In [1]:
```
import pandas as pd
import numpy as np

import seaborn as sn
import matplotlib.pyplot as plt
%matplotlib inline
```

Extracting Data

In [2]:
```
p = pd.read_csv("Placement_Data_Full_Class.csv")
p_copy = pd.read_csv("Placement_Data_Full_Class.csv")
```

Examining the dataset

In [3]:
```
p.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 215 entries, 0 to 214
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   sl_no           215 non-null    int64  
 1   gender          215 non-null    object 
 2   ssc_p           215 non-null    float64
 3   ssc_b           215 non-null    object 
 4   hsc_p           215 non-null    float64
 5   hsc_b           215 non-null    object 
 6   hsc_s           215 non-null    object 
 7   degree_p        215 non-null    float64
 8   degree_t        215 non-null    object 
 9   workex          215 non-null    object 
 10  etest_p         215 non-null    float64
 11  specialisation  215 non-null    object 
 12  mba_p           215 non-null    float64
 13  status          215 non-null    object 
 14  salary          148 non-null    float64
dtypes: float64(6), int64(1), object(8)
memory usage: 25.3+ KB
```

Checking for missing data

In [4]:
```
p.isnull().sum()
```

Out[4]:
```
sl_no              0
gender             0
ssc_p              0
ssc_b              0
hsc_p              0
hsc_b              0
hsc_s              0
degree_p           0
degree_t           0
workex             0
etest_p            0
specialisation     0
mba_p              0
status             0
salary            67
dtype: int64
```

Data Cleaning

Handling Missing Values

In [5]:
```
p['salary'].fillna(value=0, inplace=True)
p.isnull().sum()
```

Out[5]:
```
sl_no             0
gender            0
ssc_p             0
ssc_b             0
hsc_p             0
hsc_b             0
hsc_s             0
degree_p          0
degree_t          0
workex            0
etest_p           0
specialisation    0
mba_p             0
status            0
salary            0
dtype: int64
```

We have successfully removed all null values.

Dropping Unwanted Features

In [6]:
```
p.drop(['sl_no','ssc_b','hsc_b'], axis = 1,inplace=True)
```

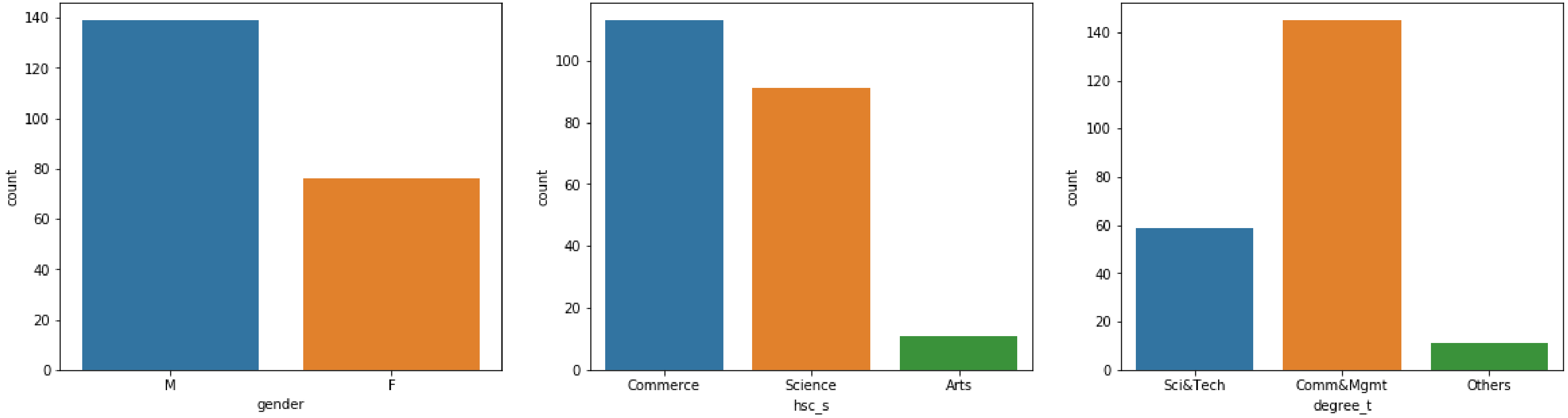
We have dropped serial number as we have index as default and we have dropped the boards of school education as we believe it doesn't matter for recruitment

