# PM2.5 Prediction with Machine Learning

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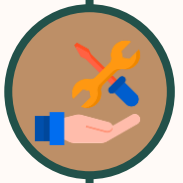
Group 7

Image sources: https://www.bangkokpost.com/life/social-and-lifestyle/2578139/thailand-clean-air-network-needs-you

# Table of Contents

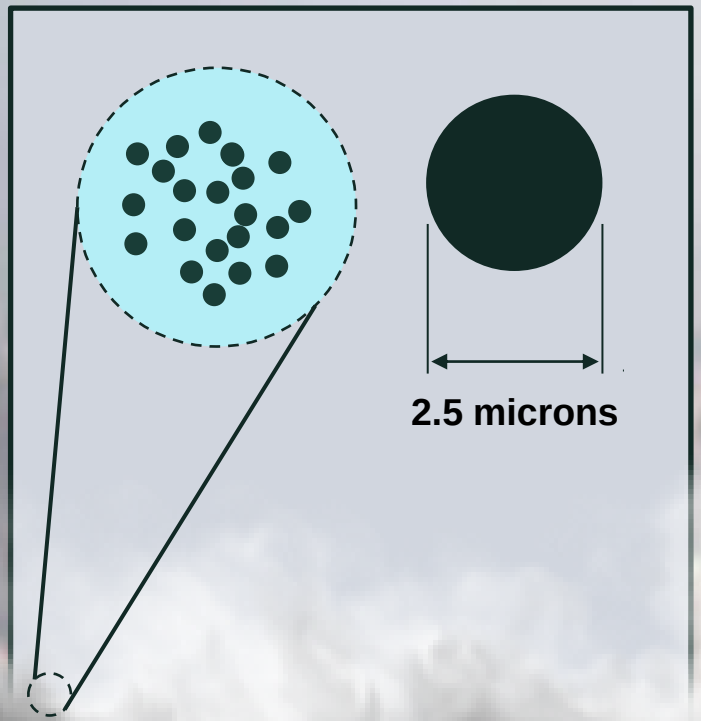




01
02
03
04
05

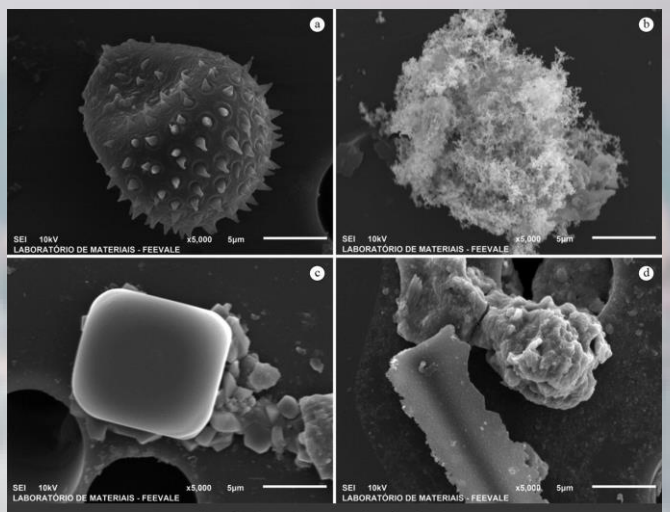
# Introduction & Problem Statement

# What is PM2.5 ?




## Particulate Matter or PM2.5

refers to tiny airborne particles or droplets with a diameter of 2.5 micrometers or smaller.




(a) Particle of biological origin, identified in the PM2.5-10
(b) Soot particle, identified in the PM2.5-10 (b)
(c) Cubic-shaped particle, identified in the PM2.5-10
(d) Particle characteristic of soil resuspension and particle possibly originated from anthropic sources, both identified in the PM2.5-10

Image Source: https://www.devex.com/news/inside-thailand-s-tussle-with-toxic-smog-104836, https://journals.sagepub.com/doi/abs/10.1177/1420326X04059280?journalCode=ibeb

# PM2.5 Perspective



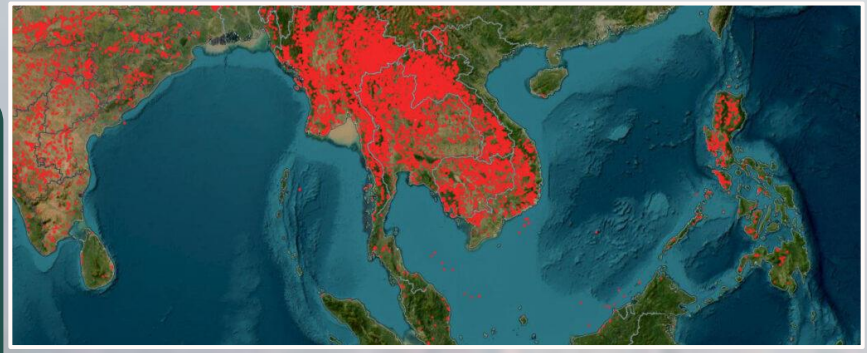
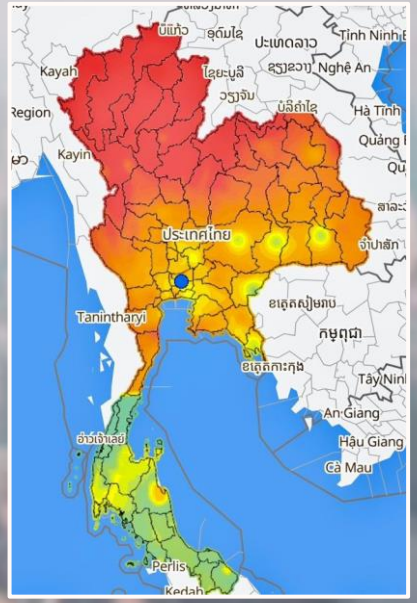


Image Source: https://bkktribune.com/the-hard-lessons-of-pm2-5-haze/

## PM2.5: Global Perspective

helps nations collaborate in addressing transboundary air pollution and sharing information to mitigate the impact of airborne particles on a global scale.




## PM2.5: Local Perspective

helps individuals make informed decisions about outdoor activities, and it assists policymakers in implementing measures to improve air quality and protect public health.

Image Source: bkktribune.com/the-hard-lessons-of-pm2-5-haze

# What is PM2.5 ?

## Why PM2.5 is important ?

***Protecting Public Health***

***Environmental Impact***

***Policy and Regulation***


***Awareness and Education***


Image Source: https://home.maefahluang.org/pm2_5_neweducatation

# Problem Statement

01

02

03

04

05

**To predict the PM2.5 values based on given weather conditions and trends of the PM2.5, Temporal Trends PM2.5 (seasonal, monthly, daily, hourly), Correlations between weather parameters and PM2.5, Weather effects (wind speed and temperature) on PM2.5**

