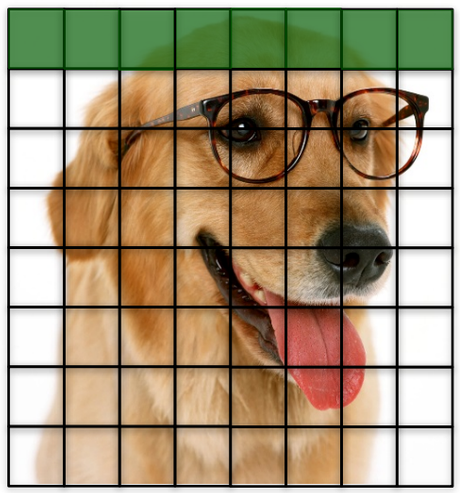
CNN for Image Classification

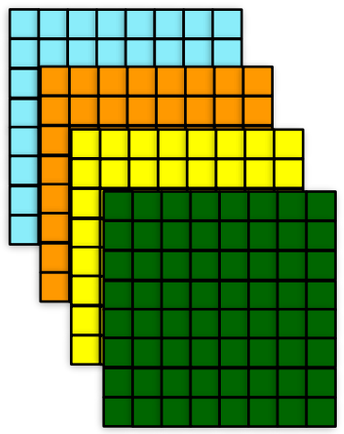




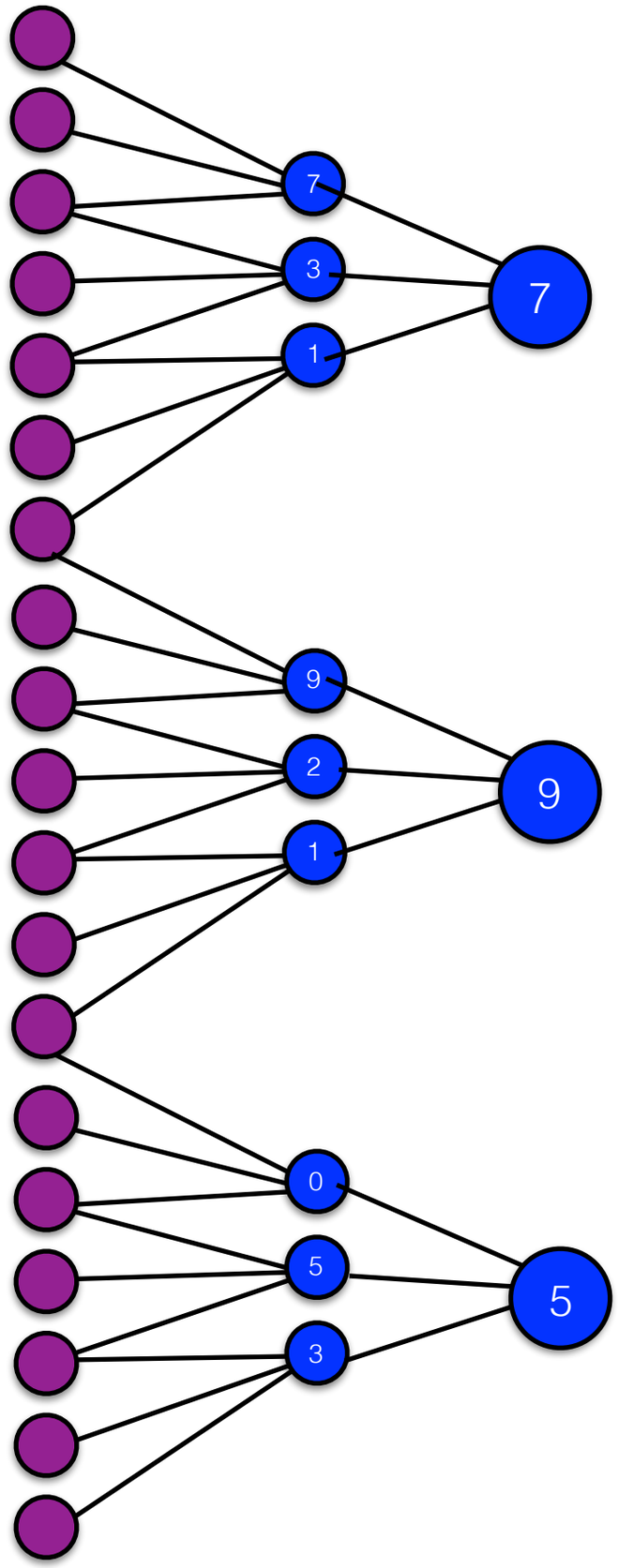
Convolutional Layer

CNN for Image Classification





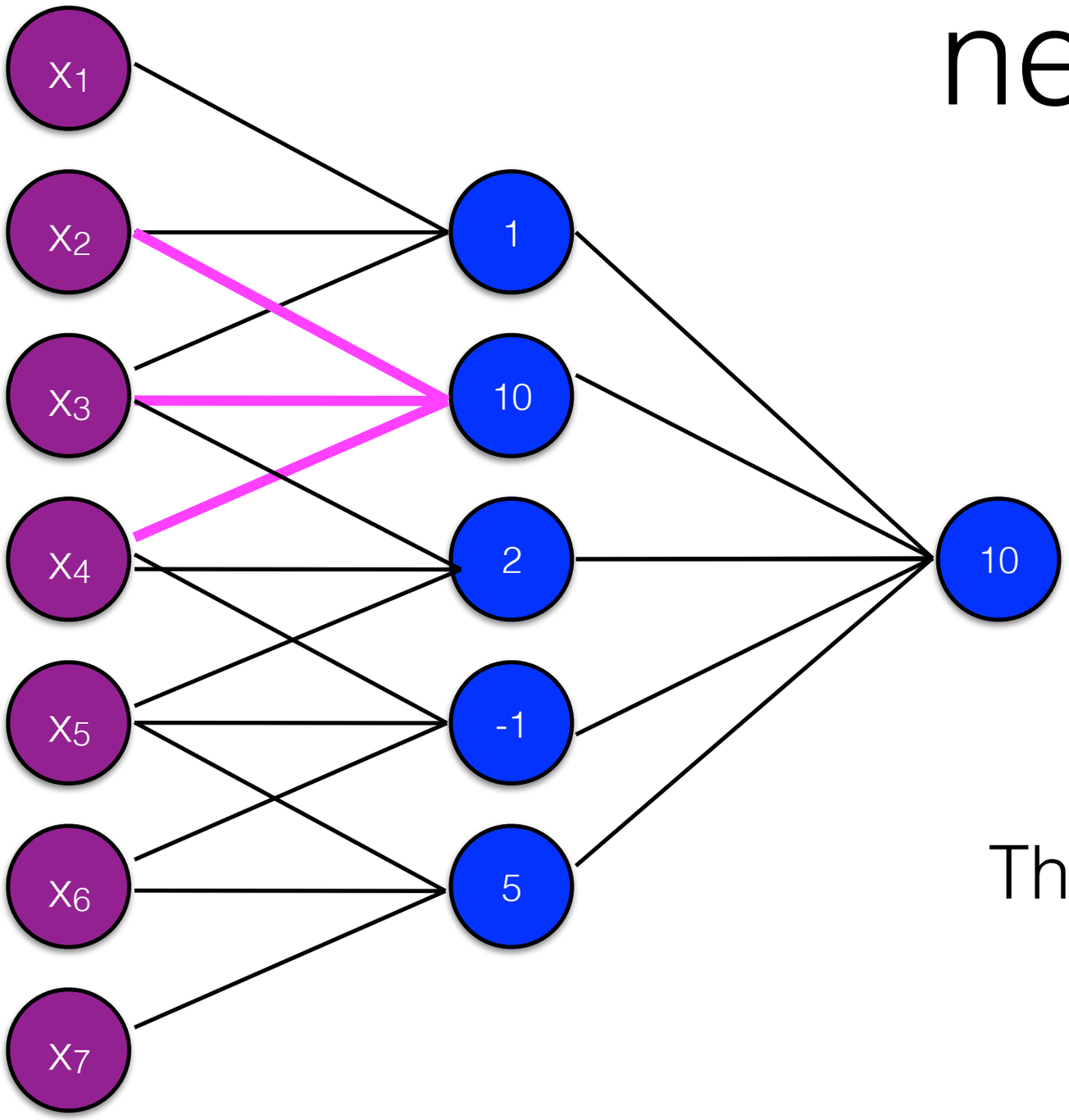
Convolutional Layer



Pooling

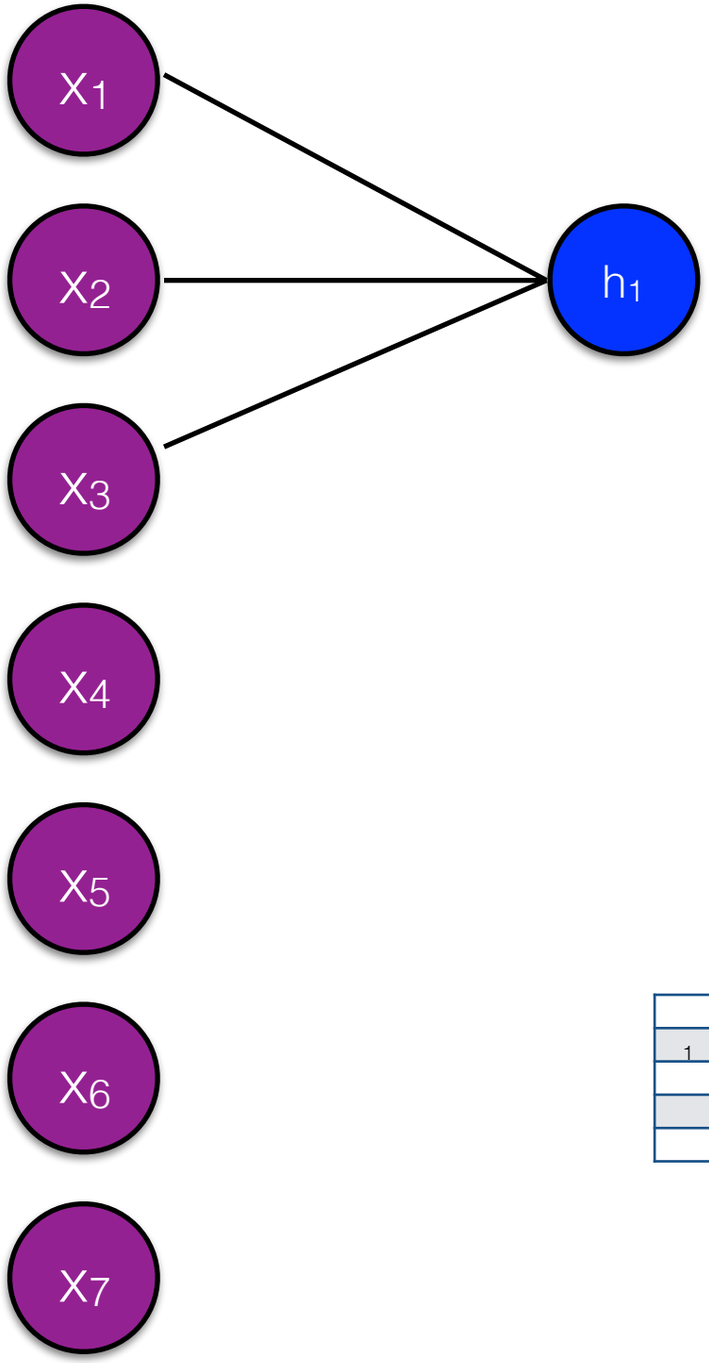
- Down-samples a layer by selecting a single point from some set
- Max-pooling selects the largest value

Convolutional networks



This defines one filter.

