EDA of Tavel package data

Dataset Attributes:

Customer details:

1. CustomerID: Unique customer ID
2. ProdTaken: Whether the customer has purchased a package or not (0: No, 1: Yes)
3. Age: Age of customer
4. TypeofContact: How customer was contacted (Company Invited or Self Inquiry)
5. CityTier: City tier depends on the development of a city, population, facilities, and living standards. The categories are ordered i.e. Tier 1 > Tier 2 > Tier 3
6. Occupation: Occupation of customer
7. Gender: Gender of customer
8. NumberOfPersonVisiting: Total number of persons planning to take the trip with the customer
9. PreferredPropertyStar: Preferred hotel property rating by customer
10. MaritalStatus: Marital status of customer
11. NumberOfTrips: Average number of trips in a year by customer
12. Passport: The customer has a passport or not (0: No, 1: Yes)
13. OwnCar: Whether the customers own a car or not (0: No, 1: Yes)
14. NumberOfChildrenVisiting: Total number of children with age less than 5 planning to take the trip with the customer
15. Designation: Designation of the customer in the current organization
16. MonthlyIncome: Gross monthly income of the customer

Customer interaction data:

1. PitchSatisfactionScore: Sales pitch satisfaction score
2. ProductPitched: Product pitched by the salesperson
3. NumberOfFollowups: Total number of follow-ups has been done by the salesperson after the sales pitch
4. DurationOfPitch: Duration of the pitch by a salesperson to the customer

Importing Necessary Libraries

In [1]:

```
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.set_option("display.max_columns", None)
# pd.set_option('display.max_rows', None)
pd.set_option("display.max_rows", 200)

from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifi
from xgboost import XGBClassifier
from sklearn import tree
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score, recall_score, precision_score
# For pandas profiling
from pandas_profiling import ProfileReport
```

Load and Explore the Data

In [2]:

```
# C:\Users\sub13\Downloads\Dataset (1)\Dataset\data1
path = 'C:/Users/sub13/Downloads/Dataset (1)/Dataset/data1/Travel.csv'
#data = pd.read_csv(path) #load the data
```

In [3]:

```
data = pd.read_csv(path) #load the data
data.head()
```

Out[3]:

	CustomerID	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	Num
0	200000	1	41.0	Self Enquiry	3	6.0	Salaried	Female	
1	200001	0	49.0	Company Invited	1	14.0	Salaried	Male	
2	200002	1	37.0	Self Enquiry	1	8.0	Free Lancer	Male	
3	200003	0	33.0	Company Invited	1	9.0	Salaried	Female	
4	200004	0	NaN	Self Enquiry	1	8.0	Small Business	Male	

In [4]:
```
data = pd.read_csv(path) #load the data
data.head()
```

Out[4]:

	CustomerID	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	Num
0	200000	1	41.0	Self Enquiry	3	6.0	Salaried	Female	
1	200001	0	49.0	Company Invited	1	14.0	Salaried	Male	
2	200002	1	37.0	Self Enquiry	1	8.0	Free Lancer	Male	
3	200003	0	33.0	Company Invited	1	9.0	Salaried	Female	
4	200004	0	NaN	Self Enquiry	1	8.0	Small Business	Male	

In [5]:
```
df= data.copy() #making a copy to avoid changes to data
print(f"There are {df.shape[0]} rows and {df.shape[1]} columns.")
#checking the shape of the dataset
np.random.seed(15)
df.sample(10) #loading random 10 rows
```

```
There are 4888 rows and 20 columns.
```

Out[5]:

	CustomerID	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	I
4019	204019	0	60.0	Company Invited	2	9.0	Salaried	Female	
1365	201365	1	29.0	Company Invited	3	30.0	Large Business	Male	
473	200473	0	49.0	Self Enquiry	1	24.0	Salaried	Male	
2554	202554	0	52.0	Company Invited	1	7.0	Small Business	Fe Male	
1492	201492	0	34.0	Self Enquiry	1	13.0	Salaried	Fe Male	
3809	203809	1	30.0	Company Invited	3	NaN	Large Business	Male	
4385	204385	0	39.0	Self Enquiry	1	17.0	Small Business	Female	
521	200521	0	27.0	Company Invited	3	NaN	Small Business	Female	
4358	204358	0	49.0	Self Enquiry	3	9.0	Small Business	Female	
475	200475	0	26.0	Self Enquiry	3	34.0	Small Business	Male	

In [6]:
```
df.info() # Looking at the structure of the data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4888 entries, 0 to 4887
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   CustomerID                4888 non-null   int64  
 1   ProdTaken                 4888 non-null   int64  
 2   Age                       4662 non-null   float64
 3   TypeofContact             4863 non-null   object 
 4   CityTier                  4888 non-null   int64  
 5   DurationOfPitch           4637 non-null   float64
 6   Occupation                4888 non-null   object 
 7   Gender                    4888 non-null   object 
 8   NumberOfPersonVisiting    4888 non-null   int64  
 9   NumberOfFollowups         4843 non-null   float64
 10  ProductPitched            4888 non-null   object 
 11  PreferredPropertyStar     4862 non-null   float64
 12  MaritalStatus             4888 non-null   object 
 13  NumberOfTrips             4748 non-null   float64
 14  Passport                  4888 non-null   int64  
 15  PitchSatisfactionScore    4888 non-null   int64  
 16  OwnCar                    4888 non-null   int64  
 17  NumberOfChildrenVisiting  4822 non-null   float64
 18  Designation               4888 non-null   object 
 19  MonthlyIncome             4655 non-null   float64
dtypes: float64(7), int64(7), object(6)
memory usage: 763.9+ KB
```

In [7]:
```
df.ProdTaken.unique()
```

Out[7]:
```
array([1, 0], dtype=int64)
```

Data Pre-Processing:

Fixing Datatypes

In [8]:
```
df.drop(['CustomerID'],axis=1,inplace=True)
```

In [9]:
```
cat_cols = ['CityTier','ProdTaken','NumberOfPersonVisiting','NumberOfChil
df[cat_cols] = df[cat_cols].astype('category')

cols = data.select_dtypes(['object']) #selecting all object datatypes and
for i in cols.columns:
    df[i] = df[i].astype('category')

df.info() #rechecking the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4888 entries, 0 to 4887
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype   
---  ------                   --------------  -----   
 0   ProdTaken                4888 non-null   category
 1   Age                      4662 non-null   float64 
 2   TypeofContact            4863 non-null   category
 3   CityTier                 4888 non-null   category
 4   DurationOfPitch          4637 non-null   float64 
 5   Occupation               4888 non-null   category
 6   Gender                   4888 non-null   category
 7   NumberOfPersonVisiting   4888 non-null   category
 8   NumberOfFollowups        4843 non-null   float64 
 9   ProductPitched           4888 non-null   category
 10  PreferredPropertyStar    4862 non-null   category
 11  MaritalStatus            4888 non-null   category
 12  NumberOfTrips            4748 non-null   float64 
 13  Passport                 4888 non-null   category
 14  PitchSatisfactionScore   4888 non-null   category
 15  OwnCar                   4888 non-null   category
 16  NumberOfChildrenVisiting 4822 non-null   category
 17  Designation              4888 non-null   category
 18  MonthlyIncome            4655 non-null   float64 
dtypes: category(14), float64(5)
memory usage: 260.2 KB
```

- The datatypes have been fixed and the memory reduced.

Missing Value Treatment:

In [10]:
```
df.isna().sum()
```

Out[10]:
```
ProdTaken                     0
Age                         226
TypeofContact                25
CityTier                      0
DurationOfPitch             251
Occupation                    0
Gender                        0
NumberOfPersonVisiting        0
NumberOfFollowups            45
ProductPitched                0
PreferredPropertyStar        26
MaritalStatus                 0
NumberOfTrips               140
Passport                      0
PitchSatisfactionScore        0
OwnCar                        0
NumberOfChildrenVisiting     66
Designation                   0
MonthlyIncome               233
dtype: int64
```

In [11]:
```
missing_numerical = df.select_dtypes(include=np.number).columns.tolist()
missing_numerical.remove('Age')
missing_numerical.remove('MonthlyIncome')
missing_numerical
```

Out[11]:
```
['DurationOfPitch', 'NumberOfFollowups', 'NumberOfTrips']
```

In [12]:
```
df.head()
```

Out[12]:

	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	NumberOfPerson\
0	1	41.0	Self Enquiry	3	6.0	Salaried	Female	
1	0	49.0	Company Invited	1	14.0	Salaried	Male	
2	1	37.0	Self Enquiry	1	8.0	Free Lancer	Male	
3	0	33.0	Company Invited	1	9.0	Salaried	Female	
4	0	NaN	Self Enquiry	1	8.0	Small Business	Male	

In [13]:
```
medianFiller = lambda x: x.fillna(x.median()) #replacing with the Median
df[missing_numerical] = df[missing_numerical].apply(medianFiller,axis=0)
```

In [14]:
```
#we will replace the missing values with median income w.r.t the customer
df["MonthlyIncome"] = df.groupby(['Designation'])['MonthlyIncome'].transf
df["Age"] = df.groupby(['Designation'])['Age'].transform(lambda x: x.fill
```

In [15]:

```
df.tail()
```

Out[15]:

	ProdTaken	Age	TypeofContact	CityTier	DurationOfPitch	Occupation	Gender	NumberOfPers
4883	1	49.0	Self Enquiry	3	9.0	Small Business	Male	
4884	1	28.0	Company Invited	1	31.0	Salaried	Male	
4885	1	52.0	Self Enquiry	3	17.0	Salaried	Female	
4886	1	19.0	Self Enquiry	3	16.0	Small Business	Male	
4887	1	36.0	Self Enquiry	1	14.0	Salaried	Male	

Summary of Numerical Columns

In [16]:

```
df.describe().T
```

Out[16]:

	count	mean	std	min	25%	50%	75%	m
Age	4888.0	37.429828	9.149822	18.0	31.0	36.0	43.00	6
DurationOfPitch	4888.0	15.362930	8.316166	5.0	9.0	13.0	19.00	12
NumberOfFollowups	4888.0	3.711129	0.998271	1.0	3.0	4.0	4.00	(
NumberOfTrips	4888.0	3.229746	1.822769	1.0	2.0	3.0	4.00	2
MonthlyIncome	4888.0	23546.843903	5266.279293	1000.0	20485.0	22413.5	25424.75	9867

In [17]:
```
cat_cols =  df.select_dtypes(['category'])
for i in cat_cols.columns:
    print(cat_cols[i].value_counts())
    print('-'*50)
    print('\n')
```

```
0    3968
1     920
Name: ProdTaken, dtype: int64
--------------------------------------------------


Self Enquiry       3444
Company Invited    1419
Name: TypeofContact, dtype: int64
--------------------------------------------------


1    3190
3    1500
2     198
Name: CityTier, dtype: int64
--------------------------------------------------


Salaried          2368
Small Business    2084
Large Business     434
Free Lancer          2
Name: Occupation, dtype: int64
--------------------------------------------------


Male       2916
Female     1817
Fe Male     155
Name: Gender, dtype: int64
--------------------------------------------------


3    2402
2    1418
4    1026
1      39
5       3
Name: NumberOfPersonVisiting, dtype: int64
--------------------------------------------------


Basic           1842
Deluxe          1732
Standard         742
Super Deluxe     342
King             230
Name: ProductPitched, dtype: int64
--------------------------------------------------
```

```
3.0    2993
5.0     956
4.0     913
Name: PreferredPropertyStar, dtype: int64
--------------------------------------------------


Married      2340
Divorced      950
Single        916
Unmarried     682
Name: MaritalStatus, dtype: int64
--------------------------------------------------


0    3466
1    1422
Name: Passport, dtype: int64
--------------------------------------------------


3    1478
5     970
1     942
4     912
2     586
Name: PitchSatisfactionScore, dtype: int64
--------------------------------------------------


1    3032
0    1856
Name: OwnCar, dtype: int64
--------------------------------------------------


1.0    2080
2.0    1335
0.0    1082
3.0     325
Name: NumberOfChildrenVisiting, dtype: int64
--------------------------------------------------


Executive         1842
Manager           1732
Senior Manager     742
AVP                342
VP                 230
Name: Designation, dtype: int64
--------------------------------------------------
```

Observations:

- In the Gender column, we have an error value Fe Male. We will treat this as an data entry issue and replace it to Female.
- Self Inquiry is the most preffered in TypeofContact feature.
- 3.0 is the highest property rating
- And 1.0 is the highest value for the NumberOfChildrenVisiting column.
- Hence we will replace the missing values in the above columns accordingly

In [18]:
```
#treating missing values in categorical variables
df['TypeofContact'] = df['TypeofContact'].fillna('Self Enquiry')
df['NumberOfChildrenVisiting'] = df['NumberOfChildrenVisiting'].fillna(1.
df['PreferredPropertyStar'] = df['PreferredPropertyStar'].fillna(3.0)

df.Gender = df.Gender.replace('Fe Male','Female') #treating error
```

In [19]:
```
df.isnull().sum()
```

Out[19]:
```
ProdTaken                   0
Age                         0
TypeofContact               0
CityTier                    0
DurationOfPitch             0
Occupation                  0
Gender                      0
NumberOfPersonVisiting      0
NumberOfFollowups           0
ProductPitched              0
PreferredPropertyStar       0
MaritalStatus               0
NumberOfTrips               0
Passport                    0
PitchSatisfactionScore      0
OwnCar                      0
NumberOfChildrenVisiting    0
Designation                 0
MonthlyIncome               0
dtype: int64
```

- All missing values are treated

Summary of Categorical Variables

In [20]:
```
1 df.describe()
```

Out[20]:

	Age	DurationOfPitch	NumberOfFollowups	NumberOfTrips	MonthlyIncome
count	4888.000000	4888.000000	4888.000000	4888.000000	4888.000000
mean	37.429828	15.362930	3.711129	3.229746	23546.843903
std	9.149822	8.316166	0.998271	1.822769	5266.279293
min	18.000000	5.000000	1.000000	1.000000	1000.000000
25%	31.000000	9.000000	3.000000	2.000000	20485.000000
50%	36.000000	13.000000	4.000000	3.000000	22413.500000
75%	43.000000	19.000000	4.000000	4.000000	25424.750000
max	61.000000	127.000000	6.000000	22.000000	98678.000000

In [21]:
```
1 df.describe().T          # T for Transposed display
```

Out[21]:

	count	mean	std	min	25%	50%	75%	m
Age	4888.0	37.429828	9.149822	18.0	31.0	36.0	43.00	6
DurationOfPitch	4888.0	15.362930	8.316166	5.0	9.0	13.0	19.00	12
NumberOfFollowups	4888.0	3.711129	0.998271	1.0	3.0	4.0	4.00	[illegible]
NumberOfTrips	4888.0	3.229746	1.822769	1.0	2.0	3.0	4.00	2
MonthlyIncome	4888.0	23546.843903	5266.279293	1000.0	20485.0	22413.5	25424.75	9867

In [22]:
```
df.describe(include="category").T
# Duration of pitch meaning time taken for presenting business ideas to a
```

Out[22]:

	count	unique	top	freq
ProdTaken	4888	2	0	3968
TypeofContact	4888	2	Self Enquiry	3469
CityTier	4888	3	1	3190
Occupation	4888	4	Salaried	2368
Gender	4888	2	Male	2916
NumberOfPersonVisiting	4888	5	3	2402
ProductPitched	4888	5	Basic	1842
PreferredPropertyStar	4888.0	3.0	3.0	3019.0
MaritalStatus	4888	4	Married	2340
Passport	4888	2	0	3466
PitchSatisfactionScore	4888	5	3	1478
OwnCar	4888	2	1	3032
NumberOfChildrenVisiting	4888.0	4.0	1.0	2146.0
Designation	4888	5	Executive	1842

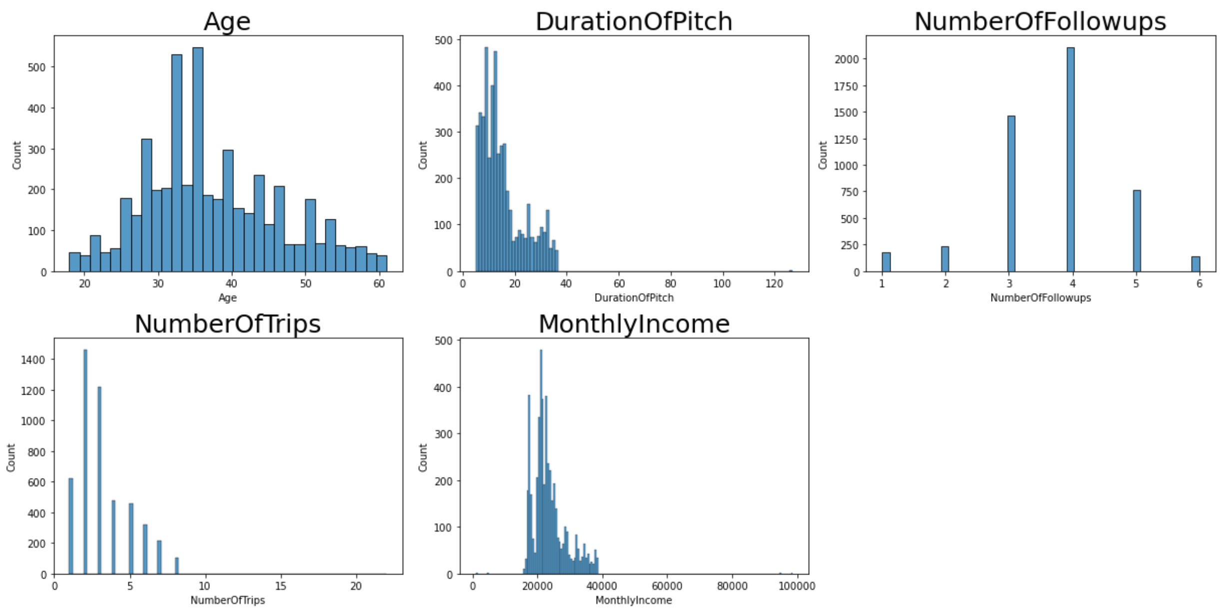
Observations:

- Self Inquiry is the most preffered Type of Contact
- ProdTaken : There is heavy imbalance in this column where atleast 80% customers did not purchase any product
- CityTier : Most customers are from Tier 1
- Occupation : Most customers earn a salary
- Gender : Male customers are slightly higher than Female Customers
- NoOfPersonsVisting: Most customers plan to take atleast 3 additional persons with them in the trip
- ProductPitched : Basic is the popular product
- MaritalStatus : Most customers are married
- Passport : Most customers dont have a passport
- PitchSatisfactionScore : Most customers have rated 3.0
- OwnCar: Most customers own a car
- NumberofChildrenVisting : Most customers plan to take atleast 1 child under five with them for the trip.
- Designation : Most customers belong to Executive designation

Exploratory Data Analysis:

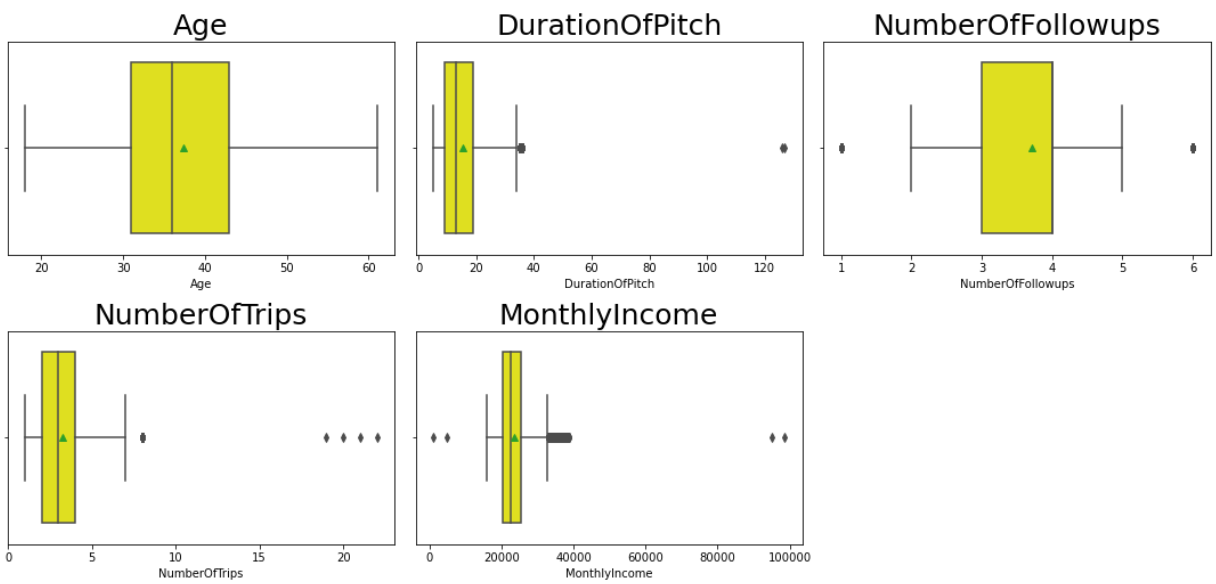
Univariate Analysis - Numerical Columns:

In [23]:
```
#Performing Univariate Analysis to study the central tendency and dispers
#Plotting histogram to study distribution
Uni_num = df.select_dtypes(include=np.number).columns.tolist()
plt.figure(figsize=(17,75))
for i in range(len(Uni_num)):     #creating a loop that will show the plo
    plt.subplot(18,3,i+1)
    sns.histplot(df[Uni_num[i]],kde=False)
    plt.tight_layout()
    plt.title(Uni_num[i],fontsize=25)

plt.show()
```



In [24]:

```
plt.figure(figsize=(15,35))
for i in range(len(Uni_num)):
    plt.subplot(10,3,i+1)
    sns.boxplot(df[Uni_num[i]],showmeans=True, color='yellow')
    plt.tight_layout()
    plt.title(Uni_num[i],fontsize=25)

plt.show()
```



Observations:

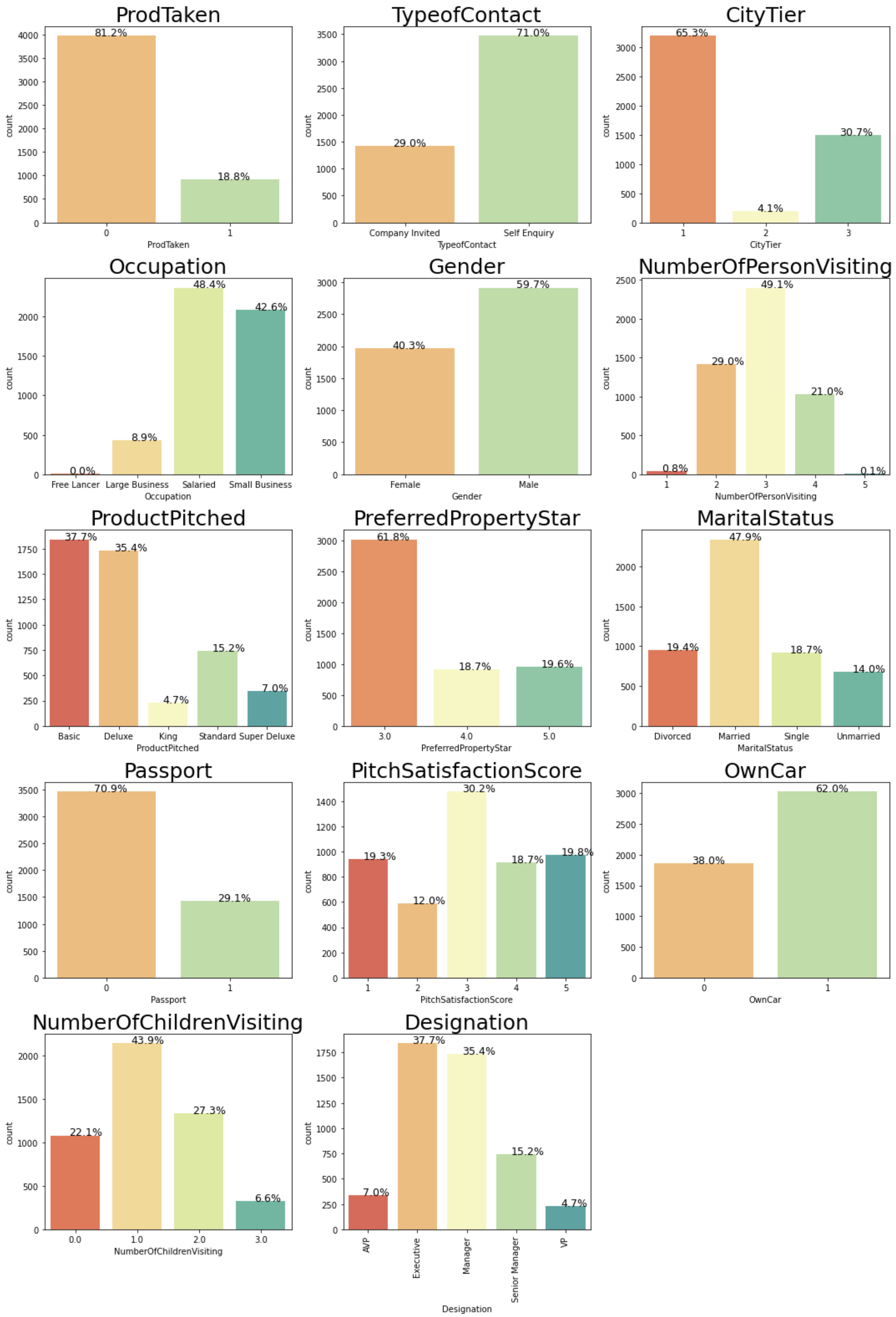
- Age variable is almost normally distributed with no outliers. we see that most customers are in the age brackets 30- 45 yrs.
- DurationofPitch is slightly right-skewed. We see that most customer's pitch duration was under 20 mins. We also see few outliers at 40 mins and at 120+ mins.
- The highest number of followups is 4.0 followed by 3.0.
- NumberofTrips is right-skwed a little and majority of the customers seem to take atleast 3 trips per year. We also see very few outliers in the higher end
- MonthlyIncome is also right-skewd. However, we see that the majority of customers are between income bracket 20K dollars and 30K dollars. We also see two outliers in the low end and on the highest end. There are several outliers after the approx 35K dollars income level.

Univariate Analysis - Categorical Columns:

In [25]:

```
categorical_val = df.select_dtypes(exclude=np.number).columns.tolist()
```

In [26]:
```
plt.figure(figsize=(15,75))
for i in range(len(categorical_val)):     #creating a loop that will show
    plt.subplot(18,3,i+1)
    ax=sns.countplot(df[categorical_val[i]],palette='Spectral')
    plt.tight_layout()
    plt.title(categorical_val[i],fontsize=25)
    total = len (df[categorical_val[i]])
    for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total) # perce
        x = p.get_x() + (p.get_width() / 2)-0.1  # width of the plot
        y = p.get_y() + p.get_height()           # hieght of the plot
        ax.annotate(percentage, (x, y), size = 12.5,color='black') # To a
plt.xticks(rotation=90)
plt.show()
```



Observations:

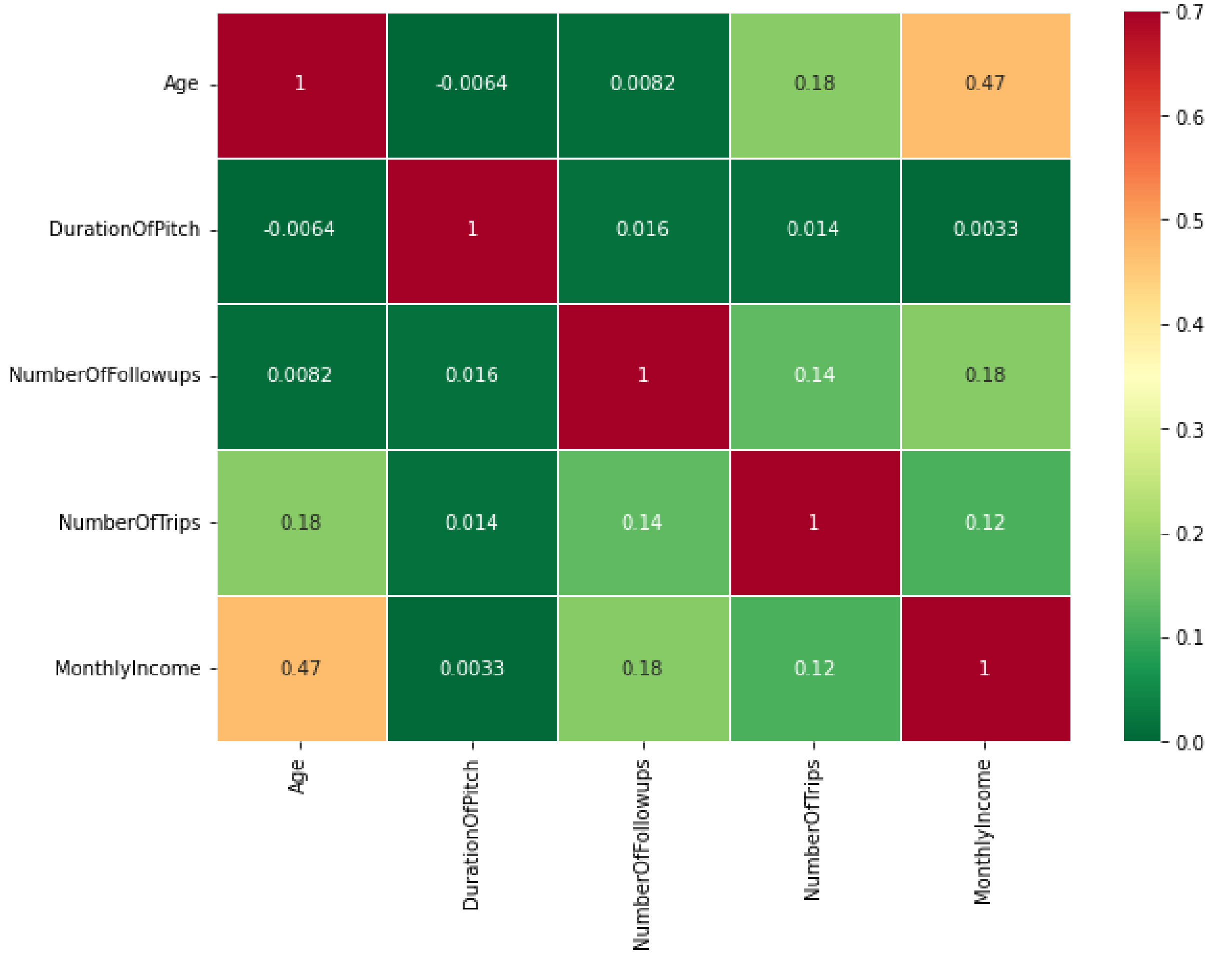
- ProdTaken is the dependent variable. We that only 18.8% of the total customers purchased any of the travel package.The plot shows heavy imbalance in the dataset

- Self-Enquiry is the most preffered contact method by the customers at 71%
- 65.3% of customers are from Tier 1 cities and Tier3 cities comes second at 30.7%.
- 48.4% of customers are Salaried, i.e work for an organization and customers with Small Business are the next highest in Occupation at 42.6%.
- Male customers(59.7%) are higher than Female customers (40.3%)
- 49.1% of customers plan to take atleast 3 persons with them during trip. Around 29% customers want to take 2 people and 21% customers want to take 4 additional persons with them during their travel
- Basic(37.7%) and Deluxe(35.4%) are the most popular travel packages. The next slightly popular one is the Standard Travel package at 15.2%
- 61.8% customers prefer a three star hotel rating compared to four (18.7%) and five (19.6%) star rating hotels
- Married customers form the bulk of the data at 47.9% with Divorced (19.4%) and Single (18.7%) coming in close second and Unmarried(with partners) customers form 14% of the data
- Only 29.1% of customers have a passport and almost 62% of customers own a car
- Only 30.2% of customers rated the Sales Pitch with a score of 3. Even though 18.7% customers rated at 4 and 19.8% rated a pitch score of 5, we also see that 19.3% rated the Sales pitch score at 1. This shows a need for improvement in this area
- Around 43.9% of customers have atleast one child under age Five, planning to accompany them in the travels
- Executive (37.7%) and Manager(35.4%) are the highest Designations of the customers in the dataset

Correlation Matrix

In [27]:

```
corr= df.corr()
plt.figure(figsize=(10,7))
sns.heatmap(corr,annot= True,vmin=0,vmax=0.7, cmap='RdYlGn_r',linewidths=
plt.show()
```



Observations:

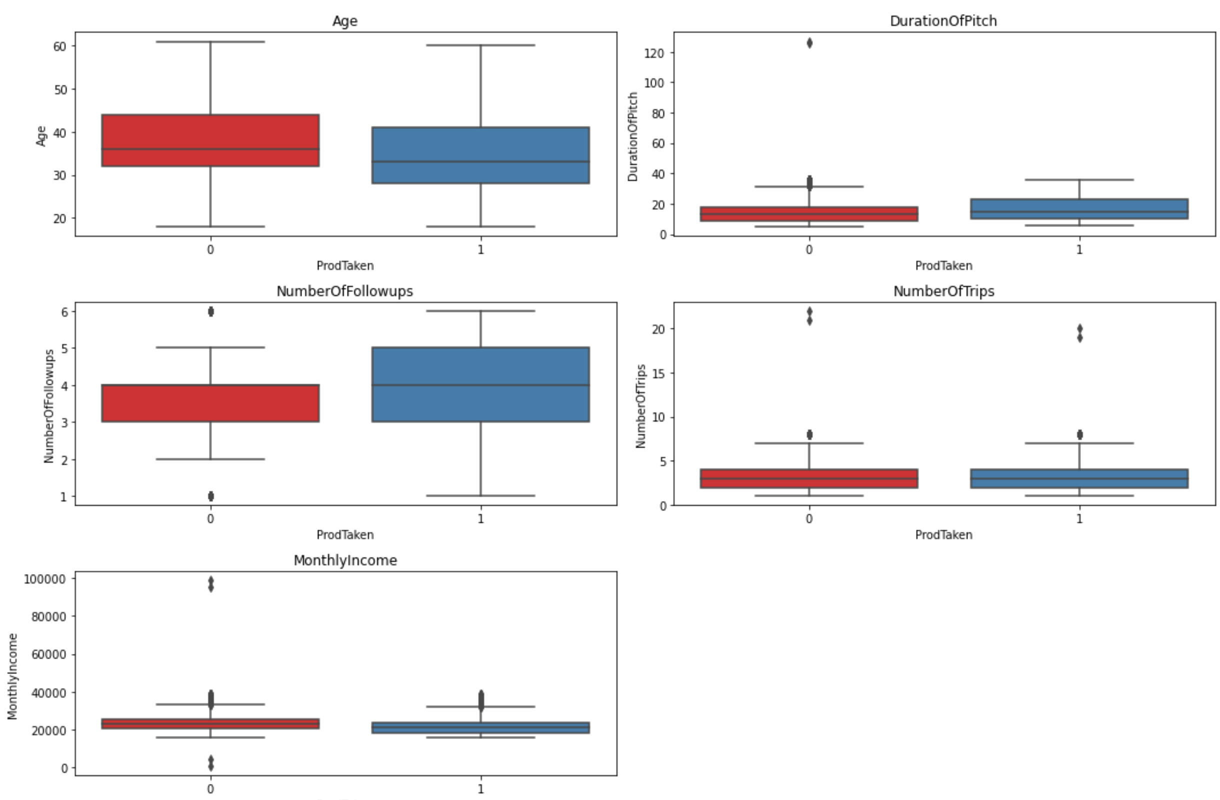
- The correlation values are quite low between all the variables.
- Only Age and DurationofPitch have a very low negative correlation.
- MonthlyIncome and Age have the highest positive correlation at 0.47; i.e as Age increases, so does MontlyIncome
- NumberofFollowups and NumberofTrips have a moderate positive correlation between them and also individually with Monthly Income.

Bivariate Analysis:

- Let's analyse the dependent variable with all the numerical and categorical features and investigate possible relationships

In [28]:

```
# For all numerical variables with Personal_Loan
plt.figure(figsize=(15,10))
for i, variable in enumerate(Uni_num):
                     plt.subplot(3,2,i+1)
                     sns.boxplot(df['ProdTaken'],df[variable],palette="Se
                     plt.tight_layout()
                     plt.title(variable)
plt.show()
```



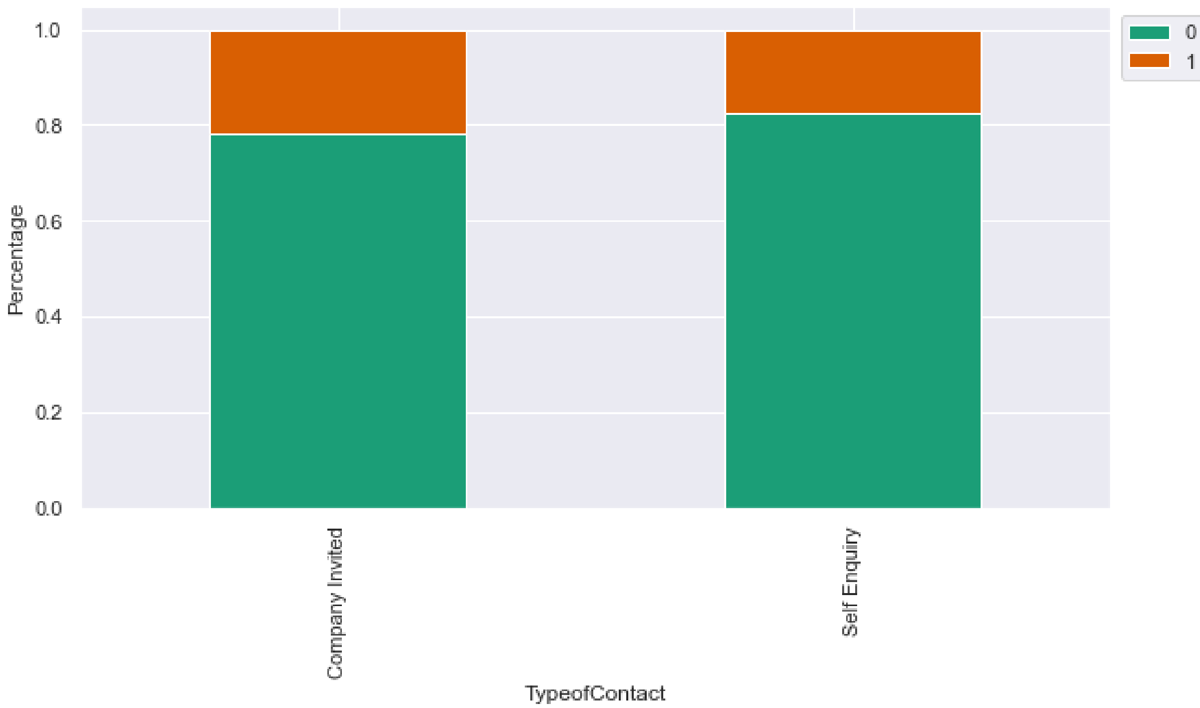
Observations:

- The mean Age for customers who purchased any Product is slightly less than those who didnt. We also see that Age variable doesnt have any outliers.
- The mean DurationofPitch for both classed of ProdTaken is almost equal. We see there are many outliers in Class '0' of ProdTaken, suggesting that longer pitch durations doesnt lead to product purchase.
- Interestingly, Customers who purchased the packages had an average of atleast four followups, compared to customers who didnt.
- The Averages for NumberofTrips and MonthlyIncome;for both Classes of ProdTaken is almost equal. MonthlyIncome variable has several outliers in the higher end for both ProdTaken classes and very few in low end of Class '0'.

In [29]:
```
#Stacked plot of categorical variables with Personal Loans
def stacked_plot(x):
    sns.set(palette='Dark2')
    tab1 = pd.crosstab(x,df['ProdTaken'],margins=True)
    print(tab1)
    print('-'*120)
    tab = pd.crosstab(x,df['ProdTaken'],normalize='index')
    tab.plot(kind='bar',stacked=True,figsize=(10,5))
    plt.legend(loc='lower left', frameon=True)
    plt.legend(loc="upper left", bbox_to_anchor=(1,1))
    plt.ylabel('Percentage')
    plt.show()
```

In [30]:
```
stacked_plot(df.TypeofContact)
```

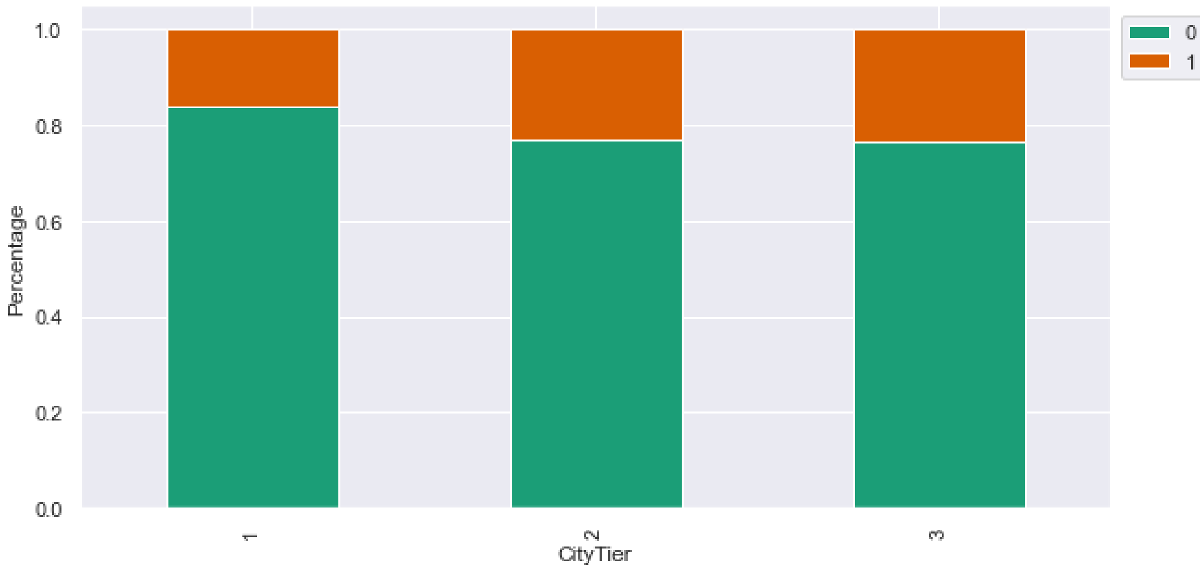
```
ProdTaken           0    1   All
TypeofContact
Company Invited  1109  310  1419
Self Enquiry     2859  610  3469
All              3968  920  4888
----------------------------------------------------------------------------
--------------------------------------------
```



- More Customers with CompanyInvited contact have bought Travel Packages

In [31]:
```
stacked_plot(df.CityTier)
```

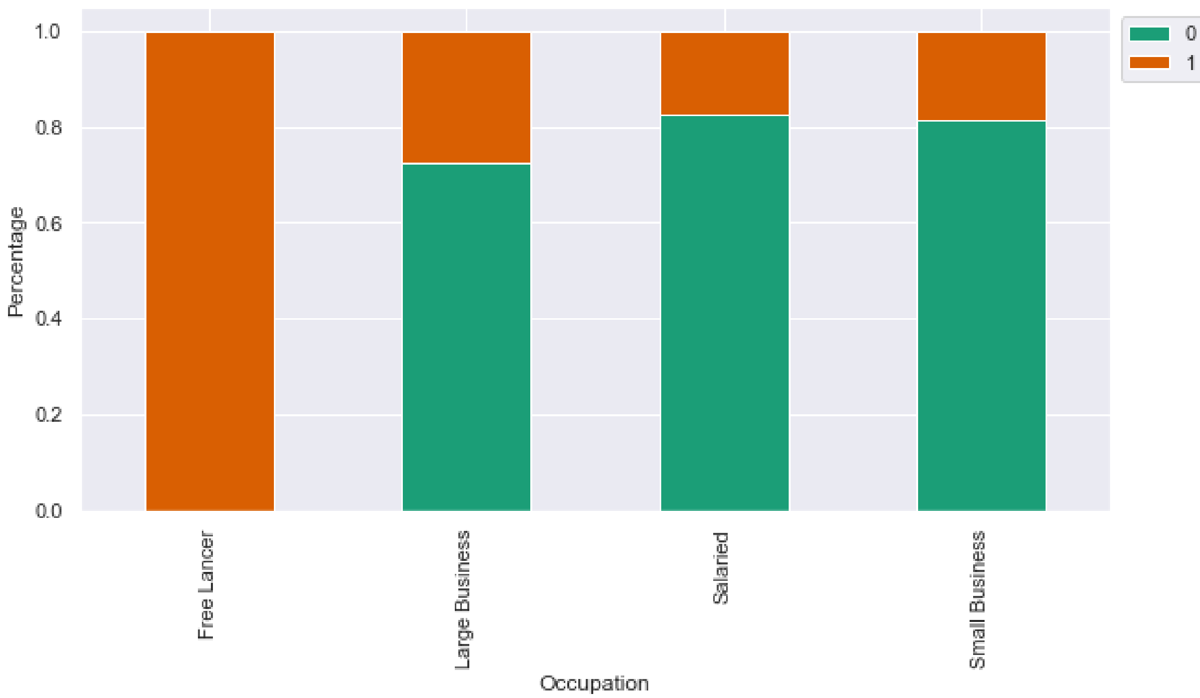
```
ProdTaken     0    1   All
CityTier
1          2670  520  3190
2           152   46   198
3          1146  354  1500
All        3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- More Customers from Tier2 and Tier3 cities have purchased Travel Packages

In [32]:
```
stacked_plot(df.Occupation)
```

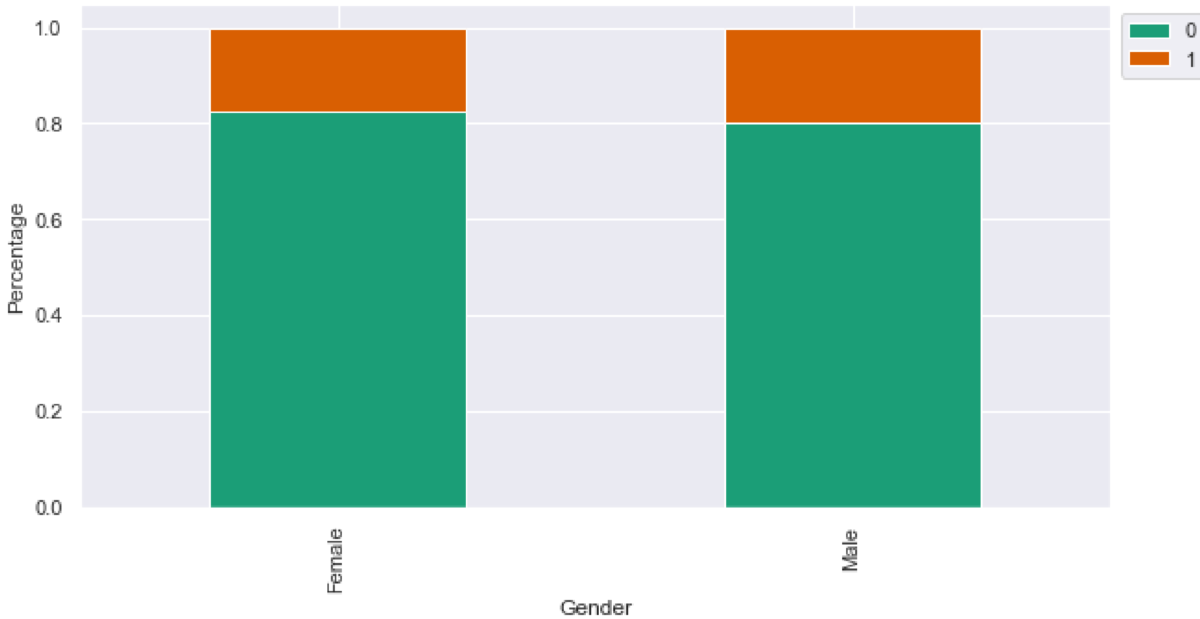
```
ProdTaken          0    1   All
Occupation
Free Lancer        0    2     2
Large Business   314  120   434
Salaried        1954  414  2368
Small Business  1700  384  2084
All             3968  920  4888
----------------------------------------------------------------------------
----------------------------------------
```



- Though customers who are Freelancers by Occupation have bought travel packages, the sample size is only two.
- Of the 434 Large Business owning customers, almost 30% bought travel packages.
- Among Salaried and Small Business owning customers,close to 20% have bought travel packages

In [33]:
```
stacked_plot(df.Gender)
```

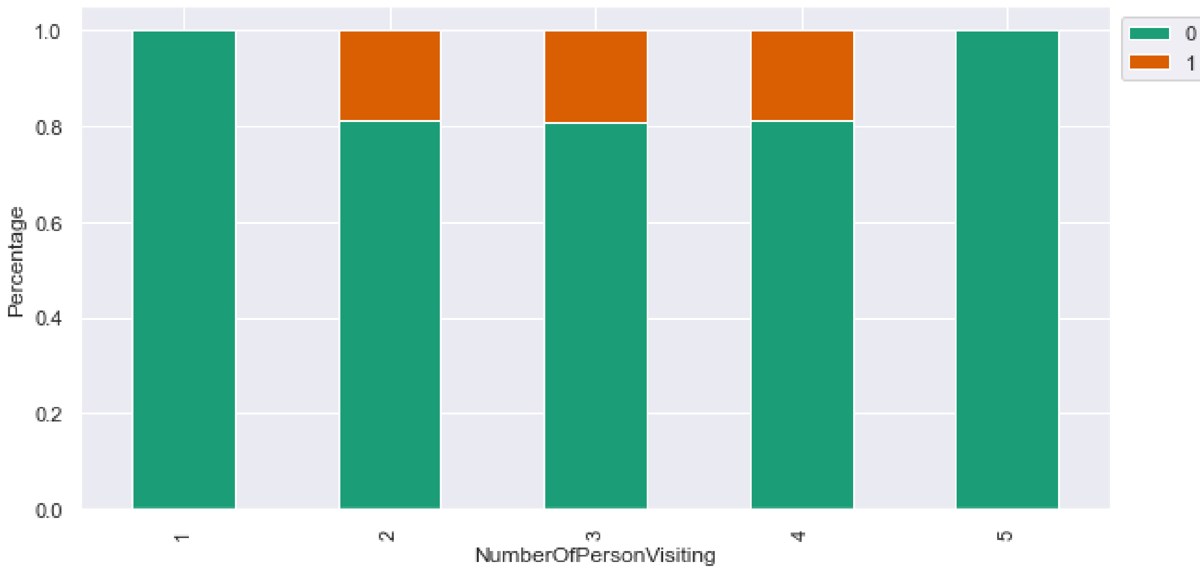
```
ProdTaken     0    1   All
Gender
Female     1630  342  1972
Male       2338  578  2916
All        3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- Despite Male customers being significantly higher than Female customer, the percentage of those who bought travel packages is almost the same(or with minimum difference).

In [34]:
```
1 stacked_plot(df.NumberOfPersonVisiting)
```

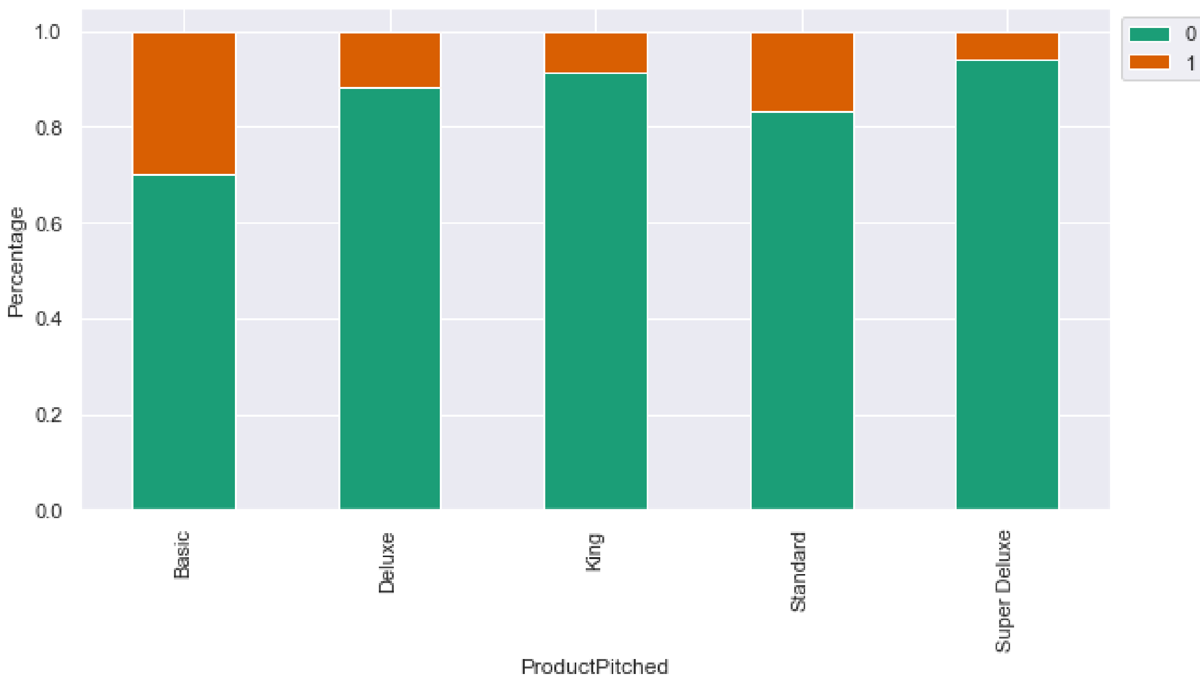
```
ProdTaken                  0    1   All
NumberOfPersonVisiting
1                         39    0    39
2                       1151  267  1418
3                       1942  460  2402
4                        833  193  1026
5                          3    0     3
All                     3968  920  4888
------------------------------------------------------------------------------
----------------------------------------
```



- Among Customers who plan to take between 2-4 persons with them during travel, close to 20% have bought a travel package product.
- Interestingly, we see that all Customers with one companion and five comapanions, did not purchase any product.
- This suugests that the products dont seem either appealing or beneficial to the customers of the above two categories. This area needs further investigation

In [35]:
```
stacked_plot(df.ProductPitched)
```

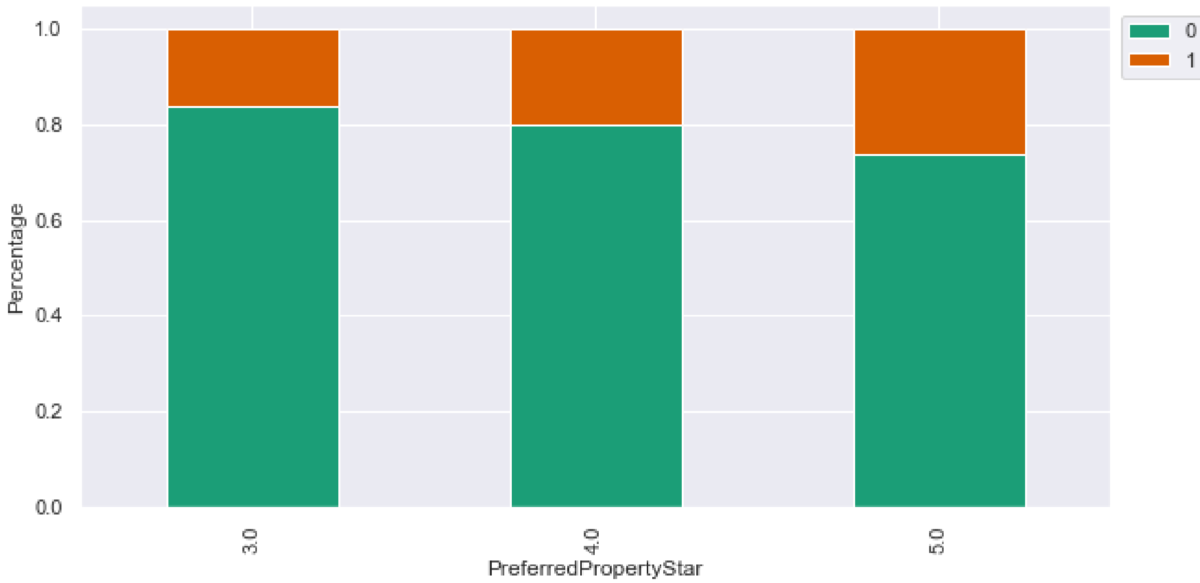
```
ProdTaken          0    1   All
ProductPitched
Basic           1290  552  1842
Deluxe          1528  204  1732
King             210   20   230
Standard         618  124   742
Super Deluxe     322   20   342
All             3968  920  4888
----------------------------------------------------------------------------
--------------------------------------------
```



- The Basic Package is the most preffered, with Standard and Deluxe following up.
- Comparitively very few customers purchased Super Deluxe products

In [36]:
```
stacked_plot(df.PreferredPropertyStar)
```

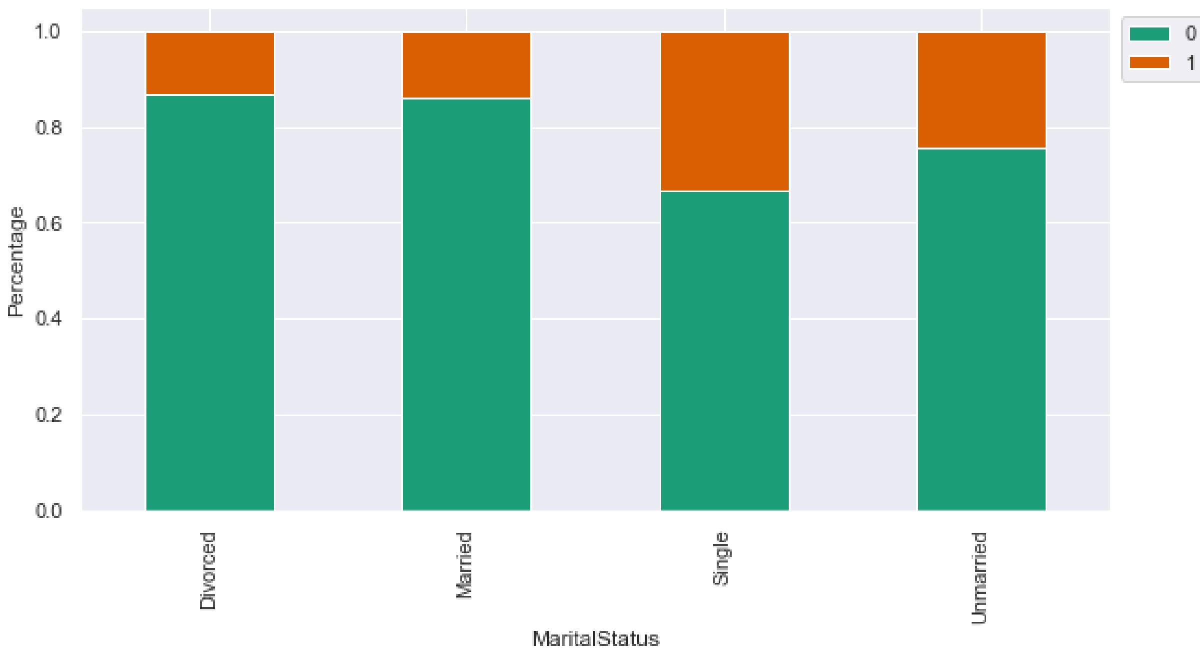
```
ProdTaken                 0    1   All
PreferredPropertyStar
3.0                    2531  488  3019
4.0                     731  182   913
5.0                     706  250   956
All                    3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- Though majority of customers prefer a 3.0 star rated Property, the percentage of customers purchasing the products is comparitively less than customers who prefer a 4.0 and 5.0 star rated property.
- The higher the proprety star rating, higher the number of customers who purchased a product

In [37]:
```
stacked_plot(df.MaritalStatus)
```

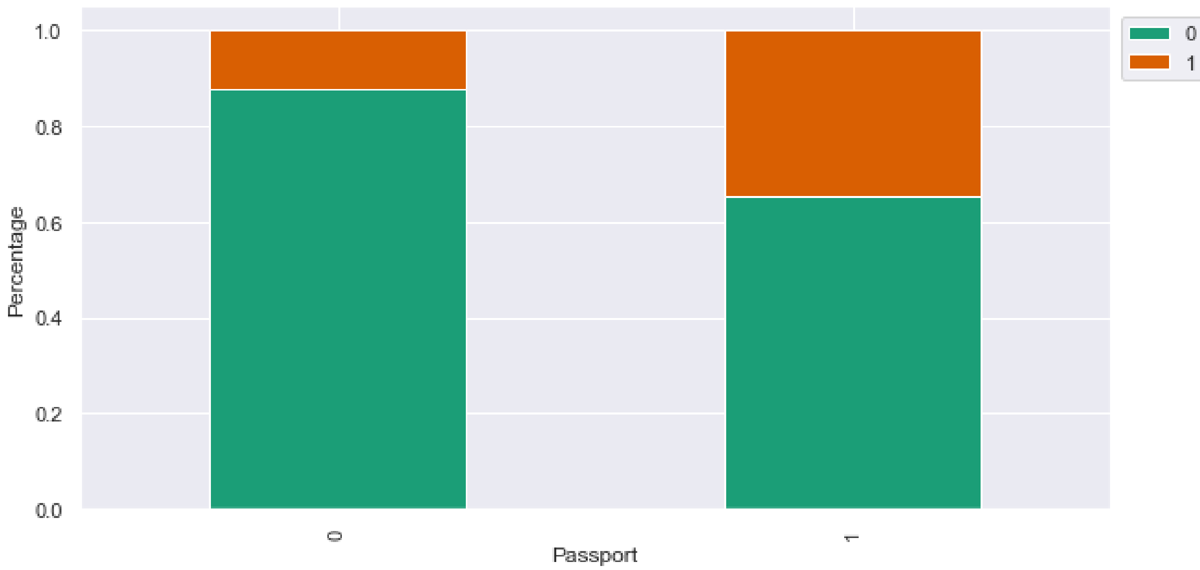
```
ProdTaken         0    1   All
MaritalStatus
Divorced        826  124   950
Married        2014  326  2340
Single          612  304   916
Unmarried       516  166   682
All            3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- Around 30% of all Single customers have bought a product and about 25% of Unmarried customers have also purchased a product
- Almost 50% of the total customers belong to the married category, but we see that only approx 15% of them have actually purchased any product.

In [38]:
```
stacked_plot(df.Passport)
```

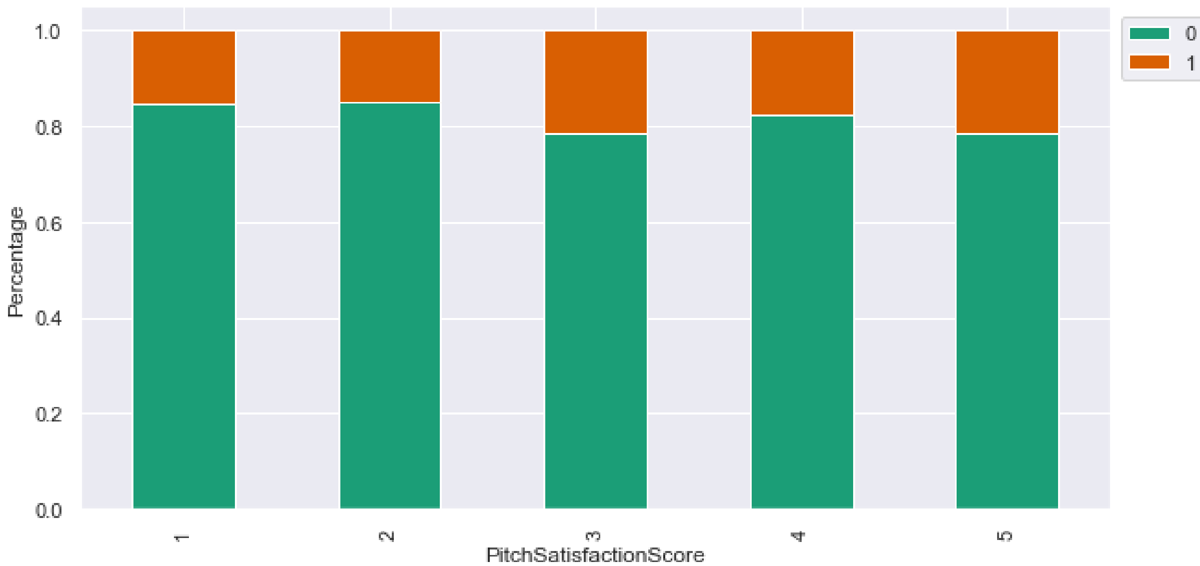
```
ProdTaken     0    1   All
Passport
0          3040  426  3466
1           928  494  1422
All        3968  920  4888
------------------------------------------------------------------------------
---------------------------------------------
```



- More customers with passport tend to purchase products than those who dont.

In [39]:
```
stacked_plot(df.PitchSatisfactionScore)
```

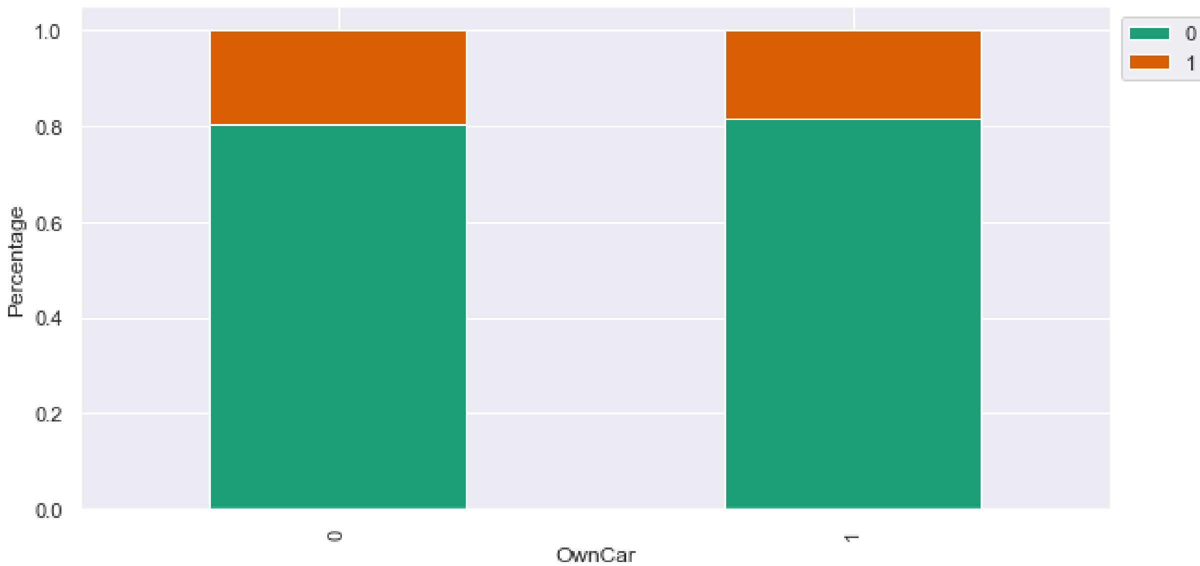
```
ProdTaken                  0    1   All
PitchSatisfactionScore                 
1                        798  144   942
2                        498   88   586
3                       1162  316  1478
4                        750  162   912
5                        760  210   970
All                     3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- Majority of customers have given a score of 3.0 to the Sale pitch for the products.
- But we observe that the number of customers who purchased any product is almost equal across all pitch scores.
- This suggests that a high product pitch score doesnt guarantee purchase

In [40]:
```
stacked_plot(df.OwnCar)
```

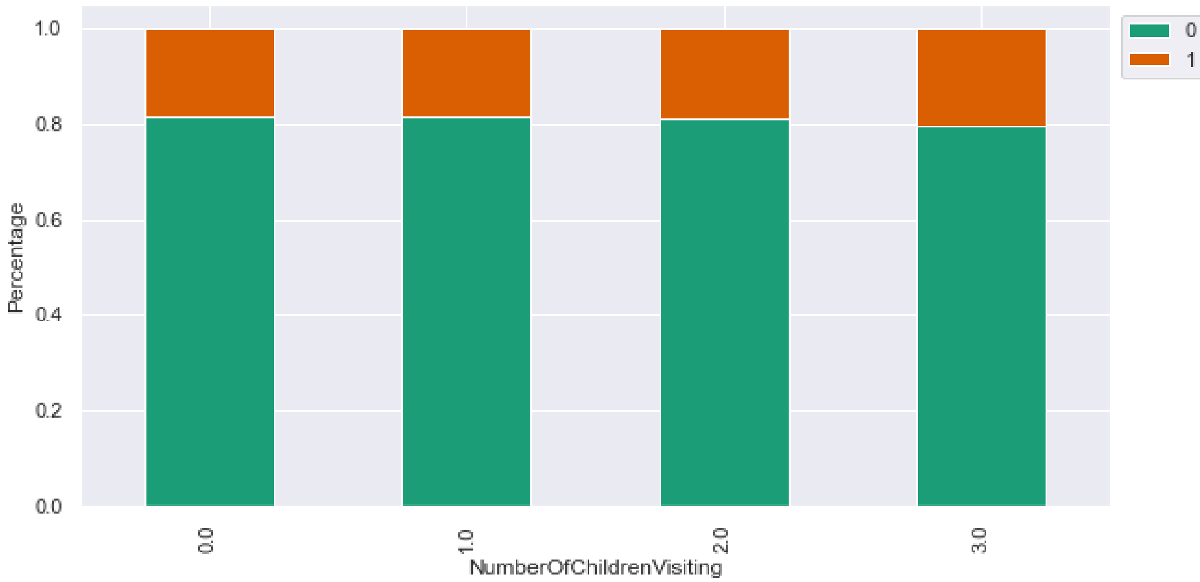
```
ProdTaken     0    1   All
OwnCar
0          1496  360  1856
1          2472  560  3032
All        3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- The number of customers who bought a product is fairly equal across both classes of OwnCar

In [41]:
```
1 stacked_plot(df.NumberOfChildrenVisiting)
```

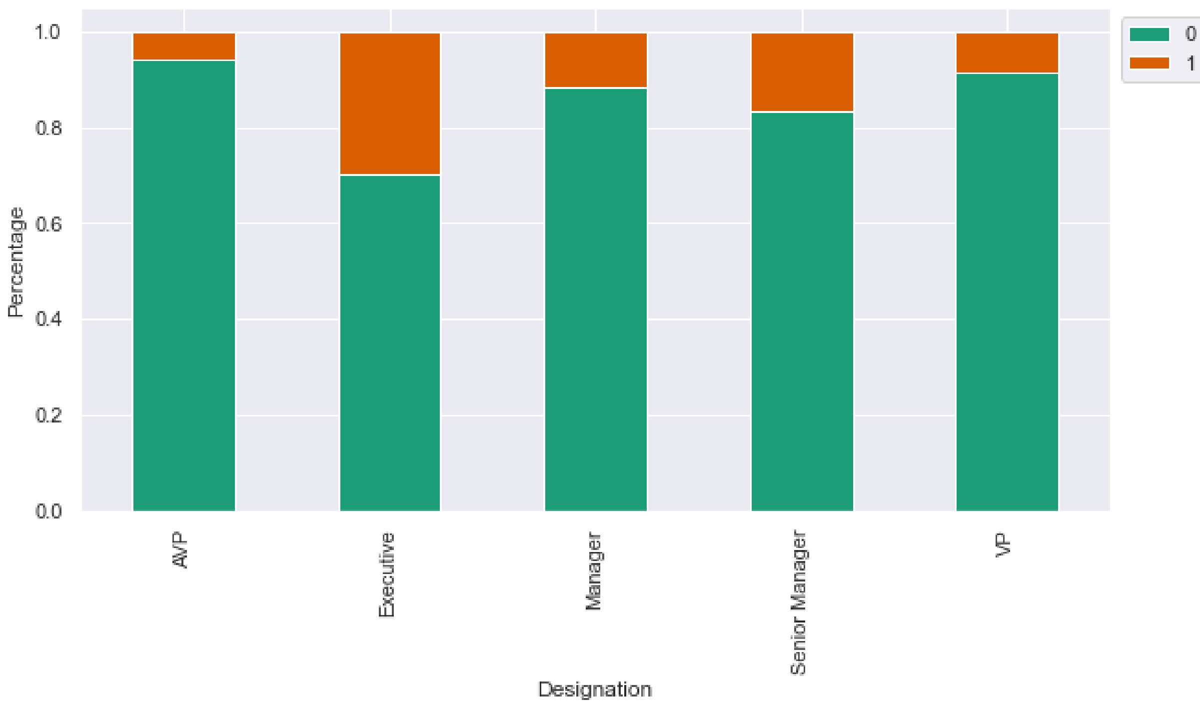
```
ProdTaken                    0    1   All
NumberOfChildrenVisiting
0.0                        880  202  1082
1.0                       1747  399  2146
2.0                       1082  253  1335
3.0                        259   66   325
All                       3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- We see that the percentage of customes who purchased a product is fairly same across all categories of variable NumberOfChildrenVisiting.

In [42]:
```
stacked_plot(df.Designation)
```

```
ProdTaken          0    1   All
Designation
AVP              322   20   342
Executive       1290  552  1842
Manager         1528  204  1732
Senior Manager   618  124   742
VP               210   20   230
All             3968  920  4888
------------------------------------------------------------------------------------------------------------------------
```



- Around 30% Customers with Executive Designation have purchased a product
- Sr. Manager(16%) and Manager(~11%) Designation customers have purchased a product.
- Very few customers of VP and AVP Designation have purchased a product.

Outliers Detection and Treatment :

In [43]:
```
#Let's find the percentage of outliers using IQR
```

In [44]:
```
Q1 = data.quantile(0.25)            #To find the 25th percentile and 75t
Q3 = data.quantile(0.75)

IQR = Q3 - Q1                          #Inter Quantile Range (75th peren

lower=Q1-1.5*IQR                       #Finding lower and upper bounds f
upper=Q3+1.5*IQR
```

In [45]:
```
outlier_num = df.select_dtypes(include=np.number)
```

In [46]:
```
outlier_num
```

Out[46]:

	Age	DurationOfPitch	NumberOfFollowups	NumberOfTrips	MonthlyIncome
0	41.0	6.0	3.0	1.0	20993.0
1	49.0	14.0	4.0	2.0	20130.0
2	37.0	8.0	4.0	7.0	17090.0
3	33.0	9.0	3.0	2.0	17909.0
4	32.0	8.0	3.0	1.0	18468.0
...	...	...	...	...	...
4883	49.0	9.0	5.0	2.0	26576.0
4884	28.0	31.0	5.0	3.0	21212.0
4885	52.0	17.0	4.0	7.0	31820.0
4886	19.0	16.0	4.0	3.0	20289.0
4887	36.0	14.0	4.0	3.0	24041.0

4888 rows × 5 columns

In [47]:
```
((outlier_num<lower)|(outlier_num>upper)).sum()/len(df)*100
```

Out[47]:
```
Age                          0.000000
CityTier                     0.000000
CustomerID                   0.000000
DurationOfPitch              0.040917
MonthlyIncome                7.058101
NumberOfChildrenVisiting     0.000000
NumberOfFollowups            6.382979
NumberOfPersonVisiting       0.000000
NumberOfTrips                2.229951
OwnCar                       0.000000
Passport                     0.000000
PitchSatisfactionScore       0.000000
PreferredPropertyStar        0.000000
ProdTaken                    0.000000
dtype: float64
```

- MonthlyIncome and NumberofFollowups have high outliers compared to the other features.
- However, we will not be treating outliers, as we will be building Decision Tree based models and Decision Tree models are not influenced by Outliers.
- Furthermore, in real case scenario, we will encounter similar outliers and that would require the model to investigate if there is any pattern among the customers

In [ ]:
```

```