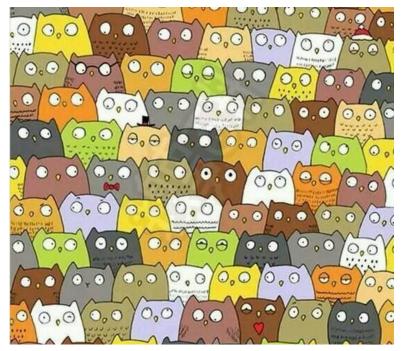
# Human face detection

Long Lin, Sina Borgi, Weiyuan Chen, and Malou Maria Nielsen

### Outline

- Motivation
- Dataset
- Models
- Results
- Discussion
- Summary

### Motivation



- 1. We are all interested in object detection
- 2. Human face detection is most relevant and practical

Where is the cat?

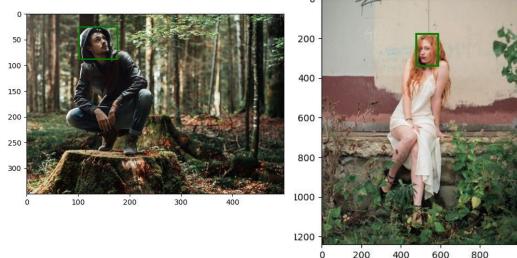
A diverse compilation of human facial images encompassing various **races**, **age** groups, and **profiles**. (N=2,204)

- High resolution
- Labeled images
- Different sizes
- Different number of faces
- Structured



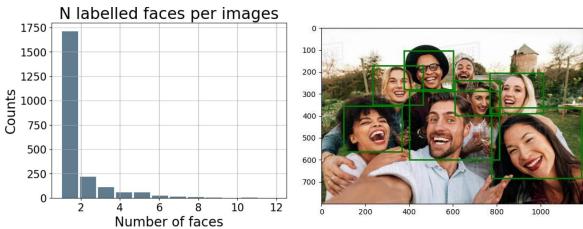
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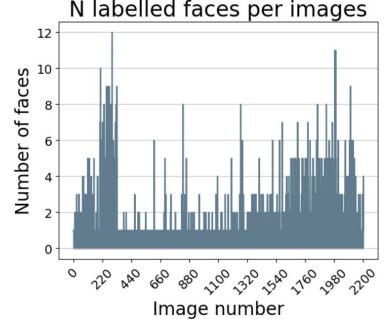
A diverse compilation of human facial images encompassing various **races**, **age** groups, and **profiles**. (N=2,204)

- High resolution
- Labeled images
- Different sizes
- Different number of faces
- Structured



A diverse compilation of human facial images encompassing various **races**, **age** groups, and **profiles**. (N=2,204) N labelled faces per images

- High resolution
- Labeled images
- Different sizes
- Different number of faces
- Structured



### **Pre-trained Models**

- InceptionResnetV2
  - CNN -- 164 layers
  - Trained on more than a million images (No human faces)
  - Classify images into 1000 object categories
  - Input size of 299-by-299
- Xception
  - CNN -- 71 layers
  - Trained on the same images dataset as above (No human faces)
  - Classify images into 1000 object categories
  - Input size of 299-by-299
- MTCNN
  - Multi-task Cascaded Convolutional Networks
  - Combined 3 CNNs for face classification, bounding box regression, facial landmark localization

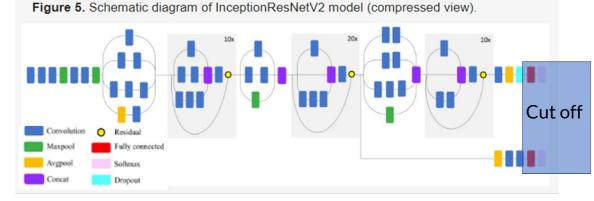
#### **Pre-trained models**

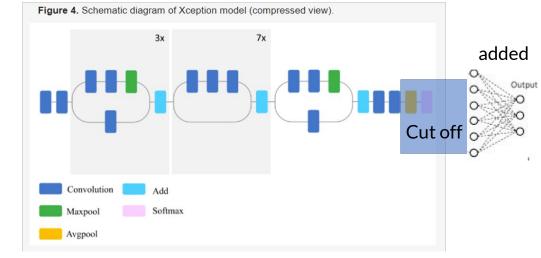
Model	Accuracy	Average_IoU
InceptionResnetV2	0%	١
Xception	0%	١
MTCNN	93%	0.43
Accuracy:	$\sum_{N} true \ positive \ rate \ per \ image$	- Area of Overlap
IoU(Intersection over Union):		IoU = Area of Union

## Implementation

- Pre-trained on Imagenet
  - Classify 1000 objects or animals
- Removed top layers (\*bottom)

   Adding our own





how many faces

• Output:

(4) max\_number\_faces + (1) corners of the box

Accuracy: IoU

## Implementation

Loss: MSE =  $(1/n) * \Sigma(xi - x)^2$ 

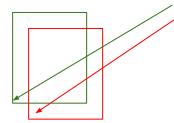
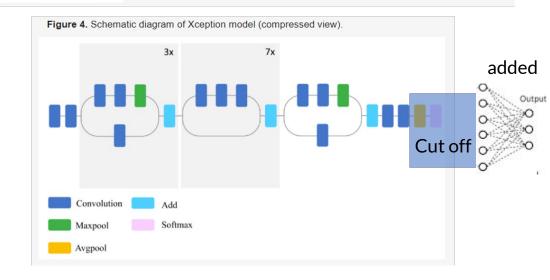


Figure 5. Schematic diagram of InceptionResNetV2 model (compressed view). 0 Cut off Convolution Residual 0 Fully connected Aaxpool 



- Training process
  - Train the added layers (Frozen) 0
  - Retrain with all layers (Unfrozen) 0

Avgpool

Concat

Softmax

Dropout

### **Results: Xception**

- Average IoU(Frozen): 0.5
- Average IoU(Unfrozen): 0.7
  - Trained on sharp images

Intersection over Union: 0.77166766

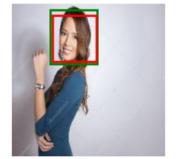


Intersection over Union: 0.47691643



Red: Predicted box Green: True box

Intersection over Union: 0.78414136





### **InceptionResnetV2**

Decent performance

Single faces

0

0

Average IoU (Unfrozen): 0.792 

Trained on clean images

Intersection over Union: 0.6732693 Intersection over Union: 0.84425384



Intersection over Union: 0.7658046

Intersection over Union: 0.7840933

Intersection over Union: 0.8151966









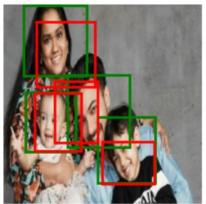


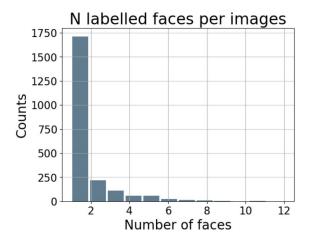
#### InceptionResnetV2

- Not so decent performance
  - $\circ \quad \text{Multiple faces} \\$

#### Intersection over Union: 0.4779279



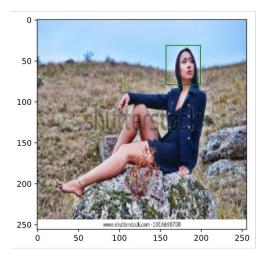




#### **InceptionResnetV2: Are all images perfect?**



#### Blur it until humans almost can't distinguish



### **Can the model still recognize faces?**

Sometimes. 

Different training needed 

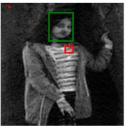
Intersection over Union: 0.007913823



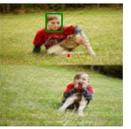


Intersection over Union: 0.6154

Intersection over Union: 0.0



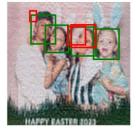
Intersection over Union: 0.0



Intersection over Union: 0.814212



Intersection over Union: 0.16921507 Intersection over Union: 0.06073324



Intersection over Union: 0.20204966 Intersection over Union: 0.25476074







### **Can the model still recognize faces?**

Sometimes.

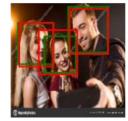
- Different training needed
  - Pre-processed + clean images 0

Intersection over Union: 0.8765532

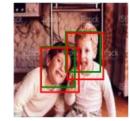


Intersection over Union: 0.56810457

Intersection over Union: 0.818023



#### Intersection over Union: 0.747998



Intersection over Union: 0.8619364



#### Intersection over Union: 0.5799238



Intersection over Union: 0.8785978



Intersection over Union: 0.88977987



- Accuracy:
- Average IOU: 0.824 (+ 0.032)





#### MTCNN – Multi-Task Cascaded Convolutional Neural Network

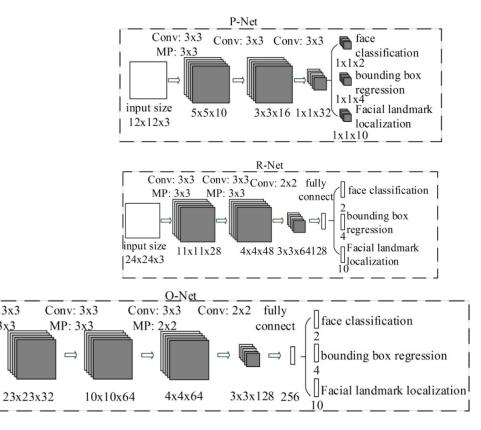
Conv: 3x3

MP: 3x3

input size

48x48x3

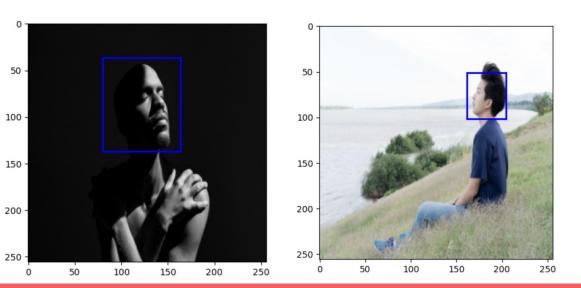
- The 3 stages:
  - 1. The proposal network (P-Net)
  - 2. The refine network (R-Net)
  - 3. The output network (O-Net)
- The 3 tasks:
  - 1. Face classification
  - 2. Bounding box regression
  - 3. Facial landmark localization
- Zhang et al. 2016

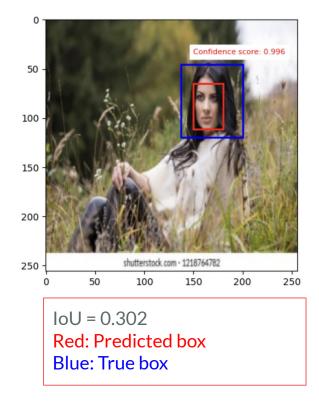


#### MTCNN - Multi-Task Cascaded Convolutional Neural Network

Problems:

- Sometimes it can't find any faces .
- Difference to the true boxes (low IoU, but is it bad?)





### Discussions

• Good at individuals

#### • Labels

• Not the best

- Overtraining • Maybe?
- Weaknesses
  - Multiple faces
  - Lower resolution (and small)

#### • Lacking comparability

Intersection over Union: 0.31416506



Intersection over Union: 0.61306775



Intersection over Union: 0.0



Intersection over Union: 0.0



Intersection over Union: 0.6192416



Intersection over Union: 0.0



Intersection over Union: 0.4179048





Intersection over Union: 0.0





- 1. InceptionResnetV2(Retrained)
  - a. Powerful on individual faces
  - b. Weaker on multiple
  - c. Stronger when trained on pre-processed images

- 2. Xception(Retrained)
  - a. Decent on individual faces
  - b. Weaker on multiple

- 3. MTCNN
  - a. Powerful on multiple faces
  - b. Independent of labels

#### Thank you for listening

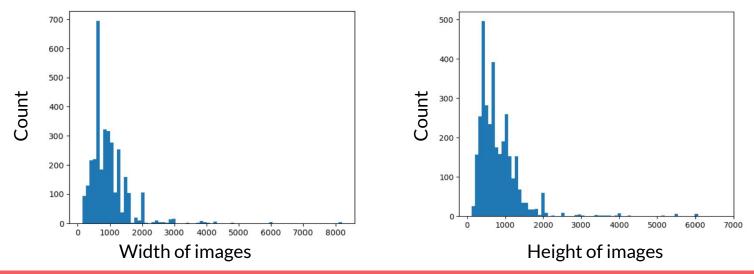
Appendix

#### **Motivation**

In this project we wanted to find a dataset of images. Find an appropriately pre-trained model that could take images and do object detection on it. If possible the final model should be able to draw a box around human faces. Once this step has been done we can see if it is possible to finetune the initial model and get better and better guesses on where the human faces are, or if they are not there.

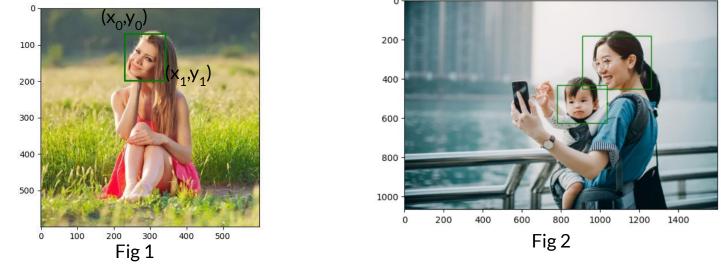
#### Data

This project will take a dataset of images from Kaggle (N = 2204). The data is photographs of people (individuals and groups), and the goal of this project is to find a pre-trained model, or multiple, to draw boxes around human faces. The data comes in different sizes as seen in the Figures below.



#### Data

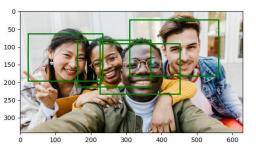
The data is also labelled with bounding boxes that gives the  $x_0$ ,  $y_0$ ,  $x_1$  and  $y_1$ , coordinates of the top-left and bottom-right corners of the box around each face in each image (shown in Fig 1). This means that images with multiple faces has multiple labels (shown in Fig 2).



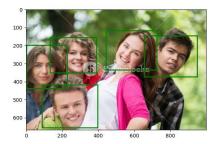
#### Data

The coordinates were produced by ssd\_mobilenet\_v2\_face\_quant\_postprocess model. There are some issues that may affect our training:

- 1. Overlapping between multiple faces coordinates. e.g. 00000562.jpg
- 2. Some images don't have all labels for all faces, possibly due to the lack of power of that model, e.g. 00000616.jpg
- 3. Some images have more labels than faces. e.g. 00002857.jpg
- 4. Duplicated/highly similar images. e.g. 00000280.jpg vs 00000377.jpg









00000562.jpg

00000616.jpg

00000280.jpg

00000377.jpg

### Data source (all Kaggle)

• Human faces:

https://www.kaggle.com/datasets/sbaghbidi/human-faces-object-detection

- Flowers: <u>https://www.kaggle.com/datasets/prasunroy/natural-images</u>
  - Subfolder:/flower

- Cats: <u>https://www.kaggle.com/datasets/prasunroy/natural-images</u>
  - Subfolder:/cat

#### Methods and thoughts: InceptionResnetV2

Then by adjusting the pre-processing phase, training of the model and doing hyper parameter tuning. The aim is to improve on basic pre-trained models accuracy on detecting faces. For InceptionResnetV2, hyperparameter tuning included tests on the learning rate, how many layers to add to the end of the pre-trained model and how many nodes on them. The optimal settings were found using a "grid" with Ir = 0.0001, 2 extra hidden layers of 256 and 128 nodes. Cross validation was not working with the way that the data/labels were setup. We had to use the:

ds = tf.data.Dataset.from\_tensor\_slices(images\_path).map(lambda x: tf.numpy\_function(load\_image\_and\_boxes, [x], [np.float32, np.float32]))

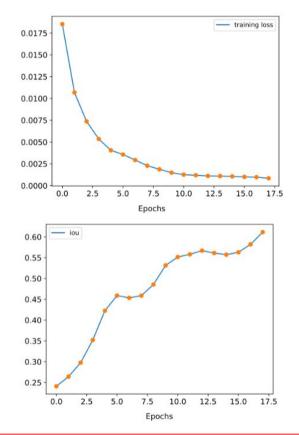
Which caused model.fit(validation\_data=val\_data) to fail same with validation\_split

#### Methods and thoughts: InceptionResnetV2

However, pre-processing was tried as a measure of improving the detection capacity of the model. Here computer vision functions such as blurring matrices, high&low pass Fourier filters were used to mess up the images. By training the model on both clean and pre-processed images the over IoU and loss functions were better. This was could have been because the versatility of different types of images made the model more robust. At least towards less "optimal" images where the there isn't only 1 face, centered, focused, and looking at the camera and with higher resolution.

#### Initial training with only the added layers

On the right, the loss and IoU score can be seen for each epoch of the initial training. This is where the end of the pre-trained model has been cut-off and the extra hidden layers has been added with the desired output layer. Clearly the weights are way off in the beginning, but without much training there is a huge improvement after just 10 epochs (on pre-processed images).

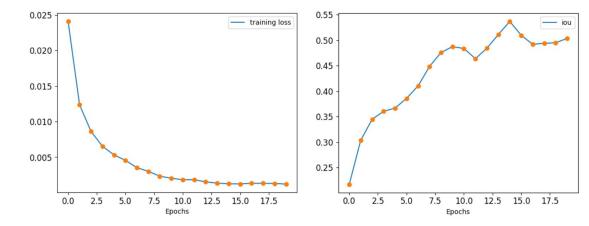


#### Methods and thoughts: Xception

Xception was trained with the same parameters as InceptionResNetV2.

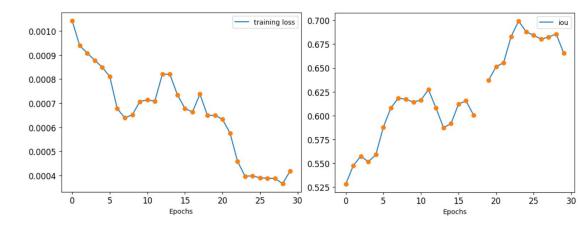
The figures on the left show loss and IoU scores for the initial training with the added layers.

The IoU score improved until it was around 0.5.



#### Methods and thoughts: Xception

After training with all the layers, the model saw improvements in IoU score until 23 epochs. At around 17 epochs in the bottom IoU figure there is a gap in the graph. This is due to the output being a NaN, which sometimes occurs because the IoU score is calculated by dividing with the area of union. If the area is 0, then IoU can't be calculated.



#### **MTCNN - Why did we choose to work with it?**

- MTCNN is currently one of the most popular detection models and known to be very accurate.
- As a completely pretrained model it is independent on the true labels, and as discussed the true labels might not be the very best, so an independent model might provide more information.
- We expected it to work really well and the idea was to compare the other models to it.

#### **MTCNN - Preprocessing and implementation**

Preprocessing:

- **input size:** doesn't matter,, but we used 256x256.
- Color format: BGR.
- Integer type: uint8.

Implementation:

• mtcnn package:

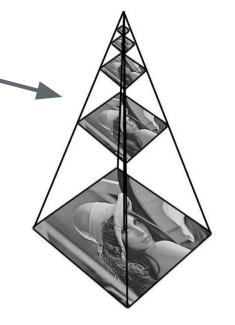
model = mtcnn.MTCNN()
faces = model.detect\_faces(Image)

The very first step:

- Resizing the image to make an image pyramid.
- This is the input of stage 1 (the P-Net).

The stride of 2:

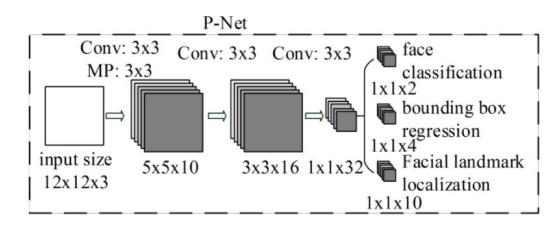
• Allows for faster runtime!





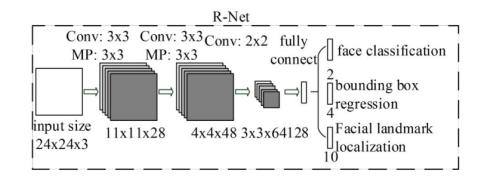
Stage 1 (P-Net):

- Fully Convolutional Network (FCN).
- Finds candidate windows and their bounding box regression vectors.
- 2. Non-Maximum Suppression (NMS):
  - Highly overlapping candidates are merged.



#### Stage 2 (R-Net):

- CNN not FCN
- It takes the candidates (as 24x24x3 image arrays) from P-Net as input.
- 2. Low confidence candidates are discarded.
- 3. Bounding box regression.
- 4. NMS ones again to discard redundant boxes.

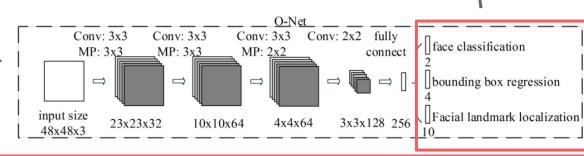


#### Stage 3 (O-Net):

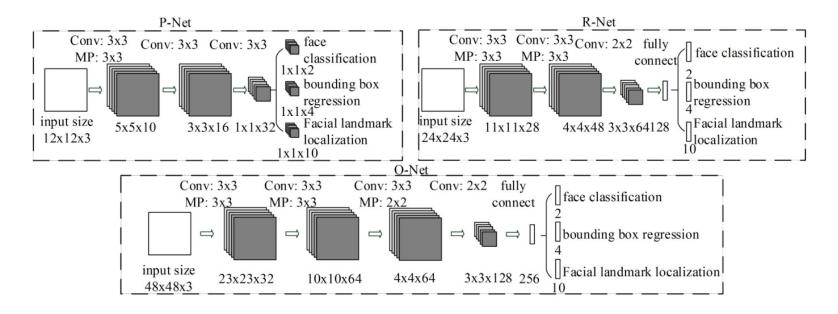
- CNN not FCN
- It takes the boxes (as 48x48x3 image arrays) from R-Net as input.
- 2. Similar to R-Net:
  - Low confidence candidates are discarded.
  - Bounding box regression.
  - NMS.
- 3. It starts finding facial landmarks.

#### Outputs:

- Face classification (binary classification is it a face or not?)
- 4 element vector representing the bounding box (x, y, width, height).
- 10 element vector representing 5 facial landmarks.

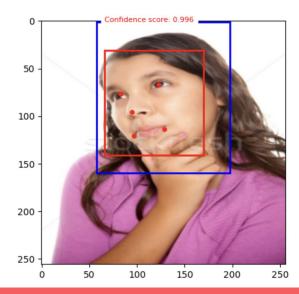


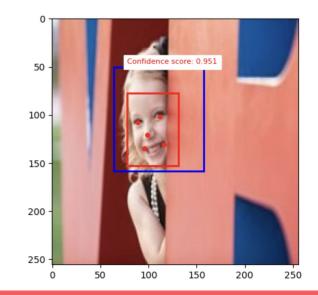
The complete model architecture image taken from Zhang et al. 2016:

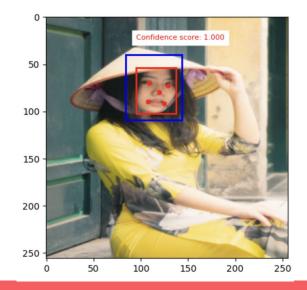


#### **MTCNN - Facial landmarks**

- MTCNN also finds 5 facial landmarks (nose, left\_eye, right\_eye, mouth\_left, mouth\_right)!
- Since the dataset doesn't have these facial landmarks labeled, we can't quantitatively look at the performance.







#### **MTCNN - How was it trained?**

- Datasets:
  - Wider Face
  - Celeb A (has annotated facial landmarks)
  - Face Detection Dataset and Benchmark (FDDB)
- Discussion (Considerations):
  - Are these diverse in terms of ethnicities, gender, and age?
  - Are these diverse in terms quality (blurring), angles, number of faces in the image, and poses etc.
  - Or is the lack of diversity the reason MTCNN sometimes can't recognize faces in our dataset?

#### **MTCNN - Sources**

- <u>https://arxiv.org/ftp/arxiv/papers/1604/1604.02878.pdf</u>(Zhang et al. 2016)
- <u>https://towardsdatascience.com/how-does-a-face-detection-program-work-using-neural-netw</u> <u>orks-17896df8e6ff</u>
- <u>https://medium.com/@iselagradilla94/multi-task-cascaded-convolutional-networks-mtcnn-for</u> <u>-face-detection-and-facial-landmark-alignment-7c21e8007923</u>
- <u>https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-ipr.2019.0141</u>

### Other models we tried

- Mask R-CNN
  - Amazing results on people and objects but.. deprecated libraries..

