One Acre Data Analytics Excersie

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Importing All the necessary Libraries needed

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import warnings
```

In [2]:
```
# Load the dataset
file_path = 'Data_Analyst_Test.xlsx'
data = pd.read_excel(file_path)
```

EXPLORATORY DATA ANALYSIS

In [3]:
```
data.head()
```

Out[3]:

	contract_reference	status	start_date	end_date	next_contract_payment_due_da
0	abc0001	Completed	2022-05-20 08:23:51.406	2022-05-20 08:23:51.406	2022-05-20 08:23:51.4
1	abc0002	Active	2022-05-25 13:28:49.874	NaT	2022-08-31 18:34:01.6
2	abc0003	Active	2022-05-31 10:02:23.159	NaT	2022-07-22 01:17:15.5
3	abc0004	Active	2022-07-05 11:49:03.802	NaT	2022-08-18 13:34:13.9
4	abc0005	Active	2022-05-31 06:31:25.977	NaT	2022-07-04 13:30:36.4

In [4]:

```
# Checking the data types within the dataframe
#data.info()
```

Cleaning the date columns

In [5]:

```
data['start_date'] = pd.to_datetime(data['start_date']).dt.normalize()
data['end_date'] = pd.to_datetime(data['end_date']).dt.normalize()
data['next_contract_payment_due_date'] =
pd.to_datetime(data['next_contract_payment_due_date']).dt.normalize()
data['birthdate'] = pd.to_datetime(data['birthdate']).dt.normalize()
```

In [6]:

```
# Confirming the date columns are clean and in correct format
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 20 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   contract_reference                1000 non-null   object
 1   status                            1000 non-null   object
 2   start_date                        1000 non-null   datetime64[ns]
 3   end_date                          246 non-null    datetime64[ns]
 4   next_contract_payment_due_date    1000 non-null   datetime64[ns]
 5   cumulative_amount_paid            1000 non-null   float64
 6   expected_cumulative_amount_paid   1000 non-null   float64
 7   nominal_contract_value            1000 non-null   float64
 8   deposit_amount                    1000 non-null   float64
 9   birthdate                         858 non-null    datetime64[ns]
 10  gender                            1000 non-null   int64
 11  l3_entity_id                      1000 non-null   int64
 12  name                              1000 non-null   object
 13  expected_payment_progression      1000 non-null   float64
 14  Region                            1000 non-null   object
 15  Agent ID                          1000 non-null   int64
 16  Loan Product Type                 1000 non-null   object
 17  Loan Interest Rate                1000 non-null   float64
 18  Repayment Frequency               1000 non-null   object
 19  Credit Score                      1000 non-null   int64
dtypes: datetime64[ns](4), float64(6), int64(4), object(6)
memory usage: 156.4+ KB
```

In [7]:

```
# How many records are there in our dataframe?
num_records, num_columns = data.shape

# Print the results in the desired format
print(f"We have {num_columns} columns and {num_records} records.")
```

```
We have 20 columns and 1000 records.
```

In [8]:

```
# Checking for missing / null values
missing_percentage = (data.isnull().sum() / len(data)) * 100

print(missing_percentage)
```

```
contract_reference                  0.0
status                              0.0
start_date                          0.0
end_date                           75.4
next_contract_payment_due_date      0.0
cumulative_amount_paid              0.0
expected_cumulative_amount_paid     0.0
nominal_contract_value              0.0
deposit_amount                      0.0
birthdate                          14.2
gender                              0.0
l3_entity_id                        0.0
name                                0.0
expected_payment_progression        0.0
Region                              0.0
Agent ID                            0.0
Loan Product Type                   0.0
Loan Interest Rate                  0.0
Repayment Frequency                 0.0
Credit Score                        0.0
dtype: float64
```

- There are no significant null values from the dataset, we shall keep the dataframe as is.

Task 1

Loan Performance and Risk Metrics

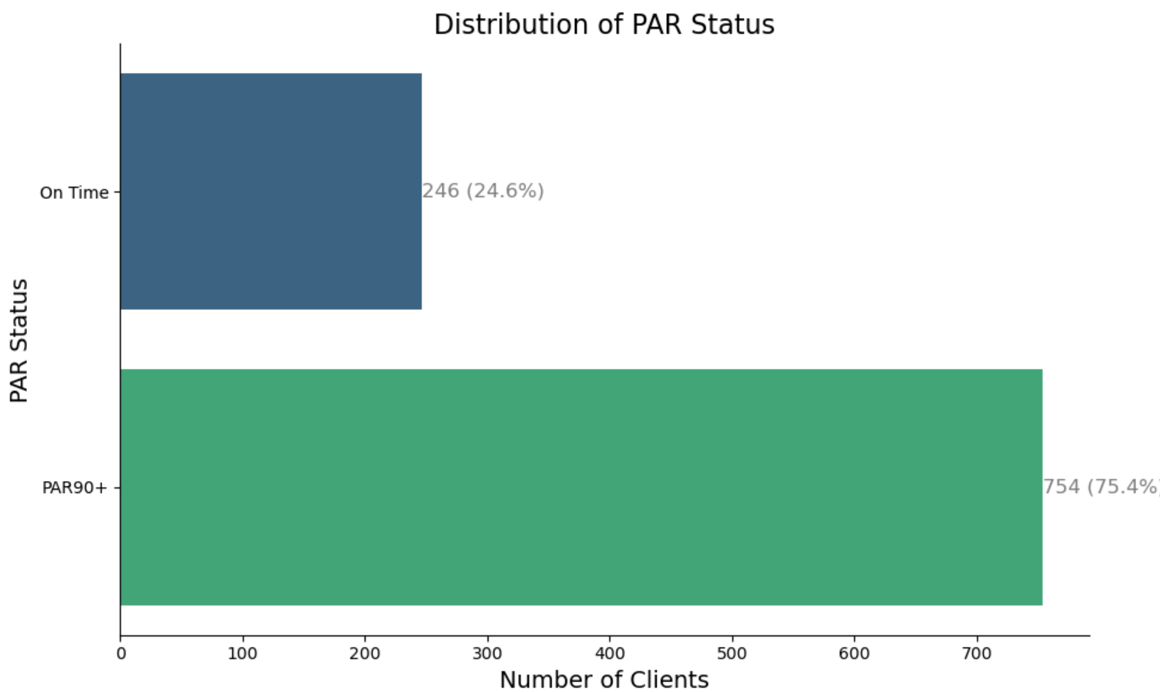
1. PAR Status based on repayment progression

In [9]:
```
# We get the current date to calculate PAR status
current_date = datetime.now()
```

In [10]:
```
def calculate_par_status(row):
    # Check if the loan status is 'Completed', these are categorized as on time records.
    if row['status'] == 'Completed':
        return 'On Time'

    # Calculate days past due based on the current date
    days_past_due = (current_date - row['next_contract_payment_due_date']).days

    # Determine the PAR status based on days past due
    if days_past_due < 0:
        return 'On Time'
    elif 0 <= days_past_due <= 7:
        return 'PAR0-7'
    elif 8 <= days_past_due <= 30:
        return 'PAR8-30'
    elif 31 <= days_past_due <= 90:
```

```
        return 'PAR31-90'
    else:
        return 'PAR90+'

# Apply the function to the DataFrame
data['PAR Status'] = data.apply(calculate_par_status, axis=1)
```

In [11]:
```
# Setting the figure size
plt.figure(figsize=(10, 6))

# Using horizontal bar plot
ax = sns.countplot(data=data, y='PAR Status', palette='viridis')

plt.title('Distribution of PAR Status', fontsize=16)
plt.xlabel('Number of Clients', fontsize=14)
plt.ylabel('PAR Status', fontsize=14)

# Calculating the total number of clients for percentage calculation
total_clients = len(data)

# Adding data labels as integers and percentages.
for p in ax.patches:
    count = int(p.get_width())  # Count
    percentage = (count / total_clients) * 100
    ax.annotate(f'{count} ({percentage:.1f}%)',
                (p.get_width() + 0.2, p.get_y() + p.get_height()/2),
                ha='left', va='center', fontsize=12, color='grey')

# Remove the top and right borders
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```



2. Current Collection Rate

The formula for the Current Collection Rate is given by:

$$\text{Current Collection Rate} = \frac{\text{Expected Cumulative Amount Paid} - \text{Deposit Amount}}{\text{Cumulative Amount Paid}}$$

In [12]:
```
data['Current Collection Rate'] = data['cumulative_amount_paid'] / (data['expected_cumulative_amount_paid'] - data['deposit_amount'])
```

3. Total Amount in Arrears

Total Amount in arrears is given by:

$$\text{Total Amount in Arrears} = \text{Expected Cumulative Amount Paid} - \text{Cumulative Amo}$$

In [13]:
```
data['Total Amount in Arrears'] = data['expected_cumulative_amount_paid'] - data['cumulative_amount_paid']
```

4. Payment Progression

The formula for Payment Progression is given by:

$$\text{Payment Progression} = \frac{\text{Cumulative Amount Paid}}{\text{Nominal Contract Value}}$$

In [14]:
```
data['Payment Progression'] = data['cumulative_amount_paid'] / data['nominal_contract_value']
```

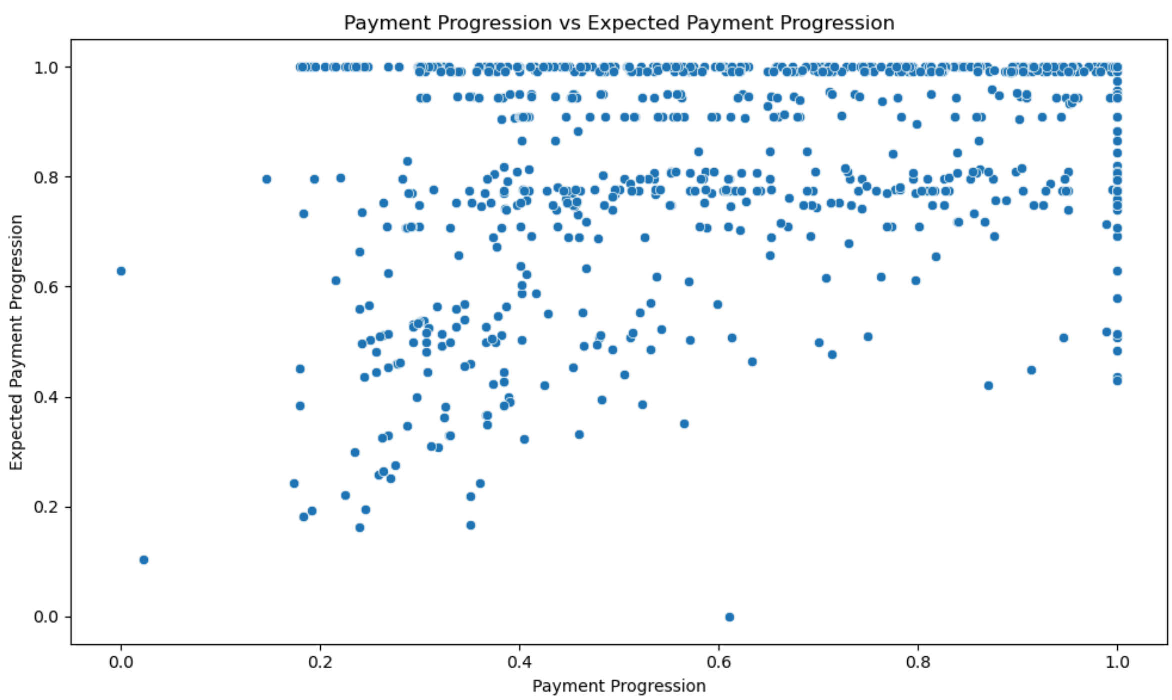
5. Expected Payment Progression

The formula for Expected Payment Progression is given by:

$$\text{Expected Payment Progression} = \frac{\text{Expected Cumulative Amount Paid}}{\text{Nominal Contract Value}}$$

In [15]:
```
data['Expected Payment Progression'] = data['expected_cumulative_amount_paid']
/ data['nominal_contract_value']
```

In [16]:
```
# Visualization: Payment Progression vs. Expected Payment Progression
plt.figure(figsize=(10,6))
sns.scatterplot(x='Payment Progression', y='Expected Payment Progression',
data=data)
plt.title('Payment Progression vs Expected Payment Progression')
plt.xlabel('Payment Progression')
plt.ylabel('Expected Payment Progression')
plt.tight_layout()
plt.show()
```



6. Loan Type Derivation

In [17]:
```
# Function to derive Loan Type
def derive_loan_type(name):
    if 'Individual' in name:
        return 'Individual Loan'
    elif 'Group' in name:
        return 'Group Loan'
    elif 'Paygo' in name:
        return 'Paygo Loan'
    elif 'Cash' in name:
        return 'Cash Sale'
```

```
    else:
        return 'Other'  # or return None if you want to leave it blank

# Apply the function to create a new column
data['Loan Type'] = data['name'].apply(derive_loan_type)
```

Confirming all the metrics are correct

In [18]:
```
#data.head()
#ata.info()
```

Task 2: Hidden Risk Analysis

- Flagging clients with high Payment Progression but low Expected Payment Progression

In [19]:
```
data['Hidden Risk Flag'] = np.where(
    (data['Payment Progression'] > 0.8) &
    (data['Expected Payment Progression'] < 0.5) &
    (data['status'] != 'Completed'),
    'Flagged',
    'Not Flagged'
)
```

- Flagging clients with a low Current Collection Rate (e.g., < 50%)

In [20]:
```
data['Collection Risk Flag'] = np.where(
    (data['Current Collection Rate'] < 0.5) &
    (data['status'] != 'Completed'),
    'Flagged',
    'Not Flagged'
)
```

In [21]:
```
# Combining both flags to generate a summary of hidden risk clients
data['Hidden Risk'] = np.where((data['Hidden Risk Flag'] == 'Flagged') |
(data['Collection Risk Flag'] == 'Flagged'), 'High Risk', 'Low Risk')
```

Summary of hidden risk clients

In [22]:
```
hidden_risk_summary = data[data['Hidden Risk'] == 'High Risk']
hidden_risk_summary_count = hidden_risk_summary.groupby('Hidden
Risk').size().reset_index(name='Count')
```

Visualizing the summary

In [23]:
```
plt.figure(figsize=(6, 4))

# Create the barplot
barplot = sns.barplot(x='Hidden Risk', y='Count',
```

```
data=hidden_risk_summary_count, palette='Set2')

# Set the title and labels
plt.title('Summary of Hidden Risk Clients', fontsize=14)
plt.xlabel('Hidden Risk', fontsize=12)
plt.ylabel('Count', fontsize=12)

# Adding labels on top of the bars
for p in barplot.patches:
    barplot.annotate(format(p.get_height(), '.0f'),
                     (p.get_x() + p.get_width() / 2., p.get_height()),
                     ha='center', va='center',
                     xytext=(0, 9),
                     textcoords='offset points',
                     fontsize=10)
barplot.spines['top'].set_visible(False)
barplot.spines['right'].set_visible(False)
plt.tight_layout()
plt.show()
```

Task 3: Identifying High Impact Agents

Calculating the total amount in arrears and total loan value per agent

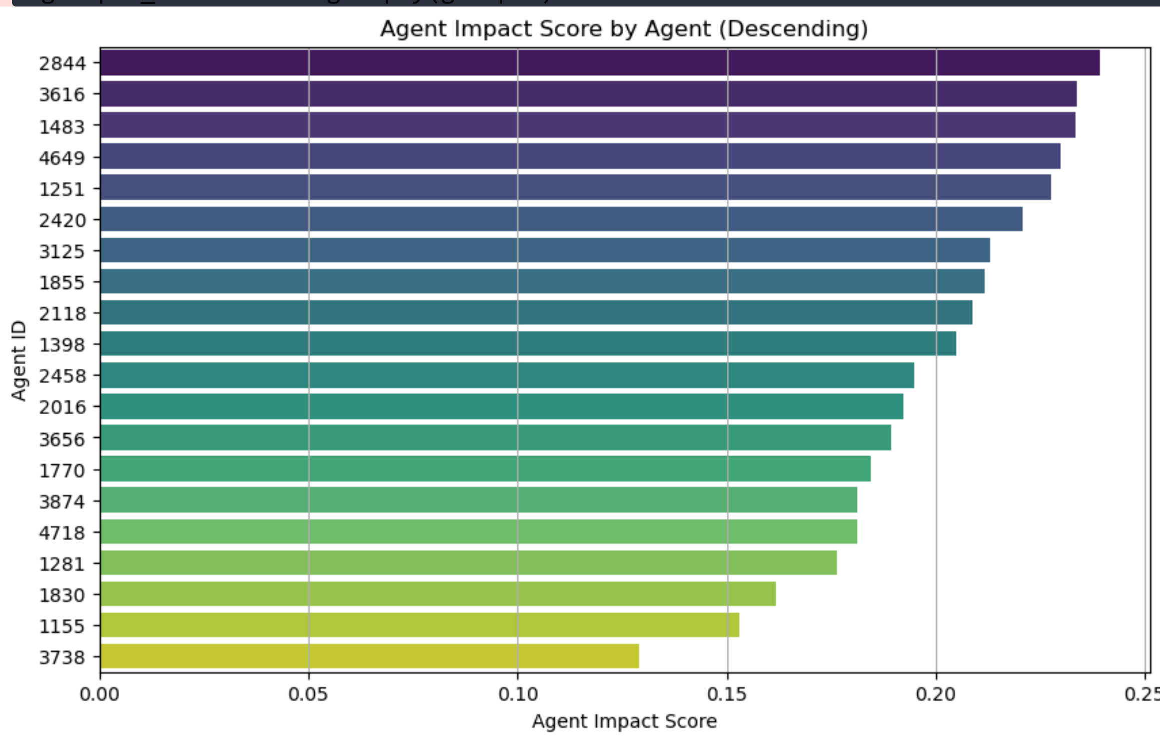
In [24]:
```
agent_impact = data.groupby('Agent ID').agg(
    total_arrears=('Total Amount in Arrears', 'sum'),
    total_loan_value=('nominal_contract_value', 'sum')
).reset_index()
```

Calculating the Agent Impact Score And Identifying Top 5 Agents

In [25]:
```
agent_impact['Agent Impact Score'] = agent_impact['total_arrears'] / 
agent_impact['total_loan_value']
```

In [26]:
```
# Sort by 'Agent Impact Score' in descending order
agent_impact_sorted = agent_impact.sort_values(by='Agent Impact Score', 
ascending=False)

# Convert 'Agent ID' to a categorical type and set the order based on the 
sorted scores
agent_impact_sorted['Agent ID'] = pd.Categorical(agent_impact_sorted['Agent 
ID'], categories=agent_impact_sorted['Agent ID'], ordered=True)

# Set up the plot with horizontal bars
plt.figure(figsize=(10, 6))
sns.barplot(x='Agent Impact Score', y='Agent ID', data=agent_impact_sorted, 
palette='viridis', orient='h')

# Add labels and title
plt.ylabel('Agent ID')
plt.xlabel('Agent Impact Score')
plt.title('Agent Impact Score by Agent (Descending)')
plt.grid(axis='x')

# Show plot
plt.show()
```

```
C:\Users\Brian.Kipkemboi2\AppData\Local\anaconda3\Lib\site-packages\seaborn\categ
orical.py:641: FutureWarning: The default of observed=False is deprecated and wil
l be changed to True in a future version of pandas. Pass observed=False to retain
current behavior or observed=True to adopt the future default and silence this wa
rning.
  grouped_vals = vals.groupby(grouper)
```



In [27]:
```
#### Identifying the top 5 high-impact agents
top_5_agents = agent_impact.nlargest(5, 'Agent Impact Score')
top_5_agents
```

Out[27]:

	Agent ID	total_arrears	total_loan_value	Agent Impact Score
12	2844	120093.76	501977.18	0.239241
14	3616	102634.47	439268.35	0.233649
4	1483	109513.72	469034.16	0.233488
18	4649	116055.60	504534.11	0.230025
1	1251	111257.43	488711.00	0.227655

Distribution of Agent Impact Scores

In [28]:
```
# Ignore the FutureWarning
warnings.simplefilter(action='ignore', category=FutureWarning)
agent_impact['Agent Impact Score'].replace([np.inf, -np.inf], np.nan,
inplace=True)
agent_impact_clean = agent_impact.dropna(subset=['Agent Impact Score'])

plt.figure(figsize=(10, 6))
# Create histogram bars
sns.histplot(agent_impact_clean['Agent Impact Score'],
             bins=20,
             color='#54C392',
             kde=True)

# Set titles and labels
plt.title('Distribution of Agent Impact Scores', fontsize=16)
plt.xlabel('Agent Impact Score', fontsize=12)
plt.ylabel('Frequency', fontsize=12)

# Adjust layout and show the plot
plt.tight_layout()
plt.show()
```

Strategy for Rebalancing Portfolios at One Acre Fund

To ensure that no single agent has disproportionate influence, I recommend implementing a **diversification strategy** across the portfolios. This can be achieved by redistributing loans based on several key factors:

1. **Loan Size Caps**: Establish maximum loan limits per agent to prevent any single agent from controlling a large portion of the portfolio. This ensures a more equitable distribution of funds.

2. **Risk Assessment**: Conduct a thorough risk assessment for each agent based on their historical performance, repayment rates, and client demographics. Allocate loans according to their risk profiles, ensuring that high-risk agents receive proportionately smaller loans.

3. **Geographic Distribution**: Redistribute loans based on geographic regions, ensuring that agents in underrepresented areas receive adequate funding. This promotes balanced growth and minimizes the risk associated with concentration in specific areas.

4. **Performance-Based Adjustments**: Regularly review agent performance and adjust loan allocations accordingly. High-performing agents could receive slightly larger allocations, while underperformers are supported with smaller loans.

By adopting these strategies, One Acre Fund can foster a more balanced and sustainable lending environment.

In [29]:
```
# Saving the updated dataset and agent impact analysis
data.to_excel('Loan_Performance_Analysis_with_Hidden_Risks.xlsx', index=False)
agent_impact.to_excel('Agent_Impact_Scores.xlsx', index=False)
```

In [30]:
```
!jupyter nbconvert --to html Brian_Kipkemboi_Exercise.ipynb
```

```
[NbConvertApp] Converting notebook Brian_Kipkemboi_Exercise.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 5 image(s).
[NbConvertApp] Writing 644486 bytes to Brian_Kipkemboi_Exercise.html
```