# PS5

### January 15, 2024

```
[1]: from shap.datasets import adult
     X, y = adult()
     print(X)
     print(y)
                                                Marital Status
                                                                   Occupation
                   Workclass
                                Education-Num
             Age
    0
            39.0
                            7
                                          13.0
                                                                             1
                                                               2
                                                                             4
    1
            50.0
                            6
                                          13.0
    2
            38.0
                            4
                                           9.0
                                                               0
                                                                             6
    3
            53.0
                            4
                                           7.0
                                                               2
                                                                             6
    4
            28.0
                            4
                                          13.0
                                                               2
                                                                            10
                                                               •••
    32556
            27.0
                                          12.0
                                                               2
                                                                            13
                            4
                                                               2
    32557
            40.0
                            4
                                           9.0
                                                                             7
                                           9.0
    32558
            58.0
                            4
                                                               6
                                                                             1
                                           9.0
    32559
            22.0
                            4
                                                               4
                                                                             1
    32560
            52.0
                            5
                                           9.0
                                                               2
                                                                             4
                            Race
                                         Capital Gain
                                                        Capital Loss
                                                                        Hours per week \
            Relationship
                                   Sex
    0
                         0
                                4
                                                2174.0
                                                                   0.0
                                                                                    40.0
                                     1
                                                                   0.0
    1
                         4
                                4
                                                   0.0
                                                                                    13.0
    2
                         0
                                4
                                                   0.0
                                                                   0.0
                                                                                    40.0
    3
                         4
                                2
                                                   0.0
                                                                   0.0
                                                                                    40.0
                                     1
    4
                         5
                                2
                                     0
                                                   0.0
                                                                   0.0
                                                                                    40.0
                         •••
    32556
                         5
                                4
                                     0
                                                   0.0
                                                                   0.0
                                                                                    38.0
    32557
                         4
                                4
                                     1
                                                   0.0
                                                                   0.0
                                                                                    40.0
    32558
                         1
                                4
                                     0
                                                   0.0
                                                                   0.0
                                                                                    40.0
                         3
                                                   0.0
                                                                   0.0
                                                                                    20.0
    32559
                                4
    32560
                                     0
                                              15024.0
                                                                   0.0
                                                                                    40.0
            Country
    0
                  39
    1
                  39
    2
                  39
```

3

39

```
4
                  5
    32556
                 39
    32557
                 39
    32558
                 39
    32559
                 39
    32560
                 39
    [32561 rows x 12 columns]
    [False False False ... False False True]
[2]: numerical_columns = ['Age', 'Education-Num', 'Capital Gain', 'Capital Loss', 'Hours_
      →per week']
     categorical_columns = ['Workclass', 'Marital__
      ⇔Status','Occupation','Relationship','Race','Sex','Country']
         Conversion of categorical data
[3]: import pandas as pd # for one-hot encoding
     from sklearn.preprocessing import StandardScaler # for normalization
[4]: # Normalization of numerical data
     for column in numerical_columns:
         scaler = StandardScaler()
         X[column] = scaler.fit_transform(X[column].values.reshape(-1,1))
     print(X)
                      Workclass
                                  Education-Num Marital Status
                                                                  Occupation
                 Age
    0
           0.030671
                              7
                                       1.134739
                                                                            1
           0.837109
                              6
                                                               2
                                                                            4
    1
                                       1.134739
    2
                              4
                                                               0
                                                                            6
          -0.042642
                                      -0.420060
    3
                              4
                                                               2
                                                                            6
           1.057047
                                      -1.197459
    4
                              4
                                                               2
          -0.775768
                                       1.134739
                                                                           10
    32556 -0.849080
                              4
                                       0.746039
                                                               2
                                                                           13
    32557 0.103983
                              4
                                      -0.420060
                                                               2
                                                                            7
    32558 1.423610
                                      -0.420060
                                                               6
                                                                            1
    32559 -1.215643
                              4
                                      -0.420060
                                                               4
                                                                            1
    32560 0.983734
                              5
                                      -0.420060
                                                               2
                                                                            4
                          Race
                                Sex
                                     Capital Gain Capital Loss
                                                                   Hours per week
           Relationship
    0
                             4
                       0
                                   1
                                          0.148453
                                                         -0.21666
                                                                         -0.035429
                       4
                                   1
    1
                                         -0.145920
                                                         -0.21666
                                                                         -2.222153
    2
                       0
                                  1
                                         -0.145920
                                                         -0.21666
                                                                        -0.035429
    3
                       4
                             2
                                   1
                                         -0.145920
                                                         -0.21666
                                                                         -0.035429
    4
                       5
                             2
                                         -0.145920
                                                         -0.21666
                                                                        -0.035429
```

```
32556
                        5
                                          -0.145920
                                                           -0.21666
                                                                           -0.197409
                                    0
    32557
                        4
                              4
                                    1
                                          -0.145920
                                                           -0.21666
                                                                           -0.035429
    32558
                        1
                               4
                                    0
                                          -0.145920
                                                           -0.21666
                                                                           -0.035429
                        3
    32559
                               4
                                    1
                                          -0.145920
                                                           -0.21666
                                                                           -1.655225
                        5
    32560
                               4
                                            1.888424
                                                           -0.21666
                                                                           -0.035429
            Country
    0
                 39
    1
                 39
    2
                 39
    3
                 39
    4
                  5
    32556
                 39
    32557
                 39
    32558
                 39
                 39
    32559
    32560
                 39
     [32561 rows x 12 columns]
[5]: # Data type change of categorical data
     for column in categorical_columns:
         X[column] = X[column].astype('category')
     print(X)
                                  Education-Num Marital Status Occupation
                 Age Workclass
    0
            0.030671
                                       1.134739
                                                                           1
                                                               2
    1
            0.837109
                               6
                                       1.134739
                                                                           4
    2
                               4
                                                               0
                                                                           6
           -0.042642
                                      -0.420060
    3
            1.057047
                               4
                                      -1.197459
                                                               2
                                                                           6
                                       1.134739
                                                               2
    4
                                                                          10
           -0.775768
                               4
                                       0.746039
                                                               2
                                                                          13
    32556 -0.849080
                               4
    32557 0.103983
                               4
                                      -0.420060
                                                               2
                                                                           7
    32558 1.423610
                               4
                                      -0.420060
                                                               6
                                                                           1
    32559 -1.215643
                               4
                                      -0.420060
                                                               4
                                                                           1
    32560 0.983734
                              5
                                      -0.420060
                                                               2
                                                                           4
                                    Capital Gain
           Relationship Race Sex
                                                   Capital Loss
                                                                  Hours per week
    0
                            4
                                        0.148453
                                                        -0.21666
                                                                        -0.035429
    1
                       4
                                                        -0.21666
                            4
                                       -0.145920
                                                                        -2.222153
    2
                       0
                            4
                                 1
                                       -0.145920
                                                        -0.21666
                                                                        -0.035429
    3
                       4
                            2
                                       -0.145920
                                                        -0.21666
                                                                        -0.035429
                                 1
    4
                       5
                            2
                                 0
                                       -0.145920
                                                        -0.21666
                                                                        -0.035429
```

```
32556
                          4 0
                                    -0.145920
                                                    -0.21666
                                                                   -0.197409
    32557
                          4 1
                                    -0.145920
                                                    -0.21666
                                                                   -0.035429
    32558
                          4 0
                                    -0.145920
                                                    -0.21666
                                                                   -0.035429
                     1
    32559
                     3
                          4 1
                                    -0.145920
                                                    -0.21666
                                                                   -1.655225
                     5
                          4
    32560
                             0
                                     1.888424
                                                    -0.21666
                                                                   -0.035429
          Country
    0
               39
    1
               39
    2
               39
    3
               39
    4
                5
    32556
               39
    32557
               39
               39
    32558
    32559
               39
    32560
               39
    [32561 rows x 12 columns]
[6]: # One-hot encoding of categorical data
     X = pd.get_dummies(X)
     # Conversion of data frame to numpy
     X = X.values
     # Converision: {False, True} --> {0., 1.}
     y = y.astype(float)
[7]: print(X.shape)
     print(y.shape)
     print(y)
    (32561, 91)
    (32561,)
    [0. 0. 0. ... 0. 0. 1.]
    0.2 train-val-test split
[8]: from sklearn.model_selection import train_test_split
     X_,X_test,y_,y_test = train_test_split(X,y,test_size=1/10,stratify=y)
     X_train,X_val,y_train,y_val = train_test_split(X_,y_,test_size=1/9,stratify=y_)
     print(X_train.shape)
     print(X_val.shape)
     print(X_test.shape)
```

```
(26048, 91)
     (3256, 91)
     (3257, 91)
     0.3 Logistic regression
 [9]: from sklearn.linear_model import LogisticRegression
[10]: | model_LR = LogisticRegression()
      # training
      model_LR.fit(X_train, y_train)
      # evaulation
      val_acc = model_LR.score(X_val, y_val)
      print(val_acc)
     0.8541154791154791
     lbfgs failed to converge (status=1):
     STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
     Increase the number of iterations (max_iter) or scale the data as shown in:
         https://scikit-learn.org/stable/modules/preprocessing.html
     Please also refer to the documentation for alternative solver options:
         https://scikit-learn.org/stable/modules/linear model.html#logistic-
     regression
[11]: from joblib import dump
      dump(model_LR, 'LR_sample.joblib')
[11]: ['LR_sample.joblib']
[12]: from joblib import load
      load('LR_sample.joblib')
[12]: LogisticRegression()
     0.4 A 2-layer DNN
[13]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense
      from tensorflow.keras.optimizers import Adam
```

model = Sequential()

model.add(Dense(128, activation='relu'))

```
model.add(Dense(1, activation='sigmoid'))
opt = Adam(learning_rate=0.01,
    beta_1 = 0.9,
    beta_2 = 0.999)
#model.compile(optimizer=opt,
     loss='binary crossentropy')
model.compile(optimizer=opt,
     loss='binary_crossentropy',
     metrics=['acc'])
model.fit(X_train,y_train, epochs=10)
Epoch 1/10
0.8516
Epoch 2/10
0.8529
Epoch 3/10
0.8579
Epoch 4/10
0.8590
Epoch 5/10
0.8612
Epoch 6/10
0.8613
Epoch 7/10
0.8660
Epoch 8/10
0.8664
Epoch 9/10
0.8674
Epoch 10/10
0.8689
```

```
[13]: <keras.callbacks.History at 0x1a10329ba30>
```

### 0.5 Regularization

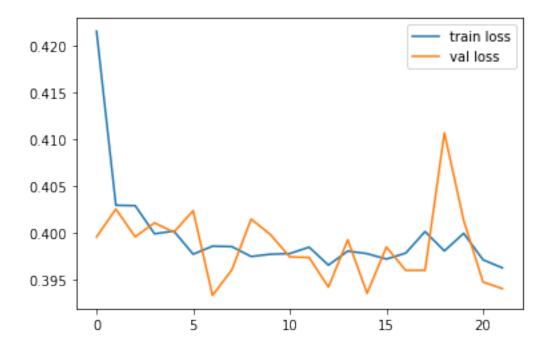
### 0.6 Early stopping

```
[16]: from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Dense
      from tensorflow.keras.optimizers import Adam
      from tensorflow.keras.callbacks import EarlyStopping
      model = Sequential()
      model.add(Dense(128,kernel_regularizer=12(0.01),
                bias_regularizer=12(0.01),
                activation='relu'))
      model.add(Dense(1,kernel_regularizer=12(0.01),
                bias_regularizer=12(0.01),
                activation='sigmoid'))
      opt = Adam(learning_rate=0.01,beta_1 = 0.9,beta_2 = 0.999)
      model.compile(optimizer=opt,
                   loss='binary_crossentropy')
      #model.compile(optimizer=opt,
                   loss='binary_crossentropy',
      #
                    metrics=['acc'])
      #es_callback = EarlyStopping(monitor='val_acc', patience=15)
      #es_callback = EarlyStopping(monitor='val_loss', patience=15)
      es_callback = EarlyStopping(monitor='val_loss', patience=15)
     hist = model.fit(X_train, y_train,
```

# validation\_data=(X\_val, y\_val), epochs=100,callbacks=[es\_callback])

```
Epoch 1/100
val_loss: 0.3996
Epoch 2/100
val_loss: 0.4026
Epoch 3/100
val_loss: 0.3996
Epoch 4/100
814/814 [============ ] - 2s 2ms/step - loss: 0.3999 -
val_loss: 0.4011
Epoch 5/100
val_loss: 0.4001
Epoch 6/100
val_loss: 0.4024
Epoch 7/100
val_loss: 0.3934
Epoch 8/100
val_loss: 0.3961
Epoch 9/100
val_loss: 0.4015
Epoch 10/100
val_loss: 0.3999
Epoch 11/100
val_loss: 0.3975
Epoch 12/100
val_loss: 0.3974
Epoch 13/100
val_loss: 0.3942
Epoch 14/100
val_loss: 0.3993
Epoch 15/100
val_loss: 0.3936
```

```
Epoch 16/100
  val_loss: 0.3985
  Epoch 17/100
  val_loss: 0.3960
  Epoch 18/100
  val_loss: 0.3960
  Epoch 19/100
  val_loss: 0.4107
  Epoch 20/100
  val_loss: 0.4014
  Epoch 21/100
  814/814 [============ ] - 2s 3ms/step - loss: 0.3972 -
  val_loss: 0.3948
  Epoch 22/100
  val_loss: 0.3941
[17]: train_loss = hist.history['loss']
   val_loss = hist.history['val_loss']
   #train_acc = hist.history['acc']
   #val_acc = hist.history['val_acc']
   import matplotlib.pyplot as plt
   plt.plot(train_loss,label='train loss')
   plt.plot(val_loss,label='val loss')
   plt.legend()
   plt.show()
```



### 0.7 Dropout

## 0.8 Weight initialization

```
[19]: from tensorflow.keras.initializers import HeNormal
   init = HeNormal()

model.add(Dense(128,kernel_regularizer=12(0.01),
        bias_regularizer=12(0.01),
        kernel_initializer=init,
        activation='relu'))
```

#### 0.9 Batch normalization

### 0.10 Learning rate decaying

```
[21]: from tensorflow.keras.initializers import HeNormal
      from tensorflow.keras.layers import BatchNormalization
      from tensorflow.keras.layers import ReLU
      from tensorflow.keras.layers import Dropout
      from tensorflow.keras.callbacks import EarlyStopping
      from tensorflow.keras.callbacks import LearningRateScheduler
      init = HeNormal()
      model = Sequential()
      model.add(Dense(128,kernel_regularizer=12(0.01),
                bias_regularizer=12(0.01),
                kernel_initializer=init))
      model.add(BatchNormalization())
      model.add(ReLU())
      model.add(Dropout(0.5))
      model.add(Dense(1,activation='sigmoid'))
      opt = Adam(learning_rate=0.01,beta_1 = 0.9,beta_2 = 0.999)
      #model.compile(optimizer=opt,
                    loss='binary_crossentropy',
                   metrics=['acc'])
      model.compile(optimizer=opt,
                   loss='binary_crossentropy')
      es_callback = EarlyStopping(monitor='val_loss', patience=15)
      #es_callback = EarlyStopping(monitor='val_acc', patience=15)
      def scheduler(epoch, lr):
          if epoch in [20,40,60]:
```

```
lr = 0.1*lr
  else:
   lr = lr
  return lr
ls_callback = LearningRateScheduler(scheduler)
hist = model.fit(X_train, y_train,
        validation_data=(X_val, y_val),
        epochs=100, callbacks=[es_callback,ls_callback])
Epoch 1/100
val_loss: 0.4659 - lr: 0.0100
Epoch 2/100
val_loss: 0.4038 - lr: 0.0100
Epoch 3/100
val_loss: 0.4165 - lr: 0.0100
Epoch 4/100
val_loss: 0.4006 - lr: 0.0100
Epoch 5/100
val_loss: 0.4203 - lr: 0.0100
Epoch 6/100
val_loss: 0.4111 - lr: 0.0100
Epoch 7/100
val_loss: 0.3966 - lr: 0.0100
Epoch 8/100
val_loss: 0.3943 - lr: 0.0100
Epoch 9/100
val_loss: 0.3920 - lr: 0.0100
Epoch 10/100
val_loss: 0.4045 - lr: 0.0100
Epoch 11/100
val_loss: 0.4148 - lr: 0.0100
Epoch 12/100
val_loss: 0.3959 - lr: 0.0100
```

```
Epoch 13/100
val_loss: 0.4031 - lr: 0.0100
Epoch 14/100
val_loss: 0.4039 - lr: 0.0100
Epoch 15/100
val_loss: 0.3973 - lr: 0.0100
Epoch 16/100
val_loss: 0.3890 - lr: 0.0100
Epoch 17/100
val_loss: 0.4017 - lr: 0.0100
Epoch 18/100
val_loss: 0.3992 - lr: 0.0100
Epoch 19/100
val_loss: 0.3931 - lr: 0.0100
Epoch 20/100
val_loss: 0.3863 - lr: 0.0100
Epoch 21/100
814/814 [============= ] - 3s 4ms/step - loss: 0.3694 -
val_loss: 0.3417 - lr: 1.0000e-03
Epoch 22/100
val_loss: 0.3389 - lr: 1.0000e-03
Epoch 23/100
val_loss: 0.3373 - lr: 1.0000e-03
Epoch 24/100
val_loss: 0.3351 - lr: 1.0000e-03
Epoch 25/100
val_loss: 0.3318 - lr: 1.0000e-03
Epoch 26/100
val_loss: 0.3328 - lr: 1.0000e-03
Epoch 27/100
val_loss: 0.3327 - lr: 1.0000e-03
Epoch 28/100
val_loss: 0.3393 - lr: 1.0000e-03
```

```
Epoch 29/100
val_loss: 0.3408 - lr: 1.0000e-03
Epoch 30/100
val_loss: 0.3379 - lr: 1.0000e-03
Epoch 31/100
val_loss: 0.3344 - lr: 1.0000e-03
Epoch 32/100
val_loss: 0.3319 - lr: 1.0000e-03
Epoch 33/100
val_loss: 0.3334 - lr: 1.0000e-03
Epoch 34/100
val_loss: 0.3366 - lr: 1.0000e-03
Epoch 35/100
val_loss: 0.3358 - lr: 1.0000e-03
Epoch 36/100
val_loss: 0.3347 - lr: 1.0000e-03
Epoch 37/100
val_loss: 0.3300 - lr: 1.0000e-03
Epoch 38/100
val_loss: 0.3356 - lr: 1.0000e-03
Epoch 39/100
val_loss: 0.3344 - lr: 1.0000e-03
Epoch 40/100
val_loss: 0.3370 - lr: 1.0000e-03
Epoch 41/100
val_loss: 0.3296 - lr: 1.0000e-04
Epoch 42/100
val_loss: 0.3290 - lr: 1.0000e-04
Epoch 43/100
val_loss: 0.3275 - lr: 1.0000e-04
Epoch 44/100
val_loss: 0.3266 - lr: 1.0000e-04
```

```
Epoch 45/100
val_loss: 0.3270 - lr: 1.0000e-04
Epoch 46/100
val_loss: 0.3248 - lr: 1.0000e-04
Epoch 47/100
val_loss: 0.3250 - lr: 1.0000e-04
Epoch 48/100
val_loss: 0.3237 - lr: 1.0000e-04
Epoch 49/100
val_loss: 0.3243 - lr: 1.0000e-04
Epoch 50/100
val_loss: 0.3255 - lr: 1.0000e-04
Epoch 51/100
val_loss: 0.3232 - lr: 1.0000e-04
Epoch 52/100
val_loss: 0.3222 - lr: 1.0000e-04
Epoch 53/100
814/814 [============= ] - 3s 3ms/step - loss: 0.3289 -
val_loss: 0.3236 - lr: 1.0000e-04
Epoch 54/100
val_loss: 0.3214 - lr: 1.0000e-04
Epoch 55/100
val_loss: 0.3223 - lr: 1.0000e-04
Epoch 56/100
val_loss: 0.3215 - lr: 1.0000e-04
Epoch 57/100
val_loss: 0.3231 - lr: 1.0000e-04
Epoch 58/100
val_loss: 0.3204 - lr: 1.0000e-04
Epoch 59/100
val_loss: 0.3211 - lr: 1.0000e-04
Epoch 60/100
val_loss: 0.3205 - lr: 1.0000e-04
```

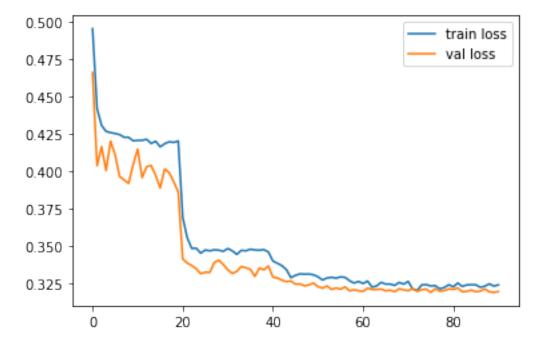
```
Epoch 61/100
val_loss: 0.3200 - lr: 1.0000e-05
Epoch 62/100
val_loss: 0.3222 - lr: 1.0000e-05
Epoch 63/100
val_loss: 0.3213 - lr: 1.0000e-05
Epoch 64/100
val_loss: 0.3213 - lr: 1.0000e-05
Epoch 65/100
val_loss: 0.3216 - lr: 1.0000e-05
Epoch 66/100
val_loss: 0.3204 - lr: 1.0000e-05
Epoch 67/100
val_loss: 0.3209 - lr: 1.0000e-05
Epoch 68/100
val_loss: 0.3198 - lr: 1.0000e-05
Epoch 69/100
814/814 [============= ] - 3s 4ms/step - loss: 0.3260 -
val_loss: 0.3218 - lr: 1.0000e-05
Epoch 70/100
val_loss: 0.3210 - lr: 1.0000e-05
Epoch 71/100
val_loss: 0.3205 - lr: 1.0000e-05
Epoch 72/100
val_loss: 0.3220 - lr: 1.0000e-05
Epoch 73/100
val_loss: 0.3200 - lr: 1.0000e-05
Epoch 74/100
val_loss: 0.3211 - lr: 1.0000e-05
Epoch 75/100
val_loss: 0.3216 - lr: 1.0000e-05
Epoch 76/100
val_loss: 0.3193 - lr: 1.0000e-05
```

```
Epoch 77/100
val_loss: 0.3218 - lr: 1.0000e-05
Epoch 78/100
val_loss: 0.3202 - lr: 1.0000e-05
Epoch 79/100
val_loss: 0.3205 - lr: 1.0000e-05
Epoch 80/100
val_loss: 0.3216 - lr: 1.0000e-05
Epoch 81/100
val_loss: 0.3213 - lr: 1.0000e-05
Epoch 82/100
val_loss: 0.3223 - lr: 1.0000e-05
Epoch 83/100
val_loss: 0.3198 - lr: 1.0000e-05
Epoch 84/100
val_loss: 0.3201 - lr: 1.0000e-05
Epoch 85/100
814/814 [============= ] - 3s 3ms/step - loss: 0.3245 -
val_loss: 0.3209 - lr: 1.0000e-05
Epoch 86/100
val_loss: 0.3198 - lr: 1.0000e-05
Epoch 87/100
val_loss: 0.3203 - lr: 1.0000e-05
Epoch 88/100
val_loss: 0.3217 - lr: 1.0000e-05
Epoch 89/100
val_loss: 0.3197 - lr: 1.0000e-05
Epoch 90/100
val_loss: 0.3193 - lr: 1.0000e-05
Epoch 91/100
val_loss: 0.3199 - lr: 1.0000e-05
```

```
[22]: train_loss = hist.history['loss']
  val_loss = hist.history['val_loss']
  #train_acc = hist.history['acc']
  #val_acc = hist.history['val_acc']

import matplotlib.pyplot as plt

plt.plot(train_loss,label='train loss')
  plt.plot(val_loss,label='val loss')
  plt.legend()
  plt.show()
```



[]: