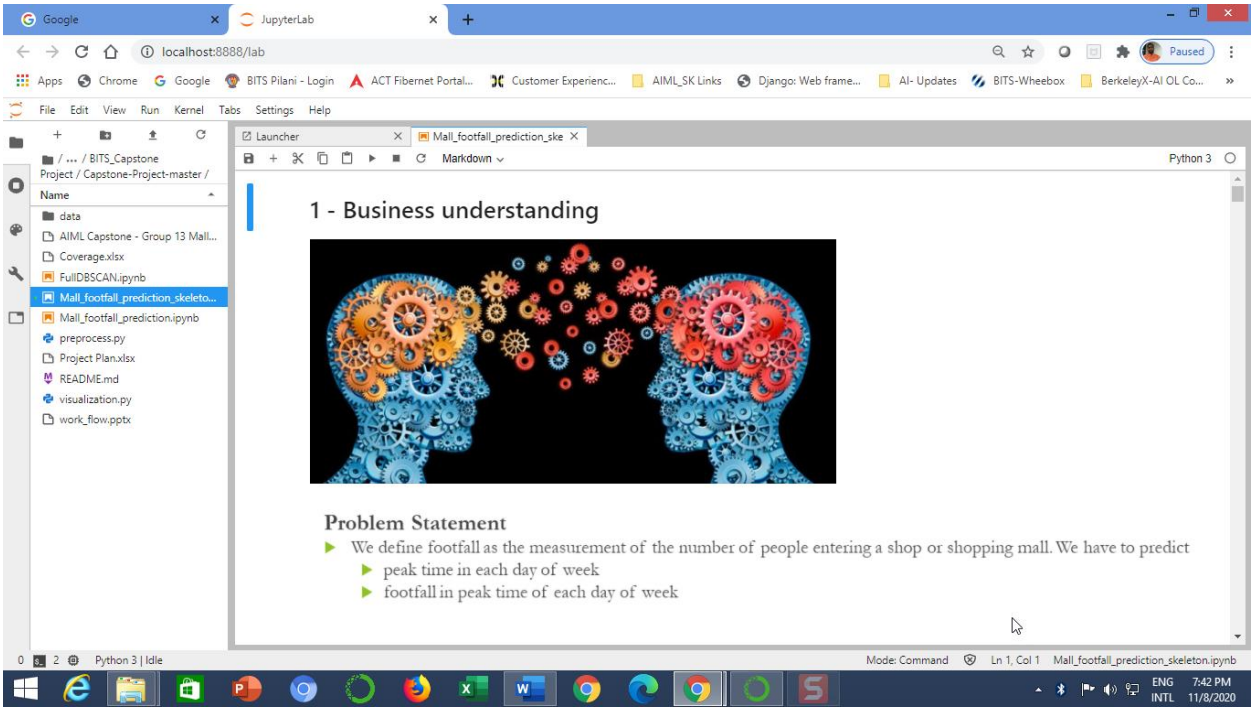
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Mall_footfall_prediction.ipynb
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
1 - Business understanding
Problem Statement
We define footfall as the measurement of the number of people entering a shop or shopping mall. We have to predict
peak time in each day of week
footfall in peak time of each day of week
Python 3 | Idle
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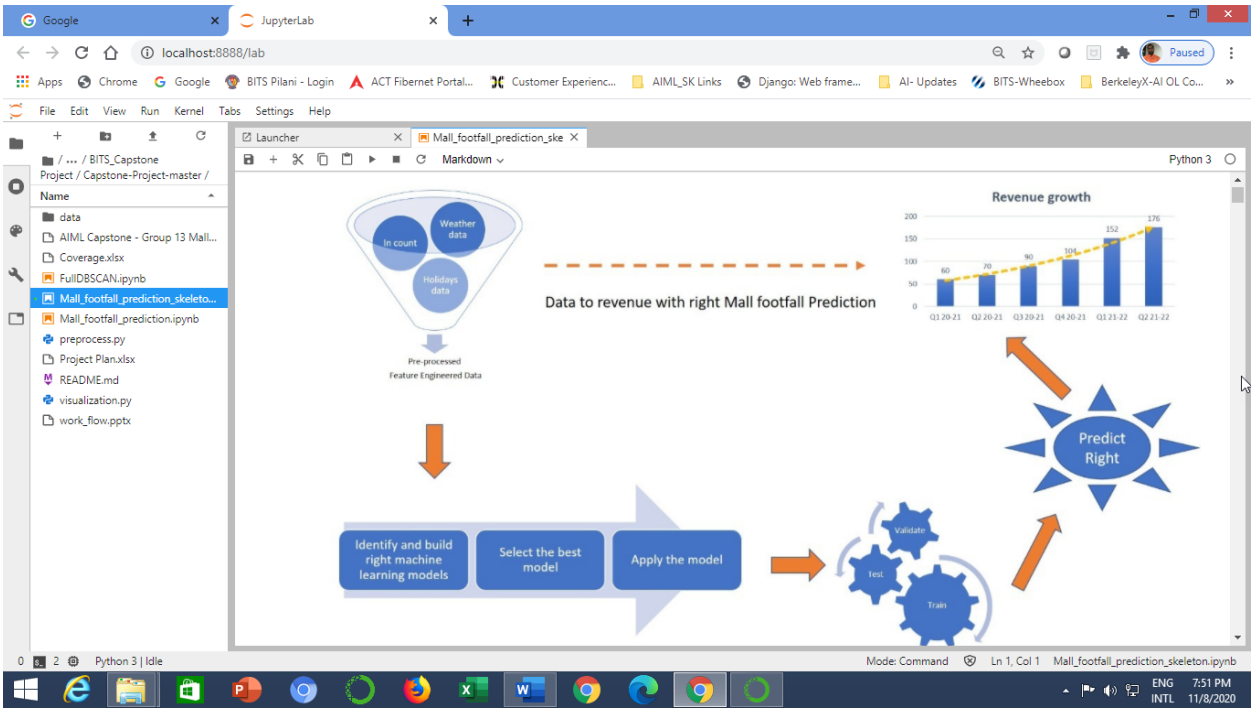
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Mall_footfall_prediction.ipynb
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
In count
Weather data
Holidays data
Pre-processed Feature Engineered Data
Data to revenue with right Mall footfall Prediction
Revenue growth
Predict Right
Identify and build right machine learning models
Select the best model
Apply the model
Validate
Test
Train
Python 3 | Idle
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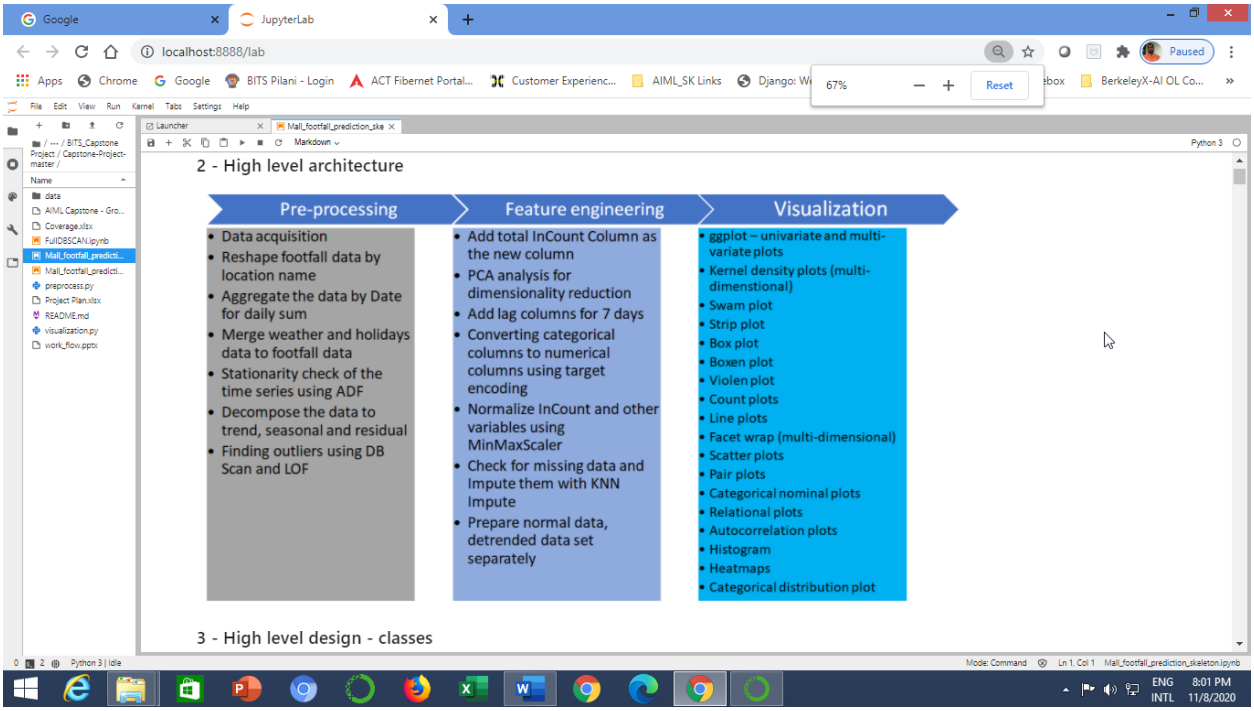
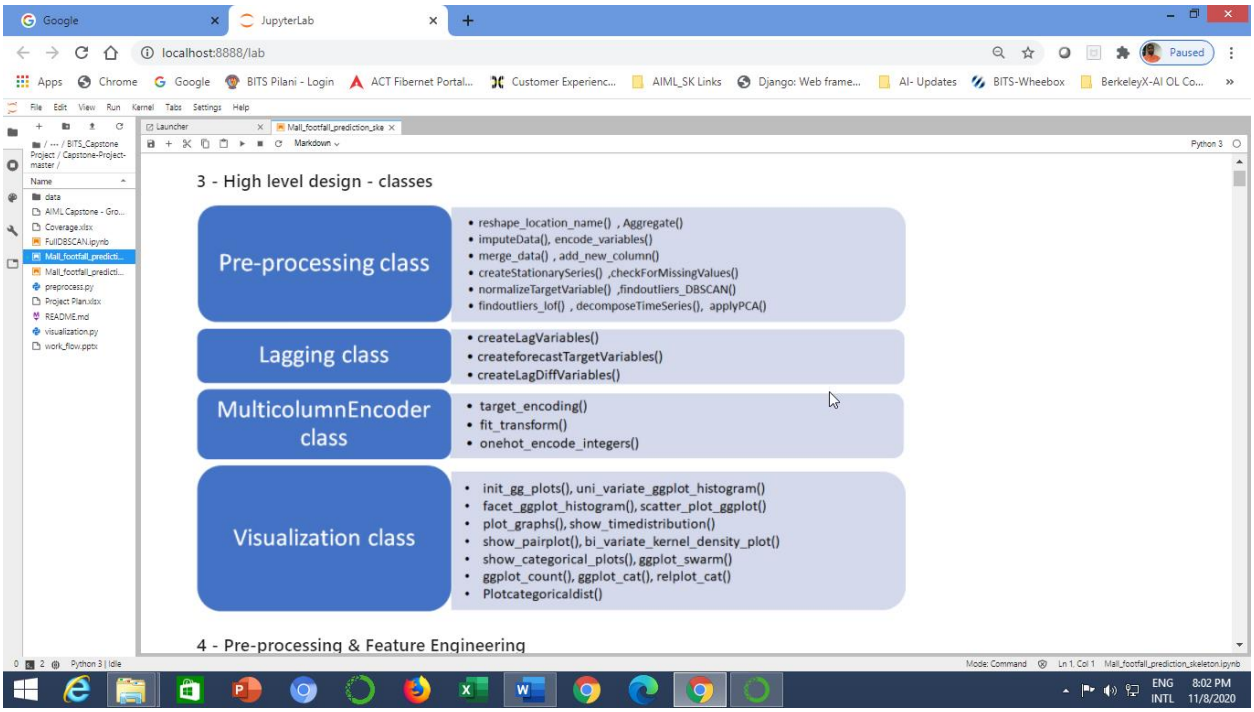
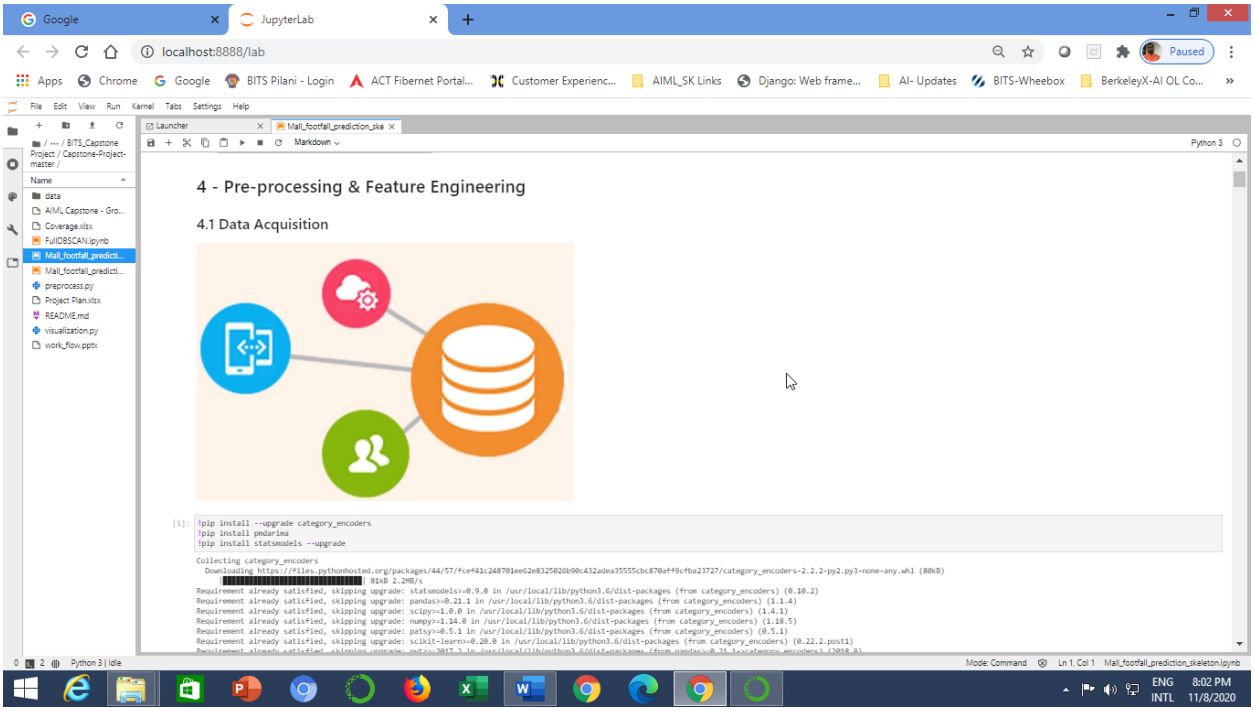

2 - High level architecture
Pre-processing
Data acquisition
Reshape footfall data by location name
Aggregate the data by Date for daily sum
Merge weather and holidays data to footfall data
Stationarity check of the time series using ADF
Decompose the data to trend, seasonal and residual
Finding outliers using DB Scan and LOF
Feature engineering
Add total InCount Column as the new column
PCA analysis for dimensionality reduction
Add lag columns for 7 days
Converting categorical columns to numerical columns using target encoding
Normalize InCount and other variables using MinMaxScaler
Check for missing data and Impute them with KNN Impute
Prepare normal data, detrended data set separately
Visualization
ggplot – univariate and multi-variate plots
Kernel density plots (multi-dimenstional)
Swam plot
Strip plot
Box plot
Boxen plot
Violen plot
Count plots
Line plots
Facet wrap (multi-dimensional)
Scatter plots
Pair plots
Categorical nominal plots
Relational plots
Autocorrelation plots
Histogram
Heatmaps
Categorical distribution plot
3 - High level design - classes


3 - High level design - classes
Pre-processing class
reshape_location_name() , Aggregate()
imputeData(), encode_variables()
merge_data() , add_new_column()
createStationarySeries() ,checkForMissingValues()
normalizeTargetVariable() ,findoutliers_DBSCAN()
findoutliers_lof() , decomposeTimeSeries(), applyPCA()
Lagging class
createLagVariables()
createforecastTargetVariables()
createLagDiffVariables()
MulticolumnEncoder class
target_encoding()
fit_transform()
onehot_encode_integers()
Visualization class
init_gg_plots(), uni_variate_ggplot_histogram()
facet_ggplot_histogram(), scatter_plot_ggplot()
plot_graphs(), show_timedistribution()
show_pairplot(), bi_variate_kernel_density_plot()
show_categorical_plots(), ggplot_swarm()
ggplot_count(), ggplot_cat(), relplot_cat()
Plotcategoricaldist()
4 - Pre-processing & Feature Engineering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Python 3
4 - Pre-processing & Feature Engineering
4.1 Data Acquisition
[1]:
!pip install --upgrade category_encoders
!pip install pmdarima
!pip install statsmodels --upgrade
Collecting category_encoders
Downloading https://files.pythonhosted.org/packages/44/57/fcef41c248701ee62e8325026b90c432adea35555cbc870aff9cfba23727/category_encoders-2.2.2-py2.py3-none-any.whl (80kB)
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Requirement already satisfied, skipping upgrade: statsmodels>=0.9.0 in /usr/local/lib/python3.6/dist-packages (from category_encoders) (0.10.2)
Requirement already satisfied, skipping upgrade: pandas>=0.21.1 in /usr/local/lib/python3.6/dist-packages (from category_encoders) (1.1.4)
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Requirement already satisfied, skipping upgrade: scikit-learn>=0.20.0 in /usr/local/lib/python3.6/dist-packages (from category_encoders) (0.22.2.post1)
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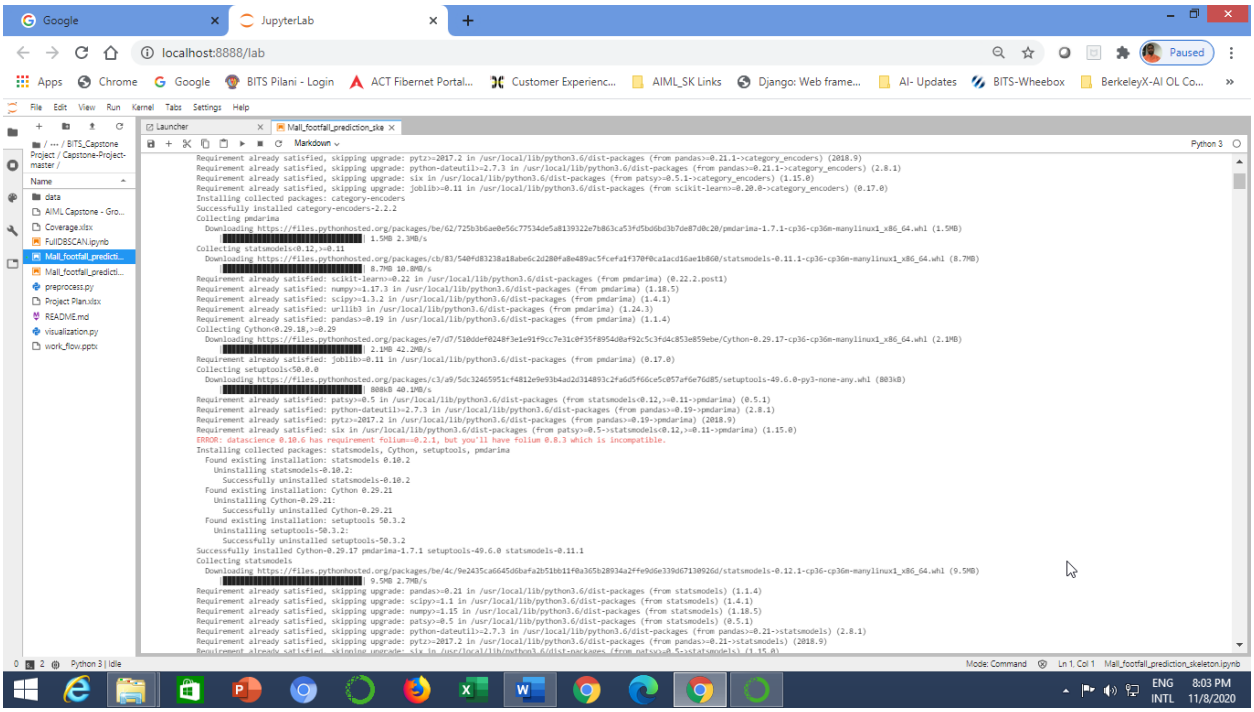
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Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.21.1->category_encoders) (2018.9)
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Requirement already satisfied, skipping upgrade: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20.0->category_encoders) (0.17.0)
Installing collected packages: category-encoders
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Collecting pmdarima
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1.5MB 2.3MB/s
Collecting statsmodels<0.12,>=0.11
Downloading https://files.pythonhosted.org/packages/cb/83/540fd83238a18abe6c2d280fa8e489ac5fcefa1f370f0ca1acd16ae1b860/statsmodels-0.11.1-cp36-cp36m-manylinux1_x86_64.whl (8.7MB)
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Collecting Cython<0.29.18,>=0.29
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2.1MB 42.2MB/s
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Collecting setuptools<50.0.0
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Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.6/dist-packages (from statsmodels<0.12,>=0.11->pmdarima) (0.5.1)
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Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas>=0.19->pmdarima) (2018.9)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from patsy>=0.5->statsmodels<0.12,>=0.11->pmdarima) (1.15.0)
ERROR: datascience 0.10.6 has requirement folium==0.2.1, but you'll have folium 0.8.3 which is incompatible.
Installing collected packages: statsmodels, Cython, setuptools, pmdarima
Found existing installation: statsmodels 0.10.2
Uninstalling statsmodels-0.10.2:
Successfully uninstalled statsmodels-0.10.2
Found existing installation: Cython 0.29.21
Uninstalling Cython-0.29.21:
Successfully uninstalled Cython-0.29.21
Found existing installation: setuptools 50.3.2
Uninstalling setuptools-50.3.2:
Successfully uninstalled setuptools-50.3.2
Successfully installed Cython-0.29.17 pmdarima-1.7.1 setuptools-49.6.0 statsmodels-0.11.1
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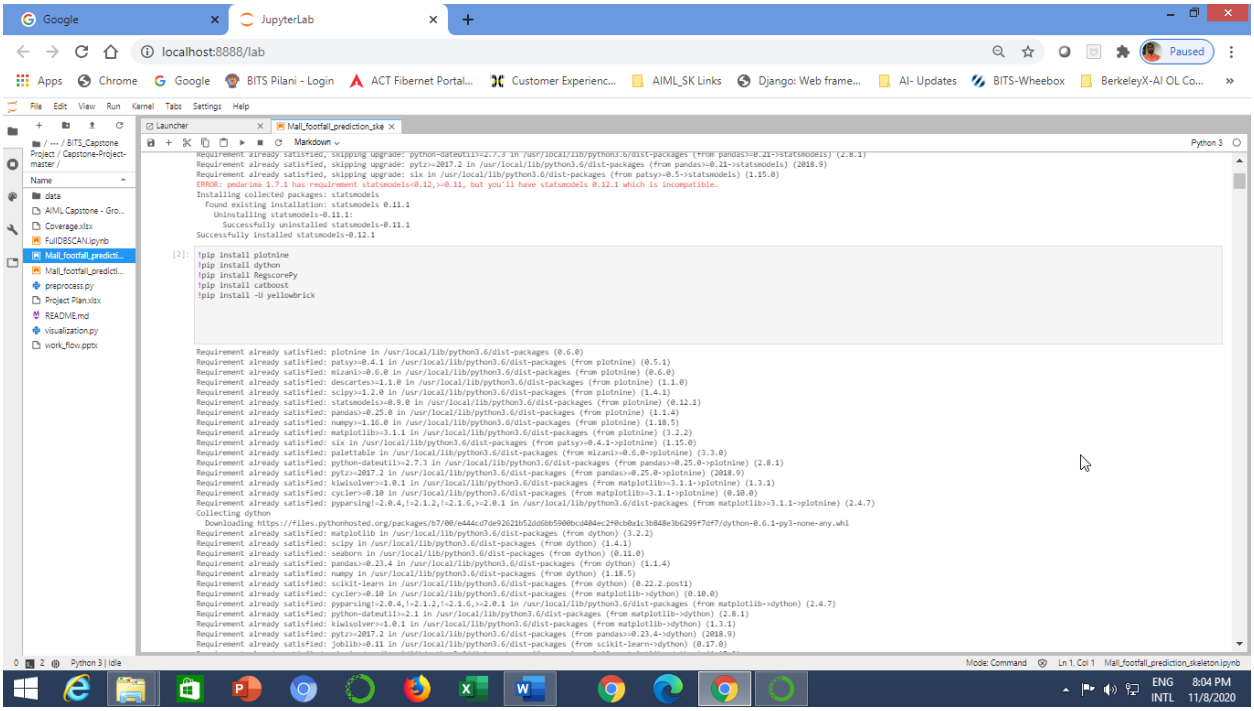
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README.md
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[2]:
!pip install plotnine
!pip install dython
!pip install RegscorePy
!pip install catboost
!pip install -U yellowbrick
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Requirement already satisfied: matplotlib>=3.1.1 in /usr/local/lib/python3.6/dist-packages (from plotnine) (3.2.2)
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Requirement already satisfied: seaborn in /usr/local/lib/python3.6/dist-packages (from dython) (0.11.0)
Requirement already satisfied: pandas>=0.23.4 in /usr/local/lib/python3.6/dist-packages (from dython) (1.1.4)
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Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn->dython) (0.17.0)
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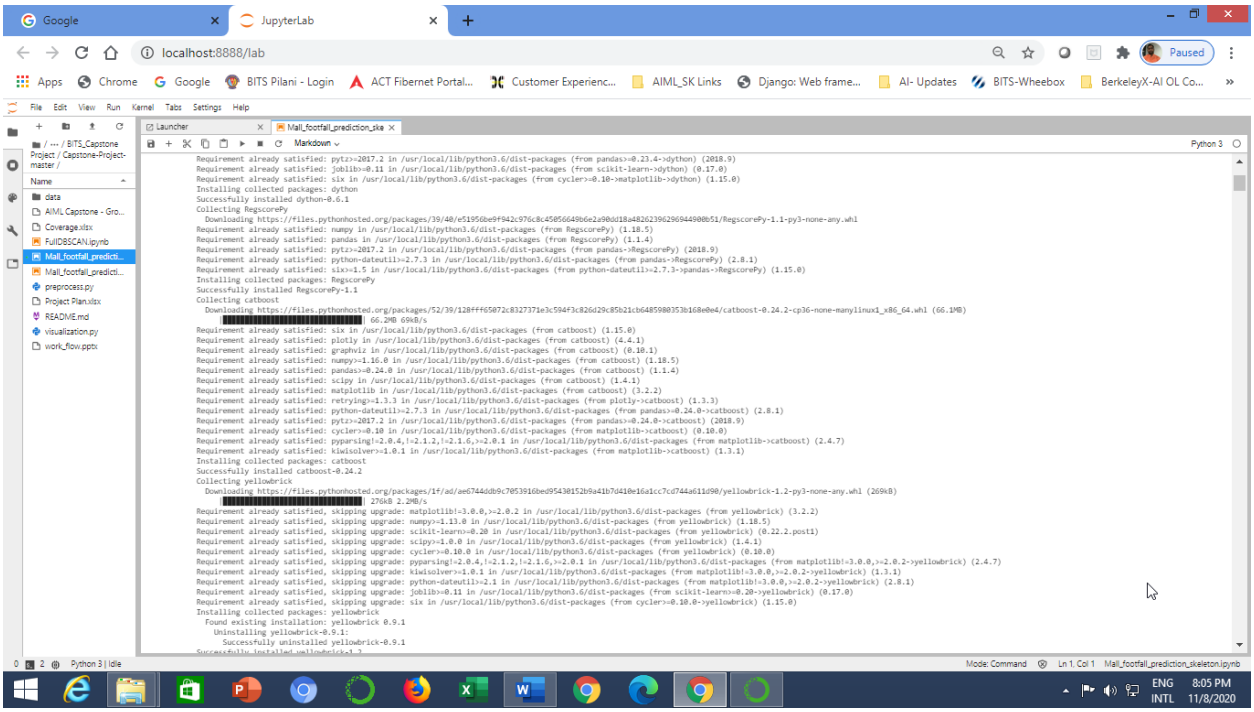
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Installing collected packages: dython
Successfully installed dython-0.6.1
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Downloading https://files.pythonhosted.org/packages/39/40/e51956be9f942c976c8c450566490b6e2a90dd18a4826239629694490b51/RegscorePy-1.1-py3-none-any.whl
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Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (from pandas->RegscorePy) (2018.9)
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Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (from catboost) (1.15.0)
Requirement already satisfied: plotly in /usr/local/lib/python3.6/dist-packages (from catboost) (4.4.1)
Requirement already satisfied: graphviz in /usr/local/lib/python3.6/dist-packages (from catboost) (0.10.1)
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Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.6/dist-packages (from plotly->catboost) (1.3.3)
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Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->catboost) (1.3.1)
Installing collected packages: catboost
Successfully installed catboost-0.24.2
Collecting yellowbrick
Downloading https://files.pythonhosted.org/packages/1f/ad/ae6744ddb9c7053916bed95430152b9a41b7d410e16a1cc7cd744a611d90/yellowbrick-1.2-py3-none-any.whl (269kB)
276kB 2.2MB/s
Requirement already satisfied, skipping upgrade: matplotlib!=3.0.0,>=2.0.2 in /usr/local/lib/python3.6/dist-packages (from yellowbrick) (3.2.2)
Requirement already satisfied, skipping upgrade: numpy>=1.13.0 in /usr/local/lib/python3.6/dist-packages (from yellowbrick) (1.18.5)
Requirement already satisfied, skipping upgrade: scikit-learn>=0.20 in /usr/local/lib/python3.6/dist-packages (from yellowbrick) (0.22.2.post1)
Requirement already satisfied, skipping upgrade: scipy>=1.0.0 in /usr/local/lib/python3.6/dist-packages (from yellowbrick) (1.4.1)
Requirement already satisfied, skipping upgrade: cycler>=0.10.0 in /usr/local/lib/python3.6/dist-packages (from yellowbrick) (0.10.0)
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.4.7)
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.3.1)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.8.1)
Requirement already satisfied, skipping upgrade: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20->yellowbrick) (0.17.0)
Requirement already satisfied, skipping upgrade: six in /usr/local/lib/python3.6/dist-packages (from cycler>=0.10.0->yellowbrick) (1.15.0)
Installing collected packages: yellowbrick
Found existing installation: yellowbrick 0.9.1
Uninstalling yellowbrick-0.9.1:
Successfully uninstalled yellowbrick-0.9.1
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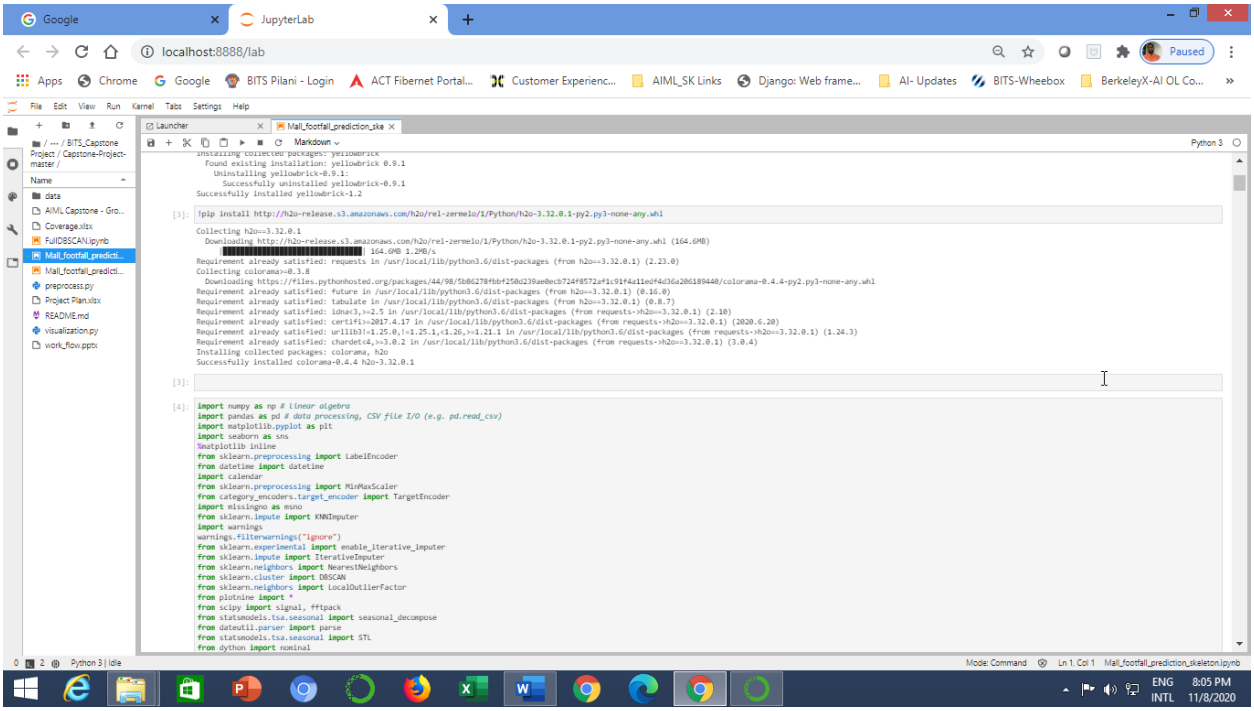
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Installing collected packages: yellowbrick
Found existing installation: yellowbrick 0.9.1
Uninstalling yellowbrick-0.9.1:
Successfully uninstalled yellowbrick-0.9.1
Successfully installed yellowbrick-1.2
[3]: !pip install http://h2o-release.s3.amazonaws.com/h2o/rel-zermelo/1/Python/h2o-3.32.0.1-py2.py3-none-any.whl
Collecting h2o==3.32.0.1
Downloading http://h2o-release.s3.amazonaws.com/h2o/rel-zermelo/1/Python/h2o-3.32.0.1-py2.py3-none-any.whl (164.6MB)
164.6MB 1.2MB/s
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from h2o==3.32.0.1) (2.23.0)
Collecting colorama>=0.3.8
Downloading https://files.pythonhosted.org/packages/44/98/5b86278fbbf250d239ae0ecb724f8572af1c91f4a11edf4d36a206189440/colorama-0.4.4-py2.py3-none-any.whl
Requirement already satisfied: future in /usr/local/lib/python3.6/dist-packages (from h2o==3.32.0.1) (0.16.0)
Requirement already satisfied: tabulate in /usr/local/lib/python3.6/dist-packages (from h2o==3.32.0.1) (0.8.7)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-packages (from requests->h2o==3.32.0.1) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (from requests->h2o==3.32.0.1) (2020.6.20)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.6/dist-packages (from requests->h2o==3.32.0.1) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6/dist-packages (from requests->h2o==3.32.0.1) (3.0.4)
Installing collected packages: colorama, h2o
Successfully installed colorama-0.4.4 h2o-3.32.0.1
[3]:
[4]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.preprocessing import LabelEncoder
from datetime import datetime
import calendar
from sklearn.preprocessing import MinMaxScaler
from category_encoders.target_encoder import TargetEncoder
import missingno as msno
from sklearn.impute import KNNImputer
import warnings
warnings.filterwarnings("ignore")
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.neighbors import NearestNeighbors
from sklearn.cluster import DBSCAN
from sklearn.neighbors import LocalOutlierFactor
from plotnine import *
from scipy import signal, fftpack
from statsmodels.tsa.seasonal import seasonal_decompose
from dateutil.parser import parse
from statsmodels.tsa.seasonal import STL
from python import nominal
0 2 Python 3 | Idle
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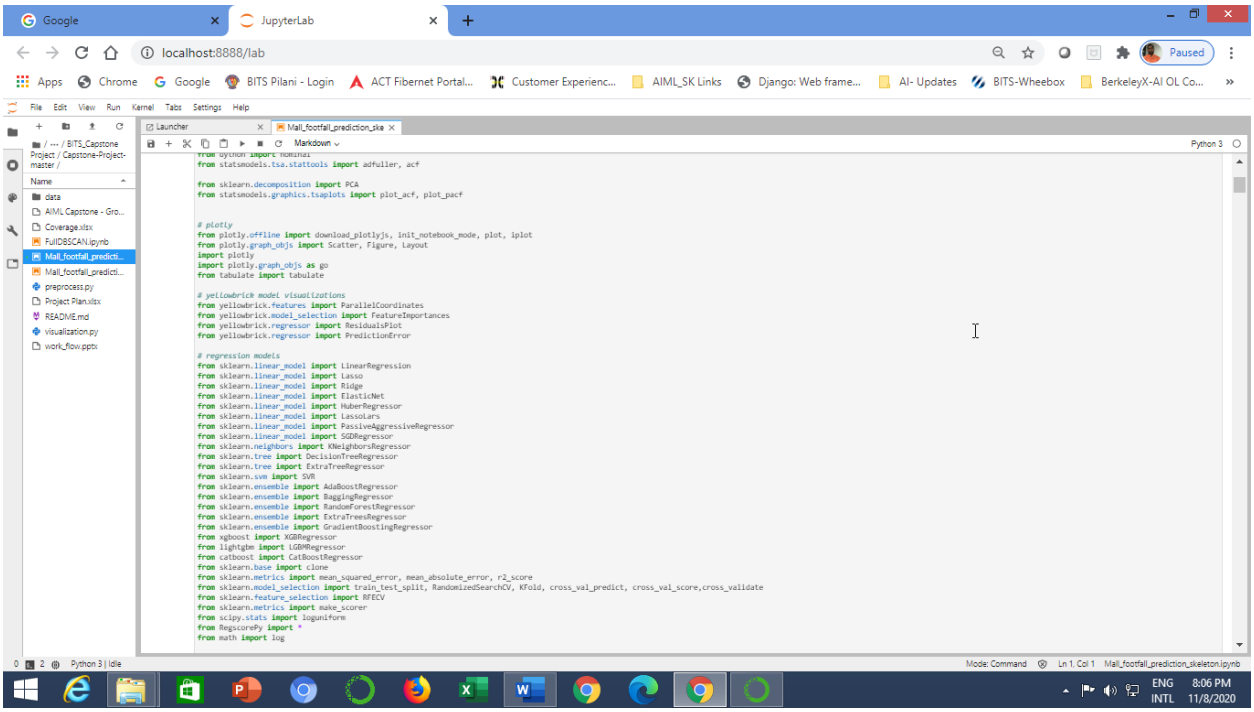
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from statsmodels.tsa.stattools import adfuller, acf
from sklearn.decomposition import PCA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
# plotly
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
from plotly.graph_objs import Scatter, Figure, Layout
import plotly
import plotly.graph_objs as go
from tabulate import tabulate
# yellowbrick model visualizations
from yellowbrick.features import ParallelCoordinates
from yellowbrick.model_selection import FeatureImportances
from yellowbrick.regressor import ResidualsPlot
from yellowbrick.regressor import PredictionError
# regression models
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import HuberRegressor
from sklearn.linear_model import LassoLars
from sklearn.linear_model import PassiveAggressiveRegressor
from sklearn.linear_model import SGDRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import ExtraTreeRegressor
from sklearn.svm import SVR
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from catboost import CatBoostRegressor
from sklearn.base import clone
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.model_selection import train_test_split, RandomizedSearchCV, KFold, cross_val_predict, cross_val_score,cross_validate
from sklearn.feature_selection import RFECV
from sklearn.metrics import make_scorer
from scipy.stats import loguniform
from RegscorePy import *
from math import log
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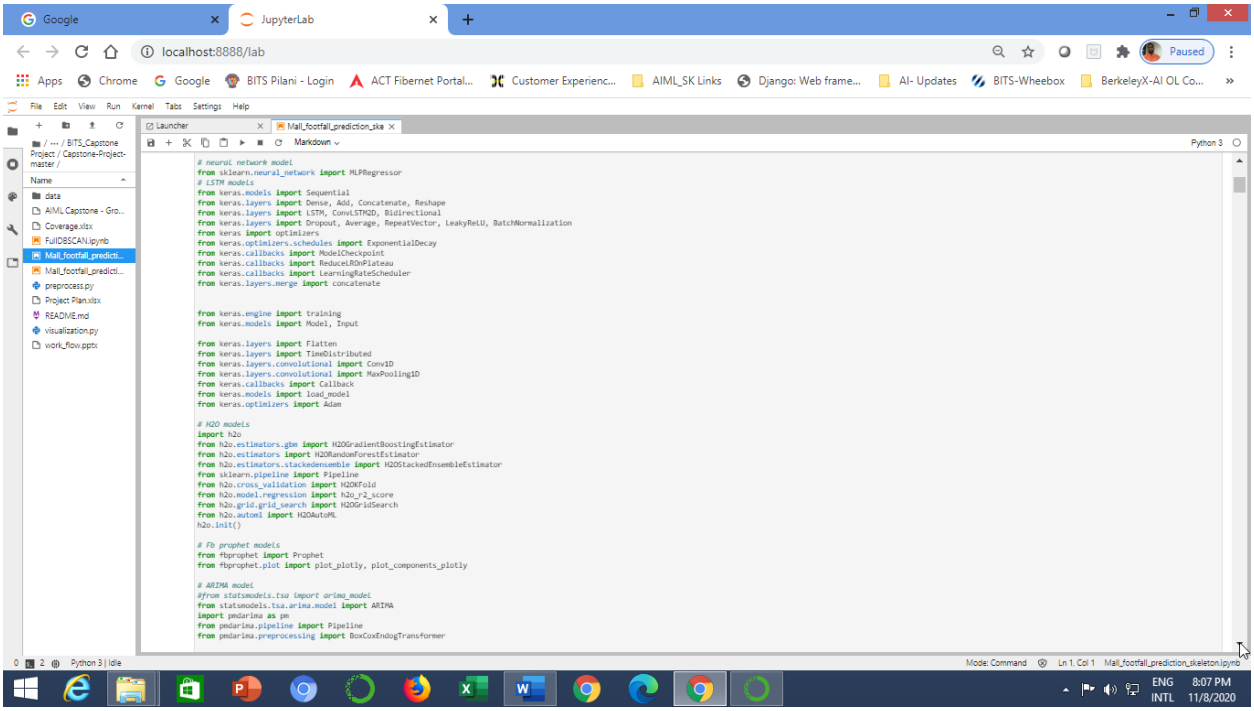
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work_flow.pptx
# neural network model
from sklearn.neural_network import MLPRegressor
# LSTM models
from keras.models import Sequential
from keras.layers import Dense, Add, Concatenate, Reshape
from keras.layers import LSTM, ConvLSTM2D, Bidirectional
from keras.layers import Dropout, Average, RepeatVector, LeakyReLU, BatchNormalization
from keras import optimizers
from keras.optimizers.schedules import ExponentialDecay
from keras.callbacks import ModelCheckpoint
from keras.callbacks import ReduceLROnPlateau
from keras.callbacks import LearningRateScheduler
from keras.layers.merge import concatenate
from keras.engine import training
from keras.models import Model, Input
from keras.layers import Flatten
from keras.layers import TimeDistributed
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.callbacks import Callback
from keras.models import load_model
from keras.optimizers import Adam
# H2O models
import h2o
from h2o.estimators.gbm import H2OGradientBoostingEstimator
from h2o.estimators import H2ORandomForestEstimator
from h2o.estimators.stackedensemble import H2OStackedEnsembleEstimator
from sklearn.pipeline import Pipeline
from h2o.cross_validation import H2OKFold
from h2o.model.regression import h2o_r2_score
from h2o.grid.grid_search import H2OGridSearch
from h2o.automl import H2OAutoML
h2o.init()
# Fb prophet models
from fbprophet import Prophet
from fbprophet.plot import plot_plotly, plot_components_plotly
# ARIMA model
#from statsmodels.tsa import arima_model
from statsmodels.tsa.arima.model import ARIMA
import pmdarima as pm
from pmdarima.pipeline import Pipeline
from pmdarima.preprocessing import BoxCoxEndogTransformer
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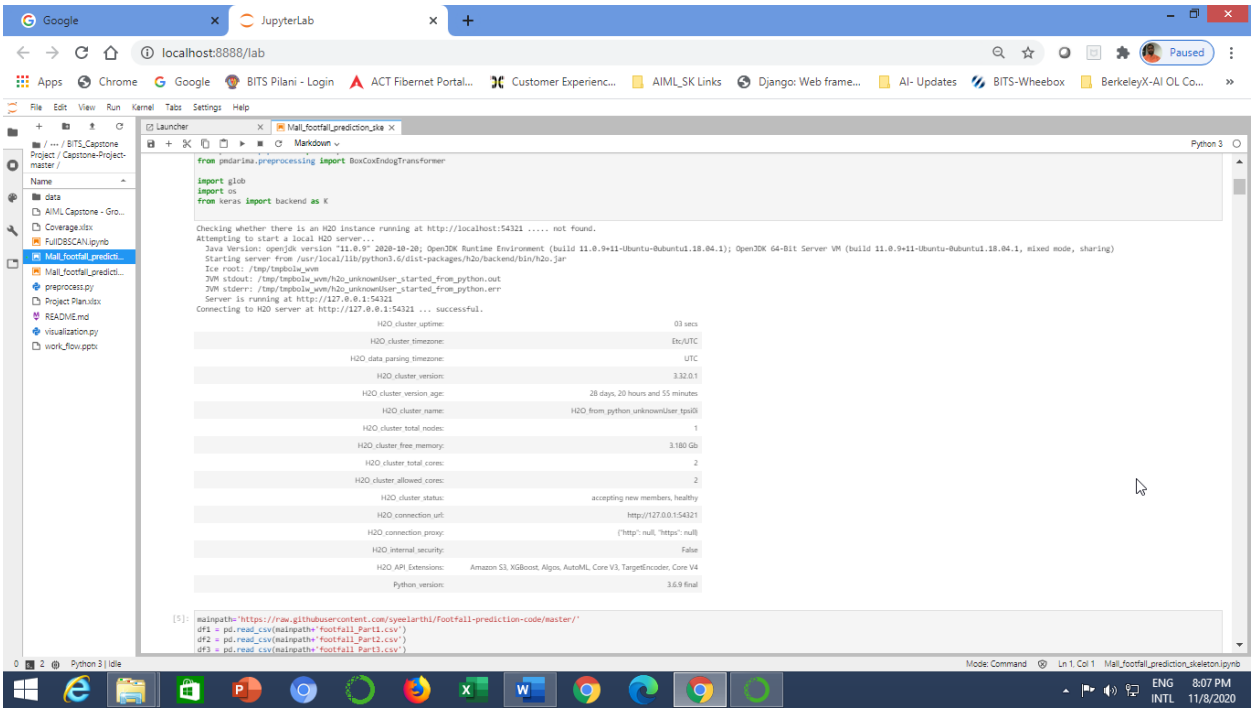
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work_flow.pptx
from pmdarima.preprocessing import BoxCoxEndogTransformer
import glob
import os
from keras import backend as K
Checking whether there is an H2O instance running at http://localhost:54321 ..... not found.
Attempting to start a local H2O server...
Java Version: openjdk version "11.0.9" 2020-10-20; OpenJDK Runtime Environment (build 11.0.9+11-Ubuntu-0ubuntu1.18.04.1); OpenJDK 64-Bit Server VM (build 11.0.9+11-Ubuntu-0ubuntu1.18.04.1, mixed mode, sharing)
Starting server from /usr/local/lib/python3.6/dist-packages/h2o/backend/bin/h2o.jar
Ice root: /tmp/tmpbolw_wvm
JVM stdout: /tmp/tmpbolw_wvm/h2o_unknownUser_started_from_python.out
JVM stderr: /tmp/tmpbolw_wvm/h2o_unknownUser_started_from_python.err
Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321 ... successful.
H2O_cluster_uptime: 03 secs
H2O_cluster_timezone: Etc/UTC
H2O_data_parsing_timezone: UTC
H2O_cluster_version: 3.32.0.1
H2O_cluster_version_age: 28 days, 20 hours and 55 minutes
H2O_cluster_name: H2O_from_python_unknownUser_tpsi0i
H2O_cluster_total_nodes: 1
H2O_cluster_free_memory: 3.180 Gb
H2O_cluster_total_cores: 2
H2O_cluster_allowed_cores: 2
H2O_cluster_status: accepting new members, healthy
H2O_connection_url: http://127.0.0.1:54321
H2O_connection_proxy: {"http": null, "https": null}
H2O_internal_security: False
H2O_API_Extensions: Amazon S3, XGBoost, Algos, AutoML, Core V3, TargetEncoder, Core V4
Python_version: 3.6.9 final
[5]:
mainpath='https://raw.githubusercontent.com/syeelarthi/Footfall-prediction-code/master/'
df1 = pd.read_csv(mainpath+'footfall_Part1.csv')
df2 = pd.read_csv(mainpath+'footfall_Part2.csv')
df3 = pd.read_csv(mainpath+'footfall_Part3.csv')
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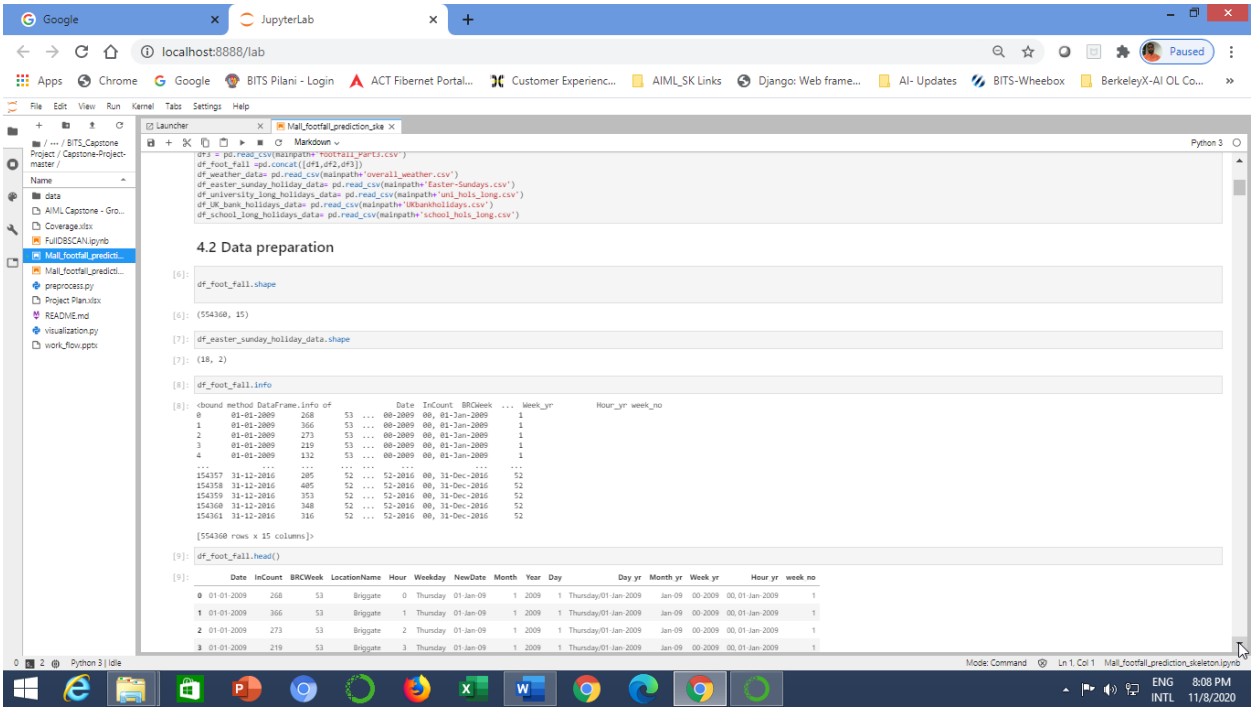
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4.2 Data preparation
df_foot_fall.shape
(554360, 15)
df_easter_sunday_holiday_data.shape
(18, 2)
df_foot_fall.info
<bound method DataFrame.info of Date InCount BRCWeek ... Week_yr Hour_yr week_no
154360 31-12-2016 348 52 ... 52-2016 00, 31-Dec-2016 52
154361 31-12-2016 316 52 ... 52-2016 00, 31-Dec-2016 52
[554360 rows x 15 columns]>
df_foot_fall.head()
Date InCount BRCWeek LocationName Hour Weekday NewDate Month Year Day Day yr Month yr Week yr Hour yr week no
0 01-01-2009 268 53 Briggate 0 Thursday 01-Jan-09 1 2009 1 Thursday/01-Jan-2009 Jan-09 00-2009 00, 01-Jan-2009 1
1 01-01-2009 366 53 Briggate 1 Thursday 01-Jan-09 1 2009 1 Thursday/01-Jan-2009 Jan-09 00-2009 00, 01-Jan-2009 1
2 01-01-2009 273 53 Briggate 2 Thursday 01-Jan-09 1 2009 1 Thursday/01-Jan-2009 Jan-09 00-2009 00, 01-Jan-2009 1
3 01-01-2009 219 53 Briggate 3 Thursday 01-Jan-09 1 2009 1 Thursday/01-Jan-2009 Jan-09 00-2009 00, 01-Jan-2009 1
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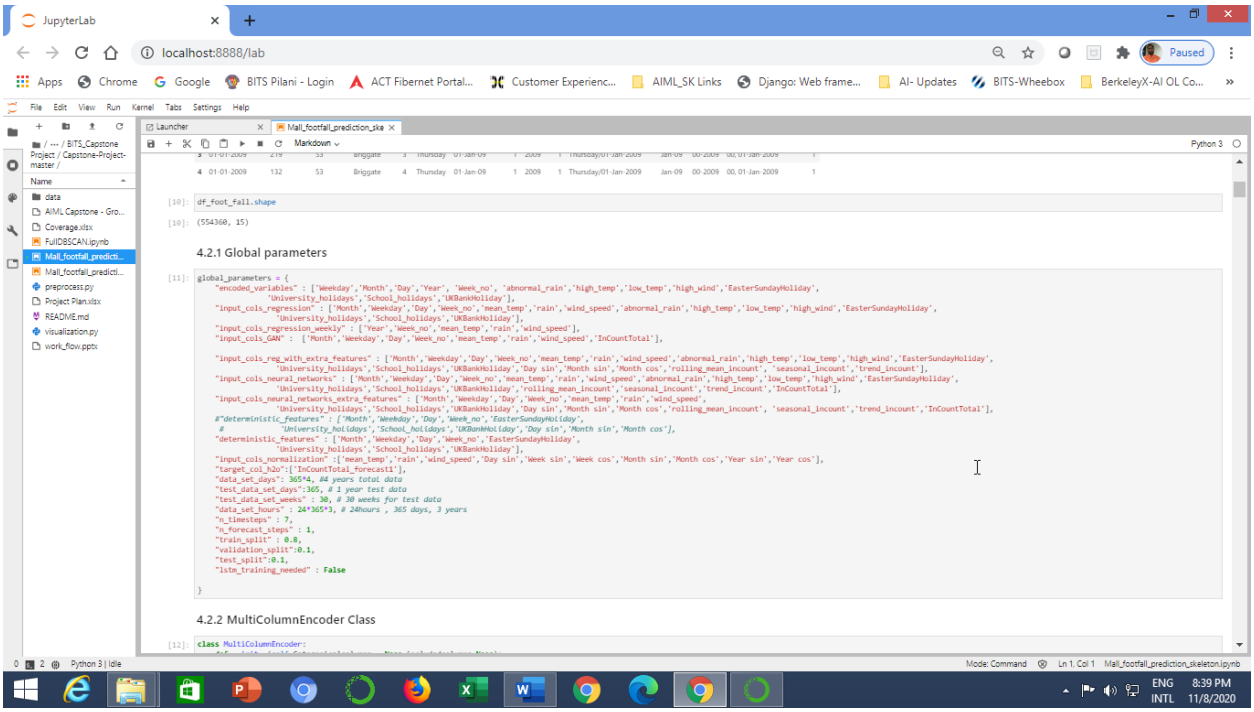
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4 01-01-2009 132 53 Briggate 4 Thursday 01-Jan-09 1 2009 1 Thursday/01-Jan-2009 Jan-09 00-2009 00, 01-Jan-2009 1
df_foot_fall.shape
(554360, 15)
4.2.1 Global parameters
global_parameters = {
"encoded_variables" : ['Weekday','Month','Day','Year', 'Week_no', 'abnormal_rain','high_temp','low_temp','high_wind','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday'],
"input_cols_regression" : ['Month','Weekday','Day','Week_no','mean_temp','rain','wind_speed','abnormal_rain','high_temp','low_temp','high_wind','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday'],
"input_cols_regression_weekly" : ['Year','Week_no','mean_temp','rain','wind_speed'],
"input_cols_GAN" : ['Month','Weekday','Day','Week_no','mean_temp','rain','wind_speed','InCountTotal'],
"input_cols_reg_with_extra_features" : ['Month','Weekday','Day','Week_no','mean_temp','rain','wind_speed','abnormal_rain','high_temp','low_temp','high_wind','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday','Day sin','Month sin','Month cos','rolling_mean_incount','seasonal_incount','trend_incount'],
"input_cols_neural_networks" : ['Month','Weekday','Day','Week_no','mean_temp','rain','wind_speed','abnormal_rain','high_temp','low_temp','high_wind','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday','rolling_mean_incount','seasonal_incount','trend_incount','InCountTotal'],
"input_cols_neural_networks_extra_features" : ['Month','Weekday','Day','Week_no','mean_temp','rain','wind_speed',
'University_holidays','School_holidays','UKBankHoliday','Day sin','Month sin','Month cos','rolling_mean_incount', 'seasonal_incount','trend_incount','InCountTotal'],
#"deterministic_features" : ['Month','Weekday','Day','Week_no','EasterSundayHoliday',
# 'University_holidays','School_holidays','UKBankHoliday','Day sin','Month sin','Month cos'],
"deterministic_features" : ['Month','Weekday','Day','Week_no','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday'],
"input_cols_normalization" :['mean_temp','rain','wind_speed','Day sin','Week sin','Week cos','Month sin','Month cos','Year sin','Year cos'],
"target_col_h2o":['InCountTotal_forecast1'],
"data_set_days": 365*4, ## years total data
"test_data_set_days":365, # 1 year test data
"test_data_set_weeks" : 30, # 30 weeks for test data
"data_set_hours" : 24*365*3, # 24hours , 365 days, 3 years
"n_timesteps" : 7,
"n_forecast_steps" : 1,
"train_split" : 0.8,
"validation_split":0.1,
"test_split":0.1,
"lstm_training_needed" : False
}
4.2.2 MultiColumnEncoder Class
class MultiColumnEncoder:
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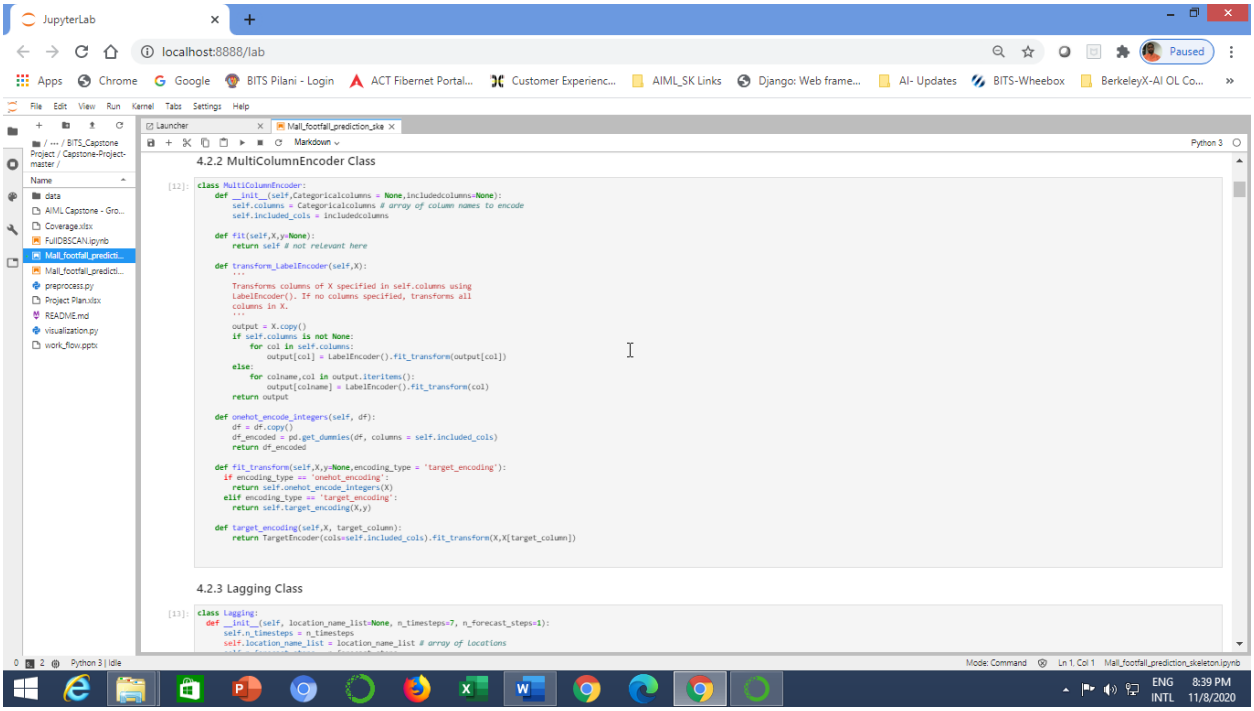


### 4.2.2 MultiColumnEncoder Class

```
class MultiColumnEncoder:
    def __init__(self,Categoricalcolumns = None,includedcolumns=None):
        self.columns = Categoricalcolumns # array of column names to encode
        self.included_cols = includedcolumns

    def fit(self,X,y=None):
        return self # not relevant here

    def transform_LabelEncoder(self,X):
        '''
        Transforms columns of X specified in self.columns using
        LabelEncoder(). If no columns specified, transforms all
        columns in X.
        '''
        output = X.copy()
        if self.columns is not None:
            for col in self.columns:
                output[col] = LabelEncoder().fit_transform(output[col])
        else:
            for colname,col in output.iteritems():
                output[colname] = LabelEncoder().fit_transform(col)
        return output

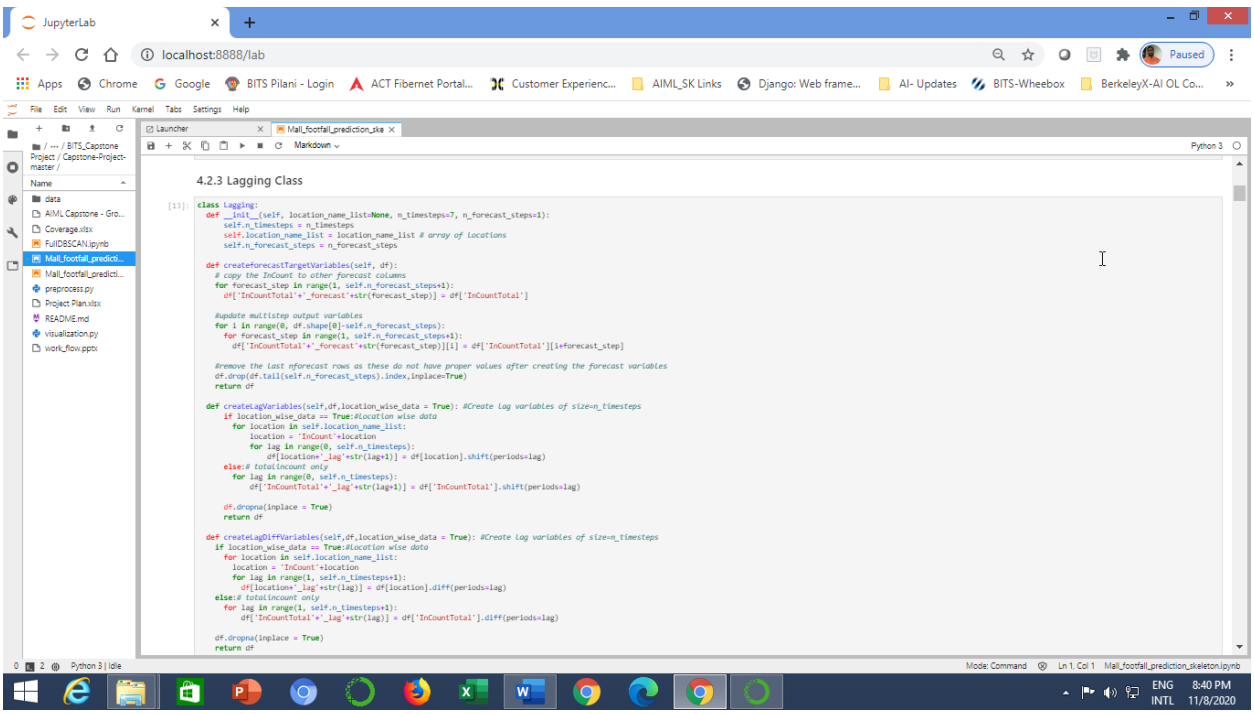
    def onehot_encode_integers(self, df):
        df = df.copy()
        df_encoded = pd.get_dummies(df, columns = self.included_cols)
        return df_encoded

    def fit_transform(self,X,y=None,encoding_type = 'target_encoding'):
      if encoding_type == 'onehot_encoding':
        return self.onehot_encode_integers(X)
      elif encoding_type == 'target_encoding':
        return self.target_encoding(X,y)

    def target_encoding(self,X, target_column):
        return TargetEncoder(cols=self.included_cols).fit_transform(X,X[target_column])
```

### 4.2.3 Lagging Class

```
class Lagging:
  def __init__(self, location_name_list=None, n_timesteps=7, n_forecast_steps=1):
      self.n_timesteps = n_timesteps
      self.location_name_list = location_name_list # array of locations
```



### 4.2.3 Lagging Class

```
class Lagging:
  def __init__(self, location_name_list=None, n_timesteps=7, n_forecast_steps=1):
      self.n_timesteps = n_timesteps
      self.location_name_list = location_name_list # array of locations
      self.n_forecast_steps = n_forecast_steps

  def createforecastTargetVariables(self, df):
    # copy the InCount to other forecast columns
    for forecast_step in range(1, self.n_forecast_steps+1):
      df['InCountTotal'+'_forecast'+str(forecast_step)] = df['InCountTotal']

    #update multistep output variables
    for i in range(0, df.shape[0]-self.n_forecast_steps):
      for forecast_step in range(1, self.n_forecast_steps+1):
        df['InCountTotal'+'_forecast'+str(forecast_step)][i] = df['InCountTotal'][i+forecast_step]

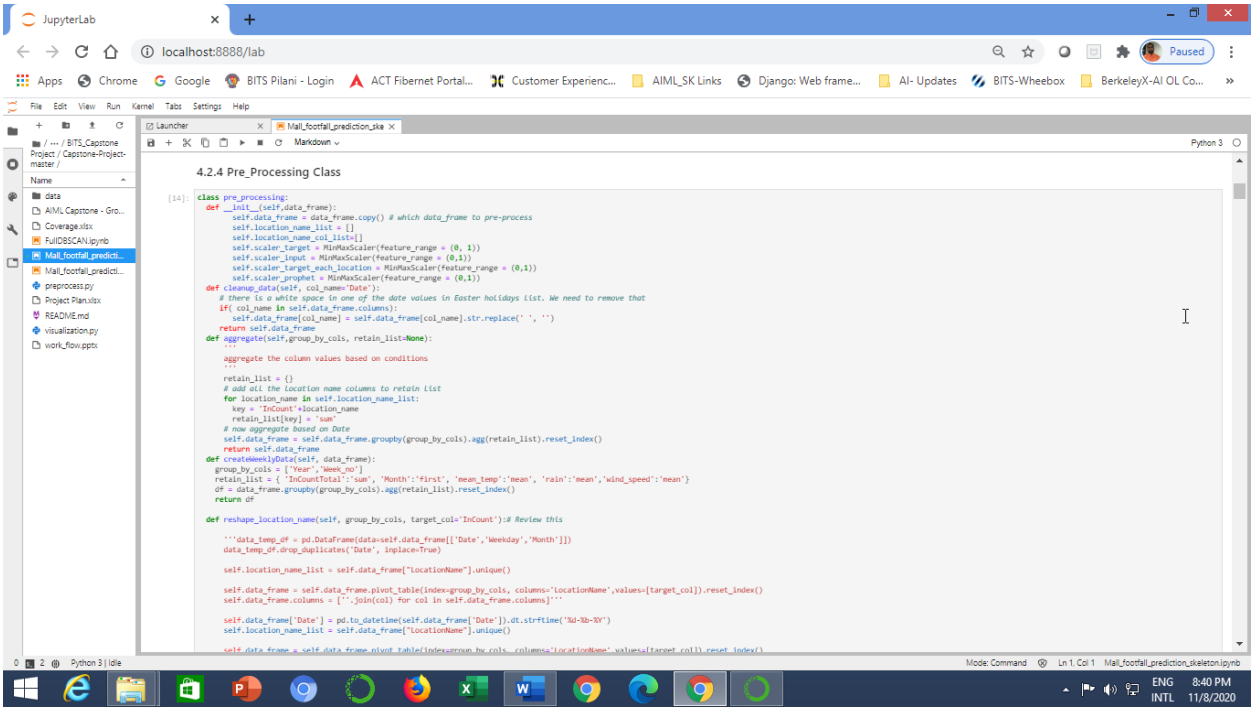
    #remove the last nforecast rows as these do not have proper values after creating the forecast variables
    df.drop(df.tail(self.n_forecast_steps).index,inplace=True)
    return df

  def createLagVariables(self,df,location_wise_data = True): #Create Lag variables of size=n_timesteps
      if location_wise_data == True:#Location wise data
        for location in self.location_name_list:
            location = 'InCount'+location
            for lag in range(0, self.n_timesteps):
                df[location+'_lag'+str(lag+1)] = df[location].shift(periods=lag)
      else:# totalincount only
        for lag in range(0, self.n_timesteps):
            df['InCountTotal'+'_lag'+str(lag+1)] = df['InCountTotal'].shift(periods=lag)

      df.dropna(inplace = True)
      return df

  def createLagDiffVariables(self,df,location_wise_data = True): #Create Lag variables of size=n_timesteps
    if location_wise_data == True:#Location wise data
      for location in self.location_name_list:
        location = 'InCount'+location
        for lag in range(1, self.n_timesteps+1):
          df[location+'_lag'+str(lag)] = df[location].diff(periods=lag)
    else:# totalincount only
      for lag in range(1, self.n_timesteps+1):
          df['InCountTotal'+'_lag'+str(lag)] = df['InCountTotal'].diff(periods=lag)

    df.dropna(inplace = True)
    return df
```


JupyterLab
localhost:8888/lab
Paused
Apps
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AIML_SK Links
Django: Web frame...
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BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
4.2.4 Pre_Processing Class
[14]:
class pre_processing:
def __init__(self,data_frame):
self.data_frame = data_frame.copy() # which data_frame to pre-process
self.location_name_list = []
self.location_name_col_list=[]
self.scaler_target = MinMaxScaler(feature_range = (0, 1))
self.scaler_temp_input = MinMaxScaler(feature_range = (0,1))
self.scaler_target_each_location = MinMaxScaler(feature_range = (0,1))
self.scaler_prophet = MinMaxScaler(feature_range = (0,1))
def cleanup_data(self, col_name='Date'):
# there is a white space in one of the date values in Easter holidays list. We need to remove that
if( col_name in self.data_frame.columns):
self.data_frame[col_name] = self.data_frame[col_name].str.replace(' ', '')
return self.data_frame
def aggregate(self,group_by_cols, retain_list=None):
'''
aggregate the column values based on conditions
'''
retain_list = {}
# add all the location name columns to retain list
for location_name in self.location_name_list:
key = 'InCount'+location_name
retain_list[key] = 'sum'
# now aggregate based on Date
self.data_frame = self.data_frame.groupby(group_by_cols).agg(retain_list).reset_index()
return self.data_frame
def createWeeklyData(self, data_frame):
group_by_cols = ['Year','Week_no']
retain_list = { 'InCountTotal':'sum', 'Month':'first', 'mean_temp':'mean', 'rain':'mean','wind_speed':'mean'}
df = data_frame.groupby(group_by_cols).agg(retain_list).reset_index()
return df
def reshape_location_name(self, group_by_cols, target_col='InCount'):# Review this
'''data_temp_df = pd.DataFrame(data=self.data_frame[['Date','Weekday','Month']])
data_temp_df.drop_duplicates('Date', inplace=True)
self.location_name_list = self.data_frame["LocationName"].unique()
self.data_frame = self.data_frame.pivot_table(index=group_by_cols, columns='LocationName',values=[target_col]).reset_index()
self.data_frame.columns = [''.join(col) for col in self.data_frame.columns]'''
self.data_frame['Date'] = pd.to_datetime(self.data_frame['Date']).dt.strftime('%d-%b-%Y')
self.location_name_list = self.data_frame["LocationName"].unique()
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
Python 3 | Idle
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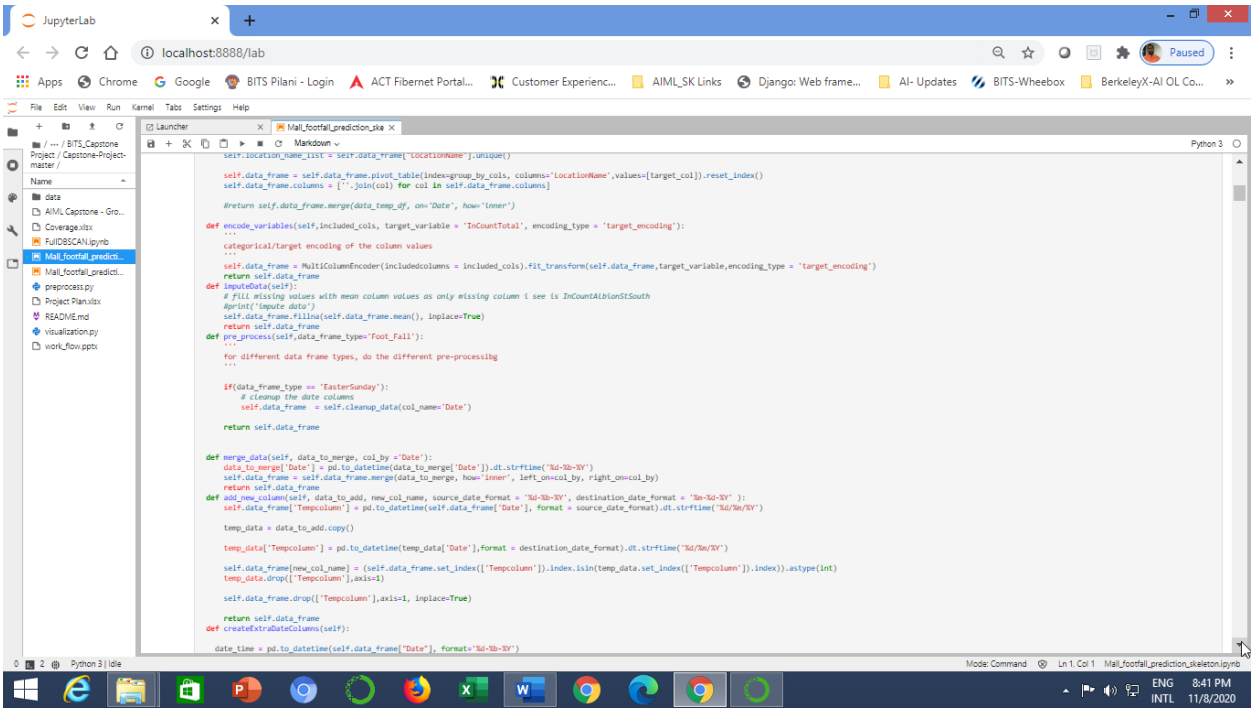
11/8/2020


JupyterLab
localhost:8888/lab
Paused
Apps
Chrome
Google
BITS Pilani - Login
ACT Fibernet Portal...
Customer Experienc...
AIML_SK Links
Django: Web frame...
AI- Updates
BITS-Wheebox
BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
self.location_name_list = self.data_frame["LocationName"].unique()
self.data_frame = self.data_frame.pivot_table(index=group_by_cols, columns='LocationName',values=[target_col]).reset_index()
self.data_frame.columns = [''.join(col) for col in self.data_frame.columns]
#return self.data_frame.merge(data_temp_df, on='Date', how='inner')
def encode_variables(self,included_cols, target_variable = 'InCountTotal', encoding_type = 'target_encoding'):
'''
categorical/target encoding of the column values
'''
self.data_frame = MultiColumnEncoder(includedcolumns = included_cols).fit_transform(self.data_frame,target_variable,encoding_type = 'target_encoding')
return self.data_frame
def imputeData(self):
# fill missing values with mean column values as only missing column i see is InCountAlbionStSouth
#print('impute data')
self.data_frame.fillna(self.data_frame.mean(), inplace=True)
return self.data_frame
def pre_process(self,data_frame_type='Foot_Fall'):
'''
for different data frame types, do the different pre-processibg
'''
if(data_frame_type == 'EasterSunday'):
# cleanup the date columns
self.data_frame = self.cleanup_data(col_name='Date')
return self.data_frame
def merge_data(self, data_to_merge, col_by ='Date'):
data_to_merge['Date'] = pd.to_datetime(data_to_merge['Date']).dt.strftime('%d-%b-%Y')
self.data_frame = self.data_frame.merge(data_to_merge, how='inner', left_on=col_by, right_on=col_by)
return self.data_frame
def add_new_column(self, data_to_add, new_col_name, source_date_format = '%d-%b-%Y', destination_date_format = '%m-%d-%Y' ):
self.data_frame['Tempcolumn'] = pd.to_datetime(self.data_frame['Date'], format = source_date_format).dt.strftime('%d/%m/%Y')
temp_data = data_to_add.copy()
temp_data['Tempcolumn'] = pd.to_datetime(temp_data['Date'],format = destination_date_format).dt.strftime('%d/%m/%Y')
self.data_frame[new_col_name] = (self.data_frame.set_index(['Tempcolumn']).index.isin(temp_data.set_index(['Tempcolumn']).index)).astype(int)
temp_data.drop(['Tempcolumn'],axis=1)
self.data_frame.drop(['Tempcolumn'],axis=1, inplace=True)
return self.data_frame
def createExtraDateColumns(self):
date_time = pd.to_datetime(self.data_frame["Date"], format='%d-%b-%Y')
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
Python 3 | Idle
ENG
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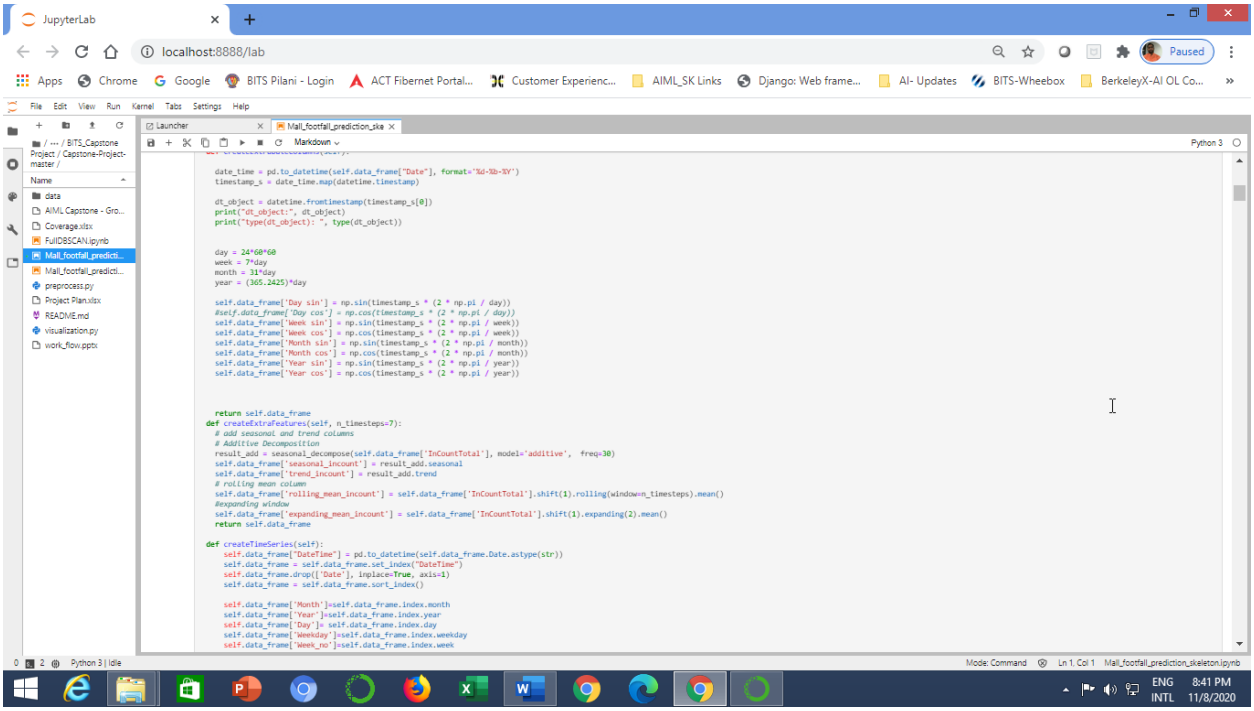


```
    date_time = pd.to_datetime(self.data_frame["Date"], format='%d-%b-%Y')
    timestamp_s = date_time.map(datetime.timestamp)

    dt_object = datetime.fromtimestamp(timestamp_s[0])
    print("dt_object:", dt_object)
    print("type(dt_object): ", type(dt_object))

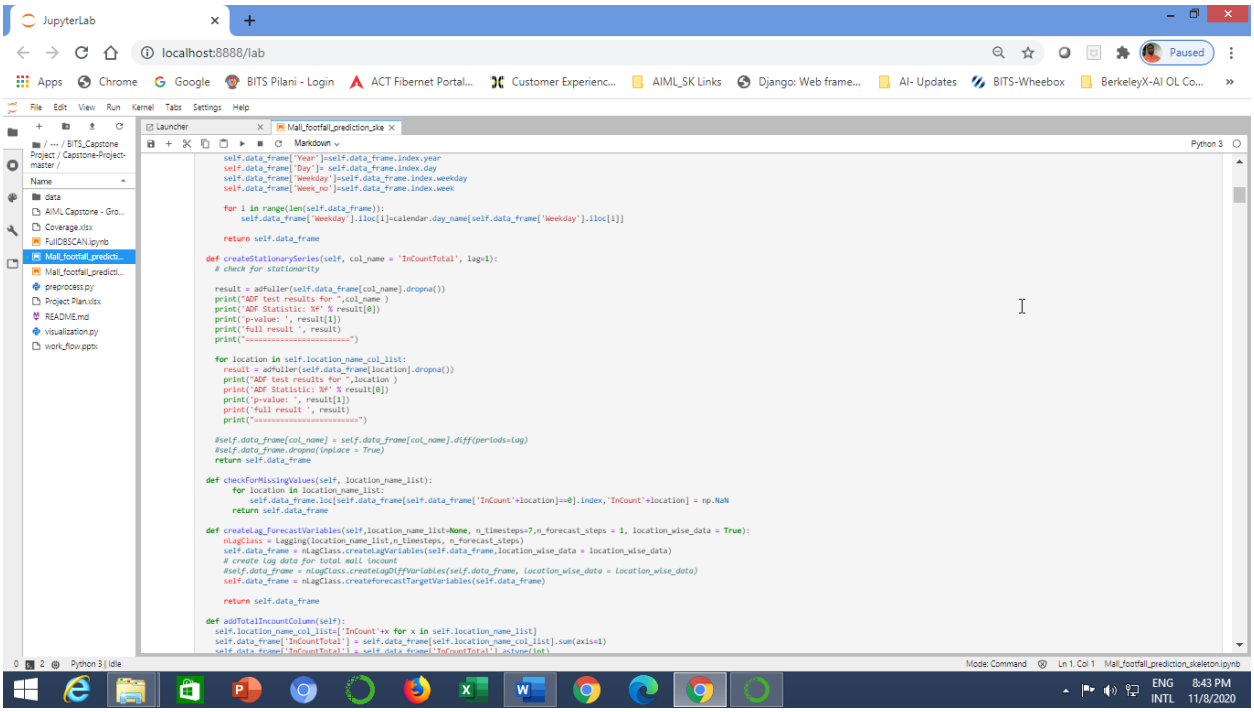

    day = 24*60*60
    week = 7*day
    month = 31*day
    year = (365.2425)*day

    self.data_frame['Day sin'] = np.sin(timestamp_s * (2 * np.pi / day))
    #self.data_frame['Day cos'] = np.cos(timestamp_s * (2 * np.pi / day))
    self.data_frame['Week sin'] = np.sin(timestamp_s * (2 * np.pi / week))
    self.data_frame['Week cos'] = np.cos(timestamp_s * (2 * np.pi / week))
    self.data_frame['Month sin'] = np.sin(timestamp_s * (2 * np.pi / month))
    self.data_frame['Month cos'] = np.cos(timestamp_s * (2 * np.pi / month))
    self.data_frame['Year sin'] = np.sin(timestamp_s * (2 * np.pi / year))
    self.data_frame['Year cos'] = np.cos(timestamp_s * (2 * np.pi / year))


    return self.data_frame
def createExtraFeatures(self, n_timesteps=7):
  # add seasonal and trend columns
  # Additive Decomposition
  result_add = seasonal_decompose(self.data_frame['InCountTotal'], model='additive',  freq=30)
  self.data_frame['seasonal_incount'] = result_add.seasonal
  self.data_frame['trend_incount'] = result_add.trend
  # rolling mean column
  self.data_frame['rolling_mean_incount'] = self.data_frame['InCountTotal'].shift(1).rolling(window=n_timesteps).mean()
  #expanding window
  self.data_frame['expanding_mean_incount'] = self.data_frame['InCountTotal'].shift(1).expanding(2).mean()
  return self.data_frame

def createTimeSeries(self):
    self.data_frame["DateTime"] = pd.to_datetime(self.data_frame.Date.astype(str))
    self.data_frame = self.data_frame.set_index("DateTime")
    self.data_frame.drop(['Date'], inplace=True, axis=1)
    self.data_frame = self.data_frame.sort_index()

    self.data_frame['Month']=self.data_frame.index.month
    self.data_frame['Year']=self.data_frame.index.year
    self.data_frame['Day']= self.data_frame.index.day
    self.data_frame['Weekday']=self.data_frame.index.weekday
    self.data_frame['Week_no']=self.data_frame.index.week
```



```
    self.data_frame['Year']=self.data_frame.index.year
    self.data_frame['Day']= self.data_frame.index.day
    self.data_frame['Weekday']=self.data_frame.index.weekday
    self.data_frame['Week_no']=self.data_frame.index.week

    for i in range(len(self.data_frame)):
        self.data_frame['Weekday'].iloc[i]=calendar.day_name[self.data_frame['Weekday'].iloc[i]]

    return self.data_frame

def createStationarySeries(self, col_name = 'InCountTotal', lag=1):
  # check for stationarity

  result = adfuller(self.data_frame[col_name].dropna())
  print("ADF test results for ",col_name )
  print('ADF Statistic: %f' % result[0])
  print('p-value: ', result[1])
  print('full result ', result)
  print("======================")

  for location in self.location_name_col_list:
    result = adfuller(self.data_frame[location].dropna())
    print("ADF test results for ",location )
    print('ADF Statistic: %f' % result[0])
    print('p-value: ', result[1])
    print('full result ', result)
    print("======================")

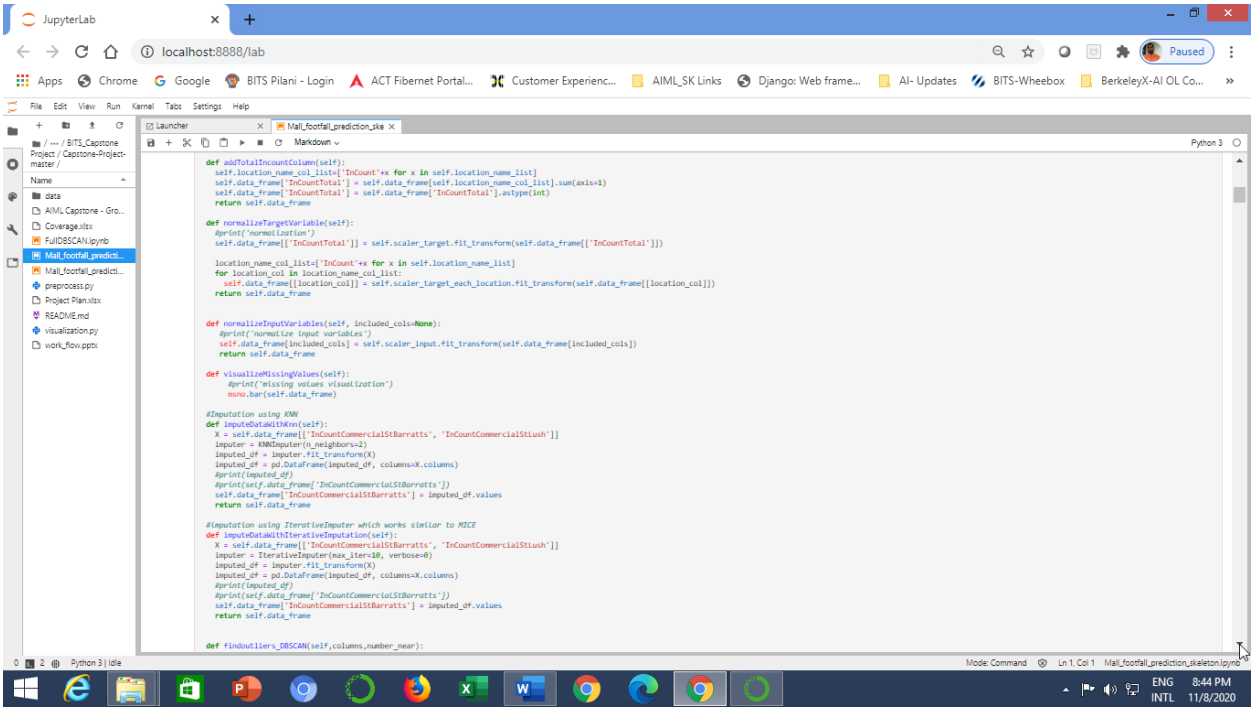
  #self.data_frame[col_name] = self.data_frame[col_name].diff(periods=Lag)
  #self.data_frame.dropna(inplace = True)
  return self.data_frame

def checkForMissingValues(self, location_name_list):
      for location in location_name_list:
          self.data_frame.loc[self.data_frame[self.data_frame['InCount'+location]==0].index,'InCount'+location] = np.NaN
      return self.data_frame

def createLag_ForecastVariables(self,location_name_list=None, n_timesteps=7,n_forecast_steps = 1, location_wise_data = True):
    nLagClass = Lagging(location_name_list,n_timesteps, n_forecast_steps)
    self.data_frame = nLagClass.createLagVariables(self.data_frame,location_wise_data = location_wise_data)
    # create lag data for total mall incount
    #self.data_frame = nLagClass.createLagDiffVariables(self.data_frame, location_wise_data = location_wise_data)
    self.data_frame = nLagClass.createforecastTargetVariables(self.data_frame)

    return self.data_frame

def addTotalIncountColumn(self):
  self.location_name_col_list=['InCount'+x for x in self.location_name_list]
  self.data_frame['InCountTotal'] = self.data_frame[self.location_name_col_list].sum(axis=1)
```



```
def addTotalIncountColumn(self):
  self.location_name_col_list=['InCount'+x for x in self.location_name_list]
  self.data_frame['InCountTotal'] = self.data_frame[self.location_name_col_list].sum(axis=1)
  self.data_frame['InCountTotal'] = self.data_frame['InCountTotal'].astype(int)
  return self.data_frame

def normalizeTargetVariable(self):
  #print('normalization')
  self.data_frame[['InCountTotal']] = self.scaler_target.fit_transform(self.data_frame[['InCountTotal']])

  location_name_col_list=['InCount'+x for x in self.location_name_list]
  for location_col in location_name_col_list:
    self.data_frame[[location_col]] = self.scaler_target_each_location.fit_transform(self.data_frame[[location_col]])
  return self.data_frame

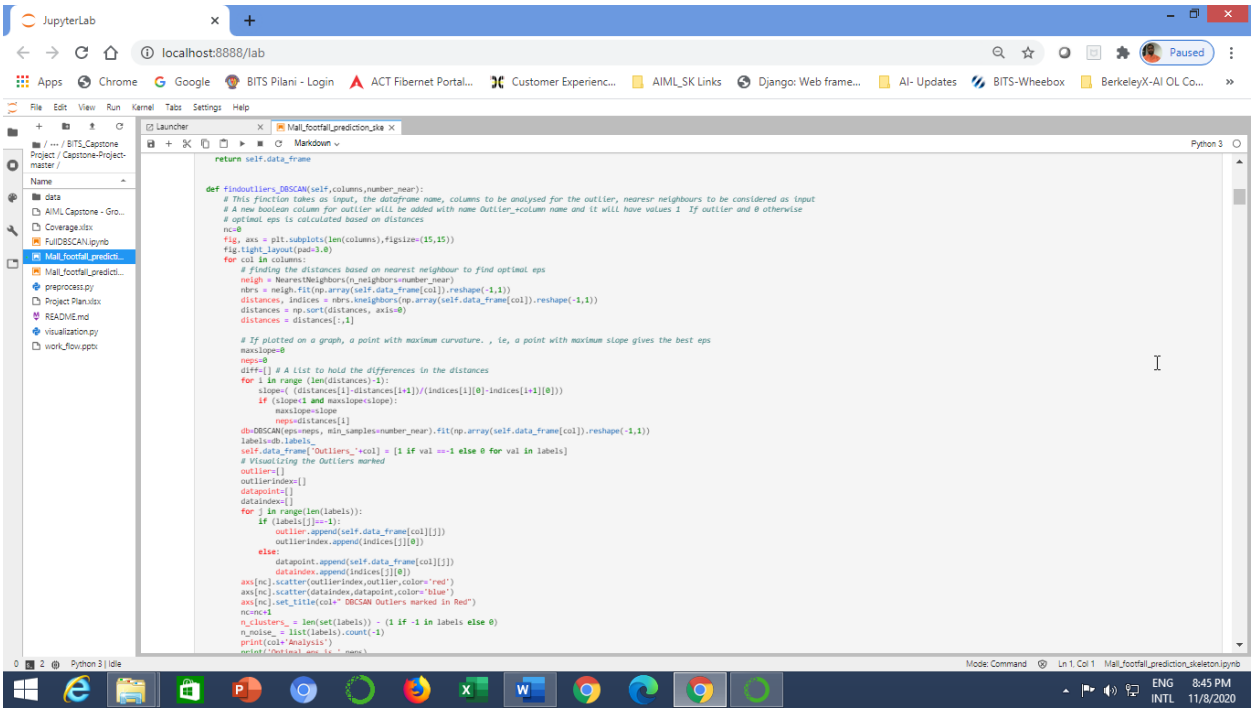

def normalizeInputVariables(self, included_cols=None):
  #print('normalize input variables')
  self.data_frame[included_cols] = self.scaler_input.fit_transform(self.data_frame[included_cols])
  return self.data_frame

def visualizeMissingValues(self):
    #print('missing values visualization')
    msno.bar(self.data_frame)

#Imputation using KNN
def imputeDataWithKnn(self):
  X = self.data_frame[['InCountCommercialStBarratts', 'InCountCommercialStLush']]
  imputer = KNNImputer(n_neighbors=2)
  imputed_df = imputer.fit_transform(X)
  imputed_df = pd.DataFrame(imputed_df, columns=X.columns)
  #print(imputed_df)
  #print(self.data_frame['InCountCommercialStBarratts'])
  self.data_frame['InCountCommercialStBarratts'] = imputed_df.values
  return self.data_frame

#imputation using IterativeImputer which works similar to MICE
def imputeDataWithIterativeImputation(self):
  X = self.data_frame[['InCountCommercialStBarratts', 'InCountCommercialStLush']]
  imputer = IterativeImputer(max_iter=10, verbose=0)
  imputed_df = imputer.fit_transform(X)
  imputed_df = pd.DataFrame(imputed_df, columns=X.columns)
  #print(imputed_df)
  #print(self.data_frame['InCountCommercialStBarratts'])
  self.data_frame['InCountCommercialStBarratts'] = imputed_df.values
  return self.data_frame

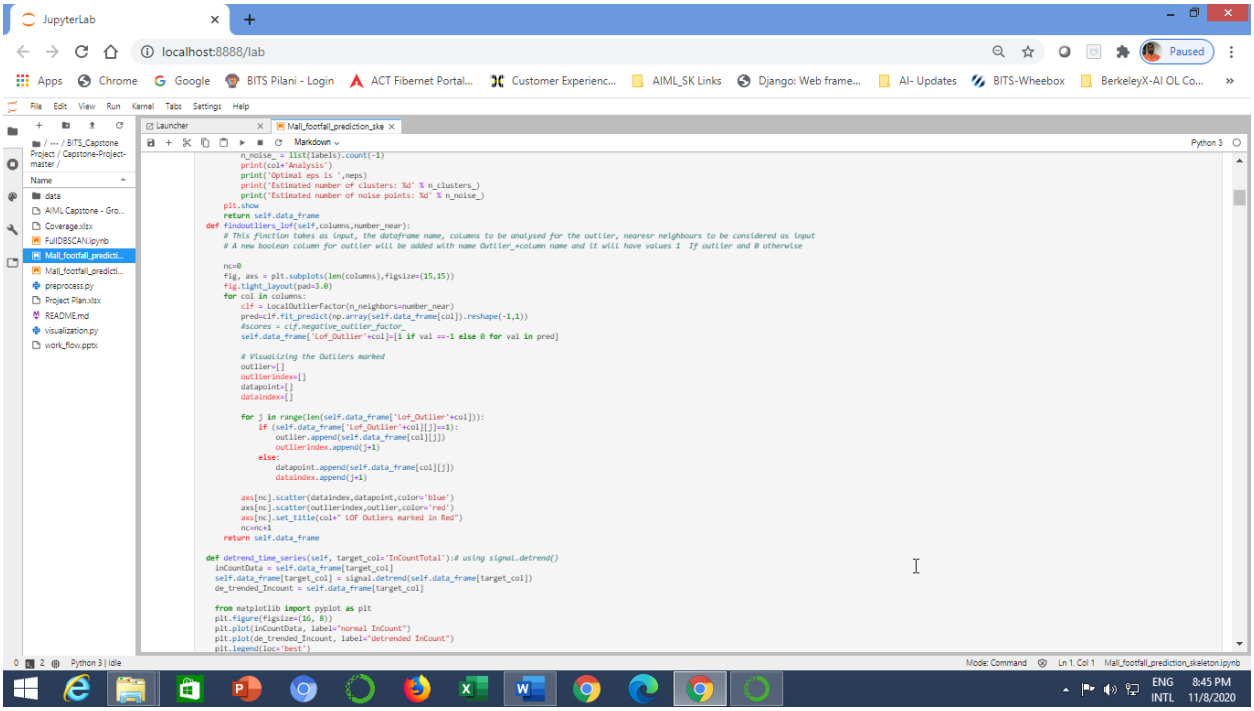

def findoutliers_DBSCAN(self,columns,number_near):
```



```
  return self.data_frame


def findoutliers_DBSCAN(self,columns,number_near):
    # This function takes as input, the dataframe name, columns to be analysed for the outlier, nearesr neighbours to be considered as input
    # A new boolean column for outlier will be added with name Outlier_+column name and it will have values 1  If outlier and 0 otherwise
    # optimal eps is calculated based on distances
    nc=0
    fig, axs = plt.subplots(len(columns),figsize=(15,15))
    fig.tight_layout(pad=3.0)
    for col in columns:
        # finding the distances based on nearest neighbour to find optimal eps
        neigh = NearestNeighbors(n_neighbors=number_near)
        nbrs = neigh.fit(np.array(self.data_frame[col]).reshape(-1,1))
        distances, indices = nbrs.kneighbors(np.array(self.data_frame[col]).reshape(-1,1))
        distances = np.sort(distances, axis=0)
        distances = distances[:,1]

        # If plotted on a graph, a point with maximum curvature. , ie, a point with maximum slope gives the best eps
        maxslope=0
        neps=0
        diff=[] # A list to hold the differences in the distances
        for i in range (len(distances)-1):
            slope=( (distances[i]-distances[i+1])/(indices[i][0]-indices[i+1][0]))
            if (slope<1 and maxslope<slope):
                maxslope=slope
                neps=distances[i]
        db=DBSCAN(eps=neps, min_samples=number_near).fit(np.array(self.data_frame[col]).reshape(-1,1))
        labels=db.labels_
        self.data_frame['Outliers_'+col] = [1 if val ==-1 else 0 for val in labels]
        # Visualizing the Outliers marked
        outlier=[]
        outlierindex=[]
        datapoint=[]
        dataindex=[]
        for j in range(len(labels)):
            if (labels[j]==-1):
                outlier.append(self.data_frame[col][j])
                outlierindex.append(indices[j][0])
            else:
                datapoint.append(self.data_frame[col][j])
                dataindex.append(indices[j][0])
        axs[nc].scatter(outlierindex,outlier,color='red')
        axs[nc].scatter(dataindex,datapoint,color='blue')
        axs[nc].set_title(col+" DBSCAN Outliers marked in Red")
        nc=nc+1
        n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
        n_noise_ = list(labels).count(-1)
        print(col+'Analysis')
        print('Optimal eps is ' neps)
```


