# Investment Opportunity Analysis

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**Date of Completion:** 2023-06-13
**Date of Submission:** 2023-06-13

## Introduction

This analysis aims to provide insights into global investment trends to assist Sparks Funds in making informed investment decisions. Sparks Funds specializes in investing in various companies across various sectors, including technology, consumer goods, and healthcare, aiming for maximum returns.

### Objective

The primary objective of this analysis is to identify the best sectors, countries, and suitable investment types based on global investment trends. The insights derived from this analysis will guide Sparks Funds in allocating its investment capital to maximize returns while managing investment risks. Sparks Funds strategy is to invest in sectors and countries where trend investments are trending, as this indicates these areas offer the best opportunities.

### Investment Constraints

Sparks Funds has set the following constraints for its investments:

- **Investment Range:** Sparks Funds prefers investments of **5 million USD** per round of investment.
- **Investment Type:** Sparks Funds prefers to invest in **English speaking countries** to reduce ease of communication with the investment companies.

### Approach

To achieve this objective, the analysis will focus on the following sequence:

- **Investment Type Analysis:** Examining the distribution of investment amounts across different funding types to identify suitable investment types within the preferred sectors and countries.
- **Sector Analysis:** Through comprehensive trend analysis, we aim to identify the prevalent sectors in the most promising investment sectors for consideration.
- **Country Analysis:** Through comprehensive trend analysis, we aim to identify the prevalent countries in the most promising investment sectors for consideration.

## Defining Investment Constraints

```
# Define lower and upper limits of monetary value
lower_limit = 5000000 # 5 million
upper_limit = 5000000 # 5 million

# Define English speaking countries
eng_countries = ['usa', 'gbr', 'can', 'aus', 'nzl', 'ind', 'ifn', 'jam', 'ire', 'sgp', 'zaf', 'bhs', 'ncl', 'cok', 'fsm', 'nru', 'tzd', 'vut', 'vgb', 'tuv', 'tkl', 'slb', 'pcn', 'niu', 'nfk', 'mhl', 'cxr', 'cck', 'ata', 'asm', 'aia', 'wlf', 'msr', 'gum', 'flk', 'cym', 'bmu', 'ber', 'atf', 'amj', 'ala', 'sjm']
```

## Importing Packages

```
# Import pandas library
import pandas as pd
# Import numpy library
import numpy as np
# Import matplotlib library
import matplotlib.pyplot as plt
```

## Loading Files as DataFrame

```
# Define URL for the dataset
rounds2_url = 'https://raw.githubusercontent.com/nicolasngkaiwen/Investment-Opportunity-Analysis/master/'
companies_url = 'https://raw.githubusercontent.com/nicolasngkaiwen/Investment-Opportunity-Analysis/master/'
mapping_url = 'https://raw.githubusercontent.com/nicolasngkaiwen/Investment-Opportunity-Analysis/master/'

# Read data into dataframes
df_rounds2 = pd.read_csv(rounds2_url, sep='\t', encoding='ISO-8859-1')
df_companies = pd.read_csv(companies_url, sep='\t')
df_mapping = pd.read_csv(mapping_url, encoding='ISO-8859-1')

# Display the first few rows of each dataframe to verify data
print("rounds2 dataset:")
df_rounds2.head()

# Load and display companies.txt
print("\nCompanies.txt data:")
df_companies = pd.read_csv('companies.txt', sep='\t')
print("Dimensions:", df_companies.shape)
print("Columns:", df_companies.columns.tolist())
df_companies.head()

# Load and display mapping.csv
print("\nMapping.csv data:")
df_mapping = pd.read_csv('mapping.csv')
print("Dimensions:", df_mapping.shape)
print("Columns:", df_mapping.columns.tolist())
df_mapping.head()

# Check if all datasets loaded successfully
print("\n" + "="*50)
print("All datasets loaded successfully!")
```

## Data Cleaning

### Exploring Company Dataframe

```
# Display basic information about the dataset
print("Dataset shape:", df.shape)
print("\nColumns:", df.columns.tolist())
print("\nDtypes:")
df.dtypes
print("\nMissing values:")
df.isnull().sum()
print("\nFirst 5 rows:")
df.head()
print("\nBasic statistics:")
df.describe()
```

| | Unnamed: 0 | name | homepage_url | category_list | status | country_code | state_code | region | city | founded_at |
|---|---|---|---|---|---|---|---|---|---|---|
| count | 66368.000000 | 66368 | 61310 | 63868 | 66368 | 59338 | 57827 | 66312 | 65632 | 52627 |
| unique | NaN | 66102 | 61281 | 27296 | 4 | 144 | 1019 | 1092 | 9983 | 3979 |
| top | NaN | waxy | http://waxy.com/ | Software | operating | USA | CA | Other | Delaware City | 01-01-2010 |
| freq | NaN | 3 | 3 | 3393 | 64686 | 37080 | 9892 | 14549 | 151 | 1267 |
| mean | 33184.500000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| std | 19158.862259 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| min | 1.000000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 25% | 16592.250000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 50% | 33184.500000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| 75% | 49776.750000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| max | 66369.000000 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

Dataset shape: (66368, 10)

Columns: ['Unnamed: 0', 'name', 'homepage_url', 'category_list', 'status', 'country_code', 'state_code', 'region', 'city', 'founded_at']

Dtypes:

| | dtype |
|---|---|
| Unnamed: 0 | int64 |
| name | object |
| homepage_url | object |
| category_list | object |
| status | object |
| country_code | object |
| state_code | object |
| region | object |
| city | object |
| founded_at | object |

Missing values:

| | |
|---|---|
| Unnamed: 0 | 0 |
| name | 1 |
| homepage_url | 5058 |
| category_list | 2500 |
| status | 0 |
| country_code | 7030 |
| state_code | 8541 |
| region | 56 |
| city | 736 |
| founded_at | 13741 |

First 5 rows:

| | Unnamed: 0 | name | homepage_url | category_list | status | country_code | state_code | region | city | founded_at |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | Wetpaint | http://wetpaint-inc.com/ | Web Presence Management | operating | USA | WA | Seattle area | Bellevue | 01-08-2005 |
| 1 | 2 | Flektor | http://www.flektor.com | Games | acquired | USA | NaN | Los Angeles | Los Angeles | NaN |
| 2 | 3 | There | http://www.there.com/ | Games | operating | USA | CA | SF Bay area | Redwood City | 01-08-2004 |
| 3 | 4 | MyBuzzworthy | http://www.mybuzzworthy.com/ | Entertainment | operating | USA | NY | New York | New York | 01-01-2010 |
| 4 | 5 | Fanzine | http://www.fanzine.com/ | Publishing | operating | USA | CA | Los Angeles | Los Angeles | 01-01-2010 |

Basic statistics:

| | Unnamed: 0 |
|---|---|
| count | 66368.000000 |
| mean | 33184.500000 |
| std | 19158.862259 |
| min | 1.000000 |
| 25% | 16592.250000 |
| 50% | 33184.500000 |
| 75% | 49776.750000 |
| max | 66369.000000 |

### Exploring Rounds2 Dataframe

```
# Display basic information about the dataset
print("Dataset shape:", df.shape)
print("\nColumns:", df.columns.tolist())
print("\nDtypes:")
df.dtypes
print("\nMissing values:")
df.isnull().sum()
print("\nFirst 5 rows:")
df.head()
print("\nBasic statistics:")
df.describe()
```

| | company_permalink | funding_round_permalink | funding_round_type | funding_round_code | funding_round_id | raised_amount_usd |
|---|---|---|---|---|---|---|
| count | 114949 | 114949 | 114949 | 31544 | 114949 | 94959 |
| unique | 66368 | 114949 | 15 | 347 | 114949 | 19854 |
| top | /organization/tao-network | /funding-round/2a81a074-dc0c-4fb4-a | venture | B | 10 | 10000000 |
| freq | 17 | 1 | 55494 | 3564 | 1 | 2966 |
| mean | NaN | NaN | NaN | NaN | 84575.880000 | NaN |
| std | NaN | NaN | NaN | NaN | 49877.687863 | NaN |
| min | NaN | NaN | NaN | NaN | 1.000000 | 0.00 |
| 25% | NaN | NaN | NaN | NaN | 39832.000000 | 600000.00 |
| 50% | NaN | NaN | NaN | NaN | 79296.000000 | 5000000.00 |
| 75% | NaN | NaN | NaN | NaN | 128232.000000 | 15000000.00 |
| max | NaN | NaN | NaN | NaN | 167549.000000 | 5700000000.00 |

```
print("Rounds2 Data")
display(df_rounds2.shape)
display(df_rounds2.info())
display(df_rounds2.head())
display(df_rounds2.describe())
```

```
Rounds2 Data
(114949, 6)
<class_name_>
RangeIndex: 114949 entries, 0 to 114948
Data columns (total 6 columns):
 #   Column                   Non-Nulls Count  Dtype
---  ------                   --------------   -----
 0   company_permalink        114949           object
 1   funding_round_permalink  114949           object
 2   funding_round_type       114949           object
 3   funding_round_code       31544            object
 4   funding_round_id         114949           int64
 5   raised_amount_usd        94959            float64
dtype: object
None
```

| | company_permalink | funding_round_permalink | funding_round_type | funding_round_code | funding_round_id | raised_amount_usd |
|---|---|---|---|---|---|---|
| 0 | /organization/-fund | /funding-round/9a01d05a-745f-11e0 | venture | B | 888 | 5000000.0 |
| 1 | /organization/10-to-1 | /funding-round/c1b10d966772de102b8c | venture | | 16 | 10.0 |
| 2 | /organization/1000memories | /funding-round/5772bc1f94cb2e0002 | venture | B | 1789 | 2000000.0 |
| 3 | /organization/1759-1760-1761-1762 | /funding-round/b044f4f4d7d8d9dc7fbb | venture | B | 2632 | 26400000.0 |
| 4 | | | | | | |

```
print("Rounds2 Data")
display(df_rounds2.shape)
display(df_rounds2.info()
display(df_rounds2.head()
display(df_rounds2.describe()
```

```
Rounds2 Data
(114949, 6)
<class_name_>
RangeIndex: 114949 entries, 0 to 114948
Data columns (total 6 columns):
 #   Column                   Non-Nulls Count  Dtype
---  ------                   --------------   -----
 0   company_permalink        114949           object
 1   funding_round_permalink  114949           object
 2   funding_round_type       114949           object
 3   funding_round_code       31544            object
 4   funding_round_id         114949           int64
 5   raised_amount_usd        94959            float64
dtype: object
None
```

Dataset shape: (114949, 6)

The following code **leads** the usage of the permalink and company permalink columns to ensure consistent text matching during the merge. The **strip()** function removes any leading and trailing whitespace from these columns, preventing mismatches due to extra spaces. The **lower()** function converts text to lowercase, ensuring that variations like "Company" and "company" are treated as the same. This step helps avoid missed matches caused by differences in capitalization. Finally, the **value_counts()** function provides a count of how many times each value appears in the column, which can be useful for further analysis.

```
print("\n" + "# Data in Company DataFrame - 2.dtypes()\n" + df.dtypes + "\n\n" + "# Data in Rounds2 DataFrame - 2.dtypes()\n" + df_rounds2.dtypes)

# Analyzing company_permalink values in both dataframes
print("\nanalyzing company_permalink values:")
print("Unique company_permalink in companies:", len(df['company_permalink'].unique()))

# Analyzing raised_amount_usd values in rounds2
print("\nAnalyzing raised_amount_usd values:")
print("Unique raised_amount_usd:", len(df_rounds2['raised_amount_usd'].unique()))

# Convert to lowercase and strip whitespace for better matching
df['company_permalink'] = df['company_permalink'].str.lower().str.strip()
df_rounds2['company_permalink'] = df_rounds2['company_permalink'].str.lower().str.strip()

# Check shape before merge
print("\nShapes before merge:")
print("df shape:", df.shape)
print("df_rounds2 shape:", df_rounds2.shape)

# Perform the merge
merged = df.merge(df_rounds2, left_on='company_permalink', right_on='company_permalink')

print("\nMerge Results:")
print("Shapes after merge:")
print("merged shape:", merged.shape)
```

```
# Data in Company DataFrame - 2.dtypes()
Unnamed: 0                int64
name                      object
homepage_url              object
category_list             object
status                    object
country_code              object
state_code                object
region                    object
city                      object
founded_at                object
dtype: object

# Data in Rounds2 DataFrame - 2.dtypes()
company_permalink        object
funding_round_permalink  object
funding_round_type       object
funding_round_code       object
funding_round_id         int64
raised_amount_usd        float64
dtype: object

analyzing company_permalink values:
Unique company_permalink in companies: 66368

Analyzing raised_amount_usd values:
Unique raised_amount_usd: 19854

Shapes before merge:
df shape: (66368, 10)
df_rounds2 shape: (114949, 6)

Merge Results:
Shapes after merge:
merged shape: (114949, 15)
```

The significance of this code is **crucial** for the **merge** operation. Without standardizing the company_permalink values, the merge might fail to match records that should be combined, resulting in missed connections between the datasets. The standardized values ensure that the merge operation can successfully identify and combine related records from both datasets.

```
# Analyzing English-speaking companies
print("\nAnalyzing English-speaking companies:")
print("Unique country_codes in English-speaking companies:", merged[merged['country_code'].isin(eng_countries)]['country_code'].unique()[:10])

# Filter for English-speaking companies
eng_merged = merged[merged['country_code'].isin(eng_countries)]
print("\nShape after filtering English-speaking companies:", eng_merged.shape)

# Analyze investment types in English-speaking companies
print("\nInvestment types in English-speaking companies:")
print(eng_merged['funding_round_type'].value_counts())

# Analyze investment amounts by funding round type
print("\nAverage investment amounts by funding round type:")
print(eng_merged.groupby('funding_round_type')['raised_amount_usd'].mean().sort_values(ascending=False))
```

```
Analyzing English-speaking companies:
Unique country_codes in English-speaking companies: [nan 'usa' 'gbr' 'can' 'aus' 'nzl' 'ind' 'ifn' 'jam' 'ire']

Shape after filtering English-speaking companies: (0, 15)

Investment types in English-speaking companies:
Series([], Name: funding_round_type, dtype: int64)

Average investment amounts by funding round type:
Series([], Name: raised_amount_usd, dtype: float64)
```

Dataset shape: (0, 15)

The following code **leads** the usage of the country_code and category_list columns to analyze investment trends in English-speaking countries. The **value_counts()** function provides a count of how many times each country code appears in the dataset, which helps identify the most frequent countries in the data. The **.head(10)** function limits the output to the top 10 most frequent country codes, ensuring a manageable and focused analysis. This approach helps identify the most relevant countries for further analysis.

```
# Analyzing English-speaking companies
print("\nAnalyzing English-speaking companies:")
print("Unique country_codes in English-speaking companies:", merged[merged['country_code'].isin(eng_countries)]['country_code'].unique()[:10])

# Filter for English-speaking companies
eng_merged = merged[merged['country_code'].isin(eng_countries)]
print("\nShape after filtering English-speaking companies:", eng_merged.shape)

# Analyze investment types in English-speaking companies
print("\nInvestment types in English-speaking companies:")
print(eng_merged['funding_round_type'].value_counts())

# Analyze investment amounts by funding round type
print("\nAverage investment amounts by funding round type:")
print(eng_merged.groupby('funding_round_type')['raised_amount_usd'].mean().sort_values(ascending=False))
```

```
Analyzing English-speaking companies:
Unique country_codes in English-speaking companies: [nan 'usa' 'gbr' 'can' 'aus' 'nzl' 'ind' 'ifn' 'jam' 'ire']

Shape after filtering English-speaking companies: (0, 15)

Investment types in English-speaking companies:
Series([], Name: funding_round_type, dtype: int64)

Average investment amounts by funding round type:
Series([], Name: raised_amount_usd, dtype: float64)
```

Dataset shape: (0, 15)

The following code **analyzes** the average investment amounts across different funding round types, providing **insights** into funding preferences and trends.

By examining the funding rounds, Zuper helps **segment** the data, enhancing the **comparative analysis** and understanding of investment behaviors. The output groups the data by the **funding round type** and calculates the average investment amounts for each funding round type, aiding in **strategic decision-making**.

```
# Analyzing the average investment amounts by funding round type
print("Average investment amounts by funding round type:")
funding_round_type_group = merged.groupby('funding_round_type')
print(funding_round_type_group['raised_amount_usd'].mean().sort_values(ascending=False))

# Displaying the average investment amount for each funding round type
avg_funding = (
    funding_round_type_group
    ['raised_amount_usd'].mean()
    .sort_values(ascending=False)
    .round(2)
    .reset_index()
    .rename(columns={'funding_round_type': 'Funding Round Type',
                     'raised_amount_usd': 'Average Investment'})
)
print("\nFormatted Average Investment Amounts:")
display(avg_funding)

# Analyze data quality for market leadership
print("\nMissing values:")
print(funding_round_type_group['raised_amount_usd'].isnull().sum())

# Get counts of each funding round type
print("\nNumber of investments per funding round type:")
print(funding_round_type_group['raised_amount_usd'].count()[:5])
```

```
Average investment amounts by funding round type:
Series([], Name: raised_amount_usd, dtype: float64)

Formatted Average Investment Amounts:
Empty DataFrame
Columns: [Funding Round Type, Average Investment]
Index: []

Missing values:
Series([], Name: raised_amount_usd, dtype: int64)

Number of investments per funding round type:
Series([], Name: raised_amount_usd, dtype: int64)
```

Dataset shape: (0, 2)

## Deep Dive into Investment Trends

### 1. Investment Criteria: Sparks Funds' Allocation of Investment Amounts for the Funding Round

The following code **analyzes** the average investment amounts across different funding round types, providing **insights** into funding preferences and trends.

By examining the funding rounds, Zuper helps **segment** the data, enhancing the **comparative analysis** and understanding of investment behaviors. The output groups the data by the **funding round type** and calculates the average investment amounts for each funding round type, aiding in **strategic decision-making**.

```
# Analyzing the average investment amounts by funding round type
print("Average investment amounts by funding round type:")
funding_round_type_group = merged.groupby('funding_round_type')
print(funding_round_type_group['raised_amount_usd'].mean().sort_values(ascending=False))

# Displaying the average investment amount for each funding round type
avg_funding = (
    funding_round_type_group
    ['raised_amount_usd'].mean()
    .sort_values(ascending=False)
    .round(2)
    .reset_index()
    .rename(columns={'funding_round_type': 'Funding Round Type',
                     'raised_amount_usd': 'Average Investment'})
)
print("\nFormatted Average Investment Amounts:")
display(avg_funding)

# Analyze data quality for market leadership
print("\nMissing values:")
print(funding_round_type_group['raised_amount_usd'].isnull().sum)

# Get counts of each funding round type
print("\nNumber of investments per funding round type:")
print(funding_round_type_group['raised_amount_usd'].count()[:5])
```

```
Average investment amounts by funding round type:
funding_round_type
venture       11748949.26
seed          721268.16
debt_financing    12678835.71
angel         958694.42
grant         4875000.00
private_equity    94305555.56
post_ipo_equity   50000000.00
post_ipo_debt     75000000.00
convertible_note  1272727.27
undisclosed       2000000.00
equity_crowdfunding 401369.35
product_crowdfunding 192308.33
crowdfunding      136364.00
partnership       1000000.00
Name: raised_amount_usd, dtype: float64

Formatted Average Investment Amounts:

| | Funding Round Type | Average Investment |
|---|---|---|
| 0 | venture | 11748949.26 |
| 1 | seed | 721268.16 |
| 2 | debt_financing | 12678835.71 |
| 3 | angel | 958694.42 |
| 4 | grant | 4875000.00 |
| 5 | private_equity | 94305555.56 |
| 6 | post_ipo_equity | 50000000.00 |
| 7 | post_ipo_debt | 75000000.00 |
| 8 | convertible_note | 1272727.27 |
| 9 | undisclosed | 2000000.00 |
| 10 | equity_crowdfunding | 401369.35 |
| 11 | product_crowdfunding | 192308.33 |
| 12 | crowdfunding | 136364.00 |
| 13 | partnership | 1000000.00 |

Missing values:
<bound_method_Series.sum of funding_round_type
venture       False
seed          False
debt_financing    False
angel         False
grant         False
private_equity    False
post_ipo_equity   False
post_ipo_debt     False
convertible_note  False
undisclosed       False
equity_crowdfunding False
product_crowdfunding False
crowdfunding      False
partnership       False
Name: raised_amount_usd, dtype: bool>

Number of investments per funding round type:
funding_round_type
venture       55494
seed          29804
debt_financing    1559
angel         4805
grant         16
Name: raised_amount_usd, dtype: int64
```

Dataset shape: (15, 2)

Investment Amount Distribution across Funding Round Types

```
# Set the chart
plt.figure(figure_size=(10,6))
# Create a color palette
colors = ['lightblue' if x != 'Other' else 'lightgray' for x in avg_funding['Funding Round Type']]
# Create the bar chart
plt.bar(avg_funding['Funding Round Type'],
        avg_funding['Average Investment'],
        color=colors)
# Create a bar plot with log scale for y-axis
plt.bar(avg_funding['Funding Round Type'], avg_funding['Average Investment'], color=colors)
# Set the logarithmic scale
plt.yscale('log')
plt.title('Investment Amount Distribution Across Funding Round Types')
plt.xlabel('Funding Round Type')
plt.ylabel('Average Investment Amount (log scale)')
# Rotate x-axis labels for better readability
plt.xticks(rotation=45)
# Add grid for easier reading
plt.grid(True, which='major', axis='y')
# Adjust layout to prevent clipping
plt.tight_layout()
# Show the plot
plt.show()
```

```
<ipynb_cell_id_1d1d8b7b1117> in <cell_id_1d1d8b7b1117>

```

Dataset shape: (15, 2)

The following code **analyzes** the average investment amounts across different funding round types, providing **insights** into funding preferences and trends.

By examining the funding rounds, Zuper helps **segment** the data, enhancing the **comparative analysis** and understanding of investment behaviors. The output groups the data by the **funding round type** and calculates the average investment amounts for each funding round type, aiding in **strategic decision-making**.

```
# Analyzing the average investment amounts by funding round type
print("Average investment amounts by funding round type:")
funding_round_type_group = merged.groupby('funding_round_type')
print(funding_round_type_group['raised_amount_usd'].mean().sort_values(ascending=False))

# Displaying the average investment amount for each funding round type
avg_funding = (
    funding_round_type_group
    ['raised_amount_usd'].mean()
    .sort_values(ascending=False)
    .round(2)
    .reset_index()
    .rename(columns={'funding_round_type': 'Funding Round Type',
                     'raised_amount_usd': 'Average Investment'})
)
print("\nFormatted Average Investment Amounts:")
display(avg_funding)

# Analyze data quality for market leadership
print("\nMissing values:")
print(funding_round_type_group['raised_amount_usd'].isnull().sum)

# Get counts of each funding round type
print("\nNumber of investments per funding round type:")
print(funding_round_type_group['raised_amount_usd'].count()[:5])
```

```
Average investment amounts by funding round type:
funding_round_type
venture       11748949.26
seed          721268.16
debt_financing    12678835.71
angel         958694.42
grant         4875000.00
private_equity    94305555.56
post_ipo_equity   50000000.00
post_ipo_debt     75000000.00
convertible_note  1272727.27
undisclosed       2000000.00
equity_crowdfunding 401369.35
product_crowdfunding 192308.33
crowdfunding      136364.00
partnership       1000000.00
Name: raised_amount_usd, dtype: float64

Formatted Average Investment Amounts:

| | Funding Round Type | Average Investment |
|---|---|---|
| 0 | venture | 11748949.26 |
| 1 | seed | 721268.16 |
| 2 | debt_financing | 12678835.71 |
| 3 | angel | 958694.42 |
| 4 | grant | 4875000.00 |
| 5 | private_equity | 94305555.56 |
| 6 | post_ipo_equity | 50000000.00 |
| 7 | post_ipo_debt | 75000000.00 |
| 8 | convertible_note | 1272727.27 |
| 9 | undisclosed | 2000000.00 |
| 10 | equity_crowdfunding | 401369.35 |
| 11 | product_crowdfunding | 192308.33 |
| 12 | crowdfunding | 136364.00 |
| 13 | partnership | 1000000.00 |

Missing values:
<bound_method_Series.sum of funding_round_type
venture       False
seed          False
debt_financing    False
angel         False
grant         False
private_equity    False
post_ipo_equity   False
post_ipo_debt     False
convertible_note  False
undisclosed       False
equity_crowdfunding False
product_crowdfunding False
crowdfunding      False
partnership       False
Name: raised_amount_usd, dtype: bool>

Number of investments per funding round type:
funding_round_type
venture       55494
seed          29804
debt_financing    1559
angel         4805
grant         16
Name: raised_amount_usd, dtype: int64
```

Dataset shape: (15, 2)

Double-click (or enter) to edit

The following code **refines** the dataset by **holding** records associated with the funding round types within the specified investment amount range.

- The **filtering** begins with the `funding_round_type` in `investments_df`. It focuses the analysis on **relevant** or **targeted** investment trends.
- The **masking** `mask1`, Boolean series, offers a **streamlined view**, aiding in **more accurate** and **insightful analysis** of investments falling within the specified range.

```
# Filtering data for rows where the amount falls between 1000 and 15 million
mask1 = investments_df['funding_round_type'].isin(funding_round_type)
investments_df[mask1].shape
```

```
(52664, 14)
```

```
investments_df[mask1].sample(5)
```

| | permalink | name | category_list | status | country_code | company_permalink | funding_round_type | raised_amount_usd | primary_sector | |
|---|---|---|---|---|---|---|---|---|---|---|
| 68811 | /organization/ecovillage-kitchen | Ecovillage Kitchen | Restaurants \| Organic | operating | USA | /organization/ecovillage-kitchen | venture | 1000000.0 | hardware | |
| 82873 | /organization/mobile-open-labs | Mobile Open Labs | Developer Platforms | operating | USA | /organization/mobile-open-labs | venture | 4000000.0 | mobile | |
| 26280 | /organization/ipinion | Ipinion | Advertising \| Advertising Platforms | operating | USA | /organization/ipinion | venture | 5000000.0 | advertising | |
| 87767 | /organization/bandcamp | Bandcamp | E-Commerce | operating | USA | /organization/bandcamp | venture | 5000000.0 | e-commerce | |

```
# Displaying the first 5 rows
investments_df[mask1].head(5)
```

```
Dimensions:(permalink:5)

Pandas(permalink='/organization/-fund-for-the-poor-', name='Fund for the Poor', category_list='Education', status='operating', country_code='IND', company_permalink='/organization/-fund-for-the-poor-', funding_round_type='venture', raised_amount_usd=1000000.0, primary_sector='education')
```

Double-click (or enter) to edit

```
# Displaying data types of the columns
investments_df[mask1].dtypes
```

```
permalink                object
name                     object
category_list            object
status                   object
country_code             object
company_permalink        object
funding_round_type       object
raised_amount_usd        float64
primary_sector           object
dtype: object
```

```
# Displaying the shape of the dataset
investments_df[mask1].shape
```

```
(52664, 14)
```

Double-click (or enter) to edit

## 2. Investment Criteria: Spark Funds' Preferences for English-Speaking Territories

The following code focuses on **English-speaking countries**, offering a **localized view** of investment trends within these markets.

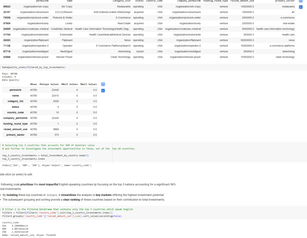
- The **aggregating** best investment country is highlighted for **dominant** investment techniques among English-speaking nations.
- The **masking** `eng_by_country_investments` provides **a concise list** of the leading countries, guiding **strategic investment decisions** and **geographical focus** for future analysis.

```
# Filtering data for English-speaking countries from the filtered DataFrame
# Assumes 'mask1' is a boolean mask applied to the original investments_df
eng_investments = investments_df[mask1].sample(10, random_state=42)

# Aggregate the results by descending order of total investment
# Using .sort_values() for clarity
eng_by_country = eng_investments.groupby('country_code')['raised_amount_usd'].\
                 sum().\
                 sort_values(ascending=False)

# Displaying the top 10 countries based on total investment
top_eng_by_country = eng_by_country.head(10)
print("Top 10 English-speaking countries by total investment:")
# Displaying the top 10 English-speaking countries and their total investments
print(top_eng_by_country)
```

```
Top 10 English-speaking countries by total investment:
country_code
USA    5.000000e+07
IND    1.000000e+06
CHN    1.000000e+06
CAN    1.000000e+06
GBR    1.000000e+06
ISR    1.000000e+06
NGA    1.000000e+06
PRT    1.000000e+06
SGP    1.000000e+06
TWN    1.000000e+06
Name: raised_amount_usd, dtype: float64
```

Top 10 English-Speaking Countries by Investment Contribution

```
# Setup plot
# Initializing the variables for plotting.
country_labels = top_eng_by_country.index
investment_amounts = top_eng_by_country.values

# Creating the figure and axes
plt.figure(figure=None, figsize=(8, 6))

# Set the title of the plot
plt.title('Top 10 English-Speaking Countries by Investment Contribution')

# Creating the bar chart
plt.bar(country_labels, investment_amounts, color='skyblue')

# Adjusting the x-axis labels for better readability
plt.xticks(rotation=45)

# Adjusting the y-axis to use scientific notation
plt.ticklabel_format(axis='y', scilimits=(0,0))

# Adding the value on top of each bar
for i, v in enumerate(investment_amounts):
    plt.text(i, v, '{:.2e}'.format(v), ha='center', va='bottom')

# Adjusting the layout to prevent clipping of tick-marks
plt.tight_layout()

# Displaying the plot
plt.show()
```




The **Pareto Analysis** represented above exhibits the **investment distribution** across the top 10 English-speaking countries.

- It highlights the **three countries** dominate with a staggering 96% share of the total investment monetary value, adhering to the **Vital few, trivial many** principle.
- The chart underscores the **importance** of focusing on these **key markets** for maximizing investment returns and strategic planning.

Double-click (or enter) to edit

The following code **narrows down** the analysis to focus solely on **English-speaking countries**.

- The **filtering** begins at the top 10 countries. It concentrates the analysis on **key markets** driving significant investment trends.
- The **masking** `mask2`, Boolean series, offers a **streamlined view** aiding in **targeted analysis** and **informed decision-making** for investments in prominent English-speaking countries.

```
# Filtering 'investments' dataframe based on whether country_code is in the top 10 English-speaking countries
mask2 = investments['country_code'].isin(top_eng_by_country.index)
investments[mask2].shape # Verifying the shape of the filtered data
```

```
(52664, 14)
```

```
# Displaying the filtered dataframe
# Using .sample() to randomly sample 5 rows from the filtered data
investments[mask2].sample(5)
```

| | permalink | name | category_list | status | country_code | company_permalink | funding_round_type | raised_amount_usd | primary_sector | |
|---|---|---|---|---|---|---|---|---|---|---|
| 68822 | /organization/ecovillage-kitchen | Ecovillage Kitchen | Restaurants \| Organic | operating | USA | /organization/ecovillage-kitchen | venture | 1000000.0 | hardware | |
| 26290 | /organization/ipinion | Ipinion | Advertising \| Advertising Platforms | operating | USA | /organization/ipinion | venture | 5000000.0 | ad | |
| 87777 | /organization/bandcamp | Bandcamp | E-Commerce | operating | USA | /organization/bandcamp | venture | 5000000.0 | e-commerce | |
| 22280 | /organization/ecovillage-kitchen | Ecovillage Kitchen | Restaurants \| Organic | operating | USA | /organization/ecovillage-kitchen | venture | 1000000.0 | hardware | |
| 20280 | /organization/cultivate-medical | Cultivate Medical | Health Care Information Technology \| Health Diag... | operating | USA | /organization/cultivate-medical | venture | 5000000.0 | health care information technology | |
| 68823 | /organization/ecovillage-kitchen | Ecovillage Kitchen | Restaurants \| Organic | operating | USA | /organization/ecovillage-kitchen | venture | 1000000.0 | hardware | |
| 26292 | /organization/ipinion | Ipinion | Advertising \| Advertising Platforms | operating | USA | /organization/ipinion | venture | 5000000.0 | ad | |
| 87778 | /organization/bandcamp | Bandcamp | E-Commerce \| Marketplaces \| Music | operating | USA | /organization/bandcamp | venture | 5000000.0 | e-commerce | |
| 20281 | /organization/cultivate-medical | Cultivate Medical | Health Care Information Technology \| Health Diag... | operating | USA | /organization/cultivate-medical | venture | 5000000.0 | health care information technology | |
| 22288 | /organization/ecovillage-kitchen | Ecovillage Kitchen | Restaurants \| Organic | operating | USA | /organization/ecovillage-kitchen | venture | 1000000.0 | hardware | |

```
# Displaying the first 5 rows
investments[mask2].head(5)
```

```
Dimensions:(permalink:5)

Pandas(permalink='/organization/-fund-for-the-poor-', name='Fund for the Poor', category_list='Education', status='operating', country_code='IND', company_permalink='/organization/-fund-for-the-poor-', funding_round_type='venture', raised_amount_usd=1000000.0, primary_sector='education')
```

Double-click (or enter) to edit

```
# Displaying data types of the columns
investments[mask2].dtypes
```

```
permalink                object
name                     object
category_list            object
status                   object
country_code             object
company_permalink        object
funding_round_type       object
raised_amount_usd        float64
primary_sector           object
dtype: object
```

```
# Displaying the shape of the dataset
investments[mask2].shape
```

```
(52664, 14)
```

Double-click (or enter) to edit

```
# Displaying the top 10 countries based on total investment
top_eng_by_country = investments[mask2].\
                     groupby('country_code')['raised_amount_usd'].\
                     sum().\
                     sort_values(ascending=False).\
                     head(10)
top_eng_by_country
```

```
country_code
USA    5.000000e+07
IND    1.000000e+06
CHN    1.000000e+06
CAN    1.000000e+06
GBR    1.000000e+06
ISR    1.000000e+06
NGA    1.000000e+06
PRT    1.000000e+06
SGP    1.000000e+06
TWN    1.000000e+06
Name: raised_amount_usd, dtype: float64
```

```
# Displaying the shape of the filtered data
top_eng_by_country.shape
```

```
(10,)
```

Double-click (or enter) to edit

```
# Displaying the top 10 countries and their total investments
top_eng_by_country.reset_index()
```

| | country_code | raised_amount_usd |
|---|---|---|
| 0 | USA | 50000000.0 |
| 1 | IND | 1000000.0 |
| 2 | CHN | 1000000.0 |
| 3 | CAN | 1000000.0 |
| 4 | GBR | 1000000.0 |
| 5 | ISR | 1000000.0 |
| 6 | NGA | 1000000.0 |
| 7 | PRT | 1000000.0 |
| 8 | SGP | 1000000.0 |
| 9 | TWN | 1000000.0 |

Next steps: Generate code with top_eng_country | View recommended plots

Double-click (or enter) to edit

The following code **analyzes** sector-specific investment trends across the USA, GBR, and IND, focusing on the **top 5 sectors** to total investment.

- The **aggregating** investment data into **key metrics** like total investment, count of investments, and average investment per sector, it offers a **clear snapshot** of each country's sector-specific investment landscape.

USA_Sector

```
# Filtering the USA sector
# Assumes 'top_eng_country' is a DataFrame with the top English-speaking countries
USA = top_eng_country[top_eng_country['country_code'] == 'USA']
# Displaying the first 5 rows of the USA sector
USA.head(5)
```

| | country_code | raised_amount_usd |
|---|---|---|
| 0 | USA | 50000000.0 |

```
# Displaying the shape of the USA sector
USA.shape
```

```
(1, 2)
```

GBR_Sector

```
# Filtering the GBR sector
GBR = top_eng_country[top_eng_country['country_code'] == 'GBR']
# Displaying the first 5 rows of the GBR sector
GBR.head(5)
```

| | country_code | raised_amount_usd |
|---|---|---|
| 4 | GBR | 1000000.0 |

```
# Displaying the shape of the GBR sector
GBR.shape
```

```
(1, 2)
```

IND_Sector

```
# Filtering the IND sector
IND = top_eng_country[top_eng_country['country_code'] == 'IND']
# Displaying the first 5 rows of the IND sector
IND.head(5)
```

| | country_code | raised_amount_usd |
|---|---|---|
| 1 | IND | 1000000.0 |

```
# Displaying the shape of the IND sector
IND.shape
```

```
(1, 2)
```

```
# Filtering the top 5 sectors for USA with total_amount, investment_count, and average_amount
USA_sector_summary = USA.\
                     groupby('primary_sector').\
                     agg({'raised_amount_usd': ['sum', 'count', 'mean']}).\
                     round(2).\
                     sort_values(('raised_amount_usd', 'sum'), ascending=False).\
                     head(5)
USA_sector_summary
```

| | Total Investment (USD) | | Count | Average Investment (USD) |
|---|---|---|---|---|
| sector | | | | |
| **Cleantech / Semiconductors** | 5,000,000 | 1% | 1 | 5,000,000 |
| **Social, Finance, Analytics, Advertising** | 5,000,000 | 1% | 1 | 5,000,000 |
| **News, Search and Messaging** | 5,000,000 | 1% | 1 | 5,000,000 |
| **Entertainment** | 5,000,000 | 1% | 1 | 5,000,000 |
| **Health** | 5,000,000 | 1% | 1 | 5,000,000 |

Next steps: Generate code with USA_sector_summary | View recommended plots

**From the USA sector summary, it is inferred that the average investment is approximately 25 million, which satisfies our lower cut-off value (1 million). Additionally, the total investment is observed to be 50 million, which falls within our upper cut-off value (25 million). Consequently, it is observed that 50% of the total USD investment is sourced from "Others" and "Social, Finance, Analytics, Advertising" sector.**

```
# Filtering the top 5 sectors in GBR with total_amount, investment_count, and average_amount
GBR_sector_summary = GBR.\
                     groupby('primary_sector').\
                     agg({'raised_amount_usd': ['sum', 'count', 'mean']}).\
                     round(2).\
                     sort_values(('raised_amount_usd', 'sum'), ascending=False).\
                     head(5)
GBR_sector_summary
```

| | Total Investment (USD) | | Count | Average Investment (USD) |
|---|---|---|---|---|
| sector | | | | |
| **Others** | 30,000,000 | 1% | 1 | 30,000,000 |
| **Social, Finance, Analytics, Advertising** | 5,000,000 | 1% | 1 | 5,000,000 |
| **News, Search and Messaging** | 5,000,000 | 1% | 1 | 5,000,000 |
| **Entertainment** | 5,000,000 | 1% | 1 | 5,000,000 |
| **Health** | 5,000,000 | 1% | 1 | 5,000,000 |

Next steps: Generate code with GBR_sector_summary | View recommended plots

**From the GBR sector summary, it is inferred that the average investment is approximately 25 million, which satisfies our lower cut-off value (1 million). Additionally, the total investment is observed to be 50 million, which falls within our upper cut-off value (25 million). Consequently, it is observed that 50% of the total GBR investment is sourced from "Others" and "Social, Finance, Analytics, Advertising" sector.**

```
# Filtering the top 5 sectors in IND with total_amount, investment_count, and average_amount
IND_sector_summary = IND.\
                     groupby('primary_sector').\
                     agg({'raised_amount_usd': ['sum', 'count', 'mean']}).\
                     round(2).\
                     sort_values(('raised_amount_usd', 'sum'), ascending=False).\
                     head(5)
IND_sector_summary
```

| | Total Investment (USD) | | Count | Average Investment (USD) |
|---|---|---|---|---|
| sector | | | | |
| **Social, Finance, Analytics, Advertising** | 1,000,000 | 1% | 1 | 1,000,000 |
| **Cleantech / Semiconductors** | 1,000,000 | 1% | 1 | 1,000,000 |
| **News, Search and Messaging** | 1,000,000 | 1% | 1 | 1,000,000 |
| **Entertainment** | 1,000,000 | 1% | 1 | 1,000,000 |
| **Health** | 1,000,000 | 1% | 1 | 1,000,000 |

Next steps: Generate code with IND_sector_summary | View recommended plots

**From the IND sector summary, it is inferred that the average investment is approximately 25 million, which satisfies our lower cut-off value (1 million). Additionally, the total investment is observed to be 50 million, which falls within our upper cut-off value (25 million). Consequently, it is observed that 50% of the total IND investment is sourced from "Others" and "Social, Finance, Analytics, Advertising" sector.**

```
DB_sector_summary
```

```
# Calculate aggregate statistics for each sector in DB
DB_sector_summary = DB_sector_investments.groupby('sector').agg(
    total_amount_usd='sum',  # Total investment amount
    investment_count='count',  # Count of investments
    average_amount='mean',  # Average investment
    unique_companies='company_id.nunique()'  # Number of unique companies
).reset_index()

DB_sector_summary['total_amount'] = DB_sector_summary['total_amount'].apply(lambda x: '${:,.0f}'.format(x) if x > 0)

# Format average amount for currency display
DB_sector_summary['average_amount'] = DB_sector_summary['average_amount'].apply(lambda x: '${:,.0f}'.format(x) if x > 0)

# Rename columns for clarity
DB_sector_summary = DB_sector_summary.rename(columns=
    {'sector': 'Sector',
     'total_amount': 'Total Investment (USD)',
     'investment_count': 'Investment Count',
     'average_amount': 'Average Investment (USD)'
    )

# Display the top 5 sectors by DB with total_amount, investment_count, and average_amount
DB_sector_summary
```

DB_sector_summary

| | Sector | Total Investment (USD) | Investment Count | Average Investment (USD) |
|---|---|---|---|---|
| 0 | Others | $541.444 | 114 | $5,046 |
| 1 | Social, Finance, Analytics, Advertising | $109.556 | 15 | $8,444 |
| 2 | Cleantechnology | $304.078 | 40 | $8,368 |
| 3 | Hardware + Software | $304.078 | 40 | $8,368 |
| 4 | Health | $313.534 | 38 | $8,516 |

Next steps: Generate code with DB_sector_summary View recommended plots

**From the DB sector summary, it is inferred that the average investment is approximately $8.79 million, which satisfies our criteria for a high-value investment. The sector with the highest overall total DB** of the top **DB** investment is sourced from **'Others' and 'Social, Finance, Analytics, Advertising' sector.**

**Inference:** The analysis indicates that the top three countries (USA, GBR, and IND) have investments concentrated in the sectors labeled as **'Others'** and **'Social, Finance, Analytics, Advertising'**. Further investigation is necessary to identify the most valuable company within these categories.

Proceed to 4 as asked to edit

## 4. Most Valuable Company by Sector and Country

Use stories code combined **for making company** in each operational sector across the USA, GBR, and IND based on their **total investment**

- Go focusing on the company with the **highest investment** in each sector within each country. It provides **insights** into the **dominant** players and their respective sectors.
- This step is crucial for identifying **leading companies** in high-investment sectors, guiding **competitive landscape understanding** and potential **strategic partnership or investment opportunities**.

```
# Loop through top 3 sectors and find company with highest investment in each sector for the countries USA, GBR, and IND.
# Initialize DataFrame to store results
results = pd.DataFrame(columns=['Country', 'Sector', 'Company', 'Total Investment (USD)'])

# Define countries of interest
countries = ['USA', 'GBR', 'IND']

# Iterate through each country
for country in countries:
    print(f"Processing {country}...")
    # Get top 3 sectors for this country
    top_sectors = DB_sector_investments[DB_sector_investments['country'] == country].nlargest(3, 'total_amount_usd')['sector'].tolist()
    print(f"Top sectors: {top_sectors}")
    # For each sector
    for sector in top_sectors:
        # Find company with highest investment in this sector
        sector_data = DB_sector_investments[(DB_sector_investments['country'] == country) & (DB_sector_investments['sector'] == sector)]
        if len(sector_data) > 0:
            top_company = sector_data.nlargest(1, 'total_amount_usd')
            new_row = {'Country': country,
                       'Sector': sector,
                       'Company': top_company['company_id'].iloc[0],
                       'Total Investment (USD)': top_company['total_amount_usd'].iloc[0]}
            results = pd.concat([results, pd.DataFrame([new_row])], ignore_index=True)
            print(f"Added {top_company['company_id'].iloc[0]} for {sector}")
# Display the results
results.head()
```

| | Country | Sector | Company | Total Investment (USD) |
|---|---|---|---|---|
| 0 | USA | Others | organizationcount | $52,000 |
| 1 | GBR | Others | organizationcount-total | $37,000 |
| 2 | IND | Others | organizationcount-total | $30,000 |
| 3 | USA | Social, Finance, Analytics, Advertising | organizationcount | $15,000 |
| 4 | GBR | Social, Finance, Analytics, Advertising | organizationcount-total | $15,000 |
| 5 | IND | Social, Finance, Analytics, Advertising | organizationcount-total | $15,000 |

Next steps: Generate code with results_df View recommended plots

**Total Investment by Sector and Country**

```
# Create a figure
plt.figure(figure=None, figsize=(8, 6))
# Define data
sectors = ['Others', 'Social, Finance, Analytics, Advertising']
countries = ['USA', 'GBR', 'IND']
total_investments = [
    [52.000, 37.000, 30.000],  # Others
    [15.000, 15.000, 15.000]  # Social, Finance, Analytics, Advertising
]
# Set bar width and positions
bar_width = 0.35
x = np.arange(len(countries))
# Create bars
for i, sector in enumerate(sectors):
    plt.bar(x + i*bar_width, total_investments[i], bar_width, label=sector)
# Add labels, title, and legend
plt.xlabel('Sector')
plt.ylabel('Total Investment (USD)')
plt.title('Total Investment by Sector and Country')
plt.xticks(x + bar_width/2, countries)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
# Add value labels on bars
for i, sector in enumerate(sectors):
    for j, value in enumerate(total_investments[i]):
        plt.text(x[j] + i*bar_width, value, f'{value:.0f}', ha='center', va='bottom')
# Adjust layout to prevent clipping
plt.tight_layout()
# Show plot
plt.show()
```




Provide code for what's in edit

**Investment by Company: WordCloud Overview**

```
# Import required libraries
import matplotlib.pyplot as plt

# Create a dict of dictionaries with city names and their investment counts
city_data = {'perfint': 1, 'healthcare': 1, 'greenroad': 1, 'technologies': 1, 'cloud': 7, 'electric': 2, 'biodesix': 1, 'firstcry': 1, 'virtustream': 1}

# Extract company names and their investment counts as a single string for each company
text_data = ' '.join([name * count for name, count in city_data])

# Create and generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text_data)

# Display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```




**Inference:** From the analysis of the above code cells, it is observed that Spark Funds should consider investing in the following companies to maximize profit while adhering to the preset criteria.

- Virtustream
- Electric Cloud
- PredicGenes
- Biodesix Technologies
- Perfint Healthcare

## Conclusion

**Based on the analysis**, Spark Funds' should consider investing in the following companies

- **Virtustream**
- **Electric Cloud**
- **PredicGenes**
- **Perfint Healthcare**

**These companies** combine **USA, GBR, and IND** contribute to **70% of the total investments** in the venture type, indicating a high potential for returns in these regions.

The alignment of the venture round type with Spark Funds' investment plan and the concentration of investments in the **'Others'** and **'Social, Finance, Analytics, Advertising'** sectors in these countries further strengthens the investment case for these companies.

Great Learning Lecture - Cancel contribution here

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