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May 12, 2022

# 1 Tuning Neural Networks with Normalization - Lab

#### 1.1 Introduction

In this lab you'll build a neural network to perform a regression task.

It is worth noting that getting regression to work with neural networks can be comparatively difficult because the output is unbounded ( $\hat{y}$  can technically range from  $-\infty$  to  $+\infty$ ), and the models are especially prone to exploding gradients. This issue makes a regression exercise the perfect learning case for tinkering with normalization and optimization strategies to ensure proper convergence!

# 1.2 Objectives

In this lab you will:

- Fit a neural network to normalized data
- Implement and observe the impact of various initialization techniques
- Implement and observe the impact of various optimization techniques

## 1.3 Load the data

First, run the following cell to import all the neccessary libraries and classes you will need in this lab.

```
[1]: # Necessary libraries and classes
  import numpy as np
  import pandas as pd
  from keras.models import Sequential
  from keras import initializers
  from keras import layers
  from sklearn.preprocessing import StandardScaler
  from sklearn.metrics import mean_squared_error
  from keras import optimizers
  from sklearn.model_selection import train_test_split
  import warnings
  warnings.filterwarnings('ignore')
```

In this lab, you'll be working with the housing prices data you saw in an earlier section. However, we did a lot of preprocessing for you so you can focus on normalizing numeric features and building

neural network models! The following preprocessing steps were taken (all the code can be found in the data\_preprocessing.ipynb notebook in this repository):

- The data was split into the training, validate, and test sets
- All the missing values in numeric columns were replaced by the median of those columns
- All the missing values in categorical columns were replaced with the word 'missing'
- All the categorical columns were one-hot encoded

Run the following cells to import the train, validate, and test sets:

```
[2]: # Load all numeric features
X_train_numeric = pd.read_csv('data/X_train_numeric.csv')
X_val_numeric = pd.read_csv('data/X_val_numeric.csv')
X_test_numeric = pd.read_csv('data/X_test_numeric.csv')

# Load all categorical features
X_train_cat = pd.read_csv('data/X_train_cat.csv')
X_val_cat = pd.read_csv('data/X_val_cat.csv')
X_test_cat = pd.read_csv('data/X_test_cat.csv')

# Load all targets
y_train = pd.read_csv('data/y_train.csv')
y_val = pd.read_csv('data/y_val.csv')
y_test = pd.read_csv('data/y_test.csv')

[3]: # Combine all features
X_train = pd.concat([X_train_numeric, X_train_cat], axis=1)
X_val = pd.concat([X_val_numeric, X_val_cat], axis=1)
```

```
[3]: # Combine all features
X_train = pd.concat([X_train_numeric, X_train_cat], axis=1)
X_val = pd.concat([X_val_numeric, X_val_cat], axis=1)
X_test = pd.concat([X_test_numeric, X_test_cat], axis=1)

# Number of features
n_features = X_train.shape[1]
```

As a refresher, preview the training data:

```
[4]: # Preview the data
X_train.head()
```

```
[4]:
        MSSubClass
                    LotFrontage LotArea
                                            OverallQual
                                                         OverallCond
                                                                       YearBuilt
     0
              80.0
                            69.0 21453.0
                                                    6.0
                                                                  5.0
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4
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   {\tt SaleCondition\_Normal}
                            SaleCondition_Partial
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1
                      1.0
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                      1.0
4
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                                                0.0
```

[5 rows x 296 columns]

#### 1.4 Build a Baseline Model

Building a naive baseline model to compare performance against is a helpful reference point. From there, you can then observe the impact of various tunning procedures which will iteratively improve your model. So, let's do just that!

In the cell below:

- Add an input layer with n\_features units
- Add two hidden layers, one with 100 and the other with 50 units (make sure you use the 'relu' activation function)
- Add an output layer with 1 unit and 'linear' activation
- Compile and fit the model

```
# Hidden layer with 50 units
baseline_model.add(layers.Dense(50, activation = "relu"))
# Output layer
baseline_model.add(layers.Dense(1, activation = "linear"))
# Compile the model
baseline_model.compile(optimizer='SGD',
            loss='mse',
            metrics=['mse'])
# Train the model
baseline_model.fit(X_train,
          y_train,
          batch_size=32,
          epochs=150,
          validation_data=(X_val, y_val))
Epoch 1/150
val_loss: nan - val_mse: nan
Epoch 2/150
val_loss: nan - val_mse: nan
Epoch 3/150
val_loss: nan - val_mse: nan
Epoch 4/150
val_loss: nan - val_mse: nan
Epoch 5/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 6/150
val_loss: nan - val_mse: nan
Epoch 7/150
val_loss: nan - val_mse: nan
Epoch 8/150
val_loss: nan - val_mse: nan
Epoch 9/150
val_loss: nan - val_mse: nan
Epoch 10/150
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val_loss: nan - val_mse: nan
Epoch 11/150
val_loss: nan - val_mse: nan
Epoch 12/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 13/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 14/150
val_loss: nan - val_mse: nan
Epoch 15/150
val_loss: nan - val_mse: nan
Epoch 16/150
val_loss: nan - val_mse: nan
Epoch 17/150
val_loss: nan - val_mse: nan
Epoch 18/150
val_loss: nan - val_mse: nan
Epoch 19/150
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Epoch 20/150
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Epoch 21/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 22/150
val_loss: nan - val_mse: nan
Epoch 23/150
val_loss: nan - val_mse: nan
Epoch 24/150
val_loss: nan - val_mse: nan
Epoch 25/150
val_loss: nan - val_mse: nan
Epoch 26/150
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val_loss: nan - val_mse: nan
Epoch 27/150
val_loss: nan - val_mse: nan
Epoch 28/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 29/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 30/150
val_loss: nan - val_mse: nan
Epoch 31/150
val_loss: nan - val_mse: nan
Epoch 32/150
val_loss: nan - val_mse: nan
Epoch 33/150
val_loss: nan - val_mse: nan
Epoch 34/150
val_loss: nan - val_mse: nan
Epoch 35/150
val_loss: nan - val_mse: nan
Epoch 36/150
val_loss: nan - val_mse: nan
Epoch 37/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 38/150
val_loss: nan - val_mse: nan
Epoch 39/150
val_loss: nan - val_mse: nan
Epoch 40/150
val_loss: nan - val_mse: nan
Epoch 41/150
val_loss: nan - val_mse: nan
Epoch 42/150
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val_loss: nan - val_mse: nan
Epoch 43/150
val_loss: nan - val_mse: nan
Epoch 44/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 45/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 46/150
val_loss: nan - val_mse: nan
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val_loss: nan - val_mse: nan
Epoch 48/150
val_loss: nan - val_mse: nan
Epoch 49/150
val_loss: nan - val_mse: nan
Epoch 50/150
val_loss: nan - val_mse: nan
Epoch 51/150
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Epoch 52/150
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Epoch 53/150
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Epoch 55/150
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Epoch 56/150
val_loss: nan - val_mse: nan
Epoch 57/150
val_loss: nan - val_mse: nan
Epoch 58/150
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val_loss: nan - val_mse: nan
Epoch 59/150
val_loss: nan - val_mse: nan
Epoch 60/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 61/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 62/150
val_loss: nan - val_mse: nan
Epoch 63/150
val_loss: nan - val_mse: nan
Epoch 64/150
val_loss: nan - val_mse: nan
Epoch 65/150
val_loss: nan - val_mse: nan
Epoch 66/150
val_loss: nan - val_mse: nan
Epoch 67/150
val_loss: nan - val_mse: nan
Epoch 68/150
val_loss: nan - val_mse: nan
Epoch 69/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 70/150
val_loss: nan - val_mse: nan
Epoch 71/150
val_loss: nan - val_mse: nan
Epoch 72/150
val_loss: nan - val_mse: nan
Epoch 73/150
val_loss: nan - val_mse: nan
Epoch 74/150
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val_loss: nan - val_mse: nan
Epoch 75/150
val_loss: nan - val_mse: nan
Epoch 76/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 77/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 78/150
val_loss: nan - val_mse: nan
Epoch 79/150
val_loss: nan - val_mse: nan
Epoch 80/150
val_loss: nan - val_mse: nan
Epoch 81/150
val_loss: nan - val_mse: nan
Epoch 82/150
val_loss: nan - val_mse: nan
Epoch 83/150
val_loss: nan - val_mse: nan
Epoch 84/150
val_loss: nan - val_mse: nan
Epoch 85/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 86/150
val_loss: nan - val_mse: nan
Epoch 87/150
val_loss: nan - val_mse: nan
Epoch 88/150
val_loss: nan - val_mse: nan
Epoch 89/150
val_loss: nan - val_mse: nan
Epoch 90/150
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val_loss: nan - val_mse: nan
Epoch 91/150
val_loss: nan - val_mse: nan
Epoch 92/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 93/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 94/150
val_loss: nan - val_mse: nan
Epoch 95/150
val_loss: nan - val_mse: nan
Epoch 96/150
val_loss: nan - val_mse: nan
Epoch 97/150
val_loss: nan - val_mse: nan
Epoch 98/150
val_loss: nan - val_mse: nan
Epoch 99/150
val_loss: nan - val_mse: nan
Epoch 100/150
val_loss: nan - val_mse: nan
Epoch 101/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 102/150
val_loss: nan - val_mse: nan
Epoch 103/150
val_loss: nan - val_mse: nan
Epoch 104/150
val_loss: nan - val_mse: nan
Epoch 105/150
val_loss: nan - val_mse: nan
Epoch 106/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
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val_loss: nan - val_mse: nan
Epoch 107/150
val_loss: nan - val_mse: nan
Epoch 108/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 109/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 110/150
val_loss: nan - val_mse: nan
Epoch 111/150
val_loss: nan - val_mse: nan
Epoch 112/150
val_loss: nan - val_mse: nan
Epoch 113/150
val_loss: nan - val_mse: nan
Epoch 114/150
val_loss: nan - val_mse: nan
Epoch 115/150
val_loss: nan - val_mse: nan
Epoch 116/150
val_loss: nan - val_mse: nan
Epoch 117/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 118/150
val_loss: nan - val_mse: nan
Epoch 119/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 120/150
val_loss: nan - val_mse: nan
Epoch 121/150
val_loss: nan - val_mse: nan
Epoch 122/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
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val_loss: nan - val_mse: nan
Epoch 123/150
val_loss: nan - val_mse: nan
Epoch 124/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val loss: nan - val mse: nan
Epoch 125/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 126/150
val_loss: nan - val_mse: nan
Epoch 127/150
val_loss: nan - val_mse: nan
Epoch 128/150
val_loss: nan - val_mse: nan
Epoch 129/150
val_loss: nan - val_mse: nan
Epoch 130/150
val_loss: nan - val_mse: nan
Epoch 131/150
val_loss: nan - val_mse: nan
Epoch 132/150
val_loss: nan - val_mse: nan
Epoch 133/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 134/150
val_loss: nan - val_mse: nan
Epoch 135/150
val_loss: nan - val_mse: nan
Epoch 136/150
val_loss: nan - val_mse: nan
Epoch 137/150
val_loss: nan - val_mse: nan
Epoch 138/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
```

```
val_loss: nan - val_mse: nan
Epoch 139/150
val_loss: nan - val_mse: nan
Epoch 140/150
val loss: nan - val mse: nan
Epoch 141/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 142/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 143/150
val_loss: nan - val_mse: nan
Epoch 144/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 145/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 146/150
val_loss: nan - val_mse: nan
Epoch 147/150
val_loss: nan - val_mse: nan
Epoch 148/150
val_loss: nan - val_mse: nan
Epoch 149/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 150/150
val_loss: nan - val_mse: nan
```

[6]: <tensorflow.python.keras.callbacks.History at 0x7ff1b7937370>

Notice this extremely problematic behavior: all the values for training and validation loss are "nan". This indicates that the algorithm did not converge. The first solution to this is to normalize the input. From there, if convergence is not achieved, normalizing the output may also be required.

## 1.5 Normalize the Input Data

It's now time to normalize the input data. In the cell below:

- Assign the column names of all numeric columns to numeric\_columns
- Instantiate a StandardScaler
- Fit and transform X\_train\_numeric. Make sure you convert the result into a DataFrame (use numeric\_columns as the column names)
- ullet Transform validate and test sets (X\_val\_numeric and X\_test\_numeric), and convert these results into DataFrames as well
- Use the provided to combine the scaled numerical and categorical features

```
[9]: # Numeric column names
numeric_columns = X_train_numeric.columns

# Instantiate StandardScaler
ss_X = StandardScaler()

# Fit and transform train data
X_train_scaled = pd.DataFrame(ss_X.fit_transform(X_train[numeric_columns]))

# Transform validate and test data
X_val_scaled = pd.DataFrame(ss_X.transform(X_val[numeric_columns]))
X_test_scaled = pd.DataFrame(ss_X.transform(X_test[numeric_columns]))

# Combine the scaled numerical features and categorical features
X_train = pd.concat([X_train_scaled, X_train_cat], axis=1)
X_val = pd.concat([X_val_scaled, X_val_cat], axis=1)
X_test = pd.concat([X_test_scaled, X_test_cat], axis=1)
```

Now run the following cell to compile a neural network model (with the same architecture as before):

In the cell below: - Train the normalized\_input\_model on normalized input (X\_train) and output (y\_train) - Set a batch size of 32 and train for 150 epochs - Specify the validation\_data argument as (X\_val, y\_val)

## validation\_data = (X\_val, y\_val))

```
Epoch 1/150
33/33 [=============== ] - Os 4ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 2/150
val_loss: nan - val_mse: nan
Epoch 3/150
val_loss: nan - val_mse: nan
Epoch 4/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 5/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 6/150
val_loss: nan - val_mse: nan
Epoch 7/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 8/150
val_loss: nan - val_mse: nan
Epoch 9/150
val_loss: nan - val_mse: nan
Epoch 10/150
val_loss: nan - val_mse: nan
Epoch 11/150
val_loss: nan - val_mse: nan
Epoch 12/150
val_loss: nan - val_mse: nan
Epoch 13/150
val_loss: nan - val_mse: nan
Epoch 14/150
val_loss: nan - val_mse: nan
Epoch 15/150
val_loss: nan - val_mse: nan
```

```
Epoch 16/150
val_loss: nan - val_mse: nan
Epoch 17/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 18/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 19/150
val_loss: nan - val_mse: nan
Epoch 20/150
val_loss: nan - val_mse: nan
Epoch 21/150
val_loss: nan - val_mse: nan
Epoch 22/150
val_loss: nan - val_mse: nan
Epoch 23/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 24/150
val_loss: nan - val_mse: nan
Epoch 25/150
val_loss: nan - val_mse: nan
Epoch 26/150
val_loss: nan - val_mse: nan
Epoch 27/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 28/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 29/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 30/150
val_loss: nan - val_mse: nan
Epoch 31/150
val_loss: nan - val_mse: nan
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```
Epoch 32/150
val_loss: nan - val_mse: nan
Epoch 33/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 34/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 35/150
val_loss: nan - val_mse: nan
Epoch 36/150
val_loss: nan - val_mse: nan
Epoch 37/150
val_loss: nan - val_mse: nan
Epoch 38/150
val_loss: nan - val_mse: nan
Epoch 39/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 40/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 41/150
val_loss: nan - val_mse: nan
Epoch 42/150
val_loss: nan - val_mse: nan
Epoch 43/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 44/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 45/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 46/150
val_loss: nan - val_mse: nan
Epoch 47/150
val_loss: nan - val_mse: nan
```

```
Epoch 48/150
val_loss: nan - val_mse: nan
Epoch 49/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 50/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 51/150
val_loss: nan - val_mse: nan
Epoch 52/150
val_loss: nan - val_mse: nan
Epoch 53/150
val_loss: nan - val_mse: nan
Epoch 54/150
val_loss: nan - val_mse: nan
Epoch 55/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 56/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 57/150
val_loss: nan - val_mse: nan
Epoch 58/150
val_loss: nan - val_mse: nan
Epoch 59/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 60/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 61/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
val_loss: nan - val_mse: nan
Epoch 63/150
val_loss: nan - val_mse: nan
```

```
Epoch 64/150
val_loss: nan - val_mse: nan
Epoch 65/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 66/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 67/150
val_loss: nan - val_mse: nan
Epoch 68/150
val_loss: nan - val_mse: nan
Epoch 69/150
val_loss: nan - val_mse: nan
Epoch 70/150
val_loss: nan - val_mse: nan
Epoch 71/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 72/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 73/150
val_loss: nan - val_mse: nan
Epoch 74/150
val_loss: nan - val_mse: nan
Epoch 75/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 76/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 77/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 78/150
val_loss: nan - val_mse: nan
Epoch 79/150
val_loss: nan - val_mse: nan
```

```
Epoch 80/150
val_loss: nan - val_mse: nan
Epoch 81/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 82/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 83/150
val_loss: nan - val_mse: nan
Epoch 84/150
val_loss: nan - val_mse: nan
Epoch 85/150
val_loss: nan - val_mse: nan
Epoch 86/150
val_loss: nan - val_mse: nan
Epoch 87/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 88/150
val_loss: nan - val_mse: nan
Epoch 89/150
val_loss: nan - val_mse: nan
Epoch 90/150
val_loss: nan - val_mse: nan
Epoch 91/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 92/150
33/33 [================== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 93/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 94/150
val_loss: nan - val_mse: nan
Epoch 95/150
val_loss: nan - val_mse: nan
```

```
Epoch 96/150
val_loss: nan - val_mse: nan
Epoch 97/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 98/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 99/150
val_loss: nan - val_mse: nan
Epoch 100/150
val_loss: nan - val_mse: nan
Epoch 101/150
val_loss: nan - val_mse: nan
Epoch 102/150
val_loss: nan - val_mse: nan
Epoch 103/150
val_loss: nan - val_mse: nan
Epoch 104/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 105/150
val_loss: nan - val_mse: nan
Epoch 106/150
val_loss: nan - val_mse: nan
Epoch 107/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 108/150
val_loss: nan - val_mse: nan
Epoch 109/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 110/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 111/150
val_loss: nan - val_mse: nan
```

```
Epoch 112/150
val_loss: nan - val_mse: nan
Epoch 113/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 114/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 115/150
val_loss: nan - val_mse: nan
Epoch 116/150
val_loss: nan - val_mse: nan
Epoch 117/150
val_loss: nan - val_mse: nan
Epoch 118/150
val_loss: nan - val_mse: nan
Epoch 119/150
val_loss: nan - val_mse: nan
Epoch 120/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 121/150
val_loss: nan - val_mse: nan
Epoch 122/150
val_loss: nan - val_mse: nan
Epoch 123/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 124/150
val_loss: nan - val_mse: nan
Epoch 125/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 126/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 127/150
val_loss: nan - val_mse: nan
```

```
Epoch 128/150
val_loss: nan - val_mse: nan
Epoch 129/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 130/150
33/33 [================ ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 131/150
val_loss: nan - val_mse: nan
Epoch 132/150
val_loss: nan - val_mse: nan
Epoch 133/150
val_loss: nan - val_mse: nan
Epoch 134/150
val_loss: nan - val_mse: nan
Epoch 135/150
val_loss: nan - val_mse: nan
Epoch 136/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 137/150
val_loss: nan - val_mse: nan
Epoch 138/150
val_loss: nan - val_mse: nan
Epoch 139/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 140/150
val_loss: nan - val_mse: nan
Epoch 141/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 142/150
val_loss: nan - val_mse: nan
Epoch 143/150
val_loss: nan - val_mse: nan
```

```
Epoch 144/150
val_loss: nan - val_mse: nan
Epoch 145/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 146/150
val_loss: nan - val_mse: nan
Epoch 147/150
33/33 [============= ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 148/150
33/33 [=============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
Epoch 149/150
val_loss: nan - val_mse: nan
Epoch 150/150
33/33 [============== ] - Os 1ms/step - loss: nan - mse: nan -
val_loss: nan - val_mse: nan
```

[12]: <tensorflow.python.keras.callbacks.History at 0x7ff198d98fa0>

Note that you still haven't achieved convergence! From here, it's time to normalize the output data.

# 1.6 Normalizing the output

Again, use StandardScaler() to:

- Fit and transform y\_train
- Transform y\_val and y\_test

```
[13]: # Instantiate StandardScaler
ss_y = StandardScaler()

# Fit and transform train labels
y_train_scaled = ss_y.fit_transform(y_train)

# Transform validate and test labels
y_val_scaled = ss_y.transform(y_val)
y_test_scaled = ss_y.transform(y_test)
```

In the cell below: - Train the normalized\_model on normalized input (X\_train) and output (y\_train\_scaled) - Set a batch size of 32 and train for 150 epochs - Specify the validation\_data as (X\_val, y\_val\_scaled)

```
[14]: # Model with all normalized inputs and outputs
   np.random.seed(123)
   normalized_model = Sequential()
   normalized_model.add(layers.Dense(100, activation='relu', u
    →input_shape=(n_features,)))
   normalized_model.add(layers.Dense(50, activation='relu'))
   normalized_model.add(layers.Dense(1, activation='linear'))
   # Compile the model
   normalized_model.compile(optimizer='SGD',
                   loss='mse',
                   metrics=['mse'])
   # Train the model
   normalized_model.fit(X_train, y_train_scaled,
               epochs = 150, batch size = 32,
               validation_data = (X_val, y_val_scaled))
   Epoch 1/150
   0.5117 - val_loss: 0.2658 - val_mse: 0.2658
   Epoch 2/150
   0.2252 - val_loss: 0.2162 - val_mse: 0.2162
   Epoch 3/150
   0.1920 - val_loss: 0.1976 - val_mse: 0.1976
   Epoch 4/150
   0.1657 - val_loss: 0.1797 - val_mse: 0.1797
   Epoch 5/150
   0.1510 - val_loss: 0.1756 - val_mse: 0.1756
   0.1395 - val_loss: 0.1702 - val_mse: 0.1702
   Epoch 7/150
   0.1260 - val_loss: 0.1651 - val_mse: 0.1651
   Epoch 8/150
   0.1182 - val_loss: 0.1642 - val_mse: 0.1642
   Epoch 9/150
   0.1096 - val_loss: 0.1680 - val_mse: 0.1680
```

Epoch 10/150

```
0.1046 - val_loss: 0.1678 - val_mse: 0.1678
Epoch 11/150
0.0979 - val_loss: 0.1652 - val_mse: 0.1652
Epoch 12/150
0.0952 - val_loss: 0.1632 - val_mse: 0.1632
Epoch 13/150
0.0860 - val_loss: 0.1667 - val_mse: 0.1667
Epoch 14/150
0.0840 - val_loss: 0.1585 - val_mse: 0.1585
Epoch 15/150
0.0810 - val_loss: 0.1627 - val_mse: 0.1627
Epoch 16/150
0.0752 - val_loss: 0.1691 - val_mse: 0.1691
Epoch 17/150
0.0747 - val_loss: 0.1664 - val_mse: 0.1664
Epoch 18/150
0.0715 - val_loss: 0.1631 - val_mse: 0.1631
Epoch 19/150
33/33 [============= ] - Os 1ms/step - loss: 0.0696 - mse:
0.0696 - val_loss: 0.1663 - val_mse: 0.1663
Epoch 20/150
0.0641 - val_loss: 0.1689 - val_mse: 0.1689
Epoch 21/150
0.0638 - val_loss: 0.1697 - val_mse: 0.1697
Epoch 22/150
0.0620 - val_loss: 0.1723 - val_mse: 0.1723
Epoch 23/150
0.0595 - val_loss: 0.1733 - val_mse: 0.1733
Epoch 24/150
0.0568 - val_loss: 0.1738 - val_mse: 0.1738
Epoch 25/150
0.0550 - val_loss: 0.1732 - val_mse: 0.1732
Epoch 26/150
```

```
0.0550 - val_loss: 0.1699 - val_mse: 0.1699
Epoch 27/150
0.0516 - val_loss: 0.1828 - val_mse: 0.1828
Epoch 28/150
0.0516 - val_loss: 0.1733 - val_mse: 0.1733
Epoch 29/150
0.0497 - val_loss: 0.1757 - val_mse: 0.1757
Epoch 30/150
0.0482 - val_loss: 0.1742 - val_mse: 0.1742
Epoch 31/150
0.0473 - val_loss: 0.1745 - val_mse: 0.1745
Epoch 32/150
0.0450 - val_loss: 0.1787 - val_mse: 0.1787
Epoch 33/150
0.0446 - val_loss: 0.1783 - val_mse: 0.1783
Epoch 34/150
0.0435 - val_loss: 0.1828 - val_mse: 0.1828
Epoch 35/150
0.0422 - val_loss: 0.1789 - val_mse: 0.1789
Epoch 36/150
0.0416 - val_loss: 0.1803 - val_mse: 0.1803
Epoch 37/150
0.0389 - val loss: 0.1816 - val mse: 0.1816
Epoch 38/150
0.0400 - val_loss: 0.1800 - val_mse: 0.1800
Epoch 39/150
0.0390 - val_loss: 0.1810 - val_mse: 0.1810
Epoch 40/150
0.0385 - val_loss: 0.1817 - val_mse: 0.1817
Epoch 41/150
0.0364 - val_loss: 0.1799 - val_mse: 0.1799
Epoch 42/150
```

```
0.0362 - val_loss: 0.1815 - val_mse: 0.1815
Epoch 43/150
0.0352 - val_loss: 0.1882 - val_mse: 0.1882
Epoch 44/150
0.0344 - val_loss: 0.1827 - val_mse: 0.1827
Epoch 45/150
0.0333 - val_loss: 0.1848 - val_mse: 0.1848
Epoch 46/150
33/33 [============= ] - Os 1ms/step - loss: 0.0334 - mse:
0.0334 - val_loss: 0.1829 - val_mse: 0.1829
Epoch 47/150
0.0333 - val_loss: 0.1854 - val_mse: 0.1854
Epoch 48/150
0.0320 - val_loss: 0.1838 - val_mse: 0.1838
Epoch 49/150
0.0312 - val_loss: 0.1849 - val_mse: 0.1849
Epoch 50/150
0.0309 - val_loss: 0.1841 - val_mse: 0.1841
Epoch 51/150
33/33 [============= ] - Os 1ms/step - loss: 0.0300 - mse:
0.0300 - val_loss: 0.1832 - val_mse: 0.1832
Epoch 52/150
0.0296 - val_loss: 0.1860 - val_mse: 0.1860
Epoch 53/150
0.0291 - val loss: 0.1828 - val mse: 0.1828
Epoch 54/150
0.0295 - val_loss: 0.1866 - val_mse: 0.1866
Epoch 55/150
0.0282 - val_loss: 0.1860 - val_mse: 0.1860
Epoch 56/150
0.0276 - val_loss: 0.1859 - val_mse: 0.1859
Epoch 57/150
0.0267 - val_loss: 0.1867 - val_mse: 0.1867
Epoch 58/150
```

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0.0267 - val_loss: 0.1880 - val_mse: 0.1880
Epoch 59/150
0.0263 - val_loss: 0.1892 - val_mse: 0.1892
Epoch 60/150
0.0259 - val_loss: 0.1889 - val_mse: 0.1889
Epoch 61/150
0.0254 - val_loss: 0.1858 - val_mse: 0.1858
Epoch 62/150
0.0246 - val_loss: 0.1855 - val_mse: 0.1855
Epoch 63/150
0.0244 - val_loss: 0.1887 - val_mse: 0.1887
Epoch 64/150
0.0240 - val_loss: 0.1881 - val_mse: 0.1881
Epoch 65/150
0.0241 - val_loss: 0.1865 - val_mse: 0.1865
Epoch 66/150
0.0230 - val_loss: 0.1876 - val_mse: 0.1876
Epoch 67/150
0.0229 - val_loss: 0.1895 - val_mse: 0.1895
Epoch 68/150
0.0224 - val_loss: 0.1887 - val_mse: 0.1887
Epoch 69/150
0.0219 - val loss: 0.1898 - val mse: 0.1898
Epoch 70/150
0.0221 - val_loss: 0.1867 - val_mse: 0.1867
Epoch 71/150
0.0212 - val_loss: 0.1902 - val_mse: 0.1902
Epoch 72/150
33/33 [============= ] - Os 2ms/step - loss: 0.0209 - mse:
0.0209 - val_loss: 0.1897 - val_mse: 0.1897
Epoch 73/150
0.0208 - val_loss: 0.1890 - val_mse: 0.1890
Epoch 74/150
```

```
0.0206 - val_loss: 0.1915 - val_mse: 0.1915
Epoch 75/150
0.0198 - val_loss: 0.1903 - val_mse: 0.1903
Epoch 76/150
33/33 [============= ] - Os 1ms/step - loss: 0.0196 - mse:
0.0196 - val_loss: 0.1904 - val_mse: 0.1904
Epoch 77/150
0.0193 - val_loss: 0.1914 - val_mse: 0.1914
Epoch 78/150
0.0194 - val_loss: 0.1909 - val_mse: 0.1909
Epoch 79/150
0.0190 - val_loss: 0.1909 - val_mse: 0.1909
Epoch 80/150
0.0187 - val_loss: 0.1926 - val_mse: 0.1926
Epoch 81/150
0.0184 - val_loss: 0.1919 - val_mse: 0.1919
Epoch 82/150
0.0188 - val_loss: 0.1945 - val_mse: 0.1945
Epoch 83/150
0.0183 - val_loss: 0.1922 - val_mse: 0.1922
Epoch 84/150
0.0174 - val_loss: 0.1937 - val_mse: 0.1937
Epoch 85/150
0.0174 - val loss: 0.1959 - val mse: 0.1959
Epoch 86/150
0.0176 - val_loss: 0.1963 - val_mse: 0.1963
Epoch 87/150
0.0173 - val_loss: 0.1937 - val_mse: 0.1937
Epoch 88/150
0.0165 - val_loss: 0.1927 - val_mse: 0.1927
Epoch 89/150
0.0163 - val_loss: 0.1933 - val_mse: 0.1933
Epoch 90/150
```

```
0.0162 - val_loss: 0.1937 - val_mse: 0.1937
Epoch 91/150
0.0159 - val_loss: 0.1968 - val_mse: 0.1968
Epoch 92/150
0.0156 - val_loss: 0.1926 - val_mse: 0.1926
Epoch 93/150
0.0157 - val_loss: 0.1933 - val_mse: 0.1933
Epoch 94/150
33/33 [============= ] - Os 1ms/step - loss: 0.0153 - mse:
0.0153 - val_loss: 0.1927 - val_mse: 0.1927
Epoch 95/150
0.0153 - val_loss: 0.1958 - val_mse: 0.1958
Epoch 96/150
0.0151 - val_loss: 0.1946 - val_mse: 0.1946
Epoch 97/150
0.0148 - val_loss: 0.1953 - val_mse: 0.1953
Epoch 98/150
0.0145 - val_loss: 0.1970 - val_mse: 0.1970
Epoch 99/150
0.0145 - val_loss: 0.1971 - val_mse: 0.1971
Epoch 100/150
0.0144 - val_loss: 0.1944 - val_mse: 0.1944
Epoch 101/150
0.0138 - val loss: 0.1951 - val mse: 0.1951
Epoch 102/150
0.0138 - val_loss: 0.1965 - val_mse: 0.1965
Epoch 103/150
0.0138 - val_loss: 0.1959 - val_mse: 0.1959
Epoch 104/150
0.0135 - val_loss: 0.1971 - val_mse: 0.1971
Epoch 105/150
0.0134 - val_loss: 0.1969 - val_mse: 0.1969
Epoch 106/150
```

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0.0131 - val_loss: 0.1967 - val_mse: 0.1967
Epoch 107/150
0.0130 - val_loss: 0.1976 - val_mse: 0.1976
Epoch 108/150
0.0131 - val_loss: 0.1995 - val_mse: 0.1995
Epoch 109/150
0.0127 - val_loss: 0.1971 - val_mse: 0.1971
Epoch 110/150
0.0126 - val_loss: 0.1973 - val_mse: 0.1973
Epoch 111/150
0.0123 - val_loss: 0.1984 - val_mse: 0.1984
Epoch 112/150
0.0123 - val_loss: 0.1983 - val_mse: 0.1983
Epoch 113/150
0.0119 - val_loss: 0.1987 - val_mse: 0.1987
Epoch 114/150
0.0120 - val_loss: 0.1973 - val_mse: 0.1973
Epoch 115/150
33/33 [============= ] - Os 1ms/step - loss: 0.0118 - mse:
0.0118 - val_loss: 0.2009 - val_mse: 0.2009
Epoch 116/150
0.0116 - val_loss: 0.1988 - val_mse: 0.1988
Epoch 117/150
0.0116 - val loss: 0.2015 - val mse: 0.2015
Epoch 118/150
0.0117 - val_loss: 0.1994 - val_mse: 0.1994
Epoch 119/150
0.0113 - val_loss: 0.2000 - val_mse: 0.2000
Epoch 120/150
0.0112 - val_loss: 0.1976 - val_mse: 0.1976
Epoch 121/150
0.0111 - val_loss: 0.2009 - val_mse: 0.2009
Epoch 122/150
```

```
0.0107 - val_loss: 0.2010 - val_mse: 0.2010
Epoch 123/150
0.0108 - val_loss: 0.2014 - val_mse: 0.2014
Epoch 124/150
0.0106 - val_loss: 0.2005 - val_mse: 0.2005
Epoch 125/150
0.0106 - val_loss: 0.1997 - val_mse: 0.1997
Epoch 126/150
0.0106 - val_loss: 0.1994 - val_mse: 0.1994
Epoch 127/150
0.0101 - val_loss: 0.2007 - val_mse: 0.2007
Epoch 128/150
0.0102 - val_loss: 0.2044 - val_mse: 0.2044
Epoch 129/150
0.0100 - val_loss: 0.1995 - val_mse: 0.1995
Epoch 130/150
0.0098 - val_loss: 0.2025 - val_mse: 0.2025
Epoch 131/150
0.0098 - val_loss: 0.2012 - val_mse: 0.2012
Epoch 132/150
0.0098 - val_loss: 0.2010 - val_mse: 0.2010
Epoch 133/150
0.0097 - val loss: 0.2035 - val mse: 0.2035
Epoch 134/150
0.0096 - val_loss: 0.2014 - val_mse: 0.2014
Epoch 135/150
0.0094 - val_loss: 0.2004 - val_mse: 0.2004
Epoch 136/150
33/33 [============= ] - Os 1ms/step - loss: 0.0093 - mse:
0.0093 - val_loss: 0.2004 - val_mse: 0.2004
Epoch 137/150
0.0094 - val_loss: 0.2024 - val_mse: 0.2024
Epoch 138/150
```

```
0.0091 - val_loss: 0.2027 - val_mse: 0.2027
Epoch 139/150
0.0091 - val_loss: 0.2021 - val_mse: 0.2021
Epoch 140/150
0.0090 - val_loss: 0.2006 - val_mse: 0.2006
Epoch 141/150
0.0087 - val_loss: 0.2014 - val_mse: 0.2014
Epoch 142/150
0.0087 - val_loss: 0.2015 - val_mse: 0.2015
Epoch 143/150
0.0084 - val_loss: 0.2030 - val_mse: 0.2030
Epoch 144/150
0.0084 - val_loss: 0.2031 - val_mse: 0.2031
Epoch 145/150
0.0085 - val_loss: 0.2043 - val_mse: 0.2043
Epoch 146/150
0.0084 - val_loss: 0.2033 - val_mse: 0.2033
Epoch 147/150
0.0083 - val_loss: 0.2013 - val_mse: 0.2013
Epoch 148/150
0.0082 - val_loss: 0.2022 - val_mse: 0.2022
Epoch 149/150
0.0081 - val loss: 0.2026 - val mse: 0.2026
Epoch 150/150
0.0080 - val_loss: 0.2051 - val_mse: 0.2051
```

[14]: <tensorflow.python.keras.callbacks.History at 0x7ff1992d4370>

Nicely done! After normalizing both the input and output, the model finally converged.

• Evaluate the model (normalized\_model) on training data (X\_train and y\_train\_scaled)

```
[15]: # Evaluate the model on training data normalized_model.evaluate(X_train, y_train_scaled)
```

0.0080

#### [15]: [0.00796041265130043, 0.00796041265130043]

• Evaluate the model (normalized\_model) on validate data (X\_val and y\_val\_scaled)

```
[16]: # Evaluate the model on validate data
normalized_model.evaluate(X_val, y_val_scaled)
```

```
9/9 [==========] - Os 692us/step - loss: 0.2051 - mse: 0.2051
```

[16]: [0.2051234394311905, 0.2051234394311905]

Since the output is normalized, the metric above is not interpretable. To remedy this:

- Generate predictions on validate data (X\_val)
- Transform these predictions back to original scale using  ${\tt ss\_y}$
- Now you can calculate the RMSE in the original units with y\_val and y\_val\_pred

```
[21]: # Generate predictions on validate data
y_val_pred_scaled = normalized_model.predict(X_val)

# Transform the predictions back to original scale
y_val_pred = ss_y.inverse_transform(y_val_pred_scaled)

# RMSE of validate data
RMSE = mean_squared_error(y_val, y_val_pred, squared = False)
RMSE
```

#### [21]: 35590.91210505595

Great! Now that you have a converged model, you can also experiment with alternative optimizers and initialization strategies to see if you can find a better global minimum. (After all, the current models may have converged to a local minimum.)

## 1.7 Using Weight Initializers

In this section you will to use alternative initialization and optimization strategies. At the end, you'll then be asked to select the model which you believe performs the best.

#### 1.8 He Initialization

In the cell below, sepcify the following in the first hidden layer:
- 100 units - 'relu' activation - input\_shape - kernel\_initializer='he\_normal'

```
[23]: np.random.seed(123)
he_model = Sequential()

# Add the first hidden layer
```

```
he_model.add(layers.Dense(100, activation = "relu",
                kernel_initializer = "he_normal",
                input_shape = (X_train.shape[1],)))
# Add another hidden layer
he_model.add(layers.Dense(50, activation='relu'))
# Add an output layer
he model.add(layers.Dense(1, activation='linear'))
# Compile the model
he_model.compile(optimizer='SGD',
          loss='mse',
          metrics=['mse'])
# Train the model
he_model.fit(X_train,
        y_train_scaled,
        batch_size=32,
        epochs=150,
        validation_data=(X_val, y_val_scaled))
Epoch 1/150
0.5365 - val_loss: 0.1936 - val_mse: 0.1936
Epoch 2/150
0.2515 - val_loss: 0.1565 - val_mse: 0.1565
Epoch 3/150
0.2123 - val_loss: 0.1445 - val_mse: 0.1445
Epoch 4/150
0.1921 - val_loss: 0.1493 - val_mse: 0.1493
0.1647 - val_loss: 0.1509 - val_mse: 0.1509
Epoch 6/150
0.1447 - val_loss: 0.1479 - val_mse: 0.1479
Epoch 7/150
0.1340 - val_loss: 0.1460 - val_mse: 0.1460
Epoch 8/150
0.1224 - val_loss: 0.1541 - val_mse: 0.1541
Epoch 9/150
```

```
0.1122 - val_loss: 0.1553 - val_mse: 0.1553
Epoch 10/150
0.1051 - val_loss: 0.1741 - val_mse: 0.1741
Epoch 11/150
0.1025 - val_loss: 0.1724 - val_mse: 0.1724
Epoch 12/150
0.0930 - val_loss: 0.1619 - val_mse: 0.1619
Epoch 13/150
0.0879 - val_loss: 0.1741 - val_mse: 0.1741
Epoch 14/150
0.0853 - val_loss: 0.1660 - val_mse: 0.1660
Epoch 15/150
0.0802 - val_loss: 0.1717 - val_mse: 0.1717
Epoch 16/150
0.0787 - val_loss: 0.1717 - val_mse: 0.1717
Epoch 17/150
0.0748 - val_loss: 0.1723 - val_mse: 0.1723
Epoch 18/150
0.0723 - val_loss: 0.1753 - val_mse: 0.1753
Epoch 19/150
0.0712 - val_loss: 0.1743 - val_mse: 0.1743
Epoch 20/150
0.0660 - val_loss: 0.1817 - val_mse: 0.1817
Epoch 21/150
0.0640 - val_loss: 0.1743 - val_mse: 0.1743
Epoch 22/150
0.0618 - val_loss: 0.1763 - val_mse: 0.1763
Epoch 23/150
33/33 [============= ] - Os 1ms/step - loss: 0.0602 - mse:
0.0602 - val_loss: 0.1824 - val_mse: 0.1824
Epoch 24/150
0.0591 - val_loss: 0.1792 - val_mse: 0.1792
Epoch 25/150
```

```
0.0568 - val_loss: 0.1825 - val_mse: 0.1825
Epoch 26/150
0.0556 - val_loss: 0.1788 - val_mse: 0.1788
Epoch 27/150
0.0540 - val_loss: 0.1795 - val_mse: 0.1795
Epoch 28/150
0.0525 - val_loss: 0.1799 - val_mse: 0.1799
Epoch 29/150
0.0510 - val_loss: 0.1794 - val_mse: 0.1794
Epoch 30/150
0.0500 - val_loss: 0.1801 - val_mse: 0.1801
Epoch 31/150
0.0488 - val_loss: 0.1778 - val_mse: 0.1778
Epoch 32/150
0.0472 - val_loss: 0.1789 - val_mse: 0.1789
Epoch 33/150
0.0458 - val_loss: 0.1790 - val_mse: 0.1790
Epoch 34/150
0.0451 - val_loss: 0.1799 - val_mse: 0.1799
Epoch 35/150
0.0440 - val_loss: 0.1816 - val_mse: 0.1816
Epoch 36/150
0.0421 - val loss: 0.1833 - val mse: 0.1833
Epoch 37/150
0.0423 - val_loss: 0.1834 - val_mse: 0.1834
Epoch 38/150
0.0405 - val_loss: 0.1874 - val_mse: 0.1874
Epoch 39/150
0.0403 - val_loss: 0.1839 - val_mse: 0.1839
Epoch 40/150
0.0397 - val_loss: 0.1826 - val_mse: 0.1826
Epoch 41/150
```

```
0.0383 - val_loss: 0.1830 - val_mse: 0.1830
Epoch 42/150
0.0370 - val_loss: 0.1850 - val_mse: 0.1850
Epoch 43/150
0.0368 - val_loss: 0.1890 - val_mse: 0.1890
Epoch 44/150
0.0368 - val_loss: 0.1857 - val_mse: 0.1857
Epoch 45/150
0.0352 - val_loss: 0.1861 - val_mse: 0.1861
Epoch 46/150
0.0343 - val_loss: 0.1862 - val_mse: 0.1862
Epoch 47/150
0.0343 - val_loss: 0.1859 - val_mse: 0.1859
Epoch 48/150
0.0335 - val_loss: 0.1866 - val_mse: 0.1866
Epoch 49/150
0.0330 - val_loss: 0.1881 - val_mse: 0.1881
Epoch 50/150
0.0324 - val_loss: 0.1900 - val_mse: 0.1900
Epoch 51/150
0.0314 - val_loss: 0.1884 - val_mse: 0.1884
Epoch 52/150
0.0312 - val loss: 0.1863 - val mse: 0.1863
Epoch 53/150
0.0307 - val_loss: 0.1874 - val_mse: 0.1874
Epoch 54/150
0.0299 - val_loss: 0.1878 - val_mse: 0.1878
Epoch 55/150
33/33 [============= ] - Os 1ms/step - loss: 0.0295 - mse:
0.0295 - val_loss: 0.1890 - val_mse: 0.1890
Epoch 56/150
0.0290 - val_loss: 0.1896 - val_mse: 0.1896
Epoch 57/150
```

```
0.0282 - val_loss: 0.1881 - val_mse: 0.1881
Epoch 58/150
0.0287 - val_loss: 0.1873 - val_mse: 0.1873
Epoch 59/150
0.0270 - val_loss: 0.1865 - val_mse: 0.1865
Epoch 60/150
0.0272 - val_loss: 0.1852 - val_mse: 0.1852
Epoch 61/150
0.0271 - val_loss: 0.1902 - val_mse: 0.1902
Epoch 62/150
0.0262 - val_loss: 0.1881 - val_mse: 0.1881
Epoch 63/150
0.0258 - val_loss: 0.1893 - val_mse: 0.1893
Epoch 64/150
0.0252 - val_loss: 0.1906 - val_mse: 0.1906
Epoch 65/150
0.0249 - val_loss: 0.1882 - val_mse: 0.1882
Epoch 66/150
33/33 [============= ] - Os 1ms/step - loss: 0.0243 - mse:
0.0243 - val_loss: 0.1898 - val_mse: 0.1898
Epoch 67/150
0.0237 - val_loss: 0.1935 - val_mse: 0.1935
Epoch 68/150
0.0237 - val loss: 0.1885 - val mse: 0.1885
Epoch 69/150
0.0234 - val_loss: 0.1911 - val_mse: 0.1911
Epoch 70/150
0.0230 - val_loss: 0.1897 - val_mse: 0.1897
Epoch 71/150
0.0226 - val_loss: 0.1906 - val_mse: 0.1906
Epoch 72/150
0.0218 - val_loss: 0.1906 - val_mse: 0.1906
Epoch 73/150
```

```
0.0221 - val_loss: 0.1921 - val_mse: 0.1921
Epoch 74/150
0.0218 - val_loss: 0.1906 - val_mse: 0.1906
Epoch 75/150
0.0211 - val_loss: 0.1900 - val_mse: 0.1900
Epoch 76/150
0.0214 - val_loss: 0.1956 - val_mse: 0.1956
Epoch 77/150
33/33 [============= ] - Os 1ms/step - loss: 0.0211 - mse:
0.0211 - val_loss: 0.1936 - val_mse: 0.1936
Epoch 78/150
0.0203 - val_loss: 0.1927 - val_mse: 0.1927
Epoch 79/150
0.0202 - val_loss: 0.1911 - val_mse: 0.1911
Epoch 80/150
0.0201 - val_loss: 0.1926 - val_mse: 0.1926
Epoch 81/150
0.0195 - val_loss: 0.1924 - val_mse: 0.1924
Epoch 82/150
0.0192 - val_loss: 0.1915 - val_mse: 0.1915
Epoch 83/150
0.0189 - val_loss: 0.1921 - val_mse: 0.1921
Epoch 84/150
0.0186 - val loss: 0.1951 - val mse: 0.1951
Epoch 85/150
0.0184 - val_loss: 0.1960 - val_mse: 0.1960
Epoch 86/150
0.0182 - val_loss: 0.1928 - val_mse: 0.1928
Epoch 87/150
0.0178 - val_loss: 0.2016 - val_mse: 0.2016
Epoch 88/150
0.0178 - val_loss: 0.1939 - val_mse: 0.1939
Epoch 89/150
```

```
0.0178 - val_loss: 0.1930 - val_mse: 0.1930
Epoch 90/150
0.0172 - val_loss: 0.1920 - val_mse: 0.1920
Epoch 91/150
0.0172 - val_loss: 0.1930 - val_mse: 0.1930
Epoch 92/150
0.0168 - val_loss: 0.1923 - val_mse: 0.1923
Epoch 93/150
33/33 [============= ] - Os 1ms/step - loss: 0.0164 - mse:
0.0164 - val_loss: 0.1947 - val_mse: 0.1947
Epoch 94/150
0.0161 - val_loss: 0.1953 - val_mse: 0.1953
Epoch 95/150
0.0162 - val_loss: 0.1952 - val_mse: 0.1952
Epoch 96/150
0.0158 - val_loss: 0.1952 - val_mse: 0.1952
Epoch 97/150
0.0155 - val_loss: 0.1933 - val_mse: 0.1933
Epoch 98/150
0.0157 - val_loss: 0.1931 - val_mse: 0.1931
Epoch 99/150
0.0154 - val_loss: 0.1943 - val_mse: 0.1943
Epoch 100/150
0.0151 - val loss: 0.1949 - val mse: 0.1949
Epoch 101/150
0.0150 - val_loss: 0.1944 - val_mse: 0.1944
Epoch 102/150
0.0147 - val_loss: 0.1947 - val_mse: 0.1947
Epoch 103/150
0.0147 - val_loss: 0.1967 - val_mse: 0.1967
Epoch 104/150
0.0145 - val_loss: 0.1951 - val_mse: 0.1951
Epoch 105/150
```

```
0.0141 - val_loss: 0.1936 - val_mse: 0.1936
Epoch 106/150
0.0141 - val_loss: 0.1933 - val_mse: 0.1933
Epoch 107/150
0.0138 - val_loss: 0.1940 - val_mse: 0.1940
Epoch 108/150
0.0139 - val_loss: 0.1944 - val_mse: 0.1944
Epoch 109/150
0.0136 - val_loss: 0.1950 - val_mse: 0.1950
Epoch 110/150
0.0133 - val_loss: 0.1967 - val_mse: 0.1967
Epoch 111/150
0.0132 - val_loss: 0.1971 - val_mse: 0.1971
Epoch 112/150
0.0132 - val_loss: 0.1945 - val_mse: 0.1945
Epoch 113/150
0.0129 - val_loss: 0.1962 - val_mse: 0.1962
Epoch 114/150
0.0127 - val_loss: 0.1959 - val_mse: 0.1959
Epoch 115/150
0.0126 - val_loss: 0.1986 - val_mse: 0.1986
Epoch 116/150
0.0125 - val loss: 0.1964 - val mse: 0.1964
Epoch 117/150
0.0124 - val_loss: 0.1976 - val_mse: 0.1976
Epoch 118/150
0.0120 - val_loss: 0.1950 - val_mse: 0.1950
Epoch 119/150
0.0120 - val_loss: 0.1996 - val_mse: 0.1996
Epoch 120/150
0.0122 - val_loss: 0.1960 - val_mse: 0.1960
Epoch 121/150
```

```
0.0120 - val_loss: 0.1967 - val_mse: 0.1967
Epoch 122/150
0.0117 - val_loss: 0.1968 - val_mse: 0.1968
Epoch 123/150
0.0117 - val_loss: 0.1962 - val_mse: 0.1962
Epoch 124/150
0.0114 - val_loss: 0.1982 - val_mse: 0.1982
Epoch 125/150
33/33 [============= ] - Os 1ms/step - loss: 0.0114 - mse:
0.0114 - val_loss: 0.1981 - val_mse: 0.1981
Epoch 126/150
0.0113 - val_loss: 0.1972 - val_mse: 0.1972
Epoch 127/150
0.0109 - val_loss: 0.1965 - val_mse: 0.1965
Epoch 128/150
0.0109 - val_loss: 0.1969 - val_mse: 0.1969
Epoch 129/150
0.0108 - val_loss: 0.1990 - val_mse: 0.1990
Epoch 130/150
33/33 [============= ] - Os 1ms/step - loss: 0.0108 - mse:
0.0108 - val_loss: 0.1977 - val_mse: 0.1977
Epoch 131/150
0.0105 - val_loss: 0.1970 - val_mse: 0.1970
Epoch 132/150
0.0105 - val loss: 0.2005 - val mse: 0.2005
Epoch 133/150
0.0103 - val_loss: 0.1972 - val_mse: 0.1972
Epoch 134/150
0.0102 - val_loss: 0.1984 - val_mse: 0.1984
Epoch 135/150
0.0101 - val_loss: 0.1977 - val_mse: 0.1977
Epoch 136/150
0.0100 - val_loss: 0.1977 - val_mse: 0.1977
Epoch 137/150
```

```
0.0099 - val_loss: 0.1968 - val_mse: 0.1968
  Epoch 138/150
  0.0098 - val_loss: 0.1968 - val_mse: 0.1968
  Epoch 139/150
  0.0097 - val_loss: 0.1977 - val_mse: 0.1977
  Epoch 140/150
  0.0096 - val_loss: 0.1974 - val_mse: 0.1974
  Epoch 141/150
  0.0095 - val_loss: 0.1988 - val_mse: 0.1988
  Epoch 142/150
  0.0094 - val_loss: 0.1988 - val_mse: 0.1988
  Epoch 143/150
  0.0091 - val_loss: 0.1973 - val_mse: 0.1973
  Epoch 144/150
  0.0090 - val_loss: 0.1984 - val_mse: 0.1984
  Epoch 145/150
  0.0090 - val_loss: 0.1986 - val_mse: 0.1986
  Epoch 146/150
  33/33 [============= ] - Os 1ms/step - loss: 0.0090 - mse:
  0.0090 - val_loss: 0.1992 - val_mse: 0.1992
  Epoch 147/150
  0.0087 - val_loss: 0.1988 - val_mse: 0.1988
  Epoch 148/150
  0.0089 - val loss: 0.1984 - val mse: 0.1984
  Epoch 149/150
  0.0088 - val_loss: 0.1989 - val_mse: 0.1989
  Epoch 150/150
  0.0084 - val_loss: 0.1979 - val_mse: 0.1979
[23]: <tensorflow.python.keras.callbacks.History at 0x7ff199e3c340>
  Evaluate the model (he model) on training data (X train and y train scaled)
[24]: # Evaluate the model on training data
   he_model.evaluate(X_train, y_train_scaled)
```

### 1.9 Lecun Initialization

In the cell below, sepcify the following in the first hidden layer:
- 100 units - 'relu' activation - input\_shape - kernel\_initializer='lecun\_normal'

```
[27]: np.random.seed(123)
      lecun_model = Sequential()
      # Add the first hidden layer
      lecun model.add(layers.Dense(100, activation = "relu",
                                  kernel_initializer = "lecun_normal",
                                  input_shape = (X_train.shape[1],)))
      # Add another hidden layer
      lecun_model.add(layers.Dense(50, activation='relu'))
      # Add an output layer
      lecun_model.add(layers.Dense(1, activation='linear'))
      # Compile the model
      lecun model.compile(optimizer='SGD',
                          loss='mse',
                          metrics=['mse'])
      # Train the model
      lecun_model.fit(X_train,
                      y_train_scaled,
                      batch_size=32,
                      epochs=150,
                      validation_data=(X_val, y_val_scaled))
```

```
0.4230 - val_loss: 0.1823 - val_mse: 0.1823
Epoch 2/150
0.2504 - val_loss: 0.1546 - val_mse: 0.1546
Epoch 3/150
0.1969 - val_loss: 0.1418 - val_mse: 0.1418
Epoch 4/150
0.1702 - val_loss: 0.1325 - val_mse: 0.1325
Epoch 5/150
0.1491 - val_loss: 0.1198 - val_mse: 0.1198
Epoch 6/150
0.1404 - val_loss: 0.1144 - val_mse: 0.1144
Epoch 7/150
0.1252 - val_loss: 0.1125 - val_mse: 0.1125
Epoch 8/150
0.1170 - val_loss: 0.1121 - val_mse: 0.1121
Epoch 9/150
0.1084 - val_loss: 0.1119 - val_mse: 0.1119
Epoch 10/150
0.1019 - val_loss: 0.1088 - val_mse: 0.1088
Epoch 11/150
0.0953 - val_loss: 0.1106 - val_mse: 0.1106
Epoch 12/150
0.0912 - val_loss: 0.1087 - val_mse: 0.1087
Epoch 13/150
0.0845 - val_loss: 0.1096 - val_mse: 0.1096
Epoch 14/150
0.0800 - val_loss: 0.1230 - val_mse: 0.1230
Epoch 15/150
0.0758 - val_loss: 0.1165 - val_mse: 0.1165
Epoch 16/150
0.0715 - val_loss: 0.1129 - val_mse: 0.1129
Epoch 17/150
```

```
0.0674 - val_loss: 0.1117 - val_mse: 0.1117
Epoch 18/150
0.0647 - val_loss: 0.1093 - val_mse: 0.1093
Epoch 19/150
0.0624 - val_loss: 0.1112 - val_mse: 0.1112
Epoch 20/150
0.0591 - val_loss: 0.1116 - val_mse: 0.1116
Epoch 21/150
0.0573 - val_loss: 0.1176 - val_mse: 0.1176
Epoch 22/150
0.0545 - val_loss: 0.1126 - val_mse: 0.1126
Epoch 23/150
0.0533 - val_loss: 0.1141 - val_mse: 0.1141
Epoch 24/150
0.0503 - val_loss: 0.1203 - val_mse: 0.1203
Epoch 25/150
0.0494 - val_loss: 0.1193 - val_mse: 0.1193
Epoch 26/150
0.0468 - val_loss: 0.1182 - val_mse: 0.1182
Epoch 27/150
0.0462 - val_loss: 0.1181 - val_mse: 0.1181
Epoch 28/150
0.0441 - val_loss: 0.1202 - val_mse: 0.1202
Epoch 29/150
0.0428 - val_loss: 0.1242 - val_mse: 0.1242
Epoch 30/150
0.0421 - val_loss: 0.1227 - val_mse: 0.1227
Epoch 31/150
33/33 [============= ] - Os 2ms/step - loss: 0.0400 - mse:
0.0400 - val_loss: 0.1227 - val_mse: 0.1227
Epoch 32/150
0.0388 - val_loss: 0.1239 - val_mse: 0.1239
Epoch 33/150
```

```
0.0391 - val_loss: 0.1239 - val_mse: 0.1239
Epoch 34/150
0.0382 - val_loss: 0.1240 - val_mse: 0.1240
Epoch 35/150
0.0368 - val_loss: 0.1255 - val_mse: 0.1255
Epoch 36/150
0.0366 - val_loss: 0.1258 - val_mse: 0.1258
Epoch 37/150
0.0352 - val_loss: 0.1281 - val_mse: 0.1281
Epoch 38/150
0.0350 - val_loss: 0.1283 - val_mse: 0.1283
Epoch 39/150
0.0339 - val_loss: 0.1263 - val_mse: 0.1263
Epoch 40/150
0.0328 - val_loss: 0.1274 - val_mse: 0.1274
Epoch 41/150
0.0322 - val_loss: 0.1304 - val_mse: 0.1304
Epoch 42/150
0.0317 - val_loss: 0.1313 - val_mse: 0.1313
Epoch 43/150
0.0312 - val_loss: 0.1316 - val_mse: 0.1316
Epoch 44/150
0.0305 - val_loss: 0.1337 - val_mse: 0.1337
Epoch 45/150
0.0298 - val_loss: 0.1308 - val_mse: 0.1308
Epoch 46/150
0.0298 - val_loss: 0.1324 - val_mse: 0.1324
Epoch 47/150
0.0288 - val_loss: 0.1314 - val_mse: 0.1314
Epoch 48/150
0.0278 - val_loss: 0.1333 - val_mse: 0.1333
Epoch 49/150
```

```
0.0280 - val_loss: 0.1349 - val_mse: 0.1349
Epoch 50/150
0.0273 - val_loss: 0.1344 - val_mse: 0.1344
Epoch 51/150
0.0264 - val_loss: 0.1345 - val_mse: 0.1345
Epoch 52/150
0.0266 - val_loss: 0.1358 - val_mse: 0.1358
Epoch 53/150
0.0256 - val_loss: 0.1358 - val_mse: 0.1358
Epoch 54/150
0.0259 - val_loss: 0.1358 - val_mse: 0.1358
Epoch 55/150
0.0247 - val_loss: 0.1378 - val_mse: 0.1378
Epoch 56/150
0.0250 - val_loss: 0.1370 - val_mse: 0.1370
Epoch 57/150
0.0238 - val_loss: 0.1374 - val_mse: 0.1374
Epoch 58/150
0.0238 - val_loss: 0.1391 - val_mse: 0.1391
Epoch 59/150
0.0239 - val_loss: 0.1363 - val_mse: 0.1363
Epoch 60/150
0.0228 - val_loss: 0.1386 - val_mse: 0.1386
Epoch 61/150
0.0229 - val_loss: 0.1398 - val_mse: 0.1398
Epoch 62/150
0.0224 - val_loss: 0.1413 - val_mse: 0.1413
Epoch 63/150
33/33 [============= ] - Os 1ms/step - loss: 0.0221 - mse:
0.0221 - val_loss: 0.1407 - val_mse: 0.1407
Epoch 64/150
0.0216 - val_loss: 0.1425 - val_mse: 0.1425
Epoch 65/150
```

```
0.0213 - val_loss: 0.1436 - val_mse: 0.1436
Epoch 66/150
0.0217 - val_loss: 0.1429 - val_mse: 0.1429
Epoch 67/150
0.0207 - val_loss: 0.1427 - val_mse: 0.1427
Epoch 68/150
0.0206 - val_loss: 0.1427 - val_mse: 0.1427
Epoch 69/150
0.0200 - val_loss: 0.1457 - val_mse: 0.1457
Epoch 70/150
0.0197 - val_loss: 0.1476 - val_mse: 0.1476
Epoch 71/150
0.0201 - val_loss: 0.1454 - val_mse: 0.1454
Epoch 72/150
0.0195 - val_loss: 0.1432 - val_mse: 0.1432
Epoch 73/150
0.0193 - val_loss: 0.1445 - val_mse: 0.1445
Epoch 74/150
0.0191 - val_loss: 0.1453 - val_mse: 0.1453
Epoch 75/150
0.0188 - val_loss: 0.1464 - val_mse: 0.1464
Epoch 76/150
0.0188 - val_loss: 0.1447 - val_mse: 0.1447
Epoch 77/150
0.0181 - val_loss: 0.1468 - val_mse: 0.1468
Epoch 78/150
0.0179 - val_loss: 0.1468 - val_mse: 0.1468
Epoch 79/150
33/33 [============= ] - Os 1ms/step - loss: 0.0176 - mse:
0.0176 - val_loss: 0.1456 - val_mse: 0.1456
Epoch 80/150
0.0175 - val_loss: 0.1463 - val_mse: 0.1463
Epoch 81/150
```

```
0.0171 - val_loss: 0.1447 - val_mse: 0.1447
Epoch 82/150
0.0174 - val_loss: 0.1457 - val_mse: 0.1457
Epoch 83/150
0.0167 - val_loss: 0.1474 - val_mse: 0.1474
Epoch 84/150
0.0164 - val_loss: 0.1458 - val_mse: 0.1458
Epoch 85/150
0.0163 - val_loss: 0.1476 - val_mse: 0.1476
Epoch 86/150
0.0161 - val_loss: 0.1473 - val_mse: 0.1473
Epoch 87/150
0.0161 - val_loss: 0.1467 - val_mse: 0.1467
Epoch 88/150
0.0154 - val_loss: 0.1450 - val_mse: 0.1450
Epoch 89/150
0.0156 - val_loss: 0.1453 - val_mse: 0.1453
Epoch 90/150
0.0152 - val_loss: 0.1472 - val_mse: 0.1472
0.0151 - val_loss: 0.1467 - val_mse: 0.1467
Epoch 92/150
0.0155 - val_loss: 0.1480 - val_mse: 0.1480
Epoch 93/150
0.0150 - val_loss: 0.1459 - val_mse: 0.1459
Epoch 94/150
0.0146 - val_loss: 0.1478 - val_mse: 0.1478
Epoch 95/150
33/33 [============= ] - Os 1ms/step - loss: 0.0144 - mse:
0.0144 - val_loss: 0.1503 - val_mse: 0.1503
Epoch 96/150
0.0143 - val_loss: 0.1475 - val_mse: 0.1475
Epoch 97/150
```

```
0.0140 - val_loss: 0.1478 - val_mse: 0.1478
Epoch 98/150
0.0142 - val_loss: 0.1489 - val_mse: 0.1489
Epoch 99/150
0.0138 - val_loss: 0.1502 - val_mse: 0.1502
Epoch 100/150
0.0138 - val_loss: 0.1502 - val_mse: 0.1502
Epoch 101/150
33/33 [============= ] - Os 1ms/step - loss: 0.0136 - mse:
0.0136 - val_loss: 0.1491 - val_mse: 0.1491
Epoch 102/150
0.0133 - val_loss: 0.1495 - val_mse: 0.1495
Epoch 103/150
0.0133 - val_loss: 0.1478 - val_mse: 0.1478
Epoch 104/150
0.0132 - val_loss: 0.1486 - val_mse: 0.1486
Epoch 105/150
0.0131 - val_loss: 0.1488 - val_mse: 0.1488
Epoch 106/150
0.0129 - val_loss: 0.1492 - val_mse: 0.1492
Epoch 107/150
0.0128 - val_loss: 0.1480 - val_mse: 0.1480
Epoch 108/150
0.0126 - val_loss: 0.1481 - val_mse: 0.1481
Epoch 109/150
0.0125 - val_loss: 0.1511 - val_mse: 0.1511
Epoch 110/150
0.0122 - val_loss: 0.1497 - val_mse: 0.1497
Epoch 111/150
33/33 [============= ] - Os 1ms/step - loss: 0.0121 - mse:
0.0121 - val_loss: 0.1489 - val_mse: 0.1489
Epoch 112/150
33/33 [============= ] - Os 1ms/step - loss: 0.0120 - mse:
0.0120 - val_loss: 0.1475 - val_mse: 0.1475
Epoch 113/150
```

```
0.0119 - val_loss: 0.1478 - val_mse: 0.1478
Epoch 114/150
0.0120 - val_loss: 0.1500 - val_mse: 0.1500
Epoch 115/150
0.0119 - val_loss: 0.1497 - val_mse: 0.1497
Epoch 116/150
0.0116 - val_loss: 0.1489 - val_mse: 0.1489
Epoch 117/150
33/33 [============= ] - Os 1ms/step - loss: 0.0116 - mse:
0.0116 - val_loss: 0.1491 - val_mse: 0.1491
Epoch 118/150
33/33 [============= ] - Os 1ms/step - loss: 0.0114 - mse:
0.0114 - val_loss: 0.1498 - val_mse: 0.1498
Epoch 119/150
0.0113 - val_loss: 0.1509 - val_mse: 0.1509
Epoch 120/150
0.0114 - val_loss: 0.1508 - val_mse: 0.1508
Epoch 121/150
0.0110 - val_loss: 0.1502 - val_mse: 0.1502
Epoch 122/150
0.0109 - val_loss: 0.1505 - val_mse: 0.1505
Epoch 123/150
0.0109 - val_loss: 0.1517 - val_mse: 0.1517
Epoch 124/150
0.0107 - val_loss: 0.1521 - val_mse: 0.1521
Epoch 125/150
0.0106 - val_loss: 0.1508 - val_mse: 0.1508
Epoch 126/150
0.0106 - val_loss: 0.1509 - val_mse: 0.1509
Epoch 127/150
33/33 [============= ] - Os 1ms/step - loss: 0.0105 - mse:
0.0105 - val_loss: 0.1513 - val_mse: 0.1513
Epoch 128/150
0.0103 - val_loss: 0.1503 - val_mse: 0.1503
Epoch 129/150
```

```
0.0102 - val_loss: 0.1521 - val_mse: 0.1521
Epoch 130/150
0.0100 - val_loss: 0.1527 - val_mse: 0.1527
Epoch 131/150
0.0101 - val_loss: 0.1510 - val_mse: 0.1510
Epoch 132/150
0.0100 - val_loss: 0.1526 - val_mse: 0.1526
Epoch 133/150
0.0096 - val_loss: 0.1523 - val_mse: 0.1523
Epoch 134/150
0.0097 - val_loss: 0.1526 - val_mse: 0.1526
Epoch 135/150
0.0095 - val_loss: 0.1519 - val_mse: 0.1519
Epoch 136/150
0.0094 - val_loss: 0.1543 - val_mse: 0.1543
Epoch 137/150
0.0096 - val_loss: 0.1523 - val_mse: 0.1523
Epoch 138/150
0.0092 - val_loss: 0.1509 - val_mse: 0.1509
Epoch 139/150
0.0093 - val_loss: 0.1510 - val_mse: 0.1510
Epoch 140/150
0.0091 - val_loss: 0.1501 - val_mse: 0.1501
Epoch 141/150
0.0091 - val_loss: 0.1529 - val_mse: 0.1529
Epoch 142/150
0.0090 - val_loss: 0.1520 - val_mse: 0.1520
Epoch 143/150
33/33 [============= ] - Os 1ms/step - loss: 0.0088 - mse:
0.0088 - val_loss: 0.1537 - val_mse: 0.1537
Epoch 144/150
33/33 [============ ] - Os 1ms/step - loss: 0.0092 - mse:
0.0092 - val_loss: 0.1519 - val_mse: 0.1519
Epoch 145/150
```

```
0.0087 - val_loss: 0.1525 - val_mse: 0.1525
   Epoch 146/150
   0.0086 - val_loss: 0.1518 - val_mse: 0.1518
   Epoch 147/150
   0.0086 - val_loss: 0.1521 - val_mse: 0.1521
   Epoch 148/150
   0.0085 - val_loss: 0.1525 - val_mse: 0.1525
   Epoch 149/150
   0.0084 - val_loss: 0.1542 - val_mse: 0.1542
   Epoch 150/150
   0.0083 - val_loss: 0.1532 - val_mse: 0.1532
[27]: <tensorflow.python.keras.callbacks.History at 0x7ff19a0f8520>
   Evaluate the model (lecun_model) on training data (X_train and y_train_scaled)
[28]: # Evaluate the model on training data
   lecun model.evaluate(X train, y train scaled)
   0.0088
[28]: [0.008768126368522644, 0.008768126368522644]
   Evaluate the model (lecun_model) on validate data (X_val and y_val_scaled)
[29]: # Evaluate the model on validate data
   lecun_model.evaluate(X_val, y_val_scaled)
```

0.1532 [29]: [0.15321286022663116, 0.15321286022663116]

Not much of a difference, but a useful note to consider when tuning your network. Next, let's investigate the impact of various optimization algorithms.

## 1.10 RMSprop

Compile the rmsprop\_model with:

- 'rmsprop' as the optimizer
- $\bullet\,$  track 'mse' as the loss and metric

```
[31]: np.random.seed(123)
   rmsprop_model = Sequential()
   rmsprop_model.add(layers.Dense(100, activation='relu',_
    →input_shape=(n_features,)))
   rmsprop_model.add(layers.Dense(50, activation='relu'))
   rmsprop_model.add(layers.Dense(1, activation='linear'))
   # Compile the model
   rmsprop_model.compile(optimizer = "rmsprop", loss = "mse", metrics = ["mse"])
   # Train the model
   rmsprop_model.fit(X_train,
             y_train_scaled,
             batch_size=32,
             epochs=150,
             validation_data=(X_val, y_val_scaled))
   Epoch 1/150
   0.3343 - val_loss: 0.1196 - val_mse: 0.1196
   Epoch 2/150
   0.1779 - val_loss: 0.1412 - val_mse: 0.1412
   Epoch 3/150
   0.1327 - val_loss: 0.1018 - val_mse: 0.1018
   Epoch 4/150
   0.0962 - val_loss: 0.1278 - val_mse: 0.1278
   Epoch 5/150
   0.0937 - val_loss: 0.1127 - val_mse: 0.1127
   Epoch 6/150
   0.0647 - val_loss: 0.1218 - val_mse: 0.1218
   Epoch 7/150
   0.0557 - val_loss: 0.1334 - val_mse: 0.1334
   Epoch 8/150
   0.0474 - val_loss: 0.1399 - val_mse: 0.1399
   Epoch 9/150
   0.0505 - val_loss: 0.1213 - val_mse: 0.1213
   Epoch 10/150
```

0.0385 - val\_loss: 0.1551 - val\_mse: 0.1551

```
Epoch 11/150
0.0347 - val_loss: 0.2104 - val_mse: 0.2104
Epoch 12/150
0.0277 - val_loss: 0.1731 - val_mse: 0.1731
Epoch 13/150
0.0264 - val_loss: 0.1319 - val_mse: 0.1319
Epoch 14/150
0.0302 - val_loss: 0.1414 - val_mse: 0.1414
Epoch 15/150
0.0248 - val_loss: 0.1347 - val_mse: 0.1347
Epoch 16/150
0.0218 - val_loss: 0.1345 - val_mse: 0.1345
Epoch 17/150
0.0242 - val_loss: 0.1596 - val_mse: 0.1596
Epoch 18/150
0.0233 - val_loss: 0.1419 - val_mse: 0.1419
Epoch 19/150
0.0195 - val_loss: 0.1324 - val_mse: 0.1324
Epoch 20/150
33/33 [============= ] - Os 2ms/step - loss: 0.0190 - mse:
0.0190 - val_loss: 0.1351 - val_mse: 0.1351
Epoch 21/150
33/33 [============= ] - Os 2ms/step - loss: 0.0191 - mse:
0.0191 - val_loss: 0.1495 - val_mse: 0.1495
Epoch 22/150
0.0174 - val_loss: 0.1304 - val_mse: 0.1304
Epoch 23/150
0.0162 - val_loss: 0.1439 - val_mse: 0.1439
Epoch 24/150
0.0175 - val_loss: 0.1517 - val_mse: 0.1517
Epoch 25/150
0.0175 - val_loss: 0.1282 - val_mse: 0.1282
Epoch 26/150
33/33 [============= ] - Os 2ms/step - loss: 0.0163 - mse:
0.0163 - val_loss: 0.1767 - val_mse: 0.1767
```

```
Epoch 27/150
0.0137 - val_loss: 0.1349 - val_mse: 0.1349
Epoch 28/150
0.0169 - val_loss: 0.1483 - val_mse: 0.1483
Epoch 29/150
0.0158 - val_loss: 0.1464 - val_mse: 0.1464
Epoch 30/150
0.0146 - val_loss: 0.1350 - val_mse: 0.1350
Epoch 31/150
0.0152 - val_loss: 0.1256 - val_mse: 0.1256
Epoch 32/150
0.0136 - val_loss: 0.1460 - val_mse: 0.1460
Epoch 33/150
0.0139 - val_loss: 0.1372 - val_mse: 0.1372
Epoch 34/150
0.0139 - val_loss: 0.1655 - val_mse: 0.1655
Epoch 35/150
0.0113 - val_loss: 0.1265 - val_mse: 0.1265
Epoch 36/150
0.0104 - val_loss: 0.1391 - val_mse: 0.1391
Epoch 37/150
33/33 [============= ] - Os 2ms/step - loss: 0.0144 - mse:
0.0144 - val_loss: 0.1722 - val_mse: 0.1722
Epoch 38/150
0.0117 - val_loss: 0.1361 - val_mse: 0.1361
Epoch 39/150
0.0099 - val_loss: 0.1364 - val_mse: 0.1364
Epoch 40/150
0.0107 - val_loss: 0.1400 - val_mse: 0.1400
0.0112 - val_loss: 0.1418 - val_mse: 0.1418
Epoch 42/150
0.0119 - val_loss: 0.1364 - val_mse: 0.1364
```

```
Epoch 43/150
0.0122 - val_loss: 0.1482 - val_mse: 0.1482
Epoch 44/150
0.0104 - val_loss: 0.1263 - val_mse: 0.1263
Epoch 45/150
0.0123 - val_loss: 0.1467 - val_mse: 0.1467
Epoch 46/150
0.0095 - val_loss: 0.1260 - val_mse: 0.1260
Epoch 47/150
0.0085 - val_loss: 0.1306 - val_mse: 0.1306
Epoch 48/150
0.0125 - val_loss: 0.1373 - val_mse: 0.1373
Epoch 49/150
0.0112 - val_loss: 0.1266 - val_mse: 0.1266
Epoch 50/150
0.0089 - val_loss: 0.1239 - val_mse: 0.1239
Epoch 51/150
0.0104 - val_loss: 0.1464 - val_mse: 0.1464
Epoch 52/150
33/33 [============= ] - Os 2ms/step - loss: 0.0088 - mse:
0.0088 - val_loss: 0.1307 - val_mse: 0.1307
Epoch 53/150
0.0084 - val_loss: 0.1604 - val_mse: 0.1604
Epoch 54/150
0.0124 - val_loss: 0.1404 - val_mse: 0.1404
Epoch 55/150
0.0094 - val_loss: 0.1420 - val_mse: 0.1420
Epoch 56/150
0.0088 - val_loss: 0.1282 - val_mse: 0.1282
Epoch 57/150
0.0082 - val_loss: 0.1341 - val_mse: 0.1341
Epoch 58/150
0.0085 - val_loss: 0.1340 - val_mse: 0.1340
```

```
Epoch 59/150
0.0087 - val_loss: 0.1250 - val_mse: 0.1250
Epoch 60/150
0.0082 - val_loss: 0.1394 - val_mse: 0.1394
Epoch 61/150
0.0100 - val_loss: 0.1387 - val_mse: 0.1387
Epoch 62/150
0.0083 - val_loss: 0.1237 - val_mse: 0.1237
Epoch 63/150
0.0073 - val_loss: 0.1586 - val_mse: 0.1586
Epoch 64/150
33/33 [============= ] - Os 2ms/step - loss: 0.0093 - mse:
0.0093 - val_loss: 0.1461 - val_mse: 0.1461
Epoch 65/150
0.0084 - val_loss: 0.1382 - val_mse: 0.1382
Epoch 66/150
0.0084 - val_loss: 0.1389 - val_mse: 0.1389
Epoch 67/150
0.0081 - val_loss: 0.1282 - val_mse: 0.1282
Epoch 68/150
0.0070 - val_loss: 0.1298 - val_mse: 0.1298
Epoch 69/150
0.0075 - val_loss: 0.1314 - val_mse: 0.1314
Epoch 70/150
0.0072 - val_loss: 0.1417 - val_mse: 0.1417
Epoch 71/150
0.0095 - val_loss: 0.1320 - val_mse: 0.1320
Epoch 72/150
0.0076 - val_loss: 0.1428 - val_mse: 0.1428
0.0071 - val_loss: 0.1361 - val_mse: 0.1361
Epoch 74/150
0.0085 - val_loss: 0.1619 - val_mse: 0.1619
```

```
Epoch 75/150
0.0073 - val_loss: 0.1248 - val_mse: 0.1248
Epoch 76/150
0.0079 - val_loss: 0.1305 - val_mse: 0.1305
Epoch 77/150
0.0070 - val_loss: 0.1410 - val_mse: 0.1410
Epoch 78/150
0.0079 - val_loss: 0.1348 - val_mse: 0.1348
Epoch 79/150
0.0057 - val_loss: 0.1297 - val_mse: 0.1297
Epoch 80/150
33/33 [============ ] - Os 2ms/step - loss: 0.0090 - mse:
0.0090 - val_loss: 0.1252 - val_mse: 0.1252
Epoch 81/150
0.0073 - val_loss: 0.1266 - val_mse: 0.1266
Epoch 82/150
0.0057 - val_loss: 0.1264 - val_mse: 0.1264
Epoch 83/150
0.0064 - val_loss: 0.1157 - val_mse: 0.1157
Epoch 84/150
0.0069 - val_loss: 0.1348 - val_mse: 0.1348
Epoch 85/150
0.0070 - val_loss: 0.1165 - val_mse: 0.1165
Epoch 86/150
0.0065 - val_loss: 0.1181 - val_mse: 0.1181
Epoch 87/150
0.0055 - val_loss: 0.1391 - val_mse: 0.1391
Epoch 88/150
0.0073 - val_loss: 0.1302 - val_mse: 0.1302
Epoch 89/150
0.0069 - val_loss: 0.1301 - val_mse: 0.1301
Epoch 90/150
33/33 [============= ] - Os 2ms/step - loss: 0.0084 - mse:
0.0084 - val_loss: 0.1220 - val_mse: 0.1220
```

```
Epoch 91/150
0.0053 - val_loss: 0.1245 - val_mse: 0.1245
Epoch 92/150
0.0063 - val_loss: 0.1281 - val_mse: 0.1281
Epoch 93/150
0.0066 - val_loss: 0.1244 - val_mse: 0.1244
Epoch 94/150
0.0058 - val_loss: 0.1300 - val_mse: 0.1300
Epoch 95/150
33/33 [============= ] - Os 2ms/step - loss: 0.0087 - mse:
0.0087 - val_loss: 0.1212 - val_mse: 0.1212
Epoch 96/150
0.0047 - val_loss: 0.1369 - val_mse: 0.1369
Epoch 97/150
0.0046 - val_loss: 0.1255 - val_mse: 0.1255
Epoch 98/150
0.0061 - val_loss: 0.1356 - val_mse: 0.1356
Epoch 99/150
0.0071 - val_loss: 0.1167 - val_mse: 0.1167
Epoch 100/150
0.0054 - val_loss: 0.1288 - val_mse: 0.1288
Epoch 101/150
0.0054 - val_loss: 0.1203 - val_mse: 0.1203
Epoch 102/150
0.0057 - val_loss: 0.1222 - val_mse: 0.1222
Epoch 103/150
0.0053 - val_loss: 0.1163 - val_mse: 0.1163
Epoch 104/150
0.0059 - val_loss: 0.1177 - val_mse: 0.1177
Epoch 105/150
0.0055 - val_loss: 0.1258 - val_mse: 0.1258
Epoch 106/150
0.0058 - val_loss: 0.1269 - val_mse: 0.1269
```

```
Epoch 107/150
0.0054 - val_loss: 0.1271 - val_mse: 0.1271
Epoch 108/150
0.0055 - val_loss: 0.1181 - val_mse: 0.1181
Epoch 109/150
0.0052 - val_loss: 0.1229 - val_mse: 0.1229
Epoch 110/150
0.0045 - val_loss: 0.1138 - val_mse: 0.1138
Epoch 111/150
0.0073 - val_loss: 0.1262 - val_mse: 0.1262
Epoch 112/150
0.0043 - val_loss: 0.1288 - val_mse: 0.1288
Epoch 113/150
0.0067 - val_loss: 0.1198 - val_mse: 0.1198
Epoch 114/150
0.0048 - val_loss: 0.1183 - val_mse: 0.1183
Epoch 115/150
0.0077 - val_loss: 0.1171 - val_mse: 0.1171
Epoch 116/150
0.0037 - val_loss: 0.1275 - val_mse: 0.1275
Epoch 117/150
33/33 [============= ] - Os 2ms/step - loss: 0.0050 - mse:
0.0050 - val_loss: 0.1145 - val_mse: 0.1145
Epoch 118/150
0.0049 - val_loss: 0.1286 - val_mse: 0.1286
Epoch 119/150
0.0053 - val_loss: 0.1130 - val_mse: 0.1130
Epoch 120/150
0.0049 - val_loss: 0.1215 - val_mse: 0.1215
Epoch 121/150
0.0047 - val_loss: 0.1246 - val_mse: 0.1246
Epoch 122/150
0.0054 - val_loss: 0.1119 - val_mse: 0.1119
```

```
Epoch 123/150
0.0041 - val_loss: 0.1084 - val_mse: 0.1084
Epoch 124/150
0.0045 - val_loss: 0.1186 - val_mse: 0.1186
Epoch 125/150
0.0049 - val_loss: 0.1176 - val_mse: 0.1176
Epoch 126/150
0.0054 - val_loss: 0.1162 - val_mse: 0.1162
Epoch 127/150
0.0057 - val_loss: 0.1269 - val_mse: 0.1269
Epoch 128/150
0.0039 - val_loss: 0.1079 - val_mse: 0.1079
Epoch 129/150
0.0048 - val_loss: 0.1122 - val_mse: 0.1122
Epoch 130/150
0.0054 - val_loss: 0.1075 - val_mse: 0.1075
Epoch 131/150
0.0063 - val_loss: 0.1139 - val_mse: 0.1139
Epoch 132/150
0.0039 - val_loss: 0.1132 - val_mse: 0.1132
Epoch 133/150
0.0035 - val_loss: 0.1160 - val_mse: 0.1160
Epoch 134/150
0.0049 - val_loss: 0.1212 - val_mse: 0.1212
Epoch 135/150
0.0036 - val_loss: 0.1103 - val_mse: 0.1103
Epoch 136/150
0.0051 - val_loss: 0.1207 - val_mse: 0.1207
Epoch 137/150
0.0043 - val_loss: 0.1091 - val_mse: 0.1091
Epoch 138/150
0.0041 - val_loss: 0.1102 - val_mse: 0.1102
```

```
0.0049 - val_loss: 0.1213 - val_mse: 0.1213
  Epoch 140/150
  0.0043 - val_loss: 0.1093 - val_mse: 0.1093
  Epoch 141/150
  0.0039 - val_loss: 0.1148 - val_mse: 0.1148
  Epoch 142/150
  0.0051 - val_loss: 0.1135 - val_mse: 0.1135
  Epoch 143/150
  0.0041 - val_loss: 0.1191 - val_mse: 0.1191
  Epoch 144/150
  0.0039 - val_loss: 0.1180 - val_mse: 0.1180
  Epoch 145/150
  0.0074 - val_loss: 0.1125 - val_mse: 0.1125
  Epoch 146/150
  0.0037 - val_loss: 0.1136 - val_mse: 0.1136
  Epoch 147/150
  0.0032 - val_loss: 0.1325 - val_mse: 0.1325
  Epoch 148/150
  0.0052 - val_loss: 0.1047 - val_mse: 0.1047
  Epoch 149/150
  33/33 [============= ] - Os 2ms/step - loss: 0.0048 - mse:
  0.0048 - val_loss: 0.1191 - val_mse: 0.1191
  Epoch 150/150
  0.0050 - val_loss: 0.1118 - val_mse: 0.1118
[31]: <tensorflow.python.keras.callbacks.History at 0x7ff19a28c670>
  Evaluate the model (rmsprop_model) on training data (X_train and y_train_scaled)
[32]: # Evaluate the model on training data
   rmsprop_model.evaluate(X_train, y_train_scaled)
  0.0028
[32]: [0.0027529627550393343, 0.0027529627550393343]
```

Epoch 139/150

Evaluate the model (rmsprop\_model) on training data (X\_train and y\_train\_scaled)

#### 1.11 Adam

Compile the adam model with:

- 'Adam' as the optimizer
- track 'mse' as the loss and metric

```
Epoch 1/150
0.3832 - val_loss: 0.1305 - val_mse: 0.1305
Epoch 2/150
0.1599 - val_loss: 0.1216 - val_mse: 0.1216
Epoch 3/150
0.1067 - val_loss: 0.1150 - val_mse: 0.1150
Epoch 4/150
0.0821 - val_loss: 0.1234 - val_mse: 0.1234
Epoch 5/150
0.0588 - val_loss: 0.1167 - val_mse: 0.1167
Epoch 6/150
```

```
0.0474 - val_loss: 0.1210 - val_mse: 0.1210
Epoch 7/150
0.0359 - val_loss: 0.1388 - val_mse: 0.1388
Epoch 8/150
0.0294 - val_loss: 0.1219 - val_mse: 0.1219
Epoch 9/150
0.0241 - val_loss: 0.1597 - val_mse: 0.1597
Epoch 10/150
0.0225 - val_loss: 0.1243 - val_mse: 0.1243
Epoch 11/150
0.0199 - val_loss: 0.1658 - val_mse: 0.1658
Epoch 12/150
0.0171 - val_loss: 0.1260 - val_mse: 0.1260
Epoch 13/150
0.0152 - val_loss: 0.1383 - val_mse: 0.1383
Epoch 14/150
0.0153 - val_loss: 0.1314 - val_mse: 0.1314
Epoch 15/150
0.0113 - val_loss: 0.1364 - val_mse: 0.1364
Epoch 16/150
0.0097 - val_loss: 0.1342 - val_mse: 0.1342
Epoch 17/150
0.0092 - val loss: 0.1308 - val mse: 0.1308
Epoch 18/150
0.0130 - val_loss: 0.1319 - val_mse: 0.1319
Epoch 19/150
0.0126 - val_loss: 0.1516 - val_mse: 0.1516
Epoch 20/150
33/33 [============= ] - Os 2ms/step - loss: 0.0119 - mse:
0.0119 - val_loss: 0.1307 - val_mse: 0.1307
Epoch 21/150
0.0259 - val_loss: 0.1378 - val_mse: 0.1378
Epoch 22/150
```

```
0.0199 - val_loss: 0.1272 - val_mse: 0.1272
Epoch 23/150
0.0210 - val_loss: 0.1419 - val_mse: 0.1419
Epoch 24/150
0.0150 - val_loss: 0.1296 - val_mse: 0.1296
Epoch 25/150
0.0084 - val_loss: 0.1235 - val_mse: 0.1235
Epoch 26/150
0.0058 - val_loss: 0.1275 - val_mse: 0.1275
Epoch 27/150
0.0047 - val_loss: 0.1306 - val_mse: 0.1306
Epoch 28/150
0.0032 - val_loss: 0.1272 - val_mse: 0.1272
Epoch 29/150
0.0027 - val_loss: 0.1305 - val_mse: 0.1305
Epoch 30/150
0.0026 - val_loss: 0.1224 - val_mse: 0.1224
Epoch 31/150
33/33 [============= ] - Os 2ms/step - loss: 0.0028 - mse:
0.0028 - val_loss: 0.1345 - val_mse: 0.1345
Epoch 32/150
0.0034 - val_loss: 0.1258 - val_mse: 0.1258
Epoch 33/150
0.0033 - val loss: 0.1291 - val mse: 0.1291
Epoch 34/150
0.0051 - val_loss: 0.1312 - val_mse: 0.1312
Epoch 35/150
0.0053 - val_loss: 0.1334 - val_mse: 0.1334
Epoch 36/150
33/33 [============= ] - Os 2ms/step - loss: 0.0054 - mse:
0.0054 - val_loss: 0.1314 - val_mse: 0.1314
Epoch 37/150
0.0085 - val_loss: 0.1416 - val_mse: 0.1416
Epoch 38/150
```

```
0.0112 - val_loss: 0.1186 - val_mse: 0.1186
Epoch 39/150
0.0085 - val_loss: 0.1336 - val_mse: 0.1336
Epoch 40/150
0.0066 - val_loss: 0.1332 - val_mse: 0.1332
Epoch 41/150
0.0073 - val_loss: 0.1276 - val_mse: 0.1276
Epoch 42/150
0.0093 - val_loss: 0.1311 - val_mse: 0.1311
Epoch 43/150
0.0067 - val_loss: 0.1206 - val_mse: 0.1206
Epoch 44/150
0.0036 - val_loss: 0.1227 - val_mse: 0.1227
Epoch 45/150
0.0020 - val_loss: 0.1223 - val_mse: 0.1223
Epoch 46/150
0.0017 - val_loss: 0.1231 - val_mse: 0.1231
Epoch 47/150
0.0016 - val_loss: 0.1248 - val_mse: 0.1248
Epoch 48/150
0.0019 - val_loss: 0.1232 - val_mse: 0.1232
Epoch 49/150
0.0045 - val_loss: 0.1207 - val_mse: 0.1207
Epoch 50/150
0.0060 - val_loss: 0.1233 - val_mse: 0.1233
Epoch 51/150
0.0099 - val_loss: 0.1229 - val_mse: 0.1229
Epoch 52/150
0.0089 - val_loss: 0.1139 - val_mse: 0.1139
Epoch 53/150
0.0060 - val_loss: 0.1216 - val_mse: 0.1216
Epoch 54/150
```

```
0.0047 - val_loss: 0.1104 - val_mse: 0.1104
Epoch 55/150
0.0028 - val_loss: 0.1235 - val_mse: 0.1235
Epoch 56/150
0.0018 - val_loss: 0.1141 - val_mse: 0.1141
Epoch 57/150
0.0011 - val_loss: 0.1147 - val_mse: 0.1147
Epoch 58/150
33/33 [============= ] - Os 2ms/step - loss: 7.9010e-04 - mse:
7.9010e-04 - val_loss: 0.1166 - val_mse: 0.1166
Epoch 59/150
6.0425e-04 - val_loss: 0.1163 - val_mse: 0.1163
Epoch 60/150
4.5378e-04 - val_loss: 0.1172 - val_mse: 0.1172
Epoch 61/150
3.7978e-04 - val_loss: 0.1146 - val_mse: 0.1146
Epoch 62/150
2.8653e-04 - val_loss: 0.1152 - val_mse: 0.1152
Epoch 63/150
33/33 [============ ] - Os 2ms/step - loss: 2.8772e-04 - mse:
2.8772e-04 - val_loss: 0.1169 - val_mse: 0.1169
Epoch 64/150
33/33 [============== ] - Os 2ms/step - loss: 3.1232e-04 - mse:
3.1232e-04 - val_loss: 0.1156 - val_mse: 0.1156
Epoch 65/150
3.2732e-04 - val_loss: 0.1165 - val_mse: 0.1165
Epoch 66/150
3.2007e-04 - val_loss: 0.1137 - val_mse: 0.1137
Epoch 67/150
3.2825e-04 - val_loss: 0.1170 - val_mse: 0.1170
Epoch 68/150
33/33 [============== ] - Os 2ms/step - loss: 3.3012e-04 - mse:
3.3012e-04 - val_loss: 0.1143 - val_mse: 0.1143
Epoch 69/150
3.9314e-04 - val_loss: 0.1177 - val_mse: 0.1177
Epoch 70/150
```

```
5.7634e-04 - val_loss: 0.1135 - val_mse: 0.1135
Epoch 71/150
6.8785e-04 - val_loss: 0.1205 - val_mse: 0.1205
Epoch 72/150
8.2294e-04 - val_loss: 0.1108 - val_mse: 0.1108
Epoch 73/150
0.0012 - val_loss: 0.1213 - val_mse: 0.1213
Epoch 74/150
0.0021 - val_loss: 0.1079 - val_mse: 0.1079
Epoch 75/150
0.0037 - val_loss: 0.1256 - val_mse: 0.1256
Epoch 76/150
0.0044 - val_loss: 0.1119 - val_mse: 0.1119
Epoch 77/150
0.0056 - val_loss: 0.1274 - val_mse: 0.1274
Epoch 78/150
0.0060 - val_loss: 0.1034 - val_mse: 0.1034
Epoch 79/150
0.0063 - val_loss: 0.1263 - val_mse: 0.1263
Epoch 80/150
0.0072 - val_loss: 0.0983 - val_mse: 0.0983
Epoch 81/150
0.0052 - val_loss: 0.1187 - val_mse: 0.1187
Epoch 82/150
0.0048 - val_loss: 0.1079 - val_mse: 0.1079
Epoch 83/150
0.0074 - val_loss: 0.1198 - val_mse: 0.1198
Epoch 84/150
0.0135 - val_loss: 0.0979 - val_mse: 0.0979
Epoch 85/150
0.0114 - val_loss: 0.1219 - val_mse: 0.1219
Epoch 86/150
```

```
0.0066 - val_loss: 0.1040 - val_mse: 0.1040
Epoch 87/150
0.0041 - val_loss: 0.1116 - val_mse: 0.1116
Epoch 88/150
0.0033 - val_loss: 0.1093 - val_mse: 0.1093
Epoch 89/150
0.0029 - val_loss: 0.1047 - val_mse: 0.1047
Epoch 90/150
0.0033 - val_loss: 0.1115 - val_mse: 0.1115
Epoch 91/150
0.0024 - val_loss: 0.1063 - val_mse: 0.1063
Epoch 92/150
0.0016 - val_loss: 0.1121 - val_mse: 0.1121
Epoch 93/150
0.0012 - val_loss: 0.1050 - val_mse: 0.1050
Epoch 94/150
7.6140e-04 - val_loss: 0.1084 - val_mse: 0.1084
Epoch 95/150
7.7036e-04 - val_loss: 0.1060 - val_mse: 0.1060
Epoch 96/150
7.4114e-04 - val_loss: 0.1061 - val_mse: 0.1061
Epoch 97/150
9.8494e-04 - val loss: 0.1098 - val mse: 0.1098
Epoch 98/150
0.0013 - val_loss: 0.1079 - val_mse: 0.1079
Epoch 99/150
0.0021 - val_loss: 0.1100 - val_mse: 0.1100
Epoch 100/150
0.0032 - val_loss: 0.1073 - val_mse: 0.1073
Epoch 101/150
0.0050 - val_loss: 0.1103 - val_mse: 0.1103
Epoch 102/150
```

```
0.0078 - val_loss: 0.1141 - val_mse: 0.1141
Epoch 103/150
0.0165 - val_loss: 0.1025 - val_mse: 0.1025
Epoch 104/150
0.0152 - val_loss: 0.1220 - val_mse: 0.1220
Epoch 105/150
0.0192 - val_loss: 0.1149 - val_mse: 0.1149
Epoch 106/150
0.0163 - val_loss: 0.1074 - val_mse: 0.1074
Epoch 107/150
0.0107 - val_loss: 0.1114 - val_mse: 0.1114
Epoch 108/150
0.0104 - val_loss: 0.1239 - val_mse: 0.1239
Epoch 109/150
0.0148 - val_loss: 0.0951 - val_mse: 0.0951
Epoch 110/150
0.0073 - val_loss: 0.1019 - val_mse: 0.1019
Epoch 111/150
33/33 [============= ] - Os 2ms/step - loss: 0.0030 - mse:
0.0030 - val_loss: 0.1002 - val_mse: 0.1002
Epoch 112/150
0.0019 - val_loss: 0.1003 - val_mse: 0.1003
Epoch 113/150
0.0013 - val loss: 0.1003 - val mse: 0.1003
Epoch 114/150
8.0570e-04 - val_loss: 0.1006 - val_mse: 0.1006
Epoch 115/150
5.6472e-04 - val_loss: 0.0999 - val_mse: 0.0999
Epoch 116/150
33/33 [============= ] - Os 2ms/step - loss: 3.9107e-04 - mse:
3.9107e-04 - val_loss: 0.0991 - val_mse: 0.0991
Epoch 117/150
2.9013e-04 - val_loss: 0.1003 - val_mse: 0.1003
Epoch 118/150
```

```
2.0509e-04 - val_loss: 0.0988 - val_mse: 0.0988
Epoch 119/150
1.9364e-04 - val_loss: 0.0992 - val_mse: 0.0992
Epoch 120/150
1.2910e-04 - val_loss: 0.0990 - val_mse: 0.0990
Epoch 121/150
1.2374e-04 - val_loss: 0.1002 - val_mse: 0.1002
Epoch 122/150
1.0726e-04 - val_loss: 0.0998 - val_mse: 0.0998
Epoch 123/150
8.0730e-05 - val_loss: 0.1002 - val_mse: 0.1002
Epoch 124/150
6.6349e-05 - val_loss: 0.0993 - val_mse: 0.0993
Epoch 125/150
7.1356e-05 - val_loss: 0.1000 - val_mse: 0.1000
Epoch 126/150
6.5658e-05 - val_loss: 0.0988 - val_mse: 0.0988
Epoch 127/150
5.9304e-05 - val_loss: 0.1002 - val_mse: 0.1002
Epoch 128/150
5.9500e-05 - val_loss: 0.0991 - val_mse: 0.0991
Epoch 129/150
5.9513e-05 - val loss: 0.1000 - val mse: 0.1000
Epoch 130/150
6.1346e-05 - val_loss: 0.0992 - val_mse: 0.0992
Epoch 131/150
6.5084e-05 - val_loss: 0.1001 - val_mse: 0.1001
Epoch 132/150
7.8508e-05 - val_loss: 0.0998 - val_mse: 0.0998
Epoch 133/150
1.0812e-04 - val_loss: 0.1005 - val_mse: 0.1005
Epoch 134/150
```

```
1.7396e-04 - val_loss: 0.0992 - val_mse: 0.0992
Epoch 135/150
2.6164e-04 - val_loss: 0.1006 - val_mse: 0.1006
Epoch 136/150
3.7319e-04 - val_loss: 0.0990 - val_mse: 0.0990
Epoch 137/150
6.0664e-04 - val_loss: 0.1027 - val_mse: 0.1027
Epoch 138/150
0.0011 - val_loss: 0.0983 - val_mse: 0.0983
Epoch 139/150
0.0023 - val_loss: 0.1027 - val_mse: 0.1027
Epoch 140/150
0.0036 - val_loss: 0.1037 - val_mse: 0.1037
Epoch 141/150
0.0039 - val_loss: 0.0958 - val_mse: 0.0958
Epoch 142/150
0.0034 - val_loss: 0.0989 - val_mse: 0.0989
Epoch 143/150
0.0033 - val_loss: 0.1068 - val_mse: 0.1068
Epoch 144/150
0.0047 - val_loss: 0.0979 - val_mse: 0.0979
Epoch 145/150
0.0055 - val loss: 0.1090 - val mse: 0.1090
Epoch 146/150
0.0051 - val_loss: 0.0900 - val_mse: 0.0900
Epoch 147/150
0.0052 - val_loss: 0.1188 - val_mse: 0.1188
Epoch 148/150
0.0054 - val_loss: 0.0923 - val_mse: 0.0923
Epoch 149/150
0.0058 - val_loss: 0.1114 - val_mse: 0.1114
Epoch 150/150
```

[34]: <tensorflow.python.keras.callbacks.History at 0x7ff19b7330a0>

Evaluate the model (adam\_model) on training data (X\_train and y\_train\_scaled)

```
[35]: # Evaluate the model on training data adam_model.evaluate(X_train, y_train_scaled)
```

[35]: [0.003275700379163027, 0.003275700379163027]

Evaluate the model (adam\_model) on training data (X\_val and y\_val\_scaled)

```
[36]: # Evaluate the model on validate data adam_model.evaluate(X_val, y_val_scaled)
```

```
9/9 [===========] - Os 677us/step - loss: 0.0999 - mse: 0.0999
```

[36]: [0.09989020228385925, 0.09989020228385925]

### 1.12 Select a Final Model

Now, select the model with the best performance based on the training and validation sets. Evaluate this top model using the test set!

```
[41]: # Evaluate the best model on test data
# They used rmsprop_model but for me adam_model looks better

print(adam_model.evaluate(X_test, y_test_scaled))
print()
print(rmsprop_model.evaluate(X_test, y_test_scaled))
```

[0.16654819250106812, 0.16654819250106812]

As earlier, this metric is hard to interpret because the output is scaled.

- Generate predictions on test data (X\_test)
- Transform these predictions back to original scale using ss\_y
- Now you can calculate the RMSE in the original units with y\_test and y\_test\_pred

```
[46]: # Generate predictions on test data
y_test_pred_scaled = adam_model.predict(X_test)

# Transform the predictions back to original scale
y_test_pred = ss_y.inverse_transform(y_test_pred_scaled)

# MSE of test data
RMSE_final = mean_squared_error(y_test, y_test_pred, squared = False)
RMSE_final
```

[46]: 30915.59986780489

# 1.13 Summary

In this lab, you worked to ensure your model converged properly by normalizing both the input and output. Additionally, you also investigated the impact of varying initialization and optimization routines.