

# 3dcarprojection

December 7, 2019

Yesterday, I read this [recent article on medium about facial keypoint detection](#). The article suggests that deep learning methods can easily be used to perform this task. It ends by suggesting that everyone should try it, since the data needed and the toolkits are all open source. This article is my attempt, since I've been interested in face detection for a long time and [written about it before](#).

This is the outline of what we'll try:

- loading the data
- analyzing the data
- building a Keras model
- checking the results
- applying the method to a fun problem

## 1 Loading the data

The data we will use comes from a [Kaggle challenge](#) called *Facial Keypoints Detection*. I've downloaded the .csv file and put it in a *data/* directory. Let's use pandas to read it.

```
In [2]: import pandas as pd
```

```
In [3]: df = pd.read_csv('vehiclereid_baseline/test1.txt', sep=",", header=None)
```

```
In [4]: df.head()
```

```
Out[4]:
```

		0	1	2	3	4	5	6	7	\
0	VeRi/image_train/0181_c001_00034295_0.jpg	-1	-1	-1	-1	367	89	190		
1	VeRi/image_train/0181_c001_00034315_0.jpg	-1	-1	-1	-1	231	58	153		
2	VeRi/image_train/0181_c001_00034340_0.jpg	-1	-1	-1	-1	130	56	114		
3	VeRi/image_train/0181_c012_00034760_0.jpg	-1	-1	-1	-1	213	71	163		
4	VeRi/image_train/0181_c012_00034765_0.jpg	-1	-1	-1	-1	192	66	151		

	8	9	...	32	33	34	35	36	37	38	39	40	41
0	205	-1	...	77	14	148	91	180	44	160	46	176	7
1	132	-1	...	32	14	94	108	108	55	100	58	114	7
2	92	-1	...	19	18	64	96	69	55	62	54	72	7
3	141	-1	...	44	22	100	123	113	67	106	70	123	7
4	124	-1	...	36	25	89	116	97	68	93	73	108	7

[5 rows x 42 columns]

```
In [5]: df.shape
```

```
Out[5]: (499, 42)
```

## 2 Analyzing the data

The Image column contains the face data for which the 30 first columns represent the keypoint data (15 x-coordinates and 15 y-coordinates). Let's try to get a feel for the data. First, let's display some faces.

```
In [6]: import numpy as np
import matplotlib.pyplot as plt
import cv2
%matplotlib inline
```

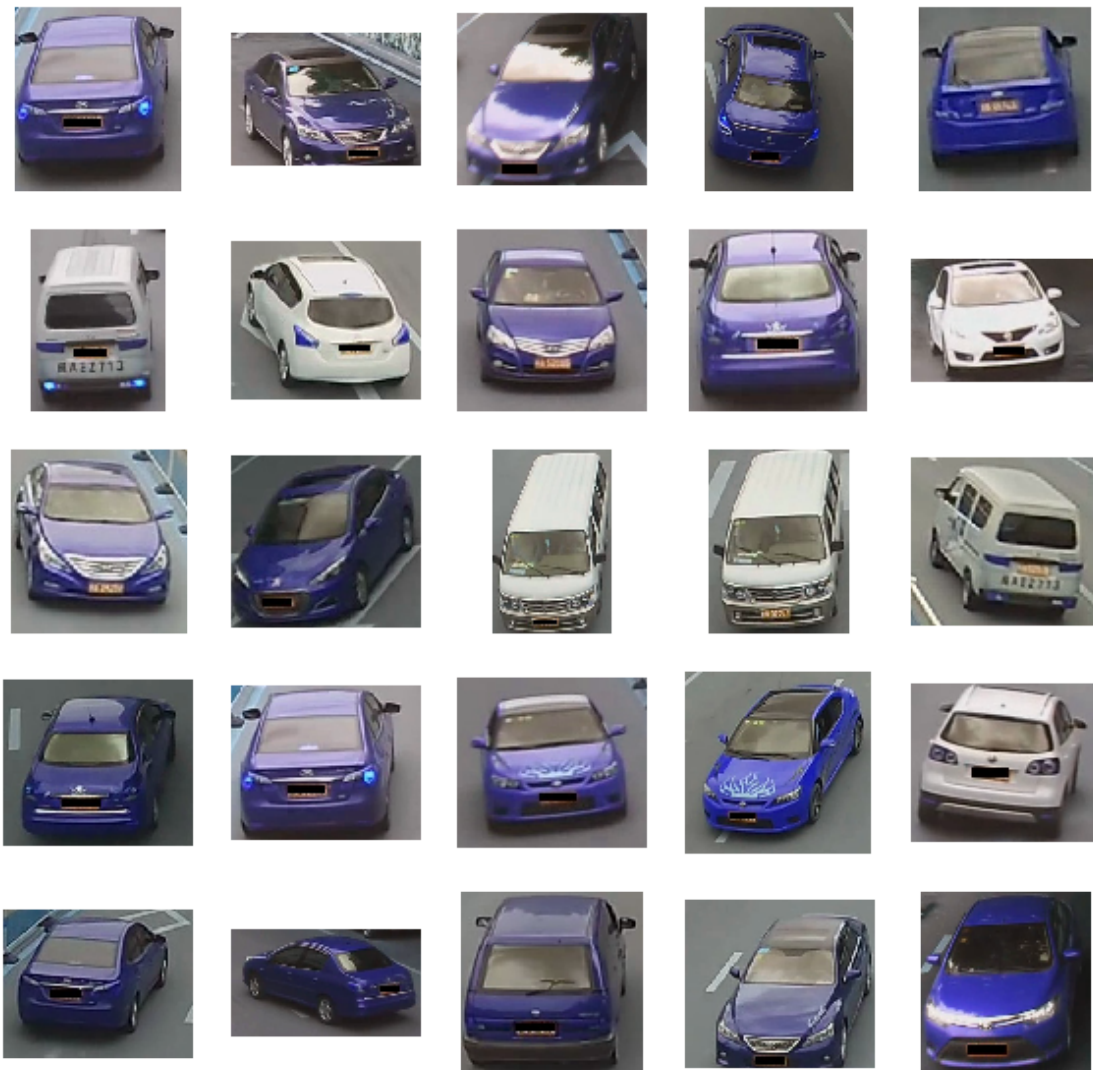
```
In [40]: def string2image(string):
    """Converts a string to a numpy array."""
    img = cv2.imread(string)
    #img = cv2.resize(img, (336, 336))
    return img
    #return np.array([int(item) for item in string.split()]).reshape((96, 96))

def plot_faces(nrows=5, ncols=5):
    """Randomly displays some faces from the training data."""
    selection = np.random.choice(df.index, size=(nrows*ncols), replace=False)
    image_strings = df.loc[selection][0]
    fig, axes = plt.subplots(figsize=(10, 10), nrows=nrows, ncols=ncols)
    for string, ax in zip(image_strings, axes.ravel()):
        print(string)
        ax.imshow(string2image(string), cmap='gray')
        ax.axis('off')
```

```
In [41]: plot_faces()
```

```
VeRi/image_train/0181_c014_00036570_0.jpg
VeRi/image_train/0185_c009_00042525_0.jpg
VeRi/image_train/0185_c008_00042440_0.jpg
VeRi/image_train/0189_c010_00003830_0.jpg
VeRi/image_train/0191_c017_00031640_0.jpg
VeRi/image_train/0297_c014_00077460_0.jpg
VeRi/image_train/0293_c006_00001500_0.jpg
VeRi/image_train/0181_c013_00034610_0.jpg
VeRi/image_train/0190_c014_00005570_0.jpg
VeRi/image_train/0293_c009_00000425_0.jpg
VeRi/image_train/0184_c015_00016750_0.jpg
VeRi/image_train/0189_c017_00000755_0.jpg
VeRi/image_train/0287_c001_00033100_0.jpg
VeRi/image_train/0287_c001_00033080_0.jpg
```

VeRi/image\_train/0297\_c015\_00068010\_0.jpg  
 VeRi/image\_train/0190\_c017\_00072295\_0.jpg  
 VeRi/image\_train/0181\_c014\_00036580\_0.jpg  
 VeRi/image\_train/0191\_c019\_00031820\_0.jpg  
 VeRi/image\_train/0191\_c010\_00027390\_0.jpg  
 VeRi/image\_train/0289\_c002\_00049960\_0.jpg  
 VeRi/image\_train/0181\_c012\_00034775\_0.jpg  
 VeRi/image\_train/0190\_c019\_00004155\_0.jpg  
 VeRi/image\_train/0194\_c003\_00052155\_0.jpg  
 VeRi/image\_train/0185\_c010\_00043035\_0.jpg  
 VeRi/image\_train/0186\_c008\_00035660\_0.jpg



Let's now add to that plot the facial keypoints that were tagged. First, let's do an example :

```
In [9]: keypoint_cols = list(df.columns)[1:-1]
```

```
In [10]: def xy_plotfilter(xy):
          y = np.empty((0,2))

          for x in xy:
              if x[0]!=-1 and x[1]!=-1:
                  y = np.append(y,[x],axis=0)
          return y

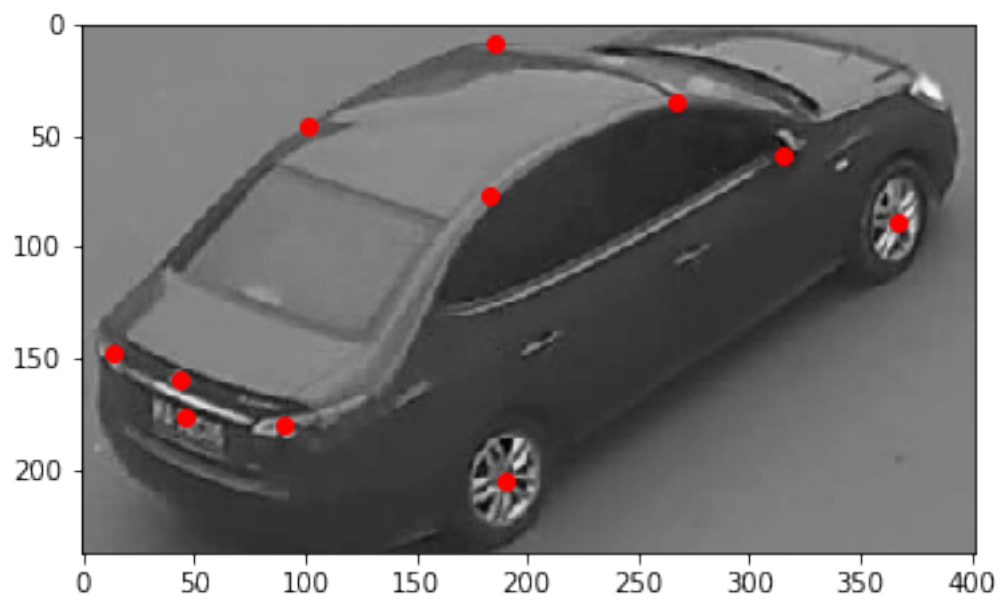
In [11]: xy = df.iloc[0][keypoint_cols].values.reshape((20, 2))

          xy = xy_plotfilter(xy)
          print(xy)
```

```
[[367 89]
 [190 205]
 [315 59]
 [267 35]
 [185 8]
 [101 46]
 [183 77]
 [14 148]
 [91 180]
 [44 160]
 [46 176]]
```

```
In [12]: plt.plot(xy[:, 0], xy[:, 1], 'ro')
          plt.imshow(string2image(df.iloc[0][0]), cmap='gray')
```

```
Out[12]: <matplotlib.image.AxesImage at 0x7fab04ebc400>
```



Now, let's add this to the function we wrote before.

```
In [13]: def plot_faces_with_keypoints(nrows=5, ncols=5):
        """Randomly displays some faces from the training data with their keypoints."""
        selection = np.random.choice(df.index, size=(nrows*ncols), replace=False)
        image_strings = df.loc[selection][0]
        keypoint_cols = list(df.columns)[1:-1]
        keypoints = df.loc[selection][keypoint_cols]
        fig, axes = plt.subplots(figsize=(10, 10), nrows=nrows, ncols=ncols)
        for string, (iloc, keypoint), ax in zip(image_strings, keypoints.iterrows(), axes):
            xy = keypoint.values.reshape((20, 2))
            xy = xy_plotfilter(xy)
            ax.imshow(string2image(string), cmap='gray')
            ax.plot(xy[:, 0], xy[:, 1], 'ro')
            ax.axis('off')

In [14]: plot_faces_with_keypoints()
```



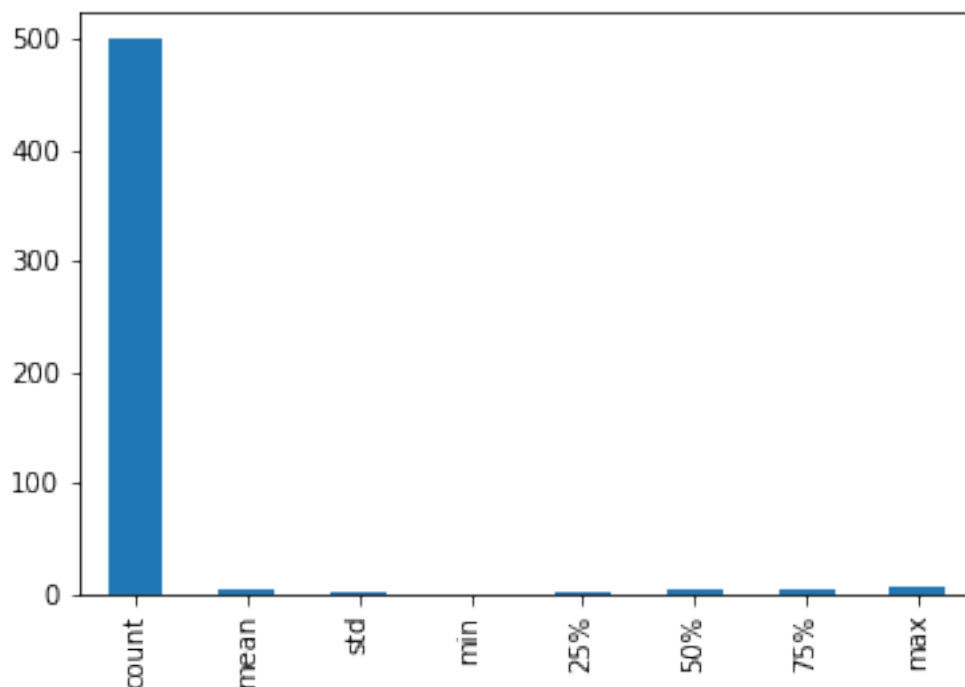
We can make several observations from this image:

- some images are high resolution, some are low
- some images have all 15 keypoints, while some have only a few

Let's do some statistics about the keypoints to investigate that last observation :

```
In [15]: df.describe().loc[:][41].plot.bar()
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fab0454ab38>
```



What this plot tells us is that in this dataset, only 2000 images are "high quality" with all keypoints, while 5000 other images are "low quality" with only 4 keypoints labelled.

Let's start training the data with the high quality images and see how far we get.

```
In [16]: fully_annotated = df.dropna()
```

```
In [17]: fully_annotated.shape
```

```
Out[17]: (499, 42)
```

```
In [18]: fully_annotated.head()
```

```
Out[18]:
```

		0	1	2	3	4	5	6	7	\
0	VeRi/image_train/0181_c001_00034295_0.jpg	-1	-1	-1	-1	367	89	190		
1	VeRi/image_train/0181_c001_00034315_0.jpg	-1	-1	-1	-1	231	58	153		
2	VeRi/image_train/0181_c001_00034340_0.jpg	-1	-1	-1	-1	130	56	114		
3	VeRi/image_train/0181_c012_00034760_0.jpg	-1	-1	-1	-1	213	71	163		
4	VeRi/image_train/0181_c012_00034765_0.jpg	-1	-1	-1	-1	192	66	151		

	8	9	...	32	33	34	35	36	37	38	39	40	41
0	205	-1	...	77	14	148	91	180	44	160	46	176	7
1	132	-1	...	32	14	94	108	108	55	100	58	114	7
2	92	-1	...	19	18	64	96	69	55	62	54	72	7
3	141	-1	...	44	22	100	123	113	67	106	70	123	7
4	124	-1	...	36	25	89	116	97	68	93	73	108	7

```
[5 rows x 42 columns]
```

### 3 Building a Keras model

Now on to the machine learning part. Let's build a Keras model with our data. Actually, before we do that, let's do some preprocessing first, using the scikit-learn pipelines (inspired by [this great post on scalable Machine Learning by Tom Augspurger](#)).

The idea behind pipelining is that it allows you to easily keep track of the data transformations applied to our data. We need two scalings: one for the input and one for the output. Since I couldn't get the scaling to work for 3d image data, we will only use a pipeline for our outputs.

```
In [19]: X = []
         i = 0
         y = np.vstack(fully_annotated[fully_annotated.columns[1:-1]].values)
         for string in fully_annotated[:,0]:
             img = string2image(string)
             for j in range(0,40,2):
                 if y[i][j] != -1:
                     y[i][j] = y[i][j] / img.shape[1] * 336
                 if y[i][j+1] != -1:
                     y[i][j+1] = y[i][j+1] / img.shape[0] * 336
             img = cv2.resize(img,(336,336))
             X.append(img)
             #print(img.shape)
             #X = np.stack((X,[img])).astype(np.float)[:,:,:,: , np.newaxis]
             #X = np.concatenate((X,img)).astype(np.float)[:,:,:,: , np.newaxis]
             i+=1
         X = np.array(X)
         X = X.reshape(499, 336,336,1)
         X.shape

         #X = np.stack([cv2.resize(string2image(string),(336,336)) for string in fully_annotat

Out[19]: (499, 336, 336, 1)

In [20]: for i in range(0,5):
         print(y[i])
```

```
[ -1  -1  -1  -1 306 125 158 289  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1
  -1  -1  -1  -1 263  83 223  49 154  11  84  64 152 108  11 208  76 254
 36 225  38 248]
[ -1  -1  -1  -1 318 121 210 275  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1
  -1  -1  -1  -1 291  58 236  18 128   4  82  48 196  66  19 196 148 225
 75 208  79 237]
[ -1  -1  -1  -1 314 165 275 271  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1
  -1  -1  62  50 314  64 256  20  99  14  79  50 241  56  43 188 232 203
132 182 130 212]
[ -1  -1  -1  -1 307 140 235 278  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1
  -1  -1  93  41 294  75 248  35 118  21  83  65 214  86  31 197 177 223
 96 209 100 243]
[ -1  -1  -1  -1 286 134 225 252  -1  -1  -1  -1  -1  -1  -1  -1  -1  -1
```



```
-1 -1 83 40 274 67 235 32 110 20 83 52 207 73 37 181 173 197
101 189 109 219]
```

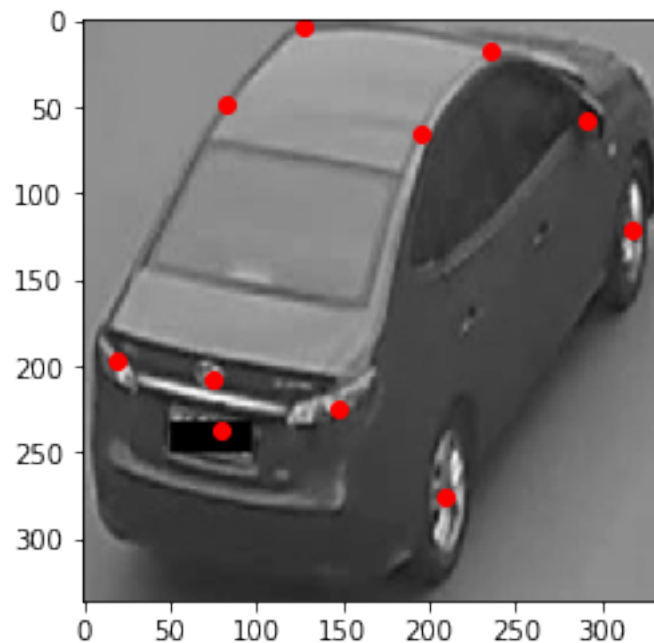
```
In [21]: xy1 = y[1].reshape((20, 2))
        xy1 = xy_plotfilter(xy1)
        xy1
```

```
Out[21]: array([[318., 121.],
               [210., 275.],
               [291., 58.],
               [236., 18.],
               [128., 4.],
               [ 82., 48.],
               [196., 66.],
               [ 19., 196.],
               [148., 225.],
               [ 75., 208.],
               [ 79., 237.]])
```

```
In [22]: #keypoint_cols = list(df.columns)[1:-1]
```

```
plt.plot(xy1[:, 0], xy1[:, 1], 'ro')
img1 = string2image(fully_annotated[:, 0][1])
img1 = cv2.resize(img1, (336, 336))
plt.imshow(img1, cmap='gray')
```

```
Out[22]: <matplotlib.image.AxesImage at 0x7fab044dbe80>
```



```
In [23]: X.shape, X.dtype
```

```
Out[23]: ((499, 336, 336, 1), dtype('uint8'))
```

```
In [24]: y.shape, y.dtype
```

```
Out[24]: ((499, 40), dtype('int64'))
```

```
In [25]: X_train = X / 255.0
```

```
In [26]: from sklearn.pipeline import make_pipeline
         from sklearn.preprocessing import MinMaxScaler
```

```
output_pipe = make_pipeline(
    MinMaxScaler(feature_range=(-1, 1))
)
```

```
y_train = output_pipe.fit_transform(y)
y_train.shape
```

```
Out[26]: (499, 40)
```

```
In [27]: for i in range(0,5):
         print(y_train[i])
```

```
[-1.          -1.          -1.          -1.          0.88343558 -0.18446602
  0.          0.84713376 -1.          -1.          -1.          -1.
 -1.          -1.          -1.          -1.          -1.          -1.
 -1.          -1.          -1.          -1.          0.6146789  -0.328
  0.47854785 -0.46236559  0.02649007 -0.87301587 -0.43143813 -0.23976608
 -0.05555556  0.26744186 -0.9266055  0.33121019 -0.53892216  0.63461538
 -0.76357827  0.65567766 -0.75316456  0.61165049]
[-1.          -1.          -1.          -1.          0.95705521 -0.21035599
  0.32704403  0.75796178 -1.          -1.          -1.          -1.
 -1.          -1.          -1.          -1.          -1.          -1.
 -1.          -1.          -1.          -1.          0.78593272 -0.528
  0.56435644 -0.79569892 -0.14569536 -0.94708995 -0.44481605 -0.42690058
  0.21604938 -0.22093023 -0.87767584  0.25477707 -0.10778443  0.44871795
 -0.514377    0.53113553 -0.49367089  0.54045307]
[-1.          -1.          -1.          -1.          0.93251534  0.07443366
  0.73584906  0.73248408 -1.          -1.          -1.          -1.
 -1.          -1.          -1.          -1.          -1.          -1.
 -1.          -1.          -0.61111111 -0.49253731  0.9266055  -0.48
  0.69636964 -0.77419355 -0.33774834 -0.84126984 -0.46488294 -0.40350877
  0.49382716 -0.3372093  -0.73088685  0.20382166  0.39520958  0.30769231
 -0.15015974  0.34065934 -0.17088608  0.37864078]
```

```

[-1.          -1.          -1.          -1.          0.88957055 -0.08737864
 0.48427673  0.77707006 -1.          -1.          -1.          -1.
-1.          -1.          -1.          -1.          -1.          -1.
-1.          -1.          -0.41975309 -0.58208955  0.80428135 -0.392
 0.64356436 -0.61290323 -0.21192053 -0.76719577 -0.43812709 -0.22807018
 0.32716049  0.01162791 -0.80428135  0.2611465  0.06586826  0.43589744
-0.38019169  0.53846154 -0.36075949  0.57928803]
[-1.          -1.          -1.          -1.          0.7607362  -0.12621359
 0.42138365  0.61146497 -1.          -1.          -1.          -1.
-1.          -1.          -1.          -1.          -1.          -1.
-1.          -1.          -0.48148148 -0.5920398  0.68195719 -0.456
 0.55775578 -0.64516129 -0.26490066 -0.77777778 -0.43812709 -0.38011696
 0.28395062 -0.13953488 -0.7675841  0.15923567  0.04191617  0.26923077
-0.34824281  0.39194139 -0.30379747  0.42394822]

```

## 4 Transfer learning for 8 classes

```

In [28]: #Importing the ResNet50 model
         from keras.applications.resnet50 import ResNet50, preprocess_input

         #Loading the ResNet50 model with pre-trained ImageNet weights
         model = ResNet50(weights='imagenet', include_top=False, input_shape=(336, 336, 3))

WARNING: Logging before flag parsing goes to stderr.
W1130 23:10:07.787857 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:07.816876 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:07.823477 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:07.845628 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:07.846690 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:07.972143 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/
W1130 23:10:08.036344 140373928044352 deprecation_wrapper.py:119] From /home/william/anaconda3/

/home/william/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras_applications/resnet50.py:
  warnings.warn('The output shape of `ResNet50(include_top=False)` '

In [29]: #Reshaping the training data
         X_train_new = np.array([np.resize(X_train[i], (336, 336, 3)) for i in range(0, len(X_t

         #Preprocessing the data, so that it can be fed to the pre-trained ResNet50 model.
         resnet_train_input = preprocess_input(X_train_new)

```

```

#Creating bottleneck features for the training data
train_features = model.predict(resnet_train_input)

#Saving the bottleneck features
np.savez('resnet_features_train', features=train_features)

In [30]: img = X_train_new[0:2]#.reshape(1, -1)
img1 = preprocess_input(img)
print(img1.shape)
print(resnet_train_input.shape)

(2, 336, 336, 3)
(499, 336, 336, 3)

In [56]: #Reshaping the testing data
X_test_new = np.array([imresize(X_test[i], (336, 336, 3)) for i in range(0, len(X_test))])

#Preprocessing the data, so that it can be fed to the pre-trained ResNet50 model.
resnet_test_input = preprocess_input(X_test_new)

#Creating bottleneck features for the testing data
test_features = model.predict(resnet_test_input)

#Saving the bottleneck features
np.savez('resnet_features_test', features=test_features)

-----

NameError                                Traceback (most recent call last)

<ipython-input-56-463595940c9c> in <module>
      1 #Reshaping the testing data
----> 2 X_test_new = np.array([imresize(X_test[i], (336, 336, 3)) for i in range(0, len(X_test))])
      3
      4 #Preprocessing the data, so that it can be fed to the pre-trained ResNet50 model.
      5 resnet_test_input = preprocess_input(X_test_new)

NameError: name 'X_test' is not defined

In [96]: from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPooling2D
from keras.layers import Dropout, Flatten, GlobalAveragePooling2D

In [114]: model = Sequential()
model.add(GlobalAveragePooling2D(input_shape=(336,336,3)))

```

```

model.add(Dropout(0.3))
model.add(Dense(8, activation='softmax'))
model.summary()

```

```

-----
Layer (type)                 Output Shape              Param #
=====
global_average_pooling2d_4 ( (None, 3)          0
-----
dropout_3 (Dropout)          (None, 3)                 0
-----
dense_5 (Dense)              (None, 8)                32
=====
Total params: 32
Trainable params: 32
Non-trainable params: 0
-----

```

```

In [115]: model.compile(loss='categorical_crossentropy', optimizer='adam',
                      metrics=['accuracy'])

```

```

In [33]: y_train1 = np.vstack(fully_annotated[fully_annotated.columns[-1]].values)
y_train1 = np.resize(y_train1, (499))
num_classes = 8
from keras.utils import np_utils
y_train1 = np_utils.to_categorical(y_train1, num_classes)
y_train1

```

```

Out[33]: array([[0., 0., 0., ..., 0., 0., 1.],
                [0., 0., 0., ..., 0., 0., 1.],
                [0., 0., 0., ..., 0., 0., 1.],
                ...,
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.],
                [0., 0., 0., ..., 0., 0., 0.]], dtype=float32)

```

```

In [117]: import keras
checkpointer = keras.callbacks.ModelCheckpoint(filepath='scratchmodel.best.hdf5',
                                              verbose=1, save_best_only=True)

```

```

In [118]: model.fit(train_features, y_train1, batch_size=32, epochs=200,
                    validation_split=0.2, callbacks=[checkpointer], verbose=1, shuffle=True)

```

-----

ValueError

Traceback (most recent call last)

```

<ipython-input-118-248459b92ea6> in <module>
    1 model.fit(train_features, y_train1, batch_size=32, epochs=200,
----> 2             validation_split=0.2, callbacks=[checkpointer], verbose=1, shuffle=True)

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training.py in fit(self,
950             sample_weight=sample_weight,
951             class_weight=class_weight,
--> 952             batch_size=batch_size)
953     # Prepare validation data.
954     do_validation = False

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training.py in _standardize_input_data
749     feed_input_shapes,
750     check_batch_axis=False, # Don't enforce the batch size.
--> 751     exception_prefix='input')
752
753     if y is not None:

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training_utils.py in standardize_input_data
136         ': expected ' + names[i] + ' to have shape ' +
137         str(shape) + ' but got array with shape ' +
--> 138         str(data_shape))
139     return data
140

```

ValueError: Error when checking input: expected global\_average\_pooling2d\_4\_input to have

In [103]: X\_train[0:2].shape

Out[103]: (2, 336, 336, 1)

```

In [110]: from keras.applications.resnet50 import ResNet50, preprocess_input
model_input_shape = (1,)+model.get_input_shape_at(0)[1:]
img = X_train_new[0:2].reshape(1, -1)
img1 = preprocess_input(X_train_new)
print(img1.shape)
#prediction = model.predict(img1)
#predictions = model.predict(img)
#xy_predictions = output_pipe.inverse_transform(predictions).reshape(20, 2)
#plt.imshow(X_train[2, :, :, 0], cmap='gray')
#plt.plot(xy_predictions[:, 0], xy_predictions[:, 1], 'b*')
#prediction
score = model.evaluate(train_features, y_train1)
score[1]

```

```
(499, 336, 336, 3)
499/499 [=====] - 1s 1ms/step
```

```
Out[110]: 0.791583166810458
```

```
In [112]: test_predictions = model.predict(X_train_new)
```

```
-----

ValueError                                Traceback (most recent call last)

<ipython-input-112-098aee91bc3f> in <module>
----> 1 test_predictions = model.predict(X_train_new)

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training.py in predict
1147         'argument.')
```

```
1148         # Validate user data.
-> 1149         x, _, _ = self._standardize_user_data(x)
1150         if self.stateful:
1151             if x[0].shape[0] > batch_size and x[0].shape[0] % batch_size != 0:

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training.py in _standardize_user_data
749         feed_input_shapes,
750         check_batch_axis=False, # Don't enforce the batch size.
--> 751         exception_prefix='input')
752
753         if y is not None:

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training_utils.py in _standardize_inputs
136         ': expected ' + names[i] + ' to have shape ' +
137         str(shape) + ' but got array with shape ' +
--> 138         str(data_shape))
139     return data
140
```

```
ValueError: Error when checking input: expected global_average_pooling2d_3_input to have
```

```
In [31]: from keras.models import Model
        from keras.optimizers import Adam
        from keras.layers import GlobalAveragePooling2D
        from keras.layers import Dense
        from keras.applications.inception_v3 import InceptionV3
```

```

from keras.utils.np_utils import to_categorical

# Get the InceptionV3 model so we can do transfer learning
base_inception = InceptionV3(weights='imagenet', include_top=False,
                               input_shape=(336, 336, 3))

# Add a global spatial average pooling layer
out = base_inception.output
out = GlobalAveragePooling2D()(out)
out = Dense(512, activation='relu')(out)
out = Dense(512, activation='relu')(out)
total_classes = 8
predictions = Dense(total_classes, activation='softmax')(out)

model = Model(inputs=base_inception.input, outputs=predictions)

# only if we want to freeze layers
for layer in base_inception.layers:
    layer.trainable = False

# Compile
model.compile(Adam(lr=.0001), loss='categorical_crossentropy', metrics=['accuracy'])
model.summary()

```

W1130 23:12:33.649125 140373928044352 deprecation\_wrapper.py:119] From /home/william/anaconda3:

W1130 23:12:46.188709 140373928044352 deprecation\_wrapper.py:119] From /home/william/anaconda3:

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	(None, 336, 336, 3)	0	
conv2d_1 (Conv2D)	(None, 167, 167, 32)	864	input_2[0][0]
batch_normalization_1 (BatchNor	(None, 167, 167, 32)	96	conv2d_1[0][0]
activation_50 (Activation)	(None, 167, 167, 32)	0	batch_normalization_1[0][0]
conv2d_2 (Conv2D)	(None, 165, 165, 32)	9216	activation_50[0][0]
batch_normalization_2 (BatchNor	(None, 165, 165, 32)	96	conv2d_2[0][0]
activation_51 (Activation)	(None, 165, 165, 32)	0	batch_normalization_2[0][0]
conv2d_3 (Conv2D)	(None, 165, 165, 64)	18432	activation_51[0][0]



batch_normalization_3 (BatchNor	(None, 165, 165, 64)	192	conv2d_3[0][0]
activation_52 (Activation)	(None, 165, 165, 64)	0	batch_normalization_3[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 82, 82, 64)	0	activation_52[0][0]
conv2d_4 (Conv2D)	(None, 82, 82, 80)	5120	max_pooling2d_2[0][0]
batch_normalization_4 (BatchNor	(None, 82, 82, 80)	240	conv2d_4[0][0]
activation_53 (Activation)	(None, 82, 82, 80)	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D)	(None, 80, 80, 192)	138240	activation_53[0][0]
batch_normalization_5 (BatchNor	(None, 80, 80, 192)	576	conv2d_5[0][0]
activation_54 (Activation)	(None, 80, 80, 192)	0	batch_normalization_5[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 39, 39, 192)	0	activation_54[0][0]
conv2d_9 (Conv2D)	(None, 39, 39, 64)	12288	max_pooling2d_3[0][0]
batch_normalization_9 (BatchNor	(None, 39, 39, 64)	192	conv2d_9[0][0]
activation_58 (Activation)	(None, 39, 39, 64)	0	batch_normalization_9[0][0]
conv2d_7 (Conv2D)	(None, 39, 39, 48)	9216	max_pooling2d_3[0][0]
conv2d_10 (Conv2D)	(None, 39, 39, 96)	55296	activation_58[0][0]
batch_normalization_7 (BatchNor	(None, 39, 39, 48)	144	conv2d_7[0][0]
batch_normalization_10 (BatchNo	(None, 39, 39, 96)	288	conv2d_10[0][0]
activation_56 (Activation)	(None, 39, 39, 48)	0	batch_normalization_7[0][0]
activation_59 (Activation)	(None, 39, 39, 96)	0	batch_normalization_10[0][0]
average_pooling2d_1 (AveragePoo	(None, 39, 39, 192)	0	max_pooling2d_3[0][0]
conv2d_6 (Conv2D)	(None, 39, 39, 64)	12288	max_pooling2d_3[0][0]
conv2d_8 (Conv2D)	(None, 39, 39, 64)	76800	activation_56[0][0]
conv2d_11 (Conv2D)	(None, 39, 39, 96)	82944	activation_59[0][0]
conv2d_12 (Conv2D)	(None, 39, 39, 32)	6144	average_pooling2d_1[0][0]

batch_normalization_6	(BatchNor	(None, 39, 39, 64)	192	conv2d_6[0][0]
batch_normalization_8	(BatchNor	(None, 39, 39, 64)	192	conv2d_8[0][0]
batch_normalization_11	(BatchNo	(None, 39, 39, 96)	288	conv2d_11[0][0]
batch_normalization_12	(BatchNo	(None, 39, 39, 32)	96	conv2d_12[0][0]
activation_55	(Activation)	(None, 39, 39, 64)	0	batch_normalization_6[0][0]
activation_57	(Activation)	(None, 39, 39, 64)	0	batch_normalization_8[0][0]
activation_60	(Activation)	(None, 39, 39, 96)	0	batch_normalization_11[0][0]
activation_61	(Activation)	(None, 39, 39, 32)	0	batch_normalization_12[0][0]
mixed0	(Concatenate)	(None, 39, 39, 256)	0	activation_55[0][0] activation_57[0][0] activation_60[0][0] activation_61[0][0]
conv2d_16	(Conv2D)	(None, 39, 39, 64)	16384	mixed0[0][0]
batch_normalization_16	(BatchNo	(None, 39, 39, 64)	192	conv2d_16[0][0]
activation_65	(Activation)	(None, 39, 39, 64)	0	batch_normalization_16[0][0]
conv2d_14	(Conv2D)	(None, 39, 39, 48)	12288	mixed0[0][0]
conv2d_17	(Conv2D)	(None, 39, 39, 96)	55296	activation_65[0][0]
batch_normalization_14	(BatchNo	(None, 39, 39, 48)	144	conv2d_14[0][0]
batch_normalization_17	(BatchNo	(None, 39, 39, 96)	288	conv2d_17[0][0]
activation_63	(Activation)	(None, 39, 39, 48)	0	batch_normalization_14[0][0]
activation_66	(Activation)	(None, 39, 39, 96)	0	batch_normalization_17[0][0]
average_pooling2d_2	(AveragePoo	(None, 39, 39, 256)	0	mixed0[0][0]
conv2d_13	(Conv2D)	(None, 39, 39, 64)	16384	mixed0[0][0]
conv2d_15	(Conv2D)	(None, 39, 39, 64)	76800	activation_63[0][0]
conv2d_18	(Conv2D)	(None, 39, 39, 96)	82944	activation_66[0][0]

conv2d_19 (Conv2D)	(None, 39, 39, 64)	16384	average_pooling2d_2[0][0]
batch_normalization_13 (BatchNo	(None, 39, 39, 64)	192	conv2d_13[0][0]
batch_normalization_15 (BatchNo	(None, 39, 39, 64)	192	conv2d_15[0][0]
batch_normalization_18 (BatchNo	(None, 39, 39, 96)	288	conv2d_18[0][0]
batch_normalization_19 (BatchNo	(None, 39, 39, 64)	192	conv2d_19[0][0]
activation_62 (Activation)	(None, 39, 39, 64)	0	batch_normalization_13[0][0]
activation_64 (Activation)	(None, 39, 39, 64)	0	batch_normalization_15[0][0]
activation_67 (Activation)	(None, 39, 39, 96)	0	batch_normalization_18[0][0]
activation_68 (Activation)	(None, 39, 39, 64)	0	batch_normalization_19[0][0]
mixed1 (Concatenate)	(None, 39, 39, 288)	0	activation_62[0][0] activation_64[0][0] activation_67[0][0] activation_68[0][0]
conv2d_23 (Conv2D)	(None, 39, 39, 64)	18432	mixed1[0][0]
batch_normalization_23 (BatchNo	(None, 39, 39, 64)	192	conv2d_23[0][0]
activation_72 (Activation)	(None, 39, 39, 64)	0	batch_normalization_23[0][0]
conv2d_21 (Conv2D)	(None, 39, 39, 48)	13824	mixed1[0][0]
conv2d_24 (Conv2D)	(None, 39, 39, 96)	55296	activation_72[0][0]
batch_normalization_21 (BatchNo	(None, 39, 39, 48)	144	conv2d_21[0][0]
batch_normalization_24 (BatchNo	(None, 39, 39, 96)	288	conv2d_24[0][0]
activation_70 (Activation)	(None, 39, 39, 48)	0	batch_normalization_21[0][0]
activation_73 (Activation)	(None, 39, 39, 96)	0	batch_normalization_24[0][0]
average_pooling2d_3 (AveragePoo	(None, 39, 39, 288)	0	mixed1[0][0]
conv2d_20 (Conv2D)	(None, 39, 39, 64)	18432	mixed1[0][0]
conv2d_22 (Conv2D)	(None, 39, 39, 64)	76800	activation_70[0][0]
conv2d_25 (Conv2D)	(None, 39, 39, 96)	82944	activation_73[0][0]

conv2d_26 (Conv2D)	(None, 39, 39, 64)	18432	average_pooling2d_3[0][0]
batch_normalization_20 (BatchNo	(None, 39, 39, 64)	192	conv2d_20[0][0]
batch_normalization_22 (BatchNo	(None, 39, 39, 64)	192	conv2d_22[0][0]
batch_normalization_25 (BatchNo	(None, 39, 39, 96)	288	conv2d_25[0][0]
batch_normalization_26 (BatchNo	(None, 39, 39, 64)	192	conv2d_26[0][0]
activation_69 (Activation)	(None, 39, 39, 64)	0	batch_normalization_20[0][0]
activation_71 (Activation)	(None, 39, 39, 64)	0	batch_normalization_22[0][0]
activation_74 (Activation)	(None, 39, 39, 96)	0	batch_normalization_25[0][0]
activation_75 (Activation)	(None, 39, 39, 64)	0	batch_normalization_26[0][0]
mixed2 (Concatenate)	(None, 39, 39, 288)	0	activation_69[0][0] activation_71[0][0] activation_74[0][0] activation_75[0][0]
conv2d_28 (Conv2D)	(None, 39, 39, 64)	18432	mixed2[0][0]
batch_normalization_28 (BatchNo	(None, 39, 39, 64)	192	conv2d_28[0][0]
activation_77 (Activation)	(None, 39, 39, 64)	0	batch_normalization_28[0][0]
conv2d_29 (Conv2D)	(None, 39, 39, 96)	55296	activation_77[0][0]
batch_normalization_29 (BatchNo	(None, 39, 39, 96)	288	conv2d_29[0][0]
activation_78 (Activation)	(None, 39, 39, 96)	0	batch_normalization_29[0][0]
conv2d_27 (Conv2D)	(None, 19, 19, 384)	995328	mixed2[0][0]
conv2d_30 (Conv2D)	(None, 19, 19, 96)	82944	activation_78[0][0]
batch_normalization_27 (BatchNo	(None, 19, 19, 384)	1152	conv2d_27[0][0]
batch_normalization_30 (BatchNo	(None, 19, 19, 96)	288	conv2d_30[0][0]
activation_76 (Activation)	(None, 19, 19, 384)	0	batch_normalization_27[0][0]
activation_79 (Activation)	(None, 19, 19, 96)	0	batch_normalization_30[0][0]

max_pooling2d_4 (MaxPooling2D)	(None, 19, 19, 288)	0	mixed2[0][0]
mixed3 (Concatenate)	(None, 19, 19, 768)	0	activation_76[0][0] activation_79[0][0] max_pooling2d_4[0][0]
conv2d_35 (Conv2D)	(None, 19, 19, 128)	98304	mixed3[0][0]
batch_normalization_35 (BatchNo	(None, 19, 19, 128)	384	conv2d_35[0][0]
activation_84 (Activation)	(None, 19, 19, 128)	0	batch_normalization_35[0][0]
conv2d_36 (Conv2D)	(None, 19, 19, 128)	114688	activation_84[0][0]
batch_normalization_36 (BatchNo	(None, 19, 19, 128)	384	conv2d_36[0][0]
activation_85 (Activation)	(None, 19, 19, 128)	0	batch_normalization_36[0][0]
conv2d_32 (Conv2D)	(None, 19, 19, 128)	98304	mixed3[0][0]
conv2d_37 (Conv2D)	(None, 19, 19, 128)	114688	activation_85[0][0]
batch_normalization_32 (BatchNo	(None, 19, 19, 128)	384	conv2d_32[0][0]
batch_normalization_37 (BatchNo	(None, 19, 19, 128)	384	conv2d_37[0][0]
activation_81 (Activation)	(None, 19, 19, 128)	0	batch_normalization_32[0][0]
activation_86 (Activation)	(None, 19, 19, 128)	0	batch_normalization_37[0][0]
conv2d_33 (Conv2D)	(None, 19, 19, 128)	114688	activation_81[0][0]
conv2d_38 (Conv2D)	(None, 19, 19, 128)	114688	activation_86[0][0]
batch_normalization_33 (BatchNo	(None, 19, 19, 128)	384	conv2d_33[0][0]
batch_normalization_38 (BatchNo	(None, 19, 19, 128)	384	conv2d_38[0][0]
activation_82 (Activation)	(None, 19, 19, 128)	0	batch_normalization_33[0][0]
activation_87 (Activation)	(None, 19, 19, 128)	0	batch_normalization_38[0][0]
average_pooling2d_4 (AveragePoo	(None, 19, 19, 768)	0	mixed3[0][0]
conv2d_31 (Conv2D)	(None, 19, 19, 192)	147456	mixed3[0][0]
conv2d_34 (Conv2D)	(None, 19, 19, 192)	172032	activation_82[0][0]

conv2d_39 (Conv2D)	(None, 19, 19, 192)	172032	activation_87[0][0]
conv2d_40 (Conv2D)	(None, 19, 19, 192)	147456	average_pooling2d_4[0][0]
batch_normalization_31 (BatchNo	(None, 19, 19, 192)	576	conv2d_31[0][0]
batch_normalization_34 (BatchNo	(None, 19, 19, 192)	576	conv2d_34[0][0]
batch_normalization_39 (BatchNo	(None, 19, 19, 192)	576	conv2d_39[0][0]
batch_normalization_40 (BatchNo	(None, 19, 19, 192)	576	conv2d_40[0][0]
activation_80 (Activation)	(None, 19, 19, 192)	0	batch_normalization_31[0][0]
activation_83 (Activation)	(None, 19, 19, 192)	0	batch_normalization_34[0][0]
activation_88 (Activation)	(None, 19, 19, 192)	0	batch_normalization_39[0][0]
activation_89 (Activation)	(None, 19, 19, 192)	0	batch_normalization_40[0][0]
mixed4 (Concatenate)	(None, 19, 19, 768)	0	activation_80[0][0] activation_83[0][0] activation_88[0][0] activation_89[0][0]
conv2d_45 (Conv2D)	(None, 19, 19, 160)	122880	mixed4[0][0]
batch_normalization_45 (BatchNo	(None, 19, 19, 160)	480	conv2d_45[0][0]
activation_94 (Activation)	(None, 19, 19, 160)	0	batch_normalization_45[0][0]
conv2d_46 (Conv2D)	(None, 19, 19, 160)	179200	activation_94[0][0]
batch_normalization_46 (BatchNo	(None, 19, 19, 160)	480	conv2d_46[0][0]
activation_95 (Activation)	(None, 19, 19, 160)	0	batch_normalization_46[0][0]
conv2d_42 (Conv2D)	(None, 19, 19, 160)	122880	mixed4[0][0]
conv2d_47 (Conv2D)	(None, 19, 19, 160)	179200	activation_95[0][0]
batch_normalization_42 (BatchNo	(None, 19, 19, 160)	480	conv2d_42[0][0]
batch_normalization_47 (BatchNo	(None, 19, 19, 160)	480	conv2d_47[0][0]
activation_91 (Activation)	(None, 19, 19, 160)	0	batch_normalization_42[0][0]
activation_96 (Activation)	(None, 19, 19, 160)	0	batch_normalization_47[0][0]

conv2d_43 (Conv2D)	(None, 19, 19, 160)	179200	activation_91[0][0]
conv2d_48 (Conv2D)	(None, 19, 19, 160)	179200	activation_96[0][0]
batch_normalization_43 (BatchNo	(None, 19, 19, 160)	480	conv2d_43[0][0]
batch_normalization_48 (BatchNo	(None, 19, 19, 160)	480	conv2d_48[0][0]
activation_92 (Activation)	(None, 19, 19, 160)	0	batch_normalization_43[0][0]
activation_97 (Activation)	(None, 19, 19, 160)	0	batch_normalization_48[0][0]
average_pooling2d_5 (AveragePoo	(None, 19, 19, 768)	0	mixed4[0][0]
conv2d_41 (Conv2D)	(None, 19, 19, 192)	147456	mixed4[0][0]
conv2d_44 (Conv2D)	(None, 19, 19, 192)	215040	activation_92[0][0]
conv2d_49 (Conv2D)	(None, 19, 19, 192)	215040	activation_97[0][0]
conv2d_50 (Conv2D)	(None, 19, 19, 192)	147456	average_pooling2d_5[0][0]
batch_normalization_41 (BatchNo	(None, 19, 19, 192)	576	conv2d_41[0][0]
batch_normalization_44 (BatchNo	(None, 19, 19, 192)	576	conv2d_44[0][0]
batch_normalization_49 (BatchNo	(None, 19, 19, 192)	576	conv2d_49[0][0]
batch_normalization_50 (BatchNo	(None, 19, 19, 192)	576	conv2d_50[0][0]
activation_90 (Activation)	(None, 19, 19, 192)	0	batch_normalization_41[0][0]
activation_93 (Activation)	(None, 19, 19, 192)	0	batch_normalization_44[0][0]
activation_98 (Activation)	(None, 19, 19, 192)	0	batch_normalization_49[0][0]
activation_99 (Activation)	(None, 19, 19, 192)	0	batch_normalization_50[0][0]
mixed5 (Concatenate)	(None, 19, 19, 768)	0	activation_90[0][0] activation_93[0][0] activation_98[0][0] activation_99[0][0]
conv2d_55 (Conv2D)	(None, 19, 19, 160)	122880	mixed5[0][0]
batch_normalization_55 (BatchNo	(None, 19, 19, 160)	480	conv2d_55[0][0]

activation_104 (Activation)	(None, 19, 19, 160)	0	batch_normalization_55[0][0]
conv2d_56 (Conv2D)	(None, 19, 19, 160)	179200	activation_104[0][0]
batch_normalization_56 (BatchNo	(None, 19, 19, 160)	480	conv2d_56[0][0]
activation_105 (Activation)	(None, 19, 19, 160)	0	batch_normalization_56[0][0]
conv2d_52 (Conv2D)	(None, 19, 19, 160)	122880	mixed5[0][0]
conv2d_57 (Conv2D)	(None, 19, 19, 160)	179200	activation_105[0][0]
batch_normalization_52 (BatchNo	(None, 19, 19, 160)	480	conv2d_52[0][0]
batch_normalization_57 (BatchNo	(None, 19, 19, 160)	480	conv2d_57[0][0]
activation_101 (Activation)	(None, 19, 19, 160)	0	batch_normalization_52[0][0]
activation_106 (Activation)	(None, 19, 19, 160)	0	batch_normalization_57[0][0]
conv2d_53 (Conv2D)	(None, 19, 19, 160)	179200	activation_101[0][0]
conv2d_58 (Conv2D)	(None, 19, 19, 160)	179200	activation_106[0][0]
batch_normalization_53 (BatchNo	(None, 19, 19, 160)	480	conv2d_53[0][0]
batch_normalization_58 (BatchNo	(None, 19, 19, 160)	480	conv2d_58[0][0]
activation_102 (Activation)	(None, 19, 19, 160)	0	batch_normalization_53[0][0]
activation_107 (Activation)	(None, 19, 19, 160)	0	batch_normalization_58[0][0]
average_pooling2d_6 (AveragePoo	(None, 19, 19, 768)	0	mixed5[0][0]
conv2d_51 (Conv2D)	(None, 19, 19, 192)	147456	mixed5[0][0]
conv2d_54 (Conv2D)	(None, 19, 19, 192)	215040	activation_102[0][0]
conv2d_59 (Conv2D)	(None, 19, 19, 192)	215040	activation_107[0][0]
conv2d_60 (Conv2D)	(None, 19, 19, 192)	147456	average_pooling2d_6[0][0]
batch_normalization_51 (BatchNo	(None, 19, 19, 192)	576	conv2d_51[0][0]
batch_normalization_54 (BatchNo	(None, 19, 19, 192)	576	conv2d_54[0][0]
batch_normalization_59 (BatchNo	(None, 19, 19, 192)	576	conv2d_59[0][0]



batch_normalization_60 (BatchNo	(None, 19, 19, 192)	576	conv2d_60[0][0]
activation_100 (Activation)	(None, 19, 19, 192)	0	batch_normalization_51[0][0]
activation_103 (Activation)	(None, 19, 19, 192)	0	batch_normalization_54[0][0]
activation_108 (Activation)	(None, 19, 19, 192)	0	batch_normalization_59[0][0]
activation_109 (Activation)	(None, 19, 19, 192)	0	batch_normalization_60[0][0]
mixed6 (Concatenate)	(None, 19, 19, 768)	0	activation_100[0][0] activation_103[0][0] activation_108[0][0] activation_109[0][0]
conv2d_65 (Conv2D)	(None, 19, 19, 192)	147456	mixed6[0][0]
batch_normalization_65 (BatchNo	(None, 19, 19, 192)	576	conv2d_65[0][0]
activation_114 (Activation)	(None, 19, 19, 192)	0	batch_normalization_65[0][0]
conv2d_66 (Conv2D)	(None, 19, 19, 192)	258048	activation_114[0][0]
batch_normalization_66 (BatchNo	(None, 19, 19, 192)	576	conv2d_66[0][0]
activation_115 (Activation)	(None, 19, 19, 192)	0	batch_normalization_66[0][0]
conv2d_62 (Conv2D)	(None, 19, 19, 192)	147456	mixed6[0][0]
conv2d_67 (Conv2D)	(None, 19, 19, 192)	258048	activation_115[0][0]
batch_normalization_62 (BatchNo	(None, 19, 19, 192)	576	conv2d_62[0][0]
batch_normalization_67 (BatchNo	(None, 19, 19, 192)	576	conv2d_67[0][0]
activation_111 (Activation)	(None, 19, 19, 192)	0	batch_normalization_62[0][0]
activation_116 (Activation)	(None, 19, 19, 192)	0	batch_normalization_67[0][0]
conv2d_63 (Conv2D)	(None, 19, 19, 192)	258048	activation_111[0][0]
conv2d_68 (Conv2D)	(None, 19, 19, 192)	258048	activation_116[0][0]
batch_normalization_63 (BatchNo	(None, 19, 19, 192)	576	conv2d_63[0][0]
batch_normalization_68 (BatchNo	(None, 19, 19, 192)	576	conv2d_68[0][0]
activation_112 (Activation)	(None, 19, 19, 192)	0	batch_normalization_63[0][0]

activation_117 (Activation)	(None, 19, 19, 192)	0	batch_normalization_68[0][0]
average_pooling2d_7 (AveragePool)	(None, 19, 19, 768)	0	mixed6[0][0]
conv2d_61 (Conv2D)	(None, 19, 19, 192)	147456	mixed6[0][0]
conv2d_64 (Conv2D)	(None, 19, 19, 192)	258048	activation_112[0][0]
conv2d_69 (Conv2D)	(None, 19, 19, 192)	258048	activation_117[0][0]
conv2d_70 (Conv2D)	(None, 19, 19, 192)	147456	average_pooling2d_7[0][0]
batch_normalization_61 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_61[0][0]
batch_normalization_64 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_64[0][0]
batch_normalization_69 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_69[0][0]
batch_normalization_70 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_70[0][0]
activation_110 (Activation)	(None, 19, 19, 192)	0	batch_normalization_61[0][0]
activation_113 (Activation)	(None, 19, 19, 192)	0	batch_normalization_64[0][0]
activation_118 (Activation)	(None, 19, 19, 192)	0	batch_normalization_69[0][0]
activation_119 (Activation)	(None, 19, 19, 192)	0	batch_normalization_70[0][0]
mixed7 (Concatenate)	(None, 19, 19, 768)	0	activation_110[0][0] activation_113[0][0] activation_118[0][0] activation_119[0][0]
conv2d_73 (Conv2D)	(None, 19, 19, 192)	147456	mixed7[0][0]
batch_normalization_73 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_73[0][0]
activation_122 (Activation)	(None, 19, 19, 192)	0	batch_normalization_73[0][0]
conv2d_74 (Conv2D)	(None, 19, 19, 192)	258048	activation_122[0][0]
batch_normalization_74 (BatchNormalization)	(None, 19, 19, 192)	576	conv2d_74[0][0]
activation_123 (Activation)	(None, 19, 19, 192)	0	batch_normalization_74[0][0]
conv2d_71 (Conv2D)	(None, 19, 19, 192)	147456	mixed7[0][0]

conv2d_75 (Conv2D)	(None, 19, 19, 192)	258048	activation_123[0][0]
batch_normalization_71 (BatchNo	(None, 19, 19, 192)	576	conv2d_71[0][0]
batch_normalization_75 (BatchNo	(None, 19, 19, 192)	576	conv2d_75[0][0]
activation_120 (Activation)	(None, 19, 19, 192)	0	batch_normalization_71[0][0]
activation_124 (Activation)	(None, 19, 19, 192)	0	batch_normalization_75[0][0]
conv2d_72 (Conv2D)	(None, 9, 9, 320)	552960	activation_120[0][0]
conv2d_76 (Conv2D)	(None, 9, 9, 192)	331776	activation_124[0][0]
batch_normalization_72 (BatchNo	(None, 9, 9, 320)	960	conv2d_72[0][0]
batch_normalization_76 (BatchNo	(None, 9, 9, 192)	576	conv2d_76[0][0]
activation_121 (Activation)	(None, 9, 9, 320)	0	batch_normalization_72[0][0]
activation_125 (Activation)	(None, 9, 9, 192)	0	batch_normalization_76[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 9, 9, 768)	0	mixed7[0][0]
mixed8 (Concatenate)	(None, 9, 9, 1280)	0	activation_121[0][0] activation_125[0][0] max_pooling2d_5[0][0]
conv2d_81 (Conv2D)	(None, 9, 9, 448)	573440	mixed8[0][0]
batch_normalization_81 (BatchNo	(None, 9, 9, 448)	1344	conv2d_81[0][0]
activation_130 (Activation)	(None, 9, 9, 448)	0	batch_normalization_81[0][0]
conv2d_78 (Conv2D)	(None, 9, 9, 384)	491520	mixed8[0][0]
conv2d_82 (Conv2D)	(None, 9, 9, 384)	1548288	activation_130[0][0]
batch_normalization_78 (BatchNo	(None, 9, 9, 384)	1152	conv2d_78[0][0]
batch_normalization_82 (BatchNo	(None, 9, 9, 384)	1152	conv2d_82[0][0]
activation_127 (Activation)	(None, 9, 9, 384)	0	batch_normalization_78[0][0]
activation_131 (Activation)	(None, 9, 9, 384)	0	batch_normalization_82[0][0]
conv2d_79 (Conv2D)	(None, 9, 9, 384)	442368	activation_127[0][0]