convolution max pooling



x

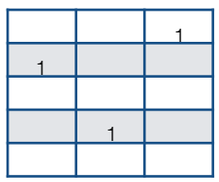
x_1 x_2 x_3

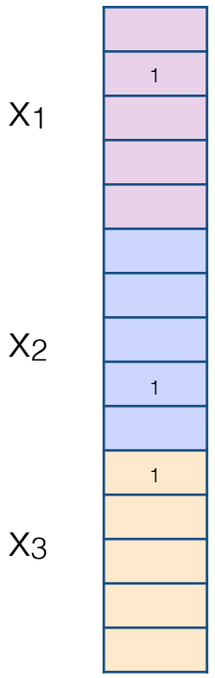
vectorize

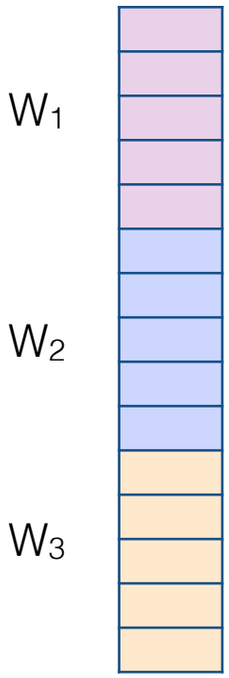
W

W_1 W_2 W_3

vectorize

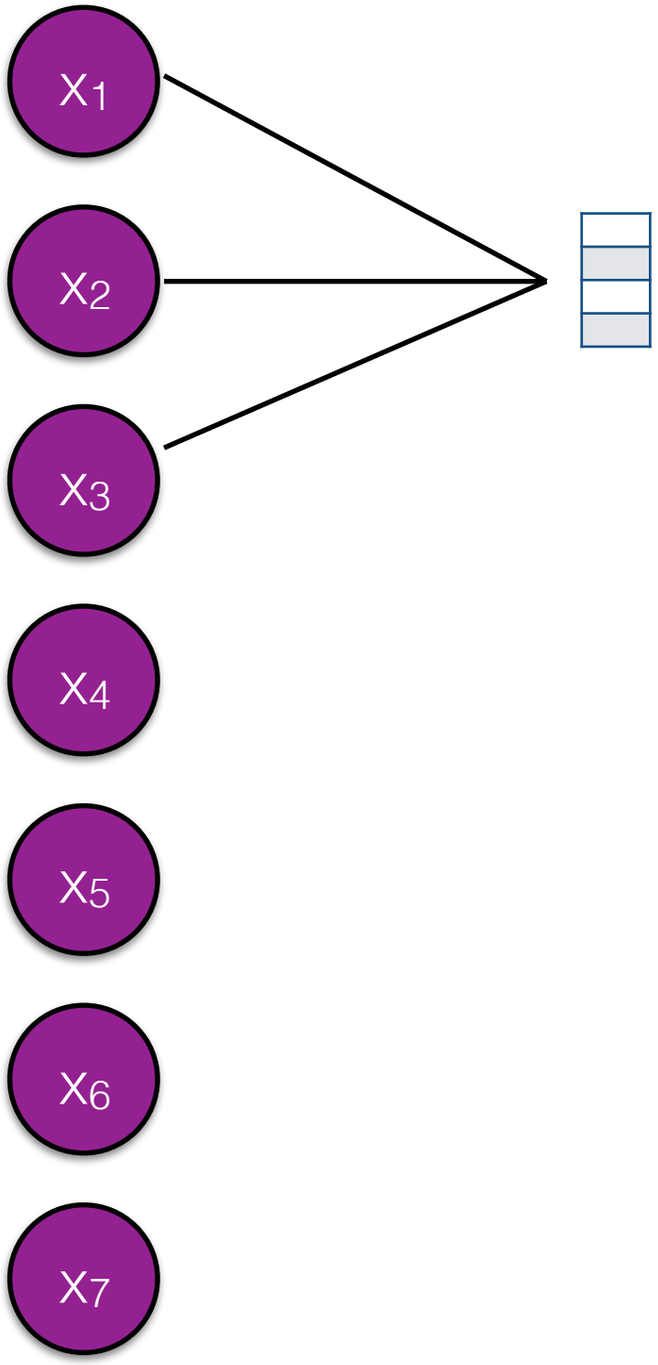


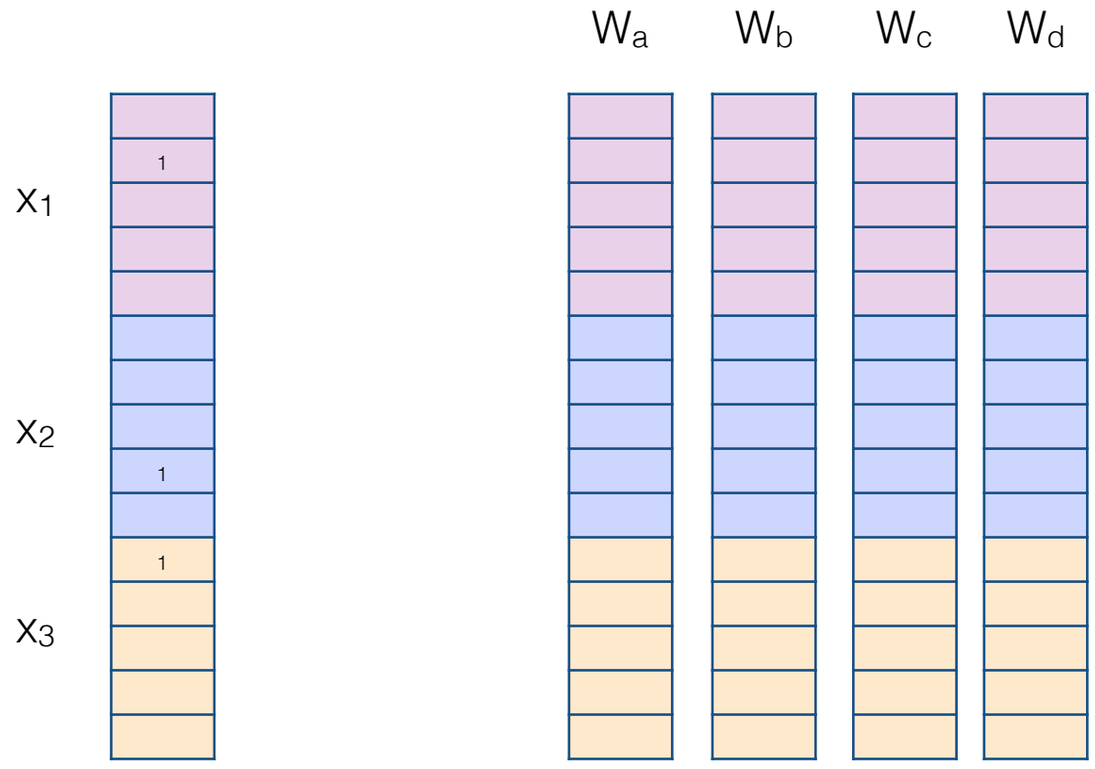




$$h_1 = \sigma(x^\top W)$$

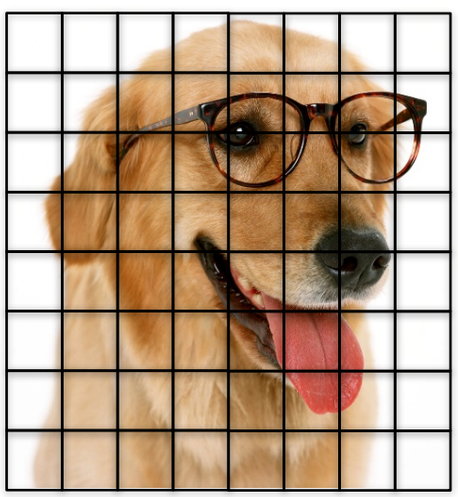
We can specify multiple filters; each filter is a separate set of parameters to be learned

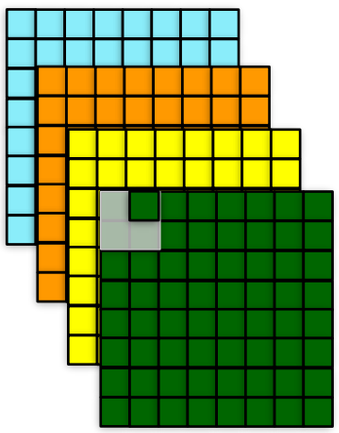


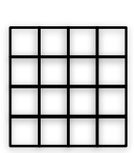


$$h_1 = \sigma(x^\top W) \in R^4$$

CNN for Image Classification

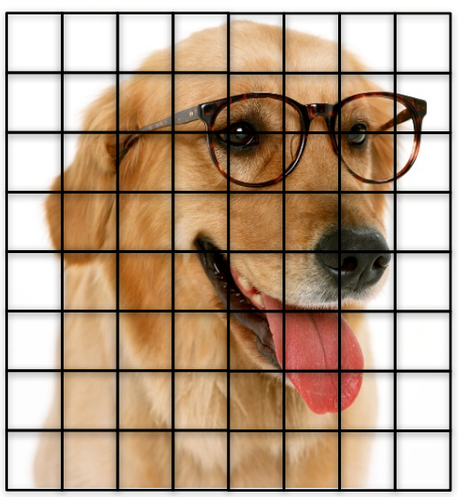


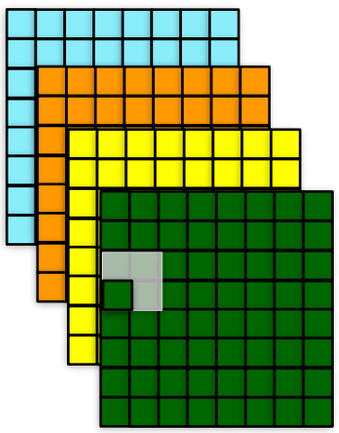


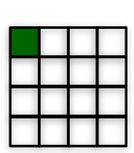


Max Pooling

CNN for Image Classification

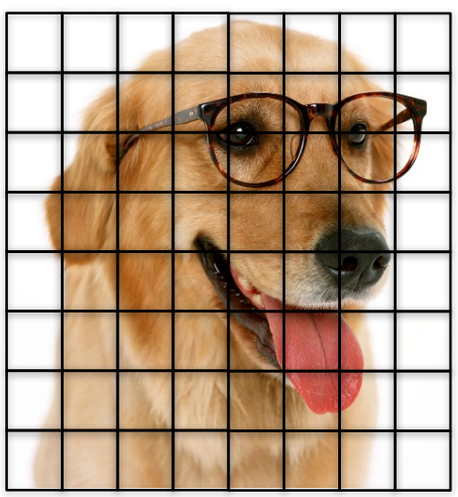


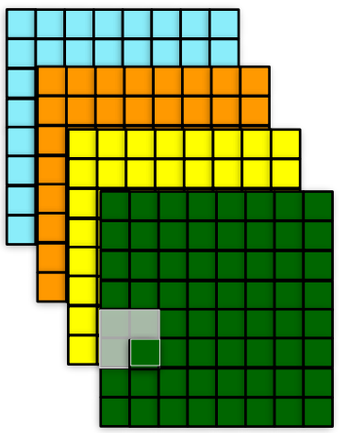


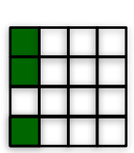


Max Pooling

CNN for Image Classification

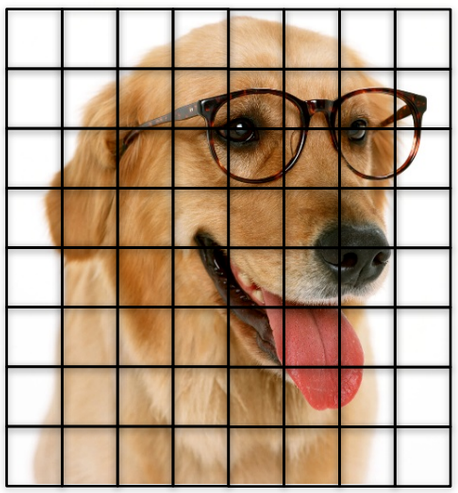


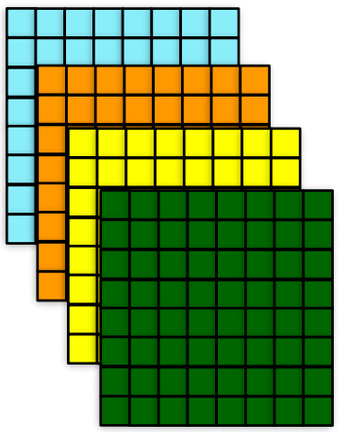


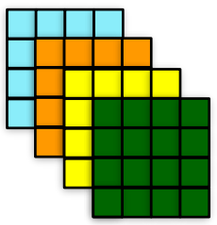


Max Pooling

CNN for Image Classification





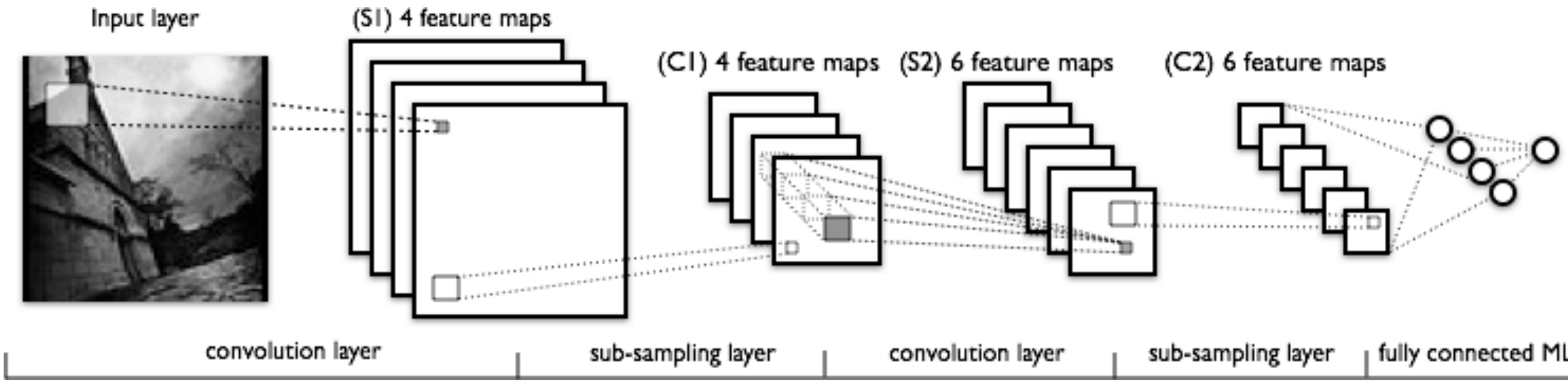


Max Pooling

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

CNN for Image Classification

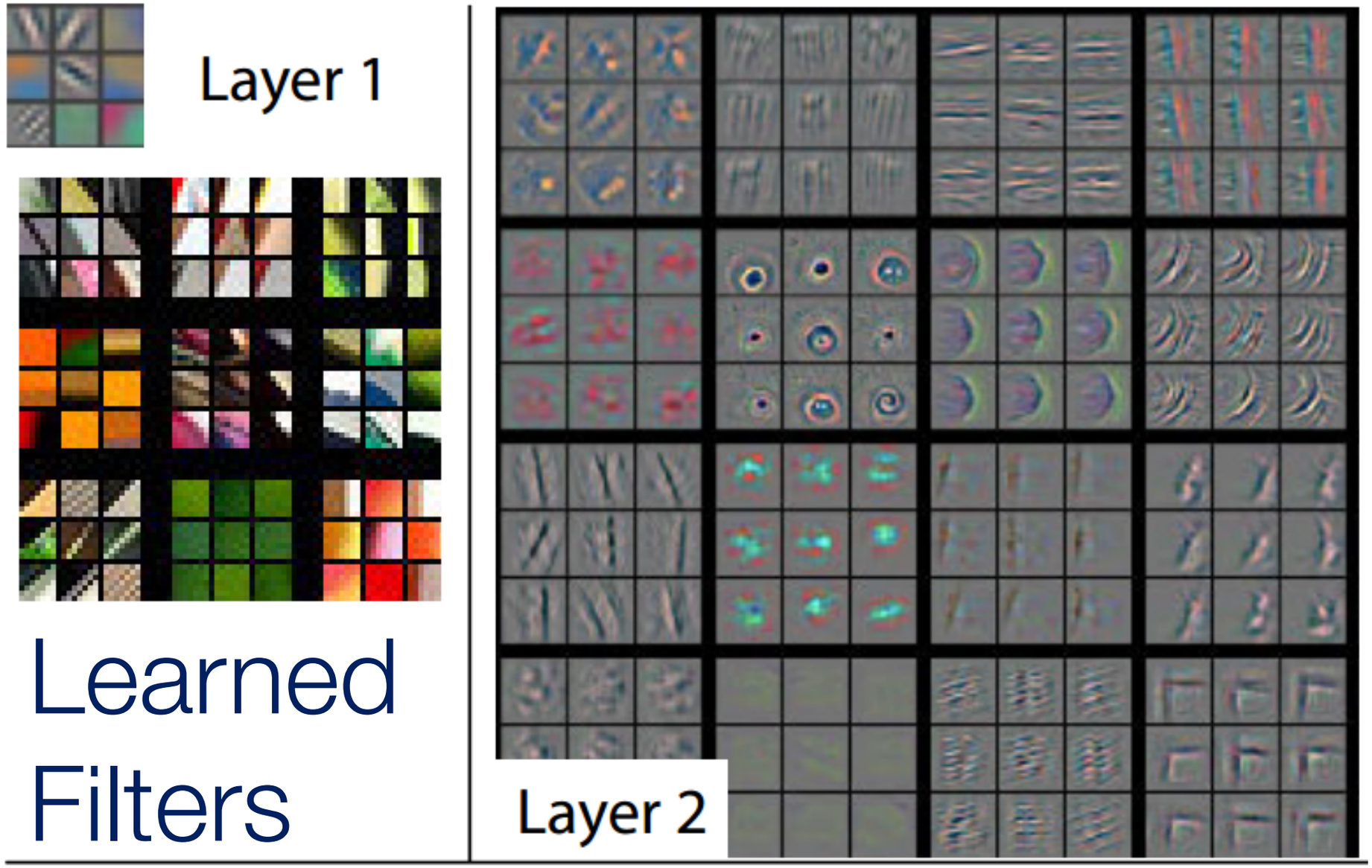


http://deeplearning.net/tutorial/lenet.html

CNN for Image Classification

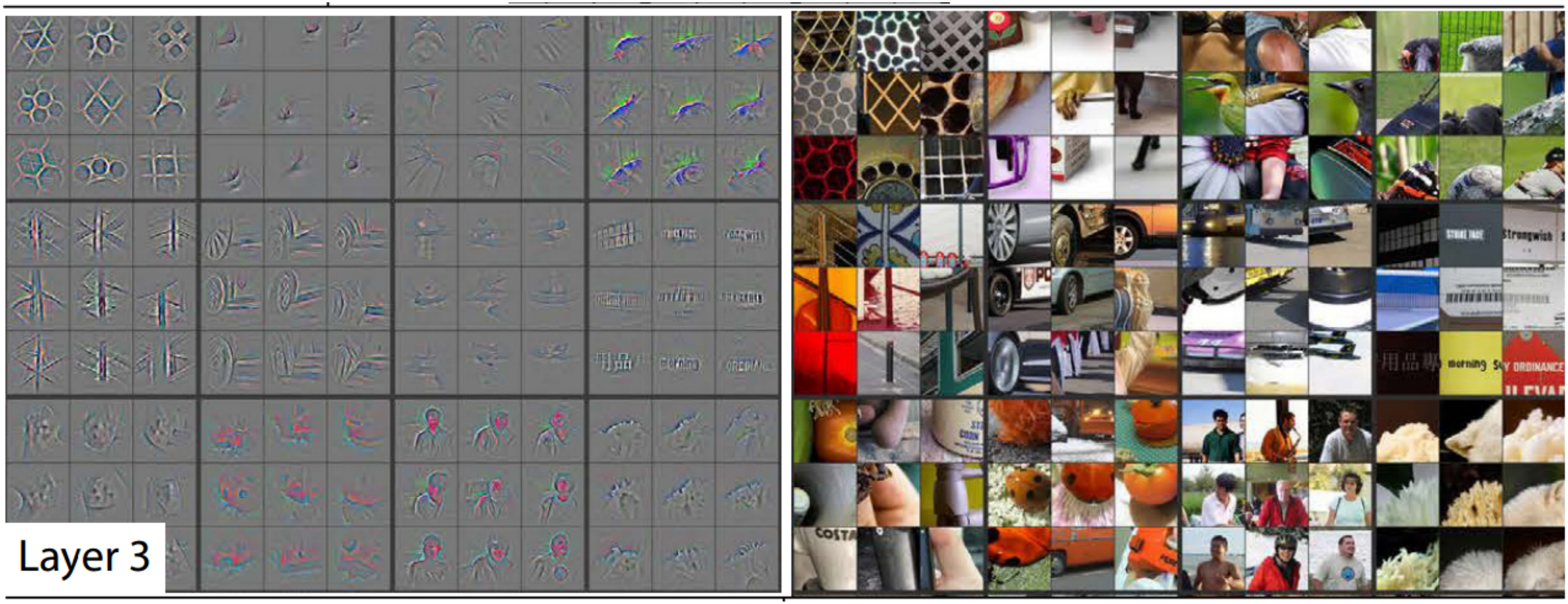
- How good are CNNs?
- “We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of **15.3%**, compared to **26.2%** achieved by the second-best entry.”
  - Krizhevsky et al., 2012: ImageNet Classification with Deep Convolutional Neural Networks
  - Competition to classify photos from ImageNet, http://www.image-net.org/

CNN for Image Classification



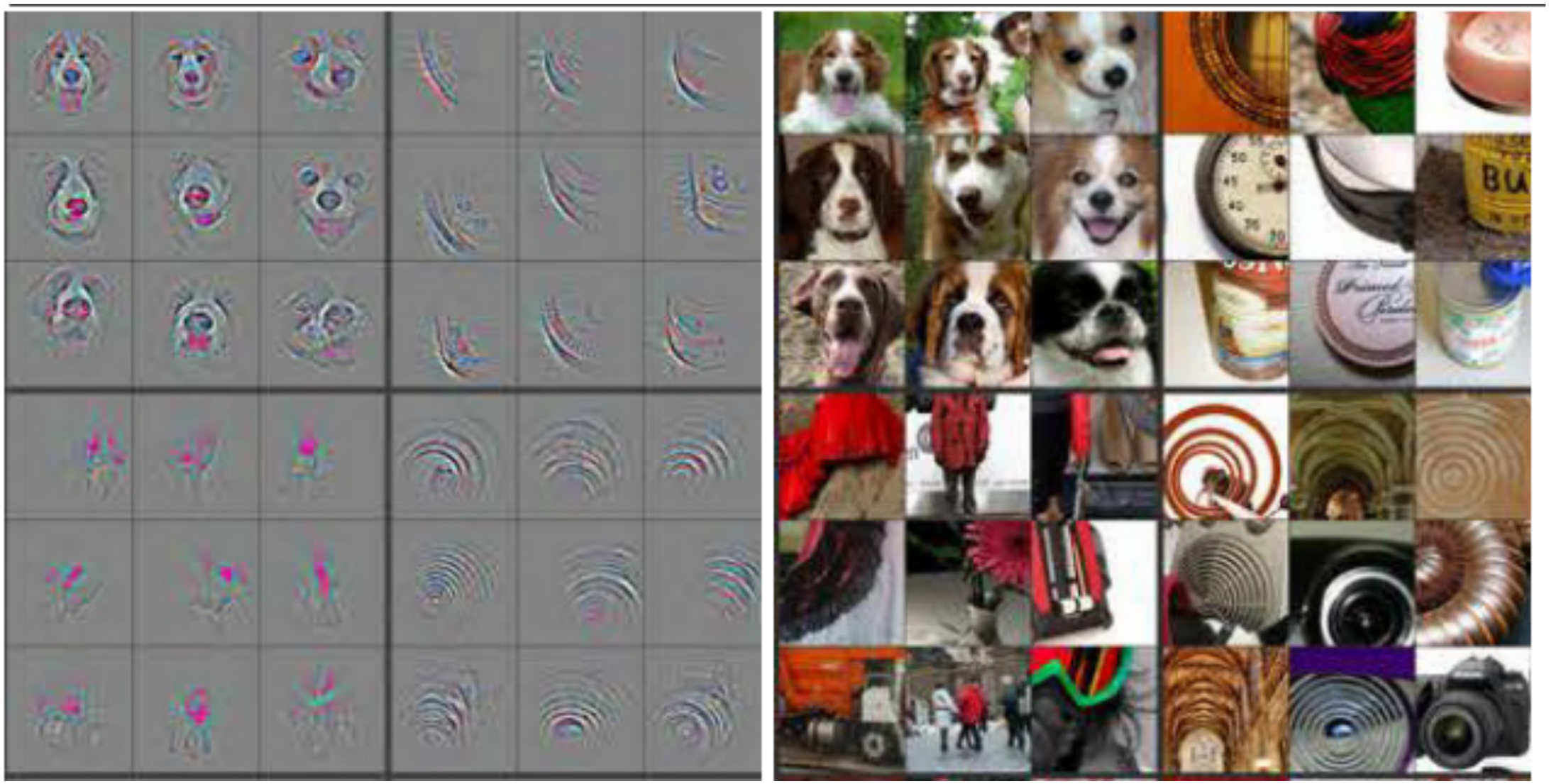
Zeiler and Fergus 2014

CNN for Image Classification



Zeiler and Fergus 2014

CNN for Image Classification



Layer 4

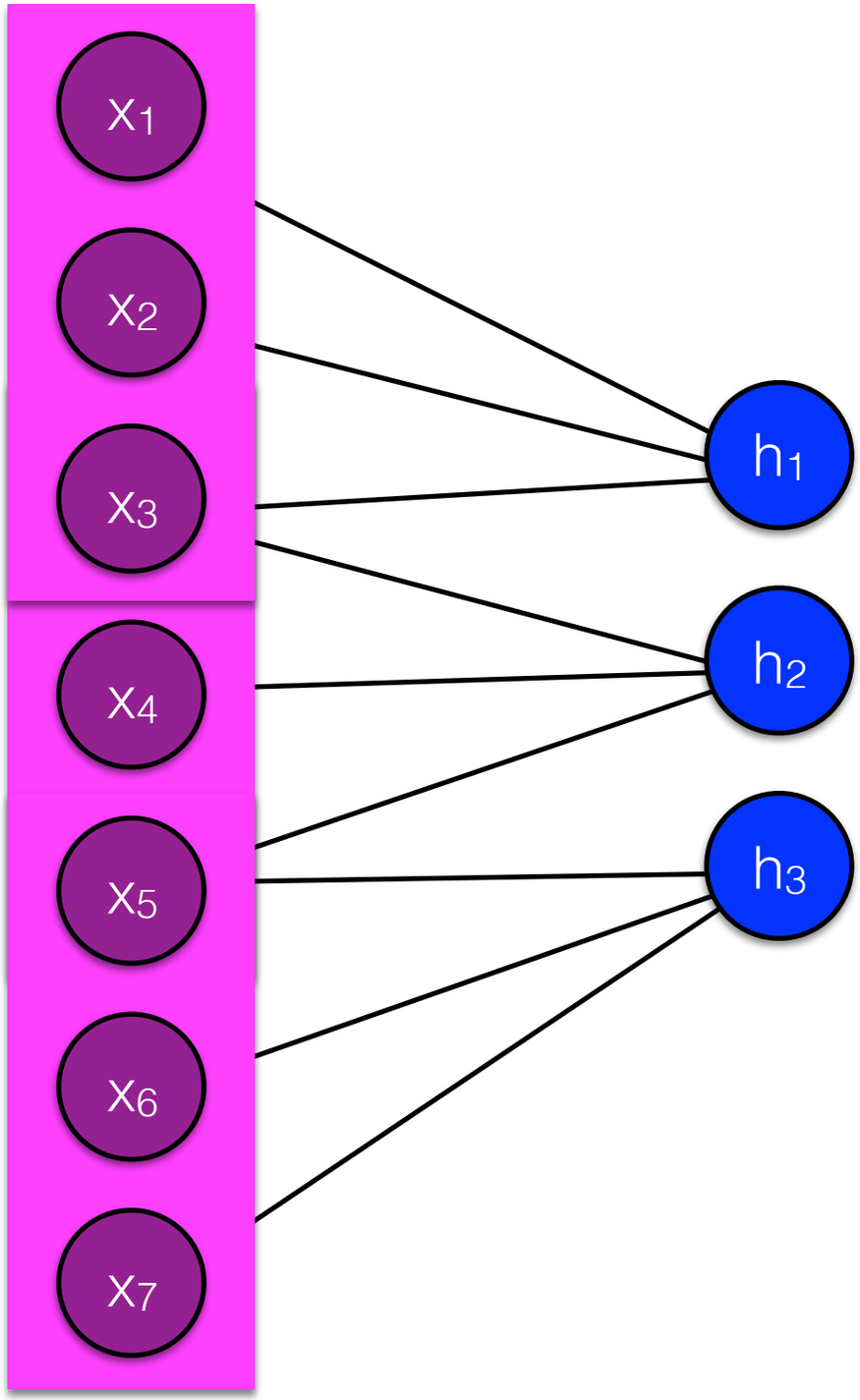
Zeiler and Fergus 2014

CNNs for NLP

- Represent words with indicator vectors
- Every token is a V-dimensional vector (size of the vocab) with a single 1 identifying the word
- We'll get to distributed representations of words next week!

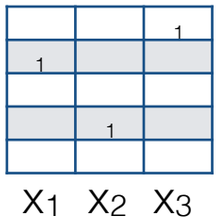
vocab item	indicator
a	0
aa	0
aal	0
aalii	0
aam	0
aardvark	1
aardwolf	0
aba	0

Convolutional networks



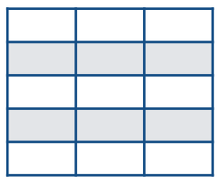
convolutional window size

x



size of vocab

W



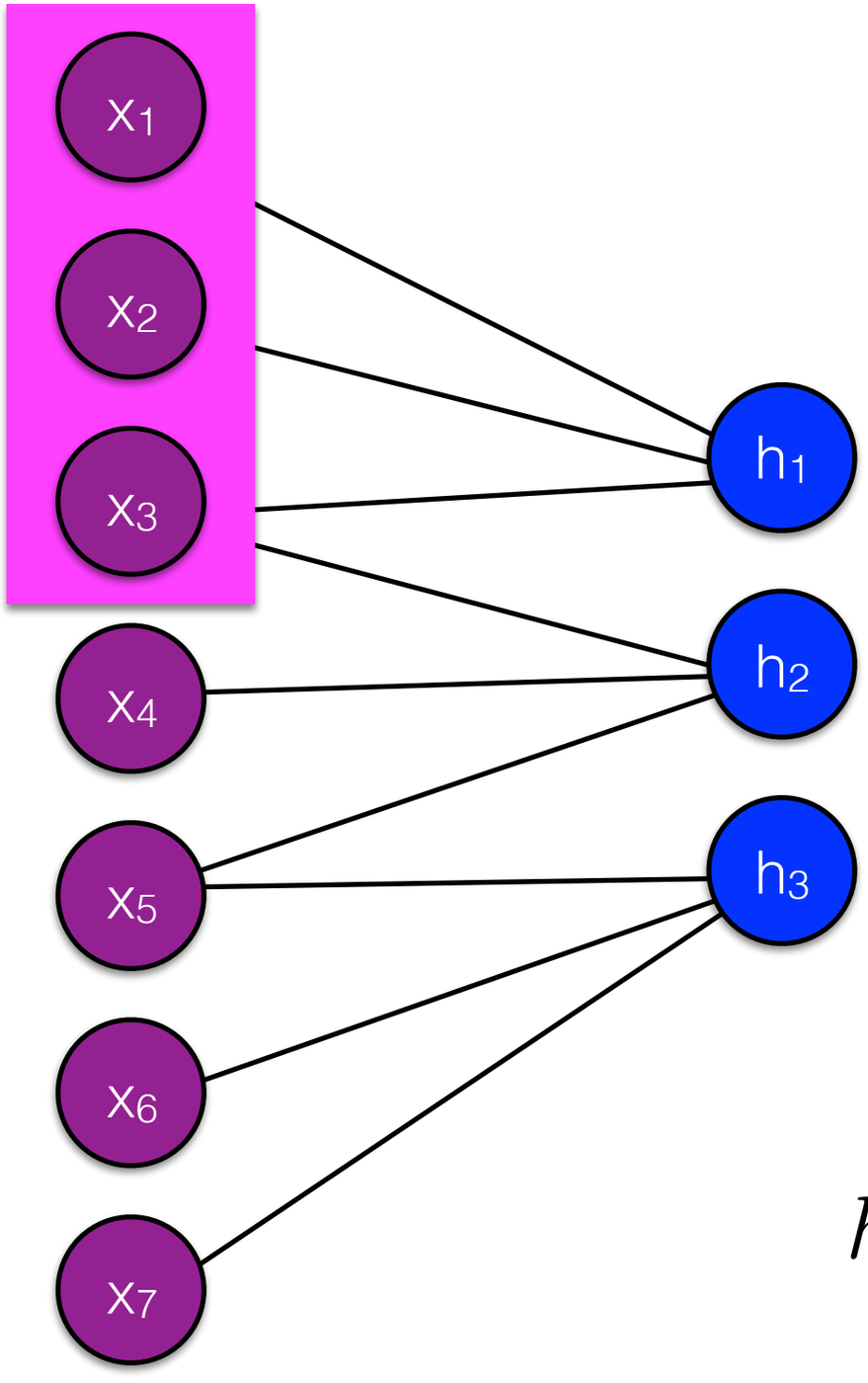
size of vocab

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

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

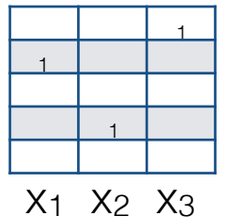
$$h_3 = \sigma(x_5 W_1 + x_6 W_2 + x_7 W_3)$$

Convolutional networks



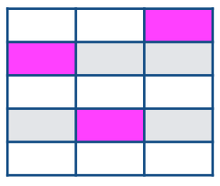
convolutional window size

x



size of vocab

W

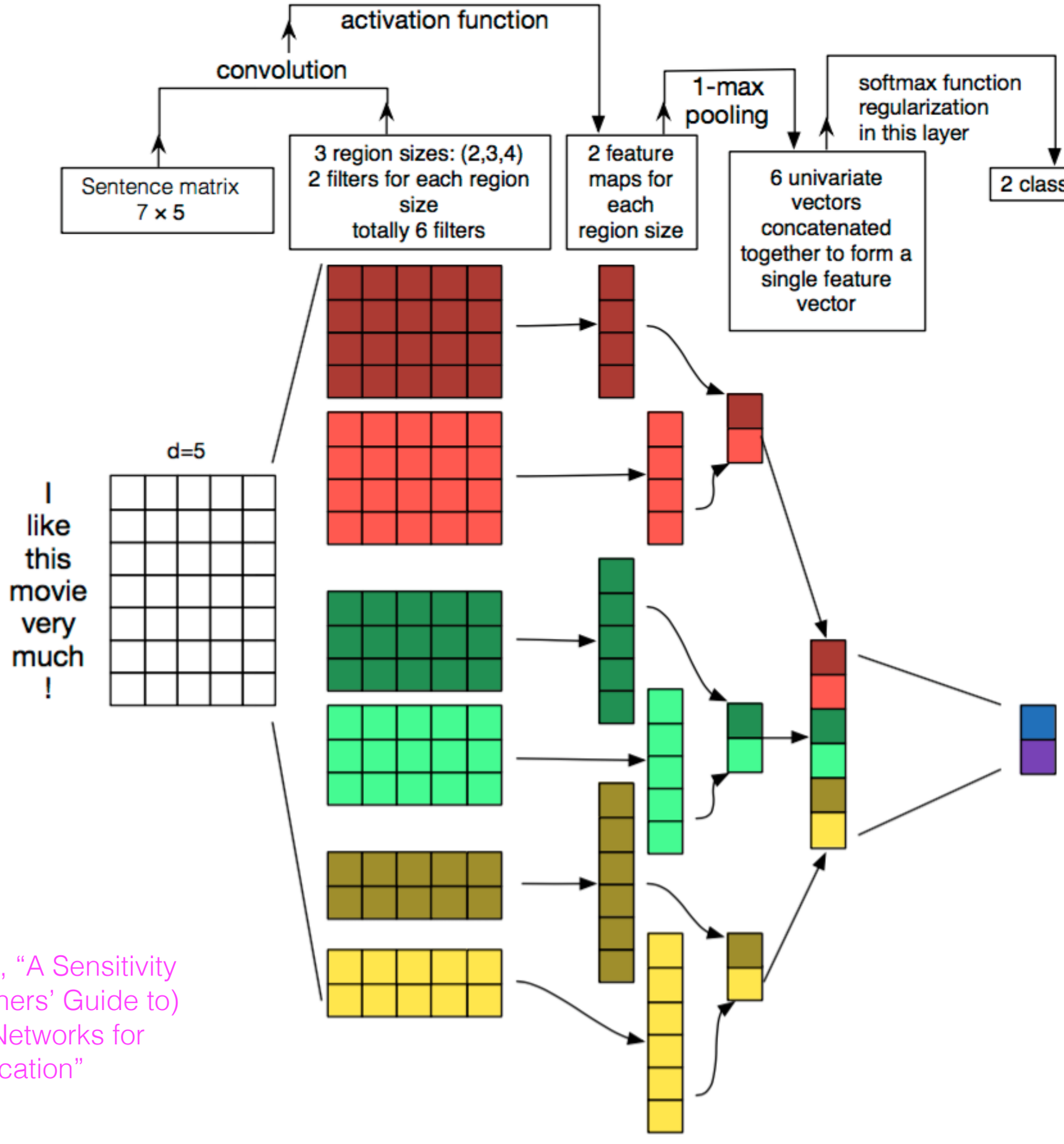


size of vocab

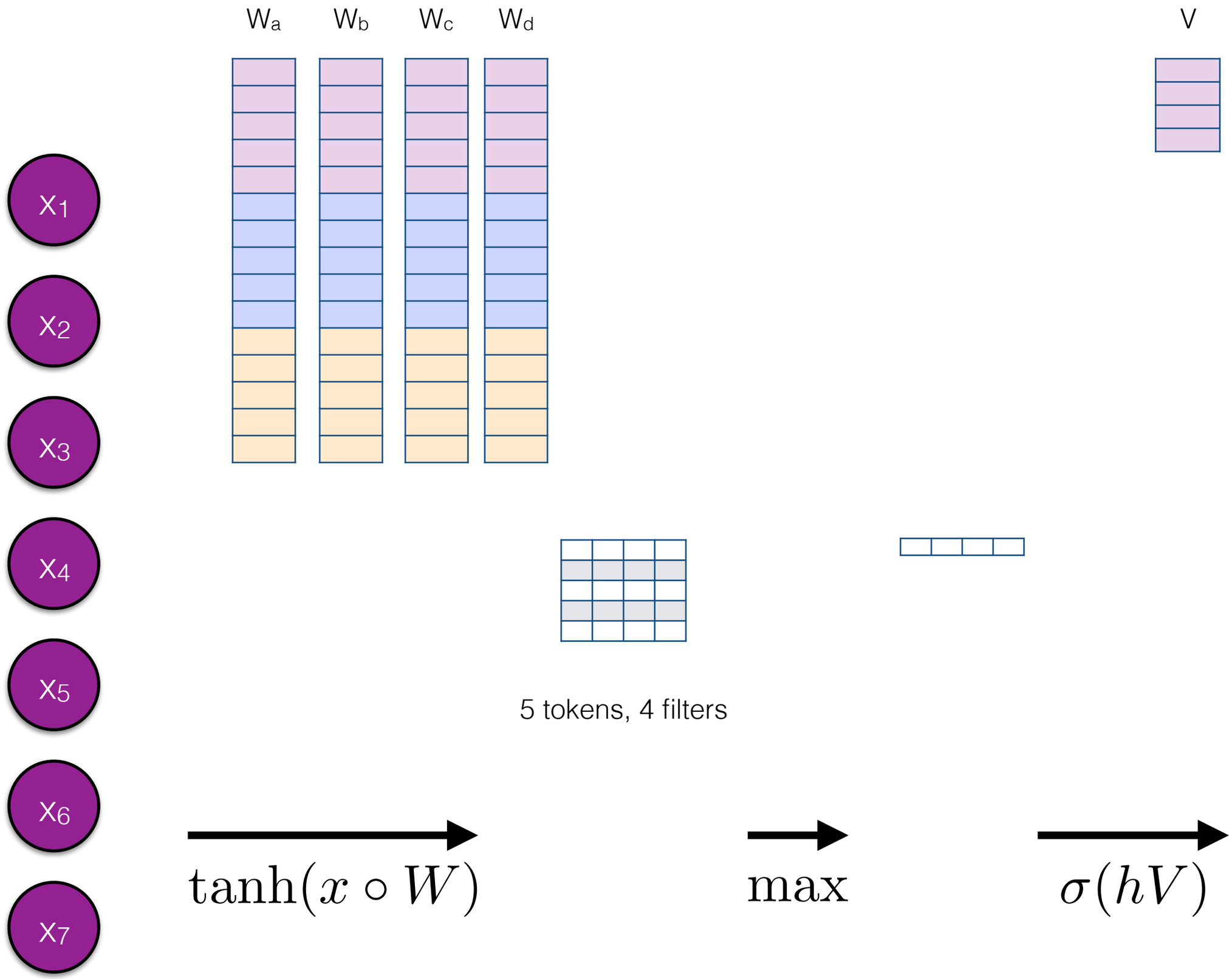
For indicator vectors, we're just adding these numbers together

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

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



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


W_a
W_b
W_c
W_d
V
x_1
x_2
x_3
x_4
x_5
x_6
x_7
y
5 tokens, 4 filters
$\tanh(x \circ W)$
$\max$
$\sigma(hV)$

CNN as important ngram detector

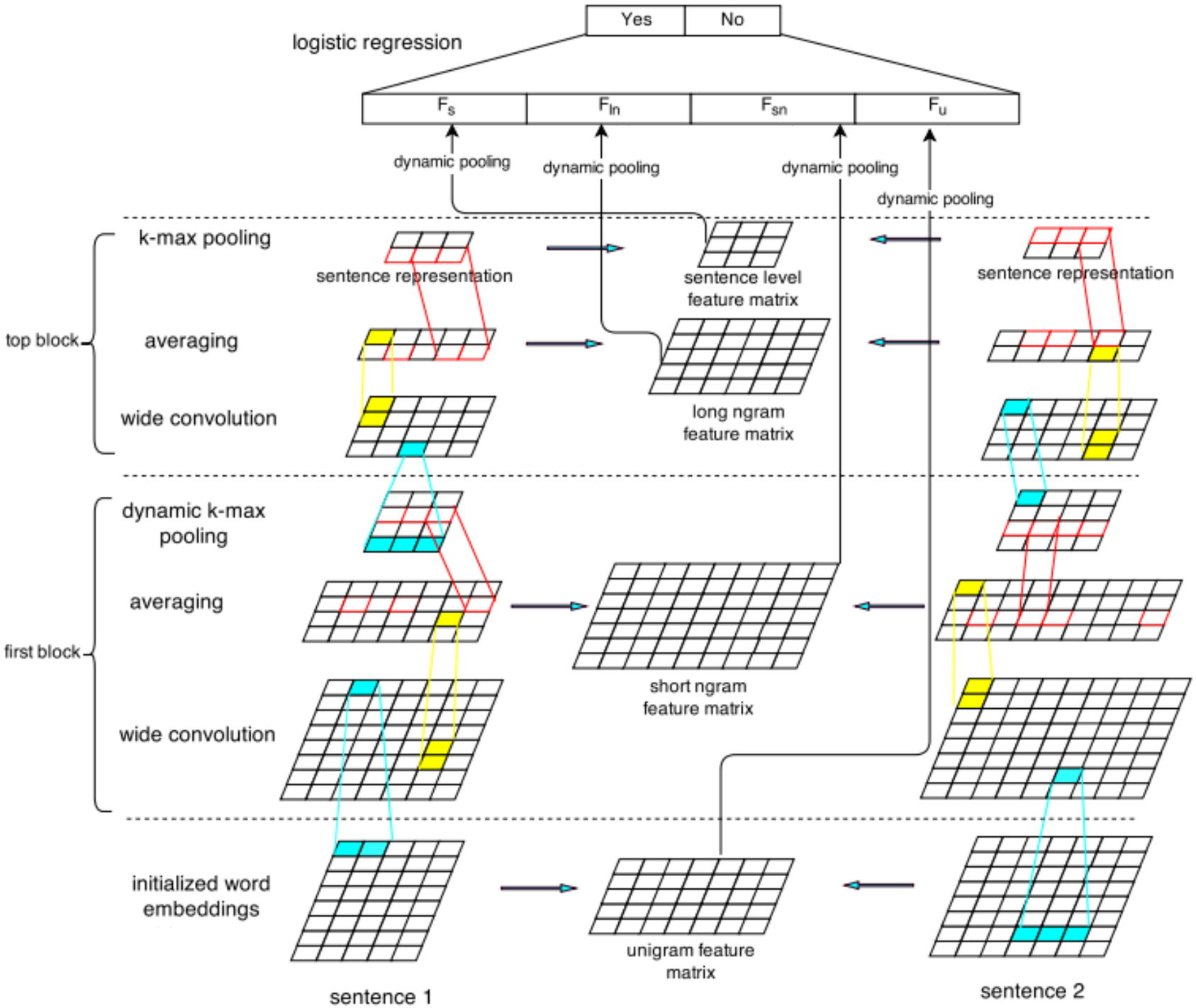
Higher-order ngrams are much more informative than just unigrams (e.g., “i don’t like this movie” [“I”, “don’t”, “like”, “this”, “movie”])

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

Example Application: Paraphrase Detection



(Yin & Schütze 2015)

So, What Can't They Do for NLP?

- Convolutional Neural Network for Paraphrase Identification (Yin & Schütze 2015)
- Summarization-based Video Caption via Deep Neural Networks (Li et al. 2015)
- Question Answering over Freebase with Multi-Column Convolutional Neural Networks (Dong et al. 2015)
- Convolutional Neural Network Architectures for Matching Natural Language Sentences (Hu et al. 2015)
- Learning Semantic Representations Using Convolutional Neural Networks for Web Search (Sheng et al. 2015)
- Deep Convolutional Neural Networks for Sentiment Analysis of Short Texts (dos Santos & Gatti 2014)
- Relation Extraction: Perspective from Convolutional Neural Networks (Nguyen & Grishman 2015)
- Modeling Mention, Context and Entity with Neural Networks for Entity Disambiguation (Sun et al. 2015)
- Modeling Interestingness with Deep Neural Networks (Gao 2015)

… and so on

Generative vs. Discriminative models

- Generative models specify a joint distribution over the labels and the data. With this you could generate new data

$$P(x, y) = P(y)\, P(x \mid y)$$

- Discriminative models specify the conditional distribution of the label y given the data x. These models focus on how to discriminate between the classes

$$P(y \mid x)$$

Summary

- Discriminative classifiers directly model the conditional, p(y|x)

- Logistic regression is a simple linear classifier, that retains a probabilistic semantics

- Parameters in LR are learned by iterative optimization (e.g. SGD)

- Regularization helps to avoid overfitting

Administrative Matters

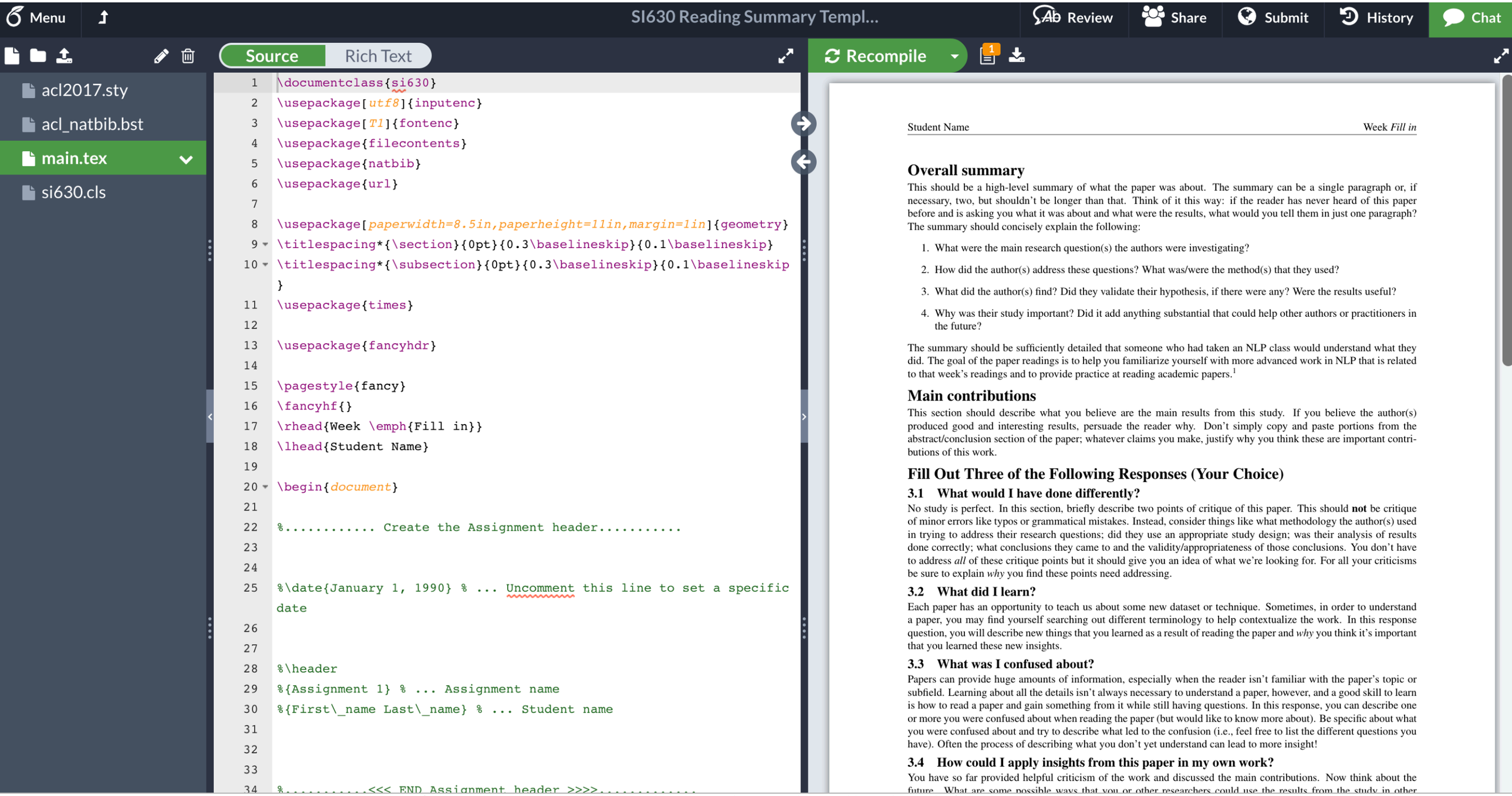
- Paper Readings will go out tonight. Reading responses will start this week

- Reminder: Regex Homework is due next Weds!

Reading Response

Student Name Week *Fill in*

Overall summary



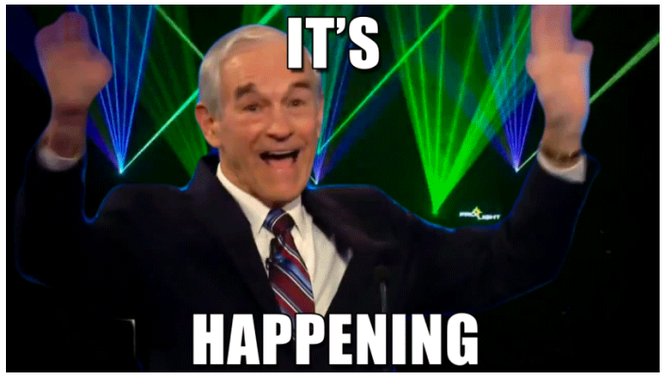
future. What are some possible ways that you or other researchers could use the results from the study in other interesting applications or as the basis for other directions of research. For example, are there future studies that could build on theories/models tested in the study? Where do you see this paper being used within your own field or for your own interests?

Reading Response

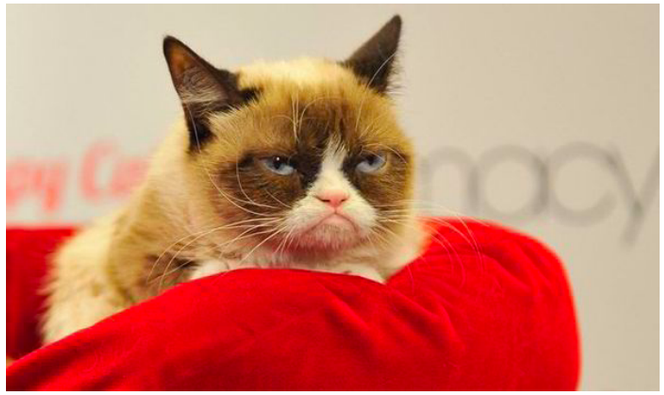
- Reminder: Goal is to get you slightly deeper knowledge into one topic covered in that week's lecture
- You're not expected to understand all of the paper!
- Some weeks will be easier than others

Homework 1 is out!

- You'll implement Naive Bayes!



- You'll implement Logistic Regression!



- You'll finally put an end to bad behavior online!