Rahul_Ranjan1_Fintech_Capstone_Project_Final_Submission_2024

November 14, 2024

[1]:
```
!pip install pingouin
!pip install --upgrade category_encoders
import pingouin as pg
from decimal import Decimal, getcontext
import numpy as np
import random
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import math
from scipy.stats import poisson, expon, geom,norm
from statsmodels.stats import weightstats as stests
import statsmodels.api as sm
from scipy.stats import ttest_1samp
from scipy.stats import ttest_ind
from scipy.stats import ttest_rel
from scipy.stats import powerlaw
from scipy.stats import chisquare # Statistical test (chistat, pvalue)
from scipy.stats import chi2
from scipy.stats import chi2_contingency
from statsmodels.stats.proportion import proportions_ztest
from scipy.stats import f_oneway
from scipy.stats import kruskal
from statsmodels.graphics.gofplots import qqplot
from scipy.stats import shapiro
from scipy.stats import levene
from scipy.stats import pearsonr,spearmanr
import warnings
warnings.filterwarnings('ignore')
from scipy.stats import skew
from scipy.stats import skew, kurtosis
from scipy.stats import kstest
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder
from category_encoders import TargetEncoder
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.preprocessing import MinMaxScaler
import scipy.stats as stats
```

```
Collecting pingouin
  Downloading pingouin-0.5.5-py3-none-any.whl.metadata (19 kB)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-
packages (from pingouin) (3.8.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from pingouin) (1.26.4)
Requirement already satisfied: pandas>=1.5 in /usr/local/lib/python3.10/dist-
packages (from pingouin) (2.2.2)
Collecting pandas-flavor (from pingouin)
  Downloading pandas_flavor-0.6.0-py3-none-any.whl.metadata (6.3 kB)
Requirement already satisfied: scikit-learn>=1.2 in
/usr/local/lib/python3.10/dist-packages (from pingouin) (1.5.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from pingouin) (1.13.1)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-
packages (from pingouin) (0.13.2)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-
packages (from pingouin) (0.14.4)
Requirement already satisfied: tabulate in /usr/local/lib/python3.10/dist-
packages (from pingouin) (0.9.0)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.5->pingouin) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.5->pingouin) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.5->pingouin) (2024.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn>=1.2->pingouin) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.2->pingouin)
(3.5.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->pingouin) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->pingouin) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->pingouin) (4.54.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->pingouin) (1.4.7)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->pingouin) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib->pingouin) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in
```

```
/usr/local/lib/python3.10/dist-packages (from matplotlib->pingouin) (3.2.0)
Requirement already satisfied: xarray in /usr/local/lib/python3.10/dist-packages
(from pandas-flavor->pingouin) (2024.10.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels->pingouin) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels->pingouin) (1.16.0)
Downloading pingouin-0.5.5-py3-none-any.whl (204 kB)
                         204.4/204.4 kB
4.7 MB/s eta 0:00:00
Downloading pandas_flavor-0.6.0-py3-none-any.whl (7.2 kB)
Installing collected packages: pandas-flavor, pingouin
Successfully installed pandas-flavor-0.6.0 pingouin-0.5.5
Collecting category_encoders
  Downloading category_encoders-2.6.4-py2.py3-none-any.whl.metadata (8.0 kB)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-
packages (from category_encoders) (1.26.4)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.10/dist-packages (from category_encoders) (1.5.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-
packages (from category_encoders) (1.13.1)
Requirement already satisfied: statsmodels>=0.9.0 in
/usr/local/lib/python3.10/dist-packages (from category_encoders) (0.14.4)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.10/dist-
packages (from category_encoders) (2.2.2)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-
packages (from category_encoders) (0.5.6)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.0.5->category_encoders)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.0.5->category_encoders) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
packages (from pandas>=1.0.5->category_encoders) (2024.2)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn>=0.20.0->category_encoders) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-
learn>=0.20.0->category_encoders) (3.5.0)
Requirement already satisfied: packaging>=21.3 in
/usr/local/lib/python3.10/dist-packages (from
statsmodels>=0.9.0->category_encoders) (24.2)
Downloading category_encoders-2.6.4-py2.py3-none-any.whl (82 kB)
                         82.0/82.0 kB
2.9 MB/s eta 0:00:00
Installing collected packages: category_encoders
```

```
Successfully installed category_encoders-2.6.4
```

[2]:
```
df = pd.read_csv("/content/investments_VC.csv", encoding='ISO-8859-1')
df
```

[2]:

	permalink	name	homepage_url	category_list	market	funding_total_usd	status	country_code	state_code	region
0	/organization/waywire	#waywire	http://www.waywire.com	|Entertainment|Politics|Social Media|News|	News	17,50,000	acquired	USA	NY	New York City
1	/organization/tv-communications	&TV Communications	http://enjoyandtv.com	|Games|	Games	40,00,000	operating	USA	CA	Los Angeles
2	/organization/rock-your-paper	'Rock' Your Paper	http://www.rockyourpaper.org	|Publishing|Education|	Publishing					
3	/organization/in-touch-network	(In)Touch Network	http://www.InTouchNetwork.com	|Electronics|Guides|Coffee|Restaurants|Music|i…	Electronics					
4	/organization/r-ranch-and-mine	-R- Ranch and Mine	NaN	|Tourism|Entertainment|Games|	Tourism					
…	…	…	…	…	…					
54289	NaN	NaN	NaN	NaN	NaN					
54290	NaN	NaN	NaN	NaN	NaN					
54291	NaN	NaN	NaN	NaN	NaN					
54292	NaN	NaN	NaN	NaN	NaN					
54293	NaN	NaN	NaN	NaN	NaN					

```
2                  40,000   operating          EST        NaN        Tallinn
3               15,00,000   operating          GBR        NaN         London
4                  60,000   operating          USA         TX         Dallas
…                      …        …           …         …             …
54289                 NaN        NaN          NaN        NaN            NaN
54290                 NaN        NaN          NaN        NaN            NaN
54291                 NaN        NaN          NaN        NaN            NaN
54292                 NaN        NaN          NaN        NaN            NaN
54293                 NaN        NaN          NaN        NaN            NaN

       … secondary_market  product_crowdfunding round_A round_B round_C  \
0      …               0.0                   0.0     0.0     0.0     0.0
1      …               0.0                   0.0     0.0     0.0     0.0
2      …               0.0                   0.0     0.0     0.0     0.0
3      …               0.0                   0.0     0.0     0.0     0.0
4      …               0.0                   0.0     0.0     0.0     0.0
…    …                 …                     …       …       …       …
54289  …               NaN                   NaN     NaN     NaN     NaN
54290  …               NaN                   NaN     NaN     NaN     NaN
54291  …               NaN                   NaN     NaN     NaN     NaN
54292  …               NaN                   NaN     NaN     NaN     NaN
54293  …               NaN                   NaN     NaN     NaN     NaN

       round_D round_E round_F  round_G  round_H
0          0.0     0.0     0.0      0.0      0.0
1          0.0     0.0     0.0      0.0      0.0
2          0.0     0.0     0.0      0.0      0.0
3          0.0     0.0     0.0      0.0      0.0
4          0.0     0.0     0.0      0.0      0.0
…        …     …       …        …        …
54289      NaN     NaN     NaN      NaN      NaN
54290      NaN     NaN     NaN      NaN      NaN
54291      NaN     NaN     NaN      NaN      NaN
54292      NaN     NaN     NaN      NaN      NaN
54293      NaN     NaN     NaN      NaN      NaN

[54294 rows x 39 columns]
```

[3]:
```python
# Strip whitespace from all column names
df.columns = df.columns.str.strip()

# Rename the column
df.rename(columns={'funding_total_usd': 'amount_USD'}, inplace=True)
df.rename(columns={'founded_month': 'month'}, inplace=True)
df.rename(columns={'founded_year': 'year'}, inplace=True)
```

Performing EDA on the categorical columns of the dataset - and the numerical columns

of the dataset.

Evaluating -Datatypes, Missing Data, and Summary Statistics.

[4]:
```
df = df.dropna()
df
```

[4]:

	permalink	name	homepage_url	category_list	market	amount_USD	status	country_code
0	/organization/waywire	#waywire	http://www.waywire.com	|Entertainment|Politics|Social Media|News|	News	17,50,000	acquired	USA
8	/organization/004-technologies	004 Technologies	http://004gmbh.de/en/004-interact	|Software|				
12	/organization/1-800-dentist	1-800-DENTIST	http://www.1800dentist.com	|Health and Wellness|				
13	/organization/1-800-doctors	1-800-DOCTORS	http://1800doctors.com	|Health and Wellness|				
16	/organization/10-20-media	10-20 Media	http://www.10-20media.com	|E-Commerce|				
…	…	…	…	…				
49425	/organization/zynerba-pharmaceuticals	Zynerba Pharmaceuticals	http://zynerba.com	|Pharmaceuticals|				
49426	/organization/zynga	Zynga	http://www.zynga.com	|Technology|Facebook Applications|Networking|G…				
49427	/organization/zyngenia	Zyngenia	http://www.zyngenia.com	|Biotechnology|				
49429	/organization/zyomyx-inc	ZYOMYX	http://www.zyomyx.com	|Biotechnology|				
49437	/organization/x	[x+1]	http://www.xplusone.com/	|Enterprise Software|				

```
8                  Software             -     operating          USA
12      Health and Wellness             -     operating          USA
13      Health and Wellness       17,50,000   operating          USA
16                E-Commerce      20,50,000   operating          USA
…                        …            …       …          …
49425       Pharmaceuticals    1,30,00,000   operating          USA
49426            Technology   86,65,50,786   operating          USA
49427          Biotechnology    2,50,00,000   operating          USA
49429          Biotechnology    3,42,75,015   operating          USA
49437   Enterprise Software     4,50,00,000   operating          USA

      state_code                  region  … secondary_market  \
0             NY           New York City  …              0.0
8             IL   Springfield, Illinois  …              0.0
12            CA              Los Angeles  …              0.0
13            NJ                   Newark  …              0.0
16            MD                Baltimore  …              0.0
…          …                        …  …             …
49425         PA             Philadelphia  …              0.0
49426         CA              SF Bay Area  …              0.0
49427         MD        Washington, D.C.  …              0.0
49429         MO               MO - Other  …              0.0
49437         NY           New York City  …              0.0

       product_crowdfunding     round_A      round_B      round_C  round_D  \
0                       0.0         0.0          0.0          0.0      0.0
8                       0.0         0.0          0.0          0.0      0.0
12                      0.0         0.0          0.0          0.0      0.0
13                      0.0         0.0          0.0          0.0      0.0
16                      0.0         0.0          0.0          0.0      0.0
…                       …           …            …            …        …
49425                   0.0         0.0          0.0          0.0      0.0
49426                   0.0  15026000.0  355187000.0  490000000.0      0.0
49427                   0.0  25000000.0          0.0          0.0      0.0
49429                   0.0         0.0   12000000.0          0.0      0.0
49437                   0.0  16000000.0   10000000.0          0.0      0.0

      round_E round_F  round_G  round_H
0         0.0     0.0      0.0      0.0
8         0.0     0.0      0.0      0.0
12        0.0     0.0      0.0      0.0
13        0.0     0.0      0.0      0.0
16        0.0     0.0      0.0      0.0
…       …     …       …        …
49425     0.0     0.0      0.0      0.0
49426     0.0     0.0      0.0      0.0
49427     0.0     0.0      0.0      0.0
```

```
49429     0.0     0.0      0.0      0.0
49437     0.0     0.0      0.0      0.0

[21840 rows x 39 columns]
```

[5]:
```
#Reviewing few samples
df.sample(15)
```

[5]:
```
                                permalink                  name  \
15759                  /organization/foko                  FoKo
25784              /organization/mdxhealth              MDxHealth
1191                 /organization/adtonik                AdTonik
32006           /organization/pet-airways            Pet Airways
26339           /organization/messagegate            MessageGate
5124           /organization/binary-thumb           Binary Thumb
7367               /organization/carlypso               Carlypso
41773  /organization/taiga-biotechnologies  Taiga Biotechnologies
8566       /organization/claytonstress-com      ClaytonStress.com
39851              /organization/sparefoot              SpareFoot
3445          /organization/ask-the-doctor         Ask The Doctor
10883             /organization/dailybooth             DailyBooth
2181                /organization/ambature               Ambature
42299              /organization/telekenex              Telekenex
8278                /organization/cimetrix               Cimetrix

                    homepage_url  \
15759          http://www.foko.co
25784        http://mdxhealth.com
1191          http://adtonik.com/
32006   http://www.PetAirways.com
26339  http://www.messagegate.com
5124   http://www.binarythumb.com
7367      http://www.carlypso.com
41773     http://taigabiotech.com
8566     http://ClaytonStress.com
39851    http://www.sparefoot.com
3445      http://askthedoctor.com
10883       http://dailybooth.com
2181          http://ambature.com
42299    http://www.telekenex.com
8278          http://cimetrix.com

                                        category_list  \
15759                               |Enterprise Software|
25784                                    |Biotechnology|
1191   |Television|Mobile Analytics|Analytics|Mobile …
32006                                    |Pets|Travel|
```

```
26339                                        |Messaging|
5124                                  |Technology|Mobile|
7367                                         |Automotive|
41773                                      |Biotechnology|
8566                     |Health and Wellness|Curated Web|
39851  |Startups|Sales and Marketing|Software|B2B|Mar…
3445                                       |Curated Web|
10883                    |Photo Sharing|Public Relations|
2181                                  |Clean Technology|
42299                                       |Web Hosting|
8278                                      |Semiconductors|
```

	market	amount_USD	status	country_code	\
15759	Enterprise Software	4,50,000	operating	CAN	
25784	Biotechnology	2,36,00,000	operating	USA	
1191	Mobile Advertising	5,00,000	operating	USA	
32006	Travel	-	operating	USA	
26339	Messaging	56,00,000	closed	USA	
5124	Technology	-	operating	USA	
7367	Automotive	13,20,000	operating	USA	
41773	Biotechnology	34,45,997	operating	USA	
8566	Health and Wellness	75,000	operating	USA	
39851	Software	1,63,50,000	operating	USA	
3445	Curated Web	30,00,000	operating	CAN	
10883	Photo Sharing	70,15,000	acquired	USA	
2181	Clean Technology	33,10,000	operating	USA	
42299	Web Hosting	-	operating	USA	
8278	Semiconductors	8,18,750	operating	USA	

	state_code	region	…	secondary_market	product_crowdfunding	\
15759	QC	Gatineau	…	0.0	0.0	
25784	CA	Anaheim	…	0.0	0.0	
1191	CA	SF Bay Area	…	0.0	0.0	
32006	FL	Palm Beaches	…	0.0	0.0	
26339	WA	Seattle	…	0.0	0.0	
5124	WA	Seattle	…	0.0	0.0	
7367	CA	SF Bay Area	…	0.0	0.0	
41773	CO	Denver	…	0.0	0.0	
8566	MO	St. Louis	…	0.0	0.0	
39851	TX	Austin	…	0.0	0.0	
3445	ON	Toronto	…	0.0	0.0	
10883	CA	SF Bay Area	…	0.0	0.0	
2181	CA	SF Bay Area	…	0.0	0.0	
42299	CA	SF Bay Area	…	0.0	0.0	
8278	UT	Salt Lake City	…	0.0	0.0	

	round_A	round_B	round_C	round_D	round_E	round_F	round_G	\

```
15759         0.0        0.0         0.0      0.0     0.0     0.0      0.0
25784  23600000.0        0.0         0.0      0.0     0.0     0.0      0.0
1191          0.0        0.0         0.0      0.0     0.0     0.0      0.0
32006         0.0        0.0         0.0      0.0     0.0     0.0      0.0
26339         0.0        0.0         0.0      0.0     0.0     0.0      0.0
5124          0.0        0.0         0.0      0.0     0.0     0.0      0.0
7367          0.0        0.0         0.0      0.0     0.0     0.0      0.0
41773         0.0        0.0         0.0      0.0     0.0     0.0      0.0
8566          0.0        0.0         0.0      0.0     0.0     0.0      0.0
39851    850000.0  3500000.0  10000000.0      0.0     0.0     0.0      0.0
3445          0.0        0.0         0.0      0.0     0.0     0.0      0.0
10883   6000000.0        0.0         0.0      0.0     0.0     0.0      0.0
2181          0.0        0.0         0.0      0.0     0.0     0.0      0.0
42299         0.0        0.0         0.0      0.0     0.0     0.0      0.0
8278          0.0        0.0         0.0      0.0     0.0     0.0      0.0

       round_H
15759      0.0
25784      0.0
1191       0.0
32006      0.0
26339      0.0
5124       0.0
7367       0.0
41773      0.0
8566       0.0
39851      0.0
3445       0.0
10883      0.0
2181       0.0
42299      0.0
8278       0.0

[15 rows x 39 columns]
```

[6]:
```
#Reviewing shape of data
df.shape
```

[6]:
```
(21840, 39)
```

[7]:
```
#Checking dtype of All Columns
df.dtypes
```

[7]:
```
permalink                object
name                     object
homepage_url             object
category_list            object
```

```
market                  object
amount_USD              object
status                  object
country_code            object
state_code              object
region                  object
city                    object
funding_rounds         float64
founded_at              object
month                   object
founded_quarter         object
year                   float64
first_funding_at        object
last_funding_at         object
seed                   float64
venture                float64
equity_crowdfunding    float64
undisclosed            float64
convertible_note       float64
debt_financing         float64
angel                  float64
grant                  float64
private_equity         float64
post_ipo_equity        float64
post_ipo_debt          float64
secondary_market       float64
product_crowdfunding   float64
round_A                float64
round_B                float64
round_C                float64
round_D                float64
round_E                float64
round_F                float64
round_G                float64
round_H                float64
dtype: object
```

[8]:
```
#Checking for NaN across all columns
df.isnull().sum().sort_values(ascending = False)
```

[8]:
```
permalink              0
secondary_market       0
convertible_note       0
debt_financing         0
angel                  0
grant                  0
private_equity         0
```

```
post_ipo_equity          0
post_ipo_debt            0
product_crowdfunding     0
equity_crowdfunding      0
round_A                  0
round_B                  0
round_C                  0
round_D                  0
round_E                  0
round_F                  0
round_G                  0
undisclosed              0
venture                  0
name                     0
region                   0
homepage_url             0
category_list            0
market                   0
amount_USD               0
status                   0
country_code             0
state_code               0
city                     0
seed                     0
funding_rounds           0
founded_at               0
month                    0
founded_quarter          0
year                     0
first_funding_at         0
last_funding_at          0
round_H                  0
dtype: int64
```

[9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21840 entries, 0 to 49437
Data columns (total 39 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   permalink             21840 non-null  object
 1   name                  21840 non-null  object
 2   homepage_url          21840 non-null  object
 3   category_list         21840 non-null  object
 4   market                21840 non-null  object
 5   amount_USD            21840 non-null  object
```

```
 6   status                 21840 non-null  object
 7   country_code           21840 non-null  object
 8   state_code             21840 non-null  object
 9   region                 21840 non-null  object
 10  city                   21840 non-null  object
 11  funding_rounds         21840 non-null  float64
 12  founded_at             21840 non-null  object
 13  month                  21840 non-null  object
 14  founded_quarter        21840 non-null  object
 15  year                   21840 non-null  float64
 16  first_funding_at       21840 non-null  object
 17  last_funding_at        21840 non-null  object
 18  seed                   21840 non-null  float64
 19  venture                21840 non-null  float64
 20  equity_crowdfunding    21840 non-null  float64
 21  undisclosed            21840 non-null  float64
 22  convertible_note       21840 non-null  float64
 23  debt_financing         21840 non-null  float64
 24  angel                  21840 non-null  float64
 25  grant                  21840 non-null  float64
 26  private_equity         21840 non-null  float64
 27  post_ipo_equity        21840 non-null  float64
 28  post_ipo_debt          21840 non-null  float64
 29  secondary_market       21840 non-null  float64
 30  product_crowdfunding   21840 non-null  float64
 31  round_A                21840 non-null  float64
 32  round_B                21840 non-null  float64
 33  round_C                21840 non-null  float64
 34  round_D                21840 non-null  float64
 35  round_E                21840 non-null  float64
 36  round_F                21840 non-null  float64
 37  round_G                21840 non-null  float64
 38  round_H                21840 non-null  float64
dtypes: float64(23), object(16)
memory usage: 6.7+ MB
```

[10]:
```
df= df.applymap(lambda x: x.lstrip() if isinstance(x, str) else x)
df
```

[10]:

	permalink	name	\
0	/organization/waywire	#waywire	
8	/organization/004-technologies	004 Technologies	
12	/organization/1-800-dentist	1-800-DENTIST	
13	/organization/1-800-doctors	1-800-DOCTORS	
16	/organization/10-20-media	10-20 Media	
…	…	…	
49425	/organization/zynerba-pharmaceuticals	Zynerba Pharmaceuticals	

```
49426                   /organization/zynga                    Zynga
49427                 /organization/zyngenia                  Zyngenia
49429               /organization/zyomyx-inc                    ZYOMYX
49437                         /organization/x                     [x+1]

                           homepage_url  \
0                  http://www.waywire.com
8       http://004gmbh.de/en/004-interact
12             http://www.1800dentist.com
13                 http://1800doctors.com
16              http://www.10-20media.com
…                                     …
49425                  http://zynerba.com
49426                http://www.zynga.com
49427              http://www.zyngenia.com
49429                http://www.zyomyx.com
49437             http://www.xplusone.com/

                                          category_list  \
0               |Entertainment|Politics|Social Media|News|
8                                            |Software|
12                                 |Health and Wellness|
13                                 |Health and Wellness|
16                                          |E-Commerce|
…                                                   …
49425                                   |Pharmaceuticals|
49426  |Technology|Facebook Applications|Networking|G…
49427                                     |Biotechnology|
49429                                     |Biotechnology|
49437                                |Enterprise Software|

                     market     amount_USD     status country_code state_code  \
0                      News      17,50,000    acquired          USA         NY
8                  Software              -     operating          USA         IL
12     Health and Wellness              -     operating          USA         CA
13     Health and Wellness      17,50,000    operating          USA         NJ
16               E-Commerce      20,50,000    operating          USA         MD
…                         …              …           …          …          …
49425      Pharmaceuticals    1,30,00,000    operating          USA         PA
49426           Technology   86,65,50,786    operating          USA         CA
49427        Biotechnology    2,50,00,000    operating          USA         MD
49429        Biotechnology    3,42,75,015    operating          USA         MO
49437  Enterprise Software    4,50,00,000    operating          USA         NY

                      region  … secondary_market  product_crowdfunding  \
0               New York City  …              0.0                   0.0
8       Springfield, Illinois  …              0.0                   0.0
```

```
12              Los Angeles  …              0.0                   0.0
13                   Newark  …              0.0                   0.0
16                Baltimore  …              0.0                   0.0
…                       …  …              …                     …
49425           Philadelphia  …              0.0                   0.0
49426            SF Bay Area  …              0.0                   0.0
49427      Washington, D.C.   …              0.0                   0.0
49429             MO - Other  …              0.0                   0.0
49437          New York City  …              0.0                   0.0

          round_A      round_B      round_C  round_D round_E round_F  round_G  \
0             0.0          0.0          0.0      0.0     0.0     0.0      0.0
8             0.0          0.0          0.0      0.0     0.0     0.0      0.0
12            0.0          0.0          0.0      0.0     0.0     0.0      0.0
13            0.0          0.0          0.0      0.0     0.0     0.0      0.0
16            0.0          0.0          0.0      0.0     0.0     0.0      0.0
…             …            …            …        …       …       …        …
49425         0.0          0.0          0.0      0.0     0.0     0.0      0.0
49426  15026000.0  355187000.0  490000000.0      0.0     0.0     0.0      0.0
49427  25000000.0          0.0          0.0      0.0     0.0     0.0      0.0
49429         0.0   12000000.0          0.0      0.0     0.0     0.0      0.0
49437  16000000.0   10000000.0          0.0      0.0     0.0     0.0      0.0

       round_H
0          0.0
8          0.0
12         0.0
13         0.0
16         0.0
…          …
49425      0.0
49426      0.0
49427      0.0
49429      0.0
49437      0.0

[21840 rows x 39 columns]
```

[11]:
```
# Statisctical summary of numerical data type columns
df.describe(include="all")
```

[11]:
```
                    permalink   name         homepage_url category_list  \
count                   21840  21840                21840         21840
unique                  21840  21817                21800          8980
top     /organization/waywire  Spire  http://ivillage.com    |Software|
freq                        1      3                    2          1868
mean                      NaN    NaN                  NaN           NaN
```

```
std                     NaN    NaN                 NaN           NaN
min                     NaN    NaN                 NaN           NaN
25%                     NaN    NaN                 NaN           NaN
50%                     NaN    NaN                 NaN           NaN
75%                     NaN    NaN                 NaN           NaN
max                     NaN    NaN                 NaN           NaN

           market amount_USD     status country_code state_code       region  \
count       21840      21840      21840        21840      21840        21840
unique        666       7155          3            2         61          281
top     Software          -  operating          USA         CA  SF Bay Area
freq        2419       2728      18448        20863       7611         5405
mean         NaN        NaN        NaN          NaN        NaN          NaN
std          NaN        NaN        NaN          NaN        NaN          NaN
min          NaN        NaN        NaN          NaN        NaN          NaN
25%          NaN        NaN        NaN          NaN        NaN          NaN
50%          NaN        NaN        NaN          NaN        NaN          NaN
75%          NaN        NaN        NaN          NaN        NaN          NaN
max          NaN        NaN        NaN          NaN        NaN          NaN

        … secondary_market  product_crowdfunding       round_A  \
count   …     2.184000e+04          2.184000e+04  2.184000e+04
unique  …              NaN                   NaN           NaN
top     …              NaN                   NaN           NaN
freq    …              NaN                   NaN           NaN
mean    …     4.182715e+04          1.022974e+04  1.639491e+06
std     …     3.206989e+06          6.214429e+05  5.794835e+06
min     …     0.000000e+00          0.000000e+00  0.000000e+00
25%     …     0.000000e+00          0.000000e+00  0.000000e+00
50%     …     0.000000e+00          0.000000e+00  0.000000e+00
75%     …     0.000000e+00          0.000000e+00  0.000000e+00
max     …     4.000000e+08          7.200000e+07  2.250000e+08

             round_B       round_C       round_D       round_E       round_F  \
count   2.184000e+04  2.184000e+04  2.184000e+04  2.184000e+04  2.184000e+04
unique           NaN           NaN           NaN           NaN           NaN
top              NaN           NaN           NaN           NaN           NaN
freq             NaN           NaN           NaN           NaN           NaN
mean    2.218391e+06  1.880059e+06  1.277402e+06  5.885045e+05  2.853710e+05
std     9.721395e+06  9.892003e+06  1.392027e+07  6.906438e+06  8.673690e+06
min     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%     0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
max     5.420000e+08  4.900000e+08  1.200000e+09  4.000000e+08  1.060000e+09

             round_G       round_H
```

```
count   2.184000e+04  2.184000e+04
unique           NaN           NaN
top              NaN           NaN
freq             NaN           NaN
mean    5.246412e+04  2.289377e+03
std     3.154128e+06  3.383325e+05
min     0.000000e+00  0.000000e+00
25%     0.000000e+00  0.000000e+00
50%     0.000000e+00  0.000000e+00
75%     0.000000e+00  0.000000e+00
max     4.000000e+08  5.000000e+07

[11 rows x 39 columns]
```

[11]:

[12]:
```
# Checking for duplicates
df.duplicated().value_counts()
```

[12]:
```
False    21840
Name: count, dtype: int64
```

Insights

1. There are no duplicate entries in the dataset.

[13]:
```
#Counting Distinct across each dataframe column
a=df.nunique(axis=0)
print("No.of.unique values in each column :\n\n",a)
```

```
No.of.unique values in each column :

 permalink              21840
name                    21817
homepage_url            21800
category_list            8980
market                    666
amount_USD               7155
status                      3
country_code                2
state_code                 61
region                    281
city                     1913
funding_rounds             16
founded_at               2388
month                     386
founded_quarter           200
year                       92
```

```
first_funding_at         3228
last_funding_at          2805
seed                     1216
venture                  5129
equity_crowdfunding       120
undisclosed               147
convertible_note          207
debt_financing           1333
angel                     328
grant                     242
private_equity            493
post_ipo_equity           110
post_ipo_debt              30
secondary_market           12
product_crowdfunding       74
round_A                   901
round_B                   703
round_C                   451
round_D                   336
round_E                   188
round_F                    82
round_G                    23
round_H                     2
dtype: int64
```

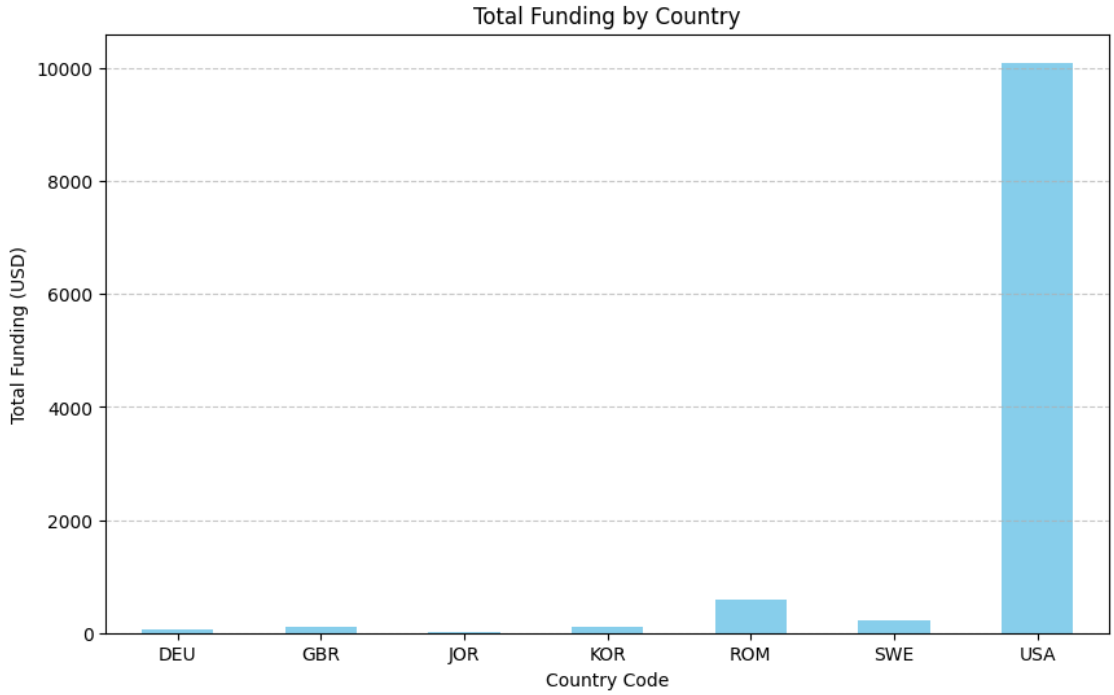
[14]:
```
### Changing the datatype
df.permalink=df.permalink.astype('string')
df.name=df.name.astype('string')
df.homepage_url=df.homepage_url.astype('string')
df.category_list=df.category_list.astype('string')
df.status=df.status.astype('string')
df.country_code=df.country_code.astype('string')
df.state_code=df.state_code.astype('string')
df.region=df.region.astype('string')
df.city=df.city.astype('string')
df.funding_rounds=df.funding_rounds.astype('int')
df['founded_at'] = pd.to_datetime(df['founded_at'], errors='coerce')
df['month'] = pd.to_datetime(df['month'], errors='coerce').dt.month
df.founded_quarter=df.founded_quarter.astype('string')
df.year=df.year.astype('int')
df['first_funding_at'] = pd.to_datetime(df['first_funding_at'], errors='coerce')
df['last_funding_at'] = pd.to_datetime(df['last_funding_at'], errors='coerce')
df.seed=df.seed.astype('float')
df.venture=df.venture.astype('float')
df.equity_crowdfunding=df.equity_crowdfunding.astype('float')
df.undisclosed=df.undisclosed.astype('float')
df.convertible_note=df.convertible_note.astype('float')
```

```
df.debt_financing=df.debt_financing.astype('float')
df.angel=df.angel.astype('float')
df.grant=df.grant.astype('float')
df.private_equity=df.private_equity.astype('float')
df.post_ipo_equity=df.post_ipo_equity.astype('float')
df.post_ipo_debt=df.post_ipo_debt.astype('float')
df.secondary_market=df.secondary_market.astype('float')
df.product_crowdfunding=df.product_crowdfunding.astype('float')
df.round_A=df.round_A.astype('float')
df.round_B=df.round_B.astype('float')
df.round_C=df.round_C.astype('float')
df.round_D=df.round_D.astype('float')
df.round_E=df.round_E.astype('float')
df.round_F=df.round_F.astype('float')
```

Determining total funding across different countries.

[33]:
```
df1 = pd.read_csv("/content/investments_VC.csv", encoding='ISO-8859-1')
df1
# Strip whitespace from all column names
df1.columns = df1.columns.str.strip()

# Rename the column
df1.rename(columns={'funding_total_usd': 'amount_USD1'}, inplace=True)
df1.rename(columns={'founded_month': 'month'}, inplace=True)
df1.rename(columns={'founded_year': 'year'}, inplace=True)

import pandas as pd
import matplotlib.pyplot as plt

# Assuming your DataFrame is called df1 and has columns 'country_code' and␣
 ↪'amount_USD'

# Convert 'amount_USD' to numeric, coerce errors to NaN
df1['amount_USD1'] = pd.to_numeric(df1['amount_USD1'], errors='coerce')

# Drop rows with NaN in 'amount_USD' if any
df1 = df1.dropna(subset=['amount_USD1'])

# Group by 'country_code' and calculate the sum of 'amount_USD' for each country
country_funding = df1.groupby('country_code')['amount_USD1'].sum()

# Plotting the bar plot
country_funding.plot(kind='bar', figsize=(10, 6), color='skyblue')

# Adding titles and labels
plt.title('Total Funding by Country')
```

```
plt.xlabel('Country Code')
plt.ylabel('Total Funding (USD)')
plt.xticks(rotation=0)  # Rotate x-axis labels for clarity
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



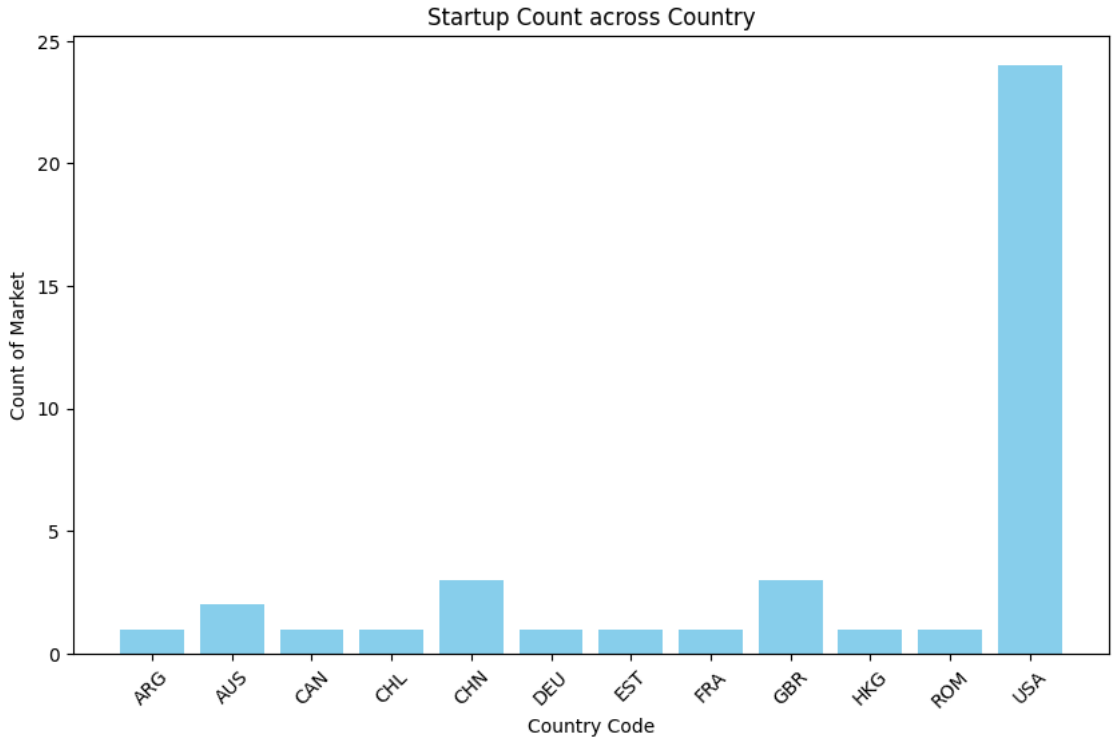
Insights

1. USA received maximum funding while Germany received very less funding.

Determining the total number of startups across different countries

[ ]:
```
import matplotlib.pyplot as plt

# Sample data
data = {
    'country_code': ['ARG', 'AUS', 'CAN', 'CHL', 'CHN', 'DEU', 'EST', 'FRA',␣
 ↪'GBR', 'HKG', 'ROM', 'USA'],
    'Count of market': [1, 2, 1, 1, 3, 1, 1, 1, 3, 1, 1, 24]
}

# Create a dataframe
import pandas as pd
df = pd.DataFrame(data)
```

```
# Plotting the bar chart
plt.figure(figsize=(10,6))
plt.bar(df['country_code'], df['Count of market'], color='skyblue')
plt.xlabel('Country Code')
plt.ylabel('Count of Market')
plt.title('Startup Count across Country')
plt.xticks(rotation=45)
plt.show()
```



Insights

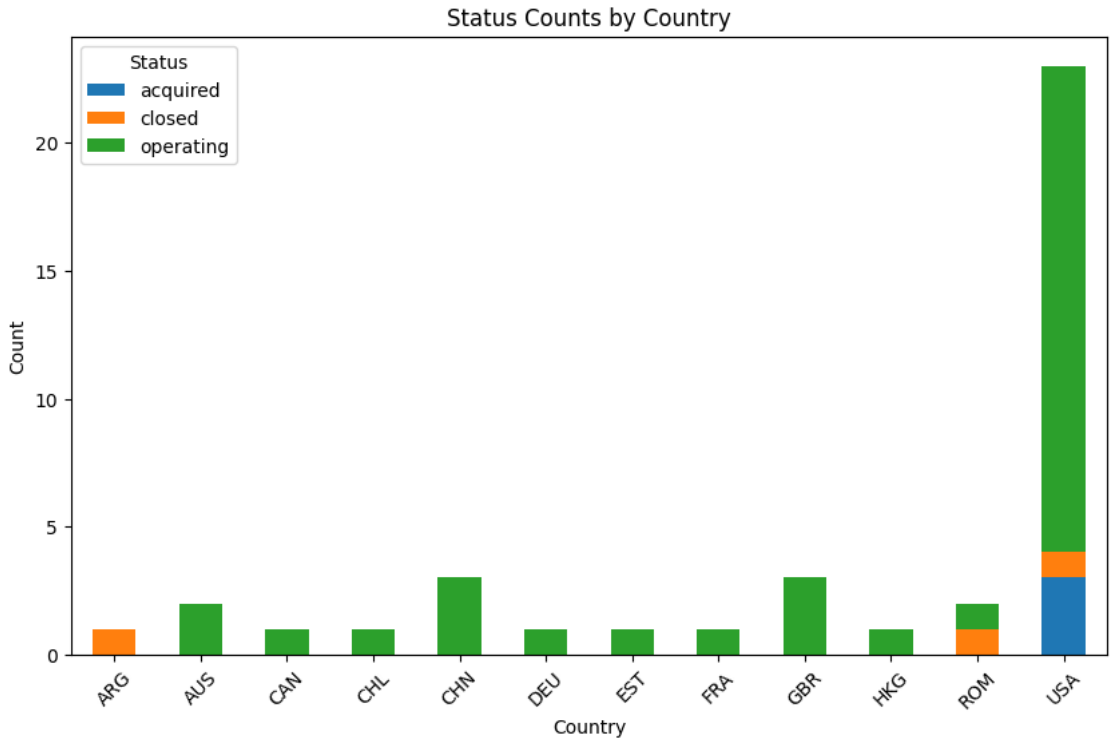
1. USA has the highest number of startups.
2. Argentina ,Canada,France,Hong Kong have nominal number of startups .

Determining the current status of startups across different countries.

[ ]:

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Define the data
data = {
```

```
    'Country': ['ARG', 'AUS', 'CAN', 'CHL', 'CHN', 'DEU', 'EST', 'FRA', 'GBR',␣
 ↪'HKG', 'ROM', 'USA'],
    'acquired': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3],
    'closed': [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
    'operating': [0, 2, 1, 1, 3, 1, 1, 1, 3, 1, 1, 19]
}

# Convert data to DataFrame
df = pd.DataFrame(data)

# Set 'Country' as index for easy plotting
df.set_index('Country', inplace=True)

# Plotting
df.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Status Counts by Country')
plt.xlabel('Country')
plt.ylabel('Count')
plt.legend(title='Status')
plt.xticks(rotation=45)
plt.show()
```

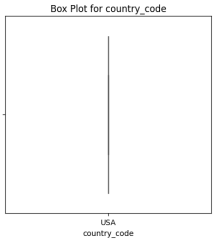


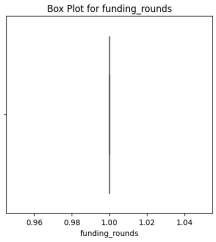
Insights

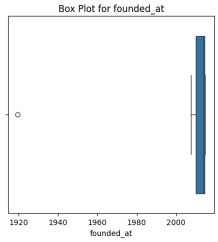
1. Argentina contribution in number of startups are very low and almost all of them are in closed sate.
2. USA has maximum number of startups and majority of them are in operating status.

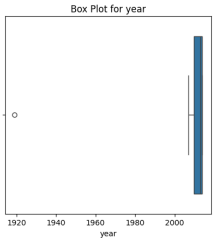
Outliers Detection

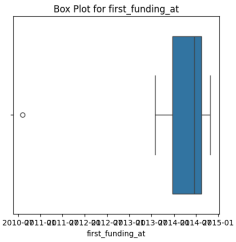
[18]:
```
columns_to_check = ['country_code',
                    'funding_rounds', 'founded_at',  'year',
                    'first_funding_at', 'last_funding_at', 'seed', 'venture',␣
 ↪'equity_crowdfunding',
                    'undisclosed', 'convertible_note', 'debt_financing',␣
 ↪'angel', 'grant', 'private_equity',
                    'post_ipo_equity', 'post_ipo_debt', 'secondary_market',␣
 ↪'product_crowdfunding']

# Creating a box plot for each column
num_columns = len(columns_to_check)
num_rows = (num_columns // 3) + (num_columns % 3)  # Adjusting the number of␣
 ↪rows based on 3 columns per row

plt.figure(figsize=(15, num_rows * 5))  # Adjust the figure height to␣
 ↪accommodate three plots per row

for i, column in enumerate(columns_to_check, 1):
    plt.subplot(num_rows, 3, i)  # Automatically adjust the number of rows and␣
 ↪columns (3 per row)
    sns.boxplot(x=df[column])
    plt.title(f'Box Plot for {column}')

plt.tight_layout()  # Automatically adjust layout to prevent overlap
plt.subplots_adjust(hspace=0.4, wspace=0.4)  # Adjust space between subplots
plt.show()
```

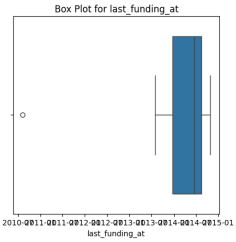

Box Plot for country_code
USA
country_code

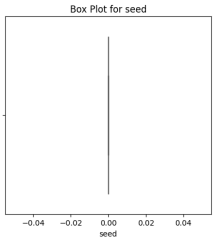

Box Plot for funding_rounds
0.96
0.98
1.00
1.02
1.04
funding_rounds

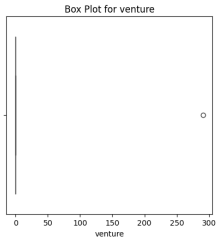

Box Plot for founded_at
1920
1940
1960
1980
2000
founded_at

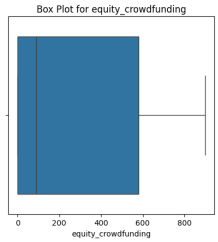

Box Plot for year
1920
1940
1960
1980
2000
year

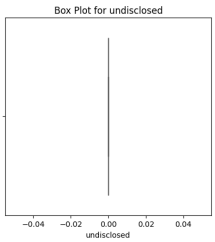

Box Plot for first_funding_at
first_funding_at

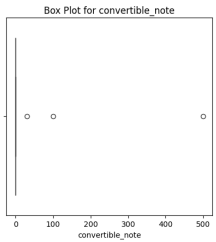

Box Plot for last_funding_at
last_funding_at

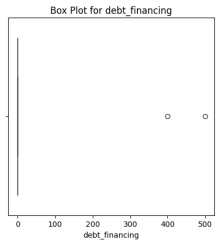

Box Plot for seed
−0.04
−0.02
0.00
0.02
0.04
seed

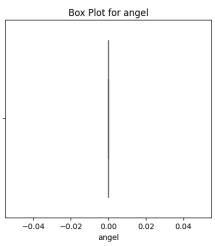

Box Plot for venture
0
50
100
150
200
250
300
venture

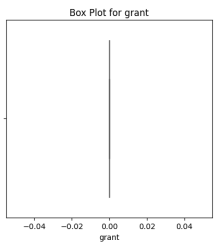

Box Plot for equity_crowdfunding
0
200
400
600
800
equity_crowdfunding

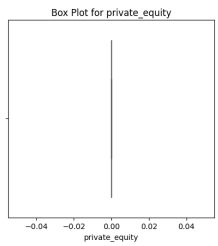

Box Plot for undisclosed
−0.04
−0.02
0.00
0.02
0.04
undisclosed

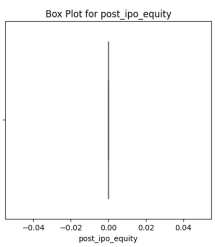

Box Plot for convertible_note
0
100
200
300
400
500
convertible_note

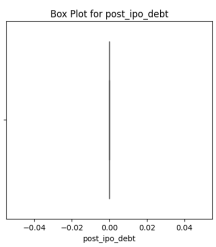

Box Plot for debt_financing
0
100
200
300
400
500
debt_financing

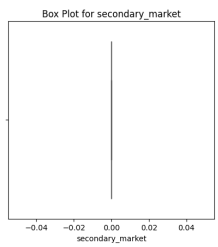

Box Plot for angel
−0.04
−0.02
0.00
0.02
0.04
angel

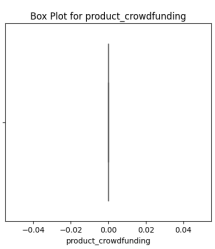

Box Plot for grant
−0.04
−0.02
0.00
0.02
0.04
grant


Box Plot for private_equity
−0.04
−0.02
0.00
0.02
0.04
private_equity


Box Plot for post_ipo_equity
−0.04
−0.02
0.00
0.02
0.04
post_ipo_equity


Box Plot for post_ipo_debt
−0.04
−0.02
0.00
0.02
0.04
post_ipo_debt


Box Plot for secondary_market
−0.04
−0.02
0.00
0.02
0.04
secondary_market


Box Plot for product_crowdfunding
−0.04
−0.02
0.00
0.02
0.04
product_crowdfunding

Insights from Boxplots

1. **Distribution of Funding Data** (Applicable for Columns like 'funding_rounds', 'seed', 'venture', 'angel', and 'private_equity') : it indicate that companies with exceptionally large funding rounds compared to others.
2. **Time-Related Funding Insights** (Applicable for Columns like 'founded_at', 'first_funding_at', and 'last_funding_at') : it suggests that many startups are receiving funding in the same period, possibly indicating a trend or a boom in funding during that period.

How Does the Funding Ecosystem Changes with Respect to Time?

[19]:
```
# Convert 'amount_USD' to numeric, forcing errors to NaN for invalid entries
df['amount_USD'] = pd.to_numeric(df['amount_USD'], errors='coerce')

# Now aggregate the data by year and month
monthly_funding = df.groupby(['year', 'month']).agg(
    total_funding=('amount_USD', 'sum'),
    number_of_investments=('amount_USD', 'count'),
    average_funding=('amount_USD', 'mean')
).reset_index()

# Display the result
monthly_funding.head()
```

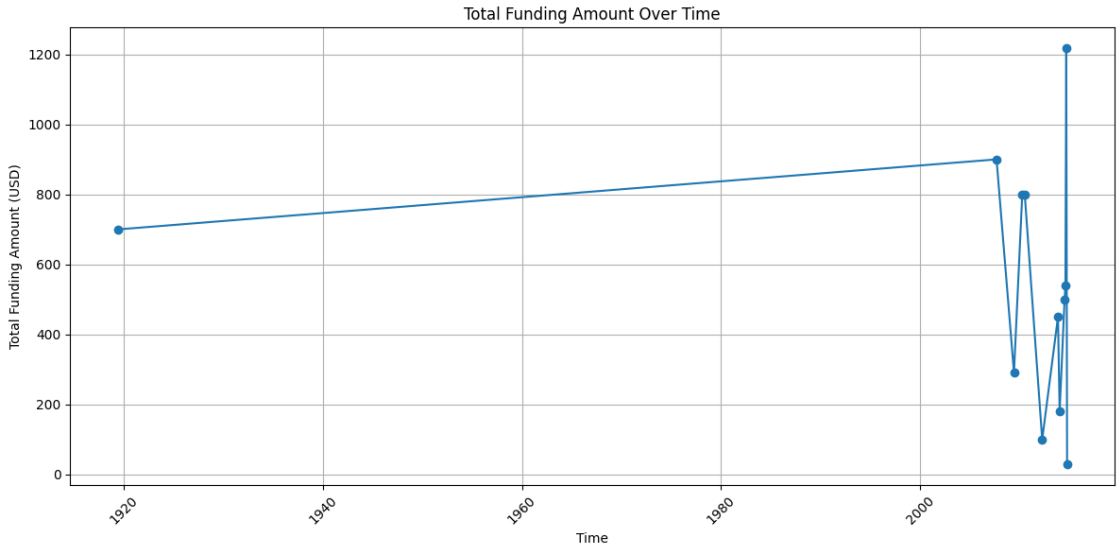
[19]:

	year	month	total_funding	number_of_investments	average_funding
0	1919	6	700.0	1	700.0
1	2007	9	900.0	2	450.0
2	2009	6	291.0	1	291.0
3	2010	4	800.0	1	800.0
4	2010	7	800.0	1	800.0

[20]:
```
# Create a 'year_month' column for plotting
monthly_funding['year_month'] = pd.to_datetime(monthly_funding[['year',␣
 ↪'month']].assign(day=1))
```

[21]:
```
# Combine 'year' and 'month' into a single datetime column
monthly_funding['year_month'] = pd.to_datetime(monthly_funding[['year',␣
 ↪'month']].assign(day=1))

# Sort by the new 'year_month' column to ensure the timeline is sequential
monthly_funding = monthly_funding.sort_values(by='year_month')

# Plot total funding amount over time
plt.figure(figsize=(12, 6))
```

```
plt.plot(monthly_funding['year_month'], monthly_funding['total_funding'],␣
 ↪marker='o', linestyle='-')
plt.title('Total Funding Amount Over Time')
plt.xlabel('Time')
plt.ylabel('Total Funding Amount (USD)')
plt.xticks(rotation=45)  # Rotate x-axis labels for better readability
plt.grid(True)
plt.tight_layout()  # Adjust layout to prevent overlap
plt.show()
```

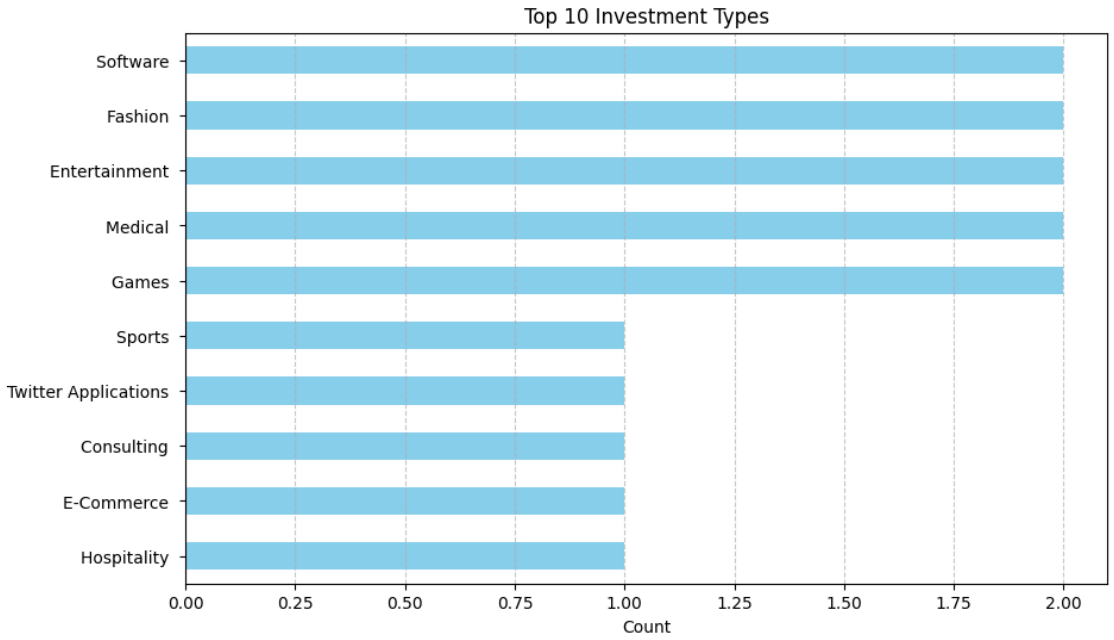


Insights

1. **Fluctuations**: Noticeable fluctuations in total funding amounts between 1900 and 2010.
2. **Peak**: Peak funding amount was observed in 217.
3. **Low Activity**: Low funding activity in late 1900 and early 2000.

Determining top 10 investment types

[22]:
```
# Calculate the count of each investment type and select the top 10

top_investment_types = df['market'].value_counts().head(10).
 ↪sort_values(ascending=True)
plt.figure(figsize=(10, 6))
top_investment_types.plot(kind='barh', color='skyblue')
plt.title('Top 10 Investment Types')
plt.xlabel('Count')
plt.ylabel('')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```

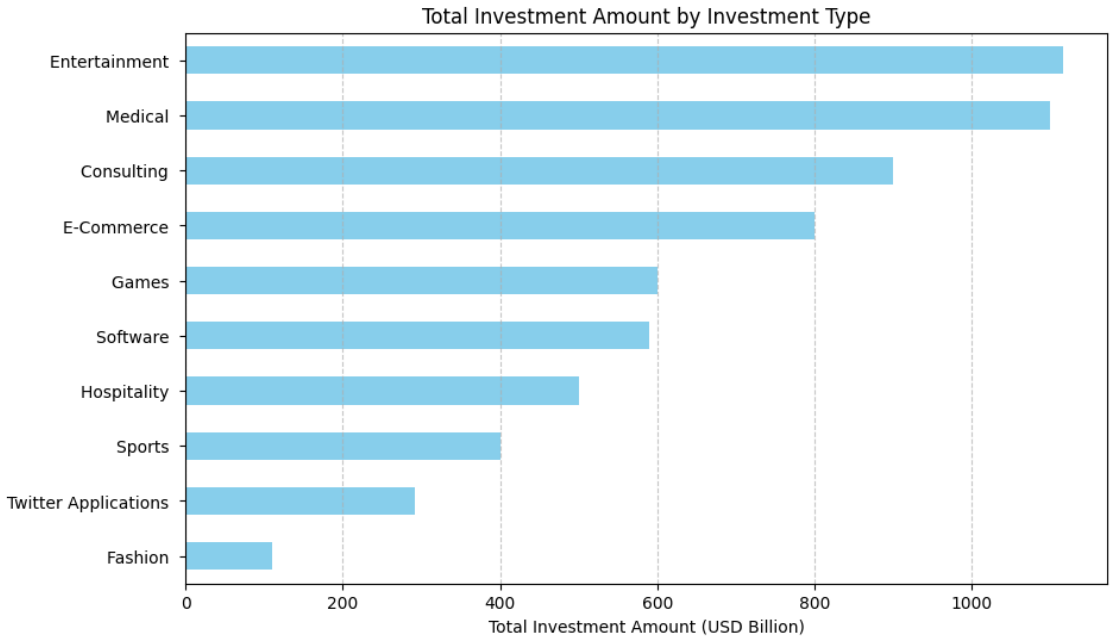


Insights

1. Software,Biotechnology and mobile hold first,second and third place respectively in terms of investment types.

Determining top 10 total investment amount by investment type

[23]:
```
# Calculate the sum of investment amount for each investment type and select␣
 ↪the top 10

top_investment_amounts = df.groupby('market')['amount_USD'].sum().nlargest(10).
 ↪sort_values(ascending=True)
plt.figure(figsize=(10, 6))
top_investment_amounts.plot(kind='barh', color='skyblue')
plt.title('Total Investment Amount by Investment Type')
plt.xlabel('Total Investment Amount (USD Billion)')
plt.ylabel('')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```

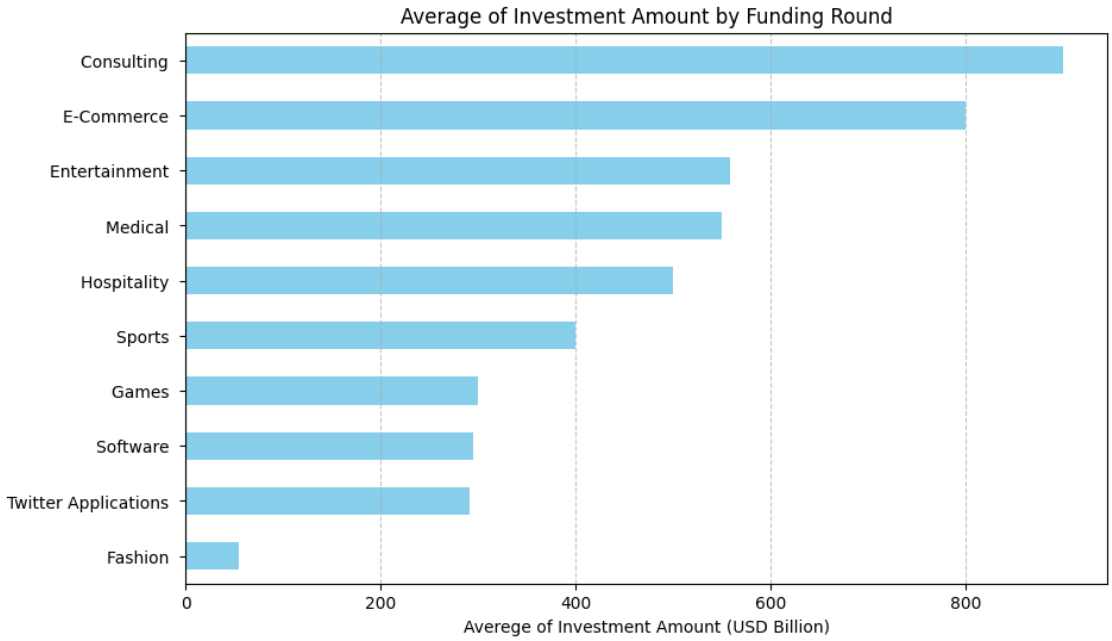


Insights

1. Highest investment was made for Entertainment category.
2. Lowest investment was made for Fashion category.

Determining the total investment amount for each investment type and identify the top 10 highest investment types.

[24]:
```
# Calculate the sum of investment amount for each investment type and select␣
 ↪the top 10

top_investment_amounts = df.groupby('market')['amount_USD'].sum().nlargest(10).
 ↪index

# Calculate the mean investment amount for these top investment types
mean_investment_amounts = df[df['market'].isin(top_investment_amounts)].
 ↪groupby('market')['amount_USD'].mean().sort_values(ascending=True)

# Create the bar chart
plt.figure(figsize=(10, 6))
mean_investment_amounts.plot(kind='barh', color='skyblue')
plt.title('Average of Investment Amount by Funding Round')
plt.xlabel('Averege of Investment Amount (USD Billion)')
plt.ylabel('')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```

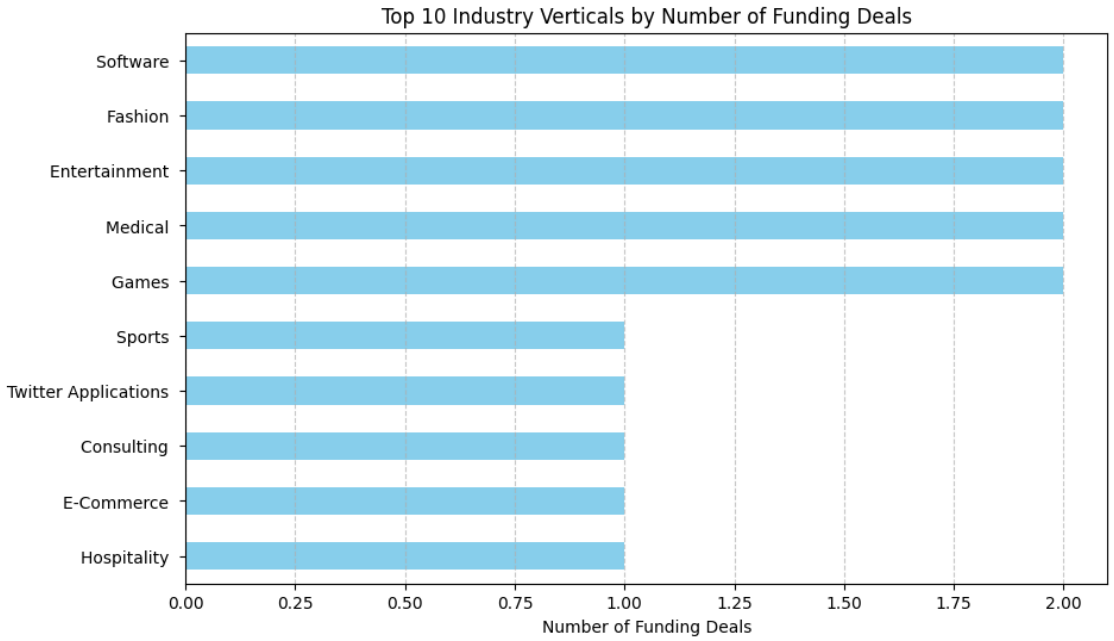


Insights

High Investment in Consulting, E-commerce, and Entertainment Sectors:Consulting, E-commerce, and Entertainment lead in investment amounts, reflecting strong investor confidence driven by technological advancements, digital transformation, and growing consumer demand.

What types of industries are most favorable for startups?

[25]:
```
# Calculate the number of funding deals for each industry vertical and select the top 10
top_industry_verticals = df['market'].value_counts().nlargest(10).sort_values(ascending=True)

# Create the bar chart
plt.figure(figsize=(10, 6))
top_industry_verticals.plot(kind='barh', color='skyblue')
plt.title('Top 10 Industry Verticals by Number of Funding Deals')
plt.xlabel('Number of Funding Deals')
plt.ylabel('')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```



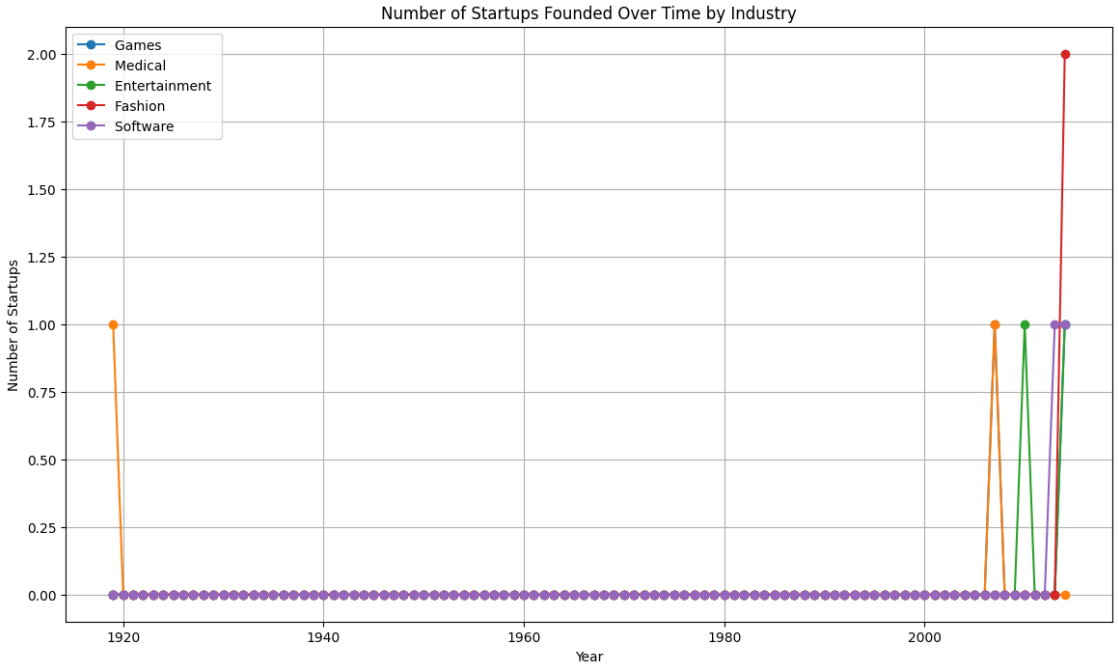
Insights

1. **Software**: Leading with the highest number of funding rounds.
2. **Technology**: Second most active funding rounds.
3. **Clean Technology**: Least significant in terms of funding rounds.

[26]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Filter out unknown markets and get the top 10 industries
top_industries = df[df['market'] != 'unknown']['market'].value_counts().
 ↪head(10).reset_index()

# Print column names of top_industries to confirm
print("Columns in top_industries:", top_industries.columns)

# Use the appropriate column name based on the printed output
industry_column = top_industries.columns[0]  # This should hold the industry␣
 ↪names
top_industries_list = top_industries[industry_column].head(5)

# Group by year and industry, and fill missing values
yearly_industry_count = df.groupby(['year', 'market']).size().unstack().
 ↪fillna(0)

# Reindex to include all years, filling in any gaps
all_years = pd.Index(range(df['year'].min(), df['year'].max() + 1), name='year')
```

```
yearly_industry_count = yearly_industry_count.reindex(all_years, fill_value=0)

# Plotting the line plots for the top industries over time
plt.figure(figsize=(14, 8))
for industry in top_industries_list:
    if industry in yearly_industry_count.columns:  # Check to avoid KeyError
        plt.plot(yearly_industry_count.index, yearly_industry_count[industry],␣
↪marker='o', label=industry)
plt.title('Number of Startups Founded Over Time by Industry')
plt.xlabel('Year')
plt.ylabel('Number of Startups')
plt.legend()
plt.grid(True)
plt.show()
```

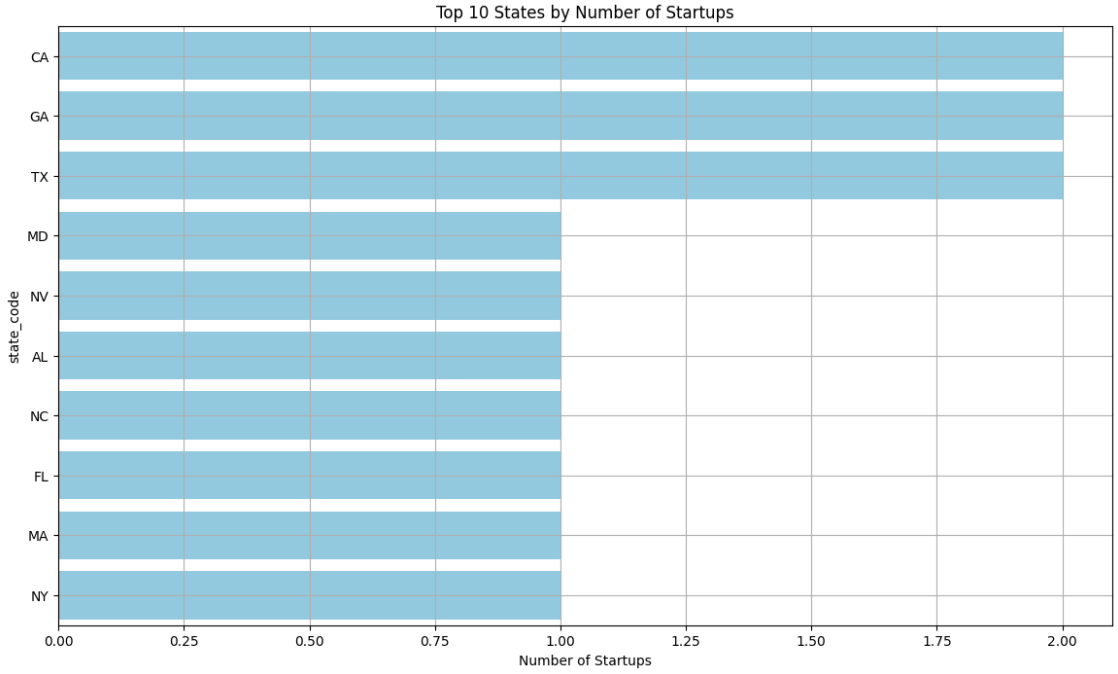
```
Columns in top_industries: Index(['market', 'count'], dtype='object')
```



How does location influence the growth trajectory of a startup?

[27]:
```
# Count the number of startups in each city
top_cities_count = df['state_code'].value_counts().head(10).reset_index()
top_cities_count.columns = ['state_code', 'Count']

# Plot the number of startups by city
plt.figure(figsize=(14, 8))
sns.barplot(x='Count', y='state_code', data=top_cities_count, color='skyblue')
```

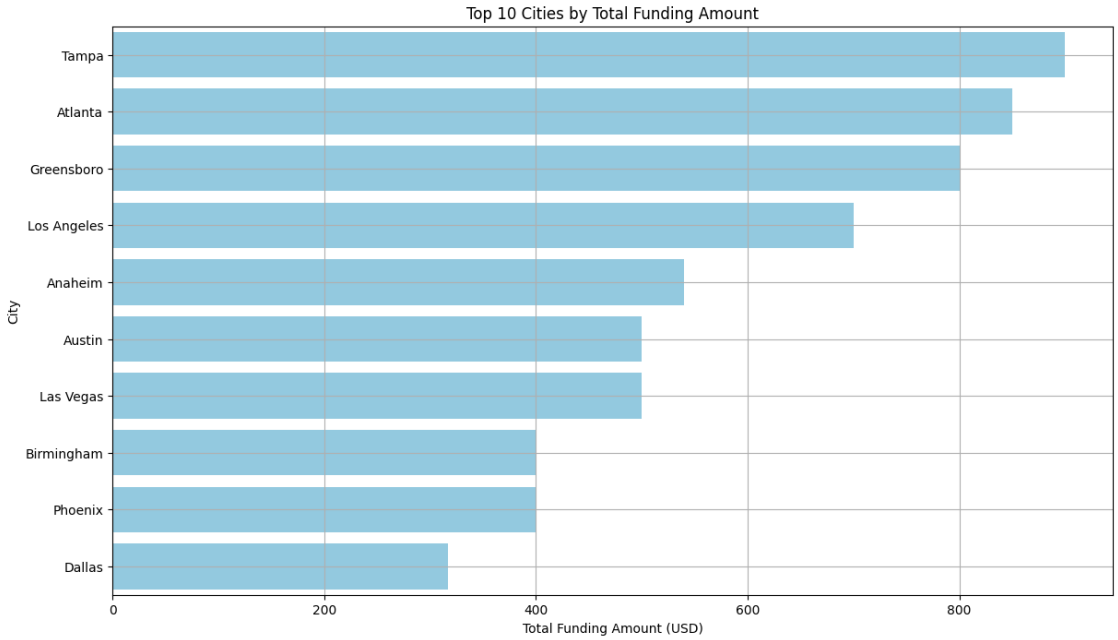
```
plt.title('Top 10 States by Number of Startups')
plt.xlabel('Number of Startups')
plt.ylabel('state_code')
plt.grid(True)
plt.show()
```



Insight

1. Maximum number of startups were in state CA,USA.
2. Minimum number of startups were in state ON,USA.

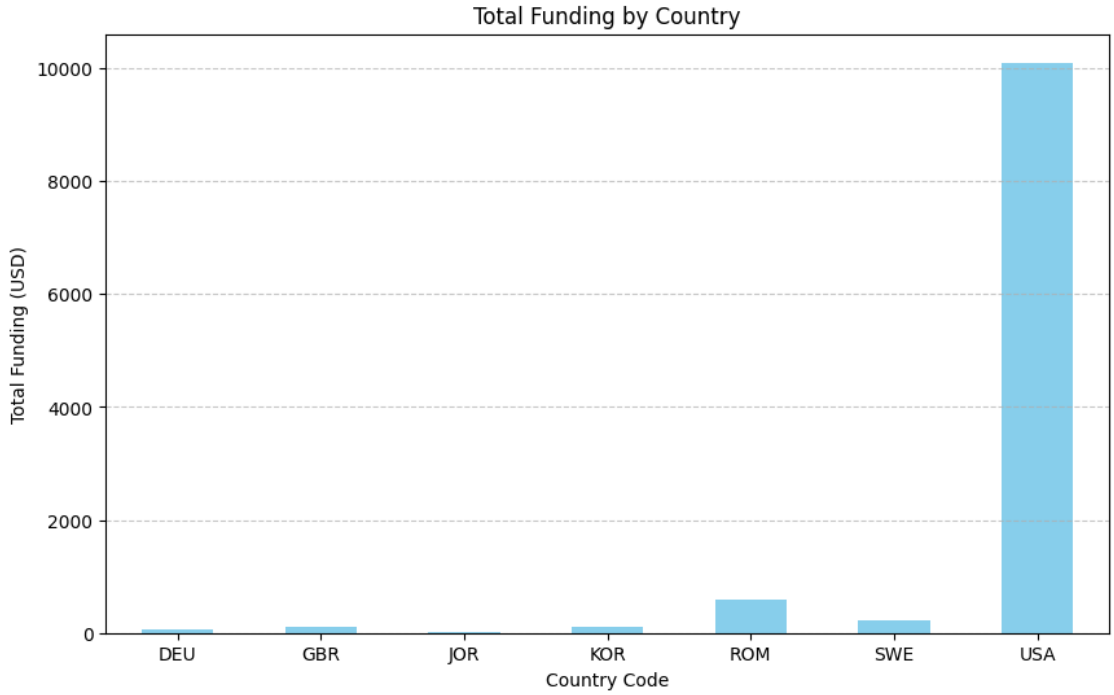
[28]:
```
# Calculate the total funding amount received by startups in each city
top_cities_funding = df.groupby('region')['amount_USD'].sum().reset_index()
top_cities_funding = top_cities_funding.sort_values(by='amount_USD',␣
 ↪ascending=False).head(10)
top_cities_funding.columns = ['City', 'Total Funding Amount']

# Plot the total funding amount by city
plt.figure(figsize=(14, 8))
sns.barplot(x='Total Funding Amount', y='City', data=top_cities_funding,␣
 ↪color='skyblue')
plt.title('Top 10 Cities by Total Funding Amount')
plt.xlabel('Total Funding Amount (USD)')
plt.ylabel('City')
plt.grid(True)
plt.show()
```



Determining total funding across different countries.

[29]:
```
df1 = pd.read_csv("/content/investments_VC.csv", encoding='ISO-8859-1')
df1
# Strip whitespace from all column names
df1.columns = df1.columns.str.strip()

# Rename the column
df1.rename(columns={'funding_total_usd': 'amount_USD1'}, inplace=True)
df1.rename(columns={'founded_month': 'month'}, inplace=True)
df1.rename(columns={'founded_year': 'year'}, inplace=True)

import pandas as pd
import matplotlib.pyplot as plt

# Assuming your DataFrame is called df1 and has columns 'country_code' and␣
 ↪'amount_USD'

# Convert 'amount_USD' to numeric, coerce errors to NaN
df1['amount_USD1'] = pd.to_numeric(df1['amount_USD1'], errors='coerce')

# Drop rows with NaN in 'amount_USD' if any
df1 = df1.dropna(subset=['amount_USD1'])

# Group by 'country_code' and calculate the sum of 'amount_USD' for each country
country_funding = df1.groupby('country_code')['amount_USD1'].sum()
```

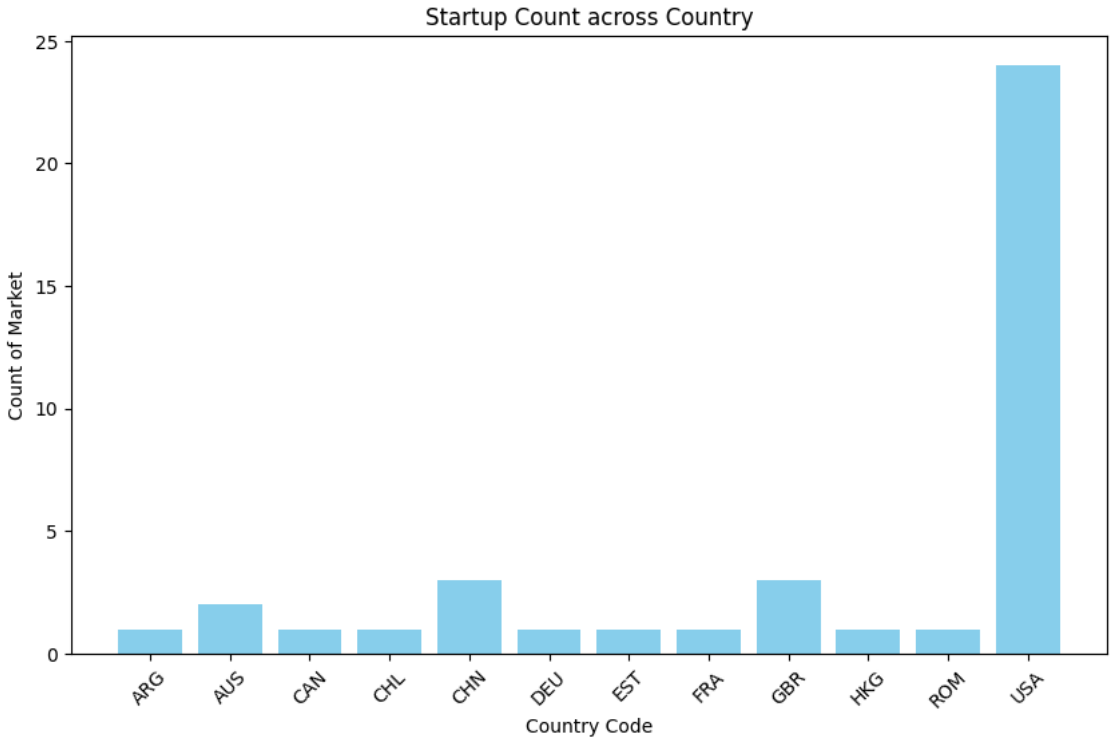
```
# Plotting the bar plot
country_funding.plot(kind='bar', figsize=(10, 6), color='skyblue')

# Adding titles and labels
plt.title('Total Funding by Country')
plt.xlabel('Country Code')
plt.ylabel('Total Funding (USD)')
plt.xticks(rotation=0)  # Rotate x-axis labels for clarity
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



Determining the total number of startups across different countries

[30]:
```
import matplotlib.pyplot as plt

# Sample data
data = {
    'country_code': ['ARG', 'AUS', 'CAN', 'CHL', 'CHN', 'DEU', 'EST', 'FRA',␣
 ↪'GBR', 'HKG', 'ROM', 'USA'],
    'Count of market': [1, 2, 1, 1, 3, 1, 1, 1, 3, 1, 1, 24]
}
```

```
# Create a dataframe
import pandas as pd
df = pd.DataFrame(data)

# Plotting the bar chart
plt.figure(figsize=(10,6))
plt.bar(df['country_code'], df['Count of market'], color='skyblue')
plt.xlabel('Country Code')
plt.ylabel('Count of Market')
plt.title('Startup Count across Country')
plt.xticks(rotation=45)
plt.show()
```



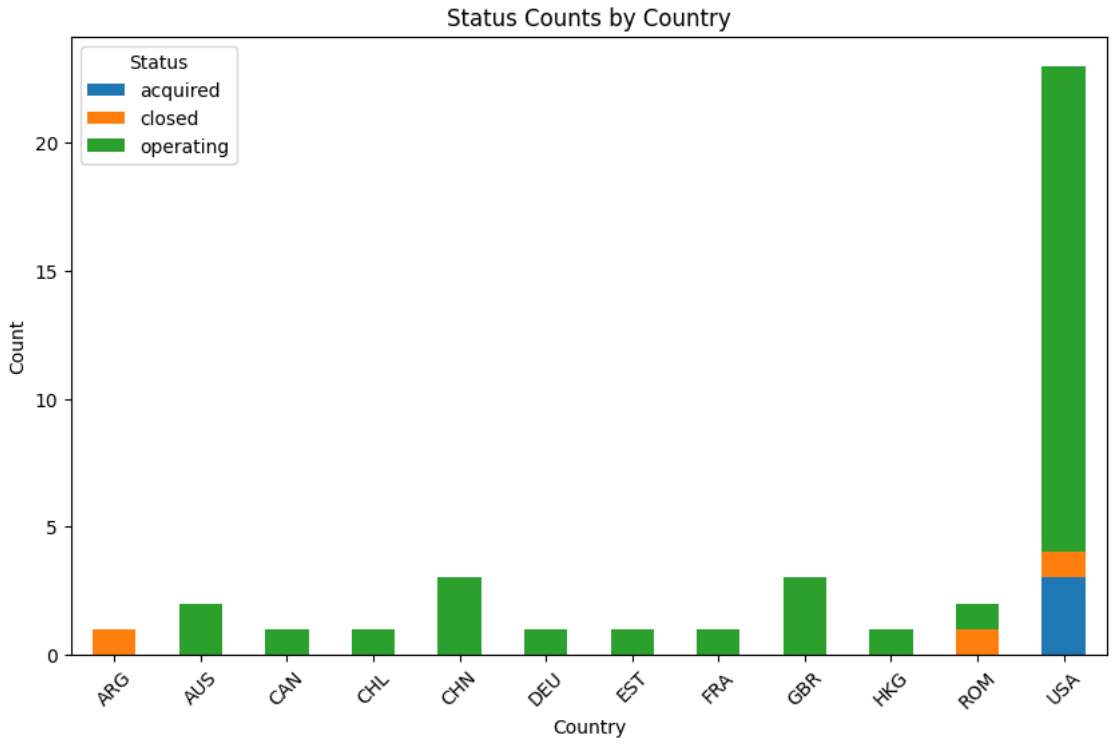
Insights

1. Most of the startups are in healthy and are in opearting phase.
2. A very small portion of startups have been completed closed.

Determining the current status of startups across different countries.

[31]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Define the data
```

```
data = {
    'Country': ['ARG', 'AUS', 'CAN', 'CHL', 'CHN', 'DEU', 'EST', 'FRA', 'GBR',␣
 ↪'HKG', 'ROM', 'USA'],
    'acquired': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3],
    'closed': [1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1],
    'operating': [0, 2, 1, 1, 3, 1, 1, 1, 3, 1, 1, 19]
}

# Convert data to DataFrame
df = pd.DataFrame(data)

# Set 'Country' as index for easy plotting
df.set_index('Country', inplace=True)

# Plotting
df.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Status Counts by Country')
plt.xlabel('Country')
plt.ylabel('Count')
plt.legend(title='Status')
plt.xticks(rotation=45)
plt.show()
```



Insights

1. Argentina contribution in number of startups are very low and almost all of them are in closed sate.
2. USA has maximum number of startups and majority of them are in operating status.

Observations: 1. **Funding Trends Over Time**: A clear trend in the funding levels for startups is observed, with certain years showing marked spikes, reflecting periods of strong investor interest and economic growth. 2. **General Funding Levels**: The analysis highlights a broad spectrum of funding amounts, with a notable share of startups receiving substantial investments. Most startups, however, secured funding within specific ranges, indicating typical investment sizes. 3. **Industry Preferences**: Sectors such as Software, Biotechnology, Mobile, and Curated Web were among the top recipients of funding, suggesting strong investor preference for these industries due to their high growth potential and market demand. 4. **Geographical Influence**: Cities like Tampa, Atlanta, and Greensboro emerged as top locations for startup funding, likely due to their supportive ecosystems, strong infrastructure, and proximity to investors. 5. **Key Players in the Ecosystem**: The analysis identified prominent investors actively contributing to the startup ecosystem. These investors have not only provided capital but also mentorship and networking opportunities, playing a pivotal role in nurturing startup growth. 6. **Types of Funding**: Various funding types, including Seed Funding and Equity Crowdfunding, were identified. Each funding type supports different growth stages, from initial product development to scaling and market expansion.

Recommendations:

1. **For Startups**:

   Target High-Growth Sectors: Focus on sectors with strong investor interest like Software and Biotechnology.
   Leverage Geographic Hubs: Operate in startup-friendly cities to access better funding and resources.
   Diversify Funding Sources: Seek multiple funding types to secure capital at various growth stages.
   Enhance Investor Readiness: Develop solid business plans and market strategies to attract investors.
   Focus on Sustainable Growth: Balance growth with profitability for long-term resilience.
   Cultivate Strong Networks: Attend industry events and competitions to connect with investors and mentors.

2. **For Investors**:

   Monitor Emerging Sectors: Keep abreast of high-growth sectors like AI and Clean Energy.
   Strengthen Ecosystem Infrastructure: Support local incubators and accelerators to develop startup ecosystems.
   Support Diverse Funding Rounds: Participate across different funding stages to diversify risk.
   Prioritize Sustainable Investments: Focus on startups with sustainable, ethical practices aligned with ESG goals.
   Foster Long-Term Partnerships: Offer mentorship and networking to build enduring relationships with startups.

Promote Innovation in New Areas: Invest in underrepresented sectors and regions to diversify and drive innovation.