New York City Leading Causes of Death

The data consider 6 features; year, leading cause of death, sex, race, deaths, death rate and age-adjusted death rate.

Data Extraction and Exploration

```
In [1]: import types
        import pandas as pd
        from botocore.client import Config
        import ibm boto3
        def __iter__(self): return 0
        # @hidden cell
        # The following code accesses a file in your IBM Cloud Object Storage. It
        includes your credentials.
        # You might want to remove those credentials before you share the notebook
        client_11c432be10854a9b9869f676bfc39db7 = ibm_boto3.client(service_name='s
            ibm_api_key_id='RoQ3a72rfJwtvFJsCDXKv8HQVkgk8r819S0k9ES0wc1e',
            ibm_auth_endpoint="https://iam.ng.bluemix.net/oidc/token",
            config=Config(signature version='oauth'),
            endpoint_url='https://s3-api.us-geo.objectstorage.service.networklayer
        .com')
        body = client_11c432be10854a9b9869f676bfc39db7.get_object(Bucket='nyc-dono
        tdelete-pr-0ua42fmkmna1sa', Key='NYCity.csv')['Body']
        # add missing __iter__ method, so pandas accepts body as file-like object
        if not hasattr(body, "__iter___"): body.__iter__ = types.MethodType( __iter
        __, body )
        # If you are reading an Excel file into a pandas DataFrame, replace `read_
        csv` by `read_excel` in the next statement.
        df_data_0 = pd.read_csv(body)
        df_data_0.head()
```

Out[1]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281	107.3	170.5
1	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Hispanic	1146	96	143.5
2	2014	Influenza (Flu) and Pneumonia (J09-J18)	Male	Hispanic	199	16.7	26.6
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191	16	16.6
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186	15.6	23.2

```
In [2]: # The dataframe is renamed df_ny from the original name df_data_0
    df_ny = df_data_0
    df_ny.head()
```

Out[2]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281	107.3	170.5
1	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Hispanic	1146	96	143.5
2	2014	Influenza (Flu) and Pneumonia (J09-J18)	Male	Hispanic	199	16.7	26.6
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191	16	16.6
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186	15.6	23.2

In [3]: # A description of the dataset

df_ny.describe(include = 'all')

Out[3]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
count	1094.000000	1094	1094	1094	1094	1094	1094
unique	NaN	27	2	6	465	442	427
top	NaN	Diseases of Heart (100-109, 111, 113, 120-151)	Female	Not Stated/Unknown			
freq	NaN	96	554	200	138	386	386
mean	2010.477148	NaN	NaN	NaN	NaN	NaN	NaN
std	2.293419	NaN	NaN	NaN	NaN	NaN	NaN
min	2007.000000	NaN	NaN	NaN	NaN	NaN	NaN
25%	2008.000000	NaN	NaN	NaN	NaN	NaN	NaN
50%	2010.000000	NaN	NaN	NaN	NaN	NaN	NaN
75%	2012.000000	NaN	NaN	NaN	NaN	NaN	NaN
max	2014.000000	NaN	NaN	NaN	NaN	NaN	NaN

In [4]: # Data grouping according to leading cause of death in New York

df_grp4 = df_ny[["Deaths", "Leading_Cause", "Year"]].groupby(["Leading_Cause"], as_index = False).mean()
 df_grp4

Out[4]:

	Leading_Cause	Year
0	Accidents Except Drug Poisoning (V01-X39, X43,	2010.350000
1	All Other Causes	2010.500000
2	Alzheimer's Disease (G30)	2011.093750

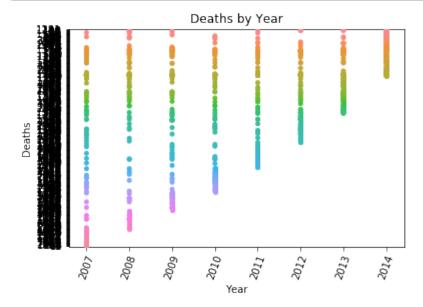
3	Aortic Aneurysm and Dissection (I71)	2009.000000
4	Assault (Homicide: Y87.1, X85-Y09)	2009.650000
5	Atherosclerosis (I70)	2008.666667
6	Cerebrovascular Disease (Stroke: I60-I69)	2010.544444
7	Certain Conditions originating in the Perinata	2010.500000
8	Chronic Liver Disease and Cirrhosis (K70, K73)	2010.551724
9	Chronic Lower Respiratory Diseases (J40-J47)	2010.488636
10	Congenital Malformations, Deformations, and Ch	2010.875000
11	Diabetes Mellitus (E10-E14)	2010.543478
12	Diseases of Heart (I00-I09, I11, I13, I20-I51)	2010.500000
13	Essential Hypertension and Renal Diseases (I10	2010.586667
14	Human Immunodeficiency Virus Disease (HIV: B20	2010.186047
15	In Situ or Benign / Uncertain Neoplasms (D00-D48)	2008.500000
16	In situ or Benign / Uncertain Neoplasms (D00-D48)	2008.000000
17	Influenza (Flu) and Pneumonia (J09-J18)	2010.500000
18	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	2010.578947
19	Malignant Neoplasms (Cancer: C00-C97)	2010.500000
20	Mental and Behavioral Disorders due to Acciden	2010.435897
21	Mental and Behavioral Disorders due to Use of	2008.500000
22	Nephritis, Nephrotic Syndrome and Nephrosis (N	2010.294118
23	Parkinson's Disease (G20)	2011.000000
24	Septicemia (A40-A41)	2011.076923
25	Tuberculosis (A16-A19)	2011.000000
26	Viral Hepatitis (B15-B19)	2010.400000

Out[5]: Year int64
Leading_Cause object
Sex object
Race object
Deaths object
Death_Rate object
AADR object

dtype: object

In [6]: # In this cell libraries and modules required for plotting are imported an
 d a swarm plot is drawn;
the swarm plot shows that some data such as deaths that would be conside

```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
plot = sns.swarmplot(x = "Year", y = 'Deaths', data = df_ny)
plt.setp(plot.get_xticklabels(), rotation = 70)
plt.title('Deaths by Year')
plt.show()
```



```
In [7]: # Missing values in the dataset are being checked for
    missing_data = df_ny.isnull()
    missing_data.head(30)
```

Out[7]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
5	False	False	False	False	False	False	False
6	False	False	False	False	False	False	False
7	False	False	False	False	False	False	False
8	False	False	False	False	False	False	False
9	False	False	False	False	False	False	False
10	False	False	False	False	False	False	False
11	False	False	False	False	False	False	False
12	False	False	False	False	False	False	False

| 13 | False |
|----|-------|-------|-------|-------|-------|-------|-------|
| 14 | False |
| 15 | False |
| 16 | False |
| 17 | False |
| 18 | False |
| 19 | False |
| 20 | False |
| 21 | False |
| 22 | False |
| 23 | False |
| 24 | False |
| 25 | False |
| 26 | False |
| 27 | False |
| 28 | False |
| 29 | False |

```
In [8]: missing_data2 = df_ny.notnull()
missing_data2.head()
```

Out[8]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	True	True	True	True	True	True	True
1	True	True	True	True	True	True	True
2	True	True	True	True	True	True	True
3	True	True	True	True	True	True	True
4	True	True	True	True	True	True	True

```
In [9]: # Counting the missing values

for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print("")
Year
```

False 1094

Name: Year, dtype: int64

Leading_Cause False 1094

Name: Leading Cause, dtype: int64

Sex

False 1094

Name: Sex, dtype: int64

Race

False 1094

Name: Race, dtype: int64

Deaths

False 1094

Name: Deaths, dtype: int64

Death_Rate False 1094

Name: Death_Rate, dtype: int64

AADR

False 1094

Name: AADR, dtype: int64

In [10]: df_ny.head(50)

Out[10]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281	107.3	170.5
1	2014	Malignant Neoplasms (Cancer: C00- C97)	Male	Hispanic	1146	96	143.5
2	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Hispanic	199	16.7	26.6
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191	16	16.6
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186	15.6	23.2
5	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Hispanic	176	14.7	16.9
6	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Hispanic	165	13.8	20.4
7	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Hispanic	164	13.7	16.7
8	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Hispanic	145	12.1	19.3
9	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Hispanic	92	7.7	8.7
10	2014	All Other Causes	Male	Hispanic	1195	100.1	143.3
11	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Asian and Pacific Islander	657	114.5	129.5
		Diseases of Heart (I00-I09, I11, I13, I20-		Asian and Pacific			

12	2014	I51)	Male	Islander	554	96.5	118.5
13	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Asian and Pacific Islander	105	18.3	25
14	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Asian and Pacific Islander	95	16.6	22.9
15	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Asian and Pacific Islander	91	15.9	19.3
16	2014	Diabetes Mellitus (E10-E14)	Male	Asian and Pacific Islander	71	12.4	14.2
17	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Asian and Pacific Islander	68	11.9	13.3
18	2014	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	Male	Asian and Pacific Islander	50	8.7	8.7
19	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Asian and Pacific Islander	31	5.4	5.3
20	2014	Nephritis, Nephrotic Syndrome and Nephrosis (N	Male	Asian and Pacific Islander	28	4.9	5.8
21	2014	All Other Causes	Male	Asian and Pacific Islander	424	73.9	90.4
22	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	White Non- Hispanic	3990	297.1	238.4
23	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	White Non- Hispanic	3142	234	195.1
24	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	White Non- Hispanic	502	37.4	29.7
25	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	White Non- Hispanic	399	29.7	24
26	2014	Mental and Behavioral Disorders due to Acciden	Male	White Non- Hispanic	314	23.4	21.4
27	2014	Diabetes Mellitus (E10-E14)	Male	White Non- Hispanic	292	21.7	18.1
28	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	White Non- Hispanic	277	20.6	16.8
29	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	White Non- Hispanic	258	19.2	16.4
30	2014	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	Male	White Non- Hispanic	204	15.2	13.4
31	2014	Essential Hypertension and Renal Diseases (I10	Male	White Non- Hispanic	175	13	10.5
32	2014	All Other Causes	Male	White Non- Hispanic	2275	169.4	141.3
33	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Black Non-Hispanic	1958	226.8	264.7

34	2014	Malignant Neoplasms (Cancer: C00- C97)	Male	Black Non-Hispanic	1532	177.5	199.6
35	2014	Diabetes Mellitus (E10-E14)	Male	Black Non-Hispanic	318	36.8	42.2
36	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Black Non-Hispanic	242	28	33.9
37	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Black Non-Hispanic	197	22.8	26.4
38	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Black Non-Hispanic	196	22.7	21.7
39	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Black Non-Hispanic	186	21.5	25.4
40	2014	Assault (Homicide: Y87.1, X85-Y09)	Male	Black Non-Hispanic	186	21.5	21.5
41	2014	Essential Hypertension and Renal Diseases (I10	Male	Black Non-Hispanic	155	18	21.6
42	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Black Non-Hispanic	148	17.1	17.7
43	2014	All Other Causes	Male	Black Non-Hispanic	1375	159.3	177.8
44	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Other Race/ Ethnicity	63		
45	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Other Race/ Ethnicity	50		
46	2014	Diabetes Mellitus (E10-E14)	Male	Other Race/ Ethnicity	18		
47	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Other Race/ Ethnicity	12		
48	2014	Mental and Behavioral Disorders due to Acciden	Male	Other Race/ Ethnicity	12		
49	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Other Race/ Ethnicity	11		

In [28]: df_ny = df_ny.fillna(df_ny.mean())
 df_ny.head(50)

Out[28]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281.0	107.300000	170.500000
1	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Hispanic	1146.0	96.000000	143.500000
2	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Hispanic	199.0	16.700000	26.600000
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191.0	16.000000	16.600000
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186.0	15.600000	23.200000

5	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Hispanic	176.0	14.700000	16.900000
6	2014	Cerebrovascular Disease (Stroke: 160-169)	Male	Hispanic	165.0	13.800000	20.400000
7	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Hispanic	164.0	13.700000	16.700000
8	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Hispanic	145.0	12.100000	19.300000
9	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Hispanic	92.0	7.700000	8.700000
10	2014	All Other Causes	Male	Hispanic	1195.0	100.100000	143.300000
11	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Asian and Pacific Islander	657.0	114.500000	129.500000
12	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Asian and Pacific Islander	554.0	96.500000	118.500000
13	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Asian and Pacific Islander	105.0	18.300000	25.000000
14	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Asian and Pacific Islander	95.0	16.600000	22.900000
15	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Asian and Pacific Islander	91.0	15.900000	19.300000
16	2014	Diabetes Mellitus (E10-E14)	Male	Asian and Pacific Islander	71.0	12.400000	14.200000
17	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Asian and Pacific Islander	68.0	11.900000	13.300000
18	2014	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	Male	Asian and Pacific Islander	50.0	8.700000	8.700000
19	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Asian and Pacific Islander	31.0	5.400000	5.300000
20	2014	Nephritis, Nephrotic Syndrome and Nephrosis (N	Male	Asian and Pacific Islander	28.0	4.900000	5.800000
21	2014	All Other Causes	Male	Asian and Pacific Islander	424.0	73.900000	90.400000
22	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	White Non- Hispanic	3990.0	297.100000	238.400000
23	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	White Non- Hispanic	3142.0	234.000000	195.100000
24	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	White Non- Hispanic	502.0	37.400000	29.700000
25	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	White Non- Hispanic	399.0	29.700000	24.000000
26	2014	Mental and Behavioral Disorders due to Acciden	Male	White Non- Hispanic	314.0	23.400000	21.400000

White Non-

27	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	292.0	21.700000	18.100000
28	2014	Cerebrovascular Disease (Stroke: 160-169)	Male	White Non- Hispanic	277.0	20.600000	16.800000
29	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	White Non- Hispanic	258.0	19.200000	16.400000
30	2014	Intentional Self-Harm (Suicide: X60- X84, Y87.0)	Male	White Non- Hispanic	204.0	15.200000	13.400000
31	2014	Essential Hypertension and Renal Diseases (I10	Male	White Non- Hispanic	175.0	13.000000	10.500000
32	2014	All Other Causes	Male	White Non- Hispanic	2275.0	169.400000	141.300000
33	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Black Non- Hispanic	1958.0	226.800000	264.700000
34	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Black Non- Hispanic	1532.0	177.500000	199.600000
35	2014	Diabetes Mellitus (E10-E14)	Male	Black Non- Hispanic	318.0	36.800000	42.200000
36	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Black Non- Hispanic	242.0	28.000000	33.900000
37	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Black Non- Hispanic	197.0	22.800000	26.400000
38	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Black Non- Hispanic	196.0	22.700000	21.700000
39	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Black Non- Hispanic	186.0	21.500000	25.400000
40	2014	Assault (Homicide: Y87.1, X85-Y09)	Male	Black Non- Hispanic	186.0	21.500000	21.500000
41	2014	Essential Hypertension and Renal Diseases (I10	Male	Black Non- Hispanic	155.0	18.000000	21.600000
42	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Black Non- Hispanic	148.0	17.100000	17.700000
43	2014	All Other Causes	Male	Black Non- Hispanic	1375.0	159.300000	177.800000
44	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Other Race/ Ethnicity	63.0	53.438842	53.462288
45	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Other Race/ Ethnicity	50.0	53.438842	53.462288
46	2014	Diabetes Mellitus (E10-E14)	Male	Other Race/ Ethnicity	18.0	53.438842	53.462288
47	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Other Race/ Ethnicity	12.0	53.438842	53.462288
48	2014	Mental and Behavioral Disorders due to Acciden	Male	Other Race/ Ethnicity	12.0	53.438842	53.462288

```
Influenza (Flu) and Pneumonia (J09-
          49 2014
                                                                  11.0
                                                                        53.438842 53.462288
                                             Male
                                                         Ethnicity
In [29]: # Determining the value_counts for each sex
         df_ny["Sex"].value_counts()
Out[29]: Female
                    554
         Male
                    540
         Name: Sex, dtype: int64
In [30]: # Determining the value_counts for each race
         df_ny["Race"].value_counts()
Out[30]: Not Stated/Unknown
                                          200
         Other Race/ Ethnicity
                                          186
         Black Non-Hispanic
                                          178
         Hispanic
                                          177
         Asian and Pacific Islander
                                          177
         White Non-Hispanic
                                          176
         Name: Race, dtype: int64
```

Other Race/

Extract, Transform, Load (ETL)

```
In [31]: # Data types
         df_ny.dtypes
Out[31]: Year
                             int64
         Leading_Cause
                            object
         Sex
                            object
         Race
                            object
         Deaths
                           float64
                           float64
         Death_Rate
         AADR
                           float64
         dtype: object
In [32]: df_ny.describe(include = "all")
Out[32]:
```

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
count	1094.000000	1094	1094	1094	1094.000000	1094.000000	1094.000000
unique	NaN	27	2	6	NaN	NaN	NaN
top	NaN	Diseases of Heart (100-109, I11, I13, I20-I51)	Female	Not Stated/Unknown	NaN	NaN	NaN
freq	NaN	96	554	200	NaN	NaN	NaN
mean	2010.477148	NaN	NaN	NaN	444.558577	53.438842	53.462288
std	2.293419	NaN	NaN	NaN	822.673477	61.546202	55.575360

min	2007.000000	NaN	NaN	NaN	5.000000	2.400000	2.500000
25%	2008.000000	NaN	NaN	NaN	47.000000	15.800000	16.950000
50%	2010.000000	NaN	NaN	NaN	186.000000	53.438842	53.462288
75%	2012.000000	NaN	NaN	NaN	444.558577	53.438842	53.462288
max	2014.000000	NaN	NaN	NaN	7050.000000	491.400000	350.700000

```
In [33]: df_ny["Deaths"].min()
Out[33]: 5.0
In [34]: df_ny["Deaths"].max()
Out[34]: 7050.0
In [35]: import numpy as np
         df_ny.replace(".", np.nan, inplace = True)
In [36]: df_ny["Deaths"] = df_ny["Deaths"].astype(float)
In [37]: df_ny["Death_Rate"] = df_ny["Death_Rate"].astype(float)
In [38]: df_ny["Deaths"].mean()
Out[38]: 444.55857740585924
In [39]: df_ny["Death_Rate"].mean()
Out[39]: 53.43884180790981
In [40]: df_ny["AADR"].mean()
Out[40]: 53.46228813559277
In [41]: df_ny["AADR"] = df_ny["AADR"].astype(float)
In [42]: df_grp1 = df_ny[["Deaths", "Sex"]].groupby(['Sex'], as_index = False).mean
         df_grp1
Out[42]:
                     Deaths
              Sex
          0 Female 464.848070
              Male 423.743061
In [45]: import scipy.stats
         scipy.stats.pearsonr(df_ny["Deaths"], df_ny["Death_Rate"])
Out[45]: (0.9324294842131633, 0.0)
```

```
In [46]: | scipy.stats.pearsonr(df_ny["Deaths"], df_ny["AADR"])
Out[46]: (0.7931153989191558, 2.1919824608206278e-237)
In [47]: scipy.stats.pearsonr(df_ny["Death_Rate"], df_ny["AADR"])
Out[47]: (0.9195200324490621, 0.0)
In [48]: # Average number of Deaths per year
          df_grp2 = df_ny[["Deaths", "Year"]].groupby(['Year'], as_index = False).me
          an()
          df_grp2
Out[48]:
                     Deaths
             Year
           0 2007 464.925695
           1 2008 460.180978
           2 2009 463.705842
           3 2010 451.342672
           4 2011 449.612808
           5 2012 431.005246
           6 2013 421.461289
          7 2014 412.631691
In [49]: # Average number of Deaths per race
          df_grp5 = df_ny[["Deaths", "Race"]].groupby(['Race'], as_index = False).me
          an()
          df_grp5
Out[49]:
                            Race
                                     Deaths
          0 Asian and Pacific Islander
                                  148.898305
           1
                 Black Non-Hispanic
                                  624.247191
           2
                         Hispanic
                                  422.610169
           3
                 Not Stated/Unknown
                                 140.525816
                Other Race/ Ethnicity
                                  212.268390
           5
                 White Non-Hispanic 1173.221591
In [50]: # Average number of Deaths by sex
          df_grp6 = df_ny[["Deaths", "Sex"]].groupby(['Sex'], as_index = False).mean
          ( )
          df_grp6
```

```
Out[50]:
               Sex
                      Deaths
          0 Female 464.848070
          1
               Male 423.743061
In [51]: # In this cell, the mean of all variables by race is indicated
          df_ny.groupby("Race").mean()
Out[51]:
                                     Year
                                              Deaths Death_Rate
                                                                 AADR
                          Race
          Asian and Pacific Islander 2010.485876
                                           148.898305
                                                      27.313559 34.387006
               Black Non-Hispanic 2010.460674
                                          624.247191
                                                      65.946629 69.571348
                       Hispanic 2010.491525
                                           422.610169
                                                      35.858757 49.824294
              Not Stated/Unknown 2010.480000
                                           140.525816
                                                     53.438842 53.462288
              Other Race/ Ethnicity 2010.446237
                                                      53.438842 53.462288
                                           212.268390
               White Non-Hispanic 2010.500000 1173.221591
                                                     84.742614 60.012500
In [52]: # Collections-extended library is installed to enable proper variable coun
          ting
          !pip install collections-extended
         Collecting collections-extended
            Downloading https://files.pythonhosted.org/packages/4e/1e/3440dfc8036621
          832e33634bd8ae6fe691c0ee951441903417c8879c242e/collections_extended-1.0.3-
         py2.py3-none-any.whl
         Requirement already satisfied: setuptools in /opt/conda/envs/Python36/lib/
         python3.6/site-packages (from collections-extended) (40.8.0)
          Installing collected packages: collections-extended
         Successfully installed collections-extended-1.0.3
In [53]: from collections import Counter
          import collections, numpy
          df_sex = df_ny["Sex"]
          collections.Counter(df_sex)
Out[53]: Counter({'Male': 540, 'Female': 554})
In [54]: from collections import Counter
          import collections, numpy
          df_Leading = df_ny["Leading_Cause"]
          collections.Counter(df_Leading)
Out[54]: Counter({'Diseases of Heart (I00-I09, I11, I13, I20-I51)': 96,
                    'Malignant Neoplasms (Cancer: C00-C97)': 96,
                   'Influenza (Flu) and Pneumonia (J09-J18)': 96,
                    'Mental and Behavioral Disorders due to Accidental Poisoning and
         Other Psychoactive Substance Use (F11-F16, F18-F19, X40-X42, X44): 39,
```

```
'Diabetes Mellitus (E10-E14)': 92,
                  'Accidents Except Drug Poisoning (V01-X39, X43, X45-X59, Y85-Y86)
         ': 80,
                  'Cerebrovascular Disease (Stroke: I60-I69)': 90,
                  'Chronic Liver Disease and Cirrhosis (K70, K73)': 29,
                  'Chronic Lower Respiratory Diseases (J40-J47)': 88,
                  'Human Immunodeficiency Virus Disease (HIV: B20-B24)': 43,
                  'All Other Causes': 96,
                  'Intentional Self-Harm (Suicide: X60-X84, Y87.0)': 38,
                  'Nephritis, Nephrotic Syndrome and Nephrosis (N00-N07, N17-N19, N
         25-N27)': 17,
                  'Essential Hypertension and Renal Diseases (I10, I12)': 75,
                  'Assault (Homicide: Y87.1, X85-Y09)': 20,
                  'Certain Conditions originating in the Perinatal Period (P00-P96)
         ': 26,
                  'Septicemia (A40-A41)': 13,
                  "Alzheimer's Disease (G30)": 32,
                  'Congenital Malformations, Deformations, and Chromosomal Abnormal
         ities (Q00-Q99)': 8,
                  'Viral Hepatitis (B15-B19)': 5,
                  'Aortic Aneurysm and Dissection (I71)': 3,
                  "Parkinson's Disease (G20)": 1,
                  'Tuberculosis (A16-A19)': 1,
                  'Mental and Behavioral Disorders due to Use of Alcohol (F10)': 2,
                  'In Situ or Benign / Uncertain Neoplasms (D00-D48)': 4,
                  'Atherosclerosis (I70)': 3,
                   'In situ or Benign / Uncertain Neoplasms (D00-D48)': 1})
In [55]: from collections import Counter
         import collections, numpy
         df race = df ny["Race"]
         collections.Counter(df_race)
Out[55]: Counter({'Hispanic': 177,
                  'Asian and Pacific Islander': 177,
                   'White Non-Hispanic': 176,
                  'Black Non-Hispanic': 178,
                  'Other Race/ Ethnicity': 186,
                  'Not Stated/Unknown': 200})
```

Transforming the data

dtype: float64

In [65]: df_ny.mean()

Out[65]: Year

2010.477148 Deaths 444.558577 Death_Rate 53.438842 AADR 53.462288

dtype: float64

In [66]: # Missing numerical variables (NaN) are being replaced by the column means

df_ny = df_ny.fillna(df_ny.mean())

df_ny.head(50)

Out[66]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281.0	107.300000	170.500000
1	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Hispanic	1146.0	96.000000	143.500000
2	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Hispanic	199.0	16.700000	26.600000
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191.0	16.000000	16.600000
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186.0	15.600000	23.200000
5	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Hispanic	176.0	14.700000	16.900000
6	2014	Cerebrovascular Disease (Stroke: 160-169)	Male	Hispanic	165.0	13.800000	20.400000
7	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Hispanic	164.0	13.700000	16.700000
8	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Hispanic	145.0	12.100000	19.300000
9	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Hispanic	92.0	7.700000	8.700000
10	2014	All Other Causes	Male	Hispanic	1195.0	100.100000	143.300000
11	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Asian and Pacific Islander	657.0	114.500000	129.500000
12	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Asian and Pacific Islander	554.0	96.500000	118.500000
13	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Asian and Pacific Islander	105.0	18.300000	25.000000
14	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Asian and Pacific Islander	95.0	16.600000	22.900000
15	2014	Cerebrovascular Disease (Stroke: 160-169)	Male	Asian and Pacific Islander	91.0	15.900000	19.300000

16	2014	Diabetes Mellitus (E10-E14)	Male	Asian and Pacific Islander	71.0	12.400000	14.200000
17	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Asian and Pacific Islander	68.0	11.900000	13.300000
18	2014	Intentional Self-Harm (Suicide: X60-X84, Y87.0)	Male	Asian and Pacific Islander	50.0	8.700000	8.700000
19	2014	Chronic Liver Disease and Cirrhosis (K70, K73)	Male	Asian and Pacific Islander	31.0	5.400000	5.300000
20	2014	Nephritis, Nephrotic Syndrome and Nephrosis (N	Male	Asian and Pacific Islander	28.0	4.900000	5.800000
21	2014	All Other Causes	Male	Asian and Pacific Islander	424.0	73.900000	90.400000
22	2014	Diseases of Heart (100-109, 111, 113, 120-151)	Male	White Non- Hispanic	3990.0	297.100000	238.400000
23	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	White Non- Hispanic	3142.0	234.000000	195.100000
24	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	White Non- Hispanic	502.0	37.400000	29.700000
25	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	White Non- Hispanic	399.0	29.700000	24.000000
26	2014	Mental and Behavioral Disorders due to Acciden	Male	White Non- Hispanic	314.0	23.400000	21.400000
27	2014	Diabetes Mellitus (E10-E14)	Male	White Non- Hispanic	292.0	21.700000	18.100000
28	2014	Cerebrovascular Disease (Stroke: 160-169)	Male	White Non- Hispanic	277.0	20.600000	16.800000
29	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	White Non- Hispanic	258.0	19.200000	16.400000
30	2014	Intentional Self-Harm (Suicide: X60- X84, Y87.0)	Male	White Non- Hispanic	204.0	15.200000	13.400000
31	2014	Essential Hypertension and Renal Diseases (I10	Male	White Non- Hispanic	175.0	13.000000	10.500000
32	2014	All Other Causes	Male	White Non- Hispanic	2275.0	169.400000	141.300000
33	2014	Diseases of Heart (100-109, 111, 113, 120-151)	Male	Black Non- Hispanic	1958.0	226.800000	264.700000
34	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Black Non- Hispanic	1532.0	177.500000	199.600000
35	2014	Diabetes Mellitus (E10-E14)	Male	Black Non- Hispanic	318.0	36.800000	42.200000
36	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Black Non- Hispanic	242.0	28.000000	33.900000
37	2014	Cerebrovascular Disease (Stroke: I60-I69)	Male	Black Non- Hispanic	197.0	22.800000	26.400000

38	2014	Human Immunodeficiency Virus Disease (HIV: B20	Male	Black Non- Hispanic	196.0	22.700000	21.700000
39	2014	Chronic Lower Respiratory Diseases (J40-J47)	Male	Black Non- Hispanic	186.0	21.500000	25.400000
40	2014	Assault (Homicide: Y87.1, X85-Y09)	Male	Black Non- Hispanic	186.0	21.500000	21.500000
41	2014	Essential Hypertension and Renal Diseases (I10	Male	Black Non- Hispanic	155.0	18.000000	21.600000
42	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Black Non- Hispanic	148.0	17.100000	17.700000
43	2014	All Other Causes	Male	Black Non- Hispanic	1375.0	159.300000	177.800000
44	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Other Race/ Ethnicity	63.0	53.438842	53.462288
45	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Other Race/ Ethnicity	50.0	53.438842	53.462288
46	2014	Diabetes Mellitus (E10-E14)	Male	Other Race/ Ethnicity	18.0	53.438842	53.462288
47	2014	Accidents Except Drug Poisoning (V01-X39, X43,	Male	Other Race/ Ethnicity	12.0	53.438842	53.462288
48	2014	Mental and Behavioral Disorders due to Acciden	Male	Other Race/ Ethnicity	12.0	53.438842	53.462288
49	2014	Influenza (Flu) and Pneumonia (J09- J18)	Male	Other Race/ Ethnicity	11.0	53.438842	53.462288

In [67]: df_ny.mean()

Out[67]: Year

2010.477148 444.558577 Deaths 53.438842 Death_Rate 53.462288 AADR

dtype: float64

In [68]: df_ny.groupby("Race").mean()

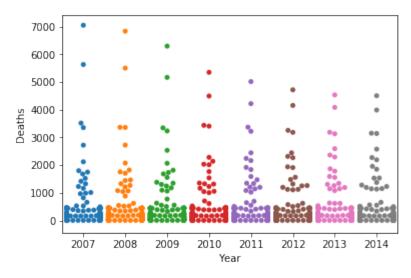
Out[68]:

	Year	Deaths	Death_Rate	AADR
Race				
Asian and Pacific Islander	2010.485876	148.898305	27.313559	34.387006
Black Non-Hispanic	2010.460674	624.247191	65.946629	69.571348
Hispanic	2010.491525	422.610169	35.858757	49.824294
Not Stated/Unknown	2010.480000	140.525816	53.438842	53.462288
Other Race/ Ethnicity	2010.446237	212.268390	53.438842	53.462288
White Non-Hispanic	2010.500000	1173.221591	84.742614	60.012500

More visualizations of the data

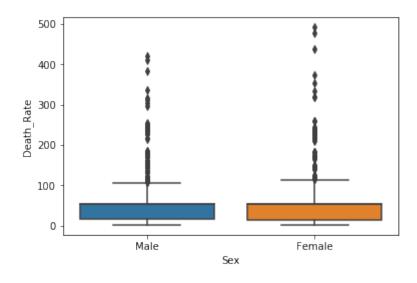
```
In [70]: # A swarm plot re-drawn after replacing the missing data by the column mea
    ns

plot = sns.swarmplot(x = "Year", y = "Deaths", data = df_ny)
```



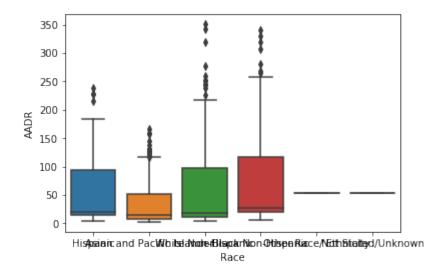
```
In [71]: sns.boxplot(x = "Sex", y = "Death_Rate", data = df_ny)
```

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6718ae07f0>



```
In [72]: sns.boxplot(x = "Race", y = "AADR", data = df_ny)
```

Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6718a52a90>



```
In [73]: df_ny.mean()
```

Out[73]: Year 2010.477148

Deaths 444.558577

Death_Rate 53.438842 AADR 53.462288

dtype: float64

In [74]: # The features are undergoing scaling since they are of different scales i
 n the original dataset

from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

SCALE = StandardScaler()
SCALE.fit(df_ny[["Deaths", "Death_Rate", "AADR"]])

Out[74]: StandardScaler(copy=True, with_mean=True, with_std=True)

In [75]: df_ny.head()

Out[75]:

	Year	Leading_Cause	Sex	Race	Deaths	Death_Rate	AADR
0	2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	Male	Hispanic	1281.0	107.3	170.5
1	2014	Malignant Neoplasms (Cancer: C00-C97)	Male	Hispanic	1146.0	96.0	143.5
2	2014	Influenza (Flu) and Pneumonia (J09-J18)	Male	Hispanic	199.0	16.7	26.6
3	2014	Mental and Behavioral Disorders due to Acciden	Male	Hispanic	191.0	16.0	16.6
4	2014	Diabetes Mellitus (E10-E14)	Male	Hispanic	186.0	15.6	23.2

The encoding of categorical variables

```
In [76]: X = df_ny[["Sex", "Race"]].values
```

```
X[0:5]
Out[76]: array([['Male', 'Hispanic'],
                ['Male', 'Hispanic'],
                ['Male', 'Hispanic'],
                ['Male', 'Hispanic'],
                ['Male', 'Hispanic']], dtype=object)
In [77]: le_Sex = preprocessing.LabelEncoder()
         le_Sex.fit(['Female', 'Male'])
         X[:,0] = le_Sex.transform(X[:,0])
In [78]: df_ny["Race"].value_counts()
Out[78]: Not Stated/Unknown
                                        200
         Other Race/ Ethnicity
                                        186
         Black Non-Hispanic
                                        178
         Hispanic
                                        177
         Asian and Pacific Islander
                                        177
         White Non-Hispanic
                                        176
         Name: Race, dtype: int64
In [79]: le_Race = preprocessing.LabelEncoder()
         le_Race.fit(['Not Stated/Unknown', 'Other Race/ Ethnicity', 'Black Non-His
         panic', 'Hispanic',
                                'Asian and Pacific Islander', 'White Non-Hispanic'])
         X[:,1] = le Race.transform(X[:,1])
In [80]: X[0:5]
Out[80]: array([[1, 2],
                [1, 2],
                [1, 2],
                [1, 2],
                [1, 2]], dtype=object)
         Creation of dependent variables (the y's)
```

```
In [81]: y1 = df_ny["Deaths"]
         y1[0:5]
Out[81]: 0
              1281.0
         1
              1146.0
         2
              199.0
               191.0
         3
               186.0
         Name: Deaths, dtype: float64
In [82]: y2 = df_ny["Death_Rate"]
         y2[0:5]
Out[82]: 0
              107.3
         1
               96.0
         2
               16.7
         3
               16.0
```

Model Definition and Training

Analysis of variance (ANOVA)

```
In [84]: from scipy import stats
    df_anova = df_ny[['Sex', "AADR"]]
    grouped_anova = df_anova.groupby(['Sex'])
    f_val,p_val = stats.f_oneway(grouped_anova.get_group("Male")["AADR"], grou
    ped_anova.get_group("Female")["AADR"])
    print("ANOVA results:F=", f_val, "P=", p_val)
```

ANOVA results:F= 15.79910032940535 P= 7.506366410092774e-05

Model Definition and Training: Linear Regression

Given the nature of the data, supervised learning machine learning algorithms and/or linear regression models were used with race and sex as the dependent variables. In this section, the Scikit-Learn library was used for ordinary linear regression. The dependent variables were number of deaths, death rate and age-adjusted death rate (AADR). The latter three were not included together in a single regression model since they represent the same outcome presented in different numerical formats. The data set are first split into train and test sets. A linear regression model is then instantiated and using this object, the model is trained using the train sets. The intercept and beta-coefficient are derived. These steps are carried out for all the three models with number of deaths, death rate and AADR as dependent variables.

```
Out[86]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
                  normalize=False)
In [87]: lr1.coef
Out[87]: array([-69.85160475, 90.9792418])
In [88]: | 1r1.intercept
Out[88]: 240.6707119535052
In [89]: X_train, X_test, y2_train, y2_test = train_test_split(X, y2, test_size = 0)
         .3)
         from sklearn.linear_model import LinearRegression
         lr2 = LinearRegression()
         lr2.fit(X train, y2 train)
         lr2.coef
Out[89]: array([8.71536122, 7.07887758])
In [90]: |lr2.intercept_
Out[90]: 31.16505123956901
In [91]: X_train, X_test, y3_train, y3_test = train_test_split(X, y3, test_size = 0)
         .3)
         from sklearn.linear_model import LinearRegression
         lr3 = LinearRegression()
         lr3.fit(X_train, y3_train)
         lr3.coef
Out[91]: array([15.58854644, 2.32053421])
In [92]: |lr3.intercept_
Out[92]: 37.83718940881997
```

In order to include more linear regression estimates and/or parameters the Scipy library 'statsmodels.api' was imported. From it, the module 'stats' was imported to allow calculation of the estimates. This first required one-hot encoding or creation of dummy variables before writing the code to derive the estimates.

							isianuei	Ilispaili
0 2014	Diseases of Heart (I00-I09, I11, I13, I20-I51)	1281.0	107.3	170.5	0	1	0	

Malignant

	1 2014 (Neoplasms Cancer: C00- C97)	1146.0	96.0	143.5	0	1	0
		nfluenza (Flu) d Pneumonia (J09-J18)	199.0	16.7	26.6	0	1	0
	3 2014 Disc	Mental and Behavioral orders due to Acciden	191.0	16.0	16.6	0	1	0
	4 2014 N	Diabetes Mellitus (E10- E14)	186.0	15.6	23.2	0	1	0
In [94]:	X4 = df_ny "Race_Blac White Non- y4 = df_ny	k Non-His "Race_Not Hispanic"	panic", Stated]].value	"Race_His /Unknown	spanic",			Islander",
In [95]:	<pre>import sta from scipy X5 = sm.ad est = sm.C est2 = est print(est2</pre>	import state decimport state deconstant of the state of t	cats c(X4)		cession Re	sults		
				=======	=======		======	
	======================================	hlo:		7 7 7	DD D GOLL	arad:		======:
	Dep. Varia .000 Model:	======= ble:		IAA IO	_	ared: R-squared	:	====== ()
	Dep. Varia .000 Model: .000 Method:	======== ble:	Lea		LS Adj.		:	
	Dep. Varia .000 Model: .000 Method: nan Date: nan	======== ble:		OI st Square 1 Dec 201	LS Adj. : es F-sta	R-squared tistic: (F-statis	tic):	(
	Dep. Varia .000 Model: .000 Method: nan Date: nan Time: .096			OI st Square	Adj.: es F-sta Prob Log-L	R-squared	tic):	-28
	Dep. Varia .000 Model: .000 Method: nan Date: nan Time:	ations:		OI st Square 1 Dec 201	LS Adj. : es F-sta	R-squared tistic: (F-statis	tic):	(
	Dep. Varia .000 Model: .000 Method: nan Date: nan Time: .096 No. Observ 8.19	ations:		OI st Square 1 Dec 201	Adj. : Es F-sta Prob Log-L AIC:	R-squared tistic: (F-statis	tic):	-28 <u>.</u>
	Dep. Varia000 Model:000 Method: nan Date: nan Time:096 No. Observ 8.19 Df Residua.7.80	ations: ls:		OI st Square 1 Dec 201	Adj. : Es F-sta Prob Log-L AIC: BIC:	R-squared tistic: (F-statis	tic):	-28 <u>.</u>
	Dep. Varia000 Model: .000 Method: nan Date: nan Time: .096 No. Observ 8.19 Df Residua 7.80 Df Model: Covariance	ations: ls: Type:	Wed, 1	OI st Square 1 Dec 201 07:56:0	Adj.: Es F-sta Prob Log-L AIC: BIC: 0	R-squared tistic: (F-statistic) ikelihood	tic): :	-28 <u>•</u>

const	-7.631e-15	3.34e-15	-2.281	0.085	-1.69e-14	1.66
e-15						
x1	38.0400	16.674	2.281	0.085	-8.256	84
.336						
x2	0	0	nan	nan	0	
0						
x3	0	0	nan	nan	0	
0						
x4	38.0400	16.674	2.281	0.085	-8.256	84
.336						
x5	0	0	nan	nan	0	
0	_				_	
хб	0	0	nan	nan	0	
0	0	0			0	
x7	0	0	nan	nan	0	
0						
=====	========	========	=======	=======	========	======
Omnibus:			nan Durk	oin-Watson:		0
.654			nan Duri	JIII-WatsoII.		U
Prob(Omni	hug):		nan Jaro	que-Bera (JI	2):	0
.787	Dus / •		man dark	que bera (or	5,7•	O
Skew:		0	.451 Prol	o(JB):		0
.675		0.	. 131 110	3(02)		Ŭ
Kurtosis:		1.	.278 Cond	d. No.		
inf		Ξ.	3			
=======	========	========	=======	========	:=======	:======
====						

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The input rank is higher than the number of observations.
- [3] The smallest eigenvalue is 0. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/stats/stattools.py:72: ValueWarning: omni_normtest is not valid with less than 8 observations; 5 samples were given.

"samples were given." % int(n), ValueWarning)

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/regressio
n/linear_model.py:1633: RuntimeWarning: divide by zero encountered in doub
le_scalars

return np.sqrt(eigvals[0]/eigvals[-1])

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/regressio
n/linear_model.py:1554: RuntimeWarning: invalid value encountered in doubl
e_scalars

return self.ess/self.df_model

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/base/mode
l.py:1100: RuntimeWarning: invalid value encountered in true_divide
 return self.params / self.bse

/opt/conda/envs/Python36/lib/python3.6/site-packages/scipy/stats/_distn_in
frastructure.py:877: RuntimeWarning: invalid value encountered in greater
 return (self.a < x) & (x < self.b)</pre>

/opt/conda/envs/Python36/lib/python3.6/site-packages/scipy/stats/_distn_in

```
frastructure.py:877: RuntimeWarning: invalid value encountered in less
         return (self.a < x) & (x < self.b)
       /opt/conda/envs/Python36/lib/python3.6/site-packages/scipy/stats/_distn_in
       frastructure.py:1831: RuntimeWarning: invalid value encountered in less_eq
         cond2 = cond0 & (x <= self.a)
In [96]: X4 = df_ny2[["Sex_Female", "Sex_Male", "Race_Asian and Pacific Islander",
       "Race Black Non-Hispanic", "Race Hispanic",
                 "Race_Not Stated/Unknown", "Race_Other Race/ Ethnicity", "Race_
       White Non-Hispanic"]].values
       y5 = df_ny2[["Deaths"]]
In [97]: import statsmodels.api as sm
       from scipy import stats
       X5 = sm.add\_constant(X4)
       est = sm.OLS(y5, X5)
       est2 = est.fit()
       print(est2.summary())
                               OLS Regression Results
       ______
       Dep. Variable:
                                 Deaths R-squared:
                                                                    0
       .000
       Model:
                                    OLS
                                        Adj. R-squared:
                                                                    0
       .000
       Method:
                           Least Squares F-statistic:
        inf
                        Wed, 11 Dec 2019 Prob (F-statistic):
       Date:
        nan
       Time:
                               07:56:22 Log-Likelihood:
                                                                   -38
       .190
       No. Observations:
                                     5
                                       AIC:
                                                                    7
       8.38
                                         BIC:
                                                                    7
       Df Residuals:
                                      4
       7.99
       Df Model:
       Covariance Type:
                              nonrobust
       ______
       ====
                     coef std err
                                         t P>|t| [0.025
                                                                    0.
       9751
       _____
                -6.024e-14 2.52e-14 -2.392 0.075 -1.3e-13 9.69
       const
       e-15
                  300.3000 125.566
                                      2.392
                                               0.075
                                                        -48.328
                                                                 648
       x1
       .928
                        0
                                 0
                                        nan
                                                  nan
                                                              0
          0
       x3
                        0
                                 0
                                                              0
                                        nan
                                                  nan
          0
```

```
2.392
                                         0.075
                                                            648
x4
           300.3000
                     125.566
                                                  -48.328
.928
                 0
                          0
                                                       0
                                  nan
                                           nan
хб
                 0
                          0
                                                       0
                                  nan
                                           nan
x7
                 \cap
                                  nan
                                           nan
_______
Omnibus:
                                  Durbin-Watson:
                                                              0
                             nan
.726
Prob(Omnibus):
                                  Jarque-Bera (JB):
                             nan
.818
                                                              0
Skew:
                           0.430
                                  Prob(JB):
.664
Kurtosis:
                           1.215
                                  Cond. No.
 inf
```

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The input rank is higher than the number of observations.
- [3] The smallest eigenvalue is 0. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/stats/stattools.py:72: ValueWarning: omni_normtest is not valid with less than 8 observations; 5 samples were given.

"samples were given." % int(n), ValueWarning)

/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/regressio
n/linear_model.py:1554: RuntimeWarning: divide by zero encountered in doub
le scalars

return self.ess/self.df model

In [99]: import statsmodels.api as sm from scipy import stats X5 = sm.add_constant(X4) est = sm.OLS(y6, X5) est2 = est.fit() print(est2.summary())

OLS Regression Results

Model: OLS Adj. R-squared: 0

.000							
Method:	: Least Square		res	F-statistic:			
nan							
		ed, 11 Dec 2	2019	Prob	(F-statisti	.c):	
nan		07:56:27		Log-Likelihood: -25			٥٦
Time: .791		07:56	1:2/	rog-r	ikelinood:		-25
No. Observations:			5	AIC:			5
3.58			5	AIC.			3
Df Residuals:			4	BIC:			5
3.19							
Df Model:			0				
Covariance Type:		nonrok	ust				
========	========	========	:====:	======	========	========	======
	coef	std err		+	D> +	[0 025	0.
975]	2021	BCG CII		C	1, 101	[0.025	0.
const	-5.047e-15	2.11e-15	- 2	2.393	0.075	-1.09e-14	8.1
e-16	05 1600	10 516			0 000	4 005	- 4
x1 .357	25.1600	10.516	2	2.393	0.075	-4.037	54
.35/ x2	0	0		nan	nan	0	
0	O	O		IIaII	IIaII	O	
x3	0	0		nan	nan	0	
0							
x4	25.1600	10.516	2	2.393	0.075	-4.037	54
.357							
x5	0	0		nan	nan	0	
0	0	2				0	
хб 0	0	0		nan	nan	0	
x7	0	0		nan	nan	0	
0	Ŭ	· ·		11011	IIdII	O	
=======		========	====	======	=======	========	=====
====							
Omnibus:			nan	Durbin-Watson: 0			
.725	,						
	·		nan	Jarque-Bera (JB): 0			
.818		42A	Drob/	TD \ •		0	
Skew: 0.430 .664				Prob(٠ (ط ٥		U
Kurtosis:		1	215	Cond.	No.		
inf							
=======		========	====	======	=======	========	=====
====							

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The input rank is higher than the number of observations.
- [3] The smallest eigenvalue is 0. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

```
/opt/conda/envs/Python36/lib/python3.6/site-packages/statsmodels/stats/sta
ttools.py:72: ValueWarning: omni_normtest is not valid with less than 8 ob
servations; 5 samples were given.
   "samples were given." % int(n), ValueWarning)
```

Analysis of variance (ANOVA) with race as predictor and AADR as dependent variable (outcome)

```
In [100]: groups = df_ny.groupby("Race").groups
   Race_Asian = df_ny["AADR"][groups["Asian and Pacific Islander"]]
   Race_Black = df_ny["AADR"][groups["Black Non-Hispanic"]]
   Race_Hispanic = df_ny["AADR"][groups["Hispanic"]]
   Race_Unknown = df_ny["AADR"][groups["Not Stated/Unknown"]]
   Race_Other = df_ny["AADR"][groups["Other Race/ Ethnicity"]]
   Race_WNonH = df_ny["AADR"][groups["White Non-Hispanic"]]
   stats.f_oneway(Race_Asian, Race_Black, Race_Hispanic, Race_Unknown, Race_Other, Race_WNonH)
Out[100]: F_onewayResult(statistic=8.053927751980025, pvalue=1.8008655089838347e-07)
```

Model Evaluation

Model evaluation was carried out for the three models using R-squared score, mean absolute error and mean squared error.

```
In [101]: from sklearn import metrics
          from sklearn.metrics import r2_score
          from sklearn.metrics import mean_absolute_error
          from sklearn.metrics import mean_squared_error
          predict1 = lr1.predict(X_test)
          predict1[0:5]
Out[101]: array([625.71531619, 331.64995375, 170.8191072, 534.73607439,
                 331.64995375])
In [102]: | r2_score(y1_test, predict1)
Out[102]: -0.027907825501596983
In [103]: mean_absolute_error(y1_test, predict1)
Out[103]: 496.89717202034194
In [104]: | mean_squared_error(y1_test, predict1)
Out[104]: 912405.9000953499
In [105]: predict2 = lr2.predict(X_test)
          predict2[0:5]
Out[105]: array([75.27480038, 38.24392882, 39.88041246, 68.19592279, 38.24392882])
```

```
In [106]: r2_score(y2_test, predict2)
Out[106]: -0.045601730810380214

In [107]: mean_absolute_error(y2_test, predict2)
Out[107]: 39.23727315032904

In [108]: mean_squared_error(y2_test, predict2)
Out[108]: 4296.122475885754

In [109]: predict3 = lr3.predict(X_test)
    predict3[0:5]
Out[109]: array([65.02840692, 40.15772362, 53.42573585, 62.7078727 , 40.15772362])

In [110]: r2_score(y3_test, predict3)
Out[110]: -0.008479573873794166

In [111]: mean_absolute_error(y3_test, predict3)
Out[111]: 37.78903980756004

In [112]: mean_squared_error(y3_test, predict3)
Out[112]: 3287.687455471314
```

The R-squared scores show that sex and race explain no variation in the dependent variables 'number of deaths' and 'death rate' and very low variation in the dependent variable 'AADR'. To improve the model, more variables would have to be added. This would entail more data collection, which at the moment is not possible since the data were sourced from a fixed database. However, the results are highly informative in so many ways despite the results of the regression analysis. They explain the differential distribution of leading causes of disease by race and sex and the differences by year. The coefficients are also a guide to further data collection.

Model Definition and Training Using TensorFlow

Machine learning alorithms/models were used with race and sex as the dependent variables. In this section, gradient descent with TensorFlow was used. Like with the ordinary linear regression above, the dependent/output variables were either number of deaths, death rate or age-adjusted death rate (AADR); these were not included together in a single regression model because they represent the same outcome presented in different numerical formats. The necessary libraries for computation of estimates were imported. Fixed seeds for both Numpy

and TensorFlow were set to make the random numbers predictable. Models creation was started by defining placeholders for x and y in order to feed the training examples x and y (y1, y2 and y3) into the optimizer during the process of training. Next, two trainable TensorFlow variables were declared for the weights (w) and bias (b) and initialized using np.random.randn(). Hyperparameters learning rate (0.001) and number of epochs (1000) were then defined. The predictions/hypotheses, cost function and optimizer were then built and the variables were then initialized. The training process was then started insider a TensorFlow and predictions were computed. These steps are carried out for all the three models with number of deaths, death rate and AADR as dependent variables.

```
In [113]: import numpy as np
          import tensorflow as tf
          import matplotlib.pyplot as plt
          np.random.seed(101)
          tf.set_random_seed(101)
In [114]: x = X
          x_new = np.reshape(x, (2,1094)) # Reshaping x for Tensorflow computations
          (x_new is the reshaped x)
          y = y3
          n = len(x)
In [115]: x_new.shape
Out[115]: (2, 1094)
In [116]: X1 = tf.placeholder("float")
          Y1 = tf.placeholder("float")
          W = tf.Variable(np.random.randn(), name="W")
          b = tf.Variable(np.random.randn(), name="b")
          WARNING: tensorflow: From /opt/conda/envs/Python36/lib/python3.6/site-packag
          es/tensorflow/python/framework/op_def_library.py:263: colocate_with (from
          tensorflow.python.framework.ops) is deprecated and will be removed in a fu
          ture version.
          Instructions for updating:
          Colocations handled automatically by placer.
In [117]: learning_rate = 0.001
          training_epochs = 1000
In [118]: y_pred = tf.add(tf.multiply(X1,W),b)
In [119]: |cost = tf.reduce_sum(tf.pow(y_pred - Y1, 2))/(2*n)
In [120]: optimizer = tf.train.GradientDescentOptimizer(learning_rate).minimize(cost
          WARNING:tensorflow:From /opt/conda/envs/Python36/lib/python3.6/site-packag
          es/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.pytho
```

n.ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.

```
In [121]: init = tf.global variables initializer()
In [122]: # Starting the Tensorflow Session
          with tf.Session() as sess:
              # Initializing the Variables
              sess.run(init)
              # Iterating through all the epochs
              for epoch in range(training_epochs):
                   # Feeding each data point into the optimizer using Feed Dictionary
                  for (_x_new, _y) in zip(x_new, y):
                       sess.run(optimizer, feed_dict = {X1 : _x_new, Y1 : _y})
                   # Displaying the result after every 50 epochs
                  if (epoch + 1) % 50 == 0:
                       # Calculating the cost a every epoch
                       c = sess.run(cost, feed_dict = {X1 : x_new, Y1 : y})
                       print("Epoch", (epoch + 1), ": cost =", c, "W =", sess.run(W),
           "b =", sess.run(b))
              # Storing necessary values to be used outside the Session
              training_cost = sess.run(cost, feed_dict = {X1: x_new, Y1: y})
              weight = sess.run(W)
              bias = sess.run(b)
          Epoch 50 : cost = 4158.2227 W = 19.483673 b = 13.794002
          Epoch 100 : cost = 5328.8564 W = 28.44038 b = 23.91537
          Epoch 150 : cost = 6644.1567 W = 32.87008 b = 32.144875
          Epoch 200 : cost = 7606.429 \text{ W} = 34.69387 \text{ b} = 39.160885
          Epoch 250: cost = 8221.636 W = 35.031773 b = 45.36466
          Epoch 300 : cost = 8593.332 \text{ W} = 34.53612 \text{ b} = 50.99536
          Epoch 350 : cost = 8815.213 W = 33.58625 b = 56.19722
          Epoch 400 : cost = 8952.373 W = 32.40207 b = 61.058945
          Epoch 450: cost = 9045.73 W = 31.110634 b = 65.636475
          Epoch 500 : cost = 9119.416 W = 29.784683 b = 69.96659
          Epoch 550: cost = 9187.019 W = 28.465393 b = 74.07447
          Epoch 600 : cost = 9255.769 W = 27.175564 b = 77.9785
          Epoch 650: cost = 9329.231 W = 25.927294 b = 81.69293
          Epoch 700 : cost = 9408.74 \text{ W} = 24.72651 \text{ b} = 85.22937
          Epoch 750 : cost = 9494.54 \text{ W} = 23.575575 \text{ b} = 88.59774
          Epoch 800 : cost = 9586.174 W = 22.474842 b = 91.8069
          Epoch 850: cost = 9682.982 W = 21.423529 b = 94.86477
          Epoch 900 : cost = 9784.096 W = 20.42023 b = 97.77881
          Epoch 950 : cost = 9888.653 W = 19.46322 b = 100.55594
          Epoch 1000 : cost = 9995.885 W = 18.550661 b = 103.2027
In [123]: predictions = weight*x + bias
          print("Training cost is", training_cost, "Weight=", weight, "bias=", bias,
```

Training cost is 9995.885 Weight= 18.550661 bias= 103.2027

```
In [124]: # Starting the Tensorflow Session
          with tf.Session() as sess:
              # Initializing the Variables
              sess.run(init)
              # Iterating through all the epochs
              for epoch in range(training_epochs):
                  # Feeding each data point into the optimizer using Feed Dictionary
                  for (_x_new, _y1) in zip(x_new, y1):
                      sess.run(optimizer, feed_dict = {X1 : _x_new, Y1 : _y1})
                  # Displaying the result after every 50 epochs
                  if (epoch + 1) % 50 == 0:
                      # Calculating the cost a every epoch
                      c = sess.run(cost, feed dict = {X1 : x new, Y1 : y1})
                      print("Epoch", (epoch + 1), ": cost =", c, "W =", sess.run(W),
           "b =", sess.run(b))
              # Storing necessary values to be used outside the Session
              training_cost = sess.run(cost, feed_dict ={X1: x_new, Y1: y1})
              weight = sess.run(W)
              bias = sess.run(b)
          Epoch 50 : cost = 747745.8 W = 139.73703 b = 104.83377
          Epoch 100 : cost = 804070.8 W = 213.27309 b = 184.4595
          Epoch 150 : cost = 878154.5 W = 250.03694 b = 248.85182
          Epoch 200 : cost = 933742.06 W = 265.6181 b = 303.5097
          Epoch 250 : cost = 969199.9 W = 269.10623 b = 351.6835
          Epoch 300 : cost = 990172.25 W = 265.79593 b = 395.3087
          Epoch 350: cost = 1002148.3 W = 258.76663 b = 435.5513
          Epoch 400: cost = 1009027.9 W = 249.80476 b = 473.1261
          Epoch 450 : cost = 1013281.25 W = 239.94202 b = 508.48303
          Epoch 500 : cost = 1016374.3 W = 229.7705 b = 541.9158
          Epoch 550 : cost = 1019137.9 W = 219.62547 b = 573.6251
          Epoch 600 : cost = 1022011.0 W = 209.69316 b = 603.75714
          Epoch 650: cost = 1025209.94 W = 200.07306 b = 632.423
          Epoch 700 : cost = 1028817.8 W = 190.81436 b = 659.71356
          Epoch 750 : cost = 1032849.25 W = 181.93752 b = 685.7063
          Epoch 800 : cost = 1037276.4 W = 173.44637 b = 710.46936
          Epoch 850: cost = 1042057.75 W = 165.33545 b = 734.0655
          Epoch 900 : cost = 1047142.3 W = 157.59457 b = 756.5514
          Epoch 950 : cost = 1052475.2 \text{ W} = 150.21053 \text{ b} = 777.9806
          Epoch 1000 : cost = 1058007.8 W = 143.16925 b = 798.4038
In [125]: predictions = weight*x + bias
          print("Training cost is", training_cost, "Weight=", weight, "bias=", bias,
```

Training cost is 1058007.8 Weight= 143.16925 bias= 798.4038

```
In [126]: # Starting the Tensorflow Session
          with tf.Session() as sess:
              # Initializing the Variables
              sess.run(init)
              # Iterating through all the epochs
              for epoch in range(training_epochs):
                  # Feeding each data point into the optimizer using Feed Dictionary
                  for (_x_new, _y2) in zip(x_new, y2):
                      sess.run(optimizer, feed_dict = {X1 : _x_new, Y1 : _y2})
                  # Displaying the result after every 50 epochs
                  if (epoch + 1) % 50 == 0:
                      # Calculating the cost a every epoch
                      c = sess.run(cost, feed\_dict = {X1 : x_new, Y1 : y2})
                      print("Epoch", (epoch + 1), ": cost =", c, "W =", sess.run(W),
           "b =", sess.run(b))
              # Storing necessary values to be used outside the Session
              training_cost = sess.run(cost, feed_dict ={X1: x_new, Y1: y2})
              weight = sess.run(W)
              bias = sess.run(b)
          Epoch 50 : cost = 4741.0156 W = 13.185323 b = 9.025084
          Epoch 100 : cost = 4650.8057 W = 18.759716 b = 15.505519
          Epoch 150 : cost = 4821.548 W = 21.49601 b = 20.792898
          Epoch 200 : cost = 4973.959 \text{ W} = 22.599386 \text{ b} = 25.313112
          Epoch 250 : cost = 5061.64 \text{ W} = 22.772444 \text{ b} = 29.318174
          Epoch 300 : cost = 5096.7666 W = 22.42435 b = 32.958397
          Epoch 350 : cost = 5099.4224 W = 21.79301 b = 36.324543
          Epoch 400: cost = 5085.3896 W = 21.016352 b = 39.47249
          Epoch 450: cost = 5064.901 W = 20.17397 b = 42.43755
          Epoch 500: cost = 5043.9946 W = 19.311445 b = 45.242992
          Epoch 550: cost = 5025.916 W = 18.45454 b = 47.90483
          Epoch 600 : cost = 5012.22 W = 17.617483 b = 50.434853
          Epoch 650 : cost = 5003.502 W = 16.807806 b = 52.84213
          Epoch 700 : cost = 4999.7715 W = 16.029161 b = 55.134117
          Epoch 750 : cost = 5000.7593 W = 15.282984 b = 57.317223
          Epoch 800 : cost = 5006.0586 W = 14.56943 b = 59.39716
          Epoch 850 : cost = 5015.1987 W = 13.887956 b = 61.37909
          Epoch 900 : cost = 5027.695 W = 13.237631 b = 63.267796
          Epoch 950 : cost = 5043.087 W = 12.617332 b = 65.067764
          Epoch 1000 : cost = 5060.9463 W = 12.025838 b = 66.78324
In [127]: predictions = weight*x + bias
          print("Training cost is", training_cost, "Weight=", weight, "bias=", bias,
           '\n')
```

Training cost is 5060.9463 Weight= 12.025838 bias= 66.78324

Model Definition and Training using Keras

```
In [134]: from keras.models import Sequential
      from keras.layers import Dense, Activation
      from keras.optimizers import SGD
      # create model
      model = Sequential()
      model.add(Dense(1, input_shape=(2,)))
      model.add(Activation('linear'))
In [135]: model.summary()
      Layer (type)
                       Output Shape
                                      Param #
      ______
      dense_3 (Dense)
                       (None, 1)
      activation 3 (Activation) (None, 1)
      ______
      Total params: 3
      Trainable params: 3
     Non-trainable params: 0
In [136]: sqd = SGD(0.0001)
      model.compile(loss='mse', optimizer=sgd, metrics=['mse'])
      H = model.fit(X, y3, epochs = 1000)
      plt.plot(H.history['mean_squared_error'])
      plt.title("Graph of Loss vs Number of Epochs")
      plt.xlabel("Number of Epochs")
      plt.ylabel("Loss")
      Epoch 1/1000
      99 - mean_squared_error: 5827.8099
      Epoch 2/1000
      3 - mean_squared_error: 5534.7903
      Epoch 3/1000
      5 - mean_squared_error: 5274.0145
      Epoch 4/1000
      5 - mean_squared_error: 5037.2325
      Epoch 5/1000
      1 - mean_squared_error: 4843.1951
     Epoch 6/1000
      6 - mean_squared_error: 4672.6866
      Epoch 7/1000
      1 - mean_squared_error: 4526.3321
      Epoch 8/1000
```

```
6 - mean_squared_error: 4398.5486
Epoch 9/1000
7 - mean_squared_error: 4288.4557
Epoch 10/1000
4 - mean_squared_error: 4190.0494
Epoch 11/1000
6 - mean_squared_error: 4105.2246
Epoch 12/1000
8 - mean_squared_error: 4030.4178
Epoch 13/1000
8 - mean_squared_error: 3965.3258
Epoch 14/1000
0 - mean_squared_error: 3907.6510
Epoch 15/1000
9 - mean_squared_error: 3855.4159
Epoch 16/1000
4 - mean_squared_error: 3812.6464
Epoch 17/1000
3 - mean_squared_error: 3775.9903
Epoch 18/1000
9 - mean_squared_error: 3742.5739
Epoch 19/1000
2 - mean_squared_error: 3713.2582
Epoch 20/1000
0 - mean_squared_error: 3687.1860
Epoch 21/1000
9 - mean_squared_error: 3665.1509
Epoch 22/1000
9 - mean_squared_error: 3643.0259
Epoch 23/1000
8 - mean_squared_error: 3624.4888
Epoch 24/1000
8 - mean squared error: 3608.9878
Epoch 25/1000
0 - mean_squared_error: 3594.8650
Epoch 26/1000
5 - mean_squared_error: 3582.1925
Epoch 27/1000
```

```
2 - mean_squared_error: 3571.1432
Epoch 28/1000
6 - mean_squared_error: 3561.1736
Epoch 29/1000
5 - mean_squared_error: 3551.4145
Epoch 30/1000
6 - mean_squared_error: 3541.1746
Epoch 31/1000
8 - mean_squared_error: 3534.4898
Epoch 32/1000
2 - mean_squared_error: 3528.1322
Epoch 33/1000
3 - mean_squared_error: 3521.8413
Epoch 34/1000
9 - mean_squared_error: 3516.2549
Epoch 35/1000
6 - mean_squared_error: 3510.8746
Epoch 36/1000
1 - mean_squared_error: 3505.2601
Epoch 37/1000
3 - mean squared error: 3500.8453
Epoch 38/1000
7 - mean_squared_error: 3496.6577
Epoch 39/1000
1 - mean_squared_error: 3492.7341
Epoch 40/1000
6 - mean_squared_error: 3488.3836
Epoch 41/1000
3 - mean squared error: 3484.6293
Epoch 42/1000
8 - mean_squared_error: 3481.0788
Epoch 43/1000
0 - mean_squared_error: 3477.9770
Epoch 44/1000
3 - mean_squared_error: 3474.2683
Epoch 45/1000
8 - mean_squared_error: 3471.1518
Epoch 46/1000
```

```
6 - mean_squared_error: 3468.0396
Epoch 47/1000
1 - mean_squared_error: 3465.0871
Epoch 48/1000
1 - mean_squared_error: 3462.2071
Epoch 49/1000
2 - mean_squared_error: 3459.7142
Epoch 50/1000
5 - mean_squared_error: 3456.8305
Epoch 51/1000
8 - mean_squared_error: 3454.3948
Epoch 52/1000
4 - mean_squared_error: 3452.0254
Epoch 53/1000
5 - mean_squared_error: 3449.4255
Epoch 54/1000
9 - mean_squared_error: 3447.1599
Epoch 55/1000
5 - mean_squared_error: 3444.6525
Epoch 56/1000
2 - mean squared error: 3442.2042
Epoch 57/1000
2 - mean_squared_error: 3439.9452
Epoch 58/1000
4 - mean_squared_error: 3437.6224
Epoch 59/1000
9 - mean_squared_error: 3435.2149
Epoch 60/1000
1 - mean_squared_error: 3433.0731
Epoch 61/1000
5 - mean_squared_error: 3430.5165
Epoch 62/1000
4 - mean_squared_error: 3428.3144
Epoch 63/1000
7 - mean_squared_error: 3426.0027
Epoch 64/1000
7 - mean_squared_error: 3423.7407
Epoch 65/1000
```

```
1 - mean_squared_error: 3421.5371
Epoch 66/1000
2 - mean_squared_error: 3419.2282
Epoch 67/1000
6 - mean_squared_error: 3417.1326
Epoch 68/1000
4 - mean_squared_error: 3414.9134
Epoch 69/1000
6 - mean_squared_error: 3412.7916
Epoch 70/1000
1 - mean_squared_error: 3410.5401
Epoch 71/1000
0 - mean_squared_error: 3408.4810
Epoch 72/1000
5 - mean_squared_error: 3406.4665
Epoch 73/1000
2 - mean_squared_error: 3404.4322
Epoch 74/1000
4 - mean_squared_error: 3402.3024
Epoch 75/1000
4 - mean squared error: 3400.2734
Epoch 76/1000
4 - mean_squared_error: 3398.3184
Epoch 77/1000
3 - mean_squared_error: 3396.3143
Epoch 78/1000
3 - mean_squared_error: 3394.3253
Epoch 79/1000
0 - mean_squared_error: 3392.2340
Epoch 80/1000
8 - mean_squared_error: 3390.3368
Epoch 81/1000
1 - mean_squared_error: 3388.3781
Epoch 82/1000
3 - mean_squared_error: 3386.4083
Epoch 83/1000
8 - mean_squared_error: 3384.5728
Epoch 84/1000
```

```
9 - mean_squared_error: 3382.6879
Epoch 85/1000
8 - mean_squared_error: 3380.5718
Epoch 86/1000
5 - mean_squared_error: 3378.6995
Epoch 87/1000
3 - mean_squared_error: 3376.8213
Epoch 88/1000
8 - mean_squared_error: 3374.9968
Epoch 89/1000
9 - mean_squared_error: 3373.0839
Epoch 90/1000
7 - mean_squared_error: 3371.2897
Epoch 91/1000
8 - mean_squared_error: 3369.4328
Epoch 92/1000
3 - mean_squared_error: 3367.5053
Epoch 93/1000
3 - mean_squared_error: 3365.6653
Epoch 94/1000
3 - mean squared error: 3363.7233
Epoch 95/1000
0 - mean_squared_error: 3361.9840
Epoch 96/1000
5 - mean_squared_error: 3360.0975
Epoch 97/1000
9 - mean_squared_error: 3358.3799
Epoch 98/1000
6 - mean_squared_error: 3356.6446
Epoch 99/1000
3 - mean_squared_error: 3354.8493
Epoch 100/1000
0 - mean_squared_error: 3353.1080
Epoch 101/1000
6 - mean_squared_error: 3351.2746
Epoch 102/1000
9 - mean_squared_error: 3349.4509
Epoch 103/1000
```

```
3 - mean_squared_error: 3347.6863
Epoch 104/1000
3 - mean_squared_error: 3345.9623
Epoch 105/1000
2 - mean_squared_error: 3344.3302
Epoch 106/1000
6 - mean_squared_error: 3342.6946
Epoch 107/1000
2 - mean_squared_error: 3341.0572
Epoch 108/1000
0 - mean_squared_error: 3339.1640
Epoch 109/1000
3 - mean_squared_error: 3337.4963
Epoch 110/1000
2 - mean_squared_error: 3335.8462
Epoch 111/1000
7 - mean_squared_error: 3334.2027
Epoch 112/1000
3 - mean_squared_error: 3332.5253
Epoch 113/1000
0 - mean squared error: 3330.9080
Epoch 114/1000
5 - mean_squared_error: 3329.3815
Epoch 115/1000
0 - mean_squared_error: 3327.7590
Epoch 116/1000
3 - mean_squared_error: 3326.2383
Epoch 117/1000
1 - mean_squared_error: 3324.2581
Epoch 118/1000
2 - mean_squared_error: 3322.7172
Epoch 119/1000
5 - mean_squared_error: 3321.1665
Epoch 120/1000
2 - mean_squared_error: 3319.6002
Epoch 121/1000
6 - mean_squared_error: 3318.0306
Epoch 122/1000
```

```
1 - mean_squared_error: 3316.4781
Epoch 123/1000
6 - mean_squared_error: 3314.8556
Epoch 124/1000
3 - mean_squared_error: 3313.2533
Epoch 125/1000
0 - mean_squared_error: 3311.5720
Epoch 126/1000
0 - mean_squared_error: 3310.1270
Epoch 127/1000
3 - mean_squared_error: 3308.6103
Epoch 128/1000
8 - mean_squared_error: 3307.0068
Epoch 129/1000
7 - mean_squared_error: 3305.4347
Epoch 130/1000
8 - mean_squared_error: 3303.9838
Epoch 131/1000
2 - mean_squared_error: 3302.5372
Epoch 132/1000
8 - mean_squared_error: 3301.1008
Epoch 133/1000
0 - mean_squared_error: 3299.6680
Epoch 134/1000
3 - mean_squared_error: 3298.0383
Epoch 135/1000
1 - mean_squared_error: 3296.6771
Epoch 136/1000
1 - mean_squared_error: 3295.2261
Epoch 137/1000
3 - mean_squared_error: 3293.8893
Epoch 138/1000
5 - mean_squared_error: 3292.4435
Epoch 139/1000
7 - mean_squared_error: 3290.9877
Epoch 140/1000
6 - mean_squared_error: 3289.6336
Epoch 141/1000
```

```
7 - mean_squared_error: 3288.2867
Epoch 142/1000
1 - mean_squared_error: 3286.9301
Epoch 143/1000
1 - mean_squared_error: 3285.5471
Epoch 144/1000
3 - mean_squared_error: 3284.0303
Epoch 145/1000
5 - mean_squared_error: 3282.7305
Epoch 146/1000
4 - mean_squared_error: 3281.4034
Epoch 147/1000
4 - mean_squared_error: 3280.1304
Epoch 148/1000
2 - mean_squared_error: 3278.8052
Epoch 149/1000
2 - mean_squared_error: 3277.5042
Epoch 150/1000
0 - mean_squared_error: 3276.2160
Epoch 151/1000
6 - mean_squared_error: 3274.9236
Epoch 152/1000
8 - mean_squared_error: 3273.6918
Epoch 153/1000
7 - mean_squared_error: 3272.2787
Epoch 154/1000
8 - mean_squared_error: 3270.9598
Epoch 155/1000
6 - mean_squared_error: 3269.7036
Epoch 156/1000
7 - mean_squared_error: 3268.2717
Epoch 157/1000
1 - mean_squared_error: 3266.9801
Epoch 158/1000
6 - mean_squared_error: 3265.7476
Epoch 159/1000
2 - mean_squared_error: 3264.5492
Epoch 160/1000
```

```
9 - mean_squared_error: 3263.0699
Epoch 161/1000
5 - mean_squared_error: 3261.6425
Epoch 162/1000
3 - mean_squared_error: 3260.3433
Epoch 163/1000
3 - mean_squared_error: 3259.0793
Epoch 164/1000
9 - mean_squared_error: 3258.0339
Epoch 165/1000
7 - mean_squared_error: 3256.7717
Epoch 166/1000
4 - mean_squared_error: 3255.6944
Epoch 167/1000
3 - mean_squared_error: 3254.4313
Epoch 168/1000
6 - mean_squared_error: 3253.2676
Epoch 169/1000
7 - mean_squared_error: 3252.0337
Epoch 170/1000
2 - mean_squared_error: 3250.9812
Epoch 171/1000
6 - mean_squared_error: 3249.7736
Epoch 172/1000
9 - mean_squared_error: 3248.7019
Epoch 173/1000
8 - mean_squared_error: 3247.4628
Epoch 174/1000
9 - mean_squared_error: 3246.2299
Epoch 175/1000
0 - mean_squared_error: 3245.1690
Epoch 176/1000
3 - mean_squared_error: 3243.9543
Epoch 177/1000
1 - mean_squared_error: 3242.9541
Epoch 178/1000
4 - mean_squared_error: 3241.8034
Epoch 179/1000
```

```
1 - mean_squared_error: 3240.6631
Epoch 180/1000
8 - mean_squared_error: 3239.5938
Epoch 181/1000
7 - mean_squared_error: 3238.4907
Epoch 182/1000
2 - mean_squared_error: 3237.4752
Epoch 183/1000
1 - mean_squared_error: 3236.3481
Epoch 184/1000
3 - mean_squared_error: 3235.2083
Epoch 185/1000
3 - mean_squared_error: 3234.0833
Epoch 186/1000
1 - mean_squared_error: 3233.1781
Epoch 187/1000
0 - mean_squared_error: 3232.0670
Epoch 188/1000
4 - mean_squared_error: 3230.9814
Epoch 189/1000
4 - mean_squared_error: 3229.8984
Epoch 190/1000
1 - mean_squared_error: 3228.7761
Epoch 191/1000
6 - mean_squared_error: 3227.8076
Epoch 192/1000
9 - mean_squared_error: 3226.7399
Epoch 193/1000
6 - mean_squared_error: 3225.8016
Epoch 194/1000
7 - mean_squared_error: 3224.7257
Epoch 195/1000
5 - mean_squared_error: 3223.7515
Epoch 196/1000
6 - mean_squared_error: 3222.6626
Epoch 197/1000
2 - mean_squared_error: 3221.8032
Epoch 198/1000
```

```
7 - mean_squared_error: 3220.6397
Epoch 199/1000
2 - mean_squared_error: 3219.6882
Epoch 200/1000
1 - mean_squared_error: 3218.6781
Epoch 201/1000
7 - mean_squared_error: 3217.6157
Epoch 202/1000
4 - mean_squared_error: 3216.7324
Epoch 203/1000
7 - mean_squared_error: 3215.7897
Epoch 204/1000
8 - mean_squared_error: 3214.8648
Epoch 205/1000
1 - mean_squared_error: 3213.8951
Epoch 206/1000
4 - mean_squared_error: 3213.0474
Epoch 207/1000
3 - mean_squared_error: 3211.9593
Epoch 208/1000
2 - mean_squared_error: 3211.0532
Epoch 209/1000
7 - mean_squared_error: 3210.1057
Epoch 210/1000
4 - mean_squared_error: 3209.0074
Epoch 211/1000
0 - mean_squared_error: 3208.1590
Epoch 212/1000
2 - mean_squared_error: 3207.2362
Epoch 213/1000
4 - mean_squared_error: 3206.2944
Epoch 214/1000
8 - mean_squared_error: 3205.4228
Epoch 215/1000
6 - mean_squared_error: 3204.5796
Epoch 216/1000
6 - mean_squared_error: 3203.3836
Epoch 217/1000
```

```
4 - mean_squared_error: 3202.4894
Epoch 218/1000
7 - mean_squared_error: 3201.6207
Epoch 219/1000
3 - mean_squared_error: 3200.7613
Epoch 220/1000
3 - mean_squared_error: 3199.8383
Epoch 221/1000
3 - mean_squared_error: 3199.0013
Epoch 222/1000
0 - mean_squared_error: 3198.0670
Epoch 223/1000
7 - mean_squared_error: 3197.2747
Epoch 224/1000
6 - mean_squared_error: 3196.2286
Epoch 225/1000
0 - mean_squared_error: 3195.5080
Epoch 226/1000
1 - mean_squared_error: 3194.5621
Epoch 227/1000
9 - mean squared error: 3193.6179
Epoch 228/1000
4 - mean_squared_error: 3192.6814
Epoch 229/1000
2 - mean_squared_error: 3191.8922
Epoch 230/1000
4 - mean_squared_error: 3191.1154
Epoch 231/1000
0 - mean_squared_error: 3190.2710
Epoch 232/1000
8 - mean_squared_error: 3189.5338
Epoch 233/1000
7 - mean_squared_error: 3188.5497
Epoch 234/1000
5 - mean_squared_error: 3187.7765
Epoch 235/1000
3 - mean_squared_error: 3186.9163
Epoch 236/1000
```

```
3 - mean_squared_error: 3186.1423
Epoch 237/1000
1 - mean_squared_error: 3185.4041
Epoch 238/1000
4 - mean_squared_error: 3184.4884
Epoch 239/1000
4 - mean_squared_error: 3183.7414
Epoch 240/1000
9 - mean_squared_error: 3183.0029
Epoch 241/1000
6 - mean_squared_error: 3182.2586
Epoch 242/1000
9 - mean_squared_error: 3181.5079
Epoch 243/1000
5 - mean_squared_error: 3180.7635
Epoch 244/1000
1 - mean_squared_error: 3179.8091
Epoch 245/1000
7 - mean_squared_error: 3179.0587
Epoch 246/1000
3 - mean_squared_error: 3178.4093
Epoch 247/1000
7 - mean_squared_error: 3177.6187
Epoch 248/1000
9 - mean_squared_error: 3176.8899
Epoch 249/1000
9 - mean_squared_error: 3176.0869
Epoch 250/1000
8 - mean_squared_error: 3175.4008
Epoch 251/1000
1 - mean_squared_error: 3174.7141
Epoch 252/1000
1 - mean_squared_error: 3174.0271
Epoch 253/1000
5 - mean_squared_error: 3173.2055
Epoch 254/1000
2 - mean_squared_error: 3172.4752
Epoch 255/1000
```

```
2 - mean_squared_error: 3171.6822
Epoch 256/1000
8 - mean_squared_error: 3171.0268
Epoch 257/1000
0 - mean_squared_error: 3170.3380
Epoch 258/1000
7 - mean_squared_error: 3169.7077
Epoch 259/1000
8 - mean_squared_error: 3168.9998
Epoch 260/1000
8 - mean_squared_error: 3168.2508
Epoch 261/1000
6 - mean_squared_error: 3167.6076
Epoch 262/1000
2 - mean_squared_error: 3166.8572
Epoch 263/1000
0 - mean_squared_error: 3166.2330
Epoch 264/1000
3 - mean_squared_error: 3165.5123
Epoch 265/1000
1 - mean_squared_error: 3164.6291
Epoch 266/1000
7 - mean_squared_error: 3164.1057
Epoch 267/1000
8 - mean_squared_error: 3163.3348
Epoch 268/1000
3 - mean_squared_error: 3162.6703
Epoch 269/1000
1 - mean_squared_error: 3162.0521
Epoch 270/1000
2 - mean_squared_error: 3161.4502
Epoch 271/1000
6 - mean_squared_error: 3160.7616
Epoch 272/1000
1 - mean_squared_error: 3160.0501
Epoch 273/1000
6 - mean_squared_error: 3159.3946
Epoch 274/1000
```

```
0 - mean_squared_error: 3158.7230
Epoch 275/1000
5 - mean_squared_error: 3158.0025
Epoch 276/1000
0 - mean_squared_error: 3157.3530
Epoch 277/1000
8 - mean_squared_error: 3156.6308
Epoch 278/1000
5 - mean_squared_error: 3156.0835
Epoch 279/1000
6 - mean_squared_error: 3155.3836
Epoch 280/1000
9 - mean_squared_error: 3154.7489
Epoch 281/1000
8 - mean_squared_error: 3154.1908
Epoch 282/1000
6 - mean_squared_error: 3153.5926
Epoch 283/1000
4 - mean_squared_error: 3153.0494
Epoch 284/1000
8 - mean_squared_error: 3152.2618
Epoch 285/1000
1 - mean_squared_error: 3151.6541
Epoch 286/1000
6 - mean_squared_error: 3151.0206
Epoch 287/1000
2 - mean_squared_error: 3150.4172
Epoch 288/1000
1 - mean_squared_error: 3149.8671
Epoch 289/1000
9 - mean_squared_error: 3149.2379
Epoch 290/1000
2 - mean_squared_error: 3148.8542
Epoch 291/1000
9 - mean_squared_error: 3148.2029
Epoch 292/1000
3 - mean_squared_error: 3147.4133
Epoch 293/1000
```

```
2 - mean_squared_error: 3146.8082
Epoch 294/1000
6 - mean_squared_error: 3146.2566
Epoch 295/1000
3 - mean_squared_error: 3145.7473
Epoch 296/1000
0 - mean_squared_error: 3145.0900
Epoch 297/1000
2 - mean_squared_error: 3144.3582
Epoch 298/1000
8 - mean_squared_error: 3143.8038
Epoch 299/1000
1 - mean_squared_error: 3143.3561
Epoch 300/1000
1 - mean_squared_error: 3142.7931
Epoch 301/1000
8 - mean_squared_error: 3142.0908
Epoch 302/1000
6 - mean_squared_error: 3141.7476
Epoch 303/1000
5 - mean_squared_error: 3141.0685
Epoch 304/1000
4 - mean_squared_error: 3140.4444
Epoch 305/1000
4 - mean_squared_error: 3139.9104
Epoch 306/1000
2 - mean_squared_error: 3139.2772
Epoch 307/1000
1 - mean_squared_error: 3138.7781
Epoch 308/1000
0 - mean_squared_error: 3138.2650
Epoch 309/1000
7 - mean_squared_error: 3137.6567
Epoch 310/1000
3 - mean_squared_error: 3137.2093
Epoch 311/1000
5 - mean_squared_error: 3136.6405
Epoch 312/1000
```

```
3 - mean_squared_error: 3136.0603
Epoch 313/1000
6 - mean_squared_error: 3135.6186
Epoch 314/1000
3 - mean_squared_error: 3135.1163
Epoch 315/1000
9 - mean_squared_error: 3134.5829
Epoch 316/1000
7 - mean_squared_error: 3134.0807
Epoch 317/1000
9 - mean_squared_error: 3133.7259
Epoch 318/1000
4 - mean_squared_error: 3133.1664
Epoch 319/1000
9 - mean_squared_error: 3132.6539
Epoch 320/1000
6 - mean_squared_error: 3132.0716
Epoch 321/1000
1 - mean_squared_error: 3131.6401
Epoch 322/1000
3 - mean_squared_error: 3131.0893
Epoch 323/1000
9 - mean_squared_error: 3130.6039
Epoch 324/1000
6 - mean_squared_error: 3130.0766
Epoch 325/1000
9 - mean_squared_error: 3129.6709
Epoch 326/1000
7 - mean_squared_error: 3129.0307
Epoch 327/1000
4 - mean_squared_error: 3128.5814
Epoch 328/1000
2 - mean_squared_error: 3128.1012
Epoch 329/1000
9 - mean_squared_error: 3127.6469
Epoch 330/1000
8 - mean_squared_error: 3127.1488
Epoch 331/1000
```

```
1 - mean_squared_error: 3126.7631
Epoch 332/1000
4 - mean_squared_error: 3126.2684
Epoch 333/1000
6 - mean_squared_error: 3125.7376
Epoch 334/1000
1 - mean_squared_error: 3125.4101
Epoch 335/1000
0 - mean_squared_error: 3124.9000
Epoch 336/1000
2 - mean_squared_error: 3124.4002
Epoch 337/1000
1 - mean_squared_error: 3123.9471
Epoch 338/1000
4 - mean_squared_error: 3123.3954
Epoch 339/1000
2 - mean_squared_error: 3123.0082
Epoch 340/1000
8 - mean_squared_error: 3122.4568
Epoch 341/1000
2 - mean_squared_error: 3122.0352
Epoch 342/1000
6 - mean_squared_error: 3121.5616
Epoch 343/1000
2 - mean_squared_error: 3121.1402
Epoch 344/1000
3 - mean_squared_error: 3120.5873
Epoch 345/1000
2 - mean_squared_error: 3120.2532
Epoch 346/1000
8 - mean_squared_error: 3119.7198
Epoch 347/1000
2 - mean_squared_error: 3119.3342
Epoch 348/1000
5 - mean_squared_error: 3118.9855
Epoch 349/1000
5 - mean_squared_error: 3118.4725
Epoch 350/1000
```

```
2 - mean_squared_error: 3118.0532
Epoch 351/1000
9 - mean_squared_error: 3117.5869
Epoch 352/1000
6 - mean_squared_error: 3117.1486
Epoch 353/1000
3 - mean_squared_error: 3116.7983
Epoch 354/1000
8 - mean_squared_error: 3116.4458
Epoch 355/1000
5 - mean_squared_error: 3115.9475
Epoch 356/1000
0 - mean_squared_error: 3115.5590
Epoch 357/1000
1 - mean_squared_error: 3115.2021
Epoch 358/1000
0 - mean_squared_error: 3114.7860
Epoch 359/1000
8 - mean_squared_error: 3114.3538
Epoch 360/1000
6 - mean_squared_error: 3113.9506
Epoch 361/1000
3 - mean_squared_error: 3113.5423
Epoch 362/1000
6 - mean_squared_error: 3113.0876
Epoch 363/1000
8 - mean_squared_error: 3112.6538
Epoch 364/1000
3 - mean_squared_error: 3112.2923
Epoch 365/1000
5 - mean_squared_error: 3111.8825
Epoch 366/1000
7 - mean_squared_error: 3111.5947
Epoch 367/1000
1 - mean_squared_error: 3111.2921
Epoch 368/1000
2 - mean_squared_error: 3110.9412
Epoch 369/1000
```

```
5 - mean_squared_error: 3110.4825
Epoch 370/1000
3 - mean_squared_error: 3109.9773
Epoch 371/1000
9 - mean_squared_error: 3109.5549
Epoch 372/1000
5 - mean_squared_error: 3109.3095
Epoch 373/1000
9 - mean_squared_error: 3108.8229
Epoch 374/1000
1 - mean_squared_error: 3108.4681
Epoch 375/1000
2 - mean_squared_error: 3108.0442
Epoch 376/1000
5 - mean_squared_error: 3107.5995
Epoch 377/1000
7 - mean_squared_error: 3107.2447
Epoch 378/1000
3 - mean_squared_error: 3106.7603
Epoch 379/1000
5 - mean_squared_error: 3106.3945
Epoch 380/1000
8 - mean_squared_error: 3106.0918
Epoch 381/1000
1 - mean_squared_error: 3105.6611
Epoch 382/1000
5 - mean_squared_error: 3105.4465
Epoch 383/1000
5 - mean_squared_error: 3104.9945
Epoch 384/1000
8 - mean_squared_error: 3104.7628
Epoch 385/1000
6 - mean_squared_error: 3104.3966
Epoch 386/1000
3 - mean_squared_error: 3103.9123
Epoch 387/1000
4 - mean_squared_error: 3103.6404
Epoch 388/1000
```

```
5 - mean_squared_error: 3103.2785
Epoch 389/1000
0 - mean_squared_error: 3102.8830
Epoch 390/1000
0 - mean_squared_error: 3102.4780
Epoch 391/1000
3 - mean_squared_error: 3102.1323
Epoch 392/1000
1 - mean_squared_error: 3101.8541
Epoch 393/1000
2 - mean_squared_error: 3101.4512
Epoch 394/1000
9 - mean_squared_error: 3101.1469
Epoch 395/1000
5 - mean_squared_error: 3100.7785
Epoch 396/1000
8 - mean_squared_error: 3100.5088
Epoch 397/1000
0 - mean_squared_error: 3100.1180
Epoch 398/1000
5 - mean squared error: 3099.7695
Epoch 399/1000
5 - mean_squared_error: 3099.3645
Epoch 400/1000
0 - mean_squared_error: 3099.0930
Epoch 401/1000
8 - mean_squared_error: 3098.8998
Epoch 402/1000
4 - mean_squared_error: 3098.4424
Epoch 403/1000
2 - mean_squared_error: 3098.2052
Epoch 404/1000
8 - mean_squared_error: 3097.8058
Epoch 405/1000
3 - mean_squared_error: 3097.5173
Epoch 406/1000
6 - mean_squared_error: 3097.1416
Epoch 407/1000
```

```
5 - mean_squared_error: 3096.9675
Epoch 408/1000
4 - mean_squared_error: 3096.6164
Epoch 409/1000
4 - mean_squared_error: 3096.2964
Epoch 410/1000
6 - mean_squared_error: 3095.9866
Epoch 411/1000
6 - mean_squared_error: 3095.5856
Epoch 412/1000
3 - mean_squared_error: 3095.4193
Epoch 413/1000
8 - mean_squared_error: 3095.1438
Epoch 414/1000
4 - mean_squared_error: 3094.6744
Epoch 415/1000
3 - mean_squared_error: 3094.4833
Epoch 416/1000
4 - mean_squared_error: 3094.0484
Epoch 417/1000
8 - mean squared error: 3093.8058
Epoch 418/1000
1 - mean_squared_error: 3093.4281
Epoch 419/1000
5 - mean_squared_error: 3093.1935
Epoch 420/1000
2 - mean_squared_error: 3092.8502
Epoch 421/1000
2 - mean_squared_error: 3092.6552
Epoch 422/1000
7 - mean_squared_error: 3092.3197
Epoch 423/1000
1 - mean_squared_error: 3091.9561
Epoch 424/1000
5 - mean_squared_error: 3091.6875
Epoch 425/1000
3 - mean_squared_error: 3091.5173
Epoch 426/1000
```

```
7 - mean_squared_error: 3091.1567
Epoch 427/1000
5 - mean_squared_error: 3090.9025
Epoch 428/1000
1 - mean_squared_error: 3090.6371
Epoch 429/1000
3 - mean_squared_error: 3090.2763
Epoch 430/1000
3 - mean_squared_error: 3090.0673
Epoch 431/1000
0 - mean_squared_error: 3089.7250
Epoch 432/1000
9 - mean_squared_error: 3089.4799
Epoch 433/1000
9 - mean_squared_error: 3089.2369
Epoch 434/1000
5 - mean_squared_error: 3088.8965
Epoch 435/1000
8 - mean_squared_error: 3088.6898
Epoch 436/1000
2 - mean_squared_error: 3088.4672
Epoch 437/1000
0 - mean_squared_error: 3088.1040
Epoch 438/1000
6 - mean_squared_error: 3087.8816
Epoch 439/1000
0 - mean_squared_error: 3087.5650
Epoch 440/1000
5 - mean_squared_error: 3087.3335
Epoch 441/1000
5 - mean_squared_error: 3087.0135
Epoch 442/1000
9 - mean_squared_error: 3086.7219
Epoch 443/1000
1 - mean_squared_error: 3086.5541
Epoch 444/1000
2 - mean_squared_error: 3086.2642
Epoch 445/1000
```

```
7 - mean_squared_error: 3086.0037
Epoch 446/1000
5 - mean_squared_error: 3085.7515
Epoch 447/1000
7 - mean_squared_error: 3085.5797
Epoch 448/1000
4 - mean_squared_error: 3085.2684
Epoch 449/1000
7 - mean_squared_error: 3084.9887
Epoch 450/1000
8 - mean_squared_error: 3084.7928
Epoch 451/1000
7 - mean_squared_error: 3084.5387
Epoch 452/1000
6 - mean_squared_error: 3084.3616
Epoch 453/1000
2 - mean_squared_error: 3084.1682
Epoch 454/1000
8 - mean_squared_error: 3083.8688
Epoch 455/1000
3 - mean squared error: 3083.6963
Epoch 456/1000
2 - mean_squared_error: 3083.2832
Epoch 457/1000
4 - mean_squared_error: 3083.1424
Epoch 458/1000
5 - mean_squared_error: 3082.8065
Epoch 459/1000
4 - mean_squared_error: 3082.5324
Epoch 460/1000
4 - mean_squared_error: 3082.3104
Epoch 461/1000
1 - mean_squared_error: 3081.9591
Epoch 462/1000
1 - mean_squared_error: 3081.7561
Epoch 463/1000
5 - mean_squared_error: 3081.4995
Epoch 464/1000
```

```
9 - mean_squared_error: 3081.3549
Epoch 465/1000
2 - mean_squared_error: 3081.0982
Epoch 466/1000
3 - mean_squared_error: 3080.8563
Epoch 467/1000
8 - mean_squared_error: 3080.6098
Epoch 468/1000
3 - mean_squared_error: 3080.3943
Epoch 469/1000
3 - mean_squared_error: 3080.1133
Epoch 470/1000
3 - mean_squared_error: 3079.9543
Epoch 471/1000
7 - mean_squared_error: 3079.6487
Epoch 472/1000
5 - mean_squared_error: 3079.5575
Epoch 473/1000
9 - mean_squared_error: 3079.3039
Epoch 474/1000
6 - mean squared error: 3079.0106
Epoch 475/1000
5 - mean_squared_error: 3078.8615
Epoch 476/1000
2 - mean_squared_error: 3078.5892
Epoch 477/1000
5 - mean_squared_error: 3078.3985
Epoch 478/1000
3 - mean_squared_error: 3078.1733
Epoch 479/1000
4 - mean_squared_error: 3078.0454
Epoch 480/1000
2 - mean_squared_error: 3077.8112
Epoch 481/1000
9 - mean_squared_error: 3077.5929
Epoch 482/1000
1094/1094 [=============== ] - Os 34us/step - loss: 3077.368
5 - mean_squared_error: 3077.3685
Epoch 483/1000
```

```
0 - mean_squared_error: 3077.2160
Epoch 484/1000
8 - mean_squared_error: 3076.9368
Epoch 485/1000
2 - mean_squared_error: 3076.7212
Epoch 486/1000
2 - mean_squared_error: 3076.4052
Epoch 487/1000
4 - mean_squared_error: 3076.1254
Epoch 488/1000
1 - mean_squared_error: 3075.9811
Epoch 489/1000
4 - mean_squared_error: 3075.7794
Epoch 490/1000
0 - mean_squared_error: 3075.6060
Epoch 491/1000
4 - mean_squared_error: 3075.3134
Epoch 492/1000
3 - mean_squared_error: 3075.2413
Epoch 493/1000
8 - mean squared error: 3074.9468
Epoch 494/1000
1 - mean_squared_error: 3074.6211
Epoch 495/1000
4 - mean_squared_error: 3074.4564
Epoch 496/1000
5 - mean_squared_error: 3074.2225
Epoch 497/1000
4 - mean_squared_error: 3074.0344
Epoch 498/1000
3 - mean_squared_error: 3073.8283
Epoch 499/1000
6 - mean_squared_error: 3073.6506
Epoch 500/1000
8 - mean_squared_error: 3073.5878
Epoch 501/1000
3 - mean_squared_error: 3073.3173
Epoch 502/1000
```

```
3 - mean_squared_error: 3073.0743
Epoch 503/1000
2 - mean_squared_error: 3072.9392
Epoch 504/1000
2 - mean_squared_error: 3072.8162
Epoch 505/1000
7 - mean_squared_error: 3072.5427
Epoch 506/1000
8 - mean_squared_error: 3072.3578
Epoch 507/1000
1 - mean_squared_error: 3072.2151
Epoch 508/1000
2 - mean_squared_error: 3072.0312
Epoch 509/1000
8 - mean_squared_error: 3071.8768
Epoch 510/1000
8 - mean_squared_error: 3071.6278
Epoch 511/1000
4 - mean_squared_error: 3071.5224
Epoch 512/1000
3 - mean_squared_error: 3071.2463
Epoch 513/1000
6 - mean_squared_error: 3071.1206
Epoch 514/1000
0 - mean_squared_error: 3070.7810
Epoch 515/1000
2 - mean_squared_error: 3070.5942
Epoch 516/1000
3 - mean_squared_error: 3070.4553
Epoch 517/1000
3 - mean_squared_error: 3070.2813
Epoch 518/1000
1 - mean_squared_error: 3070.1061
Epoch 519/1000
0 - mean_squared_error: 3069.9670
Epoch 520/1000
4 - mean_squared_error: 3069.7824
Epoch 521/1000
```

```
9 - mean_squared_error: 3069.5239
Epoch 522/1000
2 - mean_squared_error: 3069.4122
Epoch 523/1000
8 - mean_squared_error: 3069.2428
Epoch 524/1000
4 - mean_squared_error: 3069.0404
Epoch 525/1000
2 - mean_squared_error: 3068.8222
Epoch 526/1000
9 - mean_squared_error: 3068.5899
Epoch 527/1000
9 - mean_squared_error: 3068.4729
Epoch 528/1000
3 - mean_squared_error: 3068.2653
Epoch 529/1000
4 - mean_squared_error: 3068.1514
Epoch 530/1000
6 - mean_squared_error: 3067.9026
Epoch 531/1000
0 - mean squared error: 3067.8080
Epoch 532/1000
4 - mean_squared_error: 3067.6614
Epoch 533/1000
8 - mean_squared_error: 3067.4748
Epoch 534/1000
2 - mean_squared_error: 3067.3552
Epoch 535/1000
4 - mean_squared_error: 3067.1094
Epoch 536/1000
4 - mean_squared_error: 3067.0354
Epoch 537/1000
2 - mean_squared_error: 3066.7492
Epoch 538/1000
8 - mean_squared_error: 3066.5918
Epoch 539/1000
8 - mean_squared_error: 3066.4838
Epoch 540/1000
```

```
6 - mean_squared_error: 3066.2756
Epoch 541/1000
3 - mean_squared_error: 3066.1933
Epoch 542/1000
5 - mean_squared_error: 3065.9795
Epoch 543/1000
6 - mean_squared_error: 3065.8426
Epoch 544/1000
0 - mean_squared_error: 3065.6910
Epoch 545/1000
4 - mean_squared_error: 3065.5214
Epoch 546/1000
7 - mean_squared_error: 3065.3027
Epoch 547/1000
3 - mean_squared_error: 3065.2583
Epoch 548/1000
7 - mean_squared_error: 3065.1127
Epoch 549/1000
8 - mean_squared_error: 3065.0098
Epoch 550/1000
8 - mean squared error: 3064.7648
Epoch 551/1000
8 - mean_squared_error: 3064.6038
Epoch 552/1000
3 - mean_squared_error: 3064.4593
Epoch 553/1000
2 - mean_squared_error: 3064.3142
Epoch 554/1000
0 - mean_squared_error: 3064.1420
Epoch 555/1000
9 - mean_squared_error: 3064.0409
Epoch 556/1000
2 - mean_squared_error: 3063.8262
Epoch 557/1000
8 - mean_squared_error: 3063.6768
Epoch 558/1000
8 - mean_squared_error: 3063.5478
Epoch 559/1000
```

```
7 - mean_squared_error: 3063.4377
Epoch 560/1000
3 - mean_squared_error: 3063.2583
Epoch 561/1000
7 - mean_squared_error: 3063.1397
Epoch 562/1000
6 - mean_squared_error: 3063.0356
Epoch 563/1000
8 - mean_squared_error: 3062.8768
Epoch 564/1000
7 - mean_squared_error: 3062.7887
Epoch 565/1000
7 - mean_squared_error: 3062.6007
Epoch 566/1000
2 - mean_squared_error: 3062.3902
Epoch 567/1000
1 - mean_squared_error: 3062.2321
Epoch 568/1000
9 - mean_squared_error: 3062.1549
Epoch 569/1000
3 - mean_squared_error: 3061.9843
Epoch 570/1000
2 - mean_squared_error: 3061.8772
Epoch 571/1000
5 - mean_squared_error: 3061.8185
Epoch 572/1000
2 - mean_squared_error: 3061.6282
Epoch 573/1000
9 - mean_squared_error: 3061.4909
Epoch 574/1000
0 - mean_squared_error: 3061.3980
Epoch 575/1000
4 - mean_squared_error: 3061.2374
Epoch 576/1000
6 - mean_squared_error: 3061.1086
Epoch 577/1000
6 - mean_squared_error: 3060.9876
Epoch 578/1000
```

```
8 - mean_squared_error: 3060.7498
Epoch 579/1000
4 - mean_squared_error: 3060.7434
Epoch 580/1000
9 - mean_squared_error: 3060.5539
Epoch 581/1000
7 - mean_squared_error: 3060.4127
Epoch 582/1000
8 - mean_squared_error: 3060.1848
Epoch 583/1000
4 - mean_squared_error: 3060.0604
Epoch 584/1000
2 - mean_squared_error: 3060.0062
Epoch 585/1000
5 - mean_squared_error: 3059.8975
Epoch 586/1000
2 - mean_squared_error: 3059.7502
Epoch 587/1000
5 - mean_squared_error: 3059.6675
Epoch 588/1000
2 - mean squared error: 3059.5662
Epoch 589/1000
5 - mean_squared_error: 3059.3555
Epoch 590/1000
8 - mean_squared_error: 3059.2528
Epoch 591/1000
9 - mean_squared_error: 3059.1369
Epoch 592/1000
7 - mean_squared_error: 3058.9507
Epoch 593/1000
3 - mean_squared_error: 3058.8933
Epoch 594/1000
7 - mean_squared_error: 3058.7217
Epoch 595/1000
4 - mean_squared_error: 3058.6954
Epoch 596/1000
0 - mean_squared_error: 3058.4410
Epoch 597/1000
```

```
6 - mean_squared_error: 3058.3736
Epoch 598/1000
5 - mean_squared_error: 3058.3215
Epoch 599/1000
8 - mean_squared_error: 3058.2078
Epoch 600/1000
0 - mean_squared_error: 3058.0100
Epoch 601/1000
8 - mean_squared_error: 3057.8638
Epoch 602/1000
1 - mean_squared_error: 3057.7511
Epoch 603/1000
2 - mean_squared_error: 3057.7312
Epoch 604/1000
6 - mean_squared_error: 3057.5266
Epoch 605/1000
9 - mean_squared_error: 3057.3679
Epoch 606/1000
4 - mean_squared_error: 3057.2874
Epoch 607/1000
0 - mean_squared_error: 3057.1810
Epoch 608/1000
5 - mean_squared_error: 3057.0865
Epoch 609/1000
5 - mean_squared_error: 3056.9915
Epoch 610/1000
9 - mean_squared_error: 3056.8779
Epoch 611/1000
8 - mean_squared_error: 3056.7698
Epoch 612/1000
7 - mean_squared_error: 3056.6307
Epoch 613/1000
5 - mean_squared_error: 3056.5545
Epoch 614/1000
4 - mean_squared_error: 3056.4994
Epoch 615/1000
1 - mean_squared_error: 3056.3531
Epoch 616/1000
```

```
9 - mean_squared_error: 3056.1759
Epoch 617/1000
5 - mean_squared_error: 3056.1285
Epoch 618/1000
0 - mean_squared_error: 3056.0030
Epoch 619/1000
3 - mean_squared_error: 3055.8613
Epoch 620/1000
5 - mean_squared_error: 3055.7315
Epoch 621/1000
4 - mean_squared_error: 3055.7064
Epoch 622/1000
8 - mean_squared_error: 3055.5558
Epoch 623/1000
6 - mean_squared_error: 3055.3506
Epoch 624/1000
9 - mean_squared_error: 3055.2949
Epoch 625/1000
9 - mean_squared_error: 3055.1979
Epoch 626/1000
4 - mean_squared_error: 3055.1324
Epoch 627/1000
0 - mean_squared_error: 3054.9910
Epoch 628/1000
4 - mean_squared_error: 3054.8534
Epoch 629/1000
7 - mean_squared_error: 3054.7837
Epoch 630/1000
6 - mean_squared_error: 3054.7076
Epoch 631/1000
5 - mean_squared_error: 3054.5455
Epoch 632/1000
9 - mean_squared_error: 3054.4949
Epoch 633/1000
2 - mean_squared_error: 3054.3322
Epoch 634/1000
8 - mean_squared_error: 3054.1998
Epoch 635/1000
```

```
4 - mean_squared_error: 3054.1554
Epoch 636/1000
9 - mean_squared_error: 3054.0099
Epoch 637/1000
8 - mean_squared_error: 3053.9328
Epoch 638/1000
0 - mean_squared_error: 3053.7890
Epoch 639/1000
3 - mean_squared_error: 3053.8233
Epoch 640/1000
4 - mean_squared_error: 3053.6644
Epoch 641/1000
4 - mean_squared_error: 3053.5254
Epoch 642/1000
0 - mean_squared_error: 3053.4750
Epoch 643/1000
5 - mean_squared_error: 3053.4105
Epoch 644/1000
4 - mean_squared_error: 3053.2854
Epoch 645/1000
5 - mean_squared_error: 3053.1765
Epoch 646/1000
6 - mean_squared_error: 3053.1096
Epoch 647/1000
6 - mean_squared_error: 3053.0256
Epoch 648/1000
5 - mean_squared_error: 3052.9155
Epoch 649/1000
0 - mean_squared_error: 3052.9030
Epoch 650/1000
2 - mean_squared_error: 3052.8172
Epoch 651/1000
0 - mean_squared_error: 3052.6270
Epoch 652/1000
1 - mean_squared_error: 3052.5031
Epoch 653/1000
1 - mean_squared_error: 3052.4691
Epoch 654/1000
```

```
3 - mean_squared_error: 3052.4293
Epoch 655/1000
6 - mean_squared_error: 3052.3136
Epoch 656/1000
1 - mean_squared_error: 3052.0701
Epoch 657/1000
5 - mean_squared_error: 3051.9995
Epoch 658/1000
2 - mean_squared_error: 3051.9022
Epoch 659/1000
4 - mean_squared_error: 3051.8904
Epoch 660/1000
2 - mean_squared_error: 3051.7592
Epoch 661/1000
4 - mean_squared_error: 3051.6754
Epoch 662/1000
4 - mean_squared_error: 3051.6084
Epoch 663/1000
5 - mean_squared_error: 3051.5255
Epoch 664/1000
3 - mean_squared_error: 3051.4133
Epoch 665/1000
1 - mean_squared_error: 3051.2541
Epoch 666/1000
9 - mean_squared_error: 3051.2269
Epoch 667/1000
7 - mean_squared_error: 3051.0987
Epoch 668/1000
5 - mean_squared_error: 3050.9665
Epoch 669/1000
3 - mean_squared_error: 3051.0263
Epoch 670/1000
8 - mean_squared_error: 3050.8948
Epoch 671/1000
0 - mean_squared_error: 3050.7220
Epoch 672/1000
0 - mean_squared_error: 3050.6470
Epoch 673/1000
```

```
4 - mean_squared_error: 3050.5714
Epoch 674/1000
0 - mean_squared_error: 3050.4780
Epoch 675/1000
4 - mean_squared_error: 3050.4954
Epoch 676/1000
9 - mean_squared_error: 3050.3739
Epoch 677/1000
4 - mean_squared_error: 3050.2844
Epoch 678/1000
5 - mean_squared_error: 3050.1495
Epoch 679/1000
7 - mean_squared_error: 3050.1227
Epoch 680/1000
3 - mean_squared_error: 3050.1073
Epoch 681/1000
1 - mean_squared_error: 3049.9721
Epoch 682/1000
9 - mean_squared_error: 3050.0139
Epoch 683/1000
5 - mean squared error: 3049.7565
Epoch 684/1000
2 - mean_squared_error: 3049.7382
Epoch 685/1000
4 - mean_squared_error: 3049.6224
Epoch 686/1000
7 - mean_squared_error: 3049.5237
Epoch 687/1000
2 - mean_squared_error: 3049.5392
Epoch 688/1000
3 - mean_squared_error: 3049.3823
Epoch 689/1000
8 - mean_squared_error: 3049.2868
Epoch 690/1000
0 - mean_squared_error: 3049.2070
Epoch 691/1000
1 - mean_squared_error: 3049.1461
Epoch 692/1000
```

```
9 - mean_squared_error: 3049.0079
Epoch 693/1000
2 - mean_squared_error: 3049.0042
Epoch 694/1000
8 - mean_squared_error: 3048.9348
Epoch 695/1000
3 - mean_squared_error: 3048.8593
Epoch 696/1000
9 - mean_squared_error: 3048.7509
Epoch 697/1000
7 - mean_squared_error: 3048.7957
Epoch 698/1000
5 - mean_squared_error: 3048.5415
Epoch 699/1000
2 - mean_squared_error: 3048.4772
Epoch 700/1000
9 - mean_squared_error: 3048.4359
Epoch 701/1000
8 - mean_squared_error: 3048.3758
Epoch 702/1000
1 - mean_squared_error: 3048.2771
Epoch 703/1000
7 - mean_squared_error: 3048.1657
Epoch 704/1000
4 - mean_squared_error: 3048.1634
Epoch 705/1000
7 - mean_squared_error: 3048.0937
Epoch 706/1000
0 - mean_squared_error: 3047.9090
Epoch 707/1000
1 - mean_squared_error: 3047.9201
Epoch 708/1000
2 - mean_squared_error: 3047.7892
Epoch 709/1000
5 - mean_squared_error: 3047.7545
Epoch 710/1000
3 - mean_squared_error: 3047.6753
Epoch 711/1000
```

```
1 - mean_squared_error: 3047.6011
Epoch 712/1000
8 - mean_squared_error: 3047.5328
Epoch 713/1000
2 - mean_squared_error: 3047.5132
Epoch 714/1000
1 - mean_squared_error: 3047.3991
Epoch 715/1000
6 - mean_squared_error: 3047.3136
Epoch 716/1000
1 - mean_squared_error: 3047.2571
Epoch 717/1000
1 - mean_squared_error: 3047.1581
Epoch 718/1000
2 - mean_squared_error: 3047.2172
Epoch 719/1000
8 - mean_squared_error: 3047.0638
Epoch 720/1000
6 - mean_squared_error: 3046.9716
Epoch 721/1000
2 - mean_squared_error: 3046.8952
Epoch 722/1000
4 - mean_squared_error: 3046.7894
Epoch 723/1000
3 - mean_squared_error: 3046.7373
Epoch 724/1000
2 - mean_squared_error: 3046.7102
Epoch 725/1000
5 - mean_squared_error: 3046.5665
Epoch 726/1000
7 - mean_squared_error: 3046.5467
Epoch 727/1000
4 - mean_squared_error: 3046.5404
Epoch 728/1000
7 - mean_squared_error: 3046.3297
Epoch 729/1000
3 - mean_squared_error: 3046.3233
Epoch 730/1000
```

```
3 - mean_squared_error: 3046.2603
Epoch 731/1000
6 - mean_squared_error: 3046.1786
Epoch 732/1000
7 - mean_squared_error: 3046.1757
Epoch 733/1000
1 - mean_squared_error: 3046.1041
Epoch 734/1000
9 - mean_squared_error: 3046.0469
Epoch 735/1000
1 - mean_squared_error: 3045.9991
Epoch 736/1000
3 - mean_squared_error: 3045.8973
Epoch 737/1000
8 - mean_squared_error: 3045.8908
Epoch 738/1000
1 - mean_squared_error: 3045.8661
Epoch 739/1000
9 - mean_squared_error: 3045.7299
Epoch 740/1000
3 - mean_squared_error: 3045.7153
Epoch 741/1000
6 - mean_squared_error: 3045.6056
Epoch 742/1000
4 - mean_squared_error: 3045.4884
Epoch 743/1000
4 - mean_squared_error: 3045.4514
Epoch 744/1000
6 - mean_squared_error: 3045.4076
Epoch 745/1000
5 - mean_squared_error: 3045.2605
Epoch 746/1000
0 - mean_squared_error: 3045.2270
Epoch 747/1000
3 - mean_squared_error: 3045.1313
Epoch 748/1000
9 - mean_squared_error: 3045.0559
Epoch 749/1000
```

```
9 - mean_squared_error: 3045.0339
Epoch 750/1000
4 - mean_squared_error: 3044.9484
Epoch 751/1000
7 - mean_squared_error: 3044.9577
Epoch 752/1000
1 - mean_squared_error: 3044.8031
Epoch 753/1000
8 - mean_squared_error: 3044.9048
Epoch 754/1000
5 - mean_squared_error: 3044.7385
Epoch 755/1000
9 - mean_squared_error: 3044.7169
Epoch 756/1000
9 - mean_squared_error: 3044.7079
Epoch 757/1000
9 - mean_squared_error: 3044.5699
Epoch 758/1000
9 - mean_squared_error: 3044.5619
Epoch 759/1000
1 - mean_squared_error: 3044.3881
Epoch 760/1000
7 - mean_squared_error: 3044.3817
Epoch 761/1000
7 - mean_squared_error: 3044.3237
Epoch 762/1000
8 - mean_squared_error: 3044.2478
Epoch 763/1000
3 - mean_squared_error: 3044.2533
Epoch 764/1000
8 - mean_squared_error: 3044.2168
Epoch 765/1000
9 - mean_squared_error: 3044.1089
Epoch 766/1000
9 - mean_squared_error: 3044.0919
Epoch 767/1000
2 - mean_squared_error: 3043.9922
Epoch 768/1000
```

```
5 - mean_squared_error: 3043.8905
Epoch 769/1000
6 - mean_squared_error: 3043.8146
Epoch 770/1000
5 - mean_squared_error: 3043.8405
Epoch 771/1000
2 - mean_squared_error: 3043.6632
Epoch 772/1000
3 - mean_squared_error: 3043.7223
Epoch 773/1000
7 - mean_squared_error: 3043.6447
Epoch 774/1000
6 - mean_squared_error: 3043.5596
Epoch 775/1000
8 - mean_squared_error: 3043.5378
Epoch 776/1000
5 - mean_squared_error: 3043.3135
Epoch 777/1000
3 - mean_squared_error: 3043.3043
Epoch 778/1000
8 - mean_squared_error: 3043.2388
Epoch 779/1000
4 - mean_squared_error: 3043.1704
Epoch 780/1000
2 - mean_squared_error: 3043.2262
Epoch 781/1000
3 - mean_squared_error: 3043.0773
Epoch 782/1000
9 - mean_squared_error: 3043.1559
Epoch 783/1000
0 - mean_squared_error: 3043.0780
Epoch 784/1000
2 - mean_squared_error: 3042.9462
Epoch 785/1000
8 - mean_squared_error: 3042.9428
Epoch 786/1000
4 - mean_squared_error: 3042.8214
Epoch 787/1000
```

```
9 - mean_squared_error: 3042.8829
Epoch 788/1000
7 - mean_squared_error: 3042.7257
Epoch 789/1000
5 - mean_squared_error: 3042.7405
Epoch 790/1000
8 - mean_squared_error: 3042.6908
Epoch 791/1000
2 - mean_squared_error: 3042.6122
Epoch 792/1000
0 - mean_squared_error: 3042.5090
Epoch 793/1000
3 - mean_squared_error: 3042.4603
Epoch 794/1000
7 - mean_squared_error: 3042.3257
Epoch 795/1000
7 - mean_squared_error: 3042.4197
Epoch 796/1000
4 - mean_squared_error: 3042.3064
Epoch 797/1000
3 - mean squared error: 3042.1983
Epoch 798/1000
5 - mean_squared_error: 3042.2385
Epoch 799/1000
1 - mean_squared_error: 3042.1641
Epoch 800/1000
6 - mean_squared_error: 3042.1316
Epoch 801/1000
7 - mean_squared_error: 3042.0447
Epoch 802/1000
7 - mean_squared_error: 3041.9497
Epoch 803/1000
7 - mean_squared_error: 3041.9427
Epoch 804/1000
9 - mean_squared_error: 3041.8989
Epoch 805/1000
6 - mean_squared_error: 3041.8196
Epoch 806/1000
```

```
7 - mean_squared_error: 3041.8147
Epoch 807/1000
1 - mean_squared_error: 3041.7161
Epoch 808/1000
2 - mean_squared_error: 3041.7592
Epoch 809/1000
6 - mean_squared_error: 3041.6166
Epoch 810/1000
7 - mean_squared_error: 3041.4927
Epoch 811/1000
7 - mean_squared_error: 3041.5127
Epoch 812/1000
9 - mean_squared_error: 3041.4329
Epoch 813/1000
1 - mean_squared_error: 3041.4591
Epoch 814/1000
1 - mean_squared_error: 3041.3791
Epoch 815/1000
8 - mean_squared_error: 3041.2848
Epoch 816/1000
4 - mean_squared_error: 3041.2464
Epoch 817/1000
8 - mean_squared_error: 3041.3398
Epoch 818/1000
5 - mean_squared_error: 3041.2595
Epoch 819/1000
7 - mean_squared_error: 3041.1447
Epoch 820/1000
4 - mean_squared_error: 3041.0534
Epoch 821/1000
9 - mean_squared_error: 3040.9549
Epoch 822/1000
9 - mean_squared_error: 3040.9889
Epoch 823/1000
7 - mean_squared_error: 3040.8877
Epoch 824/1000
3 - mean_squared_error: 3040.9603
Epoch 825/1000
```

```
5 - mean_squared_error: 3040.7735
Epoch 826/1000
8 - mean_squared_error: 3040.7158
Epoch 827/1000
2 - mean_squared_error: 3040.7002
Epoch 828/1000
6 - mean_squared_error: 3040.5816
Epoch 829/1000
2 - mean_squared_error: 3040.5992
Epoch 830/1000
9 - mean_squared_error: 3040.5719
Epoch 831/1000
2 - mean_squared_error: 3040.5122
Epoch 832/1000
7 - mean_squared_error: 3040.5117
Epoch 833/1000
7 - mean_squared_error: 3040.3727
Epoch 834/1000
8 - mean_squared_error: 3040.3638
Epoch 835/1000
1 - mean_squared_error: 3040.3811
Epoch 836/1000
0 - mean_squared_error: 3040.3400
Epoch 837/1000
1 - mean_squared_error: 3040.2631
Epoch 838/1000
0 - mean_squared_error: 3040.3310
Epoch 839/1000
3 - mean_squared_error: 3040.1893
Epoch 840/1000
6 - mean_squared_error: 3040.1426
Epoch 841/1000
1 - mean_squared_error: 3040.0381
Epoch 842/1000
1 - mean_squared_error: 3040.0301
Epoch 843/1000
7 - mean_squared_error: 3040.0617
Epoch 844/1000
```

```
2 - mean_squared_error: 3040.0742
Epoch 845/1000
8 - mean_squared_error: 3039.8948
Epoch 846/1000
4 - mean_squared_error: 3039.8134
Epoch 847/1000
3 - mean_squared_error: 3039.8683
Epoch 848/1000
7 - mean_squared_error: 3039.7097
Epoch 849/1000
9 - mean_squared_error: 3039.7559
Epoch 850/1000
0 - mean_squared_error: 3039.6350
Epoch 851/1000
7 - mean_squared_error: 3039.6767
Epoch 852/1000
8 - mean_squared_error: 3039.5208
Epoch 853/1000
4 - mean_squared_error: 3039.4974
Epoch 854/1000
3 - mean squared error: 3039.5473
Epoch 855/1000
5 - mean_squared_error: 3039.3735
Epoch 856/1000
1 - mean_squared_error: 3039.4411
Epoch 857/1000
1 - mean_squared_error: 3039.4811
Epoch 858/1000
9 - mean_squared_error: 3039.3169
Epoch 859/1000
7 - mean_squared_error: 3039.4057
Epoch 860/1000
9 - mean_squared_error: 3039.2809
Epoch 861/1000
3 - mean_squared_error: 3039.1643
Epoch 862/1000
1 - mean_squared_error: 3039.2771
Epoch 863/1000
```

```
4 - mean_squared_error: 3039.1214
Epoch 864/1000
3 - mean_squared_error: 3039.1393
Epoch 865/1000
1 - mean_squared_error: 3039.1791
Epoch 866/1000
7 - mean_squared_error: 3039.0597
Epoch 867/1000
3 - mean_squared_error: 3039.0343
Epoch 868/1000
4 - mean_squared_error: 3038.9984
Epoch 869/1000
5 - mean_squared_error: 3038.9665
Epoch 870/1000
5 - mean_squared_error: 3038.9315
Epoch 871/1000
5 - mean_squared_error: 3038.8265
Epoch 872/1000
6 - mean_squared_error: 3038.7976
Epoch 873/1000
7 - mean squared error: 3038.8577
Epoch 874/1000
1 - mean_squared_error: 3038.7971
Epoch 875/1000
1 - mean_squared_error: 3038.6731
Epoch 876/1000
3 - mean_squared_error: 3038.7713
Epoch 877/1000
5 - mean_squared_error: 3038.6735
Epoch 878/1000
6 - mean_squared_error: 3038.5836
Epoch 879/1000
0 - mean_squared_error: 3038.5660
Epoch 880/1000
8 - mean_squared_error: 3038.5458
Epoch 881/1000
5 - mean_squared_error: 3038.4615
Epoch 882/1000
```

```
2 - mean_squared_error: 3038.4742
Epoch 883/1000
0 - mean_squared_error: 3038.4920
Epoch 884/1000
3 - mean_squared_error: 3038.5443
Epoch 885/1000
2 - mean_squared_error: 3038.4292
Epoch 886/1000
9 - mean_squared_error: 3038.4419
Epoch 887/1000
2 - mean_squared_error: 3038.2972
Epoch 888/1000
1 - mean_squared_error: 3038.3471
Epoch 889/1000
3 - mean_squared_error: 3038.1643
Epoch 890/1000
0 - mean_squared_error: 3038.1550
Epoch 891/1000
4 - mean_squared_error: 3038.1274
Epoch 892/1000
3 - mean_squared_error: 3038.1413
Epoch 893/1000
6 - mean_squared_error: 3038.0696
Epoch 894/1000
7 - mean_squared_error: 3037.9977
Epoch 895/1000
6 - mean_squared_error: 3037.9656
Epoch 896/1000
5 - mean_squared_error: 3037.8525
Epoch 897/1000
5 - mean_squared_error: 3037.9035
Epoch 898/1000
5 - mean_squared_error: 3037.9385
Epoch 899/1000
6 - mean_squared_error: 3037.9246
Epoch 900/1000
8 - mean_squared_error: 3037.7538
Epoch 901/1000
```

```
7 - mean_squared_error: 3037.6927
Epoch 902/1000
2 - mean_squared_error: 3037.6982
Epoch 903/1000
6 - mean_squared_error: 3037.6596
Epoch 904/1000
9 - mean_squared_error: 3037.6129
Epoch 905/1000
5 - mean_squared_error: 3037.5555
Epoch 906/1000
9 - mean_squared_error: 3037.5319
Epoch 907/1000
9 - mean_squared_error: 3037.5389
Epoch 908/1000
1 - mean_squared_error: 3037.4661
Epoch 909/1000
2 - mean_squared_error: 3037.4482
Epoch 910/1000
8 - mean_squared_error: 3037.4368
Epoch 911/1000
9 - mean squared error: 3037.4569
Epoch 912/1000
9 - mean_squared_error: 3037.3349
Epoch 913/1000
0 - mean_squared_error: 3037.2950
Epoch 914/1000
1 - mean_squared_error: 3037.3831
Epoch 915/1000
1 - mean_squared_error: 3037.2361
Epoch 916/1000
3 - mean_squared_error: 3037.2323
Epoch 917/1000
5 - mean_squared_error: 3037.1245
Epoch 918/1000
6 - mean_squared_error: 3037.1316
Epoch 919/1000
4 - mean_squared_error: 3037.0814
Epoch 920/1000
```

```
9 - mean_squared_error: 3037.1049
Epoch 921/1000
4 - mean_squared_error: 3037.0234
Epoch 922/1000
8 - mean_squared_error: 3037.0898
Epoch 923/1000
4 - mean_squared_error: 3036.9874
Epoch 924/1000
3 - mean_squared_error: 3036.9223
Epoch 925/1000
3 - mean_squared_error: 3036.9363
Epoch 926/1000
2 - mean_squared_error: 3036.9242
Epoch 927/1000
0 - mean_squared_error: 3036.9740
Epoch 928/1000
4 - mean_squared_error: 3036.7924
Epoch 929/1000
9 - mean_squared_error: 3036.8189
Epoch 930/1000
4 - mean_squared_error: 3036.7664
Epoch 931/1000
4 - mean_squared_error: 3036.7894
Epoch 932/1000
1 - mean_squared_error: 3036.7001
Epoch 933/1000
8 - mean_squared_error: 3036.7018
Epoch 934/1000
7 - mean_squared_error: 3036.7017
Epoch 935/1000
1 - mean_squared_error: 3036.6521
Epoch 936/1000
1 - mean_squared_error: 3036.5921
Epoch 937/1000
6 - mean_squared_error: 3036.6016
Epoch 938/1000
7 - mean_squared_error: 3036.5047
Epoch 939/1000
```

```
0 - mean_squared_error: 3036.5240
Epoch 940/1000
8 - mean_squared_error: 3036.5128
Epoch 941/1000
3 - mean_squared_error: 3036.4463
Epoch 942/1000
5 - mean_squared_error: 3036.4115
Epoch 943/1000
1 - mean_squared_error: 3036.4111
Epoch 944/1000
7 - mean_squared_error: 3036.4467
Epoch 945/1000
3 - mean_squared_error: 3036.3303
Epoch 946/1000
9 - mean_squared_error: 3036.3269
Epoch 947/1000
0 - mean_squared_error: 3036.2650
Epoch 948/1000
2 - mean_squared_error: 3036.2212
Epoch 949/1000
5 - mean_squared_error: 3036.2775
Epoch 950/1000
8 - mean_squared_error: 3036.2758
Epoch 951/1000
8 - mean_squared_error: 3036.1798
Epoch 952/1000
6 - mean_squared_error: 3036.1136
Epoch 953/1000
2 - mean_squared_error: 3036.1102
Epoch 954/1000
4 - mean_squared_error: 3036.0594
Epoch 955/1000
6 - mean_squared_error: 3036.0156
Epoch 956/1000
9 - mean_squared_error: 3035.8989
Epoch 957/1000
1 - mean_squared_error: 3036.0621
Epoch 958/1000
```

```
3 - mean_squared_error: 3035.9753
Epoch 959/1000
3 - mean_squared_error: 3035.9203
Epoch 960/1000
0 - mean_squared_error: 3035.9630
Epoch 961/1000
2 - mean_squared_error: 3035.9192
Epoch 962/1000
8 - mean_squared_error: 3035.8618
Epoch 963/1000
3 - mean_squared_error: 3035.7833
Epoch 964/1000
7 - mean_squared_error: 3035.7837
Epoch 965/1000
8 - mean_squared_error: 3035.7888
Epoch 966/1000
4 - mean_squared_error: 3035.7494
Epoch 967/1000
0 - mean_squared_error: 3035.7360
Epoch 968/1000
0 - mean_squared_error: 3035.7150
Epoch 969/1000
8 - mean_squared_error: 3035.7238
Epoch 970/1000
0 - mean_squared_error: 3035.6640
Epoch 971/1000
8 - mean_squared_error: 3035.6128
Epoch 972/1000
2 - mean_squared_error: 3035.6732
Epoch 973/1000
3 - mean_squared_error: 3035.7153
Epoch 974/1000
7 - mean_squared_error: 3035.5227
Epoch 975/1000
2 - mean_squared_error: 3035.4782
Epoch 976/1000
4 - mean_squared_error: 3035.4784
Epoch 977/1000
```

```
8 - mean_squared_error: 3035.5238
Epoch 978/1000
1 - mean_squared_error: 3035.4701
Epoch 979/1000
4 - mean_squared_error: 3035.4514
Epoch 980/1000
5 - mean_squared_error: 3035.4725
Epoch 981/1000
6 - mean_squared_error: 3035.4966
Epoch 982/1000
7 - mean_squared_error: 3035.3367
Epoch 983/1000
0 - mean_squared_error: 3035.2780
Epoch 984/1000
6 - mean_squared_error: 3035.3556
Epoch 985/1000
2 - mean_squared_error: 3035.2412
Epoch 986/1000
9 - mean_squared_error: 3035.1739
Epoch 987/1000
7 - mean squared error: 3035.2737
Epoch 988/1000
3 - mean_squared_error: 3035.2523
Epoch 989/1000
5 - mean_squared_error: 3035.1475
Epoch 990/1000
7 - mean_squared_error: 3035.0647
Epoch 991/1000
6 - mean_squared_error: 3035.0656
Epoch 992/1000
5 - mean_squared_error: 3035.1205
Epoch 993/1000
9 - mean_squared_error: 3035.0599
Epoch 994/1000
3 - mean_squared_error: 3035.1613
Epoch 995/1000
2 - mean_squared_error: 3034.9622
Epoch 996/1000
```

```
7 - mean_squared_error: 3035.0067
       Epoch 997/1000
       4 - mean_squared_error: 3034.9614
       Epoch 998/1000
       5 - mean_squared_error: 3034.9175
       Epoch 999/1000
       8 - mean_squared_error: 3034.9018
       Epoch 1000/1000
       6 - mean_squared_error: 3034.9146
Out[136]: Text(0, 0.5, 'Loss')
                  Graph of Loss vs Number of Epochs
         5500
         5000
         4500
         4000
         3500
         3000
             O
                  200
                        400
                              600
                                   800
                                         1000
                       Number of Epochs
In [137]: y3_pred = model.predict(X)
       y3_pred
Out[137]: array([[58.89272],
             [58.89272],
             [58.89272],
             . . . ,
             [45.636673],
             [45.636673],
             [45.636673]], dtype=float32)
In [138]: W = model.get_weights()
       print(W)
       [array([[16.866497],
             [ 3.6104503]], dtype=float32), array([34.80532], dtype=float32)]
In [139]: import keras
        !pip install pydot
        !pip install graphviz
       import pydot as pyd
       from IPython.display import SVG
       from keras.utils.vis_utils import model_to_dot
```

```
keras.utils.vis_utils.pydot = pyd

#Visualize Model

def visualize_model(model):
    return SVG(model_to_dot(model).create(prog='dot', format='svg'))
#create your model
#then call the function on your model
visualize_model(model)
```

Collecting pydot

Downloading https://files.pythonhosted.org/packages/33/d1/b1479a770f66d9 62f545c2101630ce1d5592d90cb4f083d38862e93d16d2/pydot-1.4.1-py2.py3-none-an y.whl

Requirement already satisfied: pyparsing>=2.1.4 in /opt/conda/envs/Python3 6/lib/python3.6/site-packages (from pydot) (2.3.1)

Installing collected packages: pydot

Successfully installed pydot-1.4.1

Collecting graphviz

Downloading https://files.pythonhosted.org/packages/f5/74/dbed754c0abd63 768d3a7a7b472da35b08ac442cf87d73d5850a6f32391e/graphviz-0.13.2-py2.py3-non e-any.whl

Installing collected packages: graphviz Successfully installed graphviz-0.13.2

Out[139]: G 140080160472144 dense_3: Dense 140080160472984 activation_3: Activation 140080160472144->140080160472984 140080160470632 140080160470632 140080160470632->140080160472144