Project 1: Credit Card Fraud Detection

Phase 1: Problem Definition and Design Thinking

In order to effectively test, detect, validate, correct error and monitor control systems against fraudulent activities, businesses entities and organizations rely on specialized data analytics techniques such as data mining, data matching, the sounds like function, regression analysis, clustering analysis etc

Problem Definition:

The Credit Card Fraud Detection Problem includes modeling past credit card transactions with the knowledge of the ones that turned out to be fraud.

Design Thinking:

Data Source:

When we make any transaction while purchasing any product online a good amount of people prefer credit cards. The credit limit in credit cards sometimes helps us me making purchases even if we don't have the amount at that time.

Data Preprocessing:

Data source resulted from preprocessing affects directly the quality of data mining. The methods are not the same according to particular application fields and industries.

Feature Engineering:

Create additional features that could enhance fraud detection, such as transaction frequency and amount deviations

Model Selection:

Choose suitable machine learning algorithms (e.g., Logistic Regression, Random Forest, Gradient Boosting) for fraud detection.

Model Training:

Train the selected model using the preprocessed data.

IBM –NAAN MUDHALVAN - APPLIED DATA SCIENCE

Project name: Credit Card Fraud Detection

Phase 2: Innovation

INTRODUCTION :

Fraud detection and prevention tools involve risk mitigation by monitoring and reviewing user actions. Device fingerprinting, social media lookup, and data enrichment are part of the fraud detection and transaction fraud detection tools. I hope you got a good intuition about isolation forest algorithm and how it achieves high anomaly detection performance reducing swamping and masking by leveraging the subsampling technique.

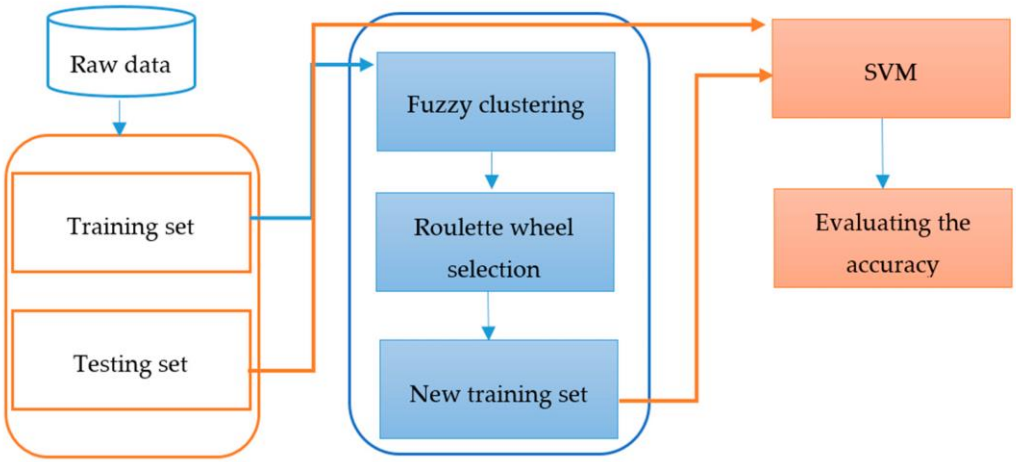
- Certainly, advanced techniques like Isolation Forest, One-Class SVM, and ensemble methods can be very effective for improving fraud detection accuracy.
- Isolation Forest is great at isolating anomalies, while One-Class SVM can be used to model the normal behavior and detect deviations. Ensembles, such as Random Forest or boosting, can combine multiple models for enhanced performance.
- If you have specific questions about implementing these techniques or need more information, feel free to ask!

- Advanced Fraud Detection TechniquesUser
  Consider exploring advanced techniques such as anomaly detection algorithms (e.g., Isolation Forest, One-Class SVM) and ensemble methods for improved fraud detection accuracy.
- Certainly, using advanced techniques like Isolation Forest, One-Class SVM, and ensemble methods can enhance fraud detection accuracy. These methods work well for anomaly detection in fraud detection systems.

  Isolation Forest: It's effective at isolating anomalies by creating a binary tree structure. Anomalies are isolated closer to the root, making them easier to detect.

  One-Class SVM: This algorithm is suitable for one-class classification, making it useful for detecting anomalies in imbalanced datasets, which is common in fraud detection.

  Ensemble Methods: Combining multiple models can improve accuracy. Techniques like Random Forest or Gradient Boosting can be used to create an ensemble of models for more robust fraud detection.



To implement these techniques:

Data Preprocessing: Ensure your data is well-preprocessed and features are properly engineered.

Model Selection: Choose the appropriate anomaly detection algorithm(s) and ensemble methods for your dataset. Experiment with different algorithms to find the best fit.

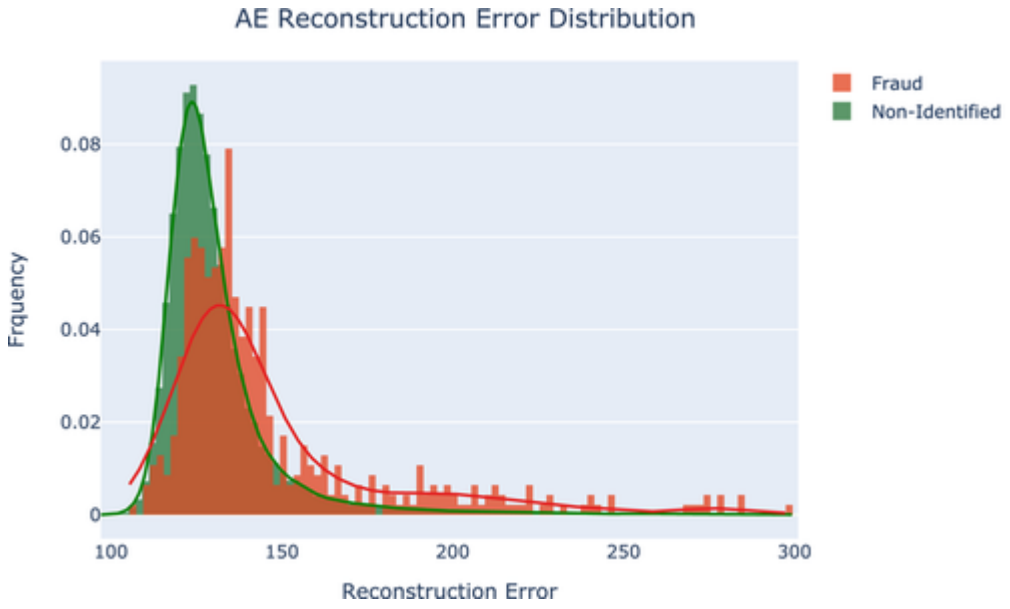
Hyperparameter Tuning: Fine-tune the hyperparameters for each algorithm to optimize performance.

Cross-Validation: Use cross-validation to assess the models' generalization and avoid overfitting.

Monitoring and Updating: Continuously monitor the performance of your fraud detection system and update it as new data becomes available.

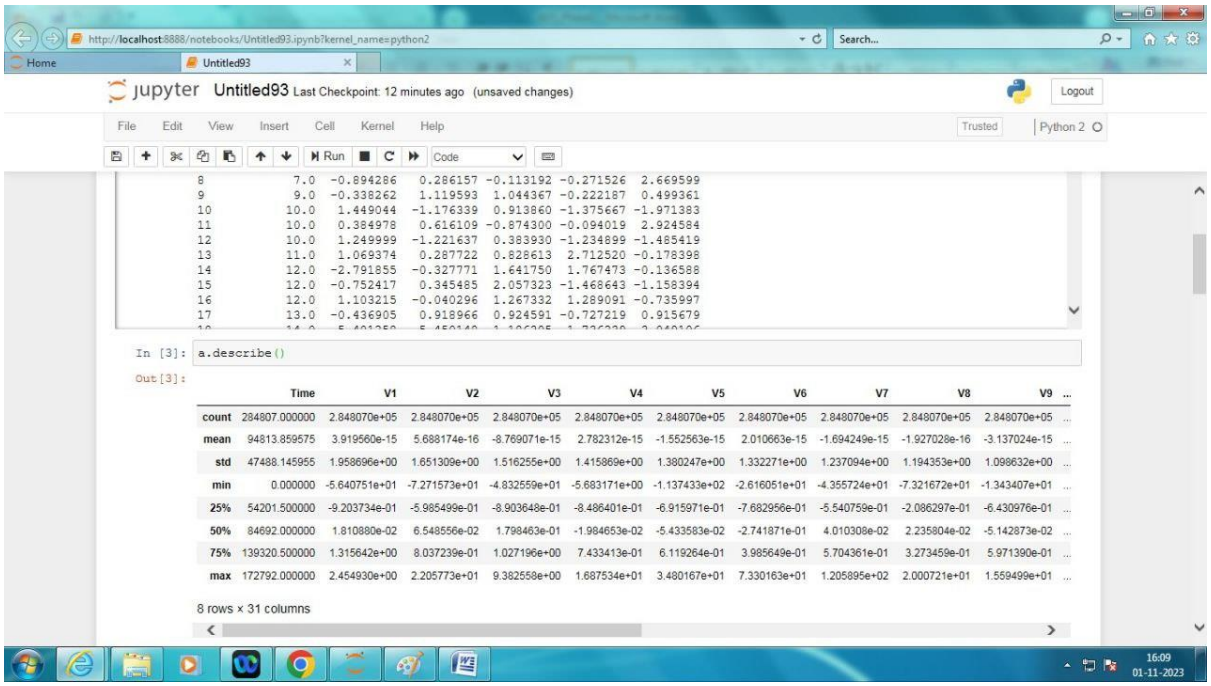
Remember that fraud patterns can change over time, so a robust and adaptable system is essential.

One-class SVM (SGD) – Builds on the one-class SVM algorithm using Stochastic Gradient Descent (SGD). Isolation forest – Uses decision trees to continuously split or divide the data to eventually isolate anomalous data points.


AE Reconstruction Error Distribution
Fraud
Non-Identified
Frquency
0.08
0.06
0.04
0.02
0
100
150
200
250
300
Reconstruction Error

Phase3:Development part1

Importing CSV file :



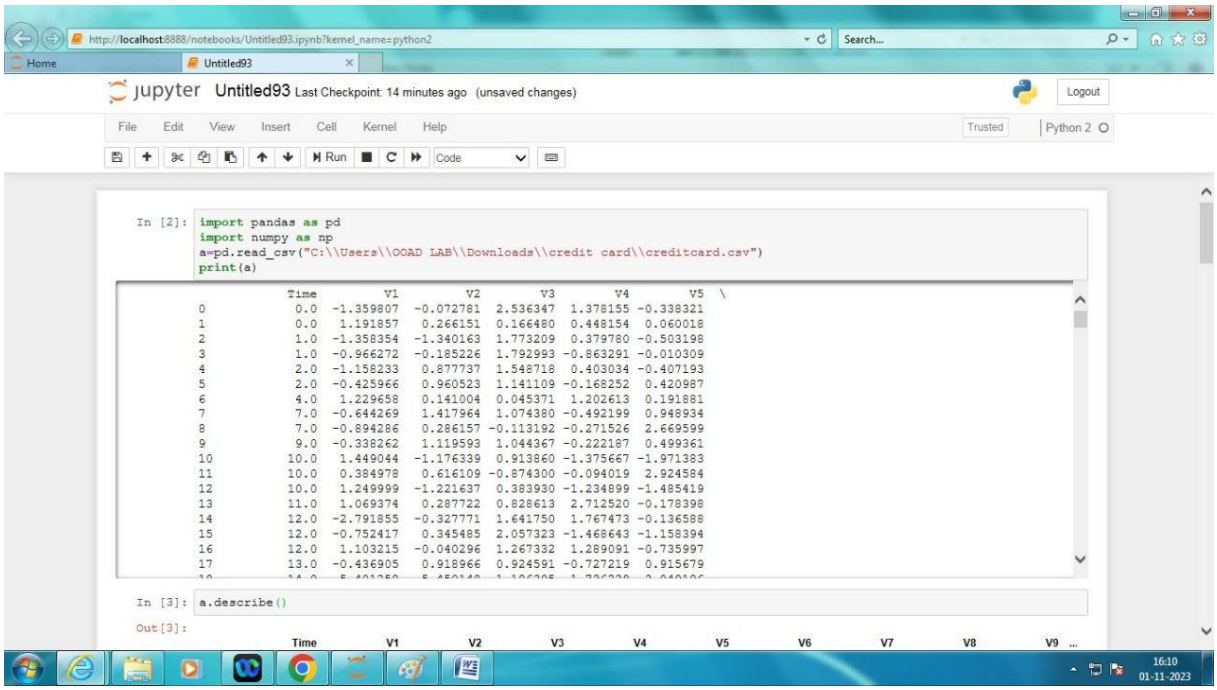
```
In [3]: a.describe()
```

Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...
count	284807.000000	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	2.848070e+05	...
mean	94813.859575	3.919560e-15	5.688174e-16	-8.769071e-15	2.782312e-15	-1.552563e-15	2.010663e-15	-1.694249e-15	-1.927028e-16	-3.137024e-15	...
std	47488.145955	1.958696e+00	1.651309e+00	1.516255e+00	1.415869e+00	1.380247e+00	1.332271e+00	1.237094e+00	1.194353e+00	1.098632e+00	...
min	0.000000	-5.640751e+01	-7.271573e+01	-4.832559e+01	-5.683171e+00	-1.137433e+02	-2.616051e+01	-4.355724e+01	-7.321672e+01	-1.343407e+01	...
25%	54201.500000	-9.203734e-01	-5.985499e-01	-8.903648e-01	-8.486401e-01	-6.915971e-01	-7.682956e-01	-5.540759e-01	-2.086297e-01	-6.430976e-01	...
50%	84692.000000	1.810880e-02	6.548556e-02	1.798463e-01	-1.984653e-02	-5.433583e-02	-2.741871e-01	4.010308e-02	2.235804e-02	-5.142873e-02	...
75%	139320.500000	1.315642e+00	8.037239e-01	1.027196e+00	7.433413e-01	6.119264e-01	3.985649e-01	5.704361e-01	3.273459e-01	5.971390e-01	...
max	172792.000000	2.454930e+00	2.205773e+01	9.382558e+00	1.687534e+01	3.480167e+01	7.330163e+01	1.205895e+02	2.000721e+01	1.559499e+01	...

8 rows × 31 columns

Preprocessing:



```
In [2]: import pandas as pd
        import numpy as np
        a=pd.read_csv("C:\\Users\\OOAD LAB\\Downloads\\credit card\\creditcard.csv")
        print(a)
```

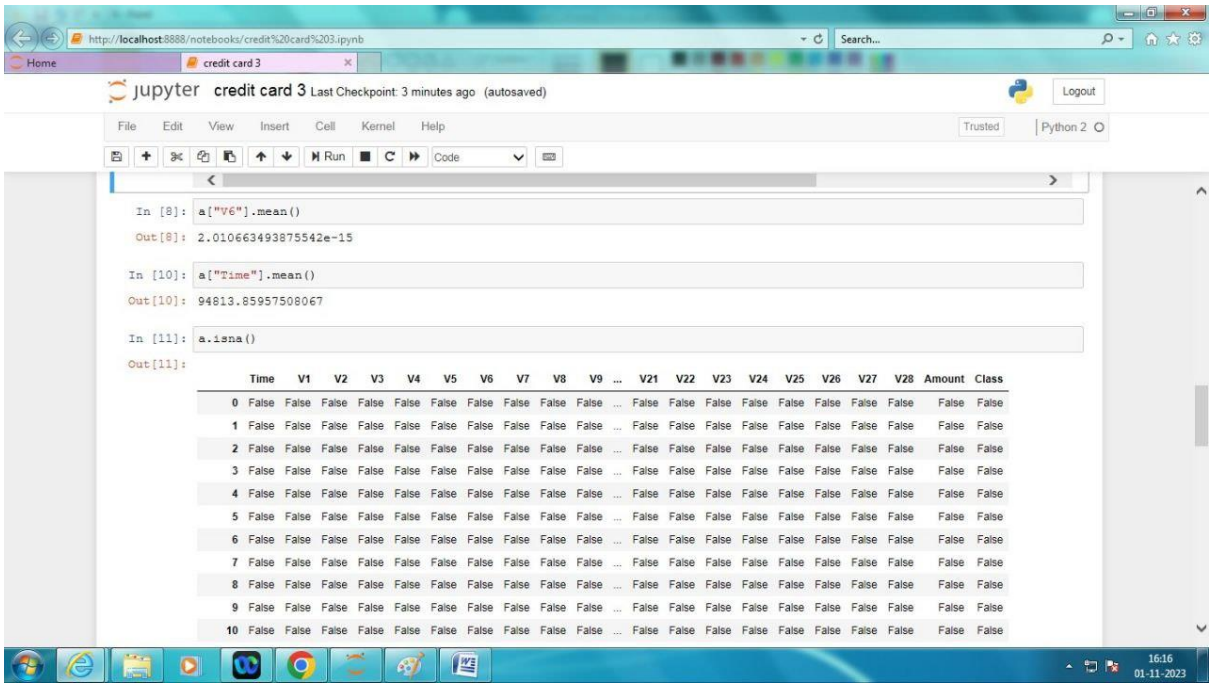
```
        Time         V1        V2        V3        V4        V5  \
0        0.0  -1.359807 -0.072781  2.536347  1.378155 -0.338321
1        0.0   1.191857  0.266151  0.166480  0.448154  0.060018
2        1.0  -1.358354 -1.340163  1.773209  0.379780 -0.503198
3        1.0  -0.966272 -0.185226  1.792993 -0.863291 -0.010309
4        2.0  -1.158233  0.877737  1.548718  0.403034 -0.407193
5        2.0  -0.425966  0.960523  1.141109 -0.168252  0.420987
6        4.0   1.229658  0.141004  0.045371  1.202613  0.191881
7        7.0  -0.644269  1.417964  1.074380 -0.492199  0.948934
8        7.0  -0.894286  0.286157 -0.113192 -0.271526  2.669599
9        9.0  -0.338262  1.119593  1.044367 -0.222187  0.499361
10      10.0   1.449044 -1.176339  0.913860 -1.375667 -1.971383
11      10.0   0.384978  0.616109 -0.874300 -0.094019  2.924584
12      10.0   1.249999 -1.221637  0.383930 -1.234899 -1.485419
13      11.0   1.069374  0.287722  0.828613  2.712520 -0.178398
14      12.0  -2.791855 -0.327771  1.641750  1.767473 -0.136588
15      12.0  -0.752417  0.345485  2.057323 -1.468643 -1.158394
16      12.0   1.103215 -0.040296  1.267332  1.289091 -0.735997
17      13.0  -0.436905  0.918966  0.924591 -0.727219  0.915679
```

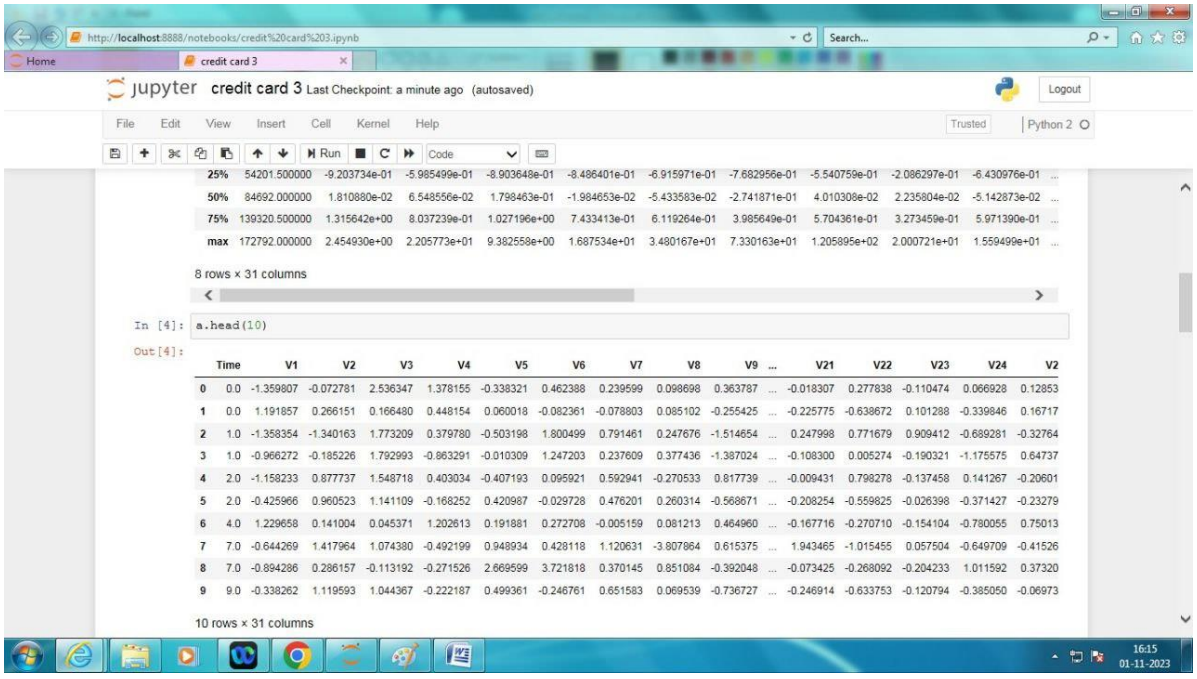
```
In [3]: a.describe()
```

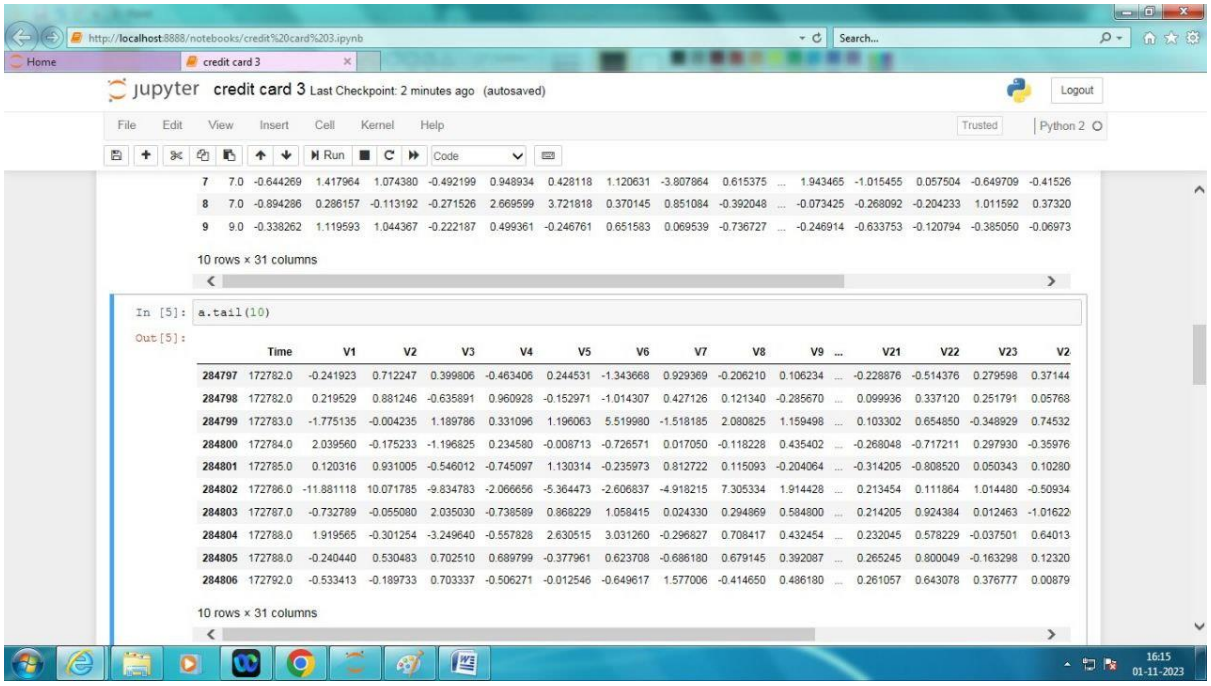
Out[3]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...

Preforming various operation:


http://localhost:8888/notebooks/credit%20card%203.ipynb
Search...
Home
credit card 3
jupyter credit card 3 Last Checkpoint: 3 minutes ago (autosaved)
Logout
File Edit View Insert Cell Kernel Help
Trusted
Python 2
Run
Code
In [8]: a["V6"].mean()
Out[8]: 2.0106634938755 42e-15
In [10]: a["Time"].mean()
Out[10]: 94813.85957508067
In [11]: a.isna()
Out[11]:
Time V1 V2 V3 V4 V5 V6 V7 V8 V9 ... V21 V22 V23 V24 V25 V26 V27 V28 Amount Class
0 False False False False False False False False False False ... False False False False False False False False False False
1 False False False False False False False False False False ... False False False False False False False False False False
2 False False False False False False False False False False ... False False False False False False False False False False
3 False False False False False False False False False False ... False False False False False False False False False False
4 False False False False False False False False False False ... False False False False False False False False False False
5 False False False False False False False False False False ... False False False False False False False False False False
6 False False False False False False False False False False ... False False False False False False False False False False
7 False False False False False False False False False False ... False False False False False False False False False False
8 False False False False False False False False False False ... False False False False False False False False False False
9 False False False False False False False False False False ... False False False False False False False False False False
10 False False False False False False False False False False ... False False False False False False False False False False
16:16
01-11-2023

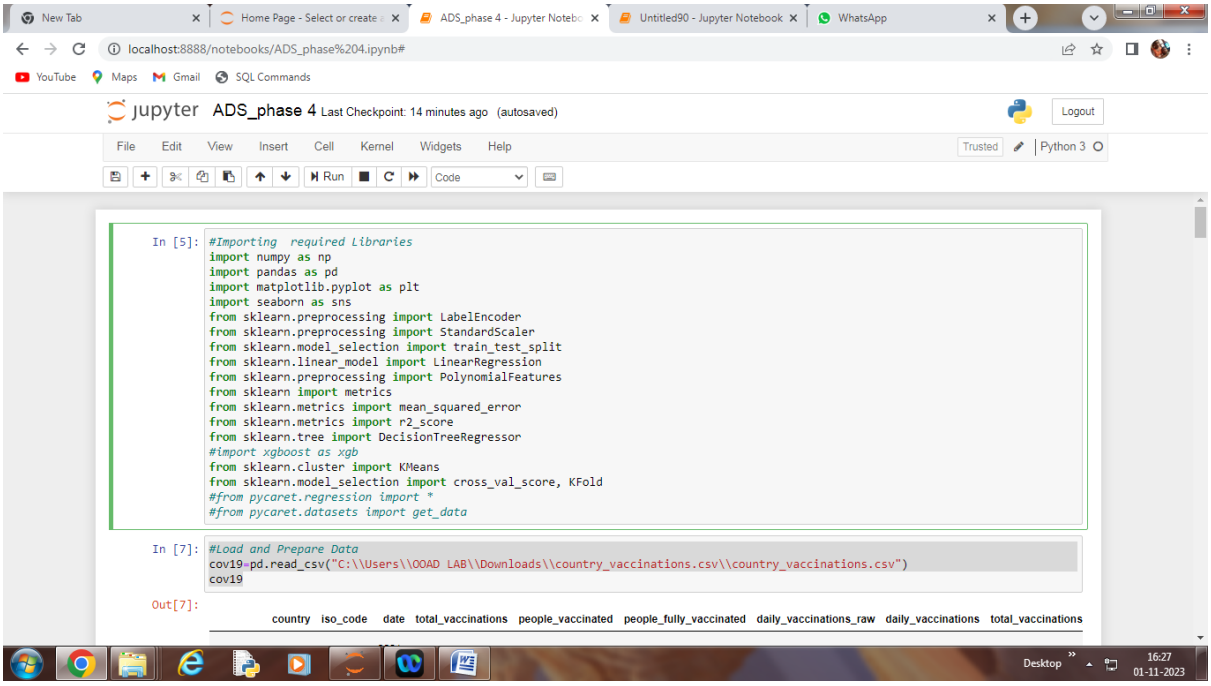

http://localhost:8888/notebooks/credit%20card%203.ipynb
Search...
Home
credit card 3
jupyter credit card 3 Last Checkpoint: a minute ago (autosaved)
Logout
File Edit View Insert Cell Kernel Help
Trusted
Python 2
Run
Code
25% 54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01 -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01 ...
50% 84692.000000 1.810880e-02 6.548556e-02 1.798463e-01 -1.984653e-02 -5.433583e-02 -2.741871e-01 4.010308e-02 2.235804e-02 -5.142873e-02 ...
75% 139320.500000 1.315642e+00 8.037239e-01 1.027196e+00 7.433413e-01 6.119264e-01 3.985649e-01 5.704361e-01 3.273459e-01 5.971390e-01 ...
max 172792.000000 2.454930e+00 2.205773e+01 9.382558e+00 1.687534e+01 3.480167e+01 7.330163e+01 1.205895e+02 2.000721e+01 1.559499e+01 ...
8 rows × 31 columns
In [4]: a.head(10)
Out[4]:
Time V1 V2 V3 V4 V5 V6 V7 V8 V9 ... V21 V22 V23 V24 V2
0 0.0 -1.359807 -0.072781 2.536347 1.378155 -0.338321 0.462388 0.239599 0.098698 0.363787 ... -0.018307 0.277838 -0.110474 0.066928 0.12853
1 0.0 1.191857 0.266151 0.166480 0.448154 0.060018 -0.082361 -0.078803 0.085102 -0.255425 ... -0.225775 -0.638672 0.101288 -0.339846 0.16717
2 1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461 0.247676 -1.514654 ... 0.247998 0.771679 0.909412 -0.689281 -0.32764
3 1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203 0.237609 0.377436 -1.387024 ... -0.108300 0.005274 -0.190321 -1.175575 0.64737
4 2.0 -1.158233 0.877737 1.548718 0.403034 -0.407193 0.095921 0.592941 -0.270533 0.817739 ... -0.009431 0.798278 -0.137458 0.141267 -0.20601
5 2.0 -0.425966 0.960523 1.141109 -0.168252 0.420987 -0.029728 0.476201 0.260314 -0.568671 ... -0.208254 -0.559825 -0.026398 -0.371427 -0.23279
6 4.0 1.229658 0.141004 0.045371 1.202613 0.191881 0.272708 -0.005159 0.081213 0.464960 ... -0.167716 -0.270710 -0.154104 -0.780055 0.75013
7 7.0 -0.644269 1.417964 1.074380 -0.492199 0.948934 0.428118 1.120631 -3.807864 0.615375 ... 1.943465 -1.015455 0.057504 -0.649709 -0.41526
8 7.0 -0.894286 0.286157 -0.113192 -0.271526 2.669599 3.721818 0.370145 0.851084 -0.392048 ... -0.073425 -0.268092 -0.204233 1.011592 0.37320
9 9.0 -0.338262 1.119593 1.044367 -0.222187 0.499361 -0.246761 0.651583 0.069539 -0.736727 ... -0.246914 -0.633753 -0.120794 -0.385050 -0.06973
10 rows × 31 columns
16:15
01-11-2023


http://localhost:8888/notebooks/credit%20card%203.ipynb
Search...
Home
credit card 3
jupyter credit card 3 Last Checkpoint: 2 minutes ago (autosaved)
Logout
File Edit View Insert Cell Kernel Help
Trusted
Python 2
Run
Code
7 7.0 -0.644269 1.417964 1.074380 -0.492199 0.948934 0.428118 1.120631 -3.807864 0.615375 ... 1.943465 -1.015455 0.057504 -0.649709 -0.41526
8 7.0 -0.894286 0.286157 -0.113192 -0.271526 2.669599 3.721818 0.370145 0.851084 -0.392048 ... -0.073425 -0.268092 -0.204233 1.011592 0.37320
9 9.0 -0.338262 1.119593 1.044367 -0.222187 0.499361 -0.246761 0.651583 0.069539 -0.736727 ... -0.246914 -0.633753 -0.120794 -0.385050 -0.06973
10 rows × 31 columns
In [5]: a.tail(10)
Out[5]:
Time V1 V2 V3 V4 V5 V6 V7 V8 V9 ... V21 V22 V23 V2
284797 172782.0 -0.241923 0.712247 0.399806 -0.463406 0.244531 -1.343668 0.929369 -0.206210 0.106234 ... -0.228876 -0.514376 0.279598 0.37144
284798 172782.0 0.219529 0.881246 -0.635891 0.960928 -0.152971 -1.014307 0.427126 0.121340 -0.285670 ... 0.099936 0.337120 0.251791 0.05768
284799 172783.0 -1.775135 -0.004235 1.189786 0.331096 1.196063 5.519980 -1.518185 2.080825 1.159498 ... 0.103302 0.654850 -0.348929 0.74532
284800 172784.0 2.039560 -0.175233 -1.196825 0.234580 -0.008713 -0.726571 0.017050 -0.118228 0.435402 ... -0.268048 -0.717211 0.297930 -0.35976
284801 172785.0 0.120316 0.931005 -0.546012 -0.745097 1.130314 -0.235973 0.812722 0.115093 -0.204064 ... -0.314205 -0.808520 0.050343 0.10280
284802 172786.0 -11.881118 10.071785 -9.834783 -2.066656 -5.364473 -2.606837 -4.918215 7.305334 1.914428 ... 0.213454 0.111864 1.014480 -0.50934
284803 172787.0 -0.732789 -0.055080 2.035030 -0.738589 0.868229 1.058415 0.024330 0.294869 0.584800 ... 0.214205 0.924384 0.012463 -1.01622
284804 172788.0 1.919565 -0.301254 -3.249640 -0.557828 2.630515 3.031260 -0.296827 0.708417 0.432454 ... 0.232045 0.578229 -0.037501 0.64013
284805 172788.0 -0.240440 0.530483 0.702510 0.689799 -0.377961 0.623708 -0.686180 0.679145 0.392087 ... 0.265245 0.800049 -0.163298 0.12320
284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546 -0.649617 1.577006 -0.414650 0.486180 ... 0.261057 0.643078 0.376777 0.00879
10 rows × 31 columns
16:15
01-11-2023

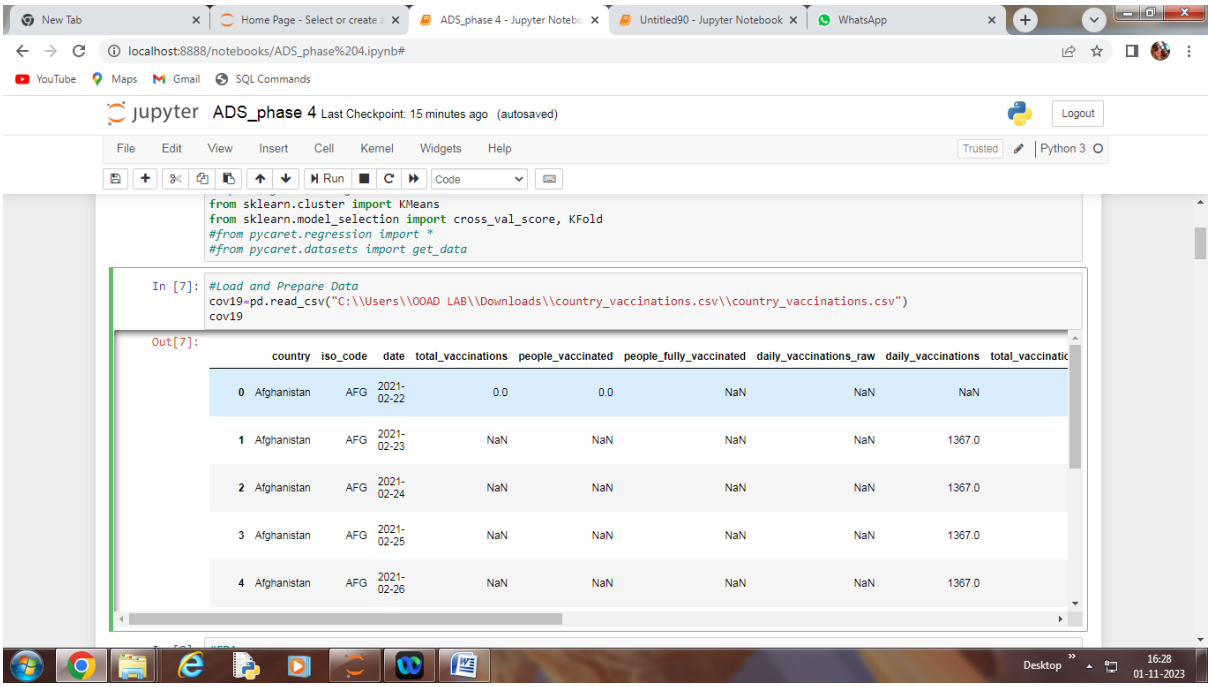
APPLIED DATA SCIENCE PHASE 4

Project: Covid-19 Vaccines Analysis

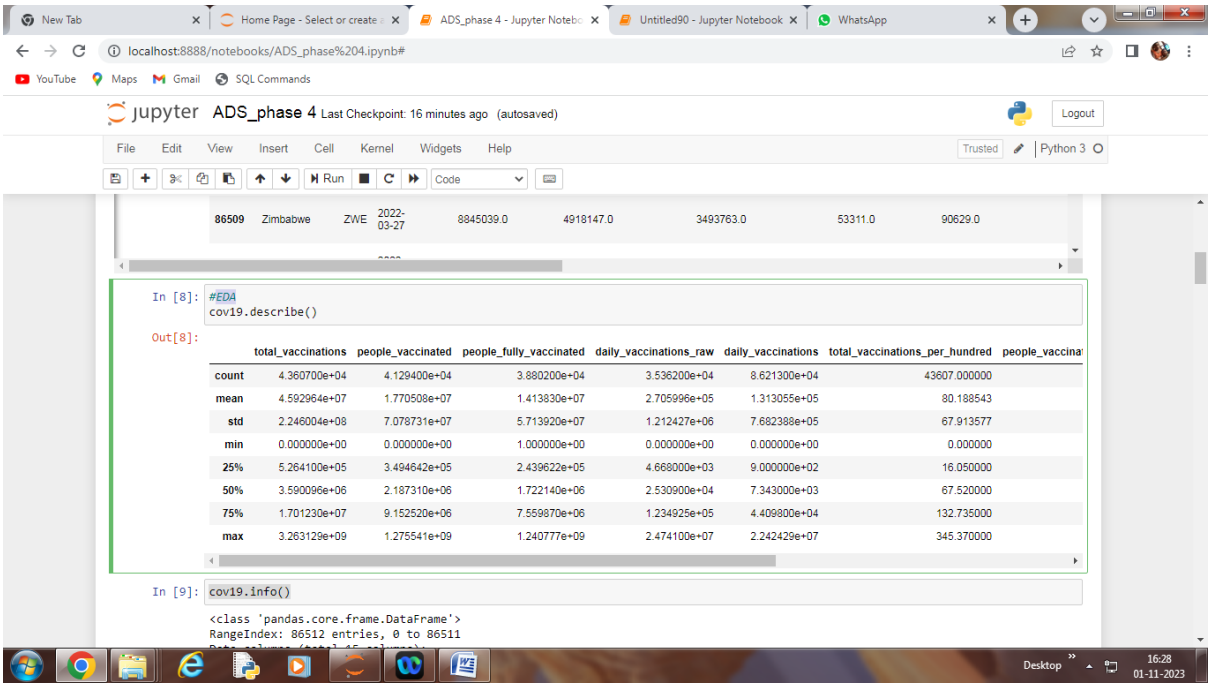
Importing Required Libraries:



Load and Prepare Data:



EDA:



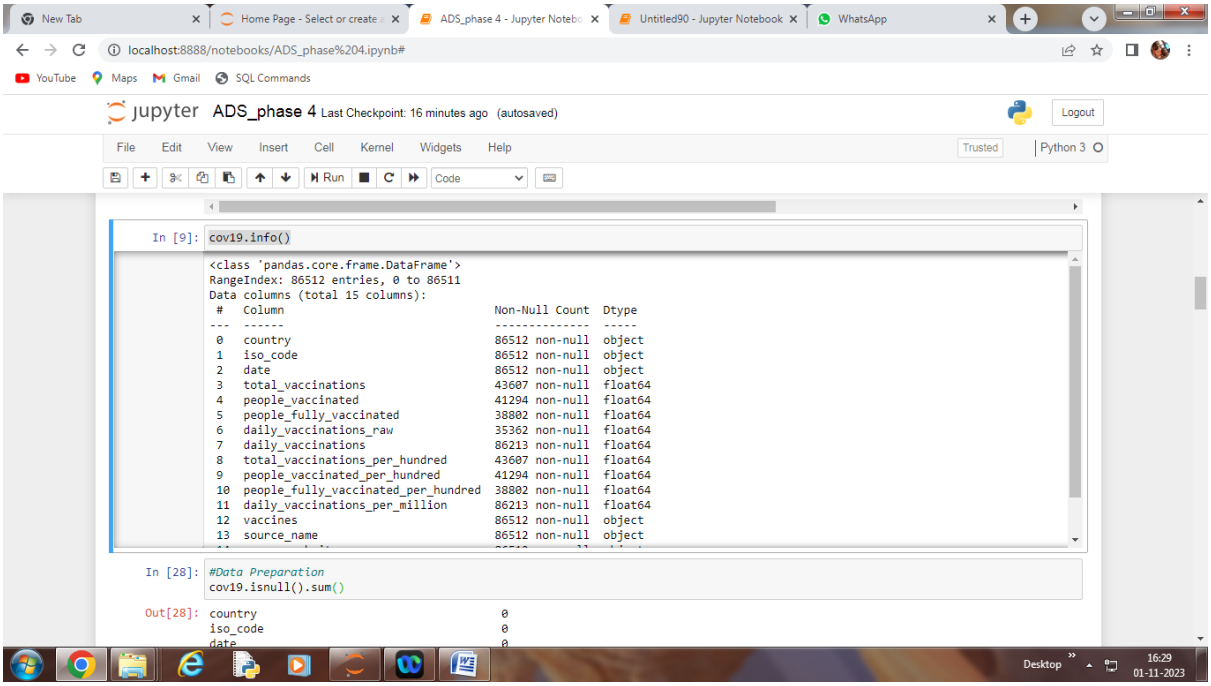
86509	Zimbabwe	ZWE	2022-03-27	8845039.0	4918147.0	3493763.0	53311.0	90629.0

```
In [8]: #EDA
        cov19.describe()
```

Out[8]:

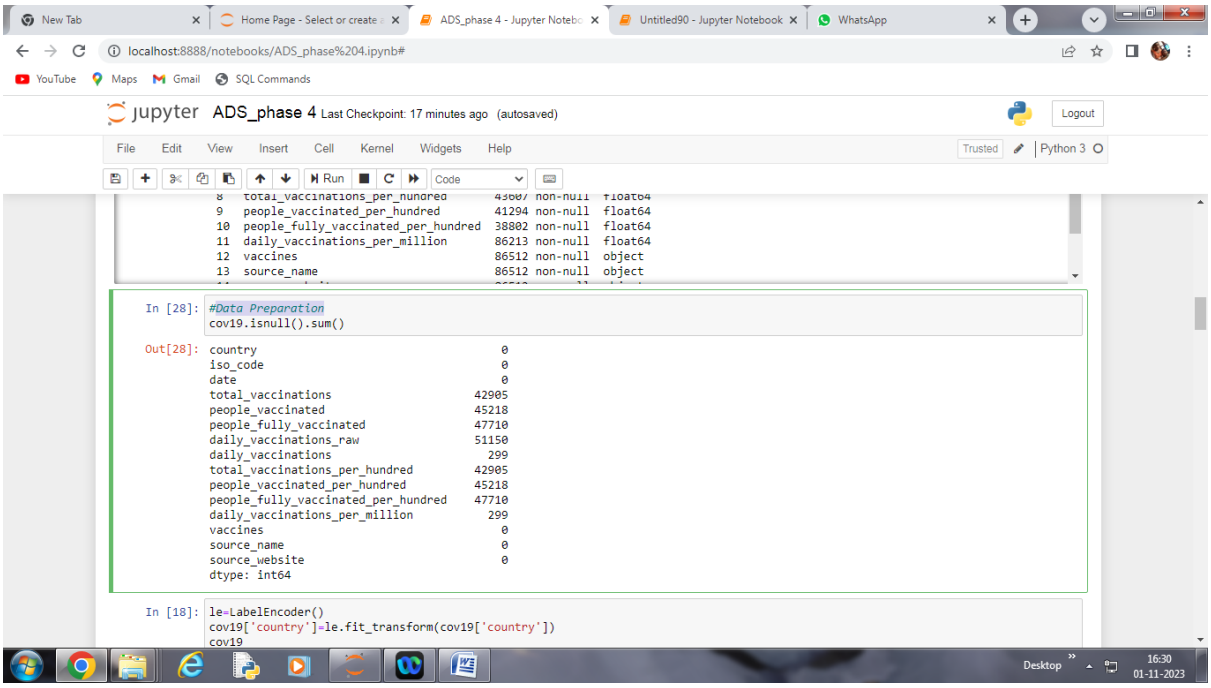
	total_vaccinations	people_vaccinated	people_fully_vaccinated	daily_vaccinations_raw	daily_vaccinations	total_vaccinations_per_hundred	people_vaccina
count	4.360700e+04	4.129400e+04	3.880200e+04	3.536200e+04	8.621300e+04	43607.000000	
mean	4.592964e+07	1.770508e+07	1.413830e+07	2.705996e+05	1.313055e+05	80.188543	
std	2.246004e+08	7.078731e+07	5.713920e+07	1.212427e+06	7.682388e+05	67.913577	
min	0.000000e+00	0.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00	0.000000	
25%	5.264100e+05	3.494642e+05	2.439622e+05	4.668000e+03	9.000000e+02	16.050000	
50%	3.590096e+06	2.187310e+06	1.722140e+06	2.530900e+04	7.343000e+03	67.520000	
75%	1.701230e+07	9.152520e+06	7.559870e+06	1.234925e+05	4.409800e+04	132.735000	
max	3.263129e+09	1.275541e+09	1.240777e+09	2.474100e+07	2.242429e+07	345.370000	

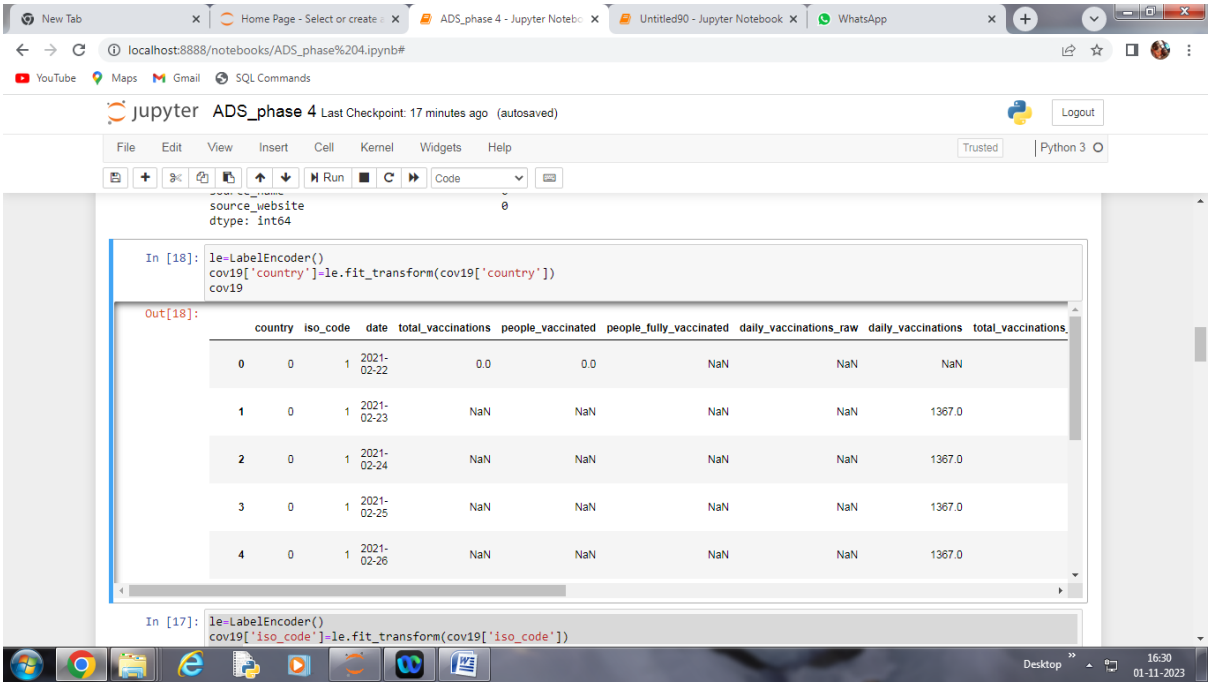
```
In [9]: cov19.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 86512 entries, 0 to 86511
```

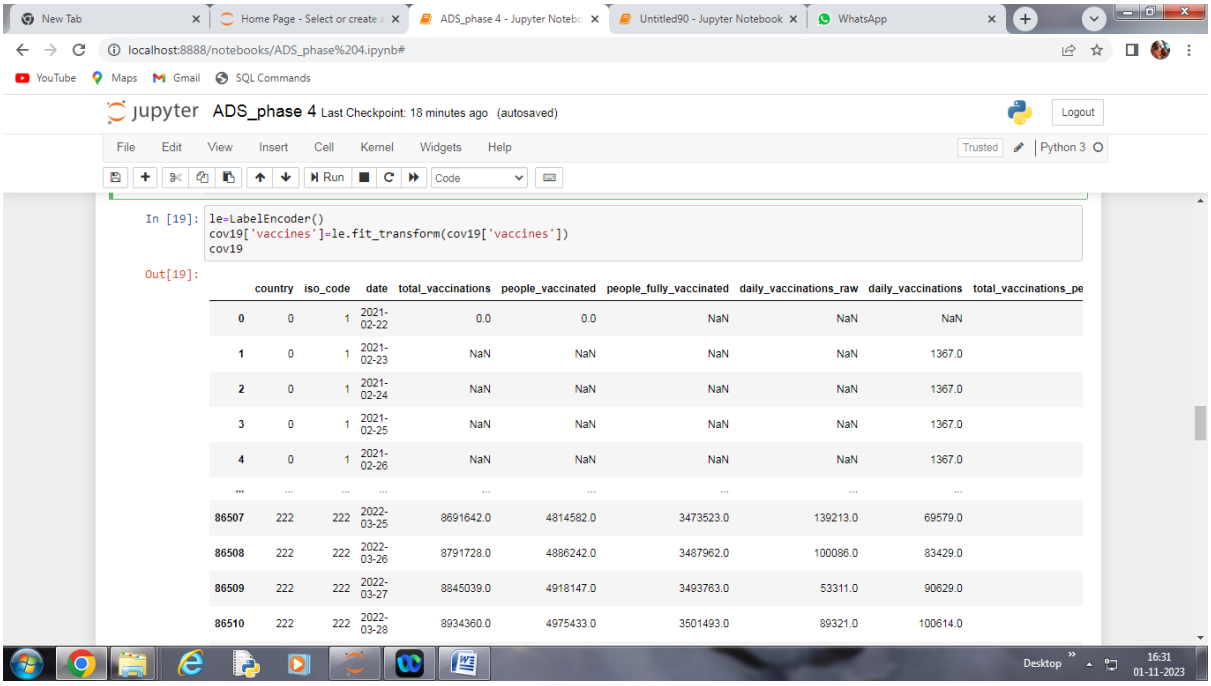


```
In [9]: cov19.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 86512 entries, 0 to 86511
        Data columns (total 15 columns):
         #   Column                             Non-Null Count  Dtype
        ---  ------                             --------------  -----
         0   country                            86512 non-null  object
         1   iso_code                           86512 non-null  object
         2   date                               86512 non-null  object
         3   total_vaccinations                 43607 non-null  float64
         4   people_vaccinated                  41294 non-null  float64
         5   people_fully_vaccinated            38802 non-null  float64
         6   daily_vaccinations_raw             35362 non-null  float64
         7   daily_vaccinations                 86213 non-null  float64
         8   total_vaccinations_per_hundred     43607 non-null  float64
         9   people_vaccinated_per_hundred      41294 non-null  float64
         10  people_fully_vaccinated_per_hundred 38802 non-null  float64
         11  daily_vaccinations_per_million     86213 non-null  float64
         12  vaccines                           86512 non-null  object
         13  source_name                        86512 non-null  object

In [28]: #Data Preparation
         cov19.isnull().sum()

Out[28]: country                            0
         iso_code                           0
         date                               0
```

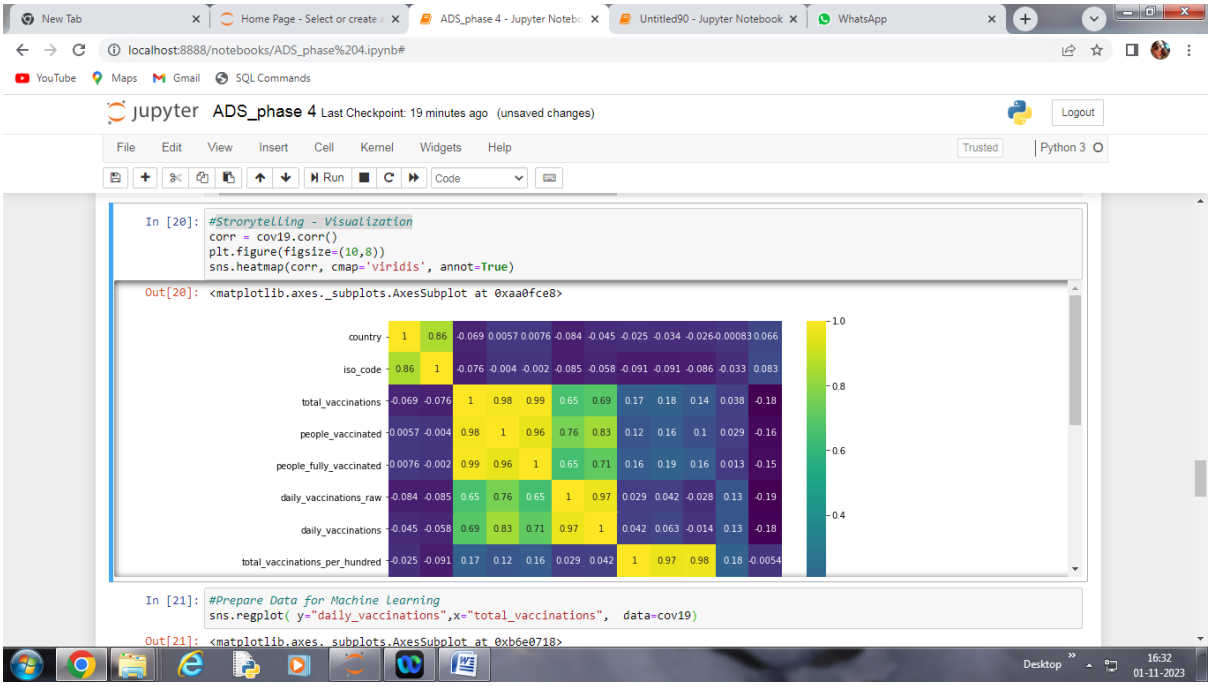
Data Preparation:







Strorytelling – Visualization:



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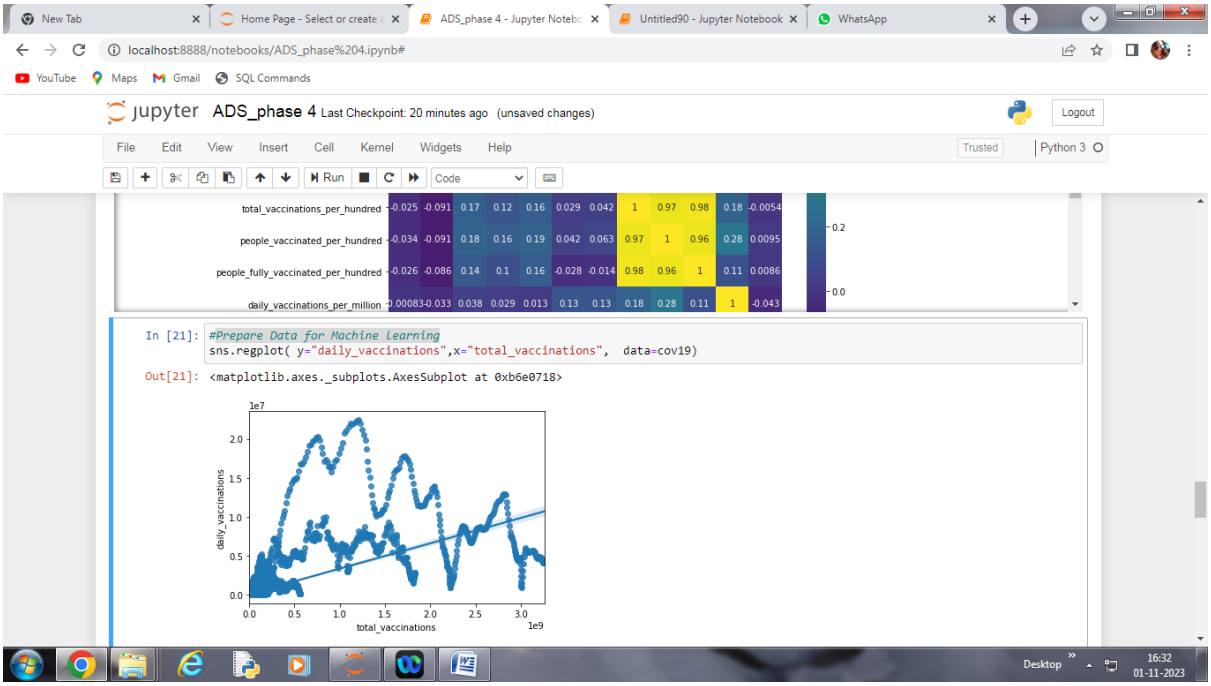
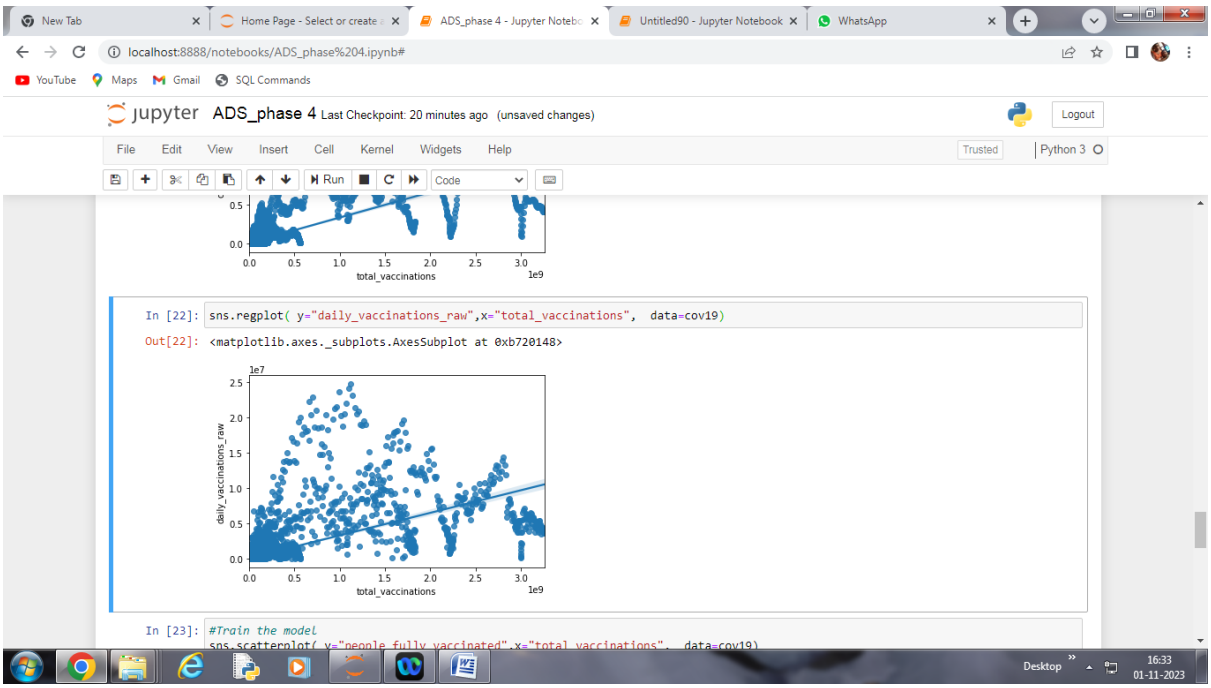
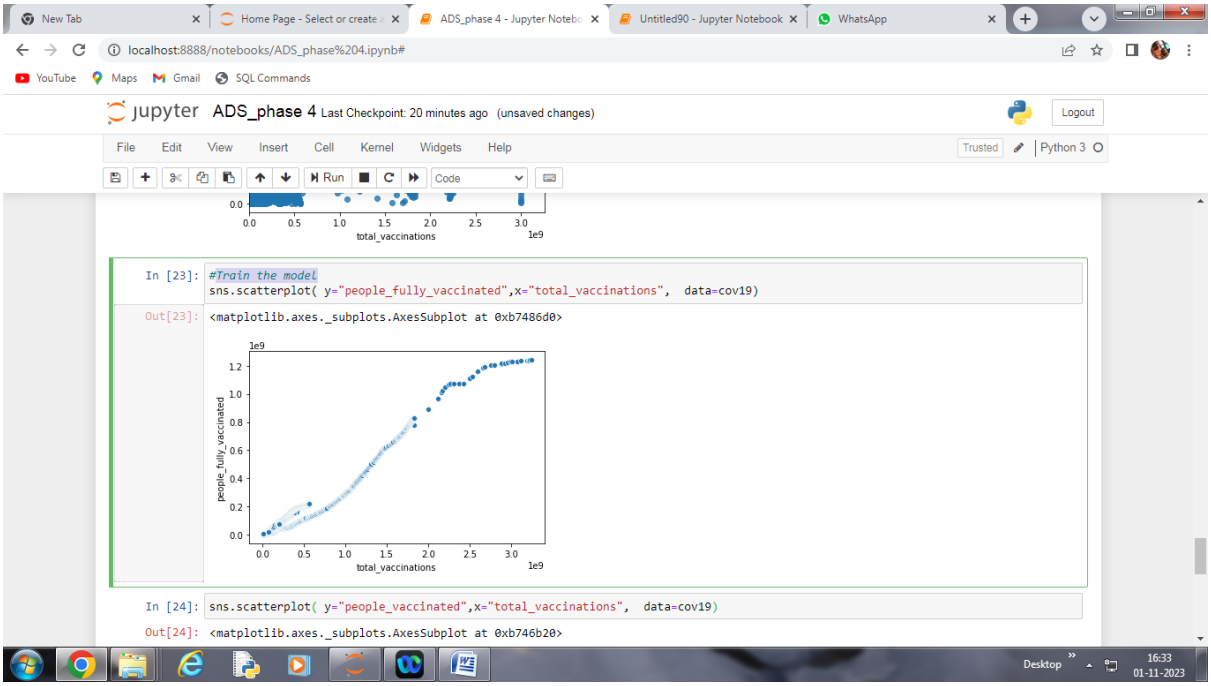
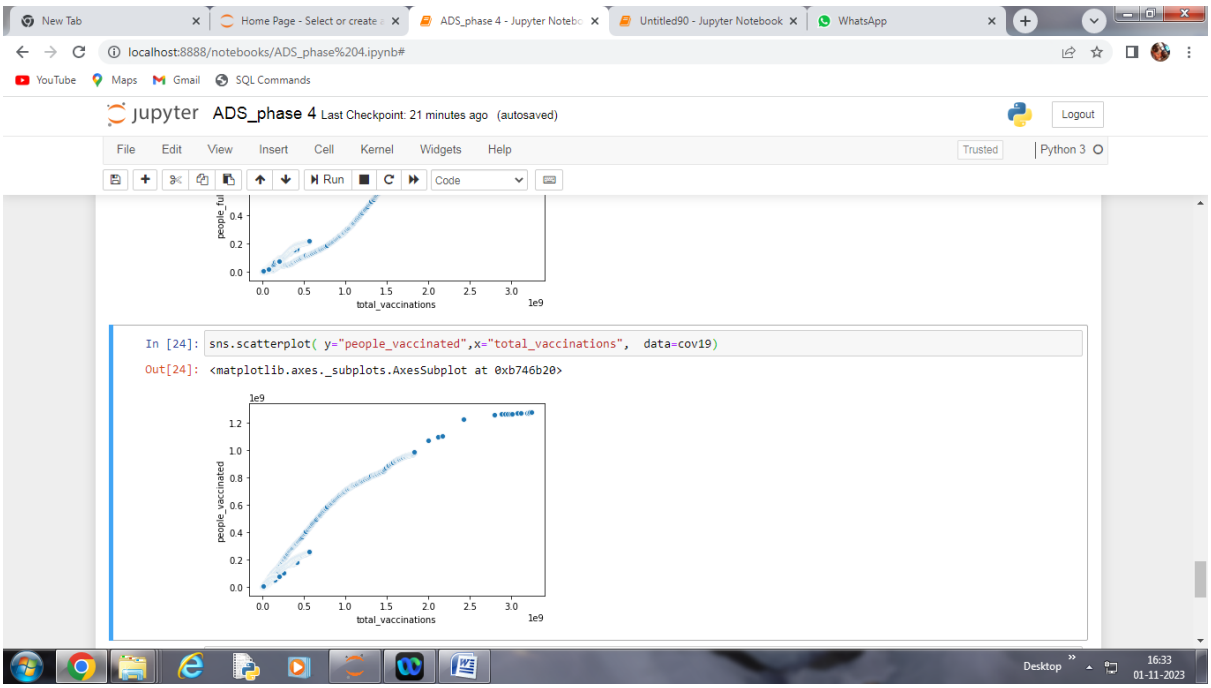
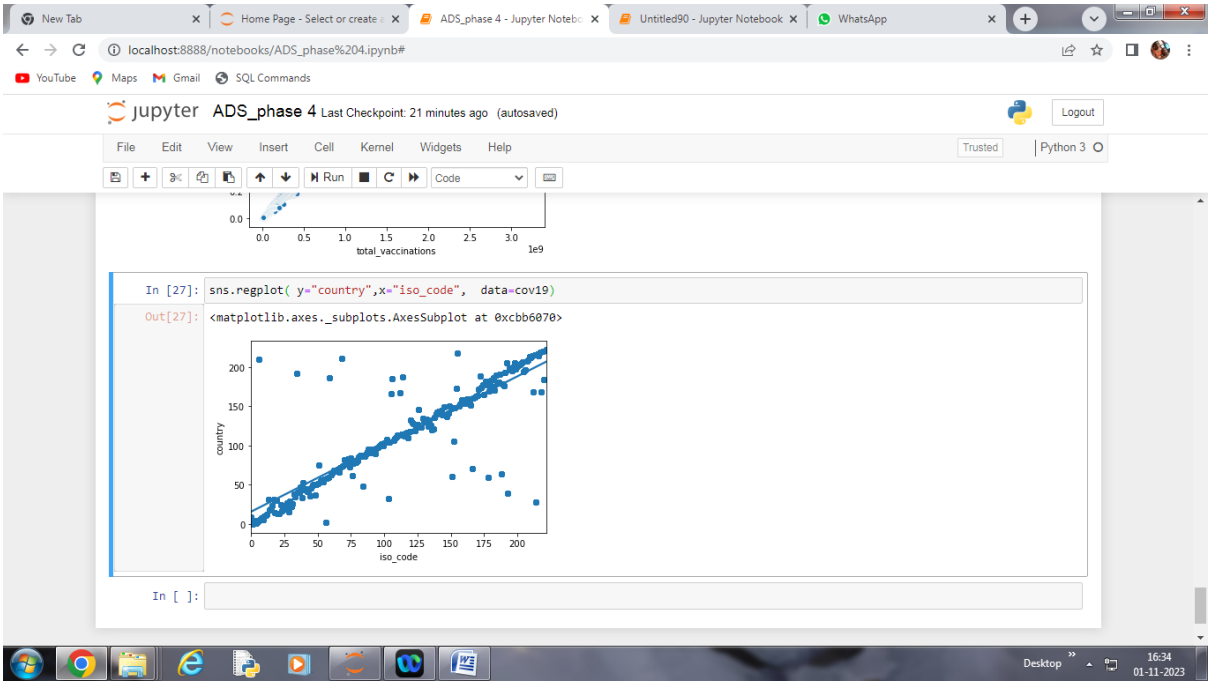




Train the model:



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01-11-2023