The final project

ISE 364

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Team:

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** Problem statement **

Find the best classification technique that predicts of whether a client will subscribe to a long-term deposit program or not.

We have different supervised motheds (output known) that can be used:

- a) The logistic regression
- b) KNearestNeighbors (KNN)
- c) Random forest
- d) SVM
- e) Neural Network using Keras

In [1]:

```
# Import all the useful libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing                    # for numeric values findin
from sklearn.linear_model import LogisticRegression  # use for logistic regressi
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import tensorflow
import pickle                    # use with Keras
%matplotlib inline
sns.set_style("darkgrid")       # the background of the plot
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarnin
g: Conversion of the second argument of issubdtype from `float` to `np.floating
` is deprecated. In future, it will be treated as `np.float64 == np.dtype(floa
t).type`.
  from ._conv import register_converters as _register_converters
```

In [2]:
```
# Read the given data:
data = pd.read_csv("data.csv")     # predict the best model
```

Understand the data and their features

- head
- describe
- info

In [3]:
```
data.head()
```

Out[3]:

	age	job	marital	education	default	housing	loan	contact	day_of_week	campaign
0	56	housemaid	married	basic.4y	no	no	no	telephone	mon	1
1	57	services	married	high.school	unknown	no	no	telephone	mon	1
2	37	services	married	high.school	no	yes	no	telephone	mon	1
3	40	admin.	married	basic.6y	no	no	no	telephone	mon	1
4	56	services	married	high.school	no	no	yes	telephone	mon	1

- All the input variables are described in the description of the project
- We need to know the output variable (desired target), has the client subscribed? (binary: "yes", "No")

In [4]:
```
data.describe()
```

Out[4]:

	age	campaign	pdays	cons_price_idx	cons_conf_idx	prime_rate
count	40181.000000	40181.000000	40181.000000	40181.000000	40181.000000	40181.000000
mean	40.009731	2.573405	964.353923	93.578309	-40.506769	3.638561
std	10.360507	2.774774	182.216275	0.577601	4.610277	1.727104
min	17.000000	1.000000	0.000000	92.201000	-50.800000	0.634000
25%	32.000000	1.000000	999.000000	93.075000	-42.700000	1.344000
50%	38.000000	2.000000	999.000000	93.798000	-41.800000	4.857000
75%	47.000000	3.000000	999.000000	93.994000	-36.400000	4.961000
max	98.000000	56.000000	999.000000	94.767000	-26.900000	5.045000

In [5]:
```
data.info()    # we do not have any missing data!
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40181 entries, 0 to 40180
Data columns (total 16 columns):
age               40181 non-null int64
job               40181 non-null object
marital           40181 non-null object
education         40181 non-null object
default           40181 non-null object
housing           40181 non-null object
loan              40181 non-null object
contact           40181 non-null object
day_of_week       40181 non-null object
campaign          40181 non-null int64
pdays             40181 non-null int64
poutcome          40181 non-null object
cons_price_idx    40181 non-null float64
cons_conf_idx     40181 non-null float64
prime_rate        40181 non-null float64
y                 40181 non-null object
dtypes: float64(3), int64(3), object(10)
memory usage: 4.9+ MB
```

In [6]:
```
data.isnull().sum()  # we do not have any missing data!
```

Out[6]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
day_of_week       0
campaign          0
pdays             0
poutcome          0
cons_price_idx    0
cons_conf_idx     0
prime_rate        0
y                 0
dtype: int64
```

In [7]:
```
# lets take a look to the education catagories
data['education'].unique()
```

Out[7]:
```
array(['basic.4y', 'high.school', 'basic.6y', 'basic.9y',
       'professional.course', 'unknown', 'university.degree',
       'illiterate'], dtype=object)
```

In [8]:
```
data['campaign'].unique()
```

Out[8]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 19, 18, 23, 14,
       22, 25, 16, 17, 15, 20, 56, 39, 35, 42, 28, 26, 27, 32, 24, 21, 29,
       31, 30, 41, 37, 40, 33, 34, 43], dtype=int64)
```

We will group ('basic.4y', 'basic.6y', 'basic.9y') together with one word 'basic' for a better modelling

In [9]:
```
data.replace(['basic.4y', 'basic.6y', 'basic.9y'], 'basic', inplace=True)
```

In [10]:
```
# lets test it again
data['education'].unique()
```

Out[10]:
```
array(['basic', 'high.school', 'professional.course', 'unknown',
       'university.degree', 'illiterate'], dtype=object)
```

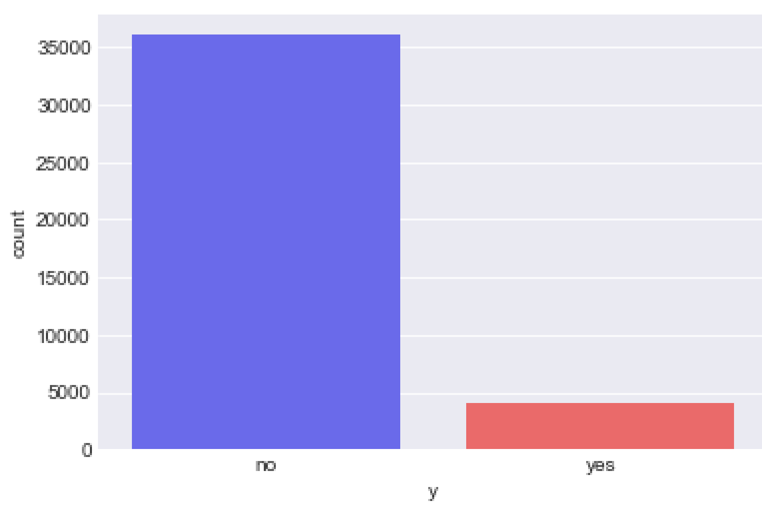
In [11]:
```
data['pdays'].unique()
```

Out[11]:
```
array([999,   6,   4,   3,   5,   1,   0,  10,   7,   8,   9,  11,   2,
        12,  13,  14,  15,  16,  21,  17,  18,  22,  25,  26,  19,  27,
        20], dtype=int64)
```

Data exploration and visualizition

In [12]:
```
# find the data output feature
sns.countplot(x='y',data=data, palette="seismic") # it can be used any color from
```

Out[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c2676419b0>
```



In [13]:
```
data['y'].value_counts()
```

Out[13]:
```
no     36065
yes     4116
Name: y, dtype: int64
```

It can be seen from the above plot, we do have imbalance data classes

Lets calculate the percentage of each one ('yes' or 'no')

In [14]:
```
Client_no_sub=len(data[data['y']=='no'])
Client_sub=len(data[data['y']=='yes'])
Total=Client_no_sub+Client_sub
percen_no_sub=Client_no_sub/Total*100
percen_sub=Client_sub/Total*100
print('The percentage of the client has NOT subscribed is:',percen_no_sub)
print('The percentage of the client has subscribed is:',percen_sub)
```

```
The percentage of the client has NOT subscribed is: 89.75635250491526
The percentage of the client has subscribed is: 10.243647495084742
```

It obvious from the percentages that we need to balance our data!

In [15]:
```
# find the mean of the data according to y
data.groupby('y').mean()
```

Out[15]:

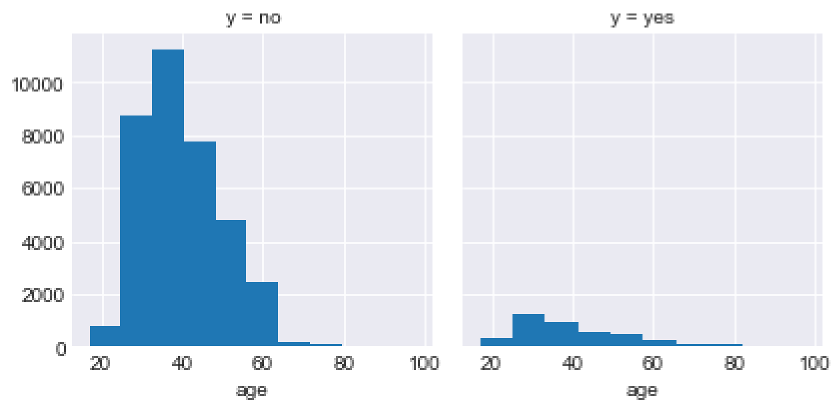
	age	campaign	pdays	cons_price_idx	cons_conf_idx	prime_rate
y						
no	39.916124	2.632968	984.079800	93.604335	-40.593978	3.812245
yes	40.829932	2.051506	791.512877	93.350263	-39.742638	2.116718

- **We need further visualization to get better understanding of our data**
- **For example,the age result above is telling us that the average age of the client who bought the long term deposit is higher than the one who did not buy it! (still not give a good picture about the data)**

Note:

Lets take a look to the features to understand which feature is important compare to other

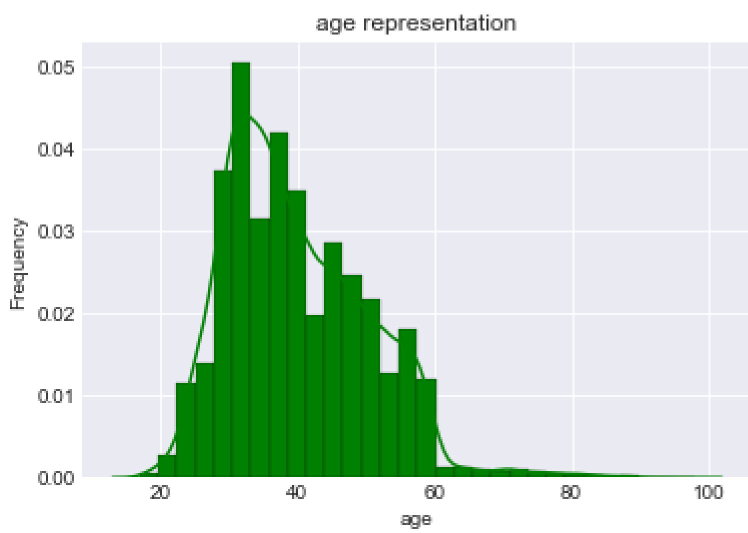
In [16]:
```
# age feature
g = sns.FacetGrid(data, col="y")
g = g.map(plt.hist, "age")
```



In [17]:
```
sns.distplot(data['age'],kde=True, bins=30,color='g',hist_kws=dict(edgecolor='k',
plt.ylabel('Frequency')
plt.title('age representation')
```

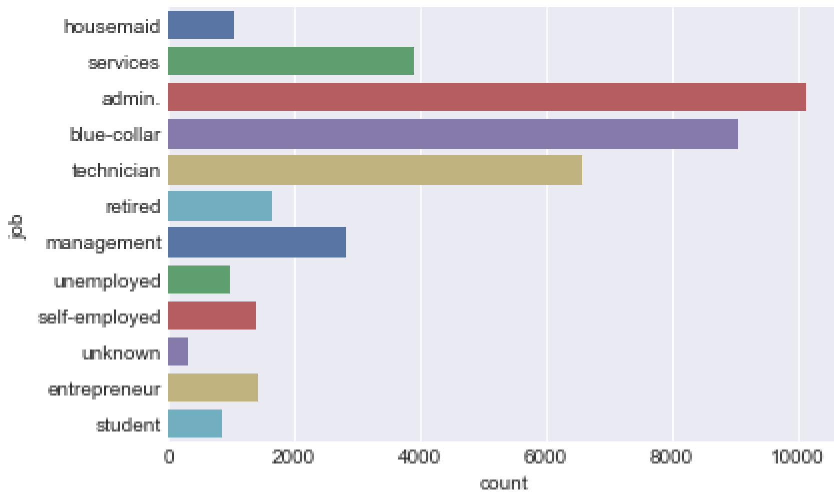
```
C:\Users\Mohanad\Anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: Use
rWarning: The 'normed' kwarg is deprecated, and has been replaced by the 'densi
ty' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[17]: `Text(0.5,1,'age representation')`



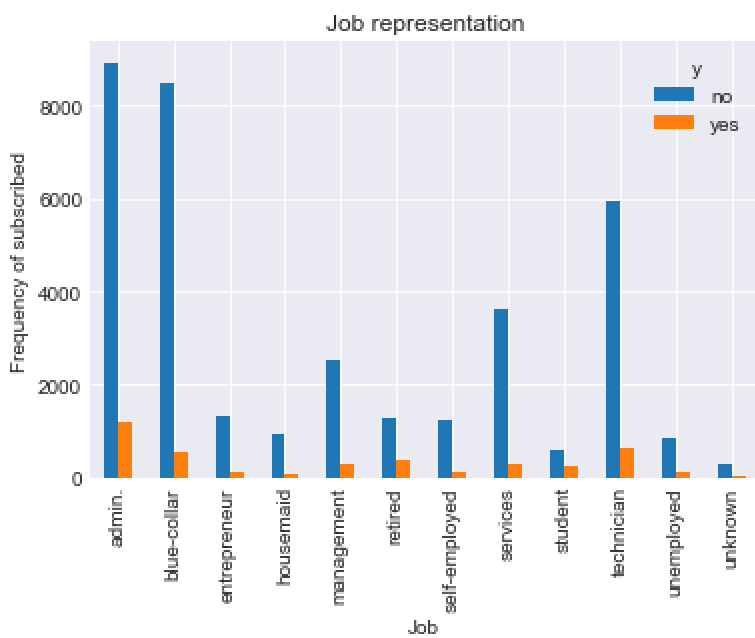
In [18]:
```
# Job feature (undestand number of participants in the subscription)
sns.countplot(y='job', data=data, palette="deep")
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1c267964f98>



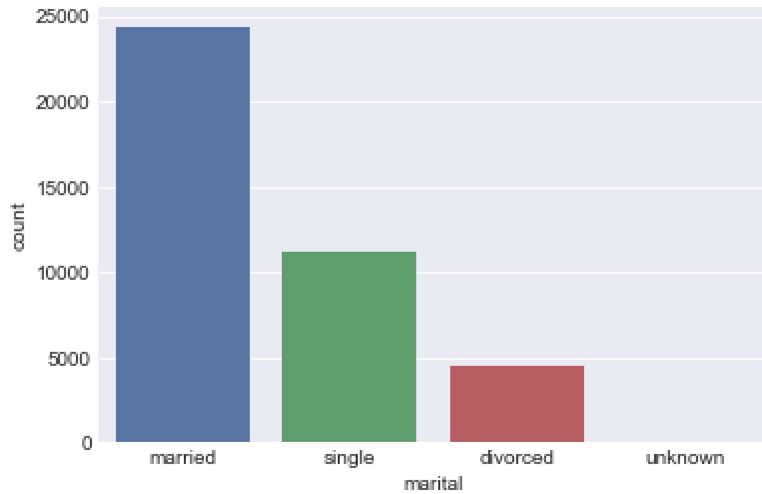
In [19]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.job,data.y).plot(kind='bar')
plt.title('Job representation')
plt.xlabel('Job')
plt.ylabel('Frequency of subscribed')
```

Out[19]: Text(0,0.5,'Frequency of subscribed')



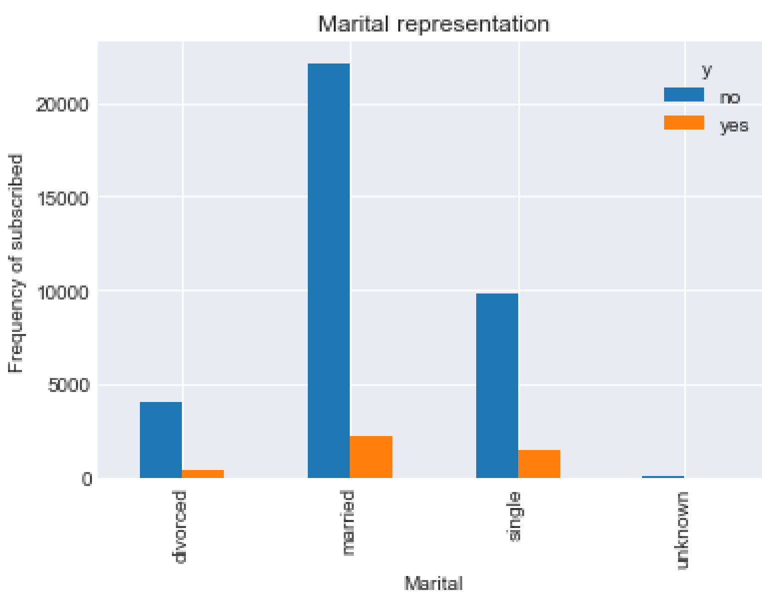
In [20]:
```
# Marital feature (undestand number of participants in the subscription)
sns.countplot(x='marital', data=data, palette="deep")
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1c267fdf208>



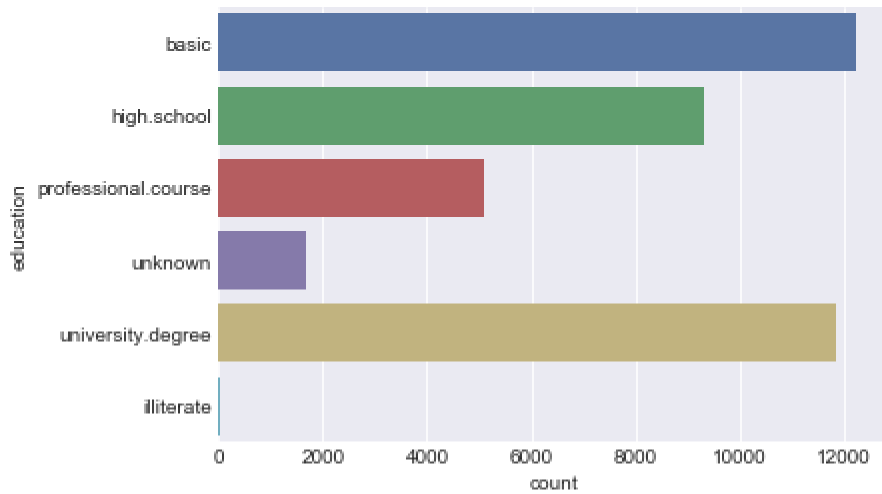
In [21]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.marital,data.y).plot(kind='bar')
plt.title('Marital representation')
plt.xlabel('Marital')
plt.ylabel('Frequency of subscribed')
```

Out[21]: Text(0,0.5,'Frequency of subscribed')



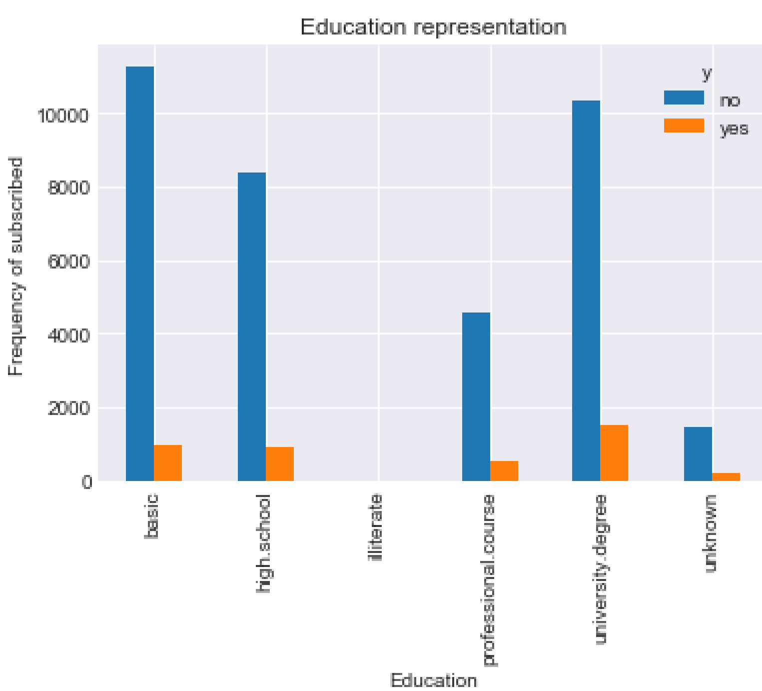
In [22]:
```
# Education feature (understand number of participants in the subscription)
sns.countplot(y='education', data=data, palette="deep")
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1c26845e0f0>



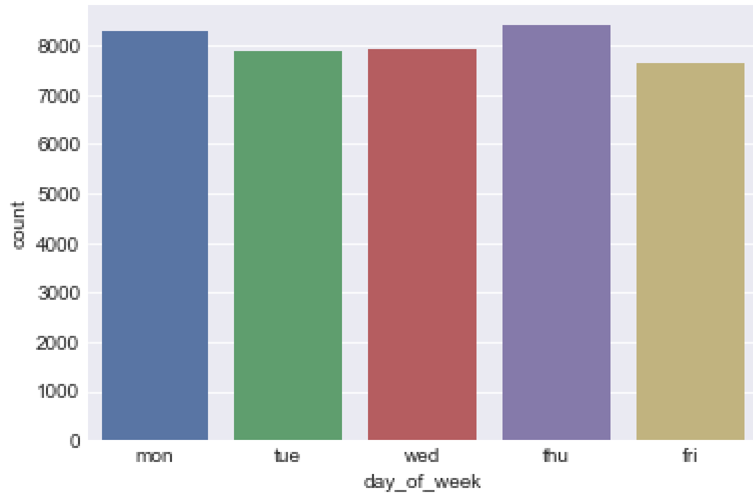
In [23]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.education,data.y).plot(kind='bar')
plt.title('Education representation')
plt.xlabel('Education')
plt.ylabel('Frequency of subscribed')
```

Out[23]: Text(0,0.5,'Frequency of subscribed')



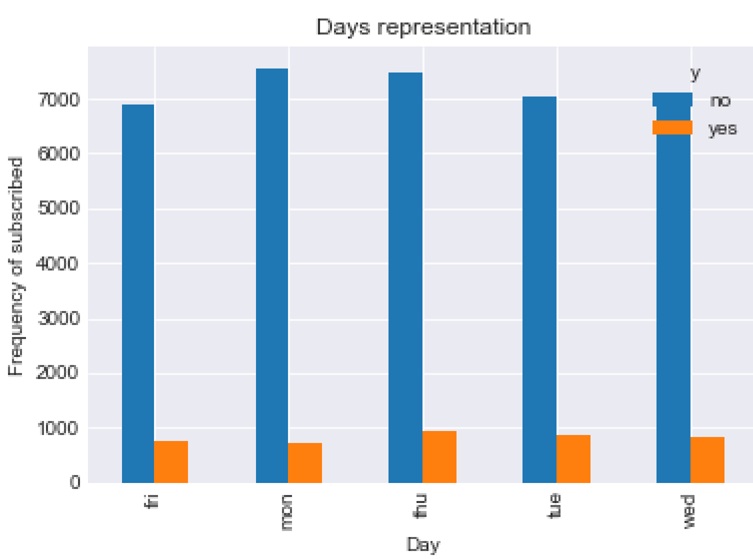
In [24]:
```
# day_of_week feature (undestand number of participants in the subscription)
sns.countplot(x='day_of_week', data=data, palette="deep")
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x1c268531ba8>



In [25]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.day_of_week,data.y).plot(kind='bar')
plt.title('Days representation')
plt.xlabel('Day')
plt.ylabel('Frequency of subscribed')
```

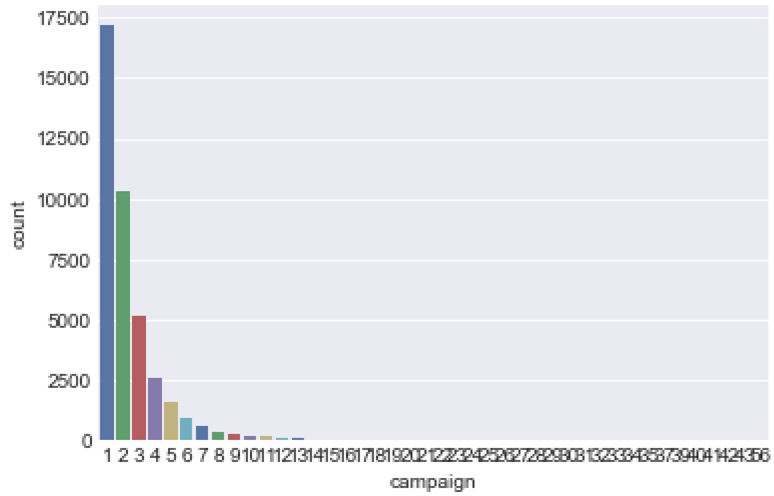
Out[25]: Text(0,0.5,'Frequency of subscribed')



