Finlatics_Project

March 29, 2024

[1]:
```
#To supress Future Warning of Pandas
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
#Importing the modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['font.size'] = 15.0
import seaborn as sns
```

[2]:
```
df = pd.read_csv("../Finlatics/DsResearch/Banking/banking_data.csv")
```

1 Data Assessment

1.1 Summary

The dataset details phone call marketing campaigns by a Portuguese bank for promoting term deposits. It aims to predict client subscription to these deposits, emphasizing the efficiency of telephonic outreach despite the costs. This focus on optimizing marketing efforts makes the dataset valuable for strategic planning in banking.

1.2 Column Descriptions

- **age**: This column represents the age of the bank client. It's a numeric variable indicating the age in years.
- **job**: This column indicates the type of job the client has. It's a categorical variable with options such as "admin.", "unknown", "unemployed", "management", etc.
- **marital**: This column represents the marital status of the client. It's a categorical variable with options such as "married", "divorced", or "single".
- **education**: This column indicates the level of education of the client. It's a categorical variable with options such as "unknown", "secondary", "primary", or "tertiary".
- **default**: This column indicates whether the client has credit in default. It's a binary variable with options "yes" or "no".
- **balance**: This column represents the average yearly balance in euros for the client. It's a numeric variable.
- **housing**: This column indicates whether the client has a housing loan. It's a binary variable with options "yes" or "no".

- **loan**: This column indicates whether the client has a personal loan. It's a binary variable with options "yes" or "no".
- **contact**: This column represents the type of communication used to contact the client. It's a categorical variable with options such as "unknown", "telephone", or "cellular".
- **day**: This column represents the last contact day of the month. It's a numeric variable.
- **month**: This column represents the last contact month of the year. It's a categorical variable with options such as "jan", "feb", "mar", etc.
- **duration**: This column represents the duration of the last contact in seconds. It's a numeric variable.
- **campaign**: This column represents the number of contacts performed during this campaign and for this client. It's a numeric variable.
- **pdays**: This column represents the number of days that passed by after the client was last contacted from a previous campaign. It's a numeric variable where -1 means the client was not previously contacted.
- **previous**: This column represents the number of contacts performed before this campaign and for this client. It's a numeric variable.
- **poutcome**: This column represents the outcome of the previous marketing campaign. It's a categorical variable with options such as "unknown", "other", "failure", or "success".
- **y**: This column is the target variable and indicates whether the client has subscribed to a term deposit. It's a binary variable with options "yes" or "no".

1.3 Issues with dataset

1. Dirty Data
   - job, marital, marital_status, education, default, housing, loan, contact, day, month, day-month, poutcome,y as assigned wrong dtype `validity`
   - marital, marital_status, education have missing values `completion`
   - replace nan in education with unknown `validity`
   - append year to day_month column `completion`
   - 5 duplicate entries `accuracy`
2. Messy Data
   - marital and marital_status represent the exact same information
   - day and month column are unecessary when day-month is present
   - rename day_month column to date once year is appended

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

[3]:

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

```
3     yes   no  unknown    5   may     5-May        92         1     -1
4      no   no  unknown    5   may     5-May       198         1     -1

   previous poutcome   y
0         0  unknown  no
1         0  unknown  no
2         0  unknown  no
3         0  unknown  no
4         0  unknown  no
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45216 entries, 0 to 45215
Data columns (total 19 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             45216 non-null  int64
 1   job             45216 non-null  object
 2   marital         45213 non-null  object
 3   marital_status  45213 non-null  object
 4   education       45213 non-null  object
 5   default         45216 non-null  object
 6   balance         45216 non-null  int64
 7   housing         45216 non-null  object
 8   loan            45216 non-null  object
 9   contact         45216 non-null  object
 10  day             45216 non-null  int64
 11  month           45216 non-null  object
 12  day_month       45216 non-null  object
 13  duration        45216 non-null  int64
 14  campaign        45216 non-null  int64
 15  pdays           45216 non-null  int64
 16  previous        45216 non-null  int64
 17  poutcome        45216 non-null  object
 18  y               45216 non-null  object
dtypes: int64(7), object(12)
memory usage: 6.6+ MB
```