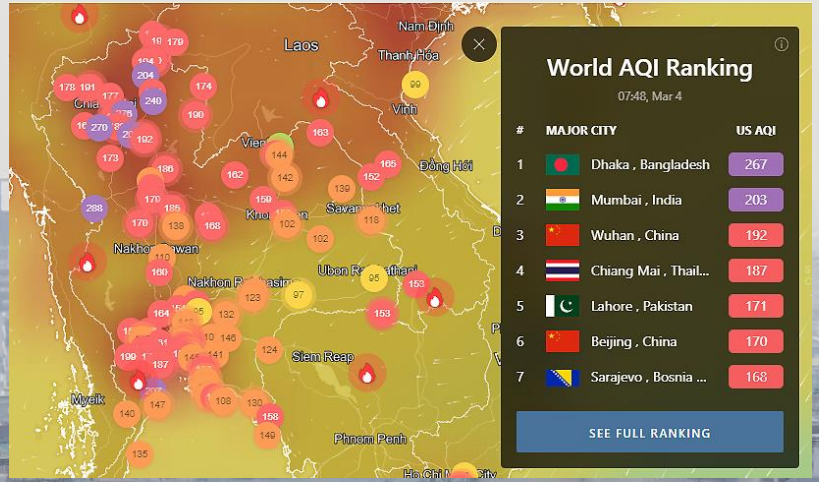


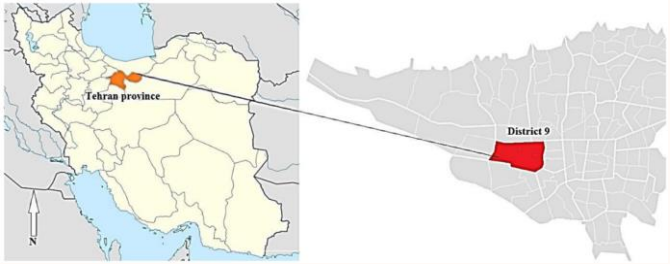


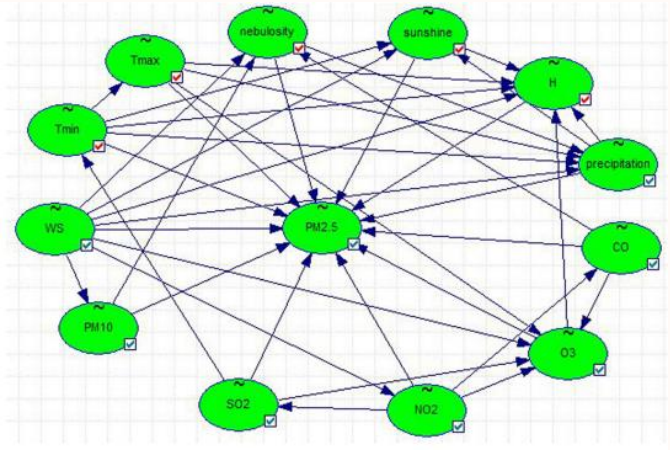
Image Source: https://stats.stackexchange.com/questions/198181/interpreting-temporal-trends-and-selecting-predictors-in-regression-models, https://www.bangkok-travel-ideas.com/weather-in-thailand.html, https://www.bangkokpost.com/thailand/general/2520020/solutions-sought-as-north-ravaged-by-toxic-pm2-5

01
02
03
04
05

# Literature Review

# Literature Review

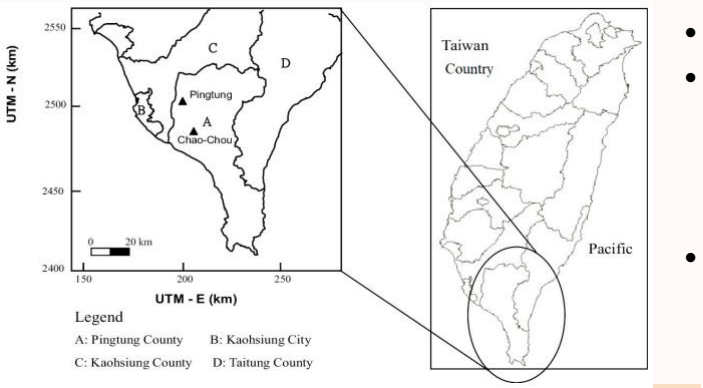



- proposed decision trees (DT), Bayesian Network (BN), and support vector machine (SVM). Using the data for over three periods,
- PM10, NO2, SO2, and O3 are critical factors for PM2.5

Image Source: Mehdipour V., Stevenson D.S., Memarianfard M. et al, "Comparing different methods for statistical modeling of particulate matter in Tehran, Iran", Air Quality Atmosphere Health 11, pp.1155—1165 (2018), https://doi.org/10.1007/s11869-018-0615-z

# Literature Review




- Taiwan Air Quality Monitoring data set.
- The model they used are random forest regressor (RFR), gradient boosting regressor GBR), k neighbors regressor (KNR), MLP regressor (MLPR), and decision tree regressor CART.
- To select the best model, they used cross-validation and determined that gradient boosting regressor model is better in forecasting air pollution in TAQMN data.

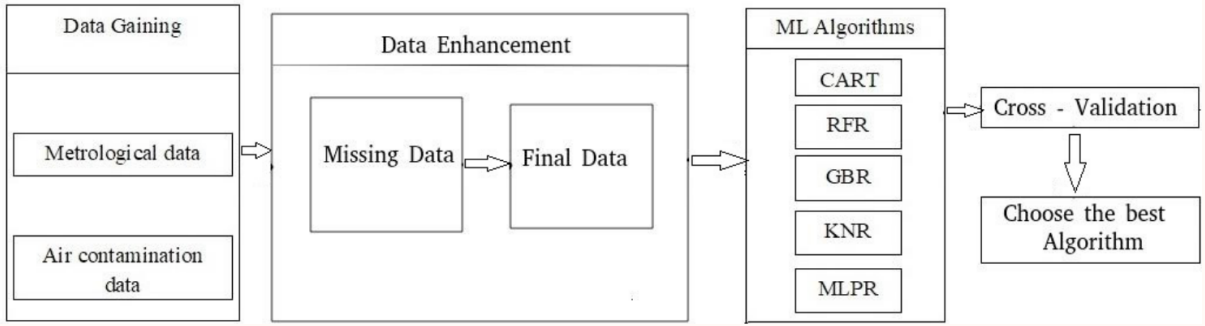



Image Source: Doreswamy, Harishkumar K. S., Yogesh K.M. and Ibrahim Gad. "Forecasting Air Pollution Particulate Matter (PM2.5) Using Machine Learning Regression Models". Procedia Computer Science. vol. 171. 2020. pp. 2057–2066. https://www.sciencedirect.com/science/article/pii/S1877050920312060

01
02
03
04
05

# Methodology

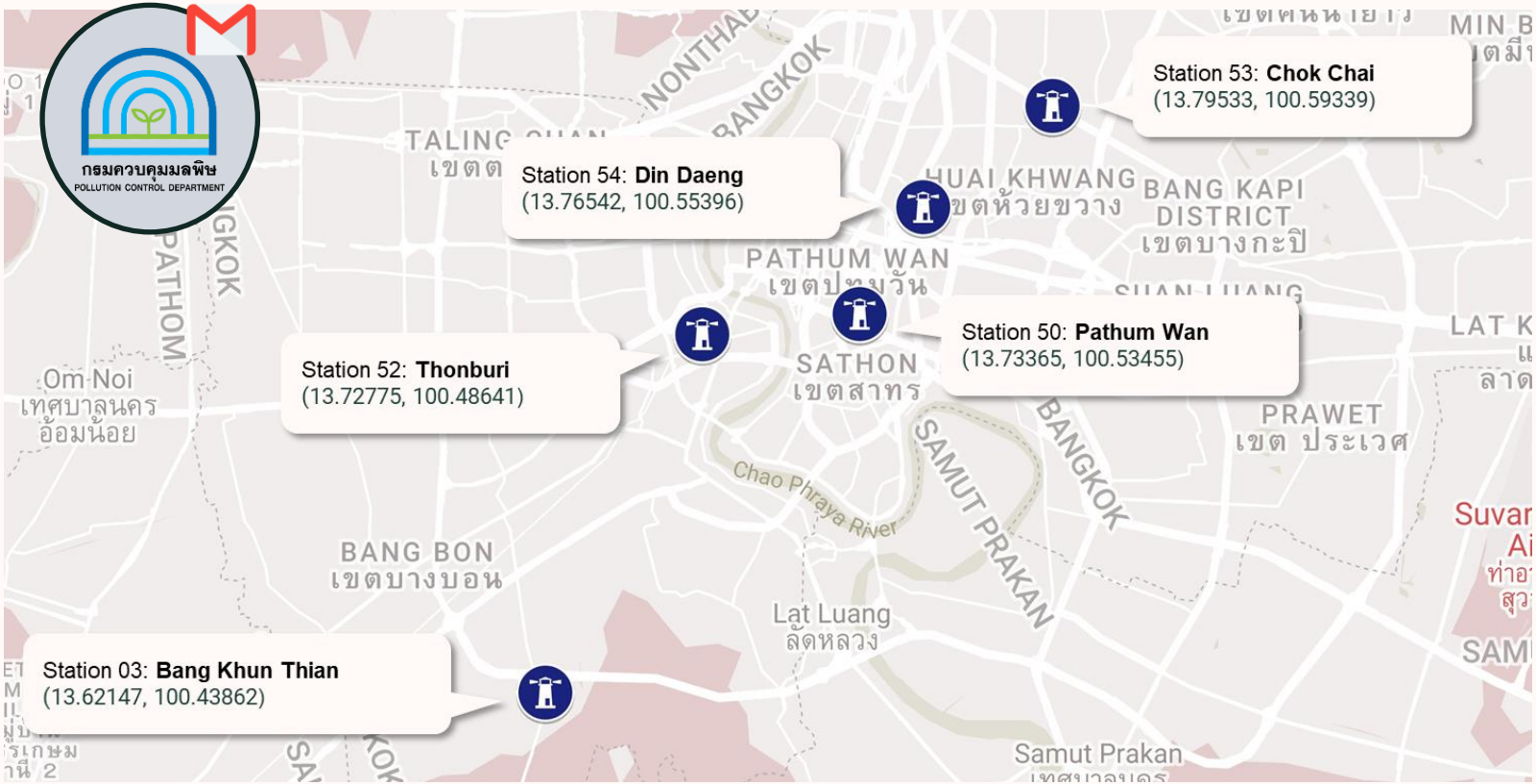


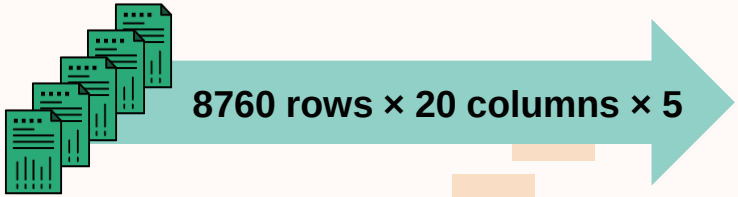

Image Source: https://www.google.co.th › maps

01
02
03
04
05
...

## Drop 2nd header not necessary

## Rename header + Add Province column because we have 5 stations

## Merge all 5 stations -> single DataFrame




| | YYMMDD | HR | CO | NO | NO2 | NOX | Windspeed | Winddir | Temp | O3 | PM10 | PM2.5 | Province | District | Relhum | Pressure | Rain | SO2 | Globrad | Netrad |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 190101 | 100 | 1.6 | 1.0 | 31.0 | 32.0 | 0.1 | 86.0 | 22.3 | 12.0 | 46 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN |
| 1 | 190101 | 200 | 1.5 | 1.0 | 28.0 | 29.0 | 0.5 | 52.0 | 20.0 | 15.0 | 57 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN |
| 2 | 190101 | 300 | NaN | NaN | NaN | NaN | 0.0 | 28.0 | 23.4 | NaN | 52 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN |
| 3 | 190101 | 400 | 1.8 | 13.0 | 38.0 | 52.0 | 0.1 | 4.0 | 23.1 | 1.0 | 61 | 29 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN |
| 4 | 190101 | 500 | 1.5 | 5.0 | 37.0 | 42.0 | 0.1 | 3.0 | 22.6 | 1.0 | 54 | 32 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 43795 | 191231 | 2000 | 1.9 | 138.0 | 45.0 | 182.0 | 0.3 | 310.0 | 31.3 | 4.0 | 41 | 27 | Bangkok | Din Daeng | 48.0 | 762.0 | 0.0 | NaN | NaN | NaN |
| 43796 | 191231 | 2100 | 2.4 | 171.0 | 48.0 | 219.0 | 0.2 | 332.0 | 31.3 | 3.0 | 51 | 29 | Bangkok | Din Daeng | 48.0 | 763.0 | 0.0 | NaN | NaN | NaN |
| 43797 | 191231 | 2200 | 2.4 | 175.0 | 52.0 | 227.0 | 0.2 | 325.0 | 31.0 | 3.0 | 58 | 30 | Bangkok | Din Daeng | 49.0 | 763.0 | 0.0 | NaN | NaN | NaN |
| 43798 | 191231 | 2300 | 2.7 | 207.0 | 56.0 | 262.0 | 0.2 | 315.0 | 30.7 | 2.0 | 68 | 32 | Bangkok | Din Daeng | 51.0 | 763.0 | 0.0 | NaN | NaN | NaN |
| 43799 | 191231 | 2400 | 2.4 | 154.0 | 52.0 | 206.0 | 0.4 | 358.0 | 30.5 | 2.0 | 70 | 38 | Bangkok | Din Daeng | 51.0 | 764.0 | 0.0 | NaN | NaN | NaN |

43800 rows × 20 columns

## Datetime formatting

(and drop YYMMDD and HR)

| | YYMMDD | HR |
|---|---|---|
| 0 | 190101 | 100 |
| 1 | 190101 | 200 |
| 2 | 190101 | 300 |
| 3 | 190101 | 400 |
| 4 | 190101 | 500 |

| Timestamp |
|---|
| 2019-01-01 01:00:00 |
| 2019-01-01 02:00:00 |
| 2019-01-01 03:00:00 |
| 2019-01-01 04:00:00 |
| 2019-01-01 05:00:00 |

Image Source:

01 02 03 04 05 ...

# Reorder the columns

**making it more readable and more manageable (move target variable to the end)**

| | CO | NO | NO2 | NOX | Windspeed | Winddir | Temp | O3 | PM10 | PM2.5 | Province | District | Relhum | Pressure | Rain | SO2 | Globrad | Netrad | Timestamp |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1.6 | 1.0 | 31.0 | 32.0 | 0.1 | 86.0 | 22.3 | 12.0 | 46 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 2019-01-01 01:00:00 |
| 1 | 1.5 | 1.0 | 28.0 | 29.0 | 0.5 | 52.0 | 20.0 | 15.0 | 57 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 2019-01-01 02:00:00 |
| 2 | NaN | NaN | NaN | NaN | 0.0 | 28.0 | 23.4 | NaN | 52 | 28 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 2019-01-01 03:00:00 |
| 3 | 1.8 | 13.0 | 38.0 | 52.0 | 0.1 | 4.0 | 23.1 | 1.0 | 61 | 29 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 2019-01-01 04:00:00 |
| 4 | 1.5 | 5.0 | 37.0 | 42.0 | 0.1 | 3.0 | 22.6 | 1.0 | 54 | 32 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 2019-01-01 05:00:00 |

| | Timestamp | Province | District | CO | NO | NO2 | NOX | SO2 | O3 | Windspeed | Winddir | Globrad | Netrad | Temp | Relhum | Rain | PM10 | PM2.5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2019-01-01 01:00:00 | Bangkok | Bang Khun Thian | 1.6 | 1.0 | 31.0 | 32.0 | NaN | 12.0 | 0.1 | 86.0 | NaN | NaN | 22.3 | NaN | NaN | 46 | 28 |
| 1 | 2019-01-01 02:00:00 | Bangkok | Bang Khun Thian | 1.5 | 1.0 | 28.0 | 29.0 | NaN | 15.0 | 0.5 | 52.0 | NaN | NaN | 20.0 | NaN | NaN | 57 | 28 |
| 2 | 2019-01-01 03:00:00 | Bangkok | Bang Khun Thian | NaN | NaN | NaN | NaN | NaN | NaN | 0.0 | 28.0 | NaN | NaN | 23.4 | NaN | NaN | 52 | 28 |
| 3 | 2019-01-01 04:00:00 | Bangkok | Bang Khun Thian | 1.8 | 13.0 | 38.0 | 52.0 | NaN | 1.0 | 0.1 | 4.0 | NaN | NaN | 23.1 | NaN | NaN | 61 | 29 |
| 4 | 2019-01-01 05:00:00 | Bangkok | Bang Khun Thian | 1.5 | 5.0 | 37.0 | 42.0 | NaN | 1.0 | 0.1 | 3.0 | NaN | NaN | 22.6 | NaN | NaN | 54 | 32 |

predictor

target

# Replace string values in numerical columns

**'Calm' in Winddir, no direction in degree recorded. So, we replace it as NaN (because same result as sensor can't record data)**

