Marketing Question 1 from sklearn.cluster import KMeans from sklearn.preprocessing import MinMaxScaler, StandardScaler, OneHotEncoder from sklearn.decomposition import PCA from sklearn.metrics import silhouette score load data df = Variables de segmentation Variables d df2 = Descripteurs Descripteu df = pd.read_csv("/Users/vincent/Desktop/school_2020/Book1.csv") df2 = pd.read_csv("/Users/vincent/Desktop/school_2020/Book2.csv") df head()

ld Networking	Reputation of the school	Changing company	Academic knowledge	Cost- driven	Location	Ranking of the program	Increasing your salary	Launching your own company	Personal dev	Changing career
0 1 5	5	1	2	2	2	3	1	5	5	5
1 2 5	5	1	2	2	2	3	1	5	5	5
2 3 1	5	3	4	4	4	2	1	1	5	1
3 4 5	5	1	5	1	2	5	5	1	5	1
4 5 4	5	5	4	1	1	2	5	1	5	5

In [143]: df2.head()

	ld	Gender	Country	Age	Experience	Financed
0	1	Male	International	44	13	Self
1	2	Male	France	37	11	Self
2	3	Male	International	43	15	Employer
3	4	Female	International	34	10	Self
4	5	Male	International	40	18	Self

```
#dropping this garbage column that starts counting at 1 ??? who counts from 1?!

df = df.drop('Id', axis=1)

df2 = df2.drop('Id', axis=1)
```

scale and PCA

we have to scale our data so that its normalized into a space that is legible by a computer

```
In [145]: ss = StandardScaler()
```

```
df scaled = ss.fit transform(df)
df scaled
 array([[ 1.11433685, 0.81228226, -1.03397878, ..., 1.34420385,
        -0.584<del>6</del>1089, 0.833<del>6</del>0904],
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       [0.31315306, -0.18162833, 0.76862139, \ldots, 0.65994504,
         1.79818245, 0.05160437]])
  df2 had strings in it, which cant be read by a comp, so lets turn those into binaryyyy
cat cols = ['Gender', 'Country', 'Financed']
#enc = OneHotEncoder(cat cols, handle unknown='ignore')
df2['bGender'] = np.where(df2['Gender'].str.contains('Male'), 1, 0)
df2['bCountry'] = np.where(df2['Country'].str.contains('France'), 1, 0)
df2['bFinanced'] = np.where(df2['Financed'].str.contains('Self'), 1, 0)
df2 = df2.drop(cat cols, axis=1)
df2.head()
   Age Experience bGender bCountry bFinanced
 0 44 13 1
2 43 15 1 0
 3 34 10
```

```
Age Experience bGender bCountry bFinanced
 4 40
       18
df2 scaled = ss.fit transform(df2)
df2 scaled
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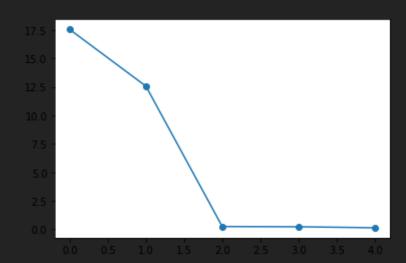
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        [ 0.71873157, 0.4315553 , 0.75894664, 0.81822462, 0.44857498],
        [-0.48731714, -2.0853774, 0.75894664, 0.81822462, 0.44857498],
        [-0.48731714, 0.71121449, -1.31761569, 0.81822462, 0.44857498],
        [-0.2461074 , 0.99087367, 0.75894664, 0.81822462, 0.44857498],
        [-0.00489766, -0.12776308, -1.31761569, 0.81822462, 0.44857498],
        [0.47752183, 0.15189611, 0.75894664, 0.81822462, 0.44857498],
        [-0.96973663, -0.12776308, 0.75894664, -1.22215829, -2.22928172],
        [-0.00489766, -1.52605903, 0.75894664, 0.81822462, 0.44857498]])
  now applying PCA to reduce the dimensionality of our data
pca1 = PCA()
pca data = pcal.fit transform(df)
new df = pd.DataFrame(pca data)
new df.columns = df.columns
plt.plot(pca1.explained_variance , "-o")
  [<matplotlib.lines.Line2D at 0x11e9f5c18>]
```

```
In [152]: pca2 = PCA()
   pca_data2 = pca2.fit_transform(df2)
   new_df2 = pd.DataFrame(pca_data2)
   new_df2.columns = df2.columns
   plt.plot(pca2.explained_variance_, "-o")

[<matplotlib.lines.Line2D at 0x11a97b4e0>]
```

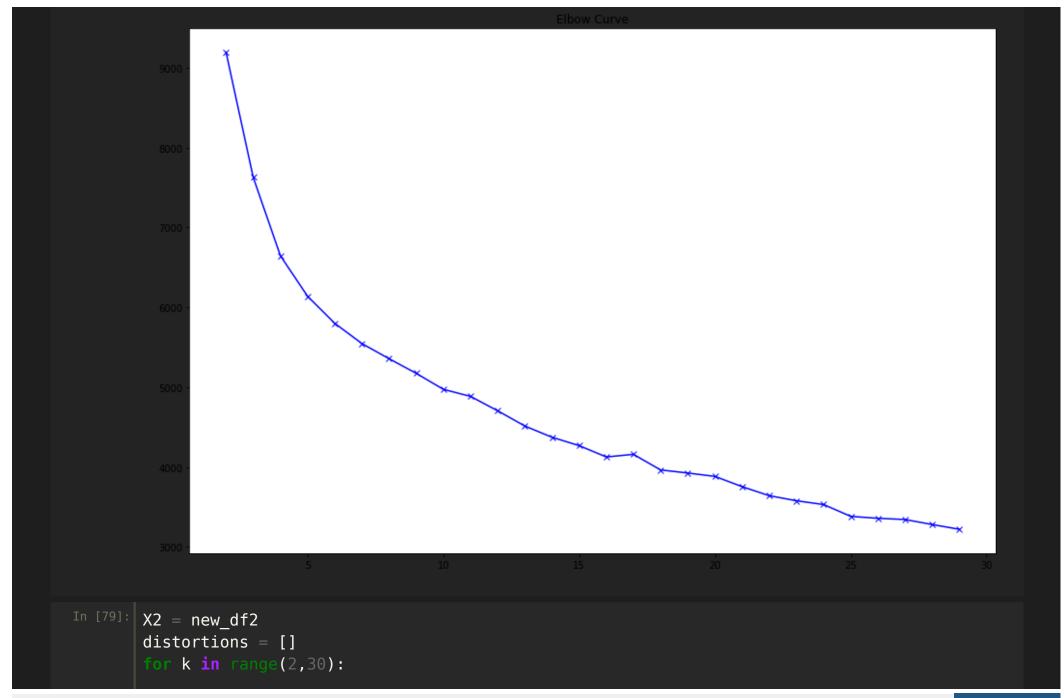


export to csv so enginius can tell us what each principle component means be im too tired to do the eigen math rn

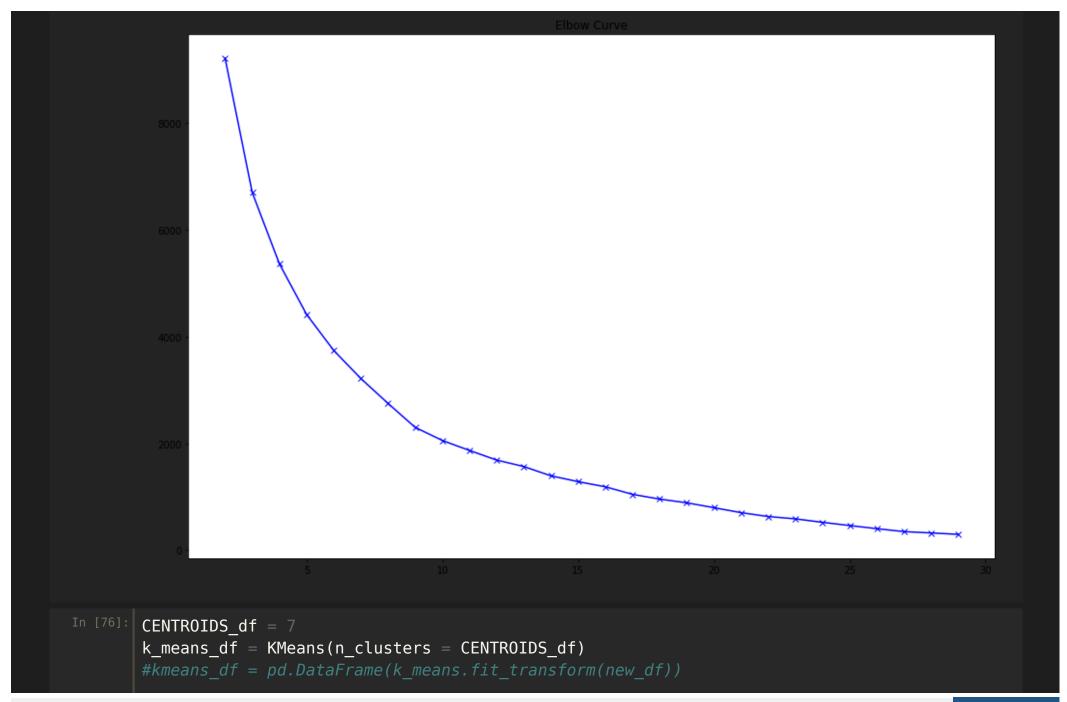
```
In [153]: new_df.head()
```

	Networking	Reputation of the	Changing	Academic	Cost-	Location	Ranking of the	Increasing your	Launching your own		Changing	c
	rtottioning	school	company	knowledge	driven	200411011	program	salary	company	dev	career	рі
	0 -0.864621	3.246970	2.977510	2.885319	0.320777	-1.566546	-0.236069	-1.886132	-0.385450	1.147241	-0.256647	1.1
	1 -0.864621	3.246970	2.977510	2.885319	0.320777	-1.566546	-0.236069	-1.886132	-0.385450	1.147241	-0.256647	1.1
	2 -2.801328	2.951599	0.075888	-1.454817	-0.736540	-1.036595	-3.259385	1.839996	-1.176350	-1.134459	0.692407	0.:
	3 -1.382418	-2.867785	2.453917	-1.144465	4.101465	2.211512	-0.672203	-0.318327	0.853783	-0.987209	-1.866509	-1
	4 4.150873	-1.447914	-1.971437	-0.262210	0.202581	-1.875030	0.538392	0.754126	0.708139	0.591011	-0.785617	-0
In [154]:	new_df2.hea	nd ()										
	Age Ex	xperience b	Gender bC	ountry bFin	anced							
	0 4.483296 -2.	.612615 -0	.711419 0.08	80674 -0.04	3393							
	1 -2.782444 -2.	.869428 0.	124746 -0.5	64251 -0.21	0609							
	2 3.983657 -0.	.434787 -0	.586350 0.09	94664 0.952	393							
	3 -5.941320 -3.	.135740 -0	.023798 0.82	24460 -0.20	9773							
	4 1.791333 3.1	196785 -C	.770411 0.10	05705 -0.03	3203							
In [155]:	new_df.to_c new_df2.to_											
kmeans clustering aka segmentation												
<pre>In [78]: X1 = new_df distortions = [] for k in range(2,30): k_means = KMeans(n_clusters = k) k_means.fit(X1)</pre>												

```
distortions append(k_means inertia_)
fig = plt.figure(figsize=(15,10))
plt.plot(range(2,30), distortions, 'bx-')
plt.title("Elbow Curve")
 Text(0.5, 1.0, 'Elbow Curve')
```



```
k_means = KMeans(n_clusters = k)
    k means fit(X2)
    distortions append(k_means inertia_)
fig = plt.figure(figsize=(15,10))
plt.plot(range(2,30), distortions, 'bx-')
plt.title("Elbow Curve")
 Text(0.5, 1.0, 'Elbow Curve')
```



```
X1['idx'] = k_means.fit_predict(new_df)
X1
```

	Networking	Reputation of the school	Changing company	Academic knowledge	Cost- driven	Location	Ranking of the program	Increasing your salary	Launching your own company	Personal dev	Changing career
0	-0.864621	3.246970	2.977510	2.885319	0.320777	-1.566546	-0.236069	-1.886132	-0.385450	1.147241	-0.256647
1	-0.864621	3.246970	2.977510	2.885319	0.320777	-1.566546	-0.236069	-1.886132	-0.385450	1.147241	-0.256647
2	-2.801328	2.951599	0.075888	-1.454817	-0.736540	-1.036595	-3.259385	1.839996	-1.176350	-1.134459	0.692407
3	-1.382418	-2.867785	2.453917	-1.144465	4.101465	2.211512	-0.672203	-0.318327	0.853783	-0.987209	-1.866509
4	4.150873	-1.447914	-1.971437	-0.262210	0.202581	-1.875030	0.538392	0.754126	0.708139	0.591011	-0.785617
192	0.764847	1.709765	-0.495760	-1.685259	-1.900965	2.936704	-1.385588	-0.111770	-2.161464	3.175317	-0.258228
193	-1.923550	5.451500	-0.827410	0.397593	-3.259149	2.147808	2.857874	1.227871	0.567607	-0.766280	-2.594120
194	0.830345	-0.157907	-0.960533	-0.753141	-0.485773	1.545426	-1.755626	-0.236817	-1.950126	-0.347470	-1.824623
195	-2.438497	-3.152476	-0.217916	1.794988	-1.921662	-2.327751	-1.206735	1.884174	-1.762781	-1.360205	-0.363577
196	-0.235236	1.476507	-3.009335	0.419355	1.852891	1.077462	-0.150166	-0.547856	-0.133756	-0.353544	-1.613892

197 rows × 19 columns

```
In [77]: CENTROIDS_df2 = 9
    k_means_df2 = KMeans(n_clusters = CENTROIDS_df2)
    #kmeans_df = pd.DataFrame(k_means.fit_transform(new_df))
    X2['idx'] = k_means.fit_predict(new_df2)
    X2
```

```
        Age
        Experience
        bGender
        bCountry
        bFinanced
        idx

        0
        4.482537
        -2.612852
        0.696923
        0.079458
        -0.0
        10
```

```
Age Experience bGender bCountry bFinanced idx
    -2.783300 -2.870050
                          -0.156407 -0.563423
                                               0.0
                                                           18
    3.988315 -0.432278
                          0.723575 0.090893
                                               -0.0
    -5.942214 -3.136531
                          -0.006289 0.824998
                                               -0.0
    1.790312 3.196426
                                    0.104350
                          0.756841
                                               0.0
                                                           28
192 -0.143063 3.688431
                          -0.042984 -0.512313
                                              -0.0
193 -0.124007 -0.430435
                          -0.712530 0.253382
                                               0.0
                                                           16
194 2.054940 0.059727
                          -0.076249 -0.525769 -0.0
                                                           16
195 -4.019042 0.505211
                          0.672207 0.064232
                                             -0.0
                                                           21
196 -1.317964 -5.289186
                          -0.178584 -0.572394 0.0
```

197 rows × 6 columns

calc silhoutte score

```
In [82]: silhouette_scores = []
    for clusters in range (2, 15):
        silhouette_scores append(silhouette_score(new_df, KMeans(n_clusters=clusters).fit_pr
        edict(new_df)))
        silhouette_scores

[0.42892582330701395,
        0.28652223843784785,
        0.20709437182422633,
        0.1918260811007373,
        0.15779337054515635,
        0.15750229565281872,
        0.14695322505321767,
        0.15289063195803013,
        0.1534116372670955,
```

```
0.1574182336056877,
   0.16146102624303493,
   0.1637853694254049,
   0.1638382889015344]
silhouette scores df2 = []
     clusters in range (2, 30):
     silhouette scores df2.append(silhouette score(new df2, KMeans(n clusters=clusters).f
it predict(new df2)))
silhouette scores df2
  [0.4399142714648029,
   0.3746435170940155,
   0.3992416318825048,
   0.40374757284722085,
   0.41214236947561456,
   0.429673620140503,
   0.4517054957124213,
   0.4666596549473109,
   0.476580665873192,
   0.4645099324809888,
   0.5021643866381706,
   0.4877915947730886,
   0.500457913538215,
   0.5297794132586645,
   0.5184083108072808,
   0.5411611485321279.
   0.5384357670475921,
   0.5475316440592597,
   0.5595342774274862.
   0.557465685179288,
   0.566994635582538,
   0.5640793604589242,
   0.5801305210593586,
   0.5795186130729701,
   0.593376673023028,
   0.5890539124089897,
```

0.5929027876984826,
0.5841578871756462]

final decision

we should use 3 or 4 clusters since 'the standard' is not to trust anything under ~0.20

In []: