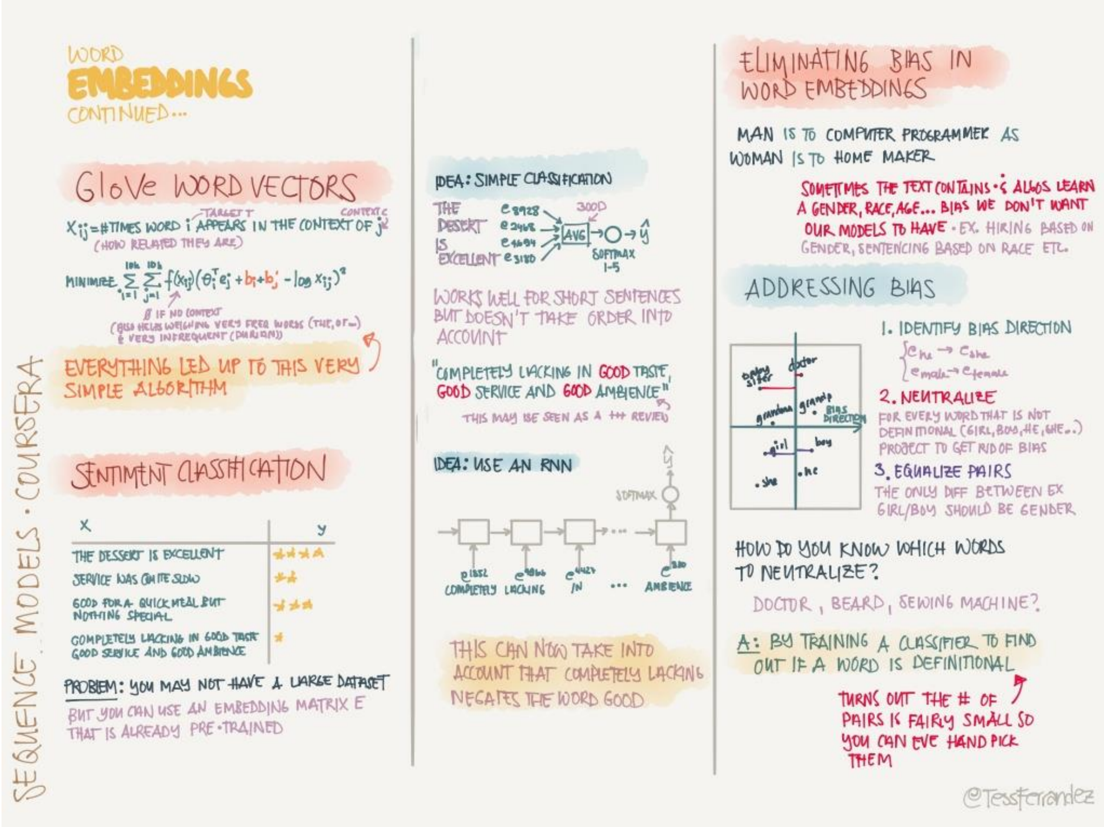
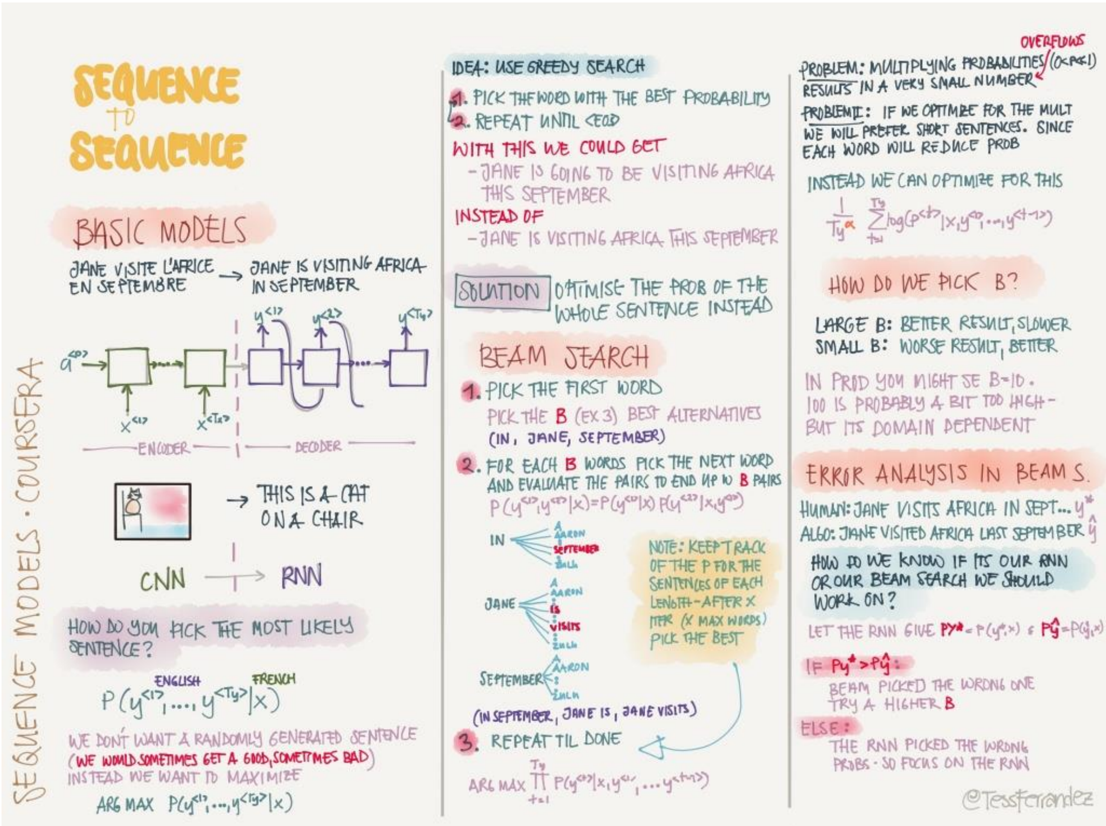
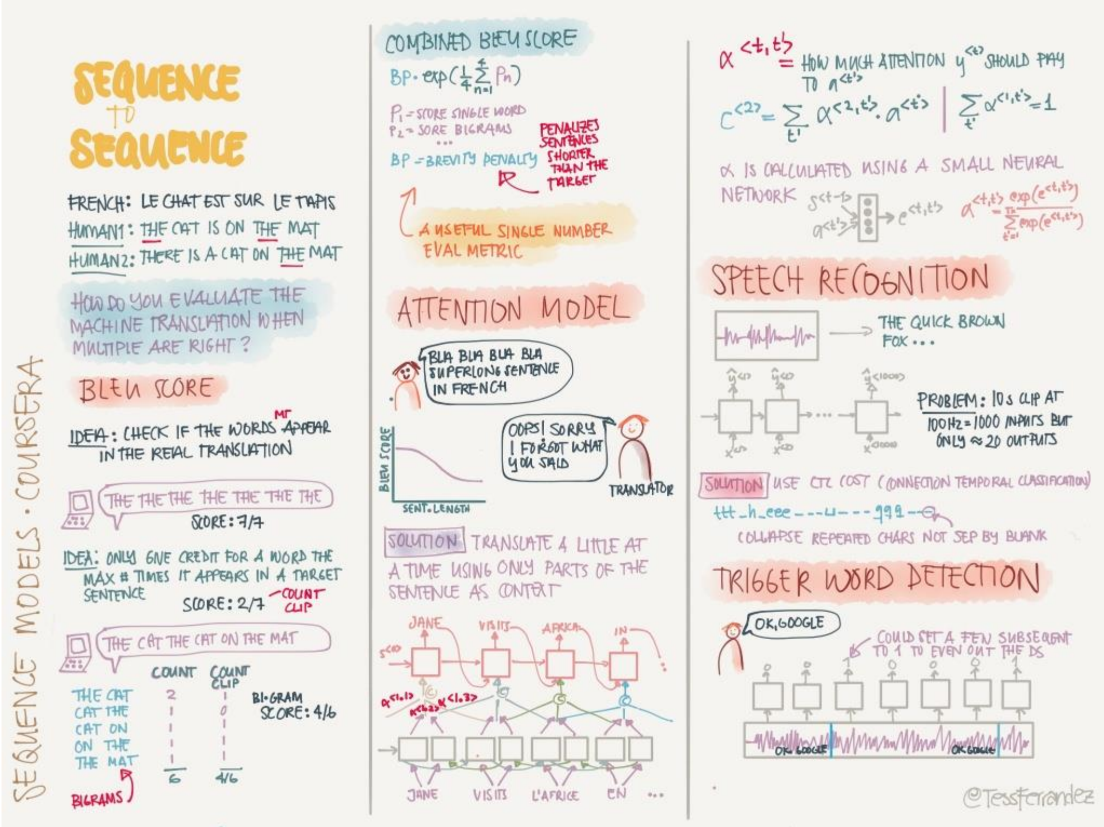
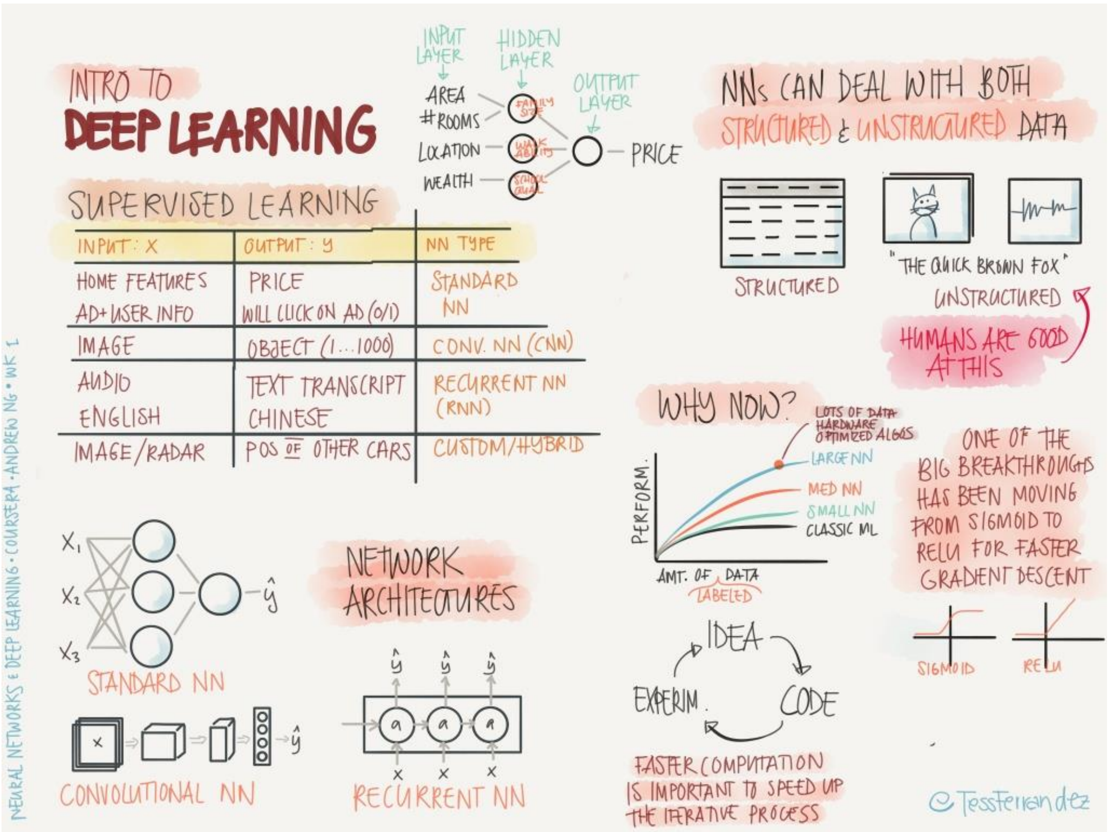
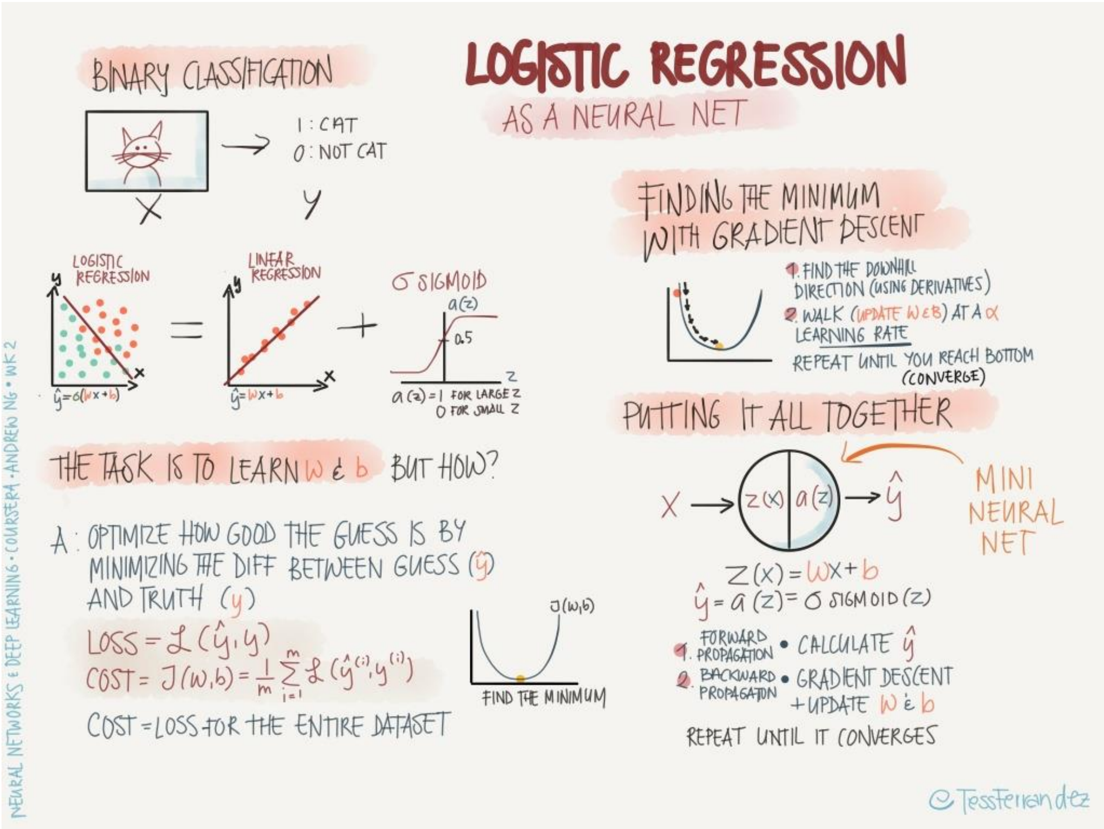

WORD EMBEDDINGS CONTINUED...
GloVe WORD VECTORS
X_{ij} = # TIMES WORD i (TARGET T) APPEARS IN THE CONTEXT OF j (CONTEXT C)
(HOW RELATED THEY ARE)
MINIMIZE $\sum_{i=1}^{10k}\sum_{j=1}^{10k} f(X_{ij})(\theta_i^T e_j + b_i + b_j' - \log X_{ij})^2$
0 IF NO CONTEXT
(ALSO HELPS WEIGHING VERY FREQ WORDS (THE, 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
THE DESERT IS EXCELLENT
e_{8928} e_{2468} e_{4694} e_{3180}
300D
AVG
SOFTMAX 1-5
$\hat{y}$
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
SOFTMAX
$\hat{y}$
e^{1852} COMPLETELY
e^{4966} LACKING
e^{4427} IN
...
e^{330} AMBIENCE
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
baby sister
doctor
grandma
grandpa
BIAS DIRECTION
girl
boy
she
he
1. IDENTIFY BIAS DIRECTION
$e_{he} \rightarrow e_{she}$
$e_{male} \rightarrow e_{female}$
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
@TessFerrandez
SEQUENCE MODELS · COURSERA


SEQUENCE TO SEQUENCE
BASIC MODELS
JANE VISITE L'AFRICE EN SEPTEMBRE → JANE IS VISITING AFRICA IN SEPTEMBER
$a^{\langle 0 \rangle}$
$x^{\langle 1 \rangle}$ $x^{\langle T_x \rangle}$
$y^{\langle 1 \rangle}$ $y^{\langle 2 \rangle}$ $y^{\langle T_y \rangle}$
ENCODER
DECODER
THIS IS A CAT ON A CHAIR
CNN → RNN
HOW DO YOU PICK THE MOST LIKELY SENTENCE?
ENGLISH FRENCH
$P(y^{\langle 1 \rangle}, \ldots, y^{\langle T_y \rangle} | x)$
WE DON'T WANT A RANDOMLY GENERATED SENTENCE
(WE WOULD SOMETIMES GET A GOOD, SOMETIMES BAD)
INSTEAD WE WANT TO MAXIMIZE
ARG MAX $P(y^{\langle 1 \rangle}, \ldots, y^{\langle T_y \rangle} | x)$
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
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
$P(y^{\langle 1 \rangle}, y^{\langle 2 \rangle} | x) = P(y^{\langle 1 \rangle}|x) P(y^{\langle 2 \rangle}|x, y^{\langle 1 \rangle})$
IN
A AARON SEPTEMBER ZULU
JANE
A AARON IS VISITS ZULU
SEPTEMBER
A AARON ZULU
NOTE: KEEP TRACK OF THE P FOR THE SENTENCES OF EACH LENGTH - AFTER X ITER (X MAX WORDS) PICK THE BEST
(IN SEPTEMBER, JANE IS, JANE VISITS)
3. REPEAT TIL DONE
ARG MAX $\prod_{t=1}^{T_y} P(y^{\langle t \rangle}|x, y^{\langle 1 \rangle}, \ldots y^{\langle t-1 \rangle})$
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
$\frac{1}{T_y^{\alpha}} \sum_{t=1}^{T_y} \log(P^{\langle t \rangle}|x, y^{\langle 1 \rangle}, \ldots, y^{\langle t-1 \rangle})$
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
@TessFerrandez
SEQUENCE MODELS · COURSERA


SEQUENCE TO SEQUENCE
SEQUENCE MODELS · COURSERA
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
COUNT
COUNT CLIP
THE CAT
CAT THE
CAT ON
ON THE
THE MAT
BIGRAMS
BI-GRAM SCORE: 4/6
COMBINED BLEU SCORE
BP · exp(1/4 Σ Pn)
P1 = SCORE SINGLE WORD
P2 = SCORE BIGRAMS
BP = BREVITY PENALTY
PENALIZES SENTENCES SHORTER THAN THE TARGET
A USEFUL SINGLE NUMBER EVAL METRIC
ATTENTION MODEL
BLA BLA BLA BLA SUPERLONG SENTENCE IN FRENCH
OOPS! SORRY I FORGOT WHAT YOU SAID
TRANSLATOR
BLEU SCORE
SENT. LENGTH
SOLUTION: TRANSLATE A LITTLE AT A TIME USING ONLY PARTS OF THE SENTENCE AS CONTEXT
JANE VISITS AFRICA IN
JANE VISITS L'AFRIQUE EN ...
α<t,t'> = HOW MUCH ATTENTION y<t> SHOULD PAY TO a<t'>
C<2> = Σ α<2,t'> · a<t'>
Σ α<1,t'> = 1
α IS CALCULATED USING A SMALL NEURAL NETWORK
SPEECH RECOGNITION
THE QUICK BROWN FOX ...
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
OK, GOOGLE
COULD SET A FEW SUBSEQUENT TO 1 TO EVEN OUT THE DS
OK GOOGLE
OK GOOGLE
@TessFerrandez


INTRO TO DEEP LEARNING
NEURAL NETWORKS & DEEP LEARNING · COURSERA · ANDREW NG · WK 1
INPUT LAYER
HIDDEN LAYER
OUTPUT LAYER
AREA
ROOMS
LOCATION
WEALTH
PRICE
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?
LOTS OF DATA
HARDWARE
OPTIMIZED ALGOS
LARGE NN
MED NN
SMALL NN
CLASSIC ML
PERFORM.
AMT. OF DATA
LABELED
ONE OF THE BIG BREAKTHROUGHS HAS BEEN MOVING FROM SIGMOID TO RELU FOR FASTER GRADIENT DESCENT
SIGMOID
RELU
x1
x2
x3
ŷ
STANDARD NN
NETWORK ARCHITECTURES
CONVOLUTIONAL NN
RECURRENT NN
IDEA
CODE
EXPERIM.
FASTER COMPUTATION IS IMPORTANT TO SPEED UP THE ITERATIVE PROCESS
@TessFerrandez


LOGISTIC REGRESSION
AS A NEURAL NET
BINARY CLASSIFICATION
1 : CAT
0 : NOT CAT
X
Y
LOGISTIC REGRESSION
LINEAR REGRESSION
σ SIGMOID
a(z)
0.5
z
$\hat{y} = \sigma(wx+b)$
$\hat{y} = wx+b$
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
J(w,b)
FIND THE MINIMUM
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
X → z(x) | a(z) → $\hat{y}$
MINI NEURAL NET
$z(x) = wx + b$
$\hat{y} = a(z) = \sigma$ SIGMOID(z)
1. FORWARD PROPAGATION • CALCULATE $\hat{y}$
2. BACKWARD PROPAGATION • GRADIENT DESCENT + UPDATE w & b
REPEAT UNTIL IT CONVERGES
NEURAL NETWORKS & DEEP LEARNING • COURSERA • ANDREW NG • WK 2
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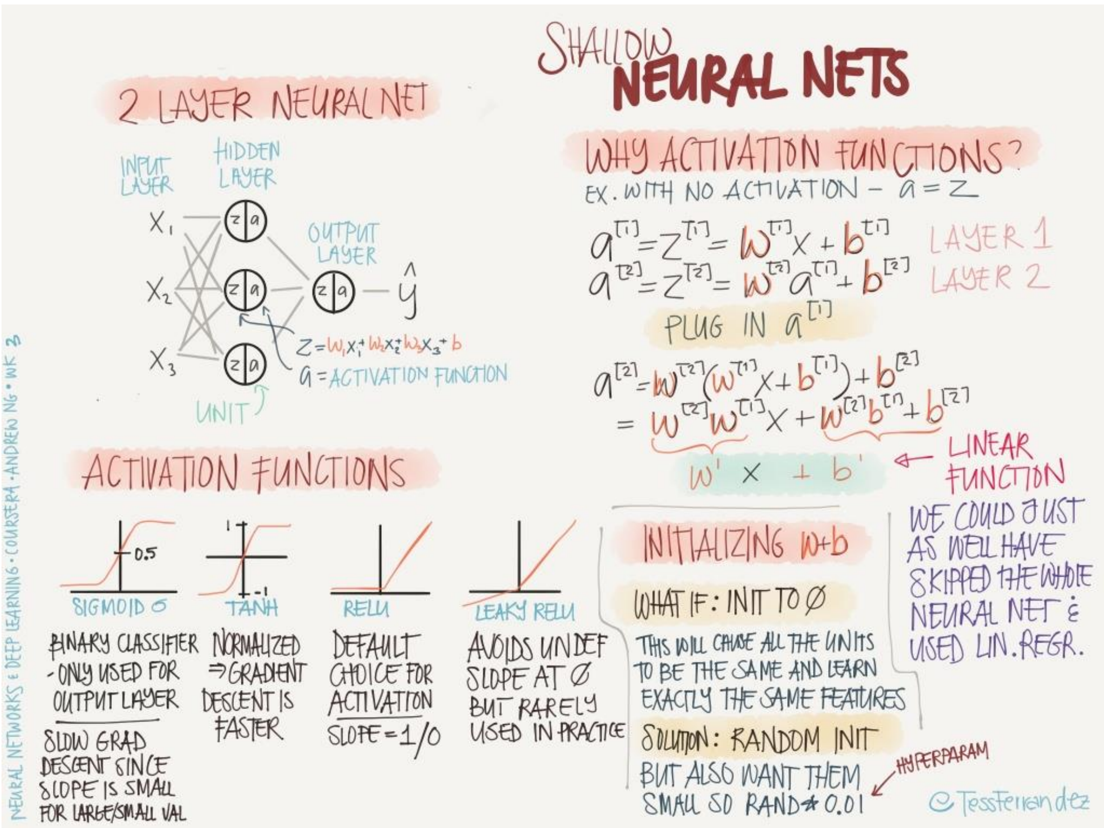
SHALLOW NEURAL NETS
2 LAYER NEURAL NET
INPUT LAYER
HIDDEN LAYER
OUTPUT LAYER
X_1
X_2
X_3
$\hat{y}$
UNIT
$Z = w_1x_1 + w_2x_2 + w_3x_3 + b$
a = ACTIVATION FUNCTION
WHY ACTIVATION FUNCTIONS?
EX. WITH NO ACTIVATION – a = z
$a^{[1]} = z^{[1]} = w^{[1]}x + b^{[1]}$ LAYER 1
$a^{[2]} = z^{[2]} = w^{[2]}a^{[1]} + b^{[2]}$ 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.
ACTIVATION FUNCTIONS
0.5
SIGMOID σ
1
-1
TANH
RELU
LEAKY RELU
BINARY CLASSIFIER - ONLY USED FOR OUTPUT LAYER
SLOW GRAD DESCENT SINCE SLOPE IS SMALL FOR LARGE/SMALL VAL
NORMALIZED ⇒ GRADIENT DESCENT IS FASTER
DEFAULT CHOICE FOR ACTIVATION
SLOPE = 1/0
AVOIDS UNDEF SLOPE AT Ø BUT RARELY USED IN PRACTICE
INITIALIZING w+b
WHAT IF: INIT TO Ø
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
NEURAL NETWORKS & DEEP LEARNING • COURSERA • ANDREW NG • WK 3
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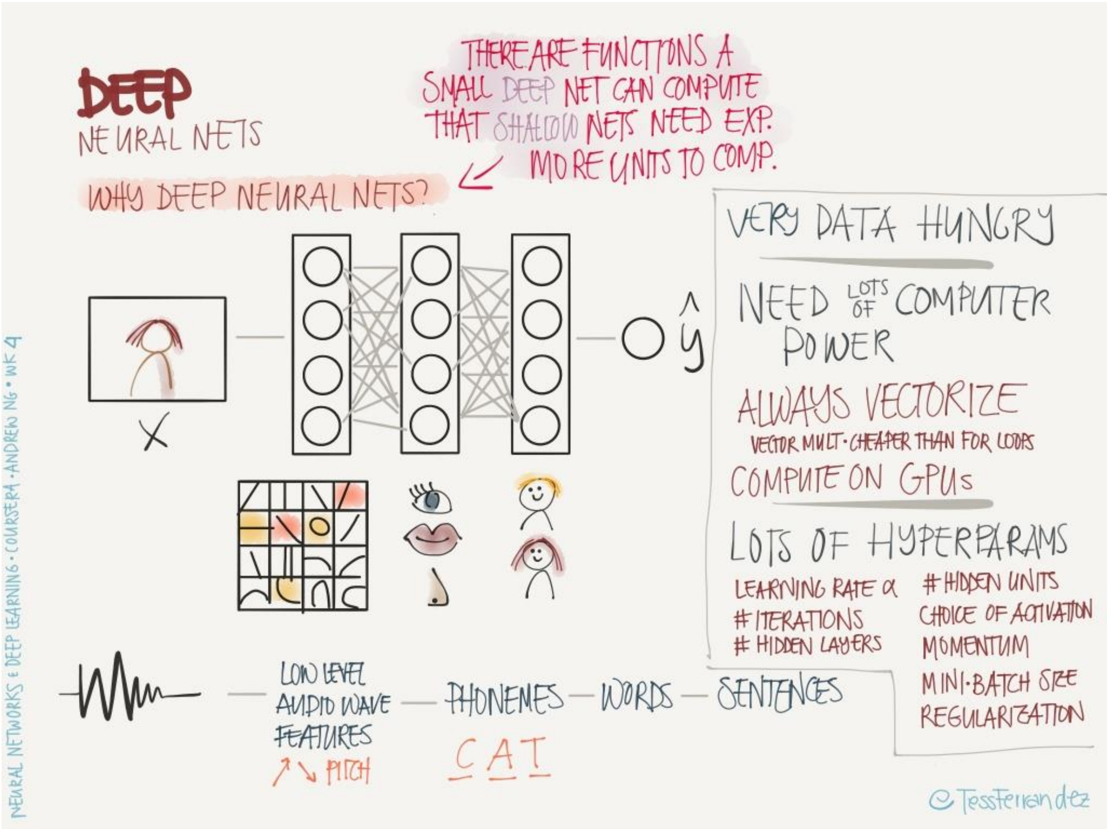
DEEP
NEURAL NETS
THERE ARE FUNCTIONS A SMALL DEEP NET CAN COMPUTE THAT SHALLOW NETS NEED EXP. MORE UNITS TO COMP.
WHY DEEP NEURAL NETS?
X
ŷ
LOW LEVEL AUDIO WAVE FEATURES
PITCH
PHONEMES
WORDS
SENTENCES
CAT
VERY DATA HUNGRY
NEED LOTS OF COMPUTER POWER
ALWAYS VECTORIZE
VECTOR MULT · CHEAPER THAN FOR LOOPS
COMPUTE ON GPUs
LOTS OF HYPERPARAMS
LEARNING RATE α
ITERATIONS
HIDDEN LAYERS
HIDDEN UNITS
CHOICE OF ACTIVATION
MOMENTUM
MINI-BATCH SIZE
REGULARIZATION
NEURAL NETWORKS & DEEP LEARNING · COURSERA · ANDREW NG · WK 4
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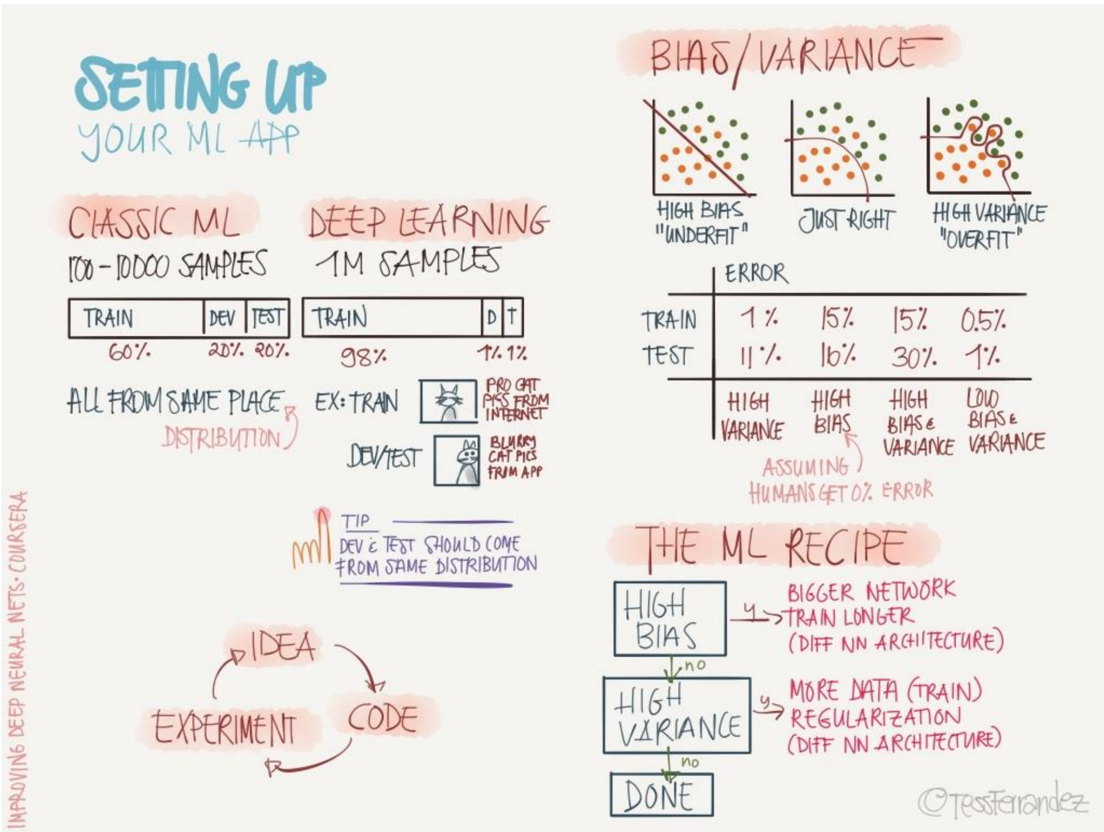
SETTING UP
YOUR ML APP
CLASSIC ML
100 – 10000 SAMPLES
TRAIN
DEV
TEST
60%
20%
20%
DEEP LEARNING
1M SAMPLES
TRAIN
D
T
98%
1%
1%
ALL FROM SAME PLACE
DISTRIBUTION
EX: TRAIN
PRO CAT PICS FROM INTERNET
DEV/TEST
BLURRY CAT PICS FROM APP
TIP
DEV & TEST SHOULD COME FROM SAME DISTRIBUTION
IDEA
CODE
EXPERIMENT
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
HIGH BIAS
y
BIGGER NETWORK
TRAIN LONGER
(DIFF NN ARCHITECTURE)
no
HIGH VARIANCE
y
MORE DATA (TRAIN)
REGULARIZATION
(DIFF NN ARCHITECTURE)
no
DONE
IMPROVING DEEP NEURAL NETS · COURSERA
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REGULARIZATION

PREVENTING OVERFITTING

L2 REGULARIZATION

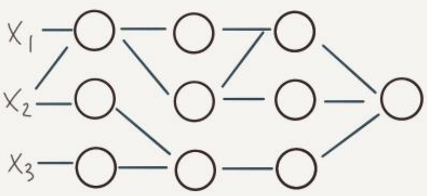
COST: $J(w,b) = \frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y},y) + \frac{\lambda}{2m}\|w\|_2^2$

EUCLIDEAN NORM

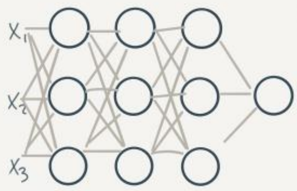
L1 REGULARIZATION

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

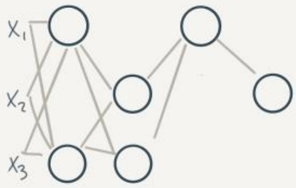
BOTH PENALIZE LARGE WEIGHTS ⇒ SOME WILL BE CLOSE TO Ø ⇒ SIMPLER NETWORKS



DROPOUT



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

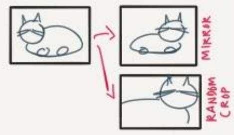


WE GET SIMPLER NWs & LESS CHANCE TO RELY ON SINGLE FEATURES

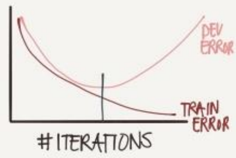
OTHER REGULARIZATION TECHNIQUES

DATA AUGMENTATION

GENERATE NEW PICS FROM EXISTING



EARLY STOPPING



PROBLEM: AFFECTS BOTH BIAS & VARIANCE

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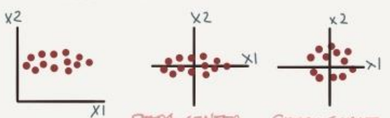
OPTIMIZING

TRAINING

NORMALIZING INPUTS

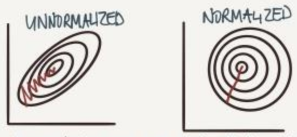


STEP1: CENTER AROUND Ø,Ø

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.

NOTE: ONLY USE WHEN DEBUGGING SINCE IT'S SLOW

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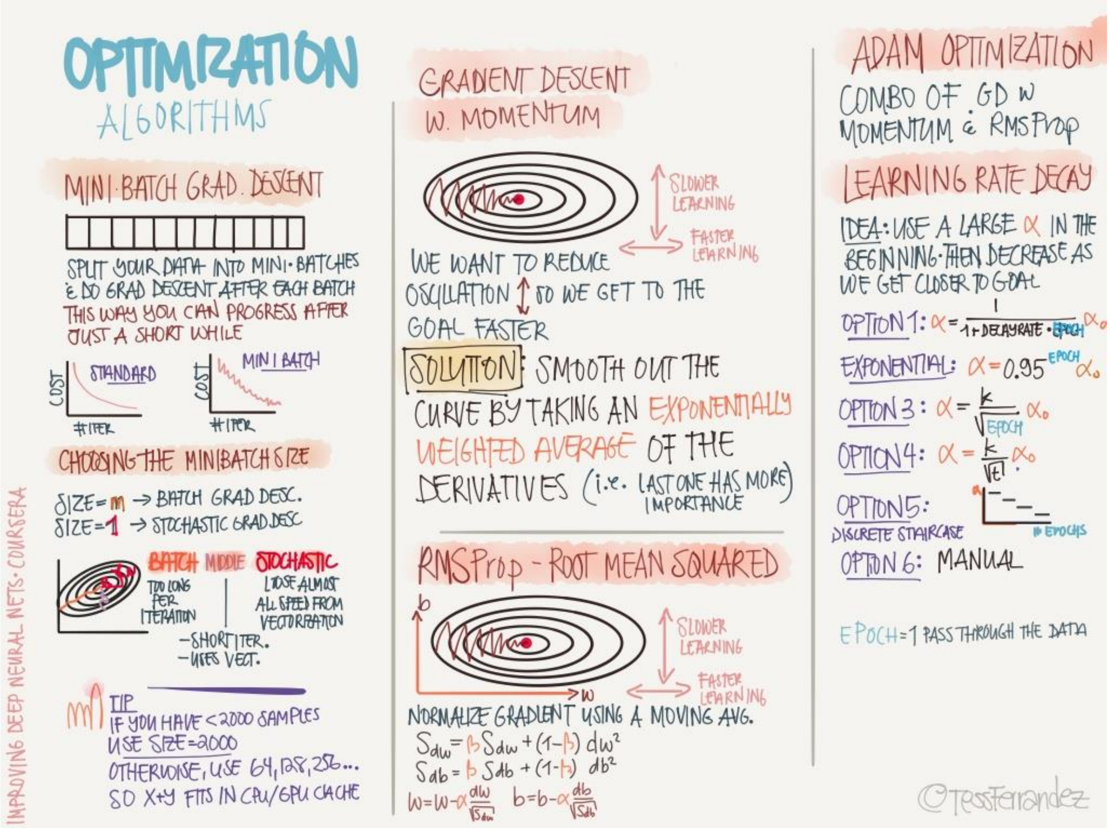
OPTIMIZATION
ALGORITHMS
MINI-BATCH GRAD. DESCENT
SPLIT YOUR DATA INTO MINI-BATCHES & DO GRAD DESCENT AFTER EACH BATCH
THIS WAY YOU CAN PROGRESS AFTER JUST A SHORT WHILE
COST
STANDARD
#ITER
COST
MINI BATCH
#ITER
CHOOSING THE MINIBATCH SIZE
SIZE=m → BATCH GRAD DESC.
SIZE=1 → STOCHASTIC GRAD DESC
BATCH MIDDLE STOCHASTIC
TOO LONG PER ITERATION
LOSE ALMOST ALL SPEED FROM VECTORIZATION
-SHORT ITER.
-USES VECT.
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
SLOWER LEARNING
FASTER LEARNING
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
b
w
SLOWER LEARNING
FASTER LEARNING
NORMALIZE GRADIENT USING A MOVING AVG.
$S_{dw} = \beta S_{dw} + (1-\beta) dw^2$
$S_{db} = \beta S_{db} + (1-\beta) db^2$
$w = w - \alpha \frac{dw}{\sqrt{S_{dw}}}$ $b = b - \alpha \frac{db}{\sqrt{S_{db}}}$
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: $\alpha = \frac{1}{1 + DECAYRATE \cdot EPOCH} \alpha_0$
EXPONENTIAL: $\alpha = 0.95^{EPOCH} \alpha_0$
OPTION 3: $\alpha = \frac{k}{\sqrt{EPOCH}} \alpha_0$
OPTION 4: $\alpha = \frac{k}{\sqrt{t}} \alpha_0$
OPTION 5: DISCRETE STAIRCASE
α
EPOCHS
OPTION 6: MANUAL
EPOCH=1 PASS THROUGH THE DATA
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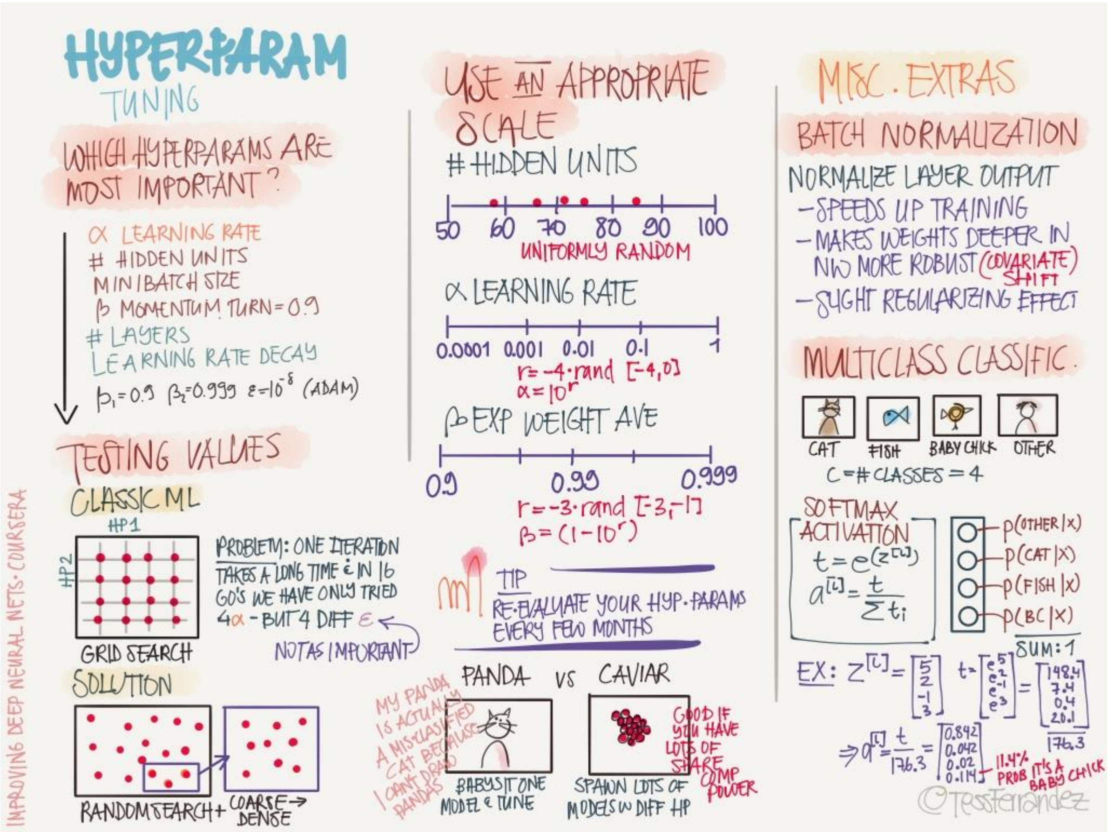
HYPERPARAM
TUNING
WHICH HYPERPARAMS ARE MOST IMPORTANT?
α LEARNING RATE
HIDDEN UNITS
MINIBATCH SIZE
β MOMENTUM TURN=0.9
LAYERS
LEARNING RATE DECAY
$\beta_1=0.9$ $\beta_2=0.999$ $\varepsilon=10^{-8}$ (ADAM)
TESTING VALUES
CLASSIC ML
HP1
HP2
GRID SEARCH
PROBLEM: ONE ITERATION TAKES A LONG TIME & IN 16 GO'S WE HAVE ONLY TRIED 4α - 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
$r = -4 \cdot rand$ [-4, 0]
$\alpha = 10^r$
β EXP WEIGHT AVE
0.9 0.99 0.999
$r = -3 \cdot rand$ [-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
SPAWN LOTS OF MODELS W DIFF HP
GOOD IF YOU HAVE LOTS OF SPARE COMP POWER
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)
EX: $z^{[L]} = \begin{bmatrix} 5 \\ 2 \\ -1 \\ 3 \end{bmatrix}$ $t = \begin{bmatrix} e^5 \\ e^2 \\ e^{-1} \\ e^3 \end{bmatrix} = \begin{bmatrix} 148.4 \\ 7.4 \\ 0.4 \\ 20.1 \end{bmatrix}$
SUM: 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
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STRUCTURING
YOUR ML PROJECTS

SETTING YOUR GOAL

★ A 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

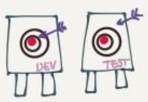
RUNTIME = SATISFICING

SELECTING YOUR DEV/TEST SETS

DATA

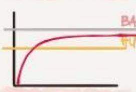
US
UK
EUROPE
S.AM
INDIA
CHINA
AUST.

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



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)

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

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
VARIANCE
DEV

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

- MORE DATA (TRAIN)
- REGULARIZATION
- NN ARCHITECTURE

	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

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ERROR
ANALYSIS

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

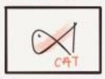
1. PICK 100 MIS-LABLED
2. COUNT ERROR REASONS

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

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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
	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

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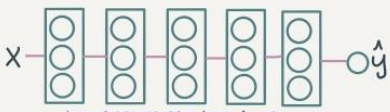
EXTENDED LEARNING

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

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

UNLIKE SOFTMAX. 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

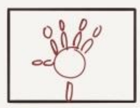
A. THE LEARNING DATA YOU HAVE FOR THE DIFF TASKS IS QUITE SIMILAR – & THE AMOUNTS (EG. 1K CARS, 1K STOP SIGNS)

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 BONELENGTH

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

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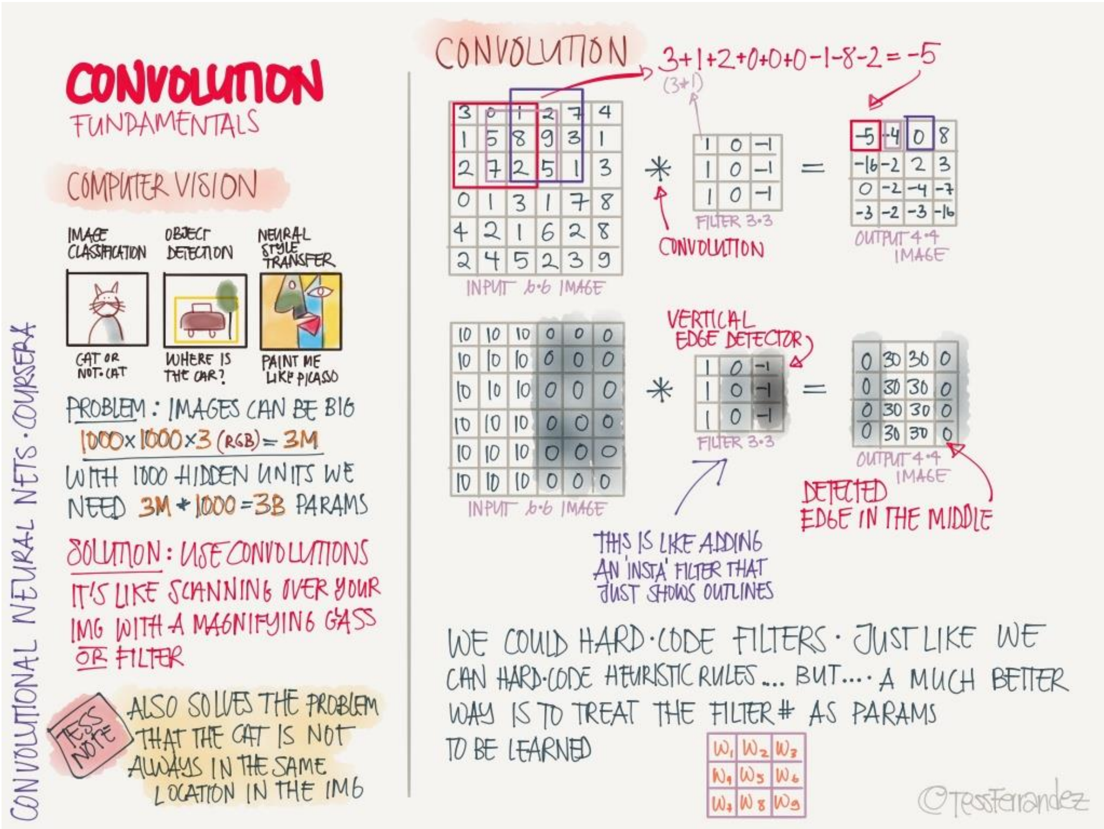
CONVOLUTION
FUNDAMENTALS
COMPUTER VISION
IMAGE CLASSIFICATION
OBJECT DETECTION
NEURAL STYLE TRANSFER
CAT OR NOT-CAT
WHERE IS THE CAR?
PAINT ME LIKE PICASSO
PROBLEM: IMAGES CAN BE BIG
1000 x 1000 x 3 (RGB) = 3M
WITH 1000 HIDDEN UNITS WE NEED 3M * 1000 = 3B PARAMS
SOLUTION: USE CONVOLUTIONS
IT'S LIKE SCANNING 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
CONVOLUTIONAL NEURAL NETS · COURSERA
CONVOLUTION
3+1+2+0+0+0-1-8-2 = -5
(3*1)
INPUT 6·6 IMAGE
FILTER 3·3
CONVOLUTION
OUTPUT 4·4 IMAGE
VERTICAL EDGE DETECTOR
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
W1 W2 W3
W4 W5 W6
W7 W8 W9
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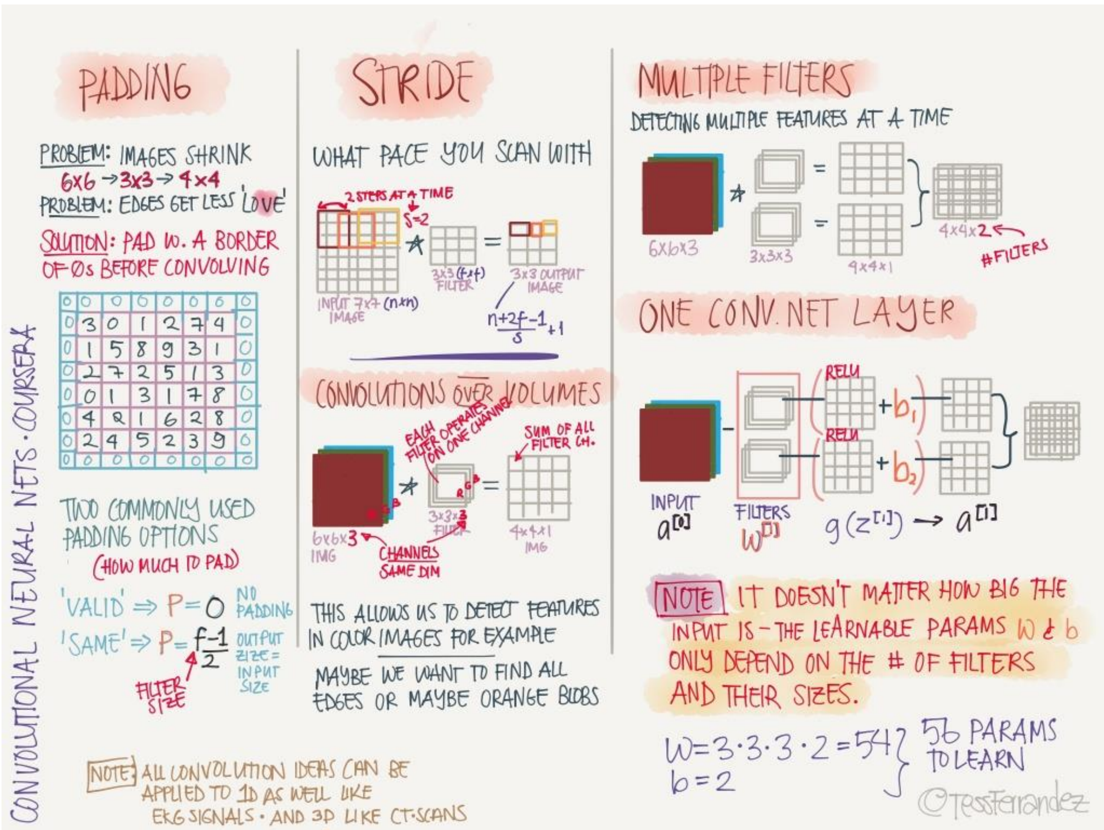
PADDING
PROBLEM: IMAGES SHRINK
6x6 → 3x3 → 4x4
PROBLEM: EDGES GET LESS 'LOVE'
SOLUTION: PAD W. A BORDER OF 0s BEFORE CONVOLVING
TWO COMMONLY USED PADDING OPTIONS
(HOW MUCH TO PAD)
'VALID' ⇒ P = 0 NO PADDING
'SAME' ⇒ P = (f-1)/2 OUTPUT SIZE = INPUT SIZE
FILTER SIZE
NOTE: ALL CONVOLUTION IDEAS CAN BE APPLIED TO 1D AS WELL LIKE EKG SIGNALS · AND 3D LIKE CT-SCANS
CONVOLUTIONAL NEURAL NETS · COURSERA
STRIDE
WHAT PACE YOU SCAN WITH
2 STEPS AT A TIME
S=2
INPUT 7x7 (nxn) IMAGE
3x3 (fxf) FILTER
3x3 OUTPUT IMAGE
(n+2f-1)/s + 1
CONVOLUTIONS OVER VOLUMES
EACH FILTER OPERATES ON ONE CHANNEL
SUM OF ALL FILTER CH.
6x6x3 IMG
3x3x3 FILTER
4x4x1 IMG
CHANNELS SAME DIM
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
6x6x3
3x3x3
4x4x1
4x4x2
#FILTERS
ONE CONV. NET LAYER
RELU
+b1
+b2
INPUT a[0]
FILTERS W[1]
g(z[1]) → 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.
W = 3·3·3·2 = 54
b = 2
56 PARAMS TO LEARN
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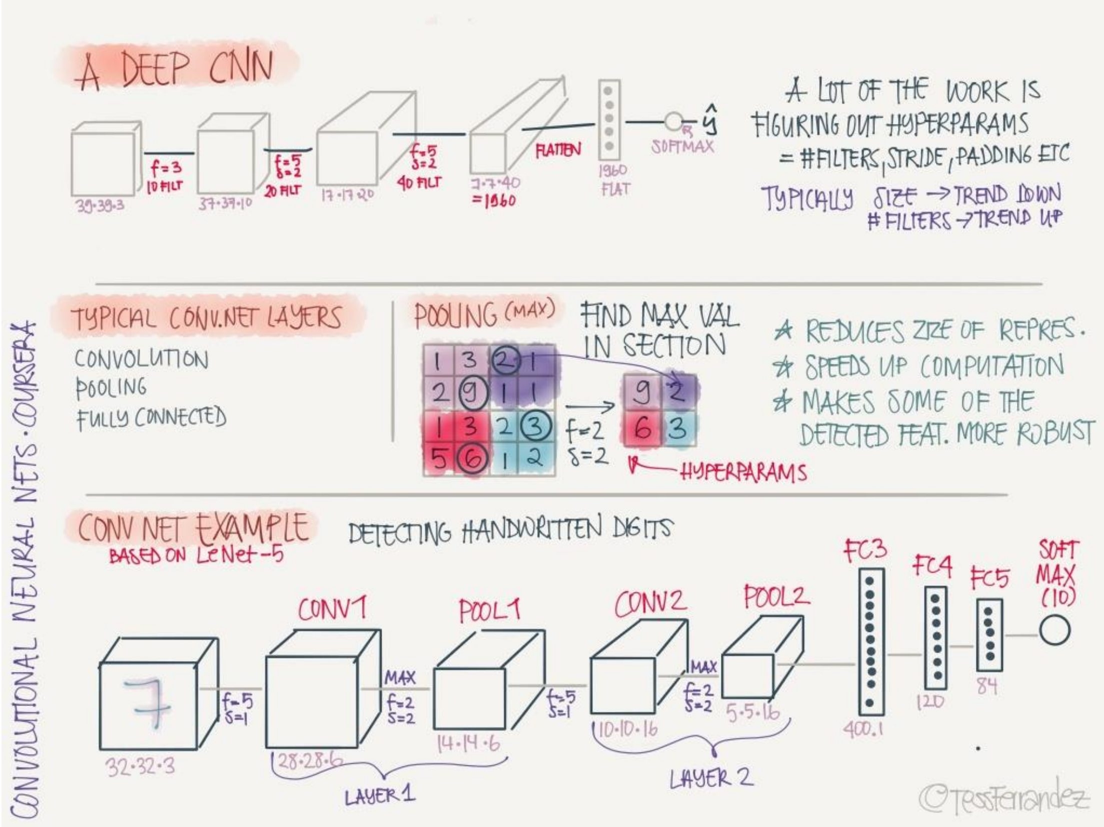
A DEEP CNN
f=3
10 FILT
f=5
s=2
20 FILT
f=5
s=2
40 FILT
FLATTEN
SOFTMAX
39·39·3
37·37·10
17·17·20
7·7·40
=1960
1960
FLAT
A LOT OF THE WORK IS FIGURING OUT HYPERPARAMS
= #FILTERS, STRIDE, PADDING ETC
TYPICALLY SIZE → TREND DOWN
#FILTERS → TREND UP
TYPICAL CONV.NET LAYERS
CONVOLUTION
POOLING
FULLY CONNECTED
POOLING (MAX)
FIND MAX VAL IN SECTION
f=2
s=2
HYPERPARAMS
* 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
CONV1
POOL1
CONV2
POOL2
FC3
FC4
FC5
SOFT MAX (10)
f=5
s=1
MAX
f=2
s=2
32·32·3
28·28·6
14·14·6
10·10·16
5·5·16
400,1
120
84
LAYER 1
LAYER 2
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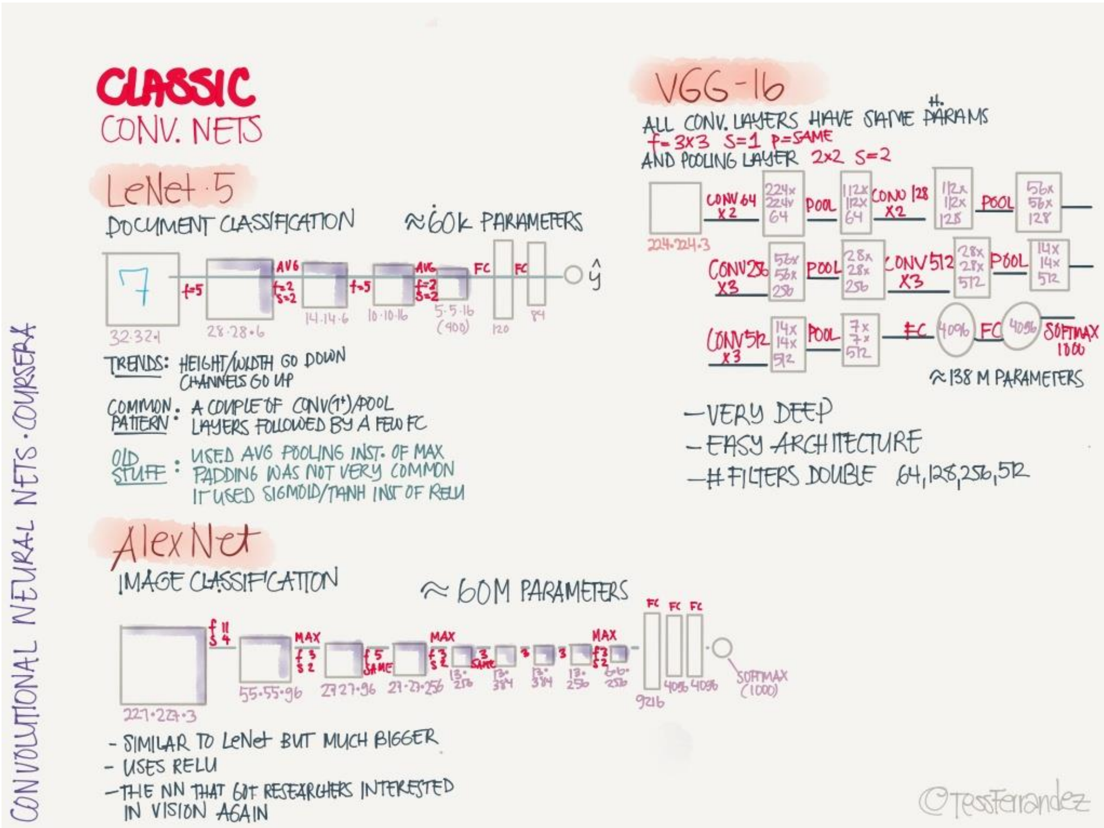
CLASSIC CONV. NETS
LeNet·5
DOCUMENT CLASSIFICATION
≈60K PARAMETERS
f=5
AVG
f=2
s=2
FC
32·32·1
28·28·6
14·14·6
10·10·16
5·5·16
(400)
120
84
TRENDS: HEIGHT/WIDTH GO DOWN
CHANNELS GO UP
COMMON PATTERN: A COUPLE OF CONV(1+)/POOL LAYERS FOLLOWED BY A FEW FC
OLD STUFF: USED AVG POOLING INST. OF MAX
PADDING WAS NOT VERY COMMON
IT USED SIGMOID/TANH INST OF RELU
AlexNet
IMAGE CLASSIFICATION
≈ 60M PARAMETERS
MAX
SAME
227·227·3
55·55·96
27·27·96
27·27·256
9216
4096
4096
SOFTMAX (1000)
- 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
CONV 64 x2
POOL
CONV 128 x2
CONV 256 x3
CONV 512 x3
FC
4096
SOFTMAX 1000
224·224·3
≈138 M PARAMETERS
- VERY DEEP
- EASY ARCHITECTURE
- # FILTERS DOUBLE 64, 128, 256, 512
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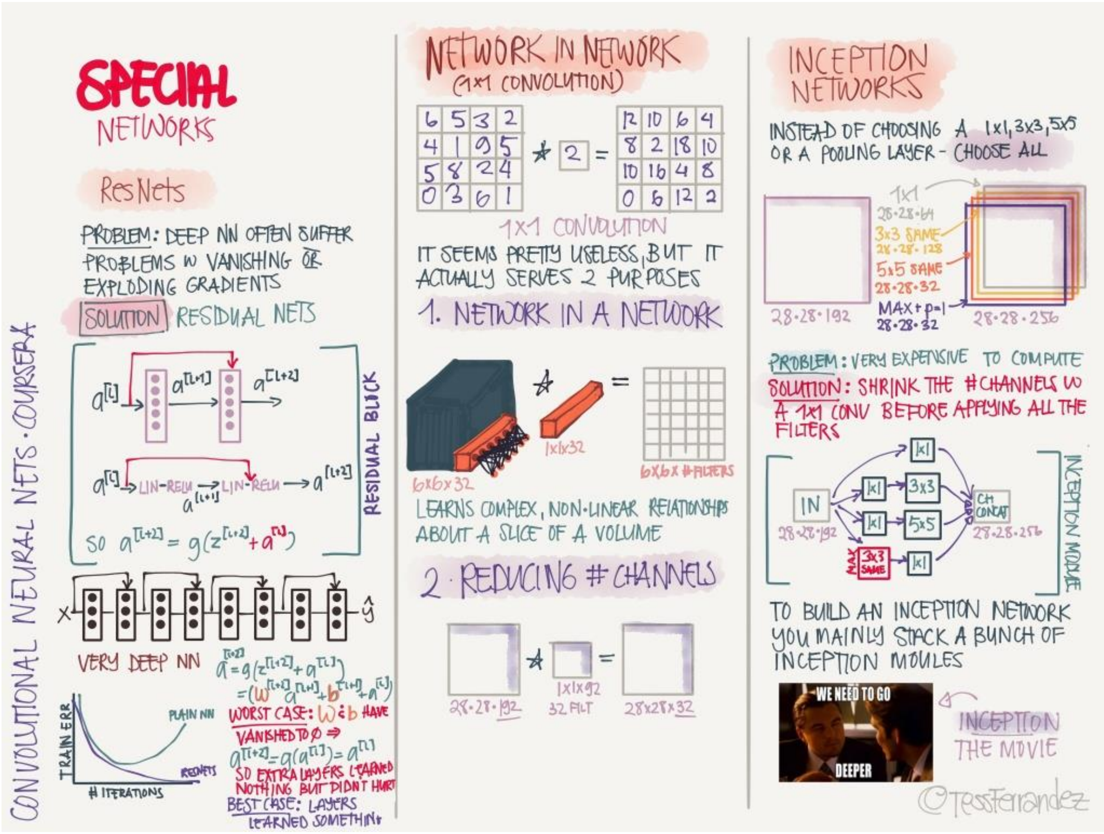
SPECIAL NETWORKS
ResNets
PROBLEM: DEEP NN OFTEN SUFFER PROBLEMS W VANISHING OR EXPLODING GRADIENTS
SOLUTION RESIDUAL NETS
RESIDUAL BLOCK
LIN-RELU
SO $a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$
VERY DEEP NN
TRAIN ERR
PLAIN NN
RESNETS
ITERATIONS
$a^{[l+2]} = g(z^{[l+2]} + a^{[l]})$
$= (W^{[l+2]} a^{[l+1]} + b^{[l+2]} + a^{[l]})$
WORST CASE: W & b HAVE VANISHED TO Ø ⇒
$a^{[l+2]} = g(a^{[l]}) = a^{[l]}$
SO EXTRA LAYERS LEARNED NOTHING BUT DIDN'T HURT
BEST CASE: LAYERS LEARNED SOMETHING
CONVOLUTIONAL NEURAL NETS · COURSERA
NETWORK IN NETWORK
(1x1 CONVOLUTION)
1x1 CONVOLUTION
IT SEEMS PRETTY USELESS, BUT IT ACTUALLY SERVES 2 PURPOSES
1. NETWORK IN A NETWORK
6x6x32
1x1x32
6x6x #FILTERS
LEARNS COMPLEX, NON-LINEAR RELATIONSHIPS ABOUT A SLICE OF A VOLUME
2. REDUCING # CHANNELS
28·28·192
1x1x32
32 FILT
28x28x32
INCEPTION NETWORKS
INSTEAD OF CHOOSING A 1x1, 3x3, 5x5 OR A POOLING LAYER - CHOOSE ALL
1x1
28·28·64
3x3 SAME
28·28·128
5x5 SAME
28·28·32
MAX + p=1
28·28·32
28·28·192
28·28·256
PROBLEM: VERY EXPENSIVE TO COMPUTE
SOLUTION: SHRINK THE # CHANNELS W A 1x1 CONV BEFORE APPLYING ALL THE FILTERS
IN
CH CONCAT
INCEPTION MODULE
TO BUILD AN INCEPTION NETWORK YOU MAINLY STACK A BUNCH OF INCEPTION MODULES
WE NEED TO GO DEEPER
INCEPTION THE MOVIE
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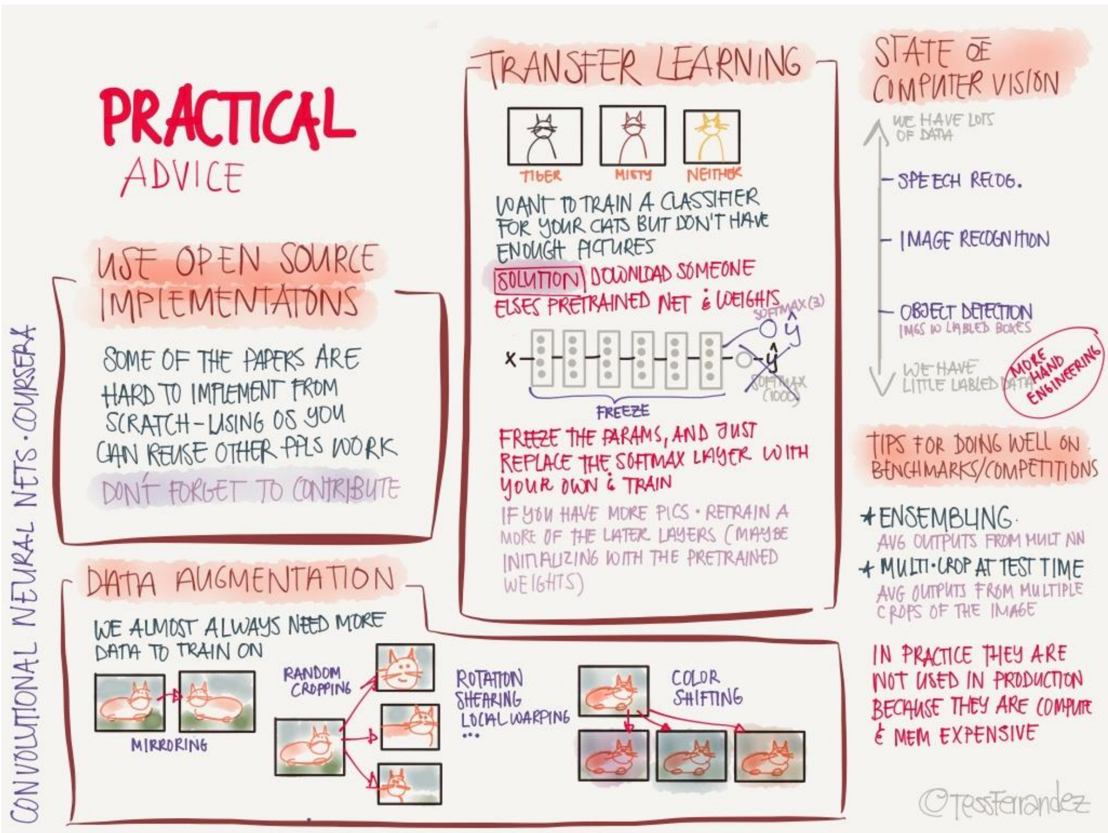
PRACTICAL ADVICE
USE OPEN SOURCE IMPLEMENTATIONS
SOME OF THE PAPERS ARE HARD TO IMPLEMENT FROM SCRATCH - USING OS YOU CAN REUSE OTHER PPLS WORK
DON'T FORGET TO CONTRIBUTE
DATA AUGMENTATION
WE ALMOST ALWAYS NEED MORE DATA TO TRAIN ON
MIRRORING
RANDOM CROPPING
ROTATION
SHEARING
LOCAL WARPING
...
COLOR SHIFTING
CONVOLUTIONAL NEURAL NETS · COURSERA
TRANSFER LEARNING
TIGER
MISTY
NEITHER
WANT TO TRAIN A CLASSIFIER FOR YOUR CATS BUT DON'T HAVE ENOUGH PICTURES
SOLUTION DOWNLOAD SOMEONE ELSES PRETRAINED NET & WEIGHTS
SOFTMAX (3)
SOFTMAX (1000)
FREEZE
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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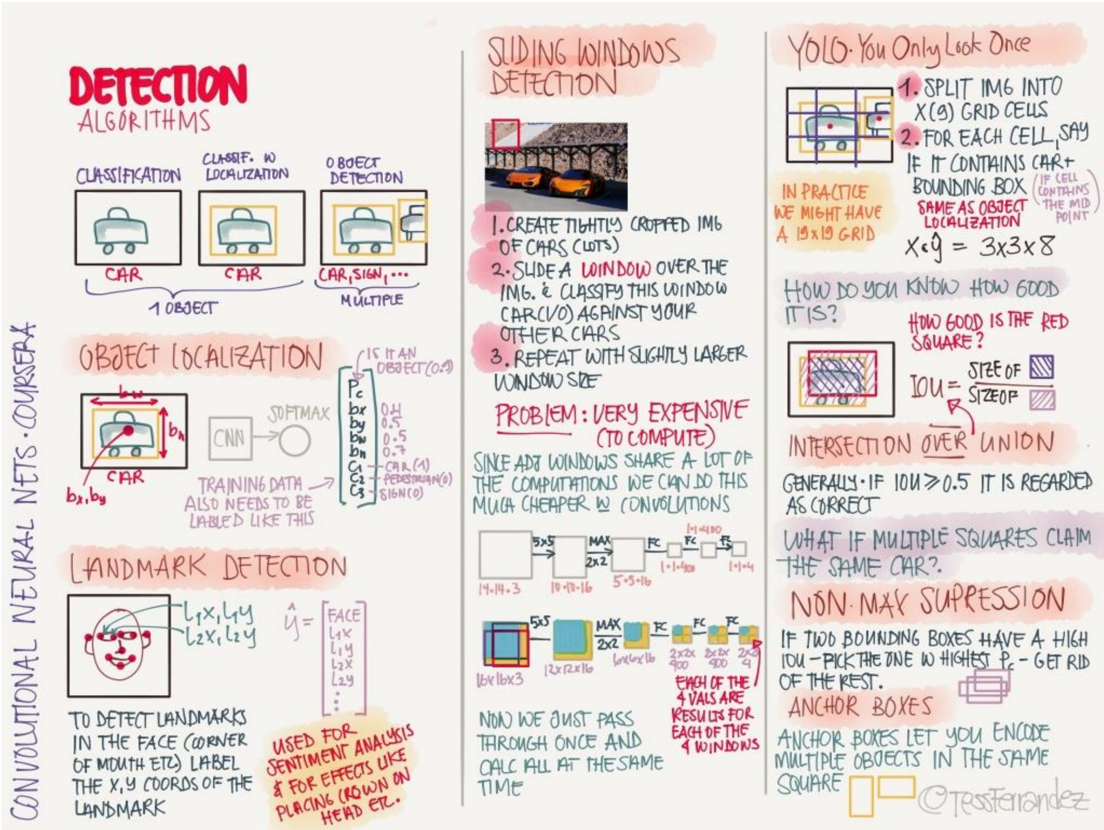
DETECTION
ALGORITHMS
CLASSIFICATION
CLASSIF. W LOCALIZATION
OBJECT DETECTION
CAR
CAR
CAR, SIGN, ...
1 OBJECT
MULTIPLE
OBJECT LOCALIZATION
bw
bh
bx, by
CAR
CNN
SOFTMAX
IS IT AN OBJECT (0,1)
Pc bx by bh bw C1 C2 C3
0.4 0.5 0.5 0.7
CAR (1)
PEDESTRIAN (0)
SIGN (0)
TRAINING DATA ALSO NEEDS TO BE LABLED LIKE THIS
LANDMARK DETECTION
L1x, L1y
L2x, L2y
ŷ = FACE L1x L1y L2x L2y ...
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.
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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
5x5
MAX 2x2
FC
FC
FC
14x14x3
10x10x16
5x5x16
1x1x400
1x1x400
1x1x4
16x16x3
5x5
12x12x16
MAX 2x2
6x6x16
FC
FC
FC
2x2x400
2x2x400
2x2x4
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 & ŷ = 3x3x8
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 SUPPRESSION
IF TWO BOUNDING BOXES HAVE A HIGH IOU — PICK THE ONE W HIGHEST Pc — GET RID OF THE REST.
ANCHOR BOXES
ANCHOR BOXES LET YOU ENCODE MULTIPLE OBJECTS IN THE SAME SQUARE
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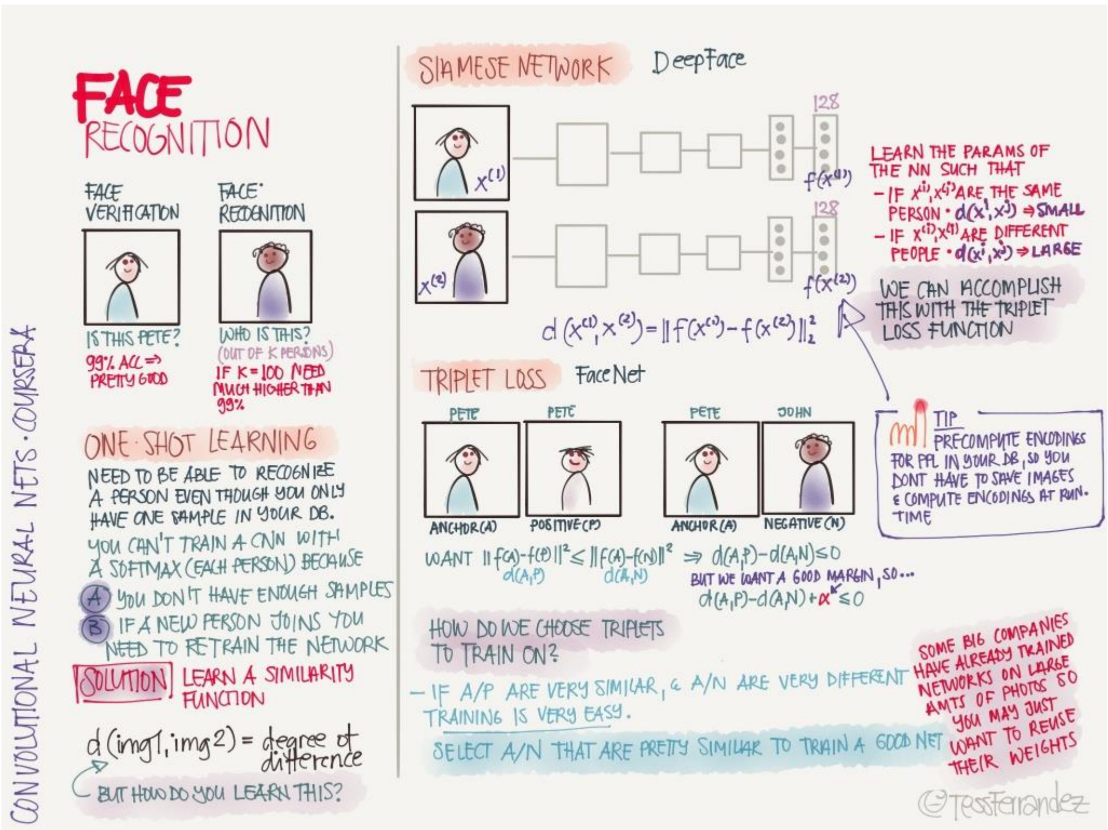
FACE RECOGNITION
FACE VERIFICATION
FACE RECOGNITION
IS THIS PETE?
99% ACC ⇒ PRETTY GOOD
WHO IS THIS? (OUT OF K PERSONS)
IF K=100 NEED MUCH HIGHER THAN 99%
ONE-SHOT LEARNING
NEED TO BE ABLE TO RECOGNIZE A PERSON EVEN THOUGH YOU ONLY HAVE ONE SAMPLE IN YOUR DB.
YOU CAN'T TRAIN A CNN WITH A SOFTMAX (EACH 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?
CONVOLUTIONAL NEURAL NETS · COURSERA
SIAMESE NETWORK
DeepFace
$x^{(1)}$
$x^{(2)}$
128
128
$f(x^{(1)})$
$f(x^{(2)})$
LEARN THE PARAMS OF THE NN SUCH THAT
- IF $x^{(i)}, x^{(j)}$ ARE THE SAME PERSON · $d(x^{(i)}, x^{(j)})$ ⇒ SMALL
- IF $x^{(i)}, x^{(j)}$ ARE DIFFERENT PEOPLE · $d(x^{(i)}, x^{(j)})$ ⇒ LARGE
WE CAN ACCOMPLISH THIS WITH THE TRIPLET LOSS FUNCTION
$d(x^{(1)}, x^{(2)}) = \|f(x^{(1)}) - f(x^{(2)})\|_2^2$
TRIPLET LOSS
FaceNet
PETE
PETE
PETE
JOHN
ANCHOR (A)
POSITIVE (P)
ANCHOR (A)
NEGATIVE (N)
WANT $\|f(A)-f(P)\|^2 \leq \|f(A)-f(N)\|^2 \Rightarrow d(A,P)-d(A,N) \leq 0$
d(A,P)
d(A,N)
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
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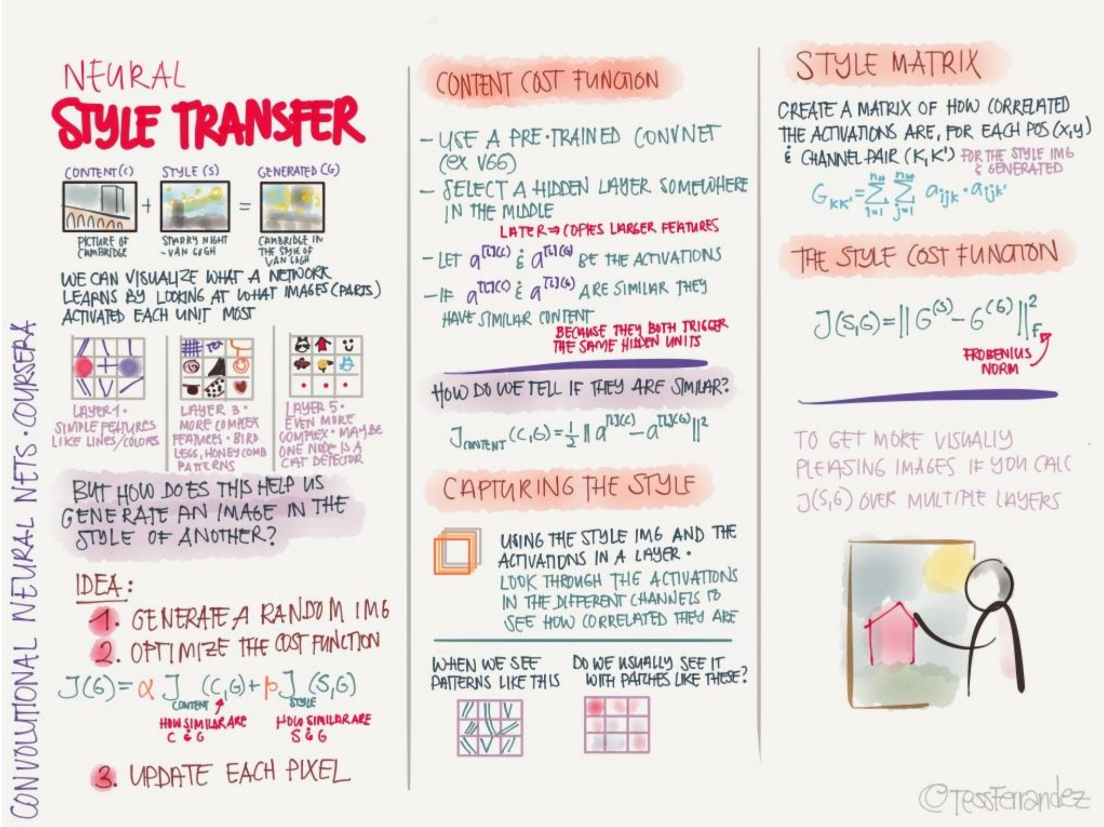

NEURAL
STYLE TRANSFER
CONTENT (C)
STYLE (S)
GENERATED (G)
PICTURE OF CAMBRIDGE
STARRY NIGHT - VAN GOGH
CAMBRIDGE IN THE STYLE OF VAN GOGH
WE CAN VISUALIZE WHAT A NETWORK LEARNS BY LOOKING AT WHAT IMAGES (PARTS) ACTIVATED EACH UNIT MOST
LAYER 1 • SIMPLE FEATURES LIKE LINES/COLORS
LAYER 3 • MORE COMPLEX 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) = α J_CONTENT(C,G) + β J_STYLE(S,G)
HOW SIMILAR ARE C & G
HOW SIMILAR ARE S & G
3. UPDATE EACH PIXEL
CONVOLUTIONAL NEURAL NETS • COURSERA
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) = 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' = Σ_{i=1}^{nH} Σ_{j=1}^{nW} a_ijk • a_ijk'
THE STYLE COST FUNCTION
J(S,G) = ‖G^(S) − G^(G)‖²_F
FROBENIUS NORM
TO GET MORE VISUALLY PLEASING IMAGES IF YOU CALC J(S,G) OVER MULTIPLE LAYERS
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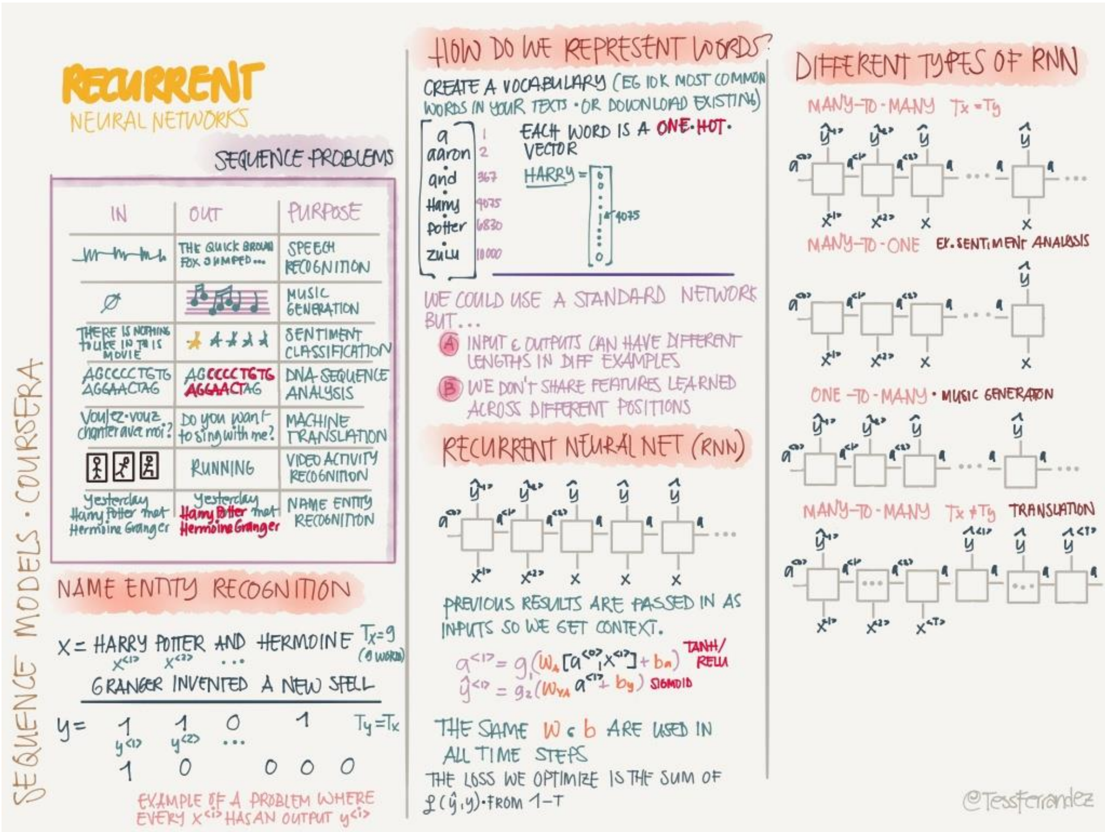

RECURRENT
NEURAL NETWORKS
SEQUENCE PROBLEMS
IN | OUT | PURPOSE
THE QUICK BROWN FOX JUMPED... | SPEECH RECOGNITION
Ø | MUSIC GENERATION
THERE IS NOTHING TO LIKE IN THIS MOVIE | SENTIMENT CLASSIFICATION
AGCCCCTGTG AGGAACTAG | AGCCCCTGTG AGGAACTAG | DNA SEQUENCE ANALYSIS
Voulez-vous chanter avec moi? | Do you want to sing with me? | MACHINE TRANSLATION
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
Tx=9 (9 words)
y = 1 1 0 ... 1 0 0 0 0
Ty=Tx
EXAMPLE OF A PROBLEM WHERE EVERY x<t> HAS AN OUTPUT y<t>
SEQUENCE MODELS • COURSERA
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
HARRY = [0 0 ... 1 ... 0] ← 4075
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.
a<t> = g1(Wa[a<t-1>, x<t>] + ba) TANH/RELU
ŷ<t> = g2(Wya a<t> + by) SIGMOID
THE SAME W & b ARE USED IN ALL TIME STEPS
THE LOSS WE OPTIMIZE IS THE SUM OF ℒ(ŷ,y) • FROM 1−T
DIFFERENT TYPES OF RNN
MANY-TO-MANY Tx = Ty
MANY-TO-ONE EX. SENTIMENT ANALYSIS
ONE-TO-MANY • MUSIC GENERATION
MANY-TO-MANY Tx ≠ Ty TRANSLATION
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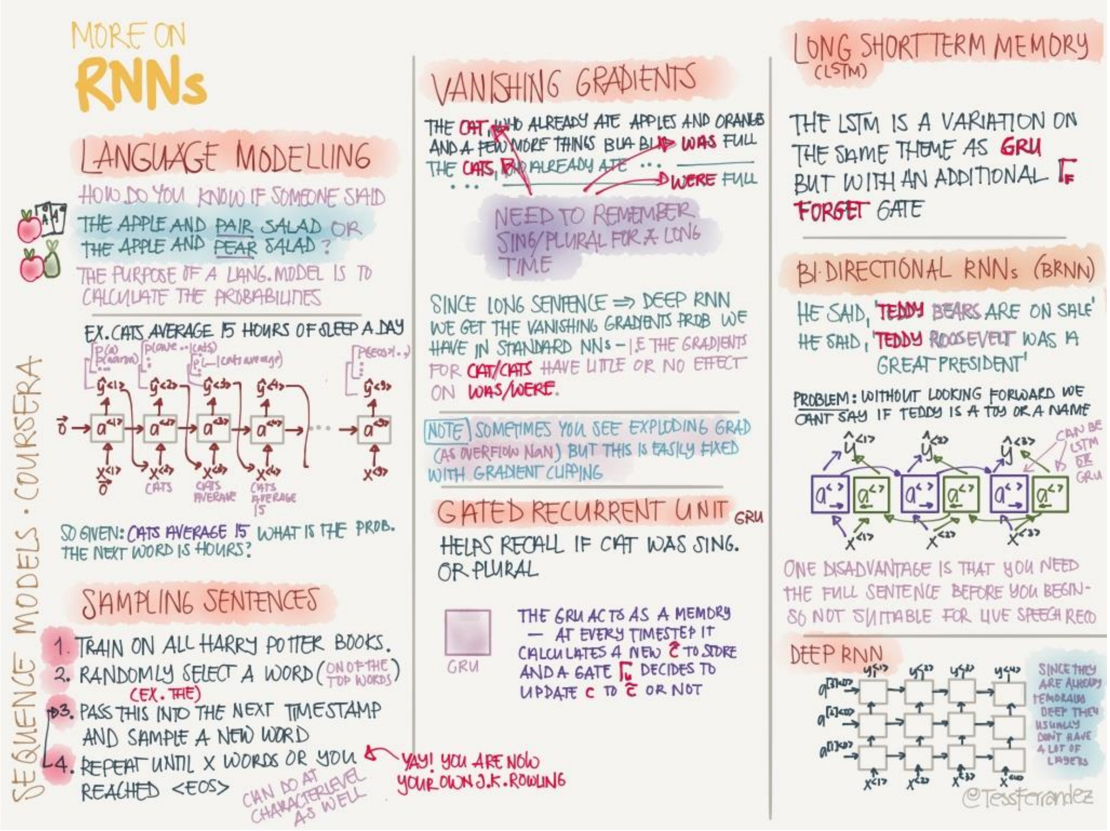

MORE ON
RNNs
LANGUAGE MODELLING
HOW DO YOU KNOW IF SOMEONE SAID
THE APPLE AND PAIR SALAD OR
THE APPLE AND PEAR SALAD ?
THE PURPOSE OF A LANG. MODEL IS TO
CALCULATE THE PROBABILITIES
EX. CATS AVERAGE 15 HOURS OF SLEEP A DAY
CATS
CATS AVERAGE
CATS AVERAGE 15
SO GIVEN: CATS AVERAGE 15 WHAT IS THE PROB.
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>
YAY! YOU ARE NOW
YOUR OWN J.K. ROWLING
CAN DO AT
CHARACTERLEVEL
AS WELL
SEQUENCE MODELS · COURSERA
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
GRU
THE GRU ACTS AS A MEMORY
— AT EVERY TIMESTEP IT
CALCULATES A NEW C̃ TO STORE
AND A GATE Γu DECIDES TO
UPDATE C TO C̃ OR NOT
LONG SHORT TERM MEMORY
(LSTM)
THE LSTM IS A VARIATION ON
THE SAME THEME AS GRU
BUT WITH AN ADDITIONAL Γf
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
CAN BE
LSTM
OR
GRU
ONE DISADVANTAGE IS THAT YOU NEED
THE FULL SENTENCE BEFORE YOU BEGIN-
SO NOT SUITABLE FOR LIVE SPEECH RECO
DEEP RNN
SINCE THEY
ARE ALREADY
TEMPORAL
DEEP THEY
USUALLY
DON'T HAVE
A LOT OF
LAYERS
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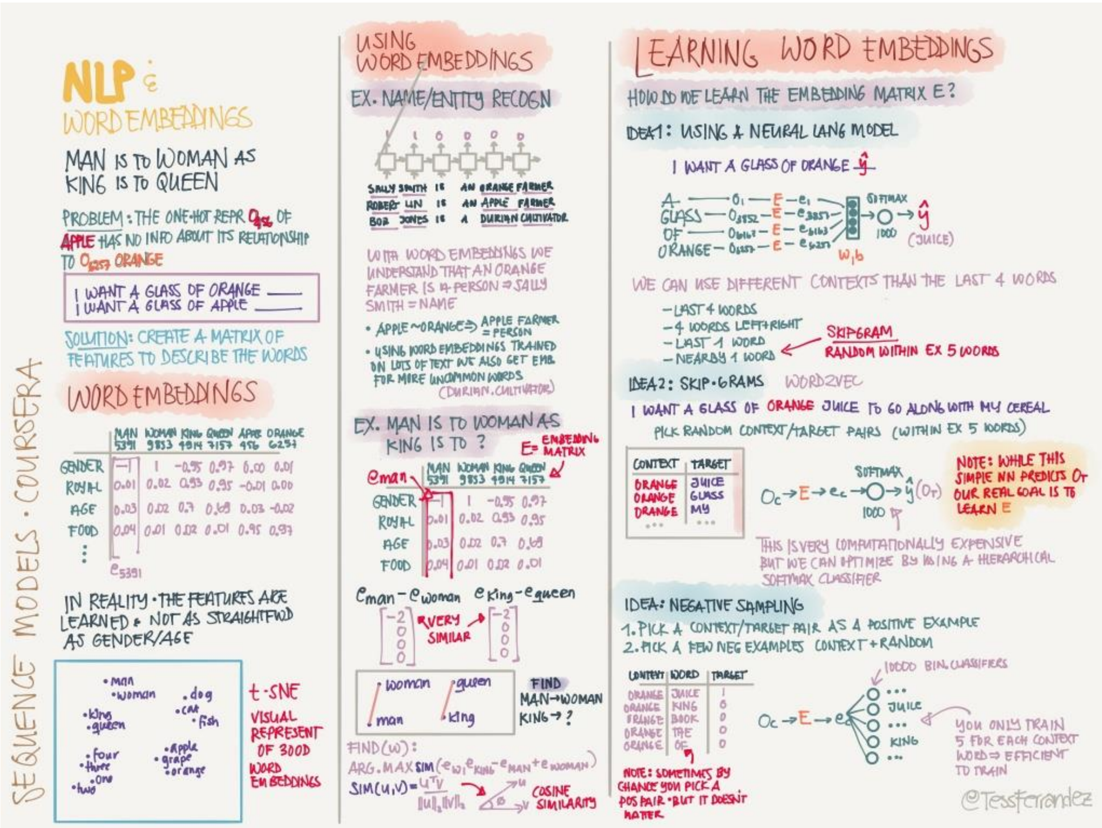

NLP &
WORD EMBEDDINGS
MAN IS TO WOMAN AS
KING IS TO QUEEN
PROBLEM: THE ONE-HOT REPR O456 OF
APPLE HAS NO INFO ABOUT ITS RELATIONSHIP
TO O6257 ORANGE
I WANT A GLASS OF ORANGE ____
I WANT A GLASS OF APPLE ____
SOLUTION: CREATE A MATRIX OF
FEATURES TO DESCRIBE THE WORDS
WORD EMBEDDINGS
MAN 5391 WOMAN 9853 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
e5391
IN REALITY - THE FEATURES ARE
LEARNED & NOT AS STRAIGHTFWD
AS GENDER/AGE
man
woman
king
queen
dog
cat
fish
four
three
two
one
apple
grape
orange
t-SNE
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   e_king - e_queen
VERY SIMILAR
woman queen
man king
FIND
MAN→WOMAN
KING→?
FIND(W):
ARG. MAX SIM(e_w, e_king - e_man + e_woman)
SIM(u,v) = uᵀv / ‖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 ŷ
A GLASS OF ORANGE
SOFTMAX
1000
(JUICE)
W, b
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
SOFTMAX
1000
NOTE: WHILE THIS
SIMPLE NN PREDICTS Ot
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
10000 BIN. CLASSIFIERS
JUICE
KING
YOU ONLY TRAIN
5 FOR EACH CONTEXT
WORD ⇒ EFFICIENT
TO TRAIN
NOTE: SOMETIMES BY
CHANCE YOU PICK A
POS PAIR - BUT IT DOESN'T
MATTER
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