**'-' in PM10 & PM2.5, no value recorded. So, we replace it as NaN (because same result as sensor can't record data)**

```
, 'Calm'],
```

```
211,
'-',
170
```

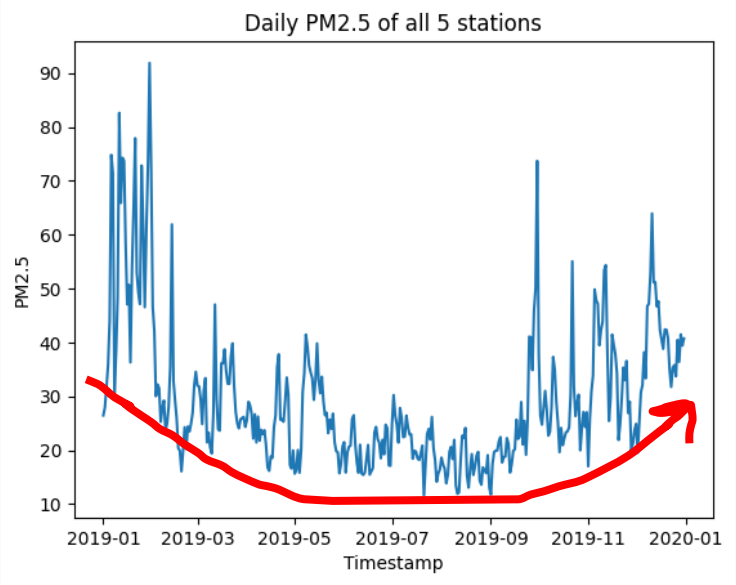
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 43800 entries, 0 to 43799
Data columns (total 18 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Timestamp  43800 non-null  datetime64[ns]
 1   Province   43800 non-null  object
 2   District   43800 non-null  object
 3   CO         39420 non-null  float64
 4   NO         39420 non-null  float64
 5   NO2        39420 non-null  float64
 6   NOX        39420 non-null  float64
 7   SO2        39420 non-null  float64
 8   O3         39420 non-null  float64
 9   Windspeed  39420 non-null  float64
 10  Winddir    34791 non-null  object
 11  Globrad    0 non-null      float64
 12  Netrad     0 non-null      float64
 13  Temp       43633 non-null  float64
 14  Relhum     34883 non-null  float64
 15  Rain       34833 non-null  float64
 16  PM10       43800 non-null  object
 17  PM2.5      43800 non-null  object
dtypes: datetime64[ns](1), float64(12), object(5)
memory usage: 6.0+ MB
```

Image Source: https://www.mathsisfun.com/geometry/images/degrees-360.svg

01
02
03
04
05

# PM2.5 (all stations)

**plotting to see the trend of average PM2.5 daily in all 5 stations. PM2.5 is quite high in the first two months. Then it drops dramatically at each its lowest in September. Then, it starts rising again up until the end of December.**



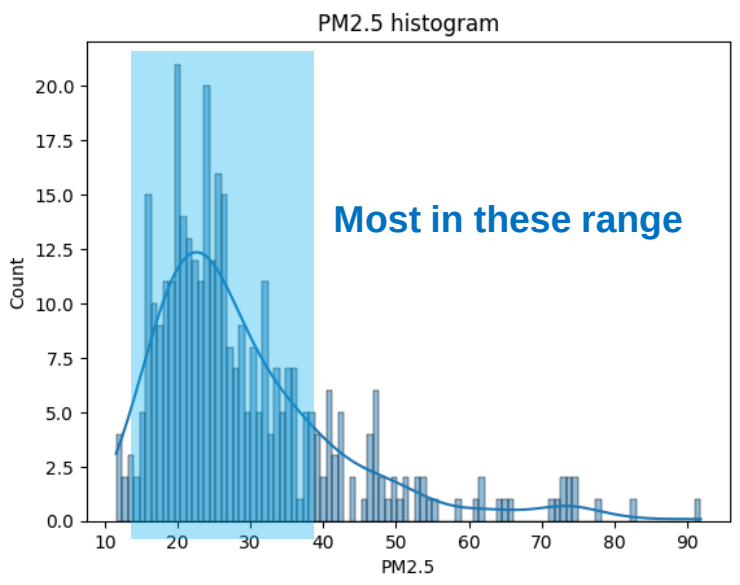




Image Source:

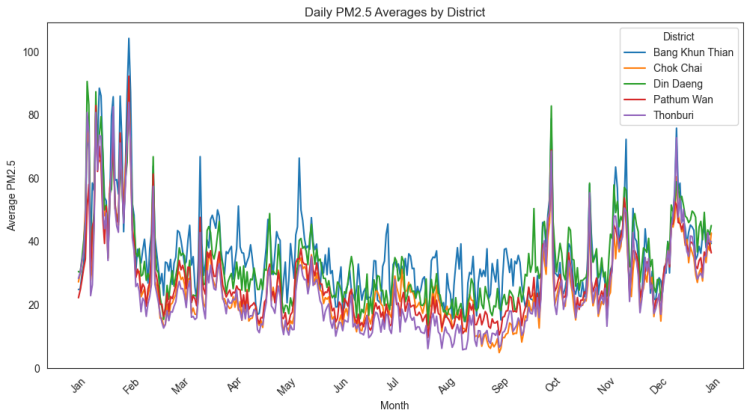
01

02

03

# PM2.5 (individual)

**we compared PM2.5 from each station that are relatively in the same province so PM2.5 should be in the same trends. However, in kde plot, it shows that stations has 2 different distributions of the PM2.5 values. Bang Khun Thian is similar with Din Daeng. The other group** is **Chok Chai, Pathum Wan, and Thonburi**.



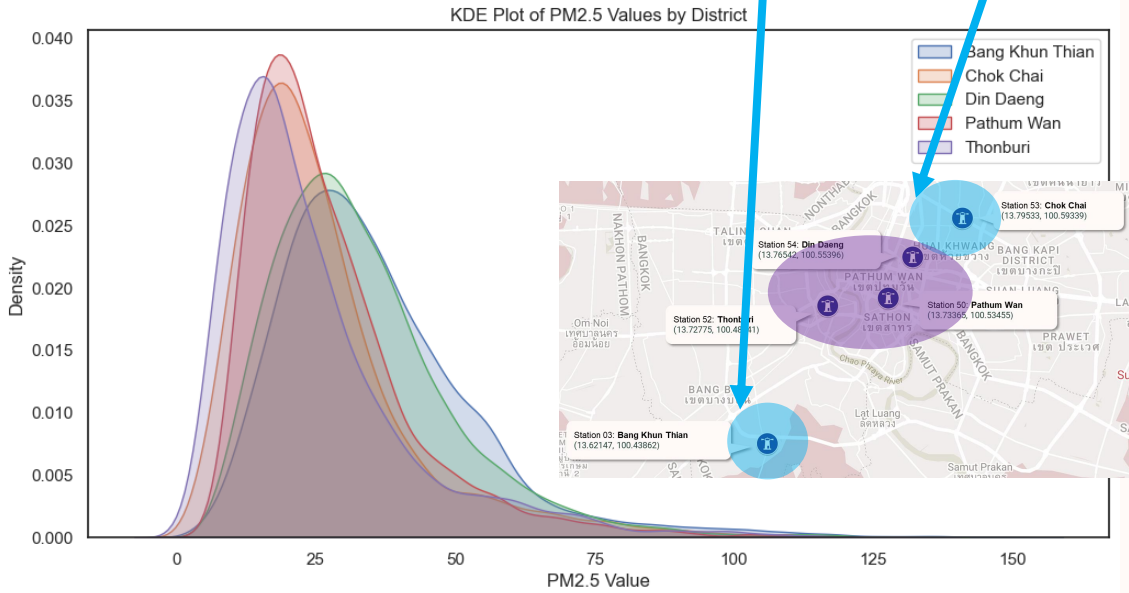
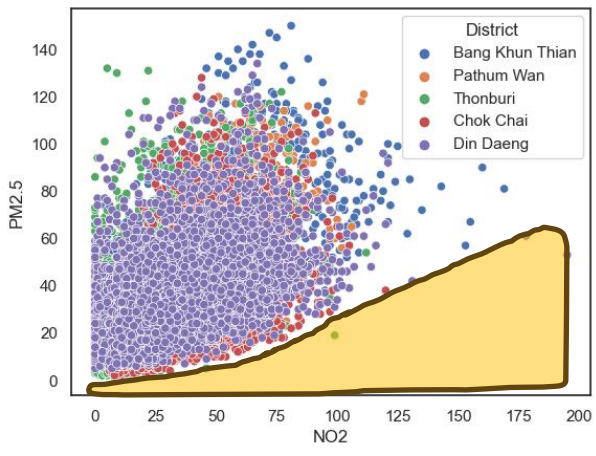
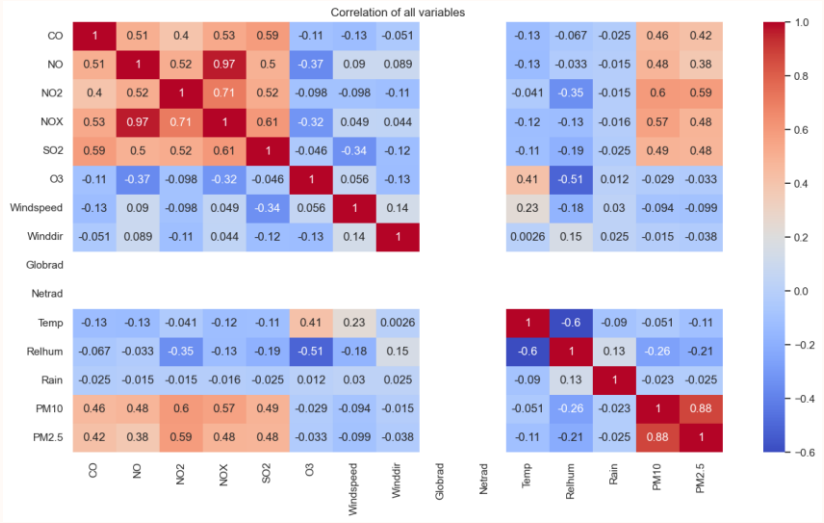




Image Source:




## PM2.5 – NO2

**If NO2 increases, it tends to increase the minimum PM2.5 value boundary. This indicates that NO2 has some effects to PM2.5.**




## Correlation Heat Map

**CO, NO, NO2, NOX, SO2, and PM10 have potential to be the predictor for PM2.5 as target variable.**

Image Source:

| | |
|---|---|
| Timestamp | 0.000000 |
| Province | 0.000000 |
| District | 0.000000 |
| CO | 5.312785 |
| NO | 10.068493 |
| NO2 | 10.068493 |
| NOX | 10.066210 |
| SO2 | 81.114155 |
| O3 | 52.506849 |
| Windspeed | 20.899543 |
| Winddir | 20.586758 |
| Globrad | 100.000000 |
| Netrad | 100.000000 |
| Temp | 0.381279 |
| Relhum | 20.358447 |
| Rain | 20.472603 |
| PM10 | 0.867580 |
| PM2.5 | 0.773973 |

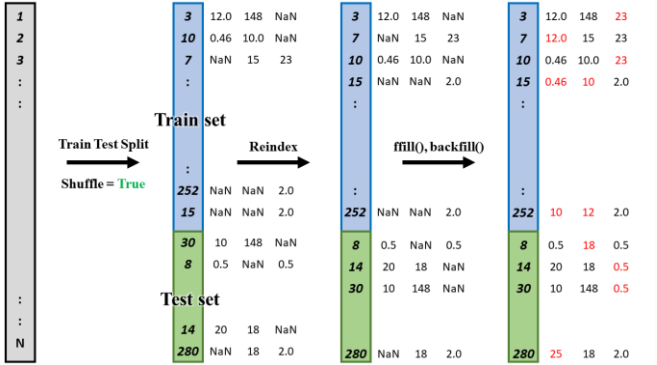
## Remove columns

- **Globrad** and **Netrad 100 % are NaN (Not a Number)**
- **SO2 less than 20 % entries**
- **Province single unique value**, Bangkok.
- **Timestamp** will also be dropped **time-independent**.

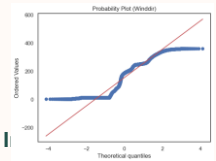
## Train-test Split with 80 : 20 train-test ratio

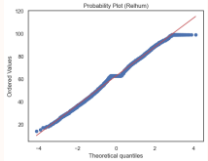
## Imputation

**Reindex then forward fill and backward fill (sensor data)**




## Scale and Encode into pipeline





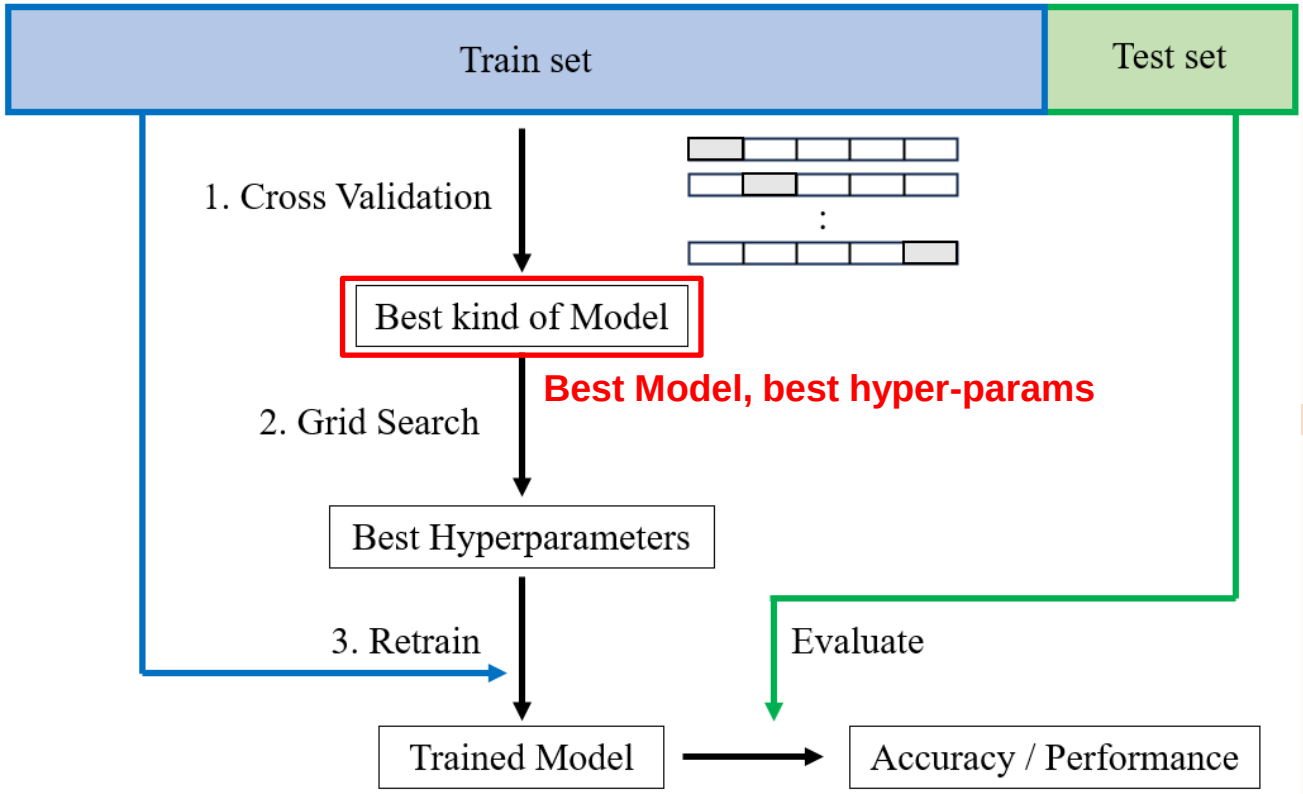
| Column Name | Pipeline Step(s) | | |
|---|---|---|---|
| | *Standard Scale* | *MinMax Scale* | *OneHot Encoder* |
| CO | ✓ | | |
| NO | | ✓ | |
| NO2 | | ✓ | |
| NOX | | ✓ | |
| O3 | | ✓ | |
| Windspeed | | ✓ | |
| Winddir | | ✓ | |
| Temp | ✓ | | |
| Relhum | ✓ | | |
| Rain | ✓ | | |
| PM10[a] | | ✓ | |
| District | | | ✓ |

[a]PM.10 will be dropped in other scenario.

Select Model → Cross Validation (K-Fold = 5) → Tune Hyper-params → GridSearchCV (K-Fold = 10) → Best Model, Best hyper-params

- *Linear Regression*
- *Ridge Regression*
- *Lasso Regression*
- *Gradient Boosting Regression*
- *Histogram-based Gradient Boosting Regression Tree*
- *Support Vector Regression (SVR)*
- *K Neighbor Regression*
- *Decision Tree Regression*
- *Random Forest Regression*
- *AdaBoost Regression*

Image Source: https://www.shutterstock.com/search/tightening-bolts,




Use R2 score

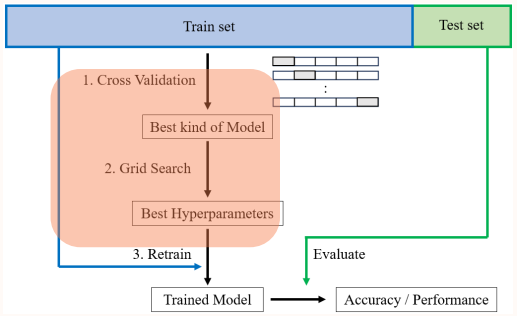
Image Source:


| | |
|---|---|
| Create | Model |
| Pickle | Model |
| Create | Web Application |
| Deploy | AWS |

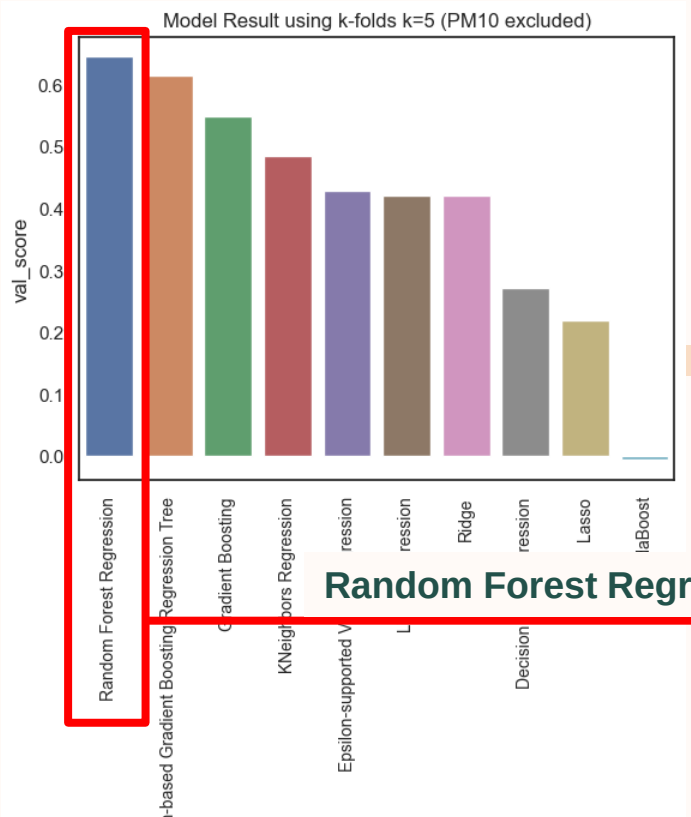
Image Source:

# Results

# Results



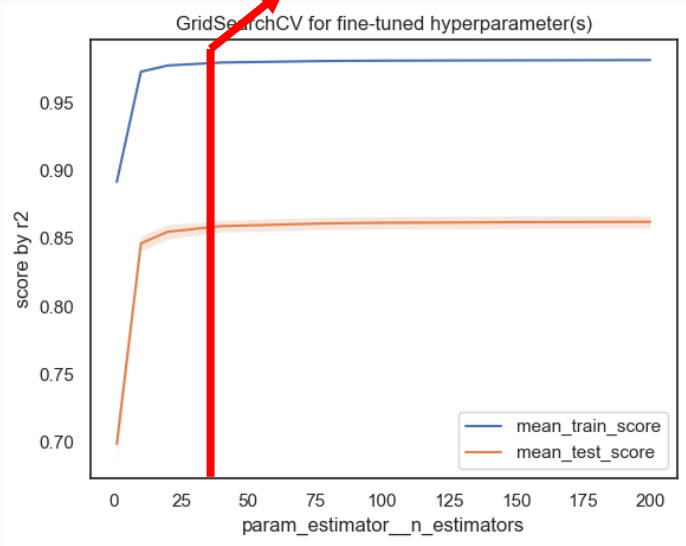

## Select Model and Hyper-parameter(s) Tuning




**Model Selection**

**Random Forest Regression**

**Hyper-parameter tuning (n_estimators = 40)**



# Results



## Train and Evaluation

