vir-projekt

July 31, 2016

Contents

1 Convolutional Network Features

1.1 Setup der Programmierumgebung

1.1.1 Python-Libraries

```
In [1]: %matplotlib inline
        import scipy.misc as sm
        import numpy as nd
        import glob as g
        import os.path as op
        import re
        import scipy.spatial.distance as sdist
        import numpy as np
```

```
import matplotlib.pyplot as plt
from skimage import io, transform
import pandas as pd

import pickle

import seaborn as sns
import functools
import itertools
from collections import namedtuple
import random
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
import h5py
import random
from tqdm import tqdm
```

```
In [2]: from keras.layers import Input, Dense, Lambda, Dropout, Flatten, MaxPooling2D
        from keras.layers import Convolution2D, MaxPooling2D, ZeroPadding2D
        from keras.models import Model, Sequential
        from keras import backend as K
        from keras import objectives
        from keras.datasets import mnist
        from keras.optimizers import SGD, Adam
```

```
Using Theano backend.
```

1.1.2 mAP

```
In [3]: def feature_distances(query, features, f_distance=sdist.cityblock):
            return np.apply_along_axis(f_distance, 1, features, query)

        def p_r_curve(X, Y, f_distance=sdist.cityblock, query_dist=feature_distances):
            pres, recal = np.zeros(len(X)), np.zeros(len(X))
            ap = np.zeros(len(X))
            for q in range(len(X)):
                distances = query_dist(X[q], X, f_distance)
                retrival = (Y == Y[q])[distances.argsort()]
                p_q = retrival.cumsum() / (np.arange(len(retrival)) + 1)
                pres  = np.add(pres, p_q)
                recal = np.add(recal, retrival.cumsum() / retrival.sum())
                ap[q] = p_q[retrival].mean()
            return recal / len(X), pres / len(X), ap
```

```
In [66]: img_shape = 3, 224, 224
         nb_training_images = 2
         angle_range = 45
```

```
crop_range = 20

sns.set_style("whitegrid", {'axes.grid' : False})
sns.set_context('talk')
```

1.2 Vorverarbeitung der Daten

- BildgröSSe skalieren, da NN-Eingangsvektor konstant
- Anordnen: RGBRGBRGB -> RRR...GGG...BBB

```
In [5]: def reorder(img):
            img = img * 255
            img[:,:,0] -= 103.939
            img[:,:,1] -= 116.779
            img[:,:,2] -= 123.68
            img = img.transpose((2,0,1))
            return img

        def preprocess(img, img_shape =(224, 224, 3)):
            return reorder(transform.resize(img , img_shape))
```

```
In [6]: paths = sorted(g.glob('./data/WebImages_71x6/*.jpg'))
        data = pd.DataFrame([(re.split('_\d+', op.basename(path))[0],path)
                             for path in paths],columns=['class', 'path'])
        classes = list(enumerate(sorted(list(set(data['class'])))))
        class_map = {name: index for index, name in classes}
        data['y'] = [class_map[name] for name in data['class']]
        data.head()
```

Out[6]:

	class	path	y
0	50	./data/WebImages_71x6/50_1.jpg	0
1	50	./data/WebImages_71x6/50_2.jpg	0
2	50	./data/WebImages_71x6/50_3.jpg	0
3	50	./data/WebImages_71x6/50_4.jpg	0
4	50	./data/WebImages_71x6/50_5.jpg	0

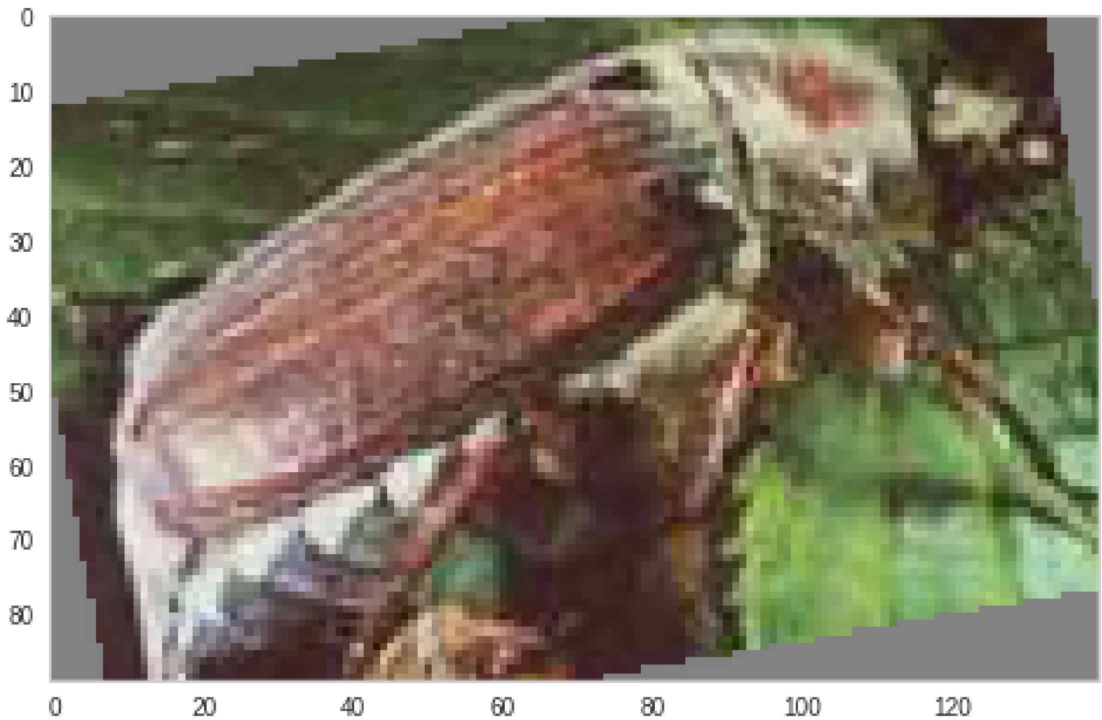
1.2.1 Trainingsdaten erzeugen

Die Trainingsdaten pro Klasse bestehen aus zwei Bildern aus dem Datenset. Aus jedem Bild werden 10 weitere Bilder erzeugt.

```
In [7]: import warnings
        warnings.filterwarnings('ignore')
```

```
In [38]: def rand_img(img):
             height, width, depth = img.shape
             if random.choice((True,False)):
                 img = np.fliplr(img)
```

```
    img = img[random.randint(0,crop_range):
              random.randint(height - crop_range,height),
              random.randint(0,crop_range):
              random.randint(width - crop_range,width)]
    img = transform.rotate(img,(random.random()-0.5) * 2 * angle_range,
                           cval=127, resize=False,mode='constant',order=2)
    return img
plt.imshow(rand_img(io.imread(data['path'].ix[200])), interpolation='none')
plt.show()
```



1.2.2 Trainings und Evaluierungsset erstellen

- Trennung von Trainingsdaten und Testdaten
- Arbeit mit NN macht sonst keinen Sinn

In [39]:
```
x_train_df = data[:0]
x_test_df  = data[:0]
for key, group in data.groupby('class'):
    x_train_df = x_train_df.append(group[0:nb_training_images])
    x_test_df  = x_test_df.append(group[nb_training_images:])
x_train_df.head()


def build_np(df, augment=0):
```

```
    nb_images = len(df) + len(df) * augment
    x = np.zeros((nb_images,) + img_shape, dtype=np.float32)
    y = np.zeros((nb_images,),dtype=np.int8)
    idx = 0
#     print(x.shape)
    for path, cId in tqdm(list(zip(df['path'],df['y']))):
        img = io.imread(path)
        x[idx] = preprocess(img)
        y[idx] = cId
        idx += 1
        for i in range(augment):
            aug_img = rand_img(img)
            x[idx] = preprocess(aug_img)
            y[idx] = cId
            idx += 1
    npy = np.zeros((len(y), max(y) + 1), dtype=np.bool)
    npy[np.arange(len(y)), y] = 1
    return x, npy

x_train, y_train = build_np(x_train_df, augment=10)
x_test, y_test   = build_np(x_test_df)

with open('data/dataset.pickle', 'wb') as feat:
    pickle.dump((x_train, y_train, x_test, y_test), feat)
```

```
100%|| 142/142 [00:37<00:00,  3.91it/s]
100%|| 284/284 [00:02<00:00, 131.28it/s]
```

```
In [ ]: with open('data/dataset.pickle', 'rb') as feat:
            x_train, y_train, x_test, y_test = pickle.load(feat)
```

2 VGG16 mit Keras laden

siehe https://arxiv.org/abs/1409.1556:

```
Very Deep Convolutional Networks for Large-Scale Image Recognition
Karen Simonyan, Andrew Zisserman
```

Parameter und Quellcode basierend auf diesem Gist

Abwandlung hier: nur eine bestimmte Anzahl von Layern werden geladen. Die Ausgabe des Netzes an diesem Punkt, kann dann als Input für eine neues Netz genutz werden, wie es in CS231n beschrieben wurde.

```
In [13]: def load_some_weighs(model, weights_path):
             f = h5py.File(weights_path, mode='r')
             nb_layers = f.attrs['nb_layers']
             for k in range(len(model.flattened_layers)):
```

```
            g = f['layer_{}'.format(k)]
            weights = [g['param_{}'.format(p)] for p in range(g.attrs['nb_params'])]
            model.flattened_layers[k].set_weights(weights)

        f.close()
        return model

    def VGG_16(weights_path=None, layer_limit=None):
        model = Sequential()
        model.add(ZeroPadding2D((1,1),input_shape=(3,224,224)))
        model.add(Convolution2D(64, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(64, 3, 3, activation='relu'))
        model.add(MaxPooling2D((2,2), strides=(2,2)))
        # img dim = 112
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(128, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(128, 3, 3, activation='relu'))
        model.add(MaxPooling2D((2,2), strides=(2,2)))
        # img dim = 56
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(256, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(256, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(256, 3, 3, activation='relu'))
        model.add(MaxPooling2D((2,2), strides=(2,2)))
        # img dim = 28
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(MaxPooling2D((2,2), strides=(2,2)))
        # img dim = 14
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(ZeroPadding2D((1,1)))
        model.add(Convolution2D(512, 3, 3, activation='relu'))
        model.add(MaxPooling2D((2,2), strides=(2,2)))
        # img dim = 7
        model.add(Flatten())
        # length 25088
        if layer_limit == 'maxpool4':
```

```
            return load_some_weighs(model, weights_path)

        model.add(Dense(4096, activation='relu'))
        model.add(Dropout(0.5))
        model.add(Dense(4096, activation='relu'))
        model.add(Dropout(0.5))

        return load_some_weighs(model, weights_path)
```

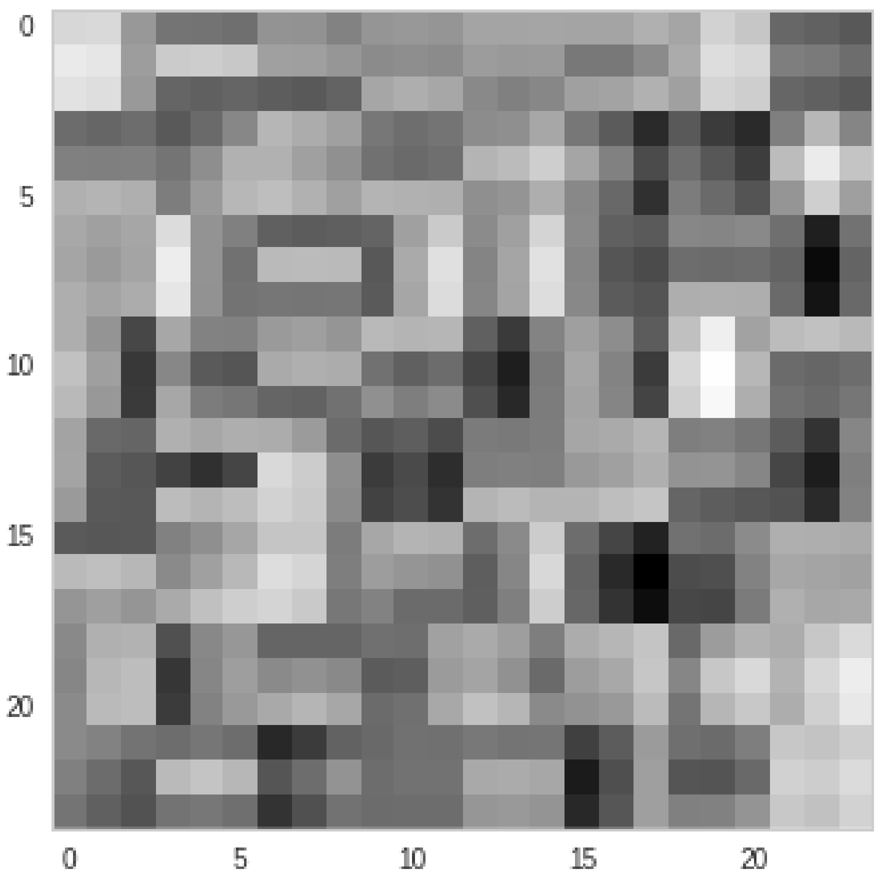
```
In [40]: f_model = VGG_16('models/vgg16/vgg16_weights.h5')
         sgd = SGD(lr=0.1, decay=1e-6, momentum=0.9, nesterov=True)
         f_model.compile(optimizer=sgd, loss='categorical_crossentropy')
```

```
In [41]: conv_model = VGG_16('models/vgg16/vgg16_weights.h5', layer_limit='maxpool4')
         sgd = SGD(lr=0.1, decay=1e-6, momentum=0.9, nesterov=True)
         conv_model.compile(optimizer=sgd, loss='categorical_crossentropy')
```

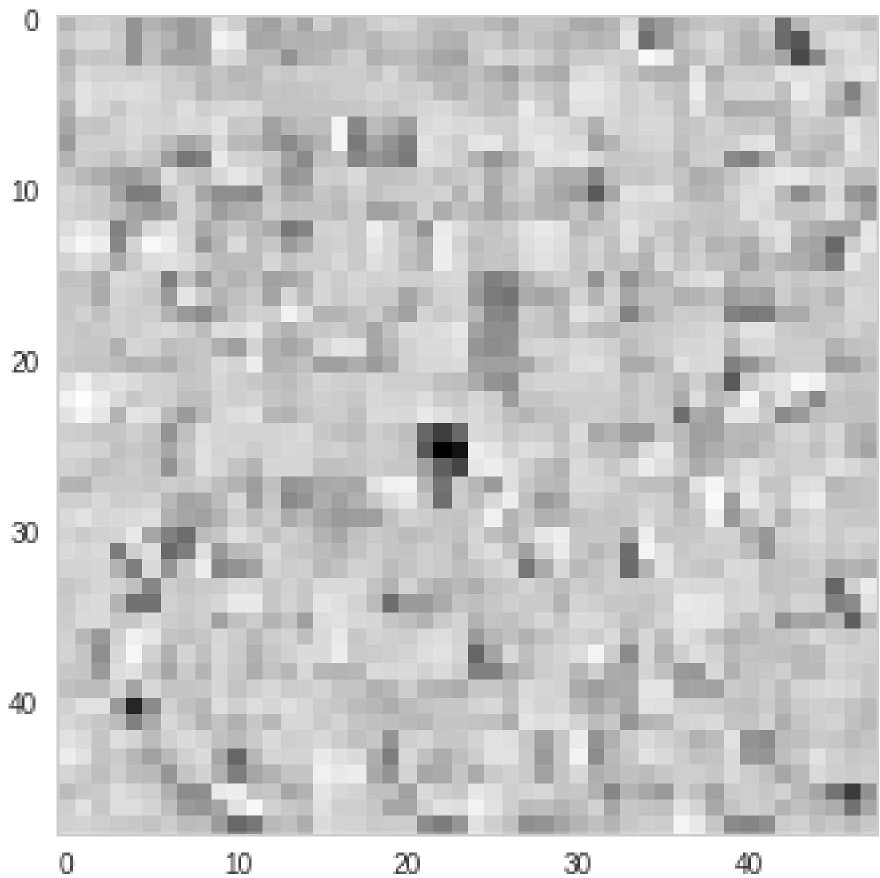
3 Visualisierung der Filter des VGG Models

Das VGG16 Netz benutzt nur 3x3-Filterkernel. Die erste Abbildung zeig die 64 Filter des ersten Layers und die zweite Abbildung zeigt die 256 Filter des siebten Layers als Beispiele.

```
In [16]: conv1 = f_model.layers[1]
         img = np.zeros((8*3, 8*3))
         for y in range(8):
             for x in range(8):
         #         print(y,x, y*8+x)
                 img[x*3:x*3+3,y*3:y*3+3] = conv1.get_weights()[0][y*8 + x,:,:,0]
         plt.imshow(img, interpolation='none')
         plt.show()
```



```
In [17]: conv2 = f_model.layers[15]
         dim = 16
         img = np.zeros((dim*3, dim*3))
         for y_f in range(dim):
             for x_f in range(dim):
                 for y in range(dim):
                     for x in range(dim):
                 #         print(y,x, y*8+x)
                         img[x*3:x*3+3,y*3:y*3+3] = conv2.get_weights()[0][y*dim + x,0,:,:]
         plt.imshow(img, interpolation='none')
         plt.show()
```



4 Feature-Vektoren

Für alle Trainings und Testdaten werden die Featurevektoren auf der Festplatte zwischengespeichert.

```
In [43]: dense_features_train = f_model.predict(x_train,verbose=1)
         dense_features_test  = f_model.predict(x_test,verbose=1)
         with open('models/vgg_dense.features', 'wb') as feat:
             pickle.dump((dense_features_train, dense_features_test), feat)

         conv_features_train = conv_model.predict(x_train,verbose=1)
         conv_features_test  = conv_model.predict(x_test,verbose=1)
         with open('models/vgg_conv.features', 'wb') as feat:
             pickle.dump((conv_features_train, conv_features_test), feat)
```

```
1562/1562 [==============================] - 920s
284/284 [==============================] - 194s
1562/1562 [==============================] - 1029s
```

```
284/284 [==============================] - 174s
```

```
In [18]: with open('models/vgg_dense.features', 'rb') as feat:
             dense_features_train, dense_features_test = pickle.load(feat)
         with open('models/vgg_conv.features', 'rb') as feat:
             conv_features_train, conv_features_test = pickle.load(feat)
```

