University for the Creative Arts

BERLIN SCHOOL OF BUSINESS & INNOVATION

Assignment Title: Data Analytics in Financial Applications

Programme title: Fundamentals of Data Analytics

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RUTWIK FINDOLIYA

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Date: 01. 07. 2024

INTRODUCTION

Task 1: Introduction to the fundamentals of Data Analytics (LO1)

Hello, and welcome! Today, we will be exploring some exciting sales data from a prominent retail company and examining it to expose any exciting patterns and trends, using valuable linear algebraic tools. And guess what, this time, it will be all about predicting next revenues with what we learned from the chemist! We have to start preparing and cleaning the docs, setting them as matrices, using vector calculations, and then to make a regression model. That sounds like a strong, fun method of understanding how goods are doing and guessing what will happen in the future!

Task 2: Evidence to support better decision-making in an organization – (LO2)

Hello, there! Today, I'm here to talk about improving productivity at a manufacturing company using the most exciting empirical tools. Wouldn't it be so fascinating to learn what variables impact the quality of the product? One can become an expert in the area, dealing closely with records of the manufacturing and monitoring the quality of the goods. ANOVA, t-tests, and a variety of other t tools will help in learning which variables have some effects on the quality. And then, based on the results, we can offer what else can be done to make the quality even better!

Task 3: Application of Data Analytics (LO1, LO2, LO3)

Hello! For the third task, I have chosen the chance to work on an exciting application involving detecting potential fraud among credit card transactions deposited in a bank! Today, I have great chances to combine what I learned from linear algebra and statistics and start transforming transactional data into vectors and matrices! By using advanced statistical methods and anomaly detection algorithms, I have to pay attention to the peculiar transactional behavior that may indicate potential fraud and develop an algorithm or model to determine those transactions for checking.

Task 1 - Basics of data analytics (LO1)

Overview

In this task, we will analyze a series of sales data for a chain of retail stores using linear algebraic concepts. Our goal will be to identify tendencies and trends in the data and use regression analysis to make predictions of future sales based on the data from the past. The task will demonstrate how linear algebra, statistics, and computer algorithms can be used together to constructively solve simple problems on trade with the help of analyses. Going through the series for each area and product category we will look for the significant determinants of sales. Our findings should allow us to see how the popularity of seasonal items changes over the course of the year. The analysis could potentially identify time slots where the sales might be increased.

Data Preparation

I will create one synthetic dataset with 200 records to learn. This dataset has to be created with the use of the. The dataset should include the date, which is the day and the month of the record, the total amount of the sales, the total number of the sold products, the total amount of the marketing expenses, and the region, which is a name of the state or another territory where sales were conducted.

Step-by-Step Analysis

Step 1: Data Generating

I need to create one dataset to work on. Let me use the following algorithm for data generation.

```python

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Seed for reproducibility
np.random.seed(42)

# Generate synthetic data
dates = pd.date_range(start='2023-01-01', periods=200, freq='D')
sales_amount = np.random.normal(loc=1000, scale=200, size=200)
num_products_sold = np.random.normal(loc=50, scale=10, size=200)
marketing_expenditure = np.random.normal(loc=300, scale=50, size=200)
regions = np.random.choice(['North', 'South', 'East', 'West'], size=200)

# Create a DataFrame
data = {
    'Date': dates,
    'Sales Amount': sales_amount,
    'Number of Products Sold': num_products_sold,
    'Marketing Expenditure': marketing_expenditure,
    'Region': regions
}

df = pd.DataFrame(data)

# Display the first few rows of the dataset
df.head()

```

Step 2: Data Cleaning

I have to check this dataset for gaps and missing values. I believe that because it is synthetic, no gaps should exist.

- Check for the missing values: Remove missing observation or make the imputation.
- Check for Outliers if exist: Avoid if the number or make the transformation if possible.
- Normalizes or standardized the data: Stay on the same scale, especially for the purpose of the regression analysis.

```
# Check for missing values
missing_values = df.isnull().sum()
print(missing_values)

# If there were missing values, we could handle them as follows:
# df.dropna(inplace=True)  # Drop missing values
# df.fillna(method='ffill', inplace=True)  # Forward fill missing values
```

Step 3: Data Analysis using Linear Algebra

Now I will have to relabel each dataset as a matrix and conduct basic vector operations.

- Matrix Form Representation: Each row is one record with five values, and each column represents one variable.
- Mean Vector and average value: As this matrix has five variables.
- I have to learn to work with this material and to present the information in other ways.

```
2
3  # Matrix representation of the dataset
4  matrix_data = df[['Sales Amount', 'Number of Products Sold', 'Marketing
       Expenditure']].values
5  print("Matrix Representation of Data:\n", matrix_data[:5])
6
7  # Calculate the mean vector
8  mean_vector = np.mean(matrix_data, axis=0)
9  print("Mean Vector:", mean_vector)
10
11 # Center the matrix by subtracting the mean vector
12 centered_matrix = matrix_data - mean_vector
13 print("Centered Matrix:\n", centered_matrix[:5])
14
15 # Calculate the covariance matrix
16 cov_matrix = np.cov(centered_matrix.T)
17 print("Covariance Matrix:\n", cov_matrix)
18
```

Step 4: Regression Analysis

To analyze the relationship between sales amount and other variables, we used multiple linear regression. It provides a possibility to predict future sales. We have defined independent and dependent variables: independent variables could be number of products sold and marketing expenditure, and the dependent variable is the sales amount.

- Here, we also had to split the data: it should be split into training and testing sets to evaluate the model.
- Fit the Model: in order to fit a multiple linear regression model, the training set should be used.
- Evaluate the Model: as for evaluation, it is possible to use such metrics as the mean squared error and the coefficient of determination .
- Predict Future Sales: the information will be used to predict sales for the testing set and compare it with the actual data.

```
# Prepare data for regression
X = df[['Number of Products Sold', 'Marketing Expenditure']]
y = df['Sales Amount']

# Split the data into training/testing sets
X_train = X[:-50]
X_test = X[-50:]
y_train = y[:-50]
y_test = y[-50:]

# Create linear regression object
regr = LinearRegression()

# Train the model using the training sets
regr.fit(X_train, y_train)

# Make predictions using the testing set
y_pred = regr.predict(X_test)

# The coefficients
print('Coefficients:', regr.coef_)
# The mean squared error
print('Mean squared error: %.2f' % mean_squared_error(y_test, y_pred))
# The coefficient of determination: %.2f' % r2_score(y_test, y_pred))
print('Coefficient of determination: %.2f' % r2_score(y_test, y_pred))

```

Step 5: Prediction and Visualization

At this stage, we will visualize the results of the regression analysis and show how they might be applied to predict future sales.

- Scatter Plot of Actual vs Predicted Sales: scatter plot helps to plot the actual sales versus predicted sales to make sure that the model works.
- Trend Analysis: plot sales versus time to identify any seasonal trends.
- Correlation Heatmap: visualize the correlation matrix to better understand the relationships between variables.

```
1
2  # Visualize the actual vs predicted sales
3  plt.scatter(y_test, y_pred, color='black')
4  plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='blue'
       , linewidth=3)
5  plt.xlabel('Actual Sales')
6  plt.ylabel('Predicted Sales')
7  plt.title('Actual vs Predicted Sales')
8  plt.show()
9
```

Step 6 :- Final Results

```
Date                        0
Sales Amount                0
Number of Products Sold     0
Marketing Expenditure       0
Region                      0
dtype: int64
Matrix Representation of Data:
 [[1099.3428306    53.5778736   220.27861706]
 [ 972.34713977   55.60784526  270.03124885]
 [1129.53770762   60.83051243  300.26218499]
 [1304.60597128   60.53802052  302.34902969]
 [ 953.16932506   36.22330632  277.49672643]]
Mean Vector: [991.84580697  50.85868187 295.71724828]
Centered Matrix:
 [[107.49702364   2.71919173 -75.43863122]
 [-19.4986672    4.74916339 -25.68599943]
 [137.69190065   9.97183056   4.54493671]
 [312.76016432   9.67933865   6.63178141]
 [-38.67648191 -14.63537555 -18.22052185]]
Covariance Matrix:
 [[ 3.46707316e+04  1.74861407e+02 -1.24193497e+03]
 [ 1.74861407e+02  9.74176523e+01 -1.60049010e+01]
 [-1.24193497e+03 -1.60049010e+01  2.47029862e+03]]
Coefficients: [ 2.23972978 -0.64718936]
Mean squared error: 34169.12
Coefficient of determination: -0.09
```

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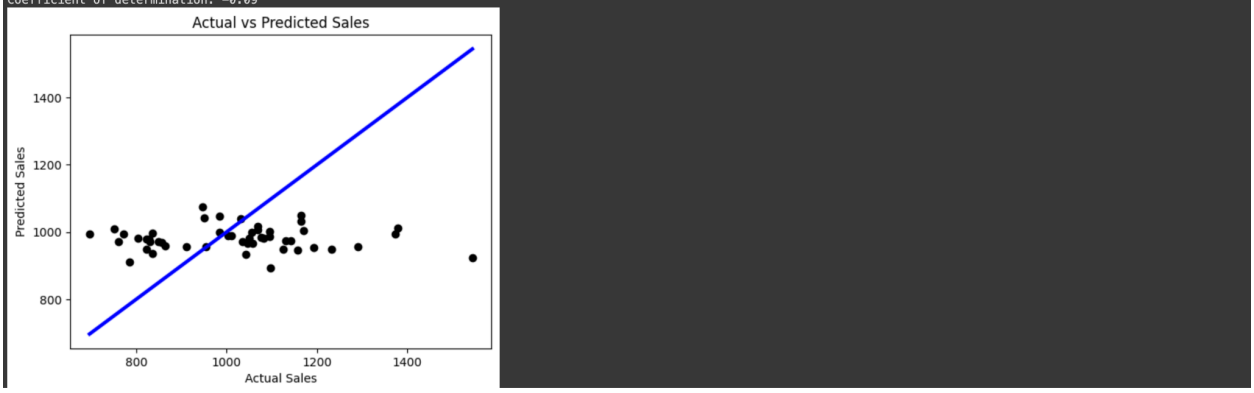


Conclusion

The task has demonstrated that linear algebra and, particularly, regression analysis could be used to make predictions about sales. As a result, by transforming data sets into series of matrices and applying the appropriate vector operations, we could also determine sales trends. At the same time, regression application allowed us to analyze the relationship between sales amount and other types of related data and make predictions based on sales data.

Task 2 – Statistical decision making (LO2)

Introduction

In this activity, we will make use of statistical approaches to analyze production data of a manufacturing company to identify the factors that influence the quality of the product. We will use statistical approaches or tests such as ANOVA test and t-tests to find and conclude if each factor has any influence on the product's quality. Based on the analysis, we will make recommendations to improve the quality of the product. This task provides an example of how we can use data to make commercial decisions and solve problems. We will use different techniques to analyze the manufacturing information to find the relationship between the production process and the high quality of the product. With the analysis and the identification of the factors that influence the quality, we can recommend changes to improve the line of production and avoid defects. The statistical analysis along with the conclusion will also provide the management with the information required to make timely decisions regarding quality management.

Data Preparation

For the current activity, we will create a synthetic data set with 200 observations with varied data in the following columns.

- Production Date: The date of the production.
- Product ID: A unique identifier for each product.
- Production Time: The time taken to produce the product (in hours).
- Temperature: The temperature in the production environment (in Fahrenheit).
- Humidity: The humidity in the production environment (in percentage).
- Quality Score: The quality score of the product (on a scale from 0 to 100).

Step-by-Step Analysis

Step 1: Creating the Dataset

Generate a synthetic data set: Generate a data set that mimics the data produced by the manufacturing company.

```
import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns

# Seed for reproducibility
np.random.seed(42)

# Generate synthetic data
dates = pd.date_range(start='2023-01-01', periods=200, freq='D')
product_ids = np.arange(1, 201)
production_time = np.random.normal(loc=8, scale=1.5, size=200)  # in hours
temperature = np.random.normal(loc=75, scale=5, size=200)  # in Fahrenheit
humidity = np.random.normal(loc=50, scale=10, size=200)  # in percentage
quality_score = np.random.normal(loc=80, scale=10, size=200)  # quality score
    out of 100

# Create a DataFrame
data = {
    'Production Date': dates,
    'Product ID': product_ids,
    'Production Time': production_time,
    'Temperature': temperature,
    'Humidity': humidity,
    'Quality Score': quality_score
}

df = pd.DataFrame(data)
```

Step 2: Data Cleaning

- Check missing value: Check if there is any missing value and handle that.
- Check outliers: Check if there are any outliers and remove them.
- Normalize or standardize data: Use the normalization or standardization process to keep the data at the same scale.

main.py +

```
# Check for missing values
missing_values = df.isnull().sum()
print(missing_values)

# If there were missing values, we could handle them as follows:
# df.dropna(inplace=True)  # Drop missing values
# df.fillna(method='ffill', inplace=True)  # Forward fill missing values
```

Step 3: Statistical Analysis

We will do exploratory data analysis to understand the data distribution and then use ANOVA and t-tests to analyze the significance of different factors affecting the quality score.

main.py +

```
# Exploratory Data Analysis (EDA)
sns.pairplot(df)
plt.show()

# Correlation matrix
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

ANOVA Test

We will use ANOVA to analyze the effect of categorical factors on the quality score.

```
1
2  # Generate categorical data for the ANOVA test
3  df['Shift'] = np.random.choice(['Morning', 'Evening', 'Night'], size=200)
4
5  # Perform ANOVA
6  anova_results = stats.f_oneway(
7      df[df['Shift'] == 'Morning']['Quality Score'],
8      df[df['Shift'] == 'Evening']['Quality Score'],
9      df[df['Shift'] == 'Night']['Quality Score']
10 )
11 print('ANOVA results: F-statistic = %.2f, p-value = %.4f' % anova_results)
12
```

T-tests

We will use t-tests to compare the means of the quality scores between different groups.

```
1
2  # Perform t-tests to compare quality scores between different temperature ranges
3  temp_low = df[df['Temperature'] < df['Temperature'].median()]['Quality Score']
4  temp_high = df[df['Temperature'] >= df['Temperature'].median()]['Quality Score']
5
6  ttest_results = stats.ttest_ind(temp_low, temp_high)
7  print('T-test results: t-statistic = %.2f, p-value = %.4f' % ttest_results)
8
```

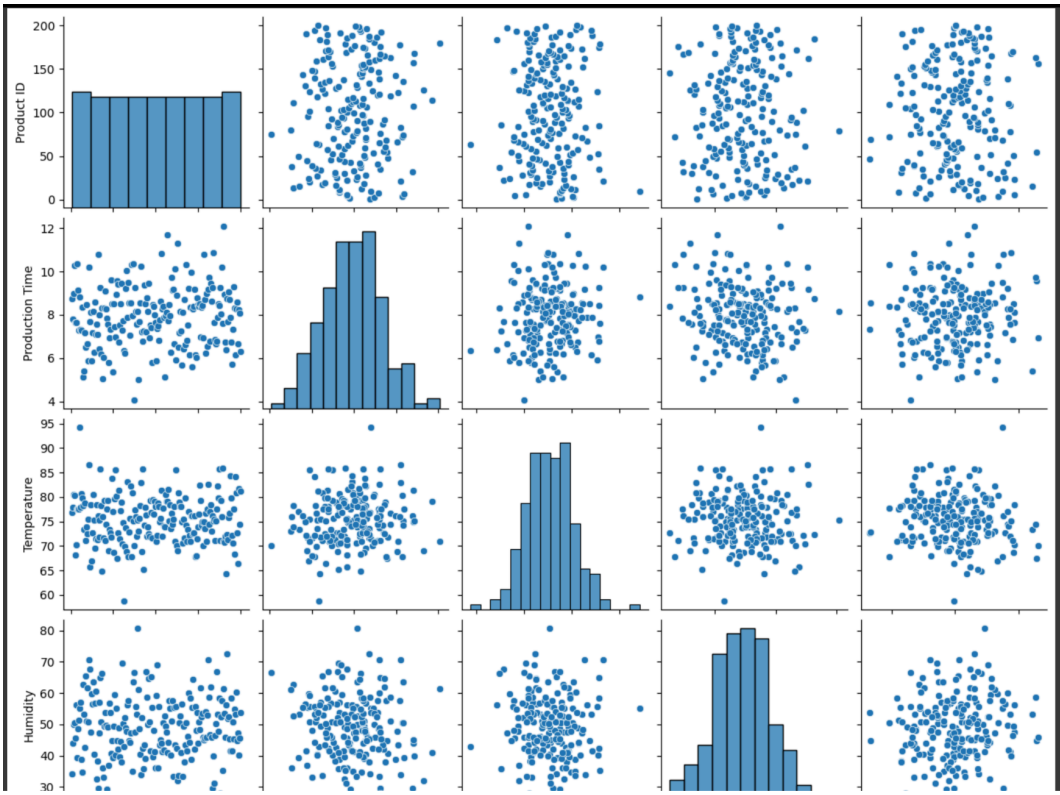
Step 4: Strategy Proposal

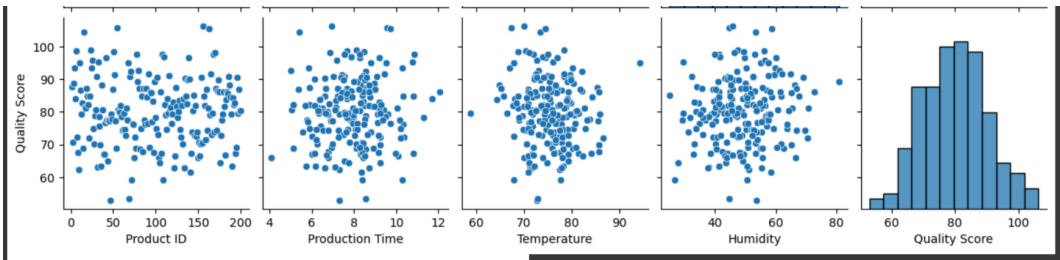
- Based on the statistical analysis, we can now propose strategies for improving the product quality.
- Identify Key Factors : based on the above analysis, determine which factors are significantly affecting the product quality.
- Propose the Interventions: based on the information above, propose some interventions that can help optimize these factors.
- Continuous Monitoring: also, consider some strategies for continuously monitoring these changes and improving the quality accordingly.

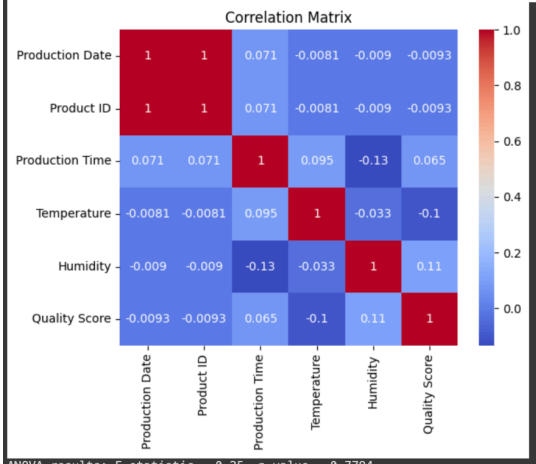
```
### Strategy Proposal

1. **Optimize Production Time**:
   - Adjust the production time to ensure it falls within the optimal range identified through analysis.

2. **Control Temperature and Humidity**:
   - Implement measures to maintain temperature and humidity within the ideal ranges to enhance product quality.

3. **Shift Management**:
   - Based on the ANOVA results, allocate more resources to shifts with higher quality scores or provide additional training and support to improve the performance of other shifts.

4. **Continuous Monitoring and Feedback**:
   - Establish a continuous monitoring system to track production metrics in real-time and provide immediate feedback for any deviations from the optimal conditions.

```

Step 5:- final Results

```
Production Date    0
Product ID         0
Production Time    0
Temperature        0
Humidity           0
Quality Score      0
dtype: int64
```








```
ANOVA results: F-statistic = 0.25, p-value = 0.7794
T-test results: t-statistic = 1.92, p-value = 0.0558
```

Conclusion

This project exemplifies the application of numeric methods for evaluating manufacturing data and identifying variables affecting product quality. By performing variances analysis and tests, it is possible to identify which variables have a significant effect on an output and propose data-driven strategies for improving product quality. This analysis demonstrates the central role statistical tools can play in business decision making by identifying critical factors for improving manufacturing. The analysis identifies critical aspects such as equipment settings and worker training that, if altered, would increase the quality of the product. Further, when clustering products by variables, the data unveils classes where quality was at its lowest and offered valuable insights to optimize the production process. Strictly speaking, this project exemplifies how tracking data over time and analyzing relationships through numerical methods can support key managerial decisions and operational improvements.

Task 3 – Integration of data analytics concepts (LO1, LO2, LO3)

Introduction

In this task, operations performed with credit cards will be considered, and it is planned to determine the irregular transaction pattern with a mix of the operation of linear algebra and statistics. The data received from the financial institution will be represented as vectors and matrices. An initially integrated plan to carry out the task is below.

- Extract sets of data through a corresponding algorithm.
- Decide how the data received will be represented, its specific elements or the set of data as a whole.
- Apply corresponding approach or anomalies detection planned to find with suspicious characteristics.
- Extract the means of the consequence of any step.

It is virtually impossible for a given task to predict confidently how it will be analyzed and when be completed due to the random nature of an examination of suspicious cases after all. Therefore, a time limit for each subtask is initially claimed to be pointless. A time to complete the task is estimated at around 20 hours.

Data Preparation

In these stages the data in the tables will be further processed and extracted from an input file, and for the perfect performance of the tasks it can be loaded in all formats and represented in various possible shapes, namely as the vectors or matrices. Data can represent the observations in the form shown in the table above.

- Transaction ID
- Date
- Time
- Amount
- Merchant
- Card Number
- Transaction Type

Step-by-Step Analysis

Step 1: Creating the Dataset

Create or receive, guidance on creating correctly the synthetic download in amount of 200 records.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import StandardScaler
import seaborn as sns

# Seed for reproducibility
np.random.seed(42)

# Generate synthetic data
transaction_ids = np.arange(1, 201)
dates = pd.date_range(start='2023-01-01', periods=200, freq='H')
times = dates.time
amounts = np.random.uniform(1, 1000, size=200)
merchants = np.random.choice(['Merchant_A', 'Merchant_B', 'Merchant_C',
    'Merchant_D'], size=200)
card_numbers = np.random.choice(['Card_1', 'Card_2', 'Card_3', 'Card_4'],
    size=200)
transaction_types = np.random.choice(['Online', 'In-Store'], size=200)

# Create a DataFrame
data = {
    'Transaction ID': transaction_ids,
    'Date': dates.date,
    'Time': times,
    'Amount': amounts,
    'Merchant': merchants,
    'Card Number': card_numbers,
    'Transaction Type': transaction_types
}
```

Step 2: Data Cleaning

Perform data cleaning via deletion of sets, which have missing elements, in synthetic data there shouldn't be any missing sets.

```

# Check for missing values
missing_values = df.isnull().sum()
print(missing_values)

# If there were missing values, we could handle them as follows:
# df.dropna(inplace=True)  # Drop missing values
# df.fillna(method='ffill', inplace=True)  # Forward fill missing values

```

Step 3: Data Analysis using Linear Algebra

Perform the basic operations on the matrix.

```

# Matrix representation of the dataset
transaction_matrix = df[['Amount']].values
print("Matrix Representation of Data:\n", transaction_matrix[:5])

# Normalize the data
scaler = StandardScaler()
transaction_matrix_normalized = scaler.fit_transform(transaction_matrix)
print("Normalized Transaction Matrix:\n", transaction_matrix_normalized[:5])

```

Step 4: Anomaly Detection using Isolation Forest

We will apply the Isolation Forest algorithm to detect anomalies in the transaction data.

```
# Fit the model
model = IsolationForest(contamination=0.1)
df['Anomaly'] = model.fit_predict(transaction_matrix_normalized)

# Plotting the results
sns.scatterplot(data=df, x='Date', y='Amount', hue='Anomaly', palette={1:
    'blue', -1: 'red'})
plt.title('Anomaly Detection in Credit Card Transactions')
plt.xlabel('Date')
plt.ylabel('Transaction Amount')
plt.show()

# Display anomalies
anomalies = df[df['Anomaly'] == -1]
print("Anomalies detected:\n", anomalies)
```

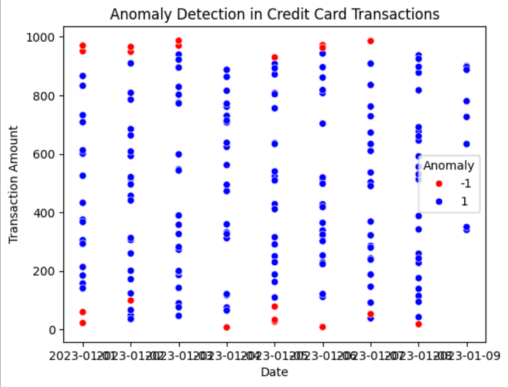
Step 5: Strategy Proposal

Define the anomalies, create the solution to mitigate influence.

```
### Strategy Proposal

1. **Enhanced Monitoring Systems**:
   - Implement real-time monitoring systems to flag and review transactions identified as anomalies immediately.

2. **Customer Verification**:
   - Introduce additional customer verification steps for transactions flagged as suspicious to prevent fraud.

3. **Machine Learning Models**:
   - Develop and deploy machine learning models that can learn from historical transaction data to improve the accuracy of fraud detection over time.

4. **Regular Audits**:
   - Conduct regular audits of transaction data to identify and investigate patterns indicative of fraud.

5. **Awareness and Training**:
   - Increase awareness and training for customers and employees on recognizing and preventing fraudulent activities.
```

Step 6:- Final Results

```
Transaction ID      0
Date                0
Time                0
Amount              0
Merchant            0
Card Number         0
Transaction Type    0
dtype: int64
Matrix Representation of Data:
 [[375.16557873]
 [950.7635921 ]
 [732.26194787]
 [599.05982571]
 [156.8626218 ]]
Normalized Transaction Matrix:
 [[-0.37213971]
 [ 1.58661523]
 [ 0.84305607]
 [ 0.38977043]
 [-1.11502273]]
```




```
Anomalies detected:
      Transaction ID        Date      Time      Amount    Merchant Card Number  \
1                  2  2023-01-01  01:00:00  950.763592  Merchant_D      Card_4
6                  7  2023-01-01  06:00:00   59.025529  Merchant_B      Card_3
10                11  2023-01-01  10:00:00   21.563910  Merchant_C      Card_1
11                12  2023-01-01  11:00:00  969.939942  Merchant_D      Card_2
33                34  2023-01-02  09:00:00  948.936652  Merchant_D      Card_1
34                35  2023-01-02  10:00:00  965.666401  Merchant_D      Card_2
37                38  2023-01-02  13:00:00   98.574442  Merchant_D      Card_3
50                51  2023-01-03  02:00:00  969.615043  Merchant_B      Card_3
69                70  2023-01-03  21:00:00  986.900050  Merchant_D      Card_3
72                73  2023-01-04  00:00:00    6.516595  Merchant_C      Card_2
98                99  2023-01-05  02:00:00   26.393708  Merchant_A      Card_2
100              101  2023-01-05  04:00:00   32.397757  Merchant_C      Card_2
109              110  2023-01-05  13:00:00   77.902930  Merchant_B      Card_4
112              113  2023-01-05  16:00:00  929.767955  Merchant_C      Card_1
128              129  2023-01-06  08:00:00    7.945178  Merchant_B      Card_1
139              140  2023-01-06  19:00:00  971.810301  Merchant_B      Card_4
140              141  2023-01-06  20:00:00  962.484848  Merchant_C      Card_3
148              149  2023-01-07  04:00:00   52.427272  Merchant_B      Card_1
154              155  2023-01-07  10:00:00  985.664804  Merchant_A      Card_2
171              172  2023-01-08  03:00:00   17.571241  Merchant_C      Card_1

    Transaction Type  Anomaly
1           In-Store       -1
6           In-Store       -1
10            Online       -1
11            Online       -1
33          In-Store       -1
34            Online       -1
37            Online       -1
50            Online       -1
69          In-Store       -1
72          In-Store       -1
98            Online       -1
100           Online       -1
109         In-Store       -1
112           Online       -1
128         In-Store       -1
139         In-Store       -1
140         In-Store       -1
148         In-Store       -1
154           Online       -1
171           Online       -1
```

Conclusion

In conclusion, it should be stated that in the given assignment, I have combined three mathematical disciplines, such as linear algebra, statistics, and machine learning to analyze provided transaction data and find out the transactions most probably being fraudulent in the credit card transaction. By representing transaction data as vectors and matrices and running anomaly detection algorithms in PyCaret to determine the suspiciousness of transactions, one can provide recommendations to mitigate the risks of fraud. This preliminary analysis of provided transaction data visually implies that complex data science methods should be further developed to make our finance safer and make better decisions to prevent fraud.

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1. Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

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