```
# create new pipeline to fit
random_forest = RandomForestRegressor(random_state=0,
                                      n_estimators=200)

deploy_pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                                  ('model', random_forest)])
```

✓ 0.0s

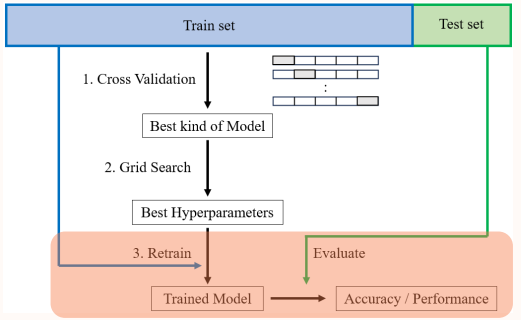
```
# training fit and transform (already include both fit and transform for train set)
# now this time, no seperation between train and val set like in GridSearchCV
deploy_pipeline.fit(X=X_train, y=y_train)
```

✓ 1m 29.3s

```
# No information leakage
yhat = deploy_pipeline.predict(X=X_test) # transform (no fit) and then predict
print(mean_squared_error(y_true=y_test, y_pred=yhat))
print(r2_score(y_true=y_test, y_pred=yhat))
```

```
162.97067793338206
0.4425220697072084
```

Image Source:



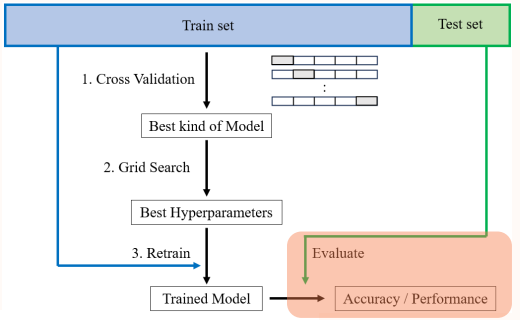

### Training

- *Val R2 score = 0.648*
*(64.8 % that model can explained)*

### Evaluation

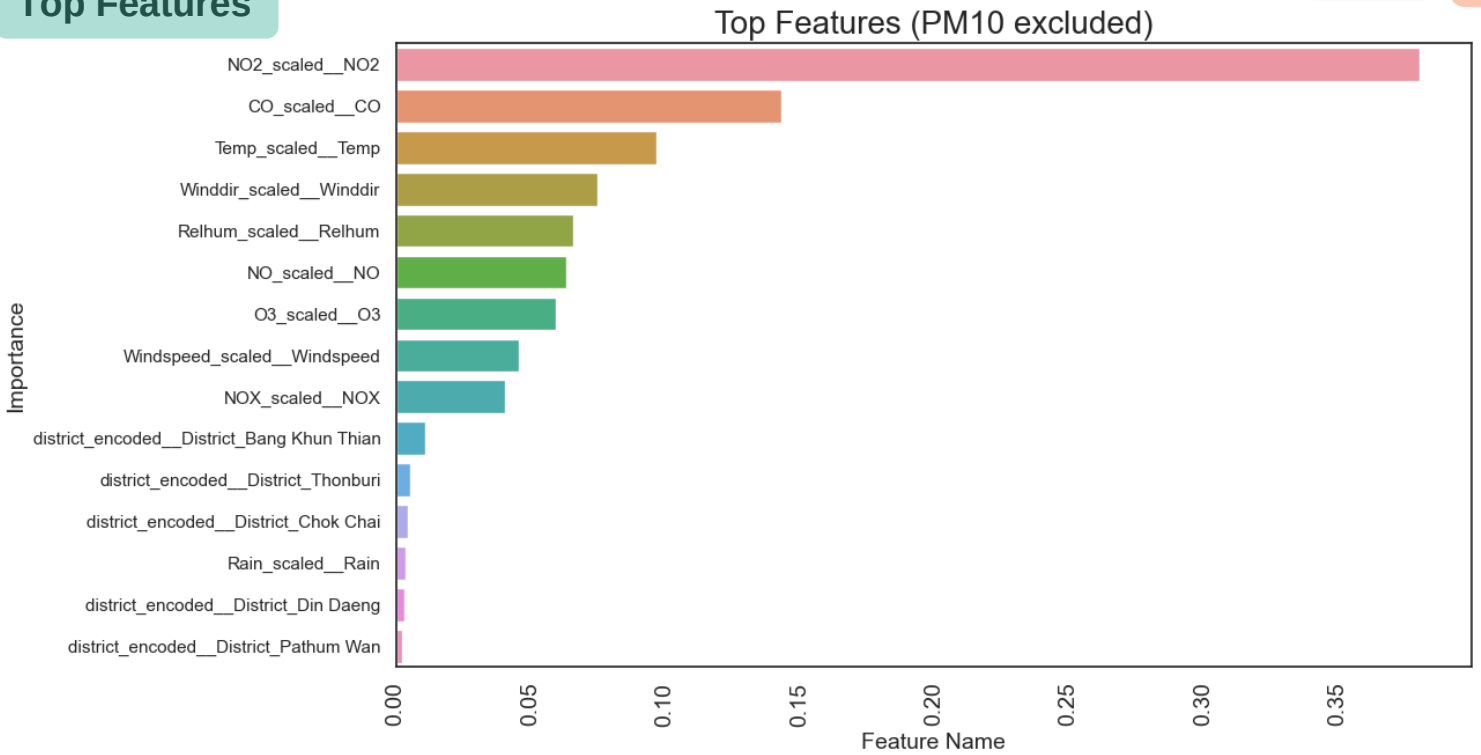
- *Test R2 score = 0.443*

# Results

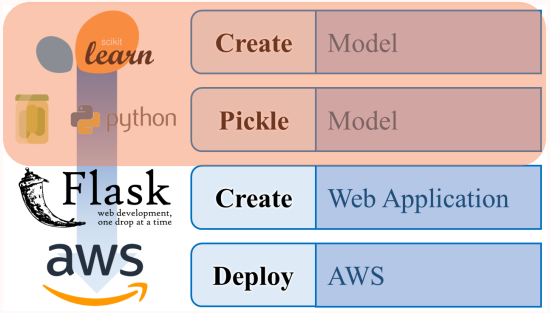



## Evaluation

### Top Features



# Results




## Create and Pickle the Model

```
import pickle

# save the model to disk
filename = 'model/pm25-prediction20231110_noPM10_v2_chronoffill.model'
pickle.dump(deploy_pipeline, open(filename, 'wb'))
```

```
# load the model from disk
loaded_model = pickle.load(open(filename, 'rb'))
```

