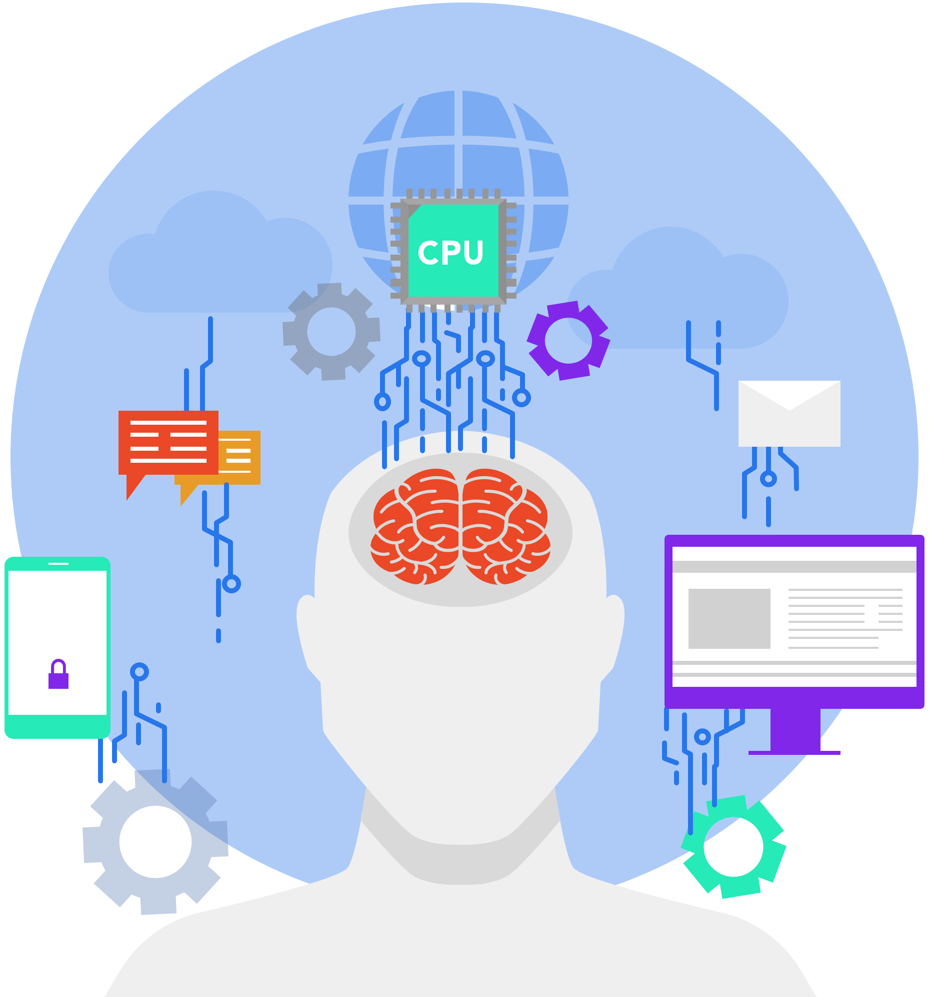


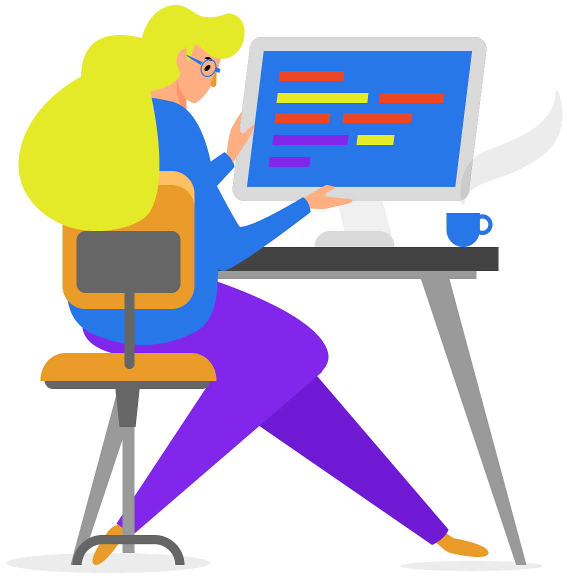
Vehicle CO_2 Emission Prediction

Deep Learning
Assignment 1

Team Members

6310412018	Pongsarat Chootai	**(25%)** Find dataset, Data cleansing and preparation, Develop Linear Regression Model, Develop initial Deep Learning Model, Result Summarization
6310412021	Theethut Narksenee	**(25%)** Experimental variation on activation fn. and learning rate
6310412024	Saranchai Angkawinijwong	**(25%)** Experimental variation on number of neuron and number of layer
6420400001	Krittipat Chuenphitthayavut	**(25%)** Experimental variation on number of epoch and batch size

Agenda



01 Team Members

02 Why CO_2 Emission ?

03 Data Exploration and Preparation

04 Linear Regression

05 Deep Learning

06 Summary

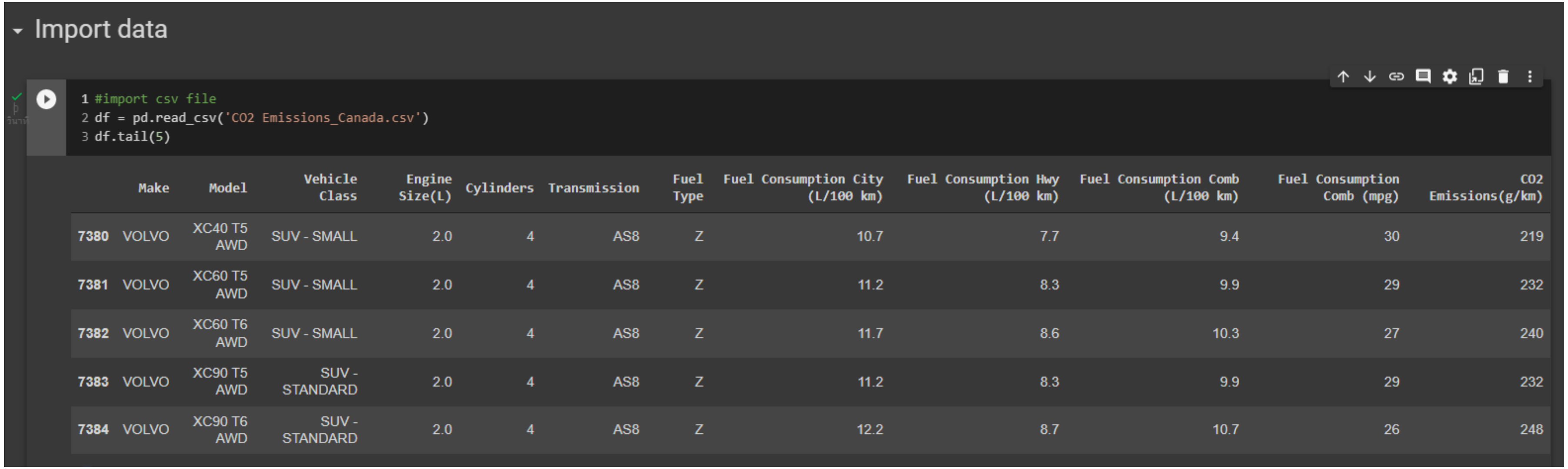
Why CO_2 Emission ?

The CO_2 emission is the most concerned environmental problem for our earth for a long
According to UN Climate Change Conference (COP26), all countries are going to achieve “Net Zero” which means the overall CO_2 emission equals to 0 with in 2040 – 2070 to ensure that the atmosphere won’t be damaged until it’ll be irreversible anymore.

The CO_2 emission from vehicles is one of the main CO2 emission source which will be benefit if we can estimate them accurately in order to plan for CO_2 net-zero in near future.

Dataset

The data source is a public data from Canada government as per below link https://www.kaggle.com/debajyotipodder/co2-emission-by-vehicles which comprises of 7385 data of vehicles with 11 features each.



Import data

```
#import csv file
df = pd.read_csv('CO2 Emissions_Canada.csv')
df.tail(5)
```

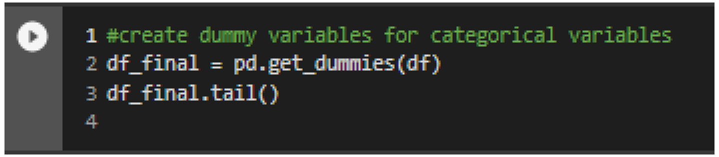
	Make	Model	Vehicle Class	Engine Size(L)	Cylinders	Transmission	Fuel Type	Fuel Consumption City (L/100 km)	Fuel Consumption Hwy (L/100 km)	Fuel Consumption Comb (L/100 km)	Fuel Consumption Comb (mpg)	CO2 Emissions(g/km)
7380	VOLVO	XC40 T5 AWD	SUV - SMALL	2.0	4	AS8	Z	10.7	7.7	9.4	30	219
7381	VOLVO	XC60 T5 AWD	SUV - SMALL	2.0	4	AS8	Z	11.2	8.3	9.9	29	232
7382	VOLVO	XC60 T6 AWD	SUV - SMALL	2.0	4	AS8	Z	11.7	8.6	10.3	27	240
7383	VOLVO	XC90 T5 AWD	SUV - STANDARD	2.0	4	AS8	Z	11.2	8.3	9.9	29	232
7384	VOLVO	XC90 T6 AWD	SUV - STANDARD	2.0	4	AS8	Z	12.2	8.7	10.7	26	248

Data Exploration and Preparation

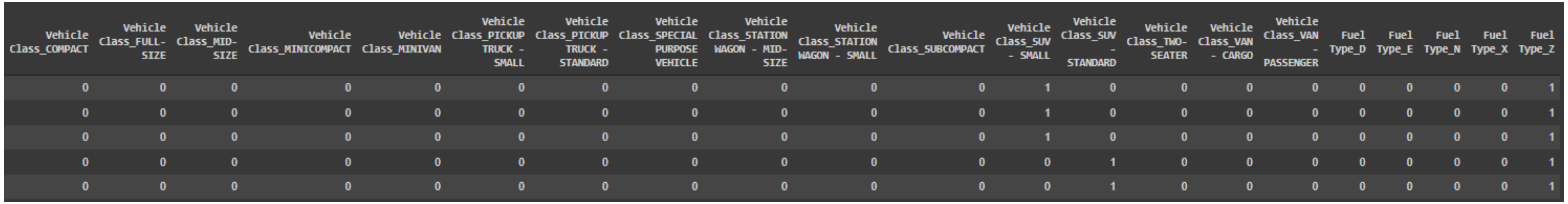
According to the data, there are some categorical data as shown below which will be converted as dummy variables.

Vehicle class
STATION WAGON - SMALL
COMPACT
MID-SIZE
SUV - SMALL
MINICOMPACT
SPECIAL PURPOSE VEHICLE
STATION WAGON - MID-SIZE
SUBCOMPACT
MINIVAN
FULL-SIZE
TWO-SEATER
PICKUP TRUCK - SMALL
PICKUP TRUCK - STANDARD
SUV - STANDARD
VAN - CARGO
VAN - PASSENGER

Fuel type
X = regular gasoline
Z = premium gasoline
D = diesel
E = ethanol (E85)
N = natural gas



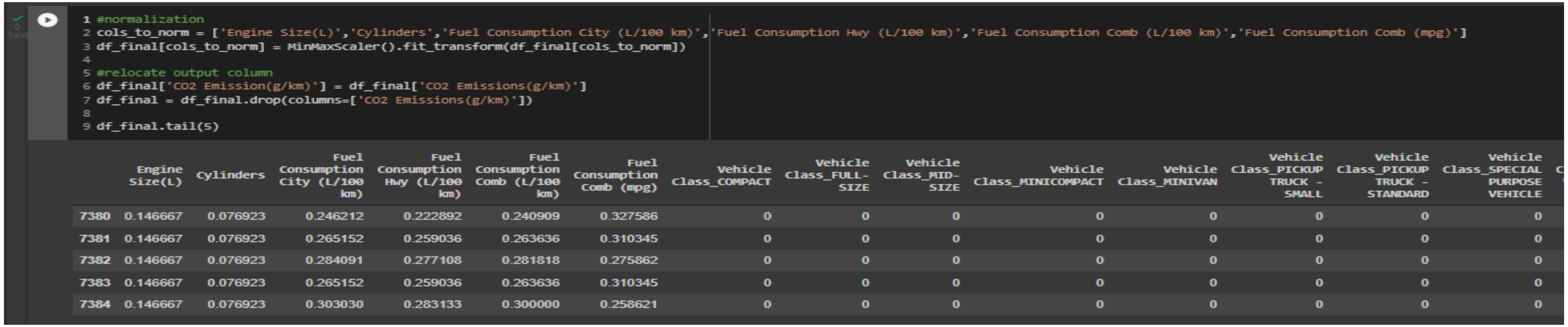
```
#create dummy variables for categorical variables
df_final = pd.get_dummies(df)
df_final.tail()

```



Vehicle Class_COMPACT	Vehicle Class_FULL-SIZE	Vehicle Class_MID-SIZE	Vehicle Class_MINICOMPACT	Vehicle Class_MINIVAN	Vehicle Class_PICKUP TRUCK - SMALL	Vehicle Class_PICKUP TRUCK - STANDARD	Vehicle Class_SPECIAL PURPOSE VEHICLE	Vehicle Class_STATION WAGON - MID-SIZE	Vehicle Class_STATION WAGON - SMALL	Vehicle Class_SUBCOMPACT	Vehicle Class_SUV - SMALL	Vehicle Class_SUV - STANDARD	Vehicle Class_TWO-SEATER	Vehicle Class_VAN - CARGO	Vehicle Class_VAN - PASSENGER	Fuel Type_D	Fuel Type_E	Fuel Type_N	Fuel Type_X	Fuel Type_Z
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1

Data Exploration and Preparation

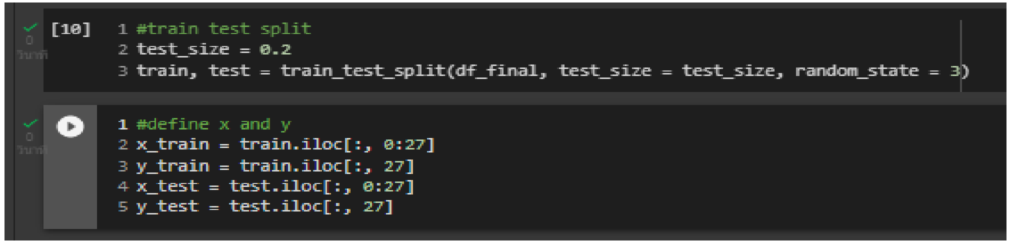
Next is to normalize the input. We select min – max scalar method to convert the input variables' value to be in range 0 – 1 since all those values shall be in positive number only.



```python
#normalization
cols_to_norm = ['Engine Size(L)','Cylinders','Fuel Consumption City (L/100 km)','Fuel Consumption Hwy (L/100 km)','Fuel Consumption Comb (L/100 km)','Fuel Consumption Comb (mpg)']
df_final[cols_to_norm] = MinMaxScaler().fit_transform(df_final[cols_to_norm])

#relocate output column
df_final['CO2 Emission(g/km)'] = df_final['CO2 Emissions(g/km)']
df_final = df_final.drop(columns=['CO2 Emissions(g/km)'])

df_final.tail(5)
```

```
                                Fuel        Fuel        Fuel                                             Vehicle      Vehicle                                               Vehicle        Vehicle         Vehicle
        Engine             Consumption Consumption Consumption        Fuel          Vehicle     Class_FULL-  Class_MID-             Vehicle          Vehicle Class_PICKUP   Class_PICKUP   Class_SPECIAL
       Size(L) Cylinders    City (L/100  Hwy (L/100  Comb (L/100  Consumption  Class_COMPACT         SIZE        SIZE  Class_MINICOMPACT  Class_MINIVAN      TRUCK -        TRUCK -         PURPOSE
                                  km)         km)         km)   Comb (mpg)                                                                                SMALL       STANDARD         VEHICLE
7380  0.146667  0.076923     0.246212    0.222892    0.240909     0.327586              0            0           0                  0              0            0              0               0
7381  0.146667  0.076923     0.265152    0.259036    0.263636     0.310345              0            0           0                  0              0            0              0               0
7382  0.146667  0.076923     0.284091    0.277108    0.281818     0.275862              0            0           0                  0              0            0              0               0
7383  0.146667  0.076923     0.265152    0.259036    0.263636     0.310345              0            0           0                  0              0            0              0               0
7384  0.146667  0.076923     0.303030    0.283133    0.300000     0.258621              0            0           0                  0              0            0              0               0
```

We performed train – test split with 80% training data and 20% test data. The variable x_train, y_train, x_test, and y_test are ready to be analyzed with linear regression as based line and deep learning onward.

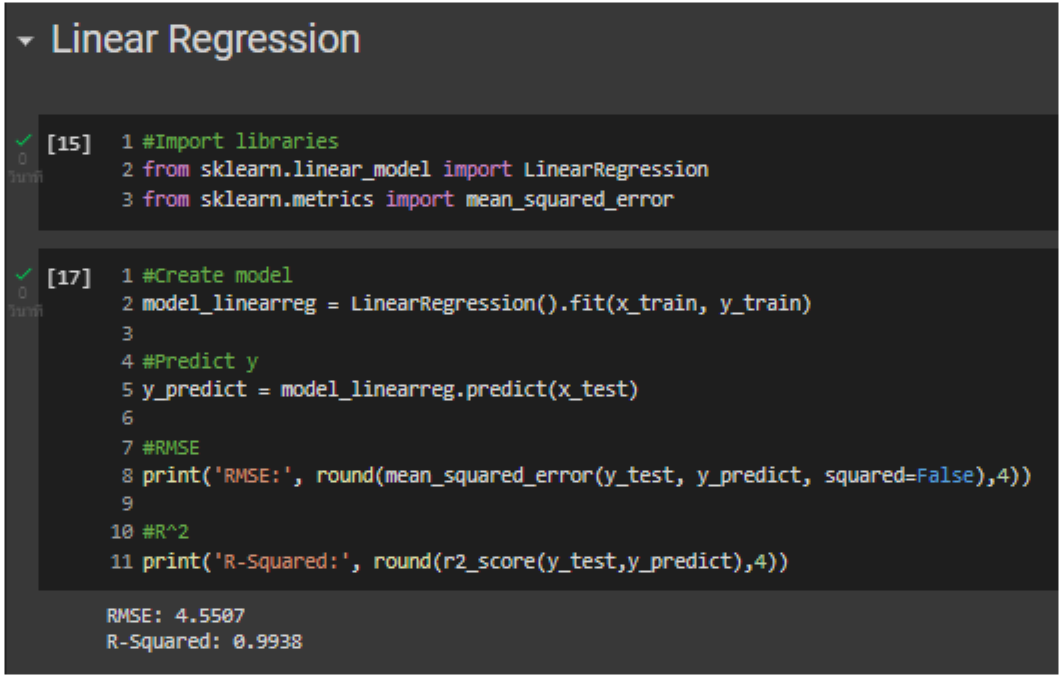


```python
[10]
#train test split
test_size = 0.2
train, test = train_test_split(df_final, test_size = test_size, random_state = 3)
```

```python
#define x and y
x_train = train.iloc[:, 0:27]
y_train = train.iloc[:, 27]
x_test = test.iloc[:, 0:27]
y_test = test.iloc[:, 27]
```

Linear Regression

After fine-tuned linear regression model, the result shows the RMSE = 4.5507 with R^2 = 0.9938



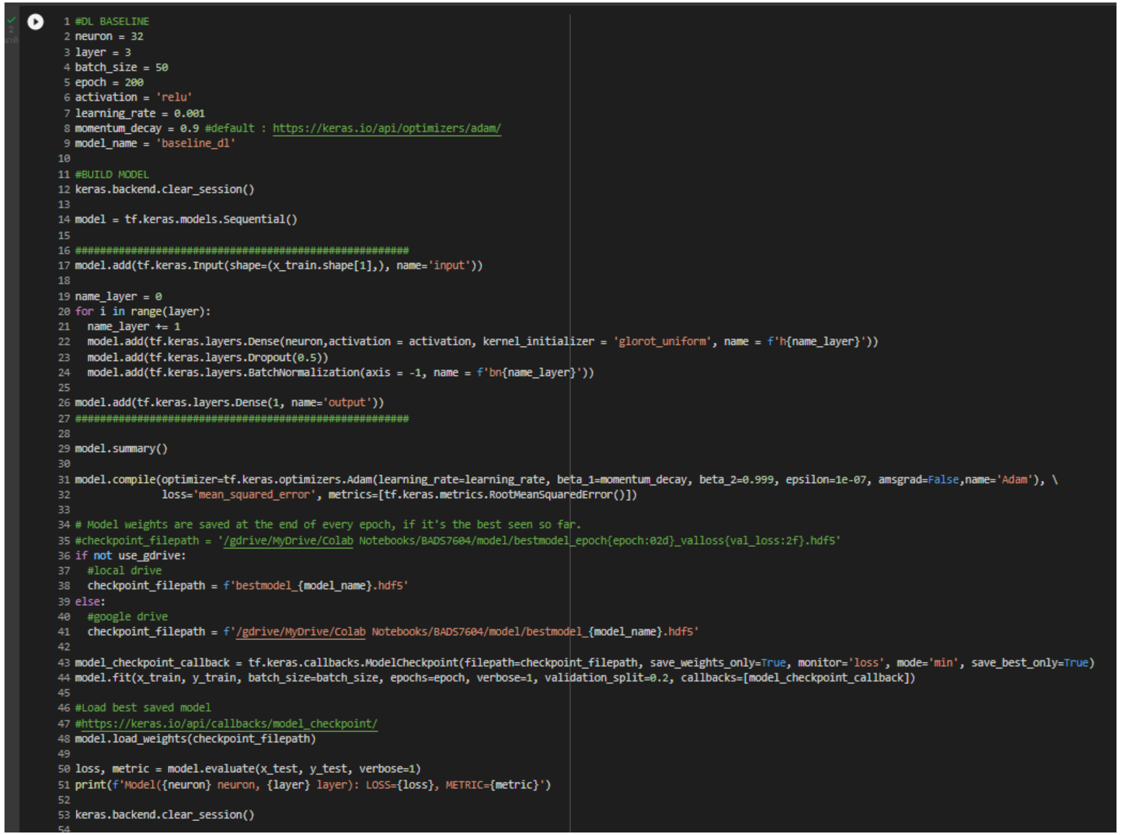
Linear Regression

[15]
```python
#Import libraries
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

[17]
```python
#Create model
model_linearreg = LinearRegression().fit(x_train, y_train)

#Predict y
y_predict = model_linearreg.predict(x_test)

#RMSE
print('RMSE:', round(mean_squared_error(y_test, y_predict, squared=False),4))

#R^2
print('R-Squared:', round(r2_score(y_test,y_predict),4))
```

```
RMSE: 4.5507
R-Squared: 0.9938
```

Deep Learning

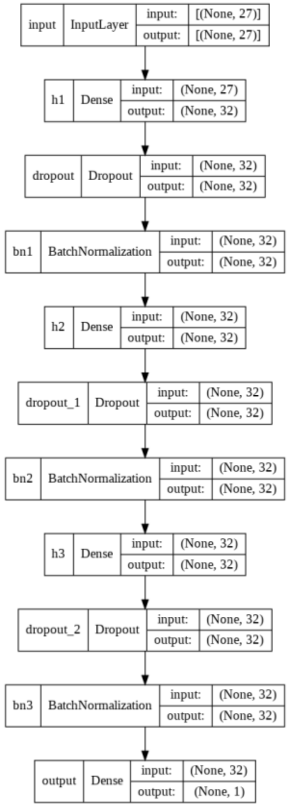


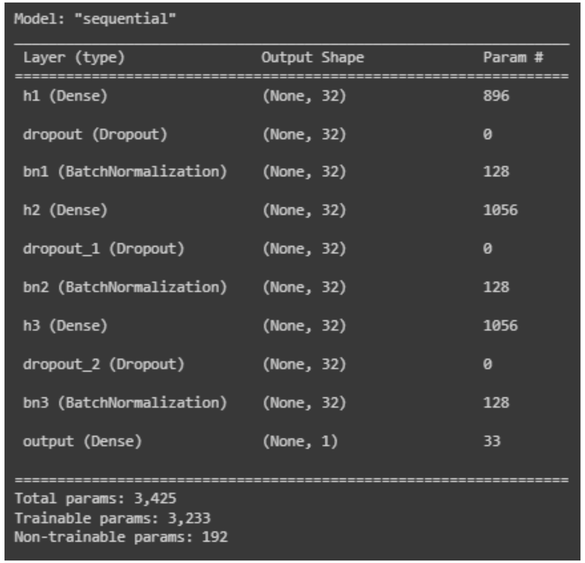
```python
#DL BASELINE
neuron = 32
layer = 3
batch_size = 50
epoch = 200
activation = 'relu'
learning_rate = 0.001
momentum_decay = 0.9 #default : https://keras.io/api/optimizers/adam/
model_name = 'baseline_dl'

#BUILD MODEL
keras.backend.clear_session()

model = tf.keras.models.Sequential()

######################################################
model.add(tf.keras.Input(shape=(x_train.shape[1],), name='input'))

name_layer = 0
for i in range(layer):
  name_layer += 1
  model.add(tf.keras.layers.Dense(neuron,activation = activation, kernel_initializer = 'glorot_uniform', name = f'h{name_layer}'))
  model.add(tf.keras.layers.Dropout(0.5))
  model.add(tf.keras.layers.BatchNormalization(axis = -1, name = f'bn{name_layer}'))

model.add(tf.keras.layers.Dense(1, name='output'))
######################################################

model.summary()

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate, beta_1=momentum_decay, beta_2=0.999, epsilon=1e-07, amsgrad=False,name='Adam'), \
              loss='mean_squared_error', metrics=[tf.keras.metrics.RootMeanSquaredError()])

# Model weights are saved at the end of every epoch, if it's the best seen so far.
#checkpoint_filepath = '/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_epoch{epoch:02d}_valloss{val_loss:2f}.hdf5'
if not use_gdrive:
  #local drive
  checkpoint_filepath = f'bestmodel_{model_name}.hdf5'
else:
  #google drive
  checkpoint_filepath = f'/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_{model_name}.hdf5'

model_checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_filepath, save_weights_only=True, monitor='loss', mode='min', save_best_only=True)
model.fit(x_train, y_train, batch_size=batch_size, epochs=epoch, verbose=1, validation_split=0.2, callbacks=[model_checkpoint_callback])

#Load best saved model
#https://keras.io/api/callbacks/model_checkpoint/
model.load_weights(checkpoint_filepath)

loss, metric = model.evaluate(x_test, y_test, verbose=1)
print(f'Model({neuron} neuron, {layer} layer): LOSS={loss}, METRIC={metric}')

keras.backend.clear_session()

```

We constructs the MLP deep learning model with initial parameters:

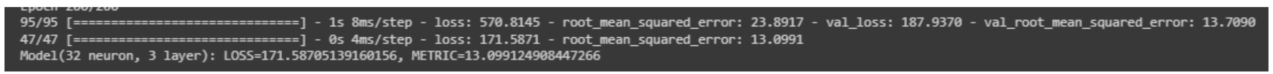
- neuron = 32
- layer = 3
- batch_size = 50
- epoch = 200
- activation = 'relu'
- learning_rate = 0.001
- momentum_decay = 0.9

Deep Learning


input | InputLayer | input: [(None, 27)] | output: [(None, 27)]
h1 | Dense | input: (None, 27) | output: (None, 32)
dropout | Dropout | input: (None, 32) | output: (None, 32)
bn1 | BatchNormalization | input: (None, 32) | output: (None, 32)
h2 | Dense | input: (None, 32) | output: (None, 32)
dropout_1 | Dropout | input: (None, 32) | output: (None, 32)
bn2 | BatchNormalization | input: (None, 32) | output: (None, 32)
h3 | Dense | input: (None, 32) | output: (None, 32)
dropout_2 | Dropout | input: (None, 32) | output: (None, 32)
bn3 | BatchNormalization | input: (None, 32) | output: (None, 32)
output | Dense | input: (None, 32) | output: (None, 1)



```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 h1 (Dense)                  (None, 32)                896

 dropout (Dropout)           (None, 32)                0

 bn1 (BatchNormalization)    (None, 32)                128

 h2 (Dense)                  (None, 32)                1056

 dropout_1 (Dropout)         (None, 32)                0

 bn2 (BatchNormalization)    (None, 32)                128

 h3 (Dense)                  (None, 32)                1056

 dropout_2 (Dropout)         (None, 32)                0

 bn3 (BatchNormalization)    (None, 32)                128

 output (Dense)              (None, 1)                 33

=================================================================
Total params: 3,425
Trainable params: 3,233
Non-trainable params: 192
```



```
95/95 [==============================] - 1s 8ms/step - loss: 570.8145 - root_mean_squared_error: 23.8917 - val_loss: 187.9370 - val_root_mean_squared_error: 13.7090
47/47 [==============================] - 0s 4ms/step - loss: 171.5871 - root_mean_squared_error: 13.0991
Model(32 neuron, 3 layer): LOSS=171.58705139160156, METRIC=13.099124908447266
```

The model architecture is shown here with initial RMSE = 13.10

Neurons and Layers Variation

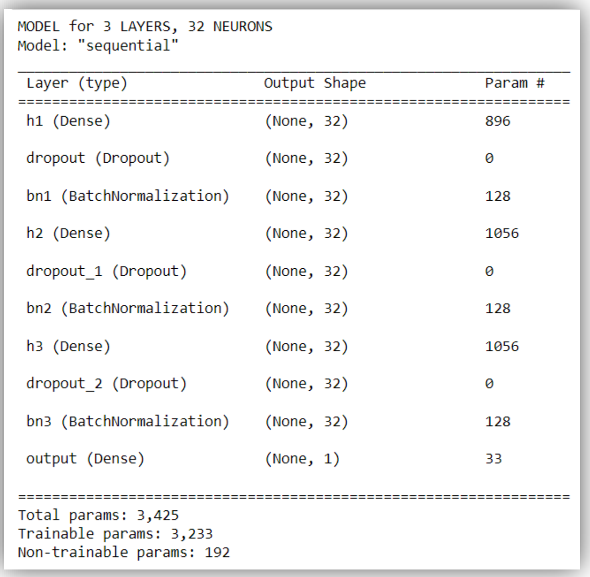
Variation Specifications

- Neuron's variation = [32, 128, 512, 2048]

- Layers variation = [3, 7, 11, 15]

- Each layer consists of

1) one Dense Layer
2) one Dropout(prob=0.5)
3) one Batch Normalization(axis=-1)



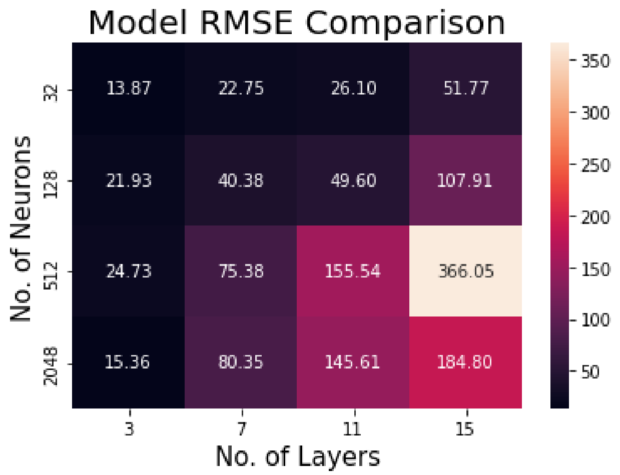
```
MODEL for 3 LAYERS, 32 NEURONS
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 h1 (Dense)                  (None, 32)                896

 dropout (Dropout)           (None, 32)                0

 bn1 (BatchNormalization)    (None, 32)                128

 h2 (Dense)                  (None, 32)                1056

 dropout_1 (Dropout)         (None, 32)                0

 bn2 (BatchNormalization)    (None, 32)                128

 h3 (Dense)                  (None, 32)                1056

 dropout_2 (Dropout)         (None, 32)                0

 bn3 (BatchNormalization)    (None, 32)                128

 output (Dense)              (None, 1)                 33

=================================================================
Total params: 3,425
Trainable params: 3,233
Non-trainable params: 192
```

Example:
Model summary of 32 neurons and 3 layers
(baseline model)

Neurons and Layers Variation

Results

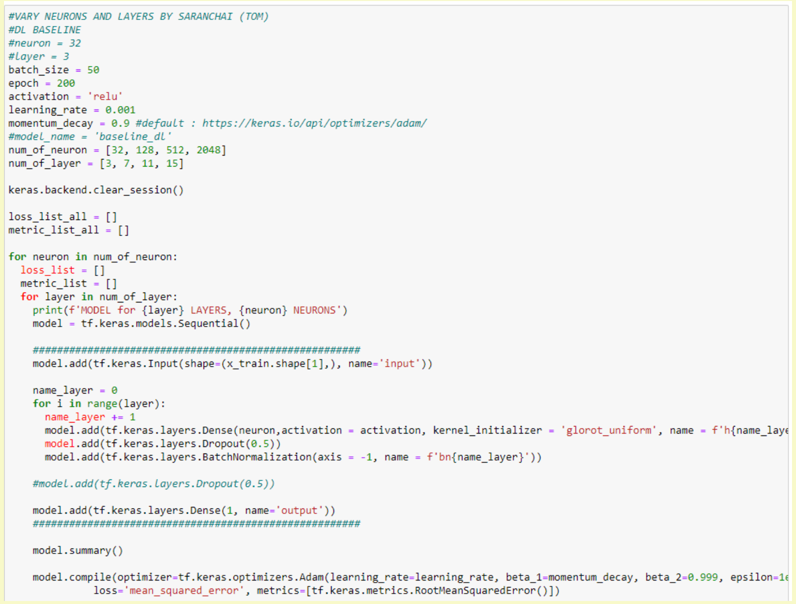
- Model with 32 neurons and 3 layers gives the best fit with 13.87 root mean square error
- Adding more neuron or more layer tend to worsen the model efficiency
- This can be caused from the data overfitting



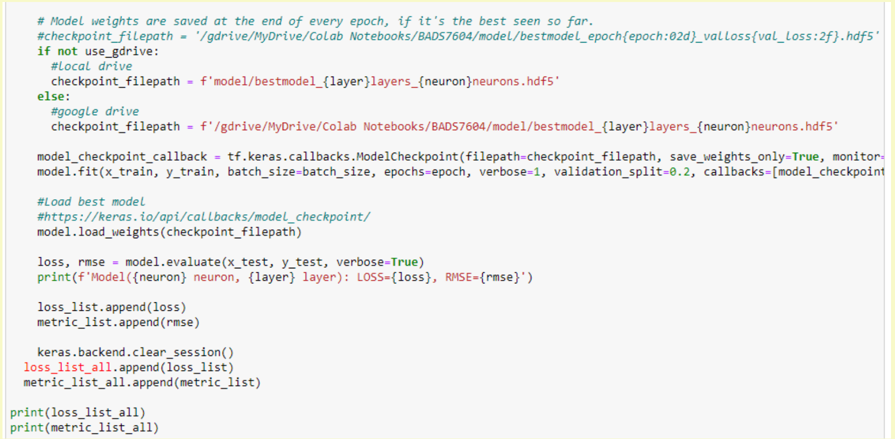
Model RMSE Comparison

Neurons and Layers Variation

Code



```
#VARY NEURONS AND LAYERS BY SARANCHAI (TOM)
#DL BASELINE
#neuron = 32
#layer = 3
batch_size = 50
epoch = 200
activation = 'relu'
learning_rate = 0.001
momentum_decay = 0.9 #default : https://keras.io/api/optimizers/adam/
#model_name = 'baseline_dl'
num_of_neuron = [32, 128, 512, 2048]
num_of_layer = [3, 7, 11, 15]

keras.backend.clear_session()

loss_list_all = []
metric_list_all = []

for neuron in num_of_neuron:
  loss_list = []
  metric_list = []
  for layer in num_of_layer:
    print(f'MODEL for {layer} LAYERS, {neuron} NEURONS')
    model = tf.keras.models.Sequential()

    ######################################################
    model.add(tf.keras.Input(shape=(x_train.shape[1],), name='input'))

    name_layer = 0
    for i in range(layer):
      name_layer += 1
      model.add(tf.keras.layers.Dense(neuron,activation = activation, kernel_initializer = 'glorot_uniform', name = f'h{name_laye
      model.add(tf.keras.layers.Dropout(0.5))
      model.add(tf.keras.layers.BatchNormalization(axis = -1, name = f'bn{name_layer}'))

    #model.add(tf.keras.layers.Dropout(0.5))

    model.add(tf.keras.layers.Dense(1, name='output'))
    ######################################################

    model.summary()

    model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate, beta_1=momentum_decay, beta_2=0.999, epsilon=1e
              loss='mean_squared_error', metrics=[tf.keras.metrics.RootMeanSquaredError()])
```

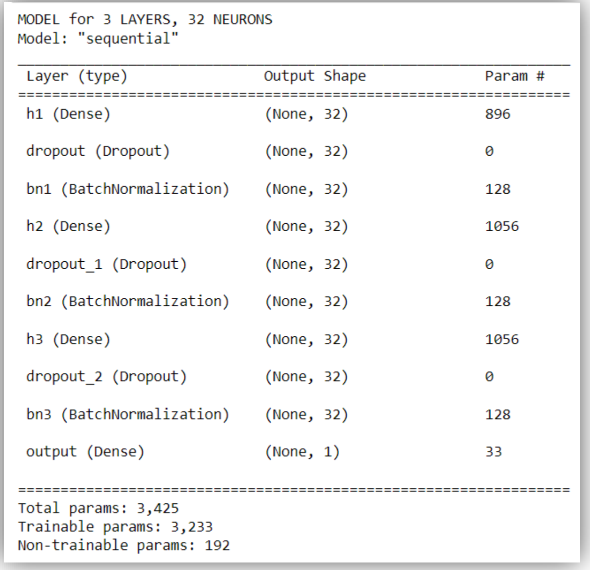


```
    # Model weights are saved at the end of every epoch, if it's the best seen so far.
    #checkpoint_filepath = '/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_epoch{epoch:02d}_valloss{val_loss:2f}.hdf5'
    if not use_gdrive:
      #local drive
      checkpoint_filepath = f'model/bestmodel_{layer}layers_{neuron}neurons.hdf5'
    else:
      #google drive
      checkpoint_filepath = f'/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_{layer}layers_{neuron}neurons.hdf5'

    model_checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_filepath, save_weights_only=True, monitor=
    model.fit(x_train, y_train, batch_size=batch_size, epochs=epoch, verbose=1, validation_split=0.2, callbacks=[model_checkpoint

    #Load best model
    #https://keras.io/api/callbacks/model_checkpoint/
    model.load_weights(checkpoint_filepath)

    loss, rmse = model.evaluate(x_test, y_test, verbose=True)
    print(f'Model({neuron} neuron, {layer} layer): LOSS={loss}, RMSE={rmse}')

    loss_list.append(loss)
    metric_list.append(rmse)

    keras.backend.clear_session()
  loss_list_all.append(loss_list)
  metric_list_all.append(metric_list)

print(loss_list_all)
print(metric_list_all)
```

Batch Size and Epoch Variation

Variation Specifications

- Batch size variation = [50, 100, 150, 200]
- Epoch variation = [50, 100, 200]
- The rest of the model follow the baseline model



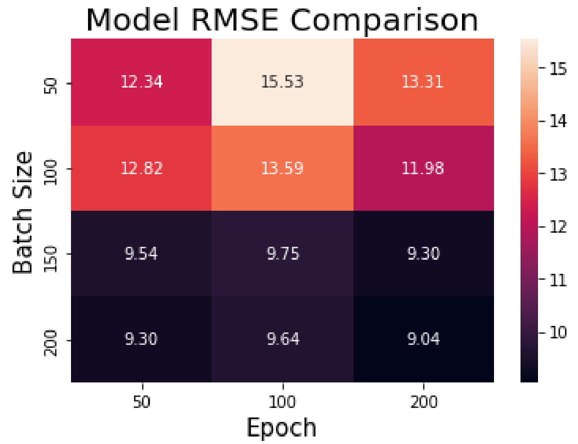
```
MODEL for 3 LAYERS, 32 NEURONS
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 h1 (Dense)                  (None, 32)                896

 dropout (Dropout)           (None, 32)                0

 bn1 (BatchNormalization)    (None, 32)                128

 h2 (Dense)                  (None, 32)                1056

 dropout_1 (Dropout)         (None, 32)                0

 bn2 (BatchNormalization)    (None, 32)                128

 h3 (Dense)                  (None, 32)                1056

 dropout_2 (Dropout)         (None, 32)                0

 bn3 (BatchNormalization)    (None, 32)                128

 output (Dense)              (None, 1)                 33

=================================================================
Total params: 3,425
Trainable params: 3,233
Non-trainable params: 192
```

Example:
Model summary of 32 neurons and 3 layers
(baseline model)

Batch Size and Epoch Variation

Results

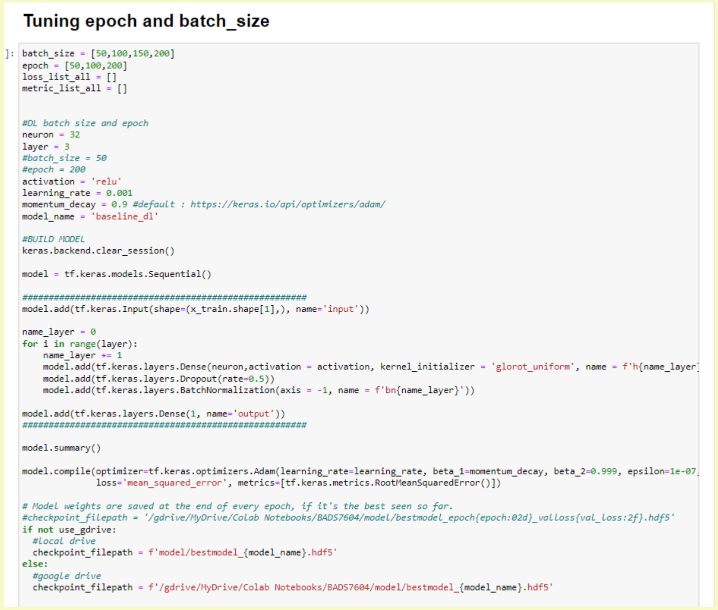
- Model with 200 batch size and 200 epochs gives the best fit with 9.04 root mean square error
- Adding more batch size or more epoch tend to improve the model efficiency



Model RMSE Comparison

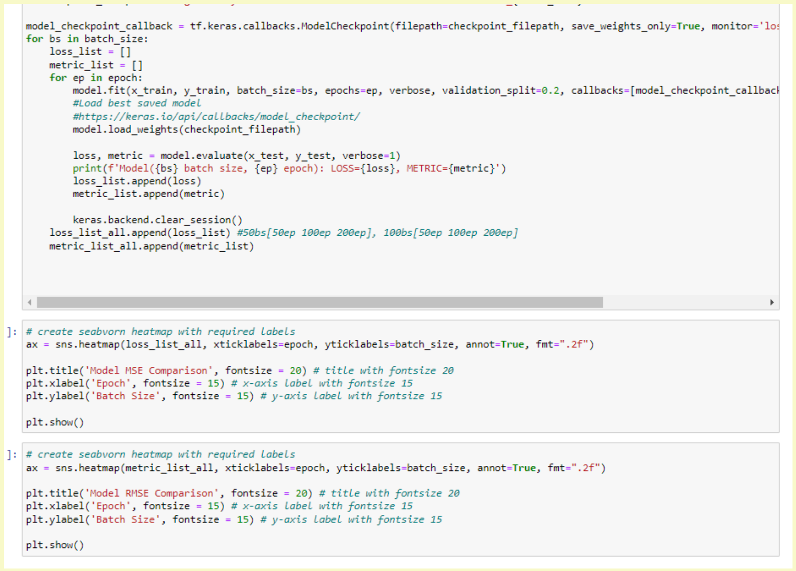
Batch Size and Epoch Variation

Code



Tuning epoch and batch_size

```
]: batch_size = [50,100,150,200]
epoch = [50,100,200]
loss_list_all = []
metric_list_all = []


#DL batch size and epoch
neuron = 32
layer = 3
#batch_size = 50
#epoch = 200
activation = 'relu'
learning_rate = 0.001
momentum_decay = 0.9 #default : https://keras.io/api/optimizers/adam/
model_name = 'baseline_dl'

#BUILD MODEL
keras.backend.clear_session()

model = tf.keras.models.Sequential()

######################################################
model.add(tf.keras.Input(shape=(x_train.shape[1],), name='input'))

name_layer = 0
for i in range(layer):
    name_layer += 1
    model.add(tf.keras.layers.Dense(neuron,activation = activation, kernel_initializer = 'glorot_uniform', name = f'h{name_layer}
    model.add(tf.keras.layers.Dropout(rate=0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = f'bn{name_layer}'))

model.add(tf.keras.layers.Dense(1, name='output'))
######################################################

model.summary()

model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate, beta_1=momentum_decay, beta_2=0.999, epsilon=1e-07,
              loss='mean_squared_error', metrics=[tf.keras.metrics.RootMeanSquaredError()])

# Model weights are saved at the end of every epoch, if it's the best seen so far.
#checkpoint_filepath = '/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_epoch{epoch:02d}_valloss{val_loss:2f}.hdf5'
if not use_gdrive:
  #local drive
  checkpoint_filepath = f'model/bestmodel_{model_name}.hdf5'
else:
  #google drive
  checkpoint_filepath = f'/gdrive/MyDrive/Colab Notebooks/BADS7604/model/bestmodel_{model_name}.hdf5'
```



```
model_checkpoint_callback = tf.keras.callbacks.ModelCheckpoint(filepath=checkpoint_filepath, save_weights_only=True, monitor='los
for bs in batch_size:
    loss_list = []
    metric_list = []
    for ep in epoch:
        model.fit(x_train, y_train, batch_size=bs, epochs=ep, verbose, validation_split=0.2, callbacks=[model_checkpoint_callback
        #Load best saved model
        #https://keras.io/api/callbacks/model_checkpoint/
        model.load_weights(checkpoint_filepath)

        loss, metric = model.evaluate(x_test, y_test, verbose=1)
        print(f'Model({bs} batch size, {ep} epoch): LOSS={loss}, METRIC={metric}')
        loss_list.append(loss)
        metric_list.append(metric)

        keras.backend.clear_session()
    loss_list_all.append(loss_list) #50bs[50ep 100ep 200ep], 100bs[50ep 100ep 200ep]
    metric_list_all.append(metric_list)
```

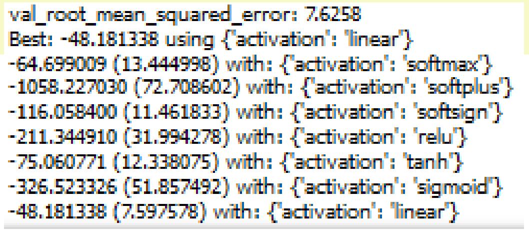
```
]: # create seabvorn heatmap with required labels
ax = sns.heatmap(loss_list_all, xticklabels=epoch, yticklabels=batch_size, annot=True, fmt=".2f")

plt.title('Model MSE Comparison', fontsize = 20) # title with fontsize 20
plt.xlabel('Epoch', fontsize = 15) # x-axis label with fontsize 15
plt.ylabel('Batch Size', fontsize = 15) # y-axis label with fontsize 15

plt.show()
```

```
]: # create seabvorn heatmap with required labels
ax = sns.heatmap(metric_list_all, xticklabels=epoch, yticklabels=batch_size, annot=True, fmt=".2f")

plt.title('Model RMSE Comparison', fontsize = 20) # title with fontsize 20
plt.xlabel('Epoch', fontsize = 15) # x-axis label with fontsize 15
plt.ylabel('Batch Size', fontsize = 15) # y-axis label with fontsize 15

plt.show()
```

Activation function and Learning rate variation

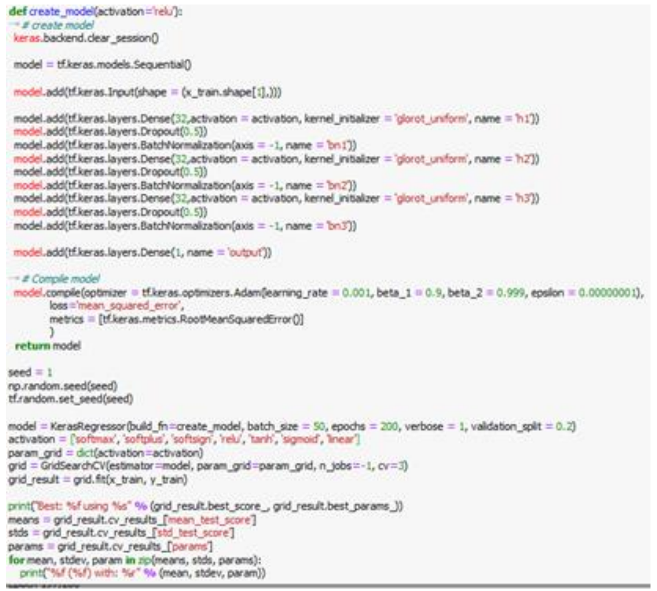
Variation Specifications

- Activation function's variation = [Softmax, Softplus, Softsign, ReLu, Tanh, sigmoid, linear]
- The scikit-learn library has a unified model scoring system where it assumes that all model scores are maximized. In order this system to work with scores that are minimized, like MSE , the scores that are minimized are inverted by making them negative. Thus, we see the negative result of MSE



```
val_root_mean_squared_error: 7.6258
Best: -48.181338 using {'activation': 'linear'}
-64.699009 (13.444998) with: {'activation': 'softmax'}
-1058.227030 (72.708602) with: {'activation': 'softplus'}
-116.058400 (11.461833) with: {'activation': 'softsign'}
-211.344910 (31.994278) with: {'activation': 'relu'}
-75.060771 (12.338075) with: {'activation': 'tanh'}
-326.523326 (51.857492) with: {'activation': 'sigmoid'}
-48.181338 (7.597578) with: {'activation': 'linear'}
```

Result of activation function Gridsearching



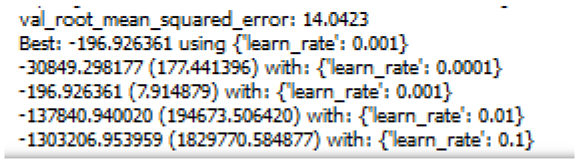
```
def create_model(activation='relu'):
    # create model
    keras.backend.clear_session()

    model = tf.keras.models.Sequential()

    model.add(tf.keras.Input(shape = (x_train.shape[1],)))

    model.add(tf.keras.layers.Dense(32,activation = activation, kernel_initializer = 'glorot_uniform', name = 'h1'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn1'))
    model.add(tf.keras.layers.Dense(32,activation = activation, kernel_initializer = 'glorot_uniform', name = 'h2'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn2'))
    model.add(tf.keras.layers.Dense(32,activation = activation, kernel_initializer = 'glorot_uniform', name = 'h3'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn3'))

    model.add(tf.keras.layers.Dense(1, name = 'output'))

    # Compile model
    model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001, beta_1 = 0.9, beta_2 = 0.999, epsilon = 0.0000001),
            loss='mean_squared_error',
            metrics = [tf.keras.metrics.RootMeanSquaredError()]
            )
    return model

seed = 1
np.random.seed(seed)
tf.random.set_seed(seed)

model = KerasRegressor(build_fn=create_model, batch_size = 50, epochs = 200, verbose = 1, validation_split = 0.2)
activation = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'linear']
param_grid = dict(activation=activation)
grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1, cv=3)
grid_result = grid.fit(x_train, y_train)

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
  print("%f (%f) with: %r" % (mean, stdev, param))
```

Code for tuning activation function parameter

Activation function and Learning rate variation

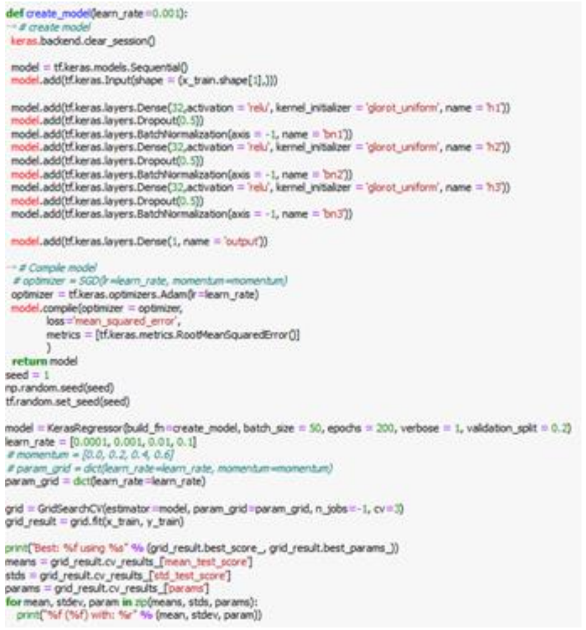
Variation Specifications

- Learning rate = [0.0001 0.001 0.01 0.1]
- Setting default learning rate to 0.001 and all hyperparameter according to baseline using Adam optimizer



```
val_root_mean_squared_error: 14.0423
Best: -196.926361 using {'learn_rate': 0.001}
-30849.298177 (177.441396) with: {'learn_rate': 0.0001}
-196.926361 (7.914879) with: {'learn_rate': 0.001}
-137840.940020 (194673.506420) with: {'learn_rate': 0.01}
-1303206.953959 (1829770.584877) with: {'learn_rate': 0.1}
```

Result of learning rate Gridsearching



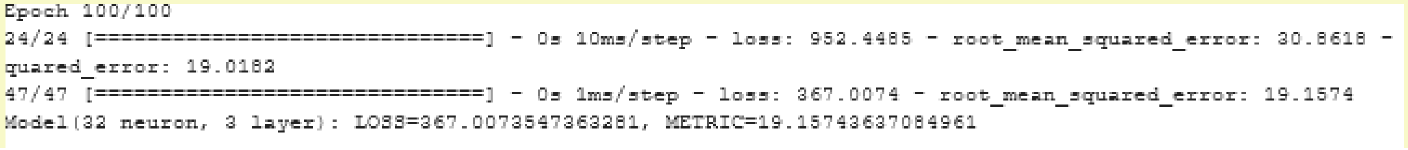
```
def create_model(learn_rate=0.001):
    # create model
    keras.backend.clear_session()

    model = tf.keras.models.Sequential()
    model.add(tf.keras.Input(shape = (x_train.shape[1],)))

    model.add(tf.keras.layers.Dense(32,activation = 'relu', kernel_initializer = 'glorot_uniform', name = 'h1'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn1'))
    model.add(tf.keras.layers.Dense(32,activation = 'relu', kernel_initializer = 'glorot_uniform', name = 'h2'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn2'))
    model.add(tf.keras.layers.Dense(32,activation = 'relu', kernel_initializer = 'glorot_uniform', name = 'h3'))
    model.add(tf.keras.layers.Dropout(0.5))
    model.add(tf.keras.layers.BatchNormalization(axis = -1, name = 'bn3'))

    model.add(tf.keras.layers.Dense(1, name = 'output'))

    # Compile model
    # optimizer = SGD(lr=learn_rate, momentum=momentum)
    optimizer = tf.keras.optimizers.Adam(lr=learn_rate)
    model.compile(optimizer = optimizer,
            loss='mean_squared_error',
            metrics = [tf.keras.metrics.RootMeanSquaredError()]
            )
    return model
seed = 1
np.random.seed(seed)
tf.random.set_seed(seed)

model = KerasRegressor(build_fn=create_model, batch_size = 50, epochs = 200, verbose = 1, validation_split = 0.2)
learn_rate = [0.0001, 0.001, 0.01, 0.1]
# momentum = [0.0, 0.2, 0.4, 0.6]
# param_grid = dict(learn_rate=learn_rate, momentum=momentum)
param_grid = dict(learn_rate=learn_rate)

grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1, cv=3)
grid_result = grid.fit(x_train, y_train)

print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

Code for tuning learning rate parameter

Deep Learning hyperparameter tuning and result

Neurons variation = [**32**, 128, 512, 2048]
Layers variation = [**3**, 7, 11, 15]
Batch_size = [**50**, 100, 150, 200]
Epoch = [100, 150, **200]**
Activation : [Softmax, Softplus, Softsign, **ReLu**, Tanh, sigmoid, linear]
Learning rate : [][0.0001, **0.001,** 0.01, 0.1]
Optimizer = **Adam**
Loss function = **MSE**
Metric = **RMSE**

Noted : Default hyperparameters setting showed in **bold** and best parameter showed in Red



```
Epoch 100/100
24/24 [==============================] - 0s 10ms/step - loss: 952.4485 - root_mean_squared_error: 30.8618 -
quared_error: 19.0182
47/47 [==============================] - 0s 1ms/step - loss: 367.0074 - root_mean_squared_error: 19.1574
Model(32 neuron, 3 layer): LOSS=367.0073547363281, METRIC=19.15743637084961
```

Result after tuning best of all parameter

Summary

According to the result, there is an interesting point needed discussion. You'll find that the result from linear regression has the RMSE = 4.55 comparing to the best result from deep learning RMSE = 19.15. It's interesting that the result from linear regression has lower RMSE value. We've discussed and found that the prediction of CO_2 from various variables may be not complex and be in the form of some correlation. Therefore, the linear regression model perform well this time.

What we learned from this experiments is how we change the deep learning parameters and monitor the performance of the model. Finally, we learned that the deep learning model won't outperform other techniques every time. We just have to pick the most suited model for each situations.