```
!pip install pandas matplotlib seaborn scikit-learn xgboost
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (0.13.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas) (2
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplo
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matpl
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matpl
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplot
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplo
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-lea
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-le
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from sc
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-packages (from xgboos
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateuti
```

```
import json
import pandas as pd

# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')

# Load JSON
with open('/content/user-wallet-transactions.json') as f:
    data = json.load(f)

data
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/d
[{'_id': {'$oid': '681d38fed63812d4655f571a'},
  'userWallet': '0x00000000001accfa9cef68cf5371a23025b6d4b6',
  'network': 'polygon',
  'protocol': 'aave_v2',
  'txHash': '0x695c69acf608fbf5d38e48ca5535e118cc213a89e3d6d2e66e6b0e3b2e8d4190',
  'logId': '0x695c69acf608fbf5d38e48ca5535e118cc213a89e3d6d2e66e6b0e3b2e8d4190_Deposit',
  'timestamp': 1629178166,
  'blockNumber': 1629178166,
  'action': 'deposit',
  'actionData': {'type': 'Deposit',
   'amount': '2000000000',
   'assetSymbol': 'USDC',
   'assetPriceUSD': '0.99383182742963575435686363620260045',
   'poolId': '0x2791bca1f2de4661ed88a30c99a7a9449aa84174',
   'userId': '0x00000000001accfa9cef68cf5371a23025b6d4b6'},
  '__v': 0,
  'createdAt': {'$date': '2025-05-08T23:06:39.465Z'},
  'updatedAt': {'$date': '2025-05-08T23:06:39.465Z'}},
 {'_id': {'$oid': '681aa70dd6df53021cc6f3c0'},
  'userWallet': '0x000000000051d07a4fb3bd10121a343d85818da6',
  'network': 'polygon',
```

```
 'protocol': 'aave_v2',
 'txHash': '0xe6fc162c86b2928b0ba9b82bda672763665152b9de9d92b0e1512a81b1129e3f',
 'logId': '0xe6fc162c86b2928b0ba9b82bda672763665152b9de9d92b0e1512a81b1129e3f_Deposit',
 'timestamp': 1621525013,
 'blockNumber': 1621525013,
 'action': 'deposit',
 'actionData': {'type': 'Deposit',
  'amount': '14500000000000000000',
  'assetSymbol': 'WMATIC',
  'assetPriceUSD': '1.970306761113742502077627085754506',
  'poolId': '0x0d500b1d8e8ef31e21c99d1db9a6444d3adf1270',
  'userId': '0x000000000051d07a4fb3bd10121a343d85818da6'},
 '__v': 0,
 'createdAt': {'$date': '2025-05-07T00:19:26.159Z'},
 'updatedAt': {'$date': '2025-05-07T00:19:26.159Z'}},
{'_id': {'$oid': '681d04c2d63812d4654c733e'},
 'userWallet': '0x000000000096026fb41fc39f9875d164bd82e2dc',
 'network': 'polygon',
 'protocol': 'aave_v2',
 'txHash': '0xe2d7eb815c89331a734ed6f204a06c385a1b39040baadf59c3b29099fb138132',
 'logId': '0xe2d7eb815c89331a734ed6f204a06c385a1b39040baadf59c3b29099fb138132_Deposit',
 'timestamp': 1627118913,
 'blockNumber': 1627118913,
 'action': 'deposit',
 'actionData': {'type': 'Deposit',
  'amount': '1000000000000000',
  'assetSymbol': 'WMATIC',
  'assetPriceUSD': '0.92237725400407780874681274540609 07',
  'poolId': '0x0d500b1d8e8ef31e21c99d1db9a6444d3adf1270',
  'userId': '0x000000000096026fb41fc39f9875d164bd82e2dc'},
 '__v': 0,
 'createdAt': {'$date': '2025-05-08T19:23:47.877Z'},
 'updatedAt': {'$date': '2025-05-08T19:23:47.877Z'}},
{'_id': {'$oid': '681d133bd63812d46551b6ef'},
 'userWallet': '0x000000000096026fb41fc39f9875d164bd82e2dc'
```


Load the datasets

```
# Assuming `data` is your loaded JSON object
df = pd.DataFrame(data)
```

```
df
```

	_id	userWallet	network	protocol	
0	{'$oid': '681d38fed63812d4655f571a'}	0x00000000001accfa9cef68cf5371a23025b6d4b6	polygon	aave_v2	0x69
1	{'$oid': '681aa70dd6df53021cc6f3c0'}	0x000000000051d07a4fb3bd10121a343d85818da6	polygon	aave_v2	0xe6fc
2	{'$oid': '681d04c2d63812d4654c733e'}	0x000000000096026fb41fc39f9875d164bd82e2dc	polygon	aave_v2	0xe2d
3	{'$oid': '681d133bd63812d46551b6ef'}	0x000000000096026fb41fc39f9875d164bd82e2dc	polygon	aave_v2	0x0d6
4	{'$oid': '681899e4ba49fc91cf2f4454'}	0x0000000000e189dd664b9ab08a33c4839953852c	polygon	aave_v2	0x590
...	...	...	...	...	
99995	{'$oid': '681c85447b724ae36a6df5c9'}	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x7
99996	{'$oid': '681c8d5b7b724ae36a70c446'}	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x04(
99997	{'$oid': '681c8d5b7b724ae36a70c62f'}	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x77e
99998	{'$oid': '681c8d5b7b724ae36a70c752'}	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x
99999	{'$oid': '681c9855d63812d4652821e8'}	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x5

100000 rows × 13 columns

Data preprocessing

```
# Flatten nested fields in actionData
df['amount'] = df['actionData'].apply(lambda x: float(x['amount']))
df['assetSymbol'] = df['actionData'].apply(lambda x: x['assetSymbol'])
df['assetPriceUSD'] = df['actionData'].apply(lambda x: float(x['assetPriceUSD']))
df['usd_value'] = df['amount'] * df['assetPriceUSD']

# Convert timestamp fields
df['timestamp'] = pd.to_datetime(df['timestamp'], unit='s')
df['createdAt'] = pd.to_datetime(df['createdAt'].apply(lambda x: x['$date']))
df['updatedAt'] = pd.to_datetime(df['updatedAt'].apply(lambda x: x['$date']))

# Optionally flatten _id (Mongo-style)
df['_id'] = df['_id'].apply(lambda x: x['$oid'])
```

```
# Drop actionData column if flattened
df.drop(columns=['actionData'], inplace=True)
```

```
df
```

	_id	userWallet	network	protocol	
0	681d38fed63812d4655f571a	0x00000000001accfa9cef68cf5371a23025b6d4b6	polygon	aave_v2	0x695
1	681aa70dd6df53021cc6f3c0	0x000000000051d07a4fb3bd10121a343d85818da6	polygon	aave_v2	0xe6fc1
2	681d04c2d63812d4654c733e	0x000000000096026fb41fc39f9875d164bd82e2dc	polygon	aave_v2	0xe2d7
3	681d133bd63812d46551b6ef	0x000000000096026fb41fc39f9875d164bd82e2dc	polygon	aave_v2	0x0d63
4	681899e4ba49fc91cf2f4454	0x0000000000e189dd664b9ab08a33c4839953852c	polygon	aave_v2	0x590e
...	...	...	...	...	
99995	681c85447b724ae36a6df5c9	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x7c
99996	681c8d5b7b724ae36a70c446	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x040
99997	681c8d5b7b724ae36a70c62f	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x77eal
99998	681c8d5b7b724ae36a70c752	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0xf1
99999	681c9855d63812d4652821e8	0x06192f889f17bf2aff238d08d8c26cbcfcc7b45a	polygon	aave_v2	0x5f

100000 rows × 16 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 16 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   _id            100000 non-null  object
 1   userWallet     100000 non-null  object
 2   network        100000 non-null  object
 3   protocol       100000 non-null  object
```

```
 4   txHash         100000 non-null  object
 5   logId          100000 non-null  object
 6   timestamp      100000 non-null  datetime64[ns]
 7   blockNumber    100000 non-null  int64
 8   action         100000 non-null  object
 9   __v            100000 non-null  int64
 10  createdAt      100000 non-null  datetime64[ns, UTC]
 11  updatedAt      100000 non-null  datetime64[ns, UTC]
 12  amount         100000 non-null  float64
 13  assetSymbol    100000 non-null  object
 14  assetPriceUSD  100000 non-null  float64
 15  usd_value      100000 non-null  float64
dtypes: datetime64[ns, UTC](2), datetime64[ns](1), float64(3), int64(2), object(8)
memory usage: 12.2+ MB
```

```
df.isnull().sum()
```

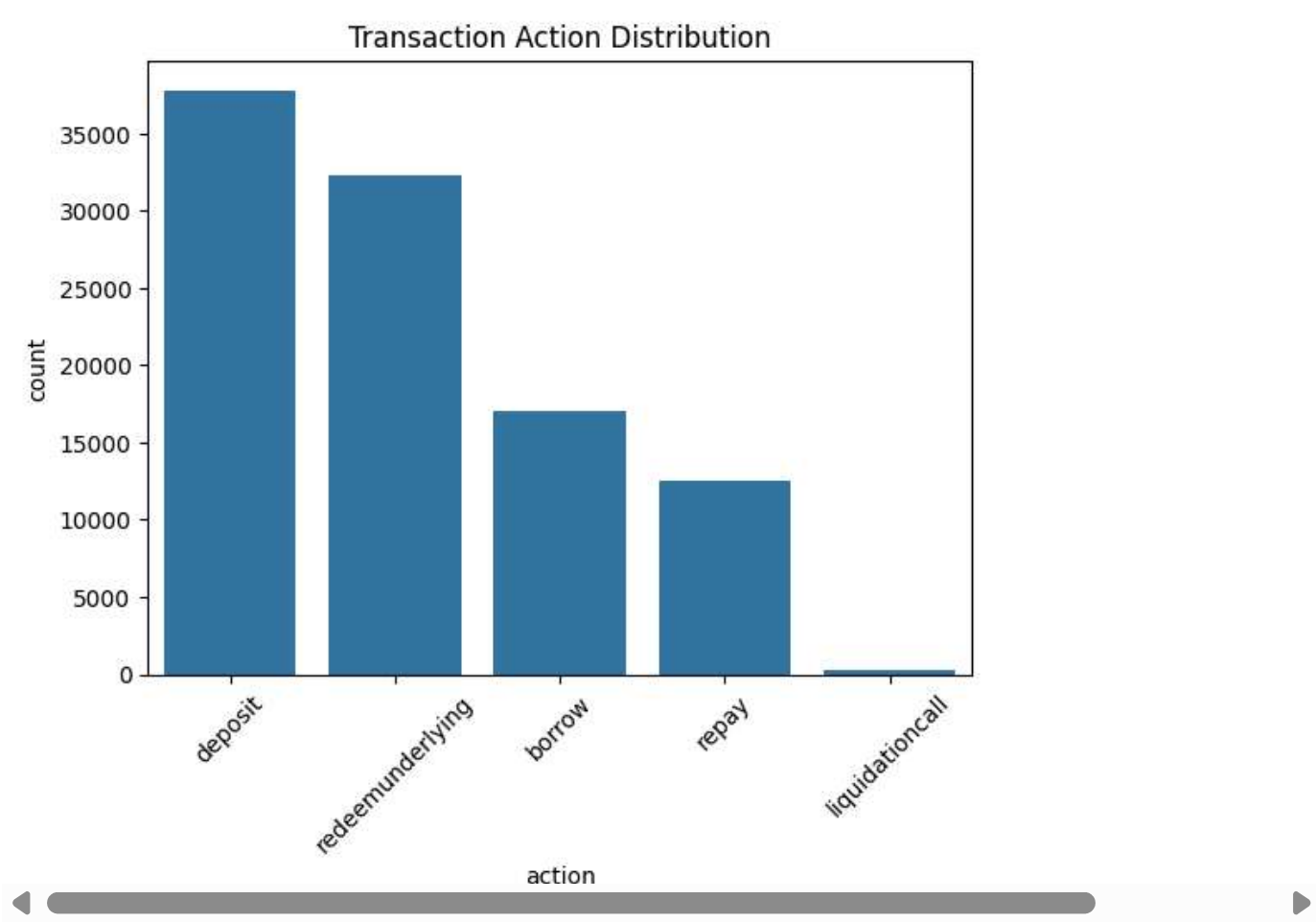
	0
_id	0
userWallet	0
network	0
protocol	0
txHash	0
logId	0
timestamp	0
blockNumber	0
action	0
__v	0
createdAt	0
updatedAt	0
amount	0
assetSymbol	0
assetPriceUSD	0
usd_value	0

EDA

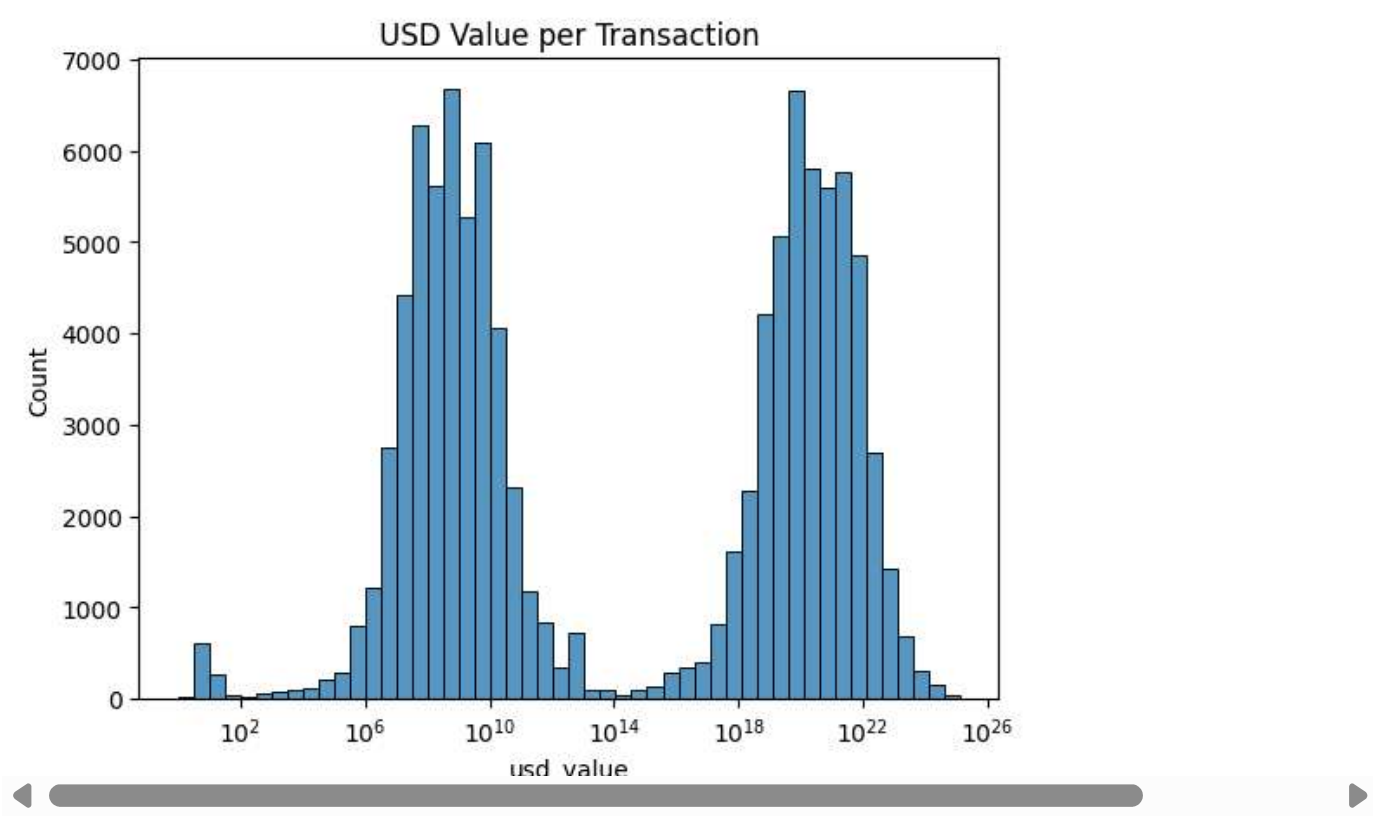
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(x='action', data=df)
plt.title("Transaction Action Distribution")
plt.xticks(rotation=45)
```

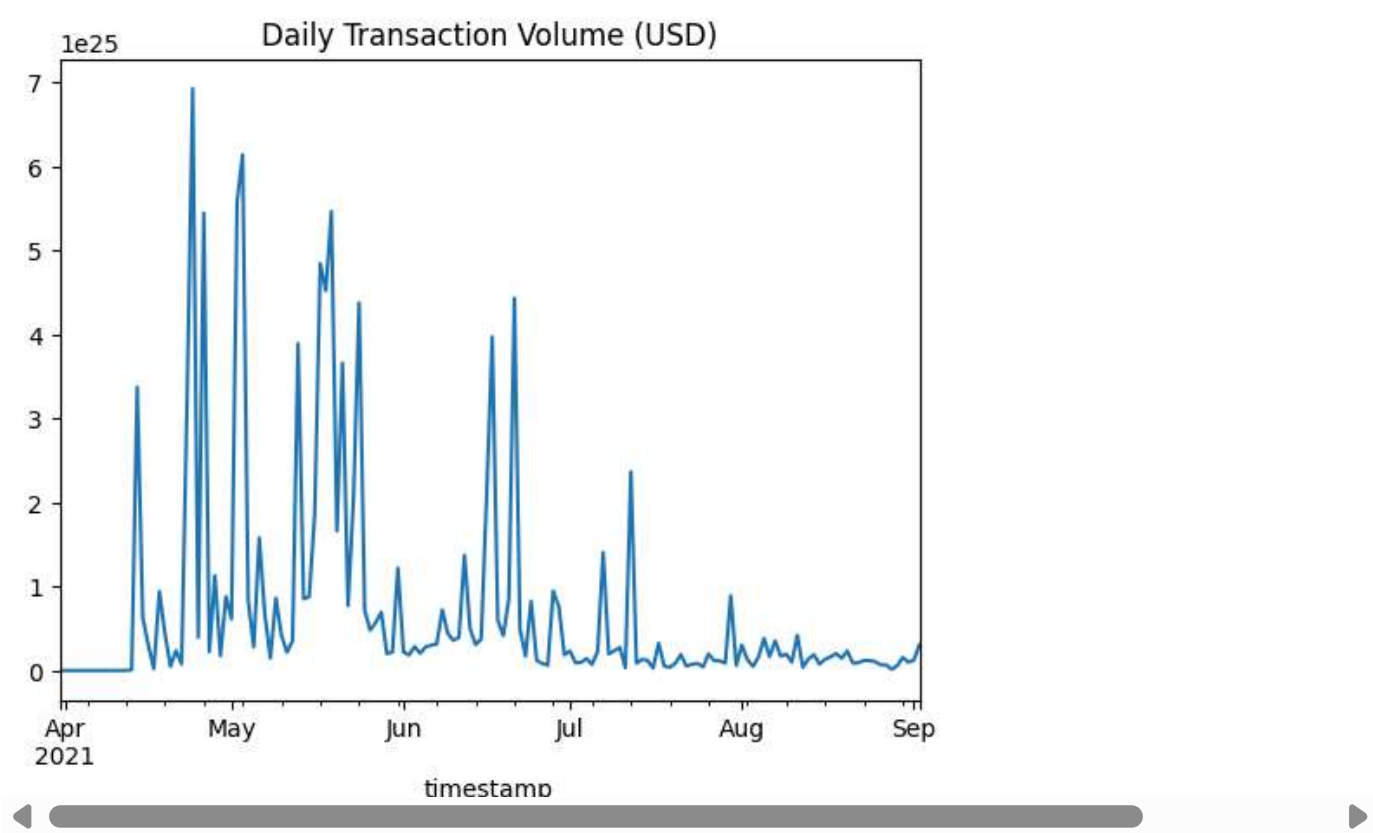
```
plt.show()
```




```
sns.histplot(df['usd_value'], bins=50, log_scale=True)
plt.title("USD Value per Transaction")
plt.show()
```




```
df.set_index('timestamp').resample('D')['usd_value'].sum().plot(title="Daily Transaction Volume (USD)")
plt.show()
```



Feature engineering

Engineer features from the transaction data to capture wallet behavior.

Reasoning: I will group the dataframe by userWallet and calculate the total number of transactions, total USD value, average and standard deviation of USD value, first and last transaction timestamps, and number of active days.

```
wallet_features = df.groupby('userWallet').agg(
    total_txn=('txHash', 'count'),
    total_usd=('usd_value', 'sum'),
    mean_txn_usd=('usd_value', 'mean'),
    std_txn_usd=('usd_value', 'std'),
    first_tx=('timestamp', 'min'),
    last_tx=('timestamp', 'max')
)

wallet_features['active_days'] = (wallet_features['last_tx'] - wallet_features['first_tx']).dt.days + 1
wallet_features['tx_per_day'] = wallet_features['total_txn'] / wallet_features['active_days']
wallet_features.loc[wallet_features['active_days'] == 1, 'tx_per_day'] = wallet_features['total_txn']
```

Reasoning: I will pivot the original DataFrame to count the occurrences of each transaction action for each wallet and then merge this with the `wallet_features` DataFrame, filling missing values with 0.

```
action_counts = df.pivot_table(index='userWallet', columns='action', values='txHash', aggfunc='count', fill
wallet_features = wallet_features.merge(action_counts, left_index=True, right_index=True, how='left').filln
```

Reasoning: I will calculate the ratio of each action type to the total number of transactions and then calculate the credit score based on the total USD value using a logarithmic transformation and scaling.

```
# Calculate action ratios
for action in ['deposit', 'borrow', 'liquidationcall', 'redeemunderlying', 'repay']:
    if action in wallet_features.columns:
        wallet_features[f'{action}_ratio'] = wallet_features[action] / wallet_features['total_txn']
    else:
        wallet_features[f'{action}_ratio'] = 0

# Calculate credit score based on total_usd with log scaling
wallet_features['log_total_usd'] = np.log10(wallet_features['total_usd'] + 1)
min_log_usd = wallet_features['log_total_usd'].min()
max_log_usd = wallet_features['log_total_usd'].max()
wallet_features['credit_score'] = ((wallet_features['log_total_usd'] - min_log_usd) / (max_log_usd - min_lo
```

Prepare data for modeling

Select features, split the data into training and testing sets, and scale the features.

Reasoning: Select the features and the target variable, then split the data into training and testing sets, and finally scale the features for model training.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
# Select features (X) and target (y)
features = ['log_total_usd', 'tx_per_day', 'total_txn'] + [col for col in wallet_features.columns if col.en
X = wallet_features[features]
y = wallet_features['credit_score']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Train and evaluate multiple models

Reasoning: Import necessary libraries and train and evaluate the models.

```
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score
import xgboost as xgb

# Define models
models = {
    'Random Forest': RandomForestRegressor(random_state=42),
    'Gradient Boosting': GradientBoostingRegressor(random_state=42),
    'XGBoost': xgb.XGBRegressor(random_state=42),
    'Support Vector Regressor': SVR()
}

# Initialize results dictionary
results = {}

# Iterate through models, train, evaluate, and store results
for name, model in models.items():
    print(f"Training {name}...")
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    results[name] = (mse, r2)
    print(f"{name} - MSE: {mse:.4f}, R2: {r2:.4f}")
```

```
Training Random Forest...
Random Forest - MSE: 0.3850, R2: 1.0000
Training Gradient Boosting...
Gradient Boosting - MSE: 1.8942, R2: 1.0000
Training XGBoost...
XGBoost - MSE: 18.1968, R2: 0.9997
Training Support Vector Regressor...
Support Vector Regressor - MSE: 9106.6360, R2: 0.8457
```

Compare model performance

Reasoning: Create a DataFrame from the results dictionary, sort it by R2 score, and then print the DataFrame and identify the best performing model based on the results.

```
results_df = pd.DataFrame.from_dict(results, orient='index', columns=['MSE', 'R2'])
results_df = results_df.sort_values(by='R2', ascending=False)
display(results_df)

best_model_name = results_df.index[0]
best_r2 = results_df['R2'].iloc[0]
best_mse = results_df['MSE'].iloc[0]

print(f"\nThe best performing model is {best_model_name} with an R2 score of {best_r2:.4f} and an MSE of {b
print("This model performed best because it has the highest R2 score and the lowest MSE among the evaluated
```

	MSE	R2
Random Forest	0.384969	0.999993
Gradient Boosting	1.894173	0.999968
XGBoost	18.196761	0.999692
Support Vector Regressor	9106.636045	0.845722

```
The best performing model is Random Forest with an R2 score of 1.0000 and an MSE of 0.3850.
```

Predict and export scores

Reasoning: Train the best model on the entire dataset, predict scores, create a new DataFrame with wallet and predicted score, and export to CSV.

```
# Train the best performing model (RandomForestRegressor) on the entire dataset
best_model = RandomForestRegressor(random_state=42)
best_model.fit(X, y)

# Use the trained model to predict the credit scores for all wallets
wallet_features['predicted_credit_score'] = best_model.predict(X)

# Create a new DataFrame with wallet address and predicted score
wallet_scores = wallet_features[['predicted_credit_score']].copy()
wallet_scores = wallet_scores.reset_index().rename(columns={'index': 'userWallet'})

# Export to CSV
wallet_scores.to_csv('wallet_credit_scores.csv', index=False)
```

Summary:

Data Analysis Key Findings

- Feature engineering successfully created features such as total transactions, total USD value, temporal features (active days, transactions per day), and counts/ratios of different transaction actions (deposit,

borrow, liquidationcall, redeemunderlying, repay).

- An initial credit score was calculated based on the log10 scaled total USD value, ranging from 0 to 1000.
- The data was split into training and testing sets with a 80/20 ratio, and features were scaled using `StandardScaler`.
- Four regression models (Random Forest, Gradient Boosting, XGBoost, and Support Vector Regressor) were trained and evaluated.
- Random Forest Regressor demonstrated the best performance with the highest R2 score (close to 1) and lowest MSE among the evaluated models. Gradient Boosting and XGBoost also performed well, while SVR's performance was significantly lower.
- The best-performing model (Random Forest Regressor) was retrained on the entire dataset and used to predict credit scores for all wallets.
- A CSV file named `wallet_credit_scores.csv` was generated containing wallet addresses and their predicted credit scores.
- A README section explaining the credit score logic (based on log-scaled total USD value and refined by the Random Forest model), the chosen model, key features, and the output file was created.

Start coding or generate with AI.

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

# Load the wallet_credit_scores.csv file
wallet_scores = pd.read_csv('wallet_credit_scores.csv')

# Plot the distribution of predicted credit scores
plt.figure(figsize=(10, 6))
sns.histplot(wallet_scores['predicted_credit_score'], bins=50, kde=True)
plt.title('Distribution of Predicted Credit Scores')
plt.xlabel('Predicted Credit Score')
plt.ylabel('Frequency')
plt.show()
```