1. Main objective of the analysis that also specifies whether your model will be focused on clustering or dimensionality reduction and the benefits that your analysis brings to the business or stakeholders of this data.

- Here we want clustering of the country based on there similar economic and social status

1. Brief description of the data set you chose, a summary of its attributes, and an outline of what you are trying to accomplish with this analysis.

In [75]:

```
import numpy as np , pandas as pd ,matplotlib.pyplot as plt
```

In [76]:

```
data = pd.read_csv('Country-data.csv')
data.head()
```

Out[76]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	5!
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	40!
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	44(
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	35:
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	122(

In [77]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   country     167 non-null    object 
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64  
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64  
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

- Country data consists of the various economic and social factor of 167 countries across the globe . One of the NGO wants to help some country with some funds and they need the name of country which needs the money most .

In [78]:

```
num_col = data.columns[data.dtypes!=np.object]
```

In [79]:

```
data[num_col].describe().T
```

Out[79]:

	count	mean	std	min	25%	50%	75%	max
child_mort	167.0	38.270060	40.328931	2.6000	8.250	19.30	62.10	208.00
exports	167.0	41.108976	27.412010	0.1090	23.800	35.00	51.35	200.00
health	167.0	6.815689	2.746837	1.8100	4.920	6.32	8.60	17.90
imports	167.0	46.890215	24.209589	0.0659	30.200	43.30	58.75	174.00
income	167.0	17144.688623	19278.067698	609.0000	3355.000	9960.00	22800.00	125000.00
inflation	167.0	7.781832	10.570704	-4.2100	1.810	5.39	10.75	104.00
life_expec	167.0	70.555689	8.893172	32.1000	65.300	73.10	76.80	82.80
total_fer	167.0	2.947964	1.513848	1.1500	1.795	2.41	3.88	7.49
gdpp	167.0	12964.155689	18328.704809	231.0000	1330.000	4660.00	14050.00	105000.00

- All above variable are quantitative in nature and there descriptive statistics are represented above

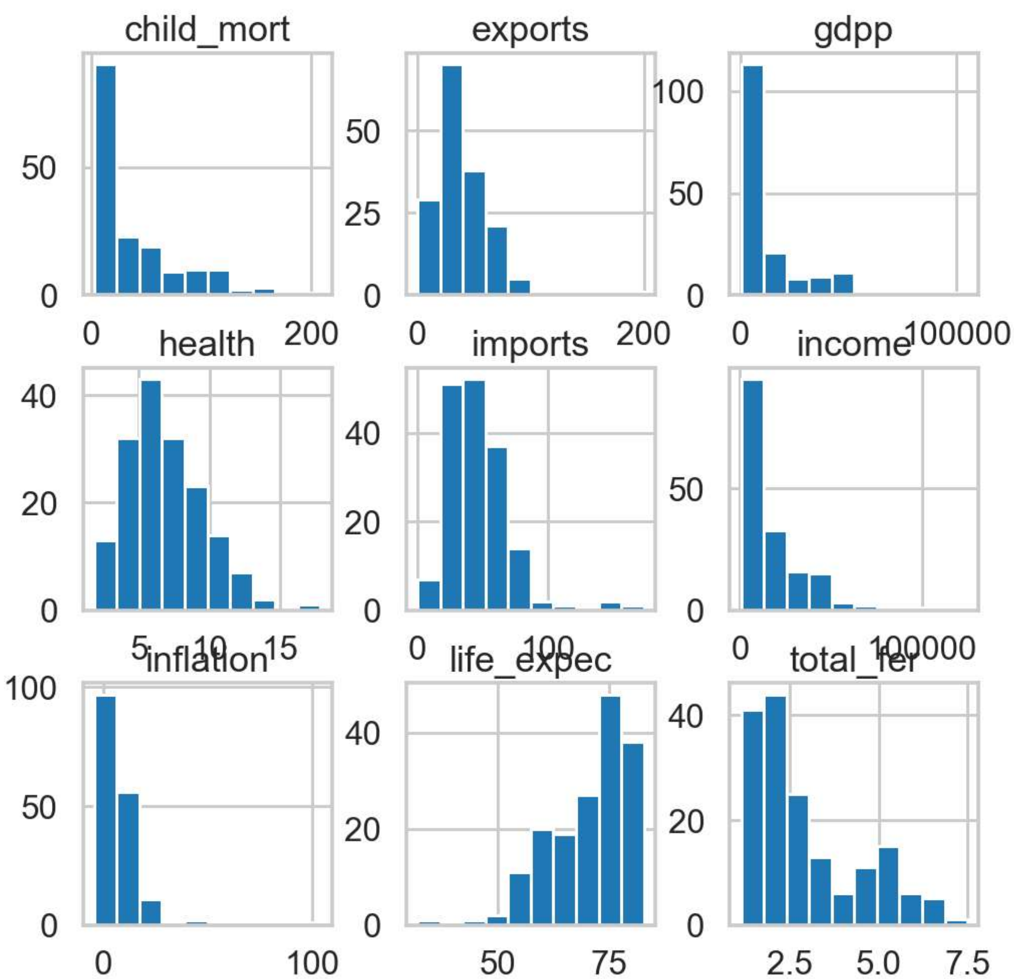
1. Brief summary of data exploration and actions taken for data cleaning orfeature engineering.

In [80]:

```
data[num_col].hist(figsize = (8,8))
```

Out[80]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001A742944EB0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A7478B32B0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A7478DA970
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001A747DF1130>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A747E188B0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A747E410D0
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001A747E4D0A0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A746745BB0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001A7471B4580
>]],
      dtype=object)
```



In [81]:

```
from sklearn.preprocessing import MinMaxScaler
s = MinMaxScaler()
X_tr = pd.DataFrame(s.fit_transform(data[num_col]))
X_tr.columns = num_col
X_tr
```

Out[81]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	0.426485	0.049482	0.358608	0.257765	0.008047	0.126144	0.475345	0.736593	0.00307
1	0.068160	0.139531	0.294593	0.279037	0.074933	0.080399	0.871795	0.078864	0.03683
2	0.120253	0.191559	0.146675	0.180149	0.098809	0.187691	0.875740	0.274448	0.04036
3	0.566699	0.311125	0.064636	0.246266	0.042535	0.245911	0.552268	0.790221	0.03148
4	0.037488	0.227079	0.262275	0.338255	0.148652	0.052213	0.881657	0.154574	0.11424
...	...	...	...	...	...	...	...	...	.
162	0.129503	0.232582	0.213797	0.302609	0.018820	0.063118	0.609467	0.370662	0.02614
163	0.070594	0.142032	0.192666	0.100809	0.127750	0.463081	0.854043	0.208202	0.12665
164	0.100779	0.359651	0.312617	0.460715	0.031200	0.150725	0.808679	0.126183	0.01029
165	0.261441	0.149536	0.209447	0.197397	0.031120	0.257000	0.698225	0.555205	0.01029
166	0.391918	0.184556	0.253574	0.177275	0.021473	0.168284	0.392505	0.670347	0.01173

167 rows × 9 columns

In [82]:

```
data_tr = pd.concat([data[['country']] ,X_tr] ,axis = 1)
data_tr.head()
```

Out[82]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fe
0	Afghanistan	0.426485	0.049482	0.358608	0.257765	0.008047	0.126144	0.475345	0.73659
1	Albania	0.068160	0.139531	0.294593	0.279037	0.074933	0.080399	0.871795	0.07886
2	Algeria	0.120253	0.191559	0.146675	0.180149	0.098809	0.187691	0.875740	0.27444
3	Angola	0.566699	0.311125	0.064636	0.246266	0.042535	0.245911	0.552268	0.79022
4	Antigua and Barbuda	0.037488	0.227079	0.262275	0.338255	0.148652	0.052213	0.881657	0.15457

1. Summary of training at least three variations of the unsupervised model you selected. For example, you can use different clustering techniques or different hyperparameters.

In [83]:

```
data_tr[num_col].describe().T
```

Out[83]:

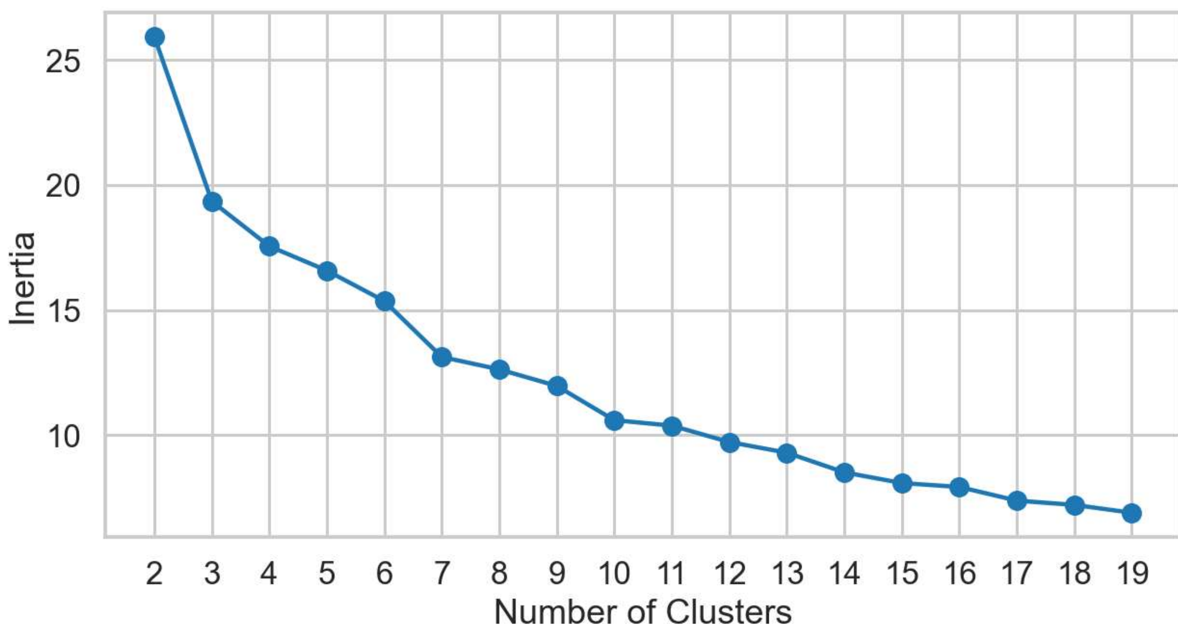
	count	mean	std	min	25%	50%	75%	max
child_mort	167.0	0.173661	0.196343	0.0	0.027507	0.081305	0.289679	1.0
exports	167.0	0.205112	0.137135	0.0	0.118520	0.174550	0.256345	1.0
health	167.0	0.311106	0.170717	0.0	0.193288	0.280298	0.422001	1.0
imports	167.0	0.269207	0.139188	0.0	0.173250	0.248566	0.337393	1.0
income	167.0	0.132933	0.154980	0.0	0.022076	0.075174	0.178397	1.0
inflation	167.0	0.110820	0.097687	0.0	0.055633	0.088716	0.138250	1.0
life_expec	167.0	0.758495	0.175408	0.0	0.654832	0.808679	0.881657	1.0
total_fer	167.0	0.283591	0.238777	0.0	0.101735	0.198738	0.430599	1.0
gdpp	167.0	0.121536	0.174944	0.0	0.010490	0.042274	0.131900	1.0

In [84]:

```
# Setup and imports
# sets backend to render higher res images
%config InlineBackend.figure_formats = ['retina']
plt.rcParams['figure.figsize'] = [10,5]
import seaborn as sns
sns.set_style("whitegrid")
sns.set_context("talk")

inertia = []
scores = []
from sklearn.cluster import KMeans
num_clusters = list(range(2,20))

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
for i in num_clusters:
    km  =  KMeans(n_clusters = i,random_state=10,n_init=1)
    km.fit(X_tr)
    inertia.append(km.inertia_)
    score = silhouette_score(X, km.labels_, metric='euclidean')
    scores.append(score)

plt.plot(num_clusters,inertia)
plt.scatter(num_clusters,inertia)
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia');
plt.xticks(num_clusters)
```

Out[84]:

```
([<matplotlib.axis.XTick at 0x1a747faa130>,
  <matplotlib.axis.XTick at 0x1a747faa100>,
  <matplotlib.axis.XTick at 0x1a747f9bdf0>,
  <matplotlib.axis.XTick at 0x1a7483d5700>,
  <matplotlib.axis.XTick at 0x1a7483d5c10>,
  <matplotlib.axis.XTick at 0x1a7483da160>,
  <matplotlib.axis.XTick at 0x1a7483da670>,
  <matplotlib.axis.XTick at 0x1a7483dab80>,
  <matplotlib.axis.XTick at 0x1a7483e00d0>,
  <matplotlib.axis.XTick at 0x1a7483e05e0>,
  <matplotlib.axis.XTick at 0x1a7483e0af0>,
  <matplotlib.axis.XTick at 0x1a7483e5040>,
  <matplotlib.axis.XTick at 0x1a7483e5550>,
  <matplotlib.axis.XTick at 0x1a7483e07c0>,
  <matplotlib.axis.XTick at 0x1a7483da850>,
  <matplotlib.axis.XTick at 0x1a7483d58e0>,
  <matplotlib.axis.XTick at 0x1a7483e5a60>,
  <matplotlib.axis.XTick at 0x1a7483e5f70>],
 <a list of 18 Text major ticklabel objects>)
```



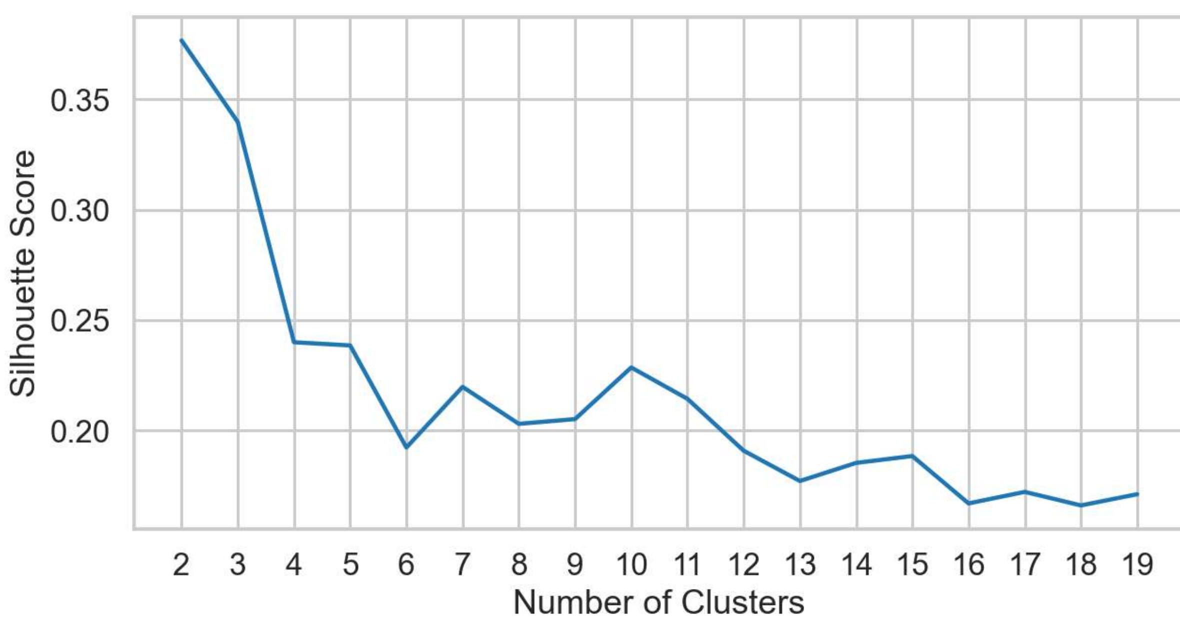
- Here the elbow method does not yield a clear decision (i.e. the elbow is not clear and sharp, or is ambiguous). In this case, we try alternatives such as the silhouette coefficient.

In [85]:

```
plt.plot(num_clusters ,scores)
plt.xlabel('Number of Clusters')
plt.ylabel('Silhouette Score');
plt.xticks(num_clusters)
```

Out[85]:

```
([<matplotlib.axis.XTick at 0x1a74840ab20>,
  <matplotlib.axis.XTick at 0x1a74840aaf0>,
  <matplotlib.axis.XTick at 0x1a748404b50>,
  <matplotlib.axis.XTick at 0x1a748d825e0>,
  <matplotlib.axis.XTick at 0x1a748d82af0>,
  <matplotlib.axis.XTick at 0x1a748d87040>,
  <matplotlib.axis.XTick at 0x1a748d87550>,
  <matplotlib.axis.XTick at 0x1a748d87a60>,
  <matplotlib.axis.XTick at 0x1a748d87fa0>,
  <matplotlib.axis.XTick at 0x1a748d875e0>,
  <matplotlib.axis.XTick at 0x1a748d82670>,
  <matplotlib.axis.XTick at 0x1a748d8c4f0>,
  <matplotlib.axis.XTick at 0x1a748d8ca00>,
  <matplotlib.axis.XTick at 0x1a748d8cf10>,
  <matplotlib.axis.XTick at 0x1a748d93460>,
  <matplotlib.axis.XTick at 0x1a748d93970>,
  <matplotlib.axis.XTick at 0x1a748d93e80>,
  <matplotlib.axis.XTick at 0x1a748d983d0>],
 <a list of 18 Text major ticklabel objects>)
```



In [86]:

```
km  =  KMeans(n_clusters = 5,random_state=10,n_init=1)
data['kmeans'] = km.fit_predict(X_tr)
data.head()
```

Out[86]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	5!
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	40!
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	44(
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	35:
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	122(

In [92]:

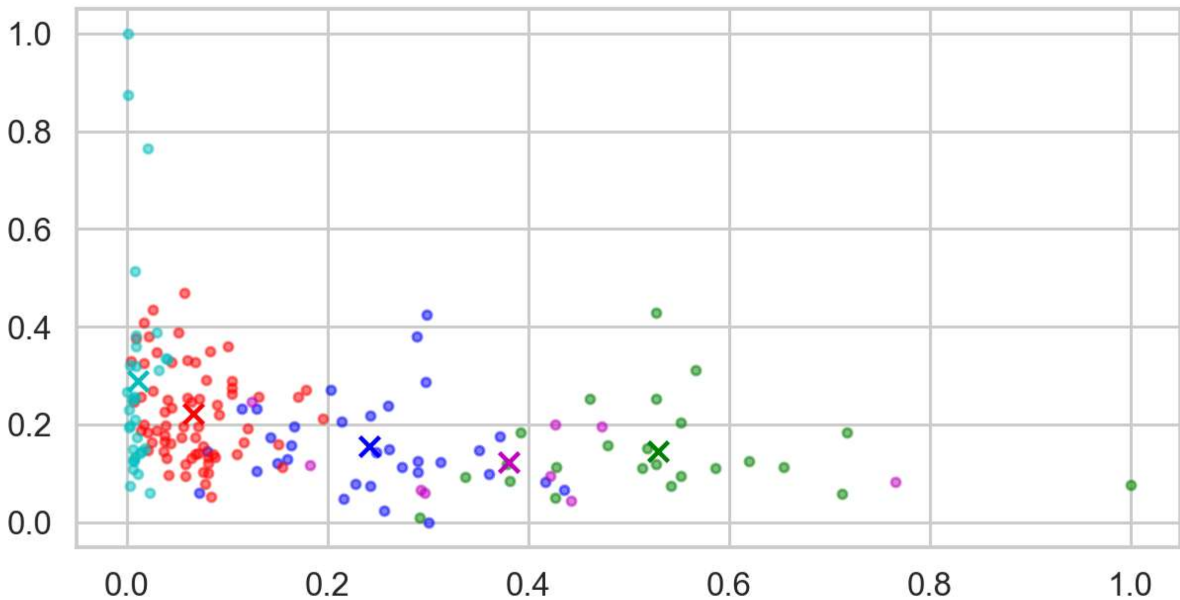
```
data.kmeans.value_counts()
```

Out[92]:

```
1    69
0    33
3    32
2    24
4     9
Name: kmeans, dtype: int64
```

In [98]:

```
X = np.array(X_tr)
color = 'brgcmyk'
alpha = 0.5
s = 20

for i in range(num_clusters):
    plt.scatter(X[km.labels_==i,0],X[km.labels_==i,1],c = color[i],alpha = alpha,s=s)
    plt.scatter(km.cluster_centers_[i][0],km.cluster_centers_[i][1],c = color[i], marker =
'x', s = 100)
```



In [87]:

```
from sklearn.cluster import AgglomerativeClustering
### BEGIN SOLUTION
ag = AgglomerativeClustering(n_clusters=5, linkage='ward', compute_full_tree=True)
ag = ag.fit(X_tr)
data['agglom'] = ag.fit_predict(X_tr)
data.head()
```

Out[87]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	5ℓ
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	40ℓ
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	44ℓ
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	35ℓ
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	122ℓ

In [89]:

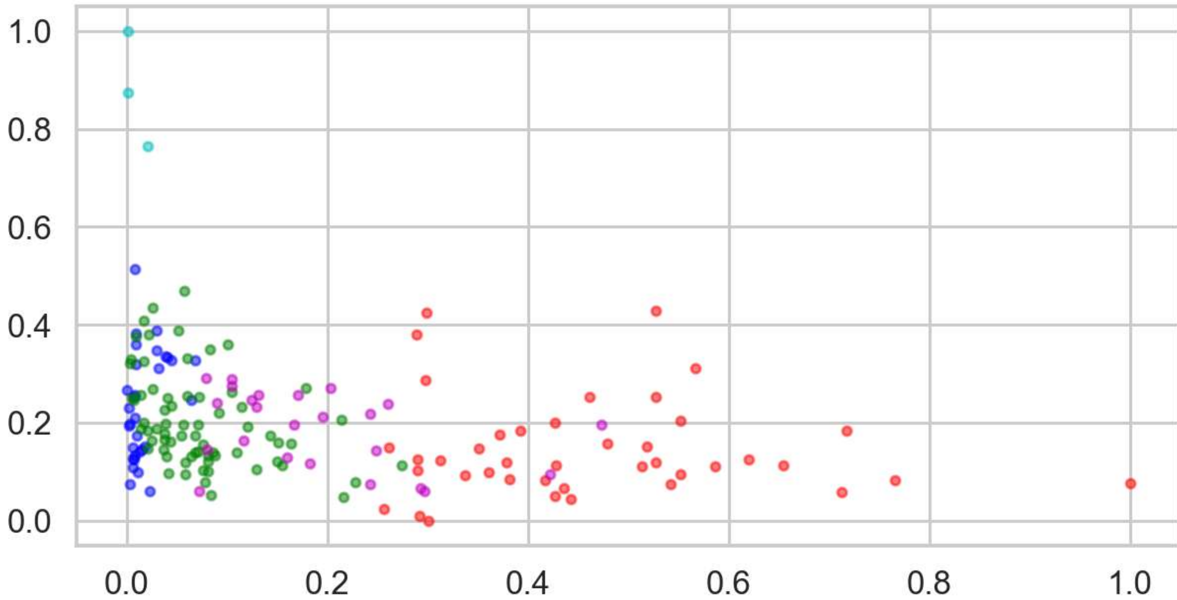
```
data.agglom.value_counts()
```

Out[89]:

```
2    68
1    41
0    31
4    24
3     3
Name: agglom, dtype: int64
```

In [100]:

```
X = np.array(X_tr)
color = 'brgcmyk'
alpha = 0.5
s = 20

for i in range(num_clusters):
    plt.scatter(X[ag.labels_==i,0],X[ag.labels_==i,1],c = color[i],alpha = alpha,s=s)
```



1. A paragraph explaining which of your Unsupervised Learning models you recommend as a final model that best fits your needs in terms. Summary Key Findings and Insights, which walks your reader through the main findings of your modeling exercise.

- We have Kmean clustering algorithm with different number of cluster ranging from 2 to 40 . After then we have checked the elbow plot and silhouette score and analysing them , I found that 5 number of cluster is optimum for the data set partition or segmentation . Further we have also fitted Agglomerative Clustering or Hierarchical clustering with same number of cluster i.e. 5 . We have found similar result approximately like kmean but one advantage with Agglomerative is that it is reproducible . So , we consider Hierarchical or Agglomerative clustering partition as final clustes

1. Suggestions for next steps in analyzing this data, which may include suggesting revisiting this model or adding specific data features to achieve a better model.

- In next step one can analyse by checking other clustering algorithm to investigate some uniqueness property of data

In [ ]:

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