Funding_in_Startup_EDA

November 23, 2024

1 Funding in startups

Problem Statement * Uncover trends and insights that guide strategic decision-making. Consider analyzing the distribution of funding across different categories, markets, and regions to identify sectors with higher investment potential.

- Explore the correlation between a startup's funding characteristics and its funding success, examining factors such as the funding rounds, funding types, and geographical locations. Additionally, assess the impact of economic factors on funding, and propose strategies for startups to optimize their funding journeys. This project has the potential to offer valuable insights for both aspiring entrepreneurs and investors in the dynamic landscape of startup financing.

[ ]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import re

pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

import warnings
warnings.filterwarnings('ignore')
```

[ ]:
```
#!pip install pandas_profiling
```

[ ]:
```
#from ydata_profiling import ProfileReport
```

[ ]:
```
!gdown 110tJaSocsCTvgqjJ3LyfzZOmhy8woTfP
```

```
Downloading…
From: https://drive.google.com/uc?id=110tJaSocsCTvgqjJ3LyfzZOmhy8woTfP
To: /content/investments_VC.csv
100% 12.5M/12.5M [00:00<00:00, 51.7MB/s]
```

[ ]:
```
df=pd.read_csv('/content/investments_VC.csv',encoding='unicode_escape')
```

[ ]:
```
df.shape
```

[ ]:
```
(54294, 39)
```

DataSet Contains 54294 rows and 39 columns

[ ]:
```
desc = ['Static hyperlink for the startup on Crunchbase\'s website','name of␣
 ↪the startup','Website address of the startup',
      'in which category the startups fall','which market the startup caters␣
 ↪to','total funding received(in USD)',
       'current operating status','country of origin','state of␣
 ↪origin','region','city of origin','total rounds of funding',
       'date of founding','month of founding','quarter of founding','year of␣
 ↪founding','date of first funding','date of last funding',
       'seed funding received(in USD)','venture funding received(in␣
 ↪USD)','funding received by diluting equity',
       'other undisclosed funding sources','funding received from convertible␣
 ↪notes','funding received from debts',
       'funding received from angel investors','funding from grants','funding␣
 ↪from private equity',
       'funding from equity dilution after IPO','funding from debts after␣
 ↪IPO','funding from secondary markets',
       'funding from crowdfunding','round A funding','round B funding','round␣
 ↪C funding','round D funding','round E funding',
      'round F funding','round G funding','round H funding']
df_details = pd.DataFrame(list(zip(df.columns, desc)), columns =['Column',␣
 ↪'Description'])
df_details
```

[ ]:

	Column	Description
0	permalink	Static hyperlink for the startup on Crunchbase…
1	name	name of the startup
2	homepage_url	Website address of the startup
3	category_list	in which category the startups fall
4	market	which market the startup caters to
5	funding_total_usd	total funding received(in USD)
6	status	current operating status
7	country_code	country of origin
8	state_code	state of origin
9	region	region
10	city	city of origin
11	funding_rounds	total rounds of funding
12	founded_at	date of founding
13	founded_month	month of founding
14	founded_quarter	quarter of founding
15	founded_year	year of founding
16	first_funding_at	date of first funding

```
17       last_funding_at                        date of last funding
18                  seed              seed funding received(in USD)
19               venture           venture funding received(in USD)
20  equity_crowdfunding            funding received by diluting equity
21           undisclosed            other undisclosed funding sources
22      convertible_note         funding received from convertible notes
23        debt_financing                  funding received from debts
24                 angel         funding received from angel investors
25                 grant                           funding from grants
26        private_equity                   funding from private equity
27       post_ipo_equity          funding from equity dilution after IPO
28         post_ipo_debt                  funding from debts after IPO
29      secondary_market                 funding from secondary markets
30  product_crowdfunding                     funding from crowdfunding
31               round_A                               round A funding
32               round_B                               round B funding
33               round_C                               round C funding
34               round_D                               round D funding
35               round_E                               round E funding
36               round_F                               round F funding
37               round_G                               round G funding
38               round_H                               round H funding
```

[ ]:
```
df.rename(columns={' funding_total_usd ': 'funding_total_usd',' market ':
 ↪'market'}, inplace=True)
```

[ ]:
```
#ProfileReport(df)
```

[ ]:
```
df=df[~df.isnull().all(axis=1)]
```

[ ]:
```
df.shape
```

[ ]:
```
(49438, 39)
```

[ ]:
```
df.duplicated().sum()
```

[ ]:
```
0
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
permalink                0
name                     1
homepage_url          3449
category_list         3961
market                3968
funding_total_usd        0
status                1314
```

```
country_code               5273
state_code                19277
region                     5273
city                       6116
funding_rounds                0
founded_at                10884
founded_month             10956
founded_quarter           10956
founded_year              10956
first_funding_at              0
last_funding_at               0
seed                          0
venture                       0
equity_crowdfunding           0
undisclosed                   0
convertible_note              0
debt_financing                0
angel                         0
grant                         0
private_equity                0
post_ipo_equity               0
post_ipo_debt                 0
secondary_market              0
product_crowdfunding          0
round_A                       0
round_B                       0
round_C                       0
round_D                       0
round_E                       0
round_F                       0
round_G                       0
round_H                       0
dtype: int64
```

[ ]:
```
round(df.isnull().sum()/len(df)*100,2)
```

[ ]:
```
permalink                  0.00
name                       0.00
homepage_url               6.98
category_list              8.01
market                     8.03
funding_total_usd          0.00
status                     2.66
country_code              10.67
state_code                38.99
region                    10.67
city                      12.37
```

```
funding_rounds           0.00
founded_at              22.02
founded_month           22.16
founded_quarter         22.16
founded_year            22.16
first_funding_at         0.00
last_funding_at          0.00
seed                     0.00
venture                  0.00
equity_crowdfunding      0.00
undisclosed              0.00
convertible_note         0.00
debt_financing           0.00
angel                    0.00
grant                    0.00
private_equity           0.00
post_ipo_equity          0.00
post_ipo_debt            0.00
secondary_market         0.00
product_crowdfunding     0.00
round_A                  0.00
round_B                  0.00
round_C                  0.00
round_D                  0.00
round_E                  0.00
round_F                  0.00
round_G                  0.00
round_H                  0.00
dtype: float64
```

[ ]:

```
df['founded_at'] = pd.to_datetime(df['founded_at'],format='%Y-%m-%d',␣
↪errors='coerce')
df['first_funding_at'] = pd.
↪to_datetime(df['first_funding_at'],format='%Y-%m-%d', errors='coerce')
df['last_funding_at'] = pd.to_datetime(df['last_funding_at'],format='%Y-%m-%d',␣
↪errors='coerce')
```

[ ]:

```
df['funding_total_usd']=df['funding_total_usd'].str.replace(' ','').str.
↪replace(',','').replace('-',np.nan).astype(float)
```

[ ]:

```
df['funding_total_usd'].isnull().sum()
```

[ ]: 8531

[ ]:

```
round(df.isnull().sum()/len(df)*100,2)
```

[ ]:
```
permalink                0.00
name                     0.00
homepage_url             6.98
category_list            8.01
market                   8.03
funding_total_usd       17.26
status                   2.66
country_code            10.67
state_code              38.99
region                  10.67
city                    12.37
funding_rounds           0.00
founded_at              22.02
founded_month           22.16
founded_quarter         22.16
founded_year            22.16
first_funding_at         0.02
last_funding_at          0.01
seed                     0.00
venture                  0.00
equity_crowdfunding      0.00
undisclosed              0.00
convertible_note         0.00
debt_financing           0.00
angel                    0.00
grant                    0.00
private_equity           0.00
post_ipo_equity          0.00
post_ipo_debt            0.00
secondary_market         0.00
product_crowdfunding     0.00
round_A                  0.00
round_B                  0.00
round_C                  0.00
round_D                  0.00
round_E                  0.00
round_F                  0.00
round_G                  0.00
round_H                  0.00
dtype: float64
```

[ ]:
```
# List of funding-related columns to sum
funding_columns = ['seed', 'venture', 'equity_crowdfunding', 'undisclosed',␣
 ↪'convertible_note',
                   'debt_financing', 'angel', 'grant', 'private_equity',␣
 ↪'post_ipo_equity',
```

```
                    'post_ipo_debt', 'secondary_market', 'product_crowdfunding',␣
↪'round_A',
                    'round_B', 'round_C', 'round_D', 'round_E', 'round_F',␣
↪'round_G', 'round_H']

# adding all values of funding columns row wise
df['total_funding_usd'] = df[funding_columns].sum(axis=1)
```

[ ]:
```
df[df['total_funding_usd']==0].sample(10)
```

[ ]:
```
                                  permalink                    name  \
homepage_url                                      category_list  \
market  funding_total_usd     status country_code state_code          region  \
city  funding_rounds founded_at founded_month founded_quarter  founded_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  round_A  \
round_B  round_C  round_D  round_E  round_F  round_G  round_H total_funding_usd
12664                    /organization/easy-food               Easy Food
http://www.easyfood.com.br                 |High Schools|Health and Wellness|
High Schools                   NaN  operating          BRA         NaN  Rio de
Janeiro  Rio De Janeiro             1.0 2011-01-01        2011-01         2011-Q1
2011.0       2013-07-01      2013-07-01   0.0       0.0                    0.0
0.0              0.0              0.0     0.0     0.0               0.0
0.0            0.0                0.0                    0.0       0.0       0.0
0.0      0.0      0.0      0.0      0.0      0.0                0.0
17640                       /organization/gotaxi           GoTaxi(Cabeo)
http://cabeo.it                                                   |Travel|
Travel                 NaN  operating          ITA         NaN            Milan
Milan              1.0 2012-05-01       2012-05          2012-Q2        2012.0
2013-09-13      2013-09-13   0.0      0.0                    0.0           0.0
0.0              0.0     0.0     0.0                0.0                0.0
0.0              0.0                   0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                  0.0
23615                     /organization/leadjini                 Leadjini
http://www.leadjini.com   |Advertising|Optimization|SEO|Lead Generation|…
Optimization                   NaN  operating          NaN         NaN
NaN              NaN              1.0 2009-03-01        2009-03          2009-Q1
2009.0        2009-03-01      2009-03-01   0.0       0.0                    0.0
0.0              0.0              0.0     0.0     0.0               0.0
0.0            0.0                0.0                    0.0       0.0       0.0
0.0      0.0      0.0      0.0      0.0      0.0                0.0
49183                       /organization/zinkia                   Zinkia
http://www.zinkia.com              |Brand Marketing|Entertainment|Games|   Brand
Marketing                   NaN  operating          ESP         NaN          Madrid
Madrid                1.0          NaT              NaN             NaN          NaN
2012-09-07      2012-09-07   0.0      0.0                    0.0           0.0
```

```
0.0             0.0    0.0    0.0              0.0               0.0
0.0               0.0                  0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                 0.0
18934                /organization/heyshops              Heyshops
http://heyshops.com                                             NaN
NaN                NaN  operating         DEU        NaN          Berlin
NaN             1.0 2014-01-01       2014-01         2014-Q1        2014.0
2014-01-01      2014-01-01   0.0      0.0                  0.0          0.0
0.0             0.0    0.0    0.0              0.0               0.0
0.0               0.0                  0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                 0.0
31823           /organization/pencil-you-in          Pencil You In
http://pencilyou.in                                             NaN
NaN                NaN  operating         NaN        NaN             NaN
NaN             1.0 2008-01-01       2008-01         2008-Q1        2008.0
2011-08-04      2011-08-04   0.0      0.0                  0.0          0.0
0.0             0.0    0.0    0.0              0.0               0.0
0.0               0.0                  0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                 0.0
8839   /organization/cloud-nine-productions  Cloud Nine Productions
http://www.cnine.com/                              |Entertainment|Games|
Entertainment                 NaN  operating         USA        CO
Denver          Denver             1.0 2012-07-22       2012-07         2012-Q3
2012.0       2012-07-22      2012-07-22   0.0      0.0                 0.0
0.0               0.0              0.0    0.0    0.0              0.0
0.0             0.0                0.0                  0.0      0.0      0.0
0.0      0.0      0.0      0.0      0.0      0.0               0.0
18904                   /organization/heroz                   HEROZ
http://heroz.co.jp/                    |Mobile|Mobile Commerce|Media|   Mobile
Commerce                 NaN  operating         NaN        NaN             NaN
NaN             1.0 2009-01-01       2009-01         2009-Q1        2009.0
2009-06-01      2009-06-01   0.0      0.0                  0.0          0.0
0.0             0.0    0.0    0.0              0.0               0.0
0.0               0.0                  0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                 0.0
41013             /organization/stylepuzzle            StylePuzzle
http://stylepuzzle.com                        |Shopping|Lifestyle|Fashion|
Fashion                 NaN  operating         USA         CA     SF Bay Area
Sunnyvale             1.0 2014-06-01       2014-06         2014-Q2        2014.0
2014-06-13      2014-06-13   0.0      0.0                  0.0          0.0
0.0             0.0    0.0    0.0              0.0               0.0
0.0               0.0                  0.0      0.0      0.0      0.0      0.0
0.0      0.0      0.0      0.0                 0.0
46612         /organization/volaris-advisors        Volaris Advisors
NaN                                                 NaN                NaN
NaN  operating          USA         NY   New York City        New York
1.0        NaT           NaN             NaN           NaN       2000-03-20
```

```
2000-03-20    0.0      0.0                     0.0           0.0                 0.0
0.0     0.0     0.0               0.0                   0.0              0.0
0.0                     0.0      0.0      0.0      0.0      0.0      0.0      0.0
0.0       0.0                   0.0
```

[ ]:
```
len(df[(df['total_funding_usd']==0) & (df['funding_total_usd'].isnull())])
```

[ ]:
```
8531
```

[ ]:
```
# since sum is 0 for all funding columns, nan value in funding_total_usd is␣
↪replaced by 0
df['funding_total_usd']=df['funding_total_usd'].replace(np.nan,0)
```

[ ]:
```
df['funding_total_usd'].isnull().sum()
```

[ ]:
```
0
```

[ ]:
```
df['name'].nunique()
```

[ ]:
```
49350
```

[ ]:
```
df['funding_total_usd'].sum()
```

[ ]:
```
650933703144.0
```

[ ]:
```
df[['name', 'funding_total_usd']].sort_values(by='funding_total_usd',␣
↪ascending=False).head(5).assign(
    funding_total_usd=lambda x: x['funding_total_usd'].apply(lambda y: f"{y:,.
↪0f}"))
```

[ ]:

	name	funding_total_usd
45815	Verizon Communications	30,079,503,000
36911	Sberbank	5,800,000,000
8664	Clearwire	5,700,000,000
7977	Charter Communications	5,162,513,431
15315	First Data Corporation	3,500,000,000

[ ]:
```
# Function to print basic useful details for a given column
def get_column_details(df,column):
    print("Details of",column,"column")

    #DataType of column
    print("\nDataType: ",df[column].dtype)

    #Check if null values are present
    count_null = df[column].isnull().sum()
    if count_null==0:
```

```
        print("\nThere are no null values")
    elif count_null>0:
        print("\nThere are ",count_null," null values")

    #Get Number of Unique Values
    print("\nNumber of Unique Values: ",df[column].nunique())

    #Get Distribution of Column
    print("\nDistribution of column:\n")
    print(df[column].value_counts())
```

[ ]:
```
get_column_details(df,'market')
```

```
Details of market column

DataType:  object

There are  3968  null values

Number of Unique Values:  753

Distribution of column:

market
Software                4620
Biotechnology           3688
Mobile                  1983
E-Commerce              1805
Curated Web             1655
                        …
Contact Centers            1
Swimming                   1
Retirement                 1
Musical Instruments        1
Rural Energy               1
Name: count, Length: 753, dtype: int64
```

[ ]:
```
get_column_details(df,'status')
```

```
Details of status column

DataType:  object

There are  1314  null values

Number of Unique Values:  3
```

```
Distribution of column:

status
operating    41829
acquired      3692
closed        2603
Name: count, dtype: int64
```

[ ]:
```python
get_column_details(df,'country_code')
```

```
Details of country_code column

DataType:  object

There are  5273  null values

Number of Unique Values:  115

Distribution of column:

country_code
USA    28793
GBR     2642
CAN     1405
CHN     1239
DEU      968
FRA      866
IND      849
ISR      682
ESP      549
RUS      368
SWE      315
AUS      314
ITA      308
NLD      307
IRL      306
SGP      299
BRA      293
CHL      285
JPN      284
KOR      246
CHE      222
DNK      210
FIN      194
BEL      149
ARG      149
HKG      126
TUR      124
```

AUT	103
NOR	98
POL	94
MEX	83
PRT	69
BGR	68
ARE	66
NZL	62
ZAF	52
IDN	52
CZE	51
MYS	48
UKR	45
EST	44
HUN	42
TWN	41
THA	38
COL	35
PHL	32
GRC	31
LTU	31
PER	30
NGA	29
KEN	24
EGY	23
LUX	22
ROM	22
VNM	21
JOR	20
DZA	20
PAK	18
ISL	16
SVK	15
LBN	13
CYP	12
LVA	12
URY	12
CYM	11
SVN	11
GHA	11
UGA	10
SRB	10
KHM	10
HRV	8
BGD	7
SAU	7
TZA	7
CRI	6

```
PAN        5
BMU        4
GTM        4
BWA        4
MAR        3
BHR        3
BLR        3
AZE        3
TUN        3
SLV        3
DOM        3
MLT        3
GIB        2
MKD        2
KWT        2
MMR        2
NIC        2
ECU        2
MDA        2
NPL        2
BHS        2
CMR        2
LAO        2
ARM        2
TTO        1
JAM        1
SYC        1
SOM        1
CIV        1
MUS        1
OMN        1
JEY        1
UZB        1
ZWE        1
MCO        1
ALB        1
MOZ        1
LIE        1
BRN        1
MAF        1
Name: count, dtype: int64
```

[ ]:
```
get_column_details(df,'state_code')
```

```
Details of state_code column

DataType:  object
```

```
There are  19277  null values

Number of Unique Values:  61

Distribution of column:

state_code
CA    9917
NY    2914
MA    1969
TX    1466
WA     974
FL     963
IL     827
PA     792
CO     723
ON     653
NJ     579
VA     553
GA     541
OH     532
MD     493
NC     476
TN     411
UT     365
MN     355
AZ     327
BC     318
CT     316
MI     313
OR     312
IN     233
MO     220
QC     219
NV     195
WI     191
DC     182
AR     177
SC     125
AB     115
KY     113
NH     112
AL     105
RI     104
KS      94
IA      78
LA      78
OK      76
```

```
NM      75
NE      75
DE      71
ID      56
HI      54
ME      52
VT      48
NS      42
MS      32
MT      30
NL      20
WY      17
WV      15
ND      15
SD      14
MB      13
AK      12
NB       8
SK       4
PE       2
Name: count, dtype: int64
```

[ ]:
```
get_column_details(df,'region')
```

```
Details of region column

DataType:  object

There are  5273  null values

Number of Unique Values:  1089

Distribution of column:

region
SF Bay Area        6804
New York City      2577
Boston             1837
London             1588
Los Angeles        1389
                   …
Palma Del Río         1
Harbin                1
Teddington            1
Borehamwood           1
Buckinghamshire       1
Name: count, Length: 1089, dtype: int64
```

[ ]:
```
get_column_details(df,'city')
```

```
Details of city column

DataType:  object

There are  6116  null values

Number of Unique Values:  4188

Distribution of column:

city
San Francisco            2615
New York                 2334
London                   1257
Palo Alto                 597
Austin                    583
                         …
Richmond Upon Thames        1
Kunming                     1
Browns Mills                1
Paducah                     1
Damansara New Village       1
Name: count, Length: 4188, dtype: int64
```

[ ]:
```
df['country_code'].isnull().sum()
```

[ ]: 5273

[ ]:
```
df.isnull().sum()/len(df)*100
```

[ ]:
```
permalink              0.000000
name                   0.002023
homepage_url           6.976415
category_list          8.012056
market                 8.026215
funding_total_usd      0.000000
status                 2.657875
country_code          10.665885
state_code            38.992273
region                10.665885
city                  12.371051
funding_rounds         0.000000
founded_at            22.017476
founded_month         22.161091
founded_quarter       22.161091
```

```
founded_year             22.161091
first_funding_at          0.020227
last_funding_at           0.012136
seed                      0.000000
venture                   0.000000
equity_crowdfunding       0.000000
undisclosed               0.000000
convertible_note          0.000000
debt_financing            0.000000
angel                     0.000000
grant                     0.000000
private_equity            0.000000
post_ipo_equity           0.000000
post_ipo_debt             0.000000
secondary_market          0.000000
product_crowdfunding      0.000000
round_A                   0.000000
round_B                   0.000000
round_C                   0.000000
round_D                   0.000000
round_E                   0.000000
round_F                   0.000000
round_G                   0.000000
round_H                   0.000000
total_funding_usd         0.000000
dtype: float64
```

[ ]:
```
ddf=df.copy()
```

[ ]:
```
# Function to extract TLD
def extract_country_domain(url):
    if pd.isna(url):
        return None
    match = re.search(r'\.([a-z]{2,3})/$', url) or re.search(r'\.([a-z]{2,3})(/
↪|$)', url)
    if match:
        tld = match.group(1)
        return tld.lower()
    return None
```

2 Replacing null values in Country Code column by country domain

[ ]:
```
df['country_domain'] = df['homepage_url'].apply(extract_country_domain)
```

[ ]:
```
df['country_domain'].unique()
```

[ ]:
```
array(['com', 'org', None, 'de', 'hk', 'tv', 'ec', 'br', 'io', 'net',
       'cn', 'ru', 'uk', 'fr', 'be', 'se', 'au', 'nz', 'it', 'es', 'co',
       'me', 'hu', 'biz', 'kr', 'to', 'fi', 'us', 'cc', 'jp', 'ae', 'in',
       'ee', 'edu', 'za', 'ro', 'ca', 'kh', 'dk', 'nl', 'eu', 'st', 'cz',
       'ly', 'pt', 'is', 'ph', 'ci', 'ie', 'tr', 'lt', 'pl', 'pa', 'cl',
       'ni', 'al', 'la', 'vn', 'ch', 'do', 'fm', 'mx', 'il', 'sh', 'gov',
       'pro', 'my', 'ai', 'as', 'sm', 'jo', 'li', 'no', 'sg', 'ar', 'gh',
       'ke', 'ad', 'ge', 'md', 'sx', 'tn', 'mp', 'pe', 'id', 'rs', 'am',
       'vc', 'im', 'cm', 'pw', 'gr', 'ws', 'bg', 'by', 'sc', 'lu', 'hiv',
       're', 'ua', 'gt', 'nr', 'at', 'pk', 'zw', 'eg', 'uy', 'tw', 'ma',
       've', 'gs', 'tt', 'lv', 'tk', 'th', 'ng', 'hr', 'sk', 'ms', 'ag',
       'gl', 'ps', 'cx', 'sr', 'ht', 'gy', 'ug', 'bz', 'nu', 'ki', 'lk',
       'hom', 'pr', 'bo', 'mn', 'hp', 'hm', 'sl', 'su', 'cr', 'pm', 'gg',
       'dj', 'bs', 'az', 'mu', 'xyz', 'gi', 'dm'], dtype=object)
```

[ ]:
```
tld_country_map = {
    'de': 'DEU', 'hk': 'HKG', 'tv': 'TUV', 'ec': 'ECU', 'br': 'BRA', 'io':␣
 ↪'IOT',
    'cn': 'CHN', 'ru': 'RUS', 'uk': 'GBR', 'fr': 'FRA', 'be': 'BEL', 'se':␣
 ↪'SWE',
    'au': 'AUS', 'nz': 'NZL', 'it': 'ITA', 'es': 'ESP', 'co': 'COL', 'me':␣
 ↪'MNE',
    'hu': 'HUN', 'kr': 'KOR', 'to': 'TON', 'fi': 'FIN', 'us': 'USA', 'cc':␣
 ↪'CCK',
    'jp': 'JPN', 'ae': 'ARE', 'in': 'IND', 'ee': 'EST', 'za': 'ZAF', 'ro':␣
 ↪'ROU',
    'ca': 'CAN', 'kh': 'KHM', 'dk': 'DNK', 'nl': 'NLD', 'eu': 'EUR', 'st':␣
 ↪'STP',
    'cz': 'CZE', 'ly': 'LBY', 'pt': 'PRT', 'is': 'ISL', 'ph': 'PHL', 'ci':␣
 ↪'CIV',
    'ie': 'IRL', 'tr': 'TUR', 'lt': 'LTU', 'pl': 'POL', 'pa': 'PAN', 'cl':␣
 ↪'CHL',
    'ni': 'NIC', 'al': 'ALB', 'la': 'LAO', 'vn': 'VNM', 'ch': 'CHE', 'do':␣
 ↪'DOM',
    'fm': 'FSM', 'mx': 'MEX', 'il': 'ISR', 'sh': 'SHN', 'my': 'MYS', 'ai':␣
 ↪'AIA',
    'as': 'ASM', 'sm': 'SMR', 'jo': 'JOR', 'li': 'LIE', 'no': 'NOR', 'sg':␣
 ↪'SGP',
    'ar': 'ARG', 'gh': 'GHA', 'ke': 'KEN', 'ad': 'AND', 'ge': 'GEO', 'md':␣
 ↪'MDA',
    'sx': 'SXM', 'tn': 'TUN', 'mp': 'MNP', 'pe': 'PER', 'id': 'IDN', 'rs':␣
 ↪'SRB',
    'am': 'ARM', 'vc': 'VCT', 'im': 'IMN', 'cm': 'CMR', 'pw': 'PLW', 'gr':␣
 ↪'GRC',
    'ws': 'WSM', 'bg': 'BGR', 'by': 'BLR', 'sc': 'SYC', 'lu': 'LUX', 're':␣
 ↪'REU',
```

```
    'ua': 'UKR', 'gt': 'GTM', 'nr': 'NRU', 'at': 'AUT', 'pk': 'PAK', 'zw':␣
 ↪'ZWE',
    'eg': 'EGY', 'uy': 'URY', 'tw': 'TWN', 'ma': 'MAR', 've': 'VEN', 'gs':␣
 ↪'SGS',
    'tt': 'TTO', 'lv': 'LVA', 'tk': 'TKL', 'th': 'THA', 'ng': 'NGA', 'hr':␣
 ↪'HRV',
    'sk': 'SVK', 'ms': 'MSR', 'ag': 'ATG', 'gl': 'GRL', 'ps': 'PSE', 'cx':␣
 ↪'CXR',
    'sr': 'SUR', 'ht': 'HTI', 'gy': 'GUY', 'ug': 'UGA', 'bz': 'BLZ', 'nu':␣
 ↪'NIU',
    'ki': 'KIR', 'lk': 'LKA', 'pr': 'PRI', 'bo': 'BOL', 'mn': 'MNG', 'hm':␣
 ↪'HMD',
    'sl': 'SLE', 'su': 'SUN', 'cr': 'CRI', 'pm': 'SPM', 'gg': 'GGY', 'dj':␣
 ↪'DJI',
    'bs': 'BHS', 'az': 'AZE', 'mu': 'MUS',  'gi': 'GIB', 'dm': 'DMA'
}
```

[ ]:
```
domain_country = {k:v for k, v in tld_country_map.items()}
```

[ ]:
```
df['country_code'] = df['country_code'].fillna(df['country_domain'].
 ↪map(domain_country))
```

[ ]:
```
df['country_code'].isnull().sum()
```

[ ]:
```
4418
```

[ ]:
```
df['country_code'].unique()
```

[ ]:
```
array(['USA', 'EST', 'GBR', 'ARG', nan, 'HKG', 'CHL', 'DEU', 'FRA', 'CHN',
       'CAN', 'ECU', 'AUS', 'BRA', 'ROM', 'NLD', 'SWE', 'RUS', 'DNK',
       'IND', 'SGP', 'NOR', 'BEL', 'IRL', 'ITA', 'ISR', 'ESP', 'THA',
       'NZL', 'CZE', 'CHE', 'COL', 'HUN', 'JPN', 'BWA', 'KOR', 'NGA',
       'MNE', 'FIN', 'TUR', 'CCK', 'ARE', 'CRI', 'PRT', 'ZAF', 'TWN',
       'KHM', 'UKR', 'LTU', 'AUT', 'STP', 'PHL', 'ISL', 'BGR', 'URY',
       'HRV', 'KEN', 'MEX', 'JOR', 'VNM', 'GHA', 'PER', 'POL', 'IDN',
       'PAN', 'LVA', 'IOT', 'ALB', 'UGA', 'LBN', 'GRC', 'FSM', 'PAK',
       'EGY', 'SVK', 'LUX', 'MYS', 'DOM', 'BHS', 'TUV', 'LIE', 'ARM',
       'DZA', 'MDA', 'EUR', 'TUN', 'LAO', 'NIC', 'TZA', 'CYP', 'NPL',
       'GEO', 'BHR', 'CMR', 'ASM', 'SRB', 'SAU', 'CYM', 'BRN', 'IMN',
       'SLV', 'MLT', 'SVN', 'BLR', 'ZWE', 'LBY', 'TTO', 'MAR', 'VEN',
       'SGS', 'MMR', 'TON', 'BGD', 'BMU', 'ATG', 'ROU', 'MOZ', 'NIU',
       'GTM', 'PRI', 'AZE', 'MCO', 'UZB', 'SPM', 'OMN', 'JEY', 'REU',
       'JAM', 'VCT', 'KWT', 'MUS', 'CIV', 'WSM', 'SOM', 'MKD', 'GIB',
       'NRU', 'SYC', 'MAF'], dtype=object)
```

[ ]:
```
df['country_code'].value_counts()
```

[ ]:
```
country_code
USA    28817
GBR     2696
CAN     1418
CHN     1293
DEU      998
FRA      878
IND      860
ISR      686
ESP      560
RUS      469
BRA      341
ITA      333
AUS      327
SWE      323
NLD      314
IRL      312
JPN      304
SGP      300
CHL      289
KOR      253
CHE      224
DNK      217
FIN      196
BEL      153
ARG      152
COL      136
HKG      129
TUR      124
AUT      105
NOR      100
POL       98
MEX       90
PRT       71
BGR       69
ARE       68
NZL       65
ZAF       57
IOT       57
CZE       53
MNE       53
IDN       53
MYS       51
EST       46
UKR       46
HUN       44
TWN       43
```

THA	38
PHL	33
GRC	32
LTU	32
NGA	31
PER	30
TUV	25
KEN	25
EGY	23
LUX	22
VNM	22
ROM	22
DZA	20
JOR	20
ISL	19
PAK	18
SVK	16
LBN	13
CYP	12
LVA	12
URY	12
GHA	11
SVN	11
CYM	11
UGA	10
KHM	10
FSM	10
SRB	10
EUR	9
LBY	9
CCK	8
HRV	8
SAU	7
BGD	7
DOM	7
CRI	7
TZA	7
ARM	6
PAN	6
BLR	6
TON	5
MDA	5
LAO	5
AZE	4
GTM	4
BWA	4
TUN	4

```
LIE        4
BMU        4
REU        3
MLT        3
MAR        3
ALB        3
ECU        3
STP        3
SLV        3
IMN        3
BHR        3
KWT        2
MMR        2
MKD        2
ATG        2
NIC        2
SGS        2
GIB        2
ZWE        2
CMR        2
GEO        2
NPL        2
BHS        2
NRU        1
SYC        1
SOM        1
WSM        1
CIV        1
MUS        1
VCT        1
JAM        1
ASM        1
JEY        1
OMN        1
SPM        1
UZB        1
MCO        1
PRI        1
NIU        1
MOZ        1
ROU        1
VEN        1
TTO        1
BRN        1
MAF        1
Name: count, dtype: int64
```

[ ]:
```
df.isnull().sum()/len(df)*100
```

[ ]:
```
permalink                0.000000
name                     0.002023
homepage_url             6.976415
category_list            8.012056
market                   8.026215
funding_total_usd        0.000000
status                   2.657875
country_code             8.936446
state_code              38.992273
region                  10.665885
city                    12.371051
funding_rounds           0.000000
founded_at              22.017476
founded_month           22.161091
founded_quarter         22.161091
founded_year            22.161091
first_funding_at         0.020227
last_funding_at          0.012136
seed                     0.000000
venture                  0.000000
equity_crowdfunding      0.000000
undisclosed              0.000000
convertible_note         0.000000
debt_financing           0.000000
angel                    0.000000
grant                    0.000000
private_equity           0.000000
post_ipo_equity          0.000000
post_ipo_debt            0.000000
secondary_market         0.000000
product_crowdfunding     0.000000
round_A                  0.000000
round_B                  0.000000
round_C                  0.000000
round_D                  0.000000
round_E                  0.000000
round_F                  0.000000
round_G                  0.000000
round_H                  0.000000
total_funding_usd        0.000000
country_domain           7.253530
dtype: float64
```

[ ]:
```
df[['region','country_code']]
```

```
[ ]:              region country_code
     0      New York City          USA
     1        Los Angeles          USA
     2            Tallinn          EST
     3             London          GBR
     4             Dallas          USA
     …                  …            …
     49433         London          GBR
     49434        Beijing          CHN
     49435          Split          HRV
     49436            NaN          NaN
     49437  New York City          USA

     [49438 rows x 2 columns]
```

```
[ ]: df['region'] = df.groupby(['country_code'])['region'].transform(lambda x: x.
      ↪fillna(x.mode()[0] if not x.mode().empty else 'Unknown'))
```

```
[ ]: df['region'].isnull().sum()/len(df)*100
```

```
[ ]: 8.936445649095837
```

```
[ ]: df['region'].value_counts()
```

```
[ ]: region
     SF Bay Area        6828
     New York City      2577
     Boston             1837
     London             1642
     Los Angeles        1389
                        …
     Maple Ridge           1
     Santander             1
     Leicestershire        1
     Leverkusen            1
     Buckinghamshire       1
     Name: count, Length: 1090, dtype: int64
```

```
[ ]: df[['founded_at','founded_year']].dtypes
```

```
[ ]: founded_at      datetime64[ns]
     founded_year           float64
     dtype: object
```

```
[ ]: df['founded_year'] = df['founded_year'].astype('datetime64[ns]')
```

```
[ ]: df['founded_year'].isnull().sum()
```

[ ]: 10956

[ ]:
```
df['founded_at'].isnull().sum()
```

[ ]: 10885

[ ]:
```
df['founded_year'] = df['founded_year'].fillna(df['founded_at'].dt.year)
```

[ ]:
```
df['founded_year'].isnull().sum()/len(df)*100
```

[ ]: 22.01747643513087

[ ]:
```
df['founded_at'].isnull().sum()/len(df)*100
```

[ ]: 22.01747643513087

[ ]:
```
df['founded_at'].value_counts()
```

[ ]:
```
founded_at
2012-01-01    2181
2011-01-01    2161
2010-01-01    1855
2009-01-01    1603
2013-01-01    1575
              …
2006-06-19       1
2002-11-20       1
2008-08-26       1
2003-05-29       1
2012-05-13       1
Name: count, Length: 3368, dtype: int64
```

[ ]:
```
df.isnull().sum()/len(df)*100
```

[ ]:
```
permalink                0.000000
name                     0.002023
homepage_url             6.976415
category_list            8.012056
market                   8.026215
funding_total_usd        0.000000
status                   2.657875
country_code             8.936446
state_code              38.992273
region                   8.936446
city                    12.371051
funding_rounds           0.000000
founded_at              22.017476
```

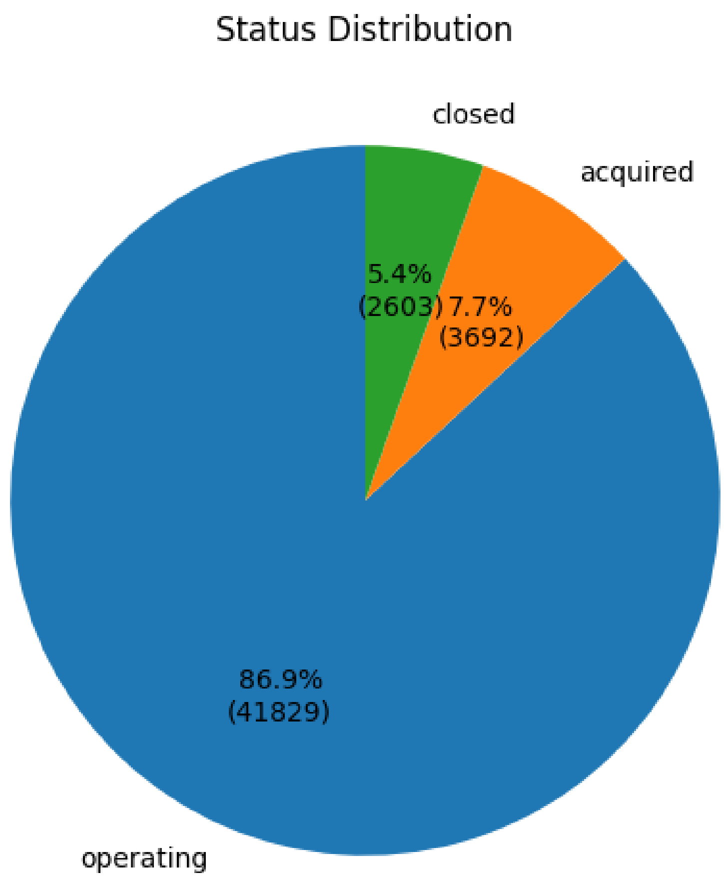
```
founded_month            22.161091
founded_quarter          22.161091
founded_year             22.017476
first_funding_at          0.020227
last_funding_at           0.012136
seed                      0.000000
venture                   0.000000
equity_crowdfunding       0.000000
undisclosed               0.000000
convertible_note          0.000000
debt_financing            0.000000
angel                     0.000000
grant                     0.000000
private_equity            0.000000
post_ipo_equity           0.000000
post_ipo_debt             0.000000
secondary_market          0.000000
product_crowdfunding      0.000000
round_A                   0.000000
round_B                   0.000000
round_C                   0.000000
round_D                   0.000000
round_E                   0.000000
round_F                   0.000000
round_G                   0.000000
round_H                   0.000000
total_funding_usd         0.000000
country_domain            7.253530
dtype: float64
```

[ ]:
```
df['status'].value_counts()
```

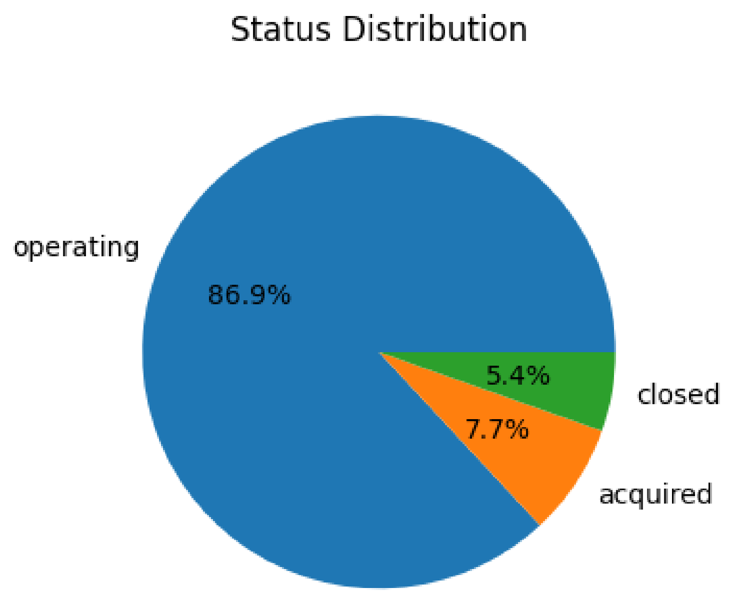
[ ]:
```
status
operating    41829
acquired      3692
closed        2603
Name: count, dtype: int64
```

[ ]:
```
plt.figure(figsize=(8, 6))

# Define a custom function to show both percentage and count
def autopct_format(pct, all_vals):
    total = sum(all_vals)
    val = int(round(pct * total / 100.0))  # Calculate the original value
    return f'{pct:.1f}%\n({val})'          # Format to show percentage and value

# Plot the pie chart
```

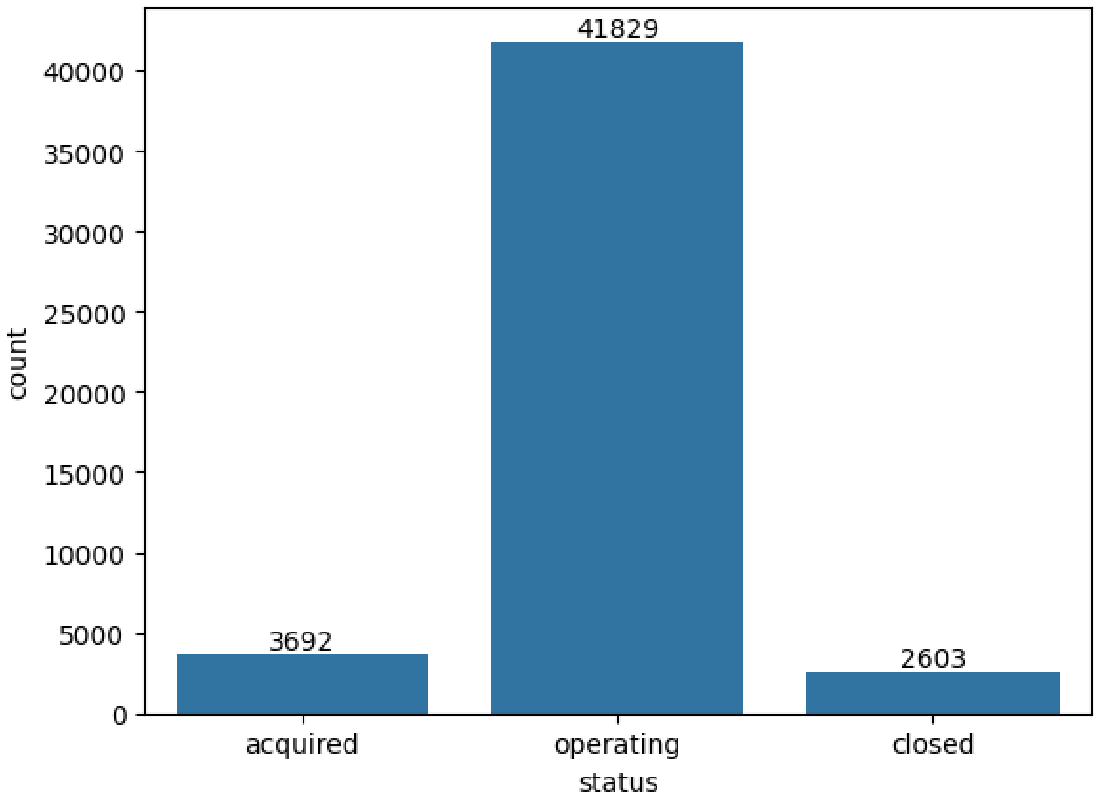
```
counts = df['status'].value_counts()  # Get the counts of each status
plt.pie(counts,
        labels=counts.index,
        autopct=lambda pct: autopct_format(pct, counts),
        startangle=90)
plt.title('Status Distribution')
plt.show()
```



[ ]:
```
plt.figure(figsize=(6,4))
plt.pie(df['status'].value_counts(), labels=df['status'].value_counts().index,␣
↪autopct='%1.1f%%')
plt.title('Status Distribution')
plt.show()
```



[ ]:
```
ax=sns.countplot(x='status',data=df)
for bars in ax.containers:
    ax.bar_label(bars)
```



30107 startups are currently operational and 2870 startups have been acquired and 1540 startups have shut down

3 Total Funding, Average Funding, Funding Count and Funding distribution by Market

[ ]:
```
def funding_statistics(data, group_by_cols, funding_col='funding_total_usd'):
    """
    This function calculates total funding, average funding, and funding␣
↪distribution statistics
    for specified grouping columns.

    Parameters:
    data (pd.DataFrame): The DataFrame containing the data.
    group_by_cols (list): List of columns to group by (e.g., ['market'],␣
↪['country'], ['region', 'state'], etc.).
    funding_col (str): The column name for funding data (default is␣
↪'funding_total_usd').

    Returns:
```

```
    pd.DataFrame: A DataFrame with the total funding, average funding, and␣
↪funding distribution.
    """

    # Check if funding column contains valid numeric data
    data[funding_col] = pd.to_numeric(data[funding_col], errors='coerce')

    # Group by the specified columns and calculate total and average funding
    funding_summary = data.groupby(group_by_cols)[funding_col].agg(
        total_funding='sum',  # Sum of funding
        avg_funding='mean',   # Average funding
        funding_count='count' # Count of funding instances
    ).reset_index()

    # Calculate the funding distribution (percentage share of each group)
    total_funding_all = funding_summary['total_funding'].sum()
    funding_summary['funding_distribution'] =(funding_summary['total_funding'] /
↪ total_funding_all) * 100
    #funding_summary['funding_distribution'] =␣
↪funding_summary['funding_distribution'].map('{:.3f}%'.format)
    #funding_summary['avg_funding'] = funding_summary['avg_funding'].
↪apply(lambda x: f"{x:,.2f}")
    #funding_summary['total_funding'] = funding_summary['total_funding'].
↪apply(lambda x: f"{x:,.2f}")

    return funding_summary
```

[ ]:
```
# For total funding, average funding, and distribution by market
market_funding_stats = funding_statistics(df, ['market'])
market_funding_stats
```

[ ]:
```
               market  total_funding   avg_funding  funding_count
funding_distribution
0                  3D     98325062.0  3.933002e+06             25
0.015723
1         3D Printing     32454000.0  3.606000e+06              9
0.005190
2       3D Technology     20645352.0  2.580669e+06              8
0.003301
3          Accounting    311455618.0  1.730309e+07             18
0.049804
4        Ad Targeting    179329558.0  1.379458e+07             13
0.028676
..                 …             …            …              …
…
748               iOS    221407342.0  4.612653e+06             48
0.035404
```

```
749            iPad      51562714.0  1.778025e+06             29
0.008245
750          iPhone     210124149.0  3.045278e+06             69
0.033600
751      iPod Touch       4338000.0  1.446000e+06              3
0.000694
752         mHealth       4902386.0  6.127982e+05              8
0.000784

[753 rows x 5 columns]
```

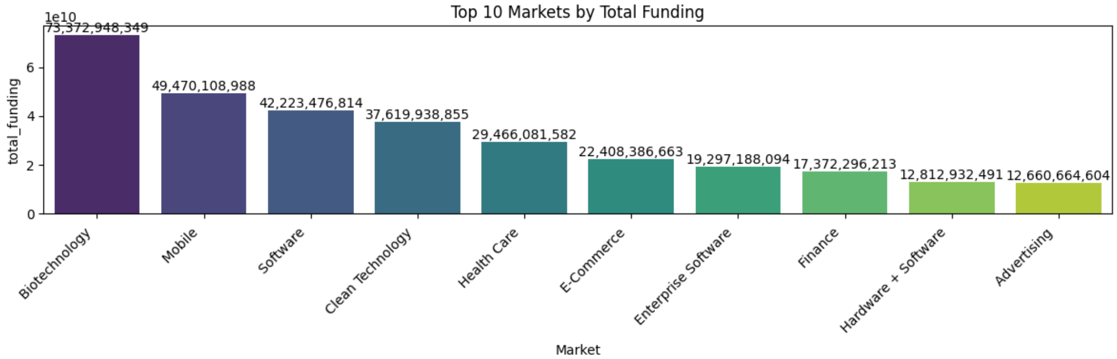
[ ]:
```
#market_funding_stats['total_funding']=pd.
 ↪to_numeric(market_funding_stats['total_funding'], errors='coerce')
#market_funding_stats['avg_funding']=pd.
 ↪to_numeric(market_funding_stats['avg_funding'], errors='coerce')
top_10_markets_funds = market_funding_stats.sort_values(by='total_funding',␣
 ↪ascending=False).head(10)
top_10_markets_avg = market_funding_stats.sort_values(by='avg_funding',␣
 ↪ascending=False).head(10)
top_10_markets_count = market_funding_stats.sort_values(by='funding_count',␣
 ↪ascending=False).head(10)
top_10_markets_dist = market_funding_stats.
 ↪sort_values(by='funding_distribution', ascending=False).head(10)
```

[ ]:
```
def plot_top_10(data, x, y, title, xlabel):
    plt.figure(figsize=(12,4))
    g=sns.barplot(x=x, y=y, data=data, palette='viridis')
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(y)
    plt.xticks(rotation=45, ha='right')
    for bars in g.containers:
      g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.
 ↪datavalues])

    plt.tight_layout()
    plt.show()
```

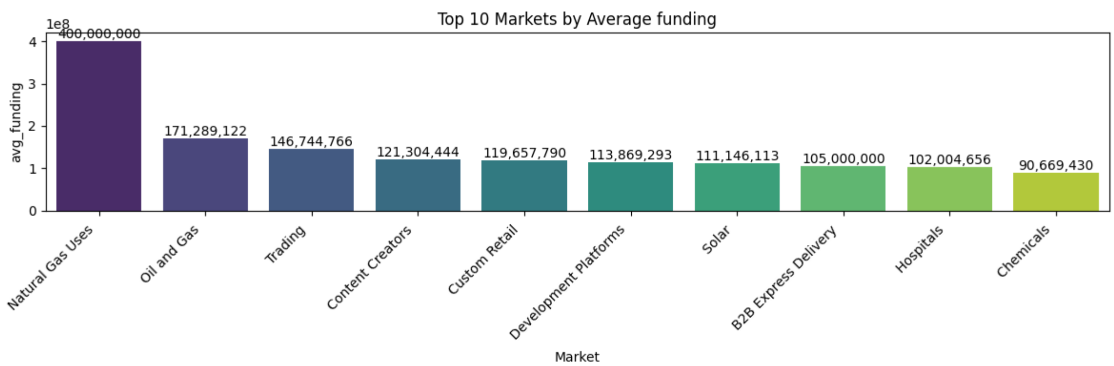
[ ]:
```
df['funding_total_usd'].sum()
```

[ ]:
```
534472078295.0
```

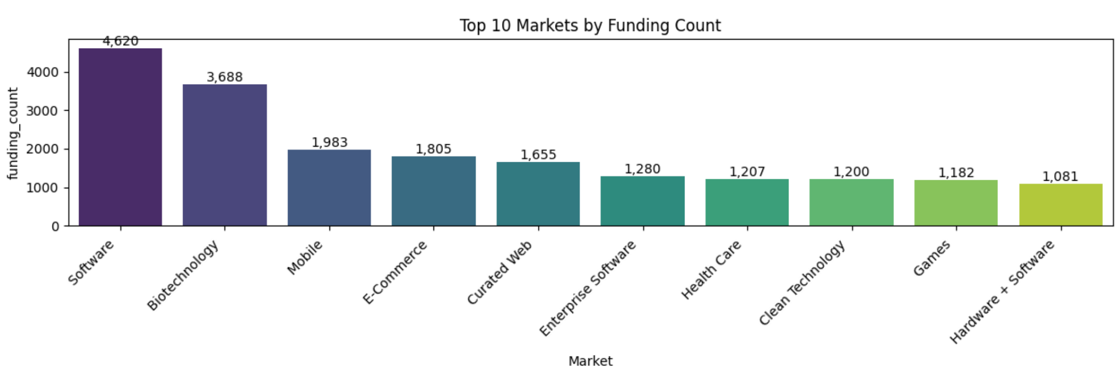
[ ]:
```
plot_top_10(top_10_markets_funds, 'market', 'total_funding', 'Top 10 Markets by␣
 ↪Total Funding', 'Market')
```



[ ]:
```
plot_top_10(top_10_markets_avg, 'market', 'avg_funding', 'Top 10 Markets by␣
↪Average funding', 'Market')
```

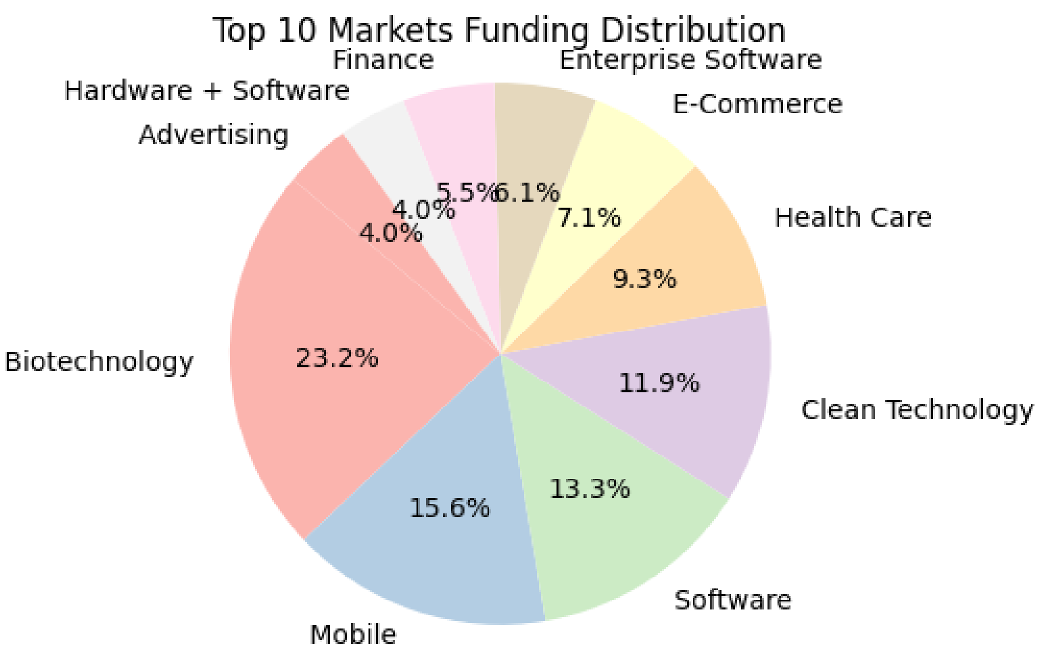


[ ]:
```
plot_top_10(top_10_markets_count, 'market', 'funding_count', 'Top 10 Markets by␣
↪Funding Count', 'Market')
```



[ ]:
```
def plot_pie_chart(data, labels_column, values_column, title):
    plt.figure(figsize=(4,4))

    # Extract labels and values for the pie chart
    labels = data[labels_column]
    values = data[values_column]

    # Plot the pie chart
    plt.pie(values, labels=labels, autopct='%1.1f%%', startangle=140,
 ↪colors=plt.cm.Pastel1.colors)
    plt.title(title)
    plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a
 ↪circle.
    plt.show()
```

[ ]:
```
plot_pie_chart(top_10_markets_dist, 'market', 'funding_distribution', 'Top 10
 ↪Markets Funding Distribution')
```



Observations: * **Top Markets by Total Funding:** Biotechnology, Mobile, Software, Clean Technology, and Healthcare. * **Top Markets by Average Funding:** Natural Gas Uses, Oil & Gas, and Trading. * **Top Markets by Funding Count:** Software, Biotechnology, and Mobile.

4 Total Funding, Average Funding, Funding Count and Funding distribution by Country

[ ]:
```
# For total funding, average funding, and distribution by country
country_funding_stats = funding_statistics(df, ['country_code'])
country_funding_stats
```

[ ]:
```
   country_code  total_funding   avg_funding  funding_count  \
funding_distribution
0           ALB   6.500000e+05  2.166667e+05              3
0.000103
1           ARE   6.489352e+08  9.543165e+06             68
0.103055
2           ARG   2.668057e+08  1.755300e+06            152
0.042371
3           ARM   3.547416e+07  5.912361e+06              6
0.005634
4           ASM   3.625000e+06  3.625000e+06              1
0.000576
5           ATG   7.444500e+06  3.722250e+06              2
0.001182
6           AUS   2.771918e+09  8.476813e+06            327
0.440199
7           AUT   4.965809e+08  4.729342e+06            105
0.078860
8           AZE   3.740000e+05  9.350000e+04              4
0.000059
9           BEL   1.245332e+09  8.139426e+06            153
0.197767
10          BGD   4.809897e+07  6.871282e+06              7
0.007638
11          BGR   4.935270e+07  7.152564e+05             69
0.007838
12          BHR   1.212690e+05  4.042300e+04              3
0.000019
13          BHS   1.010000e+07  5.050000e+06              2
0.001604
14          BLR   8.700000e+05  1.450000e+05              6
0.000138
15          BMU   7.516660e+08  1.879165e+08              4
0.119370
16          BRA   2.645856e+09  7.759110e+06            341
0.420180
17          BRN   0.000000e+00  0.000000e+00              1
0.000000
18          BWA   2.271352e+06  5.678380e+05              4
0.000361
```

19	CAN	1.403986e+10	9.901171e+06	1418
2.229623				
20	CCK	1.141240e+08	1.426550e+07	8
0.018124				
21	CHE	3.026828e+09	1.351263e+07	224
0.480680				
22	CHL	4.770288e+07	1.650619e+05	289
0.007576				
23	CHN	3.632446e+10	2.809317e+07	1293
5.768567				
24	CIV	6.000000e+04	6.000000e+04	1
0.000010				
25	CMR	1.195610e+05	5.978050e+04	2
0.000019				
26	COL	3.133751e+08	2.304229e+06	136
0.049766				
27	CRI	6.670000e+05	9.528571e+04	7
0.000106				
28	CYM	1.522579e+08	1.384162e+07	11
0.024180				
29	CYP	4.529948e+07	3.774957e+06	12
0.007194				
30	CZE	2.859428e+08	5.395148e+06	53
0.045410				
31	DEU	8.282713e+09	8.299311e+06	998
1.315350				
32	DNK	1.143982e+09	5.271807e+06	217
0.181672				
33	DOM	2.235301e+06	3.193287e+05	7
0.000355				
34	DZA	1.216828e+06	6.084140e+04	20
0.000193				
35	ECU	1.680000e+06	5.600000e+05	3
0.000267				
36	EGY	4.304398e+08	1.871477e+07	23
0.068357				
37	ESP	3.684026e+09	6.578617e+06	560
0.585048				
38	EST	8.040310e+07	1.747894e+06	46
0.012769				
39	EUR	5.753916e+07	6.393239e+06	9
0.009138				
40	FIN	1.114023e+09	5.683791e+06	196
0.176914				
41	FRA	5.217787e+09	5.942810e+06	878
0.828619				
42	FSM	1.076045e+07	1.076045e+06	10

					0.001709
43	GBR	2.380562e+10	8.829978e+06	2696	3.780491
44	GEO	0.000000e+00	0.000000e+00	2	0.000000
45	GHA	1.774615e+06	1.613286e+05	11	0.000282
46	GIB	1.994491e+07	9.972456e+06	2	0.003167
47	GRC	2.527425e+07	7.898203e+05	32	0.004014
48	GTM	9.410340e+05	2.352585e+05	4	0.000149
49	HKG	1.674290e+09	1.297899e+07	129	0.265888
50	HRV	4.463391e+06	5.579239e+05	8	0.000709
51	HUN	3.832166e+07	8.709467e+05	44	0.006086
52	IDN	3.331122e+08	6.285136e+06	53	0.052900
53	IMN	1.262954e+06	4.209847e+05	3	0.000201
54	IND	1.502775e+10	1.747412e+07	860	2.386506
55	IOT	5.348183e+07	9.382777e+05	57	0.008493
56	IRL	2.439394e+09	7.818572e+06	312	0.387392
57	ISL	5.543053e+07	2.917397e+06	19	0.008803
58	ISR	6.296680e+09	9.178833e+06	686	0.999955
59	ITA	1.168704e+09	3.509622e+06	333	0.185598
60	JAM	3.200000e+04	3.200000e+04	1	0.000005
61	JEY	0.000000e+00	0.000000e+00	1	0.000000
62	JOR	2.612336e+07	1.306168e+06	20	0.004149
63	JPN	2.928354e+09	9.632743e+06	304	0.465042
64	KEN	2.862053e+08	1.144821e+07	25	0.045451
65	KHM	4.800000e+05	4.800000e+04	10	0.000076

66	KOR	9.452182e+08	3.736040e+06	253
0.150107				
67	KWT	1.405000e+07	7.025000e+06	2
0.002231				
68	LAO	1.474340e+05	2.948680e+04	5
0.000023				
69	LBN	6.553000e+06	5.040769e+05	13
0.001041				
70	LBY	8.934000e+06	9.926667e+05	9
0.001419				
71	LIE	9.592500e+06	2.398125e+06	4
0.001523				
72	LTU	9.102098e+07	2.844406e+06	32
0.014455				
73	LUX	6.093775e+08	2.769898e+07	22
0.096773				
74	LVA	1.271740e+07	1.059784e+06	12
0.002020				
75	MAF	2.922000e+07	2.922000e+07	1
0.004640				
76	MAR	3.200000e+06	1.066667e+06	3
0.000508				
77	MCO	6.570000e+05	6.570000e+05	1
0.000104				
78	MDA	6.134000e+05	1.226800e+05	5
0.000097				
79	MEX	7.119179e+08	7.910199e+06	90
0.113057				
80	MKD	3.848400e+04	1.924200e+04	2
0.000006				
81	MLT	1.325772e+07	4.419240e+06	3
0.002105				
82	MMR	7.000000e+05	3.500000e+05	2
0.000111				
83	MNE	5.324607e+07	1.004643e+06	53
0.008456				
84	MOZ	0.000000e+00	0.000000e+00	1
0.000000				
85	MUS	2.000000e+05	2.000000e+05	1
0.000032				
86	MYS	1.248519e+09	2.448077e+07	51
0.198273				
87	NGA	2.761624e+08	8.908465e+06	31
0.043856				
88	NIC	3.519200e+06	1.759600e+06	2
0.000559				
89	NIU	0.000000e+00	0.000000e+00	1

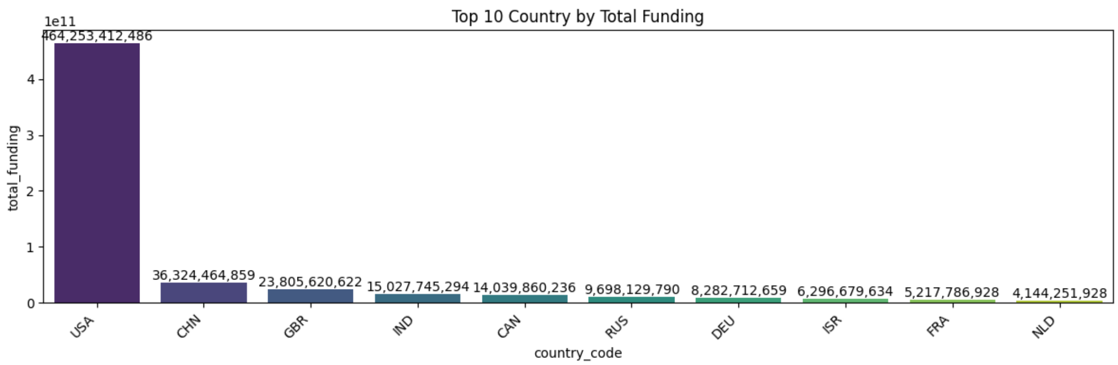
					0.000000
90	NLD	4.144252e+09	1.319825e+07	314	0.658135
91	NOR	8.566731e+08	8.566731e+06	100	0.136045
92	NPL	3.000000e+05	1.500000e+05	2	0.000048
93	NRU	1.400000e+04	1.400000e+04	1	0.000002
94	NZL	1.084639e+09	1.668675e+07	65	0.172248
95	OMN	1.000000e+04	1.000000e+04	1	0.000002
96	PAK	9.586000e+06	5.325556e+05	18	0.001522
97	PAN	5.198000e+06	8.663333e+05	6	0.000825
98	PER	2.546457e+07	8.488191e+05	30	0.004044
99	PHL	3.045943e+08	9.230130e+06	33	0.048372
100	POL	2.013283e+08	2.054371e+06	98	0.031972
101	PRI	0.000000e+00	0.000000e+00	1	0.000000
102	PRT	1.178197e+08	1.659432e+06	71	0.018711
103	REU	1.550000e+06	5.166667e+05	3	0.000246
104	ROM	1.900788e+07	8.639945e+05	22	0.003019
105	ROU	0.000000e+00	0.000000e+00	1	0.000000
106	RUS	9.698130e+09	2.067832e+07	469	1.540128
107	SAU	5.497346e+07	7.853352e+06	7	0.008730
108	SGP	1.735831e+09	5.786102e+06	300	0.275661
109	SGS	1.000000e+04	5.000000e+03	2	0.000002
110	SLV	4.400000e+05	1.466667e+05	3	0.000070
111	SOM	2.000000e+06	2.000000e+06	1	0.000318
112	SPM	4.654900e+04	4.654900e+04	1	0.000007

113	SRB	5.666244e+06	5.666244e+05	10	0.000900
114	STP	8.035000e+05	2.678333e+05	3	0.000128
115	SVK	1.070906e+07	6.693162e+05	16	0.001701
116	SVN	5.514303e+06	5.013003e+05	11	0.000876
117	SWE	2.899032e+09	8.975330e+06	323	0.460386
118	SYC	3.500000e+04	3.500000e+04	1	0.000006
119	THA	6.943664e+07	1.827280e+06	38	0.011027
120	TON	1.100369e+06	2.200738e+05	5	0.000175
121	TTO	1.500000e+05	1.500000e+05	1	0.000024
122	TUN	3.970000e+06	9.925000e+05	4	0.000630
123	TUR	7.213572e+08	5.817397e+06	124	0.114556
124	TUV	2.915789e+07	1.166316e+06	25	0.004630
125	TWN	9.146054e+08	2.126989e+07	43	0.145245
126	TZA	1.301400e+07	1.859143e+06	7	0.002067
127	UGA	3.964000e+06	3.964000e+05	10	0.000630
128	UKR	2.640100e+07	5.739348e+05	46	0.004193
129	URY	1.258000e+07	1.048333e+06	12	0.001998
130	USA	4.642534e+11	1.611040e+07	28817	73.726532
131	UZB	9.000000e+04	9.000000e+04	1	0.000014
132	VCT	6.500000e+05	6.500000e+05	1	0.000103
133	VEN	5.011600e+04	5.011600e+04	1	0.000008
134	VNM	2.149205e+08	9.769114e+06	22	0.034131
135	WSM	2.000000e+05	2.000000e+05	1	0.000032
136	ZAF	6.483570e+08	1.137468e+07	57	

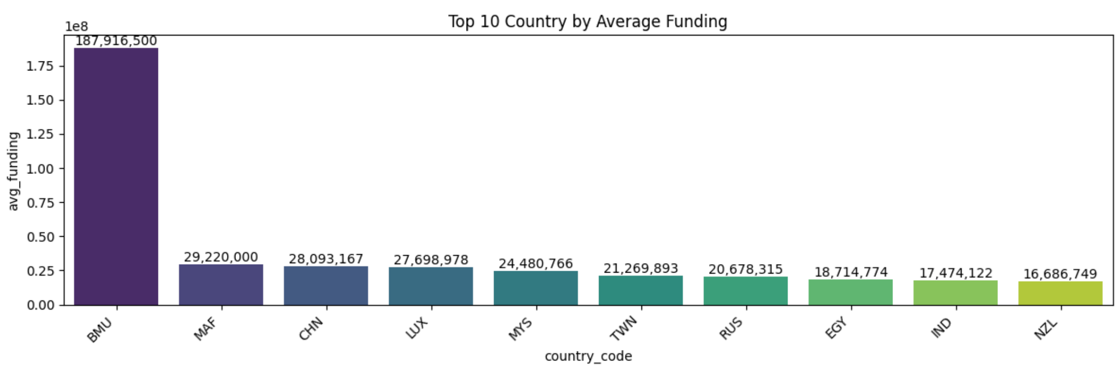
```
0.102963
137           ZWE   1.000200e+07  5.001000e+06              2
0.001588
```

[ ]:
```
top_10_country_funds = country_funding_stats.sort_values(by='total_funding', ascending=False).head(10)
top_10_country_avg = country_funding_stats.sort_values(by='avg_funding', ascending=False).head(10)
top_10_country_count = country_funding_stats.sort_values(by='funding_count', ascending=False).head(10)
top_10_country_dist = country_funding_stats.sort_values(by='funding_distribution', ascending=False).head(10)
```

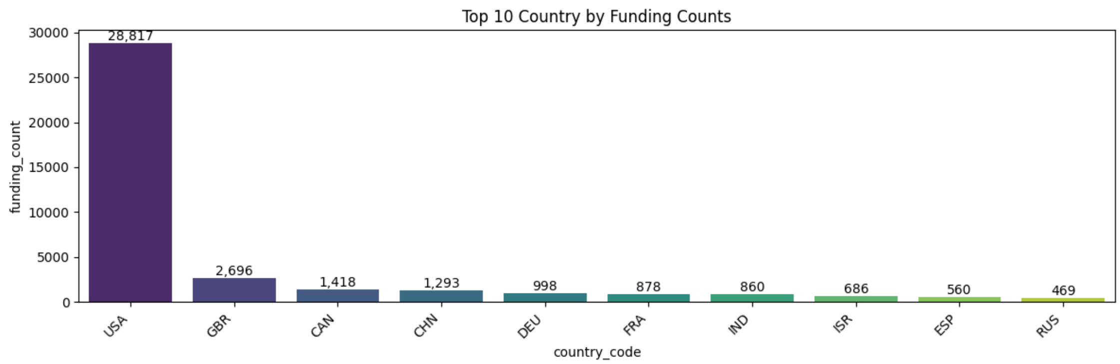
[ ]:
```
plot_top_10(top_10_country_funds, 'country_code', 'total_funding', 'Top 10 Country by Total Funding', 'country_code')
```



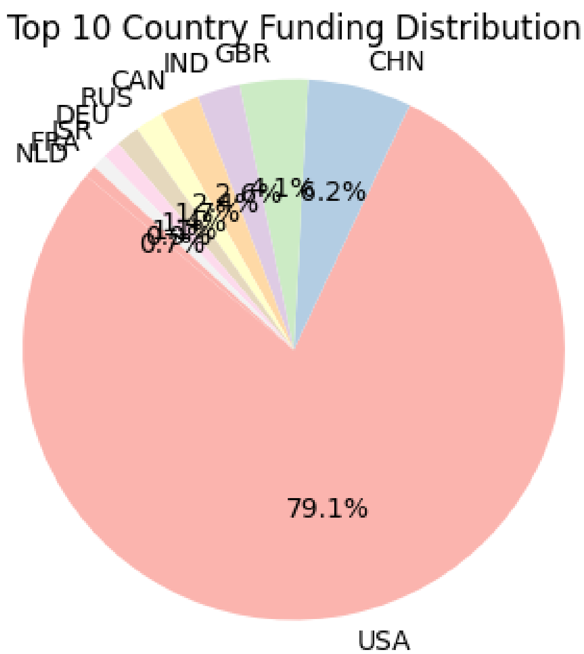
[ ]:
```
plot_top_10(top_10_country_avg, 'country_code', 'avg_funding', 'Top 10 Country by Average Funding', 'country_code')
```



```
[ ]: plot_top_10(top_10_country_count, 'country_code', 'funding_count', 'Top 10
     ↪Country by Funding Counts', 'country_code')
```




```
[ ]: plot_pie_chart(top_10_country_dist, 'country_code', 'funding_distribution',
     ↪'Top 10 Country Funding Distribution')
```



Observations:

- **Top Country by Total Funding:** USA, CHN, GBR, IND AND CAN
- **Top Country by Average Funding:** BMU,MAF, CHN
- **Top Country by Founding Count:** USA,GBR, CAN.

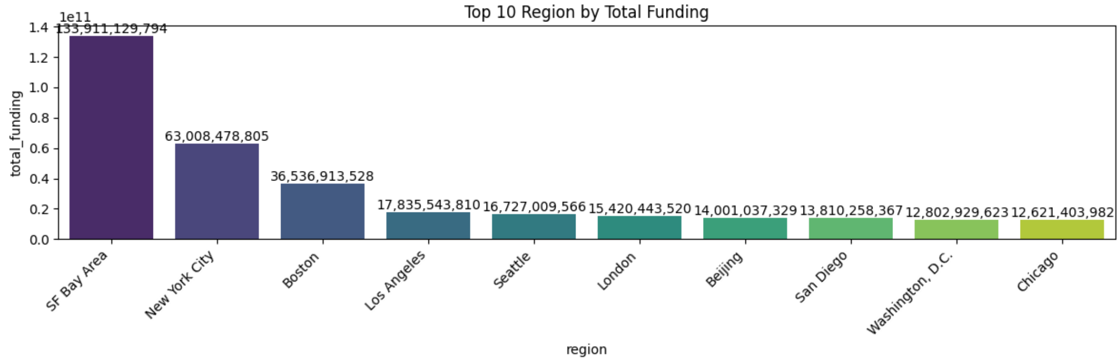
5 Total Funding, Average Funding, Funding Count and Funding distribution by Region

[ ]:
```
# For total funding, average funding, and distribution by region
region_funding_stats = funding_statistics(df, ['region'])
region_funding_stats
```

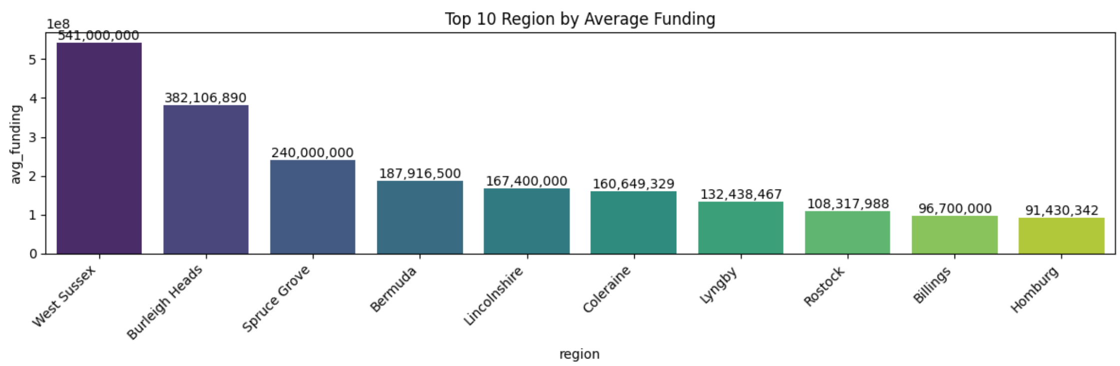
[ ]:
```
           region  total_funding   avg_funding  funding_count
funding_distribution
0        A Coruna   4.947720e+06  1.236930e+06              4
0.000786
1      AB - Other   2.307500e+07  3.296429e+06              7
0.003664
2      AK - Other   8.850000e+06  2.212500e+06              4
0.001405
3      AL - Other   1.114637e+09  6.966481e+07             16
0.177012
4      AR - Other   2.917444e+06  1.458722e+05             20
0.000463
…             …              …             …             …
…
1085    Zhengzhou   1.721373e+07  5.737911e+06              3
0.002734
1086       Zhuhai   3.042155e+08  7.605386e+07              4
0.048311
1087       Zurich   6.101537e+08  8.028338e+06             76
0.096896
1088          Çan   3.294481e+08  9.983275e+06             33
0.052319
1089         Évry   6.637540e+05  2.212513e+05              3
0.000105

[1090 rows x 5 columns]
```

[ ]:
```
top_10_region_funds = region_funding_stats.sort_values(by='total_funding',␣
 ↪ascending=False).head(10)
top_10_region_avg = region_funding_stats.sort_values(by='avg_funding',␣
 ↪ascending=False).head(10)
top_10_region_count = region_funding_stats.sort_values(by='funding_count',␣
 ↪ascending=False).head(10)
top_10_region_dist = region_funding_stats.
 ↪sort_values(by='funding_distribution', ascending=False).head(10)
```

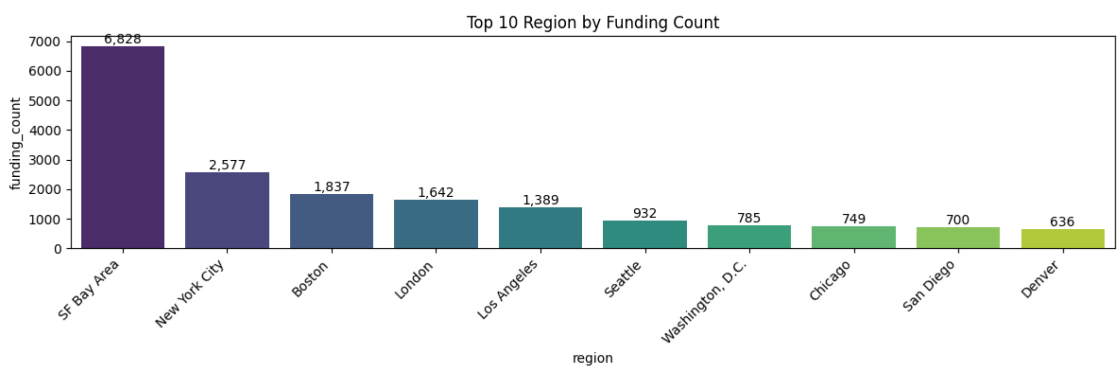
[ ]:
```
plot_top_10(top_10_region_funds, 'region', 'total_funding', 'Top 10 Region by␣
 ↪Total Funding', 'region')
```



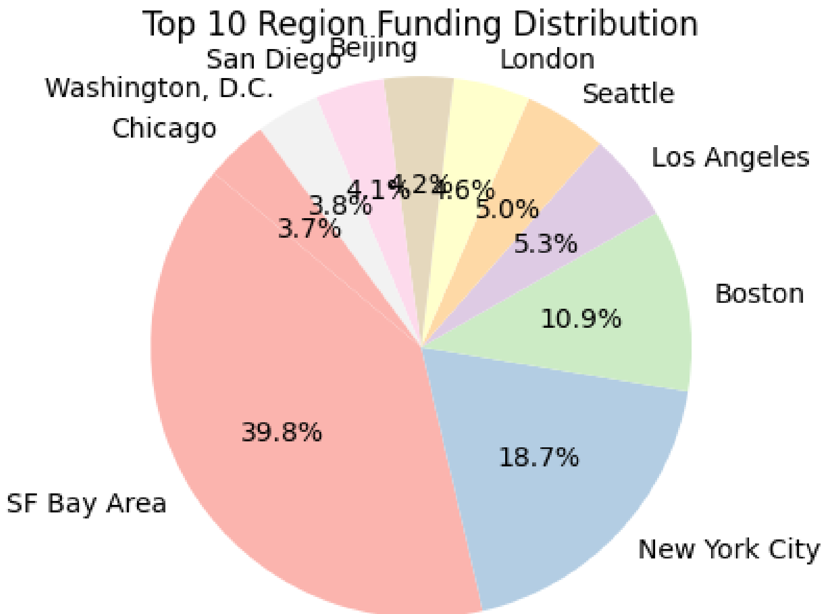
[ ]:
```
plot_top_10(top_10_region_avg, 'region', 'avg_funding', 'Top 10 Region by␣
↪Average Funding', 'region')
```



[ ]:
```
plot_top_10(top_10_region_count, 'region', 'funding_count', 'Top 10 Region by␣
↪Funding Count', 'region')
```



[ ]:
```
plot_pie_chart(top_10_region_dist, 'region', 'funding_distribution', 'Top 10␣
↪Region Funding Distribution')
```



Observations:

- **Top Region by Total Funding:** SF Bay Area, NewYork City and Boston
- **Top Region by Average Funding:** West Sussex, Butleigh Heads,
- **Top Region by Founding Count:** SF Bay Area, NewYork City and Boston.

6 Total Funding, Average Funding, Funding Count and Funding distribution by State

[ ]:
```
# For total funding, average funding, and distribution by state and city␣
↪together
state_funding_stats = funding_statistics(df, ['state_code'])
state_funding_stats
```

[ ]:

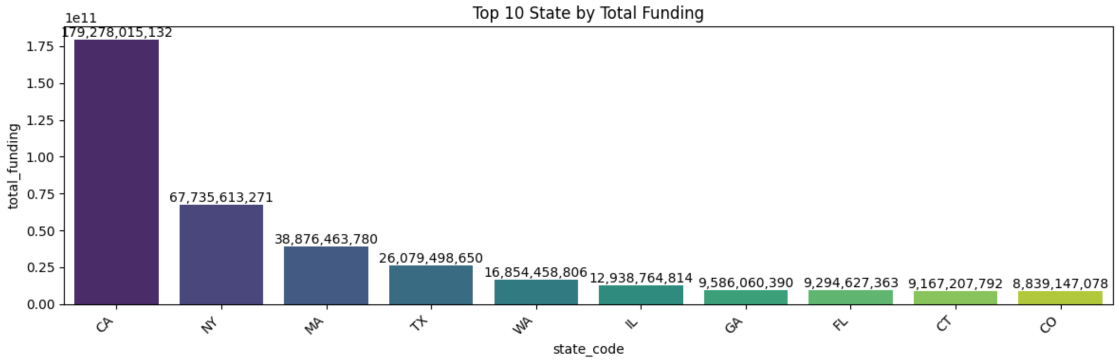
	state_code	total_funding	avg_funding	funding_count	funding_distribution
0	AB	1.886735e+09	1.640640e+07	115	0.394669
1	AK	1.485042e+07	1.237535e+06	12	0.003106
2	AL	1.674069e+09	1.594351e+07	105	0.350184
3	AR	2.855398e+08	1.613219e+06	177	0.059730
4	AZ	2.843284e+09	8.695058e+06	327	0.594761
5	BC	2.171049e+09	6.827197e+06	318	0.454142
6	CA	1.792780e+11	1.807785e+07	9917	37.501575

7	CO	8.839147e+09	1.222565e+07	723	1.848983
8	CT	9.167208e+09	2.901015e+07	316	1.917607
9	DC	2.197159e+09	1.207230e+07	182	0.459604
10	DE	4.397126e+08	6.193135e+06	71	0.091980
11	FL	9.294627e+09	9.651742e+06	963	1.944261
12	GA	9.586060e+09	1.771915e+07	541	2.005223
13	HI	1.932962e+08	3.579560e+06	54	0.040434
14	IA	1.314375e+09	1.685096e+07	78	0.274942
15	ID	3.450831e+08	6.162197e+06	56	0.072185
16	IL	1.293876e+10	1.564542e+07	827	2.706545
17	IN	1.374372e+09	5.898592e+06	233	0.287493
18	KS	1.515956e+09	1.612719e+07	94	0.317109
19	KY	5.002151e+08	4.426683e+06	113	0.104636
20	LA	3.906566e+08	5.008418e+06	78	0.081718
21	MA	3.887646e+10	1.974427e+07	1969	8.132222
22	MB	5.189950e+07	3.992269e+06	13	0.010856
23	MD	8.762863e+09	1.777457e+07	493	1.833025
24	ME	4.935310e+08	9.490980e+06	52	0.103237
25	MI	1.746275e+09	5.579152e+06	313	0.365288
26	MN	3.909698e+09	1.101323e+07	355	0.817835
27	MO	2.544634e+09	1.156652e+07	220	0.532289
28	MS	1.662880e+08	5.196500e+06	32	0.034784
29	MT	2.597309e+08	8.657698e+06	30	0.054331
30	NB	1.636982e+08	2.046228e+07	8	0.034243
31	NC	6.824440e+09	1.433706e+07	476	1.427544
32	ND	7.023632e+07	4.682422e+06	15	0.014692
33	NE	6.653848e+08	8.871797e+06	75	0.139186
34	NH	1.262294e+09	1.127048e+07	112	0.264048
35	NJ	7.881763e+09	1.361272e+07	579	1.648716
36	NL	1.000152e+08	5.000762e+06	20	0.020921
37	NM	3.969667e+08	5.292889e+06	75	0.083038
38	NS	1.572161e+08	3.743240e+06	42	0.032887
39	NV	5.935064e+08	3.043623e+06	195	0.124150
40	NY	6.773561e+10	2.324489e+07	2914	14.169011
41	OH	4.216990e+09	7.926674e+06	532	0.882115
42	OK	6.491334e+08	8.541228e+06	76	0.135786
43	ON	6.306244e+09	9.657342e+06	653	1.319147
44	OR	3.687324e+09	1.181835e+07	312	0.771319
45	PA	8.710200e+09	1.099773e+07	792	1.822009
46	PE	2.350000e+06	1.175000e+06	2	0.000492
47	QC	2.939260e+09	1.342128e+07	219	0.614838
48	RI	7.655675e+08	7.361226e+06	104	0.160142
49	SC	1.478519e+09	1.182815e+07	125	0.309278
50	SD	4.917170e+07	3.512265e+06	14	0.010286
51	SK	8.882205e+07	2.220551e+07	4	0.018580
52	TN	2.090993e+09	5.087575e+06	411	0.437396
53	TX	2.607950e+10	1.778956e+07	1466	5.455339

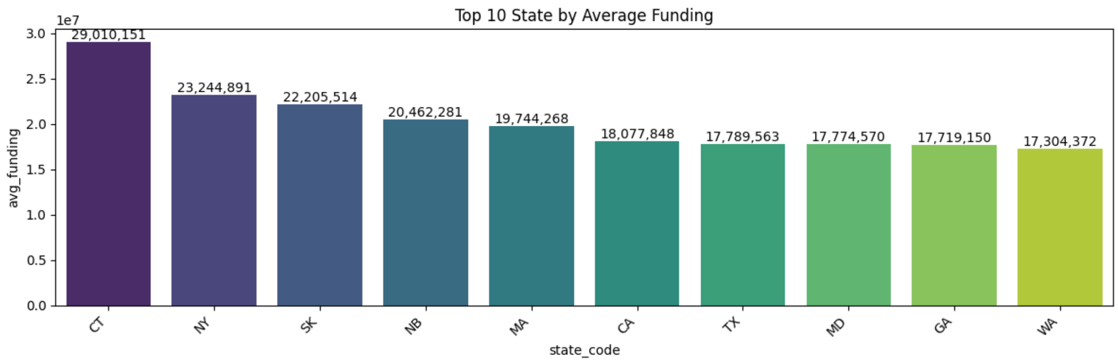
54	UT	4.925022e+09	1.349321e+07	365	1.030222
55	VA	6.671589e+09	1.206436e+07	553	1.395570
56	VT	2.843962e+08	5.924920e+06	48	0.059490
57	WA	1.685446e+10	1.730437e+07	974	3.525634
58	WI	3.261311e+09	1.707493e+07	191	0.682205
59	WV	6.723582e+07	4.482388e+06	15	0.014064
60	WY	1.385298e+07	8.148814e+05	17	0.002898

[ ]:
```
top_10_state_funds = state_funding_stats.sort_values(by='total_funding',␣
    ↪ascending=False).head(10)
top_10_state_avg = state_funding_stats.sort_values(by='avg_funding',␣
    ↪ascending=False).head(10)
top_10_state_count = state_funding_stats.sort_values(by='funding_count',␣
    ↪ascending=False).head(10)
top_10_state_dist = state_funding_stats.sort_values(by='funding_distribution',␣
    ↪ascending=False).head(10)
```

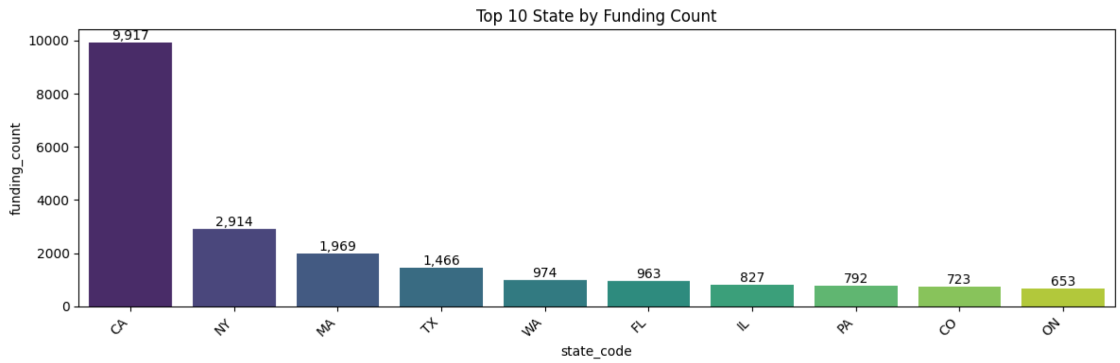
[ ]:
```
plot_top_10(top_10_state_funds, 'state_code', 'total_funding', 'Top 10 State by␣
    ↪Total Funding', 'state_code')
```



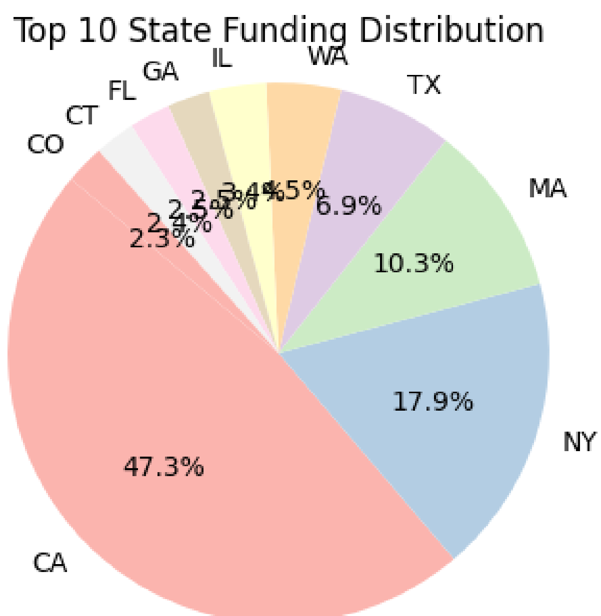
[ ]:
```
plot_top_10(top_10_state_avg, 'state_code', 'avg_funding', 'Top 10 State by␣
    ↪Average Funding', 'state_code')
```



```
[ ]: plot_top_10(top_10_state_count, 'state_code', 'funding_count', 'Top 10 State by Funding Count', 'state_code')
```




```
[ ]: plot_pie_chart(top_10_state_dist, 'state_code', 'funding_distribution', 'Top 10 State Funding Distribution')
```



Observations:

- **Top State by Total Funding:** CA,NY and MA
- **Top State by Average Funding:** CT, NY and SK
- **Top State by Founding Count:** CA, NY and MA

7 Total Funding, Average Funding, Funding Count and Funding distribution by City

[ ]:
```
funding_statistics(df,['city'])
```

[ ]:
```
                   city  total_funding   avg_funding  funding_count  
funding_distribution
0      's-hertogenbosch            0.0  0.000000e+00              1
0.000000
1        6 October City       145000.0  1.450000e+05              1
0.000024
2              A Coruña      4947720.0  1.236930e+06              4
0.000804
3                Aachen     45141916.0  6.448845e+06              7
0.007339
4               Aalborg       350000.0  1.166667e+05              3
0.000057
…                   …            …            …             …
…
4183              Évora            0.0  0.000000e+00              1
0.000000
4184               Évry       663754.0  2.212513e+05              3
0.000108
4185          Ísafjörður      4000000.0  4.000000e+06              1
0.000650
4186       Örnsköldsvik            0.0  0.000000e+00              1
0.000000
4187       Østerby Havn       855000.0  8.550000e+05              1
0.000139

[4188 rows x 5 columns]
```

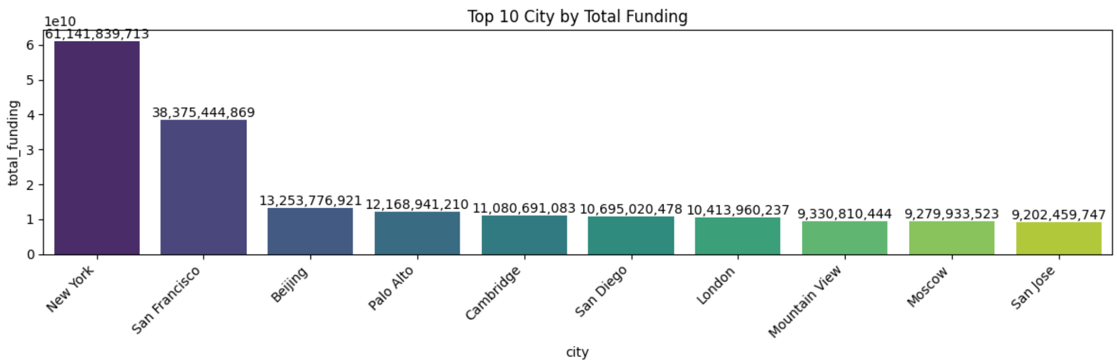
[ ]:
```
# For total funding, average funding, and distribution by state and city␣
 ↪together
city_funding_stats = funding_statistics(df, ['city'])
city_funding_stats
```

[ ]:
```
                   city  total_funding   avg_funding  funding_count  
funding_distribution
0      's-hertogenbosch            0.0  0.000000e+00              1
0.000000
1        6 October City       145000.0  1.450000e+05              1
0.000024
2              A Coruña      4947720.0  1.236930e+06              4
0.000804
3                Aachen     45141916.0  6.448845e+06              7
0.007339
```

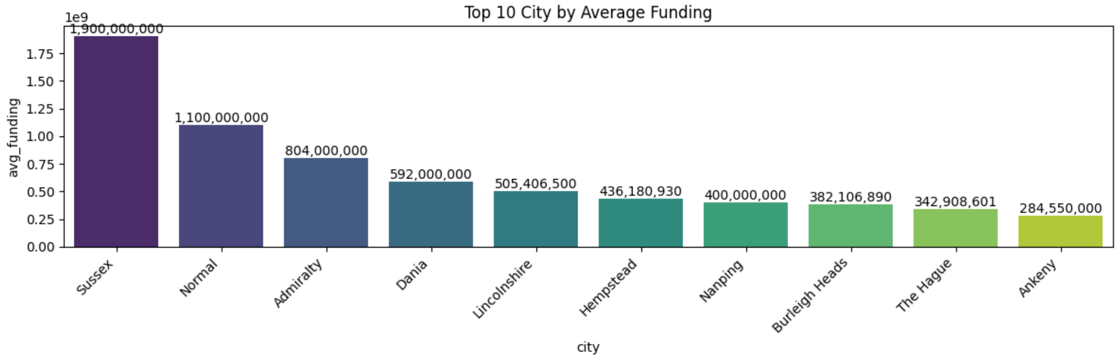
```
4           Aalborg      350000.0  1.166667e+05              3
0.000057
…               …            …            …            …
…
4183          Évora           0.0  0.000000e+00              1
0.000000
4184           Évry      663754.0  2.212513e+05              3
0.000108
4185      Ísafjörður    4000000.0  4.000000e+06              1
0.000650
4186    Örnsköldsvik          0.0  0.000000e+00              1
0.000000
4187    Østerby Havn     855000.0  8.550000e+05              1
0.000139

[4188 rows x 5 columns]
```

[ ]:
```
top_10_city_funds = city_funding_stats.sort_values(by='total_funding',␣
↪ascending=False).head(10)
top_10_city_avg = city_funding_stats.sort_values(by='avg_funding',␣
↪ascending=False).head(10)
top_10_city_count = city_funding_stats.sort_values(by='funding_count',␣
↪ascending=False).head(10)
top_10_city_dist = city_funding_stats.sort_values(by='funding_distribution',␣
↪ascending=False).head(10)
```

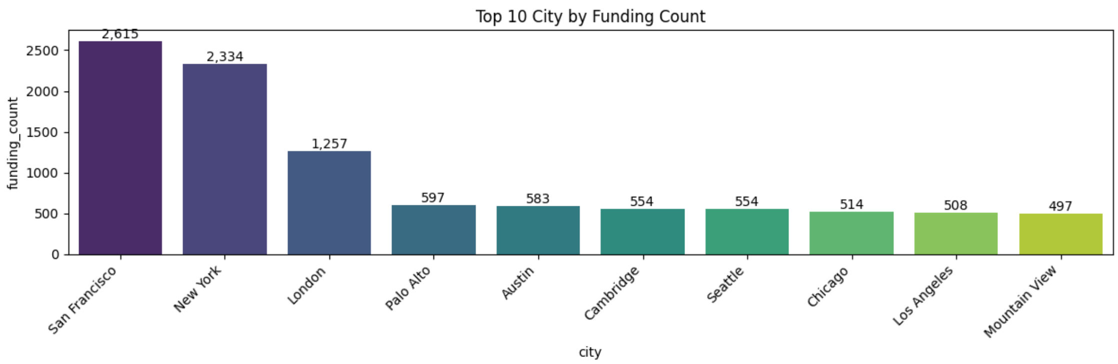
[ ]:
```
plot_top_10(top_10_city_funds, 'city', 'total_funding', 'Top 10 City by Total␣
↪Funding', 'city')
```



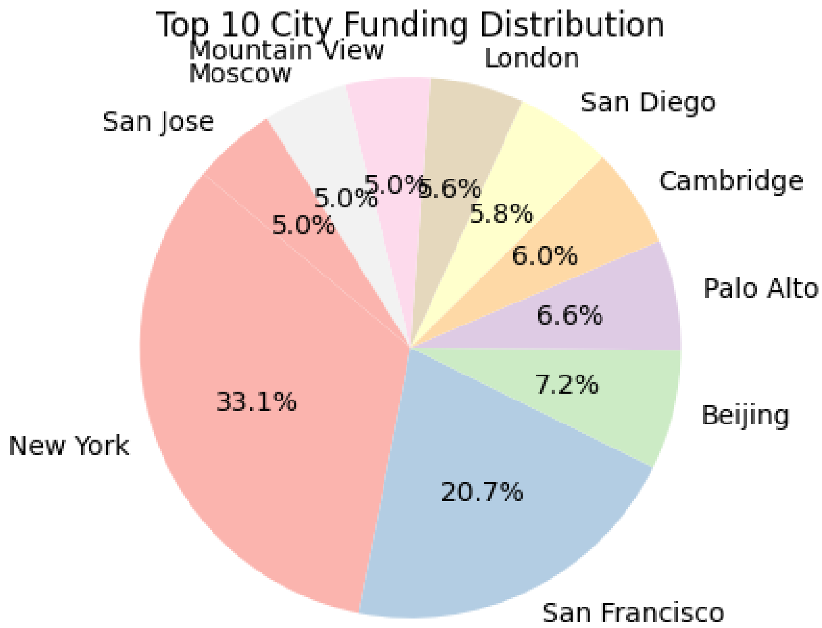
[ ]:
```
plot_top_10(top_10_city_avg, 'city', 'avg_funding', 'Top 10 City by Average␣
↪Funding', 'city')
```



[ ]:
```
plot_top_10(top_10_city_count, 'city', 'funding_count', 'Top 10 City by Funding␣
↪Count', 'city')
```



[ ]:
```
plot_pie_chart(top_10_city_dist, 'city', 'funding_distribution', 'Top 10 City␣
↪Funding Distribution')
```



Observations:

- **Top City by Total Funding:** NewYork, San Francisco and Beijing
- **Top City by Average Funding:** Sussex, Normal and Admiralty
- **Top City by Founding Count:** San Francisco, New York and London

8 Correlation between total funding vs founded year

[ ]:
```
df['founded_year']
```

[ ]:
```
0        1970-01-01 00:00:00.000002012
1                                  NaN
2        1970-01-01 00:00:00.000002012
3        1970-01-01 00:00:00.000002011
4        1970-01-01 00:00:00.000002014
                       …
49433    1970-01-01 00:00:00.000002013
49434                              NaN
49435    1970-01-01 00:00:00.000002012
49436                              NaN
49437    1970-01-01 00:00:00.000001999
Name: founded_year, Length: 49438, dtype: object
```

[ ]:
```
df[['total_funding_usd','founded_at']].corr()
```

[ ]:
```
                   total_funding_usd  founded_at
total_funding_usd           1.000000    0.013602
founded_at                  0.013602    1.000000
```

Insights: There is a very weak positive correlation (0.0136) between total_funding_usd and founded_at. This suggests that the year a company was founded has almost no direct relationship with the total funding it has received.

[ ]:
```
df['founded_year_extract'] = pd.to_datetime(df['founded_year'], format='%Y',␣
 ↪errors='coerce').dt.year
```

[ ]:
```
df['founded_year_extract']
```

[ ]:
```
0        1970.0
1           NaN
2        1970.0
3        1970.0
4        1970.0
          …
49433    1970.0
49434       NaN
49435    1970.0
49436       NaN
49437    1970.0
Name: founded_year_extract, Length: 49438, dtype: float64
```

9 Analyzing Funding Trends by Year

[ ]:
```
# Convert relevant date column to datetime if needed
df['founded_year'] = pd.to_datetime(df['founded_at']).dt.year

# Group by year and calculate total funding
funding_by_year = df.groupby('founded_year')['funding_total_usd'].sum().
 ↪reset_index()

# Drop rows with missing years
funding_by_year = funding_by_year.dropna()

# Sort data by year
funding_by_year = funding_by_year.sort_values('founded_year')

print(funding_by_year)
```

```
     founded_year  funding_total_usd
0          1785.0       2.000000e+06
1          1802.0       9.000000e+06
2          1817.0       7.700000e+06
```

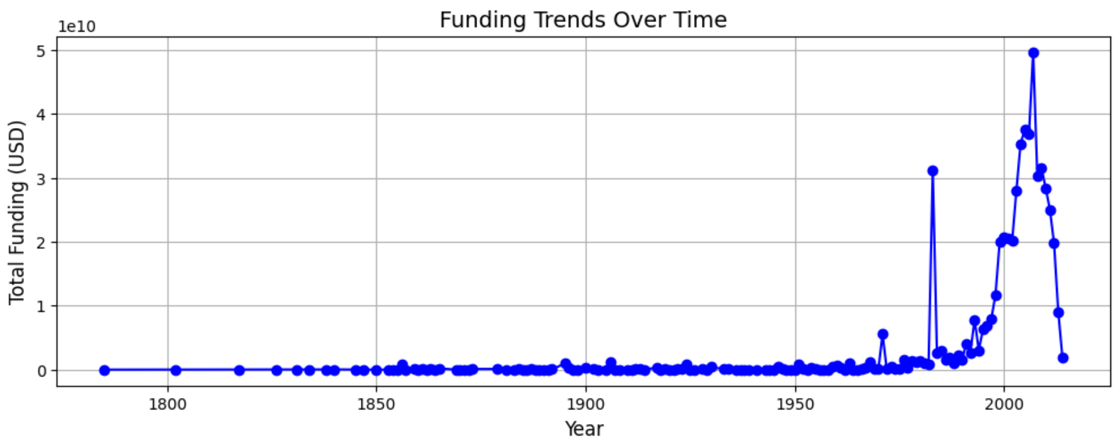
3	1826.0	5.400000e+05
4	1831.0	1.900000e+07
5	1834.0	1.200000e+07
6	1838.0	1.470000e+07
7	1840.0	3.150000e+07
8	1845.0	2.705000e+06
9	1847.0	8.900000e+06
10	1850.0	0.000000e+00
11	1853.0	8.000000e+06
12	1854.0	0.000000e+00
13	1855.0	3.900000e+06
14	1856.0	7.525000e+08
15	1857.0	0.000000e+00
16	1859.0	1.750000e+08
17	1860.0	1.730404e+07
18	1861.0	9.000000e+07
19	1862.0	1.976340e+05
20	1863.0	4.850000e+07
21	1864.0	1.340000e+07
22	1865.0	2.010000e+08
23	1869.0	2.550000e+06
24	1870.0	0.000000e+00
25	1871.0	1.400000e+06
26	1872.0	6.000000e+06
27	1873.0	9.855000e+07
28	1879.0	1.080000e+08
29	1881.0	3.329581e+07
30	1883.0	1.680000e+07
31	1884.0	1.315000e+08
32	1885.0	6.500000e+06
33	1886.0	4.500000e+06
34	1887.0	9.551000e+07
35	1888.0	2.130940e+05
36	1889.0	1.500000e+06
37	1890.0	2.000000e+06
38	1891.0	3.600000e+06
39	1892.0	5.000000e+07
40	1895.0	9.462000e+08
41	1896.0	2.650000e+08
42	1897.0	5.200000e+06
43	1898.0	2.600000e+07
44	1900.0	3.425000e+08
45	1902.0	4.167500e+07
46	1903.0	9.300000e+06
47	1905.0	6.000000e+05
48	1906.0	1.137800e+09
49	1907.0	1.100000e+07
50	1908.0	5.814700e+06

51	1910.0	1.000000e+05
52	1911.0	4.200000e+06
53	1912.0	1.486500e+08
54	1913.0	1.011508e+08
55	1914.0	3.330000e+07
56	1917.0	3.000000e+08
57	1918.0	1.570000e+05
58	1919.0	5.271126e+07
59	1920.0	2.500000e+06
60	1921.0	3.504800e+07
61	1922.0	2.157000e+08
62	1923.0	3.945237e+07
63	1924.0	8.853665e+08
64	1925.0	1.543200e+05
65	1926.0	8.070000e+05
66	1928.0	1.250800e+08
67	1929.0	0.000000e+00
68	1930.0	4.092194e+08
69	1933.0	9.015077e+07
70	1934.0	1.320000e+08
71	1936.0	0.000000e+00
72	1937.0	1.500000e+05
73	1938.0	1.300000e+07
74	1939.0	7.500000e+06
75	1941.0	2.814100e+06
76	1943.0	1.772000e+07
77	1944.0	5.000000e+06
78	1945.0	1.220000e+07
79	1946.0	4.120000e+08
80	1947.0	1.657682e+08
81	1948.0	3.144151e+07
82	1949.0	2.000000e+06
83	1950.0	2.917639e+07
84	1951.0	8.330000e+08
85	1952.0	1.943389e+08
86	1953.0	1.200000e+07
87	1954.0	3.365891e+08
88	1955.0	5.803364e+07
89	1956.0	3.347821e+07
90	1957.0	1.000000e+07
91	1958.0	2.410000e+07
92	1959.0	5.321125e+08
93	1960.0	6.696344e+08
94	1961.0	2.912576e+08
95	1962.0	1.500000e+07
96	1963.0	1.040816e+09
97	1964.0	7.300000e+06
98	1965.0	5.651345e+06

99	1966.0	1.108150e+08
100	1967.0	2.648611e+08
101	1968.0	1.224268e+09
102	1969.0	1.640146e+08
103	1970.0	5.312270e+07
104	1971.0	5.543204e+09
105	1972.0	8.334338e+07
106	1973.0	4.732727e+08
107	1974.0	1.262062e+08
108	1975.0	1.173552e+08
109	1976.0	1.468725e+09
110	1977.0	2.463475e+08
111	1978.0	1.310415e+09
112	1979.0	1.206505e+09
113	1980.0	1.322901e+09
114	1981.0	9.313513e+08
115	1982.0	7.700357e+08
116	1983.0	3.112576e+10
117	1984.0	2.673240e+09
118	1985.0	3.021623e+09
119	1986.0	1.496859e+09
120	1987.0	1.951969e+09
121	1988.0	1.036501e+09
122	1989.0	2.201268e+09
123	1990.0	1.592949e+09
124	1991.0	4.017930e+09
125	1992.0	2.690840e+09
126	1993.0	7.818241e+09
127	1994.0	3.032152e+09
128	1995.0	6.264429e+09
129	1996.0	6.882358e+09
130	1997.0	7.935088e+09
131	1998.0	1.171991e+10
132	1999.0	2.001026e+10
133	2000.0	2.065715e+10
134	2001.0	2.055311e+10
135	2002.0	2.023634e+10
136	2003.0	2.806065e+10
137	2004.0	3.532863e+10
138	2005.0	3.757720e+10
139	2006.0	3.677809e+10
140	2007.0	4.967083e+10
141	2008.0	3.024974e+10
142	2009.0	3.147555e+10
143	2010.0	2.839501e+10
144	2011.0	2.503891e+10
145	2012.0	1.973232e+10
146	2013.0	9.074411e+09

```
147        2014.0       1.893958e+09
```

[ ]:
```python
# Line Chart for Funding Trends
plt.figure(figsize=(12,4))
plt.plot(funding_by_year['founded_year'], funding_by_year['funding_total_usd'],␣
↪marker='o', color='blue')
plt.title('Funding Trends Over Time', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Total Funding (USD)', fontsize=12)
plt.grid(True)
plt.show()
```



10 Year over year growth in funding for each market

[ ]:
```python
# Step 1: Group by market and year, then sum funding
grouped_data = df.groupby(['market', 'founded_at'])['funding_total_usd'].sum().
↪reset_index()

# Step 2: Calculate Year-over-Year Growth
grouped_data['YoY_growth'] = grouped_data.
↪groupby('market')['funding_total_usd'].pct_change() * 100

# Step 3: Display the result
print(grouped_data)
```

```
      market founded_at  funding_total_usd   YoY_growth
0         3D  2002-05-17                0.0         NaN
1         3D  2005-03-01         18000000.0         inf
2         3D  2007-02-01         19679275.0    9.329306
3         3D  2010-01-01          3325000.0  -83.104052
4         3D  2010-03-01           390000.0  -88.270677
```

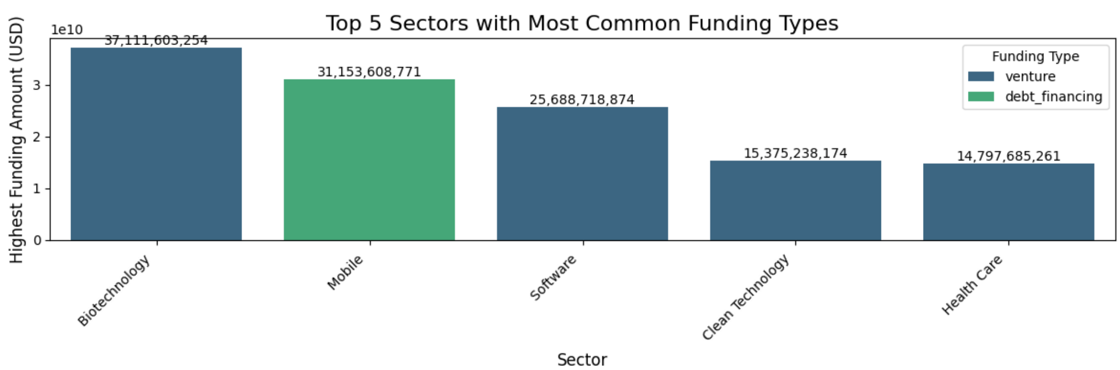
```
...          ...          ...                 ...         ...
16784    mHealth  2012-05-01           619328.0  1964.426667
16785    mHealth  2013-01-01           276672.0   -55.327064
16786    mHealth  2013-02-01          3300000.0  1092.748092
16787    mHealth  2014-02-28                0.0  -100.000000
16788    mHealth  2014-08-11            25000.0          inf

[16789 rows x 4 columns]
```

11 Most common Funding Type in Market

[ ]:
```
# Filter relevant columns for funding types and categories
funding_cols = [
    'seed', 'venture', 'equity_crowdfunding', 'undisclosed', 'convertible_note',
    'debt_financing', 'angel', 'grant', 'private_equity', 'post_ipo_equity',
    'post_ipo_debt', 'secondary_market', 'product_crowdfunding','round_A',␣
  ↪'round_B', 'round_C',
    'round_D', 'round_E', 'round_F', 'round_G', 'round_H']

relevant_data = df[['market'] + funding_cols].copy()

# Fill missing values in funding columns with 0 (assuming no funding means 0)
relevant_data[funding_cols] = relevant_data[funding_cols].fillna(0)

# Group by category_list and calculate the total funding for each type
funding_by_sector = relevant_data.groupby('market')[funding_cols].sum()

# Find the most common funding type for each sector
funding_by_sector['most_common_funding'] = funding_by_sector.idxmax(axis=1)
funding_by_sector['highest_funding_amount'] = funding_by_sector.
  ↪select_dtypes(include='number').max(axis=1)

# Reset index for visualization
funding_by_sector = funding_by_sector.reset_index()

# Display top sectors and their most common funding type
top_sectors = funding_by_sector.nlargest(10, 'highest_funding_amount')

print("Top Sectors and Their Most Common Funding Type:")
print(top_sectors[['market', 'most_common_funding', 'highest_funding_amount']])

# Visualize the results
def plot_top_funding_types(data, top_n=5):
    plt.figure(figsize=(12,4))

    # Select top N sectors by highest funding amount
```

```
    top_data = data.nlargest(top_n, 'highest_funding_amount')

    g=sns.barplot(
        data=top_data,
        x='market',
        y='highest_funding_amount',
        hue='most_common_funding',
        palette='viridis'
    )
    plt.title(f"Top {top_n} Sectors with Most Common Funding Types", fontsize=16)
    plt.xlabel("Sector", fontsize=12)
    plt.ylabel("Highest Funding Amount (USD)", fontsize=12)
    plt.xticks(rotation=45, ha='right')
    plt.legend(title="Funding Type", fontsize=10)
    for bars in g.containers:
      g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
    plt.tight_layout()
    plt.show()

# Plot the results
plot_top_funding_types(funding_by_sector)
```

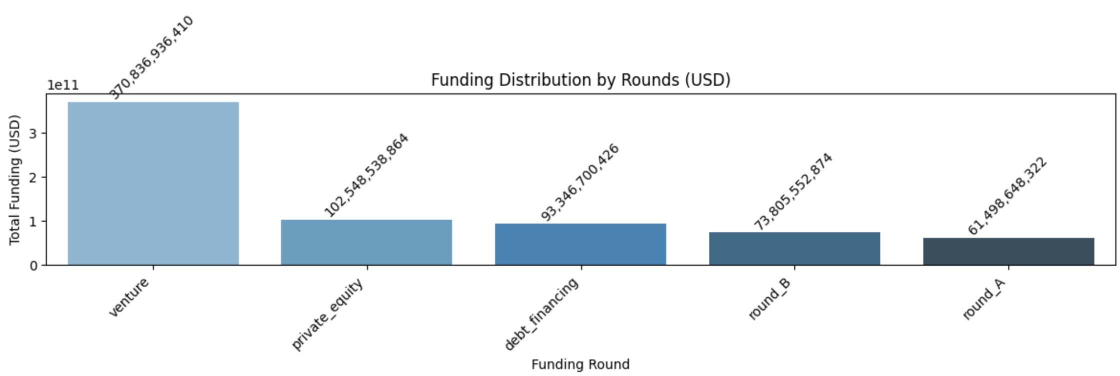
```
Top Sectors and Their Most Common Funding Type:
                    market most_common_funding  highest_funding_amount
55           Biotechnology             venture            3.711160e+10
408                 Mobile      debt_financing            3.115361e+10
610               Software             venture            2.568872e+10
88        Clean Technology             venture            1.537524e+10
293            Health Care             venture            1.479769e+10
192             E-Commerce             venture            1.301898e+10
225    Enterprise Software             venture            1.247175e+10
7              Advertising             venture            9.396025e+09
570         Semiconductors             venture            8.452689e+09
292    Hardware + Software             venture            6.999030e+09
```



Observed that most common funding type is Venture

12 Funding Rounds Analysis

[ ]:
```
# Select funding round columns
funding_rounds = ['seed', 'venture', 'equity_crowdfunding', 'undisclosed',␣
↪'convertible_note','debt_financing','angel',
                                 'grant', 'private_equity',␣
↪'post_ipo_equity','post_ipo_debt', 'secondary_market',␣
↪'product_crowdfunding',
                  'round_A', 'round_B', 'round_C', 'round_D', 'round_E',␣
↪'round_F', 'round_G', 'round_H']
rounds_data = df[funding_rounds].sum().sort_values(ascending=False).head(5)

# Visualize funding by rounds
plt.figure(figsize=(12,4))
g=sns.barplot(x=rounds_data.index, y=rounds_data.values, palette="Blues_d")
plt.title('Funding Distribution by Rounds (USD)')
plt.xlabel('Funding Round')
plt.ylabel('Total Funding (USD)')
plt.xticks(rotation=45, ha='right')
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.
↪datavalues],rotation=45)
plt.tight_layout()
plt.show()
```

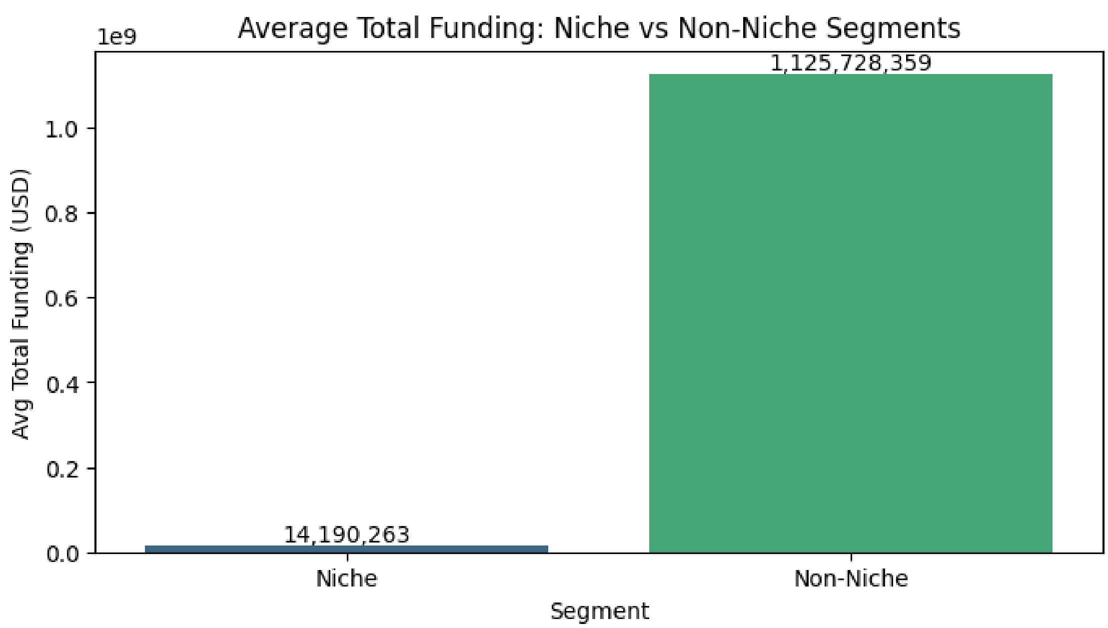


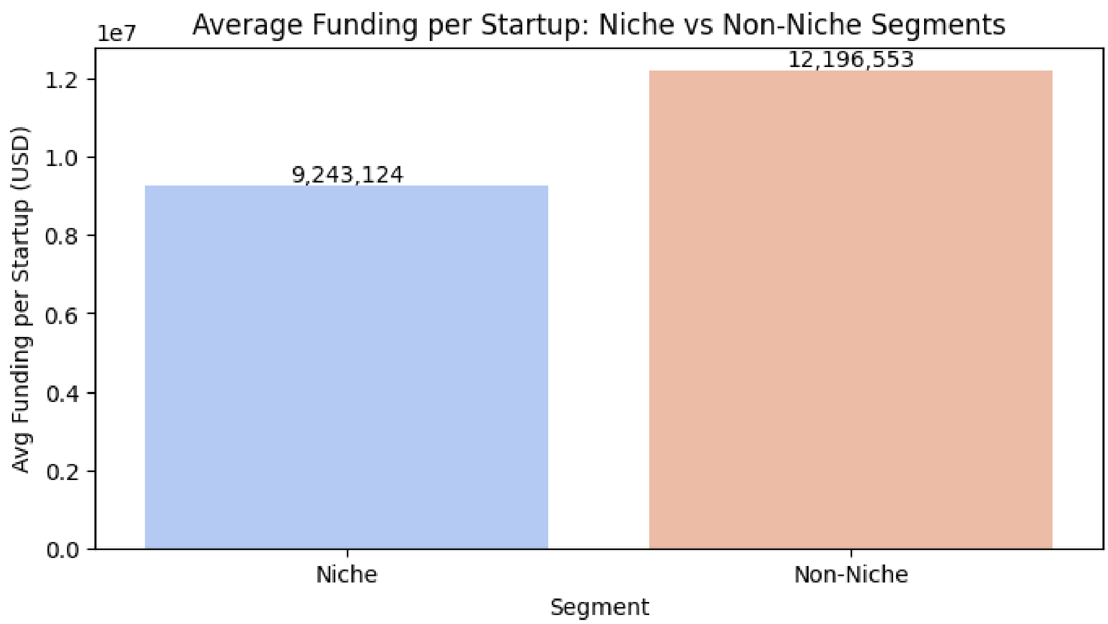
Venture Funding Dominates: The majority of funds are concentrated in the Venture funding round, indicating it as the primary source of capital for companies in this dataset.

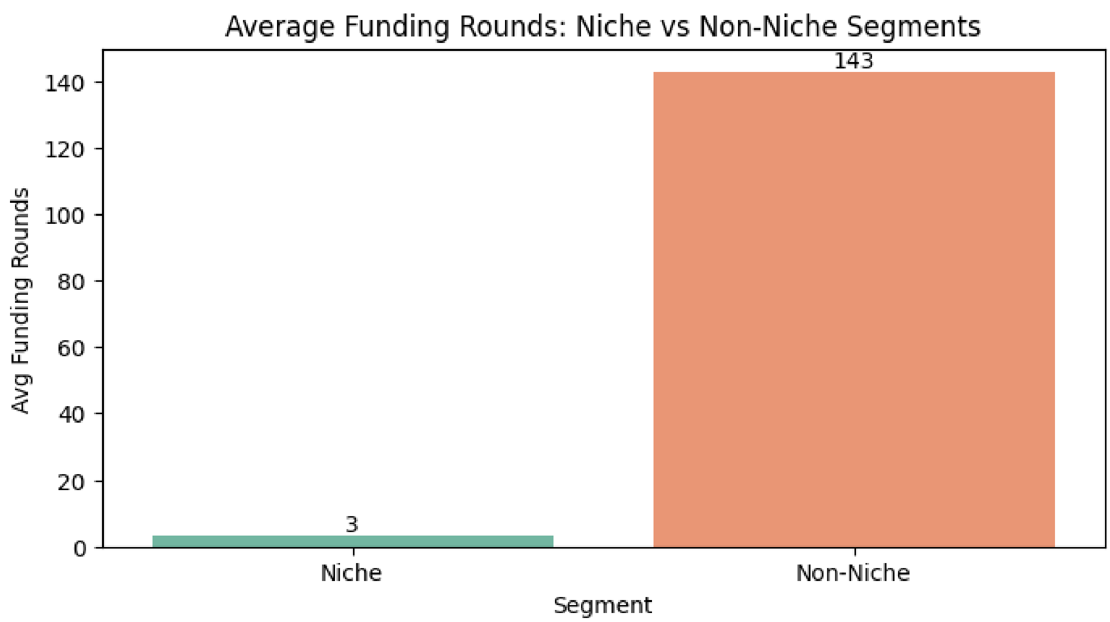
13 Niche Market Analysis

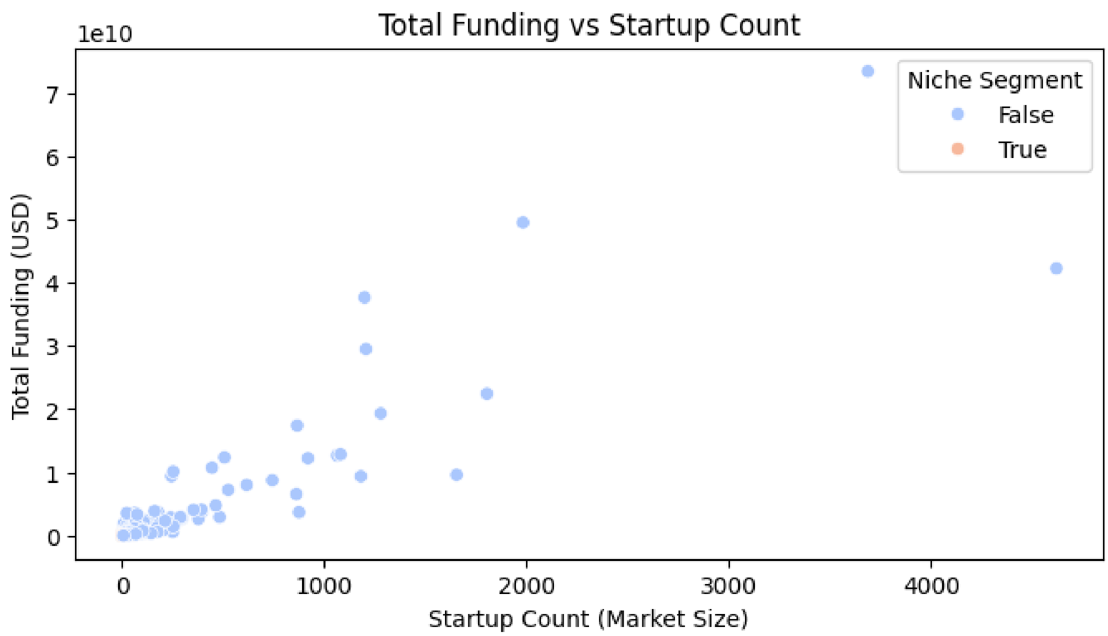
[ ]:
```
# Ensure funding_total_usd column is numeric
df['funding_total_usd'] = pd.to_numeric(df['funding_total_usd'],␣
 ↪errors='coerce')

# Step 1: Group by Market/Category
market_stats = df.groupby('market').agg(
    total_funding=('funding_total_usd', 'sum'),
    avg_funding=('funding_total_usd', 'mean'),
    funding_rounds=('funding_rounds', 'sum'),
    startup_count=('market', 'count')
).reset_index()

# Step 2: Define Niche Segments
# Set a threshold for niche segments (bottom 25% by startup count)
niche_threshold = market_stats['startup_count'].quantile(0.25)
market_stats['is_niche'] = market_stats['startup_count'] <= niche_threshold

# Step 3: Compare Metrics for Niche vs Non-Niche
niche_stats = market_stats[market_stats['is_niche'] == True]
non_niche_stats = market_stats[market_stats['is_niche'] == False]

# Calculate average funding and returns for niche vs non-niche
comparison = {
    "Segment": ["Niche", "Non-Niche"],
    "Avg Total Funding": [niche_stats['total_funding'].mean(),␣
 ↪non_niche_stats['total_funding'].mean()],
    "Avg Funding per Startup": [niche_stats['avg_funding'].mean(),␣
 ↪non_niche_stats['avg_funding'].mean()],
    "Avg Funding Rounds": [niche_stats['funding_rounds'].mean(),␣
 ↪non_niche_stats['funding_rounds'].mean()]
}
comparison_df = pd.DataFrame(comparison)

# Step 4: Visualize the Comparison
plt.figure(figsize=(8,4))
g=sns.barplot(x='Segment', y='Avg Total Funding', data=comparison_df,␣
 ↪palette='viridis')
plt.title('Average Total Funding: Niche vs Non-Niche Segments')
plt.ylabel('Avg Total Funding (USD)')
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()

plt.figure(figsize=(8,4))
```

```
g=sns.barplot(x='Segment', y='Avg Funding per Startup', data=comparison_df,␣
↪palette='coolwarm')
plt.title('Average Funding per Startup: Niche vs Non-Niche Segments')
plt.ylabel('Avg Funding per Startup (USD)')
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()

plt.figure(figsize=(8,4))
g=sns.barplot(x='Segment', y='Avg Funding Rounds', data=comparison_df,␣
↪palette='Set2')
plt.title('Average Funding Rounds: Niche vs Non-Niche Segments')
plt.ylabel('Avg Funding Rounds')
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()

# Step 5: Scatter Plot to Analyze Total Funding by Startup Count
plt.figure(figsize=(8,4))
sns.scatterplot(data=market_stats, x='startup_count', y='total_funding',␣
↪hue='is_niche', palette='coolwarm')
plt.title('Total Funding vs Startup Count')
plt.xlabel('Startup Count (Market Size)')
plt.ylabel('Total Funding (USD)')
plt.legend(title='Niche Segment')
plt.show()
```




Average Funding per Startup: Niche vs Non-Niche Segments
1e7
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Avg Funding per Startup (USD)
9,243,124
12,196,553
Niche
Non-Niche
Segment


Average Funding Rounds: Niche vs Non-Niche Segments
140
120
100
80
60
40
20
0
Avg Funding Rounds
3
143
Niche
Non-Niche
Segment




```
[ ]: niche_stats.sort_values(by='total_funding', ascending=False).head(5)
```

```
[ ]:                        market  total_funding  avg_funding  funding_rounds
     startup_count  is_niche
     456        Natural Gas Uses     400000000.0  400000000.0             1.0
     1       True
     559              Recreation     128660000.0   64330000.0             2.0
     2       True
     154           Custom Retail     119657790.0  119657790.0             1.0
     1       True
     42     B2B Express Delivery     105000000.0  105000000.0             4.0
     1       True
     102       Cloud-Based Music     104000000.0   52000000.0             2.0
     2       True
```

```
[ ]: non_niche_stats.sort_values(by='total_funding', ascending=False).head(5)
```

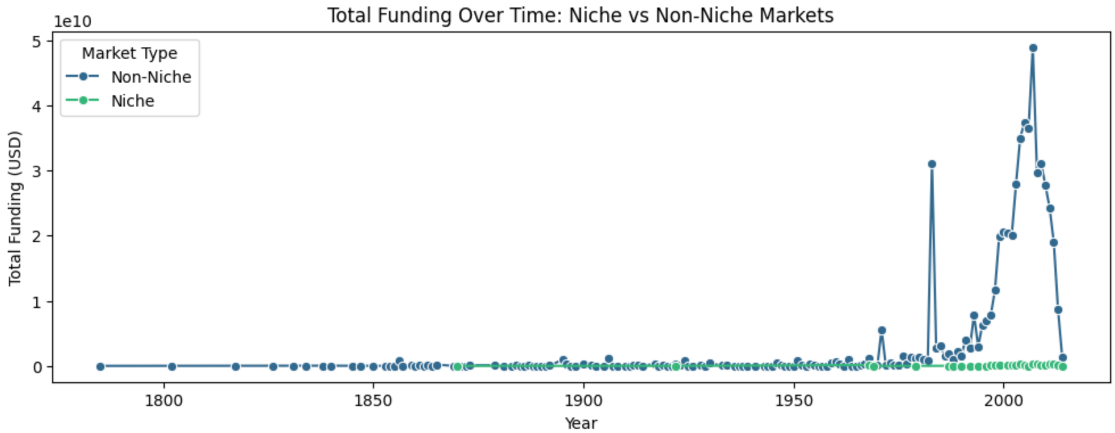
```
[ ]:                    market  total_funding   avg_funding  funding_rounds
     startup_count  is_niche
     59        Biotechnology    7.337295e+10  1.989505e+07          7652.0
     3688      False
     425              Mobile    4.947011e+10  2.494710e+07          3570.0
     1983      False
     636            Software    4.222348e+10  9.139281e+06          7633.0
     4620      False
     94     Clean Technology    3.761994e+10  3.134995e+07          2190.0
```

```
1200      False
305         Health Care     2.946608e+10   2.441266e+07           2777.0
1207      False
```

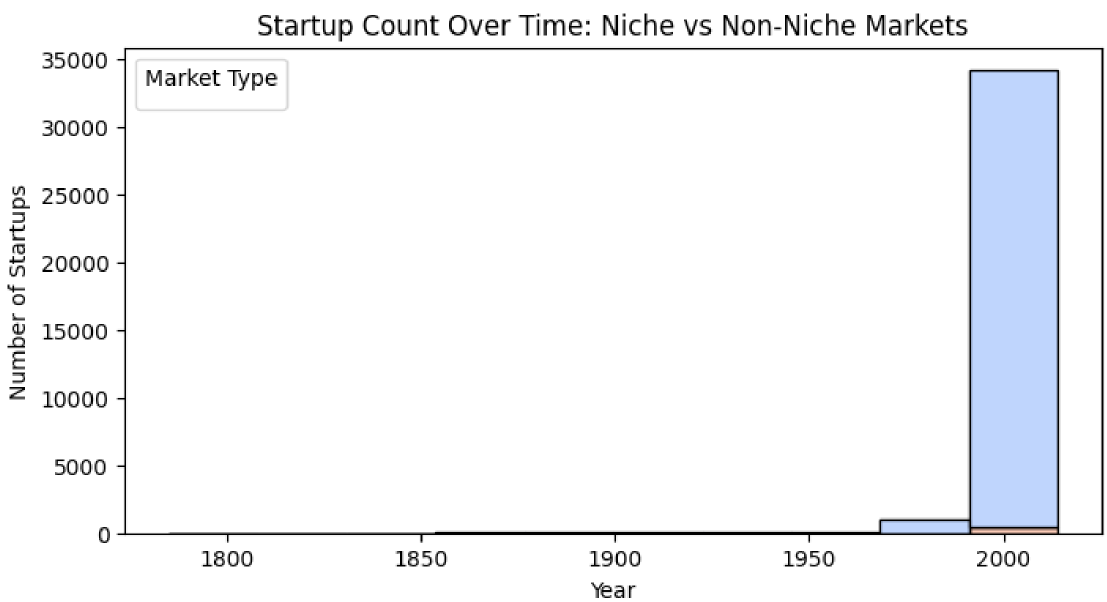
Non-Niche Markets Lead in Funding: Non-Niche markets have the highest average total funding, the highest average funding per startup, and the most funding counts, indicating that these markets attract a larger volume of investments compared to niche markets.

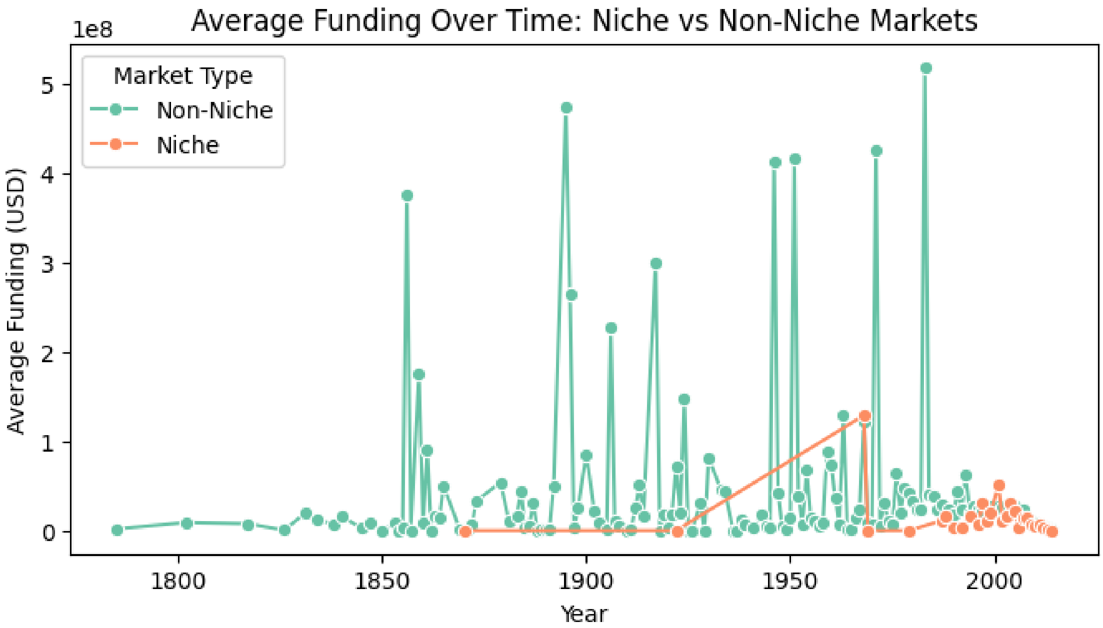
```
[ ]: # Convert founded_at to datetime and extract the year
df['founded_at'] = pd.to_datetime(df['founded_at'])
df['founded_year'] = df['founded_at'].dt.year

# Group by market to identify niche markets
market_startup_count = df.groupby('market')['name'].count().reset_index()
market_startup_count.rename(columns={'name': 'startup_count'}, inplace=True)

# Define niche markets (bottom 25%)
niche_threshold = market_startup_count['startup_count'].quantile(0.25)
niche_markets = market_startup_count[market_startup_count['startup_count'] <=␣
↪niche_threshold]['market']

# Add a column to identify niche markets
df['is_niche'] = df['market'].apply(lambda x: 'Niche' if x in niche_markets.
↪values else 'Non-Niche')

# Group by year and niche type
time_niche_analysis = df.groupby(['founded_year', 'is_niche']).agg({
    'funding_total_usd': 'sum',
    'name': 'count'
}).rename(columns={'funding_total_usd': 'total_funding', 'name':␣
↪'startup_count'}).reset_index()

# Add average funding per startup
time_niche_analysis['avg_funding'] = time_niche_analysis['total_funding'] /␣
↪time_niche_analysis['startup_count']

# Plot total funding over time
plt.figure(figsize=(12,4))
sns.lineplot(
    data=time_niche_analysis,
    x='founded_year',
    y='total_funding',
    hue='is_niche',
    marker='o',
    palette='viridis'
)
plt.title('Total Funding Over Time: Niche vs Non-Niche Markets')
```

```python
plt.xlabel('Year')
plt.ylabel('Total Funding (USD)')
plt.legend(title='Market Type')
plt.show()

# Plot startup count over time
plt.figure(figsize=(8,4))
sns.histplot(
    data=time_niche_analysis,
    x='founded_year',
    weights='startup_count',
    hue='is_niche',
    multiple='stack',
    palette='coolwarm'
)
plt.title('Startup Count Over Time: Niche vs Non-Niche Markets')
plt.xlabel('Year')
plt.ylabel('Number of Startups')
plt.legend(title='Market Type')
plt.show()

# Plot average funding over time
plt.figure(figsize=(8,4))
sns.lineplot(
    data=time_niche_analysis,
    x='founded_year',
    y='avg_funding',
    hue='is_niche',
    marker='o',
    palette='Set2'
)
plt.title('Average Funding Over Time: Niche vs Non-Niche Markets')
plt.xlabel('Year')
plt.ylabel('Average Funding (USD)')
plt.legend(title='Market Type')
plt.show()
```




```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note
that artists whose label start with an underscore are ignored when legend() is
called with no argument.
```





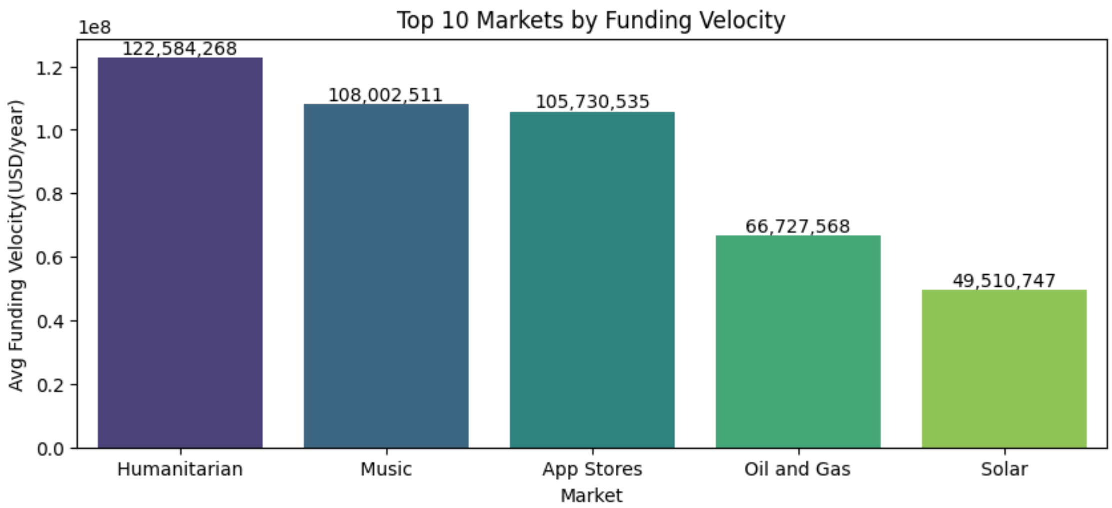
[ ]:
```
# Convert 'founded_at' and 'last_funding_at' to datetime

# Handle missing dates: Replace 'last_funding_at' with the current year if␣
↪missing
df['last_funding_at'] = df['last_funding_at'].fillna(pd.Timestamp.now())

# Calculate the total number of years (active duration)
df['total_no_years'] = (df['last_funding_at'] - df['founded_at']).dt.days / 365.
↪0

# Handle cases where 'total_no_years' is zero or negative
df['total_no_years'] = df['total_no_years'].apply(lambda x: x if x > 0 else np.
↪nan)

# Calculate Funding Velocity (funding_total_usd / total_no_years)
df['funding_total_usd'] = pd.to_numeric(df['funding_total_usd'],␣
↪errors='coerce')  # Ensure numeric funding
df['funding_velocity'] = round(df['funding_total_usd'] / df['total_no_years'],2)

# Drop rows with missing or invalid values
df = df.dropna(subset=['funding_velocity'])

# Inspect the resulting dataframe
print(df[['name', 'market', 'funding_total_usd', 'total_no_years',␣
↪'funding_velocity']].head())
```

```
# Group by market to analyze average funding velocity
market_velocity = df.groupby('market')['funding_velocity'].mean().
 ↪sort_values(ascending=False).reset_index()

# Display top 10 markets with highest funding velocity
print()
market_velocity['funding_velocity'] = market_velocity['funding_velocity'].
 ↪sort_values(ascending=False)
print("\nTop 10 Markets with Highest Funding Velocity:")
print(market_velocity.head(10))
```

```
                 name        market  funding_total_usd  total_no_years
funding_velocity
0            #waywire          News          1750000.0        0.079452
22025862.07
4   -R- Ranch and Mine       Tourism            60000.0        0.734247
81716.42
5        .Club Domains      Software          7000000.0        1.641096
4265442.40
7             0-6.com   Curated Web          2000000.0        1.213699
1647855.53
8     004 Technologies      Software                0.0        4.561644
0.00


Top 10 Markets with Highest Funding Velocity:
              market  funding_velocity
0       Humanitarian      1.225843e+08
1              Music      1.080025e+08
2         App Stores      1.057305e+08
3        Oil and Gas      6.672757e+07
4              Solar      4.951075e+07
5           Shopping      4.345072e+07
6           Hardware      3.646189e+07
7      TV Production      3.628231e+07
8    Vacation Rentals      2.901973e+07
9             Racing      2.893384e+07
```

[ ]:
```
# Plot top 10 markets by funding velocity
plt.figure(figsize=(10,4))
g=sns.barplot(x='market', y='funding_velocity', data=market_velocity.head(5),␣
 ↪palette='viridis')
plt.title('Top 10 Markets by Funding Velocity')
plt.xlabel('Market')
plt.ylabel('Avg Funding Velocity(USD/year)')
plt.xticks(rotation=0, ha='center')
for bars in g.containers:
```

```
    g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()
```



The top 10 markets with the highest funding velocity are:

- Humanitarian and Music lead, indicating rapid growth and emerging opportunities.
- Oil & Gas and Solar show strong investor interest, with a focus on traditional energy and sustainability.
- App Stores, Hardware, and Shopping reflect solid growth in tech and consumer markets.
- Niche sectors like TV Production, Vacation Rentals, and Racing are attracting steady investments.

[ ]:
```
# Example: If a FinTech industry averages a 5:1 valuation-to-funding ratio, and
↪the total funding is $10M:
df['valuation']=df['funding_total_usd'] * 5
```

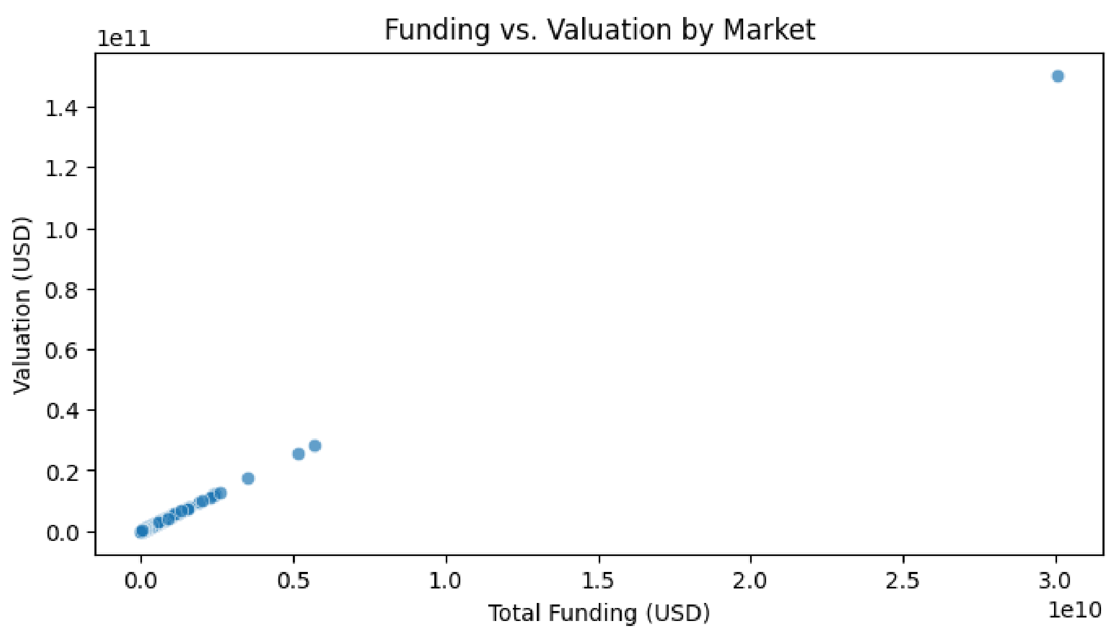
[ ]:
```
print(df[['name', 'market', 'funding_total_usd', 'valuation', 'founded_year']].
↪head())
```

```
                 name          market  funding_total_usd   valuation  \
founded_year
0            #waywire           News           1750000.0   8750000.0
2012.0
4   -R- Ranch and Mine       Tourism             60000.0    300000.0
2014.0
5        .Club Domains      Software           7000000.0  35000000.0
2011.0
7              0-6.com   Curated Web           2000000.0  10000000.0
2007.0
8     004 Technologies      Software                 0.0         0.0
2010.0
```

[ ]:
```python
# Correlation between funding and valuation
correlation = df[['funding_total_usd', 'valuation']].corr()
print("Correlation between funding and valuation:")
print(correlation)
```

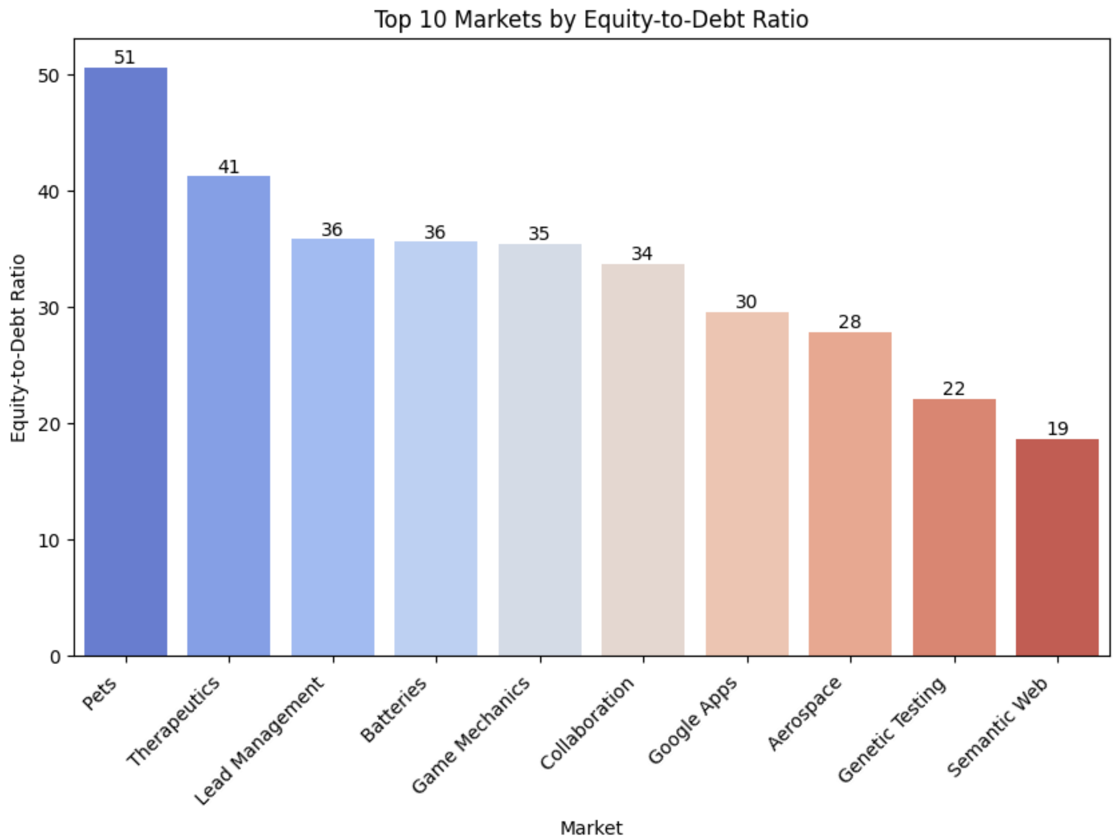
```
Correlation between funding and valuation:
                   funding_total_usd  valuation
funding_total_usd                1.0        1.0
valuation                        1.0        1.0
```

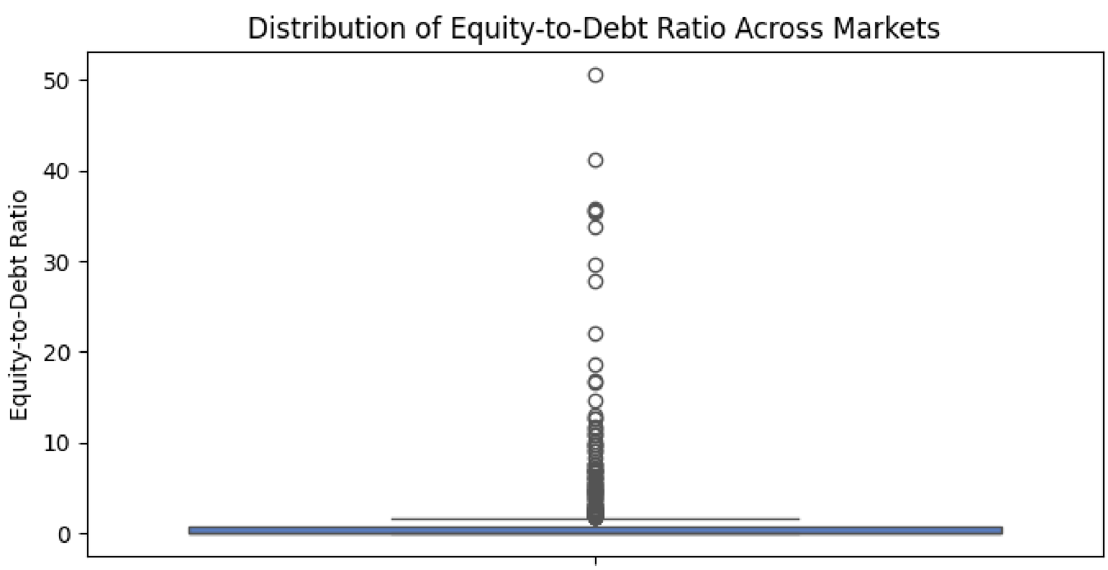
[ ]:
```python
plt.figure(figsize=(8,4))
sns.scatterplot(x='funding_total_usd', y='valuation', data=df,alpha=0.7,␣
↪palette='tab10')
plt.title('Funding vs. Valuation by Market')
plt.xlabel('Total Funding (USD)')
plt.ylabel('Valuation (USD)')
plt.show()
```



[ ]:
```python
# Calculate total equity funding (including funding rounds A to F)
df['total_equity_funding'] = (df['venture'] +  df['angel'] +␣
↪df['private_equity'] +  df['seed'] + df['equity_crowdfunding']+
                              df['post_ipo_equity'] + df['round_A'] +␣
↪df['round_B'] + df['round_C'] + df['round_D'] + df['round_E'] +
                              df['round_F'] + df['round_G'] + df['round_H'])

# Calculate total debt funding
```

```
df['total_debt_funding'] = (df['convertible_note'] + df['debt_financing'] +␣
↪df['post_ipo_debt'])

# Calculate Equity-to-Debt Ratio
df['equity_debt_ratio'] = df['total_equity_funding'] / df['total_debt_funding']

# Replace infinite or NaN values in the ratio
df['equity_debt_ratio']= df['equity_debt_ratio'].apply(lambda x: np.nan if np.
↪isinf(x) else x)
df['equity_debt_ratio'].fillna(0, inplace=True)

# Group by Market and calculate mean ratios
equity_debt_by_market = df.groupby('market')[['total_equity_funding',␣
↪'total_debt_funding', 'equity_debt_ratio']].mean().reset_index()

# Sort by Equity-to-Debt Ratio
top_markets = equity_debt_by_market.sort_values(by='equity_debt_ratio',␣
↪ascending=False).head(10)

# Plotting the Equity-to-Debt Ratio
plt.figure(figsize=(10,6))
g=sns.barplot(data=top_markets, x='market', y='equity_debt_ratio',␣
↪palette='coolwarm')
plt.title('Top 10 Markets by Equity-to-Debt Ratio')
plt.xlabel('Market')
plt.ylabel('Equity-to-Debt Ratio')
plt.xticks(rotation=45, ha='right')
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()

# Visualize the distribution of funding
plt.figure(figsize=(8,4))
sns.boxplot(data=equity_debt_by_market, y='equity_debt_ratio', palette='muted')
plt.title('Distribution of Equity-to-Debt Ratio Across Markets')
plt.ylabel('Equity-to-Debt Ratio')
plt.show()
```


Top 10 Markets by Equity-to-Debt Ratio
51
41
36
36
35
34
30
28
22
19
Equity-to-Debt Ratio
0
10
20
30
40
50
Pets
Therapeutics
Lead Management
Batteries
Game Mechanics
Collaboration
Google Apps
Aerospace
Genetic Testing
Semantic Web
Market


Distribution of Equity-to-Debt Ratio Across Markets
Equity-to-Debt Ratio
0
10
20
30
40
50

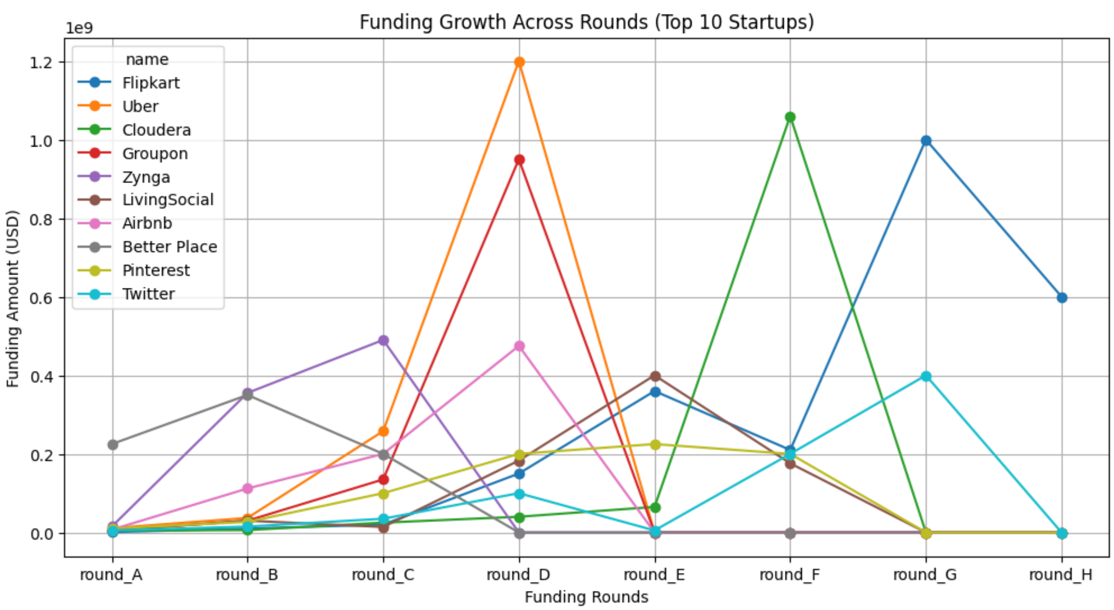
```
[ ]: ddf=df.copy()
```

```
[ ]: # Adding cumulative funding
round_columns = ['round_A', 'round_B', 'round_C', 'round_D', 'round_E',␣
↪'round_F', 'round_G', 'round_H']
ddf['total_funding'] = ddf[round_columns].sum(axis=1)
for i in range(len(round_columns) - 1):
    current_round = round_columns[i]
    next_round = round_columns[i + 1]
    ddf[f'{current_round}_to_{next_round}_growth'] = (
        (ddf[next_round] - ddf[current_round]) / ddf[current_round]
    ) * 100
# Create a boolean column to indicate if funding increased at each round
ddf['consistent_growth'] = (ddf[round_columns].diff(axis=1) > 0).all(axis=1)
```

```
[ ]: ddf['consistent_growth'].value_counts()
```

```
[ ]: consistent_growth
False    35379
Name: count, dtype: int64
```

```
[ ]: top_startups = ddf.nlargest(10, 'total_funding')  # Top 10 startups by total␣
↪funding
top_startups.set_index('name')[round_columns].T.plot(kind='line', figsize=(12,␣
↪6), marker='o')
plt.title("Funding Growth Across Rounds (Top 10 Startups)")
plt.xlabel("Funding Rounds")
plt.ylabel("Funding Amount (USD)")
plt.grid()
plt.show()
```



14 Hypothesis Testing

[ ]:
```
from scipy.stats import shapiro
stat, p = shapiro(df['funding_total_usd'])
print('Shapiro-Wilk Test: stat=%.3f, p=%.3f' % (stat, p))
```

```
Shapiro-Wilk Test: stat=0.031, p=0.000
```

[ ]:
```
from scipy.stats import levene
stat, p = levene(df['funding_total_usd'],df['market'])
print('Levene Test: stat=%.3f, p=%.3f' % (stat, p))
```

```
Levene Test: stat=nan, p=nan
```

[ ]:
```
from scipy.stats import f_oneway
# HO :  The average funding across all markets is the same.
# H1 : The average funding differs for at least one market.

# Group funding data by market
market_funding = df.groupby('market')['funding_total_usd'].apply(list)

# Perform One-Way ANOVA test
f_stat, p_value = f_oneway(*market_funding)

# Results
print(f"F-Statistic: {f_stat}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: The average funding differs across␣
↪markets.")
else:
    print("Fail to reject the null hypothesis: No significant difference in␣
↪funding across markets.")
```

```
F-Statistic: 0.23704333197345273, P-Value: 0.9999999999999999
Fail to reject the null hypothesis: No significant difference in funding across
markets.
```

[ ]:
```
from scipy.stats import kruskal

# Group funding data by region
region_funding = df.groupby('region')['funding_total_usd'].apply(list)

# Perform Kruskal-Wallis test
h_stat, p_value = kruskal(*region_funding)
```

```
# Results
print(f"H-Statistic: {h_stat}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: Funding differs significantly between␣
↪regions.")
else:
    print("Fail to reject the null hypothesis: No significant difference in␣
↪funding between regions.")
```

```
H-Statistic: 4114.422648932073, P-Value: 0.0
Reject the null hypothesis: Funding differs significantly between regions.
```

[ ]:
```
from scipy.stats import pearsonr

# Remove NaN values for testing
seed_venture_data = df[['seed', 'venture']].dropna()

# Perform Pearson correlation test
corr, p_value = pearsonr(seed_venture_data['seed'],␣
↪seed_venture_data['venture'])

# Results
print(f"Correlation Coefficient: {corr}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: Significant correlation between seed and␣
↪venture funding.")
else:
    print("Fail to reject the null hypothesis: No significant correlation␣
↪between seed and venture funding.")
```

```
Correlation Coefficient: -0.015089071076506418, P-Value: 0.0045367200624364026
Reject the null hypothesis: Significant correlation between seed and venture
funding.
```

[ ]:
```
from scipy.stats import f_oneway

# H0 :  The average funding across all status is the same.
# H1 : The average funding differs for at least one status.

# Separate funding data for active and closed startups
active_funding = df[df['status'] == 'operating']['funding_total_usd'].dropna()
closed_funding = df[df['status'] == 'closed']['funding_total_usd'].dropna()
operating_funding = df[df['status'] == 'operating']['funding_total_usd'].
↪dropna()

# Perform two-sample t-test
f_stat, p_value = f_oneway(active_funding, closed_funding,operating_funding)
```

```
# Results
print(f"F-Statistic: {f_stat}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: The average funding differs across␣
↪status of startups.")
else:
    print("Fail to reject the null hypothesis: No significant difference in␣
↪funding between status of startups.")
```

```
F-Statistic: 1.1246374509748063, P-Value: 0.3247768431056756
Fail to reject the null hypothesis: No significant difference in funding between
status of startups.
```

[ ]:
```
from scipy.stats import ttest_ind

# Separate funding data for active and closed startups
active_funding = df[df['status'] == 'operating']['funding_total_usd'].dropna()
closed_funding = df[df['status'] == 'closed']['funding_total_usd'].dropna()

# Perform two-sample t-test
t_stat, p_value = ttest_ind(active_funding, closed_funding)

# Results
print(f"T-Statistic: {t_stat}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: Funding differs significantly between␣
↪active and closed startups.")
else:
    print("Fail to reject the null hypothesis: No significant difference in␣
↪funding between active and closed startups.")
```

```
T-Statistic: 1.4986728697672715, P-Value: 0.13396849327823057
Fail to reject the null hypothesis: No significant difference in funding between
active and closed startups.
```

[ ]:
```
from scipy.stats import chi2_contingency

# Create a contingency table
contingency_table = pd.crosstab(df['market'], df['funding_rounds'])

# Perform Chi-Square test
chi2_stat, p_value, dof, expected = chi2_contingency(contingency_table)

# Results
print(f"Chi-Square Statistic: {chi2_stat}, P-Value: {p_value}")
if p_value < 0.05:
```

```
    print("Reject the null hypothesis: Funding rounds are associated with␣
↪specific markets.")
else:
    print("Fail to reject the null hypothesis: No significant association␣
↪between funding rounds and markets.")
```

```
Chi-Square Statistic: 9889.917170496228, P-Value: 1.0
Fail to reject the null hypothesis: No significant association between funding
rounds and markets.
```

[ ]:
```
# Group funding data by country
country_funding = df.groupby('country_code')['funding_total_usd'].apply(list)

# Perform Kruskal-Wallis test for non-normal distributions
h_stat, p_value = kruskal(*country_funding)

# Results
print(f"H-Statistic: {h_stat}, P-Value: {p_value}")
if p_value < 0.05:
    print("Reject the null hypothesis: Funding differs significantly between␣
↪countries.")
else:
    print("Fail to reject the null hypothesis: No significant difference in␣
↪funding between countries.")
```

```
H-Statistic: 1529.9612429227366, P-Value: 1.5245711578164713e-238
Reject the null hypothesis: Funding differs significantly between countries.
```

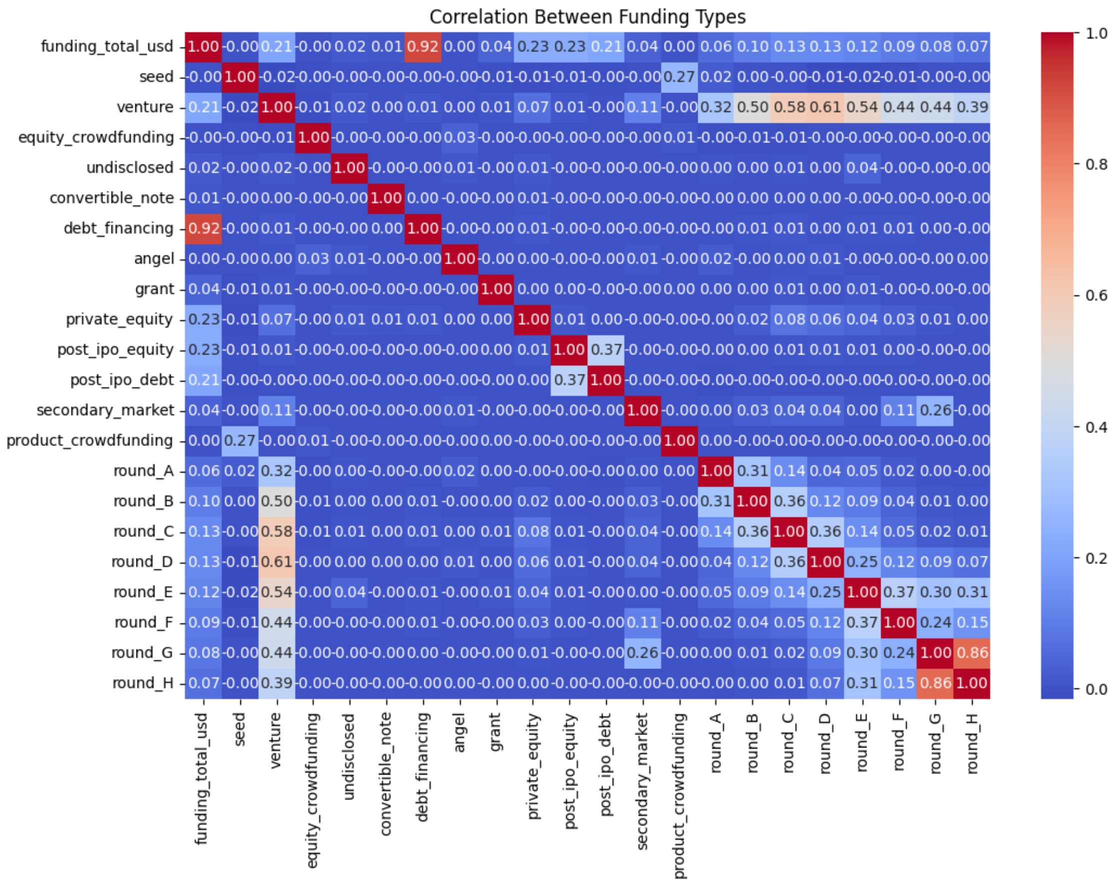
[ ]:
```
df.columns
```

[ ]:
```
Index(['permalink', 'name', 'homepage_url', 'category_list', 'market',
'funding_total_usd', 'status', 'country_code', 'state_code', 'region', 'city',
'funding_rounds', 'founded_at', 'founded_month', 'founded_quarter',
'founded_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', 'round_A', 'round_B', 'round_C',
'round_D', 'round_E', 'round_F', 'round_G', 'round_H', 'total_funding_usd',
'country_domain', 'founded_year_extract', 'is_niche', 'total_no_years',
'funding_velocity', 'valuation', 'total_equity_funding', 'total_debt_funding',
'equity_debt_ratio'], dtype='object')
```

[ ]:
```
c=df[['funding_total_usd','seed', 'venture', 'equity_crowdfunding',␣
↪'undisclosed', 'convertible_note', 'debt_financing', 'angel',
    'grant', 'private_equity', 'post_ipo_equity', 'post_ipo_debt',␣
↪'secondary_market', 'product_crowdfunding',
```

```
    'round_A', 'round_B', 'round_C', 'round_D', 'round_E', 'round_F',␣
↪'round_G', 'round_H']].corr()
```

[ ]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(c, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Between Funding Types')
plt.show()
```



[ ]:
```
pip install lifelines
```

```
Collecting lifelines
  Downloading lifelines-0.30.0-py3-none-any.whl.metadata (3.2 kB)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-
packages (from lifelines) (1.26.4)
Requirement already satisfied: scipy>=1.7.0 in /usr/local/lib/python3.10/dist-
packages (from lifelines) (1.13.1)
Requirement already satisfied: pandas>=2.1 in /usr/local/lib/python3.10/dist-
packages (from lifelines) (2.2.2)
Requirement already satisfied: matplotlib>=3.0 in
/usr/local/lib/python3.10/dist-packages (from lifelines) (3.8.0)
```

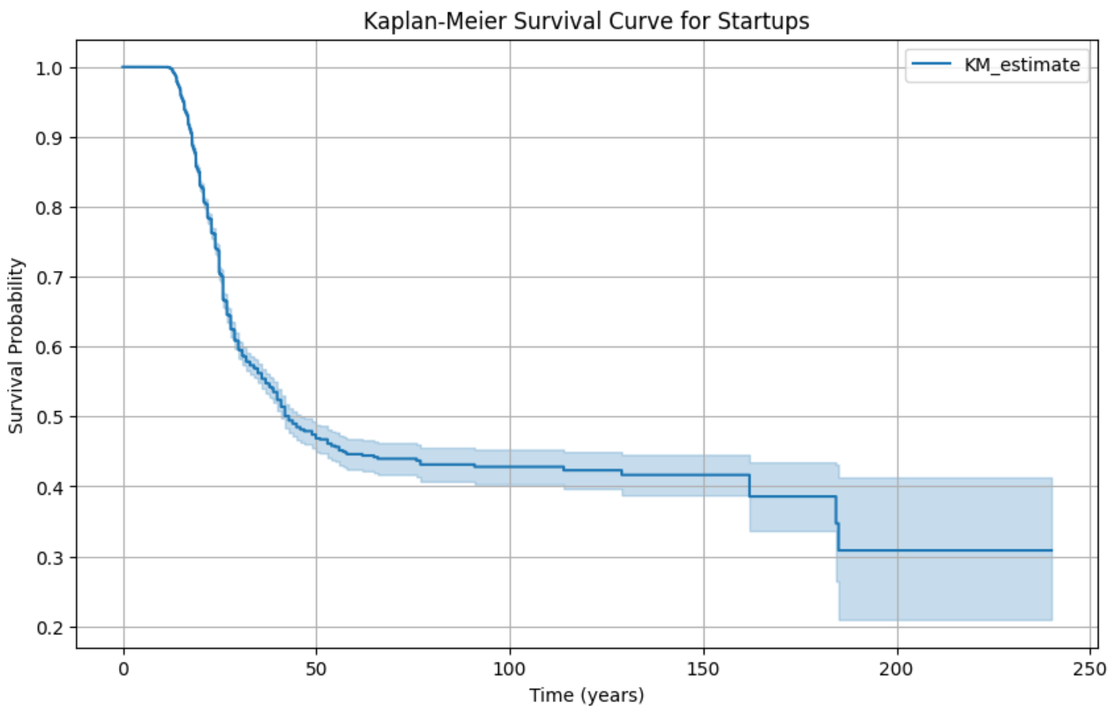
```
Requirement already satisfied: autograd>=1.5 in /usr/local/lib/python3.10/dist-
packages (from lifelines) (1.7.0)
Collecting autograd-gamma>=0.3 (from lifelines)
  Downloading autograd-gamma-0.5.0.tar.gz (4.0 kB)
  Preparing metadata (setup.py) … done
Collecting formulaic>=0.2.2 (from lifelines)
  Downloading formulaic-1.0.2-py3-none-any.whl.metadata (6.8 kB)
Collecting interface-meta>=1.2.0 (from formulaic>=0.2.2->lifelines)
  Downloading interface_meta-1.3.0-py3-none-any.whl.metadata (6.7 kB)
Requirement already satisfied: typing-extensions>=4.2.0 in
/usr/local/lib/python3.10/dist-packages (from formulaic>=0.2.2->lifelines)
(4.12.2)
Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.10/dist-
packages (from formulaic>=0.2.2->lifelines) (1.16.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
(1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib>=3.0->lifelines) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
(4.55.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
(1.4.7)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-
packages (from matplotlib>=3.0->lifelines) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
(3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas>=2.1->lifelines) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-
packages (from pandas>=2.1->lifelines) (2024.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.7->matplotlib>=3.0->lifelines) (1.16.0)
Downloading lifelines-0.30.0-py3-none-any.whl (349 kB)
                          349.3/349.3 kB
16.2 MB/s eta 0:00:00
Downloading formulaic-1.0.2-py3-none-any.whl (94 kB)
                          94.5/94.5 kB
7.2 MB/s eta 0:00:00
Downloading interface_meta-1.3.0-py3-none-any.whl (14 kB)
```

```
Building wheels for collected packages: autograd-gamma
  Building wheel for autograd-gamma (setup.py) … done
  Created wheel for autograd-gamma: filename=autograd_gamma-0.5.0-py3-none-
any.whl size=4031
sha256=aa82f40b2959c7da26a8fff4a3544540516f92084b51b27c955ff16823ed4d71
  Stored in directory: /root/.cache/pip/wheels/25/cc/e0/ef2969164144c899fedb22b3
38f6703e2b9cf46eeebf254991
Successfully built autograd-gamma
Installing collected packages: interface-meta, autograd-gamma, formulaic,
lifelines
Successfully installed autograd-gamma-0.5.0 formulaic-1.0.2 interface-meta-1.3.0
lifelines-0.30.0
```

[ ]:
```
from datetime import datetime
from lifelines import KaplanMeierFitter

# Convert dates to datetime format
ddf['founded_at'] = pd.to_datetime(ddf['founded_at'])

# Create "duration" column (time from founding to the current date or event)
current_date = datetime.now()
ddf['duration'] = (current_date - ddf['founded_at']).dt.days / 365  # Convert␣
 ↪to years

# Encode the "event" column (1 if acquired/closed, 0 if operating)
ddf['event'] = np.where(ddf['status'].isin(['acquired', 'closed']), 1, 0)

# View the prepared data
print(ddf[['name', 'market', 'founded_at', 'duration', 'event']].head(10))

# Initialize Kaplan-Meier Fitter
kmf = KaplanMeierFitter()

# Fit the data
kmf.fit(ddf['duration'], event_observed=ddf['event'])

# Plot the survival function
plt.figure(figsize=(10, 6))
kmf.plot_survival_function()
plt.title('Kaplan-Meier Survival Curve for Startups')
plt.xlabel('Time (years)')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.show()
```

```
                 name                  market founded_at   duration  event
0            #waywire                    News  2012-06-01  12.484932      1
4   -R- Ranch and Mine                Tourism  2014-01-01  10.898630      0
```

```
5          .Club Domains               Software  2011-10-10  13.128767      0
7                0-6.com            Curated Web  2007-01-01  17.904110      0
8       004 Technologies               Software  2010-01-01  14.901370      0
10           1,2,3 Listo             E-Commerce  2012-01-01  12.901370      0
12          1-800-DENTIST  Health and Wellness  1986-01-01  38.917808      0
13          1-800-DOCTORS  Health and Wellness  1984-01-01  40.920548      0
14      1.618 Technology            Real Estate  2013-12-07  10.967123      0
15        10 Minutes With             Education  2013-01-01  11.898630      0
```



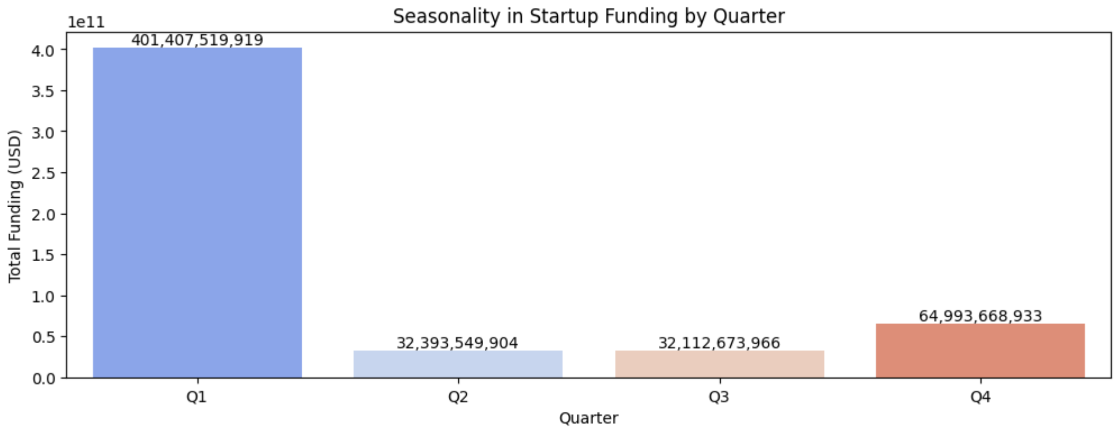
[ ]:
```
df['founded_q']=df['founded_quarter'].str.split('-').str[1]
```

[ ]:
```
quarterly_funding = df.groupby('founded_q')['funding_total_usd'].sum().
  ↪reset_index()
quarterly_funding.columns = ['Quarter', 'Total_Funding']
#quarterly_funding['Total_Funding']=quarterly_funding['Total_Funding'].
  ↪apply(lambda x: f'{x:.2f}')
quarterly_funding
```

[ ]:

	Quarter	Total_Funding
0	Q1	4.014075e+11
1	Q2	3.239355e+10
2	Q3	3.211267e+10
3	Q4	6.499367e+10

[ ]:
```
plt.figure(figsize=(12,4))
g=sns.barplot(data=quarterly_funding,x='Quarter', y='Total_Funding',␣
 ↪palette="coolwarm")
plt.title("Seasonality in Startup Funding by Quarter")
plt.xlabel("Quarter")
plt.ylabel("Total Funding (USD)")
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.datavalues])
plt.show()
```



[ ]:
```
df.sample(2)
```

[ ]:
```
                                        permalink                   name
homepage_url                                              category_list
market  funding_total_usd     status country_code state_code              region
city   funding_rounds founded_at founded_month founded_quarter  founded_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
round_A    round_B  round_C  round_D  round_E  round_F  round_G  round_H
total_funding_usd country_domain  founded_year_extract   is_niche
total_no_years  funding_velocity   valuation  total_equity_funding
total_debt_funding  equity_debt_ratio founded_q
41570  /organization/synergene-therapeutics  SynerGene Therapeutics
NaN                                        |Biotechnology|         Biotechnology
3951000.0  operating          USA          MD  Washington, D.C.     Potomac
2.0 1998-01-01        1998-01          1998-Q1         1998.0        2011-09-14
2014-04-02    0.0    3951000.0                  0.0          0.0                0.0
0.0     0.0     0.0              0.0              0.0            0.0
0.0                    0.0         0.0        0.0       0.0        0.0        0.0
0.0       0.0       0.0           3951000.0           None                1970.0
Non-Niche        16.260274        242984.84   19755000.0              3951000.0
```

```
0.0                0.0        Q1
37868     /organization/shape-the-nation                ShapeUp
http://www.shapeup.com  |Fitness|Health Care Information Technology|He…
Health and Wellness          12500000.0  operating          USA          RI
Providence  Providence             3.0 2006-01-01       2006-01          2006-Q1
2006.0       2010-08-16      2013-11-05    0.0   10000000.0                 0.0
0.0                0.0       2500000.0     0.0     0.0              0.0
0.0             0.0               0.0                     0.0  5000000.0  5000000.0
0.0       0.0       0.0       0.0       0.0       0.0        22500000.0
com                1970.0  Non-Niche        7.849315        1592495.64
62500000.0            20000000.0          2500000.0             8.0
Q1
```

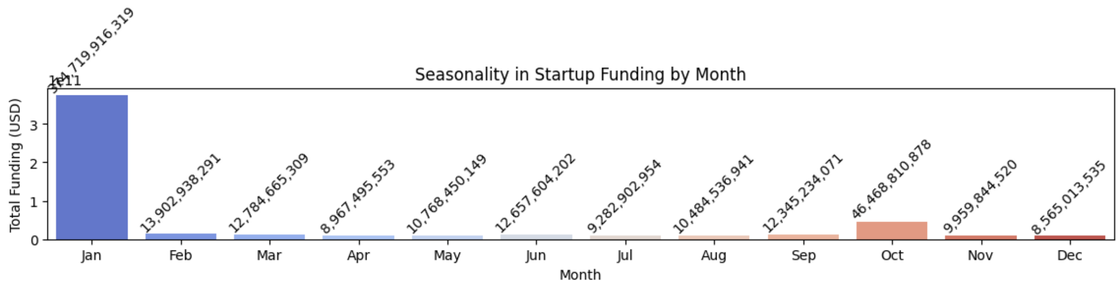
[ ]:
```
df['month']=df['founded_month'].str.split('-').str[1]
```

[ ]:
```
monthly_funding = df.groupby('month')['funding_total_usd'].sum().reset_index()
monthly_funding.columns = ['Month', 'Total_Funding']
monthly_funding['Month'] = monthly_funding['Month'].astype(int)
#monthly_funding['Total_Funding']=monthly_funding['Total_Funding'].apply(lambda␣
↪x: f'{x:.2f}' if pd.notnull(x) else x)
monthly_funding
```

[ ]:
```
    Month  Total_Funding
0       1   3.747199e+11
1       2   1.390294e+10
2       3   1.278467e+10
3       4   8.967496e+09
4       5   1.076845e+10
5       6   1.265760e+10
6       7   9.282903e+09
7       8   1.048454e+10
8       9   1.234523e+10
9      10   4.646881e+10
10     11   9.959845e+09
11     12   8.565014e+09
```

[ ]:
```
plt.figure(figsize=(14,2))
g=sns.barplot(data=monthly_funding,x='Month', y='Total_Funding',␣
↪palette="coolwarm")
plt.title("Seasonality in Startup Funding by Month")
plt.xlabel("Month")
plt.ylabel("Total Funding (USD)")
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun',␣
↪'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], fontsize=10)
for bars in g.containers:
  g.bar_label(bars, fmt='%.0f', labels=[f'{v:,.0f}' for v in bars.
↪datavalues],rotation=45)
```

```
plt.show()
```

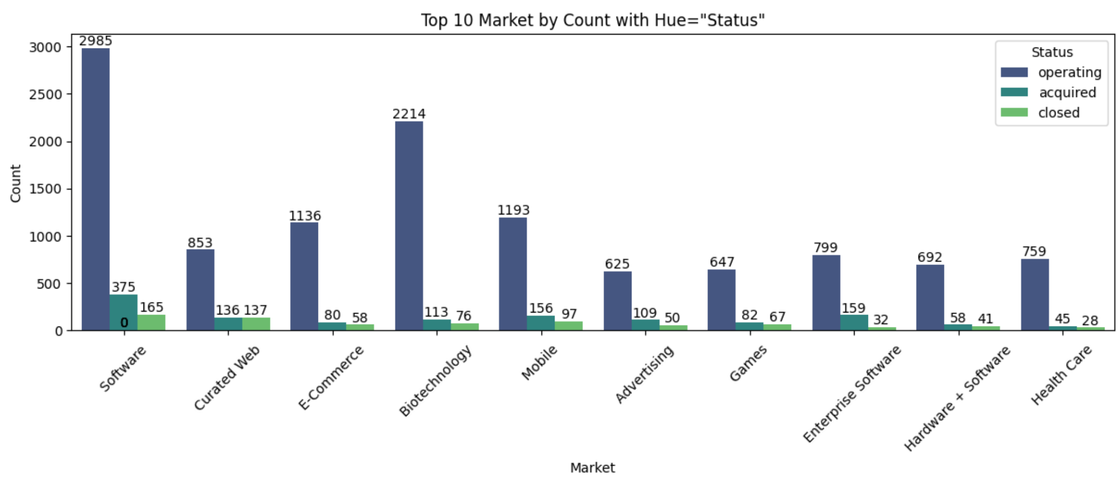


Increased Funding in Q1, Particularly in January: The data shows a significant rise in funding during the first quarter, with January seeing the highest amount of investments, indicating strong investor activity at the start of the year.

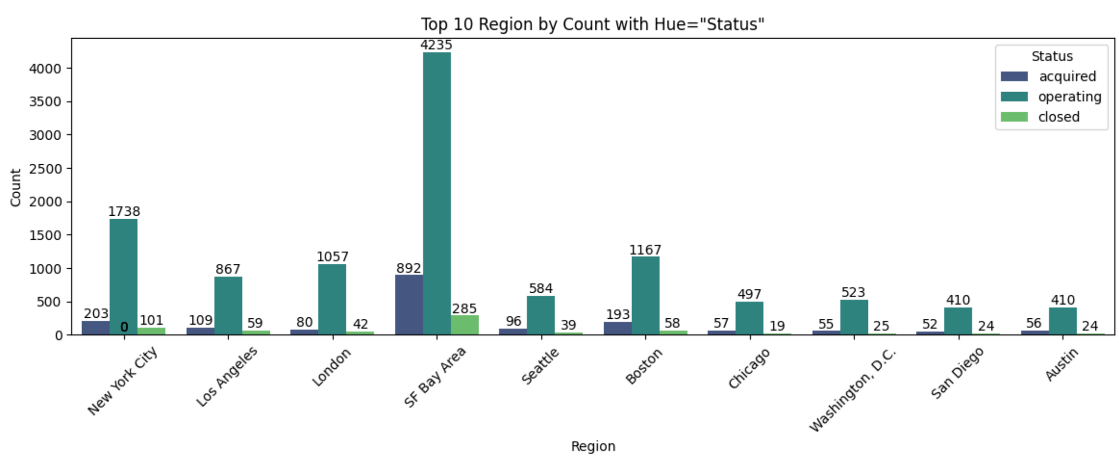
```
[ ]: def plot_top_10_counts_with_hue(df, column_name, hue_column='status'):
         """
         Plots a count plot of the top 10 most frequent values in a specified␣
     ↪column, with a hue,
         displaying counts on the bars.

         Parameters:
         - df (pd.DataFrame): The DataFrame containing the data.
         - column_name (str): The column name to analyze (e.g., 'market', 'city').
         - hue_column (str): The column name to use for hue (default is 'status').
         """
         # Get the top 10 most frequent values in the specified column excluding␣
     ↪'Unknown'
         top_10_values = df[column_name].value_counts().head(10).index

         # Filter the DataFrame for rows with top 10 values in the specified column
         df_top_10 = df[df[column_name].isin(top_10_values) & (df[column_name] !=␣
     ↪'Unknown')]

         # Count Plot with Hue
         plt.figure(figsize=(14, 4))
         ax = sns.countplot(data=df_top_10, x=column_name, hue=hue_column,␣
     ↪palette='viridis')
         plt.title(f'Top 10 {column_name.capitalize()} by Count with␣
     ↪Hue="{hue_column.capitalize()}"')
         plt.xlabel(column_name.capitalize())
         plt.ylabel('Count')
         plt.xticks(rotation=45)

         # Display the count values on top of each bar
```

```
    for p in ax.patches:
        height = p.get_height()
        ax.annotate(f'{int(height)}',
                    (p.get_x() + p.get_width() / 2., height),
                    ha='center', va='bottom', fontsize=10)

    plt.legend(title=hue_column.capitalize())
    plt.show()
```

[ ]:
```
plot_top_10_counts_with_hue(df, column_name='market', hue_column='status')
```



[ ]:
```
plot_top_10_counts_with_hue(df, column_name='region', hue_column='status')
```



14.1 Recommendations for markets and regions

Key Area	Top 10 Markets	Top 10 Regions
Investment Focus	Focus on high-activity markets like **Games**, **Software**, and **Curated Web**. Prioritize **operating** and **acquired** companies.	Focus on **NYC**, **SF Bay Area**. Prioritize **operating** companies and explore **acquired** ones for insights.
Diversification	Diversify into **E-commerce**, **Biotech**, and **Mobile** markets. Focus on **operating companies** for growth.	Diversify across **London**, **LA**, **Seattle**, and **Boston**. Focus on **operating** regions for balanced risk.
Emerging Opportunities	Explore **Hardware + Software**, **Clean Tech**, and **Health Care** for growth. Target **operating** companies.	Explore **Chicago**, **DC**, **Denver**, and **San Diego** for growth. Focus on **operating** companies in these regions.
Due Diligence	Assess **market size**, **competition**, and **regulations**. Learn from **closed** companies.	Evaluate **economic stability** and **ease of business**. Learn from **closed** regions and **acquired** companies.
Strategic Partnerships	Partner with **top-performing companies** in growth markets.	Partner with **local VCs** and **accelerators** in top regions. Focus on **operating companies** for scalability.
Long-term Strategy	Invest for **long-term growth** in high-potential markets.	Focus on **sustained growth** in mature regions and **operating companies**.

[ ]:
```
df.columns
```

[ ]:
```
Index(['permalink', 'name', 'homepage_url', 'category_list', 'market',
'funding_total_usd', 'status', 'country_code', 'state_code', 'region', 'city',
'funding_rounds', 'founded_at', 'founded_month', 'founded_quarter',
'founded_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', 'round_A', 'round_B', 'round_C',
'round_D', 'round_E', 'round_F', 'round_G', 'round_H', 'total_funding_usd',
'country_domain', 'founded_year_extract', 'is_niche', 'total_no_years',
'funding_velocity', 'valuation', 'total_equity_funding', 'total_debt_funding',
'equity_debt_ratio', 'founded_q', 'month'], dtype='object')
```

[ ]:
```
df[['name','funding_total_usd']].
↪sort_values(by='funding_total_usd',ascending=False).head(5)
```

[ ]:
```
                         name  funding_total_usd
45815  Verizon Communications       3.007950e+10
8664                Clearwire       5.700000e+09
```

```
7977   Charter Communications       5.162513e+09
15315  First Data Corporation       3.500000e+09
38289                sigmacare      2.600000e+09
```

15 Insights for Investors:

Top Markets by Funding:

Total Funding: Biotechnology, Mobile, Software, Clean Technology, and Healthcare are the leading markets, indicating robust investment opportunities in tech-driven and sustainable sectors.

Average Funding: Markets like Natural Gas Uses, Oil & Gas, and Trading offer high-value investments, suggesting these sectors provide attractive returns.

Funding Velocity: Humanitarian and Music sectors show rapid growth, while Oil & Gas, Solar, and App Stores indicate high investor interest, with quick returns. Geographic Investment Opportunities:

Top Countries by Funding: The USA, China, the UK, India, and Canada are dominant in funding, making them key regions for investors looking for well-established markets with strong startup ecosystems.

Top Regions by Funding: The SF Bay Area, New York City, and Boston offer substantial funding, while regions like West Sussex and Butleigh Heads show high average funding per startup.

Top States and Cities by Funding: California, New York, and Massachusetts lead in total funding, with cities like New York, San Francisco, and Beijing receiving the most investment, signaling strong startup activity in these regions. Emerging Investment Opportunities:

Funding Velocity: Markets with the highest funding velocity (Humanitarian, Music, Oil & Gas, and Solar) suggest emerging opportunities for investors looking for rapid growth.

Increased Funding in Q1: January shows the highest funding levels, reflecting heightened investor activity at the start of the year. Investors should consider planning major investments in Q1 for maximum returns.

Economic Trends for Investment Strategy:

Non-Niche Markets Lead: Non-niche markets (tech, healthcare) attract the highest funding, with the most funding rounds. Investors should focus on these markets for larger volumes of investment opportunities.

Venture Funding Dominates: Venture funding is the dominant source of capital, signifying that investors should focus on startups in the early to growth stages, as they attract the most capital.

Market and Regional Trends:

Regional Funding Variations: Significant funding differences across regions indicate that some areas, like the SF Bay Area and New York City, are more lucrative for investment than others. This can help investors focus on regions with better access to capital.

YoY Growth: Monitoring Year-over-Year growth in funding can reveal long-term trends, showing whether certain markets or regions are gaining or losing investor interest over time.

Insights for Startups:

Market Focus for Startups:

Top Markets by Average Funding: Startups in high average funding markets like Natural Gas Uses, Oil & Gas, and Trading can secure larger investments. Startups should consider entering these markets for higher-value investments.

Top Markets by Founding Count: Software, Biotechnology, and Mobile are the most popular markets, indicating where there is high startup activity. New startups should consider these areas for greater networking and investor interest.

Geographic Focus for Startups:

Top Countries by Funding: The USA, China, UK, and Canada receive the most funding, making them ideal locations for startups to attract international investors.

Top Regions and Cities by Funding: Startups in the SF Bay Area, New York City, and Boston have a higher likelihood of attracting funding, as these regions are startup hubs.

Top States and Cities by Founding Count: States like California and New York, along with cities like San Francisco and New York, have the highest number of startups. Startups should establish themselves in these locations for better networking and investment opportunities.

Funding Trends to Watch for Startups:

Funding Velocity: Markets with high funding velocity, like Humanitarian and Music, indicate rapid growth and emerging opportunities. Startups in these sectors may experience quick capital inflows.

Seasonality and Timing: Significant funding increases in Q1, especially in January, suggest that startups should time their fundraising efforts early in the year for maximum investor interest and availability of funds.

Funding Round Strategy:

Venture Funding Dominance: Most funds come through venture funding rounds. Startups should focus on securing venture capital for expansion and scaling, as it remains the primary source of capital.

Seed vs. Venture: A strong correlation between seed and venture funding suggests that startups securing seed funding can transition to venture funding more easily, making it crucial for early-stage startups to seek seed funding for growth.

Non-Niche vs. Niche Markets for Startups:

Non-Niche Markets Lead: Startups in non-niche markets (tech, healthcare) receive more funding on average, indicating that these sectors are more attractive to investors. Startups in these markets may have greater access to investment capital.

Niche Markets: Startups in niche markets like TV Production and Racing still attract consistent investments, though at a slower pace compared to non-niche markets. Niche markets may offer targeted opportunities with specific investor interest. Regional Funding Insights for Startups:

Funding Disparity Across Regions: Startups in regions like SF Bay Area and New York City have access to larger pools of capital. New startups may consider establishing their businesses in these regions to increase their chances of securing funding. Economic and YoY Insights for Startups:

YoY Growth: Monitoring Year-over-Year growth in funding across markets can help startups assess long-term trends and potential shifts in investor behavior. Emerging markets with strong YoY growth could provide new opportunities for investment.

Market Saturation: Some markets show no significant funding differences, suggesting that certain sectors may be saturated with competition. Startups in such markets should focus on innovation to differentiate themselves.

Recommendations For Investors:

Focus on Emerging Markets:

Humanitarian, Music, and App Stores markets are growing rapidly and offer emerging opportunities. Investors should consider allocating resources to these sectors as they exhibit high funding velocity, indicating rapid growth and potential for future returns.

Invest in Non-Niche Markets:

Non-niche markets, particularly those in technology (e.g., Software) and healthcare, are attracting the largest volumes of investment and consistently show high average funding per startup. These markets offer more mature investment opportunities with stable growth, which can be appealing for long-term investors.

Consider Traditional and Sustainable Sectors:

While Oil & Gas and Solar might appear different, both sectors offer significant investor interest. Investors should consider balancing their portfolios with investments in both traditional energy sectors (Oil & Gas) and renewable energy sectors (Solar) to mitigate risk and capitalize on global trends.

Target High Growth Periods:

Q1, particularly January, shows the highest funding activity. Investors should plan and allocate capital strategically during this period, taking advantage of increased investment momentum at the start of the year.

Diversify Geographic Exposure:

The USA, China, and the UK consistently lead in terms of total funding. However, don't overlook emerging regions such as SF Bay Area, New York City, and Boston for diversified investment portfolios, especially in rapidly growing industries.

Evaluate Funding Rounds for Better Opportunities:

There is a significant correlation between seed and venture funding. Investors should consider identifying and nurturing startups during their seed stage for better long-term investment returns as they transition to venture funding.

Recommendations For Startups:

Focus on High-Growth Markets:

If you are operating in markets like Biotechnology, Mobile, Software, Clean Technology, or Healthcare, you are in sectors that attract substantial funding. Tailor your business model to tap into these high-growth areas and stay ahead of emerging trends.

Leverage Venture Funding:

Venture funding is the dominant source of capital. Focus on refining your business model to meet the criteria that attract venture capitalists, such as scalability, innovation, and a high potential for return on investment.

Consider Timing Your Funding Rounds:

Given the increased funding in Q1, particularly January, startups should consider aligning their funding rounds during this period to increase the likelihood of securing investment when investor activity peaks.

Evaluate Market Trends:

Non-niche markets are seeing higher average total funding and funding counts. If you operate in a niche market, consider whether expanding into related non-niche areas might enhance your appeal to investors.

Seek Investments in High Funding Regions:

Focus your efforts in markets and regions that attract more funding. For example, areas like the SF Bay Area, New York City, and Boston are prominent startup hubs. Expanding your operations or networking in these areas could increase your chances of securing funding.

Maximize the Value Proposition in Traditional Sectors:

While Oil & Gas and Solar sectors have traditionally been strong investment areas, exploring sustainability and innovation within these fields can open up funding opportunities, particularly from investors focused on future growth and sustainability.

Build a Strong Investor Network:

Cultivate relationships with investors early on, especially those interested in your market. By understanding investor interests and aligning your goals with those of potential investors, you can position your startup for better funding opportunities.

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