In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings(action="ignore")
```

First View of Dataset

In [2]:
```
df=pd.read_csv('C:/application/interview_prep/bank-additional/bank-additional/bank-additional-full.csv', sep=";")
print(df.shape)
df.info()
```

```
(41188, 21)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
age               41188 non-null int64
job               41188 non-null object
marital           41188 non-null object
education         41188 non-null object
default           41188 non-null object
housing           41188 non-null object
loan              41188 non-null object
contact           41188 non-null object
month             41188 non-null object
day_of_week       41188 non-null object
duration          41188 non-null int64
campaign          41188 non-null int64
pdays             41188 non-null int64
previous          41188 non-null int64
poutcome          41188 non-null object
emp.var.rate      41188 non-null float64
cons.price.idx    41188 non-null float64
cons.conf.idx     41188 non-null float64
euribor3m         41188 non-null float64
nr.employed       41188 non-null float64
y                 41188 non-null object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

First look to the Dataset tell us that there are no missing values

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

Out[3]:

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

5 rows × 21 columns

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

Out[4]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4118
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	9
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	9
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	9
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	9
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	9
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	9

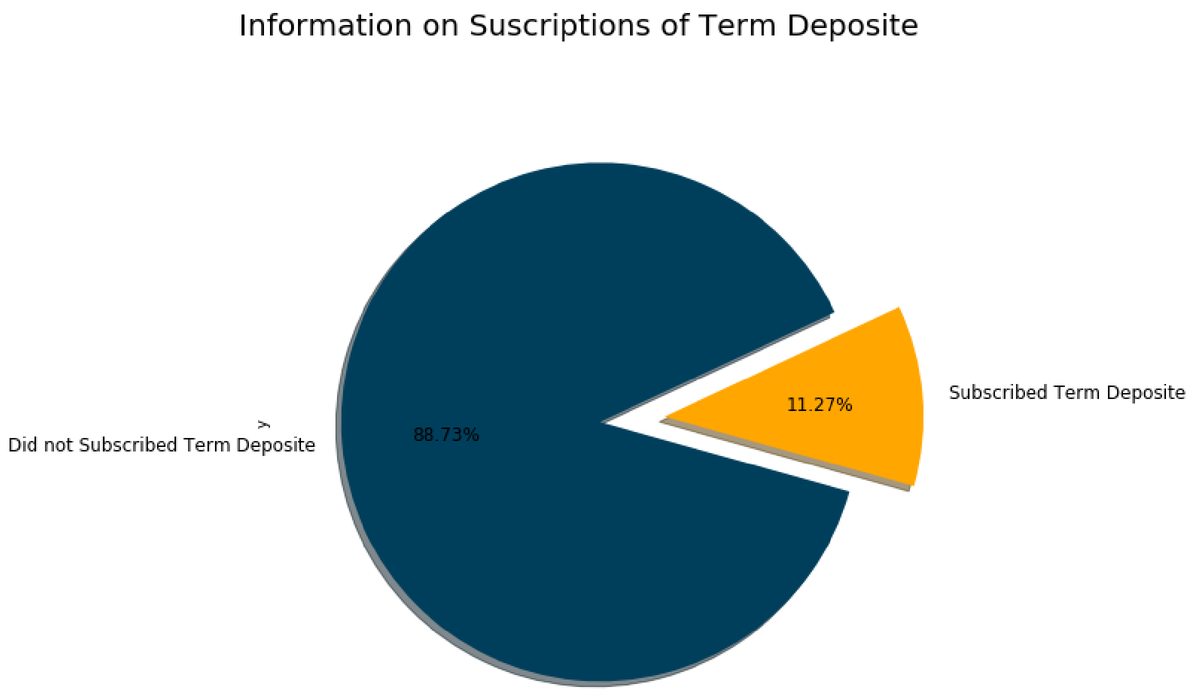
Exploratory Data Analysis:

- After Taking First Look at the Data it is decided to explore every feature to understand patterns and trend

Term Deposite Data Distribution

In [5]:
```
f, ax = plt.subplots(1, figsize=(16,8))

colors = ["#003f5c", "#ffa600"]
labels ="Did not Subscribed Term Deposite", "Subscribed Term Deposite"

plt.suptitle('Information on Suscriptions of Term Deposite', fontsize=20)

df["y"].value_counts().plot.pie(explode=[0,0.25], autopct='%1.2f%%', shadow=True, colors=colors,
                                             labels=labels, fontsize=12, startangle=25)
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1504ca1f4e0>



- From the above analysis it is clear that Data is not evenly distributed
- We will be needing some sampling technique to balance the data so that our model will perform well in actual setup

In [6]:
```
def count_plot(df,col):
    plt.figure(figsize=(10,4))
    sns.barplot(df[col].value_counts().values, df[col].value_counts().index, palette = "rocket")
    plt.title(col)
    plt.tight_layout()
```

In [7]:
```
def freq_dist(df,col):
    plt.figure(figsize=(15,10))
    sns.countplot(x=col,hue="y",data=df, order = df[col].value_counts().index, palette = "dark")
    plt.show()
```

In [8]:
```
def normalized_relative_freq(df,col):
    plt.figure(figsize=(10,4))
    #Returns counts of unique values for each outcome for each feature.
    pos_counts = df.loc[df.y.values == 'yes', col].value_counts()
    neg_counts = df.loc[df.y.values == 'no', col].value_counts()

    all_counts = list(set(list(pos_counts.index) + list(neg_counts.index)))

    #Counts of how often each outcome was recorded.
    freq_pos = (df.y.values == 'yes').sum()
    freq_neg = (df.y.values == 'no').sum()

    pos_counts = pos_counts.to_dict()
    neg_counts = neg_counts.to_dict()

    all_index = list(all_counts)
    all_counts = [pos_counts.get(k, 0) / freq_pos - neg_counts.get(k, 0) / fre
q_neg for k in all_counts]

    sns.barplot(all_counts, all_index, palette = "Spectral")
    plt.title(col)
    plt.tight_layout()
```

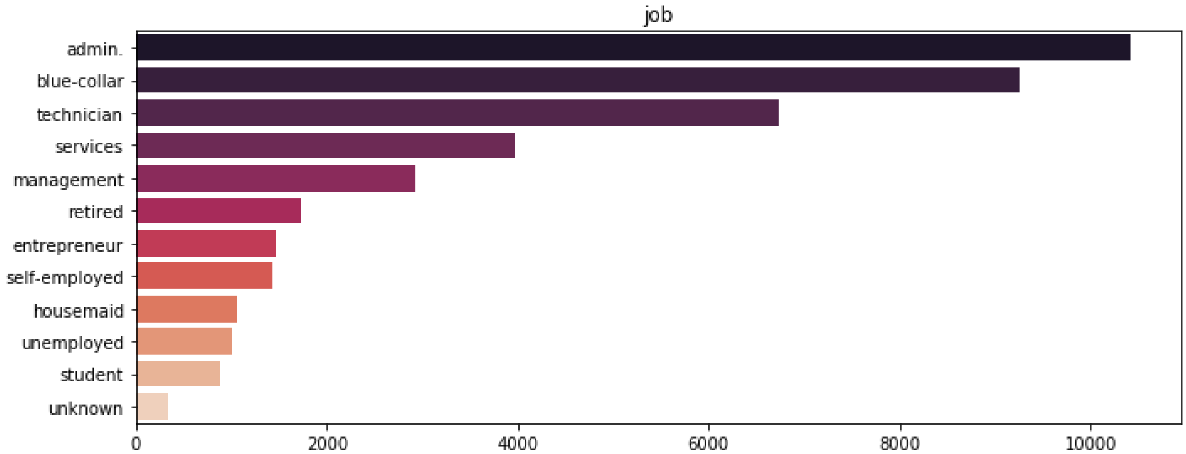
In [9]:
```
def data_analysis(df,col):
    count_plot(df,col)
    freq_dist(df,col)
    normalized_relative_freq(df,col)
```

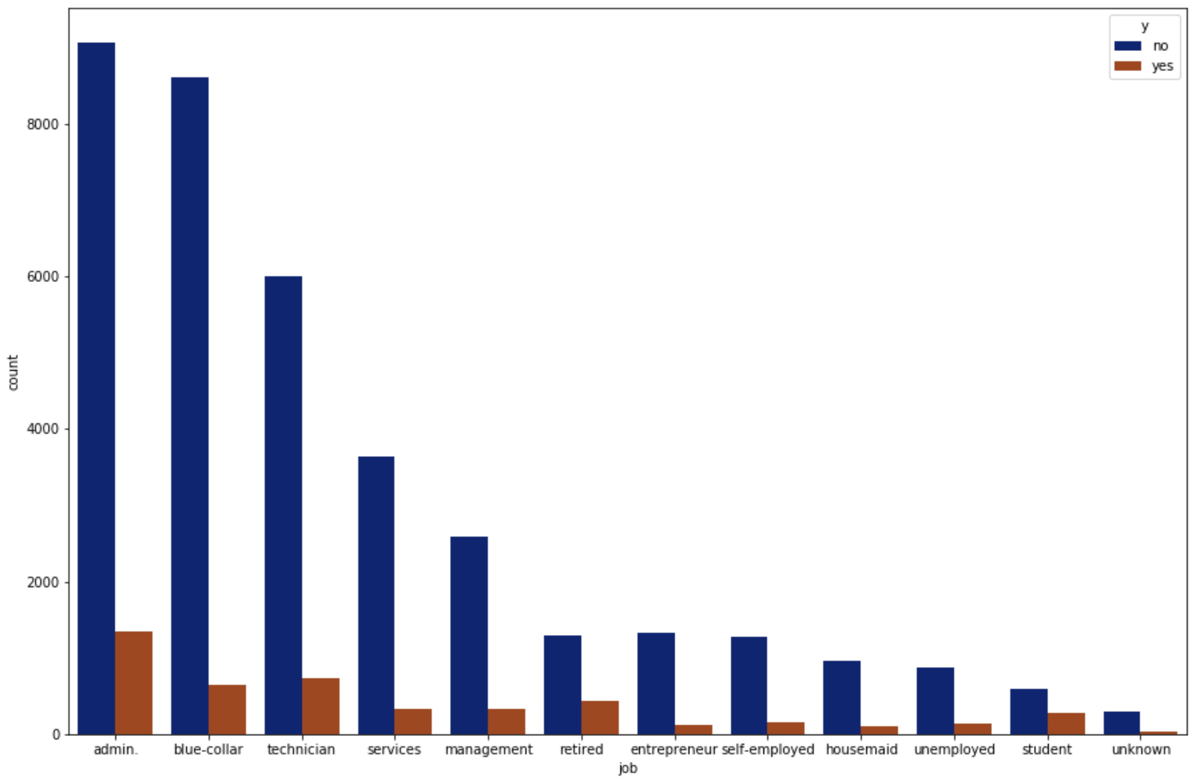
Categorical Features

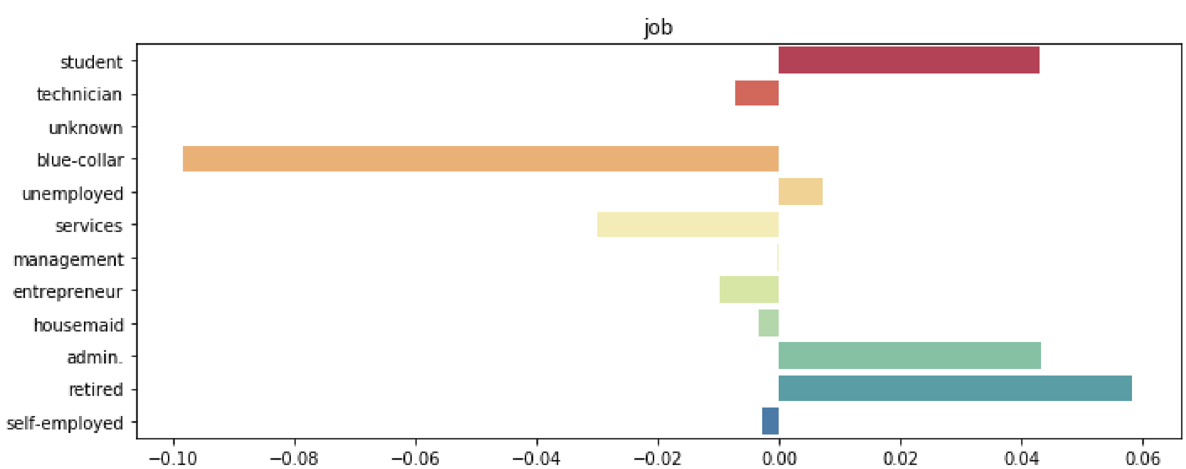
- First we will look into categorical features

Job Feature Analysis

In [10]:
```
data_analysis(df,"job")
```



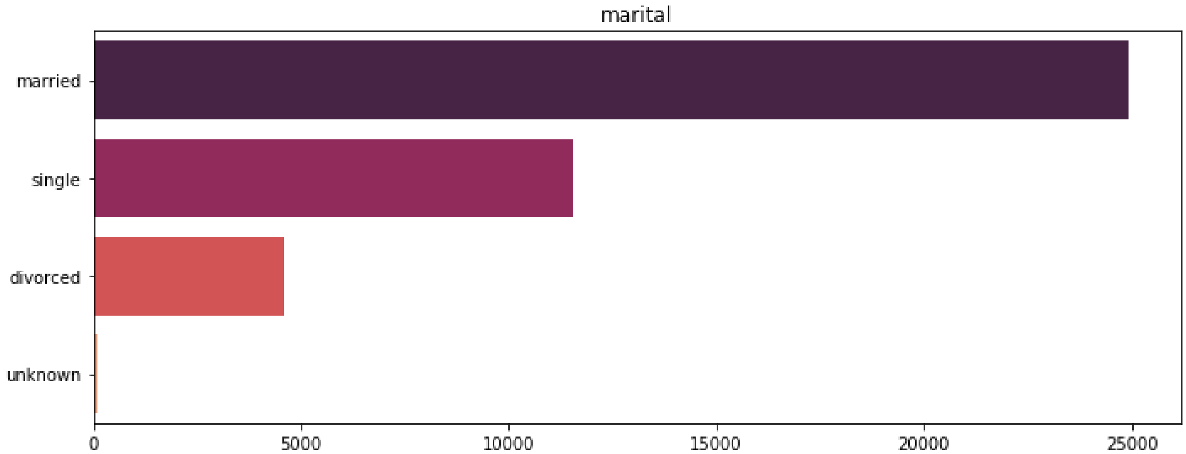


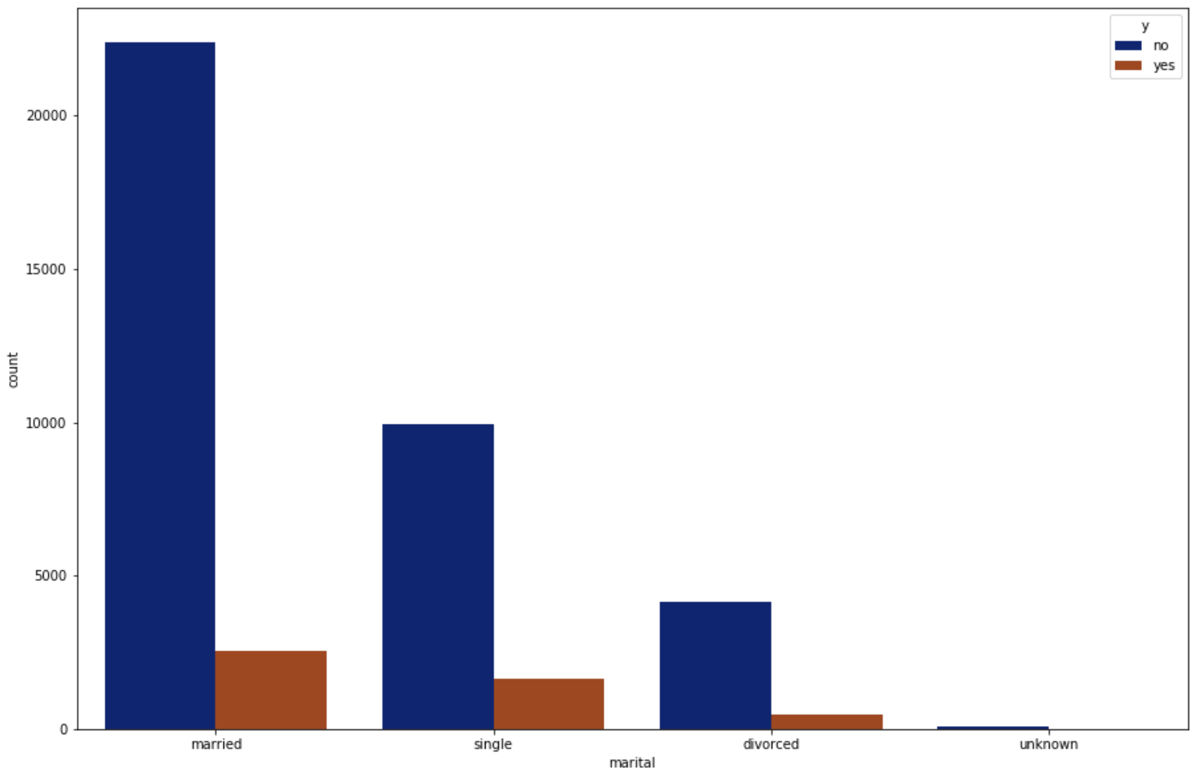


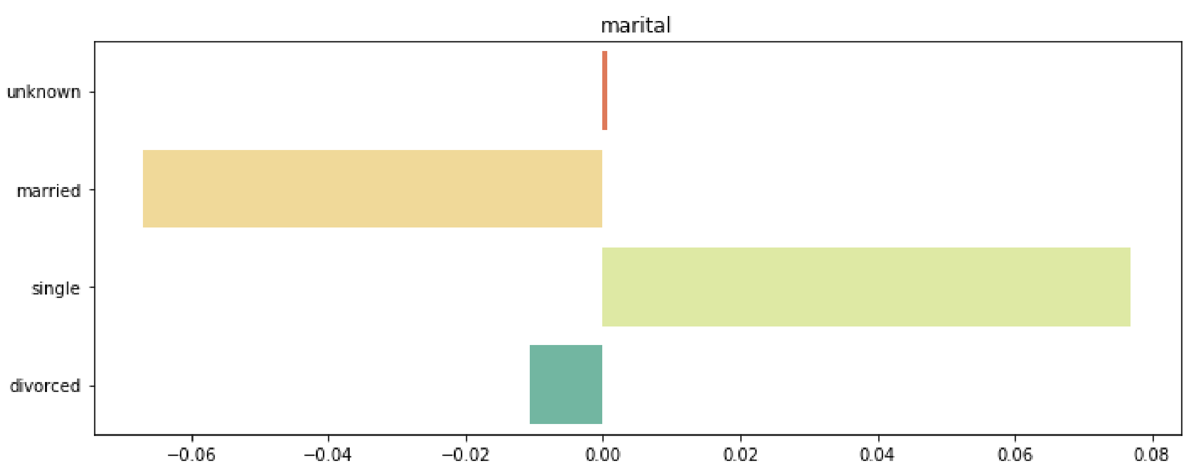
- Here by plotting normalized relative frequency we can imply that job category "retired","admin", "student" are highly likely to subscribe for Term Deposite

Marital Feature Analysis

In [11]:
```
data_analysis(df,"marital")
```



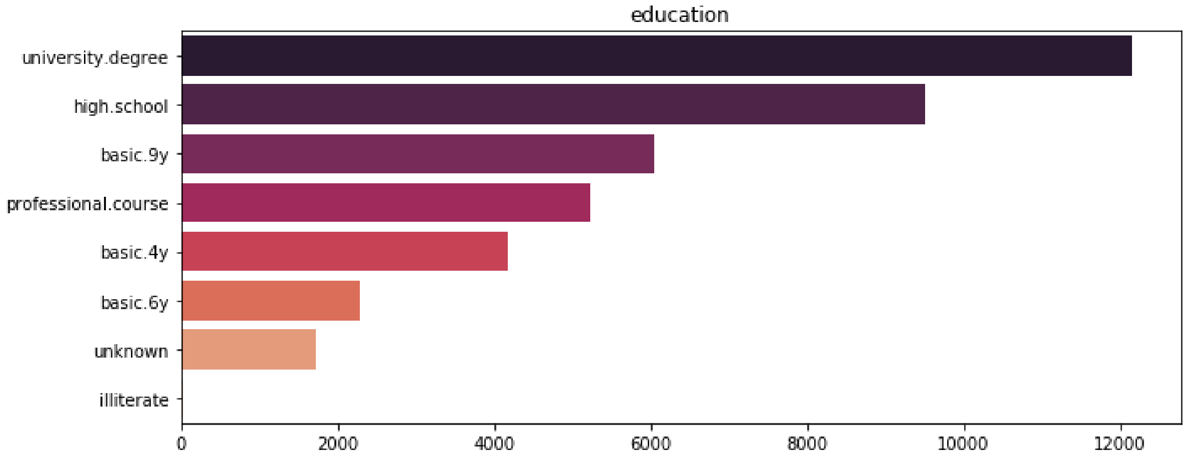


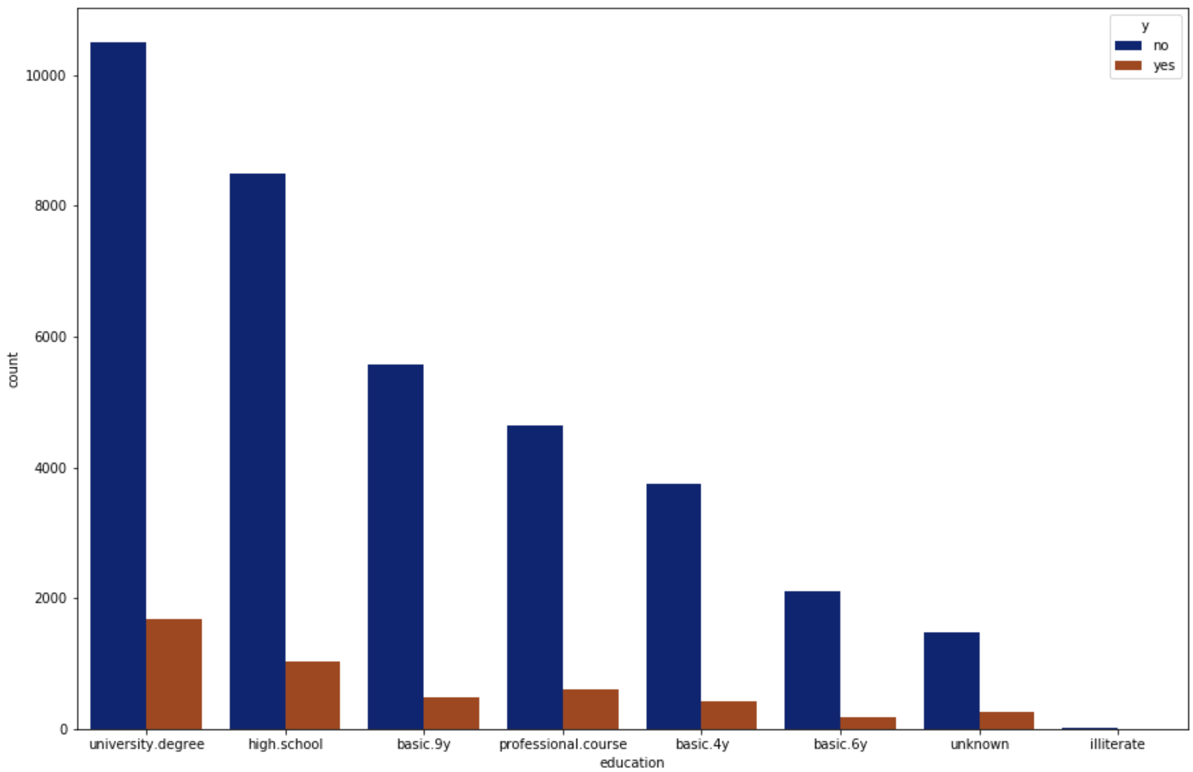


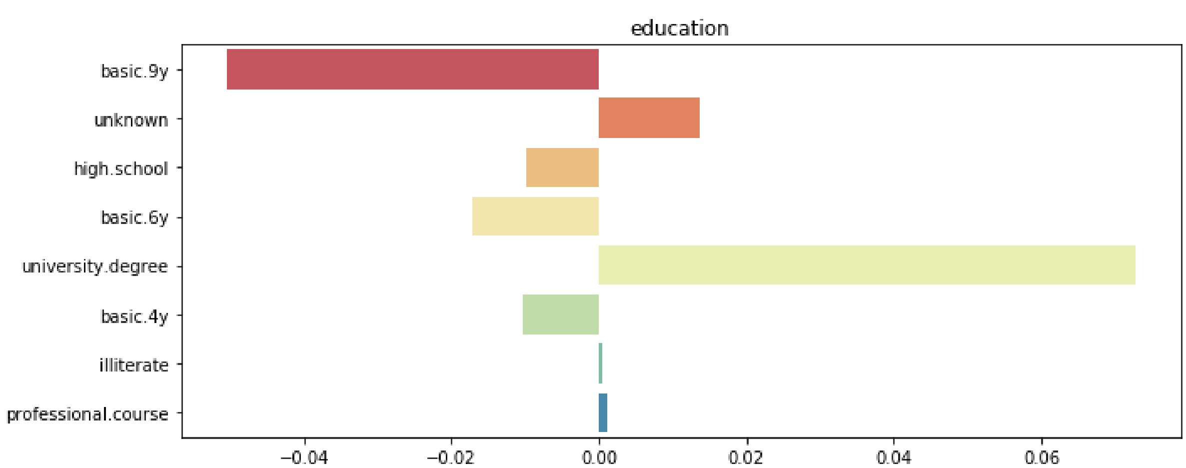
- Here our normalized frequency graph tell us that marital status"single" are highly likely to subscribe for Team Deposite

