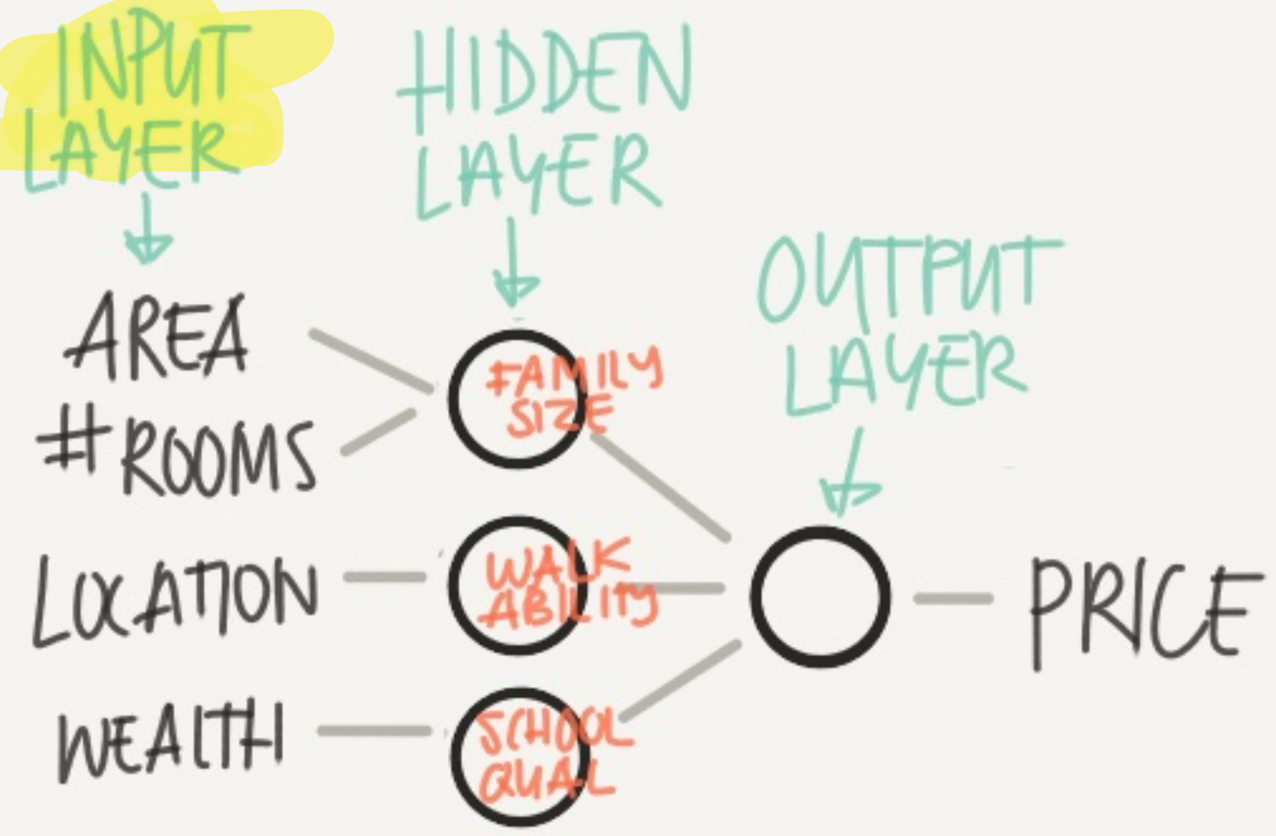
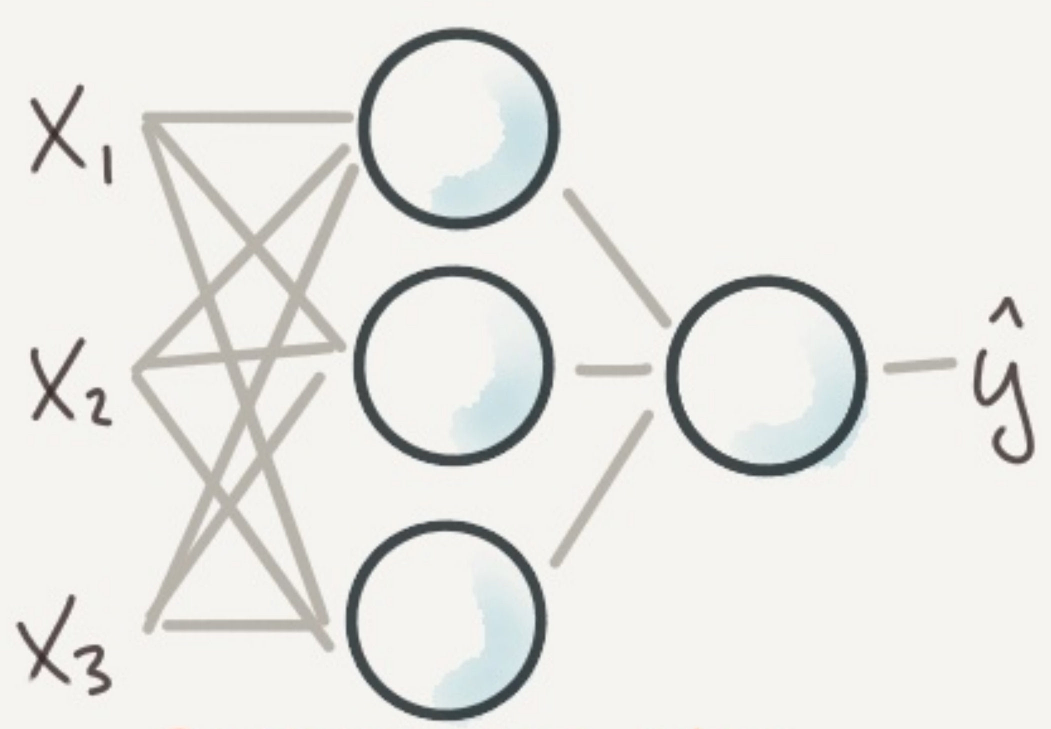
INTRO TO **DEEP LEARNING**



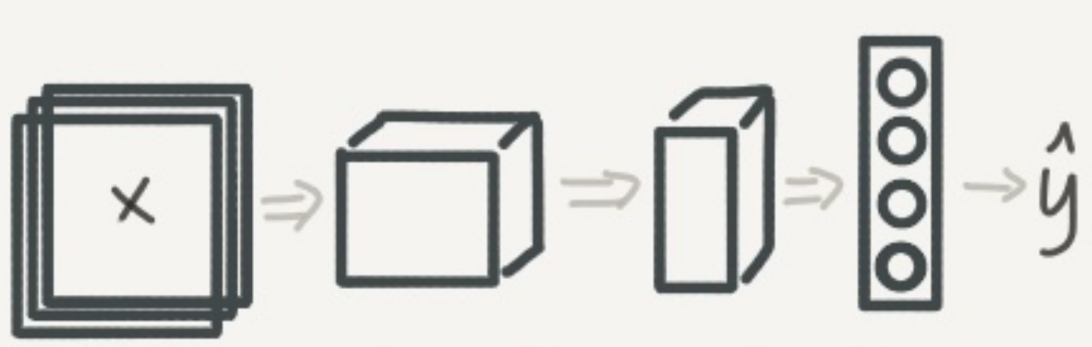
SUPERVISED LEARNING

INPUT: X	OUTPUT: y	NN TYPE
HOME FEATURES AD+USER INFO	PRICE WILL CLICK ON AD (0/1)	STANDARD NN
IMAGE	OBJECT (1...1000)	CONV. NN (CNN)
AUDIO ENGLISH	TEXT TRANSCRIPT CHINESE	RECURRENT NN (RNN)
IMAGE/RADAR	POS OF OTHER CARS	CUSTOM/HYBRID

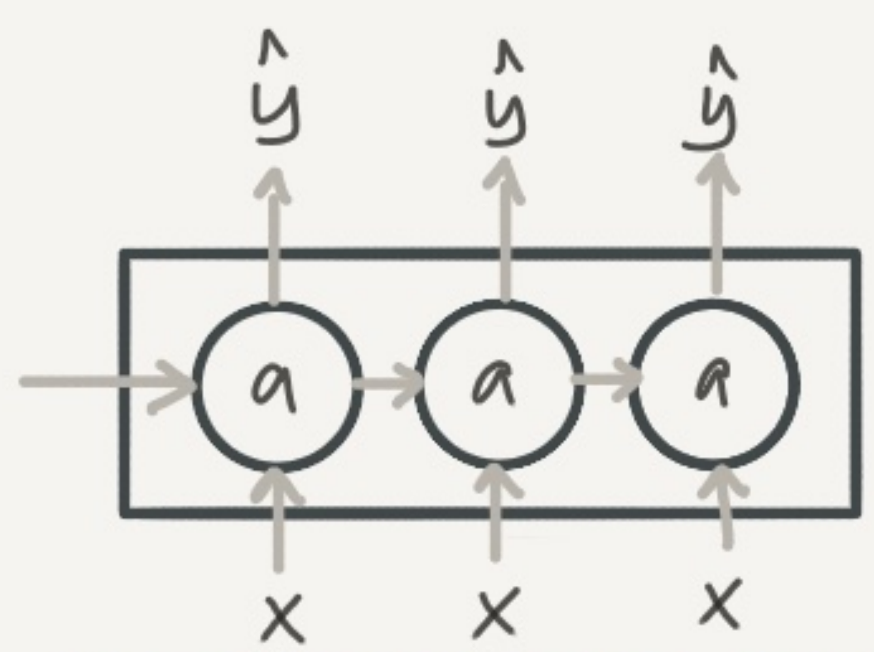
NETWORK ARCHITECTURES



STANDARD NN

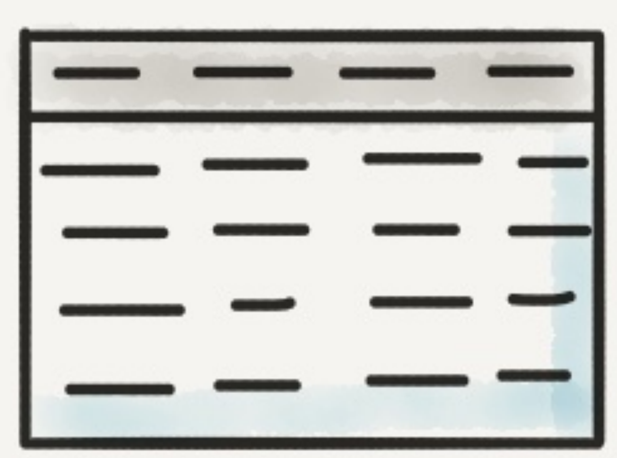


CONVOLUTIONAL NN



RECURRENT NN

NNs CAN DEAL WITH BOTH STRUCTURED & UNSTRUCTURED DATA



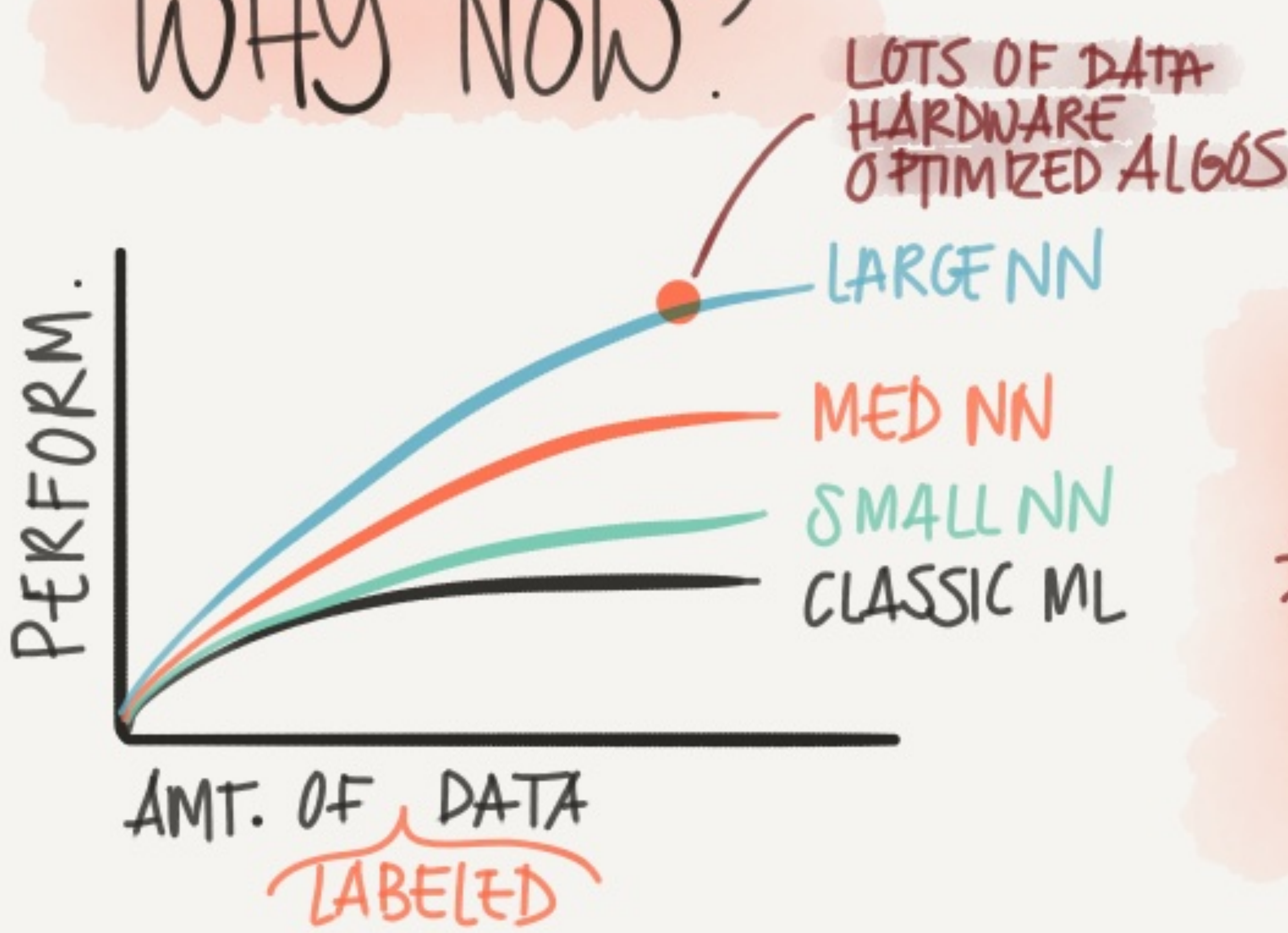
STRUCTURED

"THE QUICK BROWN FOX"

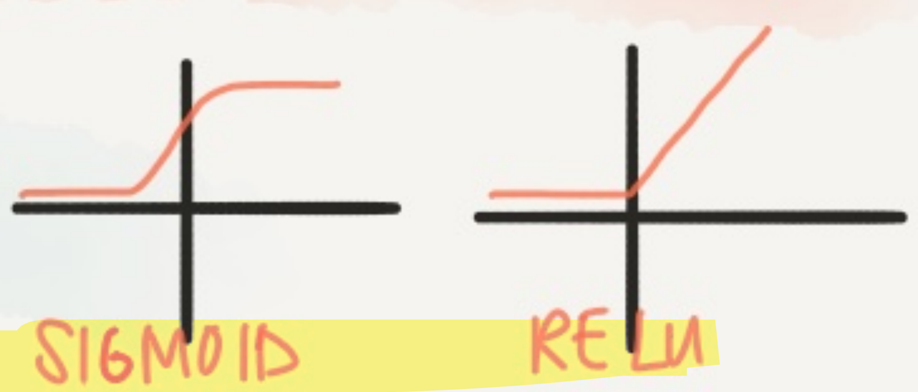
UNSTRUCTURED

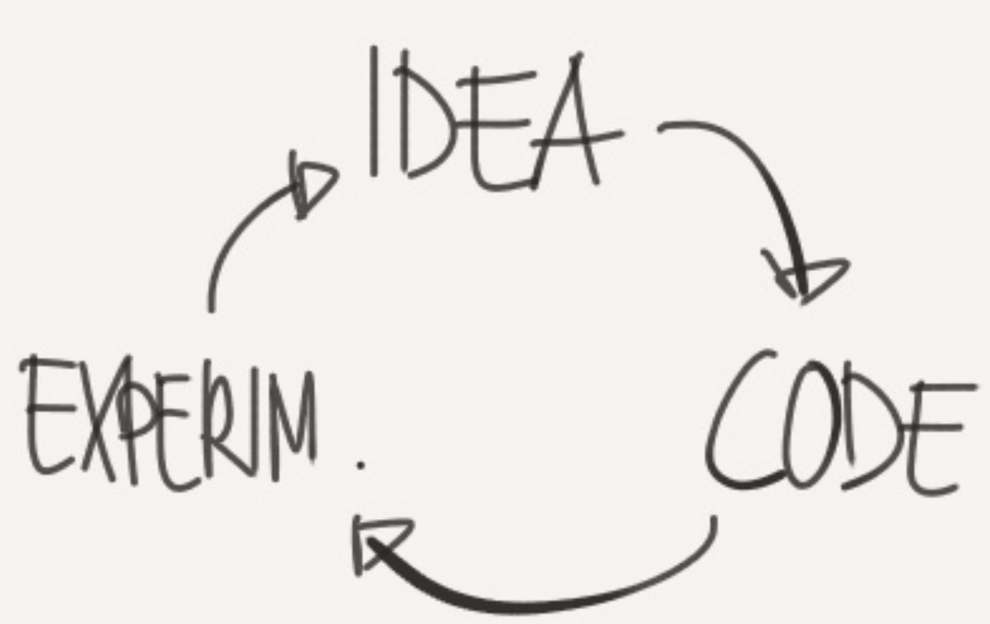
HUMANS ARE GOOD AT THIS

WHY NOW?



ONE OF THE BIG BREAKTHROUGHS HAS BEEN MOVING FROM SIGMOID TO RELU FOR FASTER GRADIENT DESCENT





FASTER COMPUTATION IS IMPORTANT TO SPEED UP THE ITERATIVE PROCESS

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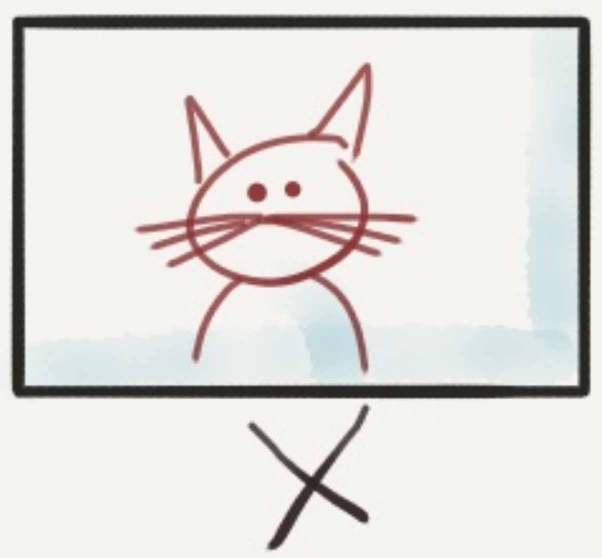
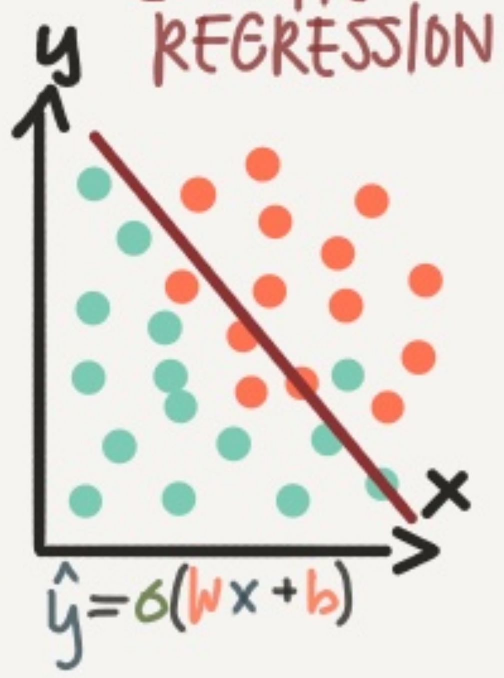
LOGISTIC REGRESSION
AS A NEURAL NET

BINARY CLASSIFICATION



→ 1 : CAT
0 : NOT CAT

y



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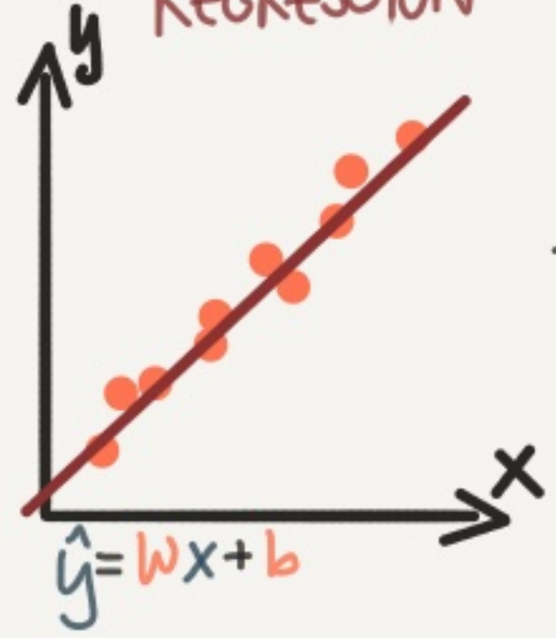

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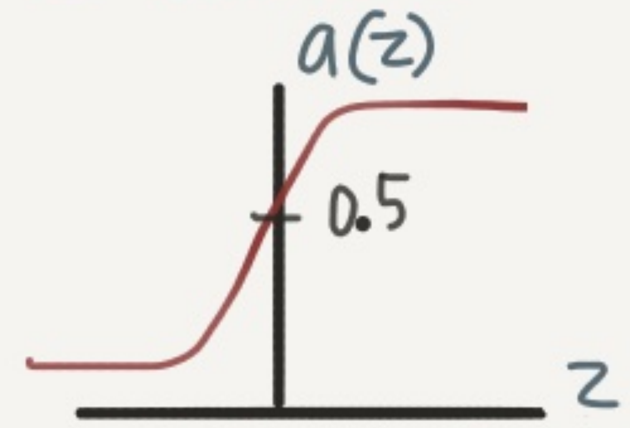


$a(z) = 1$ FOR LARGE Z
0 FOR SMALL Z

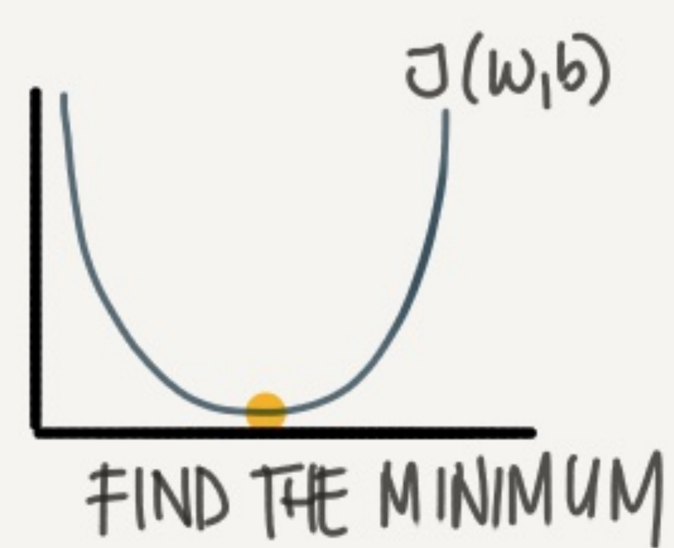
THE TASK IS TO LEARN w & b BUT HOW?

A : OPTIMIZE HOW GOOD THE GUESS IS BY MINIMIZING THE DIFF BETWEEN GUESS ($\hat{y}$) AND TRUTH (y)

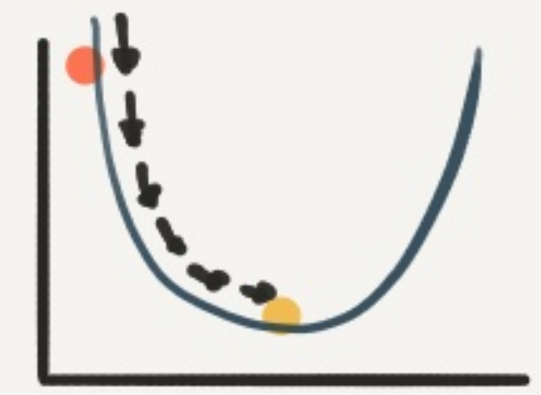
$$LOSS = \mathcal{L}(\hat{y}, y)$$

$$COST = J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

COST = LOSS FOR THE ENTIRE DATASET



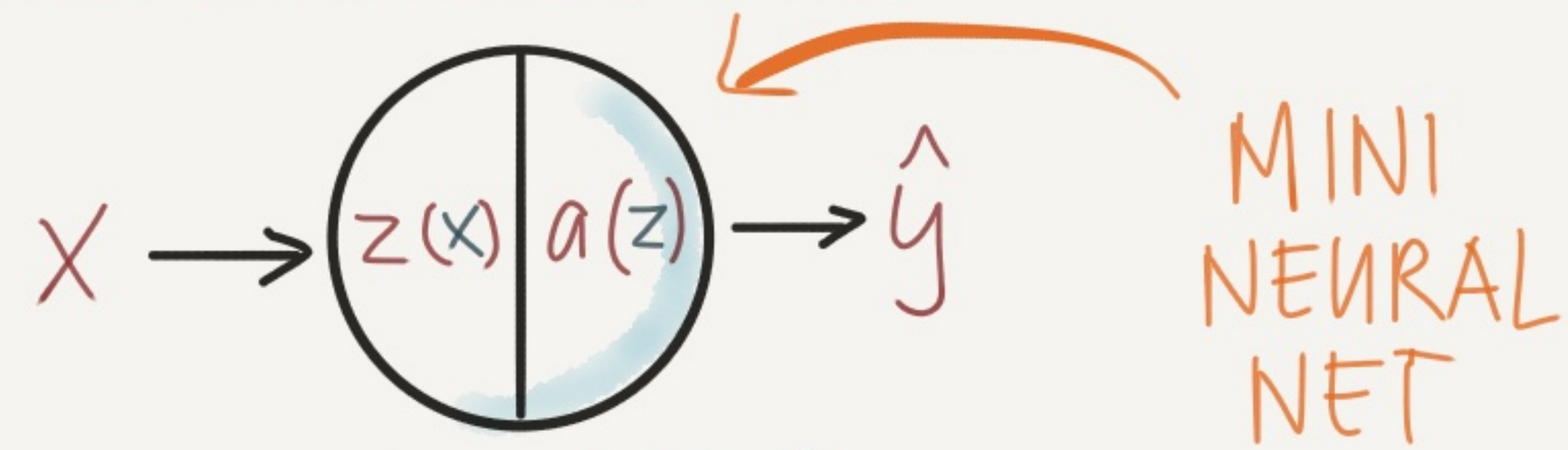
FINDING THE MINIMUM WITH GRADIENT DESCENT



1. FIND THE DOWNHILL DIRECTION (USING DERIVATIVES)
2. WALK (UPDATE W & B) AT A α LEARNING RATE

REPEAT UNTIL YOU REACH BOTTOM (CONVERGE)

PUTTING IT ALL TOGETHER



$$z(x) = wx + b$$

$$\hat{y} = a(z) = \sigma\ SIGMOID(z)$$

1. FORWARD PROPAGATION • CALCULATE $\hat{y}$
2. BACKWARD PROPAGATION • GRADIENT DESCENT + UPDATE w & b

REPEAT UNTIL IT CONVERGES

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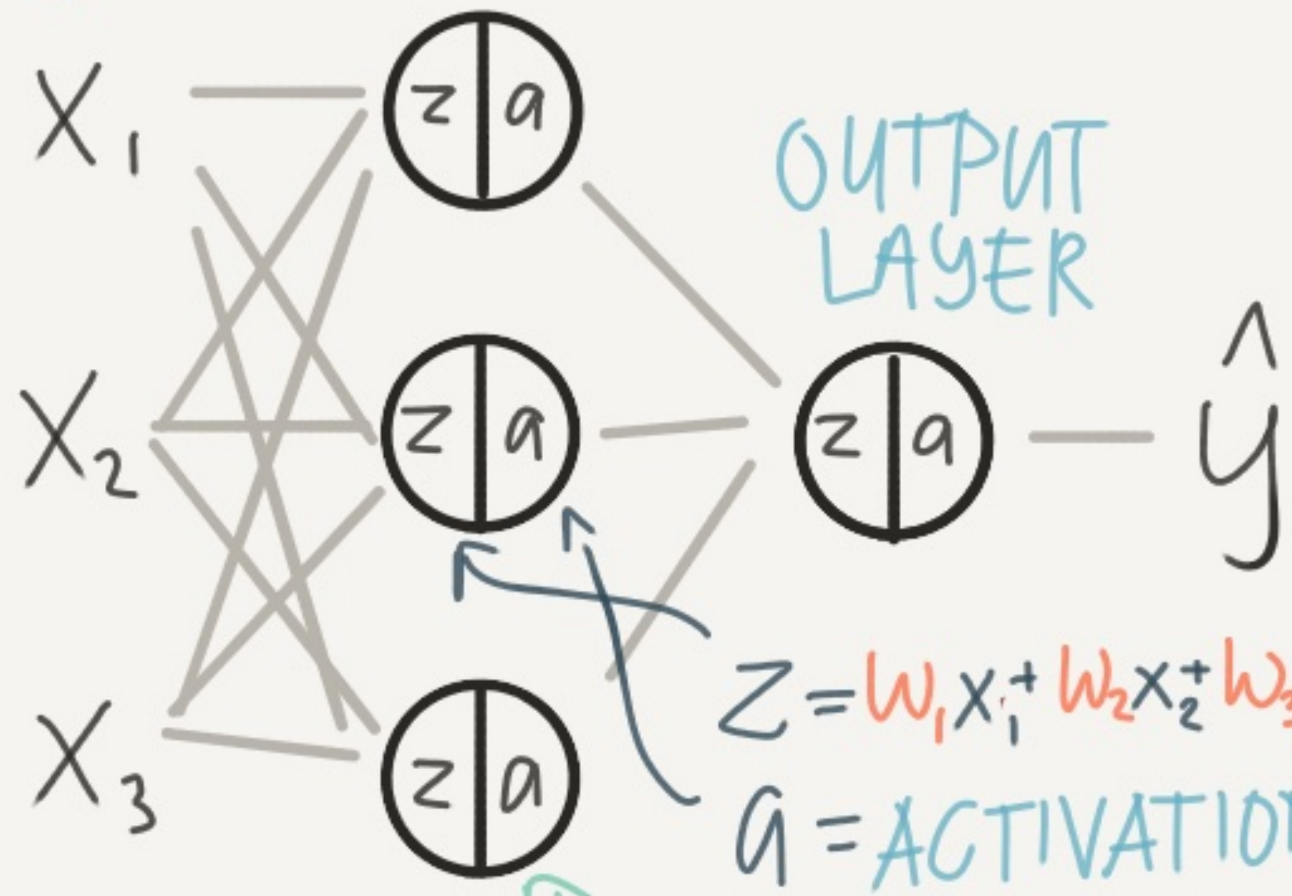
@TessFerrandez

SHALLOW NEURAL NETS

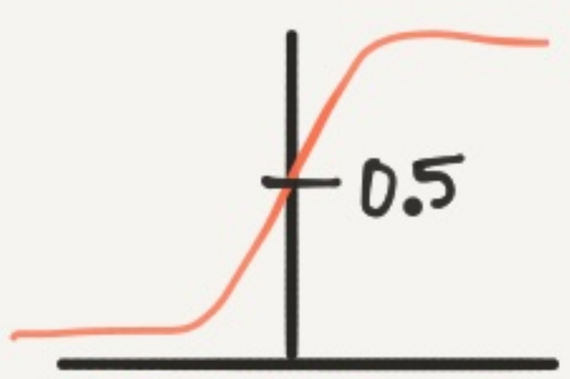
2 LAYER NEURAL NET



$Z = W_1 x_1 + W_2 x_2 + W_3 x_3 + b$

a = ACTIVATION FUNCTION

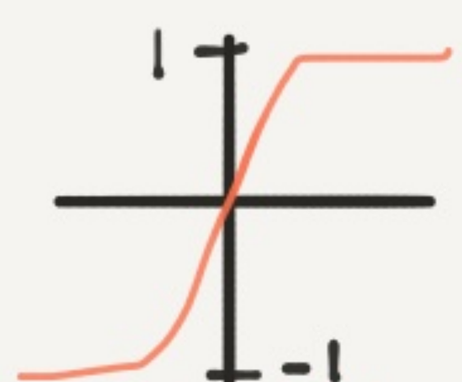
ACTIVATION FUNCTIONS



SIGMOID σ

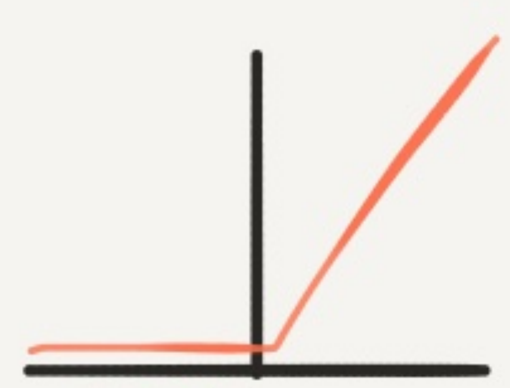
BINARY CLASSIFIER - ONLY USED FOR OUTPUT LAYER

SLOW GRAD DESCENT SINCE SLOPE IS SMALL FOR LARGE/SMALL VAL



TANH

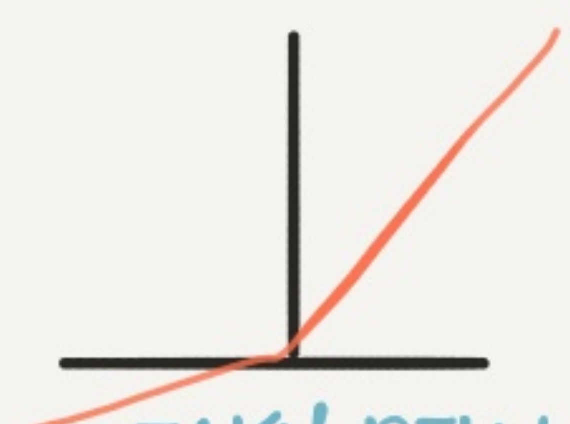
NORMALIZED ⇒ GRADIENT DESCENT IS FASTER



RELU

DEFAULT CHOICE FOR ACTIVATION

SLOPE = 1/0



LEAKY RELU

AVOIDS UNDEF SLOPE AT ∅ BUT RARELY USED IN PRACTICE

WHY ACTIVATION FUNCTIONS?

EX. WITH NO ACTIVATION - $a = z$

$a^{[1]} = z^{[1]} = w^{[1]}x + b^{[1]}$ LAYER 1

$a^{[2]} = z^{[2]} = w^{[2]}a^{[1]} + b^{[2]}$ LAYER 2

PLUG IN $a^{[1]}$

$$a^{[2]} = w^{[2]}(w^{[1]}x + b^{[1]}) + b^{[2]}$$
$$= \underbrace{w^{[2]}w^{[1]}}_{w'}x + \underbrace{w^{[2]}b^{[1]} + b^{[2]}}_{b'}$$

$w'x + b'$ ← LINEAR FUNCTION

WE COULD JUST AS WELL HAVE SKIPPED THE WHOLE NEURAL NET & USED LIN. REGR.

INITIALIZING W+b

WHAT IF: INIT TO ∅

THIS WILL CAUSE ALL THE UNITS TO BE THE SAME AND LEARN EXACTLY THE SAME FEATURES

SOLUTION: RANDOM INIT

BUT ALSO WANT THEM SMALL SO RAND * 0.01 ← HYPERPARAM

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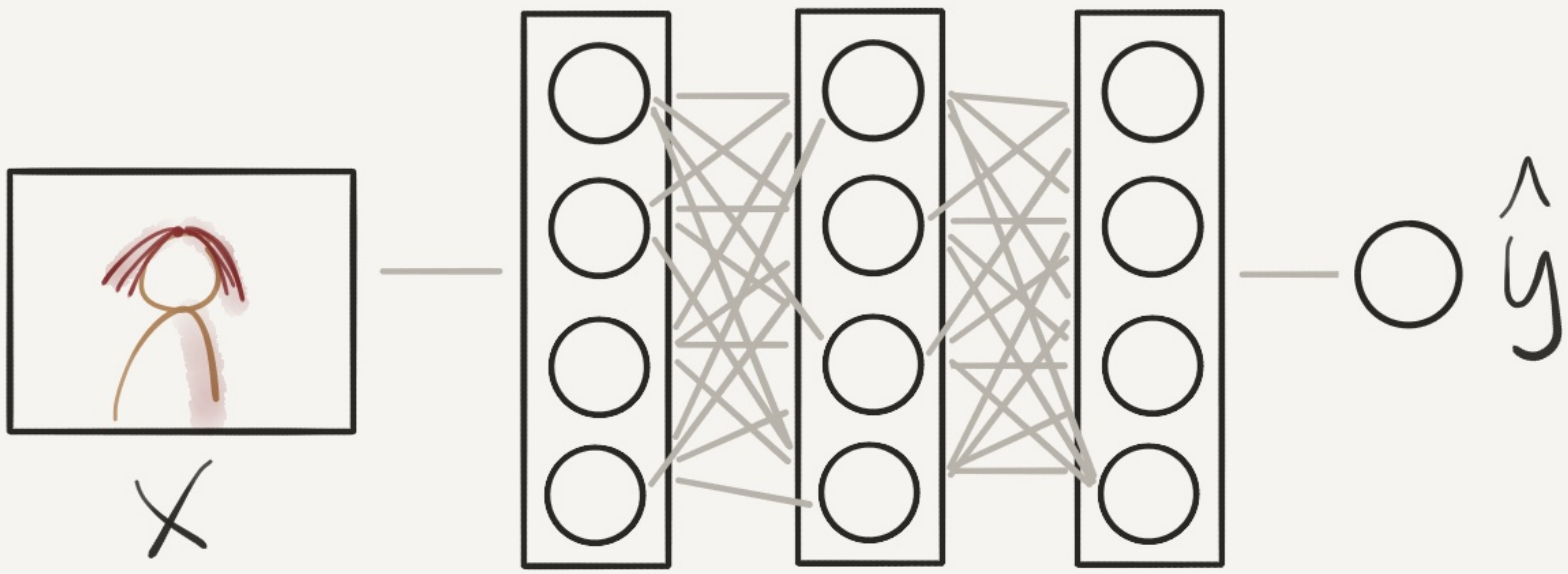
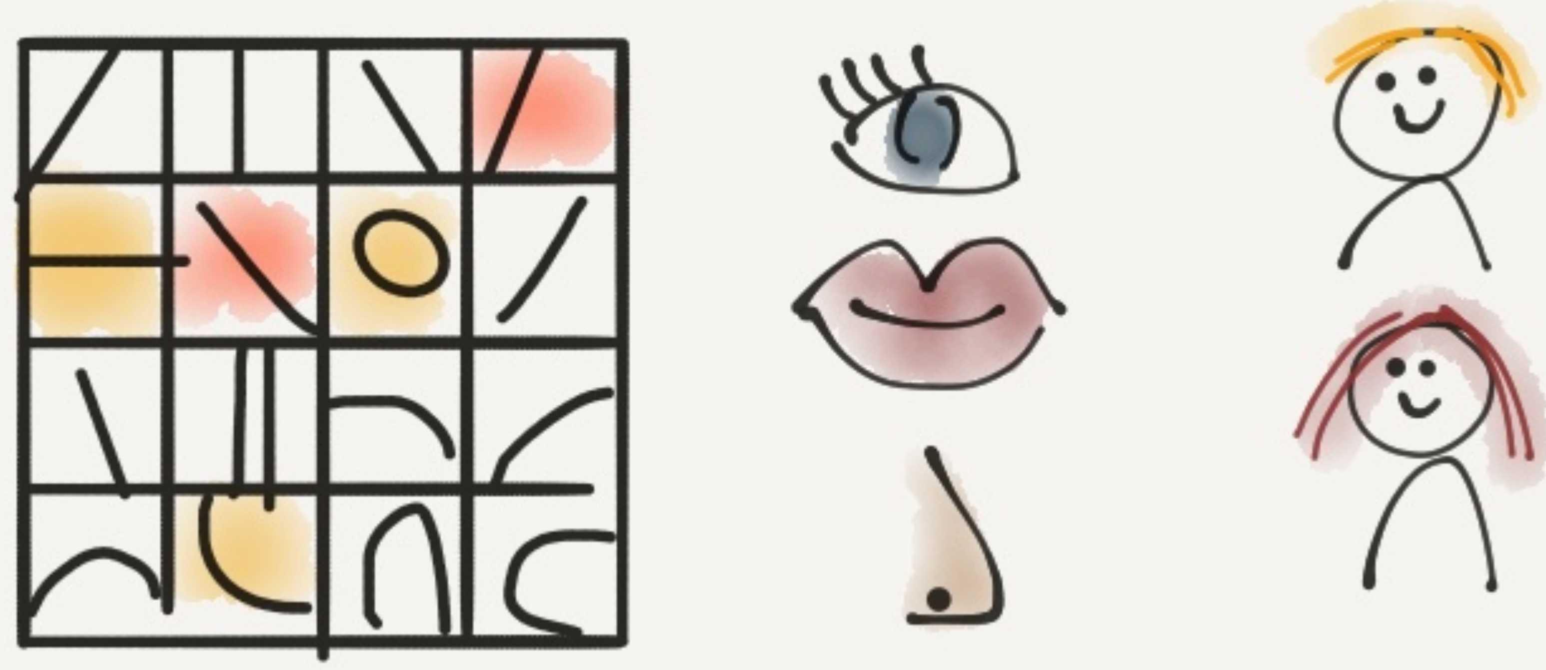
DEEP
NEURAL NETS

THERE ARE FUNCTIONS A SMALL DEEP NET CAN COMPUTE THAT SHALLOW NETS NEED EXP. MORE UNITS TO COMP.

WHY DEEP NEURAL NETS?





LOW LEVEL AUDIO WAVE FEATURES — PHONEMES — WORDS — SENTENCES

↗ ↘ PITCH

C A T

VERY DATA HUNGRY

NEED LOTS OF COMPUTER POWER

ALWAYS VECTORIZE

VECTOR MULT · CHEAPER THAN FOR LOOPS

COMPUTE ON GPUs

LOTS OF HYPERPARAMS

- LEARNING RATE α
- # ITERATIONS
- # HIDDEN LAYERS
- # HIDDEN UNITS
- CHOICE OF ACTIVATION
- MOMENTUM
- MINI-BATCH SIZE
- REGULARIZATION

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SETTING UP
YOUR ML ~~APP~~

CLASSIC ML

100 – 10000 SAMPLES

TRAIN	DEV	TEST
60%	20%	20%

ALL FROM SAME PLACE
DISTRIBUTION

DEEP LEARNING

1M SAMPLES

TRAIN	D	T
98%	1%	1%

EX: TRAIN

PRO CAT PICS FROM INTERNET

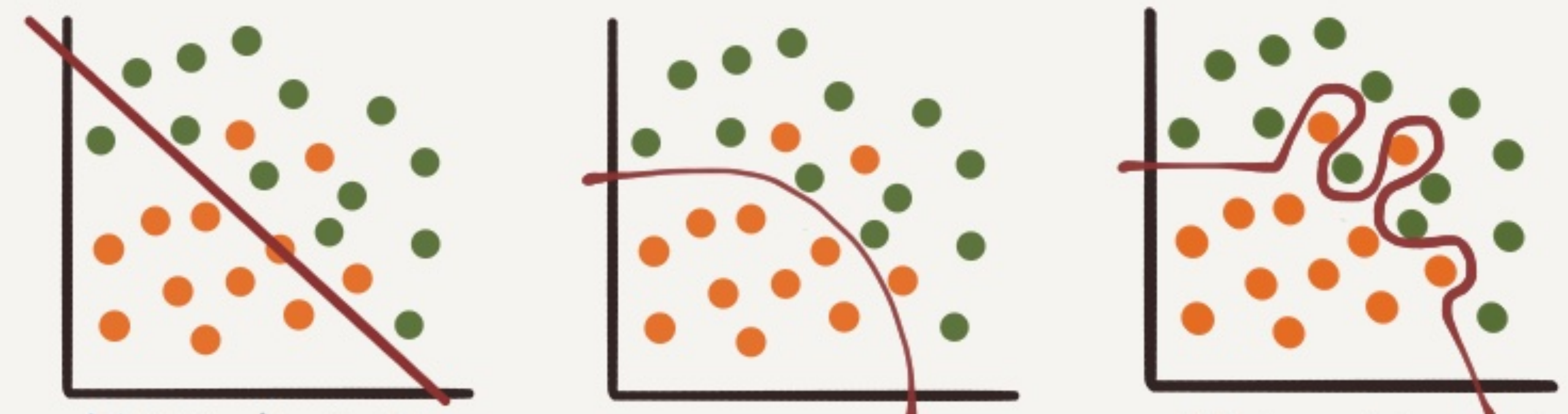
DEV/TEST

BLURRY CAT PICS FROM APP

TIP
DEV & TEST SHOULD COME FROM SAME DISTRIBUTION

IDEA → CODE → EXPERIMENT → IDEA

BIAS/VARIANCE



HIGH BIAS "UNDERFIT" | JUST RIGHT | HIGH VARIANCE "OVERFIT"

ERROR				
TRAIN	1%	15%	15%	0.5%
TEST	11%	16%	30%	1%
	HIGH VARIANCE	HIGH BIAS	HIGH BIAS & VARIANCE	LOW BIAS & VARIANCE

ASSUMING HUMANS GET 0% ERROR

THE ML RECIPE

$\boxed{\text{HIGH BIAS}}$ —y→ BIGGER NETWORK, TRAIN LONGER, (DIFF NN ARCHITECTURE)

↓ no

$\boxed{\text{HIGH VARIANCE}}$ —y→ MORE DATA (TRAIN), REGULARIZATION, (DIFF NN ARCHITECTURE)

↓ no

$\boxed{\text{DONE}}$

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REGULARIZATION

PREVENTING OVERFITTING

L2 REGULARIZATION

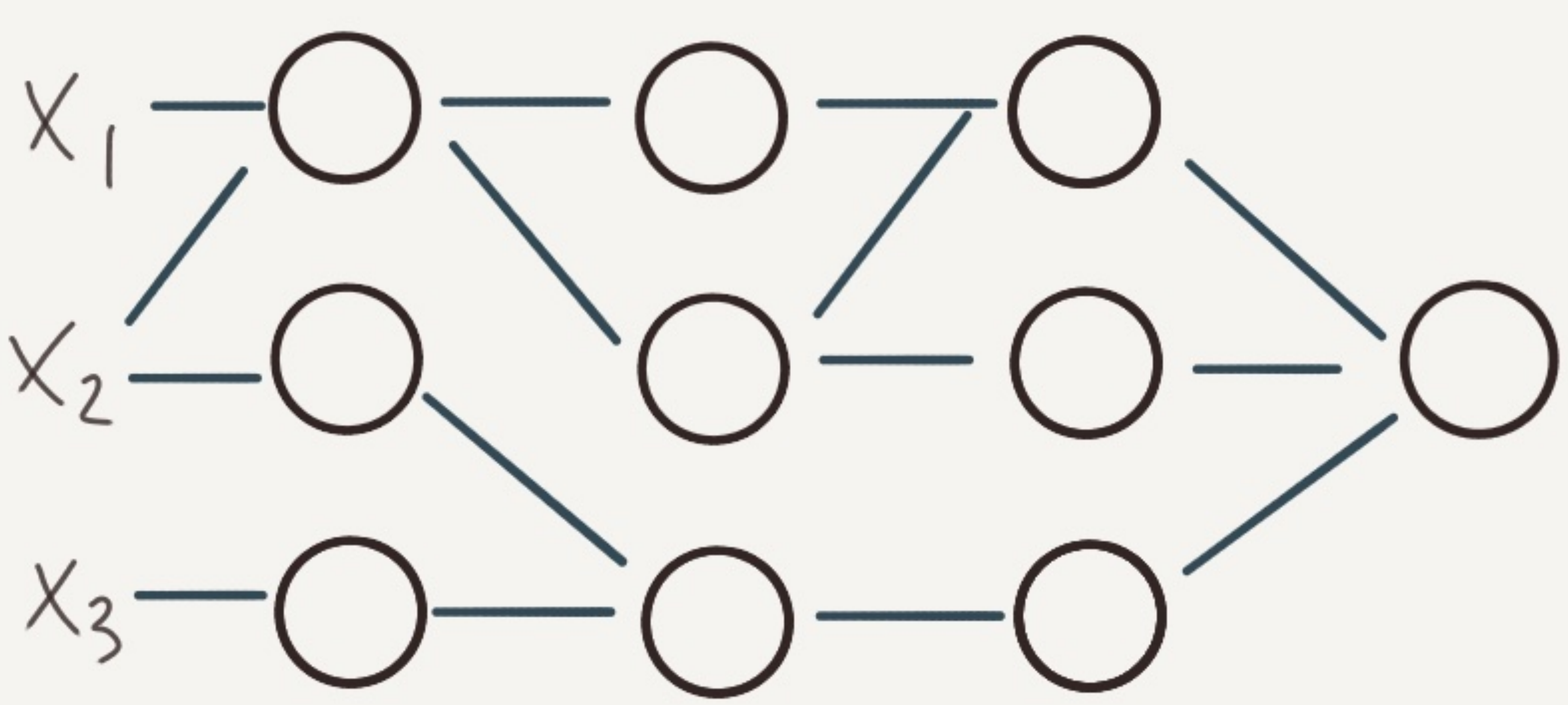
$$\text{COST}: J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y},y) + \frac{\lambda}{2m}\|w\|_2^2$$

EUCLIDEAN NORM

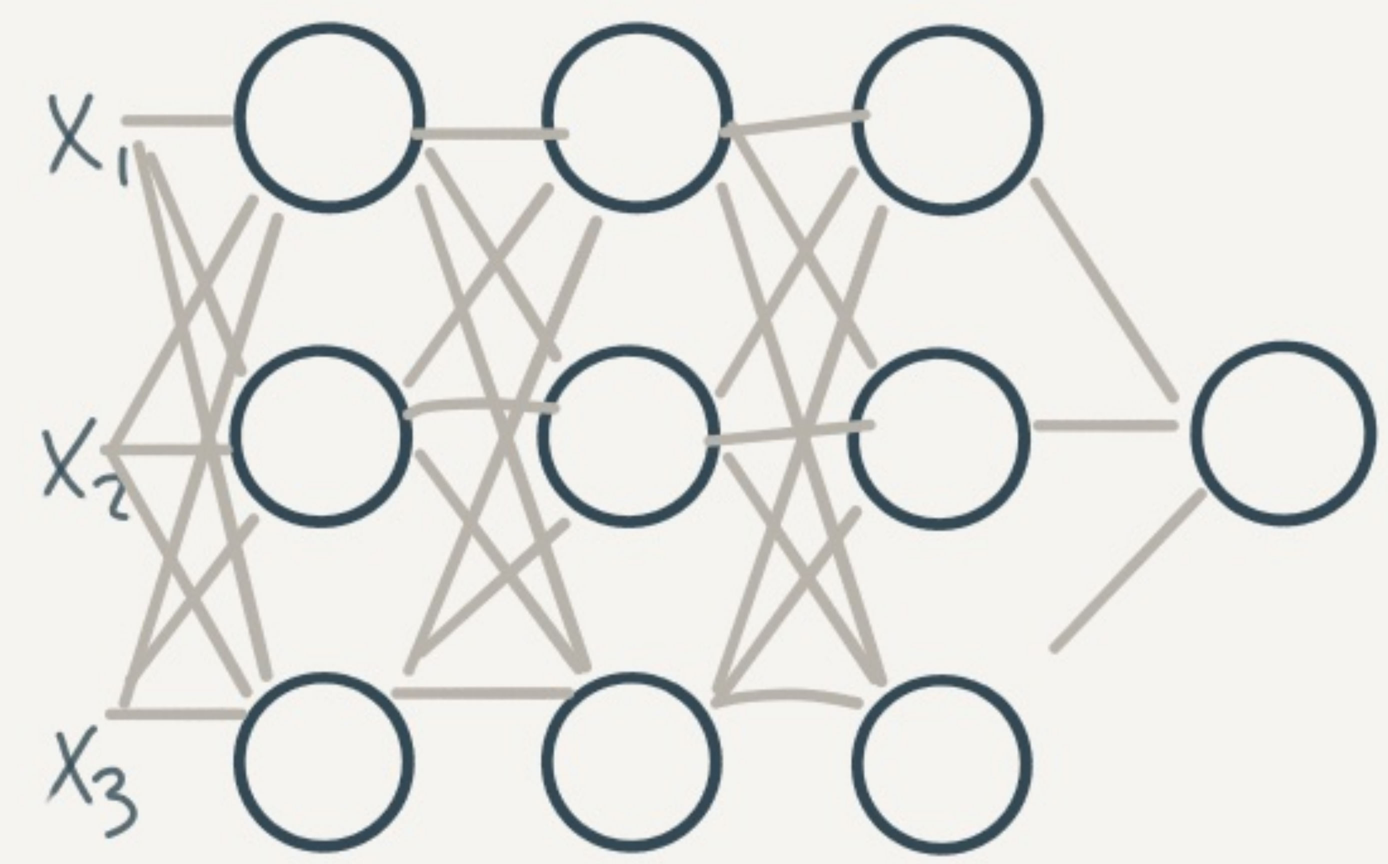
L1 REGULARIZATION

$$\text{COST}: J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y},y) + \frac{\lambda}{m}\|w\|_1$$

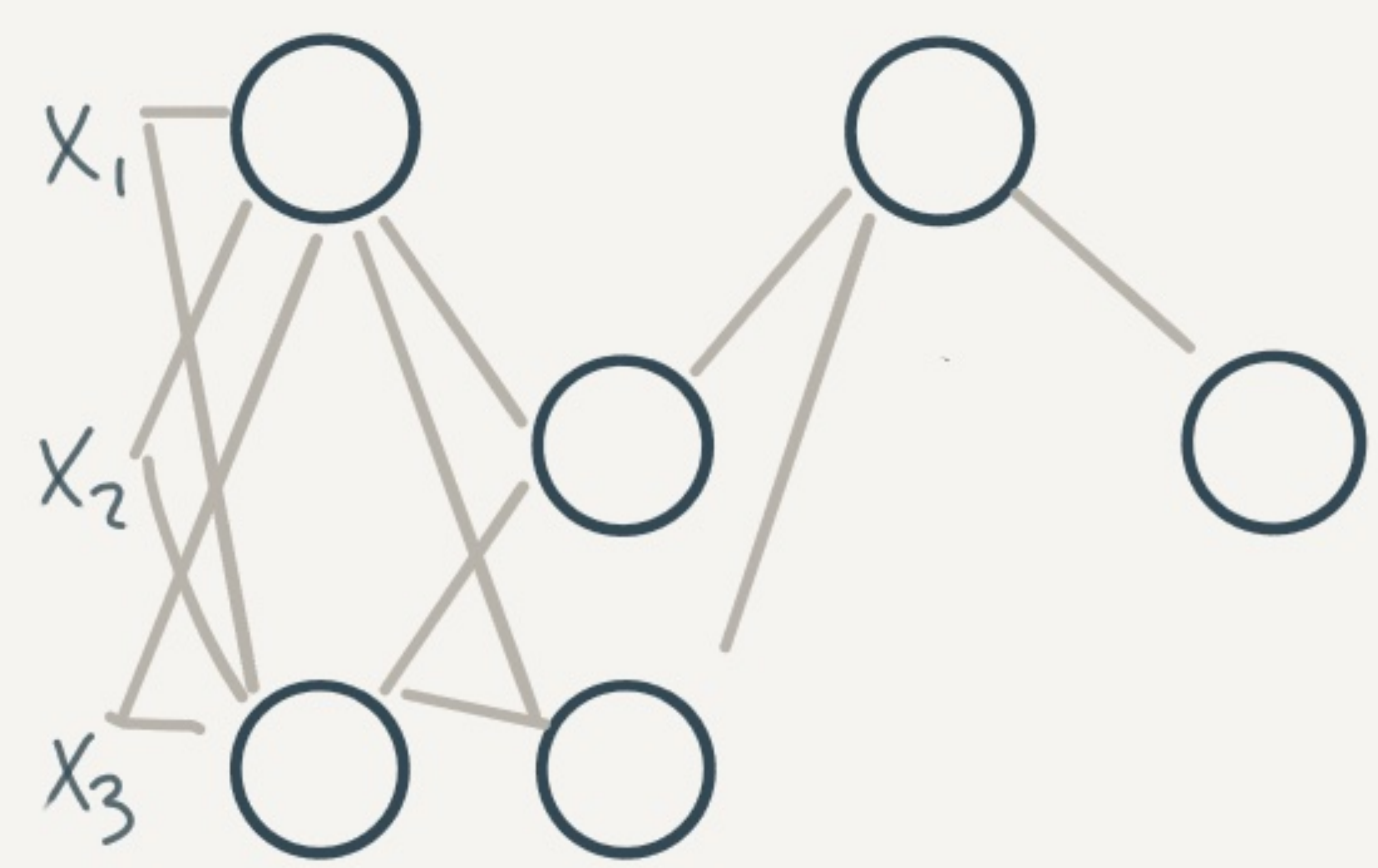
BOTH PENALIZE LARGE WEIGHTS ⇒ SOME WILL BE CLOSE TO Ø ⇒ SIMPLER NETWORKS



DROPOUT



FOR EACH ITERATION & SAMPLE SOME NODES ARE RANDOMLY DROPPED (BASED ON KEEP-PROB)

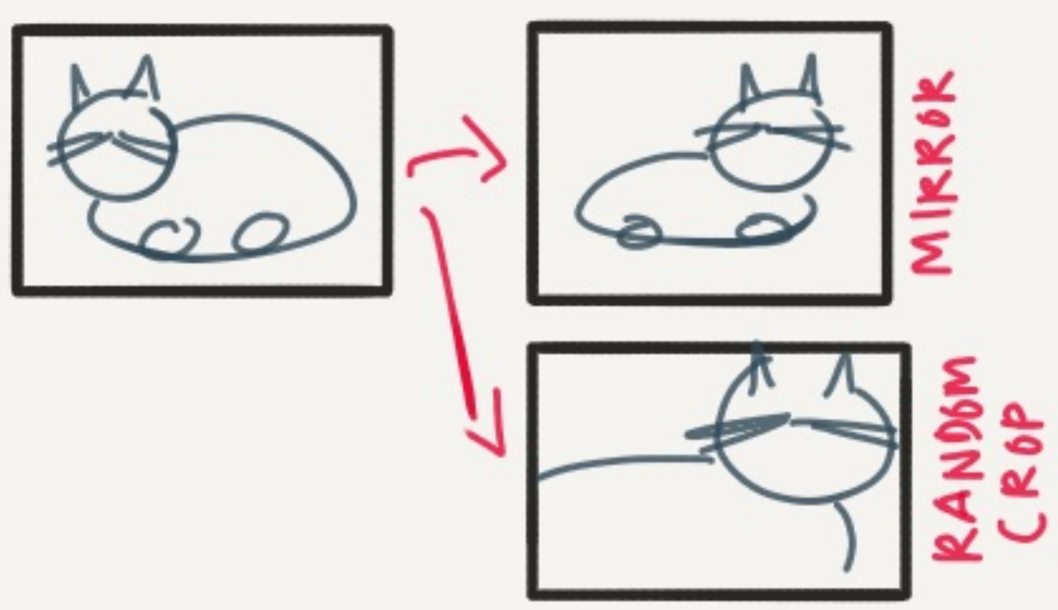


WE GET SIMPLER NWs & LESS CHANCE TO RELY ON SINGLE FEATURES

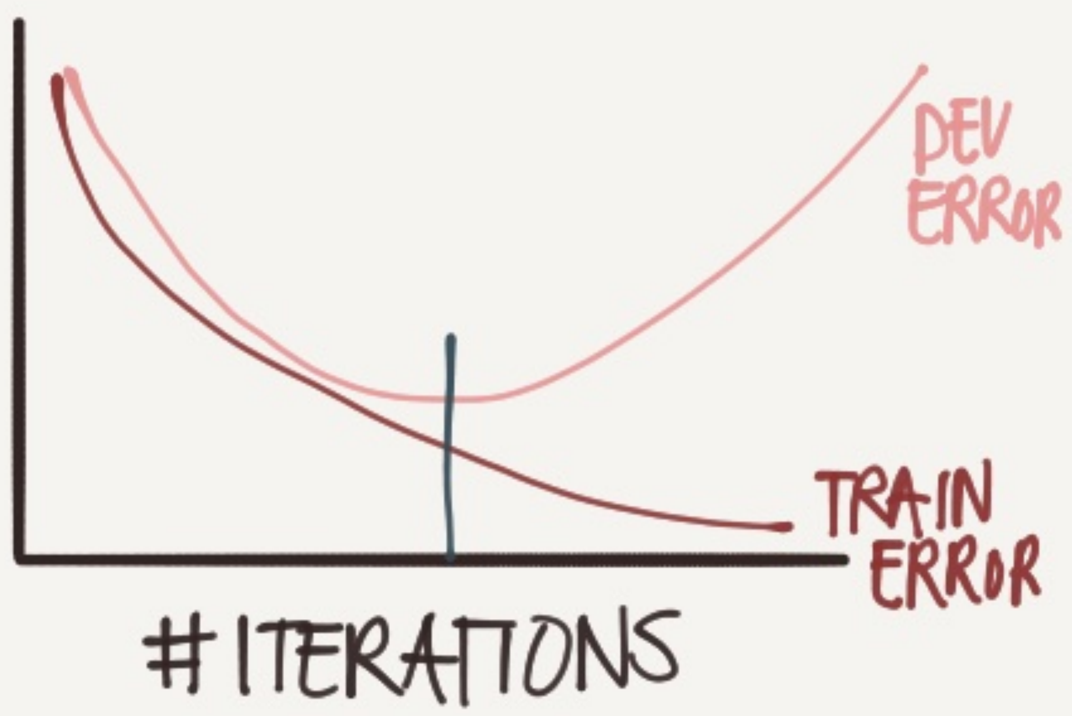
OTHER REGULARIZATION TECHNIQUES

DATA AUGMENTATION

GENERATE NEW PICS FROM EXISTING



EARLY STOPPING



PROBLEM: AFFECTS BOTH BIAS & VARIANCE

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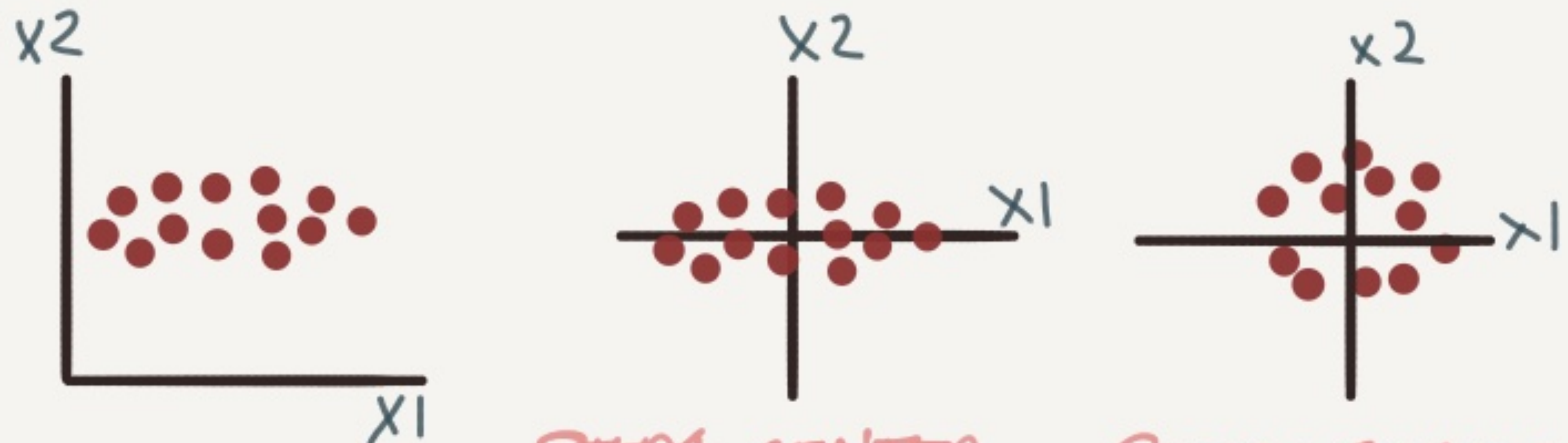
OPTIMIZING
TRAINING

NORMALIZING INPUTS



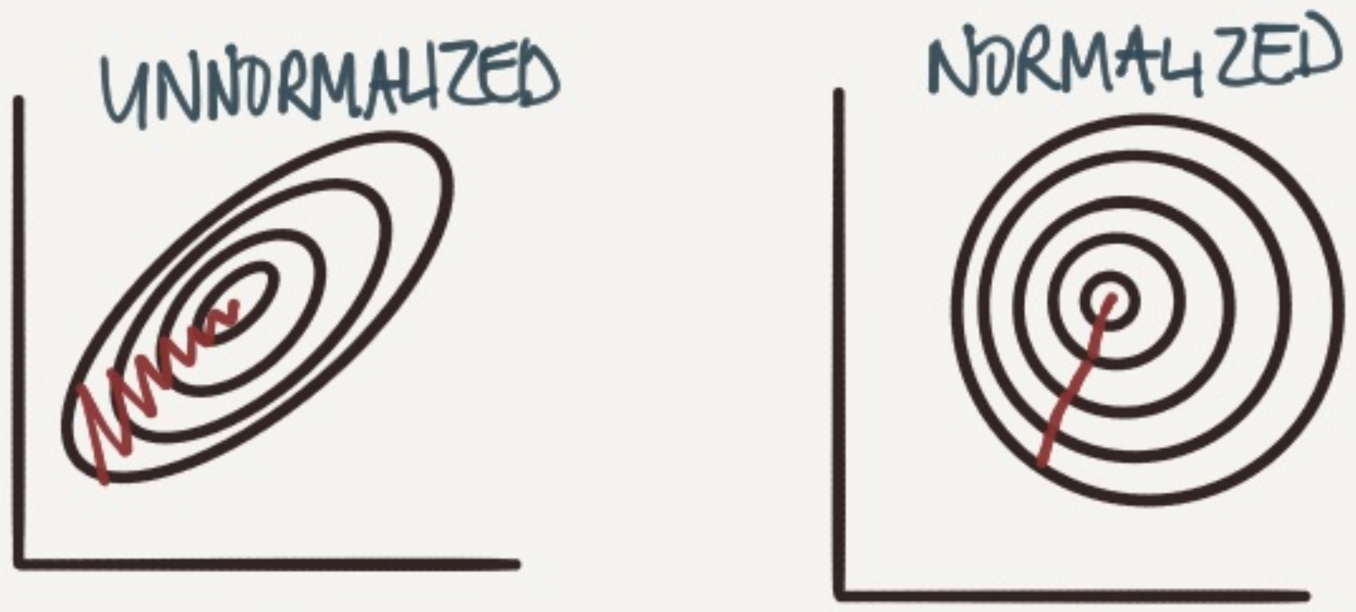
STEP1: CENTER AROUND 0,0

STEP2: SCALE SO VARIANCE IS SAME (X −1 → 1

TIP

USE SAME AVG/VAR TO NORMALIZE DEV/TEST

WHY DO WE DO THIS?



