

# Employee attrition Classification

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The issue of keeping one's employees happy and satisfied is a perennial and age-old challenge. If an employee you have invested so much time and money leaves for "greener pastures", then this would mean that you would have to spend even more time and money to hire somebody else. In the spirit of Kaggle, let us therefore turn to our predictive modelling capabilities and see if we can predict employee attrition on this synthetically generated IBM dataset.

```
In [1]: import warnings
```

```
In [2]: warnings.filterwarnings('ignore')
```

## Let's Dive into it

### Import necessary libraries

```
In [3]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

### Read 'HR-Employee-Attrition.csv' dataset and store it inside a variable

```
In [4]: df=pd.read_csv('HR-Employee-Attrition.csv')
```

### Check head

```
In [5]: pd.set_option("display.max_columns", None)
```

```
In [6]: df.head()
```

Out[6]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Lif
1	49	No	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	No	Travel_Rarely	591	Research & Development	2	1	

## Check last 5 rows

```
In [7]: df.tail()
```

Out[7]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	E
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

## Check shape

```
In [8]: df.shape
```

Out[8]: (1470, 35)

## View info about the dataset

```
In [9]: df.info()
```


```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Age                                   1470 non-null   int64
1   Attrition                           1470 non-null   object
2   BusinessTravel                      1470 non-null   object
3   DailyRate                           1470 non-null   int64
4   Department                          1470 non-null   object
5   DistanceFromHome                    1470 non-null   int64
6   Education                           1470 non-null   int64
7   EducationField                      1470 non-null   object
8   EmployeeCount                       1470 non-null   int64
9   EmployeeNumber                      1470 non-null   int64
10  EnvironmentSatisfaction              1470 non-null   int64
11  Gender                              1470 non-null   object
12  HourlyRate                          1470 non-null   int64
13  JobInvolvement                      1470 non-null   int64
14  JobLevel                            1470 non-null   int64
15  JobRole                             1470 non-null   object
16  JobSatisfaction                     1470 non-null   int64
17  MaritalStatus                      1470 non-null   object
18  MonthlyIncome                      1470 non-null   int64
19  MonthlyRate                         1470 non-null   int64
20  NumCompaniesWorked                  1470 non-null   int64
21  Over18                             1470 non-null   object
22  OverTime                           1470 non-null   object
23  PercentSalaryHike                   1470 non-null   int64
24  PerformanceRating                   1470 non-null   int64
25  RelationshipSatisfaction             1470 non-null   int64
26  StandardHours                      1470 non-null   int64
27  StockOptionLevel                    1470 non-null   int64
28  TotalWorkingYears                   1470 non-null   int64
29  TrainingTimesLastYear               1470 non-null   int64
30  WorkLifeBalance                     1470 non-null   int64
31  YearsAtCompany                      1470 non-null   int64
32  YearsInCurrentRole                  1470 non-null   int64
33  YearsSinceLastPromotion              1470 non-null   int64
34  YearsWithCurrManager                1470 non-null   int64
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

## View basic statistical information about the dataset

In [10]: `df.describe()`

Out[10]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNu
<b>count</b>	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.00
<b>mean</b>	36.923810	802.485714	9.192517	2.912925	1.0	1024.86
<b>std</b>	9.135373	403.509100	8.106864	1.024165	0.0	602.02
<b>min</b>	18.000000	102.000000	1.000000	1.000000	1.0	1.00
<b>25%</b>	30.000000	465.000000	2.000000	2.000000	1.0	491.25
<b>50%</b>	36.000000	802.000000	7.000000	3.000000	1.0	1020.50
<b>75%</b>	43.000000	1157.000000	14.000000	4.000000	1.0	1555.75
<b>max</b>	60.000000	1499.000000	29.000000	5.000000	1.0	2068.00



## Check for null values

```
In [11]: df.isna().sum()
```

```
Out[11]: Age                                0
Attrition                                  0
BusinessTravel                            0
DailyRate                                 0
Department                                0
DistanceFromHome                          0
Education                                 0
EducationField                             0
EmployeeCount                              0
EmployeeNumber                             0
EnvironmentSatisfaction                    0
Gender                                     0
HourlyRate                                 0
JobInvolvement                             0
JobLevel                                  0
JobRole                                    0
JobSatisfaction                            0
MaritalStatus                             0
MonthlyIncome                             0
MonthlyRate                               0
NumCompaniesWorked                        0
Over18                                    0
OverTime                                   0
PercentSalaryHike                         0
PerformanceRating                         0
RelationshipSatisfaction                   0
StandardHours                             0
StockOptionLevel                          0
TotalWorkingYears                         0
TrainingTimesLastYear                     0
WorkLifeBalance                           0
YearsAtCompany                            0
YearsInCurrentRole                        0
YearsSinceLastPromotion                   0
YearsWithCurrManager                      0
dtype: int64
```

## View unique values in all categorical columns

```
In [12]: pd.set_option("display.max_columns", None)
df.head()
```

```
Out[12]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Lif
1	49	No	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	No	Travel_Rarely	591	Research & Development	2	1	

```
In [13]: categorical_columns=[ 'Attrition', 'BusinessTravel', 'Department',
                                'EducationField', 'Gender', 'JobRole',
                                'MaritalStatus', 'Over18', 'OverTime']
for i in categorical_columns:
    print("unique values in ",i,"are:" ,df[i].unique())
```

```
unique values in Attrition are: ['Yes' 'No']
unique values in BusinessTravel are: ['Travel_Rarely' 'Travel_Frequently' 'N
on-Travel']
unique values in Department are: ['Sales' 'Research & Development' 'Human Re
sources']
unique values in EducationField are: ['Life Sciences' 'Other' 'Medical' 'Mar
keting' 'Technical Degree'
'Human Resources']
unique values in Gender are: ['Female' 'Male']
unique values in JobRole are: ['Sales Executive' 'Research Scientist' 'Labor
atory Technician'
'Manufacturing Director' 'Healthcare Representative' 'Manager'
'Sales Representative' 'Research Director' 'Human Resources']
unique values in MaritalStatus are: ['Single' 'Married' 'Divorced']
unique values in Over18 are: ['Y']
unique values in OverTime are: ['Yes' 'No']
```

## Check the number of unique values in all columns

```
In [14]: columns_nunique=['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department',
                        'DistanceFromHome', 'Education', 'EducationField', 'EmployeeCount',
                        'EmployeeNumber', 'EnvironmentSatisfaction', 'Gender', 'HourlyRate',
                        'JobInvolvement', 'JobLevel', 'JobRole', 'JobSatisfaction',
                        'MaritalStatus', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
                        'Over18', 'OverTime', 'PercentSalaryHike', 'PerformanceRating',
                        'RelationshipSatisfaction', 'StandardHours', 'StockOptionLevel',
                        'TotalWorkingYears', 'TrainingTimesLastYear', 'WorkLifeBalance',
                        'YearsAtCompany', 'YearsInCurrentRole', 'YearsSinceLastPromotion',
                        'YearsWithCurrManager']
```

```
In [15]: for i in columns_nunique:
          print("Number of unique elements in ",i,"are:" ,df[i].nunique())
```

```
Number of unique elements in Age are: 43
Number of unique elements in Attrition are: 2
Number of unique elements in BusinessTravel are: 3
Number of unique elements in DailyRate are: 886
Number of unique elements in Department are: 3
Number of unique elements in DistanceFromHome are: 29
Number of unique elements in Education are: 5
Number of unique elements in EducationField are: 6
Number of unique elements in EmployeeCount are: 1
Number of unique elements in EmployeeNumber are: 1470
Number of unique elements in EnvironmentSatisfaction are: 4
Number of unique elements in Gender are: 2
Number of unique elements in HourlyRate are: 71
Number of unique elements in JobInvolvement are: 4
Number of unique elements in JobLevel are: 5
Number of unique elements in JobRole are: 9
Number of unique elements in JobSatisfaction are: 4
Number of unique elements in MaritalStatus are: 3
Number of unique elements in MonthlyIncome are: 1349
Number of unique elements in MonthlyRate are: 1427
Number of unique elements in NumCompaniesWorked are: 10
Number of unique elements in Over18 are: 1
Number of unique elements in OverTime are: 2
Number of unique elements in PercentSalaryHike are: 15
Number of unique elements in PerformanceRating are: 2
Number of unique elements in RelationshipSatisfaction are: 4
Number of unique elements in StandardHours are: 1
Number of unique elements in StockOptionLevel are: 4
Number of unique elements in TotalWorkingYears are: 40
Number of unique elements in TrainingTimesLastYear are: 7
Number of unique elements in WorkLifeBalance are: 4
Number of unique elements in YearsAtCompany are: 37
Number of unique elements in YearsInCurrentRole are: 19
Number of unique elements in YearsSinceLastPromotion are: 16
Number of unique elements in YearsWithCurrManager are: 18
```

## Print out the names of the columns having only one unique values

```
In [16]: for i in columns_nunique:
         if df[i].nunique()==1:
             print(i)
```

```
EmployeeCount
Over18
StandardHours
```


## Drop these columns as they won't be useful in our prediction

```
In [17]: df.drop(columns=["EmployeeCount", 'Over18', "StandardHours"], inplace=True)
```

```
In [18]: df.head()
```

```
Out[18]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Lif
1	49	No	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	No	Travel_Rarely	591	Research & Development	2	1	



## Drop EmployeeNumber column aswell


```
In [19]: df.drop(columns=["EmployeeNumber"], inplace=True)
```



In [20]: df.head()

Out[20]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Lif
1	49	No	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	No	Travel_Rarely	591	Research & Development	2	1	



Create following groupby valuecounts

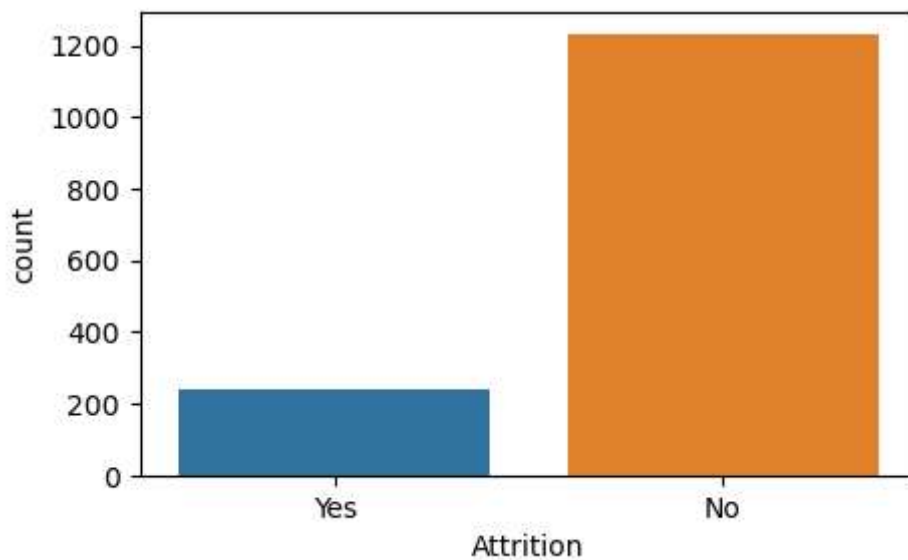
```
In [21]: df.groupby(["Department", "EducationField", "Gender"], observed=True, dropna=False)
```

Out[21]:

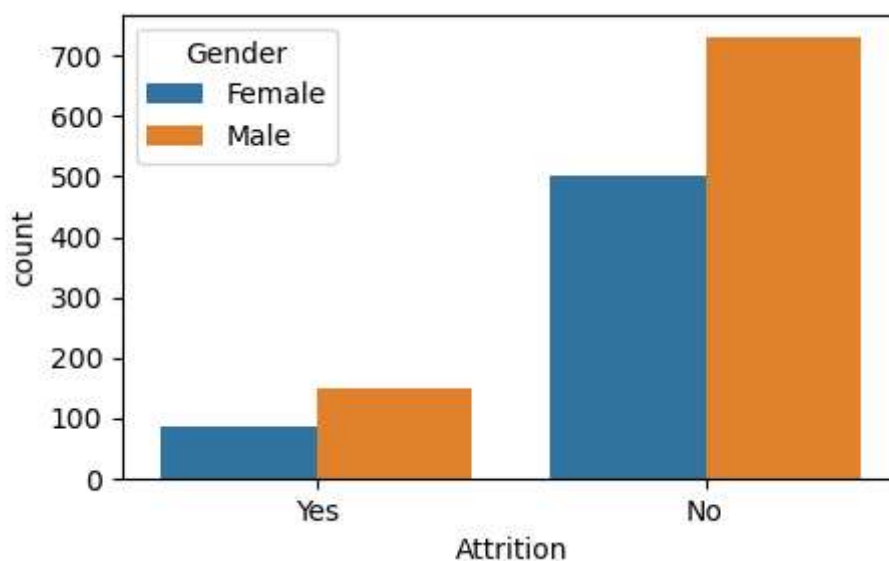
			Age	DailyRate	DistanceFromHome	Education	Environ
	Department	EducationField	Gender				
Human Resources	Human Resources		Female	310	6084	96	25
			Male	690	12148	148	59
	Life Sciences		Female	352	8293	103	28
			Male	278	3756	36	21
	Medical		Female	57	2318	28	4
			Male	461	9065	90	30
	Other		Male	104	3015	26	9
	Technical Degree		Female	34	1107	9	4
			Male	96	1561	12	7
	Research & Development	Life Sciences		Female	6060	125412	1408
Male				10219	221834	2492	787
Medical			Female	5788	125306	1523	442
			Male	7731	174434	1941	589
Other			Female	919	16866	218	71
			Male	1397	31989	357	127
Technical Degree			Female	1395	31396	303	111
			Male	2089	48147	546	165
Life Sciences			Female	2570	57199	583	196
			Male	3008	70988	805	249
Sales	Marketing		Female	2646	53745	634	217
			Male	3384	61981	973	280
	Medical		Female	1224	30600	332	85
			Male	1832	40056	426	151
	Other		Female	105	5300	38	11
			Male	375	8104	93	34
	Technical Degree		Female	490	11639	141	37
			Male	664	17311	152	49

## Plot the following

```
In [22]: plt.figure(figsize=(5,3))  
sns.countplot(x='Attrition',data=df)  
plt.show()
```

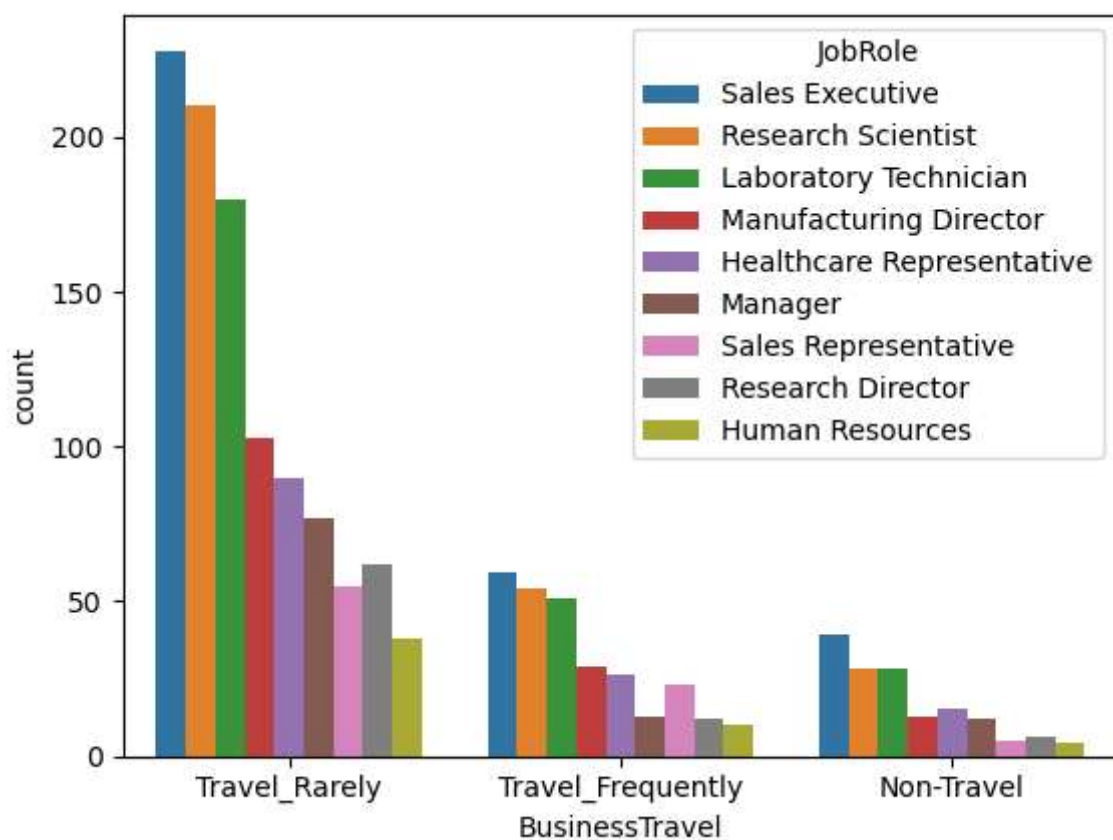


```
In [23]: plt.figure(figsize=(5,3))  
sns.countplot(x='Attrition',hue='Gender',data=df)  
plt.show()
```

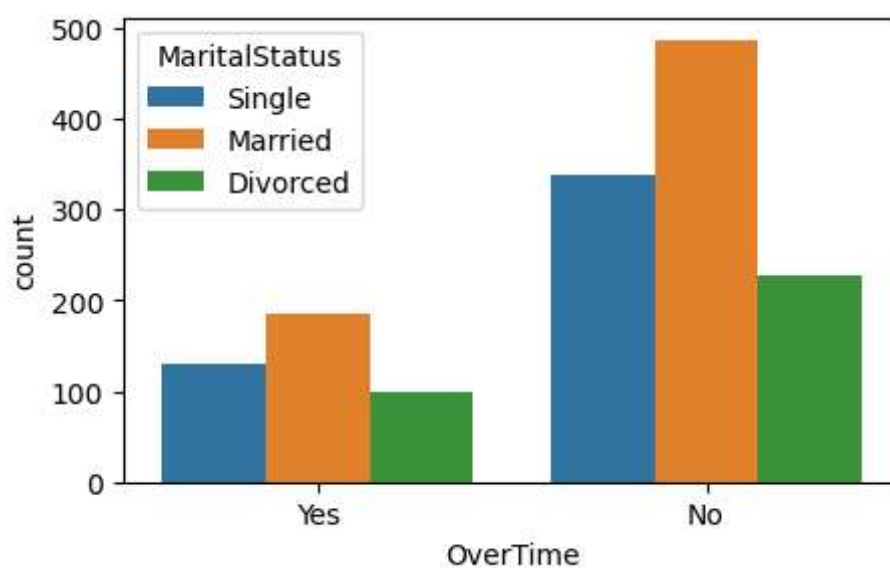


```
In [24]: sns.countplot(x='BusinessTravel',hue='JobRole',data=df)
```

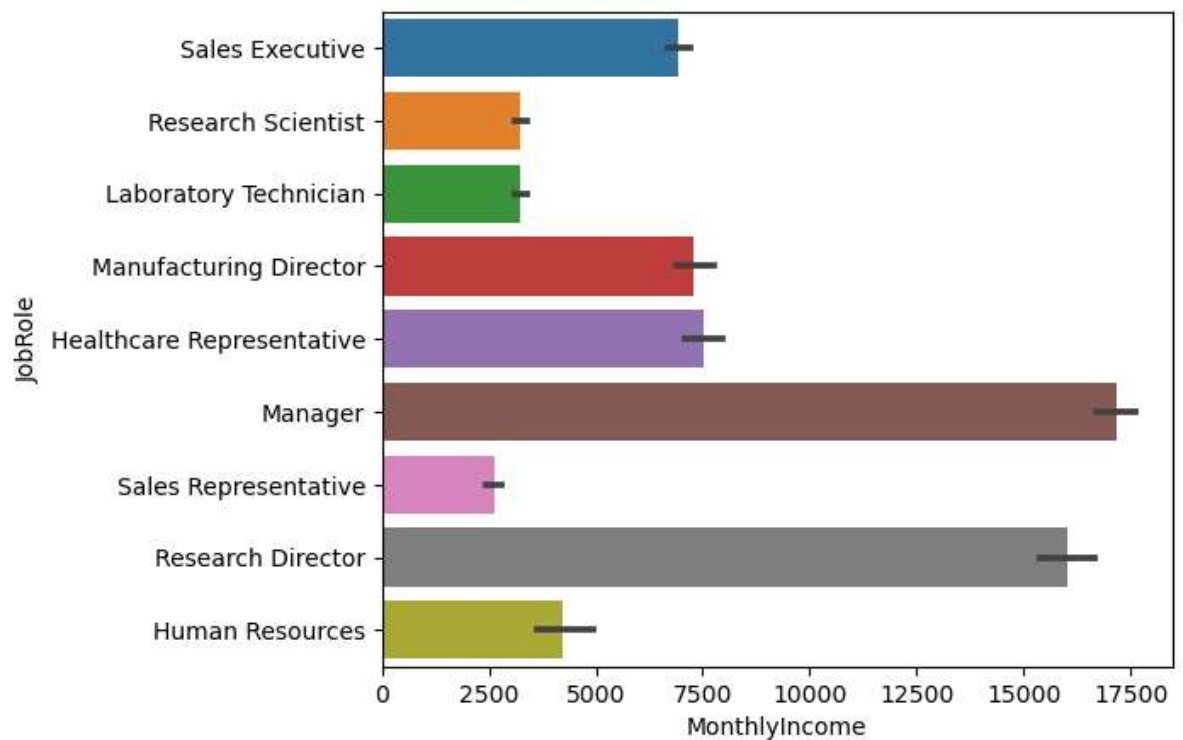
```
Out[24]: <AxesSubplot:xlabel='BusinessTravel', ylabel='count'>
```



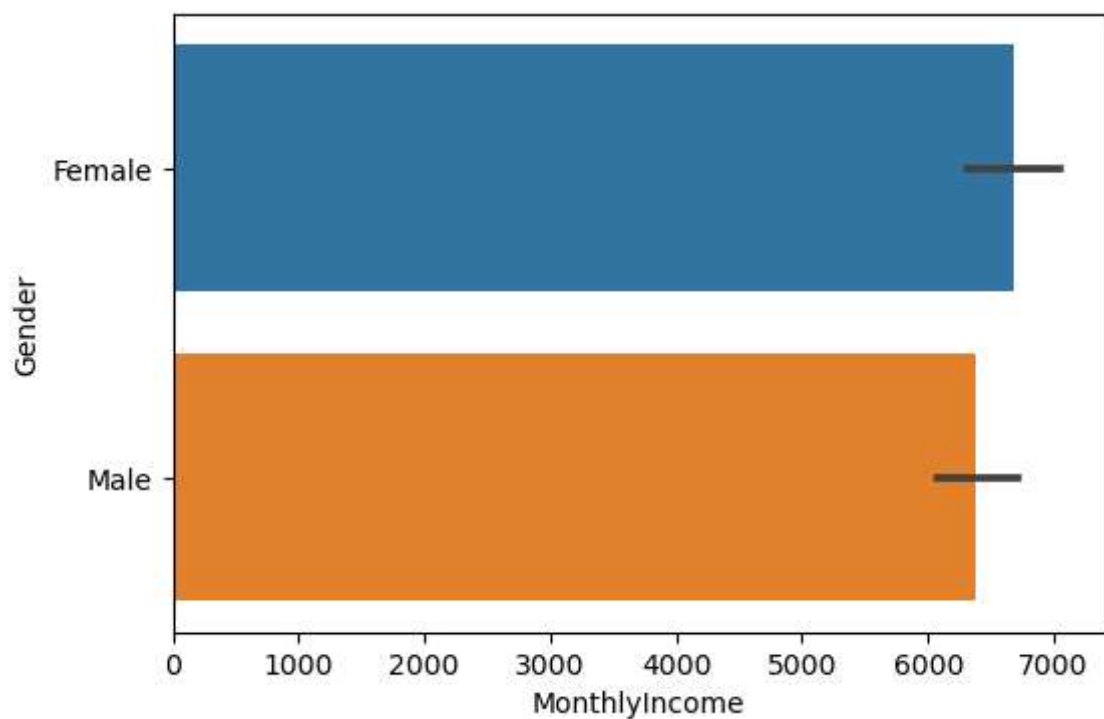
```
In [25]: plt.figure(figsize=(5,3))
sns.countplot(x='OverTime',hue='MaritalStatus',data=df)
plt.show()
```



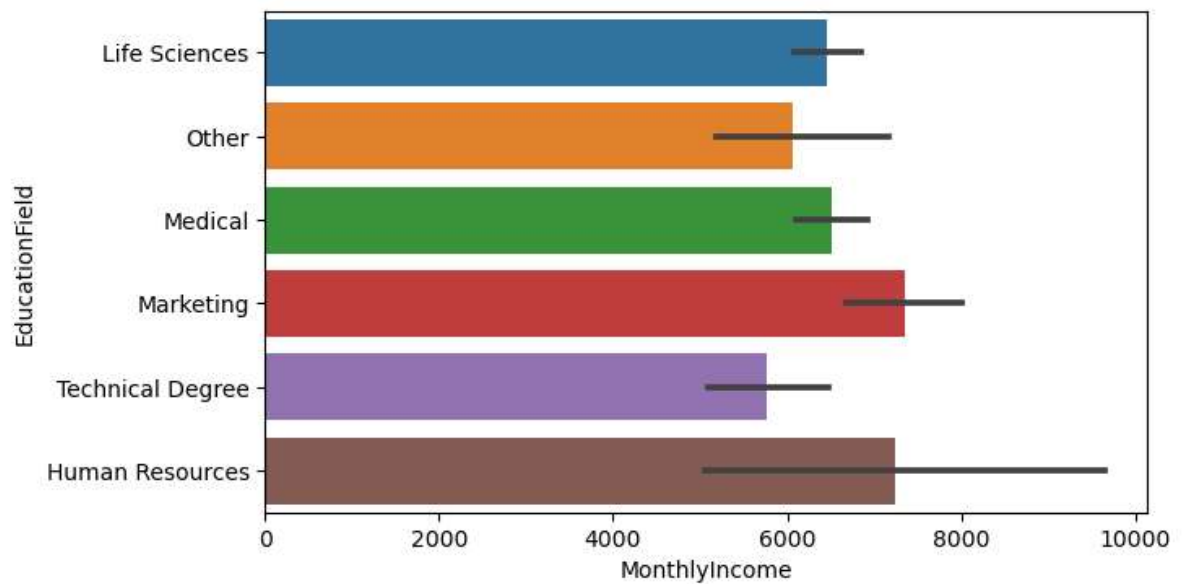
```
In [26]: plt.figure(figsize=(6,5))
sns.barplot(y='JobRole',x='MonthlyIncome',data=df)
plt.show()
```



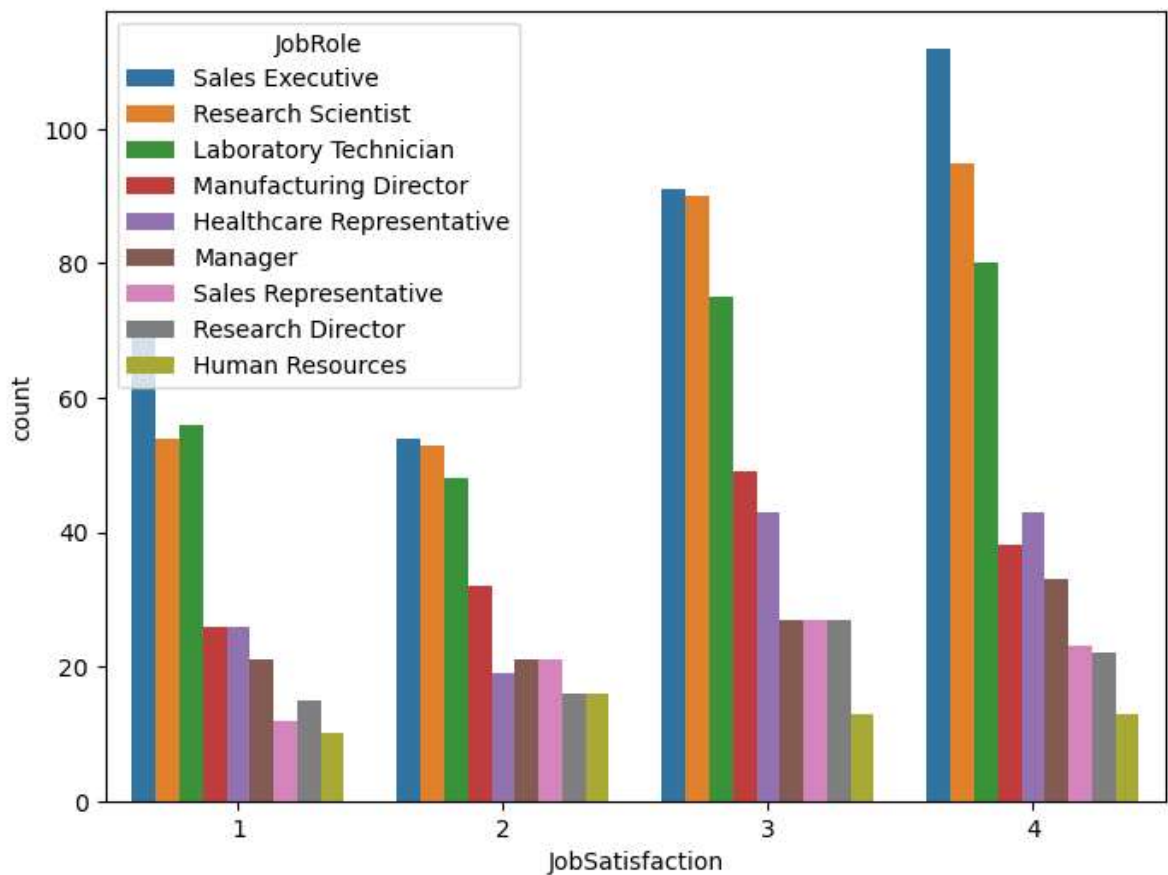
```
In [27]: plt.figure(figsize=(6,4))
sns.barplot(y='Gender',x='MonthlyIncome',data=df)
plt.show()
```



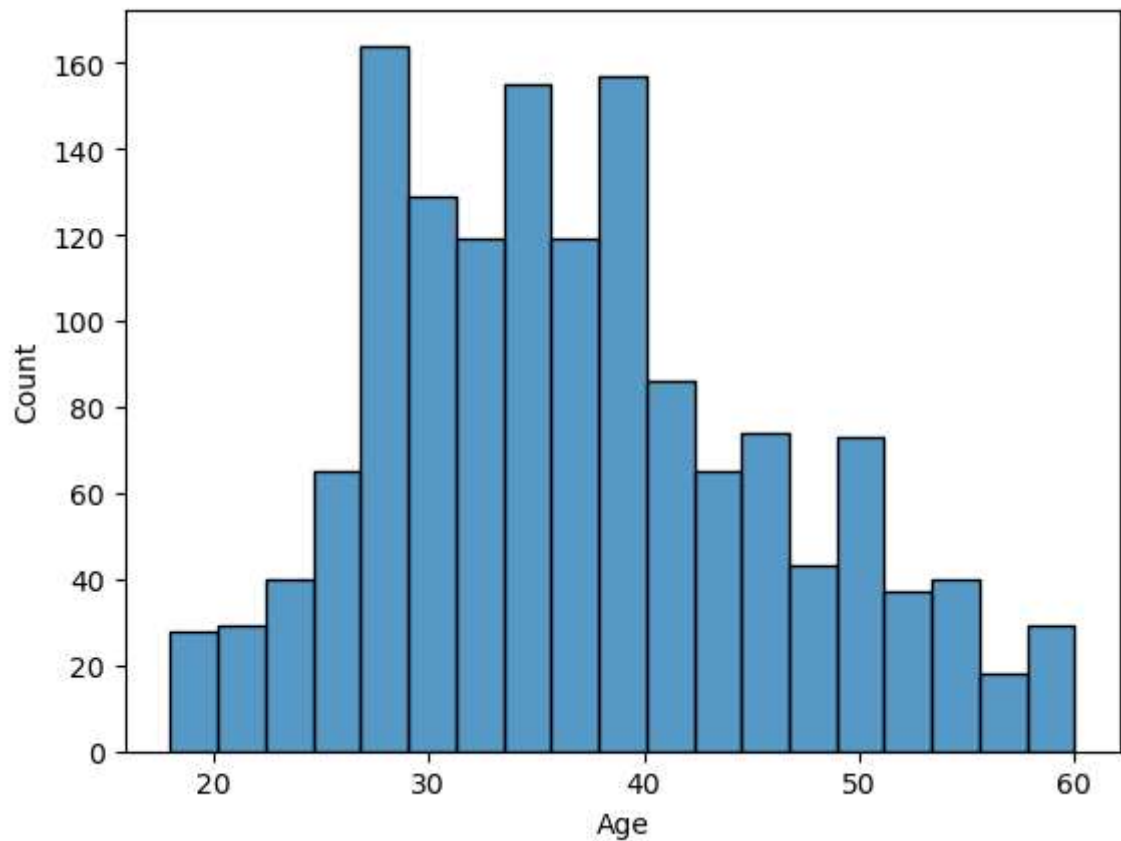
```
In [28]: plt.figure(figsize=(7,4))
sns.barplot(y='EducationField',x='MonthlyIncome',data=df)
plt.show()
```



```
In [29]: plt.figure(figsize=(8,6))
sns.countplot(x='JobSatisfaction',hue='JobRole',data=df)
plt.show()
```



```
In [30]: sns.histplot(df['Age'],kde=False);  
plt.show()
```



## Data Preprocessing

Convert Attrition from ('Yes', 'No') to (1,0)

```
In [31]: def attrition(x):  
         if x == "No":  
             return 0  
         else:  
             return 1
```

```
In [32]: df['Attrition'] = df['Attrition'].apply(attrition)
```

```
In [33]: df.head()
```

```
Out[33]:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	1	Travel_Rarely	1102	Sales	1	2	Lif
1	49	0	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	1	Travel_Rarely	1373	Research & Development	2	2	
3	33	0	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	0	Travel_Rarely	591	Research & Development	2	1	

**Convert the rest of the categorical values into numeric using dummy variables and store the results in a new dataframe called 'newdf'**

```
In [34]: newdf=pd.get_dummies(df,drop_first=True)
newdf.head()
```

```
Out[34]:
```

	Age	Attrition	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate
0	41	1	1102	1	2	2	94
1	49	0	279	8	1	3	61
2	37	1	1373	2	2	4	92
3	33	0	1392	3	4	4	56
4	27	0	591	2	1	1	40

**Check the shape of our new dataset**

```
In [35]: newdf.shape
```

```
Out[35]: (1470, 45)
```

**Print unique values in our new dataframe**



```
In [36]: ncatgegorical_columns=['Age', 'Attrition', 'DailyRate', 'DistanceFromHome', 'Ed
'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel',
'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
'YearsSinceLastPromotion', 'YearsWithCurrManager',
'BusinessTravel_Travel_Frequently', 'BusinessTravel_Travel_Rarely',
'Department_Research & Development', 'Department_Sales',
'EducationField_Life Sciences', 'EducationField_Marketing',
'EducationField_Medical', 'EducationField_Other',
'EducationField_Technical Degree', 'Gender_Male',
'JobRole_Human Resources', 'JobRole_Laboratory Technician',
'JobRole_Manager', 'JobRole_Manufacturing Director',
'JobRole_Research Director', 'JobRole_Research Scientist',
'JobRole_Sales Executive', 'JobRole_Sales Representative',
'MaritalStatus_Married', 'MaritalStatus_Single', 'OverTime_Yes']
```

```
In [37]: for i in ncatgegorical_columns:
        print("Unique values in",i,"are",newdf[i].unique())
```

```
Unique values in YearsAtCompany are [ 0 10 16 18 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402 403 404 405 406 407 408 409 410 411 412 413 414 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 447 448 449 450 451 452 453 454 455 456 457 458 459 460 461 462 463 464 465 466 467 468 469 470 471 472 473 474 475 476 477 478 479 480 481 482 483 484 485 486 487 488 489 490 491 492 493 494 495 496 497 498 499 500 501 502 503 504 505 506 507 508 509 510 511 512 513 514 515 516 517 518 519 520 521 522 523 524 525 526 527 528 529 530 531 532 533 534 535 536 537 538 539 540 541 542 543 544 545 546 547 548 549 550 551 552 553 554 555 556 557 558 559 560 561 562 563 564 565 566 567 568 569 570 571 572 573 574 575 576 577 578 579 580 581 582 583 584 585 586 587 588 589 590 591 592 593 594 595 596 597 598 599 600 601 602 603 604 605 606 607 608 609 610 611 612 613 614 615 616 617 618 619 620 621 622 623 624 625 626 627 628 629 630 631 632 633 634 635 636 637 638 639 640 641 642 643 644 645 646 647 648 649 650 651 652 653 654 655 656 657 658 659 660 661 662 663 664 665 666 667 668 669 670 671 672 673 674 675 676 677 678 679 680 681 682 683 684 685 686 687 688 689 690 691 692 693 694 695 696 697 698 699 700 701 702 703 704 705 706 707 708 709 710 711 712 713 714 715 716 717 718 719 720 721 722 723 724 725 726 727 728 729 730 731 732 733 734 735 736 737 738 739 740 741 742 743 744 745 746 747 748 749 750 751 752 753 754 755 756 757 758 759 760 761 762 763 764 765 766 767 768 769 770 771 772 773 774 775 776 777 778 779 780 781 782 783 784 785 786 787 788 789 790 791 792 793 794 795 796 797 798 799 800 801 802 803 804 805 806 807 808 809 810 811 812 813 814 815 816 817 818 819 820 821 822 823 824 825 826 827 828 829 830 831 832 833 834 835 836 837 838 839 840 841 842 843 844 845 846 847 848 849 850 851 852 853 854 855 856 857 858 859 860 861 862 863 864 865 866 867 868 869 870 871 872 873 874 875 876 877 878 879 880 881 882 883 884 885 886 887 888 889 890 891 892 893 894 895 896 897 898 899 900 901 902 903 904 905 906 907 908 909 910 911 912 913 914 915 916 917 918 919 920 921 922 923 924 925 926 927 928 929 930 931 932 933 934 935 936 937 938 939 940 941 942 943 944 945 946 947 948 949 950 951 952 953 954 955 956 957 958 959 960 961 962 963 964 965 966 967 968 969 970 971 972 973 974 975 976 977 978 979 980 981 982 983 984 985 986 987 988 989 990 991 992 993 994 995 996 997 998 999 1000 1001 1002 1003 1004 1005 1006 1007 1008 1009 1010 1011 1012 1013 1014 1015 1016 1017 1018 1019 1020 1021 1022 1023 1024 1025 1026 1027 1028 1029 1030 1031 1032 1033 1034 1035 1036 1037 1038 1039 1040 1041 1042 1043 1044 1045 1046 1047 1048 1049 1050 1051 1052 1053 1054 1055 1056 1057 1058 1059 1060 1061 1062 1063 1064 1065 1066 1067 1068 1069 1070 1071 1072 1073 1074 1075 1076 1077 1078 1079 1080 1081 1082 1083 1084 1085 1086 1087 1088 1089 1090 1091 1092 1093 1094 1095 1096 1097 1098 1099 1100 1101 1102 1103 1104 1105 1106 1107 1108 1109 1110 1111 1112 1113 1114 1115 1116 1117 1118 1119 1120 1121 1122 1123 1124 1125 1126 1127 1128 1129 1130 1131 1132 1133 1134 1135 1136 1137 1138 1139 1140 1141 1142 1143 1144 1145 1146 1147 1148 1149 1150 1151 1152 1153 1154 1155 1156 1157 1158 1159 1160 1161 1162 1163 1164 1165 1166 1167 1168 1169 1170 1171 1172 1173 1174 1175 1176 1177 1178 1179 1180 1181 1182 1183 1184 1185 1186 1187 1188 1189 1190 1191 1192 1193 1194 1195 1196 1197 1198 1199 1200 1201 1202 1203 1204 1205 1206 1207 1208 1209 1210 1211 1212 1213 1214 1215 1216 1217 1218 1219 1220 1221 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2022 2023 2024 2025 2026 2027 2028 2029 2030 2031 2032 2033 2034 2035 2036 2037 2038 2039 2040 2041 2042 2043 2044 2045 2046 2047 2048 2049 2050 2051 2052 2053 2054 2055 2056 2057 2058 2059 2060 2061 2062 2063 2064 2065 2066 2067 2068 2069 2070 2071 2072 2073 2074 2075 2076 2077 2078 2079 2080 2081 2082 2083 2084 2085 2086 2087 2088 2089 2090 2091 2092 2093 2094 2095 2096 2097 2098 2099 2100 2101 2102 2103 2104 2105 2106 2107 2108 2109 2110 2111 2112 2113 2114 2115 2116 2117 2118 2119 2120 2121 2122 2123 2124 2125 2126 2127 2128 2129 2130 2131 2132 2133 2134 2135 2136 2137 2138 2139 2140 2141 2142 2143 2144 2145 2146 2147 2148 2149 2150 2151 2152 2153 2154 2155 2156 2157 2158 2159 2160 2161 2162 2163 2164 2165 2166 2167 2168 2169 2170 2171 2172 2173 2174 2175 2176 2177 2178 2179 2180 2181 2182 2183 2184 2185 2186 2187 2188 2189 2190 2191 2192 2193 2194 2195 2196 2197 2198 2199 2200 2201 2202 2203 2204 2205 2206 2207 2208 2209 2210 2211 2212 2213 2214 2215 2216 2217 2218 2219 2220 2221 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```

```
In [39]: from sklearn.preprocessing import StandardScaler
```

```
In [40]: scalar=StandardScaler()
```

```
In [41]: X_scalar=scalar.fit_transform(X)
```

```
In [42]: scaled_X=pd.DataFrame(X_scalar,columns=X.columns)
```

```
In [43]: scaled_X.head()
```

```
Out[43]:
```

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate	Jol
0	0.446350	0.742527	-1.010909	-0.891688	-0.660531	1.383138	
1	1.322365	-1.297775	-0.147150	-1.868426	0.254625	-0.240677	
2	0.008343	1.414363	-0.887515	-0.891688	1.169781	1.284725	
3	-0.429664	1.461466	-0.764121	1.061787	1.169781	-0.486709	
4	-1.086676	-0.524295	-0.887515	-1.868426	-1.575686	-1.274014	

## Split the dataset into training and testing set

```
In [44]: from sklearn.model_selection import train_test_split
```

```
In [45]: X_test,X_train,y_test,y_train=train_test_split(X,y,test_size=0.3)
```

## Machine Learning Models

### Logistic Regression

```
In [46]: from sklearn.linear_model import LogisticRegression  
from sklearn import metrics  
from sklearn.model_selection import cross_val_score
```

```
In [47]: model=LogisticRegression()
```

```
In [48]: model.fit(X_train,y_train)
```

```
Out[48]: LogisticRegression()
```

```
In [49]: y_pred=model.predict(X_test)
```

```
In [90]: a=metrics.accuracy_score(y_test,y_pred)
a
```

```
Out[90]: 0.8347910592808552
```

```
In [51]: metrics.confusion_matrix(y_test,y_pred)
```

```
Out[51]: array([[856,   3],
                [166,   4]], dtype=int64)
```

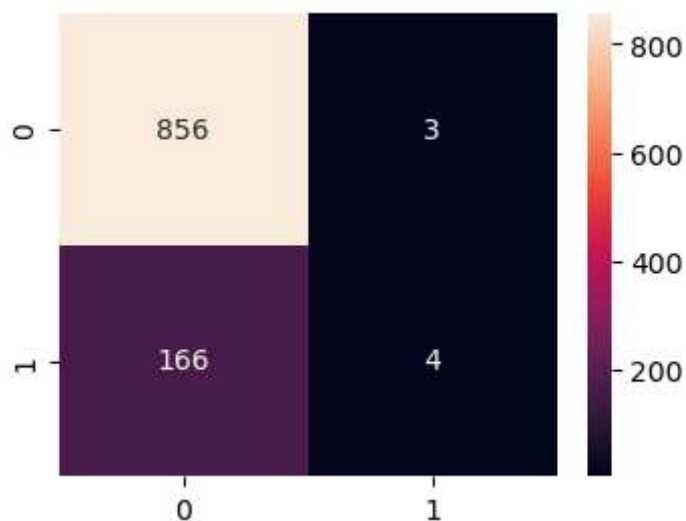
```
In [52]: print(metrics.classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.84	1.00	0.91	859
1	0.57	0.02	0.05	170
accuracy			0.84	1029
macro avg	0.70	0.51	0.48	1029
weighted avg	0.79	0.84	0.77	1029

```
In [53]: metrics.confusion_matrix(y_test,y_pred)
```

```
Out[53]: array([[856,   3],
                [166,   4]], dtype=int64)
```

```
In [54]: plt.figure(figsize=(4,3))
sns.heatmap(metrics.confusion_matrix(y_test,y_pred),annot=True,fmt='d')
plt.show()
```



## Random Forest Classifier

**\*\* Choose the best estimator and parameters :GridSearchCV\*\***

```
In [55]: from sklearn.ensemble import RandomForestClassifier
        from sklearn.model_selection import GridSearchCV
```

```
In [56]: model1 = RandomForestClassifier(n_estimators= 100)
```

```
In [57]: model1.fit(X_train, y_train)
```

```
Out[57]: RandomForestClassifier()
```

```
In [58]: forest_params = [{'max_depth': [0.5,1,5,10], 'max_features': list(range(0,14))}
```

```
In [59]: clf = GridSearchCV(model1, forest_params,scoring='accuracy')
```

```
In [60]: clf.fit(X_train, y_train)
```

```
Out[60]: GridSearchCV(estimator=RandomForestClassifier(),
                      param_grid=[{'max_depth': [0.5, 1, 5, 10],
                                   'max_features': [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10,
11,
                                                12, 13]}],
                      scoring='accuracy')
```

```
In [61]: clf.best_params_
```

```
Out[61]: {'max_depth': 10, 'max_features': 6}
```

```
In [62]: clf.best_score_
```

```
Out[62]: 0.8662665985699693
```

```
In [63]: clf.best_estimator_
```

```
Out[63]: RandomForestClassifier(max_depth=10, max_features=6)
```

Create Random forest model with the best parameters

```
In [91]: b=model1.score(X_train, y_train)
        b
```

```
Out[91]: 1.0
```

```
In [65]: y_pred = model1.predict(X_test)
```

```
In [66]: metrics.accuracy_score(y_test, y_pred)
```

```
Out[66]: 0.8425655976676385
```

```
In [67]: metrics.confusion_matrix(y_test, y_pred)
```

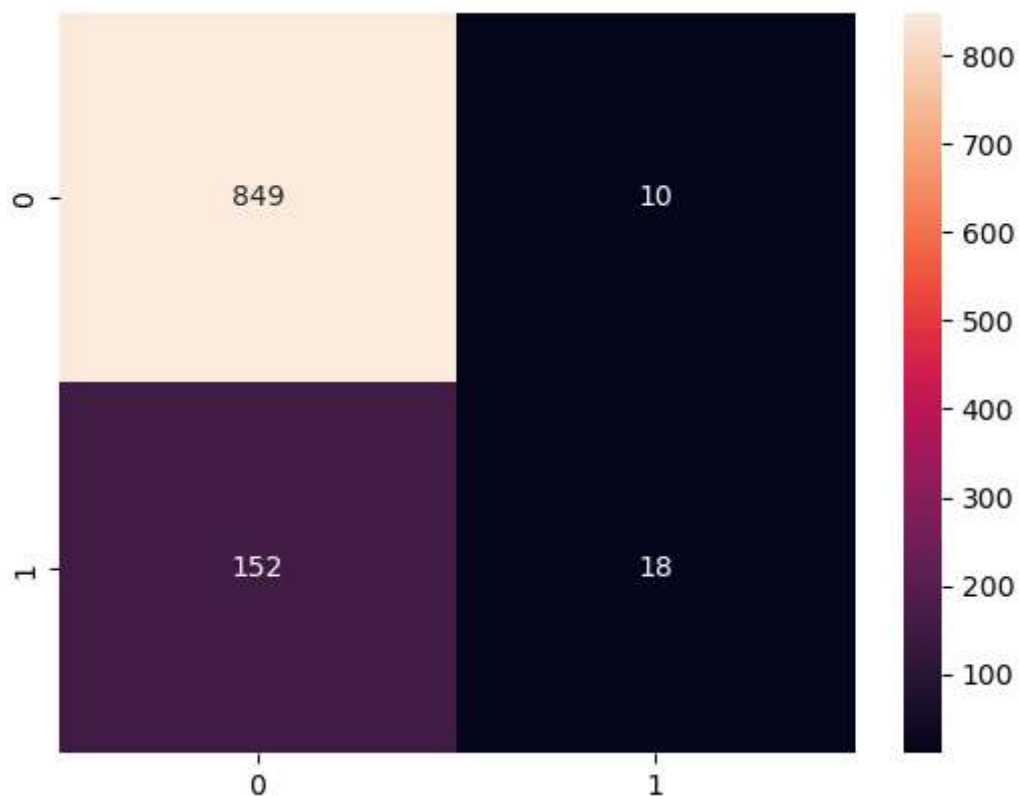
```
Out[67]: array([[849, 10],  
               [152, 18]], dtype=int64)
```

```
In [68]: print(metrics.classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.85	0.99	0.91	859
1	0.64	0.11	0.18	170
accuracy			0.84	1029
macro avg	0.75	0.55	0.55	1029
weighted avg	0.81	0.84	0.79	1029

### Visualize confusion matrix

```
In [70]: sns.heatmap(metrics.confusion_matrix(y_test,y_pred), annot = True, fmt = 'd')  
plt.show()
```



## Support Vector Machine

```
In [71]: from sklearn.svm import SVC
```

```
In [72]: model = SVC()
```

```
In [73]: model.fit(X_train, y_train)
```

```
Out[73]: SVC()
```

```
In [92]: c=model.score(X_train,y_train)
c
```

```
Out[92]: 0.8480725623582767
```

```
In [75]: y_pred = model.predict(X_test)
```

```
In [76]: from sklearn import metrics
```

```
In [77]: metrics.accuracy_score(y_test, y_pred)
```

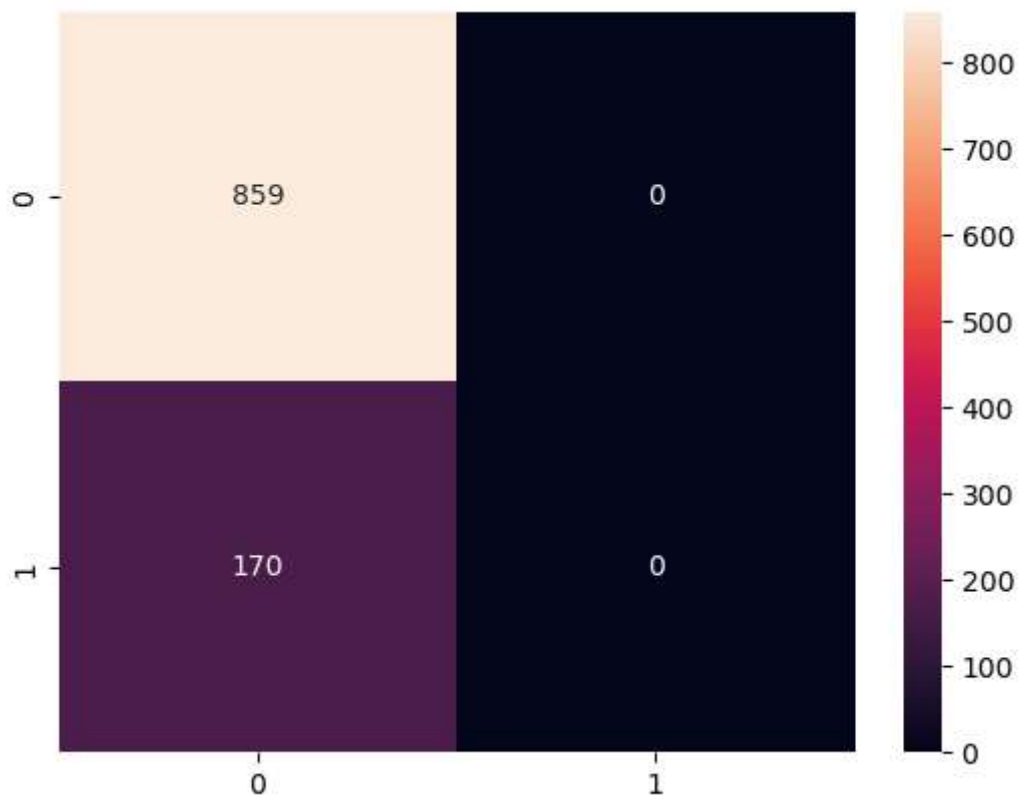
```
Out[77]: 0.8347910592808552
```

```
In [78]: metrics.confusion_matrix(y_test,y_pred)
```

```
Out[78]: array([[859,  0],
               [170,  0]], dtype=int64)
```

Visualize confusion matrix

```
In [79]: sns.heatmap(metrics.confusion_matrix(y_test,y_pred), annot = True, fmt = 'd')  
plt.show()
```



## View score of different models in one dataframe

```
In [102]: asd=([[a],[b],[c]])  
pd.DataFrame(asd)
```

```
Out[102]:
```

	0
0	0.834791
1	1.000000
2	0.848073

## Use PCA to reduce dimensionality of the data

Import PCA and fit our X\_train

```
In [ ]: from sklearn.decomposition import PCA
```

```
In [ ]: PCA(n_components = 0.95)
```

**Apply the mapping (transform) to both the training set and the test set.**

```
In [ ]: train_X = PCA.transform(X_train)
        test_X = PCA.transform(X_test)
```

**Import machine learning model of our choice, we are going with RandomForest for this problem**

```
In [ ]: from sklearn.ensemble import RandomForestClassifier
```

**Create RandomForest model with the best parameter we got earlier and train it**

```
In [112]: from sklearn.ensemble import RandomForestClassifier
          from sklearn.model_selection import GridSearchCV
          model1 = RandomForestClassifier(n_estimators= 100)
          model1.fit(X_train, y_train)
```

```
Out[112]: RandomForestClassifier()
```

**Check the score of our model**

```
In [113]: model1.score(X_train, y_train)
```

```
Out[113]: 1.0
```

**Make predictions with X\_test and check the accuracy score**

```
In [114]: metrics.accuracy_score(y_test, y_pred)
```

```
Out[114]: 0.8347910592808552
```

**Print Confusion matrix and Classification report**

```
In [115]: metrics.confusion_matrix(y_test, y_pred)
```

```
Out[115]: array([[859,  0],
                 [170,  0]], dtype=int64)
```



```
In [116]: print(metrics.classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	0.83	1.00	0.91	859
1	0.00	0.00	0.00	170
accuracy			0.83	1029
macro avg	0.42	0.50	0.45	1029
weighted avg	0.70	0.83	0.76	1029

---