Education Feature Analysis

In [12]:
```
data_analysis(df,"education")
```



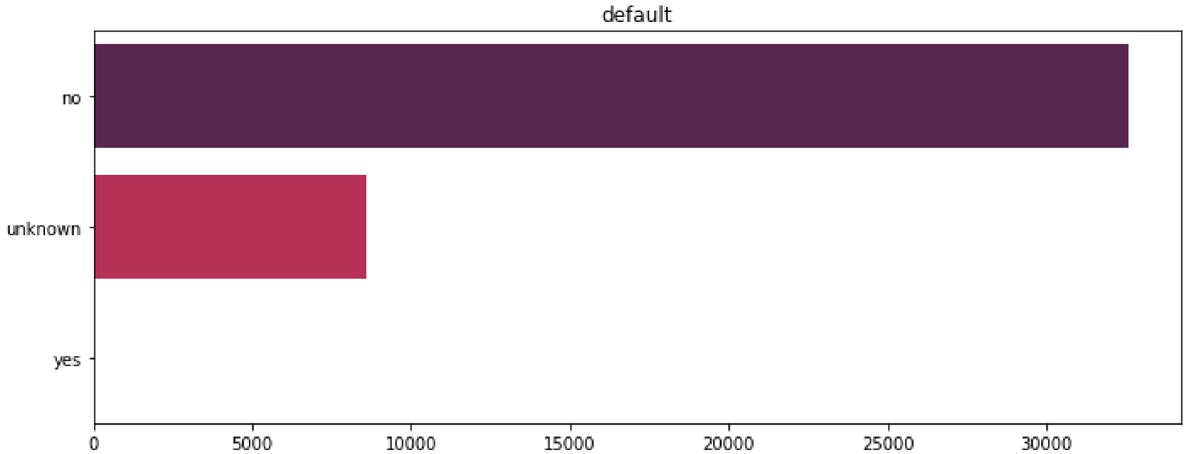


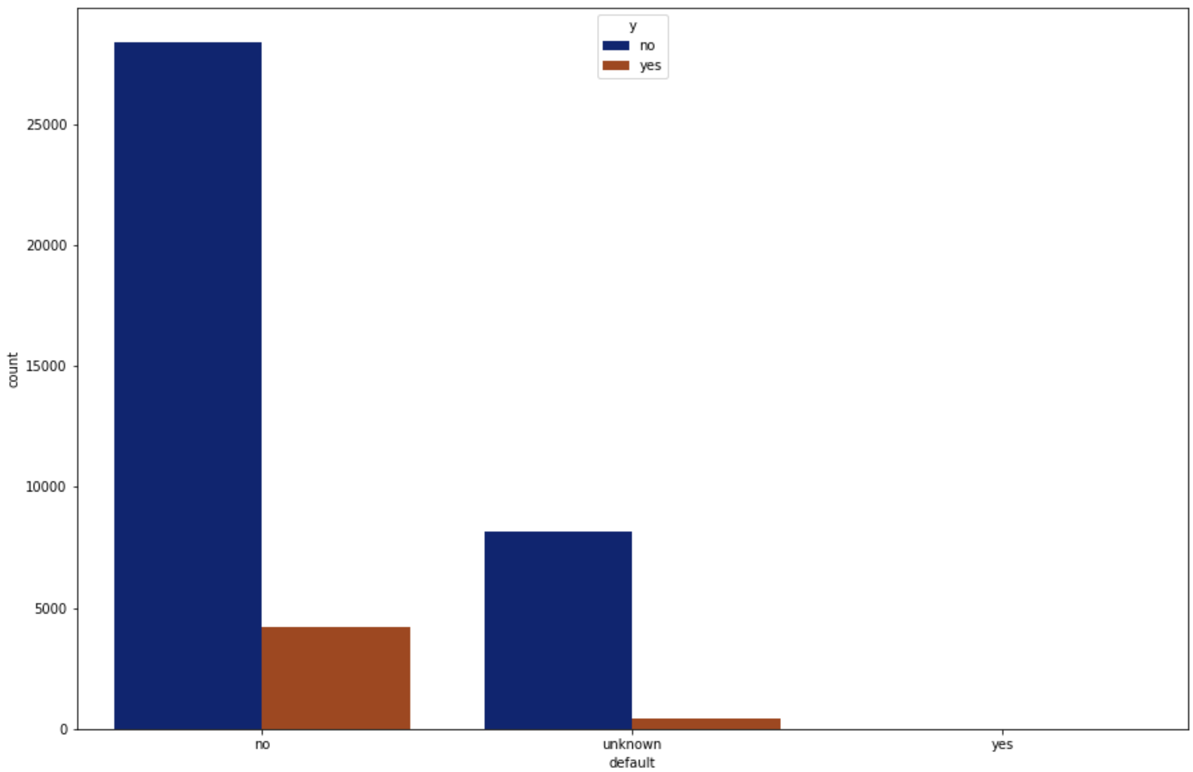


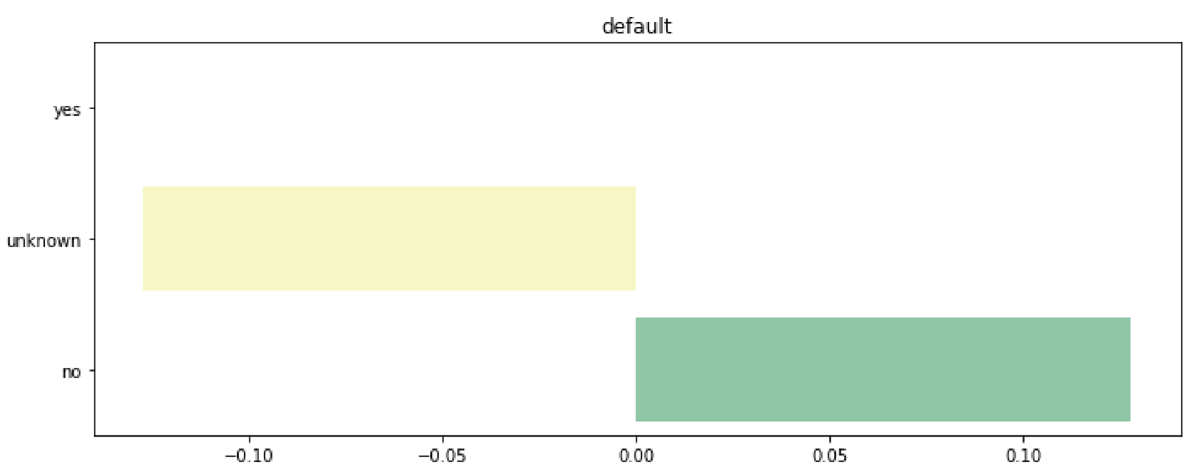
- Here our normalized frequency graph tell us that Education status "university.degree" are highly likely to subscribe for Team Deposite
- There is a variable named "unknown" which we will deal with later

Default Feature Analysis

In [13]:
```
data_analysis(df,"default")
```



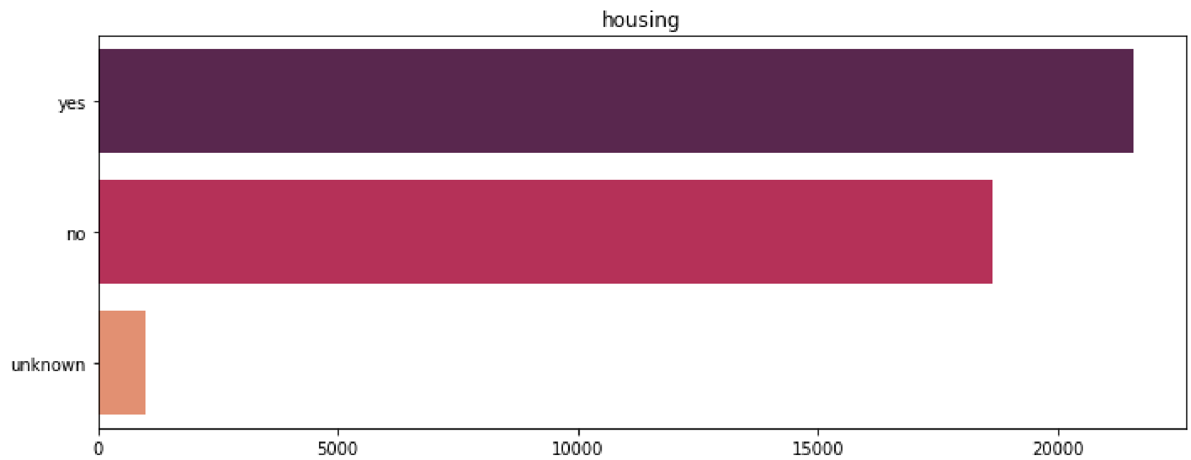


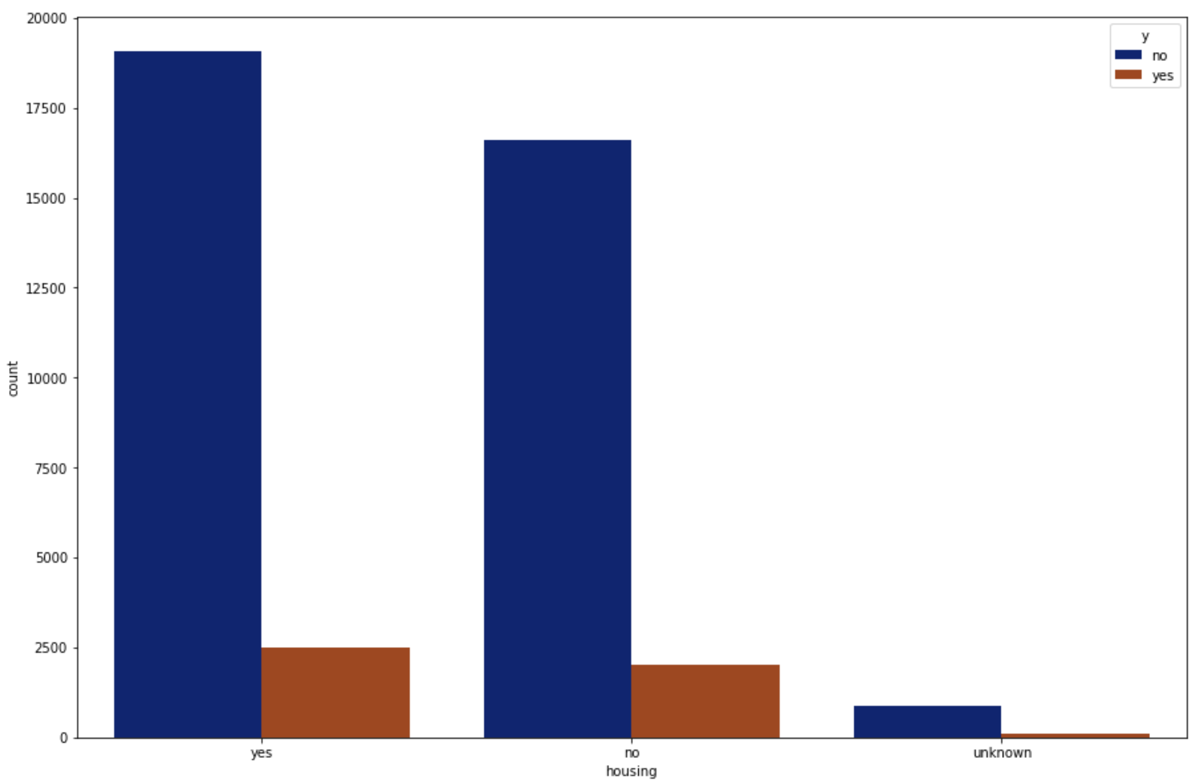


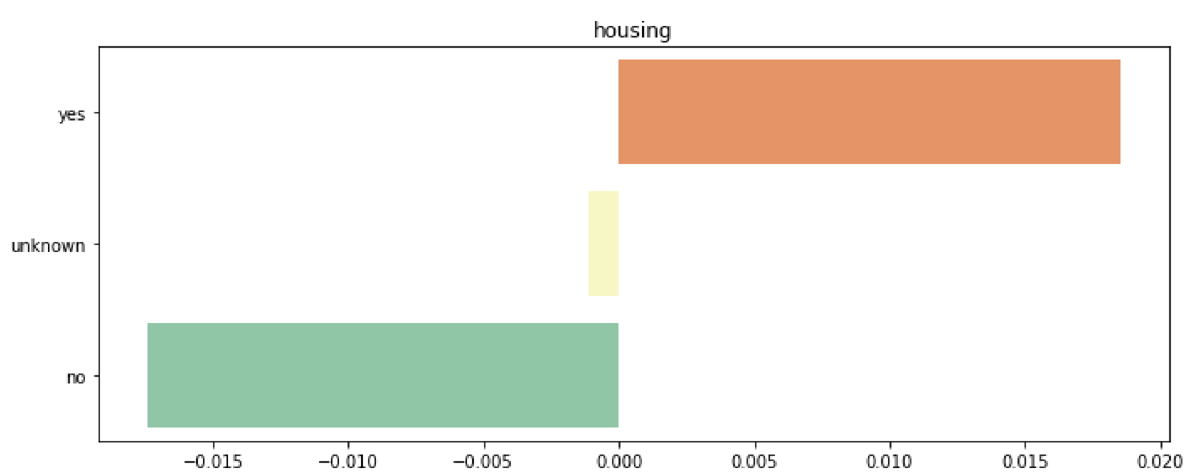
- Here our normalized frequency graph tell us that person with No defaults are highly likely to subscribe for Team Deposite

Housing Feature Analysis

In [14]:
```
data_analysis(df,"housing")
```



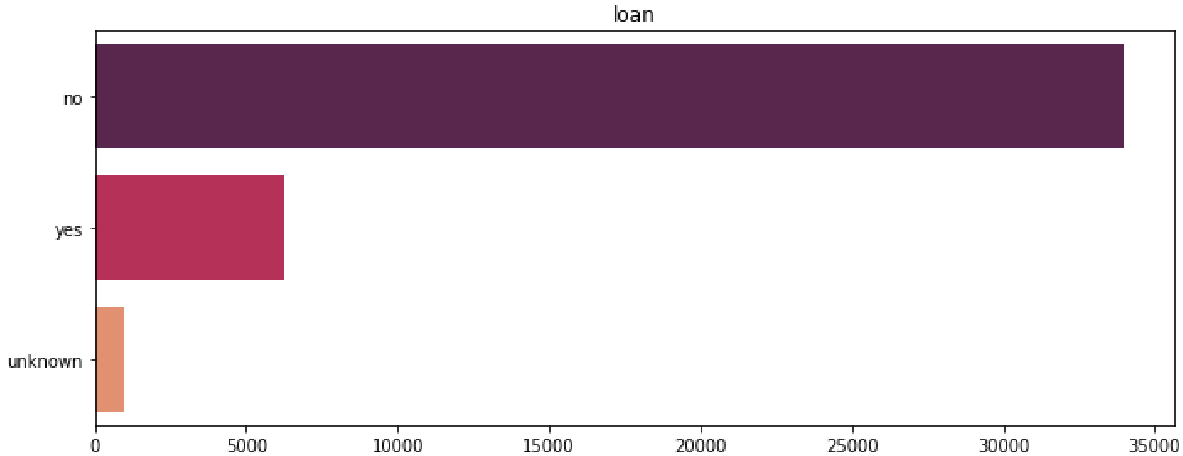


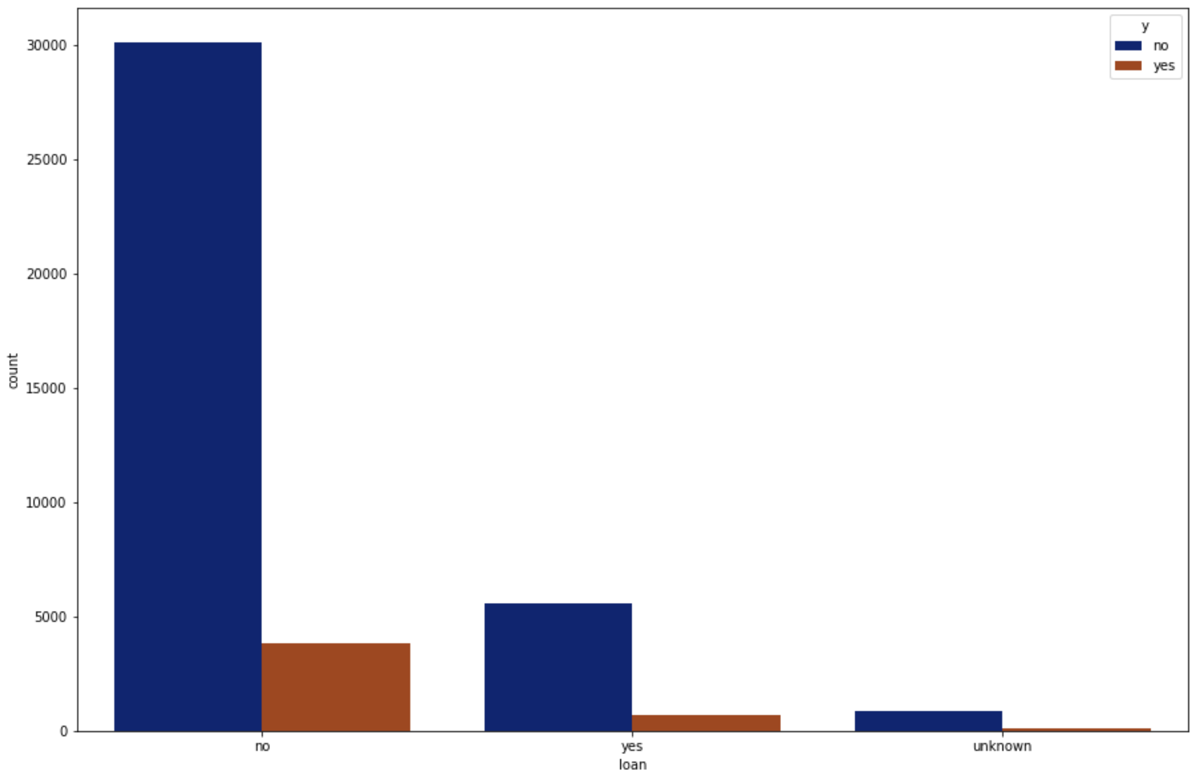


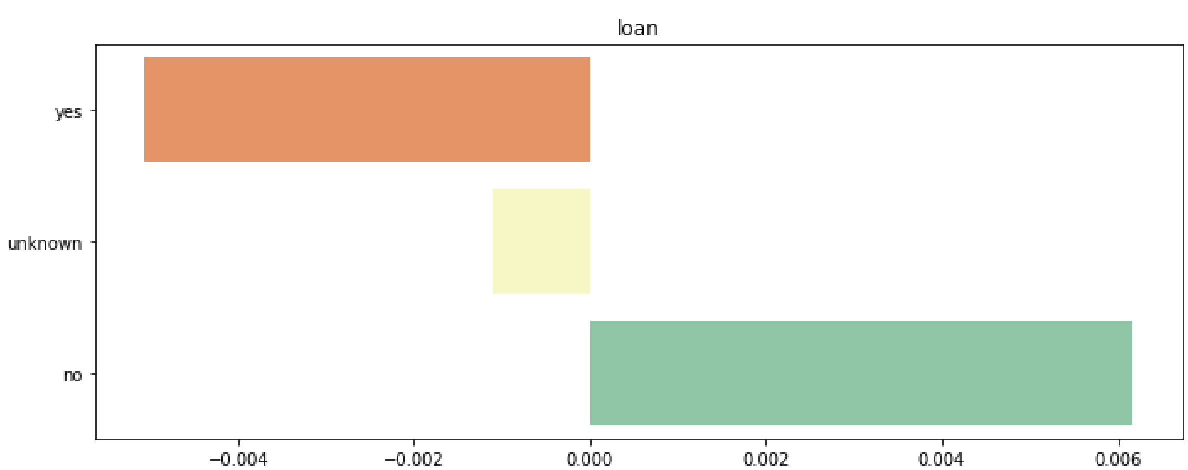
- Here our normalized frequency graph tell us that person with Housing loan are highly likely to subscribe for Team Deposite

Loan Feature Analysis

```
In [15]: data_analysis(df,"loan")
```



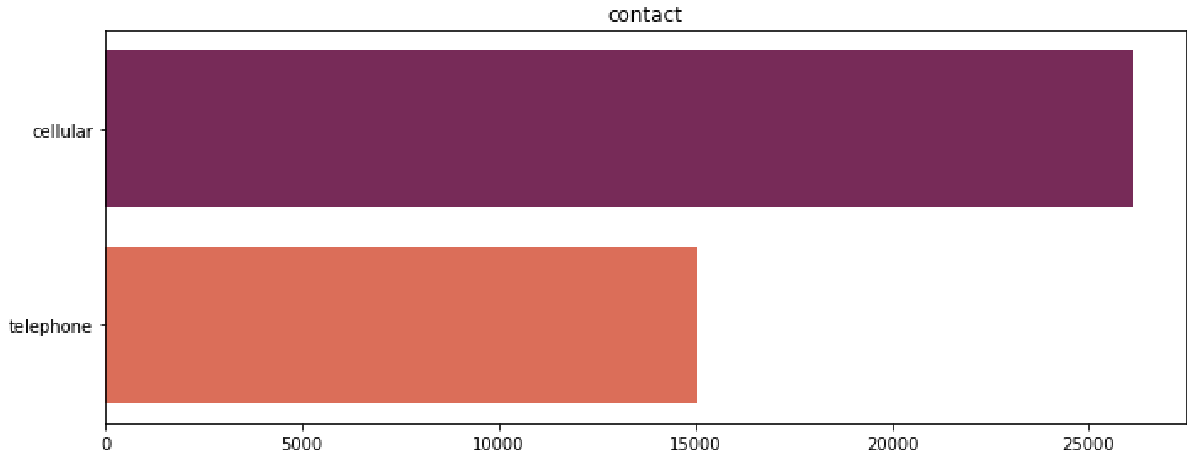


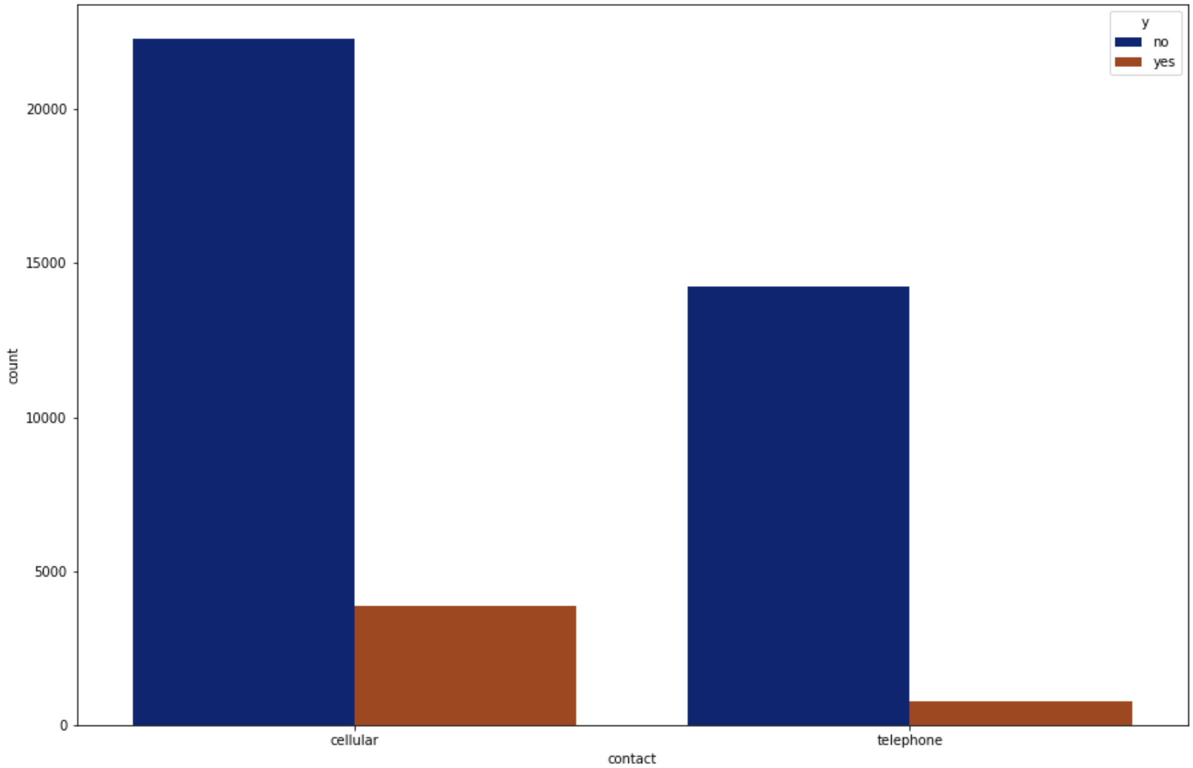


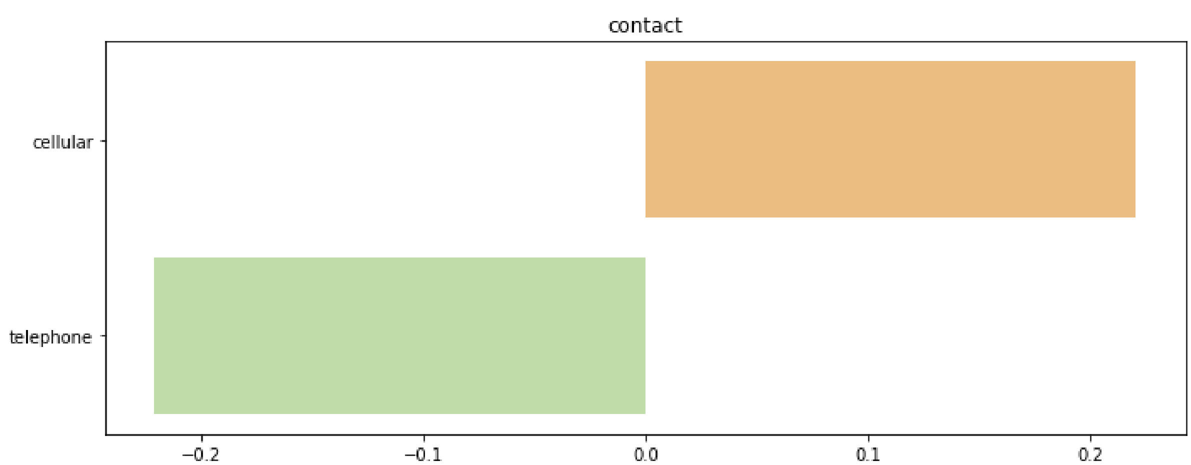
- Here our normalized frequency graph tell us that person with NO loan are highly likely to subscribe for Team Deposite

Contact Feature Analysis

In [16]:
```
data_analysis(df,"contact")
```



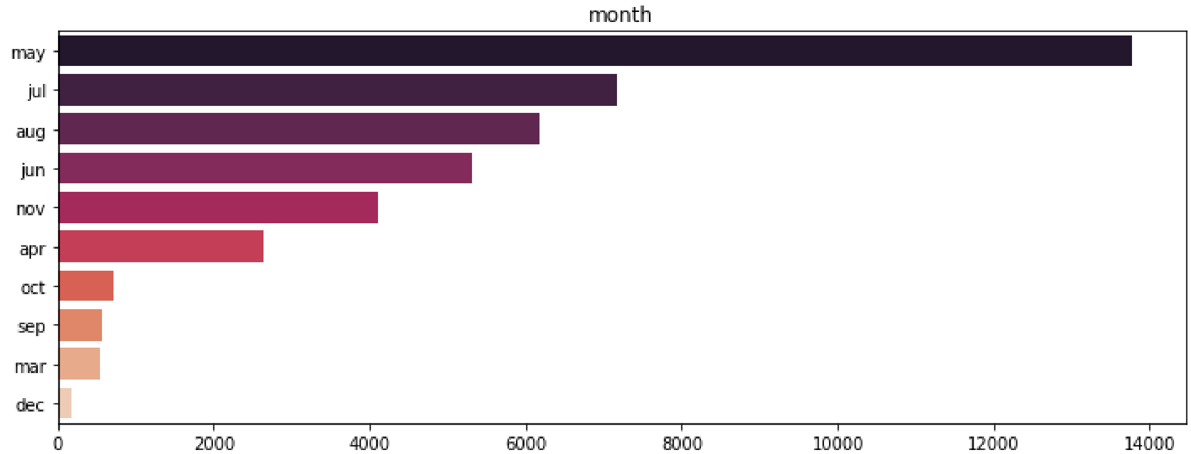


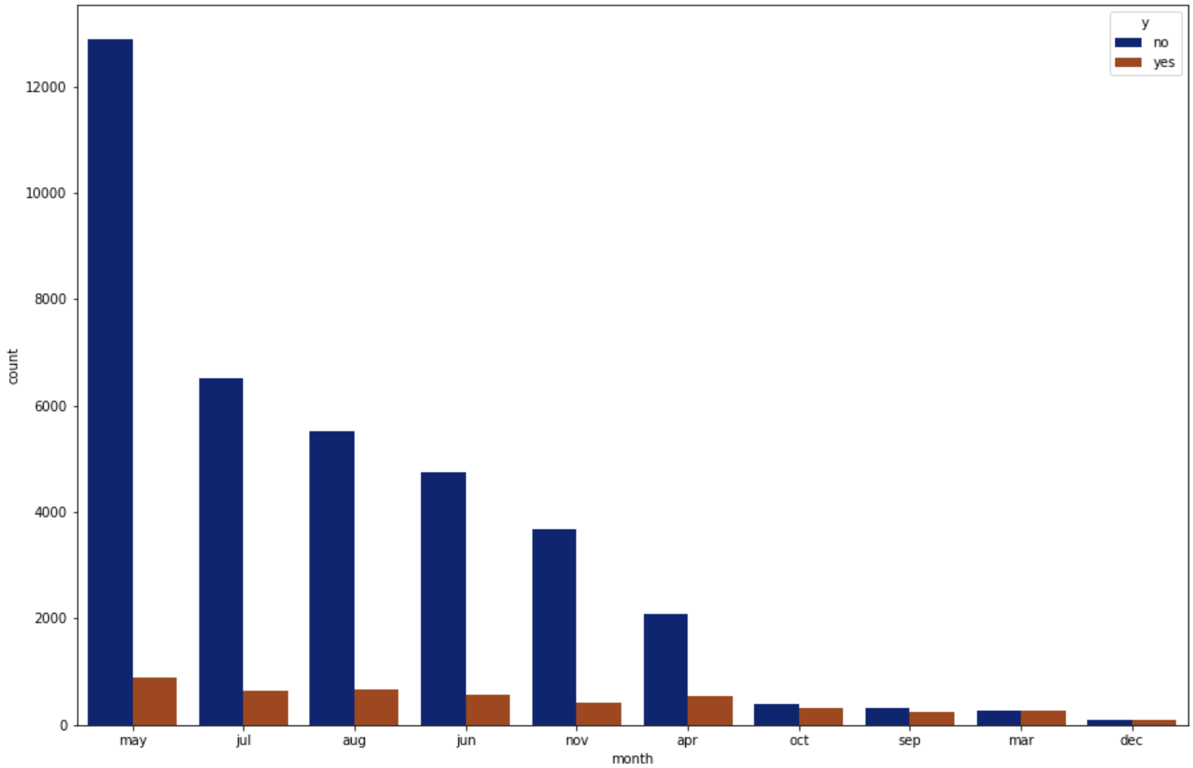


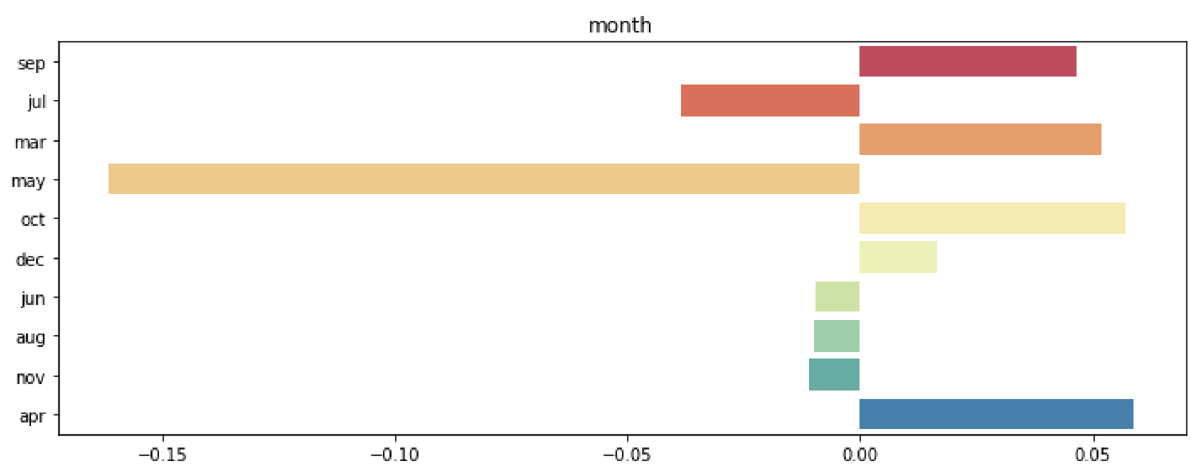
- Here our normalized frequency graph tell us that person contacted by Cellular means are highly likely to subscribe for Team Deposite

Month Feature Analysis

```
In [17]: data_analysis(df,"month")
```



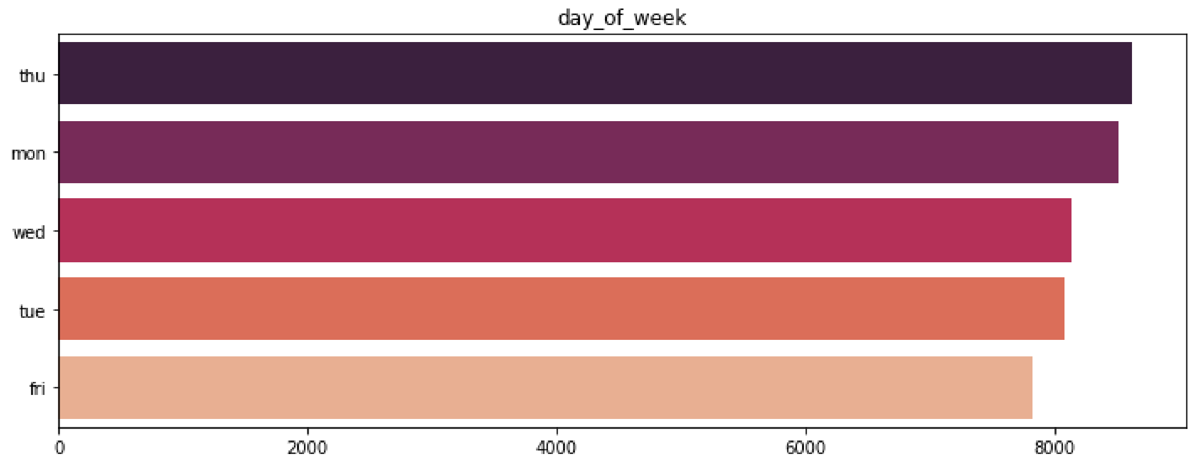


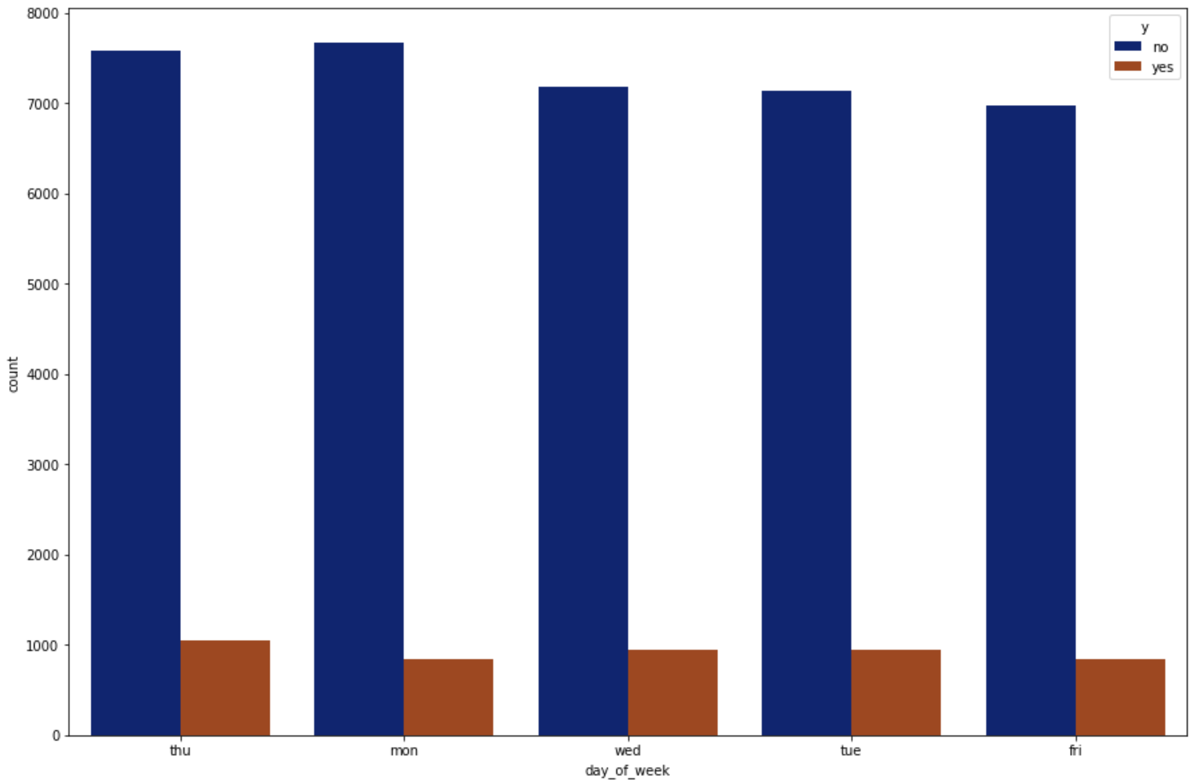


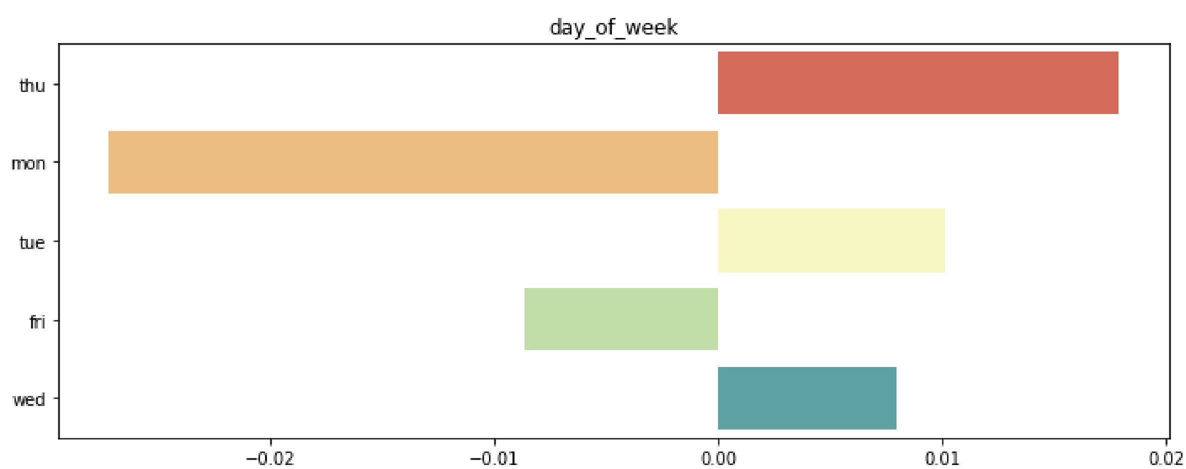
- As the normalized frequency graph shows the best month to contact any person are "March", "April", "September", "October", "December".
- The Campaign should be planed around that period of time

Day of Week Feature Analysis

In [18]:
```
data_analysis(df,"day_of_week")
```



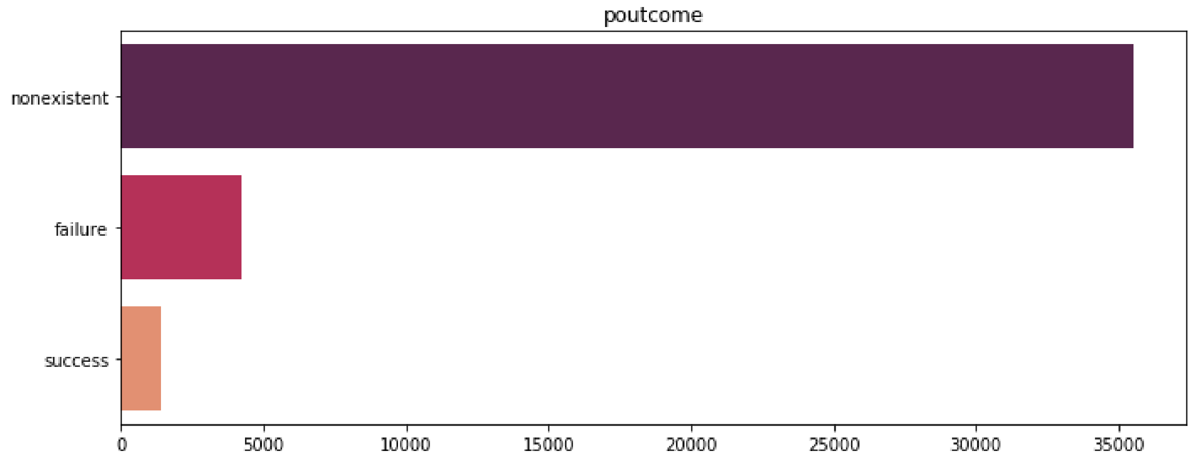


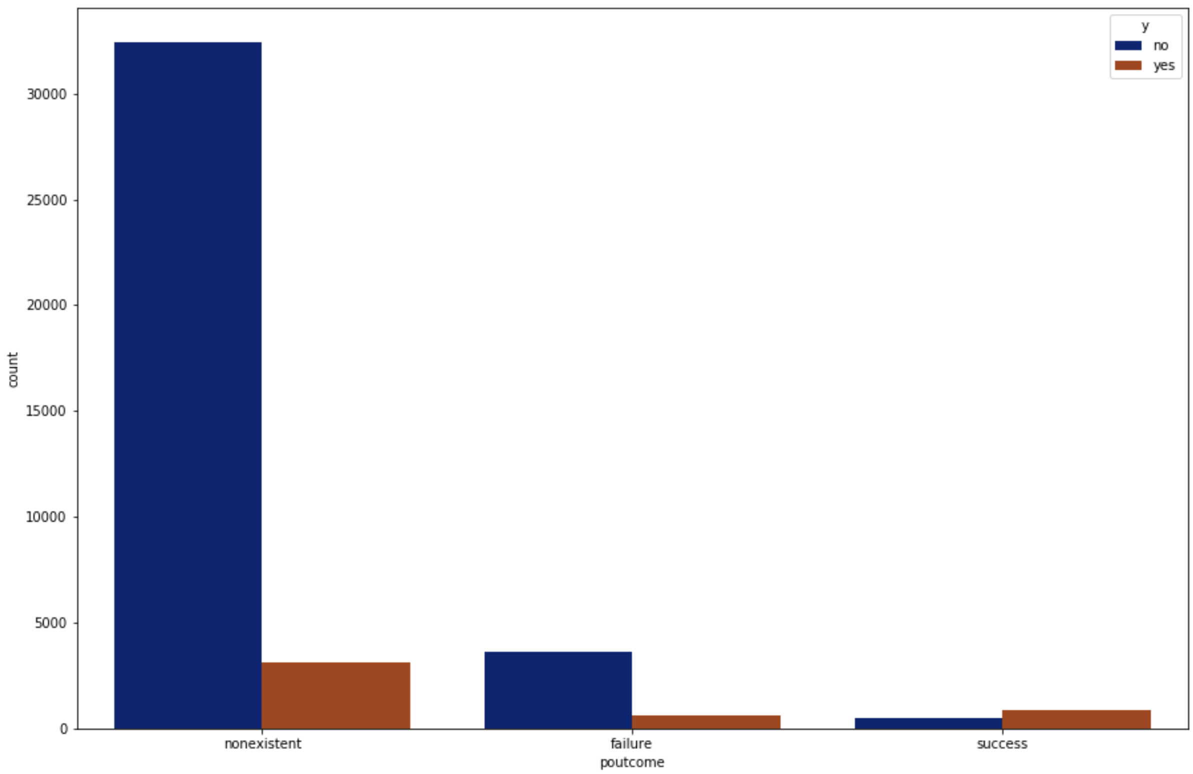


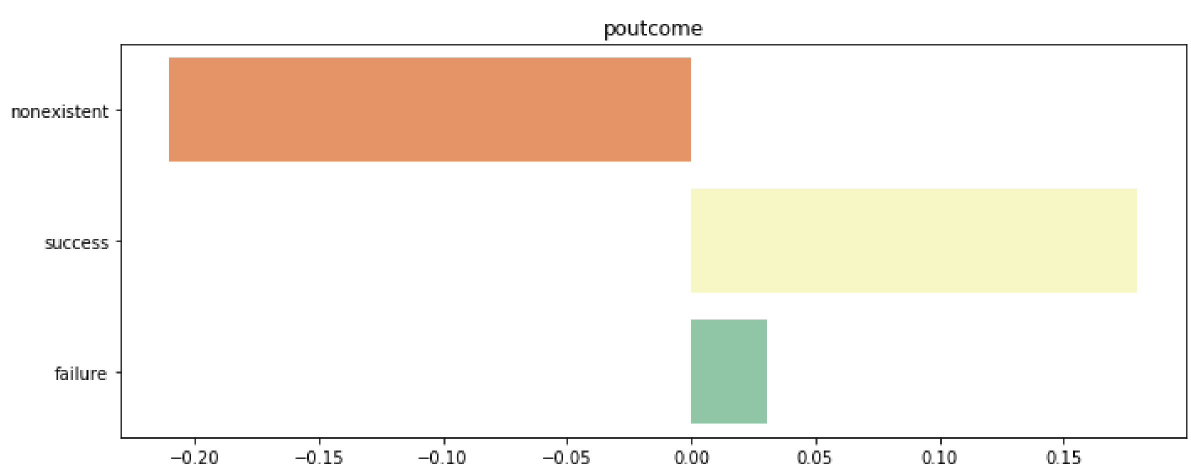
- As the normalized frequency graph shows the best day of week to contact any person are "Tuesday", "Wednesday", "Thursday".

Poutcome Feature Analysis

In [19]:
```
data_analysis(df,"poutcome")
```





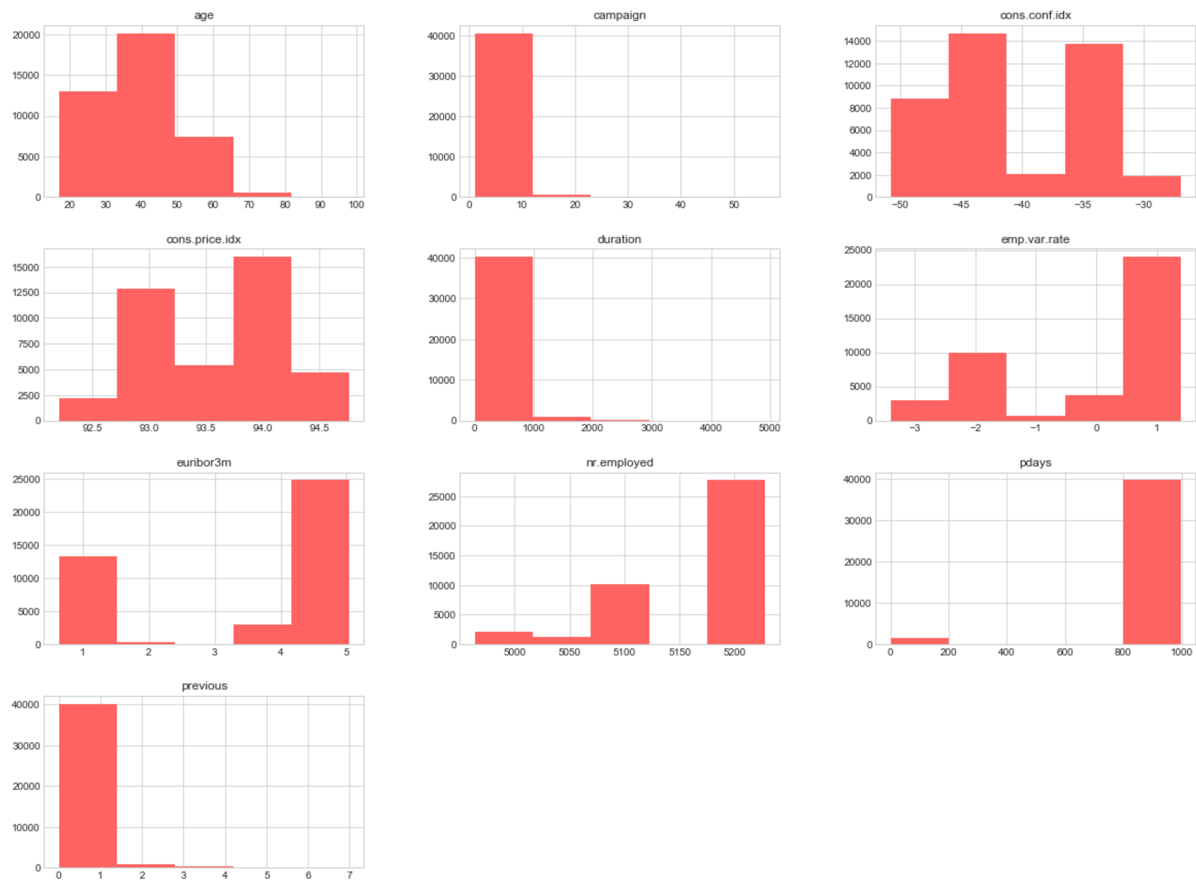


- As per the Normalize Frequency Graph if outcome of previous campaign is success then we should contact the person
- Here most of the values are having "nonexistent" value which means they were not contacted before

Numerical Feature

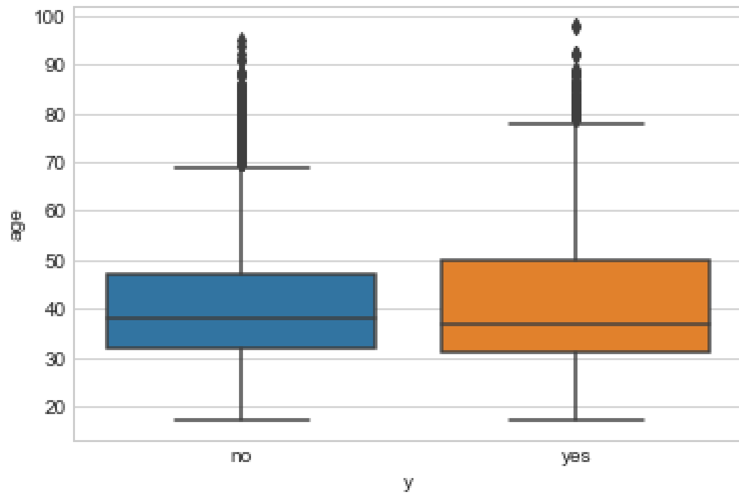
- Lets look into numeric features

In [20]:
```
plt.style.use('seaborn-whitegrid')

df.hist(bins=5, figsize=(20,15), color='#ff6361')
plt.show()
```



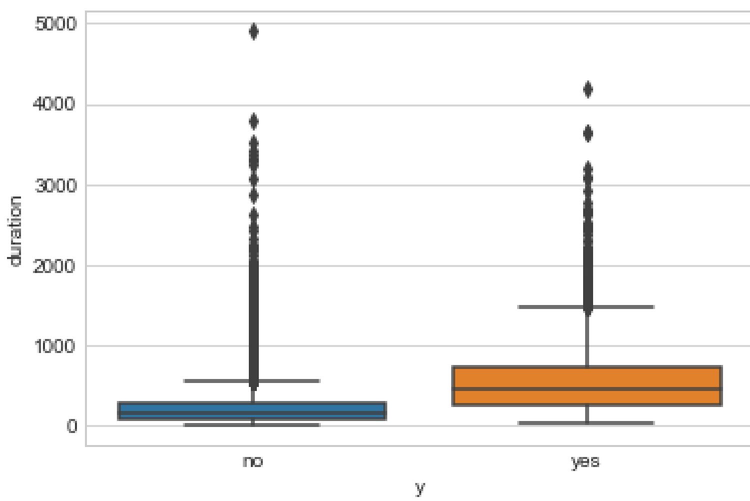
Age Feature Analysis

In [22]:
```
sns.boxplot(data=df,x='y',y='age')
plt.show()
```

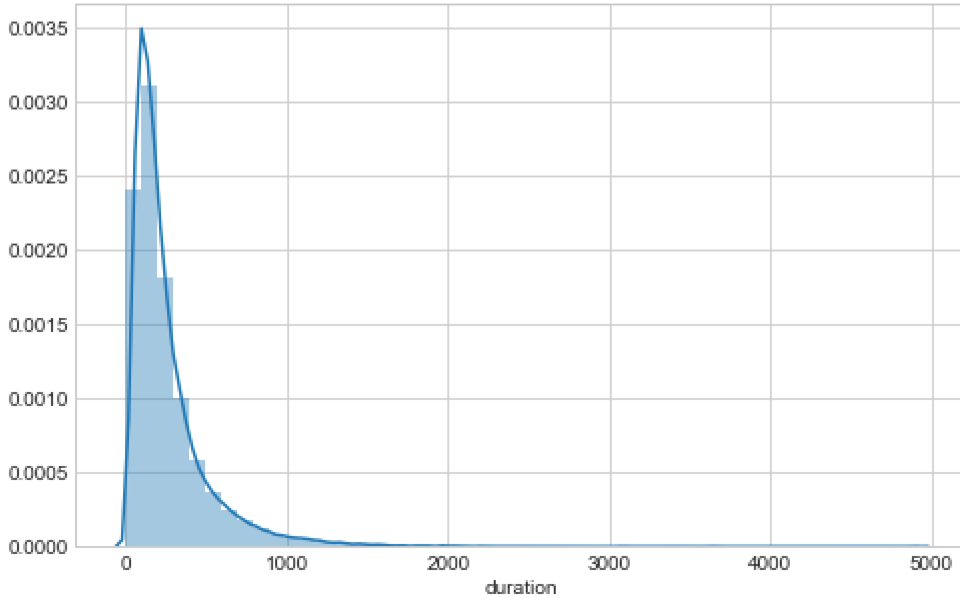


Duration Feature Analysis

In [23]:
```
sns.boxplot(data=df,x='y',y='duration')
plt.show()
```

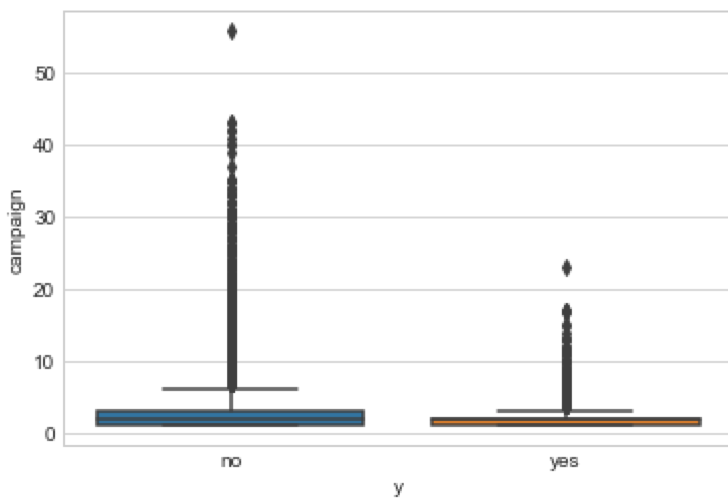


In [40]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["duration"])
plt.show()
```

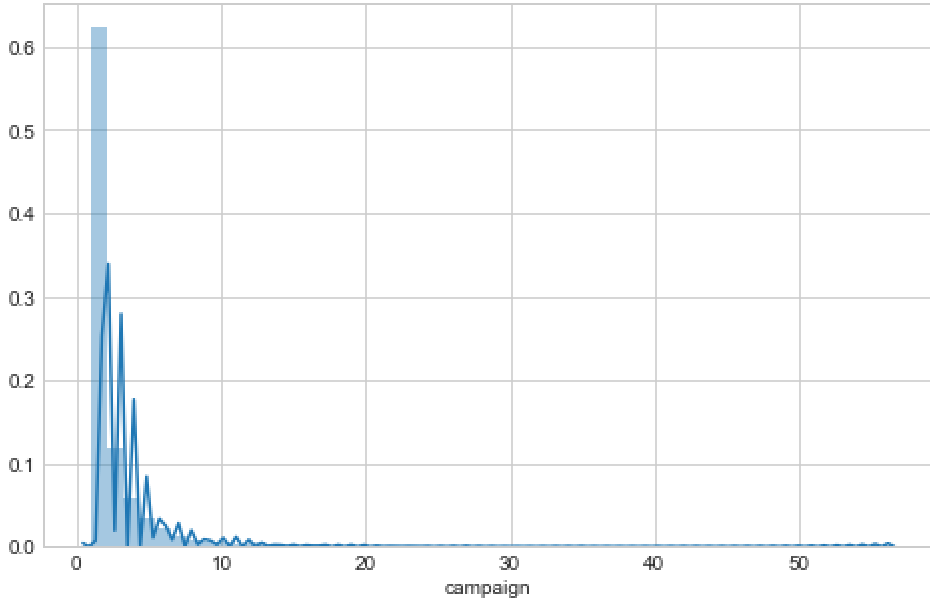


Campaign Feature Analysis

In [41]:
```
sns.boxplot(data=df,x='y',y='campaign')
plt.show()
```

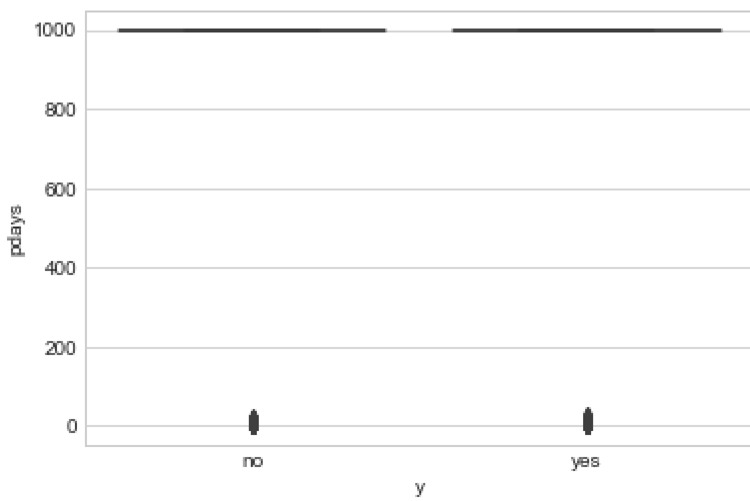


In [39]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["campaign"])
plt.show()
```

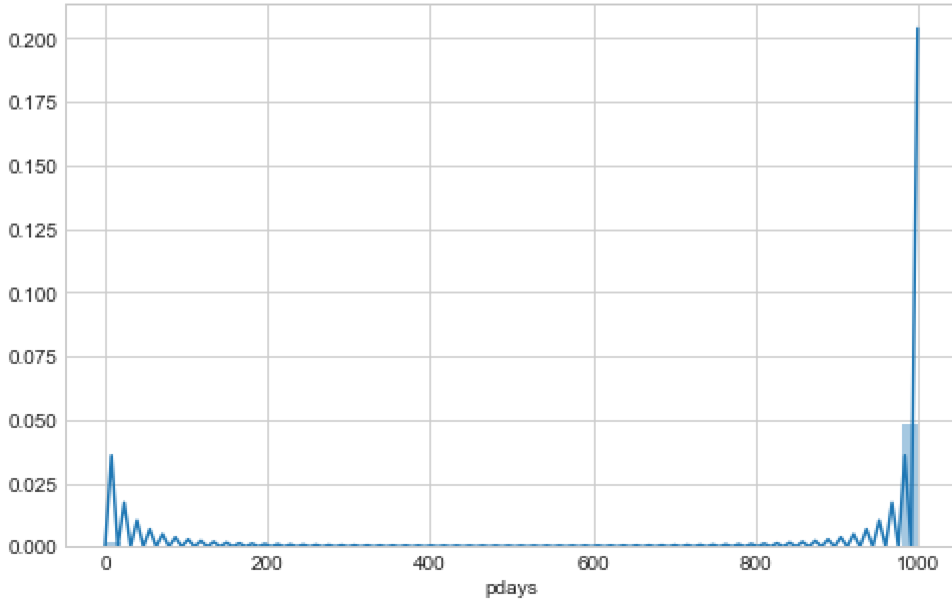


pdays Feature Analysis

In [42]:
```
sns.boxplot(data=df,x='y',y='pdays')
plt.show()
```

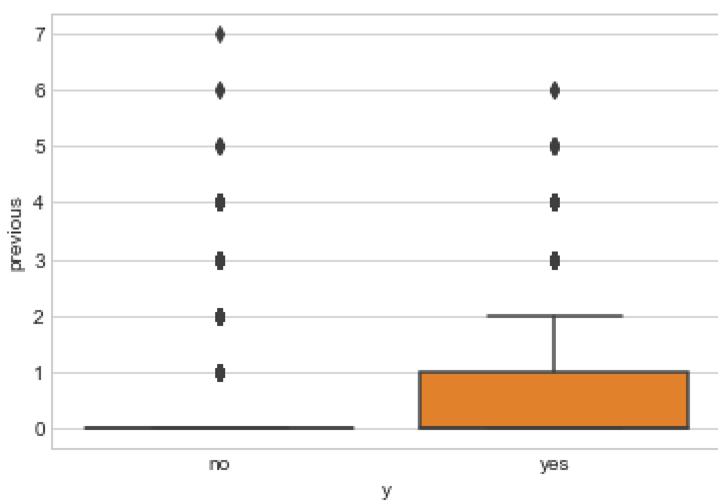


In [43]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["pdays"])
plt.show()
```

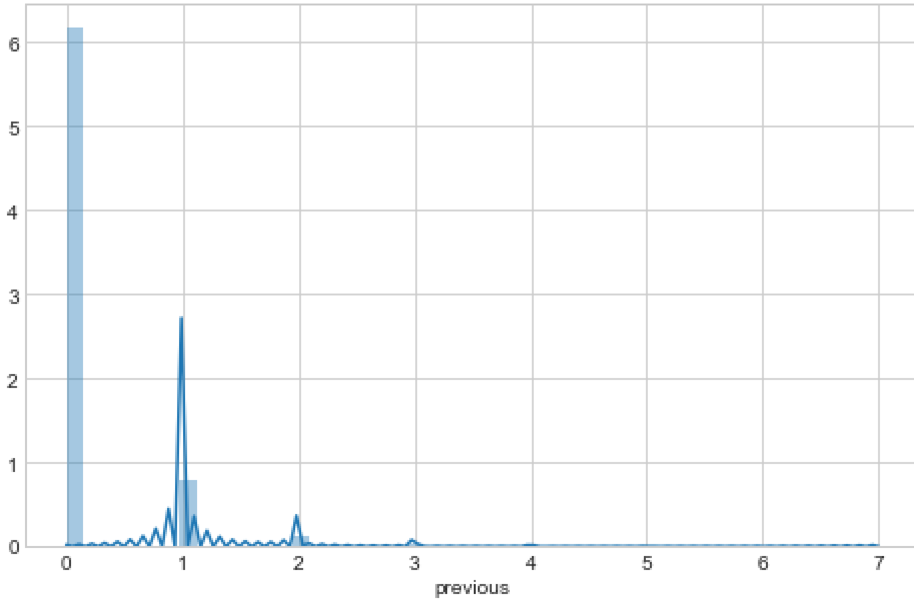


previous Feature Analysis

In [44]:
```
sns.boxplot(data=df,x='y',y='previous')
plt.show()
```

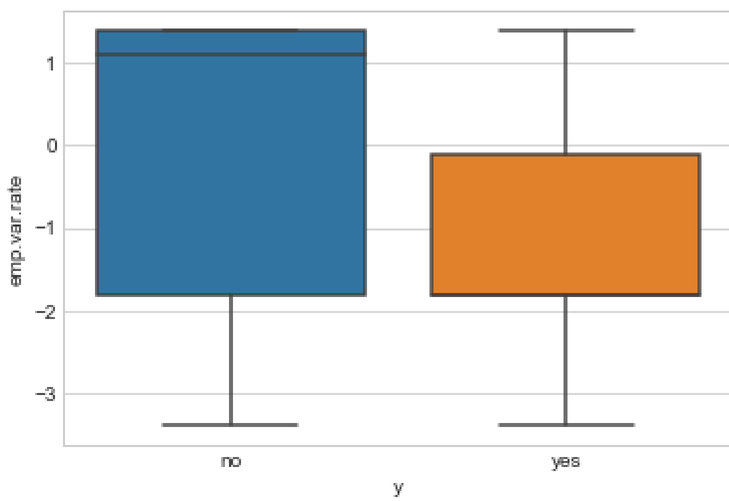


In [45]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["previous"])
plt.show()
```

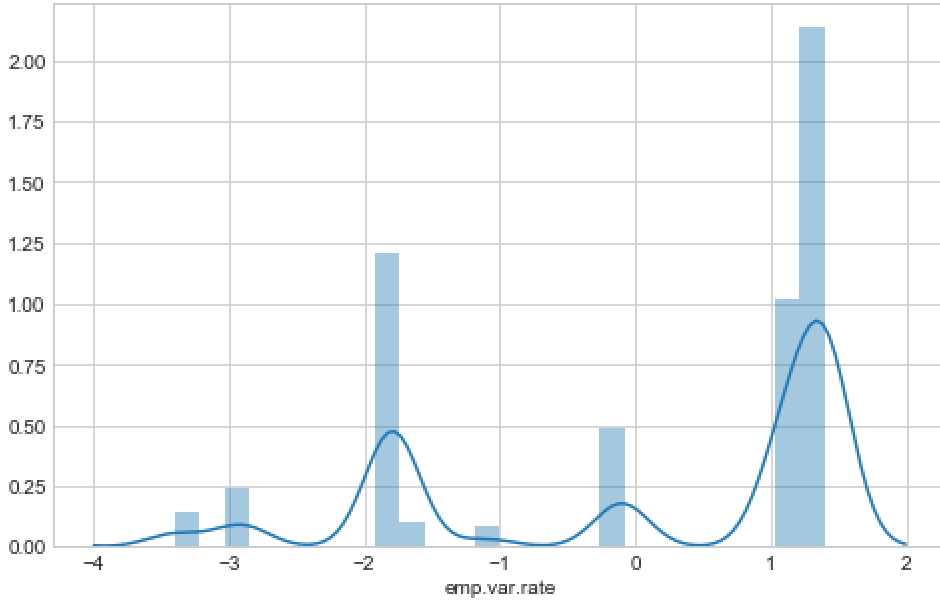


emp.var.rate Feature Analysis

In [24]:
```
sns.boxplot(data=df,x='y',y='emp.var.rate')
plt.show()
```

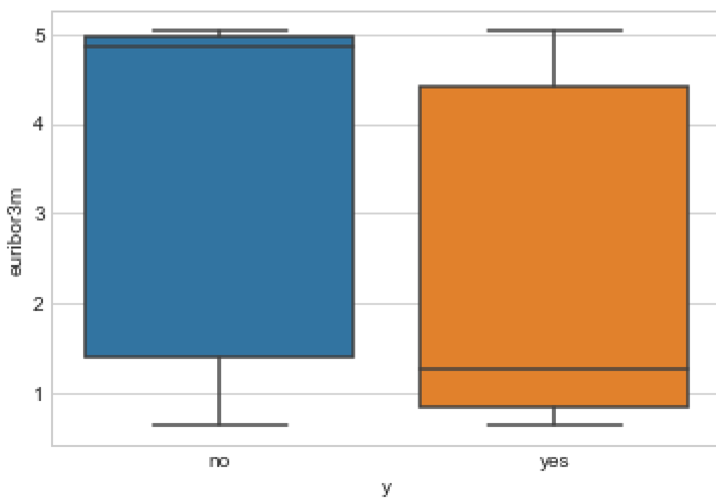


In [27]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["emp.var.rate"])
plt.show()
```



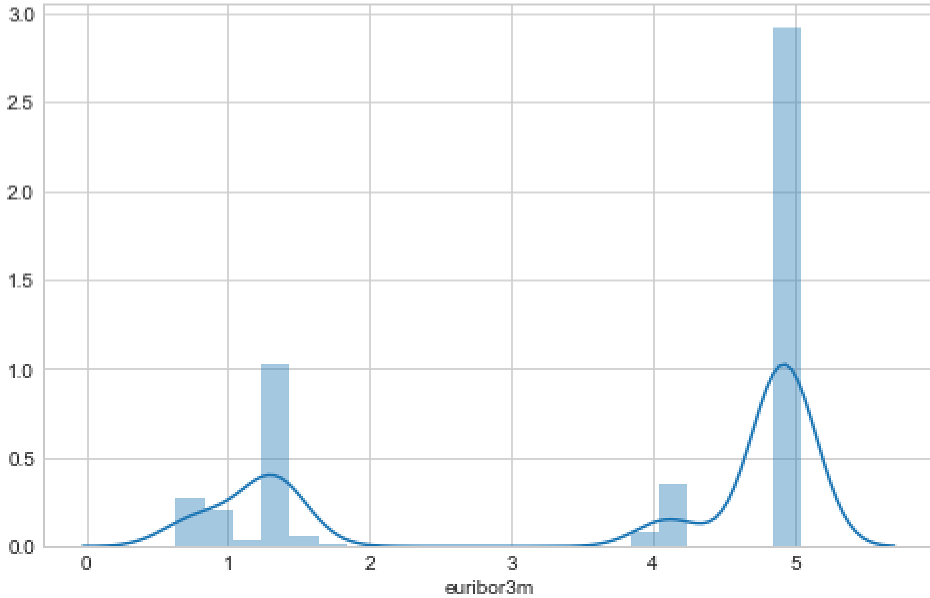
euribor3m Feature Analysis

In [29]:
```
sns.boxplot(data=df,x='y',y='euribor3m')
plt.show()
```



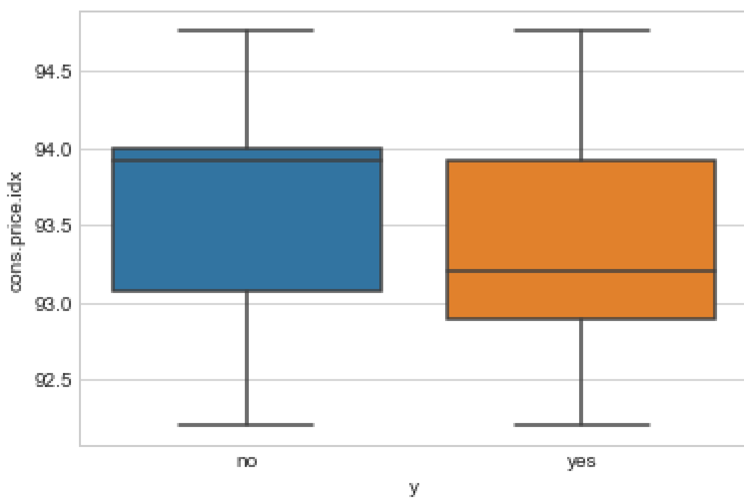
- From the above plot, we can clearly see the difference in median for both the classes. This indicates that the feature can be very useful for our case study.

In [30]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["euribor3m"])
plt.show()
```

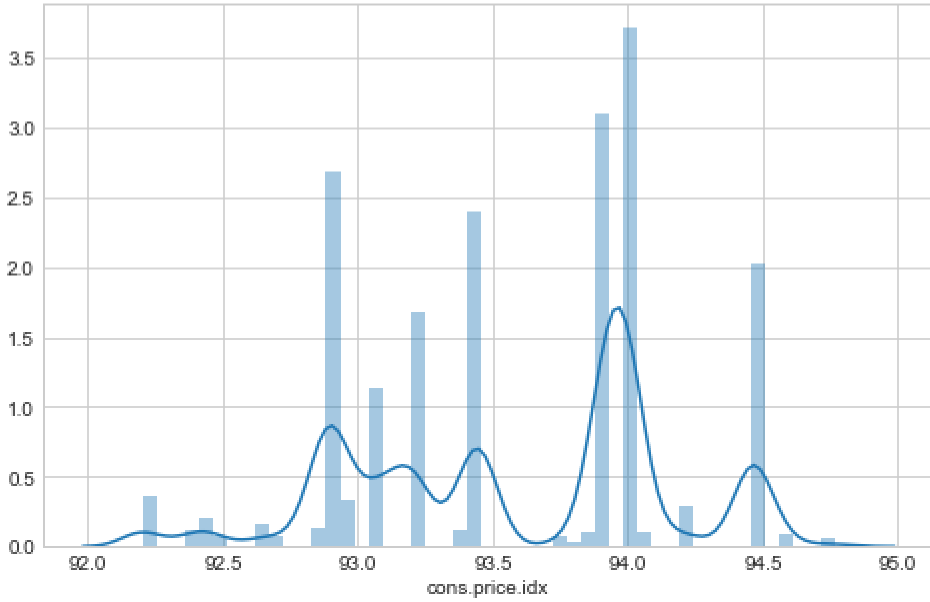


cons.price.idx Feature Analysis

In [32]:
```
sns.boxplot(data=df,x='y',y='cons.price.idx')
plt.show()
```

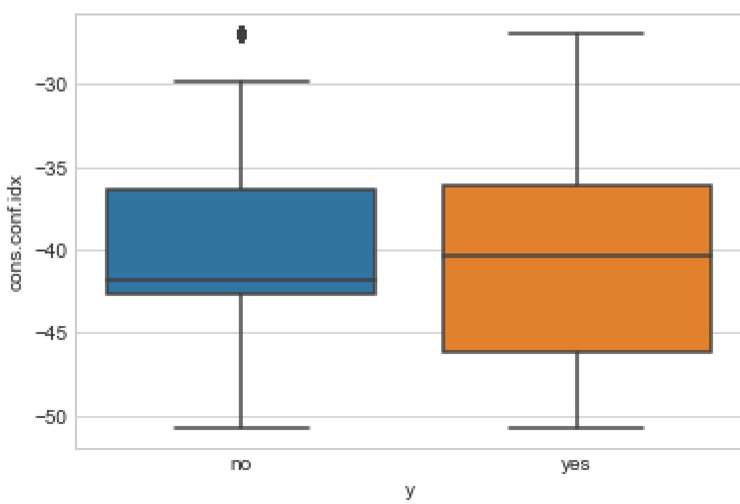


In [33]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["cons.price.idx"])
plt.show()
```

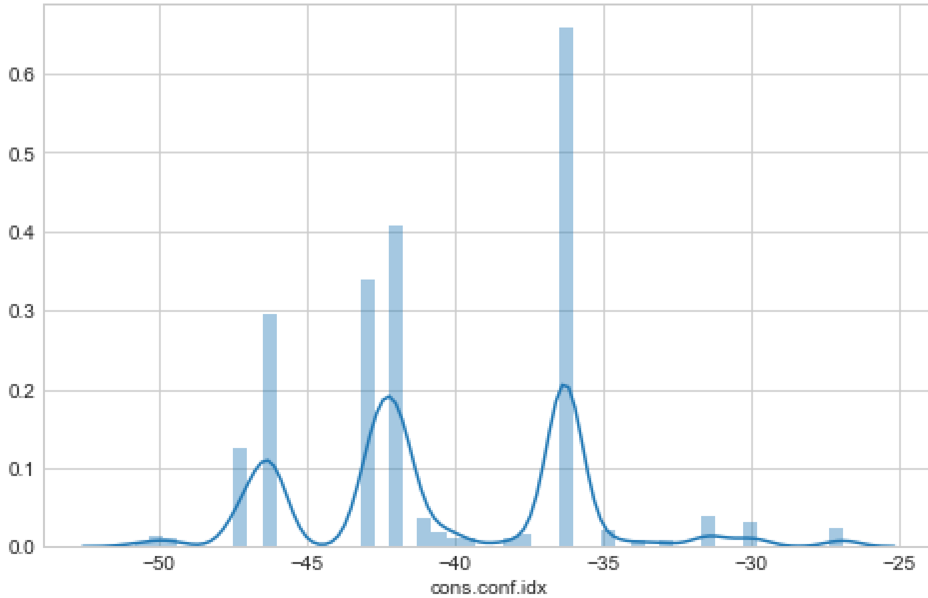


cons.conf.idx Feature Analysis

In [34]:
```
sns.boxplot(data=df,x='y',y='cons.conf.idx')
plt.show()
```

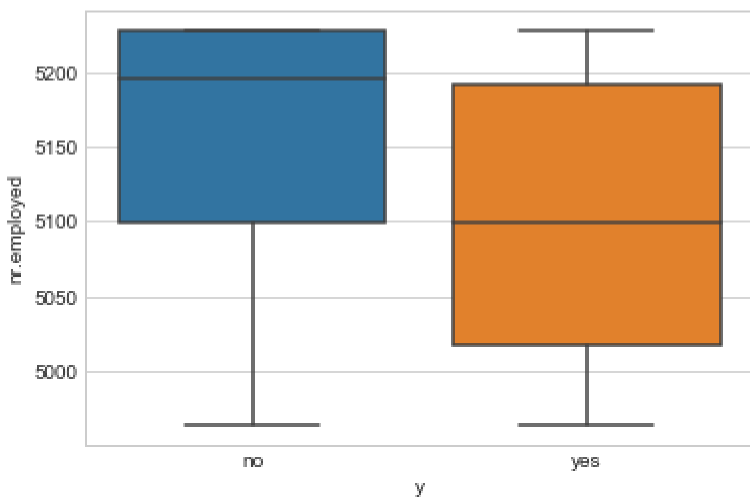


In [35]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["cons.conf.idx"])
plt.show()
```

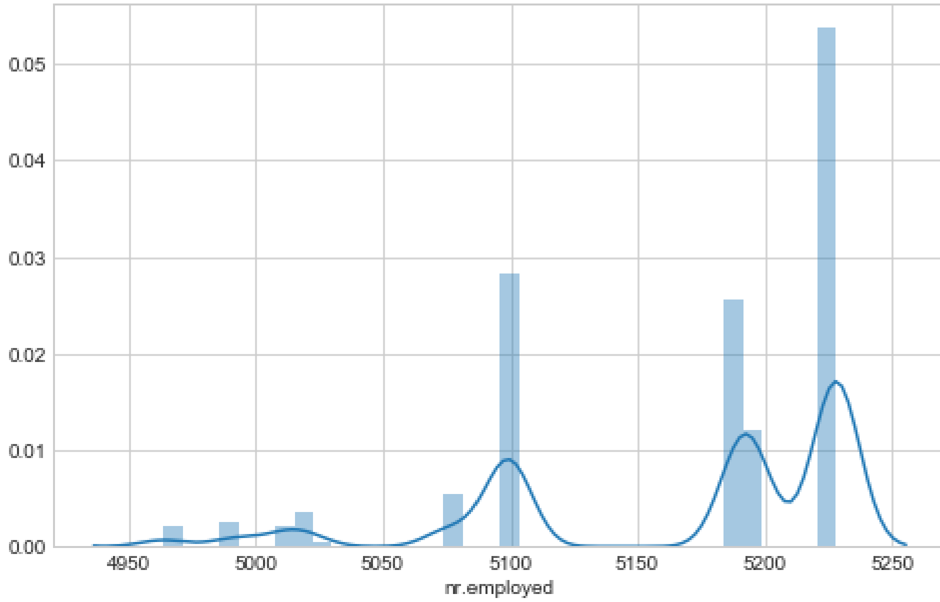


nr.employed Feature Analysis

In [37]:
```
sns.boxplot(data=df,x='y',y='nr.employed')
plt.show()
```



In [36]:
```
plt.figure(figsize=(8,5))
sns.distplot(df["nr.employed"])
plt.show()
```

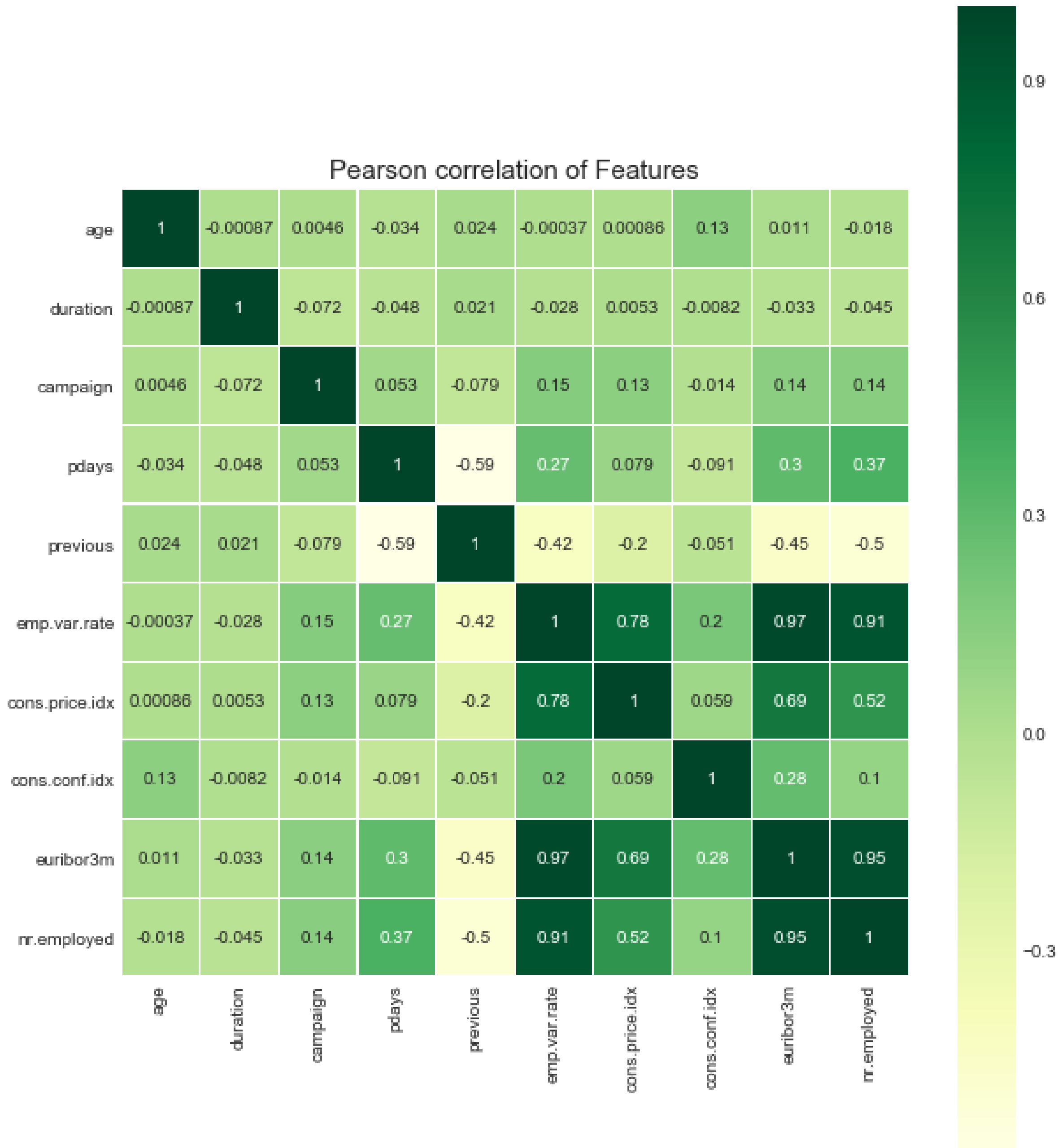


In [ ]:

Correlation Matrix of the numerical features:

In [31]:
```
corr = df.corr()

f, ax = plt.subplots(figsize=(10,12))

cmap = sns.diverging_palette(220, 10, as_cmap=True)

_ = sns.heatmap(corr, cmap="YlGn", square=True, ax=ax, annot=True, linewidth=
0.1)

plt.title("Pearson correlation of Features", y=1.05, size=15)
```

Out[31]: Text(0.5, 1.05, 'Pearson correlation of Features')



	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
age	1	-0.00087	0.0046	-0.034	0.024	-0.00037	0.00086	0.13	0.011	-0.018
duration	-0.00087	1	-0.072	-0.048	0.021	-0.028	0.0053	-0.0082	-0.033	-0.045
campaign	0.0046	-0.072	1	0.053	-0.079	0.15	0.13	-0.014	0.14	0.14
pdays	-0.034	-0.048	0.053	1	-0.59	0.27	0.079	-0.091	0.3	0.37
previous	0.024	0.021	-0.079	-0.59	1	-0.42	-0.2	-0.051	-0.45	-0.5
emp.var.rate	-0.00037	-0.028	0.15	0.27	-0.42	1	0.78	0.2	0.97	0.91
cons.price.idx	0.00086	0.0053	0.13	0.079	-0.2	0.78	1	0.059	0.69	0.52
cons.conf.idx	0.13	-0.0082	-0.014	-0.091	-0.051	0.2	0.059	1	0.28	0.1
euribor3m	0.011	-0.033	0.14	0.3	-0.45	0.97	0.69	0.28	1	0.95
nr.employed	-0.018	-0.045	0.14	0.37	-0.5	0.91	0.52	0.1	0.95	1

- The emp.var.rate, cons.price.idx, euribor3m and nr.employed features have very high correlation. With euribor3m and nr.employed having the highest correlation of 0.95!

In [21]:
```
numeric = ['age','campaign','cons.conf.idx','cons.price.idx','duration','emp.v
ar.rate','euribor3m','nr.employed','pdays','previous']
df[numeric].describe()
```

Out[21]:

	age	campaign	cons.conf.idx	cons.price.idx	duration	emp.var.rate	e
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	4118
mean	40.02406	2.567593	-40.502600	93.575664	258.285010	0.081886	
std	10.42125	2.770014	4.628198	0.578840	259.279249	1.570960	
min	17.00000	1.000000	-50.800000	92.201000	0.000000	-3.400000	
25%	32.00000	1.000000	-42.700000	93.075000	102.000000	-1.800000	
50%	38.00000	2.000000	-41.800000	93.749000	180.000000	1.100000	
75%	47.00000	3.000000	-36.400000	93.994000	319.000000	1.400000	
max	98.00000	56.000000	-26.900000	94.767000	4918.000000	1.400000	

- From the source of the data (U.C. Irvine ML Repository), we're told that the missing values, or NaNs, are encoded as '999'. - From the analysis above, it is clear that only 'pdays' has missing values. Moreover, a majority of the values for 'pdays' are missing.
- Outliers are defined as 1.5 x Q3 value (75th percentile). From the above table, it can be seen that only 'age' and 'campaign' have outliers as max('age') and max('campaign') > 1.5Q3('age') and >1.5Q3('campaign') respectively.
- But we also see that the value of these outliers are not so unrealistic (max('age')=98 and max('campaign')=56). Hence, we need not remove them since the prediction model should represent the real world. This improves the generalizability of the model and makes it robust for real world situations. The outliers, therefore, are not removed.

Conclusion of Analysis

- Analyzing the dataset we found that out of **20 Features**
  - 10 features were Numerical Features
  - 10 features were Categorical Features

- The data is highly skewed as there are **88.73%** of values for people who did not subscribed for Term Deposit

- There are **"Unknown"** values in many categorical variables in the Data Set
  - One way to handle the missing values is to remove the row but drawback of this will be reduction of dataset which will not solve our purpose
  - Good way to solve this problem will be inferring this "unknown" values by doing imputation
  - Variables with unknown values are "job","marital","education","default", "housing", "loan"

- There are **"999"** values in pdays variable which is numeric

- The **"Normalized Relavtive Frequency"** graph for each individual variable gives a very good Idea about the turn around for people subscribing the term deposit and it can be used to plan the next campaign!

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please refer to "Data Preparation - Market Campaign" for next step