In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
divorce_data = pd.read_csv('divorce_data.csv')
```

In [3]:

```
divorce_data.head()
```

Out[3]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	Atr9	Atr10	...	Atr46	Atr47	Atr48	Atr49
0	2	2	4	1	0	0	0	0	0	0	...	2	1	3	3
1	4	4	4	4	4	0	0	4	4	4	...	2	2	3	4
2	2	2	2	2	1	3	2	1	1	2	...	3	2	3	1
3	3	2	3	2	3	3	3	3	3	3	...	2	2	3	3
4	2	2	1	1	1	1	0	0	0	0	...	2	1	2	3

5 rows × 55 columns

In [4]:

```
divorce_data.tail()
```

Out[4]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	Atr9	Atr10	...	Atr46	Atr47	Atr48	Atr4
165	0	0	0	0	0	0	0	0	0	0	...	1	0	4	
166	0	0	0	0	0	0	0	0	0	0	...	4	1	2	
167	1	1	0	0	0	0	0	0	0	1	...	3	0	2	
168	0	0	0	0	0	0	0	0	0	0	...	3	3	2	
169	0	0	0	0	0	0	0	1	0	0	...	3	4	4	

5 rows × 55 columns

In [5]:

```
divorce_data.shape
```

Out[5]:

```
(170, 55)
```

In [6]:

```
divorce_data.columns
```

Out[6]:

```
Index(['Atr1', 'Atr2', 'Atr3', 'Atr4', 'Atr5', 'Atr6', 'Atr7', 'Atr8', 'At
r9',
       'Atr10', 'Atr11', 'Atr12', 'Atr13', 'Atr14', 'Atr15', 'Atr16', 'Atr
17',
       'Atr18', 'Atr19', 'Atr20', 'Atr21', 'Atr22', 'Atr23', 'Atr24', 'Atr
25',
       'Atr26', 'Atr27', 'Atr28', 'Atr29', 'Atr30', 'Atr31', 'Atr32', 'Atr
33',
       'Atr34', 'Atr35', 'Atr36', 'Atr37', 'Atr38', 'Atr39', 'Atr40', 'Atr
41',
       'Atr42', 'Atr43', 'Atr44', 'Atr45', 'Atr46', 'Atr47', 'Atr48', 'Atr
49',
       'Atr50', 'Atr51', 'Atr52', 'Atr53', 'Atr54', 'Class'],
      dtype='object')
```

In [7]:

```
divorce_data.duplicated().sum()
```

Out[7]:

```
20
```

In [8]:

```
divorce_data.isnull().sum()
```

Out[8]:

```
Atr1     0
Atr2     0
Atr3     0
Atr4     0
Atr5     0
Atr6     0
Atr7     0
Atr8     0
Atr9     0
Atr10    0
Atr11    0
Atr12    0
Atr13    0
Atr14    0
Atr15    0
Atr16    0
Atr17    0
Atr18    0
Atr19    0
Atr20    0
Atr21    0
Atr22    0
Atr23    0
Atr24    0
Atr25    0
Atr26    0
Atr27    0
Atr28    0
Atr29    0
Atr30    0
Atr31    0
Atr32    0
Atr33    0
Atr34    0
Atr35    0
Atr36    0
Atr37    0
Atr38    0
Atr39    0
Atr40    0
Atr41    0
Atr42    0
Atr43    0
Atr44    0
Atr45    0
Atr46    0
Atr47    0
Atr48    0
Atr49    0
Atr50    0
Atr51    0
Atr52    0
Atr53    0
Atr54    0
Class    0
dtype: int64
```

In [9]:

```
with open('divorce.txt') as f:
    contents = f.read()
    print(contents)
```

```
1. If one of us apologizes when our discussion deteriorates, the discussio
n ends.
2. I know we can ignore our differences, even if things get hard sometime
s.
3. When we need it, we can take our discussions with my spouse from the be
ginning and correct it.
4. When I discuss with my spouse, to contact him will eventually work.
5. The time I spent with my wife is special for us.
6. We don't have time at home as partners.
7. We are like two strangers who share the same environment at home rather
than family.
8. I enjoy our holidays with my wife.
9. I enjoy traveling with my wife.
10. Most of our goals are common to my spouse.
11. I think that one day in the future, when I look back, I see that my sp
ouse and I have been in harmony with each other.
12. My spouse and I have similar values in terms of personal freedom.
13. My spouse and I have similar sense of entertainment.
14. Most of our goals for people (children, friends, etc.) are the same.
15. Our dreams with my spouse are similar and harmonious.
16. We're compatible with my spouse about what love should be.
17. We share the same views about being happy in our life with my spouse
18. My spouse and I have similar ideas about how marriage should be
19. My spouse and I have similar ideas about how roles should be in marria
ge
20. My spouse and I have similar values in trust.
21. I know exactly what my wife likes.
22. I know how my spouse wants to be taken care of when she/he sick.
23. I know my spouse's favorite food.
24. I can tell you what kind of stress my spouse is facing in her/his lif
e.
25. I have knowledge of my spouse's inner world.
26. I know my spouse's basic anxieties.
27. I know what my spouse's current sources of stress are.
28. I know my spouse's hopes and wishes.
29. I know my spouse very well.
30. I know my spouse's friends and their social relationships.
31. I feel aggressive when I argue with my spouse.
32. When discussing with my spouse, I usually use expressions such as â€˜y
ou alwaysâ€™ or â€˜you neverâ€™ .
33. I can use negative statements about my spouse's personality during our
discussions.
34. I can use offensive expressions during our discussions.
35. I can insult my spouse during our discussions.
36. I can be humiliating when we discussions.
37. My discussion with my spouse is not calm.
38. I hate my spouse's way of open a subject.
39. Our discussions often occur suddenly.
40. We're just starting a discussion before I know what's going on.
41. When I talk to my spouse about something, my calm suddenly breaks.
42. When I argue with my spouse, Ä± only go out and I don't say a word.
43. I mostly stay silent to calm the environment a little bit.
44. Sometimes I think it's good for me to leave home for a while.
45. I'd rather stay silent than discuss with my spouse.
46. Even if I'm right in the discussion, I stay silent to hurt my spouse.
47. When I discuss with my spouse, I stay silent because I am afraid of no
t being able to control my anger.
48. I feel right in our discussions.
49. I have nothing to do with what I've been accused of.
50. I'm not actually the one who's guilty about what I'm accused of.
51. I'm not the one who's wrong about problems at home.
```

```
52. I wouldn't hesitate to tell my spouse about her/his inadequacy.
53. When I discuss, I remind my spouse of her/his inadequacy.
54. I'm not afraid to tell my spouse about her/his incompetence.
```

In [10]:

```
divorce_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 170 entries, 0 to 169
Data columns (total 55 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Atr1    170 non-null    int64
 1   Atr2    170 non-null    int64
 2   Atr3    170 non-null    int64
 3   Atr4    170 non-null    int64
 4   Atr5    170 non-null    int64
 5   Atr6    170 non-null    int64
 6   Atr7    170 non-null    int64
 7   Atr8    170 non-null    int64
 8   Atr9    170 non-null    int64
 9   Atr10   170 non-null    int64
 10  Atr11   170 non-null    int64
 11  Atr12   170 non-null    int64
 12  Atr13   170 non-null    int64
 13  Atr14   170 non-null    int64
 14  Atr15   170 non-null    int64
 15  Atr16   170 non-null    int64
 16  Atr17   170 non-null    int64
 17  Atr18   170 non-null    int64
 18  Atr19   170 non-null    int64
 19  Atr20   170 non-null    int64
 20  Atr21   170 non-null    int64
 21  Atr22   170 non-null    int64
 22  Atr23   170 non-null    int64
 23  Atr24   170 non-null    int64
 24  Atr25   170 non-null    int64
 25  Atr26   170 non-null    int64
 26  Atr27   170 non-null    int64
 27  Atr28   170 non-null    int64
 28  Atr29   170 non-null    int64
 29  Atr30   170 non-null    int64
 30  Atr31   170 non-null    int64
 31  Atr32   170 non-null    int64
 32  Atr33   170 non-null    int64
 33  Atr34   170 non-null    int64
 34  Atr35   170 non-null    int64
 35  Atr36   170 non-null    int64
 36  Atr37   170 non-null    int64
 37  Atr38   170 non-null    int64
 38  Atr39   170 non-null    int64
 39  Atr40   170 non-null    int64
 40  Atr41   170 non-null    int64
 41  Atr42   170 non-null    int64
 42  Atr43   170 non-null    int64
 43  Atr44   170 non-null    int64
 44  Atr45   170 non-null    int64
 45  Atr46   170 non-null    int64
 46  Atr47   170 non-null    int64
 47  Atr48   170 non-null    int64
 48  Atr49   170 non-null    int64
 49  Atr50   170 non-null    int64
 50  Atr51   170 non-null    int64
 51  Atr52   170 non-null    int64
 52  Atr53   170 non-null    int64
 53  Atr54   170 non-null    int64
 54  Class   170 non-null    int64
```

```
dtypes: int64(55)
memory usage: 73.2 KB
```

In [11]:

```
divorce_data.describe()
```

Out[11]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7
count	170.000000	170.000000	170.000000	170.000000	170.000000	170.000000	170.000000
mean	1.776471	1.652941	1.764706	1.482353	1.541176	0.747059	0.494118
std	1.627257	1.468654	1.415444	1.504327	1.632169	0.904046	0.898698
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	2.000000	2.000000	2.000000	1.000000	1.000000	0.000000	0.000000
75%	3.000000	3.000000	3.000000	3.000000	3.000000	1.000000	1.000000
max	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000	4.000000

8 rows × 55 columns

In [12]:

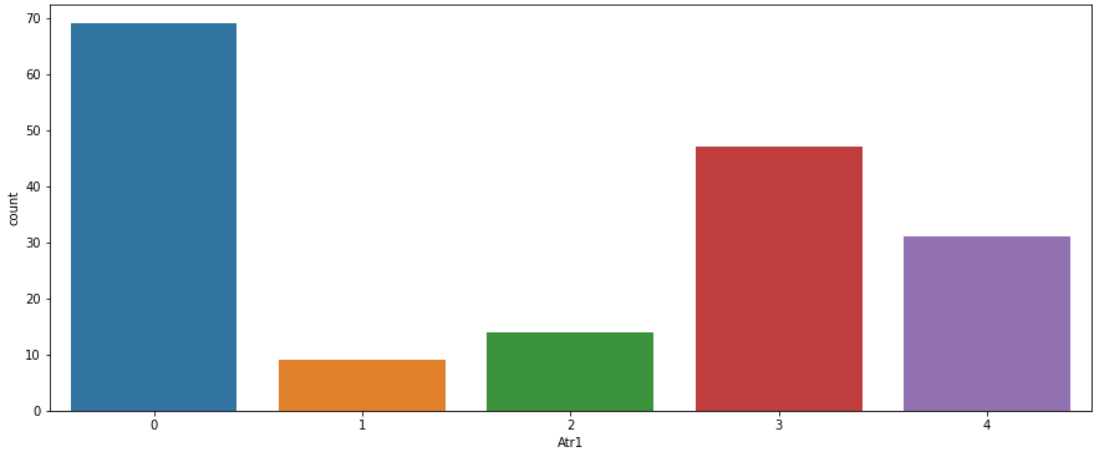
```
divorce_data.nunique()
```

Out[12]:

```
Atr1     5
Atr2     5
Atr3     5
Atr4     5
Atr5     5
Atr6     5
Atr7     5
Atr8     5
Atr9     5
Atr10    5
Atr11    5
Atr12    5
Atr13    5
Atr14    5
Atr15    5
Atr16    5
Atr17    5
Atr18    5
Atr19    5
Atr20    5
Atr21    5
Atr22    5
Atr23    5
Atr24    5
Atr25    5
Atr26    5
Atr27    5
Atr28    5
Atr29    5
Atr30    5
Atr31    5
Atr32    5
Atr33    5
Atr34    5
Atr35    5
Atr36    5
Atr37    5
Atr38    5
Atr39    5
Atr40    5
Atr41    5
Atr42    5
Atr43    5
Atr44    5
Atr45    5
Atr46    5
Atr47    5
Atr48    5
Atr49    5
Atr50    5
Atr51    5
Atr52    5
Atr53    5
Atr54    5
Class    2
dtype: int64
```

In [14]:

```
for i in divorce_data.columns:
    plt.figure(figsize=(15,6))
    sns.countplot(divorce_data[i], data = divorce_data)
    plt.show()
```



In [15]:

```
divorce_data['Class'].values
```

Out[15]:

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
```

In [16]:

```
divorce_data['Class'].unique()
```

Out[16]:

```
array([1, 0], dtype=int64)
```

In [17]:

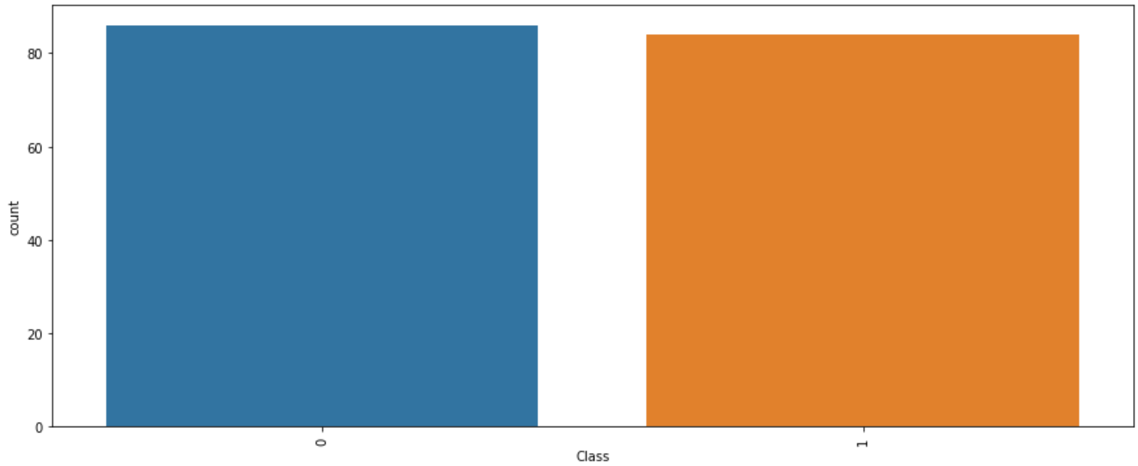
```
divorce_data['Class'].value_counts()
```

Out[17]:

```
0    86
1    84
Name: Class, dtype: int64
```

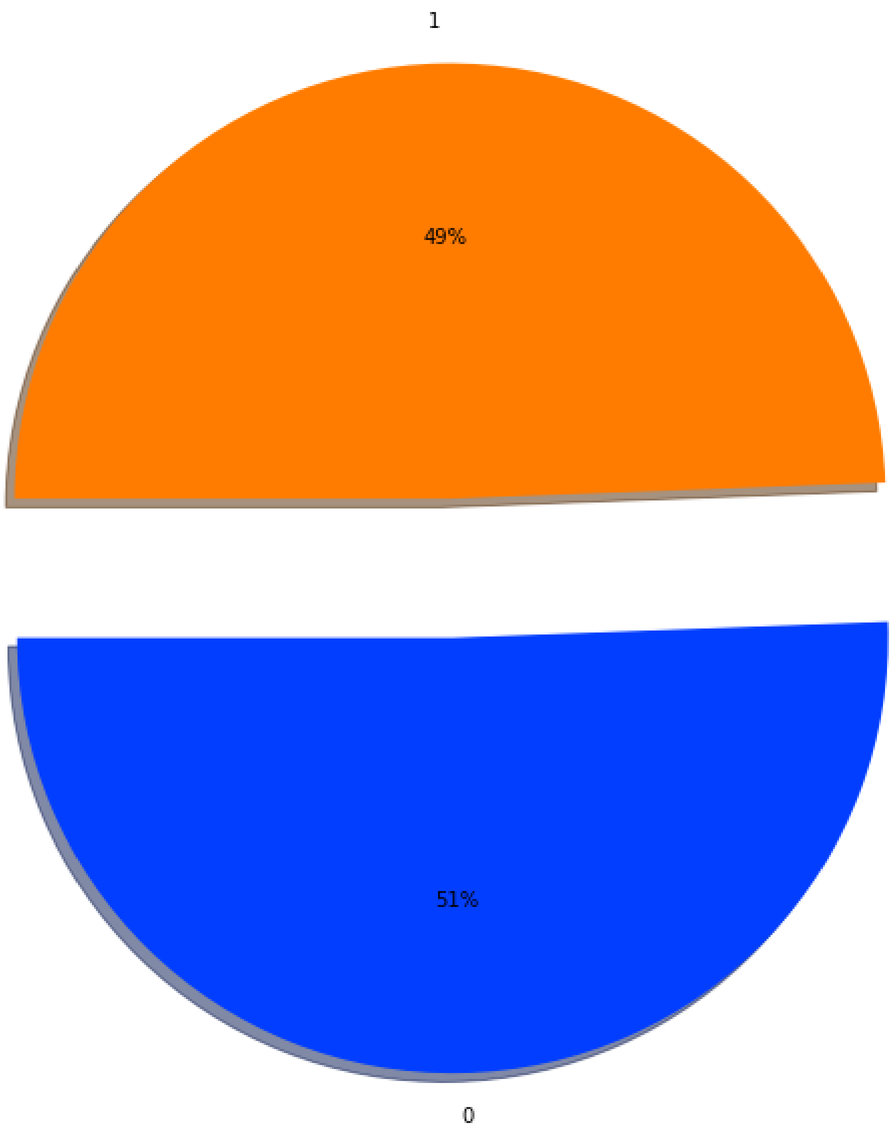
In [39]:

```
plt.figure(figsize=(15,6))
sns.countplot('Class', data = divorce_data)
plt.xticks(rotation = 90)
plt.show()
```



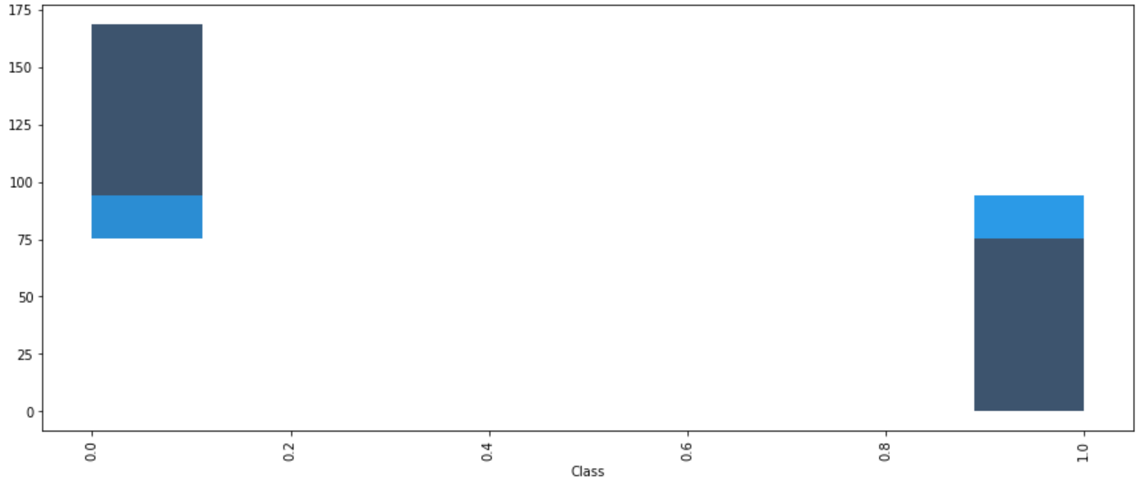
In [18]:

```
plt.figure(figsize=(20,10))
colors = sns.color_palette('bright')
explode = [0.3, 0.02]
plt.pie(divorce_data['Class'].value_counts(), colors = colors,
        labels = [0, 1], autopct = '%0.0f%%', shadow = 'True',
        explode = explode , startangle = 180)
plt.show()
```



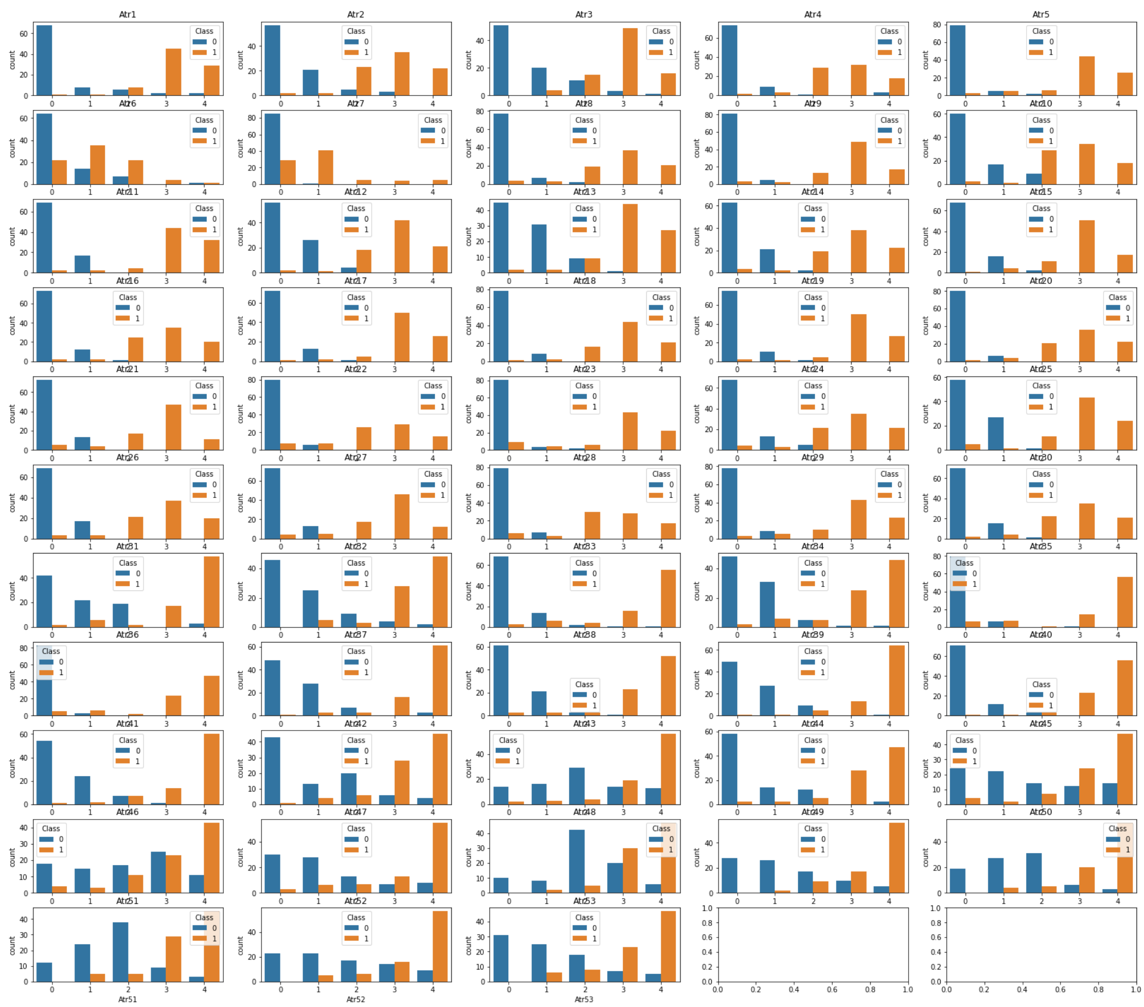
In [19]:

```
plt.figure(figsize=(15,6))
sns.histplot(x=divorce_data['Class'],y=divorce_data.index)
plt.xticks(rotation = 90)
plt.show()
```



In [20]:

```
fig, axes = plt.subplots(11,5,figsize=(28,25))
s=0
for i in range(0,11):
    for j in range(0,5):
        s+=1
        if s==54:
            break
        sns.countplot(ax = axes[i,j],x=f'Atr{s}',data=divorce_data,
                      hue='Class')
        axes[i,j].set_title(f'Atr{s}')
```



In [21]:

```
divorce_data.corr()
```

Out[21]:

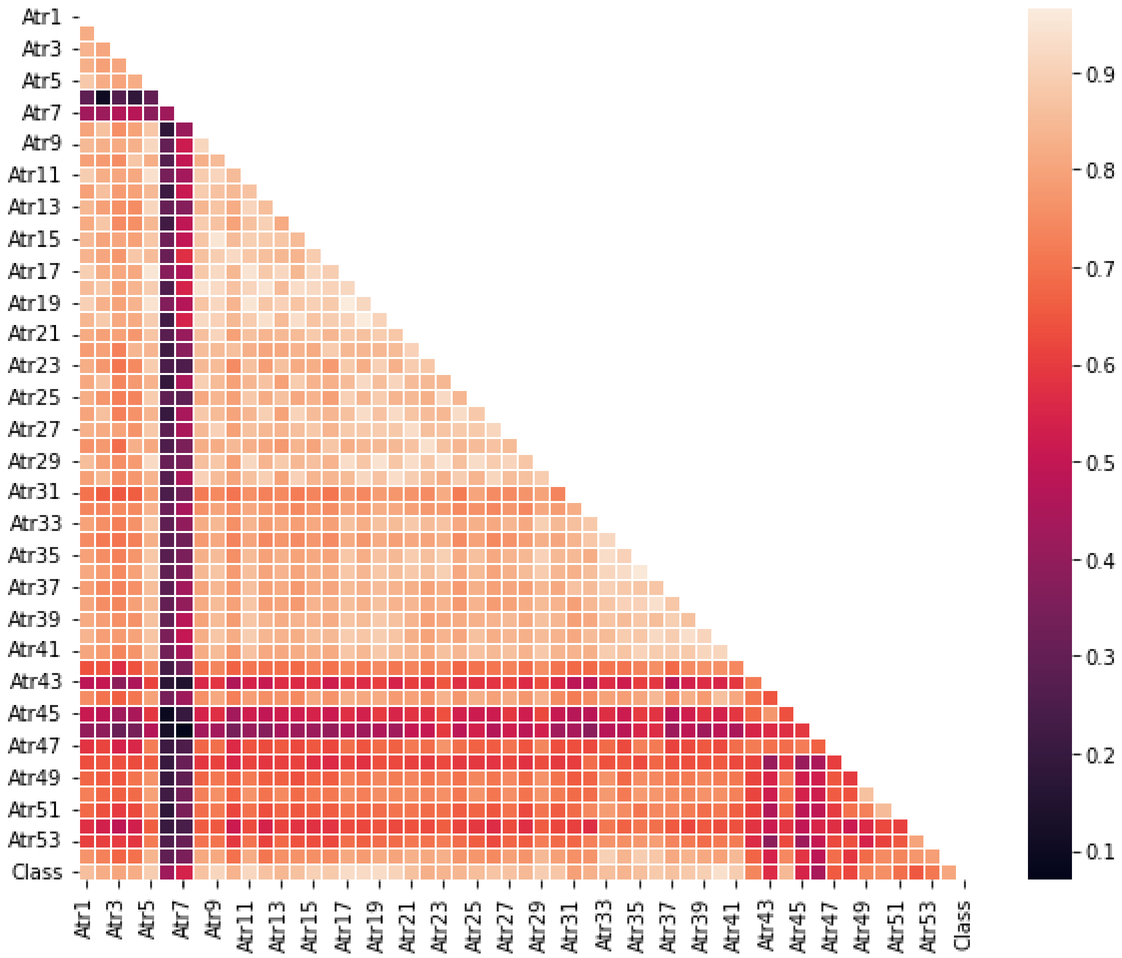
	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	A
Atr1	1.000000	0.819066	0.832508	0.825066	0.881272	0.287140	0.427989	0.802357	0.845
Atr2	0.819066	1.000000	0.805876	0.791313	0.819360	0.102843	0.417616	0.864284	0.827
Atr3	0.832508	0.805876	1.000000	0.806709	0.800774	0.263032	0.464071	0.757264	0.816
Atr4	0.825066	0.791313	0.806709	1.000000	0.818472	0.185963	0.474806	0.798347	0.829
Atr5	0.881272	0.819360	0.800774	0.818472	1.000000	0.297834	0.381378	0.877584	0.916
Atr6	0.287140	0.102843	0.263032	0.185963	0.297834	1.000000	0.424212	0.184019	0.301
Atr7	0.427989	0.417616	0.464071	0.474806	0.381378	0.424212	1.000000	0.412807	0.517
Atr8	0.802357	0.864284	0.757264	0.798347	0.877584	0.184019	0.412807	1.000000	0.915
Atr9	0.845916	0.827711	0.816653	0.829053	0.916327	0.301342	0.517522	0.915301	1.000
Atr10	0.790183	0.782286	0.753017	0.873636	0.823659	0.266076	0.498266	0.828031	0.852
Atr11	0.892253	0.823380	0.805915	0.808533	0.936955	0.340135	0.432479	0.889795	0.911
Atr12	0.794307	0.862835	0.780258	0.793992	0.846513	0.209801	0.511761	0.890338	0.869
Atr13	0.842996	0.791073	0.758969	0.751623	0.915033	0.305109	0.373361	0.840350	0.873
Atr14	0.817099	0.875800	0.750602	0.757000	0.845576	0.224459	0.491021	0.888822	0.868
Atr15	0.848754	0.801316	0.806909	0.794184	0.879461	0.323787	0.494110	0.873804	0.949
Atr16	0.831822	0.806497	0.775528	0.878416	0.853561	0.311056	0.573290	0.865680	0.893
Atr17	0.895970	0.822317	0.808161	0.809968	0.947429	0.377330	0.461450	0.881005	0.922
Atr18	0.853739	0.883856	0.797395	0.835296	0.894474	0.251856	0.544550	0.941084	0.925
Atr19	0.900446	0.829422	0.798999	0.832750	0.943349	0.365227	0.469995	0.873546	0.916
Atr20	0.840966	0.884176	0.807892	0.815896	0.892909	0.230486	0.544207	0.922465	0.902
Atr21	0.815708	0.790468	0.796069	0.775132	0.871994	0.273564	0.409827	0.861939	0.909
Atr22	0.785280	0.795406	0.727933	0.839534	0.840265	0.220010	0.378915	0.857010	0.849
Atr23	0.822534	0.773018	0.706585	0.744783	0.888584	0.246478	0.254912	0.845731	0.850
Atr24	0.813233	0.868240	0.740476	0.776640	0.833608	0.191458	0.446469	0.896841	0.851
Atr25	0.822084	0.769244	0.724506	0.736228	0.888740	0.291159	0.288867	0.809110	0.838
Atr26	0.803507	0.861421	0.728653	0.762765	0.836194	0.200634	0.443149	0.883414	0.850
Atr27	0.829037	0.817364	0.797595	0.767206	0.883768	0.283895	0.444643	0.848766	0.903
Atr28	0.762102	0.776943	0.689914	0.827847	0.809789	0.254858	0.351262	0.822361	0.818
Atr29	0.858139	0.789827	0.755491	0.781792	0.925601	0.309302	0.349379	0.860194	0.878
Atr30	0.792257	0.844007	0.752391	0.772562	0.837501	0.266464	0.448569	0.902820	0.854
Atr31	0.699223	0.661210	0.652188	0.661251	0.785038	0.247634	0.334308	0.716731	0.745
Atr32	0.739679	0.735763	0.747669	0.746677	0.832032	0.316605	0.442306	0.762425	0.803
Atr33	0.799735	0.757286	0.726481	0.764381	0.879037	0.292037	0.395764	0.818682	0.844
Atr34	0.749774	0.714360	0.702500	0.729022	0.827560	0.279789	0.328700	0.780778	0.810
Atr35	0.796413	0.753566	0.730290	0.770813	0.878289	0.276539	0.349076	0.827441	0.854
Atr36	0.812867	0.781295	0.744390	0.794636	0.887498	0.287708	0.370158	0.845435	0.871
Atr37	0.786890	0.747088	0.736984	0.760451	0.859581	0.281458	0.431979	0.800964	0.839

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	A
Atr38	0.804129	0.751705	0.740642	0.790350	0.852601	0.297791	0.401769	0.815830	0.849
Atr39	0.817035	0.787768	0.759820	0.763502	0.866293	0.296121	0.477063	0.797134	0.850
Atr40	0.838355	0.788200	0.781657	0.798520	0.871809	0.351433	0.501758	0.822302	0.875
Atr41	0.804182	0.780757	0.739967	0.768706	0.864434	0.329765	0.445483	0.821081	0.852
Atr42	0.642307	0.648539	0.569293	0.639671	0.737922	0.227993	0.333211	0.699571	0.737
Atr43	0.482223	0.503894	0.385152	0.452479	0.613142	0.171599	0.149930	0.555187	0.585
Atr44	0.752972	0.699765	0.661830	0.707212	0.799453	0.339918	0.425874	0.760016	0.808
Atr45	0.510160	0.489062	0.427409	0.446798	0.591656	0.094820	0.199548	0.542547	0.575
Atr46	0.400296	0.389519	0.308149	0.340240	0.470758	0.127759	0.069850	0.433541	0.434
Atr47	0.582693	0.616884	0.544863	0.552301	0.719899	0.212979	0.254225	0.675584	0.693
Atr48	0.633564	0.643762	0.638256	0.630205	0.659220	0.200673	0.311110	0.588531	0.611
Atr49	0.674843	0.659841	0.647961	0.699069	0.762257	0.201091	0.291325	0.674776	0.711
Atr50	0.725443	0.680538	0.663995	0.685263	0.795960	0.221100	0.332370	0.729668	0.755
Atr51	0.684143	0.636558	0.600603	0.624015	0.742664	0.179119	0.349920	0.690190	0.713
Atr52	0.575463	0.536294	0.491803	0.534264	0.663855	0.205056	0.243104	0.658613	0.652
Atr53	0.611422	0.610726	0.598749	0.588390	0.719493	0.258092	0.313725	0.705071	0.699
Atr54	0.768522	0.728897	0.673012	0.698264	0.836799	0.292428	0.347493	0.807911	0.810
Class	0.861324	0.820774	0.806709	0.819583	0.893180	0.420913	0.544835	0.869569	0.912

55 rows × 55 columns

In [22]:

```
plt.figure(figsize=(10, 8))
matrix = np.triu(divorce_data.corr())
sns.heatmap(divorce_data.corr(), annot=False, linewidth=.8, mask=matrix, cmap="rocket");
plt.show()
```



In [23]:

```
x = divorce_data.drop('Class',axis =1)
y = divorce_data['Class']
```

In [24]:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y,
                                                    test_size=0.15,
                                                    random_state=42)
```

In [32]:

```
# importing module
from sklearn.linear_model import LogisticRegression
# creating an object of LinearRegression class
LR = LogisticRegression()
# fitting the training data
LR.fit(x_train,y_train)
```

Out[32]:

```
▾ LogisticRegression
LogisticRegression()
```

In [33]:

```
y_prediction =  LR.predict(x_test)
y_prediction
```

Out[33]:

```
array([0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 1], dtype=int64)
```

In [34]:

```
print("Training Accuracy :", LR.score(x_train, y_train))
print("Testing Accuracy :", LR.score(x_test, y_test))
```

```
Training Accuracy : 1.0
Testing Accuracy : 1.0
```

In [35]:

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(x_train, y_train)
```

Out[35]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [36]:

```
y_prediction =  dt.predict(x_test)
y_prediction
```

Out[36]:

```
array([0, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 0], dtype=int64)
```

In [37]:

```
print("Training Accuracy :", dt.score(x_train, y_train))
print("Testing Accuracy :", dt.score(x_test, y_test))
```

```
Training Accuracy : 1.0
Testing Accuracy : 0.9230769230769231
```

In [31]:

```
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import cross_val_score
from tensorflow.keras.models import Sequential # initialize neural network library
from tensorflow.keras.layers import Dense # build our layers library
```

In [38]:

```
def build_classifier():
    classifier = Sequential() # initialize neural network
    classifier.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'relu',
    classifier.add(Dense(units = 4, kernel_initializer = 'uniform', activation = 'relu')
    classifier.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoi
    classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['acc
    return classifier
```

In [39]:

```
classifier = KerasClassifier(build_fn = build_classifier, epochs = 50)
accuracies = cross_val_score(estimator = classifier, X = x_train, y = y_train, cv = 2)
mean = accuracies.mean()
variance = accuracies.std()
```

```
3/3 [==============================] - 0s 3ms/step - loss: 0.6924 - acc
uracy: 0.5000
Epoch 12/50
3/3 [==============================] - 0s 0s/step - loss: 0.6922 - accu
racy: 0.5000
Epoch 13/50
3/3 [==============================] - 0s 2ms/step - loss: 0.6919 - acc
uracy: 0.5000
Epoch 14/50
3/3 [==============================] - 0s 2ms/step - loss: 0.6915 - acc
uracy: 0.5000
Epoch 15/50
3/3 [==============================] - 0s 3ms/step - loss: 0.6909 - acc
uracy: 0.5000
Epoch 16/50
3/3 [==============================] - 0s 3ms/step - loss: 0.6903 - acc
uracy: 0.5000
Epoch 17/50
3/3 [==============================] - 0s 0s/step - loss: 0.6895 - accu
racy: 0.5000
```

In [40]:

```
print("Accuracy mean: "+ str(mean))
```

```
Accuracy mean: 0.9513888955116272
```

In [41]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [42]:

```
clf = RandomForestClassifier()
```

In [43]:

```
clf.fit(x_train, y_train)
```

Out[43]:

```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [44]:

```
y_pred = clf.predict(x_test)
```

In [45]:

```
print("Training Accuracy :", clf.score(x_train, y_train))
print("Testing Accuracy :", clf.score(x_test, y_test))
```

```
Training Accuracy : 1.0
Testing Accuracy : 0.9615384615384616
```

In [46]:

```
from sklearn import metrics
print()

# using metrics module for accuracy calculation
print("ACCURACY OF THE MODEL: ", metrics.accuracy_score(y_test, y_pred))
```

```

ACCURACY OF THE MODEL:  0.9615384615384616
```