Portuguese Bank Marketing

Data Set Information:

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed. The classification goal is to predict if the client will subscribe (yes/no) a term deposit (variable y).

Attribute Information:

bank client data:

- #### 1 - age (numeric)
- #### 2 - job : type of job (categorical: "admin.","unknown","unemployed","management","housemaid","entrepreneur","student","blue-collar","self-employed","retired","technician","services")
- #### 3 - marital : marital status (categorical: "married","divorced","single"; note: "divorced" means divorced or widowed)
- #### 4 - education (categorical: "unknown","secondary","primary","tertiary")
- #### 5 - default: has credit in default? (binary: "yes","no")
- #### 6 - balance: average yearly balance, in euros (numeric)
- #### 7 - housing: has housing loan? (binary: "yes","no")
- #### 8 - loan: has personal loan? (binary: "yes","no") ## related with the last contact of the current campaign:
- #### 9 - contact: contact communication type (categorical: "unknown","telephone","cellular")
- #### 10 - day: last contact day of the month (numeric)
- #### 11 - month: last contact month of year (categorical: "jan", "feb", "mar", ..., "nov", "dec")
- #### 12 - duration: last contact duration, in seconds (numeric) ## other attributes:
- #### 13 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- #### 14 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric, -1 means client was not previously contacted)
- #### 15 - previous: number of contacts performed before this campaign and for this client (numeric)
- #### 16 - poutcome: outcome of the previous marketing campaign (categorical: "unknown","other","failure","success") ## Output variable (desired target):

- #### 17 - y - has the client subscribed a term deposit? (binary: "yes","no")

Loading the main libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv('bank-full.csv', delimiter=';')
df.head()
```

Out[2]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	du
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   age        45211 non-null  int64 
 1   job        45211 non-null  object
 2   marital    45211 non-null  object
 3   education  45211 non-null  object
 4   default    45211 non-null  object
 5   balance    45211 non-null  int64 
 6   housing    45211 non-null  object
 7   loan       45211 non-null  object
 8   contact    45211 non-null  object
 9   day        45211 non-null  int64 
 10  month      45211 non-null  object
 11  duration   45211 non-null  int64 
 12  campaign   45211 non-null  int64 
 13  pdays      45211 non-null  int64 
 14  previous   45211 non-null  int64 
 15  poutcome   45211 non-null  object
 16  y          45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

No missing values in the dataset.

In [4]:
```
df.shape
```

Out[4]:
```
(45211, 17)
```

In [5]:
```
df.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
age	45211.0	40.936210	10.618762	18.0	33.0	39.0	48.0	95.0
balance	45211.0	1362.272058	3044.765829	-8019.0	72.0	448.0	1428.0	102127.0
day	45211.0	15.806419	8.322476	1.0	8.0	16.0	21.0	31.0
duration	45211.0	258.163080	257.527812	0.0	103.0	180.0	319.0	4918.0
campaign	45211.0	2.763841	3.098021	1.0	1.0	2.0	3.0	63.0
pdays	45211.0	40.197828	100.128746	-1.0	-1.0	-1.0	-1.0	871.0
previous	45211.0	0.580323	2.303441	0.0	0.0	0.0	0.0	275.0

In [6]:
```
df.describe(include='object').T
```

Out[6]:

	count	unique	top	freq
job	45211	12	blue-collar	9732
marital	45211	3	married	27214
education	45211	4	secondary	23202
default	45211	2	no	44396
housing	45211	2	yes	25130
loan	45211	2	no	37967
contact	45211	3	cellular	29285
month	45211	12	may	13766
poutcome	45211	4	unknown	36959
y	45211	2	no	39922

In [7]:
```
print(f"Categorical Attributes Unique")
for col in df.describe(include='object'):
    print(f"{'='*75}\n{col} ({df[col].nunique()} unique):\n{df[col].unique()}"
```

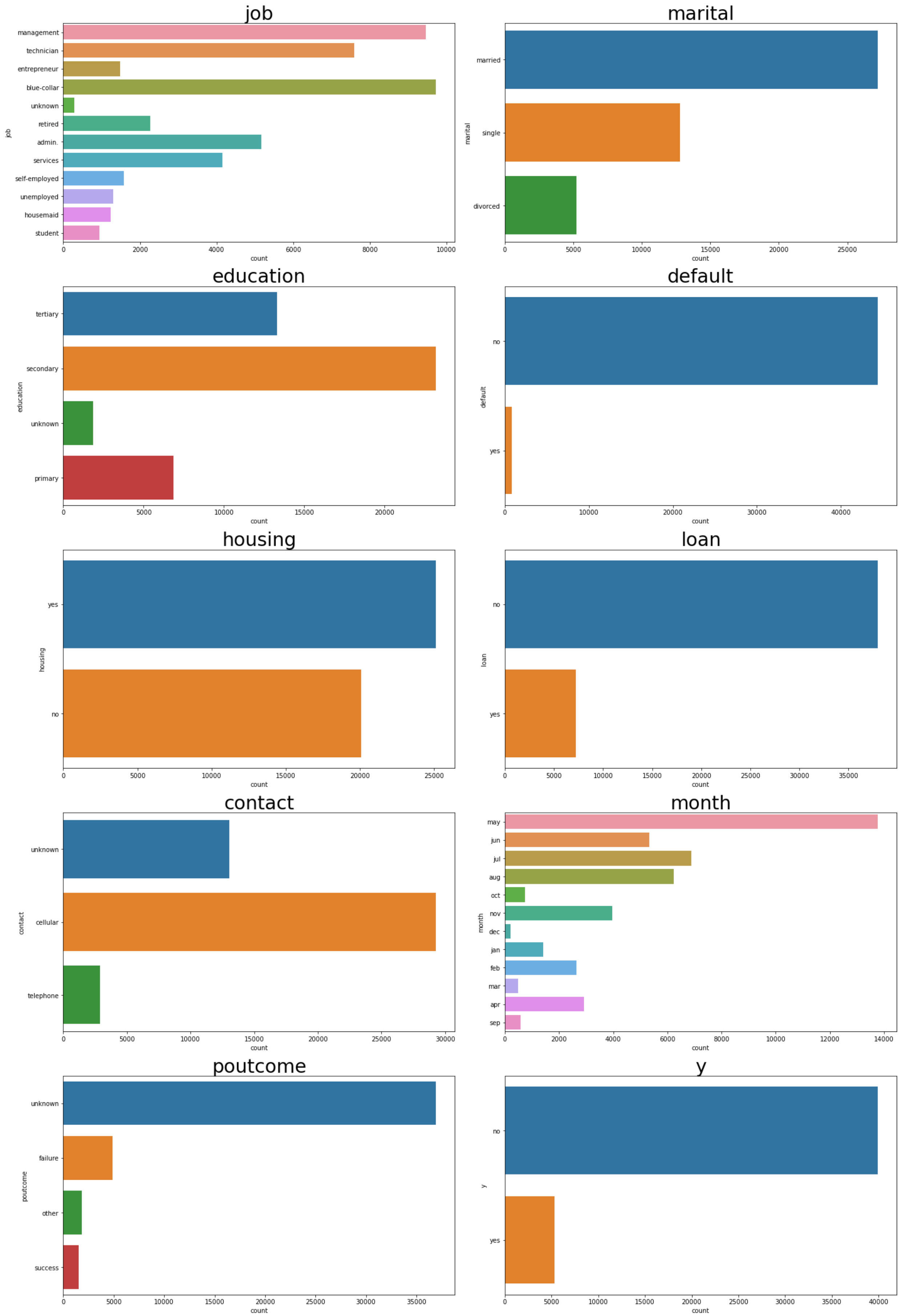
```
Categorical Attributes Unique
============================================================================
job (12 unique):
['management' 'technician' 'entrepreneur' 'blue-collar' 'unknown'
 'retired' 'admin.' 'services' 'self-employed' 'unemployed' 'housemaid'
 'student']
============================================================================
marital (3 unique):
['married' 'single' 'divorced']
============================================================================
education (4 unique):
['tertiary' 'secondary' 'unknown' 'primary']
============================================================================
default (2 unique):
['no' 'yes']
============================================================================
housing (2 unique):
['yes' 'no']
============================================================================
loan (2 unique):
['no' 'yes']
============================================================================
contact (3 unique):
['unknown' 'cellular' 'telephone']
============================================================================
month (12 unique):
['may' 'jun' 'jul' 'aug' 'oct' 'nov' 'dec' 'jan' 'feb' 'mar' 'apr' 'sep']
============================================================================
poutcome (4 unique):
['unknown' 'failure' 'other' 'success']
============================================================================
y (2 unique):
['no' 'yes']
```

Exploratory Data Analysis

Categorical Feature Count Plot

In [8]:
```
fig = plt.figure(figsize=(20,30))
plot = 1
for col in df.describe(include='object').columns:
    ax = plt.subplot(5,2,plot)
    sns.countplot(y=col, data=df, ax=ax)
    ax.set_title(col, fontsize=30)
    plot += 1
fig.suptitle('Categorical Feature Count Plot', fontsize=40, y=1)
plt.tight_layout()
plt.show()
```

Categorical Feature Count Plot

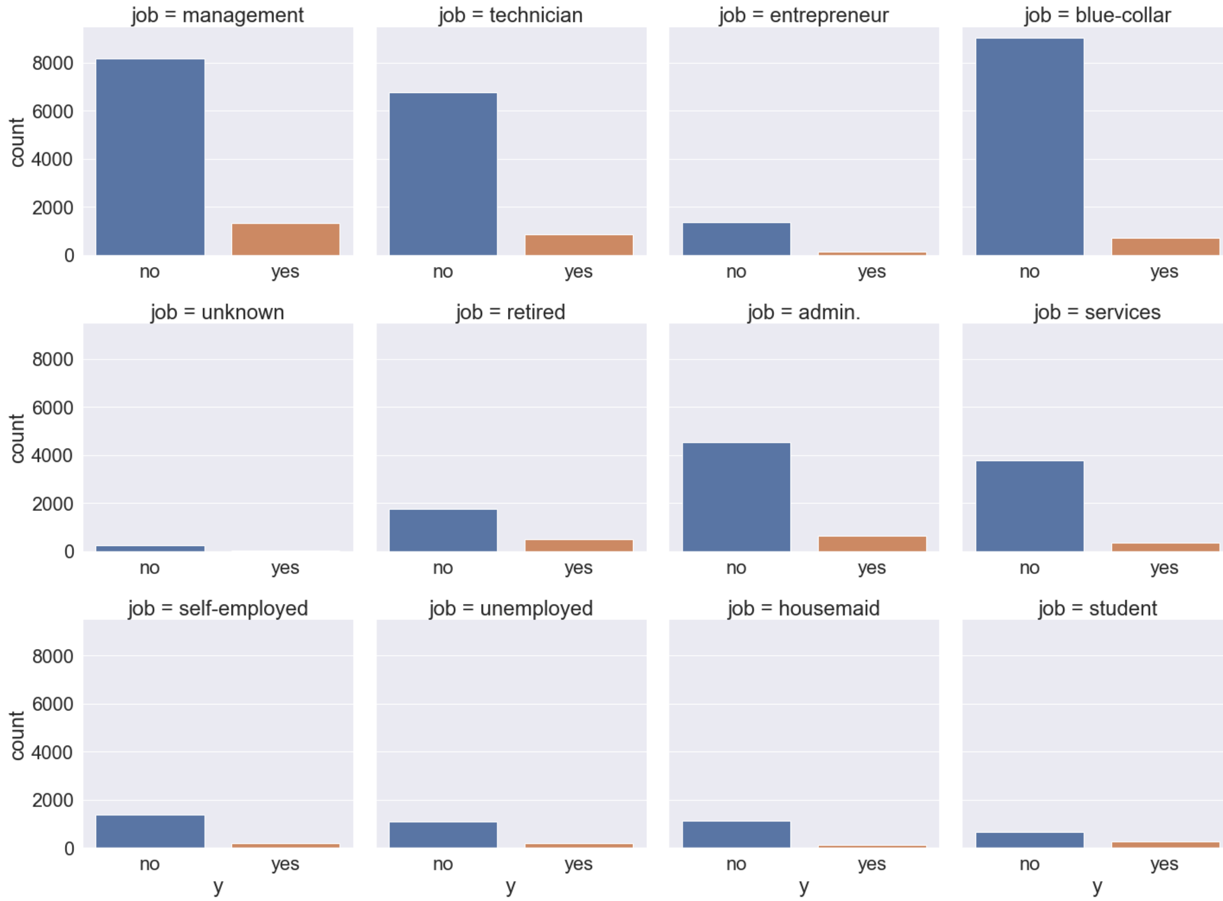


- #### Blue-collar workers are the most frequent type in this dataset, followed by management and technician.
- #### Most customers are married.
- #### Most customers have a high-school education, followed by Tertiary(College/Trade School).
- #### The vast majority of customers have not defaulted on their loans.
- #### Most customers were successfully reached via cellphone calls.
- #### Most customer contancts occur in May and the least occur in December.
- #### For most customers the outcome of the previous marketing campaign is unknown.
- #### Most clients have not subscribed for a term deposit.
- #### There is an imbalance for the dependent variable (outcome of term deposit), with significantly more rejections than acceptances.

Relationship Between Categorical Features and Label

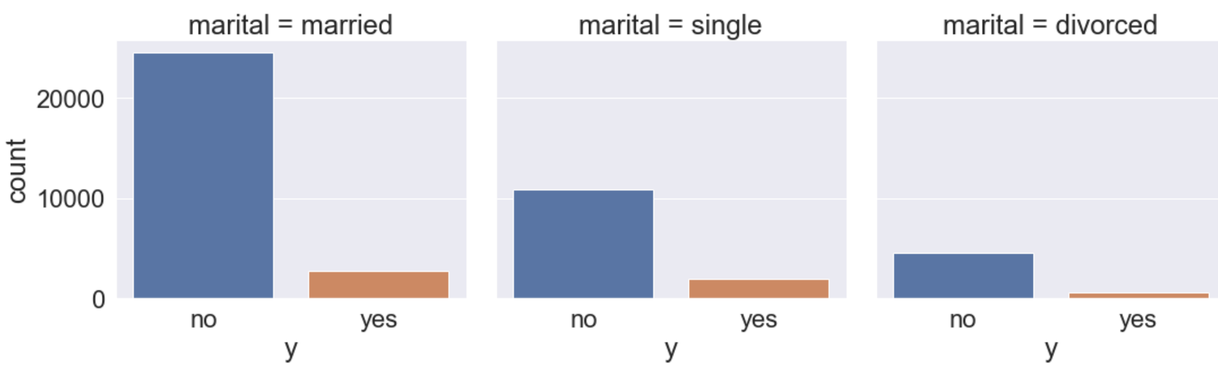
Job

In [9]:
```
sns.set(font_scale=2)
g = sns.catplot(x='y', col='job', kind='count', data=df, col_wrap=4, sharex=Fa
plt.show()
```



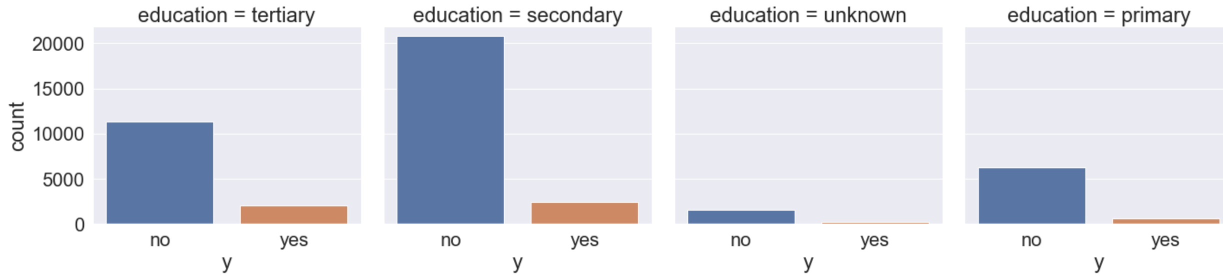
- #### Clients working in management have high interest on deposit.
- #### Blue-collar workers are least-likely to to get a term deposit.

In [10]:
```
g = sns.catplot(x='y', col='marital', kind='count', data=df, col_wrap=4)
plt.show()
```



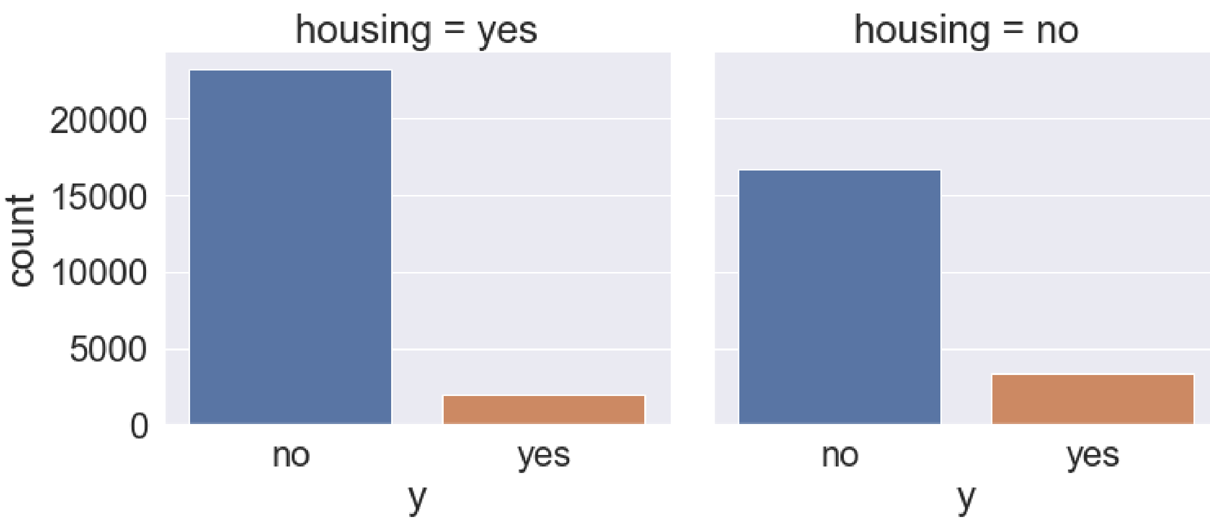
- #### Married clients are more likely to accept a term deposit.

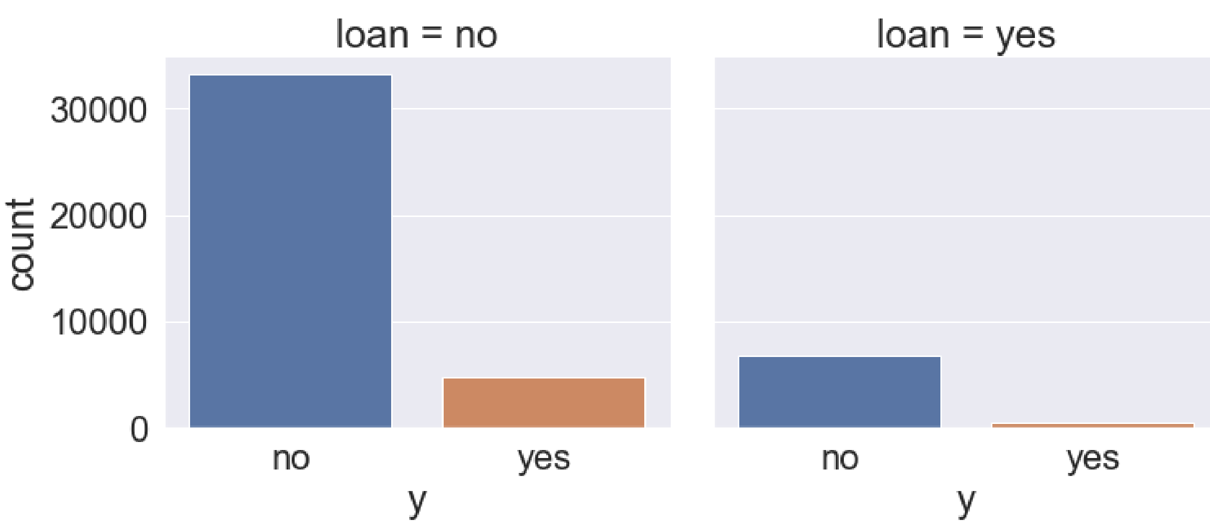
In [11]:
```
g = sns.catplot(x='y', col='education', kind='count', data=df, col_wrap=4)
plt.show()
```



- #### Clients with secondary education and above are more likely to accept a term deposit.

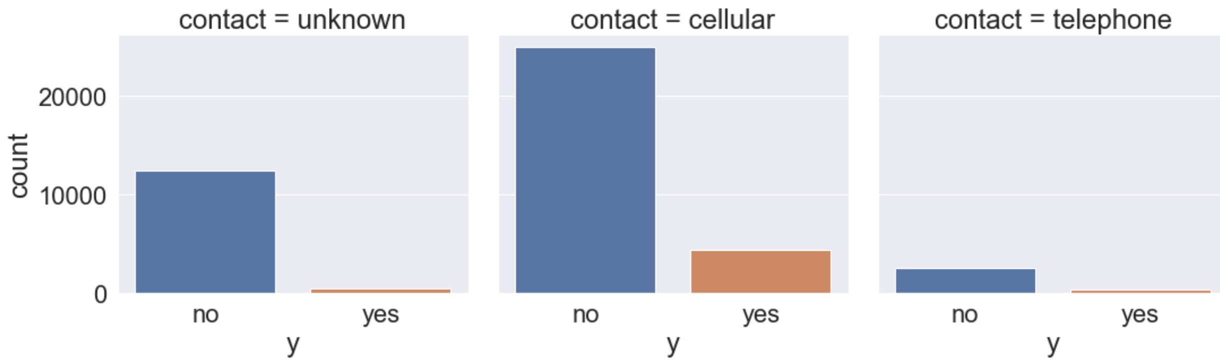
In [12]:
```python
g = sns.catplot(x='y', col='housing', kind='count', data=df, col_wrap=4)
g = sns.catplot(x='y', col='loan', kind='count', data=df, col_wrap=4)
plt.show()
```





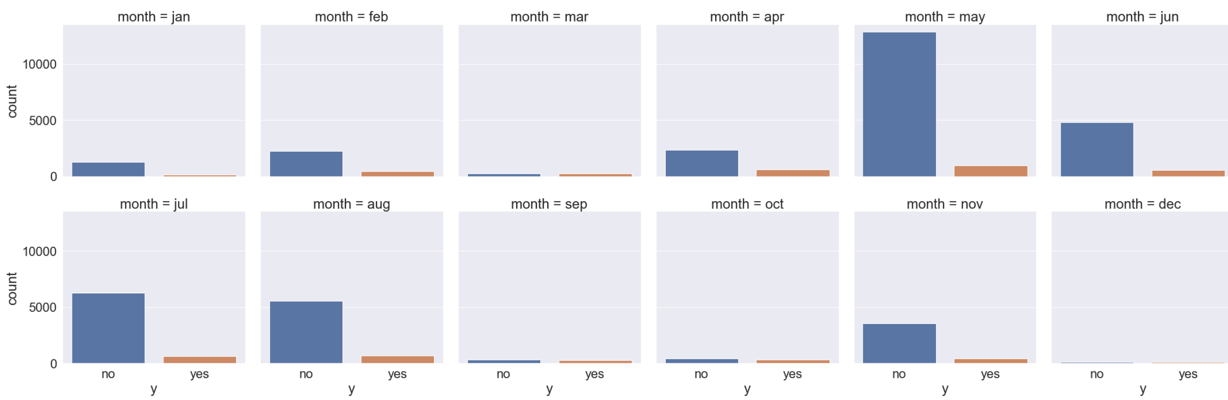
- #### Clients without a housing loan are more likely to accept a term deposit.
- #### Clients without a personal loan are more likely to accept a term deposit.

In [13]:
```python
g = sns.catplot(x='y', col='contact', kind='count', data=df, col_wrap=4)
plt.show()
```



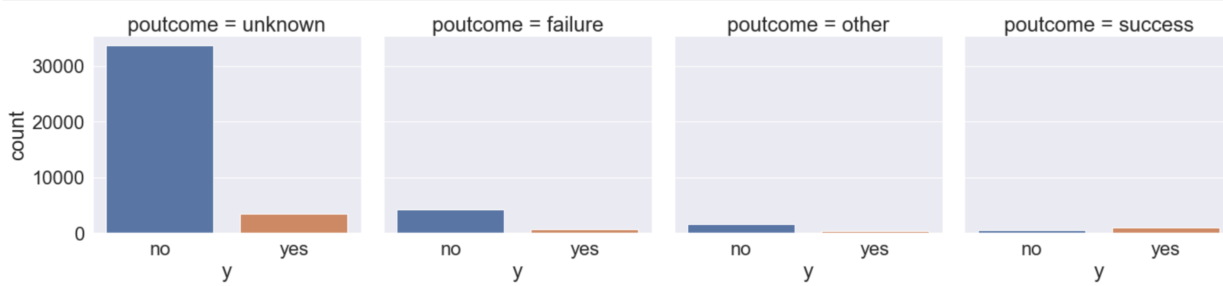
- #### Clients contacted by cellphone are more likely to accept a term deposit.

In [14]:
```
g = sns.catplot(x='y', col='month', kind='count', data=df, col_wrap=6, col_ord
plt.show()
```



- #### May is the month with the highest interest for a term deposit.
- #### December is the month with the lowest interest for a term deposit.

In [15]:
```
g = sns.catplot(x='y', col='poutcome', kind='count', data=df, col_wrap=4)
plt.show()
```



- #### If the pre-campaign outcome is successful, then there is a high chance of the client showing interest on deposit.

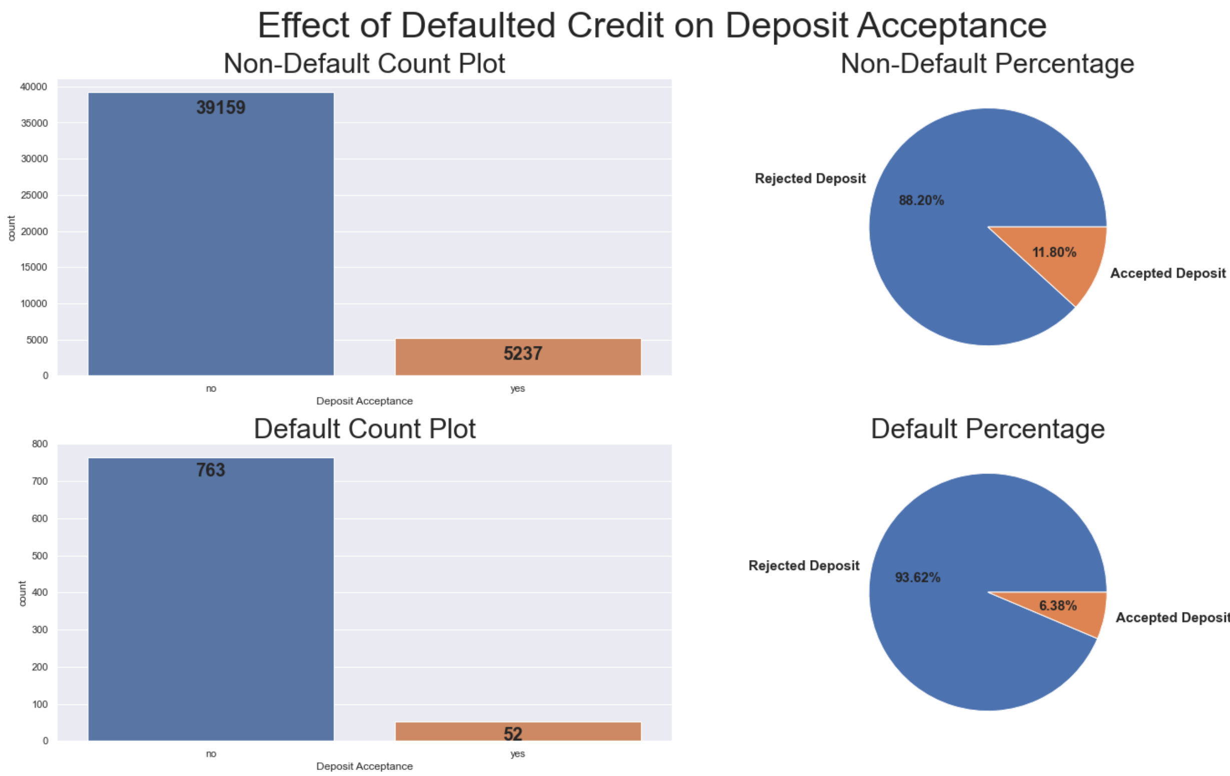
In [16]:
```
sns.set(font_scale=1)
fig, ax = plt.subplots(2,2, figsize=(20,12))

sns.countplot(df[df['default'] == 'no']['y'], ax=ax[0,0])
ax[0,0].set_title('Non-Default Count Plot', fontsize=30)
ax[0,0].set_xlabel('Deposit Acceptance')
```

```
for i in range(2):
    ax[0,0].text(i-0.05, df.groupby(['default', 'y']).size()[i]-3000,df.groupb

ax[0,1].pie(df.groupby(['default', 'y']).size()[:2], labels=['Rejected Deposit
ax[0,1].set_title('Non-Default Percentage', fontsize=30)

sns.countplot(df[df['default'] == 'yes']['y'], ax=ax[1,0])
ax[1,0].set_title('Default Count Plot', fontsize=30)
ax[1,0].set_xlabel('Deposit Acceptance')
for i in range(2):
    ax[1,0].text(i-0.05, df.groupby(['default', 'y']).size()[i+2]-50,df.groupb
ax[1,1].pie(df.groupby(['default', 'y']).size()[2:], labels=['Rejected Deposit
ax[1,1].set_title('Default Percentage', fontsize=30)
fig.suptitle('Effect of Defaulted Credit on Deposit Acceptance', fontsize=40)
fig.tight_layout()
plt.show()
```

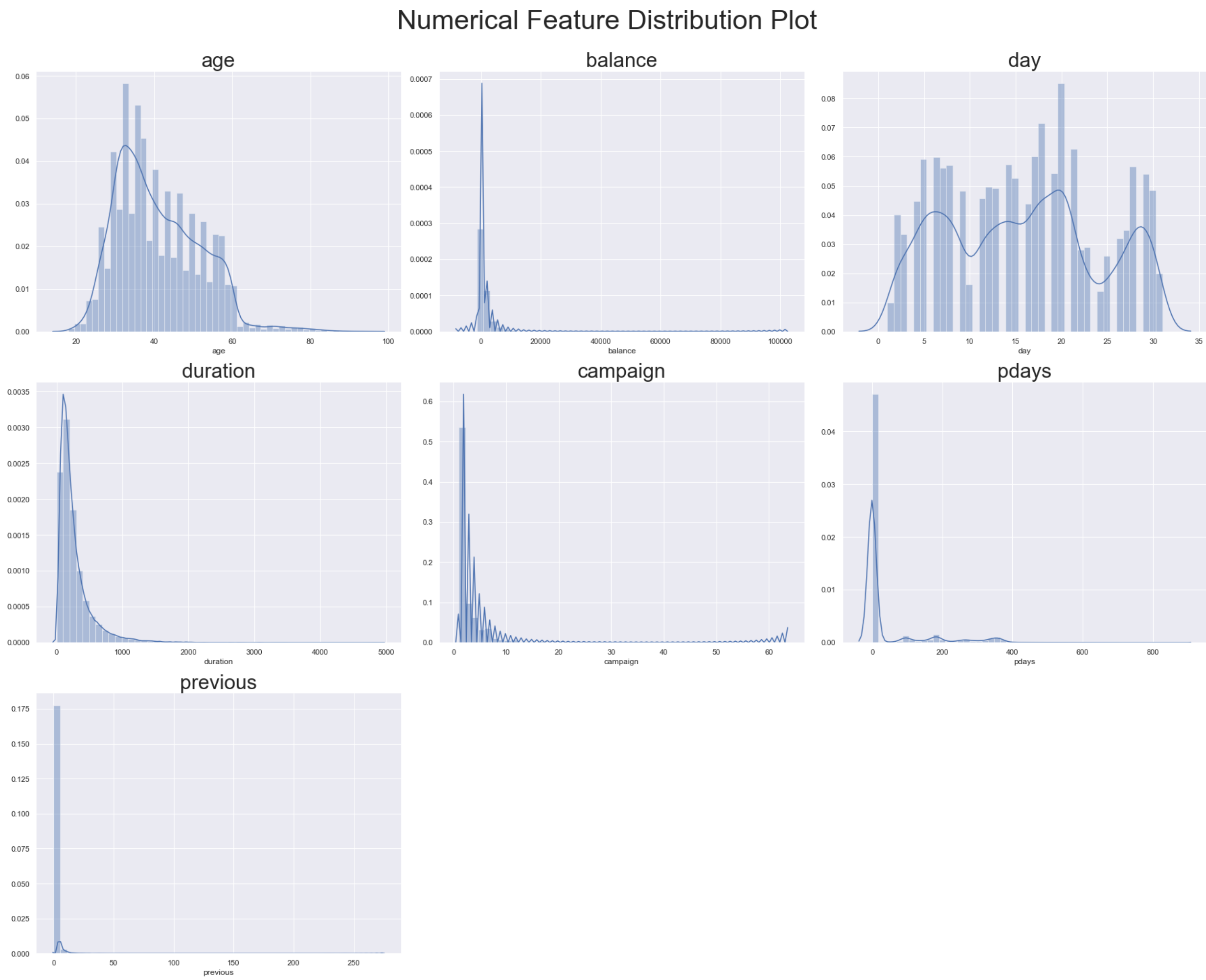


- #### Although the amount of clients in the Non-Default category are significantly larger than Default, the percentages in regards to acceptance/rejection of a deposit are very close/similar. This suggests that the "default" attribute does not play a significant role in the prediction of our dependent variable.

Exploring the Numerical Features

In [17]:
```
fig = plt.figure(figsize=(25,20))
plot = 1
for col in df.describe().columns:
    ax = plt.subplot(3,3,plot)
    sns.distplot(df[col])
    ax.set_title(col, fontsize=30)
    plot += 1
```

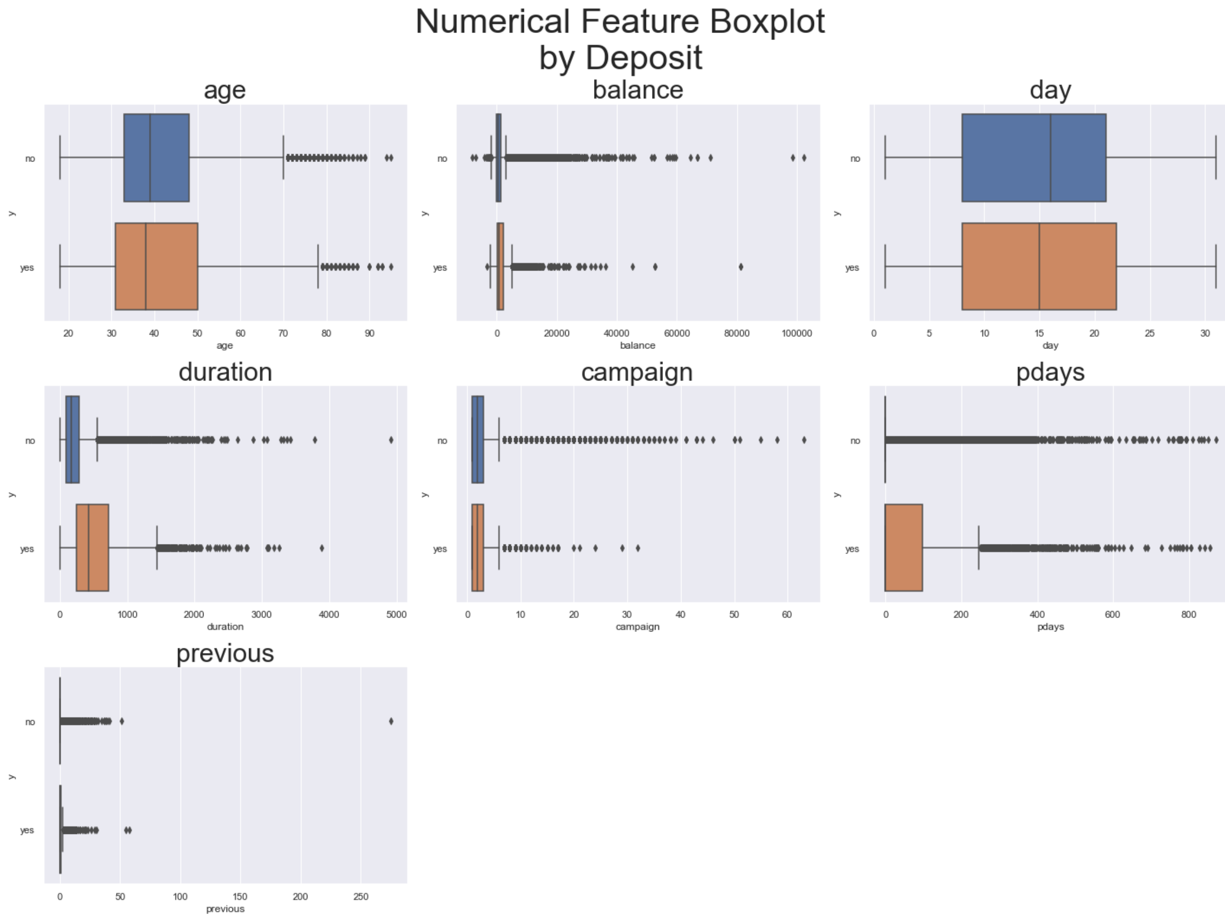
```
fig.suptitle('Numerical Feature Distribution Plot', fontsize=40, y=1)
plt.tight_layout()
plt.show()
```



- #### "age" and "day" seem approximately normally distributed.
- #### "balance", "duration", "campaign", "pdays", and "previous" are right-skewed, with the possibility of outliers present.

Numerical Feature Boxplot by Deposit

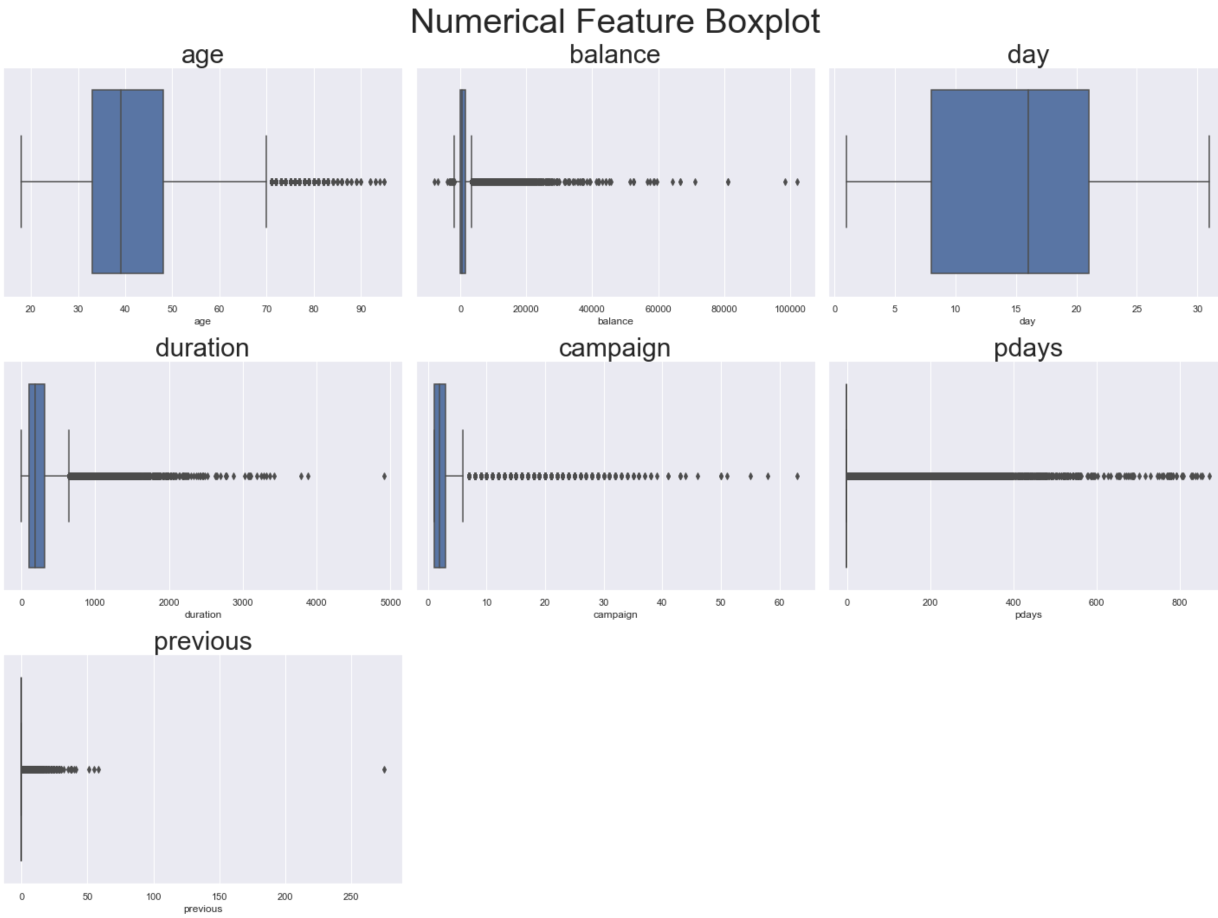
In [18]:
```
fig = plt.figure(figsize=(20,15))
plot = 1
for col in df.describe().columns:
    ax = plt.subplot(3,3,plot)
    ax.set_title(col, fontsize=30)
    sns.boxplot(x=col, y='y',data=df)
    plot += 1
fig.suptitle('Numerical Feature Boxplot\nby Deposit', fontsize=40)
fig.tight_layout()
plt.show()
```



- #### Clients who had longer call durations showed more interest towards the deposit.

Numerical Feature Boxplot

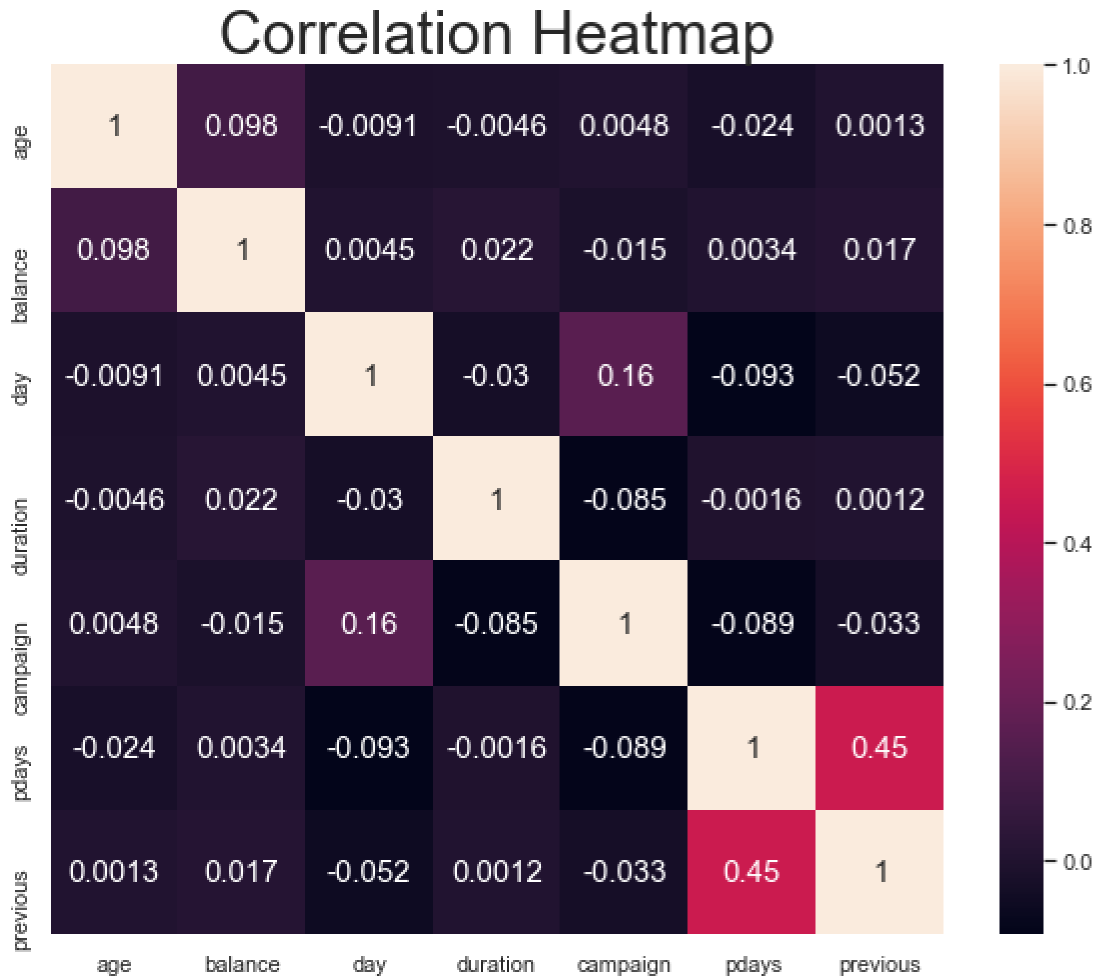
In [19]:
```
fig = plt.figure(figsize=(20,15))
plot = 1
for col in df.describe().columns:
    ax = plt.subplot(3,3,plot)
    ax.set_title(col, fontsize=30)
    sns.boxplot(x=col,data=df)
    plot += 1
fig.suptitle('Numerical Feature Boxplot', fontsize=40)
fig.tight_layout()
plt.show()
```



- #### Every attribute with the expection of "day" has outliers.

Correlation Between Numerical Features

In [20]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, annot_kws={'fontsize':15})
plt.title('Correlation Heatmap', fontsize=30)
plt.show()
```



- #### It seems no feature is heavily correlated with other features.

Feature Engineering

As per Exploratory Data Analysis:

- ##### No missing values found.
- ##### No feature found with one value.
- ##### 9 categorical features
- ##### "default" attribute does not play an important role in prediction.
- ##### There may be a presence of outliers for the numerical features.

In [21]:
```
df2 = df.copy()
df2.head()
```

Out[21]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	du
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	

Dropping irrelevant features

In [22]:

```
fig, ax = plt.subplots(1,2, figsize=(10,10))
ax[0].pie(df2.groupby(['y', 'default']).size()[:2], labels=['Rejected Deposit'
ax[1].pie(df2.groupby(['y', 'default']).size()[2:], labels=['Rejected Deposit'
fig.tight_layout()
plt.show()
```

- #### "Default" feature does not play an important role in predicting deposit.

In [23]:

```
df2.drop('default', axis=1, inplace=True)
```

In [24]:

```
print(df2.groupby(['y', 'pdays']).size())
print(f"Value -1 for pdays corresponds to {np.round(len(df[df.pdays == -1]) /
```

```
y    pdays
no   -1       33570
      1           9
      2          35
      3           1
      4           1
               ...
yes   804         1
      805         1
      828         1
      842         1
      854         1
Length: 914, dtype: int64
Value -1 for pdays corresponds to 81.74% of all pdays entries.
```

- #### "pdays" does not play an important role in predicting deposit, since over 80% of the entries are -1.

In [25]:
```
df2.drop('pdays', axis=1, inplace=True)
```

Removing Outliers

In [26]:
```
df2.groupby('age', sort=True).size()
```

Out[26]:
```
age
18     12
19     35
20     50
21     79
22    129
     ...
90      2
92      2
93      2
94      1
95      2
Length: 77, dtype: int64
```

- #### There are no significant outliers in the dataset, since the minimum age is 18 and the maximum age is 95.

In [27]:
```
df2.groupby(['y','balance'], sort=True).size()
```

Out[27]:
```
y    balance
no   -8019      1
     -6847      1
     -4057      1
     -3372      1
     -3313      1
               ..
yes   34646     1
      36252     1
      45248     1
      52587     2
      81204     2
Length: 9258, dtype: int64
```

- #### These outliers will not be removed, since they show a relationship between account balance and acceptance of deposit. Clients with low or negative balance tend to reject the deposit, and vice-verca.

In [28]:
```
df2.groupby(['y', 'campaign'], sort=True).size()
```

Out[28]:
```
y    campaign
no   1           14983
     2           11104
     3            4903
     4            3205
     5            1625
                 ...
yes  20              1
     21              1
     24              1
     29              1
     32              1
Length: 70, dtype: int64
```

- #### These outliers will not be removed, since they show a relationship between the number of contacts performed for the client and acceptance of the deposit. Clients that received more contact calls are more likely to accept a deposit, and vice-verca.

In [29]:
```
df2.groupby(['y', 'duration'], sort=True).size()
```

Out[29]:
```
y    duration
no   0            3
     1            2
     2            3
     3            4
     4           15
                 ..
yes  3094         1
     3102         1
     3183         1
     3253         1
     3881         1
Length: 2627, dtype: int64
```

- #### These outliers will not be removed, since they show a relationship between time(in seconds) spent in contact and acceptance of the deposit. Clients that stayed on the phone longer are more likely to accept a deposit, and vice-verca.

In [30]:
```
with pd.option_context('display.max_rows', None):
    print(df2.groupby(['y', 'campaign'], sort=True).size())
```

```
y    campaign
no   1           14983
     2           11104
     3            4903
     4            3205
     5            1625
     6            1199
     7             688
     8             508
     9             306
     10            252
     11            185
     12            151
     13            127
     14             89
     15             80
     16             77
     17             63
     18             51
     19             44
     20             42
     21             34
     22             23
     23             22
     24             19
     25             22
     26             13
     27             10
     28             16
     29             15
     30              8
     31             12
     32              8
     33              6
     34              5
     35              4
     36              4
     37              2
     38              3
     39              1
     41              2
     43              3
     44              1
     46              1
     50              2
     51              1
     55              1
     58              1
     63              1
yes  1            2561
     2            1401
     3             618
     4             317
     5             139
     6              92
     7              47
     8              32
     9              21
     10             14
     11             16
```

```
    12          4
    13          6
    14          4
    15          4
    16          2
    17          6
    20          1
    21          1
    24          1
    29          1
    32          1
dtype: int64
```

- #### Clients with "no" for deposit and number of campaign calls higher than clients with "yes" for deposit will be treated as outliers, since the majority of clients with no interest in a deposit get significantly less calls.

In [31]:
```
df2 = df2.loc[df2.campaign < 33]
```

In [32]:
```
with pd.option_context('display.max_rows', None):
    print(df2.groupby(['y', 'previous'], sort=True).size())
```

```
y    previous
no   0           33532
     1            2189
     2            1650
     3             848
     4             543
     5             338
     6             194
     7             151
     8              90
     9              68
     10             41
     11             50
     12             34
     13             29
     14             14
     15             19
     16             13
     17             12
     18              6
     19              9
     20              7
     21              3
     22              5
     23              7
     24              5
     25              4
     26              1
     27              5
     28              2
     29              3
     30              2
     32              1
     35              1
     37              2
     38              2
     40              1
     41              1
     51              1
     275             1
yes  0            3384
     1             583
     2             456
     3             294
     4             171
     5             121
     6              83
     7              54
     8              39
     9              24
     10             26
     11             15
     12             10
     13              9
     14              5
     15              1
     17              3
     19              2
     20              1
     21              1
```

```
      22          1
      23          1
      26          1
      29          1
      30          1
      55          1
      58          1
dtype: int64
```

- #### Clients that received more than 30 non-campaign calls will be treated as outliers.

In [33]:
```
df2 = df2.loc[df2.previous < 31]
```

Converting Categorical to Dummy/Indicator Variables

In [34]:
```
df2.head()
```

Out[34]:

	age	job	marital	education	balance	housing	loan	contact	day	month	duration	c
0	58	management	married	tertiary	2143	yes	no	unknown	5	may	261	
1	44	technician	single	secondary	29	yes	no	unknown	5	may	151	
2	33	entrepreneur	married	secondary	2	yes	yes	unknown	5	may	76	
3	47	blue-collar	married	unknown	1506	yes	no	unknown	5	may	92	
4	33	unknown	single	unknown	1	no	no	unknown	5	may	198	

In [35]:
```
df2 = pd.get_dummies(df2, columns=['job', 'marital', 'education', 'contact', '
df2.head()
```

Out[35]:

	age	balance	housing	loan	day	duration	campaign	previous	y	job_admin.	...	month_jun
0	58	2143	yes	no	5	261	1	0	no	0	...	0
1	44	29	yes	no	5	151	1	0	no	0	...	0
2	33	2	yes	yes	5	76	1	0	no	0	...	0
3	47	1506	yes	no	5	92	1	0	no	0	...	0
4	33	1	no	no	5	198	1	0	no	0	...	0

5 rows × 47 columns

Mapping Binary Categorical Variables to 0/1

In [36]:
```
for col in ['housing', 'loan', 'y']:
    df2[col] = df2[col].map({'yes': 1, 'no': 0})
df2.loc[:,['housing', 'loan', 'y']].head()
```

Out[36]:

	housing	loan	y
0	1	0	0
1	1	0	0
2	1	1	0
3	1	0	0
4	0	0	0

In [48]:
```
pd.options.display.max_columns
```

Out[48]:
```
20
```

In [50]:
```
pd.options.display.max_columns = 47
df2.head()
```

Out[50]:

	age	balance	housing	loan	day	duration	campaign	previous	y	job_admin.	job_blue-collar	job_(
0	58	2143	1	0	5	261	1	0	0	0	0	
1	44	29	1	0	5	151	1	0	0	0	0	
2	33	2	1	1	5	76	1	0	0	0	0	
3	47	1506	1	0	5	92	1	0	0	0	1	
4	33	1	0	0	5	198	1	0	0	0	0	

In [54]:
```
df2['y'].value_counts()
```

Out[54]:
```
0    39874
1     5287
Name: y, dtype: int64
```

Split Dataset into Training Set and Test Set

In [38]:
```
from sklearn.model_selection import train_test_split
X = df2.drop('y', axis=1)
y = df2['y']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
for var, txt in zip([X_train, X_test, y_train, y_test], ['X_train', 'X_test',
    print(f"{txt}.shape: {var.shape}")
```

```
X_train.shape: (36128, 46)
X_test.shape: (9033, 46)
y_train.shape: (36128,)
y_test.shape: (9033,)
```

Model Selection

We will use cross-validation to find the mean accuracy of different classification models.

In [66]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV, cross_val_score
```

In [56]:
```
models = [LogisticRegression(), SVC(), DecisionTreeClassifier(), GaussianNB(),
```

In [57]:
```
results = {
    'model': [],
    'score': []
}
for model in models:
    model_score = cross_val_score(estimator=model, X=X_train, y=y_train, cv=5)
    results['model'].append(str(model).split('(')[0])
    results['score'].append(model_score.mean())
```

```
D:\anaconda3\envs\my-env\lib\site-packages\sklearn\linear_model\_logistic.py:7
63: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
D:\anaconda3\envs\my-env\lib\site-packages\sklearn\linear_model\_logistic.py:7
63: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
D:\anaconda3\envs\my-env\lib\site-packages\sklearn\linear_model\_logistic.py:7
63: ConvergenceWarning: lbfgs failed to converge (status=1):
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
D:\anaconda3\envs\my-env\lib\site-packages\sklearn\linear_model\_logistic.py:7
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
D:\anaconda3\envs\my-env\lib\site-packages\sklearn\linear_model\_logistic.py:7
63: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regress
ion
  n_iter_i = _check_optimize_result(
D:\anaconda3\envs\my-env\lib\site-packages\xgboost\sklearn.py:888: UserWarnin
g: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
```

```
[12:42:38] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the def
ault evaluation metric used with the objective 'binary:logistic' was changed f
rom 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
D:\anaconda3\envs\my-env\lib\site-packages\xgboost\sklearn.py:888: UserWarnin
g: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[12:42:39] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the def
ault evaluation metric used with the objective 'binary:logistic' was changed f
rom 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
D:\anaconda3\envs\my-env\lib\site-packages\xgboost\sklearn.py:888: UserWarnin
g: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[12:42:40] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the def
ault evaluation metric used with the objective 'binary:logistic' was changed f
rom 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
D:\anaconda3\envs\my-env\lib\site-packages\xgboost\sklearn.py:888: UserWarnin
g: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[12:42:42] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the def
ault evaluation metric used with the objective 'binary:logistic' was changed f
rom 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
D:\anaconda3\envs\my-env\lib\site-packages\xgboost\sklearn.py:888: UserWarnin
g: The use of label encoder in XGBClassifier is deprecated and will be removed
in a future release. To remove this warning, do the following: 1) Pass option
use_label_encoder=False when constructing XGBClassifier object; and 2) Encode
your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[12:42:43] WARNING: ..\src\learner.cc:1061: Starting in XGBoost 1.3.0, the def
ault evaluation metric used with the objective 'binary:logistic' was changed f
rom 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore
the old behavior.
```

In [59]:

```python
pd.DataFrame(results).sort_values(by='score', ascending=False)
```

Out[59]:

	model	score
6	XGBClassifier	0.906084
5	RandomForestClassifier	0.905254
0	LogisticRegression	0.891663
1	SVC	0.883802
4	KNeighborsClassifier	0.877768
2	DecisionTreeClassifier	0.875498
3	GaussianNB	0.860801

XGBClassifier has the highest mean accuracy score out of all the models.

In [77]:
```
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss')
params = {
    'learning_rate': list(np.arange(0.01,0.5,0.05)),
    'max_depth': [3,5,10,20],
    'n_estimators': [10,15,25,50,75,100,150,200]
}
grid = GridSearchCV(estimator=xgb, param_grid=params, cv=5)
grid.fit(X_train, y_train)
```

Out[77]:
```
GridSearchCV(cv=5,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     eval_metric='logloss', gamma=None,
                                     gpu_id=None, importance_type='gain',
                                     interaction_constraints=None,
                                     learning_rate=None, max_delta_step=None,
                                     max_depth=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n...
                                     scale_pos_weight=None, subsample=None,
                                     tree_method=None, use_label_encoder=Fals
e,
                                     validate_parameters=None, verbosity=Non
e),
             param_grid={'learning_rate': [0.01, 0.060000000000000005, 0.11,
                                           0.16000000000000003,
                                           0.21000000000000002, 0.26,
                                           0.31000000000000005,
                                           0.36000000000000004,
                                           0.41000000000000003, 0.46],
                         'max_depth': [3, 5, 10, 20],
                         'n_estimators': [10, 15, 25, 50, 75, 100, 150, 200]})
```

In [80]:
```
xgb = grid.best_estimator_
xgb.fit(X_train, y_train)
xgb_pred = xgb.predict(X_test)
```

In [120…
```
from sklearn.metrics import accuracy_score, classification_report, confusion_m
print(f"{'='*60}\nAccuracy Score(Train): {xgb.score(X_train, y_train)}")
print(f"Accuracy Score(Test): {xgb.score(X_test, y_test)}\n{'='*60}")
```

```
print(f"{'='*60}\nClassification Report:\n{classification_report(y_test, xgb_p
print(f"{'='*60}\nConfusion Matrix:\n{pd.DataFrame(confusion_matrix(y_test, xg
```

```
============================================================
Accuracy Score(Train): 0.9288086802480071
Accuracy Score(Test): 0.905236355585077
============================================================
============================================================
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.96      0.95      7952
           1       0.64      0.47      0.54      1081

    accuracy                           0.91      9033
   macro avg       0.79      0.72      0.75      9033
weighted avg       0.90      0.91      0.90      9033

============================================================
============================================================
Confusion Matrix:
          Predicted 0  Predicted 1
Actual 0         7668          284
Actual 1          572          509
============================================================
```

With hyper-parameter turning, XGBClassifier is able to achieve 90% accuracy.

In [ ]: