Export Processing Zones of Bangladesh

Exploritory Data Analysis + Statistical Analytics

EDA is the process of investigating the dataset to discover patterns, and anomalies (outliers), and form hypotheses based on our understanding of the dataset. EDA involves generating summary statistics for numerical data in the dataset and creating various graphical representations to understand the data better.

1. Introduction ¶

The objective of this notebook is to present an extensive analysis of the Export Processing Zones of Bangladesh and to present some suggestions.

An Export Processing Zone (EPZ) is a Customs area where one is allowed to import plant, machinery, equipment and material for the manufacture of export goods under security, without payment of duty. Export processing zones (EPZs) are designated parts of Kenya that are aimed at promoting and facilitating export oriented investments and to develop an enabling environment for such investments.

At present there are 8 EPZs in Bangladesh. These are: Dhaka Export Processing Zone, Savar, Dhaka. Adamjee Export Processing Zone, Siddhirganj, Narayanganj.

The Bangladesh Export Processing Zones Authority is an agency of the Government of Bangladesh and is administered under the jurisdiction of the Prime Minister's Office. Its objective is to manage the various export processing zones in Bangladesh.

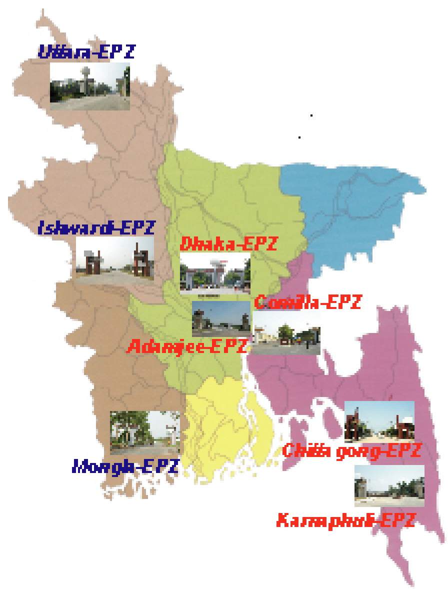
Dataset Source :

- Kaggle Dataset URL (https://www.kaggle.com/datasets/azminetoushikwasi/-epzs-of-bangladesh-investors-data)

2. Dataset Observations

2.1. Primary Observation Insights

- Location and Country data available
- Categorical Data on Products
- Total investment and Export Earned in July-September, 2020 (US$ Million) are provided of all 8 zones



3. Data, Libraries & Configurations

3.1. Import Libraries

In [1]:

```
import numpy as np
import pandas as pd
import os
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
import warnings
import json

from bokeh.io import output_notebook, show, output_file
from bokeh.plotting import figure
from bokeh.models import GeoJSONDataSource, LinearColorMapper, ColorBar
from bokeh.palettes import brewer
```

3.2. Configurations

In [2]:

```
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

warnings.filterwarnings('ignore')
```

```
/kaggle/input/country-names-with-short-codes-a2-a3-iso/country code.cs
v
/kaggle/input/-epzs-of-bangladesh-investors-data/zonal-data.csv
/kaggle/input/-epzs-of-bangladesh-investors-data/IncentivesForDevelope
rs.csv
/kaggle/input/-epzs-of-bangladesh-investors-data/data.csv
/kaggle/input/-epzs-of-bangladesh-investors-data/BSMSN/BANGABANDHU SHE
IKH MUJIB SHILPA NAGAR.txt
```

3.3. Data Loading

In [3]:

```
df=pd.read_csv("/kaggle/input/-epzs-of-bangladesh-investors-data/data.csv")
zdf=pd.read_csv("/kaggle/input/-epzs-of-bangladesh-investors-data/zonal-data.csv")
cc=pd.read_csv("/kaggle/input/country-names-with-short-codes-a2-a3-iso/country code.csv",encoding = "ISO-8859-1")
```

4. Descriptive Analysis

4.1. Dataset with 'data.csv'

4.1.1. Basic Exploration:

In [4]:

```
df.head()
```

Out[4]:

	Zone	NameOfEnterprise	InvestingCountry	Products
0	Adamjee	A.M.C.S Textiles Limited	UNITED KINGDOM	Garments
1	Adamjee	Checkpoint Systems Bangladesh Ltd.	CANADA	Garment Accessories
2	Adamjee	Epic Garments Mfg. Co. Ltd	HONGKONG	Garments
3	Adamjee	Erum Bangladesh Limited	SPAIN	Garment Accessories
4	Adamjee	French Fashion Knitting Pvt. Ltd.	HONGKONG	Garments

In [5]:

```
pd.DataFrame(df.apply(lambda col: len(col.unique())),columns=["Unique Values Count"])
```

Out[5]:

	Unique Values Count
Zone	8
NameOfEnterprise	502
InvestingCountry	34
Products	25

4.1.2. Summery:

In [6]:

```
df.describe(include=['object']).T
```

Out[6]:

	count	unique	top	freq
Zone	503	8	Chattogram	155
NameOfEnterprise	503	502	Xin Chang Shoes (BD) Limited	2
InvestingCountry	503	34	BANGLADESH	163
Products	502	24	Garments	155

4.1.3. Insights:

- All Columns are categorical on this Data
- Total 25 type of products is developed here in the EPZs
- Total 34 Country Invested here.

4.1.4. Detailed Summery

Show hidden cell

4.1.4.1 DF (Main)

Show hidden code

```
Done! Use 'show' commands to display/save.          [100%] 00:00 -> (00:00 left)
```

Sweetviz
2.1.3
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Created & maintained by Francois Bertrand
Graphic design by Jean-Francois Hains

DataFra
14
ASSOCIATIONS
DataFrame

1 Zone

VALUES: 503 (100%)
MISSING: ---
DISTINCT: 8 (2%)

2 NameOfEnterprise

VALUES: 503 (100%)
MISSING: ---
DISTINCT: 502 (>99%)

2	<1%	Xin Chang Shoes (BD) Limit
1	<1%	A.M.C.S Textiles Limited
1	<1%	Seiko Precision Parts Bang
1	<1%	FAR Chemical Industries Lt
1	<1%	Comilla Aquifer Limited
1	<1%	Sean Medal Manufacturing
1	<1%	Natway Outdoor (Banglade
495	98%	(Other)

3 InvestingCountry

VALUES: 503 (100%)
MISSING: ---
DISTINCT: 34 (7%)

4 Products

VALUES: 502 (>99%)
MISSING: 1 (<1%)

4.1.4.2 ZDF (Zonal)

Show hidden code

```
Done! Use 'show' commands to display/save.          [100%] 00:00 -> (00:00 left)
```

SweetVIZ

2.1.3

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Created & maintained by Francois Bertrand

Graphic design by Jean-Francois Hains

DataFra

ASSOCIATIONS

DataFrame

1 Zone

VALUES:	8 (100%)
MISSING:	---
DISTINCT:	8 (100%)

1	12%	Chattogram
1	12%	Dhaka
1	12%	Cumilla
1	12%	Adamjee
1	12%	Karnaphuli
1	12%	Mongla
1	12%	Uttara
1	12%	(Other)

2 Land

VALUES:	8 (100%)
MISSING:	---
DISTINCT:	2 (25%)

3 SFB

VALUES:	8 (100%)
MISSING:	---
DISTINCT:	2 (25%)

4 TotalInvestment

VALUES:	8 (100%)
MISSING:	---

4.2. Dataset with 'zonal-data.csv'

4.2.1. Basic Exploration:

In [10]:

```
zdf.head()
```

Out[10]:

	Zone	Land	SFB	TotalInvestment	ExportEarned	NewJobOpportunity
0	Chattogram	2.5	2.75	6.87	545.28	935
1	Dhaka	2.5	2.75	16.07	394.46	1773
2	Cumilla	2.5	2.75	48.83	136.39	1808
3	Adamjee	2.5	2.75	3.51	177.17	0
4	Karnaphuli	2.5	2.75	2.53	231.39	648

4.2.2. Summery:

In [11]:

```
zdf.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%
Land	8.0	2.08750	0.569304	1.40	1.400	2.50	2.5000
SFB	8.0	2.31875	0.595182	1.60	1.600	2.75	2.7500
TotalInvestment	8.0	10.13125	16.444780	0.36	1.850	3.02	9.1700
ExportEarned	8.0	197.45125	188.175461	19.52	40.875	156.78	272.1575
NewJobOpportunity	8.0	817.00000	665.295853	0.00	482.000	624.00	1144.5000

In [12]:

```
print ("Total investment in July-September, 2020",zdf['TotalInvestment'].
sum(),"M USD")
print ("Total Export earned in July-September, 2020",zdf['ExportEarned'].
sum(),"M USD")
print ("Total New Job Opportunity created in July-September, 2020",zdf['N
ewJobOpportunity'].sum(),"person")
```

```
Total investment in July-September, 2020 81.05 M USD
Total Export earned in July-September, 2020 1579.61 M USD
Total New Job Opportunity created in July-September, 2020 6536 person
```

4.2.3. Insights:

- All Columns are categorical on this Data
- Land, SFB doesn't fractuates, but others does
- Total investment in July-September, 2020 **81.05M USD**
- Total Export earned in July-September, 2020 **1579.61M USD**
- Total New Job Opportunity created in July-September, 2020 **6536 person**

5. Data Wrangling

5.1.1. Missing Values in df:

In [13]:

```
df.isna().sum()
```

Out[13]:

```
Zone                0
NameOfEnterprise    0
InvestingCountry    0
Products            1
dtype: int64
```

5.1.2. Treating Missing Values in df:

In [14]:
```
df['Products']=df['Products'].fillna("Garments")
df.isna().sum()
```

Out[14]:
```
Zone                0
NameOfEnterprise    0
InvestingCountry    0
Products            0
dtype: int64
```

5.2.1. Missing Values in zdf:

In [15]:
```
zdf.isna().sum()
```

Out[15]:
```
Zone                 0
Land                 0
SFB                  0
TotalInvestment      0
ExportEarned         0
NewJobOpportunity    0
dtype: int64
```

- no missing values

6. Statistical Analysis

6.1. Statistical Normality Tests

Normality tests are used to determine if a dataset is normally distributed and to check how likely it is for a random variable in the dataset to be normally distributed.

Popular normality tests - D'Agostino's K^2, Shapiro-Wilk, Anderson-Darling .

There are five numerical features in this dataset - **Land, SFB, TotalInvestment, ExportEarned, NewJobOpportunity**

6.1.1. D'Agostino's K^2 Test

6.1.1.1. Total Investment

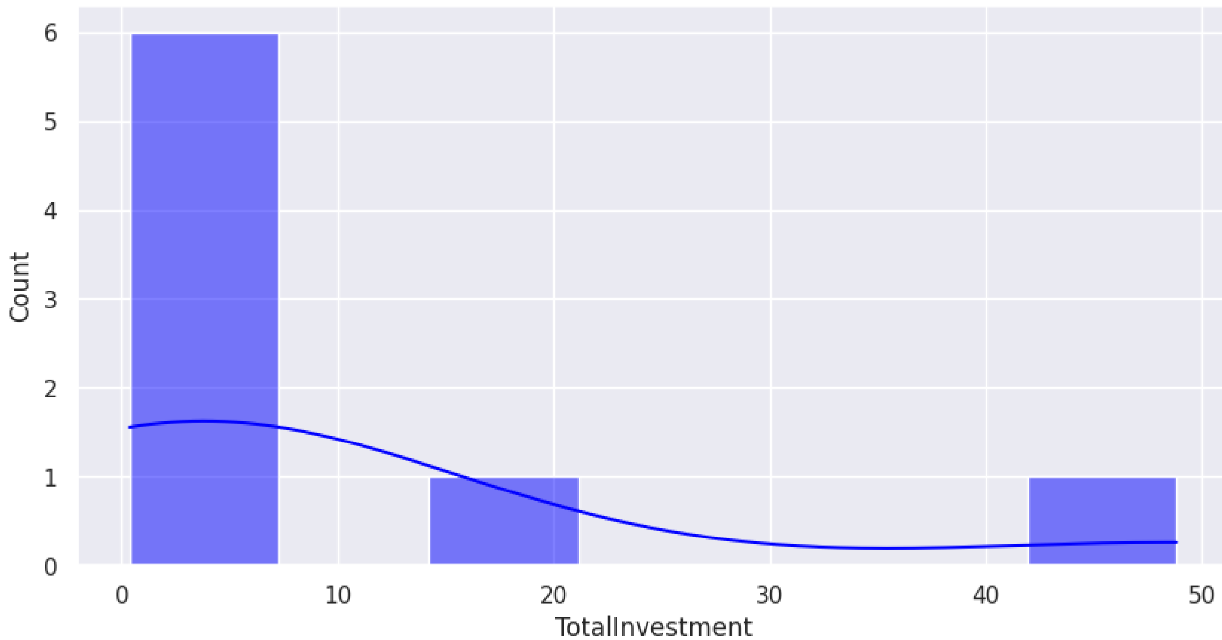
In [16]:

```
stat, p = stats.normaltest(zdf['TotalInvestment'])

print('Statistics=%.5f, p=%.3f' % (stat, p))

# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian')
else:
    print('Sample does not look Gaussian')
```

```
Statistics=16.24293, p=0.000
Sample does not look Gaussian
```

In [17]:

```
sns.set(rc={'figure.figsize':(10,5)})
p=sns.histplot(zdf["TotalInvestment"],color='blue',stat='count',kde=True,
legend=True)
```



6.1.1.2. Export Earned

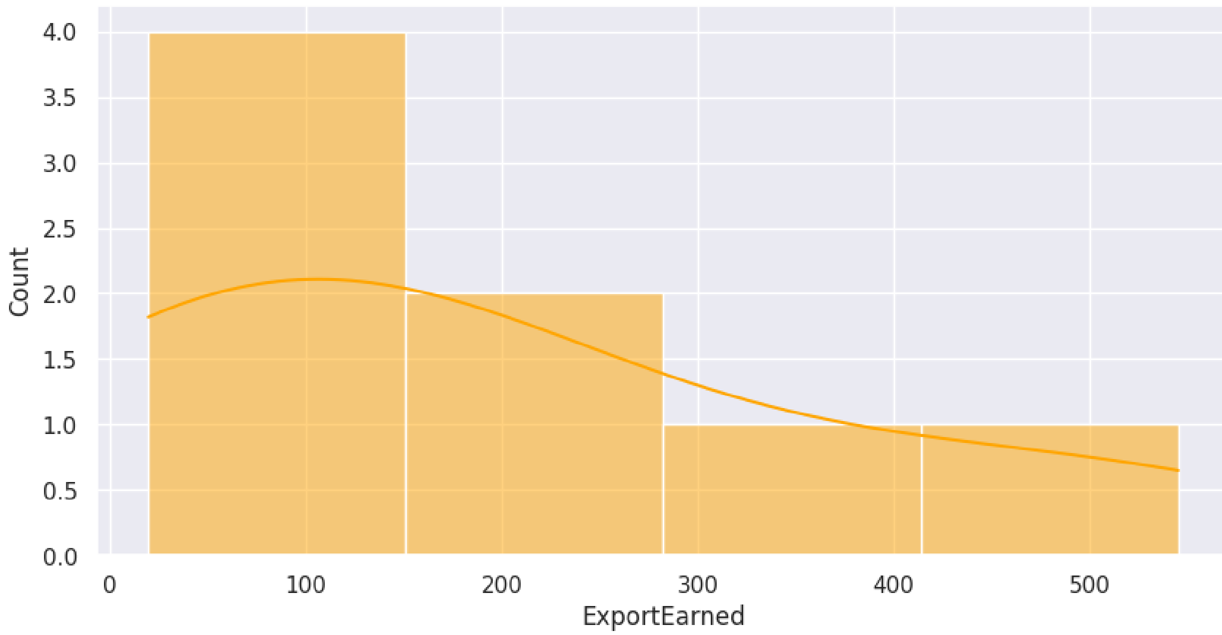
In [18]:

```
stat, p = stats.normaltest(zdf['ExportEarned'])

print('Statistics=%.5f, p=%.3f' % (stat, p))

# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian')
else:
    print('Sample does not look Gaussian')
```

```
Statistics=1.94226, p=0.379
Sample looks Gaussian
```

In [19]:

```
sns.set(rc={'figure.figsize':(10,5)})
p=sns.histplot(zdf['ExportEarned'],color='orange',stat='count',kde=True,legend=True)
```



6.1.2. Anderson-Darling Test

6.1.2.1. ExportEarned

In [20]:

```
result = stats.anderson(zdf['ExportEarned'])

print('Statistic: %.3f' % result.statistic)

p = 0

for i in range(len(result.critical_values)):
    sl, cv = result.significance_level[i], result.critical_values[i]
    if result.statistic < result.critical_values[i]:
        print(f'Significance level {sl:.2f} % : critical value {cv:.3f},
 data looks normal')
    else:
        print(f'Significance level {sl:.2f} % : critical value {cv:.3f},
 data does not look normal')
```

```
Statistic: 0.412
Significance level 15.00 % : critical value 0.519, data looks normal
Significance level 10.00 % : critical value 0.591, data looks normal
Significance level 5.00 % : critical value 0.709, data looks normal
Significance level 2.50 % : critical value 0.827, data looks normal
Significance level 1.00 % : critical value 0.984, data looks normal
```

6.1.2.1. Total Investment

In [21]:

```python
result = stats.anderson(zdf['TotalInvestment'])

print('Statistic: %.3f' % result.statistic)

p = 0

for i in range(len(result.critical_values)):
    sl, cv = result.significance_level[i], result.critical_values[i]
    if result.statistic < result.critical_values[i]:
        print(f'Significance level {sl:.2f} % : critical value {cv:.3f}, data looks normal')
    else:
        print(f'Significance level {sl:.2f} % : critical value {cv:.3f}, data does not look normal')
```

```
Statistic: 1.260
Significance level 15.00 % : critical value 0.519, data does not look normal
Significance level 10.00 % : critical value 0.591, data does not look normal
Significance level 5.00 % : critical value 0.709, data does not look normal
Significance level 2.50 % : critical value 0.827, data does not look normal
Significance level 1.00 % : critical value 0.984, data does not look normal
```

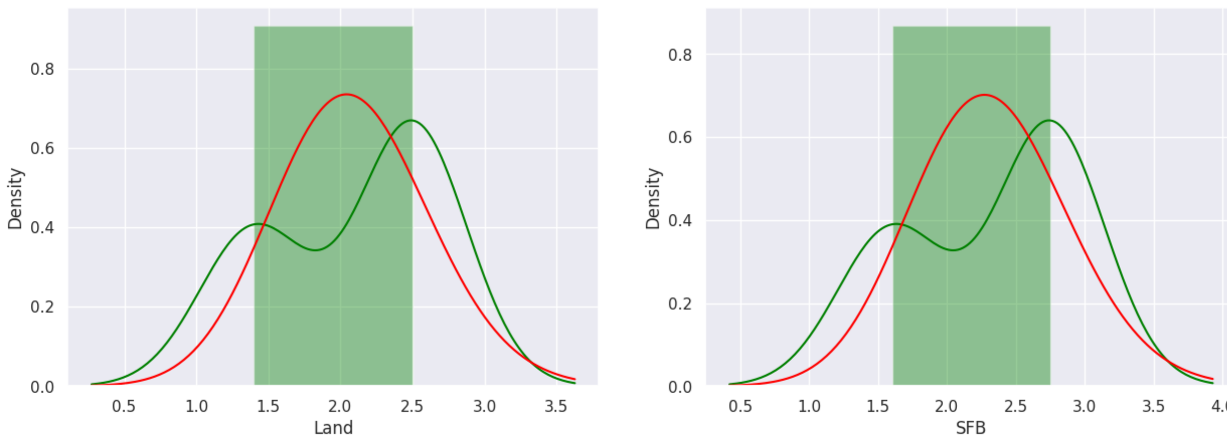
7. EDA, Data Visualization & Insights

7.1 Variables Analysis

7.1.1. ZDF numerical distributions

In [22]:

```
sns.set(rc={'figure.figsize':(15,5)})
for i, column in enumerate(["Land", "SFB"], 1):
    plt.subplot(1,2,i)
    sns.distplot(zdf[column],color='green',fit_kws={"color":"red"},fit=st
ats.gamma, label="label 1")
```

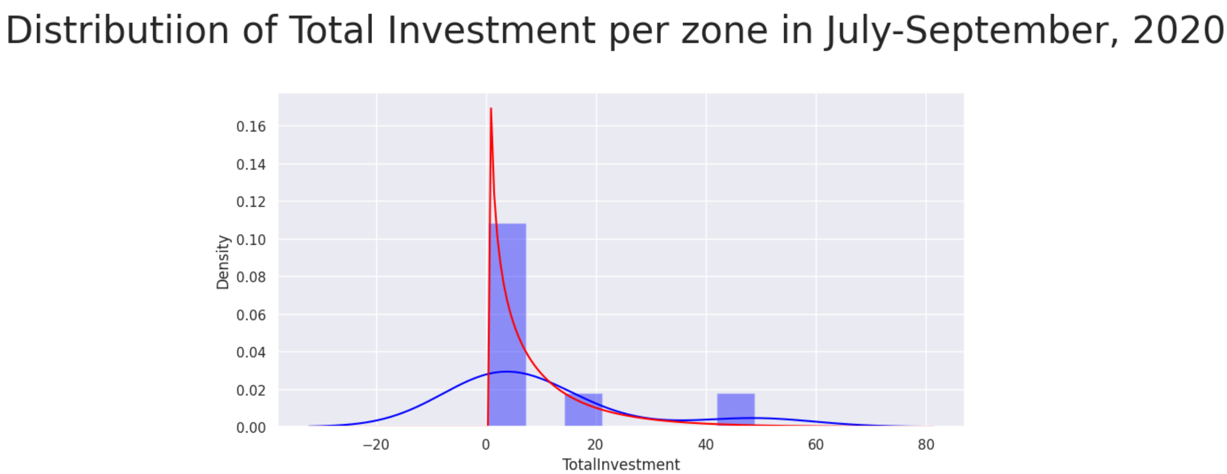


In [23]:

```
sns.set(rc={'figure.figsize':(10,5)})
p=sns.distplot(zdf["TotalInvestment"],color='blue',fit_kws={"color":"red"},fit=stats.gamma, label="label 1")
p.axes.set_title("\nDistributiion of Total Investment per zone in July-September, 2020 \n",fontsize=30)
```

Out[23]:

```
Text(0.5, 1.0, '\nDistributiion of Total Investment per zone in July-September, 2020 \n')
```

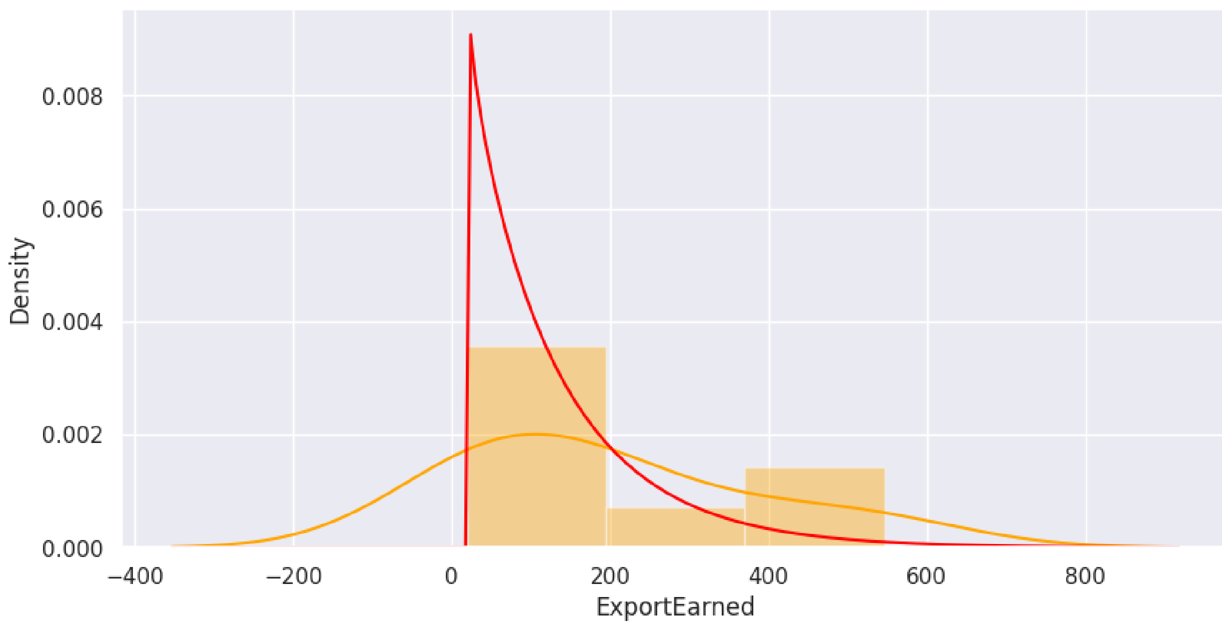


In [24]:

```
sns.distplot(zdf["ExportEarned"],color='orange',fit_kws={"color":"red"},fit=stats.gamma, label="label 1")
p.axes.set_title("\nDistributiion of Export Earned in July-September, 2020\n",fontsize=30)
```

Out[24]:

```
Text(0.5, 1.0, '\nDistributiion of Export Earned in July-September, 2020\n')
```

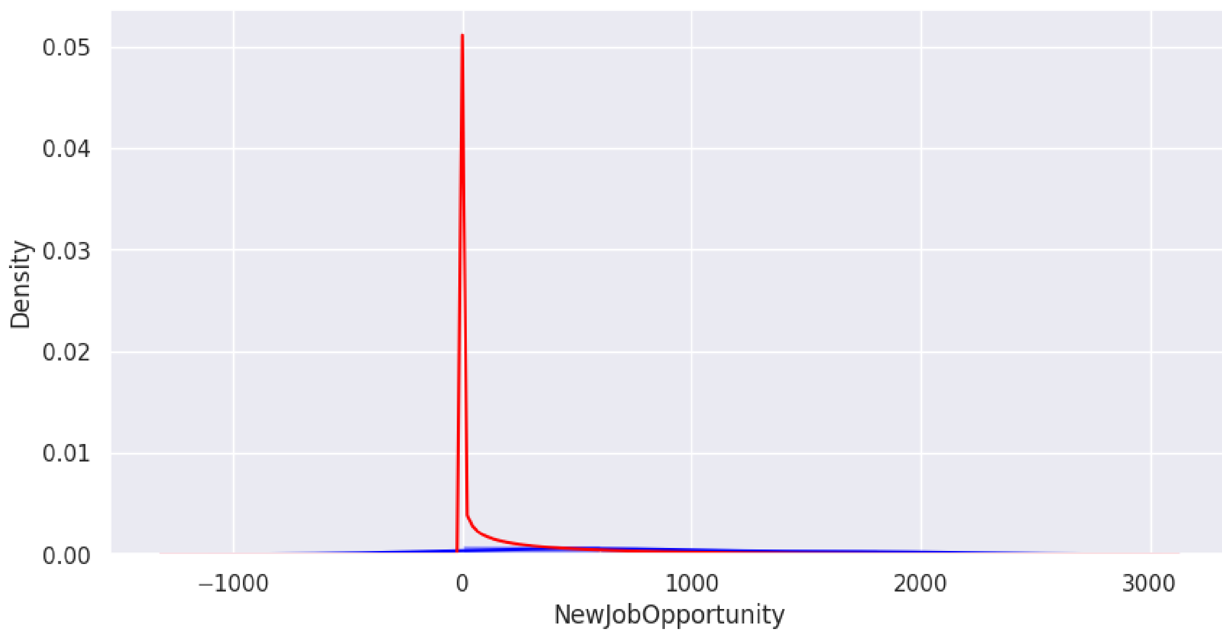


In [25]:

```
sns.distplot(zdf["NewJobOpportunity"],color='blue',fit_kws={"color":"red"
},fit=stats.gamma, label="label 1")
p.axes.set_title("\nDistributiion of New Job Opportunity created in July-
September, 2020\n",fontsize=30)
```

Out[25]:

```
Text(0.5, 1.0, '\nDistributiion of New Job Opportunity created in July
-September, 2020\n')
```



Insights

- Not properly distributed

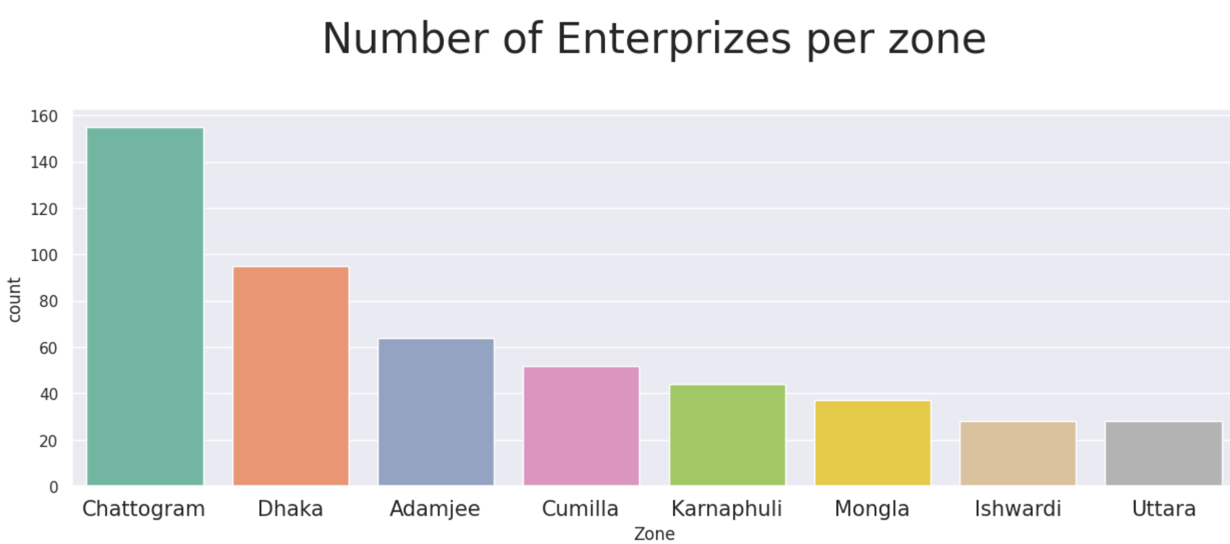
7.1.2. Number of Enterprizes per zone

In [26]:

```
sns.set(rc={'figure.figsize':(15,5)})
plt.xticks(fontsize=15)
p=sns.countplot(df['Zone'],palette="Set2",hue_order=df.groupby('Zone'),order=df.Zone.value_counts().sort_values(ascending=False).index)
p.axes.set_title("\nNumber of Enterprizes per zone\n",fontsize=30)
```

Out[26]:

```
Text(0.5, 1.0, '\nNumber of Enterprizes per zone\n')
```



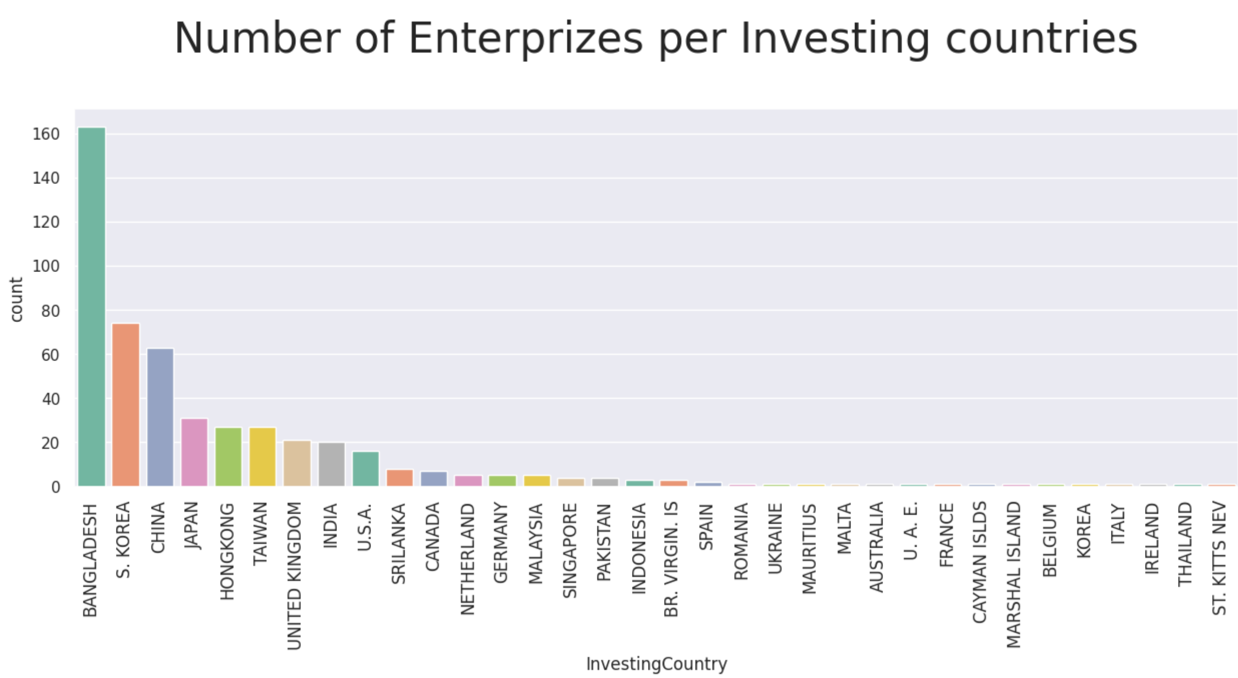
Insights

- Chattogram has highest number of factories, then comes Dhaka EPZ

7.1.3. Number of Enterprizes per Investing countries

In [27]:

```
plt.xticks(fontsize=12,rotation='vertical')
p=sns.countplot(df['InvestingCountry'],palette="Set2",hue_order=df.groupby('InvestingCountry'),order=df.InvestingCountry.value_counts().sort_values(ascending=False).index)
p.axes.set_title("\nNumber of Enterprizes per Investing countries\n",fontsize=30);
```



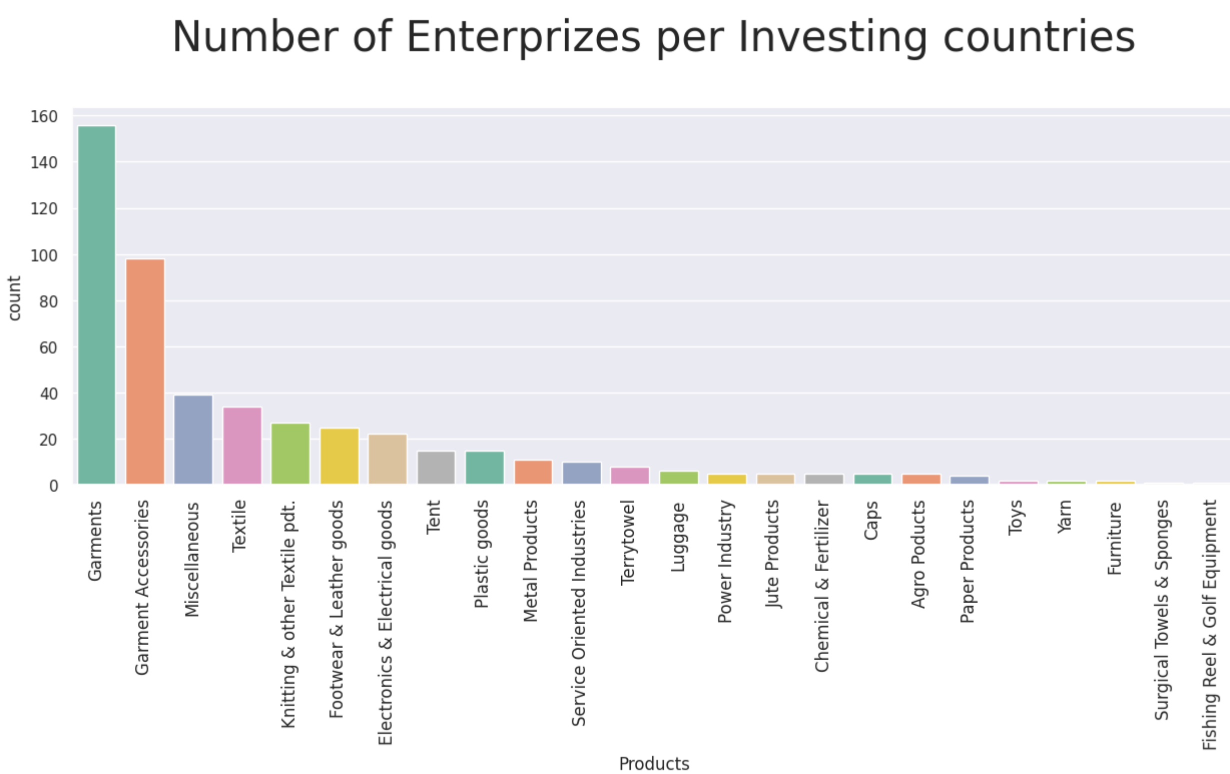
Insights

- South Korea and China are the most enterprize investors in Bangladesh EPZs based on Enterprize Numbers.
- They are asian and quite **South-East Asian Countries**.
- The list is followed by Japan, HongKong, Taiwan - all the **South-East Asian Countries**.
- **Bangladesh is a investement place for South-East Asian Countries - which are RIVALS of Bangladesh in RMG Exports.**

7.1.4. Number of Enterprizes per Products

In [28]:

```
plt.xticks(fontsize=12,rotation='vertical')
p=sns.countplot(df['Products'],palette="Set2",hue_order=df.groupby('Produ
cts'),order=df.Products.value_counts().sort_values(ascending=False).index
)
p.axes.set_title("\nNumber of Enterprizes per Investing countries\n",font
size=30);
```



Insights

- **All Garment related products are on the top**. It is normal as BD is one of the world's Garments LEADER.
- **2nd sector is Footwear** - leather related
- **3rd big one is - Electronics** - which is interesting.

7.1.5 Boxplots of ZDF

In [29]:

```
sns.set(rc={'figure.figsize':(30,3)})
for i, column in enumerate(["TotalInvestment", "ExportEarned", "NewJobOpp
ortunity"], 1):
    plt.subplot(1,5,i)
    sns.boxplot(zdf[column],palette="Set2");
```

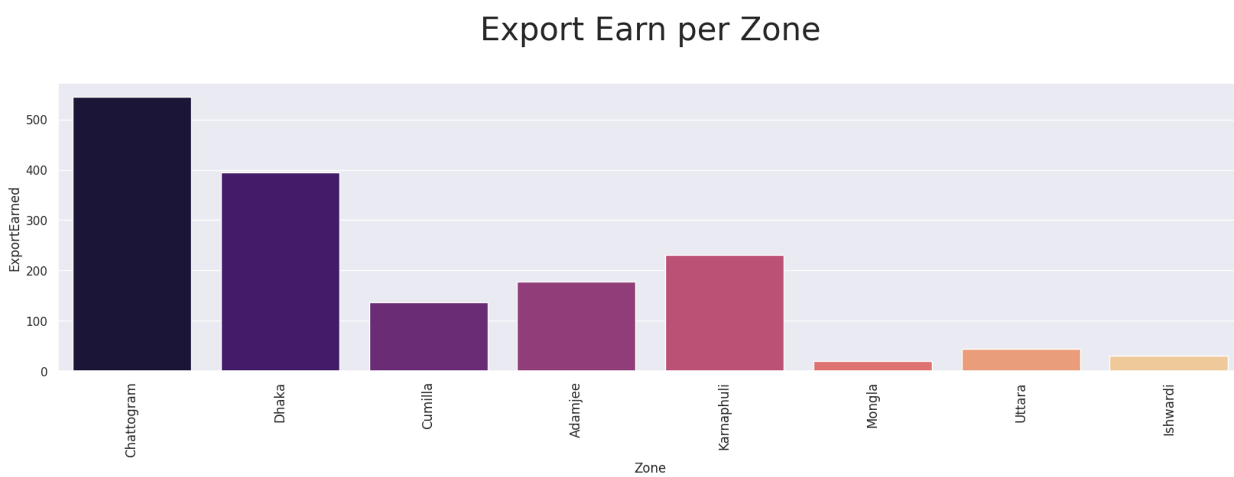
Insights

- Export earned from each area differs a lot. But 50% percentile is stable , compared to others.

7.1.6 Export Earn per Zone

In [30]:

```
sns.set(rc={'figure.figsize':(20,5)})
plt.xticks(fontsize=12,rotation='vertical')
p=sns.barplot(x="Zone", y="ExportEarned", data=zdf,palette="magma",capsiz
e=.2)
p.axes.set_title("\nExport Earn per Zone\n",fontsize=30);
```



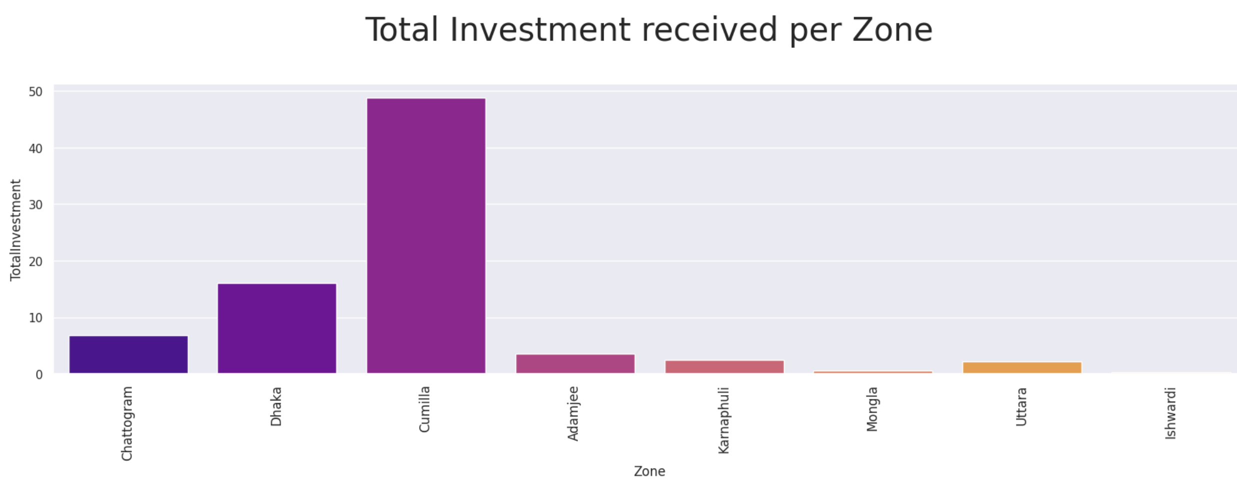
Insights

- Chattogram leads in export earnings.
- Dhaka and Karnaphuli (near to chattogram) follows..

7.1.7 Total Investment per Zone

In [31]:

```
sns.set(rc={'figure.figsize':(20,5)})
plt.xticks(fontsize=12,rotation='vertical')
p=sns.barplot(x="Zone", y="TotalInvestment", data=zdf,palette="plasma",ca
psize=.2)
p.axes.set_title("\nTotal Investment received per Zone\n",fontsize=30);
```



Insights

- Unexpected rise in Cumilla. Maybe, it was developed newly then.

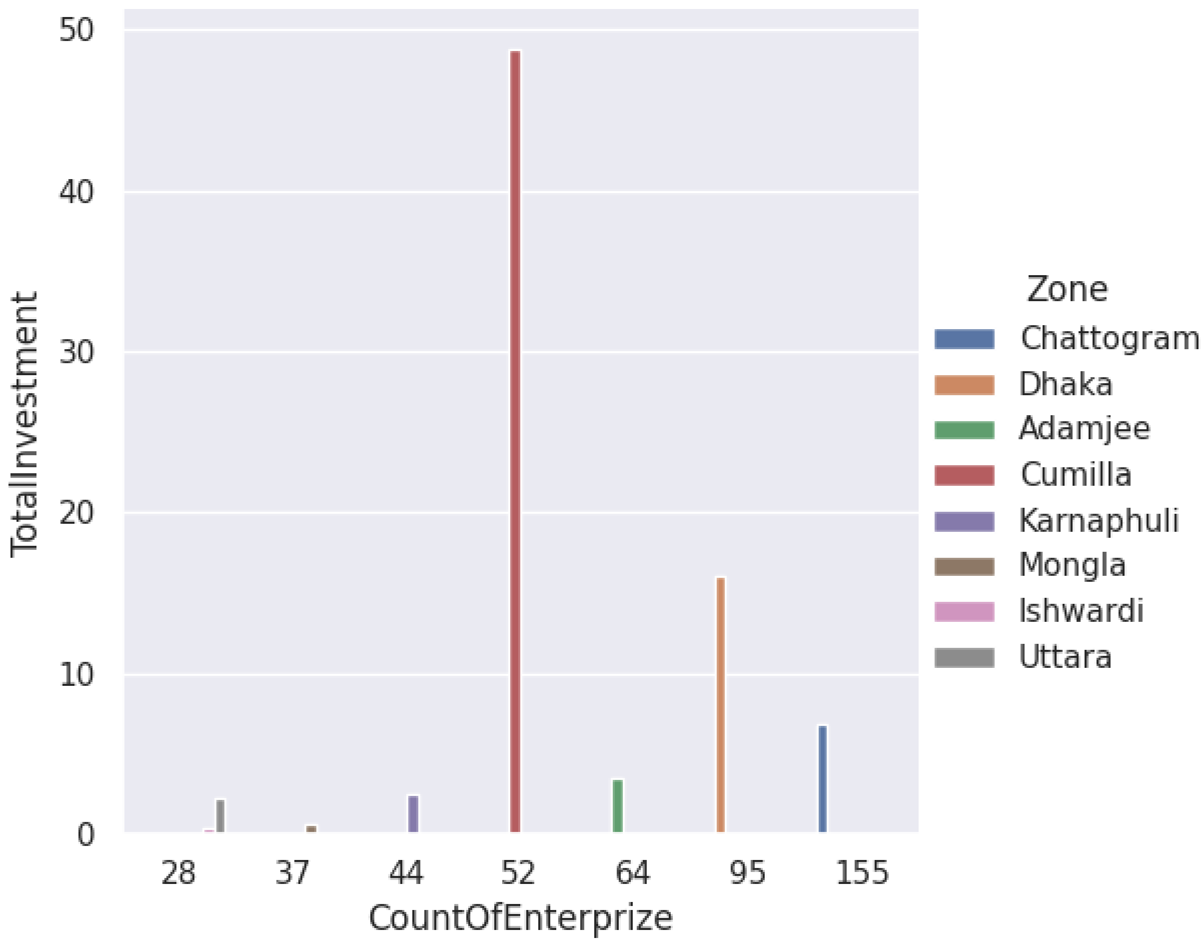
7.2 Co-Relation Analysis

7.2.1 Co-Relation Analysis of Number Of Enterprize, Total Investment, Export Earned per zone

Show hidden code

In [33]:

```
sns.set(rc={'figure.figsize':(20,5)})
g = sns.catplot(x="CountOfEnterprize", y="TotalInvestment",
                hue="Zone",
                data=export, kind="bar");
```



In [34]:

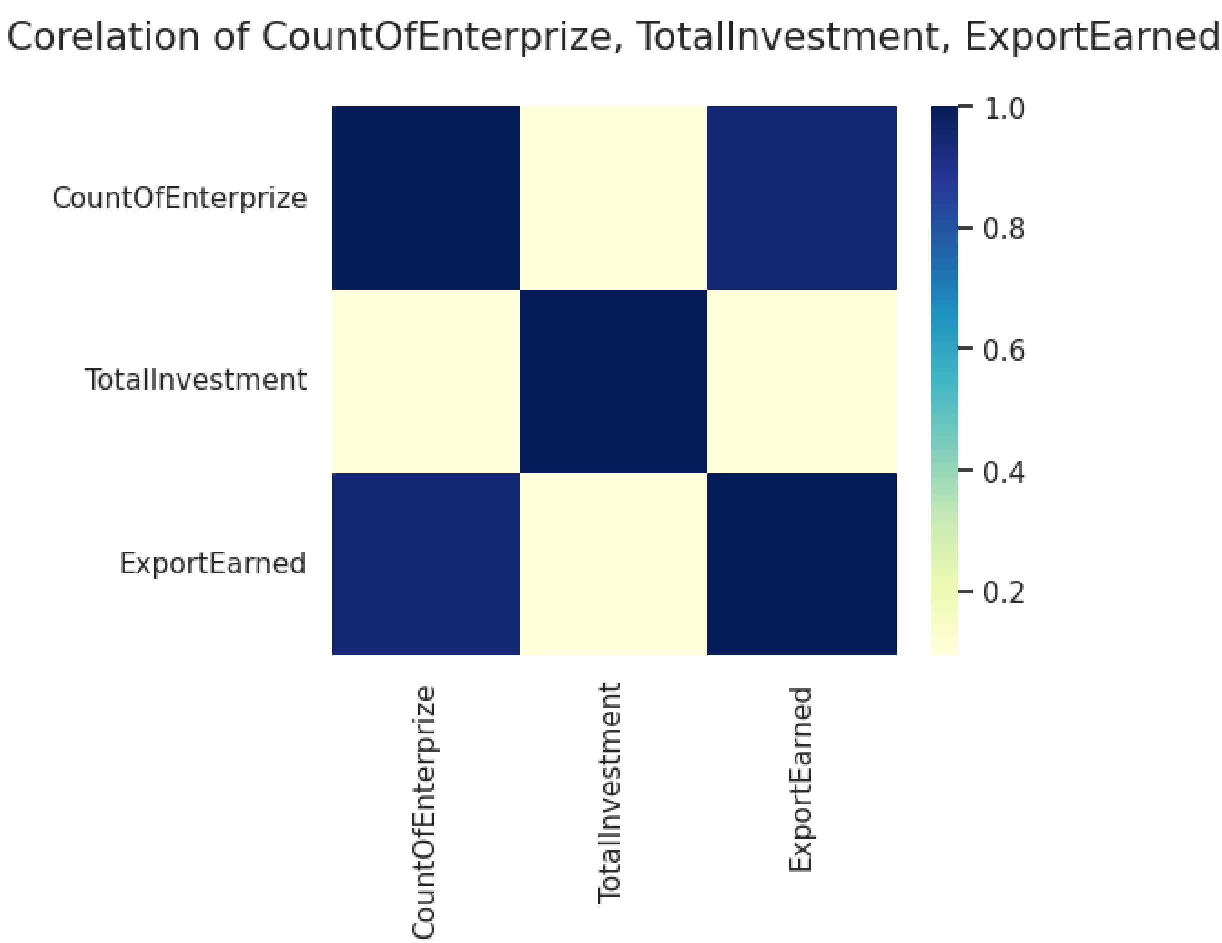
```
ex.corr()
```

Out[34]:

	CountOfEnterprize	TotalInvestment	ExportEarned
CountOfEnterprize	1.000000	0.093770	0.949863
TotalInvestment	0.093770	1.000000	0.095643
ExportEarned	0.949863	0.095643	1.000000

In [35]:

```
corr=ex.corr()
sns.set(rc={'figure.figsize':(5,4)})
p=sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns,
        cmap="YlGnBu")
p=p.axes.set_title("\nCorelation of CountOfEnterprize, TotalInvestment, E
xportEarned\n",fontsize=15);
```



Insights

- Number of Enterprizes per zone **highly co-relates** with export earned from that zone.
- But there is **no co-relation of number of interprize and total investment** there. So, we can assume there is some big investments in some enterprizes, compared to others; and this is out-numbering the co-relation.

7.2.1 Co-Relation Analysis of Number Of Enterprize, SFB, Land per zone

In [36]:

```
price = df.Zone.value_counts().to_frame('CountOfEnterprize').reset_index
()
price.rename(columns = {'index':'Zone'}, inplace = True)
price=pd.DataFrame.merge(price,zdf,on='Zone')
price.rename(index={0: 'Chattogram',1:'Dhaka',2:'Adamjee',3:'Cumilla',4:
'Karnaphuli',5:'Mongla',6:'Ishwardi',7:'Uttara',}, inplace=True)
price=price.drop(["Zone","TotalInvestment","ExportEarned","NewJobOpportun
ity"],axis=1)
price
```

Out[36]:

	CountOfEnterprize	Land	SFB
Chattogram	155	2.5	2.75
Dhaka	95	2.5	2.75
Adamjee	64	2.5	2.75
Cumilla	52	2.5	2.75
Karnaphuli	44	2.5	2.75
Mongla	37	1.4	1.60
Ishwardi	28	1.4	1.60
Uttara	28	1.4	1.60

In [37]:

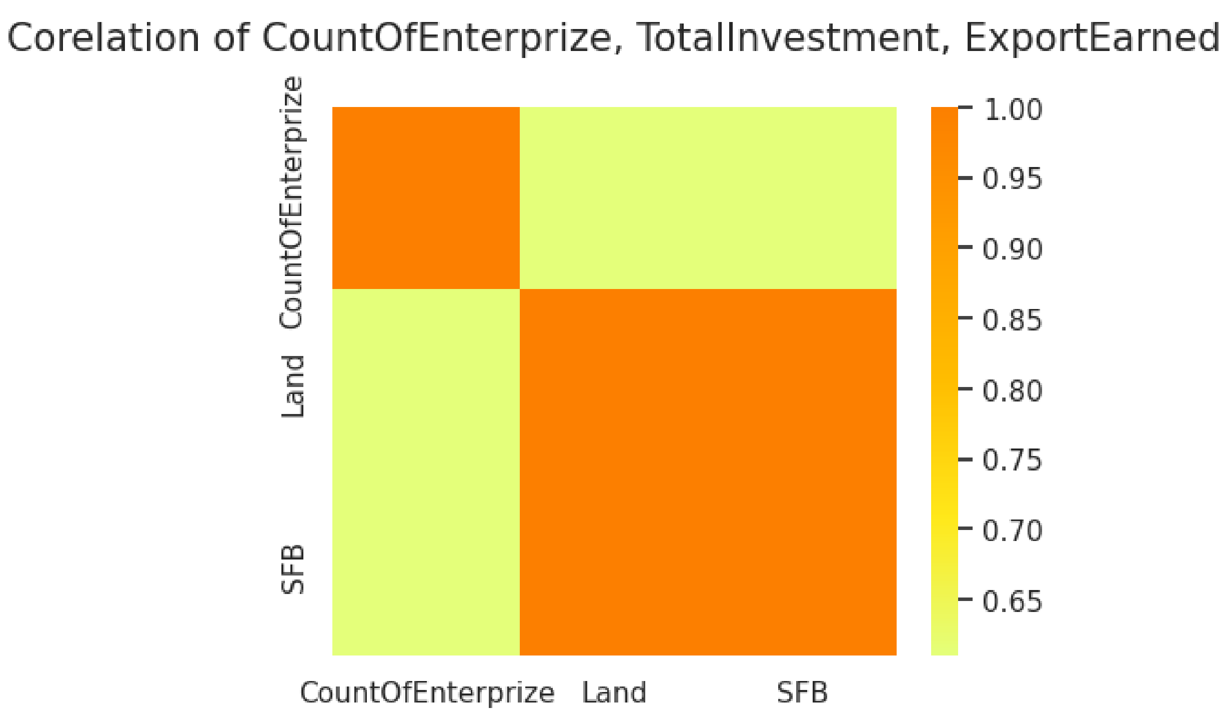
```
price.corr()
```

Out[37]:

	CountOfEnterprize	Land	SFB
CountOfEnterprize	1.000000	0.610221	0.610221
Land	0.610221	1.000000	1.000000
SFB	0.610221	1.000000	1.000000

In [38]:

```
corr=price.corr()
sns.set(rc={'figure.figsize':(5,4)})
p=sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns,
        cmap="Wistia")
p=p.axes.set_title("\nCorelation of CountOfEnterprize, TotalInvestment, E
xportEarned\n",fontsize=15)
```



Insights

- Although they corelates, I am not actually sure about it.

Assumption:

- Maybe, high priced area has better export facilities, and thats why, investors are investing there, inmstead of low-priced areas with less facilities.

8. Multivariate Analysis

8.1. Multicollinearity (Kruskal–Wallis)

For categorical and a continuous variable, multicollinearity can be measured by t-test (if the categorical variable has 2 categories, parametric) or ANOVA (more than 2 categories, parametric)

Kruskal–Wallis test is more commonly used when we have three or more levels. For two levels, the Mann Whitney U Test is appropriate

The parametric equivalent of the Kruskal–Wallis test is the one-way analysis of variance (ANOVA)

In [39]:

```
stat, p = stats.kruskal(ex['ExportEarned'], ex['TotalInvestment'], ex['Co
untOfEnterprize'])
print('Statistics=%.3f, p=%.3f' % (stat, p))

for alpha in [0.001,0.05,0.01,0.03,0.05,0.1,0.2,0.5]:
    if p > alpha:
        print("Alpha:",alpha,' -- Same distributions')
    else:
        print("Alpha:",alpha,' -- Different distributions')
```

```
Statistics=13.101, p=0.001
Alpha: 0.001  -- Same distributions
Alpha: 0.05  -- Different distributions
Alpha: 0.01  -- Different distributions
Alpha: 0.03  -- Different distributions
Alpha: 0.05  -- Different distributions
Alpha: 0.1  -- Different distributions
Alpha: 0.2  -- Different distributions
Alpha: 0.5  -- Different distributions
```

Insights

- Actually, they doesn't have same same distributions.

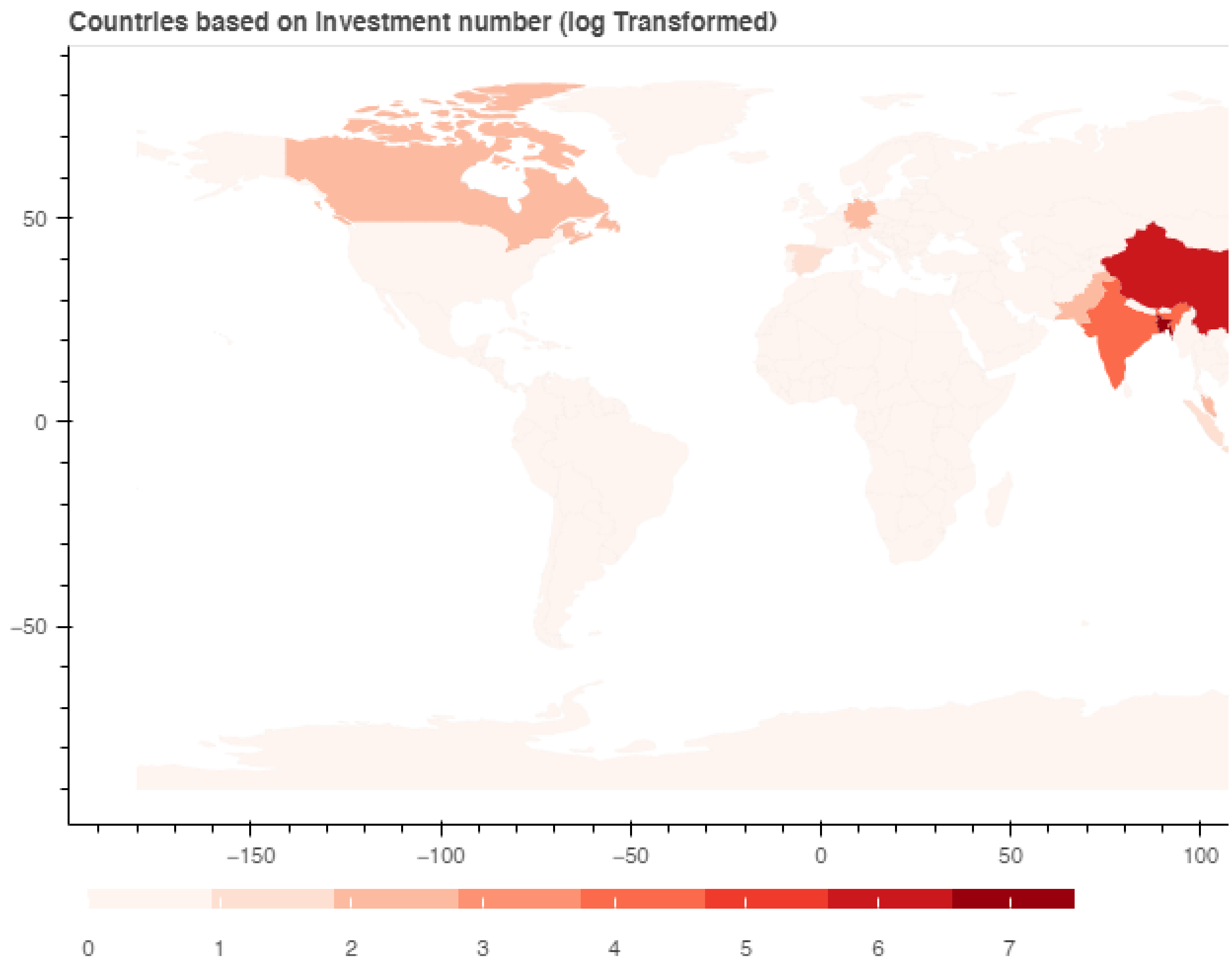
9. Map-ploting with Geopandas

In this section, we will plot the country-wise invetment data into a world map and try to visualize from which area/region/continent/sub-continent, most of the investments are coming to angladesh EPZs.

••• 6 hidden cells

Show hidden code

(https://bokeh.org) BokehJS 2.4.2 successfully loaded.



Insights

- South & South East Asian dominance.

10. Conclusions

From the above analysis, we can conclude:

1. Export number **positively relates** to number of factories.
2. Number of companies per zone is **positively corelated** with price point, which is interestng.
3. **Investment is irregular**. Maybe, some EPZs were newly built, and getting heavy investments.
4. **Chattogram, Dhaka (Capital City), and Karnaphuli (near to Chattogram) leads in export**. Reason can be, the main seaport of Bangladesh is in Chattogram.
5. Adamgee had no new job offerings, no we can assume it is old, and functioning properly - though there is some new investments.
6. **Garments and garments related sectors** leads in company types. Following by **leather-footwares and electronics** at a good distance.
7. **South Korea and China** are the most enterprize investors in Bangladesh EPZs based on Enterprize Numbers. The list is followed by **Japan, HongKong, Taiwan** - all the **South-East Asian Countries**. Bangladesh is a investement place for South-East Asian Countries - which are RIVALS of Bangladesh in RMG Exports. So, this is quite interesting.
8. Chattogram has largest number of factories.

11. References

- Notebooks of Ahmed Shahriar Sakib (https://www.kaggle.com/ahmedshahriarsakib)
- Python Statistics Fundamentals: How to Describe Your Data (https://realpython.com/python-statistics/)
- Statistics in Python (https://scipy-lectures.org/packages/statistics/index.html)
- The easiest way to plot data from Pandas on a world map (https://towardsdatascience.com/the-easiest-way-to-plot-data-from-pandas-on-a-world-map-1a62962a27f3)
- Geopandas: how to plot countries/cities? (https://stackoverflow.com/questions/65064137/geopandas-how-to-plot-countries-cities)

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