BST 261: Data Science II
Lecture 9

Object Localization and Detection, Face Recognition

Heather Mattie
Harvard T.H. Chan School of Public Health
Spring 2 2020

Recipe of the Day!

[Turkey Pot Pie]

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Paper Presentations

MULTITASK LEARNING AND BENCHMARKING WITH CLINICAL TIME SERIES DATA

Hrayr Harutyunyan, Hrant Khachatrian, David C. Kale, Greg Ver Steeg, and Aram Galstyan

Sci Data. 2019 Jun 17;6(1):96. doi: 10.1038/s41597-019-0103-9

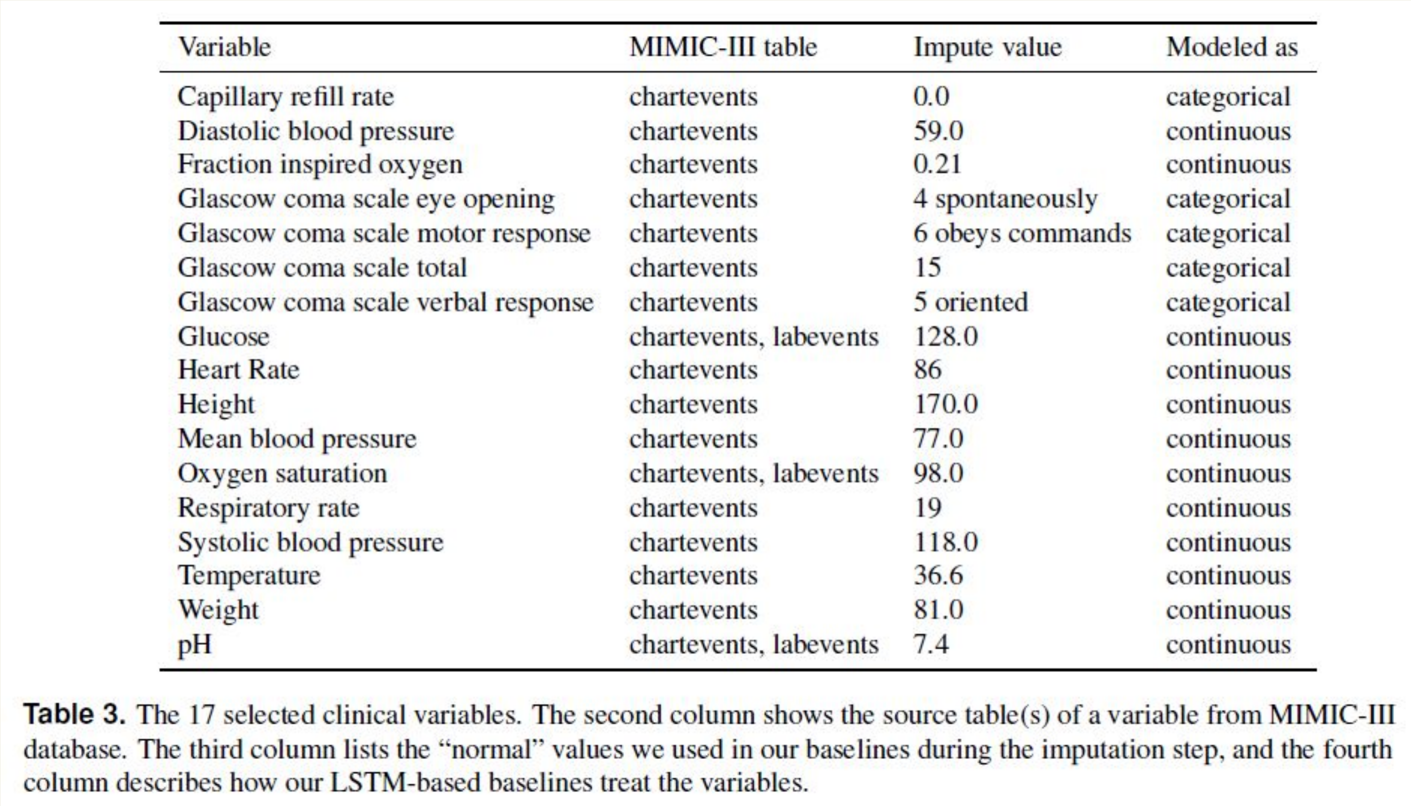
Yanghui
Sheng
4/20/20

- Derived a **benchmark dataset** from the publicly available Medical Information Mart for Intensive Care (MIMIC-III) database.

MIMIC-III:
 - A large, open source database comprising information relating to patients
admitted to critical care units at Beth Israel Deaconess Medical Center (Boston,
MA) between 2001 – 2012 (38,597 adult patients, corresponding to
49,785 hospital admissions).

- The benchmark dataset is a subset of MIMIC-III containing more than 31 million clinical events that correspond to 17 clinical variables, covering 42276 ICU stays of 33798 unique patients.

MIMIC-III, a freely accessible critical care database: Sci Data. 2016 May 24;3:160035. doi: 10.1038/sdata.2016.35.



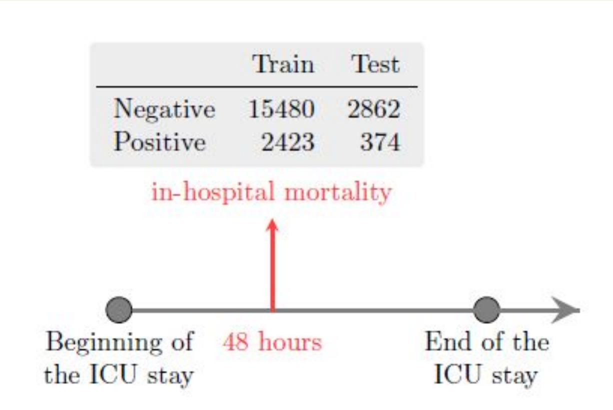
Variable	MIMIC-III table	Impute value	Modeled as
Capillary refill rate	chartevents	0.0	categorical
Diastolic blood pressure	chartevents	59.0	continuous
Fraction inspired oxygen	chartevents	0.21	continuous
Glascow coma scale eye opening	chartevents	4 spontaneously	categorical
Glascow coma scale motor response	chartevents	6 obeys commands	categorical
Glascow coma scale total	chartevents	15	categorical
Glascow coma scale verbal response	chartevents	5 oriented	categorical
Glucose	chartevents, labevents	128.0	continuous
Heart Rate	chartevents	86	continuous
Height	chartevents	170.0	continuous
Mean blood pressure	chartevents	77.0	continuous
Oxygen saturation	chartevents, labevents	98.0	continuous
Respiratory rate	chartevents	19	continuous
Systolic blood pressure	chartevents	118.0	continuous
Temperature	chartevents	36.6	continuous
Weight	chartevents	81.0	continuous
pH	chartevents, labevents	7.4	continuous

Table 3. The 17 selected clinical variables. The second column shows the source table(s) of a variable from MIMIC-III database. The third column lists the "normal" values we used in our baselines during the imputation step, and the fourth column describes how our LSTM-based baselines treat the variables.

- Derived a **benchmark dataset** from the publicly available Medical Information Mart for Intensive Care (MIMIC-III) database.

4 benchmark tasks:

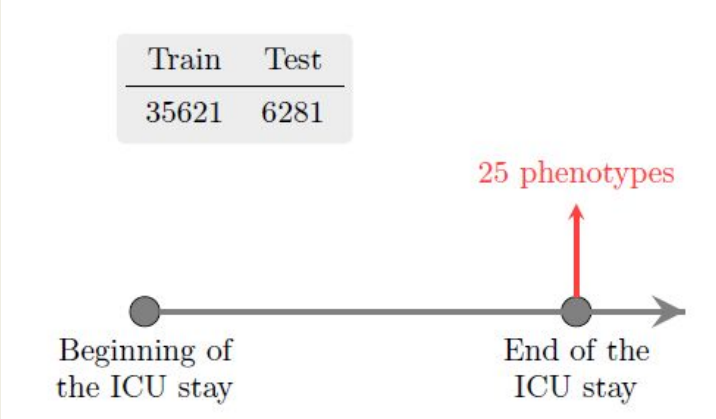
(a) In-hospital mortality prediction.



	Train	Test
Negative	15480	2862
Positive	2423	374

- Binary classification: whether patient will die in the hospital.
- Early detection of at-risk patients can improve outcomes.

(b) Phenotype classification.



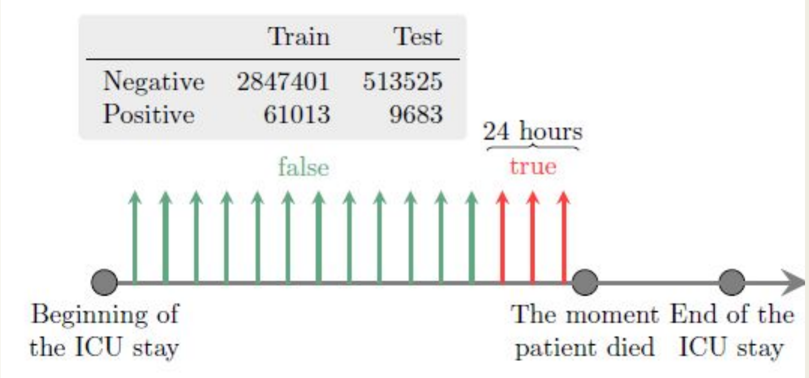
Train	Test
35621	6281

- Multilabel classification: which of the 25 acute care conditions a patient has.
- Useful for patient treatment and risk monitoring.

- Derived a **benchmark dataset** from the publicly available Medical Information Mart for Intensive Care (MIMIC-III) database.

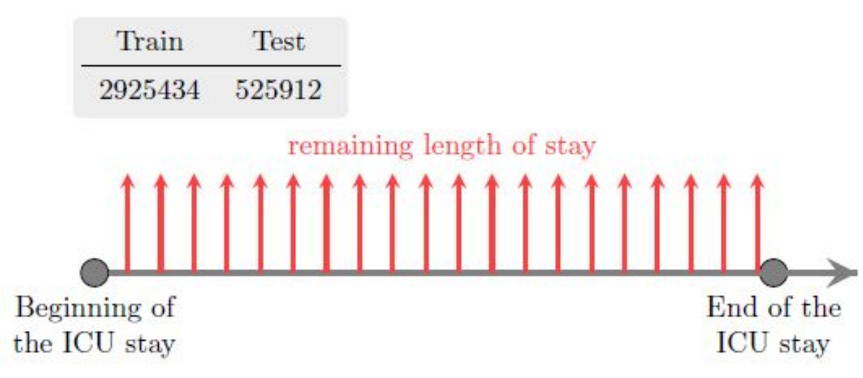
4 benchmark tasks:

(c) Decompensation prediction



	Train	Test
Negative	2847401	513525
Positive	61013	9683

(d) Length-of-stay prediction.



Train	Test
2925434	525912

- Binary classification: whether patient will die in the next 24 hrs.
- Also for early detection, related to in-hospital mortality.

- Classification: ICU stays < 1 day, each of 7 days,
between 1-2 weeks, > 2 weeks
- Useful for measuring patient acuity and resource

- Compared LSTMs vs. logistic regression using the 4 benchmark tasks on MIMIC III data.

LSTM: long short term memory, a type of recurrent neural network.

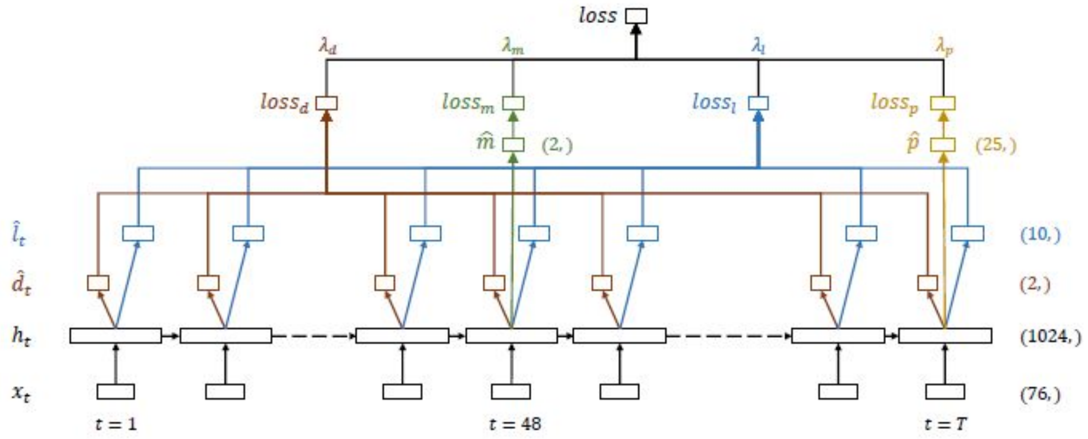
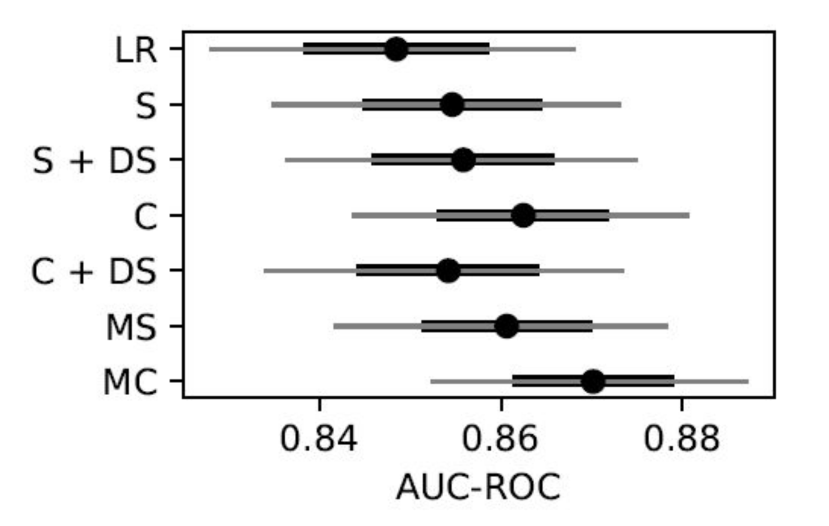


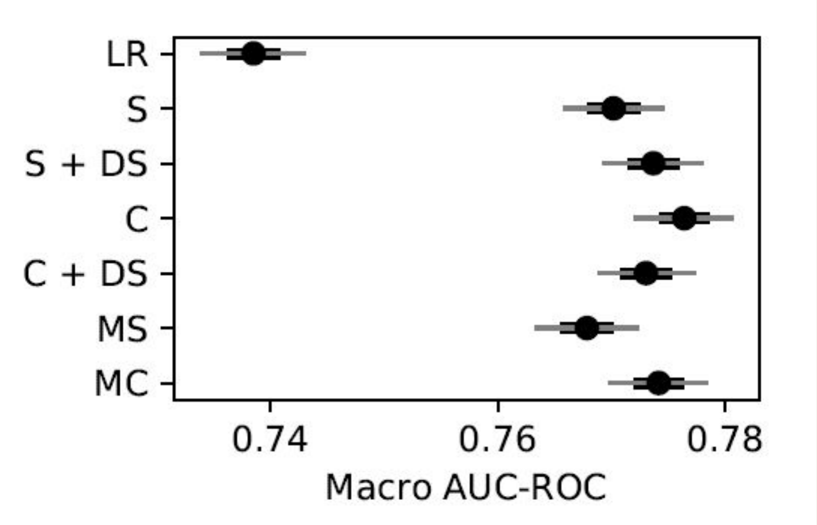
Figure 10. LSTM-based network architecture for multitask learning.

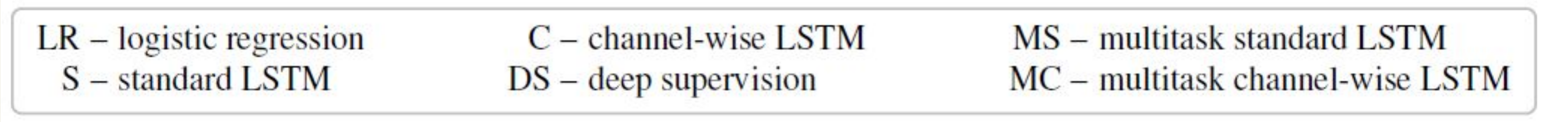
- Compared LSTMs vs. logistic regression using the 4 benchmark tasks on MIMIC III data.

(a) In-hospital mortality prediction.



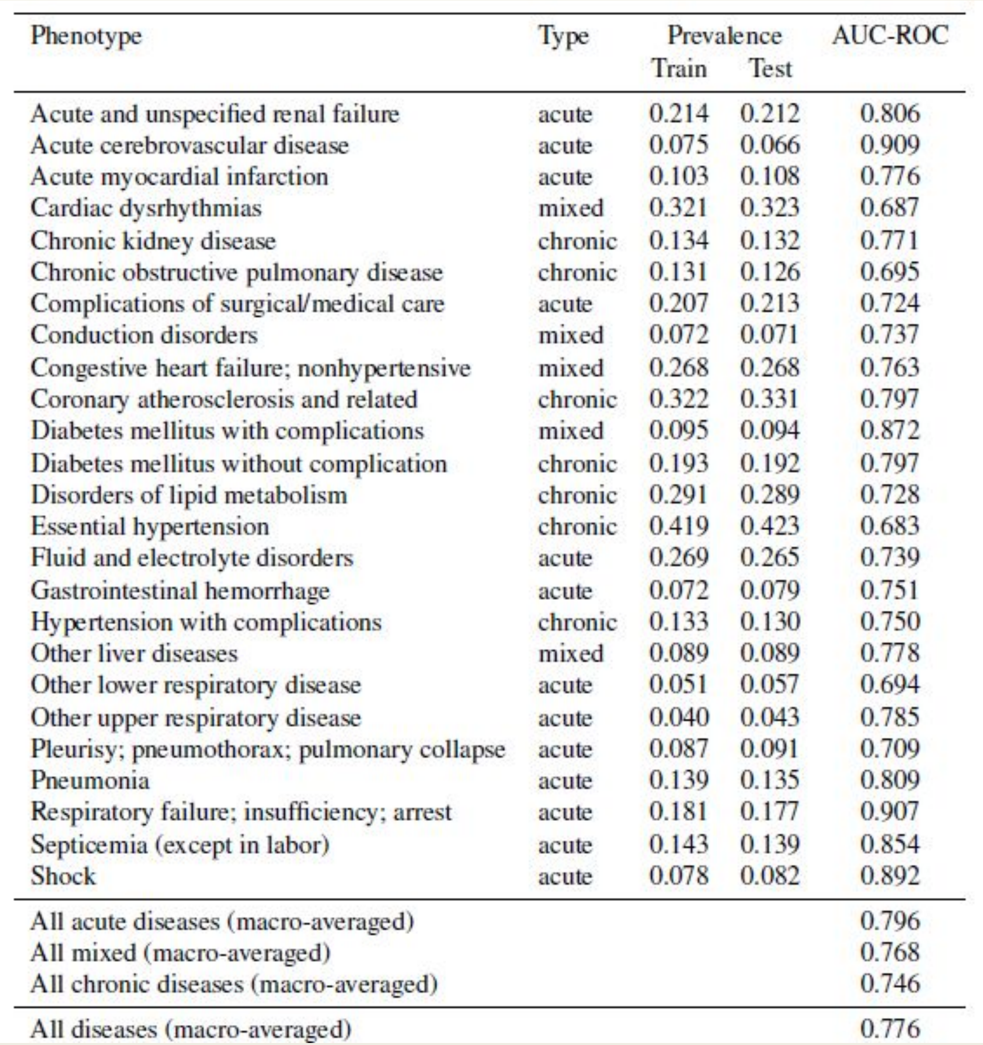
(b) Phenotype classification.





LR – logistic regression
S – standard LSTM
C – channel-wise LSTM
DS – deep supervision
MS – multitask standard LSTM
MC – multitask channel-wise LSTM

25 ICU phenotypes used in the benchmark data set, their prevalence and the per-phenotype classification performance of the best LSTM network

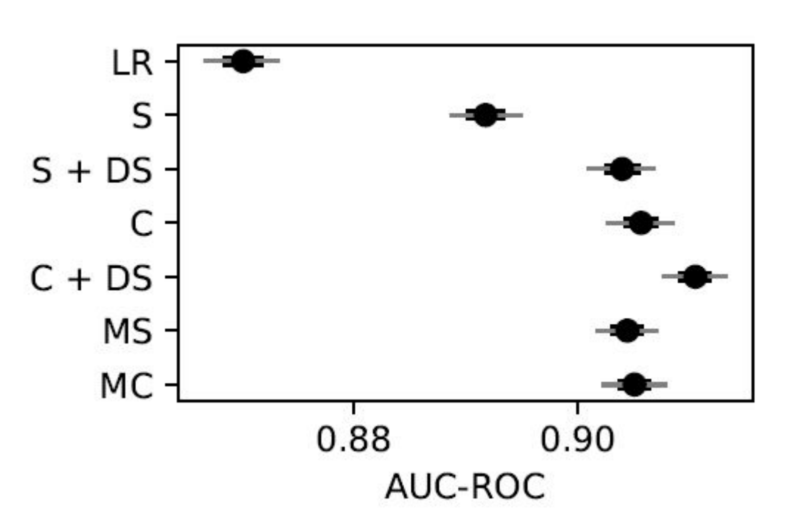


Phenotype	Type	Prevalence		AUC-ROC
		Train	Test	
Acute and unspecified renal failure	acute	0.214	0.212	0.806
Acute cerebrovascular disease	acute	0.075	0.066	0.909
Acute myocardial infarction	acute	0.103	0.108	0.776
Cardiac dysrhythmias	mixed	0.321	0.323	0.687
Chronic kidney disease	chronic	0.134	0.132	0.771
Chronic obstructive pulmonary disease	chronic	0.131	0.126	0.695
Complications of surgical/medical care	acute	0.207	0.213	0.724
Conduction disorders	mixed	0.072	0.071	0.737
Congestive heart failure; nonhypertensive	mixed	0.268	0.268	0.763
Coronary atherosclerosis and related	chronic	0.322	0.331	0.797
Diabetes mellitus with complications	mixed	0.095	0.094	0.872
Diabetes mellitus without complication	chronic	0.193	0.192	0.797
Disorders of lipid metabolism	chronic	0.291	0.289	0.728
Essential hypertension	chronic	0.419	0.423	0.683
Fluid and electrolyte disorders	acute	0.269	0.265	0.739
Gastrointestinal hemorrhage	acute	0.072	0.079	0.751
Hypertension with complications	chronic	0.133	0.130	0.750
Other liver diseases	mixed	0.089	0.089	0.778
Other lower respiratory disease	acute	0.051	0.057	0.694
Other upper respiratory disease	acute	0.040	0.043	0.785
Pleurisy; pneumothorax; pulmonary collapse	acute	0.087	0.091	0.709
Pneumonia	acute	0.139	0.135	0.809
Respiratory failure; insufficiency; arrest	acute	0.181	0.177	0.907
Septicemia (except in labor)	acute	0.143	0.139	0.854
Shock	acute	0.078	0.082	0.892
All acute diseases (macro-averaged)				0.796
All mixed (macro-averaged)				0.768
All chronic diseases (macro-averaged)				0.746
All diseases (macro-averaged)				0.776

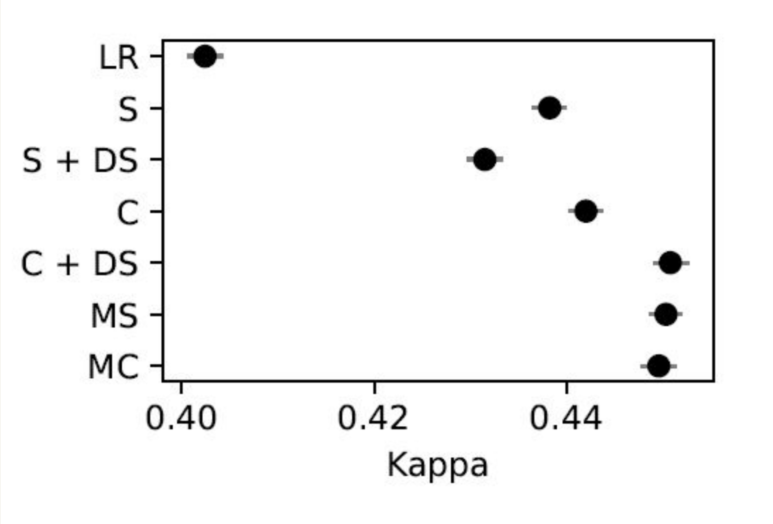
Found better performance for phenotyping acute than chronic conditions.

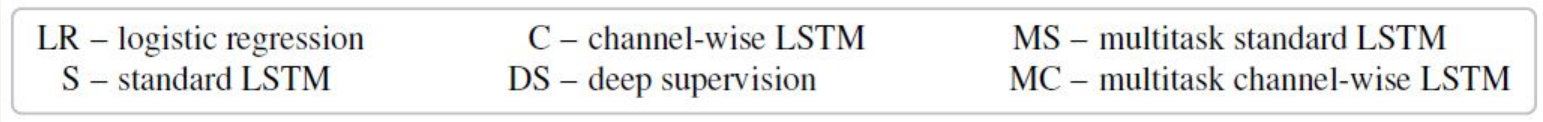
- Compared LSTM-based neural network and linear models using the 4 benchmark tasks on MIMIC III data.

(c) Decompensation prediction



(d) Length-of-stay prediction.





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Summary

- Proposed 4 standardized benchmarks for machine learning researchers interested in clinical data problems.
- Described strong linear and neural baselines for these benchmarks.
- LSTM-based models significantly outperform linear models.

Language Models are Unsupervised Multitask Learners

Carol Wei
April 20, 2020

GPT-2 Model

Generative Pre-trained Transformer 2

OpenAI

INTRODUCTION

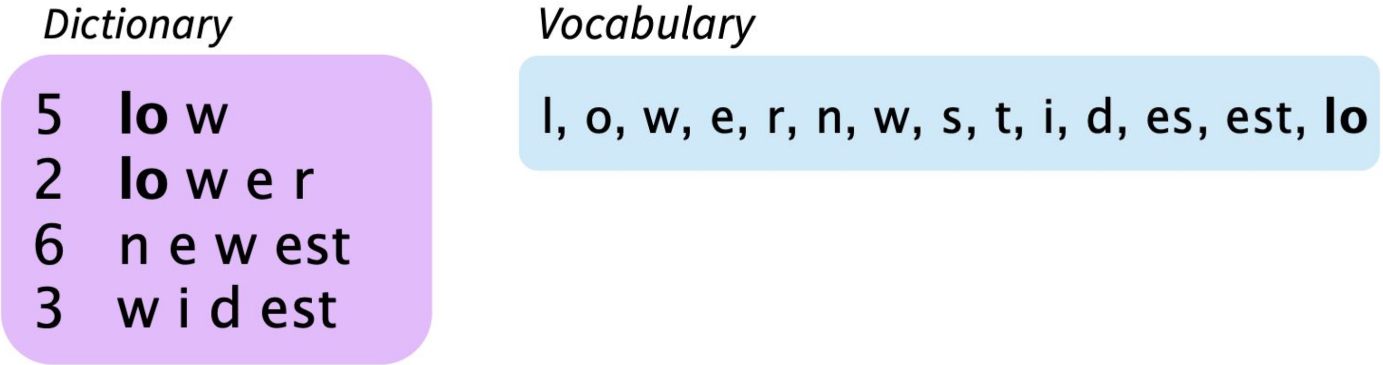
- Current models use pre-training and fine tuning
- Goal: language model without supervised fine tuning
    - Transformer-based language model
    - Solve multiple NLP tasks in a zero-shot setting

TRAINING DATASET

- Web scrape all Reddit outbound links
  - Filter ≥ 3 karma ("interesting, educational, or just funny")
- WebText
  - 45 million links
  - 8 million documents
  - 40 GB of text

INPUT REPRESENTATION

- Byte Pair Encoding (BPE)
  - Middle ground between character and word level language modeling



Dictionary

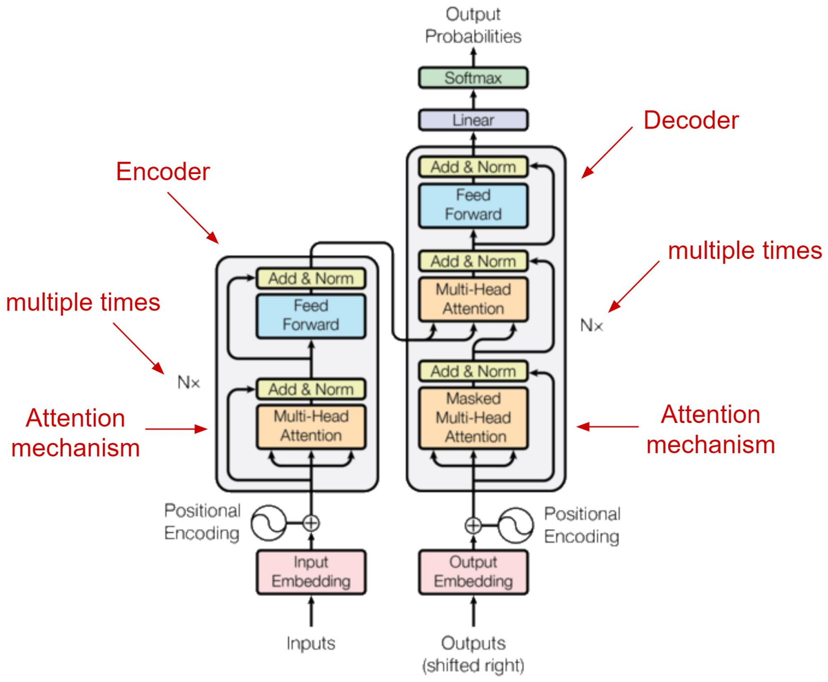
5	**lo** w
2	**lo** w e r
6	n e w est
3	w i d est

Vocabulary

l, o, w, e, r, n, w, s, t, i, d, es, est, **lo**

GPT-2 MODEL

- Improved GPT-1 model
  - Layer normalization
  - Scaled weights of residual layers
  - Expanded vocabulary
  - Increased content size and batchsize
- 1.5B parameter model

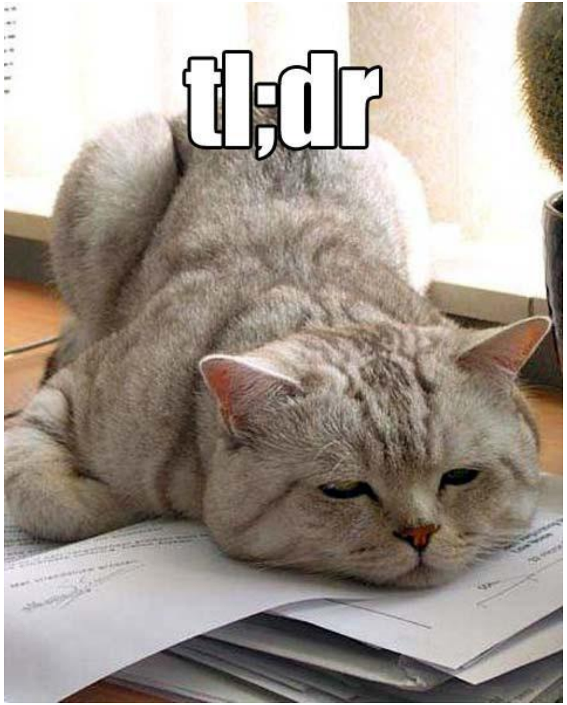


EXPERIMENTS

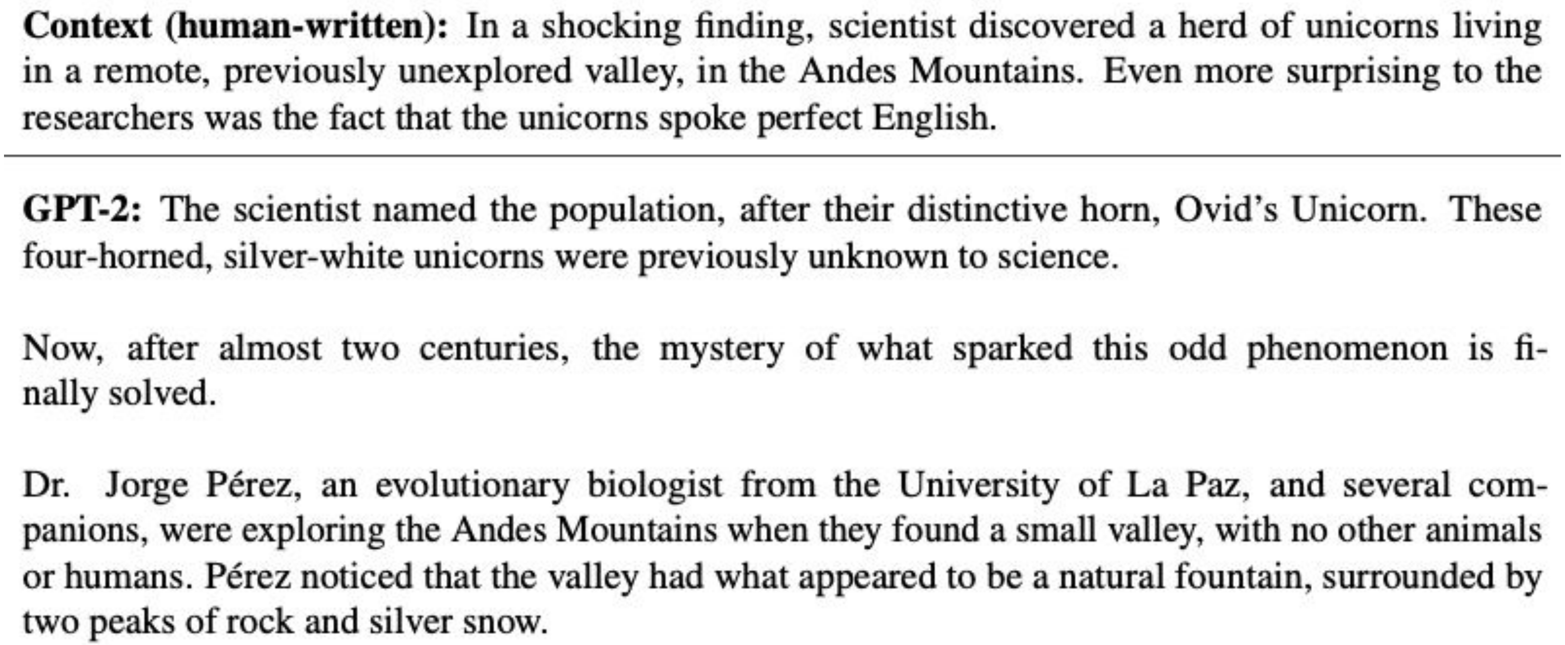
1. Language Modeling
2. Children's Book Test: fill in the blank
3. LAMBADA: predict final word
4. Winograd Schema Challenge: reasoning
5. Reading Comprehension
6. Summarization
7. Translation
8. Question Answering

SUMMARIZATION

- Summarize CNN and Daily Mail dataset
- Induce summarization behavior with “TL;DR:”
- Generate 100 tokens with Top-k random sampling with k=2
- Use first 3 generated sentences as the summary



EXAMPLE



Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

CONCLUSION

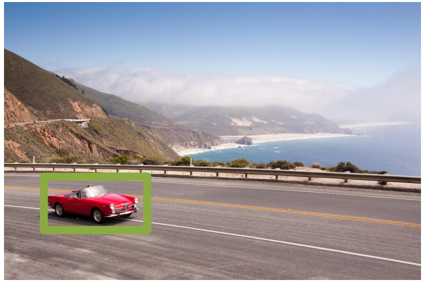
- Unsupervised task learning is a promising area of research
- Possible malicious applications
- Model available on GitHub:
    - https://github.com/openai/gpt-2

Object Detection and Location

Localization and Detection

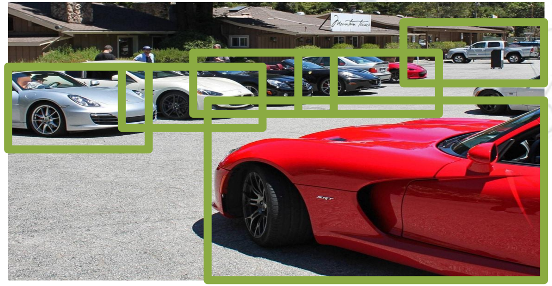
Car

(Classification)



Car, but where?

(Classification with localization)



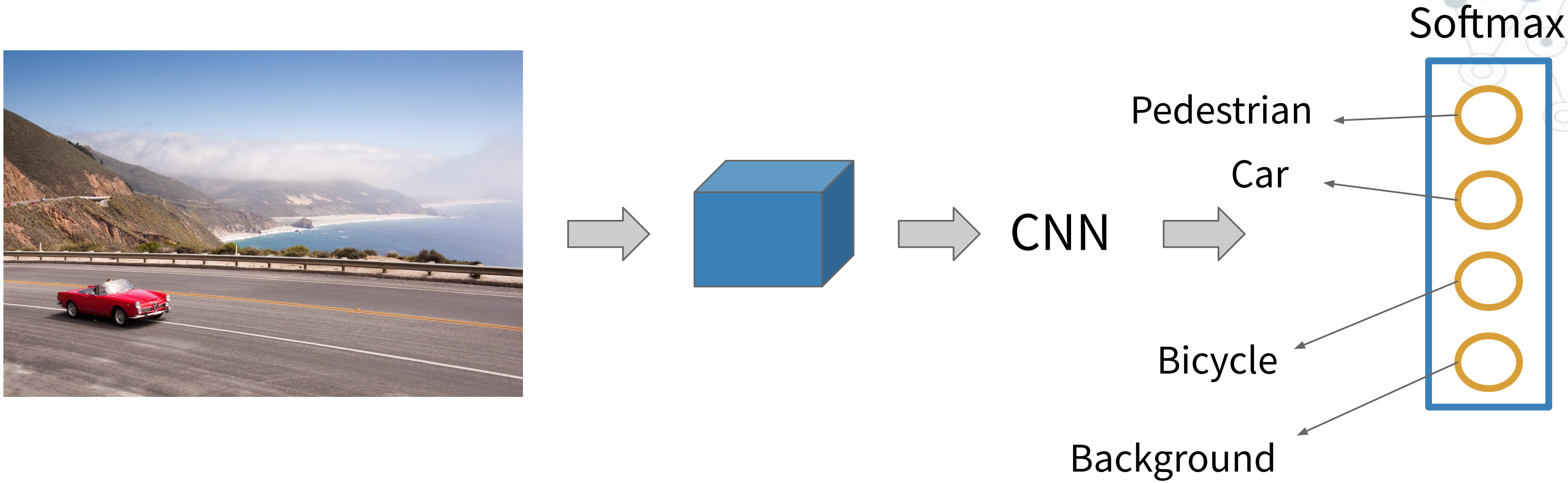
Multiple cars

(Detection)

1 object

Multiple objects; could be from different classes

Classification



CNN

Softmax

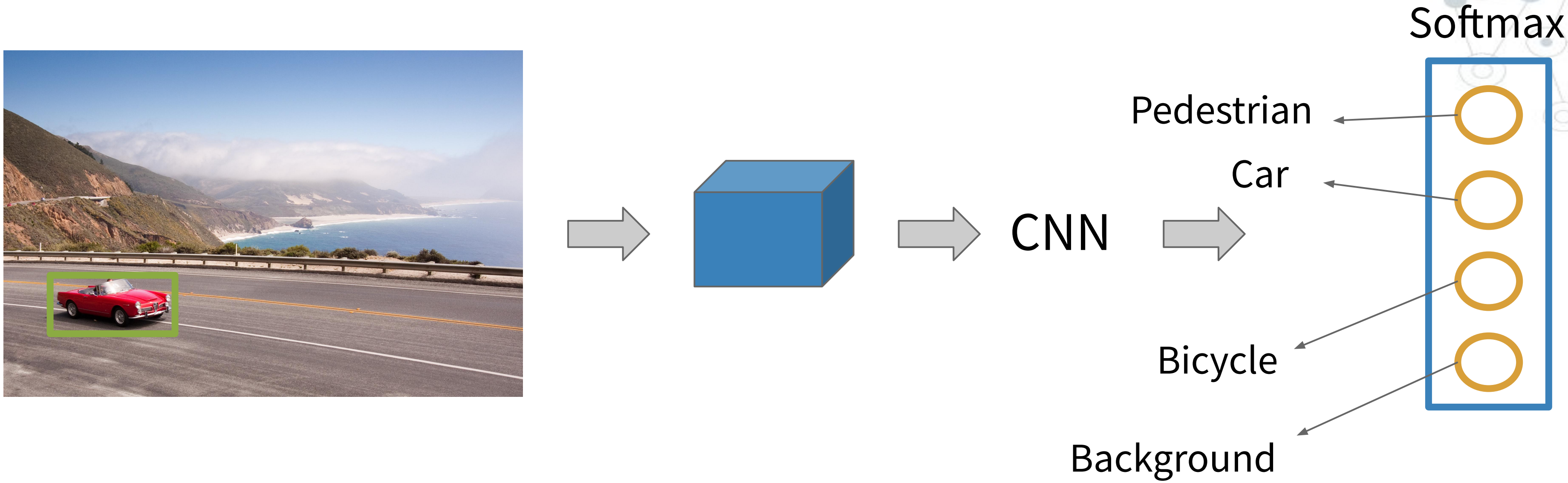
Pedestrian

Car

Bicycle

Background

Classification



Softmax

Pedestrian

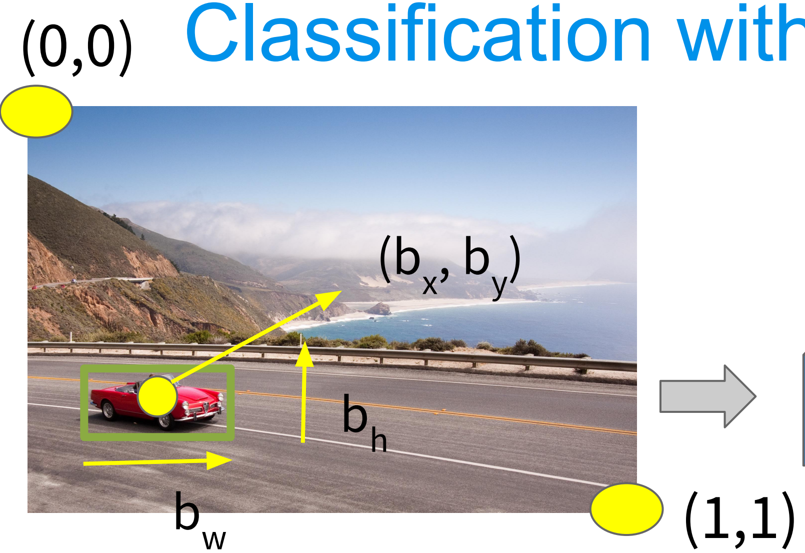
Car

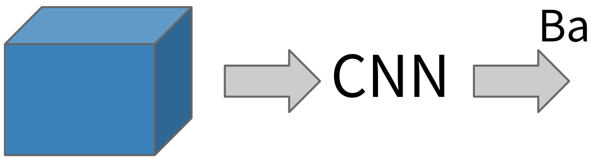
CNN

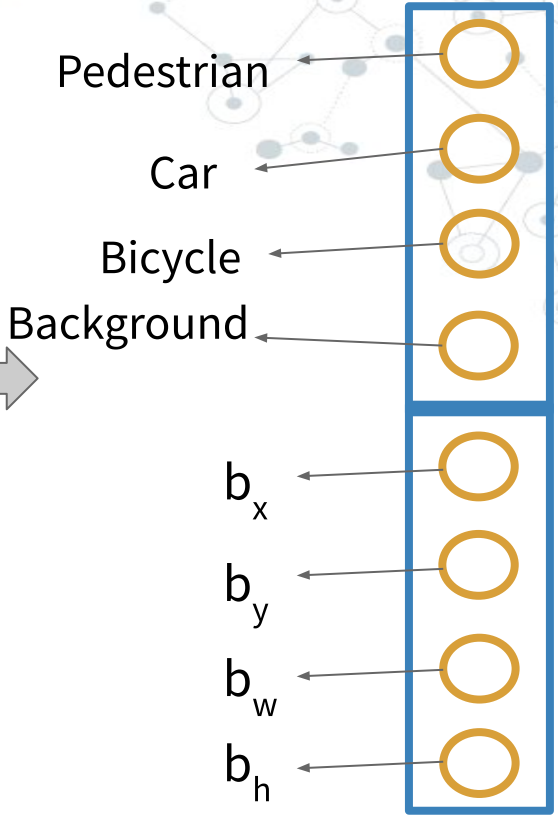
Bicycle

Background

Classification with Localization







- To train a network to detect and locate objects,

  we need a lot of training data with bounding box labels:

  - (b_x, b_y): the x and y coordinates of the center of the object
  - b_w: the width of the bounding box
  - b_h: the height of the bounding box
  - New image label: [class, b_x, b_y, b_w, b_h]

Classification with Localization

Note: assuming there is only 1 object in image

Classes

Pedestrian (c_1)

Car (c_2)

Bicycle (c_3)

Background (no object)

Probability there is an object in the image (and not just background)

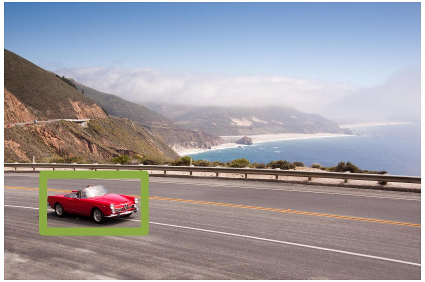
New y label: [p_d, b_x, b_y, b_w, b_h, c_1, c_2, c_3]

Loss:

$$L(\hat{y}, y) = (\hat{y}_1, y_1)^2 + (\hat{y}_2, y_2)^2 \dots (\hat{y}_8, y_8)^2 \qquad \text{if } p_d = 1$$

$$L(\hat{y}, y) = (\hat{y}_1, y_1)^2 \qquad \text{if } p_d = 0$$

Localization and Detection



Classes

Pedestrian (c_1)

Car (c_2)

Bicycle (c_3)

Background (no object)

$y = [1, 0.25, 0.75, 0.2, 0.15, 0, 1, 0]$

New y label: $[p_d, b_x, b_y, b_w, b_h, c_1, c_2, c_3]$

Loss:

$L(\hat{y}, y) = (\hat{y}_1, y_1)^2 + (\hat{y}_2, y_2)^2 \dots (\hat{y}_8, y_8)^2$ if $p_d = 1$

$L(\hat{y}, y) = (\hat{y}_1, y_1)^2$ if $p_d = 0$

Localization and Detection

Classes

Pedestrian (c_1)

Car (c_2)

Bicycle (c_3)

Background (no object)

y = [0, ?, ?, ?, ?, ?, ?, ?]

New y label: [p_d, b_x, b_y, b_w, b_h, c_1, c_2, c_3]

Loss:

$$L(\hat{y}, y) = (\hat{y}_1, y_1)^2 + (\hat{y}_2, y_2)^2 \ldots (\hat{y}_8, y_8)^2 \qquad \text{if } p_d = 1$$

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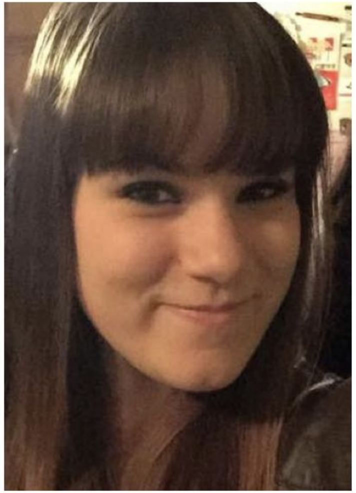
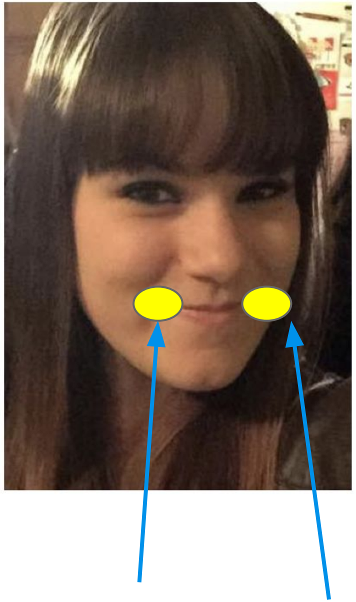
Landmark Detection

Landmark Detection

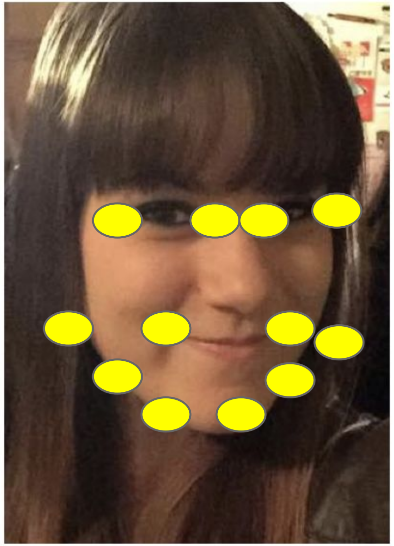


Landmark Detection



(l_{x1}, l_{y1}) (l_{x2}, l_{y2})

Landmark Detection



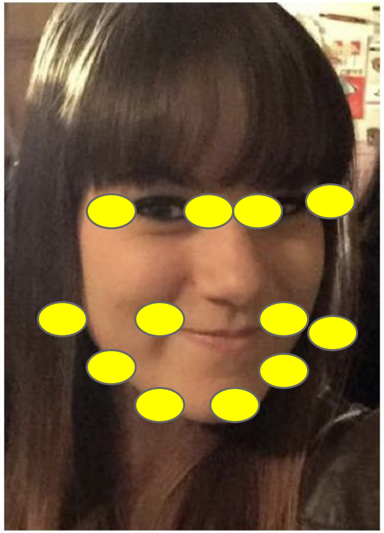
Label every point

Input: image with n landmarks
Output:
$[p_{face}, l_{x1}, l_{y1}, l_{x2}, l_{y2}, \ldots, l_{xn}, l_{yn}]$

Fit CNN to output if the image is of a face and the locations of the landmarks if it is a face

Note: landmarks have to be consistent across all training images, i.e. landmark # 1 is the left corner of the right eye, for example

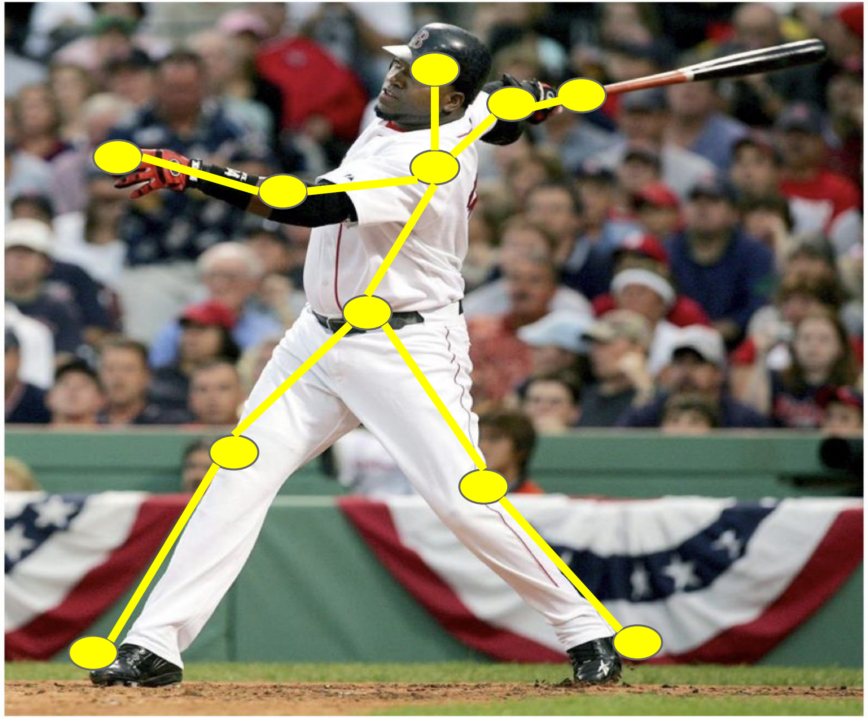
Landmark Detection



If I can detect where the landmarks are, I can add filters in appropriate places

Landmark Detection

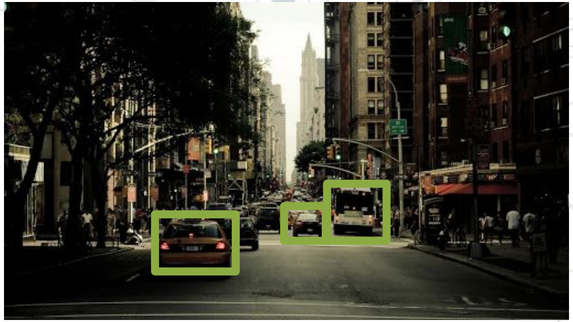
Landmark Detection



"Pose" detection

Object Detection

Object Detection



- Goal: locate and classify objects in an image
- Train CNN on cropped images of objects, where the object takes up most of the space in the image

X: image of a car

y: 1

X: image of a car

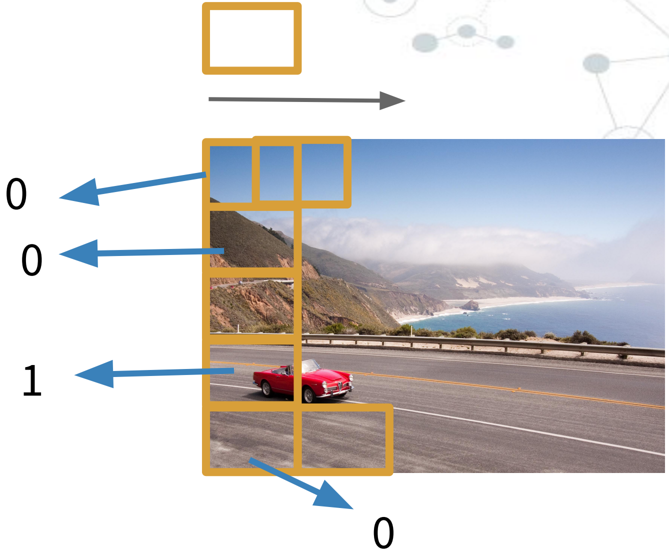
y: 1

X: image of not a car

y: 0

Object Detection

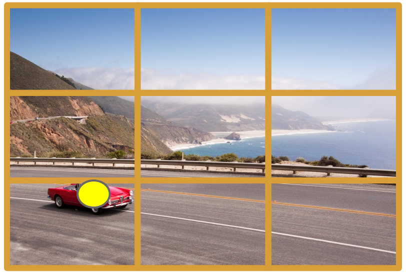
- Sliding windows detection algorithm
  - Slide a window across your image
  - In each region covered by the window, try to detect object (classify every region as containing an object or not)
  - **Very computationally expensive**, especially for small window and small stride
  - Bigger windows or strides result in fewer regions and less computational expense, but could hurt performance
  - Won’t output the most accurate bounding boxes



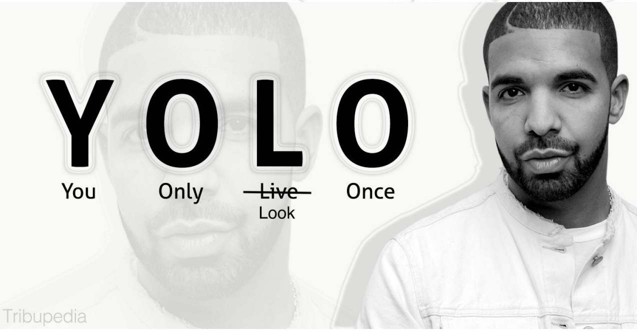
Repeat with larger and larger windows

Object Detection

- One way to predict more accurate bounding boxes is by implementing the YOLO (You Only Look Once) algorithm
  - Redmon et al. 2015
  - Overly dramatic YOLO video
- Split image into grid cells
- Assign the object to the grid cell containing the midpoint of the object
- Works well when there is only 1 object in a particular cell
- Cuts down on computational cost because it can be run as a single convolutional implementation
  - So fast it performs well for real time object detection
- GitHub repo with easy implementation in Keras



Object Detection



- One way to cut down on computational expense and predict more accurate bounding boxes is by implementing the YOLO (You Only Look Once) algorithm
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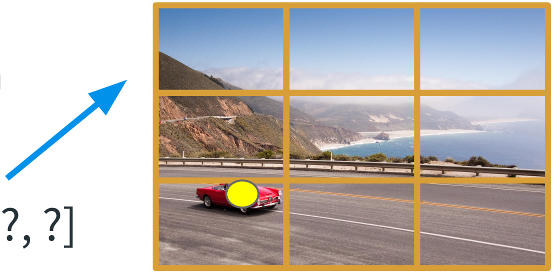
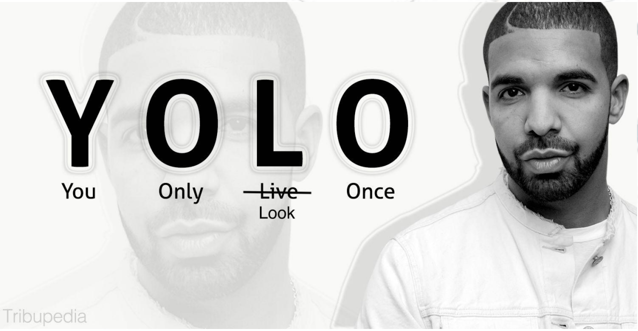


y = [0, ?, ?, ?, ?, ?, ?, ?]

Object Detection



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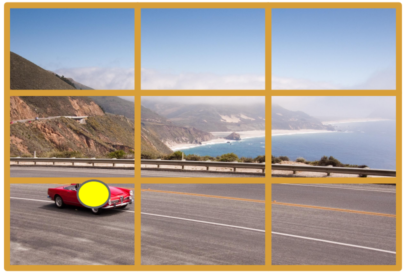
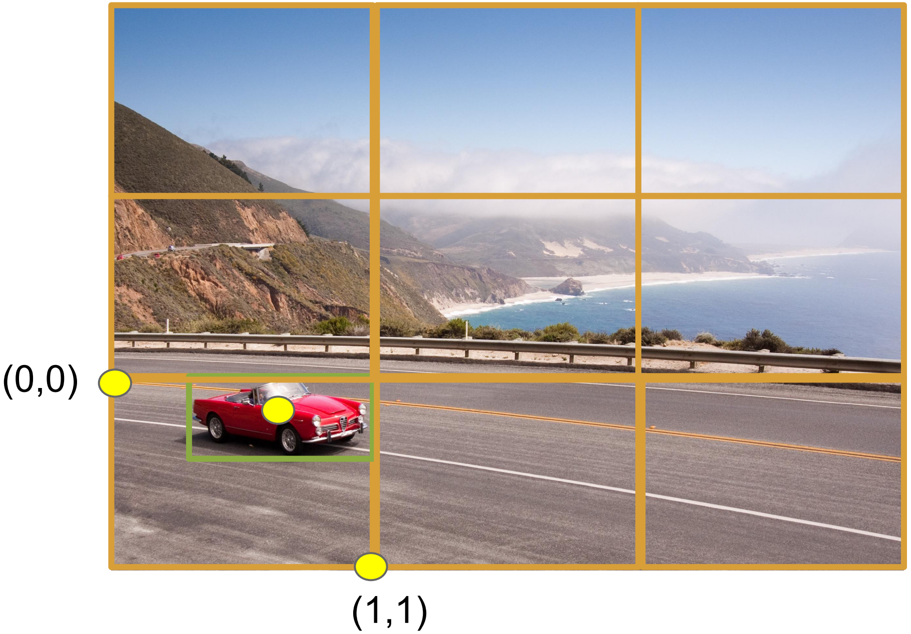
- GitHub repo with easy implementation in Keras

$y = [1, b_x, b_y, b_w, b_h, 0, 1, 0]$ →



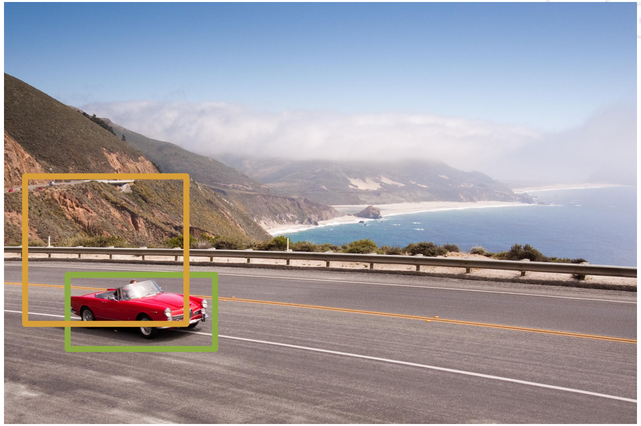
Better Bounding Boxes

- b_x, b_y, b_w, b_h are defined relative to the grid cell
- b_x, b_y will be between 0 and 1 by definition
- b_w, b_h could be greater than 1, depending on how large the object is and if it spans more than the grid cell with the midpoint



Evaluating Object Localization

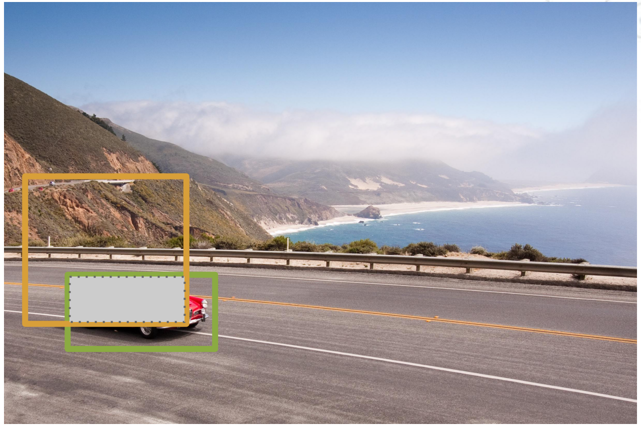
- How well is your algorithm working in terms of finding the bounding boxes?



Evaluating Object Localization

- How well is your algorithm working in terms of finding the bounding boxes?
- One metric to measure the performance of the algorithm is Intersection over Union

$$IoU = \frac{\text{size of intersection}}{\text{size of union}}$$



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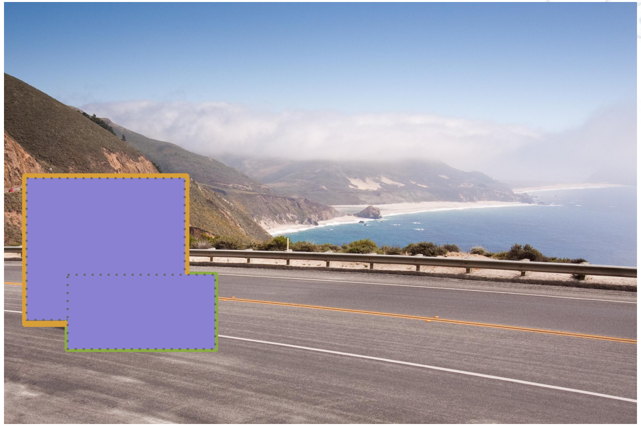

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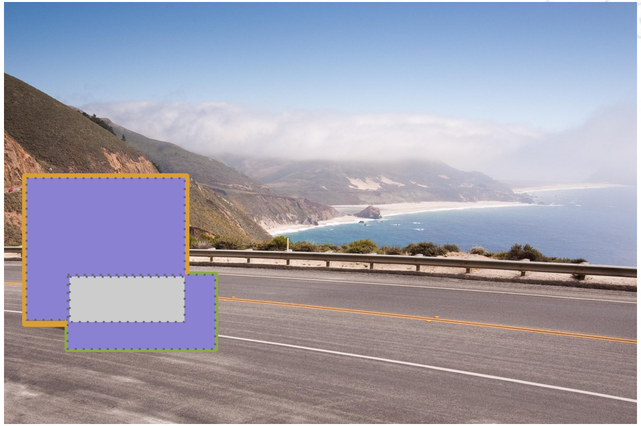

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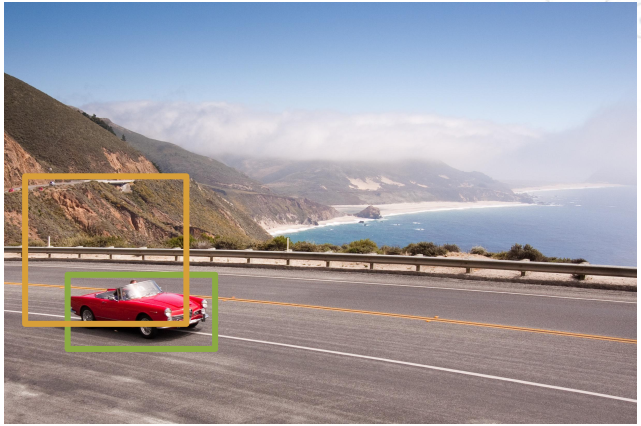
- "Correct" if , $IoU \geq 0.5$ or some other threshold
- Basically measures the overlap of the predicted bounding box with the ground truth bounding box - more overlap is better



Non-max suppression

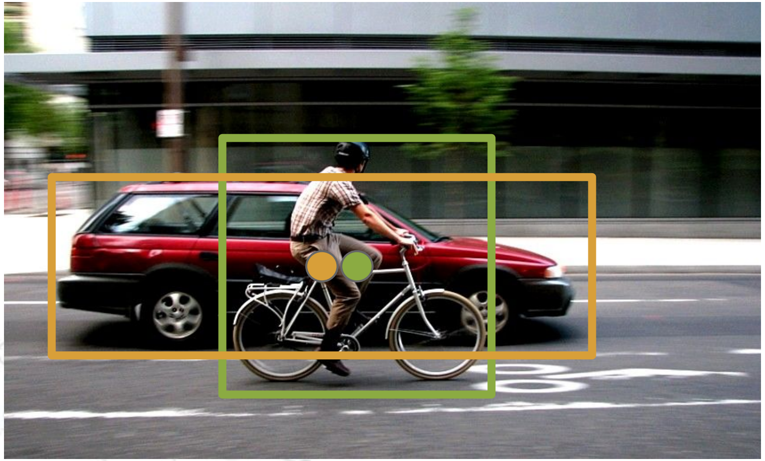
- Your algorithm may detect the same object multiple times
- Non-max suppression is a way to make sure you detect each object only once
- Steps
  - Discard all boxes with $p_d \leq 0.6$ (probability that object is detected)
  - While boxes remain: find box with highest p_d
  - Suppress (discard) all other boxes that have IoU ≥ 0.5 with the box in the previous step
  - Repeat until no more boxes remain
- Repeat this process independently for each type of object you are trying to detect

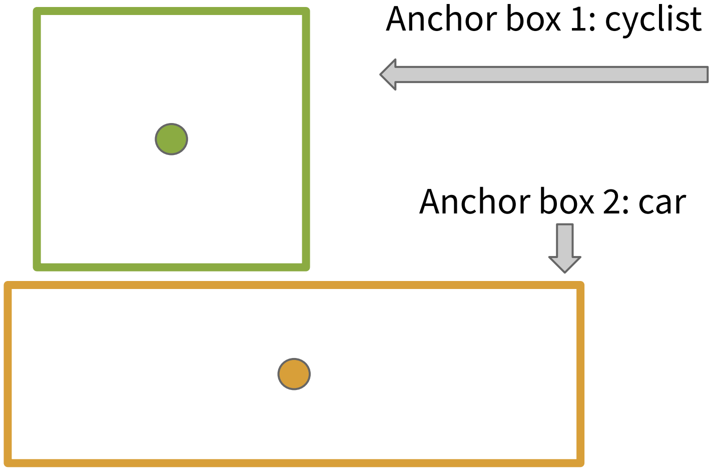
Anchor Boxes

- So far we have assumed a grid cell can only detect one object
- What if you want to **detect multiple objects in the same cell**?
- Originally, we assigned each object in an image to the grid cell that contained its midpoint
- Now, we will assign an object to a grid cell that contains its midpoint and an anchor box for that cell with the highest IoU

Anchor Boxes

$$y = [\underbrace{p_d, b_x, b_y, b_w, b_h, c_1, c_2, c_3}_{\text{Anchor box 1}}, \underbrace{p_d, b_x, b_y, b_w, b_h, c_1, c_2, c_3}_{\text{Anchor box 2}}]$$



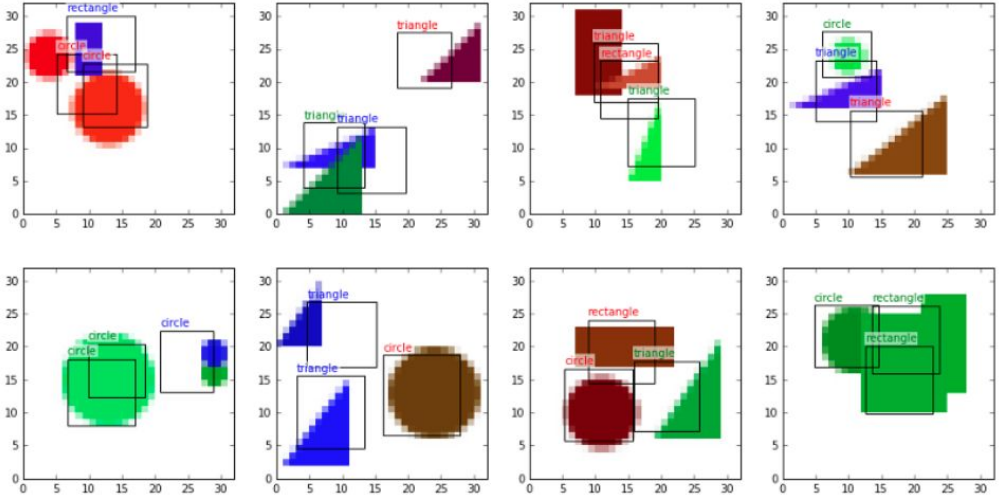


Anchor box 1: cyclist

Anchor box 2: car

Object Detection Tutorial

- [Object detection with neural networks - a simple tutorial using Keras]()



Face Recognition

Terminology

- Recognition
  - Have a database of K persons
  - Get an input image
  - Output ID if the image is any of the K persons, or “not recognized” if not like any of the K persons
- Verification
  - Input image and name/ID
  - Output whether the input image is that of the claimed person
- Andrew Ng demo video

Face Recognition

- One-shot Learning: learning from 1 example to recognize that person again
- Major downside: needs to be re-trained every time another person is added to group, only 1 example to learn from

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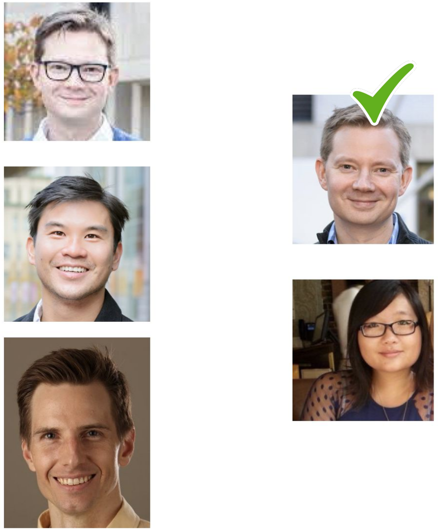

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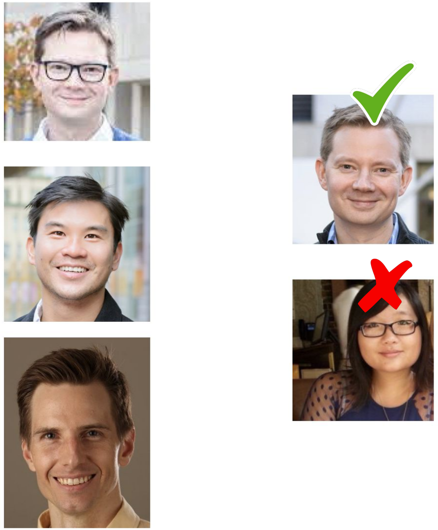


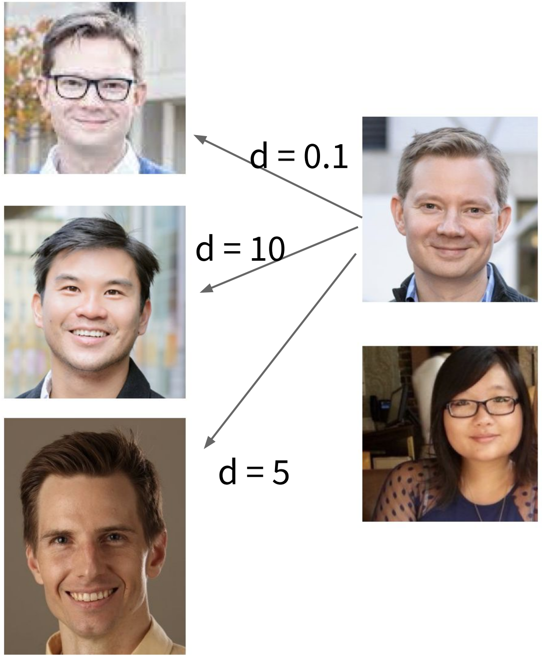
Similarity Function

- Similarity function: quantify how similar or different two images are
- If difference is large, the images are of two different people
- If difference is small, the images are of the same person
- DeepFace by Taigman et al 2014
- Define the similarity network as

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

- Learn parameters such that if $x^{(i)}$ and $x^{(j)}$ are the same person, d is small, and if $x^{(i)}$ and $x^{(j)}$ are different people, d is large
- Come up with threshold of what is “small”

Similarity Function



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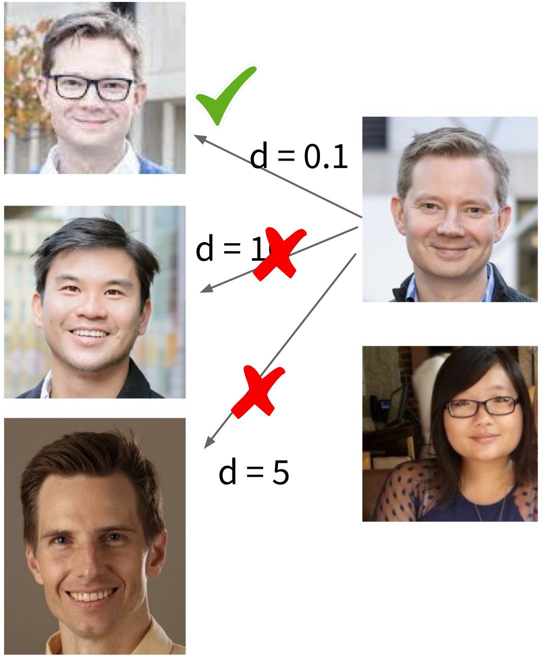
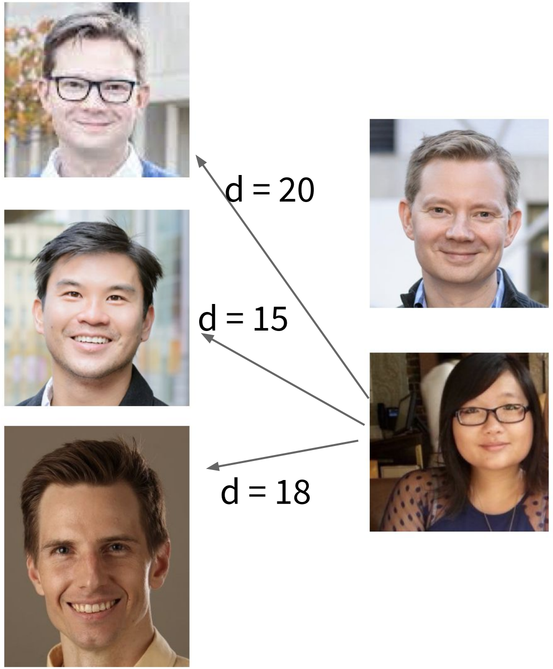


d = 0.1

d = 1

d = 5

Similarity Function



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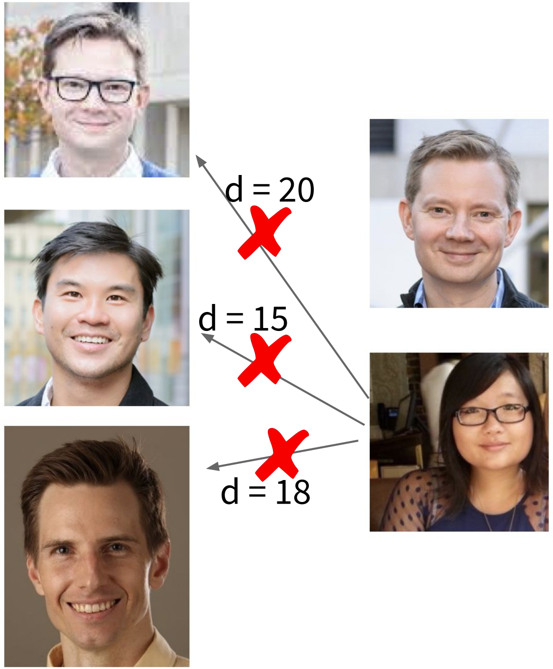


Not in database

Triplet Loss

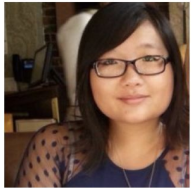
- To learn the parameters of your network (get good encodings for images), can use gradient descent to minimize the triplet loss
- Given 3 images A (anchor), P (positive) and N (negative), can we minimize the "triplet loss":

$$L(A, P, N) = \max(\|f(A) - f(P)\|_2^2 - \|f(A) - f(N)\|_2^2 + \alpha, 0)$$

- Note that multiple pictures of each person are needed for this to be effective

Anchor
(A)

Positive
(P)



Anchor
(A)

Negative
(N)

FaceNet

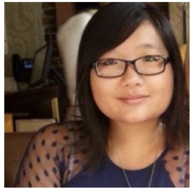
Margin parameter - ensures the network doesn’t just label every difference as 0

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

- During training, if A, P, and N are chosen randomly, is easily satisfied
  - It’s really easy to randomly pick two very different looking people (if your sample is heterogeneous)
  - It’s better to choose A, P, and N such that training is more difficult and will be better at recognizing differences on test sets

Anchor
(A)

Positive
(P)



Anchor
(A)

Negative
(N)