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

[5]:
```
                age        balance           day      duration      campaign  \
count  45216.000000   45216.000000  45216.000000  45216.000000  45216.000000
mean      40.938186    1362.277844     15.806507    258.166202      2.763668
std       10.621249    3044.609674      8.322022    257.515482      3.097896
min       18.000000   -8019.000000      1.000000      0.000000      1.000000
25%       33.000000      72.000000      8.000000    103.000000      1.000000
50%       39.000000     448.500000     16.000000    180.000000      2.000000
```

```
75%       48.000000    1428.000000     21.000000    319.000000      3.000000
max       95.000000  102127.000000     31.000000   4918.000000     63.000000

              pdays      previous
count  45216.000000  45216.000000
mean      40.202428      0.580657
std      100.128248      2.303778
min       -1.000000      0.000000
25%       -1.000000      0.000000
50%       -1.000000      0.000000
75%       -1.000000      0.000000
max      871.000000    275.000000
```

[6]:
```
df[df.duplicated()]
```

[6]:
```
       age         job   marital marital_status  education default  balance  \
45211   29  management    single         single   tertiary      no      765
45212   68     retired   married        married  secondary      no     1146
45213   53  management   married        married   tertiary      no      583
45214   73     retired   married        married  secondary      no     2850
45215   71     retired  divorced       divorced    primary      no     1729

      housing loan   contact  day month day_month  duration  campaign  pdays  \
45211      no   no  cellular   16   nov    16-Nov       238         1     -1
45212      no   no  cellular   16   nov    16-Nov       212         1    187
45213      no   no  cellular   17   nov    17-Nov       226         1    184
45214      no   no  cellular   17   nov    17-Nov       300         1     40
45215      no   no  cellular   17   nov    17-Nov       456         2     -1

       previous poutcome    y
45211         0  unknown  yes
45212         6  success  yes
45213         4  success  yes
45214         8  failure  yes
45215         0  unknown  yes
```

[7]:
```
df['age'].unique()
```

[7]:
```
array([58, 44, 33, 47, 35, 28, 42, 43, 41, 29, 53, 57, 51, 45, 60, 56, 32,
       25, 40, 39, 52, 46, 36, 49, 59, 37, 50, 54, 55, 48, 24, 38, 31, 30,
       27, 34, 23, 26, 61, 22, 21, 20, 66, 62, 83, 75, 67, 70, 65, 68, 64,
       69, 72, 71, 19, 76, 85, 63, 90, 82, 73, 74, 78, 80, 94, 79, 77, 86,
       95, 81, 18, 89, 84, 87, 92, 93, 88])
```

[8]:
```
df['job'].unique()
```

[8]:
```
array(['management', 'technician', 'entrepreneur', 'blue-collar',
       'unknown', 'retired', 'admin.', 'services', 'self-employed',
       'unemployed', 'housemaid', 'student'], dtype=object)
```

[9]:
```
df['marital'].unique()
```

[9]:
```
array(['married', 'single', 'divorced', nan], dtype=object)
```

[10]:
```
df['education'].unique()
```

[10]:
```
array(['tertiary', 'secondary', 'unknown', 'primary', nan], dtype=object)
```

[11]:
```
df['education'].value_counts()
```

[11]:
```
education
secondary    23204
tertiary     13301
primary       6851
unknown       1857
Name: count, dtype: int64
```

[12]:
```
df[df['marital'].isna()]
```

[12]:

	age	job	marital	marital_status	education	default	balance	housing	loan	contact	day	month	day_month	duration	campaign	pdays	previous	poutcome	y
44996	75	retired	NaN	NaN	secondary	no	1092	no	no	telephone	12	oct	12-Oct	250	1	431	2	failure	no
45077	20	student	NaN	NaN	secondary	no	88	no	no	telephone	21	oct	21-Oct	621	1	181	4	other	no
45209	57	blue-collar	NaN	NaN	secondary	no	668	no	no	telephone	17	nov	17-Nov	508	4	-1	0	unknown	no

[13]:
```
df[df['education'].isna()]
```

[13]:

	age	job	marital	marital_status	education	default	balance	housing	loan	contact	day	month	day_month	duration	campaign	pdays	previous	poutcome	y
44957	32	management	single	single	NaN	no	3289	no	no	cellular	8	oct	8-Oct	375	2	179	1	failure	no
45137	30	management	single	single	NaN	no	297	no	no	cellular	8	nov	8-Nov	188	1	-1	0	unknown	no
45170	19	student	single	single	NaN	no	245												

```
45170      no   no  telephone   10   nov    10-Nov        98         2    110

       previous poutcome    y
44957         2  failure   no
45137         0  unknown  yes
45170         2    other   no
```

[14]:
```
df['default'].unique()
```

[14]:
```
array(['no', 'yes'], dtype=object)
```

[15]:
```
df[df['balance']<0]
```

[15]:
```
       age           job   marital marital_status  education default  balance  \
25      44       admin.   married        married  secondary      no     -372
28      46    management    single         single  secondary      no     -246
36      25   blue-collar   married        married  secondary      no       -7
37      53    technician   married        married  secondary      no       -3
45      36       admin.    single         single    primary      no     -171
…    …           …       …              …         …      …
44626   31      services    single         single  secondary      no     -205
44629   28   blue-collar    single         single  secondary      no      -46
44836   33   blue-collar   married        married    primary      no     -195
44908   48    management  divorced       divorced   tertiary      no     -130
44964   21   blue-collar    single         single    primary      no      -42

      housing loan   contact  day month day_month  duration  campaign  pdays  \
25        yes   no   unknown    5   may     5-May       172         1     -1
28        yes   no   unknown    5   may     5-May       255         2     -1
36        yes   no   unknown    5   may     5-May       365         1     -1
37         no   no   unknown    5   may     5-May      1666         1     -1
45        yes   no   unknown    5   may     5-May       242         1     -1
…       …  …       …  …   …       …       …        …         …     …
44626      no   no  cellular    1   sep     1-Sep       481         1    579
44629     yes   no  cellular    1   sep     1-Sep       199         1     92
44836      no   no   unknown   20   sep    20-Sep         9         1     -1
44908     yes   no  cellular   29   sep    29-Sep       110         2     61
44964      no   no   unknown   10   oct    10-Oct         5         1     -1

       previous poutcome    y
25            0  unknown   no
28            0  unknown   no
36            0  unknown   no
37            0  unknown   no
45            0  unknown   no
…         …      …  …
44626         1  failure  yes
```

```
44629        14  success  yes
44836         0  unknown   no
44908         9  failure   no
44964         0  unknown   no

[3766 rows x 19 columns]
```

[16]:
```
df['balance'].sort_values()
```

[16]:
```
12909     -8019
15682     -6847
38736     -4057
7413      -3372
1896      -3313
          …
41693     71188
43393     81204
42558     81204
26227     98417
39989    102127
Name: balance, Length: 45216, dtype: int64
```

[17]:
```
df['housing'].unique()
```

[17]:
```
array(['yes', 'no'], dtype=object)
```

[18]:
```
df['loan'].unique()
```

[18]:
```
array(['no', 'yes'], dtype=object)
```

[19]:
```
df['contact'].unique()
```

[19]:
```
array(['unknown', 'cellular', 'telephone'], dtype=object)
```

[20]:
```
df['duration'].value_counts()
```

[20]:
```
duration
124     188
90      184
89      177
104     175
122     175
       …
1833      1
1545      1
1352      1
1342      1
1556      1
```

```
Name: count, Length: 1573, dtype: int64
```

[21]:
```
df[df['duration']<0]
```

[21]:
```
Empty DataFrame
Columns: [age, job, marital, marital_status, education, default, balance,
housing, loan, contact, day, month, day_month, duration, campaign, pdays,
previous, poutcome, y]
Index: []
```

[22]:
```
df['campaign'].unique()
```

[22]:
```
array([ 1,  2,  3,  5,  4,  6,  7,  8,  9, 10, 11, 12, 13, 19, 14, 24, 16,
       32, 18, 22, 15, 17, 25, 21, 43, 51, 63, 41, 26, 28, 55, 50, 38, 23,
       20, 29, 31, 37, 30, 46, 27, 58, 33, 35, 34, 36, 39, 44])
```

[23]:
```
df[df['pdays']<-1]
```

[23]:
```
Empty DataFrame
Columns: [age, job, marital, marital_status, education, default, balance,
housing, loan, contact, day, month, day_month, duration, campaign, pdays,
previous, poutcome, y]
Index: []
```

[24]:
```
df['previous'].unique()
```

[24]:
```
array([  0,   3,   1,   4,   2,  11,  16,   6,   5,  10,  12,   7,  18,
         9,  21,   8,  14,  15,  26,  37,  13,  25,  20,  27,  17,  23,
        38,  29,  24,  51, 275,  22,  19,  30,  58,  28,  32,  40,  55,
        35,  41])
```

