## Importing the Dependencies

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
```

### Data collection & Analysis

```
df = pd.read_csv("Customer_data.csv")
df.head()
```

| | Customer ID | Gender | Age | Marital Status | Income | Education | Territorial Status | Occupation | Purchase Power | Monthly Expenditure |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 8024 | Male | 1957 | Widowed | Single | Bachelor's | Rural | Retired | 3 | 5000.0 |
| 1 | 8025 | Male | 1958 | Widowed | Single | Bachelor's | Rural | Retired | 3 | 5000.0 |
| 2 | 8026 | Male | 1959 | Married | Married | Bachelor's | Rural | Retired | 3 | 5000.0 |
| 3 | 8027 | Male | 1960 | Married | Married | Bachelor's | Rural | Retired | 3 | 5000.0 |
| 4 | 8028 | Male | 1961 | Married | Married | Bachelor's | Rural | Retired | 3 | 5000.0 |

5 rows × 25 columns

```
df.tail()
```

| | Customer ID | Gender | Age | Marital Status | Income | Education | Territorial Status | Occupation | Purchase Power | Monthly Expenditure |
|---|---|---|---|---|---|---|---|---|---|---|
| 2236 | 10547 | Female | 1957 | Divorced | Single | Master's | Urban | Retired | 3 | 5000.0 |
| 2237 | 10548 | Male | 1958 | Widowed | Single | Master's | Urban | Retired | 3 | 5000.0 |
| 2238 | 10549 | Male | 1959 | Married | Married | Master's | Urban | Retired | 3 | 5000.0 |
| 2239 | 10550 | Male | 1960 | Married | Married | Master's | Urban | Retired | 3 | 5000.0 |
| 2240 | 10551 | Male | 1961 | Married | Married | Master's | Urban | Retired | 3 | 5000.0 |

5 rows × 25 columns

```
df.shape
```

```
(2241, 25)
```

### size of the dataset

```
df.size
```

```
56025
```

### statistical Measures of the dataset

```
df.describe()
```

| | Customer ID | Age | Income | Kidhome | Teenhome | Recency | MntWines |
|---|---|---|---|---|---|---|---|
| count | 2240.000000 | 2240.000000 | 2216.000000 | 2240.000000 | 2240.000000 | 2240.000000 | 2240.000000 |
| mean | 5592.159821 | 1968.805804 | 52247.251354 | 0.444196 | 0.506250 | 49.109375 | 303.935714 |
| std | 3246.662198 | 11.984069 | 25173.076661 | 0.538398 | 0.544538 | 28.962453 | 336.597393 |
| min | 0.000000 | 1893.000000 | 1730.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 2415.750000 | 1959.000000 | 35303.000000 | 0.000000 | 0.000000 | 24.000000 | 23.750000 |
| 50% | 5627.500000 | 1970.000000 | 51381.500000 | 0.000000 | 0.000000 | 49.000000 | 173.500000 |
| 75% | 8427.750000 | 1977.000000 | 68522.000000 | 1.000000 | 1.000000 | 74.000000 | 504.000000 |
| max | 11191.000000 | 1996.000000 | 666666.000000 | 2.000000 | 2.000000 | 99.000000 | 1493.000000 |

6 rows × 25 columns

## Exploratory Data Analysis

```
df.info()
```

```
<class'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 25 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(23), object(5)
memory usage: 1.5MB
```

### checking for missing values

```
df.isnull().sum()
```

```
ID                   0
Year_Birth           0
Education            0
Marital_Status       0
Income              24
Kidhome              0
Teenhome             0
Dt_Customer          0
Recency              0
MntWines             0
MntFruits            0
MntMeatProducts      0
MntFishProducts      0
MntSweetProducts     0
MntGoldProds         0
NumDealsPurchases    0
NumWebPurchases      0
NumCatalogPurchases  0
NumStorePurchases    0
NumWebVisitsMonth    0
AcceptedCmp3         0
AcceptedCmp4         0
AcceptedCmp5         0
AcceptedCmp1         0
AcceptedCmp2         0
Complain             0
Z_CostContact        0
Z_Revenue            0
Response             0
dtype: int64
```

```
df.drop('Dt_Income',1,inplace=True)
df.isnull().sum()
```

```
ID                   0
Year_Birth           0
Education            0
Marital_Status       0
Income              24
Kidhome              0
Teenhome             0
Recency              0
MntWines             0
MntFruits            0
MntMeatProducts      0
MntFishProducts      0
MntSweetProducts     0
MntGoldProds         0
NumDealsPurchases    0
NumWebPurchases      0
NumCatalogPurchases  0
NumStorePurchases    0
NumWebVisitsMonth    0
AcceptedCmp3         0
AcceptedCmp4         0
AcceptedCmp5         0
AcceptedCmp1         0
AcceptedCmp2         0
Complain             0
Z_CostContact        0
Z_Revenue            0
Response             0
dtype: int64
```

```
df['Income'].fillna(value=df['Income'].mean())
df.isnull().sum()
```

```
ID                   0
Year_Birth           0
Education            0
Marital_Status       0
Income              24
Kidhome              0
Teenhome             0
Recency              0
MntWines             0
MntFruits            0
MntMeatProducts      0
MntFishProducts      0
MntSweetProducts     0
MntGoldProds         0
NumDealsPurchases    0
NumWebPurchases      0
NumCatalogPurchases  0
NumStorePurchases    0
NumWebVisitsMonth    0
AcceptedCmp3         0
AcceptedCmp4         0
AcceptedCmp5         0
AcceptedCmp1         0
AcceptedCmp2         0
Complain             0
Z_CostContact        0
Z_Revenue            0
Response             0
dtype: int64
```

```
df.shape
```

```
(2240, 28)
```

```
df.dropna(inplace=True)
df.shape
```

```
(2216, 28)
```

```
df.isnull().sum()
```

```
ID                   0
Year_Birth           0
Education            0
Marital_Status       0
Income               0
Kidhome              0
Teenhome             0
Recency              0
MntWines             0
MntFruits            0
MntMeatProducts      0
MntFishProducts      0
MntSweetProducts     0
MntGoldProds         0
NumDealsPurchases    0
NumWebPurchases      0
NumCatalogPurchases  0
NumStorePurchases    0
NumWebVisitsMonth    0
AcceptedCmp3         0
AcceptedCmp4         0
AcceptedCmp5         0
AcceptedCmp1         0
AcceptedCmp2         0
Complain             0
Z_CostContact        0
Z_Revenue            0
Response             0
dtype: int64
```

```
plt.figure(figsize = (20,8))
sns.boxplot(df['Income'],df['Response'],palette="Set1")
plt.title('Income vs Response')
plt.show()
```

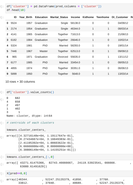
```
df.shape[:,[4,20]].value_counts
```

```
(2240, 2)
```

```
df.info()
```

```
<class'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 27 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(23), object(5)
memory usage: 1.5MB
```

```
plt.figure(figsize = (20,8))
sns.boxplot(df['Income'],df['Response'],palette="Set1")
plt.title('Income vs Response')
plt.show()
```

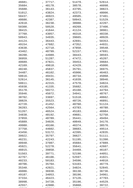



```
df.shape[:,[4,20]].value_counts
```

```
(2240, 2)
```

### elbow method

```
plt.figure(figsize = (20,8))
sns.boxplot(df['Income'],df['Response'],palette="Set1")
plt.title('Income vs Response')
plt.show()
```




```
df.shape[:,[4,20]].value_counts
```

```
(2240, 2)
```

### elbow method

```
df = df.drop(['Z_CostContact','Z_Revenue'],axis=1)
df.shape
```

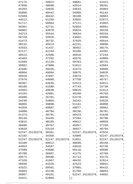
```
(2240, 26)
```

```
df.shape[:,[4,20]].value_counts
```

```
(2240, 2)
```

### clustering score

```
clustering_score = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i,init='k-means++',random_state = 42)
    kmeans.fit(df)
    clustering_score.append(kmeans.inertia_)
plt.plot(range(1,11),clustering_score)
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.title('Elbow method')
plt.show()
```




```
clustering_score
```

```
[1106988258.0,
 707744774.0,
 432030053.0,
 408797635.0,
 377672401.0,
 358875596.0,
 341359286.0,
 326781812.0,
 316348110.0,
 306445975.0,
 298090392.0]
```

```
clustering_score[3]-clustering_score[4]
```

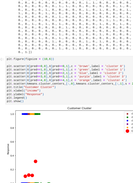
```
32878561.0
```

```
df.shape[:,[4,20]]
```

```
(2240, 2)
```

### silhouette score

```
clustering_score = []
for i in range(2,11):
    kmeans = KMeans(n_clusters=i,init='k-means++',random_state = 42)
    kmeans.fit(df)
    clustering_score.append(silhouette_score(df,kmeans.labels_))
plt.plot(range(2,11),clustering_score)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette score')
plt.title('Elbow method')
plt.show()
```




```
from sklearn.metrics import silhouette_score
clustering_score = []
for i in range(2,11):
    kmeans = KMeans(n_clusters=i,init='k-means++',random_state=42)
    kmeans.fit(df)
    clustering_score.append(silhouette_score(df,kmeans.labels_))
clustering_score_2=
```

```
[0.32473267031771,
 0.3011750201927437,
 0.2929139371054961,
 0.2728726207539472,
 0.2873922094482065,
 0.2804813283457692,
 0.2819197035403825,
 0.2828016689893617,
 0.2846029226931855,
 0.2890372751699665,
 0.2923162530103885]
```

```
clustering_score[0]
```

```
0.32473267031771
```

### Building the model

```
kmeans = KMeans(n_clusters=2,init='k-means++',random_state = 42)
kmeans.fit(df)
```

```
KMeans(n_clusters=2, random_state=42)
```

```
y = kmeans.predict(df)
df['Cluster'] = y
df
```

| | ID | Year_Birth | Education | Marital_Status | Income | Kidhome | Teenhome | Recency | MntWines | MntFruits | MntMeatProducts | MntFishProducts | MntSweetProducts | MntGoldProds | NumDealsPurchases | NumWebPurchases | NumCatalogPurchases | NumStorePurchases | NumWebVisitsMonth | AcceptedCmp3 | AcceptedCmp4 | AcceptedCmp5 | AcceptedCmp1 | AcceptedCmp2 | Complain | Z_CostContact | Z_Revenue | Response | Cluster |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 5524 | 1957 | Graduation | Single | 58138.0 | 0 | 0 | 58 | 635 | 88 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 1 | 2174 | 1954 | Graduation | Single | 46344.0 | 1 | 1 | 26 | 11 | 1 | 6 | 2 | 1 | 6 | 2 | 1 | 1 | 2 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 2 | 4141 | 1965 | Graduation | Together | 71613.0 | 0 | 0 | 26 | 426 | 49 | 127 | 111 | 21 | 42 | 1 | 8 | 2 | 10 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 3 | 6182 | 1984 | PhD | Married | 26646.0 | 1 | 0 | 26 | 11 | 4 | 20 | 10 | 3 | 5 | 2 | 2 | 0 | 4 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 4 | 5324 | 1981 | PhD | Married | 58293.0 | 1 | 0 | 94 | 173 | 43 | 118 | 46 | 27 | 15 | 5 | 5 | 3 | 6 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 2236 | 10547 | 1957 | Master's | Divorced | Single | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 2237 | 10548 | 1958 | Master's | Widowed | Single | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 2238 | 10549 | 1959 | Master's | Married | Married | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 2239 | 10550 | 1960 | Master's | Married | Married | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 2240 | 10551 | 1961 | Master's | Married | Married | 0.0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |

2240 rows × 29 columns

```
df['Cluster'].value_counts()
```

```
0    1441
1     799
Name: Cluster, dtype: int64
```

### checking of each cluster

```
df[df['Cluster']==0].shape
df[df['Cluster']==1].shape
df[df['Cluster']==2].shape
df[df['Cluster']==3].shape
df[df['Cluster']==4].shape
df[df['Cluster']==5].shape
df[df['Cluster']==6].shape
df[df['Cluster']==7].shape
df[df['Cluster']==8].shape
df[df['Cluster']==9].shape
df[df['Cluster']==10].shape
```

```
(1441, 29)
(799, 29)
```

```
df[df['Cluster']==0]
```

| | ID | Year_Birth | Education | Marital_Status | Income | Kidhome | Teenhome | Recency | MntWines | MntFruits | MntMeatProducts | MntFishProducts | MntSweetProducts | MntGoldProds | NumDealsPurchases | NumWebPurchases | NumCatalogPurchases | NumStorePurchases | NumWebVisitsMonth | AcceptedCmp3 | AcceptedCmp4 | AcceptedCmp5 | AcceptedCmp1 | AcceptedCmp2 | Complain | Z_CostContact | Z_Revenue | Response | Cluster |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 5524 | 1957 | Graduation | Single | 58138.0 | 0 | 0 | 58 | 635 | 88 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 1 | 2174 | 1954 | Graduation | Single | 46344.0 | 1 | 1 | 26 | 11 | 1 | 6 | 2 | 1 | 6 | 2 | 1 | 1 | 2 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 3 | 6182 | 1984 | PhD | Married | 26646.0 | 1 | 0 | 26 | 11 | 4 | 20 | 10 | 3 | 5 | 2 | 2 | 0 | 4 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 4 | 5324 | 1981 | PhD | Married | 58293.0 | 1 | 0 | 94 | 173 | 43 | 118 | 46 | 27 | 15 | 5 | 5 | 3 | 6 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 5 | 7424 | 1955 | Graduation | Divorced | 62513.0 | 0 | 1 | 16 | 520 | 42 | 98 | 300 | 26 | 60 | 2 | 6 | 4 | 10 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 6 | 8557 | 1965 | PhD | Married | 55914.0 | 1 | 1 | 23 | 709 | 43 | 182 | 214 | 62 | 81 | 1 | 7 | 2 | 8 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 7 | 10870 | 1967 | Graduation | Married | 33812.0 | 1 | 0 | 30 | 309 | 3 | 67 | 23 | 2 | 44 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 8 | 4071 | 1951 | PhD | Married | 70951.0 | 0 | 1 | 61 | 383 | 59 | 239 | 239 | 59 | 482 | 2 | 6 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 9 | 1970 | 1954 | PhD | Married | 54356.0 | 0 | 1 | 60 | 618 | 82 | 241 | 78 | 43 | 62 | 3 | 8 | 3 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 10 | 4693 | 1954 | 2n Cycle | Married | 67445.0 | 0 | 0 | 23 | 390 | 59 | 304 | 123 | 59 | 215 | 2 | 7 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 11 | 6095 | 1955 | PhD | Married | 62499.0 | 1 | 1 | 92 | 418 | 78 | 505 | 62 | 78 | 160 | 3 | 9 | 5 | 10 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 12 | 1617 | 1943 | PhD | Married | 96547.0 | 0 | 0 | 82 | 1035 | 76 | 641 | 91 | 68 | 364 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 13 | 5679 | 1943 | Graduation | Divorced | 165797.0 | 0 | 0 | 38 | 1690 | 59 | 1546 | 186 | 89 | 827 | 2 | 3 | 8 | 13 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 14 | 1049 | 1965 | Graduation | Married | 56304.0 | 0 | 0 | 65 | 571 | 60 | 372 | 65 | 60 | 239 | 3 | 6 | 4 | 11 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 15 | 5854 | 1953 | 2n Cycle | Married | 69235.0 | 0 | 1 | 54 | 418 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 16 | 8268 | 1961 | PhD | Married | 61331.0 | 0 | 1 | 99 | 499 | 81 | 380 | 152 | 39 | 170 | 3 | 7 | 4 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 17 | 7655 | 1975 | Graduation | Married | 30351.0 | 1 | 0 | 19 | 368 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 18 | 5555 | 1975 | Graduation | Married | 36099.0 | 1 | 1 | 65 | 50 | 16 | 624 | 61 | 21 | 62 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 19 | 4202 | 1951 | PhD | Married | 65324.0 | 0 | 0 | 74 | 850 | 87 | 351 | 549 | 144 | 395 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 20 | 7500 | 1965 | PhD | Together | 70666.0 | 1 | 0 | 12 | 655 | 75 | 488 | 239 | 78 | 781 | 3 | 8 | 4 | 10 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 21 | 1501 | 1982 | PhD | Married | 60182.0 | 0 | 1 | 23 | 800 | 99 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 22 | 8475 | 1973 | PhD | Married | 26779.0 | 1 | 0 | 23 | 225 | 1 | 544 | 62 | 51 | 123 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 23 | 2339 | 1949 | PhD | Married | 62499.0 | 1 | 1 | 96 | 413 | 116 | 953 | 687 | 48 | 359 | 3 | 9 | 5 | 10 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 24 | 8268 | 1961 | PhD | Married | 61331.0 | 0 | 1 | 99 | 499 | 81 | 380 | 152 | 39 | 170 | 3 | 7 | 4 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 25 | 7424 | 1955 | Graduation | Divorced | 62513.0 | 0 | 1 | 16 | 520 | 42 | 98 | 300 | 26 | 60 | 2 | 6 | 4 | 10 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 26 | 8557 | 1965 | PhD | Married | 55914.0 | 1 | 1 | 23 | 709 | 43 | 182 | 214 | 62 | 81 | 1 | 7 | 2 | 8 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 27 | 10870 | 1967 | Graduation | Married | 33812.0 | 1 | 0 | 30 | 309 | 3 | 67 | 23 | 2 | 44 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 28 | 4071 | 1951 | PhD | Married | 70951.0 | 0 | 1 | 61 | 383 | 59 | 239 | 239 | 59 | 482 | 2 | 6 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 29 | 1970 | 1954 | PhD | Married | 54356.0 | 0 | 1 | 60 | 618 | 82 | 241 | 78 | 43 | 62 | 3 | 8 | 3 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 30 | 4693 | 1954 | 2n Cycle | Married | 67445.0 | 0 | 0 | 23 | 390 | 59 | 304 | 123 | 59 | 215 | 2 | 7 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 31 | 6095 | 1955 | PhD | Married | 62499.0 | 1 | 1 | 92 | 418 | 78 | 505 | 62 | 78 | 160 | 3 | 9 | 5 | 10 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 32 | 1617 | 1943 | PhD | Married | 96547.0 | 0 | 0 | 82 | 1035 | 76 | 641 | 91 | 68 | 364 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 33 | 5679 | 1943 | Graduation | Divorced | 165797.0 | 0 | 0 | 38 | 1690 | 59 | 1546 | 186 | 89 | 827 | 2 | 3 | 8 | 13 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 34 | 1049 | 1965 | Graduation | Married | 56304.0 | 0 | 0 | 65 | 571 | 60 | 372 | 65 | 60 | 239 | 3 | 6 | 4 | 11 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 35 | 5854 | 1953 | 2n Cycle | Married | 69235.0 | 0 | 1 | 54 | 418 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 36 | 8268 | 1961 | PhD | Married | 61331.0 | 0 | 1 | 99 | 499 | 81 | 380 | 152 | 39 | 170 | 3 | 7 | 4 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 37 | 7655 | 1975 | Graduation | Married | 30351.0 | 1 | 0 | 19 | 368 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 38 | 5555 | 1975 | Graduation | Married | 36099.0 | 1 | 1 | 65 | 50 | 16 | 624 | 61 | 21 | 62 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 39 | 4202 | 1951 | PhD | Married | 65324.0 | 0 | 0 | 74 | 850 | 87 | 351 | 549 | 144 | 395 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 40 | 7500 | 1965 | PhD | Together | 70666.0 | 1 | 0 | 12 | 655 | 75 | 488 | 239 | 78 | 781 | 3 | 8 | 4 | 10 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 41 | 1501 | 1982 | PhD | Married | 60182.0 | 0 | 1 | 23 | 800 | 99 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 42 | 8475 | 1973 | PhD | Married | 26779.0 | 1 | 0 | 23 | 225 | 1 | 544 | 62 | 51 | 123 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 43 | 2339 | 1949 | PhD | Married | 62499.0 | 1 | 1 | 96 | 413 | 116 | 953 | 687 | 48 | 359 | 3 | 9 | 5 | 10 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 44 | 8268 | 1961 | PhD | Married | 61331.0 | 0 | 1 | 99 | 499 | 81 | 380 | 152 | 39 | 170 | 3 | 7 | 4 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 45 | 7424 | 1955 | Graduation | Divorced | 62513.0 | 0 | 1 | 16 | 520 | 42 | 98 | 300 | 26 | 60 | 2 | 6 | 4 | 10 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 46 | 8557 | 1965 | PhD | Married | 55914.0 | 1 | 1 | 23 | 709 | 43 | 182 | 214 | 62 | 81 | 1 | 7 | 2 | 8 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 47 | 10870 | 1967 | Graduation | Married | 33812.0 | 1 | 0 | 30 | 309 | 3 | 67 | 23 | 2 | 44 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 48 | 4071 | 1951 | PhD | Married | 70951.0 | 0 | 1 | 61 | 383 | 59 | 239 | 239 | 59 | 482 | 2 | 6 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 49 | 1970 | 1954 | PhD | Married | 54356.0 | 0 | 1 | 60 | 618 | 82 | 241 | 78 | 43 | 62 | 3 | 8 | 3 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 50 | 4693 | 1954 | 2n Cycle | Married | 67445.0 | 0 | 0 | 23 | 390 | 59 | 304 | 123 | 59 | 215 | 2 | 7 | 4 | 8 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 51 | 6095 | 1955 | PhD | Married | 62499.0 | 1 | 1 | 92 | 418 | 78 | 505 | 62 | 78 | 160 | 3 | 9 | 5 | 10 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 52 | 1617 | 1943 | PhD | Married | 96547.0 | 0 | 0 | 82 | 1035 | 76 | 641 | 91 | 68 | 364 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 53 | 5679 | 1943 | Graduation | Divorced | 165797.0 | 0 | 0 | 38 | 1690 | 59 | 1546 | 186 | 89 | 827 | 2 | 3 | 8 | 13 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 54 | 1049 | 1965 | Graduation | Married | 56304.0 | 0 | 0 | 65 | 571 | 60 | 372 | 65 | 60 | 239 | 3 | 6 | 4 | 11 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 55 | 5854 | 1953 | 2n Cycle | Married | 69235.0 | 0 | 1 | 54 | 418 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 56 | 8268 | 1961 | PhD | Married | 61331.0 | 0 | 1 | 99 | 499 | 81 | 380 | 152 | 39 | 170 | 3 | 7 | 4 | 8 | 6 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 57 | 7655 | 1975 | Graduation | Married | 30351.0 | 1 | 0 | 19 | 368 | 78 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 58 | 5555 | 1975 | Graduation | Married | 36099.0 | 1 | 1 | 65 | 50 | 16 | 624 | 61 | 21 | 62 | 1 | 3 | 1 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 1 |
| 59 | 4202 | 1951 | PhD | Married | 65324.0 | 0 | 0 | 74 | 850 | 87 | 351 | 549 | 144 | 395 | 2 | 4 | 6 | 12 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 60 | 7500 | 1965 | PhD | Together | 70666.0 | 1 | 0 | 12 | 655 | 75 | 488 | 239 | 78 | 781 | 3 | 8 | 4 | 10 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 0 | 0 |
| 61 | 1501 | 1982 | PhD | Married | 60182.0 | 0 | 1 | 23 | 800 | 99 | 546 | 172 | 88 | 88 | 3 | 8 | 10 | 4 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 11 | 1 | 0 |
| 62 | 8475 | 1973 | PhD | Married