Machine Learning on Polutions from Transportation

In the following program, we would guide you through using Pandas to process the emission data for Tensorflow Machine Learning. Then we would teach you how to create and train your Tensorflow model. Answer the questions when you see $\underline{\mathbf{Q}}$; follow the steps in **To-do**. When you see something like D1 or M1 next to problems, you should refer to the rubrics to see how the the problems will be graded as those problems are worth points.

Note: Hit the "Run" button to run the program block by block. We don't recommend you to use "Run All" in "Cell" because the first few blocks only need to be run once and they take some time to run.

Import Libraries

The following block is used in Python to import necessary libraries. You might encounter error while trying to import tensorflow. This is because Tensorflow is not a default library that comes with the Python package you installed. Go to this link https://www.tensorflow.org/install/pip#system-install and follow the instructions on installing Tensorflow. If you encounter problems while trying to install Tensorflow you can add —user after pip install. This is because you did not create a virtual environment for your python packages. You can follow Step 2 on the website to create a virtual environment (recommended) or you can just install the package in your HOME environment. You might encounter error while trying to import other libraries. Please use the same pip method described above.

- pandas is used to process our data.
- numpy is a great tool for mathematical processing and array creations.
- sklearn is used to split the data into Training, Testing, and Validation set.

```
In [1]: # Import Libraries
  import pandas as pd
  import numpy as np
  import tensorflow as tf
  from tensorflow.keras import layers
  from sklearn.model_selection import train_test_split
  import seaborn as sns
  from matplotlib import pyplot as plt
```

Load and Clean up the Dataset

Load the Dataset

To process the data, save the .csv file you downloaded from the Google Drive to the same directory where this Notebook is at.

- pd.read_csv("file path") reads the data into emission_train
 - Note that we call pd directly becuase we import pandas as pd
- .head() returns the first 100 rows of data. Note that when displaying, some rows are truncated. It is normal since the rows are too long.
- .describe() shows statistical data for our data frame.

```
# loading the large data set, it may takes a while.
emission_train = pd.read_csv("UC-Emission.csv", delimiter=",", quoting = 3)
```

Here is a link that contains information about meaning of the columns in "emission.csv": https://sumo.dlr.de/docs/Simulation/Output/EmissionOutput.html

```
display(emission_train.head(100))
display(emission_train.describe())
```

	timestep_time	vehicle_CO	vehicle_CO2	vehicle_HC	vehicle_NOx	vehicle_PMx	vehicle_a
0	0.0	15.20	7380.56	0.00	84.89	2.21	5
1	0.0	0.00	2416.04	0.01	0.72	0.01	4
2	1.0	17.92	9898.93	0.00	103.38	2.49	5
3	1.0	0.00	0.00	0.00	0.00	0.00	4
4	1.0	164.78	2624.72	0.81	1.20	0.07	35
•••							
95	7.0	23.44	2578.06	0.15	0.64	0.05	
96	7.0	732.32	18759.70	3.34	3.79	1.19	17
97	7.0	294.68	6949.38	1.29	1.47	0.43	17
98	7.0	236.07	4292.19	0.97	0.93	0.30	
99	7.0	179.19	1228.61	0.64	0.31	0.17	18

100 rows × 20 columns

	timestep_time	vehicle_CO	vehicle_CO2	vehicle_HC	vehicle_NOx	vehicle_PM)
count	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07
mean	4.112561e+03	5.764304e+01	4.919050e+03	7.284125e-01	1.769589e+01	4.227491e-0 ⁻
std	2.168986e+03	8.854365e+01	7.959043e+03	1.589816e+00	5.993168e+01	1.164065e+0(
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	2.291000e+03	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
50%	4.133000e+03	2.017000e+01	2.624720e+03	1.500000e-01	1.200000e+00	6.000000e-02
75%	5.903000e+03	1.034400e+02	6.161010e+03	7.600000e-01	2.710000e+00	1.500000e-0 ⁻
max	1.441800e+04	3.932950e+03	1.153026e+05	1.729000e+01	8.864200e+02	1.432000e+0 ⁻

Visualize the Dataset

Below we use sns.pairplot() to show you the 2D plots between datasets. We only use 0.5% of the randomly extracted data from emission_train to make plots becuase using too many data might crash the program. .sample(frac=0.01) takes a fraction of sample from DataFrame randomly.

 del frees up memory for Python. However, it won't release memory back to the computer.

From the pair plots you can visualize the relationships between the data in the dataset. For example, vehicle_C02 and vehicle_fuel have a linear relationship. vehicle_C02 and vehicle_pos have a parabolic or exponential like relationship. Some data might have a relationship that is not easily identified from pair plots.

 D1 Q: What do you find from the Pairplot? Find three pairs of data and list what you observe from their pair plots.

<u>Type your questions to Q:</u> Upon observating the various plots generated below, we observed trends between the data. Three observations include:

- We observed a directly proportional linear relationship between vehicle fuel and vehicle CO2, where vehicle fuel increased by 20 for every 50,000 increase in vehicle CO2.
- Vehicle noise generally tends to increase with vehicle fuel, and vehicle noise also tends to increase with vehicle CO2.
- A majority of vehicle waiting tends to occur in a certain cross-section (near the center of the city), where x-coordinates range from 20,000 to 30,000 and y-coordinates range from 20,000 to 30,000.

```
correlation_graph_data = emission_train.sample(frac=0.05).reset_index(drop=Tr
print(len(emission_train), 'emission_train')
print(len(correlation_graph_data), 'correlation_graph_data')
sns.pairplot(correlation_graph_data[['vehicle_CO2', 'vehicle_angle', 'vehicle_
#Free up memory for Python
del correlation_graph_data
```

Clean up the Dataset

Note that there are emission data like vehicle_CO, vehicle_CO2, vehicle_HC, vehicle_NOx, vehicle_PMx in the dataset. In this lab, we only want to look at vehicle_CO2.

After looking at the data, you might notice there are a lot of data we don't want for our machine learning. For example, all the vehicle_electricity are zeros, and vehicle_route data are only used to keep track of the unique route each vehicle goes through.

Below, unwanted data are dropped. vehicle_id data are dropped because they are only used to keep track of different vehicles. vehicle_lane data are the name of the road. We dropped vehicle_lane data becuase we believed the data might not affect vehicle emissions. In practice, you should only drop the data if you have clear reasonings. For example vehicle_electricity are all zeros, so you can drop them. Even if you do not drop them, the machine learning program might be able to figure the relationship out. vehicle_route data are dropped due to the reasoning above. timestep_time data are dropped becuase they are the simulation time.

To-do:

1. D2 Drop the data we mentioned above. Also, drop the data that you think might not affect the machine learning. Q: Provide your reasonings.

<u>Type your questions to Q:</u> In addition to dropping columns vehicle_CO, vehicle_HC, vehicle_NOx, vehicle_PMx, timestep_time, and vehicle_id, we decided to drop vehicle_route, vehicle_lane, and vehicle_electricity since these values were respectively used to keep track of each vehicle's unique routes, the name of the road, and vehicle_electricity data were all zeros. Dropping these data fields will not affect vehicle_CO2 output, and thus will not affect the machine learning.

```
emission_train = emission_train.drop(columns=["vehicle_CO", "vehicle_HC", "vehicle_id", "vehicle_electricity"])
```

We seperated the block above from the block below becuase we don't want you to run pd.read_csv and emission_train.drop() twice. Reading a large csv file as you might have experienced a few minutes ago take up quite some RAM and CPU, and running .drop() twice will cause an error message to be printed out.

To-do:

1. D3 Display the **last** 100 rows of your new emission_train data. It is okay if the displayed rows are truncated in the middle.

```
display(emission_train.head(100))
display(emission_train.describe())

### Insert your code below ###
display(emission_train.tail(100))
```

	vehicle_CO2	vehicle_angle	vehicle_eclass	vehicle_fuel	vehicle_noise	vehicle_pos	V
0	7380.56	50.28	HBEFA3/HDV	3.13	67.11	7.20	
1	2416.04	42.25	HBEFA3/PC_G_EU4	1.04	65.15	5.10	
2	9898.93	50.28	HBEFA3/HDV	4.20	73.20	8.21	
3	0.00	42.25	HBEFA3/PC_G_EU4	0.00	62.72	18.85	
4	2624.72	357.00	HBEFA3/PC_G_EU4	1.13	55.94	5.10	
•••					•••	•••	
95	2578.06	0.13	HBEFA3/LDV_G_EU6	1.11	63.24	35.78	
96	18759.70	179.93	HBEFA3/LDV_G_EU6	8.07	81.67	30.96	
97	6949.38	179.93	HBEFA3/LDV_G_EU6	2.99	72.45	11.88	
98	4292.19	1.91	HBEFA3/LDV_G_EU6	1.85	71.73	5.60	
99	1228.61	180.06	HBEFA3/LDV_G_EU6	0.53	55.94	2.30	

100 rows × 11 columns

	vehicle_CO2	vehicle_angle	V	ehicle_fuel	vehicle_noise	vehicle_pos	vehicle_speed
count	1.633101e+07	1.633101e+07	1.6	33101e+07	1.633101e+07	1.633101e+07	1.633101e+07
mean	4.919050e+03	1.633698e+02	2.10	05266e+00	6.636207e+01	2.162082e+02	1.331140e+01
std	7.959043e+03	1.051232e+02	3.38	89028e+00	7.389330e+00	6.034189e+02	8.833069e+00
min	0.000000e+00	0.000000e+00	0.0	00000e+00	1.258000e+01	0.000000e+00	0.000000e+00
25%	0.000000e+00	9.031000e+01	0.00	00000e+00	6.249000e+01	2.383000e+01	6.550000e+00
50%	2.624720e+03	1.799600e+02	1.13	30000e+00	6.711000e+01	7.199000e+01	1.337000e+01
75%	6.161010e+03	2.703500e+02	2.6	50000e+00	7.112000e+01	1.780600e+02	1.999000e+01
max	1.153026e+05	3.600000e+02	4.8	88000e+01	1.019600e+02	1.943554e+04	5.013000e+01
	vehicle_C	O2 vehicle_an	gle	vehicle_ecla	ass vehicle_f	uel vehicle_nois	e vehicle_pos
16330	908 5293	3.91 1	.98	HBEFA3/I	Bus 2.	26 67.19	9 77.83
16330	909 6541	.73 2	2.07	HBEFA3/I	Bus 2.	79 71.2	1 0.69
16330	910 10387.	.44 2	.06	HBEFA3/I	Bus 4.	43 74.5	3 2.58
16330	911 12058.	.39	.62	HBEFA3/I	Bus 5	.14 73.88	5.45
16330	912 13307	.66 1	.06	HBEFA3/I	Bus 5	67 73.64	9.19
	•••						
16331	003 19817	7.16	.45	HBEFA3/I	Bus 8.	45 76.50	6 185.84
16331	004 0	.00 0	.45	HBEFA3/I	Bus 0.	00 74.1	4 199.17
16331	005 23192	.37 0	.45	HBEFA3/I	Bus 9.	89 77.18	3 212.90
16331	006 0	.00 0	.45	HBEFA3/I	Bus 0.	00 74.10	226.29
16331	007 N	laN N	NaN	N	laN N	aN Naf	N NaN

100 rows × 11 columns

By now, you would have already done some cleanups by dropping unwanted data. Below we used a for loop to cast the data in vehicle_eclass and vehicle_type to string. As you might notice that the values in both columns are texts. However, we found that the data in our csv file cannot be read correctly into Tensorflow so we added the for loop.

• .dropna().reset_index(drop=True) drops the rows that contain NaN in any columns and reset the row index.

To-do:

- 1. D4 Shuffle emission_train and save a new copy to emission_train_shuffle . Hint: Look at the function we used to extract data for the correlation graph.
- 2. D5 Display the first 100 rows of the shuffled data. It is okay if the displayed rows are truncated in the middle.
- 3. D6 Display the statistic (count, mean, std...) on the shuffled data. D7 Q: Does anything change?

<u>Type your answers to Q:</u> After comparing the statistics like count, mean, std, min, 25%, 50%, 75%, and max for both the unshuffled and shuffled data, we observed no changes; the statistics remained the same when frac=1. However, if frac is set to another value, say 0.5, certain statistics like count, mean, and std change.

```
for header in ["vehicle_eclass", "vehicle_type"]:
    emission_train[header] = emission_train[header].astype(str)

emission_train = emission_train.dropna().reset_index(drop=True)

# Shuffle the dataset
emission_train_shuffle = emission_train.sample(frac=1) #FILL IN THE CODE

### Insert your code below ###

# Display the data pre- and post- shuffle
display(emission_train.head(100))
###FILL IN THE CODE
display(emission_train_shuffle.head(100))

# Get info of the dataframe
###FILL IN THE CODE
display(emission_train_shuffle.describe())
```

	vehicle_CO2	vehicle_angle	vehicle_eclass	vehicle_fuel	vehicle_noise	vehicle_pos	V
(7380.56	50.28	HBEFA3/HDV	3.13	67.11	7.20	
,	2416.04	42.25	HBEFA3/PC_G_EU4	1.04	65.15	5.10	
2	9898.93	50.28	HBEFA3/HDV	4.20	73.20	8.21	
3	0.00	42.25	HBEFA3/PC_G_EU4	0.00	62.72	18.85	

4	2624.72	357.00	HBEFA3/PC_G_EU4	1.13	55.94	5.10
•••						
95	2578.06	0.13	HBEFA3/LDV_G_EU6	1.11	63.24	35.78
96	18759.70	179.93	HBEFA3/LDV_G_EU6	8.07	81.67	30.96
97	6949.38	179.93	HBEFA3/LDV_G_EU6	2.99	72.45	11.88
98	4292.19	1.91	HBEFA3/LDV_G_EU6	1.85	71.73	5.60
99	1228.61	180.06	HBEFA3/LDV_G_EU6	0.53	55.94	2.30

100 rows × 11 columns

	vehicle_CO2	vehicle_angle	vehicle_eclass	vehicle_fuel	vehicle_noise	vehicle_
15886555	2709.26	272.11	HBEFA3/PC_G_EU4	1.16	60.01	{
9005659	7645.30	180.42	HBEFA3/PC_G_EU4	3.29	69.02	3
13455892	0.00	272.16	HBEFA3/PC_G_EU4	0.00	60.22	160
8736385	2544.18	308.17	HBEFA3/PC_G_EU4	1.09	63.65	4,
6900660	2397.80	302.55	HBEFA3/PC_G_EU4	1.03	64.85	81
•••						
13204731	2457.83	0.88	HBEFA3/PC_G_EU4	1.06	60.54	4
7337242	2624.72	89.84	HBEFA3/PC_G_EU4	1.13	55.94	64
10371264	0.00	90.15	HBEFA3/PC_G_EU4	0.00	63.65	1
1334692	0.00	0.08	HBEFA3/PC_G_EU4	0.00	67.21	5
4381848	0.00	120.44	HBEFA3/PC_G_EU4	0.00	55.92	1;

100 rows × 11 columns

	vehicle_CO2	vehicle_angle	vehicle_fuel	vehicle_noise	vehicle_pos	vehicle_speed
count	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07
mean	4.919050e+03	1.633698e+02	2.105266e+00	6.636207e+01	2.162082e+02	1.331140e+01
std	7.959043e+03	1.051232e+02	3.389028e+00	7.389330e+00	6.034189e+02	8.833069e+00
min	0.000000e+00	0.000000e+00	0.000000e+00	1.258000e+01	0.000000e+00	0.000000e+00
25%	0.000000e+00	9.031000e+01	0.000000e+00	6.249000e+01	2.383000e+01	6.550000e+00
50%	2.624720e+03	1.799600e+02	1.130000e+00	6.711000e+01	7.199000e+01	1.337000e+01
75%	6.161010e+03	2.703500e+02	2.650000e+00	7.112000e+01	1.780600e+02	1.999000e+01
max	1.153026e+05	3.600000e+02	4.888000e+01	1.019600e+02	1.943554e+04	5.013000e+01

```
In [9]:
```

```
emission_train_shuffle = emission_train.sample(frac=0.5) #Re-set frac value
display(emission_train.describe())
display(emission_train_shuffle.describe())
```

	vehicle_CO2	vehicle_angle	vehicle_fuel	vehicle_noise	vehicle_pos	vehicle_speed
count	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07	1.633101e+07
mean	4.919050e+03	1.633698e+02	2.105266e+00	6.636207e+01	2.162082e+02	1.331140e+01
std	7.959043e+03	1.051232e+02	3.389028e+00	7.389330e+00	6.034189e+02	8.833069e+00
min	0.000000e+00	0.000000e+00	0.000000e+00	1.258000e+01	0.000000e+00	0.000000e+00
25%	0.000000e+00	9.031000e+01	0.000000e+00	6.249000e+01	2.383000e+01	6.550000e+00
50%	2.624720e+03	1.799600e+02	1.130000e+00	6.711000e+01	7.199000e+01	1.337000e+01
75%	6.161010e+03	2.703500e+02	2.650000e+00	7.112000e+01	1.780600e+02	1.999000e+01
max	1.153026e+05	3.600000e+02	4.888000e+01	1.019600e+02	1.943554e+04	5.013000e+01
	vehicle CO2	vehicle angle	vehicle fuel	vehicle noise	vehicle nos	vehicle speed
	vehicle_CO2	vehicle_angle	vehicle_fuel	vehicle_noise	vehicle_pos	vehicle_speed
count	vehicle_CO2 8.165504e+06	vehicle_angle 8.165504e+06	vehicle_fuel 8.165504e+06	vehicle_noise 8.165504e+06	vehicle_pos 8.165504e+06	vehicle_speed 8.165504e+06
count	_			_		
	8.165504e+06	8.165504e+06	8.165504e+06	8.165504e+06	8.165504e+06	8.165504e+06
mean	8.165504e+06 4.923362e+03	8.165504e+06 1.634167e+02	8.165504e+06 2.107105e+00	8.165504e+06 6.636414e+01	8.165504e+06 2.160551e+02	8.165504e+06 1.331269e+01
mean std	8.165504e+06 4.923362e+03 7.965866e+03	8.165504e+06 1.634167e+02 1.051208e+02	8.165504e+06 2.107105e+00 3.391924e+00	8.165504e+06 6.636414e+01 7.389251e+00	8.165504e+06 2.160551e+02 6.030814e+02	8.165504e+06 1.331269e+01 8.831753e+00
mean std min	8.165504e+06 4.923362e+03 7.965866e+03 0.000000e+00	8.165504e+06 1.634167e+02 1.051208e+02 0.000000e+00	8.165504e+06 2.107105e+00 3.391924e+00 0.000000e+00	8.165504e+06 6.636414e+01 7.389251e+00 1.258000e+01	8.165504e+06 2.160551e+02 6.030814e+02 0.000000e+00	8.165504e+06 1.331269e+01 8.831753e+00 0.000000e+00
mean std min 25%	8.165504e+06 4.923362e+03 7.965866e+03 0.000000e+00	8.165504e+06 1.634167e+02 1.051208e+02 0.000000e+00 9.031000e+01	8.165504e+06 2.107105e+00 3.391924e+00 0.000000e+00 0.000000e+00	8.165504e+06 6.636414e+01 7.389251e+00 1.258000e+01 6.249000e+01	8.165504e+06 2.160551e+02 6.030814e+02 0.000000e+00 2.381000e+01	8.165504e+06 1.331269e+01 8.831753e+00 0.000000e+00 6.560000e+00

Stop

Before you proceed, make sure you finish reading "Machine Learning Introduction" in Step 3 of the lab. You should complete the Tensorflow playground exercise and take a screenshot of your results.

Split Data for Machine Learning

In machine learning, we often want to split our data into Training Set, Validation Set, and Test Set.

- **Training Set**: Training Set is used to train our machine learning model while the Validation and Test Set aren't.
- Validation Set: Having a Validation Set prevents overfitting of our machine learning model. Overfitting is when our model is tuned perfectly for a specific set of data, but is fitted poorly for other set of data. Take our traffic emission data for example. If the data predicts CO_2 emission data within 10 mse (mean squared error) from Training Set, but predicts emission data over 50 mse from Validation data. Then we could see that the model is overfitted.
- **Test Set**: Test set is used to evaluate the final model.

A typical workflow will be:

- 1. Train your model using Training Set.
- 2. Validate your model using Validation Set.
- 3. Adjust your model using results from Validation Set.
- 4. Pick the model that produces best results from using *Validation Set*.
- 5. Confirm your model with *Test Set*.

To-Do:

- 1. Don't change the test_size=0.99 in the first split.
- 2. Tweak the test_size= values for spilitting train_df, test_df, and val_df.
- 3. You will come back and change some codes after you finish your first training. Instructions will be provided in the "Train the Model" section.

```
train_df, backup_df = train_test_split(emission_train_shuffle, test_size=0.99
# Edit the test_size below.

# train_df, test_df = train_test_split(emission_train_shuffle, test_size=0.1)
train_df, test_df = train_test_split(train_df, test_size=0.1) # Comment for 1
train_df, val_df = train_test_split(train_df, test_size=0.2)

print(len(backup_df), 'backup data')
print(len(train_df), 'train examples')
print(len(val_df), 'validation examples')
print(len(test_df), 'test examples')

# del emission_train
```

Normalize the Input Data (Optional)

Sometimes when there are huge value differences between input features, we want to scale them to get a better training result. In this lab you are not required to use normalization. But if you cannot get a nice machine learning result, you can try normalizing the data. Below, we used Z normalization. It is just a normalization method. If you normalize your training data, make sure to also **normalize the validation and test data**. Note that train_df_norm = train_df won't copy train_df to train_df_norm. Changing the values in train_df_norm will affect the values in train_df . So if you decide to revert the normalization after you run the code block below, run the code block under "Split Data for Machine Learning" again and run only the train_df_norm = train_df below. (Comment out the code using # sign.)

Z Normalization Equation:

$$z = \frac{x - \mu}{\sigma}$$

z: Normalized Data x: Original Data

 μ : Mean of x

 σ : Standard Deviation of x

```
In [205...
# Z-Score Normalizing
# train_df_norm = train_df

# for header in ["vehicle_electricity", "vehicle_fuel", "vehicle_noise", "veh

# train_df_norm[header] = (train_df[header] - train_df[header].mean()) /
# train_df_norm[header] = train_df_norm[header].fillna(0)

### Insert your code below (optional) ###
# Normalize the validation data

# Normalize the test data

# print(train_df_norm.head())
```

Organize Features

Classify Features

We need to define our feature columns so that the program knows what type of features are used in the training. In emission data, there are two types of features: numeric (floating point, int, etc.) and categorical/indicator (for example, 'color', 'gender'; 'color' column can contain 'red', 'blue', etc.).

To Do:

1. M¹Organize the numeric columns. Also fill in the numeric columns' names in your dataset. Remember that you dropped some values already. Only put the names of the columns that are still in your dataset. Refer to "Classify structured data with feature columns" under "Tensorflow Tutorials" section on the Tensorflow website. Link: https://www.tensorflow.org/tutorials/structured_data/feature_columns

```
In [206...
          # Create an empty list
          feature cols = []
          # Numeric Columns
          numeric_col_names = ["vehicle_fuel", "vehicle_speed"]
          for header in numeric_col_names: ### Finish the list on the left
              ### Insert your code ###
              numeric column = tf.feature column.numeric column(header)
              feature_cols.append(numeric_column)
          # Indicator Columns
          indicator_col_names = ["vehicle_type"] # removed "vehicle_eclass"
          for col name in indicator col names:
              categorical column = tf.feature column.categorical column with vocabulary
              indicator column = tf.feature column.indicator column(categorical column)
              feature cols.append(indicator column)
          print("Feature columns: ", feature cols, "\n")
```

Feature columns: [NumericColumn(key='vehicle_fuel', shape=(1,), default_value =None, dtype=tf.float32, normalizer_fn=None), NumericColumn(key='vehicle_speed ', shape=(1,), default_value=None, dtype=tf.float32, normalizer_fn=None), Indi catorColumn(categorical_column=VocabularyListCategoricalColumn(key='vehicle_ty pe', vocabulary_list=('pt_bus', 'veh_passenger', 'moto_motorcycle', 'bus_bus', 'truck truck'), dtype=tf.string, default value=-1, num oov buckets=0))]

Create a Feature Layer

Feature layer will the input to our machine learning. We need to create a feature layer to be added into the machine learning model.

```
# Create a feature layer for tf
feature_layer = tf.keras.layers.DenseFeatures(feature_cols, name='Features')
```

Create and Train the Model

Create Model

- model.add(): add layer to model
- In tf.keras.layers.Dense()
 - units: number of nodes in that layer
 - activation : activation function used in that layer
 - kernel_regularizer : regularization function used in that layer
 - name : is just for us to keep track and debug
- In model.compile()
 - optimizer=tf.keras.optimizers.Adam(lr=learning_rate) : Used to improve performance of the training
 - Adam : stochastic gradient descent method
 - loss: update the model according to specified loss function
 - metrics : evaluate the model according specified metrics

Train the Model

- We first split our Pandas dataframe into features and labels.
- Then model.fit() trains our model.
- logdir, tensorboard_callback is to save training logs to be used in Tensorboard.
- Notice that there are 2 model.fit() function calls with one being commented out. The one without callbacks=[tensorboard_callback] is used in this program for large dataset training.

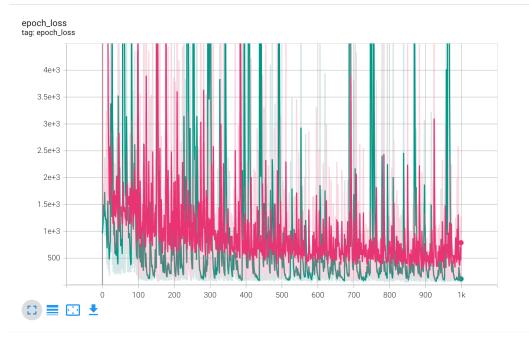
Instructions for Training Small and Large Data

As we mentioned in the lab document, hyperparameters affect the performance of your model. In the following blocks, you would be training your model. We also want you to experience training both a small dataset and a large dataset.

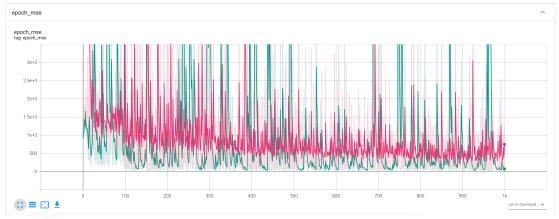
To-do:

Small Dataset:

- 1. The program cells you ran until now prepare you for small dataset training. You don't need to adjust the test_size=0.99 in "Split Data for Machine Learning".
- 2. Adjust the Hyperparameters (learning rate, batch size, epochs, hidden layer number, node number). Add in additional hidden layers as needed. Remember, a large learning rate might cause the model to never converge, but a very small learning rate would cause the model to converge very slow. If your mse (mean squared error) is decreasing but your program finishes before the mse reaches a small number, increase your epochs. Lastly, start with a small batch size. Smaller batch size often gives a better training result. A large batch size often causes poor convergence, and it might also lead to poor generalization and slow training speed. Try batch sizes of 100, 500, 1000.
- 3. In the function definitions (previous code block):
 - Press the stop button (interrupt the kernal) next to Run before you change the values in the functions above.
 - Add or reduce Hidden layers if your model turns our poorly.
 - Adjust the amount of nodes in each Hidden layer.
 - Try out different activation functions.
 - Try different regularizers.
 - You should aim to get an mse < 100. Note, we will grade your results based on mse.
- 4. M2 Once you get a result with nice mse, run the block %tensorboard --logdir logs . Then take screenshots that show your **epoch_loss** and your **epoch_mse**.
 - Screenshot showing Epoch Loss



Screenshot showing Epoch MSE



Large Dataset:

- 1. Adjust the codes in "Split Data for Machine Learning" so that no data go to backup_df.
- 2. Go to previous code block and use the model.fit() without callbacks= [tensorboard_callback]. Remember to comment out the one with callbacks=[tensorboard_callback].
- 3. Adjust the Hyperparameters (learning rate, batch size, epochs, hidden layer number, node number). Remember, a large learning rate might cause the model to never converge, but a very small learning rate would cause the model to converge very slow. If your mse (mean squared error) is decreasing but your program finishes before the mse reaches a small number, increase your epochs. Smaller batch size often gives a better training result. A large batch size often causes poor convergence, and it might also lead to poor generalization and slow training speed. Try batch sizes of 1000, 10000, 200000. M3Q: Do you notice any difference

- 4. In the function definitions:
 - Press the stop button (interrupt the kernal) next to Run before you change the values in the functions above.
 - Add or reduce Hidden layers if your model turns our poorly.
 - Adjust the amount of nodes in each Hidden layer.
 - Try out different activation functions.
 - Try different regularizers.
 - You should aim to get an mse < 200. Note, we will grade your results based on mse.
- 5. M4 The program will run for a longer time with large dataset input. Once you get a result with nice mse, you don't have to run %tensorboard --logdir logs. Move on to sections below. We would have you save a PDF once you reach the end of this Notebook. We will look at your training for the large dataset based on the logs printed out during each epoch.

Note: Ignore the warnings at the beginning and at the end.

Type your answers to Q: While adjusting the hyperparameters, including learning rate, epochs, batch size, the number of hidden layers and the node numbers, we observed that training with smaller batch sizes took much longer to train. For instance, a batch size of 1000 takes around 400-500 seconds per epoch during training. Training with larger batch sizes like 20,000 was much faster, averaging ~28 seconds per epoch. Meanwhile, training with a batch size of 200,000 took 3-4 seconds per epoch. The batch size I settled on (10,000) took ~50 seconds per epoch. Each test with these varying batch sizes had a parameter value of 50 epochs, and we observe that larger batch sizes (20,000 and 200,000) yielded test mse of 793.2882 and 4994.9922 respectively. Larger batch sizes require more epochs to converge and reach the desired mse.

```
In [208...
```

```
activation='relu',
                          kernel regularizer=tf.keras.regularizers.l1(l=0.3),
                          name='Hidden1'),
    # Additional hidden layers
    tf.keras.layers.Dense(units=7,
                          activation='relu',
                          kernel_regularizer=tf.keras.regularizers.11(1=0.3),
                          name='Hidden2'),
    tf.keras.layers.Dense(units=4,
                          activation='relu',
                          kernel regularizer=tf.keras.regularizers.11(1=0.3),
                          name='Hidden3'),
    # Output layer
    tf.keras.layers.Dense(units=1,
                          activation='linear',
                          name='Output')
1)
model.compile(optimizer=tf.keras.optimizers.Adam(lr=learning rate),
              loss=tf.keras.losses.MeanSquaredError(),
              metrics=['mse'])
#---Train the Model---#
# Keras TensorBoard callback.
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=logdir)
print(logdir)
train lbl = np.array(train df["vehicle CO2"])
train_df = train_df.drop(columns=["vehicle_CO2"])
# Split the datasets into features and label.
train_ft = {name:np.array(value) for name, value in train_df.items()}
# train lbl = np.array(train ft.pop(label name))
val lbl = np.array(val df["vehicle CO2"])
val df = val df.drop(columns=["vehicle CO2"])
val ft = {name:np.array(value) for name, value in val df.items()}
# Keras TensorBoard callback.
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=logdir)
print(logdir)
model.fit(x=train ft, y=train lbl, batch size=batch size,
          epochs=epochs, callbacks=[tensorboard_callback], validation_data=(v
# Training function for large training set
# model.fit(x=train ft, y=train lbl, batch size=batch size,
            epochs=epochs, verbose=2, validation data=(val ft, val lbl), shuf
```

```
WARNING:tensorflow:Layers in a Sequential model should only have a single inpu
t tensor, but we receive a <class 'dict'> input: {'vehicle angle': <tf.Tensor
'ExpandDims:0' shape=(None, 1) dtype=float32>, 'vehicle_eclass': <tf.Tensor 'E
xpandDims_1:0' shape=(None, 1) dtype=string>, 'vehicle_fuel': <tf.Tensor 'Expa
ndDims_2:0' shape=(None, 1) dtype=float32>, 'vehicle_noise': <tf.Tensor 'Expan</pre>
dDims_3:0' shape=(None, 1) dtype=float32>, 'vehicle_pos': <tf.Tensor 'ExpandDi</pre>
ms_4:0' shape=(None, 1) dtype=float32>, 'vehicle_speed': <tf.Tensor 'ExpandDim
s_5:0' shape=(None, 1) dtype=float32>, 'vehicle_type': <tf.Tensor 'ExpandDims_</pre>
6:0' shape=(None, 1) dtype=string>, 'vehicle_waiting': <tf.Tensor 'ExpandDims_
7:0' shape=(None, 1) dtype=float32>, 'vehicle x': <tf.Tensor 'ExpandDims 8:0'
shape=(None, 1) dtype=float32>, 'vehicle y': <tf.Tensor 'ExpandDims 9:0' shape</pre>
=(None, 1) dtype=float32>}
Consider rewriting this model with the Functional API.
WARNING:tensorflow:Layers in a Sequential model should only have a single inpu
t tensor, but we receive a <class 'dict'> input: {'vehicle angle': <tf.Tensor
'ExpandDims:0' shape=(None, 1) dtype=float32>, 'vehicle_eclass': <tf.Tensor 'E
xpandDims_1:0' shape=(None, 1) dtype=string>, 'vehicle_fuel': <tf.Tensor 'Expa</pre>
ndDims_2:0' shape=(None, 1) dtype=float32>, 'vehicle_noise': <tf.Tensor 'Expan dDims_3:0' shape=(None, 1) dtype=float32>, 'vehicle_pos': <tf.Tensor 'ExpandDi
ms_4:0' shape=(None, 1) dtype=float32>, 'vehicle_speed': <tf.Tensor 'ExpandDim</pre>
s_5:0' shape=(None, 1) dtype=float32>, 'vehicle_type': <tf.Tensor 'ExpandDims
6:0' shape=(None, 1) dtype=string>, 'vehicle_waiting': <tf.Tensor 'ExpandDims_ 7:0' shape=(None, 1) dtype=float32>, 'vehicle_x': <tf.Tensor 'ExpandDims_8:0'
shape=(None, 1) dtype=float32>, 'vehicle y': <tf.Tensor 'ExpandDims 9:0' shape
=(None, 1) dtype=float32>}
Consider rewriting this model with the Functional API.
: 15588300.0000WARNING:tensorflow:Layers in a Sequential model should only hav
e a single input tensor, but we receive a <class 'dict'> input: {'vehicle angl
e': <tf.Tensor 'ExpandDims:0' shape=(None, 1) dtype=float32>, 'vehicle_eclass'
: <tf.Tensor 'ExpandDims 1:0' shape=(None, 1) dtype=string>, 'vehicle fuel': <
tf.Tensor 'ExpandDims_2:0' shape=(None, 1) dtype=float32>, 'vehicle_noise': <t
f.Tensor 'ExpandDims 3:0' shape=(None, 1) dtype=float32>, 'vehicle pos': <tf.T
ensor 'ExpandDims_4:0' shape=(None, 1) dtype=float32>, 'vehicle_speed': <tf.Te</pre>
nsor 'ExpandDims_5:0' shape=(None, 1) dtype=float32>, 'vehicle_type': <tf.Tens</pre>
or 'ExpandDims 6:0' shape=(None, 1) dtype=string>, 'vehicle waiting': <tf.Tens
or 'ExpandDims 7:0' shape=(None, 1) dtype=float32>, 'vehicle x': <tf.Tensor 'E
xpandDims 8:0' shape=(None, 1) dtype=float32>, 'vehicle y': <tf.Tensor 'Expand
Dims 9:0' shape=(None, 1) dtype=float32>}
Consider rewriting this model with the Functional API.
mse: 14390173.0000 - val_loss: 960.7873 - val_mse: 896.9650
460/460 [=============] - 1s 1ms/step - loss: 1294.2542 - mse
: 1230.7958 - val loss: 1123.5656 - val mse: 1060.4581
Epoch 3/1000
: 1225.7668 - val loss: 1311.1069 - val mse: 1248.7766
Epoch 4/1000
: 1401.7129 - val loss: 1876.9619 - val mse: 1813.3413
: 1452.0614 - val loss: 1152.3872 - val mse: 1090.7985
Epoch 6/1000
: 1326.1233 - val loss: 1177.6323 - val mse: 1117.3474
Epoch 7/1000
: 1553.1210 - val loss: 2383.4263 - val mse: 2324.0308
```

```
Epoch 8/1000
: 2123.1831 - val loss: 916.6105 - val mse: 858.4507
Epoch 9/1000
: 1656.6272 - val loss: 1067.9589 - val mse: 1010.7408
Epoch 10/1000
: 1694.5151 - val_loss: 1135.1104 - val_mse: 1078.8667
Epoch 11/1000
: 1455.2994 - val loss: 1255.6201 - val mse: 1200.1117
Epoch 12/1000
: 3183.3303 - val loss: 919.7274 - val mse: 863.6814
Epoch 13/1000
460/460 [=============] - 1s 1ms/step - loss: 1666.7347 - mse
: 1610.0166 - val loss: 568.8065 - val mse: 511.1476
Epoch 14/1000
: 1147.1099 - val loss: 378.3917 - val mse: 322.1206
Epoch 15/1000
: 1656.3112 - val_loss: 2361.5061 - val_mse: 2306.5371
Epoch 16/1000
: 3840.8374 - val loss: 1893.3291 - val mse: 1840.0050
Epoch 17/1000
638.2205 - val loss: 289.6559 - val mse: 235.8215
Epoch 18/1000
: 1424.2133 - val loss: 484.1295 - val mse: 432.0246
Epoch 19/1000
: 1823.4003 - val loss: 448.2324 - val mse: 395.8971
Epoch 20/1000
689.2108 - val loss: 174.5670 - val mse: 122.6398
Epoch 21/1000
: 1133.0519 - val loss: 713.9376 - val mse: 660.7907
Epoch 22/1000
: 4163.3896 - val loss: 1013.4846 - val mse: 961.7798
Epoch 23/1000
: 1698.9542 - val loss: 934.5901 - val mse: 883.2675
Epoch 24/1000
460/460 [============] - 1s 1ms/step - loss: 2747.9924 - mse
: 2696.9097 - val loss: 7222.8096 - val mse: 7171.9258
Epoch 25/1000
: 1054.3271 - val loss: 961.4768 - val mse: 909.2204
Epoch 26/1000
: 2811.6987 - val_loss: 610.2139 - val mse: 557.6967
Epoch 27/1000
734.7916 - val loss: 627.4996 - val mse: 575.1221
Epoch 28/1000
```

```
460/460 [=============] - 1s 1ms/step - loss: 1564.3864 - mse
: 1512.9224 - val loss: 10536.7598 - val mse: 10485.6084
Epoch 29/1000
: 1684.3579 - val loss: 375.4037 - val mse: 324.8468
Epoch 30/1000
472.8238 - val loss: 1941.9749 - val mse: 1891.8575
Epoch 31/1000
: 964.6384 - val loss: 237.5023 - val mse: 187.7878
Epoch 32/1000
: 2556.9282 - val loss: 661.1423 - val mse: 611.5719
Epoch 33/1000
925.9935 - val loss: 391.1174 - val mse: 340.3965
Epoch 34/1000
: 2222.5825 - val loss: 1578.4456 - val mse: 1527.7898
Epoch 35/1000
576.9225 - val_loss: 301.7124 - val_mse: 251.8843
Epoch 36/1000
: 1197.5847 - val loss: 208.9788 - val mse: 159.2604
Epoch 37/1000
460/460 [==============] - 0s 1ms/step - loss: 2260.6301 - mse
: 2208.1606 - val loss: 798.9533 - val mse: 745.7689
Epoch 38/1000
592.0671 - val loss: 941.6177 - val mse: 889.5788
Epoch 39/1000
: 1463.8884 - val loss: 198.4297 - val mse: 147.0544
Epoch 40/1000
: 2710.7290 - val loss: 1741.1089 - val_mse: 1690.4199
Epoch 41/1000
: 2158.3601 - val loss: 514.5925 - val mse: 463.8033
Epoch 42/1000
: 1624.1238 - val loss: 271.2199 - val mse: 220.8976
Epoch 43/1000
642.1431 - val loss: 339.6877 - val mse: 289.9935
Epoch 44/1000
: 1023.8126 - val loss: 214.4813 - val mse: 165.6025
Epoch 45/1000
695.4609 - val loss: 8245.6104 - val mse: 8196.0703
Epoch 46/1000
: 1908.8632 - val loss: 400.2506 - val mse: 350.8480
Epoch 47/1000
se: 4892.5947 - val loss: 203.6978 - val_mse: 151.4023
Epoch 48/1000
```

```
: 1034.1498 - val loss: 296.7823 - val mse: 244.8236
Epoch 49/1000
460/460 [============] - 1s 1ms/step - loss: 771.5824 - mse:
720.0629 - val loss: 3995.5208 - val mse: 3944.3279
Epoch 50/1000
: 1204.2615 - val loss: 275.8482 - val mse: 225.1096
Epoch 51/1000
460/460 [=============] - 1s 1ms/step - loss: 1394.7828 - mse
: 1344.7786 - val loss: 546.5143 - val mse: 497.0962
Epoch 52/1000
: 1409.8949 - val loss: 201.6817 - val mse: 152.0665
Epoch 53/1000
: 1408.4475 - val loss: 1060.0891 - val_mse: 1008.6887
Epoch 54/1000
: 973.1761 - val loss: 667.6844 - val mse: 617.1738
Epoch 55/1000
: 1270.0144 - val loss: 748.1354 - val mse: 697.8074
Epoch 56/1000
828.8986 - val loss: 292.3968 - val mse: 241.7715
Epoch 57/1000
: 1220.9498 - val loss: 2945.2275 - val mse: 2895.2854
Epoch 58/1000
460/460 [=============] - 1s 1ms/step - loss: 2376.1338 - mse
: 2326.5557 - val loss: 59981.6289 - val_mse: 59930.5117
Epoch 59/1000
: 2266.6943 - val loss: 223.3981 - val mse: 171.1778
Epoch 60/1000
710.0620 - val loss: 256.7050 - val mse: 204.9143
Epoch 61/1000
460/460 [============] - 1s 1ms/step - loss: 1218.0142 - mse
: 1166.1620 - val loss: 6922.7910 - val mse: 6871.4819
Epoch 62/1000
: 1548.9817 - val loss: 2425.6064 - val mse: 2374.1289
Epoch 63/1000
: 1356.8448 - val loss: 548.9406 - val mse: 497.8929
Epoch 64/1000
: 1010.6998 - val loss: 222.9275 - val mse: 169.8481
Epoch 65/1000
: 1075.6151 - val loss: 622.9378 - val mse: 570.9710
Epoch 66/1000
: 1661.2683 - val loss: 2009.3076 - val mse: 1959.4753
Epoch 67/1000
e: 575.4349 - val loss: 576.8279 - val mse: 527.7664
Epoch 68/1000
: 1396.5839 - val loss: 5891.9438 - val mse: 5840.5200
```

```
Epoch 69/1000
: 1747.2133 - val loss: 1611.8829 - val mse: 1563.2845
Epoch 70/1000
: 2442.8552 - val loss: 779.2023 - val mse: 730.0289
Epoch 71/1000
460/460 [=============] - Os 987us/step - loss: 911.7769 - ms
e: 862.1813 - val_loss: 242.9234 - val_mse: 193.4585
Epoch 72/1000
: 1537.1934 - val loss: 1851.2977 - val mse: 1800.1724
Epoch 73/1000
: 1784.9506 - val loss: 1059.1156 - val mse: 1009.6906
Epoch 74/1000
460/460 [=============] - Os 961us/step - loss: 1234.8743 - m
se: 1185.7045 - val loss: 233.3353 - val_mse: 184.2990
Epoch 75/1000
460/460 [============== ] - Os 960us/step - loss: 1928.9265 - m
se: 1879.8883 - val loss: 922.9743 - val mse: 873.6453
Epoch 76/1000
se: 1143.7738 - val loss: 1079.3337 - val_mse: 1029.8055
Epoch 77/1000
e: 568.4607 - val loss: 572.2305 - val mse: 523.8123
Epoch 78/1000
460/460 [============== ] - 0s 978us/step - loss: 2827.6089 - m
se: 2778.0940 - val loss: 238.0903 - val mse: 188.8351
Epoch 79/1000
e: 898.1538 - val loss: 329.2023 - val mse: 280.0887
Epoch 80/1000
823.8572 - val loss: 245.7016 - val mse: 196.2513
Epoch 81/1000
: 1015.3140 - val loss: 403.2919 - val mse: 353.9266
Epoch 82/1000
: 3017.3577 - val loss: 12777.2695 - val mse: 12725.7002
Epoch 83/1000
929.1993 - val loss: 1579.8522 - val mse: 1529.6796
Epoch 84/1000
460/460 [============] - 1s 1ms/step - loss: 2172.7415 - mse
: 2122.3394 - val loss: 312.4846 - val mse: 262.6520
Epoch 85/1000
676.9226 - val loss: 707.5283 - val mse: 658.2956
Epoch 86/1000
460/460 [=============] - 1s 1ms/step - loss: 661.2540 - mse:
611.9364 - val loss: 1029.7213 - val mse: 980.0208
Epoch 87/1000
: 2716.1318 - val_loss: 394.0341 - val mse: 342.5018
Epoch 88/1000
460/460 [=============] - 0s 1ms/step - loss: 659.8021 - mse:
609.2512 - val loss: 1865.2859 - val mse: 1815.5050
Epoch 89/1000
```

```
460/460 [=============] - 0s 1ms/step - loss: 1322.0189 - mse
: 1272.3318 - val loss: 3637.9617 - val mse: 3588.3979
Epoch 90/1000
: 1581.4272 - val loss: 235.1797 - val mse: 184.6083
Epoch 91/1000
: 3208.4763 - val loss: 4370.0347 - val mse: 4319.2852
Epoch 92/1000
544.0009 - val loss: 640.8410 - val mse: 590.7892
Epoch 93/1000
: 985.6686 - val loss: 875.0453 - val mse: 822.9418
Epoch 94/1000
: 1165.6509 - val loss: 335.7108 - val mse: 284.8501
Epoch 95/1000
: 2476.5271 - val loss: 371.6035 - val mse: 322.1002
Epoch 96/1000
326.3900 - val_loss: 184.5673 - val mse: 136.7040
Epoch 97/1000
432.3899 - val loss: 650.1774 - val mse: 602.3512
Epoch 98/1000
567.2964 - val loss: 337.1521 - val mse: 288.4509
Epoch 99/1000
937.3680 - val loss: 10170.5625 - val mse: 10122.3701
Epoch 100/1000
460/460 [=============] - 1s 1ms/step - loss: 10696.2510 - ms
e: 10645.9541 - val loss: 224.8307 - val mse: 173.3170
Epoch 101/1000
88.4757 - val loss: 101.8801 - val mse: 50.5226
Epoch 102/1000
190.5260 - val loss: 114.2101 - val mse: 58.3109
Epoch 103/1000
135.0211 - val loss: 151.0190 - val mse: 96.0117
Epoch 104/1000
603.7629 - val loss: 208.1917 - val mse: 154.0405
Epoch 105/1000
630.9188 - val loss: 1188.9437 - val mse: 1135.6766
Epoch 106/1000
: 3517.1331 - val loss: 122.5677 - val mse: 69.2304
Epoch 107/1000
491.7803 - val_loss: 284.6560 - val_mse: 231.5450
Epoch 108/1000
103.8660 - val loss: 1213.0405 - val_mse: 1160.3528
Epoch 109/1000
```

```
314.6303 - val loss: 90.3454 - val mse: 36.0994
Epoch 110/1000
460/460 [=============] - 1s 1ms/step - loss: 1679.7371 - mse
: 1625.8530 - val loss: 135.6545 - val mse: 82.8500
Epoch 111/1000
215.3907 - val loss: 353.6375 - val mse: 301.8412
Epoch 112/1000
460/460 [=============] - 1s 1ms/step - loss: 1806.3469 - mse
: 1754.3085 - val loss: 1608.2721 - val mse: 1556.8375
Epoch 113/1000
768.8496 - val loss: 126.2044 - val mse: 75.7999
Epoch 114/1000
: 2178.1035 - val loss: 111.8483 - val mse: 60.6931
Epoch 115/1000
132.4662 - val loss: 90.3904 - val mse: 40.1322
Epoch 116/1000
: 1706.2161 - val loss: 6187.2720 - val mse: 6134.7500
Epoch 117/1000
: 4560.6777 - val loss: 91.9943 - val mse: 39.9335
Epoch 118/1000
179.5363 - val_loss: 152.2725 - val_mse: 100.2121
Epoch 119/1000
312.4240 - val_loss: 79.5733 - val mse: 27.5114
Epoch 120/1000
184.1289 - val loss: 267.1060 - val mse: 215.1384
Epoch 121/1000
533.5479 - val loss: 80.6053 - val mse: 29.0933
Epoch 122/1000
460/460 [============] - 1s 1ms/step - loss: 1420.2031 - mse
: 1368.6241 - val loss: 1005.1153 - val mse: 953.2596
Epoch 123/1000
: 8207.4248 - val loss: 94.9780 - val mse: 41.0368
Epoch 124/1000
66.2456 - val loss: 86.6216 - val mse: 32.4577
Epoch 125/1000
66.7550 - val loss: 111.8060 - val mse: 57.7925
Epoch 126/1000
219.7029 - val loss: 113.9387 - val mse: 60.3424
Epoch 127/1000
668.1927 - val loss: 242.8870 - val mse: 189.8576
Epoch 128/1000
: 2223.5061 - val loss: 86.5145 - val mse: 33.8581
Epoch 129/1000
145.7237 - val loss: 112.3299 - val mse: 60.4779
```

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Epoch 130/1000
: 4303.4888 - val loss: 107.5920 - val mse: 56.2971
Epoch 131/1000
128.1729 - val_loss: 146.3504 - val_mse: 95.4134
Epoch 132/1000
440.7247 - val loss: 119.8533 - val mse: 70.3921
Epoch 133/1000
275.6212 - val loss: 465.4424 - val mse: 416.1082
Epoch 134/1000
: 1092.4138 - val loss: 3484.6392 - val mse: 3434.7612
Epoch 135/1000
: 1605.5233 - val loss: 346.0750 - val mse: 296.3015
Epoch 136/1000
173.4433 - val loss: 80.9882 - val mse: 32.1956
Epoch 137/1000
460/460 [============== ] - 1s 2ms/step - loss: 3543.4790 - mse
: 3493.8113 - val_loss: 235.1815 - val_mse: 183.3550
Epoch 138/1000
167.8754 - val loss: 81.7970 - val mse: 32.0637
Epoch 139/1000
806.4368 - val loss: 456.4990 - val mse: 407.4980
Epoch 140/1000
144.7291 - val loss: 271.2065 - val mse: 222.4369
Epoch 141/1000
: 5076.2939 - val loss: 134.1582 - val mse: 83.0288
Epoch 142/1000
109.4488 - val loss: 120.4715 - val mse: 71.7835
Epoch 143/1000
84.5941 - val loss: 226.3530 - val mse: 177.8814
Epoch 144/1000
925.6999 - val loss: 121.7869 - val mse: 73.2763
Epoch 145/1000
460/460 [============] - 1s 1ms/step - loss: 1152.0637 - mse
: 1103.3726 - val loss: 144.9227 - val_mse: 95.8952
Epoch 146/1000
610.3392 - val loss: 479.6227 - val mse: 429.9487
Epoch 147/1000
: 2003.4163 - val loss: 166.0742 - val mse: 117.5289
Epoch 148/1000
202.0186 - val_loss: 1310.6703 - val_mse: 1262.0022
Epoch 149/1000
460/460 [=============] - 1s 1ms/step - loss: 2368.1533 - mse
: 2319.2520 - val loss: 290.2663 - val_mse: 239.8308
Epoch 150/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 178.5998 - mse:
129.6281 - val loss: 270.9373 - val mse: 222.4954
Epoch 151/1000
840.3101 - val loss: 149.1367 - val mse: 100.4426
Epoch 152/1000
: 3345.6682 - val loss: 39396.9336 - val mse: 39345.6172
Epoch 153/1000
e: 31401.9883 - val loss: 131.5951 - val mse: 78.5730
Epoch 154/1000
54.0006 - val loss: 87.0796 - val mse: 34.4986
Epoch 155/1000
46.8161 - val loss: 92.8828 - val mse: 40.3177
Epoch 156/1000
44.9782 - val loss: 84.8533 - val mse: 32.4248
Epoch 157/1000
47.4345 - val loss: 204.5307 - val_mse: 151.9381
Epoch 158/1000
102.1365 - val loss: 94.5660 - val mse: 42.4814
Epoch 159/1000
170.2154 - val loss: 80.9298 - val mse: 29.2087
Epoch 160/1000
460/460 [============] - 1s 2ms/step - loss: 990.9495 - mse:
939.1592 - val loss: 4517.5151 - val_mse: 4465.9058
Epoch 161/1000
: 5022.3999 - val_loss: 303.4742 - val_mse: 252.8883
Epoch 162/1000
159.6855 - val loss: 175.6870 - val mse: 125.5247
Epoch 163/1000
172.9256 - val loss: 109.1469 - val mse: 59.1763
Epoch 164/1000
405.6472 - val loss: 96.8075 - val mse: 47.5153
Epoch 165/1000
: 2727.5740 - val loss: 1544.1398 - val mse: 1493.4331
Epoch 166/1000
246.6080 - val loss: 121.4065 - val mse: 71.3503
Epoch 167/1000
500.6678 - val loss: 138.0867 - val mse: 86.9439
Epoch 168/1000
105.9029 - val loss: 522.1022 - val mse: 472.0273
Epoch 169/1000
: 1363.1448 - val loss: 114.1958 - val mse: 64.4539
Epoch 170/1000
```

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: 1252.9497 - val loss: 114.3895 - val mse: 64.4871
Epoch 171/1000
460/460 [============] - 1s 1ms/step - loss: 428.5204 - mse:
379.4000 - val loss: 1053.0092 - val mse: 1004.0618
Epoch 172/1000
460/460 [=============] - 1s 1ms/step - loss: 967.2920 - mse:
918.3471 - val loss: 75.5755 - val mse: 26.7300
Epoch 173/1000
460/460 [=============] - 1s 1ms/step - loss: 1965.7314 - mse
: 1916.6366 - val loss: 117.3198 - val mse: 68.1308
Epoch 174/1000
103.4207 - val loss: 146.3622 - val mse: 97.4945
Epoch 175/1000
: 962.2739 - val loss: 1773.2653 - val mse: 1723.2142
Epoch 176/1000
: 973.8664 - val_loss: 94.0248 - val_mse: 45.2649
Epoch 177/1000
158.4399 - val loss: 128.2240 - val mse: 79.7501
Epoch 178/1000
e: 12993.4463 - val loss: 138.5692 - val mse: 85.7248
Epoch 179/1000
79.2120 - val loss: 87.1552 - val mse: 34.6626
Epoch 180/1000
54.9667 - val loss: 90.6986 - val mse: 38.0659
Epoch 181/1000
232.2970 - val loss: 154.5736 - val mse: 101.5708
Epoch 182/1000
115.3848 - val loss: 693.8549 - val mse: 640.9402
Epoch 183/1000
460/460 [=============] - 1s 1ms/step - loss: 193.4111 - mse:
140.7975 - val loss: 149.7393 - val mse: 97.2895
Epoch 184/1000
: 4383.8633 - val loss: 619.0811 - val mse: 565.7881
Epoch 185/1000
165.1570 - val loss: 88.7812 - val mse: 36.4030
Epoch 186/1000
721.0225 - val loss: 543.0204 - val mse: 491.1728
Epoch 187/1000
141.7068 - val loss: 85.8408 - val mse: 34.2346
Epoch 188/1000
691.7120 - val loss: 162.3410 - val mse: 110.6719
Epoch 189/1000
: 1718.2266 - val loss: 247.2819 - val mse: 196.6505
Epoch 190/1000
174.0966 - val loss: 174.8983 - val mse: 124.8969
```

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Epoch 191/1000
811.8827 - val loss: 381.3926 - val mse: 331.3649
Epoch 192/1000
378.7380 - val loss: 93.1291 - val mse: 43.6434
Epoch 193/1000
: 5175.0781 - val loss: 1365.2506 - val mse: 1315.4447
Epoch 194/1000
91.8636 - val loss: 91.0764 - val mse: 41.6199
Epoch 195/1000
138.4414 - val loss: 2120.7441 - val mse: 2071.4255
Epoch 196/1000
: 1894.0706 - val loss: 478.1071 - val mse: 426.0498
Epoch 197/1000
456.2489 - val loss: 166.0968 - val mse: 115.3593
Epoch 198/1000
225.9846 - val_loss: 505.8831 - val_mse: 455.8748
Epoch 199/1000
389.1852 - val loss: 2323.1121 - val mse: 2273.9307
Epoch 200/1000
: 3816.6169 - val loss: 89.8965 - val mse: 40.8314
Epoch 201/1000
84.2307 - val loss: 113.9126 - val mse: 65.2040
Epoch 202/1000
292.1852 - val loss: 83.3812 - val mse: 34.8831
Epoch 203/1000
437.3228 - val loss: 90.5196 - val mse: 42.2835
Epoch 204/1000
: 3740.4265 - val loss: 147.0137 - val mse: 95.5386
Epoch 205/1000
66.2286 - val loss: 78.7801 - val_mse: 29.5163
Epoch 206/1000
460/460 [=============] - 1s 1ms/step - loss: 509.0663 - mse:
460.5147 - val loss: 493.4564 - val mse: 445.2609
Epoch 207/1000
121.6891 - val loss: 938.5179 - val mse: 890.6669
Epoch 208/1000
460/460 [=============] - 1s 1ms/step - loss: 608.3502 - mse:
560.2742 - val loss: 1428.4768 - val mse: 1380.6475
Epoch 209/1000
: 8042.1069 - val loss: 263.7880 - val mse: 211.9897
Epoch 210/1000
82.7505 - val loss: 83.2956 - val_mse: 32.9416
Epoch 211/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 122.8695 - mse:
72.6992 - val loss: 97.3515 - val mse: 47.3030
Epoch 212/1000
460/460 [=============] - 1s 1ms/step - loss: 263.4599 - mse:
212.9061 - val loss: 103.0705 - val mse: 52.4098
Epoch 213/1000
148.5231 - val loss: 133.3314 - val mse: 83.1245
Epoch 214/1000
: 4133.3154 - val loss: 4022.2490 - val mse: 3969.4951
Epoch 215/1000
297.3872 - val loss: 384.0786 - val mse: 331.3847
Epoch 216/1000
210.3789 - val loss: 86.5394 - val mse: 34.5923
Epoch 217/1000
: 977.4537 - val loss: 103.0976 - val mse: 51.5644
Epoch 218/1000
631.5117 - val loss: 84.3800 - val mse: 33.9169
Epoch 219/1000
509.1540 - val loss: 277.1803 - val mse: 225.8474
Epoch 220/1000
: 2621.3291 - val loss: 1408.6907 - val mse: 1358.8691
Epoch 221/1000
340.5406 - val loss: 133.1494 - val mse: 83.4442
Epoch 222/1000
: 1199.0944 - val loss: 212.3658 - val mse: 161.4259
Epoch 223/1000
382.3018 - val loss: 320.4186 - val mse: 269.6006
Epoch 224/1000
: 4394.0854 - val loss: 208.3929 - val mse: 155.9782
Epoch 225/1000
99.7625 - val loss: 112.1265 - val mse: 60.6711
Epoch 226/1000
79.7725 - val loss: 119.6935 - val mse: 68.9304
Epoch 227/1000
: 2414.1128 - val loss: 254.5222 - val mse: 203.3172
Epoch 228/1000
280.0712 - val loss: 7556.6372 - val mse: 7506.3481
Epoch 229/1000
: 1339.0959 - val loss: 107.7722 - val mse: 57.9989
Epoch 230/1000
84.7090 - val loss: 215.1629 - val mse: 165.5863
Epoch 231/1000
```

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790.3157 - val loss: 181.1005 - val mse: 131.3909
Epoch 232/1000
460/460 [============] - 1s 1ms/step - loss: 1107.9554 - mse
: 1058.2189 - val loss: 3840.6028 - val mse: 3790.7114
Epoch 233/1000
: 1581.2784 - val loss: 100.7297 - val mse: 49.5502
Epoch 234/1000
460/460 [=============] - 1s 1ms/step - loss: 3155.9004 - mse
: 3105.0122 - val loss: 486.9540 - val mse: 436.7742
Epoch 235/1000
121.4994 - val loss: 128.1583 - val mse: 78.2132
Epoch 236/1000
124.7946 - val loss: 90.6507 - val mse: 40.6330
Epoch 237/1000
374.8716 - val loss: 55103.3711 - val mse: 55052.9375
Epoch 238/1000
: 1872.4512 - val loss: 96.8857 - val mse: 47.1125
Epoch 239/1000
200.9066 - val loss: 616.5516 - val mse: 566.9201
Epoch 240/1000
: 3176.6550 - val loss: 808.8340 - val mse: 756.1902
Epoch 241/1000
399.2613 - val_loss: 309.1816 - val mse: 257.5183
Epoch 242/1000
: 1632.2002 - val loss: 288.0334 - val mse: 236.0912
Epoch 243/1000
569.0763 - val loss: 770.4210 - val mse: 718.7485
Epoch 244/1000
460/460 [=============] - 1s 1ms/step - loss: 175.6707 - mse:
124.2406 - val loss: 276.1696 - val mse: 224.7984
Epoch 245/1000
: 1297.7629 - val loss: 5731.2559 - val mse: 5679.5557
Epoch 246/1000
460/460 [============== ] - 1s 1ms/step - loss: 1092.7039 - mse
: 1041.9091 - val loss: 103.3489 - val mse: 52.6184
Epoch 247/1000
460/460 [=============] - 1s 1ms/step - loss: 591.7978 - mse:
541.2543 - val loss: 94.6572 - val mse: 44.3511
Epoch 248/1000
: 2433.4368 - val loss: 112.6074 - val mse: 61.3345
Epoch 249/1000
62.4167 - val loss: 85.8536 - val mse: 35.0344
Epoch 250/1000
112.4456 - val loss: 275.5723 - val mse: 225.0845
Epoch 251/1000
: 1922.0547 - val loss: 148.4650 - val mse: 97.1241
```

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Epoch 252/1000
223.7070 - val loss: 332.7793 - val mse: 282.1779
Epoch 253/1000
426.7683 - val_loss: 2549.4097 - val_mse: 2498.9558
Epoch 254/1000
: 1732.2296 - val loss: 29861.1289 - val mse: 29809.0117
Epoch 255/1000
: 1982.0026 - val loss: 108.4413 - val mse: 57.2530
Epoch 256/1000
: 1041.1567 - val loss: 1114.1469 - val mse: 1063.6124
Epoch 257/1000
460/460 [=============] - 1s 1ms/step - loss: 361.7957 - mse:
311.3341 - val loss: 215.5937 - val mse: 165.2531
Epoch 258/1000
381.1918 - val loss: 1162.8954 - val mse: 1112.4347
Epoch 259/1000
334.8210 - val_loss: 2984.7908 - val_mse: 2932.7988
Epoch 260/1000
460/460 [============] - 1s 1ms/step - loss: 2443.4897 - mse
: 2391.7371 - val loss: 160.4087 - val mse: 109.5085
Epoch 261/1000
145.6784 - val loss: 190.1190 - val mse: 139.8280
Epoch 262/1000
169.6357 - val loss: 102.2783 - val mse: 52.6451
Epoch 263/1000
: 1359.5607 - val loss: 166.2194 - val mse: 116.2495
Epoch 264/1000
569.9672 - val loss: 7159.4360 - val mse: 7108.9980
Epoch 265/1000
629.7050 - val loss: 1598.4327 - val mse: 1549.0166
Epoch 266/1000
: 1234.1331 - val loss: 1355.6405 - val mse: 1304.9617
Epoch 267/1000
686.4941 - val loss: 86.5990 - val mse: 36.4718
Epoch 268/1000
: 2512.4170 - val loss: 159.1938 - val mse: 109.1006
Epoch 269/1000
: 1500.3540 - val loss: 840.1555 - val mse: 788.4342
Epoch 270/1000
216.0901 - val_loss: 84.1153 - val_mse: 33.8338
Epoch 271/1000
147.1108 - val loss: 87.2845 - val mse: 37.3084
Epoch 272/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 2768.1975 - mse
: 2717.7170 - val loss: 145.3070 - val mse: 93.9779
Epoch 273/1000
97.1452 - val loss: 242.1342 - val mse: 192.3539
Epoch 274/1000
84.8792 - val loss: 175.8362 - val mse: 126.2974
Epoch 275/1000
: 6586.9458 - val loss: 110.6605 - val mse: 57.2302
Epoch 276/1000
88.4577 - val loss: 90.9161 - val mse: 39.3074
Epoch 277/1000
129.8997 - val loss: 173.2307 - val mse: 122.4675
Epoch 278/1000
283.6669 - val loss: 83.5221 - val mse: 33.1586
Epoch 279/1000
204.0584 - val_loss: 234.7229 - val mse: 184.5672
Epoch 280/1000
460/460 [============] - 1s 1ms/step - loss: 1158.9950 - mse
: 1108.5431 - val loss: 87.2924 - val mse: 37.1544
Epoch 281/1000
460/460 [============== ] - 1s 1ms/step - loss: 2660.7092 - mse
: 2609.7593 - val loss: 91.2510 - val mse: 40.5383
Epoch 282/1000
216.5524 - val loss: 81.9629 - val mse: 32.1188
Epoch 283/1000
: 7475.4131 - val_loss: 1236.4683 - val_mse: 1183.7966
Epoch 284/1000
149.4268 - val loss: 109.0127 - val mse: 57.5335
Epoch 285/1000
239.0222 - val loss: 165.2098 - val mse: 113.7745
Epoch 286/1000
99.8225 - val loss: 87.2556 - val mse: 36.2985
Epoch 287/1000
166.0116 - val loss: 94.1057 - val mse: 43.3734
Epoch 288/1000
298.6185 - val loss: 113.2553 - val mse: 62.5766
Epoch 289/1000
590.3793 - val loss: 1131.1829 - val mse: 1081.1337
Epoch 290/1000
: 3508.1418 - val loss: 82.4614 - val mse: 30.7059
Epoch 291/1000
65.4387 - val loss: 85.4789 - val mse: 33.4208
Epoch 292/1000
```

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240.5934 - val loss: 422.9982 - val mse: 370.9495
Epoch 293/1000
460/460 [============] - 1s 1ms/step - loss: 2930.1785 - mse
: 2877.7649 - val loss: 685.5585 - val mse: 633.4683
Epoch 294/1000
113.2559 - val loss: 228.5683 - val mse: 177.3971
Epoch 295/1000
: 1087.9061 - val loss: 38554.0938 - val mse: 38502.4180
Epoch 296/1000
: 1466.1244 - val loss: 91.4844 - val mse: 41.2290
Epoch 297/1000
87.7026 - val loss: 95.5219 - val mse: 45.1603
Epoch 298/1000
196.1030 - val loss: 100.5500 - val mse: 50.3678
Epoch 299/1000
: 1411.0146 - val loss: 4706.4165 - val mse: 4655.0698
Epoch 300/1000
: 1568.4388 - val loss: 38419.5586 - val mse: 38366.9141
Epoch 301/1000
: 1229.7756 - val loss: 903.9978 - val mse: 852.9892
Epoch 302/1000
300.3181 - val loss: 148.2352 - val mse: 97.5606
Epoch 303/1000
370.3183 - val loss: 155.8310 - val mse: 104.4170
Epoch 304/1000
472.3393 - val loss: 986.7201 - val mse: 936.0247
Epoch 305/1000
460/460 [=============] - 1s 1ms/step - loss: 4650.4175 - mse
: 4597.9502 - val loss: 94.2868 - val mse: 42.2114
Epoch 306/1000
87.7772 - val loss: 112.9041 - val mse: 61.8665
Epoch 307/1000
133.6626 - val loss: 79.7691 - val mse: 29.0689
Epoch 308/1000
: 1917.7330 - val loss: 538.0690 - val mse: 487.1286
Epoch 309/1000
256.8152 - val loss: 148.9315 - val mse: 98.4882
Epoch 310/1000
: 5025.4741 - val loss: 114.5714 - val mse: 61.2381
Epoch 311/1000
89.4894 - val loss: 162.4326 - val mse: 110.9705
Epoch 312/1000
57.0071 - val loss: 80.5006 - val mse: 29.9873
```

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Epoch 313/1000
671.5491 - val loss: 82.8348 - val mse: 32.2463
Epoch 314/1000
687.6453 - val loss: 85.6083 - val mse: 35.2159
Epoch 315/1000
: 1274.5972 - val loss: 1110.4393 - val mse: 1060.2961
Epoch 316/1000
652.5529 - val loss: 151.9307 - val mse: 101.9709
Epoch 317/1000
257.3964 - val loss: 87.3456 - val mse: 37.1876
Epoch 318/1000
460/460 [=============] - 1s 1ms/step - loss: 831.3943 - mse:
780.7769 - val loss: 79.6886 - val mse: 29.3845
Epoch 319/1000
484.7499 - val loss: 257.1573 - val mse: 205.9782
Epoch 320/1000
: 1412.2800 - val loss: 514.9243 - val mse: 464.7031
Epoch 321/1000
377.2703 - val loss: 142.8057 - val mse: 92.2770
Epoch 322/1000
: 1256.4342 - val loss: 2167.2671 - val mse: 2115.7415
Epoch 323/1000
715.7559 - val loss: 122.3543 - val mse: 72.1508
Epoch 324/1000
661.1891 - val loss: 103.0499 - val mse: 52.9750
Epoch 325/1000
178.4046 - val loss: 432.3512 - val mse: 381.9024
Epoch 326/1000
: 2684.4238 - val loss: 92.3130 - val mse: 39.1526
Epoch 327/1000
150.1865 - val loss: 94.8602 - val mse: 42.6957
Epoch 328/1000
869.4348 - val loss: 9268.2686 - val mse: 9215.5381
Epoch 329/1000
760.9555 - val loss: 222.8280 - val mse: 172.2286
Epoch 330/1000
239.3791 - val loss: 467.4023 - val mse: 416.7854
Epoch 331/1000
: 6480.6885 - val loss: 128.9830 - val mse: 77.6046
Epoch 332/1000
460/460 [============] - 1s 1ms/step - loss: 161.7230 - mse:
110.8046 - val loss: 165.9625 - val mse: 115.3451
Epoch 333/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 406.6814 - mse:
356.1477 - val loss: 106.4100 - val mse: 55.9544
Epoch 334/1000
460/460 [=============] - 1s 1ms/step - loss: 153.7670 - mse:
103.3862 - val loss: 187.2821 - val mse: 136.8518
Epoch 335/1000
259.6688 - val loss: 1782.4354 - val mse: 1731.8445
Epoch 336/1000
: 1512.5457 - val loss: 262.1313 - val mse: 211.6098
Epoch 337/1000
460/460 [==============] - 1s 1ms/step - loss: 422.8324 - mse:
372.5035 - val loss: 570.8513 - val mse: 520.7833
Epoch 338/1000
: 4471.5283 - val loss: 293.0437 - val mse: 242.3021
Epoch 339/1000
89.6702 - val loss: 85.5948 - val mse: 35.9469
Epoch 340/1000
76.8792 - val loss: 84.7037 - val mse: 35.0066
Epoch 341/1000
99.4035 - val loss: 196.9919 - val mse: 147.1243
Epoch 342/1000
692.9614 - val loss: 107.3661 - val mse: 56.8157
Epoch 343/1000
749.9400 - val loss: 21245.8223 - val mse: 21195.0762
Epoch 344/1000
: 1310.7046 - val loss: 171.8308 - val mse: 121.7421
Epoch 345/1000
254.8326 - val loss: 131.0200 - val mse: 80.3470
Epoch 346/1000
589.6249 - val loss: 535.8035 - val mse: 484.1995
Epoch 347/1000
936.7850 - val loss: 92.5268 - val mse: 42.1383
Epoch 348/1000
: 1603.6698 - val loss: 226.3653 - val mse: 175.6780
Epoch 349/1000
436.8979 - val loss: 81.3765 - val mse: 31.3130
Epoch 350/1000
585.8247 - val loss: 79.5173 - val mse: 29.6343
Epoch 351/1000
: 2341.1438 - val loss: 104.5180 - val mse: 52.4605
Epoch 352/1000
104.8098 - val loss: 106.2623 - val mse: 56.2872
Epoch 353/1000
```

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482.5633 - val loss: 511.7230 - val mse: 461.5353
Epoch 354/1000
460/460 [============] - 1s 1ms/step - loss: 716.7970 - mse:
666.1306 - val loss: 451.7562 - val mse: 401.3182
Epoch 355/1000
344.8998 - val loss: 2123.5952 - val mse: 2072.3792
Epoch 356/1000
529.8051 - val loss: 87.7647 - val mse: 37.6456
Epoch 357/1000
433.0993 - val loss: 107.8212 - val mse: 57.3204
Epoch 358/1000
680.7777 - val loss: 1042.5171 - val mse: 992.3988
Epoch 359/1000
: 1297.5133 - val_loss: 249.6905 - val_mse: 199.3238
Epoch 360/1000
796.5557 - val loss: 80.7329 - val mse: 30.9928
Epoch 361/1000
279.7309 - val loss: 133.9051 - val mse: 84.3464
Epoch 362/1000
: 1250.2969 - val loss: 94.4159 - val mse: 42.7102
Epoch 363/1000
126.1815 - val_loss: 90.2915 - val mse: 39.7289
Epoch 364/1000
794.4510 - val loss: 1179.0251 - val mse: 1129.3330
Epoch 365/1000
657.8044 - val loss: 221.6655 - val mse: 172.1163
Epoch 366/1000
460/460 [=============] - 1s 2ms/step - loss: 497.2292 - mse:
447.3622 - val loss: 148.9350 - val mse: 98.6707
Epoch 367/1000
501.2879 - val loss: 222.3750 - val mse: 171.1439
Epoch 368/1000
: 1754.5712 - val loss: 1395.4132 - val mse: 1345.7487
Epoch 369/1000
238.3747 - val loss: 214.7276 - val mse: 165.1573
Epoch 370/1000
464.8027 - val loss: 973.0176 - val mse: 922.6269
Epoch 371/1000
: 5226.9463 - val loss: 204.0875 - val mse: 150.7240
Epoch 372/1000
105.1205 - val loss: 766.5322 - val mse: 713.8104
Epoch 373/1000
113.4528 - val loss: 101.9699 - val mse: 49.9928
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Epoch 374/1000
160.2253 - val loss: 272.9564 - val mse: 221.4270
Epoch 375/1000
667.8509 - val loss: 159.2755 - val mse: 108.2185
Epoch 376/1000
159.6584 - val loss: 641.2985 - val mse: 591.0008
Epoch 377/1000
: 1598.0977 - val loss: 531.5876 - val mse: 481.0588
Epoch 378/1000
309.3278 - val loss: 110.0939 - val mse: 59.6297
Epoch 379/1000
426.2575 - val loss: 116.3250 - val mse: 65.8332
Epoch 380/1000
: 2921.7173 - val loss: 100.3992 - val mse: 48.6643
Epoch 381/1000
460/460 [=============] - 1s 1ms/step - loss: 125.2831 - mse:
74.0352 - val loss: 80.1639 - val mse: 29.1356
Epoch 382/1000
161.1427 - val loss: 88.0696 - val mse: 37.9149
Epoch 383/1000
253.0193 - val loss: 228.9567 - val mse: 178.8103
Epoch 384/1000
406.5942 - val loss: 197.3353 - val mse: 147.4264
Epoch 385/1000
460/460 [==============] - 1s 1ms/step - loss: 18444.7852 - ms
e: 18391.4355 - val loss: 110.5005 - val mse: 56.8594
Epoch 386/1000
40.5028 - val loss: 87.8770 - val mse: 34.5723
Epoch 387/1000
44.0077 - val loss: 83.0991 - val mse: 30.4265
Epoch 388/1000
40.1995 - val loss: 79.3547 - val mse: 26.7197
Epoch 389/1000
80.6219 - val loss: 80.2751 - val mse: 28.1559
Epoch 390/1000
111.2372 - val loss: 109.4815 - val mse: 57.3455
Epoch 391/1000
460/460 [=============] - 1s 1ms/step - loss: 306.1833 - mse:
254.0942 - val loss: 5205.6968 - val mse: 5153.7183
Epoch 392/1000
: 1205.4875 - val_loss: 95.5997 - val_mse: 44.1428
Epoch 393/1000
460/460 [=============] - 1s 1ms/step - loss: 334.5917 - mse:
283.3452 - val loss: 2182.7136 - val_mse: 2131.3386
Epoch 394/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 712.2692 - mse:
661.4639 - val loss: 96.4211 - val mse: 45.9410
Epoch 395/1000
404.6669 - val loss: 82.1124 - val mse: 32.7099
Epoch 396/1000
: 1776.6012 - val loss: 14950.0137 - val mse: 14899.6973
Epoch 397/1000
: 1665.7958 - val loss: 79.8777 - val mse: 30.4380
Epoch 398/1000
63.8528 - val loss: 198.4628 - val mse: 149.2896
Epoch 399/1000
89.4279 - val loss: 115.5984 - val mse: 66.4354
Epoch 400/1000
: 1949.3206 - val loss: 429.2128 - val mse: 379.7509
Epoch 401/1000
117.8277 - val_loss: 186.3438 - val_mse: 137.4808
Epoch 402/1000
274.3459 - val loss: 90.1455 - val mse: 41.4304
Epoch 403/1000
837.8048 - val loss: 95.2389 - val mse: 45.6855
Epoch 404/1000
148.0620 - val loss: 856.6410 - val mse: 806.5160
Epoch 405/1000
: 2256.7202 - val_loss: 334.9552 - val_mse: 283.8845
Epoch 406/1000
117.2287 - val loss: 86.1954 - val mse: 35.8491
Epoch 407/1000
313.9765 - val loss: 734.8287 - val mse: 684.6859
Epoch 408/1000
: 1854.4363 - val loss: 49437.4805 - val mse: 49385.2930
Epoch 409/1000
: 1157.3561 - val_loss: 88.5357 - val_mse: 38.1073
Epoch 410/1000
64.1559 - val loss: 243.9322 - val mse: 193.6405
Epoch 411/1000
100.7675 - val loss: 114.9011 - val mse: 64.6791
Epoch 412/1000
329.4162 - val_loss: 86.1600 - val_mse: 35.6660
Epoch 413/1000
727.7148 - val loss: 861.1555 - val mse: 809.4501
Epoch 414/1000
```

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414.1164 - val loss: 77.8754 - val mse: 27.5666
Epoch 415/1000
460/460 [==============] - 1s 1ms/step - loss: 4221.0522 - mse
: 4170.1294 - val loss: 140.0560 - val mse: 88.7000
Epoch 416/1000
117.3665 - val loss: 1122.2385 - val mse: 1071.7057
Epoch 417/1000
105.7864 - val loss: 161.5965 - val mse: 111.7550
Epoch 418/1000
148.5916 - val loss: 489.2244 - val mse: 439.3548
Epoch 419/1000
806.9924 - val loss: 142.7560 - val mse: 91.5319
Epoch 420/1000
115.3343 - val loss: 113.6793 - val mse: 63.4176
Epoch 421/1000
772.4645 - val loss: 78.9101 - val mse: 28.7921
Epoch 422/1000
163.4535 - val loss: 1014.9153 - val mse: 965.3613
Epoch 423/1000
: 2113.9827 - val loss: 79.8353 - val mse: 28.9097
Epoch 424/1000
72.3813 - val loss: 159.4172 - val mse: 109.6562
Epoch 425/1000
401.8678 - val loss: 160.5327 - val mse: 110.8597
Epoch 426/1000
390.5605 - val loss: 123.7098 - val mse: 74.6497
Epoch 427/1000
460/460 [=============] - 1s 1ms/step - loss: 2112.1248 - mse
: 2062.0908 - val loss: 101.7205 - val mse: 48.8794
Epoch 428/1000
64.5592 - val loss: 312.1273 - val mse: 261.5660
Epoch 429/1000
161.2469 - val loss: 81.6659 - val mse: 32.1262
Epoch 430/1000
460/460 [=============] - 1s 1ms/step - loss: 924.5272 - mse:
874.7726 - val loss: 88.0808 - val mse: 38.6763
Epoch 431/1000
167.8962 - val loss: 260.3535 - val mse: 210.9669
Epoch 432/1000
: 2867.6699 - val loss: 105.6180 - val mse: 55.1378
Epoch 433/1000
105.1418 - val loss: 82.2660 - val mse: 33.0383
Epoch 434/1000
188.4384 - val loss: 83.7270 - val mse: 34.7784
```

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Epoch 435/1000
: 2448.5708 - val loss: 98.1219 - val mse: 48.8277
Epoch 436/1000
61.4370 - val loss: 79.4599 - val mse: 30.3804
Epoch 437/1000
309.3130 - val loss: 94.7945 - val mse: 45.6016
Epoch 438/1000
868.5947 - val loss: 82.6317 - val mse: 32.9626
Epoch 439/1000
765.3176 - val loss: 22377.6523 - val mse: 22327.4395
Epoch 440/1000
460/460 [=============] - 1s 1ms/step - loss: 846.1685 - mse:
795.9824 - val loss: 103.6677 - val mse: 53.3582
Epoch 441/1000
272.1956 - val loss: 87.0038 - val mse: 37.1689
Epoch 442/1000
: 1352.8038 - val_loss: 91.2286 - val_mse: 39.4189
Epoch 443/1000
460/460 [============] - 1s 1ms/step - loss: 387.7661 - mse:
335.9868 - val loss: 12956.3750 - val mse: 12904.5654
Epoch 444/1000
358.6897 - val loss: 77.1012 - val mse: 25.9096
Epoch 445/1000
: 955.6957 - val loss: 92.9634 - val mse: 41.8520
Epoch 446/1000
176.7721 - val loss: 162.1897 - val mse: 111.1794
Epoch 447/1000
: 3857.4214 - val loss: 86.9946 - val mse: 35.1533
Epoch 448/1000
43.0119 - val loss: 163.4144 - val mse: 111.6988
Epoch 449/1000
58.4364 - val loss: 82.6772 - val_mse: 31.1317
Epoch 450/1000
193.1427 - val loss: 233.3488 - val mse: 181.9172
Epoch 451/1000
294.8466 - val loss: 3309.9888 - val mse: 3259.1873
Epoch 452/1000
603.7919 - val loss: 170.7271 - val mse: 119.6726
Epoch 453/1000
: 1272.5568 - val loss: 88.1946 - val mse: 37.3014
Epoch 454/1000
172.4751 - val loss: 196.5835 - val_mse: 146.3553
Epoch 455/1000
```

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460/460 [============] - 1s 1ms/step - loss: 342.4546 - mse:
292.2957 - val loss: 4299.8330 - val mse: 4249.8945
Epoch 456/1000
460/460 [============== ] - 1s 1ms/step - loss: 5072.1831 - mse
: 5021.2749 - val loss: 81.6045 - val mse: 31.1910
Epoch 457/1000
49.3618 - val loss: 379.1072 - val mse: 329.3997
Epoch 458/1000
117.2175 - val loss: 874.1065 - val mse: 823.8516
Epoch 459/1000
301.0521 - val loss: 97.1338 - val mse: 47.0239
Epoch 460/1000
302.9659 - val loss: 102.6465 - val mse: 52.3626
Epoch 461/1000
402.9042 - val loss: 1870.9615 - val mse: 1820.7465
Epoch 462/1000
540.3569 - val_loss: 146.7921 - val_mse: 96.3146
Epoch 463/1000
412.0253 - val loss: 2228.0686 - val mse: 2177.2139
Epoch 464/1000
460/460 [============== ] - 1s 1ms/step - loss: 1424.0953 - mse
: 1372.8112 - val loss: 163.2357 - val mse: 111.7652
Epoch 465/1000
297.2458 - val loss: 83.4902 - val mse: 32.8608
Epoch 466/1000
: 1487.0486 - val loss: 194.6895 - val mse: 143.9838
Epoch 467/1000
93.9520 - val loss: 79.3268 - val mse: 29.5461
Epoch 468/1000
745.0250 - val loss: 128.6040 - val mse: 78.1205
Epoch 469/1000
: 2383.5034 - val loss: 4102.7944 - val mse: 4049.7019
Epoch 470/1000
321.4420 - val loss: 118.1942 - val mse: 67.6544
Epoch 471/1000
108.0924 - val loss: 536.0283 - val mse: 485.3745
Epoch 472/1000
827.8106 - val loss: 128.3481 - val mse: 76.4536
Epoch 473/1000
617.0509 - val loss: 92.8373 - val mse: 42.5440
Epoch 474/1000
794.0392 - val loss: 5283.5972 - val mse: 5233.0952
Epoch 475/1000
```

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201.1921 - val loss: 1789.9532 - val mse: 1739.7861
Epoch 476/1000
679.2191 - val loss: 89.1237 - val mse: 39.2571
Epoch 477/1000
: 970.5644 - val loss: 1120.1816 - val mse: 1069.9647
Epoch 478/1000
460/460 [============== ] - 1s 1ms/step - loss: 1061.6538 - mse
: 1011.4793 - val loss: 77.5625 - val mse: 27.6719
Epoch 479/1000
92.1043 - val loss: 83.6628 - val mse: 34.2105
Epoch 480/1000
: 2858.6055 - val loss: 147.2331 - val mse: 95.4219
Epoch 481/1000
138.8417 - val_loss: 123.7224 - val_mse: 72.9858
Epoch 482/1000
218.1408 - val loss: 3376.2302 - val mse: 3325.6638
Epoch 483/1000
: 1031.2721 - val loss: 83.8607 - val mse: 34.1993
Epoch 484/1000
177.3851 - val_loss: 130.0545 - val_mse: 80.5563
Epoch 485/1000
492.9365 - val_loss: 216.6935 - val mse: 167.6890
Epoch 486/1000
398.7196 - val_loss: 115.6108 - val_mse: 65.5008
Epoch 487/1000
127.7863 - val loss: 224.3035 - val mse: 174.4185
Epoch 488/1000
460/460 [============] - 1s 1ms/step - loss: 4761.6377 - mse
: 4710.7988 - val loss: 124.4448 - val mse: 71.8895
Epoch 489/1000
141.5774 - val loss: 139.7971 - val mse: 87.7841
Epoch 490/1000
51.2382 - val loss: 178.8725 - val mse: 127.6391
Epoch 491/1000
306.9607 - val loss: 77.2310 - val mse: 26.3213
Epoch 492/1000
271.0273 - val loss: 29089.5410 - val mse: 29038.8281
Epoch 493/1000
825.1433 - val loss: 555.1165 - val mse: 504.9252
Epoch 494/1000
: 1798.6833 - val loss: 726.2256 - val mse: 675.8423
Epoch 495/1000
69.6259 - val loss: 113.2869 - val mse: 63.5920
```

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Epoch 496/1000
105.6464 - val loss: 114.1607 - val mse: 63.8975
Epoch 497/1000
: 3112.1104 - val loss: 176.3065 - val mse: 123.4840
Epoch 498/1000
180.6227 - val loss: 102.0504 - val mse: 50.3996
Epoch 499/1000
94.4313 - val loss: 123.3523 - val mse: 71.9441
Epoch 500/1000
455.2975 - val loss: 763.0007 - val mse: 711.9459
Epoch 501/1000
460/460 [============] - 1s 1ms/step - loss: 762.3638 - mse:
711.4916 - val loss: 266.2919 - val mse: 215.2930
Epoch 502/1000
106.1688 - val loss: 123.0003 - val mse: 72.5710
Epoch 503/1000
460/460 [============== ] - 1s 1ms/step - loss: 1258.0709 - mse
: 1207.4907 - val loss: 341.1750 - val mse: 290.8839
Epoch 504/1000
183.7674 - val loss: 1950.6249 - val mse: 1900.6989
Epoch 505/1000
786.3657 - val loss: 221.6925 - val mse: 172.0627
Epoch 506/1000
476.7180 - val loss: 101.9072 - val mse: 52.4258
Epoch 507/1000
: 1741.1964 - val loss: 156.3531 - val mse: 106.9152
Epoch 508/1000
93.1240 - val loss: 84.7014 - val mse: 35.5689
Epoch 509/1000
330.6604 - val loss: 132.8819 - val mse: 83.9701
Epoch 510/1000
852.1513 - val loss: 201.3220 - val mse: 152.4198
Epoch 511/1000
211.2162 - val loss: 101.0151 - val mse: 51.8248
Epoch 512/1000
460/460 [============] - 1s 1ms/step - loss: 4958.6040 - mse
: 4908.6724 - val loss: 115.2338 - val mse: 63.9972
Epoch 513/1000
60.6531 - val loss: 86.2387 - val mse: 35.5929
Epoch 514/1000
120.7244 - val loss: 114.2834 - val mse: 63.9346
Epoch 515/1000
510.6320 - val loss: 126.7301 - val mse: 77.0314
Epoch 516/1000
```

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460/460 [=============] - 1s 1ms/step - loss: 391.1924 - mse:
341.4656 - val loss: 96.2639 - val mse: 46.1816
Epoch 517/1000
: 1318.7744 - val loss: 83.8548 - val mse: 34.2131
Epoch 518/1000
181.1953 - val loss: 83.8894 - val mse: 34.6102
Epoch 519/1000
417.4627 - val loss: 89.4984 - val mse: 40.4713
Epoch 520/1000
111.3827 - val loss: 125.7036 - val mse: 76.1920
Epoch 521/1000
: 1673.9441 - val loss: 190.2945 - val mse: 141.2596
Epoch 522/1000
85.3481 - val loss: 106.7303 - val mse: 57.1857
Epoch 523/1000
892.7056 - val loss: 87.0311 - val mse: 37.6561
Epoch 524/1000
399.7517 - val loss: 225.8900 - val mse: 176.4800
Epoch 525/1000
385.5001 - val loss: 2303.0110 - val mse: 2253.8176
Epoch 526/1000
: 1468.1349 - val loss: 123.4987 - val mse: 72.7021
Epoch 527/1000
448.0068 - val loss: 225.4393 - val mse: 175.7007
Epoch 528/1000
853.2728 - val loss: 939.0333 - val mse: 889.8045
Epoch 529/1000
801.2378 - val loss: 3492.5557 - val mse: 3443.1265
Epoch 530/1000
282.0596 - val loss: 261.6746 - val mse: 212.1954
Epoch 531/1000
441.4308 - val loss: 466.8147 - val mse: 417.8413
Epoch 532/1000
748.4157 - val loss: 94.2128 - val mse: 44.8364
Epoch 533/1000
658.3586 - val loss: 130.9948 - val mse: 82.1208
Epoch 534/1000
539.4395 - val loss: 92.8743 - val mse: 43.7834
Epoch 535/1000
: 1596.1548 - val loss: 87.8231 - val mse: 38.9187
Epoch 536/1000
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149.8273 - val loss: 85.2945 - val mse: 36.7102
Epoch 537/1000
162.2145 - val loss: 298.7397 - val mse: 249.8489
Epoch 538/1000
460/460 [=============] - 1s 1ms/step - loss: 1665.9677 - mse
: 1617.0837 - val loss: 334.5762 - val mse: 285.0767
Epoch 539/1000
85.9353 - val loss: 273.5170 - val mse: 224.9391
Epoch 540/1000
400.6515 - val loss: 305.3639 - val mse: 257.1451
Epoch 541/1000
522.0768 - val loss: 459.4114 - val mse: 410.2997
Epoch 542/1000
: 3409.9072 - val_loss: 174.5968 - val_mse: 124.6486
Epoch 543/1000
68.6190 - val loss: 116.1904 - val mse: 66.6698
Epoch 544/1000
133.7675 - val loss: 110.7059 - val mse: 61.4901
Epoch 545/1000
143.1324 - val_loss: 518.7092 - val mse: 468.9623
Epoch 546/1000
409.7583 - val_loss: 92.4845 - val mse: 43.1120
Epoch 547/1000
260.6295 - val loss: 290.1259 - val mse: 241.1073
Epoch 548/1000
: 2414.9604 - val loss: 115.7475 - val mse: 66.6455
Epoch 549/1000
460/460 [=============] - 1s 1ms/step - loss: 123.0359 - mse:
74.2555 - val loss: 143.4411 - val mse: 94.8969
Epoch 550/1000
221.6273 - val loss: 203.9700 - val mse: 156.0053
Epoch 551/1000
502.9411 - val loss: 90.8032 - val mse: 42.9031
Epoch 552/1000
617.8649 - val loss: 80.3571 - val mse: 32.2067
Epoch 553/1000
772.5087 - val loss: 85.5627 - val mse: 37.6536
Epoch 554/1000
132.2951 - val loss: 7170.2598 - val mse: 7122.4829
Epoch 555/1000
775.9850 - val loss: 112.3514 - val mse: 65.0122
Epoch 556/1000
: 2173.4673 - val loss: 1909.7065 - val mse: 1861.0312
```

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Epoch 557/1000
87.3261 - val loss: 91.8293 - val mse: 44.1458
Epoch 558/1000
169.6448 - val_loss: 100.1490 - val mse: 52.6266
Epoch 559/1000
286.1378 - val loss: 77.2912 - val mse: 29.0413
Epoch 560/1000
: 1333.3086 - val loss: 346.0654 - val mse: 298.3914
Epoch 561/1000
176.1180 - val loss: 98.1276 - val mse: 50.5015
Epoch 562/1000
714.6002 - val loss: 92.8461 - val mse: 45.4558
Epoch 563/1000
296.8439 - val loss: 140.3401 - val mse: 92.9342
Epoch 564/1000
460/460 [=============] - 1s 1ms/step - loss: 1992.5570 - mse
: 1944.1556 - val loss: 84.3885 - val mse: 36.2773
Epoch 565/1000
460/460 [============] - 1s 1ms/step - loss: 176.7686 - mse:
129.0611 - val loss: 205.1459 - val mse: 157.8487
Epoch 566/1000
366.4175 - val loss: 117.0685 - val mse: 68.9508
Epoch 567/1000
490.2453 - val loss: 2810.3845 - val mse: 2762.5195
Epoch 568/1000
428.7783 - val loss: 687.7275 - val mse: 640.4531
Epoch 569/1000
410.8826 - val loss: 90.8219 - val mse: 43.1520
Epoch 570/1000
252.8557 - val loss: 92.4366 - val mse: 43.9854
Epoch 571/1000
410.1435 - val loss: 86.9469 - val mse: 38.1725
Epoch 572/1000
460/460 [=============] - 1s 1ms/step - loss: 551.2108 - mse:
502.4800 - val loss: 137.3766 - val mse: 88.9137
Epoch 573/1000
436.4928 - val loss: 89.2502 - val mse: 40.8657
Epoch 574/1000
698.9586 - val loss: 102.3608 - val mse: 53.0788
Epoch 575/1000
158.7698 - val_loss: 86.1440 - val_mse: 37.6084
Epoch 576/1000
460/460 [=============] - 1s 1ms/step - loss: 2859.6387 - mse
: 2811.1868 - val loss: 688.6320 - val mse: 640.4126
Epoch 577/1000
```

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127.5986 - val loss: 92.3570 - val mse: 44.9019
Epoch 578/1000
121.8844 - val loss: 83.7041 - val mse: 36.6051
Epoch 579/1000
455.9927 - val loss: 317.3773 - val mse: 269.9629
Epoch 580/1000
260.8700 - val loss: 124.3137 - val mse: 77.3649
Epoch 581/1000
703.6967 - val loss: 86.6251 - val mse: 39.6606
Epoch 582/1000
485.1113 - val loss: 93.3378 - val mse: 45.8835
Epoch 583/1000
348.3589 - val loss: 72.6598 - val mse: 25.4979
Epoch 584/1000
625.2758 - val_loss: 103.5293 - val mse: 56.7593
Epoch 585/1000
559.3563 - val loss: 418.3818 - val mse: 371.7117
Epoch 586/1000
255.2399 - val loss: 74.4376 - val mse: 27.2364
Epoch 587/1000
460/460 [=============] - 1s 1ms/step - loss: 1616.6875 - mse
: 1569.2438 - val loss: 1652.2507 - val mse: 1604.3574
Epoch 588/1000
190.5011 - val loss: 187.1084 - val mse: 140.4808
Epoch 589/1000
341.7115 - val loss: 107.1927 - val mse: 59.0289
Epoch 590/1000
: 1606.0452 - val loss: 148.7607 - val mse: 100.9574
Epoch 591/1000
531.9251 - val loss: 171.9879 - val mse: 124.8140
Epoch 592/1000
128.6207 - val loss: 123.8986 - val mse: 76.9987
Epoch 593/1000
310.8255 - val loss: 1099.3234 - val mse: 1052.1831
Epoch 594/1000
521.9863 - val loss: 907.6030 - val mse: 859.9639
Epoch 595/1000
: 1351.1064 - val loss: 242.3533 - val mse: 194.2571
Epoch 596/1000
126.9356 - val loss: 100.4456 - val mse: 53.1346
Epoch 597/1000
```

```
: 3264.0955 - val loss: 692.4985 - val mse: 643.4922
Epoch 598/1000
151.6417 - val loss: 77.5336 - val mse: 29.6652
Epoch 599/1000
216.2539 - val loss: 87.5832 - val mse: 40.3715
Epoch 600/1000
134.2933 - val loss: 225.5740 - val mse: 178.4160
Epoch 601/1000
188.3352 - val loss: 80.9184 - val mse: 33.8808
Epoch 602/1000
: 1107.5217 - val loss: 108.9532 - val mse: 61.4668
Epoch 603/1000
86.5149 - val loss: 80.6692 - val mse: 33.4305
Epoch 604/1000
804.9789 - val loss: 85.2944 - val mse: 38.8394
Epoch 605/1000
: 2489.9673 - val loss: 106.5979 - val mse: 58.9497
Epoch 606/1000
59.5737 - val loss: 93.4115 - val mse: 46.2238
Epoch 607/1000
346.2866 - val loss: 4503.2974 - val mse: 4456.7334
Epoch 608/1000
522.9461 - val loss: 1002.3351 - val mse: 956.0580
Epoch 609/1000
193.1235 - val loss: 135.7857 - val mse: 89.0893
Epoch 610/1000
: 1174.8724 - val loss: 93.7725 - val mse: 46.7615
Epoch 611/1000
131.4378 - val loss: 98.0891 - val mse: 51.2342
Epoch 612/1000
696.2904 - val loss: 1782.0963 - val mse: 1734.7319
Epoch 613/1000
431.8546 - val loss: 115.9240 - val mse: 67.5183
Epoch 614/1000
535.1237 - val loss: 129.1976 - val mse: 82.6922
Epoch 615/1000
461.8301 - val loss: 534.9319 - val mse: 487.8505
Epoch 616/1000
: 2223.4895 - val loss: 155.5540 - val mse: 108.3870
Epoch 617/1000
44.8998 - val loss: 101.9741 - val mse: 55.1101
```

```
Epoch 618/1000
576.6298 - val loss: 583.8955 - val mse: 536.2423
Epoch 619/1000
292.1880 - val_loss: 584.8121 - val_mse: 536.7693
Epoch 620/1000
: 1042.6189 - val loss: 77.6256 - val mse: 29.5536
Epoch 621/1000
169.3629 - val loss: 3944.4355 - val mse: 3896.7966
Epoch 622/1000
: 1845.2449 - val loss: 98.6549 - val mse: 50.4562
Epoch 623/1000
460/460 [=============] - 1s 1ms/step - loss: 467.5877 - mse:
419.9269 - val loss: 144.5929 - val mse: 97.5690
Epoch 624/1000
273.6808 - val loss: 237.2269 - val mse: 190.3268
Epoch 625/1000
: 2947.9075 - val_loss: 994.7816 - val_mse: 947.2385
Epoch 626/1000
103.5315 - val loss: 91.3084 - val mse: 44.5103
Epoch 627/1000
161.8614 - val loss: 783.2408 - val mse: 736.8832
Epoch 628/1000
124.9099 - val loss: 126.7565 - val mse: 80.1491
Epoch 629/1000
214.2939 - val loss: 206.8121 - val mse: 160.4407
Epoch 630/1000
945.0437 - val loss: 96.6055 - val mse: 49.2782
Epoch 631/1000
342.8695 - val loss: 160.2456 - val mse: 113.8749
Epoch 632/1000
797.1068 - val loss: 80.1032 - val mse: 34.0858
Epoch 633/1000
460/460 [============] - 1s 1ms/step - loss: 2199.5461 - mse
: 2153.1079 - val loss: 89.1579 - val mse: 42.4472
Epoch 634/1000
85.5801 - val loss: 177.4553 - val mse: 131.5814
Epoch 635/1000
177.3367 - val loss: 630.7582 - val mse: 584.6993
Epoch 636/1000
310.6218 - val_loss: 161.1357 - val_mse: 115.3275
Epoch 637/1000
578.6144 - val loss: 104.5183 - val mse: 58.3974
Epoch 638/1000
```

```
460/460 [=============] - 1s 1ms/step - loss: 1962.9542 - mse
: 1916.8578 - val loss: 527.9730 - val mse: 481.9995
Epoch 639/1000
460/460 [=============] - 1s 1ms/step - loss: 552.6096 - mse:
506.7839 - val loss: 1071.2374 - val mse: 1025.0162
Epoch 640/1000
94.6975 - val loss: 77.7414 - val mse: 31.9402
Epoch 641/1000
296.6544 - val loss: 82.4205 - val mse: 36.1065
Epoch 642/1000
290.0962 - val loss: 233.6304 - val mse: 187.6873
Epoch 643/1000
507.7299 - val loss: 79.6124 - val mse: 33.3427
Epoch 644/1000
: 1480.6200 - val loss: 1018.6410 - val mse: 972.7449
Epoch 645/1000
159.4236 - val_loss: 140.4936 - val mse: 95.0838
Epoch 646/1000
341.8297 - val loss: 595.1749 - val mse: 548.5901
Epoch 647/1000
449.3933 - val loss: 1008.6375 - val mse: 962.4974
Epoch 648/1000
366.0854 - val loss: 275.5164 - val mse: 228.8745
Epoch 649/1000
734.6924 - val loss: 221.3288 - val mse: 175.1374
Epoch 650/1000
460/460 [=============] - 1s 1ms/step - loss: 1275.6473 - mse
: 1229.2083 - val loss: 91.3210 - val mse: 45.3671
Epoch 651/1000
172.4838 - val loss: 255.7255 - val mse: 210.0144
Epoch 652/1000
178.2834 - val loss: 149.1596 - val mse: 103.4281
Epoch 653/1000
534.7352 - val loss: 76.8800 - val mse: 30.8044
Epoch 654/1000
: 2248.5090 - val loss: 87.9246 - val mse: 42.3664
Epoch 655/1000
81.4864 - val loss: 73.7245 - val mse: 27.6694
Epoch 656/1000
553.7827 - val_loss: 485.4267 - val_mse: 439.3843
Epoch 657/1000
: 1832.1165 - val loss: 232.1462 - val mse: 185.3854
Epoch 658/1000
```

```
49.2523 - val loss: 77.2322 - val mse: 30.9871
Epoch 659/1000
460/460 [=============] - 1s 1ms/step - loss: 781.2130 - mse:
735.2625 - val loss: 194.4515 - val mse: 148.8362
Epoch 660/1000
797.5824 - val loss: 108.2300 - val mse: 63.3401
Epoch 661/1000
72.2345 - val loss: 851.3175 - val mse: 806.7351
Epoch 662/1000
907.5358 - val loss: 134.7565 - val mse: 89.9338
Epoch 663/1000
110.2137 - val loss: 73.8595 - val mse: 28.9321
Epoch 664/1000
603.8551 - val_loss: 71.0704 - val_mse: 26.8194
Epoch 665/1000
83.6699 - val loss: 169.5223 - val mse: 125.4229
Epoch 666/1000
: 1018.6387 - val loss: 133.6917 - val mse: 89.1244
Epoch 667/1000
368.9663 - val_loss: 126.8507 - val_mse: 82.9581
Epoch 668/1000
: 2099.4956 - val loss: 154.8264 - val mse: 111.0102
Epoch 669/1000
68.5415 - val loss: 115.8867 - val mse: 71.9496
Epoch 670/1000
286.1770 - val loss: 91.0653 - val mse: 47.5665
Epoch 671/1000
460/460 [=============] - 1s 1ms/step - loss: 514.4247 - mse:
470.1388 - val loss: 73.8622 - val mse: 29.7367
Epoch 672/1000
628.9088 - val loss: 105.2639 - val mse: 60.5538
Epoch 673/1000
246.8880 - val loss: 81.1067 - val mse: 37.0983
Epoch 674/1000
311.5356 - val loss: 75.9029 - val mse: 32.1293
Epoch 675/1000
: 1690.1611 - val loss: 77.1934 - val mse: 33.4650
Epoch 676/1000
119.5775 - val loss: 1946.9711 - val mse: 1902.9193
Epoch 677/1000
441.0981 - val loss: 253.8753 - val mse: 210.2754
Epoch 678/1000
519.1752 - val loss: 1267.6658 - val mse: 1223.9303
```

```
Epoch 679/1000
513.5441 - val loss: 84.4256 - val mse: 40.5979
Epoch 680/1000
: 968.1702 - val loss: 84.5532 - val mse: 40.0624
Epoch 681/1000
125.4242 - val_loss: 387.2974 - val mse: 343.5422
Epoch 682/1000
760.8529 - val loss: 81.6099 - val mse: 38.1771
Epoch 683/1000
699.2660 - val loss: 131.9561 - val mse: 88.2919
Epoch 684/1000
: 1912.9893 - val loss: 216.4588 - val mse: 171.3060
Epoch 685/1000
59.1961 - val loss: 75.4835 - val mse: 31.4745
Epoch 686/1000
460/460 [=============] - 1s 1ms/step - loss: 128.1042 - mse:
84.3117 - val loss: 253.1945 - val mse: 209.4257
Epoch 687/1000
297.2093 - val loss: 224.2979 - val mse: 180.4588
Epoch 688/1000
446.9262 - val loss: 93.3098 - val mse: 49.1645
Epoch 689/1000
421.9755 - val loss: 62823.1875 - val mse: 62779.5547
Epoch 690/1000
460/460 [=============] - 1s 1ms/step - loss: 2709.4758 - mse
: 2664.6069 - val loss: 80.9412 - val mse: 36.4642
Epoch 691/1000
55.7427 - val loss: 148.7801 - val mse: 104.8036
Epoch 692/1000
439.0724 - val loss: 127.9933 - val mse: 84.1412
Epoch 693/1000
: 8572.4775 - val loss: 239.3160 - val mse: 192.8659
Epoch 694/1000
460/460 [============] - 1s 1ms/step - loss: 147.2298 - mse:
101.4070 - val loss: 114.9355 - val mse: 69.5811
Epoch 695/1000
49.1813 - val loss: 74.5696 - val mse: 29.8615
Epoch 696/1000
54.9512 - val loss: 79.9120 - val mse: 35.4908
Epoch 697/1000
55.1243 - val_loss: 71.2250 - val_mse: 27.1507
Epoch 698/1000
105.1829 - val loss: 105.1982 - val_mse: 61.3851
Epoch 699/1000
```

```
460/460 [=============] - 1s 1ms/step - loss: 1120.0312 - mse
: 1075.9618 - val loss: 224.3423 - val mse: 180.6476
Epoch 700/1000
460/460 [=============] - 1s 1ms/step - loss: 182.8186 - mse:
139.3629 - val loss: 236.8121 - val mse: 193.1976
Epoch 701/1000
362.4229 - val loss: 3818.7622 - val mse: 3774.6106
Epoch 702/1000
: 2330.6519 - val loss: 85.5137 - val mse: 42.0449
Epoch 703/1000
90.6769 - val loss: 224.2349 - val mse: 181.4302
Epoch 704/1000
68.8157 - val loss: 75.7946 - val mse: 32.9516
Epoch 705/1000
129.9176 - val loss: 4741.9346 - val mse: 4698.8667
Epoch 706/1000
: 1541.7754 - val_loss: 192.5850 - val_mse: 149.3387
Epoch 707/1000
59.0273 - val loss: 79.3281 - val mse: 36.5694
Epoch 708/1000
460/460 [=============] - 1s 1ms/step - loss: 4346.7358 - mse
: 4304.0044 - val loss: 223.8334 - val mse: 180.7591
Epoch 709/1000
62.6499 - val loss: 100.7728 - val mse: 58.0350
Epoch 710/1000
44.4025 - val loss: 75.2059 - val mse: 32.1008
Epoch 711/1000
67.5076 - val loss: 217.9029 - val mse: 175.6147
Epoch 712/1000
198.1659 - val loss: 236.8469 - val mse: 194.3953
Epoch 713/1000
358.2998 - val loss: 156.3265 - val mse: 113.3381
Epoch 714/1000
: 1520.6234 - val loss: 84.9046 - val mse: 41.4060
Epoch 715/1000
66.4167 - val loss: 94.9015 - val mse: 51.7514
Epoch 716/1000
778.7943 - val loss: 102.1300 - val mse: 59.6017
Epoch 717/1000
159.2922 - val loss: 110.8153 - val mse: 68.7859
Epoch 718/1000
: 2582.0789 - val loss: 997.7914 - val mse: 954.9282
Epoch 719/1000
```

```
108.7301 - val loss: 94.0018 - val mse: 51.7294
Epoch 720/1000
65.6590 - val loss: 172.6853 - val mse: 130.9894
Epoch 721/1000
813.0757 - val loss: 117.1112 - val mse: 75.0278
Epoch 722/1000
924.3611 - val loss: 70.8108 - val mse: 28.8449
Epoch 723/1000
169.1581 - val loss: 93.5336 - val mse: 51.7359
Epoch 724/1000
623.5024 - val loss: 201.9622 - val mse: 160.4139
Epoch 725/1000
126.6086 - val_loss: 73.3961 - val_mse: 31.3231
Epoch 726/1000
: 982.9858 - val loss: 80.0687 - val mse: 38.3938
Epoch 727/1000
347.3286 - val loss: 129.2315 - val mse: 86.4648
Epoch 728/1000
: 2504.4717 - val loss: 76.1554 - val mse: 33.5539
Epoch 729/1000
77.9930 - val loss: 258.9755 - val mse: 216.6449
Epoch 730/1000
82.6747 - val loss: 75.6838 - val mse: 33.3491
Epoch 731/1000
452.9593 - val loss: 74.9102 - val mse: 32.4100
Epoch 732/1000
460/460 [=============] - 1s 1ms/step - loss: 584.4227 - mse:
541.9434 - val loss: 86.2583 - val mse: 43.4210
Epoch 733/1000
: 973.5407 - val loss: 86.1437 - val mse: 43.5959
Epoch 734/1000
144.7586 - val_loss: 109.6629 - val_mse: 67.2006
Epoch 735/1000
: 1098.4091 - val loss: 460.8648 - val mse: 418.0941
Epoch 736/1000
152.9344 - val loss: 82.3519 - val mse: 40.2703
Epoch 737/1000
425.6432 - val loss: 73.1487 - val mse: 31.4558
Epoch 738/1000
177.1386 - val loss: 686.7335 - val mse: 644.8991
Epoch 739/1000
360.7863 - val loss: 128.1162 - val mse: 86.2197
```

```
Epoch 740/1000
: 1013.2613 - val loss: 133.3688 - val mse: 91.3316
Epoch 741/1000
112.5699 - val_loss: 811.0610 - val_mse: 769.1341
Epoch 742/1000
860.2830 - val_loss: 427.0591 - val mse: 384.7263
Epoch 743/1000
712.1387 - val loss: 139.9329 - val mse: 97.7701
Epoch 744/1000
151.2581 - val loss: 68.1091 - val mse: 26.1911
Epoch 745/1000
460/460 [=============] - 1s 1ms/step - loss: 1384.1886 - mse
: 1342.3325 - val loss: 100.5734 - val mse: 58.9718
Epoch 746/1000
85.4364 - val loss: 381.7630 - val mse: 340.2044
Epoch 747/1000
307.8657 - val_loss: 137.1026 - val_mse: 95.5208
Epoch 748/1000
: 1389.4894 - val loss: 32949.3984 - val mse: 32907.6172
Epoch 749/1000
785.9838 - val loss: 944.6813 - val mse: 903.1843
Epoch 750/1000
224.4573 - val loss: 1195.2605 - val mse: 1153.5693
Epoch 751/1000
228.0002 - val loss: 125.4927 - val mse: 83.3304
Epoch 752/1000
: 1296.0555 - val loss: 103.1915 - val mse: 61.2871
Epoch 753/1000
473.2125 - val loss: 118.5703 - val mse: 76.8158
Epoch 754/1000
658.0156 - val loss: 87.3555 - val mse: 45.2745
Epoch 755/1000
460/460 [============] - 1s 1ms/step - loss: 115.1325 - mse:
73.1096 - val loss: 495.1215 - val mse: 453.0403
Epoch 756/1000
917.8038 - val loss: 21118.3477 - val mse: 21075.5605
Epoch 757/1000
796.7283 - val loss: 108.8205 - val mse: 66.0905
Epoch 758/1000
460/460 [============== ] - 1s 1ms/step - loss: 1113.9590 - mse
: 1071.2554 - val loss: 179.6134 - val mse: 137.0715
Epoch 759/1000
460/460 [============] - 1s 1ms/step - loss: 204.1427 - mse:
161.3975 - val loss: 205.3587 - val_mse: 162.9356
Epoch 760/1000
```

```
460/460 [=============] - 1s 1ms/step - loss: 358.4240 - mse:
315.3808 - val loss: 82.5662 - val mse: 39.8722
Epoch 761/1000
460/460 [=============] - 1s 2ms/step - loss: 288.3062 - mse:
245.8363 - val loss: 318.0726 - val mse: 275.8862
Epoch 762/1000
: 1135.6548 - val loss: 150.3723 - val mse: 108.9285
Epoch 763/1000
114.3015 - val loss: 722.7451 - val mse: 681.0468
Epoch 764/1000
: 3771.0955 - val loss: 204.2096 - val mse: 161.5330
Epoch 765/1000
72.1047 - val loss: 71.3556 - val mse: 29.5022
Epoch 766/1000
48.5590 - val loss: 123.1568 - val mse: 81.5929
Epoch 767/1000
140.9865 - val_loss: 277.0580 - val mse: 235.5905
Epoch 768/1000
308.8775 - val loss: 157.1134 - val mse: 115.6432
Epoch 769/1000
738.0328 - val loss: 215.7779 - val mse: 174.2199
Epoch 770/1000
787.2018 - val loss: 88.1123 - val mse: 45.9870
Epoch 771/1000
276.4483 - val_loss: 72.8639 - val_mse: 31.5293
Epoch 772/1000
182.4779 - val loss: 631.4195 - val mse: 590.1005
Epoch 773/1000
777.7408 - val loss: 276.1659 - val mse: 234.6609
Epoch 774/1000
234.5777 - val loss: 76.5860 - val mse: 35.1697
Epoch 775/1000
394.1791 - val loss: 174.3698 - val mse: 133.0036
Epoch 776/1000
237.9638 - val loss: 966.3652 - val mse: 925.3516
Epoch 777/1000
: 1556.9120 - val loss: 70.2455 - val mse: 29.1478
Epoch 778/1000
153.3448 - val_loss: 101.4322 - val_mse: 60.3518
Epoch 779/1000
543.2067 - val loss: 1832.6144 - val mse: 1790.3484
Epoch 780/1000
```

```
225.8688 - val loss: 4707.3091 - val mse: 4664.9053
Epoch 781/1000
244.2160 - val loss: 77.5325 - val mse: 35.8733
Epoch 782/1000
460/460 [=============] - 1s 1ms/step - loss: 1809.6372 - mse
: 1767.2566 - val loss: 206.4824 - val mse: 163.6037
Epoch 783/1000
85.4263 - val loss: 252.7989 - val mse: 210.4677
Epoch 784/1000
296.5928 - val loss: 333.9813 - val mse: 292.0493
Epoch 785/1000
: 5296.6602 - val loss: 89.1154 - val mse: 45.9069
Epoch 786/1000
77.9079 - val loss: 77.9800 - val mse: 35.5223
Epoch 787/1000
56.8001 - val loss: 748.8997 - val mse: 706.8444
Epoch 788/1000
106.5401 - val loss: 200.9846 - val mse: 159.1975
Epoch 789/1000
867.8849 - val loss: 90.9220 - val mse: 49.2538
Epoch 790/1000
177.9724 - val_loss: 77.5178 - val mse: 36.0149
Epoch 791/1000
304.1343 - val_loss: 324.6105 - val mse: 283.5561
Epoch 792/1000
285.5955 - val loss: 170.1079 - val mse: 128.4105
Epoch 793/1000
460/460 [=============] - 1s 1ms/step - loss: 679.6778 - mse:
638.2471 - val loss: 70.8905 - val mse: 29.5250
Epoch 794/1000
326.1111 - val loss: 67.7387 - val mse: 26.6201
Epoch 795/1000
500.9503 - val loss: 5447.1392 - val mse: 5406.0938
Epoch 796/1000
611.1970 - val loss: 67.7747 - val mse: 26.9641
Epoch 797/1000
208.5775 - val loss: 189.0772 - val mse: 147.7556
Epoch 798/1000
: 1129.2504 - val loss: 113.7969 - val mse: 72.0981
Epoch 799/1000
151.5036 - val loss: 574.4130 - val mse: 533.1719
Epoch 800/1000
: 1246.0144 - val loss: 146.6914 - val mse: 105.4832
```

```
Epoch 801/1000
151.7359 - val loss: 71.2010 - val mse: 30.2318
Epoch 802/1000
: 1138.7305 - val loss: 112.8609 - val mse: 71.2734
Epoch 803/1000
180.4093 - val loss: 291.6163 - val mse: 250.7571
Epoch 804/1000
784.8695 - val loss: 1138.2224 - val mse: 1096.2175
Epoch 805/1000
111.5884 - val loss: 90.9037 - val mse: 49.9973
Epoch 806/1000
229.0117 - val loss: 153.3444 - val mse: 112.1697
Epoch 807/1000
: 2150.7830 - val loss: 82.0680 - val mse: 38.8290
Epoch 808/1000
361.1917 - val_loss: 77.0351 - val_mse: 33.7977
Epoch 809/1000
235.6003 - val loss: 72.2672 - val_mse: 29.4619
Epoch 810/1000
230.3568 - val loss: 311.8893 - val mse: 269.3257
Epoch 811/1000
516.7456 - val loss: 4729.5659 - val mse: 4687.3262
Epoch 812/1000
460/460 [=============] - 1s 1ms/step - loss: 1098.8794 - mse
: 1056.7955 - val loss: 88.1315 - val mse: 46.2491
Epoch 813/1000
: 2659.3918 - val loss: 84.5693 - val mse: 41.8878
Epoch 814/1000
72.1673 - val loss: 110.6140 - val mse: 68.6852
Epoch 815/1000
63.6264 - val_loss: 111.5148 - val_mse: 70.0922
Epoch 816/1000
460/460 [=============] - 1s 1ms/step - loss: 686.0236 - mse:
644.3851 - val loss: 939.9489 - val mse: 898.3436
Epoch 817/1000
496.0436 - val loss: 99.4758 - val mse: 58.3372
Epoch 818/1000
136.2511 - val loss: 104.1102 - val mse: 62.9965
Epoch 819/1000
263.6237 - val loss: 661.9817 - val mse: 620.9958
Epoch 820/1000
460/460 [============] - 0s 1ms/step - loss: 289.6576 - mse:
248.9394 - val loss: 1620.9379 - val_mse: 1580.3014
Epoch 821/1000
```

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460/460 [=============] - 0s 1ms/step - loss: 1768.8624 - mse
: 1727.6766 - val loss: 208.4731 - val mse: 167.2250
Epoch 822/1000
460/460 [=============] - 0s 1ms/step - loss: 201.3227 - mse:
160.3851 - val loss: 140.3753 - val mse: 99.4667
Epoch 823/1000
103.1425 - val loss: 101.5203 - val mse: 60.8578
Epoch 824/1000
284.9241 - val loss: 85.4793 - val mse: 44.5083
Epoch 825/1000
: 1436.2545 - val loss: 179.3003 - val mse: 138.6382
Epoch 826/1000
433.0357 - val loss: 247.0400 - val mse: 206.3849
Epoch 827/1000
141.5079 - val loss: 808.2906 - val mse: 767.8255
Epoch 828/1000
369.3141 - val_loss: 109.9547 - val mse: 69.3997
Epoch 829/1000
: 1214.1971 - val loss: 89.6051 - val mse: 48.7447
Epoch 830/1000
66.0023 - val loss: 219.3770 - val mse: 178.9212
Epoch 831/1000
400.6638 - val loss: 501.7253 - val mse: 461.0932
Epoch 832/1000
307.5325 - val loss: 81.7480 - val mse: 41.2491
Epoch 833/1000
: 1269.2686 - val loss: 434.1508 - val mse: 393.4950
Epoch 834/1000
87.9479 - val loss: 68.9130 - val mse: 28.7790
Epoch 835/1000
126.4918 - val loss: 349.2800 - val mse: 309.3262
Epoch 836/1000
821.1047 - val loss: 89.3955 - val mse: 48.8970
Epoch 837/1000
676.5222 - val loss: 1410.0876 - val mse: 1369.3636
Epoch 838/1000
496.9832 - val loss: 165.6775 - val mse: 125.4495
Epoch 839/1000
287.2820 - val loss: 94.5071 - val mse: 54.0763
Epoch 840/1000
234.6470 - val loss: 5668.2637 - val mse: 5628.0454
Epoch 841/1000
```

```
: 1019.0087 - val loss: 116.1415 - val mse: 76.4342
Epoch 842/1000
89.8819 - val loss: 75.9569 - val mse: 36.2635
Epoch 843/1000
: 1940.5078 - val loss: 68.4236 - val mse: 28.3643
Epoch 844/1000
460/460 [==============] - 0s 1ms/step - loss: 429.7003 - mse:
389.9360 - val loss: 141.2470 - val mse: 101.7888
Epoch 845/1000
91.3720 - val loss: 72.3917 - val mse: 33.0651
Epoch 846/1000
176.5812 - val loss: 86.1064 - val mse: 46.6892
Epoch 847/1000
563.3671 - val_loss: 68.5456 - val_mse: 29.0182
Epoch 848/1000
213.2480 - val loss: 71.0013 - val mse: 31.8095
Epoch 849/1000
393.0154 - val loss: 742.6755 - val mse: 702.9860
Epoch 850/1000
352.1561 - val loss: 66.9282 - val mse: 28.2071
Epoch 851/1000
: 4959.3315 - val loss: 77.4946 - val mse: 37.1609
Epoch 852/1000
53.0047 - val loss: 67.4864 - val mse: 27.1764
Epoch 853/1000
41.5739 - val loss: 68.5233 - val mse: 28.5183
Epoch 854/1000
460/460 [============] - 0s 1ms/step - loss: 104.9723 - mse:
65.1464 - val loss: 163.5887 - val mse: 124.1297
Epoch 855/1000
94.0068 - val loss: 181.5902 - val mse: 142.7904
Epoch 856/1000
460/460 [==============] - 0s 1ms/step - loss: 206.7636 - mse:
168.0151 - val loss: 830.6842 - val mse: 792.0539
Epoch 857/1000
460/460 [=============] - 0s 1ms/step - loss: 978.3616 - mse:
939.5037 - val loss: 136.5518 - val mse: 97.7406
Epoch 858/1000
131.6138 - val loss: 88.7499 - val mse: 50.0207
Epoch 859/1000
463.7589 - val loss: 233.9419 - val mse: 195.0611
Epoch 860/1000
377.7726 - val loss: 872.4516 - val mse: 833.6351
Epoch 861/1000
: 966.8326 - val loss: 599.6281 - val mse: 560.7460
```

```
Epoch 862/1000
136.2606 - val loss: 69.5728 - val mse: 30.9594
Epoch 863/1000
156.8041 - val loss: 225.5752 - val mse: 186.3862
Epoch 864/1000
607.1332 - val loss: 129.9398 - val mse: 91.2961
Epoch 865/1000
404.4400 - val loss: 524.2974 - val mse: 485.4934
Epoch 866/1000
: 1449.4550 - val loss: 469.5039 - val mse: 430.6004
Epoch 867/1000
176.8246 - val loss: 77.8046 - val mse: 38.1453
Epoch 868/1000
674.9432 - val loss: 180.2666 - val mse: 139.8219
Epoch 869/1000
119.4627 - val_loss: 72.9383 - val_mse: 33.3794
Epoch 870/1000
460/460 [=============] - 0s 1ms/step - loss: 329.7756 - mse:
290.4397 - val loss: 18182.6855 - val mse: 18143.4004
Epoch 871/1000
: 1774.5345 - val loss: 68.0504 - val mse: 29.0177
Epoch 872/1000
111.4202 - val loss: 246.1924 - val mse: 206.1013
Epoch 873/1000
404.1124 - val loss: 69.8156 - val mse: 30.2282
Epoch 874/1000
124.7726 - val loss: 210.2542 - val mse: 171.0325
Epoch 875/1000
248.8755 - val loss: 2910.9243 - val mse: 2871.8384
Epoch 876/1000
: 1654.4879 - val loss: 82.4427 - val mse: 43.5135
Epoch 877/1000
135.0447 - val loss: 142.5157 - val mse: 103.6726
Epoch 878/1000
151.0979 - val loss: 326.6219 - val mse: 287.6538
Epoch 879/1000
228.8325 - val loss: 70.9899 - val mse: 31.4156
Epoch 880/1000
460/460 [=============] - 0s 1ms/step - loss: 1504.7620 - mse
: 1465.3862 - val loss: 125.0058 - val mse: 85.8614
Epoch 881/1000
70.4337 - val loss: 96.6076 - val_mse: 57.8264
Epoch 882/1000
```

```
460/460 [=============] - 0s 1ms/step - loss: 241.5009 - mse:
202.7146 - val loss: 870.0770 - val mse: 831.1949
Epoch 883/1000
460/460 [=============] - 0s 1ms/step - loss: 406.8000 - mse:
367.9392 - val loss: 464.7564 - val mse: 425.9460
Epoch 884/1000
: 4907.1870 - val loss: 112.8816 - val mse: 72.3050
Epoch 885/1000
53.1342 - val loss: 68.5463 - val mse: 29.3624
Epoch 886/1000
44.4735 - val loss: 67.3440 - val mse: 28.3634
Epoch 887/1000
157.0969 - val loss: 335.7484 - val mse: 296.7747
Epoch 888/1000
343.6247 - val loss: 82.2539 - val mse: 43.3715
Epoch 889/1000
84.0124 - val_loss: 99.1669 - val mse: 60.2230
Epoch 890/1000
115.9965 - val loss: 1548.7043 - val mse: 1509.5236
Epoch 891/1000
: 2072.8577 - val loss: 368.9382 - val mse: 329.7481
Epoch 892/1000
208.2679 - val loss: 279.1917 - val mse: 239.9962
Epoch 893/1000
508.6929 - val_loss: 299.6041 - val mse: 260.2881
Epoch 894/1000
73.1589 - val loss: 64.9173 - val mse: 25.9562
Epoch 895/1000
170.8182 - val loss: 211.5668 - val mse: 172.4215
Epoch 896/1000
496.6414 - val loss: 1531.8824 - val mse: 1493.2833
Epoch 897/1000
358.4045 - val loss: 1545.1633 - val mse: 1506.2876
Epoch 898/1000
: 1299.8140 - val loss: 3071.8743 - val mse: 3033.4307
Epoch 899/1000
549.6414 - val loss: 69.5334 - val mse: 30.1775
Epoch 900/1000
136.4212 - val loss: 963.4727 - val mse: 923.9686
Epoch 901/1000
320.1304 - val loss: 66.4291 - val mse: 27.3148
Epoch 902/1000
460/460 [=============] - 0s 1ms/step - loss: 397.2143 - mse:
```

```
358.2751 - val loss: 142.2691 - val mse: 102.6561
Epoch 903/1000
137.9192 - val loss: 284.0092 - val mse: 245.0283
Epoch 904/1000
825.3125 - val loss: 66.8399 - val mse: 27.5010
Epoch 905/1000
706.2772 - val loss: 305.7231 - val mse: 266.3110
Epoch 906/1000
97.9784 - val loss: 71.3547 - val mse: 32.2397
Epoch 907/1000
569.6235 - val loss: 80.1380 - val mse: 41.1986
Epoch 908/1000
602.9998 - val loss: 165.9542 - val mse: 127.1162
Epoch 909/1000
166.9962 - val loss: 133.1502 - val mse: 94.4267
Epoch 910/1000
315.1913 - val loss: 494.3716 - val mse: 455.8286
Epoch 911/1000
148.5162 - val_loss: 367.4444 - val mse: 328.9745
Epoch 912/1000
: 963.8745 - val loss: 508.5178 - val mse: 469.9861
Epoch 913/1000
516.4604 - val loss: 88.9922 - val mse: 50.6215
Epoch 914/1000
166.7303 - val loss: 1541.1708 - val mse: 1502.2908
Epoch 915/1000
460/460 [=============] - 0s 1ms/step - loss: 1231.9366 - mse
: 1193.2206 - val loss: 160.8688 - val mse: 122.0919
Epoch 916/1000
92.5452 - val loss: 68.2937 - val mse: 29.3752
Epoch 917/1000
241.8935 - val loss: 3223.9910 - val mse: 3185.2273
Epoch 918/1000
460/460 [=============] - 0s 1ms/step - loss: 418.7351 - mse:
379.9459 - val loss: 268.1154 - val mse: 229.2244
Epoch 919/1000
: 1903.8339 - val loss: 169.5253 - val mse: 129.9777
Epoch 920/1000
58.0246 - val loss: 66.6870 - val mse: 27.7320
Epoch 921/1000
169.4375 - val loss: 551.6633 - val mse: 512.7723
Epoch 922/1000
200.1644 - val loss: 127.6757 - val mse: 88.9192
```

```
Epoch 923/1000
473.0558 - val loss: 123.5139 - val mse: 84.4569
Epoch 924/1000
157.7159 - val loss: 77.6402 - val mse: 38.9417
Epoch 925/1000
460/460 [=============] - 0s 1ms/step - loss: 7239.6484 - mse
: 7199.9395 - val loss: 124.0286 - val mse: 83.7457
Epoch 926/1000
47.0362 - val loss: 100.7227 - val mse: 60.9805
Epoch 927/1000
40.8668 - val loss: 71.0157 - val mse: 31.6253
Epoch 928/1000
48.4511 - val loss: 65.5982 - val mse: 26.6010
Epoch 929/1000
115.3761 - val loss: 65.5611 - val mse: 26.6073
Epoch 930/1000
460/460 [============] - 0s 1ms/step - loss: 1123.4650 - mse
: 1084.5093 - val_loss: 65.2569 - val_mse: 26.4514
Epoch 931/1000
53.2633 - val loss: 71.3967 - val mse: 32.9489
Epoch 932/1000
105.9197 - val loss: 219.1971 - val mse: 180.6514
Epoch 933/1000
310.7163 - val loss: 102.6192 - val mse: 64.1449
Epoch 934/1000
575.6423 - val loss: 142.7822 - val mse: 104.3348
Epoch 935/1000
136.6591 - val loss: 162.2560 - val mse: 123.9464
Epoch 936/1000
: 1022.7894 - val loss: 484.8983 - val mse: 446.2977
Epoch 937/1000
147.3051 - val loss: 65.1291 - val mse: 26.5814
Epoch 938/1000
460/460 [=============] - 0s 1ms/step - loss: 509.1679 - mse:
470.6306 - val_loss: 153.9638 - val mse: 115.3143
Epoch 939/1000
460/460 [=============] - 0s 1ms/step - loss: 1131.1581 - mse
: 1092.8046 - val loss: 1097.7924 - val mse: 1059.4922
Epoch 940/1000
579.5827 - val loss: 85.6649 - val mse: 47.5902
Epoch 941/1000
81.7456 - val_loss: 532.1691 - val_mse: 494.2078
Epoch 942/1000
834.2179 - val loss: 109.5599 - val mse: 71.2729
Epoch 943/1000
```

```
460/460 [=============] - 0s 1ms/step - loss: 200.4323 - mse:
161.9762 - val loss: 92.3181 - val mse: 53.6980
Epoch 944/1000
348.4689 - val loss: 1798.5692 - val mse: 1759.7638
Epoch 945/1000
: 1475.0850 - val loss: 70.3279 - val mse: 31.2978
Epoch 946/1000
132.9476 - val loss: 70.8655 - val mse: 32.0351
Epoch 947/1000
160.5724 - val loss: 107.7091 - val mse: 68.7093
Epoch 948/1000
460/460 [============] - 0s 1ms/step - loss: 2326.6648 - mse
: 2287.2549 - val loss: 72.9595 - val mse: 32.9281
Epoch 949/1000
87.8970 - val loss: 67.9164 - val mse: 28.8273
Epoch 950/1000
53.8368 - val_loss: 64.3327 - val mse: 25.6796
Epoch 951/1000
196.0800 - val loss: 103.0358 - val mse: 64.2507
Epoch 952/1000
157.2309 - val loss: 98.1247 - val mse: 59.4257
Epoch 953/1000
: 1378.3719 - val loss: 84.2982 - val mse: 45.9979
Epoch 954/1000
303.9666 - val_loss: 168.1701 - val_mse: 129.4773
Epoch 955/1000
301.6365 - val loss: 1772.6716 - val mse: 1734.4491
Epoch 956/1000
: 2940.3921 - val loss: 659.7546 - val mse: 621.1738
Epoch 957/1000
55.4183 - val loss: 76.2819 - val mse: 37.4087
Epoch 958/1000
93.0898 - val loss: 85.1503 - val mse: 46.2524
Epoch 959/1000
800.9672 - val loss: 9571.8398 - val mse: 9532.9424
Epoch 960/1000
810.0748 - val loss: 99.3410 - val mse: 60.4714
Epoch 961/1000
63.2173 - val loss: 86.0378 - val mse: 47.5648
Epoch 962/1000
905.4486 - val loss: 70.5107 - val mse: 31.9831
Epoch 963/1000
460/460 [=============] - 0s 1ms/step - loss: 847.9873 - mse:
```

```
809.3985 - val loss: 110526.9453 - val mse: 110488.1953
Epoch 964/1000
460/460 [==============] - 0s 1ms/step - loss: 1331.3408 - mse
: 1290.6575 - val loss: 75.6073 - val mse: 35.0095
Epoch 965/1000
50.5782 - val loss: 78.7491 - val mse: 38.4606
Epoch 966/1000
60.3251 - val loss: 97.2470 - val mse: 57.2657
Epoch 967/1000
207.1627 - val loss: 102.0366 - val mse: 62.3255
Epoch 968/1000
: 2355.2346 - val loss: 67.5914 - val mse: 27.8942
Epoch 969/1000
59.8355 - val loss: 482.4589 - val mse: 443.0247
Epoch 970/1000
200.4577 - val loss: 66.4887 - val mse: 27.3826
Epoch 971/1000
467.4444 - val loss: 115.2120 - val mse: 76.1722
Epoch 972/1000
182.9819 - val_loss: 71.5391 - val_mse: 32.6673
Epoch 973/1000
: 2219.8923 - val loss: 113.4463 - val mse: 74.2425
Epoch 974/1000
74.2280 - val loss: 100.0037 - val mse: 61.2826
Epoch 975/1000
339.3423 - val loss: 183.6350 - val mse: 145.4097
Epoch 976/1000
438.8578 - val loss: 767.8154 - val mse: 728.6188
Epoch 977/1000
506.7739 - val loss: 281.9064 - val mse: 243.2408
Epoch 978/1000
123.4316 - val loss: 151.5421 - val mse: 113.0016
Epoch 979/1000
617.7108 - val loss: 71.5989 - val mse: 33.1122
Epoch 980/1000
610.4622 - val loss: 136.8685 - val mse: 97.2862
Epoch 981/1000
391.2620 - val loss: 75.8231 - val mse: 36.7299
Epoch 982/1000
405.2554 - val loss: 75.8405 - val mse: 37.1111
Epoch 983/1000
53.9386 - val loss: 75.2766 - val mse: 36.5223
```

```
Epoch 984/1000
    : 1069.6677 - val loss: 95.4683 - val mse: 56.3172
    Epoch 985/1000
    : 1221.5792 - val loss: 110.4247 - val mse: 71.8384
    Epoch 986/1000
    102.6620 - val_loss: 122.8185 - val_mse: 84.4096
    Epoch 987/1000
    458.1534 - val loss: 112.9518 - val mse: 74.2129
    Epoch 988/1000
    181.4094 - val_loss: 218.4552 - val mse: 179.6421
    Epoch 989/1000
    : 1951.4618 - val loss: 80.3585 - val mse: 41.4684
    Epoch 990/1000
    132.7480 - val loss: 73.5617 - val mse: 34.9539
    Epoch 991/1000
    460/460 [=============] - 0s 1ms/step - loss: 119.2053 - mse:
    80.4816 - val_loss: 98.8374 - val_mse: 60.0255
    Epoch 992/1000
    : 2548.1533 - val loss: 70.8902 - val mse: 32.4599
    Epoch 993/1000
    47.4482 - val loss: 97.2551 - val mse: 59.0100
    Epoch 994/1000
    55.0049 - val loss: 702.2338 - val mse: 663.5891
    Epoch 995/1000
    133.0251 - val loss: 79.4218 - val mse: 40.9616
    Epoch 996/1000
    280.2671 - val loss: 174.8932 - val mse: 136.2465
    Epoch 997/1000
    562.9774 - val loss: 81.7137 - val mse: 42.9752
    Epoch 998/1000
    : 1048.1473 - val loss: 66.5185 - val mse: 28.1874
    Epoch 999/1000
    49.8686 - val loss: 114.4537 - val mse: 75.8210
    Epoch 1000/1000
    : 1243.1416 - val loss: 107.8623 - val mse: 69.3026
Out[208... <keras.callbacks.History at 0x7fb058731e80>
```

Evaluate the Model with Test Data

Below you will evaluate the performance of your model using the test data.

```
In [209...
         test_lbl = np.array(test_df["vehicle_CO2"])
         test_df = test_df.drop(columns=["vehicle_CO2"])
         test_ft = {key:np.array(value) for key, value in test_df.items()}
         # test lbl = np.array(test ft.pop(label name))
         print("Model evaluation: \n")
         model.evaluate(x=test_ft, y=test_lbl, batch_size=batch_size)
        Model evaluation:
        Out[209... [95.02432250976562, 56.46455383300781]
In [210...
         #Get a summary of your model
         model.summary()
        Model: "sequential 35"
        Layer (type)
                                  Output Shape
                                                         Param #
                                        ______
        Features (DenseFeatures)
                                  multiple
        Hidden1 (Dense)
                                  multiple
                                                         80
        Hidden2 (Dense)
                                  multiple
                                                         77
        Hidden3 (Dense)
                                  multiple
                                                         32
                                                         5
        Output (Dense)
                                  multiple
```

Use the Trained-Model and Visualize the results

Below we provide you with tables and figures for you to visualize your training results.

TensorBoard

Total params: 194
Trainable params: 194
Non-trainable params: 0

From TensorBoard, you can see the loss and mse curve of your training. Go to graph and under "Tag", select "keras". You can see your network. Note that you will see error under "Tag: Default". You can ignore the warning.

```
In [211... logdir = "./logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
    tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=logdir)
In [212... %tensorboard --logdir logs
```

Reusing TensorBoard on port 6006 (pid 53704), started 0:51:50 ago. (Use '!kill 53704' to kill it.)

Predict CO_2 From Trained-Model

Below, your trained-model is used to make prediction on the test set. Remember, test set is not used in training the model so it would give you a nice indication of how your model is doing.

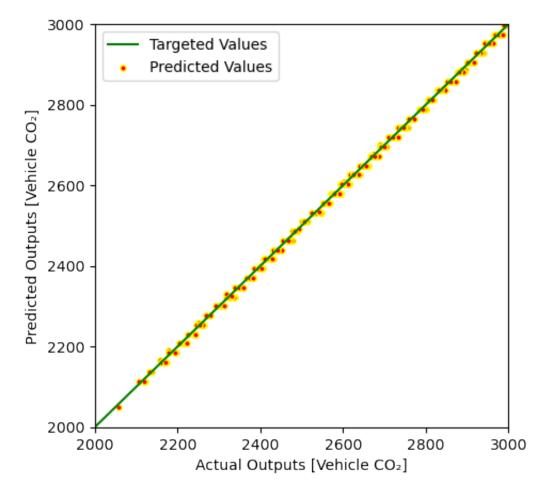
- .predict(): predicts the output values from features given.
- ullet predicted_labels: contains the values (CO_2) our model predicts. After the predicted and actual values are obtained. We create a plot for you to visualize the results. The dots show the predicted values and the line shows the targeted values.

```
In [213...
          %%time
          # Get the features from the test set
          test_features = test_ft
          # Get the actual CO2 output for the test set
          actual_labels = test_lbl
          # Make prediction on the test set
          predicted_labels = model.predict(x=test_features).flatten()
          # Define the graph
          Figure1 = plt.figure(figsize=(5,5), dpi=100)
          plt.xlabel('Actual Outputs [Vehicle CO\u2082]')
          plt.ylabel('Predicted Outputs [Vehicle CO\u2082]')
          plt.scatter(actual_labels, predicted_labels, s=15, c='Red', edgecolors='Yello
          # Take the output data from 2000 to 3000 as an instance to visualize
          lims = [2000, 3000]
          plt.xlim(lims)
          plt.ylim(lims)
          plt.plot(lims, lims, color='Green', label='Targeted Values')
          plt.legend()
```

WARNING:tensorflow:Layers in a Sequential model should only have a single input tensor, but we receive a <class 'dict'> input: {'vehicle_angle': <tf.Tensor 'ExpandDims:0' shape=(None, 1) dtype=float32>, 'vehicle_eclass': <tf.Tensor 'ExpandDims_1:0' shape=(None, 1) dtype=string>, 'vehicle_fuel': <tf.Tensor 'ExpandDims_2:0' shape=(None, 1) dtype=float32>, 'vehicle_noise': <tf.Tensor 'ExpandDims_3:0' shape=(None, 1) dtype=float32>, 'vehicle_pos': <tf.Tensor 'ExpandDims_4:0' shape=(None, 1) dtype=float32>, 'vehicle_speed': <tf.Tensor 'ExpandDims_5:0' shape=(None, 1) dtype=float32>, 'vehicle_type': <tf.Tensor 'ExpandDims_6:0' shape=(None, 1) dtype=string>, 'vehicle_waiting': <tf.Tensor 'ExpandDims_7:0' shape=(None, 1) dtype=float32>, 'vehicle_x': <tf.Tensor 'ExpandDims_8:0' shape=(None, 1) dtype=float32>, 'vehicle_y': <tf.Tensor 'ExpandDims_9:0' shape=(None, 1) dtype=float32>, 'vehicle_y': <tf.Tensor 'ExpandDims_9:0' shape=(None, 1) dtype=float32>, 'vehicle_y': <tf.Tensor 'ExpandDims_9:0' shape=(None, 1) dtype=float32>}

Consider rewriting this model with the Functional API. CPU times: user 327 ms, sys: 48.6 ms, total: 375 ms Wall time: 269 ms

Out[213... <matplotlib.legend.Legend at 0x7fb0aca2e640>



Error Count Histogram

Below, the graph shows a Histogram of errors between predicted and actual values. If the error counts locate mostly around 0, the trained-model is pretty accurate.

```
error = actual_labels - predicted_labels
Figure2 = plt.figure(figsize=(8,3), dpi=100)
plt.hist(error, bins=50, color='Red', edgecolor='Green')
plt.xlabel('Prediction Error [Vehicle CO\u2082]')
plt.ylabel('Count')
```

```
Out[214... Text(0, 0.5, 'Count')
```

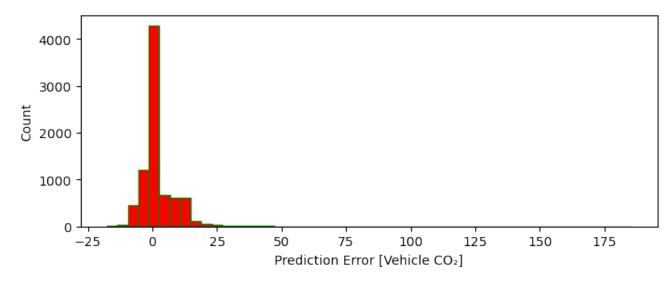


Table of Actual and Predicted Values

Below, a table puts the actual and predicted values side by side. Html is used in this case.

```
In [215...
         from IPython.display import HTML, display
         def display_table(data_x, data_y):
            html = ""
            html += ""
            html += "<h3>%s</h3>"%"Actual Vehicle CO\u2082"
            html += "<h3>%s</h3>"%"Predicted Vehicle CO\u2082"
            html += ""
            for i in range(len(data_x)):
                html += ""
                html += "<h4>%s</h4>"%(int(data x[i]))
                html += "<h4>%s</h4>"%(int(data_y[i]))
                html += ""
            html += ""
            display(HTML(html))
         display table(actual labels[0:100], predicted labels[0:100])
```

Actual Vehicle CO₂ Predicted Vehicle CO₂

5286 5287

4156 4161

0	0
0	0
0	0
0	0
6581	6568
0	0
2934	2928
2624	2626
2386	2393
0	0
0	0
0	0
0	0
2624	2626
3953	3951
0	0
0	0
10442	10441
2262	2254
0	0
0	0
0	0

0	0
0	0
0	0
2624	2626
2624	2626
26520	26494
0	0
0	0
0	0
8700	8696
0	0
2624	2626
0	0
2886	2881
17291	17279
3738	3742
0	0
0	0
0	0
2624	2626
5587	5580
2715	2719
4079	4068

2624	2626
9403	9394
37472	37424
6228	6231
10682	10674
0	0
5286	5287
0	0
5286	5284
7064	7068
0	0
0	0
0	0
0	0
0	0
0	0
17717	17712
8188	8185
6146	6138
19318	19297
0	0
44813	44805
5718	5719

5286	5287
0	0
5226	5231
2624	2626
9754	9743
0	0
5286	5287
0	0
32506	32503
5839	5835
6064	6068
0	0
0	0
0	0
0 24658	0 24659
0 24658 5286	0 24659 5287
0 24658 5286 2624	0 24659 5287 2626
0 24658 5286 2624 9048	0 24659 5287 2626 9045
0 24658 5286 2624 9048 4125	0 24659 5287 2626 9045 4114
0 24658 5286 2624 9048 4125 5888	0 24659 5287 2626 9045 4114 5882

3463	3469
0	0
10255	10266
3184	3176
34819	34858
6045	6043
0	0
0	0

Well Done!

Congradulation on finishing the lab. Please click on "File -> Print Preview" and a separate page should open. Press Cmd/Ctrl + p to print. Select "Save as PDF". Submit this .ipnyb Notebook file, the PDF, and loss graph screenshots to the link specified in the Google Doc.