Data Science Challenge 2021 - Jane Holland

This kernel aims to predict car insurance cold call success. It shows data exploration, feature engineering, visualization and different classifier selection.

The kernel is split into 6 main sections:

1. Viewing the data - what are we working with.
2. Cleaning the data - preprocessing the data we are working with.
3. Data Analysis and Visualisation - what trends and patterns we can see in the data.
4. Prepare Data for Machine Learning - change category columns into numerical data.
5. Machine Learning Classifiers - using different machine learning techniques to predict the cold call success
6. Testing the Trained Model - examine the model on the test data (CarInsurance_test.csv)

Import necessary libraries

In [48]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import operator
import itertools
from itertools import product

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder

# Regression & Classification Models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split,cross_val_score, GridSearch
from sklearn.ensemble import AdaBoostClassifier,GradientBoostingClassifier,Rando
from xgboost import XGBClassifier
from sklearn import tree

#Metrics
from sklearn.metrics import classification_report,confusion_matrix,accuracy_sco
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score

sns.set_theme(style="whitegrid")
```

1. Viewing the data

Read in csv files and show first 5 rows

In [49]:
```
df_train = pd.read_csv('carInsurance_train.csv', sep=',')
df_test = pd.read_csv('carInsurance_test.csv', sep=',')
```

```
df_train.head()
```

Out[49]:

	Id	Age	Job	Marital	Education	Default	Balance	HHInsurance	CarLoan	Communicatio
0	1	32	management	single	tertiary	0	1218	1	0	telephon
1	2	32	blue-collar	married	primary	0	1156	1	0	NaI
2	3	29	management	single	tertiary	0	637	1	0	cellula
3	4	25	student	single	primary	0	373	1	0	cellula
4	5	30	management	married	tertiary	0	2694	0	0	cellula

Display the number of rows and columns as a tuple

In [50]:
```
df_train.shape
```

Out[50]:
```
(4000, 19)
```

Display information about dataframe; columns, datatypes, etc.

In [51]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 19 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Id                4000 non-null   int64
 1   Age               4000 non-null   int64
 2   Job               3981 non-null   object
 3   Marital           4000 non-null   object
 4   Education         3831 non-null   object
 5   Default           4000 non-null   int64
 6   Balance           4000 non-null   int64
 7   HHInsurance       4000 non-null   int64
 8   CarLoan           4000 non-null   int64
 9   Communication     3098 non-null   object
 10  LastContactDay    4000 non-null   int64
 11  LastContactMonth  4000 non-null   object
 12  NoOfContacts      4000 non-null   int64
 13  DaysPassed        4000 non-null   int64
 14  PrevAttempts      4000 non-null   int64
 15  Outcome           958 non-null    object
 16  CallStart         4000 non-null   object
 17  CallEnd           4000 non-null   object
 18  CarInsurance      4000 non-null   int64
dtypes: int64(11), object(8)
memory usage: 593.9+ KB
```

2. Cleaning the data (preprocessing)

This involves:

- removing any data that is not considered important.

- filling in missing data.
- checking for duplicates (and removing if present).
- converting datatypes to the correct datatype.
- dealing with outliers.

Show any null values in dataframe

We will need to clean any NA values in the dataframe by either 1) dropping the column, or 2) filling in the missing data with the mode or the mean.

In [52]:
```
df_train.isnull().sum()
```

Out[52]:
```
Id                     0
Age                    0
Job                   19
Marital                0
Education            169
Default                0
Balance                0
HHInsurance            0
CarLoan                0
Communication        902
LastContactDay         0
LastContactMonth       0
NoOfContacts           0
DaysPassed             0
PrevAttempts           0
Outcome             3042
CallStart              0
CallEnd                0
CarInsurance           0
dtype: int64
```

Show any duplicates in dataframe

In [53]:
```
duplicates = df_train.duplicated()
print(duplicates.sum())
```

```
0
```

Remove and fill columns

- As we are not conducting any time series on individuals, the Id column can be removed.
- The Outcome column has 3042/4000 missing values, so this column can also be dropped.
- The Job, Education, and Communication columns are missing only a small amount of data so we will fill them with the most common attributes.

In [54]:
```
# Drop ID (not sequential, independent) and Outcome (too much missing data) colu
df_train= df_train.drop(['Id'], axis=1)
df_train= df_train.drop(['Outcome'], axis=1)

# Fill NA values with the most common atttribute for each column
for column in ['Job', 'Education','Communication']:
        df_train[column] = df_train[column].fillna(df_train[column].mode()[0])
```

```
df_train.isnull().sum()
```

Out[54]:
```
Age                 0
Job                 0
Marital             0
Education           0
Default             0
Balance             0
HHInsurance         0
CarLoan             0
Communication       0
LastContactDay      0
LastContactMonth    0
NoOfContacts        0
DaysPassed          0
PrevAttempts        0
CallStart           0
CallEnd             0
CarInsurance        0
dtype: int64
```

Converting datatypes

The CallStart and CallEnd need to be changed from objects to the time format.

In [55]:
```
# Conver to time datatype
df_train[['CallStart','CallEnd']]=df_train[['CallStart','CallEnd']].astype('date

# While we are dealing with the time attributes we will create a new column call

#Total Call Duration
df_train['CallDuration']=df_train['CallEnd']-df_train['CallStart']

# To make the CallDuration more comprehensible, we will convert it to seconds (c
df_train['CallDuration']=df_train['CallDuration'].dt.components['minutes']*60 +
```

Taking a closer look at the string objects in dataframe

In [56]:
```
df_train.describe(include=['O'])
```

Out[56]:

	Job	Marital	Education	Communication	LastContactMonth
count	4000	4000	4000	4000	4000
unique	11	3	3	2	12
top	management	married	secondary	cellular	may
freq	912	2304	2157	3733	1049

Do the same with the numerical datatypes

In [57]:
```
df_train.describe(datetime_is_numeric=True)
```

Out[57]:

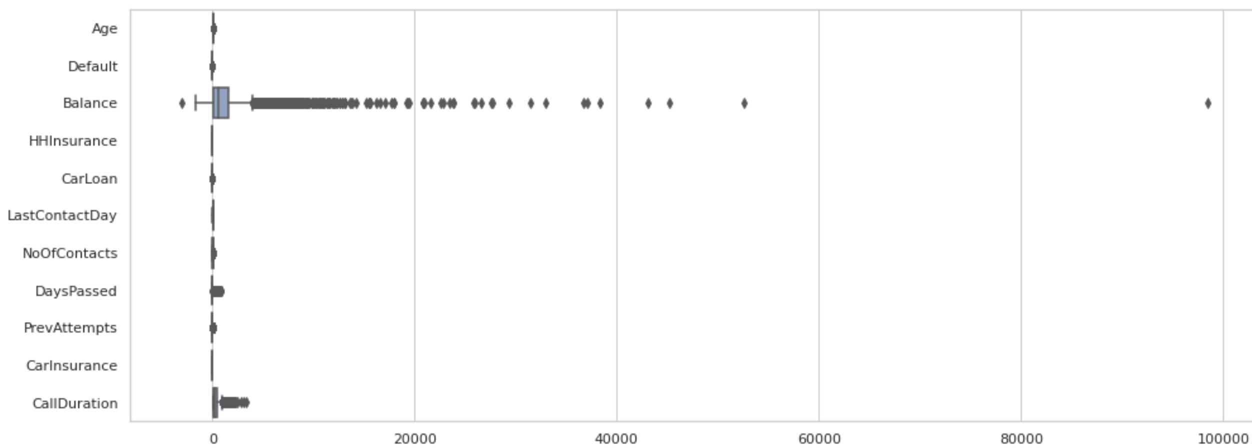
	Age	Default	Balance	HHInsurance	CarLoan	LastContactDay	NoOfCon
count	4000.000000	4000.000000	4000.000000	4000.00000	4000.000000	4000.000000	4000.00

	Age	Default	Balance	HHInsurance	CarLoan	LastContactDay	NoOfCon
mean	41.214750	0.014500	1532.937250	0.49275	0.133000	15.721250	2.60
min	18.000000	0.000000	-3058.000000	0.00000	0.000000	1.000000	1.00
25%	32.000000	0.000000	111.000000	0.00000	0.000000	8.000000	1.00
50%	39.000000	0.000000	551.500000	0.00000	0.000000	16.000000	2.00
75%	49.000000	0.000000	1619.000000	1.00000	0.000000	22.000000	3.00
max	95.000000	1.000000	98417.000000	1.00000	1.000000	31.000000	43.00
std	11.550194	0.119555	3511.452489	0.50001	0.339617	8.425307	3.06

Handling the outliers

In the above describtion we can see that the mean of the balance is 1532, but the min value is -3058 and the max value is 98417. This seems like a large range so we will take a closer look and use a boxplot to see what the spread is like.

In [58]:
```python
plt.figure(figsize=(16, 6))
ax = sns.boxplot(data=df_train, orient="h", palette="Set2")
```



As suspected the Balance column has some outliers. we will create a function to remove the outliers and only use the values betwen the 1st and 3rd quartile

In [59]:
```python
# remove outliers in Balance column
def remove_outliers(col):
    sorted(col)
    Q1,Q3=col.quantile([0.25,0.75])
    # Use interquartile range (IQR) to find outliers.
    IQR=Q3-Q1
    #  Values lower than the lower boundary are outliers.
    lower_range=Q1-(1.5*IQR)
    #  Values greater than the upper boundary are outliers.
    upper_range=Q3+(1.5*IQR)
    return lower_range, upper_range
```

In [60]:
```
# Redefining the Balance column - removing the outliers
low_bal, upp_bal = remove_outliers(df_train['Balance'])
df_train['Balance']=np.where(df_train['Balance'] > upp_bal, upp_bal, df_train['B
df_train['Balance']=np.where(df_train['Balance'] < low_bal, low_bal, df_train['B
```