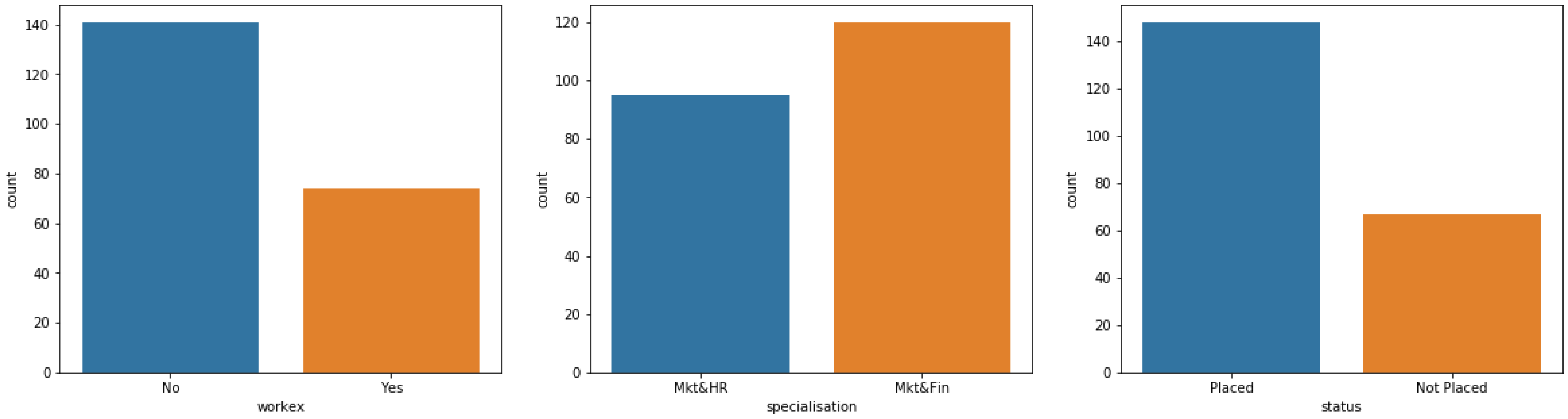
Data Visualization

Count Plots

In [7]:
```
fig, axs = plt.subplots(ncols=3,figsize=(20,5))
sn.countplot(p['gender'], ax = axs[0])
sn.countplot(p['hsc_s'], ax = axs[1])
sn.countplot(p['degree_t'], ax = axs[2])
fig, axs = plt.subplots(ncols=3,figsize=(20,5))
sn.countplot(p['workex'], ax = axs[0])
sn.countplot(p['specialisation'], ax = axs[1])
sn.countplot(p['status'], ax = axs[2])
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x250977f9d48>

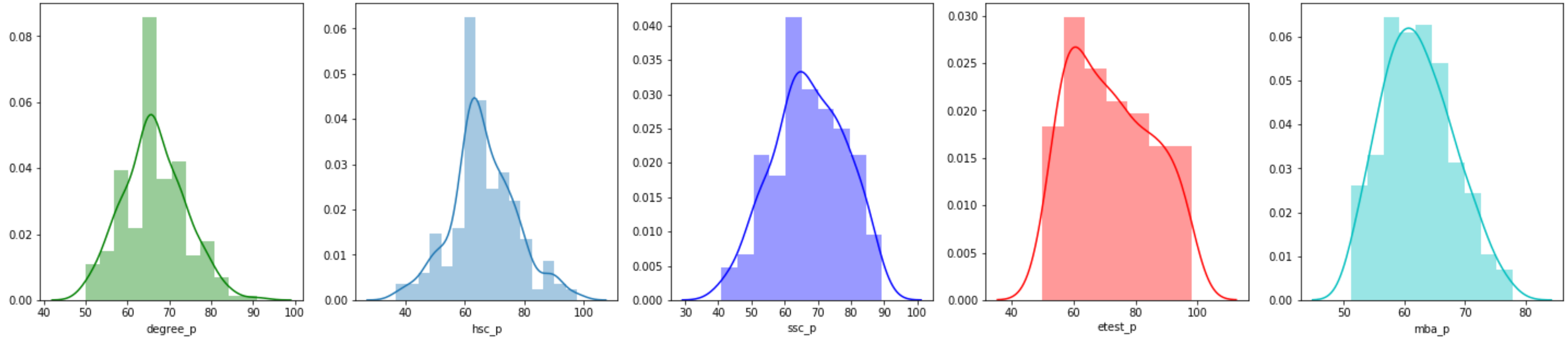




Dist Plots

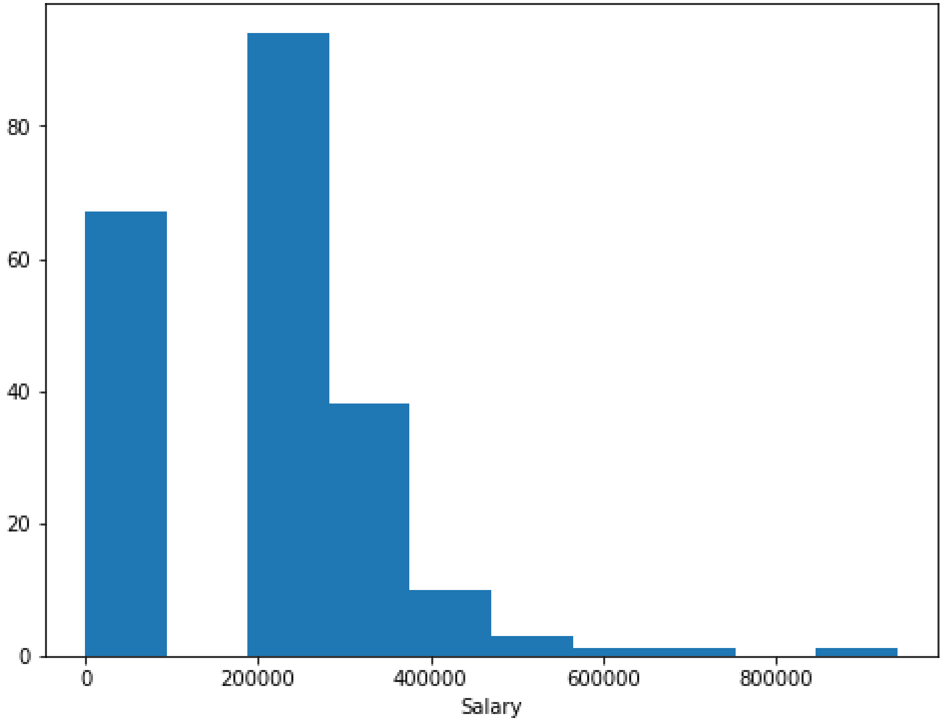
In [8]:
```
fig, axs = plt.subplots(ncols=5,figsize=(25,5))
sn.distplot(p['degree_p'], ax= axs[0], color = 'g')
sn.distplot(p['hsc_p'], ax= axs[1])
sn.distplot(p['ssc_p'],  ax= axs[2], color = 'b')
sn.distplot(p['etest_p'],  ax= axs[3], color = 'r')
sn.distplot(p['mba_p'],  ax= axs[4], color = 'c')
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x25097981ac8>



Hist Plot

In [9]:
```
plt.figure(figsize=(8,6))
plt.hist(p['salary'], bins = 10)
plt.xlabel("Salary")
plt.show()
```



Feature Engineering

In [10]:
```
#gender
gen = [1 if x=='M' else 0 for x in p['gender']]
p['gender']=gen

#hsc_s
hsc_A = [1 if x=='Arts' else 0 for x in p['hsc_s']]
p['hsc_s_Arts']=hsc_A
hsc_C = [1 if x=='Commerce' else 0 for x in p['hsc_s']]
p['hsc_s_Com']=hsc_C
hsc_S = [1 if x=='Science' else 0 for x in p['hsc_s']]
p['hsc_s_Sci']=hsc_S

#degree_t
deg_Sci = [1 if x=='Sci&Tech' else 0 for x in p['degree_t']]
p['deg_t_Sci']=deg_Sci
deg_Comm = [1 if x=='Comm&Mgmt' else 0 for x in p['degree_t']]
p['deg_t_Comm']=deg_Comm
deg_Others = [1 if x=='Others' else 0 for x in p['degree_t']]
p['deg_t_Others']=deg_Others

#specialisation
spec = [1 if x=='Mkt&HR' else 0 for x in p['specialisation']]
p['specialisation']=spec

#status
status = [1 if x=='Placed' else 0 for x in p['status']]
p['status'] = status

#workex
WorkEx = [1 if x=='Yes' else 0 for x in p['workex']]
p['workex'] = WorkEx
```

We derive numerical values from object values as it will be better for training the model

In [11]:
```
p = p.drop(axis=1, columns=['hsc_s', 'degree_t'])
```

We drop the rest of the unwanted features as we have alrady derived features from these features. Let us have a look at the data now.

In [12]:
```
p
```

Out[12]:

	gender	ssc_p	hsc_p	degree_p	workex	etest_p	specialisation	mba_p	status	salary	hsc_s_Arts	hsc_s_Com	hsc_s_Sci	deg_t_Sci	de
0	1	67.00	91.00	58.00	0	55.0	1	58.80	1	270000.0	0	1	0	1	
1	1	79.33	78.33	77.48	1	86.5	0	66.28	1	200000.0	0	0	1	1	
2	1	65.00	68.00	64.00	0	75.0	0	57.80	1	250000.0	1	0	0	0	
3	1	56.00	52.00	52.00	0	66.0	1	59.43	0	0.0	0	0	1	1	
4	1	85.80	73.60	73.30	0	96.8	0	55.50	1	425000.0	0	1	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
210	1	80.60	82.00	77.60	0	91.0	0	74.49	1	400000.0	0	1	0	0	
211	1	58.00	60.00	72.00	0	74.0	0	53.62	1	275000.0	0	0	1	1	
212	1	67.00	67.00	73.00	1	59.0	0	69.72	1	295000.0	0	1	0	0	
213	0	74.00	66.00	58.00	0	70.0	1	60.23	1	204000.0	0	1	0	0	
214	1	62.00	58.00	53.00	0	89.0	1	60.22	0	0.0	0	0	1	0	

215 rows × 16 columns

Assigning Independent and Dependent Variables

In [13]:
```
X = p[['gender','ssc_p', 'hsc_p', 'hsc_p','workex','etest_p','mba_p','hsc_s_Arts','hsc_s_Com','hsc_s_Sci','deg_t_Sci','de
y = p['status']
```

Here X conatains all independent variables and y contains the dependent variable.

Train & Test Split

In [14]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.25,random_state=0)
```

Machine Learning Models

Logistic Regression

In [15]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics

logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
```

```
D:\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (sta
tus=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessing.h
tml)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/modu
les/linear_model.html#logistic-regression)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Accuracy

In [16]:
```
logreg.score(X_test, y_test)
```

Out[16]:
```
0.8333333333333334
```

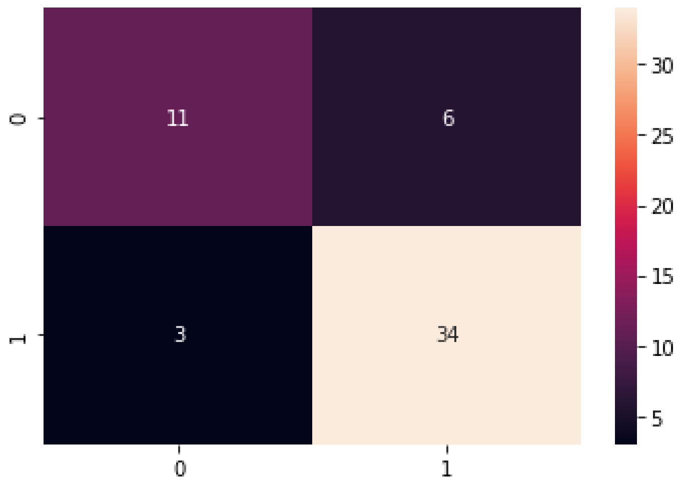
Confusion Matrix and Classification Report

In [17]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix,"\n")
from sklearn.metrics import classification_report
print("Classification Report:\n",classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[11  6]
 [ 3 34]]

Classification Report:
               precision    recall  f1-score   support

           0       0.79      0.65      0.71        17
           1       0.85      0.92      0.88        37

    accuracy                           0.83        54
   macro avg       0.82      0.78      0.80        54
weighted avg       0.83      0.83      0.83        54
```

In [18]:
```
sn.heatmap(confusion_matrix, annot=True)
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x25097f875c8>



KNN Classification

In [19]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import GridSearchCV
import math

knn = KNeighborsClassifier(n_neighbors=-1)
#Hyper Parameters Set

params = {'n_neighbors':[math.floor(math.sqrt(X_train.shape[0])), math.ceil(math.sqrt(X_train.shape[0]))],
          'leaf_size':[1,2,3,5], 'p':[1,2],
          'weights':['uniform', 'distance'],
          'algorithm':['auto', 'ball_tree','kd_tree','brute'],
          'n_jobs':[-1]}
#Making model with hyper parameters sets
knn = GridSearchCV(knn, param_grid=params, n_jobs=1)
knn.fit(X_train,y_train)

#knn.fit(X_train,y_train)
y_pred=knn.predict(X_test)
```

Accuracy

In [20]:
```
knn.score(X_test,y_test)
```

Out[20]:
```
0.7777777777777778
```

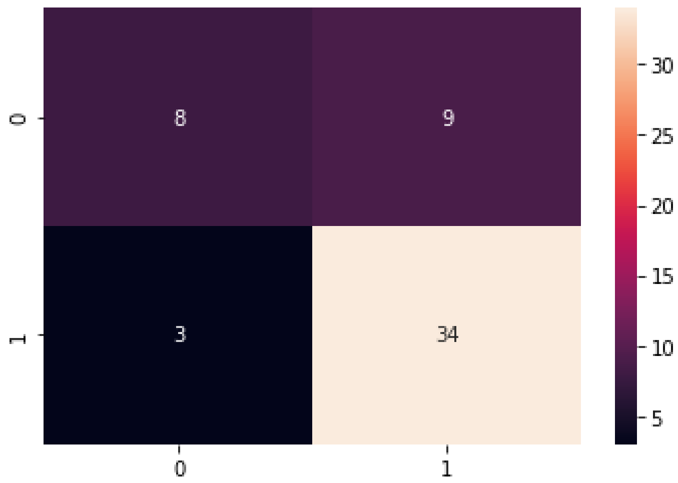
Confusion Matrix and Classification Report

In [21]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix,"\n")
from sklearn.metrics import classification_report
print("Classification Report:\n",classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[ 8  9]
 [ 3 34]]

Classification Report:
               precision    recall  f1-score   support

           0       0.73      0.47      0.57        17
           1       0.79      0.92      0.85        37

    accuracy                           0.78        54
   macro avg       0.76      0.69      0.71        54
weighted avg       0.77      0.78      0.76        54
```

In [22]:
```
sn.heatmap(confusion_matrix, annot=True)
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x25098494848>



Random Forest Classification

In [23]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report
from sklearn import metrics

clf=RandomForestClassifier(n_estimators=20)
clf.fit(X_train,y_train)
y_pred=clf.predict(X_test)
```

Accuracy

In [24]:
```
metrics.accuracy_score(y_test,y_pred)
```

Out[24]:
```
0.7777777777777778
```

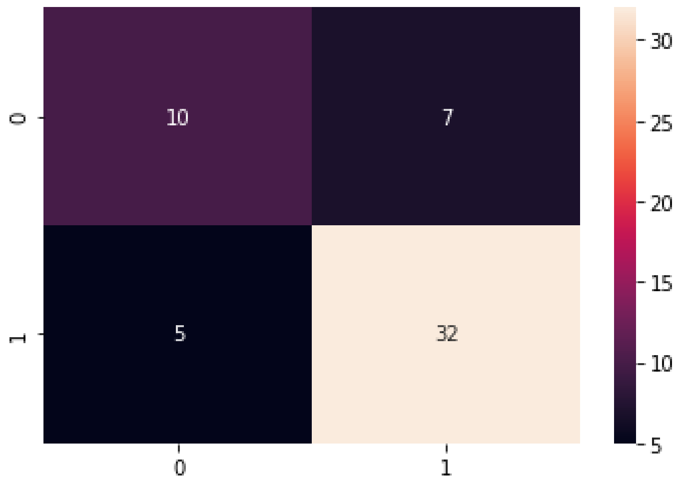
Confusion Matrix and Classification Report

In [25]:
```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:\n",confusion_matrix,"\n")
from sklearn.metrics import classification_report
print("Classification Report:\n",classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[10  7]
 [ 5 32]]

Classification Report:
               precision    recall  f1-score   support

           0       0.67      0.59      0.62        17
           1       0.82      0.86      0.84        37

    accuracy                           0.78        54
   macro avg       0.74      0.73      0.73        54
weighted avg       0.77      0.78      0.77        54
```

In [26]:
```
sn.heatmap(confusion_matrix, annot=True)
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x25098731508>



Comparing Accuracy of 3 models

We see the best model is **Logistic Regression** with **83%** accuracy, followed by **KNN Classification** with **78%** accuracy and **Random Forest Classifier** with **74%** accuracy.

Logistic Regression from Scratch

In [27]:
```
from random import seed
from random import randrange
from csv import reader
from math import exp
```

Writing Functions

In [28]:
```
# Load a CSV file
def load_csv(filename):
    dataset = list()
    with open(filename, 'r') as file:
        csv_reader = reader(file)
        for row in csv_reader:
            if not row:
                continue
            dataset.append(row)
    return dataset

# Convert string column to float
def str_column_to_float(dataset, column):
    for row in dataset:
        row[column] = float(row[column].strip())

# Find the min and max values for each column
def dataset_minmax(dataset):
    minmax = list()
    for i in range(len(dataset[0])):
        col_values = [row[i] for row in dataset]
        value_min = min(col_values)
        value_max = max(col_values)
        minmax.append([value_min, value_max])
    return minmax

# Rescale dataset columns to the range 0-1
def normalize_dataset(dataset, minmax):
    for row in dataset:
        for i in range(len(row)):
            row[i] = (row[i] - minmax[i][0]) / (minmax[i][1] - minmax[i][0])

# Split a dataset into k folds
def cross_validation_split(dataset, n_folds):
    dataset_split = list()
    dataset_copy = list(dataset)
    fold_size = int(len(dataset) / n_folds)
    for i in range(n_folds):
        fold = list()
        while len(fold) < fold_size:
            index = randrange(len(dataset_copy))
```

```
            fold.append(dataset_copy.pop(index))
        dataset_split.append(fold)
    return dataset_split

# Calculate accuracy percentage
def accuracy_metric(actual, predicted):
    correct = 0
    for i in range(len(actual)):
        if actual[i] == predicted[i]:
            correct += 1
    return correct / float(len(actual)) * 100.0

# Evaluate an algorithm using a cross validation split
def evaluate_algorithm(dataset, algorithm, n_folds, *args):
    folds = cross_validation_split(dataset, n_folds)
    scores = list()
    for fold in folds:
        train_set = list(folds)
        train_set.remove(fold)
        train_set = sum(train_set, [])
        test_set = list()
        for row in fold:
            row_copy = list(row)
            test_set.append(row_copy)
            row_copy[-1] = None
        predicted = algorithm(train_set, test_set, *args)
        actual = [row[-1] for row in fold]
        accuracy = accuracy_metric(actual, predicted)
        scores.append(accuracy)
    return scores

# Make a prediction with coefficients
def predict(row, coefficients):
    yhat = coefficients[0]
    for i in range(len(row)-1):
        yhat += coefficients[i + 1] * row[i]
    return 1.0 / (1.0 + exp(-yhat))

# Estimate logistic regression coefficients using stochastic gradient descent
def coefficients_sgd(train, l_rate, n_epoch):
    coef = [0.0 for i in range(len(train[0]))]
    for epoch in range(n_epoch):
```

```
        for row in train:
            yhat = predict(row, coef)
            error = row[-1] - yhat
            coef[0] = coef[0] + l_rate * error * yhat * (1.0 - yhat)
            for i in range(len(row)-1):
                coef[i + 1] = coef[i + 1] + l_rate * error * yhat * (1.0 - yhat) * row[i]
    return coef

# Linear Regression Algorithm With Stochastic Gradient Descent
def logistic_regression(train, test, l_rate, n_epoch):
    predictions = list()
    coef = coefficients_sgd(train, l_rate, n_epoch)
    for row in test:
        yhat = predict(row, coef)
        yhat = round(yhat)
        predictions.append(yhat)
    return(predictions)
```

Making a new CSV file of the customised DataSet

In [29]:
```
p.to_csv("Placement_Data_Full_Class_LR.csv",header=False)
```

Load and Prepare Data

In [30]:
```
dataset = load_csv("Placement_Data_Full_Class_LR.csv")

for i in range(len(dataset[0])):
    str_column_to_float(dataset, i)
```

Normalization

In [31]:
```
minmax = dataset_minmax(dataset)
normalize_dataset(dataset, minmax)
```

Evaluate Algorithm

In [32]:
```
n_folds = 5
l_rate = 0.1
n_epoch = 100
scores = evaluate_algorithm(dataset, logistic_regression, n_folds, l_rate, n_epoch)
print('Scores: %s' % scores)
print('Mean Accuracy: %.3f%%' % (sum(scores)/float(len(scores))))
```

```
Scores: [97.67441860465115, 100.0, 100.0, 97.67441860465115, 100.0]
Mean Accuracy: 99.070%
```

Deleting the New File

In [33]:
```
import os
os.remove("Placement_Data_Full_Class_LR.csv")
```

Questions

1. To get placed with highest Salary Which Degree should be Opted?

In [34]:
```
p_copy
```

Out[34]:

	sl_no	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	workex	etest_p	specialisation	mba_p	status	salary
0	1	M	67.00	Others	91.00	Others	Commerce	58.00	Sci&Tech	No	55.0	Mkt&HR	58.80	Placed	270000.0
1	2	M	79.33	Central	78.33	Others	Science	77.48	Sci&Tech	Yes	86.5	Mkt&Fin	66.28	Placed	200000.0
2	3	M	65.00	Central	68.00	Central	Arts	64.00	Comm&Mgmt	No	75.0	Mkt&Fin	57.80	Placed	250000.0
3	4	M	56.00	Central	52.00	Central	Science	52.00	Sci&Tech	No	66.0	Mkt&HR	59.43	Not Placed	NaN
4	5	M	85.80	Central	73.60	Central	Commerce	73.30	Comm&Mgmt	No	96.8	Mkt&Fin	55.50	Placed	425000.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
210	211	M	80.60	Others	82.00	Others	Commerce	77.60	Comm&Mgmt	No	91.0	Mkt&Fin	74.49	Placed	400000.0
211	212	M	58.00	Others	60.00	Others	Science	72.00	Sci&Tech	No	74.0	Mkt&Fin	53.62	Placed	275000.0
212	213	M	67.00	Others	67.00	Others	Commerce	73.00	Comm&Mgmt	Yes	59.0	Mkt&Fin	69.72	Placed	295000.0
213	214	F	74.00	Others	66.00	Others	Commerce	58.00	Comm&Mgmt	No	70.0	Mkt&HR	60.23	Placed	204000.0
214	215	M	62.00	Central	58.00	Others	Science	53.00	Comm&Mgmt	No	89.0	Mkt&HR	60.22	Not Placed	NaN

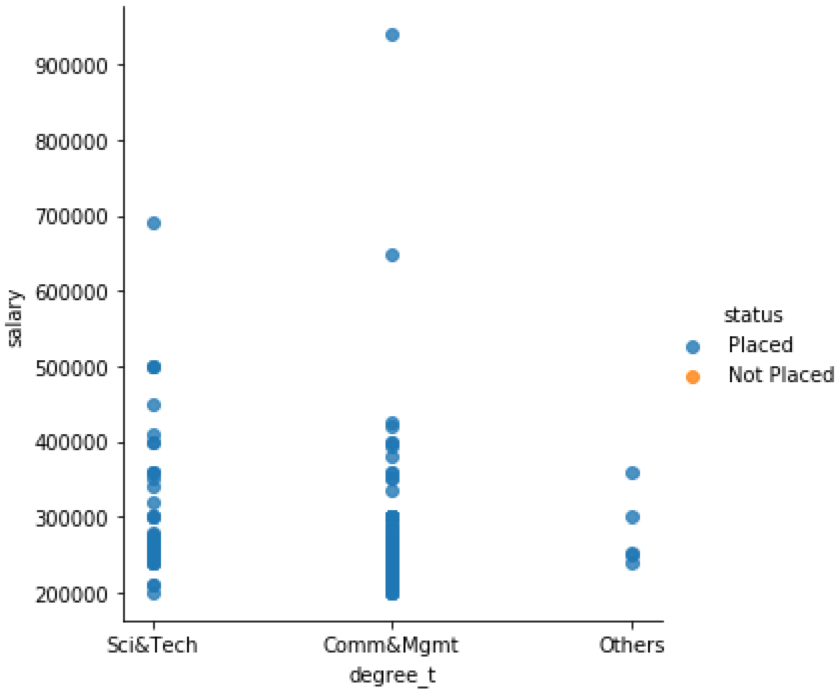
215 rows × 15 columns

In [35]:
```
status_record = p_copy.status.groupby([p_copy.degree_t])
status_record.value_counts()
```

Out[35]:
```
degree_t   status
Comm&Mgmt  Placed        102
           Not Placed     43
Others     Not Placed      6
           Placed          5
Sci&Tech   Placed         41
           Not Placed     18
Name: status, dtype: int64
```

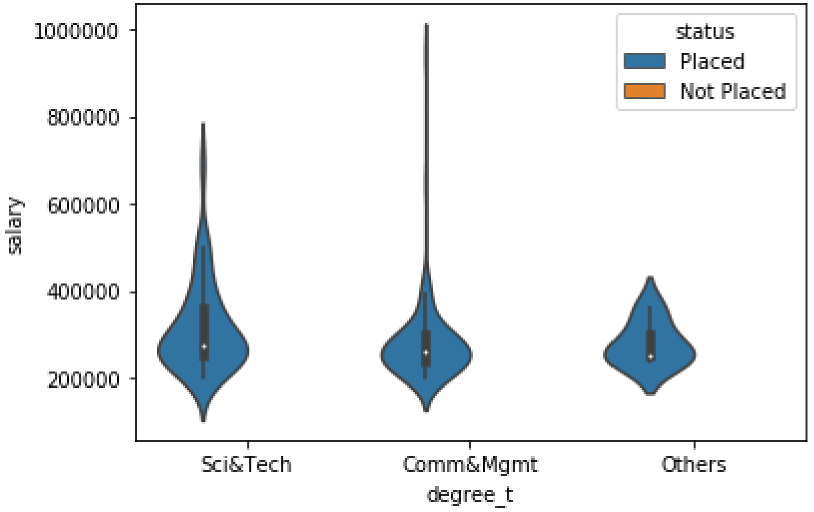
In [36]:
```
sn.lmplot(x ='degree_t', y ='salary', fit_reg = False, hue = 'status', data = p_copy)
```

Out[36]: <seaborn.axisgrid.FacetGrid at 0x250987d3d08>



In [37]:
```
#countplot for above observation
sn.violinplot(x="degree_t", y="salary", data=p_copy, hue='status')
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x25098804b88>



From the above plot, we can say that **Commerce and Management** people are placed with highest salary of all. So most people opt for it.

2. people with which degree and specialisation are more likely to be placed?

In [38]:
```
status_record_2 = p_copy.status.groupby([p_copy.degree_t,p_copy.specialisation])
status_record_2.value_counts()
#placed =1 not placed=0 MKT&HR =1 Mkt&Fin =0
```

Out[38]:
```
degree_t   specialisation  status
Comm&Mgmt  Mkt&Fin         Placed        68
                           Not Placed    18
           Mkt&HR          Placed        34
                           Not Placed    25
Others     Mkt&Fin         Not Placed     2
                           Placed         2
           Mkt&HR          Not Placed     4
                           Placed         3
Sci&Tech   Mkt&Fin         Placed        25
                           Not Placed     5
           Mkt&HR          Placed        16
                           Not Placed    13
Name: status, dtype: int64
```

In [39]:
```
#prob_1 is of people placed, who have degree in comm&mgmt and specialisation in Mkt&Fin
prob_1=68/(68+18)
print("probabability of people placed,who have a degree in comm&mgmt and specialisation in Mkt&Fin",prob_1)
#prob_2 is of people placed , who have degree in comm&mgmt and specialisation in Mkt&HR
prob_2=34/(34+25)
print("probabability of people placed,who have a degree in comm&mgmt and specialisation in Mkt&HR",prob_2)
#prob_3 is of people placed , who have degree in others and specialisation in Mkt&fin
prob_3=2/(2+2)
print("probabability of people placed,who have a degree in others and specialisation in Mkt&Fin",prob_3)
#prob_4 is of people placed , who have degree in others and specialisation in Mkt&HR
prob_4=3/(3+4)
print("probabability of people placed,who have a degree in others and specialisation in Mkt&HR",prob_4)
#prob_5 is of people placed , who have degree in Sci&Tech and specialisation in Mkt&Fin
prob_5=25/(25+5)
print("probabability of people placed,who have a degree in Sci&Tech and specialisation in Mkt&Fin",prob_5)
#prob_6 is of people placed , who have degree in Sci&Tech and specialisation in Mkt&HR
prob_6=16/(16+13)
print("probabability of people placed,who have a degree in Sci&Tech and specialisation in Mkt&HR",prob_6)
```

```
probabability of people placed,who have a degree in comm&mgmt and specialisation in Mkt&Fin 0.7906976744186046
probabability of people placed,who have a degree in comm&mgmt and specialisation in Mkt&HR 0.576271186440678
probabability of people placed,who have a degree in others and specialisation in Mkt&Fin 0.5
probabability of people placed,who have a degree in others and specialisation in Mkt&HR 0.42857142857142855
probabability of people placed,who have a degree in Sci&Tech and specialisation in Mkt&Fin 0.8333333333333334
probabability of people placed,who have a degree in Sci&Tech and specialisation in Mkt&HR 0.5517241379310345
```

In [40]:
```
max(prob_1,prob_2,prob_3,prob_4,prob_5,prob_6)
```

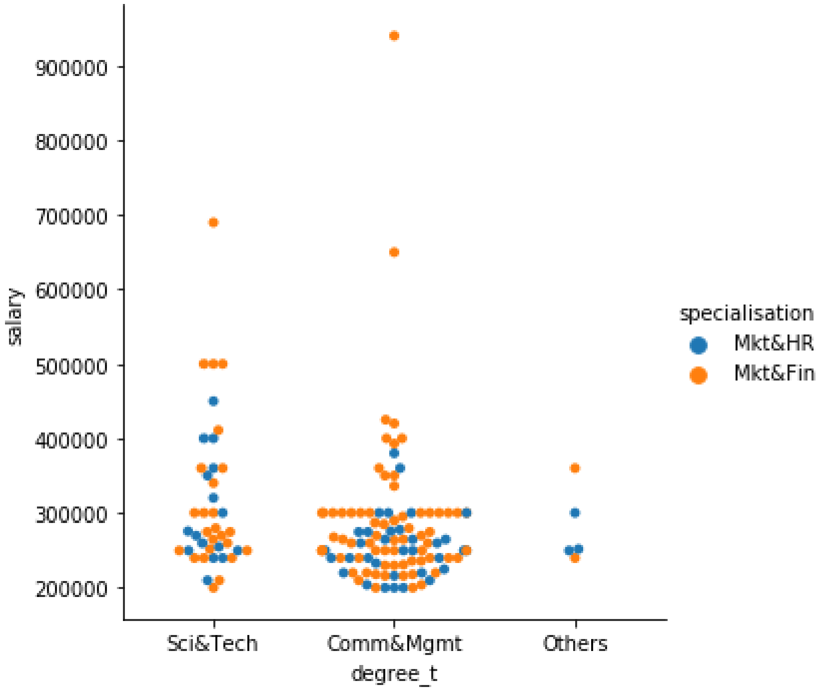
Out[40]:
```
0.8333333333333334
```

Therefore, the people with a degree in Sci&Tech and specialisation in Mkt&Fin are most probably placed.

In [41]:
```
sn.catplot(x="degree_t", y="salary", hue="specialisation", kind="swarm", data=p_copy)
#Mkt&HR is 1 and Mkt&Fin is 0
```

```
D:\anaconda3\lib\site-packages\seaborn\categorical.py:1326: RuntimeWarning: invalid value encountered in less
  off_low = points < low_gutter
D:\anaconda3\lib\site-packages\seaborn\categorical.py:1330: RuntimeWarning: invalid value encountered in greater
  off_high = points > high_gutter
```

Out[41]: <seaborn.axisgrid.FacetGrid at 0x25095ac3608>



According to this dataset, we can see that the highest salary is of the person, who has a degree in Comm&Mgmt and specialisation in Mkt&Fin.

Among people who are not placed, most of them have a specialisation in Mkt&HR.