Exercise Sheet 1

Read the Dataset

- Use Pandas to read the 'covertype.csv' file
- The dataset contains information on different forest cover types
- Look at the columns. Which of them contain meaningful features?

Seperate Features and Labels

- Define x as the vectors of meaningful features
- Define y as the labels (Cover_Type)

Split the dataset into two disjoint datasets for training and testing

- Randomly split the dataset. Use 70% for training and 30% for testing.
- Define x_train and x_test as the feature vectors
- Define y_train and y_test as the labels
    - Hint: Have a look at the sklearn package

In [120]:

```python
import os
import os.path
import sys
# python_package_path = os.path.split(sys.executable)[0] + "\\Lib\\site-packages\\"
# sys.path.append(python_package_path)

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split

file_dir = os.path.abspath(r'..\\Blatt 1') + "\\"
# file_dir = 'D:\\Dropbox\\Dropbox\\Master Theoretische Informatik\\Very Deep Learning\\WiSe 18_19\\VDL_Python\\Blatt 1\\'
# print(file_dir)
csv_path = file_dir + 'covertype.csv'
# print(csv_path)
file = pd.read_csv(file_dir + 'covertype.csv')
# print(file.columns)



values = np.array(file)
num_col = values[0].__len__()

num_features = 12
# num_features = num_col

header = file.columns.values[1:num_col]
# Describing which columns are features and what column is the label column
print ("The columns 2, 3, 4, ...,", num_features-1 , "are the features and the last column describes the labels")
# Notice, the first column is just an index. Therefore it does not contain to the features


df = pd.DataFrame(columns=header, index=values[:,0], data=values[:,list(range(1, num_col))])


train, test = train_test_split(df, test_size=0.3)
train = np.array(train)
test = np.array(test)
# print(train)
x_train = train[:,:num_features-2]
x_test = test[:,:num_features-2]
print(x_train)
y_train = train[:, num_col-2]
y_test = test[:,num_col-2]
```

```
The columns 2, 3, 4, ..., 11 are the features and the last column describes the labels
[[2235   93   16 ...  213   94 1679]
 [2005   29    6 ...  226  144  376]
 [2915   69   12 ...  216  113  295]
 ...
 [2363  176   14 ...  247  150  994]
 [2910  323   10 ...  230  174  765]
 [3109   26    7 ...  225  144 2962]]
```

Train a simple deep neural network

- Use Keras to define a simple Multi-Layer Perceptron with at least 3 layers and a Softmax classifier
    - You have to explicitly give the input shape of the first layer
    - The other layer shapes are inferred
    - The last layer should have as many neurons as there are classes
        - How many classes are there?
- Define 'accuracy' as performance metric when compiling the network model
- Train the MLP with x_train, y_train
    - Make sure to save the training history for later assessment
- Evaluate the performance on x_test, y_test

In [123]:
```
import keras
import os



# For Reproducing Traings etc.
from numpy.random import seed
seed(1)
from tensorflow import set_random_seed
set_random_seed(2)

# ---------------- Setting Hyperparameter ----------------
batch_size = 32
epochs = 10      # we choose the number so small, because we train later much longer to get a nicer visualization
lr = 0.01
decay = 1e-12             # decay works over batch-update, i.e. after each batch, the lr decreases
# --------------------------------------------------------


print(y_train.shape)

number_of_classes = np.max([np.max(y_test), np.max(y_train)]) + 1
print(number_of_classes)


print(y_train.shape)

print(y_train)

for i in range(len(y_train)):
    y_train[i] -= 1

print("\n\n\n", y_train)

for i in range(len(y_test)):
    y_test[i] -= 1

def create_model():
    model = keras.Sequential()
    model.add(keras.layers.Dense(input_dim=num_features-2, units=1024, activation='tanh'))
    model.add(keras.layers.Dense(units=512, activation='tanh'))
    model.add(keras.layers.Dense(units=256, activation='tanh'))
    model.add(keras.layers.Dense(units=128, activation='tanh'))
    model.add(keras.layers.Dense(units=64, activation='tanh'))
    model.add(keras.layers.Dense(units=32, activation='tanh'))
    model.add(keras.layers.Dense(units=number_of_classes, activation='softmax'))

    opt = keras.optimizers.adagrad(lr=lr)
    model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])

    return model


model = create_model()

print(type(x_train))

one_hot_labels_train = keras.utils.to_categorical(y_train, num_classes=number_of_classes)
one_hot_labels_test = keras.utils.to_categorical(y_test, num_classes=number_of_classes)

# Train the model
train_history = model.fit(x_train, one_hot_labels_train, epochs=epochs, batch_size=batch_size)
loss_history = train_history.history["loss"]
acc_history = train_history.history["acc"]

# print(loss_history)
# print(acc_history)

log_dir = file_dir + "\\LogFiles\\"
if not (os.path.exists(log_dir)):
    os.makedirs(log_dir)

# Write Header of Log_File:
file = open(log_dir + "train_log.csv", "w+")
file.write("Epoch\tLoss\tAccuracy\n")
file.close()

# Write Loss and Accuracy:
file = open(log_dir + "train_log.csv", "a+")
for i in range(epochs):
    file.write(str(i) + "\t" + str(loss_history[i]) + "\t" + str(acc_history[i]) + "\n")

file.close()

# Test the model
score = model.evaluate(x_test, one_hot_labels_test, batch_size=batch_size)
print(score)
```

```
(10584,)
6
(10584,)
[ 2  2 -1 ...  4  3 -1]



 [ 1  1 -2 ...  3  2 -2]
<class 'numpy.ndarray'>
Epoch 1/10
10584/10584 [==============================] - 5s 490us/step - loss: 1.7336 - acc: 0.2799
Epoch 2/10
10584/10584 [==============================] - 4s 421us/step - loss: 1.5897 - acc: 0.3184
Epoch 3/10
10584/10584 [==============================] - 4s 402us/step - loss: 1.5494 - acc: 0.3387
Epoch 4/10
10584/10584 [==============================] - 4s 386us/step - loss: 1.5296 - acc: 0.3415
Epoch 5/10
10584/10584 [==============================] - 4s 385us/step - loss: 1.5131 - acc: 0.3498
Epoch 6/10
10584/10584 [==============================] - 4s 394us/step - loss: 1.4799 - acc: 0.3725
Epoch 7/10
10584/10584 [==============================] - 4s 388us/step - loss: 1.4242 - acc: 0.4168
Epoch 8/10
10584/10584 [==============================] - 4s 383us/step - loss: 1.3599 - acc: 0.4405
Epoch 9/10
10584/10584 [==============================] - 4s 387us/step - loss: 1.2888 - acc: 0.4741 0s - loss: 1.
Epoch 10/10
10584/10584 [==============================] - 4s 388us/step - loss: 1.2357 - acc: 0.4988
4536/4536 [==============================] - 1s 156us/step
[1.160508728006319, 0.5291005291005291]
```

Debug

- If your loss is NaN, either your network architecture or your data is faulty
    - Check your network architecture
    - Check your data
        - Are there any NaN or infinite features or labels?
    - Print the labels.
        - How many unique labels do you have?
        - Are they [0, ..., n-1]?
            - If not, align them

In [124]:
```
import numpy as np
```

Train again

- Reinitialize or redefine your MLP from above and train it again

In [ ]:
```
```

Does it work?

- The loss should now be a number.
- Does the network converge?

Inspect the data

- Compute the min, max, mean and standard deviation of each feature
- What data type do the columns have?
- Use Pandas to print the statistics in a table
- What could be problematic with the dataset?

In [125]:
```
# import numpy as np
pd.options.display.float_format = '{:.2f}'.format


stats = pd.DataFrame(columns=["Type", "Min", "Max", "Mean", "Std"])


for col in df.columns:
    stats.loc[col] = {"Type": df[col].dtype,
                      "Min": df[col].min(),
                      "Max": df[col].max(),
                      "Mean": df[col].mean(),
                      "Std": df[col].std()
                      }

df.describe(include='all', percentiles=[])
display(stats)


# -------------------------------------------------
# Alternative Version:
# print(df.dtypes)
# df.describe(include='all', percentiles=[])
# -------------------------------------------------
```

	Type	Min	Max	Mean	Std
Elevation	int64	1863	3849	2749.32	417.68
Aspect	int64	0	360	156.68	110.09
Slope	int64	0	52	16.50	8.45
Horizontal_Distance_To_Hydrology	int64	0	1343	227.20	210.08
Vertical_Distance_To_Hydrology	int64	-146	554	51.08	61.24
Horizontal_Distance_To_Roadways	int64	0	6890	1714.02	1325.07
Hillshade_9am	int64	0	254	212.70	30.56
Hillshade_Noon	int64	99	254	218.97	22.80
Hillshade_3pm	int64	0	248	135.09	45.90
Horizontal_Distance_To_Fire_Points	int64	0	6993	1511.15	1099.94
Wilderness_Area1	int64	0	1	0.24	0.43
Wilderness_Area2	int64	0	1	0.03	0.18
Wilderness_Area3	int64	0	1	0.42	0.49
Wilderness_Area4	int64	0	1	0.31	0.46
Soil_Type1	int64	0	1	0.02	0.15
Soil_Type2	int64	0	1	0.04	0.20
Soil_Type3	int64	0	1	0.06	0.24
Soil_Type4	int64	0	1	0.06	0.23
Soil_Type5	int64	0	1	0.01	0.10
Soil_Type6	int64	0	1	0.04	0.20
Soil_Type7	int64	0	0	0.00	0.00
Soil_Type8	int64	0	1	0.00	0.01
Soil_Type9	int64	0	1	0.00	0.03
Soil_Type10	int64	0	1	0.14	0.35
Soil_Type11	int64	0	1	0.03	0.16
Soil_Type12	int64	0	1	0.02	0.12
Soil_Type13	int64	0	1	0.03	0.17
Soil_Type14	int64	0	1	0.01	0.11
Soil_Type15	int64	0	0	0.00	0.00
Soil_Type16	int64	0	1	0.01	0.09
Soil_Type17	int64	0	1	0.04	0.20
Soil_Type18	int64	0	1	0.00	0.06
Soil_Type19	int64	0	1	0.00	0.06
Soil_Type20	int64	0	1	0.01	0.10
Soil_Type21	int64	0	1	0.00	0.03
Soil_Type22	int64	0	1	0.02	0.15
Soil_Type23	int64	0	1	0.05	0.22
Soil_Type24	int64	0	1	0.02	0.13
Soil_Type25	int64	0	1	0.00	0.01
Soil_Type26	int64	0	1	0.00	0.06
Soil_Type27	int64	0	1	0.00	0.03
Soil_Type28	int64	0	1	0.00	0.02
Soil_Type29	int64	0	1	0.09	0.28
Soil_Type30	int64	0	1	0.05	0.21
Soil_Type31	int64	0	1	0.02	0.15
Soil_Type32	int64	0	1	0.05	0.21
Soil_Type33	int64	0	1	0.04	0.20
Soil_Type34	int64	0	1	0.00	0.04
Soil_Type35	int64	0	1	0.01	0.08
Soil_Type36	int64	0	1	0.00	0.03
Soil_Type37	int64	0	1	0.00	0.05
Soil_Type38	int64	0	1	0.05	0.21
Soil_Type39	int64	0	1	0.04	0.20
Soil_Type40	int64	0	1	0.03	0.17
Cover_Type	int64	1	7	4.00	2.00

Preprocess the Data

- Normalize or standardize your data, so all features are at the same scale.
  - This will help your network to use all available features and not be biased by some features with large values
  - Does it make sense to normalize all columns, or only some?
- Hint: Again, look if you find something useful in sklearn

- Never use test data to optimize your training! This includes the preprocessing
  - Find preprocessing parameters on your training data only!
  - Transform all your data with the computed parameters
  - You have to remember which of your samples are used for training and which are for testing

In [126]:
```
from sklearn import preprocessing
x_train_scaled = preprocessing.scale(x_train)
x_test_scaled = preprocessing.scale(x_test)
```

Inspect data again

- Print the statistics of the preprocessed data using the code from above

In [127]:
```
stats = pd.DataFrame(columns=["Type", "Min", "Max", "Mean", "Std"])
"""
# Alternative Version:
for col in df.columns:
    stats.loc[col] = {"Type": df[col].dtype,
                      "Min": df[col].min(),
                      "Max": df[col].max(),
                      "Mean": df[col].mean(),
                      "Std": df[col].std()
                      }
"""

featureNames = list(df.columns[0:num_features-2])
# print(featureNames)

# Create DataFrame from preprocessed (or normalized) Data:
x_train_scaledDF = pd.DataFrame(data=x_train_scaled, columns=featureNames)
x_test_scaledDF = pd.DataFrame(data=x_test_scaled, columns=featureNames)



x_scaledDF.describe(include='all', percentiles=[])
```

Out[127]:

	Elevation	Aspect	Slope	Horizontal_Distance_To_Hydrology	Vertical_Distance_To_Hydrology	Horizontal_Distance_To_Roadways	Hillshade_9am	Hillshade_Noon	Hillshade_3pm	Horizontal_Distance_To_Fire_Points
count	10584.00	10584.00	10584.00	10584.00	10584.00	10584.00	10584.00	10584.00	10584.00	10584.00
mean	0.00	-0.00	0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	-2.12	-1.41	-1.96	-1.07	-3.01	-1.30	-6.95	-5.30	-2.94	-1.38
50%	0.01	-0.28	-0.18	-0.23	-0.30	-0.30	0.23	0.13	0.05	-0.22
max	2.61	1.86	4.21	5.24	8.16	3.88	1.34	1.55	2.47	5.01

Train the network again

- Reinitialize or redefine your MLP from above and train it again

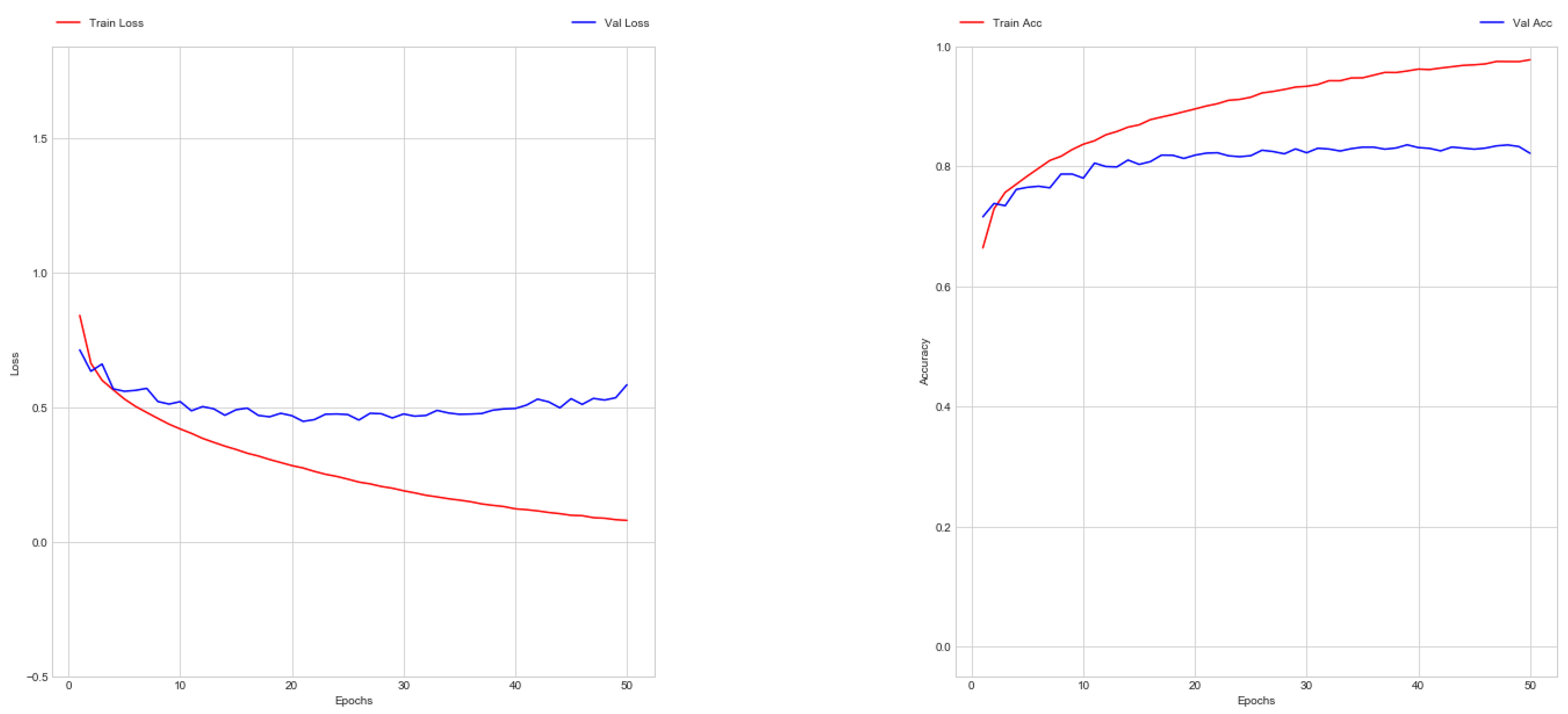
In [130]:
```
epochs = 50

model = create_model()

train_history = {'train_loss' : [], 'train_acc' : [], 'train_epochs' : []}
val_history = {'val_loss' : [], 'val_acc' : [], 'val_epochs' : []}
for i in range(epochs):
    print("Epoch", (i+1) , "of", epochs)
    train_history_temp = model.fit(x_train_scaledDF, one_hot_labels_train, epochs=1, batch_size=batch_size)
    val_history_temp = model.evaluate(x_test_scaledDF, one_hot_labels_test, batch_size=batch_size)
    print("val loss =", val_history_temp[0])
    print("val acc =", val_history_temp[1])
    print("\n")
    # print("train_history_temp =", train_history_temp.history)
    # print("val_history_temp =", val_history_temp)
    train_history['train_loss'].append(train_history_temp.history['loss'][0])
    train_history['train_acc'].append(train_history_temp.history['acc'][0])
    train_history['train_epochs'].append(i+1)
    val_history['val_loss'].append(val_history_temp[0])
    val_history['val_acc'].append(val_history_temp[1])
    val_history['val_epochs'].append(i+1)
# print(train_history)
# print(val_history)
```

```
Epoch 1 of 50
Epoch 1/1
10584/10584 [==============================] - 5s 491us/step - loss: 0.8415 - acc: 0.6640
4536/4536 [==============================] - 1s 164us/step
val loss = 0.713256541698698
val acc = 0.7158289241622575


Epoch 2 of 50
Epoch 1/1
10584/10584 [==============================] - 4s 409us/step - loss: 0.6649 - acc: 0.7291
4536/4536 [==============================] - 0s 96us/step
val loss = 0.635145267061035
val acc = 0.7380952382003609


Epoch 3 of 50
Epoch 1/1
10584/10584 [==============================] - 4s 384us/step - loss: 0.6017 - acc: 0.7566
```

Visualize the training

- use matplotlib.pyplot to visualize the keras history
- plot both the training accuracy and the validation accuracy

In [131]:
```
import matplotlib.pyplot as plt
%matplotlib inline

train_epochs = train_history['train_epochs']
train_loss = train_history['train_loss']
train_acc = train_history['train_acc']

val_epochs = val_history['val_epochs']
val_loss = val_history['val_loss']
val_acc = val_history['val_acc']


plt.figure(num=1, figsize=(20, 10),  facecolor='w', edgecolor='k')
plt.subplots_adjust(left = 0.05, right= 0.95, wspace=0.5, )

# Beginn des plottens:
plt.style.use('seaborn-whitegrid')
plt.subplot(121)

# Plot Axes-Labeling
plt.xlabel('Epochs')
plt.ylabel('Loss')

# Plot range of y-axes
plt.gca().set_ylim([-0.5, train_loss[0]+1])

# Plot Curve
plt.plot(train_epochs, train_loss, 'r', label="Train Loss")
plt.plot(train_epochs, val_loss, 'b', label="Val Loss")

# Plot Legend
plt.legend(bbox_to_anchor=(0., 1.02, 1., .102), loc=3, ncol=2, mode="expand", borderaxespad=0.)
# plt.show()


plt.subplot(122)

# Plot Axes-Labeling# Plot Legend
plt.xlabel('Epochs')
plt.ylabel('Accuracy')

# Plot range of y-axes
plt.gca().set_ylim([-0.05, 1.0])

# Plot Curve
plt.plot(val_epochs, train_acc, 'r', label="Train Acc")
plt.plot(val_epochs, val_acc, 'b', label="Val Acc")

# Plot Legend
plt.legend(bbox_to_anchor=(0., 1.02, 1., .102), loc=3, ncol=2, mode="expand", borderaxespad=0.)
plt.show()
```



In [ ]:
```
"""
Here you can see overfiting. A meaningful number of epochs could be around 20. All epochs > 20 produce a larger
train loss, than the loss by epoch 20.
"""
```