# DATA SCIENCE - OST

EDA - REPORT 2


BY:

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## Problem Statement: -

1) Finding a relation between the daily minimum and maximum temperature during the World War Two period.
2) Predicting the maximum temperature given the minimum temperature.

## Objective: -

**Weather conditions in the event of World War 2 –**

This dataset has been taken from the website Kaggle.

Our main objective is to find a correlation between the daily minimum and maximum temperature during the World War Two period. Along with this we also want to plot the heatmap to show the correlation between different attributes and construct a regplot to see the regression line fit of the maximum and minimum temperature values. We also want to see the distribution of data points more clearly by constructing the bar plots, box plots and Distplots too. Our aim is to also do a null analysis to remove as much noise as possible and clean the data so that we don't have columns which are of no use to us. We also want to use some statistical functions to find out some important values of the dataset.

## Dataset: -

Weather conditions in the event of World War 2

Source: - The dataset was taken from the famous Machine Learning and Data science community Kaggle.
https://www.kaggle.com/smid80/weatherww2/code

| Column Name | Description |
| --- | --- |
| STA | Weather Station |
| Date | Date |
| Precip | Precipitation in mm |
| WindGustSpd | Peak wind gust speed in km/h |
| MaxTemp | Maximum temperature in degrees Celsius |
| MinTemp | Minimum temperature in degrees Celsius |
| MeanTemp | Mean temperature in degrees Celsius |
| Snowfall | Snowfall and Ice Pellets in mm |
| PoorWeather | Repeated column |
| YR | Year of Observation |
| MO | Month of Observation |
| DA | Day of Observation |
| PRCP | Precipitation in inches and hundredths |

| | |
|---|---|
| DR | Peak wind gust direction in tens of degrees |
| SPD | Peak wind gust speed in knots |
| MAX | Maximum temperature in degrees Fahrenheit |
| MIN | Minimum temperature in degrees Fahrenheit |
| MEA | Mean temperature in degrees Fahrenheit |
| SNF | Snowfall in inches and tenths |
| SND | Snow depth in inches and tenths |
| FT | Frozen Ground Base (depth in inches) |
| ITH | Ice Thickness on Water (in inches and tenths) |
| PGT | Peak wind gust time (in hours and tenths) |
| TSHDSBRSGF | Day with:<br><br>Thunder; Sleet; Hail; Dust or Sand; Smoke or Haze; Blowing Snow; Rain; Snow; Glaze; Fog. |
| SD3 | Snow depth in inches and tenths |
| RHX | 24-hour Maximum relative humidity, as a whole percent |
| RHN | 24-hour Minimum relative humidity, as a whole percent |
| RVG | River gauge in feet and inches |

| | |
|---|---|
| WTE | Water equivalent of snow and ice on ground (in inches and hundredths) |

Author: Shane Smith (smid80 - A kaggle expert from Victoria, Melbourne)

Size: - The dataset contains 119041 rows and 31 columns and is a 11 MB file.

Repository -

1. https://www.ncdc.noaa.gov/data-access/land-based-station-data/land-based-datasets/world-war-ii-era-data
2. https://www.kaggle.com/smid80/weatherww2#:~:text=sort-,Weather%20Station,calendar_today,-Date

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## Literature Survey: -

Temperature prediction is one of the most difficult challenges in weather forecasting. Accurate temperature predictions can be extremely useful in preparing for ongoing battles, wars, building projects, transportation activities, aviation operations, among other things. Weather forecasting is the practice of predicting the state of the atmosphere for a given location based on different weather parameters. Weather forecasts are made by gathering data about the current state of the atmosphere. Accurate weather forecasting has proven to be a challenging task for meteorologists and researchers. Weather information is essential in every facet of life like agriculture, tourism, airport system, mining industry, and power generation. Weather forecasting has now entered the era of Big Data due to the advancement of climate observing systems like satellite meteorological observation and also because of the fast boom in the volume of weather data. So, the traditional computational intelligence models are not adequate to predict the weather accurately. Hence, deep learning-based techniques are employed to process massive datasets that can learn and make predictions more effectively based on past data.

Here in this dataset, we see the importance of a machine learning model capable of predicting the maximum temperature on any day given the minimum temperature. It helps the soldiers and armies in general to plan out their current strategies and improvise to better their

## Steps wise methods Used (From downloading of dataset, processing. Plot and Analysis)

1. Heading over to the website .
2. Downloaded the dataset (2 files)
3. Created a separate folder which includes all the codes and datasets for easy navigation and import operations
4. Created a Jupyter notebook file (with an .ipynb extension)
5. Used Jupyter Notebook and Visual Studio Code as the document for executing code.
6. Imported the necessary libraries like pandas, numpy, folium, seaborn, matplotlib, sklearn.

```
import folium
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import r2_score
from sklearn.linear_model import LinearRegression
```

7. Imported the data using the read_csv method of pandas and also passing parameter of parse_dates to parse the dates present in the data file.

```
df = pd.read_csv("./archive/Summary of Weather.csv", parse_dates=["Date"])
stationLocation = pd.read_csv("./archive/Weather Station Locations.csv")
```

8. Inspected the data using the head method.

```
df.head()  # displays the first 5 rows of dataset 'df'
```

| | STA | Date | Precip | WindGustSpd | MaxTemp | MinTemp | MeanTemp | Snowfall | PoorWeather | YR | ... | FB | FTI | ITH | PGT | TSHDSBRSGF | SD3 | RHX | RHN | RVG | WTE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 10001 | 1942-07-01 | 1.016 | NaN | 25.555556 | 22.222222 | 23.888889 | 0.0 | NaN | 42 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 1 | 10001 | 1942-07-02 | 0 | NaN | 28.888889 | 21.666667 | 25.555556 | 0.0 | NaN | 42 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 2 | 10001 | 1942-07-03 | 2.54 | NaN | 26.111111 | 22.222222 | 24.444444 | 0.0 | NaN | 42 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 3 | 10001 | 1942-07-04 | 2.54 | NaN | 26.666667 | 22.222222 | 24.444444 | 0.0 | NaN | 42 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 4 | 10001 | 1942-07-05 | 0 | NaN | 26.666667 | 21.666667 | 24.444444 | 0.0 | NaN | 42 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

5 rows × 31 columns

```
stationLocation.head()  # displays the first 5 rows of dataset 'stationLocation'
```

| | WBAN | NAME | STATE/COUNTRY ID | LAT | LON | ELEV | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|
| 0 | 33013 | AIN EL | AL | 3623N | 00637E | 611 | 36.383333 | 6.650000 |
| 1 | 33031 | LA SENIA | AL | 3537N | 00037E | 88 | 35.616667 | 0.583333 |
| 2 | 33023 | MAISON BLANCHE | AL | 3643N | 00314E | 23 | 36.716667 | 3.216667 |
| 3 | 33044 | TELERGMA | AL | 3607N | 00621E | 754 | 36.116667 | 6.416667 |
| 4 | 12001 | TINDOUF | AL | 2741N | 00809W | 443 | 27.683333 | -8.083333 |

9. Understood the shape of the dataframe using the shape method. Here, we get the rows and columns of the dataframe

Understanding the shape and columns of the dataframe

```
df.shape  # tuple of the dimensions of the dataframe
```

```
(119040, 31)
```

```
stationLocation.shape
```

```
(161, 8)
```

10. Listed all the columns in the data frame along with their data type

```
df.dtypes   # data types of all columns in the dataframe.

STA                    int64
Date          datetime64[ns]
Precip                object
WindGustSpd          float64
MaxTemp              float64
MinTemp              float64
MeanTemp             float64
Snowfall              object
PoorWeather           object
YR                     int64
MO                     int64
DA                     int64
PRCP                  object
DR                   float64
SPD                  float64
MAX                  float64
MIN                  float64
MEA                  float64
SNF                   object
SND                  float64
FT                   float64
FB                   float64
FTI                  float64
ITH                  float64
PGT                  float64

show more (open the raw output data in a text editor) ...

SD3                  float64
RHX                  float64
RHN                  float64
RVG                  float64
WTE                  float64
dtype: object
```

11. Used the info method to see the number of null values in the data frame

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119040 entries, 0 to 119039
Data columns (total 31 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   STA          119040 non-null  int64
 1   Date         119040 non-null  datetime64[ns]
 2   Precip       119040 non-null  object
 3   WindGustSpd  532 non-null     float64
 4   MaxTemp      119040 non-null  float64
 5   MinTemp      119040 non-null  float64
 6   MeanTemp     119040 non-null  float64
 7   Snowfall     117877 non-null  object
 8   PoorWeather  34237 non-null   object
 9   YR           119040 non-null  int64
 10  MO           119040 non-null  int64
 11  DA           119040 non-null  int64
 12  PRCP         117108 non-null  object
 13  DR           533 non-null     float64
 14  SPD          532 non-null     float64
 15  MAX          118566 non-null  float64
 16  MIN          118572 non-null  float64
 17  MEA          118542 non-null  float64
 18  SNF          117877 non-null  object
 19  SND          5563 non-null    float64

show more (open the raw output data in a text editor) ...

 28  RHN          0 non-null       float64
 29  RVG          0 non-null       float64
 30  WTE          0 non-null       float64
dtypes: datetime64[ns](1), float64(20), int64(4), object(6)
memory usage: 28.2+ MB
```

12. Calculated the percentages of null value in each column and sorted them

```
# Calculating the percentages of null values in each column
naPercentMiss = df.isnull().sum() * 100 / len(df)
missingDF = pd.DataFrame({"column_name": df.columns, "percent_missing": naPercentMiss})

naPercentMiss.sort_values(
    ascending=False
)  # printing the percentages of null values in each column in a sorted manner
```

```
WTE           100.000000
FT            100.000000
RVG           100.000000
FB            100.000000
RHN           100.000000
RHX           100.000000
SD3           100.000000
FTI           100.000000
ITH           100.000000
PGT            99.558972
SPD            99.553091
WindGustSpd    99.553091
DR             99.552251
SND            95.326781
TSHDSBRSGF     71.239079
PoorWeather    71.239079
PRCP            1.622984
Snowfall        0.976983
SNF             0.976983
MEA             0.418347
MAX             0.398185
MIN             0.393145
Date            0.000000
DA              0.000000
MO              0.000000

show more (open the raw output data in a text editor) ...

MeanTemp        0.000000
MinTemp         0.000000
MaxTemp         0.000000
```

13. Grouped on the column STA (Weather Station) to get the mean of each column for each station.

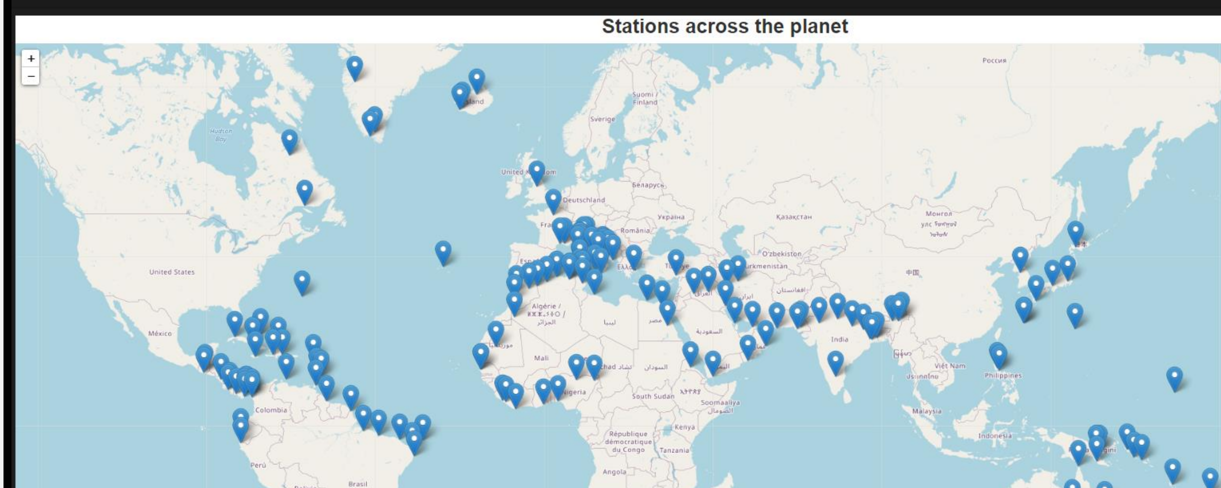
```
df.groupby("STA").mean()  # displays the mean of each column for each station
```

| STA | WindGustSpd | MaxTemp | MinTemp | MeanTemp | YR | MO | DA | DR | SPD | MAX | ... | FT | FB | FTI | ITH | PGT | SD3 | RHX | RHN | RVG | WTE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 10001 | NaN | 30.496975 | 22.520407 | 26.514933 | 43.576491 | 6.578220 | 15.758859 | NaN | NaN | 86.894555 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 10002 | NaN | 28.715983 | 23.565062 | 26.137255 | 44.172193 | 7.094118 | 15.859893 | NaN | NaN | 83.688770 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 10101 | NaN | 29.979889 | 22.375566 | 26.153008 | 43.924585 | 6.594268 | 15.790347 | NaN | NaN | 85.963801 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 10102 | NaN | 30.367892 | 22.199475 | 26.286527 | 43.725984 | 6.948819 | 15.828346 | NaN | NaN | 86.662205 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 10502 | NaN | 30.877901 | 21.409445 | 26.138034 | 43.309758 | 6.925344 | 15.768828 | NaN | NaN | 87.580223 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 82405 | NaN | 26.687042 | 16.312823 | 21.505026 | 44.002445 | 6.485330 | 15.853301 | NaN | NaN | 80.036675 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 82501 | NaN | 24.741935 | 11.430108 | 18.097969 | 43.513978 | 6.556989 | 15.881720 | NaN | NaN | 76.535484 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 82502 | NaN | 26.584119 | 12.229429 | 19.390723 | 43.870283 | 6.272406 | 15.786557 | NaN | NaN | 79.851415 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 82503 | NaN | 29.087981 | 16.085493 | 22.583077 | 44.140975 | 6.583663 | 15.776021 | NaN | NaN | 84.358366 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 82506 | NaN | 26.883534 | 15.677376 | 21.255689 | 44.802410 | 7.272289 | 15.961446 | NaN | NaN | 80.390361 | ... | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

159 rows × 23 columns

14. Used folium to add markets on the world map to see the location of each weather station.

