IBM HR Analytics Employee Attrition Modeling .

DESCRIPTION

- IBM is an American MNC operating in around 170 countries with major business vertical as computing, software, and hardware.
- Attrition is a major risk to service-providing organizations where trained and experienced people are the assets of the company. The organization would like to identify the factors which influence the attrition of employees.

Data Dictionary

- Age: Age of employee
- Attrition: Employee attrition status
- Department: Department of work
- DistanceFromHome
- Education: 1-Below College; 2- College; 3-Bachelor; 4-Master; 5-Doctor;
- EducationField
- EnvironmentSatisfaction: 1-Low; 2-Medium; 3-High; 4-Very High;
- JobSatisfaction: 1-Low; 2-Medium; 3-High; 4-Very High;
- MaritalStatus
- MonthlyIncome
- NumCompaniesWorked: Number of companies worked prior to IBM
- WorkLifeBalance: 1-Bad; 2-Good; 3-Better; 4-Best;
- YearsAtCompany: Current years of service in IBM

Analysis Task:

- Import attrition dataset and import libraries such as pandas, matplotlib.pyplot, numpy, and seaborn.
- Exploratory data analysis

  1. Find the age distribution of employees in IBM
  2. Explore attrition by age
  3. Explore data for Left employees
  4. Find out the distribution of employees by the education field
  5. Give a bar chart for the number of married and unmarried employees

- Build up a logistic regression model to predict which employees are likely to attrite.

In [20]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline
```

In [3]:
```
dataset = pd.read_csv('../datasets/IBM Attrition Data.csv')
```

In [11]:
```
dataset.shape
```

Out[11]:
```
(1470, 13)
```

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

Out[43]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCon
0	41	Yes	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	No	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Yes	Research & Development	2	2	Other	4	3	Single	2090	
3	33	No	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	No	Research & Development	2	1	Medical	1	2	Married	3468	

Find the age distribution of employees in IBM

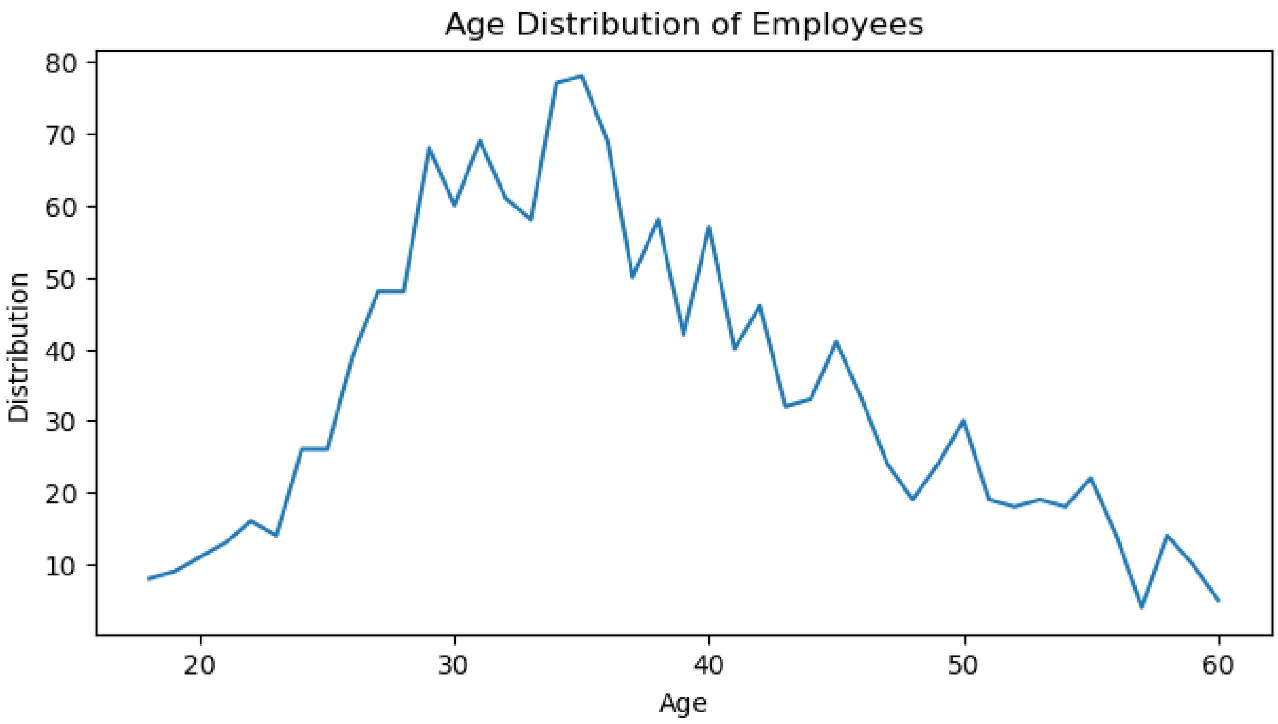
In [12]:
```
age_grouped = dataset.groupby('Age')
```

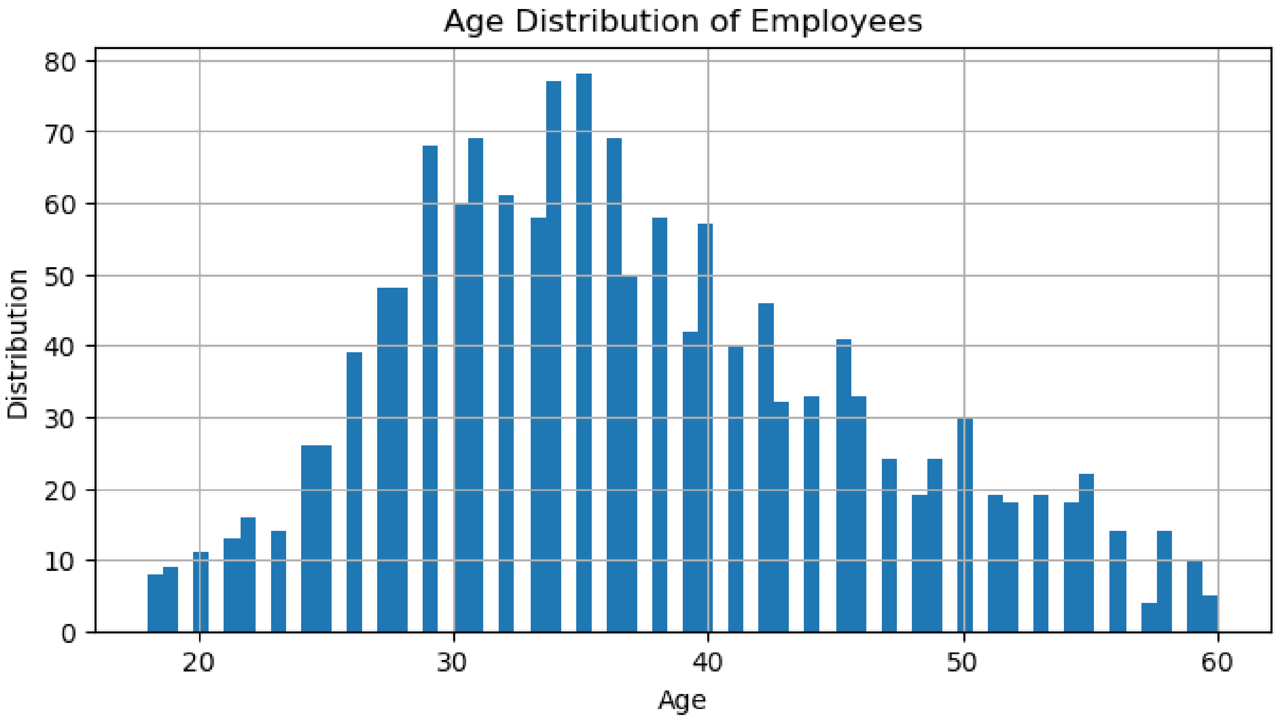
In [30]:
```
index = age_grouped.size().index
```

In [37]:
```
data = age_grouped.size().values
```

In [86]:

```
plt.figure(figsize=(8,4))
plt.plot(age_grouped.size())
plt.title("Age Distribution of Employees")
plt.xlabel('Age')
plt.ylabel('Distribution')
plt.figure(figsize=(8,4))
dataset['Age'].hist(bins=70)
plt.title("Age Distribution of Employees")
plt.xlabel('Age')
plt.ylabel('Distribution')
plt.show()
```





explore attrition by age

```
In [55]: attrition_grouped = dataset.groupby(['Age','Attrition'])
```

In [56]:

```
attrition_grouped.size()
```

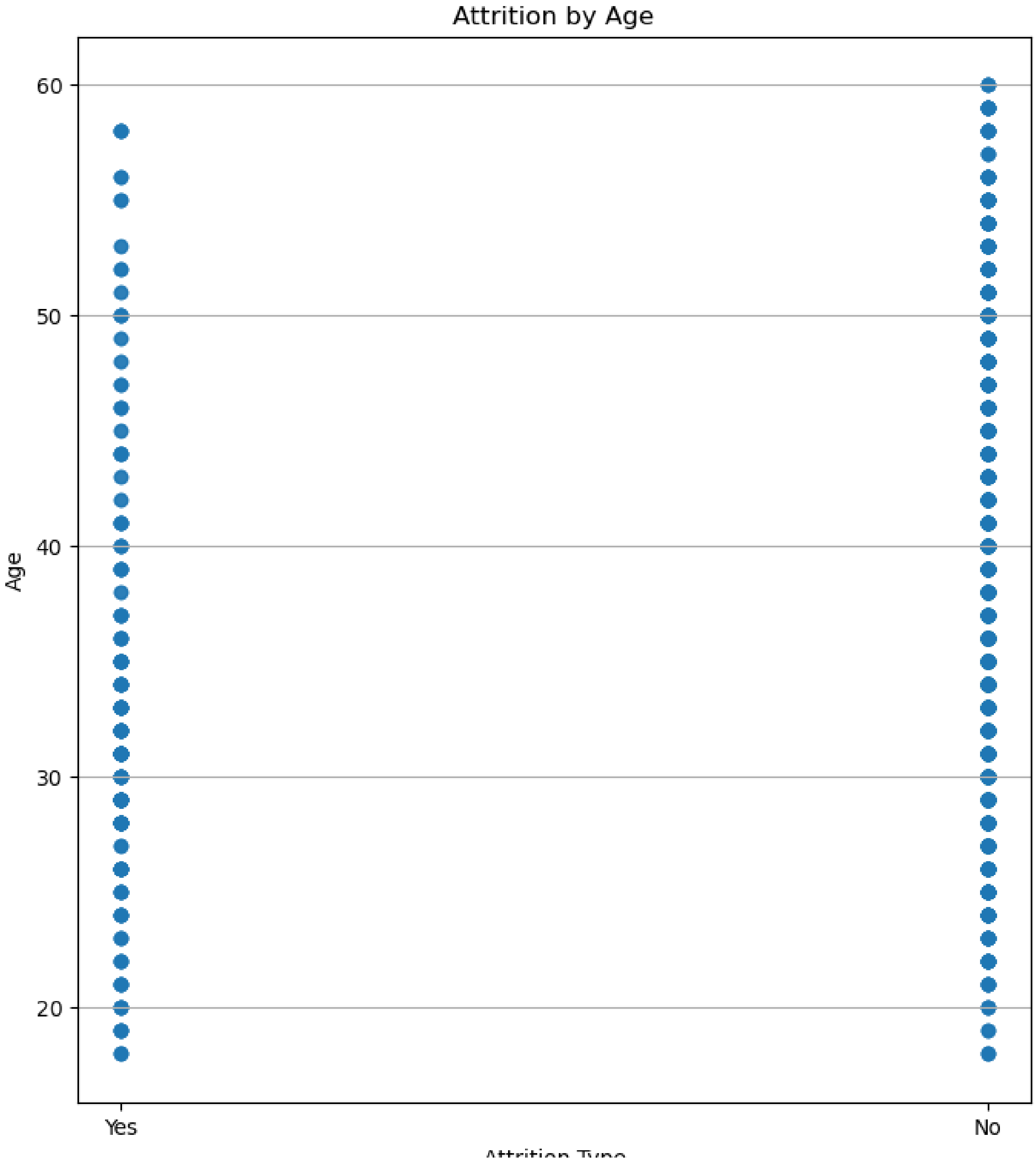
Out[56]:

```
Age  Attrition
18   No             4
     Yes            4
19   No             3
     Yes            6
20   No             5
                   ..
57   No             4
58   No             9
     Yes            5
59   No            10
60   No             5
Length: 82, dtype: int64
```

In [92]:

```
plt.figure(figsize=(8,9))
plt.scatter(dataset.Attrition,dataset.Age,alpha=.75)
plt.title("Attrition by Age")
plt.ylabel('Age')
plt.xlabel('Attrition Type')
plt.grid(b=True,which='major',axis='y')
plt.show()
```

```
/var/folders/tm/ffwlhhvs4hjbp97q0xdt53r80000gn/T/ipykernel_9047/4294918261.py:6: MatplotlibDeprecationWarning: The
'b' parameter of grid() has been renamed 'visible' since Matplotlib 3.5; support for the old name will be dropped tw
o minor releases later.
  plt.grid(b=True,which='major',axis='y')
```


Attrition by Age
Age
60
50
40
30
20
Yes
No
Attrition Type

Attrition Type

In [57]:
```
attrition_grouped.first()
```

Out[57]:

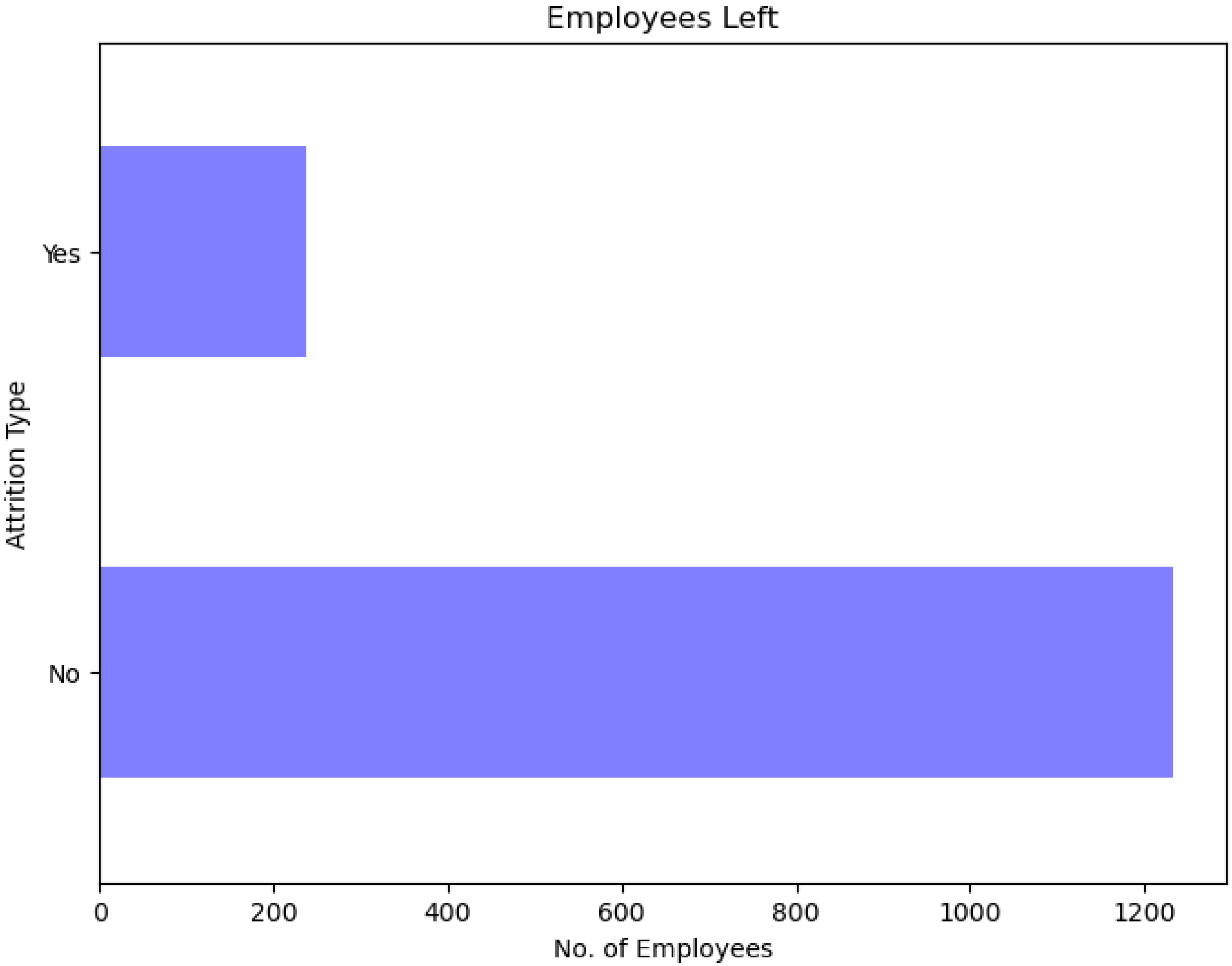
		Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompa
Age	**Attrition**									
18	**No**	Sales	10	3	Medical	4	3	Single	1200	
	Yes	Research & Development	3	3	Life Sciences	3	3	Single	1420	
19	**No**	Research & Development	3	1	Medical	2	2	Single	1483	
	Yes	Sales	22	1	Marketing	4	3	Single	1675	
20	**No**	Research & Development	1	3	Life Sciences	4	2	Single	2836	
...	**...**	...	...	...	...	...	...	...	...	
57	**No**	Research & Development	24	2	Life Sciences	3	4	Divorced	9439	
58	**No**	Sales	10	4	Medical	4	3	Single	13872	
	Yes	Research & Development	23	4	Medical	4	4	Married	10312	
59	**No**	Research & Development	3	3	Medical	3	1	Married	2670	
60	**No**	Research & Development	7	3	Life Sciences	1	1	Married	19566	

82 rows × 11 columns

Explore data for Left employees

In [128]:

```
plt.figure(figsize=(8,6))
dataset.Attrition.value_counts().plot(kind='barh',color='b',alpha=.5)
plt.title('Employees Left')
plt.xlabel('No. of Employees')
plt.ylabel('Attrition Type')
plt.show()
```



Find out the distribution of employees by the education field

In [63]:

```
education_field = dataset.groupby('EducationField')
```

In [64]:

```
education_field.size()
```

Out[64]:

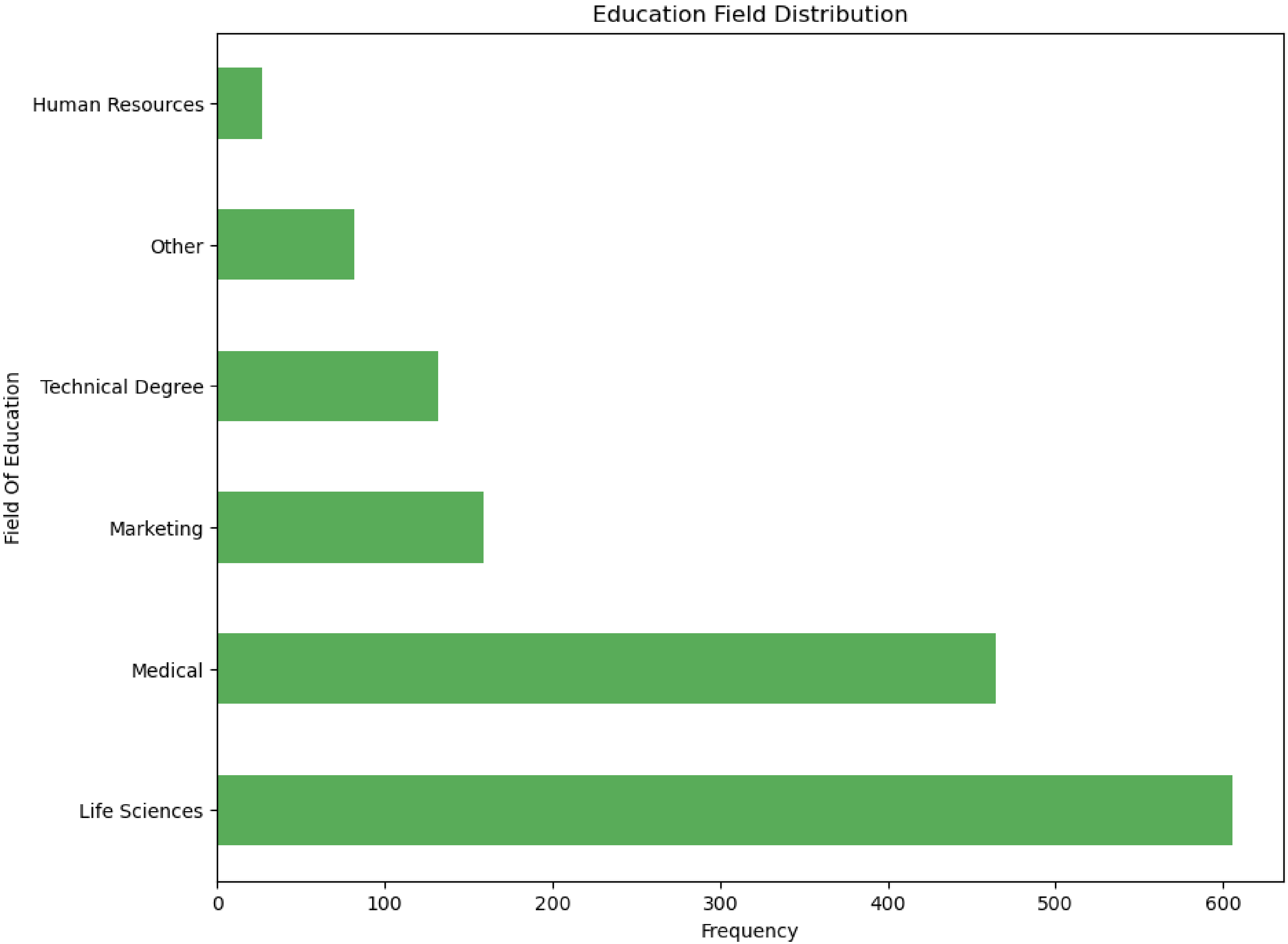
```
EducationField
Human Resources      27
Life Sciences       606
Marketing           159
Medical             464
Other                82
Technical Degree    132
dtype: int64
```

In [122]:

```
plt.figure(figsize=(10,8))
dataset.EducationField.value_counts().plot(kind='barh',color='g',alpha=0.65)
plt.title('Education Field Distribution')
plt.xlabel('Frequency')
plt.ylabel('Field Of Education')
```

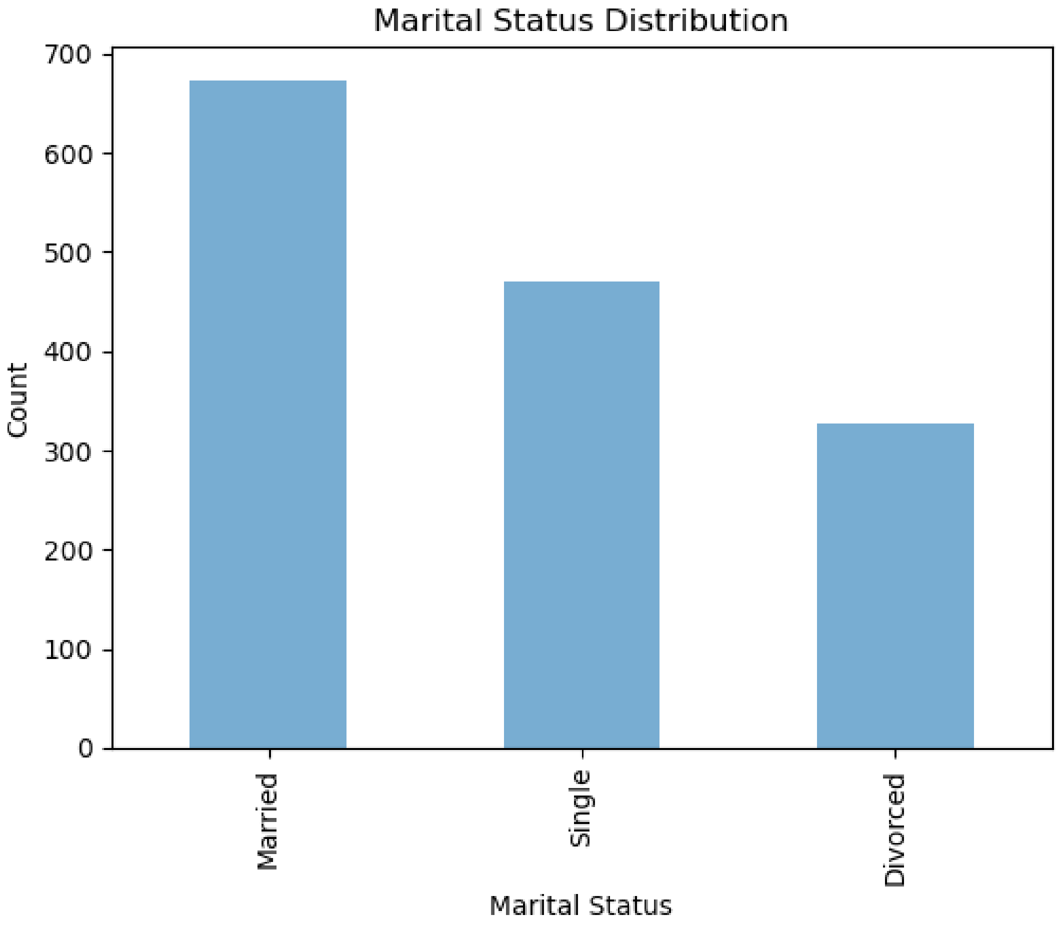
Out[122]:

```
Text(0, 0.5, 'Field Of Education')
```


Education Field Distribution
Human Resources
Other
Technical Degree
Marketing
Medical
Life Sciences
Field Of Education
0
100
200
300
400
500
600
Frequency

Give a bar chart for the number of married and unmarried employees

```
In [130]: plt.title('Marital Status Distribution')
          dataset.MaritalStatus.value_counts().plot(kind='bar',alpha=.6)
          plt.ylabel('Count')
          plt.xlabel('Marital Status')
          plt.show()
```



Model Building

Pre Processing data

In [152]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [133]:

```
dataFrame = dataset
```

In [134]:

```
dataFrame.head()
```

Out[134]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCon
0	41	Yes	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	No	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Yes	Research & Development	2	2	Other	4	3	Single	2090	
3	33	No	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	No	Research & Development	2	1	Medical	1	2	Married	3468	

In [138]:

```
dataFrame['Attrition'].replace('Yes',1,inplace=True)
dataFrame['Attrition'].replace('No',0,inplace=True)
```

In [139]:

```
dataFrame.head()
```

Out[139]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCon
0	41	1	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	0	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	1	Research & Development	2	2	Other	4	3	Single	2090	
3	33	0	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	0	Research & Development	2	1	Medical	1	2	Married	3468	

In [140]:

```
dataFrame.Department.value_counts()
```

Out[140]:

```
Research & Development    961
Sales                     446
Human Resources            63
Name: Department, dtype: int64
```

In [142]:

```
dataFrame['Department'].replace('Research & Development',1, inplace=True)
dataFrame['Department'].replace('Sales',2, inplace=True)
dataFrame['Department'].replace('Human Resources', 3, inplace=True)
```

In [143]:

```
dataFrame.head()
```

Out[143]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCom
0	41	1	2	1	2	Life Sciences	2	4	Single	5993	
1	49	0	1	8	1	Life Sciences	3	2	Married	5130	
2	37	1	1	2	2	Other	4	3	Single	2090	
3	33	0	1	3	4	Life Sciences	4	3	Married	2909	
4	27	0	1	2	1	Medical	1	2	Married	3468	

In [144]:
```
dataFrame.EducationField.value_counts()
```

Out[144]:
```
Life Sciences       606
Medical             464
Marketing           159
Technical Degree    132
Other                82
Human Resources      27
Name: EducationField, dtype: int64
```

In [145]:
```
dataFrame['EducationField'].replace('Life Sciences',1, inplace=True)
dataFrame['EducationField'].replace('Medical',2, inplace=True)
dataFrame['EducationField'].replace('Marketing', 3, inplace=True)
dataFrame['EducationField'].replace('Other',4, inplace=True)
dataFrame['EducationField'].replace('Technical Degree',5, inplace=True)
dataFrame['EducationField'].replace('Human Resources', 6, inplace=True)
```

In [146]:
```
dataFrame.head()
```

Out[146]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCom
0	41	1	2	1	2	1	2	4	Single	5993	
1	49	0	1	8	1	1	3	2	Married	5130	
2	37	1	1	2	2	4	4	3	Single	2090	
3	33	0	1	3	4	1	4	3	Married	2909	
4	27	0	1	2	1	2	1	2	Married	3468	

In [147]:
```
dataFrame.MaritalStatus.value_counts()
```

Out[147]:
```
Married     673
Single      470
Divorced    327
Name: MaritalStatus, dtype: int64
```

In [148]:

```
dataFrame['MaritalStatus'].replace('Married',1, inplace=True)
dataFrame['MaritalStatus'].replace('Single',2, inplace=True)
dataFrame['MaritalStatus'].replace('Divorced',3, inplace=True)
```

In [149]:

```
dataFrame.head()
```

Out[149]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCom
0	41	1	2	1	2	1	2	4	2	5993	
1	49	0	1	8	1	1	3	2	1	5130	
2	37	1	1	2	2	4	4	3	2	2090	
3	33	0	1	3	4	1	4	3	1	2909	
4	27	0	1	2	1	2	1	2	1	3468	

In [150]:

```
dataFrame.dtypes
```

Out[150]:

```
Age                        int64
Attrition                  int64
Department                 int64
DistanceFromHome           int64
Education                  int64
EducationField             int64
EnvironmentSatisfaction    int64
JobSatisfaction            int64
MaritalStatus              int64
MonthlyIncome              int64
NumCompaniesWorked         int64
WorkLifeBalance            int64
YearsAtCompany             int64
dtype: object
```

In [157]:

```
X = dataFrame.drop('Attrition',axis=1).values
y = dataFrame.Attrition.values
```

In [161]:

```
X = StandardScaler().fit_transform(X)
```

```
In [164]: X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,random_state=0)
```

```
In [166]: classifier = LogisticRegression().fit(X_train,y_train)
```

```
In [167]: y_pred = classifier.predict(X_test)
```

```
In [168]: accuracy_score(y_test,y_pred)

Out[168]: 0.8435374149659864
```

```
In [169]: confusion_matrix(y_test,y_pred)

Out[169]: array([[367,   4],
                 [ 65,   5]])
```

```
In [171]: print(classification_report(y_test,y_pred))

                        precision    recall  f1-score   support

                     0       0.85      0.99      0.91       371
                     1       0.56      0.07      0.13        70

              accuracy                           0.84       441
             macro avg       0.70      0.53      0.52       441
          weighted avg       0.80      0.84      0.79       441
```

```
In [ ]:
```