4.1 Modelkonstruktion 1

Zuerst wurde versucht zwei Netzwerke auf Basis des
CNN-Tensors(7, 7, 512) als Eingabe zu trainieren.

```
In [81]: t_model = Sequential()
         t_model.add(Dense(71, input_shape=(25088,),activation='softmax'))
         adam1 = Adam(lr=0.00003)
         t_model.compile(optimizer=adam1,
                         loss='categorical_crossentropy',
                         metrics=['accuracy'])

         t_model_multi = Sequential()
         t_model_multi.add(Dense(4096, input_shape=(25088,),activation='relu'))
         t_model_multi.add(Dropout(0.5))
         t_model_multi.add(Dense(4096, activation='relu'))
         t_model_multi.add(Dropout(0.5))
         t_model_multi.add(Dense(71, activation='softmax'))
         adam2 = Adam(lr=0.00003)
         t_model_multi.compile(optimizer=adam2,
                               loss='categorical_crossentropy',
                               metrics=['accuracy'])
```

4.2 Trainingsergebniss

Sehr zeitaufwendig ohne GPU. Nur das Netzwerk mit 3 Layern war erfolgsversprechend und wurde länger trainiert.

```
In [90]: def train_model(model,n=1):
             history = model.fit(conv_features_train, y_train,
                     verbose=0,
                     shuffle=True,
                     nb_epoch=10,
                     batch_size=32)

             loss, acc = model.evaluate(conv_features_test,y_test, verbose=0)
             return history, loss, acc
```

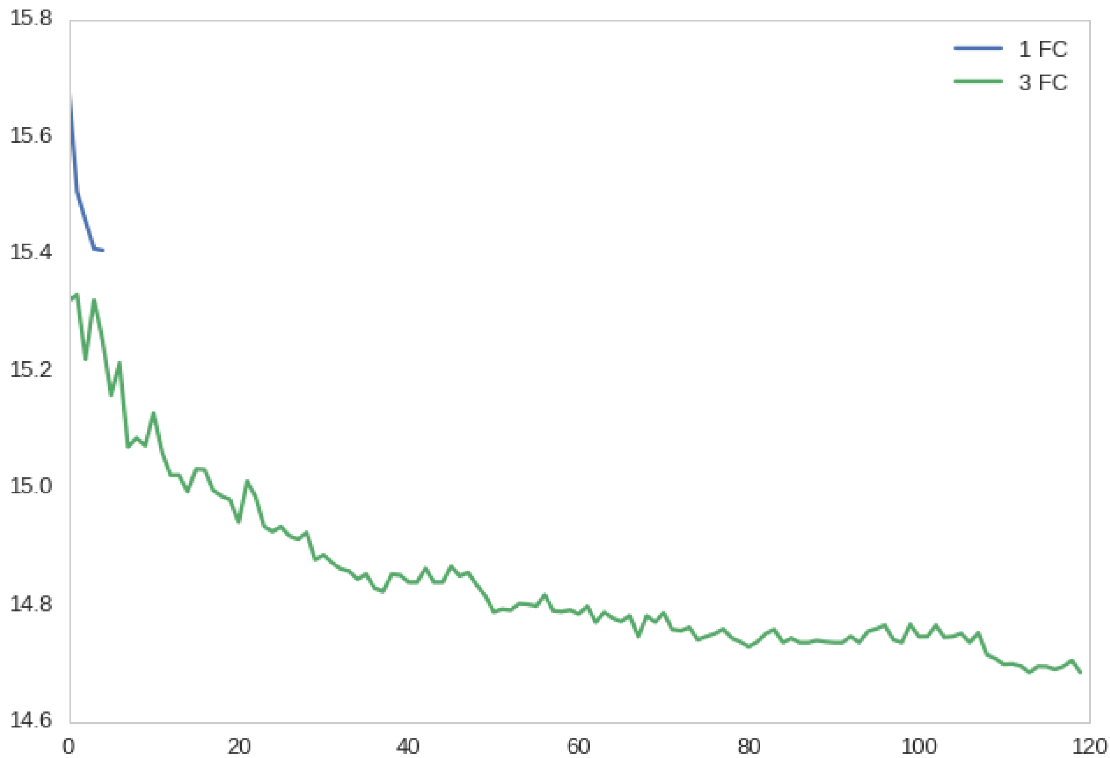
```
In [82]: t_model_eval = train_model(t_model)
```

```
In [91]: batched_training = []
         for idx in tqdm(range(12)):
             batched_training.append(train_model(t_model_multi,n=1))
```

```
100%|| 12/12 [4:51:01<00:00, 2135.03s/it]
```

```
In [105]: line, = plt.plot(t_model_eval[0].history['loss'], label="1 FC")
          line, = plt.plot(h, label="3 FC")
          plt.legend()
```

```
Out[105]: <matplotlib.legend.Legend at 0x7f8c43bc4c50>
```



4.3 Genauigkeit

```
In [111]: evaluations = []
          loss, acc = t_model.evaluate(conv_features_test,y_test, verbose=1)
          evaluations.append(('1 FC', loss, acc))
          loss, acc = t_model_multi.evaluate(conv_features_test,y_test, verbose=1)
          evaluations.append(('3 FC', loss, acc))
          pd.DataFrame(evaluations, columns=['Name','Loss', 'Genauigkeit'])
```

```
284/284 [==============================] - 0s
284/284 [==============================] - 0s
```

```
Out[111]:    Name       Loss  Genauigkeit
          0  1 FC  12.929887     0.084507
          1  3 FC   6.155772     0.556338
```

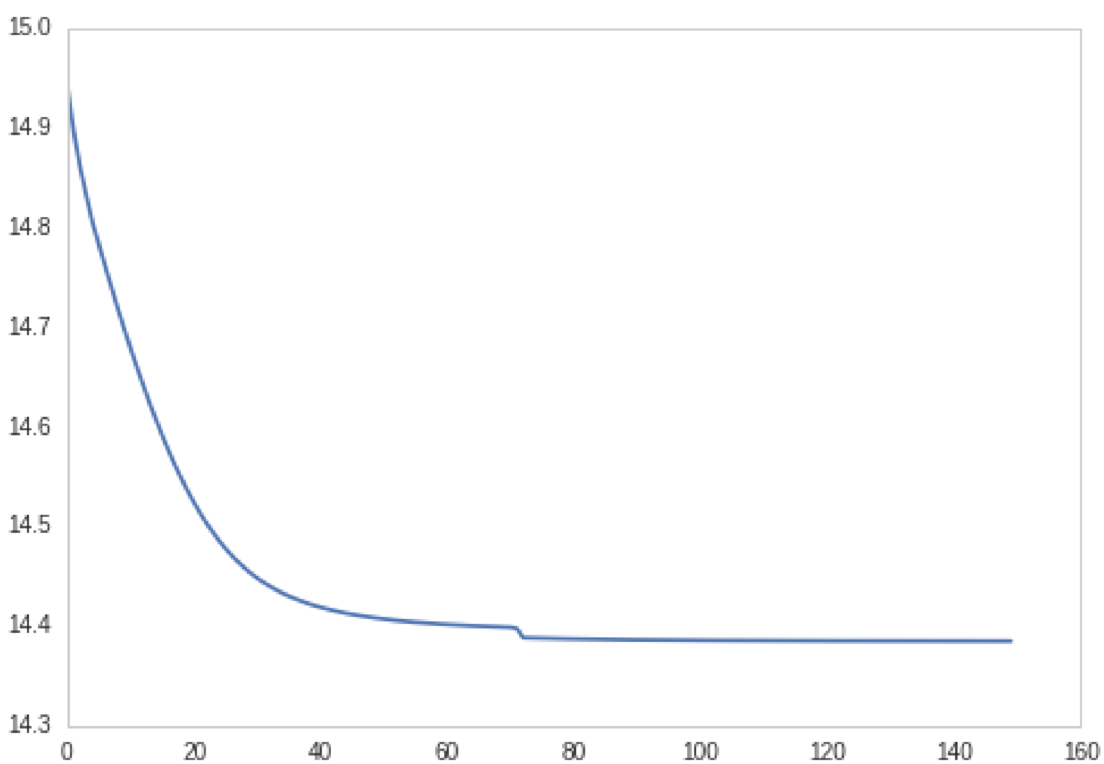
4.4 Modelkonstruktion 2

Dieses Model verwendet die Ausgabe des Fully Connected Layers als Feature (4096 Werte)

```
In [47]: dense_model = Sequential()
         dense_model.add(Dense(71, input_shape=(4096,),activation='softmax'))
         adam = Adam(lr=0.000006)
         dense_model.compile(optimizer=adam,
                             loss='categorical_crossentropy',
                             metrics=['accuracy'])
         history = dense_model.fit(dense_features_train, y_train,
                 verbose=0,
                 shuffle=True,
                 nb_epoch=150,
                 batch_size=16)

         loss, acc = dense_model.evaluate(dense_features_test,y_test, verbose=0)
         print(acc)
         plt.plot(history.history['loss'])
         plt.show()
```

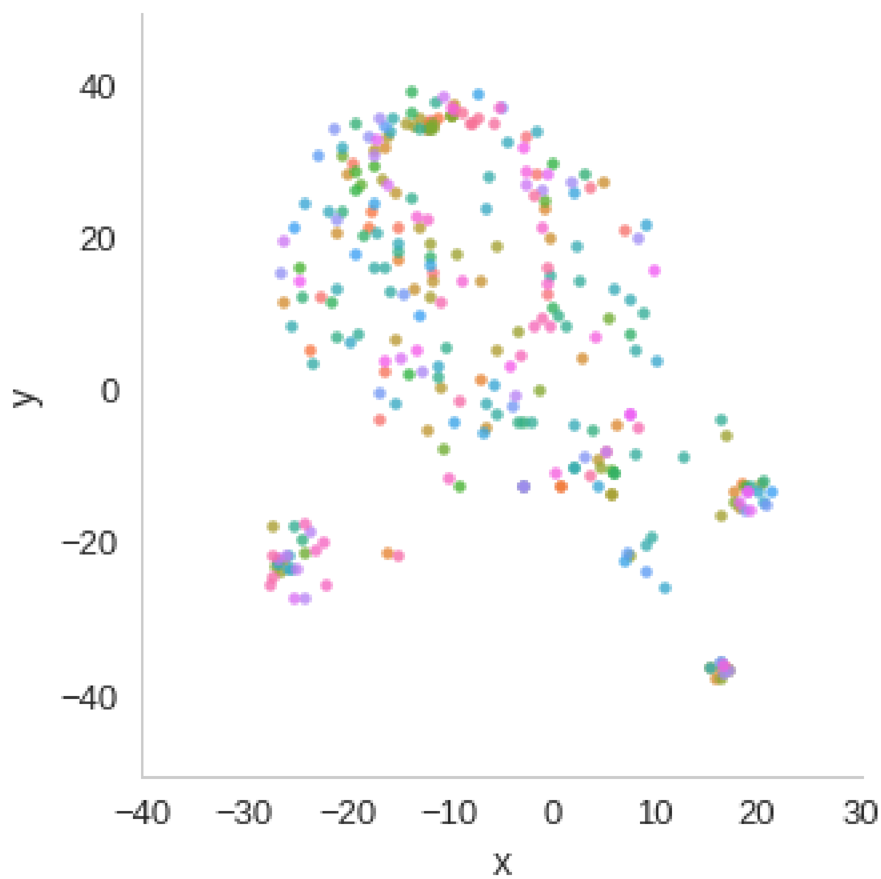
```
0.823943660293
```



5 Evaluierung

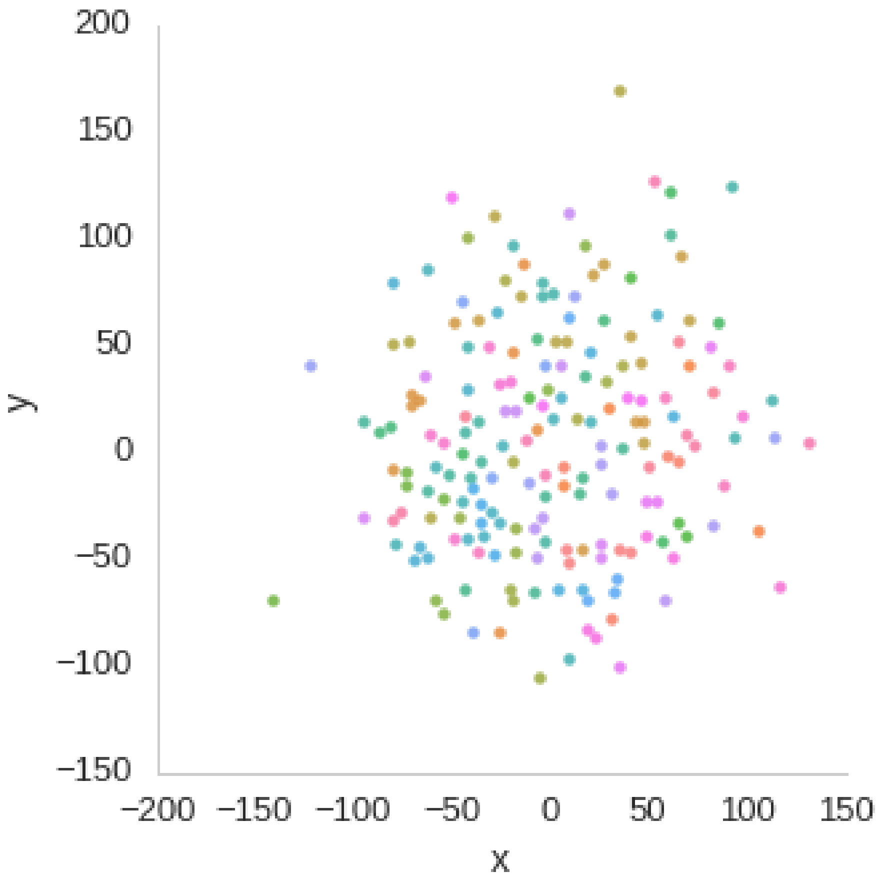
Zur Evaluierung wurde zuerst eine PCA durchgeführt. Danach wurde diese reduzierte Parameterraum mittels t-SNE visualisiert. Die erste Abbildung zeigt die Trainingsdaten im neuen Parameterraum und die Zweite zeigt die Testdaten. Die Cluster in der ersten Abbildung entstehen wahrscheinlich dürch die erzeugten Trainingsdaten.

```
In [75]: preds = dense_model.predict(dense_features_train)
         pca = PCA(n_components=50)
         pca.fit(preds)
         tsne = TSNE(n_components=2, random_state=0)
         np.set_printoptions(suppress=True)
         transformed = tsne.fit_transform(pca.transform(preds))
         data = pd.DataFrame(transformed, columns=['x', 'y'])
         data['class'] = pd.Series(x_test_df['y'])
         g = sns.lmplot(x='x', y='y', data=data, hue='class', fit_reg=False,legend=False)
```



```
In [76]: preds = dense_model.predict(dense_features_test)
         pca.fit(preds)
         np.set_printoptions(suppress=True)
         transformed = tsne.fit_transform(pca.transform(preds))
         data = pd.DataFrame(transformed, columns=['x', 'y'])
         data['class'] = pd.Series(x_test_df['y'])
         sns.lmplot(x='x', y='y', data=data, hue='class', fit_reg=False,legend=False)
```

```
Out[76]: <seaborn.axisgrid.FacetGrid at 0x7f8c46190f60>
```



5.1 Visualisierung der Erkennungsleistung

Um die Erkennungsleistung des Netzwerks zu visualisieren wurde die Sensibilität gegenüber Verdeckungen gemessen.

```
In [50]: def gray_slide(test_img, y_test_img, n = 200, r = 20, step=5):
             coordinates = []
             for height, i in enumerate(range(r, test_img.shape[0] - r,step)):
                 for width, j in enumerate(range(r, test_img.shape[1] - r,step)):
```

```
                coordinates.append((i,j))
        occluded = np.zeros((len(coordinates),) + img_shape, dtype=np.float32)
        idx = 0
        for idx in range(len(coordinates)):
                i, j = coordinates[idx]
                occ = test_img.copy()
                occ[i-r:i+r,j - r: j + r] = 127
                occluded[idx] = preprocess(occ)
        x_o_class = dense_model.predict(f_model.predict(occluded))
        z = x_o_class[:,y_test_img]
        return np.reshape(z - z.mean(),(height + 1, width + 1))
```

```
In [305]: gray_slide_img = gray_slide(io.imread(x_test_df['path'][n]), x_test_df['y'][n])
```

```
In [51]: slide_image_paths = random.sample(list(zip(x_test_df['path'], x_test_df['y'])), 5)
```

```
In [52]: slide_images = [gray_slide(io.imread(path), y) for path, y in tqdm(slide_image_paths)]
```

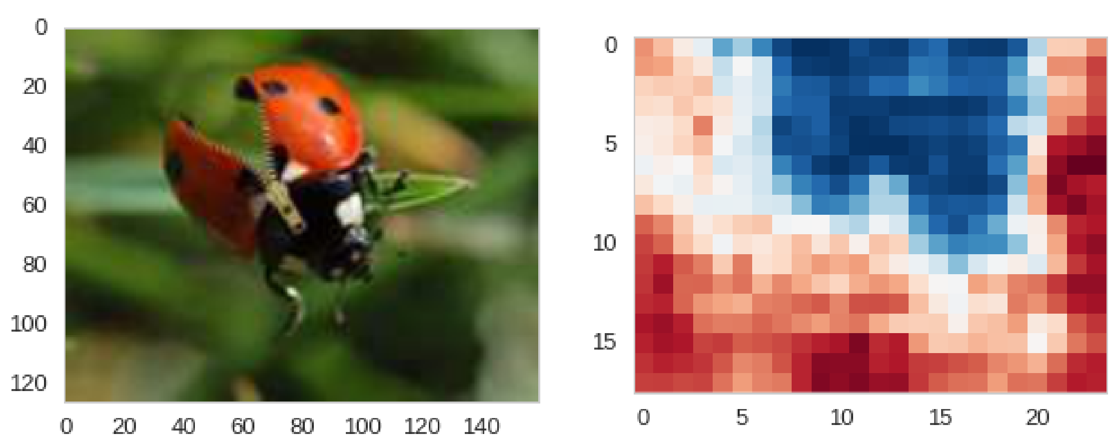
```
100%|| 5/5 [24:13<00:00, 300.25s/it]
```

```
In [336]: (slide_image_paths[0])
```

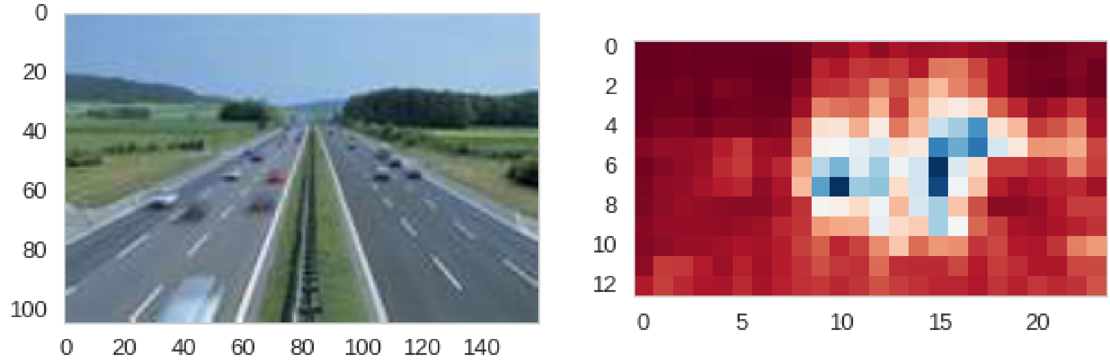
```
Out[336]: ('./data/WebImages_71x6/himbeere_6.jpg', 25)
```

```
In [77]: def plot_side_by_side(i):
                plt.subplot(121)
                plt.imshow(io.imread(slide_image_paths[i][0]))
                plt.subplot(122)
                plt.imshow(slide_images[i],cmap='RdBu_r', interpolation='none')
```