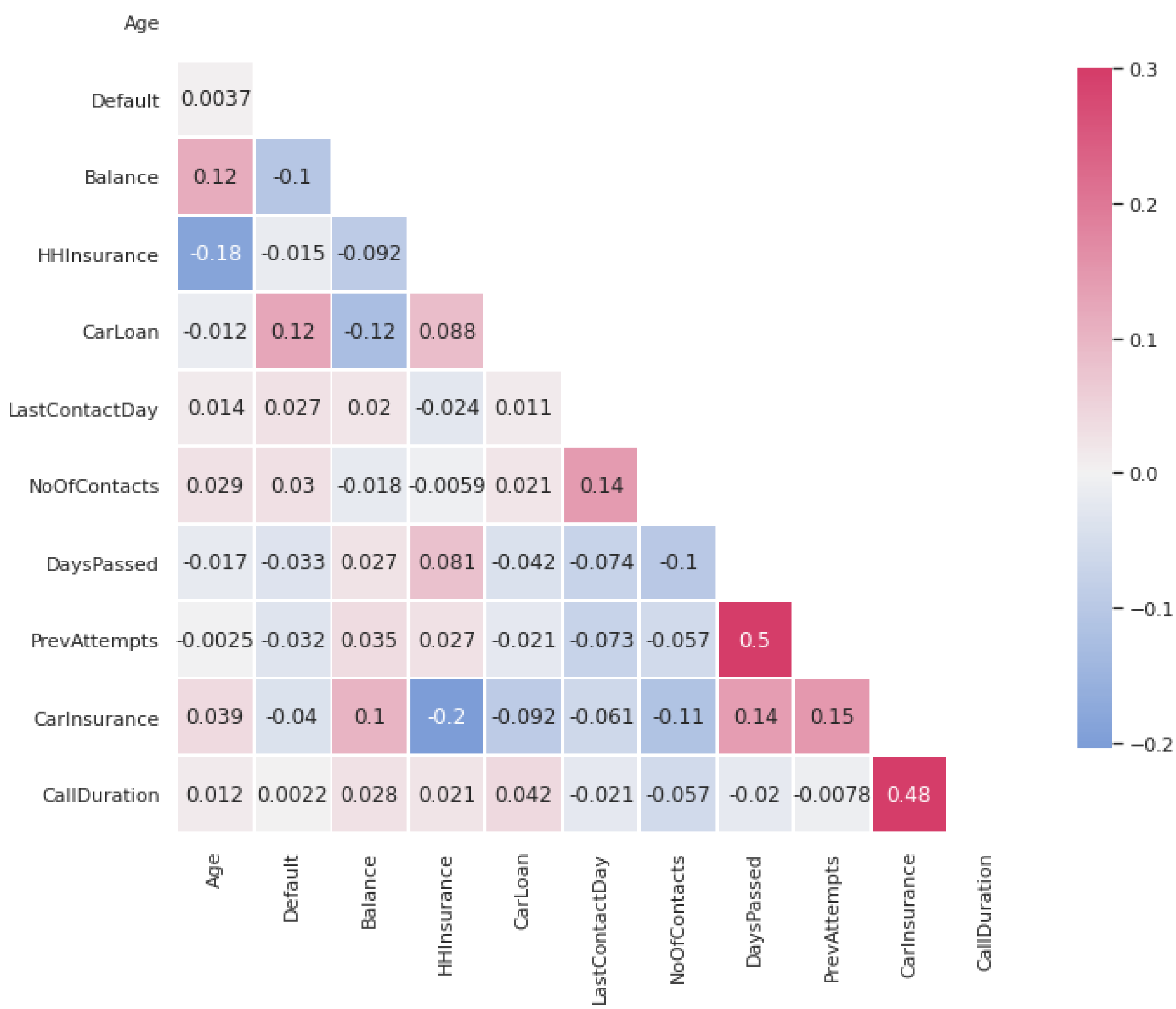
3. Data Analysis and Visualisation

Here we will explore the data in more detail and visualise any significant observations.

Data Correlation

In [61]:
```
# Display the correlated data as a heatmap - this will show the positive and neg
corr = df_train.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(255, 0, as_cmap=True)

sns.heatmap(corr, annot=True, fmt=".2", mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.8, cbar_kws={"shrink": .8})
```

Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x7f19fcdf9190>



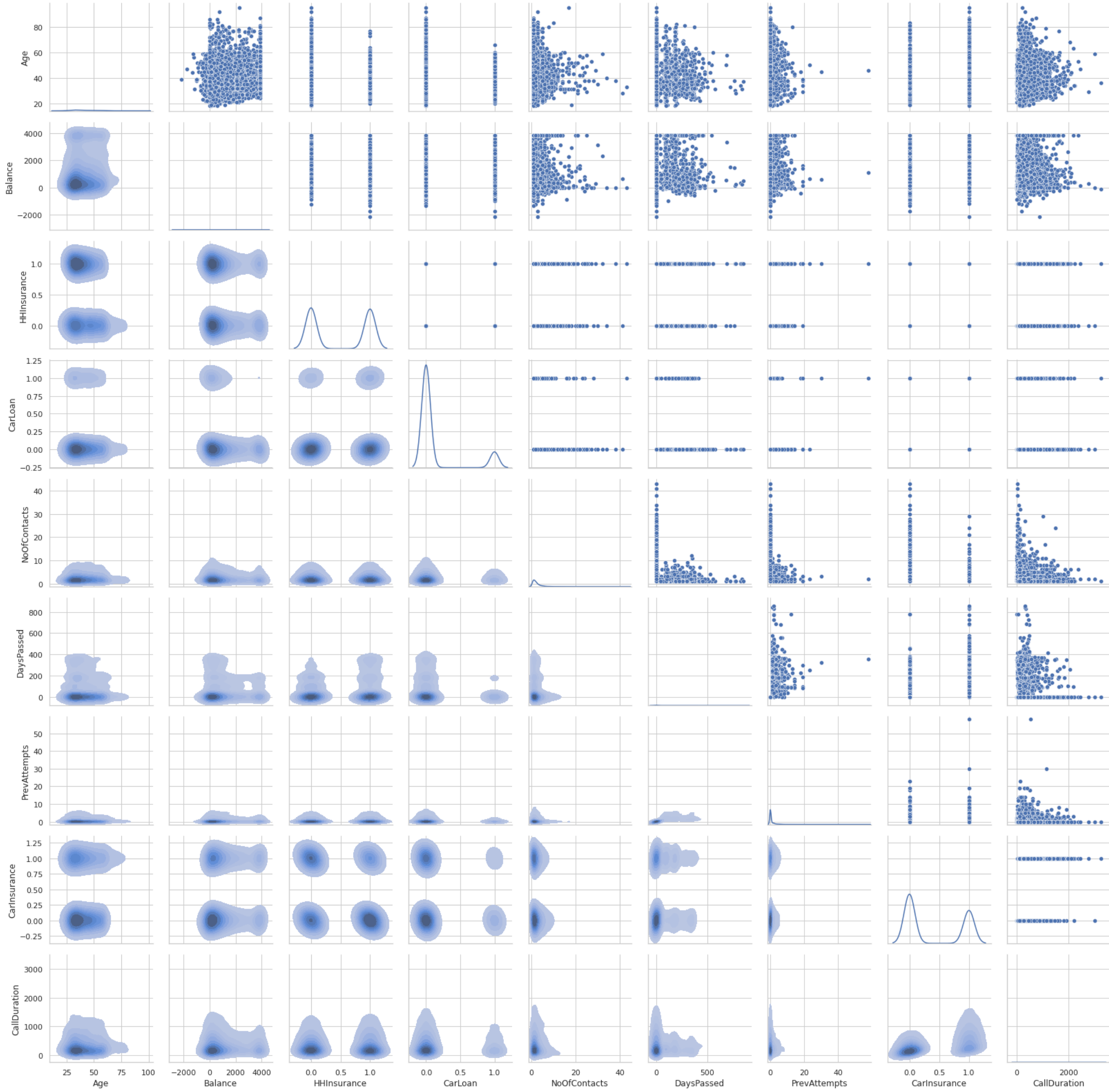
From this heatmap correlation matrix we can see that:

- There are Strong Positive correlations between the CarInsurance and CallDuration, as well as PrevAttempts and DaysPassed. Negative correlations can be seen with the LastContactDay and CarInsurance, as well as the Age and HHinsurance.
- Perhaps a longer CallDuration increases the odds of subscribing car insurance.
- Furthermore, the more times an individual is contacted, the less likely they are to subscribe to car insurance.
- Other attributes are fairly independent.

Looking more closely at the pairwise relationships in a dataset

In [62]:
```
# Plot some of the more important attribute features
df_pair_feats = ['Age','Balance','HHInsurance', 'CarLoan','NoOfContacts','DaysPa
g = sns.PairGrid(df_train[df_pair_feats])
g.map_upper(sns.scatterplot)
g.map_lower(sns.kdeplot, fill=True)
g.map_diag(sns.kdeplot)
g.add_legend()
```

Out[62]:
```
<seaborn.axisgrid.PairGrid at 0x7f19f53ed280>
```



Here we can see a few different observations:

- Younger people (<40) are less likely to have a car loan or car insurance subscribed. They are more likely to have house insurance and have a smaller balance.
- People with house insurance are less likely to have car insurance subscribed.
- The longer the Call Duration the more likely car insurance will be subscribed.
- The more frequently the number of times contacted during this campaign, the less likely that car insurance will be subscribed to the individual.
- The more previous attempts in the previous campaign, the more likely of subscribing insurance.

Category Analysis and Visualisation

In [63]:

```
# Display the number and percentage of jobs that have car insurance subscribed
job_insured=pd.crosstab(df_train['Job'],df_train['CarInsurance'],colnames=['Car
```

```
job_insured['% with Car Insurance']=round(job_insured[1]/(job_insured[0]+job_ins
job_insured
```

Out[63]:

Car Insurance	0	1	% with Car Insurance
Job			
admin.	274	185	40.31
blue-collar	540	219	28.85
entrepreneur	86	35	28.93
housemaid	72	37	33.94
management	511	401	43.97
retired	103	146	58.63
self-employed	86	54	38.57
services	218	112	33.94
student	44	87	66.41
technician	406	254	38.48
unemployed	56	74	56.92

In [64]:

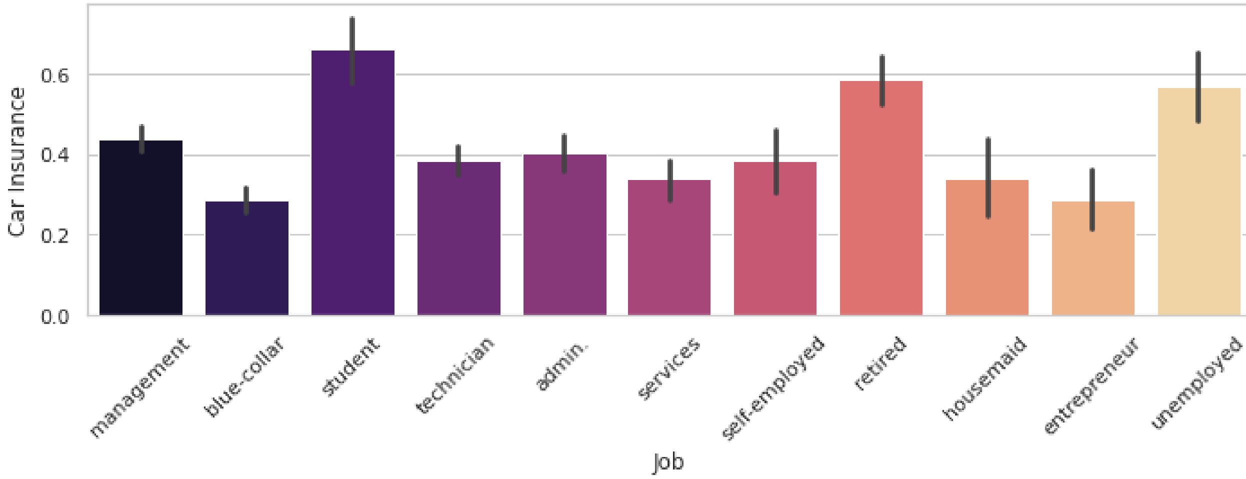
```
# Display the number and percentage of different marital statuses that have car
marital_insured=pd.crosstab(df_train['Marital'],df_train['CarInsurance'],colname
marital_insured['% with Car Insurance']=round(marital_insured[1]/(marital_insure
marital_insured
```

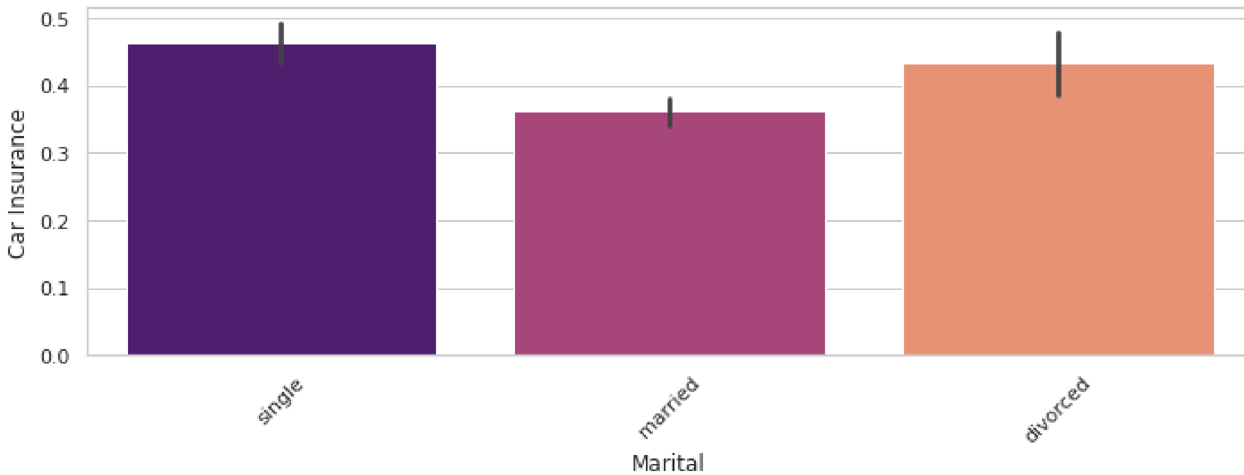
Out[64]:

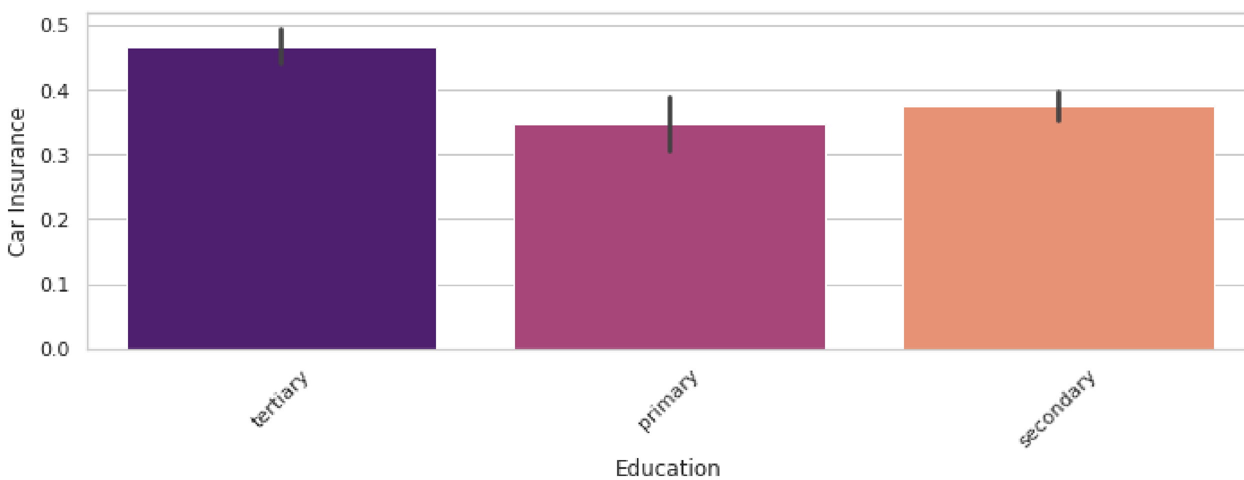
Car Insurance	0	1	% with Car Insurance
Marital			
divorced	273	210	43.48
married	1471	833	36.15
single	652	561	46.25

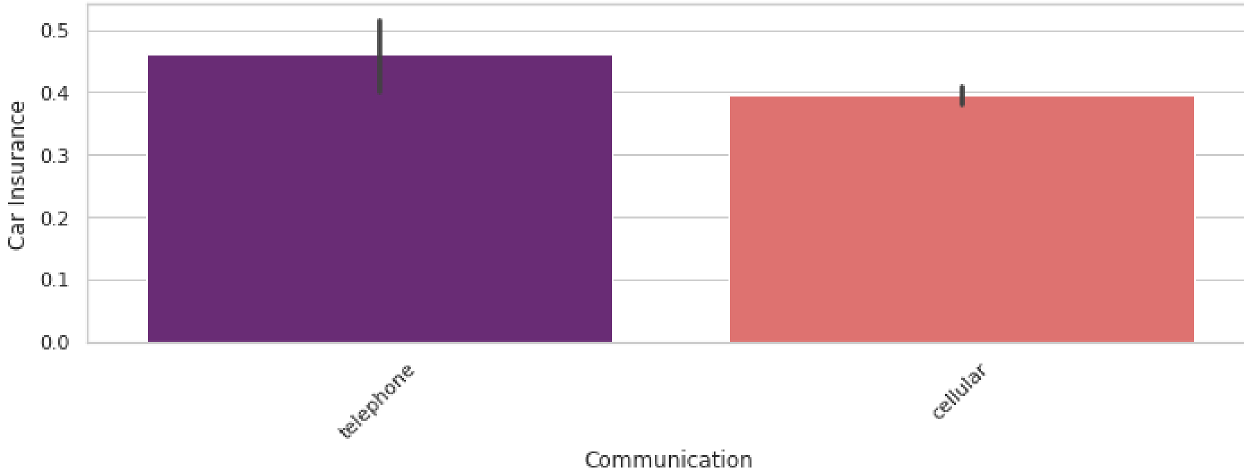
In [65]:

```
# Plot the amount of catergory features that have car insurance subscribed
df_category_feats = df_train[['Job','Marital','Education','Communication']]

for feature in df_category_feats:
    plt.figure(figsize=(10,4))
    sns.barplot(x=feature, y='CarInsurance', data= df_train, palette='magma')
    plt.xticks(rotation=45)
    plt.ylabel('Car Insurance')
    plt.tight_layout()
```

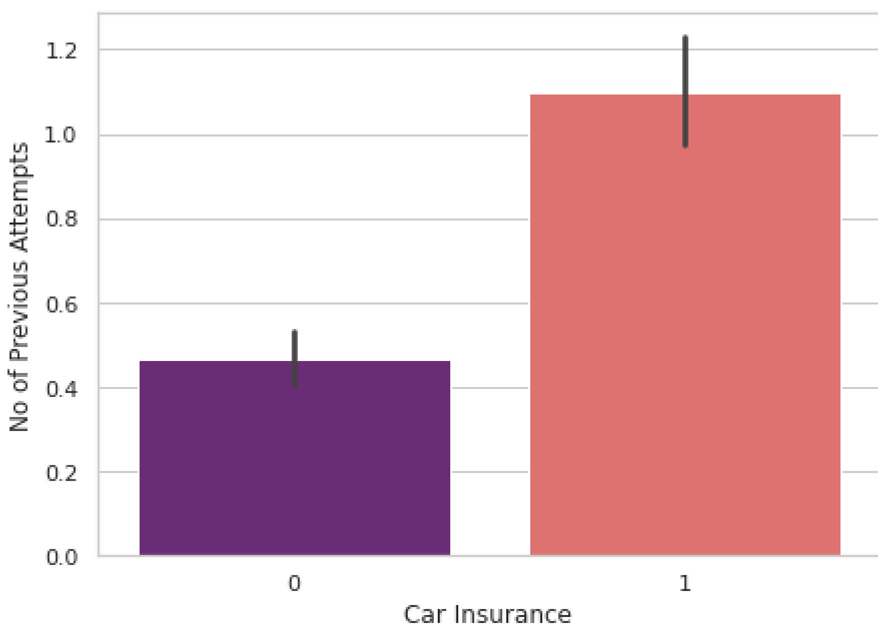

Car Insurance
0.0
0.2
0.4
0.6
management
blue-collar
student
technician
admin.
services
self-employed
retired
housemaid
entrepreneur
unemployed
Job

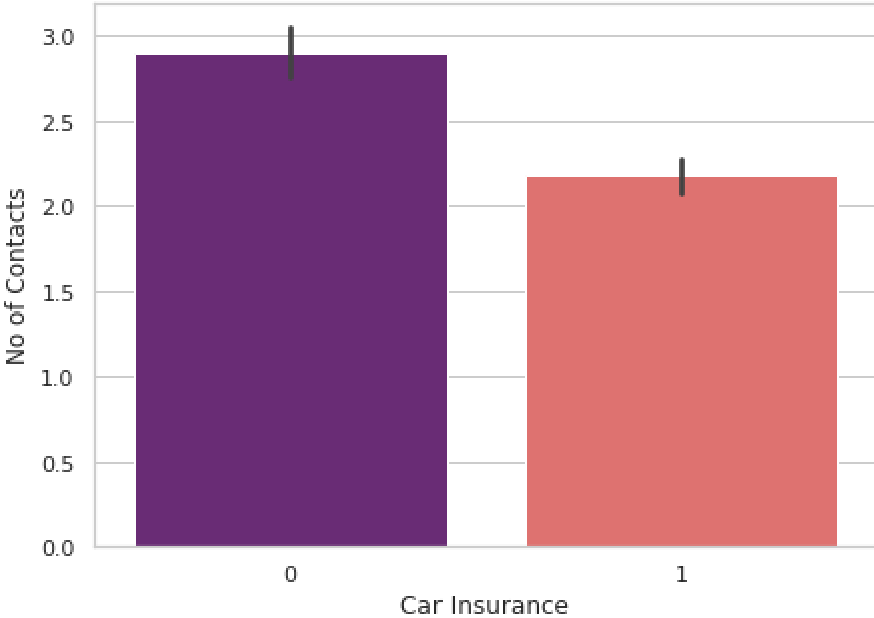

Car Insurance
0.0
0.1
0.2
0.3
0.4
0.5
single
married
divorced
Marital


Car Insurance
0.0
0.1
0.2
0.3
0.4
0.5
tertiary
primary
secondary
Education



In [66]:
```
# Plotting the previous campaign (PrevAttempts) vs the current campaign (NoOfCon

# Plot how the number of previous attempts affects the outcome of car insurance
plt.figure(figsize=(7,5))
sns.barplot( x='CarInsurance', y='PrevAttempts', data=df_train, palette='magma')
plt.ylabel('No of Previous Attempts')
plt.xlabel('Car Insurance')
plt.show()

# Plot how the number of contacts affects the outcome of car insurance subscripti
plt.figure(figsize=(7,5))
sns.barplot( x='CarInsurance', y='NoOfContacts', data=df_train, palette='magma')
plt.ylabel('No of Contacts')
plt.xlabel('Car Insurance')
plt.show()
```





Feature Engingeering

By using feature engingeering we can create more features that can be further analysed as well as for grouping attributes.

The Balance, Age, LastContactDay, and CallStart attributes are good examples of attributes to discretise it into equal-sized buckets. This produces a Category object where each quantile or bracket has a membership for each datapoint.

In [67]:
```
# Here I will create the bins and give each one a label.
# For e.g. if your balance -500 you will be in the 'Negative Balance' bracket

# Whats the min and max balances - this can inform decision on how many bins to
print("Train:", df_train['Balance'].min(), df_train['Balance'].max())
print("Test:", df_test['Balance'].min(), df_test['Balance'].max()) # outliers he

# Create and label bins
train_bal_bins= [-3000,0,1295,2590,3885]
train_bal_labels = ['Negative Balance','Low','Mid','High']

# Create a new column 'BalanceBracket' that shows the balance groups
df_train['BalanceBracket'] = pd.cut(df_train['Balance'], bins=train_bal_bins, la

# Display the number and percentage of different balance brackets that have car
balance_insured=pd.crosstab(df_train['BalanceBracket'],df_train['CarInsurance'],
balance_insured['% with Car Insurance']=round(balance_insured[1]/(balance_insure
balance_insured
```

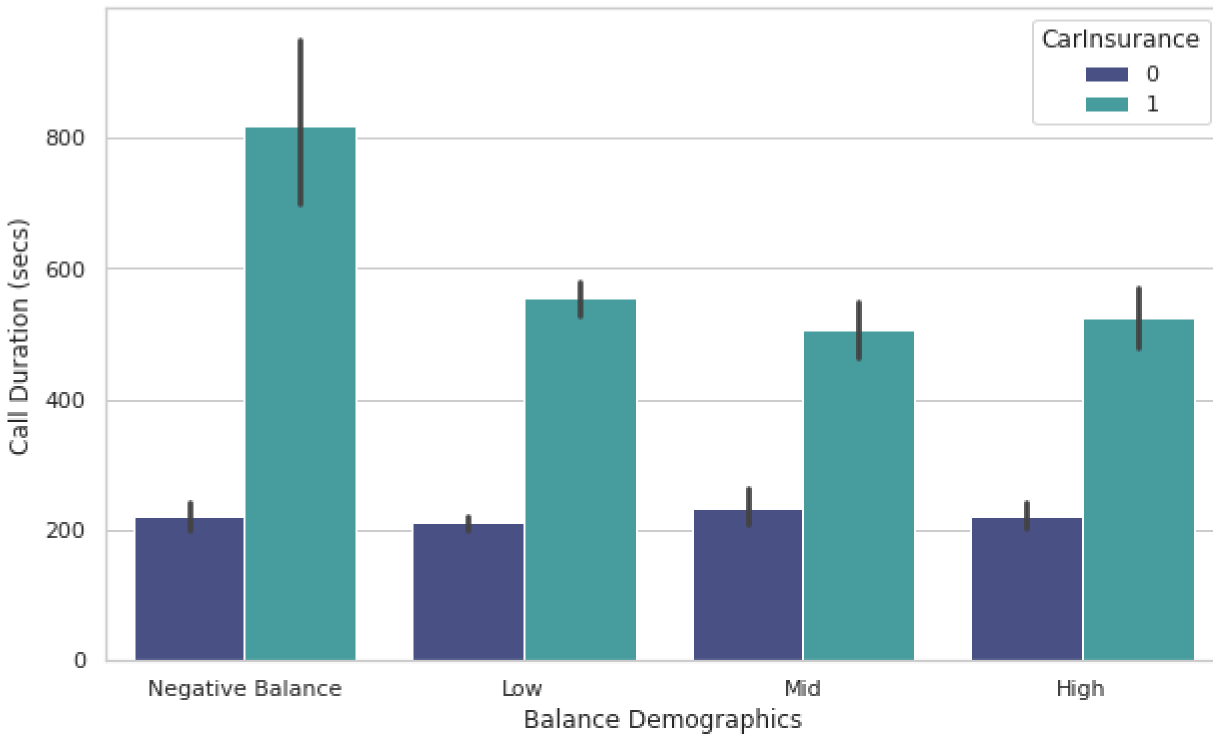
```
Train: -2151.0 3881.0
Test: -1980 41630
```

Out[67]:

Car Insurance	0	1	% with Car Insurance
BalanceBracket			
Negative Balance	207	58	21.89
Low	1571	995	38.78

Car Insurance	0	1	% with Car Insurance
BalanceBracket			
Mid	270	245	47.57
High	348	306	46.79

In [68]:
```
# Plotting how the call duration affects the likelyhood of subscribing to car in
# for different balance groups

plt.figure(figsize=(10,6))
sns.barplot(x='BalanceBracket', y='CallDuration', hue='CarInsurance', data=df_tr
plt.ylabel('Call Duration (secs)')
plt.xlabel('Balance Demographics')
plt.show()
```



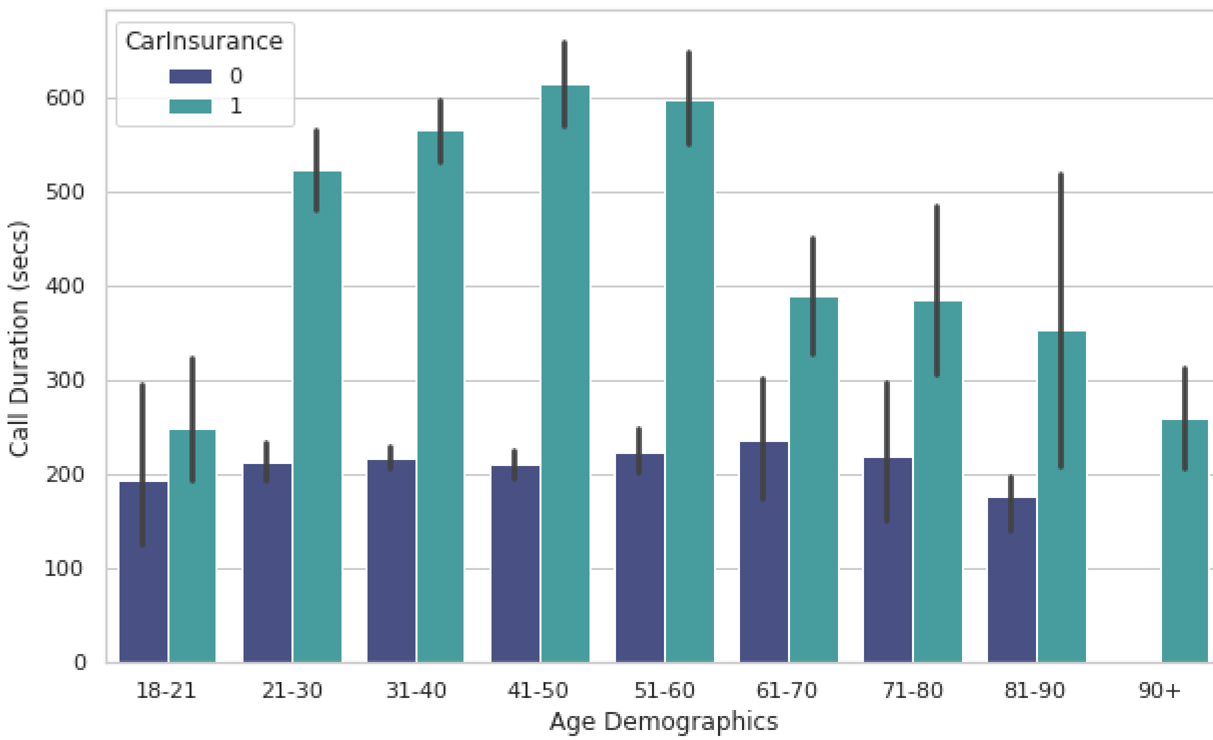
In [69]:
```
# For the age brackets I chose intervals of 10 in order to make the data more cl

# Create the bins and give each one a label.
train_age_bins= [18,21,31,41,51,61,71,81,91,101]
train_age_labels = ['18-21','21-30','31-40','41-50','51-60','61-70','71-80','81-

# Create a new column 'AgeBracket' that shows the age groups
df_train['AgeBracket'] = pd.cut(df_train['Age'], bins=train_age_bins, labels=tra

# Display the number and percentage of different age brackets that have car insu
age_insured=pd.crosstab(df_train['AgeBracket'],df_train['CarInsurance'],colnames
age_insured['% with Car Insurance']=round(age_insured[1]/(age_insured[0]+age_ins
age_insured
```

Out[69]:

Car Insurance	0	1	% with Car Insurance
AgeBracket			
18-21	7	16	69.57

Car Insurance	0	1	% with Car Insurance
AgeBracket			
21-30	342	313	47.79
31-40	955	544	36.29
41-50	618	331	34.88
51-60	434	250	36.55
61-70	21	95	81.90
71-80	16	45	73.77
81-90	3	8	72.73
90+	0	2	100.00

In [70]:
```
# Plotting how the call duration affects the likelyhood of subscribing to car in
# for different age demographics

plt.figure(figsize=(10,6))
sns.barplot(x='AgeBracket', y='CallDuration', hue='CarInsurance', data=df_train,
plt.ylabel('Call Duration (secs)')
plt.xlabel('Age Demographics')
plt.show()
```



In [71]:
```
# For the LastContactDay brackets I chose every 11 days to make the data more cl

# Create the bins and give each one a label.
train_day_bins= [0,10,21,32]
train_day_labels = ['Start','Middle','End']

# Create a new column 'DayBracket' that shows the age groups
df_train['DayBracket'] = pd.cut(df_train['LastContactDay'], bins=train_day_bins,
```

```
# Display the number and percentage of different contact day brackets that have
day_insured=pd.crosstab(df_train['DayBracket'],df_train['CarInsurance'],colnames
day_insured['% with Car Insurance']=round(day_insured[1]/(day_insured[0]+day_ins
day_insured
```

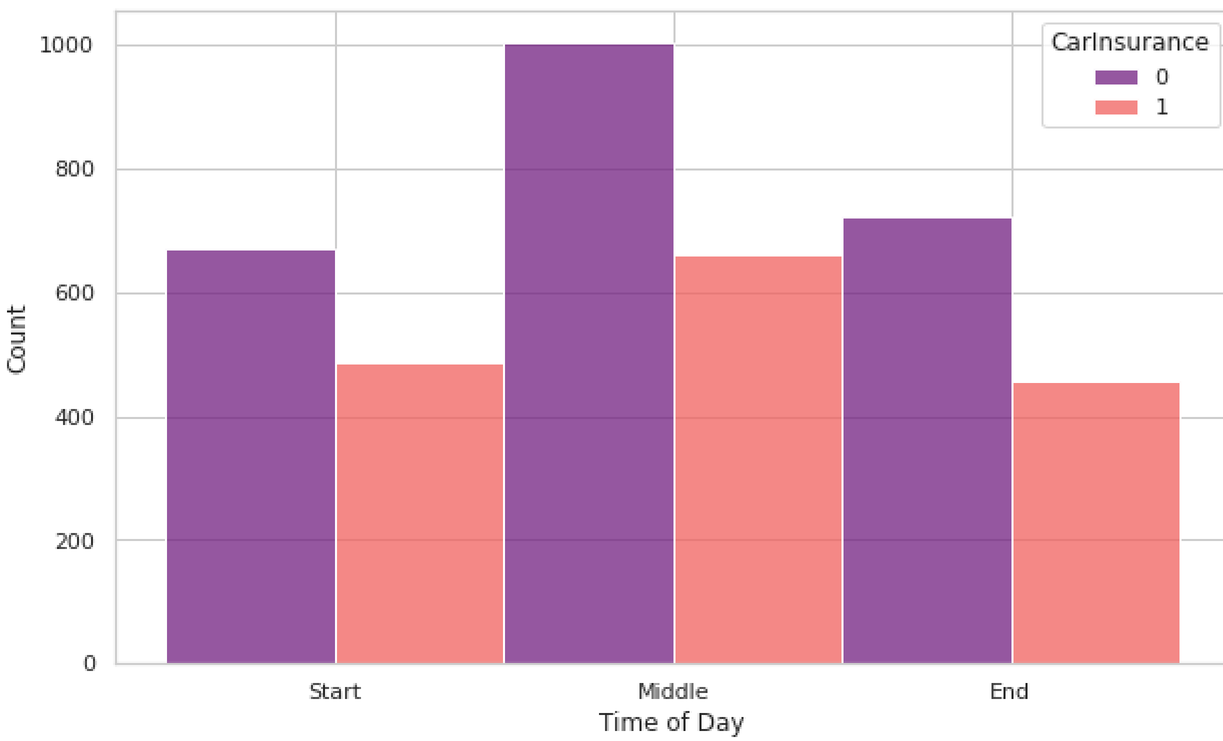
Out[71]:

Car Insurance	0	1	% with Car Insurance
DayBracket			
Start	670	487	42.09
Middle	1005	660	39.64
End	721	457	38.79

In [72]:

```
# Plotting how the time of the month affects the likelyhood of subscribing to ca
# for different age demographics

plt.figure(figsize=(10,6))
sns.histplot(x='DayBracket', hue='CarInsurance', data=df_train, multiple="dodge"
plt.ylabel('Count')
plt.xlabel('Time of Day')
plt.show
```

Out[72]: <function matplotlib.pyplot.show(*args, **kw)>



In [73]:

```
# Get the working hours for calls
print(df_train["CallStart"].dt.time.min(), df_train["CallStart"].dt.time.max())

# Based on the working hours (9am-6pm), I chose morning (9am-12), afternoon (12p
# day brackets.
# Create the bins and give each one a label.

df_train['TimeBracket']=pd.cut(df_train["CallStart"].dt.hour,
               [9,12,15,24],
               labels=['Morning','Afternoon','Evening'],
               right=False, include_lowest=True)
```

```
# Display the number and percentage of different contact day brackets that have
time_insured=pd.crosstab(df_train['TimeBracket'],df_train['CarInsurance'],colnam
time_insured['% with Car Insurance']=round(time_insured[1]/(time_insured[0]+time
time_insured
```

09:00:00 17:59:58

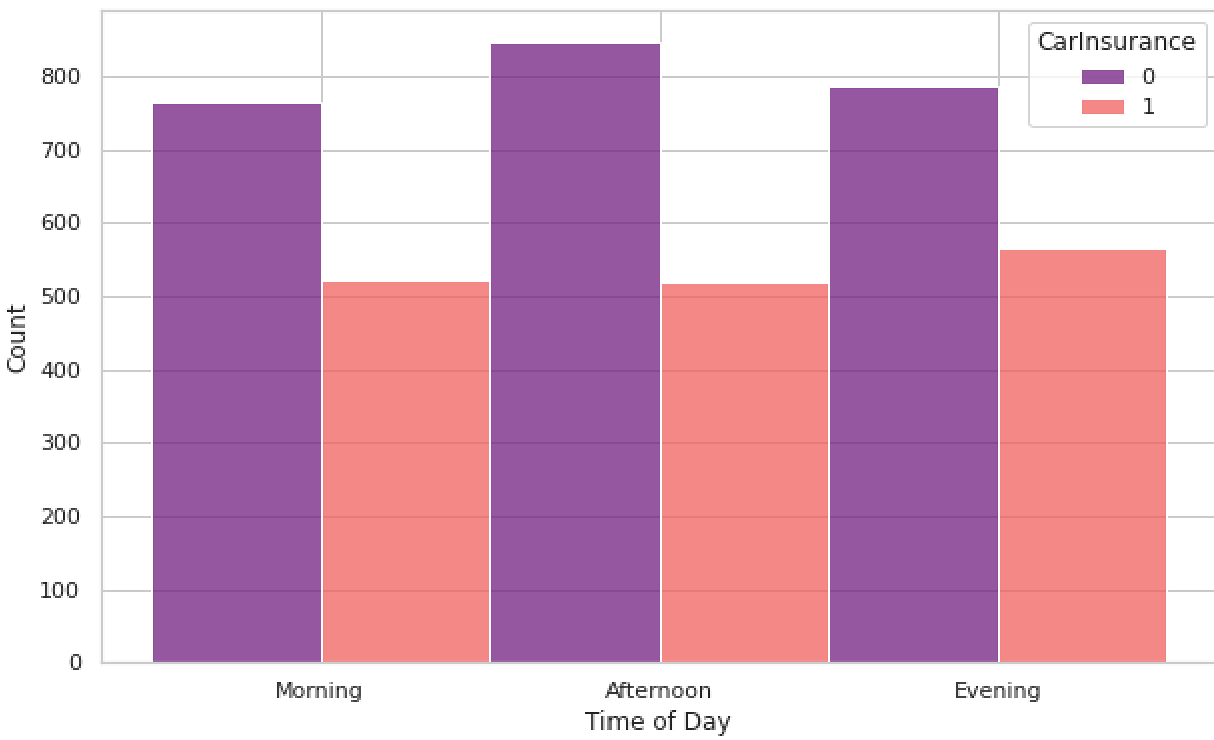
Out[73]:

Car Insurance	0	1	% with Car Insurance
TimeBracket			
Morning	763	521	40.58
Afternoon	847	518	37.95
Evening	786	565	41.82

In [74]:

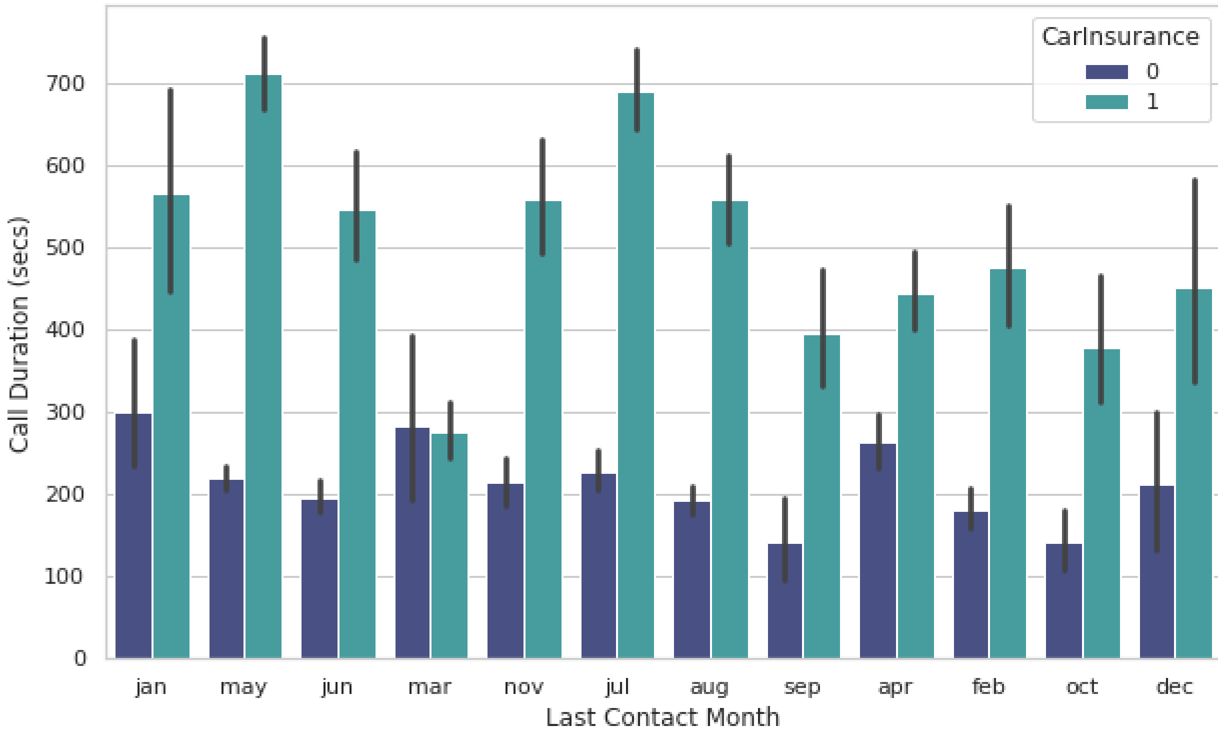
```
# Plotting how the time of the day affects the likelyhood of subscribing to car
# for different age demographics

plt.figure(figsize=(10,6))
sns.histplot(x='TimeBracket', hue='CarInsurance', data=df_train, multiple="dodge
plt.ylabel('Count')
plt.xlabel('Time of Day')
plt.show
```

Out[74]: <function matplotlib.pyplot.show(*args, **kw)>



In [75]:

```
# Plotting how the call duration affects the likelyhood of subscribing to car in
# for different months

plt.figure(figsize=(10,6))
sns.barplot(x='LastContactMonth', y='CallDuration', hue='CarInsurance', data=df_
plt.ylabel('Call Duration (secs)')
plt.xlabel('Last Contact Month')
plt.show()
```



4. Prepare Data for Machine Learning

In [76]:
```
#Drop columns used for exploratory analysis
df_train= df_train.drop(['Age'], axis=1)
df_train=df_train.drop(['Balance'], axis=1)
df_train=df_train.drop(['CallStart'], axis=1)
df_train=df_train.drop(['CallEnd'], axis=1)
df_train=df_train.drop(['LastContactDay'], axis=1)
df_train.head()
```

Out[76]:

	Job	Marital	Education	Default	HHInsurance	CarLoan	Communication	LastContactMont
0	management	single	tertiary	0	1	0	telephone	ja
1	blue-collar	married	primary	0	1	0	cellular	ma
2	management	single	tertiary	0	1	0	cellular	ju
3	student	single	primary	0	1	0	cellular	ma
4	management	married	tertiary	0	0	0	cellular	ju

In [77]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Job               4000 non-null   object
 1   Marital           4000 non-null   object
 2   Education         4000 non-null   object
 3   Default           4000 non-null   int64
 4   HHInsurance       4000 non-null   int64
 5   CarLoan           4000 non-null   int64
```

```
 6   Communication     4000 non-null   object
 7   LastContactMonth  4000 non-null   object
 8   NoOfContacts      4000 non-null   int64
 9   DaysPassed        4000 non-null   int64
 10  PrevAttempts      4000 non-null   int64
 11  CarInsurance      4000 non-null   int64
 12  CallDuration      4000 non-null   int64
 13  BalanceBracket    4000 non-null   category
 14  AgeBracket        4000 non-null   category
 15  DayBracket        4000 non-null   category
 16  TimeBracket       4000 non-null   category
dtypes: category(4), int64(8), object(5)
memory usage: 422.8+ KB
```

Encoding categorical values

Machine learning classifiers need numerical values, so category data need to be encoded to numbers before we can fit and evaluate a model.

In [78]:

```
# Label for category values
le = LabelEncoder()

df_train_cats = df_train.select_dtypes(include=['category']).columns

for i in df_train_cats:
    df_train[i] = le.fit_transform(df_train[i])


# Apply one-hot encoder to objects
df_train_objs = df_train.select_dtypes(include=['object']).columns

OH_encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)
train_oh = pd.DataFrame(OH_encoder.fit_transform(df_train[df_train_objs])).astyp

# Get feature columns
train_oh.columns = OH_encoder.get_feature_names(df_train_objs)

# One-hot encoding removed index; put it back
train_oh.index = df_train.index

# Add one-hot encoded columns to our main df
df_train = pd.concat([df_train, train_oh], axis=1)

df_train = df_train.drop(df_train_objs, axis = 1)
```

In [79]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 43 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Default                 4000 non-null   int64
 1   HHInsurance             4000 non-null   int64
 2   CarLoan                 4000 non-null   int64
 3   NoOfContacts            4000 non-null   int64
 4   DaysPassed              4000 non-null   int64
 5   PrevAttempts            4000 non-null   int64
 6   CarInsurance            4000 non-null   int64
 7   CallDuration            4000 non-null   int64
```

```
 8   BalanceBracket          4000 non-null   int64
 9   AgeBracket              4000 non-null   int64
 10  DayBracket              4000 non-null   int64
 11  TimeBracket             4000 non-null   int64
 12  Job_admin.              4000 non-null   int64
 13  Job_blue-collar         4000 non-null   int64
 14  Job_entrepreneur        4000 non-null   int64
 15  Job_housemaid           4000 non-null   int64
 16  Job_management          4000 non-null   int64
 17  Job_retired             4000 non-null   int64
 18  Job_self-employed       4000 non-null   int64
 19  Job_services            4000 non-null   int64
 20  Job_student             4000 non-null   int64
 21  Job_technician          4000 non-null   int64
 22  Job_unemployed          4000 non-null   int64
 23  Marital_divorced        4000 non-null   int64
 24  Marital_married         4000 non-null   int64
 25  Marital_single          4000 non-null   int64
 26  Education_primary       4000 non-null   int64
 27  Education_secondary     4000 non-null   int64
 28  Education_tertiary      4000 non-null   int64
 29  Communication_cellular  4000 non-null   int64
 30  Communication_telephone  4000 non-null   int64
 31  LastContactMonth_apr    4000 non-null   int64
 32  LastContactMonth_aug    4000 non-null   int64
 33  LastContactMonth_dec    4000 non-null   int64
 34  LastContactMonth_feb    4000 non-null   int64
 35  LastContactMonth_jan    4000 non-null   int64
 36  LastContactMonth_jul    4000 non-null   int64
 37  LastContactMonth_jun    4000 non-null   int64
 38  LastContactMonth_mar    4000 non-null   int64
 39  LastContactMonth_may    4000 non-null   int64
 40  LastContactMonth_nov    4000 non-null   int64
 41  LastContactMonth_oct    4000 non-null   int64
 42  LastContactMonth_sep    4000 non-null   int64
dtypes: int64(43)
memory usage: 1.3 MB
```

Update the test set to match the training set

In [80]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 19 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Id                1000 non-null   int64
 1   Age               1000 non-null   int64
 2   Job               995 non-null    object
 3   Marital           1000 non-null   object
 4   Education         953 non-null    object
 5   Default           1000 non-null   int64
 6   Balance           1000 non-null   int64
 7   HHInsurance       1000 non-null   int64
 8   CarLoan           1000 non-null   int64
 9   Communication     779 non-null    object
 10  LastContactDay    1000 non-null   int64
 11  LastContactMonth  1000 non-null   object
 12  NoOfContacts      1000 non-null   int64
 13  DaysPassed        1000 non-null   int64
 14  PrevAttempts      1000 non-null   int64
 15  Outcome           243 non-null    object
 16  CallStart         1000 non-null   object
```

```
 17  CallEnd           1000 non-null   object
 18  CarInsurance      0 non-null      float64
dtypes: float64(1), int64(10), object(8)
memory usage: 148.6+ KB
```

In [81]:

```
# A lot of redundant code doing it this way.
# Tried concatinating the training and test sets at the beginning, but kept havi
# For time reasons I just did the test set separately here:

df_test= df_test.drop(['Id'], axis=1)
df_test= df_test.drop(['Outcome'], axis=1)

df_test[['CallStart','CallEnd']]=df_test[['CallStart','CallEnd']].astype('dateti

# Fill NA values with the most common atttribute for each column
for column in ['Job', 'Education','Communication', 'Balance']:
        df_test[column] = df_test[column].fillna(df_test[column].mode()[0])

# Total Call Duration
df_test['CallDuration']=df_test['CallEnd']-df_test['CallStart']

# Extracting the time & converting it to seconds
df_test['CallDuration']=df_test['CallDuration'].dt.components['minutes']*60 + df

# Redefining the Balance column - removing the outliers
low_bal, upp_bal = remove_outliers(df_test['Balance'])
df_test['Balance']=np.where(df_test['Balance'] > upp_bal, upp_bal, df_test['Bala
df_test['Balance']=np.where(df_test['Balance'] < low_bal, low_bal, df_test['Bala

# Bins for Balance Bracket
test_bal_bins= [-3000,0,1295,2590,3885]
test_bal_labels = ['Negative Balance','Low','Mid','High']
df_test['BalanceBracket'] = pd.cut(df_test['Balance'], bins=test_bal_bins, label

# Bins for Age Bracket
test_age_bins= [18,21,31,41,51,61,71,81,91,101]
test_age_labels = ['18-21','21-30','31-40','41-50','51-60','61-70','71-80','81-9
df_test['AgeBracket'] = pd.cut(df_test['Age'], bins=test_age_bins, labels=test_a

# Bins for Day Bracket
test_day_bins= [0,10,21,32]
test_day_labels = ['Start','Middle','End']
df_test['DayBracket'] = pd.cut(df_test['LastContactDay'], bins=test_day_bins, la

# Bins for Time Bracket
df_test['TimeBracket']=pd.cut(df_test["CallStart"].dt.hour,
               [9,12,15,24],
               labels=['Morning','Afternoon','Evening'],
               right=False, include_lowest=True)

# Drop columns used for exploratory analysis
df_test= df_test.drop(['Age'], axis=1)
df_test=df_test.drop(['Balance'], axis=1)
df_test=df_test.drop(['CallStart'], axis=1)
df_test=df_test.drop(['CallEnd'], axis=1)
df_test=df_test.drop(['LastContactDay'], axis=1)

df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
```

```
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Job               1000 non-null   object
 1   Marital           1000 non-null   object
 2   Education         1000 non-null   object
 3   Default           1000 non-null   int64
 4   HHInsurance       1000 non-null   int64
 5   CarLoan           1000 non-null   int64
 6   Communication     1000 non-null   object
 7   LastContactMonth  1000 non-null   object
 8   NoOfContacts      1000 non-null   int64
 9   DaysPassed        1000 non-null   int64
 10  PrevAttempts      1000 non-null   int64
 11  CarInsurance      0 non-null      float64
 12  CallDuration      1000 non-null   int64
 13  BalanceBracket    1000 non-null   category
 14  AgeBracket        1000 non-null   category
 15  DayBracket        1000 non-null   category
 16  TimeBracket       1000 non-null   category
dtypes: category(4), float64(1), int64(7), object(5)
memory usage: 106.4+ KB
```

In [82]:

```
# Label the category values for Test Set
test_le = LabelEncoder()

df_test_cats = df_train.select_dtypes(include=['category']).columns

for i in df_train_cats:
    df_test[i] = test_le.fit_transform(df_test[i])


# Apply one-hot encoder to objects for Test Set
df_test_objs = df_test.select_dtypes(include=['object']).columns

OH_encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)
test_oh = pd.DataFrame(OH_encoder.fit_transform(df_test[df_test_objs])).astype('

# Get feature column
test_oh.columns = OH_encoder.get_feature_names(df_test_objs)

# One-hot encoding removed index; put it back
test_oh.index = df_test.index

# Add one-hot encoded columns to our main df
df_test = pd.concat([df_test, test_oh], axis=1)

df_test = df_test.drop(df_test_objs, axis = 1)

df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 43 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Default                  1000 non-null   int64
 1   HHInsurance              1000 non-null   int64
 2   CarLoan                  1000 non-null   int64
 3   NoOfContacts             1000 non-null   int64
 4   DaysPassed               1000 non-null   int64
 5   PrevAttempts             1000 non-null   int64
 6   CarInsurance             0 non-null      float64
```

```
 7   CallDuration               1000 non-null   int64
 8   BalanceBracket             1000 non-null   int64
 9   AgeBracket                 1000 non-null   int64
 10  DayBracket                 1000 non-null   int64
 11  TimeBracket                1000 non-null   int64
 12  Job_admin.                 1000 non-null   int64
 13  Job_blue-collar            1000 non-null   int64
 14  Job_entrepreneur           1000 non-null   int64
 15  Job_housemaid              1000 non-null   int64
 16  Job_management             1000 non-null   int64
 17  Job_retired                1000 non-null   int64
 18  Job_self-employed          1000 non-null   int64
 19  Job_services               1000 non-null   int64
 20  Job_student                1000 non-null   int64
 21  Job_technician             1000 non-null   int64
 22  Job_unemployed             1000 non-null   int64
 23  Marital_divorced           1000 non-null   int64
 24  Marital_married            1000 non-null   int64
 25  Marital_single             1000 non-null   int64
 26  Education_primary          1000 non-null   int64
 27  Education_secondary        1000 non-null   int64
 28  Education_tertiary         1000 non-null   int64
 29  Communication_cellular     1000 non-null   int64
 30  Communication_telephone    1000 non-null   int64
 31  LastContactMonth_apr       1000 non-null   int64
 32  LastContactMonth_aug       1000 non-null   int64
 33  LastContactMonth_dec       1000 non-null   int64
 34  LastContactMonth_feb       1000 non-null   int64
 35  LastContactMonth_jan       1000 non-null   int64
 36  LastContactMonth_jul       1000 non-null   int64
 37  LastContactMonth_jun       1000 non-null   int64
 38  LastContactMonth_mar       1000 non-null   int64
 39  LastContactMonth_may       1000 non-null   int64
 40  LastContactMonth_nov       1000 non-null   int64
 41  LastContactMonth_oct       1000 non-null   int64
 42  LastContactMonth_sep       1000 non-null   int64
dtypes: float64(1), int64(42)
memory usage: 336.1 KB
```

Split training set

X is used for the features y for CarInsurance (this is the target value we want to predict)

The Train Test split is of a 80:20 ratio respectively.

In [83]:
```
X=df_train.drop(['CarInsurance'],axis=1).values
# Including only the Target for y
y=df_train['CarInsurance'].values

#Splitting the Training and Testing data having 20% of Test data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,random_
```

Define a function that will plot a confusion matrix for each classifier

5. Machine Learning Classifiers

In [84]:
```
# This confusion matrix was sourced from the sklearn documentation
```

```
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    # Show all ticks
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    # Loop over data dimensions
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

class_names = ['Success','Failure']
```

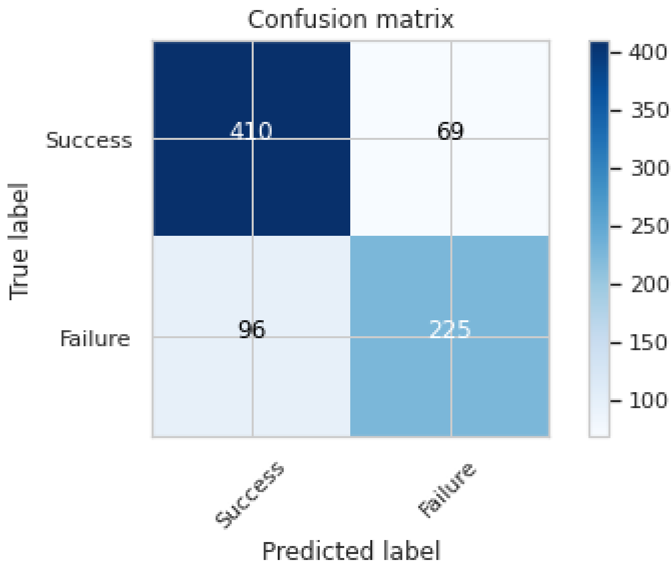
K-Nearest Neighbour

In [85]:

```
knn = KNeighborsClassifier()

# Use GridSearchCV to search over parameter values for the estimator
# This takes some time to run so can always be scaled back
parameters = {'n_neighbors':[5,6,7,8],
              'p':[1,2],
              'weights':['uniform','distance']}

knn_clf = GridSearchCV(knn, parameters)
knn_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", knn_clf.best_params_, '\n')

# Accuracy
print ("kNN Accuracy: %2.2f" % accuracy_score(y_test, knn_clf.predict(X_test)))

# Evaluate score (10-fold cross validation)
score_knn = cross_val_score(knn_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_knn)

# Prediction
y_pred= knn_clf.predict(X_test)
print(classification_report(y_test, y_pred))

# Confusion matrix for K-Nearest Neighbour
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm, classes=class_names, title='Confusion matrix')
```

```
Best parameters:  {'n_neighbors': 7, 'p': 1, 'weights': 'distance'}

kNN Accuracy: 0.79
```

```
Cross Validation Score: 0.77
              precision    recall  f1-score   support

           0       0.81      0.86      0.83       479
           1       0.77      0.70      0.73       321

    accuracy                           0.79       800
   macro avg       0.79      0.78      0.78       800
weighted avg       0.79      0.79      0.79       800
```



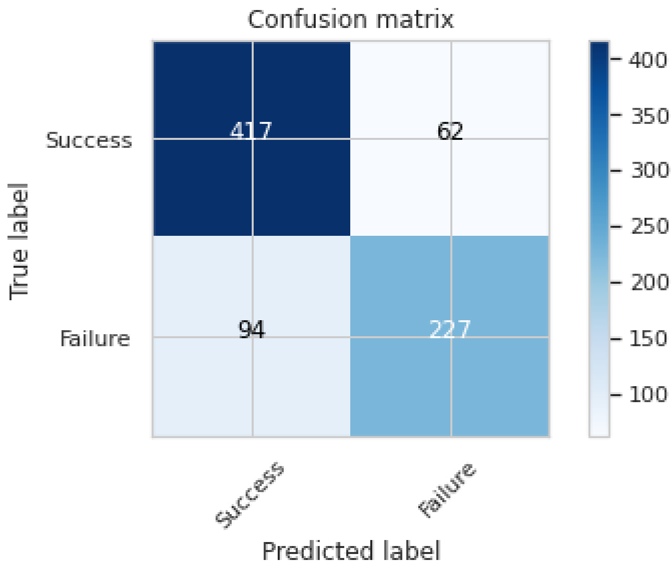
Logistic Regression Classifier

In [86]:

```
LR = LogisticRegression(max_iter=1500)

# Use GridSearchCV
parameters = {'C':[0.7,0.8,0.9,1]}

lr_clf = GridSearchCV(LR, parameters)
lr_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", lr_clf.best_params_, '\n')

# Accuracy
print ("Logistic Accuracy: %2.2f" % accuracy_score(y_test, lr_clf.predict(X_test

# Evaluate score (10-fold cross validation)
score_LR = cross_val_score(lr_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_LR)

# Prediction
y_pred = lr_clf.predict(X_test)
print(classification_report(y_test, y_pred))

# Confusion matrix for Logistical Regression
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm, classes=class_names, title='Confusion matrix')
```

```
Best parameters:  {'C': 0.8}

Logistic Accuracy: 0.81
```

```
Cross Validation Score: 0.80
              precision    recall  f1-score   support

           0       0.82      0.87      0.84       479
           1       0.79      0.71      0.74       321

    accuracy                           0.81       800
   macro avg       0.80      0.79      0.79       800
weighted avg       0.80      0.81      0.80       800
```

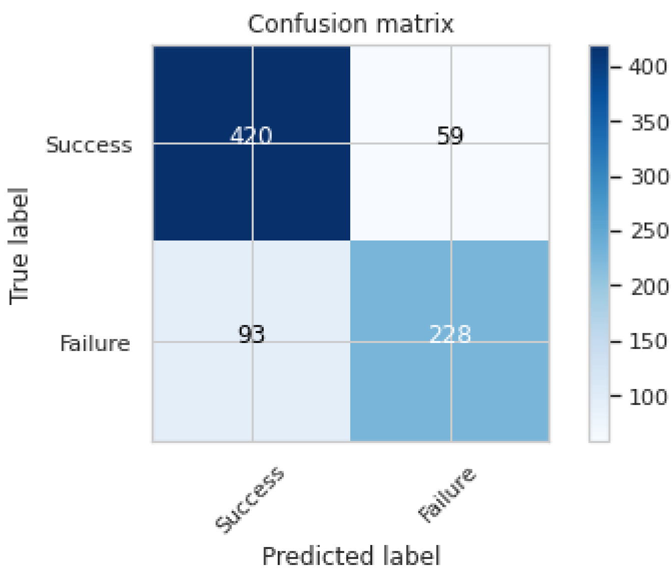


Decision Tree Classifier

In [87]:
```
DT = tree.DecisionTreeClassifier(random_state=21, criterion='gini')

# Use GridSearchCV
parameters = {'class_weight':[None,'balanced'],
              'min_weight_fraction_leaf':[0.0,0.01],
              'max_depth':[None,6,8,9]}

dt_clf = GridSearchCV(DT, parameters)
dt_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", dt_clf.best_params_,'\n')

# Accuracy
print ("Decision Tree Accuracy: %2.2f" % accuracy_score(y_test, dt_clf.predict(X

# Evaluate score (10-fold cross validation)
score_DT = cross_val_score(dt_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_DT, "\n")

# Prediction
y_pred = dt_clf.predict(X_test)
print(classification_report(y_test, y_pred))

# Confusion Matrix for Decision Tree
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm, classes=class_names, title='Confusion matrix')
```

```
Best parameters:  {'class_weight': None, 'max_depth': 6, 'min_weight_fraction_le
```

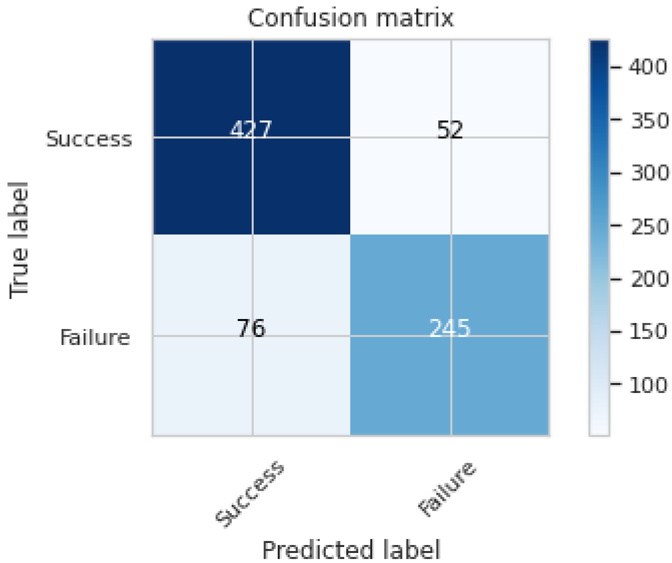
```
af': 0.01}

Decision Tree Accuracy: 0.81
Cross Validation Score: 0.79

              precision    recall  f1-score   support

           0       0.82      0.88      0.85       479
           1       0.79      0.71      0.75       321

    accuracy                           0.81       800
   macro avg       0.81      0.79      0.80       800
weighted avg       0.81      0.81      0.81       800
```



Random Forest Classifier

In [88]:
```
rfc = RandomForestClassifier(n_estimators=1000, criterion='gini', class_weight=N

# Use GridSearchCV
parameters = {'min_samples_split': [8, 10, 12]}

rfc_clf = GridSearchCV(rfc, parameters)
rfc_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", rfc_clf.best_params_, '\n')

# Accuracy
print ("Random Forest Accuracy: %2.2f" % accuracy_score(y_test, rfc_clf.predict(

# Evaluate score (10-fold cross validation)
score_rfc = cross_val_score(rfc_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_rfc)

# Prediction
y_pred = rfc_clf.predict(X_test)
print(classification_report(y_test,y_pred ))

# Confusion Matrix for Random Forest
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm, classes=class_names, title='Confusion matrix')
```

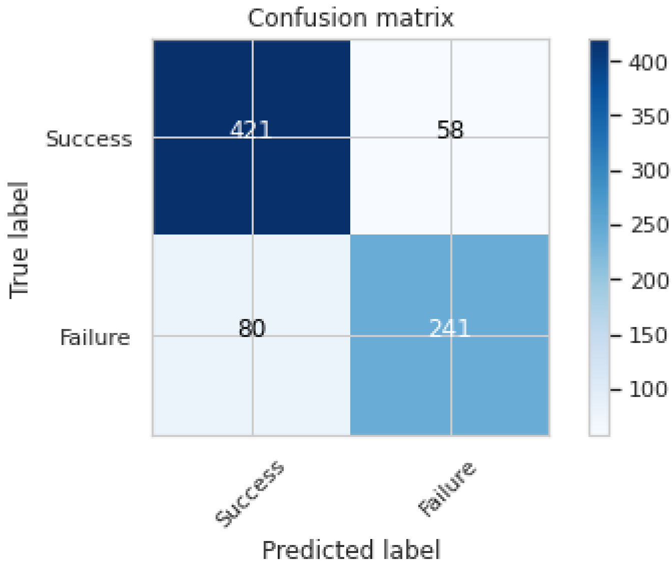
```
Best parameters:  {'min_samples_split': 12}

Random Forest Accuracy: 0.84
Cross Validation Score: 0.82
              precision    recall  f1-score   support

           0       0.85      0.89      0.87       479
           1       0.82      0.76      0.79       321

    accuracy                           0.84       800
   macro avg       0.84      0.83      0.83       800
weighted avg       0.84      0.84      0.84       800
```



AdaBoost Classifier

In [43]:
```
ada = AdaBoostClassifier(random_state=21, n_estimators=500)

# Use GridSearchCV
parameters = {'learning_rate': [0.05,0.1,0.15]}

ada_clf = GridSearchCV(ada, parameters)
ada_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", ada_clf.best_params_, '\n')

# Accuracy
print ("AdaBoost Accuracy: %2.2f" % accuracy_score(y_test,ada_clf.predict(X_test

# Evaluate score (10-fold cross validation)
score_ada = cross_val_score(ada_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_ada)

# Make prediction
y_pred = ada_clf.predict(X_test)
print(classification_report(y_test,y_pred ))

# Confusion Marix for AdaBoost
cm = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm, classes=class_names, title='Confusion matrix')
```

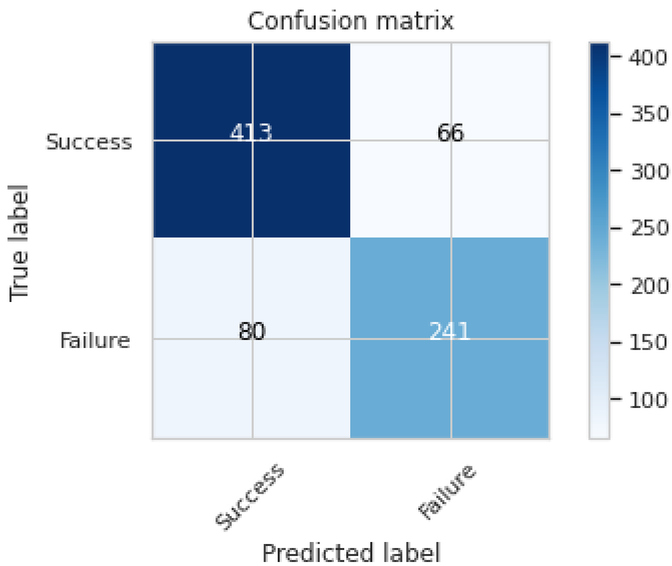
```
Best parameters:  {'learning_rate': 0.15}

AdaBoost Accuracy: 0.83
Cross Validation Score: 0.82
              precision    recall  f1-score   support

           0       0.84      0.88      0.86       479
           1       0.81      0.75      0.78       321

    accuracy                           0.83       800
   macro avg       0.82      0.81      0.82       800
weighted avg       0.83      0.83      0.83       800
```



XGBoost Classifier

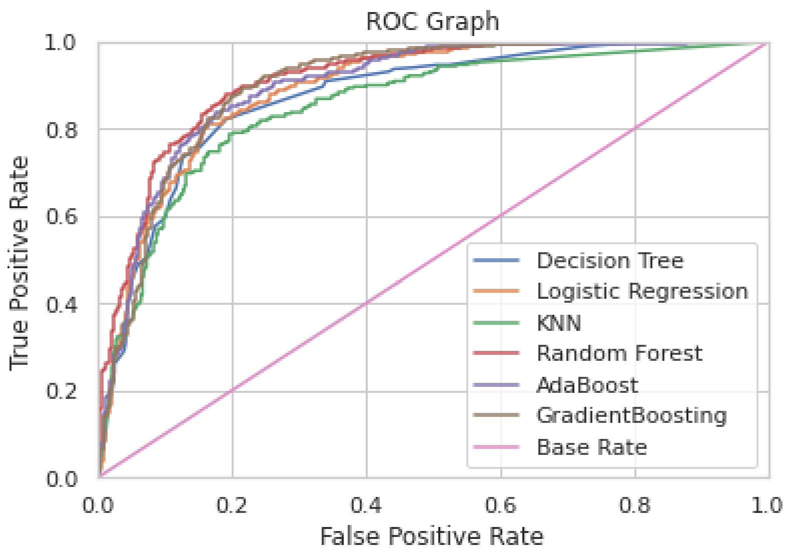
In [89]:
```
xgb = GradientBoostingClassifier(random_state=21, n_estimators=1000, max_depth=8

# Use GridSearchCV
parameters = {'subsample':[0.8,0.9,1]}

xgb_clf = GridSearchCV(xgb, parameters)
xgb_clf.fit(X_train,y_train)

# Get best parameters
print("Best parameters: ", xgb_clf.best_params_, '\n')

# Accuracy
print ("GradientBoost Accuracy: %2.2f" % accuracy_score(y_test,xgb_clf.predict(X

# Evaluate score (10-fold cross validation)
score_xgb = cross_val_score(xgb_clf, X_train, y_train, cv=10).mean()
print("Cross Validation Score: %2.2f" % score_ada)

# Prediction
y_pred = xgb_clf.predict(X_test)
print(classification_report(y_test,y_pred))

# Confusion Matrix for XGBoost
cm_xg = confusion_matrix(y_test,y_pred)
plot_confusion_matrix(cm_xg, classes=class_names, title='Confusion matrix')
```

```
Best parameters:  {'subsample': 0.8}

GradientBoost Accuracy: 0.82
Cross Validation Score: 0.82
              precision    recall  f1-score   support

           0       0.84      0.86      0.85       479
           1       0.79      0.75      0.77       321

    accuracy                           0.82       800
   macro avg       0.81      0.81      0.81       800
weighted avg       0.82      0.82      0.82       800
```



ROC Curves for each classifier

In [91]:
```
# False Positive Rate, True Positive Rate and Threshold for classifiers
knn_fpr, knn_tpr, thresholds = roc_curve(y_test, knn_clf.predict_proba(X_test)[:
LR_fpr, LR_tpr, thresholds = roc_curve(y_test, lr_clf.predict_proba(X_test)[:,1]
DT_fpr, DT_tpr, thresholds = roc_curve(y_test, dt_clf.predict_proba(X_test)[:,1]
rfc_fpr, rfc_tpr, thresholds = roc_curve(y_test, rfc_clf.predict_proba(X_test)[:
ada_fpr, ada_tpr, thresholds = roc_curve(y_test, ada_clf.predict_proba(X_test)[:
xgb_fpr, xgb_tpr, thresholds = roc_curve(y_test, xgb_clf.predict_proba(X_test)[:

# Plotting ROC Curves for all classifiers
plt.plot(DT_fpr, DT_tpr, label='Decision Tree')
plt.plot(LR_fpr, LR_tpr, label='Logistic Regression')
plt.plot(knn_fpr, knn_tpr, label='KNN' )
plt.plot(rfc_fpr, rfc_tpr, label='Random Forest')
plt.plot(ada_fpr, ada_tpr, label='AdaBoost')
plt.plot(xgb_fpr, xgb_tpr, label='GradientBoosting')

# Plot Base Rate ROC
plt.plot([0,1],[0,1],label='Base Rate')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Graph')
plt.legend(loc="lower right")
plt.show()
```



6. Testing the Trained Model

Use the best two classifers -- Random Forest and XGBoost -- on the test data (CarInsurance_test.csv)

In [93]:
```
#Random Forest Classifier
rfc.fit(X_train,y_train)
X_test = df_test.drop("CarInsurance", axis = 1)
df_test["CarInsurance"] = rfc.predict(X_test)
df_test["CarInsurance"] = df_test["CarInsurance"].apply(lambda x: "No. that will
df_test["CarInsurance"].value_counts()
```

Out[93]:
```
No. that will not buy insurance [0]    602
No. that will buy insurance [1]        398
Name: CarInsurance, dtype: int64
```

In [94]:
```
#XGBoost Classifier
xgb.fit(X_train,y_train)
X_test = df_test.drop("CarInsurance", axis = 1)
df_test["CarInsurance"] = xgb.predict(X_test)
df_test["CarInsurance"] = df_test["CarInsurance"].apply(lambda x: "No that will
df_test["CarInsurance"].value_counts()
```

Out[94]:
```
No that will not buy insurance [0]    594
No. that will buy insurance [1]       406
Name: CarInsurance, dtype: int64
```