KNN

June 22, 2021

1 Künstliche Neuronale Netze

2 mit Tensorflow / Keras

2.1 Beispiel 1: XOR-Verknüpfung

Mit Hilfe eines KNNs soll die XOR-Verknüpfung nachgebildet werden:

X1	X2	у
0	0	0
0	1	1
1	0	1
1	1	0

```
[1]: import numpy as np
  from tensorflow.keras.optimizers import *
  from tensorflow.keras.models import *
  from tensorflow.keras.layers import *
  from tensorflow.keras.losses import *
  from tensorflow.keras.utils import *
```

```
[2]: # Daten

X = [[0,0],[0,1],[1,0],[1,1]]

y = [[0], [1], [0]]
```

```
[3]: model = Sequential()
  model.add(Dense(8, input_dim=2)) # Input-Layer
  model.add(Activation("relu"))

model.add(Dense(10)) # Hidden-Layer
  model.add(Activation("tanh"))

model.add(Dense(10)) # Hidden-Layer
  model.add(Activation("tanh"))

model.add(Dense(1)) # Output-Layer
  model.add(Activation("sigmoid"))
```

```
sgd = SGD(lr=0.1) # Stochastic Gradient Descent
model.compile(loss="binary_crossentropy", optimizer=sgd, metrics="accuracy")
model.fit(X,y, epochs=100)
Epoch 1/100
0.7500
Epoch 2/100
0.7500
Epoch 3/100
0.7500
Epoch 4/100
0.7500
Epoch 5/100
0.7500
Epoch 6/100
0.7500
Epoch 7/100
0.7500
Epoch 8/100
0.7500
Epoch 9/100
0.7500
Epoch 10/100
0.7500
Epoch 11/100
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Epoch 12/100
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Epoch 13/100
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Epoch 14/100
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Epoch 15/100
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Epoch 16/100
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Epoch 17/100
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Epoch 47/100
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Epoch 74/100
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Epoch 78/100
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Epoch 79/100
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Epoch 94/100
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Epoch 95/100
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  Epoch 96/100
  1.0000
  Epoch 97/100
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  Epoch 98/100
  1.0000
  Epoch 99/100
  Epoch 100/100
  [3]: <tensorflow.python.keras.callbacks.History at 0x24ac42d40d0>
[4]: (model.predict(X)>0.5).astype(int)
[4]: array([[0],
     [1],
     [1],
     [0]])
[5]: model.summary()
  Model: "sequential"
     -----
  Layer (type)
               Output Shape
  ______
  dense (Dense)
               (None, 8)
                            24
  activation (Activation)
               (None, 8)
  dense_1 (Dense)
               (None, 10)
                            90
  activation_1 (Activation) (None, 10)
  dense_2 (Dense)
               (None, 10)
                            110
  activation_2 (Activation) (None, 10)
  dense_3 (Dense)
               (None, 1)
```

```
activation_3 (Activation) (None, 1) 0
```

Total params: 235 Trainable params: 235 Non-trainable params: 0

2.2 Beispiel 2: Vorhersage Brustkrebs

```
[6]: from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split

data = load_breast_cancer()
print(data.DESCR)
```

.. _breast_cancer_dataset:

```
Breast cancer wisconsin (diagnostic) dataset
```

Data Set Characteristics:

:Number of Instances: 569

:Number of Attributes: 30 numeric, predictive attributes and the class

:Attribute Information:

- radius (mean of distances from center to points on the perimeter)
- texture (standard deviation of gray-scale values)
- perimeter
- area
- smoothness (local variation in radius lengths)
- compactness (perimeter^2 / area 1.0)
- concavity (severity of concave portions of the contour)
- concave points (number of concave portions of the contour)
- symmetry
- fractal dimension ("coastline approximation" 1)

The mean, standard error, and "worst" or largest (mean of the three worst/largest values) of these features were computed for each image, resulting in 30 features. For instance, field 0 is Mean Radius, field 10 is Radius SE, field 20 is Worst Radius.

- class:
 - WDBC-Malignant
 - WDBC-Benign

:Summary Statistics:

```
Max
                                     Min
radius (mean):
                                    6.981 28.11
texture (mean):
                                    9.71
                                           39.28
perimeter (mean):
                                    43.79 188.5
                                    143.5 2501.0
area (mean):
smoothness (mean):
                                    0.053 0.163
compactness (mean):
                                    0.019 0.345
concavity (mean):
                                    0.0
                                           0.427
concave points (mean):
                                    0.0
                                           0.201
symmetry (mean):
                                    0.106 0.304
fractal dimension (mean):
                                    0.05
                                           0.097
radius (standard error):
                                    0.112 2.873
texture (standard error):
                                    0.36 4.885
perimeter (standard error):
                                    0.757 21.98
area (standard error):
                                    6.802 542.2
smoothness (standard error):
                                    0.002 0.031
compactness (standard error):
                                    0.002 0.135
concavity (standard error):
                                           0.396
                                    0.0
concave points (standard error):
                                    0.0
                                           0.053
symmetry (standard error):
                                    0.008 0.079
fractal dimension (standard error):
                                    0.001 0.03
radius (worst):
                                    7.93
                                           36.04
texture (worst):
                                    12.02 49.54
                                    50.41 251.2
perimeter (worst):
area (worst):
                                    185.2 4254.0
                                    0.071 0.223
smoothness (worst):
compactness (worst):
                                    0.027 1.058
concavity (worst):
                                    0.0
                                           1.252
concave points (worst):
                                    0.0
                                           0.291
symmetry (worst):
                                    0.156 0.664
fractal dimension (worst):
                                    0.055 0.208
:Missing Attribute Values: None
:Class Distribution: 212 - Malignant, 357 - Benign
:Creator: Dr. William H. Wolberg, W. Nick Street, Olvi L. Mangasarian
:Donor: Nick Street
:Date: November, 1995
```

This is a copy of UCI ML Breast Cancer Wisconsin (Diagnostic) datasets. $\verb|https://goo.gl/U2Uwz2||$ Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.

Separating plane described above was obtained using Multisurface Method-Tree (MSM-T) [K. P. Bennett, "Decision Tree Construction Via Linear Programming." Proceedings of the 4th Midwest Artificial Intelligence and Cognitive Science Society, pp. 97-101, 1992], a classification method which uses linear programming to construct a decision tree. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

The actual linear program used to obtain the separating plane in the 3-dimensional space is that described in:
[K. P. Bennett and O. L. Mangasarian: "Robust Linear Programming Discrimination of Two Linearly Inseparable Sets", Optimization Methods and Software 1, 1992, 23-34].

This database is also available through the UW CS ftp server:

ftp ftp.cs.wisc.edu
cd math-prog/cpo-dataset/machine-learn/WDBC/

- .. topic:: References
 - W.N. Street, W.H. Wolberg and O.L. Mangasarian. Nuclear feature extraction for breast tumor diagnosis. IS&T/SPIE 1993 International Symposium on Electronic Imaging: Science and Technology, volume 1905, pages 861-870, San Jose, CA, 1993.
- O.L. Mangasarian, W.N. Street and W.H. Wolberg. Breast cancer diagnosis and prognosis via linear programming. Operations Research, 43(4), pages 570-577,

July-August 1995.

- W.H. Wolberg, W.N. Street, and O.L. Mangasarian. Machine learning techniques

to diagnose breast cancer from fine-needle aspirates. Cancer Letters 77 (1994)

163-171.

```
[7]: # Aufteilen in Trainings- und Testdaten
X = data.data
y = data.target

X_train, X_test, y_train, y_test = train_test_split(X,y,shuffle=True,
→test_size=0.3)
```

```
[8]: # KNN erstellen und trainieren
   # Wir verwenden hier "ADAM" als Optimizer (Adaptive moment estimation)
   model2 = Sequential()
   model2.add(Dense(30, input_dim=X_train.shape[1])) # Input-Layer
   model2.add(Activation("relu"))
   model2.add(Dense(50)) # Hidden-Layer
   model2.add(Activation("relu"))
   model2.add(Dense(50)) # Hidden-Layer
   model2.add(Activation("relu"))
   model2.add(Dense(50)) # Hidden-Layer
   model2.add(Activation("relu"))
   model2.add(Dense(1)) # Output-Layer
   model2.add(Activation("sigmoid"))
   model2.compile(loss="binary_crossentropy", optimizer=Adam(lr=0.001), __

→metrics="accuracy")
   model2.fit(x=X_train,y=y_train, epochs=100, validation_data=(X_test, y_test))
  Epoch 1/100
  0.4523 - val_loss: 1.3917 - val_accuracy: 0.6374
  Epoch 2/100
  0.7161 - val_loss: 0.5259 - val_accuracy: 0.7778
  Epoch 3/100
  0.8367 - val_loss: 0.2381 - val_accuracy: 0.9064
  Epoch 4/100
  0.8769 - val_loss: 0.3617 - val_accuracy: 0.8889
  Epoch 5/100
  0.8920 - val_loss: 0.2201 - val_accuracy: 0.9181
  Epoch 6/100
  0.8995 - val_loss: 0.5024 - val_accuracy: 0.8129
  Epoch 7/100
  0.8794 - val_loss: 0.4182 - val_accuracy: 0.8304
  Epoch 8/100
  0.9045 - val_loss: 0.2200 - val_accuracy: 0.9006
  Epoch 9/100
```

```
0.9121 - val_loss: 0.2749 - val_accuracy: 0.9123
Epoch 10/100
0.9221 - val_loss: 0.2086 - val_accuracy: 0.9123
Epoch 11/100
0.9221 - val_loss: 0.4479 - val_accuracy: 0.8655
Epoch 12/100
0.9095 - val_loss: 0.3020 - val_accuracy: 0.8713
Epoch 13/100
0.9095 - val_loss: 0.3032 - val_accuracy: 0.8889
Epoch 14/100
0.9121 - val_loss: 0.2743 - val_accuracy: 0.8713
Epoch 15/100
0.9171 - val_loss: 0.2055 - val_accuracy: 0.9298
Epoch 16/100
0.9196 - val_loss: 0.2838 - val_accuracy: 0.8713
Epoch 17/100
0.9347 - val_loss: 0.3048 - val_accuracy: 0.8713
Epoch 18/100
0.9121 - val_loss: 0.1919 - val_accuracy: 0.9357
Epoch 19/100
0.9095 - val_loss: 0.3296 - val_accuracy: 0.8655
Epoch 20/100
0.9095 - val_loss: 0.2209 - val_accuracy: 0.9181
Epoch 21/100
0.8995 - val_loss: 0.2571 - val_accuracy: 0.8889
Epoch 22/100
0.9271 - val_loss: 0.2378 - val_accuracy: 0.9006
Epoch 23/100
0.9196 - val_loss: 0.1851 - val_accuracy: 0.9240
Epoch 24/100
0.9347 - val_loss: 0.2058 - val_accuracy: 0.9181
Epoch 25/100
```

```
0.9372 - val_loss: 0.1910 - val_accuracy: 0.9064
Epoch 26/100
0.9322 - val_loss: 0.2325 - val_accuracy: 0.9006
Epoch 27/100
0.9095 - val_loss: 0.3626 - val_accuracy: 0.8596
Epoch 28/100
0.8518 - val_loss: 0.6961 - val_accuracy: 0.8246
Epoch 29/100
0.9020 - val_loss: 0.1973 - val_accuracy: 0.9064
Epoch 30/100
0.8819 - val_loss: 0.3667 - val_accuracy: 0.8713
Epoch 31/100
0.8693 - val_loss: 0.3353 - val_accuracy: 0.8947
Epoch 32/100
0.9196 - val_loss: 0.1905 - val_accuracy: 0.9415
Epoch 33/100
0.9271 - val_loss: 0.2273 - val_accuracy: 0.9123
Epoch 34/100
0.9347 - val_loss: 0.1809 - val_accuracy: 0.9357
Epoch 35/100
0.9397 - val_loss: 0.2520 - val_accuracy: 0.9006
Epoch 36/100
0.9146 - val_loss: 0.1892 - val_accuracy: 0.9298
Epoch 37/100
0.9121 - val_loss: 0.3544 - val_accuracy: 0.8596
Epoch 38/100
0.8920 - val_loss: 0.1711 - val_accuracy: 0.9415
Epoch 39/100
0.9221 - val_loss: 0.1811 - val_accuracy: 0.9181
Epoch 40/100
0.9196 - val_loss: 0.3103 - val_accuracy: 0.8889
Epoch 41/100
```

```
0.9146 - val_loss: 0.2454 - val_accuracy: 0.9181
Epoch 42/100
0.8869 - val_loss: 0.1891 - val_accuracy: 0.9298
Epoch 43/100
0.8668 - val_loss: 0.2748 - val_accuracy: 0.8947
Epoch 44/100
0.8844 - val_loss: 0.3118 - val_accuracy: 0.9064
Epoch 45/100
0.9121 - val_loss: 0.3464 - val_accuracy: 0.8713
Epoch 46/100
0.8945 - val_loss: 0.2578 - val_accuracy: 0.9181
Epoch 47/100
0.9246 - val_loss: 0.2413 - val_accuracy: 0.9006
Epoch 48/100
0.9271 - val_loss: 0.1727 - val_accuracy: 0.9357
Epoch 49/100
0.9372 - val_loss: 0.1708 - val_accuracy: 0.9357
Epoch 50/100
0.9322 - val_loss: 0.1725 - val_accuracy: 0.9181
Epoch 51/100
0.9095 - val_loss: 0.2127 - val_accuracy: 0.9181
Epoch 52/100
0.9397 - val_loss: 0.1708 - val_accuracy: 0.9298
Epoch 53/100
0.9347 - val_loss: 0.1711 - val_accuracy: 0.9240
Epoch 54/100
0.9296 - val_loss: 0.1934 - val_accuracy: 0.9240
Epoch 55/100
0.9397 - val_loss: 0.1668 - val_accuracy: 0.9357
Epoch 56/100
0.9246 - val_loss: 0.1793 - val_accuracy: 0.9298
Epoch 57/100
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0.9447 - val_loss: 0.1673 - val_accuracy: 0.9298
Epoch 58/100
0.9347 - val_loss: 0.2204 - val_accuracy: 0.9123
Epoch 59/100
0.9070 - val_loss: 0.1658 - val_accuracy: 0.9415
Epoch 60/100
0.9271 - val_loss: 0.2113 - val_accuracy: 0.9181
Epoch 61/100
0.9296 - val_loss: 0.1735 - val_accuracy: 0.9298
Epoch 62/100
0.9347 - val_loss: 0.1726 - val_accuracy: 0.9240
Epoch 63/100
0.9422 - val_loss: 0.2131 - val_accuracy: 0.9181
Epoch 64/100
0.9271 - val_loss: 0.1744 - val_accuracy: 0.9298
Epoch 65/100
0.9372 - val_loss: 0.1636 - val_accuracy: 0.9298
Epoch 66/100
0.9322 - val_loss: 0.1904 - val_accuracy: 0.9357
Epoch 67/100
0.9095 - val_loss: 0.2546 - val_accuracy: 0.9006
Epoch 68/100
0.8794 - val_loss: 0.7587 - val_accuracy: 0.7485
Epoch 69/100
0.8668 - val_loss: 0.5992 - val_accuracy: 0.8363
Epoch 70/100
0.8819 - val_loss: 0.1651 - val_accuracy: 0.9415
Epoch 71/100
- 0s 2ms/step - loss: 0.2080 - accuracy: 0.9171 - val_loss: 0.1633 -
val_accuracy: 0.9415
Epoch 72/100
0.9221 - val_loss: 0.2850 - val_accuracy: 0.9006
```

```
Epoch 73/100
0.9372 - val_loss: 0.1708 - val_accuracy: 0.9357
Epoch 74/100
0.9372 - val_loss: 0.1818 - val_accuracy: 0.9123
Epoch 75/100
- 0s 2ms/step - loss: 0.1764 - accuracy: 0.9246 - val_loss: 0.1654 -
val_accuracy: 0.9298
Epoch 76/100
0.9221 - val_loss: 0.2615 - val_accuracy: 0.9064
Epoch 77/100
0.9347 - val_loss: 0.1873 - val_accuracy: 0.9123
Epoch 78/100
0.9347 - val_loss: 0.1660 - val_accuracy: 0.9240
Epoch 79/100
0.9347 - val_loss: 0.1686 - val_accuracy: 0.9298
Epoch 80/100
- 0s 2ms/step - loss: 0.1466 - accuracy: 0.9422 - val_loss: 0.1689 -
val_accuracy: 0.9240
Epoch 81/100
0.9472 - val_loss: 0.1966 - val_accuracy: 0.9240
Epoch 82/100
0.9472 - val_loss: 0.1742 - val_accuracy: 0.9298
Epoch 83/100
0.9347 - val_loss: 0.2047 - val_accuracy: 0.9240
Epoch 84/100
0.9347 - val_loss: 0.1663 - val_accuracy: 0.9357
Epoch 85/100
0.9372 - val_loss: 0.1704 - val_accuracy: 0.9357
Epoch 86/100
0.9397 - val_loss: 0.1886 - val_accuracy: 0.9357
Epoch 87/100
0.9397 - val_loss: 0.1665 - val_accuracy: 0.9357
Epoch 88/100
```

```
0.9397 - val_loss: 0.1956 - val_accuracy: 0.9240
  Epoch 89/100
  0.9497 - val_loss: 0.1831 - val_accuracy: 0.9357
  Epoch 90/100
  0.9422 - val_loss: 0.1609 - val_accuracy: 0.9357
  Epoch 91/100
  0.9447 - val_loss: 0.1609 - val_accuracy: 0.9415
  Epoch 92/100
  0.9497 - val_loss: 0.1598 - val_accuracy: 0.9298
  Epoch 93/100
  0.9372 - val_loss: 0.1617 - val_accuracy: 0.9357
  Epoch 94/100
  0.9221 - val_loss: 0.2267 - val_accuracy: 0.8947
  Epoch 95/100
  0.9523 - val_loss: 0.2254 - val_accuracy: 0.9123
  Epoch 96/100
  0.9523 - val_loss: 0.2502 - val_accuracy: 0.9064
  Epoch 97/100
  0.9296 - val_loss: 0.1645 - val_accuracy: 0.9298
  Epoch 98/100
  0.9447 - val_loss: 0.1751 - val_accuracy: 0.9357
  Epoch 99/100
  0.9296 - val loss: 0.3674 - val accuracy: 0.8538
  Epoch 100/100
  0.9121 - val_loss: 0.3149 - val_accuracy: 0.8947
[8]: <tensorflow.python.keras.callbacks.History at 0x24ac683b8e0>
[9]: from sklearn.metrics import confusion_matrix, accuracy_score
  pred = (model2.predict(X_test)>0.5).astype(int)
  print(confusion_matrix(pred, y_test))
  print(accuracy_score(pred, y_test))
  [[ 52
     1]
  [ 17 101]]
```

0.8947368421052632