```
predicted_pm25 = loaded_model.predict(sample)
predicted_pm25
```

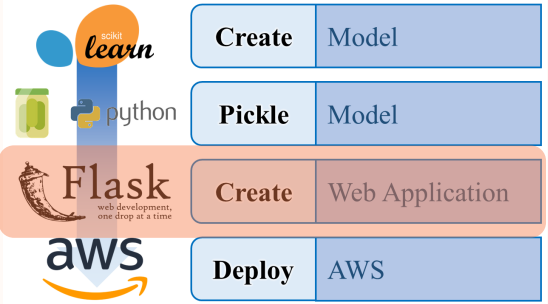
```
array([38.235, 40.9  , 46.825, 41.015, 41.015, 40.4  ])
```

**Sample DataFrame**

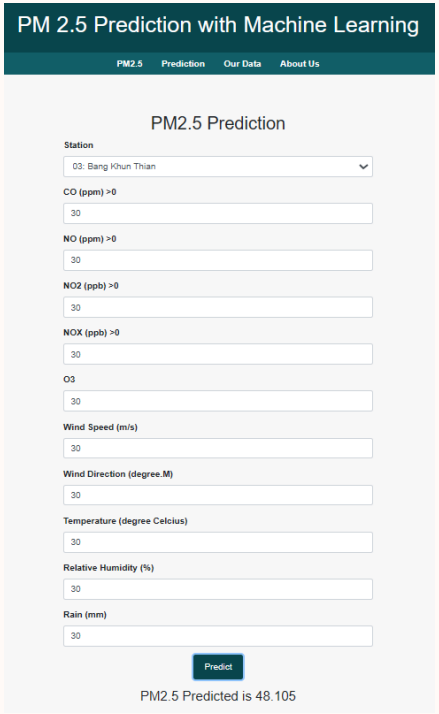
| | District | CO | NO | NO2 | NOX | O3 | Windspeed | Winddir | Temp | Relhum | Rain |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Pathum Wan | 24 | 25 | 34 | 10 | 25 | 20 | 120 | 32 | 20 | 0.2 |
| 1 | Pathum Wan | 30 | 30 | 30 | 20 | 5 | 2 | 0 | 30 | 1 | 0.8 |
| 2 | Bang Khun Thian | 30 | 30 | 30 | 20 | 5 | 2 | 0 | 30 | 1 | 0.8 |
| 3 | Chok Chai | 30 | 30 | 30 | 20 | 5 | 2 | 0 | 30 | 1 | 0.8 |
| 4 | Thonburi | 30 | 30 | 30 | 20 | 5 | 2 | 0 | 30 | 1 | 0.8 |
| 5 | Din Daeng | 30 | 30 | 30 | 20 | 5 | 2 | 0 | 30 | 1 | 0.8 |

Image Source:

# Results




## Web Application in local host



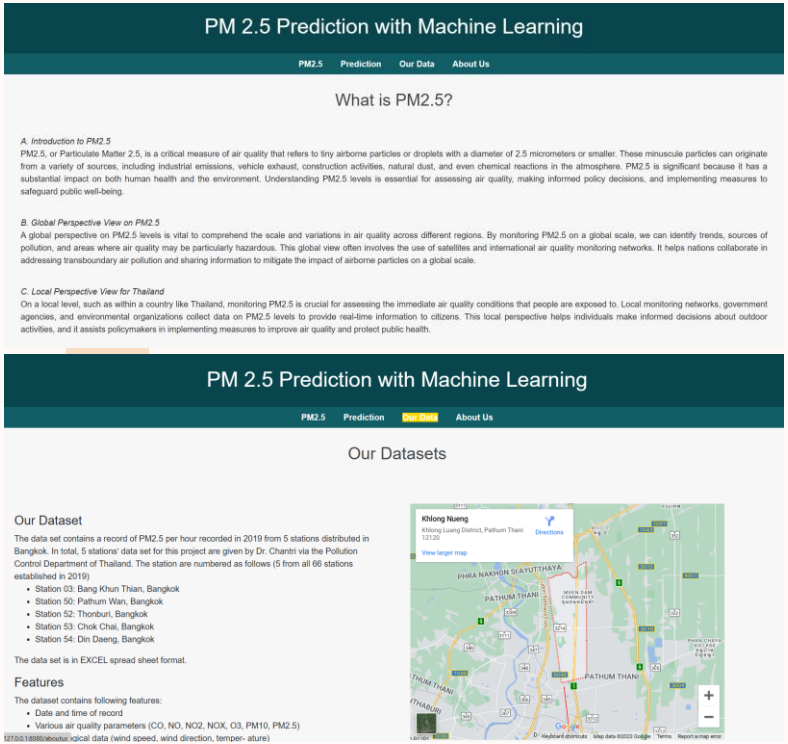




Image Source:

# Results

01

02

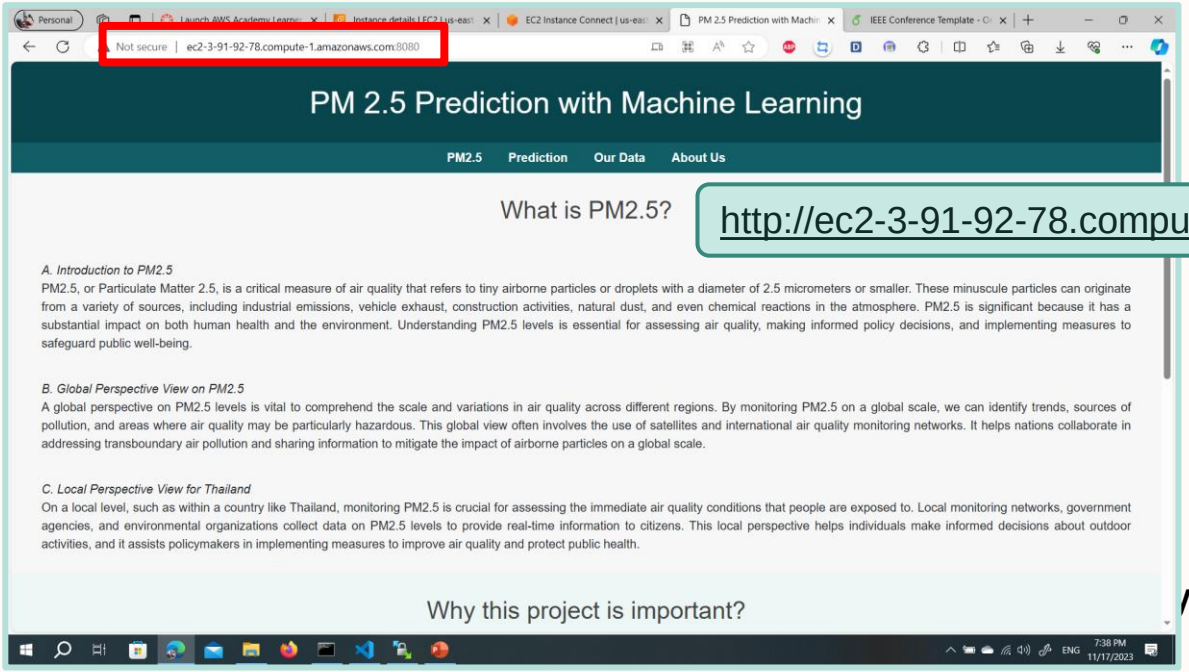
03

04

05

Deployment in aws

| | |
|---|---|
| Create | Model |
| Pickle | Model |
| Create | Web Application |
| Deploy | AWS |




http://ec2-3-91-92-78.compute-1.amazonaws.com:8080/

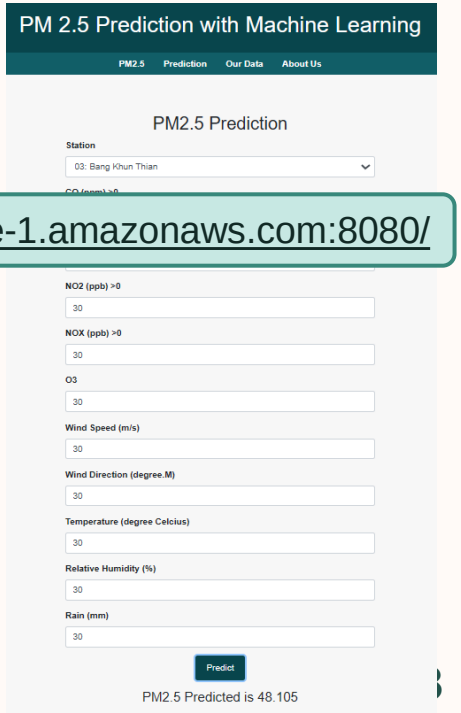



Image Source:

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# Conclusion & Future Works

# Conclusion

01

02

03

04

05

- The main benefit of this project is predicting the PM2.5 value based on given weather conditions, specializing scikit-learn library to create a machine learning model to achieve that task and deploying it to the website for end-users to use.

- This model can also be used with other station data too, to further enhance the performance of the model, making it able to predict various data from other places.

Image Source:

# Future Works

01
02
03
04
05

- **Time-series Analysis**

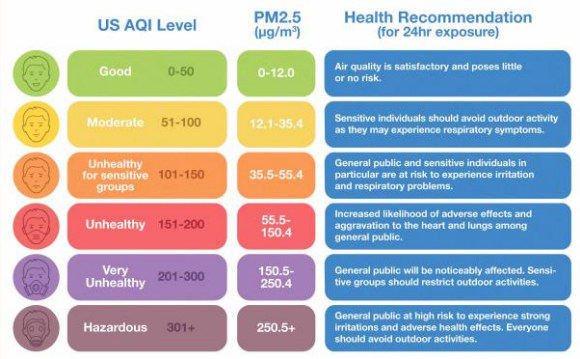
since the problem can be involved forecast with time-series.

- **Air Quality Index**

giving the users know more on how should they act and prepared (Decision-Making)

- **Include Weather data**

From other stations would give more in-depth details in PM2.5 data in Thailand will strengthen the model further in predicting PM2.5 in more diverged places



| | US AQI Level | PM2.5 (μg/m³) | Health Recommendation (for 24hr exposure) |
|---|---|---|---|
| | Good 0-50 | 0-12.0 | Air quality is satisfactory and poses little or no risk. |
| | Moderate 51-100 | 12.1-35.4 | Sensitive individuals should avoid outdoor activity as they may experience respiratory symptoms. |
| | Unhealthy for sensitive groups 101-150 | 35.5-55.4 | General public and sensitive individuals in particular are at risk to experience irritation and respiratory problems. |
| | Unhealthy 151-200 | 55.5-150.4 | Increased likelihood of adverse effects and aggravation to the heart and lungs among general public. |
| | Very Unhealthy 201-300 | 150.5-250.4 | General public will be noticeably affected. Sensitive groups should restrict outdoor activities. |
| | Hazardous 301+ | 250.5+ | General public at high risk to experience strong irritations and adverse health effects. Everyone should avoid outdoor activities. |

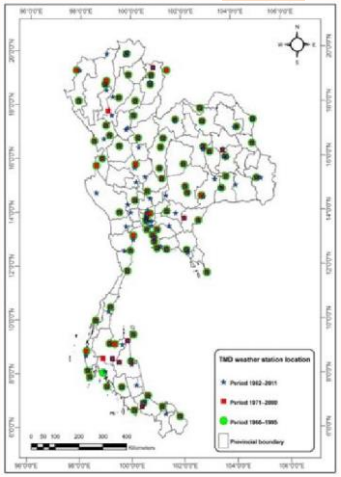



Image Source: https://www.researchgate.net/publication/294670317_Comparison_and_Recalibration_of_Equations_for_Estimating_Reference_Crop_Evapotranspiration_in_Thailand/figures?lo=1


THANK
YOU