IF WE NORMALIZE, WE CAN USE A MUCH LARGER LEARNING RATE α

DEALING WITH VANISHING/EXPLODING GRADIENTS

EX: DEEP NW (L LAYERS)

$$\hat{y} = W^{[L-1]} W^{[L-2]} \cdots W^{[1]} x + b$$

IF $W = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \Rightarrow 0.5^{L-1} \Rightarrow$ VANISHING

OR $W = \begin{bmatrix} 1.5 & 0 \\ 0 & 1.5 \end{bmatrix} \Rightarrow 1.5^{L-1} \Rightarrow$ EXPLODING

IN BOTH CASES GRADIENT DESCENT TAKES A VERY LONG TIME

PARTIAL SOLUTION: CHOOSE INITIAL VALUES CAREFULLY

$w^{[l]} = \text{rand} * \sqrt{\frac{2}{n^{[l-1]}}}$ (FOR RELU)

#inputs

XAVIER $\sqrt{\frac{1}{n^{[l-1]}}}$ (FOR TANH)

SETS THE VARIANCE

GRADIENT CHECKING

IF YOUR COST DOES NOT DECREASE ON EACH ITER YOU MAY HAVE A BACKPROP BUG.

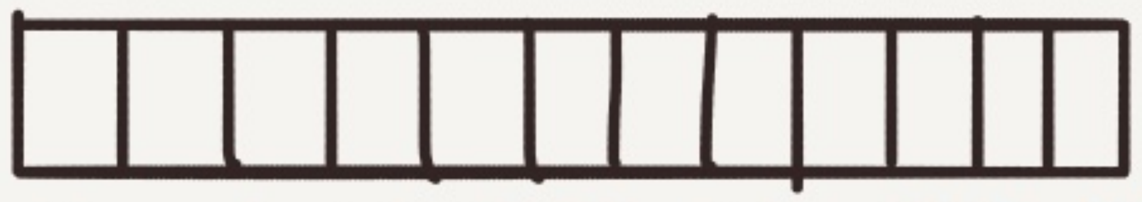
GRADIENT CHECKING APPROXIMATES THE GRADIENTS SO YOU CAN VERIFY CALC.

$\boxed{\text{NOTE}}$ ONLY USE WHEN DEBUGGING SINCE IT'S SLOW

IMPROVING DEEP NEURAL NETS · COURSERA

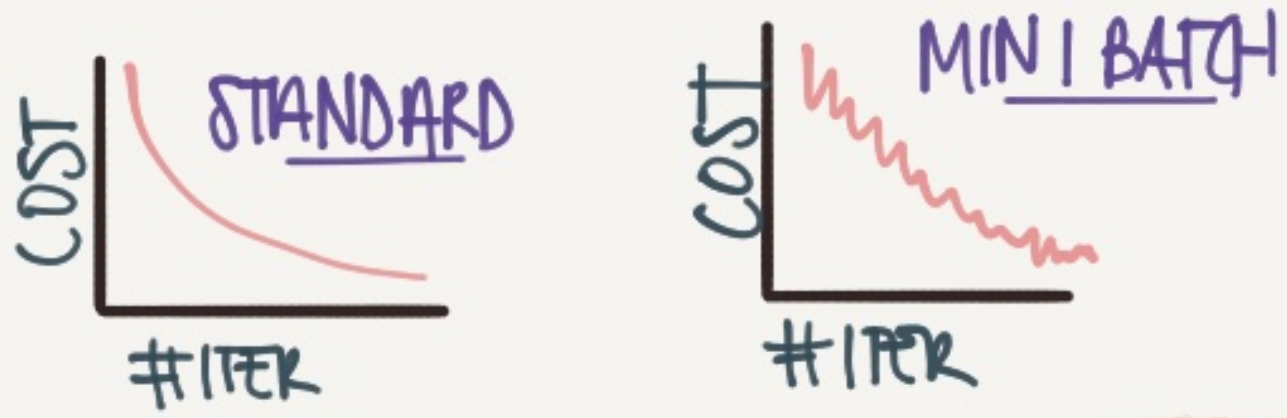
OPTIMIZATION ALGORITHMS

MINI-BATCH GRAD. DESCENT



SPLIT YOUR DATA INTO MINI-BATCHES & DO GRAD DESCENT AFTER EACH BATCH

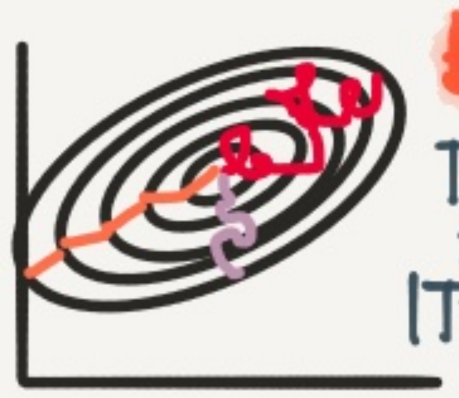
THIS WAY YOU CAN PROGRESS AFTER JUST A SHORT WHILE



CHOOSING THE MINIBATCH SIZE

SIZE = m → BATCH GRAD DESC.

SIZE = 1 → STOCHASTIC GRAD DESC



BATCH	MIDDLE	STOCHASTIC
TOO LONG PER ITERATION	-SHORT ITER. -USES VECT.	LOOSE ALMOST ALL SPEED FROM VECTORIZATION

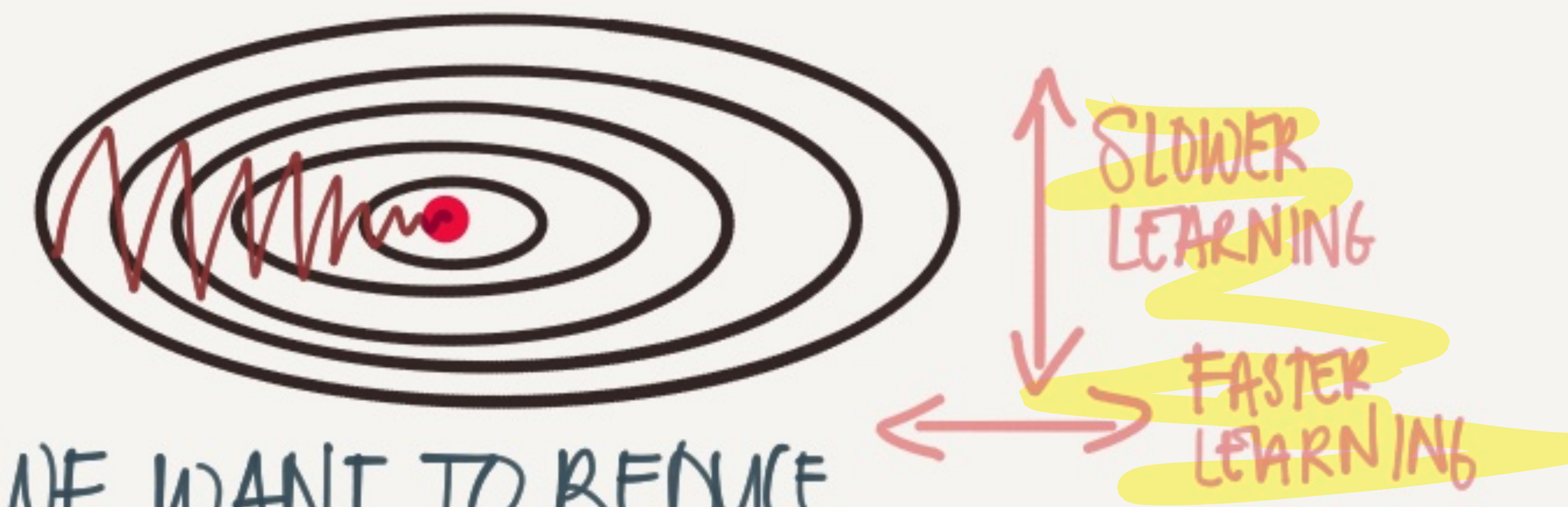
TIP

IF YOU HAVE < 2000 SAMPLES USE SIZE = 2000

OTHERWISE, USE 64, 128, 256...

SO X+Y FITS IN CPU/GPU CACHE

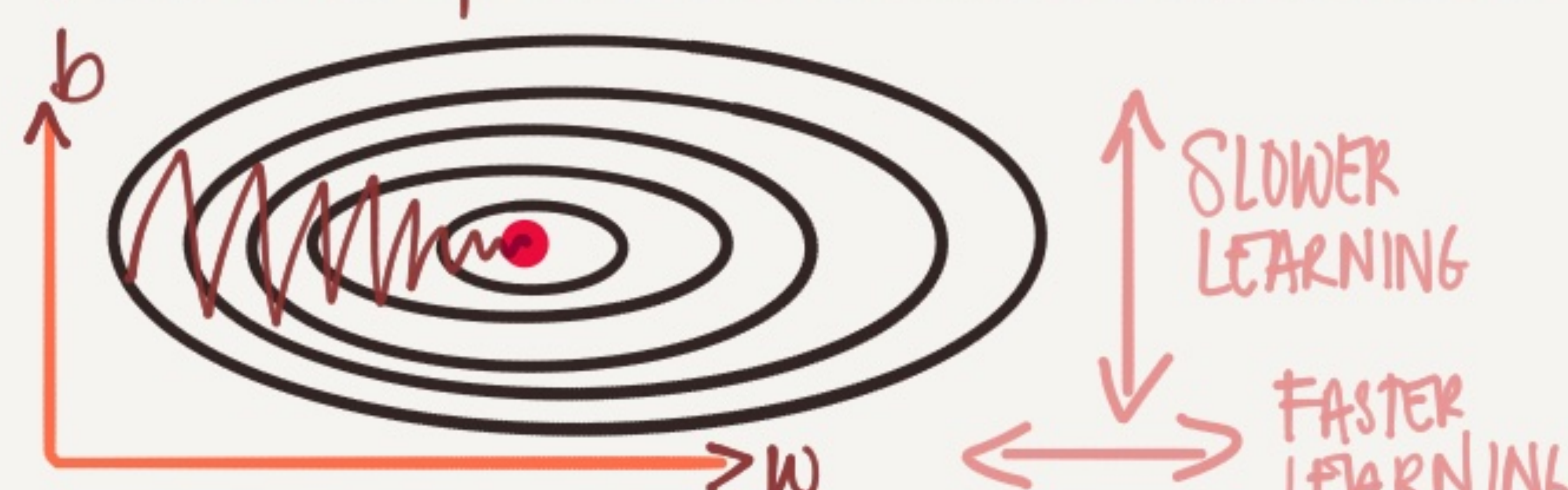
GRADIENT DESCENT W. MOMENTUM



WE WANT TO REDUCE OSCILLATION ↕ SO WE GET TO THE GOAL FASTER

SOLUTION: SMOOTH OUT THE CURVE BY TAKING AN EXPONENTIALLY WEIGHTED AVERAGE OF THE DERIVATIVES (i.e. LAST ONE HAS MORE IMPORTANCE)

RMSProp - ROOT MEAN SQUARED



NORMALIZE GRADIENT USING A MOVING AVG.

$S_{dw} = \beta S_{dw} + (1-\beta)\, dw^2$

$S_{db} = \beta S_{db} + (1-\beta)\, db^2$

$w = w - \alpha \frac{dw}{\sqrt{S_{dw}}}$ $\quad b = b - \alpha \frac{db}{\sqrt{S_{db}}}$

ADAM OPTIMIZATION

COMBO OF GD W MOMENTUM & RMSProp

LEARNING RATE DECAY

IDEA: USE A LARGE α IN THE BEGINNING. THEN DECREASE AS WE GET CLOSER TO GOAL

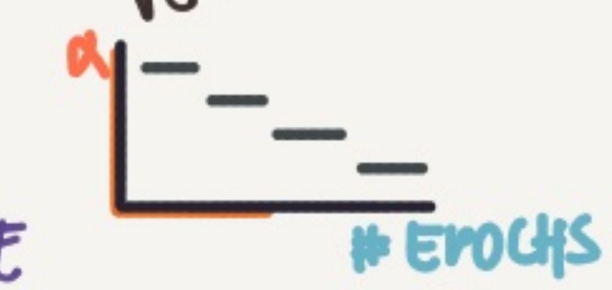
OPTION 1: $\alpha = \frac{1}{1 + \text{DECAYRATE} \cdot \text{EPOCH}} \alpha_0$

EXPONENTIAL: $\alpha = 0.95^{\text{EPOCH}} \cdot \alpha_0$

OPTION 3: $\alpha = \frac{k}{\sqrt{\text{EPOCH}}} \alpha_0$

OPTION 4: $\alpha = \frac{k}{\sqrt{t}} \alpha_0$

OPTION 5: DISCRETE STAIRCASE



OPTION 6: MANUAL

EPOCH = 1 PASS THROUGH THE DATA

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HYPERPARAM TUNING

WHICH HYPERPARAMS ARE MOST IMPORTANT?

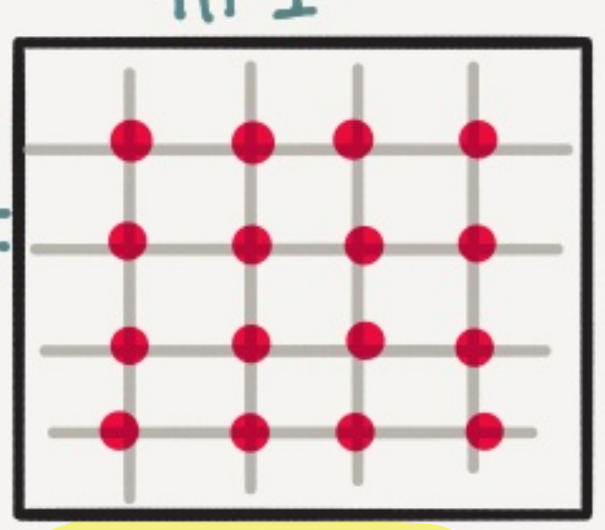
- α LEARNING RATE
- # HIDDEN UNITS
- MINIBATCH SIZE
- β MOMENTUM TURN = 0.9
- # LAYERS
- LEARNING RATE DECAY
- $\beta_1 = 0.9$ $\beta_2 = 0.999$ $\varepsilon = 10^{-8}$ (ADAM)

TESTING VALUES

CLASSIC ML

HP1

HP2

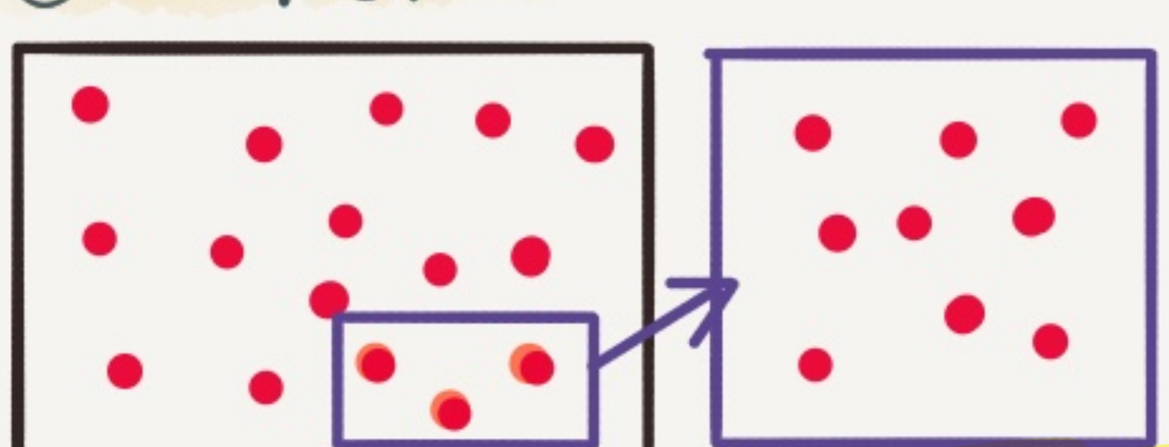


GRID SEARCH

PROBLEM: ONE ITERATION TAKES A LONG TIME & IN 16 GO'S WE HAVE ONLY TRIED 4 α - BUT 4 DIFF ε

NOT AS IMPORTANT

SOLUTION



RANDOM SEARCH + COARSE → DENSE

USE AN APPROPRIATE SCALE

HIDDEN UNITS

50 60 70 80 90 100

UNIFORMLY RANDOM

α LEARNING RATE

0.0001 0.001 0.01 0.1 1

$r = -4 \cdot \text{rand}\ [-4, 0]$

$\alpha = 10^r$

β EXP WEIGHT AVE

0.9 0.99 0.999

$r = -3 \cdot \text{rand}\ [-3, -1]$

$\beta = (1 - 10^r)$

TIP

RE-EVALUATE YOUR HYP. PARAMS EVERY FEW MONTHS

PANDA vs CAVIAR

MY PANDA IS ACTUALLY A MISCLASSIFIED CAT BECAUSE I CAN'T DRAW PANDAS

BABYSIT ONE MODEL & TUNE

GOOD IF YOU HAVE LOTS OF SPARE COMP POWER

SPAWN LOTS OF MODELS W DIFF HP

MISC. EXTRAS

BATCH NORMALIZATION

NORMALIZE LAYER OUTPUT

- SPEEDS UP TRAINING
- MAKES WEIGHTS DEEPER IN NW MORE ROBUST (COVARIATE SHIFT)
- SLIGHT REGULARIZING EFFECT

MULTICLASS CLASSIFIC.

CAT FISH BABY CHICK OTHER

C = # CLASSES = 4

SOFTMAX ACTIVATION

$t = e^{(z^{[L]})}$

$a^{[L]} = \frac{t}{\sum t_i}$

- p(OTHER | X)
- p(CAT | X)
- p(FISH | X)
- p(BC | X)

SUM: 1

EX: $z^{[L]} = \begin{bmatrix} 5 \\ 2 \\ -1 \\ 3 \end{bmatrix}$ $t = \begin{bmatrix} e^5 \\ e^2 \\ e^{-1} \\ e^3 \end{bmatrix} = \begin{bmatrix} 148.4 \\ 7.4 \\ 0.4 \\ 20.1 \end{bmatrix}$

176.3

$\Rightarrow a^{[L]} = \frac{t}{176.3} = \begin{bmatrix} 0.842 \\ 0.042 \\ 0.02 \\ 0.114 \end{bmatrix}$

11.4% PROB IT'S A BABY CHICK

IMPROVING DEEP NEURAL NETS · COURSERA

STRUCTURING
YOUR ML PROJECTS

SETTING YOUR GOAL

★ GOAL SHOULD BE A SINGLE #

	PRECISION	RECALL
A	95%	90%
B	98%	85%

IS A OR B BEST?

	PRECISION	RECALL	F1
A	95%	90%	92.4%
B	98%	85%	91%

A IS BEST

F1 = HARMONIC MEAN BETW. RECALL & PRECISION

★ DEFINE OPTIMIZING VS SATISFICING METRICS

	ACCURACY	RUNTIME
A	90%	80ms
B	92%	95ms
C	~~95%~~	~~1500 ms~~

MAXIMIZE ACC. GIVEN TIME ≤ 100ms

ACCURACY = OPTIMIZING

RUNTIME = SATISFICING

SELECTING YOUR DEV/TEST SETS

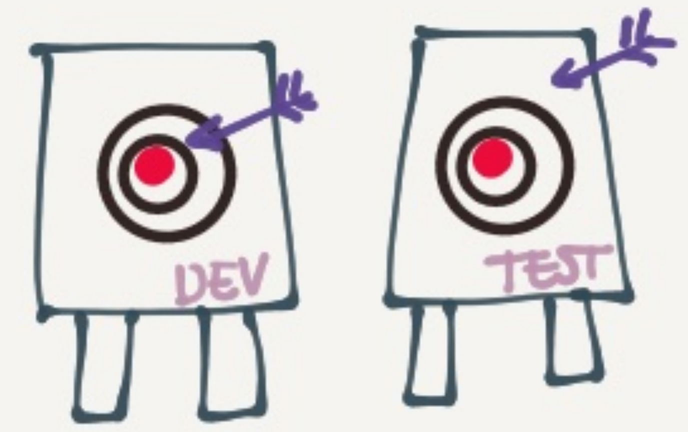
DATA

- US
- UK
- EUROPE
- S.AM
- INDIA
- CHINA
- AUST.

OPTION 1:

DEV = UK, US, EUR

TEST = REST



IF DEV & TEST ARE DIFF & WE OPTIMIZE FOR DEV WE WILL MISS THE TEST TARGET

HUMAN LEVEL PERF

WHY DOES ACC SLOW DOWN WHEN WE SURPASS HUMAN LEVEL PERF?

MEDICAL IMG CLASS

TYPICAL HUMAN	3%
TYPICAL DOCTOR	1%
EXPERIENCED DR.	0.7%
TEAM OF EXP DRs.	0.5%

HUMAN LEV PERF (PROXY FOR BAYES)

1. OFTEN CLOSE TO BAYES
2. A HUMAN CAN NO LONGER HELP IMPROVE (INSIGHTS)
3. DIFFICULT TO ANALYSE BIAS/VARIANCE

CAT CLASSIFICATION

	A	B
HUMAN	1%	7.5%
TRAIN ERR	8%	8%
DEV ERR	10%	10%
	FOCUS ON BIAS	FOCUS ON VARIANCE

BLURRY

AVOIDABLE BIAS

VARIANCE

HUMAN

AVOIDABLE BIAS

- TRAIN BIGGER NETW.
- TRAIN LONGER / BETTER OPT. ALGOS (RMSProp ADAM)
- CHANGE NN ARCH OR HYPERPARAMS

TRAIN

VARIANCE

- MORE DATA (TRAIN)
- REGULARIZATION
- NN ARCHITECTURE

DEV

	A	B
HUMAN	0.5	0.5
TRAIN ERR	0.6	0.3
DEV ERR	0.8	0.4
AVOID. BIAS	0.1	?

AVOIDABLE BIAS

VARIANCE

DON'T KNOW IF WE OVERFIT OR IF WE'RE CLOSE TO BAYES

OPTIONS TO PROCEED ARE UNCLEAR

ERROR
ANALYSIS

YOU HAVE 10% ERRORS, SOME ARE DOGS MIS-CLASSIFIED AS CATS. SHOULD YOU TRAIN ON MORE DOG PICS?

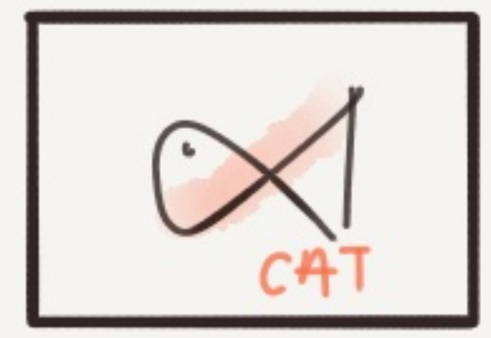
1. PICK 100 MIS-LABLED
2. COUNT ERROR REASONS

	DOG	BLURRY	INSTA FILTER	BIG CAT	...
1	1		1		
2				1	
3		1			
...					
100			1		
	5	...			

5% OF ALL ERRORS

FOCUSING ON DOGS. THE BEST WE CAN HOPE FOR IS 9.5% ERROR

YOU FIND SOME INCORR. LABLED DATA IN THE DEV SET. SHOULD YOU FIX IT?



DL ALGORITHMS ARE PRETTY ROBUST TO RANDOM ERRORS. BUT NOT TO SYSTEMATIC ERR.

(EX. ALL WHITE CATS INCORR LABLED AS MICE)

ADD EXTRA COL. IN ERROR ANALYSIS AND USE SAME CRITERIA

NOTE IF YOU FIX DEV YOU SHOULD FIX TEST AS WELL.

FOR NEW PROJ: BUILD 1st SYSTEM QUICK & ITERATE

EX: SPEECH RECOGNITION

WHAT SHOULD YOU FOCUS ON?

NOISE
ACCENTS
FAR FROM MIKE

1. START QUICKLY
   DEV/TEST METRICS
2. GET TRAIN-SET
3. TRAIN
4. BIAS/VARIANCE ANAL
5. ERROR ANALYSIS
6. PRIORITIZE NEXT STEP

TRAIN vs DEV/TEST
MISMATCH

AVAILABLE DATA

200 k PRO CAT PICS FROM INTERNET

10 k BLURRY CAT PICS FROM APP $\boxed{\text{WHAT WE CARE ABT}}$

HOW DO WE SPLIT → TRAIN/DEV/TEST?

OPTION 1: SHUFFLE ALL

205 k (TRAIN)	D	T

2.5 k

PROBLEM: DEV/TEST IS NOW MOSTLY WEB IMG (NOT REPRES. OF END SCENARIO)

SOLUTION: LET DEV/TEST COME FROM APP · THEN SHUFFLE 5k OF APP PICS w WEB FOR TRAIN

205 k	2.5	2.5
WEB + APP	APP	APP

BIAS & VARIANCE w MISMATCHED TRAIN/DEV

HUMANS ~0%
TRAIN 1%
DEV ERR 10%

IS THIS DIFF DUE TO THE MODEL NOT GENERALIZING OR IS DEV DATA MUCH HARDER

A: CREATE A TRAIN-DEV SET THAT WE DON'T TRAIN ON

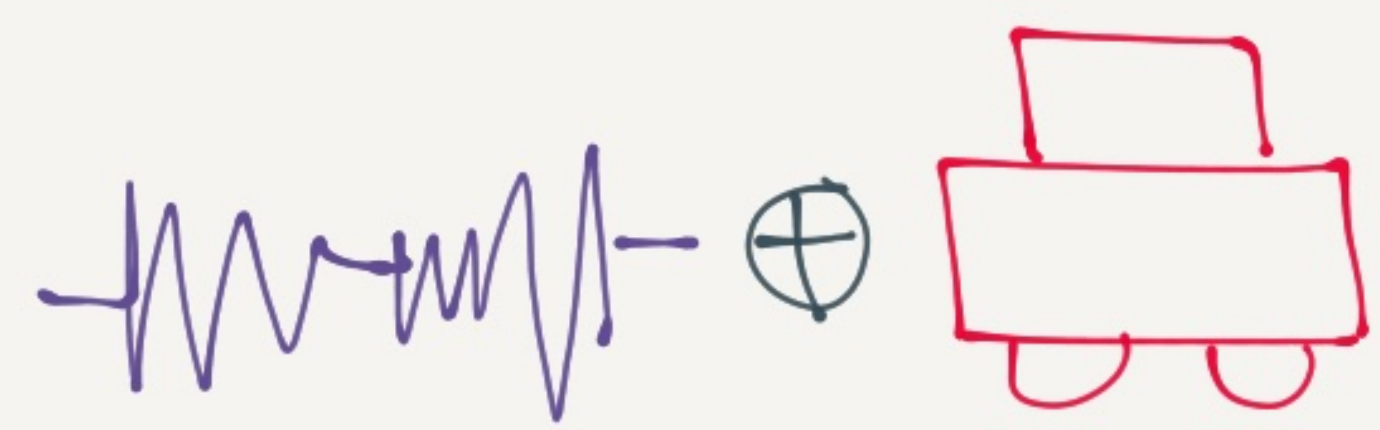
TRAIN	TD	D	T

	A	B	C	D
TRAIN	1%	1%	10%	10%
TRAIN-DEV	9%	1.5%	11%	11%
DEV	10%	10%	12%	20%
	VARIANCE	TRAIN/DEV MISMATCH	BIAS	BIAS + DATA MISMATCH

ADDRESSING DATA MISMATCH

EX. CAR GPS · TRAINING DATA IS 10.000H OF GENERAL SPEECH DATA

1. CARRY OUT MANUAL ERROR ANALYSIS TO UNDERSTAND THE DIFFERENCE (EX NOISE, STREET NUMBERS)
2. TRY TO MAKE TRAIN MORE SIMILAR TO DEV OR GATHER MORE DEV-LIKE TRAIN-DATA



⇒ AUDIO W CAR NOISE

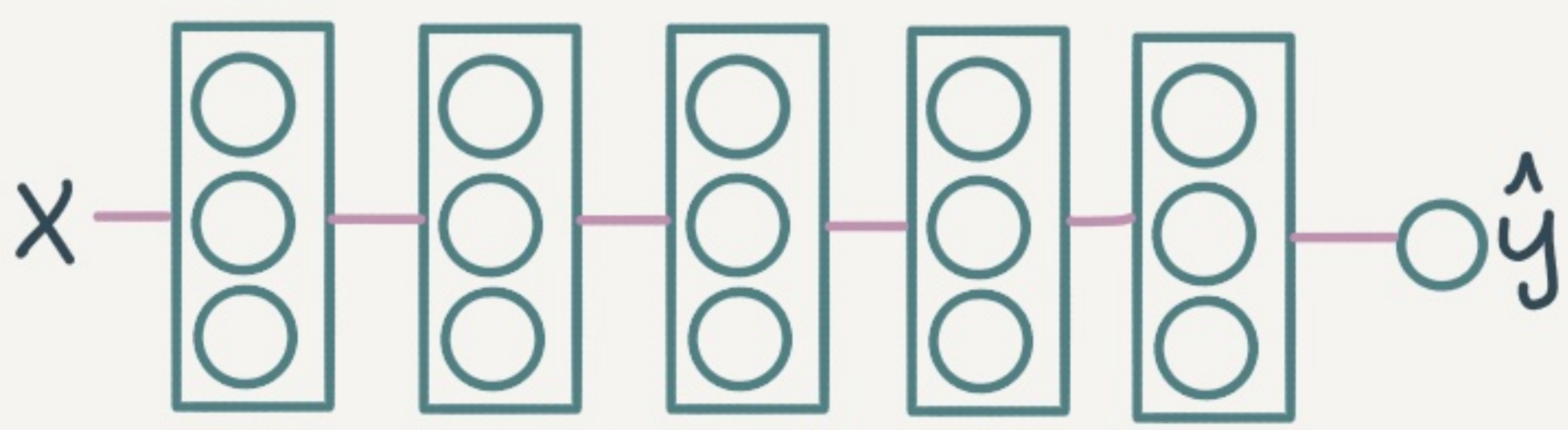
NOTE BE CAREFUL · IF YOU ONLY HAVE 1 HR OF CAR NOISE & APPLY IT TO 10K HR SPEECH YOU MAY OVERFIT TO THE CAR NOISE

STRUCTURING ML PROJECTS · COURSERA

EXTENDED LEARNING

TRANSFER LEARNING

PROBLEM: YOU WANT TO CLASSIFY SOME MEDICAL IMG. YOU HAVE AN NN THAT CLASSIFIES CATS



NN TO CLASSIFY CATS/DOGS/CARS

OPTION 1: YOU ONLY HAVE A FEW RADIOLOGY IMAGES

SOLUTION: INIT W. WEIGHTS FROM CAT NN
ONLY RETRAIN LAST LAYER(S) ON RADIOLOGY IMAGES

OPTION 2: YOU HAVE LOTS OF RADIOLOGY IMG.

