

Neural Network Modeling

This notebook contains the logic for neural network regression and classification tasks.

```
1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
```

```
1 from google.colab import drive
2 drive.mount('/content/drive')

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
1 !ls

drive sample_data
```

```
1 cleaned = pd.read_csv("/content/drive/SharedDrives/Data Science 303 Group Project/csv/cleaned_fires_data_with_four_closest_stations_nov21.csv")
2 cleaned = cleaned.replace([np.inf, -np.inf], np.nan)
3 cleaned = cleaned.dropna()
```

```
1 display(cleaned.head())
2 display(cleaned.info(verbose=True))
3
4 STATION_LIST = ["BOGIE", "BROOKS", "COHASSET", "EEL_RIVER", "HELL_HOLE", "HERNANDEZ"]
5 STATION_LIST += ["HUNTER_MOUNTAIN", "JUANITA_LAKE", "LADDER_BUTTE", "LAS_TABLAS", "LA_HONDA", "OAK_CREEK"]
6 STATION_LIST += ["PANAMINT", "PILOT_HILL", "SCORPION", "SOLDIER_MOUNTAIN", "SQUAM_LAKE", "STAMPEDE", "VAN_BREMNER", "WOLVERTON"]
7 STATION_LIST = set(STATION_LIST)
```

Unnamed: 0	BODIE	BROOKS	COHASSET	CONTAINMENT_MONTH	CONT_DATE	CONT_DOY	CONT_TIME	DISCOVERY_DATE	DISCOVERY_DOY	DISCOVERY_MONTH	DISCOVERY_TIME	REL_RIVER	FIRE_SIZE	FIRE_SIZE_CLASS	FIRE_YEAR	FOD_ID	HELL_HOLE	HERNANDEZ	HUNTER_MOUNTAIN	JUANITA_LAKE	LADDER_BUTTE	LAS_TABLAS	LATITUDE	LA_HONDA	LONGITUDE	NWCG_REPORTING_AGENCY	
0	0	-0.501752	-0.841998	-1.128433	2	2453403.5	33.0	1730.0	2453403.5	33	2	1300.0	-0.848324	0.10	A	2005	1	-1.000659	0.195610	0.434939	-0.886032	-1.114178	0.448456	40.036944	-0.394781	-121.005833	
1	1	-1.237103	-0.939629	-0.802799	5	2453137.5	133.0	1530.0	2453137.5	133	5	845.0	-0.597768	0.25	A	2004	2	-1.471873	-0.562875	-0.243079	-0.487813	-0.669480	-0.281374	38.933056	-0.869095	-120.404444	
2	2	-1.070104	-1.059637	-0.891098	6	2453156.5	152.0	2024.0	2453156.5	152	6	1921.0	-0.695749	0.10	A	2004	3	-1.410920	-0.543260	-0.109734	-0.533929	-0.714976	-0.262071	38.984167	-0.950563	-120.735556	
3	3	-1.588084	-0.752356	-0.586044	7	2453189.5	185.0	1400.0	2453184.5	180	6	1600.0	-0.401895	0.10	A	2004	4	-1.213089	-0.755069	-0.564467	-0.322165	-0.486222	-0.477673	38.559167	-0.836997	-119.913333	
4	4	-1.578681	-0.759860	-0.590604	7	2453189.5	185.0	1200.0	2453184.5	180	6	1600.0	-0.407106	0.10	A	2004	5	-1.217813	-0.758604	-0.557924	-0.324379	-0.488626	-0.480494	38.559167	-0.845502	-119.933056	
5 rows x 301 columns																											
<class 'pandas.core.frame.DataFrame'>																											
Int64Index: 87106 entries, 0 to 87105																											
Data columns (total 301 columns):																											
#	Column																										Dtype
0	Unnamed: 0																										int64
1	BODIE																										float64
2	BROOKS																										float64
3	COHASSET																										float64
4	CONTAINMENT_MONTH																										int64
5	CONT_DATE																										float64
6	CONT_DOY																										float64
7	CONT_TIME																										float64
8	DISCOVERY_DATE																										float64
9	DISCOVERY_DOY																										int64
10	DISCOVERY_MONTH																										int64
11	DISCOVERY_TIME																										float64
12	REL_RIVER																										float64
13	FIRE_SIZE																										float64
14	FIRE_SIZE_CLASS																										object
15	FIRE_YEAR																										int64
16	FOD_ID																										int64
17	HELL_HOLE																										float64
18	HERNANDEZ																										float64
19	HUNTER_MOUNTAIN																										float64
20	JUANITA_LAKE																										float64
21	LADDER_BUTTE																										float64
22	LAS_TABLAS																										float64
23	LATITUDE																										float64
24	LA_HONDA																										float64
25	LONGITUDE																										float64
26	NWCG_REPORTING_AGENCY																										object
27	NWCG_REPORTING_UNIT_NAME																										object
28	OAK_CREEK																										float64
29	OWNER_DESCR																										object
30	PANAMINT																										float64
31	PILOT_HILL																										float64
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202	PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MAX_TEMP_ABOVE_90_FAHRENHEIT	float64
203	PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_0_FAHRENHEIT	float64
204	PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT	float64
205	PRIMARY_STATION_4_MONTHS_PRIOR_TEMPERATURE_AVERAGE	float64
206	PRIMARY_STATION_4_MONTHS_PRIOR_TEMPERATURE_MAX	float64
207	PRIMARY_STATION_4_MONTHS_PRIOR_TEMPERATURE_MIN	float64
208	PRIMARY_STATION_5_MONTHS_PRIOR_ELEVATION	float64
209	PRIMARY_STATION_5_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH	float64
210	PRIMARY_STATION_5_MONTHS_PRIOR_EXTREME_MINIMUM_TEMPERATURE_FOR_MONTH	float64
211	PRIMARY_STATION_5_MONTHS_PRIOR_HEATING_DEGREE_DAYS_TO_DATE	float64
212	PRIMARY_STATION_5_MONTHS_PRIOR_LATITUDE	float64
213	PRIMARY_STATION_5_MONTHS_PRIOR_LONGITUDE	float64
214	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY	float64
215	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY_CUMULATIVE	float64
216	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT	float64
217	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MAX_TEMP_ABOVE_70_FAHRENHEIT	float64
218	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MAX_TEMP_ABOVE_90_FAHRENHEIT	float64
219	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_0_FAHRENHEIT	float64
220	PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT	float64
221	PRIMARY_STATION_5_MONTHS_PRIOR_TEMPERATURE_AVERAGE	float64

Final Part of Normalization: MinMax scaling latitude and longitude

```
1 from sklearn.preprocessing import MinMaxScaler
2 scaler = MinMaxScaler()
3
4 lat = scaler.fit_transform(np.array(cleaned["LATITUDE"]).reshape(-1, 1))
5 long = scaler.fit_transform(np.array(cleaned["LONGITUDE"]).reshape(-1, 1))
6
7 # DROP ALL LATITUDE LONGITUDE COLUMNS, THEN READD THE SCALED LATITUDE AND LONGITUDE
8 drops = []
9 for col in cleaned.columns:
10     if "LATITUDE" in col or "LONGITUDE" in col:
11         drops.append(col)
12
13 for col in drops:
14     del cleaned[col]
15
16 cleaned["S_LATITUDE"] = lat
17 cleaned["S_LONGITUDE"] = long
18
19 246 PRIMARY STATION 7 MONTHS PRIOR NUM COOLING DEGREE DAY float64
20
21 # Elevation for the primary station is redundant. Drop all elevation columns from the primary station, except for one
22 elevation = cleaned["PRIMARY_STATION_1_MONTHS_PRIOR_ELEVATION"]
23
24 drops = []
25 for col in cleaned.columns:
26     if "PRIMARY_STATION" in col and "ELEVATION" in col:
27         drops.append(col)
28
29 for col in drops:
30     del cleaned[col]
31
32 cleaned["PRIMARY_STATION_ELEVATION"] = elevation
33
34 262 PRIMARY STATION 8 MONTHS PRIOR NUM COOLING DEGREE DAY float64
35
36 # We should have a large number of fires. If not, fail
37 print(len(cleaned))
38 assert(len(cleaned) > 70000)
39
40 87106
41 209 PRIMARY_STATION_0_MONTHS_PRIOR_TEMPERATURE_AVERAGE float64
42
43 1 print( (1 - 360) % 365)
44
45 6
46 214 PRIMARY_STATION_9_MONTHS_PRIOR_EXTREME_MINIMUM_TEMPERATURE_FOR_MONTH float64
47
48 1 cleaned['DURATION'] = (cleaned['CONT_DOY']-cleaned['DISCOVERY_DOY'])%365
49
50 211 PRIMARY_STATION_9_MONTHS_PRIOR_LONGITUDE float64
51
52 1 cleaned['DURATION'].max()
53
54 335.0
55 282 PRIMARY_STATION_9_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT float64
56
57 1 from sklearn.linear_model import LinearRegression, Ridge
58
59 285 PRIMARY STATION 9 MONTHS PRIOR TEMPERATURE AVERAGE float64
60
61 # Working off of closest_station_1 for now, we can replicate later with other stations if we want
62 # 1. Get number of days that the fire was going (containment date - discovery date)
63 # Model 1a: fire duration
64 290 SHARLS_RESPONDING_URL_NAME object
65
66 1 numerical = cleaned.select_dtypes(include="number")
67 2 numerical.head()
68 3 numerical.info(verbose=True)
69
70 <class 'pandas.core.frame.DataFrame'>
71 Int64Index: 87106 entries, 0 to 87105
72 Data columns (total 246 columns):
73 # Column Dtype
74 ---
75 0 Unnamed: 0 int64
76 1 BODIE float64
77 2 BROOKS float64
78 3 COHASSET float64
79 4 CONTAINMENT_MONTH int64
80 5 CONT_DATE float64
81 6 CONT_DOY float64
82 7 CONT_TIME float64
83 8 DISCOVERY_DATE float64
84 9 DISCOVERY_DOY int64
85 10 DISCOVERY_MONTH int64
86 11 DISCOVERY_TIME float64
87 12 EEL_RIVER float64
88 13 FIRE_SIZE float64
89 14 FIRE_YEAR int64
90 15 FOD_ID int64
91 16 HELL_HOLE float64
92 17 HERNANDEZ float64
93 18 HUNTER_MOUNTAIN float64
94 19 JUANITA_LAKE float64
95 20 LADDER_BUTTE float64
96 21 LAS_TABLAS float64
97 22 LA_HONDA float64
98 23 OAK_CREEK float64
99 24 PANAMINT float64
100 25 PILOT_HILL float64
101 26 PRIMARY_STATION_10_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH float64
102 27 PRIMARY_STATION_10_MONTHS_PRIOR_EXTREME_MINIMUM_TEMPERATURE_FOR_MONTH float64
103 28 PRIMARY_STATION_10_MONTHS_PRIOR_HEATING_DEGREE_DAYS_TO_DATE float64
104 29 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY float64
105 30 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY_CUMULATIVE float64
106 31 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_DAYS_WHERE_AVG_TEMP_BELOW_65_FAHRENHEIT float64
107 32 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_70_FAHRENHEIT float64
108 33 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT float64
109 34 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_DAYS_WITH_MIN_TEMP_BELOW_0_FAHRENHEIT float64
110 35 PRIMARY_STATION_10_MONTHS_PRIOR_NUM_DAYS_WITH_MIN_TEMP_BELOW_32_FAHRENHEIT float64
111 36 PRIMARY_STATION_10_MONTHS_PRIOR_TEMPERATURE_AVERAGE float64
112 37 PRIMARY_STATION_10_MONTHS_PRIOR_TEMPERATURE_MAX float64
113 38 PRIMARY_STATION_10_MONTHS_PRIOR_TEMPERATURE_MIN float64
114 39 PRIMARY_STATION_11_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH float64
115 40 PRIMARY_STATION_11_MONTHS_PRIOR_EXTREME_MINIMUM_TEMPERATURE_FOR_MONTH float64
116 41 PRIMARY_STATION_11_MONTHS_PRIOR_HEATING_DEGREE_DAYS_TO_DATE float64
117 42 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY float64
118 43 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_COOLING_DEGREE_DAY_CUMULATIVE float64
119 44 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_DAYS_WHERE_AVG_TEMP_BELOW_65_FAHRENHEIT float64
```

```
45 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_70_FAHRENHEIT float64
46 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT float64
47 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_DAYS_WITH_MIN_TEMP_BELOW_0_FAHRENHEIT float64
48 PRIMARY_STATION_11_MONTHS_PRIOR_NUM_DAYS_WITH_MIN_TEMP_BELOW_32_FAHRENHEIT float64
49 PRIMARY_STATION_11_MONTHS_PRIOR_TEMPERATURE_AVERAGE float64
50 PRIMARY_STATION_11_MONTHS_PRIOR_TEMPERATURE_MAX float64
51 PRIMARY_STATION_11_MONTHS_PRIOR_TEMPERATURE_MIN float64
52 PRIMARY_STATION_12_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH float64

1 cols = numerical.columns
2 closest = []
3
4 for col in cols:
5     if (col[:16] == 'CLOSEST_STATION_' or col in STATION_LIST or col == "S_LATITUDE" or col == "S_LONGITUDE"):
6         closest.append(col)

1 primary_station_data_cols = []
2 for col in cols:
3     if ("PRIMARY_STATION" in col or col in STATION_LIST or col == "S_LATITUDE" or col == "S_LONGITUDE"):
4         primary_station_data_cols.append(col)
5
6 primary_station_df = pd.DataFrame()
7 for col in primary_station_data_cols:
8     primary_station_df[col] = numerical[col]
9
10 primary_station_df["FIRE_SIZE"] = numerical["FIRE_SIZE"]
11 primary_station_df["DURATION"] = numerical["DURATION"]
12

1 NUM_FEATURES_TO_KEEP = 300 + 2
2 correlation = primary_station_df.corr(method='pearson')
3 highest_correlation = (correlation.nlargest(NUM_FEATURES_TO_KEEP, 'FIRE_SIZE').index)
4 print(f"TOP {NUM_FEATURES_TO_KEEP} FEATURES WITH HIGHEST CORRELATION TO FIRE SIZE")
5 print(list(highest_correlation))
6
7 print(f"TOP 10 FEATURES WITH HIGHEST CORRELATION TO FIRE SIZE")
8 display(highest_correlation[2:12])
9 display(correlation.nlargest(NUM_FEATURES_TO_KEEP, 'FIRE_SIZE')[2:12][["FIRE_SIZE"]])
10
11 fire_size_prediction_df = primary_station_df[highest_correlation]
12 del fire_size_prediction_df["FIRE_SIZE"]
13 del fire_size_prediction_df["DURATION"]

TOP 302 FEATURES WITH HIGHEST CORRELATION TO FIRE SIZE
['FIRE_SIZE', 'DURATION', 'PRIMARY_STATION_13_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH', 'PRIMARY_STATION_1_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH', 'PRIMARY_STATION_13_MONTHS_PRIOR_TEMPERATURE_MAX', 'PRIMARY_STATION_1_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH', 'PRIMARY_STATION_13_MONTHS_PRIOR_TEMPERATURE_MAX', 'PRIMARY_STATION_1_MONTHS_PRIOR_TEMPERATURE_MAX', 'PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_70_FAHRENHEIT', 'PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT', 'PRIMARY_STATION_13_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT', 'PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT', 'PRIMARY_STATION_1_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT', 'PRIMARY_STATION_12_MONTHS_PRIOR_TEMPERATURE_MAX', 'PRIMARY_STATION_12_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH'],
dtype=object)
PRIMARY_STATION_13_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH    0.022363
PRIMARY_STATION_1_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH    0.022363
PRIMARY_STATION_13_MONTHS_PRIOR_TEMPERATURE_MAX                    0.020201
PRIMARY_STATION_1_MONTHS_PRIOR_TEMPERATURE_MAX                    0.020201
PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_70_FAHRENHEIT    0.019643
PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT    0.019516
PRIMARY_STATION_13_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT    0.019503
PRIMARY_STATION_1_MONTHS_PRIOR_NUM_DAYS_WITH_MAX_TEMP_ABOVE_90_FAHRENHEIT    0.019503
PRIMARY_STATION_12_MONTHS_PRIOR_TEMPERATURE_MAX                    0.019122
PRIMARY_STATION_12_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH    0.018295
Name: FIRE_SIZE, dtype: float64

1 display(fire_size_prediction_df)

ITH_MIN_TEMP_BELOW_32_FAHRENHEIT    PRIMARY_STATION_ELEVATION    PRIMARY_STATION_12_MONTHS_PRIOR_NUM_DAYS_WITH_MIN_TEMP_BELOW_32_FAHRENHEIT    PRIMARY_STATION_2_MONTHS_PRIOR_NUM_DAYS_WHERE_AVG_TEMP_BELOW_65_FAHRENHEIT    PRIMARY_STATION_14_MONTHS
1.574436                            1.192259                            1.643791                            1.877825
-0.935826                            0.525056                            0.501069                            0.161437
-0.935826                            0.525056                            -0.935826                            1.374855
1.088624                            1.808604                            1.088624                            1.563838
1.088624                            1.808604                            1.088624                            1.563838
...                                ...                                ...                                ...
-0.935826                            -1.008744                            -0.935826                            -0.276662
-0.935826                            0.180489                            -0.935826                            -1.143144
-0.935826                            -1.008744                            -0.935826                            -1.130569
-0.935826                            -1.266260                            -0.935826                            -0.354108
-0.935826                            0.180489                            -0.935826                            -1.143144

1 NUM_FEATURES_TO_KEEP = 300 + 2
2 correlation = primary_station_df.corr(method='pearson')
3 highest_correlation = (correlation.nlargest(NUM_FEATURES_TO_KEEP, 'DURATION').index)
4 print(f"TOP {NUM_FEATURES_TO_KEEP} FEATURES WITH HIGHEST CORRELATION TO FIRE DURATION")
5 display(highest_correlation)
6
7 print(f"TOP 10 FEATURES WITH HIGHEST CORRELATION TO FIRE DURATION")
8 display(highest_correlation[2:12])
9 display(correlation.nlargest(NUM_FEATURES_TO_KEEP, 'DURATION')[2:12][["DURATION"]])
10
11 fire_duration_prediction_df = primary_station_df[highest_correlation]
12 del fire_duration_prediction_df["FIRE_SIZE"]
13 del fire_duration_prediction_df["DURATION"]
```

```
TOP 102 FEATURES WITH HIGHEST CORRELATION TO FIRE DURATION
Index(['DURATION', 'FIRE_SIZE',
      'PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_ELEVATION',
      'PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_16_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      ...
      'PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WITH MAX_TEMP_ABOVE_70_FAHRENHEIT',
      'PRIMARY_STATION_5_MONTHS_PRIOR_TEMPERATURE_MIN',
      'PRIMARY_STATION_5_MONTHS_PRIOR_TEMPERATURE_AVERAGE',
      'PRIMARY_STATION_7_MONTHS_PRIOR_TEMPERATURE_AVERAGE',
      'PRIMARY_STATION_7_MONTHS_PRIOR_TEMPERATURE_MIN',
      'PRIMARY_STATION_6_MONTHS_PRIOR_TEMPERATURE_MAX',
      'PRIMARY_STATION_6_MONTHS_PRIOR_TEMPERATURE_MIN',
      'PRIMARY_STATION_7_MONTHS_PRIOR_EXTREME_MINIMUM_TEMPERATURE_FOR_MONTH',
      'PRIMARY_STATION_6_MONTHS_PRIOR_TEMPERATURE_AVERAGE',
      'PRIMARY_STATION_6_MONTHS_PRIOR_EXTREME_MAXIMUM_TEMPERATURE_MONTH'],
      dtype='object', length=233)

TOP 10 FEATURES WITH HIGHEST CORRELATION TO FIRE DURATION
Index(['PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_ELEVATION',
      'PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT',
      'PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_16_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT',
      'PRIMARY_STATION_3_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT'],
      dtype='object')
PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT    0.072410
PRIMARY_STATION_6_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT    0.070551
PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT    0.066327
PRIMARY_STATION_ELEVATION                                                    0.065809
PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT    0.064962
PRIMARY_STATION_5_MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT    0.064641
PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT    0.064181
PRIMARY_STATION_16_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT    0.059995
PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT    0.059995

1 display(fire_duration_prediction_df)
```

MONTHS_PRIOR_NUM_DAYS WHERE AVG_TEMP_BELOW_65_FAHRENHEIT	PRIMARY_STATION_7_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT	PRIMARY_STATION_16_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT	PRIMARY_STATION_4_MONTHS_PRIOR_NUM_DAYS WITH MIN_TEMP_BELOW_32_FAHRENHEIT
-0.288093	-0.935826		1.031302
1.506884	-0.232580		1.243994
1.321414	1.291149		1.609640
2.798891	1.643791		1.643791
2.798891	1.643791		1.643791
...
0.425497	-0.232580		-0.232580
-0.093192	-0.028466		-0.935826
-0.335247	0.837331		0.136035
0.060843	-0.935826		-0.935826
-0.093192	-0.028466		-0.935826

```
1 closest_df = pd.DataFrame()
2
3 for col in closest:
4     closest_df[col] = numerical[col]

1 closest_df.head()
```

	BODIE	BROOKS	CONASSET	EEL_RIVER	HELL_HOLE	HERNANDEZ	HUNTER_MOUNTAIN	JUANITA_LAKE	LADDER_BUTTE	LAS_TABLAS	LA_HONDA	OAK_CREEK	PANAMINT	PILOT_HILL	SCORPION	SOLDIER_MOUNTAIN	SQUAM_LAKE	STAMPEDE	VAN_BREMNER	WOLVERTON	S_
0	-0.501752	-0.841098	-1.128433	-0.848324	-1.000659	0.195610	0.434939	-0.886032	-1.114178	0.448456	-0.394781	0.297877	0.545114	-0.914818	-0.846454	-1.044163	0.687200	-1.139269	-0.918627	0.410736	
1	-1.237103	-0.939829	-0.802799	-0.597768	-1.471873	-0.562875	-0.243079	-0.487813	-0.669480	-0.281374	-0.869095	-0.451833	-0.057172	-1.280961	-0.473194	-0.612901	0.315528	-1.287797	-0.513504	-0.311271	
2	-1.070104	-1.059637	-0.891098	-0.695749	-1.410920	-0.543260	-0.109734	-0.533929	-0.714976	-0.262071	-0.950563	-0.317057	0.059122	-1.392229	-0.537641	-0.663661	0.382606	-1.233892	-0.557916	-0.204482	
3	-1.588084	-0.752356	-0.586044	-0.401895	-1.213089	-0.755069	-0.564467	-0.322165	-0.486222	-0.477673	-0.836997	-0.795000	-0.341413	-1.070171	-0.296636	-0.431126	0.143227	-1.125369	-0.346639	-0.618217	
4	-1.578681	-0.759860	-0.590604	-0.407106	-1.217813	-0.758604	-0.557924	-0.324379	-0.488626	-0.480494	-0.845502	-0.788869	-0.335760	-1.077584	-0.299859	-0.433722	0.146406	-1.126335	-0.348787	-0.614275	

• Model 1: Linear Regression

```
1 from sklearn.model_selection import train_test_split
2 from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, median_absolute_error, r2_score
3 from sklearn.metrics import explained_variance_score
4 from sklearn import svm
5 from sklearn.preprocessing import PowerTransformer
6 from sklearn.ensemble import RandomForestRegressor
7
8 # def log_transform(column):
9 #     """
10 #     Transforms a feature so that it is scaled logarithmically. Useful for correcting floating point errors
11 #     """
12
13
14 # def min_max_transform(column):
15 #     """
16 #     Transforms a feature using min-max scaling
17 #     """
18 #     pass
19
20 def run_full_linear_regression_with_accuracy(features, response, n_highest = 0):
```

```

21 print(f"Response Minimum: {response.min()}")
22 print(f"Response Maximum: {response.max()}")
23
24 model = LinearRegression()
25 # model = Ridge()
26 # model = svm.SVR()
27 # Split into test and training set
28 X_train, X_test, y_train, y_test = train_test_split(features, response, test_size=0.2, random_state=2020)
29 model.fit(X_train, y_train)
30
31 training_predictions = model.predict(X_train)
32 test_predictions = model.predict(X_test)
33 print(f"Linear Regression Coefficients: { model.coef_ }\nLinear Regression Intercept: { model.intercept_}\n")
34
35 print("Training: mean absolute error: ", mean_absolute_error(y_train, training_predictions))
36 print("Test mean absolute error: ", mean_absolute_error(y_test, test_predictions))
37
38 print("Training average error rate: ", median_absolute_error(y_train, training_predictions))
39 print("Test average error rate: ", median_absolute_error(y_test, test_predictions))
40
41 print("Explained variance in training set is: ", explained_variance_score(y_train, training_predictions))
42 print("Explained variance in test set is: ", explained_variance_score(y_test, test_predictions))
43
44 print("R2 Score training set: ", r2_score(y_train, training_predictions))
45 print("R2 Score testing set: ", r2_score(y_test, test_predictions))
46
47 fig = plt.figure()
48 ax1 = fig.add_subplot()
49 ax1.set_xlabel("True Value from Test Set")
50 ax1.set_ylabel("Prediction from Test Set")
51 ax1.set_title("True Value vs Predicted Value for Test Set: Linear Regression")
52 ax1.scatter(y_test, test_predictions)
53 plt.show()
54
55 fig = plt.figure()
56 ax1 = fig.add_subplot()
57 ax1.set_xlabel("Predicted Value from Test Set")
58 ax1.set_ylabel("Residual Value from Test Set")
59 ax1.set_title("Test Set Residual Values vs Predicted Values")
60 ax1.scatter(y_train, training_predictions)
61 plt.show()
62
63
64 # Residual plot against predictor
65 fig = plt.figure()
66 ax1 = fig.add_subplot()
67 ax1.set_xlabel("Test Set Prediction")
68 ax1.set_ylabel("Prediction from Training Set")
69 ax1.set_title("Residual Graph: Linear Regression")
70 ax1.scatter(training_predictions, y_train - training_predictions)
71 plt.show()
72
73
74
75 def run_full_ridge_regression_with_accuracy(features, response, n_highest = 0):
76     print(f"Response Minimum: {response.min()}")
77     print(f"Response Maximum: {response.max()}")
78
79
80     model = Ridge()
81     # Split into test and training set
82     X_train, X_test, y_train, y_test = train_test_split(features, response, test_size=0.2, random_state=2020)
83     model.fit(X_train, y_train)
84
85     training_predictions = model.predict(X_train)
86     test_predictions = model.predict(X_test)
87     print(f"Ridge Regression Coefficients: { model.coef_ }\nRidge Regression Intercept: { model.intercept_}\n")
88
89     print("Training: mean absolute error: ", mean_absolute_error(y_train, training_predictions))
90     print("Test mean absolute error: ", mean_absolute_error(y_test, test_predictions))
91
92     print("Training average error rate: ", median_absolute_error(y_train, training_predictions))
93     print("Test average error rate: ", median_absolute_error(y_test, test_predictions))
94
95     print("Explained variance in training set is: ", explained_variance_score(y_train, training_predictions))
96     print("Explained variance in test set is: ", explained_variance_score(y_test, test_predictions))
97
98     print("R2 Score training set: ", r2_score(y_train, training_predictions))
99     print("R2 Score testing set: ", r2_score(y_test, test_predictions))
100
101     fig = plt.figure()
102     ax1 = fig.add_subplot()
103     ax1.set_xlabel("True Value from Test Set")
104     ax1.set_ylabel("Prediction from Test Set")
105     ax1.set_title("True Value vs Predicted Value for Test Set: Ridge Regression")
106     ax1.scatter(y_test, test_predictions)
107     plt.show()
108
109     fig = plt.figure()
110
111     ax1 = fig.add_subplot()
112     ax1.set_xlabel("True Value from Training Set")
113     ax1.set_ylabel("Prediction from Training Set")
114     ax1.set_title("True Value vs Predicted Value for Training Set: Ridge Regression")
115     ax1.scatter(y_train, training_predictions)
116     plt.show()
117
118     fig = plt.figure()
119     ax1 = fig.add_subplot()
120     ax1.set_xlabel("Test Set Prediction")
121     ax1.set_ylabel("Prediction from Training Set")
122     ax1.set_title("Residual Graph: Ridge Regression")
123     ax1.scatter(training_predictions, y_train - training_predictions)
124     plt.show()
125
126 def run_full_svm_regression_with_accuracy(features, response, n_highest = 0):
127     print(f"Response Minimum: {response.min()}")
128     print(f"Response Maximum: {response.max()}")
129
130
131     model = svm.SVR()

```

```
132 # Split into test and training set
133 X_train, X_test, y_train, y_test = train_test_split(features, response, test_size=0.2, random_state=2020)
134 model.fit(X_train, y_train)
135
136 training_predictions = model.predict(X_train)
137 test_predictions = model.predict(X_test)
138
139 print('Training: mean absolute error: ', mean_absolute_error(y_train, training_predictions))
140 print('Test mean absolute error: ', mean_absolute_error(y_test, test_predictions))
141
142 print('Training average error rate: ', median_absolute_error(y_train, training_predictions))
143 print('Test average error rate: ', median_absolute_error(y_test, test_predictions))
144
145 print('Explained variance in training set is: ', explained_variance_score(y_train, training_predictions))
146 print('Explained variance in test set is: ', explained_variance_score(y_test, test_predictions))
147
148 fig = plt.figure()
149 ax1 = fig.add_subplot()
150 ax1.set_xlabel('True Value from Test Set')
151 ax1.set_ylabel('Prediction from Test Set')
152 ax1.set_title('True Value vs Predicted Value for Test Set: SVM Regression')
153 ax1.scatter(y_test, test_predictions)
154 plt.show()
155
156 fig = plt.figure()
157
158 ax1 = fig.add_subplot()
159 ax1.set_xlabel('True Value from Training Set')
160 ax1.set_ylabel('Prediction from Training Set')
161 ax1.set_title('True Value vs Predicted Value for Training Set: SVM Regression')
162 ax1.scatter(y_train, training_predictions)
163 plt.show()
164
165 def run_full_random_forest_regression_with_accuracy(features, response, n_highest = 0):
166     print(f'Response Minimum: {response.min()}')
167     print(f'Response Maximum: {response.max()}')
168
169
170     model = RandomForestRegressor(n_estimators=100)
171     # Split into test and training set
172     X_train, X_test, y_train, y_test = train_test_split(features, response, test_size=0.2, random_state=2020)
173     model.fit(X_train, y_train)
174
175     training_predictions = model.predict(X_train)
176     test_predictions = model.predict(X_test)
177
178     print('Training: mean absolute error: ', mean_absolute_error(y_train, training_predictions))
179     print('Test mean absolute error: ', mean_absolute_error(y_test, test_predictions))
180
181     print('Training average error rate: ', median_absolute_error(y_train, training_predictions))
182     print('Test average error rate: ', median_absolute_error(y_test, test_predictions))
183
184     print('Explained variance in training set is: ', explained_variance_score(y_train, training_predictions))
185     print('Explained variance in test set is: ', explained_variance_score(y_test, test_predictions))
186
187     fig = plt.figure()
188     ax1 = fig.add_subplot()
189     ax1.set_xlabel('True Value from Test Set')
190     ax1.set_ylabel('Prediction from Test Set')
191     ax1.set_title('True Value vs Predicted Value for Test Set: Random Forest Regression')
192     ax1.scatter(y_test, test_predictions)
193     plt.show()
194
195     fig = plt.figure()
196
197     ax1 = fig.add_subplot()
198     ax1.set_xlabel('True Value from Training Set')
199     ax1.set_ylabel('Prediction from Training Set')
200     ax1.set_title('True Value vs Predicted Value for Training Set: Random Forest Regression')
201     ax1.scatter(y_train, training_predictions)
202     plt.show()
```

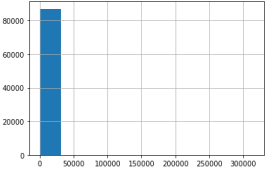
1 SUBSET = -1

▼ Fire Size Prediction using Linear Regression and Ridge Regression

Here, we predict the size of a fire using linear regression

```
1 FIRE_SIZE = numerical["FIRE_SIZE"]
2 FIRE_SIZE.hist()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f1061ebab10>



```
1 log_fire_size = pd.DataFrame(np.log(FIRE_SIZE))
2 log_fire_size = log_fire_size.replace([np.inf, -np.inf], np.nan)
3 log_fire_size = log_fire_size.fillna(0)
4 log_fire_size = (log_fire_size - log_fire_size.mean()) / log_fire_size.std()
5 log_fire_size.hist()
6 plt.show()
7
8 run_full_linear_regression_with_accuracy(fire_size_prediction_df[SUBSET], log_fire_size[SUBSET])
9 run_full_ridge_regression_with_accuracy(fire_size_prediction_df[SUBSET], log_fire_size[SUBSET])
```



```

# Histogram of FIRE_SIZE
plt.hist(FIRE_SIZE)
plt.show()

# Linear Regression
model = LinearRegression()
model.fit(X_train, Y_train)

# Predictions on test set
Y_pred = model.predict(X_test)

# Mean Absolute Error (MAE)
mae = mean_absolute_error(Y_test, Y_pred)

# R-squared value
r2 = model.score(X_test, Y_test)

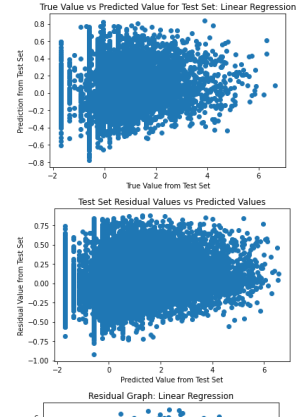
# Print results
print("Training: mean absolute error: ", mae)
print("Test mean absolute error: ", mae)
print("Training average error rate: ", mae)
print("Test average error rate: ", mae)
print("Explained variance in training set is: ", r2)
print("Explained variance in test set is: ", r2)
print("R2 Score training set: ", r2)
print("R2 Score testing set: ", r2)

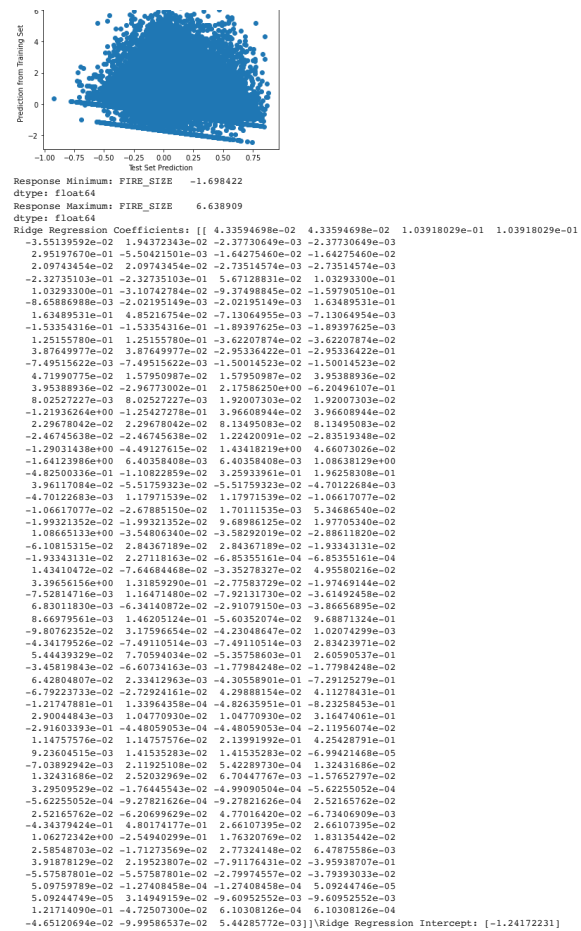
# True Value vs Predicted Value for Test Set: Linear Regression
plt.figure()
plt.scatter(Y_test, Y_pred)
plt.xlabel("True Value from Test Set")
plt.ylabel("Predicted from Test Set")
plt.title("True Value vs Predicted Value for Test Set: Linear Regression")

# Test Set Residual Values vs Predicted Values
plt.figure()
plt.scatter(Y_pred, Y_test - Y_pred)
plt.xlabel("Predicted Value from Test Set")
plt.ylabel("Residual Value from Test Set")
plt.title("Test Set Residual Values vs Predicted Values")

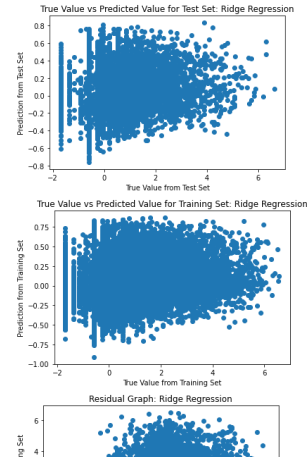
# Residual Graph: Linear Regression
plt.figure()
plt.scatter(Y_pred, Y_test - Y_pred)
plt.xlabel("Predicted Value from Test Set")
plt.ylabel("Residual Value from Test Set")
plt.title("Residual Graph: Linear Regression")
```

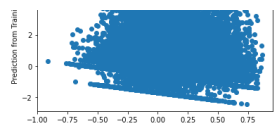
Training: mean absolute error: 0.7022413703548958
Test mean absolute error: 0.700650561286869
Training average error rate: 0.5480948672942414
Test average error rate: 0.538445372454226
Explained variance in training set is: 0.049671639216195884
Explained variance in test set is: 0.04495804308808271
R2 Score training set: 0.0496716390921026
R2 Score testing set: 0.044928275789205





Training: mean absolute error: 0.7025343078227769
Test: mean absolute error: 0.700932062396999
Training average error rate: 0.5407735980566852
Test average error rate: 0.5394821140280315
Explained variance in training set is: 0.04953417446802133
Explained variance in test set is: 0.04486034715527376
R2 Score training set: 0.04953417446802111
R2 Score testing set: 0.04482933788042309





Basic Neural Network Model

```
1 import tensorflow as tf

2 log_fire_size = pd.DataFrame(np.log(FIRE_SIZE))
3 log_fire_size = log_fire_size.replace([np.inf, -np.inf], np.nan)
4 log_fire_size = log_fire_size.fillna(0)
5 log_fire_size = (log_fire_size - log_fire_size.mean()) / log_fire_size.std()
6 X_train, X_test, y_train, y_test = train_test_split(log_fire_size, test_size=0.2, random_state=2020)

7 from tensorflow.keras.layers import *
8 from tensorflow.keras.losses import MeanSquaredError
9 print(X_train.shape)
10
11 model = tf.keras.models.Sequential([Dense(231, activation="relu"),
12                                     Dropout(0.2),
13                                     Dense(231, activation="relu"),
14                                     Dense(231, activation="relu"),
15                                     Dense(1)])
16
17 loss_function = MeanSquaredError()
18 model.compile(optimizer="adam", loss=loss_function, metrics=["mean_squared_error", "mean_absolute_error"])
19 model.fit(X_train, y_train, epochs = 300)
20 model.evaluate(X_test, y_test, verbose=2)
21
22 test_predictions = model.predict(X_test)
23 fig = plt.figure()
24 ax1 = fig.add_subplot(1,1,1)
25 ax1.set_xlabel('True Value from Test Set')
26 ax1.set_ylabel('Prediction from Test Set')
27 ax1.set_title('True Value vs Predicted Value for Test Set: Simple Neural Network')
28 ax1.scatter(y_test, test_predictions)
29 plt.show()
30
31 print(model.summary())
```

```
(69684, 231)
Epoch 1/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.9930 - mean_squared_error: 0.9930 - mean_absolute_error: 0.7215
Epoch 2/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9731 - mean_squared_error: 0.9731 - mean_absolute_error: 0.7130
Epoch 3/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9692 - mean_squared_error: 0.9692 - mean_absolute_error: 0.7113
Epoch 4/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9647 - mean_squared_error: 0.9647 - mean_absolute_error: 0.7087
Epoch 5/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9621 - mean_squared_error: 0.9621 - mean_absolute_error: 0.7080
Epoch 6/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9584 - mean_squared_error: 0.9584 - mean_absolute_error: 0.7058
Epoch 7/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9554 - mean_squared_error: 0.9554 - mean_absolute_error: 0.7046
Epoch 8/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9539 - mean_squared_error: 0.9539 - mean_absolute_error: 0.7047
Epoch 9/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9513 - mean_squared_error: 0.9513 - mean_absolute_error: 0.7026
Epoch 10/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9495 - mean_squared_error: 0.9495 - mean_absolute_error: 0.7023
Epoch 11/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9483 - mean_squared_error: 0.9483 - mean_absolute_error: 0.7020
Epoch 12/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9466 - mean_squared_error: 0.9466 - mean_absolute_error: 0.7011
Epoch 13/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9457 - mean_squared_error: 0.9457 - mean_absolute_error: 0.7005
Epoch 14/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9438 - mean_squared_error: 0.9438 - mean_absolute_error: 0.6997
Epoch 15/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9429 - mean_squared_error: 0.9429 - mean_absolute_error: 0.6992
Epoch 16/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9409 - mean_squared_error: 0.9409 - mean_absolute_error: 0.6985
Epoch 17/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9407 - mean_squared_error: 0.9407 - mean_absolute_error: 0.6981
Epoch 18/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9387 - mean_squared_error: 0.9387 - mean_absolute_error: 0.6972
Epoch 19/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9379 - mean_squared_error: 0.9379 - mean_absolute_error: 0.6969
Epoch 20/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9371 - mean_squared_error: 0.9371 - mean_absolute_error: 0.6966
Epoch 21/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9352 - mean_squared_error: 0.9352 - mean_absolute_error: 0.6965
Epoch 22/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9344 - mean_squared_error: 0.9344 - mean_absolute_error: 0.6955
Epoch 23/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9329 - mean_squared_error: 0.9329 - mean_absolute_error: 0.6946
Epoch 24/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9334 - mean_squared_error: 0.9334 - mean_absolute_error: 0.6945
Epoch 25/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9320 - mean_squared_error: 0.9320 - mean_absolute_error: 0.6941
Epoch 26/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9306 - mean_squared_error: 0.9306 - mean_absolute_error: 0.6933
Epoch 27/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9305 - mean_squared_error: 0.9305 - mean_absolute_error: 0.6933
Epoch 28/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9296 - mean_squared_error: 0.9296 - mean_absolute_error: 0.6936
Epoch 29/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9289 - mean_squared_error: 0.9289 - mean_absolute_error: 0.6931
Epoch 30/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9274 - mean_squared_error: 0.9274 - mean_absolute_error: 0.6920
Epoch 31/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9279 - mean_squared_error: 0.9279 - mean_absolute_error: 0.6925
Epoch 32/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9240 - mean_squared_error: 0.9240 - mean_absolute_error: 0.6907
Epoch 33/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9234 - mean_squared_error: 0.9234 - mean_absolute_error: 0.6905
Epoch 34/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9240 - mean_squared_error: 0.9240 - mean_absolute_error: 0.6908
Epoch 35/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9238 - mean_squared_error: 0.9238 - mean_absolute_error: 0.6905
Epoch 36/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9235 - mean_squared_error: 0.9235 - mean_absolute_error: 0.6905
Epoch 37/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9222 - mean_squared_error: 0.9222 - mean_absolute_error: 0.6890
Epoch 38/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9208 - mean_squared_error: 0.9208 - mean_absolute_error: 0.6890
Epoch 39/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9195 - mean_squared_error: 0.9195 - mean_absolute_error: 0.6881
Epoch 40/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.9193 - mean_squared_error: 0.9193 - mean_absolute_error: 0.6878
Epoch 41/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9189 - mean_squared_error: 0.9189 - mean_absolute_error: 0.6877
Epoch 42/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9188 - mean_squared_error: 0.9188 - mean_absolute_error: 0.6880
Epoch 43/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9166 - mean_squared_error: 0.9166 - mean_absolute_error: 0.6870
Epoch 44/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9154 - mean_squared_error: 0.9154 - mean_absolute_error: 0.6867
Epoch 45/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9159 - mean_squared_error: 0.9159 - mean_absolute_error: 0.6864
Epoch 46/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9127 - mean_squared_error: 0.9127 - mean_absolute_error: 0.6849
Epoch 47/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.9136 - mean_squared_error: 0.9136 - mean_absolute_error: 0.6856
Epoch 48/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9139 - mean_squared_error: 0.9139 - mean_absolute_error: 0.6862
Epoch 49/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.9144 - mean_squared_error: 0.9144 - mean_absolute_error: 0.6857
Epoch 50/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9117 - mean_squared_error: 0.9117 - mean_absolute_error: 0.6850
Epoch 51/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9110 - mean_squared_error: 0.9110 - mean_absolute_error: 0.6844
Epoch 52/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9095 - mean_squared_error: 0.9095 - mean_absolute_error: 0.6842
Epoch 53/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9094 - mean_squared_error: 0.9094 - mean_absolute_error: 0.6832
Epoch 54/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9073 - mean_squared_error: 0.9073 - mean_absolute_error: 0.6832
Epoch 55/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9072 - mean_squared_error: 0.9072 - mean_absolute_error: 0.6827
Epoch 56/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9075 - mean_squared_error: 0.9075 - mean_absolute_error: 0.6836
Epoch 57/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9049 - mean_squared_error: 0.9049 - mean_absolute_error: 0.6820
Epoch 58/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9045 - mean_squared_error: 0.9045 - mean_absolute_error: 0.6812
Epoch 59/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9039 - mean_squared_error: 0.9039 - mean_absolute_error: 0.6808
Epoch 60/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9038 - mean_squared_error: 0.9038 - mean_absolute_error: 0.6812
Epoch 61/300
```

```
Epoch 62/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9022 - mean_squared_error: 0.9022 - mean_absolute_error: 0.6802
Epoch 63/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9021 - mean_squared_error: 0.9021 - mean_absolute_error: 0.6797
Epoch 64/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9029 - mean_squared_error: 0.9029 - mean_absolute_error: 0.6809
Epoch 65/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9023 - mean_squared_error: 0.9023 - mean_absolute_error: 0.6792
Epoch 66/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9014 - mean_squared_error: 0.9014 - mean_absolute_error: 0.6799
Epoch 67/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9004 - mean_squared_error: 0.9004 - mean_absolute_error: 0.6788
Epoch 68/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8998 - mean_squared_error: 0.8998 - mean_absolute_error: 0.6793
Epoch 69/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.9001 - mean_squared_error: 0.9001 - mean_absolute_error: 0.6782
Epoch 70/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8967 - mean_squared_error: 0.8967 - mean_absolute_error: 0.6783
Epoch 71/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8981 - mean_squared_error: 0.8981 - mean_absolute_error: 0.6781
Epoch 72/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8969 - mean_squared_error: 0.8969 - mean_absolute_error: 0.6773
Epoch 73/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8962 - mean_squared_error: 0.8962 - mean_absolute_error: 0.6778
Epoch 74/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8967 - mean_squared_error: 0.8967 - mean_absolute_error: 0.6771
Epoch 75/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8967 - mean_squared_error: 0.8967 - mean_absolute_error: 0.6779
Epoch 76/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8954 - mean_squared_error: 0.8954 - mean_absolute_error: 0.6768
Epoch 77/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8928 - mean_squared_error: 0.8928 - mean_absolute_error: 0.6771
Epoch 78/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8917 - mean_squared_error: 0.8917 - mean_absolute_error: 0.6752
Epoch 79/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8938 - mean_squared_error: 0.8938 - mean_absolute_error: 0.6767
Epoch 80/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8941 - mean_squared_error: 0.8941 - mean_absolute_error: 0.6757
Epoch 81/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8930 - mean_squared_error: 0.8930 - mean_absolute_error: 0.6760
Epoch 82/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8937 - mean_squared_error: 0.8937 - mean_absolute_error: 0.6765
Epoch 83/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8926 - mean_squared_error: 0.8926 - mean_absolute_error: 0.6758
Epoch 84/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.8903 - mean_squared_error: 0.8903 - mean_absolute_error: 0.6738
Epoch 85/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.8921 - mean_squared_error: 0.8921 - mean_absolute_error: 0.6755
Epoch 86/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8887 - mean_squared_error: 0.8887 - mean_absolute_error: 0.6739
Epoch 87/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8912 - mean_squared_error: 0.8912 - mean_absolute_error: 0.6750
Epoch 88/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8888 - mean_squared_error: 0.8888 - mean_absolute_error: 0.6741
Epoch 89/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8874 - mean_squared_error: 0.8874 - mean_absolute_error: 0.6736
Epoch 90/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8896 - mean_squared_error: 0.8896 - mean_absolute_error: 0.6745
Epoch 91/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8871 - mean_squared_error: 0.8871 - mean_absolute_error: 0.6732
Epoch 92/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8855 - mean_squared_error: 0.8855 - mean_absolute_error: 0.6722
Epoch 93/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8865 - mean_squared_error: 0.8865 - mean_absolute_error: 0.6736
Epoch 94/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8863 - mean_squared_error: 0.8863 - mean_absolute_error: 0.6724
Epoch 95/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8850 - mean_squared_error: 0.8850 - mean_absolute_error: 0.6709
Epoch 96/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8828 - mean_squared_error: 0.8828 - mean_absolute_error: 0.6714
Epoch 97/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8837 - mean_squared_error: 0.8837 - mean_absolute_error: 0.6716
Epoch 98/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8846 - mean_squared_error: 0.8846 - mean_absolute_error: 0.6710
Epoch 99/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8872 - mean_squared_error: 0.8872 - mean_absolute_error: 0.6725
Epoch 100/300
2178/2178 [=====] - 8s 3ms/step - loss: 0.8827 - mean_squared_error: 0.8827 - mean_absolute_error: 0.6702
Epoch 101/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8817 - mean_squared_error: 0.8817 - mean_absolute_error: 0.6704
Epoch 102/300
2178/2178 [=====] - 7s 3ms/step - loss: 0.8816 - mean_squared_error: 0.8816 - mean_absolute_error: 0.6707
Epoch 103/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8835 - mean_squared_error: 0.8835 - mean_absolute_error: 0.6711
Epoch 104/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8813 - mean_squared_error: 0.8813 - mean_absolute_error: 0.6697
Epoch 105/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8798 - mean_squared_error: 0.8798 - mean_absolute_error: 0.6692
Epoch 106/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8797 - mean_squared_error: 0.8797 - mean_absolute_error: 0.6697
Epoch 107/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8782 - mean_squared_error: 0.8782 - mean_absolute_error: 0.6685
Epoch 108/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8785 - mean_squared_error: 0.8785 - mean_absolute_error: 0.6690
Epoch 109/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8802 - mean_squared_error: 0.8802 - mean_absolute_error: 0.6692
Epoch 110/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8782 - mean_squared_error: 0.8782 - mean_absolute_error: 0.6691
Epoch 111/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8788 - mean_squared_error: 0.8788 - mean_absolute_error: 0.6695
Epoch 112/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8793 - mean_squared_error: 0.8793 - mean_absolute_error: 0.6690
Epoch 113/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8787 - mean_squared_error: 0.8787 - mean_absolute_error: 0.6688
Epoch 114/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8775 - mean_squared_error: 0.8775 - mean_absolute_error: 0.6686
Epoch 115/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8781 - mean_squared_error: 0.8781 - mean_absolute_error: 0.6686
Epoch 116/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8789 - mean_squared_error: 0.8789 - mean_absolute_error: 0.6683
Epoch 117/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8762 - mean_squared_error: 0.8762 - mean_absolute_error: 0.6680
Epoch 118/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8756 - mean_squared_error: 0.8756 - mean_absolute_error: 0.6670
Epoch 119/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8754 - mean_squared_error: 0.8754 - mean_absolute_error: 0.6669
Epoch 120/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8769 - mean_squared_error: 0.8769 - mean_absolute_error: 0.6682
Epoch 121/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8749 - mean_squared_error: 0.8749 - mean_absolute_error: 0.6671
Epoch 122/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8742 - mean_squared_error: 0.8742 - mean_absolute_error: 0.6664
```

<https://colab.research.google.com/drive/15bbyiGWmUWng1YPyrxfLLIrY-yoRi84G#scrollTo=q2NunVS7RIjj&printMode=true>

```
2178/2178 [=====] - 8s 4ms/step - loss: 0.8525 - mean_squared_error: 0.8525 - mean_absolute_error: 0.6571
Epoch 184/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8534 - mean_squared_error: 0.8534 - mean_absolute_error: 0.6567
Epoch 185/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8539 - mean_squared_error: 0.8539 - mean_absolute_error: 0.6580
Epoch 186/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8555 - mean_squared_error: 0.8555 - mean_absolute_error: 0.6579
Epoch 187/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8504 - mean_squared_error: 0.8504 - mean_absolute_error: 0.6556
Epoch 188/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8562 - mean_squared_error: 0.8562 - mean_absolute_error: 0.6584
Epoch 189/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8546 - mean_squared_error: 0.8546 - mean_absolute_error: 0.6574
Epoch 190/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8516 - mean_squared_error: 0.8516 - mean_absolute_error: 0.6566
Epoch 191/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8532 - mean_squared_error: 0.8532 - mean_absolute_error: 0.6574
Epoch 192/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8536 - mean_squared_error: 0.8536 - mean_absolute_error: 0.6569
Epoch 193/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8504 - mean_squared_error: 0.8504 - mean_absolute_error: 0.6554
Epoch 194/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8503 - mean_squared_error: 0.8503 - mean_absolute_error: 0.6560
Epoch 195/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8529 - mean_squared_error: 0.8529 - mean_absolute_error: 0.6580
Epoch 196/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8522 - mean_squared_error: 0.8522 - mean_absolute_error: 0.6562
Epoch 197/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8503 - mean_squared_error: 0.8503 - mean_absolute_error: 0.6560
Epoch 198/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8524 - mean_squared_error: 0.8524 - mean_absolute_error: 0.6566
Epoch 199/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8480 - mean_squared_error: 0.8480 - mean_absolute_error: 0.6555
Epoch 200/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8498 - mean_squared_error: 0.8498 - mean_absolute_error: 0.6552
Epoch 201/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8503 - mean_squared_error: 0.8503 - mean_absolute_error: 0.6553
Epoch 202/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8488 - mean_squared_error: 0.8488 - mean_absolute_error: 0.6548
Epoch 203/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8494 - mean_squared_error: 0.8494 - mean_absolute_error: 0.6558
Epoch 204/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8516 - mean_squared_error: 0.8516 - mean_absolute_error: 0.6568
Epoch 205/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8479 - mean_squared_error: 0.8479 - mean_absolute_error: 0.6542
Epoch 206/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8478 - mean_squared_error: 0.8478 - mean_absolute_error: 0.6547
Epoch 207/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8486 - mean_squared_error: 0.8486 - mean_absolute_error: 0.6548
Epoch 208/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8490 - mean_squared_error: 0.8490 - mean_absolute_error: 0.6543
Epoch 209/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8438 - mean_squared_error: 0.8438 - mean_absolute_error: 0.6532
Epoch 210/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8473 - mean_squared_error: 0.8473 - mean_absolute_error: 0.6544
Epoch 211/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8471 - mean_squared_error: 0.8471 - mean_absolute_error: 0.6530
Epoch 212/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8467 - mean_squared_error: 0.8467 - mean_absolute_error: 0.6533
Epoch 213/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8468 - mean_squared_error: 0.8468 - mean_absolute_error: 0.6534
Epoch 214/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8456 - mean_squared_error: 0.8456 - mean_absolute_error: 0.6537
Epoch 215/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8465 - mean_squared_error: 0.8465 - mean_absolute_error: 0.6543
Epoch 216/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8459 - mean_squared_error: 0.8459 - mean_absolute_error: 0.6540
Epoch 217/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8455 - mean_squared_error: 0.8455 - mean_absolute_error: 0.6542
Epoch 218/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8466 - mean_squared_error: 0.8466 - mean_absolute_error: 0.6527
Epoch 219/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8445 - mean_squared_error: 0.8445 - mean_absolute_error: 0.6522
Epoch 220/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8449 - mean_squared_error: 0.8449 - mean_absolute_error: 0.6529
Epoch 221/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8453 - mean_squared_error: 0.8453 - mean_absolute_error: 0.6531
Epoch 222/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8429 - mean_squared_error: 0.8429 - mean_absolute_error: 0.6518
Epoch 223/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8428 - mean_squared_error: 0.8428 - mean_absolute_error: 0.6512
Epoch 224/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8433 - mean_squared_error: 0.8433 - mean_absolute_error: 0.6515
Epoch 225/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8434 - mean_squared_error: 0.8434 - mean_absolute_error: 0.6522
Epoch 226/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8432 - mean_squared_error: 0.8432 - mean_absolute_error: 0.6523
Epoch 227/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8433 - mean_squared_error: 0.8433 - mean_absolute_error: 0.6515
Epoch 228/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8434 - mean_squared_error: 0.8434 - mean_absolute_error: 0.6532
Epoch 229/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8412 - mean_squared_error: 0.8412 - mean_absolute_error: 0.6515
Epoch 230/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8408 - mean_squared_error: 0.8408 - mean_absolute_error: 0.6509
Epoch 231/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8437 - mean_squared_error: 0.8437 - mean_absolute_error: 0.6531
Epoch 232/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8400 - mean_squared_error: 0.8400 - mean_absolute_error: 0.6506
Epoch 233/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8414 - mean_squared_error: 0.8414 - mean_absolute_error: 0.6512
Epoch 234/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8439 - mean_squared_error: 0.8439 - mean_absolute_error: 0.6521
Epoch 235/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8398 - mean_squared_error: 0.8398 - mean_absolute_error: 0.6502
Epoch 236/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8403 - mean_squared_error: 0.8403 - mean_absolute_error: 0.6508
Epoch 237/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8406 - mean_squared_error: 0.8406 - mean_absolute_error: 0.6510
Epoch 238/300
2178/2178 [=====] - 11s 5ms/step - loss: 0.8419 - mean_squared_error: 0.8419 - mean_absolute_error: 0.6516
Epoch 239/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8411 - mean_squared_error: 0.8411 - mean_absolute_error: 0.6510
Epoch 240/300
2178/2178 [=====] - 10s 5ms/step - loss: 0.8406 - mean_squared_error: 0.8406 - mean_absolute_error: 0.6503
Epoch 241/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8390 - mean_squared_error: 0.8390 - mean_absolute_error: 0.6495
Epoch 242/300
2178/2178 [=====] - 10s 4ms/step - loss: 0.8386 - mean_squared_error: 0.8386 - mean_absolute_error: 0.6497
Epoch 243/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8415 - mean_squared_error: 0.8415 - mean_absolute_error: 0.6513
Epoch 244/300
```

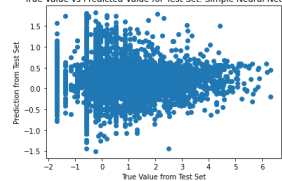
```

2178/2178 [=====] - 8s 4ms/step - loss: 0.8413 - mean_squared_error: 0.8413 - mean_absolute_error: 0.6512
Epoch 245/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8398 - mean_squared_error: 0.8398 - mean_absolute_error: 0.6502
Epoch 246/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8392 - mean_squared_error: 0.8392 - mean_absolute_error: 0.6502
Epoch 247/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8397 - mean_squared_error: 0.8397 - mean_absolute_error: 0.6506
Epoch 248/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8378 - mean_squared_error: 0.8378 - mean_absolute_error: 0.6495
Epoch 249/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8369 - mean_squared_error: 0.8369 - mean_absolute_error: 0.6497
Epoch 250/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8375 - mean_squared_error: 0.8375 - mean_absolute_error: 0.6489
Epoch 251/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8392 - mean_squared_error: 0.8392 - mean_absolute_error: 0.6506
Epoch 252/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8369 - mean_squared_error: 0.8369 - mean_absolute_error: 0.6490
Epoch 253/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8378 - mean_squared_error: 0.8378 - mean_absolute_error: 0.6496
Epoch 254/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8358 - mean_squared_error: 0.8358 - mean_absolute_error: 0.6486
Epoch 255/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8368 - mean_squared_error: 0.8368 - mean_absolute_error: 0.6484
Epoch 256/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8389 - mean_squared_error: 0.8389 - mean_absolute_error: 0.6506
Epoch 257/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8379 - mean_squared_error: 0.8379 - mean_absolute_error: 0.6494
Epoch 258/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8374 - mean_squared_error: 0.8374 - mean_absolute_error: 0.6491
Epoch 259/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8357 - mean_squared_error: 0.8357 - mean_absolute_error: 0.6480
Epoch 260/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8357 - mean_squared_error: 0.8357 - mean_absolute_error: 0.6488
Epoch 261/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8339 - mean_squared_error: 0.8339 - mean_absolute_error: 0.6474
Epoch 262/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8356 - mean_squared_error: 0.8356 - mean_absolute_error: 0.6480
Epoch 263/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8331 - mean_squared_error: 0.8331 - mean_absolute_error: 0.6467
Epoch 264/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8353 - mean_squared_error: 0.8353 - mean_absolute_error: 0.6480
Epoch 265/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8365 - mean_squared_error: 0.8365 - mean_absolute_error: 0.6489
Epoch 266/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8337 - mean_squared_error: 0.8337 - mean_absolute_error: 0.6480
Epoch 267/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8322 - mean_squared_error: 0.8322 - mean_absolute_error: 0.6466
Epoch 268/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8336 - mean_squared_error: 0.8336 - mean_absolute_error: 0.6467
Epoch 269/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8359 - mean_squared_error: 0.8359 - mean_absolute_error: 0.6487
Epoch 270/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8323 - mean_squared_error: 0.8323 - mean_absolute_error: 0.6474
Epoch 271/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8347 - mean_squared_error: 0.8347 - mean_absolute_error: 0.6477
Epoch 272/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8333 - mean_squared_error: 0.8333 - mean_absolute_error: 0.6472
Epoch 273/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8332 - mean_squared_error: 0.8332 - mean_absolute_error: 0.6477
Epoch 274/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8347 - mean_squared_error: 0.8347 - mean_absolute_error: 0.6476
Epoch 275/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8354 - mean_squared_error: 0.8354 - mean_absolute_error: 0.6484
Epoch 276/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8306 - mean_squared_error: 0.8306 - mean_absolute_error: 0.6456
Epoch 277/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8325 - mean_squared_error: 0.8325 - mean_absolute_error: 0.6473
Epoch 278/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8323 - mean_squared_error: 0.8323 - mean_absolute_error: 0.6463
Epoch 279/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8291 - mean_squared_error: 0.8291 - mean_absolute_error: 0.6460
Epoch 280/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8335 - mean_squared_error: 0.8335 - mean_absolute_error: 0.6476
Epoch 281/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8327 - mean_squared_error: 0.8327 - mean_absolute_error: 0.6466
Epoch 282/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8295 - mean_squared_error: 0.8295 - mean_absolute_error: 0.6455
Epoch 283/300
2178/2178 [=====] - 8s 4ms/step - loss: 0.8303 - mean_squared_error: 0.8303 - mean_absolute_error: 0.6456
Epoch 284/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8280 - mean_squared_error: 0.8280 - mean_absolute_error: 0.6446
Epoch 285/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8301 - mean_squared_error: 0.8301 - mean_absolute_error: 0.6462
Epoch 286/300
2178/2178 [=====] - 9s 4ms/step - loss: 0.8278 - mean_squared_error: 0.8278 - mean_absolute_error: 0.6443

```

1

True Value vs Predicted Value for Test Set: Simple Neural Network

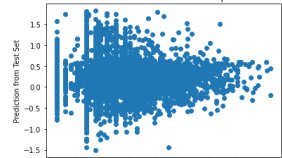


```

2178/2178 [=====] - 9s 4ms/step - loss: 0.8281 - mean_squared_error: 0.8281 - mean_absolute_error: 0.6454
1 # 60 epochs, 231, 50, 50, 50, 50
2 model.evaluate(X_test, y_test, verbose=2)
3
4 test_predictions = model.predict(X_test)
5
6 fig = plt.figure()
7 ax1 = fig.add_subplot()
8 ax1.set_xlabel('True Value from Test Set')
9 ax1.set_ylabel('Prediction from Test Set')
10 ax1.set_title('True Value vs Predicted Value for Test Set: Simple Neural Network')
11 ax1.scatter(y_test, test_predictions)
12 plt.show()

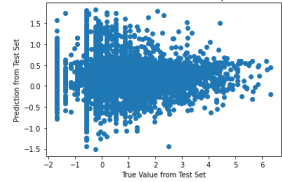
```


545/545 - 1s - loss: 1.1828 - mean_squared_error: 1.1828 - mean_absolute_error: 0.8530 - 816ms/epoch - 1ms/step
True Value vs Predicted Value for Test Set: Simple Neural Network



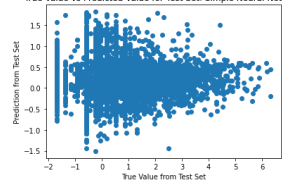
```
1 model.evaluate(X_test, y_test, verbose=2)
2
3 test_predictions = model.predict(X_test)
4
5 fig = plt.figure()
6 ax1 = fig.add_subplot()
7 ax1.set_xlabel("True Value from Test Set")
8 ax1.set_ylabel("Prediction from Test Set")
9 ax1.set_title("True Value vs Predicted Value for Test Set: Simple Neural Network")
10 ax1.scatter(y_test, test_predictions)
11 plt.show()
```

545/545 - 1s - loss: 1.1828 - mean_squared_error: 1.1828 - mean_absolute_error: 0.8530 - 824ms/epoch - 2ms/step
True Value vs Predicted Value for Test Set: Simple Neural Network



```
1 # model = tf.keras.models.Sequential([Dense(231, activation="relu"),
2 #                                     Dropout(0.2),
3 #                                     Dense(50, activation="relu"),
4 #                                     Dense(25, activation="relu"),
5 #                                     Dense(1)])
6
7 model.evaluate(X_test, y_test, verbose=2)
8
9 test_predictions = model.predict(X_test)
10
11 fig = plt.figure()
12 ax1 = fig.add_subplot()
13 ax1.set_xlabel("True Value from Test Set")
14 ax1.set_ylabel("Prediction from Test Set")
15 ax1.set_title("True Value vs Predicted Value for Test Set: Simple Neural Network")
16 ax1.scatter(y_test, test_predictions)
17 plt.show()
```

545/545 - 1s - loss: 1.1828 - mean_squared_error: 1.1828 - mean_absolute_error: 0.8530 - 881ms/epoch - 2ms/step
True Value vs Predicted Value for Test Set: Simple Neural Network



```
1 # model = tf.keras.models.Sequential([Dense(231, activation="relu"),
2 #                                     Dropout(0.2),
3 #                                     Dense(50, activation="relu"),
4 #                                     Dense(25, activation="relu"),
5 #                                     Dense(1)])
6
7 # loss_function = MeanSquaredError()
8 # model.compile(optimizer="adam", loss=loss_function, metrics=["mean_squared_error", "mean_absolute_error"])
9 # model.fit(X_train, y_train, epochs = 1000)
10
11 model.evaluate(X_test, y_test, verbose=2)
12
13 test_predictions = model.predict(X_test)
14
15 fig = plt.figure()
16 ax1 = fig.add_subplot()
17 ax1.set_xlabel("True Value from Test Set")
18 ax1.set_ylabel("Prediction from Test Set")
19 ax1.set_title("True Value vs Predicted Value for Test Set: Simple Neural Network")
20 ax1.scatter(y_test, test_predictions)
21 plt.show()
```



Neural Network Classifier

First, we want to remove the status cause code from out dataframe, and convert it to a one-hot encoding.

```
1
2 # cleaned.info(verbose=True)
3 cause_codes = cleaned["STAT_CAUSE_CODE"]
4
5 features = primary_station_df.copy()
6
7 if "STAT_CAUSE_CODE" in features:
8     del features["STAT_CAUSE_CODE"]
9 if "STAT_CAUSE_DESCR" in features:
10     del features["STAT_CAUSE_DESCR"]
11
12 # encoder = OneHotEncoder()
13 # cause_codes = np.array(cause_codes)
14 # cause_codes = cause_codes.reshape(-1, 1)
15 # cause_codes_encoded = encoder.fit_transform(cause_codes).toarray() * 1.0
16 # print(cause_codes_encoded)

1 import tensorflow as tf
2 from tensorflow.keras.layers import *
3 from tensorflow.keras.losses import SparseCategoricalCrossentropy
4
5 def run_full_classification_neural_net(features, predictors, epochs = 10, model=None):
6     X_train, X_test, y_train, y_test = train_test_split(np.array(X), Y, test_size=0.2, random_state=2020)
7     # Classification into 12 different fire cause code classes.
8     if model is None:
9         model = tf.keras.models.Sequential([Dense(233, activation="relu"),
10                                             Dense(25, activation="relu"),
11                                             Dropout(0.2),
12                                             Dense(25, activation="relu"),
13                                             Dense(25, activation="relu"),
14                                             Dense(14, activation="relu")])
15
16
17 # Make a quick untrained prediction
18 predictions = model(X_train[:1]).numpy()
19 print(predictions)
20 print(tf.nn.softmax(predictions).numpy()) # Probability of each class
21
22 loss_function = SparseCategoricalCrossentropy(from_logits=True)
23 model.compile(optimizer="adam", loss=loss_function, metrics=["accuracy"])
24 print(model.summary())
25 model.fit(X_train, y_train, epochs = epochs)
26 print("EVALUATION:")
27 print(model.evaluate(X_test, y_test))
28

1 # These are the variables to learn against
2 X = features
3 Y = cause_codes
4
5 run_full_classification_neural_net(X, Y, epochs = 200)

[[0.48183015 0.53273875 0.         1.0898234  0.14692128 0.
 0.         0.35303557 0.54752827 0.18044797 0.2152055  0.1799257
 0.13928226 0.00763759]]
[[0.08345924 0.08781805 0.05154876 0.15329307 0.05970702 0.05154876
 0.05154876 0.07323757 0.08912648 0.06174273 0.06392648 0.06171049
 0.05925265 0.05194398]]
Model: "sequential_14"

Layer (type)                 Output Shape              Param #
=====
dense_65 (Dense)              (1, 233)                  54522
dense_66 (Dense)              (1, 400)                  93600
dropout_11 (Dropout)          (1, 400)                  0
dense_67 (Dense)              (1, 400)                  160400
dense_68 (Dense)              (1, 400)                  160400
dense_69 (Dense)              (1, 14)                   5614
=====
Total params: 474,536
Trainable params: 474,536
Non-trainable params: 0

None
Epoch 1/60
2178/2178 [=====] - 22s 10ms/step - loss: 2.1051 - accuracy: 0.3800
Epoch 2/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.7774 - accuracy: 0.4077
Epoch 3/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.8005 - accuracy: 0.4172
Epoch 4/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.7298 - accuracy: 0.4244
Epoch 5/60
2178/2178 [=====] - 20s 9ms/step - loss: 1.7021 - accuracy: 0.4312
Epoch 6/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.8003 - accuracy: 0.4348
Epoch 7/60
2178/2178 [=====] - 22s 10ms/step - loss: 1.6759 - accuracy: 0.4395
Epoch 8/60
2178/2178 [=====] - 22s 10ms/step - loss: 1.6603 - accuracy: 0.4434
Epoch 9/60
2178/2178 [=====] - 21s 9ms/step - loss: 1.6528 - accuracy: 0.4443
Epoch 10/60
2178/2178 [=====] - 22s 10ms/step - loss: 1.6422 - accuracy: 0.4470
```

```
Epoch 11/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.6381 - accuracy: 0.4508
Epoch 12/60
2178/2178 [=====] - 21s 10ms/step - loss: 1.6242 - accuracy: 0.4548
Epoch 13/60
2178/2178 [=====] - 20s 9ms/step - loss: 1.6264 - accuracy: 0.4560
Epoch 14/60
2178/2178 [=====] - 20s 9ms/step - loss: 1.6141 - accuracy: 0.4574
Epoch 15/60
2178/2178 [=====] - 19s 9ms/step - loss: 1.6028 - accuracy: 0.4595
```

Next, we will try to train and test ignoring fires that have unknown cause.

```
1 cause_codes = cleaned["STAT_CAUSE_CODE"]
2 features = primary_station_df.copy()
3
4 known_cause_index = (cause_codes != 9) & (cause_codes != 13)
5
6 known_cause_codes = cause_codes[known_cause_index]
7 known_features = features[known_cause_index]
8
9 run_full_classification_neural_net(known_features, known_cause_codes, epochs = 100)

Epoch 11/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5643 - accuracy: 0.4726
Epoch 48/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5654 - accuracy: 0.4697
Epoch 49/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5604 - accuracy: 0.4725
Epoch 50/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5594 - accuracy: 0.4736
Epoch 51/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5583 - accuracy: 0.4721
Epoch 52/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5768 - accuracy: 0.4739
Epoch 53/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5550 - accuracy: 0.4722
Epoch 54/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5539 - accuracy: 0.4741
Epoch 55/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5543 - accuracy: 0.4750
Epoch 56/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5515 - accuracy: 0.4753
Epoch 57/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5525 - accuracy: 0.4741
Epoch 58/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5505 - accuracy: 0.4755
Epoch 59/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5485 - accuracy: 0.4756
Epoch 60/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5464 - accuracy: 0.4766
Epoch 61/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5464 - accuracy: 0.4771
Epoch 62/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5483 - accuracy: 0.4763
Epoch 63/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5442 - accuracy: 0.4771
Epoch 64/100
2178/2178 [=====] - 6s 3ms/step - loss: 1.5412 - accuracy: 0.4779
Epoch 65/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5757 - accuracy: 0.4762
Epoch 66/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5442 - accuracy: 0.4785
Epoch 67/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5395 - accuracy: 0.4782
Epoch 68/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5395 - accuracy: 0.4788
Epoch 69/100
2178/2178 [=====] - 5s 3ms/step - loss: 1.5386 - accuracy: 0.4796
Epoch 70/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5341 - accuracy: 0.4807
Epoch 71/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5378 - accuracy: 0.4795
Epoch 72/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5345 - accuracy: 0.4799
Epoch 73/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5339 - accuracy: 0.4796
Epoch 74/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5393 - accuracy: 0.4796
Epoch 75/100
2178/2178 [=====] - 5s 2ms/step - loss: 1.5310 - accuracy: 0.4789
Epoch 76/100
```

```
1 # trying a more complex architecture
2 model = tf.keras.models.Sequential([Dense(233, activation="relu"),
3                                     Dense(233, activation="relu"),
4                                     Dropout(0.1),
5                                     Dense(233, activation="relu"),
6                                     Dropout(0.2),
7                                     Dense(14, activation="relu")])
8 run_full_classification_neural_net(known_features, known_cause_codes, epochs = 400, model=model)

Epoch 11/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4925 - accuracy: 0.4967
Epoch 44/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.5050 - accuracy: 0.4910
Epoch 45/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.5036 - accuracy: 0.4923
Epoch 46/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4985 - accuracy: 0.4920
Epoch 47/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4946 - accuracy: 0.4937
Epoch 48/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4897 - accuracy: 0.4966
Epoch 49/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4856 - accuracy: 0.4970
Epoch 50/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4789 - accuracy: 0.4988
Epoch 51/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4899 - accuracy: 0.4942
Epoch 52/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4813 - accuracy: 0.4954
Epoch 53/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4756 - accuracy: 0.5033
Epoch 54/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4689 - accuracy: 0.4998
Epoch 55/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4669 - accuracy: 0.5036
Epoch 56/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4688 - accuracy: 0.5032
Epoch 57/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4708 - accuracy: 0.5013
```

```
41/0/41/0 [=====] - 8s 4ms/step - loss: 1.4708 - accuracy: 0.5043
Epoch 58/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4628 - accuracy: 0.5045
Epoch 59/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4661 - accuracy: 0.5036
Epoch 60/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4620 - accuracy: 0.5032
Epoch 61/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4615 - accuracy: 0.5052
Epoch 62/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4555 - accuracy: 0.5043
Epoch 63/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4522 - accuracy: 0.5085
Epoch 64/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4488 - accuracy: 0.5075
Epoch 65/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4522 - accuracy: 0.5065
Epoch 66/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4502 - accuracy: 0.5084
Epoch 67/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4756 - accuracy: 0.5024
Epoch 68/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4486 - accuracy: 0.5082
Epoch 69/400
2178/2178 [=====] - 9s 4ms/step - loss: 1.4497 - accuracy: 0.5062
Epoch 70/400
2178/2178 [=====] - 9s 4ms/step - loss: 1.4512 - accuracy: 0.5073
Epoch 71/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4506 - accuracy: 0.5057
Epoch 72/400
2178/2178 [=====] - 8s 4ms/step - loss: 1.4480 - accuracy: 0.5053
```

```
1 # probability_model = tf.keras.Sequential([
2 #     model,
3 #     tf.keras.layers.Softmax(),
4 # ])
```

```
1 # probability_model(X_test[:5])

<tf.Tensor: shape=(5, 14), dtype=float32, numpy=
array([[3.29549704e-03, 1.66717973e-02, 2.67233163e-01, 3.45799029e-02,
        4.54233326e-02, 6.08601756e-02, 3.29549704e-03, 9.02952263e-02,
        4.02569845e-02, 3.03870469e-01, 3.29549704e-03, 5.01898900e-02,
        3.29549704e-03, 7.74330422e-02],
       [6.72030510e-05, 9.49687421e-01, 8.00500251e-03, 3.49900965e-03,
        7.98075087e-03, 2.22626817e-03, 6.72030510e-05, 2.14828923e-03,
        1.18853315e-03, 2.42914725e-02, 6.72030510e-05, 6.72030510e-05,
        6.72030510e-05, 6.37105783e-04],
       [1.72957775e-03, 1.41575588e-02, 1.70311946e-02, 1.72957775e-03,
        5.11530787e-02, 8.17846507e-02, 1.72957775e-03, 7.08773196e-01,
        7.14560365e-03, 9.76177081e-02, 1.72957775e-03, 1.72957775e-03,
        1.72957775e-03, 1.19594922e-02],
       [7.89784535e-04, 5.61121881e-01, 4.12679579e-02, 3.99304330e-02,
        1.66325241e-01, 1.64578483e-02, 7.89784535e-04, 1.33630764e-02,
        1.30247315e-02, 1.40769288e-01, 7.89784535e-04, 7.89784535e-04,
        7.89784535e-04, 3.79060791e-03],
       [1.20075094e-03, 1.16253376e-01, 1.08798437e-01, 5.24045490e-02,
        2.79174715e-01, 3.31705734e-02, 1.20075094e-03, 7.25342333e-02,
        4.18527313e-02, 2.71965116e-01, 1.20075094e-03, 1.56444055e-03,
        1.20075094e-03, 1.74788609e-02]], dtype=float32)>
```