```
stationMap = folium.Map(width=1920, height=1080, zoom_start=6)

for _, row in stationLocation.iterrows():
    folium.Marker(location=[row["Latitude"], row["Longitude"]]).add_to(stationMap)

title_html = f"""
            <h1 align="center" style="font-size:30px"><b>{"Stations across the planet"}</b></h1>
            """

# Adding title to the map
stationMap.get_root().html.add_child(folium.Element(title_html))

stationMap
```



15. Displayed the summary of MaxTemp, MinTemp and STA.

```python
df[
    ["STA", "MaxTemp", "MinTemp"]
].describe()  # displays the summary of MaxTemp, MinTemp for each station
```

| | STA | MaxTemp | MinTemp |
|---|---|---|---|
| count | 119040.000000 | 119040.000000 | 119040.000000 |
| mean | 29659.435795 | 27.045111 | 17.789511 |
| std | 20953.209402 | 8.717817 | 8.334572 |
| min | 10001.000000 | -33.333333 | -38.333333 |
| 25% | 11801.000000 | 25.555556 | 15.000000 |
| 50% | 22508.000000 | 29.444444 | 21.111111 |
| 75% | 33501.000000 | 31.666667 | 23.333333 |
| max | 82506.000000 | 50.000000 | 34.444444 |

16. Described the summary statistics of all columns in the dataframe.

```python
df.describe()  # summary statistics of all columns in the dataframe.
```

Python

| | STA | WindGustSpd | MaxTemp | MinTemp | MeanTemp | YR | MO | DA | DR | SPD |
|---|---|---|---|---|---|---|---|---|---|---|
| count | 119040.000000 | 532.000000 | 119040.000000 | 119040.000000 | 119040.000000 | 119040.000000 | 119040.000000 | 119040.000000 | 533.000000 | 532.000000 |
| mean | 29659.435795 | 37.774534 | 27.045111 | 17.789511 | 22.411631 | 43.805284 | 6.726016 | 15.797530 | 26.998124 | 20.396617 |
| std | 20953.209402 | 10.297808 | 8.717817 | 8.334572 | 8.297982 | 1.136718 | 3.425561 | 8.794541 | 15.221732 | 5.560371 |
| min | 10001.000000 | 18.520000 | -33.333333 | -38.333333 | -35.555556 | 40.000000 | 1.000000 | 1.000000 | 2.000000 | 10.000000 |
| 25% | 11801.000000 | 29.632000 | 25.555556 | 15.000000 | 20.555556 | 43.000000 | 4.000000 | 8.000000 | 11.000000 | 16.000000 |
| 50% | 22508.000000 | 37.040000 | 29.444444 | 21.111111 | 25.555556 | 44.000000 | 7.000000 | 16.000000 | 32.000000 | 20.000000 |
| 75% | 33501.000000 | 43.059000 | 31.666667 | 23.333333 | 27.222222 | 45.000000 | 10.000000 | 23.000000 | 34.000000 | 23.250000 |
| max | 82506.000000 | 75.932000 | 50.000000 | 34.444444 | 40.000000 | 45.000000 | 12.000000 | 31.000000 | 78.000000 | 41.000000 |

| | ... | FT | FB | FTI | ITH | PGT | SD3 | RHX | RHN | RVG | WTE |
|---|---|---|---|---|---|---|---|---|---|---|---|
| count | ... | 0.0 | 0.0 | 0.0 | 0.0 | 525.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| mean | ... | NaN | NaN | NaN | NaN | 12.085333 | NaN | NaN | NaN | NaN | NaN |
| std | ... | NaN | NaN | NaN | NaN | 5.731328 | NaN | NaN | NaN | NaN | NaN |
| min | ... | NaN | NaN | NaN | NaN | 0.000000 | NaN | NaN | NaN | NaN | NaN |
| 25% | ... | NaN | NaN | NaN | NaN | 8.500000 | NaN | NaN | NaN | NaN | NaN |
| 50% | ... | NaN | NaN | NaN | NaN | 11.600000 | NaN | NaN | NaN | NaN | NaN |
| 75% | ... | NaN | NaN | NaN | NaN | 15.000000 | NaN | NaN | NaN | NaN | NaN |
| max | ... | NaN | NaN | NaN | NaN | 23.900000 | NaN | NaN | NaN | NaN | NaN |

8 rows × 24 columns

17. Displayed the count of null values in each column

```
df.isnull().sum()  # count of null values in each column
```

```
STA                 0
Date                0
Precip              0
WindGustSpd    118508
MaxTemp             0
MinTemp             0
MeanTemp            0
Snowfall         1163
PoorWeather     84803
YR                  0
MO                  0
DA                  0
PRCP             1932
DR             118507
SPD            118508
MAX               474
MIN               468
MEA               498
SNF              1163
SND            113477
FT             119040
FB             119040
FTI            119040
ITH            119040
PGT            118515
show more (open the raw output data in a text editor) ...
SD3            119040
RHX            119040
RHN            119040
RVG            119040
WTE            119040
dtype: int64
```

18. Selected all indian stations

```
# Station locations in India
indianStations = stationLocation[stationLocation["STATE/COUNTRY ID"] == "IN"]
indianStations
```

| | WBAN | NAME | STATE/COUNTRY ID | LAT | LON | ELEV | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|
| 66 | 32701 | AGRA | IN | 2710N | 07802E | 167 | 27.166667 | 78.100000 |
| 67 | 32801 | BAMRAULI | IN | 2526N | 08150E | 98 | 25.433333 | 81.833333 |
| 68 | 31701 | BANGALORE | IN | 1257N | 07738E | 897 | 12.950000 | 77.583333 |
| 69 | 32815 | BARRACKPORE | IN | 2246N | 08822E | 7 | 22.766667 | 88.366667 |
| 70 | 32907 | BINDUKURI | IN | 2643N | 09248E | 75 | 26.716667 | 92.716667 |
| 71 | 32803 | CHAKULIA | IN | 2227N | 08642E | 131 | 22.450000 | 86.716667 |
| 72 | 32805 | GAYA | IN | 2445N | 08457E | 115 | 24.750000 | 84.966667 |
| 73 | 32702 | JODHPUR | IN | 2616N | 07303E | 228 | 26.266667 | 73.133333 |
| 74 | 32904 | JORHAT | IN | 2643N | 09410E | 93 | 26.716667 | 94.166667 |
| 75 | 32812 | KALAIKUNDA | IN | 2220N | 08713E | 61 | 22.333333 | 87.233333 |
| 76 | 32906 | MOHANBERI | IN | 2729N | 09501E | 111 | 27.483333 | 95.116667 |

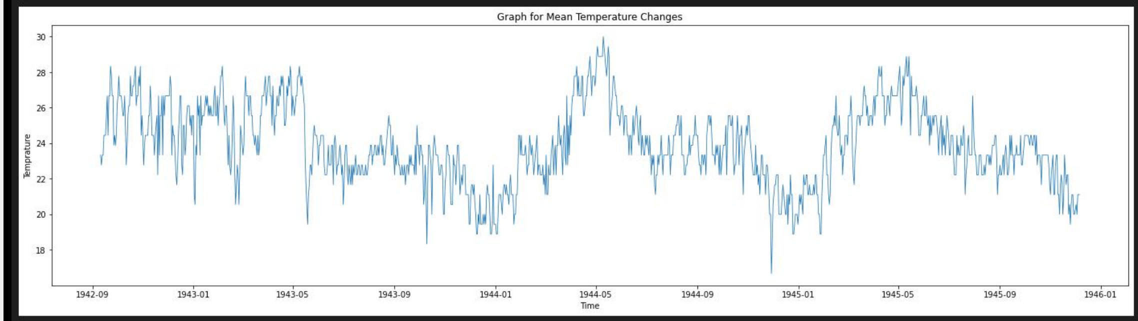
19. Out of all the above ones, selected the Bangalore station.

```
# Selecting the station in Bangalore.

blrStation = stationLocation[stationLocation["NAME"] == "BANGALORE"]
blrStation
```

| | WBAN | NAME | STATE/COUNTRY ID | LAT | LON | ELEV | Latitude | Longitude |
|---|---|---|---|---|---|---|---|---|
| 68 | 31701 | BANGALORE | IN | 1257N | 07738E | 897 | 12.95 | 77.583333 |

20. Displayed the graph for Mean Temperature changes.

```
plt.figure(figsize = (24,6))
plt.plot(blr.Date, blr.MeanTemp, linewidth = 0.8);

title = 'Graph for Mean Temperature Changes'
x_label = 'Time'
y_label = 'Temprature'

plt.title(title)
plt.xlabel(x_label)
plt.ylabel(y_label)
plt.show()
```



21. Cleaned the dataset by removing columns with High amount of Null values and the ones which are very less correlated with the target variable (Here, maxTemp.)

```python
# storing the unnecessary columns in a list
unnecessaryCols = [
    "MO",
    "YR",
    "DA",
    "Precip",
    "STA",
    "PoorWeather",
    "WindGustSpd",
    "TSHDSBRSGF",
    "Date",
    "PRCP",
    "DR",
    "Snowfall",
    "SPD",
    "SNF",
    "SND",
    "FT",
    "FB",
    "FTI",
    "ITH",
    "PGT",
    "SD3",
    "RHX",
    "RHN",
    "RVG",
    "WTE",
]


# dropping the unnecessary columns in df and storing new dataframe in newDf
newDf = df.drop(unnecessaryCols, axis=1)
```

22. Displayed the new dataframe after cleaning

```
newDf.head()
```

| | MaxTemp | MinTemp | MeanTemp | MAX | MIN | MEA |
|---|---|---|---|---|---|---|
| 0 | 25.555556 | 22.222222 | 23.888889 | 78.0 | 72.0 | 75.0 |
| 1 | 28.888889 | 21.666667 | 25.555556 | 84.0 | 71.0 | 78.0 |
| 2 | 26.111111 | 22.222222 | 24.444444 | 79.0 | 72.0 | 76.0 |
| 3 | 26.666667 | 22.222222 | 24.444444 | 80.0 | 72.0 | 76.0 |
| 4 | 26.666667 | 21.666667 | 24.444444 | 80.0 | 71.0 | 76.0 |

23. Checking for count of null values in this new dataframe.

```
# count of null values in newDf column-wise
newDf.isnull().sum()
```

```
MaxTemp       0
MinTemp       0
MeanTemp      0
MAX         474
MIN         468
MEA         498
dtype: int64
```

24. Removing any null/missing values

```python
# removing any null/missing values
newDf = newDf[~newDf["MAX"].isna()]
newDf = newDf[~newDf["MIN"].isna()]
newDf = newDf[~newDf["MEA"].isna()]
```

```python
newDf.isnull().sum() #number of null values in column-wise in newDf
```

```
MaxTemp     0
MinTemp     0
MeanTemp    0
MAX         0
MIN         0
MEA         0
dtype: int64
```

25. Used the info method on the new dataframe after cleaning

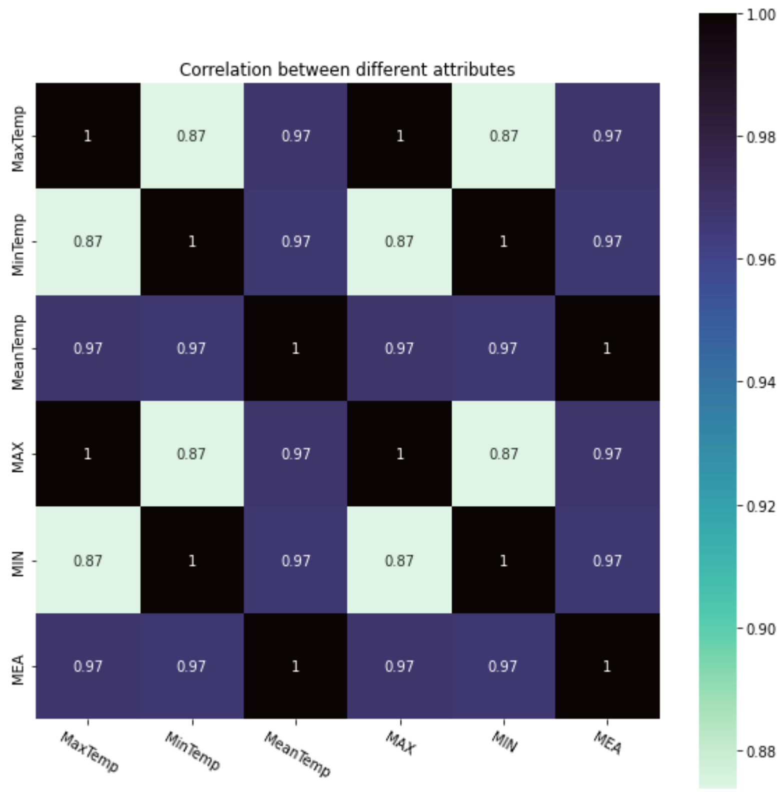
```python
newDf.info()  # printing summary of new dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 118540 entries, 0 to 119039
Data columns (total 6 columns):
 #   Column    Non-Null Count   Dtype  
---  ------    --------------   -----  
 0   MaxTemp   118540 non-null  float64
 1   MinTemp   118540 non-null  float64
 2   MeanTemp  118540 non-null  float64
 3   MAX       118540 non-null  float64
 4   MIN       118540 non-null  float64
 5   MEA       118540 non-null  float64
dtypes: float64(6)
memory usage: 6.3 MB
```

26. Started to visualize the data using Matplotlib, Seaborn.

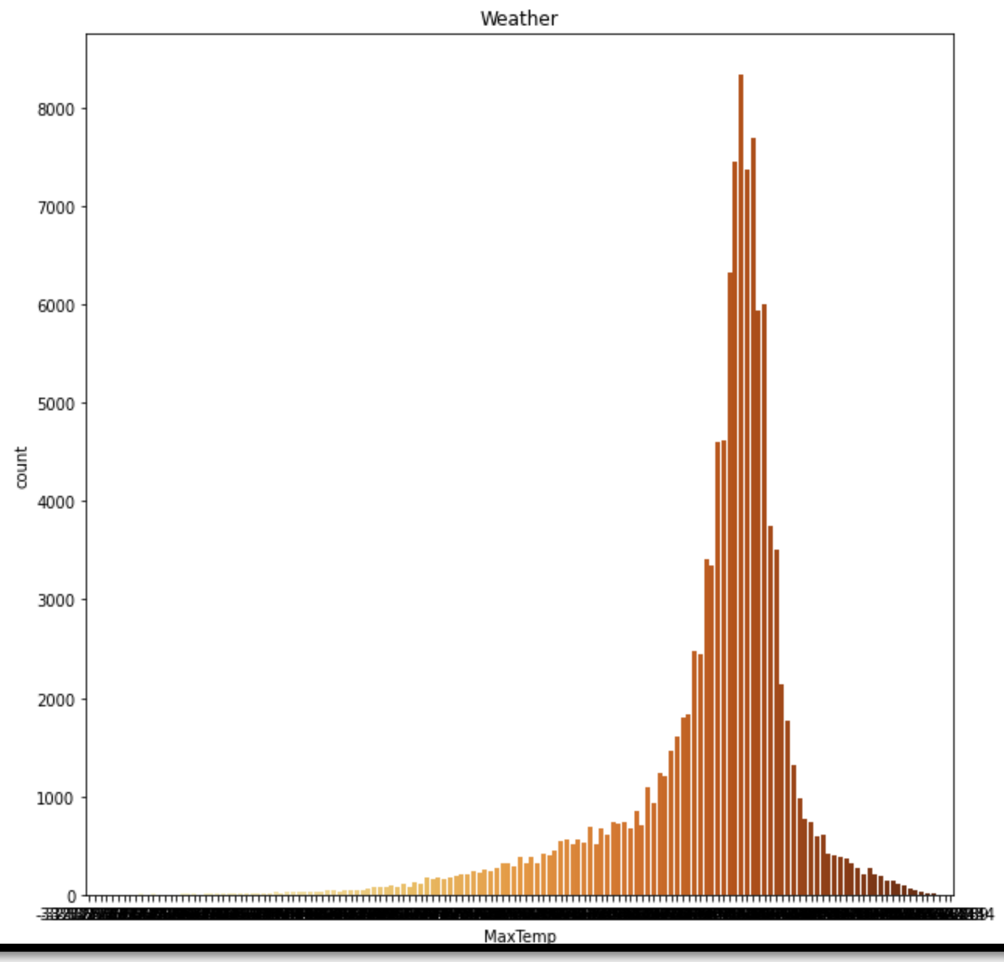
27. Generated heatmap for understanding correlation between the temperatures

```
# Generating heatmap for understanding correlation between the temperatures
plt.figure(figsize=(10, 10))
sns.heatmap(newDf.corr(),vmax=1, annot=True,square=True,cmap='mako_r')
plt.title("Correlation between different attributes")
plt.xticks(rotation=-30)
plt.show()
```



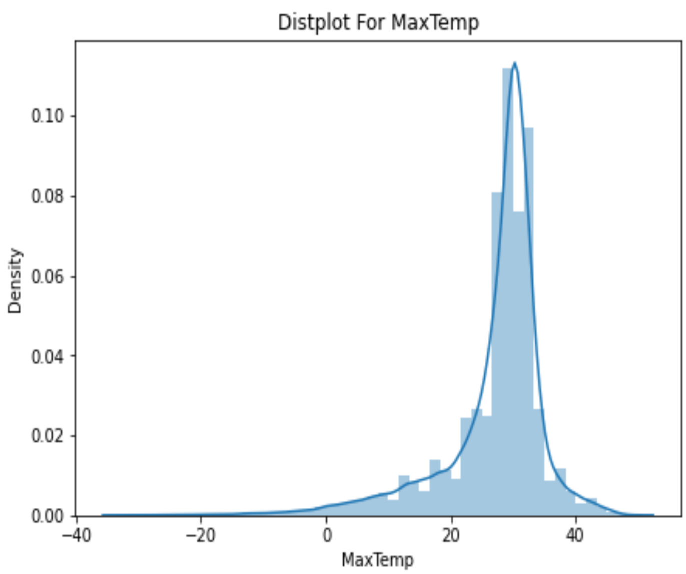
28. Generated the countplot for maxTemp

```
# Generating the countplot for Maxtemp
plt.figure(figsize=(10, 10))
sns.countplot(x="MaxTemp", data=newDf, palette="YlOrBr")
plt.title("Weather")
plt.show()
```



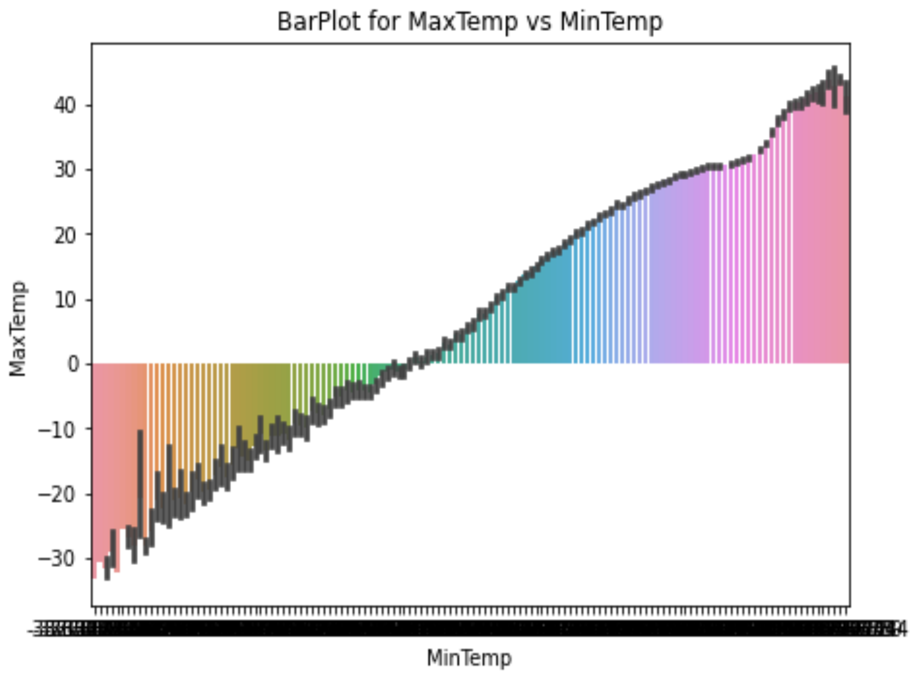
29. Generated the distplot for MaxTemp

```
# Generating the distplot for MaxTemp (density wise distribution)
plt.figure(figsize=(7,5))
plt.title("Distplot For MaxTemp")
sns.distplot(newDf["MaxTemp"])
plt.show()
```



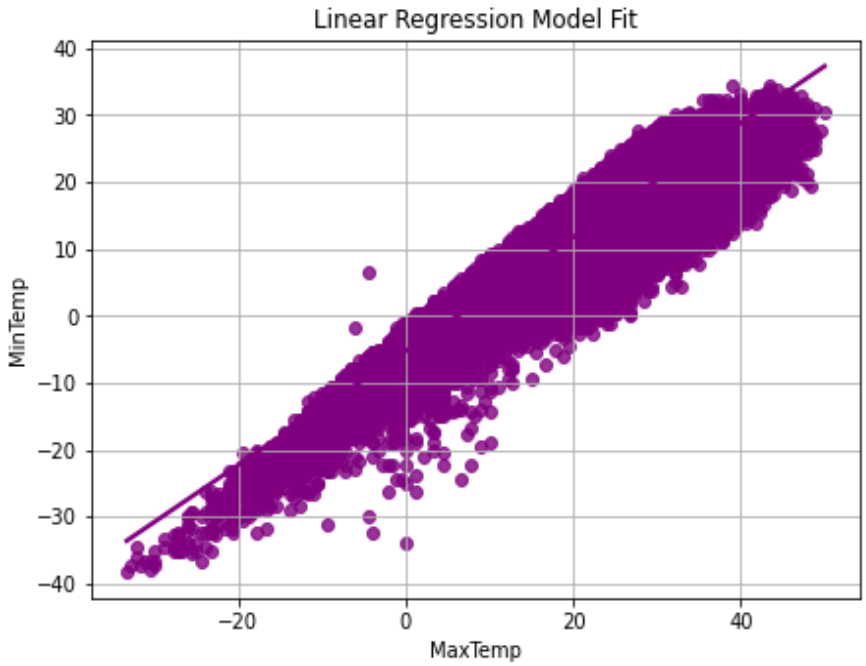
30. Generated the barplot for MinTemp vs MaxTemp

```
# Barplot for MaxTemp vs MinTemp
plt.figure(figsize=(7,5))
sns.barplot(x="MinTemp", y="MaxTemp", data=newDf)
plt.title("BarPlot for MaxTemp vs MinTemp")
plt.show()
```



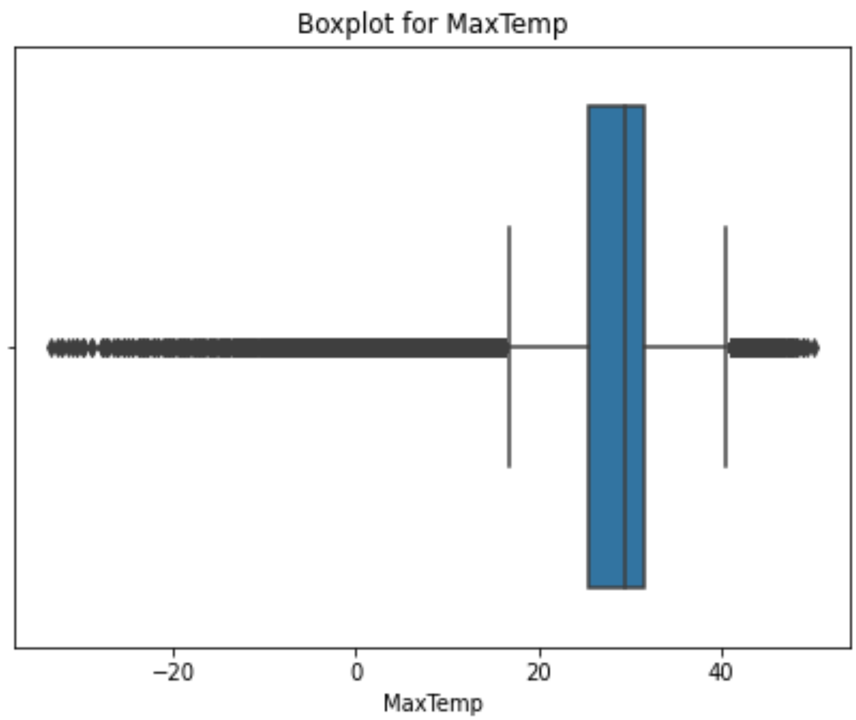
31. Displayed a Regplot to see the Linear Regression model fit

```
# Regplot generated to see the Linear regression model fit
plt.figure(figsize=(7,5))
sns.regplot(x="MaxTemp", y="MinTemp", data=newDf,color='purple')
plt.title("Linear Regression Model Fit")
plt.grid()
plt.show()
```



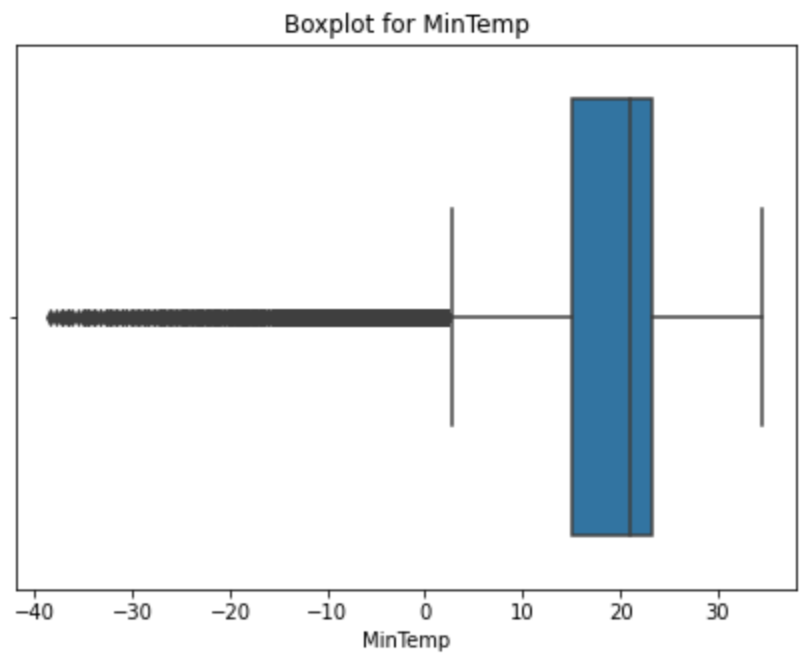
32. Displayed the boxplot for maxTemp

```python
# BoxPlot for Max Temp
plt.figure(figsize=(7,5))
plt.title("Boxplot for MaxTemp")
sns.boxplot(x="MaxTemp", data=newDf)
plt.show()
```



33. Displayed the boxplot for minTemp

```
# Boxplot for Min Temp
plt.figure(figsize=(7,5))
plt.title("Boxplot for MinTemp")
sns.boxplot(x=newDf["MinTemp"])
plt.show()
```




34. Split the dataset into training and testing by making use of the model_selection found in sklearn.

```
X = np.array(newDf["MinTemp"]).reshape(-1, 1)  # dataframe containing all MinTemp values
y = np.array(newDf["MaxTemp"])  # dataframe containing all MaxTemp values
```

```
# Using the train_test_split function from sklearn to split the data for training and testing
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

35. Built a Linear Regression model for this by making use of sklearn library.

```
# Performing Linear regression
LinearRegressor = LinearRegression()
LinearRegressor.fit(X_train, y_train)
[46]
... LinearRegression()

y_pred = LinearRegressor.predict(X_test)
print(y_pred)  # displaying the predictions of Max temperatures
[47]
... [29.58951776 16.64451689 29.58951776 ... 31.08317171 32.57682565
 26.10432522]
```

36. Evaluating the model using a custom function which calls sklearn methods and displays the R2 Score, Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)

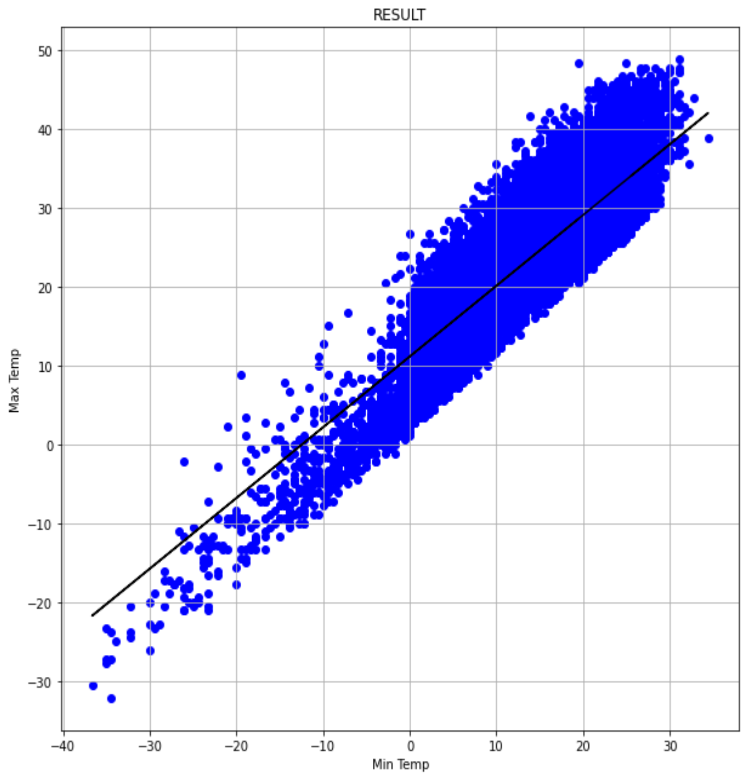
```
from sklearn.metrics import mean_squared_error, r2_score


def all_metrics(y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    report = f"""
    R2 Score: {r2_score(y_test,y_pred):.3f}
    MSE: {mse:.3f}
    RMSE: {np.sqrt(mse):.3f}
    """

    return report
```

37. Running the function along with the graph

```
all_metrics(y_test,y_pred)
```

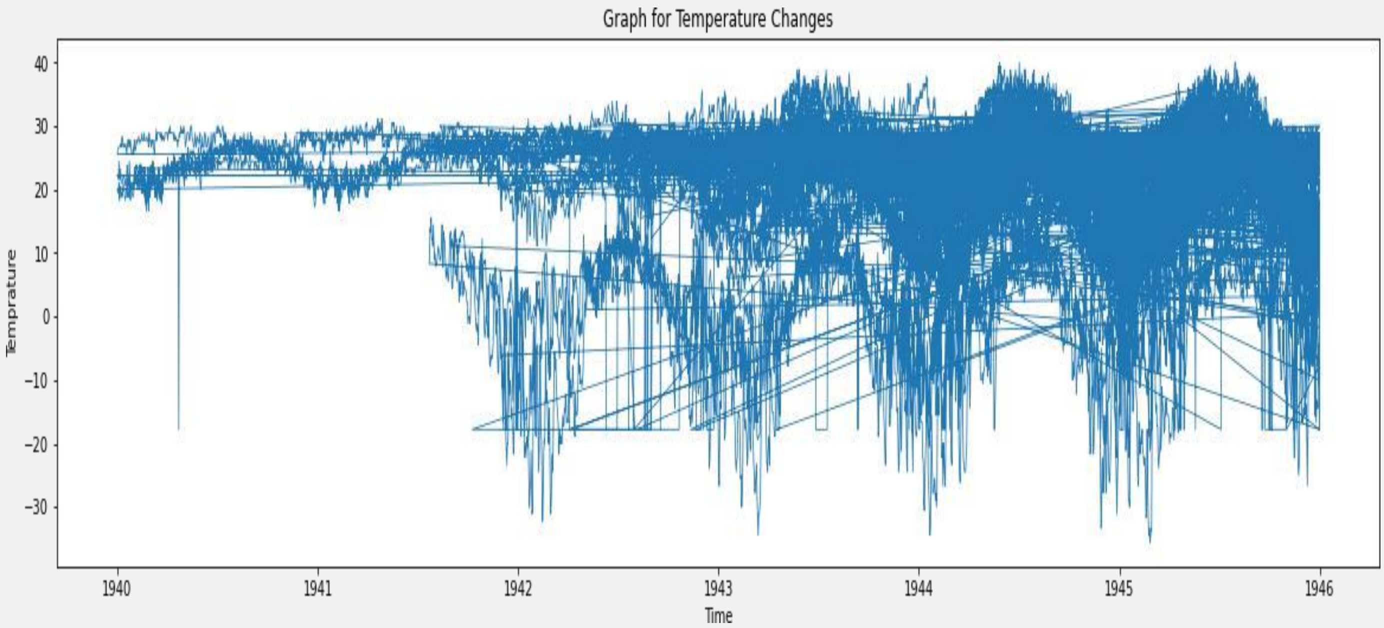
```
'R2 Score: 0.764     MSE: 15.967     RMSE: 3.996'
```

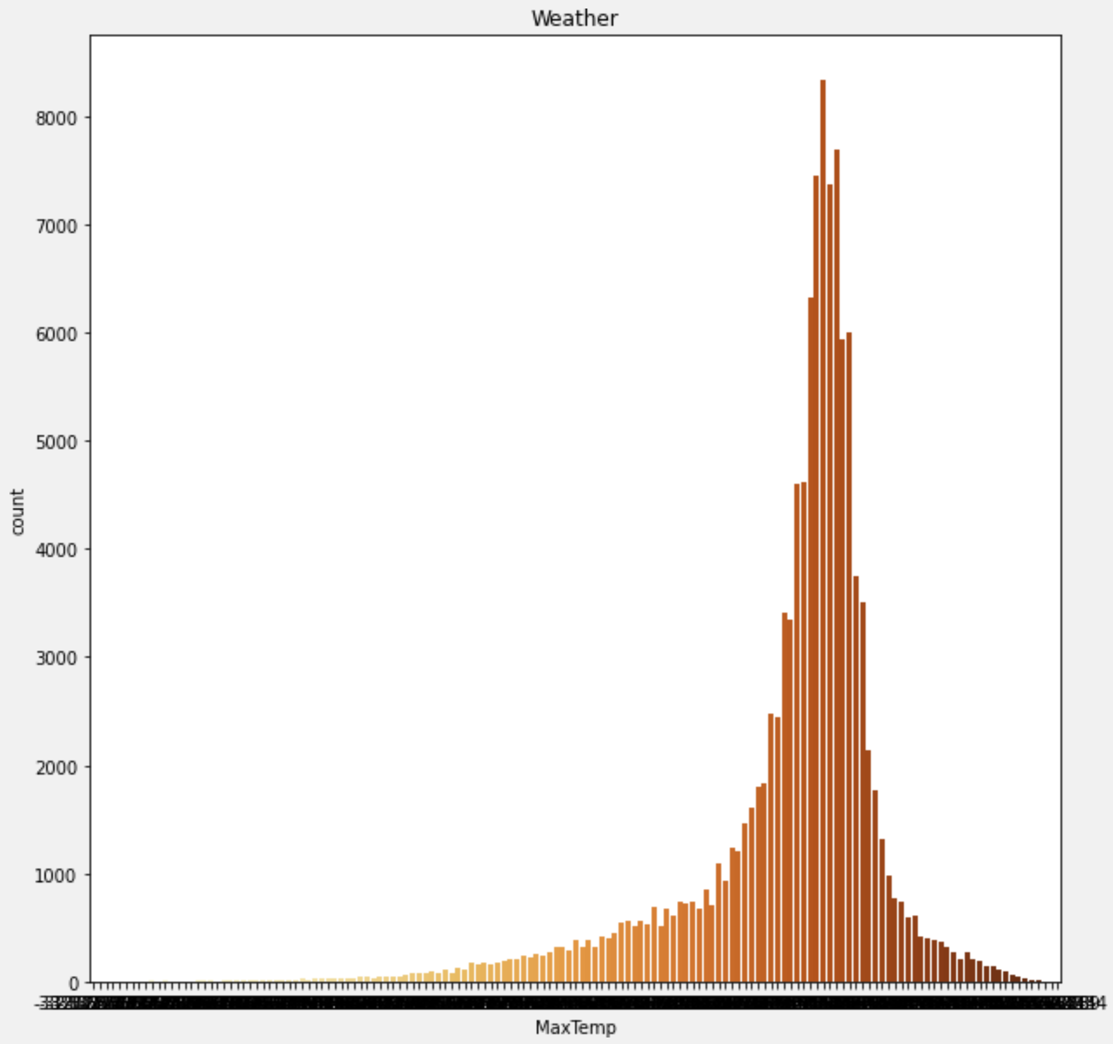
```
plt.figure(figsize=(10,10))
plt.scatter(X_test, y_test, color="b")
plt.plot(X_test, y_pred, color="k")
plt.xlabel("Min Temp")
plt.ylabel("Max Temp")
plt.title("RESULT")
plt.grid()
plt.show()
```