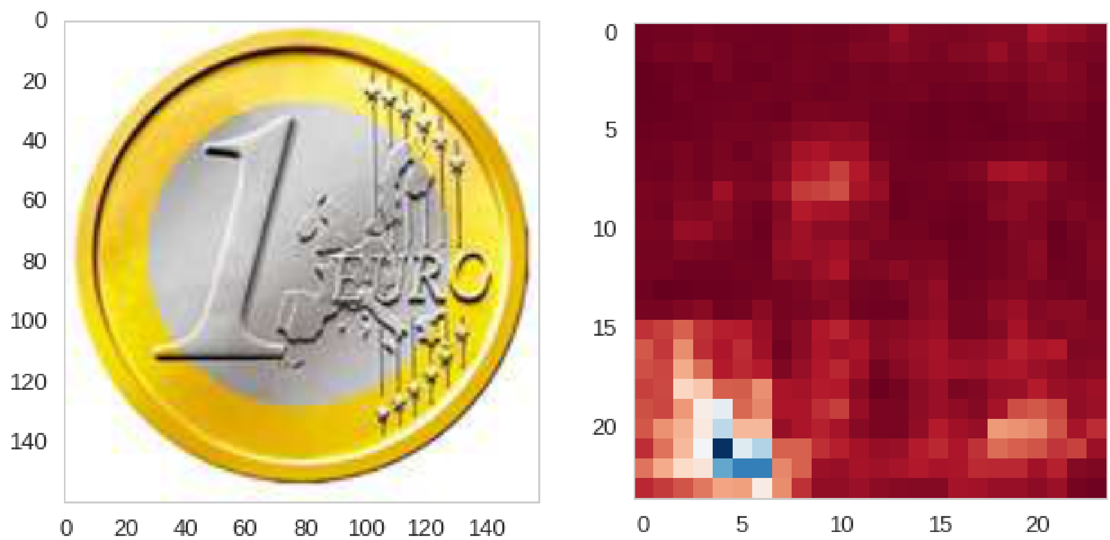
```
In [71]: plot_side_by_side(0)
```



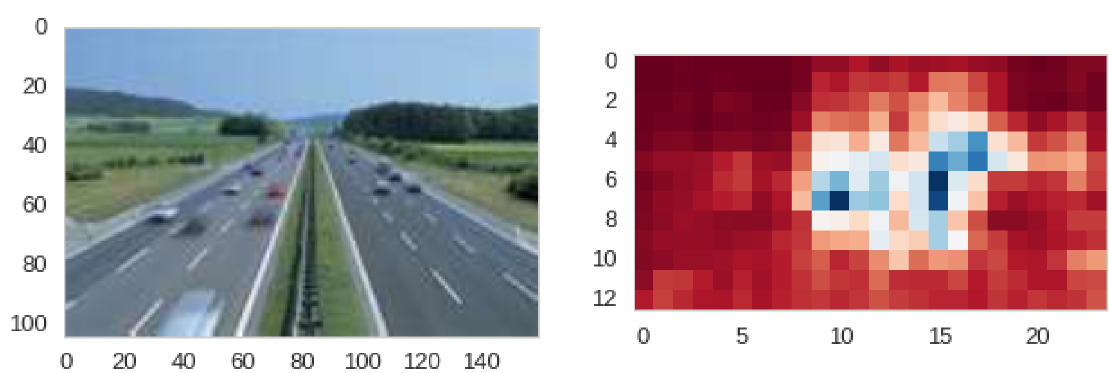
```
In [70]: plot_side_by_side(1)
```



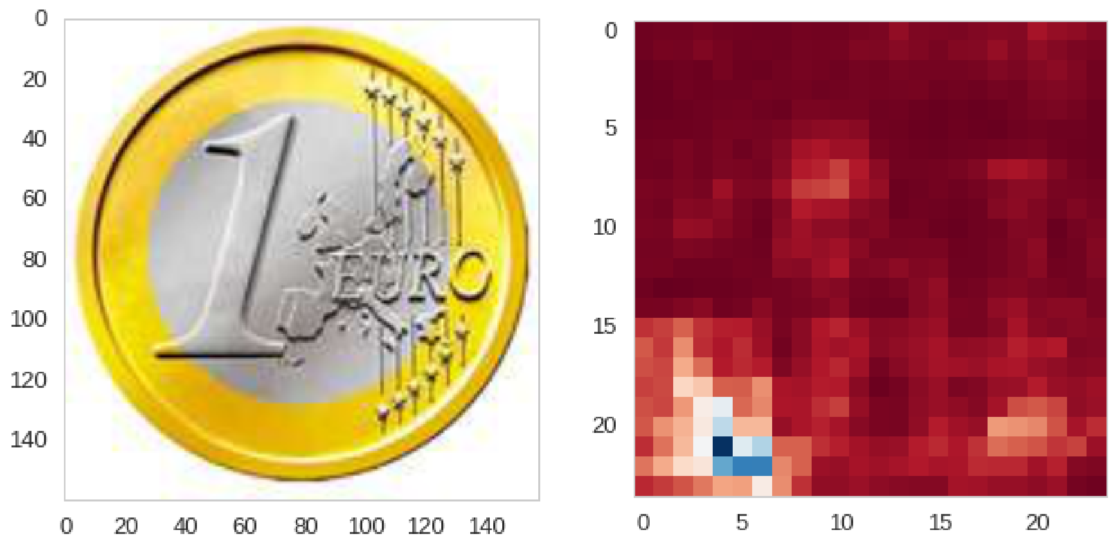

```
In [69]: plot_side_by_side(2)
```




```
In [68]: plot_side_by_side(3)
```



```
In [72]: plot_side_by_side(4)
```



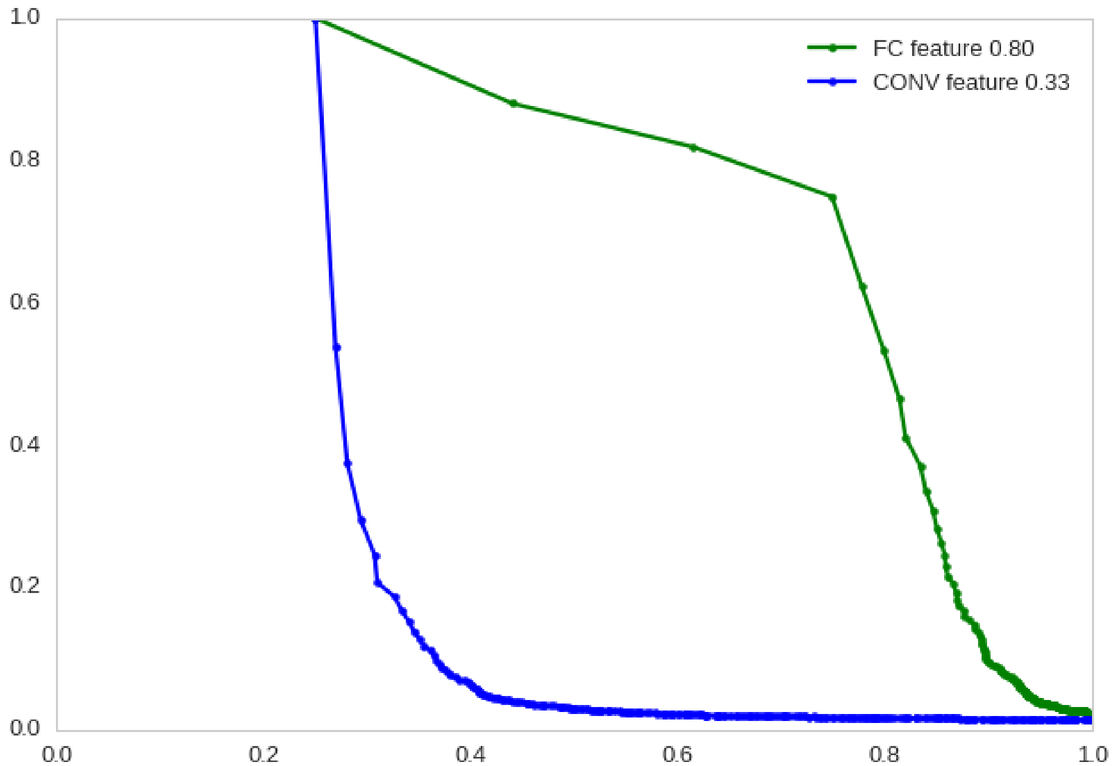
5.2 Precision-Recall

```
In [112]: x_features = dense_model.predict(dense_features_test)
          recal, pres, mAP = p_r_curve(x_features,np.array(x_test_df['y']),sdist.euclidean)
          plt.plot(recal, pres,'.-g',label='FC feature {:.2f}'.format(mAP.mean()))

          x_features = t_model.predict(conv_features_test)
          recal, pres, mAP = p_r_curve(x_features,np.array(x_test_df['y']),sdist.euclidean)
          plt.plot(recal, pres,'.-b', label='CONV feature {:.2f}'.format(mAP.mean()))

          plt.xlim([0,1])
          plt.ylim([0,1])
          mAP.mean()
          plt.legend()

Out[112]: <matplotlib.legend.Legend at 0x7f8c43a4fa90>
```


1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
FC feature 0.80
CONV feature 0.33