Face in Point

Facial Keypoint Detection, Kaggle Challenge

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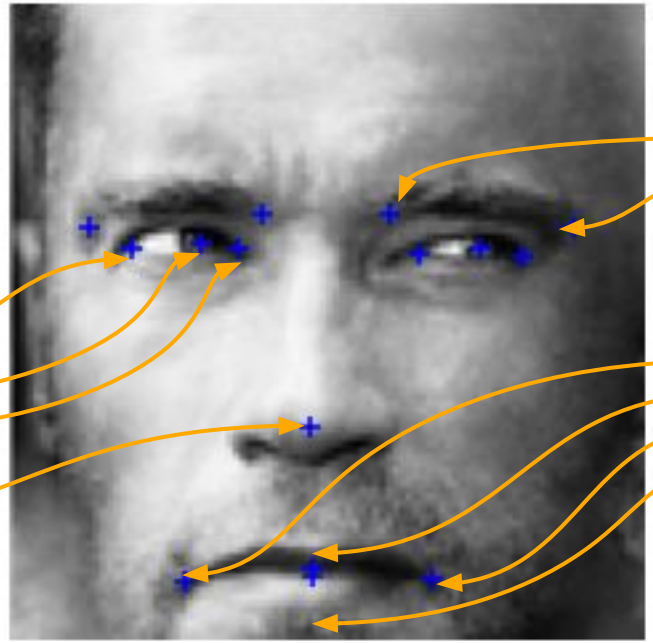
Objective

Given a facial image, identify 15 facial keypoints' (X, Y coord)

15 KP x 2 coordinates = 30



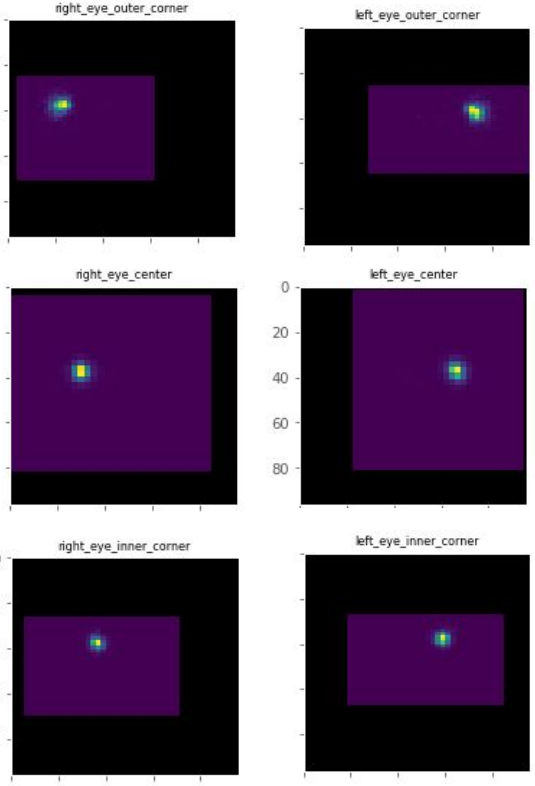
Left & right eyebrows
- Inner end
- Outer end

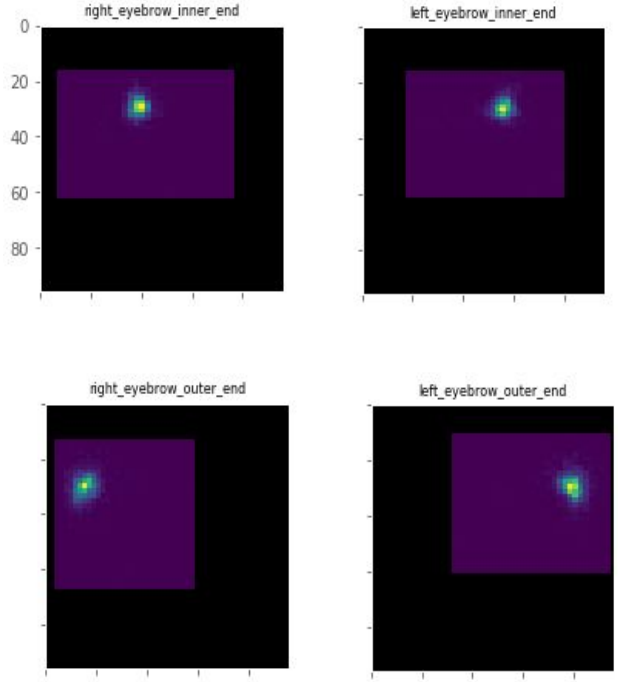
Left & right eyes
- Outer corner
- Center
- Inner corner

Mouth
- Left corner
- Center top lip
- Right corner
- Center bottom lip

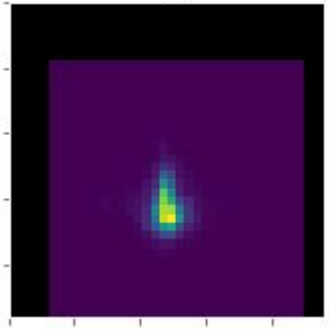
Nose
- Tip

96 px

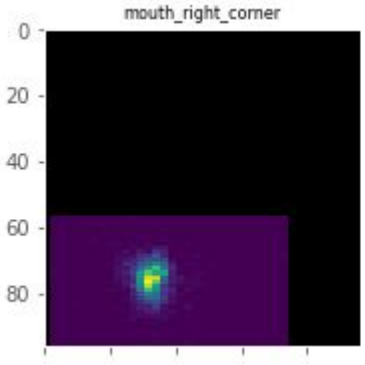

right_eye_outer_corner
left_eye_outer_corner
right_eye_center
left_eye_center
right_eye_inner_corner
left_eye_inner_corner
0
20
40
60
80


right_eyebrow_inner_end
left_eyebrow_inner_end
right_eyebrow_outer_end
left_eyebrow_outer_end
0
20
40
60
80

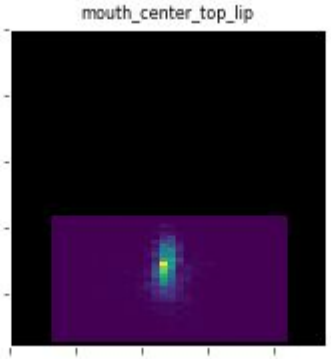
nose_tip



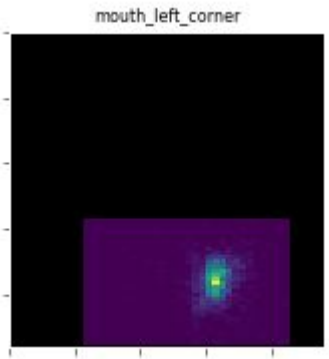
mouth_right_corner



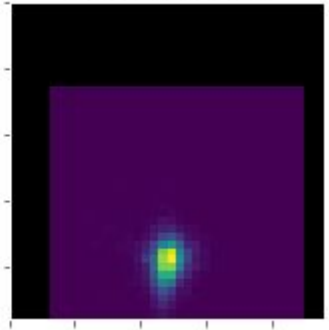
mouth_center_top_lip



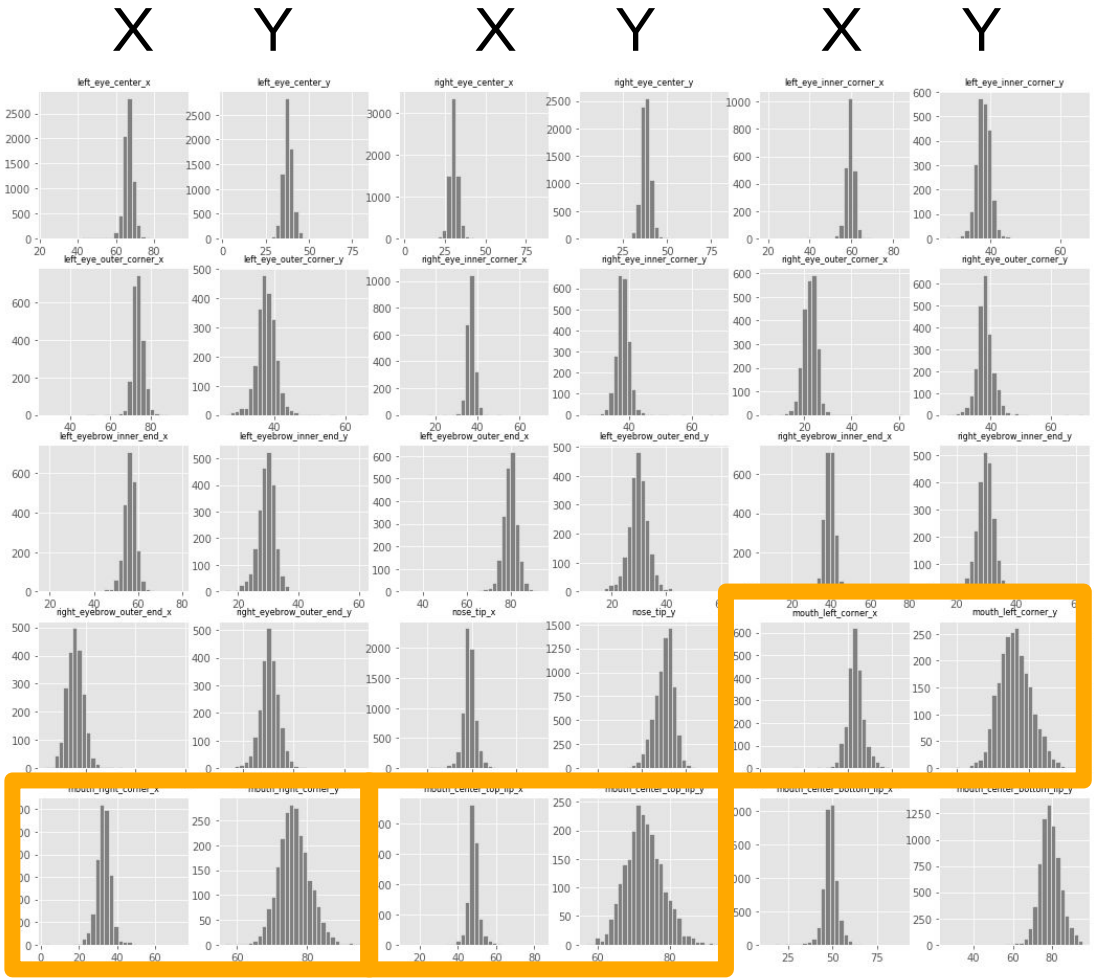
mouth_left_corner



mouth_center_bottom_lip



- Normal distributions
- Greater variance vertically (Y axis) than horizontally (X)
- Greatest variance near mouth KPs: Smiling & opening mouths



But data's missing!

5K out of 7K training images were missing KP data

Column	Non-Null Count
left_eye_center_x	7039
left_eye_center_y	7039
right_eye_center_x	7036
right_eye_center_y	7036
left_eye_inner_corner_x	2271
left_eye_inner_corner_y	2271
left_eye_outer_corner_x	2267
left_eye_outer_corner_y	2267
right_eye_inner_corner_x	2268
right_eye_inner_corner_y	2268
right_eye_outer_corner_x	2268
right_eye_outer_corner_y	2268
left_eyebrow_inner_end_x	2270
left_eyebrow_inner_end_y	2270
left_eyebrow_outer_end_x	2225
left_eyebrow_outer_end_y	2225
right_eyebrow_inner_end_x	2270
right_eyebrow_inner_end_y	2270
right_eyebrow_outer_end_x	2236
right_eyebrow_outer_end_y	2236
nose_tip_x	7049
nose_tip_y	7049
mouth_left_corner_x	2269
mouth_left_corner_y	2269
mouth_right_corner_x	2270
mouth_right_corner_y	2270
mouth_center_top_lip_x	2275
mouth_center_top_lip_y	2275
mouth_center_bottom_lip_x	7016
mouth_center_bottom_lip_y	7016

Only 2K for highlighted!

Dealing with Missing Data

Forward Fill (`ffill`)

Use the last data available in previous non-empty row

Not ideal, as 70% images are missing at least one point

👎

⭐ Original kp data from kaggle

➕ Extrapolated data to fill missing kps

Median

Use the median value of the respective point of interest

Works surprisingly well but not when faces are tilted

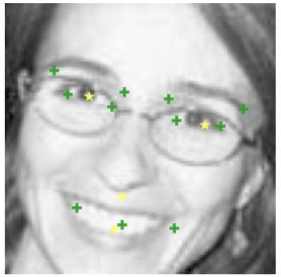
⭐ Original kp data from kaggle

➕ Extrapolated data to fill missing kps

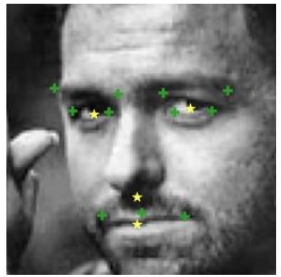
KNN

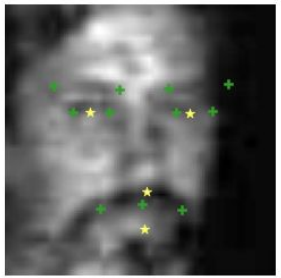
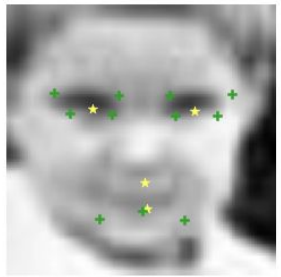
Find appropriate value to use using k-nearest neighbors, k = 9

Better performance than both previous attempt. Decent on tilted or turned faces





Original kp data from kaggle

Extrapolated data to fill missing kps

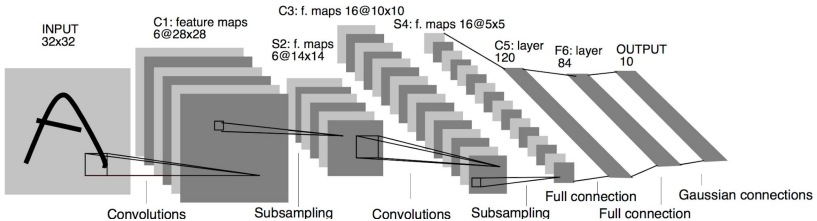
CNN Architectures

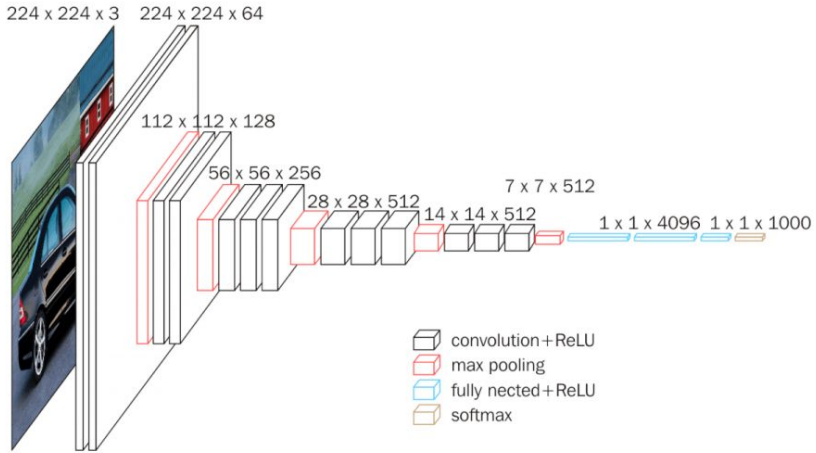
CNN

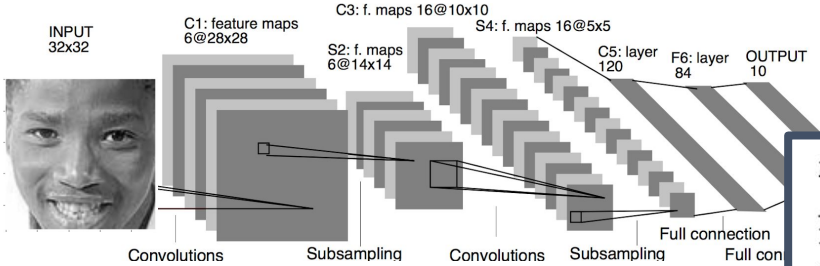
"special kind of multi-layer neural networks, designed to recognize visual patterns directly from pixel images with minimal preprocessing."

Architectures we used

1. LeNet-5
2. VGG-16





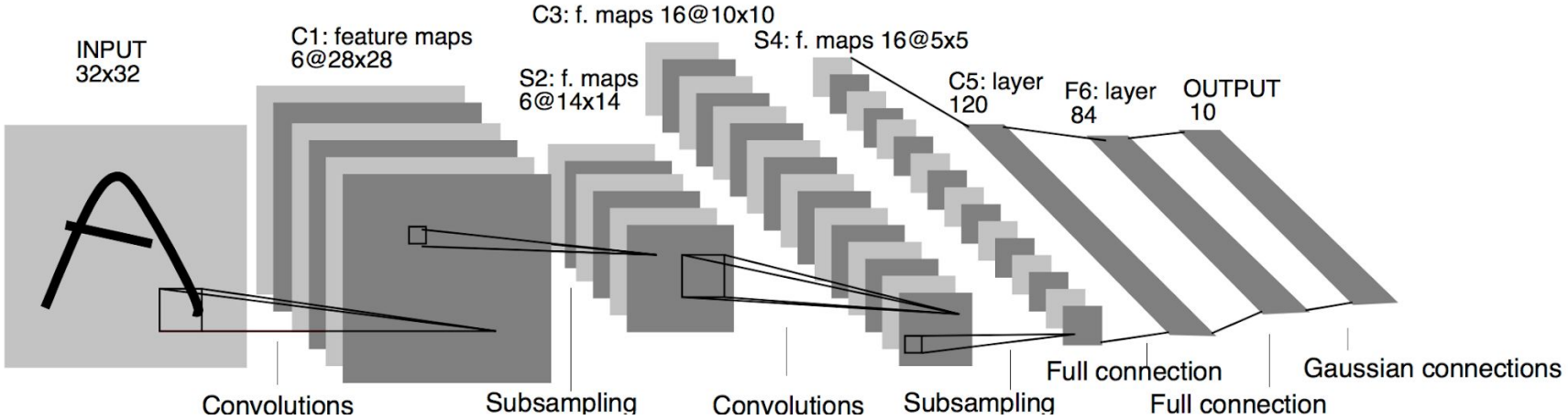


Input: (Num. Images, 96, 96, 1)

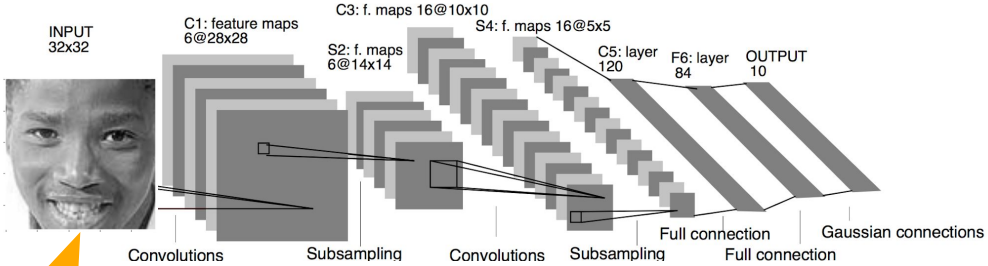
```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape
=================================================================
conv2d_4 (Conv2D)            (None, 94, 94, 6)
_________________________________________________________________
average_pooling2d_4 (Average (None, 47, 47, 6)
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 45, 45, 16)
_________________________________________________________________
average_pooling2d_5 (Average (None, 22, 22, 16)
_________________________________________________________________
flatten_2 (Flatten)          (None, 7744)
_________________________________________________________________
dense_6 (Dense)              (None, 120)
_________________________________________________________________
dense_7 (Dense)              (None, 84)
_________________________________________________________________
dense_8 (Dense)              (None, 30)
=================================================================
Total params: 943,054
Trainable params: 943,054
Non-trainable params: 0
_________________________________________________________________
None
```

LeNet-5

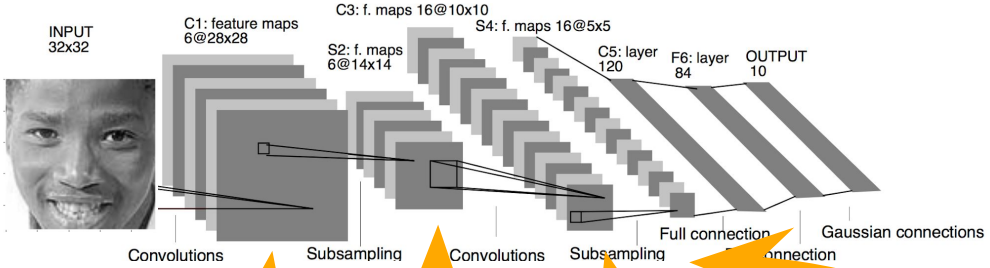
Layer shape changes from a full **96-by-96 image** to just **30 numbers** representing the KP

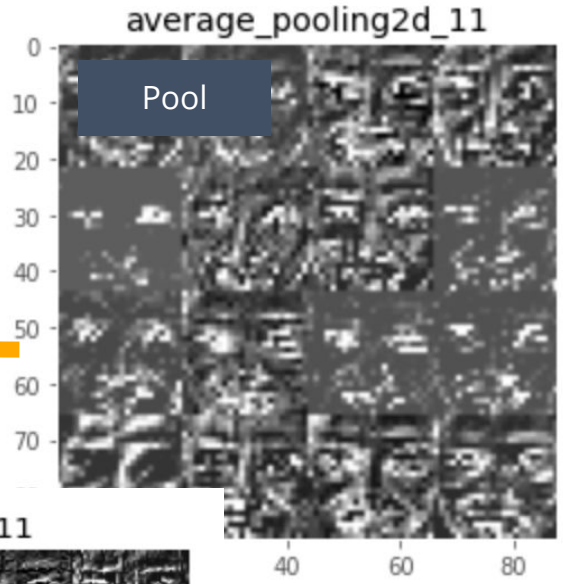


What does an ML model "see"?
LeNet5 activation layers

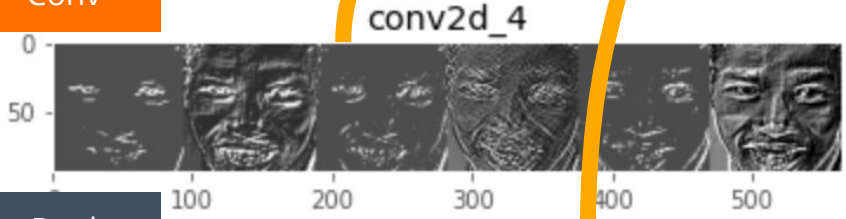


Each image: **96 by 96**

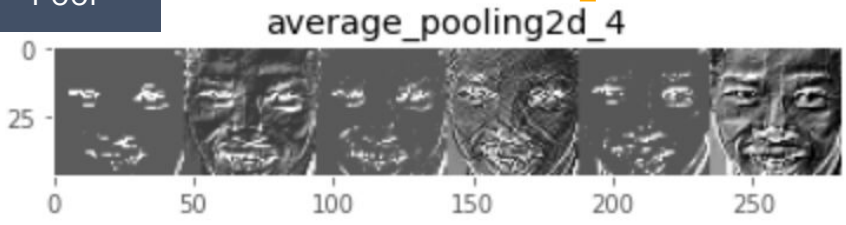


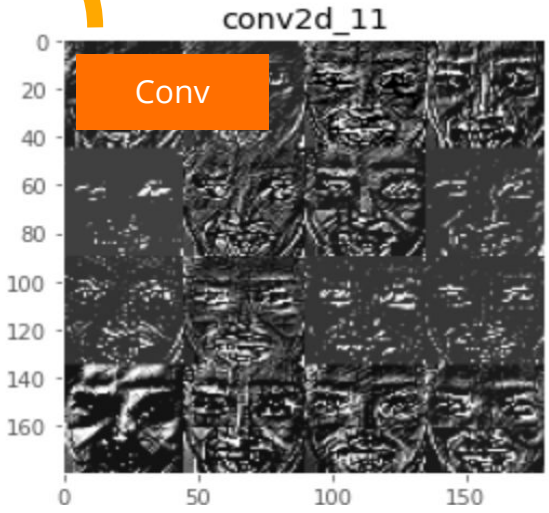


Conv



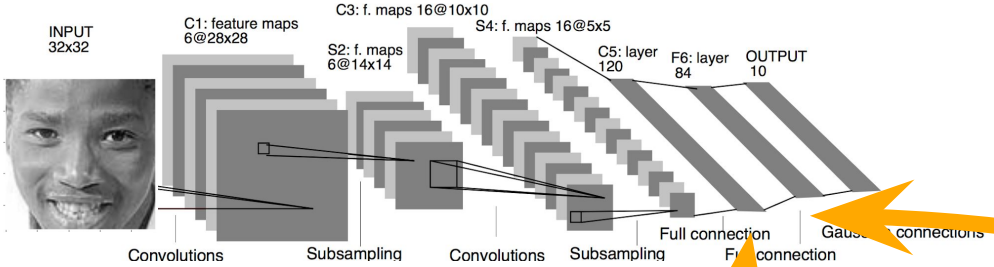
Pool





Conv detects features

Pooling reduces the size while preserving characteristics



120 numbers

FC

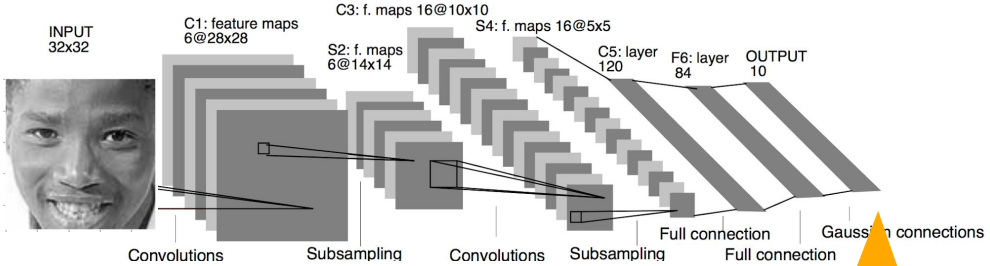
```
array([41.70368  ,  0.       , 11.684497 ,  0.       ,  0.       ,
        0.       ,  0.       ,  8.607626 ,  0.       ,  0.       ,
        0.       , 15.292818 ,  9.94827  ,  0.       ,  0.       ,
        6.8089824,  0.       ,  0.       ,  0.       ,  0.       ,
       16.973673 , 15.360426 ,  0.       ,  0.       ,  0.       ,
        9.47765  ,  0.       ,  0.       ,  0.       , 42.24256  ,
       12.297037 ,  0.       , 22.879719 ,  0.       ,  0.       ,
        6.487142 ,  0.       ,  0.       , 10.376771 ,  0.       ,
        0.       ,  0.       , 17.08813  ,  0.       ,  0.       ,
        0.       ,  0.       ,  0.       , 11.450783 , 12.42491  ,
        0.       ,  8.61066  , 17.49668  ,  0.       ,  0.       ,
       11.233514 ,  0.       ,  0.       ,  0.       ,  0.       ,
       12.334232 ,  0.       ,  1.8129607,  0.       ,  0.       ,
        0.       ,  9.862995 , 10.680107 ,  0.       , 18.863989 ,
        0.       ,  0.       , 13.35074  ,  0.       ,  0.       ,
       14.71458  ,  0.       ,  0.       , 16.032688 ,  0.       ,
       10.024964 ,  7.21192  ,  0.       ,  0.       ,  0.       ,
        6.149487 ,  0.       ,  0.       ,  0.       ,  0.       ,
       10.679127 ,  0.       ,  0.       ,  0.       ,  0.       ,
        0.       , 11.183755 ,  0.       ,  0.       ,  4.282765 ,
       19.137138 ,  0.       ,  0.       , 15.075655 ,  0.       ,
        0.       ,  0.       , 25.42046  , 18.232054 , 13.407069 ,
        0.       , 16.235718 ,  0.       ,  0.       ,  0.       ,
       10.614934 ,  0.       ,  0.       , 11.432421 ,  0.       ],
      dtype=float32)
```

84 numbers

FC

```
array([16.63355  ,  0.       , 39.939404 , 32.804752 ,  0.       ,
        0.       , 15.08051  , 43.02604  ,  0.       , 18.524906 ,
        0.       ,  0.       ,  0.       ,  0.       ,  8.178034 ,
        0.       ,  0.       ,  0.       ,  2.4489286,  0.       ,
       54.874302 ,  0.       ,  0.       , 42.76598  ,  0.       ,
       42.408684 , 48.62112  ,  0.4575051,  0.       ,  0.       ,
        0.21308264,  0.       ,  0.       ,  0.       ,  0.       ,
       39.96471  ,  0.       , 22.610771 , 46.044735 ,  0.2078133,
       32.51241  , 33.131916 ,  0.       ,  0.       , 33.57893  ,
        0.       ,  0.       ,  0.       ,  0.       ,  0.       ,
        0.       ,  0.       ,  0.       , 46.528843 ,  0.       ,
        0.       , 26.983    , 39.674263 , 37.154236 ,  0.       ,
       34.24934  ,  0.       , 20.362234 ,  0.       , 30.49593  ,
        0.       ,  0.       ,  0.       ,  0.       ,  0.       ,
        0.       ,  1.4448502, 25.033195 , 29.471706 , 38.308865 ,
        0.       ,  0.       ,  2.6136963,  0.       ,  0.       ,
        0.       ,  0.       ,  0.       , 30.762205 ], dtype=float32)
```

All we know is tha
number means ac



Output:

30 numbers for 15 KP

```
array([64.37013 , 36.601883, 28.56574 , 34.96842 , 56.406677, 36.769264,
       70.383644, 34.404564, 34.708054, 37.653595, 20.951923, 37.264774,
       52.6065  , 28.457956, 76.40988 , 29.269268, 37.388195, 29.48214 ,
       13.806782, 26.73549 , 45.301773, 60.582985, 59.48615 , 74.35807 ,
       30.009727, 73.12003 , 45.17569 , 72.86695 , 45.625507, 77.04493 ],
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```
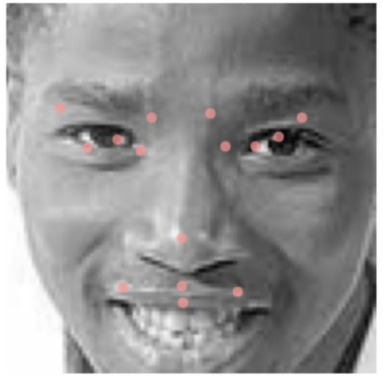
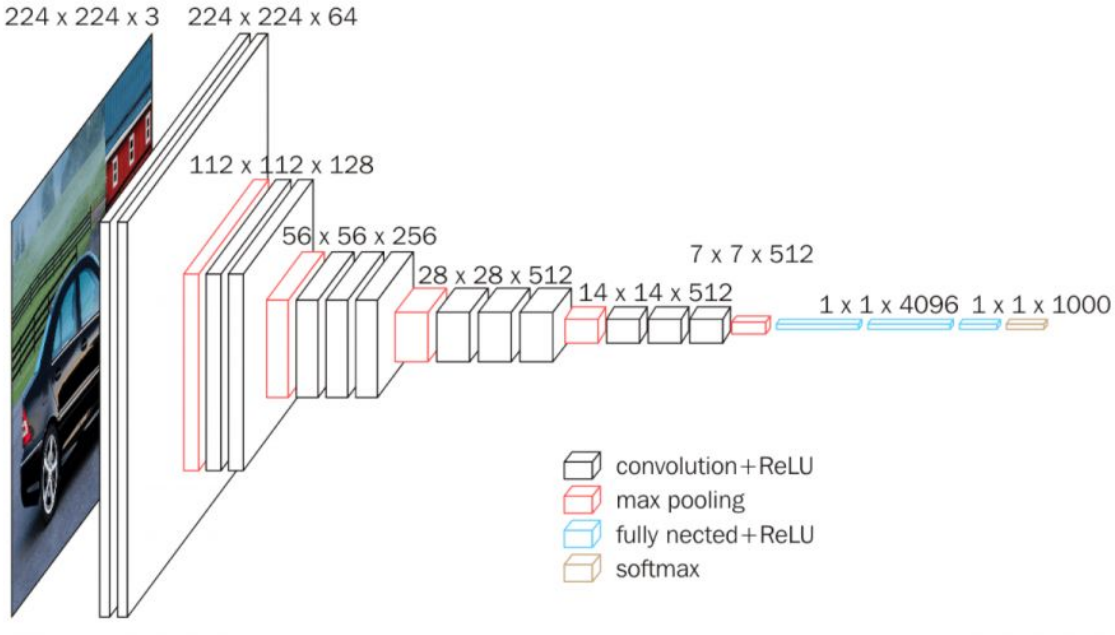
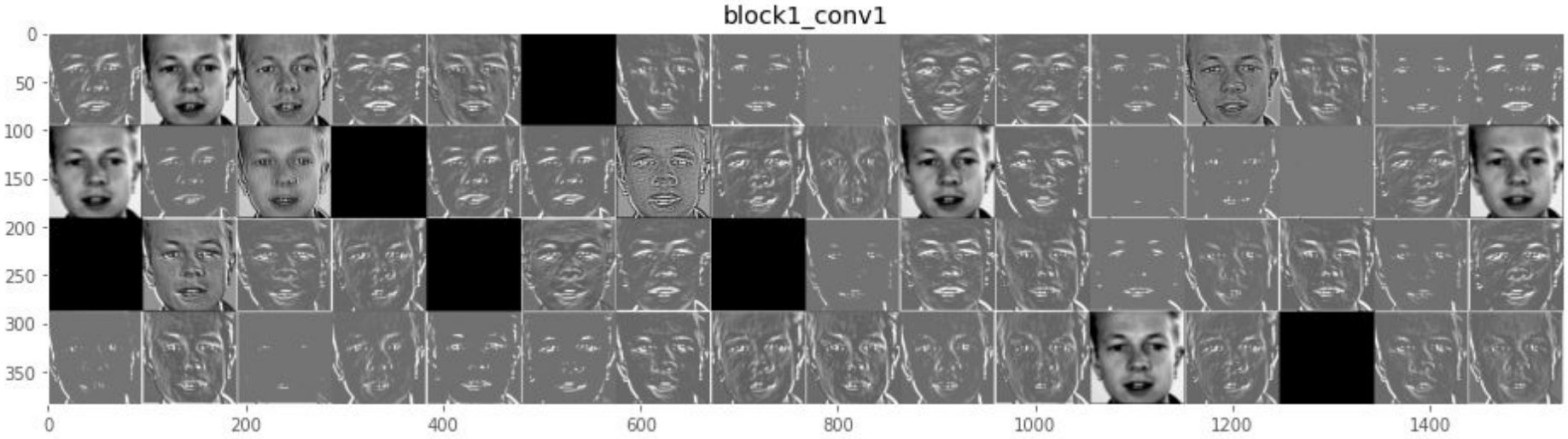





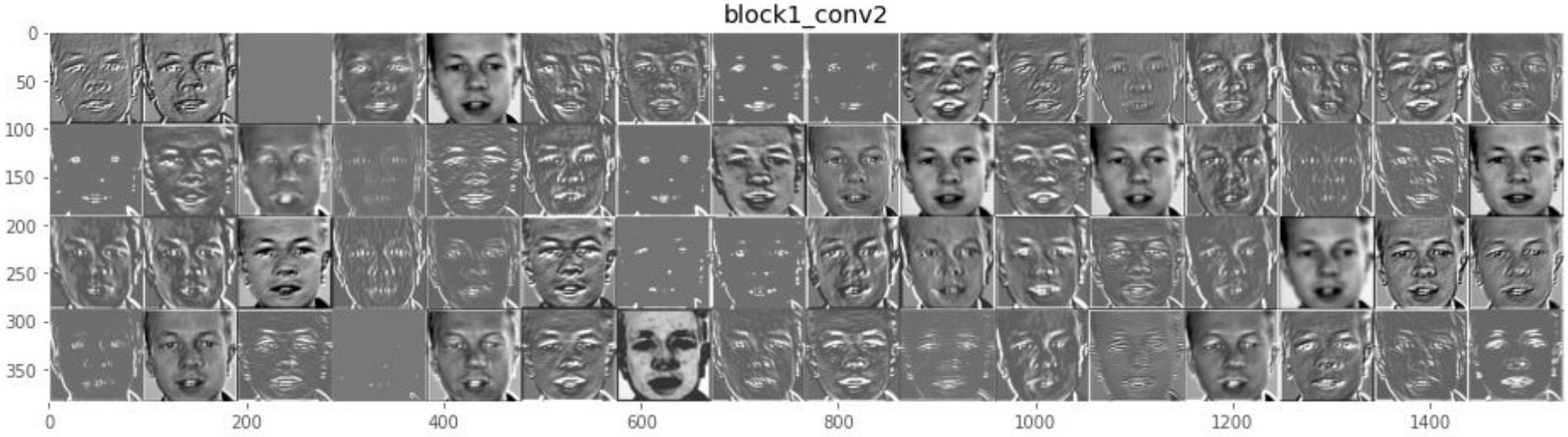
More activation layers!

VGG-16



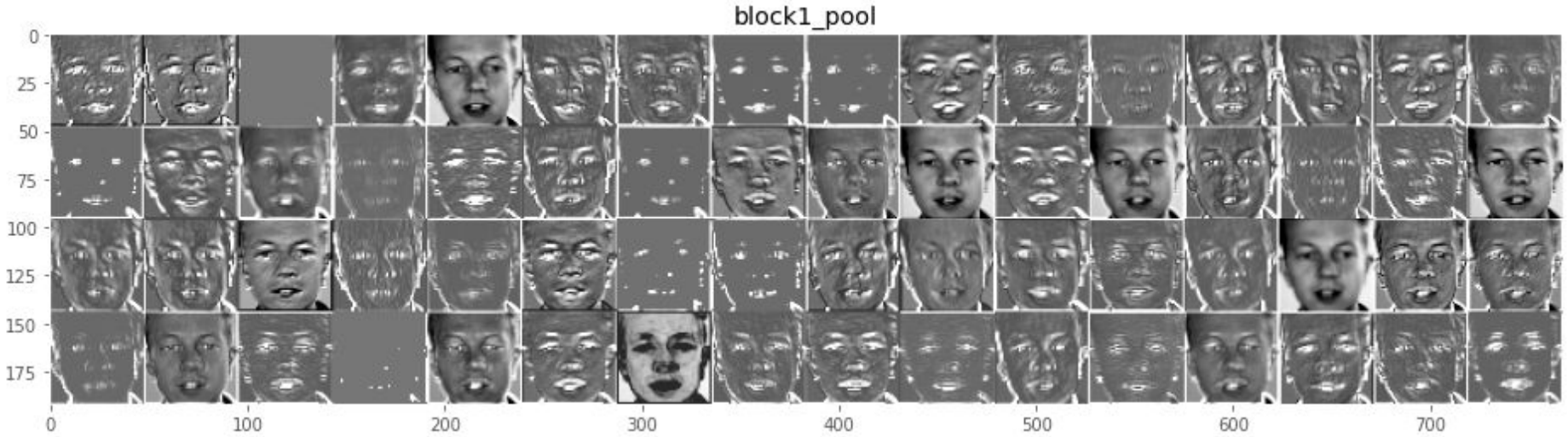
Conv

(Identify important characteristics)



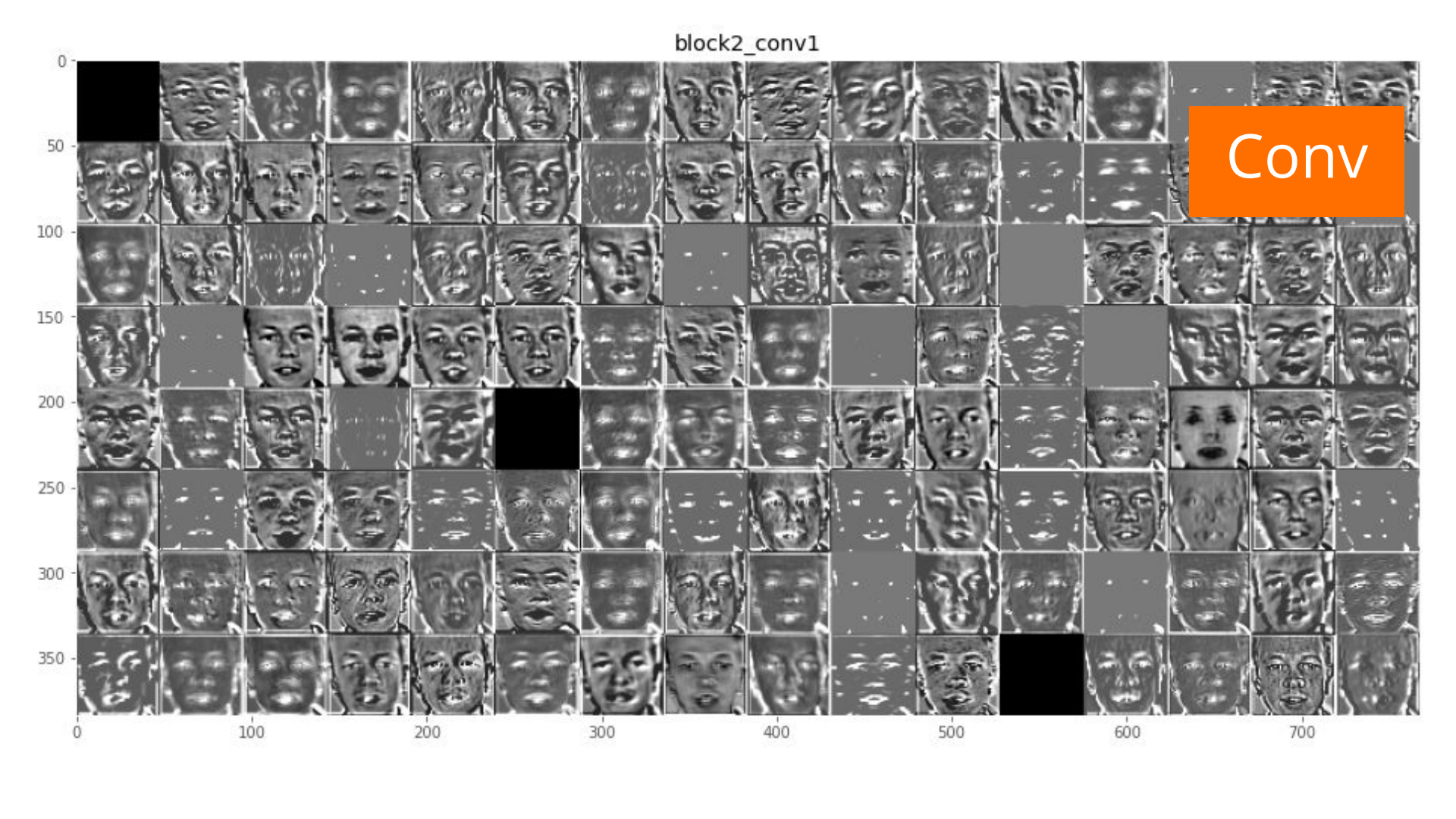
Conv

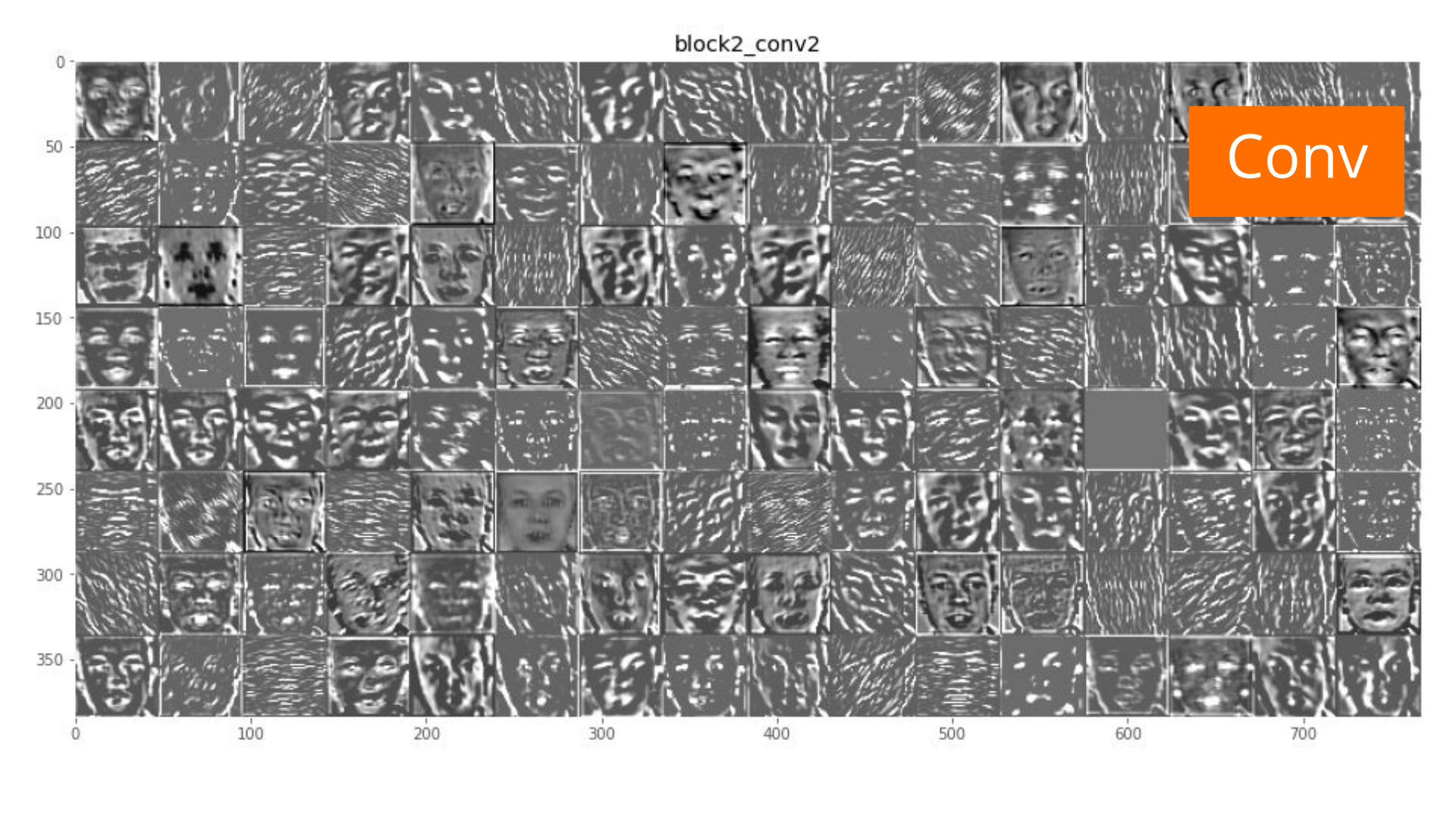
(Identify important characteristics)

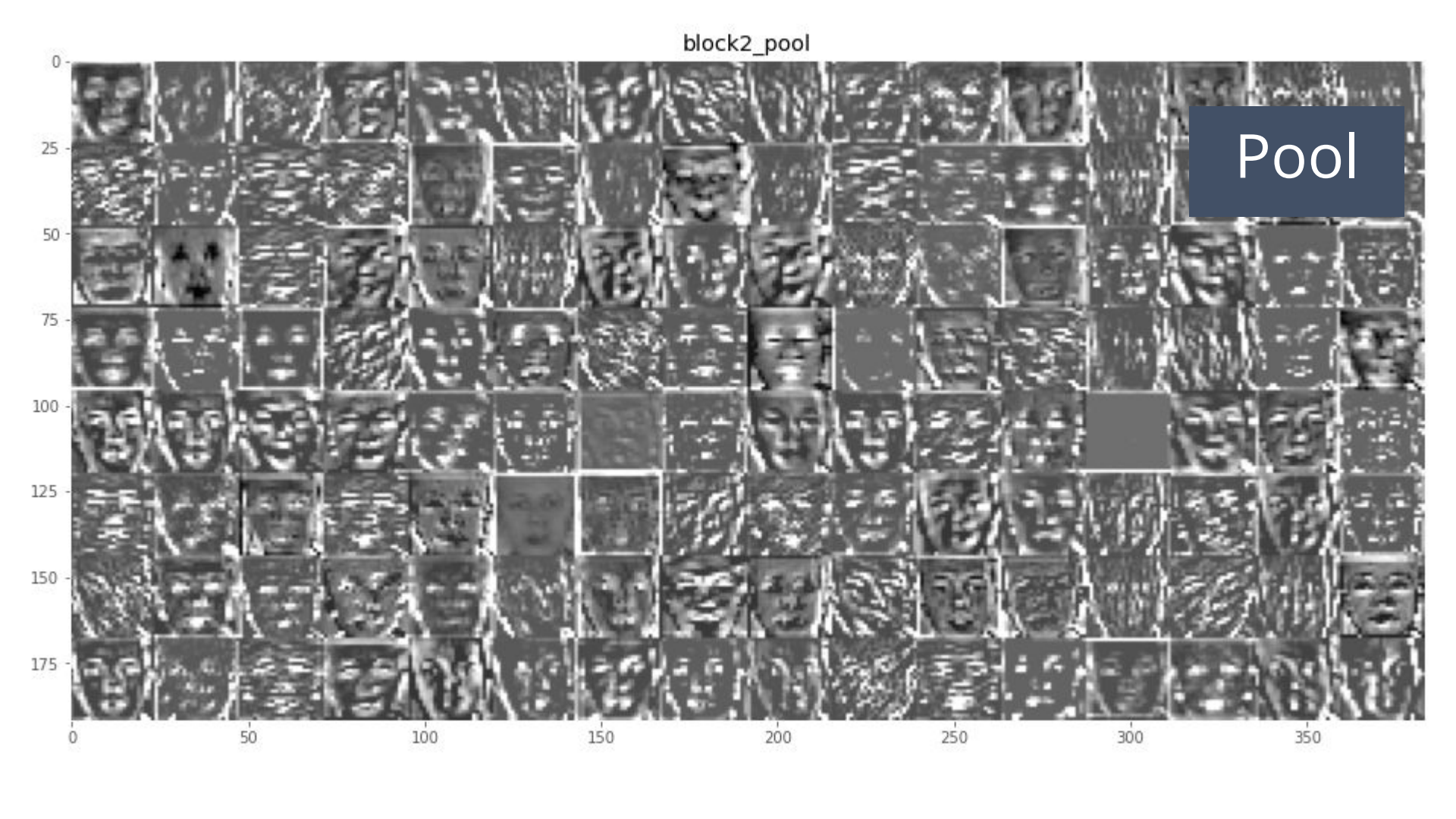


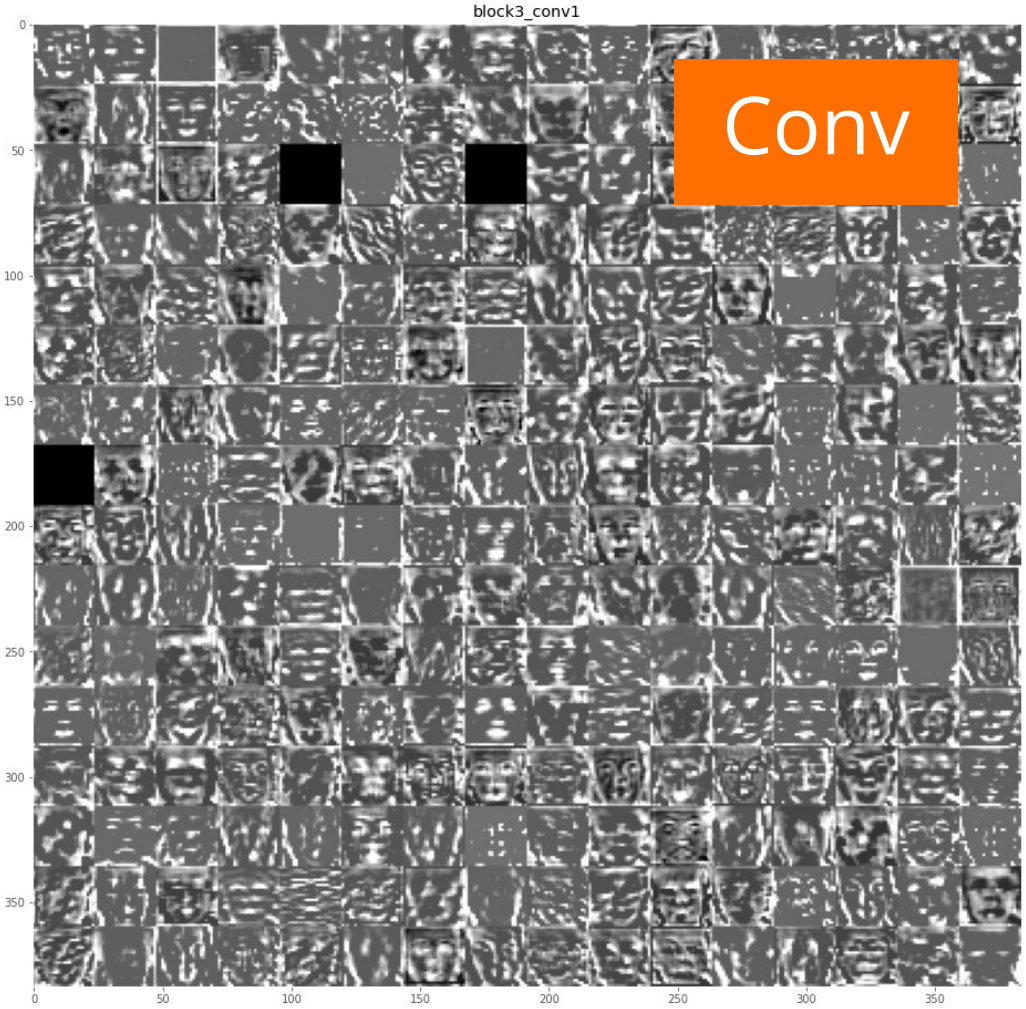
Pool

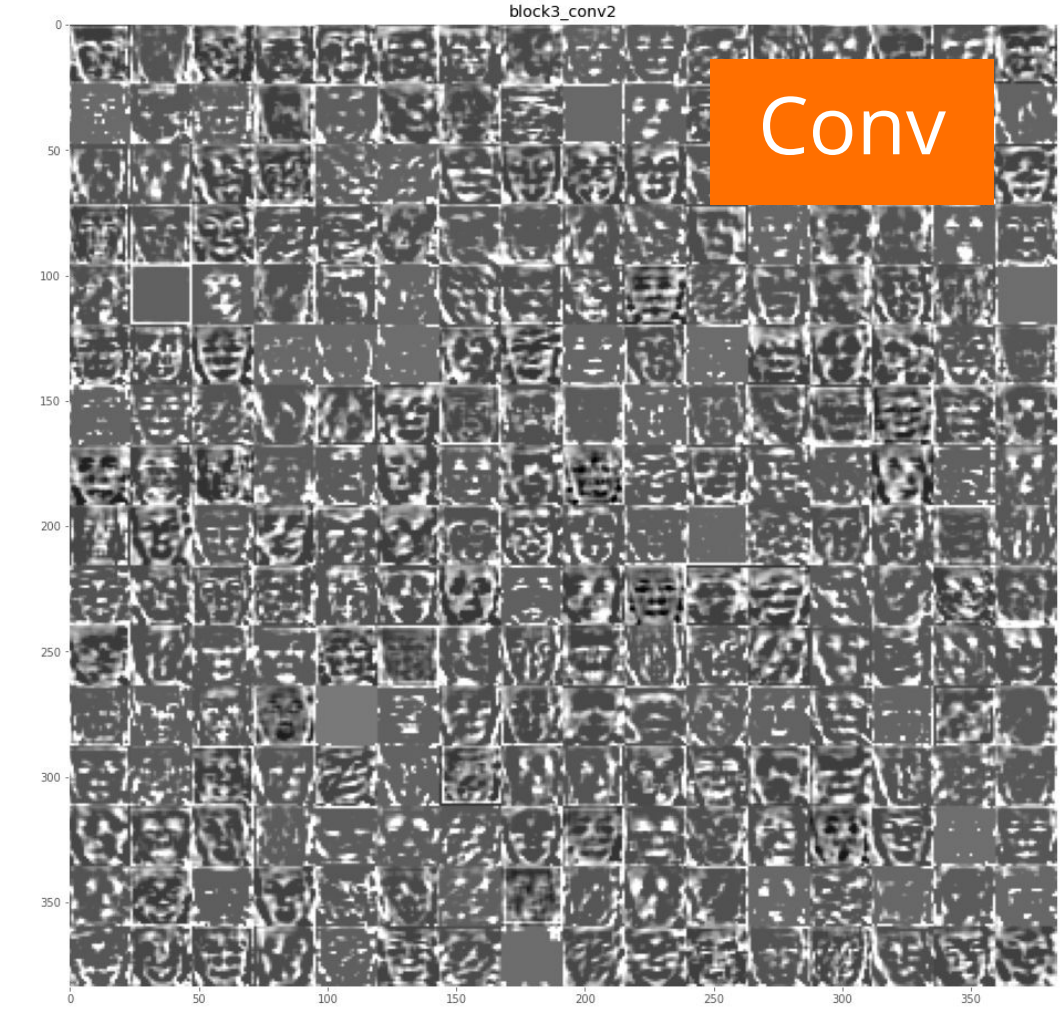
(Preserves characteristics, lower res)

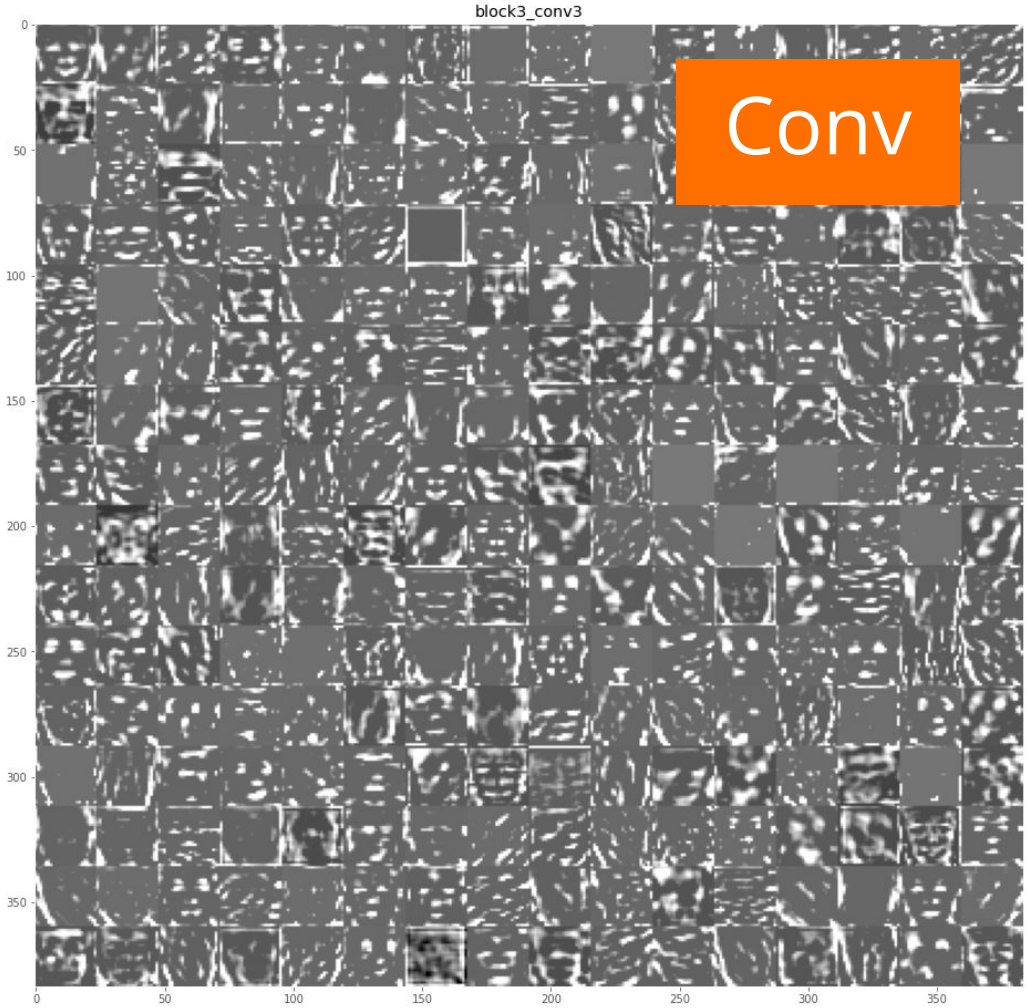

block2_conv1
Conv
0
50
100
150
200
250
300
350
0
100
200
300
400
500
600
700


block2_conv2
0
50
100
150
200
250
300
350
0
100
200
300
400
500
600
700
Conv

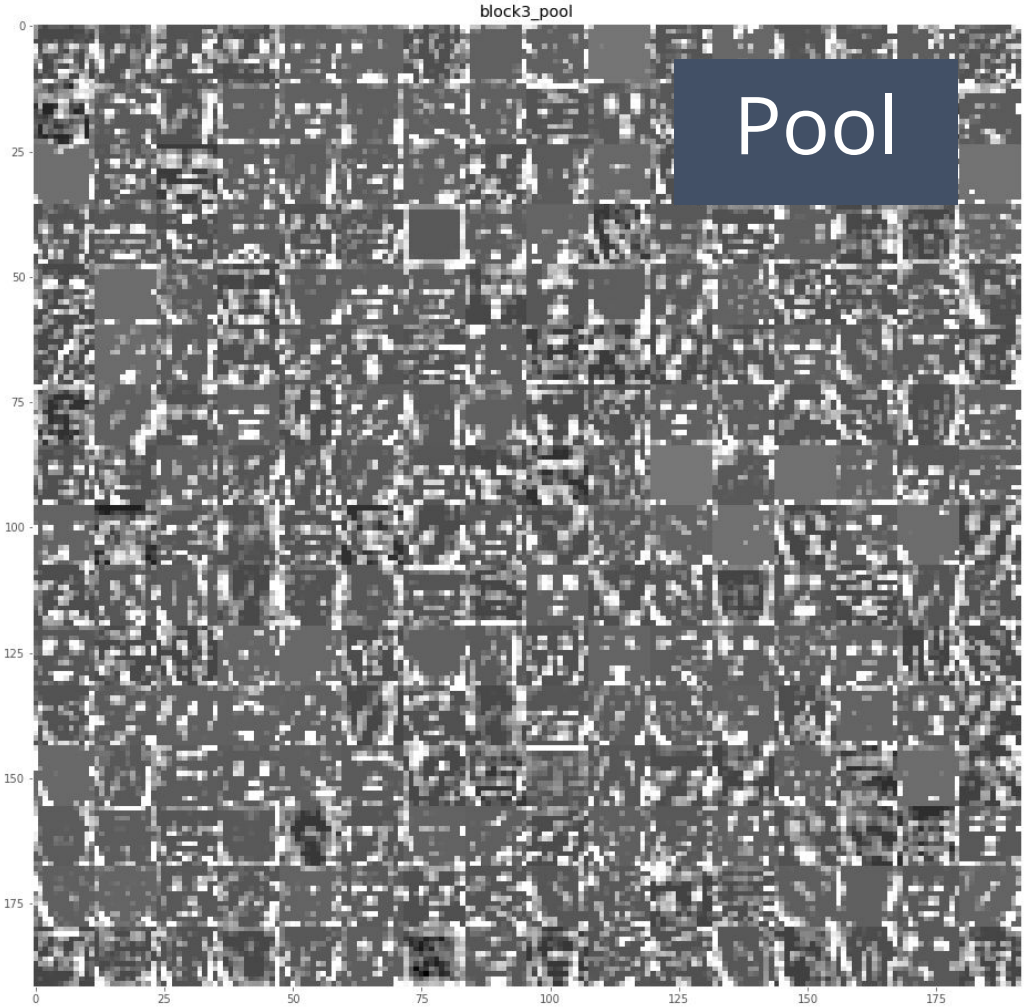

block2_pool
0
25
50
75
100
125
150
175
0
50
100
150
200
250
300
350
Pool

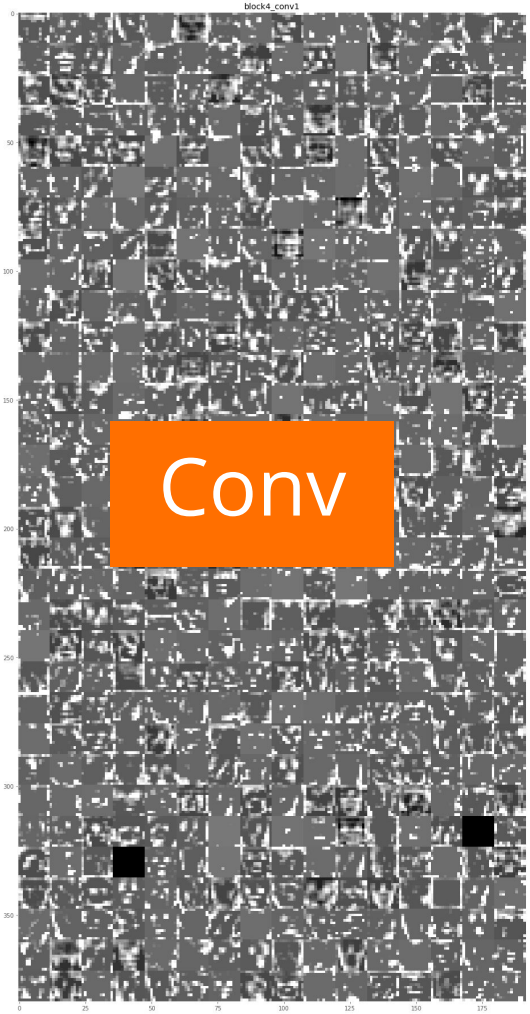

block3_conv1
Conv
0
50
100
150
200
250
300
350
0
50
100
150
200
250
300
350


block3_conv2
Conv
0
50
100
150
200
250
300
350
0
50
100
150
200
250
300
350

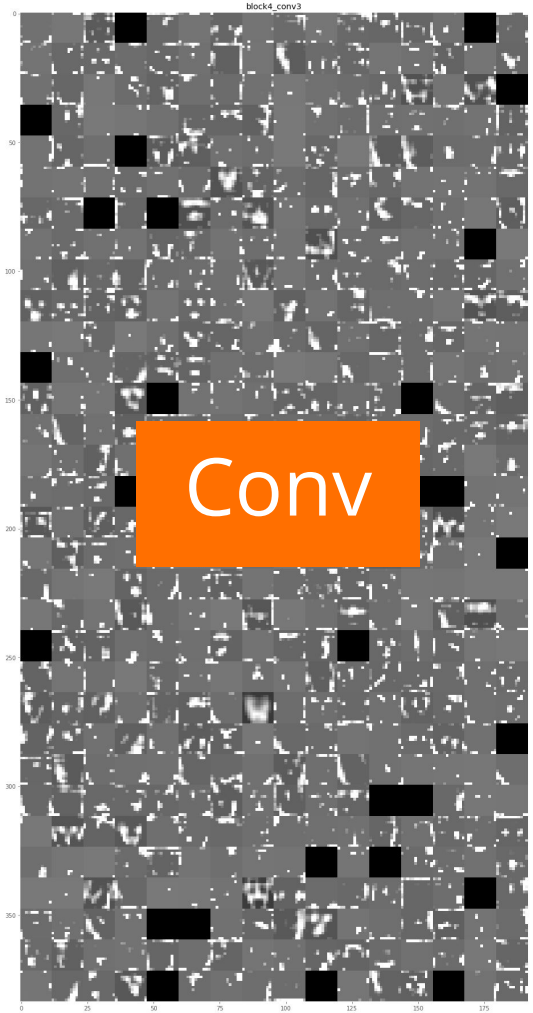


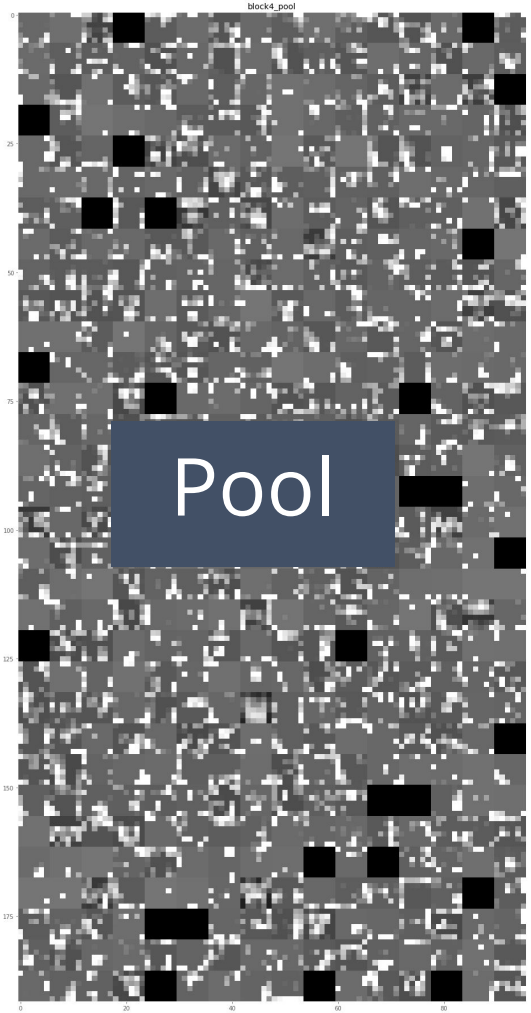
You can kinda see a face or facial features.


block3_pool
0
25
50
75
100
125
150
175
Pool

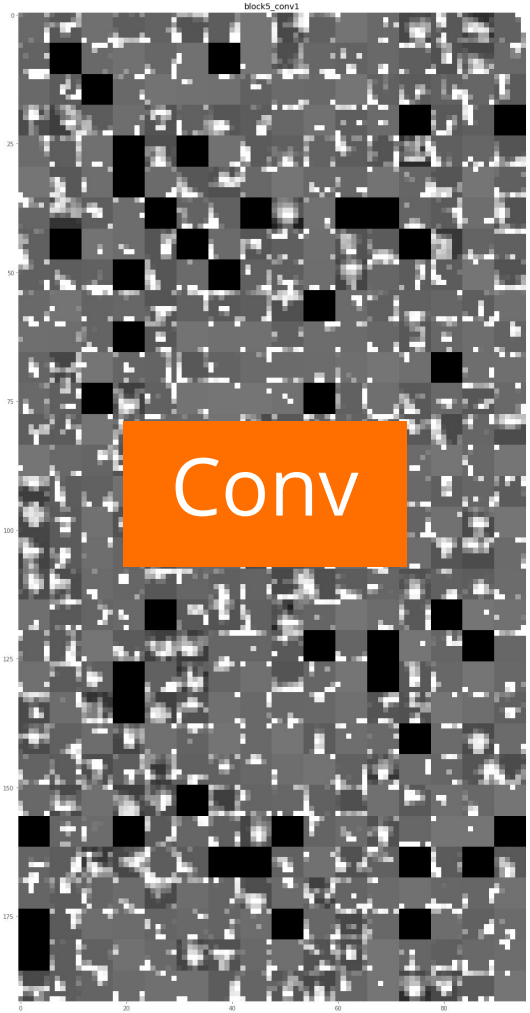

block4_conv1
Conv

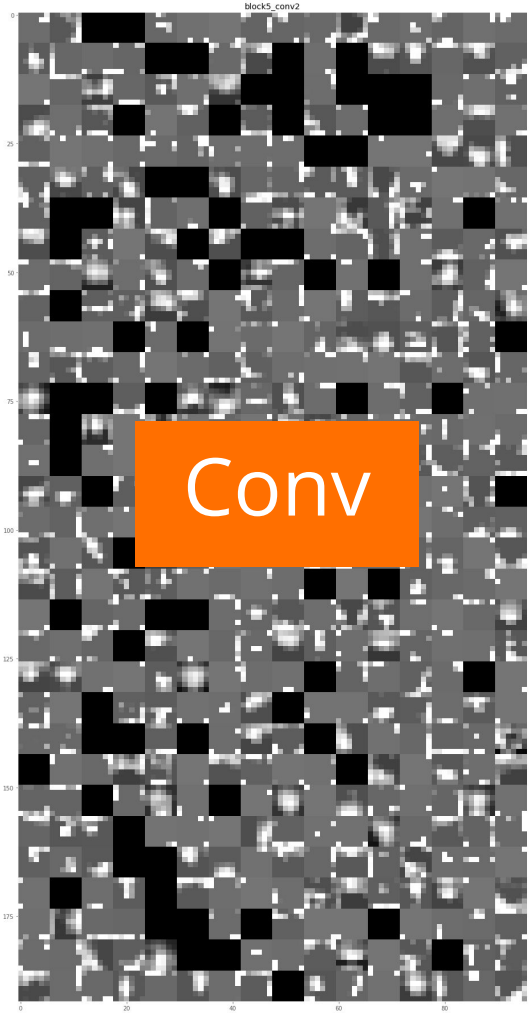

block4_conv2
Conv





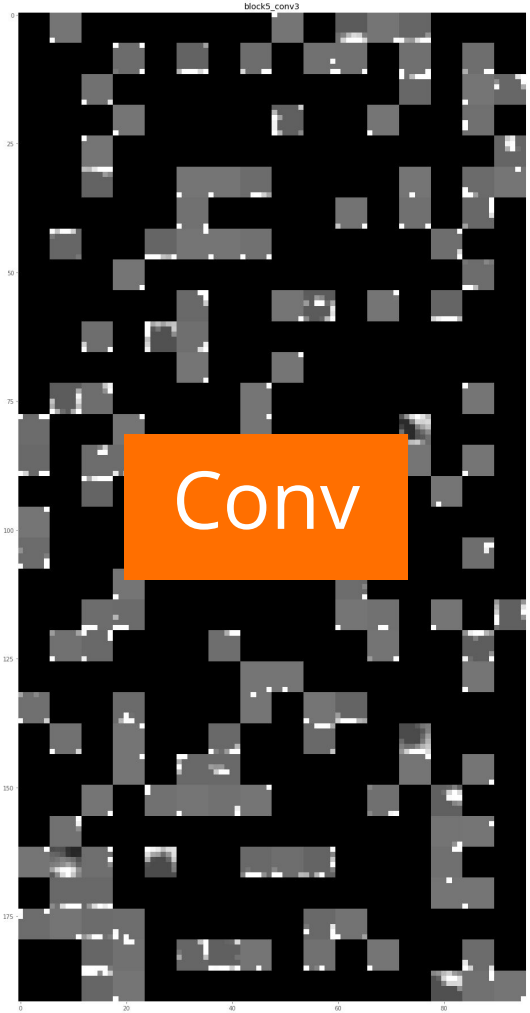
Now, each image is hardly a face.

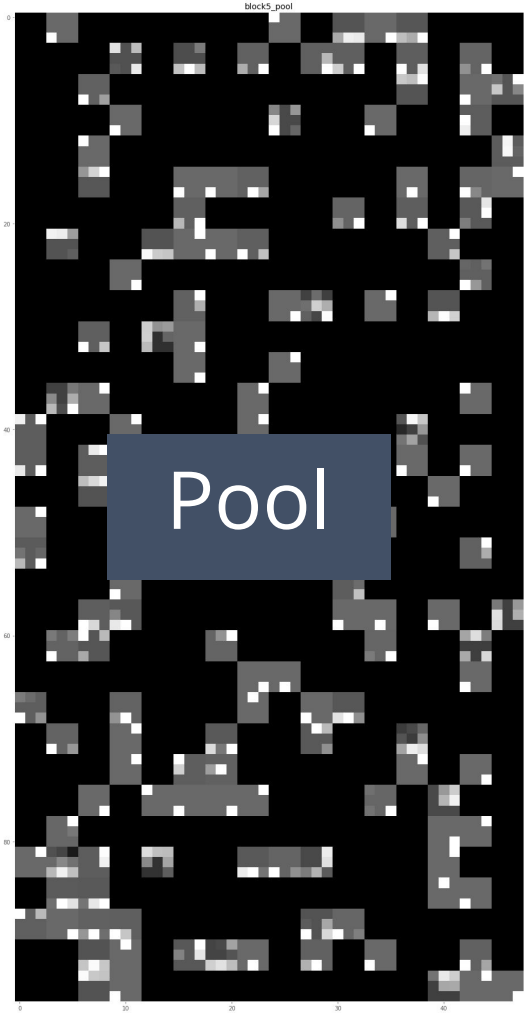

block5_conv1
Conv

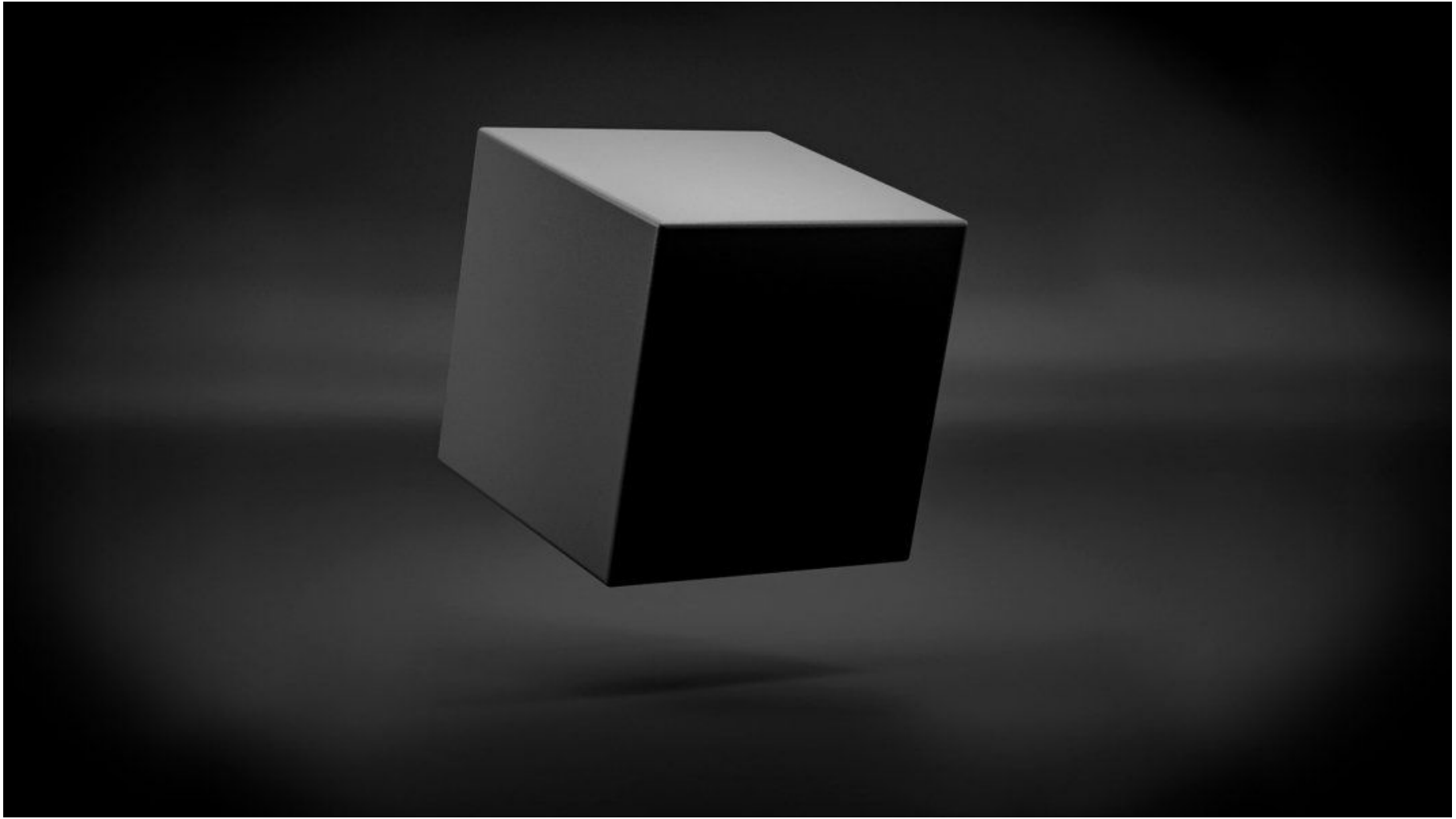

block5_conv2
Conv

Each "image" less meaningful to humans.

Closer to vectors of numbers, not images.







CNN Models

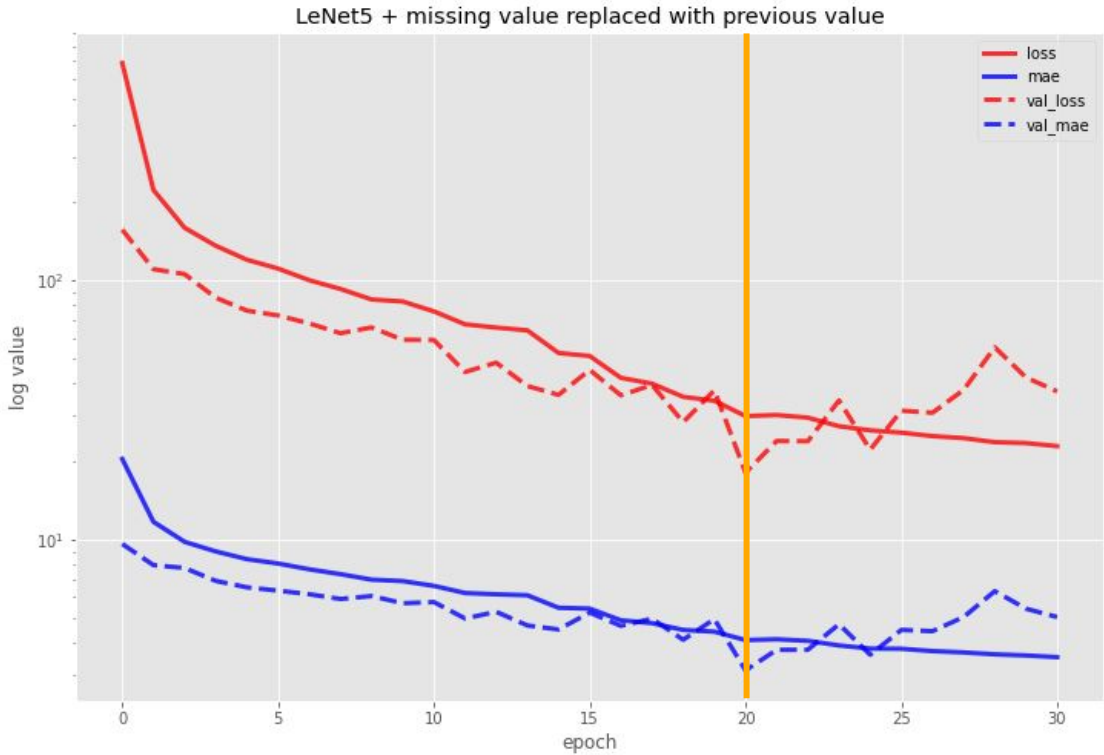
Sang

Procedure

- Neural Network weights are randomized in the beginning, bad initial values may lead to high loss
- Created and trained 50 models for each variant
  - For each model, train up to 200 epochs
  - Use an callback to save check points at each epoch, and to track the lowest val_loss achieved for the variant
  - Use an EarlyStopping callback to stop training early and prevent overfitting
  - Use regularization technique (drop-out) to prevent overfitting
  - Use Adam optimizer to speed up the convergence
- Used the weights at the epoch that had the minimal val_loss
- 6000 data points used from training set for training, remaining 1039 from the training set divided between training validation and final evaluation set.

LeNet-5 & ffill() Missing Data

- Reached min val_loss at epoch 20
- Best performance during training:
  - loss ≈ 29.92
  - mae ≈ 4.08
  - val_loss ≈ 18.10
  - val_mae ≈ 3.12
- Evaluation of final model:
  - loss ≈ 20.01
  - MAE ≈ 3.29

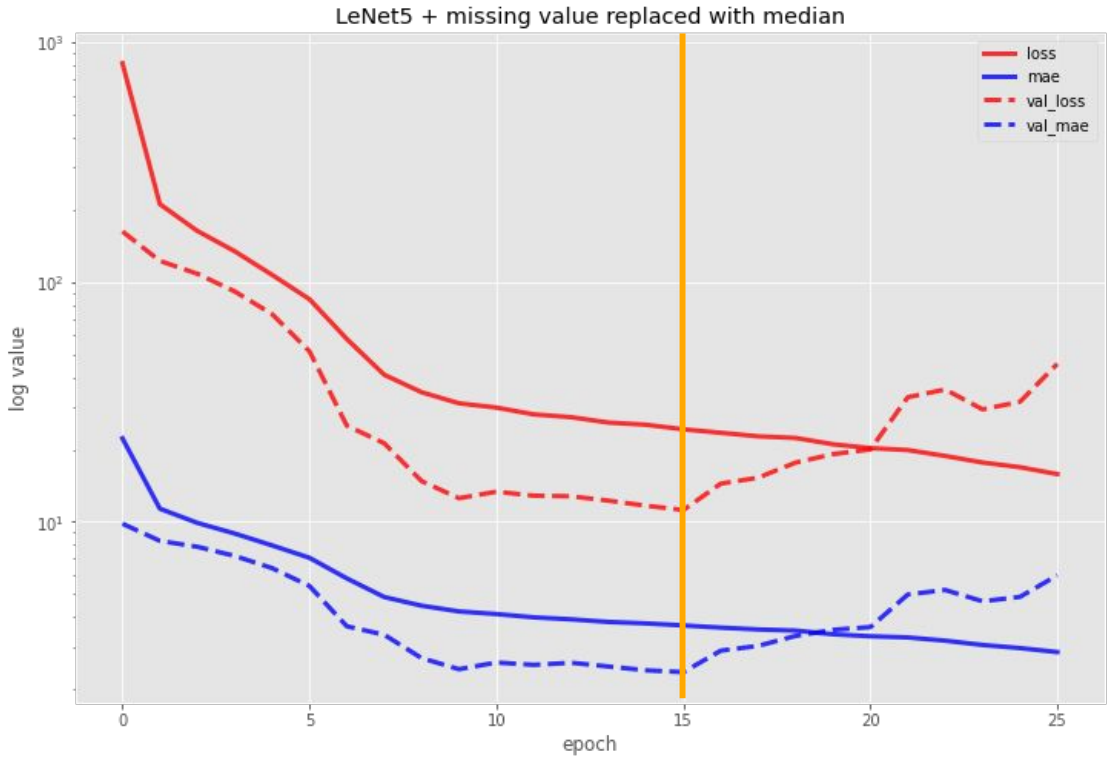


LeNet-5 & ffill()

- Dev output (contains filled missing values)
- Predicted output

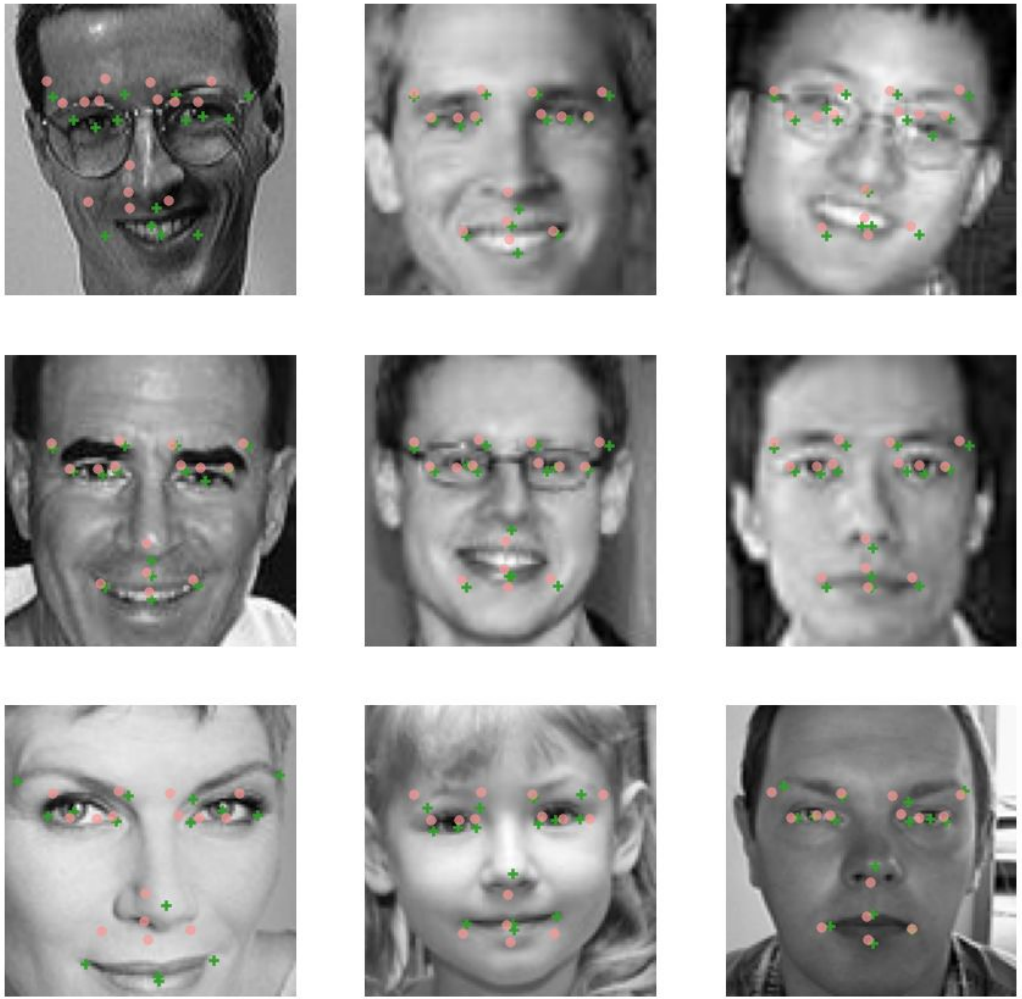
LeNet-5 & Using Median for Missing Data

- Reached min val_loss at epoch 15
- Best performance during training:
  - loss ≈ 24.29
  - mae ≈ 3.69
  - val_loss ≈ 11.19
  - val_mae ≈ 2.36
- Evaluation of final model:
  - loss ≈ 13.61
  - MAE ≈ 2.52



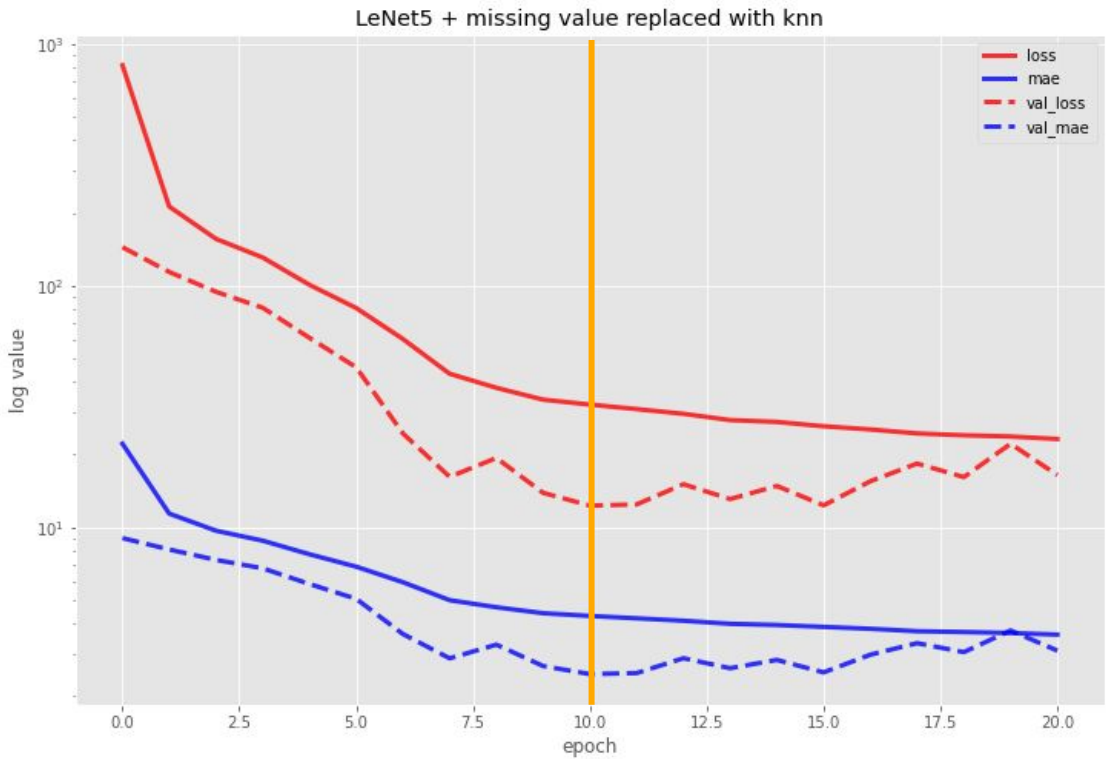
LeNet-5 & median

- Dev output (contains filled missing values)
- Predicted output



LeNet-5 & Using KNN to Fill Missing Data

- Reached min val_loss at epoch 10
- Best performance during training:
  - loss ≈ 32.22
  - mae ≈ 4.30
  - val_loss ≈ 12.30
  - val_mae ≈ 2.47
- Evaluation of final model:
  - loss ≈ 19.95
  - MAE ≈ 2.83

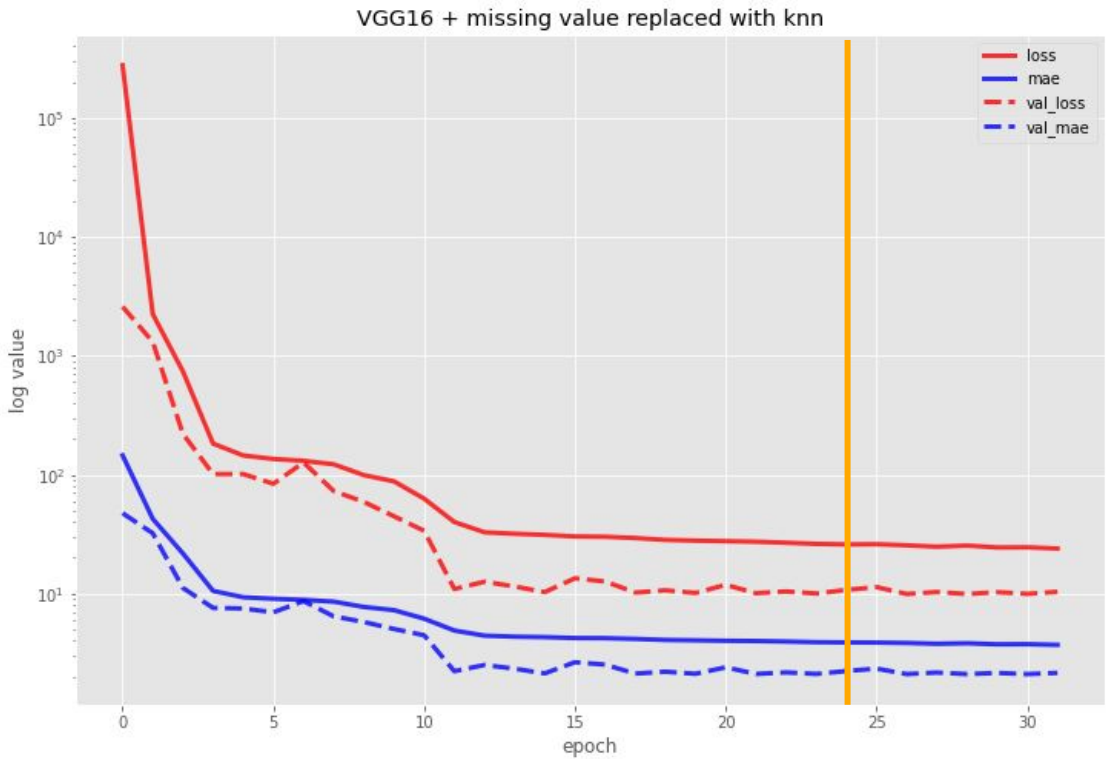


LeNet-5 & KNN

- Dev output (contains filled missing values)
- Predicted output

VGG-16 + KNN

- Reached min val_loss at epoch 24
- Best performance during training:
  - loss ≈ 28.19
  - mae ≈ 3.99
  - val_loss ≈ 9.79
  - val_mae ≈ 2.10
- Evaluation of final model:
  - loss ≈ 13.17
  - MAE ≈ 2.26

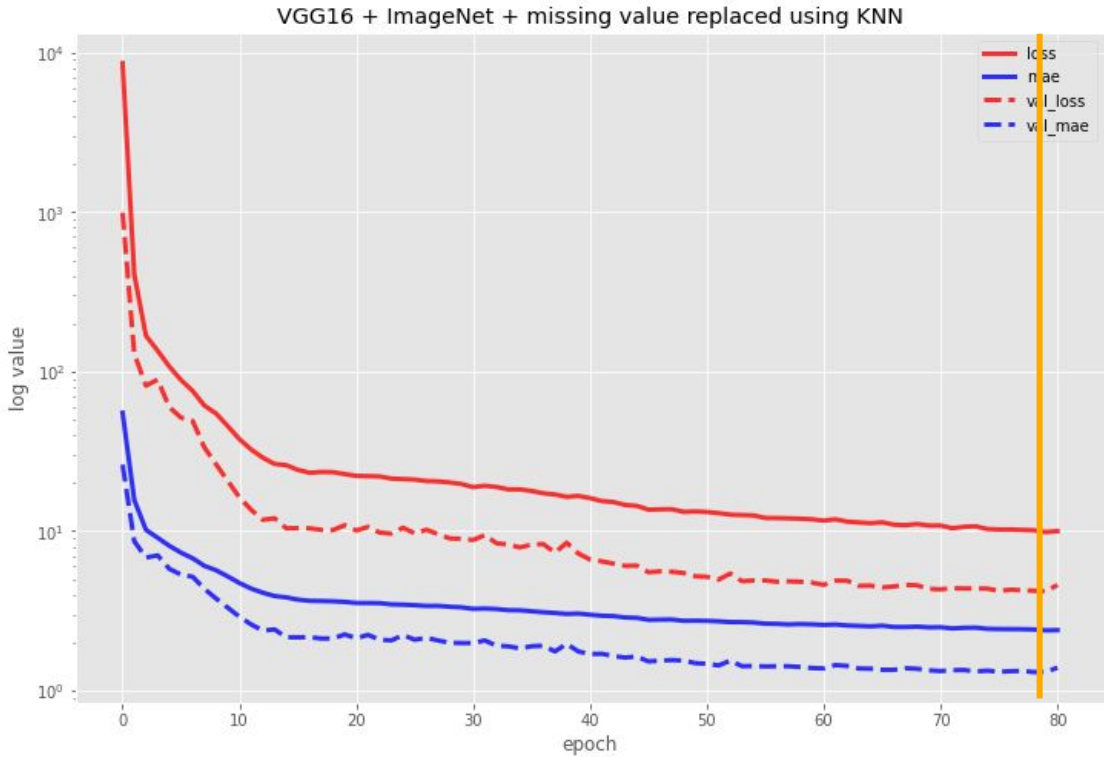


VGG16 & KNN

- Dev output (contains filled missing values)
- Predicted output

VGG-16 + Transfer Learning + KNN

- Reached min val_loss at epoch 79
- Best performance during training:
  - loss ≈ 9.86
  - mae ≈ 2.39
  - val_loss ≈ 4.20
  - val_mae ≈ 1.31
- Evaluation of final model:
  - loss ≈ 4.37
  - MAE ≈ 1.32

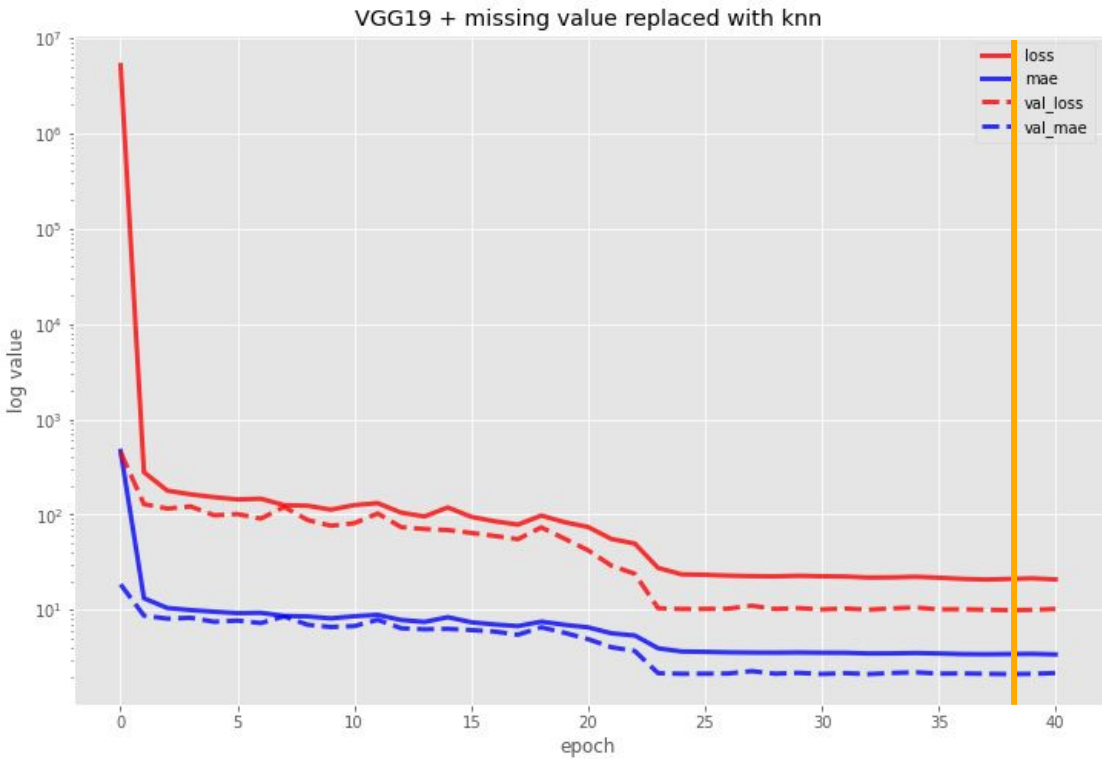


VGG16+Image Net & KNN

- Dev output (contains filled missing values)
- Predicted output

VGG-19 + KNN

- Reached min val_loss at epoch 38
- Best performance during training:
  - loss ≈ 21.06
  - mae ≈ 3.43
  - val_loss ≈ 9.92
  - val_mae ≈ 2.11
- Evaluation of final model:
  - loss ≈ 13.18
  - MAE ≈ 2.28

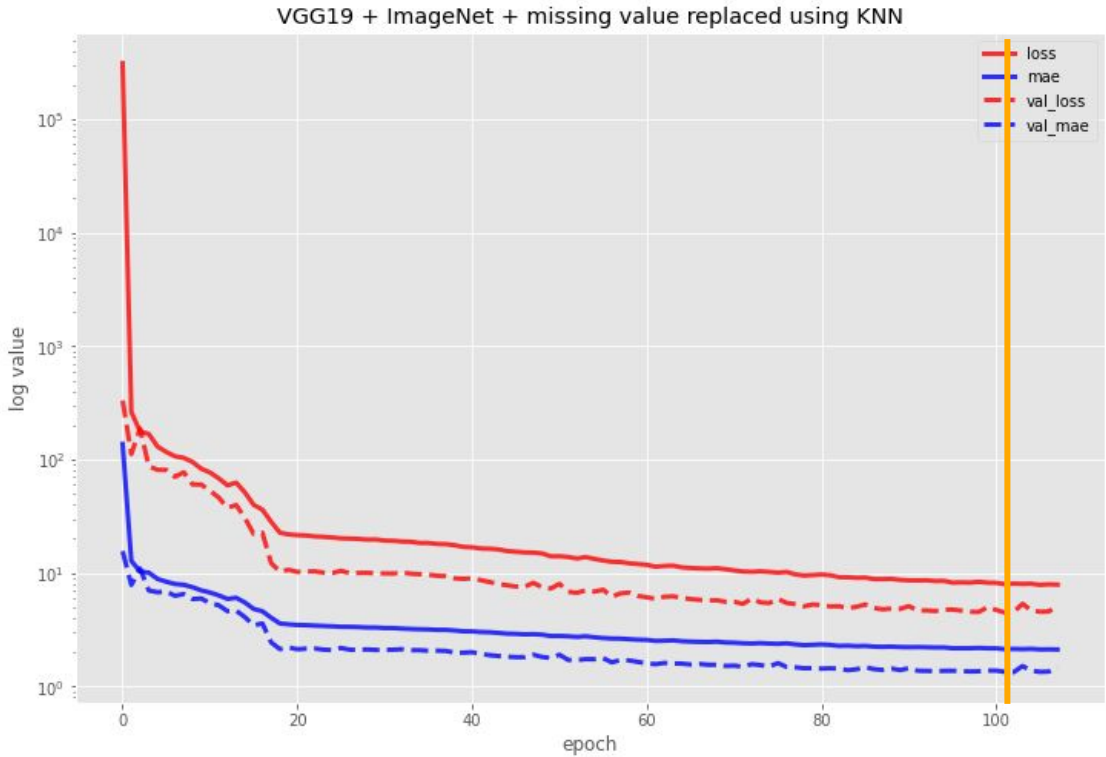


VGG19+Image Net & KNN

- Dev output (contains filled missing values)
- Predicted output

VGG-19 + Transfer Learning + KNN

- Reached min val_loss at epoch 101
- Best performance during training:
  - loss ≈ 7.96
  - mae ≈ 2.13
  - val_loss ≈ 4.47
  - val_mae ≈ 1.34
- Evaluation of final model:
  - loss ≈ 4.29
  - MAE ≈ 1.34



VGG19+Image Net & KNN

- Dev output (contains filled missing values)
- Predicted output

Baseline

Julia

Baseline

KNN regression (k = 9)

- Evaluated on entire dev output
  - MSE ≈ 11.32
  - MAE ≈ 1.97
- Evaluated on original data only
  - MSE ≈ 17.24
  - MAE ≈ 2.43

Performance Summary

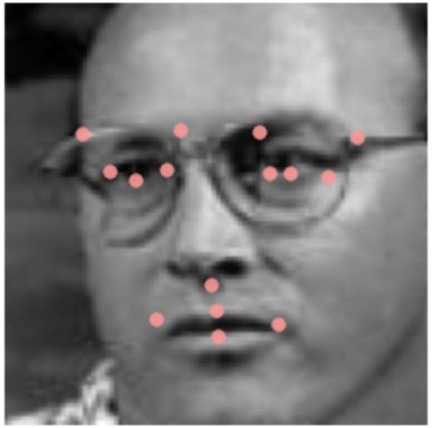
Model	KNN	LeNet5			VGG16		VGG19	
transfer learning	-	-	-	-	-	Yes	-	Yes
missing data	KNN	ffill	median	KNN	KNN	KNN	KNN	KNN
# of epochs	-	20	15	10	24	79	38	101
train loss (MSE)	-	29.92	24.29	32.22	28.19	9.86	21.06	7.96
train val_loss	-	18.10	11.19	12.30	9.79	4.20	9.92	4.47
dev val_loss	17.24	20.01	13.61	19.95	13.17	4.37	13.18	4.29

Data Augmentation

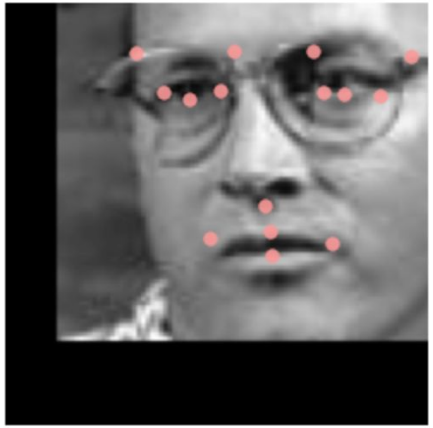
Data Augmentation

- Data Augmentation preprocesses images to create more unique training data
- Challenge: Keras's ImageDataGenerator() class does not transform Y
- Solution: custom generator class that also processes keypoint coordinates

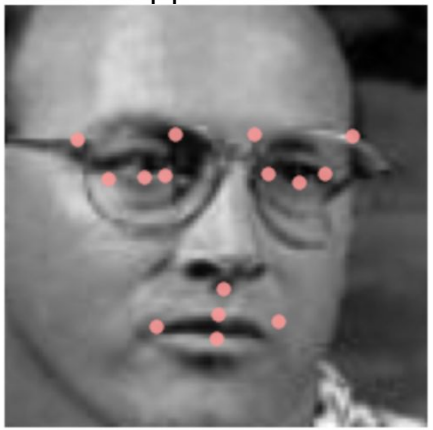
No change



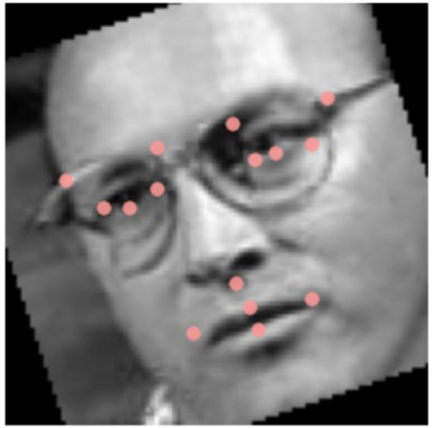
Shifted



Flipped

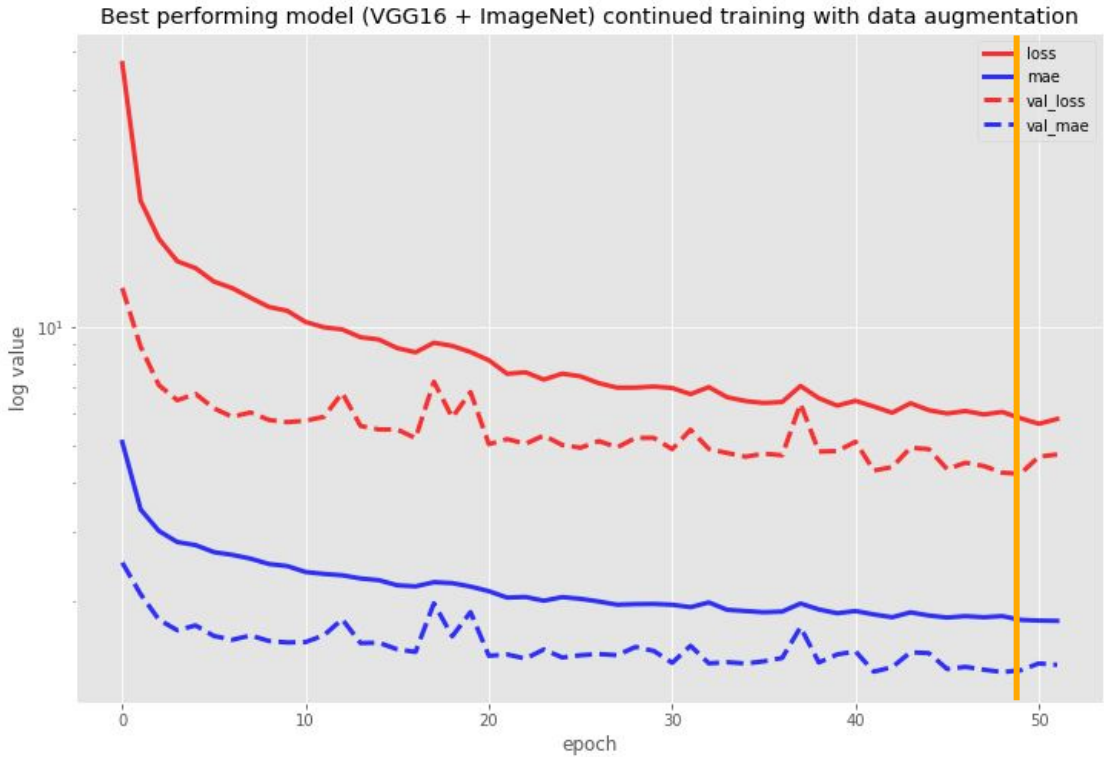


Rotated



VGG-16 + Transfer Learning + Data Augmentation

- Reached min loss_val at epoch 49
- Best performance during training:
  - loss ≈ 5.85
  - mae ≈ 1.80
  - val_loss ≈ 4.23
  - val_mae ≈ 1.34
- Dev set performance:
  - loss ≈ 3.97
  - MAE ≈ 1.33

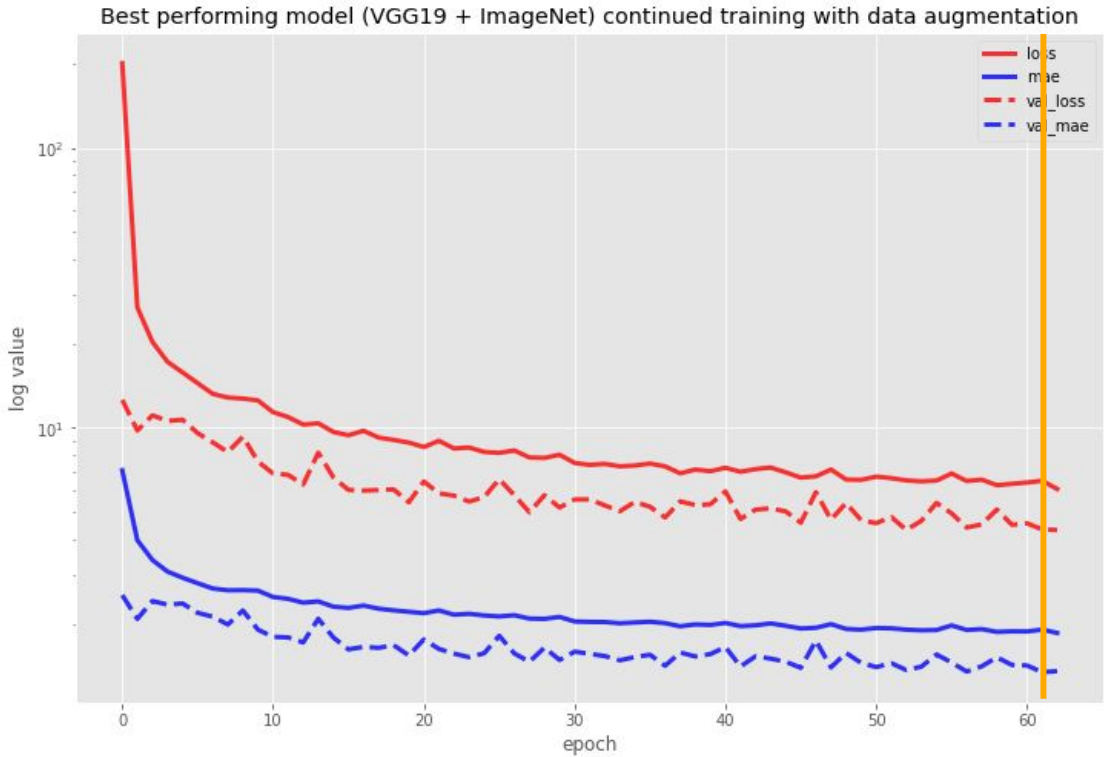


VGG-16 + Transfer Learning + Data Augmentation

- Dev output (contains filled missing values)
- Predicted output

VGG-19 + Transfer Learning + Data Augmentation

- Reached min loss_val at epoch 62
- Best performance during training:
  - loss ≈ 6.05
  - mae ≈ 1.86
  - val_loss ≈ 4.32
  - val_mae ≈ 1.35
- Dev set performance:
  - loss ≈ 4.31
  - MAE ≈ 1.35

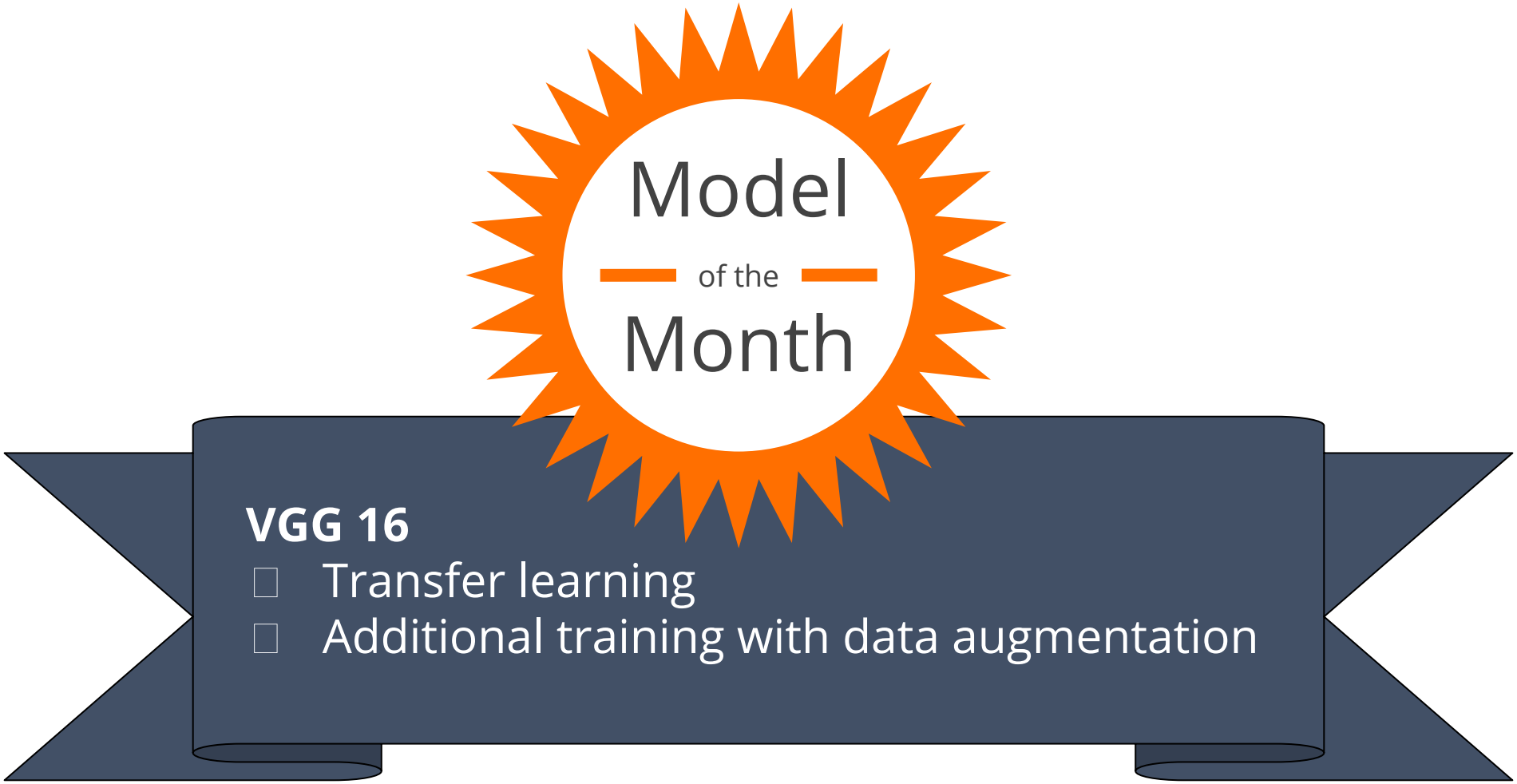


VGG-19 + Transfer Learning + Data Augmentation

- Dev output (contains filled missing values)
- Predicted output

Performance Summary

Model	VGG16		VGG19	
transfer learning	Yes	Yes	Yes	Yes
missing data	KNN	KNN	KNN	KNN
data augmentation	-	Yes	-	Yes
# of epochs	79	49	101	62
train loss (MSE)	9.86	5.85	7.96	6.05
train val_loss	4.20	4.23	4.47	4.32
dev val_loss	4.37	3.97	4.29	4.31


Model
of the
Month
VGG 16
Transfer learning
Additional training with data augmentation

How Well Does It Work?

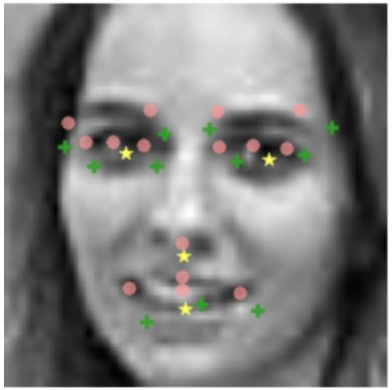
Error Analysis

- Challenge: some of the large errors is when the model gets it right, but the training key point coordinates were missing and filled erroneously

★ Original kp data from kaggle

✚ Extrapolated data to fill missing kps

● CNN predicted output



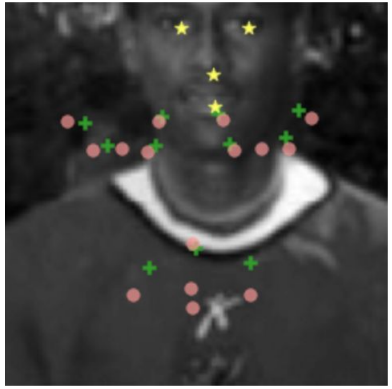
Error Analysis

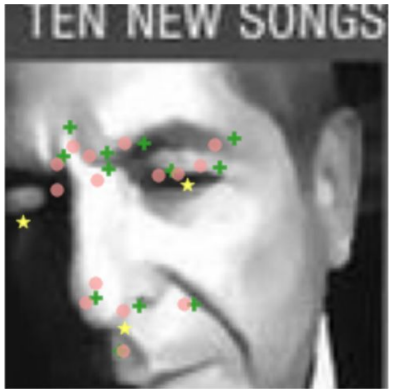
- Solution: manually calculate MSE for only the keypoint coordinates from original dataset, exclude any filled in coordinates
    - We discovered 2 images where the original data from kaggle was incorrect

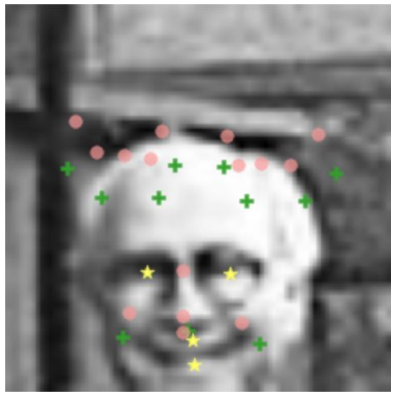
★ Original kp data from kaggle

Error Analysis

- Many common images across all models, mostly faces far off center
- Extrapolating the missing points to complete training output also performed poorly







★ Original kp data from kaggle

✚ Extrapolated data to fill missing kps

● CNN predicted output

Error Analysis: VGG

- VGG16/VGG19 tend to have a hard time with highly pixelated images
- Extrapolated missing points were relatively closer to actual locations
- May be able to address this by adding in blurring to training data

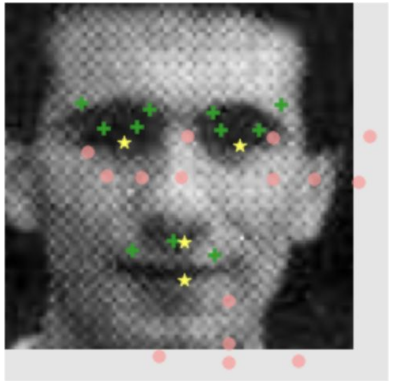
Original kp data from kaggle

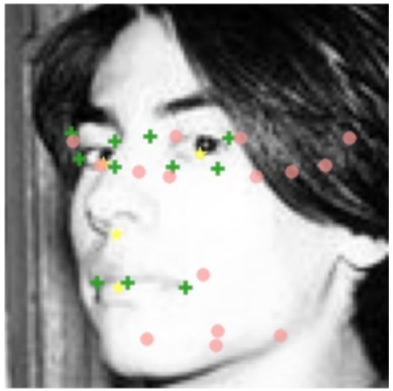
Extrapolated data to fill missing kps

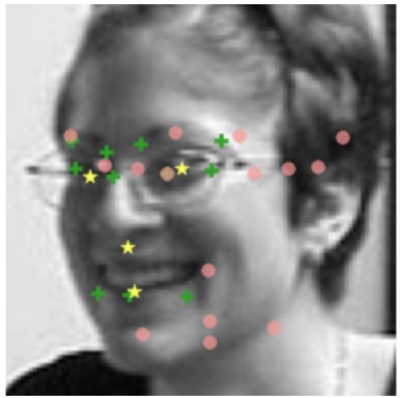
CNN predicted output

Error Analysis: LeNet5

- LeNet5 has difficulty with highly pixelated images as well
- Also have trouble with images with padded edges
- More problems with tilted faces comparing to VGG16/VGG19







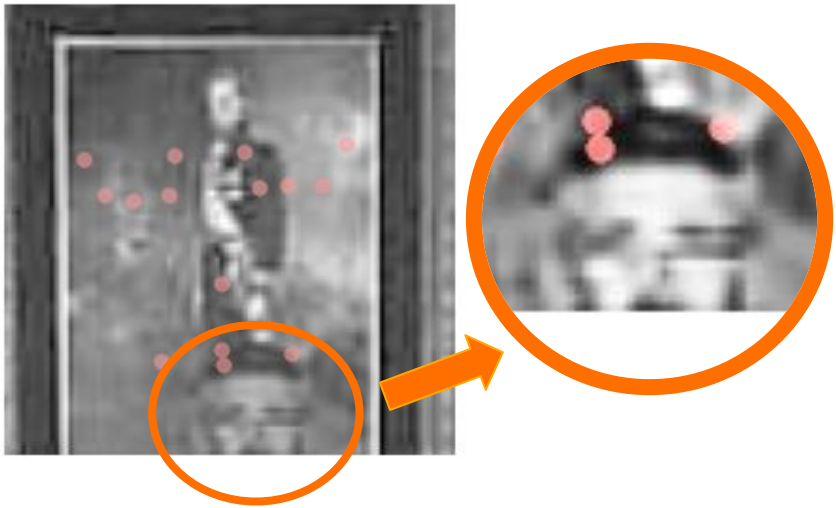
Original kp data from kaggle

Extrapolated data to fill missing kps

CNN predicted output

Test Set Results 💯

Test Set Results



🆗 on drawings

👎 on adversarial images

Show Time!

Here's a web app. Try it!
http://doctortensorflow.pythonanywhere.com/

References

- Numerous Coursera classes by Andrew Ng
- https://medium.com/@pechyonkin/key-deep-learning-architectures-lenet-5-6fc3c59e6f4
- https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5
- https://towardsdatascience.com/understand-the-architecture-of-cnn-90a25e244c7
- Black box image source: https://singularityhub.com/2019/04/17/in-defense-of-black-box-ai/
- Cherry on top image: https://www.flickr.com/photos/sharisberries/19440746753