SDP Poject

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In [106]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import seaborn as sns
```

In [107]:

```
data= pd.read_csv('investments_VC.csv',encoding='unicode_escape')
```

In [108]:

```
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54294 entries, 0 to 54293
Data columns (total 39 columns):
     Column
                           Non-Null Count Dtype
     -----
                           -----
 0
     permalink
                           49438 non-null
                                           object
 1
     name
                           49437 non-null
                                           object
 2
     homepage_url
                           45989 non-null
                                           object
 3
     category_list
                           45477 non-null
                                           object
 4
                           45470 non-null
                                           object
     market
 5
     funding_total_usd
                           49438 non-null
                                           object
 6
     status
                           48124 non-null
                                           object
 7
                           44165 non-null
                                           object
     country_code
 8
     state_code
                           30161 non-null
                                           object
 9
     region
                           44165 non-null
                                           object
 10
     city
                           43322 non-null
                                           object
 11
     funding_rounds
                           49438 non-null
                                           float64
 12
     founded_at
                           38554 non-null
                                           object
 13
     founded_month
                           38482 non-null
                                           object
 14
    founded_quarter
                           38482 non-null
                                           object
 15
     founded year
                           38482 non-null
                                           float64
     first_funding_at
                           49438 non-null
                                           object
                           49438 non-null
                                           object
 17
     last_funding_at
 18
     seed
                           49438 non-null
                                           float64
 19
     venture
                           49438 non-null
                                           float64
     equity_crowdfunding
                           49438 non-null float64
     undisclosed
                           49438 non-null float64
 22
     convertible_note
                           49438 non-null float64
 23
     debt_financing
                           49438 non-null
                                           float64
 24
     angel
                           49438 non-null
                                           float64
                           49438 non-null float64
 25
     grant
 26
     private equity
                           49438 non-null float64
 27
     post_ipo_equity
                           49438 non-null float64
                           49438 non-null float64
    post_ipo_debt
 29
     secondary_market
                           49438 non-null float64
 30
     product_crowdfunding 49438 non-null
                                           float64
 31
     round A
                           49438 non-null
                                           float64
 32
     round B
                           49438 non-null
                                           float64
 33
     round C
                           49438 non-null
                                           float64
 34
                           49438 non-null
     round D
                                           float64
 35
     round E
                           49438 non-null
                                           float64
 36
     round_F
                           49438 non-null
                                           float64
 37
     round G
                           49438 non-null
                                           float64
                           49438 non-null
                                           float64
 38
     round H
dtypes: float64(23), object(16)
memory usage: 16.2+ MB
In [109]:
data.rename(columns={' market ':'market',' funding_total_usd ':'funding_total_usd'},inplace
```

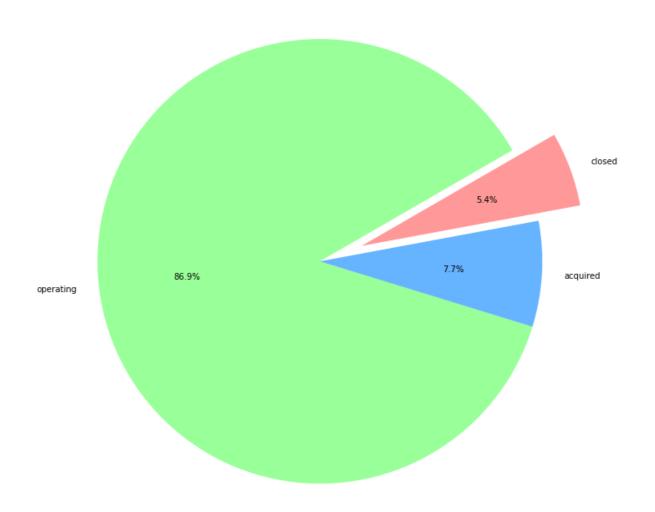
data.dropna(how='all',inplace=True)

In [110]:

Data visualization

In [111]:

What is start up companies current status



In [112]:

```
data['market'].value_counts()[:5]
```

Out[112]:

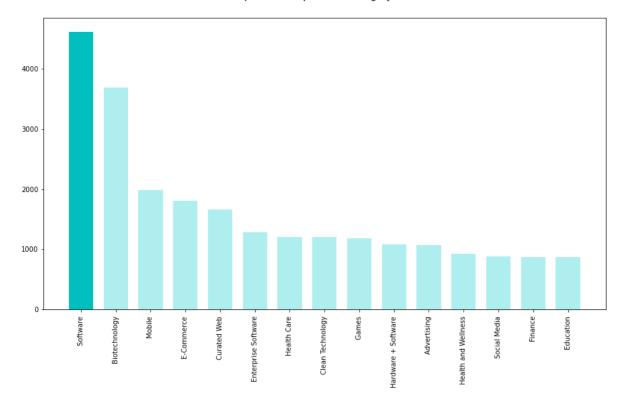
Software 4620
Biotechnology 3688
Mobile 1983
E-Commerce 1805
Curated Web 1655
Name: market, dtype: int64

In [113]:

```
plt.rcParams['figure.figsize'] = 15,8

height = data['market'].value_counts()[:15].tolist()
bars = data['market'].value_counts()[:15].index.tolist()
y_pos = np.arange(len(bars))
plt.bar(y_pos, height , width=0.7 ,color= ['c']+['paleturquoise']*14)
plt.xticks(y_pos, bars)
plt.xticks(rotation=90)
plt.title("Top 15 Start-Up market category", fontdict=None, position= [0.48,1.05], size = 'plt.show()
```

Top 15 Start-Up market category



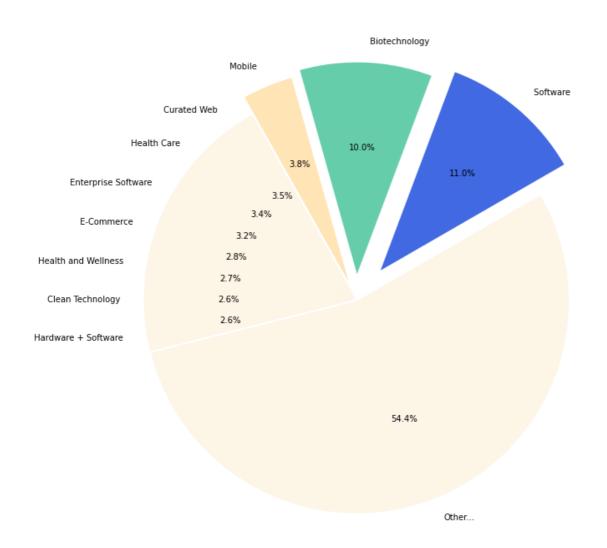
In [114]:

In [115]:

```
USA_market_pct = country_market_pct[country_market_pct['country_code'] == "USA"]
USA_market_pct = USA_market_pct.sort_values('count',ascending = False)[0:10]
```

In [116]:

USA start up market



In [117]:

```
data.drop(columns=['permalink','name','homepage_url','category_list','state_code','region',
```

In [118]:

data.head()

Out[118]:

	market	funding_total_usd	status	country_code	funding_rounds	seed	venture
0	News	17,50,000	acquired	USA	1.0	1750000.0	0.0
1	Games	40,00,000	operating	USA	2.0	0.0	4000000.0
2	Publishing	40,000	operating	EST	1.0	40000.0	0.0
3	Electronics	15,00,000	operating	GBR	1.0	1500000.0	0.0
4	Tourism	60,000	operating	USA	2.0	0.0	0.0

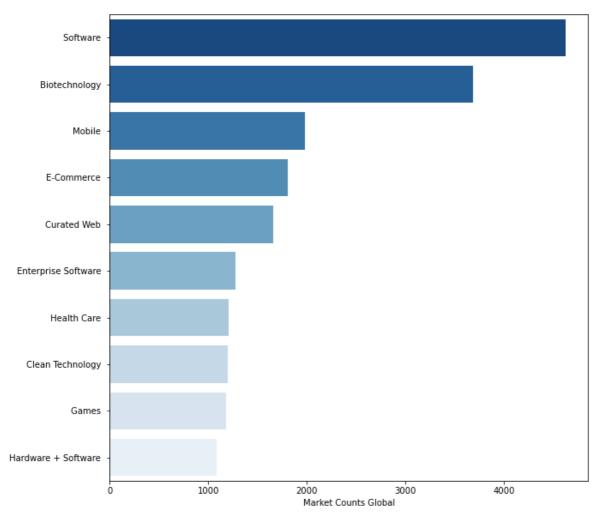
5 rows × 27 columns

localhost:8888/notebooks/Funding.ipynb#

In [119]:

```
market=data.market.value_counts()
market[(market>1000)][0:10]
market=market[(market>1000)][0:10].to_frame()
plt.figure()
ax1=sns.barplot(y=market.index,x=market.market,orient='h',palette='Blues_r')
ax1.set_title('Top 10 Market Counts of Start-Ups',pad=20)
ax1.set_xlabel('Market Counts Global')
plt.show()
```

Top 10 Market Counts of Start-Ups



In [120]:

```
data.funding_total_usd=data.funding_total_usd.str.replace(",",'').str.replace(' ',"")
data.funding_total_usd=data.funding_total_usd.replace("-",np.nan).astype('float',errors='ig
```

In [121]:

```
data['funding_total_usd']=data['funding_total_usd'].fillna(value=0)
data['status']=data['status'].fillna(value='closed')
```

In [122]:

```
data['market']= data['market'].fillna(value='Not sure')
data['country_code']= data['country_code'].fillna(value='NA')
```

```
In [123]:
```

```
X=data.iloc[:,:]
y=data.iloc[:,2]
```

In [124]:

```
X.drop(['status'],axis=1,inplace=True)
```

In [125]:

```
X.head()
```

Out[125]:

	market	funding_total_usd	country_code	funding_rounds	seed	venture	equity_cr
0	News	1750000.0	USA	1.0	1750000.0	0.0	_
1	Games	4000000.0	USA	2.0	0.0	4000000.0	
2	Publishing	40000.0	EST	1.0	40000.0	0.0	
3	Electronics	1500000.0	GBR	1.0	1500000.0	0.0	
4	Tourism	60000.0	USA	2.0	0.0	0.0	

5 rows × 26 columns

→

In [126]:

```
у
```

Out[126]:

```
0 acquired
1 operating
2 operating
3 operating
4 operating
...
49433 operating
49434 operating
```

49434 operating 49435 operating 49436 operating 49437 operating

Name: status, Length: 49438, dtype: object

In [127]:

```
markets= pd.get_dummies(X['market'],drop_first=True)
```

In [94]:

```
country=pd.get_dummies(X['country_code'],drop_first=True)
```

In [95]:

```
X=pd.concat([X,markets,country],axis=1)
```

In [96]:

```
X.drop(columns=['market','country_code'],axis=1,inplace=True)
```

In [97]:

X.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 49438 entries, 0 to 49437

Columns: 892 entries, funding_total_usd to ZWE dtypes: float64(23), int64(1), uint8(868)

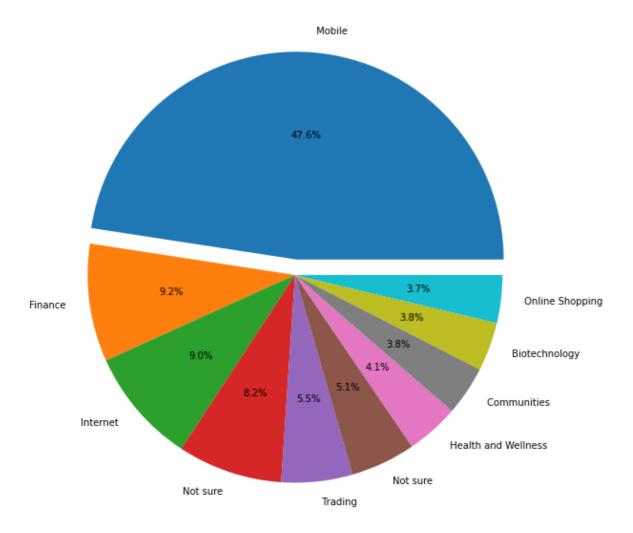
memory usage: 50.4 MB

In [103]:

```
lar=data.nlargest(n=10,columns='funding_total_usd')
explode = (0.075,0,0,0,0,0,0,0,0,0)
plt.pie(x=lar['funding_total_usd'],explode=explode,labels=lar['market'],autopct='%1.1f%%')
plt.xticks(rotation=90)
```

Out[103]:

(array([], dtype=float64), <a list of 0 Text major ticklabel objects>)



In [23]:

```
X_train,X_test,y_train,y_test= train_test_split(X,y,test_size=0.3,random_state=0)
```

In [24]:

```
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
```

```
In [25]:
sc=StandardScaler()
X_train= sc.fit_transform(X_train)
X_test= sc.fit_transform(X_test)
print(y_test)
23184
         operating
11254
         operating
35091
          acquired
23796
         operating
33448
         operating
23284
         operating
26573
         operating
30035
         operating
40811
         operating
15453
         operating
Name: status, Length: 14832, dtype: object
In [26]:
y=y.str.replace('operating','0').str.replace('acquired','1').str.replace('closed','2')
In [28]:
y=y.astype(int)
In [29]:
У
Out[29]:
0
         1
1
         0
2
         0
3
         0
         0
49433
         0
49434
         0
49435
         0
49436
         0
49437
         0
Name: status, Length: 49438, dtype: int32
```

Support Vector

```
In [ ]:
cls=svm.SVC()
cls.fit(X_train,y_train)
```

```
In [31]:

y_pred= cls.predict(X_test)

In [32]:

print('accuracy :' , 100*accuracy_score(y_test, y_pred))

accuracy : 84.00755124056096
```

Random Forest

```
In [30]:
```

from sklearn.ensemble import RandomForestClassifier

```
In [32]:
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.5,random_state=0)
rf=RandomForestClassifier(criterion='entropy',n_estimators=50,random_state=0)
```

```
In [34]:
```

```
rf.fit(X_train,y_train)
```

```
Out[34]:
```

In [35]:

```
y_pred=rf.predict(X_test)
print("Random forest accuracy: ",100*accuracy_score(y_test,y_pred))
```

Random forest accuracy: 82.70965653950402

Logistic Regression

```
In [37]:
```

```
from sklearn.linear_model import LogisticRegression
```

In [38]:

```
regressor = LogisticRegression()
regressor.fit(X_train,y_train)
y_pred=regressor.predict(X_test)
```

C:\Users\aftab\Anaconda3\lib\site-packages\sklearn\linear_model_logistic.p
y:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
 https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)

extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

In [40]:

```
from sklearn.metrics import classification_report
print("Classification report by Logistic Regression:")
print(classification_report(y_test,y_pred))
```

Classification report by Logistic Regression:

	precision	recall	†1-score	support
0	0.84	1.00	0.91	20850
1	0.18	0.01	0.03	1881
2	0.00	0.00	0.00	1988
accuracy			0.84	24719
macro avg	0.34	0.34	0.31	24719
weighted avg	0.73	0.84	0.77	24719

C:\Users\aftab\Anaconda3\lib\site-packages\sklearn\metrics_classification.p y:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and be ing set to 0.0 in labels with no predicted samples. Use `zero_division` para meter to control this behavior.

warn prf(average, modifier, msg start, len(result))

In [41]:

```
print(accuracy_score(y_test,y_pred)*100)
```

84.06893482746067