JupyterLab
localhost:8888/lab
Paused
Apps
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Google
BITS Pilani - Login
ACT Fibernet Portal...
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AIML_SK Links
Django: Web frame...
AI- Updates
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BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_prediction_ske...
Mall_footfall_prediction_skeleton.ipynb
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
def findoutliers_lof(self,columns,number_near):
# This function takes as input, the dataframe name, columns to be analysed for the outlier, nearesr neighbours to be considered as input
# A new boolean column for outlier will be added with name Outlier_+column name and it will have values 1 If outlier and 0 otherwise
nc=0
fig, axs = plt.subplots(len(columns),figsize=(15,15))
fig.tight_layout(pad=3.0)
for col in columns:
clf = LocalOutlierFactor(n_neighbors=number_near)
pred=clf.fit_predict(np.array(self.data_frame[col]).reshape(-1,1))
#scores = clf.negative_outlier_factor_
self.data_frame['Lof_Outlier'+col]=[1 if val ==-1 else 0 for val in pred]
# Visualizing the Outliers marked
outlier=[]
outlierindex=[]
datapoint=[]
dataindex=[]
for j in range(len(self.data_frame['Lof_Outlier'+col])):
if (self.data_frame['Lof_Outlier'+col][j]==1):
outlier.append(self.data_frame[col][j])
outlierindex.append(j+1)
else:
datapoint.append(self.data_frame[col][j])
dataindex.append(j+1)
axs[nc].scatter(dataindex,datapoint,color='blue')
axs[nc].scatter(outlierindex,outlier,color='red')
axs[nc].set_title(col+" LOF Outlers marked in Red")
nc=nc+1
return self.data_frame
def detrend_time_series(self, target_col='InCountTotal'):# using signal.detrend()
inCountData = self.data_frame[target_col]
self.data_frame[target_col] = signal.detrend(self.data_frame[target_col])
de_trended_Incount = self.data_frame[target_col]
from matplotlib import pyplot as plt
plt.figure(figsize=(16, 8))
plt.plot(inCountData, label="normal InCount")
plt.plot(de_trended_Incount, label="detrended InCount")
plt.legend(loc='best')
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG INTL
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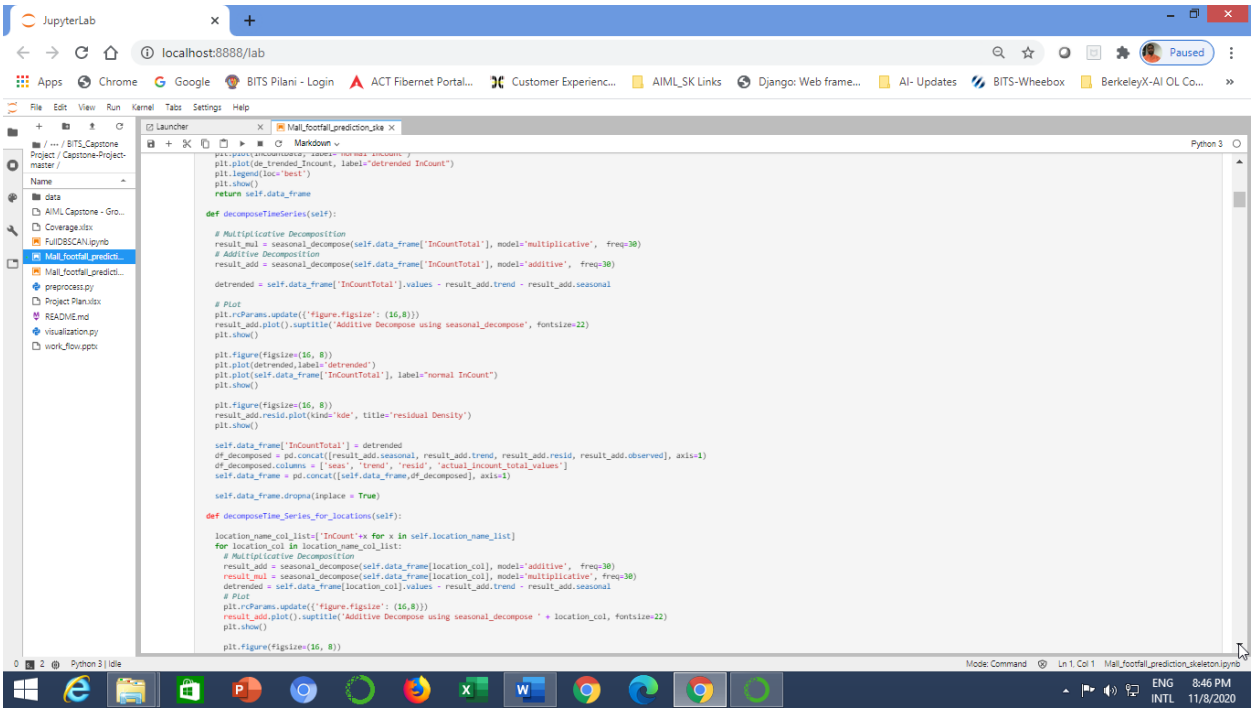
11/8/2020


JupyterLab
localhost:8888/lab
Paused
plt.plot(de_trended_Incount, label="detrended InCount")
plt.legend(loc='best')
plt.show()
return self.data_frame
def decomposeTimeSeries(self):
# Multiplicative Decomposition
result_mul = seasonal_decompose(self.data_frame['InCountTotal'], model='multiplicative', freq=30)
# Additive Decomposition
result_add = seasonal_decompose(self.data_frame['InCountTotal'], model='additive', freq=30)
detrended = self.data_frame['InCountTotal'].values - result_add.trend - result_add.seasonal
# Plot
plt.rcParams.update({'figure.figsize': (16,8)})
result_add.plot().suptitle('Additive Decompose using seasonal_decompose', fontsize=22)
plt.show()
plt.figure(figsize=(16, 8))
plt.plot(detrended,label='detrended')
plt.plot(self.data_frame['InCountTotal'], label="normal InCount")
plt.show()
plt.figure(figsize=(16, 8))
result_add.resid.plot(kind='kde', title='residual Density')
plt.show()
self.data_frame['InCountTotal'] = detrended
df_decomposed = pd.concat([result_add.seasonal, result_add.trend, result_add.resid, result_add.observed], axis=1)
df_decomposed.columns = ['seas', 'trend', 'resid', 'actual_incount_total_values']
self.data_frame = pd.concat([self.data_frame,df_decomposed], axis=1)
self.data_frame.dropna(inplace = True)
def decomposeTime_Series_for_locations(self):
location_name_col_list=['InCount'+x for x in self.location_name_list]
for location_col in location_name_col_list:
# Multiplicative Decomposition
result_add = seasonal_decompose(self.data_frame[location_col], model='additive', freq=30)
result_mul = seasonal_decompose(self.data_frame[location_col], model='multiplicative', freq=30)
detrended = self.data_frame[location_col].values - result_add.trend - result_add.seasonal
# Plot
plt.rcParams.update({'figure.figsize': (16,8)})
result_add.plot().suptitle('Additive Decompose using seasonal_decompose ' + location_col, fontsize=22)
plt.show()
plt.figure(figsize=(16, 8))
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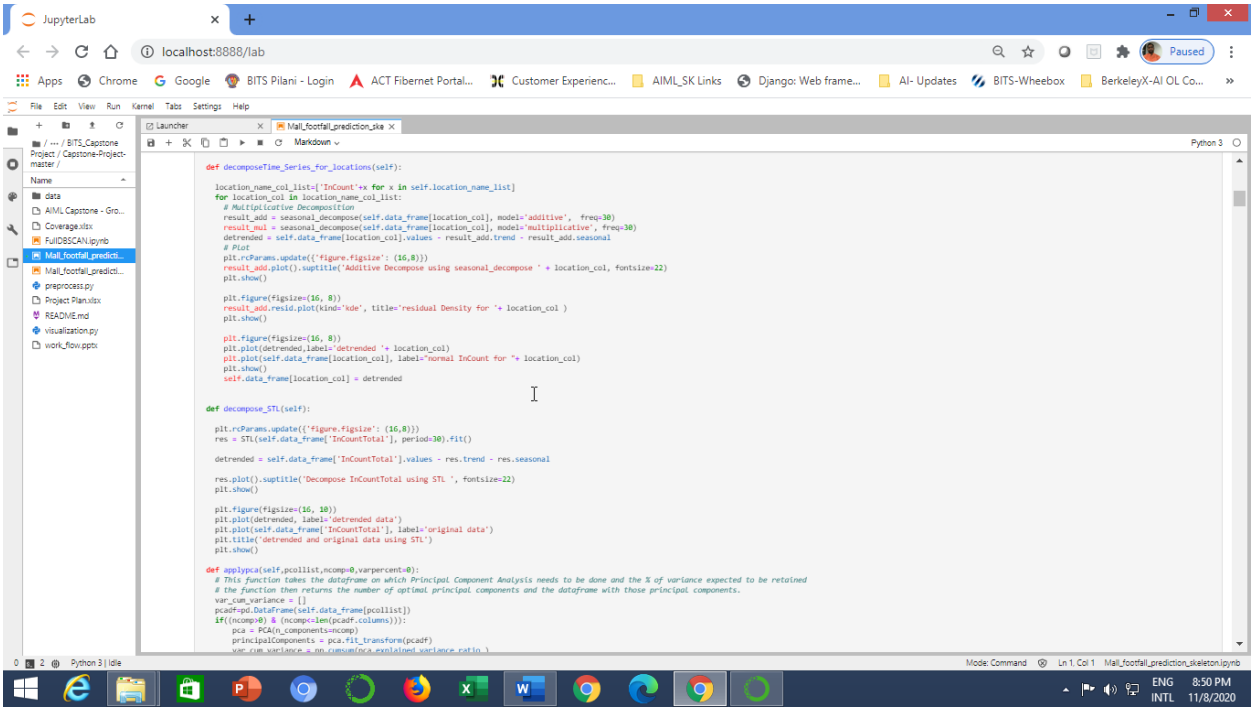


```
def decomposeTime_Series_for_locations(self):

  location_name_col_list=['InCount'+x for x in self.location_name_list]
  for location_col in location_name_col_list:
    # Multiplicative Decomposition
    result_add = seasonal_decompose(self.data_frame[location_col], model='additive',  freq=30)
    result_mul = seasonal_decompose(self.data_frame[location_col], model='multiplicative', freq=30)
    detrended = self.data_frame[location_col].values - result_add.trend - result_add.seasonal
    # Plot
    plt.rcParams.update({'figure.figsize': (16,8)})
    result_add.plot().suptitle('Additive Decompose using seasonal_decompose ' + location_col, fontsize=22)
    plt.show()

    plt.figure(figsize=(16, 8))
    result_add.resid.plot(kind='kde', title='residual Density for '+ location_col )
    plt.show()

    plt.figure(figsize=(16, 8))
    plt.plot(detrended,label='detrended '+ location_col)
    plt.plot(self.data_frame[location_col], label="normal InCount for "+ location_col)
    plt.show()
    self.data_frame[location_col] = detrended


def decompose_STL(self):

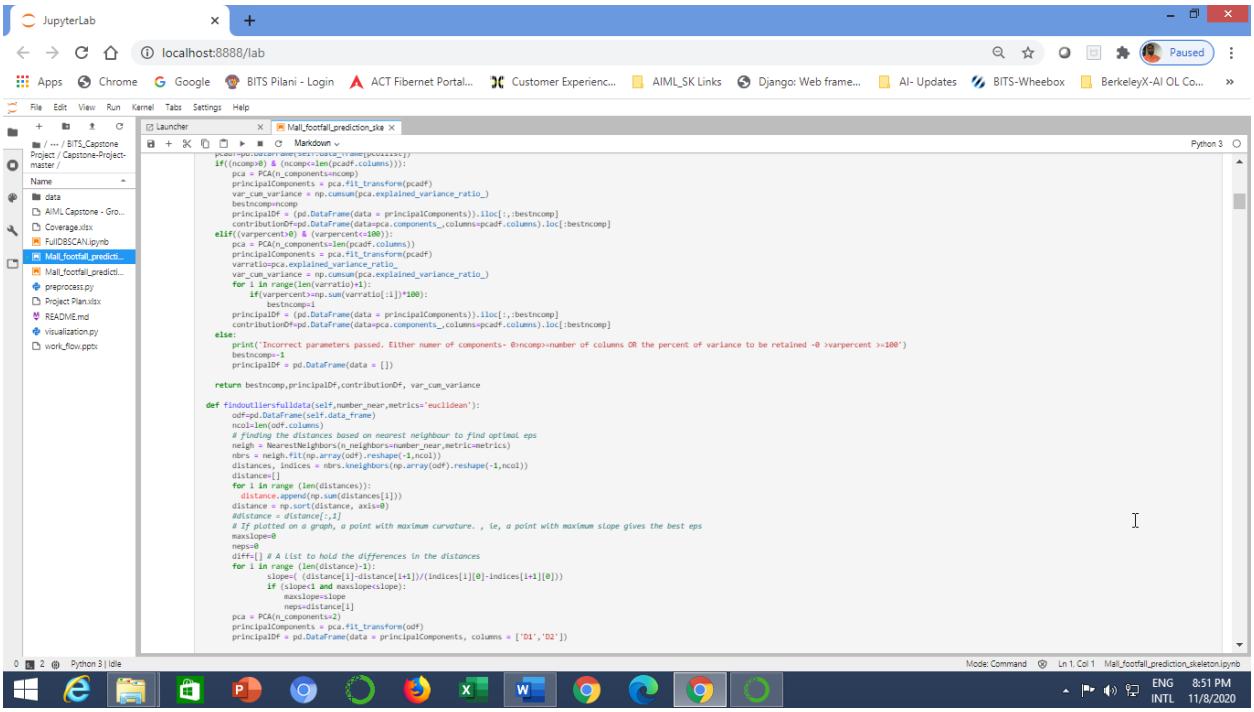
  plt.rcParams.update({'figure.figsize': (16,8)})
  res = STL(self.data_frame['InCountTotal'], period=30).fit()

  detrended = self.data_frame['InCountTotal'].values - res.trend - res.seasonal

  res.plot().suptitle('Decompose InCountTotal using STL ', fontsize=22)
  plt.show()

  plt.figure(figsize=(16, 10))
  plt.plot(detrended, label='detrended data')
  plt.plot(self.data_frame['InCountTotal'], label='original data')
  plt.title('detrended and original data using STL')
  plt.show()

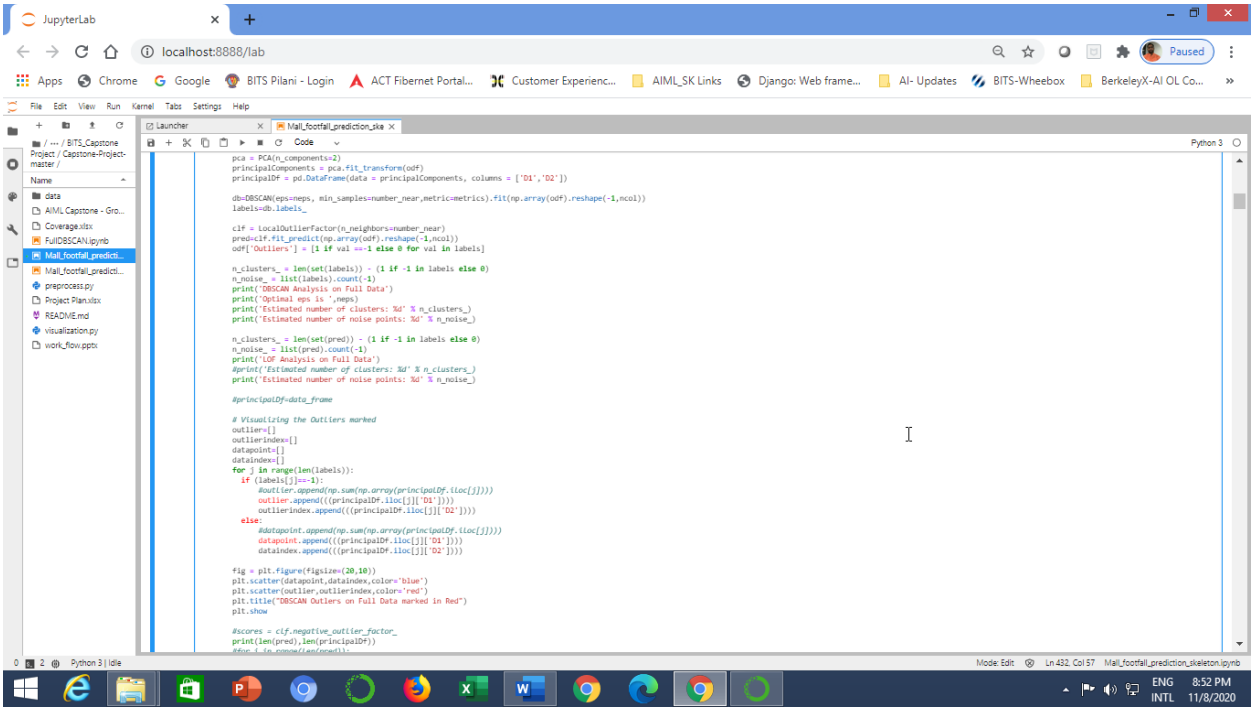
def applypca(self,pcollist,ncomp=0,varpercent=0):
  # This function takes the dataframe on which Principal Component Analysis needs to be done and the % of variance expected to be retained
  # the function then returns the number of optimal principal components and the dataframe with those principal components.
  var_cum_variance = []
  pcadf=pd.DataFrame(self.data_frame[pcollist])
  if((ncomp>0) & (ncomp<=len(pcadf.columns))):
      pca = PCA(n_components=ncomp)
      principalComponents = pca.fit_transform(pcadf)
      var_cum_variance = np.cumsum(pca.explained_variance_ratio_)
```



```
  if((ncomp>0) & (ncomp<=len(pcadf.columns))):
      pca = PCA(n_components=ncomp)
      principalComponents = pca.fit_transform(pcadf)
      var_cum_variance = np.cumsum(pca.explained_variance_ratio_)
      bestncomp=ncomp
      principalDF = (pd.DataFrame(data = principalComponents)).iloc[:,:bestncomp]
      contributionDF=pd.DataFrame(data=pca.components_,columns=pcadf.columns).loc[:bestncomp]
  elif((varpercent>0) & (varpercent<=100)):
      pca = PCA(n_components=len(pcadf.columns))
      principalComponents = pca.fit_transform(pcadf)
      varratio=pca.explained_variance_ratio_
      var_cum_variance = np.cumsum(pca.explained_variance_ratio_)
      for i in range(len(varratio)+1):
          if(varpercent>=np.sum(varratio[:i])*100):
              bestncomp=i
      principalDF = (pd.DataFrame(data = principalComponents)).iloc[:,:bestncomp]
      contributionDF=pd.DataFrame(data=pca.components_,columns=pcadf.columns).loc[:bestncomp]
  else:
      print('Incorrect parameters passed. Either numer of components- 0<ncomp>number of columns OR the percent of variance to be retained <0 >varpercent >=100')
      bestncomp=-1
      principalDF = pd.DataFrame(data = [])

  return bestncomp,principalDF,contributionDF, var_cum_variance

def findoutliersfulldata(self,number_near,metrics='euclidean'):
      odf=pd.DataFrame(self.data_frame)
      ncol=len(odf.columns)
      # finding the distances based on nearest neighbour to find optimal eps
      neigh = NearestNeighbors(n_neighbors=number_near,metric=metrics)
      nbrs = neigh.fit(np.array(odf).reshape(-1,ncol))
      distances, indices = nbrs.kneighbors(np.array(odf).reshape(-1,ncol))
      distance=[]
      for i in range (len(distances)):
        distance.append(np.sum(distances[i]))
      distance = np.sort(distance, axis=0)
      #distance = distance[:,1]
      # If plotted on a graph, a point with maximum curvature. , ie, a point with maximum slope gives the best eps
      maxslope=0
      neps=0
      diff=[] # A list to hold the differences in the distances
      for i in range (len(distance)-1):
              slope=( (distance[i]-distance[i+1])/(indices[i][0]-indices[i+1][0]))
              if (slope>1 and maxslope<slope):
                  maxslope=slope
                  neps=distance[i]
      pca = PCA(n_components=2)
      principalComponents = pca.fit_transform(odf)
      principalDF = pd.DataFrame(data = principalComponents, columns = ['D1','D2'])
```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Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(odf)
principalDf = pd.DataFrame(data = principalComponents, columns = ['D1','D2'])
db=DBSCAN(eps=neps, min_samples=number_near,metric=metrics).fit(np.array(odf).reshape(-1,ncol))
labels=db.labels_
clf = LocalOutlierFactor(n_neighbors=number_near)
pred=clf.fit_predict(np.array(odf).reshape(-1,ncol))
odf['Outliers'] = [1 if val ==-1 else 0 for val in labels]
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_noise_ = list(labels).count(-1)
print('DBSCAN Analysis on Full Data')
print('Optimal eps is ',neps)
print('Estimated number of clusters: %d' % n_clusters_)
print('Estimated number of noise points: %d' % n_noise_)
n_clusters_ = len(set(pred)) - (1 if -1 in labels else 0)
n_noise_ = list(pred).count(-1)
print('LOF Analysis on Full Data')
#print('Estimated number of clusters: %d' % n_clusters_)
print('Estimated number of noise points: %d' % n_noise_)
#principalDf=data_frame
# Visualizing the Outliers marked
outlier=[]
outlierindex=[]
datapoint=[]
dataindex=[]
for j in range(len(labels)):
if (labels[j]==-1):
#outlier.append(np.sum(np.array(principalDf.iloc[j])))
outlier.append(((principalDf.iloc[j]['D1'])))
outlierindex.append(((principalDf.iloc[j]['D2'])))
else:
#datapoint.append(np.sum(np.array(principalDf.iloc[j])))
datapoint.append(((principalDf.iloc[j]['D1'])))
dataindex.append(((principalDf.iloc[j]['D2'])))
fig = plt.figure(figsize=(20,10))
plt.scatter(datapoint,dataindex,color='blue')
plt.scatter(outlier,outlierindex,color='red')
plt.title("DBSCAN Outlers on Full Data marked in Red")
plt.show
#scores = clf.negative_outlier_factor_
print(len(pred),len(principalDf))
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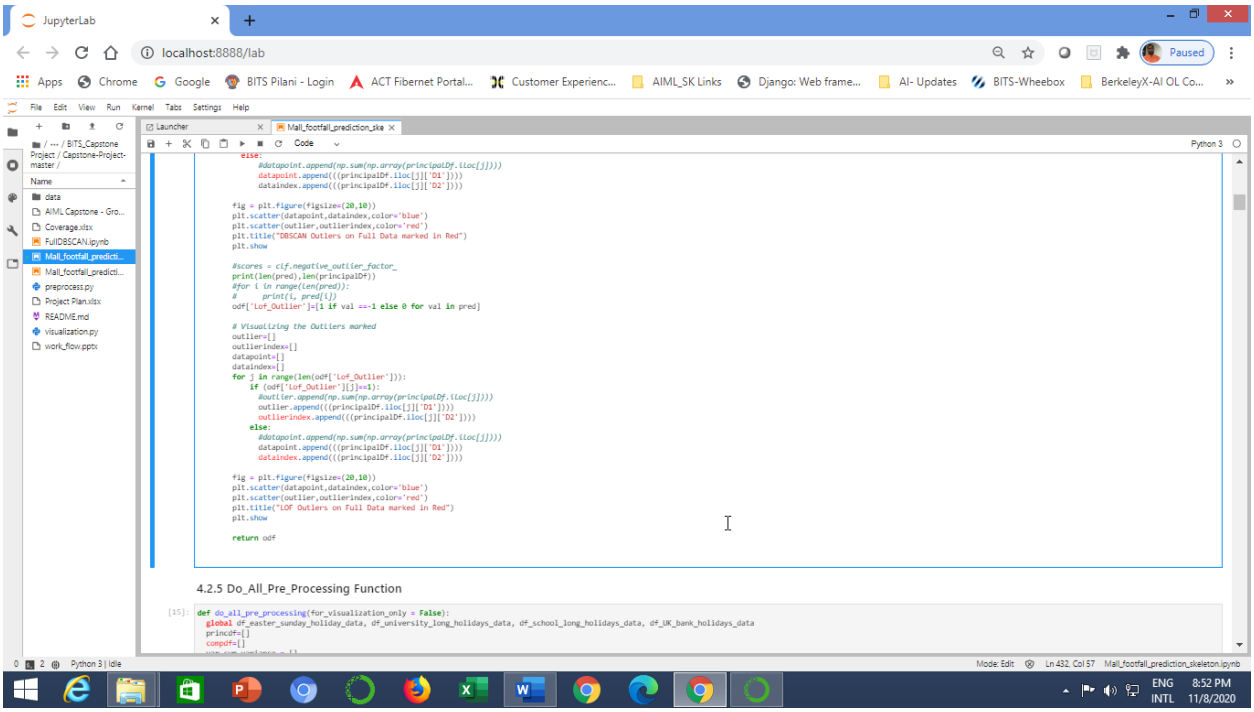
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else:
#datapoint.append(np.sum(np.array(principalDf.iloc[j])))
datapoint.append(((principalDf.iloc[j]['D1'])))
dataindex.append(((principalDf.iloc[j]['D2'])))
fig = plt.figure(figsize=(20,10))
plt.scatter(datapoint,dataindex,color='blue')
plt.scatter(outlier,outlierindex,color='red')
plt.title("DBSCAN Outlers on Full Data marked in Red")
plt.show
#scores = clf.negative_outlier_factor_
print(len(pred),len(principalDf))
#for i in range(len(pred)):
# print(i, pred[i])
odf['Lof_Outlier']=[1 if val ==-1 else 0 for val in pred]
# Visualizing the Outliers marked
outlier=[]
outlierindex=[]
datapoint=[]
dataindex=[]
for j in range(len(odf['Lof_Outlier'])):
if (odf['Lof_Outlier'][j]==1):
#outlier.append(np.sum(np.array(principalDf.iloc[j])))
outlier.append(((principalDf.iloc[j]['D1'])))
outlierindex.append(((principalDf.iloc[j]['D2'])))
else:
#datapoint.append(np.sum(np.array(principalDf.iloc[j])))
datapoint.append(((principalDf.iloc[j]['D1'])))
dataindex.append(((principalDf.iloc[j]['D2'])))
fig = plt.figure(figsize=(20,10))
plt.scatter(datapoint,dataindex,color='blue')
plt.scatter(outlier,outlierindex,color='red')
plt.title("LOF Outlers on Full Data marked in Red")
plt.show
return odf
4.2.5 Do_All_Pre_Processing Function
[15]:
def do_all_pre_processing(for_visualization_only = False):
global df_easter_sunday_holiday_data, df_university_long_holidays_data, df_school_long_holidays_data, df_UK_bank_holidays_data
princdf=[]
compdf=[]
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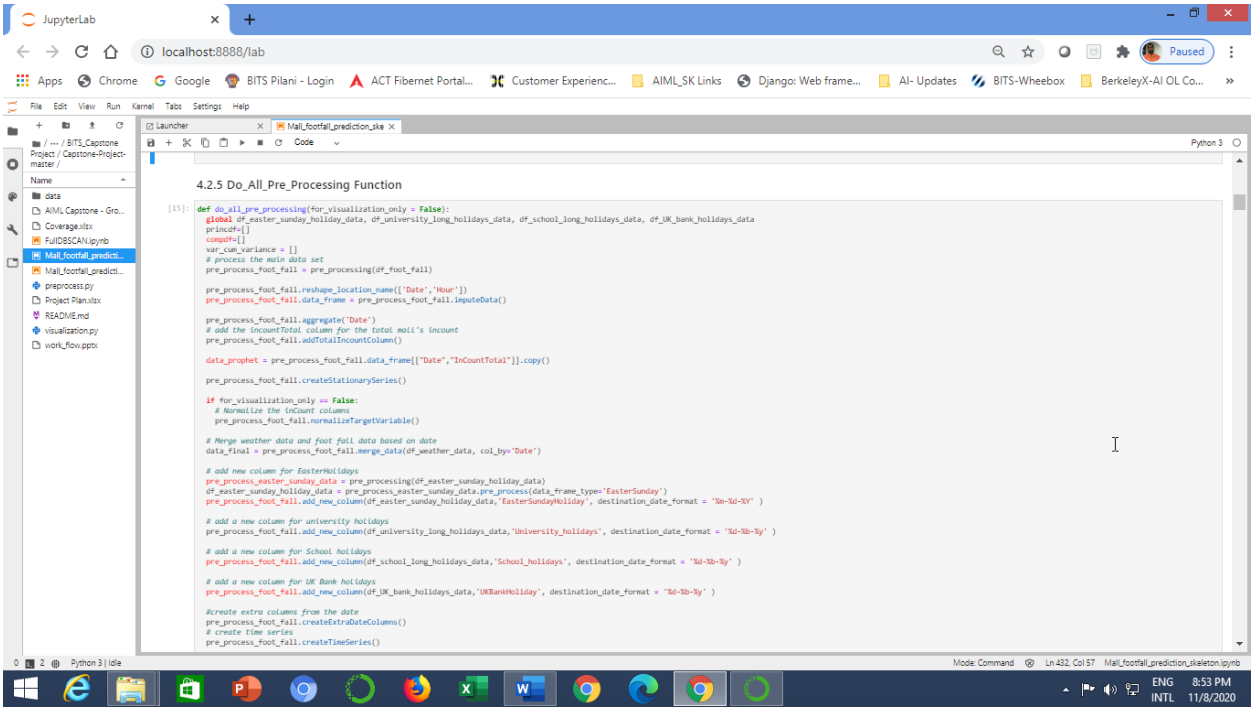
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4.2.5 Do_All_Pre_Processing Function
[15]:
def do_all_pre_processing(for_visualization_only = False):
global df_easter_sunday_holiday_data, df_university_long_holidays_data, df_school_long_holidays_data, df_UK_bank_holidays_data
princdf=[]
compdf=[]
var_cum_variance = []
# process the main data set
pre_process_foot_fall = pre_processing(df_foot_fall)
pre_process_foot_fall.reshape_location_name(['Date','Hour'])
pre_process_foot_fall.data_frame = pre_process_foot_fall.imputeData()
pre_process_foot_fall.aggregate('Date')
# add the incountTotal column for the total mall's incount
pre_process_foot_fall.addTotalIncountColumn()
data_prophet = pre_process_foot_fall.data_frame[["Date","InCountTotal"]].copy()
pre_process_foot_fall.createStationarySeries()
if for_visualization_only == False:
# Normalize the inCount columns
pre_process_foot_fall.normalizeTargetVariable()
# Merge weather data and foot fall data based on date
data_final = pre_process_foot_fall.merge_data(df_weather_data, col_by='Date')
# add new column for EasterHolidays
pre_process_easter_sunday_data = pre_processing(df_easter_sunday_holiday_data)
df_easter_sunday_holiday_data = pre_process_easter_sunday_data.pre_process(data_frame_type='EasterSunday')
pre_process_foot_fall.add_new_column(df_easter_sunday_holiday_data,'EasterSundayHoliday', destination_date_format = '%m-%d-%Y' )
# add a new column for university holidays
pre_process_foot_fall.add_new_column(df_university_long_holidays_data,'University_holidays', destination_date_format = '%d-%b-%y' )
# add a new column for School holidays
pre_process_foot_fall.add_new_column(df_school_long_holidays_data,'School_holidays', destination_date_format = '%d-%b-%y' )
# add a new column for UK Bank holidays
pre_process_foot_fall.add_new_column(df_UK_bank_holidays_data,'UKBankHoliday', destination_date_format = '%d-%b-%y' )
#create extra columns from the date
pre_process_foot_fall.createExtraDateColumns()
# create time series
pre_process_foot_fall.createTimeSeries()
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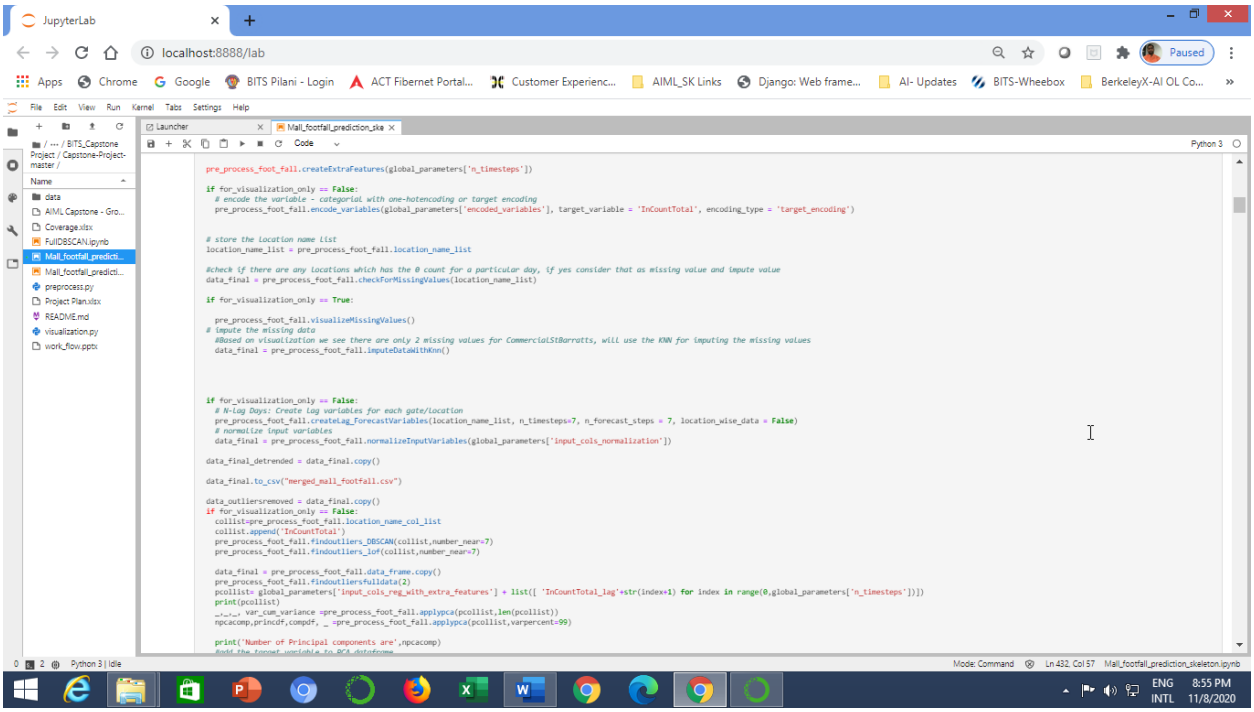
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pre_process_foot_fall.createExtraFeatures(global_parameters['n_timesteps'])
if for_visualization_only == False:
# encode the variable - categorial with one-hotencoding or target encoding
pre_process_foot_fall.encode_variables(global_parameters['encoded_variables'], target_variable = 'InCountTotal', encoding_type = 'target_encoding')
# store the location name list
location_name_list = pre_process_foot_fall.location_name_list
#check if there are any locations which has the 0 count for a particular day, if yes consider that as missing value and impute value
data_final = pre_process_foot_fall.checkForMissingValues(location_name_list)
if for_visualization_only == True:
pre_process_foot_fall.visualizeMissingValues()
# impute the missing data
#Based on visualization we see there are only 2 missing values for CommercialStBarratts, will use the KNN for imputing the missing values
data_final = pre_process_foot_fall.imputeDataWithKnn()
if for_visualization_only == False:
# N-lag Days: Create Lag variables for each gate/Location
pre_process_foot_fall.createLag_forecastVariables(location_name_list, n_timesteps=7, n_forecast_steps = 7, location_wise_data = False)
# normalize input variables
data_final = pre_process_foot_fall.normalizeInputVariables(global_parameters['input_cols_normalization'])
data_final_detrended = data_final.copy()
data_final.to_csv("merged_mall_footfall.csv")
data_outliersremoved = data_final.copy()
if for_visualization_only == False:
collist=pre_process_foot_fall.location_name_col_list
collist.append('InCountTotal')
pre_process_foot_fall.findoutliers_DBSCAN(collist,number_near=7)
pre_process_foot_fall.findoutliers_lof(collist,number_near=7)
data_final = pre_process_foot_fall.data_frame.copy()
pre_process_foot_fall.findoutliers=fulldata(2)
pcollist= global_parameters['input_cols_reg_with_extra_features'] + list([ 'InCountTotal_lag'+str(index+1) for index in range(0,global_parameters['n_timesteps'])])
print(pcollist)
_,_,_, var_cum_variance =pre_process_foot_fall.applypca(pcollist,len(pcollist))
npcacomp,princdf,compdf, _ =pre_process_foot_fall.applypca(pcollist,varpercent=99)
print('Number of Principal components are',npcacomp)
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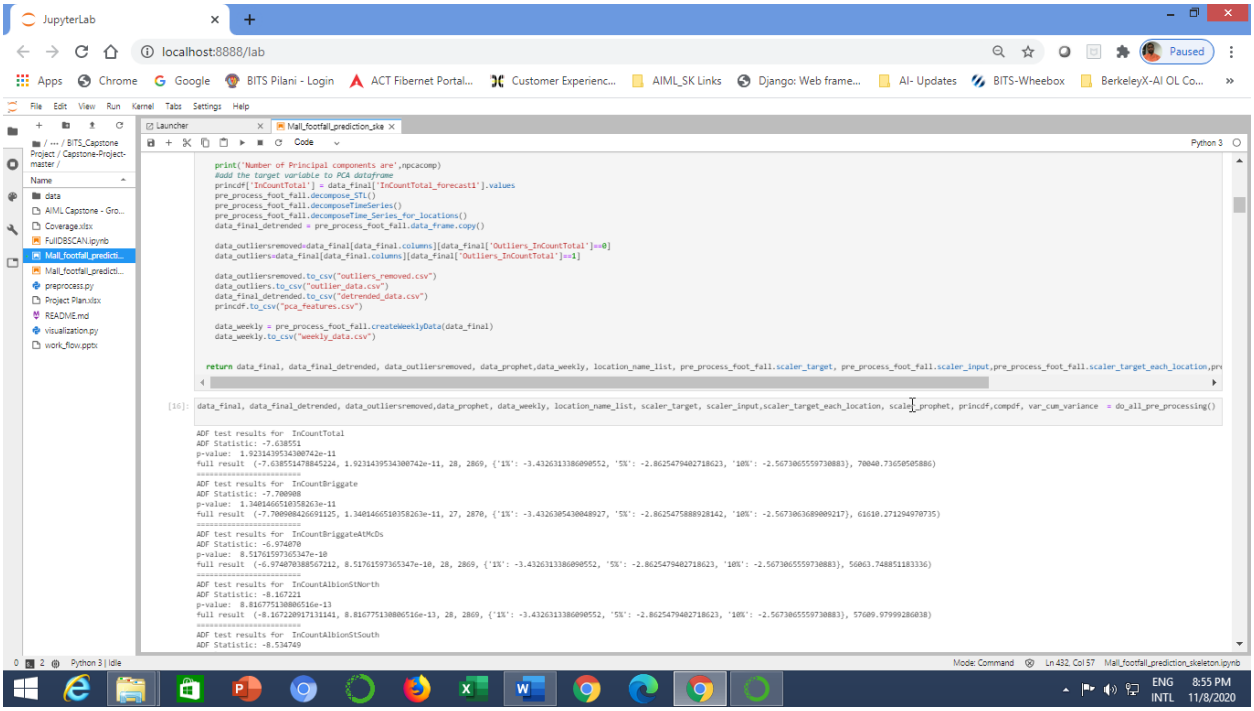
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print('Number of Principal components are',npcacomp)
Add the target variable to PCA dataframe
princdf['InCountTotal'] = data_final['InCountTotal_forecast1'].values
pre_process_foot_fall.decompose_STL()
pre_process_foot_fall.decomposeTimeSeries()
pre_process_foot_fall.decomposeTime_Series_for_locations()
data_final_detrended = pre_process_foot_fall.data_frame.copy()
data_outliersremoved=data_final[data_final.columns][data_final['Outliers_InCountTotal']==0]
data_outliers=data_final[data_final.columns][data_final['Outliers_InCountTotal']==1]
data_outliersremoved.to_csv("outliers_removed.csv")
data_outliers.to_csv("outlier_data.csv")
data_final_detrended.to_csv("detrended_data.csv")
princdf.to_csv("pca_features.csv")
data_weekly = pre_process_foot_fall.createWeeklyData(data_final)
data_weekly.to_csv("weekly_data.csv")
return data_final, data_final_detrended, data_outliersremoved, data_prophet,data_weekly, location_name_list, pre_process_foot_fall.scaler_target, pre_process_foot_fall.scaler_input,pre_process_foot_fall.scaler_target_each_location,pre
[16]: data_final, data_final_detrended, data_outliersremoved,data_prophet, data_weekly, location_name_list, scaler_target, scaler_input,scaler_target_each_location, scaler_prophet, princdf,compdf, var_cum_variance = do_all_pre_processing()
ADF test results for InCountTotal
ADF Statistic: -7.638551
p-value: 1.9231439513430074e-11
full result (-7.638551478845224, 1.9231439534300742e-11, 28, 2869, {'1%': -3.4326313386090552, '5%': -2.8625479402718623, '10%': -2.5673065559730883}, 70040.73650505886)
ADF test results for InCountBriggate
ADF Statistic: -7.700908
p-value: 1.3401466510358263e-11
full result (-7.700908426691125, 1.3401466510358263e-11, 27, 2870, {'1%': -3.4326305430048927, '5%': -2.8625475888928142, '10%': -2.5673063689009217}, 61610.271294970735)
ADF test results for InCountBriggateAtMcDs
ADF Statistic: -6.974070
p-value: 8.51761597365347e-10
full result (-6.974070388567212, 8.51761597365347e-10, 28, 2869, {'1%': -3.4326313386090552, '5%': -2.8625479402718623, '10%': -2.5673065559730883}, 56063.748851183336)
ADF test results for InCountAlbionStNorth
ADF Statistic: -8.167221
p-value: 8.816775130806516e-13
full result (-8.167220917131141, 8.816775130806516e-13, 28, 2869, {'1%': -3.4326313386090552, '5%': -2.8625479402718623, '10%': -2.5673065559730883}, 57609.97999286038)
ADF test results for InCountAlbionStSouth
ADF Statistic: -8.534749
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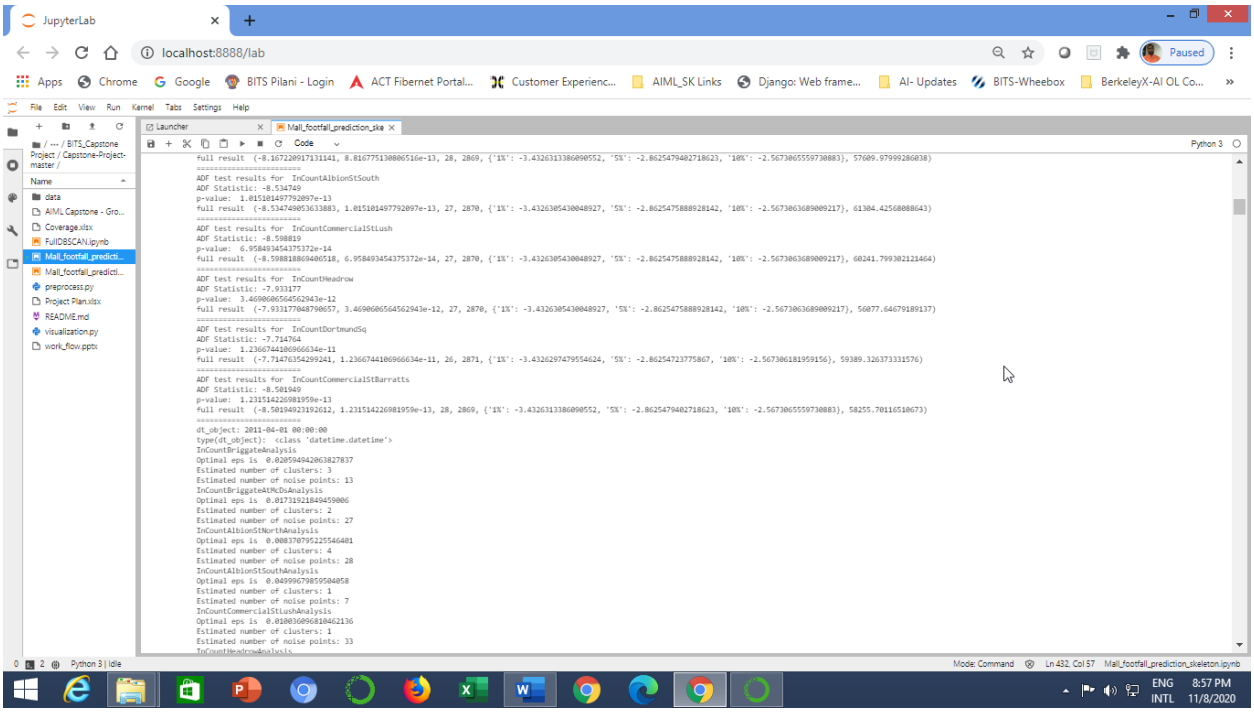
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full result (-8.167220917131141, 8.816775130806516e-13, 28, 2869, {'1%': -3.4326313386090552, '5%': -2.8625479402718623, '10%': -2.5673065559730883}, 57609.97999286038)
ADF test results for InCountAlbionStSouth
ADF Statistic: -8.534749
p-value: 1.0151014977923097e-13
full result (-8.534749053633883, 1.0151014977923097e-13, 27, 2870, {'1%': -3.4326305430048927, '5%': -2.8625475888928142, '10%': -2.5673063689009217}, 61304.42568088643)
ADF test results for InCountCommercialStLush
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p-value: 6.958493454375372e-14
full result (-8.598818869406518, 6.958493454375372e-14, 27, 2870, {'1%': -3.4326305430048927, '5%': -2.8625475888928142, '10%': -2.5673063689009217}, 60241.799302121464)
ADF test results for InCountHeadrow
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p-value: 3.4690606564562943e-12
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ADF test results for InCountDortmundSq
ADF Statistic: -7.714764
p-value: 1.2366744106966634e-11
full result (-7.714763542999241, 1.2366744106966634e-11, 26, 2871, {'1%': -3.4326297479554624, '5%': -2.8625472377585867, '10%': -2.5673061819591569}, 59389.326373331576)
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Estimated number of clusters: 3
Estimated number of noise points: 13
InCountBriggateAtMcDsAnalysis
Optimal eps is 0.017319218494559006
Estimated number of clusters: 2
Estimated number of noise points: 27
InCountAlbionStNorthAnalysis
Optimal eps is 0.008370795225546401
Estimated number of clusters: 4
Estimated number of noise points: 28
InCountAlbionStSouthAnalysis
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Estimated number of clusters: 1
Estimated number of noise points: 7
InCountCommercialStLushAnalysis
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Estimated number of clusters: 1
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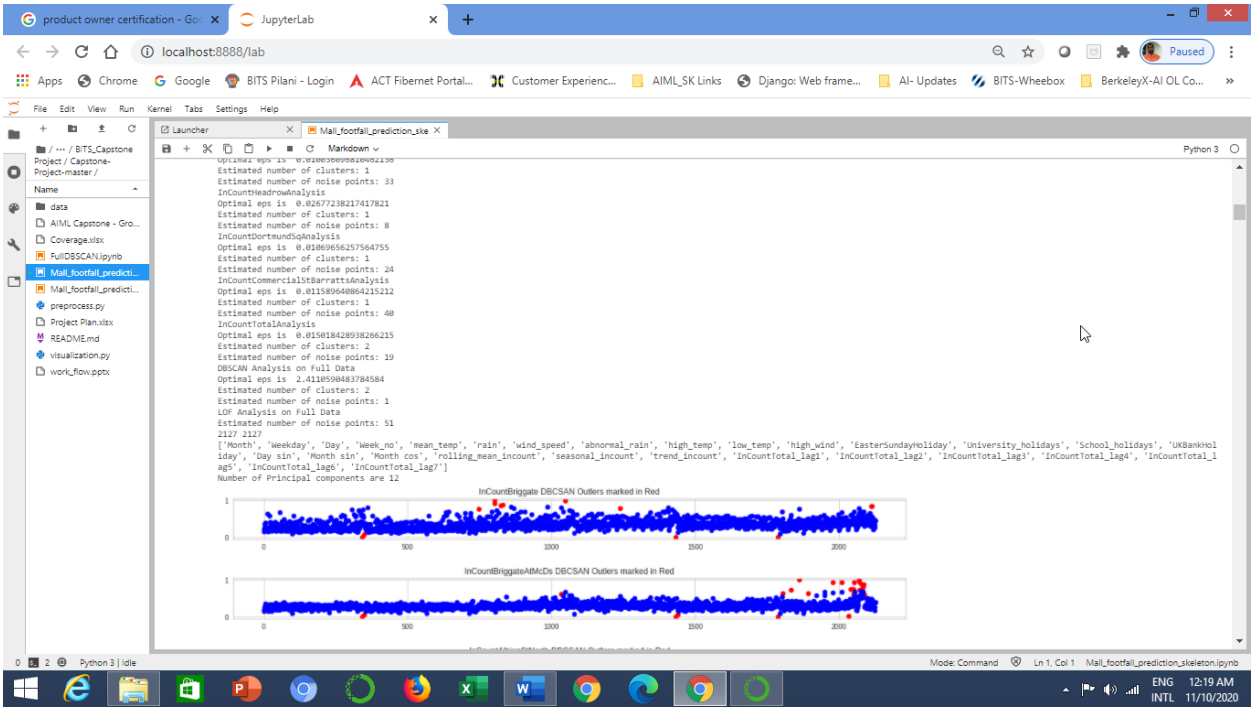
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Estimated number of clusters: 1
Estimated number of noise points: 33
InCountHeadrowAnalysis
Optimal eps is 0.026772382174178 21
Estimated number of clusters: 1
Estimated number of noise points: 8
InCountDortmundSqAnalysis
Optimal eps is 0.010696562575647 55
Estimated number of clusters: 1
Estimated number of noise points: 24
InCountCommercialStBarrattsAnalysis
Optimal eps is 0.011589640864215212
Estimated number of clusters: 1
Estimated number of noise points: 40
InCountTotalAnalysis
Optimal eps is 0.015018428938266215
Estimated number of clusters: 2
Estimated number of noise points: 19
DBSCAN Analysis on Full Data
Optimal eps is 2.4110590483784584
Estimated number of clusters: 2
Estimated number of noise points: 1
LOF Analysis on Full Data
Estimated number of noise points: 51
2127 2127
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InCountBriggate DBCSAN Outlers marked in Red
InCountBriggateAtMcDs DBCSAN Outlers marked in Red
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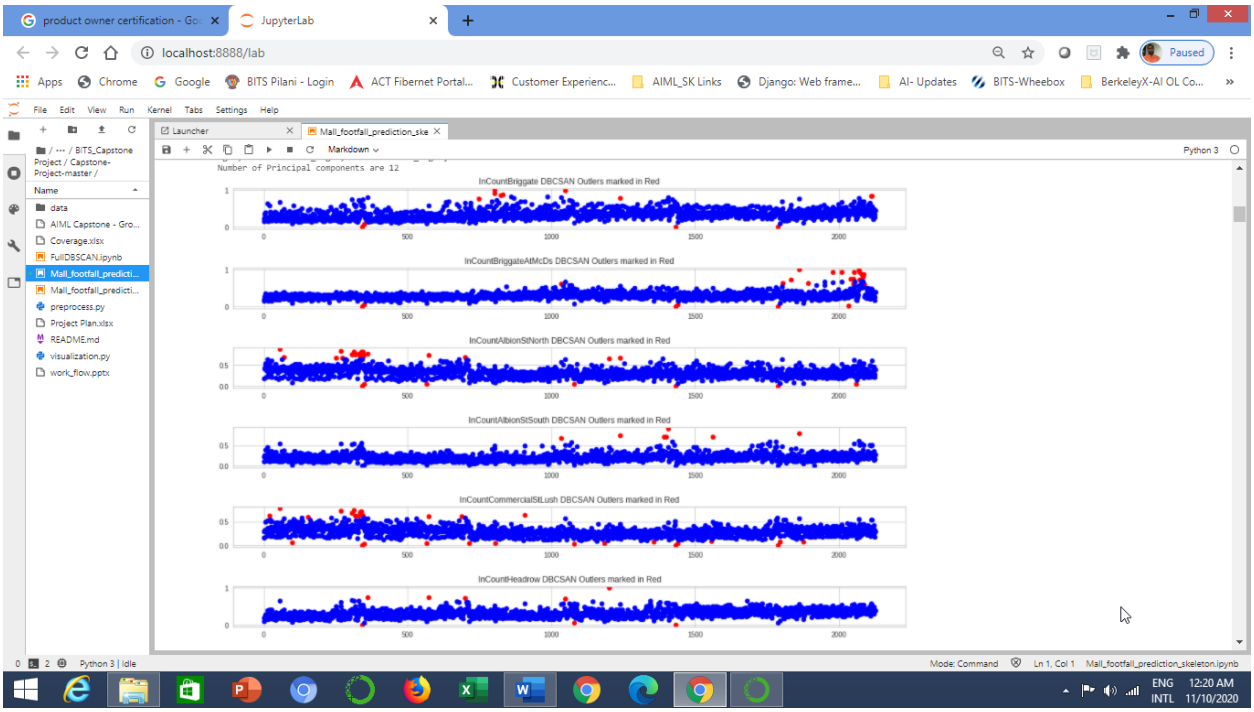
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InCountAlbionStSouth DBCSAN Outlers marked in Red
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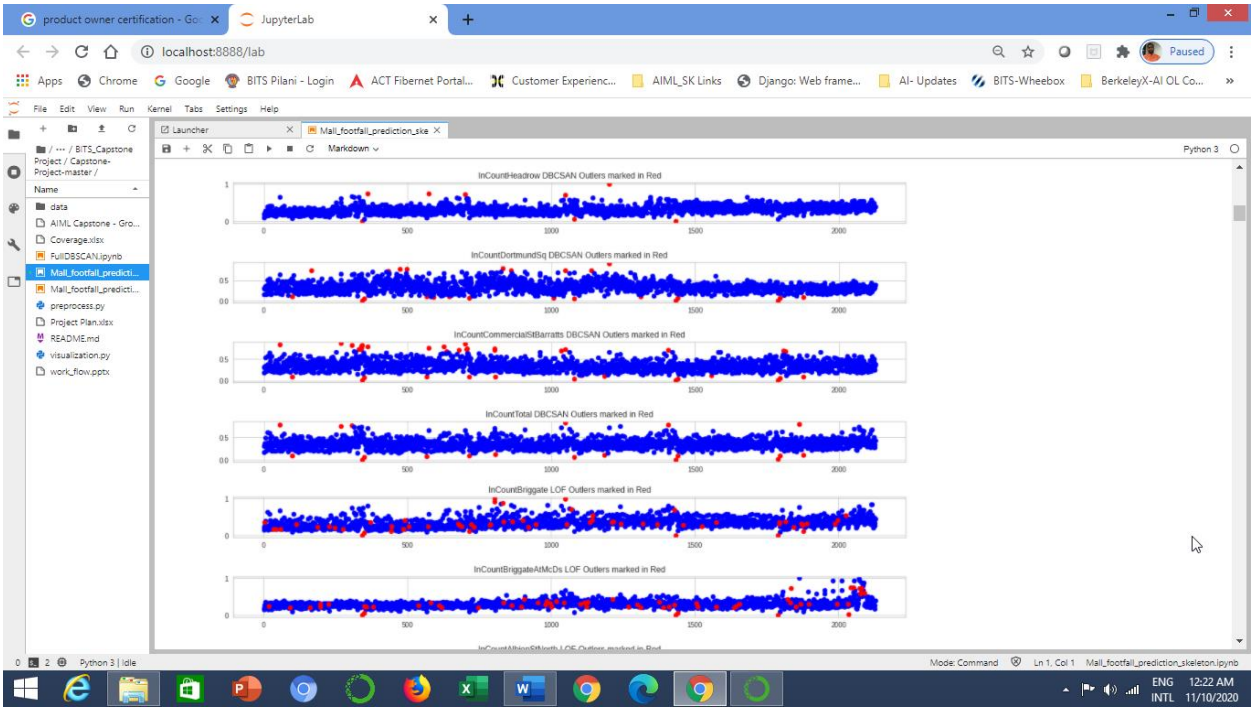
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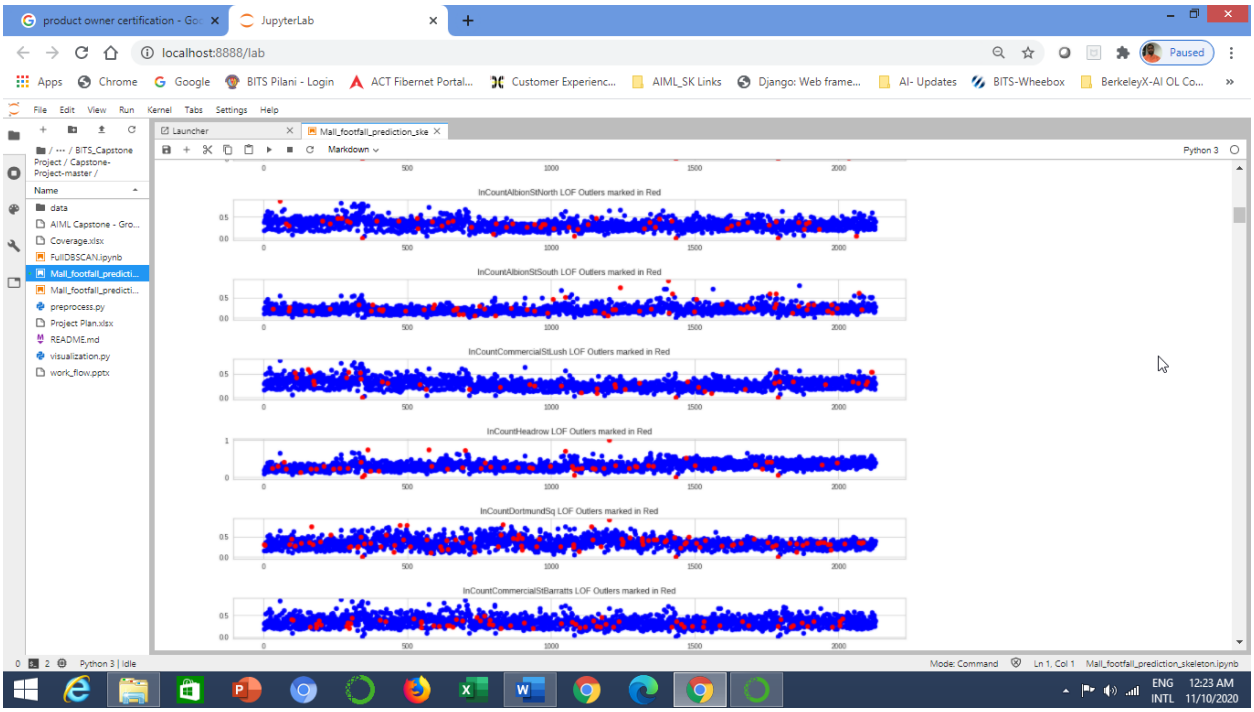
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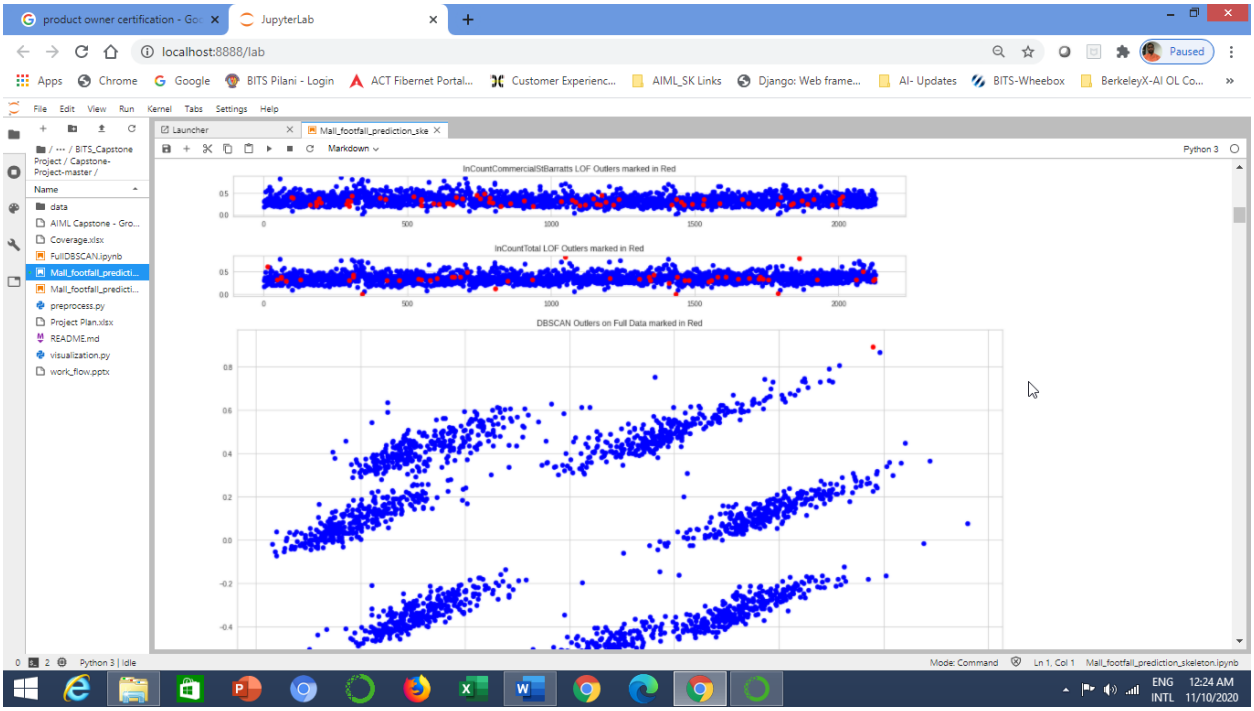
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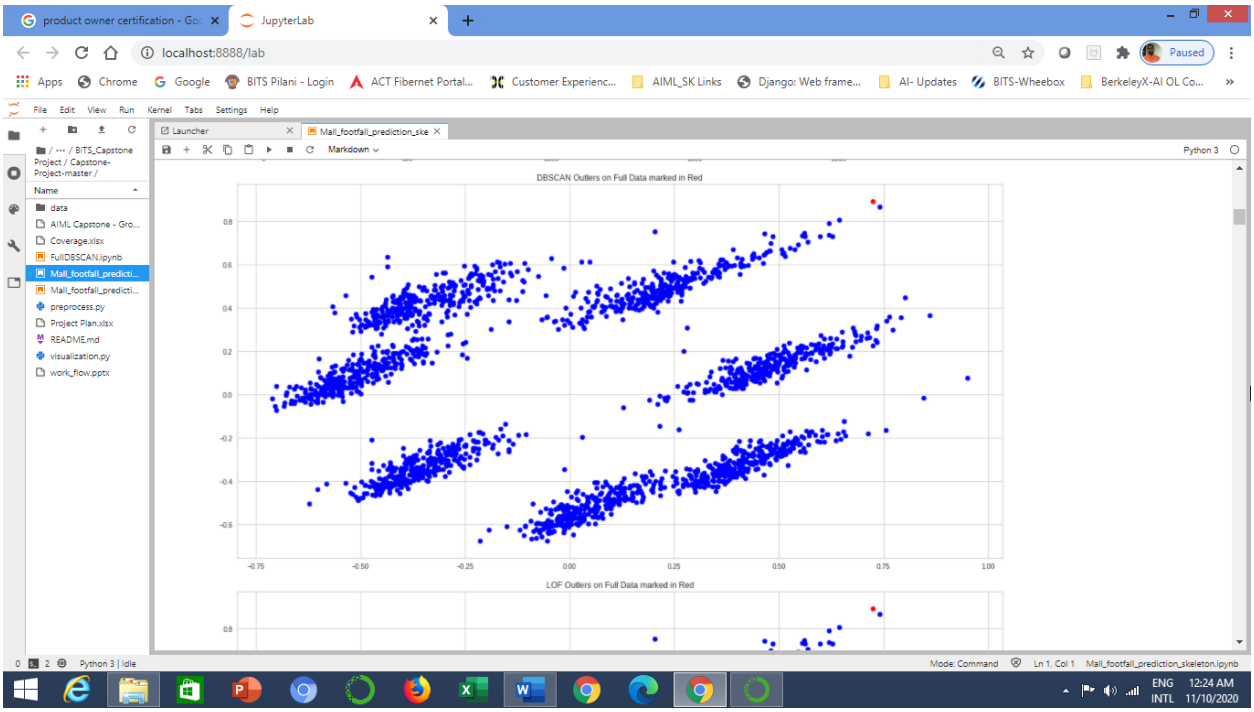
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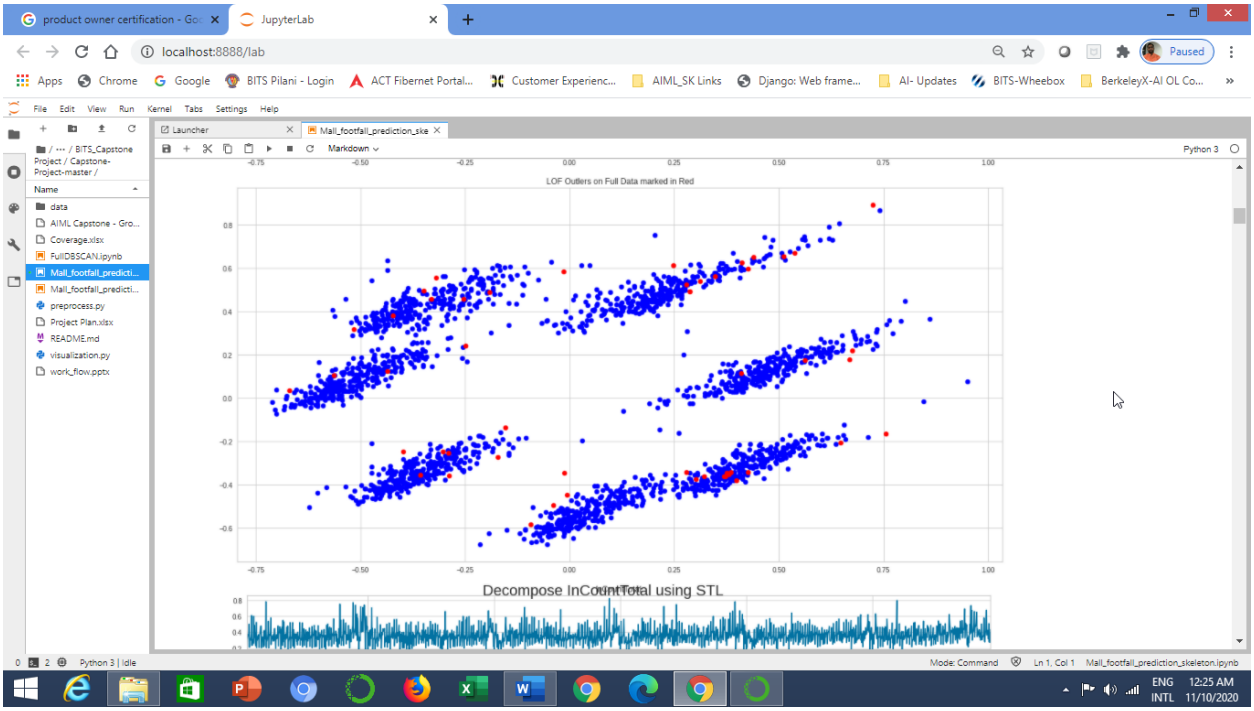
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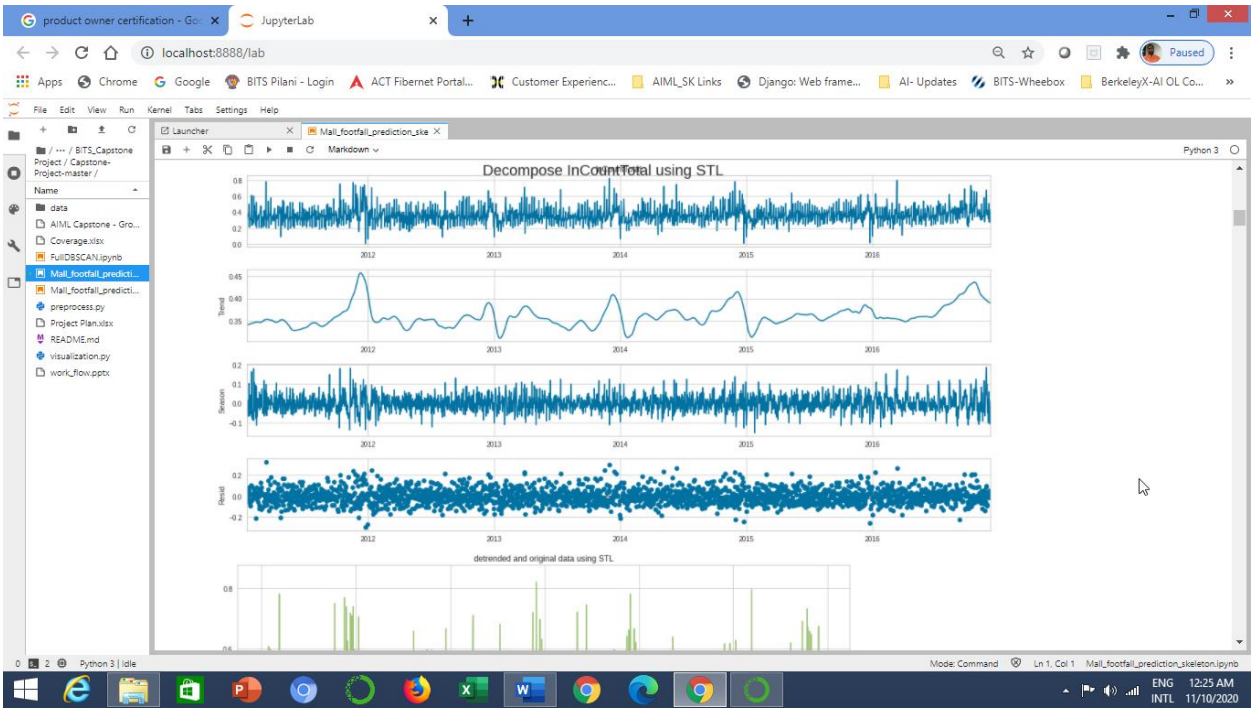
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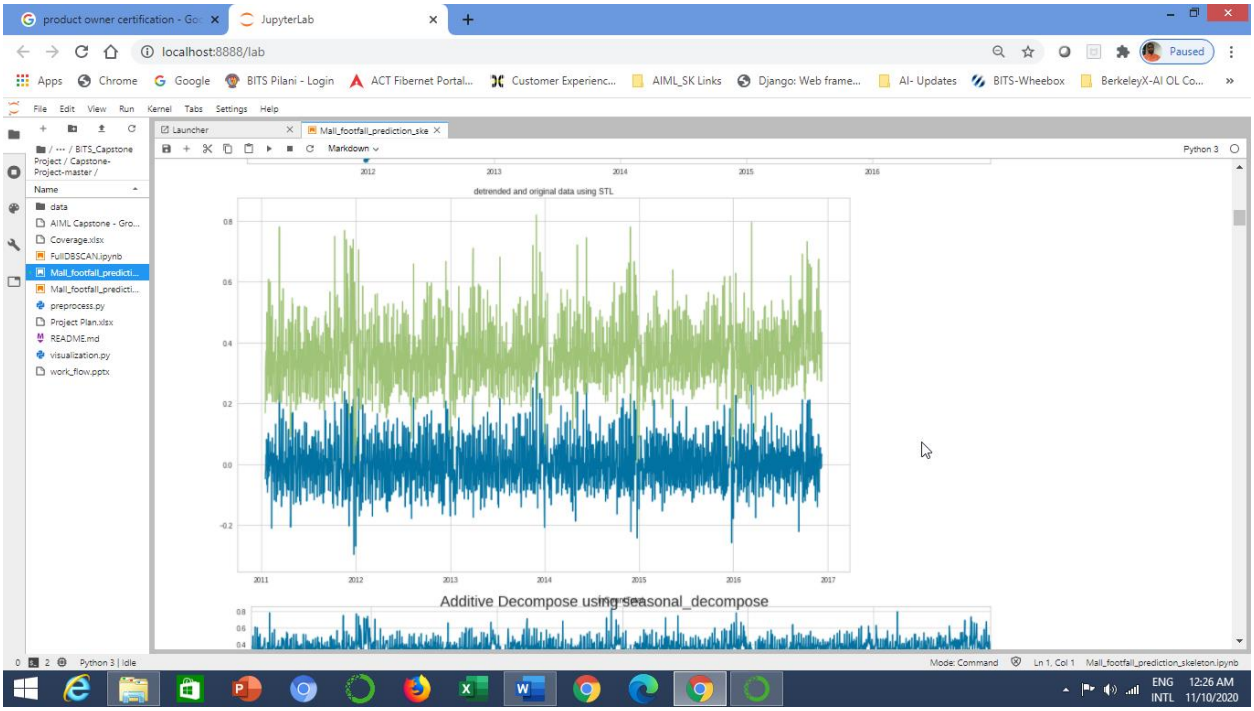
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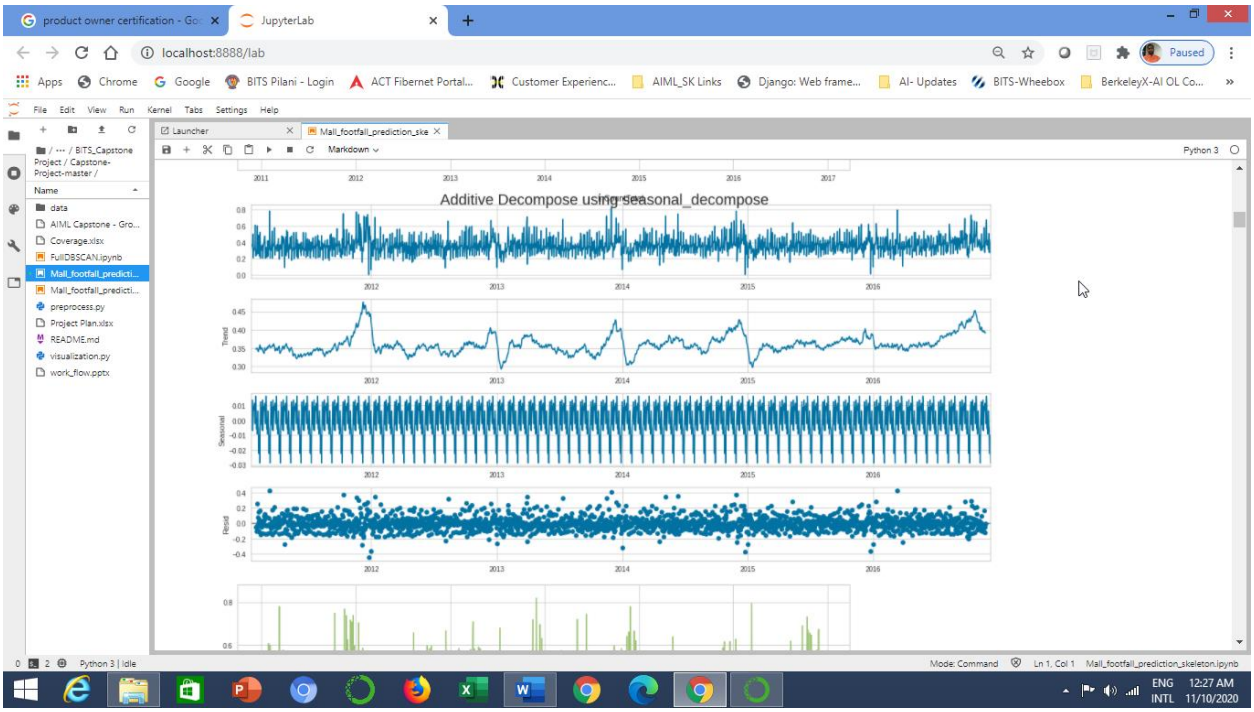
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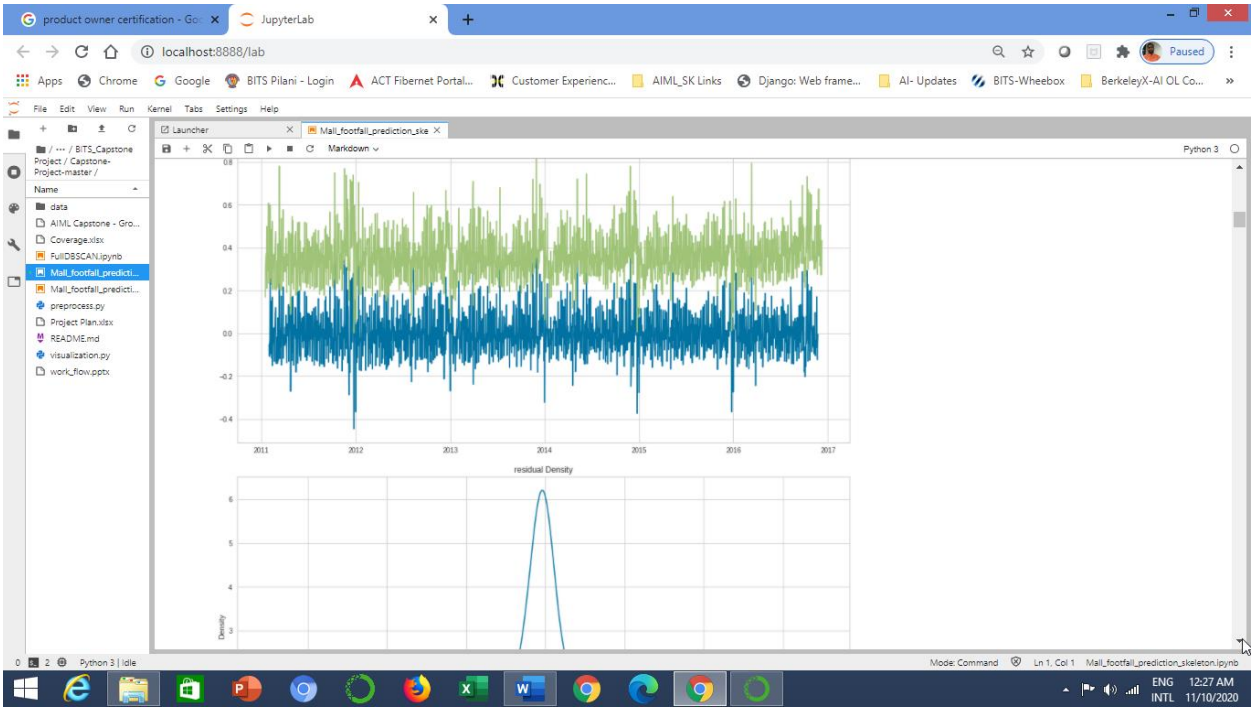
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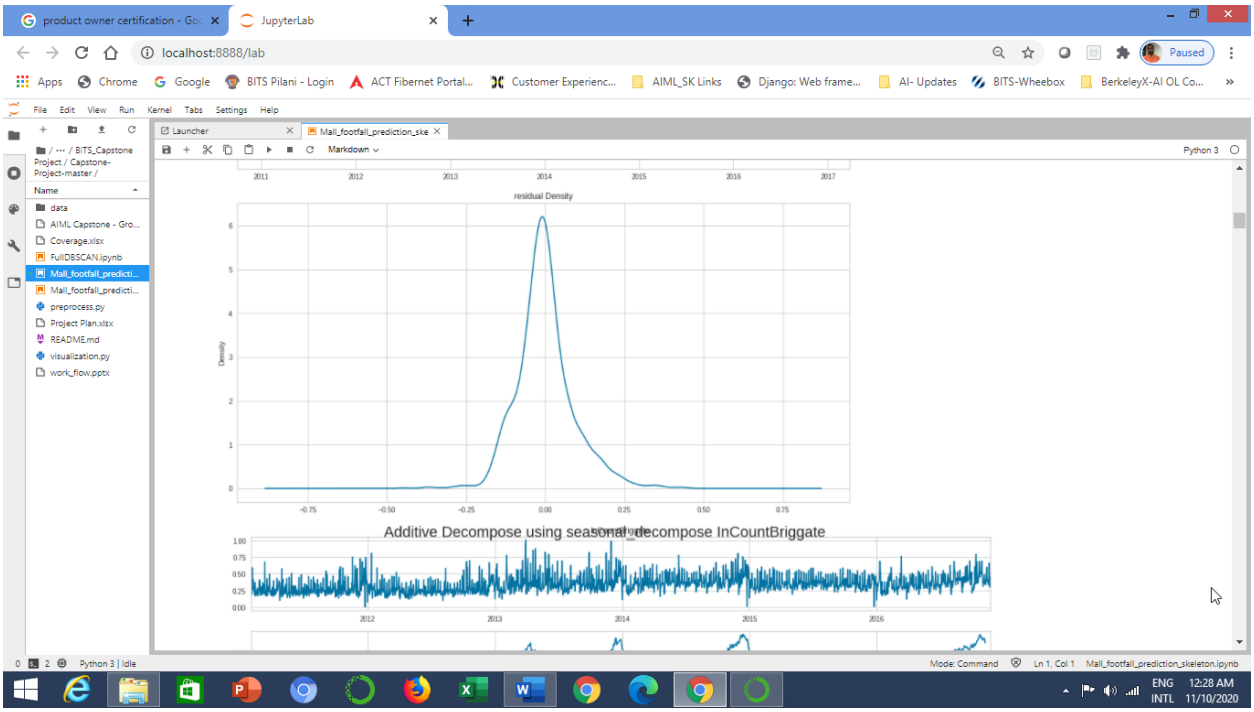
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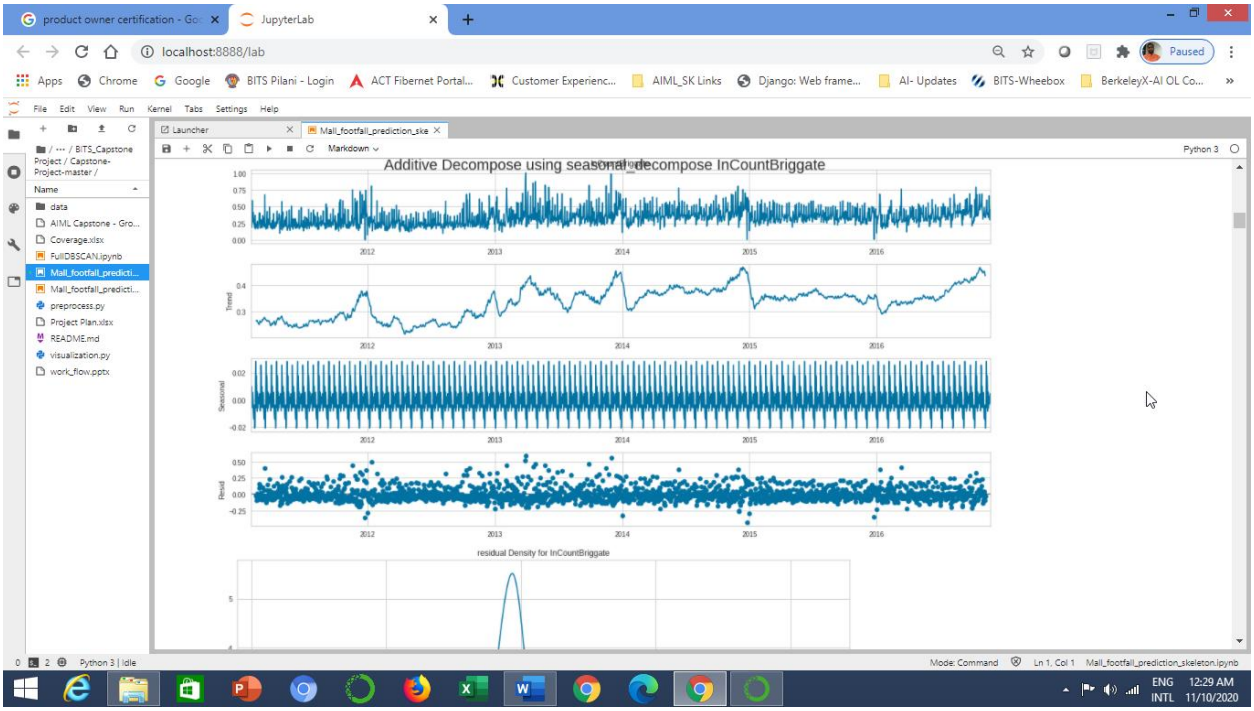
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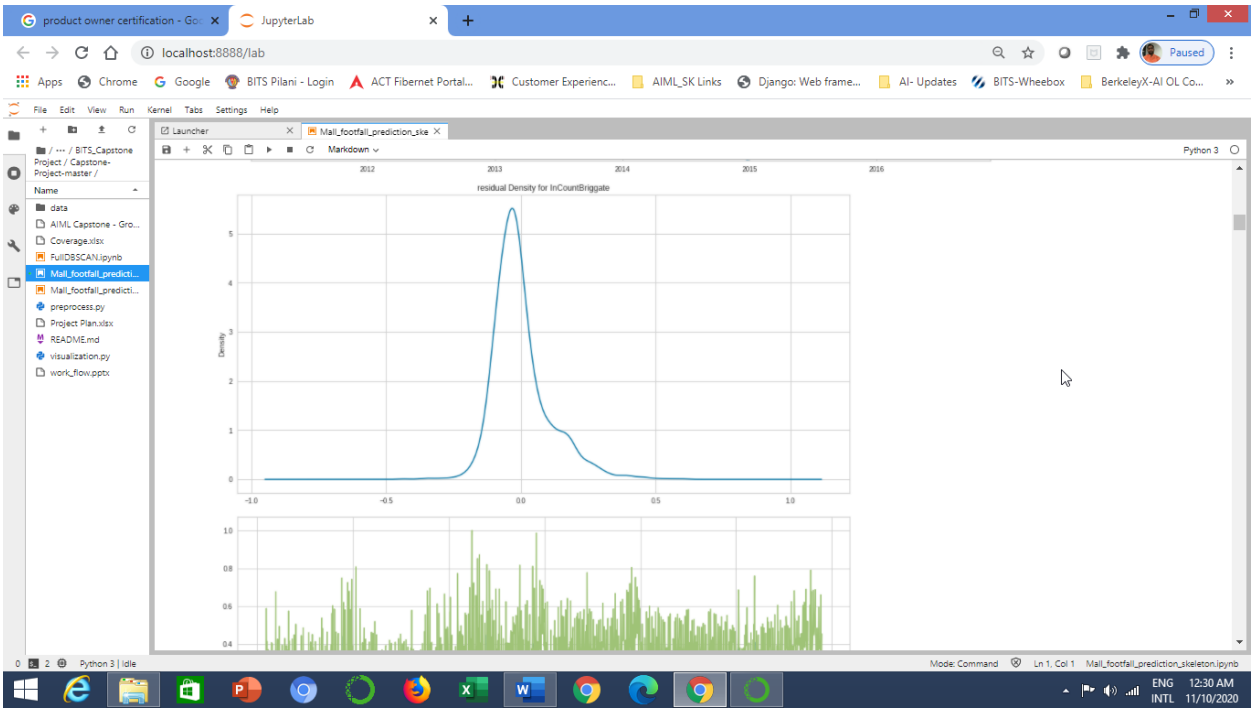
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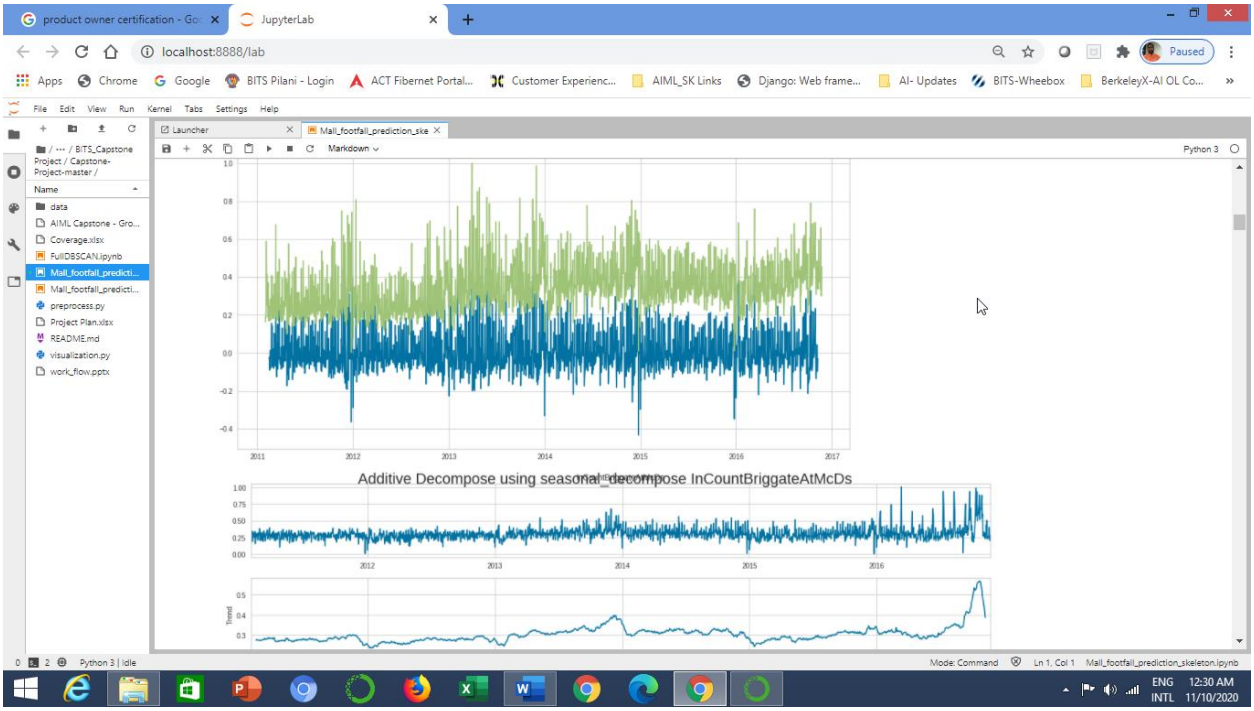
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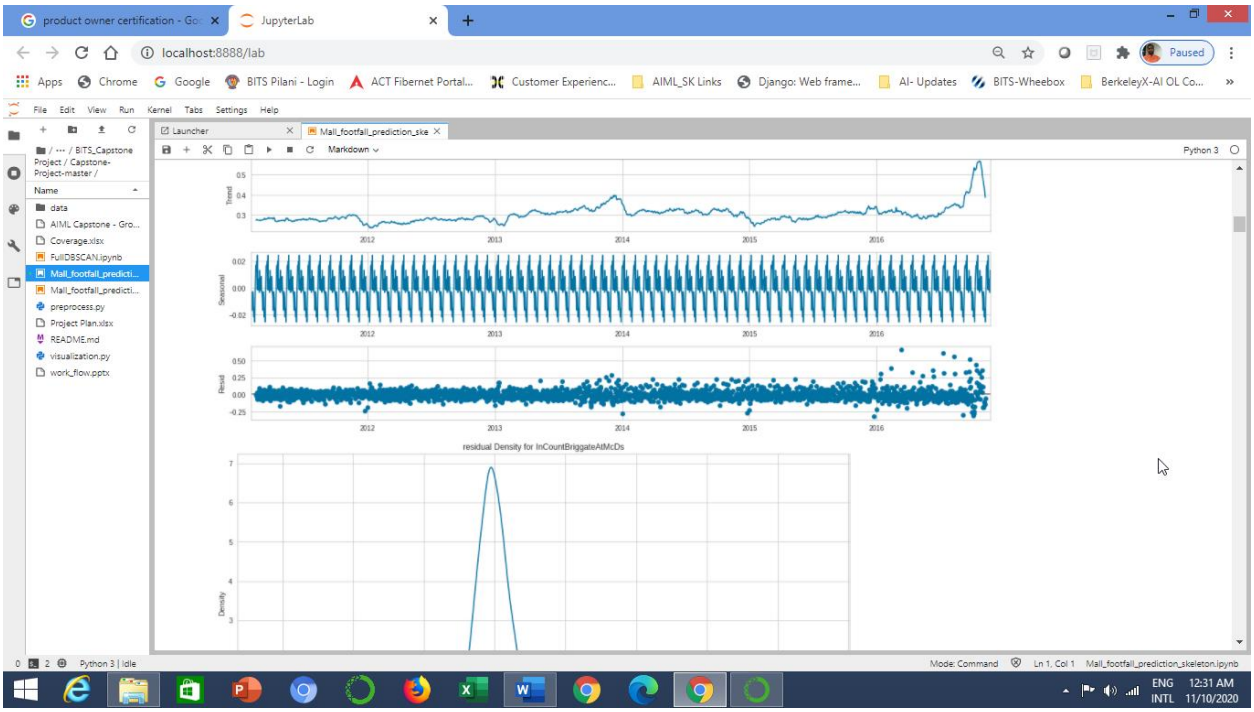
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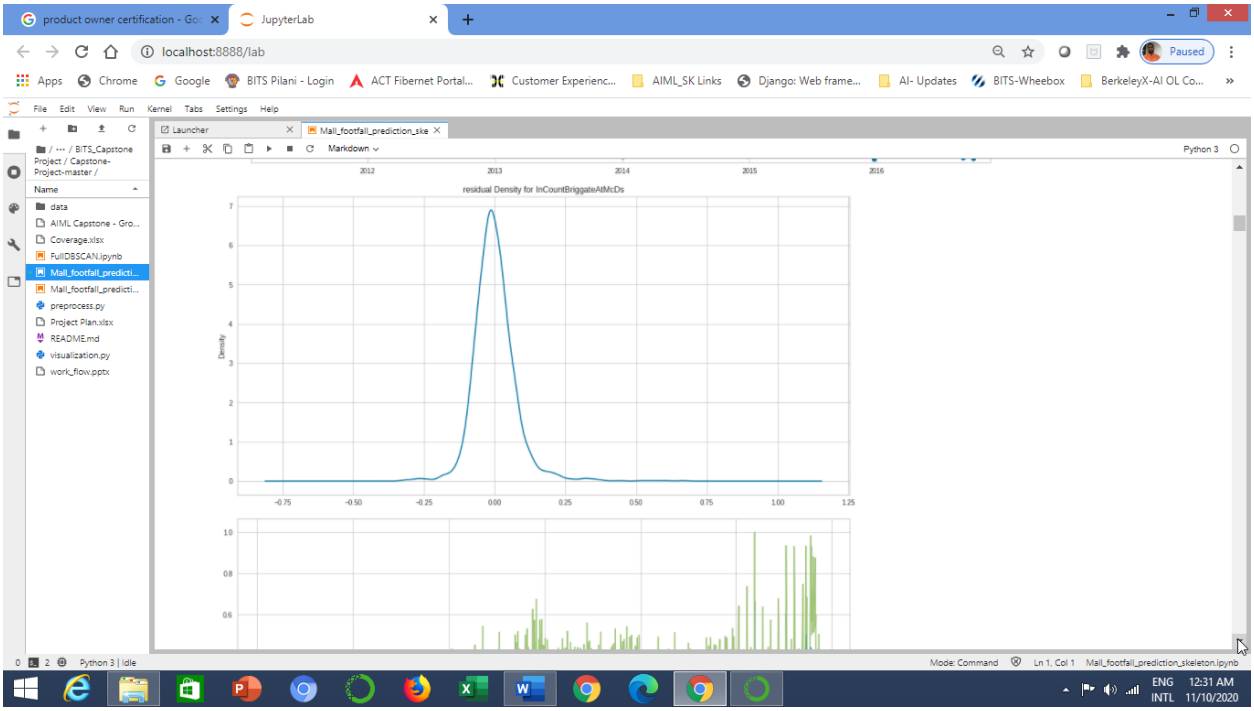
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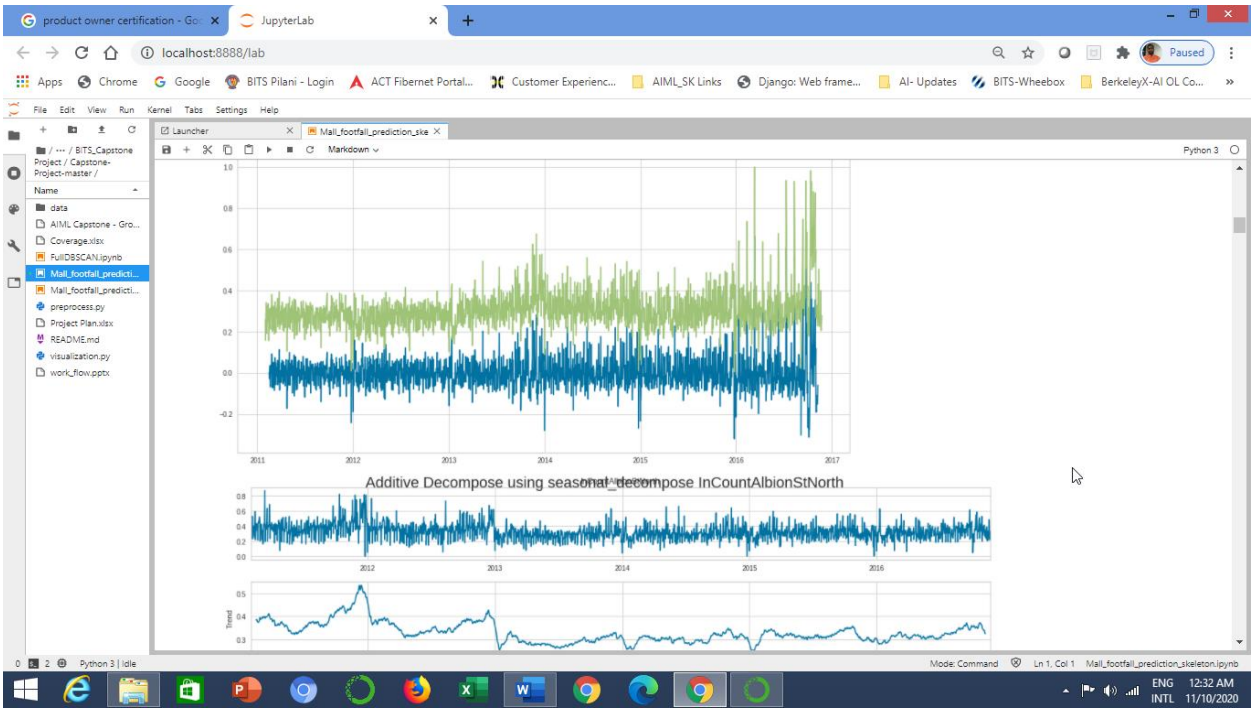
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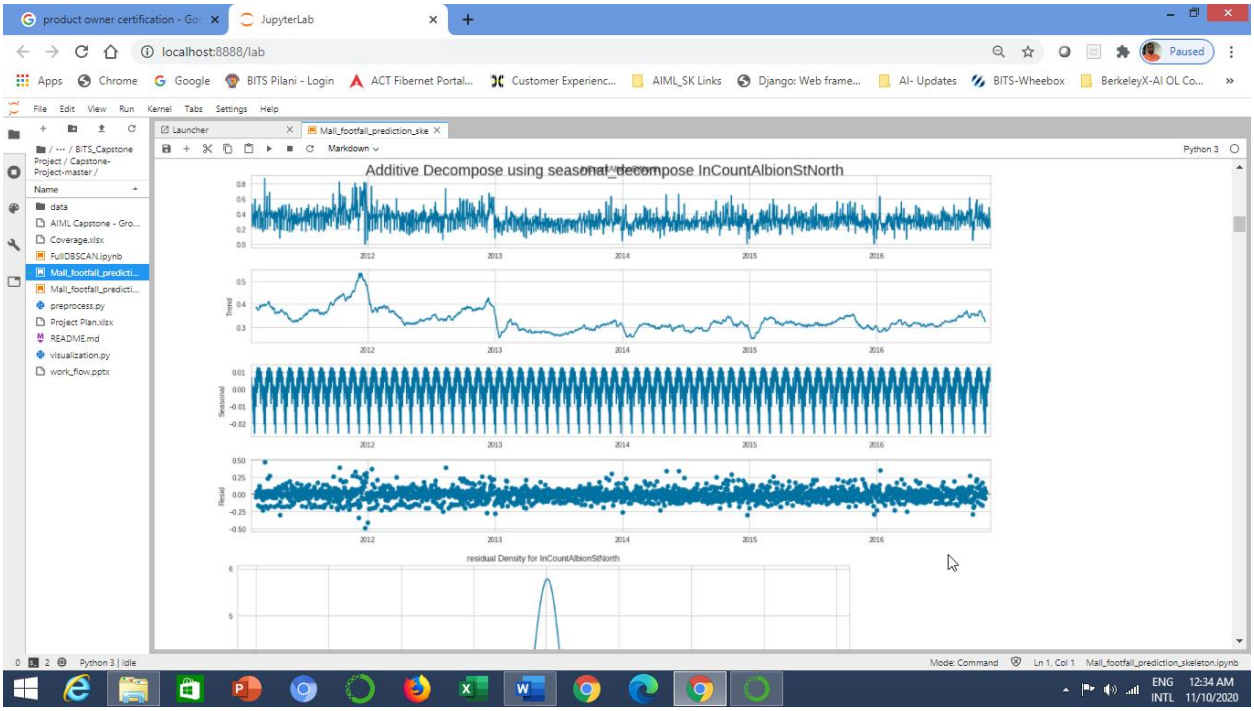
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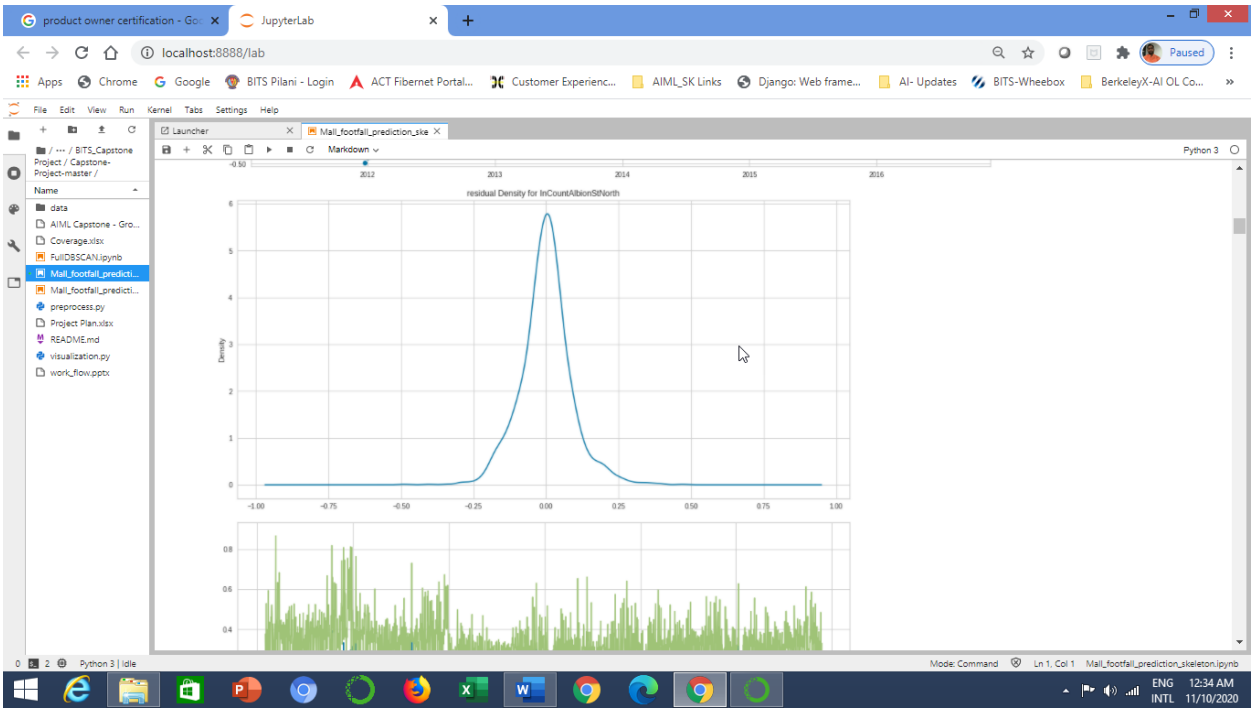
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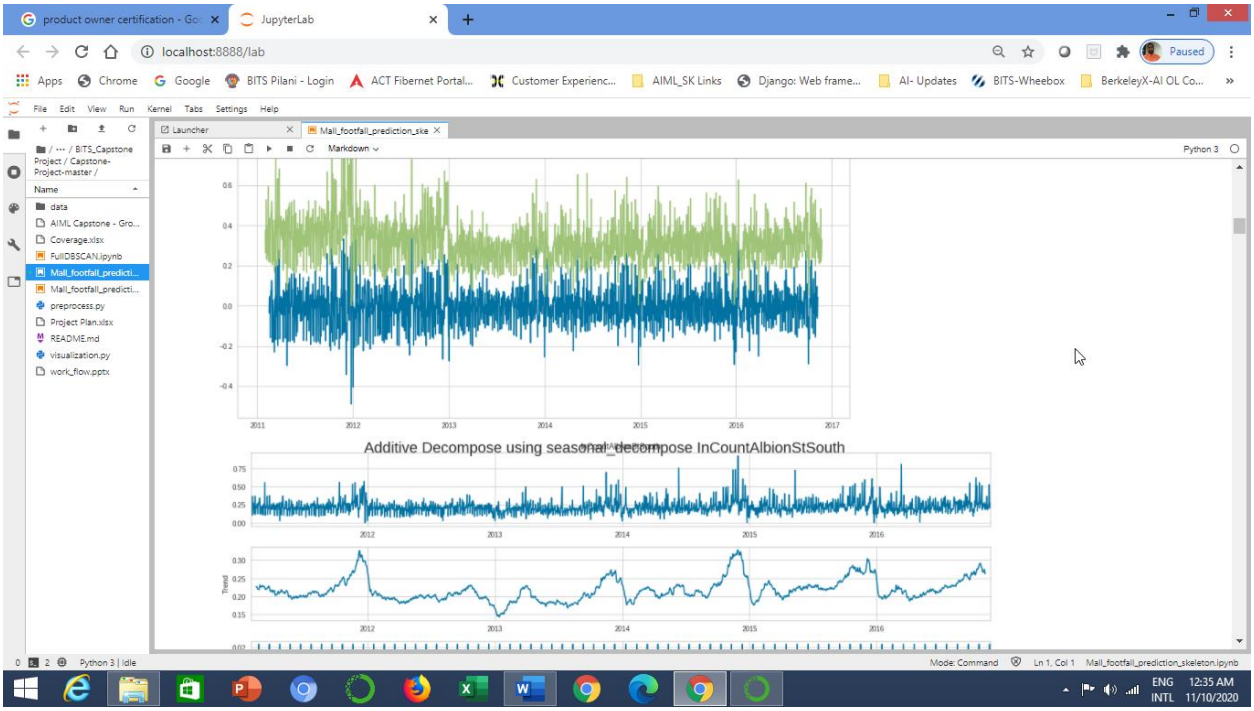
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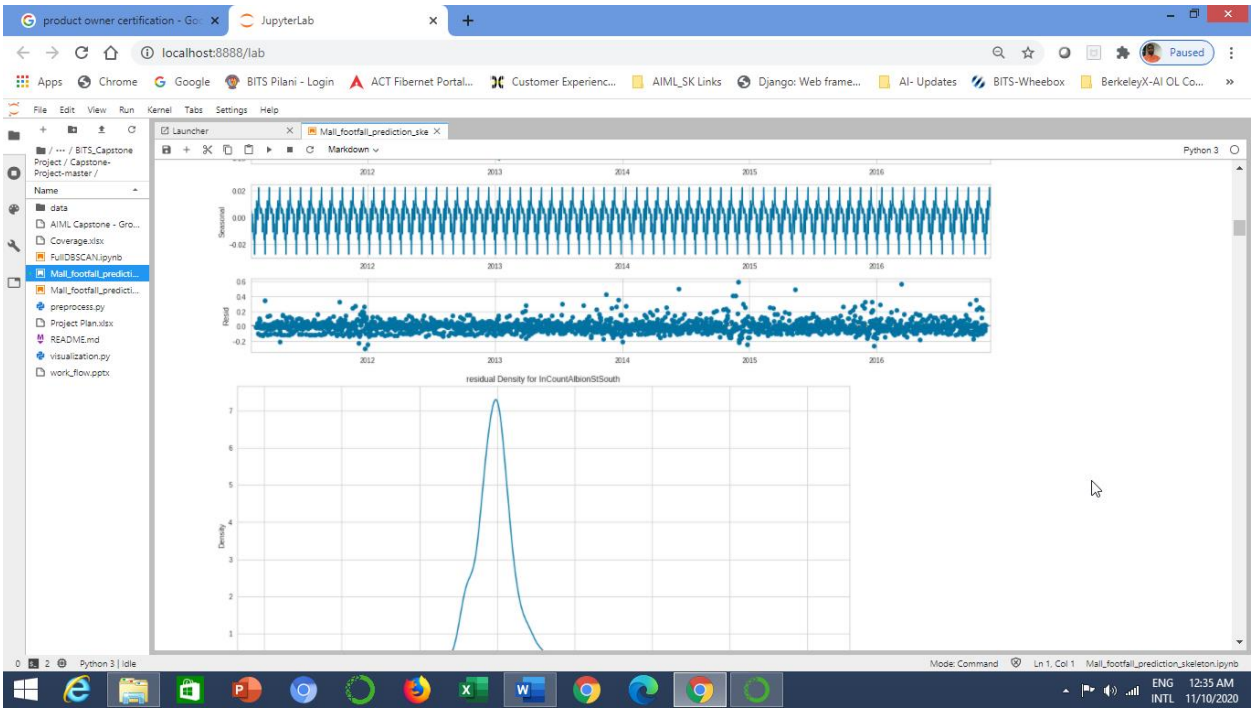
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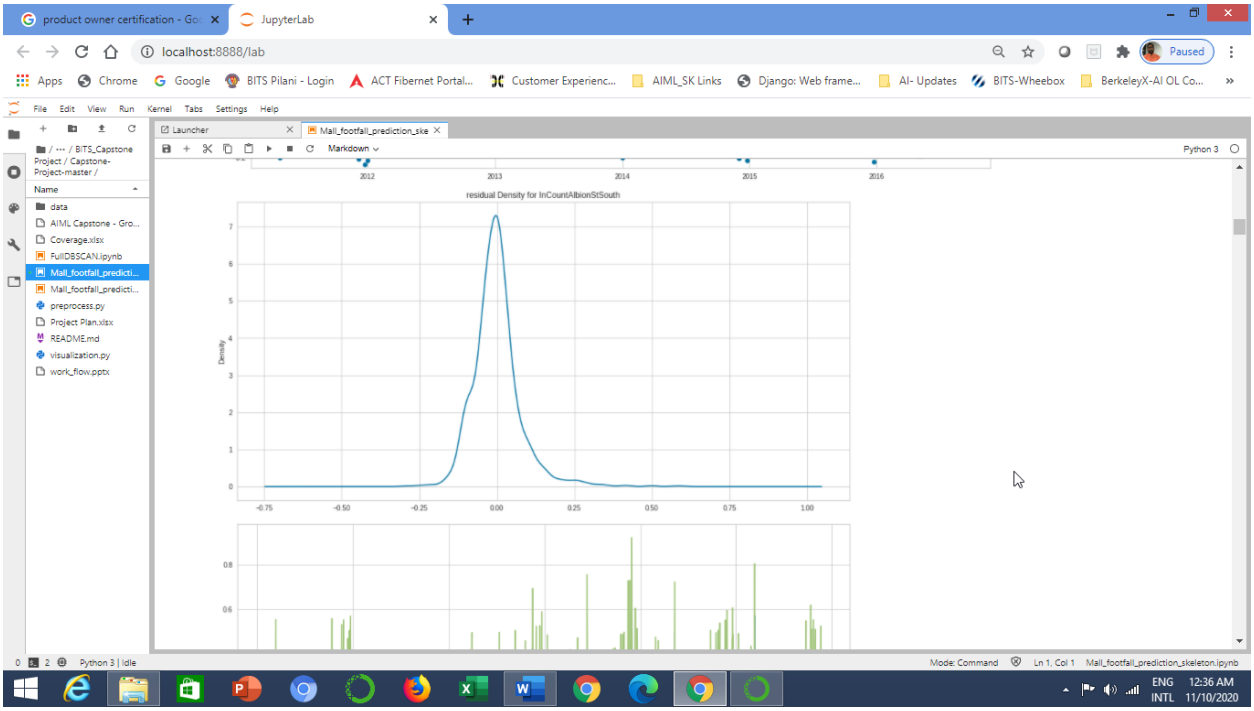
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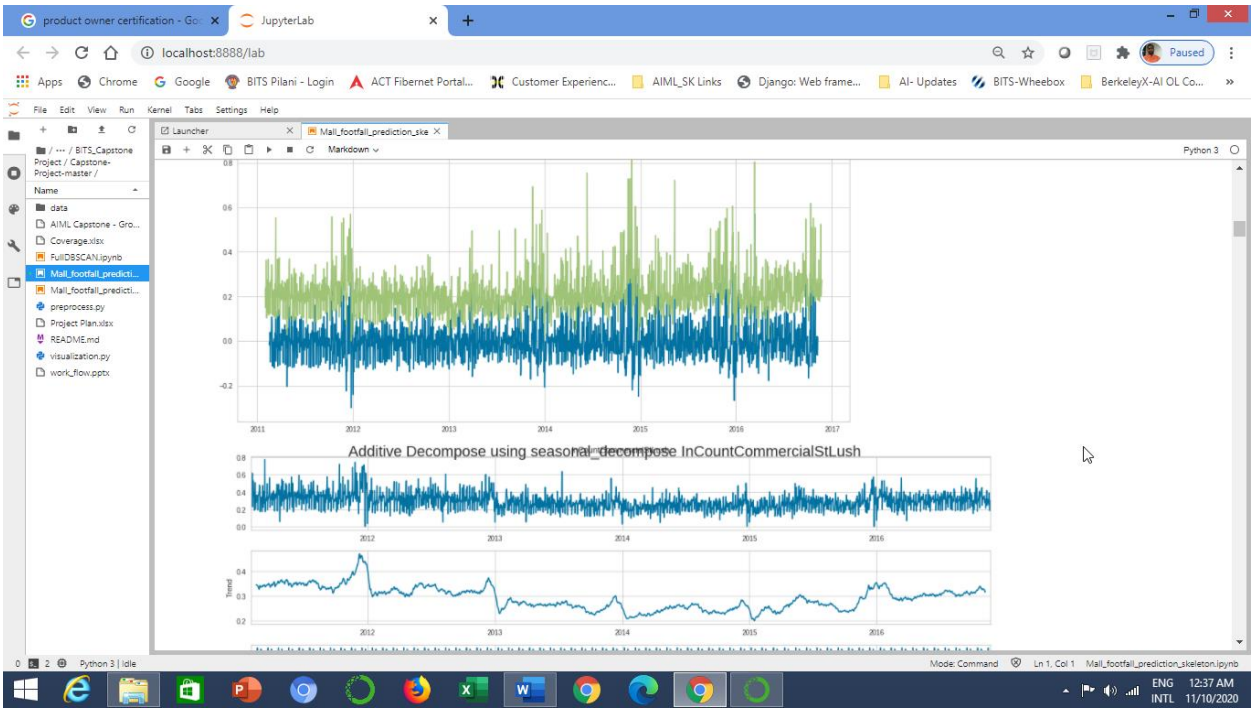
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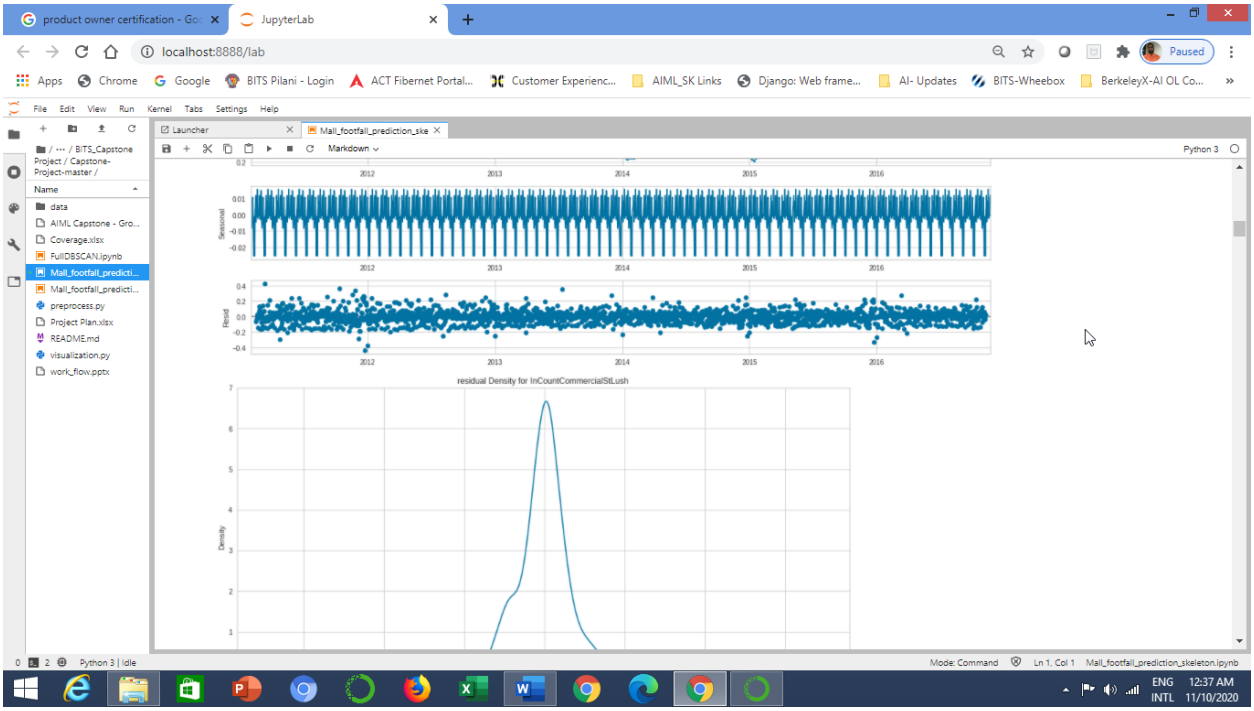
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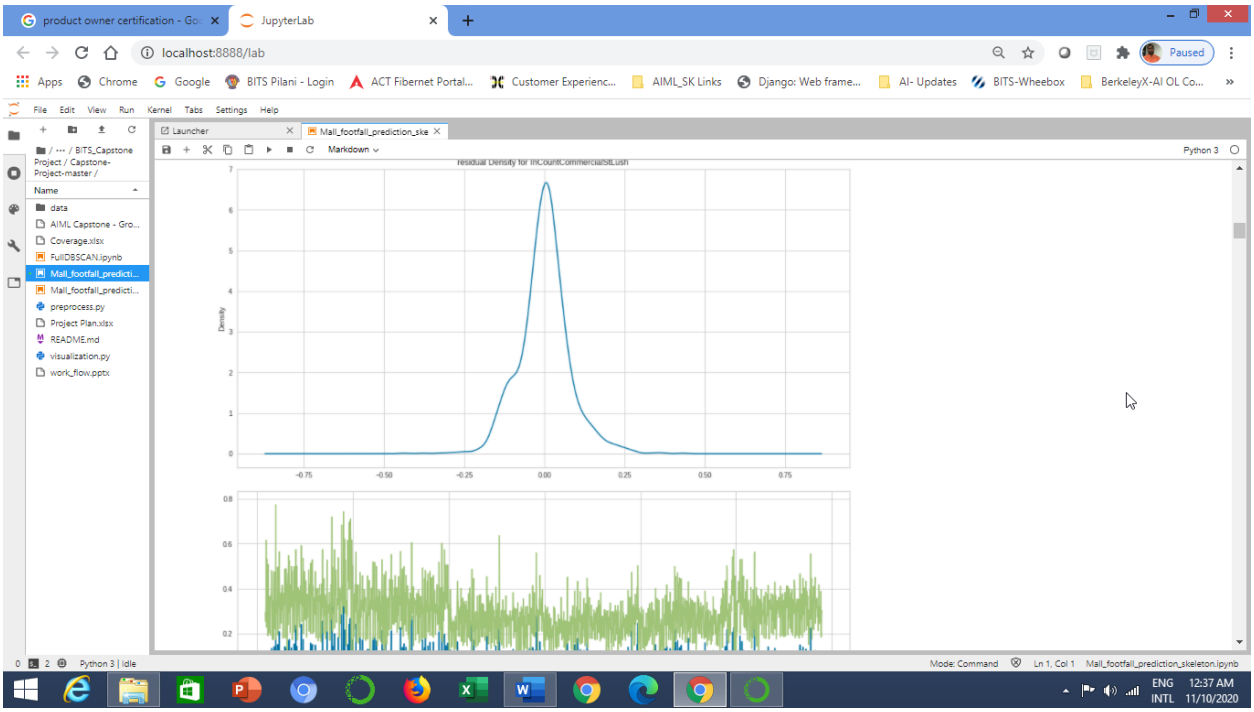
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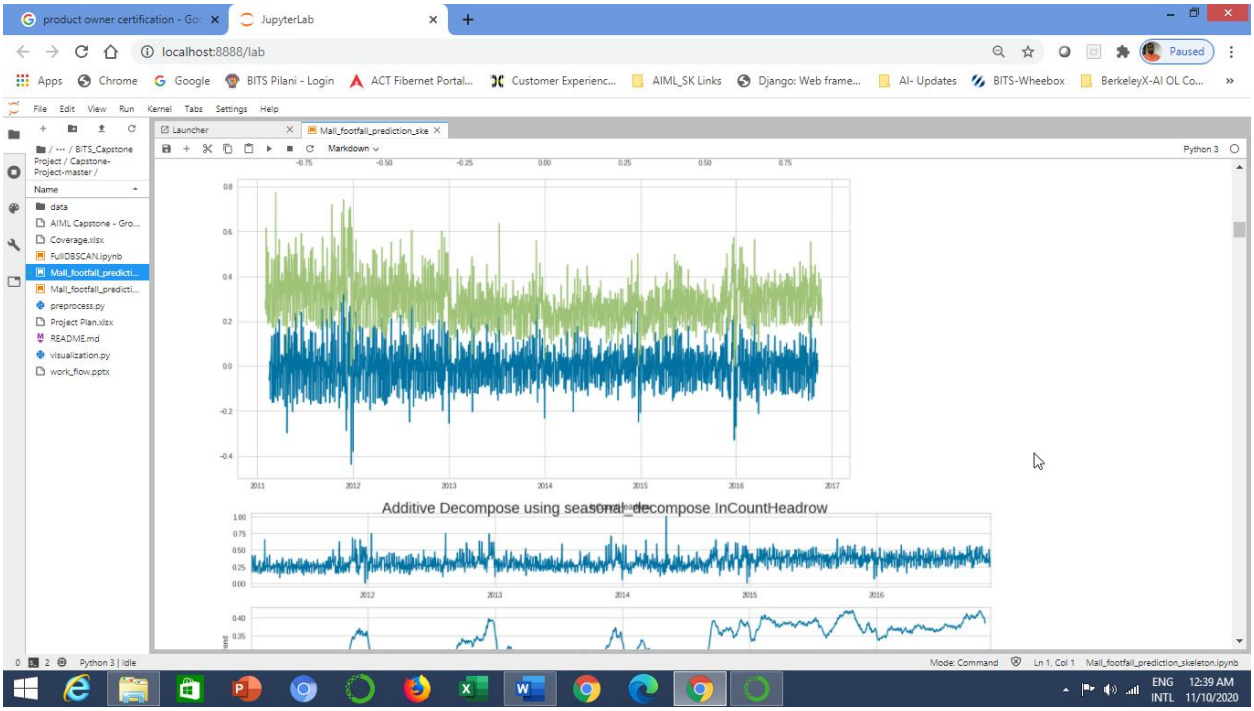
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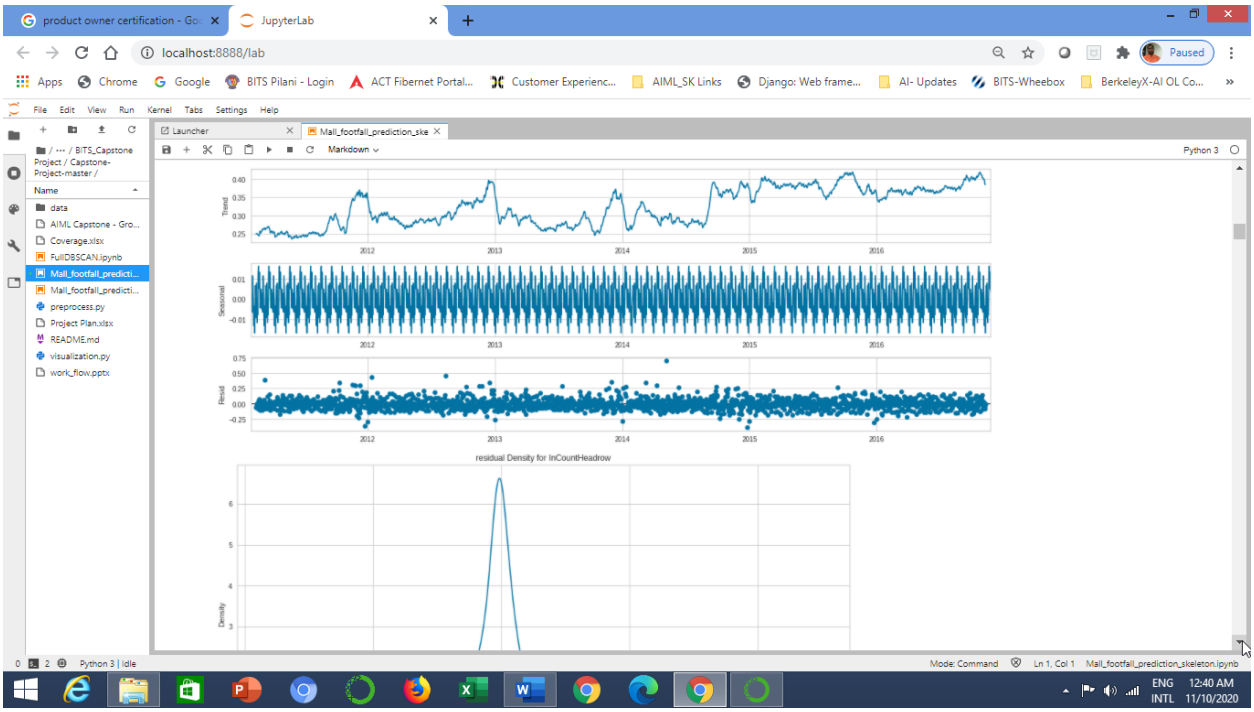
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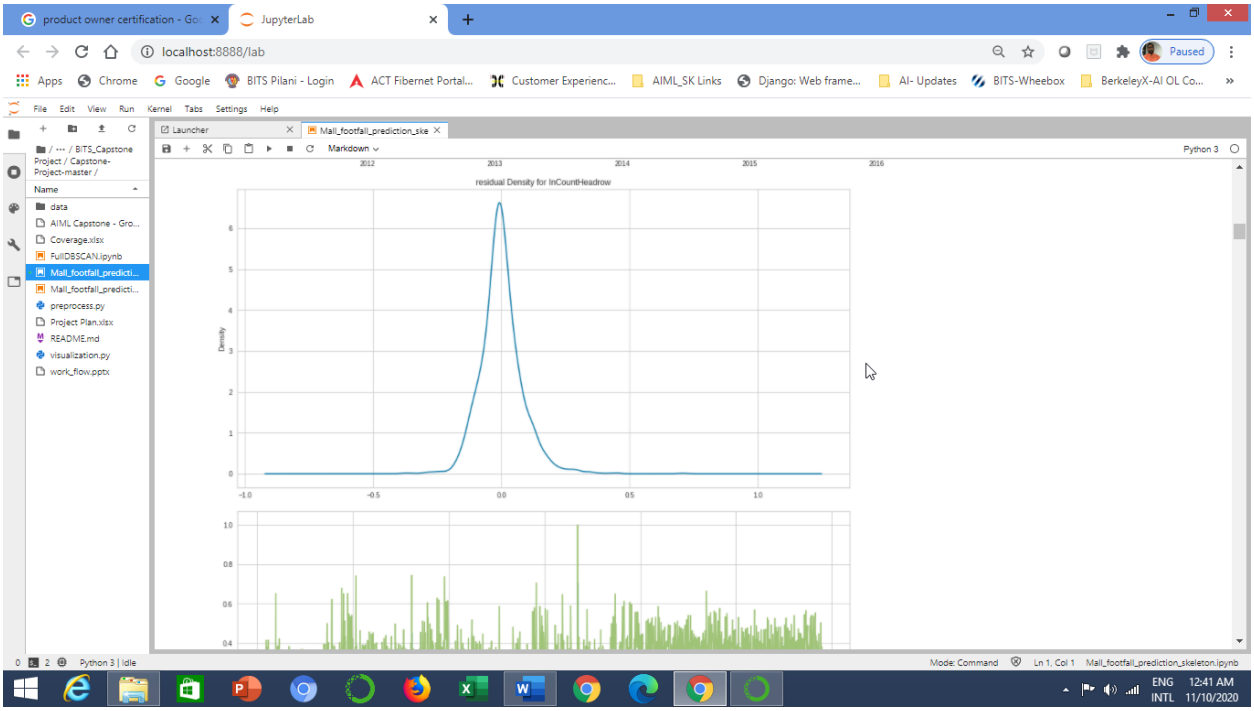
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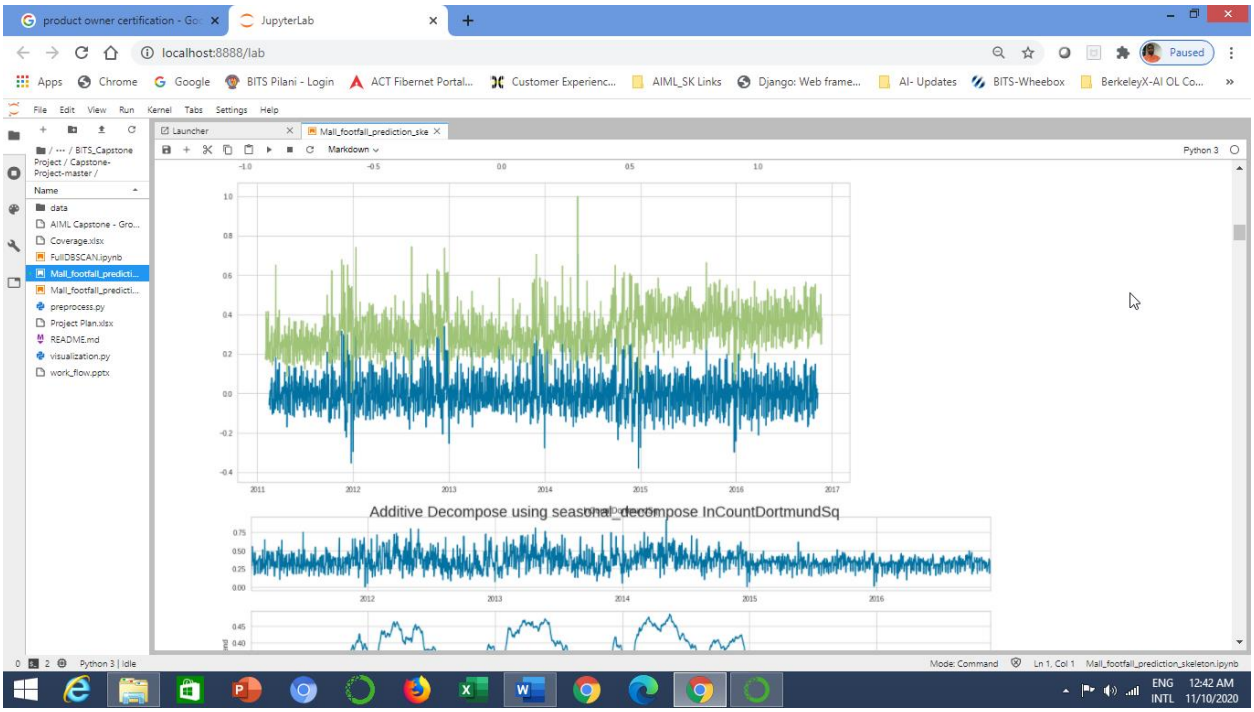
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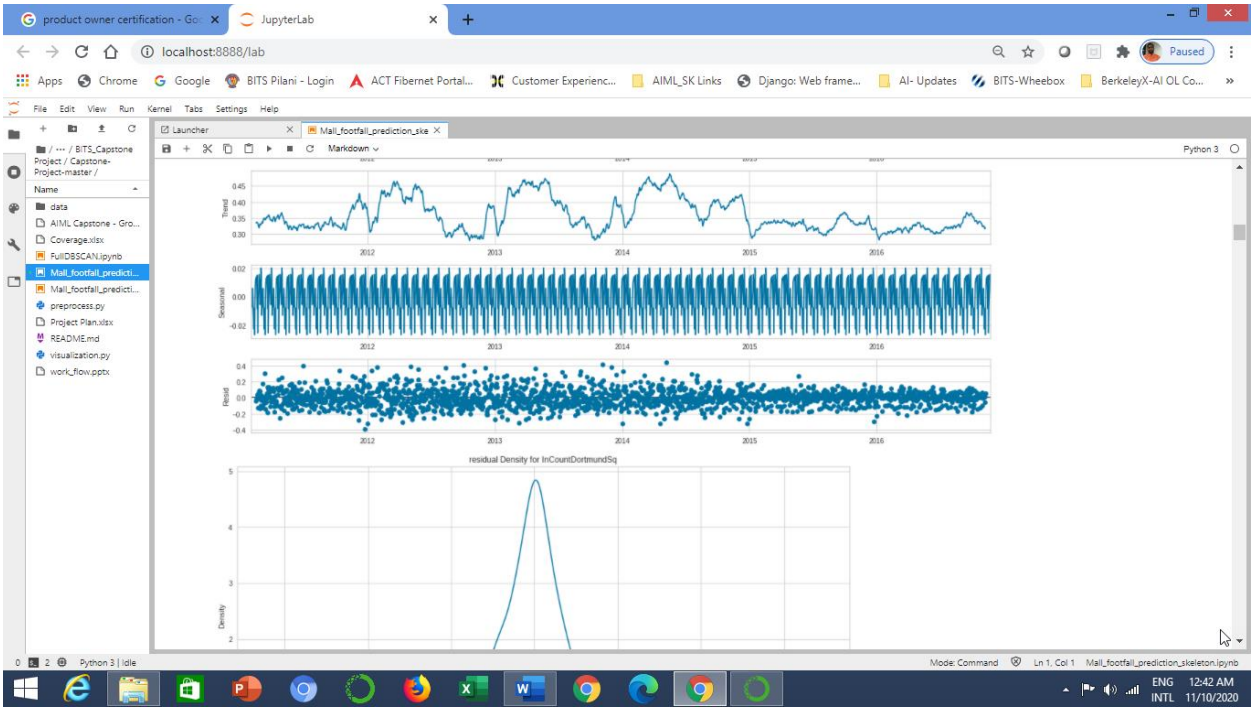
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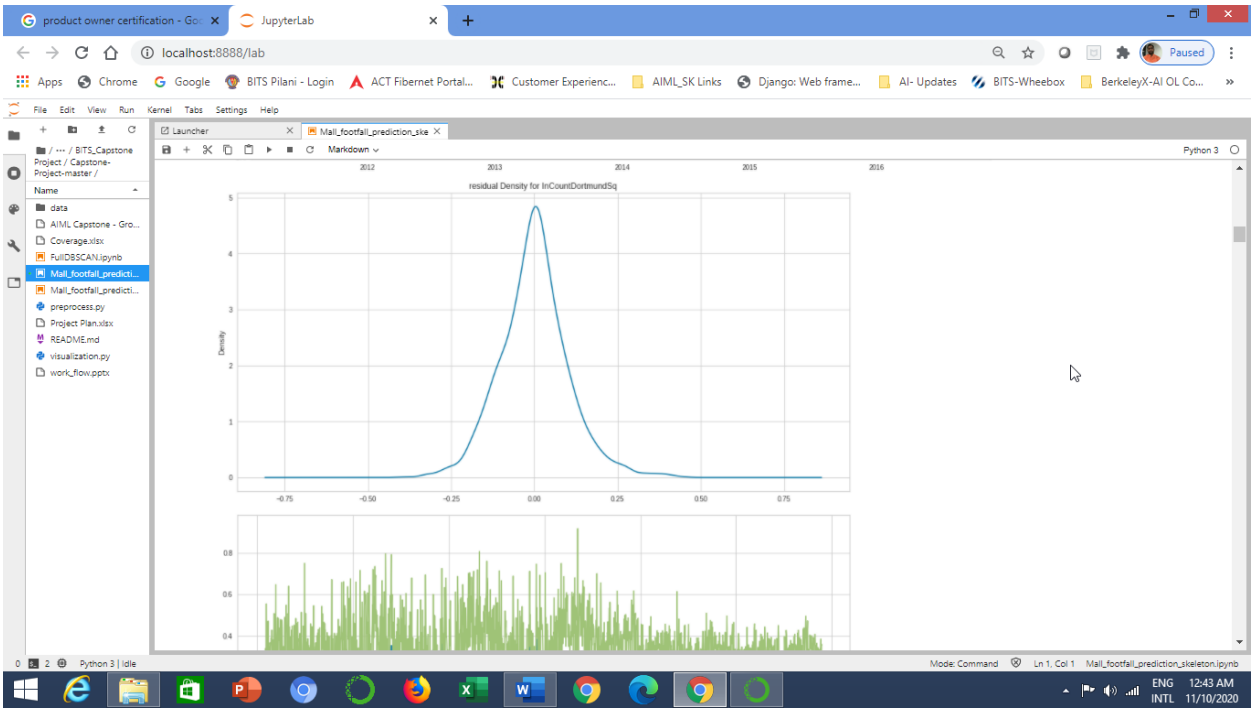
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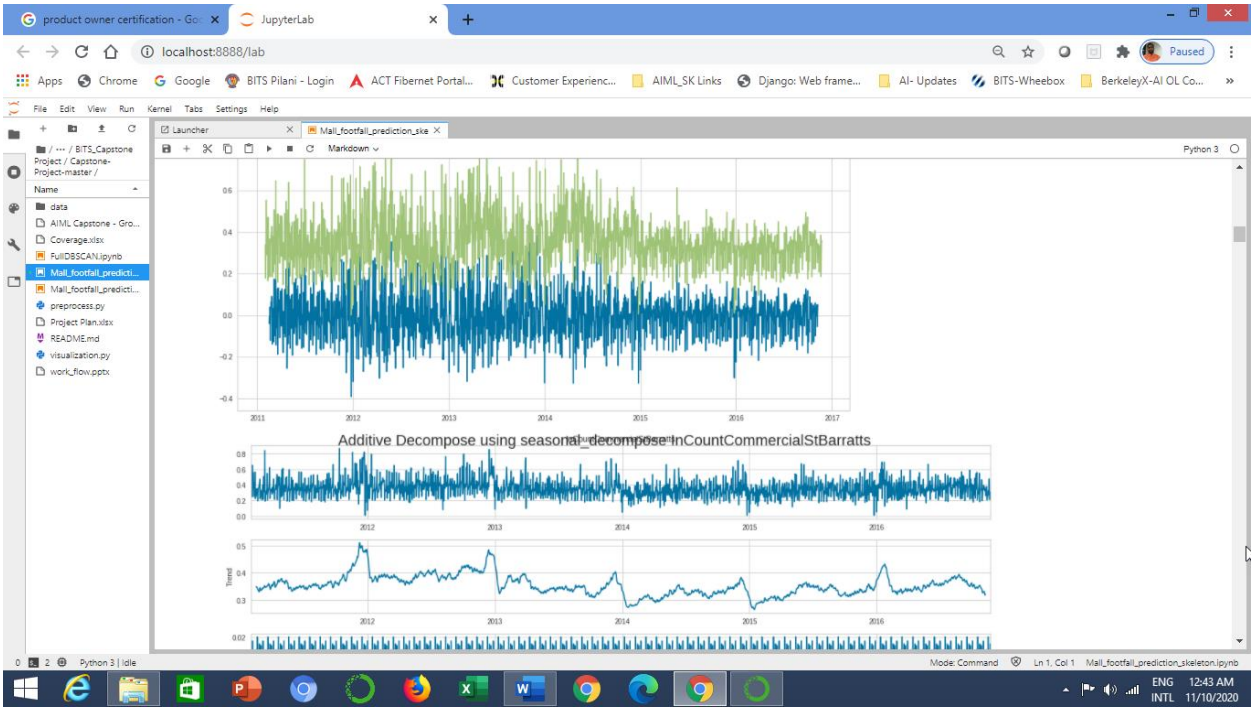
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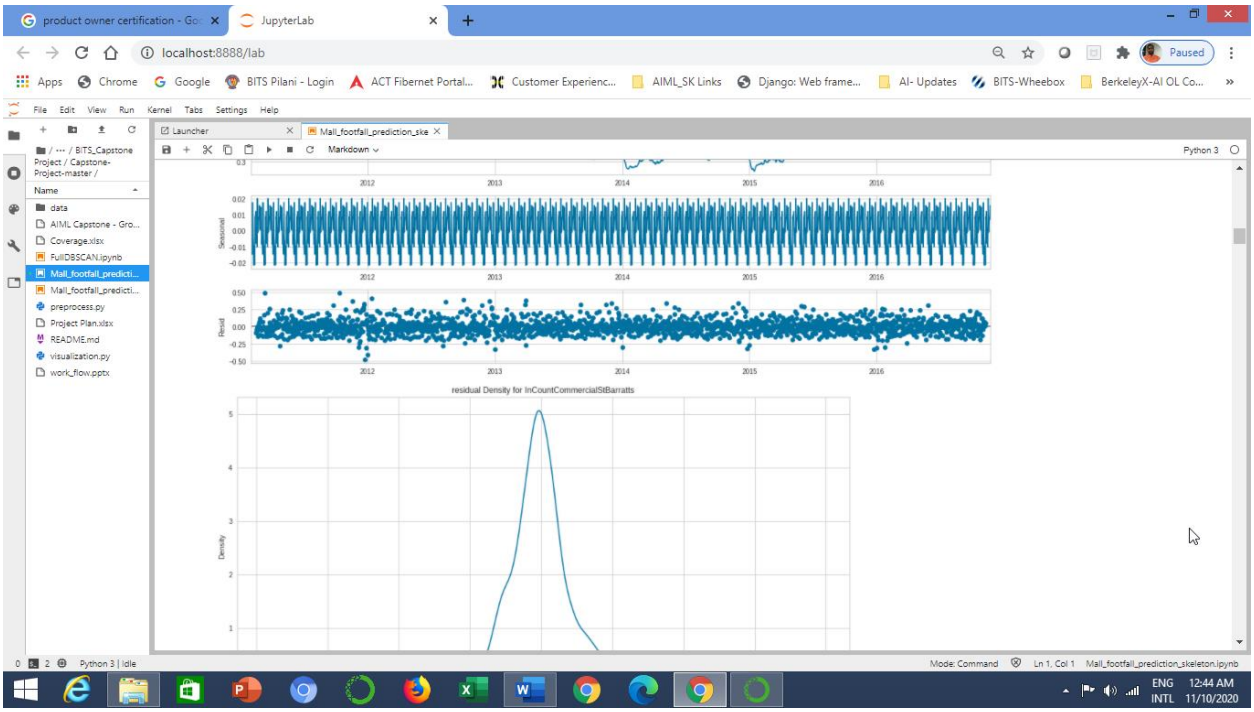
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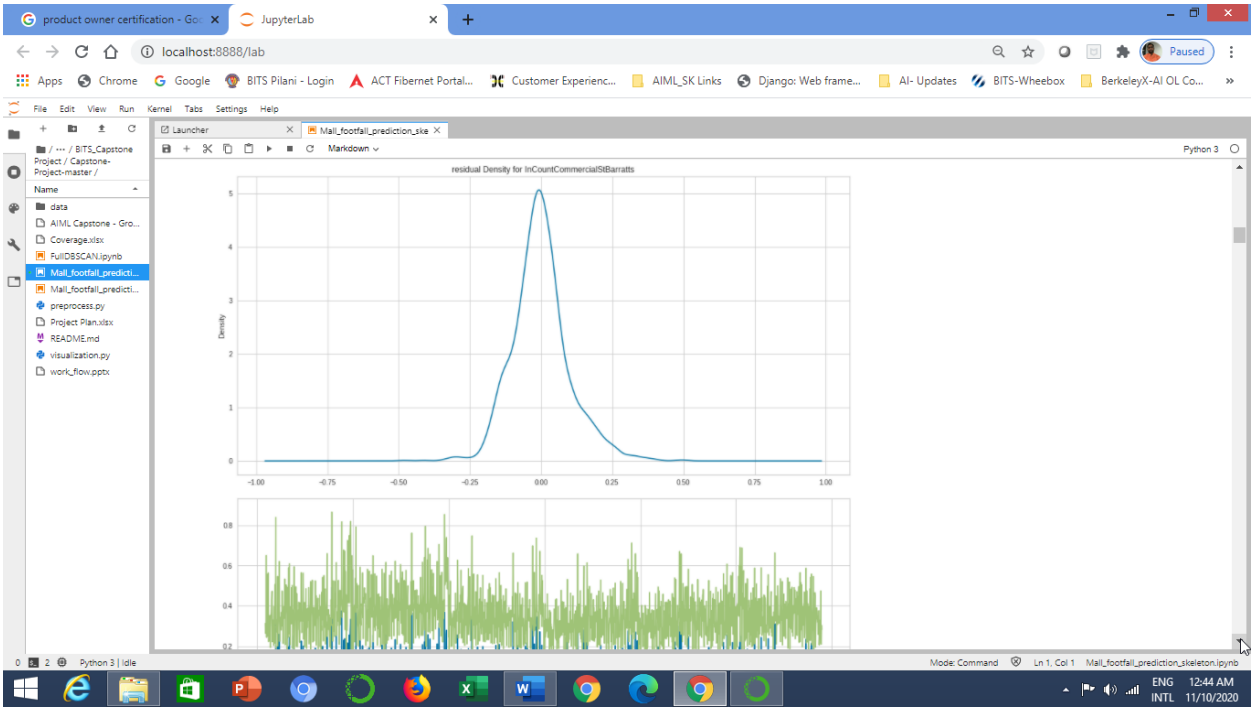
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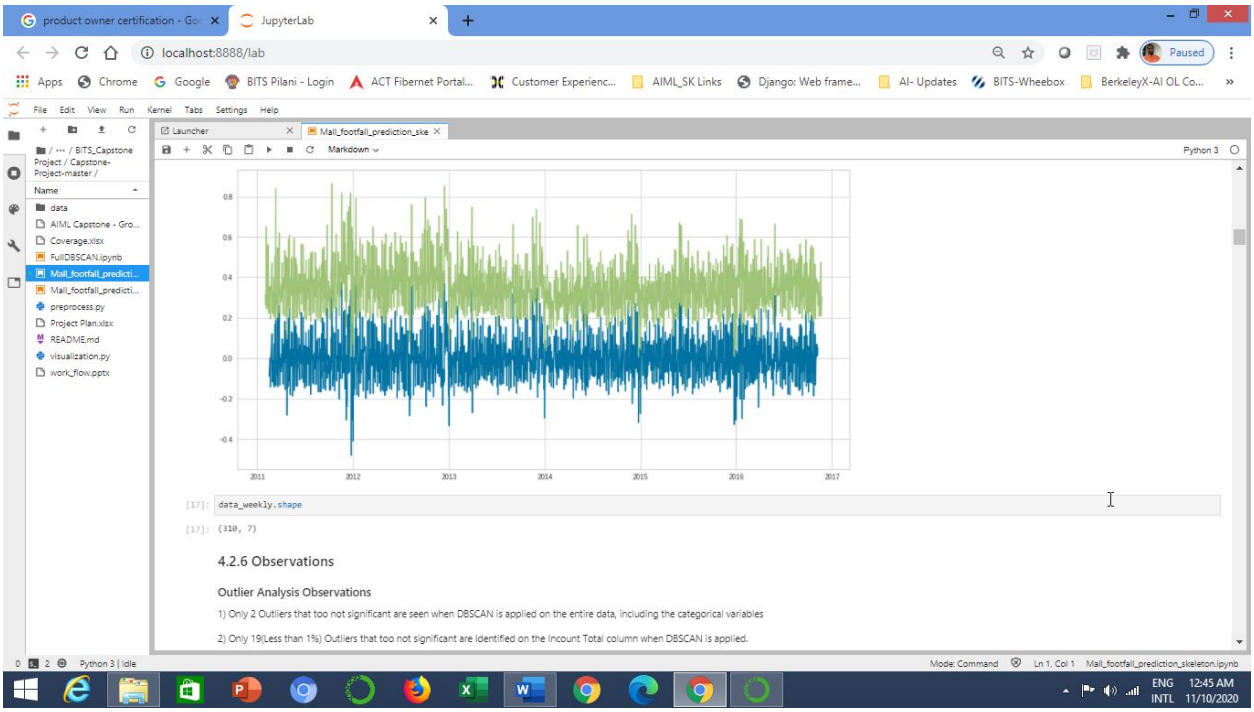
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[17]: data_weekly.shape
[17]: (310, 7)
4.2.6 Observations
Outlier Analysis Observations
1) Only 2 Outliers that too not significant are seen when DBSCAN is applied on the entire data, including the categorical variables
2) Only 19(Less than 1%) Outliers that too not significant are identified on the Incount Total column when DBSCAN is applied.
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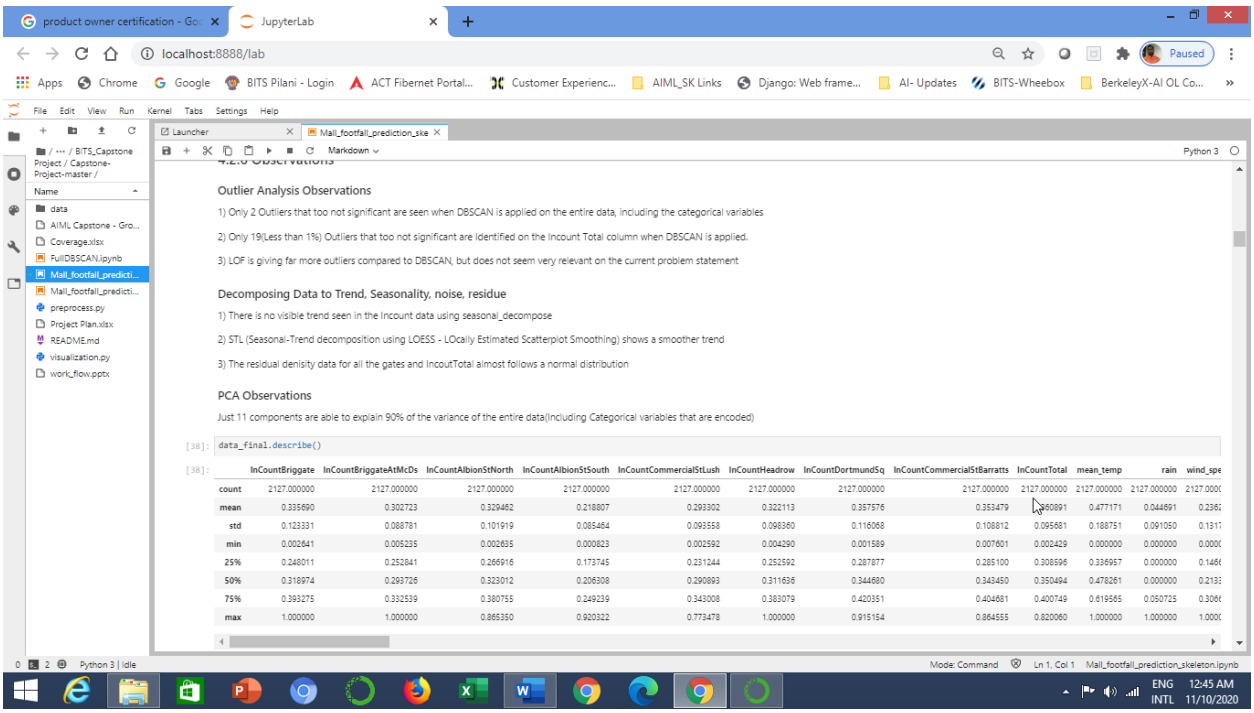


### Outlier Analysis Observations

1) Only 2 Outliers that too not significant are seen when DBSCAN is applied on the entire data, including the categorical variables

2) Only 19(Less than 1%) Outliers that too not significant are identified on the Incount Total column when DBSCAN is applied.

3) LOF is giving far more outliers compared to DBSCAN, but does not seem very relevant on the current problem statement

### Decomposing Data to Trend, Seasonality, noise, residue

1) There is no visible trend seen in the Incount data using seasonal_decompose

2) STL (Seasonal-Trend decomposition using LOESS - LOcally Estimated Scatterplot Smoothing) shows a smoother trend

3) The residual denisity data for all the gates and IncoutTotal almost follows a normal distribution

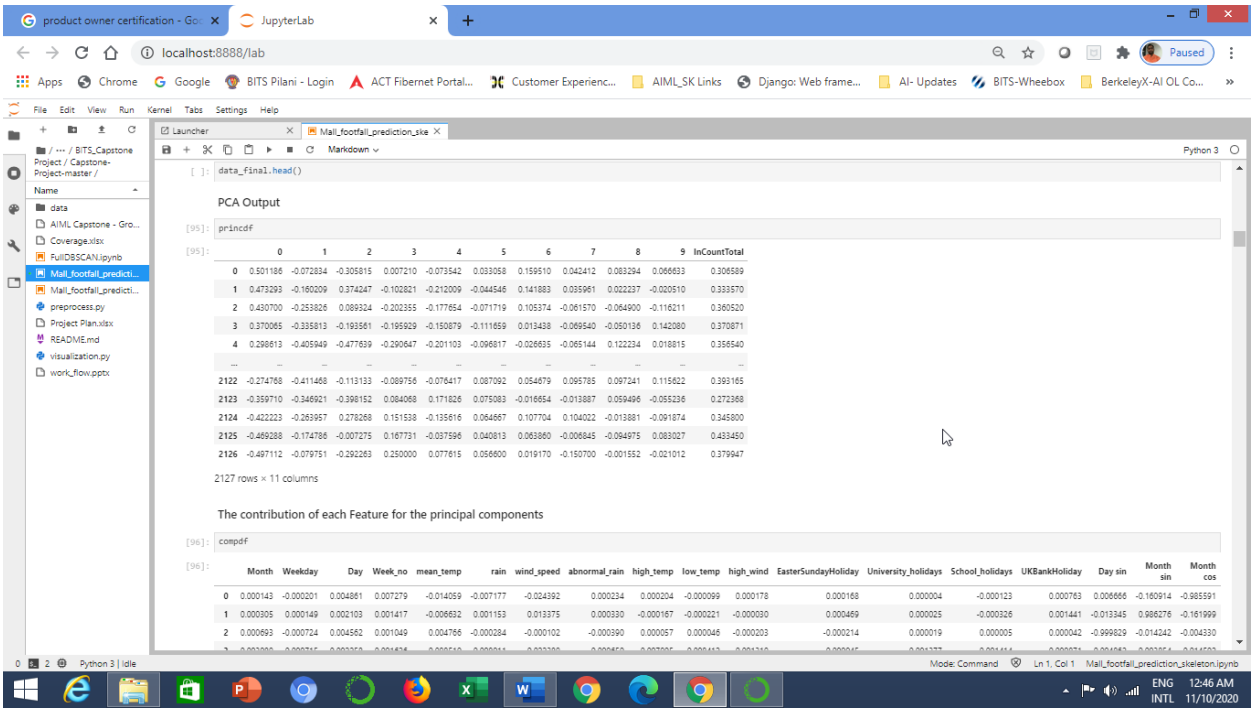
### PCA Observations

Just 11 components are able to explain 90% of the variance of the entire data(Including Categorical variables that are encoded)

```
[38]: data_final.describe()
```

[38]:

| | InCountBriggate | InCountBriggateAtMcDs | InCountAlbionStNorth | InCountAlbionStSouth | InCountCommercialStLush | InCountHeadrow | InCountDortmundSq | InCountCommercialStBarratts | InCountTotal | mean_temp | rain | wind_spe |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000000 | 2127.000 |
| mean | 0.335690 | 0.302723 | 0.329462 | 0.218807 | 0.293302 | 0.322113 | 0.357576 | 0.353479 | 0.360891 | 0.477171 | 0.044691 | 0.236 |
| std | 0.123331 | 0.088781 | 0.101919 | 0.085464 | 0.093558 | 0.098360 | 0.116068 | 0.108812 | 0.095681 | 0.188751 | 0.091050 | 0.131 |
| min | 0.002641 | 0.005235 | 0.002635 | 0.000823 | 0.002592 | 0.004290 | 0.001589 | 0.007601 | 0.002429 | 0.000000 | 0.000000 | 0.000 |
| 25% | 0.248011 | 0.252841 | 0.266916 | 0.173745 | 0.231244 | 0.252592 | 0.287877 | 0.285100 | 0.308596 | 0.336957 | 0.000000 | 0.146 |
| 50% | 0.318974 | 0.293726 | 0.323012 | 0.206308 | 0.290893 | 0.311636 | 0.344680 | 0.343450 | 0.350494 | 0.478261 | 0.000000 | 0.213 |
| 75% | 0.393275 | 0.332539 | 0.380755 | 0.249239 | 0.343008 | 0.383079 | 0.420351 | 0.404681 | 0.400749 | 0.619565 | 0.050725 | 0.306 |
| max | 1.000000 | 1.000000 | 0.865350 | 0.920322 | 0.773478 | 1.000000 | 0.915154 | 0.864555 | 0.820060 | 1.000000 | 1.000000 | 1.000 |



### PCA Output

```
[95]: princdf
```

[95]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | InCountTotal |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.501186 | -0.072834 | -0.305815 | 0.007210 | -0.073542 | 0.033058 | 0.159510 | 0.042412 | 0.083294 | 0.066633 | 0.306589 |
| 1 | 0.473293 | -0.160209 | 0.374247 | -0.102821 | -0.212009 | -0.044546 | 0.141883 | 0.035961 | 0.022237 | -0.020510 | 0.333570 |
| 2 | 0.430700 | -0.253826 | 0.089324 | -0.202355 | -0.177654 | -0.071719 | 0.105374 | -0.061570 | -0.064900 | -0.116211 | 0.360520 |
| 3 | 0.370065 | -0.335813 | -0.193561 | -0.195929 | -0.150879 | -0.111659 | 0.013438 | -0.069540 | -0.050136 | 0.142080 | 0.370871 |
| 4 | 0.298613 | -0.405949 | -0.477639 | -0.290647 | -0.201103 | -0.096817 | -0.026635 | -0.065144 | 0.122234 | 0.018815 | 0.356540 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 2122 | -0.274768 | -0.411468 | -0.113133 | -0.089756 | -0.076417 | 0.087092 | 0.054679 | 0.095785 | 0.097241 | 0.115622 | 0.393165 |
| 2123 | -0.359710 | -0.346921 | -0.398152 | 0.084068 | 0.171826 | 0.075083 | -0.016654 | -0.013887 | 0.059496 | -0.055236 | 0.272368 |
| 2124 | -0.422223 | -0.263957 | 0.278268 | 0.151538 | -0.135616 | 0.064667 | 0.107704 | 0.104022 | -0.013881 | -0.091874 | 0.345800 |
| 2125 | -0.469288 | -0.174786 | -0.007275 | 0.167731 | -0.037596 | 0.040813 | 0.063860 | -0.006845 | -0.094975 | 0.083027 | 0.433450 |
| 2126 | -0.497112 | -0.079751 | -0.292263 | 0.250000 | 0.077615 | 0.056600 | 0.019170 | -0.150700 | -0.001552 | -0.021012 | 0.379947 |

2127 rows × 11 columns

### The contribution of each Feature for the principal components

```
[96]: compdf
```

[96]:

| | Month | Weekday | Day | Week_no | mean_temp | rain | wind_speed | abnormal_rain | high_temp | low_temp | high_wind | EasterSundayHoliday | University_holidays | School_holidays | UKBankHoliday | Day sin | Month sin | Month cos |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.000143 | -0.000201 | 0.004861 | 0.007279 | -0.014059 | -0.007177 | -0.024392 | 0.000234 | 0.000204 | -0.000099 | 0.000178 | 0.000168 | 0.000004 | -0.000123 | 0.000763 | 0.006666 | -0.160914 | -0.985591 |
| 1 | 0.000305 | 0.000149 | 0.002103 | 0.001417 | -0.005632 | 0.001153 | 0.013375 | 0.000330 | -0.000167 | -0.000221 | -0.000030 | 0.000469 | 0.000025 | -0.000326 | 0.001441 | -0.013345 | 0.986276 | -0.161999 |
| 2 | 0.000693 | -0.000724 | 0.004562 | 0.001049 | 0.004766 | -0.000284 | -0.000102 | -0.000390 | 0.000057 | 0.000046 | -0.000203 | -0.000214 | 0.000019 | 0.000005 | 0.000042 | -0.999829 | -0.014242 | -0.004330 |

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- Mall_footfall_predicti...
- preprocess.py
- Project Plan.xlsx
- README.md
- visualization.py
- work_flow.pptx

[96]:
```
compdf
```

[96]:

| | Month | Weekday | Day | Week_no | mean_temp | rain | wind_speed | abnormal_rain | high_temp | low_temp | high_wind | EasterSundayHoliday | University_holidays | School_holidays | UKBankHoliday | Day sin | Month sin | Month cos |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.000143 | -0.000201 | 0.004861 | 0.007279 | -0.014059 | -0.007177 | -0.024392 | 0.000234 | 0.000204 | -0.000099 | 0.000178 | 0.000168 | 0.000004 | -0.000123 | 0.000763 | 0.006666 | -0.160914 | -0.985591 |
| 1 | 0.000305 | 0.000149 | 0.002103 | 0.001417 | -0.006632 | 0.001153 | 0.013375 | 0.000330 | -0.000167 | -0.000221 | -0.000030 | 0.000469 | 0.000025 | -0.000326 | 0.001441 | -0.013345 | 0.986276 | -0.161999 |
| 2 | 0.000693 | -0.000724 | 0.004562 | 0.001049 | 0.004766 | -0.000284 | -0.000102 | -0.000390 | 0.000057 | 0.000046 | -0.000203 | -0.000214 | 0.000019 | 0.000005 | 0.000042 | -0.999829 | -0.014242 | -0.004330 |
| 3 | -0.003089 | -0.000715 | -0.002258 | -0.001626 | 0.998510 | -0.008011 | -0.022389 | 0.000650 | -0.007905 | 0.008412 | 0.001319 | -0.000045 | 0.001377 | 0.001414 | 0.000871 | 0.004862 | 0.003854 | -0.014502 |
| 4 | 0.020332 | -0.000998 | -0.004046 | 0.014581 | 0.025544 | 0.193777 | 0.969184 | -0.013037 | 0.001565 | 0.003163 | -0.011864 | -0.000972 | 0.000206 | 0.000899 | -0.002978 | 0.000043 | -0.013477 | -0.019622 |
| 5 | 0.081877 | -0.013730 | 0.006713 | 0.112470 | 0.010910 | -0.112346 | -0.088966 | 0.008718 | 0.000297 | 0.000940 | 0.000422 | 0.000249 | -0.000267 | 0.001099 | -0.000662 | 0.002111 | 0.026341 | 0.039503 |
| 6 | -0.009098 | -0.148497 | -0.047704 | -0.041389 | 0.034172 | 0.165891 | -0.097310 | -0.012942 | -0.000866 | -0.000167 | 0.001315 | -0.000972 | -0.000074 | 0.000867 | -0.011650 | -0.005536 | 0.015080 | -0.009263 |
| 7 | -0.007176 | -0.134106 | -0.031610 | -0.000490 | -0.018104 | 0.245692 | -0.106679 | -0.019633 | -0.000127 | -0.000618 | 0.001201 | -0.006844 | 0.000035 | -0.000662 | -0.003525 | -0.003524 | -0.001363 | 0.001930 |
| 8 | 0.002127 | -0.090142 | -0.013567 | 0.006591 | 0.003781 | 0.119543 | -0.038346 | -0.008967 | 0.000371 | 0.000170 | 0.000423 | -0.005415 | 0.000096 | 0.000367 | -0.002419 | 0.004137 | 0.002531 | -0.000226 |
| 9 | -0.004048 | -0.066067 | -0.009104 | 0.005205 | -0.015090 | -0.067714 | -0.013227 | 0.005955 | 0.000167 | 0.000358 | 0.000256 | -0.002074 | -0.000199 | -0.001343 | 0.005811 | 0.000916 | -0.000247 | 0.001273 |
| 10 | 0.008006 | -0.053799 | -0.007368 | 0.014352 | -0.001175 | 0.391317 | -0.071588 | -0.028317 | 0.000669 | 0.001022 | 0.000379 | -0.002824 | 0.000134 | 0.000366 | 0.007288 | -0.000934 | 0.001979 | 0.000653 |

[98]:
```
print(var_cum_variance[0:8])
# Plotting the scree plot with a mark on 85 percentile of variance being captured
fig = plt.figure(figsize=[10,8])
plt.vlines(x=5, ymax=1, ymin=0, colors="r", linestyles="--")
plt.hlines(y=0.85, xmax=20, xmin=0, colors="g", linestyles="--")
plt.plot(var_cum_variance)
plt.ylabel("Cumulative Variance")
plt.xlabel("number of components")
plt.title("PCA cumulative variance of different components")
plt.show()
```

```
[0.27410066 0.54519011 0.71412958 0.79147247 0.83003109 0.85913497
 0.8816237  0.90256698]
```


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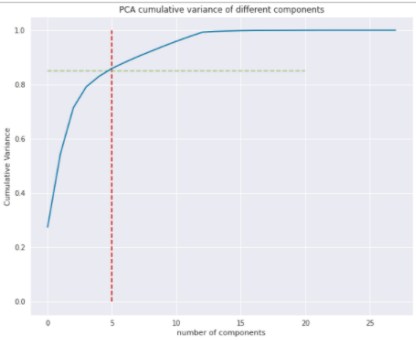


### Observation from PCA cumulative variance

Just 6 components are able to explain 85% of the variance in the data

[ ]:
```
data_for_visualization,_,_,_,_,_,_,_,_,_,_,_ = do_all_pre_processing(for_visualization_only = True)
```

### Missing Data Observation

1. Only Missing data in column InCountCommercialStBarrats for two days

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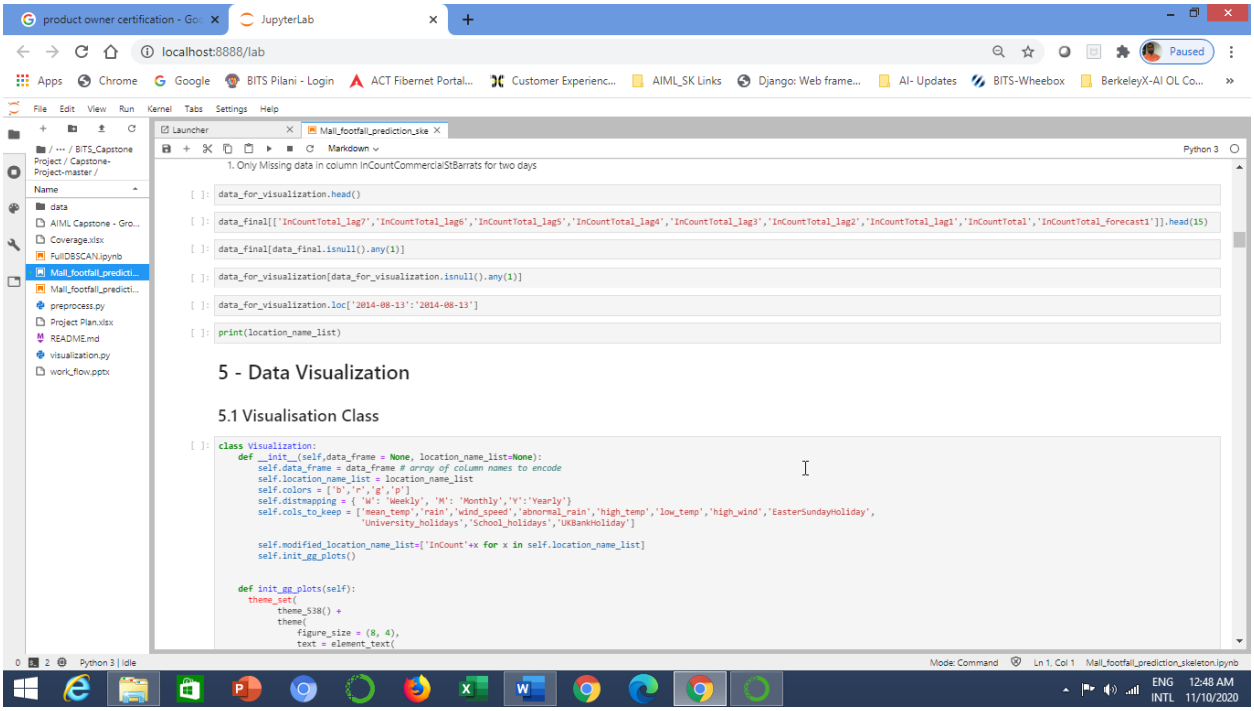
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File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
1. Only Missing data in column InCountCommercialStBarrats for two days
data_for_visualization.head()
data_final[['InCountTotal_lag7','InCountTotal_lag6','InCountTotal_lag5','InCountTotal_lag4','InCountTotal_lag3','InCountTotal_lag2','InCountTotal_lag1','InCountTotal','InCountTotal_forecast1']].head(15)
data_final[data_final.isnull().any(1)]
data_for_visualization[data_for_visualization.isnull().any(1)]
data_for_visualization.loc['2014-08-13':'2014-08-13']
print(location_name_list)
5 - Data Visualization
5.1 Visualisation Class
class Visualization:
def __init__(self,data_frame = None, location_name_list=None):
self.data_frame = data_frame # array of column names to encode
self.location_name_list = location_name_list
self.colors = ['b','r','g','p']
self.distmapping = { 'W': 'Weekly', 'M': 'Monthly','Y':'Yearly'}
self.cols_to_keep = ['mean_temp','rain','wind_speed','abnormal_rain','high_temp','low_temp','high_wind','EasterSundayHoliday',
'University_holidays','School_holidays','UKBankHoliday']
self.modified_location_name_list=['InCount'+x for x in self.location_name_list]
self.init_gg_plots()
def init_gg_plots(self):
theme_set(
theme_538() +
theme(
figure_size = (8, 4),
text = element_text(
Mode: Command
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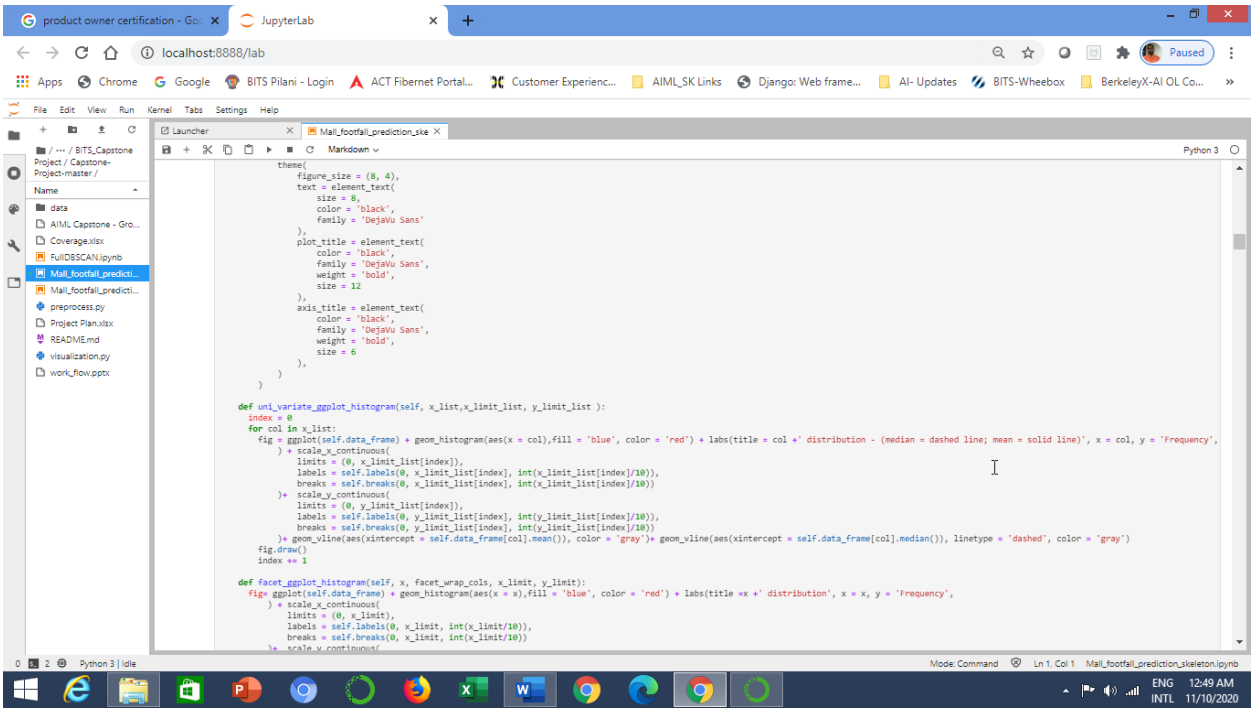
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Markdown
Python 3
theme(
figure_size = (8, 4),
text = element_text(
size = 8,
color = 'black',
family = 'DejaVu Sans'
),
plot_title = element_text(
color = 'black',
family = 'DejaVu Sans',
weight = 'bold',
size = 12
),
axis_title = element_text(
color = 'black',
family = 'DejaVu Sans',
weight = 'bold',
size = 6
),
)
)
def uni_variate_ggplot_histogram(self, x_list,x_limit_list, y_limit_list ):
index = 0
for col in x_list:
fig = ggplot(self.data_frame) + geom_histogram(aes(x = col),fill = 'blue', color = 'red') + labs(title = col +' distribution - (median = dashed line; mean = solid line)', x = col, y = 'Frequency',
) + scale_x_continuous(
limits = (0, x_limit_list[index]),
labels = self.labels(0, x_limit_list[index], int(x_limit_list[index]/10)),
breaks = self.breaks(0, x_limit_list[index], int(x_limit_list[index]/10))
)+ scale_y_continuous(
limits = (0, y_limit_list[index]),
labels = self.labels(0, y_limit_list[index], int(y_limit_list[index]/10)),
breaks = self.breaks(0, y_limit_list[index], int(y_limit_list[index]/10))
)+ geom_vline(aes(xintercept = self.data_frame[col].mean()), color = 'gray')+ geom_vline(aes(xintercept = self.data_frame[col].median()), linetype = 'dashed', color = 'gray')
fig.draw()
index += 1
def facet_ggplot_histogram(self, x, facet_wrap_cols, x_limit, y_limit):
fig= ggplot(self.data_frame) + geom_histogram(aes(x = x),fill = 'blue', color = 'red') + labs(title =x +' distribution', x = x, y = 'Frequency',
) + scale_x_continuous(
limits = (0, x_limit),
labels = self.labels(0, x_limit, int(x_limit/10)),
breaks = self.breaks(0, x_limit, int(x_limit/10))
)+ scale_y_continuous(
Mode: Command
Ln 1, Col 1
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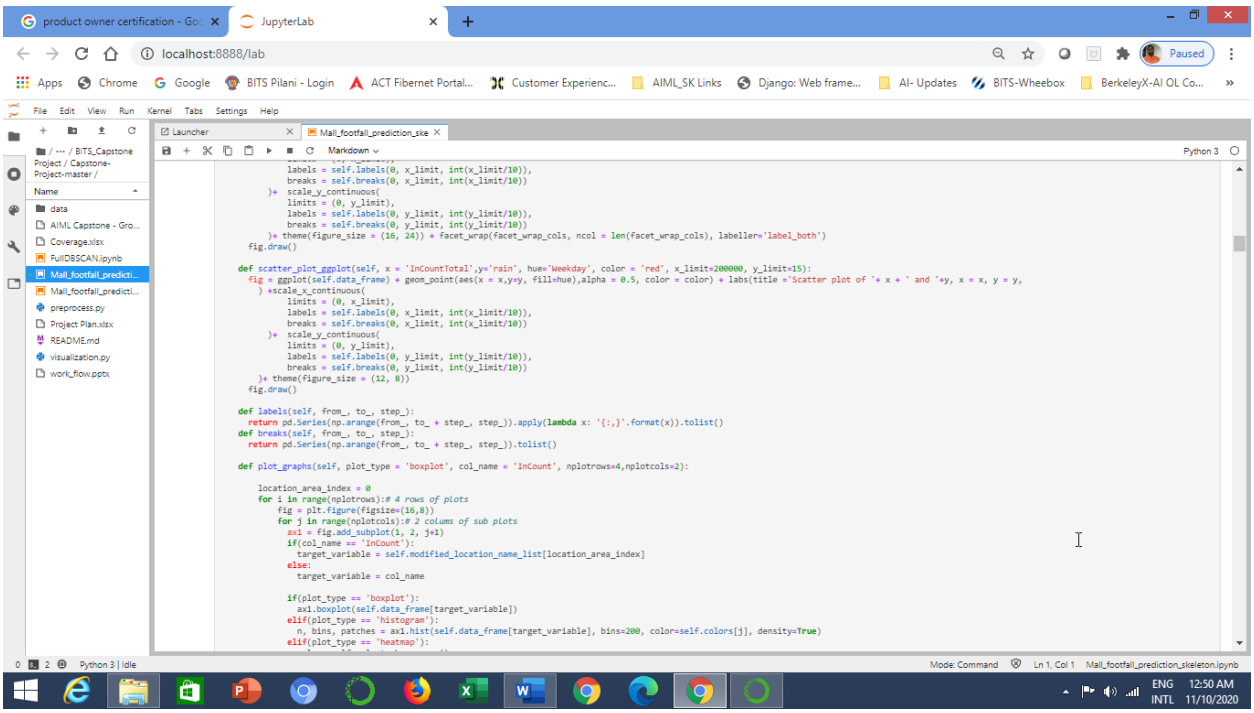


```
                labels = self.labels(0, x_limit, int(x_limit/10)),
                breaks = self.breaks(0, x_limit, int(x_limit/10))
            )+ scale_y_continuous(
                limits = (0, y_limit),
                labels = self.labels(0, y_limit, int(y_limit/10)),
                breaks = self.breaks(0, y_limit, int(y_limit/10))
            )+ theme(figure_size = (16, 24)) + facet_wrap(facet_wrap_cols, ncol = len(facet_wrap_cols), labeller='label_both')
        fig.draw()

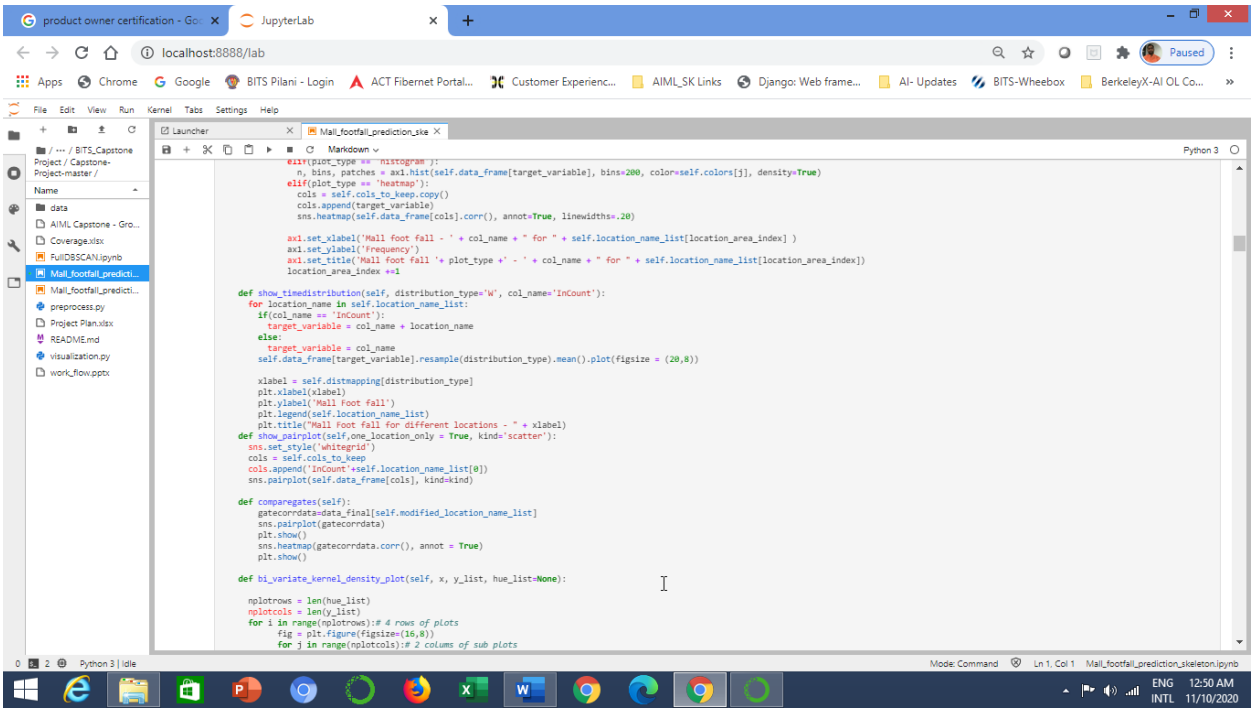
    def scatter_plot_ggplot(self, x = 'InCountTotal',y='rain', hue='Weekday', color = 'red', x_limit=200000, y_limit=15):
        fig = ggplot(self.data_frame) + geom_point(aes(x = x,y=y, fill=hue),alpha = 0.5, color = color) + labs(title ='Scatter plot of '+ x + ' and '+y, x = x, y = y,
         ) +scale_x_continuous(
                limits = (0, x_limit),
                labels = self.labels(0, x_limit, int(x_limit/10)),
                breaks = self.breaks(0, x_limit, int(x_limit/10))
            )+ scale_y_continuous(
                limits = (0, y_limit),
                labels = self.labels(0, y_limit, int(y_limit/10)),
                breaks = self.breaks(0, y_limit, int(y_limit/10))
            )+ theme(figure_size = (12, 8))
        fig.draw()

    def labels(self, from_, to_, step_):
        return pd.Series(np.arange(from_, to_ + step_, step_)).apply(lambda x: '{:,}'.format(x)).tolist()
    def breaks(self, from_, to_, step_):
        return pd.Series(np.arange(from_, to_ + step_, step_)).tolist()

    def plot_graphs(self, plot_type = 'boxplot', col_name = 'InCount', nplotrows=4,nplotcols=2):

        location_area_index = 0
        for i in range(nplotrows):# 4 rows of plots
            fig = plt.figure(figsize=(16,8))
            for j in range(nplotcols):# 2 colums of sub plots
                ax1 = fig.add_subplot(1, 2, j+1)
                if(col_name == 'InCount'):
                    target_variable = self.modified_location_name_list[location_area_index]
                else:
                    target_variable = col_name

                if(plot_type == 'boxplot'):
                    ax1.boxplot(self.data_frame[target_variable])
                elif(plot_type == 'histogram'):
                    n, bins, patches = ax1.hist(self.data_frame[target_variable], bins=200, color=self.colors[j], density=True)
                elif(plot_type == 'heatmap'):
```



```
                elif(plot_type == 'histogram'):
                    n, bins, patches = ax1.hist(self.data_frame[target_variable], bins=200, color=self.colors[j], density=True)
                elif(plot_type == 'heatmap'):
                    cols = self.cols_to_keep.copy()
                    cols.append(target_variable)
                    sns.heatmap(self.data_frame[cols].corr(), annot=True, linewidths=.20)

                ax1.set_xlabel('Mall foot fall - ' + col_name + " for " + self.location_name_list[location_area_index] )
                ax1.set_ylabel('Frequency')
                ax1.set_title('Mall foot fall '+ plot_type +' - ' + col_name + " for " + self.location_name_list[location_area_index])
                location_area_index +=1

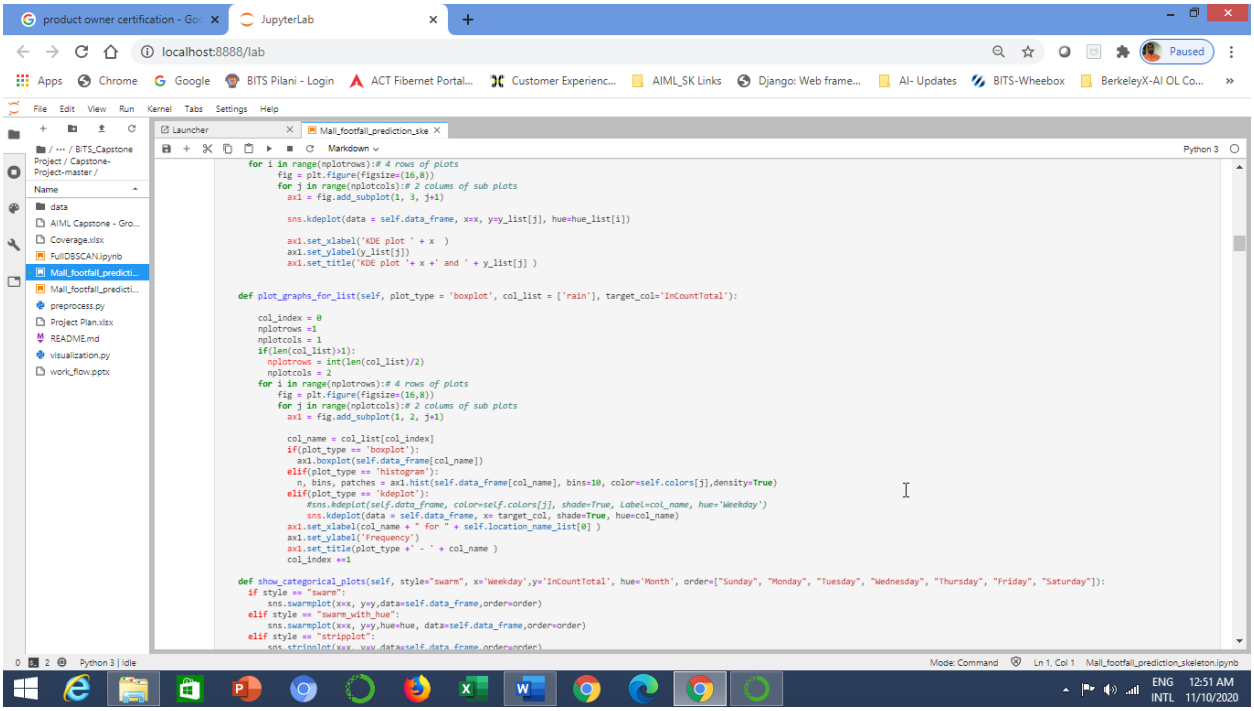
    def show_timedistribution(self, distribution_type='W', col_name='InCount'):
        for location_name in self.location_name_list:
            if(col_name == 'InCount'):
                target_variable = col_name + location_name
            else:
                target_variable = col_name
            self.data_frame[target_variable].resample(distribution_type).mean().plot(figsize = (20,8))

            xlabel = self.distmapping[distribution_type]
            plt.xlabel(xlabel)
            plt.ylabel('Mall Foot fall')
            plt.legend(self.location_name_list)
            plt.title("Mall Foot fall for different locations - " + xlabel)
    def show_pairplot(self,one_location_only = True, kind='scatter'):
        sns.set_style('whitegrid')
        cols = self.cols_to_keep
        cols.append('InCount'+self.location_name_list[0])
        sns.pairplot(self.data_frame[cols], kind=kind)

    def comparegates(self):
        gatecorrdata=data_final[self.modified_location_name_list]
        sns.pairplot(gatecorrdata)
        plt.show()
        sns.heatmap(gatecorrdata.corr(), annot = True)
        plt.show()

    def bi_variate_kernel_density_plot(self, x, y_list, hue_list=None):

        nplotrows = len(hue_list)
        nplotcols = len(y_list)
        for i in range(nplotrows):# 4 rows of plots
            fig = plt.figure(figsize=(16,8))
            for j in range(nplotcols):# 2 colums of sub plots
```



```
        for i in range(nplotrows):# 4 rows of plots
             fig = plt.figure(figsize=(16,8))
             for j in range(nplotcols):# 2 columns of sub plots
               ax1 = fig.add_subplot(1, 3, j+1)

               sns.kdeplot(data = self.data_frame, x=x, y=y_list[j], hue=hue_list[i])

               ax1.set_xlabel('KDE plot ' + x  )
               ax1.set_ylabel(y_list[j])
               ax1.set_title('KDE plot '+ x +' and ' + y_list[j] )


    def plot_graphs_for_list(self, plot_type = 'boxplot', col_list = ['rain'], target_col='InCountTotal'):

        col_index = 0
        nplotrows =1
        nplotcols = 1
        if(len(col_list)>1):
          nplotrows = int(len(col_list)/2)
          nplotcols = 2
        for i in range(nplotrows):# 4 rows of plots
             fig = plt.figure(figsize=(16,8))
             for j in range(nplotcols):# 2 columns of sub plots
               ax1 = fig.add_subplot(1, 2, j+1)

               col_name = col_list[col_index]
               if(plot_type == 'boxplot'):
                 ax1.boxplot(self.data_frame[col_name])
               elif(plot_type == 'histogram'):
                 n, bins, patches = ax1.hist(self.data_frame[col_name], bins=10, color=self.colors[j],density=True)
               elif(plot_type == 'kdeplot'):
                   #sns.kdeplot(self.data_frame, color=self.colors[j], shade=True, label=col_name, hue='Weekday')
                   sns.kdeplot(data = self.data_frame, x= target_col, shade=True, hue=col_name)
               ax1.set_xlabel(col_name + " for " + self.location_name_list[0] )
               ax1.set_ylabel('Frequency')
               ax1.set_title(plot_type +' - ' + col_name )
               col_index +=1

    def show_categorical_plots(self, style="swarm", x='Weekday',y='InCountTotal', hue='Month', order=["Sunday", "Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday"]):
      if style == "swarm":
          sns.swarmplot(x=x, y=y,data=self.data_frame,order=order)
      elif style == "swarm_with_hue":
          sns.swarmplot(x=x, y=y,hue=hue, data=self.data_frame,order=order)
      elif style == "stripplot":
          sns.stripplot(x=x, y=y,data=self.data_frame,order=order)
      elif style == "stripplot_with_hue":
          sns.stripplot(x=x, y=y,hue=hue, data=self.data_frame,order=order)
      elif style == "box":
          sns.boxplot(x=x, y=y, data=self.data_frame, whis=np.inf,order=order)
      elif style == "box_with_hue":
          sns.boxplot(x=x, y=y, hue=hue, data=self.data_frame, whis=np.inf,order=order)
      elif style == "violen":
          sns.violinplot(x=x, y=y, data=self.data_frame,order=order)
      elif style == "boxen":
          sns.boxenplot(x=x, y=y, data=self.data_frame,order=order)
      else:
          print("no style is selected")

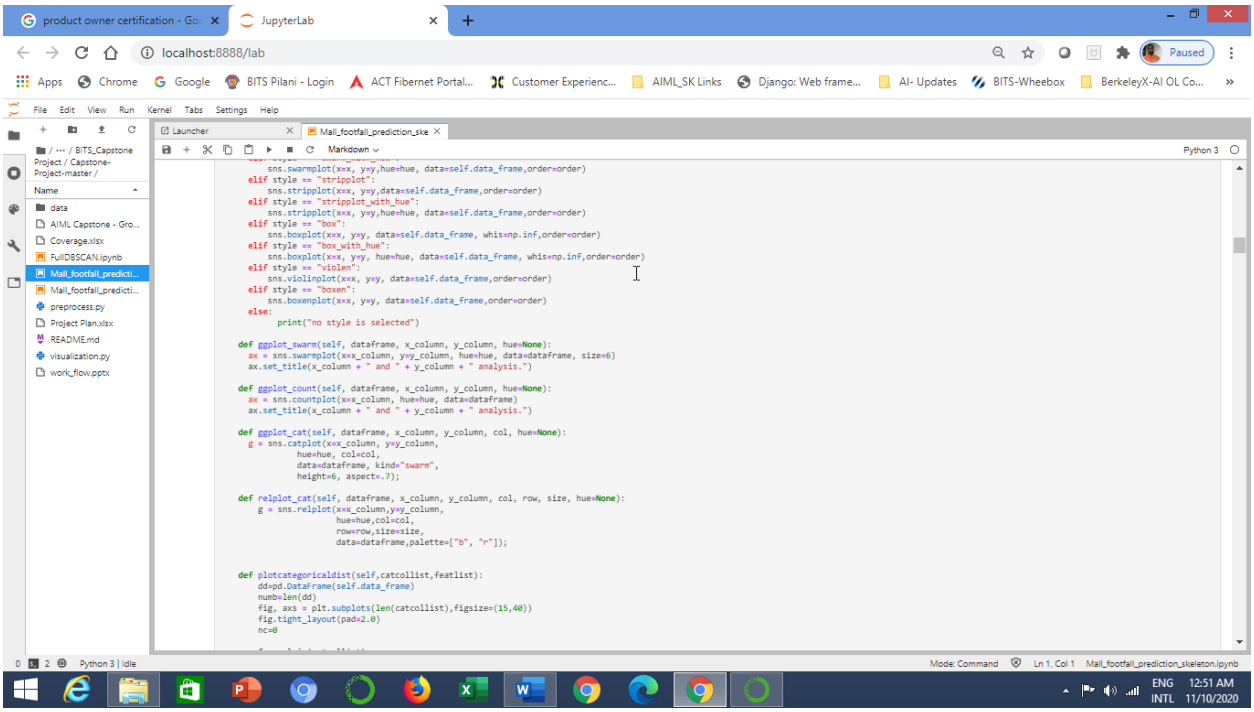
    def ggplot_swarm(self, dataframe, x_column, y_column, hue=None):
      ax = sns.swarmplot(x=x_column, y=y_column, hue=hue, data=dataframe, size=6)
      ax.set_title(x_column + " and " + y_column + " analysis.")

    def ggplot_count(self, dataframe, x_column, y_column, hue=None):
      ax = sns.countplot(x=x_column, hue=hue, data=dataframe)
      ax.set_title(x_column + " and " + y_column + " analysis.")

    def ggplot_cat(self, dataframe, x_column, y_column, col, hue=None):
      g = sns.catplot(x=x_column, y=y_column,
                  hue=hue, col=col,
                  data=dataframe, kind="swarm",
                  height=6, aspect=.7);

    def relplot_cat(self, dataframe, x_column, y_column, col, row, size, hue=None):
        g = sns.relplot(x=x_column,y=y_column,
                        hue=hue,col=col,
                        row=row,size=size,
                        data=dataframe,palette=["b", "r"]);


    def plotcategoricaldist(self,catcollist,featlist):
        dd=pd.DataFrame(self.data_frame)
        numb=len(dd)
        fig, axs = plt.subplots(len(catcollist),figsize=(15,40))
        fig.tight_layout(pad=2.0)
        nc=0
```




```
      elif style == "stripplot":
          sns.stripplot(x=x, y=y,data=self.data_frame,order=order)
      elif style == "stripplot_with_hue":
          sns.stripplot(x=x, y=y,hue=hue, data=self.data_frame,order=order)
      elif style == "box":
          sns.boxplot(x=x, y=y, data=self.data_frame, whis=np.inf,order=order)
      elif style == "box_with_hue":
          sns.boxplot(x=x, y=y, hue=hue, data=self.data_frame, whis=np.inf,order=order)
      elif style == "violen":
          sns.violinplot(x=x, y=y, data=self.data_frame,order=order)
      elif style == "boxen":
          sns.boxenplot(x=x, y=y, data=self.data_frame,order=order)
      else:
          print("no style is selected")

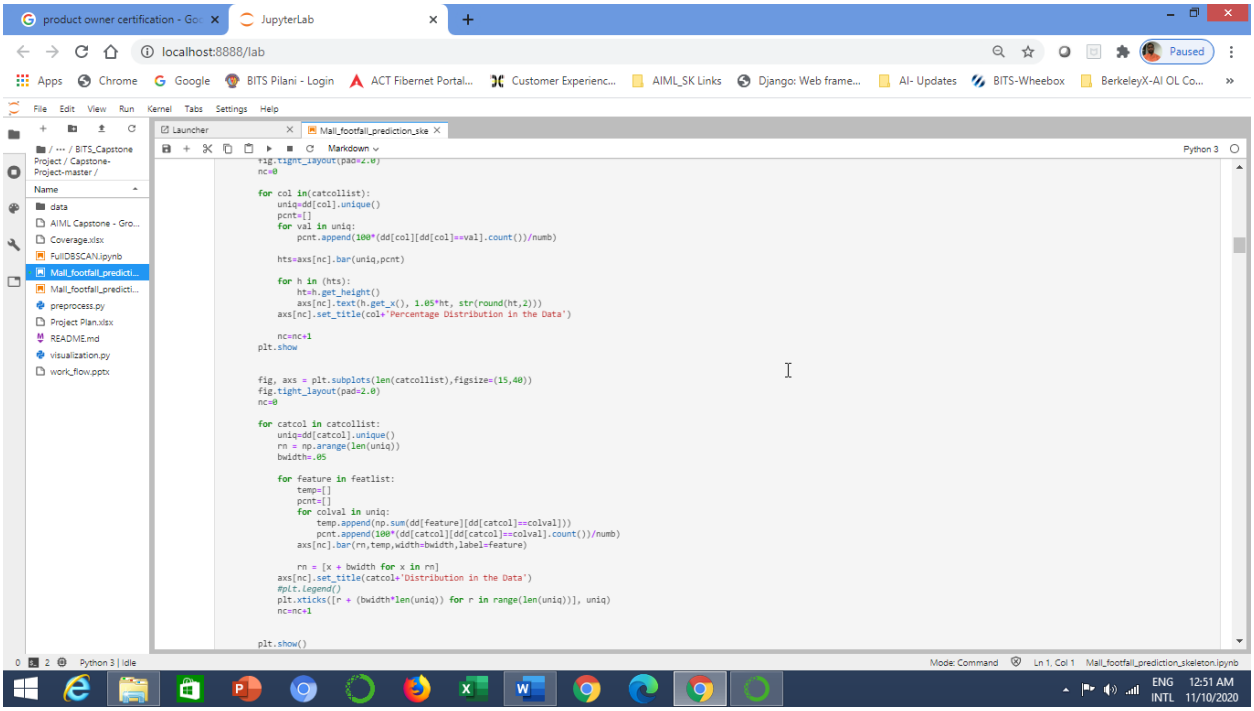
    def ggplot_swarm(self, dataframe, x_column, y_column, hue=None):
      ax = sns.swarmplot(x=x_column, y=y_column, hue=hue, data=dataframe, size=6)
      ax.set_title(x_column + " and " + y_column + " analysis.")

    def ggplot_count(self, dataframe, x_column, y_column, hue=None):
      ax = sns.countplot(x=x_column, hue=hue, data=dataframe)
      ax.set_title(x_column + " and " + y_column + " analysis.")

    def ggplot_cat(self, dataframe, x_column, y_column, col, hue=None):
      g = sns.catplot(x=x_column, y=y_column,
                  hue=hue, col=col,
                  data=dataframe, kind="swarm",
                  height=6, aspect=.7);

    def relplot_cat(self, dataframe, x_column, y_column, col, row, size, hue=None):
        g = sns.relplot(x=x_column,y=y_column,
                        hue=hue,col=col,
                        row=row,size=size,
                        data=dataframe,palette=["b", "r"]);


    def plotcategoricaldist(self,catcollist,featlist):
        dd=pd.DataFrame(self.data_frame)
        numb=len(dd)
        fig, axs = plt.subplots(len(catcollist),figsize=(15,40))
        fig.tight_layout(pad=2.0)
        nc=0
```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preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
fig.tight_layout(pad=2.0)
nc=0
for col in(catcollist):
uniq=dd[col].unique()
pcnt=[]
for val in uniq:
pcnt.append(100*(dd[col][dd[col]==val].count())/numb)
hts=axs[nc].bar(uniq,pcnt)
for h in (hts):
ht=h.get_height()
axs[nc].text(h.get_x(), 1.05*ht, str(round(ht,2)))
axs[nc].set_title(col+'Percentage Distribution in the Data')
nc=nc+1
plt.show
fig, axs = plt.subplots(len(catcollist),figsize=(15,40))
fig.tight_layout(pad=2.0)
nc=0
for catcol in catcollist:
uniq=dd[catcol].unique()
rn = np.arange(len(uniq))
bwidth=.05
for feature in featlist:
temp=[]
pcnt=[]
for colval in uniq:
temp.append(np.sum(dd[feature][dd[catcol]==colval]))
pcnt.append(100*(dd[catcol][dd[catcol]==colval].count())/numb)
axs[nc].bar(rn,temp,width=bwidth,label=feature)
rn = [x + bwidth for x in rn]
axs[nc].set_title(catcol+'Distribution in the Data')
#plt.legend()
plt.xticks([r + (bwidth*len(uniq)) for r in range(len(uniq))], uniq)
nc=nc+1
plt.show()
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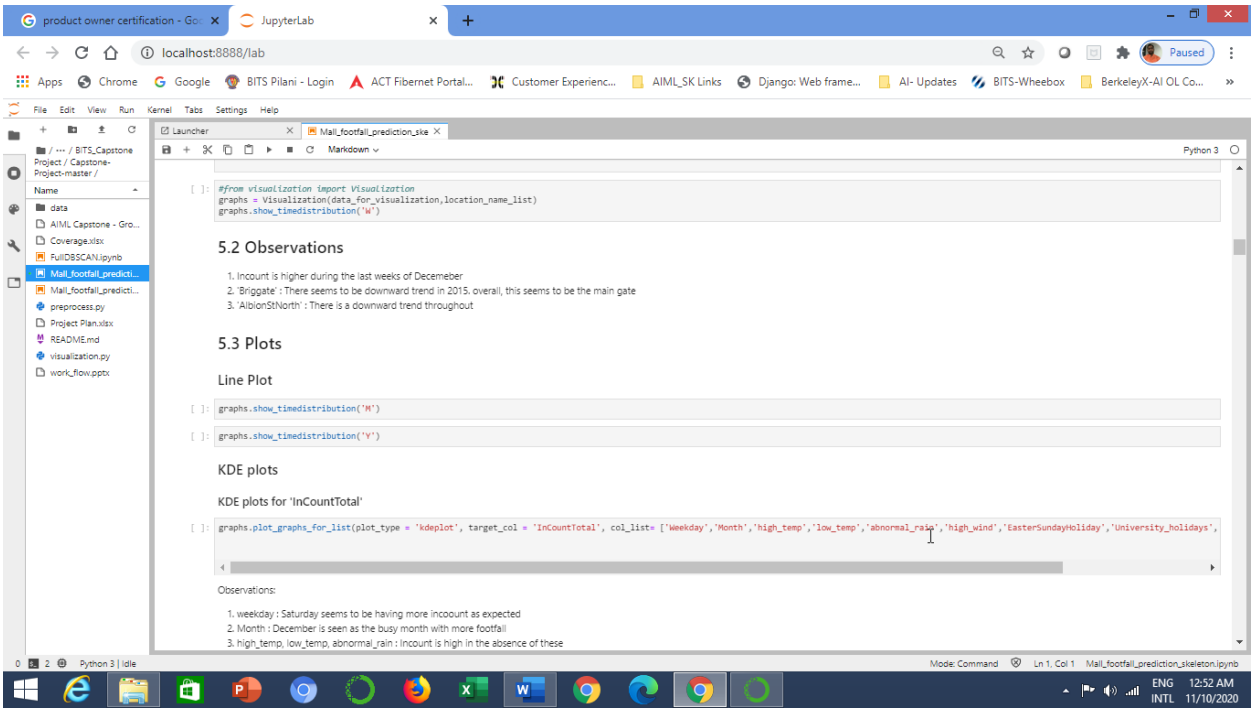
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Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
#from visualization import Visualization
graphs = Visualization(data_for_visualization,location_name_list)
graphs.show_timedistribution('W')
5.2 Observations
1. Incount is higher during the last weeks of Decemeber
2. 'Briggate' : There seems to be downward trend in 2015. overall, this seems to be the main gate
3. 'AlbionStNorth' : There is a downward trend throughout
5.3 Plots
Line Plot
graphs.show_timedistribution('M')
graphs.show_timedistribution('Y')
KDE plots
KDE plots for 'InCountTotal'
graphs.plot_graphs_for_list(plot_type = 'kdeplot', target_col = 'InCountTotal', col_list= ['Weekday','Month','high_temp','low_temp','abnormal_rain','high_wind','EasterSundayHoliday','University_holidays',
Observations:
1. weekday : Saturday seems to be having more incoount as expected
2. Month : December is seen as the busy month with more footfall
3. high_temp, low_temp, abnormal_rain : Incount is high in the absence of these
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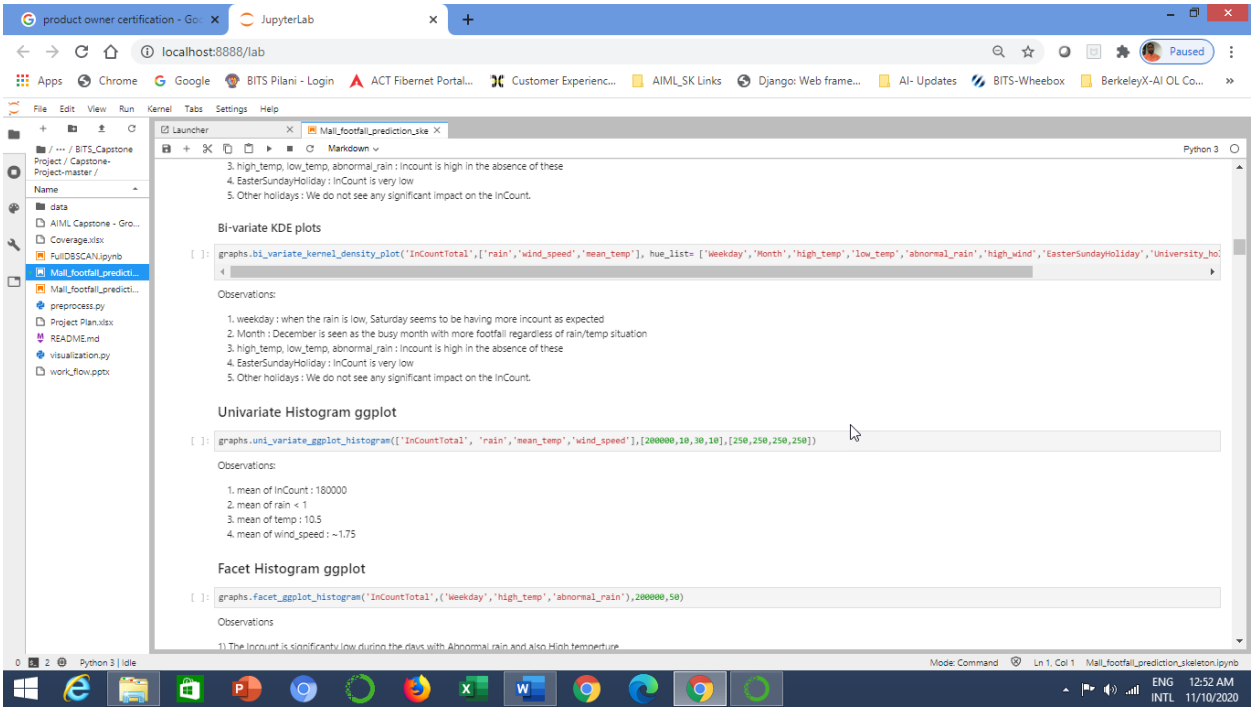
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3. high_temp, low_temp, abnormal_rain : Incount is high in the absence of these
4. EasterSundayHoliday : InCount is very low
5. Other holidays : We do not see any significant impact on the InCount.
Bi-variate KDE plots
graphs.bi_variate_kernel_density_plot('InCountTotal',['rain','wind_speed','mean_temp'], hue_list= ['Weekday','Month','high_temp','low_temp','abnormal_rain','high_wind','EasterSundayHoliday','University_ho
Observations:
1. weekday : when the rain is low, Saturday seems to be having more incount as expected
2. Month : December is seen as the busy month with more footfall regardless of rain/temp situation
3. high_temp, low_temp, abnormal_rain : Incount is high in the absence of these
4. EasterSundayHoliday : InCount is very low
5. Other holidays : We do not see any significant impact on the InCount.
Univariate Histogram ggplot
graphs.uni_variate_ggplot_histogram(['InCountTotal', 'rain','mean_temp','wind_speed'],[200000,10,30,10],[250,250,250,250])
Observations:
1. mean of InCount : 180000
2. mean of rain < 1
3. mean of temp : 10.5
4. mean of wind_speed : ~1.75
Facet Histogram ggplot
graphs.facet_ggplot_histogram('InCountTotal',('Weekday','high_temp','abnormal_rain'),200000,50)
Observations
1) The Incount is significanty low during the days with Abnormal rain and also High temperture
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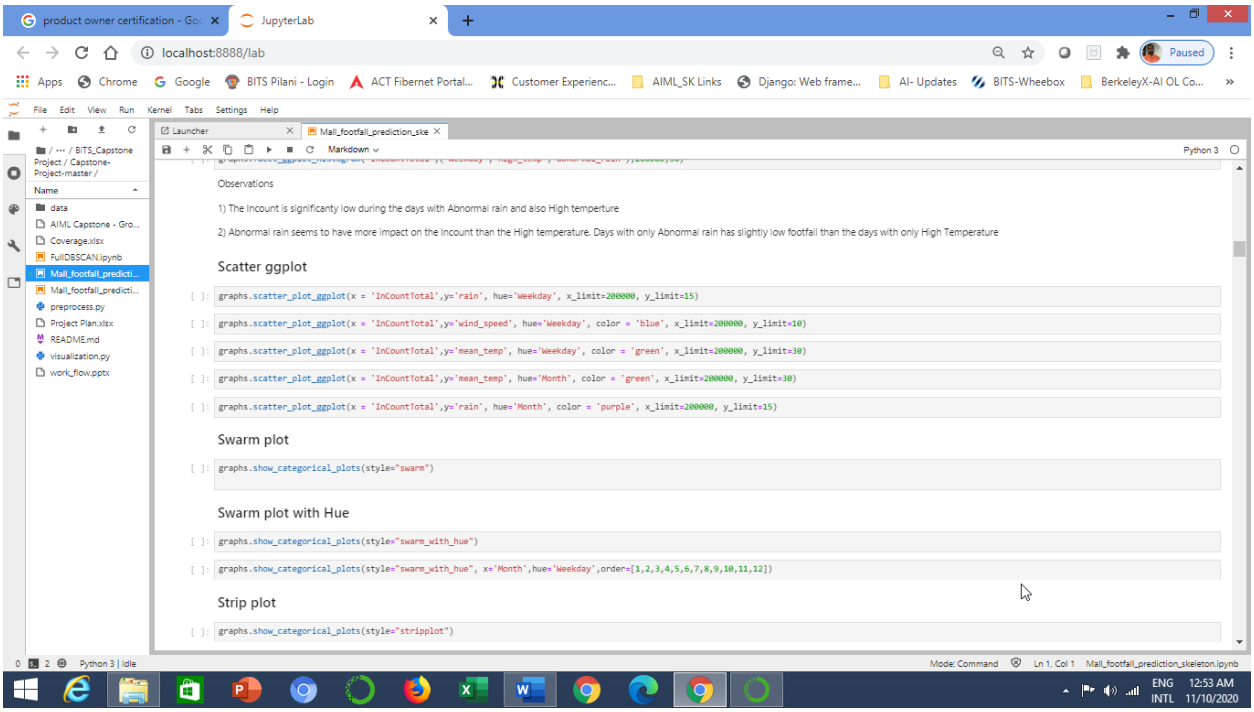
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Observations
1) The Incount is significanty low during the days with Abnormal rain and also High temperture
2) Abnormal rain seems to have more impact on the Incount than the High temperature. Days with only Abnormal rain has slightly low footfall than the days with only High Temperature
Scatter ggplot
graphs.scatter_plot_ggplot(x = 'InCountTotal',y='rain', hue='Weekday', x_limit=200000, y_limit=15)
graphs.scatter_plot_ggplot(x = 'InCountTotal',y='wind_speed', hue='Weekday', color = 'blue', x_limit=200000, y_limit=10)
graphs.scatter_plot_ggplot(x = 'InCountTotal',y='mean_temp', hue='Weekday', color = 'green', x_limit=200000, y_limit=30)
graphs.scatter_plot_ggplot(x = 'InCountTotal',y='mean_temp', hue='Month', color = 'green', x_limit=200000, y_limit=30)
graphs.scatter_plot_ggplot(x = 'InCountTotal',y='rain', hue='Month', color = 'purple', x_limit=200000, y_limit=15)
Swarm plot
graphs.show_categorical_plots(style="swarm")
Swarm plot with Hue
graphs.show_categorical_plots(style="swarm_with_hue")
graphs.show_categorical_plots(style="swarm_with_hue", x='Month',hue='Weekday',order=[1,2,3,4,5,6,7,8,9,10,11,12])
Strip plot
graphs.show_categorical_plots(style="stripplot")
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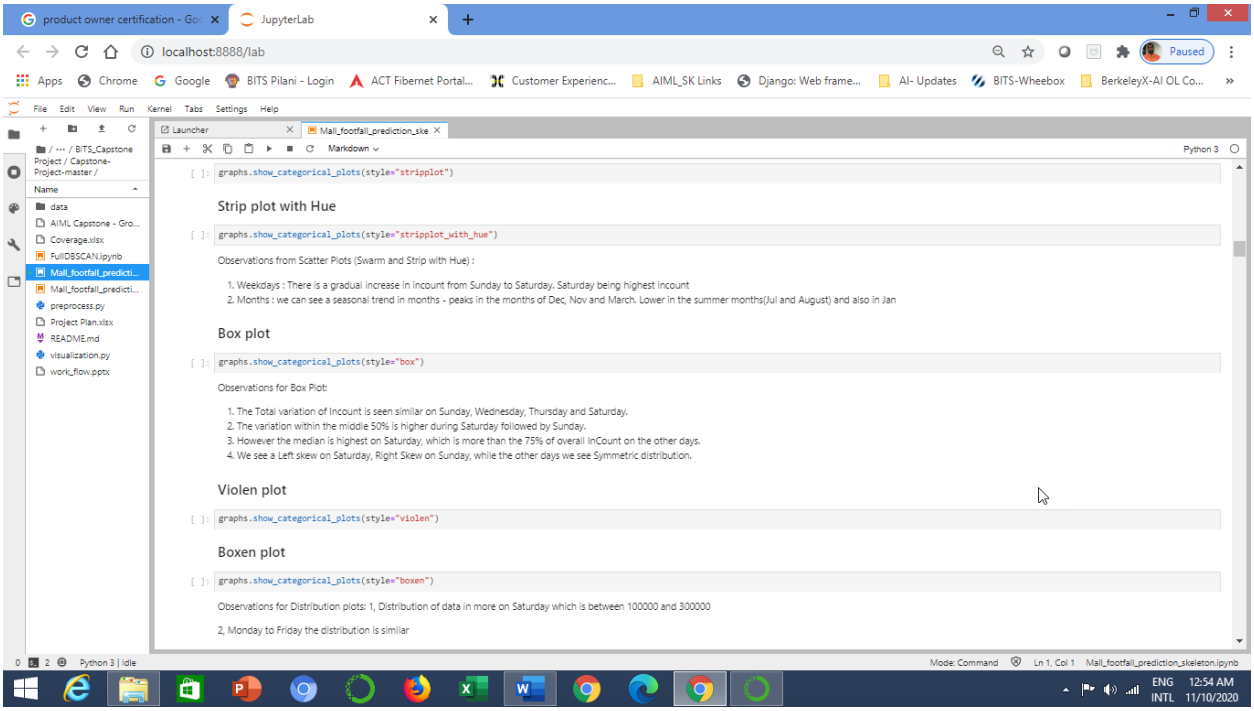
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graphs.show_categorical_plots(style="stripplot")
Strip plot with Hue
graphs.show_categorical_plots(style="stripplot_with_hue")
Observations from Scatter Plots (Swarm and Strip with Hue) :
1. Weekdays : There is a gradual increase in incount from Sunday to Saturday. Saturday being highest incount
2. Months : we can see a seasonal trend in months - peaks in the months of Dec, Nov and March. Lower in the summer months(Jul and August) and also in Jan
Box plot
graphs.show_categorical_plots(style="box")
Observations for Box Plot:
1. The Total variation of Incount is seen similar on Sunday, Wednesday, Thursday and Saturday.
2. The variation within the middle 50% is higher during Saturday followed by Sunday.
3. However the median is highest on Saturday, which is more than the 75% of overall InCount on the other days.
4. We see a Left skew on Saturday, Right Skew on Sunday, while the other days we see Symmetric distribution.
Violen plot
graphs.show_categorical_plots(style="violen")
Boxen plot
graphs.show_categorical_plots(style="boxen")
Observations for Distribution plots: 1, Distribution of data in more on Saturday which is between 100000 and 300000
2, Monday to Friday the distribution is similar
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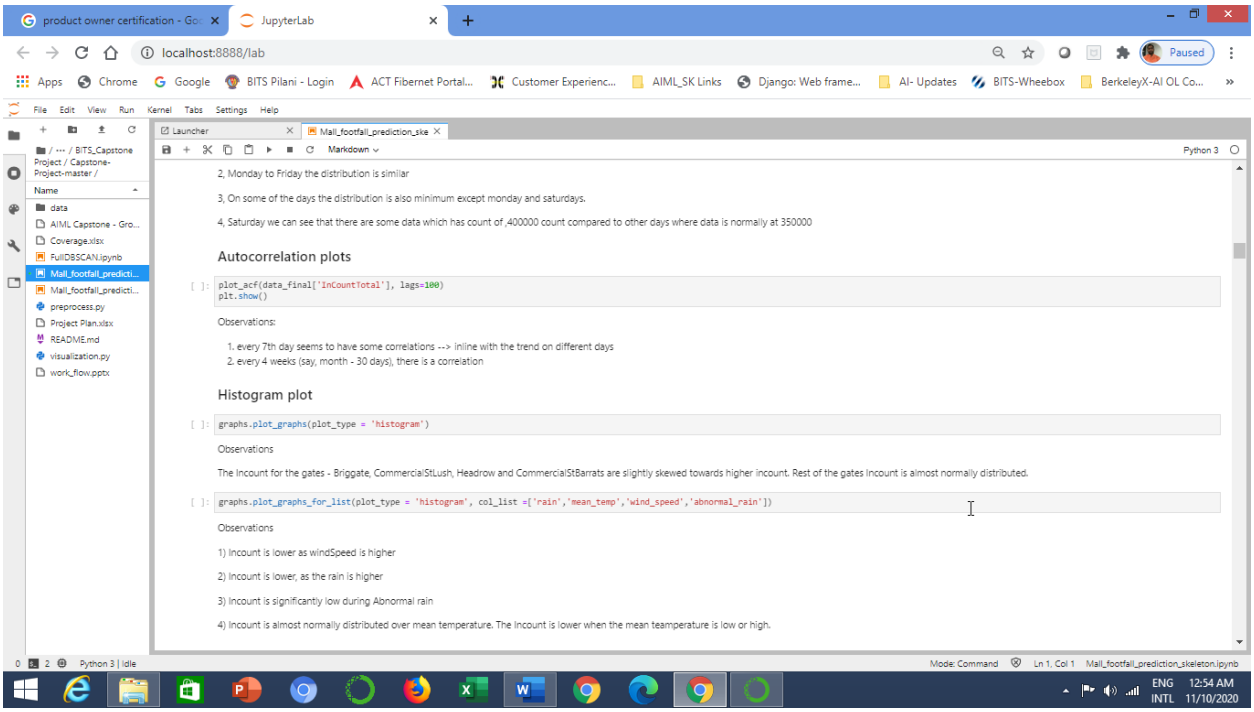
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2, Monday to Friday the distribution is similar
3, On some of the days the distribution is also minimum except monday and saturdays.
4, Saturday we can see that there are some data which has count of ,400000 count compared to other days where data is normally at 350000
Autocorrelation plots
plot_acf(data_final['InCountTotal'], lags=100)
plt.show()
Observations:
1. every 7th day seems to have some correlations --> inline with the trend on different days
2. every 4 weeks (say, month - 30 days), there is a correlation
Histogram plot
graphs.plot_graphs(plot_type = 'histogram')
Observations
The Incount for the gates - Briggate, CommercialStLush, Headrow and CommercialStBarrats are slightly skewed towards higher incount. Rest of the gates Incount is almost normally distributed.
graphs.plot_graphs_for_list(plot_type = 'histogram', col_list =['rain','mean_temp','wind_speed','abnormal_rain'])
Observations
1) Incount is lower as windSpeed is higher
2) Incount is lower, as the rain is higher
3) Incount is significantly low during Abnormal rain
4) Incount is almost normally distributed over mean temperature. The Incount is lower when the mean teamperature is low or high.
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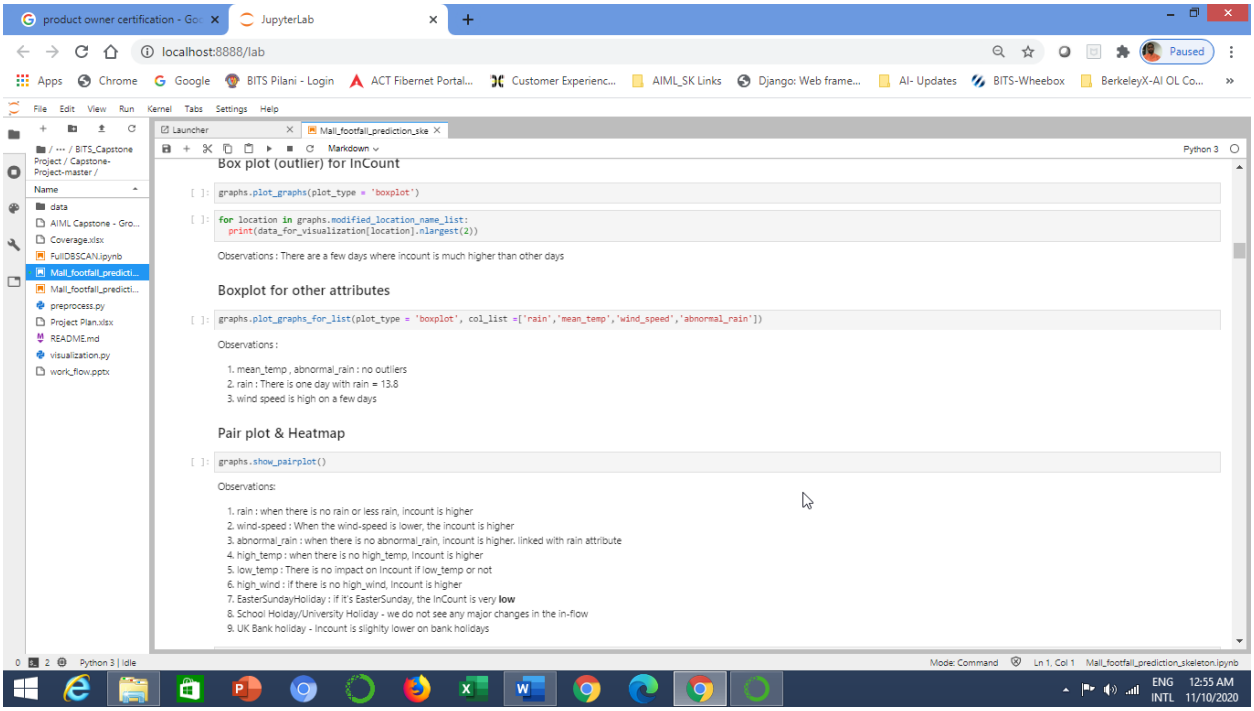
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Box plot (outlier) for InCount
graphs.plot_graphs(plot_type = 'boxplot')
for location in graphs.modified_location_name_list:
print(data_for_visualization[location].nlargest(2))
Observations : There are a few days where incount is much higher than other days
Boxplot for other attributes
graphs.plot_graphs_for_list(plot_type = 'boxplot', col_list =['rain','mean_temp','wind_speed','abnormal_rain'])
Observations :
1. mean_temp , abnormal_rain : no outliers
2. rain : There is one day with rain = 13.8
3. wind speed is high on a few days
Pair plot & Heatmap
graphs.show_pairplot()
Observations:
1. rain : when there is no rain or less rain, incount is higher
2. wind-speed : When the wind-speed is lower, the incount is higher
3. abnormal_rain : when there is no abnormal_rain, incount is higher. linked with rain attribute
4. high_temp : when there is no high_temp, incount is higher
5. low_temp : There is no impact on incount if low_temp or not
6. high_wind : If there is no high_wind, incount is higher
7. EasterSundayHoliday : if it's EasterSunday, the InCount is very low
8. School Holday/University Holiday - we do not see any major changes in the in-flow
9. UK Bank holiday - incount is slighity lower on bank holidays
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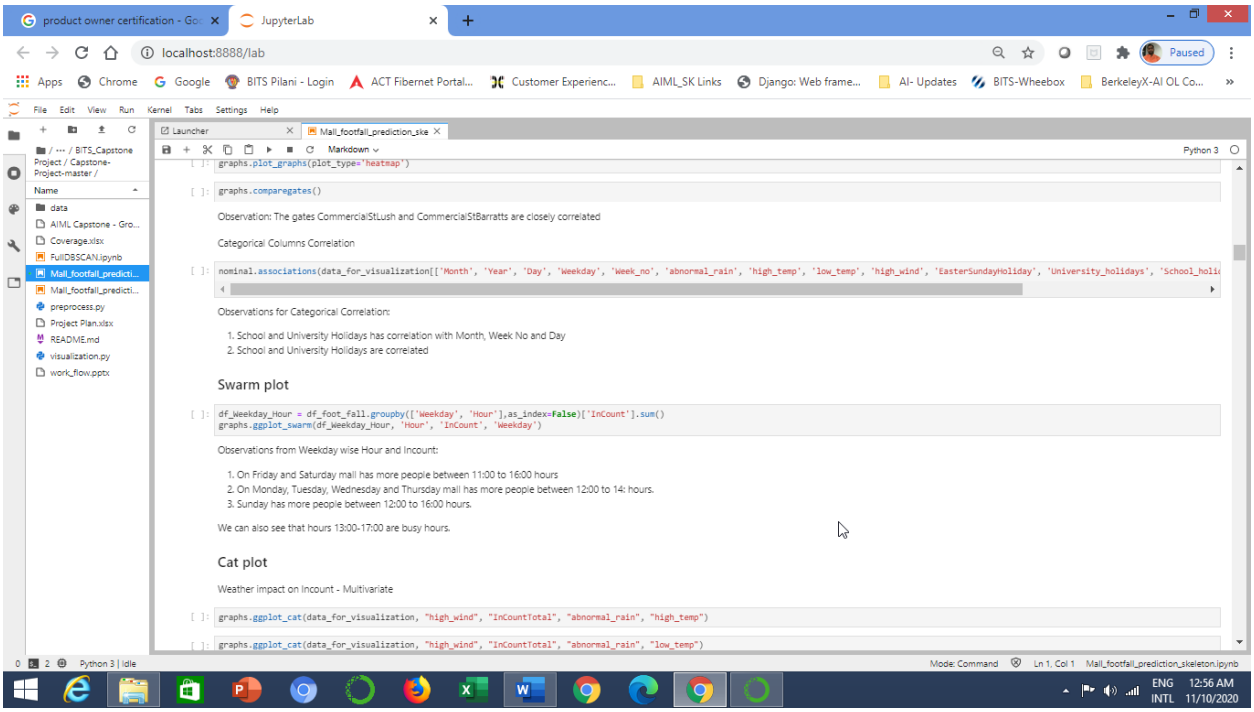
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graphs.plot_graphs(plot_type='heatmap')
graphs.comparegates()
Observation: The gates CommercialStLush and CommercialStBarratts are closely correlated
Categorical Columns Correlation
nominal.associations(data_for_visualization[['Month', 'Year', 'Day', 'Weekday', 'Week_no', 'abnormal_rain', 'high_temp', 'low_temp', 'high_wind', 'EasterSundayHoliday', 'University_holidays', 'School_holi
Observations for Categorical Correlation:
1. School and University Holidays has correlation with Month, Week No and Day
2. School and University Holidays are correlated
Swarm plot
df_Weekday_Hour = df_foot_fall.groupby(['Weekday', 'Hour'],as_index=False)['InCount'].sum()
graphs.ggplot_swarm(df_Weekday_Hour, 'Hour', 'InCount', 'Weekday')
Observations from Weekday wise Hour and Incount:
1. On Friday and Saturday mall has more people between 11:00 to 16:00 hours
2. On Monday, Tuesday, Wednesday and Thursday mall has more people between 12:00 to 14: hours.
3. Sunday has more people between 12:00 to 16:00 hours.
We can also see that hours 13:00-17:00 are busy hours.
Cat plot
Weather impact on Incount - Multivariate
graphs.ggplot_cat(data_for_visualization, "high_wind", "InCountTotal", "abnormal_rain", "high_temp")
graphs.ggplot_cat(data_for_visualization, "high_wind", "InCountTotal", "abnormal_rain", "low_temp")
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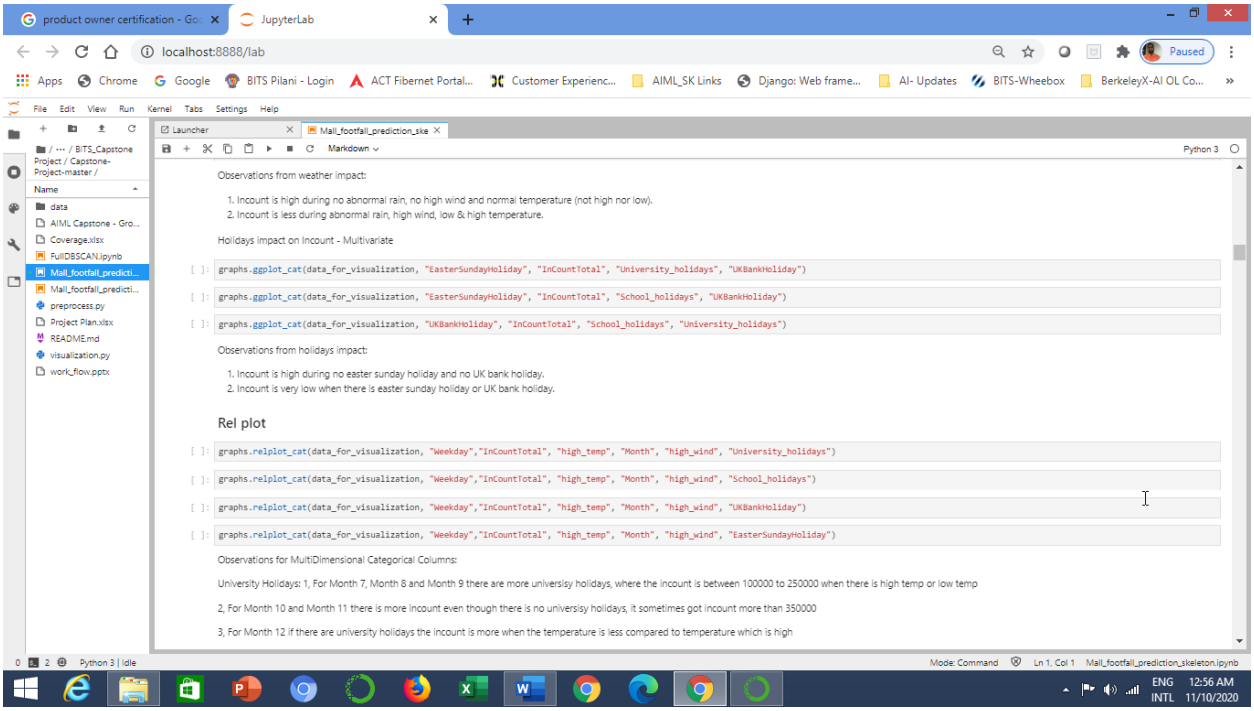
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Observations from weather impact:
1. Incount is high during no abnormal rain, no high wind and normal temperature (not high nor low).
2. Incount is less during abnormal rain, high wind, low & high temperature.
Holidays impact on Incount - Multivariate
graphs.ggplot_cat(data_for_visualization, "EasterSundayHoliday", "InCountTotal", "University_holidays", "UKBankHoliday")
graphs.ggplot_cat(data_for_visualization, "EasterSundayHoliday", "InCountTotal", "School_holidays", "UKBankHoliday")
graphs.ggplot_cat(data_for_visualization, "UKBankHoliday", "InCountTotal", "School_holidays", "University_holidays")
Observations from holidays impact:
1. Incount is high during no easter sunday holiday and no UK bank holiday.
2. Incount is very low when there is easter sunday holiday or UK bank holiday.
Rel plot
graphs.relplot_cat(data_for_visualization, "Weekday","InCountTotal", "high_temp", "Month", "high_wind", "University_holidays")
graphs.relplot_cat(data_for_visualization, "Weekday","InCountTotal", "high_temp", "Month", "high_wind", "School_holidays")
graphs.relplot_cat(data_for_visualization, "Weekday","InCountTotal", "high_temp", "Month", "high_wind", "UKBankHoliday")
graphs.relplot_cat(data_for_visualization, "Weekday","InCountTotal", "high_temp", "Month", "high_wind", "EasterSundayHoliday")
Observations for MultiDimensional Categorical Columns:
University Holidays: 1, For Month 7, Month 8 and Month 9 there are more universisy holidays, where the incount is between 100000 to 250000 when there is high temp or low temp
2, For Month 10 and Month 11 there is more incount even though there is no universisy holidays, it sometimes got incount more than 350000
3, For Month 12 if there are university holidays the incount is more when the temperature is less compared to temperature which is high
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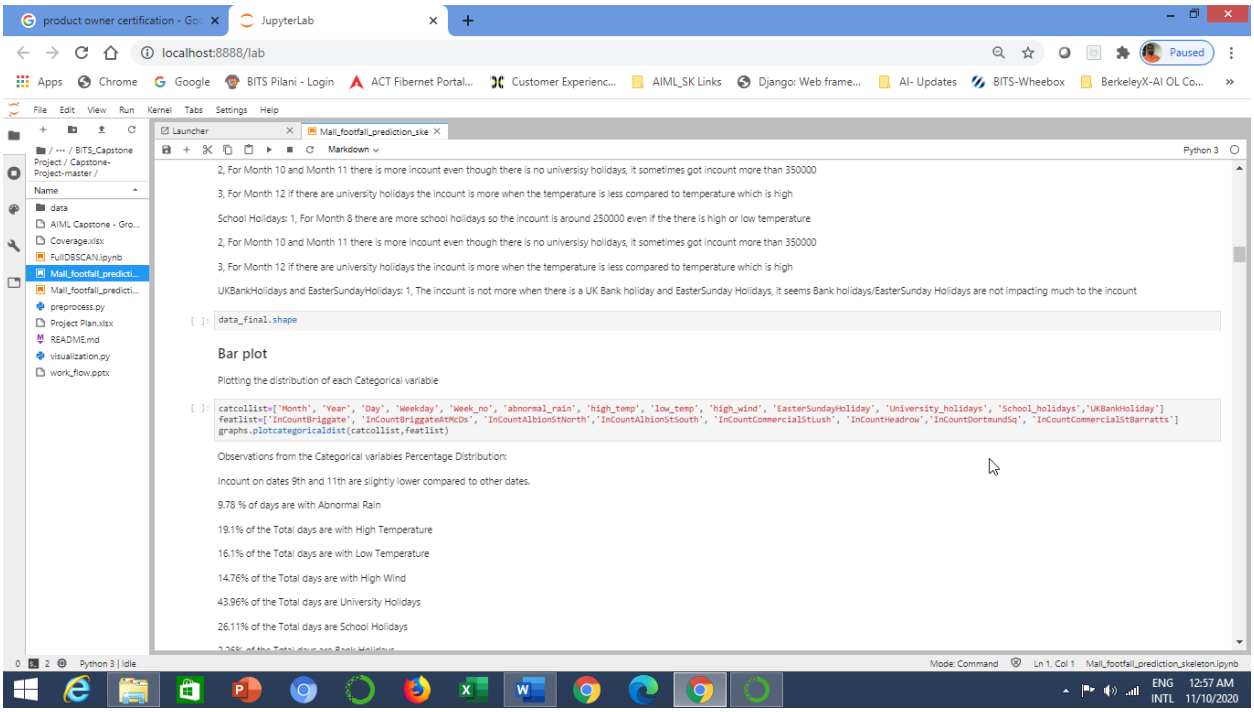
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2, For Month 10 and Month 11 there is more incount even though there is no universisy holidays, it sometimes got incount more than 350000
3, For Month 12 if there are university holidays the incount is more when the temperature is less compared to temperature which is high
School Holidays: 1, For Month 8 there are more school holidays so the incount is around 250000 even if the there is high or low temperature
2, For Month 10 and Month 11 there is more incount even though there is no universisy holidays, it sometimes got incount more than 350000
3, For Month 12 if there are university holidays the incount is more when the temperature is less compared to temperature which is high
UKBankHolidays and EasterSundayHolidays: 1, The incount is not more when there is a UK Bank holiday and EasterSunday Holidays, it seems Bank holidays/EasterSunday Holidays are not impacting much to the incount
data_final.shape
Bar plot
Plotting the distribution of each Categorical variable
catcollist=['Month', 'Year', 'Day', 'Weekday', 'Week_no', 'abnormal_rain', 'high_temp', 'low_temp', 'high_wind', 'EasterSundayHoliday', 'University_holidays', 'School_holidays','UKBankHoliday']
featlist=['InCountBriggate', 'InCountBriggateAtMcDs', 'InCountAlbionStNorth','InCountAlbionStSouth', 'InCountCommercialStLush', 'InCountHeadrow','InCountDortmundSq', 'InCountCommercialStBarratts']
graphs.plotcategoricaldist(catcollist,featlist)
Observations from the Categorical variables Percentage Distribution:
Incount on dates 9th and 11th are slightly lower compared to other dates.
9.78 % of days are with Abnormal Rain
19.1% of the Total days are with High Temperature
16.1% of the Total days are with Low Temperature
14.76% of the Total days are with High Wind
43.96% of the Total days are University Holidays
26.11% of the Total days are School Holidays
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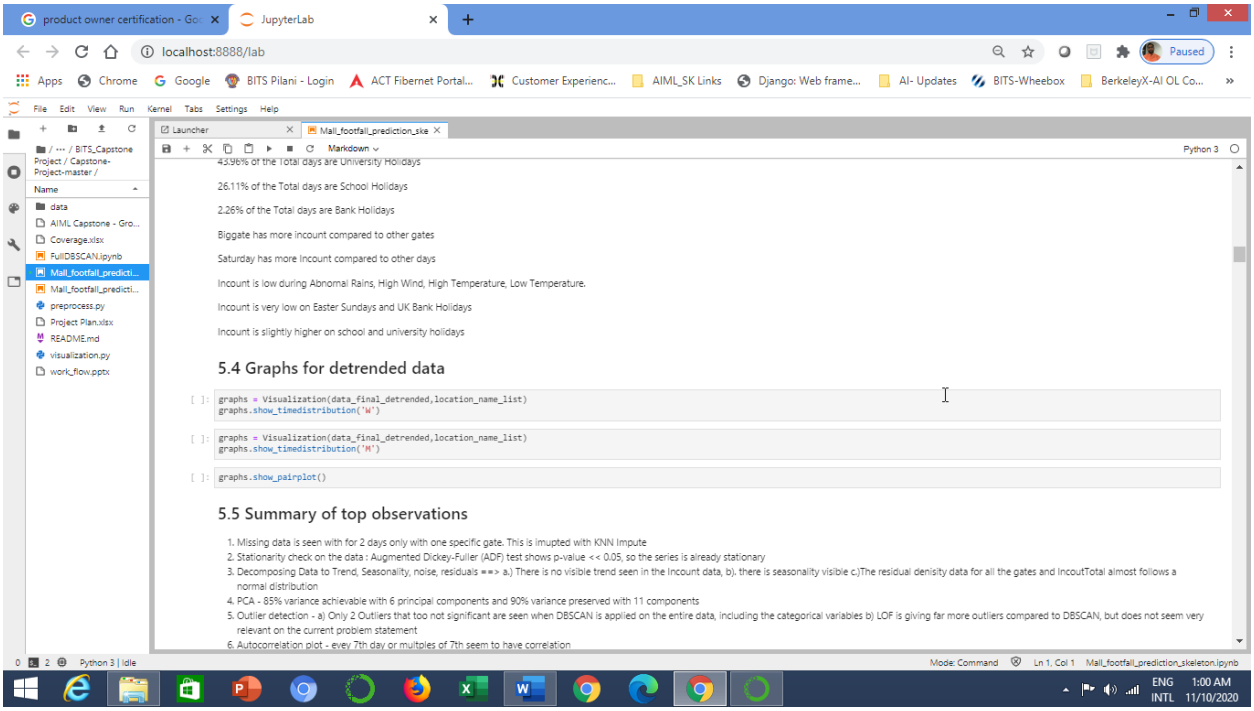
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43.96% of the Total days are University Holidays
26.11% of the Total days are School Holidays
2.26% of the Total days are Bank Holidays
Biggate has more incount compared to other gates
Saturday has more Incount compared to other days
Incount is low during Abnormal Rains, High Wind, High Temperature, Low Temperature.
Incount is very low on Easter Sundays and UK Bank Holidays
Incount is slightly higher on school and university holidays
5.4 Graphs for detrended data
graphs = Visualization(data_final_detrended,location_name_list)
graphs.show_timedistribution('W')
graphs = Visualization(data_final_detrended,location_name_list)
graphs.show_timedistribution('M')
graphs.show_pairplot()
5.5 Summary of top observations
1. Missing data is seen with for 2 days only with one specific gate. This is imupted with KNN Impute
2. Stationarity check on the data : Augmented Dickey-Fuller (ADF) test shows p-value << 0.05, so the series is already stationary
3. Decomposing Data to Trend, Seasonality, noise, residuals ==> a.) There is no visible trend seen in the Incount data, b). there is seasonality visible c.)The residual denisity data for all the gates and IncoutTotal almost follows a normal distribution
4. PCA - 85% variance achievable with 6 principal components and 90% variance preserved with 11 components
5. Outlier detection - a) Only 2 Outliers that too not significant are seen when DBSCAN is applied on the entire data, including the categorical variables b) LOF is giving far more outliers compared to DBSCAN, but does not seem very relevant on the current problem statement
6. Autocorrelation plot - evey 7th day or multples of 7th seem to have correlation
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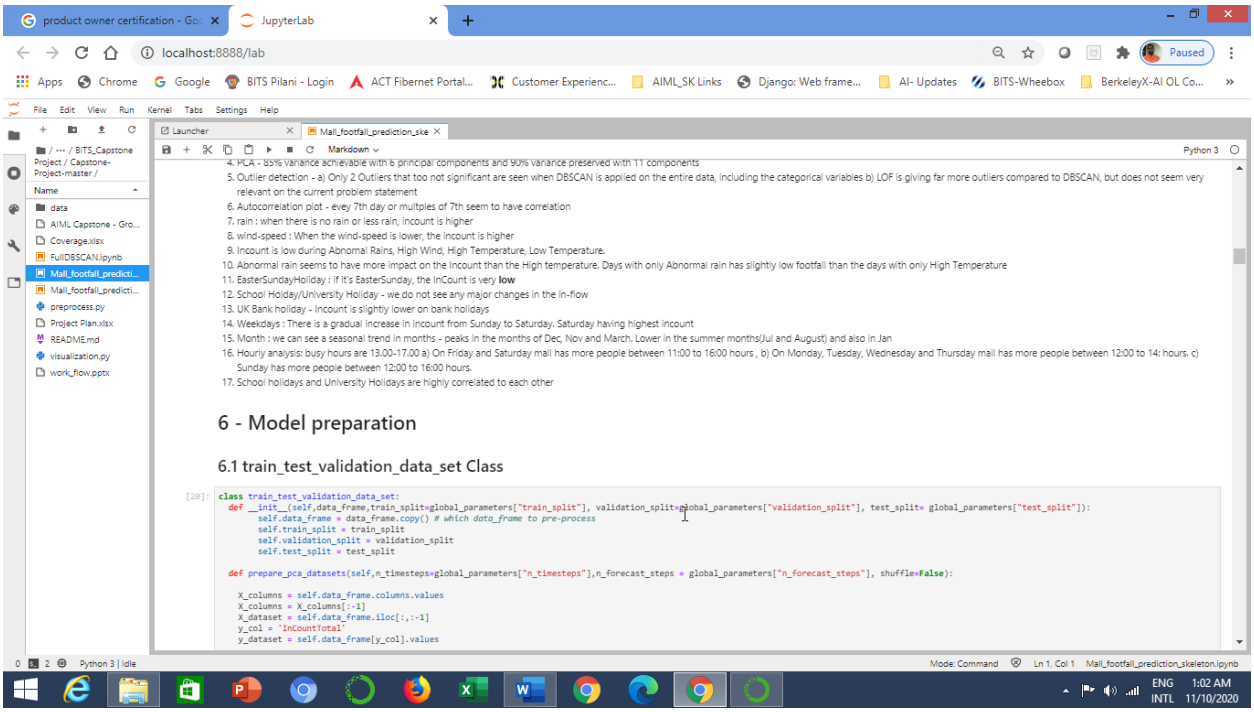
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4. PCA - 85% variance achievable with 6 principal components and 90% variance preserved with 11 components
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6. Autocorrelation plot - evey 7th day or multples of 7th seem to have correlation
7. rain : when there is no rain or less rain, incount is higher
8. wind-speed : When the wind-speed is lower, the incount is higher
9. Incount is low during Abnormal Rains, High Wind, High Temperature, Low Temperature.
10. Abnormal rain seems to have more impact on the Incount than the High temperature. Days with only Abnormal rain has slightly low footfall than the days with only High Temperature
11. EasterSundayHolidiay : if it's EasterSunday, the InCount is very low
12. School Holday/University Holiday - we do not see any major changes in the in-flow
13. UK Bank holiday - Incount is slightly lower on bank holidays
14. Weekdays : There is a gradual increase in Incount from Sunday to Saturday. Saturday having highest incount
15. Month : we can see a seasonal trend in months - peaks in the months of Dec, Nov and March. Lower in the summer months(Jul and August) and also in Jan
16. Hourly analysis: busy hours are 13.00-17.00 a) On Friday and Saturday mall has more people between 11:00 to 16:00 hours , b) On Monday, Tuesday, Wednesday and Thursday mall has more people between 12:00 to 14: hours. c) Sunday has more people between 12:00 to 16:00 hours.
17. School holidays and University Holidays are highly correlated to each other
6 - Model preparation
6.1 train_test_validation_data_set Class
class train_test_validation_data_set:
def __init__(self,data_frame,train_split=global_parameters["train_split"], validation_split=global_parameters["validation_split"], test_split= global_parameters["test_split"]):
self.data_frame = data_frame.copy() # which data_frame to pre-process
self.train_split = train_split
self.validation_split = validation_split
self.test_split = test_split
def prepare_pca_datasets(self,n_timesteps=global_parameters["n_timesteps"],n_forecast_steps = global_parameters["n_forecast_steps"], shuffle=False):
X_columns = self.data_frame.columns.values
X_columns = X_columns[:-1]
X_dataset = self.data_frame.iloc[:,:-1]
y_col = 'InCountTotal'
y_dataset = self.data_frame[y_col].values
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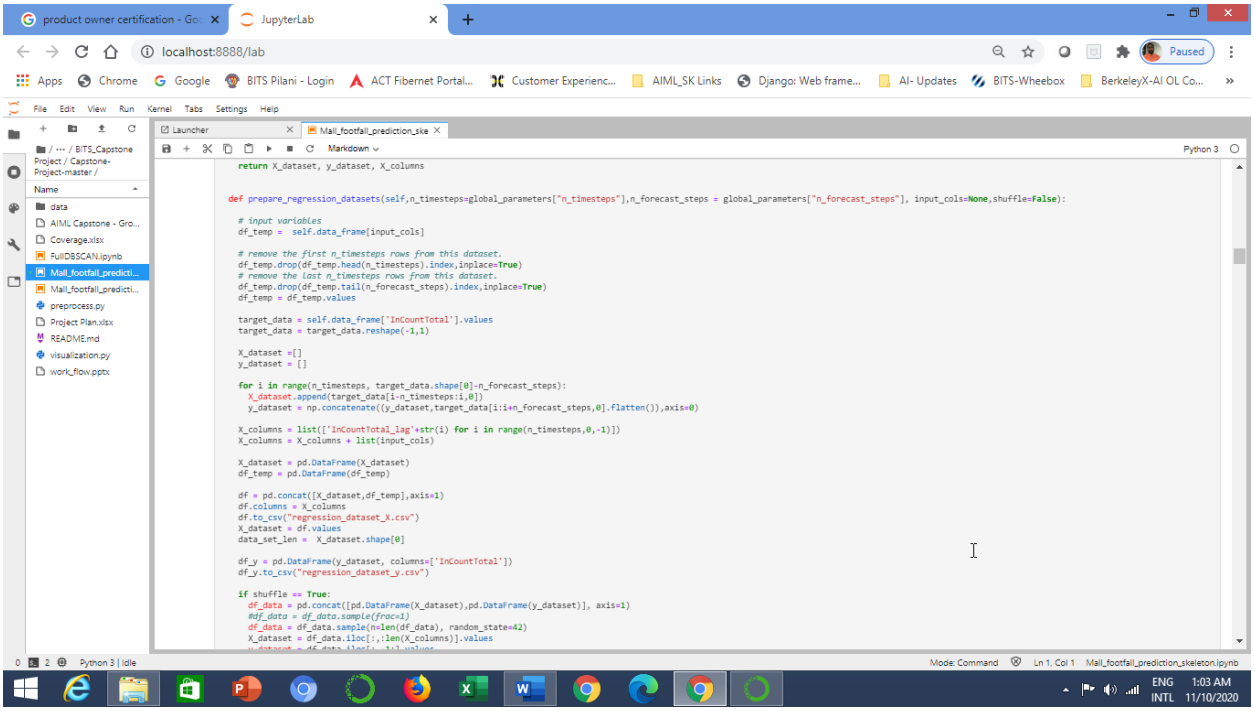
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return X_dataset, y_dataset, X_columns
def prepare_regression_datasets(self,n_timesteps=global_parameters["n_timesteps"],n_forecast_steps = global_parameters["n_forecast_steps"], input_cols=None,shuffle=False):
# input variables
df_temp = self.data_frame[input_cols]
# remove the first n_timesteps rows from this dataset.
df_temp.drop(df_temp.head(n_timesteps).index,inplace=True)
# remove the last n_timesteps rows from this dataset.
df_temp.drop(df_temp.tail(n_forecast_steps).index,inplace=True)
df_temp = df_temp.values
target_data = self.data_frame['InCountTotal'].values
target_data = target_data.reshape(-1,1)
X_dataset =[]
y_dataset = []
for i in range(n_timesteps, target_data.shape[0]-n_forecast_steps):
X_dataset.append(target_data[i-n_timesteps:i,0])
y_dataset = np.concatenate((y_dataset,target_data[i:i+n_forecast_steps,0].flatten()),axis=0)
X_columns = list(['InCountTotal_lag'+str(i) for i in range(n_timesteps,0,-1)])
X_columns = X_columns + list(input_cols)
X_dataset = pd.DataFrame(X_dataset)
df_temp = pd.DataFrame(df_temp)
df = pd.concat([X_dataset,df_temp],axis=1)
df.columns = X_columns
df.to_csv("regression_dataset_X.csv")
X_dataset = df.values
data_set_len = X_dataset.shape[0]
df_y = pd.DataFrame(y_dataset, columns=['InCountTotal'])
df_y.to_csv("regression_dataset_y.csv")
if shuffle == True:
df_data = pd.concat([pd.DataFrame(X_dataset),pd.DataFrame(y_dataset)], axis=1)
#df_data = df_data.sample(frac=1)
df_data = df_data.sample(n=len(df_data), random_state=42)
X_dataset = df_data.iloc[:,:len(X_columns)].values
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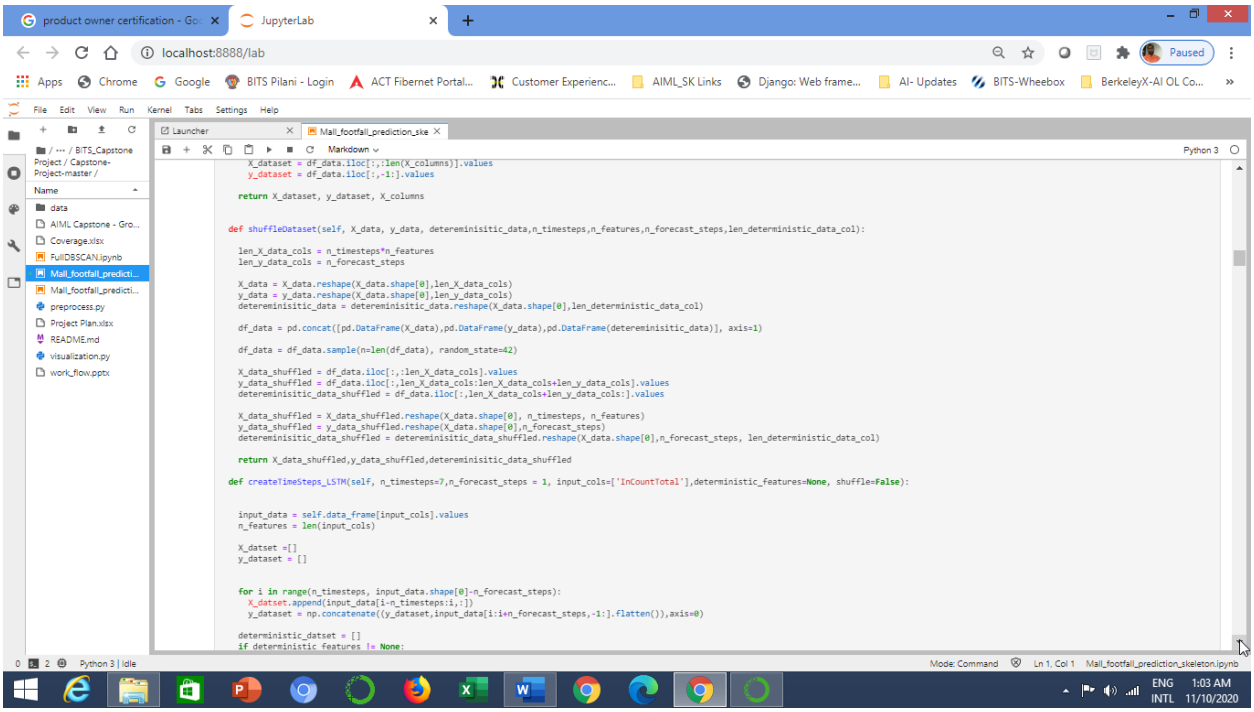
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X_dataset = df_data.iloc[:,:len(X_columns)].values
y_dataset = df_data.iloc[:,-1:].values
return X_dataset, y_dataset, X_columns
def shuffleDataset(self, X_data, y_data, detereminisitic_data,n_timesteps,n_features,n_forecast_steps,len_deterministic_data_col):
len_X_data_cols = n_timesteps*n_features
len_y_data_cols = n_forecast_steps
X_data = X_data.reshape(X_data.shape[0],len_X_data_cols)
y_data = y_data.reshape(X_data.shape[0],len_y_data_cols)
detereminisitic_data = detereminisitic_data.reshape(X_data.shape[0],len_deterministic_data_col)
df_data = pd.concat([pd.DataFrame(X_data),pd.DataFrame(y_data),pd.DataFrame(detereminisitic_data)], axis=1)
df_data = df_data.sample(n=len(df_data), random_state=42)
X_data_shuffled = df_data.iloc[:,:len_X_data_cols].values
y_data_shuffled = df_data.iloc[:,len_X_data_cols:len_X_data_cols+len_y_data_cols].values
detereminisitic_data_shuffled = df_data.iloc[:,len_X_data_cols+len_y_data_cols:].values
X_data_shuffled = X_data_shuffled.reshape(X_data.shape[0], n_timesteps, n_features)
y_data_shuffled = y_data_shuffled.reshape(X_data.shape[0],n_forecast_steps)
detereminisitic_data_shuffled = detereminisitic_data_shuffled.reshape(X_data.shape[0],n_forecast_steps, len_deterministic_data_col)
return X_data_shuffled,y_data_shuffled,detereminisitic_data_shuffled
def createTimeSteps_LSTM(self, n_timesteps=7,n_forecast_steps = 1, input_cols=['InCountTotal'],deterministic_features=None, shuffle=False):
input_data = self.data_frame[input_cols].values
n_features = len(input_cols)
X_datset =[]
y_dataset = []
for i in range(n_timesteps, input_data.shape[0]-n_forecast_steps):
X_datset.append(input_data[i-n_timesteps:i,:])
y_dataset = np.concatenate((y_dataset,input_data[i:i+n_forecast_steps,-1:].flatten()),axis=0)
deterministic_datset = []
if deterministic_features != None:
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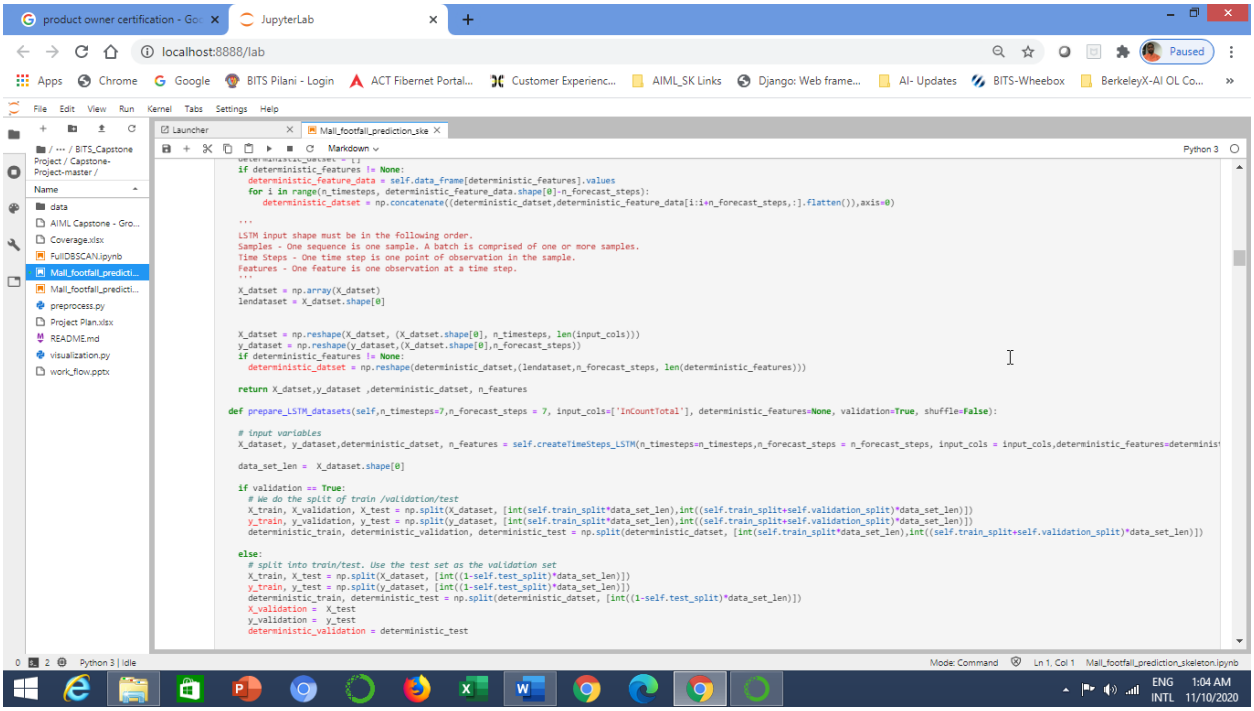
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if deterministic_features != None:
deterministic_feature_data = self.data_frame[deterministic_features].values
for i in range(n_timesteps, deterministic_feature_data.shape[0]-n_forecast_steps):
deterministic_datset = np.concatenate((deterministic_datset,deterministic_feature_data[i:i+n_forecast_steps,:].flatten()),axis=0)
'''
LSTM input shape must be in the following order.
Samples - One sequence is one sample. A batch is comprised of one or more samples.
Time Steps - One time step is one point of observation in the sample.
Features - One feature is one observation at a time step.
'''
X_datset = np.array(X_datset)
lendataset = X_datset.shape[0]
X_datset = np.reshape(X_datset, (X_datset.shape[0], n_timesteps, len(input_cols)))
y_dataset = np.reshape(y_dataset,(X_datset.shape[0],n_forecast_steps))
if deterministic_features != None:
deterministic_datset = np.reshape(deterministic_datset,(lendataset,n_forecast_steps, len(deterministic_features)))
return X_datset,y_dataset ,deterministic_datset, n_features
def prepare_LSTM_datasets(self,n_timesteps=7,n_forecast_steps = 7, input_cols=['InCountTotal'], deterministic_features=None, validation=True, shuffle=False):
# input variables
X_dataset, y_dataset,deterministic_datset, n_features = self.createTimeSteps_LSTM(n_timesteps=n_timesteps,n_forecast_steps = n_forecast_steps, input_cols = input_cols,deterministic_features=determinist
data_set_len = X_dataset.shape[0]
if validation == True:
# We do the split of train /validation/test
X_train, X_validation, X_test = np.split(X_dataset, [int(self.train_split*data_set_len),int((self.train_split+self.validation_split)*data_set_len)])
y_train, y_validation, y_test = np.split(y_dataset, [int(self.train_split*data_set_len),int((self.train_split+self.validation_split)*data_set_len)])
deterministic_train, deterministic_validation, deterministic_test = np.split(deterministic_datset, [int(self.train_split*data_set_len),int((self.train_split+self.validation_split)*data_set_len)])
else:
# split into train/test. Use the test set as the validation set
X_train, X_test = np.split(X_dataset, [int((1-self.test_split)*data_set_len)])
y_train, y_test = np.split(y_dataset, [int((1-self.test_split)*data_set_len)])
deterministic_train, deterministic_test = np.split(deterministic_datset, [int((1-self.test_split)*data_set_len)])
X_validation = X_test
y_validation = y_test
deterministic_validation = deterministic_test
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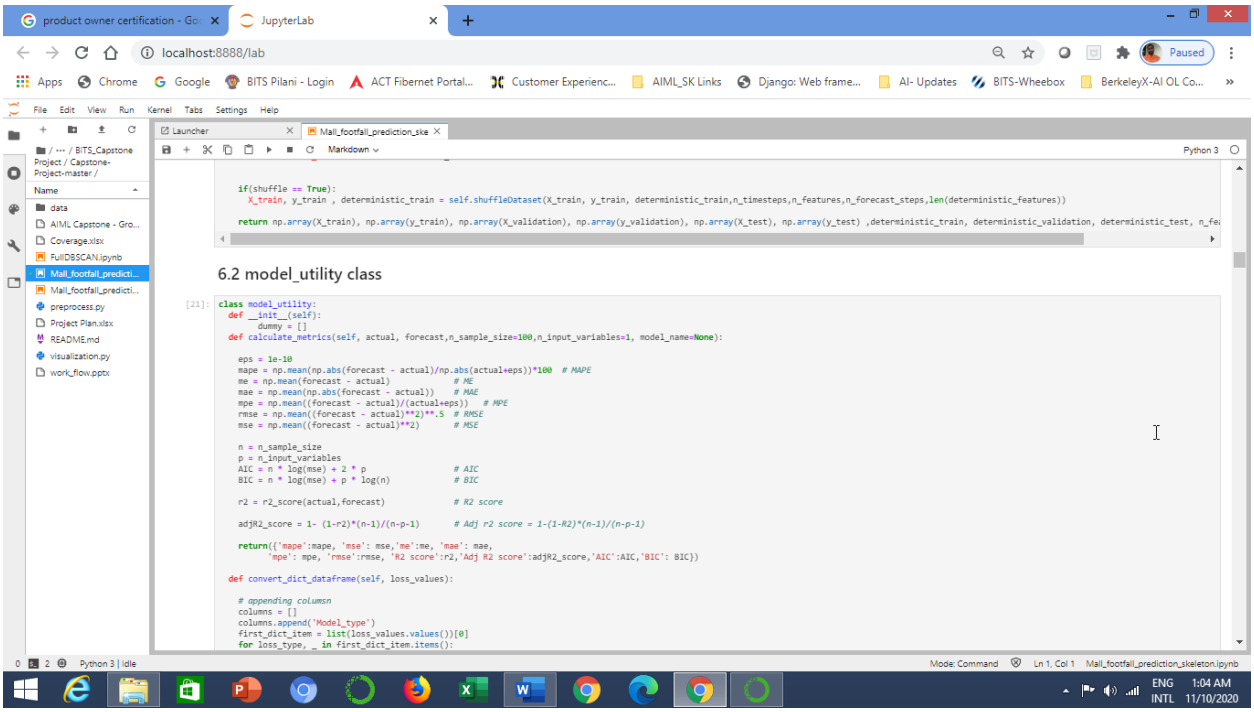
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if(shuffle == True):
X_train, y_train , deterministic_train = self.shuffleDataset(X_train, y_train, deterministic_train,n_timesteps,n_features,n_forecast_steps,len(deterministic_features))
return np.array(X_train), np.array(y_train), np.array(X_validation), np.array(y_validation), np.array(X_test), np.array(y_test) ,deterministic_train, deterministic_validation, deterministic_test, n_fe
6.2 model_utility class
[21]:
class model_utility:
def __init__(self):
dummy = []
def calculate_metrics(self, actual, forecast,n_sample_size=100,n_input_variables=1, model_name=None):
eps = 1e-10
mape = np.mean(np.abs(forecast - actual)/np.abs(actual+eps))*100 # MAPE
me = np.mean(forecast - actual) # ME
mae = np.mean(np.abs(forecast - actual)) # MAE
mpe = np.mean((forecast - actual)/(actual+eps)) # MPE
rmse = np.mean((forecast - actual)**2)**.5 # RMSE
mse = np.mean((forecast - actual)**2) # MSE
n = n_sample_size
p = n_input_variables
AIC = n * log(mse) + 2 * p # AIC
BIC = n * log(mse) + p * log(n) # BIC
r2 = r2_score(actual,forecast) # R2 score
adjR2_score = 1- (1-r2)*(n-1)/(n-p-1) # Adj r2 score = 1-(1-R2)*(n-1)/(n-p-1)
return({'mape':mape, 'mse': mse,'me':me, 'mae': mae,
'mpe': mpe, 'rmse':rmse, 'R2 score':r2,'Adj R2 score':adjR2_score,'AIC':AIC,'BIC': BIC})
def convert_dict_dataframe(self, loss_values):
# appending columsn
columns = []
columns.append('Model_type')
first_dict_item = list(loss_values.values())[0]
for loss_type, _ in first_dict_item.items():
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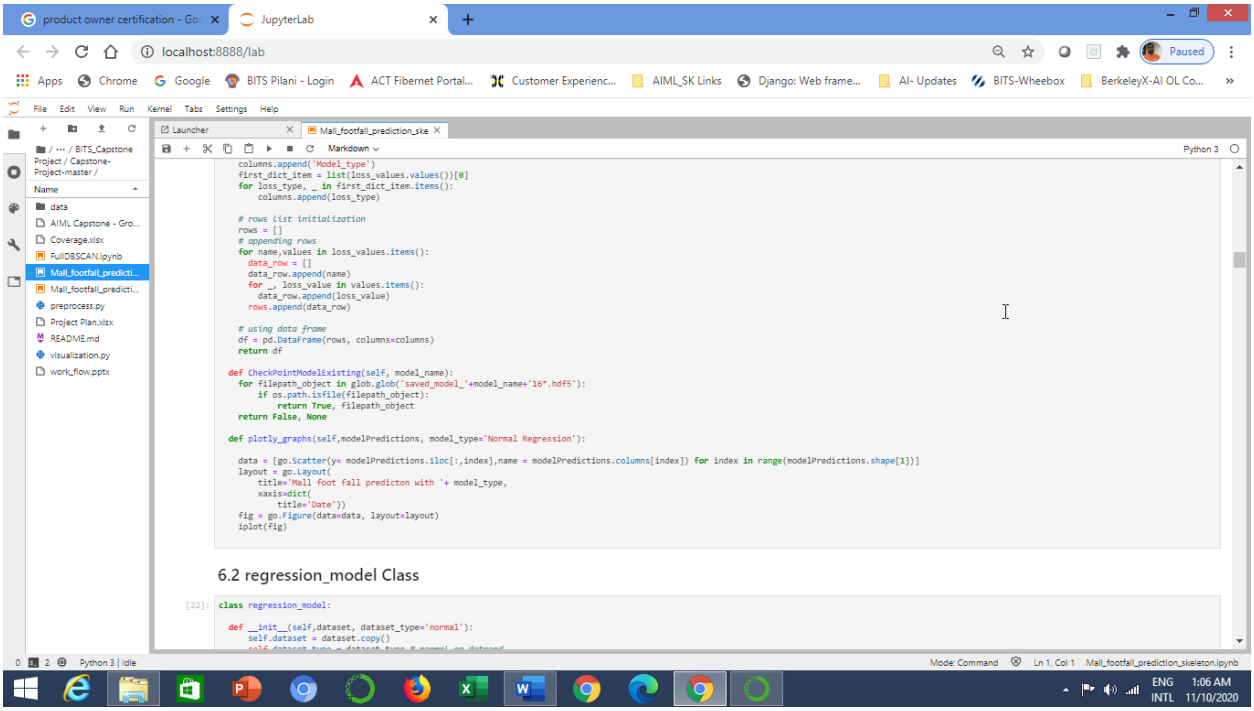
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columns.append('Model_type')
first_dict_item = list(loss_values.values())[0]
for loss_type, _ in first_dict_item.items():
columns.append(loss_type)
# rows list initialization
rows = []
# appending rows
for name,values in loss_values.items():
data_row = []
data_row.append(name)
for _, loss_value in values.items():
data_row.append(loss_value)
rows.append(data_row)
# using data frame
df = pd.DataFrame(rows, columns=columns)
return df
def CheckPointModelExisting(self, model_name):
for filepath_object in glob.glob('saved_model_'+model_name+'16*.hdf5'):
if os.path.isfile(filepath_object):
return True, filepath_object
return False, None
def plotly_graphs(self,modelPredictions, model_type='Normal Regression'):
data = [go.Scatter(y= modelPredictions.iloc[:,index],name = modelPredictions.columns[index]) for index in range(modelPredictions.shape[1])]
layout = go.Layout(
title='Mall foot fall prediction with '+ model_type,
xaxis=dict(
title='Date'))
fig = go.Figure(data=data, layout=layout)
iplot(fig)
6.2 regression_model Class
[22]:
class regression_model:
def __init__(self,dataset, dataset_type='normal'):
self.dataset = dataset.copy()
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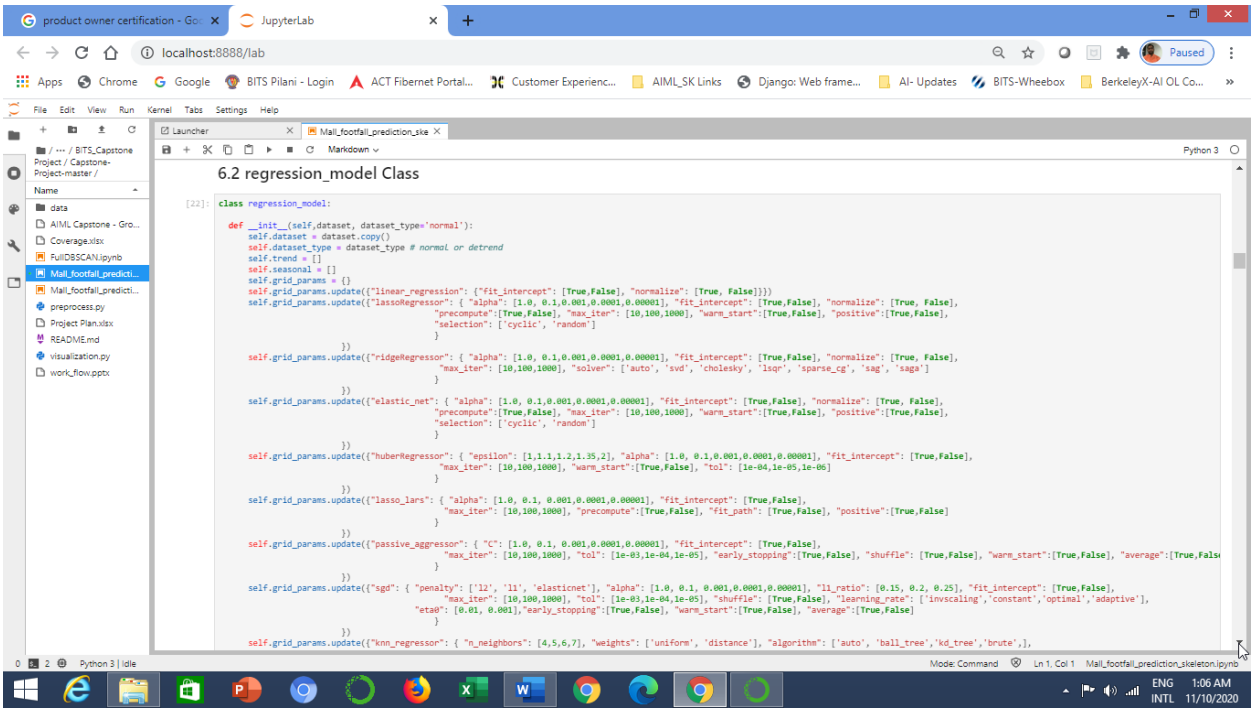
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6.2 regression_model Class
[22]:
class regression_model:
def __init__(self,dataset, dataset_type='normal'):
self.dataset = dataset.copy()
self.dataset_type = dataset_type # normal or detrend
self.trend = []
self.seasonal = []
self.grid_params = {}
self.grid_params.update({"linear_regression": {"fit_intercept": [True,False], "normalize": [True, False]}})
self.grid_params.update({"lassoRegressor": { "alpha": [1.0, 0.1,0.001,0.0001,0.00001], "fit_intercept": [True,False], "normalize": [True, False],
"precompute":[True,False], "max_iter": [10,100,1000], "warm_start":[True,False], "positive":[True,False],
"selection": ['cyclic', 'random']
}
})
self.grid_params.update({"ridgeRegressor": { "alpha": [1.0, 0.1,0.001,0.0001,0.00001], "fit_intercept": [True,False], "normalize": [True, False],
"max_iter": [10,100,1000], "solver": ['auto', 'svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga']
}
})
self.grid_params.update({"elastic_net": { "alpha": [1.0, 0.1,0.001,0.0001,0.00001], "fit_intercept": [True,False], "normalize": [True, False],
"precompute":[True,False], "max_iter": [10,100,1000], "warm_start":[True,False], "positive":[True,False],
"selection": ['cyclic', 'random']
}
})
self.grid_params.update({"huberRegressor": { "epsilon": [1,1.1,1.2,1.35,2], "alpha": [1.0, 0.1,0.001,0.0001,0.00001], "fit_intercept": [True,False],
"max_iter": [10,100,1000], "warm_start":[True,False], "tol": [1e-04,1e-05,1e-06]
}
})
self.grid_params.update({"lasso_lars": { "alpha": [1.0, 0.1, 0.001,0.0001,0.00001], "fit_intercept": [True,False],
"max_iter": [10,100,1000], "precompute":[True,False], "fit_path": [True,False], "positive":[True,False]
}
})
self.grid_params.update({"passive_aggressor": { "C": [1.0, 0.1, 0.001,0.0001,0.00001], "fit_intercept": [True,False],
"max_iter": [10,100,1000], "tol": [1e-03,1e-04,1e-05], "early_stopping":[True,False], "shuffle": [True,False], "warm_start":[True,False], "average":[True,Fals
}
})
self.grid_params.update({"sgd": { "penalty": ['l2', 'l1', 'elasticnet'], "alpha": [1.0, 0.1, 0.001,0.0001,0.00001], "l1_ratio": [0.15, 0.2, 0.25], "fit_intercept": [True,False],
"max_iter": [10,100,1000], "tol": [1e-03,1e-04,1e-05], "shuffle": [True,False], "learning_rate": ['invscaling','constant','optimal','adaptive'],
"eta0": [0.01, 0.001],"early_stopping":[True,False], "warm_start":[True,False], "average":[True,False]
}
})
self.grid_params.update({"knn_regressor": { "n_neighbors": [4,5,6,7], "weights": ['uniform', 'distance'], "algorithm": ['auto', 'ball_tree','kd_tree','brute',],
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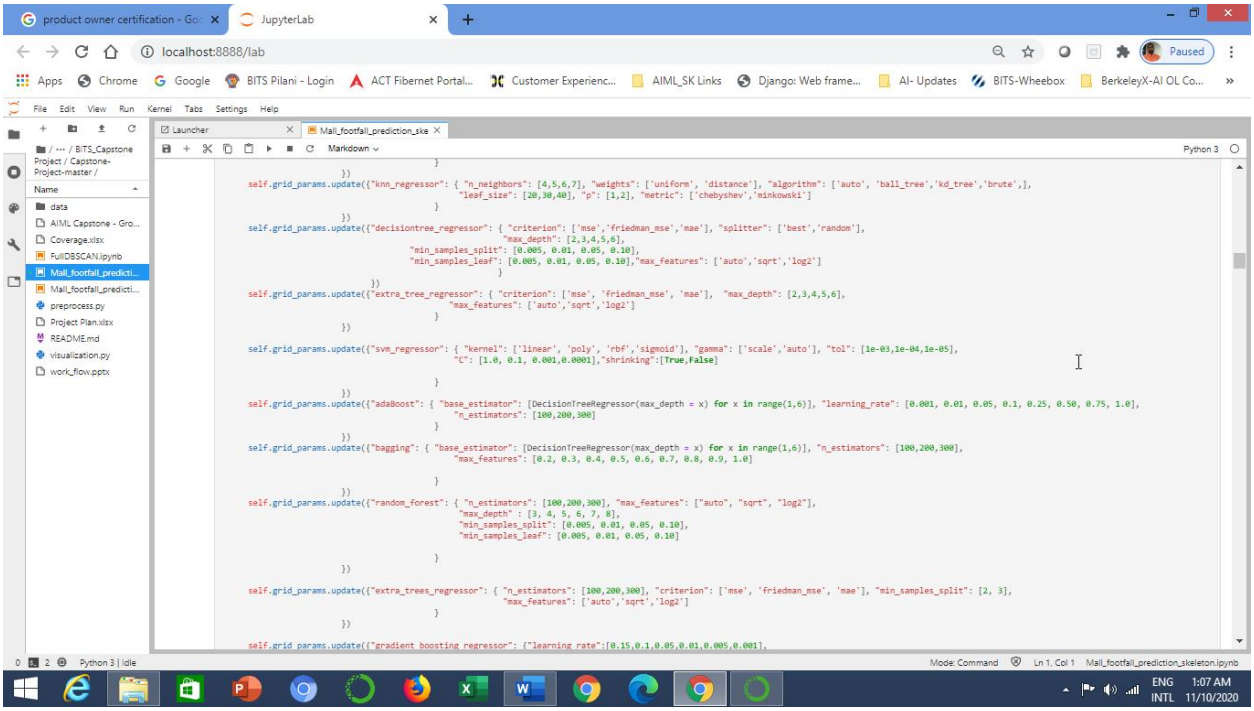
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self.grid_params.update({"knn_regressor": { "n_neighbors": [4,5,6,7], "weights": ['uniform', 'distance'], "algorithm": ['auto', 'ball_tree','kd_tree','brute',],
"leaf_size": [20,30,40], "p": [1,2], "metric": ['chebyshev','minkowski']
}
})
self.grid_params.update({"decisiontree_regressor": { "criterion": ['mse','friedman_mse','mae'], "splitter": ['best','random'],
"max_depth": [2,3,4,5,6],
"min_samples_split": [0.005, 0.01, 0.05, 0.10],
"min_samples_leaf": [0.005, 0.01, 0.05, 0.10],"max_features": ['auto','sqrt','log2']
}
})
self.grid_params.update({"extra_tree_regressor": { "criterion": ['mse', 'friedman_mse', 'mae'], "max_depth": [2,3,4,5,6],
"max_features": ['auto','sqrt','log2']
}
})
self.grid_params.update({"svm_regressor": { "kernel": ['linear', 'poly', 'rbf','sigmoid'], "gamma": ['scale','auto'], "tol": [1e-03,1e-04,1e-05],
"C": [1.0, 0.1, 0.001,0.0001],"shrinking":[True,False]
}
})
self.grid_params.update({"adaBoost": { "base_estimator": [DecisionTreeRegressor(max_depth = x) for x in range(1,6)], "learning_rate": [0.001, 0.01, 0.05, 0.1, 0.25, 0.50, 0.75, 1.0],
"n_estimators": [100,200,300]
}
})
self.grid_params.update({"bagging": { "base_estimator": [DecisionTreeRegressor(max_depth = x) for x in range(1,6)], "n_estimators": [100,200,300],
"max_features": [0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]
}
})
self.grid_params.update({"random_forest": { "n_estimators": [100,200,300], "max_features": ["auto", "sqrt", "log2"],
"max_depth" : [3, 4, 5, 6, 7, 8],
"min_samples_split": [0.005, 0.01, 0.05, 0.10],
"min_samples_leaf": [0.005, 0.01, 0.05, 0.10]
}
})
self.grid_params.update({"extra_trees_regressor": { "n_estimators": [100,200,300], "criterion": ['mse', 'friedman_mse', 'mae'], "min_samples_split": [2, 3],
"max_features": ['auto','sqrt','log2']
}
})
self.grid_params.update({"gradient_boosting_regressor": {"learning_rate":[0.15,0.1,0.05,0.01,0.005,0.001],
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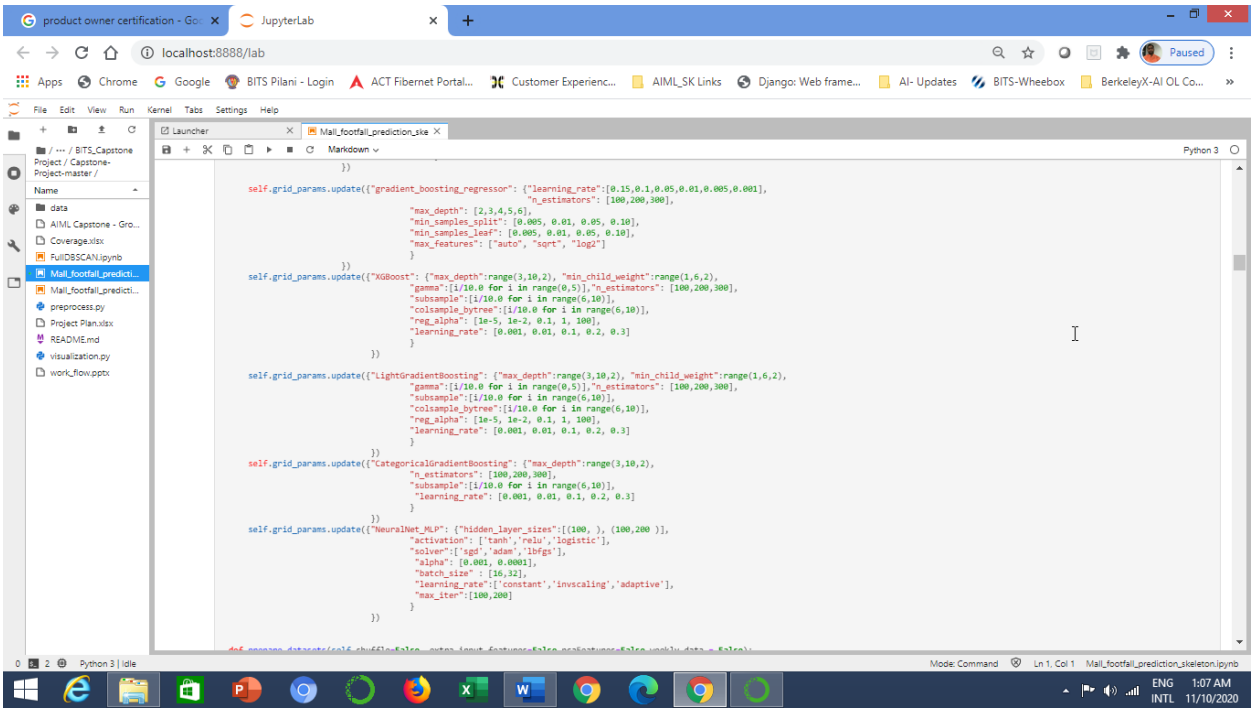
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self.grid_params.update({"gradient_boosting_regressor": {"learning_rate":[0.15,0.1,0.05,0.01,0.005,0.001],
"n_estimators": [100,200,300],
"max_depth": [2,3,4,5,6],
"min_samples_split": [0.005, 0.01, 0.05, 0.10],
"min_samples_leaf": [0.005, 0.01, 0.05, 0.10],
"max_features": ["auto", "sqrt", "log2"]
}
})
self.grid_params.update({"XGBoost": {"max_depth":range(3,10,2), "min_child_weight":range(1,6,2),
"gamma":[i/10.0 for i in range(0,5)],"n_estimators": [100,200,300],
"subsample":[i/10.0 for i in range(6,10)],
"colsample_bytree":[i/10.0 for i in range(6,10)],
"reg_alpha": [1e-5, 1e-2, 0.1, 1, 100],
"learning_rate": [0.001, 0.01, 0.1, 0.2, 0.3]
}
})
self.grid_params.update({"LightGradientBoosting": {"max_depth":range(3,10,2), "min_child_weight":range(1,6,2),
"gamma":[i/10.0 for i in range(0,5)],"n_estimators": [100,200,300],
"subsample":[i/10.0 for i in range(6,10)],
"colsample_bytree":[i/10.0 for i in range(6,10)],
"reg_alpha": [1e-5, 1e-2, 0.1, 1, 100],
"learning_rate": [0.001, 0.01, 0.1, 0.2, 0.3]
}
})
self.grid_params.update({"CategoricalGradientBoosting": {"max_depth":range(3,10,2),
"n_estimators": [100,200,300],
"subsample":[i/10.0 for i in range(6,10)],
"learning_rate": [0.001, 0.01, 0.1, 0.2, 0.3]
}
})
self.grid_params.update({"NeuralNet_MLP": {"hidden_layer_sizes":[(100, ), (100,200 )],
"activation": ['tanh','relu','logistic'],
"solver":['sgd','adam','lbfgs'],
"alpha": [0.001, 0.0001],
"batch_size" : [16,32],
"learning_rate":['constant','invscaling','adaptive'],
"max_iter":[100,200]
}
})
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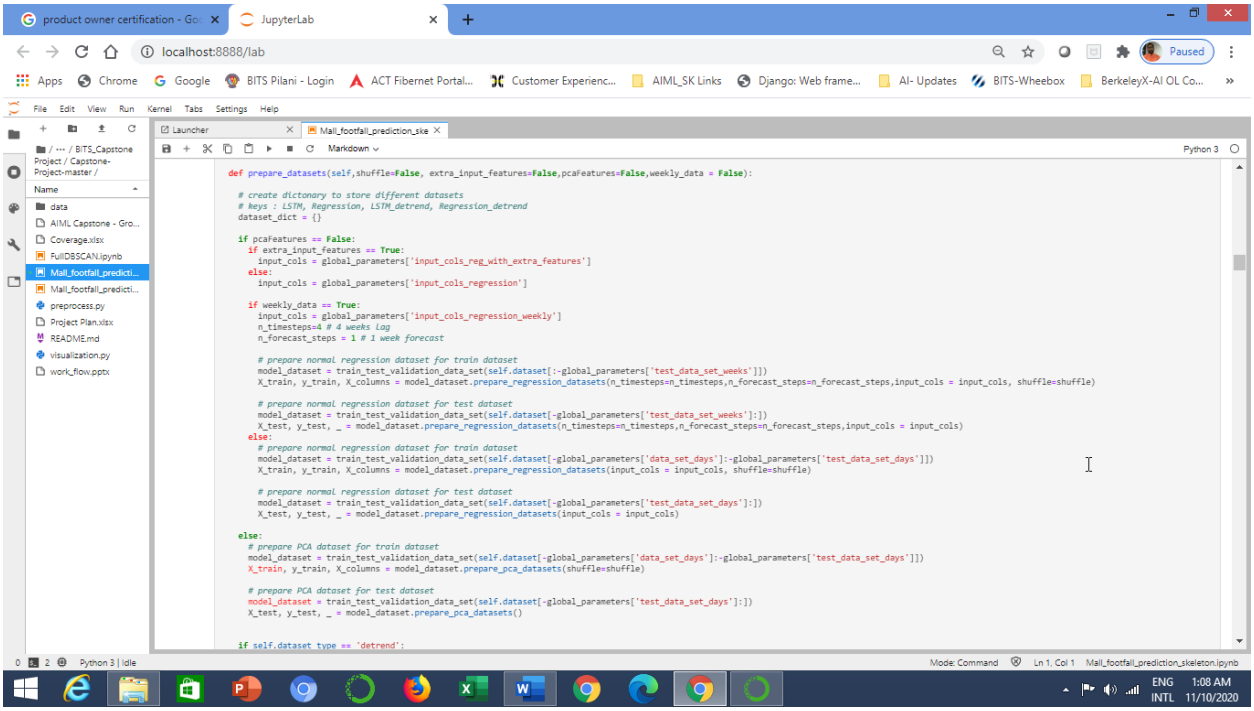


```
def prepare_datasets(self,shuffle=False, extra_input_features=False,pcaFeatures=False,weekly_data = False):

  # create dictonary to store different datasets
  # keys : LSTM, Regression, LSTM_detrend, Regression_detrend
  dataset_dict = {}

  if pcaFeatures == False:
    if extra_input_features == True:
      input_cols = global_parameters['input_cols_reg_with_extra_features']
    else:
      input_cols = global_parameters['input_cols_regression']

    if weekly_data == True:
      input_cols = global_parameters['input_cols_regression_weekly']
      n_timesteps=4 # 4 weeks lag
      n_forecast_steps = 1 # 1 week forecast

      # prepare normal regression dataset for train dataset
      model_dataset = train_test_validation_data_set(self.dataset[:-global_parameters['test_data_set_weeks']])
      X_train, y_train, X_columns = model_dataset.prepare_regression_datasets(n_timesteps=n_timesteps,n_forecast_steps=n_forecast_steps,input_cols = input_cols, shuffle=shuffle)

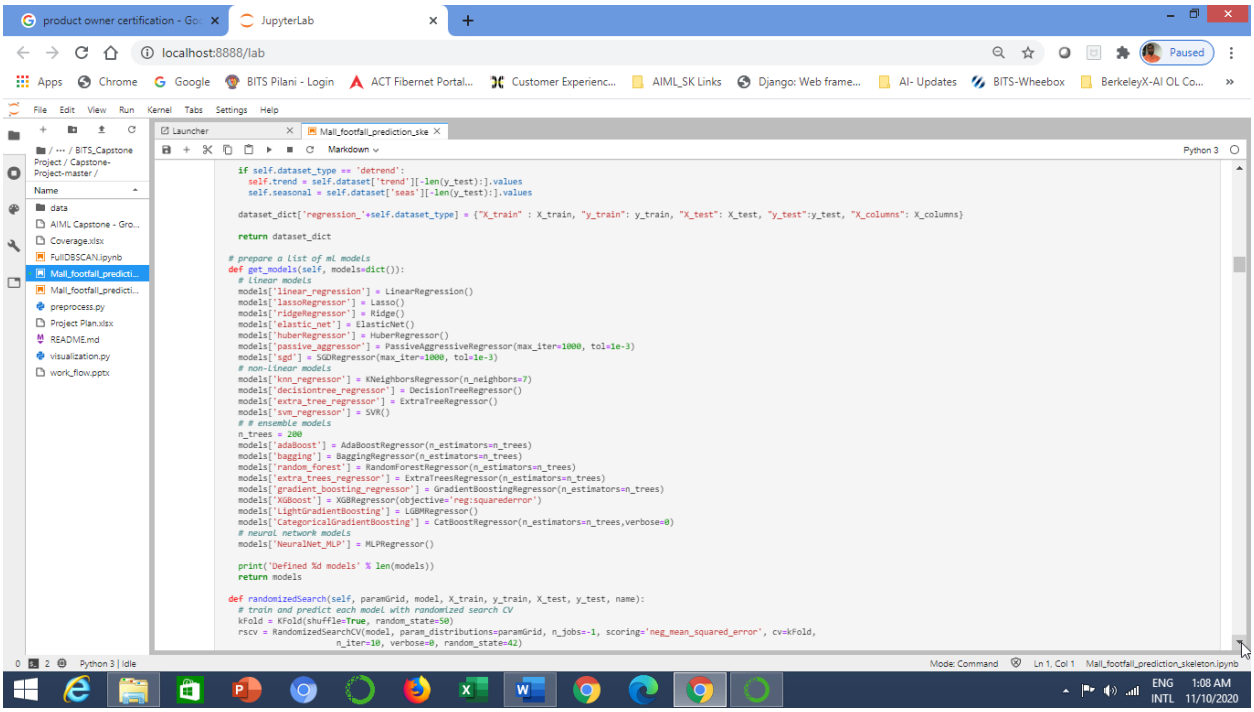
      # prepare normal regression dataset for test dataset
      model_dataset = train_test_validation_data_set(self.dataset[-global_parameters['test_data_set_weeks']:])
      X_test, y_test, _ = model_dataset.prepare_regression_datasets(n_timesteps=n_timesteps,n_forecast_steps=n_forecast_steps,input_cols = input_cols)
    else:
      # prepare normal regression dataset for train dataset
      model_dataset = train_test_validation_data_set(self.dataset[-global_parameters['data_set_days']:-global_parameters['test_data_set_days']])
      X_train, y_train, X_columns = model_dataset.prepare_regression_datasets(input_cols = input_cols, shuffle=shuffle)

      # prepare normal regression dataset for test dataset
      model_dataset = train_test_validation_data_set(self.dataset[-global_parameters['test_data_set_days']:])
      X_test, y_test, _ = model_dataset.prepare_regression_datasets(input_cols = input_cols)

  else:
    # prepare PCA dataset for train dataset
    model_dataset = train_test_validation_data_set(self.dataset[-global_parameters['data_set_days']:-global_parameters['test_data_set_days']])
    X_train, y_train, X_columns = model_dataset.prepare_pca_datasets(shuffle=shuffle)

    # prepare PCA dataset for test dataset
    model_dataset = train_test_validation_data_set(self.dataset[-global_parameters['test_data_set_days']:])
    X_test, y_test, _ = model_dataset.prepare_pca_datasets()


  if self.dataset_type == 'detrend':
```



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  if self.dataset_type == 'detrend':
    self.trend = self.dataset['trend'][-len(y_test):].values
    self.seasonal = self.dataset['seas'][-len(y_test):].values

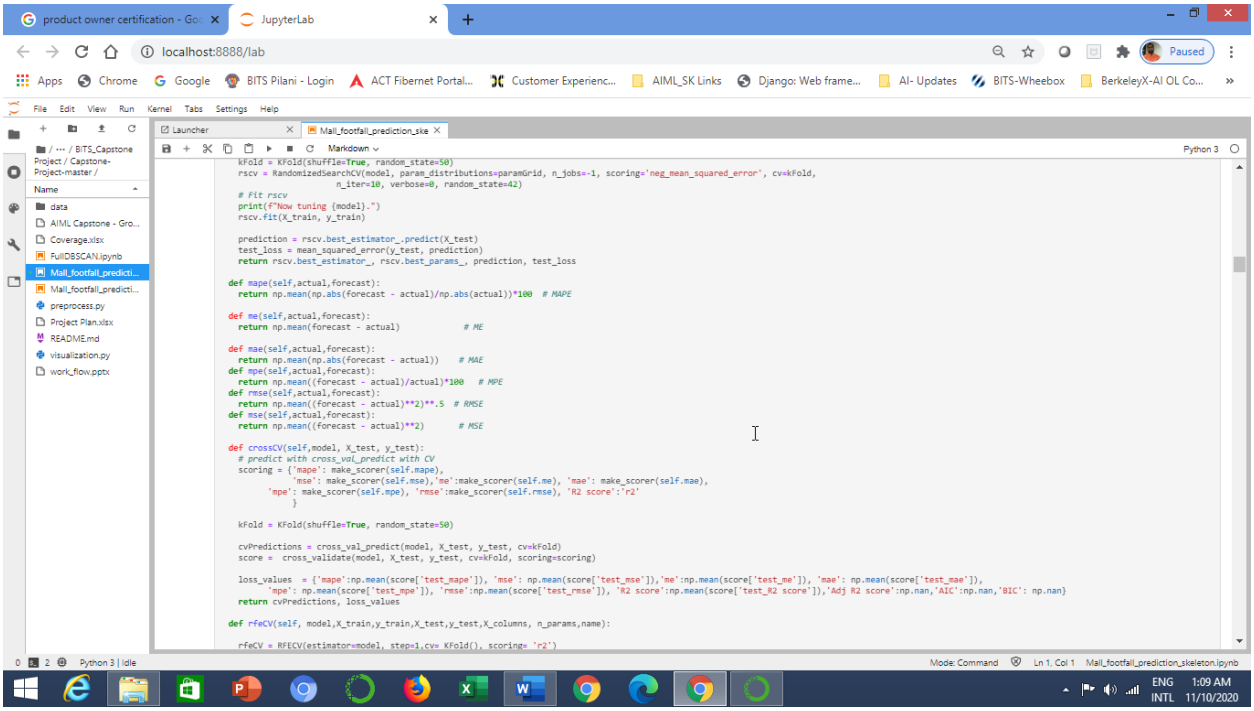
  dataset_dict['regression_'+self.dataset_type] = {"X_train" : X_train, "y_train": y_train, "X_test": X_test, "y_test":y_test, "X_columns": X_columns}

  return dataset_dict

# prepare a list of ml models
def get_models(self, models=dict()):
  # linear models
  models['linear_regression'] = LinearRegression()
  models['lassoRegressor'] = Lasso()
  models['ridgeRegressor'] = Ridge()
  models['elastic_net'] = ElasticNet()
  models['huberRegressor'] = HuberRegressor()
  models['passive_aggressor'] = PassiveAggressiveRegressor(max_iter=1000, tol=1e-3)
  models['sgd'] = SGDRegressor(max_iter=1000, tol=1e-3)
  # non-linear models
  models['knn_regressor'] = KNeighborsRegressor(n_neighbors=7)
  models['decisiontree_regressor'] = DecisionTreeRegressor()
  models['extra_tree_regressor'] = ExtraTreeRegressor()
  models['svm_regressor'] = SVR()
  # # ensemble models
  n_trees = 200
  models['adaBoost'] = AdaBoostRegressor(n_estimators=n_trees)
  models['bagging'] = BaggingRegressor(n_estimators=n_trees)
  models['random_forest'] = RandomForestRegressor(n_estimators=n_trees)
  models['extra_trees_regressor'] = ExtraTreesRegressor(n_estimators=n_trees)
  models['gradient_boosting_regressor'] = GradientBoostingRegressor(n_estimators=n_trees)
  models['XGBoost'] = XGBRegressor(objective='reg:squarederror')
  models['LightGradientBoosting'] = LGBMRegressor()
  models['CategoricalGradientBoosting'] = CatBoostRegressor(n_estimators=n_trees,verbose=0)
  # neural network models
  models['NeuralNet_MLP'] = MLPRegressor()

  print('Defined %d models' % len(models))
  return models

def randomizedSearch(self, paramGrid, model, X_train, y_train, X_test, y_test, name):
  # train and predict each model with randomized search CV
  kFold = KFold(shuffle=True, random_state=50)
  rscv = RandomizedSearchCV(model, param_distributions=paramGrid, n_jobs=-1, scoring='neg_mean_squared_error', cv=kFold,
                            n_iter=10, verbose=0, random_state=42)
```



```
    kFold = KFold(shuffle=True, random_state=50)
    rscv = RandomizedSearchCV(model, param_distributions=paramGrid, n_jobs=-1, scoring='neg_mean_squared_error', cv=kFold,
                              n_iter=10, verbose=0, random_state=42)

    # Fit rscv
    print(f"Now tuning {model}.")
    rscv.fit(X_train, y_train)

    prediction = rscv.best_estimator_.predict(X_test)
    test_loss = mean_squared_error(y_test, prediction)
    return rscv.best_estimator_, rscv.best_params_, prediction, test_loss

  def mape(self,actual,forecast):
    return np.mean(np.abs(forecast - actual)/np.abs(actual))*100  # MAPE

  def me(self,actual,forecast):
    return np.mean(forecast - actual)             # ME

  def mae(self,actual,forecast):
    return np.mean(np.abs(forecast - actual))    # MAE
  def mpe(self,actual,forecast):
    return np.mean((forecast - actual)/actual)*100   # MPE
  def rmse(self,actual,forecast):
    return np.mean((forecast - actual)**2)**.5  # RMSE
  def mse(self,actual,forecast):
    return np.mean((forecast - actual)**2)       # MSE

  def crossCV(self,model, X_test, y_test):
    # predict with cross_val_predict with CV
    scoring = {'mape': make_scorer(self.mape),
               'mse': make_scorer(self.mse),'me':make_scorer(self.me), 'mae': make_scorer(self.mae),
          'mpe': make_scorer(self.mpe), 'rmse':make_scorer(self.rmse), 'R2 score':'r2'
               }

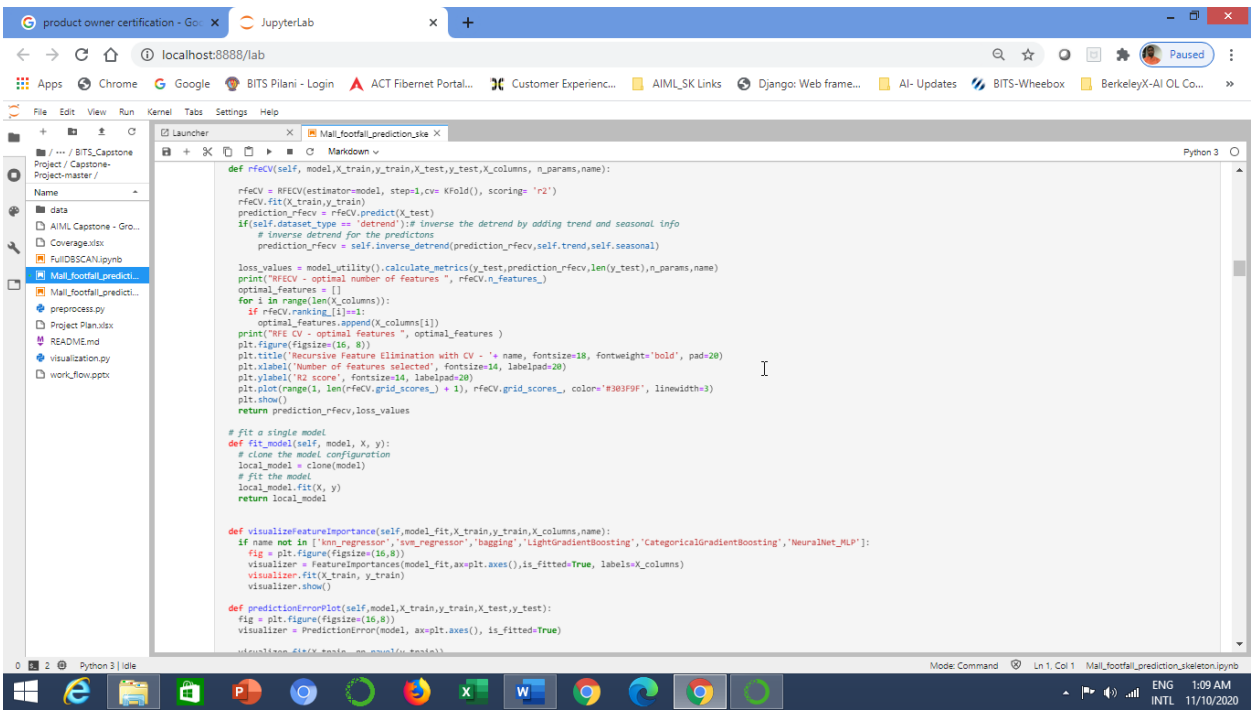
    kFold = KFold(shuffle=True, random_state=50)

    cvPredictions = cross_val_predict(model, X_test, y_test, cv=kFold)
    score =  cross_validate(model, X_test, y_test, cv=kFold, scoring=scoring)

    loss_values  = {'mape':np.mean(score['test_mape']), 'mse': np.mean(score['test_mse']),'me':np.mean(score['test_me']), 'mae': np.mean(score['test_mae']),
            'mpe': np.mean(score['test_mpe']), 'rmse':np.mean(score['test_rmse']), 'R2 score':np.mean(score['test_R2 score']),'Adj R2 score':np.nan,'AIC':np.nan,'BIC': np.nan}
    return cvPredictions, loss_values

  def rfeCV(self, model,X_train,y_train,X_test,y_test,X_columns, n_params,name):

    rfeCV = RFECV(estimator=model, step=1,cv= KFold(), scoring= 'r2')
```



```
  def rfeCV(self, model,X_train,y_train,X_test,y_test,X_columns, n_params,name):

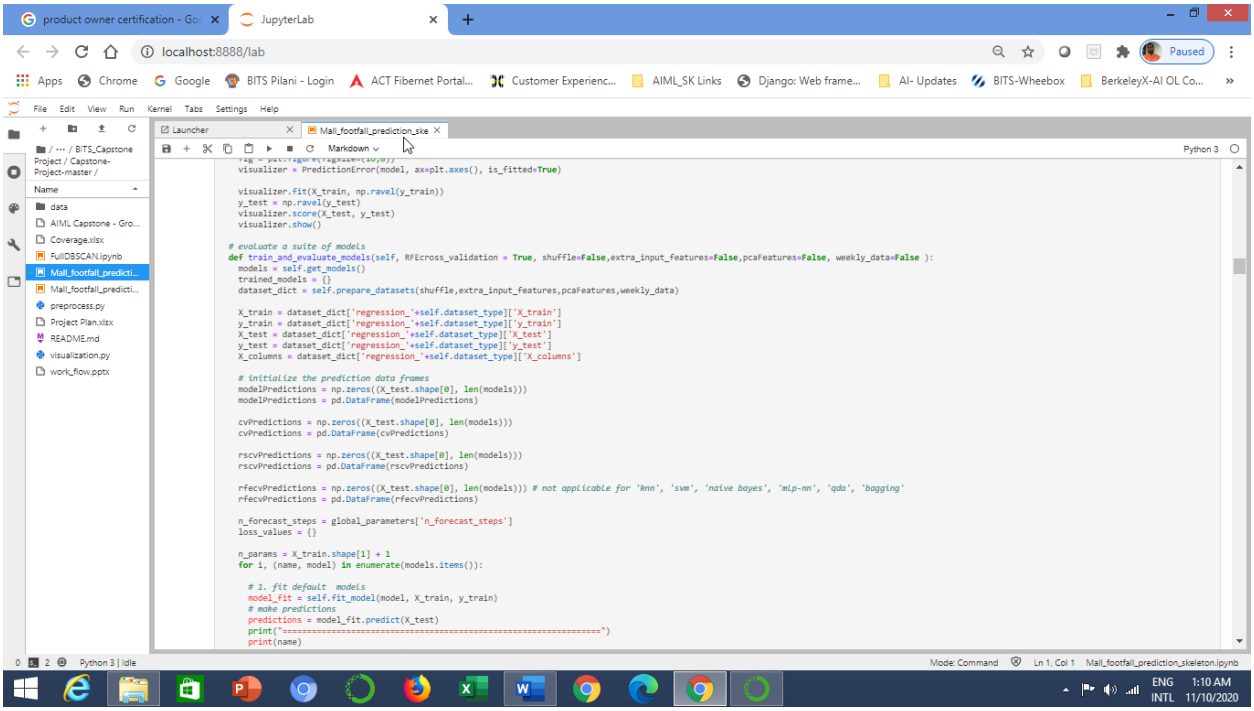
    rfeCV = RFECV(estimator=model, step=1,cv= KFold(), scoring= 'r2')
    rfeCV.fit(X_train,y_train)
    prediction_rfecv = rfeCV.predict(X_test)
    if(self.dataset_type == 'detrend'):# inverse the detrend by adding trend and seasonal info
        # inverse detrend for the predictons
        prediction_rfecv = self.inverse_detrend(prediction_rfecv,self.trend,self.seasonal)

    loss_values = model_utility().calculate_metrics(y_test,prediction_rfecv,len(y_test),n_params,name)
    print("RFECV - optimal number of features ", rfeCV.n_features_)
    optimal_features = []
    for i in range(len(X_columns)):
      if rfeCV.ranking_[i]==1:
        optimal_features.append(X_columns[i])
    print("RFE CV - optimal features ", optimal_features )
    plt.figure(figsize=(16, 8))
    plt.title('Recursive Feature Elimination with CV - '+ name, fontsize=18, fontweight='bold', pad=20)
    plt.xlabel('Number of features selected', fontsize=14, labelpad=20)
    plt.ylabel('R2 score', fontsize=14, labelpad=20)
    plt.plot(range(1, len(rfeCV.grid_scores_) + 1), rfeCV.grid_scores_, color='#303F9F', linewidth=3)
    plt.show()
    return prediction_rfecv,loss_values

  # fit a single model
  def fit_model(self, model, X, y):
    # clone the model configuration
    local_model = clone(model)
    # fit the model
    local_model.fit(X, y)
    return local_model


  def visualizeFeatureImportance(self,model_fit,X_train,y_train,X_columns,name):
    if name not in ['knn_regressor','svm_regressor','bagging','LightGradientBoosting','CategoricalGradientBoosting','NeuralNet_MLP']:
      fig = plt.figure(figsize=(16,8))
      visualizer = FeatureImportances(model_fit,ax=plt.axes(),is_fitted=True, labels=X_columns)
      visualizer.fit(X_train, y_train)
      visualizer.show()

  def predictionErrorPlot(self,model,X_train,y_train,X_test,y_test):
    fig = plt.figure(figsize=(16,8))
    visualizer = PredictionError(model, ax=plt.axes(), is_fitted=True)
```



```
visualizer = PredictionError(model, ax=plt.axes(), is_fitted=True)

visualizer.fit(X_train, np.ravel(y_train))
y_test = np.ravel(y_test)
visualizer.score(X_test, y_test)
visualizer.show()

# evaluate a suite of models
def train_and_evaluate_models(self, RFEcross_validation = True, shuffle=False,extra_input_features=False,pcaFeatures=False, weekly_data=False ):
  models = self.get_models()
  trained_models = {}
  dataset_dict = self.prepare_datasets(shuffle,extra_input_features,pcaFeatures,weekly_data)

  X_train = dataset_dict['regression_'+self.dataset_type]['X_train']
  y_train = dataset_dict['regression_'+self.dataset_type]['y_train']
  X_test = dataset_dict['regression_'+self.dataset_type]['X_test']
  y_test = dataset_dict['regression_'+self.dataset_type]['y_test']
  X_columns = dataset_dict['regression_'+self.dataset_type]['X_columns']

  # initialize the prediction data frames
  modelPredictions = np.zeros((X_test.shape[0], len(models)))
  modelPredictions = pd.DataFrame(modelPredictions)

  cvPredictions = np.zeros((X_test.shape[0], len(models)))
  cvPredictions = pd.DataFrame(cvPredictions)

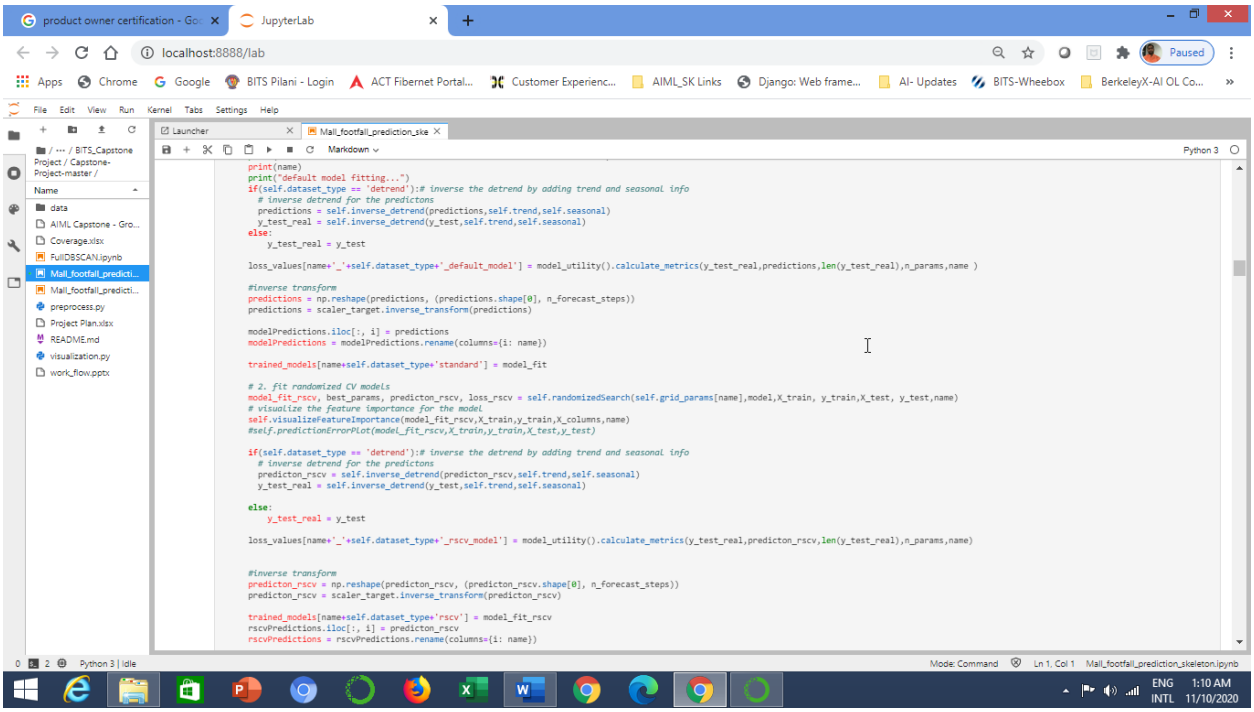
  rscvPredictions = np.zeros((X_test.shape[0], len(models)))
  rscvPredictions = pd.DataFrame(rscvPredictions)

  rfecvPredictions = np.zeros((X_test.shape[0], len(models))) # not applicable for 'knn', 'svm', 'naive bayes', 'mlp-nn', 'qda', 'bagging'
  rfecvPredictions = pd.DataFrame(rfecvPredictions)

  n_forecast_steps = global_parameters['n_forecast_steps']
  loss_values = {}

  n_params = X_train.shape[1] + 1
  for i, (name, model) in enumerate(models.items()):

    # 1. fit default  models
    model_fit = self.fit_model(model, X_train, y_train)
    # make predictions
    predictions = model_fit.predict(X_test)
    print("==========================================================")
    print(name)
```



```
    print(name)
    print("default model fitting...")
    if(self.dataset_type == 'detrend'):# inverse the detrend by adding trend and seasonal info
      # inverse detrend for the predictons
      predictions = self.inverse_detrend(predictions,self.trend,self.seasonal)
      y_test_real = self.inverse_detrend(y_test,self.trend,self.seasonal)
    else:
        y_test_real = y_test

    loss_values[name+'_'+self.dataset_type+'_default_model'] = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),n_params,name )

    #inverse transform
    predictions = np.reshape(predictions, (predictions.shape[0], n_forecast_steps))
    predictions = scaler_target.inverse_transform(predictions)

    modelPredictions.iloc[:, i] = predictions
    modelPredictions = modelPredictions.rename(columns={i: name})

    trained_models[name+self.dataset_type+'standard'] = model_fit

    # 2. fit randomized CV models
    model_fit_rscv, best_params, predicton_rscv, loss_rscv = self.randomizedSearch(self.grid_params[name],model,X_train, y_train,X_test, y_test,name)
    # visualize the feature importance for the model
    self.visualizeFeatureImportance(model_fit_rscv,X_train,y_train,X_columns,name)
    #self.predictionErrorPlot(model_fit_rscv,X_train,y_train,X_test,y_test)

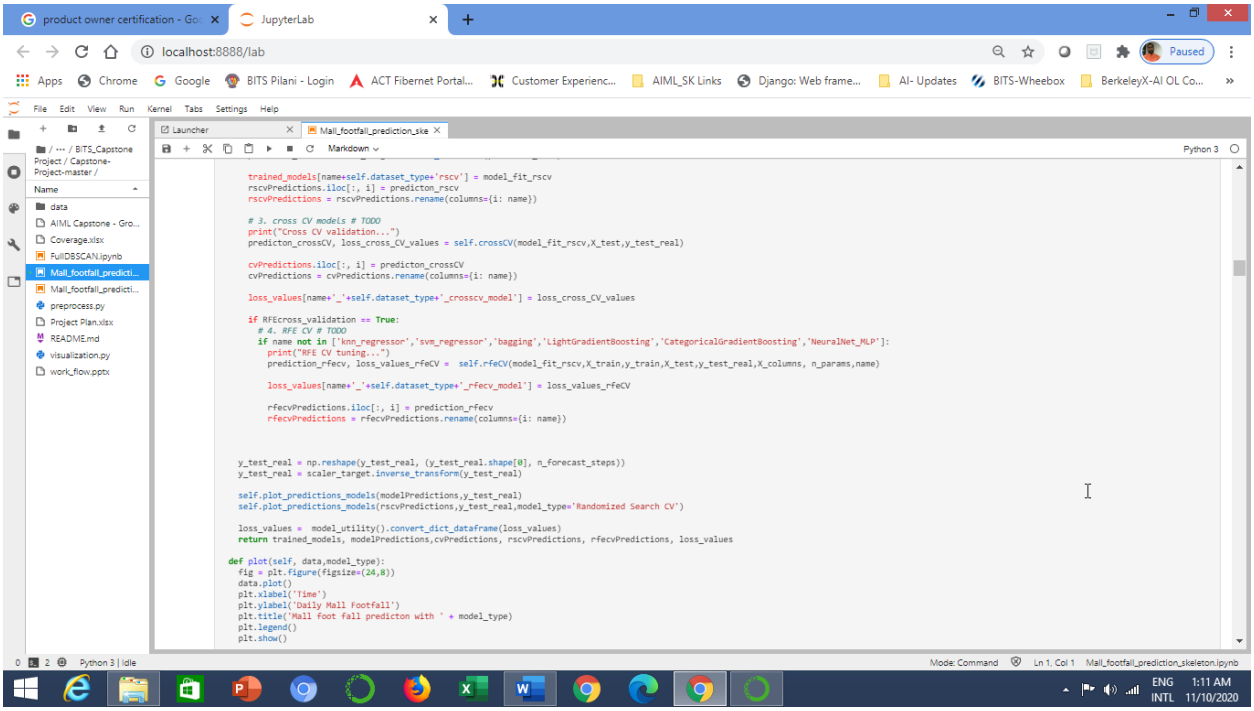
    if(self.dataset_type == 'detrend'):# inverse the detrend by adding trend and seasonal info
      # inverse detrend for the predictons
      predicton_rscv = self.inverse_detrend(predicton_rscv,self.trend,self.seasonal)
      y_test_real = self.inverse_detrend(y_test,self.trend,self.seasonal)

    else:
        y_test_real = y_test

    loss_values[name+'_'+self.dataset_type+'_rscv_model'] = model_utility().calculate_metrics(y_test_real,predicton_rscv,len(y_test_real),n_params,name)


    #inverse transform
    predicton_rscv = np.reshape(predicton_rscv, (predicton_rscv.shape[0], n_forecast_steps))
    predicton_rscv = scaler_target.inverse_transform(predicton_rscv)

    trained_models[name+self.dataset_type+'rscv'] = model_fit_rscv
    rscvPredictions.iloc[:, i] = predicton_rscv
    rscvPredictions = rscvPredictions.rename(columns={i: name})
```



```
        trained_models[name+self.dataset_type+'rscv'] = model_fit_rscv
        rscvPredictions.iloc[:, i] = predicton_rscv
        rscvPredictions = rscvPredictions.rename(columns={i: name})

        # 3. cross CV models # TODO
        print("Cross CV validation...")
        predicton_crossCV, loss_cross_CV_values = self.crossCV(model_fit_rscv,X_test,y_test_real)

        cvPredictions.iloc[:, i] = predicton_crossCV
        cvPredictions = cvPredictions.rename(columns={i: name})

        loss_values[name+'_'+self.dataset_type+'_crosscv_model'] = loss_cross_CV_values

        if RFEcross_validation == True:
          # 4. RFE CV # TODO
          if name not in ['knn_regressor','svm_regressor','bagging','LightGradientBoosting','CategoricalGradientBoosting','NeuralNet_MLP']:
            print("RFE CV tuning...")
            prediction_rfecv, loss_values_rfeCV =  self.rfeCV(model_fit_rscv,X_train,y_train,X_test,y_test_real,X_columns, n_params,name)

            loss_values[name+'_'+self.dataset_type+'_rfecv_model'] = loss_values_rfeCV

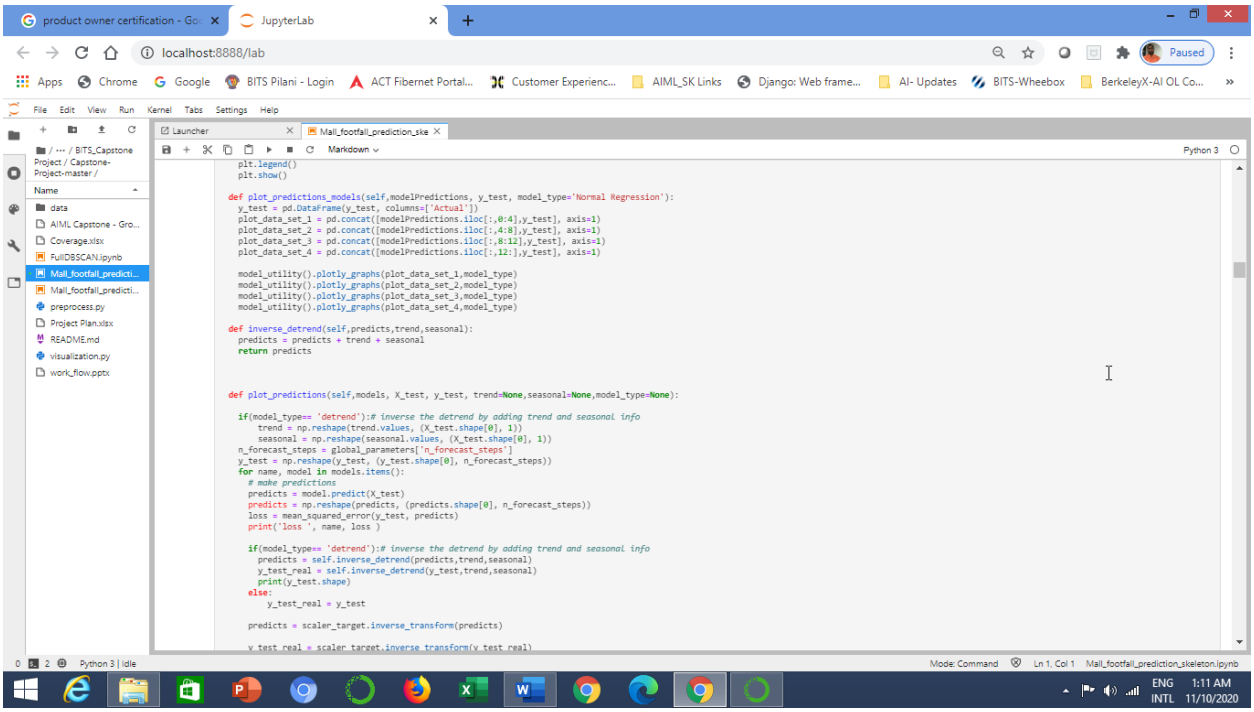
            rfecvPredictions.iloc[:, i] = prediction_rfecv
            rfecvPredictions = rfecvPredictions.rename(columns={i: name})


      y_test_real = np.reshape(y_test_real, (y_test_real.shape[0], n_forecast_steps))
      y_test_real = scaler_target.inverse_transform(y_test_real)

      self.plot_predictions_models(modelPredictions,y_test_real)
      self.plot_predictions_models(rscvPredictions,y_test_real,model_type='Randomized Search CV')

      loss_values =  model_utility().convert_dict_dataframe(loss_values)
      return trained_models, modelPredictions,cvPredictions, rscvPredictions, rfecvPredictions, loss_values

    def plot(self, data,model_type):
      fig = plt.figure(figsize=(24,8))
      data.plot()
      plt.xlabel('Time')
      plt.ylabel('Daily Mall Footfall')
      plt.title('Mall foot fall predicton with ' + model_type)
      plt.legend()
      plt.show()
```



```
      plt.legend()
      plt.show()

    def plot_predictions_models(self,modelPredictions, y_test, model_type='Normal Regression'):
      y_test = pd.DataFrame(y_test, columns=['Actual'])
      plot_data_set_1 = pd.concat([modelPredictions.iloc[:,0:4],y_test], axis=1)
      plot_data_set_2 = pd.concat([modelPredictions.iloc[:,4:8],y_test], axis=1)
      plot_data_set_3 = pd.concat([modelPredictions.iloc[:,8:12],y_test], axis=1)
      plot_data_set_4 = pd.concat([modelPredictions.iloc[:,12:],y_test], axis=1)

      model_utility().plotly_graphs(plot_data_set_1,model_type)
      model_utility().plotly_graphs(plot_data_set_2,model_type)
      model_utility().plotly_graphs(plot_data_set_3,model_type)
      model_utility().plotly_graphs(plot_data_set_4,model_type)

    def inverse_detrend(self,predicts,trend,seasonal):
      predicts = predicts + trend + seasonal
      return predicts

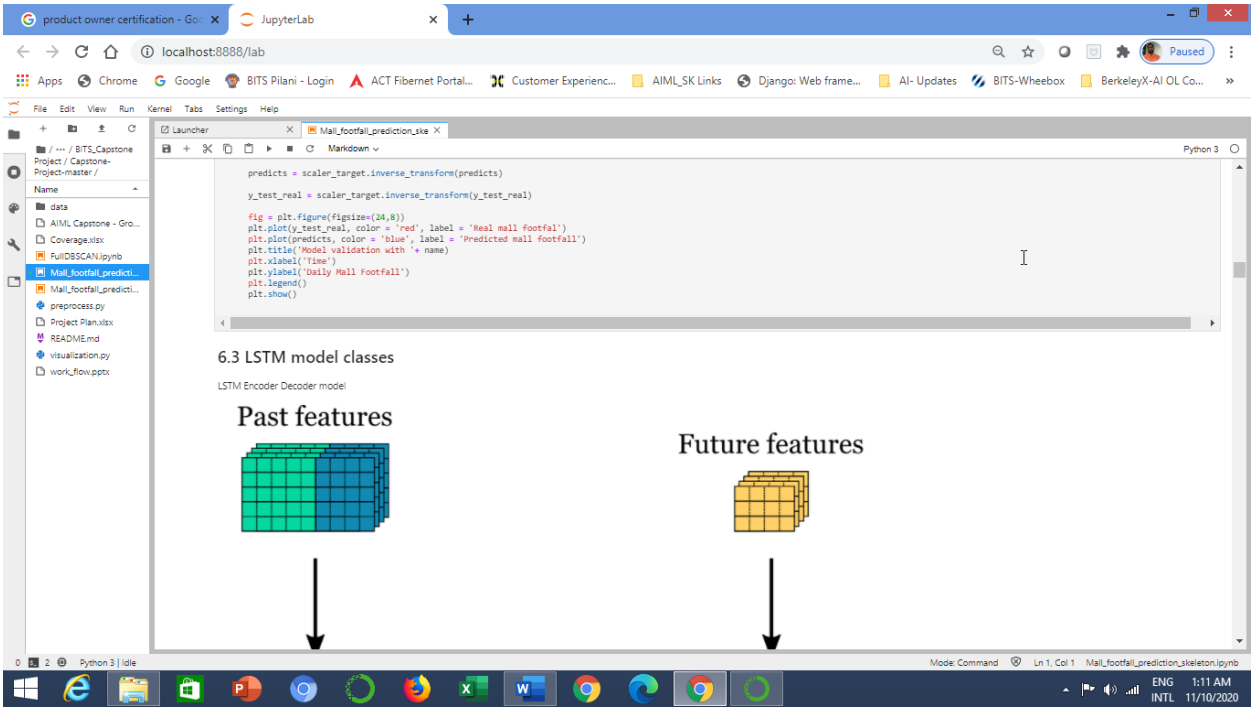

    def plot_predictions(self,models, X_test, y_test, trend=None,seasonal=None,model_type=None):

      if(model_type== 'detrend'):# inverse the detrend by adding trend and seasonal info
          trend = np.reshape(trend.values, (X_test.shape[0], 1))
          seasonal = np.reshape(seasonal.values, (X_test.shape[0], 1))
      n_forecast_steps = global_parameters['n_forecast_steps']
      y_test = np.reshape(y_test, (y_test.shape[0], n_forecast_steps))
      for name, model in models.items():
        # make predictions
        predicts = model.predict(X_test)
        predicts = np.reshape(predicts, (predicts.shape[0], n_forecast_steps))
        loss = mean_squared_error(y_test, predicts)
        print('loss ', name, loss )

        if(model_type== 'detrend'):# inverse the detrend by adding trend and seasonal info
          predicts = self.inverse_detrend(predicts,trend,seasonal)
          y_test_real = self.inverse_detrend(y_test,trend,seasonal)
          print(y_test.shape)
        else:
            y_test_real = y_test

        predicts = scaler_target.inverse_transform(predicts)

        y_test_real = scaler_target.inverse_transform(y_test_real)
```


product owner certification - Go
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Python 3
predicts = scaler_target.inverse_transform(predicts)
y_test_real = scaler_target.inverse_transform(y_test_real)
fig = plt.figure(figsize=(24,8))
plt.plot(y_test_real, color = 'red', label = 'Real mall footfal')
plt.plot(predicts, color = 'blue', label = 'Predicted mall footfall')
plt.title('Model validation with ' + name)
plt.xlabel('Time')
plt.ylabel('Daily Mall Footfall')
plt.legend()
plt.show()
6.3 LSTM model classes
LSTM Encoder Decoder model
Past features
Future features
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
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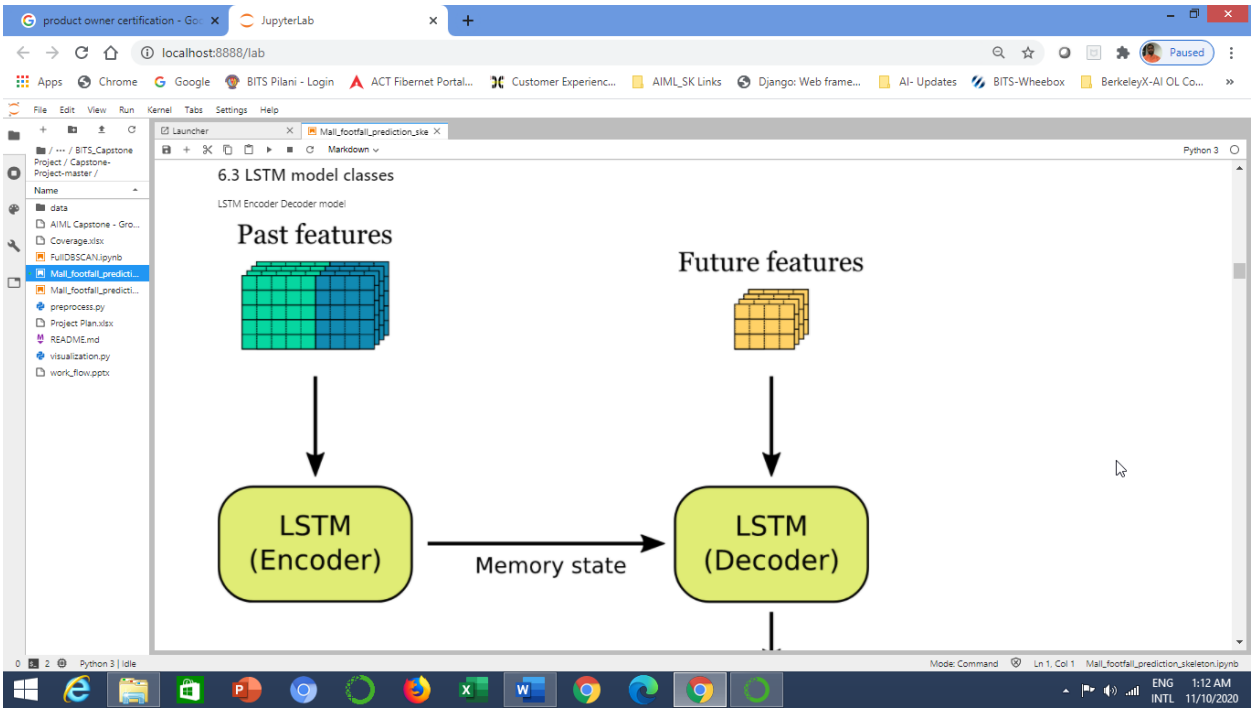
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ACT Fibernet Portal...
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AI- Updates
BITS-Wheebox
BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
6.3 LSTM model classes
LSTM Encoder Decoder model
Past features
Future features
LSTM (Encoder)
Memory state
LSTM (Decoder)
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
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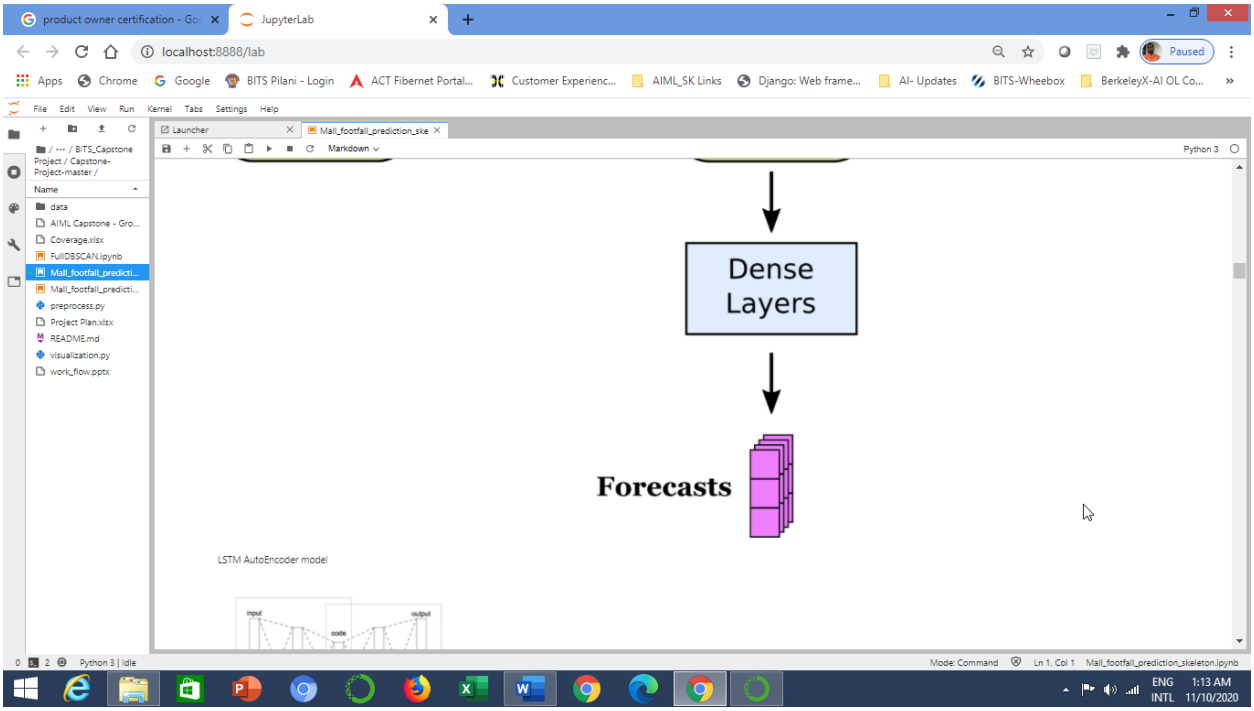
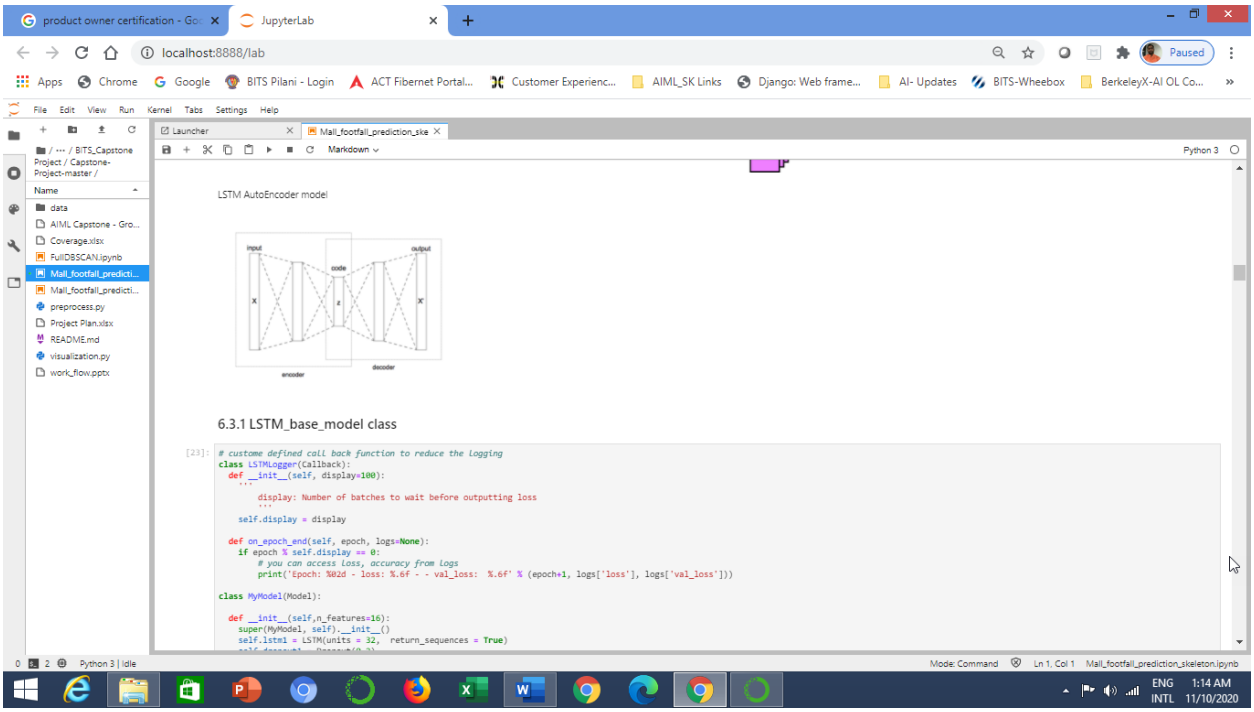
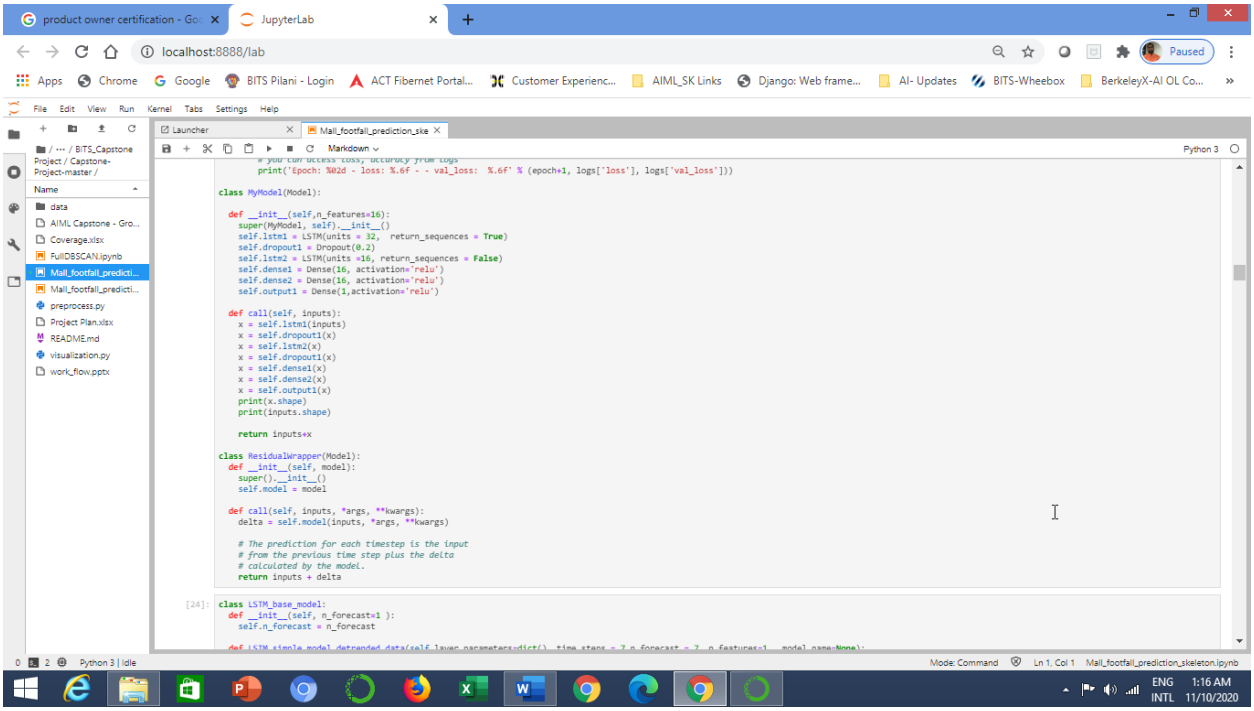

Dense Layers
Forecasts
LSTM AutoEncoder model


LSTM AutoEncoder model
6.3.1 LSTM_base_model class
# custome defined call back function to reduce the logging
class LSTMLogger(Callback):
def __init__(self, display=100):
display: Number of batches to wait before outputting loss
self.display = display
def on_epoch_end(self, epoch, logs=None):
if epoch % self.display == 0:
# you can access loss, accuracy from logs
print('Epoch: %02d - loss: %.6f - - val_loss: %.6f' % (epoch+1, logs['loss'], logs['val_loss']))
class MyModel(Model):
def __init__(self,n_features=16):
super(MyModel, self).__init__()
self.lstm1 = LSTM(units = 32, return_sequences = True)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Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
print('Epoch: %02d - loss: %.6f - - val_loss: %.6f' % (epoch+1, logs['loss'], logs['val_loss']))
class MyModel(Model):
def __init__(self,n_features=16):
super(MyModel, self).__init__()
self.lstm1 = LSTM(units = 32, return_sequences = True)
self.dropout1 = Dropout(0.2)
self.lstm2 = LSTM(units =16, return_sequences = False)
self.dense1 = Dense(16, activation='relu')
self.dense2 = Dense(16, activation='relu')
self.output1 = Dense(1,activation='relu')
def call(self, inputs):
x = self.lstm1(inputs)
x = self.dropout1(x)
x = self.lstm2(x)
x = self.dropout1(x)
x = self.dense1(x)
x = self.dense2(x)
x = self.output1(x)
print(x.shape)
print(inputs.shape)
return inputs+x
class ResidualWrapper(Model):
def __init__(self, model):
super().__init__()
self.model = model
def call(self, inputs, *args, **kwargs):
delta = self.model(inputs, *args, **kwargs)
# The prediction for each timestep is the input
# from the previous time step plus the delta
# calculated by the model.
return inputs + delta
[24]:
class LSTM_base_model:
def __init__(self, n_forecast=1 ):
self.n_forecast = n_forecast
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
Python 3 | Idle
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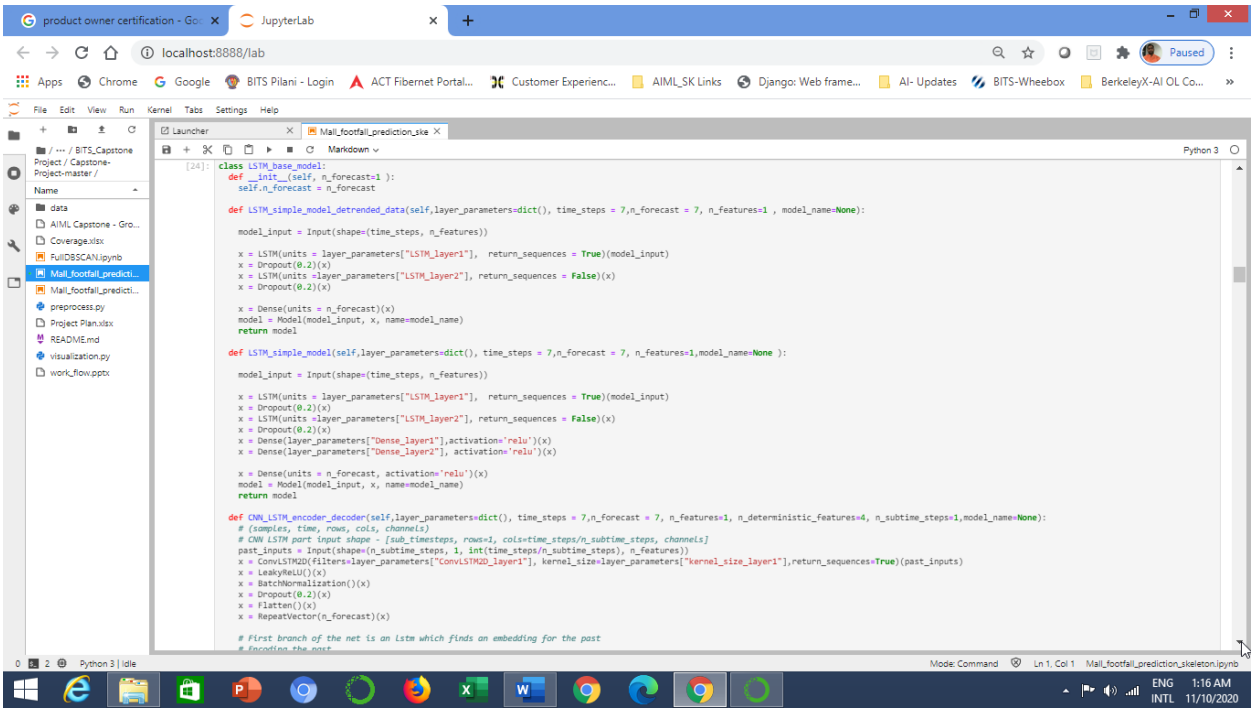
11/10/2020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AI- Updates
BITS-Wheebox
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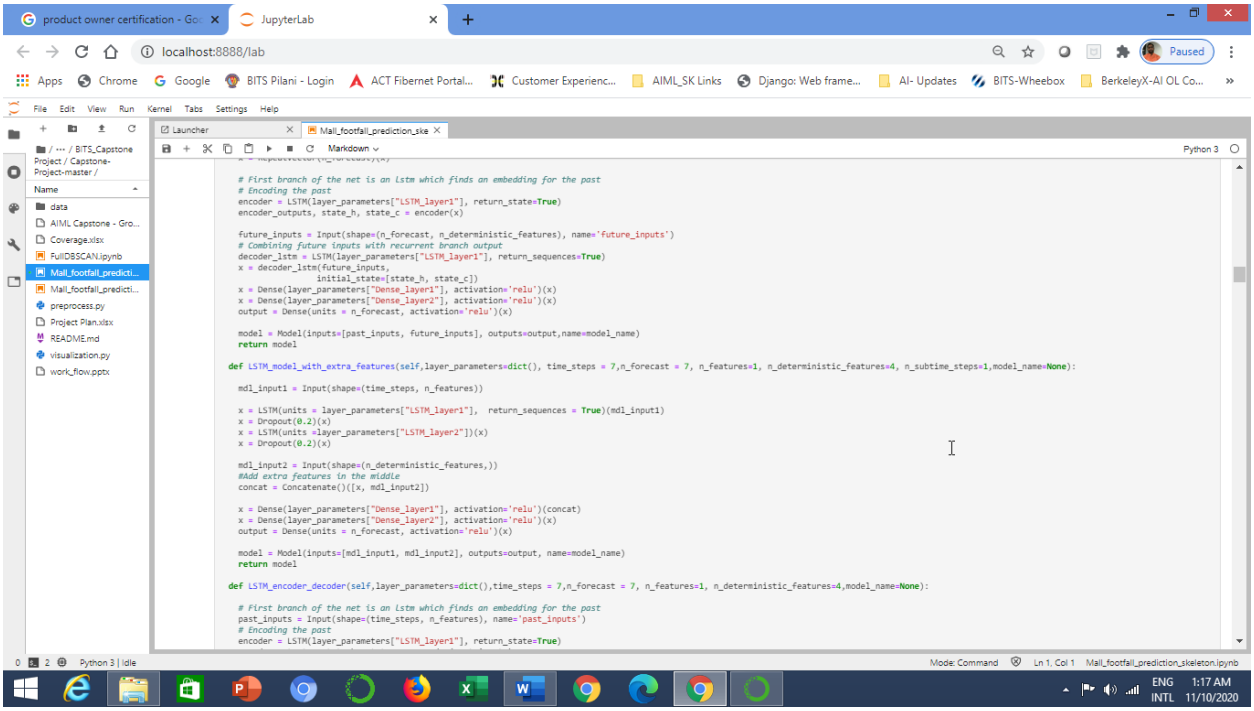
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
[24]:
class LSTM_base_model:
def __init__(self, n_forecast=1 ):
self.n_forecast = n_forecast
def LSTM_simple_model_detrended_data(self,layer_parameters=dict(), time_steps = 7,n_forecast = 7, n_features=1 , model_name=None):
model_input = Input(shape=(time_steps, n_features))
x = LSTM(units = layer_parameters["LSTM_layer1"], return_sequences = True)(model_input)
x = Dropout(0.2)(x)
x = LSTM(units =layer_parameters["LSTM_layer2"], return_sequences = False)(x)
x = Dropout(0.2)(x)
x = Dense(units = n_forecast)(x)
model = Model(model_input, x, name=model_name)
return model
def LSTM_simple_model(self,layer_parameters=dict(), time_steps = 7,n_forecast = 7, n_features=1,model_name=None ):
model_input = Input(shape=(time_steps, n_features))
x = LSTM(units = layer_parameters["LSTM_layer1"], return_sequences = True)(model_input)
x = Dropout(0.2)(x)
x = LSTM(units =layer_parameters["LSTM_layer2"], return_sequences = False)(x)
x = Dropout(0.2)(x)
x = Dense(layer_parameters["Dense_layer1"],activation='relu')(x)
x = Dense(layer_parameters["Dense_layer2"], activation='relu')(x)
x = Dense(units = n_forecast, activation='relu')(x)
model = Model(model_input, x, name=model_name)
return model
def CNN_LSTM_encoder_decoder(self,layer_parameters=dict(), time_steps = 7,n_forecast = 7, n_features=1, n_deterministic_features=4, n_subtime_steps=1,model_name=None):
# (samples, time, rows, cols, channels)
# CNN LSTM part input shape - [sub_timesteps, rows=1, cols=time_steps/n_subtime_steps, channels]
past_inputs = Input(shape=(n_subtime_steps, 1, int(time_steps/n_subtime_steps), n_features))
x = ConvLSTM2D(filters=layer_parameters["ConvLSTM2D_layer1"], kernel_size=layer_parameters["kernel_size_layer1"],return_sequences=True)(past_inputs)
x = LeakyReLU()(x)
x = BatchNormalization()(x)
x = Dropout(0.2)(x)
x = Flatten()(x)
x = RepeatVector(n_forecast)(x)
# First branch of the net is an lstm which finds an embedding for the past
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
Python 3 | Idle
ENG
INTL
1:16 AM
11/10/2020



```
    # First branch of the net is an Lstm which finds an embedding for the past
    # Encoding the past
    encoder = LSTM(layer_parameters["LSTM_layer1"], return_state=True)
    encoder_outputs, state_h, state_c = encoder(x)

    future_inputs = Input(shape=(n_forecast, n_deterministic_features), name='future_inputs')
    # Combining future inputs with recurrent branch output
    decoder_lstm = LSTM(layer_parameters["LSTM_layer1"], return_sequences=True)
    x = decoder_lstm(future_inputs,
                     initial_state=[state_h, state_c])
    x = Dense(layer_parameters["Dense_layer1"], activation='relu')(x)
    x = Dense(layer_parameters["Dense_layer2"], activation='relu')(x)
    output = Dense(units = n_forecast, activation='relu')(x)

    model = Model(inputs=[past_inputs, future_inputs], outputs=output,name=model_name)
    return model

def LSTM_model_with_extra_features(self,layer_parameters=dict(), time_steps = 7,n_forecast = 7, n_features=1, n_deterministic_features=4, n_subtime_steps=1,model_name=None):

    mdl_input1 = Input(shape=(time_steps, n_features))

    x = LSTM(units = layer_parameters["LSTM_layer1"],  return_sequences = True)(mdl_input1)
    x = Dropout(0.2)(x)
    x = LSTM(units =layer_parameters["LSTM_layer2"])(x)
    x = Dropout(0.2)(x)

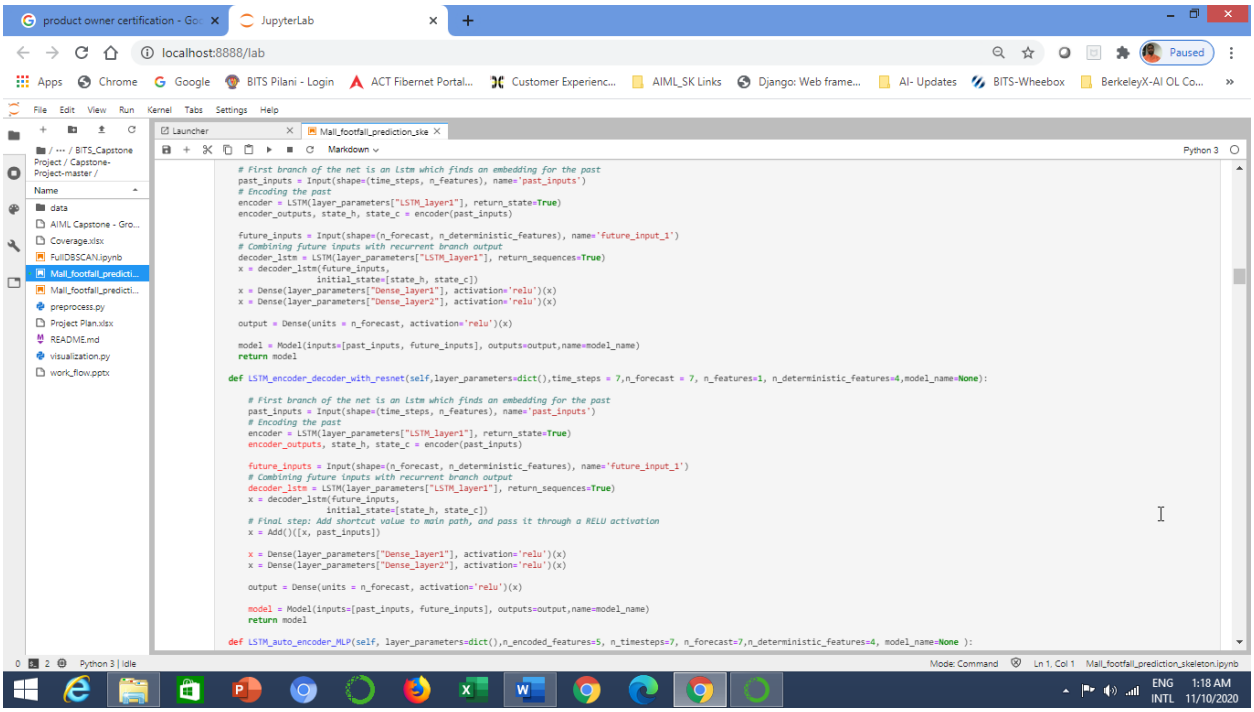
    mdl_input2 = Input(shape=(n_deterministic_features,))
    #Add extra features in the middle
    concat = Concatenate()([x, mdl_input2])

    x = Dense(layer_parameters["Dense_layer1"], activation='relu')(concat)
    x = Dense(layer_parameters["Dense_layer2"], activation='relu')(x)
    output = Dense(units = n_forecast, activation='relu')(x)

    model = Model(inputs=[mdl_input1, mdl_input2], outputs=output, name=model_name)
    return model

def LSTM_encoder_decoder(self,layer_parameters=dict(),time_steps = 7,n_forecast = 7, n_features=1, n_deterministic_features=4,model_name=None):

    # First branch of the net is an Lstm which finds an embedding for the past
    past_inputs = Input(shape=(time_steps, n_features), name='past_inputs')
    # Encoding the past
    encoder = LSTM(layer_parameters["LSTM_layer1"], return_state=True)
```



```
    # First branch of the net is an Lstm which finds an embedding for the past
    past_inputs = Input(shape=(time_steps, n_features), name='past_inputs')
    # Encoding the past
    encoder = LSTM(layer_parameters["LSTM_layer1"], return_state=True)
    encoder_outputs, state_h, state_c = encoder(past_inputs)

    future_inputs = Input(shape=(n_forecast, n_deterministic_features), name='future_input_1')
    # Combining future inputs with recurrent branch output
    decoder_lstm = LSTM(layer_parameters["LSTM_layer1"], return_sequences=True)
    x = decoder_lstm(future_inputs,
                     initial_state=[state_h, state_c])
    x = Dense(layer_parameters["Dense_layer1"], activation='relu')(x)
    x = Dense(layer_parameters["Dense_layer2"], activation='relu')(x)

    output = Dense(units = n_forecast, activation='relu')(x)

    model = Model(inputs=[past_inputs, future_inputs], outputs=output,name=model_name)
    return model

def LSTM_encoder_decoder_with_resnet(self,layer_parameters=dict(),time_steps = 7,n_forecast = 7, n_features=1, n_deterministic_features=4,model_name=None):

    # First branch of the net is an Lstm which finds an embedding for the past
    past_inputs = Input(shape=(time_steps, n_features), name='past_inputs')
    # Encoding the past
    encoder = LSTM(layer_parameters["LSTM_layer1"], return_state=True)
    encoder_outputs, state_h, state_c = encoder(past_inputs)

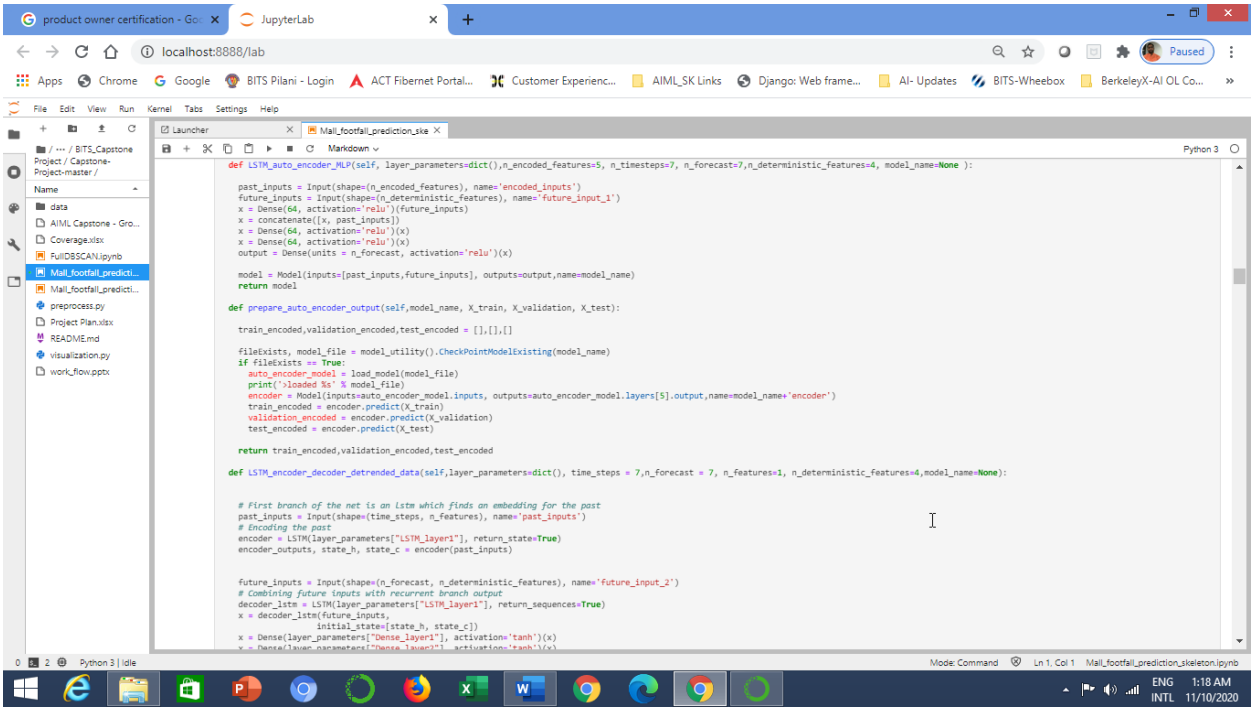
    future_inputs = Input(shape=(n_forecast, n_deterministic_features), name='future_input_1')
    # Combining future inputs with recurrent branch output
    decoder_lstm = LSTM(layer_parameters["LSTM_layer1"], return_sequences=True)
    x = decoder_lstm(future_inputs,
                     initial_state=[state_h, state_c])
    # Final step: Add shortcut value to main path, and pass it through a RELU activation
    x = Add()([x, past_inputs])

    x = Dense(layer_parameters["Dense_layer1"], activation='relu')(x)
    x = Dense(layer_parameters["Dense_layer2"], activation='relu')(x)

    output = Dense(units = n_forecast, activation='relu')(x)

    model = Model(inputs=[past_inputs, future_inputs], outputs=output,name=model_name)
    return model

def LSTM_auto_encoder_MLP(self, layer_parameters=dict(),n_encoded_features=5, n_timesteps=7, n_forecast=7,n_deterministic_features=4, model_name=None ):
```



```
def LSTM_auto_encoder_MLP(self, layer_parameters=dict(),n_encoded_features=5, n_timesteps=7, n_forecast=7,n_deterministic_features=4, model_name=None ):

  past_inputs = Input(shape=(n_encoded_features), name='encoded_inputs')
  future_inputs = Input(shape=(n_deterministic_features), name='future_input_1')
  x = Dense(64, activation='relu')(future_inputs)
  x = concatenate([x, past_inputs])
  x = Dense(64, activation='relu')(x)
  x = Dense(64, activation='relu')(x)
  output = Dense(units = n_forecast, activation='relu')(x)

  model = Model(inputs=[past_inputs,future_inputs], outputs=output,name=model_name)
  return model

def prepare_auto_encoder_output(self,model_name, X_train, X_validation, X_test):

  train_encoded,validation_encoded,test_encoded = [],[],[]

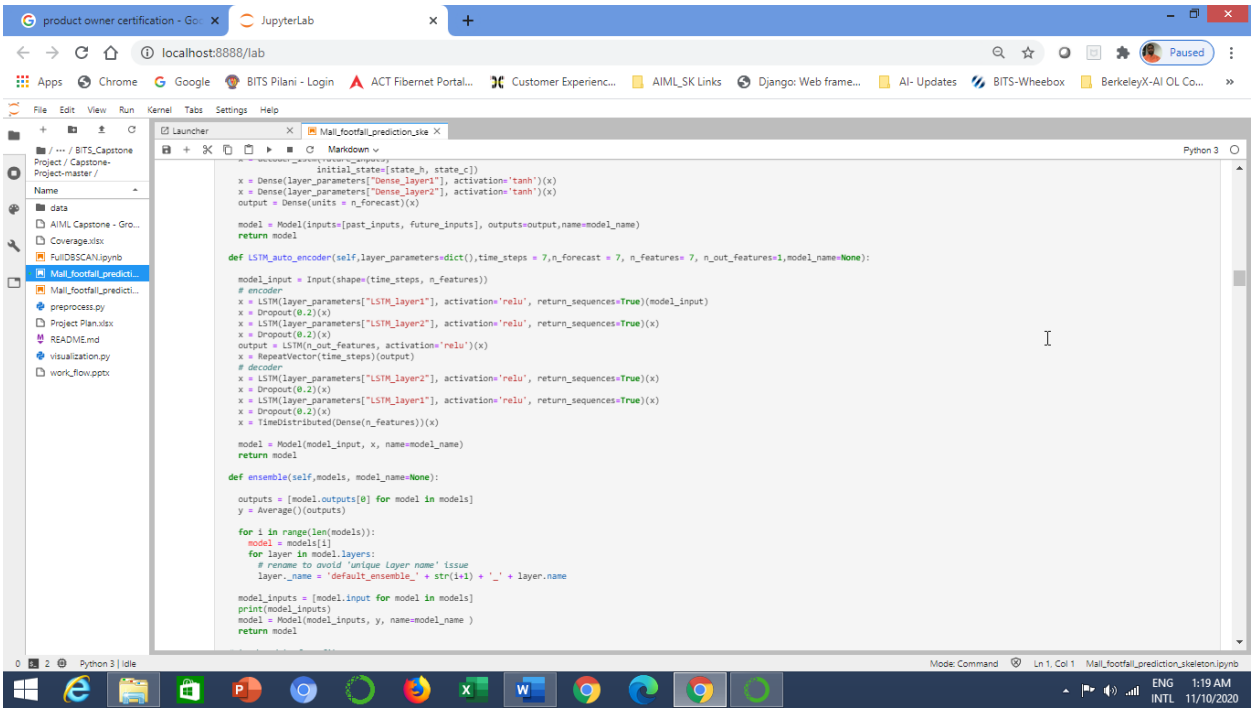
  fileExists, model_file = model_utility().CheckPointModelExisting(model_name)
  if fileExists == True:
    auto_encoder_model = load_model(model_file)
    print('>loaded %s' % model_file)
    encoder = Model(inputs=auto_encoder_model.inputs, outputs=auto_encoder_model.layers[5].output,name=model_name+'encoder')
    train_encoded = encoder.predict(X_train)
    validation_encoded = encoder.predict(X_validation)
    test_encoded = encoder.predict(X_test)

  return train_encoded,validation_encoded,test_encoded

def LSTM_encoder_decoder_detrended_data(self,layer_parameters=dict(), time_steps = 7,n_forecast = 7, n_features=1, n_deterministic_features=4,model_name=None):


  # First branch of the net is an lstm which finds an embedding for the past
  past_inputs = Input(shape=(time_steps, n_features), name='past_inputs')
  # Encoding the past
  encoder = LSTM(layer_parameters["LSTM_layer1"], return_state=True)
  encoder_outputs, state_h, state_c = encoder(past_inputs)


  future_inputs = Input(shape=(n_forecast, n_deterministic_features), name='future_input_2')
  # Combining future inputs with recurrent branch output
  decoder_lstm = LSTM(layer_parameters["LSTM_layer1"], return_sequences=True)
  x = decoder_lstm(future_inputs,
                   initial_state=[state_h, state_c])
  x = Dense(layer_parameters["Dense_layer1"], activation='tanh')(x)
  x = Dense(layer_parameters["Dense_layer2"], activation='tanh')(x)
```



```
                   initial_state=[state_h, state_c])
  x = Dense(layer_parameters["Dense_layer1"], activation='tanh')(x)
  x = Dense(layer_parameters["Dense_layer2"], activation='tanh')(x)
  output = Dense(units = n_forecast)(x)

  model = Model(inputs=[past_inputs, future_inputs], outputs=output,name=model_name)
  return model

def LSTM_auto_encoder(self,layer_parameters=dict(),time_steps = 7,n_forecast = 7, n_features= 7, n_out_features=1,model_name=None):

  model_input = Input(shape=(time_steps, n_features))
  # encoder
  x = LSTM(layer_parameters["LSTM_layer1"], activation='relu', return_sequences=True)(model_input)
  x = Dropout(0.2)(x)
  x = LSTM(layer_parameters["LSTM_layer2"], activation='relu', return_sequences=True)(x)
  x = Dropout(0.2)(x)
  output = LSTM(n_out_features, activation='relu')(x)
  x = RepeatVector(time_steps)(output)
  # decoder
  x = LSTM(layer_parameters["LSTM_layer2"], activation='relu', return_sequences=True)(x)
  x = Dropout(0.2)(x)
  x = LSTM(layer_parameters["LSTM_layer1"], activation='relu', return_sequences=True)(x)
  x = Dropout(0.2)(x)
  x = TimeDistributed(Dense(n_features))(x)

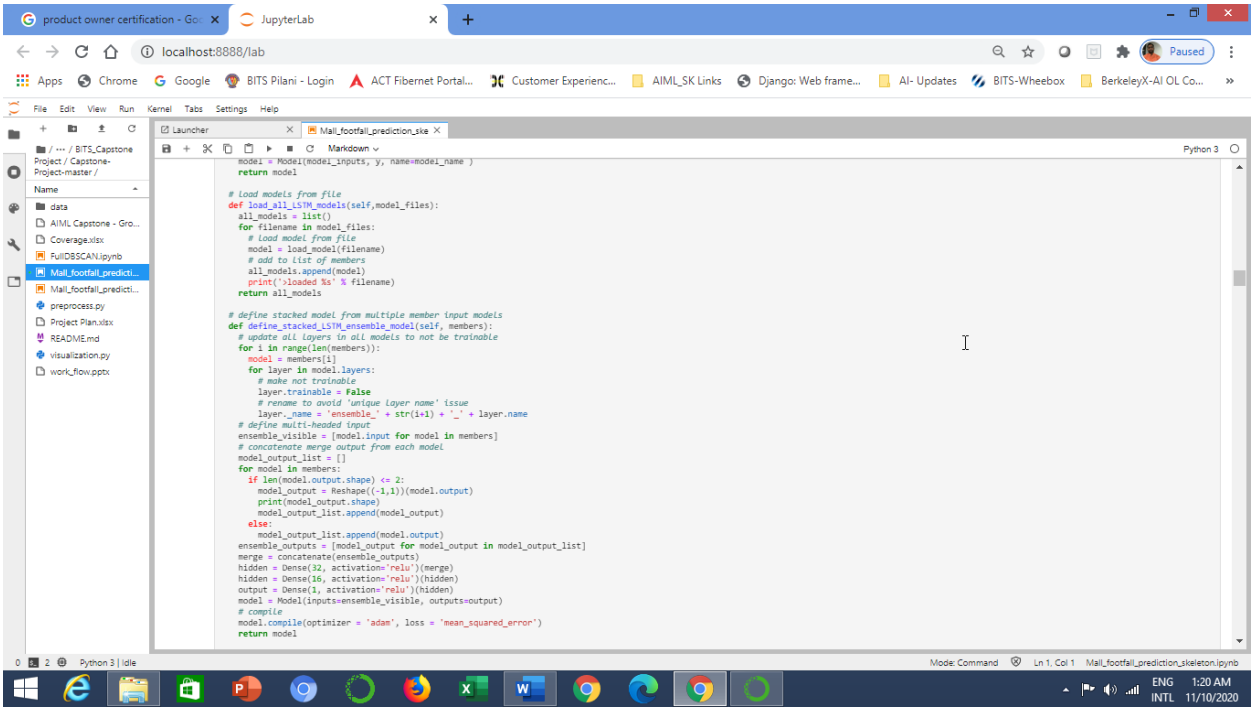
  model = Model(model_input, x, name=model_name)
  return model

def ensemble(self,models, model_name=None):

  outputs = [model.outputs[0] for model in models]
  y = Average()(outputs)

  for i in range(len(models)):
    model = models[i]
    for layer in model.layers:
      # rename to avoid 'unique layer name' issue
      layer._name = 'default_ensemble_' + str(i+1) + '_' + layer.name

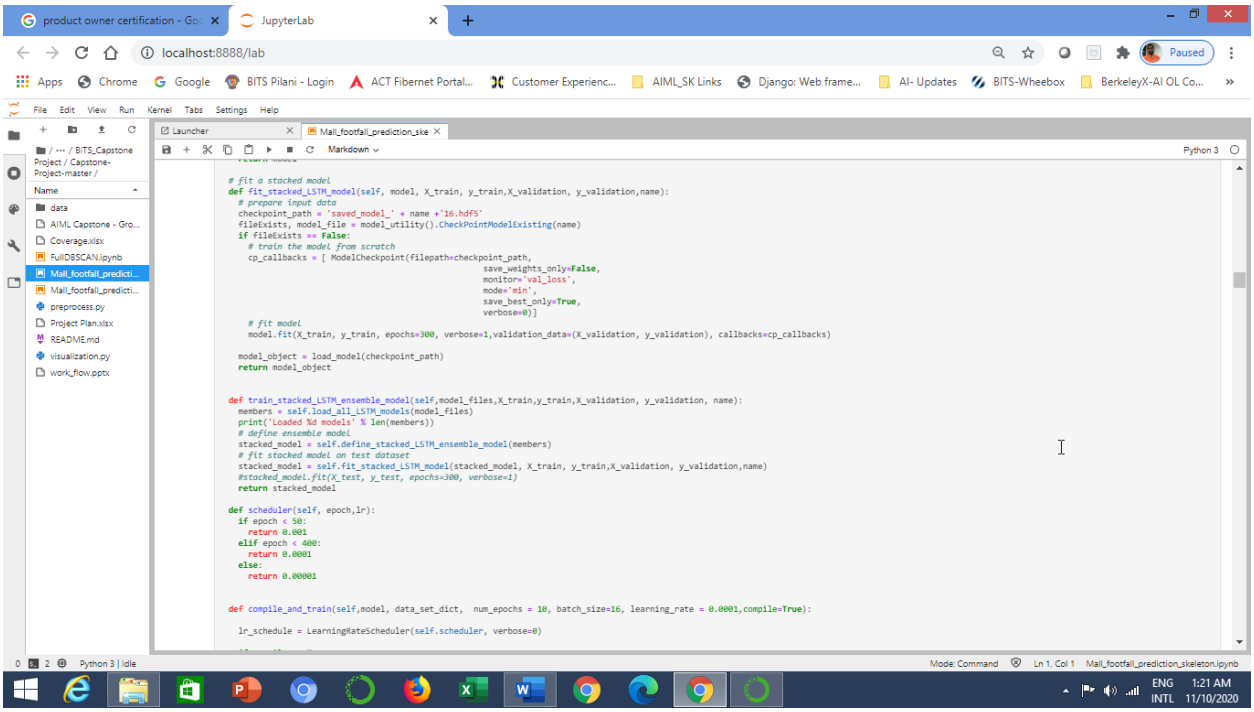
  model_inputs = [model.input for model in models]
  print(model_inputs)
  model = Model(model_inputs, y, name=model_name )
  return model
```



```
    model = Model(model_inputs, y, name=model_name )
    return model

  # Load models from file
  def load_all_LSTM_models(self,model_files):
    all_models = list()
    for filename in model_files:
      # Load model from file
      model = load_model(filename)
      # add to list of members
      all_models.append(model)
      print('>loaded %s' % filename)
    return all_models

  # define stacked model from multiple member input models
  def define_stacked_LSTM_ensemble_model(self, members):
    # update all layers in all models to not be trainable
    for i in range(len(members)):
      model = members[i]
      for layer in model.layers:
        # make not trainable
        layer.trainable = False
        # rename to avoid 'unique layer name' issue
        layer._name = 'ensemble_' + str(i+1) + '_' + layer.name
    # define multi-headed input
    ensemble_visible = [model.input for model in members]
    # concatenate merge output from each model
    model_output_list = []
    for model in members:
      if len(model.output.shape) <= 2:
        model_output = Reshape((-1,1))(model.output)
        print(model_output.shape)
        model_output_list.append(model_output)
      else:
        model_output_list.append(model.output)
    ensemble_outputs = [model_output for model_output in model_output_list]
    merge = concatenate(ensemble_outputs)
    hidden = Dense(32, activation='relu')(merge)
    hidden = Dense(16, activation='relu')(hidden)
    output = Dense(1, activation='relu')(hidden)
    model = Model(inputs=ensemble_visible, outputs=output)
    # compile
    model.compile(optimizer = 'adam', loss = 'mean_squared_error')
    return model
```



```
    return model

  # fit a stacked model
  def fit_stacked_LSTM_model(self, model, X_train, y_train,X_validation, y_validation,name):
    # prepare input data
    checkpoint_path = 'saved_model_' + name +'16.hdf5'
    fileExists, model_file = model_utility().CheckPointModelExisting(name)
    if fileExists == False:
      # train the model from scratch
      cp_callbacks = [ ModelCheckpoint(filepath=checkpoint_path,
                                       save_weights_only=False,
                                       monitor='val_loss',
                                       mode='min',
                                       save_best_only=True,
                                       verbose=0)]

      # fit model
      model.fit(X_train, y_train, epochs=300, verbose=1,validation_data=(X_validation, y_validation), callbacks=cp_callbacks)

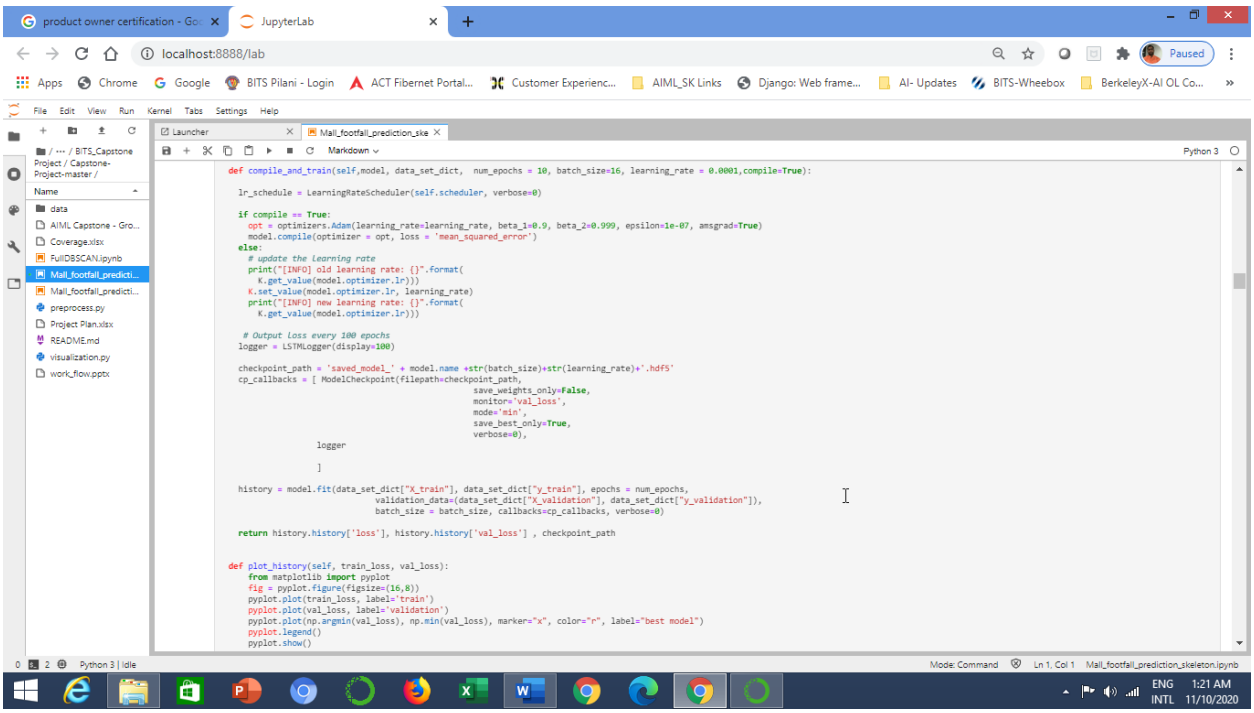
    model_object = load_model(checkpoint_path)
    return model_object


  def train_stacked_LSTM_ensemble_model(self,model_files,X_train,y_train,X_validation, y_validation, name):
    members = self.load_all_LSTM_models(model_files)
    print('Loaded %d models' % len(members))
    # define ensemble model
    stacked_model = self.define_stacked_LSTM_ensemble_model(members)
    # fit stacked model on test dataset
    stacked_model = self.fit_stacked_LSTM_model(stacked_model, X_train, y_train,X_validation, y_validation,name)
    #stacked_model.fit(X_test, y_test, epochs=300, verbose=1)
    return stacked_model

  def scheduler(self, epoch,lr):
    if epoch < 50:
      return 0.001
    elif epoch < 400:
      return 0.0001
    else:
      return 0.00001


  def compile_and_train(self,model, data_set_dict,  num_epochs = 10, batch_size=16, learning_rate = 0.0001,compile=True):

    lr_schedule = LearningRateScheduler(self.scheduler, verbose=0)
```



```
def compile_and_train(self,model, data_set_dict,  num_epochs = 10, batch_size=16, learning_rate = 0.0001,compile=True):

  lr_schedule = LearningRateScheduler(self.scheduler, verbose=0)

  if compile == True:
    opt = optimizers.Adam(learning_rate=learning_rate, beta_1=0.9, beta_2=0.999, epsilon=1e-07, amsgrad=True)
    model.compile(optimizer = opt, loss = 'mean_squared_error')
  else:
    # update the learning rate
    print("[INFO] old learning rate: {}".format(
      K.get_value(model.optimizer.lr)))
    K.set_value(model.optimizer.lr, learning_rate)
    print("[INFO] new learning rate: {}".format(
      K.get_value(model.optimizer.lr)))

  # Output Loss every 100 epochs
  logger = LSTMLogger(display=100)

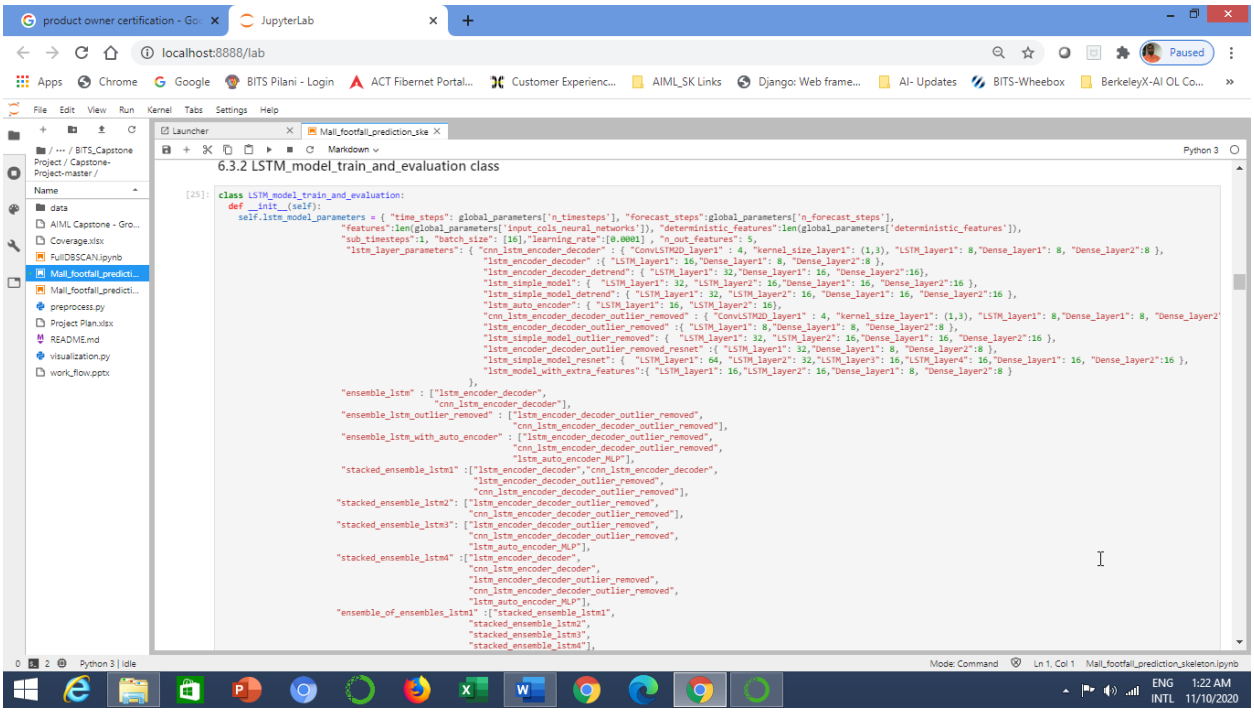
  checkpoint_path = 'saved_model_' + model.name +str(batch_size)+str(learning_rate)+'.hdf5'
  cp_callbacks = [ ModelCheckpoint(filepath=checkpoint_path,
                                   save_weights_only=False,
                                   monitor='val_loss',
                                   mode='min',
                                   save_best_only=True,
                                   verbose=0),
                  logger

                  ]

  history = model.fit(data_set_dict["X_train"], data_set_dict["y_train"], epochs = num_epochs,
                      validation_data=(data_set_dict["X_validation"], data_set_dict["y_validation"]),
                      batch_size = batch_size, callbacks=cp_callbacks, verbose=0)

  return history.history['loss'], history.history['val_loss'] , checkpoint_path


def plot_history(self, train_loss, val_loss):
    from matplotlib import pyplot
    fig = pyplot.figure(figsize=(16,8))
    pyplot.plot(train_loss, label='train')
    pyplot.plot(val_loss, label='validation')
    pyplot.plot(np.argmin(val_loss), np.min(val_loss), marker="x", color="r", label="best model")
    pyplot.legend()
    pyplot.show()
```



6.3.2 LSTM_model_train_and_evaluation class

```
[25]:
class LSTM_model_train_and_evaluation:
  def __init__(self):
    self.lstm_model_parameters = { "time_steps": global_parameters['n_timesteps'], "forecast_steps":global_parameters['n_forecast_steps'],
                                   "features":len(global_parameters['input_cols_neural_networks']), "deterministic_features":len(global_parameters['deterministic_features']),
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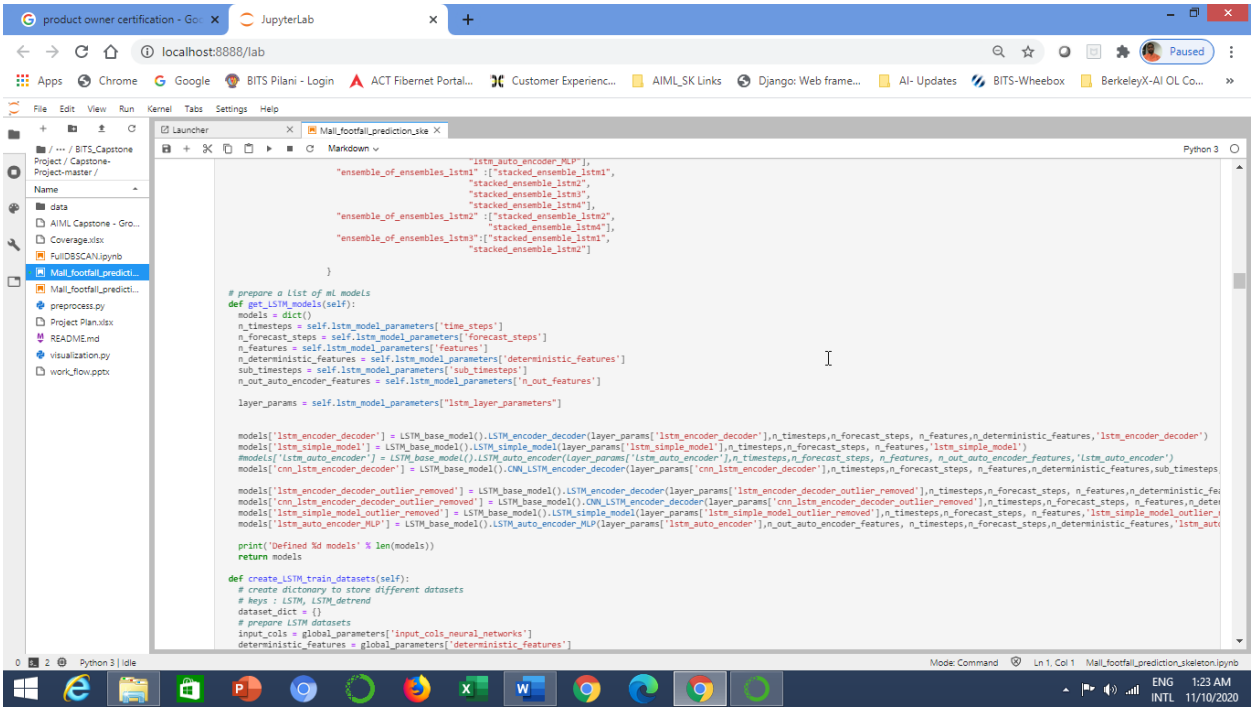
                                                                   "stacked_ensemble_lstm4"],
```



```
                                                    'lstm_auto_encoder_MLP'],
                        "ensemble_of_ensembles_lstm1" :["stacked_ensemble_lstm1",
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                                                        "stacked_ensemble_lstm4"],
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                                                        "stacked_ensemble_lstm4"],
                        "ensemble_of_ensembles_lstm3":["stacked_ensemble_lstm1",
                                                       "stacked_ensemble_lstm2"]

                       }

    # prepare a list of ml models
    def get_LSTM_models(self):
      models = dict()
      n_timesteps = self.lstm_model_parameters['time_steps']
      n_forecast_steps = self.lstm_model_parameters['forecast_steps']
      n_features = self.lstm_model_parameters['features']
      n_deterministic_features = self.lstm_model_parameters['deterministic_features']
      sub_timesteps = self.lstm_model_parameters['sub_timesteps']
      n_out_auto_encoder_features = self.lstm_model_parameters['n_out_features']

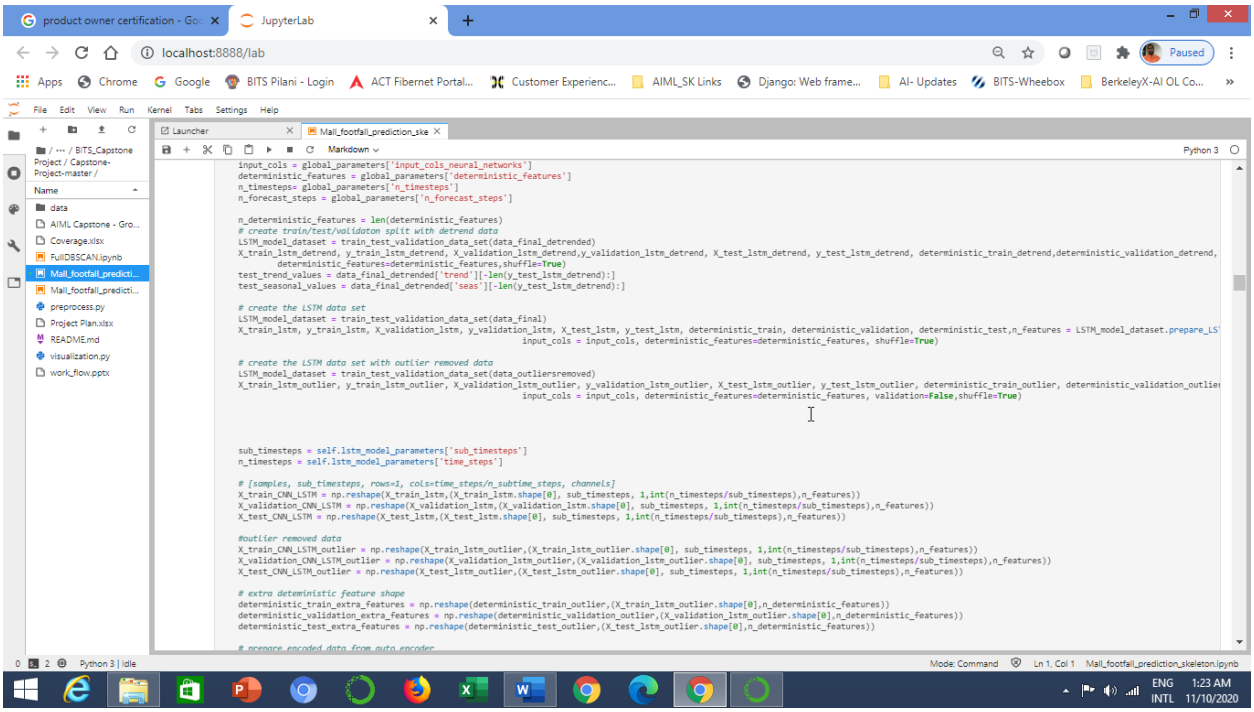
      layer_params = self.lstm_model_parameters["lstm_layer_parameters"]


      models['lstm_encoder_decoder'] = LSTM_base_model().LSTM_encoder_decoder(layer_params['lstm_encoder_decoder'],n_timesteps,n_forecast_steps, n_features,n_deterministic_features,'lstm_encoder_decoder')
      models['lstm_simple_model'] = LSTM_base_model().LSTM_simple_model(layer_params['lstm_simple_model'],n_timesteps,n_forecast_steps, n_features,'lstm_simple_model')
      #models['lstm_auto_encoder'] = LSTM_base_model().LSTM_auto_encoder(layer_params['lstm_auto_encoder'],n_timesteps,n_forecast_steps, n_features, n_out_auto_encoder_features,'lstm_auto_encoder')
      models['cnn_lstm_encoder_decoder'] = LSTM_base_model().CNN_LSTM_encoder_decoder(layer_params['cnn_lstm_encoder_decoder'],n_timesteps,n_forecast_steps, n_features,n_deterministic_features,sub_timesteps,

      models['lstm_encoder_decoder_outlier_removed'] = LSTM_base_model().LSTM_encoder_decoder(layer_params['lstm_encoder_decoder_outlier_removed'],n_timesteps,n_forecast_steps, n_features,n_deterministic_fea
      models['cnn_lstm_encoder_decoder_outlier_removed'] = LSTM_base_model().CNN_LSTM_encoder_decoder(layer_params['cnn_lstm_encoder_decoder_outlier_removed'],n_timesteps,n_forecast_steps, n_features,n_dete
      models['lstm_simple_model_outlier_removed'] = LSTM_base_model().LSTM_simple_model(layer_params['lstm_simple_model_outlier_removed'],n_timesteps,n_forecast_steps, n_features,'lstm_simple_model_outlier_
      models['lstm_auto_encoder_MLP'] = LSTM_base_model().LSTM_auto_encoder_MLP(layer_params['lstm_auto_encoder'],n_out_auto_encoder_features, n_timesteps,n_forecast_steps,n_deterministic_features,'lstm_aut

      print('Defined %d models' % len(models))
      return models

    def create_LSTM_train_datasets(self):
      # create dictonary to store different datasets
      # keys : LSTM, LSTM_detrend
      dataset_dict = {}
      # prepare LSTM datasets
      input_cols = global_parameters['input_cols_neural_networks']
      deterministic_features = global_parameters['deterministic_features']
```



```
    input_cols = global_parameters['input_cols_neural_networks']
    deterministic_features = global_parameters['deterministic_features']
    n_timesteps= global_parameters['n_timesteps']
    n_forecast_steps = global_parameters['n_forecast_steps']

    n_deterministic_features = len(deterministic_features)
    # create train/test/validaton split with detrend data
    LSTM_model_dataset = train_test_validation_data_set(data_final_detrended)
    X_train_lstm_detrend, y_train_lstm_detrend, X_validation_lstm_detrend,y_validation_lstm_detrend, X_test_lstm_detrend, y_test_lstm_detrend, deterministic_train_detrend,deterministic_validation_detrend,
            deterministic_features=deterministic_features,shuffle=True)
    test_trend_values = data_final_detrended['trend'][-len(y_test_lstm_detrend):]
    test_seasonal_values = data_final_detrended['seas'][-len(y_test_lstm_detrend):]

    # create the LSTM data set
    LSTM_model_dataset = train_test_validation_data_set(data_final)
    X_train_lstm, y_train_lstm, X_validation_lstm, y_validation_lstm, X_test_lstm, y_test_lstm, deterministic_train, deterministic_validation, deterministic_test,n_features = LSTM_model_dataset.prepare_LS
                                                    input_cols = input_cols, deterministic_features=deterministic_features, shuffle=True)

    # create the LSTM data set with outlier removed data
    LSTM_model_dataset = train_test_validation_data_set(data_outliersremoved)
    X_train_lstm_outlier, y_train_lstm_outlier, X_validation_lstm_outlier, y_validation_lstm_outlier, X_test_lstm_outlier, y_test_lstm_outlier, deterministic_train_outlier, deterministic_validation_outlie
                                                    input_cols = input_cols, deterministic_features=deterministic_features, validation=False,shuffle=True)



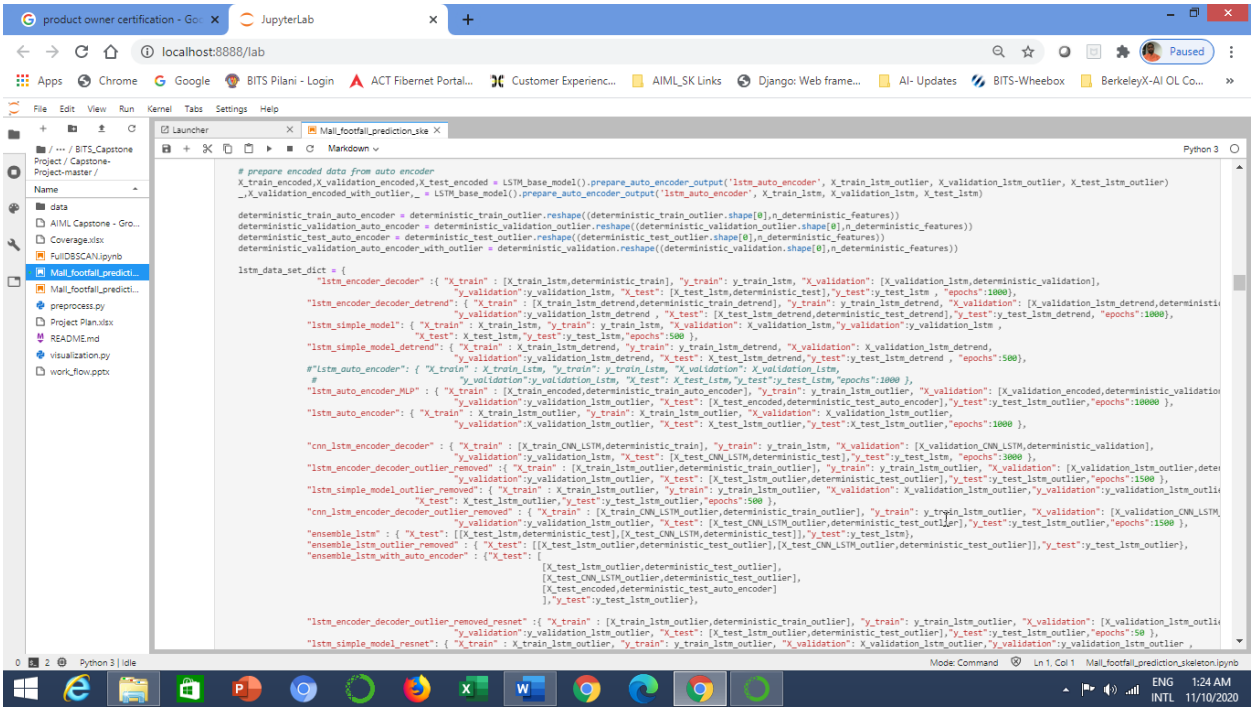
    sub_timesteps = self.lstm_model_parameters['sub_timesteps']
    n_timesteps = self.lstm_model_parameters['time_steps']

    # [samples, sub_timesteps, rows=1, cols=time_steps/n_subtime_steps, channels]
    X_train_CNN_LSTM = np.reshape(X_train_lstm,(X_train_lstm.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))
    X_validation_CNN_LSTM = np.reshape(X_validation_lstm,(X_validation_lstm.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))
    X_test_CNN_LSTM = np.reshape(X_test_lstm,(X_test_lstm.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))

    #outlier removed data
    X_train_CNN_LSTM_outlier = np.reshape(X_train_lstm_outlier,(X_train_lstm_outlier.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))
    X_validation_CNN_LSTM_outlier = np.reshape(X_validation_lstm_outlier,(X_validation_lstm_outlier.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))
    X_test_CNN_LSTM_outlier = np.reshape(X_test_lstm_outlier,(X_test_lstm_outlier.shape[0], sub_timesteps, 1,int(n_timesteps/sub_timesteps),n_features))

    # extra deteministic feature shape
    deterministic_train_extra_features = np.reshape(deterministic_train_outlier,(X_train_lstm_outlier.shape[0],n_deterministic_features))
    deterministic_validation_extra_features = np.reshape(deterministic_validation_outlier,(X_validation_lstm_outlier.shape[0],n_deterministic_features))
    deterministic_test_extra_features = np.reshape(deterministic_test_outlier,(X_test_lstm_outlier.shape[0],n_deterministic_features))

    # prepare encoded data from auto encoder
```



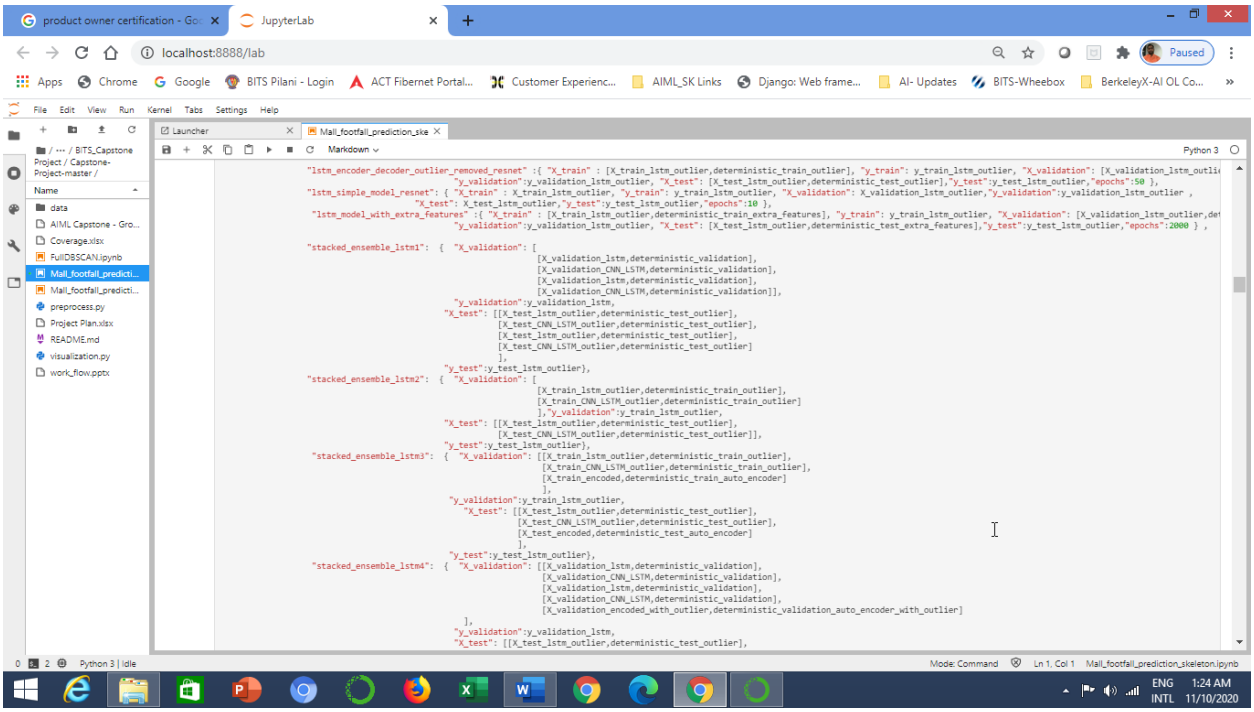
```
# prepare encoded data from auto encoder
X_train_encoded,X_validation_encoded,X_test_encoded = LSTM_base_model().prepare_auto_encoder_output('lstm_auto_encoder', X_train_lstm_outlier, X_validation_lstm_outlier, X_test_lstm_outlier)
_,X_validation_encoded_with_outlier,_ = LSTM_base_model().prepare_auto_encoder_output('lstm_auto_encoder', X_train_lstm, X_validation_lstm, X_test_lstm)

deterministic_train_auto_encoder = deterministic_train_outlier.reshape((deterministic_train_outlier.shape[0],n_deterministic_features))
deterministic_validation_auto_encoder = deterministic_validation_outlier.reshape((deterministic_validation_outlier.shape[0],n_deterministic_features))
deterministic_test_auto_encoder = deterministic_test_outlier.reshape((deterministic_test_outlier.shape[0],n_deterministic_features))
deterministic_validation_auto_encoder_with_outlier = deterministic_validation.reshape((deterministic_validation.shape[0],n_deterministic_features))

lstm_data_set_dict = {
                "lstm_encoder_decoder" :{ "X_train" : [X_train_lstm,deterministic_train], "y_train": y_train_lstm, "X_validation": [X_validation_lstm,deterministic_validation],
                                          "y_validation":y_validation_lstm, "X_test": [X_test_lstm,deterministic_test],"y_test":y_test_lstm , "epochs":1000},
            "lstm_encoder_decoder_detrend": { "X_train" : [X_train_lstm_detrend,deterministic_train_detrend], "y_train": y_train_lstm_detrend, "X_validation": [X_validation_lstm_detrend,deterministi
                                              "y_validation":y_validation_lstm_detrend , "X_test": [X_test_lstm_detrend,deterministic_test_detrend],"y_test":y_test_lstm_detrend, "epochs":1000},
            "lstm_simple_model": { "X_train" : X_train_lstm, "y_train": y_train_lstm, "X_validation": X_validation_lstm,"y_validation":y_validation_lstm ,
                                   "X_test": X_test_lstm,"y_test":y_test_lstm,"epochs":500 },
            "lstm_simple_model_detrend": { "X_train" : X_train_lstm_detrend, "y_train": y_train_lstm_detrend, "X_validation": X_validation_lstm_detrend,
                                           "y_validation":y_validation_lstm_detrend, "X_test": X_test_lstm_detrend,"y_test":y_test_lstm_detrend , "epochs":500},
            #"lstm_auto_encoder": { "X_train" : X_train_lstm, "y_train": y_train_lstm, "X_validation": X_validation_lstm,
             #                      "y_validation":y_validation_lstm, "X_test": X_test_lstm,"y_test":y_test_lstm,"epochs":1000 },
            "lstm_auto_encoder_MLP" : { "X_train" : [X_train_encoded,deterministic_train_auto_encoder], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_encoded,deterministic_validatio
                                        "y_validation":y_validation_lstm_outlier, "X_test": [X_test_encoded,deterministic_test_auto_encoder],"y_test":y_test_lstm_outlier,"epochs":10000 },
            "lstm_auto_encoder": { "X_train" : X_train_lstm_outlier, "y_train": X_train_lstm_outlier, "X_validation": X_validation_lstm_outlier,
                                   "y_validation":X_validation_lstm_outlier, "X_test": X_test_lstm_outlier,"y_test":X_test_lstm_outlier,"epochs":1000 },


            "cnn_lstm_encoder_decoder" : { "X_train" : [X_train_CNN_LSTM,deterministic_train], "y_train": y_train_lstm, "X_validation": [X_validation_CNN_LSTM,deterministic_validation],
                                           "y_validation":y_validation_lstm, "X_test": [X_test_CNN_LSTM,deterministic_test],"y_test":y_test_lstm, "epochs":3000 },
            "lstm_encoder_decoder_outlier_removed" :{ "X_train" : [X_train_lstm_outlier,deterministic_train_outlier], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_lstm_outlier,dete
                                                      "y_validation":y_validation_lstm_outlier, "X_test": [X_test_lstm_outlier,deterministic_test_outlier],"y_test":y_test_lstm_outlier,"epochs":1500 },
            "lstm_simple_model_outlier_removed": { "X_train" : X_train_lstm_outlier, "y_train": y_train_lstm_outlier, "X_validation": X_validation_lstm_outlier,"y_validation":y_validation_lstm_outli
                                                   "X_test": X_test_lstm_outlier,"y_test":y_test_lstm_outlier,"epochs":500 },
            "cnn_lstm_encoder_decoder_outlier_removed" : { "X_train" : [X_train_CNN_LSTM_outlier,deterministic_train_outlier], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_CNN_LSTM
                                                           "y_validation":y_validation_lstm_outlier, "X_test": [X_test_CNN_LSTM_outlier,deterministic_test_outlier],"y_test":y_test_lstm_outlier,"epochs":1500 },
            "ensemble_lstm" : { "X_test": [[X_test_lstm,deterministic_test],[X_test_CNN_LSTM,deterministic_test]],"y_test":y_test_lstm},
            "ensemble_lstm_outlier_removed" : { "X_test": [[X_test_lstm_outlier,deterministic_test_outlier],[X_test_CNN_LSTM_outlier,deterministic_test_outlier]],"y_test":y_test_lstm_outlier},
            "ensemble_lstm_with_auto_encoder" : {"X_test": [
                                                            [X_test_lstm_outlier,deterministic_test_outlier],
                                                            [X_test_CNN_LSTM_outlier,deterministic_test_outlier],
                                                            [X_test_encoded,deterministic_test_auto_encoder]
                                                            ],"y_test":y_test_lstm_outlier},


            "lstm_encoder_decoder_outlier_removed_resnet" :{ "X_train" : [X_train_lstm_outlier,deterministic_train_outlier], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_lstm_outli
                                                             "y_validation":y_validation_lstm_outlier, "X_test": [X_test_lstm_outlier,deterministic_test_outlier],"y_test":y_test_lstm_outlier,"epochs":50 },
            "lstm_simple_model_resnet": { "X_train" : X_train_lstm_outlier, "y_train": y_train_lstm_outlier, "X_validation": X_validation_lstm_outlier,"y_validation":y_validation_lstm_outlier ,
                                          "X_test": X_test_lstm_outlier,"y_test":y_test_lstm_outlier,"epochs":500 },
```



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            "lstm_encoder_decoder_outlier_removed_resnet" :{ "X_train" : [X_train_lstm_outlier,deterministic_train_outlier], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_lstm_outli
                                                             "y_validation":y_validation_lstm_outlier, "X_test": [X_test_lstm_outlier,deterministic_test_outlier],"y_test":y_test_lstm_outlier,"epochs":50 },
            "lstm_simple_model_resnet": { "X_train" : X_train_lstm_outlier, "y_train": y_train_lstm_outlier, "X_validation": X_validation_lstm_outlier,"y_validation":y_validation_lstm_outlier ,
                                          "X_test": X_test_lstm_outlier,"y_test":y_test_lstm_outlier,"epochs":10 },
             "lstm_model_with_extra_features" :{ "X_train" : [X_train_lstm_outlier,deterministic_train_extra_features], "y_train": y_train_lstm_outlier, "X_validation": [X_validation_lstm_outlier,det
                                                 "y_validation":y_validation_lstm_outlier, "X_test": [X_test_lstm_outlier,deterministic_test_extra_features],"y_test":y_test_lstm_outlier,"epochs":2000 } ,

            "stacked_ensemble_lstm1":  {  "X_validation": [
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                                                   [X_test_lstm_outlier,deterministic_test_outlier],
                                                   [X_test_CNN_LSTM_outlier,deterministic_test_outlier]
                                                   ],
                                        "y_test":y_test_lstm_outlier},
            "stacked_ensemble_lstm2":  {  "X_validation": [
                                                           [X_train_lstm_outlier,deterministic_train_outlier],
                                                           [X_train_CNN_LSTM_outlier,deterministic_train_outlier]
                                                           ],"y_validation":y_train_lstm_outlier,
                                        "X_test": [[X_test_lstm_outlier,deterministic_test_outlier],
                                                   [X_test_CNN_LSTM_outlier,deterministic_test_outlier]],
                                        "y_test":y_test_lstm_outlier},
             "stacked_ensemble_lstm3":  {  "X_validation": [[X_train_lstm_outlier,deterministic_train_outlier],
                                                            [X_train_CNN_LSTM_outlier,deterministic_train_outlier],
                                                            [X_train_encoded,deterministic_train_auto_encoder]
                                                            ],
                                           "y_validation":y_train_lstm_outlier,
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                                                        ],
                                           "y_test":y_test_lstm_outlier},
            "stacked_ensemble_lstm4":  {  "X_validation": [[X_validation_lstm,deterministic_validation],
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                                                           [X_validation_lstm,deterministic_validation],
                                                           [X_validation_CNN_LSTM,deterministic_validation],
                                                           [X_validation_encoded_with_outlier,deterministic_validation_auto_encoder_with_outlier]
                                             ],
                                          "y_validation":y_validation_lstm,
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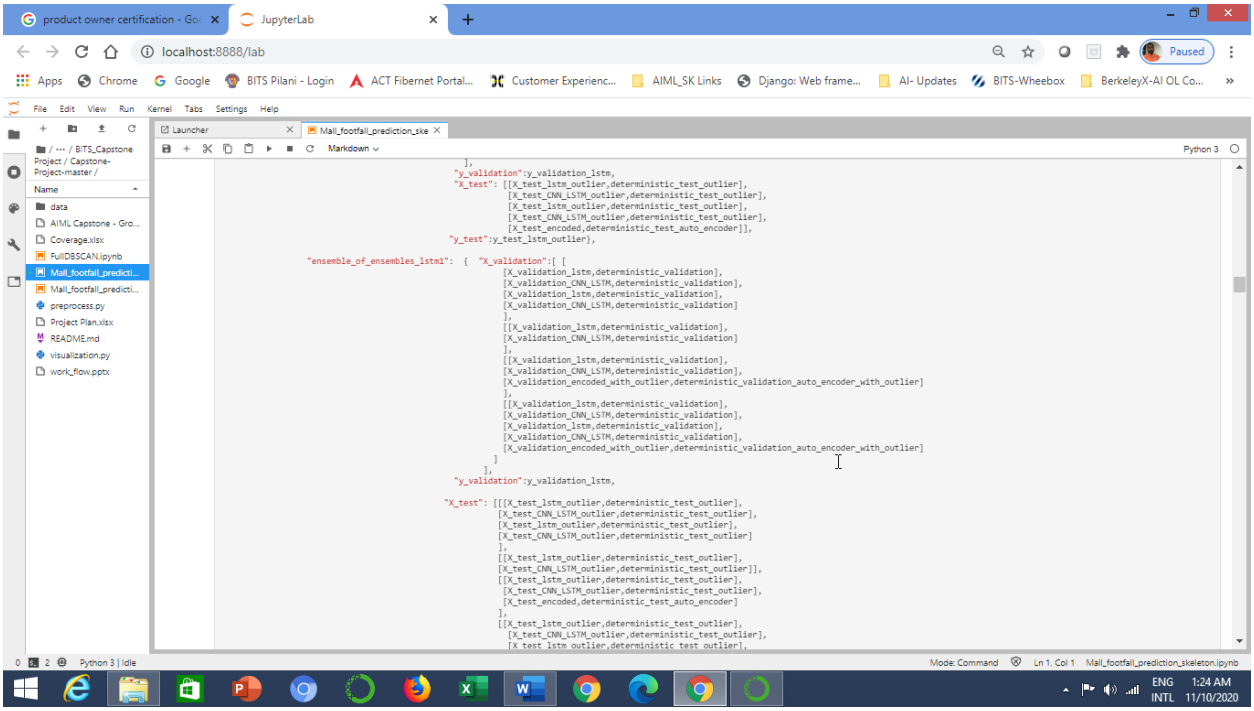
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ACT Fibernet Portal...
Customer Experienc...
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Mall_footfall_predicti...
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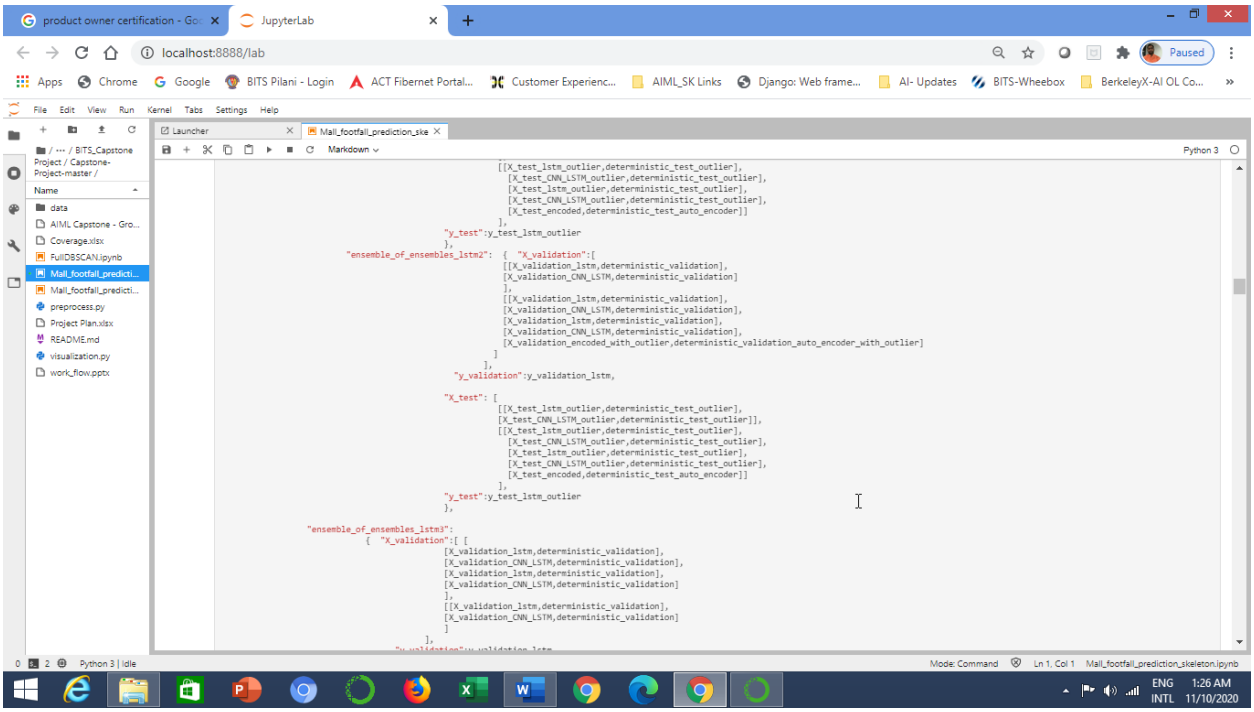
product owner certification - Go
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FullDBSCAN.ipynb
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Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
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},
"ensemble_of_ensembles_lstm2": { "X_validation":[
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[X_validation_CNN_LSTM,deterministic_validation]
],
[[X_validation_lstm,deterministic_validation],
[X_validation_CNN_LSTM,deterministic_validation],
[X_validation_lstm,deterministic_validation],
[X_validation_CNN_LSTM,deterministic_validation],
[X_validation_encoded_with_outlier,deterministic_validation_auto_encoder_with_outlier]
]
],
"y_validation":y_validation_lstm,
"X_test": [
[[X_test_lstm_outlier,deterministic_test_outlier],
[X_test_CNN_LSTM_outlier,deterministic_test_outlier]],
[[X_test_lstm_outlier,deterministic_test_outlier],
[X_test_CNN_LSTM_outlier,deterministic_test_outlier],
[X_test_lstm_outlier,deterministic_test_outlier],
[X_test_CNN_LSTM_outlier,deterministic_test_outlier],
[X_test_encoded,deterministic_test_auto_encoder]]
],
"y_test":y_test_lstm_outlier
},
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[X_validation_lstm,deterministic_validation],
[X_validation_CNN_LSTM,deterministic_validation]
],
[[X_validation_lstm,deterministic_validation],
[X_validation_CNN_LSTM,deterministic_validation]
]
],
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Mall_footfall_prediction_skeleton.ipynb
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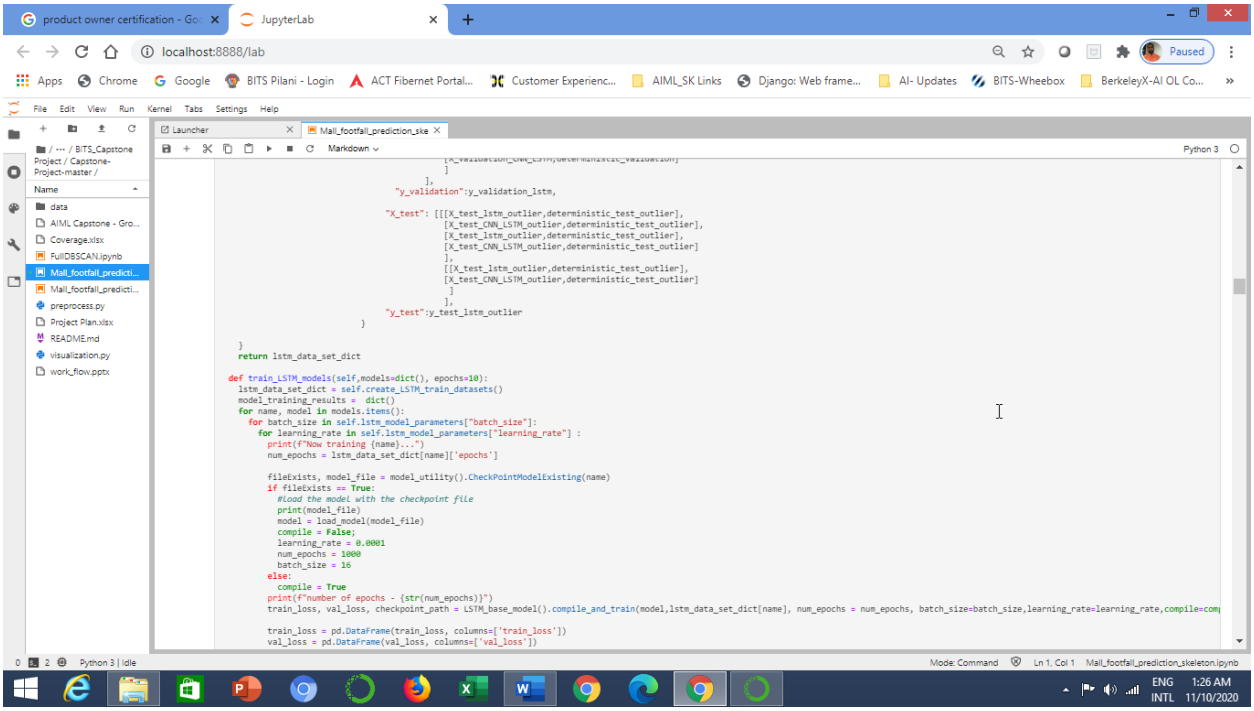


```
                                    ]
                                },
                                "y_validation":y_validation_lstm,

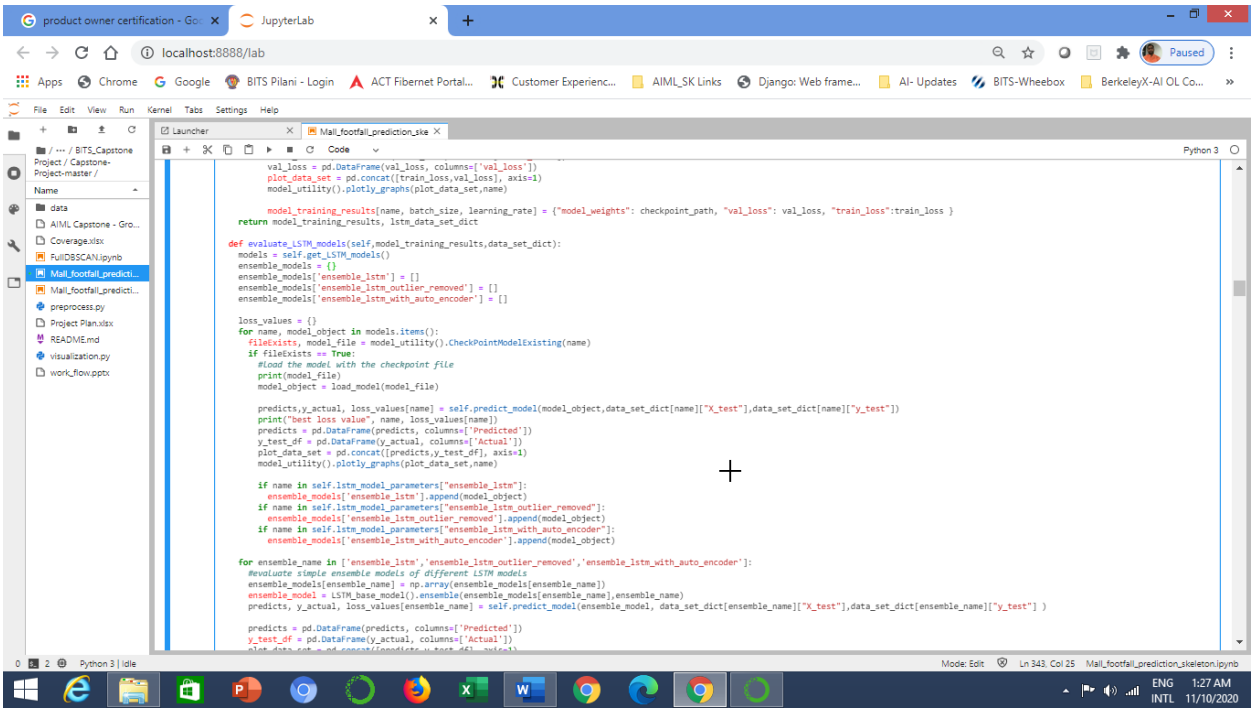
                                "X_test": [[[X_test_lstm_outlier,deterministic_test_outlier],
                                            [X_test_CNN_LSTM_outlier,deterministic_test_outlier],
                                            [X_test_lstm_outlier,deterministic_test_outlier],
                                            [X_test_CNN_LSTM_outlier,deterministic_test_outlier]
                                            ],
                                            [[X_test_lstm_outlier,deterministic_test_outlier],
                                            [X_test_CNN_LSTM_outlier,deterministic_test_outlier]
                                            ]
                                            ],
                                "y_test":y_test_lstm_outlier
                            }

    }
    return lstm_data_set_dict

def train_LSTM_models(self,models=dict(), epochs=10):
    lstm_data_set_dict = self.create_LSTM_train_datasets()
    model_training_results =  dict()
    for name, model in models.items():
      for batch_size in self.lstm_model_parameters["batch_size"]:
        for learning_rate in self.lstm_model_parameters["learning_rate"] :
          print(f"Now training {name}...")
          num_epochs = lstm_data_set_dict[name]['epochs']

          fileExists, model_file = model_utility().CheckPointModelExisting(name)
          if fileExists == True:
            #load the model with the checkpoint file
            print(model_file)
            model = load_model(model_file)
            compile = False;
            learning_rate = 0.0001
            num_epochs = 1000
            batch_size = 16
          else:
            compile = True
          print(f"number of epochs - {str(num_epochs)}")
          train_loss, val_loss, checkpoint_path = LSTM_base_model().compile_and_train(model,lstm_data_set_dict[name], num_epochs = num_epochs, batch_size=batch_size,learning_rate=learning_rate,compile=com

          train_loss = pd.DataFrame(train_loss, columns=['train_loss'])
          val_loss = pd.DataFrame(val_loss, columns=['val_loss'])
```



```
          val_loss = pd.DataFrame(val_loss, columns=['val_loss'])
          plot_data_set = pd.concat([train_loss,val_loss], axis=1)
          model_utility().plotly_graphs(plot_data_set,name)

          model_training_results[name, batch_size, learning_rate] = {"model_weights": checkpoint_path, "val_loss": val_loss, "train_loss":train_loss }
    return model_training_results, lstm_data_set_dict

def evaluate_LSTM_models(self,model_training_results,data_set_dict):
    models = self.get_LSTM_models()
    ensemble_models = {}
    ensemble_models['ensemble_lstm'] = []
    ensemble_models['ensemble_lstm_outlier_removed'] = []
    ensemble_models['ensemble_lstm_with_auto_encoder'] = []

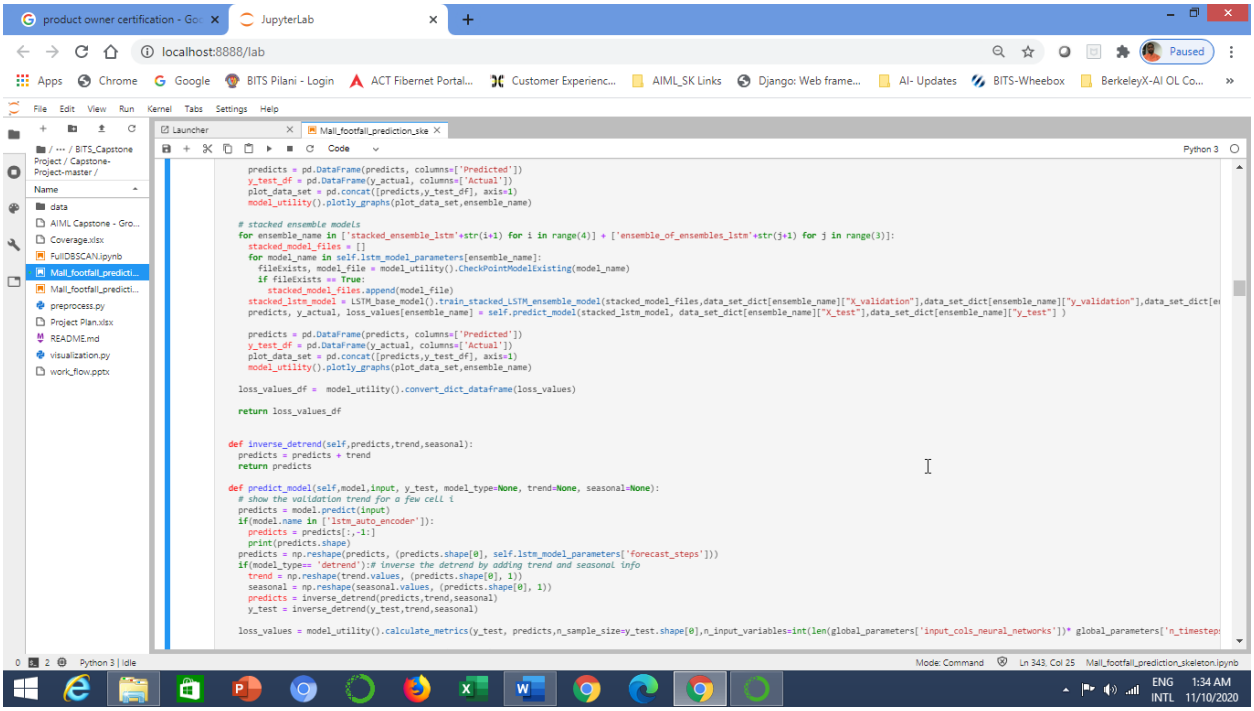
    loss_values = {}
    for name, model_object in models.items():
      fileExists, model_file = model_utility().CheckPointModelExisting(name)
      if fileExists == True:
        #load the model with the checkpoint file
        print(model_file)
        model_object = load_model(model_file)

        predicts,y_actual, loss_values[name] = self.predict_model(model_object,data_set_dict[name]["X_test"],data_set_dict[name]["y_test"])
        print("best loss value", name, loss_values[name])
        predicts = pd.DataFrame(predicts, columns=['Predicted'])
        y_test_df = pd.DataFrame(y_actual, columns=['Actual'])
        plot_data_set = pd.concat([predicts,y_test_df], axis=1)
        model_utility().plotly_graphs(plot_data_set,name)

        if name in self.lstm_model_parameters["ensemble_lstm"]:
          ensemble_models['ensemble_lstm'].append(model_object)
        if name in self.lstm_model_parameters["ensemble_lstm_outlier_removed"]:
          ensemble_models['ensemble_lstm_outlier_removed'].append(model_object)
        if name in self.lstm_model_parameters["ensemble_lstm_with_auto_encoder"]:
          ensemble_models['ensemble_lstm_with_auto_encoder'].append(model_object)

    for ensemble_name in ['ensemble_lstm','ensemble_lstm_outlier_removed','ensemble_lstm_with_auto_encoder']:
      #evaluate simple ensemble models of different LSTM models
      ensemble_models[ensemble_name] = np.array(ensemble_models[ensemble_name])
      ensemble_model = LSTM_base_model().ensemble(ensemble_models[ensemble_name],ensemble_name)
      predicts, y_actual, loss_values[ensemble_name] = self.predict_model(ensemble_model, data_set_dict[ensemble_name]["X_test"],data_set_dict[ensemble_name]["y_test"] )

      predicts = pd.DataFrame(predicts, columns=['Predicted'])
      y_test_df = pd.DataFrame(y_actual, columns=['Actual'])
```



```
        predicts = pd.DataFrame(predicts, columns=['Predicted'])
        y_test_df = pd.DataFrame(y_actual, columns=['Actual'])
        plot_data_set = pd.concat([predicts,y_test_df], axis=1)
        model_utility().plotly_graphs(plot_data_set,ensemble_name)

      # stacked ensemble models
      for ensemble_name in ['stacked_ensemble_lstm'+str(i+1) for i in range(4)] + ['ensemble_of_ensembles_lstm'+str(j+1) for j in range(3)]:
        stacked_model_files = []
        for model_name in self.lstm_model_parameters[ensemble_name]:
          fileExists, model_file = model_utility().CheckPointModelExisting(model_name)
          if fileExists == True:
            stacked_model_files.append(model_file)
        stacked_lstm_model = LSTM_base_model().train_stacked_LSTM_ensemble_model(stacked_model_files,data_set_dict[ensemble_name]["X_validation"],data_set_dict[ensemble_name]["y_validation"],data_set_dict[e
        predicts, y_actual, loss_values[ensemble_name] = self.predict_model(stacked_lstm_model, data_set_dict[ensemble_name]["X_test"],data_set_dict[ensemble_name]["y_test"] )

        predicts = pd.DataFrame(predicts, columns=['Predicted'])
        y_test_df = pd.DataFrame(y_actual, columns=['Actual'])
        plot_data_set = pd.concat([predicts,y_test_df], axis=1)
        model_utility().plotly_graphs(plot_data_set,ensemble_name)

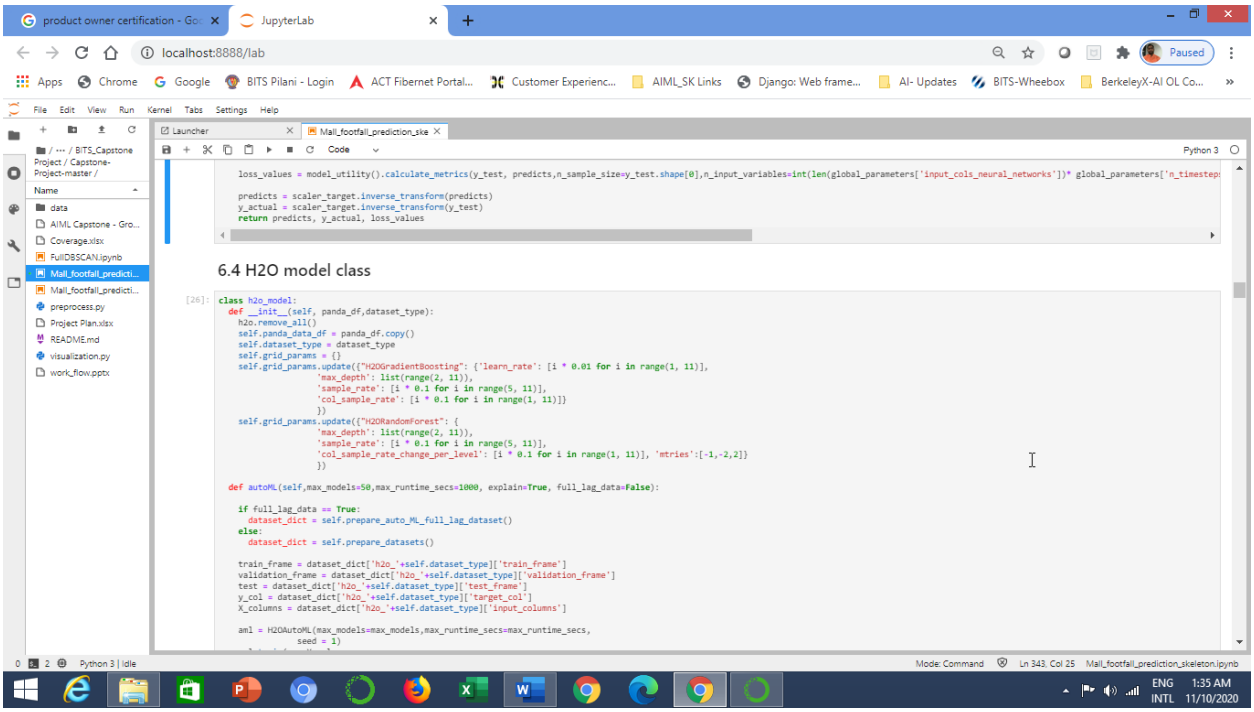
      loss_values_df =  model_utility().convert_dict_dataframe(loss_values)

      return loss_values_df


    def inverse_detrend(self,predicts,trend,seasonal):
      predicts = predicts + trend
      return predicts

    def predict_model(self,model,input, y_test, model_type=None, trend=None, seasonal=None):
      # show the validation trend for a few cell 1
      predicts = model.predict(input)
      if(model.name in ['lstm_auto_encoder']):
        predicts = predicts[:,-1:]
        print(predicts.shape)
      predicts = np.reshape(predicts, (predicts.shape[0], self.lstm_model_parameters['forecast_steps']))
      if(model_type== 'detrend'):# inverse the detrend by adding trend and seasonal info
        trend = np.reshape(trend.values, (predicts.shape[0], 1))
        seasonal = np.reshape(seasonal.values, (predicts.shape[0], 1))
        predicts = inverse_detrend(predicts,trend,seasonal)
        y_test = inverse_detrend(y_test,trend,seasonal)

      loss_values = model_utility().calculate_metrics(y_test, predicts,n_sample_size=y_test.shape[0],n_input_variables=int(len(global_parameters['input_cols_neural_networks'])* global_parameters['n_timestep
```



```
    loss_values = model_utility().calculate_metrics(y_test, predicts,n_sample_size=y_test.shape[0],n_input_variables=int(len(global_parameters['input_cols_neural_networks'])* global_parameters['n_timestep

    predicts = scaler_target.inverse_transform(predicts)
    y_actual = scaler_target.inverse_transform(y_test)
    return predicts, y_actual, loss_values
```

## 6.4 H2O model class

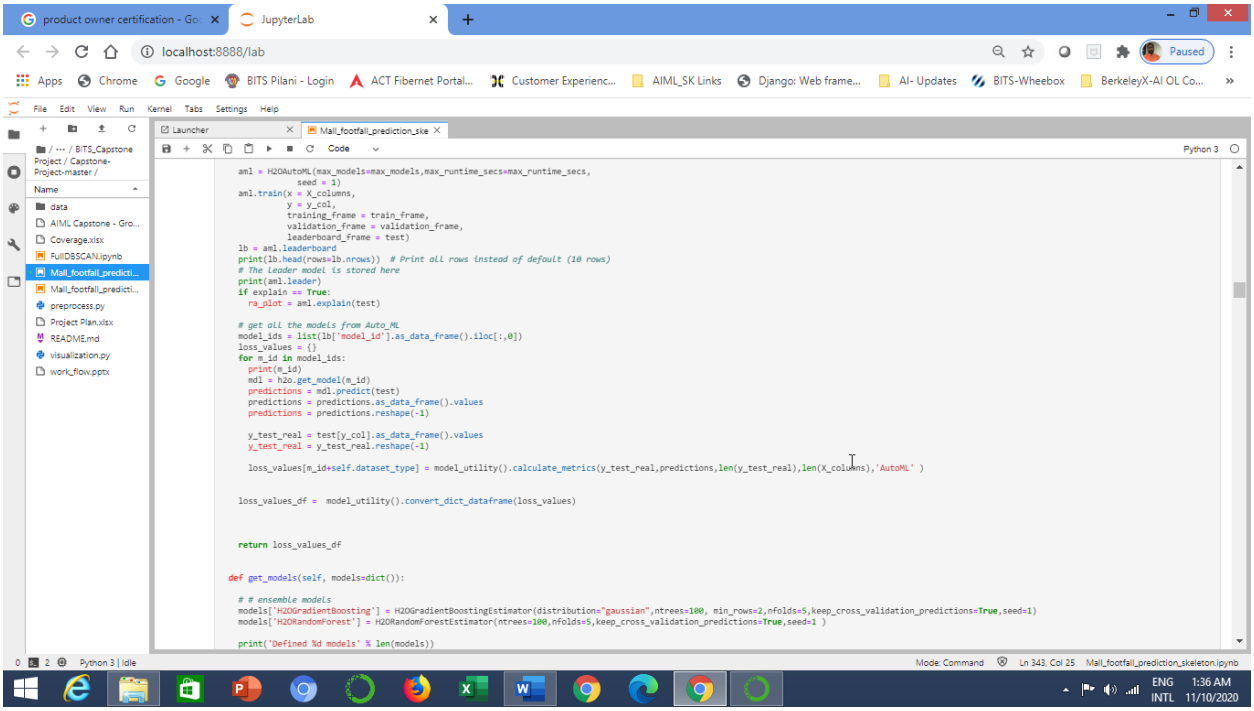
```
[26]:
class h2o_model:
  def __init__(self, panda_df,dataset_type):
    h2o.remove_all()
    self.panda_data_df = panda_df.copy()
    self.dataset_type = dataset_type
    self.grid_params = {}
    self.grid_params.update({"H2OGradientBoosting": {'learn_rate': [i * 0.01 for i in range(1, 11)],
                    'max_depth': list(range(2, 11)),
                    'sample_rate': [i * 0.1 for i in range(5, 11)],
                    'col_sample_rate': [i * 0.1 for i in range(1, 11)]}
                    })
    self.grid_params.update({"H2ORandomForest": {
                    'max_depth': list(range(2, 11)),
                    'sample_rate': [i * 0.1 for i in range(5, 11)],
                    'col_sample_rate_change_per_level': [i * 0.1 for i in range(1, 11)], 'mtries':[-1,-2,2]}
                    })

  def autoML(self,max_models=50,max_runtime_secs=1000, explain=True, full_lag_data=False):

    if full_lag_data == True:
      dataset_dict = self.prepare_auto_ML_full_lag_dataset()
    else:
      dataset_dict = self.prepare_datasets()

    train_frame = dataset_dict['h2o_'+self.dataset_type]['train_frame']
    validation_frame = dataset_dict['h2o_'+self.dataset_type]['validation_frame']
    test = dataset_dict['h2o_'+self.dataset_type]['test_frame']
    y_col = dataset_dict['h2o_'+self.dataset_type]['target_col']
    X_columns = dataset_dict['h2o_'+self.dataset_type]['input_columns']

    aml = H2OAutoML(max_models=max_models,max_runtime_secs=max_runtime_secs,
                    seed = 1)
```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Customer Experienc...
AIML_SK Links
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FullDBSCAN.ipynb
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Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
aml = H2OAutoML(max_models=max_models,max_runtime_secs=max_runtime_secs,
seed = 1)
aml.train(x = X_columns,
y = y_col,
training_frame = train_frame,
validation_frame = validation_frame,
leaderboard_frame = test)
lb = aml.leaderboard
print(lb.head(rows=lb.nrows)) # Print all rows instead of default (10 rows)
# The Leader model is stored here
print(aml.leader)
if explain == True:
ra_plot = aml.explain(test)
# get all the models from Auto_ML
model_ids = list(lb['model_id'].as_data_frame().iloc[:,0])
loss_values = {}
for m_id in model_ids:
print(m_id)
md1 = h2o.get_model(m_id)
predictions = md1.predict(test)
predictions = predictions.as_data_frame().values
predictions = predictions.reshape(-1)
y_test_real = test[y_col].as_data_frame().values
y_test_real = y_test_real.reshape(-1)
loss_values[m_id+self.dataset_type] = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),len(X_columns),'AutoML' )
loss_values_df = model_utility().convert_dict_dataframe(loss_values)
return loss_values_df
def get_models(self, models=dict()):
# # ensemble models
models['H2OGradientBoosting'] = H2OGradientBoostingEstimator(distribution="gaussian",ntrees=100, min_rows=2,nfolds=5,keep_cross_validation_predictions=True,seed=1)
models['H2ORandomForest'] = H2ORandomForestEstimator(ntrees=100,nfolds=5,keep_cross_validation_predictions=True,seed=1 )
print('Defined %d models' % len(models))
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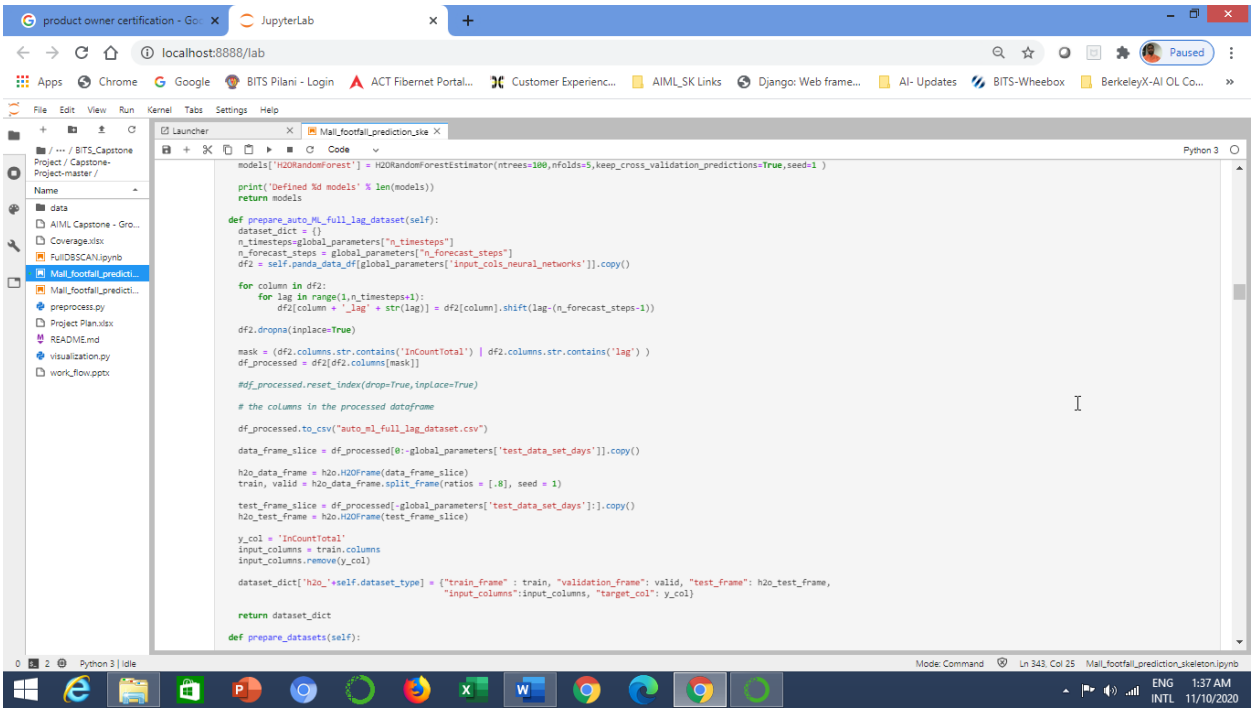
product owner certification - Go
JupyterLab
localhost:8888/lab
Paused
Apps
Chrome
Google
BITS Pilani - Login
ACT Fibernet Portal...
Customer Experienc...
AIML_SK Links
Django: Web frame...
AI- Updates
BITS-Wheebox
BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Code
Python 3
/ BITS_Capstone Project / Capstone-Project-master /
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
models['H2ORandomForest'] = H2ORandomForestEstimator(ntrees=100,nfolds=5,keep_cross_validation_predictions=True,seed=1 )
print('Defined %d models' % len(models))
return models
def prepare_auto_ML_full_lag_dataset(self):
dataset_dict = {}
n_timesteps=global_parameters["n_timesteps"]
n_forecast_steps = global_parameters["n_forecast_steps"]
df2 = self.panda_data_df[global_parameters['input_cols_neural_networks']].copy()
for column in df2:
for lag in range(1,n_timesteps+1):
df2[column + '_lag' + str(lag)] = df2[column].shift(lag-(n_forecast_steps-1))
df2.dropna(inplace=True)
mask = (df2.columns.str.contains('InCountTotal') | df2.columns.str.contains('lag') )
df_processed = df2[df2.columns[mask]]
#df_processed.reset_index(drop=True,inplace=True)
# the columns in the processed dataframe
df_processed.to_csv("auto_ml_full_lag_dataset.csv")
data_frame_slice = df_processed[0:-global_parameters['test_data_set_days']].copy()
h2o_data_frame = h2o.H2OFrame(data_frame_slice)
train, valid = h2o_data_frame.split_frame(ratios = [.8], seed = 1)
test_frame_slice = df_processed[-global_parameters['test_data_set_days']:].copy()
h2o_test_frame = h2o.H2OFrame(test_frame_slice)
y_col = 'InCountTotal'
input_columns = train.columns
input_columns.remove(y_col)
dataset_dict['h2o_'+self.dataset_type] = {"train_frame" : train, "validation_frame": valid, "test_frame": h2o_test_frame,
"input_columns":input_columns, "target_col": y_col}
return dataset_dict
def prepare_datasets(self):
Python 3 | Idle
Mode: Command
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Mall_footfall_prediction_skeleton.ipynb
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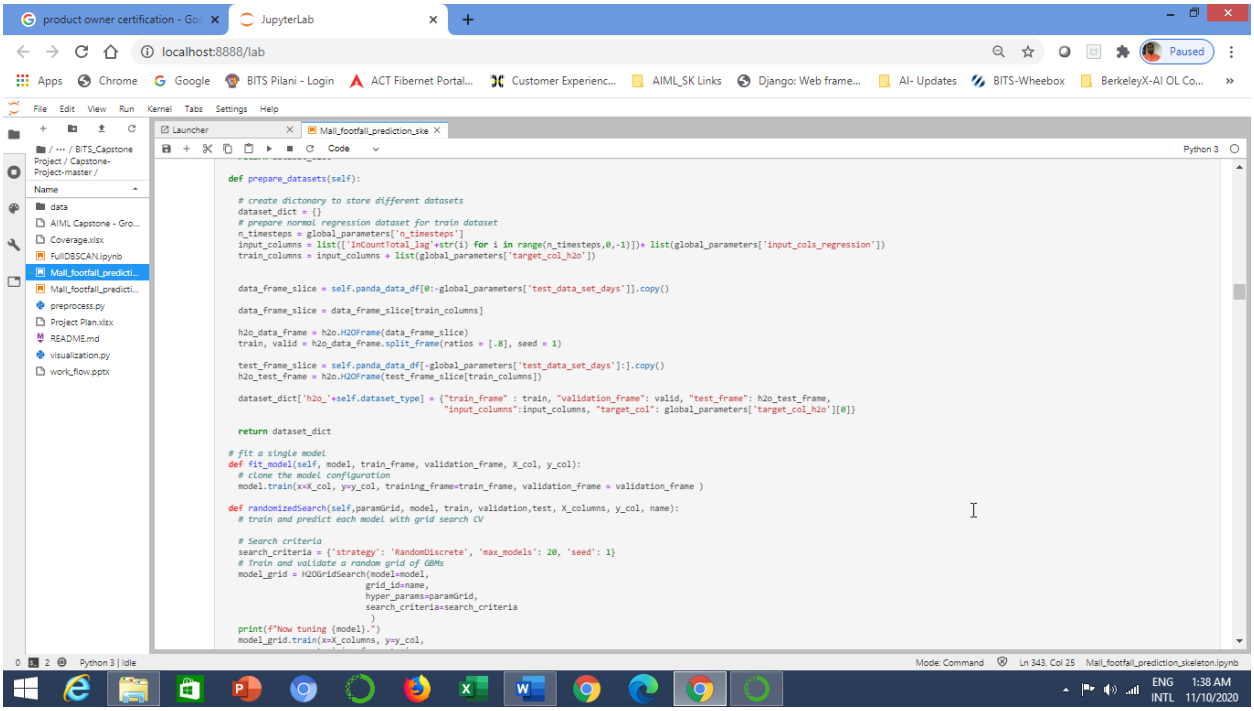
1:37 AM
11/10/2020



```
def prepare_datasets(self):

  # create dictonary to store different datasets
  dataset_dict = {}
  # prepare normal regression dataset for train dataset
  n_timesteps = global_parameters['n_timesteps']
  input_columns = list(['InCountTotal_lag'+str(i) for i in range(n_timesteps,0,-1)])+ list(global_parameters['input_cols_regression'])
  train_columns = input_columns + list(global_parameters['target_col_h2o'])


  data_frame_slice = self.panda_data_df[0:-global_parameters['test_data_set_days']].copy()

  data_frame_slice = data_frame_slice[train_columns]

  h2o_data_frame = h2o.H2OFrame(data_frame_slice)
  train, valid = h2o_data_frame.split_frame(ratios = [.8], seed = 1)

  test_frame_slice = self.panda_data_df[-global_parameters['test_data_set_days']:].copy()
  h2o_test_frame = h2o.H2OFrame(test_frame_slice[train_columns])

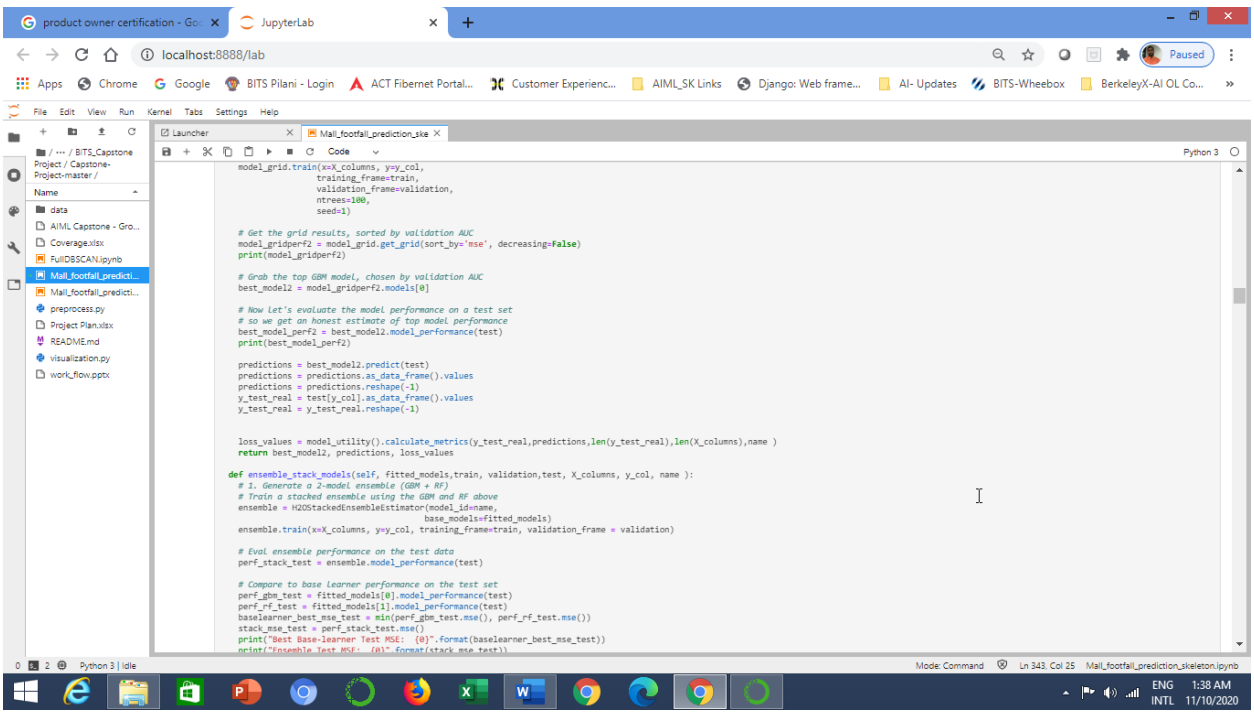
  dataset_dict['h2o_'+self.dataset_type] = {"train_frame" : train, "validation_frame": valid, "test_frame": h2o_test_frame,
                                            "input_columns":input_columns, "target_col": global_parameters['target_col_h2o'][0]}


  return dataset_dict

# fit a single model
def fit_model(self, model, train_frame, validation_frame, X_col, y_col):
  # clone the model configuration
  model.train(x=X_col, y=y_col, training_frame=train_frame, validation_frame = validation_frame )

def randomizedSearch(self,paramGrid, model, train, validation,test, X_columns, y_col, name):
  # train and predict each model with grid search CV

  # Search criteria
  search_criteria = {'strategy': 'RandomDiscrete', 'max_models': 20, 'seed': 1}
  # Train and validate a random grid of GBMs
  model_grid = H2OGridSearch(model=model,
                             grid_id=name,
                             hyper_params=paramGrid,
                             search_criteria=search_criteria
                             )
  print(f"Now tuning {model}.")
  model_grid.train(x=X_columns, y=y_col,
```



```
  model_grid.train(x=X_columns, y=y_col,
                   training_frame=train,
                   validation_frame=validation,
                   ntrees=100,
                   seed=1)

  # Get the grid results, sorted by validation AUC
  model_gridperf2 = model_grid.get_grid(sort_by='mse', decreasing=False)
  print(model_gridperf2)

  # Grab the top GBM model, chosen by validation AUC
  best_model2 = model_gridperf2.models[0]

  # Now let's evaluate the model performance on a test set
  # so we get an honest estimate of top model performance
  best_model_perf2 = best_model2.model_performance(test)
  print(best_model_perf2)

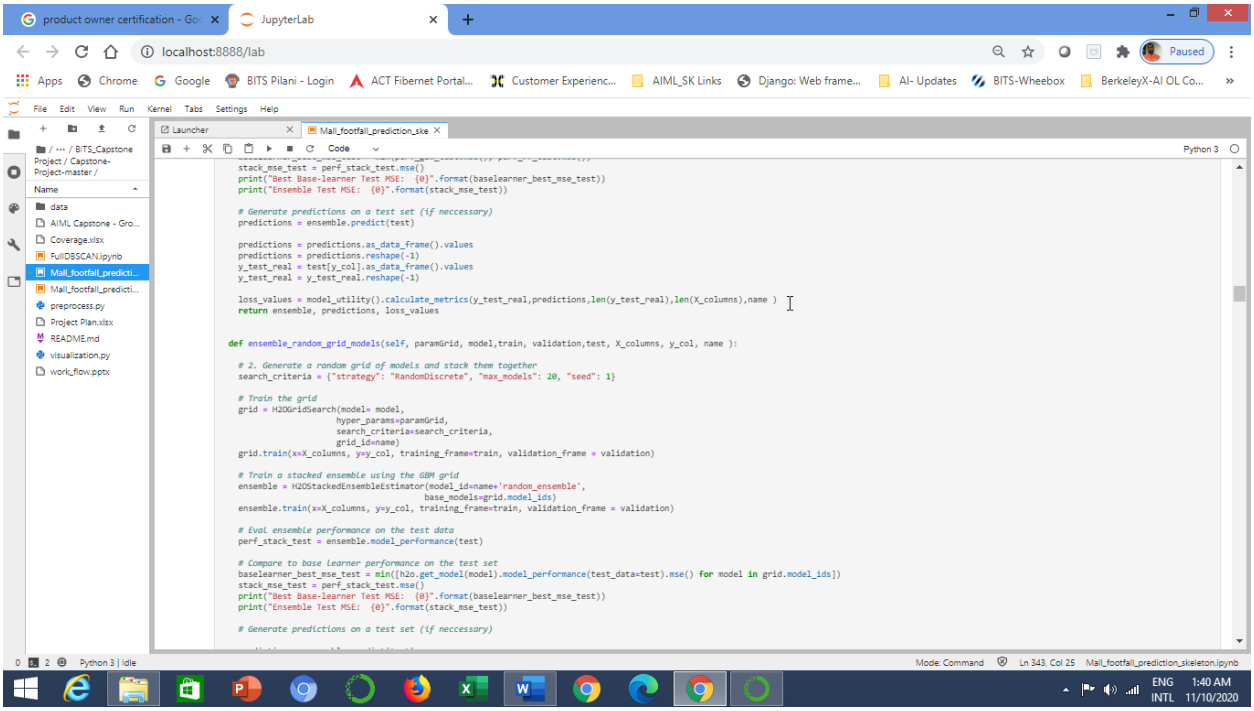
  predictions = best_model2.predict(test)
  predictions = predictions.as_data_frame().values
  predictions = predictions.reshape(-1)
  y_test_real = test[y_col].as_data_frame().values
  y_test_real = y_test_real.reshape(-1)


  loss_values = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),len(X_columns),name )
  return best_model2, predictions, loss_values

def ensemble_stack_models(self, fitted_models,train, validation,test, X_columns, y_col, name ):
  # 1. Generate a 2-model ensemble (GBM + RF)
  # Train a stacked ensemble using the GBM and RF above
  ensemble = H2OStackedEnsembleEstimator(model_id=name,
                                         base_models=fitted_models)
  ensemble.train(x=X_columns, y=y_col, training_frame=train, validation_frame = validation)

  # Eval ensemble performance on the test data
  perf_stack_test = ensemble.model_performance(test)

  # Compare to base learner performance on the test set
  perf_gbm_test = fitted_models[0].model_performance(test)
  perf_rf_test = fitted_models[1].model_performance(test)
  baselearner_best_mse_test = min(perf_gbm_test.mse(), perf_rf_test.mse())
  stack_mse_test = perf_stack_test.mse()
  print("Best Base-learner Test MSE:  {0}".format(baselearner_best_mse_test))
  print("Ensemble Test MSE:  {0}".format(stack_mse_test))
```



```
    stack_mse_test = perf_stack_test.mse()
    print("Best Base-learner Test MSE:  {0}".format(baselearner_best_mse_test))
    print("Ensemble Test MSE:  {0}".format(stack_mse_test))

    # Generate predictions on a test set (if neccessary)
    predictions = ensemble.predict(test)

    predictions = predictions.as_data_frame().values
    predictions = predictions.reshape(-1)
    y_test_real = test[y_col].as_data_frame().values
    y_test_real = y_test_real.reshape(-1)

    loss_values = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),len(X_columns),name )
    return ensemble, predictions, loss_values


def ensemble_random_grid_models(self, paramGrid, model,train, validation,test, X_columns, y_col, name ):

    # 2. Generate a random grid of models and stack them together
    search_criteria = {"strategy": "RandomDiscrete", "max_models": 20, "seed": 1}

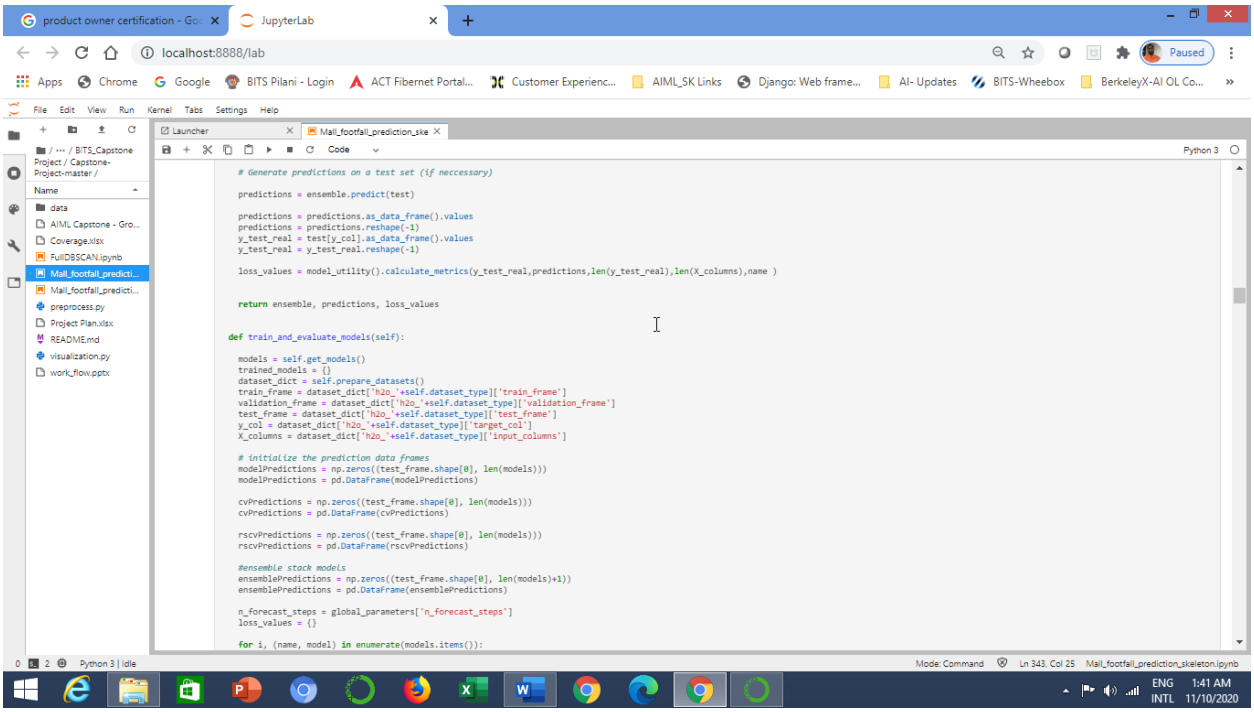
    # Train the grid
    grid = H2OGridSearch(model= model,
                         hyper_params=paramGrid,
                         search_criteria=search_criteria,
                         grid_id=name)
    grid.train(x=X_columns, y=y_col, training_frame=train, validation_frame = validation)

    # Train a stacked ensemble using the GBM grid
    ensemble = H2OStackedEnsembleEstimator(model_id=name+'random_ensemble',
                                           base_models=grid.model_ids)
    ensemble.train(x=X_columns, y=y_col, training_frame=train, validation_frame = validation)

    # Eval ensemble performance on the test data
    perf_stack_test = ensemble.model_performance(test)

    # Compare to base learner performance on the test set
    baselearner_best_mse_test = min([h2o.get_model(model).model_performance(test_data=test).mse() for model in grid.model_ids])
    stack_mse_test = perf_stack_test.mse()
    print("Best Base-learner Test MSE:  {0}".format(baselearner_best_mse_test))
    print("Ensemble Test MSE:  {0}".format(stack_mse_test))

    # Generate predictions on a test set (if neccessary)
```



```
    # Generate predictions on a test set (if neccessary)

    predictions = ensemble.predict(test)

    predictions = predictions.as_data_frame().values
    predictions = predictions.reshape(-1)
    y_test_real = test[y_col].as_data_frame().values
    y_test_real = y_test_real.reshape(-1)

    loss_values = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),len(X_columns),name )


    return ensemble, predictions, loss_values


def train_and_evaluate_models(self):

    models = self.get_models()
    trained_models = {}
    dataset_dict = self.prepare_datasets()
    train_frame = dataset_dict['h2o_'+self.dataset_type]['train_frame']
    validation_frame = dataset_dict['h2o_'+self.dataset_type]['validation_frame']
    test_frame = dataset_dict['h2o_'+self.dataset_type]['test_frame']
    y_col = dataset_dict['h2o_'+self.dataset_type]['target_col']
    X_columns = dataset_dict['h2o_'+self.dataset_type]['input_columns']

    # initialize the prediction data frames
    modelPredictions = np.zeros((test_frame.shape[0], len(models)))
    modelPredictions = pd.DataFrame(modelPredictions)

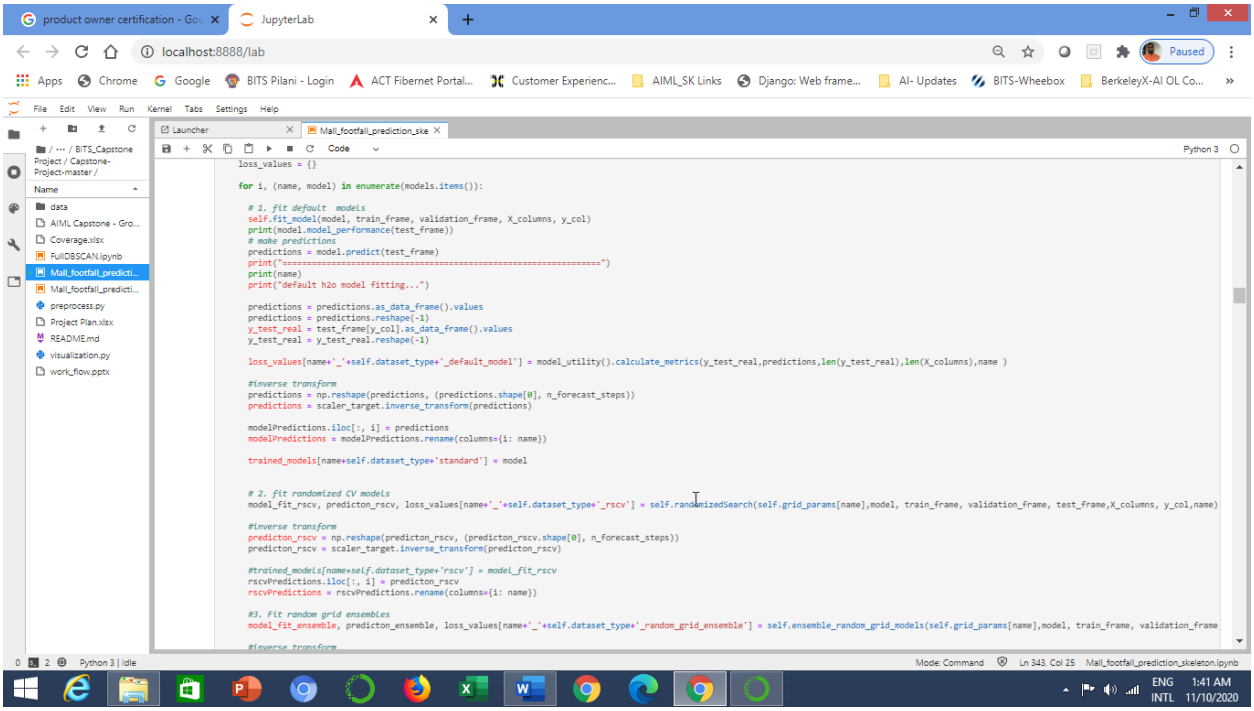
    cvPredictions = np.zeros((test_frame.shape[0], len(models)))
    cvPredictions = pd.DataFrame(cvPredictions)

    rscvPredictions = np.zeros((test_frame.shape[0], len(models)))
    rscvPredictions = pd.DataFrame(rscvPredictions)

    #ensemble stack models
    ensemblePredictions = np.zeros((test_frame.shape[0], len(models)+1))
    ensemblePredictions = pd.DataFrame(ensemblePredictions)

    n_forecast_steps = global_parameters['n_forecast_steps']
    loss_values = {}

    for i, (name, model) in enumerate(models.items()):
```



```
loss_values = {}

for i, (name, model) in enumerate(models.items()):

  # 1. fit default  models
  self.fit_model(model, train_frame, validation_frame, X_columns, y_col)
  print(model.model_performance(test_frame))
  # make predictions
  predictions = model.predict(test_frame)
  print("================================================================")
  print(name)
  print("default h2o model fitting...")

  predictions = predictions.as_data_frame().values
  predictions = predictions.reshape(-1)
  y_test_real = test_frame[y_col].as_data_frame().values
  y_test_real = y_test_real.reshape(-1)

  loss_values[name+'_'+self.dataset_type+'_default_model'] = model_utility().calculate_metrics(y_test_real,predictions,len(y_test_real),len(X_columns),name )

  #inverse transform
  predictions = np.reshape(predictions, (predictions.shape[0], n_forecast_steps))
  predictions = scaler_target.inverse_transform(predictions)

  modelPredictions.iloc[:, i] = predictions
  modelPredictions = modelPredictions.rename(columns={i: name})

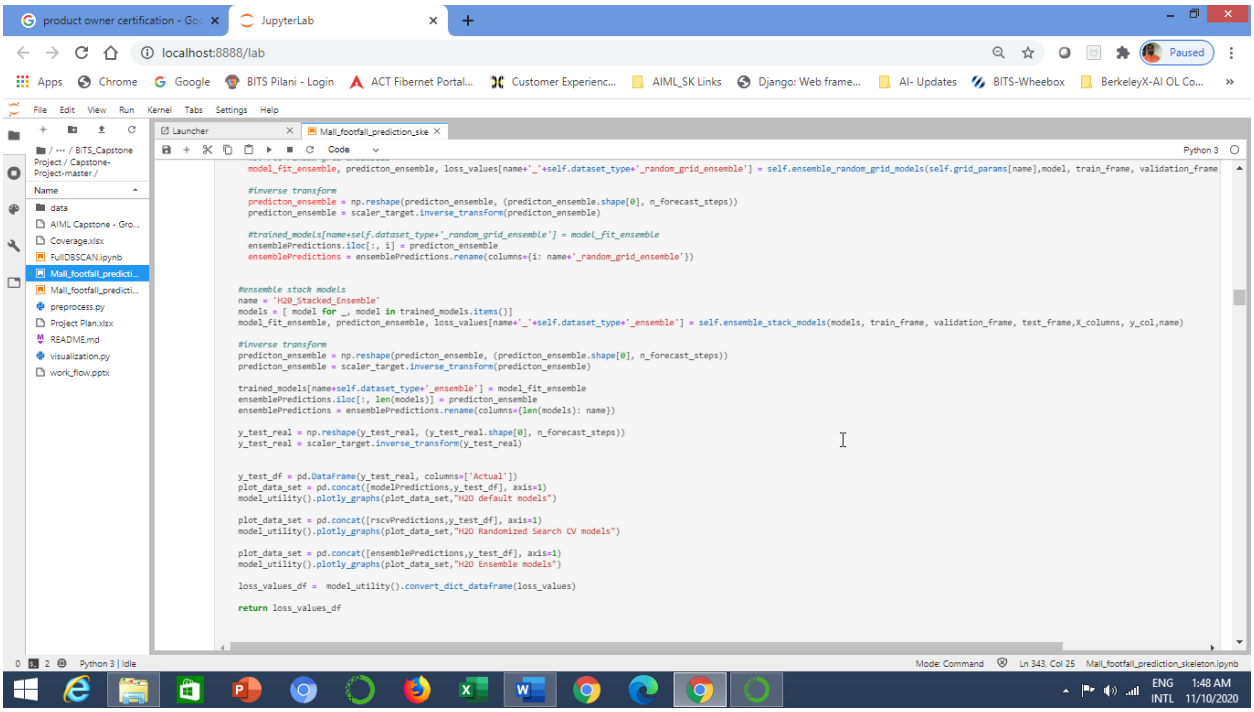
  trained_models[name+self.dataset_type+'standard'] = model


  # 2. fit randomized CV models
  model_fit_rscv, predicton_rscv, loss_values[name+'_'+self.dataset_type+'_rscv'] = self.randomizedSearch(self.grid_params[name],model, train_frame, validation_frame, test_frame,X_columns, y_col,name)

  #inverse transform
  predicton_rscv = np.reshape(predicton_rscv, (predicton_rscv.shape[0], n_forecast_steps))
  predicton_rscv = scaler_target.inverse_transform(predicton_rscv)

  #trained_models[name+self.dataset_type+'rscv'] = model_fit_rscv
  rscvPredictions.iloc[:, i] = predicton_rscv
  rscvPredictions = rscvPredictions.rename(columns={i: name})

  #3. Fit random grid ensembles
  model_fit_ensemble, predicton_ensemble, loss_values[name+'_'+self.dataset_type+'_random_grid_ensemble'] = self.ensemble_random_grid_models(self.grid_params[name],model, train_frame, validation_frame
  #inverse transform
```



```
  model_fit_ensemble, predicton_ensemble, loss_values[name+'_'+self.dataset_type+'_random_grid_ensemble'] = self.ensemble_random_grid_models(self.grid_params[name],model, train_frame, validation_frame

  #inverse transform
  predicton_ensemble = np.reshape(predicton_ensemble, (predicton_ensemble.shape[0], n_forecast_steps))
  predicton_ensemble = scaler_target.inverse_transform(predicton_ensemble)

  #trained_models[name+self.dataset_type+'_random_grid_ensemble'] = model_fit_ensemble
  ensemblePredictions.iloc[:, i] = predicton_ensemble
  ensemblePredictions = ensemblePredictions.rename(columns={i: name+'_random_grid_ensemble'})


#ensemble stack models
name = 'H20_Stacked_Ensemble'
models = [ model for _, model in trained_models.items()]
model_fit_ensemble, predicton_ensemble, loss_values[name+'_'+self.dataset_type+'_ensemble'] = self.ensemble_stack_models(models, train_frame, validation_frame, test_frame,X_columns, y_col,name)

#inverse transform
predicton_ensemble = np.reshape(predicton_ensemble, (predicton_ensemble.shape[0], n_forecast_steps))
predicton_ensemble = scaler_target.inverse_transform(predicton_ensemble)

trained_models[name+self.dataset_type+'_ensemble'] = model_fit_ensemble
ensemblePredictions.iloc[:, len(models)] = predicton_ensemble
ensemblePredictions = ensemblePredictions.rename(columns={len(models): name})

y_test_real = np.reshape(y_test_real, (y_test_real.shape[0], n_forecast_steps))
y_test_real = scaler_target.inverse_transform(y_test_real)


y_test_df = pd.DataFrame(y_test_real, columns=['Actual'])
plot_data_set = pd.concat([modelPredictions,y_test_df], axis=1)
model_utility().plotly_graphs(plot_data_set,"H2O default models")

plot_data_set = pd.concat([rscvPredictions,y_test_df], axis=1)
model_utility().plotly_graphs(plot_data_set,"H2O Randomized Search CV models")

plot_data_set = pd.concat([ensemblePredictions,y_test_df], axis=1)
model_utility().plotly_graphs(plot_data_set,"H2O Ensemble models")

loss_values_df =  model_utility().convert_dict_dataframe(loss_values)

return loss_values_df
```

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Code | Python 3

## 6.5 FB Prophet class

[27]:
```
class fb_prophet:
  def __init__(self, data):
      self.data = data.copy()

  def createFB_prophet_dataset(self,test_data_days=365):

    self.data["Date"] = pd.to_datetime(self.data.Date.astype(str))
    self.data =  self.data.set_index('Date')
    self.data = self.data.sort_index()
    self.data["Date"] = self.data.index

    # Rename the features: These names are NEEDED for the model fitting
    self.data = self.data.rename(columns = {"Date":"ds","InCountTotal":"y"}) #renaming the columns of the dataset

    data_train = self.data[0:-test_data_days]
    data_test = self.data[-test_data_days:]

    return data_train, data_test

  def train(self):
    test_data_days = global_parameters['test_data_set_days']
    data_train, data_test = self.createFB_prophet_dataset(test_data_days)
    model_train = Prophet(daily_seasonality = True) # the Prophet class (model)
    model_train.fit(data_train)

    future = model_train.make_future_dataframe(periods=test_data_days) #we need to specify the number of days in future
    prediction = model_train.predict(future)

    yhat = np.array(prediction['yhat'].tail(test_data_days)).reshape(-1,1)
    y_test = data_test['y'].values.reshape(-1,1)


    y_test_df = pd.DataFrame(y_test, columns=['Actual'])
    predictions = pd.DataFrame(yhat, columns=['Predicted'])

    plot_data_set = pd.concat([predictions,y_test_df], axis=1)
    model_utility().plotly_graphs(plot_data_set,"FB Prophet Model")

    fig = plot_plotly(model_train, prediction)
    fig.show()
```

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Code | Python 3

```
    loss_values = {}
    loss_values['FB prophet Model'] = model_utility().calculate_metrics(y_test, yhat,len(y_test),n_input_variables=data_train.shape[1], model_name='FB Prophet Model')

    loss_values_df =  model_utility().convert_dict_dataframe(loss_values)
    return loss_values_df
```

# 7 - Model training and evaluation

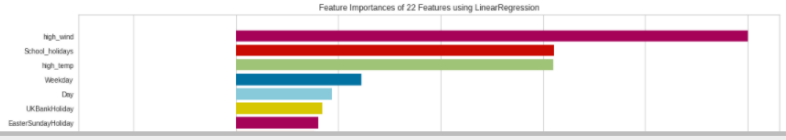
## 7.1 Model Training with Regression and Ensemble models

### 7.1.1 Model training with normal data

[28]:
```
loss_values_all_models = []
```

[29]:
```
reg_models = regression_model(data_final,dataset_type='normal_shuffled')
_,_,_, _, _, loss_normal_df = reg_models.train_and_evaluate_models(shuffle=True)
loss_values_all_models.append(loss_normal_df)
```

```
Defined 20 models
============================================================
linear_regression
default model fitting...
Now tuning LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False).
```

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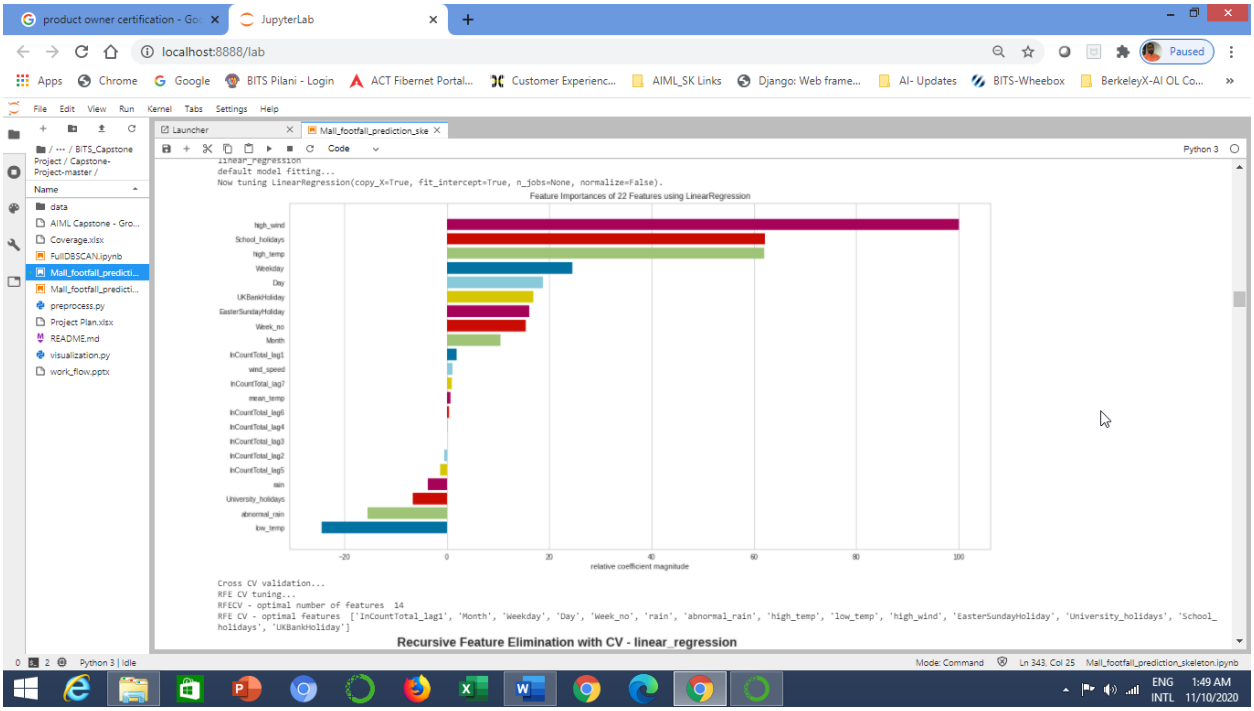
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Mall_footfall_prediction_ske
Code
Python 3
default model fitting...
Now tuning LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False).
Feature Importances of 22 Features using LinearRegression
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
EasterSundayHoliday
Week_no
Month
lnCountTotal_lag1
wind_speed
lnCountTotal_lag7
mean_temp
lnCountTotal_lag6
lnCountTotal_lag4
lnCountTotal_lag3
lnCountTotal_lag2
lnCountTotal_lag5
rain
University_holidays
abnormal_rain
low_temp
-20
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 14
RFE CV - optimal features ['lnCountTotal_lag1', 'Month', 'Weekday', 'Day', 'Week_no', 'rain', 'abnormal_rain', 'high_temp', 'low_temp', 'high_wind', 'EasterSundayHoliday', 'University_holidays', 'School_holidays', 'UKBankHoliday']
Recursive Feature Elimination with CV - linear_regression
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
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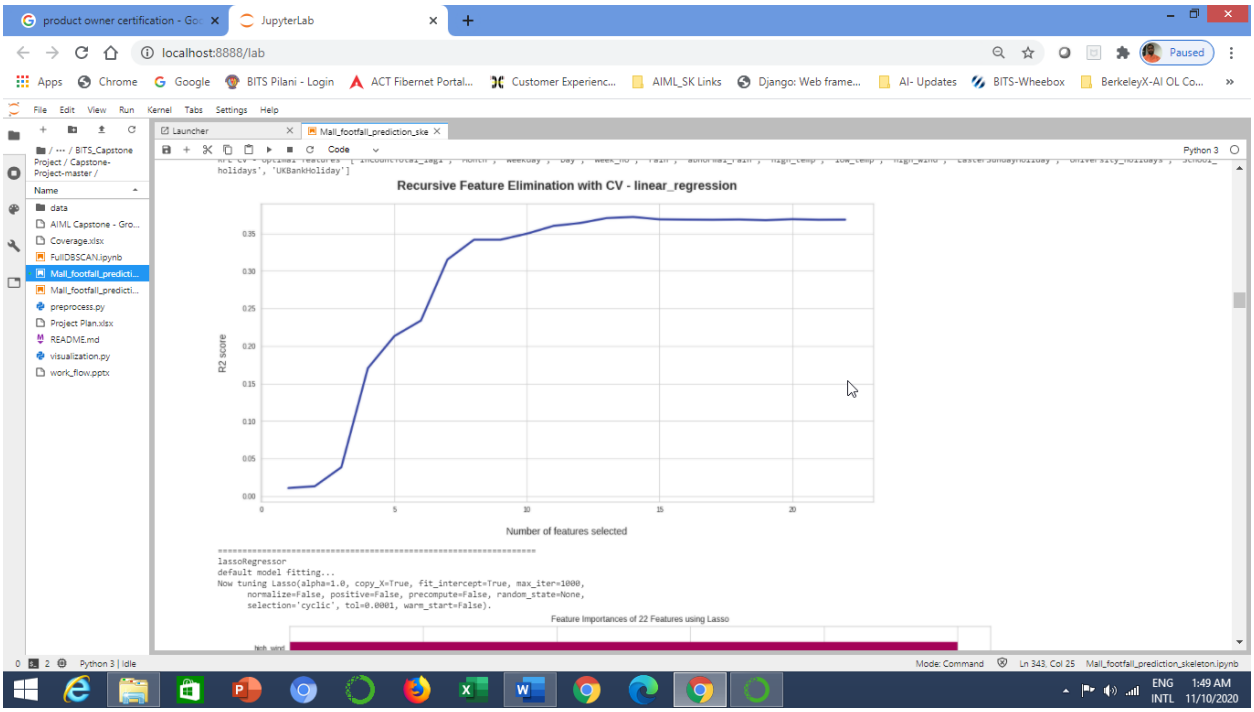
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Launcher
Mall_footfall_prediction_ske
Code
Python 3
holidays', 'UKBankHoliday']
Recursive Feature Elimination with CV - linear_regression
R2 score
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
5
10
15
20
Number of features selected
LassoRegressor
default model fitting...
Now tuning Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
normalize=False, positive=False, precompute=False, random_state=None,
selection='cyclic', tol=0.0001, warm_start=False).
Feature Importances of 22 Features using Lasso
high_wind
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
1:49 AM
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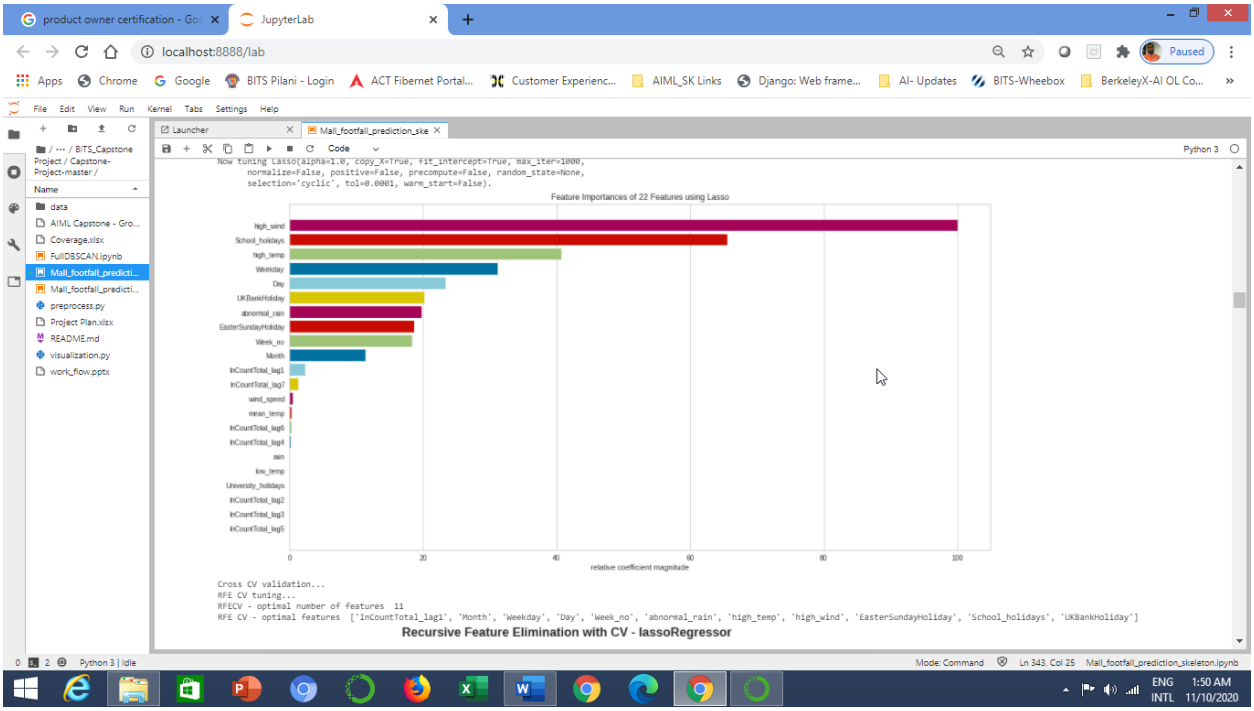
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Launcher
Mall_footfall_prediction_ske
Code
Python 3
Now tuning Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
normalize=False, positive=False, precompute=False, random_state=None,
selection='cyclic', tol=0.0001, warm_start=False).
Feature Importances of 22 Features using Lasso
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
abnormal_rain
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
rain
low_temp
University_holidays
InCountTotal_lag2
InCountTotal_lag3
InCountTotal_lag5
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 11
RFE CV - optimal features ['InCountTotal_lag1', 'Month', 'Weekday', 'Day', 'Week_no', 'abnormal_rain', 'high_temp', 'high_wind', 'EasterSundayHoliday', 'School_holidays', 'UKBankHoliday']
Recursive Feature Elimination with CV - lassoRegressor
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
ENG
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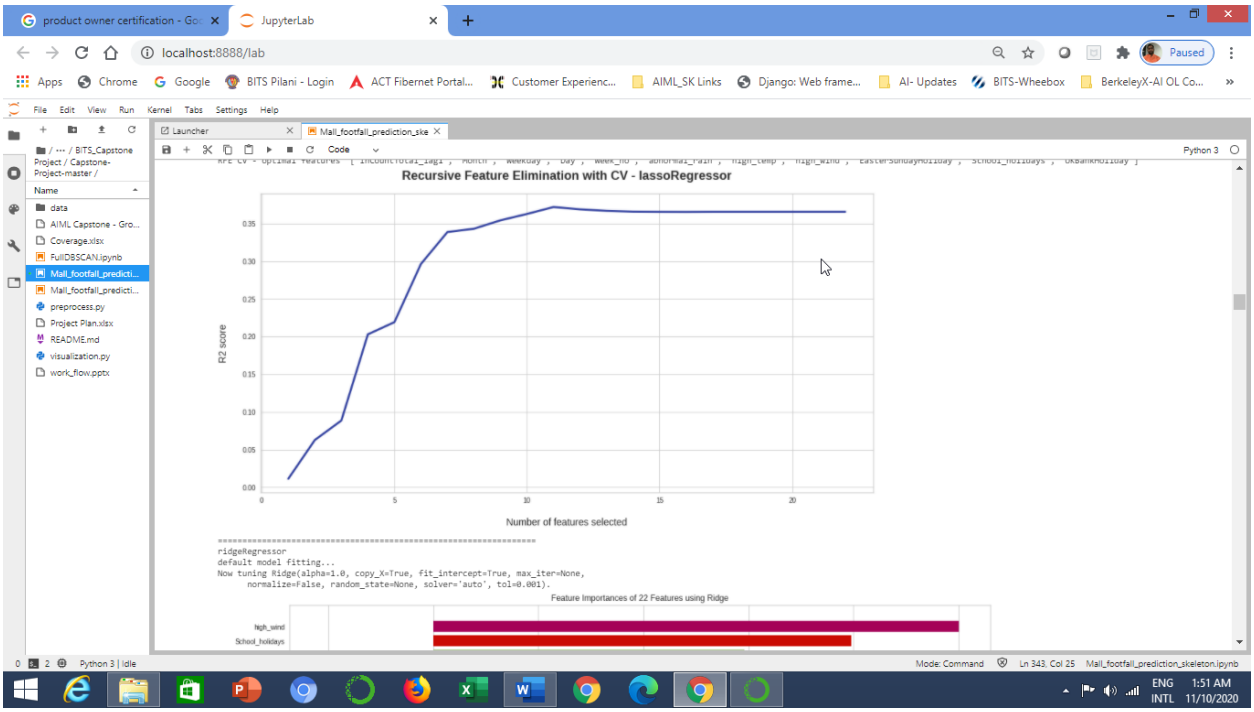
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BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
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Mall_footfall_prediction_ske
Code
Python 3
Recursive Feature Elimination with CV - lassoRegressor
R2 score
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
5
10
15
20
Number of features selected
ridgeRegressor
default model fitting...
Now tuning Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
normalize=False, random_state=None, solver='auto', tol=0.001).
Feature Importances of 22 Features using Ridge
high_wind
School_holidays
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
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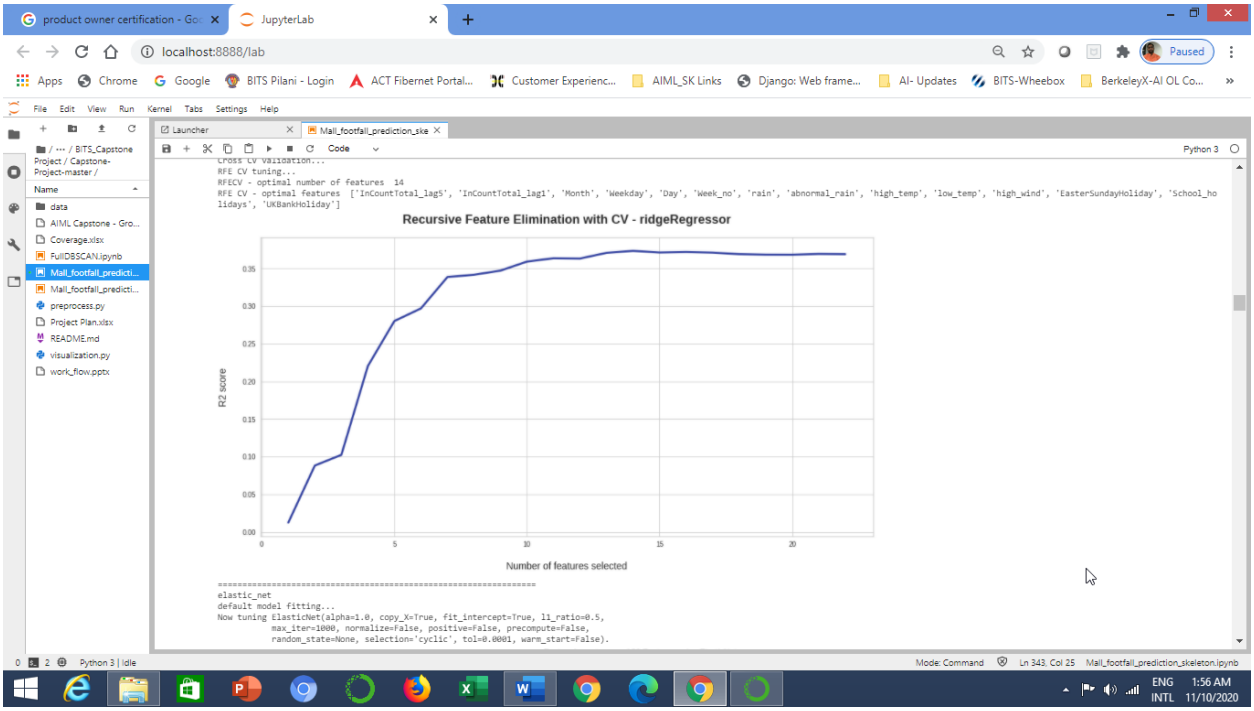
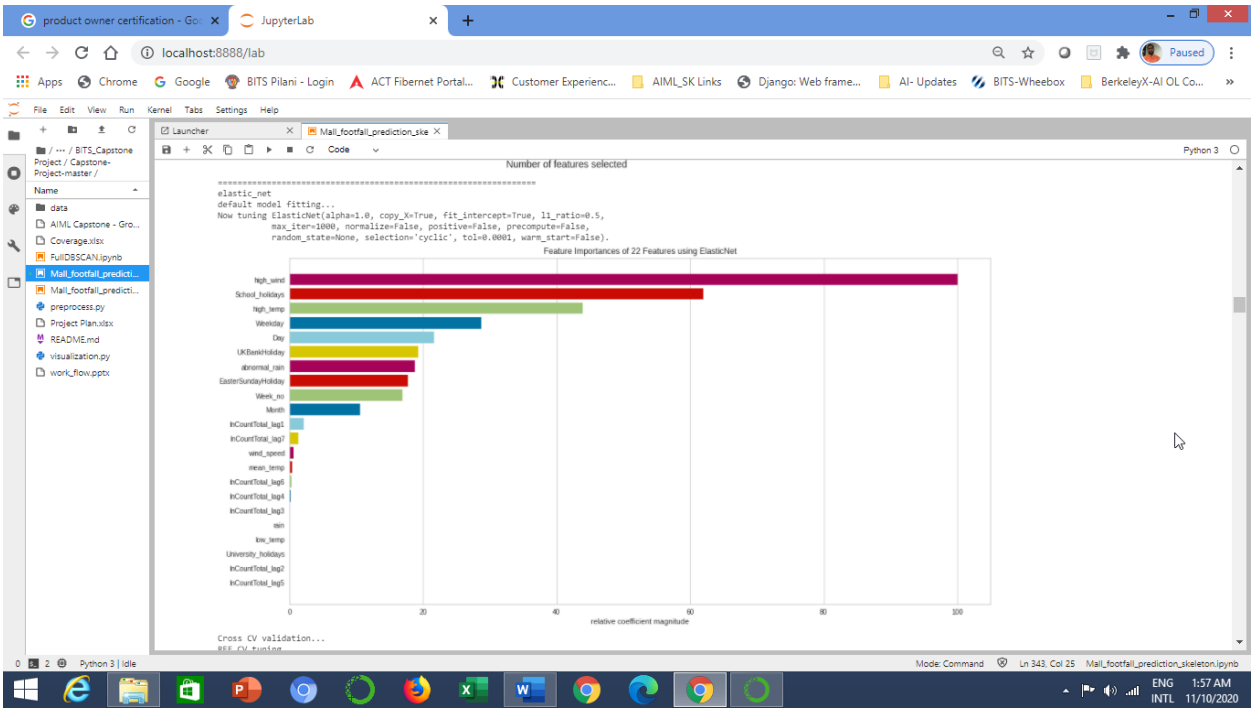
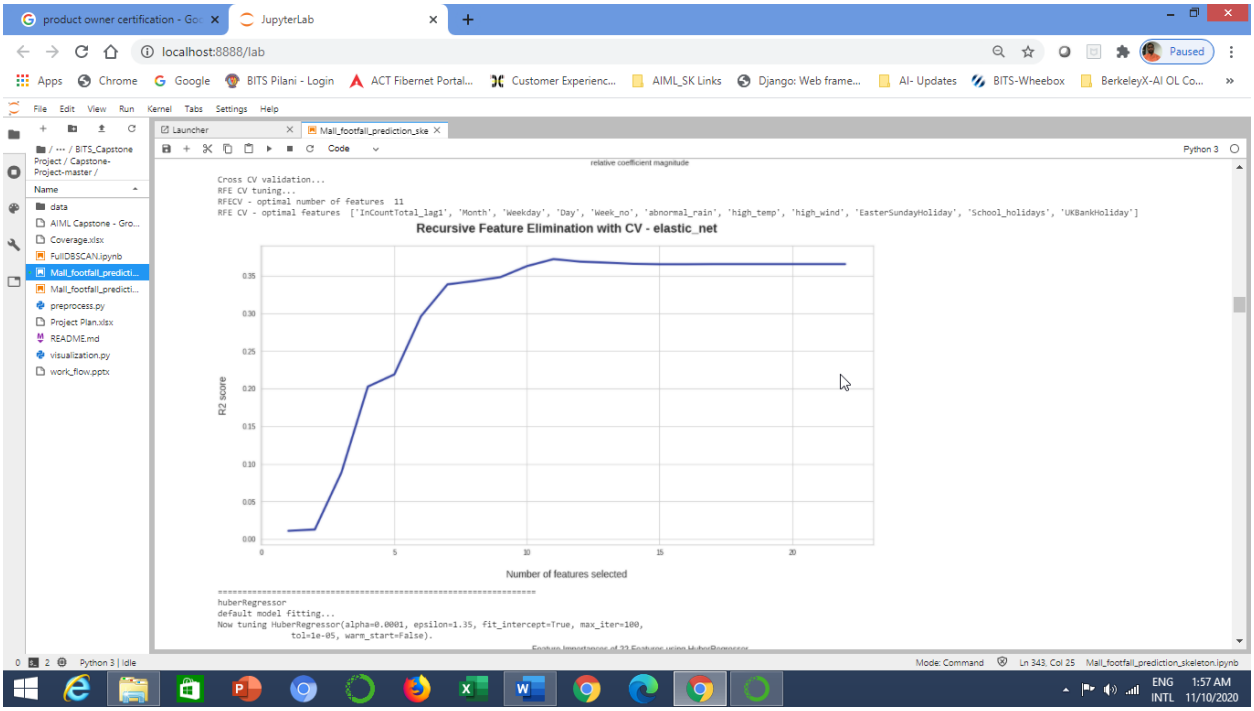
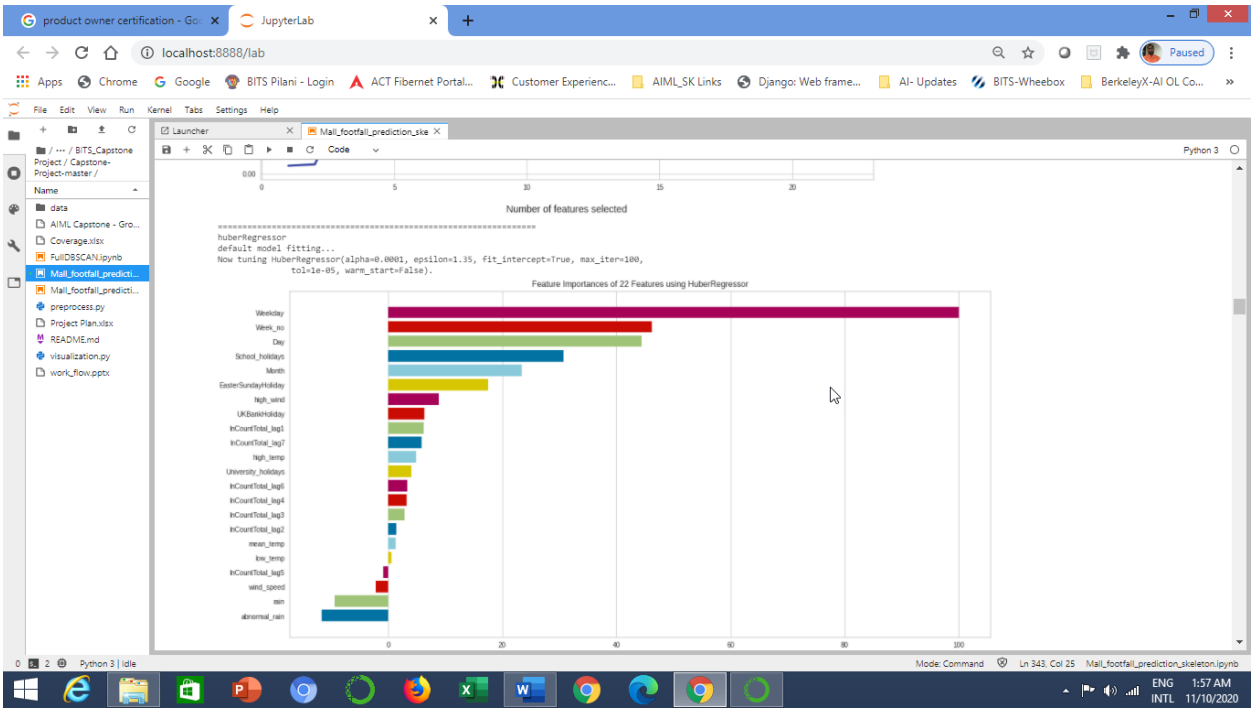
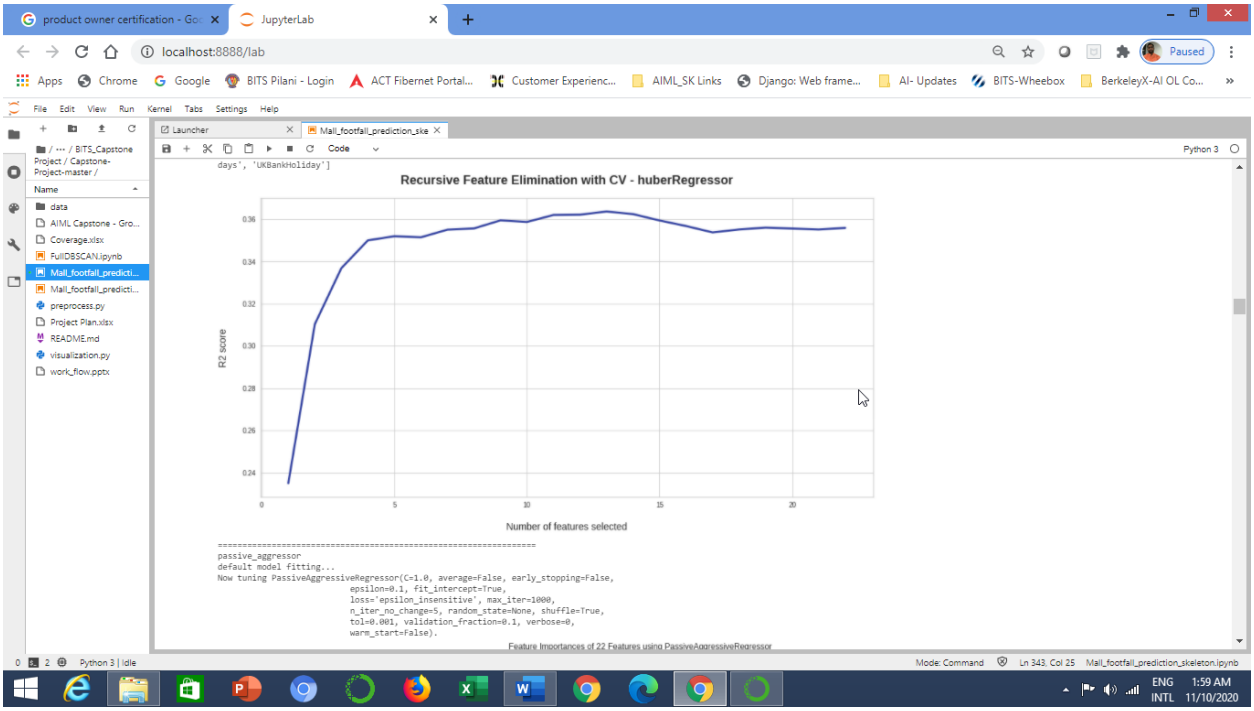
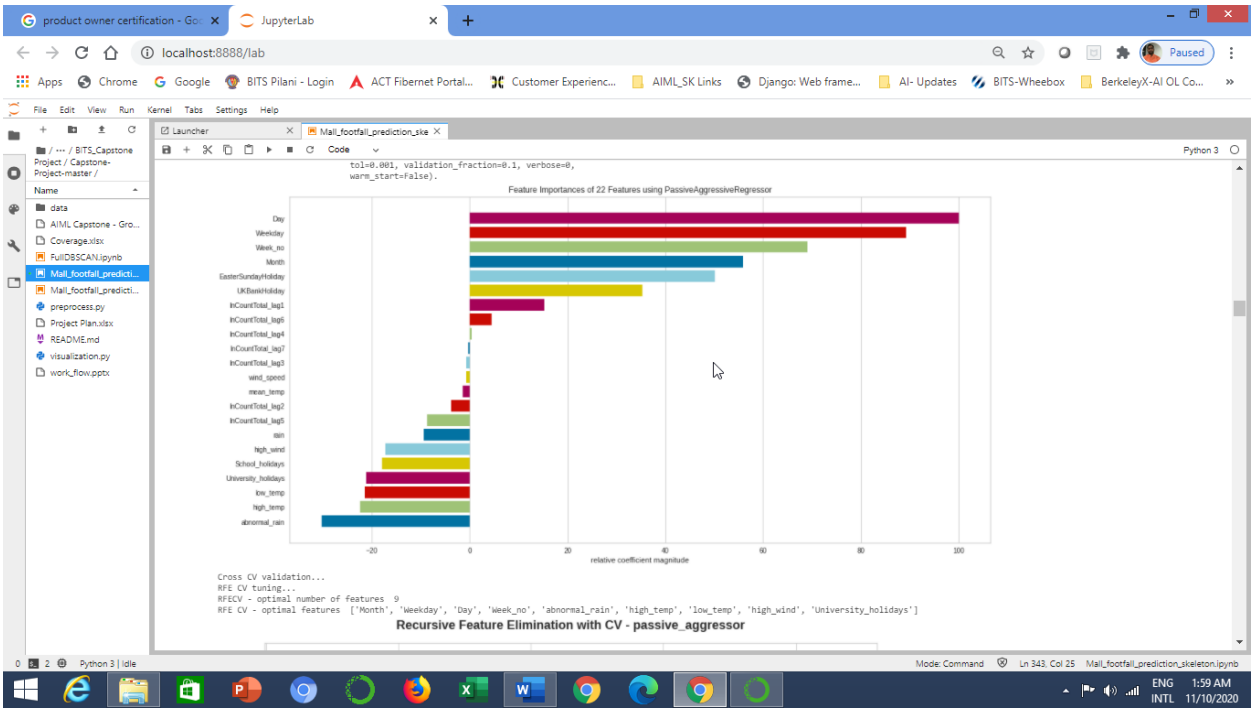

Recursive Feature Elimination with CV - ridgeRegressor
R2 score
Number of features selected
RFECV - optimal number of features 14
RFE CV - optimal features ['InCountTotal_lag5', 'InCountTotal_lag1', 'Month', 'Weekday', 'Day', 'Week_no', 'rain', 'abnormal_rain', 'high_temp', 'low_temp', 'high_wind', 'EasterSundayHoliday', 'School_holidays', 'UKBankHoliday']
elastic_net
default model fitting...
Now tuning ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
max_iter=1000, normalize=False, positive=False, precompute=False,
random_state=None, selection='cyclic', tol=0.0001, warm_start=False).

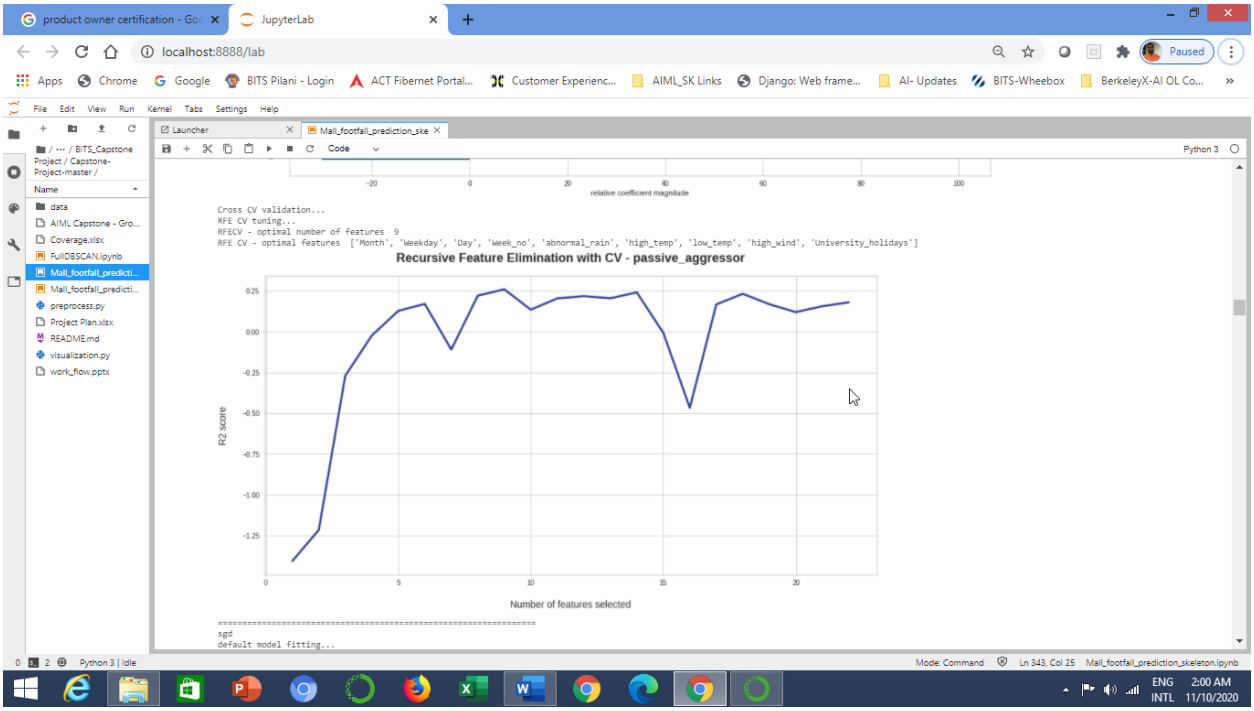

Number of features selected
Feature Importances of 22 Features using ElasticNet
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
abnormal_rain
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag3
rain
low_temp
University_holidays
InCountTotal_lag2
InCountTotal_lag5
relative coefficient magnitude
Cross CV validation...


Recursive Feature Elimination with CV - elastic_net
R2 score
Number of features selected


Feature Importances of 22 Features using HuberRegressor
Weekday
Week_no
Day
School_holidays
Month
EasterSundayHoliday
high_wind
UKBankHoliday
InCountTotal_lag1
InCountTotal_lag7
high_temp
University_holidays
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
mean_temp
low_temp
InCountTotal_lag5
wind_speed
rain
abnormal_rain


Recursive Feature Elimination with CV - huberRegressor
R2 score
Number of features selected
Feature Importances of 22 Features using PassiveAggressiveRegressor


Feature Importances of 22 Features using PassiveAggressiveRegressor
Day
Weekday
Week_no
Month
EasterSundayHoliday
UKBankHoliday
InCountTotal_lag1
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag7
InCountTotal_lag3
wind_speed
mean_temp
InCountTotal_lag2
InCountTotal_lag5
rain
high_wind
School_holidays
University_holidays
low_temp
high_temp
abnormal_rain
relative coefficient magnitude
Recursive Feature Elimination with CV - passive_aggressor


product owner certification - Go
JupyterLab
localhost:8888/lab
Paused
Apps
Chrome
Google
BITS Pilani - Login
ACT Fibernet Portal...
Customer Experienc...
AIML_SK Links
Django: Web frame...
AI- Updates
BITS-Wheebox
BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Code
Python 3
relative coefficient magnitude
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 9
RFE CV - optimal features ['Month', 'Weekday', 'Day', 'Week_no', 'abnormal_rain', 'high_temp', 'low_temp', 'high_wind', 'University_holidays']
Recursive Feature Elimination with CV - passive_aggressor
R2 score
Number of features selected
sgd
default model fitting...
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
ENG
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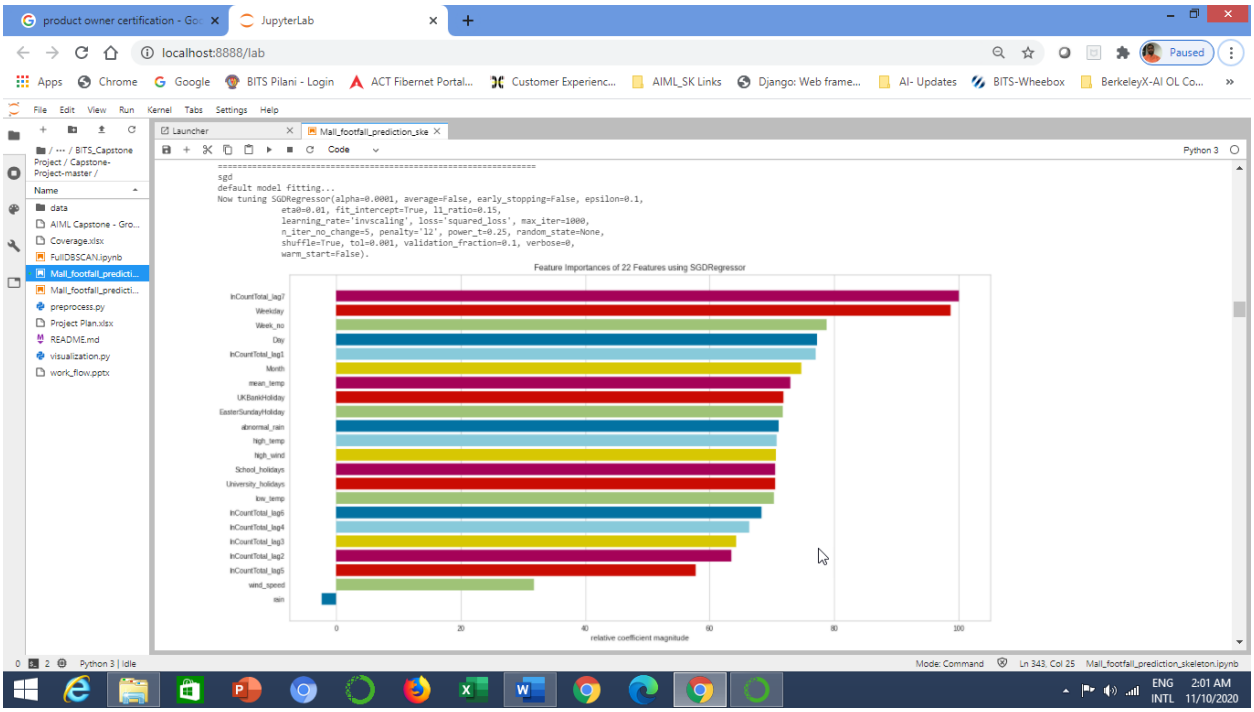
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Django: Web frame...
AI- Updates
BITS-Wheebox
BerkeleyX-AI OL Co...
File Edit View Run Kernel Tabs Settings Help
Launcher
Mall_footfall_prediction_ske
Code
Python 3
sgd
default model fitting...
Now tuning SGDRegressor(alpha=0.0001, average=False, early_stopping=False, epsilon=0.1,
eta0=0.01, fit_intercept=True, l1_ratio=0.15,
learning_rate='invscaling', loss='squared_loss', max_iter=1000,
n_iter_no_change=5, penalty='l2', power_t=0.25, random_state=None,
shuffle=True, tol=0.001, validation_fraction=0.1, verbose=0,
warm_start=False).
Feature Importances of 22 Features using SGDRegressor
lnCountTotal_lag7
Weekday
Week_no
Day
lnCountTotal_lag1
Month
mean_temp
UKBankHoliday
EasterSundayHoliday
abnormal_rain
high_temp
high_wind
School_holidays
University_holidays
low_temp
lnCountTotal_lag6
lnCountTotal_lag4
lnCountTotal_lag3
lnCountTotal_lag2
lnCountTotal_lag5
wind_speed
rain
relative coefficient magnitude
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
Python 3 | Idle
Mode: Command
Ln 343, Col 25
Mall_footfall_prediction_skeleton.ipynb
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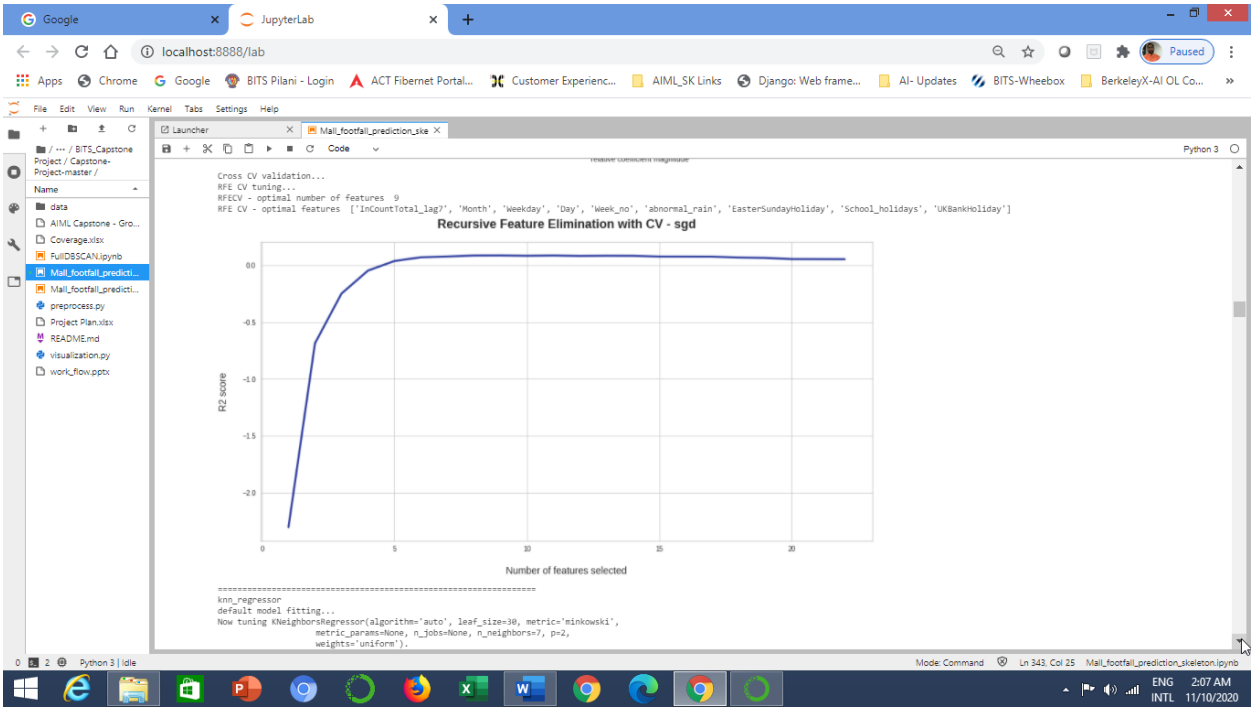
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localhost:8888/lab
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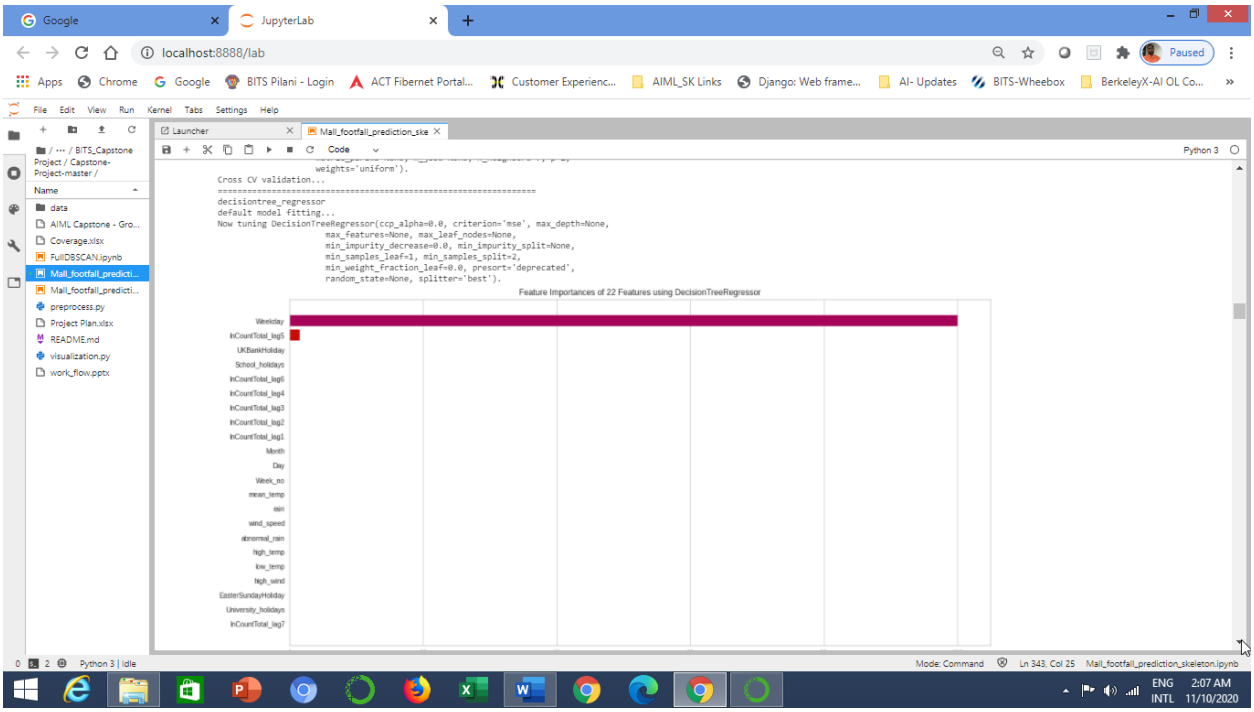
Launcher
Mall_footfall_prediction_ske
Code
Python 3
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 9
RFE CV - optimal features ['InCountTotal_lag7', 'Month', 'Weekday', 'Day', 'Week_no', 'abnormal_rain', 'EasterSundayHoliday', 'School_holidays', 'UKBankHoliday']
Recursive Feature Elimination with CV - sgd
R2 score
Number of features selected
knn_regressor
default model fitting...
Now tuning KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
metric_params=None, n_jobs=None, n_neighbors=7, p=2,
weights='uniform').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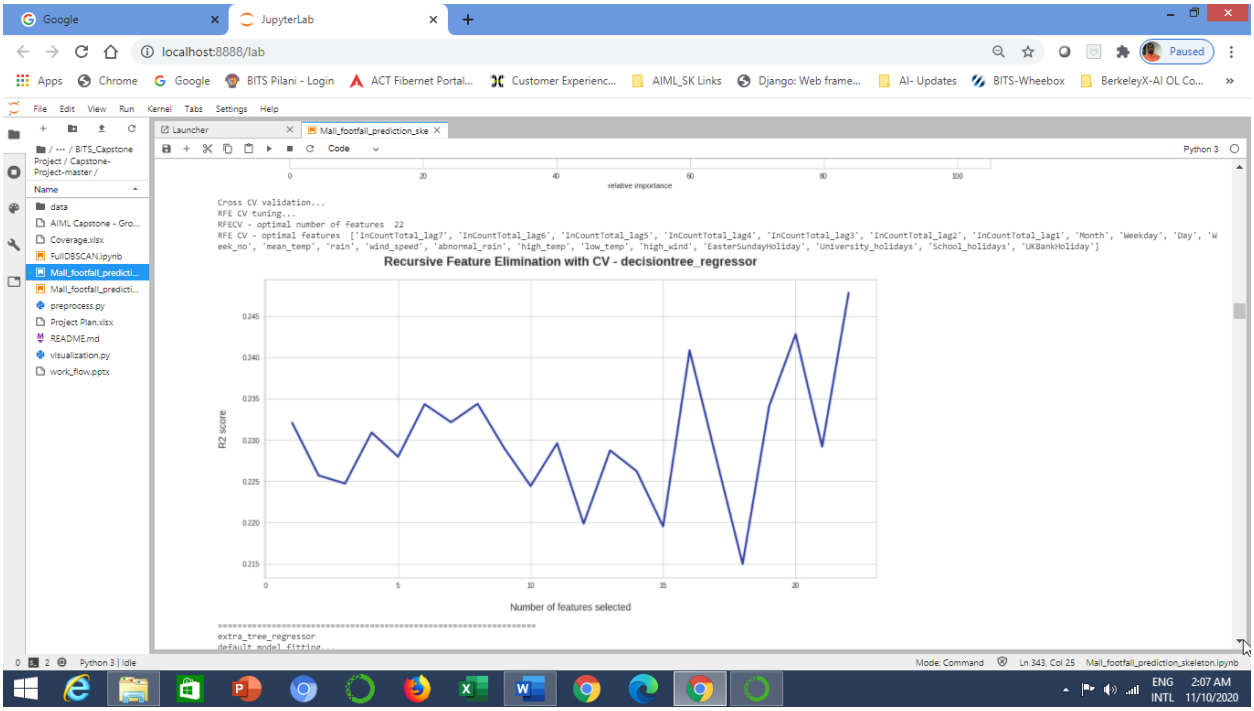
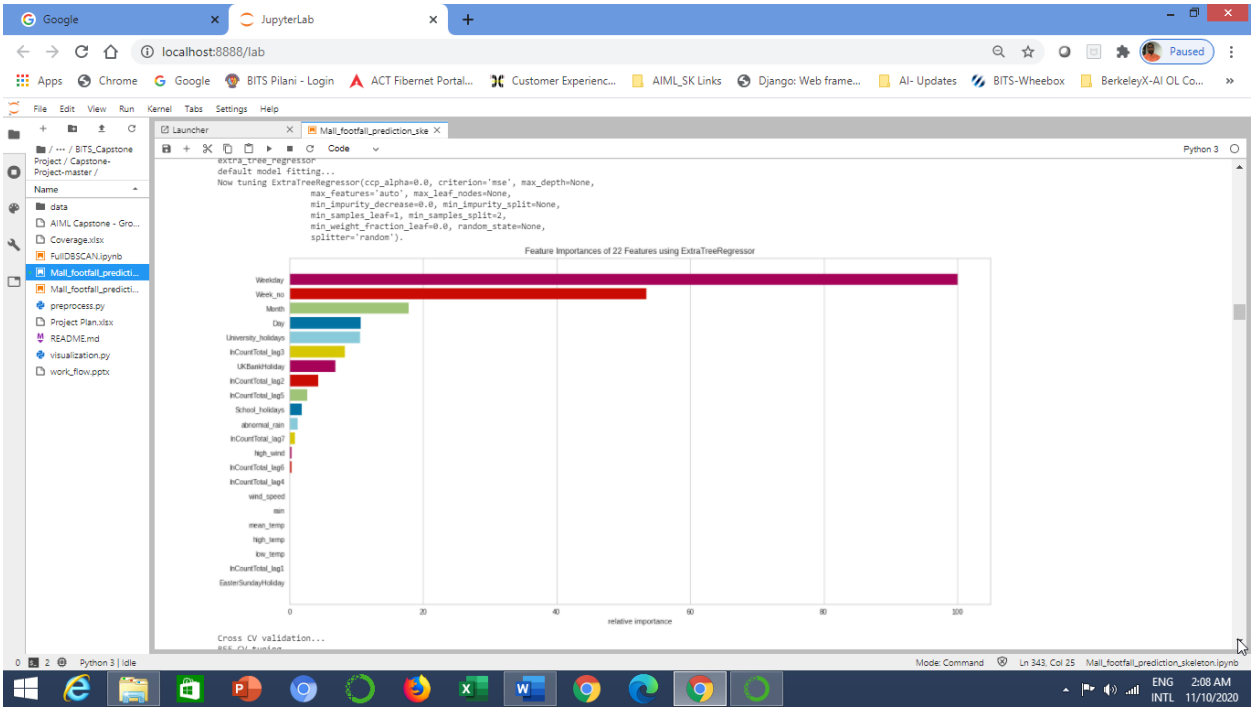
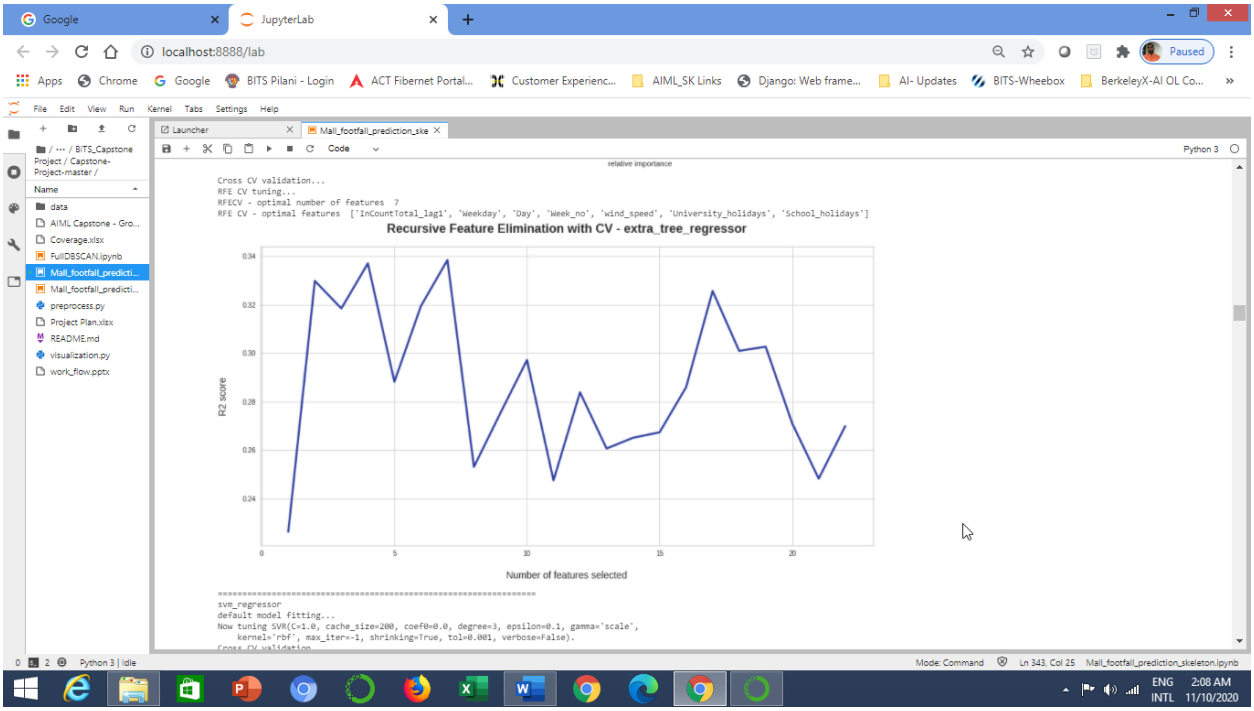
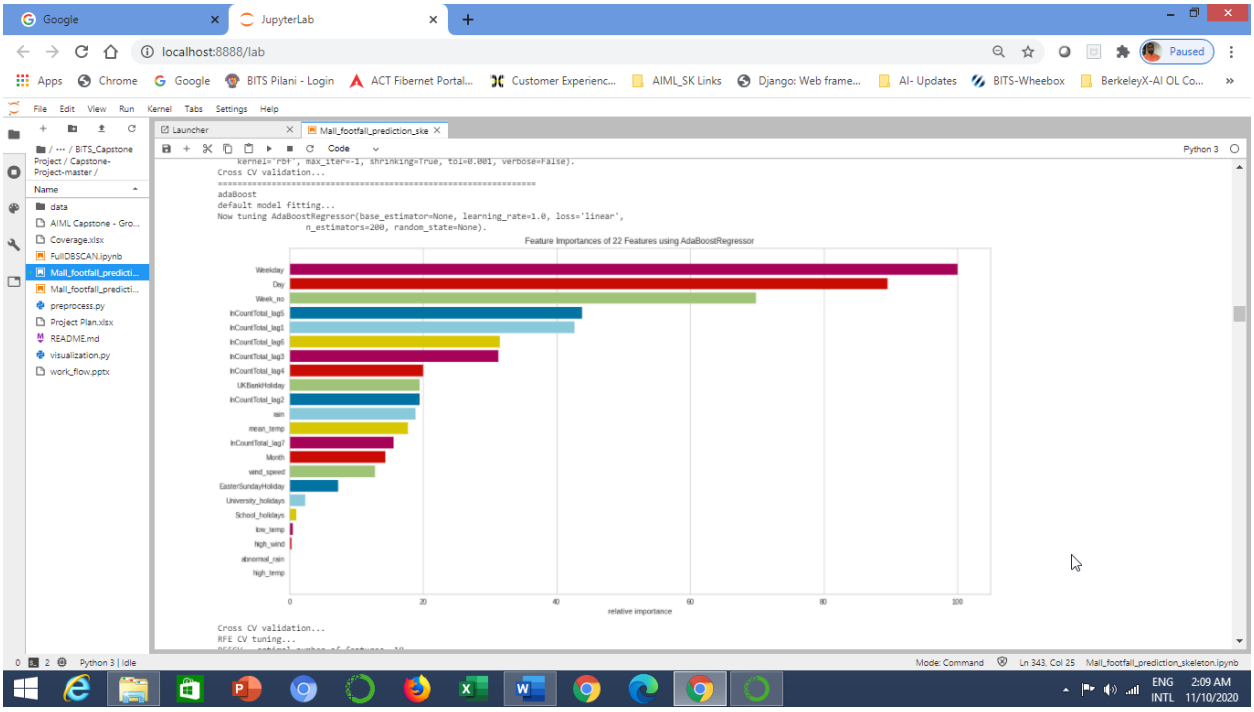
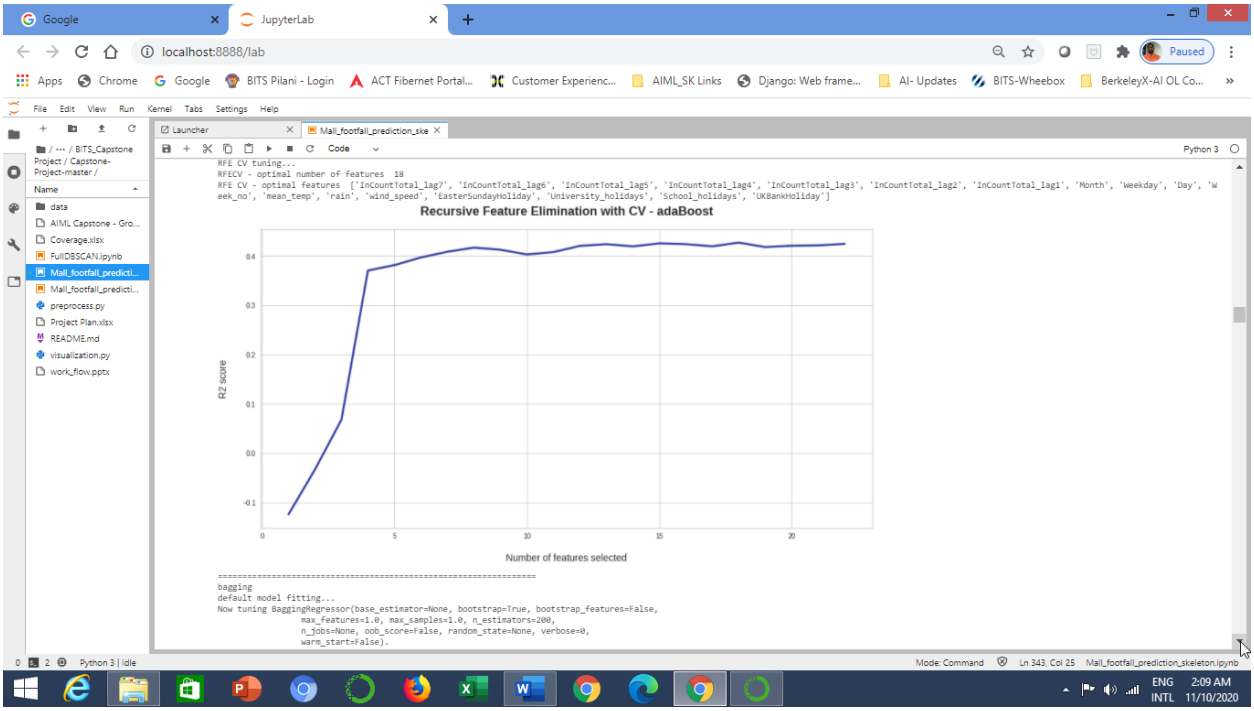
JupyterLab
localhost:8888/lab
Paused
Launcher
Mall_footfall_prediction_ske
Code
Python 3
Cross CV validation...
decisiontree_regressor
default model fitting...
Now tuning DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort='deprecated',
random_state=None, splitter='best').
Feature Importances of 22 Features using DecisionTreeRegressor
Weekday
InCountTotal_lag5
UKBankHoliday
School_holidays
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
InCountTotal_lag1
Month
Day
Week_no
mean_temp
rain
wind_speed
abnormal_rain
high_temp
low_temp
high_wind
EasterSundayHoliday
University_holidays
InCountTotal_lag7

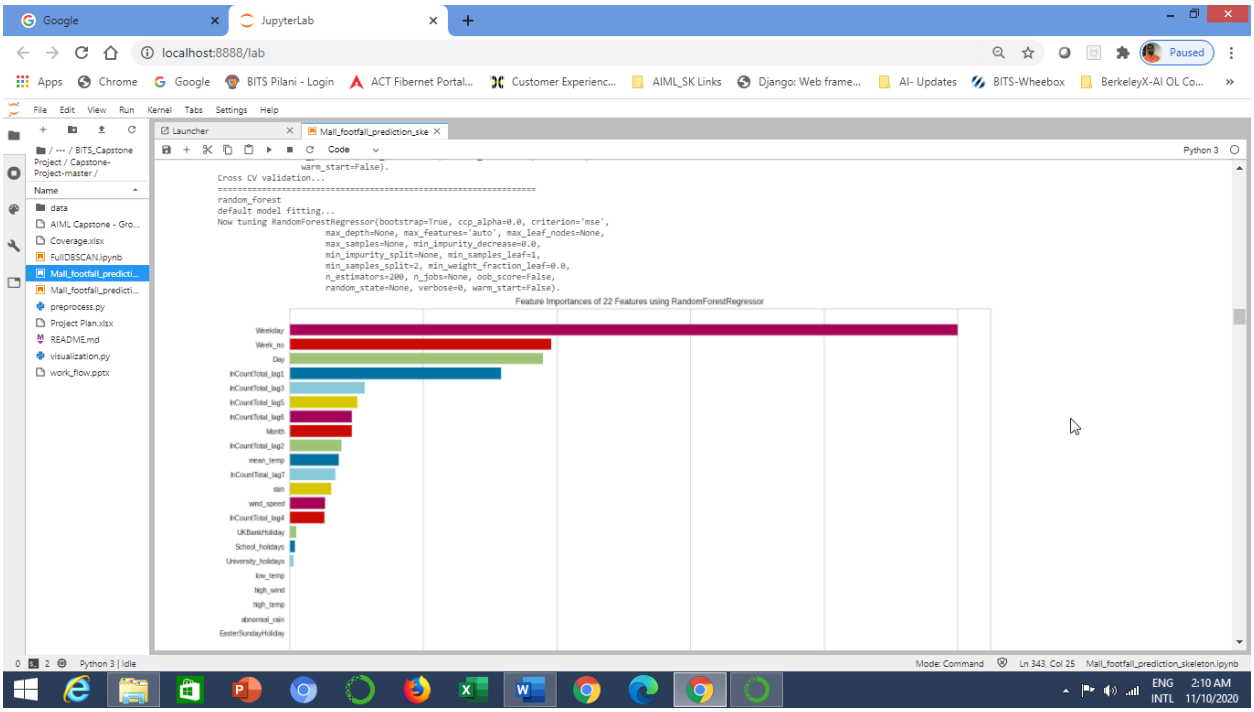

Recursive Feature Elimination with CV - decisiontree_regressor
R2 score
Number of features selected
relative importance

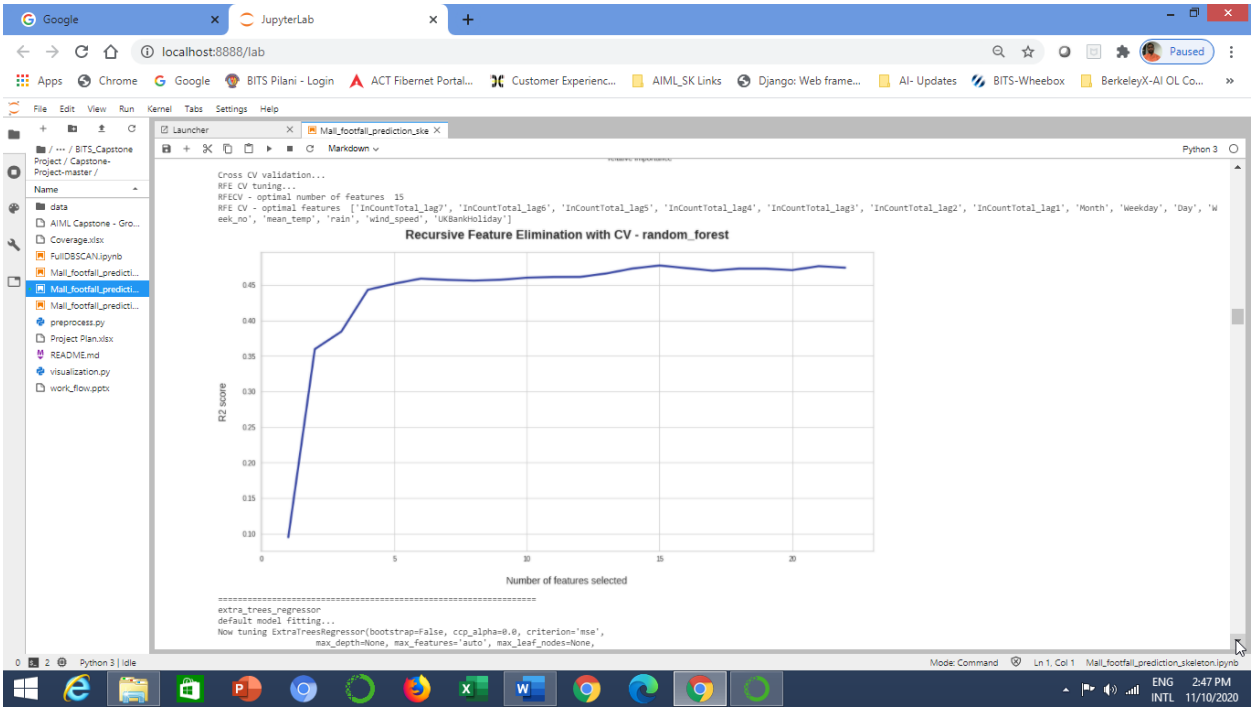

Feature Importances of 22 Features using ExtraTreeRegressor
Weekday
Week_no
Month
Day
University_holidays
lnCountTotal_lag3
UKBankHoliday
lnCountTotal_lag2
lnCountTotal_lag5
School_holidays
abnormal_rain
lnCountTotal_lag7
high_wind
lnCountTotal_lag6
lnCountTotal_lag4
wind_speed
rain
mean_temp
high_temp
low_temp
lnCountTotal_lag1
EasterSundayHoliday
relative importance

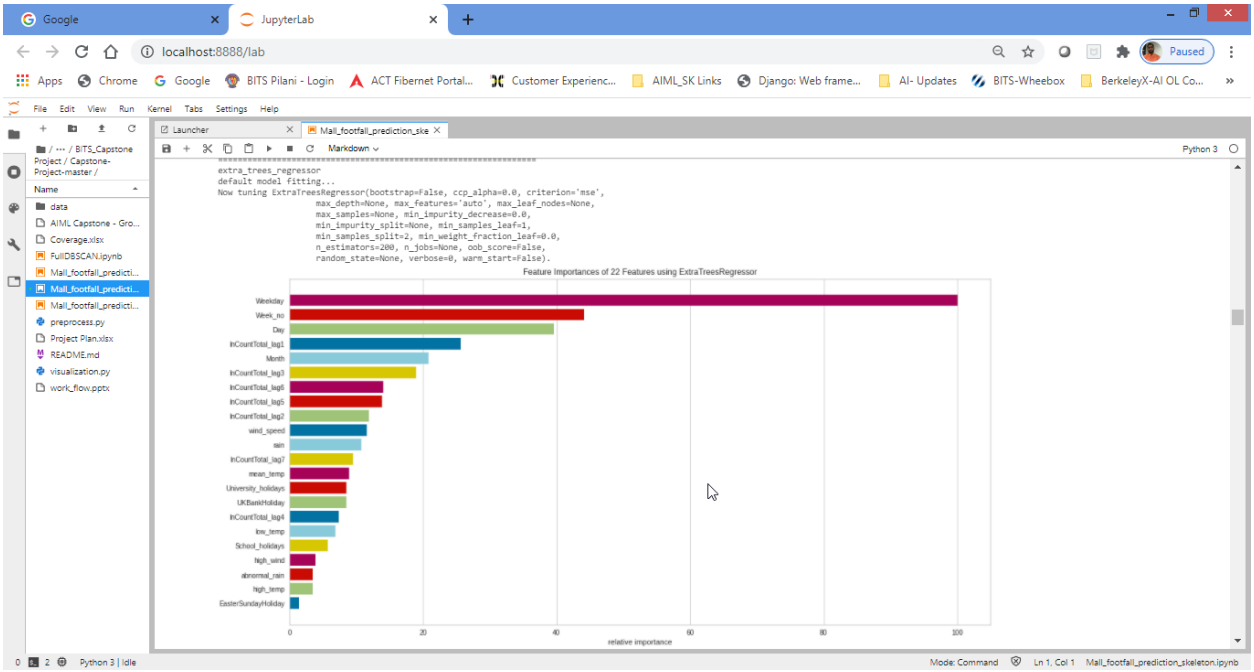

Recursive Feature Elimination with CV - extra_tree_regressor
R2 score
Number of features selected

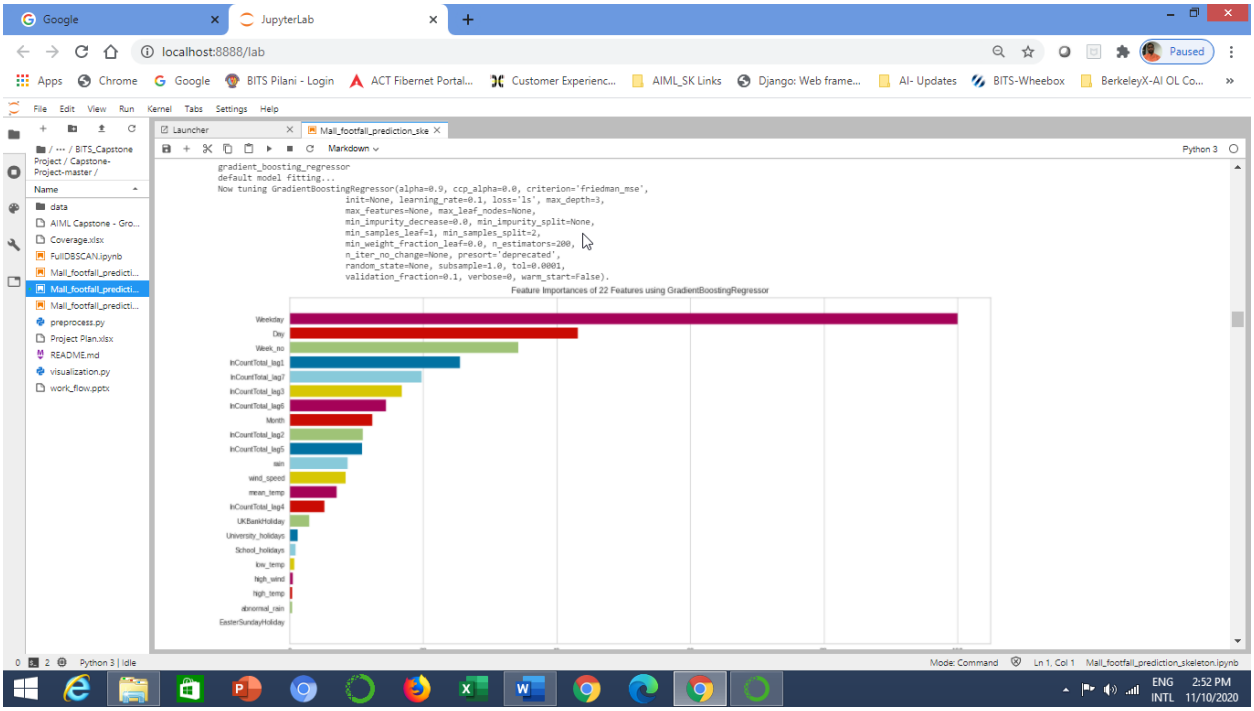

Feature Importances of 22 Features using AdaBoostRegressor
relative importance


Recursive Feature Elimination with CV - adaBoost
R2 score
Number of features selected


Feature Importances of 22 Features using RandomForestRegressor
Weekday
Week_no
Day
InCountTotal_lag1
InCountTotal_lag3
InCountTotal_lag5
InCountTotal_lag6
Month
InCountTotal_lag2
mean_temp
InCountTotal_lag7
rain
wind_speed
InCountTotal_lag4
UKBankHoliday
School_holidays
University_holidays
low_temp
high_wind
high_temp
abnormal_rain
EasterSundayHoliday


Recursive Feature Elimination with CV - random_forest
R2 score
Number of features selected


Feature Importances of 22 Features using ExtraTreesRegressor
relative importance


Google
JupyterLab
localhost:8888/lab
Paused
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
gradient_boosting_regressor
default model fitting...
Now tuning GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
init=None, learning_rate=0.1, loss='ls', max_depth=3,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, n_estimators=200,
n_iter_no_change=None, presort='deprecated',
random_state=None, subsample=1.0, tol=0.0001,
validation_fraction=0.1, verbose=0, warm_start=False).
Feature Importances of 22 Features using GradientBoostingRegressor
Weekday
Day
Week_no
InCountTotal_lag1
InCountTotal_lag7
InCountTotal_lag3
InCountTotal_lag6
Month
InCountTotal_lag2
InCountTotal_lag5
rain
wind_speed
mean_temp
InCountTotal_lag4
UKBankHoliday
University_holidays
School_holidays
low_temp
high_wind
high_temp
abnormal_rain
EasterSundayHoliday
Python 3 | Idle
Mode: Command
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Mall_footfall_prediction_skeleton.ipynb
ENG
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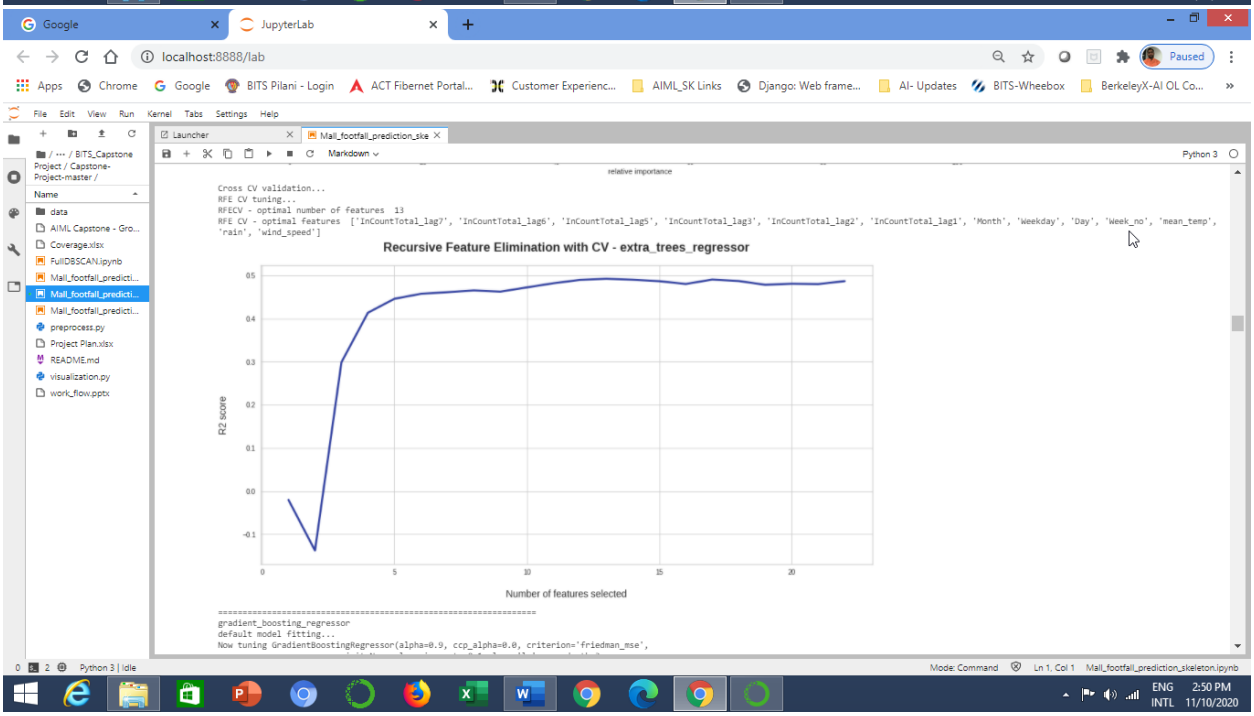
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JupyterLab
localhost:8888/lab
Paused
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
relative importance
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 13
RFE CV - optimal features ['InCountTotal_lag7', 'InCountTotal_lag6', 'InCountTotal_lag5', 'InCountTotal_lag3', 'InCountTotal_lag2', 'InCountTotal_lag1', 'Month', 'Weekday', 'Day', 'Week_no', 'mean_temp',
'rain', 'wind_speed']
Recursive Feature Elimination with CV - extra_trees_regressor
R2 score
Number of features selected
gradient_boosting_regressor
default model fitting...
Now tuning GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
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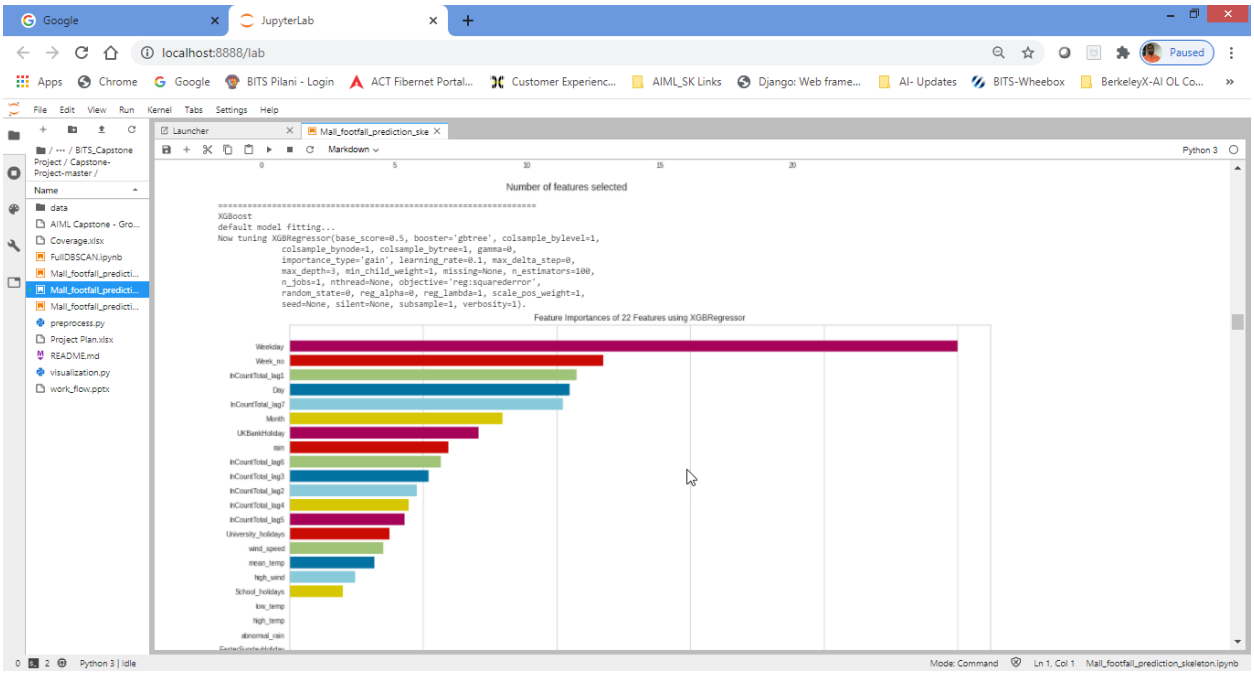
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AIML_SK Links
Django: Web frame...
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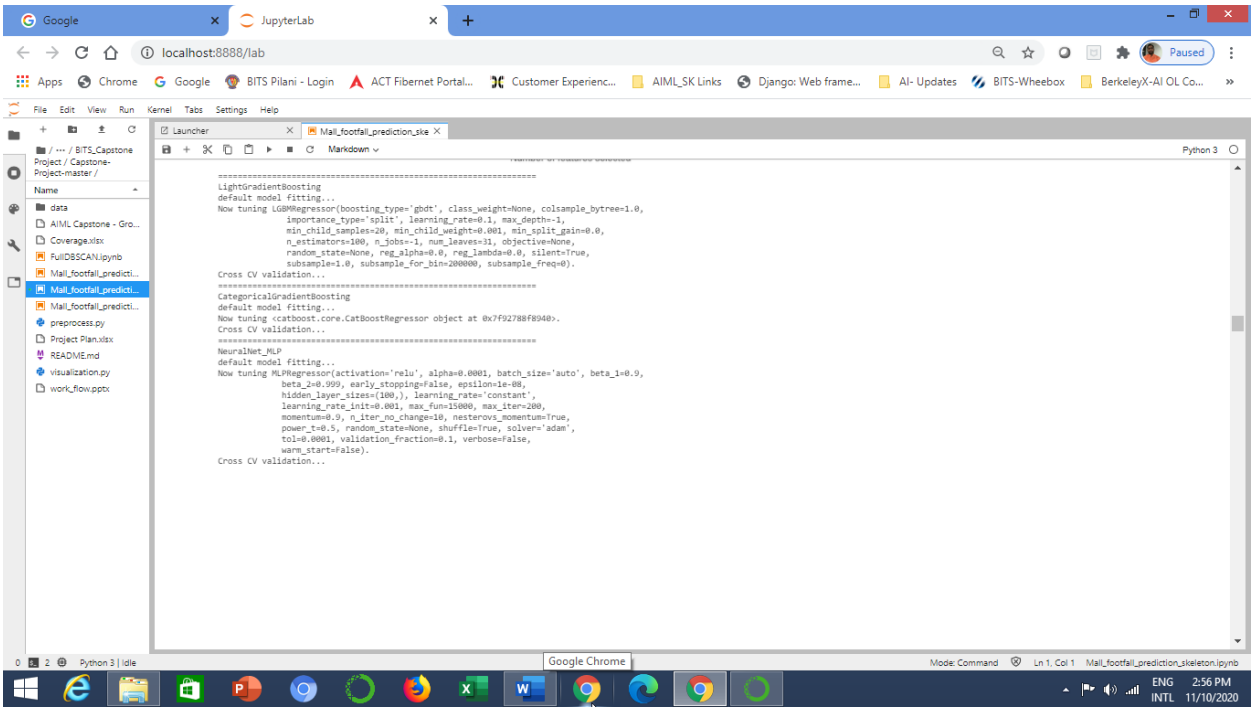
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
Number of features selected
XGBoost
default model fitting...
Now tuning XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
colsample_bynode=1, colsample_bytree=1, gamma=0,
importance_type='gain', learning_rate=0.1, max_delta_step=0,
max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
n_jobs=-1, nthread=None, objective='reg:squarederror',
random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
seed=None, silent=None, subsample=1, verbosity=1).
Feature Importances of 22 Features using XGBRegressor
Weekday
Week_no
InCountTotal_lag1
Day
InCountTotal_lag7
Month
UKBankHoliday
min
InCountTotal_lag6
InCountTotal_lag3
InCountTotal_lag2
InCountTotal_lag4
InCountTotal_lag5
University_holidays
wind_speed
mean_temp
high_wind
School_holidays
low_temp
high_temp
abnormal_rain
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb


Google
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AIML_SK Links
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preprocess.py
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visualization.py
work_flow.pptx
LightGradientBoosting
default model fitting...
Now tuning LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
importance_type='split', learning_rate=0.1, max_depth=-1,
min_child_samples=20, min_child_weight=0.001, min_split_gain=0.0,
n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
subsample=1.0, subsample_for_bin=200000, subsample_freq=0).
Cross CV validation...
CategoricalGradientBoosting
default model fitting...
Now tuning <catboost.core.CatBoostRegressor object at 0x7f92788f8940>.
Cross CV validation...
NeuralNet_MLP
default model fitting...
Now tuning MLPRegressor(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
beta_2=0.999, early_stopping=False, epsilon=1e-08,
hidden_layer_sizes=(100,), learning_rate='constant',
learning_rate_init=0.001, max_fun=15000, max_iter=200,
momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True,
power_t=0.5, random_state=None, shuffle=True, solver='adam',
tol=0.0001, validation_fraction=0.1, verbose=False,
warm_start=False).
Cross CV validation...
Python 3 | Idle
Google Chrome
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
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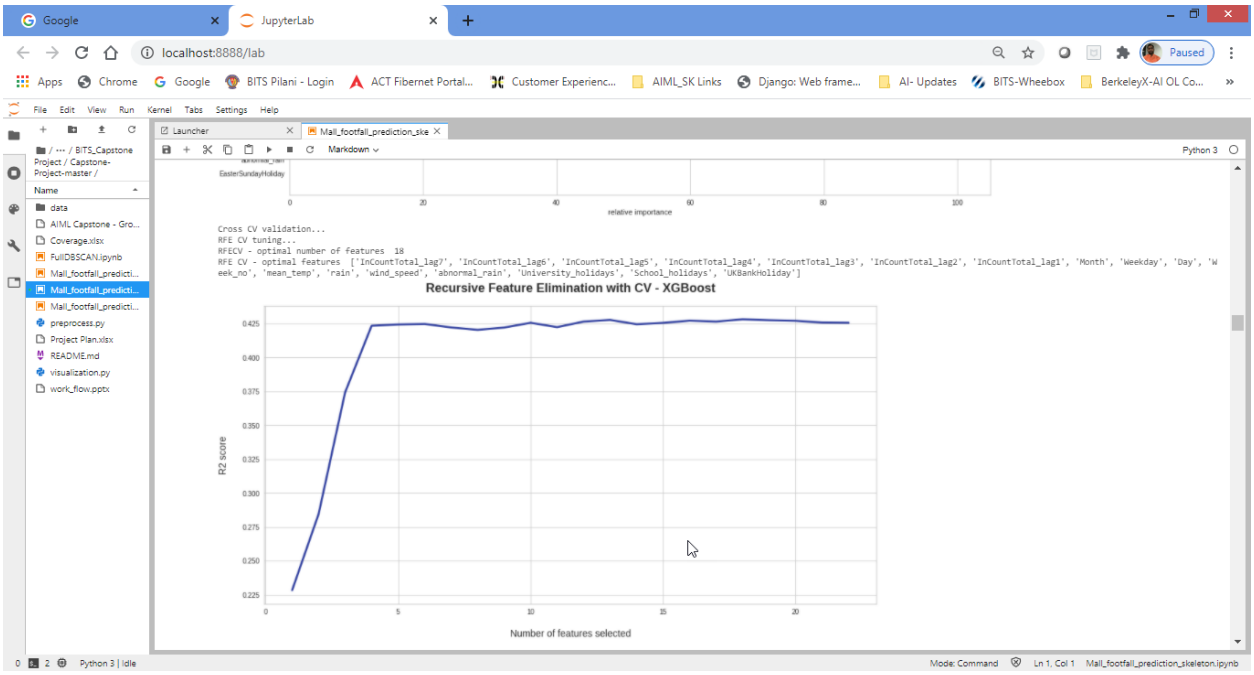
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Mall_footfall_predicti...
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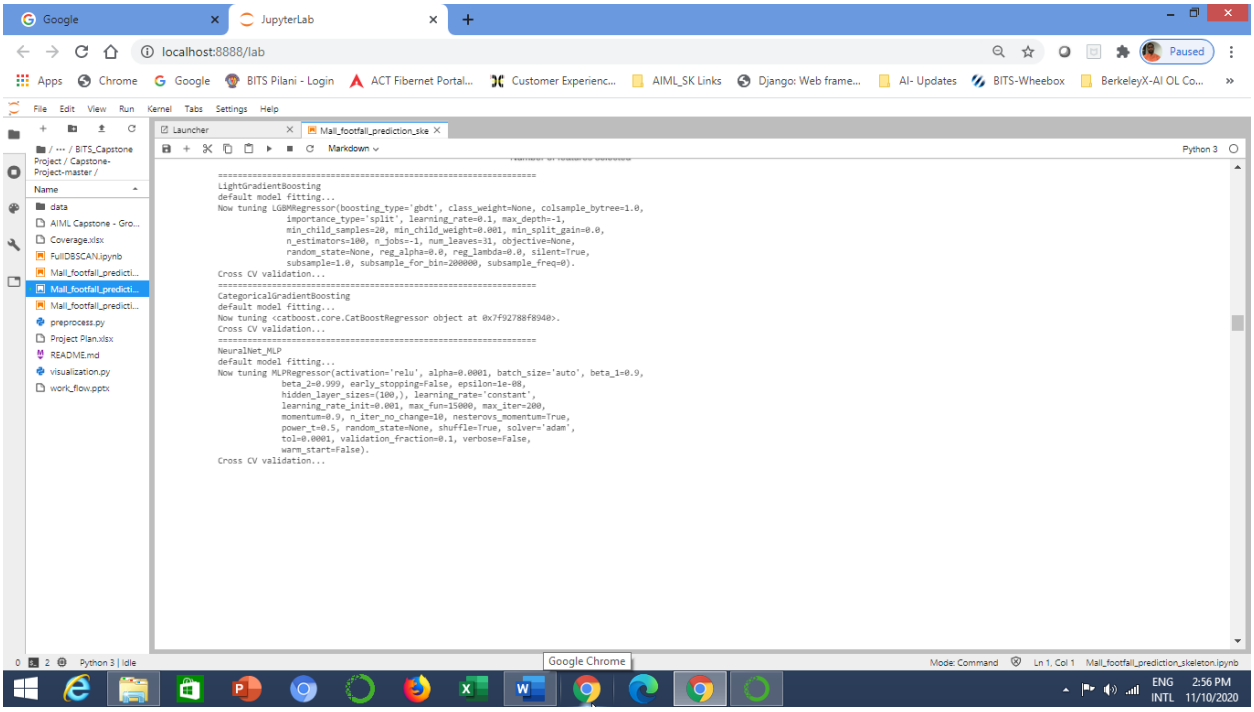
work_flow.pptx
relative importance
Cross CV validation...
RFE CV tuning...
RFECV - optimal number of features 18
RFE CV - optimal features ['InCountTotal_lag7', 'InCountTotal_lag6', 'InCountTotal_lag5', 'InCountTotal_lag4', 'InCountTotal_lag3', 'InCountTotal_lag2', 'InCountTotal_lag1', 'Month', 'Weekday', 'Day', 'Week_no', 'mean_temp', 'rain', 'wind_speed', 'abnormal_rain', 'University_holidays', 'School_holidays', 'UKBankHoliday']
Recursive Feature Elimination with CV - XGBoost
R2 score
Number of features selected
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb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ACT Fibernet Portal...
Customer Experienc...
AIML_SK Links
Django: Web frame...
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BerkeleyX-AI OL Co...
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Coverage.xlsx
FullDBSCAN.ipynb
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Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
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visualization.py
work_flow.pptx
LightGradientBoosting
default model fitting...
Now tuning LGBMRegressor(boosting_type='gbdt', class_weight=None, colsample_bytree=1.0,
importance_type='split', learning_rate=0.1, max_depth=-1,
min_child_samples=20, min_child_weight=0.001, min_split_gain=0.0,
n_estimators=100, n_jobs=-1, num_leaves=31, objective=None,
random_state=None, reg_alpha=0.0, reg_lambda=0.0, silent=True,
subsample=1.0, subsample_for_bin=200000, subsample_freq=0).
Cross CV validation...
CategoricalGradientBoosting
default model fitting...
Now tuning <catboost.core.CatBoostRegressor object at 0x7f92788f8940>.
Cross CV validation...
NeuralNet_MLP
default model fitting...
Now tuning MLPRegressor(activation='relu', alpha=0.0001, batch_size='auto', beta_1=0.9,
beta_2=0.999, early_stopping=False, epsilon=1e-08,
hidden_layer_sizes=(100,), learning_rate='constant',
learning_rate_init=0.001, max_fun=15000, max_iter=200,
momentum=0.9, n_iter_no_change=10, nesterovs_momentum=True,
power_t=0.5, random_state=None, shuffle=True, solver='adam',
tol=0.0001, validation_fraction=0.1, verbose=False,
warm_start=False).
Cross CV validation...
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
Google Chrome
ENG
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Markdown | Python 3

```
[30]: loss_normal_df.sort_values('mape').head(25)
```

[30]:

| | Model_type | mape | mse | me | mae | mpe | rmse | R2 score | Adj R2 score | AIC | BIC |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 69 | CategoricalGradientBoosting_normal_shuffled_rs... | 18.263525 | 0.005194 | -0.015631 | 0.049655 | 0.038009 | 0.072067 | 0.434226 | 0.395149 | -1831.931066 | -1742.743143 |
| 57 | gradient_boosting_regressor_normal_shuffled_de... | 18.629808 | 0.005615 | -0.019362 | 0.052390 | 0.027793 | 0.074936 | 0.388287 | 0.346036 | -1804.060158 | -1714.872235 |
| 68 | CategoricalGradientBoosting_normal_shuffled_de... | 19.332720 | 0.004999 | -0.014414 | 0.048720 | 0.055079 | 0.070706 | 0.455398 | 0.417783 | -1845.546436 | -1756.358513 |
| 49 | random_forest_normal_shuffled_default_model | 19.427948 | 0.004767 | -0.012446 | 0.047276 | 0.064320 | 0.069042 | 0.480725 | 0.444859 | -1862.547285 | -1773.359362 |
| 46 | bagging_normal_shuffled_default_model | 19.517288 | 0.004732 | -0.012377 | 0.046801 | 0.066487 | 0.068793 | 0.484467 | 0.448860 | -1865.129562 | -1775.941639 |
| 61 | XGBoost_normal_shuffled_default_model | 19.616281 | 0.005520 | -0.017470 | 0.052288 | 0.044728 | 0.074295 | 0.398706 | 0.357175 | -1810.193359 | -1721.005436 |
| 60 | gradient_boosting_regressor_normal_shuffled_rf... | 19.814619 | 0.005433 | -0.017211 | 0.051460 | 0.048572 | 0.073708 | 0.408174 | 0.367297 | -1815.859485 | -1726.671562 |
| 53 | extra_trees_regressor_normal_shuffled_default_... | 19.972139 | 0.005094 | -0.014785 | 0.049404 | 0.058715 | 0.071372 | 0.445091 | 0.406764 | -1838.853078 | -1749.665155 |
| 45 | adaBoost_normal_shuffled_rfecv_model | 20.124316 | 0.005237 | -0.005556 | 0.050963 | 0.083739 | 0.072364 | 0.429550 | 0.390149 | -1828.992344 | -1739.804421 |
| 65 | LightGradientBoosting_normal_shuffled_default_... | 20.169817 | 0.005365 | -0.015131 | 0.050980 | 0.055039 | 0.073246 | 0.415568 | 0.375202 | -1820.347930 | -1731.160007 |
| 66 | LightGradientBoosting_normal_shuffled_rscv_model | 20.187940 | 0.005135 | -0.015762 | 0.049409 | 0.059171 | 0.071660 | 0.440596 | 0.401959 | -1835.973252 | -1746.785329 |
| 43 | adaBoost_normal_shuffled_rscv_model | 20.418929 | 0.005255 | -0.005365 | 0.051170 | 0.086657 | 0.072488 | 0.427593 | 0.388058 | -1827.769953 | -1738.582030 |
| 58 | gradient_boosting_regressor_normal_shuffled_rs... | 20.828133 | 0.005532 | -0.018023 | 0.052252 | 0.055551 | 0.074380 | 0.397331 | 0.355705 | -1809.377964 | -1720.190041 |
| 54 | extra_trees_regressor_normal_shuffled_rscv_model | 20.863421 | 0.005201 | -0.015120 | 0.049837 | 0.065786 | 0.072115 | 0.433469 | 0.394340 | -1831.453730 | -1742.265807 |
| 52 | random_forest_normal_shuffled_rfecv_model | 21.029417 | 0.005072 | -0.013946 | 0.048512 | 0.074358 | 0.071221 | 0.447441 | 0.409276 | -1840.368442 | -1751.180519 |
| 50 | random_forest_normal_shuffled_rscv_model | 21.270546 | 0.005154 | -0.014407 | 0.048533 | 0.075950 | 0.071792 | 0.438538 | 0.399759 | -1834.662278 | -1745.474355 |
| 3 | linear_regression_normal_shuffled_rfecv_model | 21.679825 | 0.006029 | -0.019224 | 0.054694 | 0.054863 | 0.077645 | 0.343264 | 0.297904 | -1778.706762 | -1689.518839 |
| 56 | extra_trees_regressor_normal_shuffled_rfecv_model | 21.815635 | 0.005250 | -0.015162 | 0.050156 | 0.073199 | 0.072453 | 0.428146 | 0.388648 | -1828.114691 | -1738.926768 |
| 47 | bagging_normal_shuffled_rscv_model | 21.951364 | 0.005561 | -0.015518 | 0.051718 | 0.077761 | 0.074570 | 0.394243 | 0.352404 | -1807.553565 | -1718.365642 |
| 11 | ridgeRegressor_normal_shuffled_rfecv_model | 21.961029 | 0.006158 | -0.020317 | 0.055821 | 0.052536 | 0.078474 | 0.329157 | 0.282823 | -1771.119537 | -1681.931614 |
| 72 | NeuralNet_MLP_normal_shuffled_rscv_model | 22.314595 | 0.005971 | -0.016289 | 0.055082 | 0.064159 | 0.077274 | 0.349514 | 0.304585 | -1782.120210 | -1692.932287 |
| 64 | XGBoost_normal_shuffled_rfecv_model | 22.513271 | 0.005483 | -0.010013 | 0.051166 | 0.097267 | 0.074048 | 0.402699 | 0.361444 | -1812.572074 | -1723.384151 |

Python 3 | Idle | Mode: Command | Ln 1, Col 1 | Mall_footfall_prediction_skeleton.ipynb

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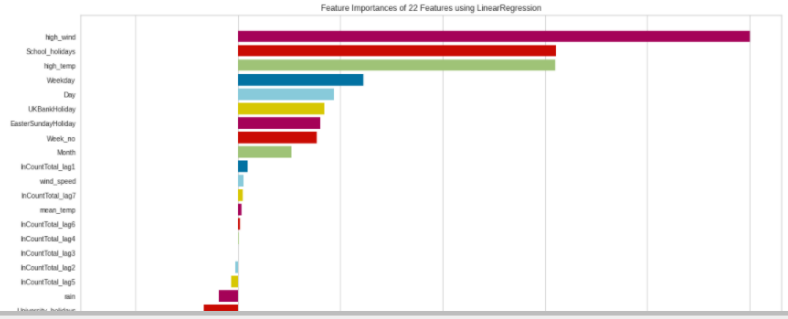
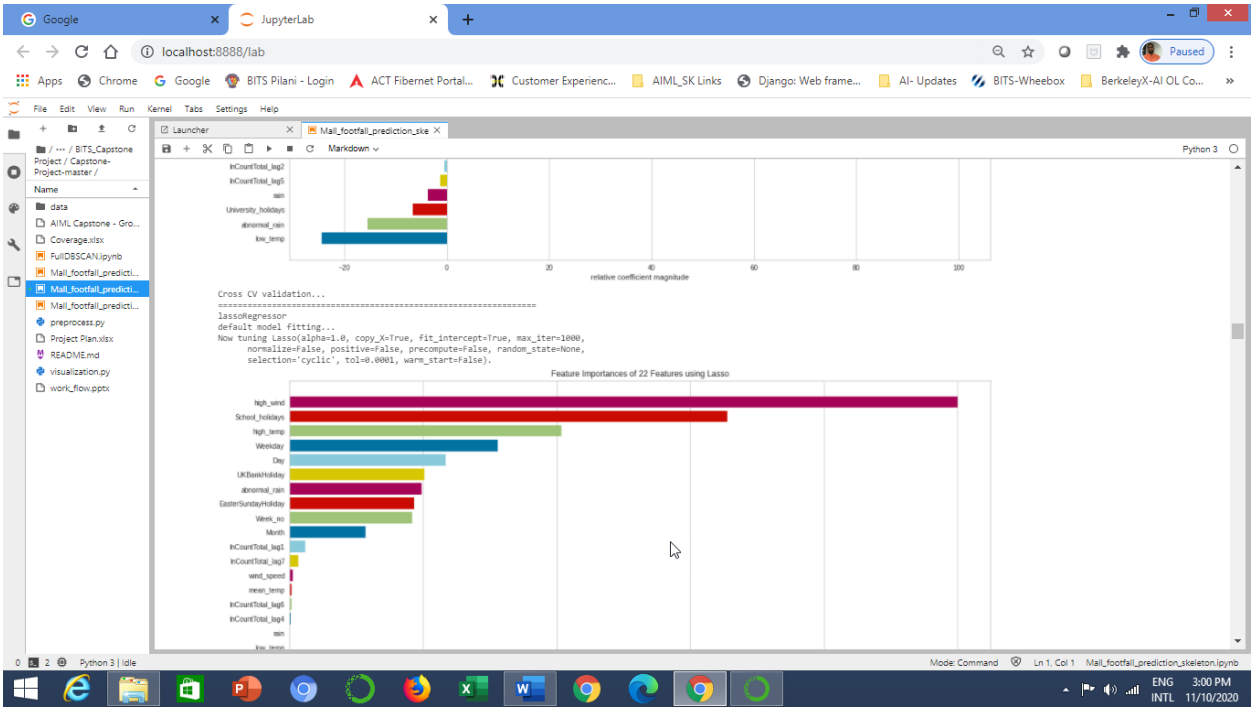
| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 15 | elastic_net_normal_shuffled_rfecv_model | 22.554926 | 0.006105 | -0.018810 | 0.055150 | 0.064095 | 0.078134 | 0.334957 | 0.289023 | -1774.219216 | -1685.031293 |
| 7 | lassoRegressor_normal_shuffled_rfecv_model | 22.580872 | 0.006112 | -0.018820 | 0.055159 | 0.064363 | 0.078181 | 0.334156 | 0.288166 | -1773.789446 | -1684.601523 |
| 62 | XGBoost_normal_shuffled_rscv_model | 22.601139 | 0.005497 | -0.010141 | 0.051270 | 0.097525 | 0.074145 | 0.401134 | 0.359771 | -1811.637863 | -1722.449940 |

```
[31]: reg_models = regression_model(data_final,dataset_type='normal')
_,_,_,_,_, loss_normal_df = reg_models.train_and_evaluate_models(RFEcross_validation=False)
loss_values_all_models.append(loss_normal_df)
```

```
Defined 20 models
================================================================
linear_regression
default model fitting...
Now tuning LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False).
```




Python 3 | Idle | Mode: Command | Ln 1, Col 1 | Mall_footfall_prediction_skeleton.ipynb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Markdown
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relative coefficient magnitude
Cross CV validation...
lassoRegressor
default model fitting...
Now tuning Lasso(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=1000,
normalize=False, positive=False, precompute=False, random_state=None,
selection='cyclic', tol=0.0001, warm_start=False).
Feature Importances of 22 Features using Lasso
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
abnormal_rain
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
rain
low_temp
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
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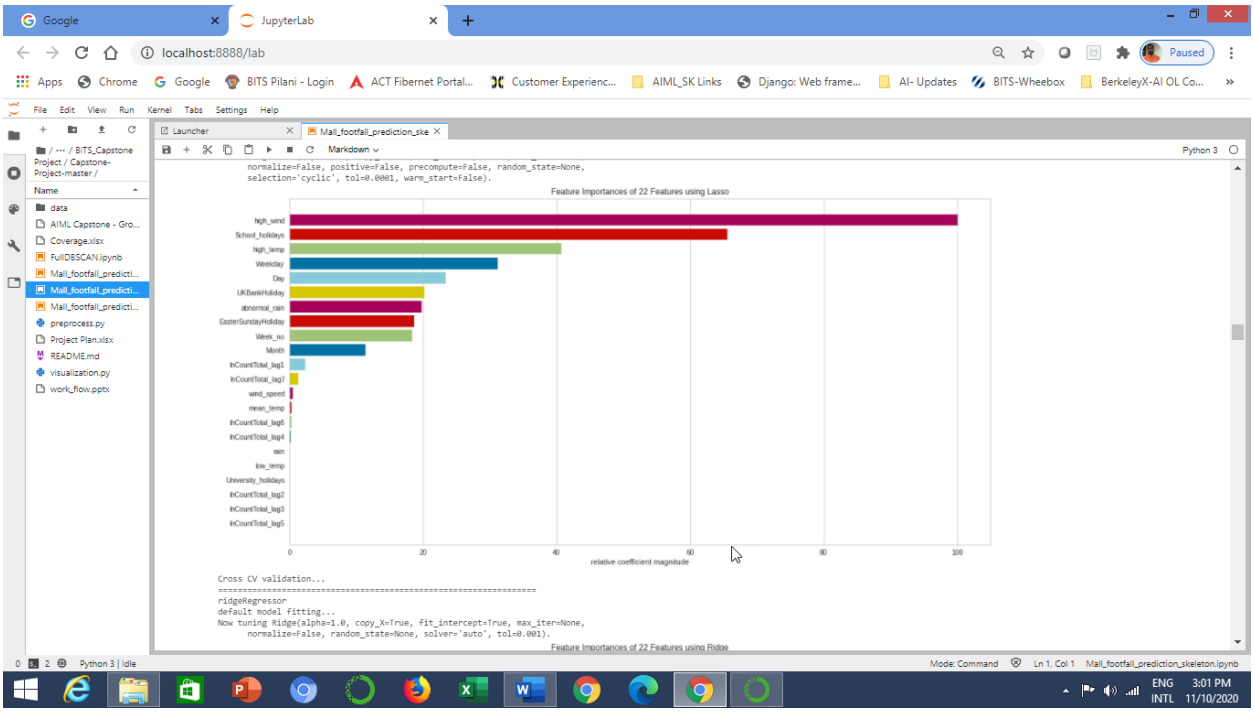
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localhost:8888/lab
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
normalize=False, positive=False, precompute=False, random_state=None,
selection='cyclic', tol=0.0001, warm_start=False).
Feature Importances of 22 Features using Lasso
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
abnormal_rain
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
rain
low_temp
University_holidays
InCountTotal_lag2
InCountTotal_lag3
InCountTotal_lag5
relative coefficient magnitude
Cross CV validation...
ridgeRegressor
default model fitting...
Now tuning Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
normalize=False, random_state=None, solver='auto', tol=0.001).
Feature Importances of 22 Features using Ridge
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
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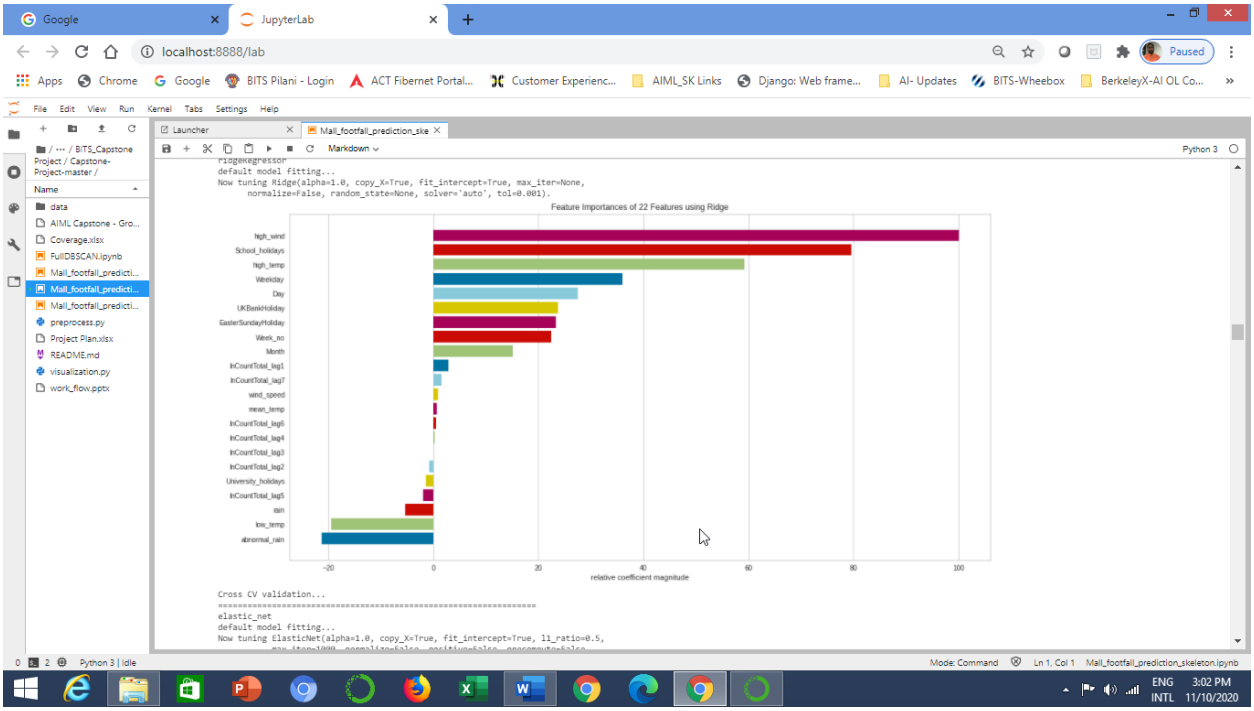
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BerkeleyX-AI OL Co...
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Markdown
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Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
RidgeRegressor
default model fitting...
Now tuning Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=None,
normalize=False, random_state=None, solver='auto', tol=0.001).
Feature Importances of 22 Features using Ridge
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
University_holidays
InCountTotal_lag5
rain
low_temp
abnormal_rain
-20
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
elastic_net
default model fitting...
Now tuning ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
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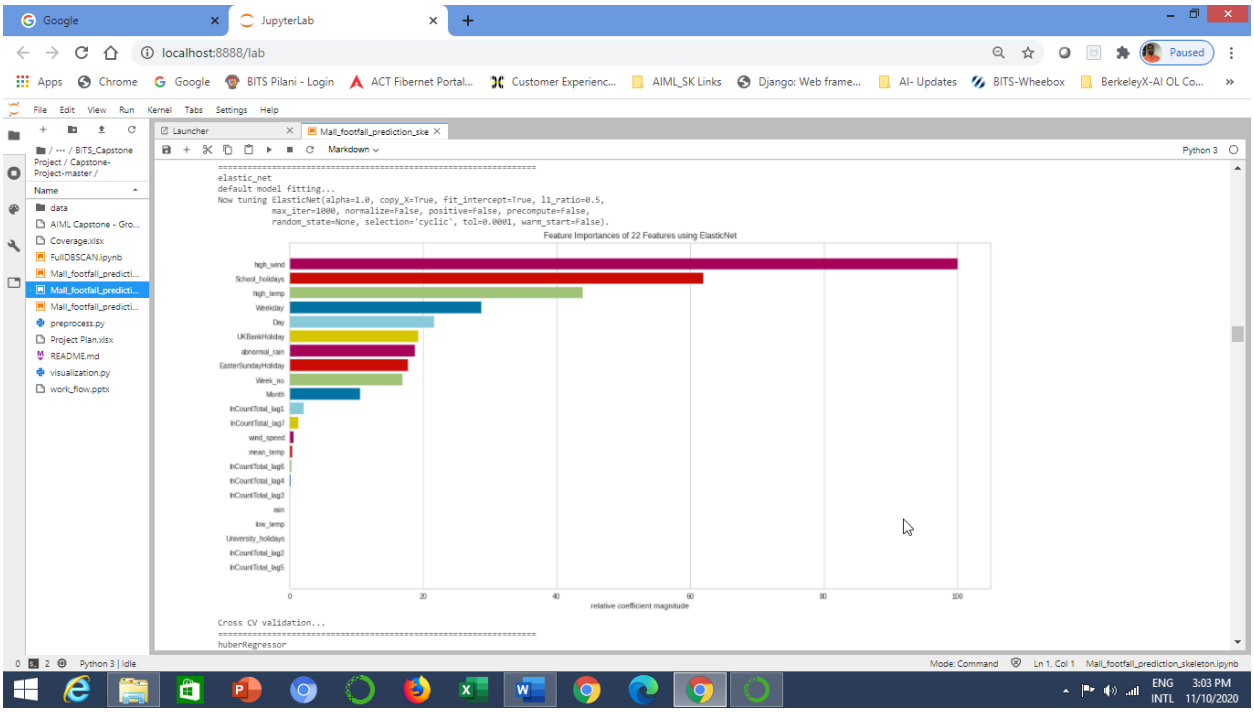
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BerkeleyX-AI OL Co...
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Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
Name
data
AIML Capstone - Gro...
Coverage.xlsx
FullDBSCAN.ipynb
Mall_footfall_predicti...
Mall_footfall_predicti...
Mall_footfall_predicti...
preprocess.py
Project Plan.xlsx
README.md
visualization.py
work_flow.pptx
elastic_net
default model fitting...
Now tuning ElasticNet(alpha=1.0, copy_X=True, fit_intercept=True, l1_ratio=0.5,
max_iter=1000, normalize=False, positive=False, precompute=False,
random_state=None, selection='cyclic', tol=0.0001, warm_start=False).
Feature Importances of 22 Features using ElasticNet
high_wind
School_holidays
high_temp
Weekday
Day
UKBankHoliday
abnormal_rain
EasterSundayHoliday
Week_no
Month
InCountTotal_lag1
InCountTotal_lag7
wind_speed
mean_temp
InCountTotal_lag6
InCountTotal_lag4
InCountTotal_lag3
rain
low_temp
University_holidays
InCountTotal_lag2
InCountTotal_lag5
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
huberRegressor
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
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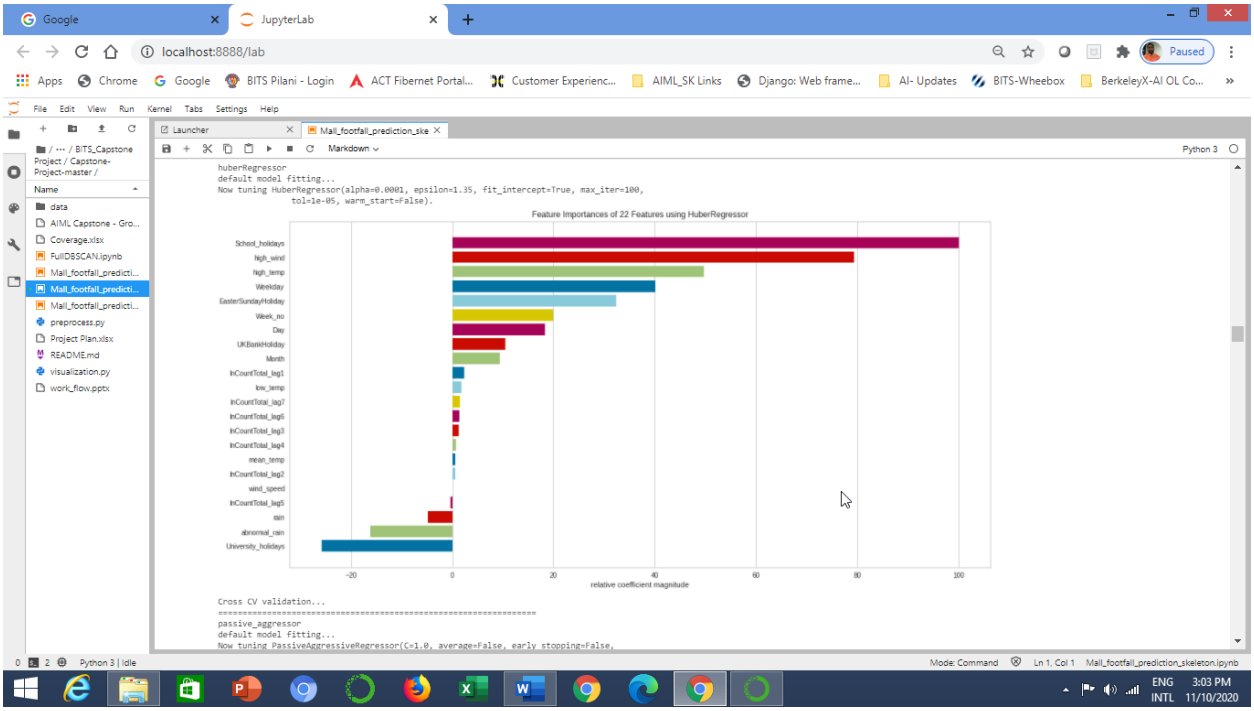
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BerkeleyX-AI OL Co...
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Mall_footfall_prediction_ske
Markdown
Python 3
huberRegressor
default model fitting...
Now tuning HuberRegressor(alpha=0.0001, epsilon=1.35, fit_intercept=True, max_iter=100,
tol=1e-05, warm_start=False).
Feature Importances of 22 Features using HuberRegressor
School_holidays
high_wind
high_temp
Weekday
EasterSundayHoliday
Week_no
Day
UKBankHoliday
Month
InCountTotal_lag1
low_temp
InCountTotal_lag7
InCountTotal_lag6
InCountTotal_lag3
InCountTotal_lag4
mean_temp
InCountTotal_lag2
wind_speed
InCountTotal_lag5
rain
abnormal_rain
University_holidays
-20
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
passive_aggressor
default model fitting...
Now tuning PassiveAggressiveRegressor(C=1.0, average=False, early_stopping=False,
Python 3 | Idle
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
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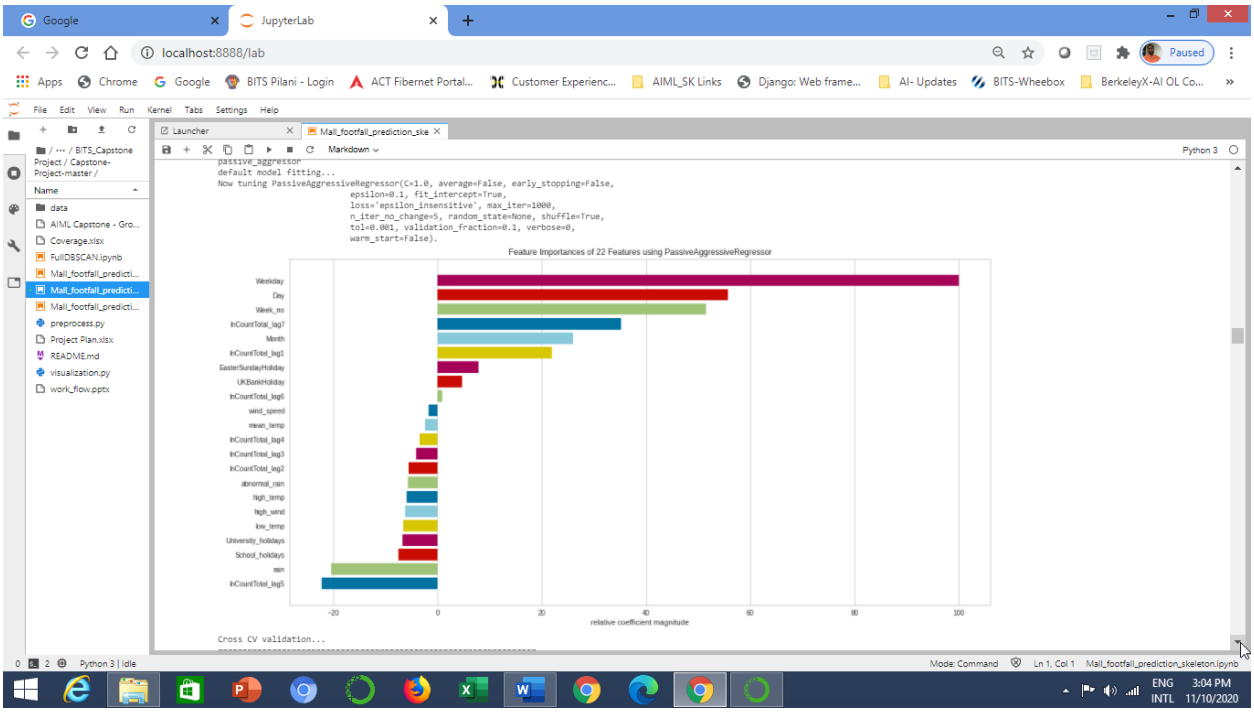
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Customer Experienc...
AIML_SK Links
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BerkeleyX-AI OL Co...
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Markdown
Python 3
passive_aggressor
default model fitting...
Now tuning PassiveAggressiveRegressor(C=1.0, average=False, early_stopping=False,
epsilon=0.1, fit_intercept=True,
loss='epsilon_insensitive', max_iter=1000,
n_iter_no_change=5, random_state=None, shuffle=True,
tol=0.001, validation_fraction=0.1, verbose=0,
warm_start=False).
Feature Importances of 22 Features using PassiveAggressiveRegressor
Weekday
Day
Week_no
InCountTotal_lag7
Month
InCountTotal_lag1
EasterSundayHoliday
UKBankHoliday
InCountTotal_lag6
wind_speed
mean_temp
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
abnormal_rain
high_temp
high_wind
low_temp
University_holidays
School_holidays
rain
InCountTotal_lag5
-20
0
20
40
60
80
100
relative coefficient magnitude
Cross CV validation...
Python 3 | Idle
Mode: Command
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Mall_footfall_prediction_skeleton.ipynb
ENG
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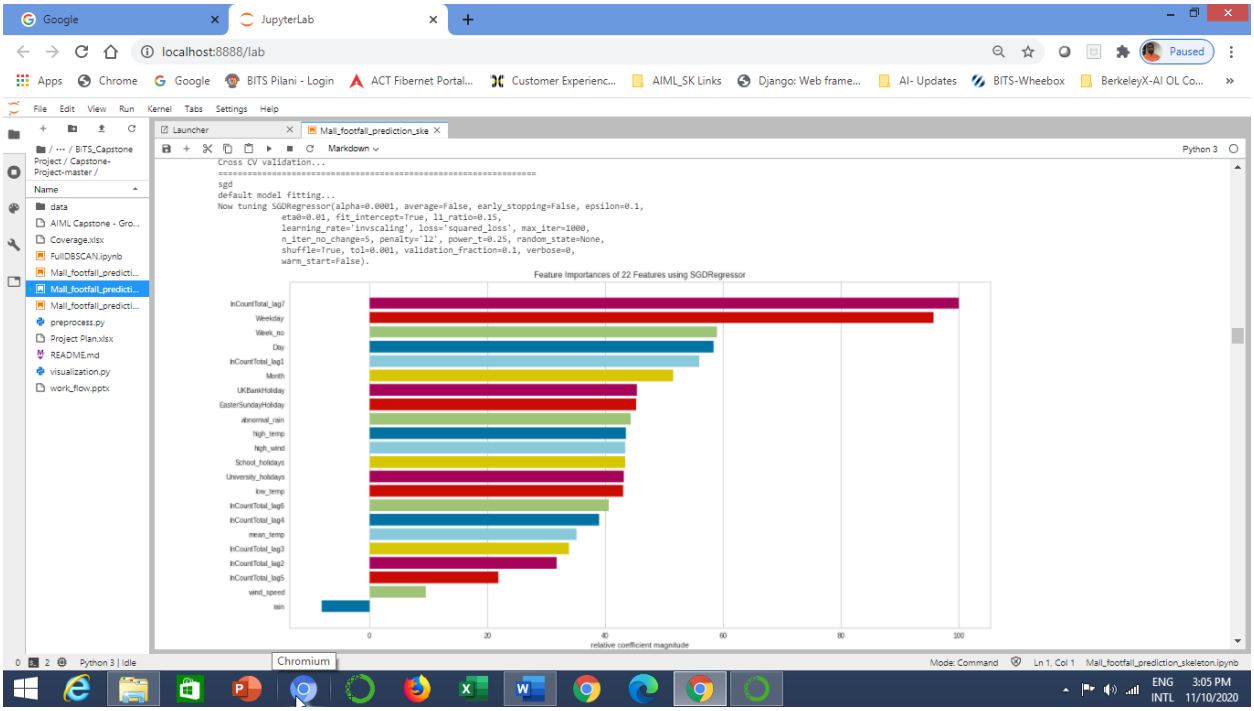
Google
JupyterLab
localhost:8888/lab
Paused
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
Cross CV validation...
sgd
default model fitting...
Now tuning SGDRegressor(alpha=0.0001, average=False, early_stopping=False, epsilon=0.1,
eta0=0.01, fit_intercept=True, l1_ratio=0.15,
learning_rate='invscaling', loss='squared_loss', max_iter=1000,
n_iter_no_change=5, penalty='l2', power_t=0.25, random_state=None,
shuffle=True, tol=0.001, validation_fraction=0.1, verbose=0,
warm_start=False).
Feature Importances of 22 Features using SGDRegressor
InCountTotal_lag7
Weekday
Week_no
Day
InCountTotal_lag1
Month
UKBankHoliday
EasterSundayHoliday
abnormal_rain
high_temp
high_wind
School_holidays
University_holidays
low_temp
InCountTotal_lag6
InCountTotal_lag4
mean_temp
InCountTotal_lag3
InCountTotal_lag2
InCountTotal_lag5
wind_speed
rain
0
20
40
60
80
100
relative coefficient magnitude
Chromium
Mode: Command
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Mall_footfall_prediction_skeleton.ipynb
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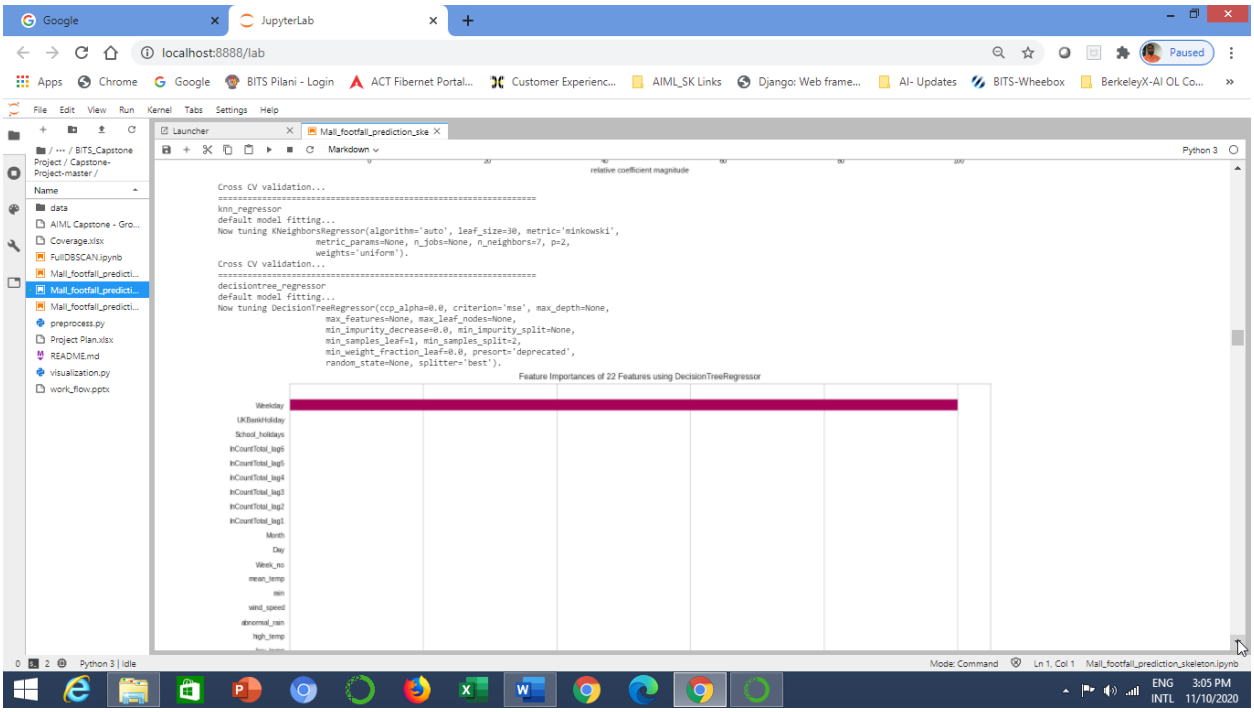
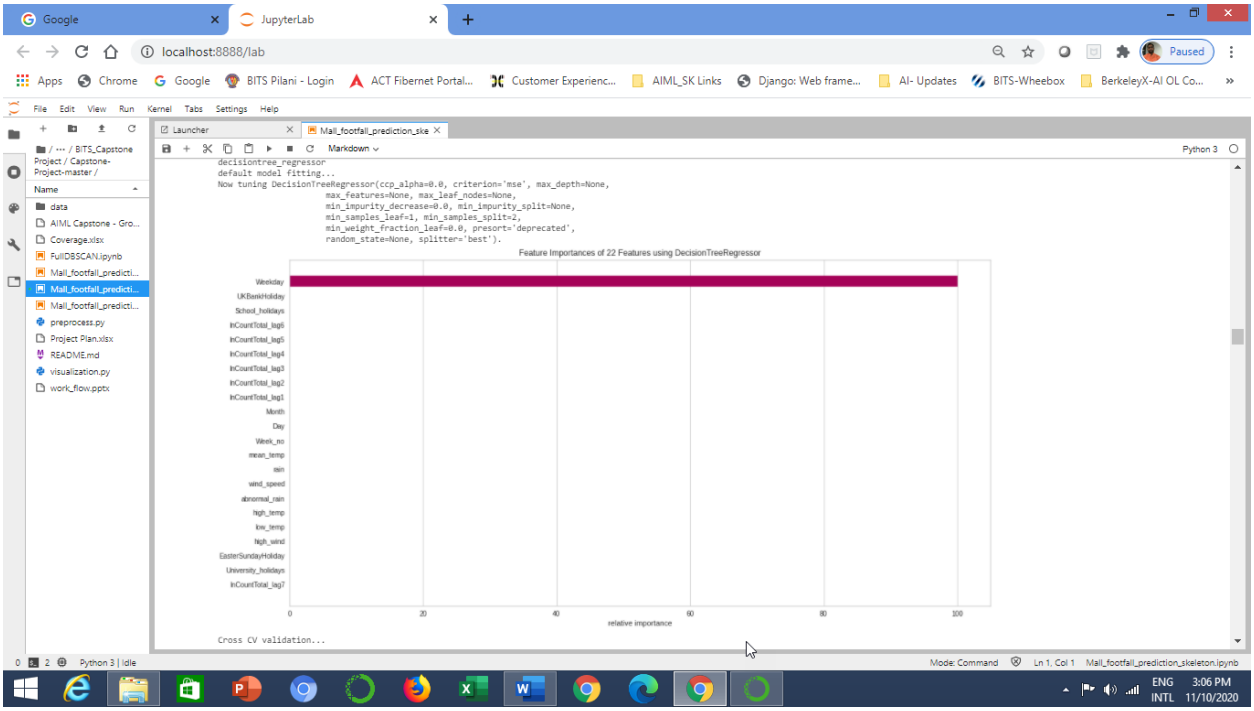
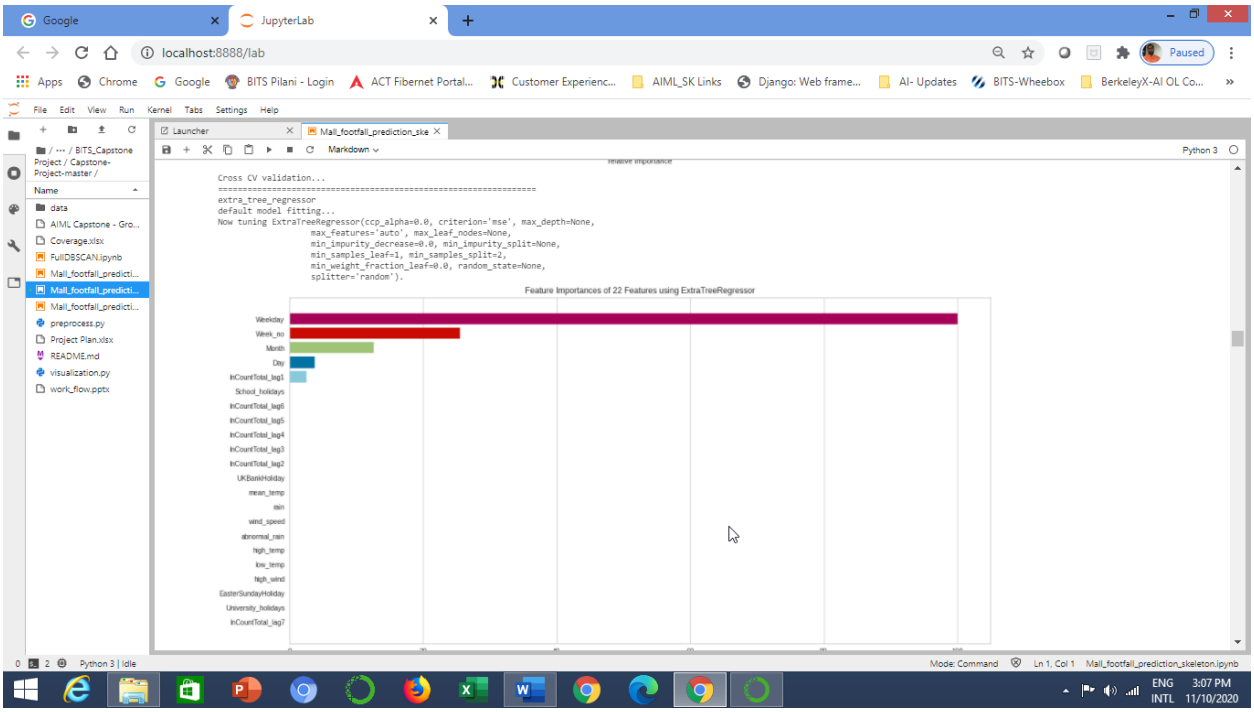

Google
JupyterLab
localhost:8888/lab
Paused
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
relative coefficient magnitude
Cross CV validation...
knn_regressor
default model fitting...
Now tuning KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
metric_params=None, n_jobs=None, n_neighbors=7, p=2,
weights='uniform').
Cross CV validation...
decisiontree_regressor
default model fitting...
Now tuning DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort='deprecated',
random_state=None, splitter='best').
Feature Importances of 22 Features using DecisionTreeRegressor
Weekday
UKBankHoliday
School_holidays
InCountTotal_lag6
InCountTotal_lag5
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
InCountTotal_lag1
Month
Day
Week_no
mean_temp
rain
wind_speed
abnormal_rain
high_temp
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
3:05 PM
11/10/2020


Google
JupyterLab
localhost:8888/lab
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
decisiontree_regressor
default model fitting...
Now tuning DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort='deprecated',
random_state=None, splitter='best').
Feature Importances of 22 Features using DecisionTreeRegressor
Weekday
UKBankHoliday
School_holidays
InCountTotal_lag6
InCountTotal_lag5
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
InCountTotal_lag1
Month
Day
Week_no
mean_temp
rain
wind_speed
abnormal_rain
high_temp
low_temp
high_wind
EasterSundayHoliday
University_holidays
InCountTotal_lag7
0
20
40
60
80
100
relative importance
Cross CV validation...
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
3:06 PM
11/10/2020


Google
JupyterLab
localhost:8888/lab
Launcher
Mall_footfall_prediction_ske
Markdown
Python 3
Cross CV validation...
extra_tree_regressor
default model fitting...
Now tuning ExtraTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
max_features='auto', max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, random_state=None,
splitter='random').
Feature Importances of 22 Features using ExtraTreeRegressor
Weekday
Week_no
Month
Day
InCountTotal_lag1
School_holidays
InCountTotal_lag6
InCountTotal_lag5
InCountTotal_lag4
InCountTotal_lag3
InCountTotal_lag2
UKBankHoliday
mean_temp
rain
wind_speed
abnormal_rain
high_temp
low_temp
high_wind
EasterSundayHoliday
University_holidays
InCountTotal_lag7
Mode: Command
Ln 1, Col 1
Mall_footfall_prediction_skeleton.ipynb
ENG
INTL
3:07 PM
11/10/2020