```
# import csv file
import pandas as pd
credit card data = pd.read csv('credit card data.csv')
print(credit card data)
                                                   ٧4
                       ٧1
                                 V2
                                          V3
           Time
V5 \
            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
            2.0 -1.158233
                           0.877737 1.548718 0.403034 -0.407193
284802 172786.0 -11.881118 10.071785 -9.834783 -2.066656 -5.364473
284803
      172787.0 -0.732789
                          -0.055080 2.035030 -0.738589 0.868229
284804
      172788.0 1.919565
                         -0.301254 -3.249640 -0.557828 2.630515
284805
      172788.0 -0.240440
                          0.530483 0.702510 0.689799 -0.377961
284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546
            V6 V7
                               V8 V9 ...
                                                     V21
V22 \
       0.462388 0.239599 0.098698 0.363787 ... -0.018307
0.277838
      -0.082361 -0.078803 0.085102 -0.255425 ... -0.225775 -
0.638672
       1.800499 0.791461 0.247676 -1.514654 ... 0.247998
0.771679
3
       1.247203 0.237609 0.377436 -1.387024 ... -0.108300
0.005274
       0.095921 0.592941 -0.270533 0.817739 ... -0.009431
0.798278
                                        284802 -2.606837 -4.918215 7.305334 1.914428 ...
                                                 0.213454
0.111864
284803 1.058415 0.024330 0.294869 0.584800 ...
                                                 0.214205
0.924384
284804 3.031260 -0.296827 0.708417 0.432454 ...
                                                 0.232045
0.578229
284805 0.623708 -0.686180 0.679145 0.392087 ...
                                                 0.265245
```

```
0.800049
284806 -0.649617 1.577006 -0.414650 0.486180 ...
                                                    0.261057
0.643078
            V23
                      V24
                                V25
                                          V26
                                                    V27
                                                              V28
Amount
       -0.110474 0.066928 0.128539 -0.189115 0.133558 -0.021053
149.62
        0.101288 - 0.339846 \quad 0.167170 \quad 0.125895 - 0.008983 \quad 0.014724
2.69
       0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
378.66
3
       -0.190321 - 1.175575 0.647376 - 0.221929 0.062723 0.061458
123.50
       -0.137458 0.141267 -0.206010 0.502292 0.219422 0.215153
69.99
. . .
. . .
284802 1.014480 -0.509348 1.436807 0.250034 0.943651 0.823731
0.77
284803 0.012463 -1.016226 -0.606624 -0.395255 0.068472 -0.053527
24.79
284804 -0.037501 0.640134 0.265745 -0.087371 0.004455 -0.026561
67.88
284805 -0.163298 0.123205 -0.569159 0.546668 0.108821 0.104533
10.00
284806  0.376777  0.008797  -0.473649  -0.818267  -0.002415  0.013649
217.00
        Class
0
           0
           0
1
2
           0
3
           0
4
           0
284802
           0
284803
           0
           0
284804
           0
284805
284806
           0
[284807 rows x 31 columns]
# Split the data into features (X) and target (Y)
import pandas as pd
credit card data = pd.read csv('credit card data.csv')
X = credit card data.drop(columns='Class', axis=1)
Y = credit card data['Class']
```

```
print("Features (X):")
print(X.head())
print("\nTarget (Y):")
print(Y.head())
Features (X):
         Time V1
                                                                            ٧2
                                                                                                          V3 V4 V5
                                                                                                                                                                                                      V6
V7 \
            0.0 - 1.359807 - 0.072781 \ 2.536347 \ 1.378155 - 0.338321 \ 0.462388
0.239599
            0.0 \quad 1.191857 \quad 0.266151 \quad 0.166480 \quad 0.448154 \quad 0.060018 \quad -0.082361 \quad -0.
0.078803
            1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499
0.791461
            1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203
0.237609
         2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
0.592941
                                                         V9 ...
                                                                                                    V20
                                                                                                                                  V21
                                                                                                                                                                 V22
                                                                                                                                                                                                V23
                           V8
V24 \
0 \quad 0.098698 \quad 0.363787 \quad \dots \quad 0.251412 \quad -0.018307 \quad 0.277838 \quad -0.110474
0.066928
1 0.085102 -0.255425 ... -0.069083 -0.225775 -0.638672 0.101288 -
0.339846
2 0.247676 -1.514654 ... 0.524980 0.247998 0.771679 0.909412 -
0.689281
3 0.377436 -1.387024 ... -0.208038 -0.108300 0.005274 -0.190321 -
1.175575
4 -0.270533  0.817739  ...  0.408542 -0.009431  0.798278 -0.137458
0.141267
                                                      V26
                                                                                     V27
                        V25
                                                                                                                    V28
                                                                                                                                   Amount
         0.128539 -0.189115
                                                                      0.133558 -0.021053
                                                                                                                                   149.62
1 0.167170 0.125895 -0.008983 0.014724
                                                                                                                                         2.69
2 -0.327642 -0.139097 -0.055353 -0.059752
                                                                                                                                  378.66
3 0.647376 -0.221929 0.062723 0.061458
                                                                                                                                   123.50
4 -0.206010 0.502292 0.219422 0.215153
                                                                                                                                      69.99
[5 rows x 30 columns]
Target (Y):
0
               0
1
               0
2
               0
3
               0
4
               0
Name: Class, dtype: int64
```

```
import pandas as pd
from imblearn.over sampling import RandomOverSampler
ros = RandomOverSampler(random state=42)
X resampled, Y resampled = ros.fit resample(X, Y)
print("Resampled Features (X):")
print(X resampled.head())
print("\nResampled Target (Y):")
print(Y resampled.head())
Resampled Features (X):
                                                                                                    ٧3
                                                                                                                                  ٧4
                                                                                                                                                               ۷5
                                                                       ٧2
                                                                                                                                                                                            ۷6
        Time
                                V1
V7
        \
           0.0 - 1.359807 - 0.072781 \ 2.536347 \ 1.378155 - 0.338321 \ 0.462388
0.239599
           0.0 \quad 1.191857 \quad 0.266151 \quad 0.166480 \quad 0.448154 \quad 0.060018 \quad -0.082361 \quad -0.08261 \quad -0.08261
0.078803
           1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499
0.791461
           1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203
0.237609
           2.0 -1.158233 0.877737 1.548718 0.403034 -0.407193 0.095921
0.592941
                         ٧8
                                                      V9 ...
                                                                                               V20
                                                                                                                            V21
                                                                                                                                                         V22
                                                                                                                                                                                      V23
V24 \
0 \quad 0.098698 \quad 0.363787 \quad \dots \quad 0.251412 \quad -0.018307 \quad 0.277838 \quad -0.110474
0.066928
1 0.085102 -0.255425 ... -0.069083 -0.225775 -0.638672 0.101288 -
0.339846
2 0.247676 -1.514654 ... 0.524980 0.247998 0.771679 0.909412 -
0.689281
        0.377436 -1.387024 ... -0.208038 -0.108300
                                                                                                                                          0.005274 -0.190321 -
1.175575
4 -0.270533  0.817739  ...  0.408542 -0.009431  0.798278 -0.137458
0.141267
                       V25
                                                   V26
                                                                                 V27
                                                                                                             V28
                                                                                                                            Amount
        0.128539 -0.189115
                                                                  0.133558 -0.021053
                                                                                                                            149.62
1 0.167170 0.125895 -0.008983 0.014724
                                                                                                                                  2.69
2 -0.327642 -0.139097 -0.055353 -0.059752
                                                                                                                            378.66
3 0.647376 -0.221929 0.062723 0.061458
                                                                                                                            123.50
4 -0.206010 0.502292 0.219422 0.215153
                                                                                                                               69.99
[5 rows x 30 columns]
Resampled Target (Y):
              0
1
              0
```

```
2
     0
3
     0
Name: Class, dtype: int64
import pandas as pd
from sklearn.model selection import train test split
from imblearn.over sampling import RandomOverSampler
ros = RandomOverSampler(random state=42)
X resampled, Y resampled = ros.fit resample(X, Y)
X_train, X_test, Y_train, Y_test = train_test_split(X_resampled,
Y resampled, test size=0.2, random state=42)
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)
X train shape: (454904, 30)
X test shape: (113726, 30)
Y train shape: (454904,)
Y test shape: (113726,)
# Create a Logistic Regression model
from sklearn.linear model import LogisticRegression
model = LogisticRegression()
print(model)
LogisticRegression()
from sklearn.linear model import LogisticRegression
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from imblearn.over sampling import RandomOverSampler
ros = RandomOverSampler(random state=42)
X resampled, Y resampled = ros.fit resample(X, Y)
X_train, X_test, Y_train, Y_test = train_test_split(X_resampled,
Y resampled, test size=0.2, random state=42)
scaler = StandardScaler()
X train scaled = scaler.fit transform(X train)
X_test_scaled = scaler.transform(X_test)
model = LogisticRegression(max iter=1000)
model.fit(X train scaled, Y train)
print("Model training completed.")
Model training completed.
```

```
# Evaluate the model on the training data
from sklearn.linear model import LogisticRegression
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy score
from imblearn.over sampling import RandomOverSampler
ros = RandomOverSampler(random state=42)
X resampled, Y resampled = ros.fit resample(X, Y)
X train, X test, Y train, Y test = train test split(X resampled,
Y resampled, test size=0.2, random state=42)
scaler = StandardScaler()
X train scaled = scaler.fit transform(X train)
X test scaled = scaler.transform(X test)
model = LogisticRegression(max iter=1000)
model.fit(X train scaled, Y train)
X train prediction = model.predict(X train scaled)
training data accuracy = accuracy score(X train prediction, Y train)
print('Accuracy on Training data:', training_data_accuracy)
Accuracy on Training data: 0.9493849251710251
# Evaluate the model on the testing data
from sklearn.metrics import accuracy score
X test prediction = model.predict(X test scaled)
test data accuracy = accuracy score(X test prediction, Y test)
print('Accuracy score on Test Data:', test_data_accuracy)
Accuracy score on Test Data: 0.9495541916536236
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear model import LogisticRegression
from sklearn.metrics import accuracy_score
from imblearn.over_sampling import RandomOverSampler
import matplotlib.pyplot as plt
credit card data = pd.read csv('credit card data.csv')
X = credit card data.drop(columns='Class', axis=1)
Y = credit card data['Class']
ros = RandomOverSampler(random state=42)
X resampled, Y resampled = ros.fit resample(X, Y)
```

```
X_train, X_test, Y_train, Y_test = train_test_split(X_resampled,
Y resampled, test size=0.2, random state=42)
model = LogisticRegression(max iter=1000, solver='saga')
model.fit(X train, Y train)
training_data_accuracy = accuracy_score(Y_train,
model.predict(X train))
test data accuracy = accuracy score(Y test, model.predict(X test))
plt.bar(['Training Data', 'Testing Data'], [training_data_accuracy,
test data accuracy], color=['#1f77b4', '#ff7f0e'])
plt.xlabel('Data Set')
plt.ylabel('Accuracy')
plt.title('Accuracy of Logistic Regression Model')
plt.legend(['Training Data', 'Testing Data'])
plt.show()
C:\Users\dell\AppData\Local\Programs\Python\Python312\Lib\site-
packages\sklearn\linear_model\_sag.py:350: ConvergenceWarning: The
max_iter was reached which means the coef_ did not converge
  warnings.warn(
```

Accuracy of Logistic Regression Model



```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(20, 10))
sns.heatmap(credit_card_data.corr(), annot=True, cmap='Blues')
plt.title('Correlation Heatmap')
plt.show()
```

Correlation Heatmap

```
Time - 1 0.12 -0.011-0.42 -0.11 0.17 -0.0630.085-0.0370.00870.037 -0.25 0.12 -0.0660.099-0.18 0.012-0.073 0.09 0.029-0.0510.045 0.14 0.051-0.016-0.23 -0.0430.0050.00940.011-0.012
                        VI - 0.12 1 8.8e-12.1e-1127e-1335e-123e-131e-121e-124.6e-129e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-126e-12.2e-12.2e-126e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e
                          V2 -0.0118.8e-1 1 ... 3e-122.3e-122.8e-124.8e-124.1e-1342e-1354e-122.1e-1342e-135e-122.3e-124.2e-134e-124.2e-132e-132e-132.9e-1242e-1538e-123.3e-122.5e-1489e-124.4e-148.1e-1341e-1349e-124.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-134.2e-
                        V5 - 0.173.5e-1128e-124e-12.6e-1 1 5.9e-146e-112e-121e-127.2e-139e-139e-139e-127e-14.1e-1156e-147e-1181e-13e-121.7e-138e-127le-136e-12.8e-135e-12.8e-135e-12.9e-121e-12e-11 -0.39-0.09
                       V6 -0.06d_3e_B4e_1B6e_IB1e_IB.ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_ee_IB_
                  V13 - 0.066.6e-1B.2e-1B.e-1B.2e-1B.e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e-1B.2e
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               - 0.2
                   V17 -0.073.7e-12e-121.1e-12ze-1247e-184e-15.2e-12e-131.5e-132e-1325e-152e-132e-15.5e-14e-14.1e-1 1.1.1e-13e-122.2e-132e-123e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1329e-1
                  - 0.0
                   V21 -0.0453.3e-1223e-1227e-1227e-1228e-123e-124e-123e-125.5e-1331e-1331e-1331e-132e-133.6e-1331e-132e-1331e-128e-123e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-1331e-13
                   V22 - 0.142.3e-12.5e-129e-133e-131e-13.1e-12.1e-123e-123e-123e-123e-123e-121e-12.3e-121e-12.3e-121e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12
                   V24 -0.0161e-18.4e-194e-12.4e-12.4e-12.6e-12.1e-12.6e-12.1e-12.6e-12.1e-12.4e-12.1e-12.4e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-12.1e-
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                -0.2
                   V25 - -0.23, 1e-19.4e-557e-1B6e-125e-12.7e-124e-1B3e-126e-128e-126e-121e-12.5e-12.5e-12.5e-12.7e-126e-125-124e-19.3e-1B6e-121e-12e-12.8e-129e-1
                  V26 -0.041.8e-12.1e-1286e-12e-13.9e-134e-14.5e-12e-127.7e-1278e-128e-12.8e-12.e-128.e-128.e-128.e-12.8e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.e-128.
                   V28 -0.009$.8e-255e-152e-12.8e-12e-136.1e-13e-13.9e-12.4e-152e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.2e-12.
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                           - -0.4
Amount -0.011-0.23 -0.53 -0.21 0.099 -0.39 0.22 0.4 -0.1 -0.044 -0.1 0.0000 0.095.0053.034-0.0030.0073.036-0.056 0.34 0.11 -0.065-0.110.00510.0480.00320.029 0.01 1 0.0056
              Class -0.012 -0.1 0.091 -0.19 0.13 -0.0950.044-0.19 0.02 -0.098-0.22 0.15 -0.260.0046-0.3-0.0042-0.2 -0.33 -0.11 0.035 0.02 0.040.00080.0028.0078.0038.00450.0180.0098.0056 1
```

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

credit_card_data = pd.read_csv('credit_card_data.csv')

plt.figure(figsize=(8, 6))
sns.countplot(data=credit_card_data, x='Class')
plt.title('Distribution of Fraudulent vs. Non-Fraudulent
Transactions')
plt.xlabel('Class (0: Non-Fraudulent, 1: Fraudulent)')
plt.ylabel('Count')
plt.show()
```

Distribution of Fraudulent vs. Non-Fraudulent Transactions