## FEATURE ENGINEERING

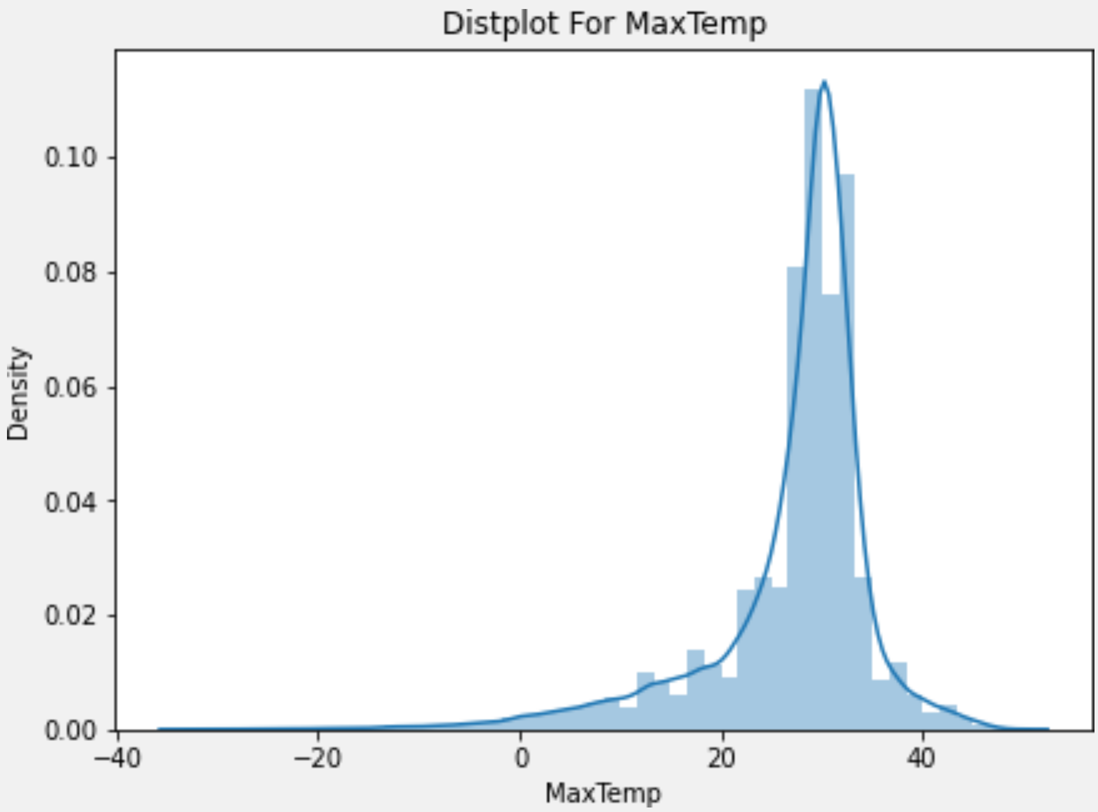
```
[ ]: #Graph that shows the temperature changes over the years
    plt.figure(figsize = (20,5))
    plt.plot(df.Date, df.MeanTemp, linewidth = 0.8);

    title = 'Graph for Temperature
    Changes' x_label = 'Time'
    y_label = 'Temprature'

    plt.title(title)
    plt.xlabel(x_la
    bel)
    plt.ylabel(y_la
    bel)
    plt.show()
```





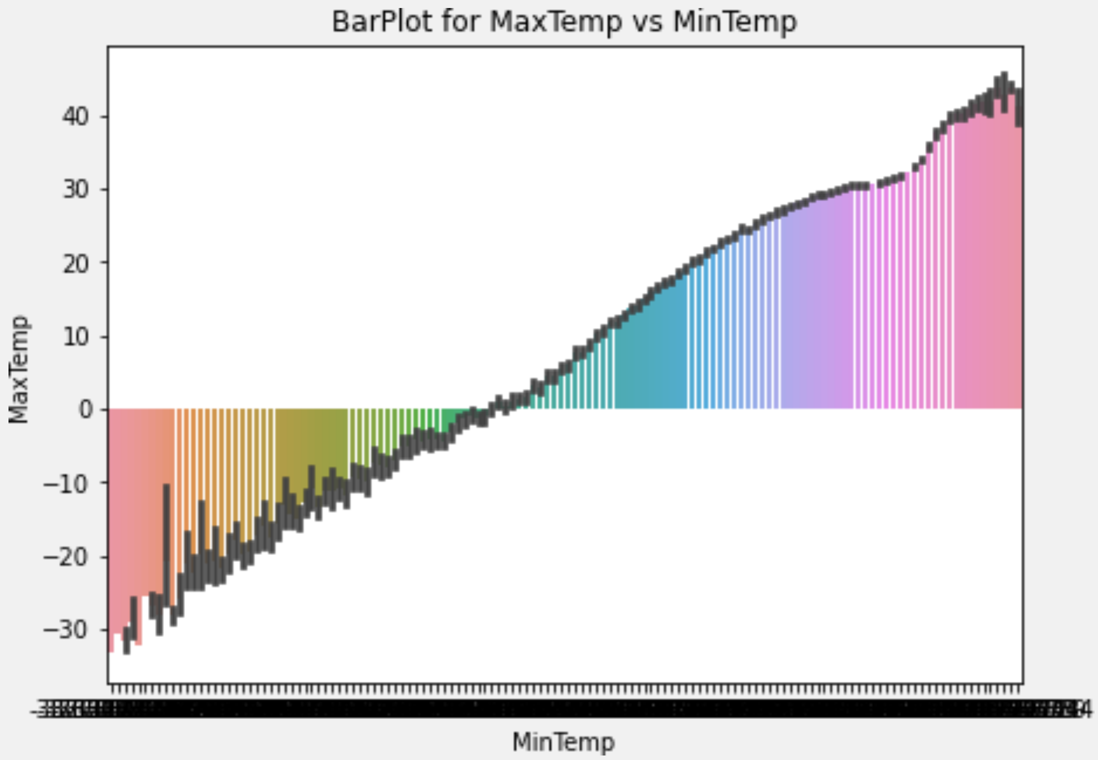

[ ]:

```
# Generating the countplot for Maxtemp
plt.figure(figsize=(10, 10))
sns.countplot(x="MaxTemp", data=newDf, palette="YlOrBr")
plt.title("Weather")
plt.show()
```

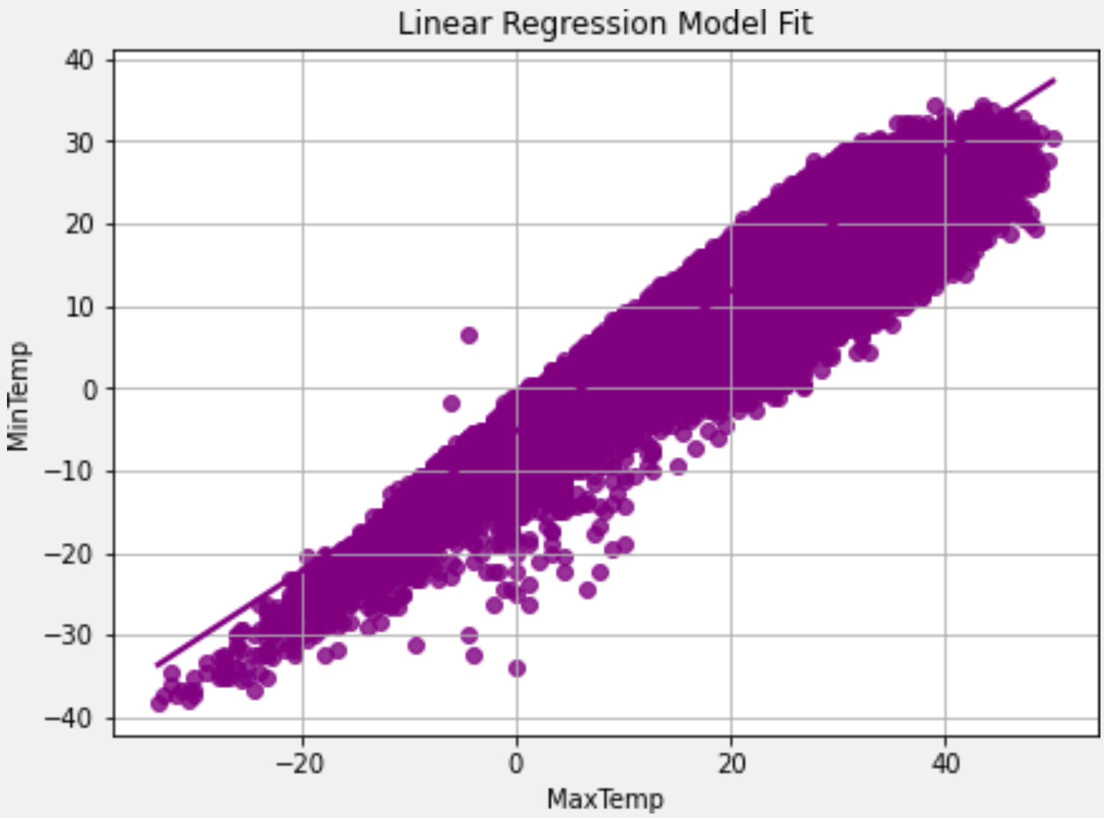



[ ]:

```
# Generating the distplot for MaxTemp (density wise distribution)
plt.figure(figsize=(7,5)) plt.title("Distplot
For MaxTemp")
sns.distplot(newDf["MaxTemp"])
plt.show()
```

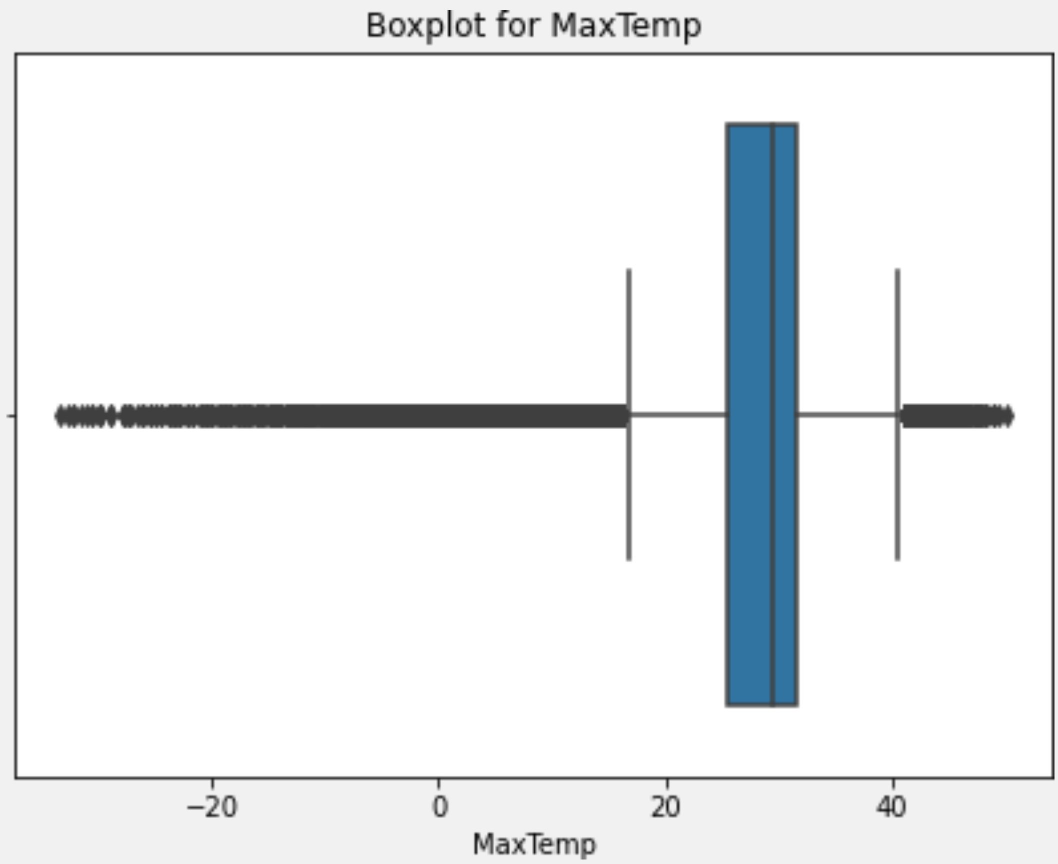



```
# Barplot for MaxTemp vs MinTemp
plt.figure(figsize=(7,5)) sns.barplot(x="MinTemp",
y="MaxTemp", data=newDf) plt.title("BarPlot for MaxTemp vs
MinTemp") plt.show()
```