It can be seen that the day of the week is does not matter

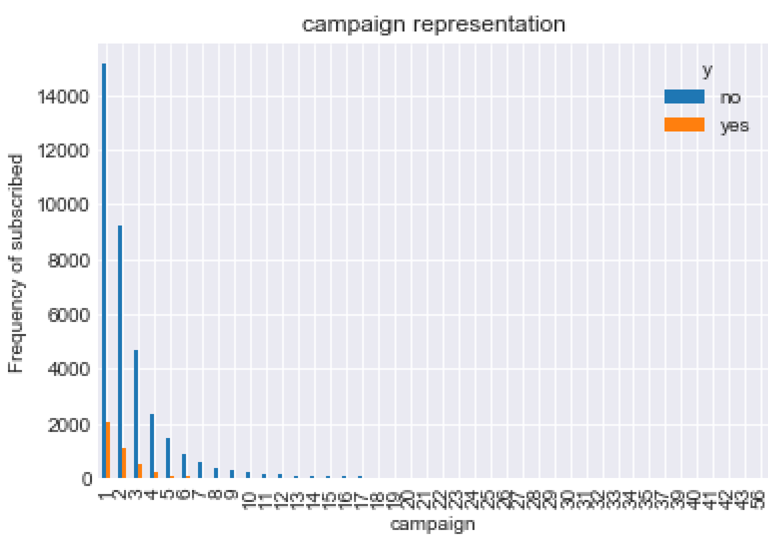
In [26]:
```
# campaign feature (undestand number of participants in the subscription)
sns.countplot(x='campaign', data=data, palette="deep")
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1c26854d668>



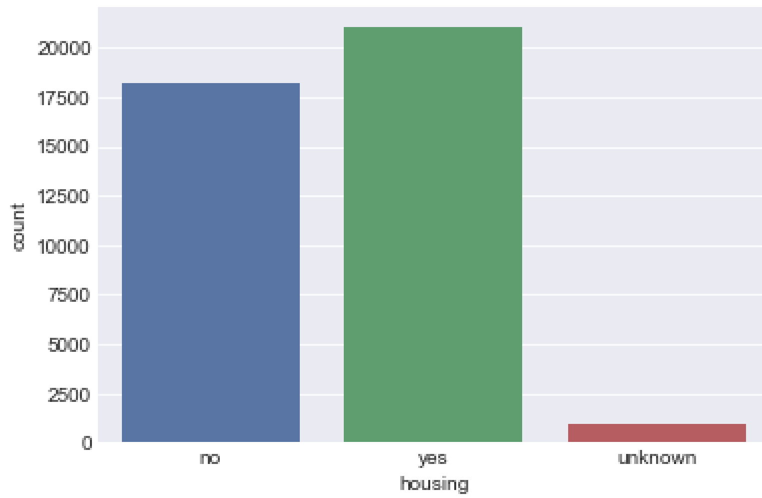
In [27]:
```
pd.crosstab(data.campaign,data.y).plot(kind='bar')
plt.title('campaign representation')
plt.xlabel('campaign')
plt.ylabel('Frequency of subscribed')
```

Out[27]: Text(0,0.5,'Frequency of subscribed')



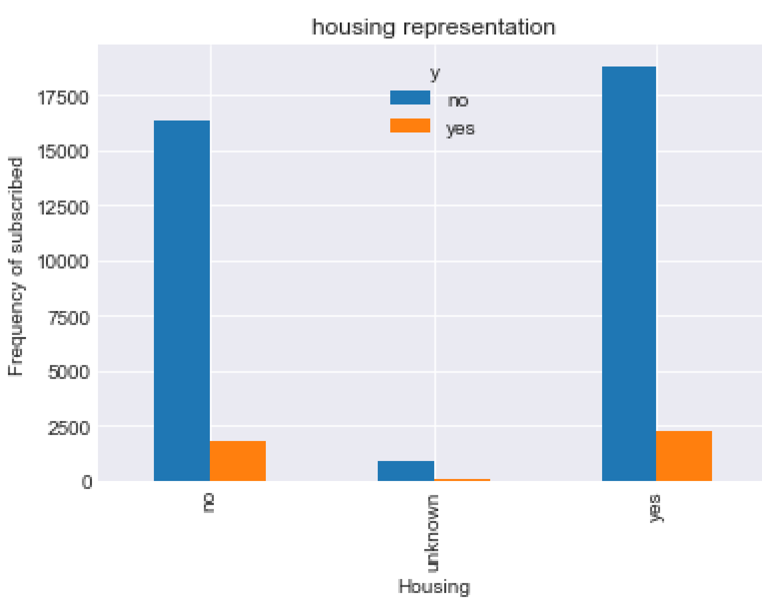
In [28]:
```python
# housing feature (undestand number of participants in the subscription)
sns.countplot(x='housing', data=data, palette="deep")
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1c26872c710>



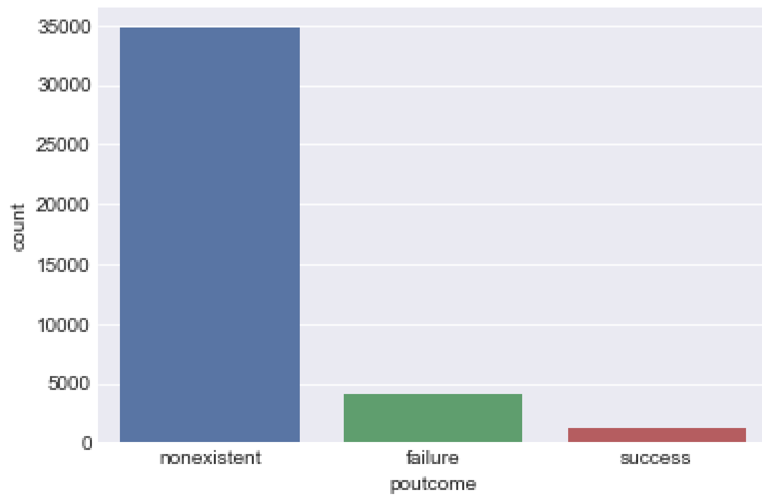
In [29]:
```python
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.housing,data.y).plot(kind='bar')
plt.title('housing representation')
plt.xlabel('Housing')
plt.ylabel('Frequency of subscribed')
```

Out[29]: Text(0,0.5,'Frequency of subscribed')



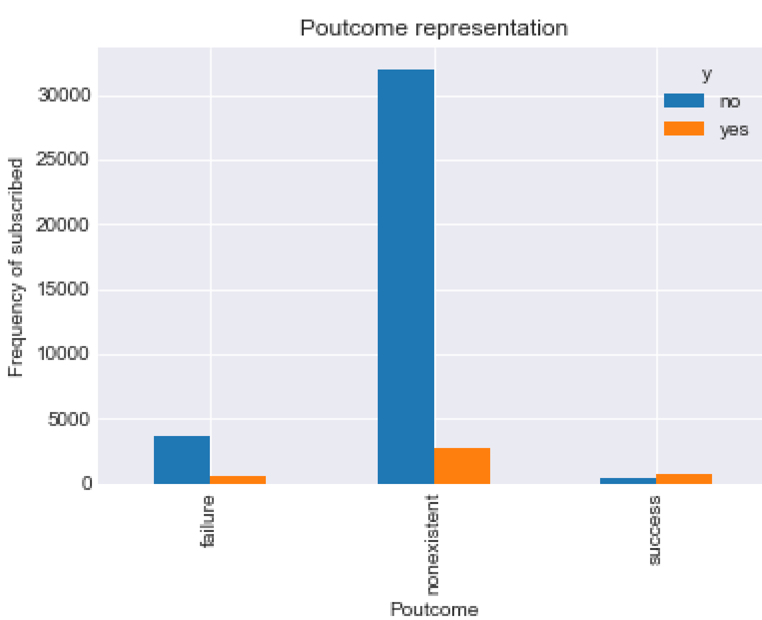
In [30]:
```
# Poutcome: outcome of the previous marketing campaign
# Poutcome feature (undestand number of participants in the subscription)
sns.countplot(x='poutcome', data=data, palette="deep")
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x1c268974048>



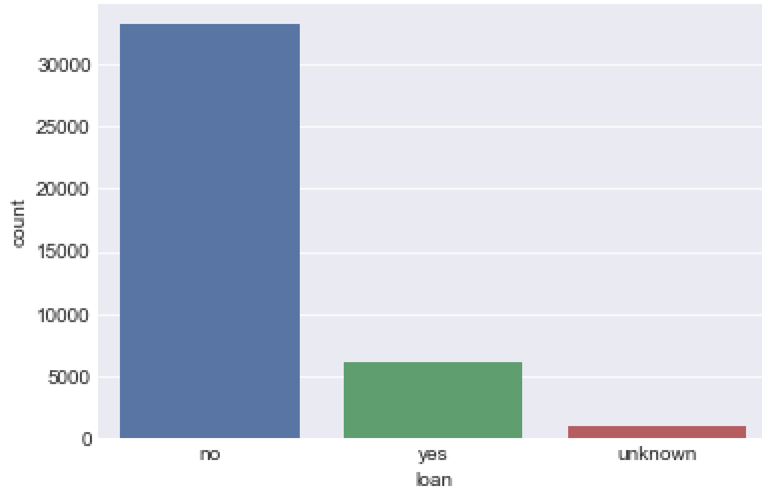
In [31]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.poutcome,data.y).plot(kind='bar')
plt.title('Poutcome representation')
plt.xlabel('Poutcome')
plt.ylabel('Frequency of subscribed')
```

Out[31]: Text(0,0.5,'Frequency of subscribed')



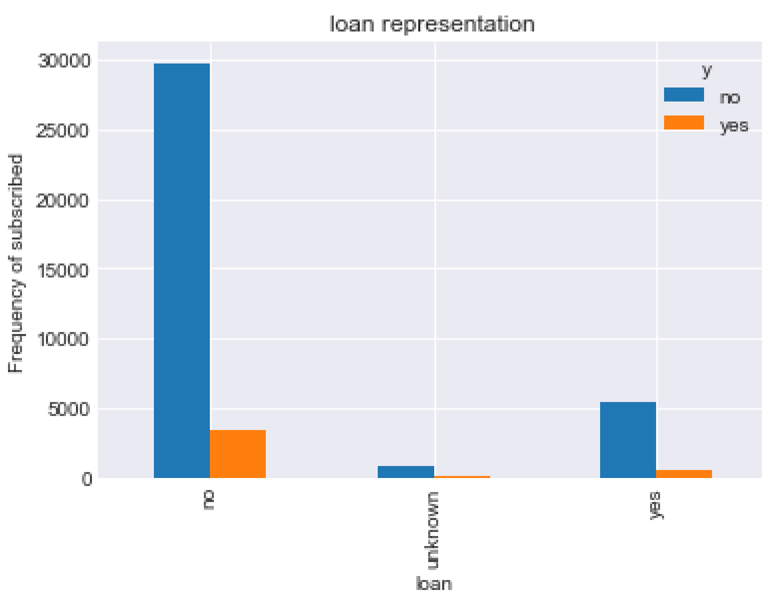
In [32]:
```
# loan feature (undestand number of participants in the subscription)
sns.countplot(x='loan', data=data, palette="deep")
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2689db198>



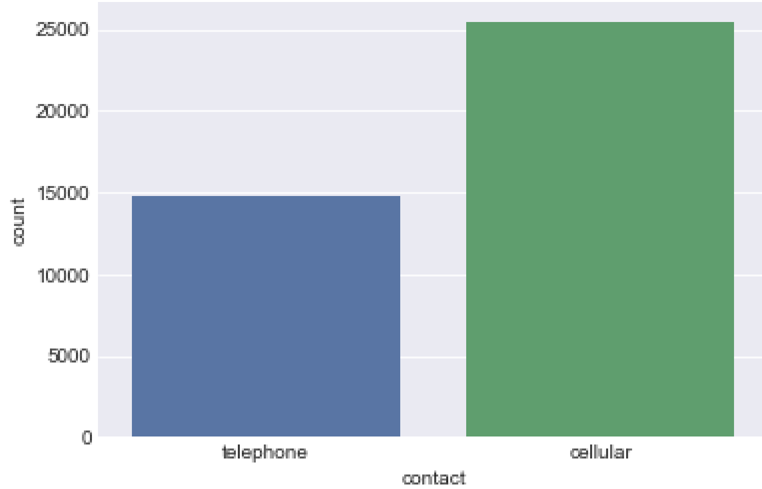
In [33]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.loan,data.y).plot(kind='bar')
plt.title('loan representation')
plt.xlabel('loan')
plt.ylabel('Frequency of subscribed')
```

Out[33]: Text(0,0.5,'Frequency of subscribed')



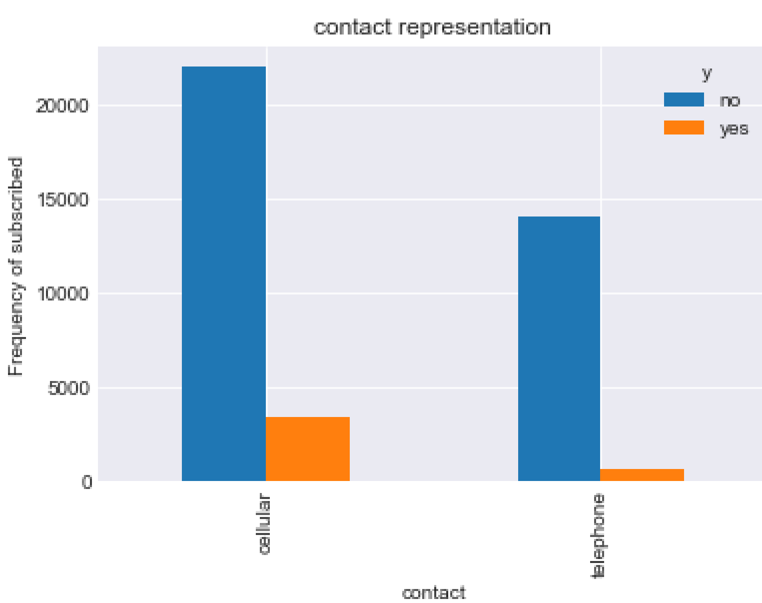
In [34]:
```
# contact feature (undestand number of participants in the subscription)
sns.countplot(x='contact', data=data, palette="deep")
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1c268b08ac8>



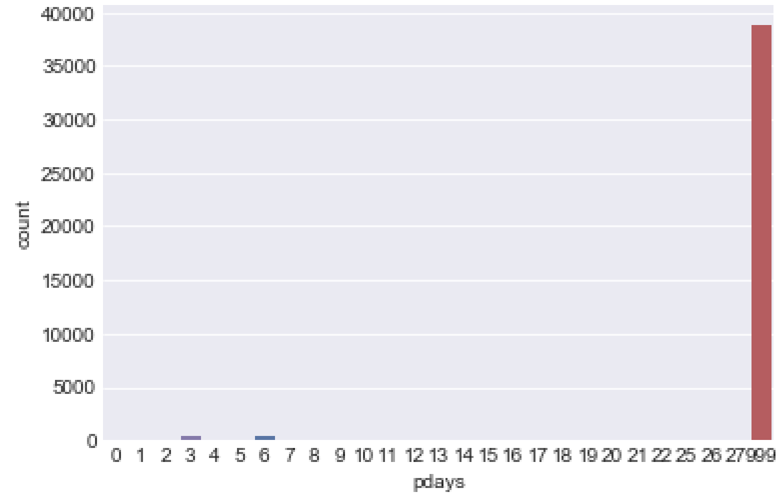
In [35]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.contact,data.y).plot(kind='bar')
plt.title('contact representation')
plt.xlabel('contact')
plt.ylabel('Frequency of subscribed')
```

Out[35]: Text(0,0.5,'Frequency of subscribed')



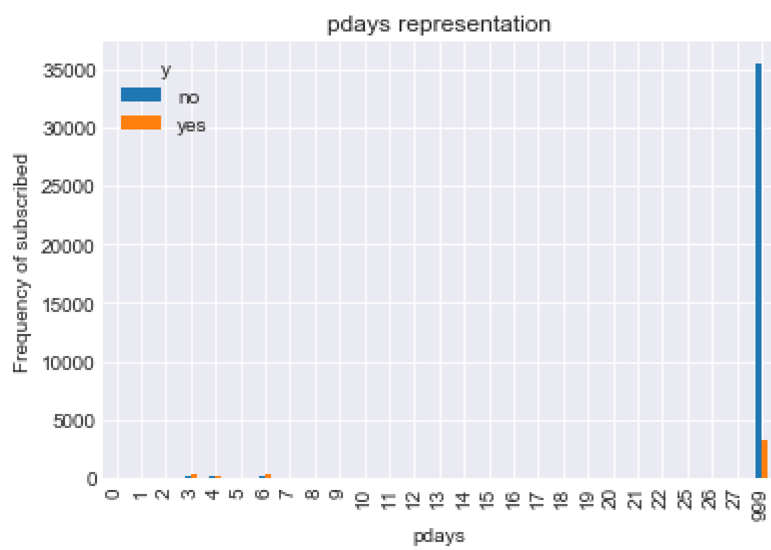
In [36]:
```
# contact feature (undestand number of participants in the subscription)
sns.countplot(x='pdays', data=data, palette="deep")
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1c268bcc128>



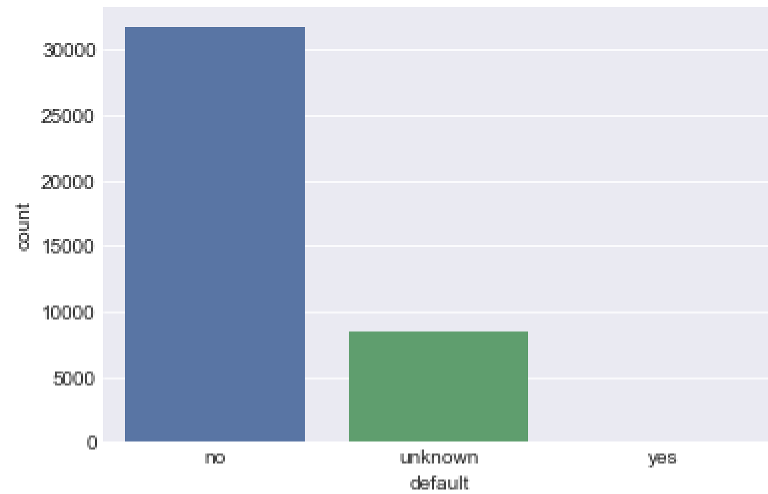
In [37]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.pdays,data.y).plot(kind='bar')
plt.title('pdays representation')
plt.xlabel('pdays')
plt.ylabel('Frequency of subscribed')
```

Out[37]: Text(0,0.5,'Frequency of subscribed')



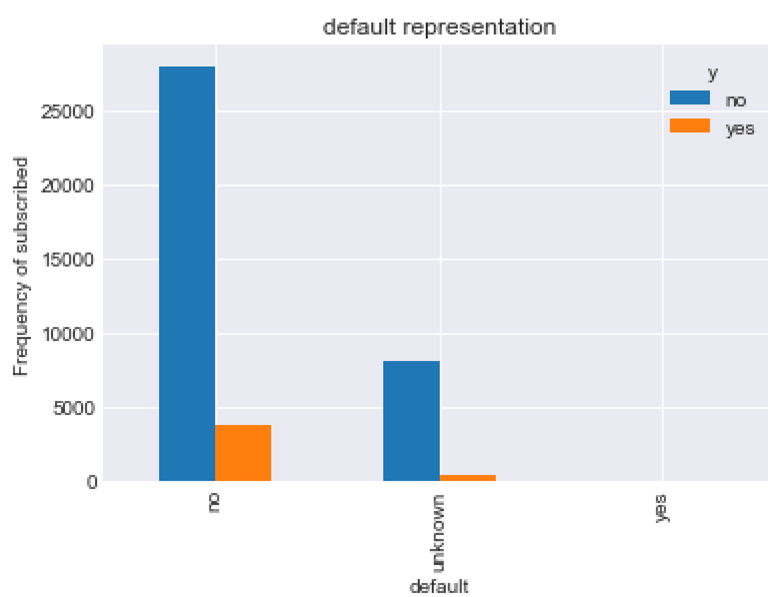
In [38]:
```
# default feature (undestand number of participants in the subscription)
sns.countplot(x='default', data=data, palette="deep")
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x1c268cf5be0>



In [39]:
```
# pandas.crosstab(index, columns, values=None, rownames=None, colnames=None, aggf
pd.crosstab(data.default,data.y).plot(kind='bar')
plt.title('default representation')
plt.xlabel('default')
plt.ylabel('Frequency of subscribed')
```

Out[39]: Text(0,0.5,'Frequency of subscribed')



Other features:

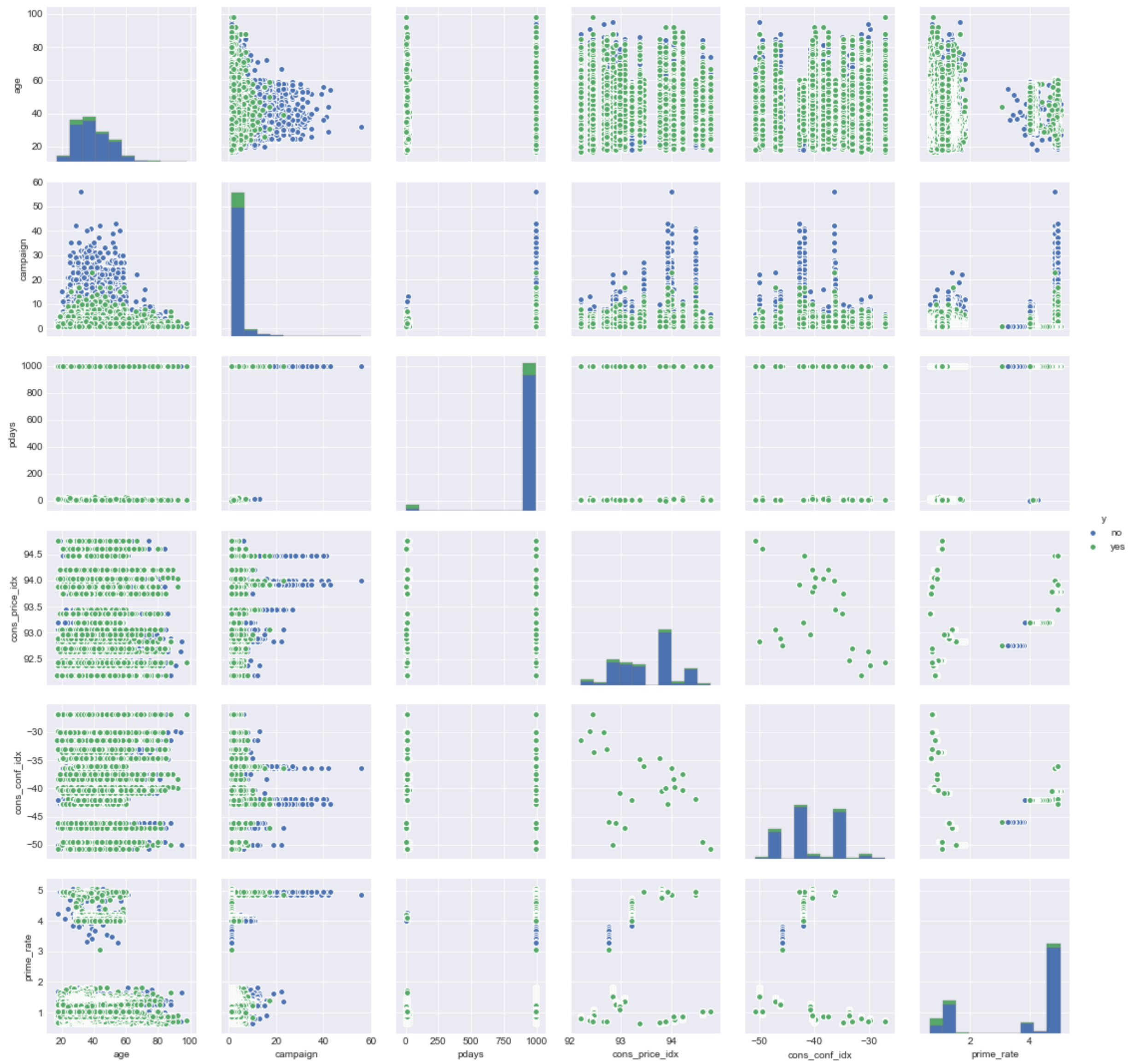
***By looking at other features (i.e., day of week, and Pdays (most are 999)) will not affect our model significantly. So it can be neglected from the model (drop) (it can be included and see how will ghange the results)**

Summary of the Visualizations:

- **1) The job feature has a great impact on our output (see the figure titled "Job representation")**
- **2) The marital feature (i.e. married) has an impact on our output (see the figure titled "Marital representation"), but it is not significan**
- **3) The Education feature seems to have an obvious impact on our output (see the figure titled "Education representation")**
- **4) The day of the week feature seems to have a very weak impact on our output (see the figure titled "days representation") so it can be neglected**
- **5) The cotact feature seems to have an acceptable impact on our output (see the figure titled "contact representation")**
- **6) The housing, poutcome and loan features seem to have a good impact on our output, but with less weight compared to (1,2 and 3) (see the figures titled "housing representation, poutcome representation, and loan representation")**

In [40]:
```
sns.pairplot(data,hue="y", palette='deep', diag_kws=dict(edgecolor='gray',linewid
```

Out[40]: <seaborn.axisgrid.PairGrid at 0x1c268df6e48>



- **Visualization Summary**

Pre-processing the data

- Lets eleminate the features that have less affect on the model (recall the visualization for which features are important)
- we will drop 2 features (pdays and day_of_week)

In [41]:
```
data.drop(['day_of_week','pdays'], axis=1, inplace=True)
data.head()
```

Out[41]:

	age	job	marital	education	default	housing	loan	contact	campaign	poutcome
0	56	housemaid	married	basic	no	no	no	telephone	1	nonexistent
1	57	services	married	high.school	unknown	no	no	telephone	1	nonexistent
2	37	services	married	high.school	no	yes	no	telephone	1	nonexistent
3	40	admin.	married	basic	no	no	no	telephone	1	nonexistent
4	56	services	married	high.school	no	no	yes	telephone	1	nonexistent

To predict a good result we need to make our data smooth and uniform

- **Convert all the categorical features to numeric features (i.e the dummy variable (0,1) or the most efficient technique "LabelEncoder")**
- class sklearn.preprocessing.LabelEncoder
- Encode labels with value between 0 and n_classes-1
- [https://scikit-learn.org/stable/modules/preprocessing_targets.html#preprocessing-targets (https://scikit-learn.org/stable/modules/preprocessing_targets.html#preprocessing-targets)](https://scikit-learn.org/stable/modules/preprocessing_targets.html#preprocessing-targets)

In [42]:
```
## call the LabelEncoder as le
le = preprocessing.LabelEncoder()
```

In [43]:
```
# fit and transform all the features to numeric order!
data.job = le.fit_transform(data.job)
data.marital = le.fit_transform(data.marital)
data.education = le.fit_transform(data.education)
data.default = le.fit_transform(data.default)
data.housing = le.fit_transform(data.housing)
data.loan = le.fit_transform(data.loan)
data.contact = le.fit_transform(data.contact)
data.poutcome = le.fit_transform(data.poutcome)
data.y = le.fit_transform(data.y)
#data.y = le.inverse_transform(data.y)       # to go back to the categorical case
```

In [44]:
```
data.head()
```

Out[44]:

	age	job	marital	education	default	housing	loan	contact	campaign	poutcome	cons_price_
0	56	3	1	0	0	0	0	1	1	1	93.!
1	57	7	1	1	1	0	0	1	1	1	93.!
2	37	7	1	1	0	2	0	1	1	1	93.!
3	40	0	1	0	0	0	0	1	1	1	93.!
4	56	7	1	1	0	0	2	1	1	1	93.!

Visualize the new data

In [45]:
```
data['job'].unique()    # we have 12 categorical job types
```

Out[45]:
```
array([ 3,  7,  0,  1,  9,  5,  4, 10,  6, 11,  2,  8], dtype=int64)
```

In [46]:
```
data['marital'].unique()    # we have 4 categorical marital types
```

Out[46]:
```
array([1, 2, 0, 3], dtype=int64)
```

In [47]:
```
data['education'].unique()    # we have 6 categorical education types
```

Out[47]:
```
array([0, 1, 3, 5, 4, 2], dtype=int64)
```

In [48]:
```
data['default'].unique()    # we have 3 categorical default types
```

Out[48]:
```
array([0, 1, 2], dtype=int64)
```

In [49]:
```
data['housing'].unique()    # we have 3 categorical housing types
```

Out[49]:
```
array([0, 2, 1], dtype=int64)
```

In [50]:
```
data['loan'].unique()    # we have 3 categorical loan types
```

Out[50]:
```
array([0, 2, 1], dtype=int64)
```

In [51]:
```
data['contact'].unique()   # we have 2 categorical contact types
```

Out[51]: array([1, 0], dtype=int64)

In [52]:
```
data['poutcome'].unique()   # we have 3 categorical poutcome types
```

Out[52]: array([1, 0, 2], dtype=int64)

In [53]:
```
# The output
data['y'].unique()   # we have 2 categorical output types
```

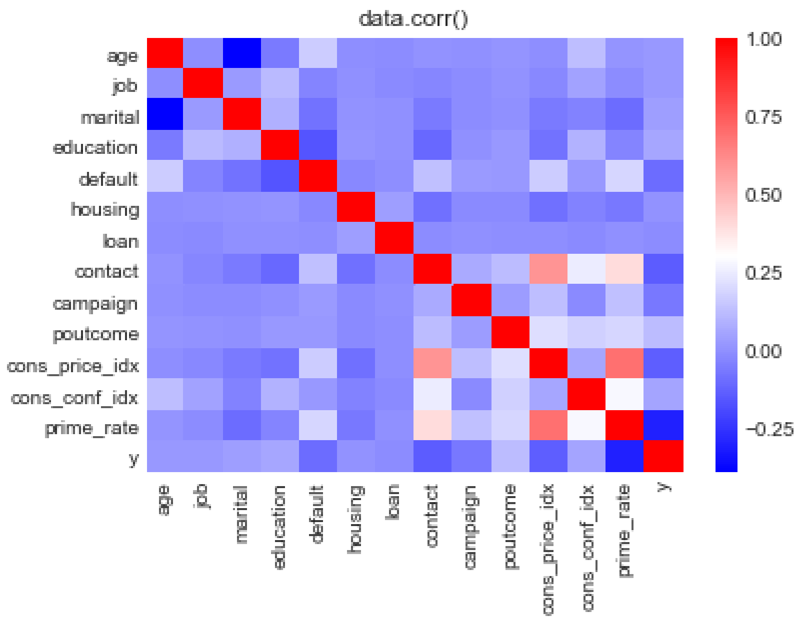
Out[53]: array([0, 1], dtype=int64)

In [54]:
```
sns.pairplot(data,hue="y", palette='deep', diag_kws=dict(edgecolor='gray',linewid
```

Out[54]: <seaborn.axisgrid.PairGrid at 0x1c268cede10>

In [55]:
```
# Matrix form for correlation data
sns.heatmap(data.corr(),cmap='bwr',annot=False) #annot = true we get the number i
plt.title('data.corr()')
```

Out[55]: `Text(0.5,1,'data.corr()')`



Eleminate the imbalance in the data

Imbalanced data typically refers to a problem with classification problems where the classes are not represented equally. As we we saw previously with the client responses:

- **Clients response with approximately 90% of "no"and 10% of "yes"**

Lets perfom the prediction with the logistic regression on our current data. It is expected to have a high accuracy since we have imblance data

In [56]:
```
# test
from sklearn.metrics import accuracy_score
y_train=data.y
X_train=data.drop('y', axis=1)
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
predictions = logmodel.predict(X_train)
print(accuracy_score(predictions, y_train))
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)

0.9051292899629177
```

Is it a good accuracy?

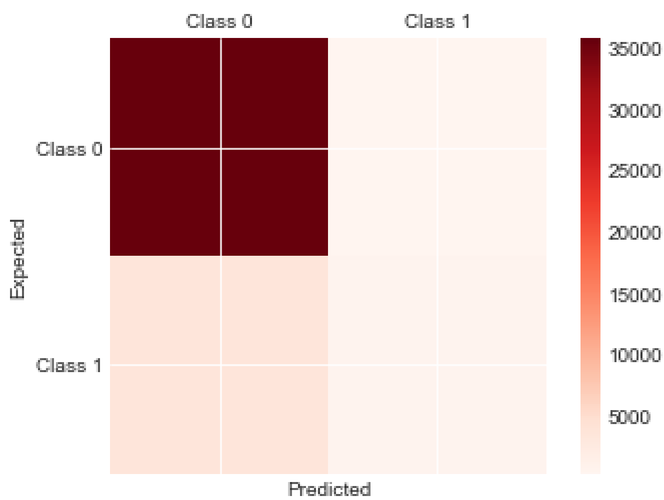
- Since we have imbalance data, its expected the majority of prediction to be only one class ('no')

There are several ways to balance the data (Resampling):

- Oversample the data (just increase the "yes" sample)
- undersample the data (just decrease the "no" sample)
- Changing your performance metric by using, The Receiver Operating Characteristic (ROC)
- SMOTE (This object is an implementation of SMOTE - Synthetic Minority Over-sampling Technique), for more info: https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.SMOTE.html (https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.SMOTE.html)
- XG Boost
- For more information about imbalance:
- https://www.kaggle.com/rafjaa/resampling-strategies-for-imbalanced-datasets (https://www.kaggle.com/rafjaa/resampling-strategies-for-imbalanced-datasets)
- **Find the representation of the confusion matrix before oversampling:**

In [57]:
```
# https://www.kaggle.com/rafjaa/resampling-strategies-for-imbalanced-datasets

from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=y_train, y_pred=predictions)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[35763   302]
 [ 3510   606]]
```



Oversampling:

- **Upsample minority class**

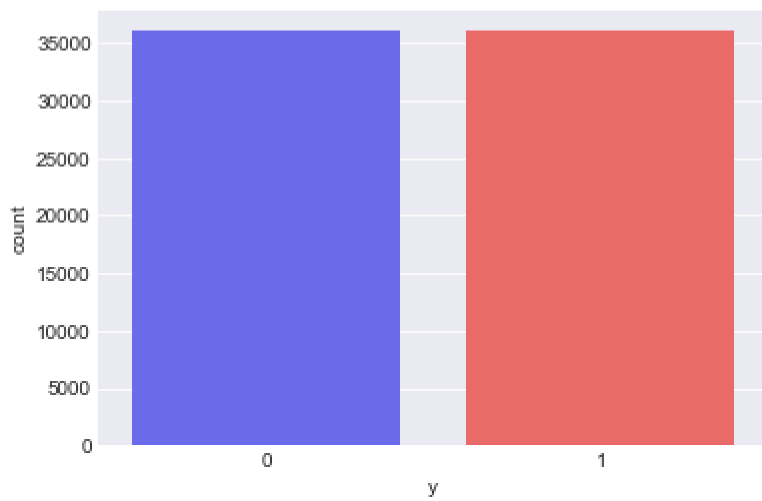
In [58]:
```
from sklearn.utils import resample
```

In [59]:
```
# Separate majority and minority classes
data_majority = data[data.y==0]
data_minority = data[data.y==1]

# Upsample minority class
data_minority_upsampled = resample(data_minority,
                                 replace=True,             # sample with replacem
                                 n_samples=Client_no_sub,  # to match majority cl
                                 random_state=123)         # reproducible results

# Combine results of the samples
data_upsampled = pd.concat([data_majority, data_minority_upsampled])

# Display new class counts
data_upsampled.y.value_counts()
```

Out[59]:
```
1    36065
0    36065
Name: y, dtype: int64
```

In [60]:
```
# find the data output feature
sns.countplot(x='y',data=data_upsampled, palette="seismic") # it can be used any
```

Out[60]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c201d0b710>
```



In [61]:
```
# test the new data
y_train=data_upsampled.y
X_train=data_upsampled.drop('y', axis=1)
logmodel = LogisticRegression()
logmodel.fit(X_train,y_train)
predictions = logmodel.predict(X_train)
print(accuracy_score(predictions, y_train))
```

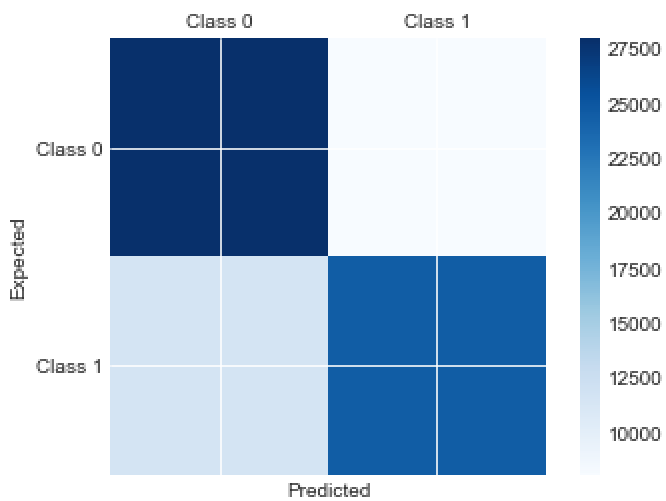
```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)

0.7272840704283932
```

In [62]:
```
predictions
```

Out[62]:
```
array([0, 0, 0, ..., 1, 0, 1])
```

In [63]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=y_train, y_pred=predictions)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Blues)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[27973  8092]
 [11579 24486]]
```



To have a higher diagonal values of the confusion matrix, the better indication can be acheived!

In [64]:
```
data.head()
```

Out[64]:

	age	job	marital	education	default	housing	loan	contact	campaign	poutcome	cons_price_
0	56	3	1	0	0	0	0	1	1	1	93.!
1	57	7	1	1	1	0	0	1	1	1	93.!
2	37	7	1	1	0	2	0	1	1	1	93.!
3	40	0	1	0	0	0	0	1	1	1	93.!
4	56	7	1	1	0	0	2	1	1	1	93.!

In [65]:
```
# We can do undersampling by following the same procedure with oversampling, but
# SMOTE Modeling
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
sm=SMOTE(random_state=0)
y=data.y
X=data.drop('y', axis=1)
data_train_x, data_test_x, data_train_y, data_test_y=train_test_split(X,y,test_si
columns=data_train_x.columns
columns
```

Out[65]:
```
Index(['age', 'job', 'marital', 'education', 'default', 'housing', 'loan',
       'contact', 'campaign', 'poutcome', 'cons_price_idx', 'cons_conf_idx',
       'prime_rate'],
      dtype='object')
```

In [66]:
```
# now we can use SMOTE to balance our data
sm_data_x,sm_data_y =sm.fit_sample(data_train_x,data_train_y)
sm_data_x=pd.DataFrame(data=sm_data_x, columns=columns)
sm_data_y=pd.DataFrame(data=sm_data_y, columns=['y'])

# we can now check our data
print('length of oversampled data is:',len(sm_data_x))
print('Number of no subscribed client within new data is:',len(sm_data_y[sm_data_
print('Number of subscribed client within new data is:',len(sm_data_y[sm_data_y['
print("Percentage of no subscription within new data is ",len(sm_data_y[sm_data_y
print("Percentage of subscription within new data is ",len(sm_data_y[sm_data_y['y
```

```
length of oversampled data is: 50504
Number of no subscribed client within new data is: 25252
Number of subscribed client within new data is: 25252
Percentage of no subscription within new data is  0.5
Percentage of subscription within new data is  0.5
```

We can see that we have balance classes!

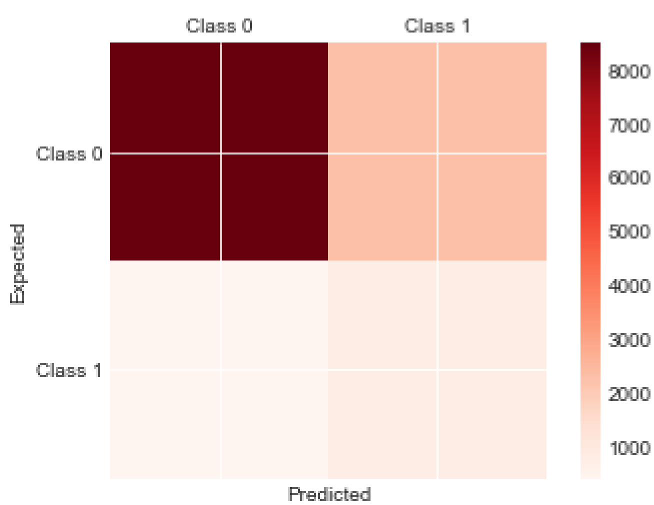
In [67]:
```
logmodel = LogisticRegression()
logmodel.fit(sm_data_x,sm_data_y)
predictions = logmodel.predict(data_test_x)
print(accuracy_score(predictions, data_test_y))
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: D
ataConversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

```
0.7723766072169225
```

In [68]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=predictions)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[8497 2316]
 [ 428  814]]
```



Implementing the model

- **Here we will use the data that we got from SMOTE (higher accuracy compare to oversampling) after oversampling to remove the imbalance**

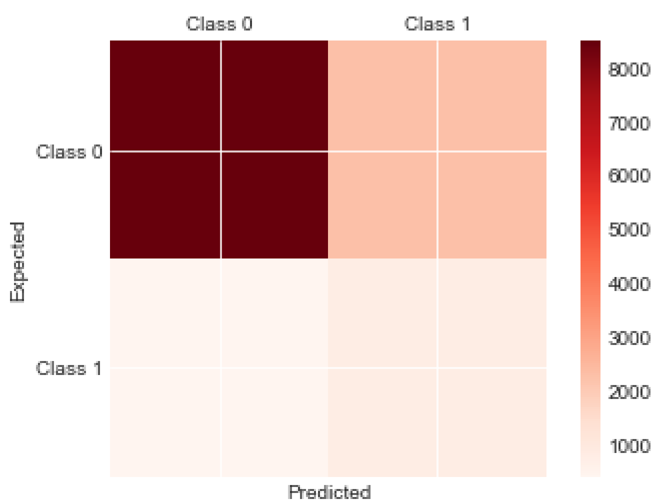
- **a) The logistic regression**

In [69]:
```
# call the previous libraries
logmodel = LogisticRegression()
logmodel.fit(sm_data_x,sm_data_y)        # these data after we did oversampling b
predictions = logmodel.predict(data_test_x)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\linear_model\logistic.py:4
33: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. Specify a
solver to silence this warning.
  FutureWarning)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: D
ataConversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [70]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=predictions)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

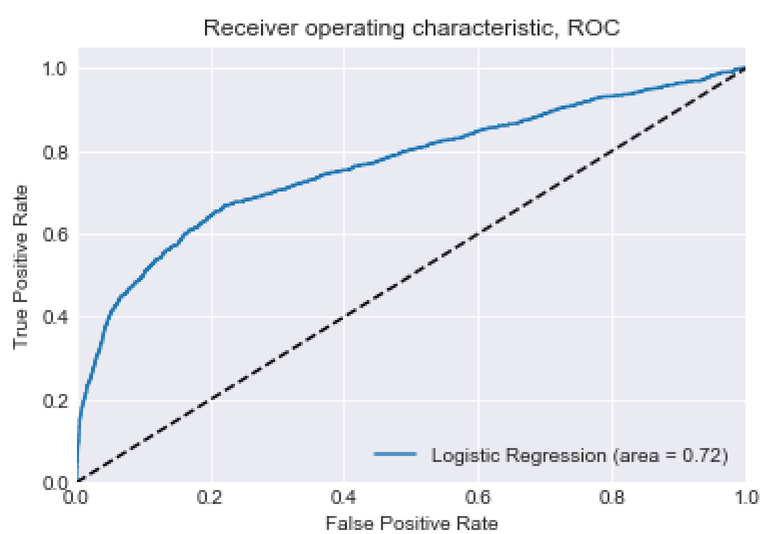
```
Confusion matrix:
 [[8497 2316]
 [ 428  814]]
```



In [71]:
```
from sklearn.metrics import classification_report, confusion_matrix
print('classification_report is:')
print(classification_report(data_test_y,predictions))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,predictions))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.95      0.79      0.86     10813
           1       0.26      0.66      0.37      1242

   micro avg       0.77      0.77      0.77     12055
   macro avg       0.61      0.72      0.62     12055
weighted avg       0.88      0.77      0.81     12055

confusion_matrix is:
[[8497 2316]
 [ 428  814]]
```

In [72]:
```
## Lets try ROC and see if we can find any diffrence
# Compare our results with the results that have published by Susan Li, sep,28,20

from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
logit_roc_auc = roc_auc_score(data_test_y, logmodel.predict(data_test_x))
fpr, tpr, thresholds = roc_curve(data_test_y, logmodel.predict_proba(data_test_x)
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



We can conclude that the selected metrics evaluation can lead to different results (i.e,

accuracy score, classification report, and ROC).

b) KNearestNeighbors (KNN) classifier

In [73]:
```
sm_data_x[0:10]
```

Out[73]:

	age	job	marital	education	default	housing	loan	contact	campaign	poutcome	cons_price_
0	29.0	0.0	2.0	0.0	1.0	2.0	0.0	1.0	2.0	1.0	93.
1	29.0	2.0	1.0	0.0	0.0	0.0	0.0	0.0	3.0	1.0	92.
2	39.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	4.0	1.0	93.
3	43.0	1.0	1.0	0.0	1.0	2.0	0.0	0.0	6.0	1.0	93.
4	59.0	5.0	1.0	0.0	1.0	0.0	0.0	1.0	5.0	1.0	94.
5	38.0	2.0	0.0	4.0	1.0	2.0	0.0	1.0	2.0	1.0	93.
6	33.0	0.0	2.0	1.0	0.0	2.0	0.0	0.0	2.0	1.0	93.
7	33.0	1.0	1.0	0.0	0.0	2.0	0.0	1.0	2.0	1.0	93.
8	32.0	0.0	1.0	4.0	1.0	2.0	0.0	0.0	1.0	1.0	93.
9	24.0	8.0	2.0	4.0	0.0	0.0	0.0	0.0	1.0	1.0	92.

In [74]:
```
scaler = StandardScaler()
scaler.fit(sm_data_x)
scaled_x_train = scaler.fit_transform(sm_data_x)
scaled_x_test = scaler.fit_transform(data_test_x)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625:
DataConversionWarning: Data with input dtype int32, int64, float64 were all con
verted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversio
nWarning: Data with input dtype int32, int64, float64 were all converted to flo
at64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [75]:
```
scaled_x_train.shape
```

Out[75]: (50504, 13)

In [76]:
```
scaled_x_test.shape
```

Out[76]: (12055, 13)

In [77]:
```
scaled_x_train.mean(0)
```

Out[77]:
```
array([ 1.04865746e-14,  3.53146503e-15, -9.90996934e-15, -3.49880904e-14,
       -5.30307709e-14, -6.05628594e-15,  7.71051913e-15,  9.99870892e-14,
        3.41675640e-14,  2.97048453e-14, -1.15880440e-11, -4.11210803e-13,
       -5.72560264e-14])
```

In [78]:
```
scaled_x_test.mean(0)
```

Out[78]:
```
array([-9.81380054e-17, -1.65036886e-17, -3.83121342e-18, -2.35766980e-18,
        2.59343678e-17,  3.30073772e-17,  8.95914524e-17,  3.50703383e-17,
       -7.54454336e-17, -3.59544644e-17, -2.26306830e-15, -5.77629101e-16,
        3.24179597e-17])
```

In [79]:
```
scaled_x_train.var(0)
```

Out[79]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

In [80]:
```
scaled_x_test.var(0)
```

Out[80]:
```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

In [81]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=1)  # K=1
## we do not need to split the data... it already splited when we used SMOTE
knn.fit(scaled_x_train,sm_data_y)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DataConve
rsionWarning: A column-vector y was passed when a 1d array was expected. Please
change the shape of y to (n_samples, ), for example using ravel().
  after removing the cwd from sys.path.
```

Out[81]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=None, n_neighbors=1, p=2,
           weights='uniform')
```

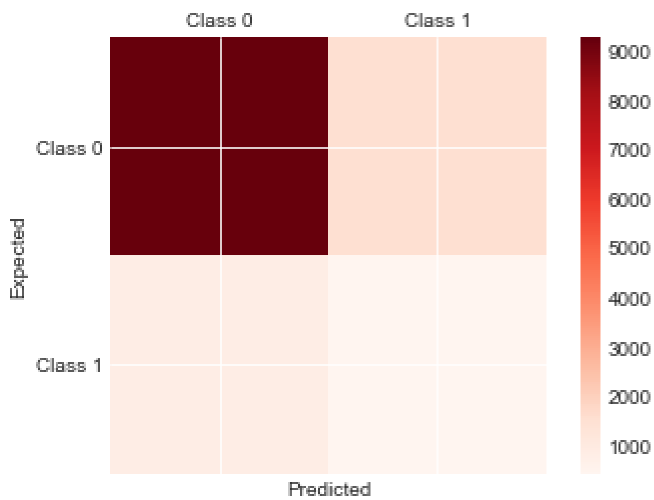
Use the predict method to predict values using your KNN model and X_test.

In [82]:
```
pred = knn.predict(scaled_x_test)
print('classification_report is:')
print(classification_report(data_test_y,pred))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,pred))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.92      0.86      0.89     10813
           1       0.22      0.34      0.27      1242

   micro avg       0.81      0.81      0.81     12055
   macro avg       0.57      0.60      0.58     12055
weighted avg       0.85      0.81      0.82     12055

confusion_matrix is:
[[9291 1522]
 [ 816  426]]
```

In [83]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=pred)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[9291 1522]
 [ 816  426]]
```



Choosing a K Value

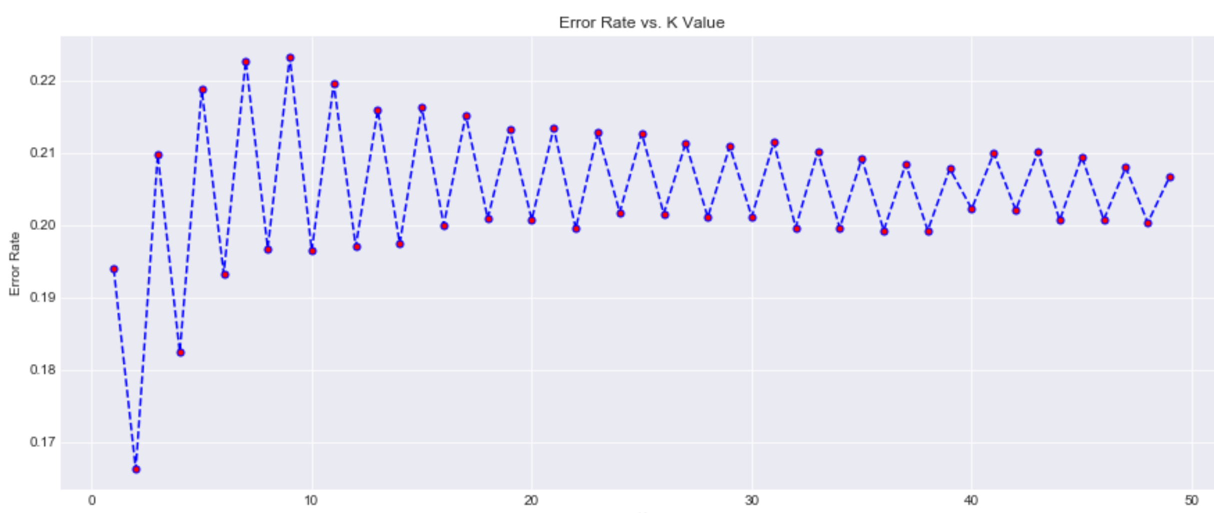
Use the elbow method to pick a good K Value!

In [84]:
```
error_rate = []

for i in range(1,50):

    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(scaled_x_train,sm_data_y)
    pred_i = knn.predict(scaled_x_test)
    error_rate.append(np.mean(pred_i != data_test_y))
```

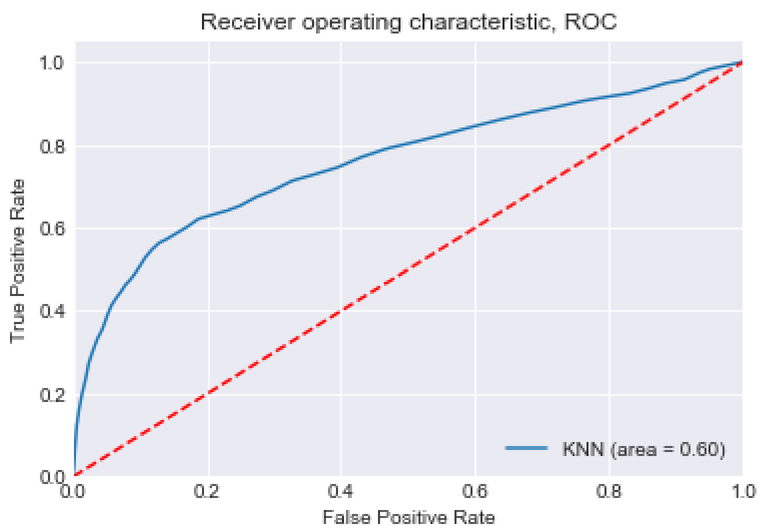
```
versionWarning: A column-vector y was passed when a 1d array was expected. Pl
ease change the shape of y to (n_samples, ), for example using ravel().

C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataCon
versionWarning: A column-vector y was passed when a 1d array was expected. Pl
ease change the shape of y to (n_samples, ), for example using ravel().

C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataCon
versionWarning: A column-vector y was passed when a 1d array was expected. Pl
ease change the shape of y to (n_samples, ), for example using ravel().

C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataCon
versionWarning: A column-vector y was passed when a 1d array was expected. Pl
ease change the shape of y to (n_samples, ), for example using ravel().

C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:6: DataCon
versionWarning: A column-vector y was passed when a 1d array was expected. Pl
ease change the shape of y to (n_samples, ), for example using ravel().
```

In [85]:
```
plt.figure(figsize=(15,6))
plt.plot(range(1,50),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=5)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

Out[85]: Text(0,0.5,'Error Rate')



In [86]:
```
logit_roc_auc = roc_auc_score(data_test_y, pred)
fpr, tpr, thresholds = roc_curve(data_test_y, knn.predict_proba(scaled_x_test)[:,
plt.figure()
plt.plot(fpr, tpr, label='KNN (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



c) Random forest classifier

- We know that the random forest classifier leads to best prediction compare to other Decision tree classifiers!

In [87]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
```

In [88]:
```
rfc.fit(sm_data_x, sm_data_y)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:246: Fu
tureWarning: The default value of n_estimators will change from 10 in version
0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: DataConve
rsionWarning: A column-vector y was passed when a 1d array was expected. Please
change the shape of y to (n_samples,), for example using ravel().
  """Entry point for launching an IPython kernel.
```

Out[88]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

Predictions and Evaluation

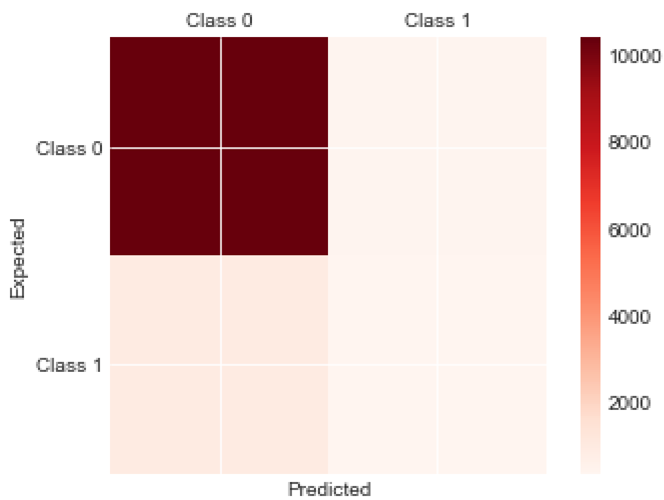
Let's predict off the y_test values and evaluate our model.

Predict the class of not.fully.paid for the X_test data.

In [89]:
```
rfc_pred = rfc.predict(data_test_x)
```

In [90]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=rfc_pred)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

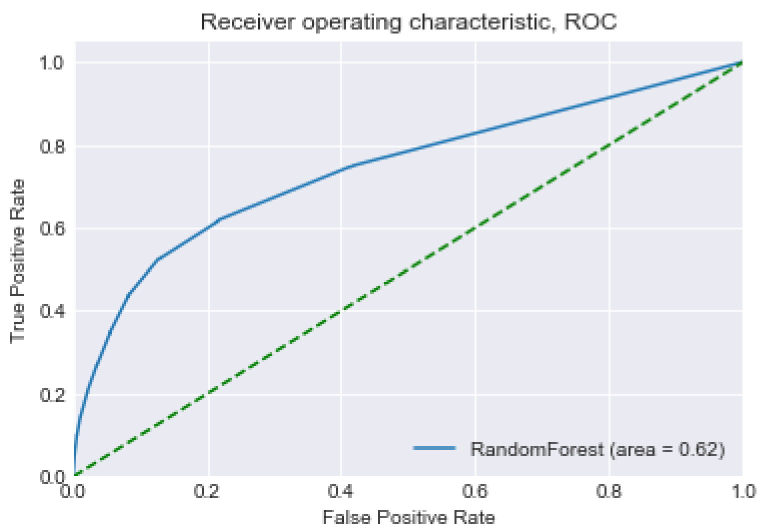
```
Confusion matrix:
 [[10423   390]
 [  906   336]]
```



In [91]:
```
print('classification_report is:')
print(classification_report(data_test_y,rfc_pred))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,rfc_pred))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.92      0.96      0.94     10813
           1       0.46      0.27      0.34      1242

   micro avg       0.89      0.89      0.89     12055
   macro avg       0.69      0.62      0.64     12055
weighted avg       0.87      0.89      0.88     12055

confusion_matrix is:
[[10423   390]
 [  906   336]]
```

In [92]:
```
logit_roc_auc = roc_auc_score(data_test_y, rfc_pred)
fpr, tpr, thresholds = roc_curve(data_test_y, rfc.predict_proba(data_test_x)[:,1]
plt.figure()
plt.plot(fpr, tpr, label='RandomForest (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



d) SVM Modelling

In [93]:
```
from sklearn.svm import SVC
model = SVC()
```

In [94]:
```
model.fit(sm_data_x, sm_data_y)      ##X_train,y_train= sm_data_x, sm_data_y
```

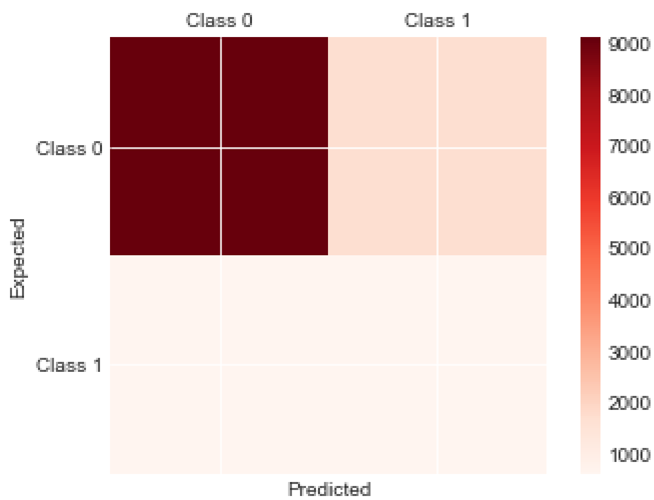
```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\utils\validation.py:761: D
ataConversionWarning: A column-vector y was passed when a 1d array was expecte
d. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\svm\base.py:196: FutureWar
ning: The default value of gamma will change from 'auto' to 'scale' in version
0.22 to account better for unscaled features. Set gamma explicitly to 'auto' or
'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)
```

Out[94]:
```
SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False)
```

In [95]:
```
pred_svm = model.predict(data_test_x)
```

In [96]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=pred_svm)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

```
Confusion matrix:
 [[9109 1704]
 [ 626  616]]
```



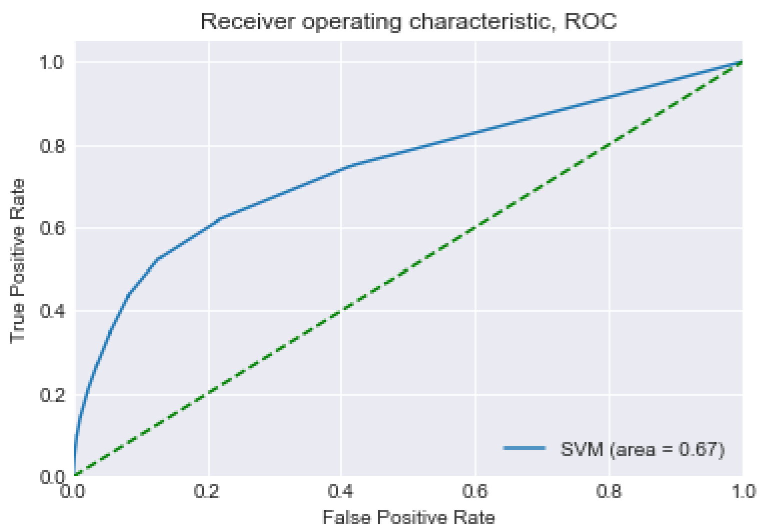
In [97]:
```
print('classification_report is:')
print(classification_report(data_test_y,pred_svm))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,pred_svm))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.94      0.84      0.89     10813
           1       0.27      0.50      0.35      1242

   micro avg       0.81      0.81      0.81     12055
   macro avg       0.60      0.67      0.62     12055
weighted avg       0.87      0.81      0.83     12055

confusion_matrix is:
[[9109 1704]
 [ 626  616]]
```

In [98]:
```
pred_svm
```

Out[98]:
```
array([0, 0, 0, ..., 0, 1, 0])
```

In [99]:
```
logit_roc_auc = roc_auc_score(data_test_y, pred_svm)
#fpr, tpr, thresholds = roc_curve(data_test_y, model.predict_proba(data_test_x)[:,
plt.figure()
plt.plot(fpr, tpr, label='SVM (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



e) Neural Network using Keras

In [100]:
```
scaler = StandardScaler()
scaler.fit(sm_data_x)
scaled_x_train = scaler.fit_transform(sm_data_x)
scaled_x_test = scaler.transform(data_test_x)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: DataConve
rsionWarning: Data with input dtype int32, int64, float64 were all converted to
float64 by StandardScaler.
  after removing the cwd from sys.path.
```

In [101]:
```
from tensorflow.contrib.keras import models, layers
from tensorflow.contrib.keras import activations, optimizers, losses
```

Note:

- **If you run the data marke as Data.csv, use input_dim=13**

In [102]:
```
dnn = models.Sequential()
dnn.add( layers.Dense(input_dim=13, units=10, activation='relu' ))  # grid search
dnn.add( layers.Dense(units=8, activation='relu' ))
dnn.add( layers.Dense(units=8, activation='relu' ))
dnn.add( layers.Dense(units=1, activation='sigmoid' ))
```

In [103]:
```
dnn.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [104]:
```
dnn.fit(scaled_x_train, sm_data_y, epochs=300, batch_size=100, verbose=0)
```

Out[104]:
```
<tensorflow.python.keras.callbacks.History at 0x1c218683860>
```

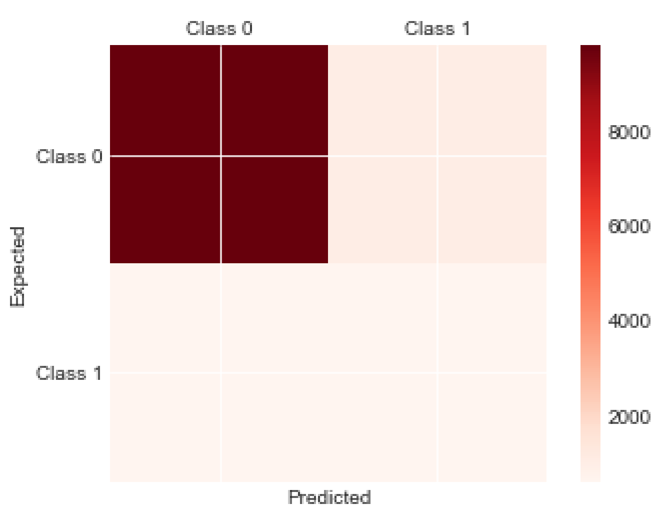
In [105]:
```
pred_keras = dnn.predict_classes(scaled_x_test)
```

In [106]:
```
sum(data_test_y==1)
```

Out[106]:
```
1242
```

In [107]:
```
from sklearn.metrics import confusion_matrix
conf_mat = confusion_matrix(y_true=data_test_y, y_pred=pred_keras)
print('Confusion matrix:\n', conf_mat)

labels = ['Class 0', 'Class 1']
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(conf_mat, cmap=plt.cm.Reds)
fig.colorbar(cax)
ax.set_xticklabels([''] + labels)
ax.set_yticklabels([''] + labels)
plt.xlabel('Predicted')
plt.ylabel('Expected')
plt.show()
```

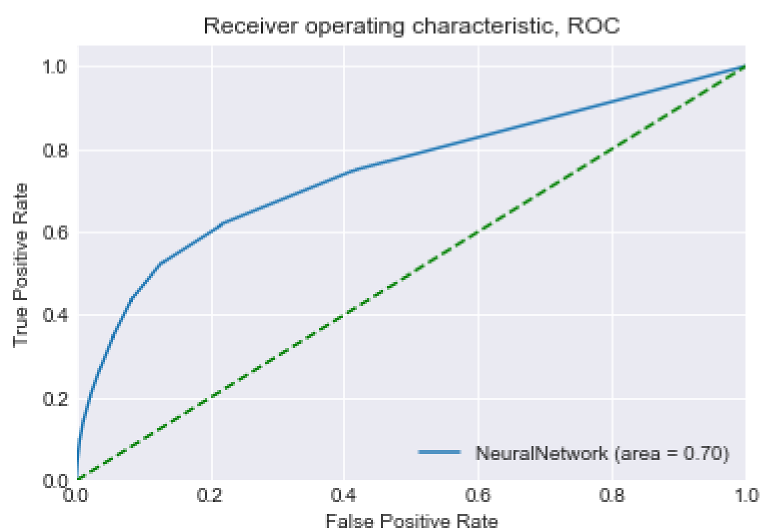
```
Confusion matrix:
 [[9790 1023]
 [ 616  626]]
```



In [108]:
```
# Evaluation
print('classification_report is:')
print(classification_report(data_test_y,pred_keras))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,pred_keras))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.94      0.91      0.92     10813
           1       0.38      0.50      0.43      1242

   micro avg       0.86      0.86      0.86     12055
   macro avg       0.66      0.70      0.68     12055
weighted avg       0.88      0.86      0.87     12055

confusion_matrix is:
[[9790 1023]
 [ 616  626]]
```

In [109]:
```
logit_roc_auc = roc_auc_score(data_test_y, pred_keras)
#fpr, tpr, thresholds = roc_curve(data_test_y, dnn.predict_proba(scaled_x_test)[:
plt.figure()
plt.plot(fpr, tpr, label='NeuralNetwork (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



Lets try with different activation function

- **If you run the data marke as Data.csv, use input_dim=13**
- **If you run the data marke as futures.csv, use input_dim=13**

In [110]:
```
model = models.Sequential()
model.add(layers.Dense(10, input_dim=13, activation='tanh'))   # just one layer

model.add(layers.Dense(1, activation='sigmoid'))
```

In [111]:
```
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

In [112]:
```
x_train_keras = np.array(scaled_x_train)
y_train_keras = np.array(sm_data_y)
#print(x_train_keras.shape)
y_train_keras = y_train_keras.reshape(y_train_keras.shape[0], 1)
```

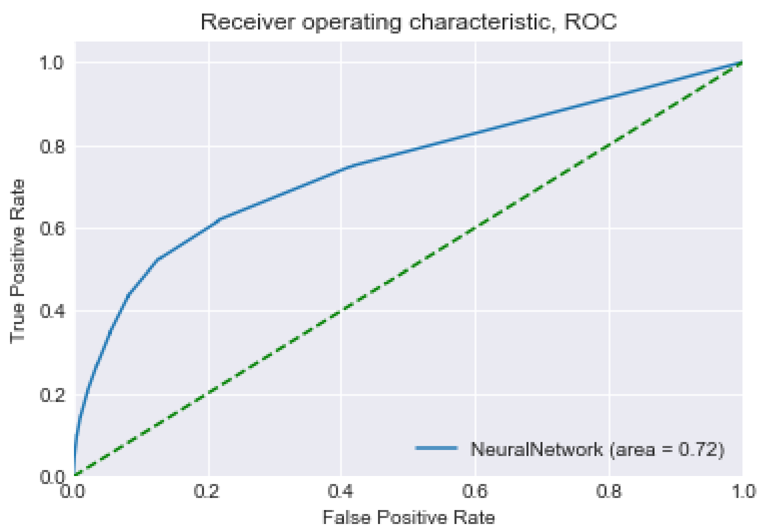
In [113]:
```
model.fit(np.array(x_train_keras), np.array(y_train_keras), epochs=200, batch_siz
```

Out[113]:
```
<tensorflow.python.keras.callbacks.History at 0x1c218fbb7f0>
```

In [114]:
```
# Evaluation
pred_keras_n = model.predict_classes(scaled_x_test)
print('classification_report is:')
print(classification_report(data_test_y,pred_keras_n))
print('confusion_matrix is:')
print(confusion_matrix(data_test_y,pred_keras_n))
```

```
classification_report is:
              precision    recall  f1-score   support

           0       0.95      0.86      0.90     10813
           1       0.33      0.58      0.42      1242

   micro avg       0.83      0.83      0.83     12055
   macro avg       0.64      0.72      0.66     12055
weighted avg       0.88      0.83      0.85     12055

confusion_matrix is:
[[9337 1476]
 [ 524  718]]
```

In [115]:
```
logit_roc_auc = roc_auc_score(data_test_y, pred_keras_n)
#fpr, tpr, thresholds = roc_curve(data_test_y, model.predict_proba(scaled_x_test)
plt.figure()
plt.plot(fpr, tpr, label='NeuralNetwork (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic, ROC')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
```



Well, we can conclude that the rectified linear function with three layers gave us a good prediction compare to tan function

Note that:

Based on the all 5 model classifiers that have been used, the Neural network using Keras has given the best prediction!

- **The results have varified with some academic papers (i.e., Jiong Chen, Yucen Han, Zhao Hu, Yicheng Lu and Mengni Sun, Dec-7,2014)**

call the output

Here the data still oversampled

- **Create txt file, and save the output pred_keras**

In [116]:
```
output_y=le.inverse_transform(pred_keras)  # convert the binary number to the cha
output_y
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:27
3: DataConversionWarning: A column-vector y was passed when a 1d array was expe
cted. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

Out[116]:
```
array(['no', 'no', 'no', ..., 'no', 'yes', 'no'], dtype=object)
```

In [117]:
```
pred_keras
```

Out[117]:
```
array([[0],
       [0],
       [0],
       ...,
       [0],
       [1],
       [0]])
```

In [118]:
```
np.savetxt('futures_output_num.out', pred_keras, fmt='%0.1f')
```

In [119]:
```
with open('futures_output.out','w') as f:
    for s in output_y:
        f.write(str(s)+'\n')
print(output_y)
```

```
['no' 'no' 'no' ... 'no' 'yes' 'no']
```

In [120]:
```
output_y
```

Out[120]:
```
array(['no', 'no', 'no', ..., 'no', 'yes', 'no'], dtype=object)
```

In [121]:
```
output_y=pd.DataFrame(output_y)
print('The "yes" value is')
print((output_y[0]=='yes').sum())
print('The "no" value is')
print((output_y[0]=='no').sum())
```

```
The "yes" value is
1649
The "no" value is
10406
```

In [122]:
```
len(output_y)
```

Out[122]:
```
12055
```

Predict the futures with Neural network by Keras

- **Since we do not have confidence about our oversampling data(We do not know exactly which features dublicated to increse the number of samples. We used two type of data**

(feeding) in out predictions

- **1) The oversampled data (sm_data_x and sm_data_y) throgh SMOTE**
- **2) Our original data before resampling (Data.cvs) with (data_train_x and data_train_y)**

In [123]:
```
X_new=  pd.read_csv("futures.csv")
X_new.head()
```

Out[123]:

	age	job	marital	education	default	housing	loan	contact	day_of_week	campai
0	42	blue-collar	married	basic.9y	unknown	no	no	telephone	mon	
1	41	management	married	basic.6y	no	no	no	telephone	mon	
2	34	technician	married	high.school	no	no	no	telephone	mon	
3	54	retired	married	high.school	unknown	no	no	telephone	mon	
4	48	blue-collar	married	basic.4y	no	yes	no	telephone	mon	

In [124]:
```
X_new.replace(['basic.4y', 'basic.6y', 'basic.9y'], 'basic', inplace=True)
```

In [125]:
```
le = preprocessing.LabelEncoder()
X_new.job = le.fit_transform(X_new.job)
X_new.marital = le.fit_transform(X_new.marital)
X_new.education = le.fit_transform(X_new.education)
X_new.default = le.fit_transform(X_new.default)
X_new.housing = le.fit_transform(X_new.housing)
X_new.loan = le.fit_transform(X_new.loan)
X_new.contact = le.fit_transform(X_new.contact)
X_new.poutcome = le.fit_transform(X_new.poutcome)
X_new.day_of_week = le.fit_transform(X_new.day_of_week)
```

In [126]:
```
X_new.head()
```

Out[126]:

	age	job	marital	education	default	housing	loan	contact	day_of_week	campaign	pdays	p
0	42	1	1	0	1	0	0	1	1	1	999	
1	41	4	1	0	0	0	0	1	1	2	999	
2	34	9	1	1	0	0	0	1	1	1	999	
3	54	5	1	1	1	0	0	1	1	1	999	
4	48	1	1	0	0	2	0	1	1	1	999	

In [127]:
```
X_new.drop(['day_of_week','pdays'], axis=1, inplace=True)
```

In [128]:
```
X_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1007 entries, 0 to 1006
Data columns (total 13 columns):
age                 1007 non-null int64
job                 1007 non-null int32
marital             1007 non-null int32
education           1007 non-null int32
default             1007 non-null int32
housing             1007 non-null int32
loan                1007 non-null int32
contact             1007 non-null int32
campaign            1007 non-null int64
poutcome            1007 non-null int32
cons_price_idx      1007 non-null float64
cons_conf_idx       1007 non-null float64
prime_rate          1007 non-null float64
dtypes: float64(3), int32(8), int64(2)
memory usage: 70.9 KB
```

1) The oversampled data (sm_data_x and sm_data_y) throgh SMOTE

In [129]:
```
dnn.fit(scaled_x_train, sm_data_y, epochs=300, batch_size=100, verbose=0)
```

Out[129]:
```
<tensorflow.python.keras.callbacks.History at 0x1c2196b7978>
```

In [130]:
```
scaler.fit(X_new)
scaled_x_new = scaler.fit_transform(X_new)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625:
DataConversionWarning: Data with input dtype int32, int64, float64 were all con
verted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625:
DataConversionWarning: Data with input dtype int32, int64, float64 were all con
verted to float64 by StandardScaler.
  return self.partial_fit(X, y)
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversio
nWarning: Data with input dtype int32, int64, float64 were all converted to flo
at64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [131]:
```
y_pred_future=dnn.predict_classes(scaled_x_new)
y_pred_future
```

Out[131]:
```
array([[0],
       [0],
       [0],
       ...,
       [1],
       [1],
       [1]])
```

In [132]:
```
np.savetxt('y_pred_future_oversampled.out', y_pred_future, fmt='%0.1f')
```

In [133]:
```
output_future_req = list(y_pred_future)
output_future_reqn = ['yes' if i == 1 else 'no' for i in output_future_req]
```

In [134]:
```
with open('output_future_oversampled.out','w') as f:
    for s in output_future_reqn:
        f.write(str(s)+'\n')
```

In [135]:
```
output_future_reqn=pd.DataFrame(output_future_reqn)
print('The "yes" value is')
print((output_future_reqn[0]=='yes').sum())
print('The "no" value is')
print((output_future_reqn[0]=='no').sum())
```

```
The "yes" value is
680
The "no" value is
327
```

2) Our original data before resampling (Data.cvs) with (data_train_x and data_train_y)

In [136]:
```
scaler.fit(data_train_x)
scaled_x_train = scaler.fit_transform(data_train_x)
```

```
C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\preprocessing\data.py:625:
DataConversionWarning: Data with input dtype int32, int64, float64 were all con
verted to float64 by StandardScaler.
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C:\Users\Mohanad\Anaconda3\lib\site-packages\sklearn\base.py:462: DataConversio
nWarning: Data with input dtype int32, int64, float64 were all converted to flo
at64 by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```

In [137]:
```
dnn.fit(scaled_x_train, data_train_y, epochs=300, batch_size=100, verbose=0)
```

Out[137]:
```
<tensorflow.python.keras.callbacks.History at 0x1c2196b7748>
```

In [138]:
```
y_pred_future=dnn.predict_classes(scaled_x_new)
y_pred_future
```

Out[138]:
```
array([[0],
       [0],
       [0],
       ...,
       [1],
       [1],
       [0]])
```

In [139]:
```
np.savetxt('y_pred_future_original.out', y_pred_future, fmt='%0.1f')
```

In [140]:
```
output_future_req_original = list(y_pred_future)
output_future_req_originaln = ['yes' if i == 1 else 'no' for i in output_future_r
```

In [141]:
```
with open('output_future_original.out','w') as f:
    for s in output_future_req_originaln:
        f.write(str(s)+'\n')
```

In [142]:
```
output_future_req_originaln=pd.DataFrame(output_future_req_originaln)
print('The "yes" value is')
print((output_future_req_originaln[0]=='yes').sum())
print('The "no" value is')
print((output_future_req_originaln[0]=='no').sum())
```

```
The "yes" value is
269
The "no" value is
738
```

In [143]:
```
X_new['y']=output_future_req_originaln
```

In [144]:
```
X_new.head()
```

Out[144]:

	age	job	marital	education	default	housing	loan	contact	campaign	poutcome	cons_price_
0	42	1	1	0	1	0	0	1	1	1	93.!
1	41	4	1	0	0	0	0	1	2	1	93.!
2	34	9	1	1	0	0	0	1	1	1	93.!
3	54	5	1	1	1	0	0	1	1	1	93.!
4	48	1	1	0	0	2	0	1	1	1	93.!

In [145]:
```
X_new.to_csv('future_pred.csv')
```

In [ ]: