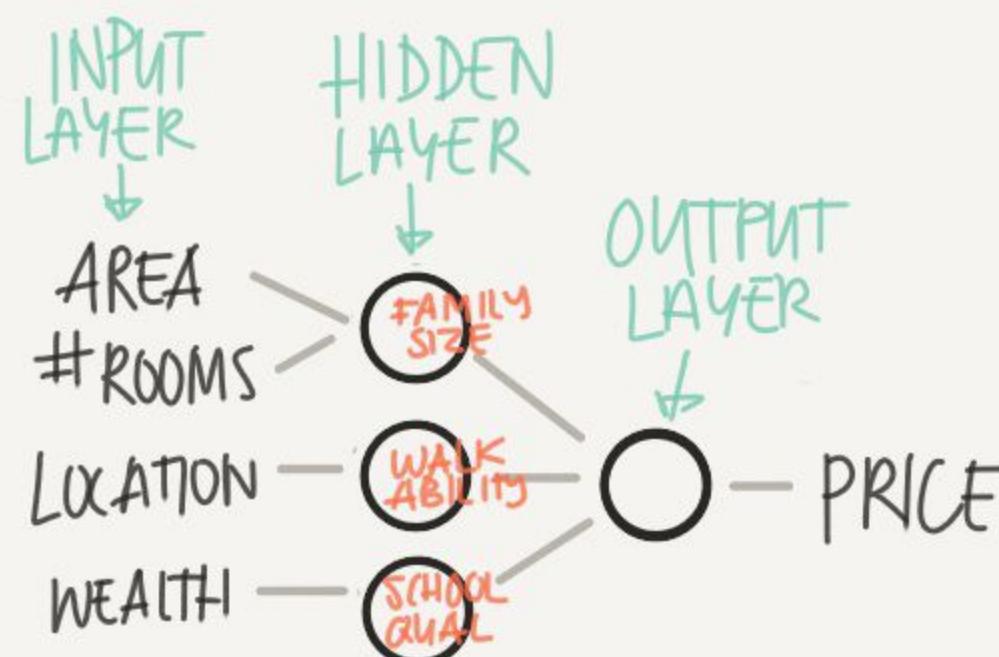
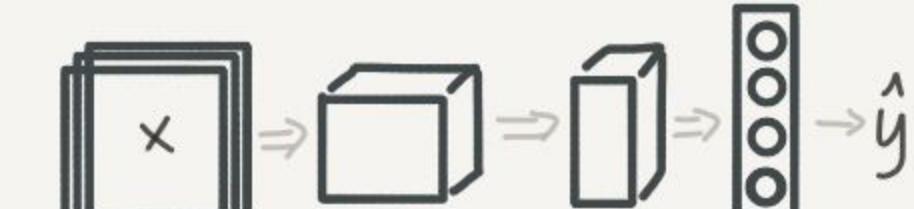
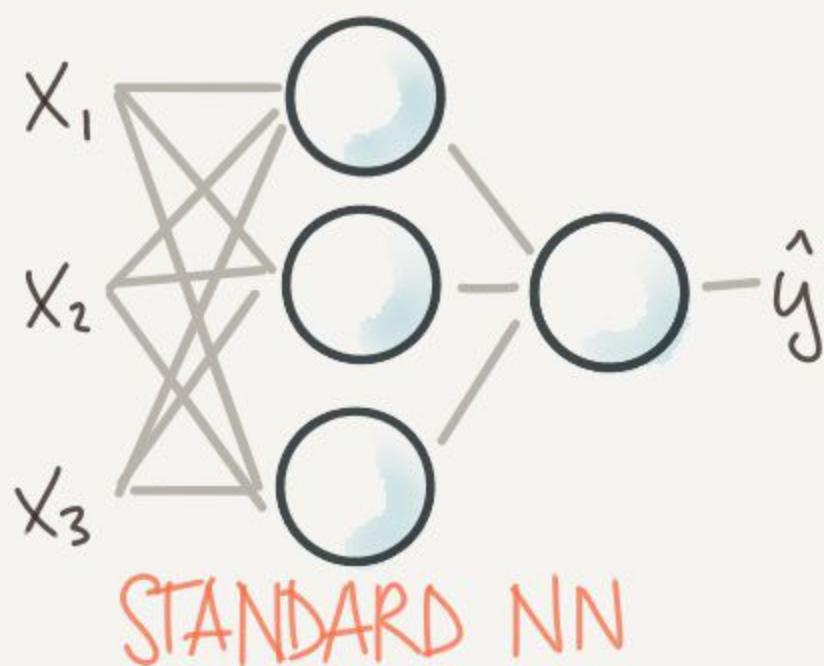


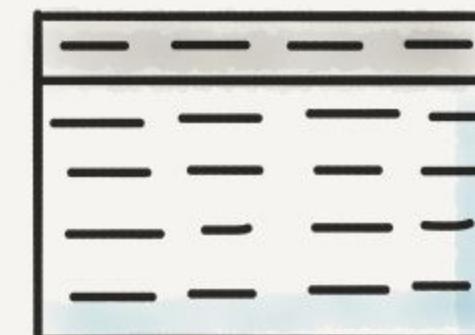
INTRO TO DEEP LEARNING

SUPERVISED LEARNING

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



NNs CAN DEAL WITH BOTH
STRUCTURED & UNSTRUCTURED DATA



STRUCTURED



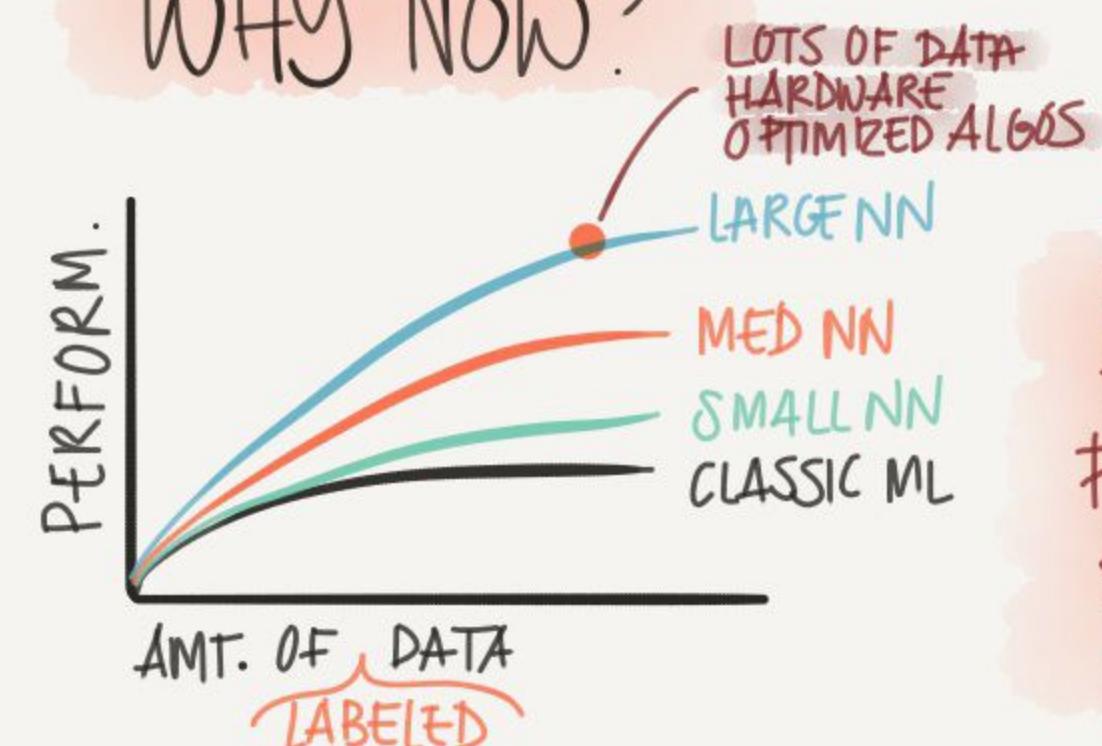
"THE QUICK BROWN FOX"



UNSTRUCTURED

HUMANS ARE GOOD
AT THIS

WHY NOW?

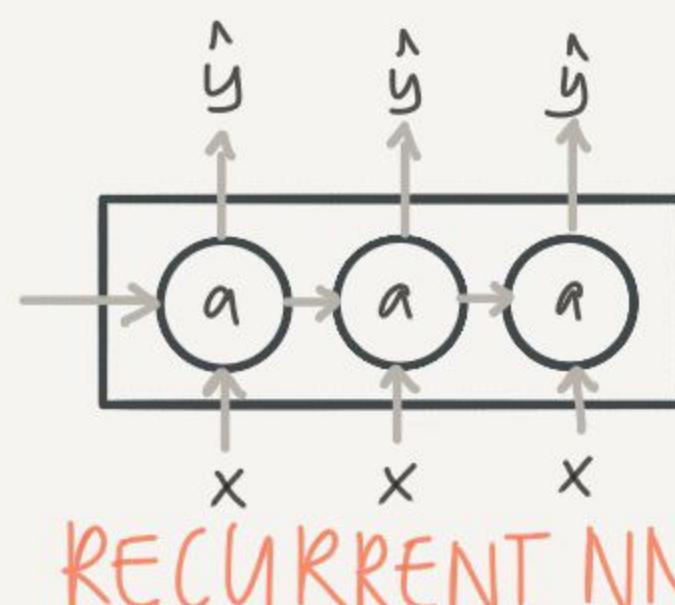


ONE OF THE
BIG BREAKTHROUGHS
HAS BEEN MOVING
FROM SIGMOID TO
RELU FOR FASTER
GRADIENT DESCENT

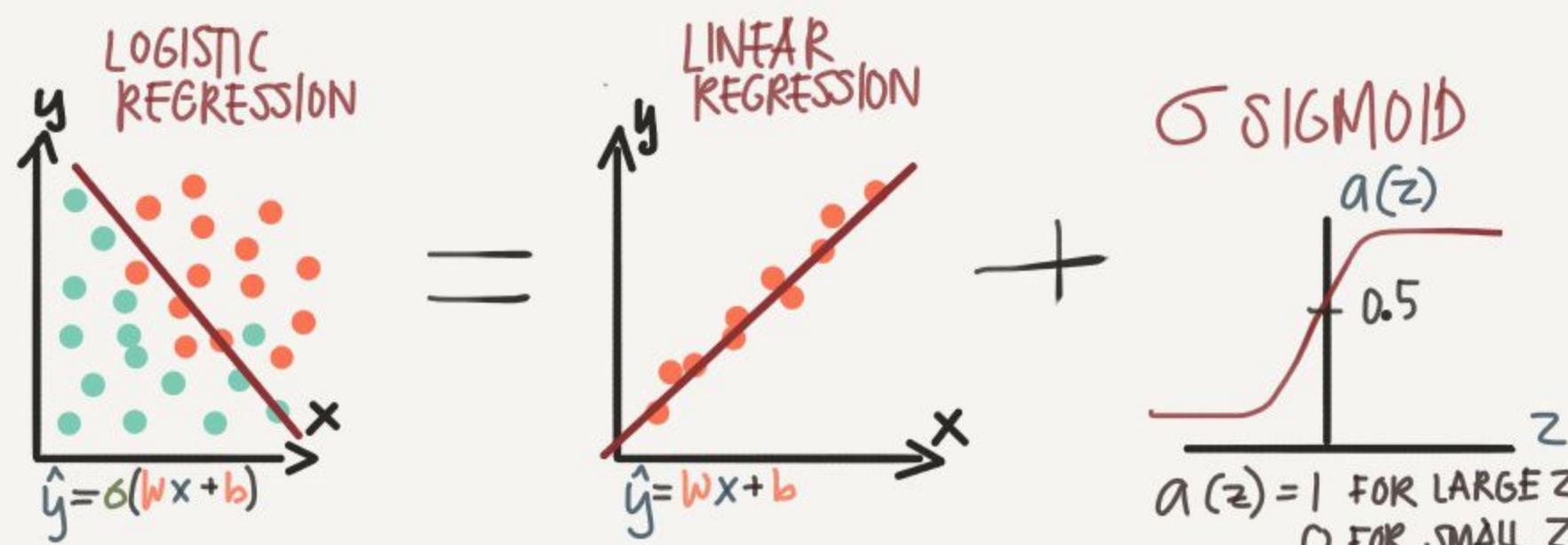
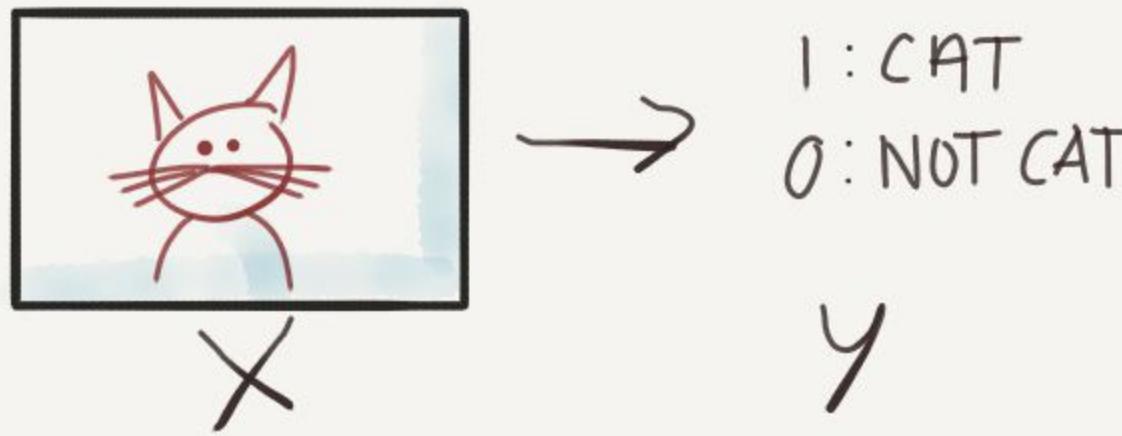


FASTER COMPUTATION
IS IMPORTANT TO SPEED UP
THE ITERATIVE PROCESS

NETWORK ARCHITECTURES



BINARY CLASSIFICATION



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)

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

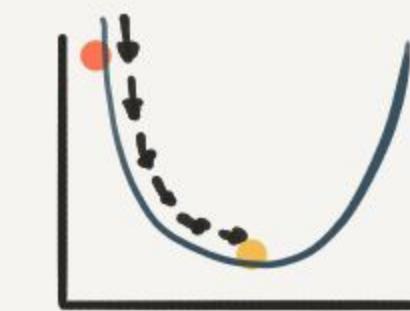
$$\text{COST} = J(w, b) = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

COST = LOSS FOR THE ENTIRE DATASET

LOGISTIC REGRESSION

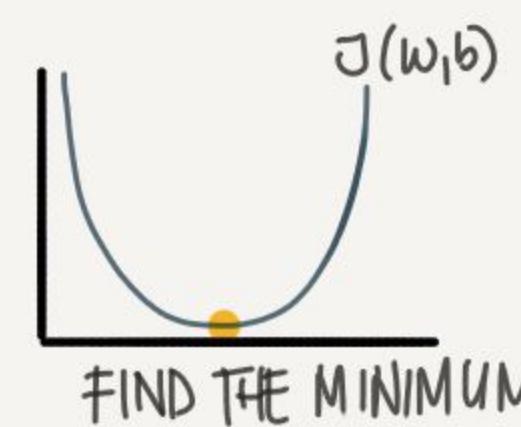
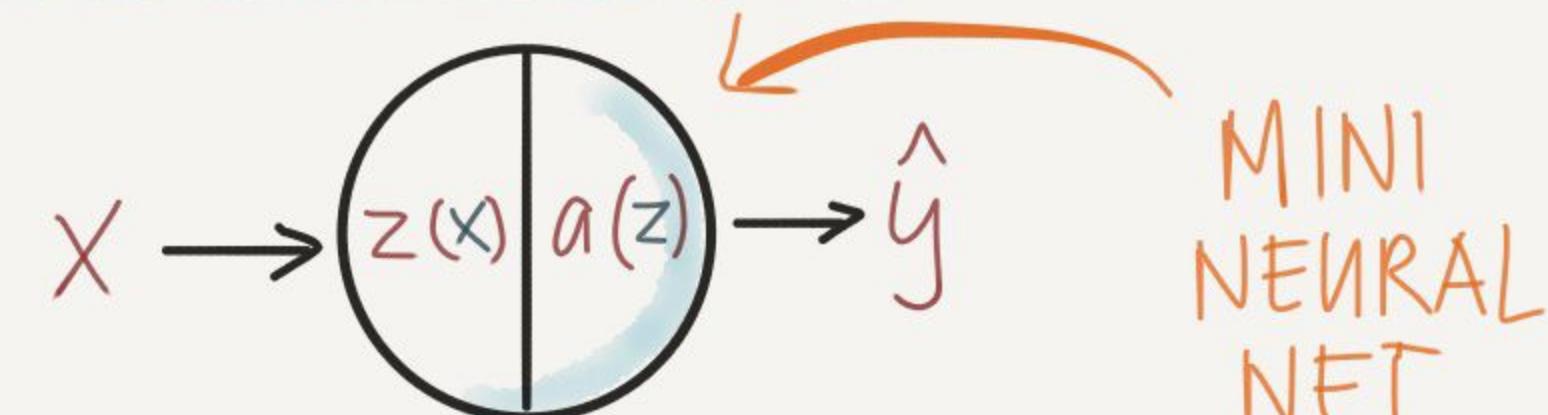
AS A NEURAL NET

FINDING THE MINIMUM WITH GRADIENT DESCENT



1. FIND THE DOWNSHILL DIRECTION (USING DERIVATIVES)
 2. WALK (UPDATE w & b) AT A α LEARNING RATE
- REPEAT UNTIL YOU REACH BOTTOM (CONVERGE)

PUTTING IT ALL TOGETHER



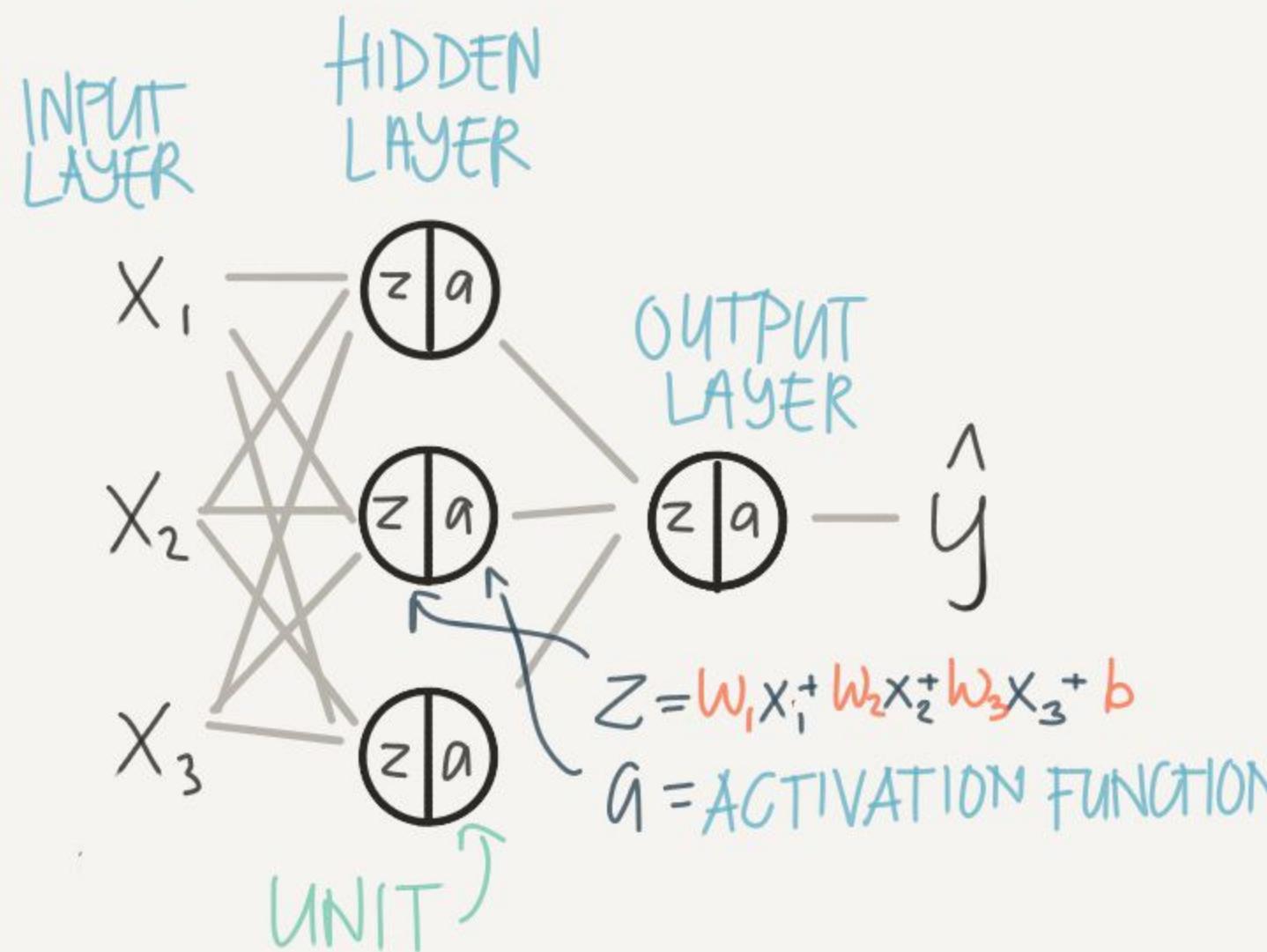
$$z(x) = wx + b$$

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

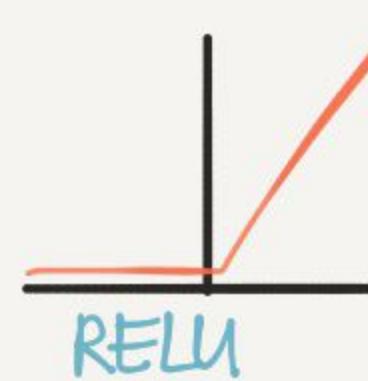
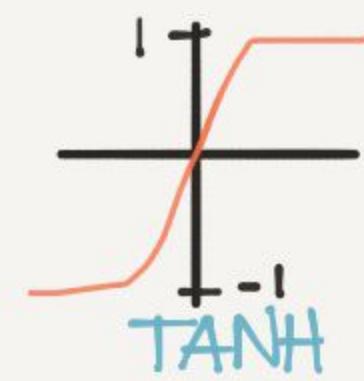
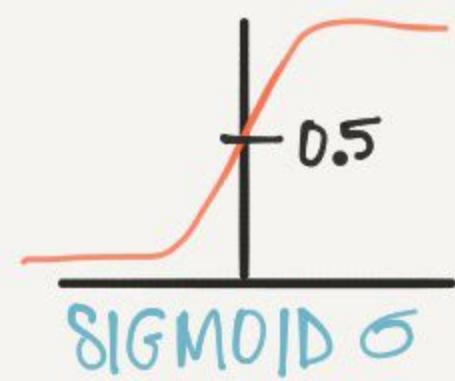
1. FORWARD PROPAGATION • CALCULATE \hat{y}
2. BACKWARD PROPAGATION • GRADIENT DESCENT + UPDATE w & b

REPEAT UNTIL IT CONVERGES

2 LAYER NEURAL NET



ACTIVATION FUNCTIONS



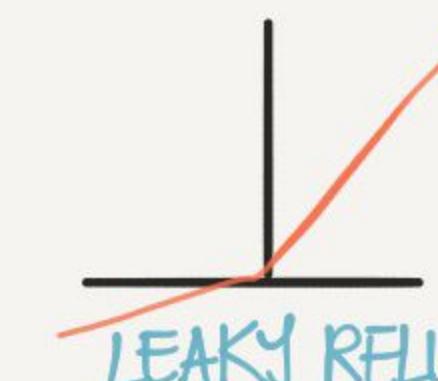
BINARY CLASSIFIER
ONLY USED FOR
OUTPUT LAYER

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

NORMALIZED
 \Rightarrow GRADIENT
DESCENT IS
FASTER

DEFAULT
CHOICE FOR
ACTIVATION
SLOPE = 1/0

AVOIDS UNDEF
SLOPE AT 0
BUT RARELY
USED IN PRACTICE



SHALLOW NEURAL NETS

WHY ACTIVATION FUNCTIONS?

EX. WITH NO ACTIVATION - $a = z$

$$\begin{aligned} a^{[1]} &= z^{[1]} = w^{[1]} x + b^{[1]} \\ a^{[2]} &= z^{[2]} = w^{[2]} a^{[1]} + b^{[2]} \end{aligned}$$

LAYER 1
LAYER 2

PLUG IN $a^{[1]}$

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

LINEAR FUNCTION

INITIALIZING $w+b$

WHAT IF: INIT TO 0

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

SOLUTION: RANDOM INIT
BUT ALSO WANT THEM
SMALL SD RAND ≈ 0.01

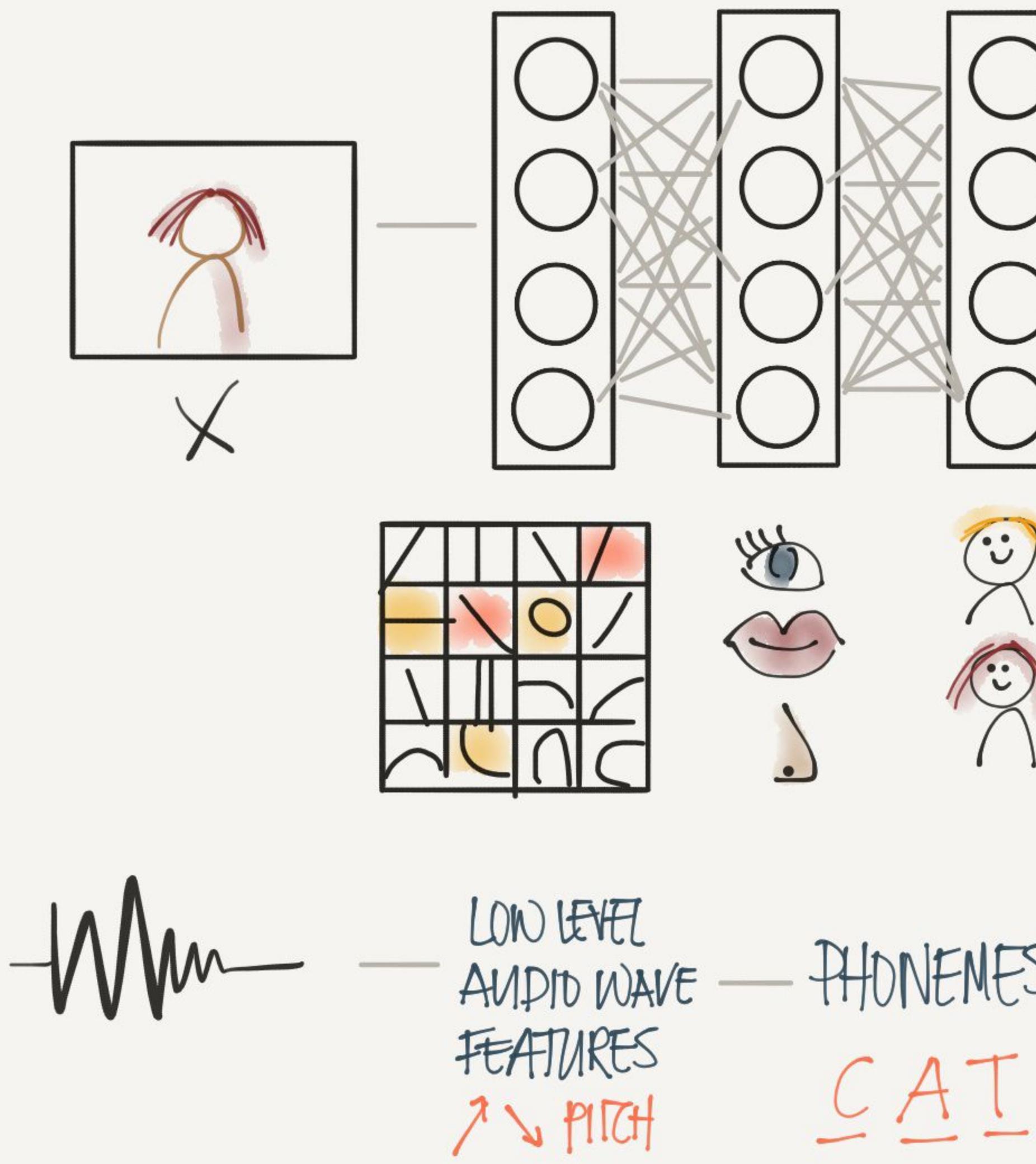
HYPERPARAM

© Tess Ferrandez

DEEP NEURAL NETS

WHY DEEP NEURAL NETS?

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



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

SETTING UP YOUR ML APP

CLASSIC ML

100 - 1000 SAMPLES

TRAIN	DEV	TEST
60%	20%	20%

ALL FROM SAME PLACE
DISTRIBUTION

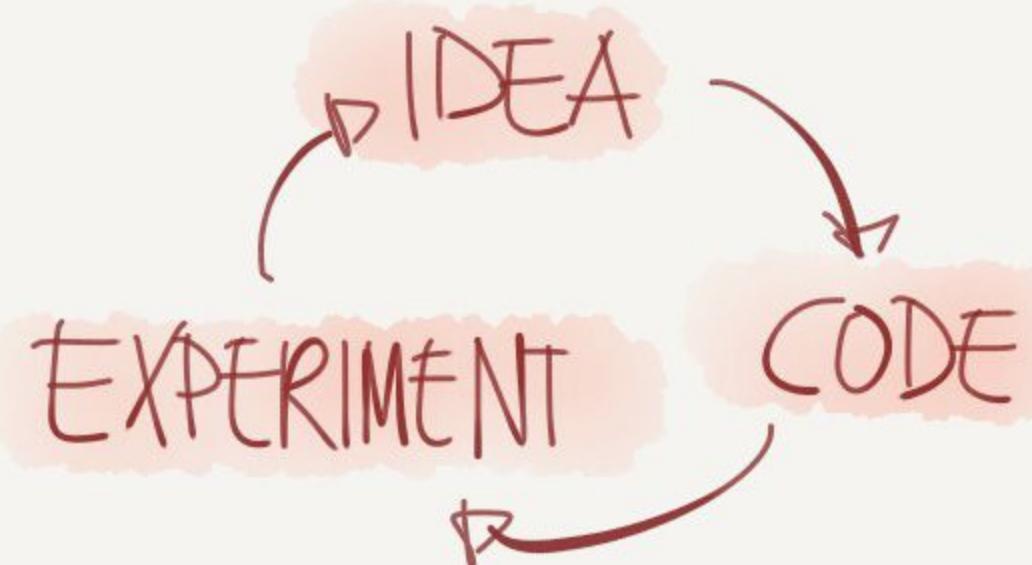
DEEP LEARNING

1M SAMPLES

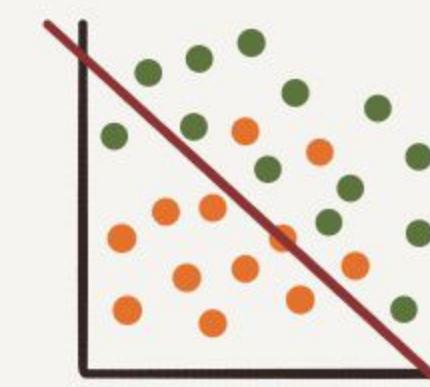
TRAIN	D	T
98%	1%	1%



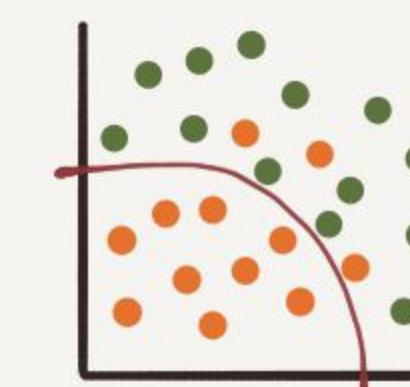
 TIP
DEV & TEST SHOULD COME
FROM SAME DISTRIBUTION



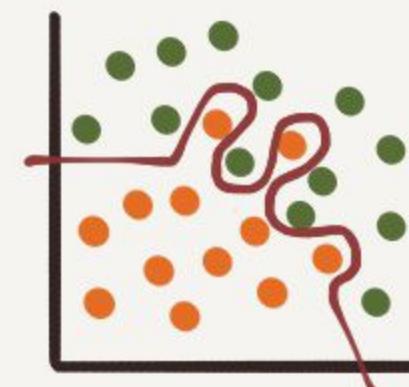
BIAS / VARIANCE



HIGH BIAS
"UNDERFIT"



JUST RIGHT



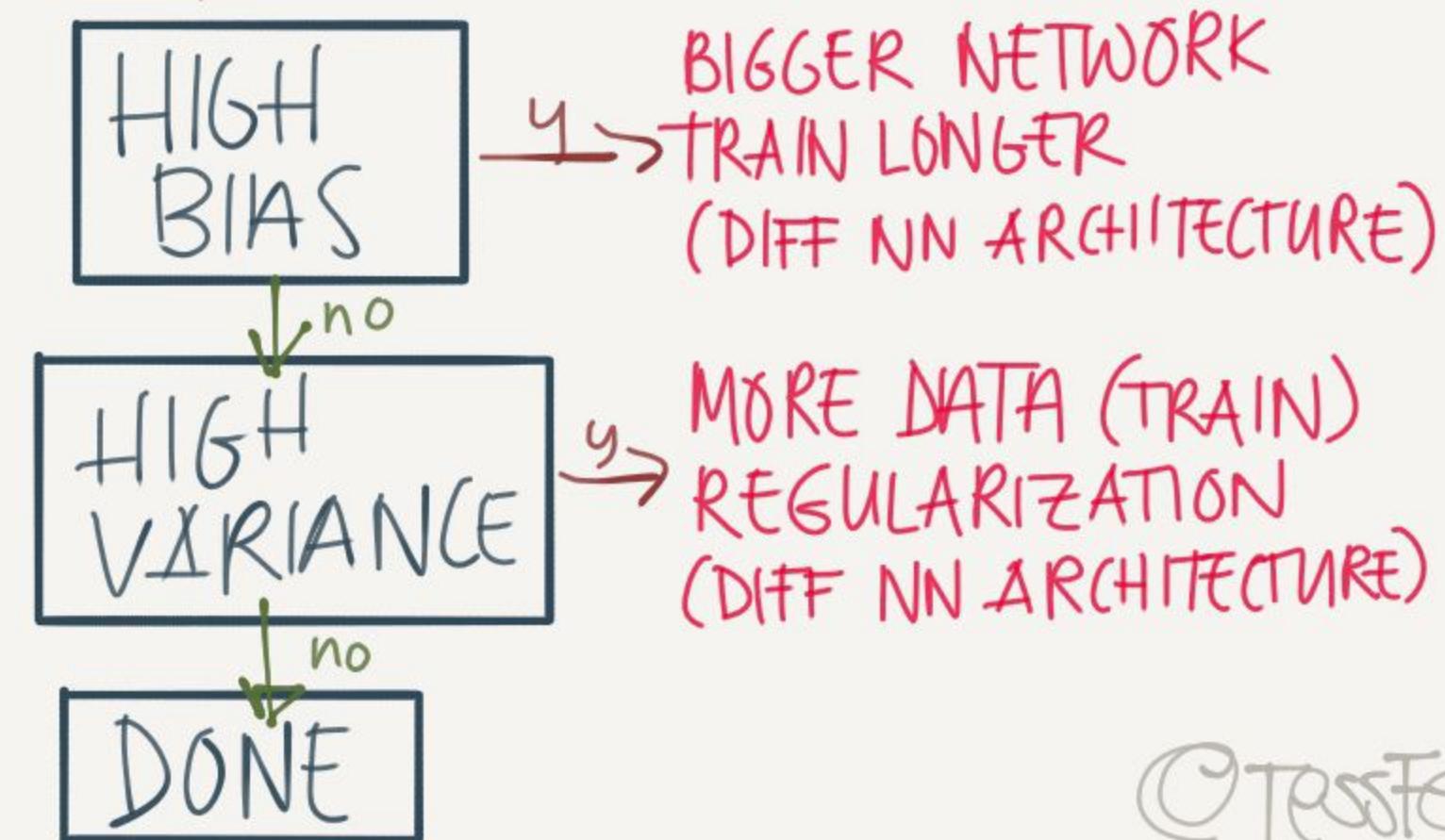
HIGH VARIANCE
"OVERFIT"

	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



REGULARIZATION

PREVENTING OVERTFITTING

L2 REGULARIZATION

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

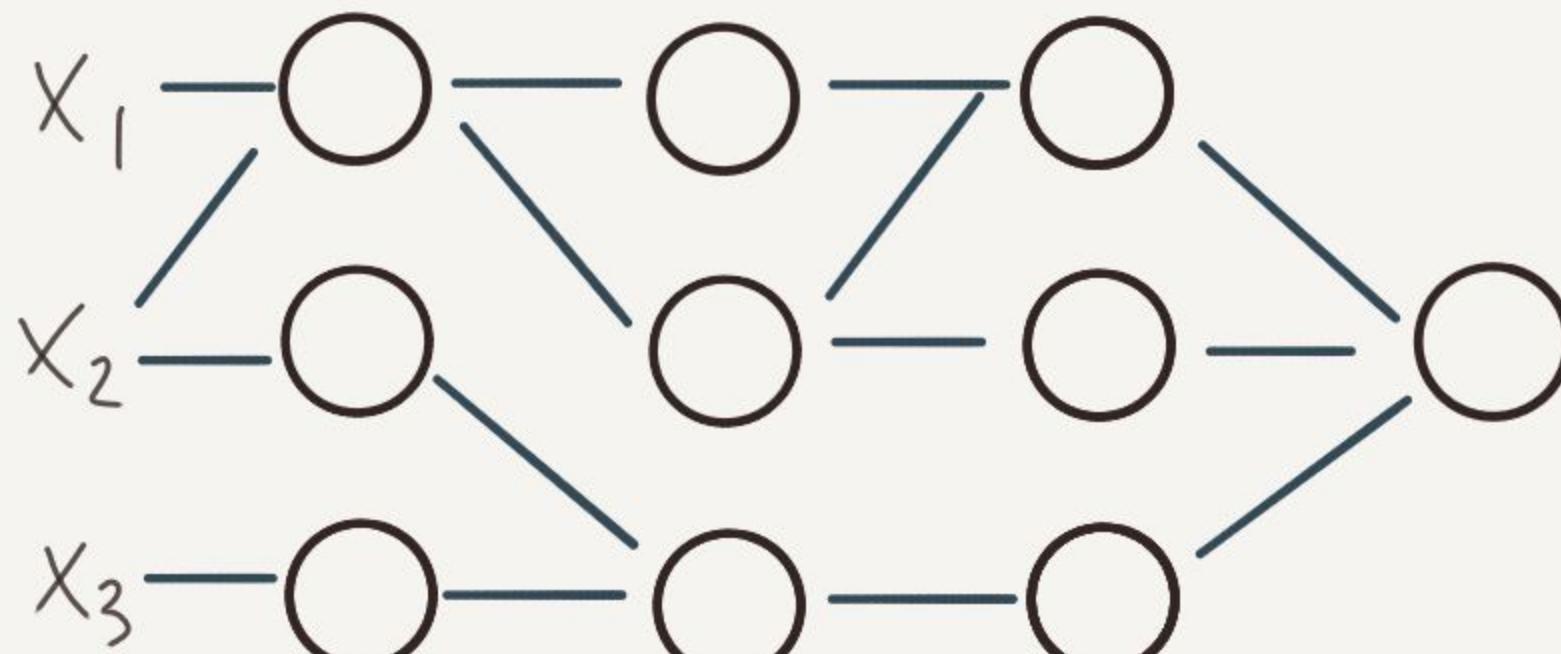
EUCLIDEAN NORM

L1 REGULARIZATION

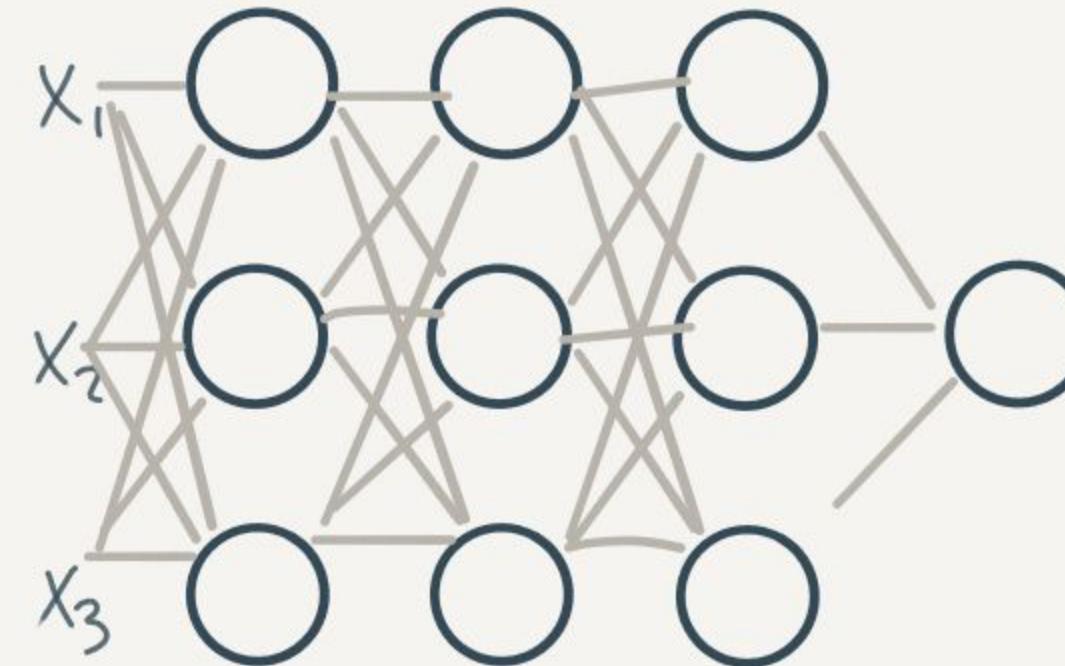
$$\text{COST: } J(w, b) = \frac{1}{m} \sum_{i=1}^m \ell(\hat{y}_i, y_i) + \frac{\lambda}{m} \|w\|_1$$

BOTH PENALIZE LARGE WEIGHTS \Rightarrow

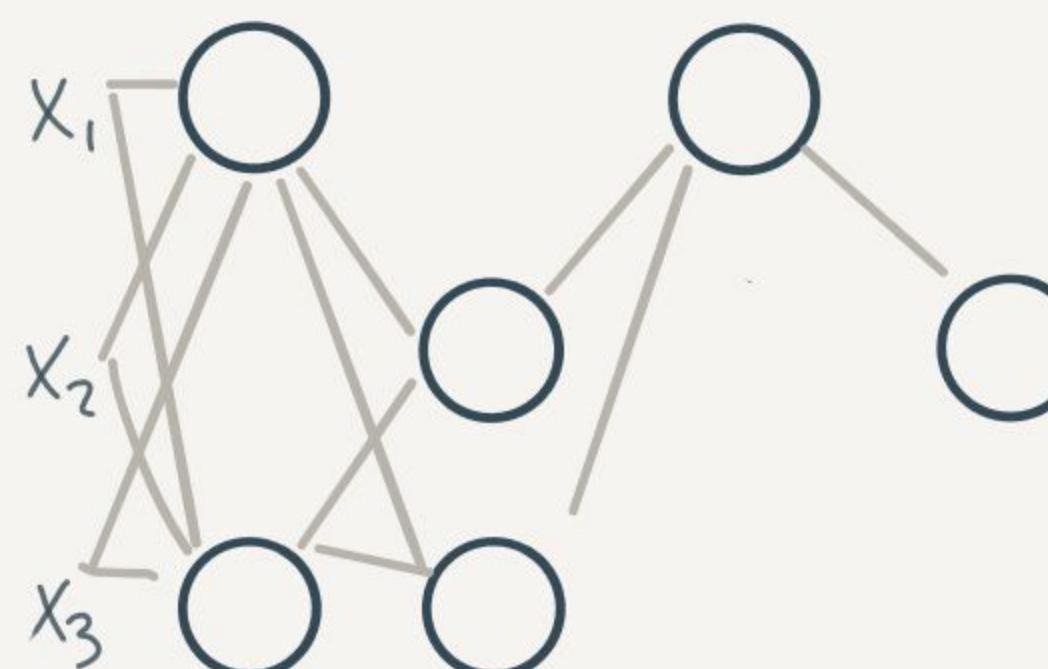
SOME WILL BE CLOSE TO $0 \Rightarrow$
SIMPLER NETWORKS



DROPOUT



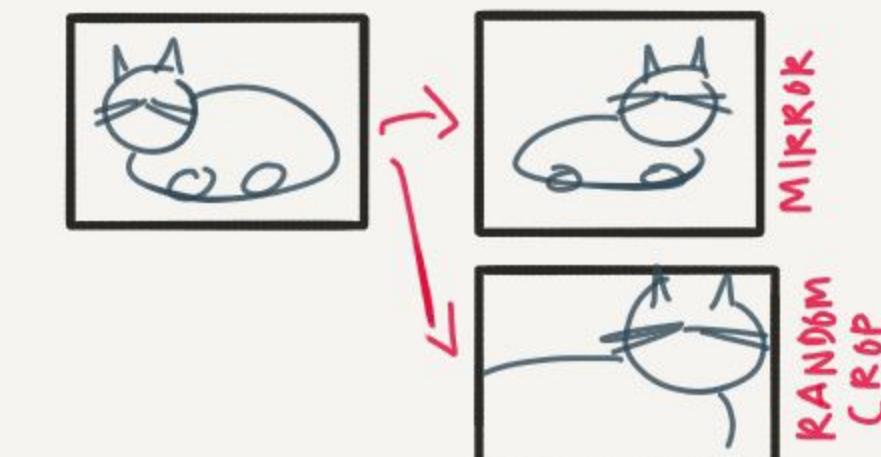
FOR EACH ITERATION i SAMPLE
SOME NODES ARE RANDOMLY
DROPPED (BASED ON KEEP-PROB)



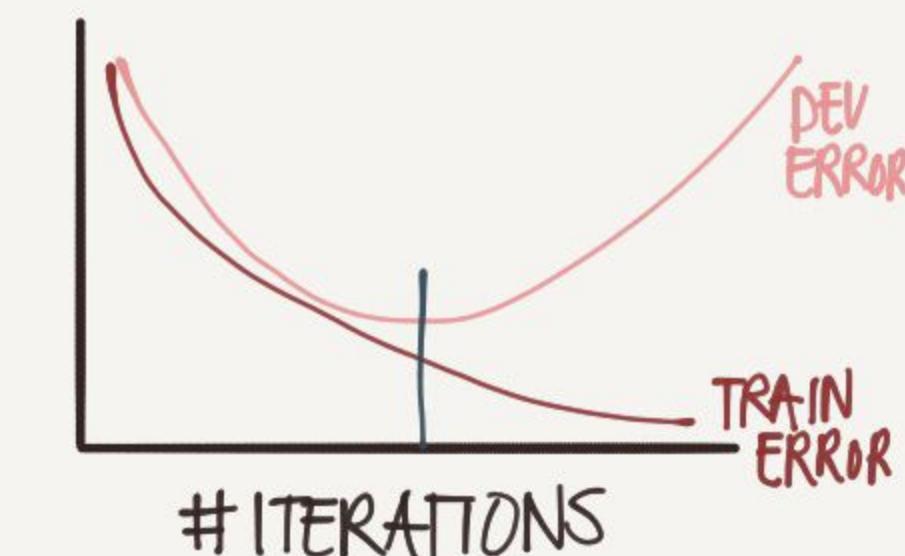
WE GET SIMPLER NWs
& LESS CHANCE TO RELY ON
SINGLE FEATURES

OTHER REGULARIZATION TECHNIQUES

DATA AUGMENTATION
GENERATE NEW PICS FROM EXISTING



EARLY STOPPING

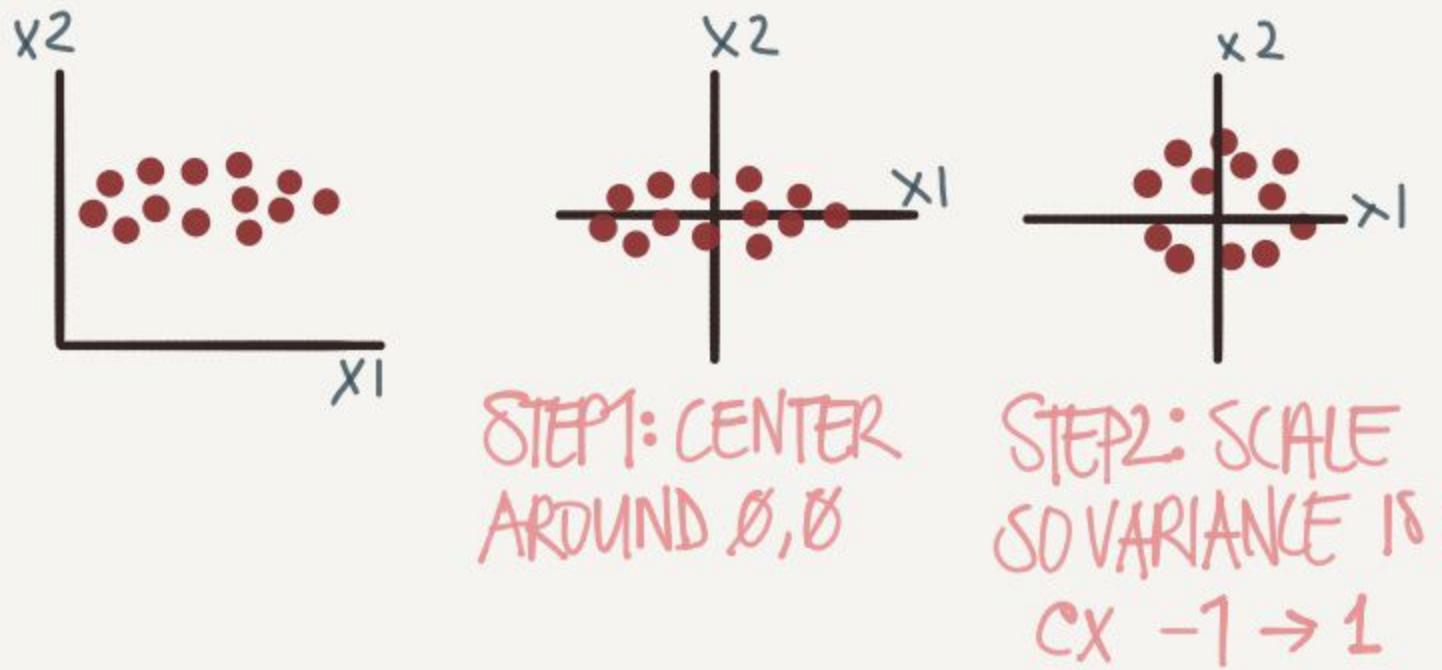


PROBLEM: AFFECTS BOTH
BIAS & VARIANCE

OPTIMIZING

TRAINING

NORMALIZING INPUTS



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)

$$\hat{y} = \underbrace{w^{[L-1]} w^{[L-2]} \cdots w^{[0]}}_{w} x + b$$

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

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

$$\text{XAVIER } \sqrt{\frac{1}{n^l}} \quad (\text{FOR TANH})$$

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.

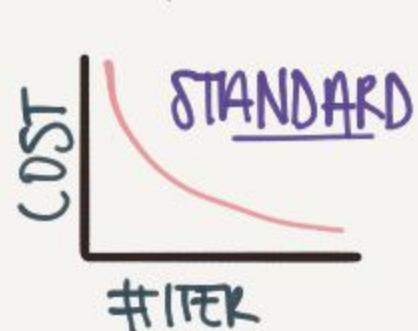
NOTE ONLY USE WHEN DEBUGGING SINCE IT'S SLOW

OPTIMIZATION ALGORITHMS

MINI-BATCH GRAD. DESCENT

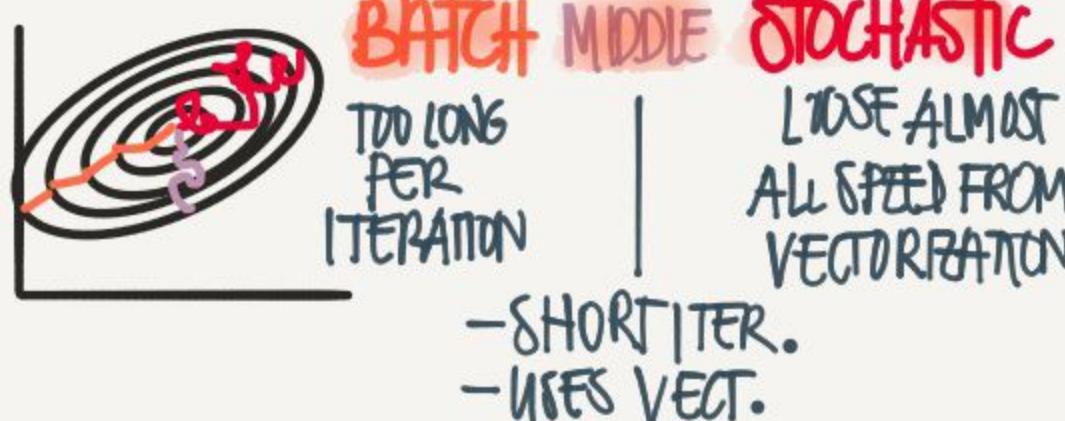


SPLIT YOUR DATA INTO MINI-BATCHES & DO GRAD DESCENT AFTER EACH BATCH THIS WAY YOU CAN PROGRESS AFTER JUST A SHORT WHILE



CHOOSING THE MINIBATCH SIZE

$\text{SIZE} = m \rightarrow$ BATCH GRAD DESC.
 $\text{SIZE} = 1 \rightarrow$ STOCHASTIC GRAD DESC



TIP
 IF YOU HAVE < 2000 SAMPLES
 USE $\text{SIZE}=2000$

OTHERWISE, USE 64, 128, 256...
 SO X+Y FITS IN CPU/GPU CACHE

GRADIENT DESCENT W. MOMENTUM



WE WANT TO REDUCE OSCILLATION \updownarrow 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

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

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

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

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

$$\text{OPTION 5: DISCRETE STAIRCASE}$$

$$\text{OPTION 6: MANUAL}$$

EPOCH = 1 PASS THROUGH THE DATA

HYPERPARAM TUNING

WHICH HYPERPARAMS ARE MOST IMPORTANT?

α LEARNING RATE

HIDDEN UNITS

MINIBATCH SIZE

β MOMENTUM, TURN = 0.9

LAYERS

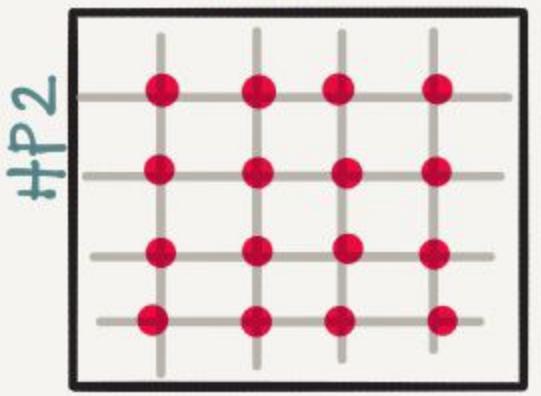
LEARNING RATE DECAY

$\beta_1 = 0.9 \quad \beta_2 = 0.999 \quad \epsilon = 10^{-8}$ (ADAM)

TESTING VALUES

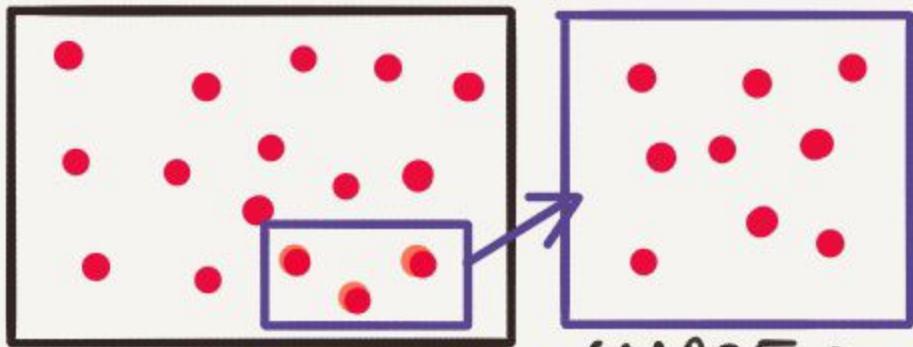
CLASSIC ML

HP1



GRID SEARCH

SOLUTION



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

NOT AS IMPORTANT

MY PANDA IS ACTUALLY A MIS-CATEGORIZED CAT BECAUSE I CAN'T DRAW PANDAS



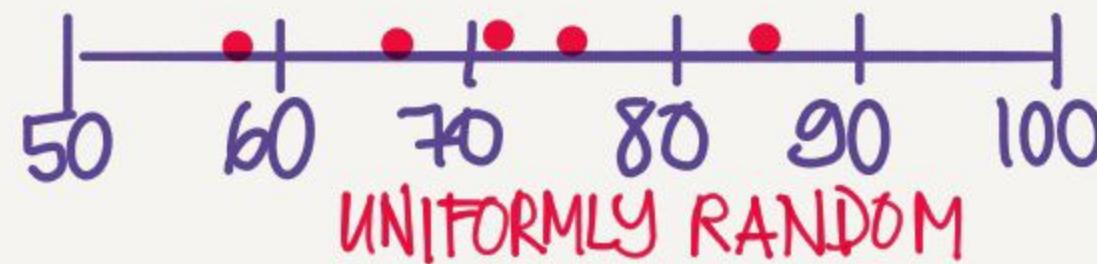
BABYSIT ONE MODEL & TUNE



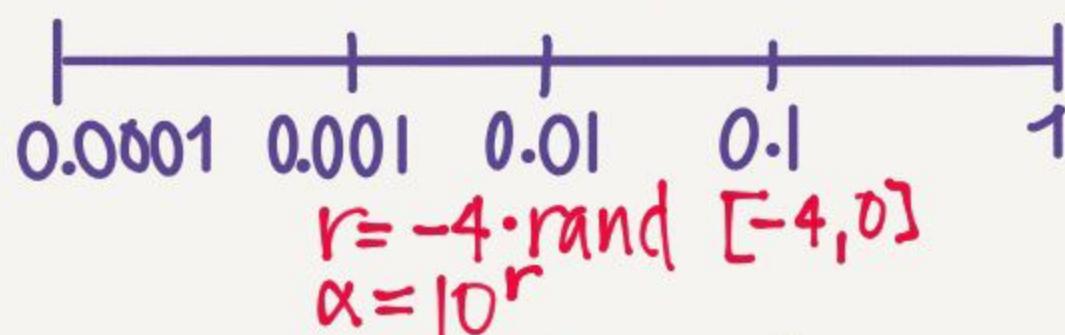
SPAWN LOTS OF MODELS W DIFF HP
GOOD IF YOU HAVE LOTS OF SHARE COMP POWER

USE AN APPROPRIATE SCALE

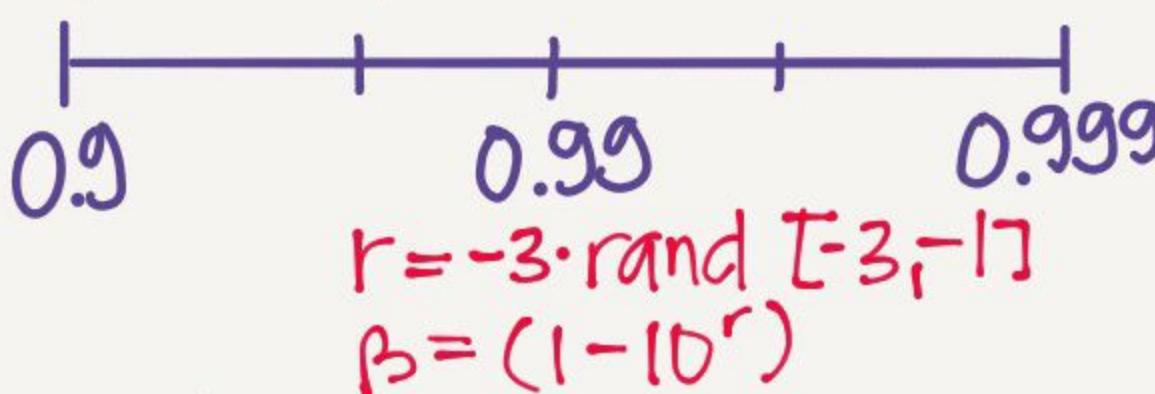
HIDDEN UNITS



α LEARNING RATE



β EXP WEIGHT AVE



TIP
RE-EVALUATE YOUR HYP. PARAMS EVERY FEW MONTHS

PANDA VS CAVIAR

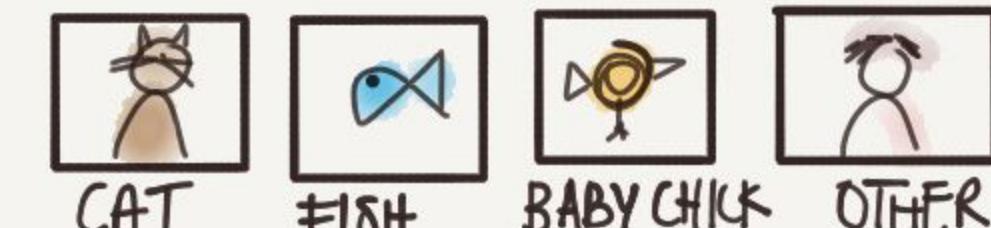
MISC. EXTRAS

BATCH NORMALIZATION

NORMALIZE LAYER OUTPUT

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

MULTICLASS CLASSIFIC.

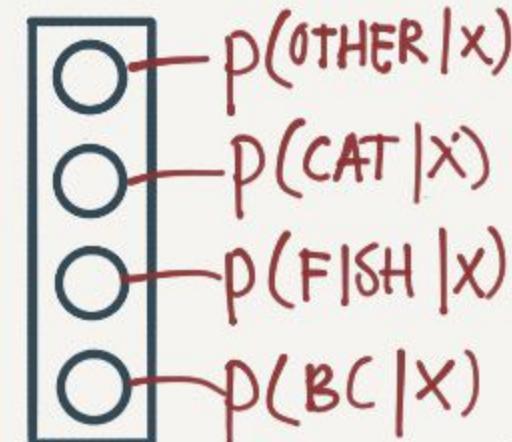


C = # CLASSES = 4

SOFTMAX ACTIVATION

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

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



SUM: 1

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

$$\Rightarrow a^{[i]} = \frac{t}{176.3} = \begin{bmatrix} 0.842 \\ 0.042 \\ 0.02 \\ 0.114 \end{bmatrix} = 11.4\% \text{ PROB IT'S A BABY CHICK}$$

© TessFerrandez

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%	

F1 = HARMONIC MEAN BETW.
RECALL & PRECISION

* DEFINE OPTIMIZING VS
SATISFYING METRICS

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

MAXIMIZE ACC.
GIVEN TIME \leq 100ms

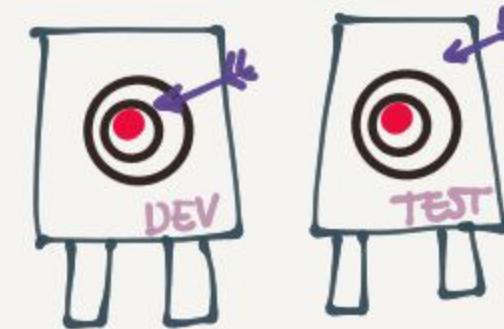
ACCURACY =
OPTIMIZING
RUNTIME =
SATISFYING

SELECTING YOUR DEV/TEST SETS

DATA

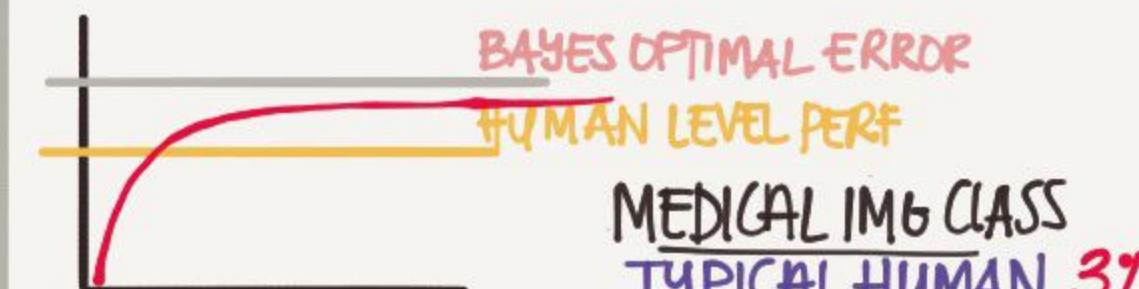
US
UK
EUROPE
S.AM
INDIA
CHINA
AUST.

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 IM6 CLASS
TYPICAL HUMAN 3%
TYPICAL DOCTOR 1%
EXPERIENCED DR. 0.7%
TEAM OF EXP DRs. 0.5%

↑ HUMAN LEV PERF
(PROXY FOR BAYES)

- OFTEN CLOSE TO BAYES
- A HUMAN CAN NO LONGER
HELP IMPROVE (INSIGHTS)
- DIFFICULT TO ANALYSE
BIAS/VARIANCE

CAT CLASSIFICATION

	A	B	BLURRY
HUMAN	1%	7.5%	
TRAIN ERR	8%	8%	AVOIDABLE BIAS
DEV ERR	10%	10%	VARIANCE

FOCUS
ON
BIAS
FOCUS
ON
VARIANCE

HUMAN TRAIN BIGGER NETW.
| AVOIDABLE BIAS } TRAIN LONGER/BETTER OPT. (RMSprop, ADAM)
TRAIN | ALSO
| VARIANCE } CHANGE NN ARCH OR HYPERPARAMS
DEV MORE DATA (TRAIN)
REGULARIZATION
NN ARCHITECTURE

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

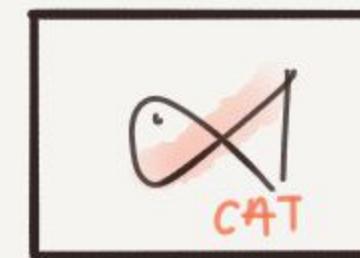
1. PICK 100 MIS-LABELED
2. COUNT ERROR REASONS

Dog	Blurry	Insta Filter	Big Cat	...
1	1		1	
2			1	
3	1			
...				
100		1		
5	...		1	

5% OF ALL ERRORS

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

YOU FIND SOME INCORR. LABELED 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 LABELED 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
WHAT WE CARE ABT

HOW DO WE SPLIT → TRAIN/DEV/TEST?

OPTION 1: SHUFFLE ALL

205 k (TRAIN)	D	T
	1%	2.5%

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

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

205 k	25	25
WEB+APP	APP	APP

BIAS & VARIANCE IN 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

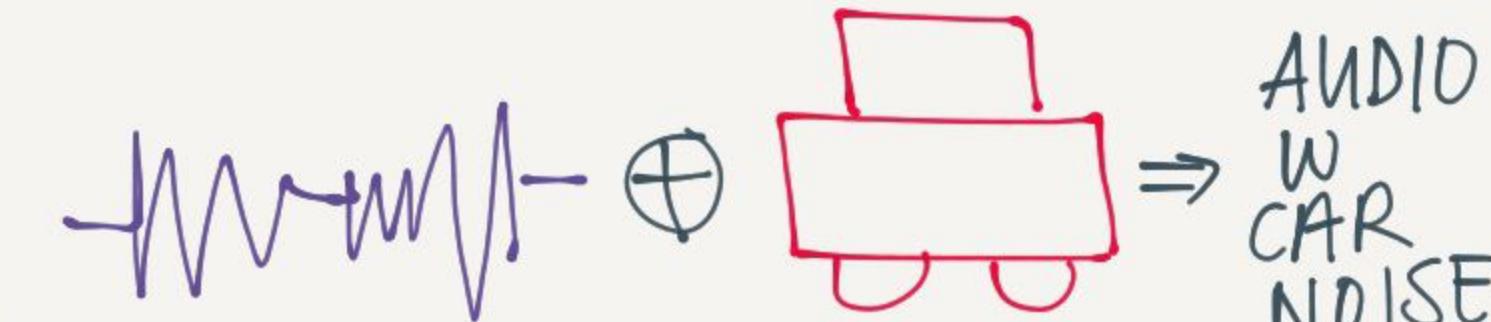
TRAIN	FD	D	T

	A	B	C	D
TRAIN	1%	1%	10%	10%
TRAIN-DEV	9%	15%	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



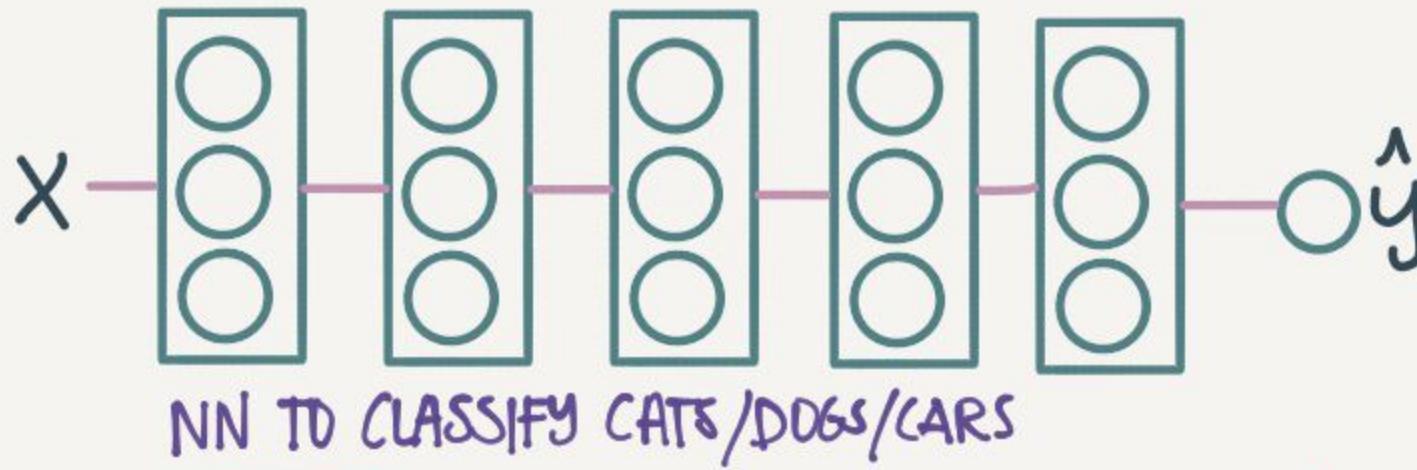
NOTE

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

EXTENDED LEARNING

TRANSFER LEARNING

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



[OPTION 1]: YOU ONLY HAVE A FEW RADIOLOGY IMAGES

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

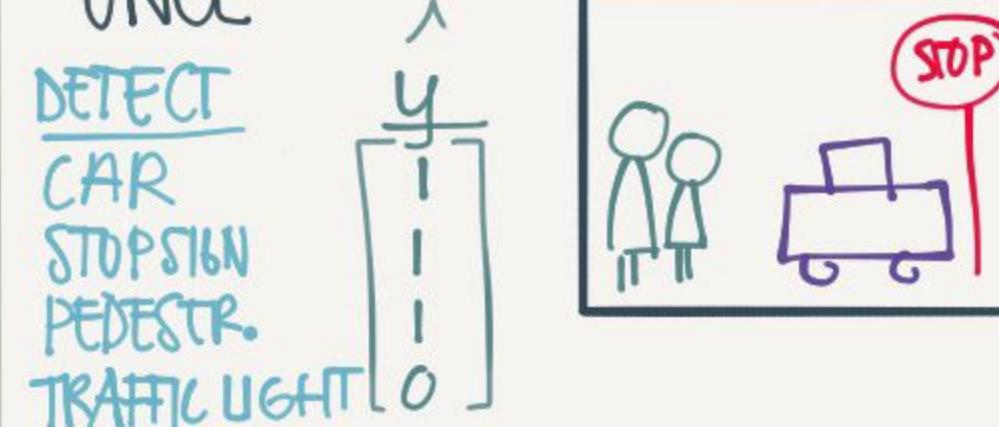
[OPTION 2] YOU HAVE LOTS OF RADIOLOGY IMGS.

SOLUTION: INIT WITH WEIGHTS FROM CAT NN
RETRAIN ALL LAYERS

THIS IS MICROSOFT CUSTOM VISION

MULTI TASK LEARNING

TRAINING ON MULT. TASKS AT ONCE



UNLIKE SOFTMAX • MANY THINGS CAN BE TRUE

$$\text{COST: } J(w, b) = \frac{1}{m} \sum_{i=1}^m \sum_{j=1}^4 f(y_i^{(j)}, \hat{y}_i^{(j)})$$

SUMMING OVER ALL OUTP OPTIONS

WE COULD HAVE JUST TRAINED 4 NN'S INSTEAD BUT... MT LEARNING MAKES SENSE WHEN

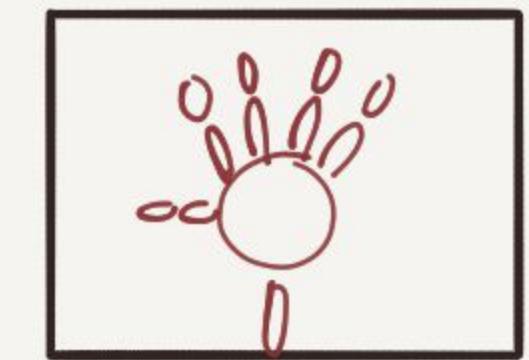
A. THE LEARNING DATA YOU HAVE FOR THE DIFF TASKS IS QUITE SIMILAR - & THE AMOUNTS (EG. 1K CARS, 1K STOP SIGNS)

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 STEPS:

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

END-TO-END

RADIOLOGY → 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 ($X \rightarrow Y$)
- EXCLUDES POTENTIALLY USEFUL HAND-MADE COMPONENTS

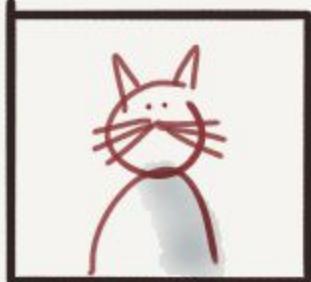
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CONVOLUTION

FUNDAMENTALS

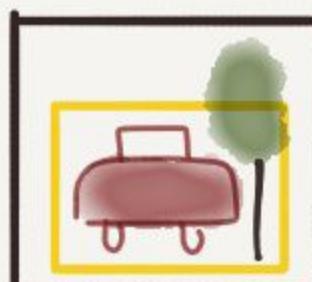
COMPUTER VISION

IMAGE
CLASSIFICATION



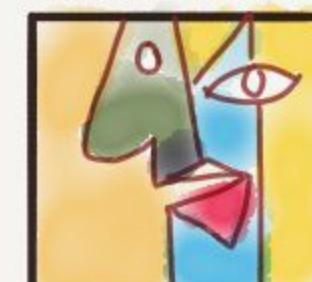
CAT OR
NOT-CAT

OBJECT
DETECTION



WHERE IS
THE CAR?

NEURAL
STYLE
TRANSFER



PAINT ME
LIKE PICASSO

PROBLEM: IMAGES CAN BE BIG

$$1000 \times 1000 \times 3 (\text{RGB}) = 3\text{M}$$

WITH 1000 HIDDEN UNITS WE
NEED $3\text{M} \times 1000 = 3\text{B}$ PARAMS

SOLUTION: USE CONVOLUTIONS

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



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

CONVOLUTION

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 6x6 IMAGE

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

(3x1)

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

FILTER 3x3

* CONVOLUTION

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

OUTPUT 4x4 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 6x6 IMAGE

VERTICAL
EDGE DETECTOR

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

FILTER 3x3

*

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

OUTPUT 4x4 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

CONVENTIONAL NEURAL NETS • COURSEPART

PADDING

PROBLEM: IMAGES SHRINK
 $6 \times 6 \rightarrow 3 \times 3 \rightarrow 4 \times 4$

PROBLEM: EDGES GET LESS 'LOVE'

SOLUTION: PAD W. A BORDER OF 0s BEFORE CONVOLVING

0	0	0	6	0	0	6	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)

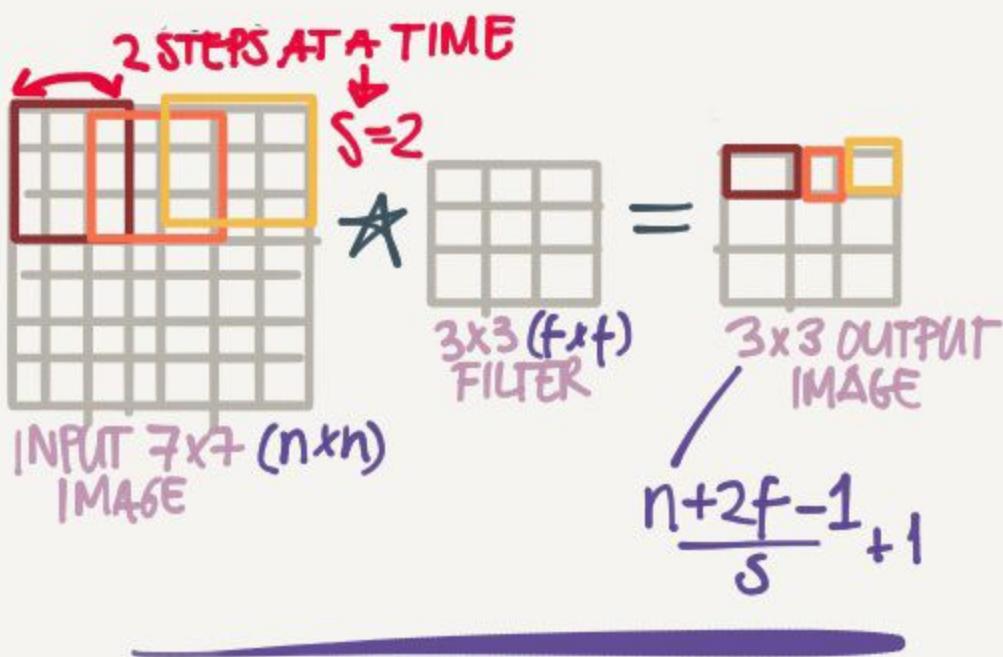
'VALID' $\Rightarrow P=0$ NO
PADDING

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

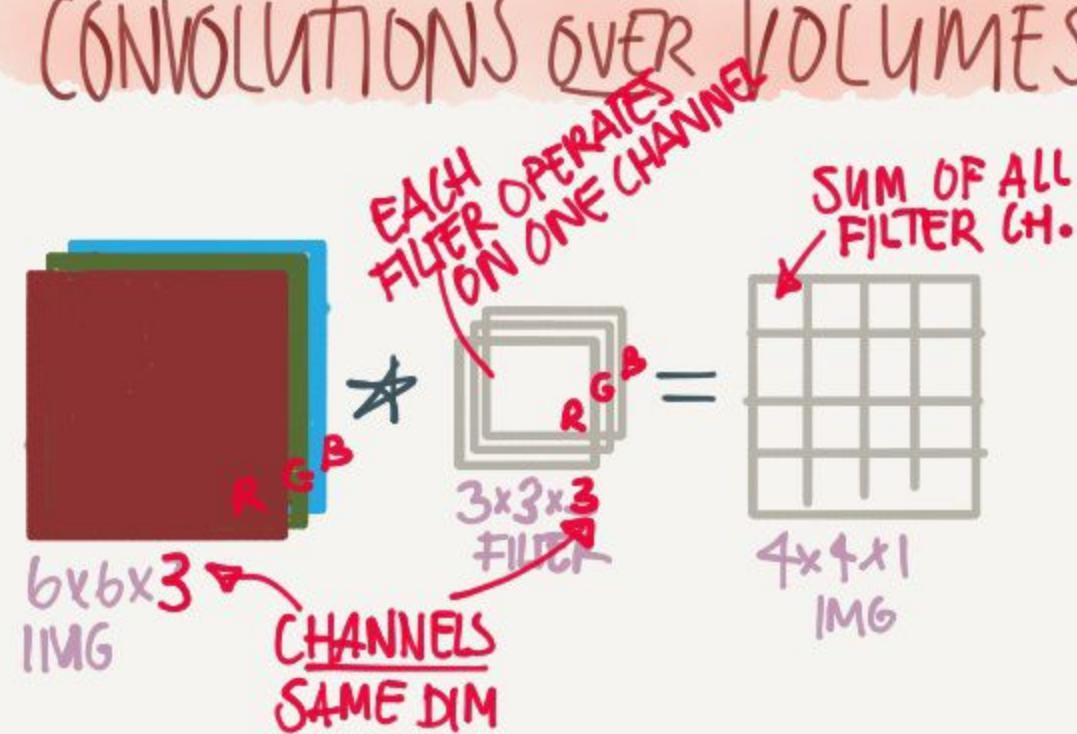
NOTE ALL CONVOLUTION IDEAS CAN BE
APPLIED TO 1D AS WELL LIKE
EKG SIGNALS • AND 3D LIKE CT-SCANS

STRIDE

WHAT PACE YOU SCAN WITH



CONVOLUTIONS OVER VOLUMES

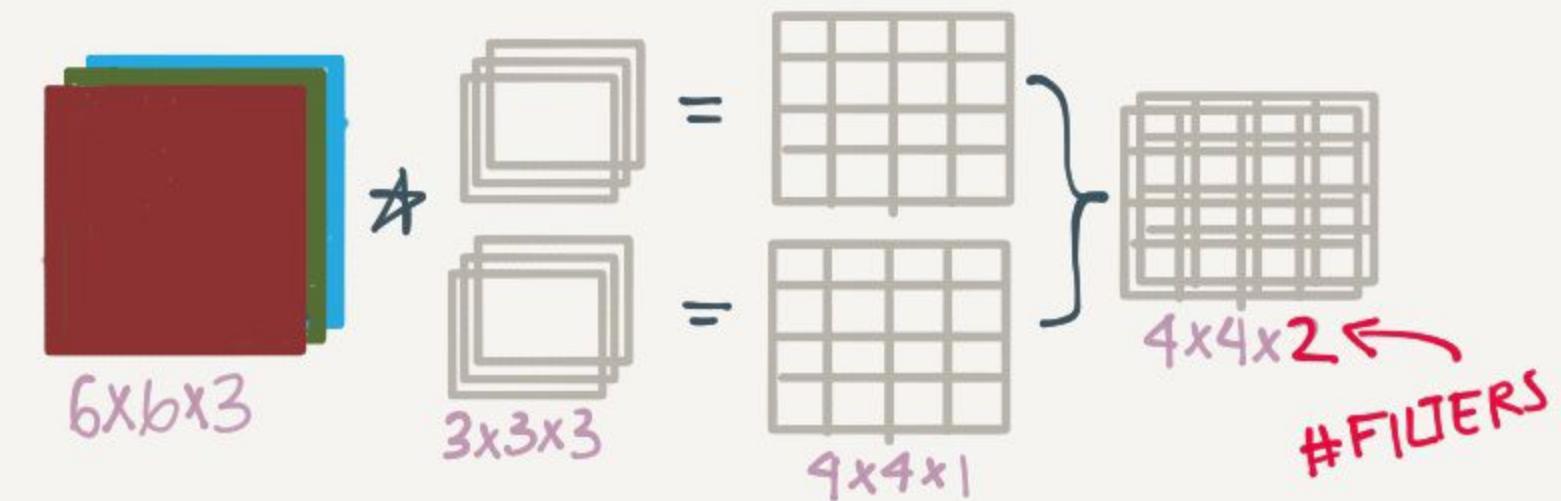


THIS ALLOWS US TO DETECT FEATURES
IN COLOR IMAGES FOR EXAMPLE

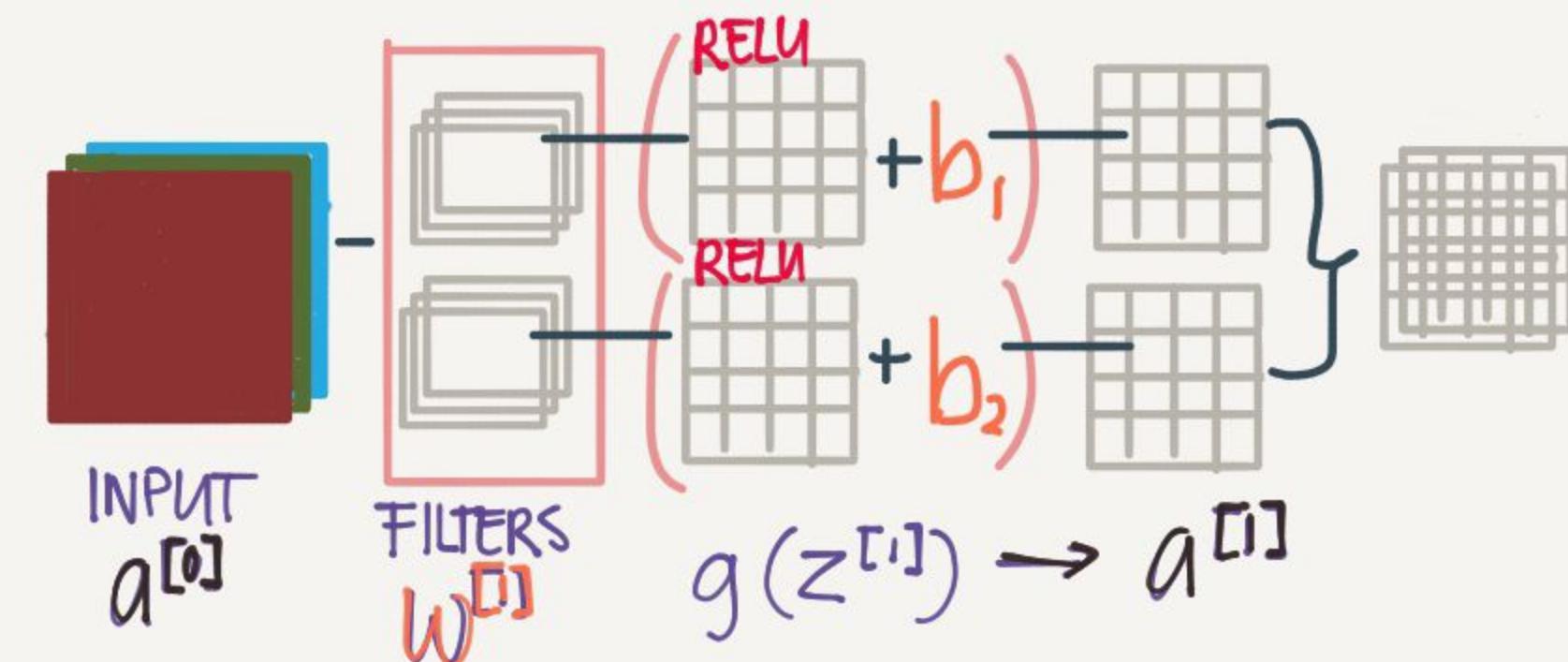
MAYBE WE WANT TO FIND ALL
EDGES OR MAYBE ORANGE BLOBS

MULTIPLE FILTERS

DETECTING MULTIPLE FEATURES AT A TIME



ONE CONV. NET LAYER



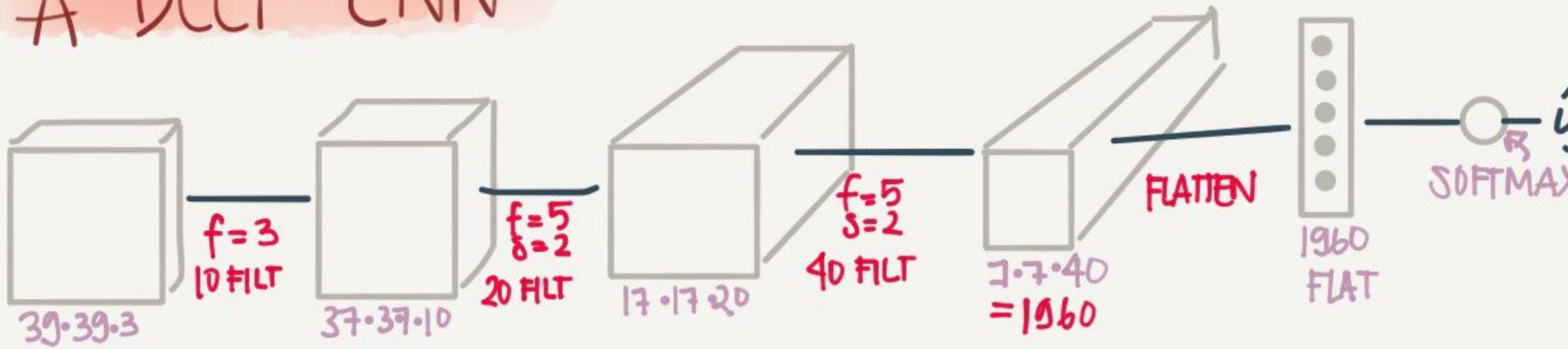
NOTE IT DOESN'T MATTER HOW BIG THE
INPUT IS - THE LEARNABLE PARAMS W & b
ONLY DEPEND ON THE # OF FILTERS
AND THEIR SIZES.

$$W = 3 \cdot 3 \cdot 3 \cdot 2 = 54 \quad \left\{ \begin{array}{l} 56 \text{ PARAMS} \\ \text{TO LEARN} \end{array} \right.$$

$$b = 2$$

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A DEEP CNN

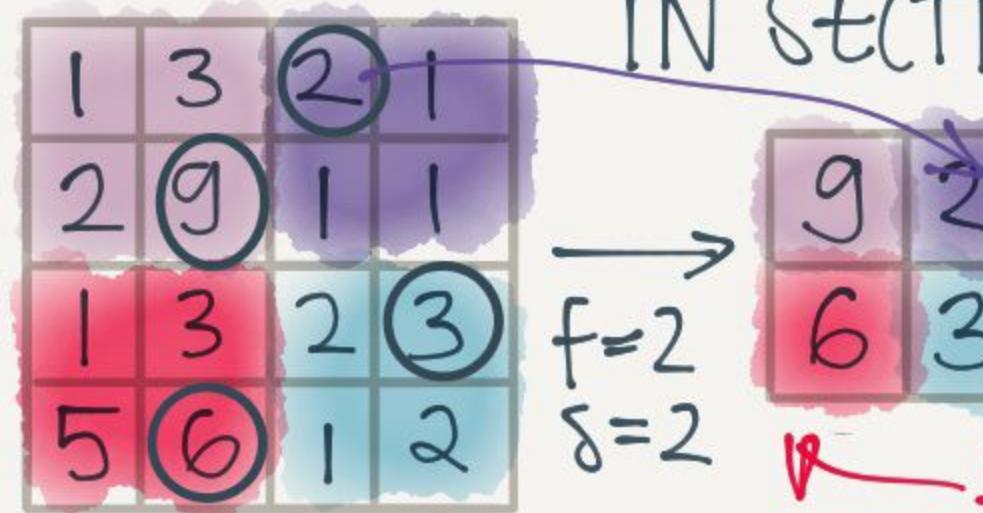


A LOT OF THE WORK IS FIGURING OUT HYPERPARAMS
= #FILTERS, STRIDE, PADDING ETC
TYPICALLY SIZE → TREND DOWN
#FILTERS → TREND UP

TYPICAL CONV.NET LAYERS

CONVOLUTION
POOLING
FULLY CONNECTED

POOLING (MAX)

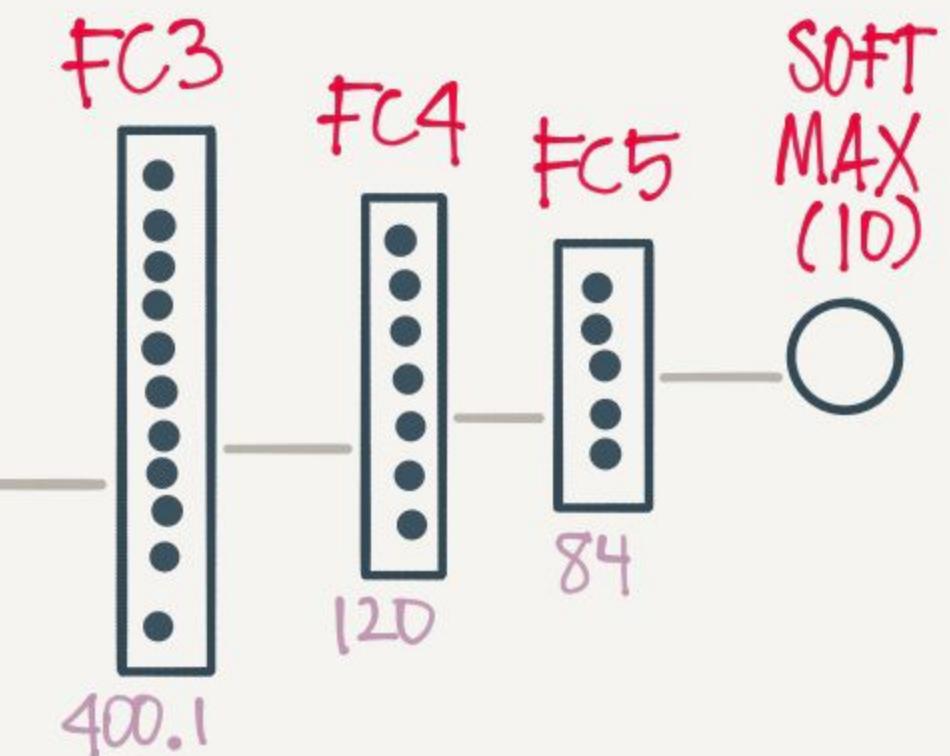
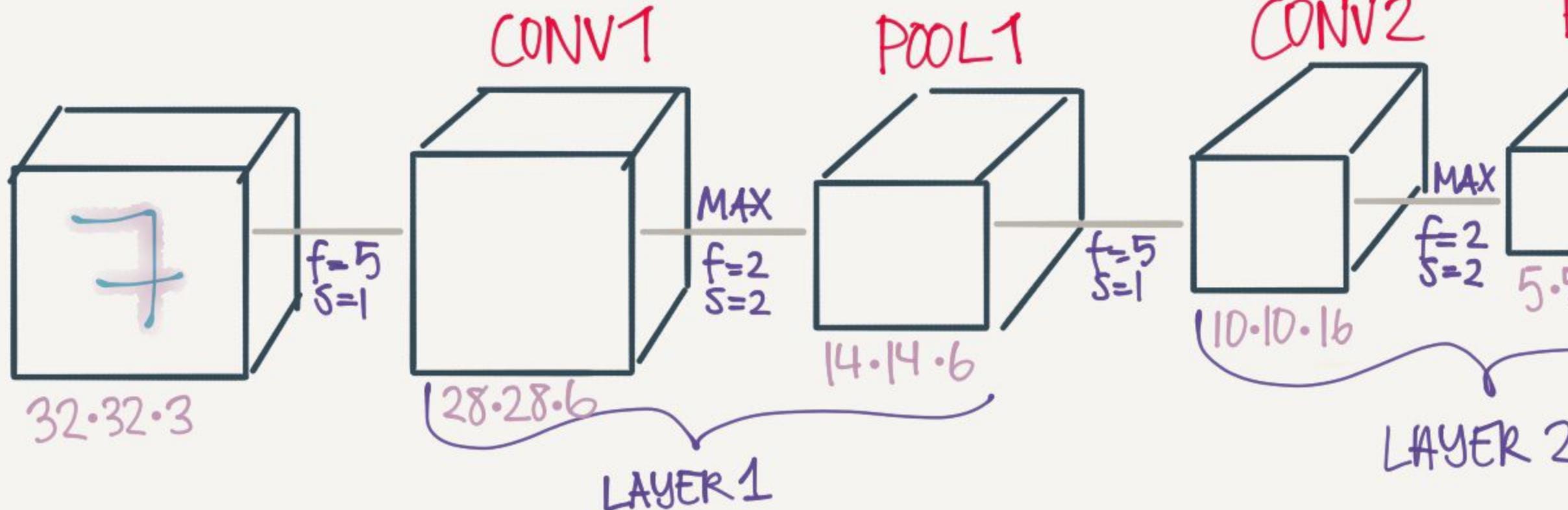


FIND MAX VAL
IN SECTION

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

CONV NET EXAMPLE BASED ON LeNet-5

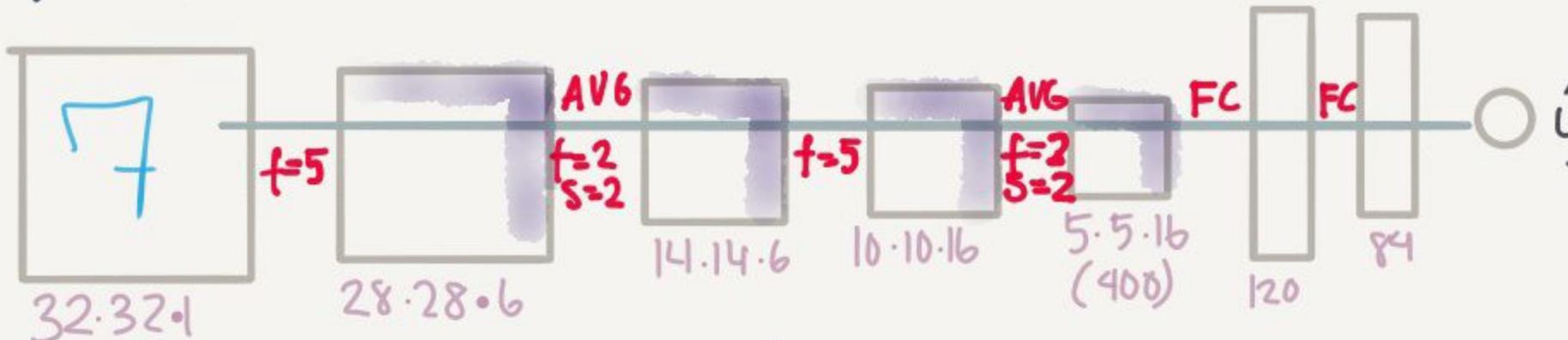
DETECTING HANDWRITTEN DIGITS



CLASSIC CONV. NETS

LeNet-5

DOCUMENT CLASSIFICATION



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

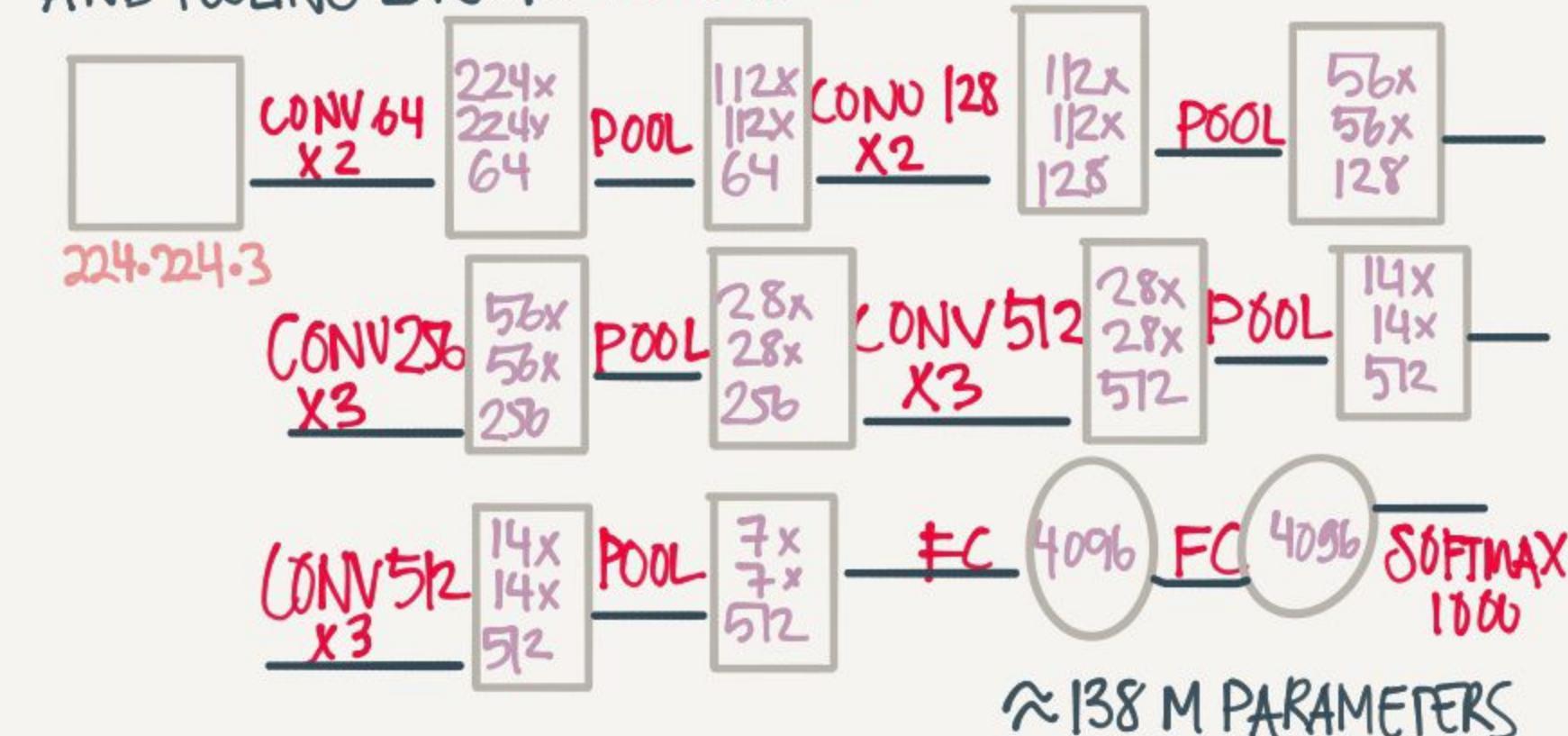
IMAGE CLASSIFICATION



- 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
 $f=3 \times 3, s=1, p=\text{SAME}$
AND POOLING LAYER $2 \times 2, s=2$



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

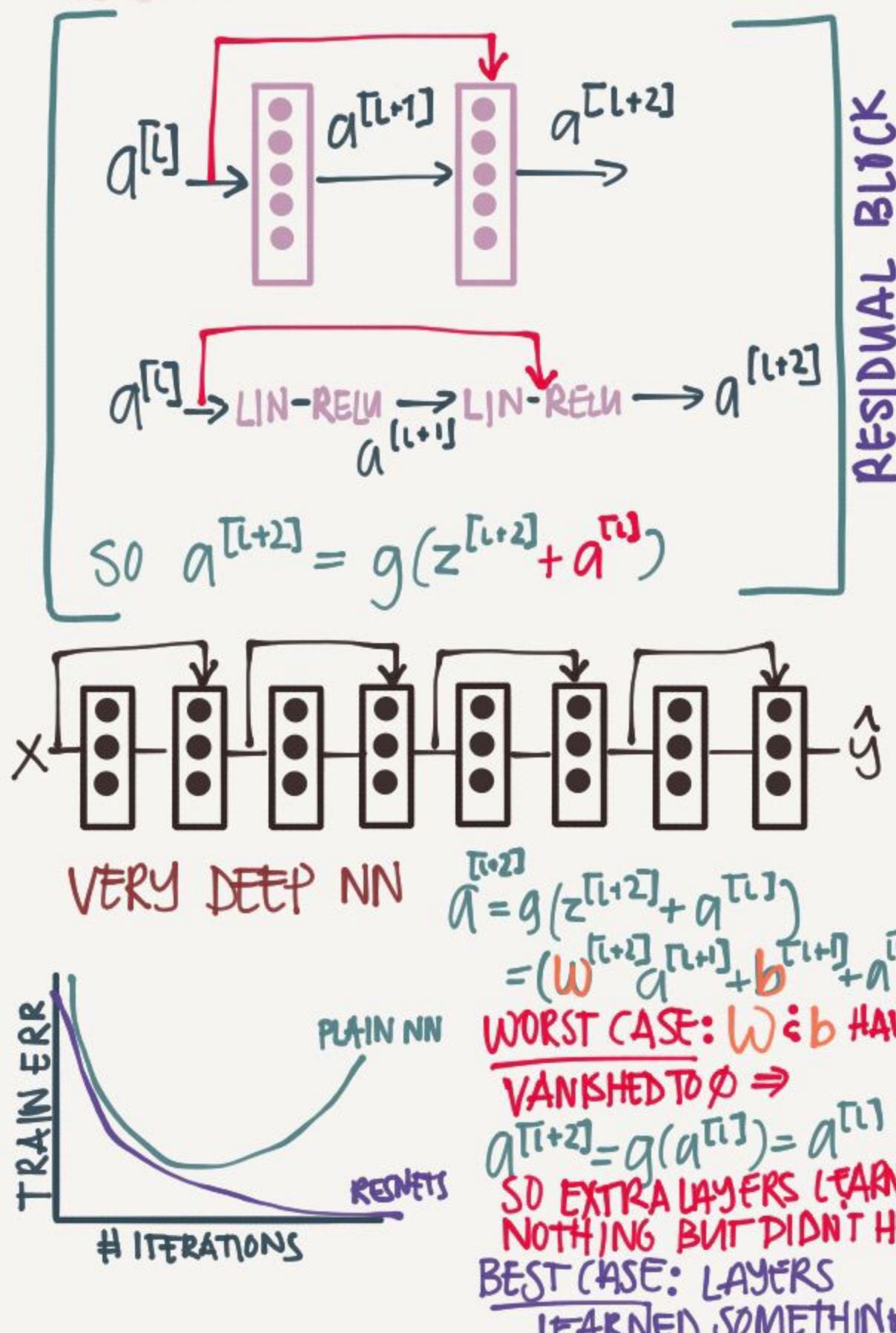
CONVENTIONAL NEURAL NETS · COURSE PART

SPECIAL NETWORKS

ResNets

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

SOLUTION: RESIDUAL NETS



NETWORK IN NETWORK (1x1 CONVOLUTION)

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

$\star 2 =$

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

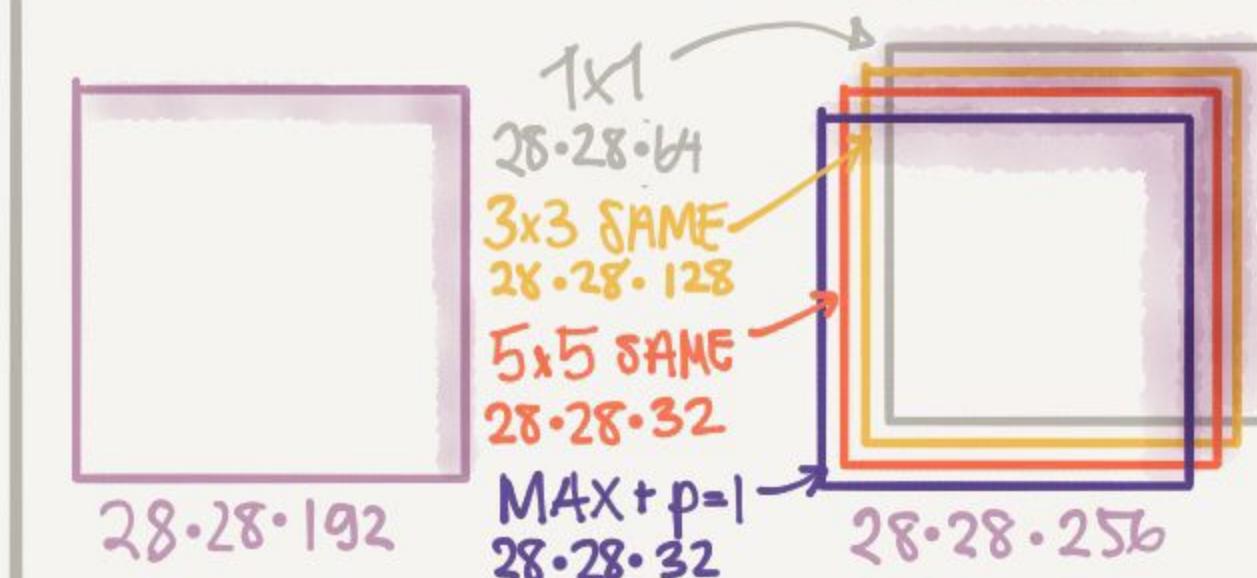
2. REDUCING # CHANNELS

$28 \times 28 \times 192$	\star	$1 \times 1 \times 92$	$=$	$28 \times 28 \times 32$
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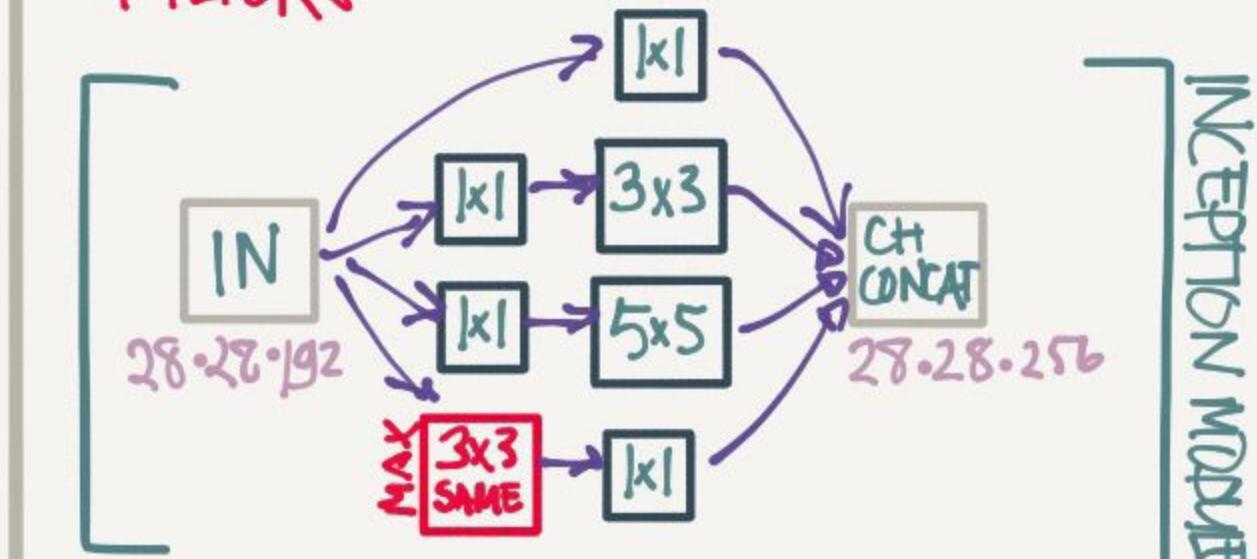
32 FILT

INCEPTION NETWORKS

INSTEAD OF CHOOSING A $1 \times 1, 3 \times 3, 5 \times 5$ OR A POOLING LAYER - CHOOSE ALL



PROBLEM: VERY EXPENSIVE TO COMPUTE
SOLUTION: SHRINK THE # CHANNELS W A 1×1 CONV BEFORE APPLYING ALL THE FILTERS



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



WE NEED TO GO
DEEPER

INCEPTION
THE MOVIE

© TessFerrandez

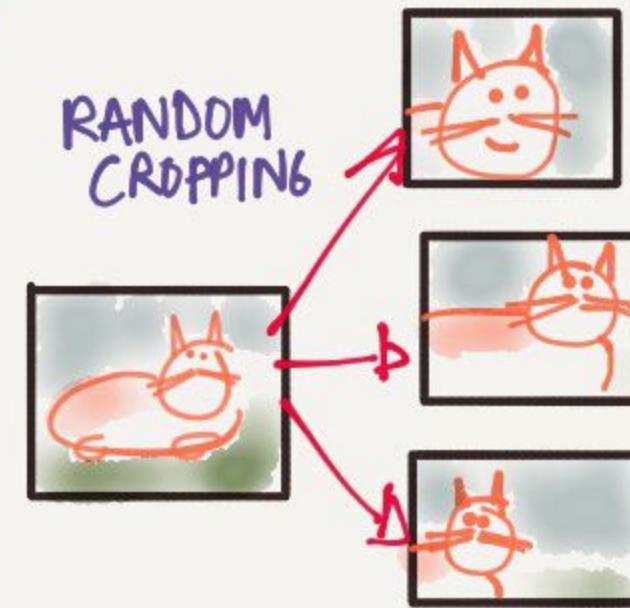
PRACTICAL ADVICE

USE OPEN SOURCE IMPLEMENTATIONS

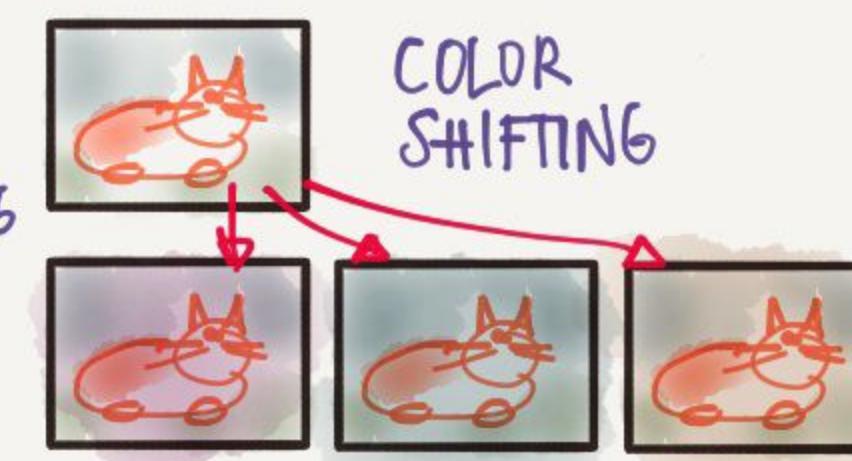
SOME OF THE PAPERS ARE HARD TO IMPLEMENT FROM SCRATCH - USING OS YOU CAN REUSE OTHER PPLS WORK
DON'T FORGET TO CONTRIBUTE

DATA AUGMENTATION

WE ALMOST ALWAYS NEED MORE DATA TO TRAIN ON

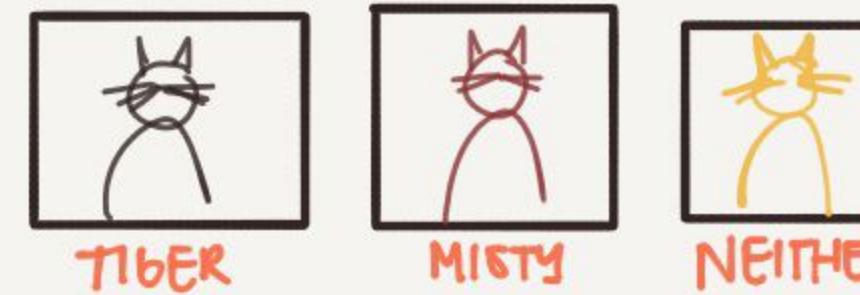


RANDOM CROPPING
ROTATION
SHEARING
LOCAL WARPING
...



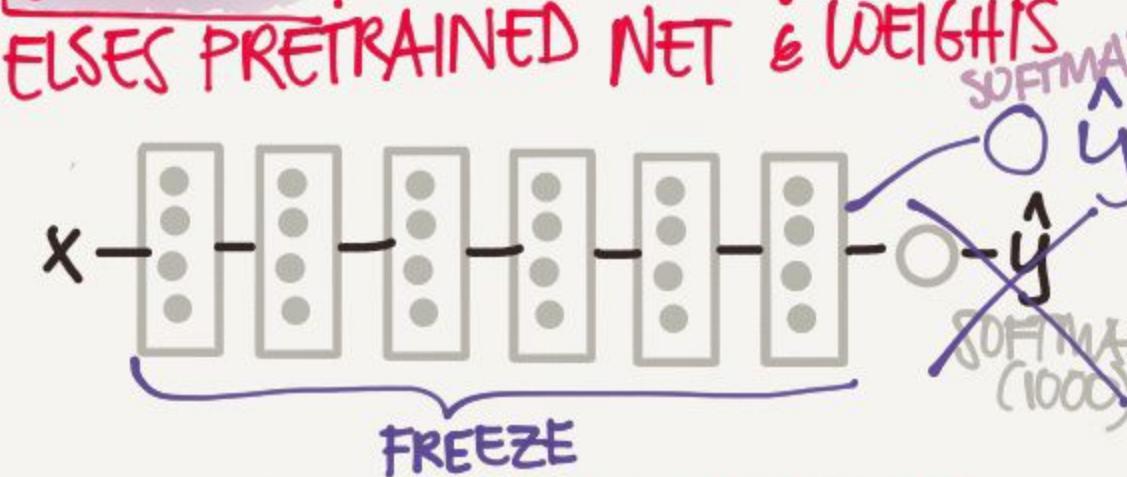
COLOR SHIFTING

TRANSFER LEARNING



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

SOLUTION DOWNLOAD SOMEONE ELSE'S PRETRAINED NET & WEIGHTS



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

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

STATE OF COMPUTER VISION

WE HAVE LOTS OF DATA

- SPEECH RECDG.

- IMAGE RECOGNITION

- OBJECT DETECTION
IMGS IN LABELED BOXES

WE HAVE LITTLE LABELED DATA

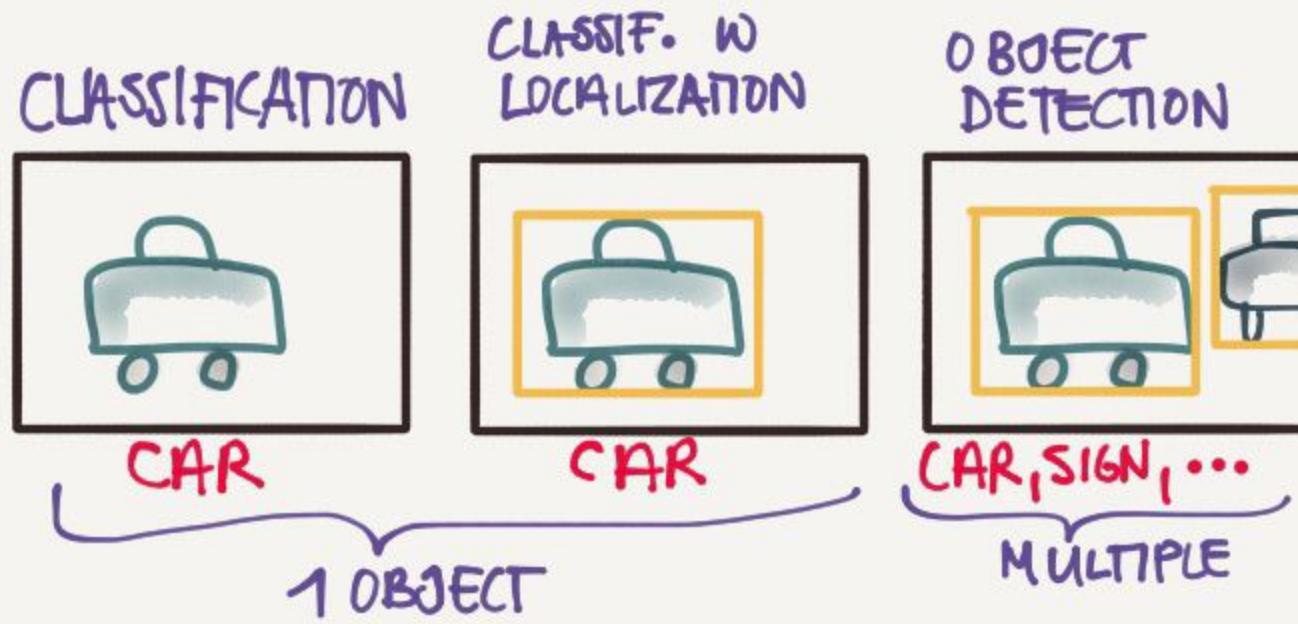
MORE HAND ENGINEERING

TIPS FOR DOING WELL ON BENCHMARKS/COMPETITIONS

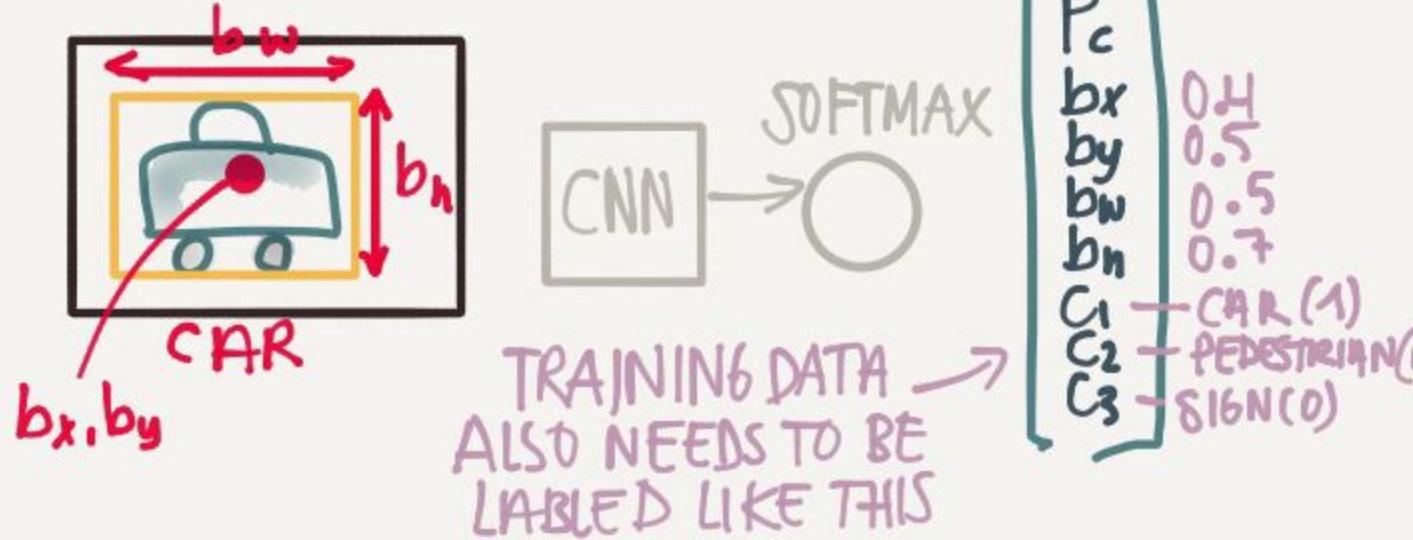
- * ENSEMBLING.
AVG OUTPUTS FROM MULT NN
- * MULTI-CROP AT TEST TIME
AVG OUTPUTS FROM MULTIPLE CROPS OF THE IMAGE

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

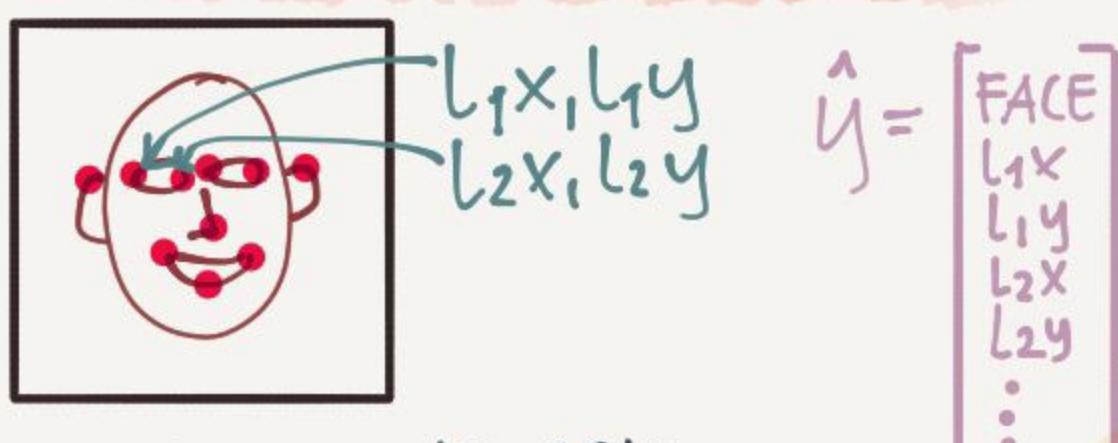
DETECTION ALGORITHMS



OBJECT LOCALIZATION



LANDMARK DETECTION



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

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

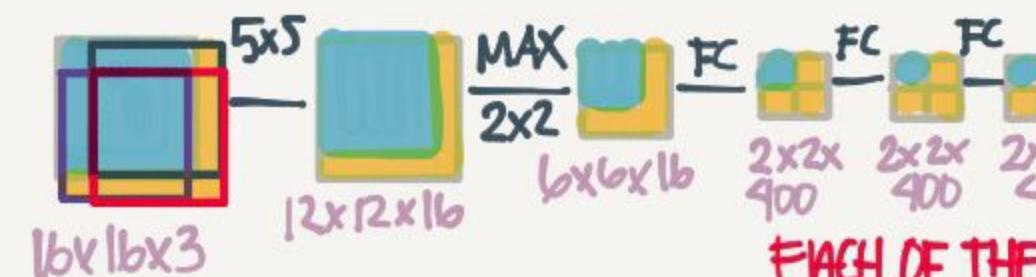
SLIDING WINDOWS DETECTION



1. CREATE SLIGHTLY CROPPED IMGS 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)

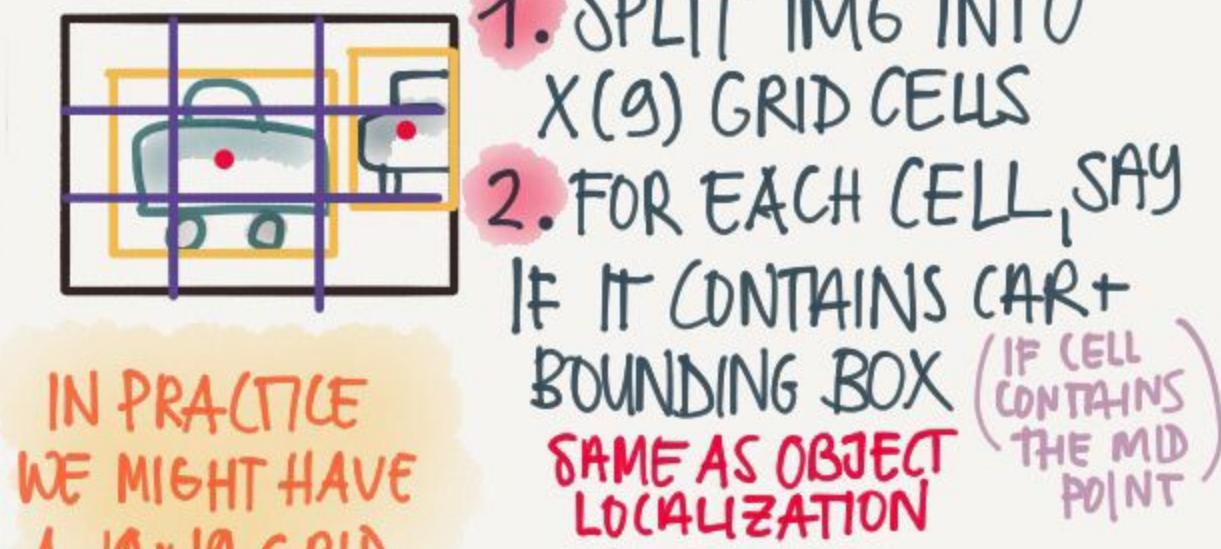
SINCE ADJ WINDOWS SHARE A LOT OF THE COMPUTATIONS WE CAN DO THIS MUCH CHEAPER W CONVOLUTIONS



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

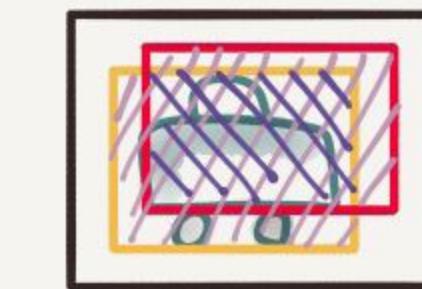
EACH OF THE 4 VALS ARE RESULTS FOR EACH OF THE 4 WINDOWS

YOLO: You Only Look Once



HOW DO YOU KNOW HOW GOOD IT IS?

HOW GOOD IS THE RED SQUARE?



$$IOU = \frac{\text{SIZE OF INTERSECTION}}{\text{SIZE OF UNION}}$$

INTERSECTION OVER UNION

GENERALLY · IF $IOU \geq 0.5$ IT IS REGARDED AS CORRECT

WHAT IF MULTIPLE SQUARES CLAIM THE SAME CAR?

NON-MAX SUPPRESSION

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



FACE RECOGNITION

FACE
VERIFICATION



IS THIS PETE?
99% ACC \Rightarrow
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

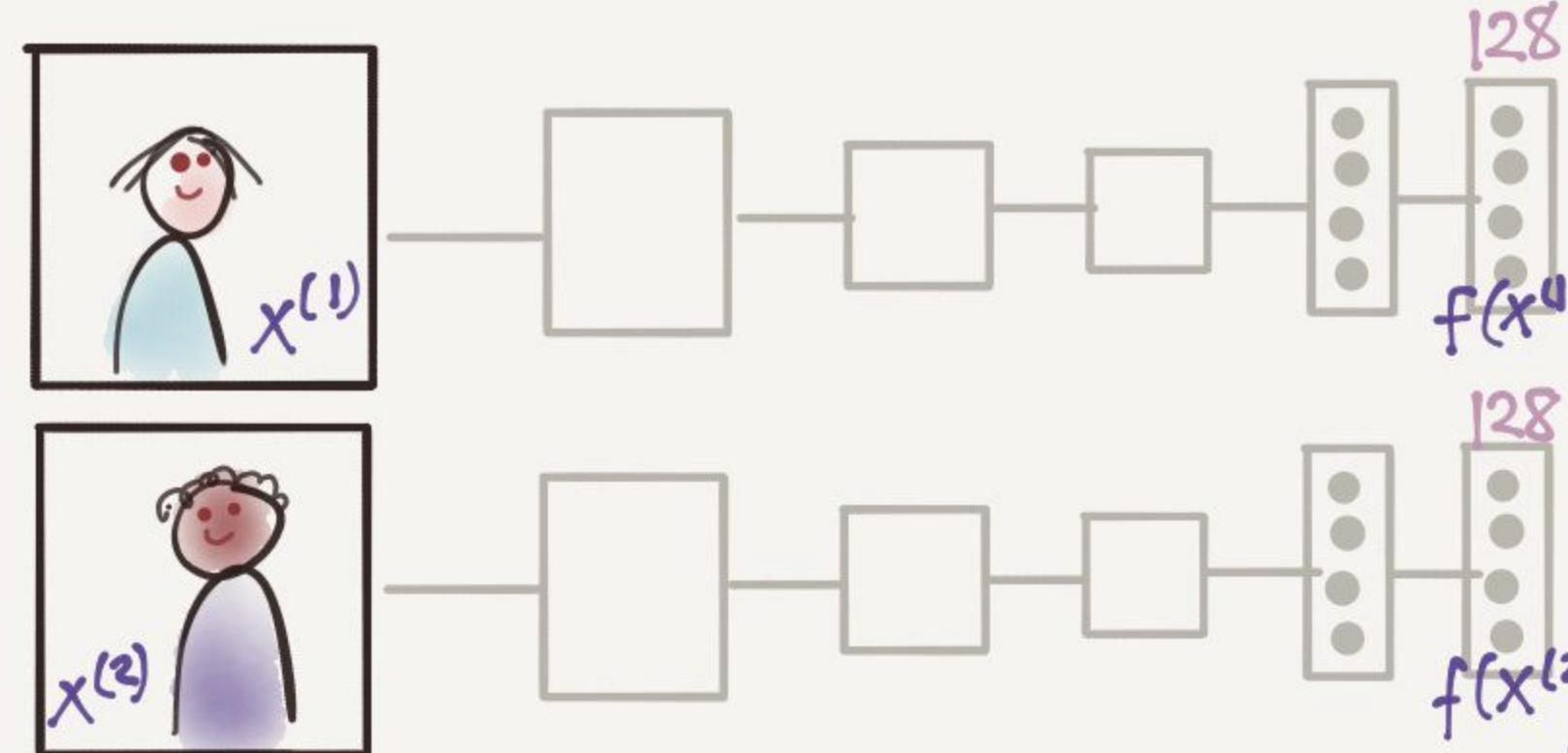
SOLUTION: LEARN A SIMILARITY
FUNCTION

$$d(\text{img}1, \text{img}2) = \text{degree of difference}$$

BUT HOW DO YOU LEARN THIS?

SIAMESE NETWORK

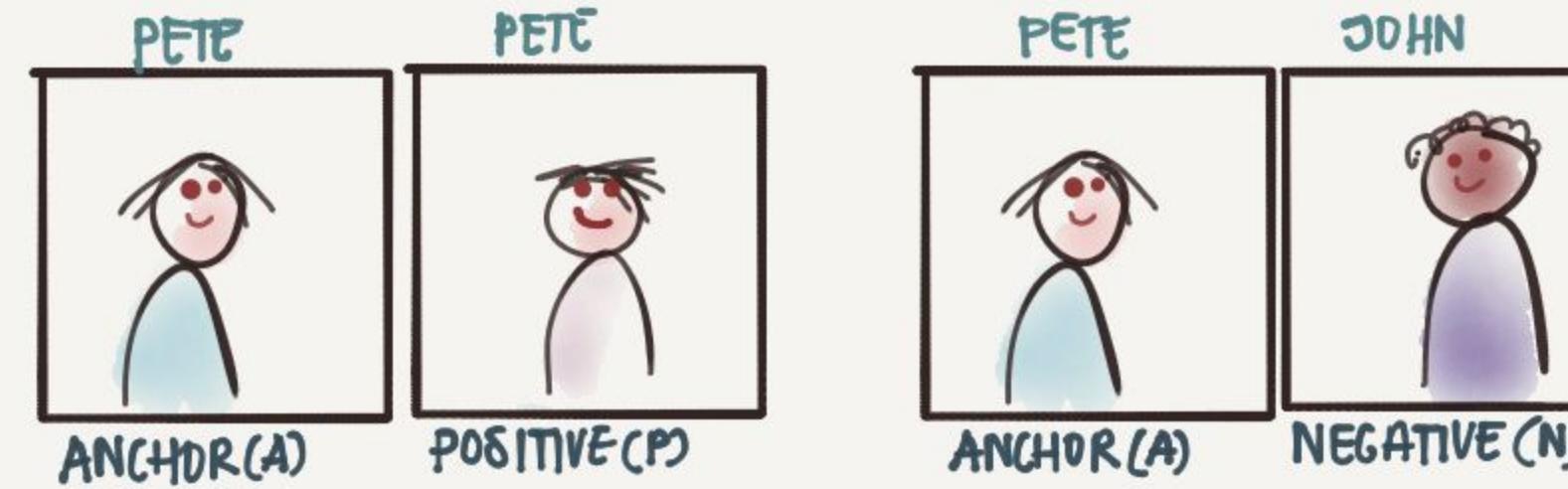
DeepFace



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

TRIPLET LOSS

FaceNet



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

BUT WE WANT A GOOD MARGIN, SO...
 $d(A, P) - d(A, N) + \alpha \leq 0$

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

LEARN THE PARAMS OF
THE NN SUCH THAT

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

WE CAN ACCOMPLISH
THIS WITH THE TRIPLET
LOSS FUNCTION

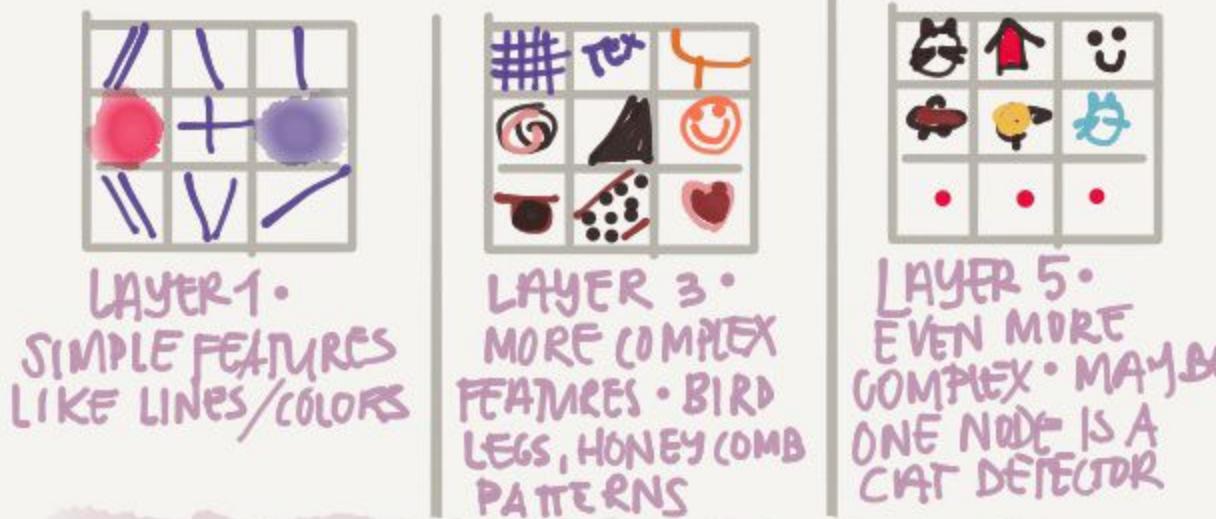
TIP PRECOMPUTE ENCODINGS
FOR PPL IN YOUR DB, SO YOU
DON'T HAVE TO SAVE IMAGES
& COMPUTE ENCODINGS AT RUN-
TIME

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

NEURAL STYLE TRANSFER



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



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

IDEA:

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

$$J(G) = \alpha J_{\text{CONTENT}}(C, G) + \beta J_{\text{STYLE}}(S, G)$$

HOW SIMILAR ARE $C \text{ & } G$ HOW SIMILAR ARE $S \text{ & } G$

3. UPDATE EACH PIXEL

CONTENT COST FUNCTION

- USE A PRE-TRAINED CONVNET (ex VGG)
- SELECT A HIDDEN LAYER SOMEWHERE IN THE MIDDLE
LATER \Rightarrow COPIES LARGER FEATURES
- LET $a^{[l]c(c)}$ & $a^{[l]k(g)}$ BE THE ACTIVATIONS
- IF $a^{[l]c(c)} \approx a^{[l]k(g)}$ ARE SIMILAR THEY HAVE SIMILAR CONTENT
BECAUSE THEY BOTH TRIGGER THE SAME HIDDEN UNITS

HOW DO WE TELL IF THEY ARE SIMILAR?

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

CAPTURING THE STYLE



USING THE STYLE IM_G 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 IM_G
 & 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 PROBLEMS

IN	OUT	PURPOSE
Mr. Brown	THE QUICK BROWN FOX JUMPED...	SPEECH RECOGNITION
∅	Music notes	MUSIC GENERATION
THERE IS NOTHING TO LIKE IN THIS MOVIE	★ + + + +	SENTIMENT CLASSIFICATION
AGCCCCCTGTG AGGAACCTAG	AGCCCCCTGTG AGGAACCTAG	DNA SEQUENCE ANALYSIS
Voulez-vous chanter avec moi?	Do you want to sing with me?	MACHINE TRANSLATION
🏃‍♂️🏃‍♀️🏃‍♂️	RUNNING	VIDEO ACTIVITY RECOGNITION
Yesterday Harry Potter met Hermione Granger	Yesterday Harry Potter met Hermione Granger	NAME ENTITY RECOGNITION

NAME ENTITY RECOGNITION

$x = \text{HARRY POTTER AND HERMIONE}$ $T_x = 9$
 $x^{<1>} x^{<2>} \dots$ (9 words)

GRANGER INVENTED A NEW SPELL

$$y = \begin{matrix} 1 & 1 & 0 & 1 & T_y = T_x \\ y^{<1>} & y^{<2>} & \dots & y^{<T>} & \end{matrix}$$

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

HOW DO WE REPRESENT WORDS?

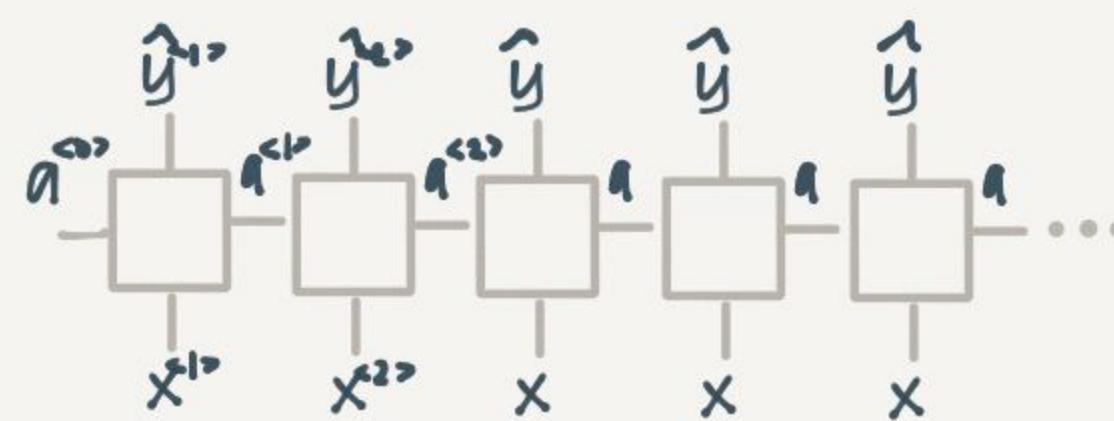
CREATE A VOCABULARY (EG 10K MOST COMMON WORDS IN YOUR TEXTS • OR DOWNLOAD EXISTING)

a	1	EACH WORD IS A ONE-HOT.
aaron	2	VECTOR
and	367	
Harry	4075	HARRY = $\begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$
Potter	6830	
zulu	10000	

WE COULD USE A STANDARD NETWORK BUT...

- (A) INPUT & OUTPUTS CAN HAVE DIFFERENT LENGTHS IN DIFF EXAMPLES
- (B) WE DON'T SHARE FEATURES LEARNED ACROSS DIFFERENT POSITIONS

RECURRENT NEURAL NET (RNN)



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

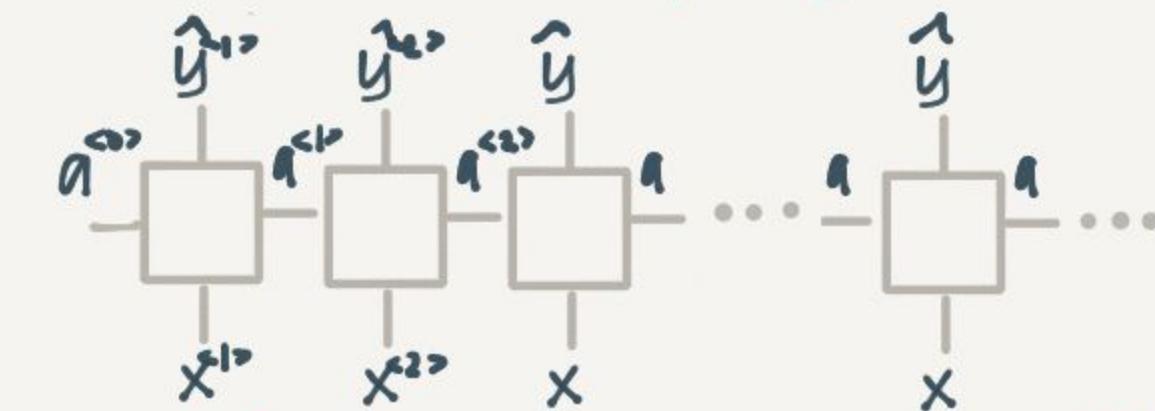
$$\begin{aligned} q^{<1>} &= g_1(W_1 [a^{<0>} | x^{<1>}] + b_1) && \text{TANH / RELU} \\ \hat{y}^{<1>} &= g_2(W_{21} q^{<1>} + b_2) && \text{SIGMOID} \end{aligned}$$

THE SAME W & b ARE USED IN ALL TIME STEPS

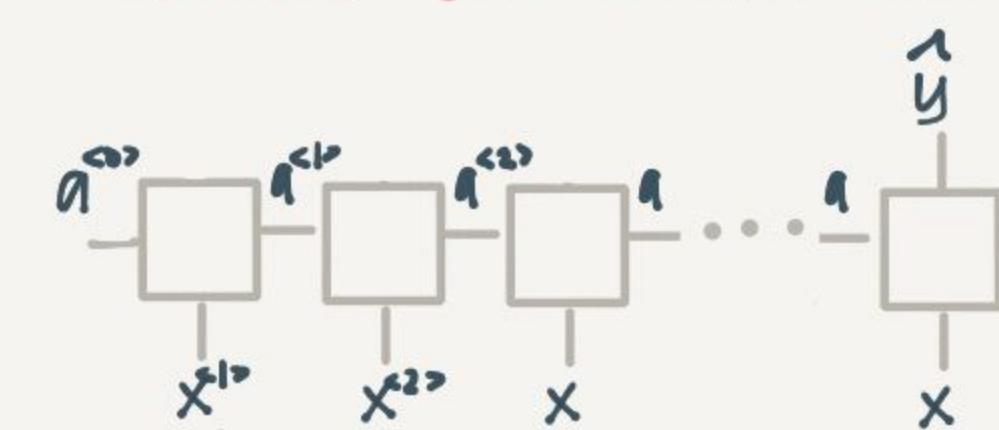
THE LOSS WE OPTIMIZE IS THE SUM OF $\ell(\hat{y}, y)$ FROM 1-T

DIFFERENT TYPES OF RNN

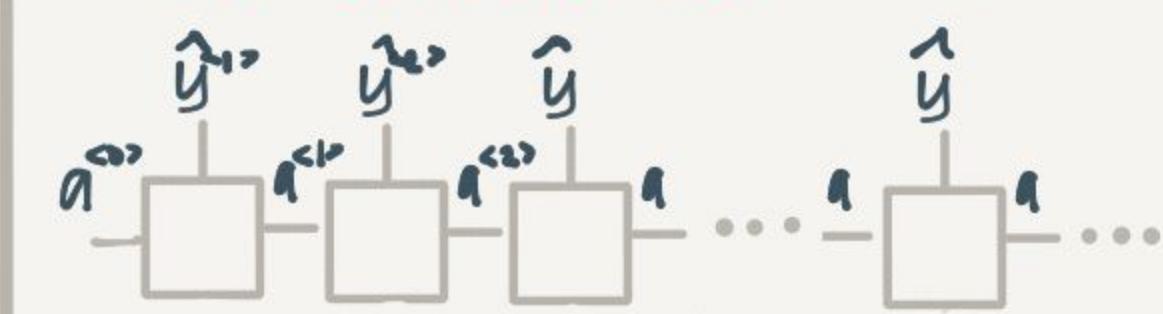
MANY-TO-MANY $T_x = T_y$



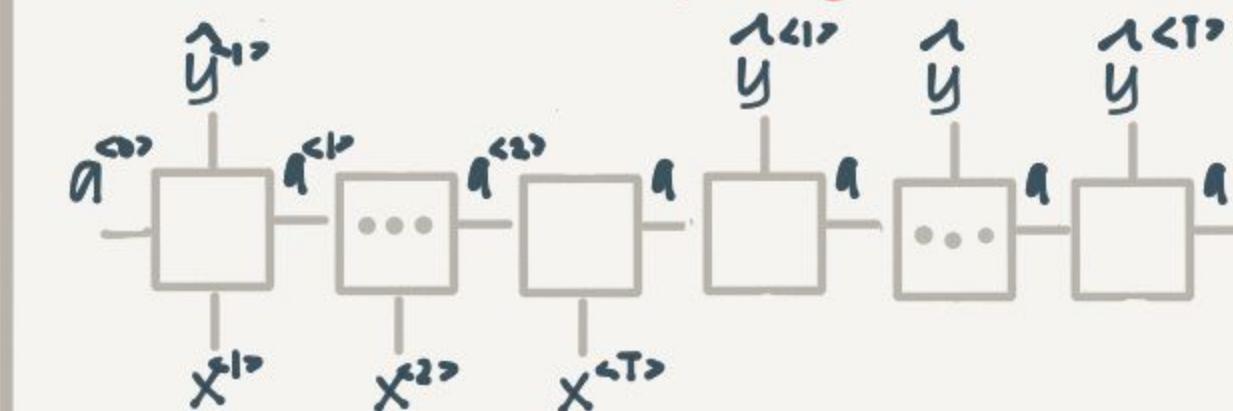
MANY-TO-ONE $EX. SENTIMENT ANALYSIS$



ONE-TO-MANY • MUSIC GENERATION



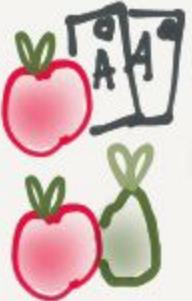
MANY-TO-MANY $T_x \neq T_y$ TRANSLATION



MORE ON RNNs

LANGUAGE MODELLING

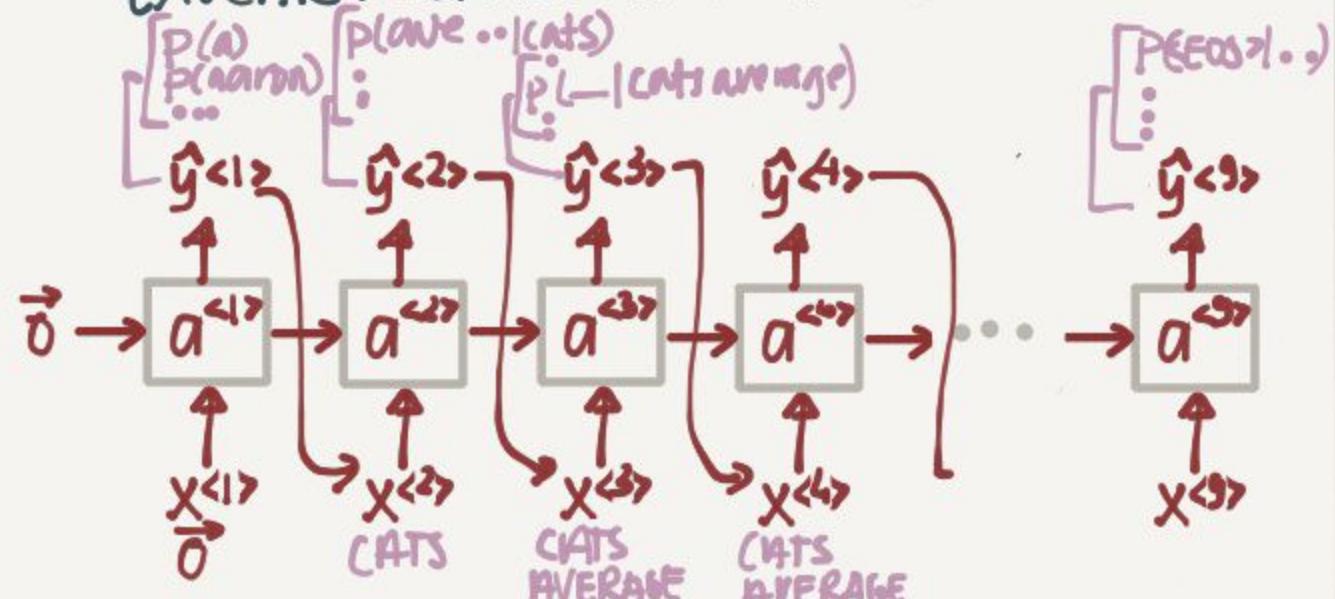
HOW DO YOU KNOW IF SOMEONE SAID



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 (ON 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 INTERLEVEL FLY



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

CAN DO AT
CHARACTER LEVEL
AS WELL

VANISHING GRADIENTS

THE CAT, WHO ALREADY ATE APPLES AND ORANGES
AND A FEW MORE THINGS BUT ~~BU~~ WAS FULL
THE CATS, ~~WHO~~ ALREADY ATE ... WERE FULL

NEED TO REMEMBER
SING/PLURAL FOR A LONG
TIME

SINCE LONG SENTENCE \Rightarrow 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_b DECIDES TO
UPDATE c TO \tilde{c} OR NOT

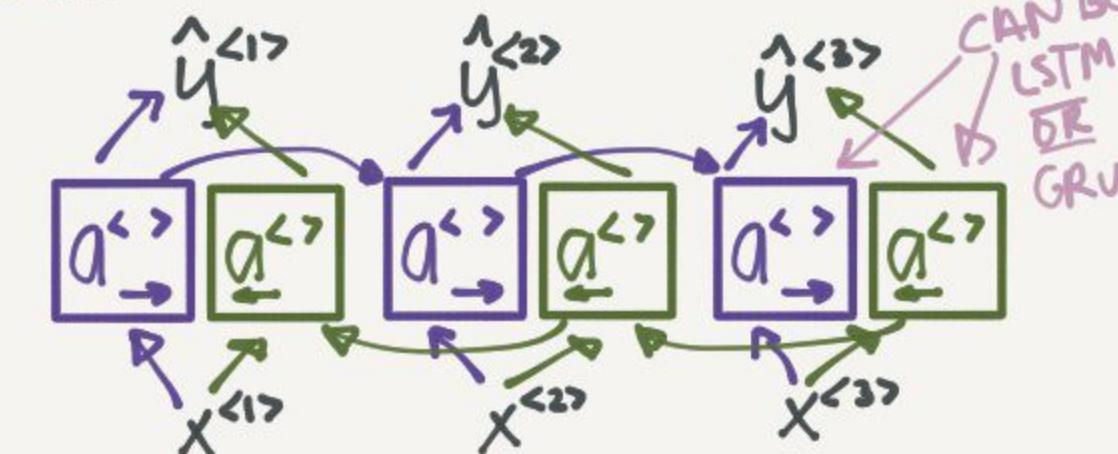
LONG SHORT TERM MEMORY (LSTM)

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

BI-DIRECTIONAL RNNs (BRNN)

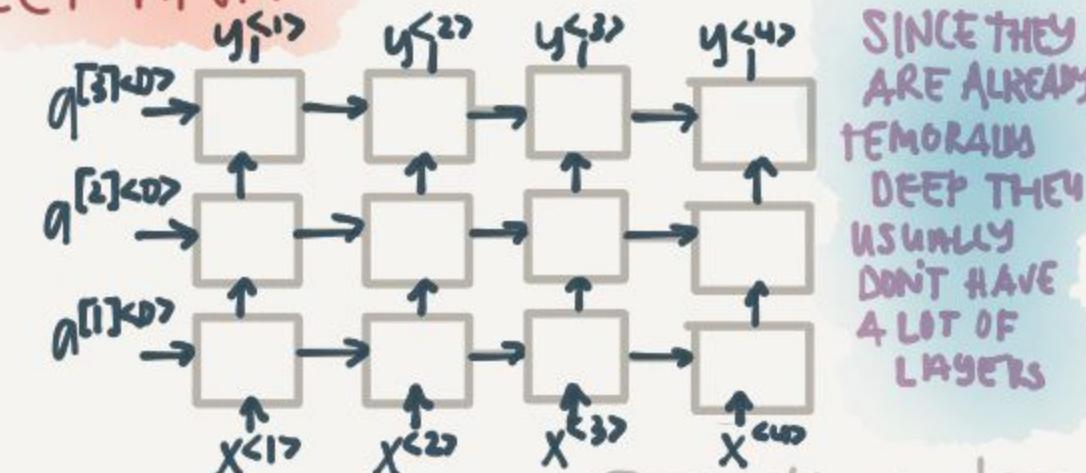
HE SAID, 'TEDDY BEARS ARE ON SALE'
HE SAID, 'TEDDY ROOSEVELT WAS A
GREAT PRESIDENT'

PROBLEM: WITHOUT LOOKING FORWARD WE
CAN'T 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 READING

DEEP RNN



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

 TessFernandez

SEQUENCE MODELS • COURSERA

NLP & WORD EMBEDDINGS

MAN IS TO WOMAN AS
KING IS TO QUEEN

PROBLEM: THE ONE-HOT REPR \mathbf{q}_apple OF
APPLE HAS NO INFO ABOUT ITS RELATIONSHIP
TO $\mathbf{o}_{\text{orange}}$ 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	WOMAN	KING	QUEEN	APPLE	ORANGE
GENDER	-1	1	-0.95	0.97	6.00	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}						

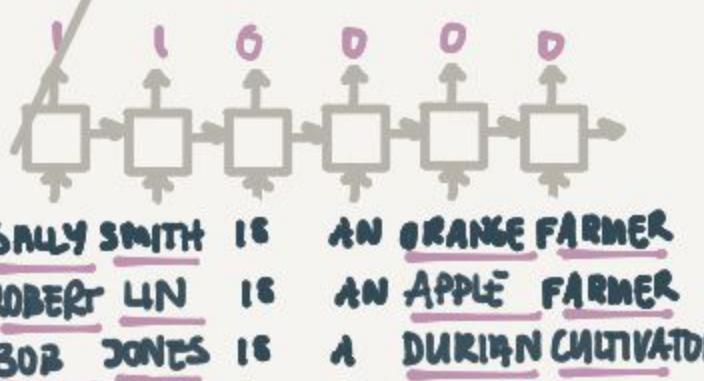
IN REALITY • THE FEATURES ARE
LEARNED & NOT AS STRAIGHTFWD
AS GENDER/AGE

	MAN	WOMAN	dog
king	.	.	.
queen	.	.	.
four	.	.	.
three	.	.	.
one	.	.	.
two	.	.	.
			cat
			fish
			apple
			grape
			orange

t-SNE
VISUAL
REPRESENT
OF 3000
WORD
EMBEDDINGS

USING WORD EMBEDDINGS

EX. NAME/ENTITY RECOGN



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

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

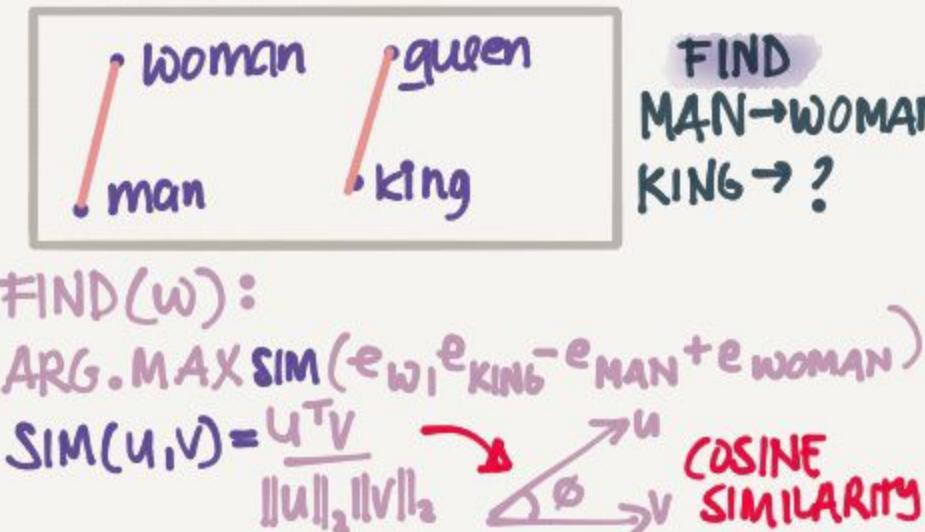
EX. MAN IS TO WOMAN AS
KING IS TO ?

$E = \text{EMBEDDING MATRIX}$

	MAN	WOMAN	KING	QUEEN
e_{man}	5391	9853	9914	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_{5391}				

$$e_{\text{man}} - e_{\text{woman}} \quad e_{\text{King}} - e_{\text{Queen}}$$

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

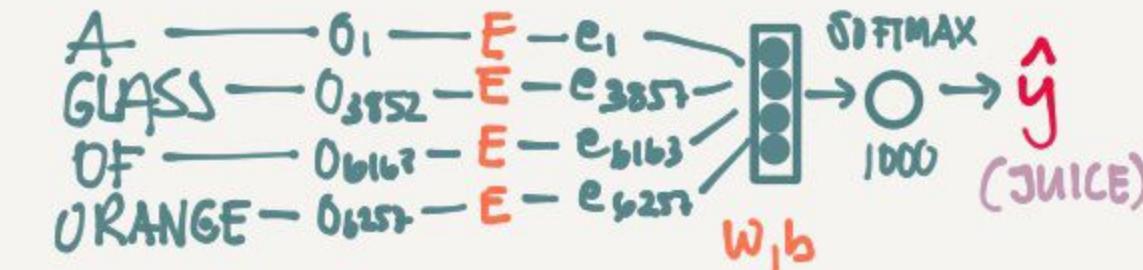


LEARNING WORD EMBEDDINGS

HOW DO WE LEARN THE EMBEDDING MATRIX E ?

IDEA1: USING A NEURAL LANG MODEL

I WANT A GLASS OF ORANGE \hat{y}



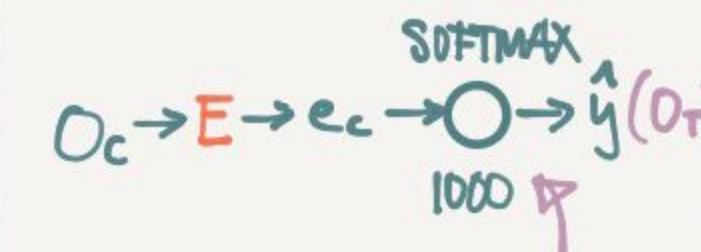
WE CAN USE DIFFERENT CONTEXTS THAN THE LAST 4 WORDS

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

IDEA2: 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
...	...



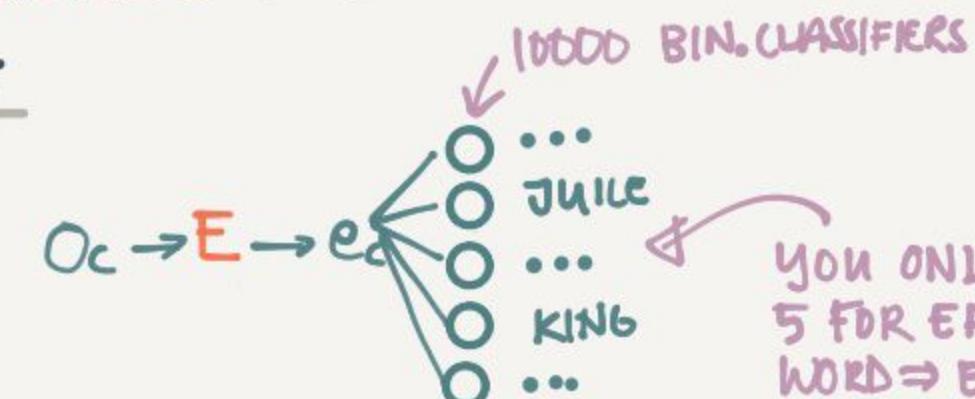
NOTE: WHILE THIS
SIMPLE NN PREDICTS O_T
OUR REAL GOAL IS TO
LEARN E

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

YOU ONLY TRAIN
5 FOR EACH CONTEXT
WORD \Rightarrow EFFICIENT
TO TRAIN

@TessFernandez

WORD EMBEDDINGS

CONTINUED...

Glove WORD VECTORS

$x_{ij} = \# \text{TIMES WORD } i \text{ APPEARS IN THE CONTEXT OF } j$

TARGET CONTEXT
(HOW RELATED THEY ARE)

$$\text{MINIMIZE } \sum_{i=1}^{10k} \sum_{j=1}^{10k} f(x_{ij})(\theta_i^T e_j + b_i + b_j - \log x_{ij})^2$$

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

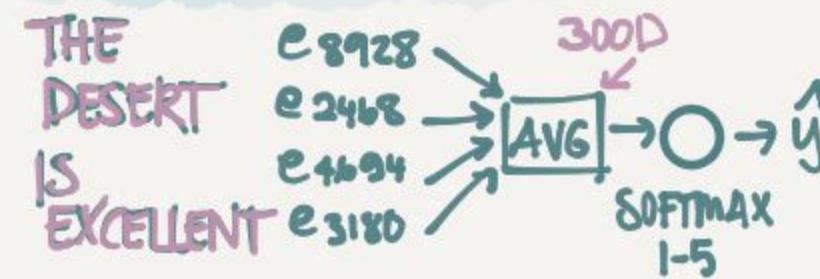
EVERYTHING LED UP TO THIS VERY SIMPLE ALGORITHM

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

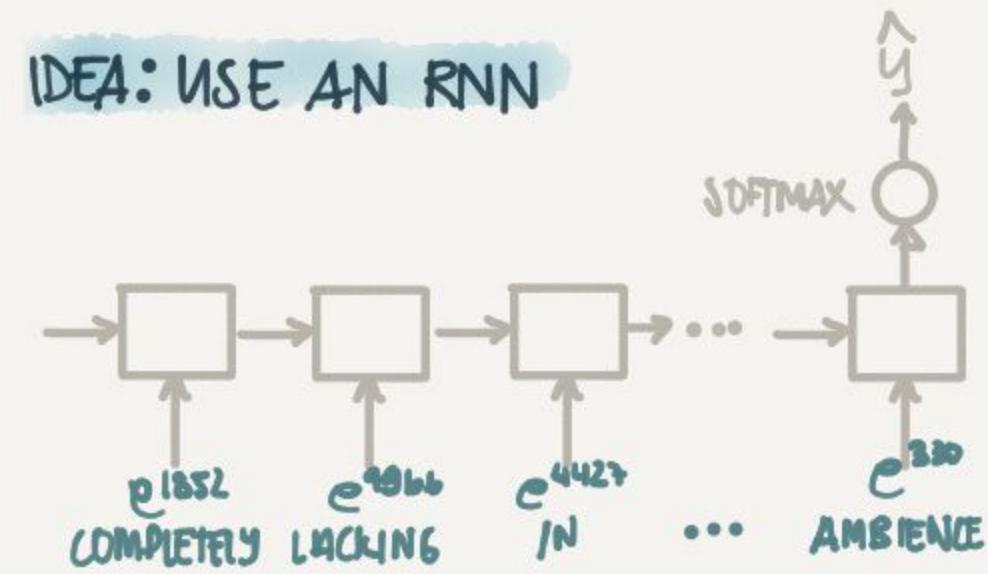


WORKS WELL FOR SHORT SENTENCES
BUT DOESN'T TAKE ORDER INTO ACCOUNT

"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 ♂ ALLOWS 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

$\{ \text{he} \rightarrow \text{she} \}$
 $\{ \text{male} \rightarrow \text{female} \}$

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?

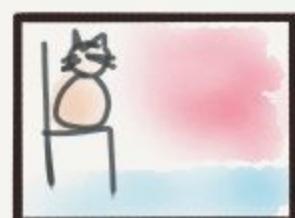
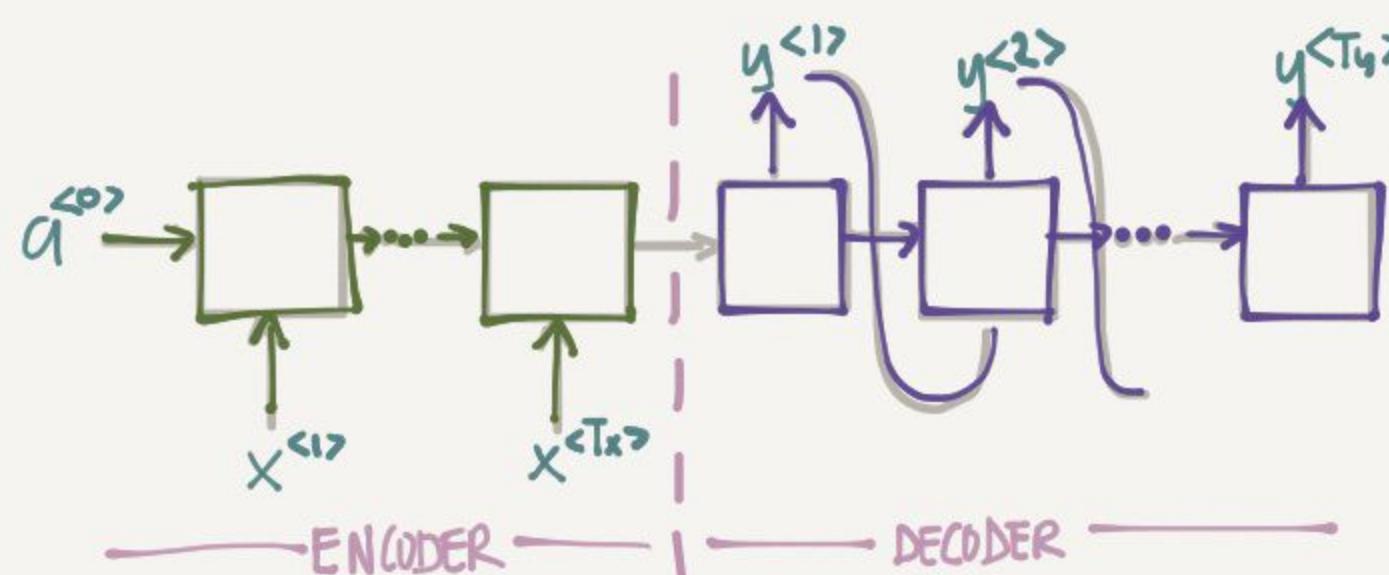
A: BY TRAINING A CLASSIFIER TO FIND OUT IF A WORD IS DEFINITIONAL

URNS OUT THE # OF PAIRS IS FAIRLY SMALL SO YOU CAN EVEN HAND PICK THEM

SEQUENCE TO SEQUENCE

BASIC MODELS

JANE VISITE L'AFRICA
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?

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

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 DEAD

WITH THIS WE COULD GET

- JANE IS GOING TO BE VISITING AFRICA
THIS SEPTEMBER

INSTEAD OF

- JANE IS VISITING AFRICA THIS SEPTEMBER

SOLUTION

OPTIMISE THE PROB OF THE
WHOLE SENTENCE INSTEAD

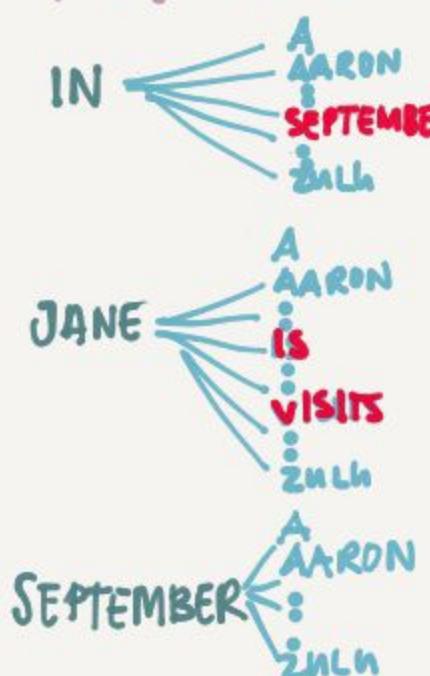
BEAM SEARCH

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

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



3. REPEAT TIL DONE

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

OVERFLOWS

PROBLEM: MULTIPLYING PROBABILITIES ($0 < p \ll 1$)
RESULTS IN A VERY SMALL NUMBER

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 SEE 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^*
ALSO: JANE VISITED AFRICA LAST SEPTEMBER \hat{y}

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

$$\text{LET THE RNN GIVE } P_{\text{Y}}^* = P(y^*, x) \text{ & } P_{\text{Y}}^{\hat{y}} = P(\hat{y}, x)$$

IF $P_{\text{Y}}^* > P_{\text{Y}}^{\hat{y}}$:

BEAM PICKED THE WRONG ONE
TRY A HIGHER B

ELSE:

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

