In [1]:

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

In [2]:

```python
# Reading dataset
mkt_data = pd.read_csv(r'C:\Users\mannu\Desktop\bank.csv')
```

In [3]:

```python
# First view
mkt_data.head()
```

Out[3]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
0	59	admin.	married	secondary	no	2343	yes	no	unknown	5	may	1042	1	-1	0	unknown	yes
1	56	admin.	married	secondary	no	45	no	no	unknown	5	may	1467	1	-1	0	unknown	yes
2	41	technician	married	secondary	no	1270	yes	no	unknown	5	may	1389	1	-1	0	unknown	yes
3	55	services	married	secondary	no	2476	yes	no	unknown	5	may	579	1	-1	0	unknown	yes
4	54	admin.	married	tertiary	no	184	no	no	unknown	5	may	673	2	-1	0	unknown	yes

In [4]:

```python
# Checking for null values
mkt_data.isnull().sum().sum()
```

Out[4]:

0

In [5]:

```python
# finding qualitative and quantitative columns
quant_columns = []
qual_columns = []
for column in mkt_data.columns:
    if mkt_data[column].dtype == 'int64':
        quant_columns.append(column)
    else:
        qual_columns.append(column)
print(f' There are {len(quant_columns)} Quantitative columns, namely: {quant_columns}')
print(f'There are {len(qual_columns)} Qualitative columns, namely: {qual_columns}')
```

```
 There are 7 Quantitative columns, namely: ['age', 'balance', 'day', 'duration', 'campaign', 'pdays', 'previous']
There are 10 Qualitative columns, namely: ['job', 'marital', 'education', 'default', 'housing', 'loan', 'contact', 'month', 'poutcome', 'deposit']
```

In [6]:

```python
# A high level review of quantitative columns:
mkt_data.describe()
```

Out[6]:

	age	balance	day	duration	campaign	pdays	previous
count	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000	11162.000000
mean	41.231948	1528.538524	15.658036	371.993818	2.508421	51.330407	0.832557
std	11.913369	3225.413326	8.420740	347.128386	2.722077	108.758282	2.292007
min	18.000000	-6847.000000	1.000000	2.000000	1.000000	-1.000000	0.000000
25%	32.000000	122.000000	8.000000	138.000000	1.000000	-1.000000	0.000000
50%	39.000000	550.000000	15.000000	255.000000	2.000000	-1.000000	0.000000
75%	49.000000	1708.000000	22.000000	496.000000	3.000000	20.750000	1.000000
max	95.000000	81204.000000	31.000000	3881.000000	63.000000	854.000000	58.000000

- #### The mean age is 41 with a standard deviation of 11~12

In [7]:

```python
# High level view of unique values in qualitative columns:
for names in qual_columns:
    print(f'{names.upper()}:{mkt_data[names].unique()}')
```

```
JOB:['admin.' 'technician' 'services' 'management' 'retired' 'blue-collar'
 'unemployed' 'entrepreneur' 'housemaid' 'unknown' 'self-employed'
 'student']
MARITAL:['married' 'single' 'divorced']
EDUCATION:['secondary' 'tertiary' 'primary' 'unknown']
DEFAULT:['no' 'yes']
HOUSING:['yes' 'no']
LOAN:['no' 'yes']
CONTACT:['unknown' 'cellular' 'telephone']
MONTH:['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar' 'apr' 'sep']
POUTCOME:['unknown' 'other' 'failure' 'success']
DEPOSIT:['yes' 'no']
```

In [8]:

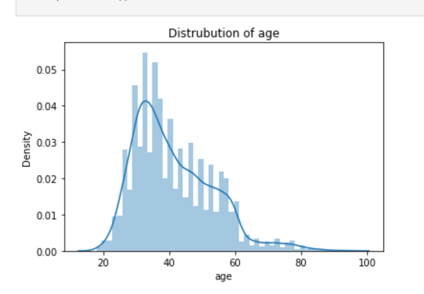
```python
# Binary Columns:
for names in qual_columns:
    if mkt_data[names].nunique() == 2:
        print(names)
```

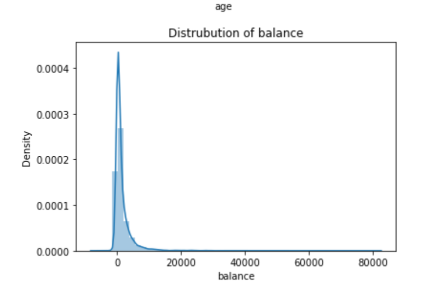
```
default
housing
loan
deposit
```

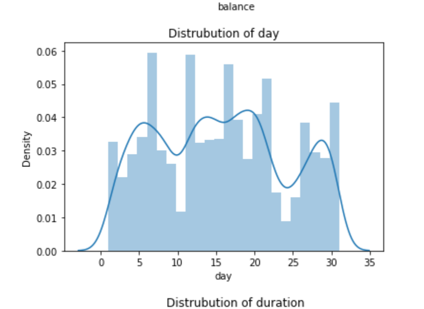
To get a feel of data we use distribution plots for quantitative values

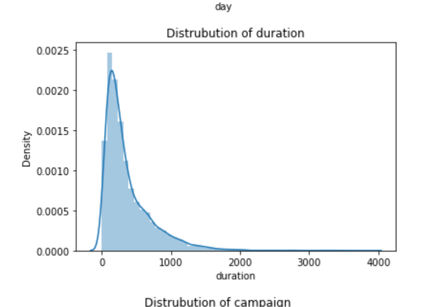
In [9]:

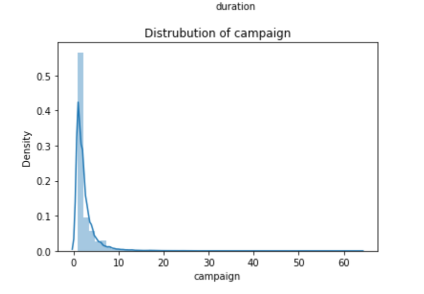
```python
for column in quant_columns:
    sns.distplot(mkt_data[column])
    plt.title(f'Distrubution of {column}')
    plt.show()
```

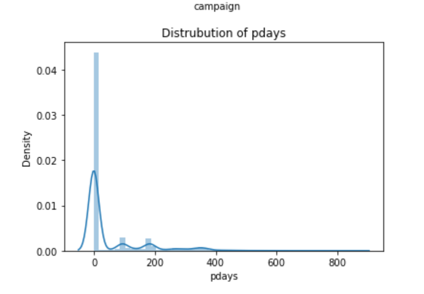


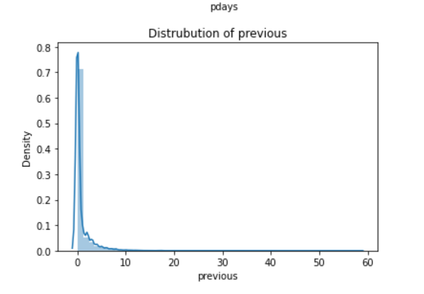












In [10]:

```python
# Finding overall conversion rate for marketing campaign
len((mkt_data[mkt_data['poutcome'] == 'success']))/len(mkt_data) * 100
```

Out[10]:

9.595054649704354

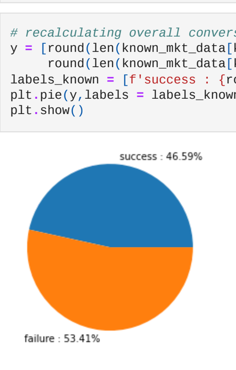
- #### Over-all conversion rate is low.
  - However this is mis-leading, since there are unknown values in poutcome column, which means that these audiences' decisions are not known and that may be due to many reasons
- #### To fix this, I will create a sub-database of where values in poutcome are either success or failure.

