Ausgangslage

- Datensatz mit 202'599 Gesichtsbilder von Celebrities (JPG, 178x218)
- 40 binäre Features pro Bild
- Augen, Mund etc. normalisiert (gleiche Position)
- Training eines neuronalen Netzes zur Feature-Erkennung

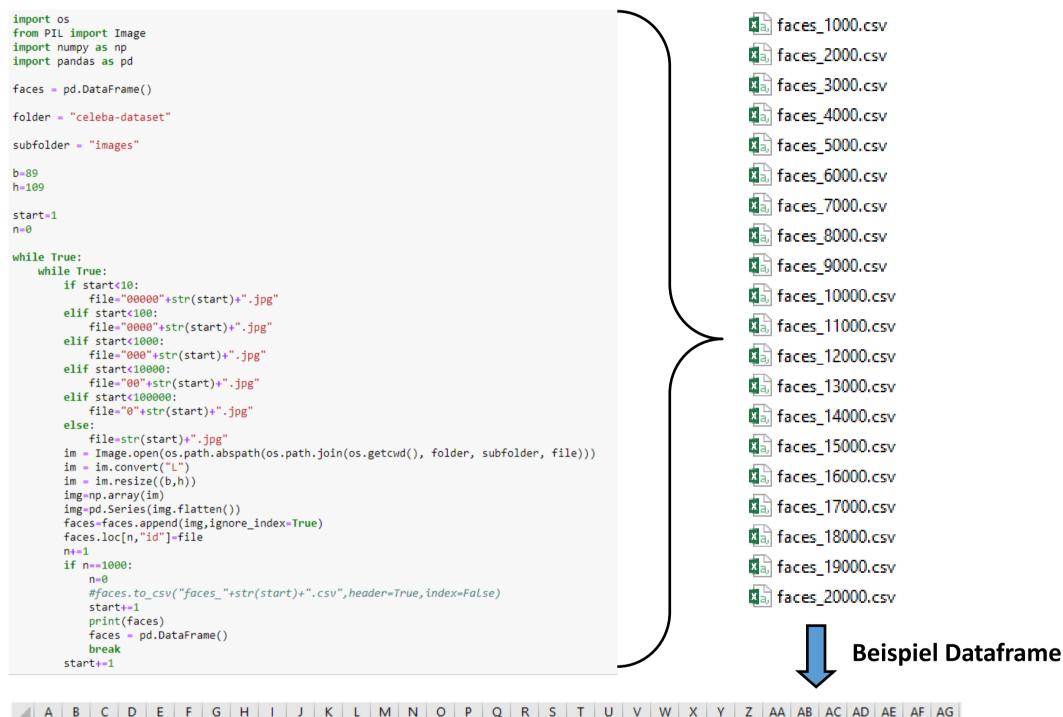
Voranalyse

['5_o_Clock_Shadow', 'Arched_Eyebrows', 'Attractive', 'Bags_Under_Eyes', 'Bald', 'Bangs', 'Big_Lips', 'Big_Nose', 'Black_Hair', 'Blond_Hair', 'Blurry', 'Brown_Hair', 'Bushy_Eyebrows', 'Chubby', 'Double_Chin', 'Eyeglasses', 'Goatee', 'Gray_Hair', 'Heavy_Makeup', 'High_Cheekbones', 'Male', 'Mouth_Slightly_Open', 'Mustache', 'Narrow_Eyes', 'No_Beard', 'Oval_Face', 'Pale_Skin', 'Pointy_Nose', 'Receding_Hairline', 'Rosy_Cheeks', 'Sideburns', 'Smiling', 'Straight_Hair', 'Wavy_Hair', 'Wearing_Earrings', 'Wearing_Hat', 'Wearing_Lipstick', 'Wearing_Necklace', 'Wearing_Necktie', 'Young']



Datenaufbereitung

- Bilder in Graustufen konvertieren zur Dimensionsreduktion
- Reduktion der Bildergrösse zu 89x109
- Transformation der Bilder in ein Dataframe mit Pixelwerten
 - Aufteilung in 1'000er Bins (CSV, ~50MB pro File)



Z AA AB AC AD AE 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 29 92 102 112 118 122 128 130 130 123 117 110 101 90 71 83 79 69 66 61 71 79 87 90 94 96 66 67 40 88 150 178 75 71 61 65 136 97 47 38 37 19 22 28 17 38 10 29 35 21 6 10 20 8 6 | 184 | 185 | 186 | 186 | 184 | 192 | 196 | 213 | 217 | 207 | 199 | 192 | 191 | 205 | 229 | 231 | 232 | 233 | 234 | 234 | 234 | 233 | 233 | 233 | 235 | 235 | 230 | 168 | 188 | 188 | 188 | 189 | 191 86 87 87 88 84 87 87 114 160 147 90 96 101 103 102 95 121 165 101 110 100 110 103 98 109 122 169 129 95 106 105 109 104 27 27 28 29 34 25 145 167 118 41 49 42 46 40 38 37 34 36 33 93 171 162 45 43 42 40 41 38 40 51 43 166 170 77 77 78 80 81 84 87 88 92 96 102 105 109 111 109 111 105 100 97 91 80 67 64 61 67 66 64 64 7 8 8 8 9 10 10 10 11 12 12 13 15 16 17 18 20 23 25 26 30 33 34 36 6 6 6 6 6 12 | 230 | 230 | 230 | 231 | 232 | 231 | 232 | 231 | 230 | 229 | 229 | 229 | 229 | 230 | 231 | 233 | 234 | 232 | 232 | 232 | 232 | 232 | 231 | 231 | 231 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 232 | 23 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 14 | 138 | 138 | 138 | 138 | 148 | 150 | 152 | 151 | 147 | 142 | 141 | 143 | 148 | 152 | 154 | 153 | 151 | 148 | 143 | 140 | 120 | 93 | 71 | 49 | 31 | 30 | 30 | 40 | 37 | 53 | 43 | 45 | 47 | 15 | 175 | 180 | 183 | 188 | 190 | 191 | 195 | 195 | 198 | 199 | 200 | 204 | 205 | 207 | 206 | 205 | 204 | 208 | 201 | 148 | 133 | 130 | 127 | 126 | 124 | 122 | 119 | 121 | 119 | 120 | 117 | 119 | 116 16 | 178 | 178 | 178 | 178 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 176 | 17 18 | 197 | 196 | 196 | 195 | 195 | 194 | 194 | 193 | 196 | 195 | 194 | 194 | 194 | 194 | 194 | 194 | 194 | 194 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 195 | 19 20 | 130 | 132 | 130 | 146 | 180 | 226 | 244 | 248 | 237 | 224 | 216 | 207 | 201 | 192 | 188 | 183 | 193 | 209 | 220 | 228 | 239 | 251 | 254 | 254 | 252 | 250 | 243 | 234 | 204 | 183 | 183 | 184 | 183 |

Netzarchitektur / Training

```
model = Sequential()
model.add(Convolution2D(8, (3, 3), input_shape=(109, 89, 1)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Convolution2D(8, (3, 3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Convolution2D(16, (3,3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Convolution2D(16, (3, 3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Convolution2D(32, (3,3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Convolution2D(32, (3, 3)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())
model.add(Dropout(0.2))
model.add(Dense(2240))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1120))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1120))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(1))
model.add(BatchNormalization())
model.add(Activation('sigmoid'))
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

```
#Parameter
goal="Smiling"
modelname="defmod"
#Trainingsdateinummern auflisten [2000,3000,4000,5000 etc.]
dateiset=[32000]
from keras.models import load model as loadm
   model = loadm(modelname+".h5")
except:
   print("NO SAVED MODEL FOUND!")
for m in dateiset:
    datei="faces "+str(m)+".csv"
    file=os.path.abspath(os.path.join(os.getcwd(),datei))
    data=pd.DataFrame(pd.read_csv(file))
    data2=attrs[["image_id",goal]]
    data2=data2.replace(-1, 0)
    datadef=data.merge(data2,left_on="id", right_on="image_id")
    datadef=datadef.drop(columns=["id","image_id"])
    [train,test]=sklms.train_test_split(datadef)
    train_x=train.loc[:, train.columns != goal]
    train_x=np.array(train_x)
    train_x=train_x.reshape(750,109,89,1)
    train_y=np.array(train[goal])
    test_x=test.loc[:, test.columns != goal]
    test_x=np.array(test_x)
    test_x=test_x.reshape(250,109,89,1)
    test_y=np.array(test[goal])
    trained_on=datei
    print("Training on",trained_on,"...")
    model.fit(train_x,train_y,epochs=anzepoch, batch_size=25,validation_data=[test_x, test_y])
    model.save(modelname+".h5")
```

Layer (type)	Output	Shape	Param #
conv2d_1 (Conv2D)	(None,	107, 87, 8)	80
batch_normalization_1 (Batch	(None,	107, 87, 8)	32
activation_1 (Activation)	(None,	107, 87, 8)	0
conv2d_2 (Conv2D)	(None,	105, 85, 8)	584
batch_normalization_2 (Batch	(None,	105, 85, 8)	32
activation_2 (Activation)	(None,	105, 85, 8)	0
max_pooling2d_1 (MaxPooling2	(None,	52, 42, 8)	0
conv2d_3 (Conv2D)	(None,	50, 40, 16)	1168
batch_normalization_3 (Batch	(None,	50, 40, 16)	64
activation_3 (Activation)	(None,	50, 40, 16)	0
conv2d_4 (Conv2D)	(None,	48, 38, 16)	2320
batch_normalization_4 (Batch	(None,	48, 38, 16)	64
activation_4 (Activation)	(None,	48, 38, 16)	0
max_pooling2d_2 (MaxPooling2	(None,	24, 19, 16)	0
conv2d_5 (Conv2D)	(None,	22, 17, 32)	4640
batch_normalization_5 (Batch	(None,	22, 17, 32)	128
activation_5 (Activation)	(None,	22, 17, 32)	0
conv2d_6 (Conv2D)	(None,	20, 15, 32)	9248
batch_normalization_6 (Batch	(None,	20, 15, 32)	128
activation_6 (Activation)	(None,	20, 15, 32)	0
max_pooling2d_3 (MaxPooling2	(None,	10, 7, 32)	0
flatten_1 (Flatten)	(None,	2240)	0
dropout_1 (Dropout)	(None,	2240)	0
dense_1 (Dense)	(None,	2240)	5019840
batch_normalization_7 (Batch	(None,	2240)	8960
activation_7 (Activation)	(None,	2240)	0
dropout_2 (Dropout)	(None,	2240)	0
dense_2 (Dense)	(None,	1120)	2509920
batch_normalization_8 (Batch	(None,	1120)	4480
activation_8 (Activation)	(None,	1120)	0
dropout_3 (Dropout)	(None,	1120)	0
dense_3 (Dense)	(None,	1120)	1255520
batch_normalization_9 (Batch	(None,	1120)	4480
activation_9 (Activation)	(None,	1120)	0
dropout_4 (Dropout)	(None,	1120)	0
dense_4 (Dense)	(None,	1)	1121
batch_normalization_10 (Batc	(None,	1)	4
activation_10 (Activation)	(None,	1)	0
Total params: 8,822,813 Trainable params: 8,813,627 Non-trainable params: 9,186	=====		

Resultate

_	•	•	c · ·		
νro	CIC	ınn	THIR	Feat	'IIro
	CIS		IUI	Lac	.ui C

'Male'

Kat. 0 94.7%

Kat. 1 93.3%

Recall für Feature

'Male'

Kat. 0 95.2%

Kat. 1 92.6%

Precision für Feature

'Mouth_Slightly_Open'

Kat. 0 93.4%

Kat. 1 88.2%

Precision für Feature

'Smiling'

Kat. 0 90.7%

Kat. 1 90.9%

Recall für Feature

'Mouth_Slightly_Open'

Kat. 0 89.4%

Kat. 1 92.6%

Recall für Feature

'Smiling'

Kat. 0 91.4%

Kat. 1 90.2%

Beispiele von Fehlklassifizierung für Feature "Male"







Beispiele von Fehlklassifizierung für Feature "Smiling"