conv2d_80 (Conv2D)	(None, 9, 9, 384)	442368	activation_127[0][0]
conv2d_83 (Conv2D)	(None, 9, 9, 384)	442368	activation_131[0][0]
conv2d_84 (Conv2D)	(None, 9, 9, 384)	442368	activation_131[0][0]
average_pooling2d_8 (AveragePoo	(None, 9, 9, 1280)	0	mixed8[0][0]
conv2d_77 (Conv2D)	(None, 9, 9, 320)	409600	mixed8[0][0]
batch_normalization_79 (BatchNo	(None, 9, 9, 384)	1152	conv2d_79[0][0]
batch_normalization_80 (BatchNo	(None, 9, 9, 384)	1152	conv2d_80[0][0]
batch_normalization_83 (BatchNo	(None, 9, 9, 384)	1152	conv2d_83[0][0]
batch_normalization_84 (BatchNo	(None, 9, 9, 384)	1152	conv2d_84[0][0]
conv2d_85 (Conv2D)	(None, 9, 9, 192)	245760	average_pooling2d_8[0][0]
batch_normalization_77 (BatchNo	(None, 9, 9, 320)	960	conv2d_77[0][0]
activation_128 (Activation)	(None, 9, 9, 384)	0	batch_normalization_79[0][0]
activation_129 (Activation)	(None, 9, 9, 384)	0	batch_normalization_80[0][0]
activation_132 (Activation)	(None, 9, 9, 384)	0	batch_normalization_83[0][0]
activation_133 (Activation)	(None, 9, 9, 384)	0	batch_normalization_84[0][0]
batch_normalization_85 (BatchNo	(None, 9, 9, 192)	576	conv2d_85[0][0]
activation_126 (Activation)	(None, 9, 9, 320)	0	batch_normalization_77[0][0]
mixed9_0 (Concatenate)	(None, 9, 9, 768)	0	activation_128[0][0] activation_129[0][0]
concatenate_1 (Concatenate)	(None, 9, 9, 768)	0	activation_132[0][0] activation_133[0][0]
activation_134 (Activation)	(None, 9, 9, 192)	0	batch_normalization_85[0][0]
mixed9 (Concatenate)	(None, 9, 9, 2048)	0	activation_126[0][0] mixed9_0[0][0] concatenate_1[0][0] activation_134[0][0]
conv2d_90 (Conv2D)	(None, 9, 9, 448)	917504	mixed9[0][0]

batch_normalization_90 (BatchNo	(None, 9, 9, 448)	1344	conv2d_90[0][0]
activation_139 (Activation)	(None, 9, 9, 448)	0	batch_normalization_90[0][0]
conv2d_87 (Conv2D)	(None, 9, 9, 384)	786432	mixed9[0][0]
conv2d_91 (Conv2D)	(None, 9, 9, 384)	1548288	activation_139[0][0]
batch_normalization_87 (BatchNo	(None, 9, 9, 384)	1152	conv2d_87[0][0]
batch_normalization_91 (BatchNo	(None, 9, 9, 384)	1152	conv2d_91[0][0]
activation_136 (Activation)	(None, 9, 9, 384)	0	batch_normalization_87[0][0]
activation_140 (Activation)	(None, 9, 9, 384)	0	batch_normalization_91[0][0]
conv2d_88 (Conv2D)	(None, 9, 9, 384)	442368	activation_136[0][0]
conv2d_89 (Conv2D)	(None, 9, 9, 384)	442368	activation_136[0][0]
conv2d_92 (Conv2D)	(None, 9, 9, 384)	442368	activation_140[0][0]
conv2d_93 (Conv2D)	(None, 9, 9, 384)	442368	activation_140[0][0]
average_pooling2d_9 (AveragePoo	(None, 9, 9, 2048)	0	mixed9[0][0]
conv2d_86 (Conv2D)	(None, 9, 9, 320)	655360	mixed9[0][0]
batch_normalization_88 (BatchNo	(None, 9, 9, 384)	1152	conv2d_88[0][0]
batch_normalization_89 (BatchNo	(None, 9, 9, 384)	1152	conv2d_89[0][0]
batch_normalization_92 (BatchNo	(None, 9, 9, 384)	1152	conv2d_92[0][0]
batch_normalization_93 (BatchNo	(None, 9, 9, 384)	1152	conv2d_93[0][0]
conv2d_94 (Conv2D)	(None, 9, 9, 192)	393216	average_pooling2d_9[0][0]
batch_normalization_86 (BatchNo	(None, 9, 9, 320)	960	conv2d_86[0][0]
activation_137 (Activation)	(None, 9, 9, 384)	0	batch_normalization_88[0][0]
activation_138 (Activation)	(None, 9, 9, 384)	0	batch_normalization_89[0][0]
activation_141 (Activation)	(None, 9, 9, 384)	0	batch_normalization_92[0][0]
activation_142 (Activation)	(None, 9, 9, 384)	0	batch_normalization_93[0][0]

batch_normalization_94 (BatchNo	(None, 9, 9, 192)	576	conv2d_94[0][0]
activation_135 (Activation)	(None, 9, 9, 320)	0	batch_normalization_86[0][0]
mixed9_1 (Concatenate)	(None, 9, 9, 768)	0	activation_137[0][0] activation_138[0][0]
concatenate_2 (Concatenate)	(None, 9, 9, 768)	0	activation_141[0][0] activation_142[0][0]
activation_143 (Activation)	(None, 9, 9, 192)	0	batch_normalization_94[0][0]
mixed10 (Concatenate)	(None, 9, 9, 2048)	0	activation_135[0][0] mixed9_1[0][0] concatenate_2[0][0] activation_143[0][0]
global_average_pooling2d_1 (Glo	(None, 2048)	0	mixed10[0][0]
dense_1 (Dense)	(None, 512)	1049088	global_average_pooling2d_1[0]
dense_2 (Dense)	(None, 512)	262656	dense_1[0][0]
dense_3 (Dense)	(None, 8)	4104	dense_2[0][0]

=====  
 Total params: 23,118,632  
 Trainable params: 1,315,848  
 Non-trainable params: 21,802,784  
 =====

```

In [34]: from keras.preprocessing.image import ImageDataGenerator

BATCH_SIZE = 32
train_datagen = ImageDataGenerator(
    rotation_range=0,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip = 'false')
train_generator = train_datagen.flow(X_train_new, y_train1, shuffle=False,
    batch_size=BATCH_SIZE, seed=1)

batch_size = BATCH_SIZE
train_steps_per_epoch = X_train_new.shape[0] // batch_size
#val_steps_per_epoch = x_val.shape[0] // batch_size

history = model.fit_generator(train_generator,
    steps_per_epoch=train_steps_per_epoch,

```

```
epochs=15, verbose=1)
```

```
W1130 23:14:17.456909 140373928044352 deprecation.py:323] From /home/william/anaconda3/envs/tf
```

```
Instructions for updating:
```

```
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

```
Epoch 1/15
```

```
15/15 [=====] - 66s 4s/step - loss: 1.9972 - acc: 0.2208
```

```
Epoch 2/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.7412 - acc: 0.2945
```

```
Epoch 3/15
```

```
15/15 [=====] - 59s 4s/step - loss: 1.6464 - acc: 0.3605
```

```
Epoch 4/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.5584 - acc: 0.4535
```

```
Epoch 5/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.4642 - acc: 0.5021
```

```
Epoch 6/15
```

```
15/15 [=====] - 58s 4s/step - loss: 1.4143 - acc: 0.5501
```

```
Epoch 7/15
```

```
15/15 [=====] - 56s 4s/step - loss: 1.3564 - acc: 0.5230
```

```
Epoch 8/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.2873 - acc: 0.5515
```

```
Epoch 9/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.2444 - acc: 0.5556
```

```
Epoch 10/15
```

```
15/15 [=====] - 58s 4s/step - loss: 1.1553 - acc: 0.6224
```

```
Epoch 11/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.1491 - acc: 0.5744
```

```
Epoch 12/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.1275 - acc: 0.5780
```

```
Epoch 13/15
```

```
15/15 [=====] - 56s 4s/step - loss: 1.0410 - acc: 0.6232
```

```
Epoch 14/15
```

```
15/15 [=====] - 58s 4s/step - loss: 0.9893 - acc: 0.6733
```

```
Epoch 15/15
```

```
15/15 [=====] - 57s 4s/step - loss: 1.0144 - acc: 0.6490
```

```
In [48]: im = string2image(fully_annotated[:,0][9])
```

```
        im = cv2.resize(im,(336,336))
```

```
        plt.imshow(im)
```

```
        im = np.expand_dims(im, axis =0)
```

```
        img = X_train_new[0:2]#.reshape(1, -1)
```

```
        #img1 = preprocess_input(X_train_new)
```

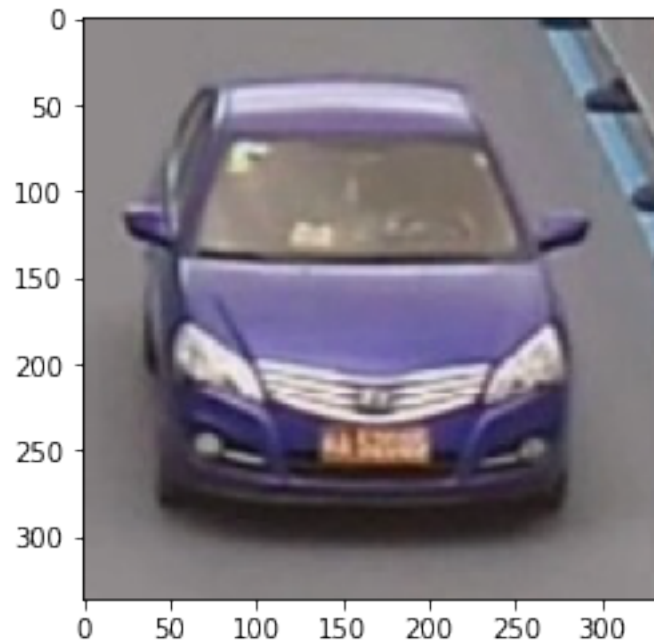
```
        #print(img1.shape)
```

```
        #prediction = model.predict(img1)
```

```
        predictions = model.predict(im)
```

```
        predictions
```

```
Out[48]: array([[4.8218969e-19, 5.7204437e-27, 0.0000000e+00, 9.9999201e-01,
                7.6653373e-15, 2.9607233e-30, 9.5904443e-25, 8.0103518e-06]],
              dtype=float32)
```



In this case, the pipelining process is, how to say this, not very spectacular. Let's move on and train a Keras model! We will start with a simple model, as found [in this blog post](#) with a fully connected layer and 100 hidden units.

```
In [41]: from keras.models import Sequential
         from keras.layers import BatchNormalization, Conv2D, Activation, MaxPooling2D, Dense,
```

Using TensorFlow backend.

```
In [42]: model = Sequential()
         model.add(Dense(100, activation="relu", input_shape=(336*336,)))
         model.add(Activation('relu'))
         model.add(Dense(8))
```

WARNING: Logging before flag parsing goes to stderr.

W1129 20:54:58.370776 139950289872704 deprecation\_wrapper.py:119] From /home/william/anaconda3:

W1129 20:54:58.394842 139950289872704 deprecation\_wrapper.py:119] From /home/william/anaconda3:

W1129 20:54:58.398083 139950289872704 deprecation\_wrapper.py:119] From /home/william/anaconda3:



Now let's compile the model and run the training.

```
In [43]: from keras import optimizers
```

```
sgd = optimizers.SGD(lr=1e-5, decay=1e-4, momentum=0.9, nesterov=True)
adam = optimizers.Adam(lr=10e-3, beta_1=0.9, beta_2=0.999, amsgrad=True)

model.compile(optimizer=sgd, loss='mse', metrics=['accuracy'])
epochs = 100
history = model.fit(X_train.reshape(y_train.shape[0], -1), y_train,
                    validation_split=0.2, shuffle=True,
                    epochs=epochs, batch_size=20)
```

```
W1129 20:55:00.433584 139950289872704 deprecation_wrapper.py:119] From /home/william/anaconda3
```

```
W1129 20:55:00.620710 139950289872704 deprecation_wrapper.py:119] From /home/william/anaconda3
```

```
W1129 20:55:00.650210 139950289872704 deprecation_wrapper.py:119] From /home/william/anaconda3
```

Train on 399 samples, validate on 100 samples

Epoch 1/100

```
399/399 [=====] - 3s 7ms/step - loss: 0.6493 - acc: 0.0677 - val_loss
```

Epoch 2/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.5099 - acc: 0.0000e+00 - val_
```

Epoch 3/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4775 - acc: 0.0025 - val_loss
```

Epoch 4/100

```
399/399 [=====] - 2s 6ms/step - loss: 0.4643 - acc: 0.0050 - val_loss
```

Epoch 5/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4546 - acc: 0.0025 - val_loss
```

Epoch 6/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4476 - acc: 0.0025 - val_loss
```

Epoch 7/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4425 - acc: 0.0000e+00 - val_
```

Epoch 8/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4386 - acc: 0.0000e+00 - val_
```

Epoch 9/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4357 - acc: 0.0025 - val_loss
```

Epoch 10/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4331 - acc: 0.0050 - val_loss
```

Epoch 11/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4310 - acc: 0.0025 - val_loss
```

Epoch 12/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4289 - acc: 0.0075 - val_loss
```

Epoch 13/100

```
399/399 [=====] - 2s 5ms/step - loss: 0.4273 - acc: 0.0050 - val_loss
```

Epoch 14/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4252 - acc: 0.0050 - val\_loss

Epoch 15/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4235 - acc: 0.0075 - val\_loss

Epoch 16/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4218 - acc: 0.0050 - val\_loss

Epoch 17/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4200 - acc: 0.0050 - val\_loss

Epoch 18/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4181 - acc: 0.0050 - val\_loss

Epoch 19/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4163 - acc: 0.0075 - val\_loss

Epoch 20/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4147 - acc: 0.0025 - val\_loss

Epoch 21/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4128 - acc: 0.0050 - val\_loss

Epoch 22/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4115 - acc: 0.0050 - val\_loss

Epoch 23/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4099 - acc: 0.0050 - val\_loss

Epoch 24/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4080 - acc: 0.0025 - val\_loss

Epoch 25/100  
399/399 [=====] - 2s 6ms/step - loss: 0.4067 - acc: 0.0050 - val\_loss

Epoch 26/100  
399/399 [=====] - 2s 6ms/step - loss: 0.4053 - acc: 0.0050 - val\_loss

Epoch 27/100  
399/399 [=====] - 2s 6ms/step - loss: 0.4036 - acc: 0.0050 - val\_loss

Epoch 28/100  
399/399 [=====] - 2s 5ms/step - loss: 0.4022 - acc: 0.0050 - val\_loss

Epoch 29/100  
399/399 [=====] - 2s 6ms/step - loss: 0.4005 - acc: 0.0100 - val\_loss

Epoch 30/100  
399/399 [=====] - 2s 6ms/step - loss: 0.3986 - acc: 0.0100 - val\_loss

Epoch 31/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3969 - acc: 0.0125 - val\_loss

Epoch 32/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3955 - acc: 0.0125 - val\_loss

Epoch 33/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3941 - acc: 0.0125 - val\_loss

Epoch 34/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3929 - acc: 0.0201 - val\_loss

Epoch 35/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3915 - acc: 0.0175 - val\_loss

Epoch 36/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3904 - acc: 0.0251 - val\_loss

Epoch 37/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3892 - acc: 0.0301 - val\_loss

Epoch 38/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3883 - acc: 0.0351 - val\_loss  
Epoch 39/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3867 - acc: 0.0376 - val\_loss  
Epoch 40/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3855 - acc: 0.0301 - val\_loss  
Epoch 41/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3845 - acc: 0.0401 - val\_loss  
Epoch 42/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3834 - acc: 0.0501 - val\_loss  
Epoch 43/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3823 - acc: 0.0476 - val\_loss  
Epoch 44/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3811 - acc: 0.0426 - val\_loss  
Epoch 45/100  
399/399 [=====] - 2s 6ms/step - loss: 0.3802 - acc: 0.0526 - val\_loss  
Epoch 46/100  
399/399 [=====] - 2s 6ms/step - loss: 0.3794 - acc: 0.0526 - val\_loss  
Epoch 47/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3781 - acc: 0.0602 - val\_loss  
Epoch 48/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3773 - acc: 0.0627 - val\_loss  
Epoch 49/100  
399/399 [=====] - 2s 6ms/step - loss: 0.3762 - acc: 0.0576 - val\_loss  
Epoch 50/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3752 - acc: 0.0627 - val\_loss  
Epoch 51/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3745 - acc: 0.0702 - val\_loss  
Epoch 52/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3732 - acc: 0.0602 - val\_loss  
Epoch 53/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3726 - acc: 0.0702 - val\_loss  
Epoch 54/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3719 - acc: 0.0777 - val\_loss  
Epoch 55/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3710 - acc: 0.0752 - val\_loss  
Epoch 56/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3700 - acc: 0.0677 - val\_loss  
Epoch 57/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3692 - acc: 0.0752 - val\_loss  
Epoch 58/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3682 - acc: 0.0777 - val\_loss  
Epoch 59/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3675 - acc: 0.0727 - val\_loss  
Epoch 60/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3666 - acc: 0.0752 - val\_loss  
Epoch 61/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3658 - acc: 0.0727 - val\_loss

Epoch 62/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3651 - acc: 0.0802 - val\_loss

Epoch 63/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3644 - acc: 0.0802 - val\_loss

Epoch 64/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3635 - acc: 0.0752 - val\_loss

Epoch 65/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3628 - acc: 0.0802 - val\_loss

Epoch 66/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3621 - acc: 0.0752 - val\_loss

Epoch 67/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3616 - acc: 0.0802 - val\_loss

Epoch 68/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3607 - acc: 0.0702 - val\_loss

Epoch 69/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3600 - acc: 0.0827 - val\_loss

Epoch 70/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3592 - acc: 0.0777 - val\_loss

Epoch 71/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3587 - acc: 0.0752 - val\_loss

Epoch 72/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3578 - acc: 0.0852 - val\_loss

Epoch 73/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3572 - acc: 0.0877 - val\_loss

Epoch 74/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3568 - acc: 0.0877 - val\_loss

Epoch 75/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3559 - acc: 0.0902 - val\_loss

Epoch 76/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3551 - acc: 0.0927 - val\_loss

Epoch 77/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3546 - acc: 0.0902 - val\_loss

Epoch 78/100  
399/399 [=====] - 2s 4ms/step - loss: 0.3539 - acc: 0.0802 - val\_loss

Epoch 79/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3532 - acc: 0.0952 - val\_loss

Epoch 80/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3526 - acc: 0.0952 - val\_loss

Epoch 81/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3519 - acc: 0.0877 - val\_loss

Epoch 82/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3513 - acc: 0.0852 - val\_loss

Epoch 83/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3506 - acc: 0.0927 - val\_loss

Epoch 84/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3500 - acc: 0.0977 - val\_loss

Epoch 85/100  
399/399 [=====] - 2s 5ms/step - loss: 0.3495 - acc: 0.1028 - val\_loss

```

Epoch 86/100
399/399 [=====] - 2s 5ms/step - loss: 0.3488 - acc: 0.0927 - val_loss
Epoch 87/100
399/399 [=====] - 2s 5ms/step - loss: 0.3483 - acc: 0.0927 - val_loss
Epoch 88/100
399/399 [=====] - 2s 5ms/step - loss: 0.3476 - acc: 0.0977 - val_loss
Epoch 89/100
399/399 [=====] - 2s 5ms/step - loss: 0.3472 - acc: 0.1003 - val_loss
Epoch 90/100
399/399 [=====] - 2s 5ms/step - loss: 0.3466 - acc: 0.1028 - val_loss
Epoch 91/100
399/399 [=====] - 2s 5ms/step - loss: 0.3459 - acc: 0.0952 - val_loss
Epoch 92/100
399/399 [=====] - 2s 4ms/step - loss: 0.3455 - acc: 0.1053 - val_loss
Epoch 93/100
399/399 [=====] - 2s 4ms/step - loss: 0.3450 - acc: 0.1078 - val_loss
Epoch 94/100
399/399 [=====] - 2s 5ms/step - loss: 0.3444 - acc: 0.1078 - val_loss
Epoch 95/100
399/399 [=====] - 2s 5ms/step - loss: 0.3438 - acc: 0.0902 - val_loss
Epoch 96/100
399/399 [=====] - 2s 4ms/step - loss: 0.3432 - acc: 0.1128 - val_loss
Epoch 97/100
399/399 [=====] - 2s 4ms/step - loss: 0.3426 - acc: 0.1003 - val_loss
Epoch 98/100
399/399 [=====] - 2s 5ms/step - loss: 0.3423 - acc: 0.1028 - val_loss
Epoch 99/100
399/399 [=====] - 2s 5ms/step - loss: 0.3414 - acc: 0.0977 - val_loss
Epoch 100/100
399/399 [=====] - 2s 5ms/step - loss: 0.3410 - acc: 0.1003 - val_loss

```

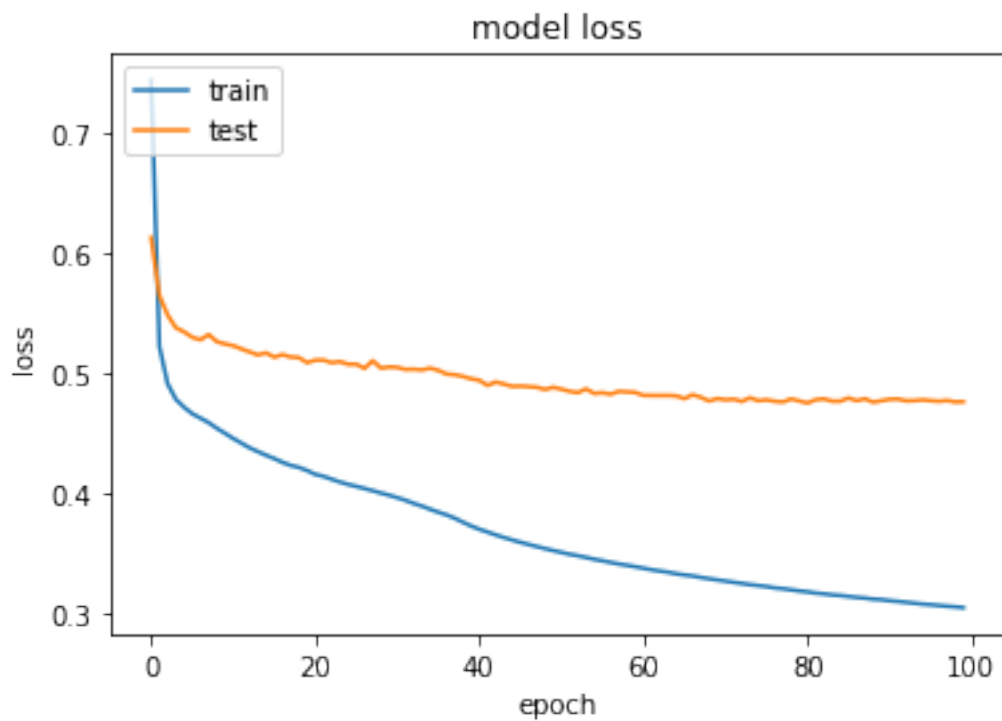
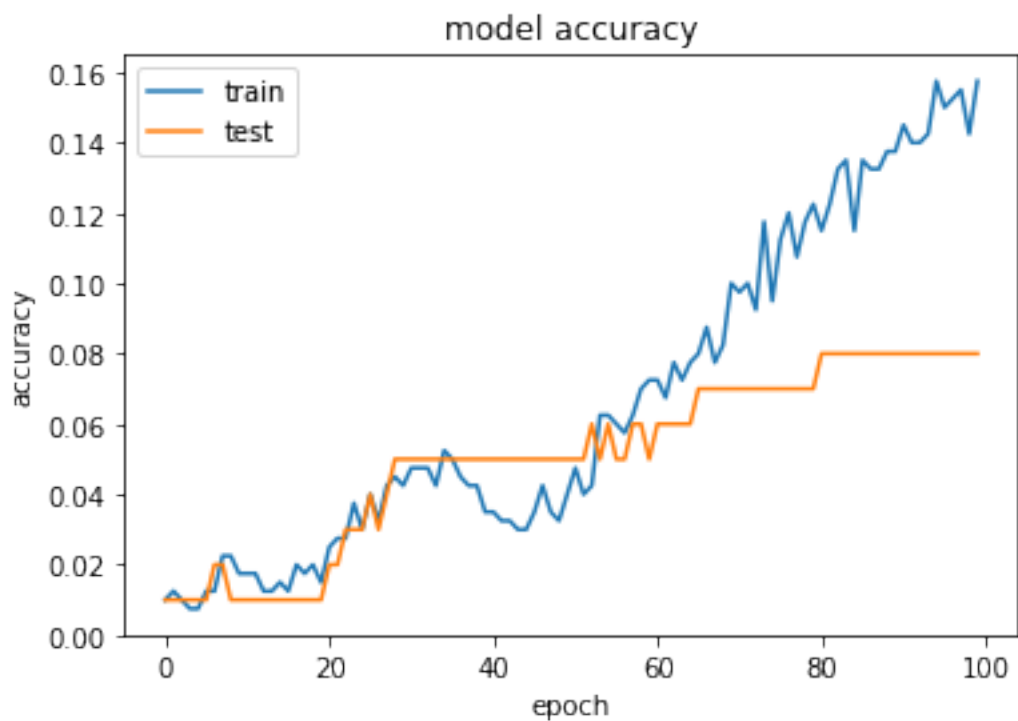
Let's plot our training curves with this model.

```

In [30]: # summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')

```

```
plt.legend(['train', 'test'], loc='upper left')  
plt.show()
```



What we see here is that with this model, the learning quickly gets on a plateau. How can we improve this? There are a lot of options:

- adjust the optimizer settings
  - learning rate
  - batch size
  - momentum
- change the model

However, one thing that is pretty clear from the above plot is that our model overfits: the train and test losses are not comparable (the test loss is 3 times higher). Let's see what the results of the net are on some samples from our data.

```
In [35]: img = X_train[2, :, :, :].reshape(1, -1)
         predictions = model.predict(img)
```

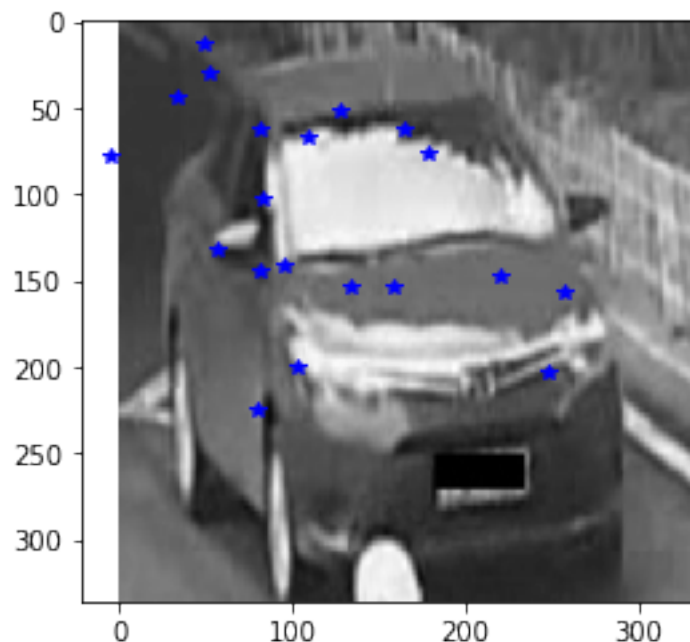
```
In [36]: img
```

```
Out[36]: array([[0.34117647, 0.34117647, 0.34509804, ..., 0.44313725, 0.44705882,
                  0.45098039]])
```

```
In [37]: xy_predictions = output_pipe.inverse_transform(predictions).reshape(20, 2)
```

```
In [38]: plt.imshow(X_train[2, :, :, 0], cmap='gray')
         plt.plot(xy_predictions[:, 0], xy_predictions[:, 1], 'b*')
```

```
Out[38]: [<matplotlib.lines.Line2D at 0x7f7bac22f940>]
```



```

In [39]: def plot_faces_with_keypoints_and_predictions(model, nrows=5, ncols=5, model_input='f
        """Plots sampled faces with their truth and predictions."""
        selection = np.random.choice(np.arange(X.shape[0]), size=(nrows*ncols), replace=F
        fig, axes = plt.subplots(figsize=(10, 10), nrows=nrows, ncols=ncols)
        for ind, ax in zip(selection, axes.ravel()):
            img = X_train[ind, :, :, 0]
            if model_input == 'flat':
                predictions = model.predict(img.reshape(1, -1))
            else:
                predictions = model.predict(img[np.newaxis, :, :, np.newaxis])
            xy_predictions = output_pipe.inverse_transform(predictions).reshape(20, 2)
            ax.imshow(img, cmap='gray')
            ax.plot(xy_predictions[:, 0], xy_predictions[:, 1], 'bo')
            ax.axis('off')

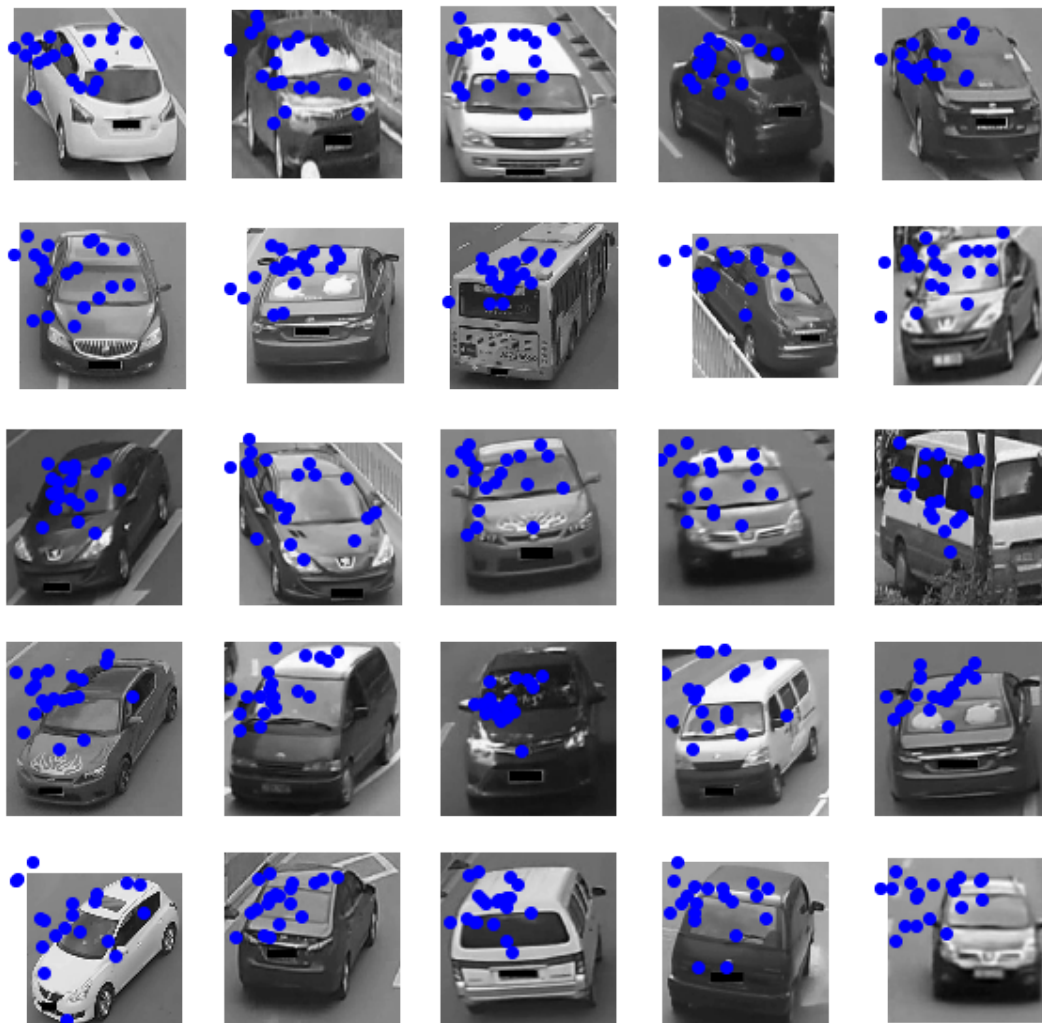
```

```

In [40]: plot_faces_with_keypoints_and_predictions(model)

```





Actually, this looks pretty good already. Let's try to train a more complicated model, this time following the initial model description found in Peter Skvarenina's article.

## 5 Towards more complicated models

```
In [41]: from keras.layers import Dropout, Flatten
```

```
In [43]: import math, json, os, sys
```

```
import keras
from keras.callbacks import EarlyStopping, ModelCheckpoint
from keras.layers import Dense
from keras.models import Model
from keras.optimizers import Adam
```

```

from keras.preprocessing import image

DATA_DIR = 'VeRi'
TRAIN_DIR = os.path.join(DATA_DIR, 'image_train')
VALID_DIR = os.path.join(DATA_DIR, 'image_test')
SIZE = (336, 336)
BATCH_SIZE = 16

num_train_samples = sum([500 for r, d, files in os.walk(TRAIN_DIR)])
num_valid_samples = sum([50 for r, d, files in os.walk(VALID_DIR)])

num_train_steps = math.floor(num_train_samples/BATCH_SIZE)
num_valid_steps = math.floor(num_valid_samples/BATCH_SIZE)

gen = keras.preprocessing.image.ImageDataGenerator()
val_gen = keras.preprocessing.image.ImageDataGenerator(horizontal_flip=True, vertical_flip=True)

batches = gen.flow_from_directory(TRAIN_DIR, target_size=SIZE, class_mode='categorical')
val_batches = val_gen.flow_from_directory(VALID_DIR, target_size=SIZE, class_mode='categorical')

model = keras.applications.resnet50.ResNet50()

classes = list(iter(batches.class_indices))
model.layers.pop()
for layer in model.layers:
    layer.trainable=False
last = model.layers[-1].output
x = Dense(len(classes), activation="softmax")(last)
finetuned_model = Model(model.input, x)
finetuned_model.compile(optimizer=Adam(lr=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
for c in batches.class_indices:
    classes[batches.class_indices[c]] = c
finetuned_model.classes = classes

early_stopping = EarlyStopping(patience=10)
checkpointer = ModelCheckpoint('resnet50_best.h5', verbose=1, save_best_only=True)

finetuned_model.fit_generator(batches, steps_per_epoch=num_train_steps, epochs=1000, validation_data=(val_batches, val_batches.class_indices),
                             callbacks=[early_stopping, checkpointer],
                             save_dir='resnet50_final.h5')

```

Found 0 images belonging to 0 classes.

Found 0 images belonging to 0 classes.

Downloading data from [https://github.com/fchollet/deep-learning-models/releases/download/v0.2/resnet50\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels\\_notop.h5](https://github.com/fchollet/deep-learning-models/releases/download/v0.2/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h5)  
102858752/102853048 [=====] - 9s 0us/step

```

-----

AttributeError                                Traceback (most recent call last)

<ipython-input-43-bf498f084cf9> in <module>
    46 checkpointer = ModelCheckpoint('resnet50_best.h5', verbose=1, save_best_only=True)
    47
---> 48 finetuned_model.fit_generator(batches, steps_per_epoch=num_train_steps, epochs=1000)
    49 finetuned_model.save('resnet50_final.h5')

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/legacy/interfaces.py in wrapper
    89         warnings.warn('Update your `' + object_name + '` call to the `' +
    90             'Keras 2 API: ' + signature, stacklevel=2)
---> 91         return func(*args, **kwargs)
    92     wrapper._original_function = func
    93     return wrapper

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/engine/training.py in fit_generator
   1416         use_multiprocessing=use_multiprocessing,
   1417         shuffle=shuffle,
-> 1418         initial_epoch=initial_epoch)
   1419
   1420     @interfaces.legacy_generator_methods_support

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/engine/training_generator.py in fit_generator
    38
    39     do_validation = bool(validation_data)
---> 40     model._make_train_function()
    41     if do_validation:
    42         model._make_test_function()

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/engine/training.py in _make_train_function
   507         training_updates = self.optimizer.get_updates(
   508             params=self._collected_trainable_weights,
--> 509             loss=self.total_loss)
   510         updates = (self.updates +
   511                   training_updates +

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/legacy/interfaces.py in wrapper
    89         warnings.warn('Update your `' + object_name + '` call to the `' +
    90             'Keras 2 API: ' + signature, stacklevel=2)
---> 91         return func(*args, **kwargs)

```

```

92         wrapper._original_function = func
93         return wrapper

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/optimizers.py in get_updates(
503             p_t = p - lr_t * m_t / (K.sqrt(v_t) + self.epsilon)
504
--> 505         self.updates.append(K.update(m, m_t))
506         self.updates.append(K.update(v, v_t))
507         new_p = p_t

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py
971         The variable `x` updated.
972         """
--> 973         return tf.assign(x, new_x)
974
975

~/anaconda3/envs/tfgpu/lib/python3.6/site-packages/tensorflow/python/ops/state_ops.py :
220         ref, value, use_locking=use_locking, name=name,
221         validate_shape=validate_shape)
--> 222     return ref.assign(value, name=name)
223
224

```

AttributeError: 'Tensor' object has no attribute 'assign'

```

In [60]: model = Sequential()
         # input layer
         model.add(BatchNormalization(input_shape=(336, 336, 1)))
         model.add(Conv2D(24, (5, 5), kernel_initializer='he_normal'))
         model.add(Activation('relu'))
         model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
         model.add(Dropout(0.2))
         # layer 2
         model.add(Conv2D(36, (5, 5)))
         model.add(Activation('relu'))
         model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
         model.add(Dropout(0.2))
         # layer 3
         model.add(Conv2D(48, (5, 5)))
         model.add(Activation('relu'))
         model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
         model.add(Dropout(0.2))

```

```

# layer 4
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.2))
# layer 5
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(Flatten())
# layer 6
model.add(Dense(500, activation="relu"))
# layer 7
model.add(Dense(120, activation="relu"))
# layer 8
model.add(Dense(40))

```

```

In [61]: sgd = optimizers.SGD(lr=1e-6, decay=1e-6, momentum=0.95, nesterov=True)
model.compile(optimizer=sgd, loss='mse', metrics=['accuracy'])
epochs = 110
history = model.fit(X_train, y_train,
                    validation_split=0.2, shuffle=True,
                    epochs=epochs, batch_size=10)

```

Train on 400 samples, validate on 100 samples

```

Epoch 1/110
400/400 [=====] - 49s 123ms/step - loss: 0.8674 - acc: 0.0150 - val_loss: 0.8674
Epoch 2/110
400/400 [=====] - 56s 141ms/step - loss: 0.8432 - acc: 0.0200 - val_loss: 0.8432
Epoch 3/110
400/400 [=====] - 51s 126ms/step - loss: 0.8003 - acc: 0.0100 - val_loss: 0.8003
Epoch 4/110
400/400 [=====] - 51s 127ms/step - loss: 0.7700 - acc: 0.0100 - val_loss: 0.7700
Epoch 5/110
400/400 [=====] - 51s 127ms/step - loss: 0.7482 - acc: 0.0225 - val_loss: 0.7482
Epoch 6/110
400/400 [=====] - 50s 126ms/step - loss: 0.7278 - acc: 0.0175 - val_loss: 0.7278
Epoch 7/110
400/400 [=====] - 50s 124ms/step - loss: 0.7063 - acc: 0.0175 - val_loss: 0.7063
Epoch 8/110
400/400 [=====] - 49s 121ms/step - loss: 0.6998 - acc: 0.0175 - val_loss: 0.6998
Epoch 9/110
400/400 [=====] - 51s 127ms/step - loss: 0.6803 - acc: 0.0075 - val_loss: 0.6803
Epoch 10/110
400/400 [=====] - 49s 123ms/step - loss: 0.6744 - acc: 0.0150 - val_loss: 0.6744
Epoch 11/110
340/400 [=====>...] - ETA: 6s - loss: 0.6633 - acc: 0.0088

```

-----

KeyboardInterrupt

Traceback (most recent call last)

```
<ipython-input-61-63ad94e2956e> in <module>
      4 history = model.fit(X_train, y_train,
      5                       validation_split=0.2, shuffle=True,
----> 6                       epochs=epochs, batch_size=10)

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training.py in fit(self,
1037         initial_epoch=initial_epoch,
1038         steps_per_epoch=steps_per_epoch,
-> 1039         validation_steps=validation_steps)
1040
1041     def evaluate(self, x=None, y=None,

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/engine/training_arrays.py in
197         ins_batch[i] = ins_batch[i].toarray()
198
--> 199         outs = f(ins_batch)
200         outs = to_list(outs)
201         for l, o in zip(out_labels, outs):

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py
2713         return self._legacy_call(inputs)
2714
-> 2715         return self._call(inputs)
2716     else:
2717         if py_any(is_tensor(x) for x in inputs):

~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/keras/backend/tensorflow_backend.py
2673         fetched = self._callable_fn(*array_vals, run_metadata=self.run_metadata)
2674     else:
-> 2675         fetched = self._callable_fn(*array_vals)
2676         return fetched[:len(self.outputs)]
2677

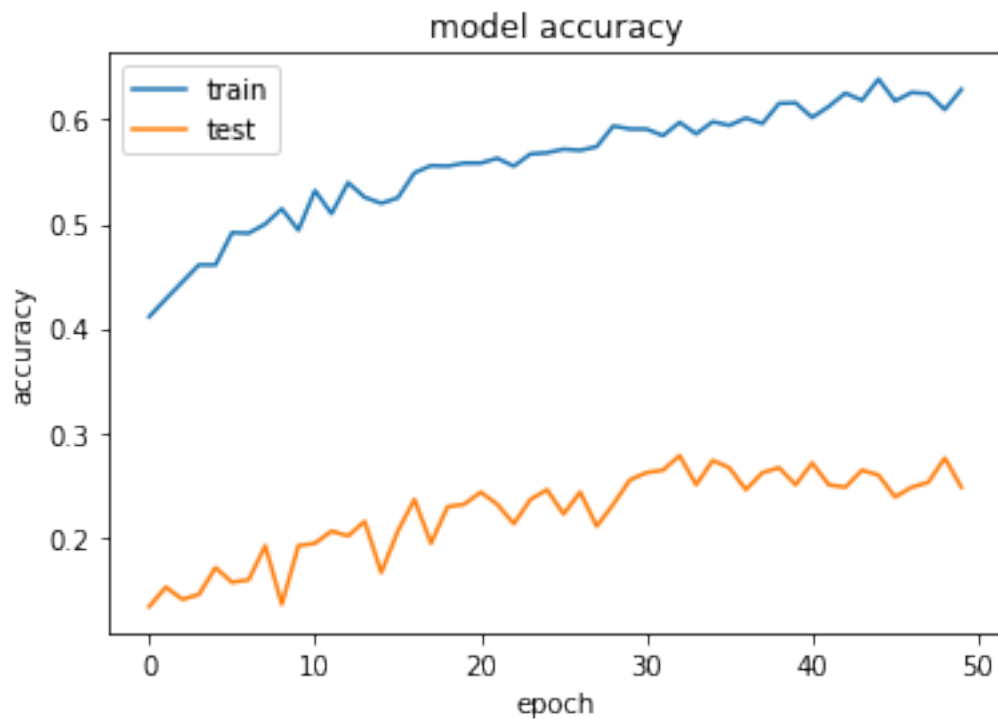
~/anaconda3/envs/tfcpu/lib/python3.6/site-packages/tensorflow/python/client/session.py
1456         ret = tf_session.TF_SessionRunCallable(self._session._session,
1457         self._handle, args,
-> 1458         run_metadata_ptr)
1459     if run_metadata:
1460         proto_data = tf_session.TF_GetBuffer(run_metadata_ptr)
```

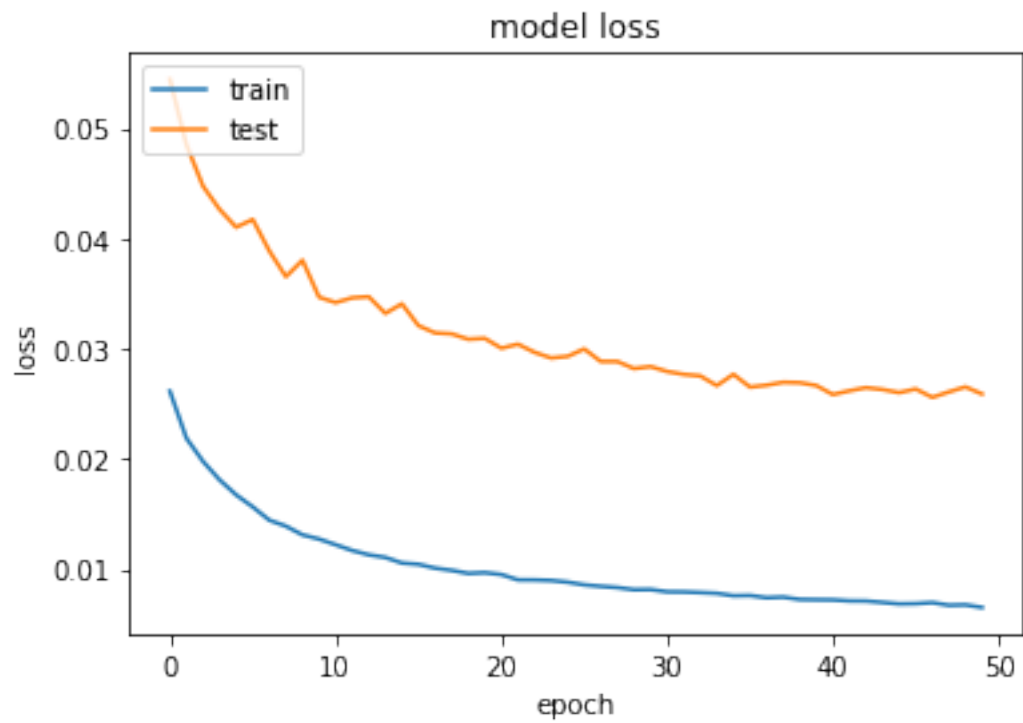
KeyboardInterrupt:

Let's see that in curves:

```
In [118]: # summarize history for accuracy
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```





How good is the result?

```
In [120]: plot_faces_with_keypoints_and_predictions(model, model_input='2d')
```





If you ask me, that's already pretty good. Even though we didn't reach the performance advertised in Peter Skvarenina's blog post, with 80% validation accuracy. I wonder what he used to reach that level of performance: longer training? better settings?

Let's move on to the last section of this blog post: applications.

## 6 Applications

### 6.1 A face mask

A first thing we can do is to apply some sort of mask on top of the detected image. Let's draw a moustache over an image for example.

First, we need an image of a moustache.

```
In [175]: import skimage.color
          from skimage.filters import median
```

```
In [337]: moustache = plt.imread('http://www.freeiconspng.com/uploads/moustache-png-by-spoonsw
moustache = skimage.color.rgb2gray(moustache)
```

```
In [338]: moustache = median(moustache, selem=np.ones((3, 3)))
```

```
/Users/kappamaki/anaconda/lib/python3.6/site-packages/skimage/util/dtype.py:122: UserWarning: I
.format(dtypeobj_in, dtypeobj_out))
```

Let's display it.

```
In [339]: plt.imshow(moustache, cmap='gray')
```

```
Out[339]: <matplotlib.image.AxesImage at 0x1388b2198>
```



Now, let's extract the boundary of this moustache.

```
In [340]: from skimage import measure
moustache_contour = measure.find_contours(moustache, 0.8)[0]
moustache_contour -= np.array([250, 250])
```

Now, let's write a function that plots a scaled moustache at a given position.

```
In [368]: def plot_scaled_moustache(ax, center_xy, dx):
    """Plots a moustache scaled by its width, dx, on current ax."""
    moustache_scaled = moustache_contour.copy()
    moustache_scaled -= moustache_contour.min(axis=0)
    moustache_scaled /= moustache_scaled.max(axis=0)[1]
```

```

deltas = moustache_scaled.max(axis=0) - moustache_scaled.min(axis=0)
moustache_scaled -= np.array([deltas[0]/2, deltas[1]/2])
moustache_scaled *= dx
moustache_scaled += center_xy[:,-1]
ax.fill(moustache_scaled[:, 1], moustache_scaled[:, 0], "g", linewidth=4)

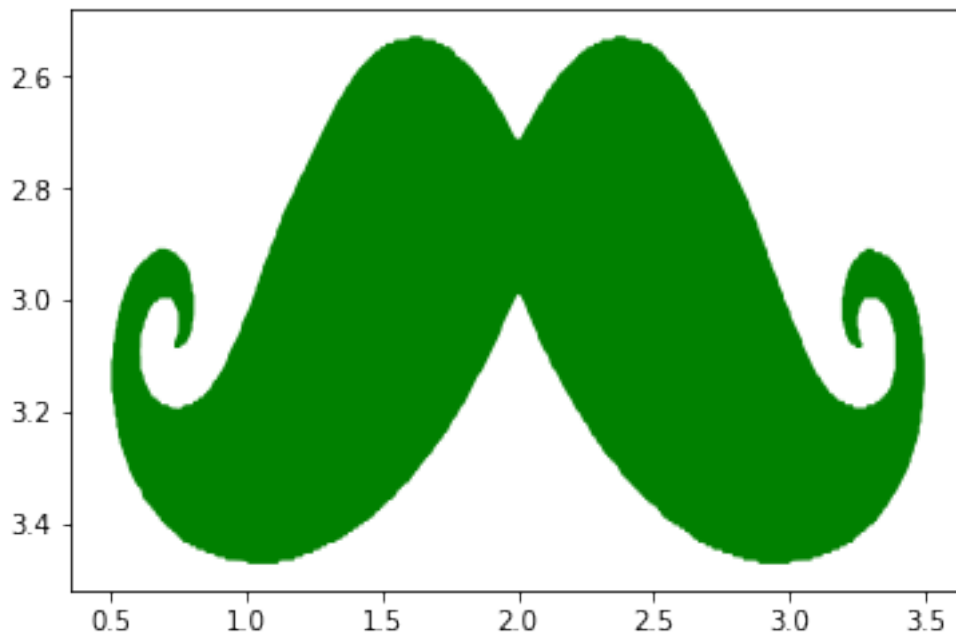
```

Let's test this:

```

In [369]: ax = plt.gca()
          plot_scaled_moustache(ax, np.array([2, 3]), dx=3)
          ax.invert_yaxis()

```



Finally, we can integrate this with a function of the predicted points. We will use the mouth location and space the moustache using the size of the mouth.

```

In [370]: def draw_moustache(predicted_points, ax):
          """Draws a moustache using the predicted face points."""
          dx = 2 * np.linalg.norm(predicted_points[12, :] - predicted_points[11, :])
          center_xy = predicted_points[13, :]
          plot_scaled_moustache(ax, center_xy, dx)

```

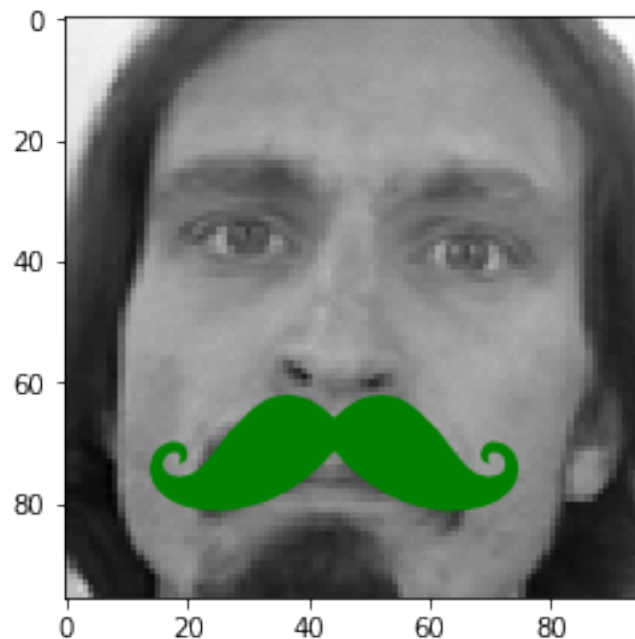
Let's try this with the first image from the training set.

```

In [371]: img = X_train[0, :, :, :][np.newaxis, :, :, :]
          predictions = model.predict(img)
          xy_predictions = output_pipe.inverse_transform(predictions).reshape(15, 2)

```

```
In [372]: fig, ax = plt.subplots()
          ax.imshow(X_train[0, :, :, 0], cmap='gray')
          draw_moustache(xy_predictions, ax)
```



Ok, looks good. Let's apply this to a grid of images.

```
In [373]: def plot_faces_with_moustaches(model, nrows=5, ncols=5, model_input='flat'):
          """Plots sampled faces with their truth and predictions."""
          selection = np.random.choice(np.arange(X.shape[0]), size=(nrows*ncols), replace=True)
          fig, axes = plt.subplots(figsize=(10, 10), nrows=nrows, ncols=ncols)
          for ind, ax in zip(selection, axes.ravel()):
              img = X_train[ind, :, :, 0]
              if model_input == 'flat':
                  predictions = model.predict(img.reshape(1, -1))
              else:
                  predictions = model.predict(img[np.newaxis, :, :, np.newaxis])
              xy_predictions = output_pipe.inverse_transform(predictions).reshape(15, 2)
              ax.imshow(img, cmap='gray')
              draw_moustache(xy_predictions, ax)
              ax.axis('off')
```

```
In [375]: plot_faces_with_moustaches(model, model_input='2d')
```



This is fun. There's a couple of ways we could better: adjust for face directions (the tilted faces in particular look strange). But that's already pretty nice. Let's make a gallery of famous faces with moustaches.

## 6.2 Famous faces with moustaches

Let's apply the skill of adding automated moustaches to some famous paintings.

```
In [501]: portrait_urls = ["https://upload.wikimedia.org/wikipedia/commons/thumb/e/ec/Mona_Lisa.jpg",
                           "https://upload.wikimedia.org/wikipedia/commons/thumb/d/d2/Hans_Holbein.jpg",
                           "https://upload.wikimedia.org/wikipedia/commons/b/b6/The_Blue_Boy.jpg",
                           "https://upload.wikimedia.org/wikipedia/commons/thumb/2/2f/Thomas_Keeble.jpg",
                           "https://upload.wikimedia.org/wikipedia/en/d/d6/GertrudeStein.JPG",
                           "https://upload.wikimedia.org/wikipedia/commons/thumb/b/b0/Ambrogio_dono.jpg"]
```

```
"https://upload.wikimedia.org/wikipedia/commons/f/f8/Martin_Luther%2F2
"https://upload.wikimedia.org/wikipedia/commons/thumb/6/60/Pierre-Aug
```

```
In [502]: portraits = {}
          for url in portrait_urls:
              if url not in portraits:
                  portraits[url] = imread(url)

In [503]: from skimage.io import imread
          import cv2

In [505]: face_cascade = cv2.CascadeClassifier('data/haarcascade_frontalface_default.xml')
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(12, 6))
for img, ax in zip(portraits.values(), axes.ravel()):
    gray = (skimage.color.rgb2gray(img) * 255).astype(dtype='uint8')
    bounding_boxes = face_cascade.detectMultiScale(gray, 1.25, 6)
    for (x,y,w,h) in bounding_boxes:
        roi_gray = gray[y:y+h, x:x+w]
        roi_rescaled = skimage.transform.resize(roi_gray, (96, 96))
        predictions = model.predict(roi_rescaled[np.newaxis, :, :, np.newaxis])
        xy_predictions = output_pipe.inverse_transform(predictions).reshape(15, 2)
        ax.imshow(roi_rescaled, cmap='gray')
        draw_moustache(xy_predictions, ax)
    ax.axis('off')
```

```
/Users/kappamaki/anaconda/lib/python3.6/site-packages/skimage/transform/_warps.py:84: UserWarning:
warn("The default mode, 'constant', will be changed to 'reflect' in "
```



For comparison's sake, here are the original paintings:



```
In [506]: face_cascade = cv2.CascadeClassifier('data/haarcascade_frontalface_default.xml')
fig, axes = plt.subplots(nrows=2, ncols=4, figsize=(12, 6))
for img, ax in zip(portraits.values(), axes.ravel()):
    ax.imshow(img)
    ax.axis('off')
```



## 7 Conclusions

Okay, that's it for this blog post. So what steps did we go through? We trained a model using Kaggle data, Keras and a deep convolutional neural network. The model was good enough that we could apply it to images from the internet without major changes.

After doing all this, I still feel that we only scratched the edge of what we could do with this. In particular, the neural network part was not very satisfying since I feel the model we trained could have been better. The reason I did not delve deeper into this (no pun intended) is that I don't own any GPU and hence the training takes quite a long time, which I was not willing to wait for better results.

As a takeaway from this post, I think the claim that a high school genius could do things like these on his own is indeed true. If you have the data, it seems that the machine learning models are powerful and simple enough to allow you to do things that were much more complicated in the past.

If I have time for a next post, I'd love to extend the work we did here but do transfer learning, using features from famous already trained neural networks.

*This post was entirely written using the IPython notebook. Its content is BSD-licensed. You can see a static view or download this notebook with the help of nbviewer at [20170914\\_FacialKeypointsDetection.ipynb](https://nbviewer.jupyter.org/github/20170914/FacialKeypointsDetection.ipynb).*