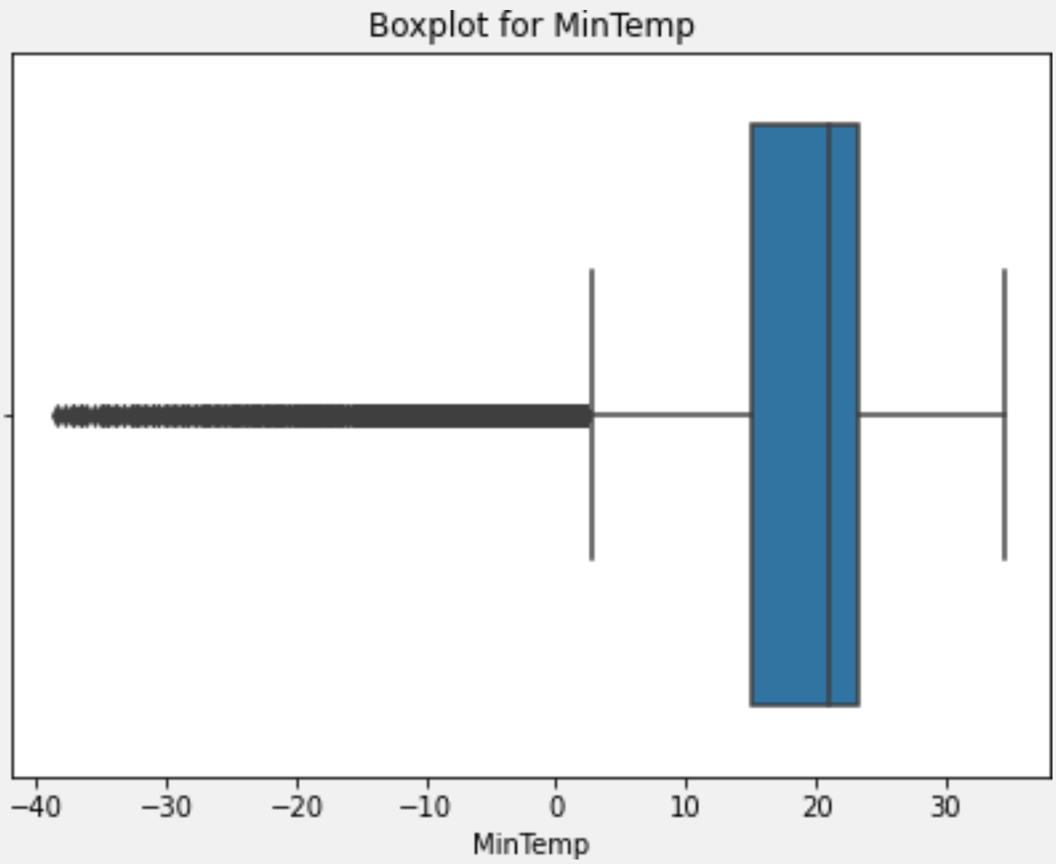

[ ]:

```
# Regplot generated to see the Linear regression model fit
plt.figure(figsize=(7,5))
sns.regplot(x="MaxTemp", y="MinTemp", data=newDf,color='purple')
plt.title("Linear Regression Model Fit")
plt.grid()
plt.show()
```




[ ]:

```
# BoxPlot for Max Temp
plt.figure(figsize=(7,5)) plt.title("Boxplot for
MaxTemp") sns.boxplot(x="MaxTemp",
data=newDf) plt.show()
```




[ ]:

```
# Boxplot for Min Temp
plt.figure(figsize=(7,5)) plt.title("Boxplot
for MinTemp")
sns.boxplot(x=newDf["MinTemp"])
plt.show()
```

# MODEL BUILDING

## 8 Building a Linear Regression Model

[ ]:
```
# Performing Linear regression
LinearRegressor = LinearRegression()
LinearRegressor.fit(X_train, y_train)
```

[ ]: LinearRegression()

[ ]:
```
y_pred = LinearRegressor.predict(X_test)
print(y_pred)         # displaying the predictions of Max temperatures
```

```
[28.58516195 16.62071917 30.57923575 ... 14.62664537 30.0807173
 34.0688649 ]
```

### 8.1 Metrics

[ ]:
```
from sklearn.metrics import mean_squared_error, r2_score


def all_metrics(y_test, y_pred):
        mse = mean_squared_error(y_test, y_pred) report
        = f"""
        R2 Score: {r2_score(y_test,y_pred):.3f}
        MSE: {mse:.3f}
        RMSE: {np.sqrt(mse):.3f}
        """

        return report
```

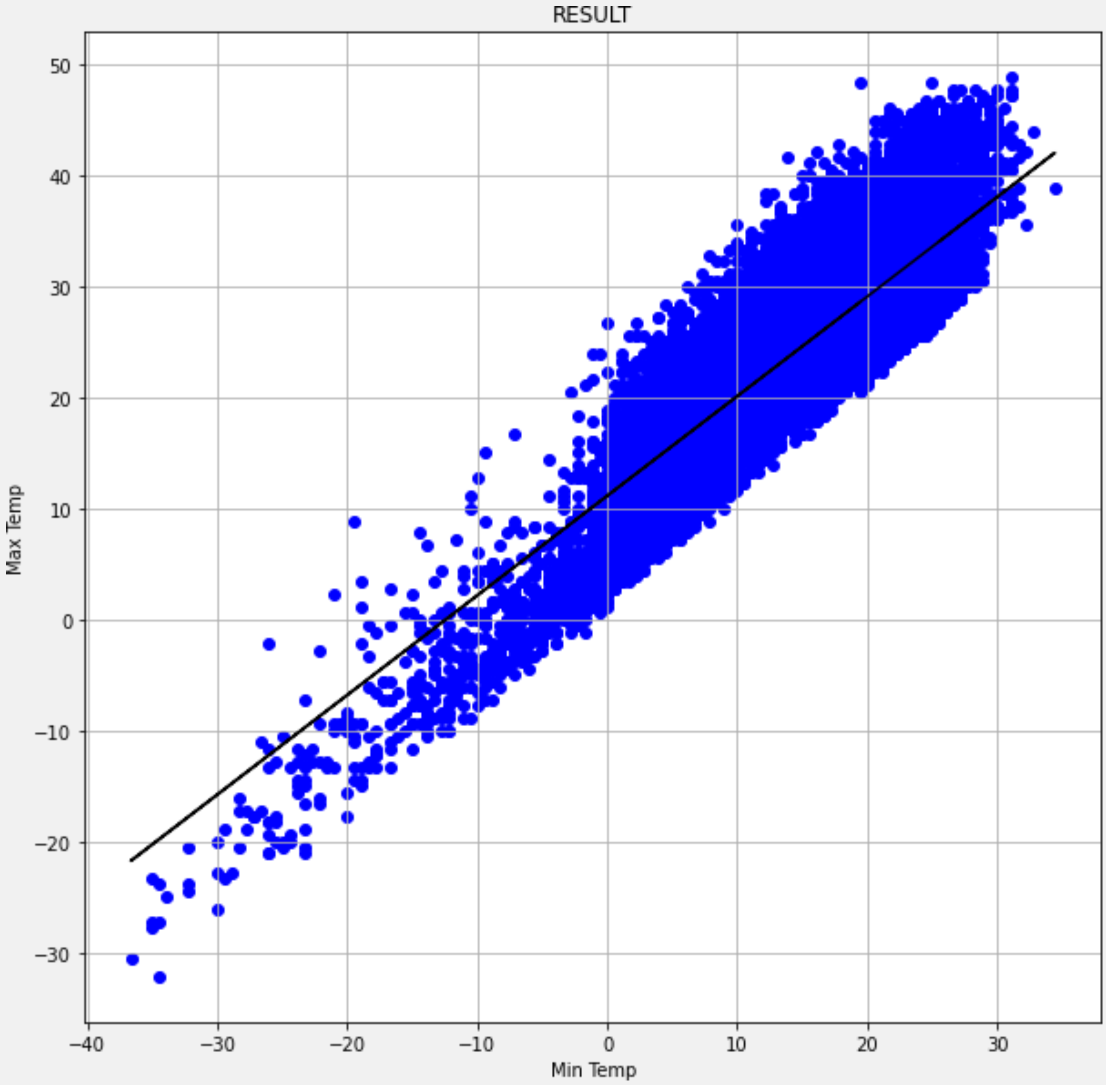
[ ]:
```
# Score function used to display the prediction accuracy of Max temp
r2_score(y_test, y_pred)
```

[ ]: 0.7636890458605848

[ ]:
```
all_metrics(y_test,y_pred)
```

[ ]: '\n          R2 Score: 0.764\n          MSE: 15.967\n          RMSE: 3.996\n          '

[ ]:
```
plt.figure(figsize=(10,10))
plt.scatter(X_test, y_test, color="b")
plt.plot(X_test, y_pred, color="k")
plt.xlabel("Min Temp")
plt.ylabel("Max Temp")
plt.title("RESULT") plt.grid()
plt.show()
```


RESULT
50
40
30
20
10
0
−10
−20
−30
Max Temp
−40
−30
−20
−10
0
10
20
30
Min Temp

# Iteration/Improving Output

## COMPARING REGRESSION MODELS

```
import os
from pandas import DataFrame,Series
from sklearn import tree
import matplotlib
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.preprocessing import StandardScaler
import statsmodels.formula.api as smf
import statsmodels.api as sm
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
from sklearn import neighbors
from sklearn import linear_model
%matplotlib inline
```

### 8.1.1 RIDGE REGRESSION

[ ]:
```
model=linear_model.Ridge()
model.fit(X_train,y_train)
y_predict=model.predict(X_train)

error=0
for i in range(len(y_train)):
	error+=(abs(y_train[i]-y_predict[i]))
train_error_ridge=error/len(y_train)
train_error_ridge
print("Average Train error (Each reading) = "'{}'.format(train_error_ridge)+"
 ↪in Ridge Regression")

y_Predict=model.predict(X_test)

error=0
for i in range(len(y_test)):
	error+=(abs(y_Predict[i]-y_test[i]))
test_error_ridge=error/len(y_test)
print("Average Test error (Each reading) = "'{}'.format(test_error_ridge)+" in
 ↪Ridge Regression")

R2_ridge = r2_score(y_test,y_Predict)
print ("R2 score of Ridge Regression = "+str(R2_ridge))
```

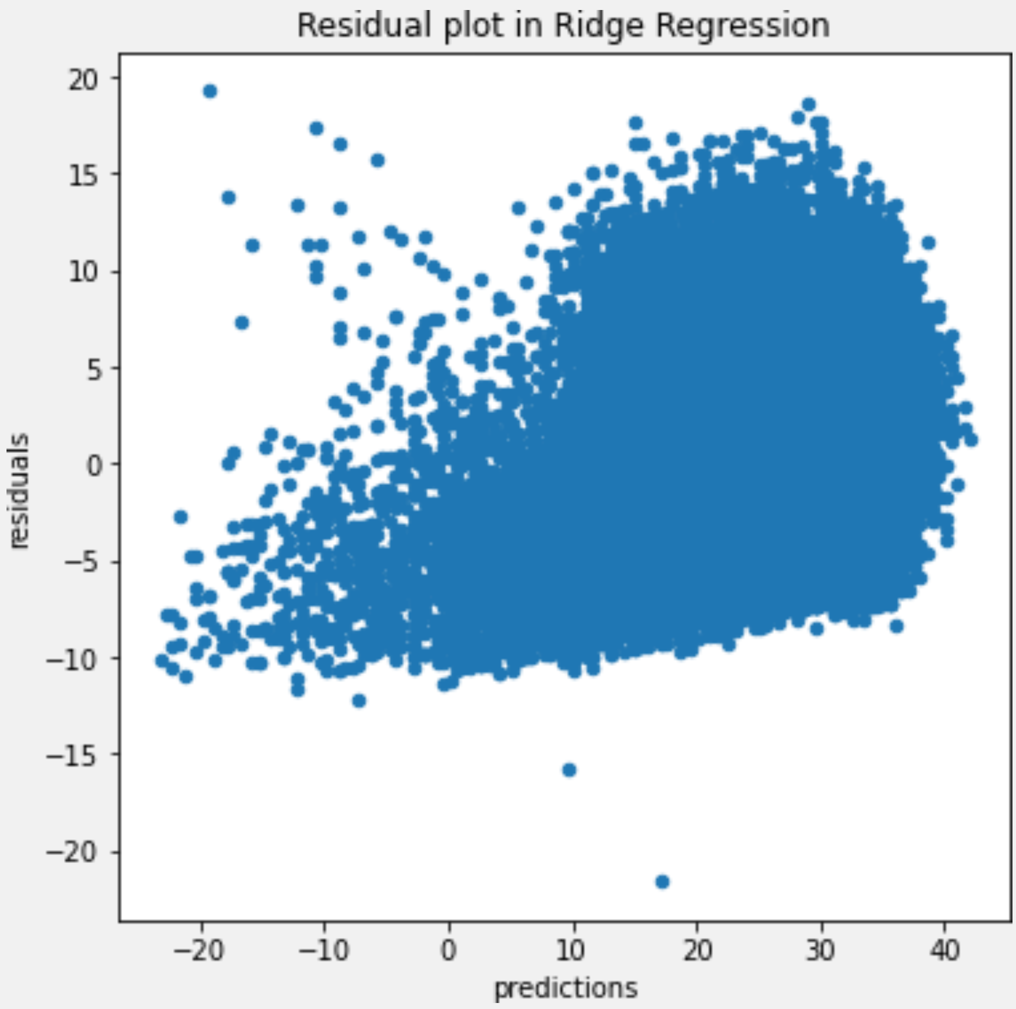
Average Train error (Each reading) = 3.1293583887776033 in Ridge Regression

Average Test error (Each reading) = 3.1119798542679393 in Ridge Regression

R2 score of Ridge Regression = 0.763689046202704

[ ]:
```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)

predictions = pd.DataFrame({"predictions":model.predict(X_train), "true":
 ↪y_train})
predictions["residuals"] = predictions["true"] - predictions["predictions"]
predictions.plot(x = "predictions", y = "residuals",kind = "scatter") plt.title("Residual plot
in Ridge Regression")
```

[ ]: Text(0.5, 1.0, 'Residual plot in Ridge Regression')




### 8.1.2 K NEIGHBOURS REGRESSOR

[ ]

```
knn=neighbors.KNeighborsRegressor(n_neighbors =2,weights='uniform')
knn.fit(X_train,y_train)
y1_knn=knn.predict(X_train)
y1_knn=list(y1_knn)

error=0
for i in range(len(y_train)):
        error+=(abs(y1_knn[i]-y_train[i]))
train_error_knn=error/len(y_train)
print("Average Train error (Each reading) = "+'{}'.format(train_error_knn)+" in→Knn algorithm")

y2_knn=knn.predict(X_test)
```

```
y2_knn=list(y2_knn)

error=0
for i in range(len(y_test)):
    error+=(abs(y2_knn[i]-y_test[i]))
test_error_knn=error/len(y_test)
print("Average Test error (Each Reading) = "'{}'.format(test_error_knn)+" in
 ↪knn algorithm")

R2_knn = r2_score(y_test,y2_knn)
print ("R2 score of K Neighbours Regression = "+str(R2_knn))
```

Average Train error (Each reading) = 3.415730508229608 in Knn algorithm

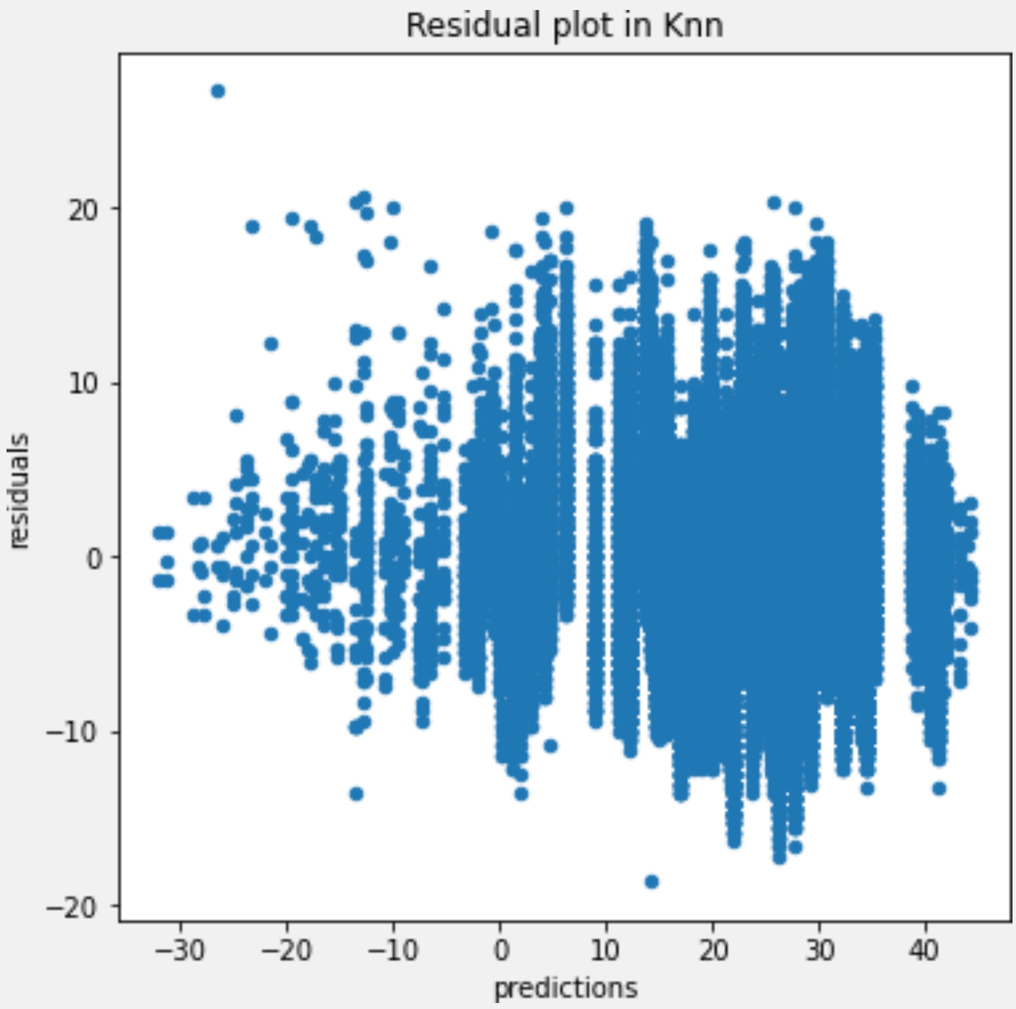
Average Test error (Each Reading) = 3.3949159214416547 in knn algorithm

R2 score of K Neighbours Regression = 0.7030949962985555

[ ]:

```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)
predictions = pd.DataFrame({"predictions":knn.predict(X_train), "true":y_train})
predictions["residuals"] = predictions["true"] - predictions["predictions"] predictions.plot(x =
"predictions", y = "residuals",kind = "scatter") plt.title("Residual plot in Knn")
```

[ ]: Text(0.5, 1.0, 'Residual plot in Knn')




### 8.1.3 BAYESIAN REGRESSION

[ ]:

```
reg = linear_model.BayesianRidge()
reg.fit(X_train,y_train)
y1_reg=reg.predict(X_train)
y1_reg=list(y1_reg)
y2_reg=reg.predict(X_test)
y2_reg=list(y2_reg)

error=0
for i in range(len(y_train)):
        error+=(abs(y1_reg[i]-y_train[i]))
train_error_bay=error/len(y_train)
print("Average Train error (Each reading) = "+'{}'.format(train_error_bay)+" in
 ↪Bayesian Regression")
```

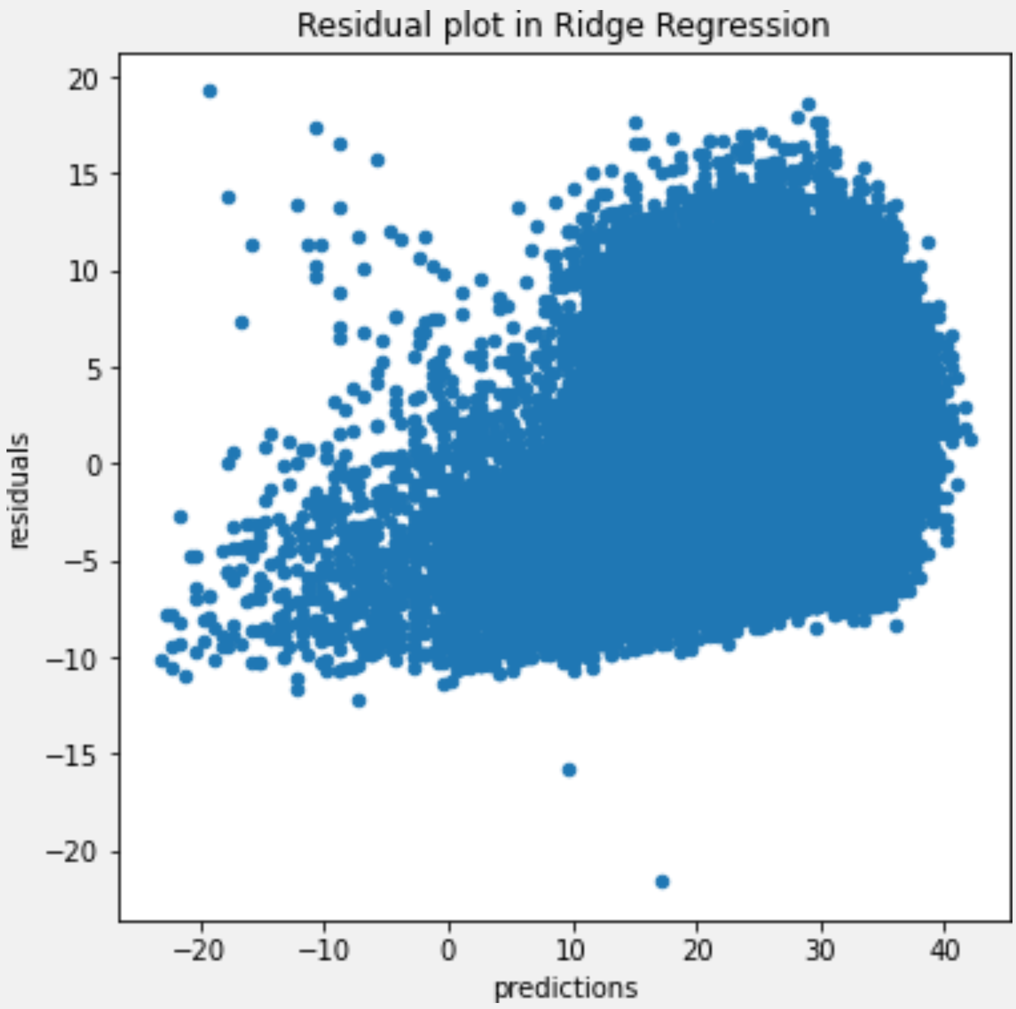
```
error=0
for i in range(len(y_test)):
        error+=(abs(y2_reg[i]-y_test[i]))
test_error_bay=(error/len(y_test))
print("Average Test error (Each reading) = "+'{}'.format(test_error_bay)+"␣
 ↪percent"+" in Bayesian Regression")

R2_bay = r2_score(y_test,y2_reg)
print ("R2 score of Bayesian Regression = "+str(R2_bay))
```

Average Train error (Each reading) = 3.129356949746602 in Bayesian Regression

Average Test error (Each reading) = 3.1119783549980546 percent in Bayesian Regression
R2 score of Bayesian Regression = 0.7636890527335571

[ ]:
```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)
predictions = pd.DataFrame({"predictions":reg.predict(X_train), "true":y_train}) predictions["residuals"]
= predictions["true"] - predictions["predictions"] predictions.plot(x = "predictions", y = "residuals",kind
= "scatter") plt.title("Residual plot in Bayesian Regression")
```

[ ]: Text(0.5, 1.0, 'Residual plot in Bayesian Regression')




### 8.1.4 Decision TreeRegressor

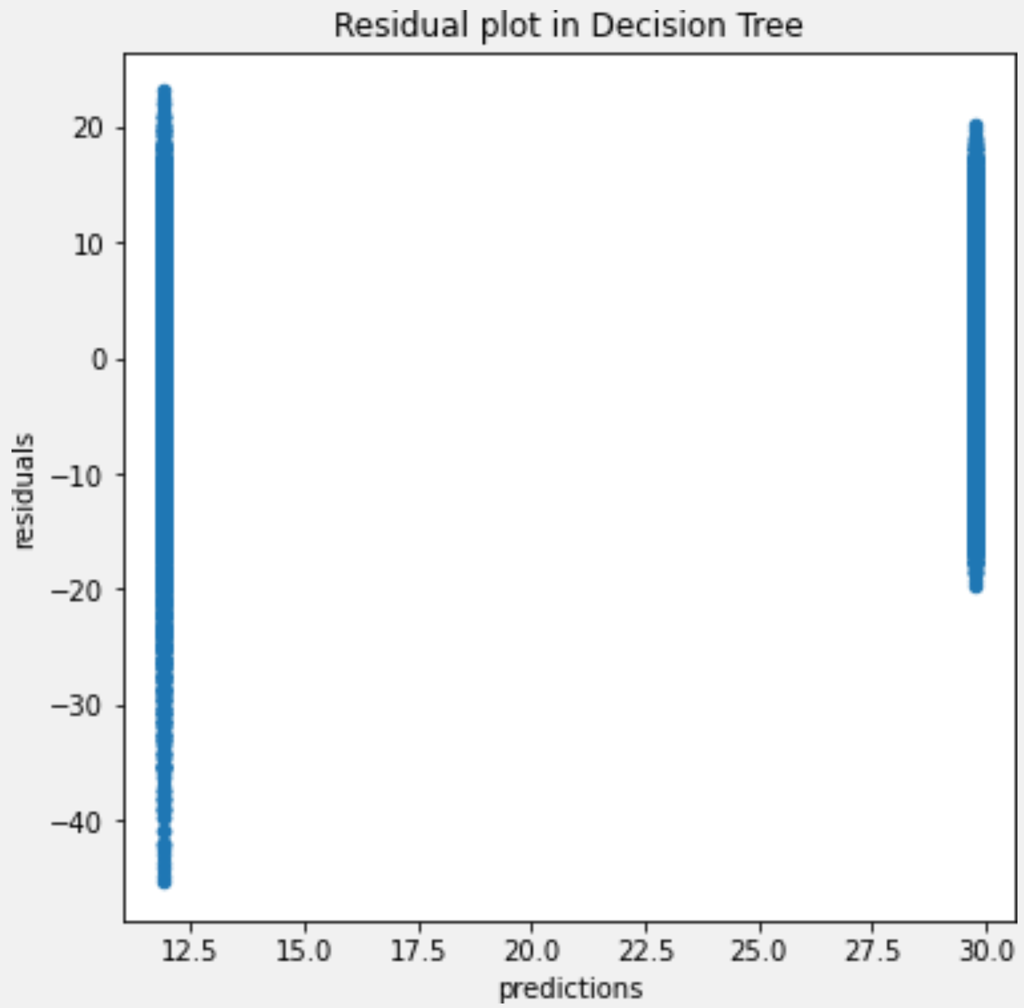
[ ]:
```
dec = tree.DecisionTreeRegressor(max_depth=1)
dec.fit(X_train,y_train)
y1_dec=dec.predict(X_train)
y1_dec=list(y1_dec)
y2_dec=dec.predict(X_test)
y2_dec=list(y2_dec)

error=0
for i in range(len(y_train)):
        error+=(abs(y1_dec[i]-y_train[i]))
train_error_tree=error/len(y_train)
print("Average Train error (Each reading) = "+'{}'.format(train_error_tree)+"
 ↪in Decision Tree Regressor")
```

```
error=0
for i in range(len(y_test)):
    error+=(abs(y1_dec[i]-y_test[i]))
test_error_tree=error/len(y_test)
print("Average Test error (Each reading) = "'{}'.format(test_error_tree)+" in
 ↪Decision Tree Regressor")

R2_dec = r2_score(y_test,y2_dec)
print ("R2 score of Decision Tree Regressor = "+str(R2_dec))
```

Average Train error (Each reading) = 3.7313379730308363 in Decision Tree Regressor
Average Test error (Each reading) = 6.745800482076615 in Decision Tree Regressor
R2 score of Decision Tree Regressor = 0.5667936810038526

[ ]:
```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)
predictions = pd.DataFrame({"predictions":dec.predict(X_train), "true":y_train})
predictions["residuals"] = predictions["true"] - predictions["predictions"] predictions.plot(x =
"predictions", y = "residuals",kind = "scatter") plt.title("Residual plot in Decision Tree")
```

[ ]: Text(0.5, 1.0, 'Residual plot in Decision Tree')




### 8.1.5 SVM (Support Vector Machines) REGRESSOR

[ ]:

```
svm_reg=svm.SVR()
svm_reg.fit(X_train,y_train)
y1_svm=svm_reg.predict(X_train)
y1_svm=list(y1_svm)
y2_svm=svm_reg.predict(X_test)
y2_svm=list(y2_svm)

error=0
for i in range(len(y_train)):
        error+=(abs(y1_svm[i]-y_train[i]))
train_error_svm=error/len(y_train)
print("Average Train error (Each reading) = "+'{}'.format(train_error_svm)+" in␣
 ↪SVM Regressor")
```

```
error=0
for i in range(len(y_test)):
	error+=(abs(y2_svm[i]-y_test[i]))
test_error_svm=error/len(y_test)
print("Average Test error (Each reading) = "'{}'.format(test_error_svm)+" in␣
 ↪SVM Regressor")

R2_svm = r2_score(y_test,y2_svm)
print ("R2 score of SVM Regressor = "+str(R2_svm))
```

Average Train error (Each reading) = 2.7814959657424465 in SVM Regressor

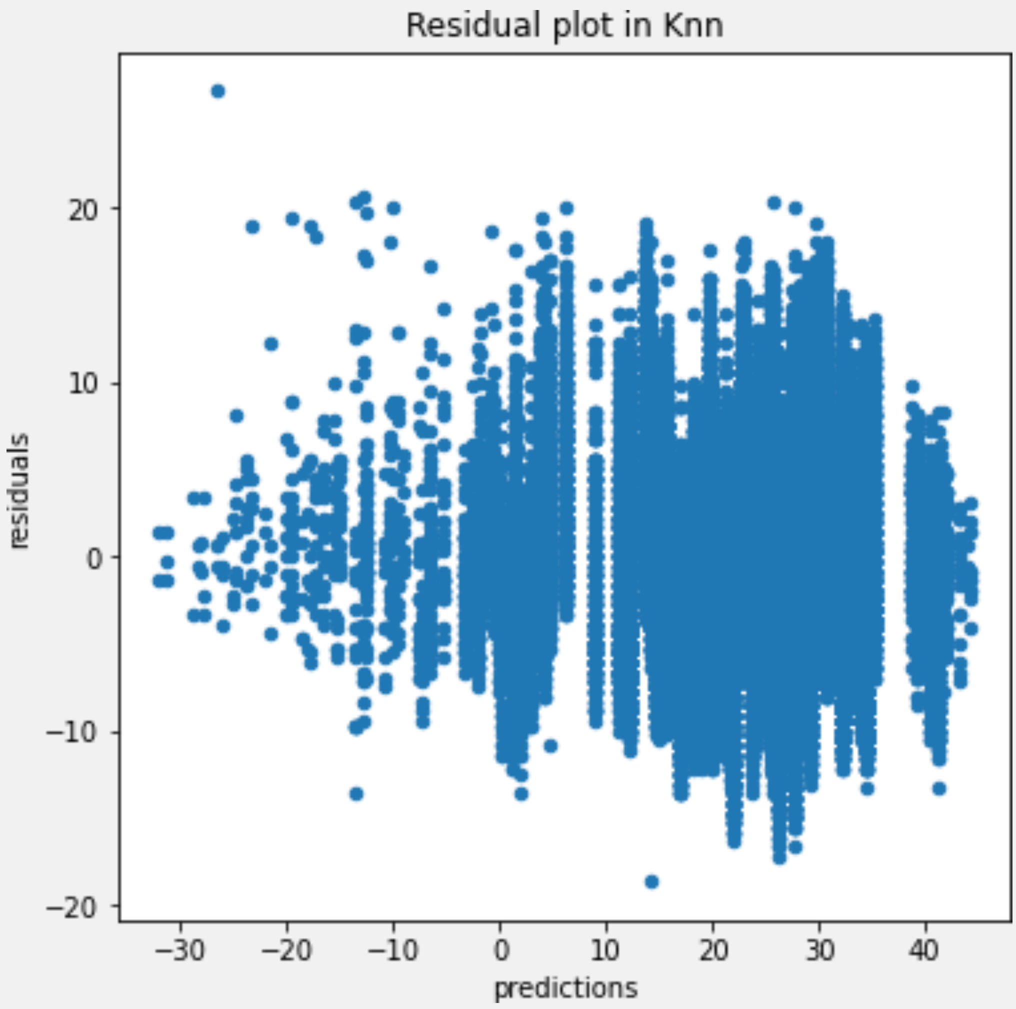
Average Test error (Each reading) = 2.7618458029537734 in SVM Regressor

R2 score of SVM Regressor = 0.7934968601870697

[ ]:

```
matplotlib.rcParams['figure.figsize'] = (6.0, 6.0)
predictions = pd.DataFrame({"predictions":knn.predict(X_train), "true":y_train})
predictions["residuals"] = predictions["true"] - predictions["predictions"] predictions.plot(x =
"predictions", y = "residuals",kind = "scatter") plt.title("Residual plot in SVM")
```

[ ]: Text(0.5, 1.0, 'Residual plot in SVM')




#### 8.1.6 SUMMARY

[ ]:
```
train_error=[train_error_ridge,train_error_knn,train_error_bay,train_error_tree,train_error_sv
test_error=[test_error_ridge,test_error_knn,test_error_bay,test_error_tree,test_error_svm]
R2_score = [R2_ridge,R2_knn,R2_bay,R2_dec,R2_svm]

col={'Train Error':train_error,'Test Error':test_error,'R2 Score': R2_score} models=['Ridge
Regression','Knn Regressor','Bayesian Regression','Decision↪Tree','SVM Regressor']

df3=DataFrame(data=col,index=models) df3
```

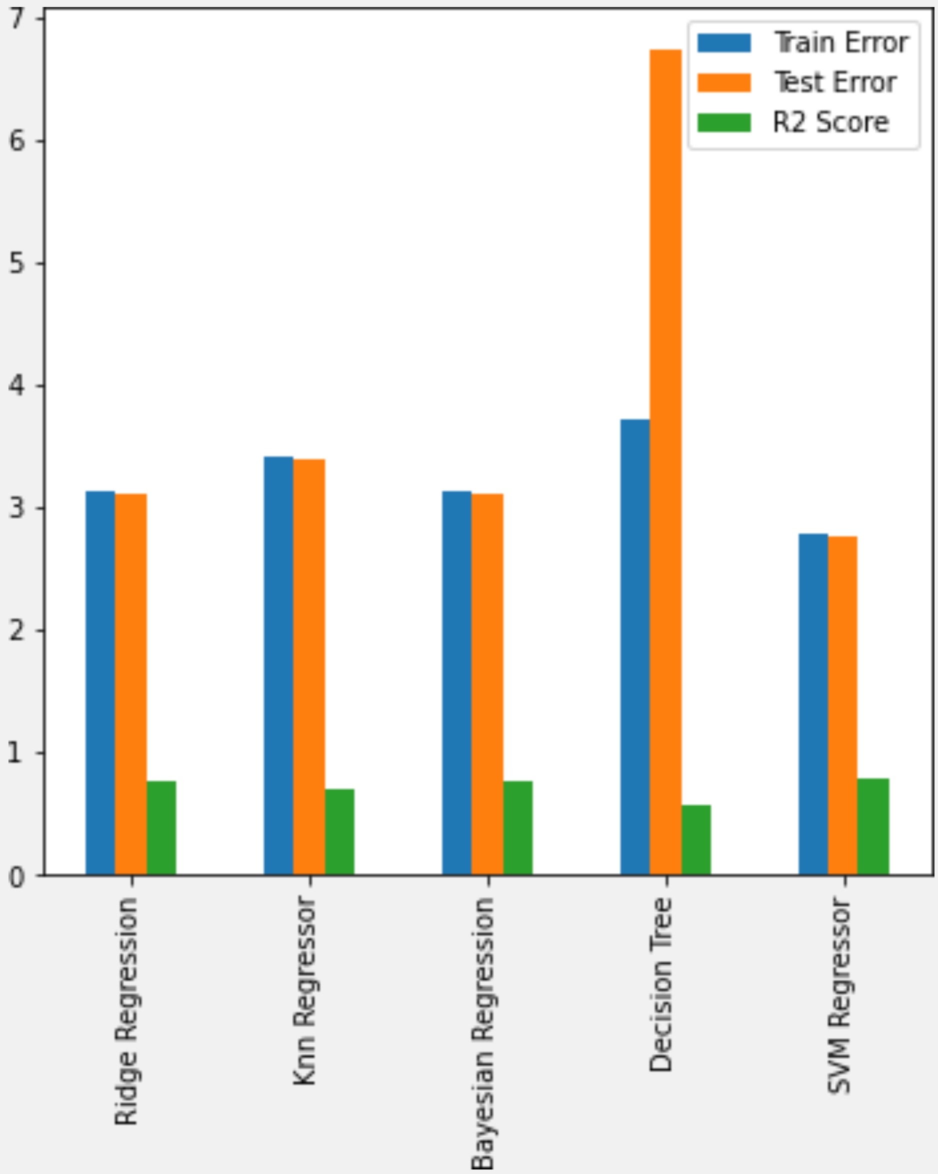
[ ]:

| | Train Error | Test Error | R2 Score |
|---|---|---|---|
| Ridge Regression | 3.129358 | 3.111980 | 0.763689 |
| Knn Regressor | 3.415731 | 3.394916 | 0.703095 |

| | | | |
|---|---|---|---|
| Bayesian Regression | 3.129357 | 3.111978 | 0.763689 |
| Decision Tree | 3.731338 | 6.745800 | 0.566794 |
| SVM Regressor | 2.781496 | 2.761846 | 0.793497 |

[ ]:
```
df3.plot(kind='bar')
```

[ ]: <AxesSubplot:>




**8.1.7 CONCLUSION : SVM Regressor Model yields the highest accuracy ataround 80% among the other regression models.**

## Conclusion

After performing exploratory data analysis on our dataset, we could successfully find out the relation between minimum and maximum temperature with an accuracy of 77%.

To improve the accuracy further, we can also use some sophisticated Machine Learning models. Which can yield better results but are also prone to overfitting.

We were able to filter out and remove noise from the dataset to work on further functions more efficiently.

We were also able to plot different graphs to display the relationship between minimum and maximum temperature and were also able to build a linear regression model.