

In [25]:

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

In [26]:

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

In [27]:

```
divorce_data.head()
```

Out[27]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	Atr9	Atr10	...	Atr46	Atr47	Atr48	Atr49	Atr
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 [28]:

```
divorce_data.tail()
```

Out[28]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	Atr9	Atr10	...	Atr46	Atr47	Atr48	Atr49	Atr
165	0	0	0	0	0	0	0	0	0	0	...	1	0	4	1	
166	0	0	0	0	0	0	0	0	0	0	...	4	1	2	2	
167	1	1	0	0	0	0	0	0	0	1	...	3	0	2	0	
168	0	0	0	0	0	0	0	0	0	0	...	3	3	2	2	
169	0	0	0	0	0	0	0	1	0	0	...	3	4	4	0	

5 rows × 55 columns

In [29]:



```
divorce_data.shape
```

Out[29]:

```
(170, 55)
```

In [30]:



```
divorce_data.columns
```

Out[30]:

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

In [31]:

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

1. If one of us apologizes when our discussion deteriorates, the discussion ends.
2. I know we can ignore our differences, even if things get hard sometimes.
3. When we need it, we can take our discussions with my spouse from the beginning 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 spouse 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 marriage
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 life.
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 "you always" or "you never" .
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, I 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 not 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 [32]:



```
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 [33]:

```
divorce_data.describe()
```

Out[33]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	
count	170.000000	170.000000	170.000000	170.000000	170.000000	170.000000	170.000000	1
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 [34]:



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

Out[34]:

```
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 [35]:



```
divorce_data.nunique()
```

Out[35]:

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

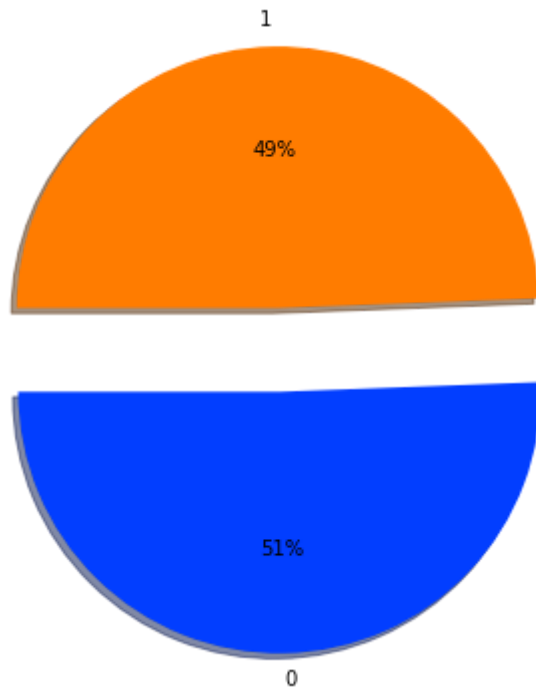


A bar chart with 'Class' on the x-axis and 'count' on the y-axis. The x-axis has two categories: '0' and '1'. The y-axis ranges from 0 to 80 with major ticks every 20 units. The bar for Class 0 is blue and reaches a height of approximately 85. The bar for Class 1 is orange and reaches a height of approximately 84.

Class	count
0	85
1	84

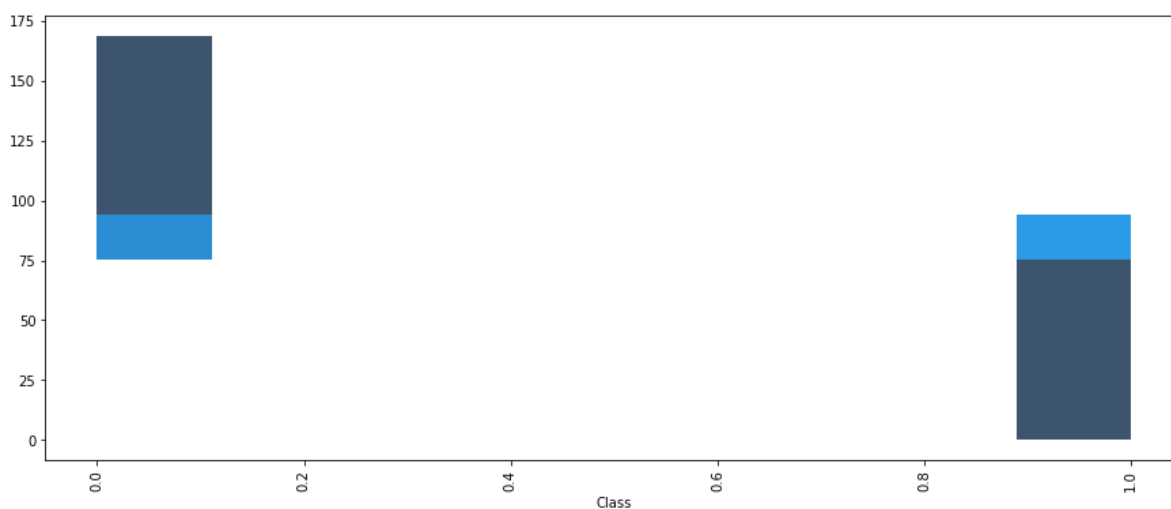
In [40]:

```
plt.figure(figsize=(15,6))
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 [41]:

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

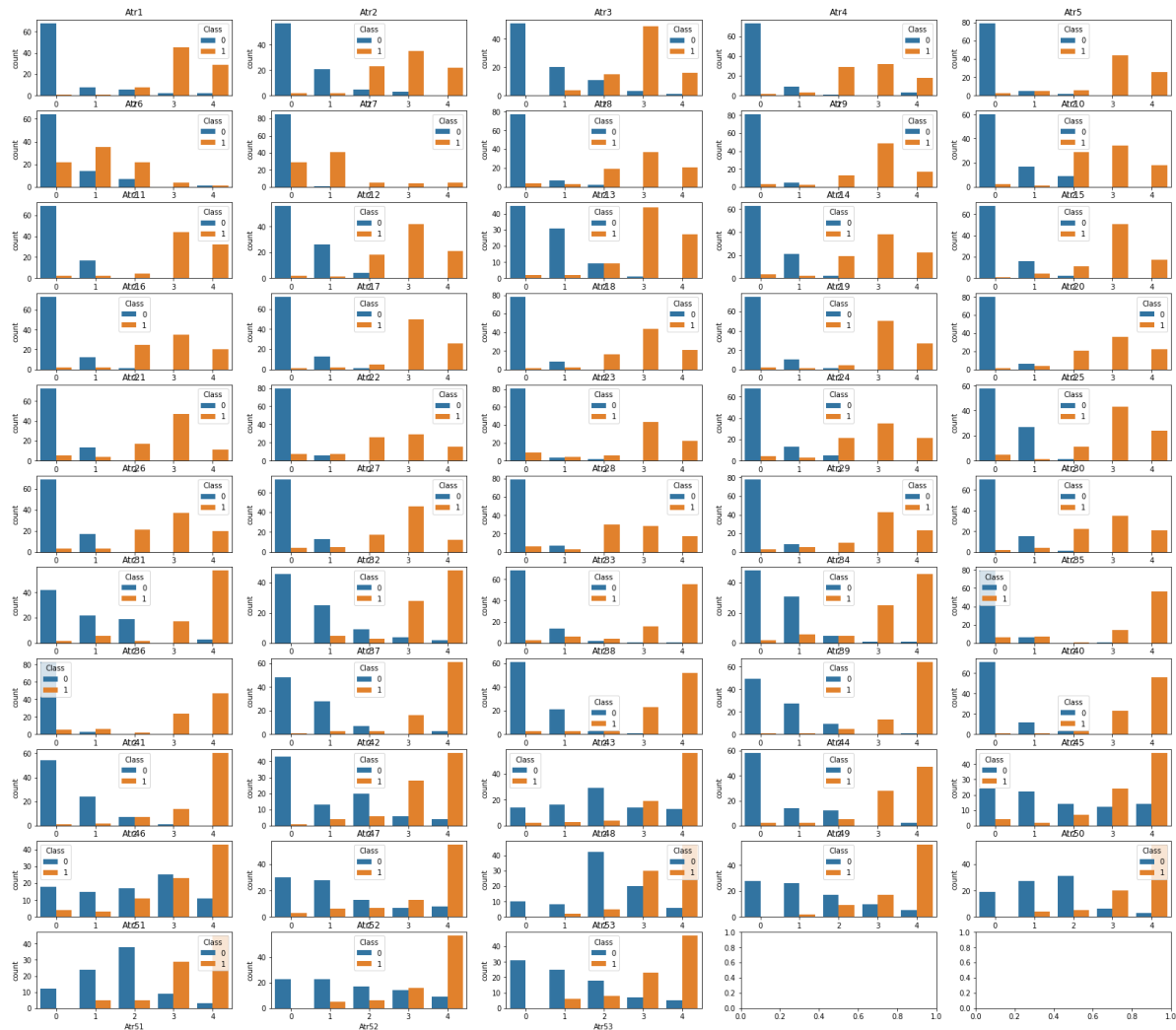


In [43]:

```

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 [44]:



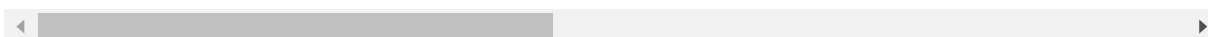
```
divorce_data.corr()
```

Out[44]:

	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	Atr9
Atr1	1.000000	0.819066	0.832508	0.825066	0.881272	0.287140	0.427989	0.802357	0.845916
Atr2	0.819066	1.000000	0.805876	0.791313	0.819360	0.102843	0.417616	0.864284	0.827711
Atr3	0.832508	0.805876	1.000000	0.806709	0.800774	0.263032	0.464071	0.757264	0.816653
Atr4	0.825066	0.791313	0.806709	1.000000	0.818472	0.185963	0.474806	0.798347	0.829053
Atr5	0.881272	0.819360	0.800774	0.818472	1.000000	0.297834	0.381378	0.877584	0.916327
Atr6	0.287140	0.102843	0.263032	0.185963	0.297834	1.000000	0.424212	0.184019	0.301342
Atr7	0.427989	0.417616	0.464071	0.474806	0.381378	0.424212	1.000000	0.412807	0.517522
Atr8	0.802357	0.864284	0.757264	0.798347	0.877584	0.184019	0.412807	1.000000	0.915301
Atr9	0.845916	0.827711	0.816653	0.829053	0.916327	0.301342	0.517522	0.915301	1.000000
Atr10	0.790183	0.782286	0.753017	0.873636	0.823659	0.266076	0.498266	0.828031	0.852381
Atr11	0.892253	0.823380	0.805915	0.808533	0.936955	0.340135	0.432479	0.889795	0.911591
Atr12	0.794307	0.862835	0.780258	0.793992	0.846513	0.209801	0.511761	0.890338	0.869018
Atr13	0.842996	0.791073	0.758969	0.751623	0.915033	0.305109	0.373361	0.840350	0.873041
Atr14	0.817099	0.875800	0.750602	0.757000	0.845576	0.224459	0.491021	0.888822	0.868111
Atr15	0.848754	0.801316	0.806909	0.794184	0.879461	0.323787	0.494110	0.873804	0.949041
Atr16	0.831822	0.806497	0.775528	0.878416	0.853561	0.311056	0.573290	0.865680	0.893371
Atr17	0.895970	0.822317	0.808161	0.809968	0.947429	0.377330	0.461450	0.881005	0.922301
Atr18	0.853739	0.883856	0.797395	0.835296	0.894474	0.251856	0.544550	0.941084	0.925541
Atr19	0.900446	0.829422	0.798999	0.832750	0.943349	0.365227	0.469995	0.873546	0.916471
Atr20	0.840966	0.884176	0.807892	0.815896	0.892909	0.230486	0.544207	0.922465	0.902241
Atr21	0.815708	0.790468	0.796069	0.775132	0.871994	0.273564	0.409827	0.861939	0.909441
Atr22	0.785280	0.795406	0.727933	0.839534	0.840265	0.220010	0.378915	0.857010	0.849971
Atr23	0.822534	0.773018	0.706585	0.744783	0.888584	0.246478	0.254912	0.845731	0.850241
Atr24	0.813233	0.868240	0.740476	0.776640	0.833608	0.191458	0.446469	0.896841	0.851041
Atr25	0.822084	0.769244	0.724506	0.736228	0.888740	0.291159	0.288867	0.809110	0.838741
Atr26	0.803507	0.861421	0.728653	0.762765	0.836194	0.200634	0.443149	0.883414	0.850241
Atr27	0.829037	0.817364	0.797595	0.767206	0.883768	0.283895	0.444643	0.848766	0.903941
Atr28	0.762102	0.776943	0.689914	0.827847	0.809789	0.254858	0.351262	0.822361	0.818041
Atr29	0.858139	0.789827	0.755491	0.781792	0.925601	0.309302	0.349379	0.860194	0.878841
Atr30	0.792257	0.844007	0.752391	0.772562	0.837501	0.266464	0.448569	0.902820	0.854441
Atr31	0.699223	0.661210	0.652188	0.661251	0.785038	0.247634	0.334308	0.716731	0.745641
Atr32	0.739679	0.735763	0.747669	0.746677	0.832032	0.316605	0.442306	0.762425	0.803341

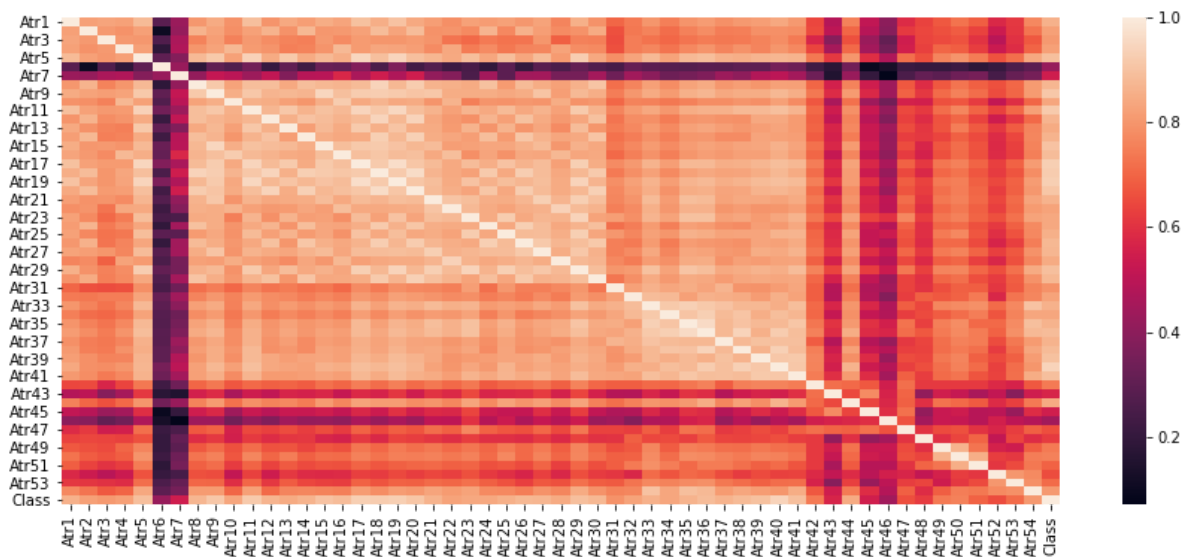
	Atr1	Atr2	Atr3	Atr4	Atr5	Atr6	Atr7	Atr8	At
<b>Atr33</b>	0.799735	0.757286	0.726481	0.764381	0.879037	0.292037	0.395764	0.818682	0.84490
<b>Atr34</b>	0.749774	0.714360	0.702500	0.729022	0.827560	0.279789	0.328700	0.780778	0.81010
<b>Atr35</b>	0.796413	0.753566	0.730290	0.770813	0.878289	0.276539	0.349076	0.827441	0.85490
<b>Atr36</b>	0.812867	0.781295	0.744390	0.794636	0.887498	0.287708	0.370158	0.845435	0.87160
<b>Atr37</b>	0.786890	0.747088	0.736984	0.760451	0.859581	0.281458	0.431979	0.800964	0.83900
<b>Atr38</b>	0.804129	0.751705	0.740642	0.790350	0.852601	0.297791	0.401769	0.815830	0.84940
<b>Atr39</b>	0.817035	0.787768	0.759820	0.763502	0.866293	0.296121	0.477063	0.797134	0.85060
<b>Atr40</b>	0.838355	0.788200	0.781657	0.798520	0.871809	0.351433	0.501758	0.822302	0.87560
<b>Atr41</b>	0.804182	0.780757	0.739967	0.768706	0.864434	0.329765	0.445483	0.821081	0.85240
<b>Atr42</b>	0.642307	0.648539	0.569293	0.639671	0.737922	0.227993	0.333211	0.699571	0.73740
<b>Atr43</b>	0.482223	0.503894	0.385152	0.452479	0.613142	0.171599	0.149930	0.555187	0.58560
<b>Atr44</b>	0.752972	0.699765	0.661830	0.707212	0.799453	0.339918	0.425874	0.760016	0.80860
<b>Atr45</b>	0.510160	0.489062	0.427409	0.446798	0.591656	0.094820	0.199548	0.542547	0.57530
<b>Atr46</b>	0.400296	0.389519	0.308149	0.340240	0.470758	0.127759	0.069850	0.433541	0.43430
<b>Atr47</b>	0.582693	0.616884	0.544863	0.552301	0.719899	0.212979	0.254225	0.675584	0.69380
<b>Atr48</b>	0.633564	0.643762	0.638256	0.630205	0.659220	0.200673	0.311110	0.588531	0.61170
<b>Atr49</b>	0.674843	0.659841	0.647961	0.699069	0.762257	0.201091	0.291325	0.674776	0.71150
<b>Atr50</b>	0.725443	0.680538	0.663995	0.685263	0.795960	0.221100	0.332370	0.729668	0.75550
<b>Atr51</b>	0.684143	0.636558	0.600603	0.624015	0.742664	0.179119	0.349920	0.690190	0.71370
<b>Atr52</b>	0.575463	0.536294	0.491803	0.534264	0.663855	0.205056	0.243104	0.658613	0.65230
<b>Atr53</b>	0.611422	0.610726	0.598749	0.588390	0.719493	0.258092	0.313725	0.705071	0.69920
<b>Atr54</b>	0.768522	0.728897	0.673012	0.698264	0.836799	0.292428	0.347493	0.807911	0.81090
<b>Class</b>	0.861324	0.820774	0.806709	0.819583	0.893180	0.420913	0.544835	0.869569	0.91230

55 rows × 55 columns



In [47]:

```
plt.figure(figsize=(15,6))
sns.heatmap(divorce_data.corr())
plt.show()
```



In [48]:

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

In [49]:

```
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 [50]:

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

Out[50]:

```
LinearRegression()
```

In [51]:

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

Out[51]:

```
array([-2.98242255e-01,  1.04218550e+00, -1.91789945e-02,  1.03862867e+00,
        7.03564733e-02, -8.35928052e-04,  2.07739887e-02,  1.00384295e+00,
        9.70405323e-02,  9.92217945e-01,  1.06361244e+00,  1.53710970e-01,
        8.89485246e-02,  1.01424057e+00,  9.14619813e-01, -1.58940064e-01,
        1.04075060e+00, -4.42718464e-02,  9.76082286e-01,  2.16106731e-01,
        1.00445617e+00,  1.06361244e+00,  9.79472390e-01,  1.06082144e+00,
        1.06929121e+00,  3.62517357e-01])
```

In [53]:

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

Training Accuracy : 0.9714138394151279

Testing Accuracy : 0.8981950750068269

In [57]:

```
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 [58]:

```
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 = 'sigmoid'))
    classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
    return classifier
```



In [59]:

```
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()
```

```
Epoch 1/50
3/3 [=====] - 0s 33ms/step - loss: 0.6931 - accuracy: 0.5417
Epoch 2/50
3/3 [=====] - 0s 4ms/step - loss: 0.6929 - accuracy: 0.5417
Epoch 3/50
3/3 [=====] - 0s 2ms/step - loss: 0.6928 - accuracy: 0.5417
Epoch 4/50
3/3 [=====] - 0s 4ms/step - loss: 0.6926 - accuracy: 0.5417
Epoch 5/50
3/3 [=====] - 0s 4ms/step - loss: 0.6923 - accuracy: 0.5417
Epoch 6/50
3/3 [=====] - 0s 4ms/step - loss: 0.6919 - accuracy: 0.5417
Epoch 7/50
```

In [61]:

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

Accuracy mean: 0.9722222089767456

In [62]:

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

In [68]:

```
clf = RandomForestClassifier()
```

In [69]:

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

Out[69]:

RandomForestClassifier()

In [70]:

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

In [71]:



```
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 [72]:



```
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