⛽ Fuel efficiency Prediction

Provided with the classic Auto MPG (https://archive.ics.uci.edu/ml/datasets/auto+mpg) dataset, we will predict the **fuel efficiency** of the late-1970s and early 1980s automobiles, leveraging features such as cylinders, displacement, horsepower, weight, etc.

It is a very small dataset and there are only a few features. We will first build a linear model and a neural network, evaluate their performances, track our experiment runs and inspect the logs using MLflow, and apply TPOT (https://github.com/EpistasisLab/tpot) to see how it can be used to search over many ML model architectures, followed by explaining the model with SHAP.

📚 Learning Objectives

By the end of this session, you will be able to

- understand the core building blocks of a neural network
- understand what dense and activation layers do
- build, train, and evaluate neural networks
- track tensorflow experiments with MLflow, access information of runs programmatically and with its tracking ui
- perform AutoML to search for optimal tree-based pipeline for a regression task

Note: State of Data Science and Machine Learning 2021 (https://www.kaggle.com/kaggle-survey-2021) by Kaggle shows that the most commonly used algorithms were linear and logtistic regressions, followed closely by decision trees, random forests, and gradient boosting machines (are you surprised?). Multilayer perceptron, or artificial neural networks are not yet the popular tools for tabular/structured data; see more technical reasons in papers: Deep Neural Networks and Tabular Data: A Survey (https://arxiv.org/abs/2110.01889), Tabular Data: Deep Learning is Not All You Need (https://arxiv.org/abs/2106.03253). For this assignment, the main purpose is for you to get familiar with the basic building blocks in constructing neural networks before we dive into more specialized neural network architectures.

IMPORTANT

You only need to run the following cells if you're completing the assignment in Google Collab. If you've already installed these libraries locally, you can skip installing these libraries.

In [1]:
```
!export PATH=/Library/TeX/texbin:$PATH
```

In [1]:
```
# this notebook run local - I did the prework provided in github
```

In [ ]:
```
# Connect colab to your Google Drive
#from google.colab import drive #coomented out
#drive.mount('/content/drive') #out
```

In [2]:
```
!pip install daal==2021.4.0 #needed to do the sns
```

```
Collecting daal==2021.4.0
  Using cached daal-2021.4.0-py2.py3-none-macosx_10_15_x86_64.macosx_
11_0_x86_64.whl (189.9 MB)
Collecting tbb==2021.*
  Using cached tbb-2021.8.0-py2.py3-none-macosx_10_15_x86_64.macosx_1
1_0_x86_64.whl (1.0 MB)
Installing collected packages: tbb, daal
  Attempting uninstall: tbb
    Found existing installation: TBB 0.2
ERROR: Cannot uninstall 'TBB'. It is a distutils installed project an
d thus we cannot accurately determine which files belong to it which
would lead to only a partial uninstall.
```

In [3]:
```
!pip install -q pluggy==1.0.0
```

In [4]:
```
!pip install -q seaborn # pairplot
!pip install -q tpot  # automl

!pip install -q mlflow # tracking
!pip install -q pyngrok # workaround to run mlflow ui in colab
!pip install -q shap
```

In [5]:
```
## one errors - most of the stuff should run
```

In [6]:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Make NumPy printouts easier to read.
np.set_printoptions(precision=3, suppress=True)
```

In [7]:

```python
import tensorflow as tf
from tensorflow.keras import layers

print(tf.__version__)
```

```
2023-01-31 18:27:06.927507: I tensorflow/core/platform/cpu_feature_gu
ard.cc:193] This TensorFlow binary is optimized with oneAPI Deep Neur
al Network Library (oneDNN) to use the following CPU instructions in
performance-critical operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appro
priate compiler flags.

2.11.0
```

Task 1 - Data: Auto MPG dataset

0. Start MLflow's automatic logging using library-specific autolog calls for tensorflow: logging metrics, parameters, and models without the need for explicit log statements.

   We will get into more details using **MLflow** after completing our experiment.

In [8]:

```python
import mlflow
mlflow.tensorflow.autolog() # MLflow Autologging
# typed conda install -c conda-forge mlflow at the terminal prompt
```

1. The dataset is available from the [UCI Machine Learning Repository (https://archive.ics.uci.edu/ml/)](https://archive.ics.uci.edu/ml/). First download and import the dataset using `pandas`:

In [9]:
```python
url = 'http://archive.ics.uci.edu/ml/machine-learning-databases/auto-m
column_names = [
  'MPG', 'Cylinders', 'Displacement', 'Horsepower', 'Weight',
  'Acceleration', 'Model Year', 'Origin'
  ]

dataset = pd.read_csv(url, names=column_names, na_values='?',
                      comment='\t', sep=' ', skipinitialspace=True)
```

In [10]:
```python
dataset.tail()
```

Out[10]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Model Year	Origin
393	27.0	4	140.0	86.0	2790.0	15.6	82	1
394	44.0	4	97.0	52.0	2130.0	24.6	82	2
395	32.0	4	135.0	84.0	2295.0	11.6	82	1
396	28.0	4	120.0	79.0	2625.0	18.6	82	1
397	31.0	4	119.0	82.0	2720.0	19.4	82	1

2. The dataset contains a few unknown values, we drop those rows to keep this initial tutorial simple. Use `pd.DataFrame.dropna()` :

In [11]:
```python
dataset.shape
```

Out[11]:
```
(398, 8)
```

In [12]:
```python
dataset = dataset.dropna() # YOUR CODE HERE
```

In [13]:
```python
dataset.shape
```

Out[13]:
```
(392, 8)
```

3. The `"Origin"` column is categorical, not numeric. So the next step is to one-hot encode the values in the column with [pd.get_dummies (https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html)](https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html).

In [14]:
```python
dataset['Origin'] = dataset['Origin'].replace({1: 'USA', 2: 'Europe',
```

In [15]:
```python
dataset = pd.get_dummies(dataset, columns=['Origin'], prefix='', prefi
dataset.tail()
```

Out[15]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Model Year	Europe	Japan
393	27.0	4	140.0	86.0	2790.0	15.6	82	0	0
394	44.0	4	97.0	52.0	2130.0	24.6	82	1	0
395	32.0	4	135.0	84.0	2295.0	11.6	82	0	0
396	28.0	4	120.0	79.0	2625.0	18.6	82	0	0
397	31.0	4	119.0	82.0	2720.0	19.4	82	0	0

4. Split the data into training and test sets. To reduce the module importing overhead, instead of `sklearn.model_selection.train_test_split()` , use `pd.DataFrame.sample()` to save 80% of the data aside to `train_dataset` , set the random state to be 0 for reproducibility.

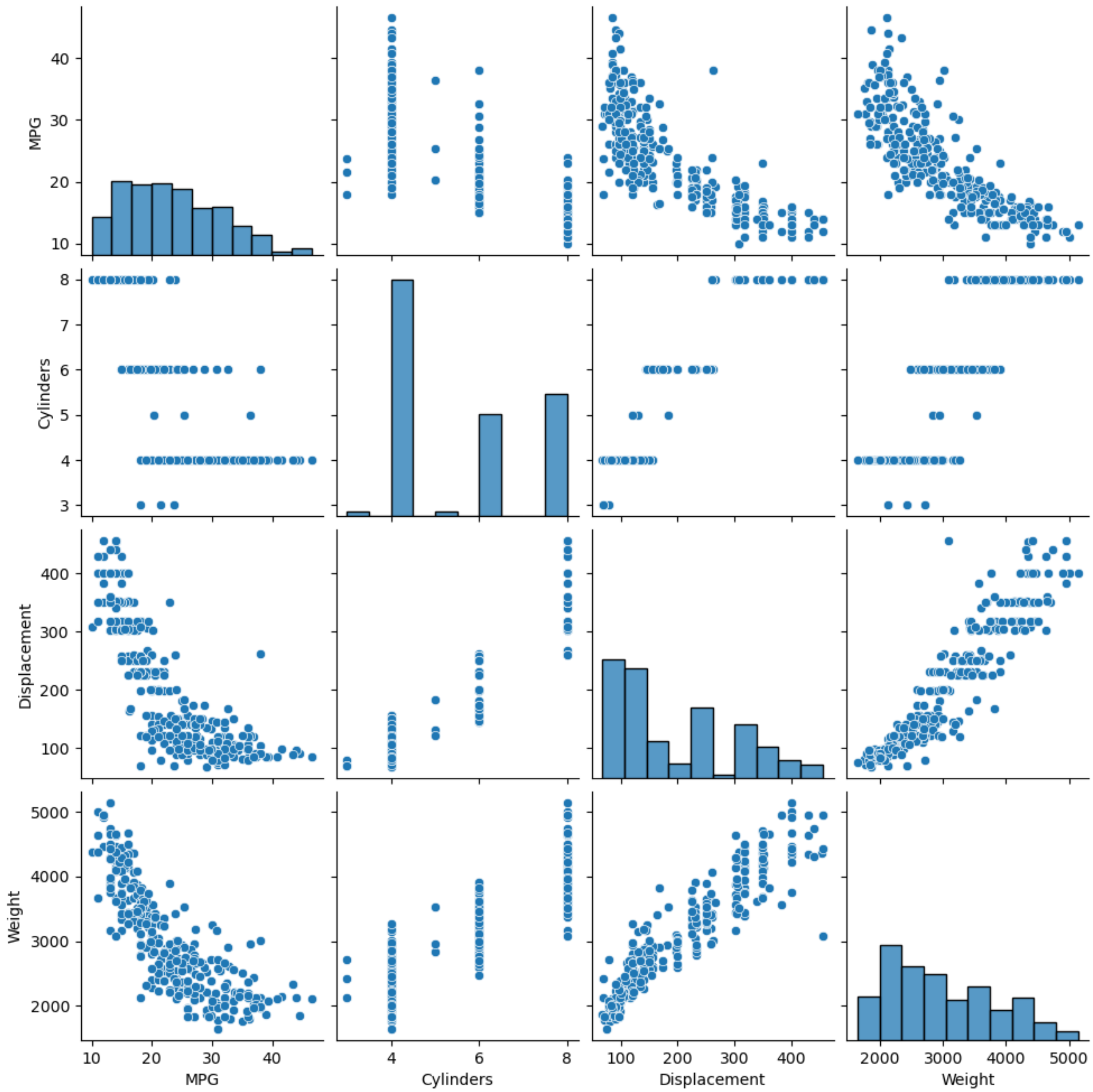
   Then use `pd.DataFrame.drop()` to obtain the `test_dataset` .

In [16]:
```python
train_dataset = dataset.sample(frac=.8,random_state=0) # YOUR CODE HER
test_dataset = dataset.drop(train_dataset.index)# YOUR CODE HERE
```

5. Review the pairwise relationships of a few pairs of columns from the training set.

   The top row suggests that the fuel efficiency (MPG) is a function of all the other parameters. The other rows indicate they are functions of each other.

In [17]:
```
###########  DEBUG THIS ##########
sns.pairplot(train_dataset[['MPG', 'Cylinders', 'Displacement', 'Weigh
```



Let's also check the overall statistics. Note how each feature covers a very different range:

In [18]:
```
train_dataset.describe().transpose()
```

Out[18]:

	count	mean	std	min	25%	50%	75%	max
MPG	314.0	23.310510	7.728652	10.0	17.00	22.0	28.95	46.6
Cylinders	314.0	5.477707	1.699788	3.0	4.00	4.0	8.00	8.0
Displacement	314.0	195.318471	104.331589	68.0	105.50	151.0	265.75	455.0
Horsepower	314.0	104.869427	38.096214	46.0	76.25	94.5	128.00	225.0
Weight	314.0	2990.251592	843.898596	1649.0	2256.50	2822.5	3608.00	5140.0
Acceleration	314.0	15.559236	2.789230	8.0	13.80	15.5	17.20	24.8
Model Year	314.0	75.898089	3.675642	70.0	73.00	76.0	79.00	82.0
Europe	314.0	0.178344	0.383413	0.0	0.00	0.0	0.00	1.0
Japan	314.0	0.197452	0.398712	0.0	0.00	0.0	0.00	1.0
USA	314.0	0.624204	0.485101	0.0	0.00	1.0	1.00	1.0

6. Split features from labels. This means, separate the target value(also called"label") from the features. Label is the value that you will train the model to predict.

In [19]:
```
train_features = train_dataset.copy() # hard copy of the dataframe - c
test_features = test_dataset.copy() # YOUR CODE HERE

train_labels = train_features.pop('MPG') # this removes the MPG variab
test_labels = test_features.pop('MPG') # and moves it in the train_lab
```

Task 2 - Normalization Layer

It is good practice to normalize features that use different scales and ranges. Although a model *might* converge without feature normalization, normalization makes training much more stable.

Similar to scikit-learn, tensorflow.keras offers a list of [preprocessing layers (https://www.tensorflow.org/guide/keras/preprocessing_layers)](https://www.tensorflow.org/guide/keras/preprocessing_layers) so that you can build and export models that are truly end-to-end.

1. The Normalization layer ([`tf.keras.layers.Normalization` (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Normalization)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Normalization) is a clean and simple way to add feature normalization into your model. The first step is to create the layer:

In [20]:
```
normalizer = tf.keras.layers.Normalization() # YOUR CODE HERE
```

2. Then, fit the state of the preprocessing layer to the data by calling `Normalization.adapt` (https://www.tensorflow.org/guide/keras/preprocessing_layers#the_adapt_method):

In [34]:
```
normalizer.adapt(train_features) # adapt blank stuff
```

We can see the feature mean and variance are stored in the layer:

In [35]:
```
print(f'feature mean: {normalizer.mean.numpy().squeeze()}\n')
print(f'feature variance: {normalizer.variance.numpy().squeeze()}')
```

```
feature mean: [   5.478  195.318  104.869 2990.252   15.559   75.898
0.178    0.197
    0.624]

feature variance: [     2.88    10850.413    1446.699 709896.9        7
.755     13.467
      0.147      0.158      0.235]
```

When the layer is called, it returns the input data, with each feature independently normalized:

In [36]:
```
first = np.array(train_features[:1])

with np.printoptions(precision=2, suppress=True):
    print('First example:', first)
    print()
    print('Normalized:', normalizer(first).numpy())
```

```
First example: [[   4.    90.    75.  2125.    14.5   74.     0.
0.     1. ]]

Normalized: [[-0.87 -1.01 -0.79 -1.03 -0.38 -0.52 -0.47 -0.5   0.78]]
```

Task 3 - Linear Regression 📈

Before building a deep neural network model, start with linear regression using all the features.

Training a model with `tf.keras` typically starts by defining the model architecture. Use a `tf.keras.Sequential` model, which [represents a sequence of steps (https://www.tensorflow.org/guide/keras/sequential_model)](https://www.tensorflow.org/guide/keras/sequential_model).

There are two steps in this multivariate linear regression model:

- Normalize all the input features using the `tf.keras.layers.Normalization` preprocessing layer. You have defined this earlier as `normalizer`.
- Apply a linear transformation ($y = mx + b$ where m is a matrix and b is a vector.) to produce one output using a linear layer ([`tf.keras.layers.Dense` (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense)).

The number of *inputs* can either be set by the `input_shape` argument, or automatically when the model is run for the first time.

1. Build the Keras Sequential model:

In [37]:
```
linear_model = tf.keras.Sequential([
                        normalizer,
                        tf.keras.layers.Dense(units=1) # could add act
                                    ])
```

In [38]:
```
linear_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 9)                19
 n)

 dense_1 (Dense)             (None, 1)                 10

=================================================================
Total params: 29
Trainable params: 10
Non-trainable params: 19
_________________________________________________________________
```

2. This model will predict `'MPG'` from all features in `train_features`. Run the untrained model on the first 10 data points / rows using `Model.predict()`. The output won't be good, but notice that it has the expected shape of `(10, 1)`:

In [39]:
```
linear_model.predict(train_features[:10])## YOUR CODE HERE
```

```
1/1 [==============================] - 0s 61ms/step
```

Out[39]:
```
array([[ 0.109],
       [ 0.373],
       [-1.933],
       [ 1.091],
       [ 1.507],
       [ 0.171],
       [ 1.69 ],
       [ 1.625],
       [-0.446],
       [ 0.566]], dtype=float32)
```

3. When you call the model, its weight matrices will be built—check that the `kernel` weights (the m in $y = mx + b$) have a shape of (9, 1):

In [40]:
```
linear_model.layers[1].kernel
```

Out[40]:
```
<tf.Variable 'dense_1/kernel:0' shape=(9, 1) dtype=float32, numpy=
array([[-0.429],
       [ 0.704],
       [-0.504],
       [-0.52 ],
       [ 0.124],
       [ 0.327],
       [ 0.53 ],
       [ 0.432],
       [ 0.251]], dtype=float32)>
```

4. Once the model is built, configure the training procedure using the Keras `Model.compile` method. The most important arguments to compile are the `loss` and the `optimizer`, since these define what will be optimized and how (using the `tf.keras.optimizers.Adam`).

   Here's a list of built-in loss functions in [`tf.keras.losses` (https://www.tensorflow.org/api_docs/python/tf/keras/losses)](https://www.tensorflow.org/api_docs/python/tf/keras/losses). For regression tasks, [common loss functions (https://towardsdatascience.com/understanding-the-3-most-common-loss-functions-for-machine-learning-regression-23e0ef3e14d3)](https://towardsdatascience.com/understanding-the-3-most-common-loss-functions-for-machine-learning-regression-23e0ef3e14d3) include mean squared error (MSE) and mean absolute error (MAE). Here, MAE is preferred such that the model is more robust against outliers.

   For optimizers, gradient descent (check this video [Gradient Descent, Step-by-Step (https://www.youtube.com/watch?v=sDv4f4s2SB8)](https://www.youtube.com/watch?v=sDv4f4s2SB8) for a refresher) is the preferred way to optimize neural networks and many other machine learning algorithms. Read [an overview of graident descent optimizer algorithms (https://ruder.io/optimizing-gradient-descent/)](https://ruder.io/optimizing-gradient-descent/) for several popular gradient descent algorithms. Here, we use the popular [`tf.keras.optimizers.Adam` (https://www.tensorflow.org/api_docs/python/tf/keras/optimizers/Adam)](https://www.tensorflow.org/api_docs/python/tf/keras/optimizers/Adam), and set the learning rate at 0.1 for faster learning.

In [41]:
```
linear_model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate = .1), # YOUR COD
    loss=tf.keras.losses.MeanAbsoluteError() # YOUR CODE HERE
    )
```

5. Use Keras `Model.fit` to execute the training for 100 epochs, set the verbose to 0 to suppress logging and keep 20% of the data for validation:

In [42]:
```
%%time
history = linear_model.fit(x=train_features,y=train_labels,epochs=100,
```

```
2023/01/31 19:14:55 INFO mlflow.utils.autologging_utils: Created MLfl
ow autologging run with ID '416c1ca789a646cba1604f5d1ec01953', which
will track hyperparameters, performance metrics, model artifacts, and
lineage information for the current tensorflow workflow

Epoch 1/100
1/8 [==>...........................] - ETA: 5s - loss: 22.7974WARNING
:tensorflow:Callback method `on_train_batch_end` is slow compared to
the batch time (batch time: 0.0022s vs `on_train_batch_end` time: 0.0
034s). Check your callbacks.

WARNING:tensorflow:Callback method `on_train_batch_end` is slow compa
red to the batch time (batch time: 0.0022s vs `on_train_batch_end` ti
me: 0.0034s). Check your callbacks.

8/8 [==============================] - 1s 44ms/step - loss: 22.9780 -
val_loss: 22.8973
Epoch 2/100
8/8 [==============================] - 0s 10ms/step - loss: 22.0896 -
val_loss: 22.1690
```

6. Visualize the model's training progress using the stats stored in the `history` object:

In [44]:
```
hist = pd.DataFrame(history.history)
hist['epoch'] = history.epoch
hist.tail()
```

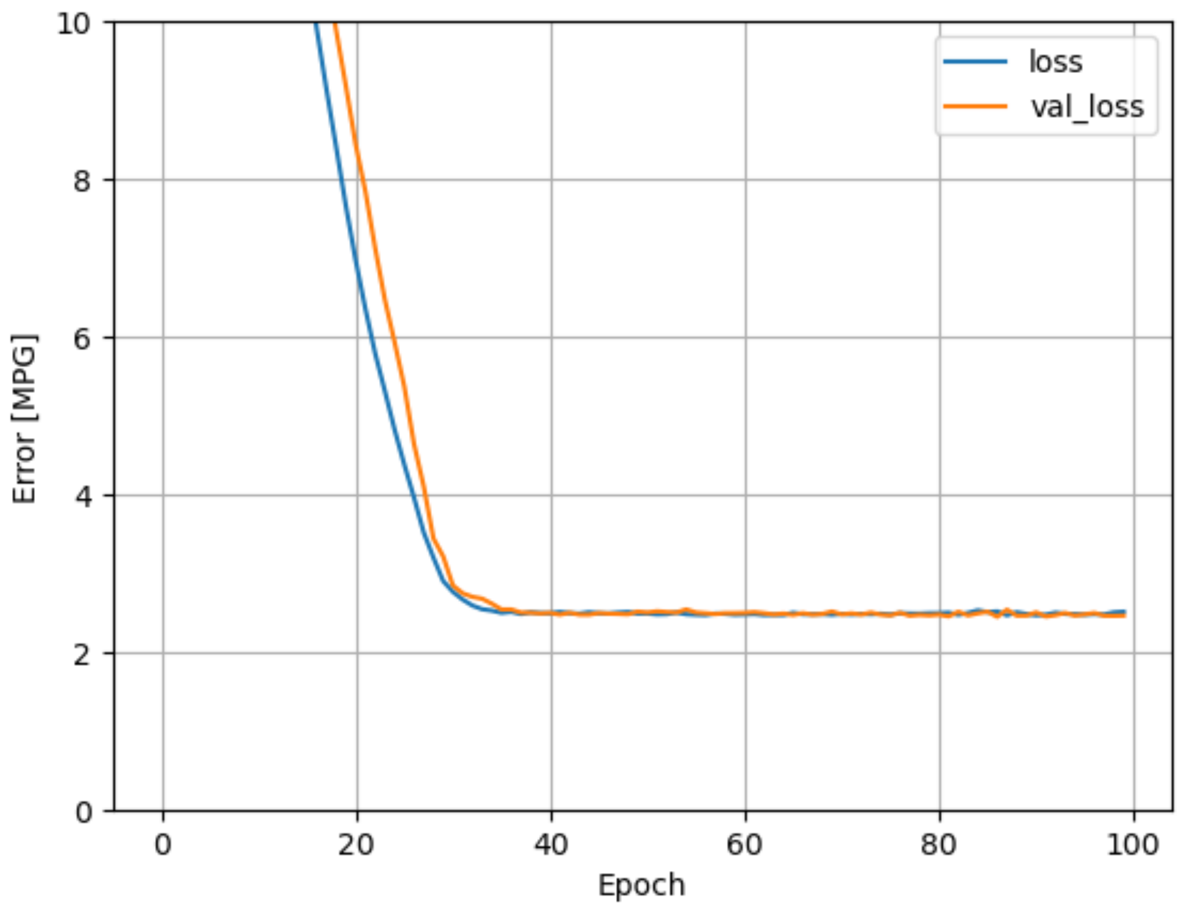
Out[44]:

	loss	val_loss	epoch
95	2.471398	2.474460	95
96	2.477598	2.491461	96
97	2.473082	2.457406	97
98	2.499563	2.455935	98
99	2.507488	2.458402	99

In [45]:
```
def plot_loss(history):
    plt.plot(history.history['loss'], label='loss')
    plt.plot(history.history['val_loss'], label='val_loss')
    plt.ylim([0, 10])
    plt.xlabel('Epoch')
    plt.ylabel('Error [MPG]')
    plt.legend()
    plt.grid(True)
```

Use `plot_loss(history)` provided to visualize the progression in loss function for training and validation data sets.

In [46]:
```
plot_loss(history)# YOUR CODE HERE
```



7. Collect the results on the test set for later using `Model.evaluate()` (https://www.tensorflow.org/api_docs/python/tf/keras/Model#evaluate)

In [47]:
```
test_results = {}

test_results['linear_model'] = linear_model.evaluate(x=test_features,
```

```
3/3 [==============================] - 0s 6ms/step - loss: 2.4612
```

In [48]:
```
test_results
```

Out[48]:
```
{'linear_model': 2.4612009525299072}
```

Task 4 - Regression with a Deep Neural Network (DNN)

You just implemented a linear model for multiple inputs. Now, you are ready to implement multiple-input DNN models.

The code is very similar except the model is expanded to include some "hidden" **non-linear** layers. The name "hidden" here just means not directly connected to the inputs or outputs.

- The normalization layer, as before (with `normalizer` for a multiple-input model).
- Two hidden, non-linear, [`Dense` (https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense)](https://www.tensorflow.org/api_docs/python/tf/keras/layers/Dense) layers with the ReLU (`relu`) activation function nonlinearity. One way is to set parameter `activation` inside `Dense` Set the number of neurons at each layer to be 64.
- A linear `Dense` single-output layer.

1. Include the model and `compile` method in the `build_and_compile_model` function below.

In [49]:
```
def build_and_compile_model(norm):
    model = tf.keras.Sequential([
        norm,
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dense(64, activation='relu'),
        tf.keras.layers.Dense(1),
    ]) # YOUR CODE HERE

    model.compile(loss='mean_absolute_error',
                  optimizer=tf.keras.optimizers.Adam())
    return model
```

2. Create a DNN model with `normalizer` (defined earlier) as the normalization layer:

In [50]:
```
dnn_model = build_and_compile_model(normalizer)# YOUR CODE HERE
```

3. Inspect the model using `Model.summary()` . This model has quite a few more trainable parameters than the linear models:

In [51]:
```
dnn_model.summary()# YOUR CODE HERE
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 normalization (Normalizatio  (None, 9)                19        
 n)                                                              
                                                                 
 dense_2 (Dense)             (None, 64)                640       
                                                                 
 dense_3 (Dense)             (None, 64)                4160      
                                                                 
 dense_4 (Dense)             (None, 1)                 65        
                                                                 
=================================================================
Total params: 4,884
Trainable params: 4,865
Non-trainable params: 19
_________________________________________________________________
```

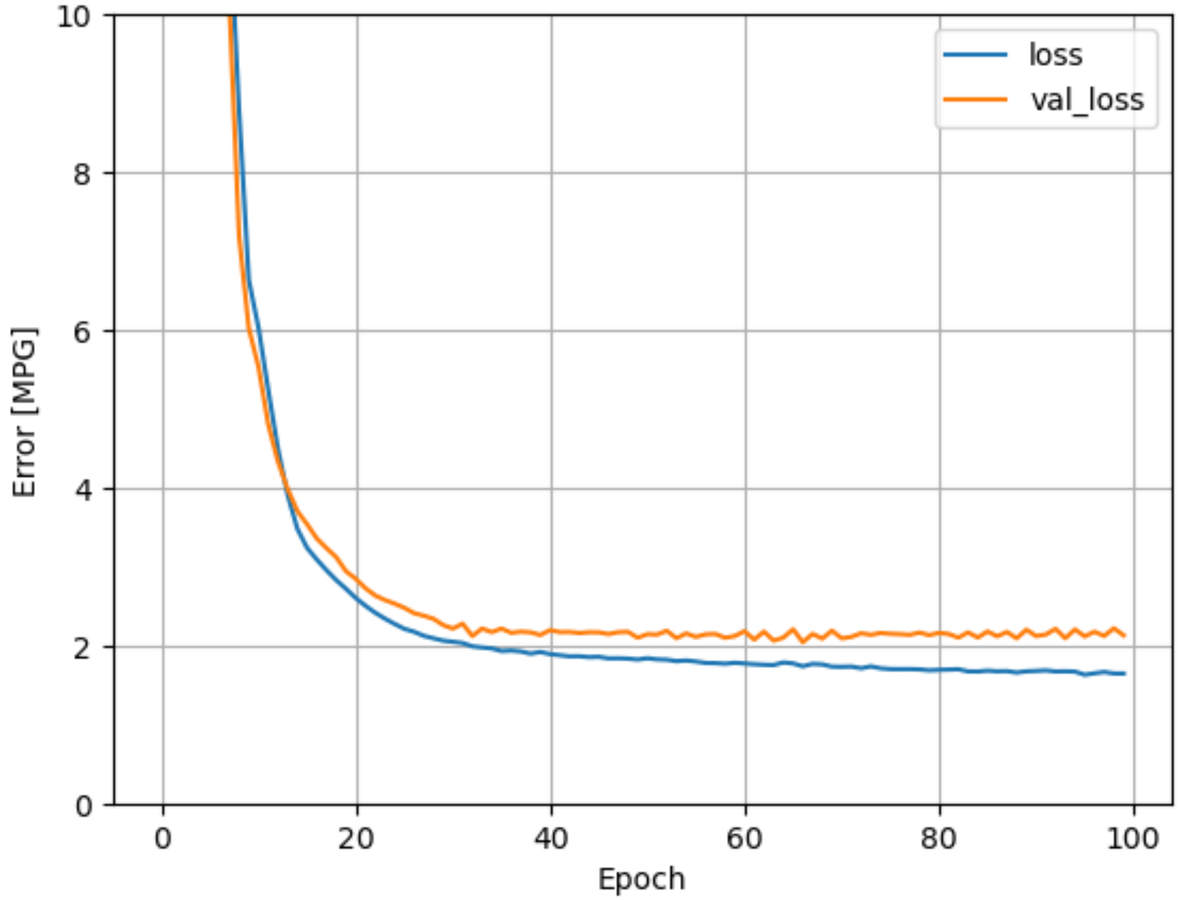
4. Train the model with Keras `Model.fit` :

In [52]:
```
%%time
history = dnn_model.fit(
    train_features,
    train_labels,
    validation_split=0.2,
    verbose=0, epochs=100)
```

```
2023/01/31 19:28:25 INFO mlflow.utils.autologging_utils: Created MLfl
ow autologging run with ID '74c24586ef67442d973256f1c6733911', which
will track hyperparameters, performance metrics, model artifacts, and
lineage information for the current tensorflow workflow
2023/01/31 19:28:33 WARNING mlflow.tensorflow: Failed to infer model
signature: could not sample data to infer model signature: Cannot log
input example or model signature for input with type <class 'pandas.c
ore.frame.DataFrame'>. TensorFlow Keras autologging can only log inpu
t examples and model signatures for the following input types: numpy.
ndarray, dict[string -> numpy.ndarray], tensorflow.keras.utils.Sequen
ce, and tensorflow.data.Dataset (TensorFlow >= 2.1.0 required)
2023/01/31 19:28:33 WARNING mlflow.tensorflow: You are saving a Tenso
rFlow Core model or Keras model without a signature. Inference with m
lflow.pyfunc.spark_udf() will not work unless the model's pyfunc repr
esentation accepts pandas DataFrames as inference inputs.
WARNING:absl:Found untraced functions such as _update_step_xla while
saving (showing 1 of 1). These functions will not be directly callabl
e after loading.

INFO:tensorflow:Assets written to: /var/folders/dx/8bzgllmx7g13k02q2z
8660kr0000gq/T/tmpubdm01t3/model/data/model/assets

INFO:tensorflow:Assets written to: /var/folders/dx/8bzgllmx7g13k02q2z
8660kr0000gq/T/tmpubdm01t3/model/data/model/assets
2023/01/31 19:28:34 WARNING mlflow.utils.environment: Encountered an
unexpected error while inferring pip requirements (model URI: /var/fo
lders/dx/8bzgllmx7g13k02q2z8660kr0000gq/T/tmpubdm01t3/model, flavor:
tensorflow), fall back to return ['tensorflow==2.11.0']. Set logging
level to DEBUG to see the full traceback.

CPU times: user 7.79 s, sys: 659 ms, total: 8.45 s
Wall time: 9.11 s
```

5. Visualize the model's training progress using the stats stored in the history object.

In [53]:
```
plot_loss(history)
```



Do you think the DNN model is overfitting? What gives away?

As the validation does not keep improving and the training keeps improving it is an ok model If the training and validation were both improving that would mean there is no difference and then it is overfitting

6. Let's save the results for later comparison.

In [54]:
```
test_results['dnn_model'] = dnn_model.evaluate(test_features, test_lab
```

In [55]:
```
test_results
```

Out[55]:
```
{'linear_model': 2.4612009525299072, 'dnn_model': 1.6599880456924438}
```

Task 5 - Make Predictions 🔮

1. Since both models have been trained, we can review their test set performance:

In [56]:
```
pd.DataFrame(test_results, index=['Mean absolute error [MPG]']).T
```

Out[56]:

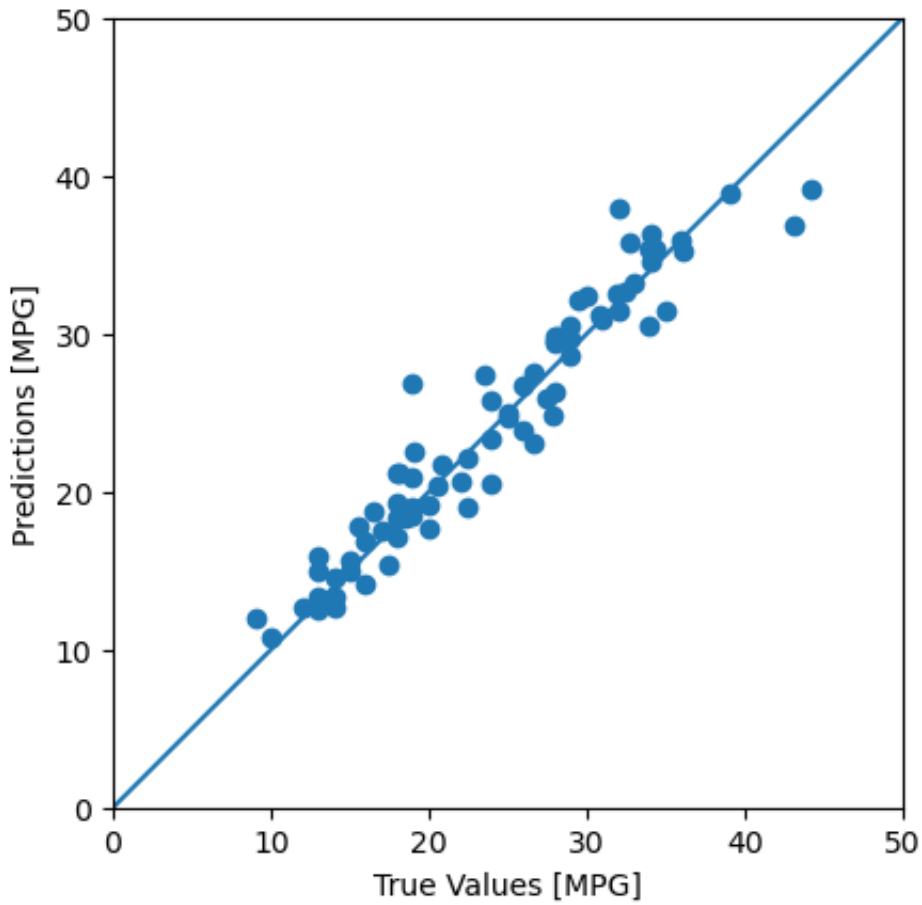
	Mean absolute error [MPG]
linear_model	2.461201
dnn_model	1.659988

These results match the validation error observed during training.

2. We can now make predictions with the `dnn_model` on the test set using Keras `Model.predict` and review the loss. Use `.flatten()` .

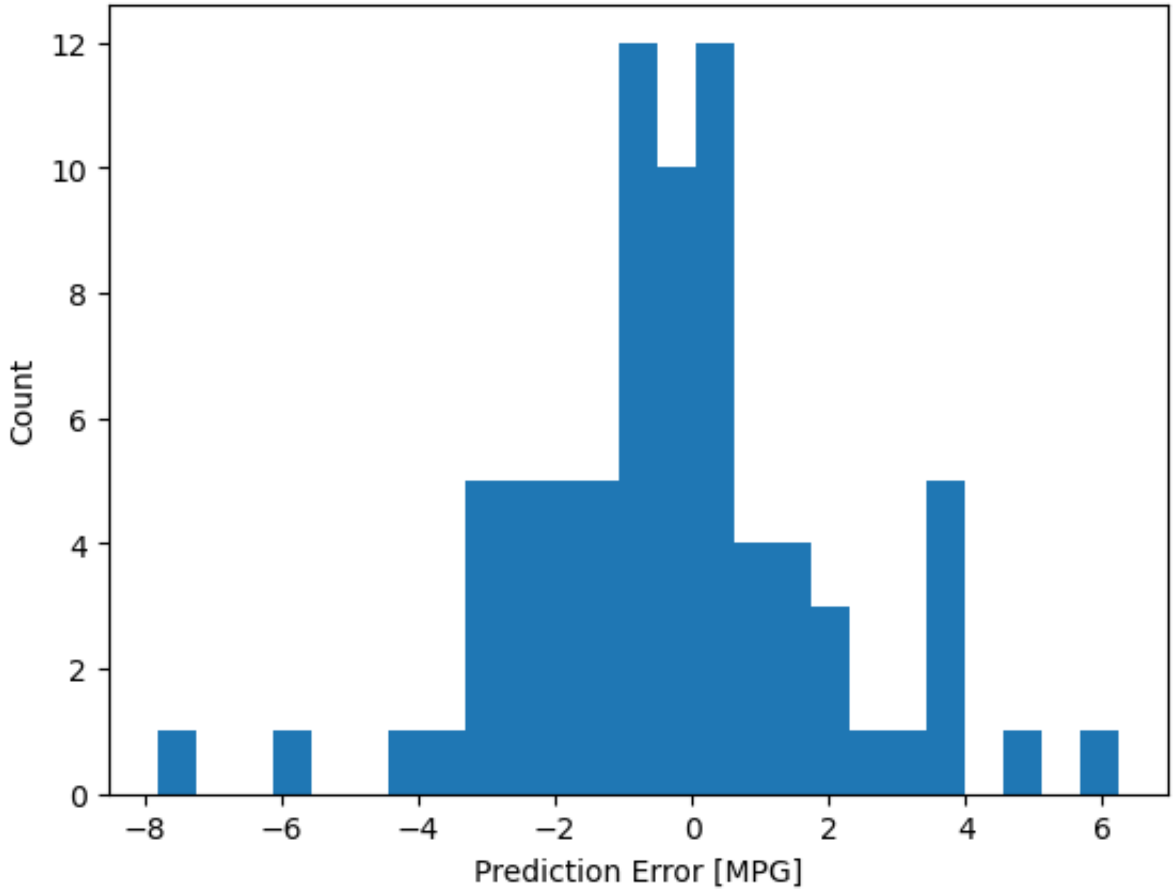
In [57]:
```
test_predictions = dnn_model.predict(test_features) # YOUR CODE HERE

a = plt.axes(aspect='equal')
plt.scatter(test_labels, test_predictions)
plt.xlabel('True Values [MPG]')
plt.ylabel('Predictions [MPG]')
lims = [0, 50]
plt.xlim(lims)
plt.ylim(lims)
_ = plt.plot(lims, lims)
```

```
3/3 [==============================] - 0s 2ms/step
```



3. It appears that the model predicts reasonably well. Now, check the error distribution:

In [58]:
```
error = (test_labels - test_predictions.squeeze()) # YOUR CODE HERE
plt.hist(error, bins=25)
plt.xlabel('Prediction Error [MPG]')
_ = plt.ylabel('Count')
```



4. Save it for later use with `Model.save`:

In [59]:
```
dnn_model.save('dnn_model')
```

```
WARNING:absl:Found untraced functions such as _update_step_xla while saving (showing 1 of 1). These functions will not be directly callabl
e after loading.

INFO:tensorflow:Assets written to: dnn_model/assets

INFO:tensorflow:Assets written to: dnn_model/assets
```

5. Reload the model with `Model.load_model`; it gives identical output:

In [60]:
```python
from tensorflow import keras
reloaded = keras.models.load_model('dnn_model') # YOUR CODE HERE

test_results['reloaded'] = reloaded.evaluate(
    test_features, test_labels, verbose=0)
```

In [61]:
```python
pd.DataFrame(test_results, index=['Mean absolute error [MPG]']).T
```

Out[61]:

	Mean absolute error [MPG]
linear_model	2.461201
dnn_model	1.659988
reloaded	1.659988

Task 6 - Nonlinearity

We mentioned that the `relu` activation function introduce non-linearity; let's visualize it. Since there are six numerical features and 1 categorical features, it is impossible to plot all the dimensions on a 2D plot; we need to simplify/isolate it.

Note: in this task, code is provided; the focus in on understanding.

1. We focus on the relationship between feature `Displacement` and target `MPG` .

   To do so, create a new dataset of the same size as `train_features` , but all other features are set at their median values; then set the `Displacement` between 0 and 500.

In [62]:
```python
fake = np.outer(np.ones(train_features.shape[0]), train_features.media
fake = pd.DataFrame(fake, columns = train_features.columns)
fake.Displacement = np.linspace(0, 500, train_features.shape[0])
```

2. Create a plotting function to:

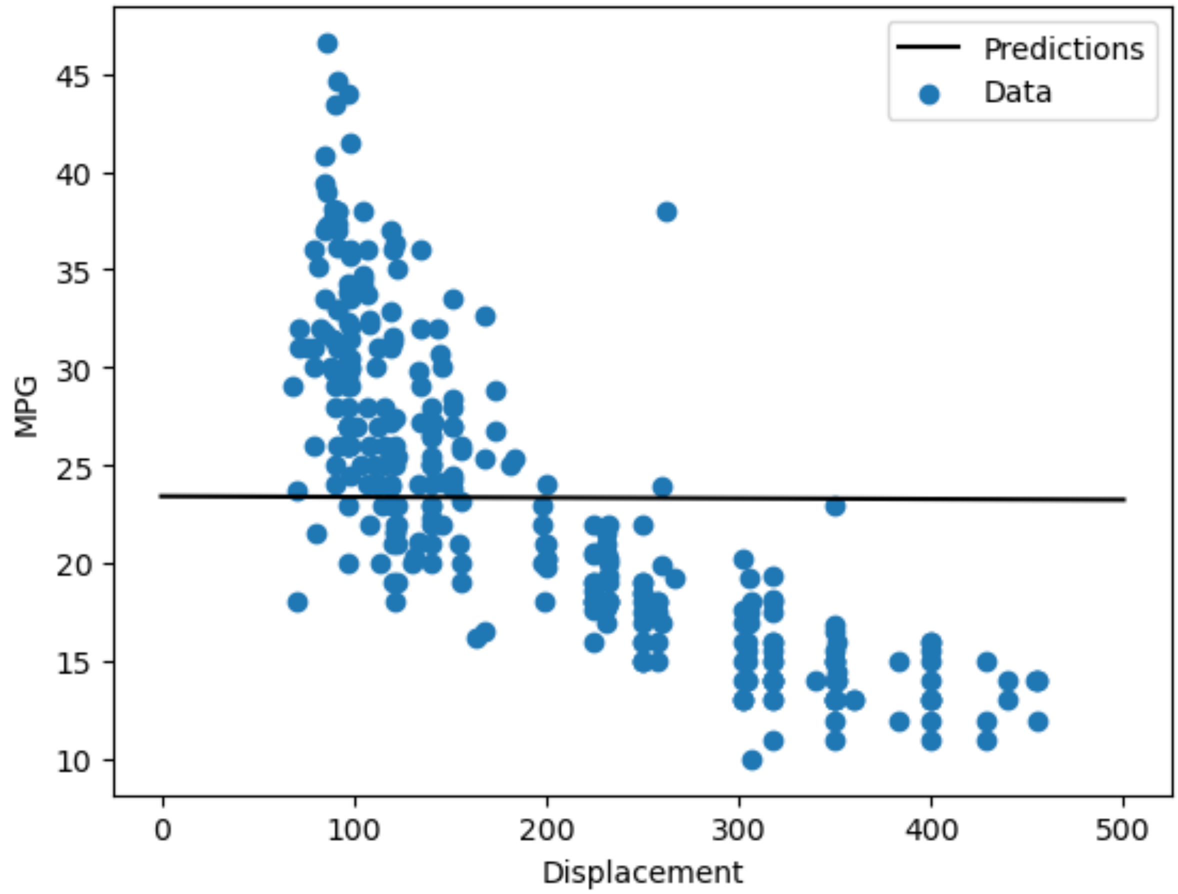
   a) visualize real values between `Displacement` and `MPG` from the training dataset in scatter plot

   b) overlay the predicted MPG from Displacement varying from 0 to 500, but holding all other features constant.

In [63]:
```
def plot_displacement(x, y):
    plt.scatter(train_features['Displacement'], train_labels, label='D
    plt.plot(x, y, color='k', label='Predictions')
    plt.xlabel('Displacement')
    plt.ylabel('MPG')
    plt.legend()
```

3. Visualize predicted MPG using the linear model.

In [64]:
```
plot_displacement(fake.Displacement, linear_model(fake))
```

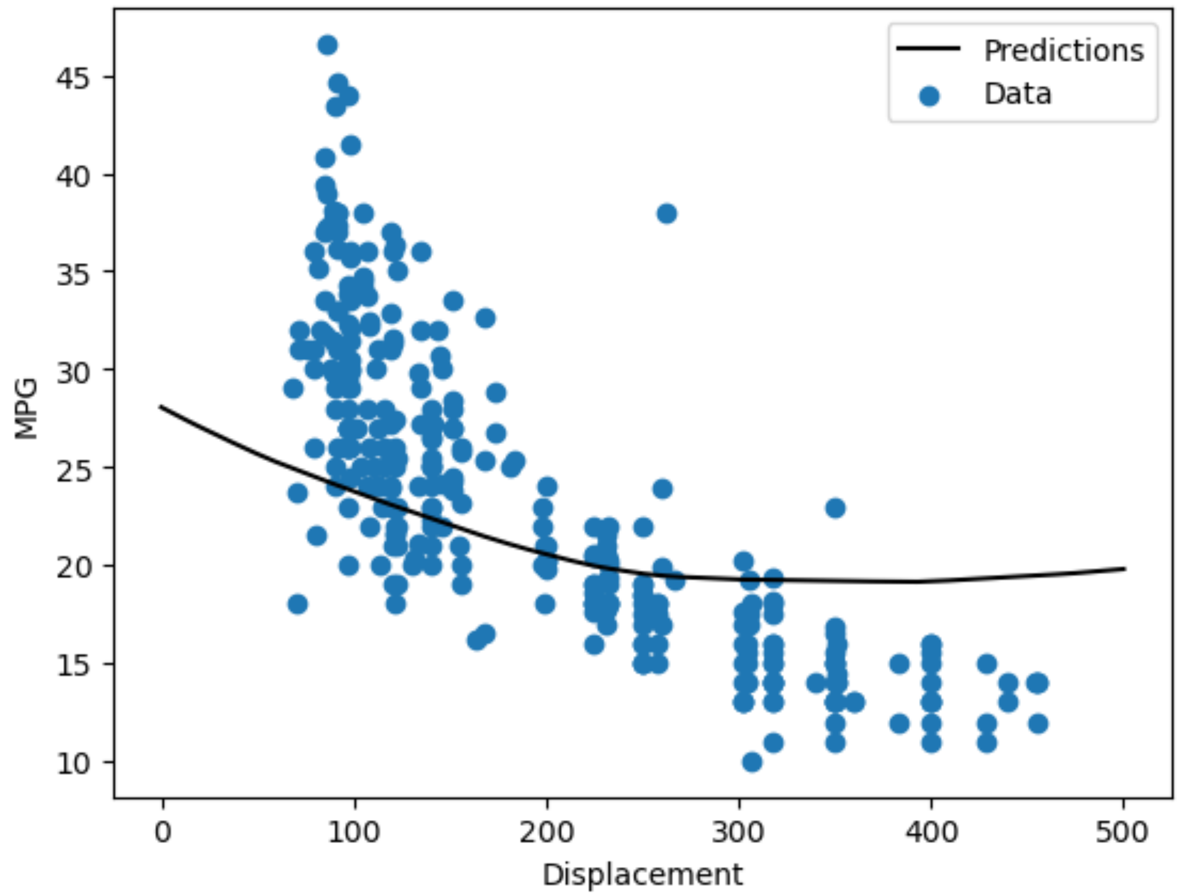


4. Visualize predicted MPG using the neural network model. Do you see an improvement/non-linearity from the linear model?

yes it imitates the trend of the results

In [65]:
```
plot_displacement(fake.Displacement, dnn_model.predict(fake))
```

```
10/10 [==============================] - 0s 3ms/step
```



5. What are the other activation functions? Check the list of [activations (https://www.tensorflow.org/api_docs/python/tf/keras/activations)](https://www.tensorflow.org/api_docs/python/tf/keras/activations).

   Optional. Modify the DNN model with a different activation function, and fit it on the data; does it perform better?

Trying with Tanh

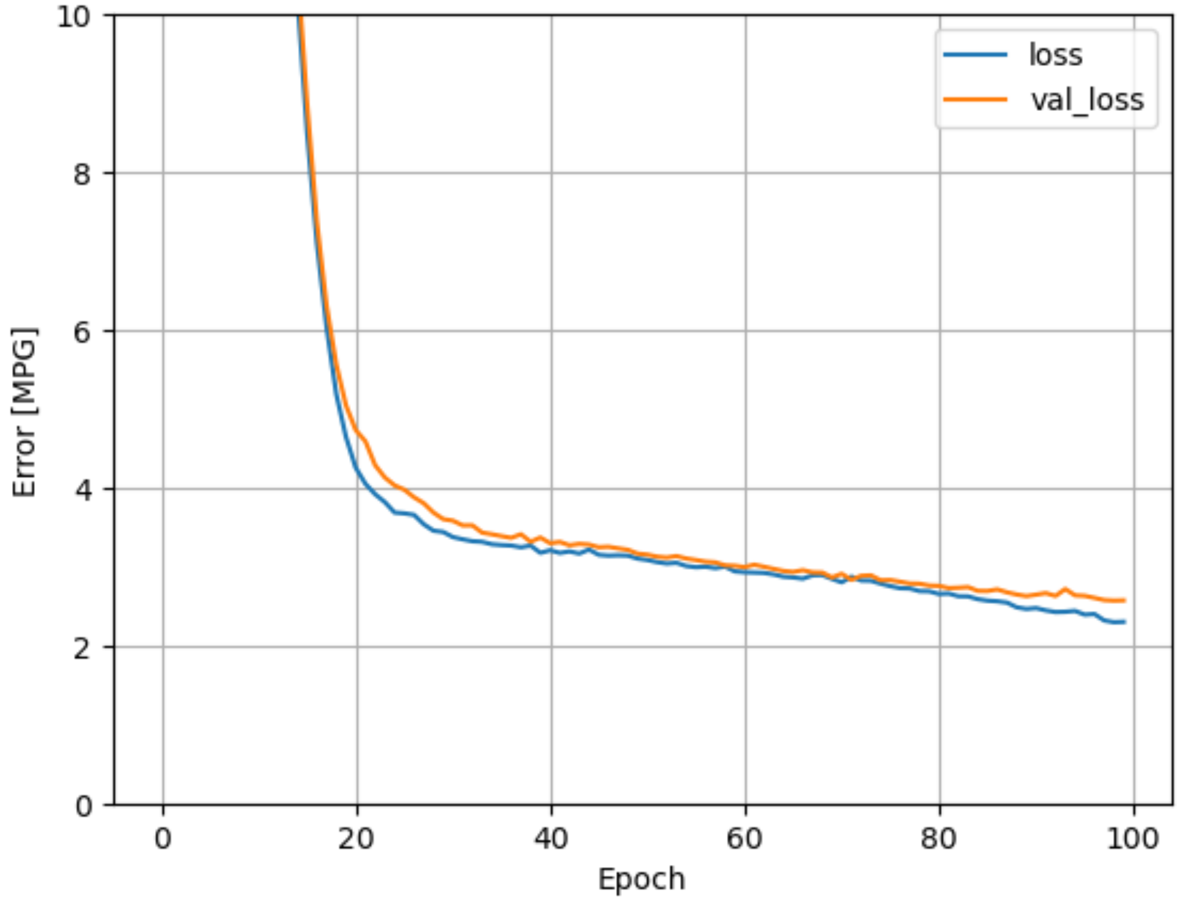
In [66]:
```python
def build_and_compile_model2(norm):
    model = tf.keras.Sequential([
        norm,
        tf.keras.layers.Dense(64, activation='tanh'),
        tf.keras.layers.Dense(64, activation='tanh'),
        tf.keras.layers.Dense(1),
    ])

    model.compile(loss='mean_absolute_error',
                  optimizer=tf.keras.optimizers.Adam())
    return model

dnn_model2 = build_and_compile_model2(normalizer)
dnn_model2.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 9)                19
 n)

 dense_5 (Dense)             (None, 64)                640

 dense_6 (Dense)             (None, 64)                4160

 dense_7 (Dense)             (None, 1)                 65

=================================================================
Total params: 4,884
Trainable params: 4,865
Non-trainable params: 19
_________________________________________________________________
```

In [67]:
```
%%time
history2 = dnn_model2.fit(
    train_features,
    train_labels,
    validation_split=0.2,
    verbose=0, epochs=100)
```

```
2023/01/31 20:05:42 INFO mlflow.utils.autologging_utils: Created MLfl
ow autologging run with ID '028b8d02ca534781996b9d0258219ec8', which
will track hyperparameters, performance metrics, model artifacts, and
lineage information for the current tensorflow workflow
2023/01/31 20:05:49 WARNING mlflow.tensorflow: Failed to infer model
signature: could not sample data to infer model signature: Cannot log
input example or model signature for input with type <class 'pandas.c
ore.frame.DataFrame'>. TensorFlow Keras autologging can only log inpu
t examples and model signatures for the following input types: numpy.
ndarray, dict[string -> numpy.ndarray], tensorflow.keras.utils.Sequen
ce, and tensorflow.data.Dataset (TensorFlow >= 2.1.0 required)
2023/01/31 20:05:49 WARNING mlflow.tensorflow: You are saving a Tenso
rFlow Core model or Keras model without a signature. Inference with m
lflow.pyfunc.spark_udf() will not work unless the model's pyfunc repr
esentation accepts pandas DataFrames as inference inputs.
WARNING:absl:Found untraced functions such as _update_step_xla while
saving (showing 1 of 1). These functions will not be directly callabl
e after loading.

INFO:tensorflow:Assets written to: /var/folders/dx/8bzgllmx7g13k02q2z
8660kr0000gq/T/tmpzz_6bi0u/model/data/model/assets

INFO:tensorflow:Assets written to: /var/folders/dx/8bzgllmx7g13k02q2z
8660kr0000gq/T/tmpzz_6bi0u/model/data/model/assets
2023/01/31 20:05:50 WARNING mlflow.utils.environment: Encountered an
unexpected error while inferring pip requirements (model URI: /var/fo
lders/dx/8bzgllmx7g13k02q2z8660kr0000gq/T/tmpzz_6bi0u/model, flavor:
tensorflow), fall back to return ['tensorflow==2.11.0']. Set logging
level to DEBUG to see the full traceback.

CPU times: user 7.6 s, sys: 633 ms, total: 8.23 s
Wall time: 8.1 s
```

In [68]:
```
plot_loss(history2)
```



In [69]:
```
test_results['dnn_model2'] = dnn_model2.evaluate(test_features, test_l
pd.DataFrame(test_results, index=['Mean absolute error [MPG]']).T
```

Out[69]:

	Mean absolute error [MPG]
linear_model	2.461201
dnn_model	1.659988
reloaded	1.659988
dnn_model2	2.289334

In [70]:
```
dnn_model2.save('dnn_model2')
```

```
WARNING:absl:Found untraced functions such as _update_step_xla while
saving (showing 1 of 1). These functions will not be directly callabl
e after loading.

INFO:tensorflow:Assets written to: dnn_model2/assets

INFO:tensorflow:Assets written to: dnn_model2/assets
```

6. Overfitting is a common problem for DNN models, how should we deal with it? Check [Regularizers (https://www.tensorflow.org/api_docs/python/tf/keras/regularizers)](https://www.tensorflow.org/api_docs/python/tf/keras/regularizers) on tf.keras. Any other techiniques that are invented for neural networks?

Task 7 - MLflow Tracking

In this task, we briefly explore [MLflow Tracking (https://www.mlflow.org/docs/latest/tracking.html#tracking)](https://www.mlflow.org/docs/latest/tracking.html#tracking), one of four primary functions that MLflow offers for managing the end-to-end machine learning lifecycle. We will access the information runs programmatically in python and then set up the MLflow UI for easy interaction.

1. Experiments.

   MLflow Tracking is organized around the concept of `runs`, which are executions of some piece of modeling code; and runs are organized into experiments.

   We set the auto logging in the beginning, we can verify that

   - there is one experiment
   - its name is `0`
   - all of its artifacts are stored at `file:///content/mlruns/0` in Google Drive.

In [71]:
```
from mlflow import MlflowClient
client = MlflowClient()
client.search_experiments()
#client.list_experiments() old code
```

Out[71]:
```
[<Experiment: artifact_location='file:///Users/Gilles/Documents/GitHu
b/week-07-intro-dl/nb/mlruns/0', creation_time=1675008942937, experim
ent_id='0', last_update_time=1675008942937, lifecycle_stage='active',
name='Default', tags={}>]
```

2. Runs.

   List information for runs that are under experiment '0' using [`mlflow.list_run_infos()` (https://www.mlflow.org/docs/latest/python_api/mlflow.html#mlflow.list_run_infos)](https://www.mlflow.org/docs/latest/python_api/mlflow.html#mlflow.list_run_infos).

In [72]:
```
client.search_runs('0')# YOUR CODE HERE
```

Out[72]:
```
[<Run: data=<RunData: metrics={'loss': 2.2992823123931885, 'val_loss'
: 2.5714523792266846}, params={'batch_size': 'None',
  'class_weight': 'None',
  'epochs': '100',
  'initial_epoch': '0',
  'max_queue_size': '10',
  'opt_amsgrad': 'False',
  'opt_beta_1': '0.9',
  'opt_beta_2': '0.999',
  'opt_clipnorm': 'None',
  'opt_clipvalue': 'None',
  'opt_ema_momentum': '0.99',
  'opt_ema_overwrite_frequency': 'None',
  'opt_epsilon': '1e-07',
  'opt_global_clipnorm': 'None',
  'opt_is_legacy_optimizer': 'False',
  'opt_jit_compile': 'False',
  'opt_learning_rate': '0.001',
  'opt_name': 'Adam',
```

3. Retrieve the currently active run, i.e., the DNN model. Hint: `mlflow.last_active_run()`

In [73]:
```
autolog_run = mlflow.last_active_run()# YOUR CODE HERE
```

4. Use function `print_auto_logged_info` provided below to fetch the auto logged parameters and metrics for `autolog_run` .

In [74]:
```
import json
def print_auto_logged_info(r):
    tags = {k: v for k, v in r.data.tags.items() if not k.startswith("
    artifacts = [f.path for f in MlflowClient().list_artifacts(r.info.
    print("run_id: {}".format(r.info.run_id))
    print("artifacts: {}".format(artifacts))
    print("params: {}".format(json.dumps(r.data.params, indent=4)))
    print("metrics: {}".format(r.data.metrics))
    print("tags: {}".format(tags))
```

In [75]:
```
print_auto_logged_info(
    autolog_run# YOUR CODE HERE
    )
```

```
run_id: 028b8d02ca534781996b9d0258219ec8
artifacts: ['model/.DS_Store', 'model/MLmodel', 'model/conda.yaml', '
model/data', 'model/python_env.yaml', 'model/requirements.txt']
params: {
    "opt_ema_momentum": "0.99",
    "opt_epsilon": "1e-07",
    "opt_clipvalue": "None",
    "validation_freq": "1",
    "validation_steps": "None",
    "shuffle": "True",
    "use_multiprocessing": "False",
    "opt_jit_compile": "False",
    "opt_is_legacy_optimizer": "False",
    "sample_weight": "None",
    "initial_epoch": "0",
    "max_queue_size": "10",
    "validation_batch_size": "None",
    "class_weight": "None",
    "opt_beta_2": "0.999",
    "validation_split": "0.2",
    "opt_weight_decay": "None",
    "steps_per_epoch": "None",
    "epochs": "100",
    "opt_name": "Adam",
    "opt_amsgrad": "False",
    "opt_use_ema": "False",
    "opt_clipnorm": "None",
    "batch_size": "None",
    "workers": "1",
    "opt_learning_rate": "0.001",
    "opt_global_clipnorm": "None",
    "opt_ema_overwrite_frequency": "None",
    "opt_beta_1": "0.9"
}
metrics: {'val_loss': 2.5714523792266846, 'loss': 2.2992823123931885}
tags: {}
```

5. Optional. Retrieve the best run using [MlflowClient().search_runs() (https://www.mlflow.org/docs/latest/search-runs.html#python)](https://www.mlflow.org/docs/latest/search-runs.html#python).

In [76]:
```
runs = MlflowClient().search_runs(experiment_ids = ['0'], order_by=['m
```

In [77]:
```
runs[0]
```

Out[77]:
```
<Run: data=<RunData: metrics={'loss': 1.6439439058303833, 'val_loss':
2.128159761428833}, params={'batch_size': 'None',
 'class_weight': 'None',
```

```
 'epochs': '100',
 'initial_epoch': '0',
 'max_queue_size': '10',
 'opt_amsgrad': 'False',
 'opt_beta_1': '0.9',
 'opt_beta_2': '0.999',
 'opt_clipnorm': 'None',
 'opt_clipvalue': 'None',
 'opt_ema_momentum': '0.99',
 'opt_ema_overwrite_frequency': 'None',
 'opt_epsilon': '1e-07',
 'opt_global_clipnorm': 'None',
 'opt_is_legacy_optimizer': 'False',
 'opt_jit_compile': 'False',
 'opt_learning_rate': '0.001',
 'opt_name': 'Adam',
 'opt_use_ema': 'False',
 'opt_weight_decay': 'None',
 'sample_weight': 'None',
 'shuffle': 'True',
 'steps_per_epoch': 'None',
 'use_multiprocessing': 'False',
 'validation_batch_size': 'None',
 'validation_freq': '1',
 'validation_split': '0.2',
 'validation_steps': 'None',
 'workers': '1'}, tags={'mlflow.autologging': 'tensorflow',
 'mlflow.log-model.history': '[{"run_id": "74c24586ef67442d973256f1c6
733911", '
                             '"artifact_path": "model", "utc_time_cre
ated": '
                             '"2023-02-01 01:28:33.418657", "flavors"
: '
                             '{"tensorflow": {"code": null, "data": "
data", '
                             '"model_type": "keras", "keras_version":
'
                             '"2.11.0", "save_format": "tf"}, '
                             '"python_function": {"loader_module": '
                             '"mlflow.tensorflow", "python_version":
"3.8.15", '
                             '"data": "data", "env": {"conda": "conda
.yaml", '
                             '"virtualenv": "python_env.yaml"}}}, '
                             '"model_uuid": '
                             '"1b96948555444e7a9046f8ef82d32ccd", '
                             '"mlflow_version": "2.1.1"}]',
 'mlflow.runName': 'rebellious-skink-608',
 'mlflow.source.name': '/Users/Gilles/anaconda3/envs/sa/lib/python3.8
/site-packages/ipykernel_launcher.py',
 'mlflow.source.type': 'LOCAL',
 'mlflow.user': 'Gilles'}>, info=<RunInfo: artifact_uri='file:///User
s/Gilles/Documents/GitHub/week-07-intro-dl/nb/mlruns/0/74c24586ef6744
```

```
2d973256f1c6733911/artifacts', end_time=1675214914366, experiment_id=
'0', lifecycle_stage='active', run_id='74c24586ef67442d973256f1c67339
11', run_name='rebellious-skink-608', run_uuid='74c24586ef67442d97325
6f1c6733911', start_time=1675214905270, status='FINISHED', user_id='G
illes'>>
```

6. To see what's logged in the file system `/content/mlruns/`, click tab `files` in the left sidepanel in Colab. For example,

```
mlruns
└── 0
    ├── 3a5aebdd35ef46fb8dc35b40e542f0a4
    │   ├── artifacts
    │   ├── meta.yaml
    │   ├── metrics
    │   ├── params
    │   └── tags
    ├── c627bc526c4a4c418a8285627e61a16d
    │   ├── artifacts
    │   ├── meta.yaml
    │   ├── metrics
    │   ├── params
    │   └── tags
    └── meta.yaml

11 directories, 3 files
```

Inspect the model summary of the DNN model you ran previously; it is located at `artifacts/model_summary.txt` of the corresponding run. Use `cat $filepath`.

In [88]:
```
!ls mlruns/0/{runs[0].info.run_id}/artifacts/model_summary.txt
```

```
mlruns/0/74c24586ef67442d973256f1c6733911/artifacts/model_summary.txt
```

In [90]:
```
!cat mlruns/0/74c24586ef67442d973256f1c6733911/artifacts/model_summary
```

```
zsh:1: unknown file attribute: b
```

It should show this (taken from collab)

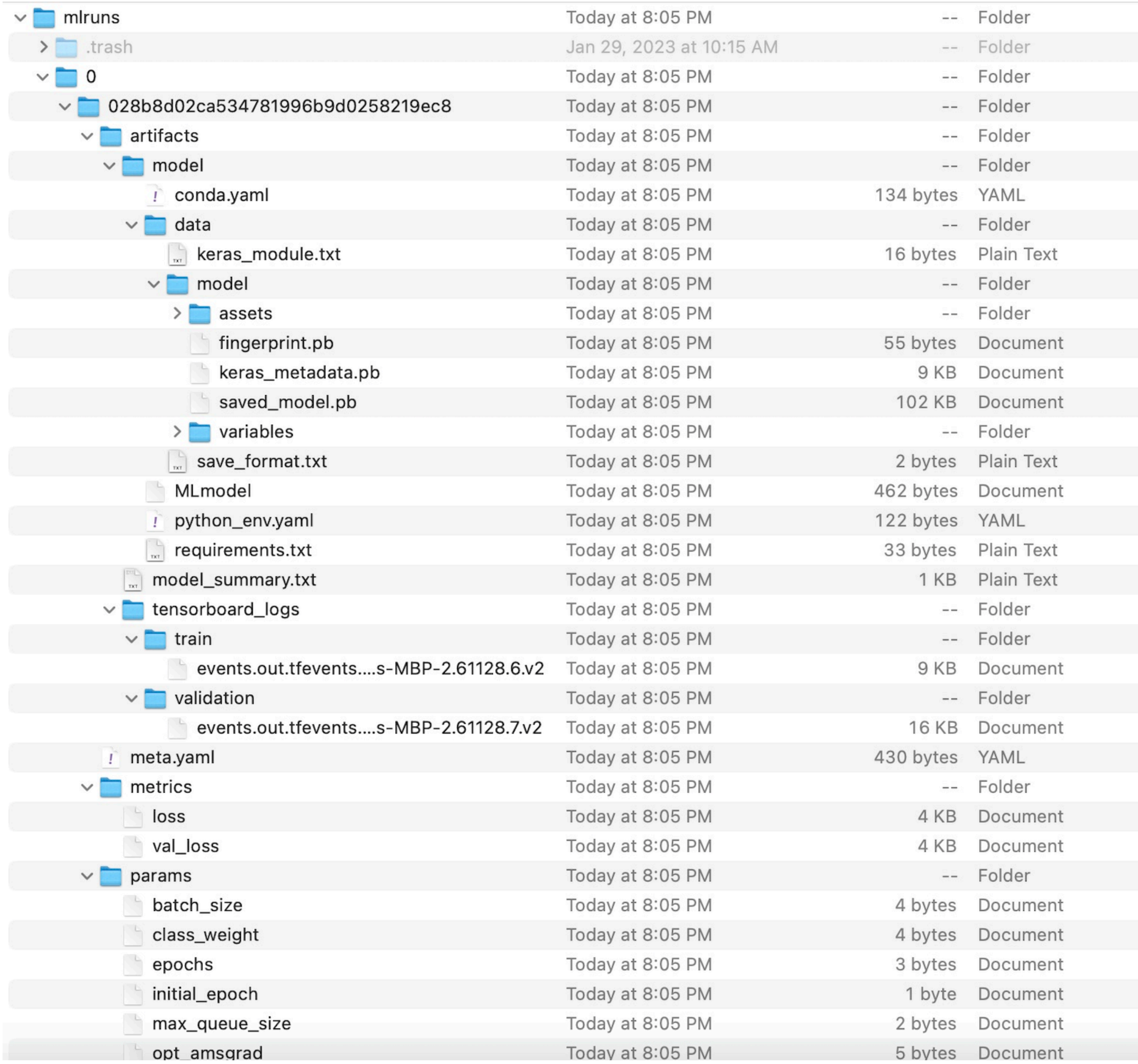
In [98]:
```python
from IPython.display import Image, display
# change the filename to wherever you downloaded/uploaded the file
filename = '../img/summary.jpg'
display(Image(filename=filename))
```

```
! cat mlruns/0/a69481b2bedd42bc9bc551ae2f373778/artifacts/model_summary.txt
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 normalization (Normalizatio  (None, 9)                19        
 n)                                                              
                                                                 
 dense_1 (Dense)             (None, 64)                640       
                                                                 
 dense_2 (Dense)             (None, 64)                4160      
                                                                 
 dense_3 (Dense)             (None, 1)                 65        
                                                                 
=================================================================
Total params: 4,884
Trainable params: 4,865
Non-trainable params: 19
_________________________________________________________________
```

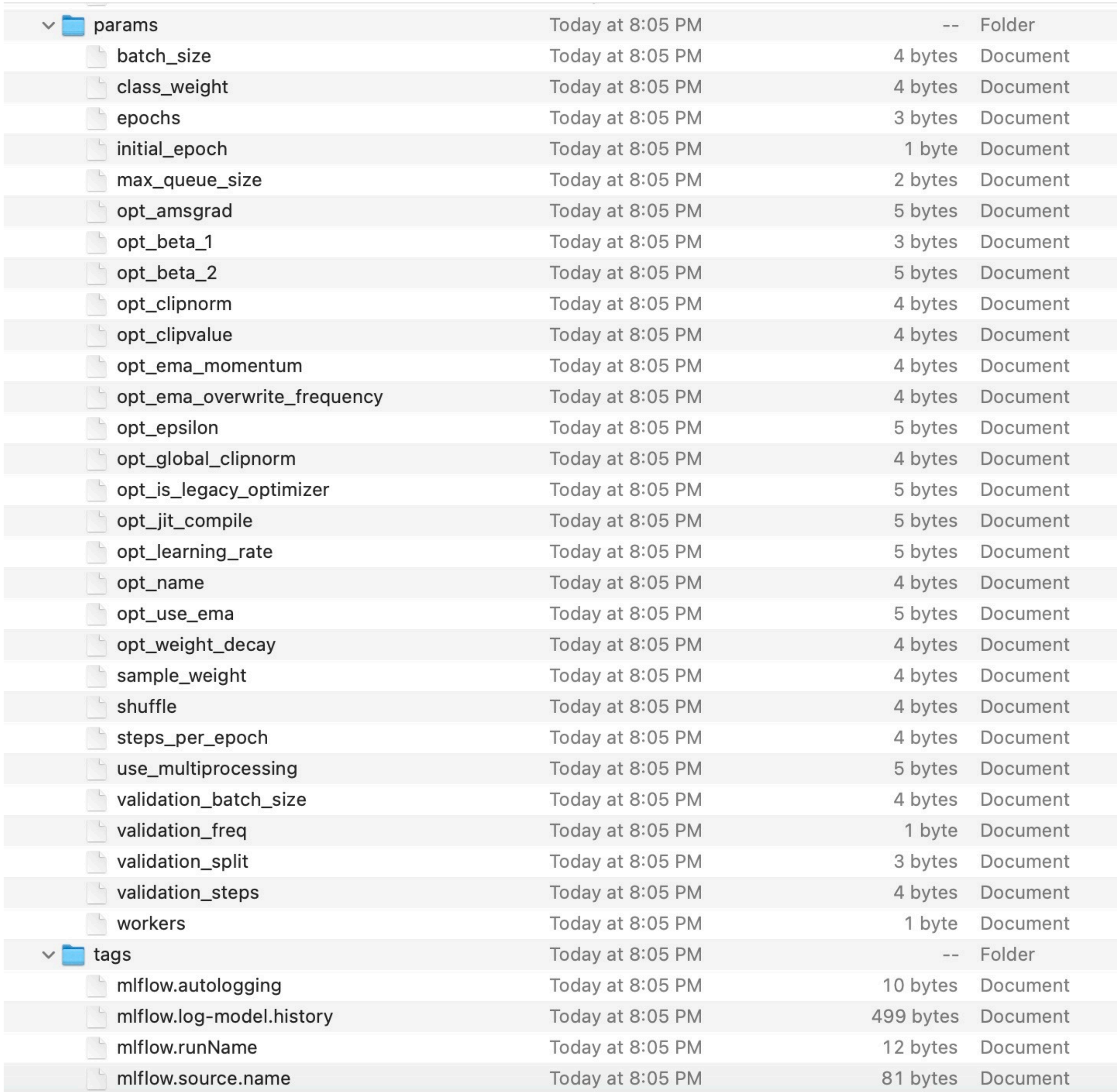
The finder that mlflow got all the experiments in mlrun

In [91]:
```python
filename = '../img/mlrunpic1.png'
display(Image(filename=filename))
```



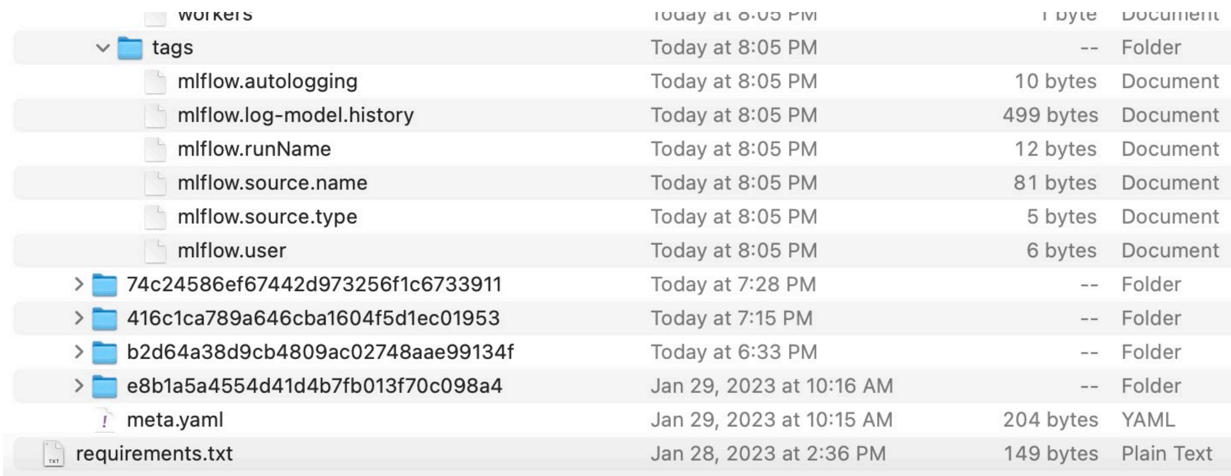
mlruns	Today at 8:05 PM	--	Folder
.trash	Jan 29, 2023 at 10:15 AM	--	Folder
0	Today at 8:05 PM	--	Folder
028b8d02ca534781996b9d0258219ec8	Today at 8:05 PM	--	Folder
artifacts	Today at 8:05 PM	--	Folder
model	Today at 8:05 PM	--	Folder
conda.yaml	Today at 8:05 PM	134 bytes	YAML
data	Today at 8:05 PM	--	Folder
keras_module.txt	Today at 8:05 PM	16 bytes	Plain Text
model	Today at 8:05 PM	--	Folder
assets	Today at 8:05 PM	--	Folder
fingerprint.pb	Today at 8:05 PM	55 bytes	Document
keras_metadata.pb	Today at 8:05 PM	9 KB	Document
saved_model.pb	Today at 8:05 PM	102 KB	Document
variables	Today at 8:05 PM	--	Folder
save_format.txt	Today at 8:05 PM	2 bytes	Plain Text
MLmodel	Today at 8:05 PM	462 bytes	Document
python_env.yaml	Today at 8:05 PM	122 bytes	YAML
requirements.txt	Today at 8:05 PM	33 bytes	Plain Text
model_summary.txt	Today at 8:05 PM	1 KB	Plain Text
tensorboard_logs	Today at 8:05 PM	--	Folder
train	Today at 8:05 PM	--	Folder
events.out.tfevents....s-MBP-2.61128.6.v2	Today at 8:05 PM	9 KB	Document
validation	Today at 8:05 PM	--	Folder
events.out.tfevents....s-MBP-2.61128.7.v2	Today at 8:05 PM	16 KB	Document
meta.yaml	Today at 8:05 PM	430 bytes	YAML
metrics	Today at 8:05 PM	--	Folder
loss	Today at 8:05 PM	4 KB	Document
val_loss	Today at 8:05 PM	4 KB	Document
params	Today at 8:05 PM	--	Folder
batch_size	Today at 8:05 PM	4 bytes	Document
class_weight	Today at 8:05 PM	4 bytes	Document
epochs	Today at 8:05 PM	3 bytes	Document
initial_epoch	Today at 8:05 PM	1 byte	Document
max_queue_size	Today at 8:05 PM	2 bytes	Document
opt_amsgrad	Today at 8:05 PM	5 bytes	Document

In [92]:
```python
from IPython.display import Image, display
# change the filename to wherever you downloaded/uploaded the file
filename = '../img/mlrunpic2.jpg'
display(Image(filename=filename))
```



params	Today at 8:05 PM	--	Folder
batch_size	Today at 8:05 PM	4 bytes	Document
class_weight	Today at 8:05 PM	4 bytes	Document
epochs	Today at 8:05 PM	3 bytes	Document
initial_epoch	Today at 8:05 PM	1 byte	Document
max_queue_size	Today at 8:05 PM	2 bytes	Document
opt_amsgrad	Today at 8:05 PM	5 bytes	Document
opt_beta_1	Today at 8:05 PM	3 bytes	Document
opt_beta_2	Today at 8:05 PM	5 bytes	Document
opt_clipnorm	Today at 8:05 PM	4 bytes	Document
opt_clipvalue	Today at 8:05 PM	4 bytes	Document
opt_ema_momentum	Today at 8:05 PM	4 bytes	Document
opt_ema_overwrite_frequency	Today at 8:05 PM	4 bytes	Document
opt_epsilon	Today at 8:05 PM	5 bytes	Document
opt_global_clipnorm	Today at 8:05 PM	4 bytes	Document
opt_is_legacy_optimizer	Today at 8:05 PM	5 bytes	Document
opt_jit_compile	Today at 8:05 PM	5 bytes	Document
opt_learning_rate	Today at 8:05 PM	5 bytes	Document
opt_name	Today at 8:05 PM	4 bytes	Document
opt_use_ema	Today at 8:05 PM	5 bytes	Document
opt_weight_decay	Today at 8:05 PM	4 bytes	Document
sample_weight	Today at 8:05 PM	4 bytes	Document
shuffle	Today at 8:05 PM	4 bytes	Document
steps_per_epoch	Today at 8:05 PM	4 bytes	Document
use_multiprocessing	Today at 8:05 PM	5 bytes	Document
validation_batch_size	Today at 8:05 PM	4 bytes	Document
validation_freq	Today at 8:05 PM	1 byte	Document
validation_split	Today at 8:05 PM	3 bytes	Document
validation_steps	Today at 8:05 PM	4 bytes	Document
workers	Today at 8:05 PM	1 byte	Document
tags	Today at 8:05 PM	--	Folder
mlflow.autologging	Today at 8:05 PM	10 bytes	Document
mlflow.log-model.history	Today at 8:05 PM	499 bytes	Document
mlflow.runName	Today at 8:05 PM	12 bytes	Document
mlflow.source.name	Today at 8:05 PM	81 bytes	Document

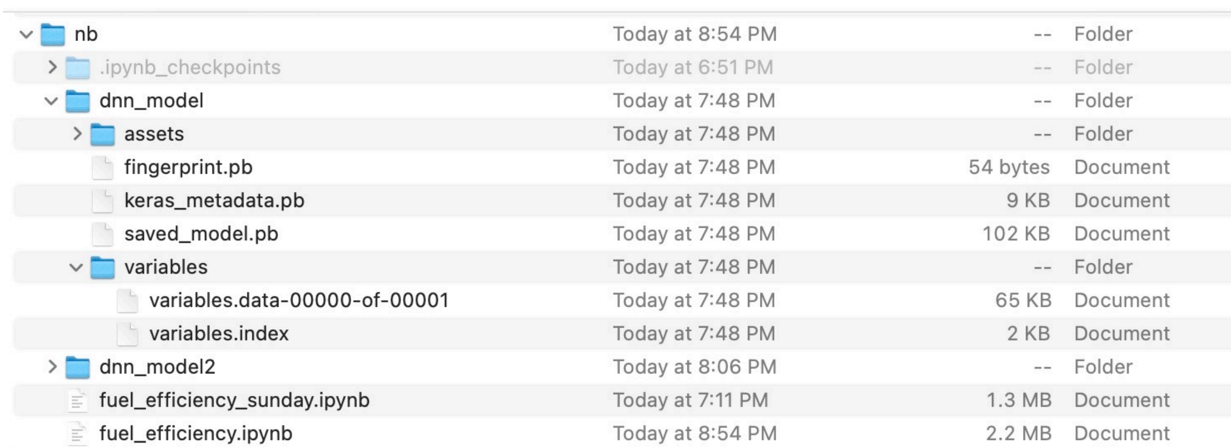
```python
In [94]: from IPython.display import Image, display
         # change the filename to wherever you downloaded/uploaded the file
         filename = '../img/mlrunpic3.jpg'
         display(Image(filename=filename))
         # the 4 next experiments (linear, redo dnn, dnn2)
```



workers	Today at 8:05 PM	1 byte	Document
tags	Today at 8:05 PM	--	Folder
mlflow.autologging	Today at 8:05 PM	10 bytes	Document
mlflow.log-model.history	Today at 8:05 PM	499 bytes	Document
mlflow.runName	Today at 8:05 PM	12 bytes	Document
mlflow.source.name	Today at 8:05 PM	81 bytes	Document
mlflow.source.type	Today at 8:05 PM	5 bytes	Document
mlflow.user	Today at 8:05 PM	6 bytes	Document
74c24586ef67442d973256f1c6733911	Today at 7:28 PM	--	Folder
416c1ca789a646cba1604f5d1ec01953	Today at 7:15 PM	--	Folder
b2d64a38d9cb4809ac02748aae99134f	Today at 6:33 PM	--	Folder
e8b1a5a4554d41d4b7fb013f70c098a4	Jan 29, 2023 at 10:16 AM	--	Folder
meta.yaml	Jan 29, 2023 at 10:15 AM	204 bytes	YAML
requirements.txt	Jan 28, 2023 at 2:36 PM	149 bytes	Plain Text

Showing what is in dnn

```python
In [97]: from IPython.display import Image, display
         # change the filename to wherever you downloaded/uploaded the file
         filename = '../img/dnnModel.jpg'
         display(Image(filename=filename))
```



nb	Today at 8:54 PM	--	Folder
.ipynb_checkpoints	Today at 6:51 PM	--	Folder
dnn_model	Today at 7:48 PM	--	Folder
assets	Today at 7:48 PM	--	Folder
fingerprint.pb	Today at 7:48 PM	54 bytes	Document
keras_metadata.pb	Today at 7:48 PM	9 KB	Document
saved_model.pb	Today at 7:48 PM	102 KB	Document
variables	Today at 7:48 PM	--	Folder
variables.data-00000-of-00001	Today at 7:48 PM	65 KB	Document
variables.index	Today at 7:48 PM	2 KB	Document
dnn_model2	Today at 8:06 PM	--	Folder
fuel_efficiency_sunday.ipynb	Today at 7:11 PM	1.3 MB	Document
fuel_efficiency.ipynb	Today at 8:54 PM	2.2 MB	Document

7. Tracking UI.

   MLflow provides an UI for us to visualize, search and compare runs, as well as download run artifacts or metadata for analysis in other tools.

   If your runs are logged to a local mlruns directory, run `mlflow ui` in the directory above it will load the corresponding runs.

   Running localhost server in Colab, however, requires a bit of extra work:

   - set up a free account on [ngrok (https://dashboard.ngrok.com/get-started/setup)](https://dashboard.ngrok.com/get-started/setup)
   - retrieve the authtoken from [https://dashboard.ngrok.com/auth (https://dashboard.ngrok.com/auth)](https://dashboard.ngrok.com/auth) and update the code cell below

   NOTE. NEVER share your secrets. Best to keep `NGROK_AUTH_TOKEN` as an environment variable and retrieve it via `os.environ.get("NGROK_AUTH_TOKEN")` .

In [99]:
```
# run tracking UI in the background
get_ipython().system_raw("mlflow ui --port 5000 &")

# create remote tunnel using ngrok.com to allow local port access
from pyngrok import ngrok
# Terminate open tunnels if exist
ngrok.kill()

# Setting the authtoken (see Note above)
NGROK_AUTH_TOKEN = "2L0umvOgkhKcI2PiJKkSWQuvvSI_42VfXjNJSxjVrUzCrKyhU"
ngrok.set_auth_token(NGROK_AUTH_TOKEN)

# Open an HTTPs tunnel on port 5000 for http://localhost:5000
ngrok_tunnel = ngrok.connect(addr="5000", proto="http", bind_tls=True)
print("MLflow Tracking UI:", ngrok_tunnel.public_url)
```

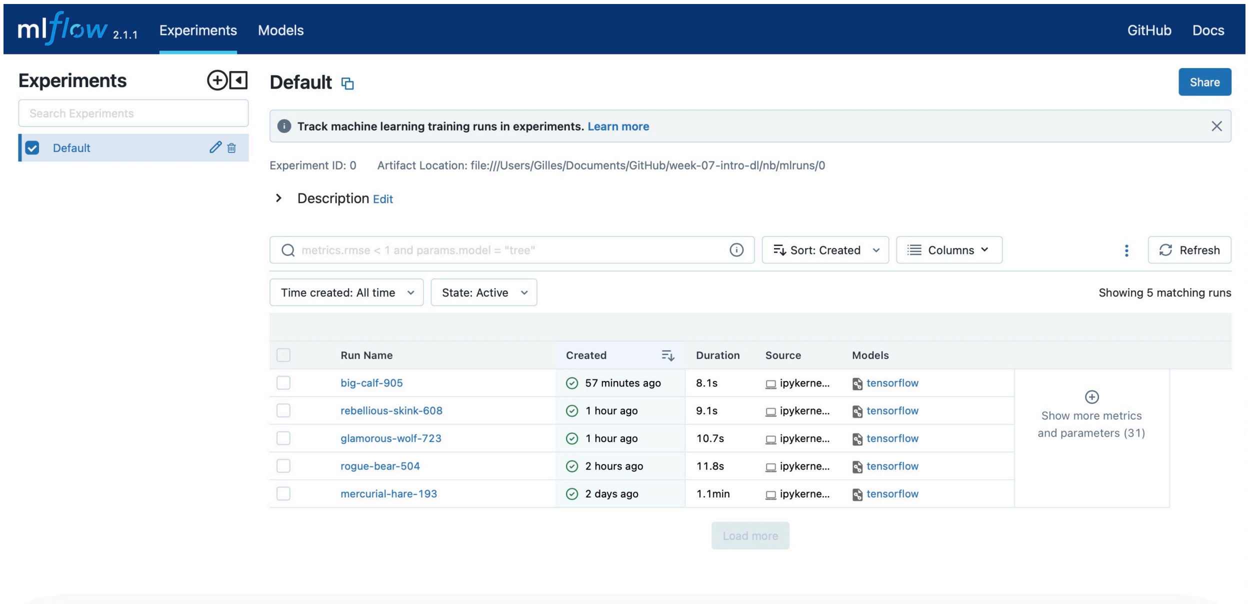
```
-----------------------------------------------------------------------
------
ModuleNotFoundError                       Traceback (most recent call
last)
Input In [99], in <cell line: 5>()
      2 get_ipython().system_raw("mlflow ui --port 5000 &")
      4 # create remote tunnel using ngrok.com to allow local port ac
cess
----> 5 from pyngrok import ngrok
      6 # Terminate open tunnels if exist
      7 ngrok.kill()

ModuleNotFoundError: No module named 'pyngrok'


[2023-01-31 21:02:50 -0600] [66666] [INFO] Starting gunicorn 20.1.0
[2023-01-31 21:02:50 -0600] [66666] [INFO] Listening at: http://127.0
.0.1:5000 (http://127.0.0.1:5000) (66666)
[2023-01-31 21:02:50 -0600] [66666] [INFO] Using worker: sync
[2023-01-31 21:02:50 -0600] [66669] [INFO] Booting worker with pid: 6
6669
[2023-01-31 21:02:50 -0600] [66670] [INFO] Booting worker with pid: 6
6670
[2023-01-31 21:02:50 -0600] [66671] [INFO] Booting worker with pid: 6
6671
[2023-01-31 21:02:50 -0600] [66672] [INFO] Booting worker with pid: 6
6672
```

8. Interact with Tracking UI.

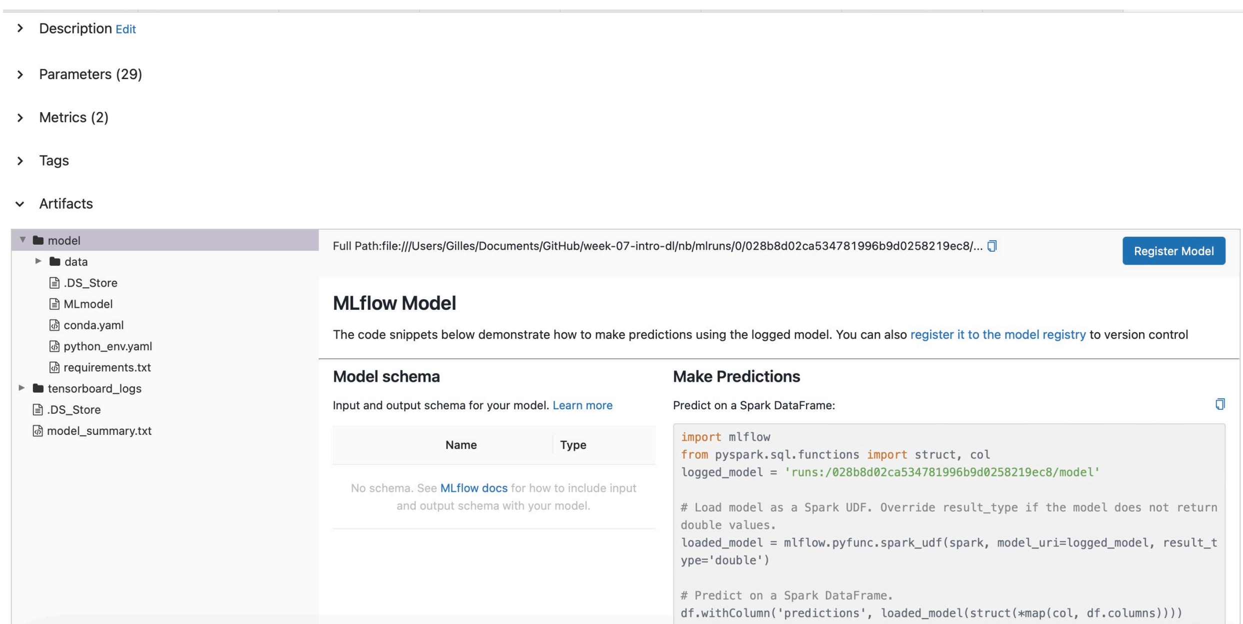
   Open the link, output from the previous cell. get oriented, `Parameters` , `Metrics` , `Artifacts` , and so on.

   When you are done, make sure to terminate the open tunnel:

In [102]:
```python
filename = '../img/mlflowexp1.jpg'
display(Image(filename=filename))
```



In [103]:
```python
filename = '../img/mlflowexp2.jpg'
display(Image(filename=filename))
```



In [104]:
```
filename = '../img/mlflowexp3.jpg'
display(Image(filename=filename))
```

Metrics (2)

Name	Value
loss	2.299
val_loss	2.571

In [106]:
```
filename = '../img/mlfowexp4.jpg'
display(Image(filename=filename))
```

Parameters (29)

Name	Value
batch_size	None
class_weight	None
epochs	100
initial_epoch	0

max_queue_size	10
opt_amsgrad	False
opt_beta_1	0.9
opt_beta_2	0.999
opt_clipnorm	None
opt_clipvalue	None

In [ ]:
```
#http://127.0.0.1:5000/#/experiments/0/runs/028b8d02ca534781996b9d025
```

In [100]:
```
# stop the kernel
ngrok.kill()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call
last)
Input In [100], in <cell line: 1>()
----> 1 ngrok.kill()

NameError: name 'ngrok' is not defined
```

Task 8 - AutoML with TPOT 🫖

1. Instantiate and train a TPOT auto-ML regressor.

   The parameters are set fairly arbitrarily (if time permits, you shall experiment with different sets of parameters after reading [what each parameter does (http://epistasislab.github.io/tpot/api/#regression)](http://epistasislab.github.io/tpot/api/#regression)). Use these parameter values:

   `generations` : 10

   `population_size` : 40

   `scoring` : negative mean absolute error; read more in [scoring functions in TPOT (http://epistasislab.github.io/tpot/using/#scoring-functions)](http://epistasislab.github.io/tpot/using/#scoring-functions)

   `verbosity` : 2 (so you can see each generation's performance)

   The final line with create a Python script tpot_products_pipeline.py with the code to create the optimal model found by TPOT.

In [168]:
```python
%%time
from tpot import TPOTRegressor
tpot = TPOTRegressor(generations=10,
                     population_size=40,
                     scoring=None, # YOUR CODE HERE scoring = 'f1' doe
                     verbosity=2,
                     random_state=42)
tpot.fit(train_features, train_labels)
print(f"Tpop score on test data: {tpot.score(test_features, test_label
tpot.export('tpot_mpg_pipeline.py')
```

```
Optimization Progress:   0%|          | 0/440 [00:00<?, ?pipeline/s]


Generation 1 - Current best internal CV score: -8.077745295810276

Generation 2 - Current best internal CV score: -8.077745295810276

Generation 3 - Current best internal CV score: -8.077745295810276

Generation 4 - Current best internal CV score: -8.00800302618326

Generation 5 - Current best internal CV score: -8.00800302618326

Generation 6 - Current best internal CV score: -7.827227772486582

Generation 7 - Current best internal CV score: -7.82722777248655

Generation 8 - Current best internal CV score: -7.82722777248655

Generation 9 - Current best internal CV score: -7.82722777248655

Generation 10 - Current best internal CV score: -7.827227772486549

Best pipeline: LassoLarsCV(ExtraTreesRegressor(MaxAbsScaler(VarianceT
hreshold(input_matrix, threshold=0.0005)), bootstrap=True, max_featur
es=0.9500000000000001, min_samples_leaf=14, min_samples_split=6, n_es
timators=100), normalize=True)
Tpop score on test data: -7.40
CPU times: user 10min 19s, sys: 7.97 s, total: 10min 27s
Wall time: 8min 11s

sklearn.metrics.SCORERS is deprecated and will be removed in v1.3. Pl
ease use sklearn.metrics.get_scorer_names to get a list of available
scorers and sklearn.metrics.get_metric to get scorer.
```

In [117]:
```python
import sklearn.metrics
sklearn.metrics.get_scorer_names()
```

Out[117]:
```
['accuracy',
 'adjusted_mutual_info_score',
 'adjusted_rand_score',
 'average_precision',
```

```
 'balanced_accuracy',
 'completeness_score',
 'explained_variance',
 'f1',
 'f1_macro',
 'f1_micro',
 'f1_samples',
 'f1_weighted',
 'fowlkes_mallows_score',
 'homogeneity_score',
 'jaccard',
 'jaccard_macro',
 'jaccard_micro',
 'jaccard_samples',
 'jaccard_weighted',
 'matthews_corrcoef',
 'max_error',
 'mutual_info_score',
 'neg_brier_score',
 'neg_log_loss',
 'neg_mean_absolute_error',
 'neg_mean_absolute_percentage_error',
 'neg_mean_gamma_deviance',
 'neg_mean_poisson_deviance',
 'neg_mean_squared_error',
 'neg_mean_squared_log_error',
 'neg_median_absolute_error',
 'neg_negative_likelihood_ratio',
 'neg_root_mean_squared_error',
 'normalized_mutual_info_score',
 'positive_likelihood_ratio',
 'precision',
 'precision_macro',
 'precision_micro',
 'precision_samples',
 'precision_weighted',
 'r2',
 'rand_score',
 'recall',
 'recall_macro',
 'recall_micro',
 'recall_samples',
 'recall_weighted',
 'roc_auc',
 'roc_auc_ovo',
 'roc_auc_ovo_weighted',
 'roc_auc_ovr',
 'roc_auc_ovr_weighted',
 'top_k_accuracy',
 'v_measure_score']
```

In [124]:
```
sklearn.metrics.get_scorer('f1')
```
Out[124]:
```
make_scorer(f1_score, average=binary)
```

In [136]:
```
dataset.head(2)
```
Out[136]:

	MPG	Cylinders	Displacement	Horsepower	Weight	Acceleration	Model Year	Europe	Japan
0	18.0	8	307.0	130.0	3504.0	12.0	70	0	0
1	15.0	8	350.0	165.0	3693.0	11.5	70	0	0

2. Examine the model pipeline that TPOT regressor offers. If you see any model, function, or class that are not familiar, look them up!

   Note: There is randomness to the way the TPOT searches, so it's possible you won't have exactly the same result as your classmate.

In [169]:
```
cat tpot_mpg_pipeline.py
```

```
import numpy as np
import pandas as pd
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.feature_selection import VarianceThreshold
from sklearn.linear_model import LassoLarsCV
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline, make_union
from sklearn.preprocessing import MaxAbsScaler
from tpot.builtins import StackingEstimator
from tpot.export_utils import set_param_recursive

# NOTE: Make sure that the outcome column is labeled 'target' in the
data file
tpot_data = pd.read_csv('PATH/TO/DATA/FILE', sep='COLUMN_SEPARATOR',
dtype=np.float64)
features = tpot_data.drop('target', axis=1)
training_features, testing_features, training_target, testing_target
= \
            train_test_split(features, tpot_data['target'], random_st
ate=42)

# Average CV score on the training set was: -7.827227772486549
exported_pipeline = make_pipeline(
    VarianceThreshold(threshold=0.0005),
    MaxAbsScaler(),
    StackingEstimator(estimator=ExtraTreesRegressor(bootstrap=True, m
ax_features=0.9500000000000001, min_samples_leaf=14, min_samples_spli
t=6, n_estimators=100)),
    LassoLarsCV(normalize=True)
)
# Fix random state for all the steps in exported pipeline
set_param_recursive(exported_pipeline.steps, 'random_state', 42)

exported_pipeline.fit(training_features, training_target)
results = exported_pipeline.predict(testing_features)
```

3. Take the appropriate lines (e.g., updating path to data and the variable names) from `tpot_mpg_pipeline.py` to build a model on our training set and make predictions on the test set. Save the predictions as `y_pred`, and compute appropriate evaluation metric. You may find that for this simple data set, the neural network we built outperforms the tree-based model, yet note it is not a conclusion that we can generalize for all tabular data.

In [170]:
```python
import numpy as np
import pandas as pd
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.feature_selection import VarianceThreshold
from sklearn.linear_model import LassoLarsCV
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline, make_union
from sklearn.preprocessing import MaxAbsScaler
from tpot.builtins import StackingEstimator
from tpot.export_utils import set_param_recursive
```

In [171]:
```python
####tpot_data = pd.read_csv('PATH/TO/DATA/FILE', sep='COLUMN_SEPARATOR
tpot_data = dataset
features = tpot_data.drop('MPG', axis=1)
training_features, testing_features, training_target, testing_target =
            train_test_split(features, tpot_data['MPG'], random_state=

exported_pipeline = make_pipeline(
    VarianceThreshold(threshold=0.0005),
    MaxAbsScaler(),
    StackingEstimator(estimator=ExtraTreesRegressor(bootstrap=True, ma
    LassoLarsCV(normalize=True)
)
# Fix random state for all the steps in exported pipeline
set_param_recursive(exported_pipeline.steps, 'random_state', 42)

exported_pipeline.fit(training_features, training_target)
results = exported_pipeline.predict(testing_features)
```

```
'normalize' was deprecated in version 1.2 and will be removed in 1.4.
If you wish to scale the data, use Pipeline with a StandardScaler in
a preprocessing stage. To reproduce the previous behavior:

from sklearn.pipeline import make_pipeline

model = make_pipeline(StandardScaler(with_mean=False), LassoLarsCV())

If you wish to pass a sample_weight parameter, you need to pass it as
a fit parameter to each step of the pipeline as follows:

kwargs = {s[0] + '__sample_weight': sample_weight for s in model.step
s}
model.fit(X, y, **kwargs)

Set parameter alpha to: original_alpha * np.sqrt(n_samples).
```

In [155]:
```
results
```

Out[155]:
```
array([28.283, 23.142, 34.006, 28.283, 28.23 , 28.283, 13.798, 34.006
,
       18.863, 28.283, 13.798, 23.142, 17.272, 28.283, 23.142, 28.23
,
       23.142, 34.006, 34.006, 28.23 , 23.142, 34.006, 34.006, 13.798
,
       28.283, 23.142, 23.142, 18.863, 28.283, 28.283, 13.798, 18.863
,
       18.863, 34.006, 13.798, 34.006, 13.798, 28.283, 13.798, 13.798
,
       13.798, 28.283, 34.006, 28.283, 13.798, 13.798, 18.863, 34.006
,
       28.283, 28.283, 13.798, 23.142, 23.142, 28.23 , 18.863, 18.863
,
       18.863, 18.863, 23.142, 23.142, 13.798, 18.863, 28.23 , 23.142
,
       23.142, 28.283, 23.142, 28.283, 18.863, 13.798, 28.283, 13.798
,
       23.142, 23.142, 18.863, 28.283, 13.798, 13.798, 23.142, 18.863
,
       23.142, 23.142, 13.798, 34.006, 17.272, 34.006, 28.23 , 18.863
,
       18.863, 18.863, 28.23 , 34.006, 34.006, 28.23 , 18.863, 23.142
,
       23.142, 13.798])
```

In [154]:
```
testing_target
```

Out[154]:
```
79     26.0
276    21.6
248    36.1
56     26.0
393    27.0
       ...
370    31.0
252    19.2
211    16.5
76     18.0
105    13.0
Name: MPG, Length: 98, dtype: float64
```

In [156]:
```
pd.DataFrame(list(results))
```

Out[156]:

	0
0	28.283333
1	23.142222
2	34.005970
3	28.283333
4	28.230435
...	...
93	28.230435
94	18.862745
95	23.142222
96	23.142222
97	13.798246

98 rows × 1 columns

In [157]:
```
results2 = pd.DataFrame(list(results))
```

In [159]:
```
testing_target2 = pd.DataFrame(testing_target)
```

In [177]:
```
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
y_true = [3, -0.5, 2, 7]
y_pred = [2.5, 0.0, 2, 8]
print('rsquare: ',r2_score(results, testing_target))
print('meanabsoluteError: ',mean_absolute_error(testing_target, result
test_results['ExtraTree']=mean_absolute_error(testing_target, results)
```

```
rsquare:  0.879077713080702
meanabsoluteError:  1.8407450367071052
```

Task 9 - Model Explainability

Last week, we introduced model explainability with SHAP and will continue to incorporate it as part our model output this week. You can use the Kernel Explainer (https://shap.readthedocs.io/en/latest/example_notebooks/tabular_examples/neural_networks for explainability of both the Neural Networks and the TPOT classifier.

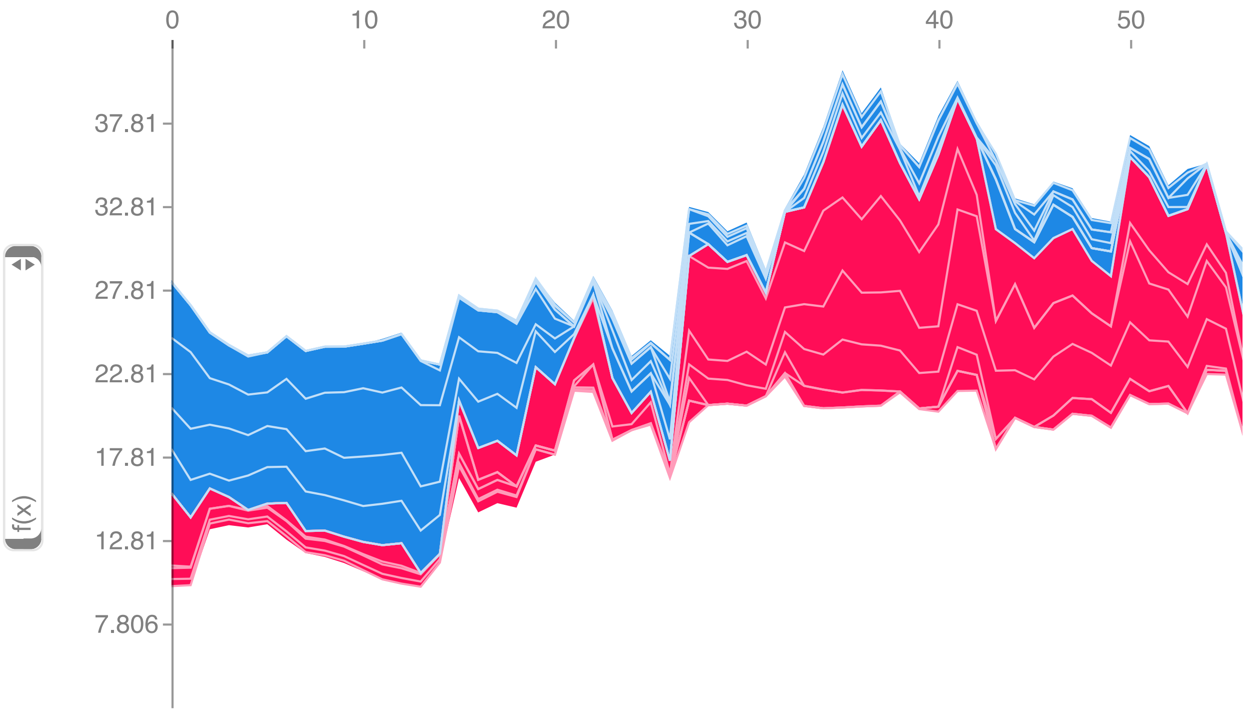
In [109]:
```
'''
copied from Explainer
#explainer = shap.KernelExplainer(f, X.iloc[:50,:])
#shap_values = explainer.shap_values(X.iloc[299,:], nsamples=500)
#shap.force_plot(explainer.expected_value, shap_values, X_display.iloc
'''

import shap
explainer = shap.KernelExplainer(lambda x: dnn_model.predict(x).flatte
shap_values = explainer.shap_values(test_features)
shap.initjs()
shap.force_plot(explainer.expected_value, np.array(shap_values), test_

# shows all explanations
```

```
2/2 [==============================] - 0s 3ms/step

  0%|          | 0/78 [00:00<?, ?it/s]

1/1 [==============================] - 0s 32ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 28ms/step
797/797 [==============================] - 2s 2ms/step
1/1 [==============================] - 0s 26ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 27ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 27ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 30ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 27ms/step
797/797 [==============================] - 1s 1ms/step
1/1 [==============================] - 0s 27ms/step
797/797 [==============================] - 1s 1ms/step
```

In [110]:
```python
shap.initjs()
shap.force_plot(explainer.expected_value, np.array(shap_values), test_
```

Out[110]:

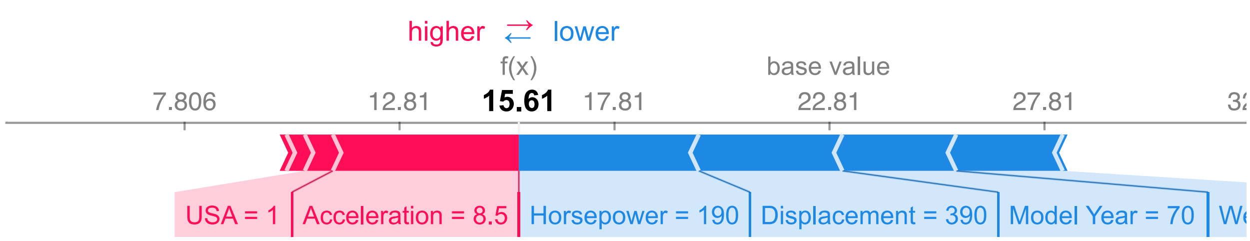
sample order by similarity



In [111]:
```python
explainer = shap.KernelExplainer(lambda x: dnn_model.predict(x).flatte
shap_values = explainer.shap_values(test_features.iloc[0,:])
shap.initjs()
shap.force_plot(explainer.expected_value, np.array(shap_values), test_
# shows the first explanation
```

```
2/2 [==============================] - 0s 3ms/step
1/1 [==============================] - 0s 36ms/step
797/797 [==============================] - 2s 2ms/step
```

Out[111]:



Task 10 - Taking it to the Next Level! 📶

Let's take our models and make a model comparison demo like we did last week, but this time you're taking the lead!

1. Save your training dataset as a CSV file so that it can be used in the Streamlit app.
2. Build a results DataFrame and save it as a CSV so that it can be used in the Streamlit app.
3. In Tab 1 - Raw Data:

- Display your training dataset in a Streamlit DataFrame (`st.DataFrame`).
- Build 1-2 interactive Plotly visualizations that explore the dataset (correlations, scatterplot, etc.)

2. In Tab 2 - Model Results:

- Display your performance metrics appropriately using 2-3 metrics for model comparison.

3. In Tab 3 - Model Explainability:

- Make local and global explainability plots to compare two models at a time side-by-side. [Here (https://www.kaggle.com/code/elsa155026/uciheart-kernel-shap-and-interactive-visualization/notebook)](https://www.kaggle.com/code/elsa155026/uciheart-kernel-shap-and-interactive-visualization/notebook) is a good example if how to create some different explainability plots using Plotly.

In [178]:
```
test_results
```

Out[178]:
```
{'linear_model': 2.4612009525299072,
 'dnn_model': 1.6599880456924438,
 'reloaded': 1.6599880456924438,
 'dnn_model2': 2.289334297180176,
 'ExtraTree': 1.8407450367071052}
```

In [179]:
```
!ls
```

```
dnn_model                                 imports.ipynb
dnn_model2                                mlruns
fuel-efficiency-prediction-streamlit.py   requirements.txt
fuel_efficiency.ipynb                     tpot_mpg_pipeline.py
fuel_efficiency_sunday.ipynb
```

In [180]:
```
cat fuel-efficiency-prediction-streamlit.py
```

```
import pandas as pd
import plotly.express as px
import plotly.figure_factory as ff
import streamlit as st
```

```
import streamlit.components.v1 as components
from PIL import Image

# Add and resize an image to the top of the app
img_fuel = Image.open("../img/fuel_efficiency.png")
st.image(img_fuel, width=700)

st.markdown("<h1 style='text-align: center; color: black;'>Fuel Effic
iency</h1>", unsafe_allow_html=True)

# Import train dataset to DataFrame
train_df = pd.read_csv("../dat/train.csv.gz", compression="gzip")
model_results_df = pd.read_csv("../dat/model_results.csv")

# Create sidebar for user selection
with st.sidebar:
    # Add FB logo
    st.image("https://user-images.githubusercontent.com/37101144/1618
36199-fdb0219d-0361-4988-bf26-48b0fad160a3.png" )

    # Available models for selection

    # YOUR CODE GOES HERE!
    models = ["DNN", "TPOT"]

    # Add model select boxes
    model1_select = st.selectbox(
        "Choose Model 1:",
        (models)
    )

    # Remove selected model 1 from model list
    # App refreshes with every selection change.
    models.remove(model1_select)

    model2_select = st.selectbox(
        "Choose Model 2:",
        (models)
    )

# Create tabs for separation of tasks
tab1, tab2, tab3 = st.tabs(["🗃️ Data", "🔎 Model Results", "🤓 Model
 Explainability"])

with tab1:
    # Data Section Header
    st.header("Raw Data")

    # Display first 100 samples of the dateframe
    st.dataframe(train_df.head(100))

    st.header("Correlations")
```

```
    # Heatmap
    corr = train_df.corr()
    fig = px.imshow(corr)
    st.write(fig)

with tab2:

    # YOUR CODE GOES HERE!

    # Columns for side-by-side model comparison
    col1, col2 = st.columns(2)

    # Build the confusion matrix for the first model.
    with col1:
        st.header(model1_select)

        # YOUR CODE GOES HERE!


    # Build confusion matrix for second model
    with col2:
        st.header(model2_select)

        # YOUR CODE GOES HERE!


with tab3:
    # YOUR CODE GOES HERE!
        # Use columns to separate visualizations for models
        # Include plots for local and global explanability!

    st.header(model1_select)

    st.header(model2_select)
```

In [184]:
```
test_results
```

Out[184]:
```
{'linear_model': 2.4612009525299072,
 'dnn_model': 1.6599880456924438,
 'reloaded': 1.6599880456924438,
 'dnn_model2': 2.289334297180176,
 'ExtraTree': 1.8407450367071052}
```

In [187]:
```
import csv
dataset.to_csv("../dat/train.csv")
dfresults = pd.DataFrame(test_results.items(), columns=['Model', 'Mear
dfresults.to_csv("../dat/model_results.csv")
```

In [190]:
```
!python fuel-efficiency-prediction-streamlit.py
```

```
Traceback (most recent call last):
  File "/Users/Gilles/Documents/GitHub/week-07-intro-dl/nb/fuel-effic
iency-prediction-streamlit.py", line 2, in <module>
    import plotly.express as px
ModuleNotFoundError: No module named 'plotly'
```

In [191]:
```
!pip install plotly
```

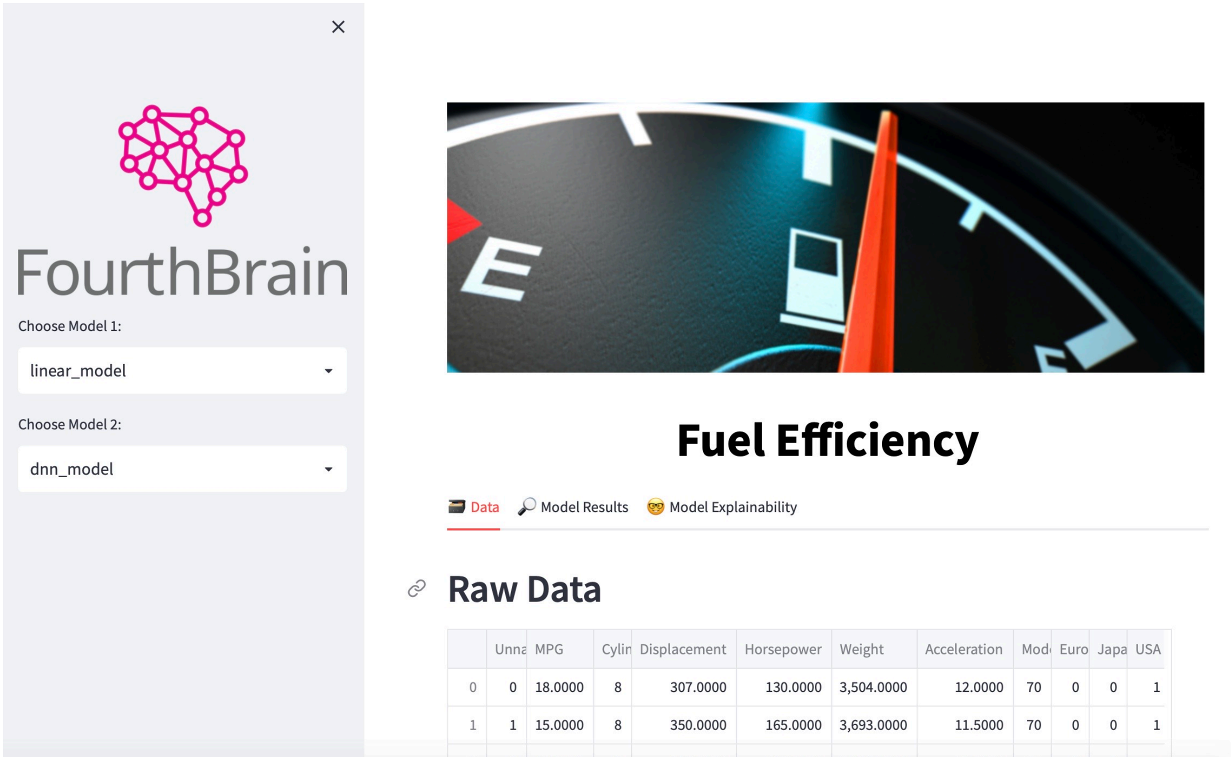
```
Collecting plotly
  Using cached plotly-5.13.0-py2.py3-none-any.whl (15.2 MB)
Collecting tenacity>=6.2.0
  Using cached tenacity-8.1.0-py3-none-any.whl (23 kB)
Installing collected packages: tenacity, plotly
Successfully installed plotly-5.13.0 tenacity-8.1.0
```

In [192]:
```
!pip install streamlit
```

```
Collecting streamlit
  Downloading streamlit-1.12.0-py2.py3-none-any.whl (9.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9.1/9.1 MB 5.6 MB/s eta
0:00:0000:0100:01
Collecting pydeck>=0.1.dev5
  Using cached pydeck-0.8.0-py2.py3-none-any.whl (4.7 MB)
Collecting pympler>=0.9
  Using cached Pympler-1.0.1-py3-none-any.whl (164 kB)
Collecting validators>=0.2
  Using cached validators-0.20.0.tar.gz (30 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: tornado>=5.0 in /Users/Gilles/anaconda
3/lib/python3.9/site-packages (from streamlit) (6.2)
Requirement already satisfied: python-dateutil in /Users/Gilles/anaco
nda3/lib/python3.9/site-packages (from streamlit) (2.8.2)
Requirement already satisfied: toml in /Users/Gilles/anaconda3/lib/py
thon3.9/site-packages (from streamlit) (0.10.2)
Collecting cachetools>=4.0
  Using cached cachetools-5.3.0-py3-none-any.whl (9.3 kB)
Requirement already satisfied: packaging>=14.1 in /Users/Gilles/anaco
```

In [ ]:
```
# type a terminal !streamlit run fuel-efficiency-prediction-streamlit.
```

In [3]:
```python
from IPython.display import Image, display
# change the filename to wherever you downloaded/uploaded the file
filename = '../img/streamlit1.jpg'
display(Image(filename=filename))
```



Additional Resources

- [Tensorflow playground (https://playground.tensorflow.org/)](https://playground.tensorflow.org/) for an interactive experience to understand how nueral networkds work.
- [An Introduction to Deep Learning for Tabular Data (https://www.fast.ai/2018/04/29/categorical-embeddings/)](https://www.fast.ai/2018/04/29/categorical-embeddings/) covers embeddings for categorical variables.
- [Imbalanced classification: credit card fraud detection (https://keras.io/examples/structured_data/imbalanced_classification/)](https://keras.io/examples/structured_data/imbalanced_classification/) demonstrates using `class_weight` to handle imbalanced classification problems.

Acknowledgement and Copyright

Acknowledgement

This notebook is adapted from [tensorflow/keras tuorial - regression (https://www.tensorflow.org/tutorials/keras/regression)](https://www.tensorflow.org/tutorials/keras/regression)