In [11]:

```python
known_mkt_data = mkt_data[mkt_data['poutcome'].isin(['success','failure'])]
```

In [12]:

```python
# recalculating overall conversion rate of campaign:
y = [round(len(known_mkt_data[known_mkt_data['poutcome'] == 'success'])/len(known_mkt_data) * 100,2),
     round(len(known_mkt_data[known_mkt_data['poutcome'] == 'failure'])/len(known_mkt_data) * 100,2)]
labels_known = [f'success : {round(y[0],2)}%',f'failure : {round(y[1],2)}%']
plt.pie(y,labels = labels_known)
plt.show()
```



- ## Methodology:
  - > I will Analyze the data on known marketing dataset i,e dataset with only success and failure values which will allow me to find actionable insights as to what are the markers of audiences which are contributing to a higher conversion rate.

In [13]:

```python
# Splitting data on the bases of poutcomes for simplicity:
success_data = known_mkt_data[known_mkt_data['poutcome'] == 'success']
failure_data = known_mkt_data[known_mkt_data['poutcome'] == 'failure']
```

- #### Calculating conversion rates for unique values in qualitative columns to find trends.

1. Job

In [14]:

```python
# Finding out Conversion Rates grouped by job types.
job_conv = (success_data.groupby('job').count()['poutcome']
            /
            known_mkt_data.groupby('job').count()['poutcome'] * 100).sort_values(ascending = False).reset_index()
```

In [15]:

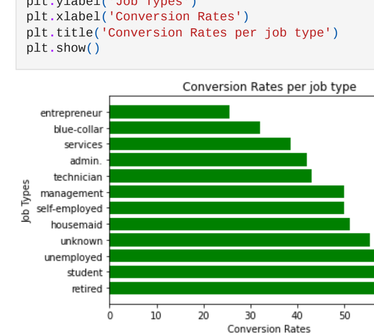
```python
job_conv
```

Out[15]:

	job	poutcome
0	retired	64.903846
1	student	60.909091
2	unemployed	59.770115
3	unknown	55.555556
4	housemaid	51.162791
5	self-employed	50.000000
6	management	49.914530
7	technician	43.013699
8	admin.	42.006270
9	services	38.509317
10	blue-collar	32.142857
11	entrepreneur	25.531915

In [16]:

```python
plt.barh(job_conv['job'],width=job_conv['poutcome'], color = 'g')
plt.ylabel('Job Types')
plt.xlabel('Conversion Rates')
plt.title('Conversion Rates per job type')
plt.show()
```



- #### Job type has a high correlation and is following a trend, to capture this trend I will create a dataframe of best performing jobs which have a conversation rate that is higher than overall conversion rate.

In [17]:

```python
#Filtering out job types that have a higher than normal conversion rate.
job_targets = job_conv[job_conv['poutcome'] >=
                       (len(known_mkt_data[known_mkt_data['poutcome'] == 'success'])/len(known_mkt_data) * 100)]
```

In [18]:

```python
job_targets
```

Out[18]:

	job	poutcome
0	retired	64.903846
1	student	60.909091
2	unemployed	59.770115
3	unknown	55.555556
4	housemaid	51.162791
5	self-employed	50.000000
6	management	49.914530

2. Marital Status

In [19]:

```python
#Calculating Conversion Rates grouped by Marital Status
marital_conv = ((success_data.groupby('marital').count()['poutcome']
                 /
                 known_mkt_data.groupby('marital').count()['poutcome']) * 100).sort_values(ascending= False).reset_index()
```

In [20]:

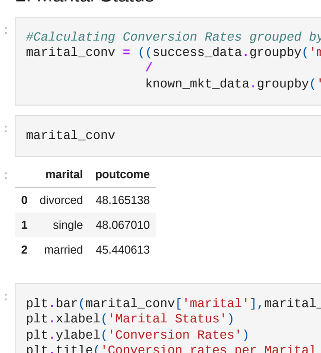
```python
marital_conv
```

Out[20]:

	marital	poutcome
0	divorced	48.165138
1	single	48.067010
2	married	45.440613

In [21]:

```python
plt.bar(marital_conv['marital'],marital_conv['poutcome'],width = 0.4)
plt.xlabel('Marital Status')
plt.ylabel('Conversion Rates')
plt.title('Conversion rates per Marital Status')
plt.show()
```



- #### Marital Status does not indicate any substantial correlation to conversion rates.

3. Education

In [22]:

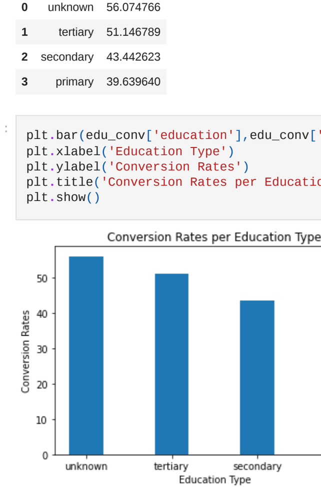
```python
# Calculating Conversion Rates grouped by Education Level/Type.
edu_conv = ((success_data.groupby('education').count()['poutcome']
             /
             known_mkt_data.groupby('education').count()['poutcome']) * 100).sort_values(ascending= False).reset_index()
edu_conv
```

Out[22]:

	education	poutcome
0	unknown	56.074766
1	tertiary	51.146789
2	secondary	43.442623
3	primary	39.639640

In [23]:

```python
plt.bar(edu_conv['education'],edu_conv['poutcome'],width = 0.4)
plt.xlabel('Education Type')
plt.ylabel('Conversion Rates')
plt.title('Conversion Rates per Education Type')
plt.show()
```



- #### Since Education has unknown values it cannot be relied upon, however we get to know that people with declared primary education are less likely to respond positively to this marketing campaign, i.e have a negative correlation

4.Default- Has a Credit Default.

In [24]:

```python
# Calculating Conversion Rates grouped by Default/Credit Default.
default_conv = ((success_data.groupby('default').count()['poutcome']
                 /
                 known_mkt_data.groupby('default').count()['poutcome']) * 100).sort_values(ascending= False).reset_index()
default_conv
```

Out[24]:

	default	poutcome
0	no	46.748145
1	yes	NaN

In [25]:

```python
known_mkt_data.groupby('default').count()['poutcome']
```

Out[25]:

```
default
no     2291
yes       8
Name: poutcome, dtype: int64
```

In [26]:

```python
success_data.groupby('default').count()
```

Out[26]:

	age	job	marital	education	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
default																
no	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071	1071

- #### Having a credit default is inconclusive, i.e. more data is required to see it's effect correctly, however there are absolutely no people who have both responded positively to marketing campaign and have a credit default.

5. Housing, whether person has a house or is on rent

In [27]:

```python
# Calculating Conversion Rates on criteria whether a person is a house-owner or not.
housing_conv = ((success_data.groupby('housing').count()['poutcome']
                 /
                 known_mkt_data.groupby('housing').count()['poutcome']) * 100).sort_values(ascending= False).reset_index()
```

In [28]:

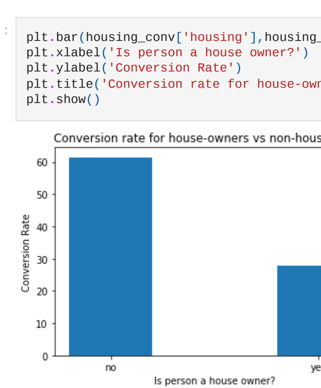
```python
housing_conv
```

Out[28]:

	housing	poutcome
0	no	61.466459
1	yes	27.826942

In [29]:

```python
plt.bar(housing_conv['housing'],housing_conv['poutcome'],width = 0.4)
plt.xlabel('Is person a house owner?')
plt.ylabel('Conversion Rate')
plt.title('Conversion rate for house-owners vs non-house-owners')
plt.show()
```



- #### Not being a house owner has a high positive correlation to conversion rates.

6. Loan: If the person has a loan or not

In [30]:

```python
# Calculating Conversion Rates on criteria of whether a person has a loan or not
loan_conv = ((success_data.groupby('loan').count()['poutcome']
              /
              known_mkt_data.groupby('loan').count()['poutcome']) * 100 ).sort_values(ascending = False).reset_index()
```

In [31]:

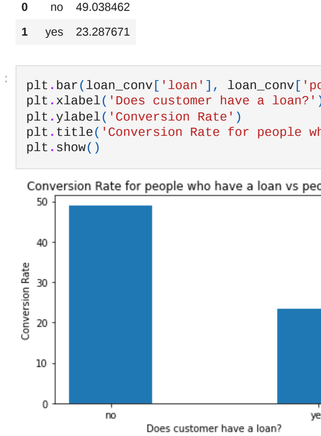
```python
loan_conv
```

Out[31]:

	loan	poutcome
0	no	49.038462
1	yes	23.287671

In [32]:

```python
plt.bar(loan_conv['loan'], loan_conv['poutcome'],width = 0.4)
plt.xlabel('Does customer have a loan?')
plt.ylabel('Conversion Rate')
plt.title('Conversion Rate for people who have a loan vs people who don\'t')
plt.show()
```



- #### People who don't have a loan are not affecting the conversion-rate in a way that is significant, however people who have a loan are doing so negatively.

7. Mode of contact

In [33]:

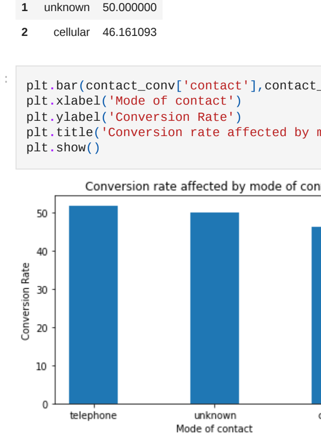
```python
# Calculating conversion rates for different mode of contacts.
contact_conv = ((success_data.groupby('contact').count()['poutcome']
                 /
                 known_mkt_data.groupby('contact').count()['poutcome']) * 100 ).sort_values(ascending = False).reset_index()
contact_conv
```

Out[33]:

	contact	poutcome
0	telephone	51.829268
1	unknown	50.000000
2	cellular	46.161093

In [34]:

```python
plt.bar(contact_conv['contact'],contact_conv['poutcome'],width=0.4)
plt.xlabel('Mode of contact')
plt.ylabel('Conversion Rate')
plt.title('Conversion rate affected by mode of contact')
plt.show()
```



- #### Despite there being an unknown value mode of contact shows no statistical value.

8. Time of year/Season/Month

In [35]:

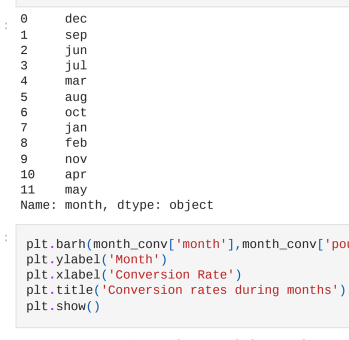
```python
# Calculating conversion rates for different months
month_conv = ((success_data.groupby('month').count()['poutcome']
               /
               known_mkt_data.groupby('month').count()['poutcome']) * 100).sort_values(ascending = False).reset_index()
month_conv['month']
```

Out[35]:

```
0     dec
1     sep
2     jun
3     jul
4     mar
5     aug
6     oct
7     jan
8     feb
9     nov
10    apr
11    may
Name: month, dtype: object
```

In [36]:

```python
plt.barh(month_conv['month'],month_conv['poutcome'], height = 0.4)
plt.ylabel('Month')
plt.xlabel('Conversion Rate')
plt.title('Conversion rates during months')
plt.show()
```



- #### Best time to contact for campaign is during holiday season.

Summary:

- ### Insights:
  - #### In relation to job it was found that there are certain jobs types that trend the conversion rate above the overall conversion rate.
  - #### In relation to housing and loans:
    - #### People who do not have a house tend to respond positively.
    - #### People who have an ongoing loan tend to respond negatively.
  - #### In relation to Defaulters:
    - #### Inconclusive
  - #### Marital Status, Education, and Mode of contact are not signifact enough to affect the target audience.
  - #### Best time to contact people is the Holiday Season
- ### Recommendations for maximizing conversion rates:
  - #### Prioritize contacting people who are from these job types:
    - retired
    - student
    - unemployed
    - housemaid
    - self-employed
    - management
  - #### Prioritize contacting people who do not own a house
  - #### Do not contact people who have a loan
  - #### Make the most contacts in Holiday Seasons ## Along with recommendations I will create a sub-set of original data for our marketing team to use.

In [37]:

```python
data_use_mkt = mkt_data[~mkt_data['poutcome'].isin(['success','failure'])]
```

In [38]:

```python
data_use_mkt = data_use_mkt[(data_use_mkt['job'].isin(job_targets['job'])) | (data_use_mkt['housing'] == 'no') & (data_use_mkt['loan'] == 'yes')]
```

In [39]:

```python
data_use_mkt
```

Out[39]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	deposit
5	42	management	single	tertiary	no	0	yes	yes	unknown	5	may	562	2	-1	0	unknown	yes
6	56	management	married	tertiary	no	830	yes	yes	unknown	6	may	1201	1	-1	0	unknown	yes
7	60	retired	divorced	secondary	no	545	yes	no	unknown	6	may	1030	1	-1	0	unknown	yes
12	29	management	married	tertiary	no	199	yes	yes	unknown	7	may	1689	4	-1	0	unknown	yes
15	35	management	divorced	tertiary	no	3837	yes	no	unknown	8	may	1084	1	-1	0	unknown	yes
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11146	30	admin.	married	secondary	yes	23	no	yes	cellular	4	feb	149	2	-1	0	unknown	no
11147	44	unemployed	married	secondary	no	0	no	no	cellular	21	nov	175	4	-1	0	unknown	no
11150	34	management	married	secondary	no	355	no	no	cellular	21	aug	314	3	-1	0	unknown	no
11151	40	management	married	tertiary	no	917	yes	no	unknown	20	may	292	1	-1	0	unknown	no
11152	34	housemaid	married	secondary	no	390	yes	no	cellular	15	jul	659	3	-1	0	unknown	no

4060 rows × 17 columns

In [40]:

```python
# Performing a test check on known data to see if insights increase the conversion rate:
test_data = known_mkt_data[(known_mkt_data['job'].isin(job_targets['job'])) | (known_mkt_data['housing'] == 'no') & (known_mkt_data['loan'] == 'no')]
```

In [41]:

```python
rate_compare = test_data.groupby('poutcome').count()['deposit']/len(test_data) * 100
```

In [42]:

```python
rate_compare = rate_compare.reset_index()
```

In [43]:

```python
rate_compare.rename(columns = {'deposit':'Conv_rates_post_analysis'}, inplace = True)
```

In [44]:

```python
rate_compare['Conv_rates_before_analysis'] = (known_mkt_data.groupby('poutcome').count()['deposit']/len(known_mkt_data) * 100).reset_index()['deposit']
```

In [45]:

```python
rate_compare
```

Out[45]:

	poutcome	Conv_rates_post_analysis	Conv_rates_before_analysis
0	failure	43.734015	53.414528
1	success	56.265985	46.585472

In [46]:

```python
plt.bar(rate_compare['poutcome'], height = rate_compare['Conv_rates_post_analysis'], width = 0.2, color = 'lime', edgecolor = 'black', align = 'edge')
plt.bar(rate_compare['poutcome'], height = rate_compare['Conv_rates_before_analysis'], width = -0.2, color = 'orangered', edgecolor = 'black', align='edge')
plt.xlabel('classification')
plt.ylabel('rates')
plt.title('Original Conversion Rates vs projected conversion rates')
plt.legend(['Projection','Original'])
plt.show()
```


- #### While the Original Conversion rate was around 46%, the projected conversion rate is 56 % and as a result marketing campaign can go a lot smoother