SOLUTION: INIT WITH WEIGHTS FROM CAT NN
RETRAIN ALL LAYERS

TESS NOTES

THIS IS MICROSOFT CUSTOM VISION

MULTI TASK LEARNING

TRAINING ON MULT. TASKS AT ONCE

DETECT — $\hat{y}$
- CAR — 1
- STOP SIGN — 1
- PEDESTR. — 1
- TRAFFIC LIGHT — 0

UNLIKE SOFMAX • MANY THINGS CAN BE TRUE

$$\text{COST: } J(w,b) = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{4}\mathcal{L}(\hat{y}_j^{(i)}, y_j^{(i)})$$

SUMMING OVER ALL OUTP OPTIONS

WE COULD HAVE JUST TRAINED 4 NNS INSTEAD BUT... MT LEARNING MAKES SENSE WHEN

A. THE LEARNING DATA YOU HAVE FOR THE DIFF TASKS IS QUITE SIMILAR – & THE AMOUNTS (EG. 1K CARS, 1K STOP SIGNS)

B. THE SUM OF THE DATA ALLOWS YOU TO TRAIN A BIG ENOUGH NN TO DO WELL ON ALL TASKS

IN REALITY TRANSFER LEARNING IS USED MORE OFTEN

END-TO-END LEARNING

FROM X-RAY OF CHILDS HAND TELL ME THE AGE OF THE CHILD

TYPICAL SOLN:
1. LOCATE BONES TO FIND LENGTHS USING ML
2. TRAIN MODEL TO PREDICT AGE BASED ON BONE LENGTH

END-TO-END

RADIOLOGY IMG → CHILD AGE

PROS:
- LET'S THE DATA SPEAK (MAYBE IT FINDS RELATIONS WE'RE UNAWARE OF)
- LESS HAND-DESIGNING OF COMPONENTS NEEDED

CONS:
- NEEDS LARGE AMTS OF LABLED DATA (X→Y)
- EXCLUDES POTENTIALLY USEFUL HAND-MADE COMPONENTS

STRUCTURING ML PROJECTS • COURSERA

CONVOLUTION
FUNDAMENTALS

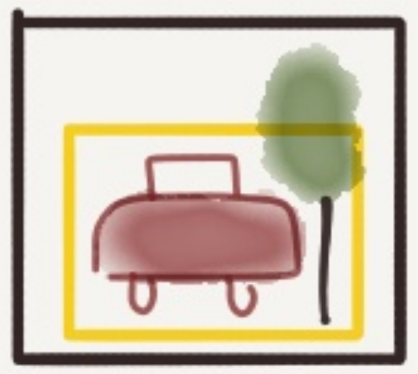
CONVOLUTIONAL NEURAL NETS · COURSERA

COMPUTER VISION

IMAGE CLASSIFICATION

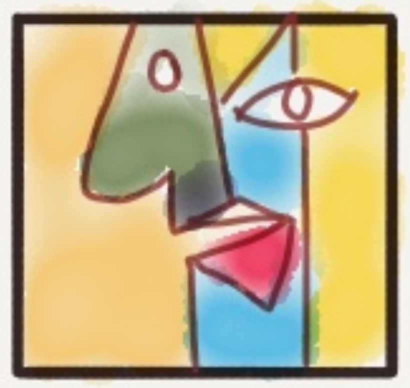
CAT OR NOT·CAT

OBJECT DETECTION



WHERE IS THE CAR?

NEURAL STYLE TRANSFER



PAINT ME LIKE PICASSO

PROBLEM: IMAGES CAN BE BIG

1000 x 1000 x 3 (RGB) = 3M

WITH 1000 HIDDEN UNITS WE NEED 3M * 1000 = 3B PARAMS

SOLUTION: USE CONVOLUTIONS

IT'S LIKE SCANNING OVER YOUR IMG WITH A MAGNIFYING GLASS OR FILTER

TESS NOTE

ALSO SOLVES THE PROBLEM THAT THE CAT IS NOT ALWAYS IN THE SAME LOCATION IN THE IMG

CONVOLUTION

3+1+2+0+0+0-1-8-2 = -5

(3*1)

3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

INPUT 6·6 IMAGE

*

CONVOLUTION

1	0	-1
1	0	-1
1	0	-1

FILTER 3·3

=

-5	-4	0	8
-16	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

OUTPUT 4·4 IMAGE

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

INPUT 6·6 IMAGE

*

VERTICAL EDGE DETECTOR

1	0	-1
1	0	-1
1	0	-1

FILTER 3·3

=

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

OUTPUT 4·4 IMAGE

DETECTED EDGE IN THE MIDDLE

THIS IS LIKE ADDING AN 'INSTA' FILTER THAT JUST SHOWS OUTLINES

WE COULD HARD·CODE FILTERS · JUST LIKE WE CAN HARD·CODE HEURISTIC RULES .... BUT.... A MUCH BETTER WAY IS TO TREAT THE FILTER # AS PARAMS TO BE LEARNED

W_1	W_2	W_3
W_4	W_5	W_6
W_7	W_8	W_9

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PADDING

PROBLEM: IMAGES SHRINK
6x6 → 3x3 → 4x4
PROBLEM: EDGES GET LESS 'LOVE'

SOLUTION: PAD W. A BORDER OF ØS BEFORE CONVOLVING

0	0	0	0	0	0	0	0
0	3	0	1	2	7	4	0
0	1	5	8	9	3	1	0
0	2	7	2	5	1	3	0
0	0	1	3	1	7	8	0
0	4	2	1	6	2	8	0
0	2	4	5	2	3	9	0
0	0	0	0	0	0	0	0

TWO COMMONLY USED PADDING OPTIONS
(HOW MUCH TO PAD)

'VALID' ⇒ $P = 0$ NO PADDING

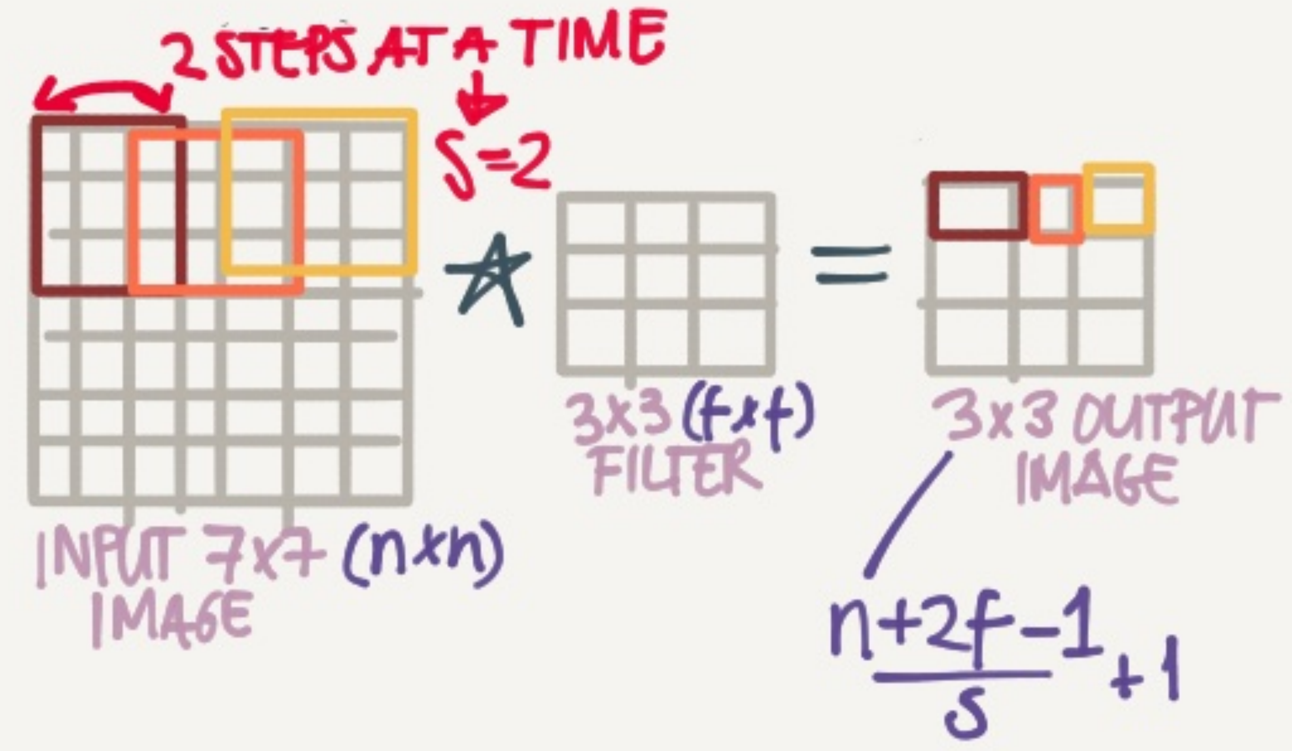
'SAME' ⇒ $P = \frac{f-1}{2}$ OUTPUT SIZE = INPUT SIZE

FILTER SIZE

NOTE: ALL CONVOLUTION IDEAS CAN BE APPLIED TO 1D AS WELL LIKE EKG SIGNALS · AND 3D LIKE CT-SCANS

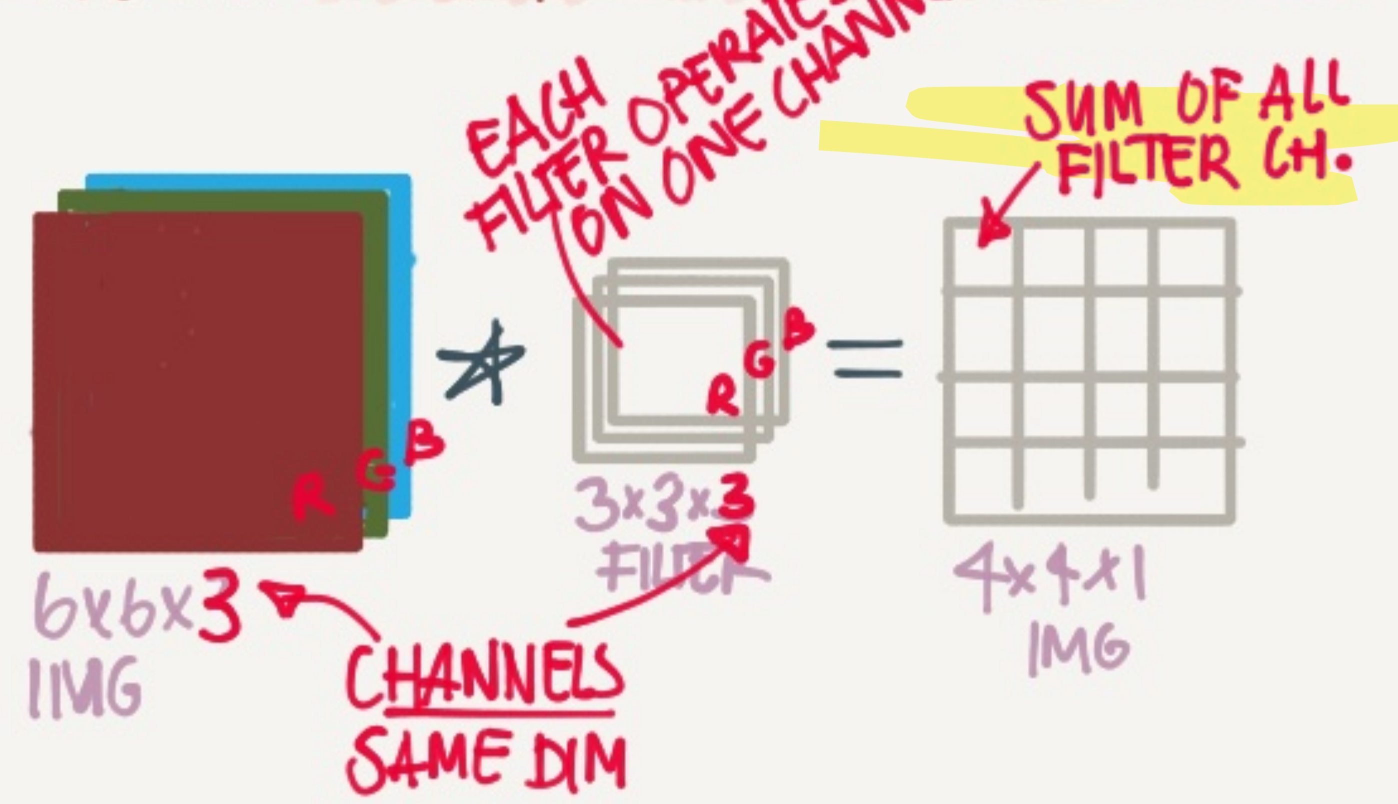
STRIDE

WHAT PACE YOU SCAN WITH



$\frac{n+2f-1}{s}+1$

CONVOLUTIONS OVER VOLUMES

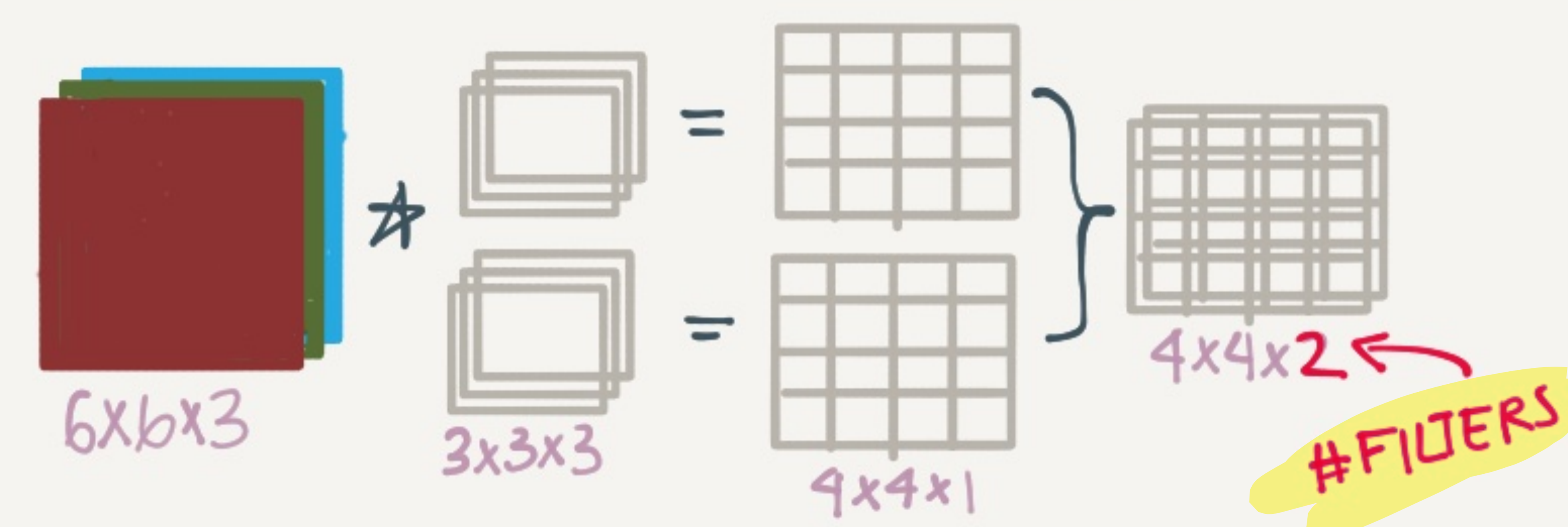


THIS ALLOWS US TO DETECT FEATURES IN COLOR IMAGES FOR EXAMPLE

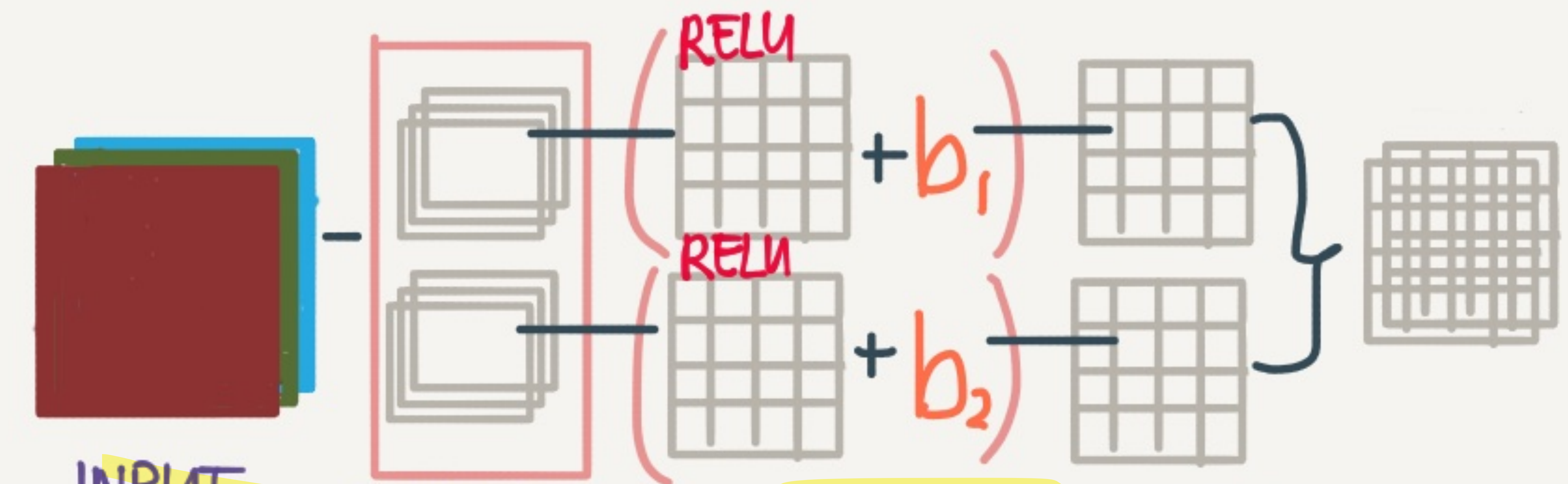
MAYBE WE WANT TO FIND ALL EDGES OR MAYBE ORANGE BLOBS

MULTIPLE FILTERS

DETECTING MULTIPLE FEATURES AT A TIME



ONE CONV. NET LAYER



INPUT $a^{[0]}$ FILTERS $W^{[1]}$ $g(z^{[1]}) \rightarrow a^{[1]}$

NOTE IT DOESN'T MATTER HOW BIG THE INPUT IS – THE LEARNABLE PARAMS W & b ONLY DEPEND ON THE # OF FILTERS AND THEIR SIZES.

$\left.\begin{array}{l} W = 3\cdot3\cdot3\cdot2 = 54 \\ b = 2 \end{array}\right\}$ 56 PARAMS TO LEARN

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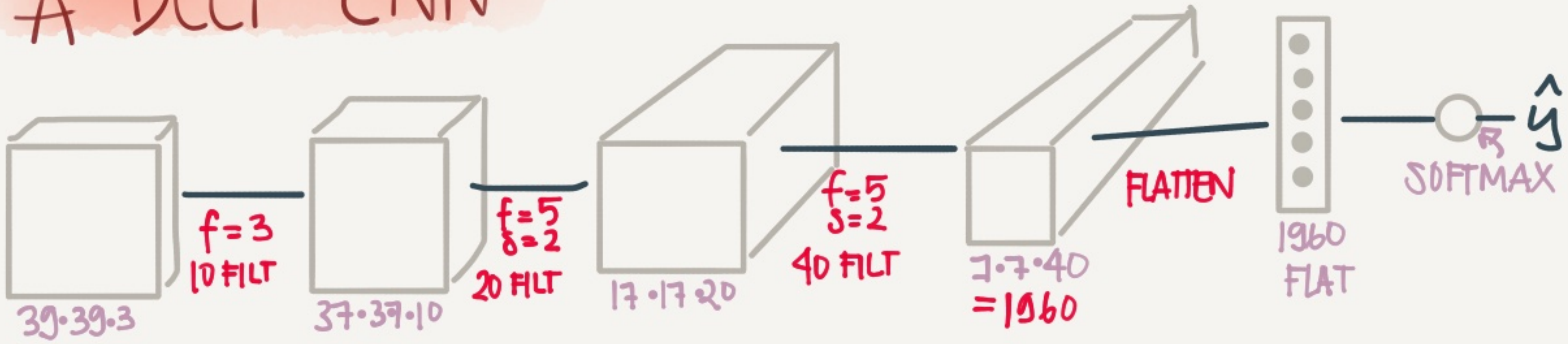
A DEEP CNN



A LOT OF THE WORK IS FIGURING OUT HYPERPARAMS
= #FILTERS, STRIDE, PADDING ETC

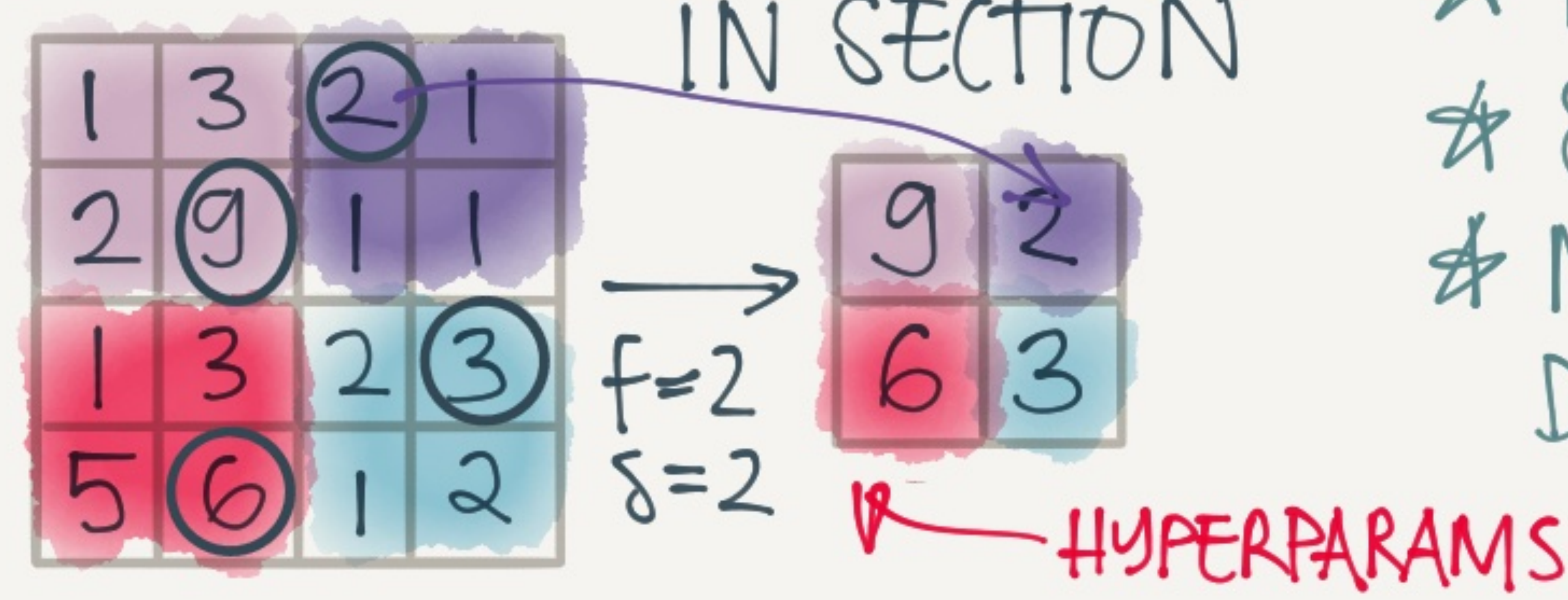
TYPICALLY SIZE → TREND DOWN
\# FILTERS → TREND UP

TYPICAL CONV.NET LAYERS

CONVOLUTION
POOLING
FULLY CONNECTED

POOLING (MAX)

FIND MAX VAL IN SECTION

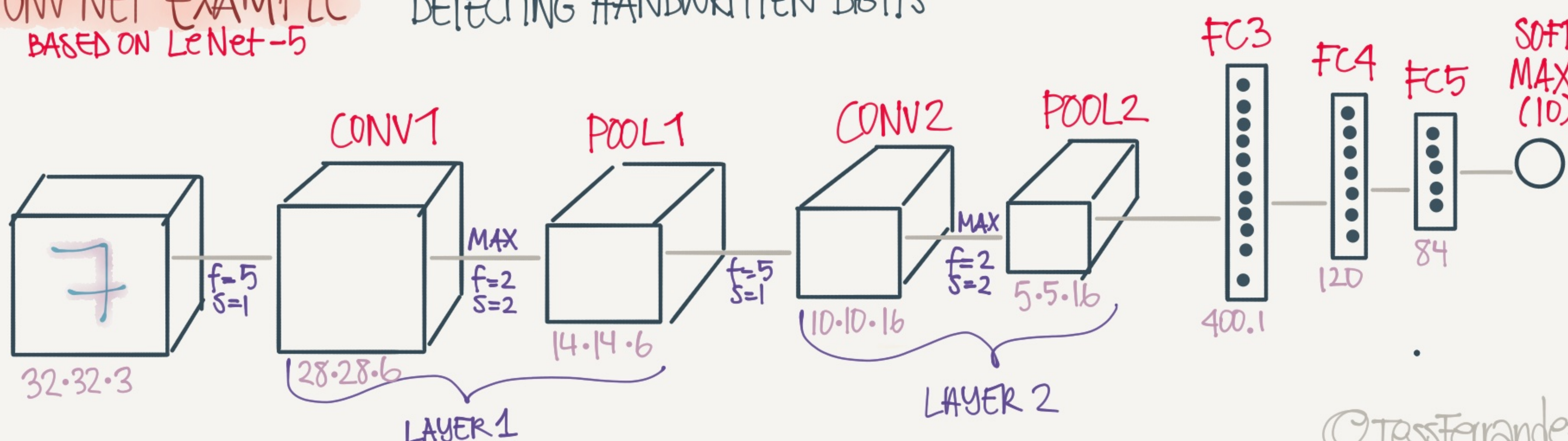


- ☆ REDUCES SIZE OF REPRES.
- ☆ SPEEDS UP COMPUTATION
- ☆ MAKES SOME OF THE DETECTED FEAT. MORE ROBUST

CONV NET EXAMPLE

BASED ON LeNet-5

DETECTING HANDWRITTEN DIGITS



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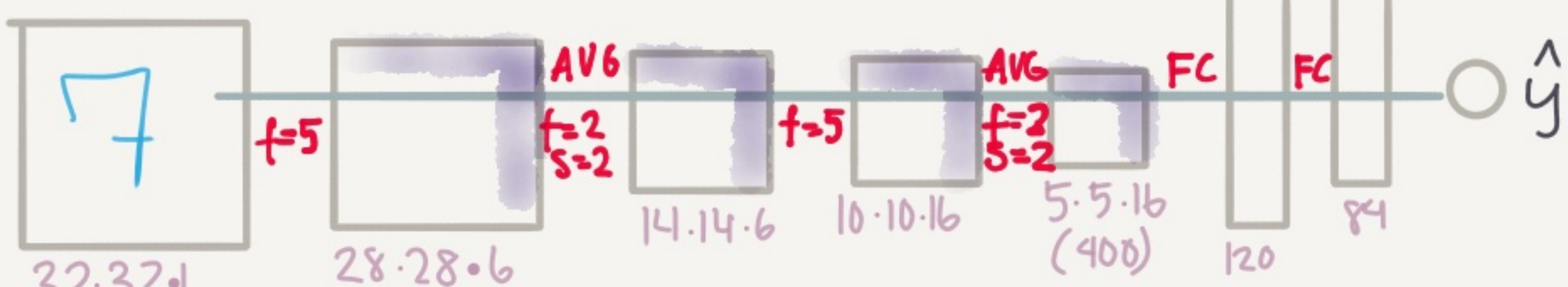
CLASSIC
CONV. NETS

LeNet-5

DOCUMENT CLASSIFICATION ≈60K PARAMETERS



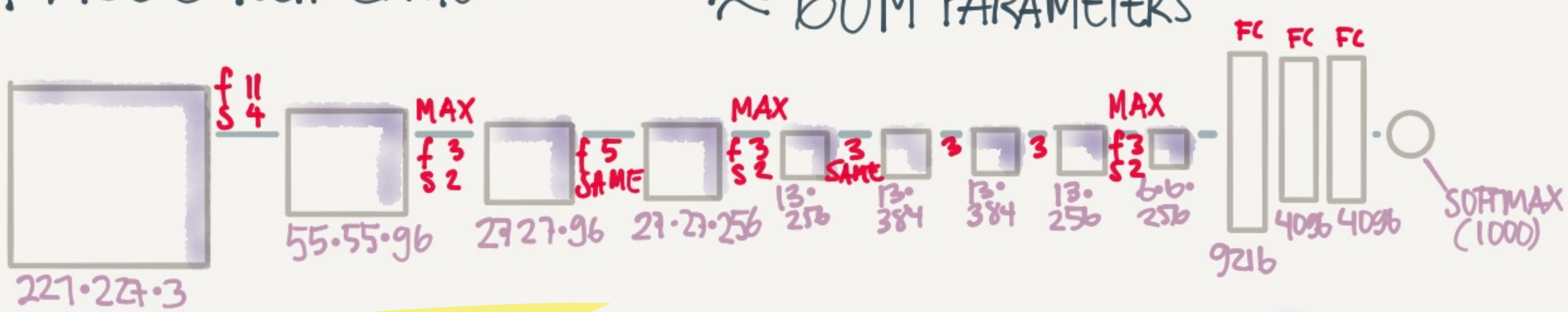
TRENDS: HEIGHT/WIDTH GO DOWN
CHANNELS GO UP

COMMON PATTERN: A COUPLE OF CONV(1+)/POOL LAYERS FOLLOWED BY A FEW FC

OLD STUFF: USED AVG POOLING INST. OF MAX
PADDING WAS NOT VERY COMMON
IT USED SIGMOID/TANH INST OF RELU

AlexNet

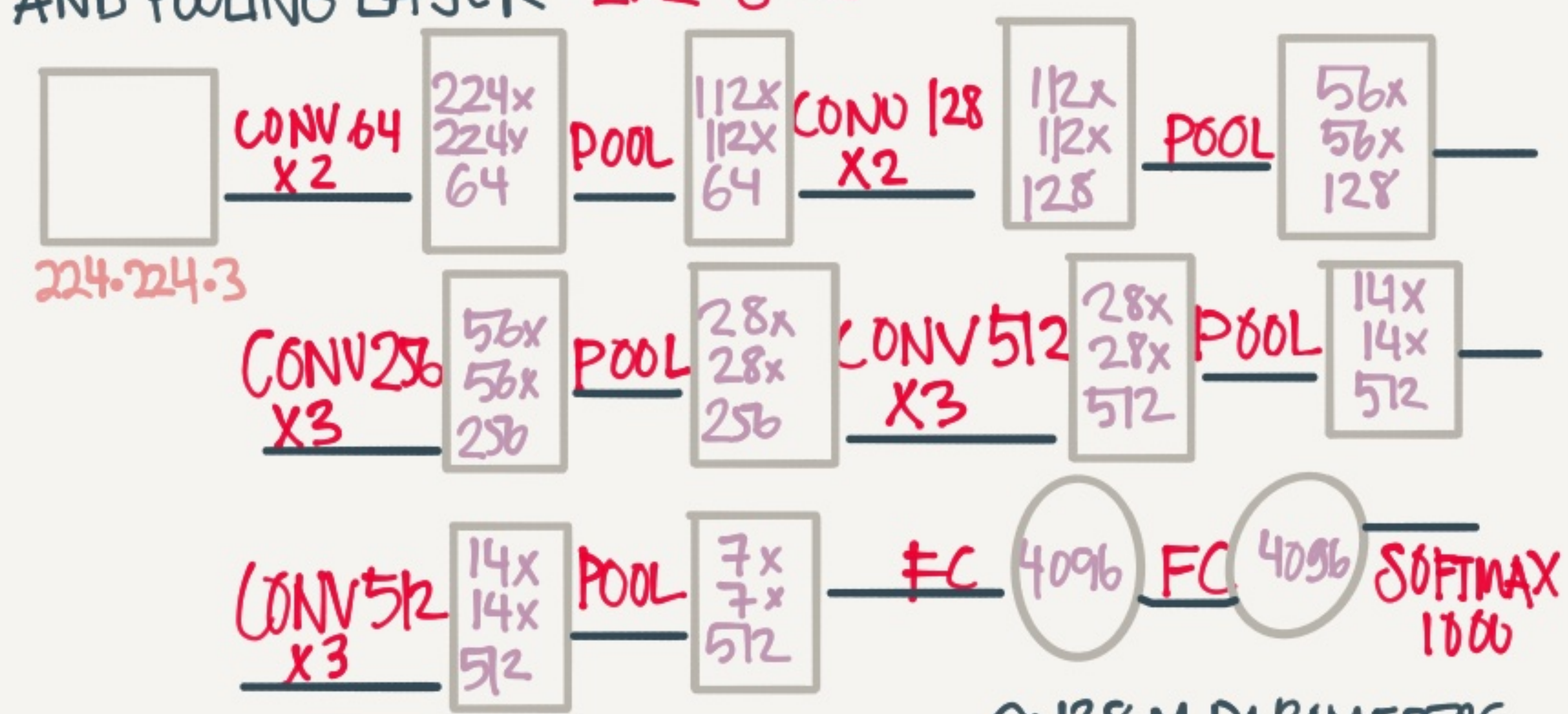
IMAGE CLASSIFICATION ≈ 60M PARAMETERS



- SIMILAR TO LeNet BUT MUCH BIGGER
- USES RELU
- THE NN THAT GOT RESEARCHERS INTERESTED IN VISION AGAIN

VGG-16

ALL CONV. LAYERS HAVE SAME #. PARAMS
f=3x3 S=1 P=SAME
AND POOLING LAYER 2x2 S=2



≈138 M PARAMETERS

- VERY DEEP
- EASY ARCHITECTURE
- # FILTERS DOUBLE 64, 128, 256, 512

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SPECIAL NETWORKS

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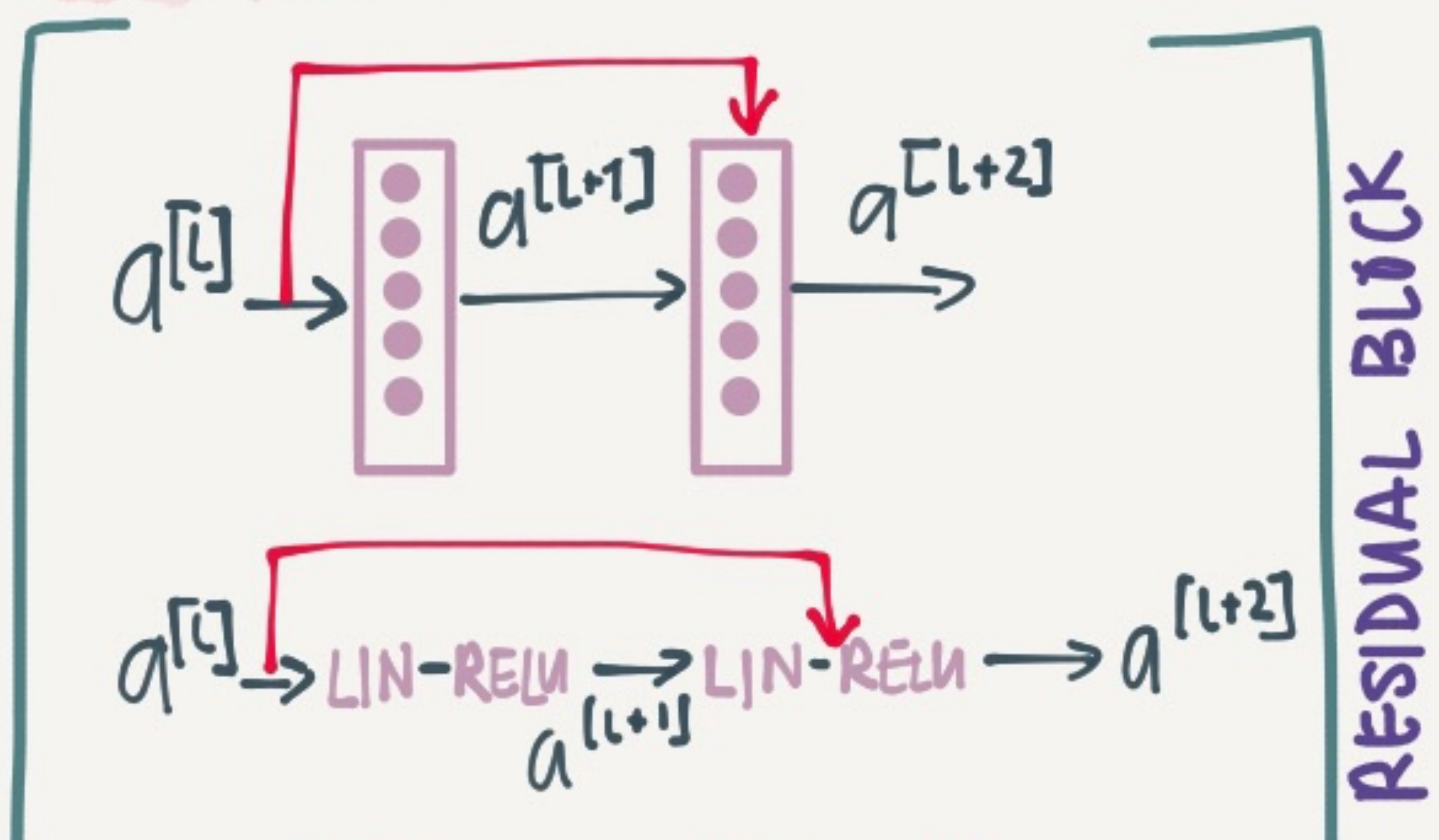
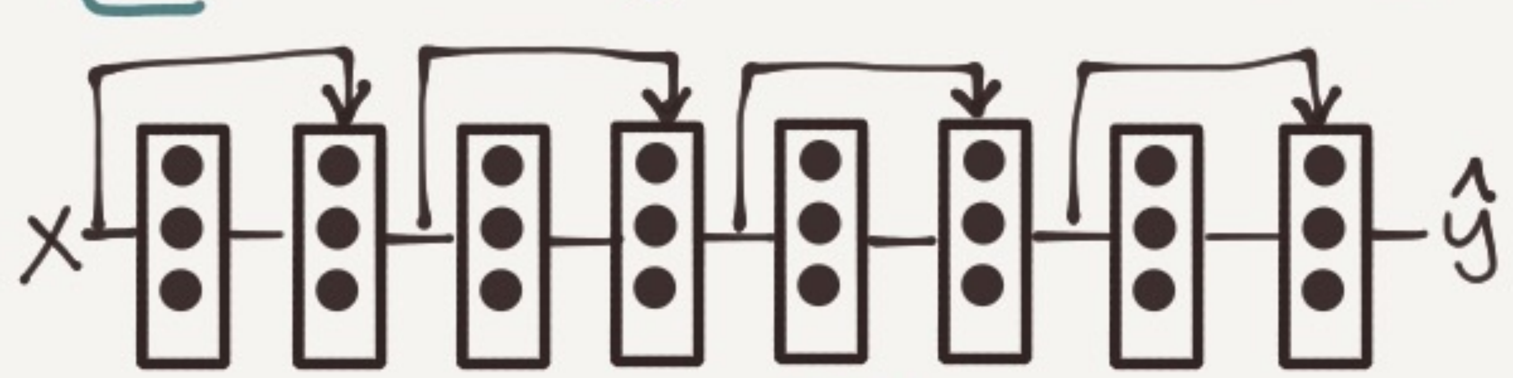
ResNets

PROBLEM: DEEP NN OFTEN SUFFER PROBLEMS W VANISHING OR EXPLODING GRADIENTS

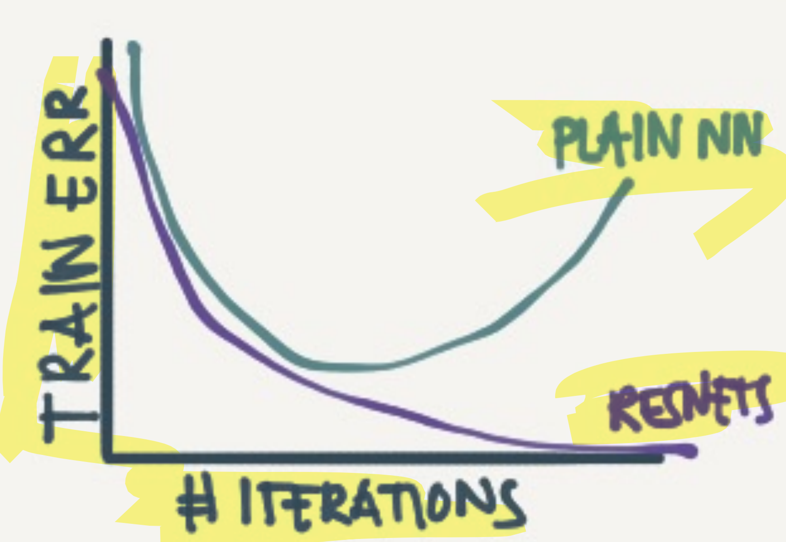
SOLUTION RESIDUAL NETS



SO $a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$



VERY DEEP NN



$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$

$= g(W^{[l+2]} a^{[l+1]} + b^{[l+1]} + a^{[l]})$

WORST CASE: W & b HAVE VANISHED TO ∅ ⇒

$a^{[l+2]} = g(a^{[l]}) = a^{[l]}$

SO EXTRA LAYERS LEARNED NOTHING BUT DIDN'T HURT

BEST CASE: LAYERS LEARNED SOMETHING

NETWORK IN NETWORK (1x1 CONVOLUTION)

6	5	3	2
4	1	9	5
5	8	2	4
0	3	6	1

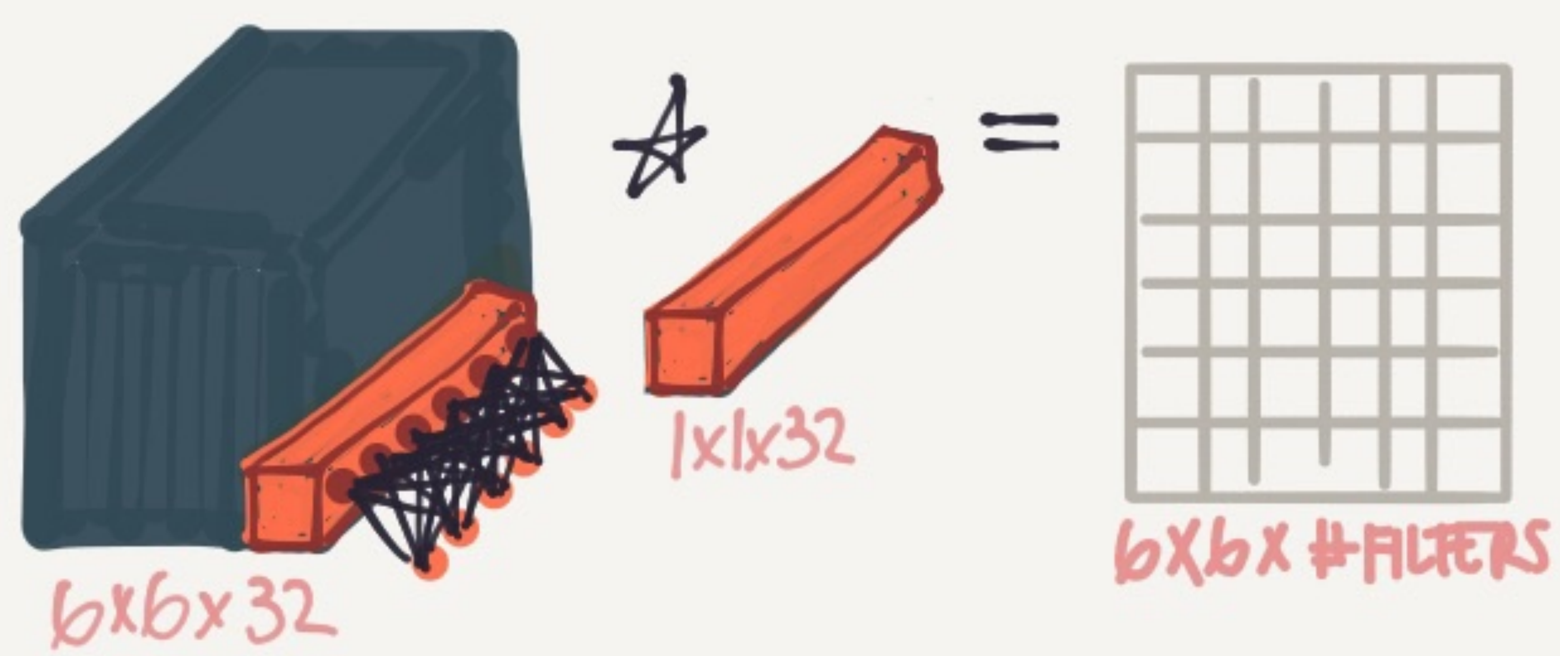
* 2 =

12	10	6	4
8	2	18	10
10	16	4	8
0	6	12	2

1x1 CONVOLUTION

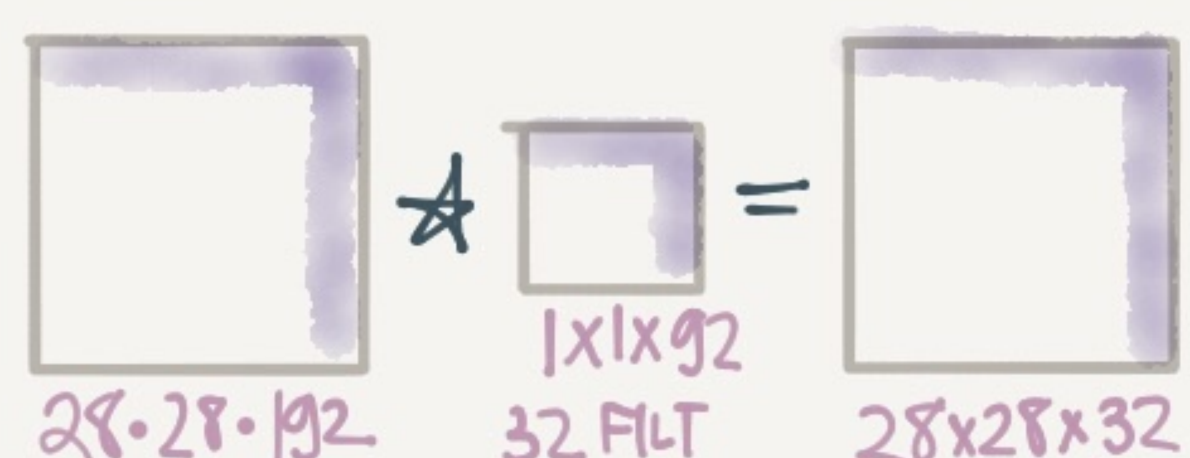
IT SEEMS PRETTY USELESS, BUT IT ACTUALLY SERVES 2 PURPOSES

1. NETWORK IN A NETWORK



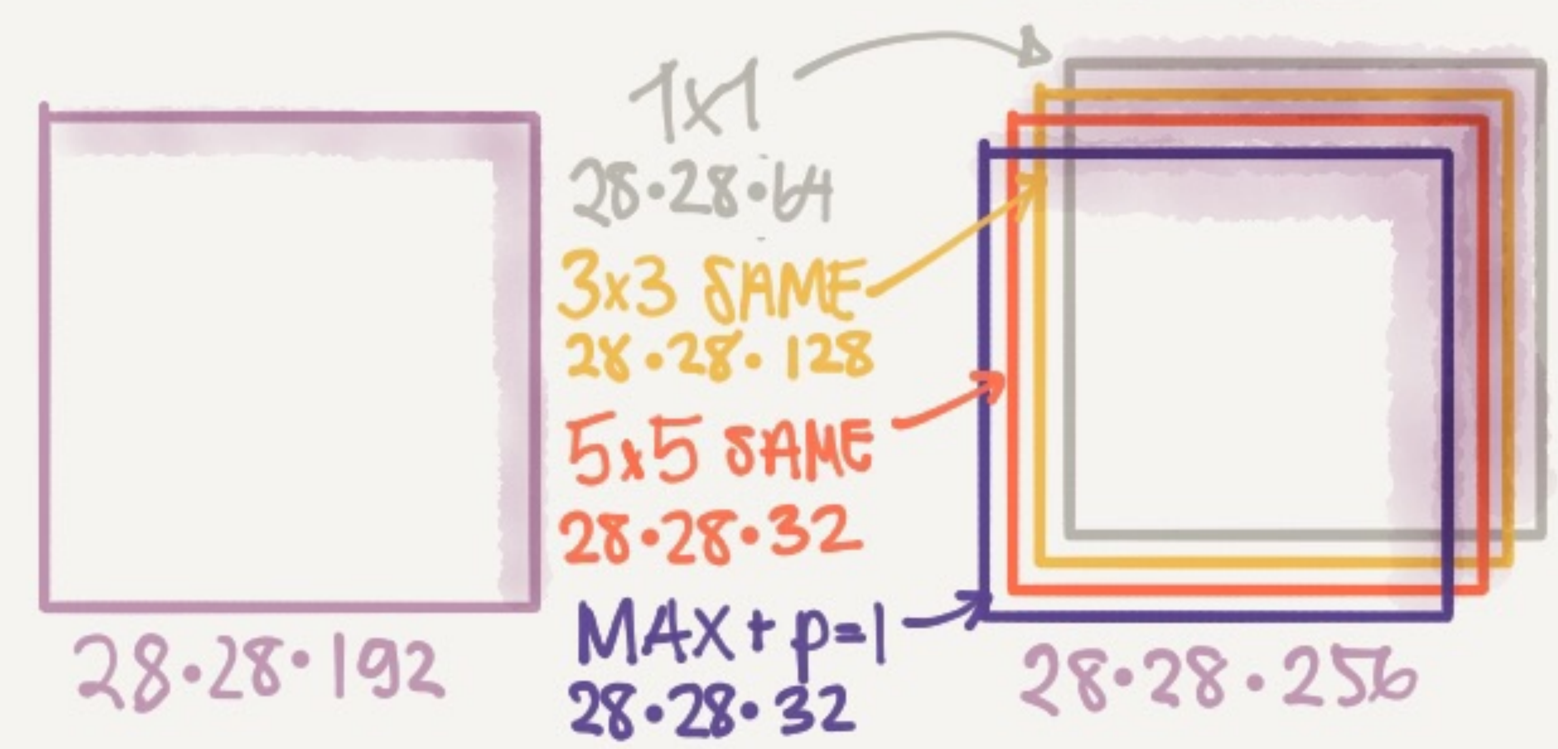
LEARNS COMPLEX, NON-LINEAR RELATIONSHIPS ABOUT A SLICE OF A VOLUME

2. REDUCING # CHANNELS



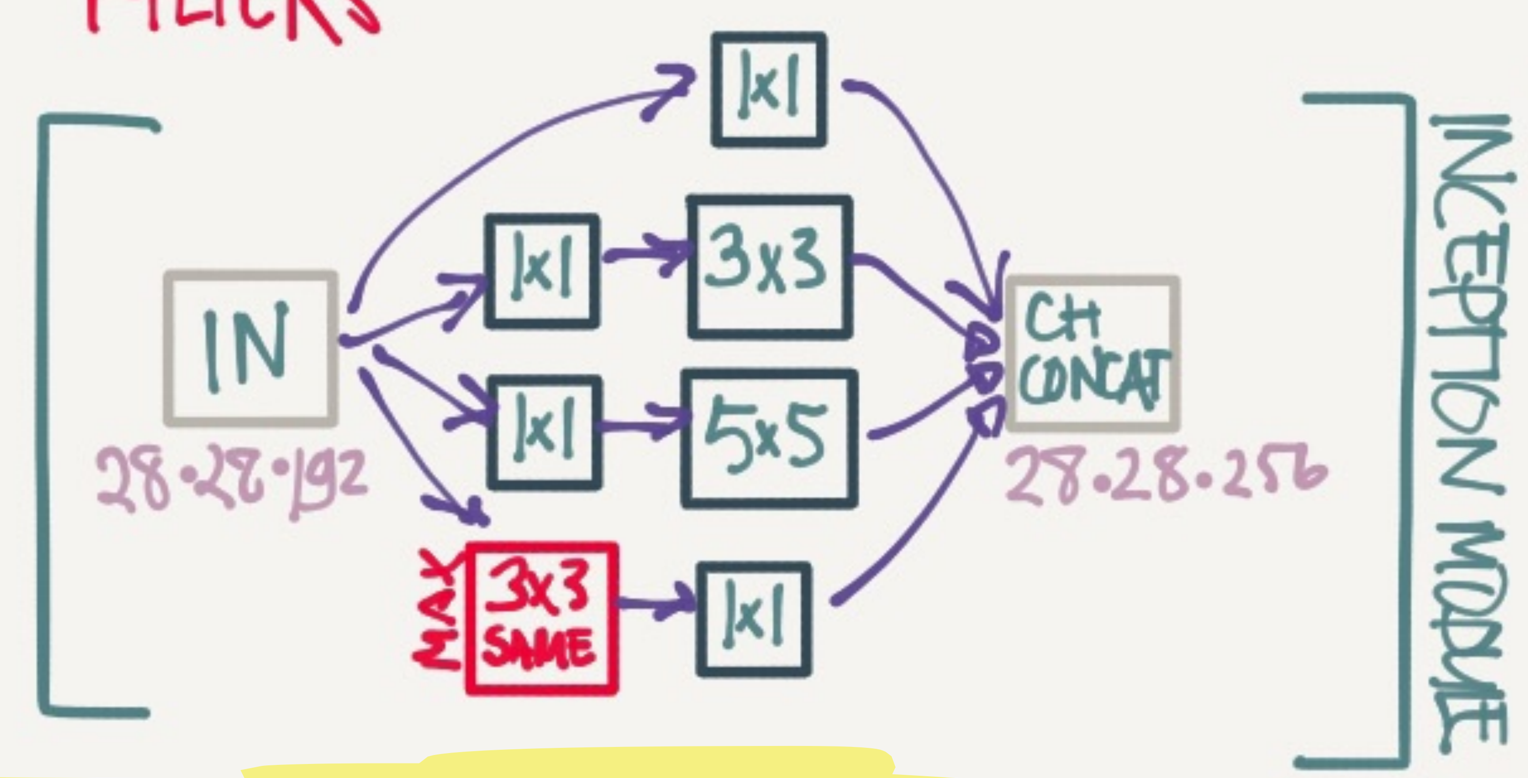
INCEPTION NETWORKS

INSTEAD OF CHOOSING A 1x1, 3x3, 5x5 OR A POOLING LAYER - CHOOSE ALL



PROBLEM: VERY EXPENSIVE TO COMPUTE

SOLUTION: SHRINK THE # CHANNELS W A 1x1 CONV BEFORE APPLYING ALL THE FILTERS



TO BUILD AN INCEPTION NETWORK YOU MAINLY STACK A BUNCH OF INCEPTION MOULES

INCEPTION THE MOVIE

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PRACTICAL
ADVICE

USE OPEN SOURCE IMPLEMENTATIONS

SOME OF THE PAPERS ARE HARD TO IMPLEMENT FROM SCRATCH - USING OS YOU CAN REUSE OTHER PPLS WORK

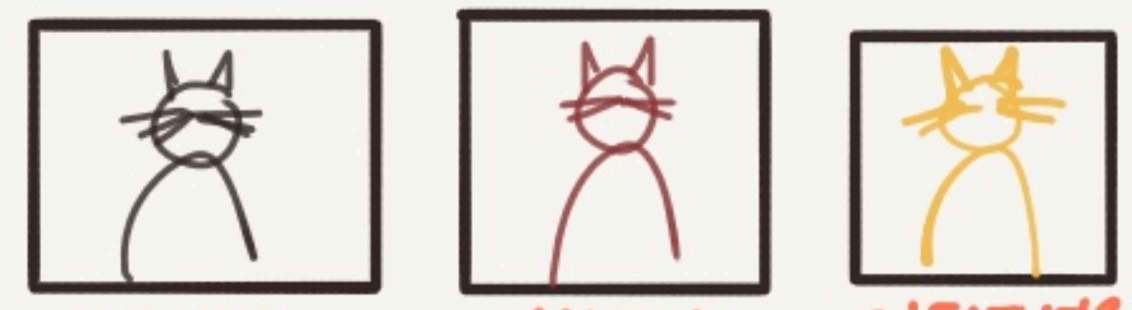
DON'T FORGET TO CONTRIBUTE

DATA AUGMENTATION

WE ALMOST ALWAYS NEED MORE DATA TO TRAIN ON

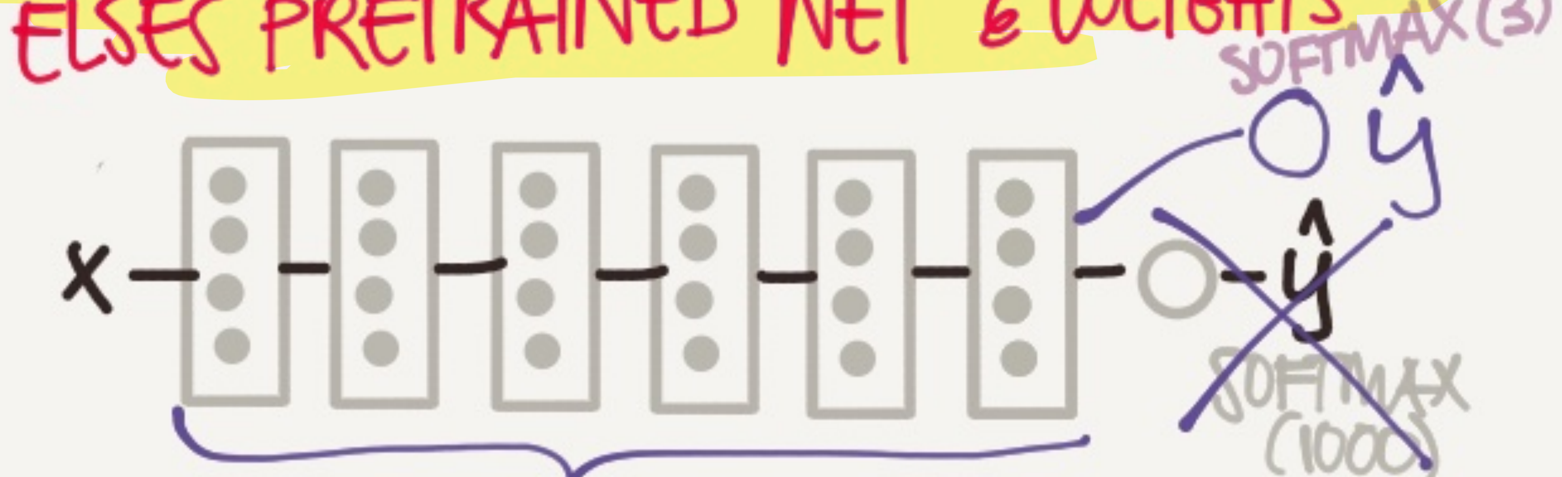
ROTATION
SHEARING
LOCAL WARPING
...

TRANSFER LEARNING



WANT TO TRAIN A CLASSIFIER FOR YOUR CATS BUT DON'T HAVE ENOUGH PICTURES

$\boxed{\text{SOLUTION}}$ DOWNLOAD SOMEONE ELSES PRETRAINED NET & WEIGHTS



FREEZE THE PARAMS, AND JUST REPLACE THE SOFTMAX LAYER WITH YOUR OWN & TRAIN

IF YOU HAVE MORE PICS · RETRAIN A MORE OF THE LATER LAYERS (MAYBE INITIALIZING WITH THE PRETRAINED WEIGHTS)

STATE OF COMPUTER VISION

WE HAVE LOTS OF DATA

- SPEECH RECOG.
- IMAGE RECOGNITION
- OBJECT DETECTION
  IMGS W LABLED BOXES

WE HAVE LITTLE LABLED DATA

MORE HAND ENGINEERING

TIPS FOR DOING WELL ON BENCHMARKS/COMPETITIONS

* ENSEMBLING
  AVG OUTPUTS FROM MULT NN
* MULTI-CROP AT TEST TIME
  AVG OUTPUTS FROM MULTIPLE CROPS OF THE IMAGE

IN PRACTICE THEY ARE NOT USED IN PRODUCTION BECAUSE THEY ARE COMPUTE & MEM EXPENSIVE

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DETECTION
ALGORITHMS

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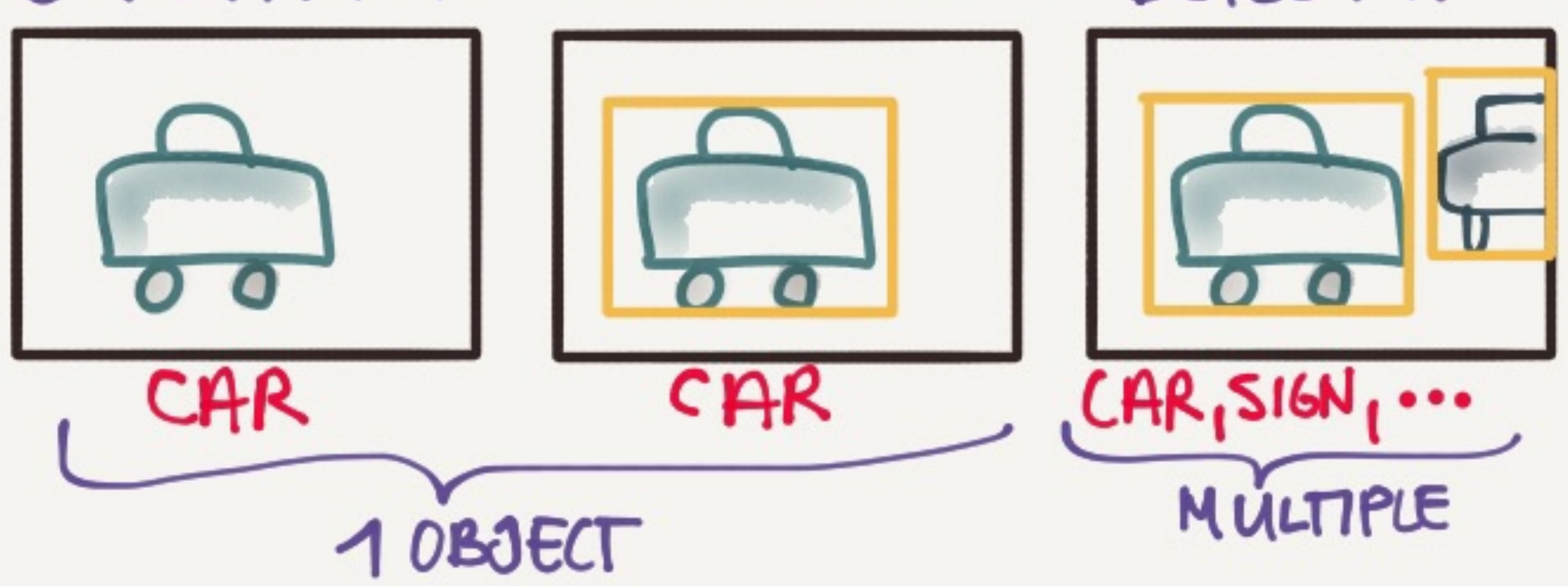
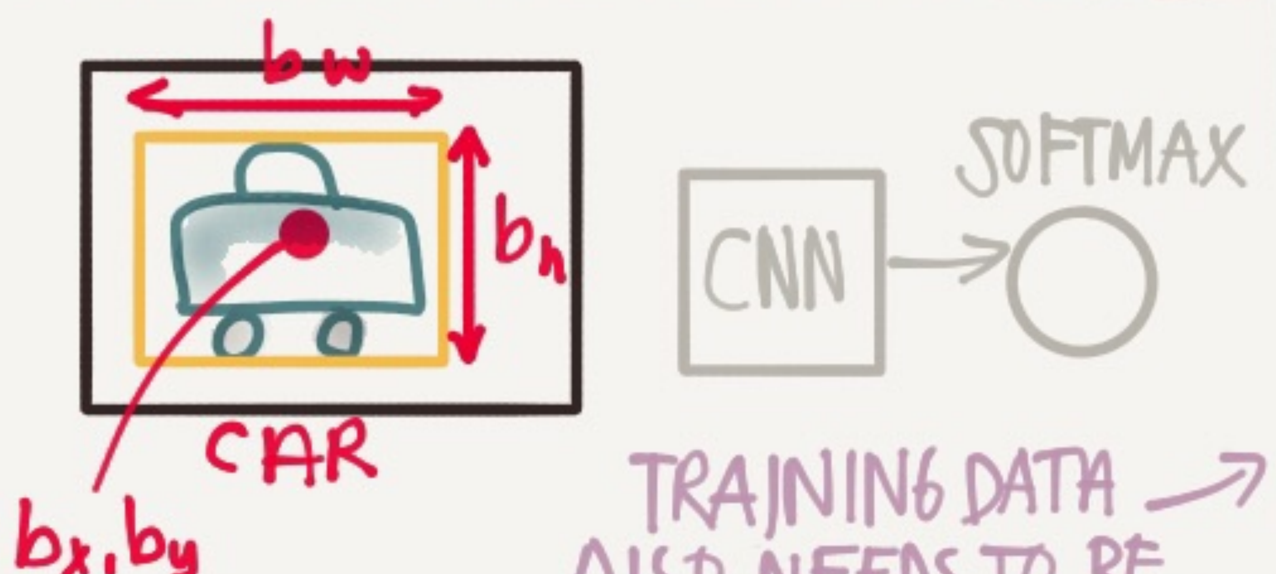
CLASSIFICATION | CLASSIF. W LOCALIZATION | OBJECT DETECTION



OBJECT LOCALIZATION

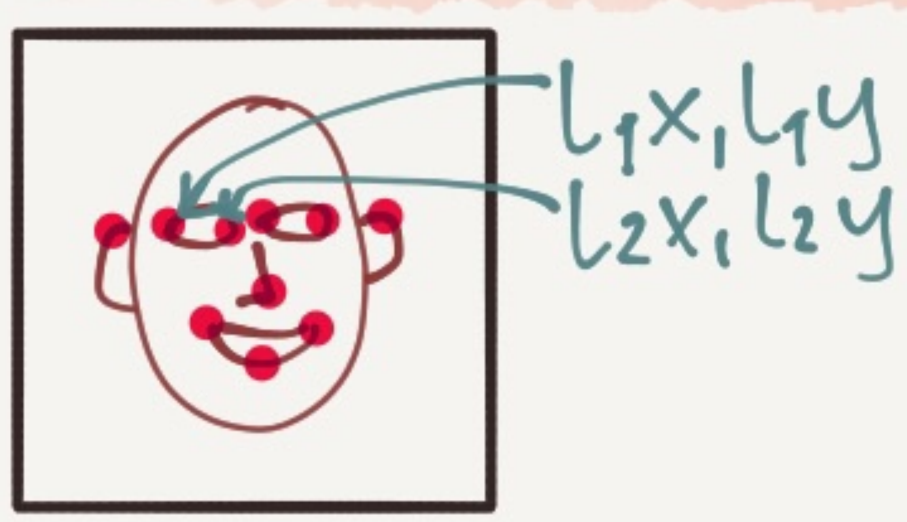


IS IT AN OBJECT (0,1)

P_c	0.4
bx	0.5
by	0.5
bw	0.5
bh	0.7
C_1	CAR (1)
C_2	PEDESTRIAN (0)
C_3	SIGN (0)

TRAINING DATA ALSO NEEDS TO BE LABLED LIKE THIS

LANDMARK DETECTION



$\hat{y} = [\text{FACE}, l_1x, l_1y, l_2x, l_2y, \vdots]$

TO DETECT LANDMARKS IN THE FACE (CORNER OF MOUTH ETC) LABEL THE X,Y COORDS OF THE LANDMARK

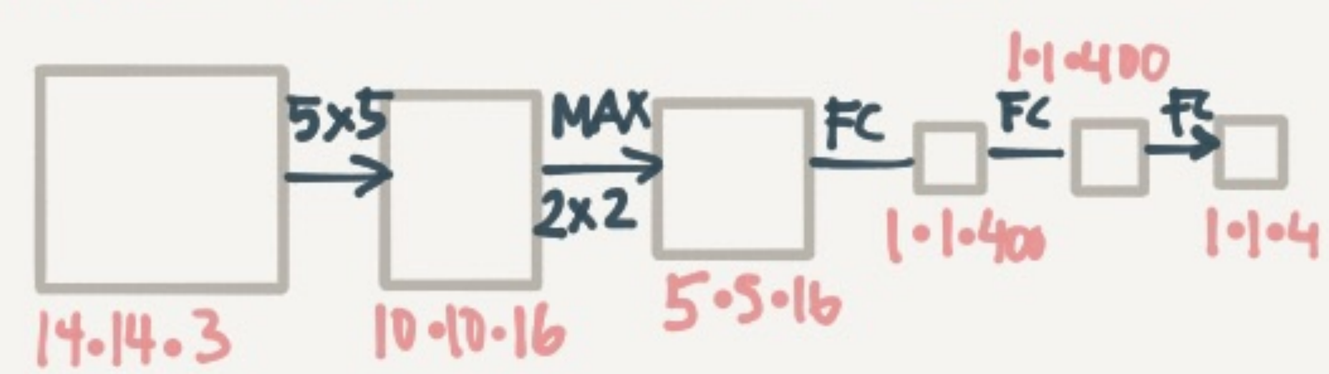
USED FOR SENTIMENT ANALYSIS & FOR EFFECTS LIKE PLACING CROWN ON HEAD ETC.

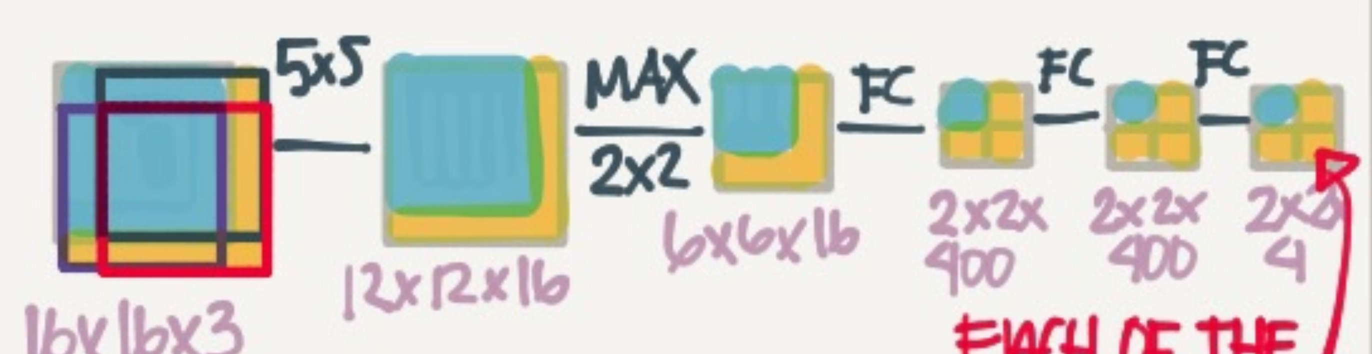
SLIDING WINDOWS DETECTION

1. CREATE TIGHTLY CROPPED IMG OF CARS (LOTS)
2. SLIDE A WINDOW OVER THE IMG. & CLASSIFY THIS WINDOW CAR (1/0) AGAINST YOUR OTHER CARS
3. REPEAT WITH SLIGHTLY LARGER WINDOW SIZE

PROBLEM: VERY EXPENSIVE (TO COMPUTE)

SINCE ADJ WINDOWS SHARE A LOT OF THE COMPUTATIONS WE CAN DO THIS MUCH CHEAPER W CONVOLUTIONS

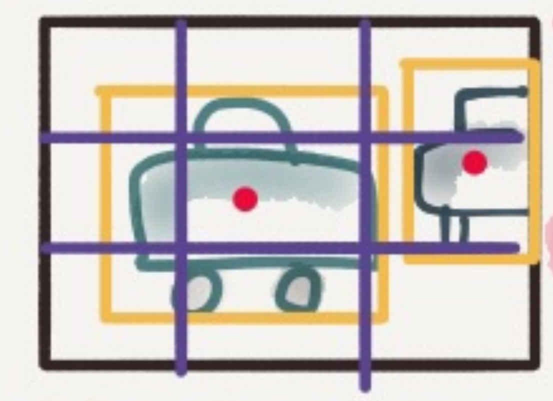




EACH OF THE 4 VALS ARE RESULTS FOR EACH OF THE 4 WINDOWS

NOW WE JUST PASS THROUGH ONCE AND CALC ALL AT THE SAME TIME

YOLO · You Only Look Once



1. SPLIT IMG INTO X (9) GRID CELLS
2. FOR EACH CELL, SAY IF IT CONTAINS CAR + BOUNDING BOX (IF CELL CONTAINS THE MID POINT)

SAME AS OBJECT LOCALIZATION

IN PRACTICE WE MIGHT HAVE A 19x19 GRID

$X \cdot \hat{y} = 3 \times 3 \times 8$

HOW DO YOU KNOW HOW GOOD IT IS?

HOW GOOD IS THE RED SQUARE?

IOU = SIZE OF / SIZE OF

INTERSECTION OVER UNION

GENERALLY · IF IOU ≥ 0.5 IT IS REGARDED AS CORRECT

WHAT IF MULTIPLE SQUARES CLAIM THE SAME CAR?

NON · MAX SUPRESSION

IF TWO BOUNDING BOXES HAVE A HIGH IOU – PICK THE ONE W HIGHEST P_c – GET RID OF THE REST.

ANCHOR BOXES

ANCHOR BOXES LET YOU ENCODE MULTIPLE OBJECTS IN THE SAME SQUARE

CONVOLUTIONAL NEURAL NETS · COURSERA

FACE RECOGNITION

FACE VERIFICATION

IS THIS PETE?

99% ACC ⇒ PRETTY GOOD

FACE RECOGNITION

WHO IS THIS? (OUT OF K PERSONS)

IF K=100 NEED MUCH HIGHER THAN 99%

ONE SHOT LEARNING

NEED TO BE ABLE TO RECOGNIZE A PERSON EVEN THOUGH YOU ONLY HAVE ONE SAMPLE IN YOUR DB.

YOU CAN'T TRAIN A CNN WITH A SOFTMAX (EACH PERSON) BECAUSE

- (A) YOU DON'T HAVE ENOUGH SAMPLES
- (B) IF A NEW PERSON JOINS YOU NEED TO RETRAIN THE NETWORK

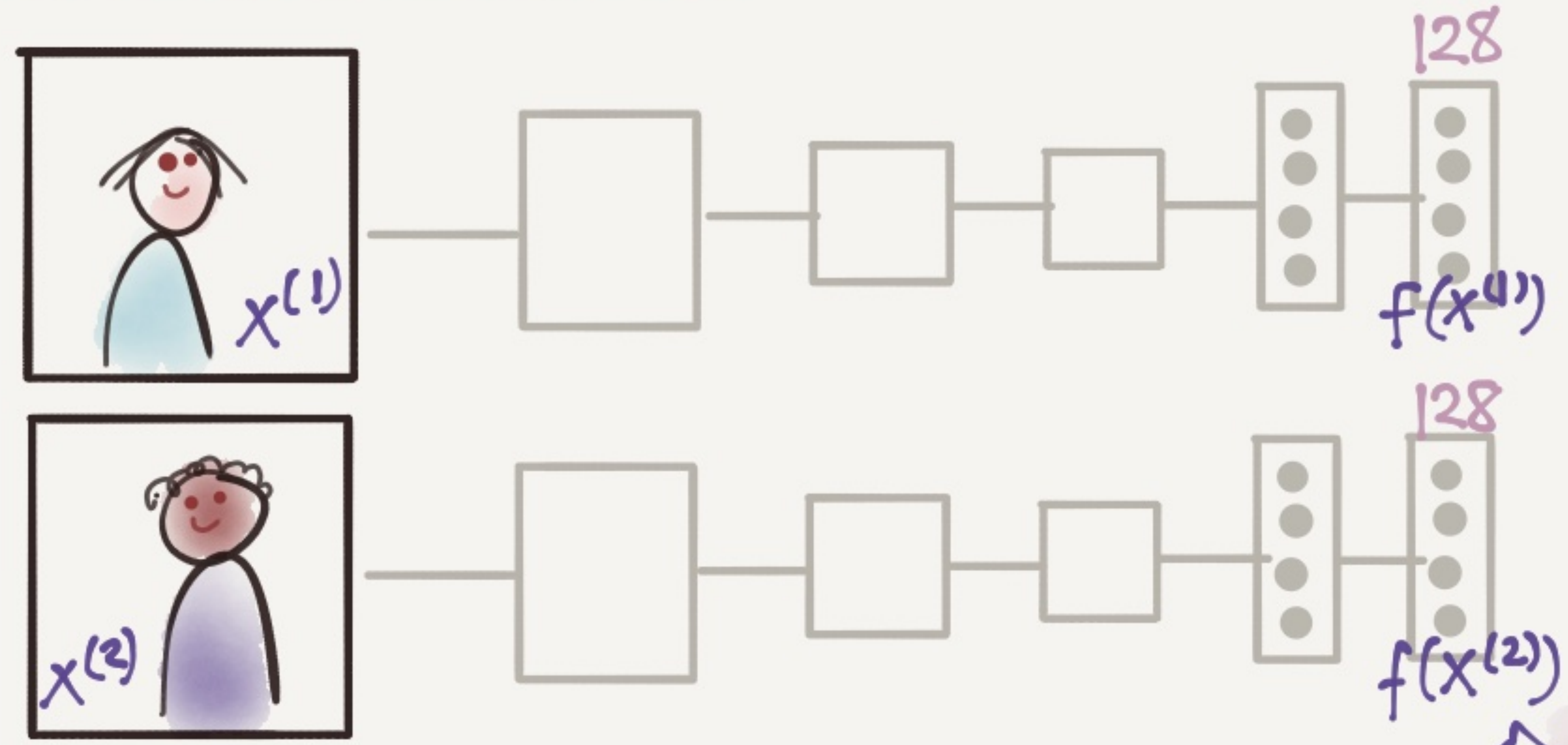
SOLUTION: LEARN A SIMILARITY FUNCTION

d(img1, img2) = degree of difference

BUT HOW DO YOU LEARN THIS?

SIAMESE NETWORK

DeepFace



$$d(x^{(1)}, x^{(2)}) = \| f(x^{(1)}) - f(x^{(2)}) \|_2^2$$

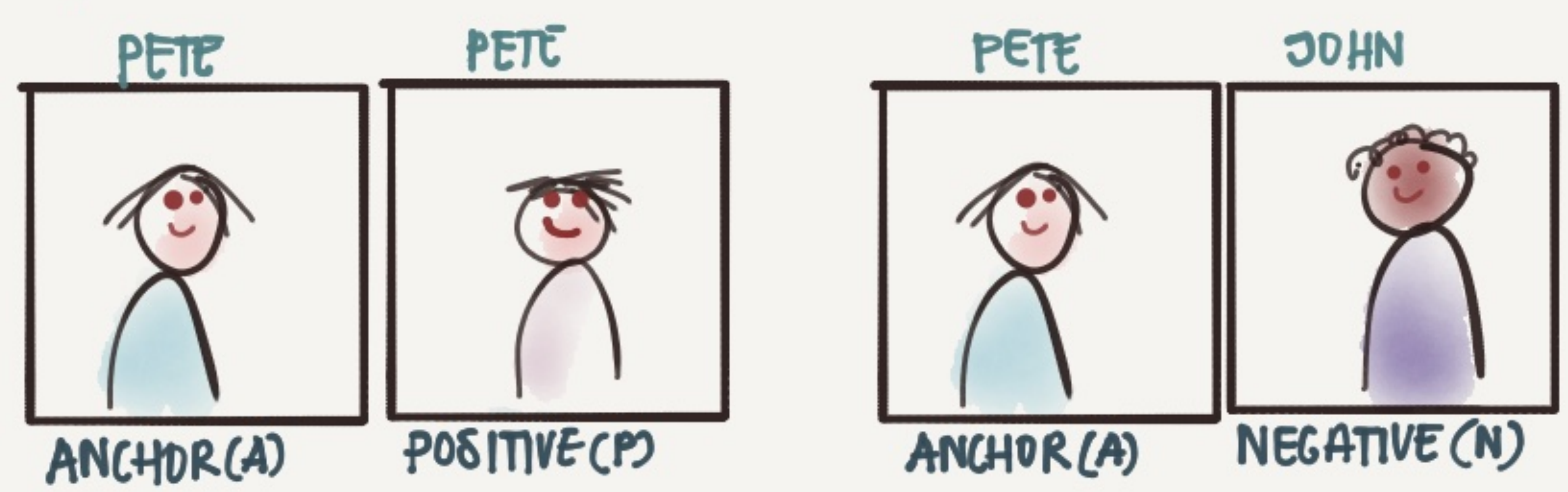
LEARN THE PARAMS OF THE NN SUCH THAT

- IF $x^{(i)}, x^{(j)}$ ARE THE SAME PERSON • $d(x^i, x^j) \Rightarrow$ SMALL
- IF $x^{(i)}, x^{(j)}$ ARE DIFFERENT PEOPLE • $d(x^i, x^j) \Rightarrow$ LARGE

WE CAN ACCOMPLISH THIS WITH THE TRIPLET LOSS FUNCTION

TRIPLET LOSS

FaceNet



WANT $\underbrace{\| f(A) - f(P) \|^2}_{d(A,P)} \leq \underbrace{\| f(A) - f(N) \|^2}_{d(A,N)} \Rightarrow d(A,P) - d(A,N) \leq 0$

BUT WE WANT A GOOD MARGIN, SO...

$d(A,P) - d(A,N) + \alpha \leq 0$

TIP: PRECOMPUTE ENCODINGS FOR PPL IN YOUR DB, SO YOU DONT HAVE TO SAVE IMAGES & COMPUTE ENCODINGS AT RUN-TIME

HOW DO WE CHOOSE TRIPLETS TO TRAIN ON?

- IF A/P ARE VERY SIMILAR, & A/N ARE VERY DIFFERENT TRAINING IS VERY EASY.

SELECT A/N THAT ARE PRETTY SIMILAR TO TRAIN A GOOD NET

SOME BIG COMPANIES HAVE ALREADY TRAINED NETWORKS ON LARGE AMTS OF PHOTOS SO YOU MAY JUST WANT TO REUSE THEIR WEIGHTS

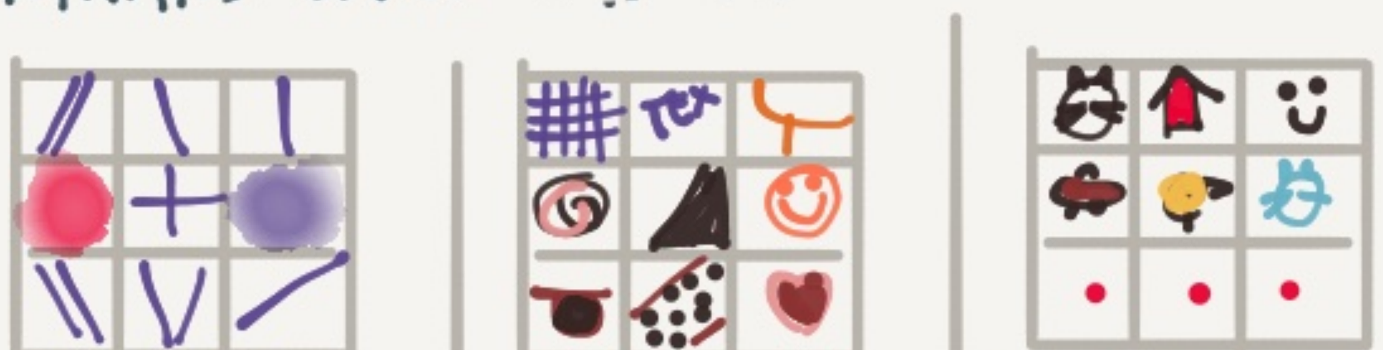
@TessFerrandez

NEURAL STYLE TRANSFER

CONTENT (C) + STYLE (S) = GENERATED (G)

PICTURE OF CAMBRIDGE | STARRY NIGHT - VAN GOGH | CAMBRIDGE IN THE STYLE OF VAN GOGH

WE CAN VISUALIZE WHAT A NETWORK LEARNS BY LOOKING AT WHAT IMAGES (PARTS) ACTIVATED EACH UNIT MOST



LAYER 1 · SIMPLE FEATURES LIKE LINES/COLORS

LAYER 3 · MORE COMPLEX FEATURES · BIRD LEGS, HONEYCOMB PATTERNS

LAYER 5 · EVEN MORE COMPLEX · MAYBE ONE NODE IS A CAT DETECTOR

BUT HOW DOES THIS HELP US GENERATE AN IMAGE IN THE STYLE OF ANOTHER?

IDEA:

1. GENERATE A RANDOM IMG
2. OPTIMIZE THE COST FUNCTION

$$J(G) = \alpha \underbrace{J_{CONTENT}(C,G)}_{\text{HOW SIMILAR ARE C \& G}} + \beta \underbrace{J_{STYLE}(S,G)}_{\text{HOW SIMILAR ARE S \& G}}$$

3. UPDATE EACH PIXEL

CONTENT COST FUNCTION

- USE A PRE-TRAINED CONVNET (EX VGG)
- SELECT A HIDDEN LAYER SOMEWHERE IN THE MIDDLE
  LATER ⇒ COPIES LARGER FEATURES
- LET $a^{[l](C)}$ & $a^{[l](G)}$ BE THE ACTIVATIONS
- IF $a^{[l](C)}$ & $a^{[l](G)}$ ARE SIMILAR THEY HAVE SIMILAR CONTENT
  BECAUSE THEY BOTH TRIGGER THE SAME HIDDEN UNITS

HOW DO WE TELL IF THEY ARE SIMILAR?

$$J_{CONTENT}(C,G) = \frac{1}{2} \| a^{[l](C)} - a^{[l](G)} \|^2$$

CAPTURING THE STYLE

USING THE STYLE IMG AND THE ACTIVATIONS IN A LAYER · LOOK THROUGH THE ACTIVATIONS IN THE DIFFERENT CHANNELS TO SEE HOW CORRELATED THEY ARE

WHEN WE SEE PATTERNS LIKE THIS | DO WE USUALLY SEE IT WITH PATCHES LIKE THESE?

STYLE MATRIX

CREATE A MATRIX OF HOW CORRELATED THE ACTIVATIONS ARE, FOR EACH POS (X,Y) & CHANNEL PAIR (K,K') FOR THE STYLE IMG & GENERATED

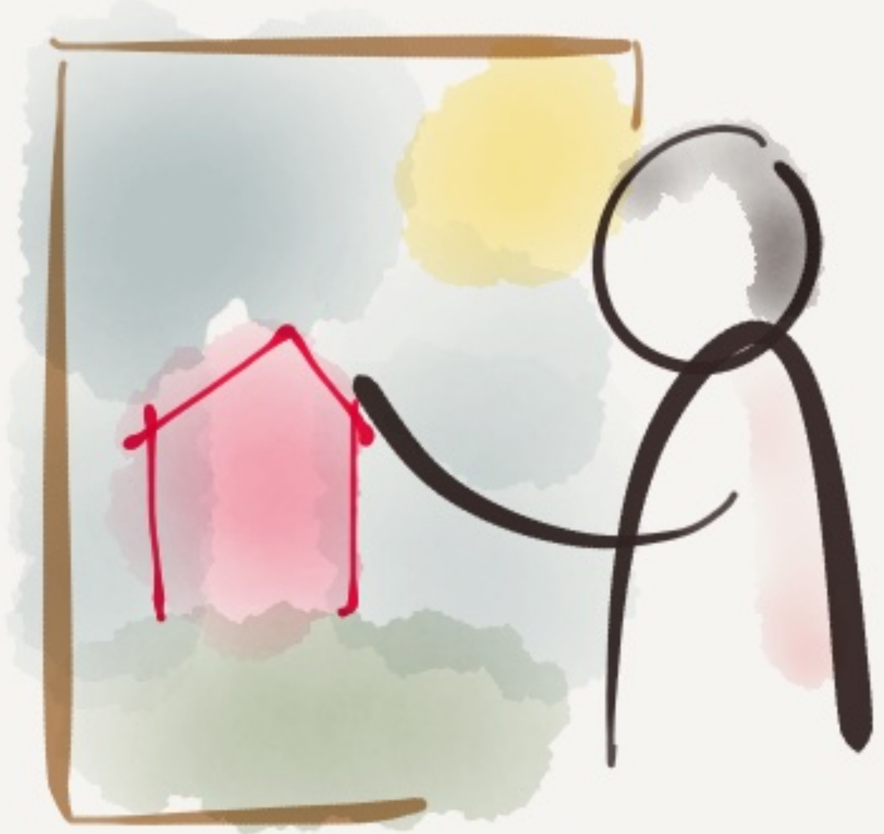
$$G_{kk'} = \sum_{i=1}^{n_H} \sum_{j=1}^{n_W} a_{ijk} \cdot a_{ijk'}$$

THE STYLE COST FUNCTION

$$J(S,G) = \| G^{(S)} - G^{(G)} \|_F^2$$

FROBENIUS NORM

TO GET MORE VISUALLY PLEASING IMAGES IF YOU CALC J(S,G) OVER MULTIPLE LAYERS



RECURRENT
NEURAL NETWORKS

SEQUENCE MODELS · COURSERA

SEQUENCE PROBLEMS

IN	OUT	PURPOSE
(audio wave)	THE QUICK BROWN FOX JUMPED...	SPEECH RECOGNITION
∅	(music notes)	MUSIC GENERATION
THERE IS NOTHING TO LIKE IN THIS MOVIE	★ ★ ★ ★ ★	SENTIMENT CLASSIFICATION
AGCCCCTGTG AGGAACTAG	AGCCCCTGTG AGGAACTAG	DNA SEQUENCE ANALYSIS
Voulez-vous chanter avec moi?	Do you want to sing with me?	MACHINE TRANSLATION
(stick figures)	RUNNING	VIDEO ACTIVITY RECOGNITION
Yesterday Harry Potter met Hermoine Granger	Yesterday **Harry Potter** met **Hermoine Granger**	NAME ENTITY RECOGNITION

NAME ENTITY RECOGNITION

X = HARRY POTTER AND HERMOINE GRANGER INVENTED A NEW SPELL $\quad T_x = 9$ (9 WORDS)

$x^{<1>}$ $x^{<2>}$ ...

y = 1 1 0 1 1 0 0 0 0 $\quad T_y = T_x$

$y^{<1>}$ $y^{<2>}$ ...

EXAMPLE OF A PROBLEM WHERE EVERY $x^{<i>}$ HAS AN OUTPUT $y^{<i>}$

HOW DO WE REPRESENT WORDS?

CREATE A VOCABULARY (EG 10K MOST COMMON WORDS IN YOUR TEXTS · OR DOWNLOAD EXISTING)

a	1
aaron	2
and	367
Harry	4075
Potter	6830
zulu	10000

EACH WORD IS A **ONE-HOT** VECTOR

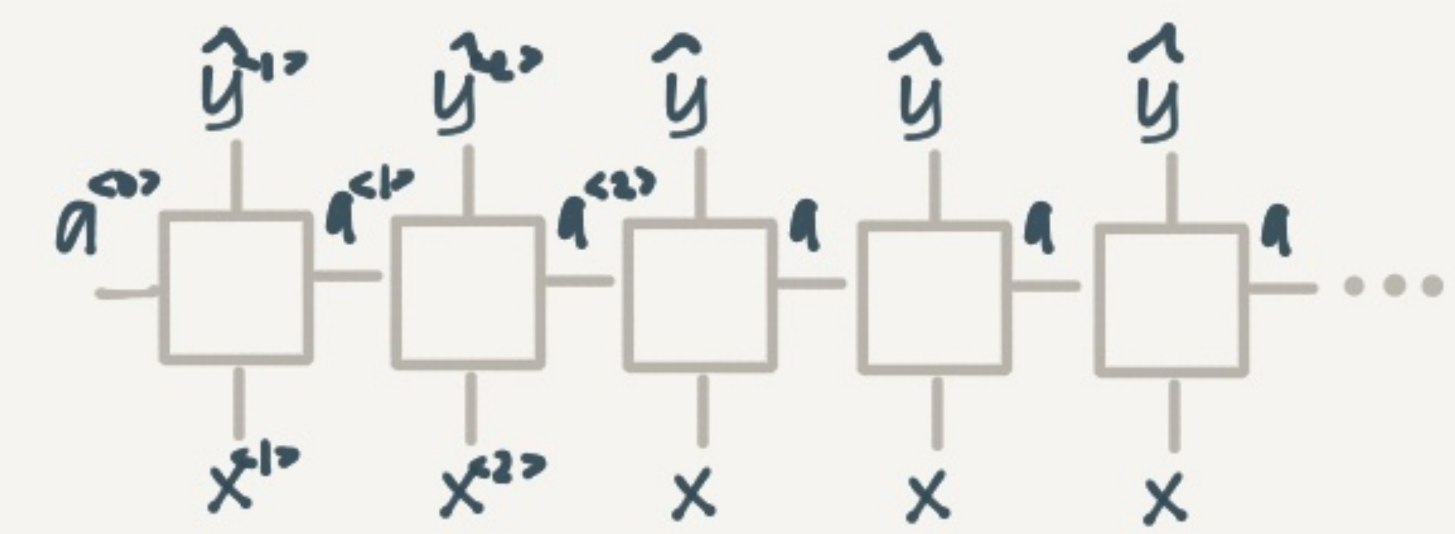
$$\text{HARRY} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{bmatrix} \leftarrow 4075$$

WE COULD USE A STANDARD NETWORK BUT...

Ⓐ INPUT & OUTPUTS CAN HAVE DIFFERENT LENGTHS IN DIFF EXAMPLES

Ⓑ WE DON'T SHARE FEATURES LEARNED ACROSS DIFFERENT POSITIONS

RECURRENT NEURAL NET (RNN)



PREVIOUS RESULTS ARE PASSED IN AS INPUTS SO WE GET CONTEXT.

$$a^{<1>} = g_1(W_a[a^{<0>}, x^{<1>}] + b_a) \quad \text{TANH/RELU}$$

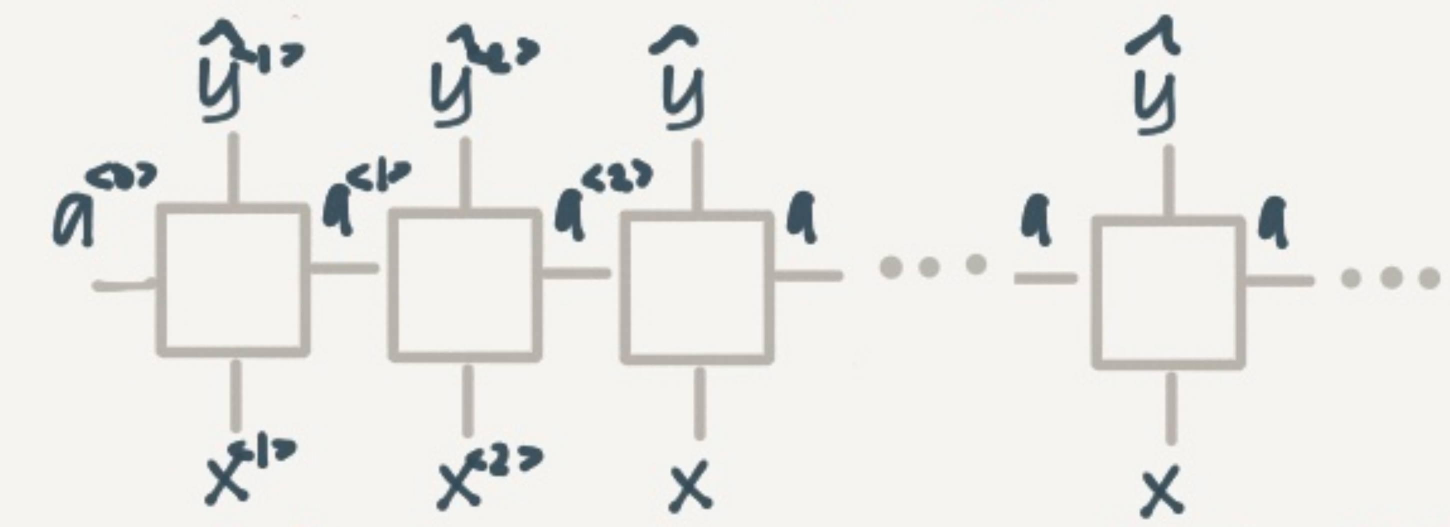
$$\hat{y}^{<1>} = g_2(W_{ya} a^{<1>} + b_y) \quad \text{SIGMOID}$$

THE SAME W & b ARE USED IN ALL TIME STEPS

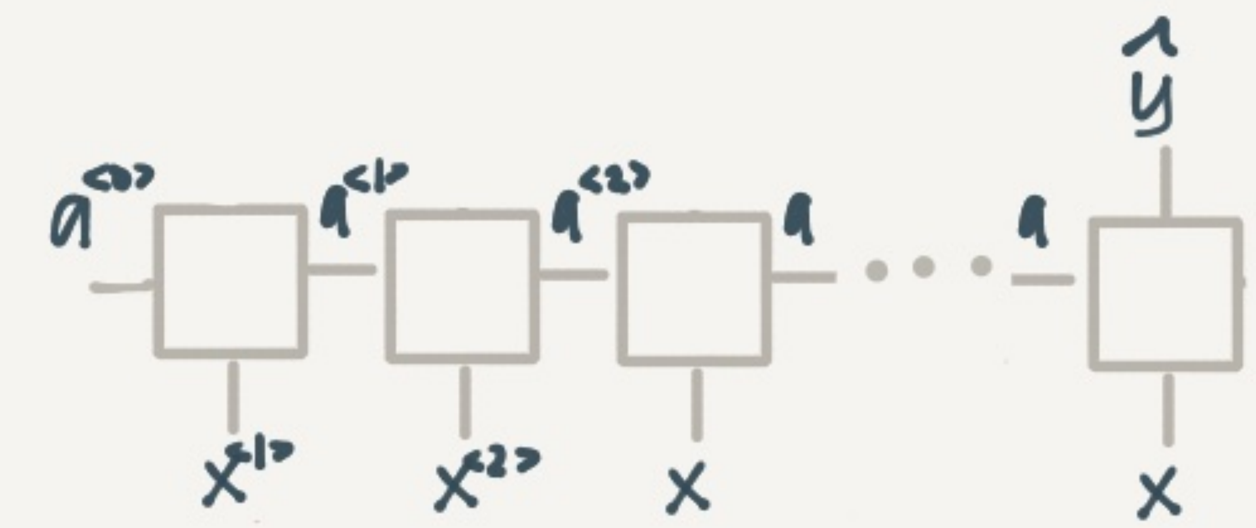
THE LOSS WE OPTIMIZE IS THE SUM OF $\mathcal{L}(\hat{y}, y)$ · FROM 1–T

DIFFERENT TYPES OF RNN

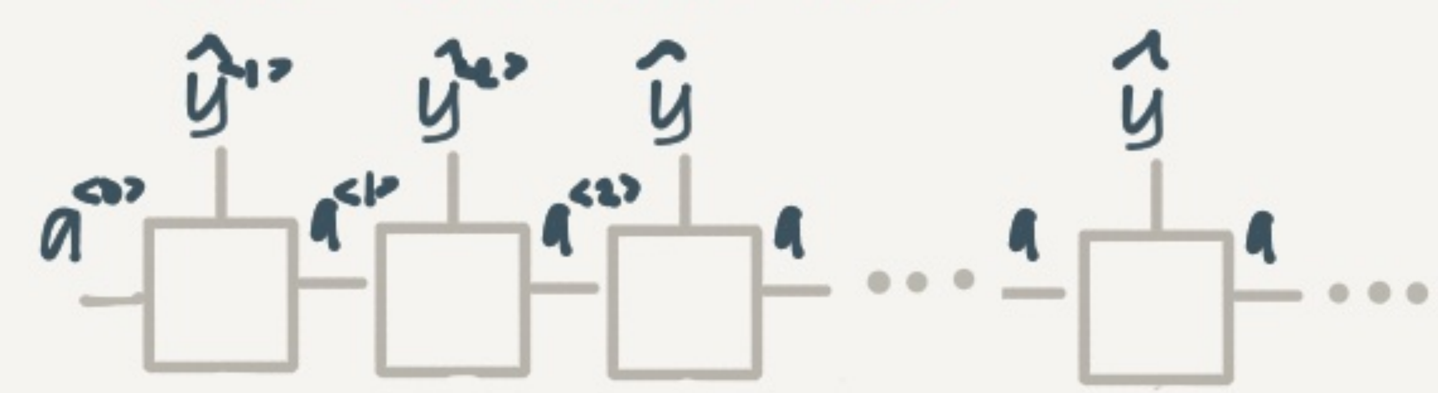
MANY-TO-MANY $T_x = T_y$



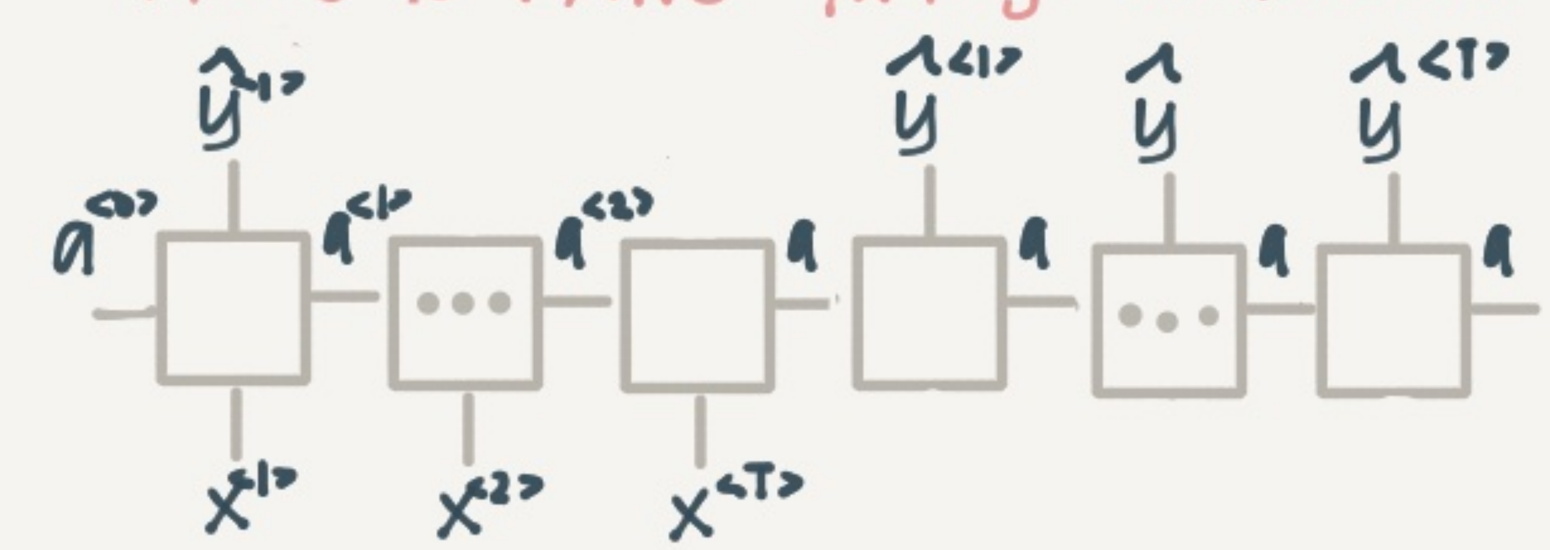
MANY-TO-ONE EX. SENTIMENT ANALYSIS



ONE-TO-MANY · MUSIC GENERATION



MANY-TO-MANY $T_x \neq T_y$ TRANSLATION



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MORE ON RNNs

SEQUENCE MODELS · COURSERA

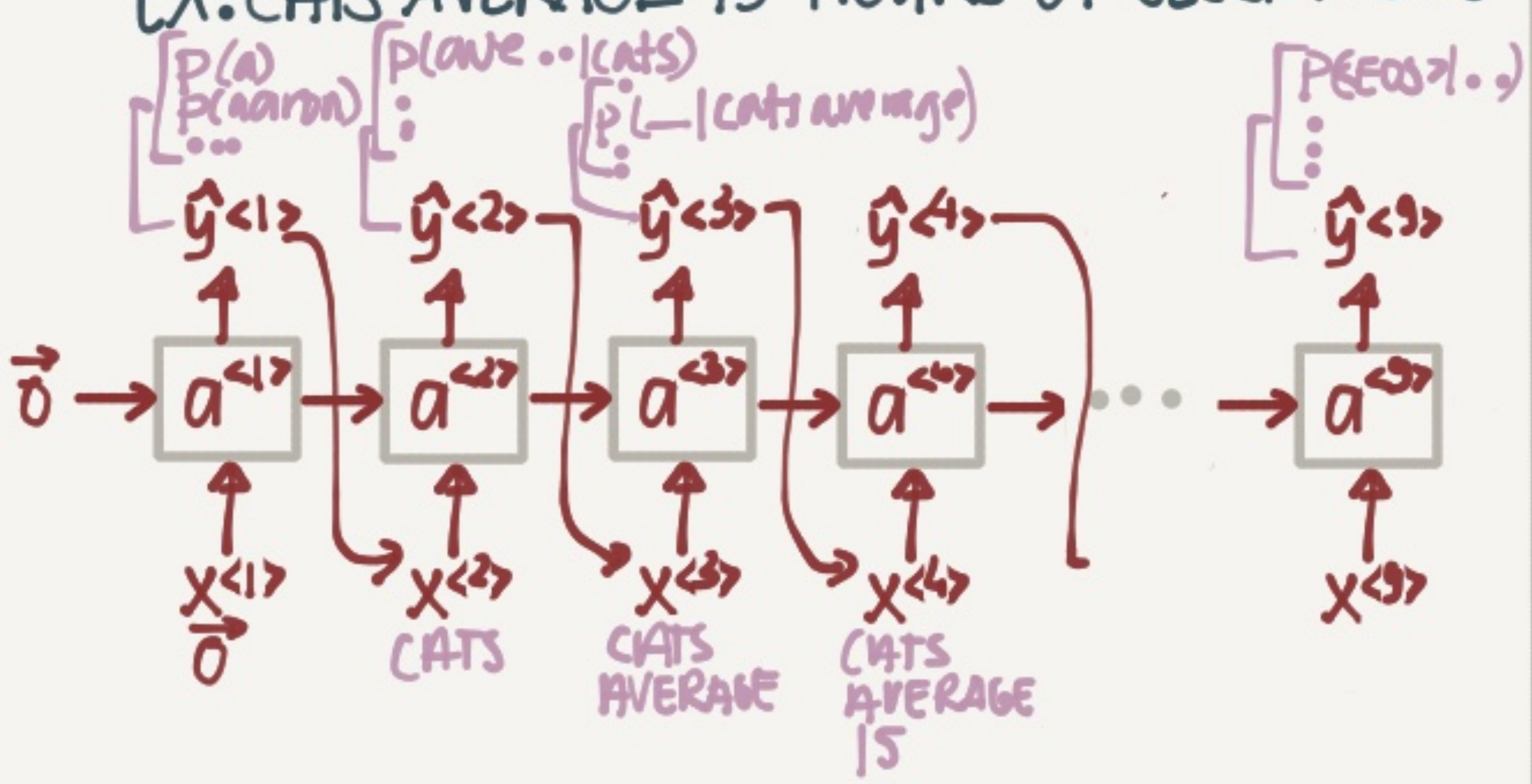
LANGUAGE MODELLING

HOW DO YOU KNOW IF SOMEONE SAID

THE APPLE AND PAIR SALAD OR
THE APPLE AND PEAR SALAD?

THE PURPOSE OF A LANG. MODEL IS TO CALCULATE THE PROBABILITIES

EX. CATS AVERAGE 15 HOURS OF SLEEP A DAY



SO GIVEN: CATS AVERAGE 15 WHAT IS THE PROB. THE NEXT WORD IS HOURS?

SAMPLING SENTENCES

1. TRAIN ON ALL HARRY POTTER BOOKS.
2. RANDOMLY SELECT A WORD (ONE OF THE TOP WORDS) (EX. THE)
3. PASS THIS INTO THE NEXT TIMESTAMP AND SAMPLE A NEW WORD
4. REPEAT UNTIL X WORDS OR YOU REACHED <EOS>

CAN DO AT CHARACTERLEVEL AS WELL

YAY! YOU ARE NOW YOUR OWN J.K. ROWLING

VANISHING GRADIENTS

THE CAT, WHO ALREADY ATE APPLES AND ORANGES AND A FEW MORE THINGS BLA BLA WAS FULL

THE CATS, WHO ALREADY ATE ... WERE FULL

NEED TO REMEMBER SING/PLURAL FOR A LONG TIME

SINCE LONG SENTENCE ⇒ DEEP RNN WE GET THE VANISHING GRADIENTS PROB WE HAVE IN STANDARD NNs – I.E THE GRADIENTS FOR CAT/CATS HAVE LITTLE OR NO EFFECT ON WAS/WERE.

NOTE: SOMETIMES YOU SEE EXPLODING GRAD (AS OVERFLOW NaN) BUT THIS IS EASILY FIXED WITH GRADIENT CLIPPING

GATED RECURRENT UNIT GRU

HELPS RECALL IF CAT WAS SING. OR PLURAL

THE GRU ACTS AS A MEMORY – AT EVERY TIMESTEP IT CALCULATES A NEW $\tilde{c}$ TO STORE AND A GATE Γ_u DECIDES TO UPDATE C TO $\tilde{c}$ OR NOT

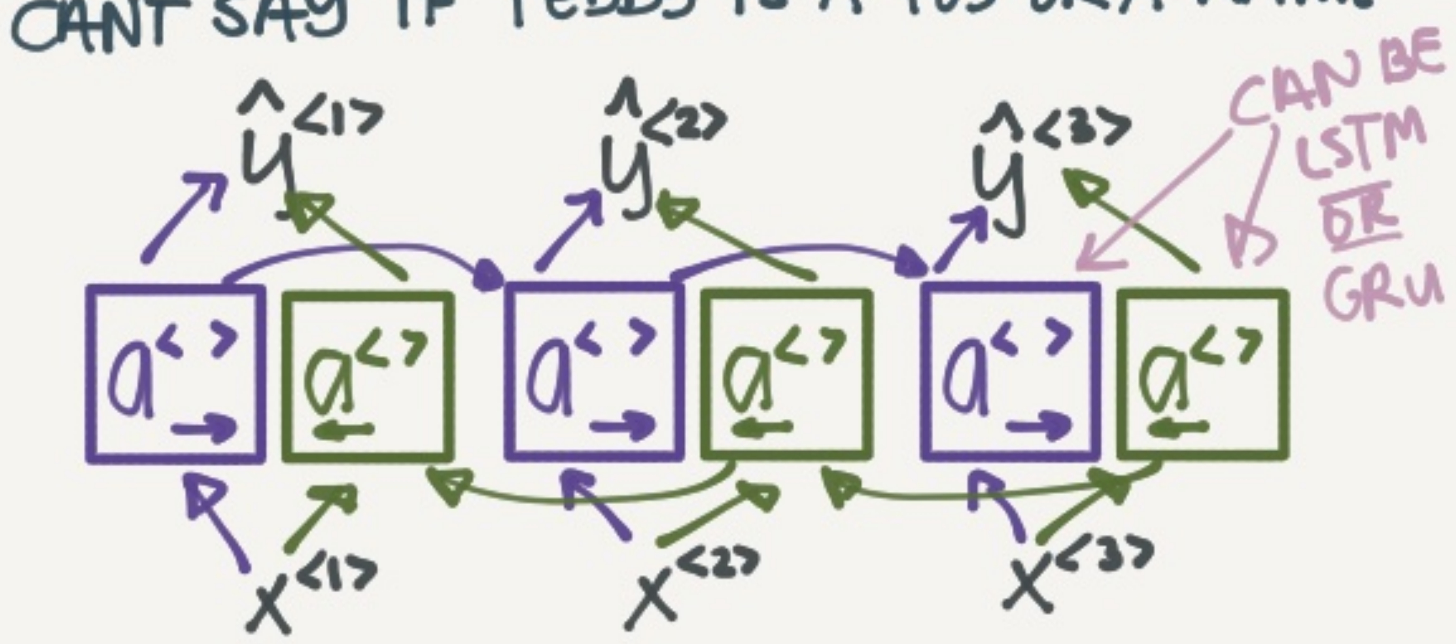
LONG SHORT TERM MEMORY (LSTM)

THE LSTM IS A VARIATION ON THE SAME THEME AS GRU BUT WITH AN ADDITIONAL Γ_F FORGET GATE

BI-DIRECTIONAL RNNs (BRNN)

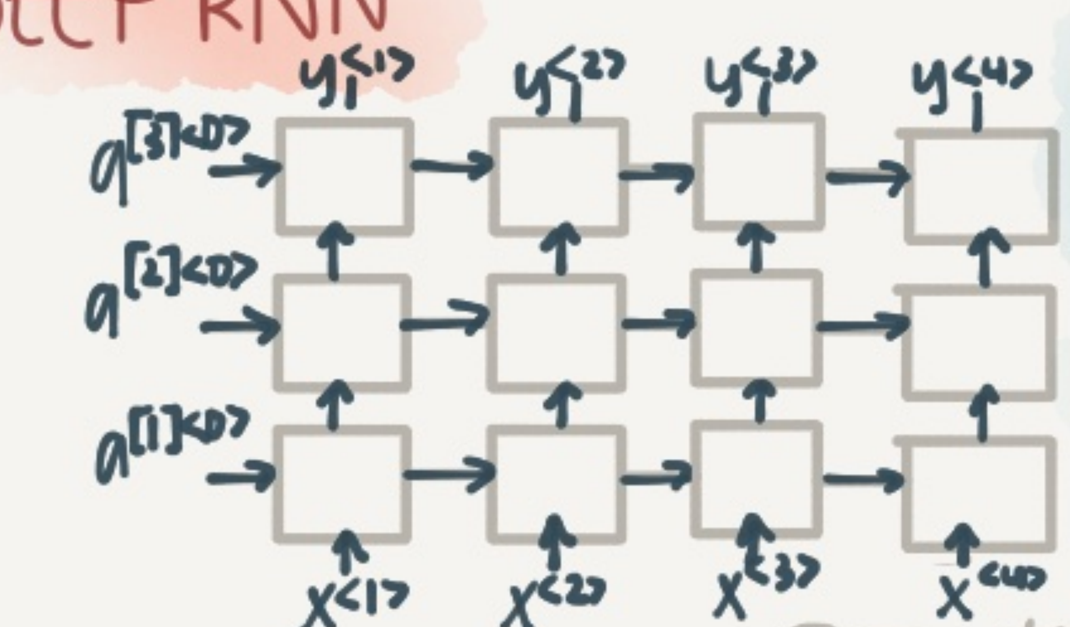
HE SAID, 'TEDDY BEARS ARE ON SALE'
HE SAID, 'TEDDY ROOSEVELT WAS A GREAT PRESIDENT'

PROBLEM: WITHOUT LOOKING FORWARD WE CANT SAY IF TEDDY IS A TOY OR A NAME



ONE DISADVANTAGE IS THAT YOU NEED THE FULL SENTENCE BEFORE YOU BEGIN – SO NOT SUITABLE FOR LIVE SPEECH REC

DEEP RNN



SINCE THEY ARE ALREADY TEMPORALLY DEEP THEY USUALLY DON'T HAVE A LOT OF LAYERS

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NLP & WORD EMBEDDINGS

MAN IS TO WOMAN AS KING IS TO QUEEN

PROBLEM: THE ONE-HOT REPR O_{456} OF APPLE HAS NO INFO ABOUT ITS RELATIONSHIP TO O_{6257} ORANGE

I WANT A GLASS OF ORANGE ____
I WANT A GLASS OF APPLE ____

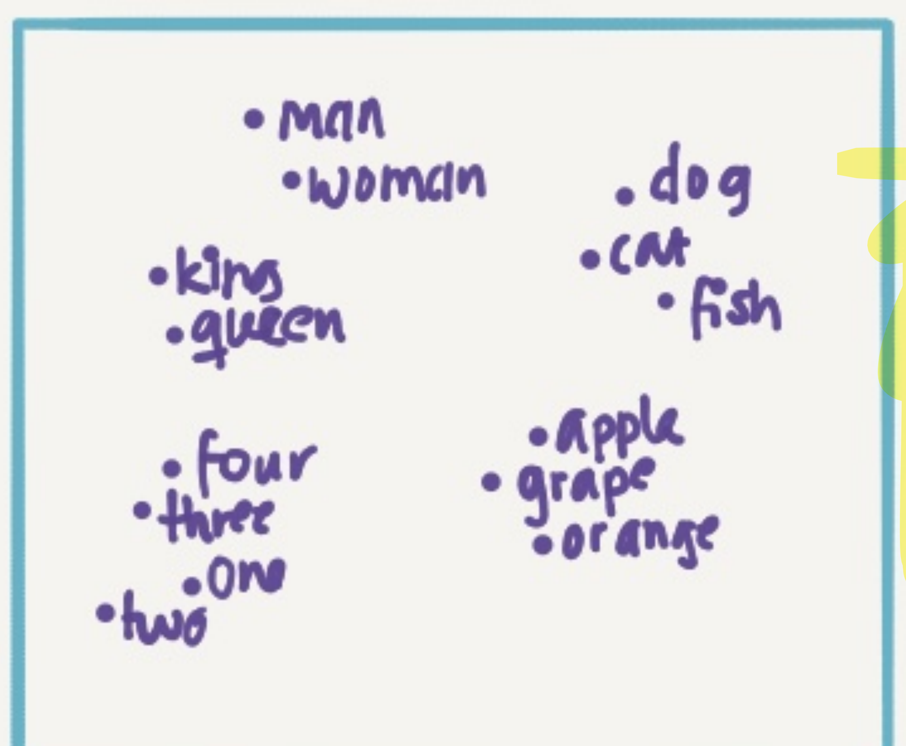
SOLUTION: CREATE A MATRIX OF FEATURES TO DESCRIBE THE WORDS

WORD EMBEDDINGS

	MAN 5391	WOMAN 9853	KING 4914	QUEEN 7157	APPLE 456	ORANGE 6257
GENDER	-1	1	-0.95	0.97	0.00	0.01
ROYAL	0.01	0.02	0.93	0.95	-0.01	0.00
AGE	0.03	0.02	0.7	0.69	0.03	-0.02
FOOD	0.04	0.01	0.02	0.01	0.95	0.97
⋮						

e_{5391}

IN REALITY THE FEATURES ARE LEARNED & NOT AS STRAIGHTFWD AS GENDER/AGE



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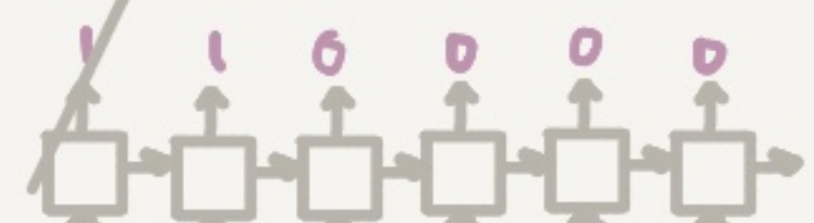
VISUAL REPRESENT OF 300D WORD EMBEDDINGS

SEQUENCE MODELS · COURSERA

USING WORD EMBEDDINGS

EX. NAME/ENTITY RECOGN



SALLY SMITH IS AN ORANGE FARMER
ROBERT LIN IS AN APPLE FARMER
BOB JONES IS A DURIAN CULTIVATOR

WITH WORD EMBEDDINGS WE UNDERSTAND THAT AN ORANGE FARMER IS A PERSON ⇒ SALLY SMITH = NAME

- APPLE ~ ORANGE ⇒ APPLE FARMER = PERSON
- USING WORD EMBEDDINGS TRAINED ON LOTS OF TEXT WE ALSO GET EMB. FOR MORE UNCOMMON WORDS (DURIAN, CULTIVATOR)

EX. MAN IS TO WOMAN AS KING IS TO ?

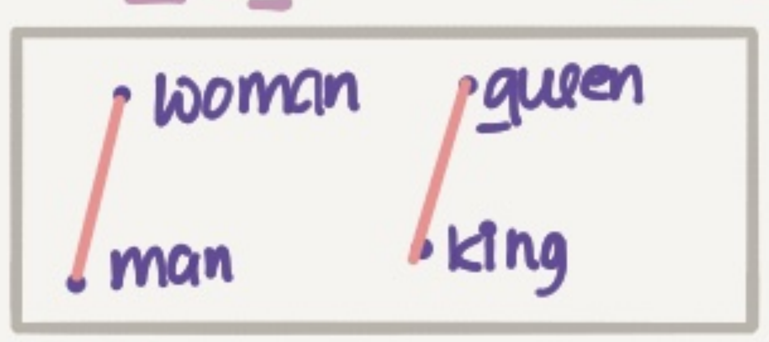
E = EMBEDDING MATRIX

e_{man}

	MAN 5391	WOMAN 9853	KING 4914	QUEEN 7157
GENDER	-1	1	-0.95	0.97
ROYAL	0.01	0.02	0.93	0.95
AGE	0.03	0.02	0.7	0.69
FOOD	0.04	0.01	0.02	0.01

$e_{man} - e_{woman}$ $\quad$ $e_{king} - e_{queen}$

$\begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$ VERY SIMILAR $\begin{bmatrix} -2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$



FIND
MAN→WOMAN
KING→?

FIND(w):
ARG.MAX SIM(e_w, $e_{king} - e_{man} + e_{woman}$)

$SIM(u,v) = \frac{u^T v}{\|u\|_2 \|v\|_2}$ COSINE SIMILARITY

LEARNING WORD EMBEDDINGS

HOW DO WE LEARN THE EMBEDDING MATRIX E?

IDEA 1: USING A NEURAL LANG MODEL

I WANT A GLASS OF ORANGE $\hat{y}$

A — O_1 — E — e_1
GLASS — O_{3852} — E — e_{3852}
OF — O_{6163} — E — e_{6163}
ORANGE — O_{6257} — E — e_{6257}
→ W, b → SOFTMAX 1000 → $\hat{y}$ (JUICE)

WE CAN USE DIFFERENT CONTEXTS THAN THE LAST 4 WORDS

- LAST 4 WORDS
- 4 WORDS LEFT+RIGHT
- LAST 1 WORD
- NEARBY 1 WORD ← SKIPGRAM RANDOM WITHIN EX 5 WORDS

IDEA 2: SKIP-GRAMS WORD2VEC

I WANT A GLASS OF ORANGE JUICE TO GO ALONG WITH MY CEREAL

PICK RANDOM CONTEXT/TARGET PAIRS (WITHIN EX 5 WORDS)

CONTEXT	TARGET
ORANGE	JUICE
ORANGE	GLASS
ORANGE	MY
...	...

$O_c \to E \to e_c \to$ ○ $\to \hat{y}(O_t)$ (SOFTMAX, 1000)

NOTE: WHILE THIS SIMPLE NN PREDICTS O_t OUR REAL GOAL IS TO LEARN E

THIS IS VERY COMPUTATIONALLY EXPENSIVE BUT WE CAN OPTIMIZE BY USING A HIERARCHICAL SOFTMAX CLASSIFIER

IDEA: NEGATIVE SAMPLING

1. PICK A CONTEXT/TARGET PAIR AS A POSITIVE EXAMPLE
2. PICK A FEW NEG EXAMPLES CONTEXT + RANDOM

CONTEXT	WORD	TARGET
ORANGE	JUICE	1
ORANGE	KING	0
ORANGE	BOOK	0
ORANGE	THE	0
ORANGE	OF	0

NOTE: SOMETIMES BY CHANCE YOU PICK A POS PAIR BUT IT DOESN'T MATTER

$O_c \to E \to e_c$ → 10000 BIN. CLASSIFIERS: ..., JUICE, ..., KING, ...

YOU ONLY TRAIN 5 FOR EACH CONTEXT WORD ⇒ EFFICIENT TO TRAIN

@TessFerrandez

WORD
EMBEDDINGS
CONTINUED...

SEQUENCE MODELS · COURSERA

GloVe WORD VECTORS

X_{ij} = #TIMES WORD i (TARGET t) APPEARS IN THE CONTEXT OF j (CONTEXT c)
(HOW RELATED THEY ARE)

MINIMIZE $\sum_{i=1}^{10k} \sum_{j=1}^{10k} f(X_{ij})(\theta_i^T e_j + b_i + b_j' - \log X_{ij})^2$

∅ IF NO CONTEXT
(ALSO HELPS WEIGHING VERY FREQ WORDS (THE, OF...) & VERY INFREQUENT (DURIAN))

EVERYTHING LED UP TO THIS VERY SIMPLE ALGORITHM

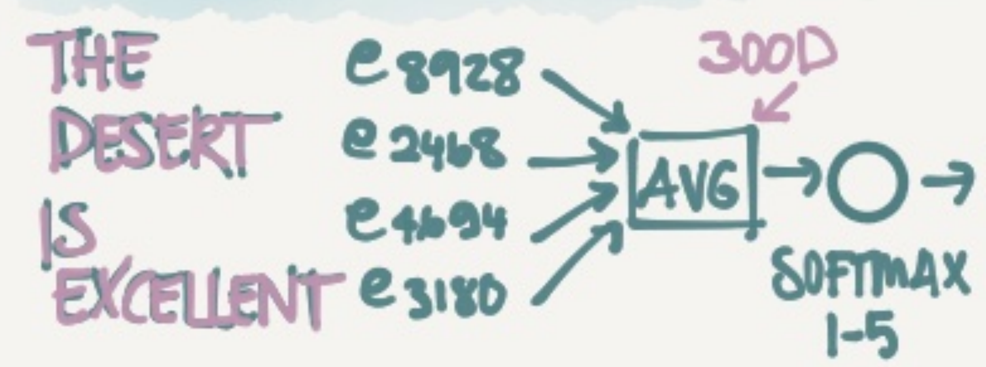
SENTIMENT CLASSIFICATION

X	y
THE DESSERT IS EXCELLENT	★★★★
SERVICE WAS QUITE SLOW	★★
GOOD FOR A QUICK MEAL BUT NOTHING SPECIAL	★★★
COMPLETELY LACKING IN GOOD TASTE GOOD SERVICE AND GOOD AMBIENCE	★

PROBLEM: YOU MAY NOT HAVE A LARGE DATASET

BUT YOU CAN USE AN EMBEDDING MATRIX E THAT IS ALREADY PRE-TRAINED

IDEA: SIMPLE CLASSIFICATION

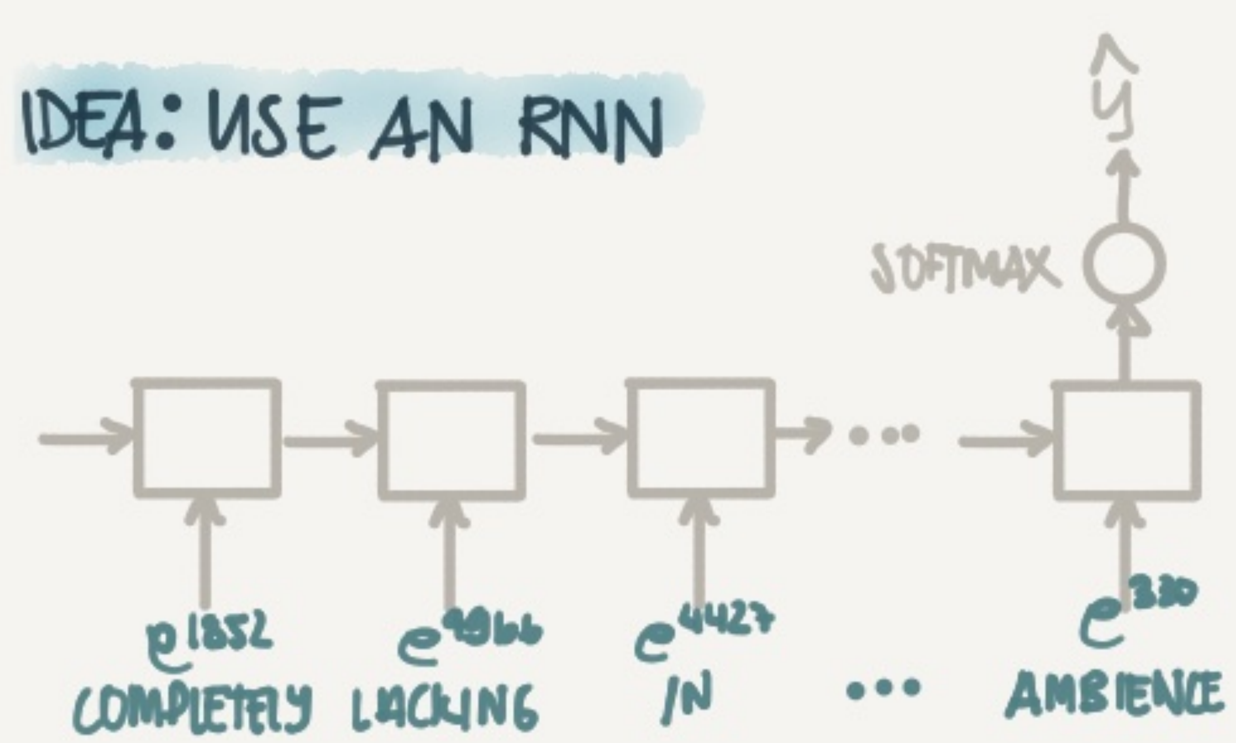


WORKS WELL FOR SHORT SENTENCES BUT DOESN'T TAKE ORDER INTO ACCOUNT

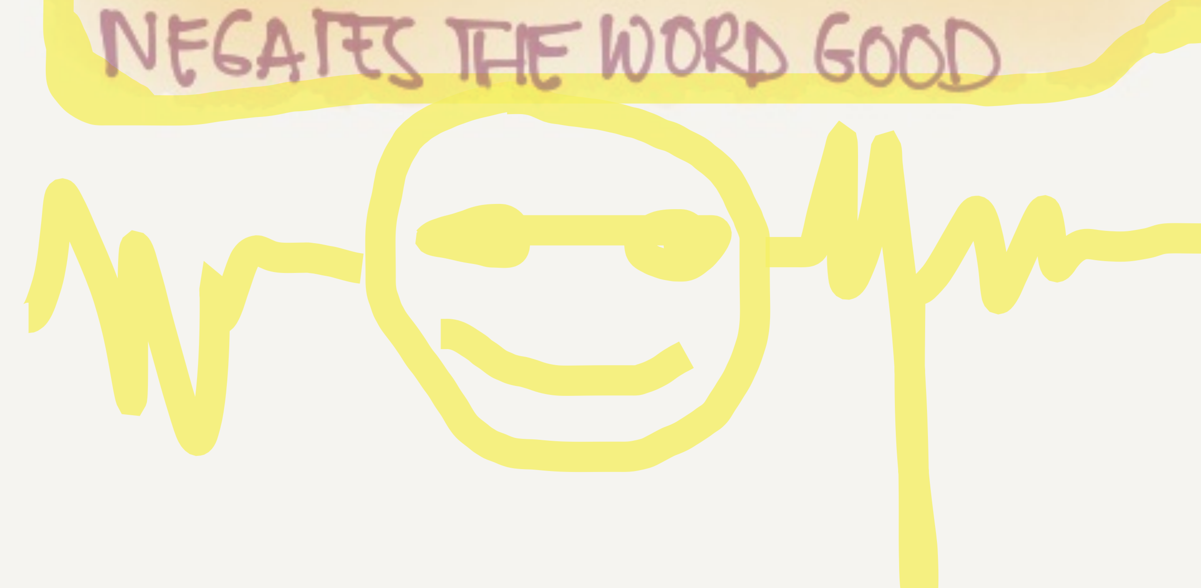
"COMPLETELY LACKING IN GOOD TASTE, GOOD SERVICE AND GOOD AMBIENCE"

THIS MAY BE SEEN AS A +++ REVIEW

IDEA: USE AN RNN



THIS CAN NOW TAKE INTO ACCOUNT THAT COMPLETELY LACKING NEGATES THE WORD GOOD

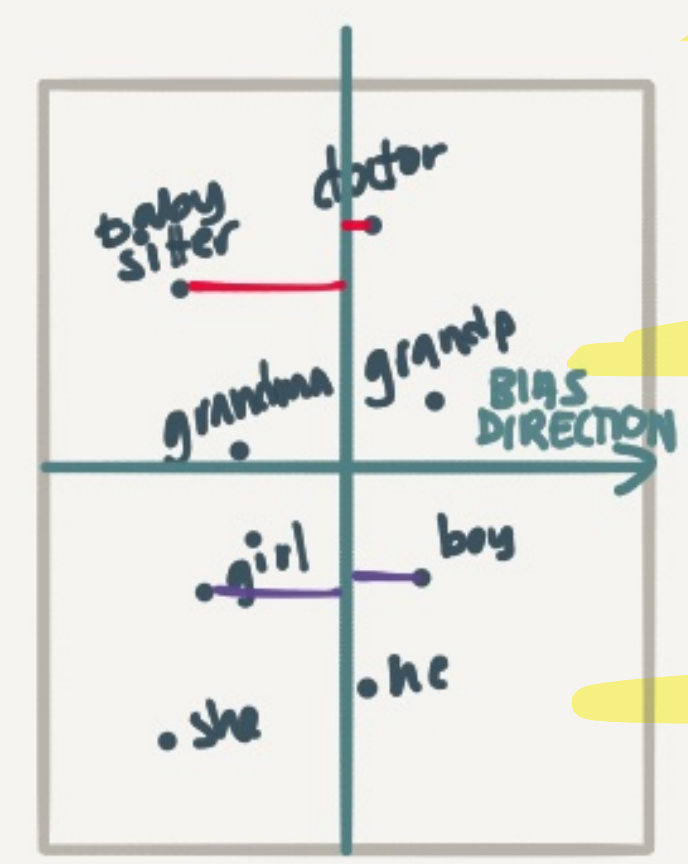


ELIMINATING BIAS IN WORD EMBEDDINGS

MAN IS TO COMPUTER PROGRAMMER AS WOMAN IS TO HOME MAKER

SOMETIMES THE TEXT CONTAINS ∴ ALGOS LEARN A GENDER, RACE, AGE... BIAS WE DON'T WANT OUR MODELS TO HAVE. EX. HIRING BASED ON GENDER, SENTENCING BASED ON RACE ETC.

ADDRESSING BIAS



1. IDENTIFY BIAS DIRECTION
   $\{ e_{he} - e_{she}$
   $\;\; e_{male} - e_{female}$
2. NEUTRALIZE
   FOR EVERY WORD THAT IS NOT DEFINITIONAL (GIRL, BOY, HE, SHE..) PROJECT TO GET RID OF BIAS
3. EQUALIZE PAIRS
   THE ONLY DIFF BETWEEN EX GIRL/BOY SHOULD BE GENDER

HOW DO YOU KNOW WHICH WORDS TO NEUTRALIZE?

DOCTOR, BEARD, SEWING MACHINE?

A: BY TRAINING A CLASSIFIER TO FIND OUT IF A WORD IS DEFINITIONAL

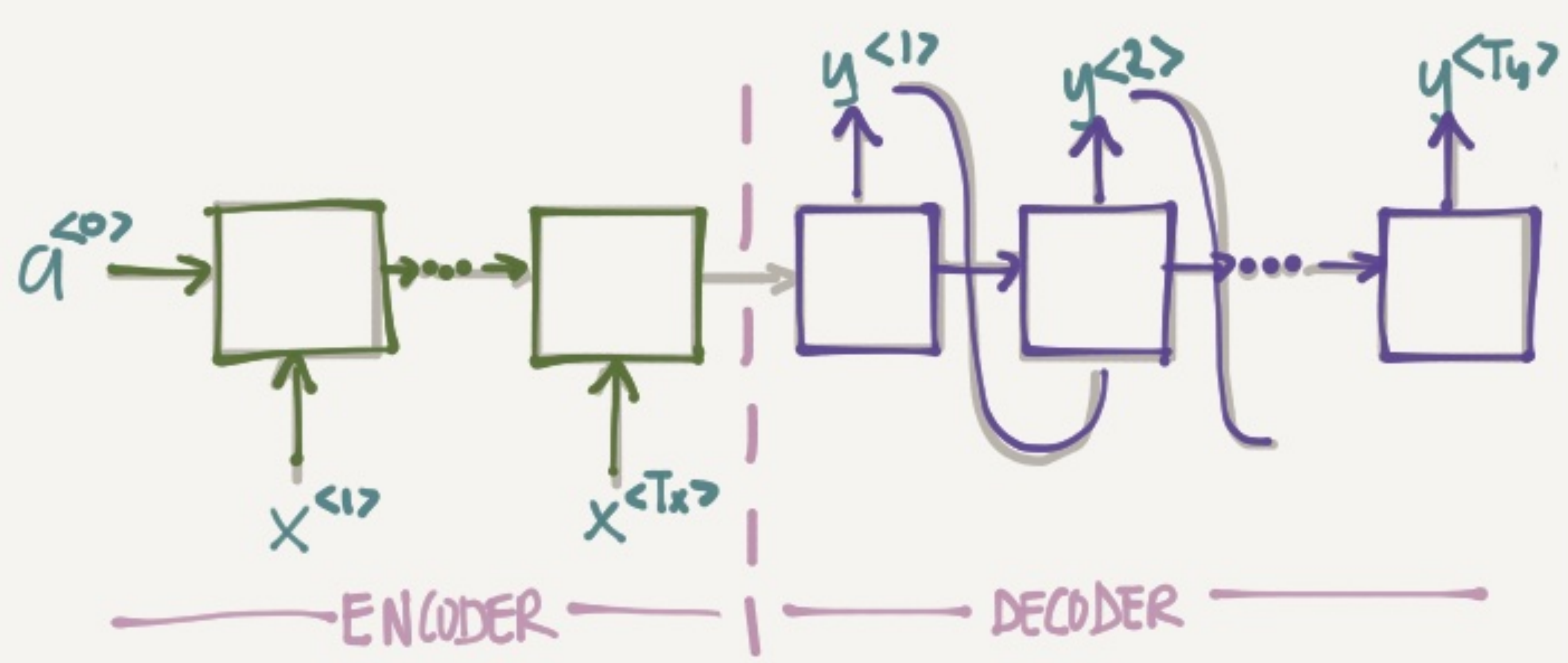
TURNS OUT THE # OF PAIRS IS FAIRLY SMALL SO YOU CAN EVE HAND PICK THEM

SEQUENCE TO SEQUENCE

SEQUENCE MODELS · COURSERA

BASIC MODELS

JANE VISITE L'AFRICE EN SEPTEMBRE → JANE IS VISITING AFRICA IN SEPTEMBER



→ THIS IS A CAT ON A CHAIR

CNN → RNN

HOW DO YOU PICK THE MOST LIKELY SENTENCE?

$$P(\underbrace{y^{<1>}, \dots, y^{<T_y>}}_{\text{ENGLISH}} | \underbrace{x}_{\text{FRENCH}})$$

WE DON'T WANT A RANDOMLY GENERATED SENTENCE (WE WOULD SOMETIMES GET A GOOD, SOMETIMES BAD)

INSTEAD WE WANT TO MAXIMIZE

$$\text{ARG MAX } P(y^{<1>}, \dots, y^{<T_y>} | x)$$

IDEA: USE GREEDY SEARCH

1. PICK THE WORD WITH THE BEST PROBABILITY
2. REPEAT UNTIL <EOS>

WITH THIS WE COULD GET

- JANE IS GOING TO BE VISITING AFRICA THIS SEPTEMBER

INSTEAD OF

- JANE IS VISITING AFRICA THIS SEPTEMBER

$\boxed{\text{SOLUTION}}$ OPTIMISE THE PROB OF THE WHOLE SENTENCE INSTEAD

BEAM SEARCH

1. PICK THE FIRST WORD

   PICK THE B (EX 3) BEST ALTERNATIVES (IN, JANE, SEPTEMBER)

2. FOR EACH B WORDS PICK THE NEXT WORD AND EVALUATE THE PAIRS TO END UP W B PAIRS

   $P(y^{<1>}, y^{<2>} | x) = P(y^{<1>} | x)\, P(y^{<2>} | x, y^{<1>})$

   IN → A, AARON, SEPTEMBER, ZULU

   JANE → A, AARON, IS, VISITS, ZULU

   SEPTEMBER → A, AARON, :, ZULU

   (IN SEPTEMBER, JANE IS, JANE VISITS)

   NOTE: KEEP TRACK OF THE P FOR THE SENTENCES OF EACH LENGTH - AFTER X ITER (X MAX WORDS) PICK THE BEST

3. REPEAT TIL DONE

$$\text{ARG MAX} \prod_{t=1}^{T_y} P(y^{<t>} | x, y^{<1>}, \dots y^{<t-1>})$$

PROBLEM: MULTIPLYING PROBABILITIES (0<P<1) RESULTS IN A VERY SMALL NUMBER ← OVERFLOWS

PROBLEM II: IF WE OPTIMIZE FOR THE MULT WE WILL PREFER SHORT SENTENCES. SINCE EACH WORD WILL REDUCE PROB

INSTEAD WE CAN OPTIMIZE FOR THIS

$$\frac{1}{T_y^{\alpha}} \sum_{t=1}^{T_y} \log(p^{<t>} | x, y^{<1>}, \dots, y^{<t-1>})$$

HOW DO WE PICK B?

LARGE B: BETTER RESULT, SLOWER

SMALL B: WORSE RESULT, BETTER

IN PROD YOU MIGHT SE B=10. 100 IS PROBABLY A BIT TOO HIGH - BUT ITS DOMAIN DEPENDENT

ERROR ANALYSIS IN BEAM S.

HUMAN: JANE VISITS AFRICA IN SEPT... y^*

ALGO: JANE VISITED AFRICA LAST SEPTEMBER $\hat{y}$

HOW DO WE KNOW IF ITS OUR RNN OR OUR BEAM SEARCH WE SHOULD WORK ON?

LET THE RNN GIVE $Py^* = P(y^*|x)$ & $P\hat{y} = P(\hat{y}|x)$

IF $Py^* > P\hat{y}$:

BEAM PICKED THE WRONG ONE

TRY A HIGHER B

ELSE:

THE RNN PICKED THE WRONG PROBS - SO FOCUS ON THE RNN

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SEQUENCE MODELS · COURSERA

SEQUENCE TO SEQUENCE

FRENCH: LE CHAT EST SUR LE TAPIS
HUMAN1: THE CAT IS ON THE MAT
HUMAN2: THERE IS A CAT ON THE MAT

HOW DO YOU EVALUATE THE MACHINE TRANSLATION WHEN MULTIPLE ARE RIGHT?

BLEU SCORE

IDEA: CHECK IF THE WORDS MT APPEAR IN THE REAL TRANSLATION

THE THE THE THE THE THE THE
SCORE: 7/7

IDEA: ONLY GIVE CREDIT FOR A WORD THE MAX # TIMES IT APPEARS IN A TARGET SENTENCE
SCORE: 2/7 — COUNT CLIP

THE CAT THE CAT ON THE MAT

BIGRAMS	COUNT	COUNT CLIP
THE CAT	2	1
CAT THE	1	0
CAT ON	1	1
ON THE	1	1
THE MAT	1	1
	6	4/6

BI-GRAM SCORE: 4/6

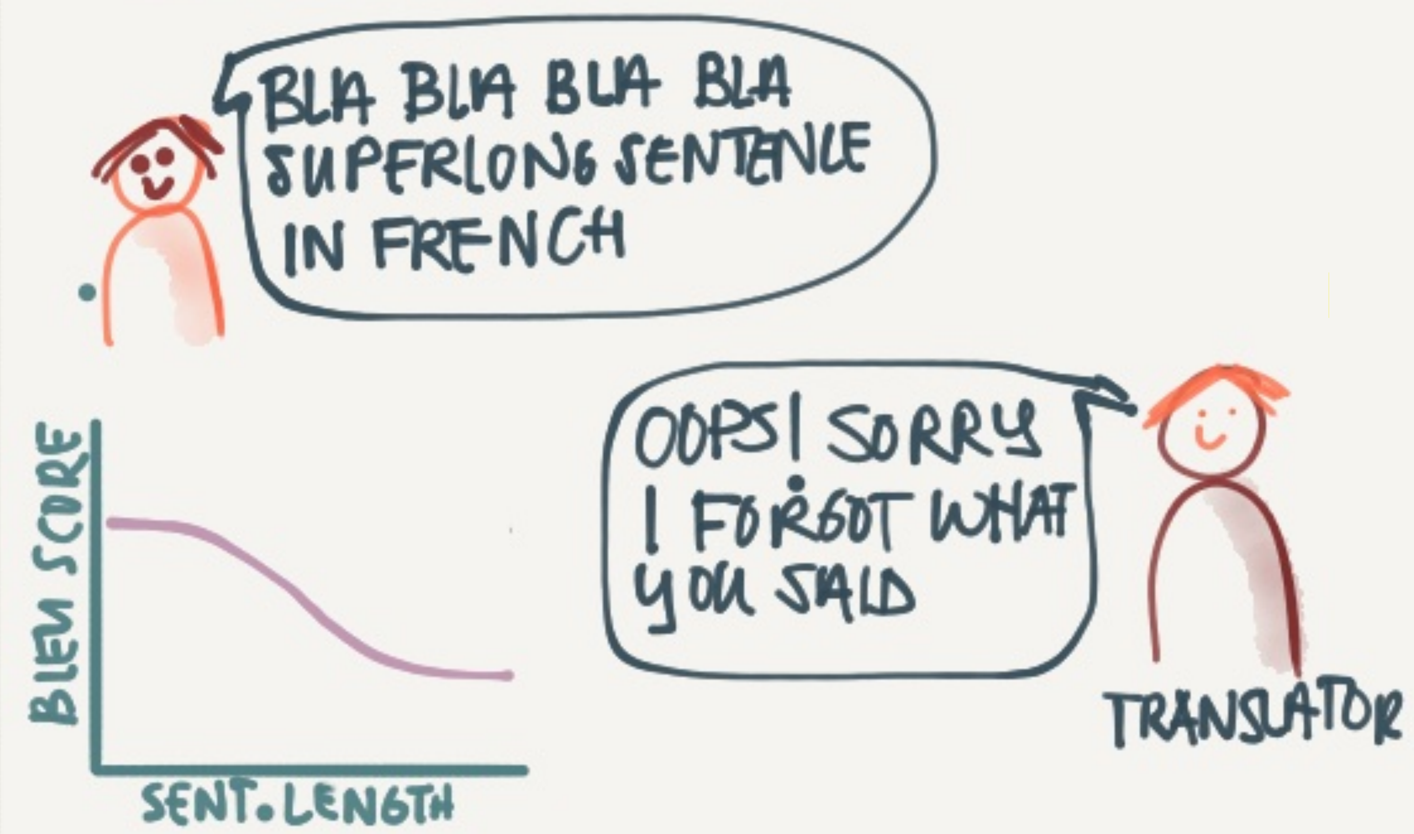
COMBINED BLEU SCORE

$$BP \cdot \exp\left(\frac{1}{4}\sum_{n=1}^{4} P_n\right)$$

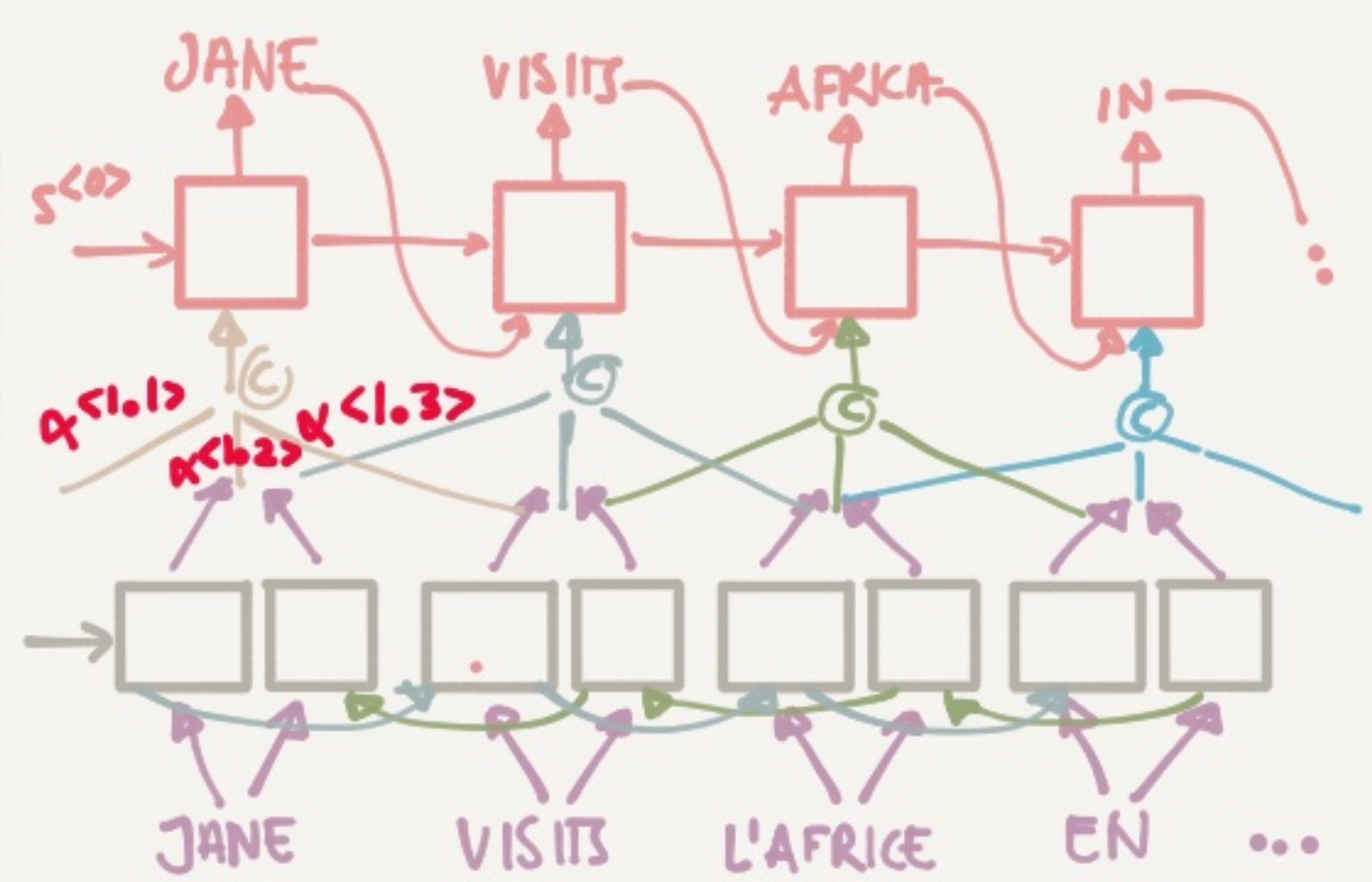
P_1 = SCORE SINGLE WORD
P_2 = SCORE BIGRAMS
...
BP = BREVITY PENALTY — PENALIZES SENTENCES SHORTER THAN THE TARGET

A USEFUL SINGLE NUMBER EVAL METRIC

ATTENTION MODEL



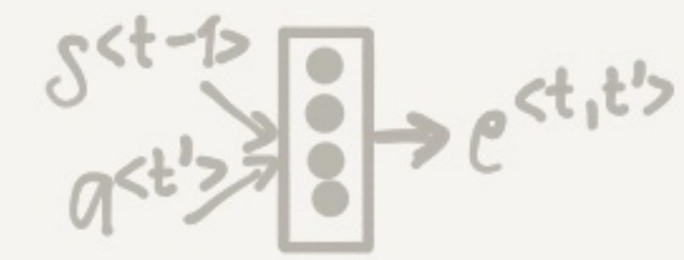
SOLUTION TRANSLATE A LITTLE AT A TIME USING ONLY PARTS OF THE SENTENCE AS CONTEXT



$\alpha^{<t,t'>}$ = HOW MUCH ATTENTION $y^{<t>}$ SHOULD PAY TO $a^{<t'>}$

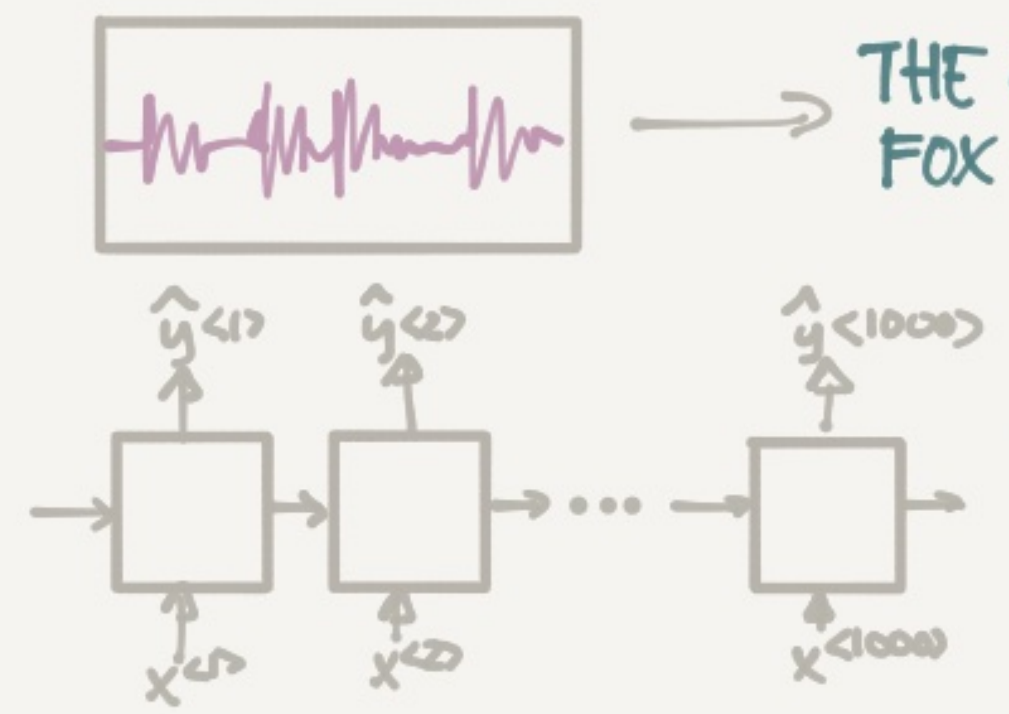
$$c^{<2>} = \sum_{t'} \alpha^{<2,t'>} \cdot a^{<t'>} \quad \Big| \quad \sum_{t'} \alpha^{<1,t'>} = 1$$

α IS CALCULATED USING A SMALL NEURAL NETWORK



$$\alpha^{<t,t'>} = \frac{\exp(e^{<t,t'>})}{\sum_{t'=1}^{T_x} \exp(e^{<t,t'>})}$$

SPEECH RECOGNITION



PROBLEM: 10s CLIP AT 100Hz = 1000 INPUTS BUT ONLY ≈ 20 OUTPUTS

SOLUTION USE CTC COST (CONNECTION TEMPORAL CLASSIFICATION)

ttt_h_eee___u___qqq__

COLLAPSE REPEATED CHARS NOT SEP BY BLANK

TRIGGER WORD DETECTION

COULD SET A FEW SUBSEQUENT TO 1 TO EVEN OUT THE DS

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