[25]:
```
df['poutcome'].unique()
```

[25]:
```
array(['unknown', 'failure', 'other', 'success'], dtype=object)
```

[26]:
```
df['y'].unique()
```

[26]:
```
array(['no', 'yes'], dtype=object)
```

2 Data Cleaning

[27]:
```
df1 = df.copy()
```

[28]:
```
#Dropping the marital_status, day, month column
df1 = df1.drop(columns=['marital_status','day','month'])
df1.head()
```

[28]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact day_month  duration  campaign  pdays  previous poutcome   y
0  unknown      5-May       261         1     -1         0  unknown  no
1  unknown      5-May       151         1     -1         0  unknown  no
2  unknown      5-May        76         1     -1         0  unknown  no
3  unknown      5-May        92         1     -1         0  unknown  no
4  unknown      5-May       198         1     -1         0  unknown  no
```

[29]:
```
#Rename day_month to date
df1 = df1.rename(columns={'day_month':'date'})
df1.head()
```

[29]:
```
   age           job  marital  education default  balance housing loan  \
0   58    management  married   tertiary      no     2143     yes   no
1   44    technician   single  secondary      no       29     yes   no
2   33  entrepreneur  married  secondary      no        2     yes  yes
3   47   blue-collar  married    unknown      no     1506     yes   no
4   33       unknown   single    unknown      no        1      no   no

   contact   date  duration  campaign  pdays  previous poutcome   y
0  unknown  5-May       261         1     -1         0  unknown  no
1  unknown  5-May       151         1     -1         0  unknown  no
2  unknown  5-May        76         1     -1         0  unknown  no
3  unknown  5-May        92         1     -1         0  unknown  no
4  unknown  5-May       198         1     -1         0  unknown  no
```

[30]:
```
#Dropping duplicate entries
df1 = df1.drop_duplicates()
df1.shape
```

[30]:
```
(45211, 16)
```

[31]:
```
#Replacing nan values of education with unknown
df1['education'] = df1['education'].fillna("unknown")
df1['education'].unique()
```

[31]:
```
array(['tertiary', 'secondary', 'unknown', 'primary'], dtype=object)
```

[32]:
```
#Appending year to the date column
df1.loc[:27728,'date'] = df1.loc[:27728,'date'] + "-2008"
df1.loc[27729:42590,'date'] = df1.loc[27729:42590,'date'] + "-2009"
df1.loc[42591:,'date'] = df1.loc[42591:,'date'] + "-2010"
```

[33]:
```
#Correcting the data types
df1['marital'] = df1['marital'].astype('category')
df1['job'] = df1['job'].astype('category')
df1['education'] = df1['education'].astype('category')
df1['default'] = df1['default'].astype('category')
df1['housing'] = df1['housing'].astype('category')
df1['loan'] = df1['loan'].astype('category')
df1['contact'] = df1['contact'].astype('category')
df1['date'] = pd.to_datetime(df1['date'],format="%d-%b-%Y")
df1['poutcome'] = df1['poutcome'].astype('category')
df1['y'] = df1['y'].astype('category')
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 45211 entries, 0 to 45210
Data columns (total 16 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   age        45211 non-null  int64
 1   job        45211 non-null  category
 2   marital    45208 non-null  category
 3   education  45211 non-null  category
 4   default    45211 non-null  category
 5   balance    45211 non-null  int64
 6   housing    45211 non-null  category
 7   loan       45211 non-null  category
 8   contact    45211 non-null  category
 9   date       45211 non-null  datetime64[ns]
 10  duration   45211 non-null  int64
 11  campaign   45211 non-null  int64
 12  pdays      45211 non-null  int64
 13  previous   45211 non-null  int64
 14  poutcome   45211 non-null  category
 15  y          45211 non-null  category
dtypes: category(9), datetime64[ns](1), int64(6)
memory usage: 4.2 MB
```

[34]:
```
df1.sample(5)
```

[34]:

	age	job	marital	education	default	balance	housing	loan	contact	date	duration	campaign	pdays	previous	poutcome	y
39925	28	technician	single	tertiary	no	4987	no	no	cellular	2009-06-02	924	2	113	21	success	yes
12543	53	services	divorced	secondary	yes	0	no	yes								
28190	32	services	single	secondary	no	486	no	no								
22086	36	management	single	tertiary	no	1246	no	no								
22861	54	management	divorced	tertiary	no	3777	no	no								

12543	unknown	2008-07-03	172	10	-1	0	unknown	no
28190	cellular	2009-01-29	1181	1	-1	0	unknown	yes
22086	cellular	2008-08-21	63	2	-1	0	unknown	no
22861	cellular	2008-08-25	56	2	-1	0	unknown	no

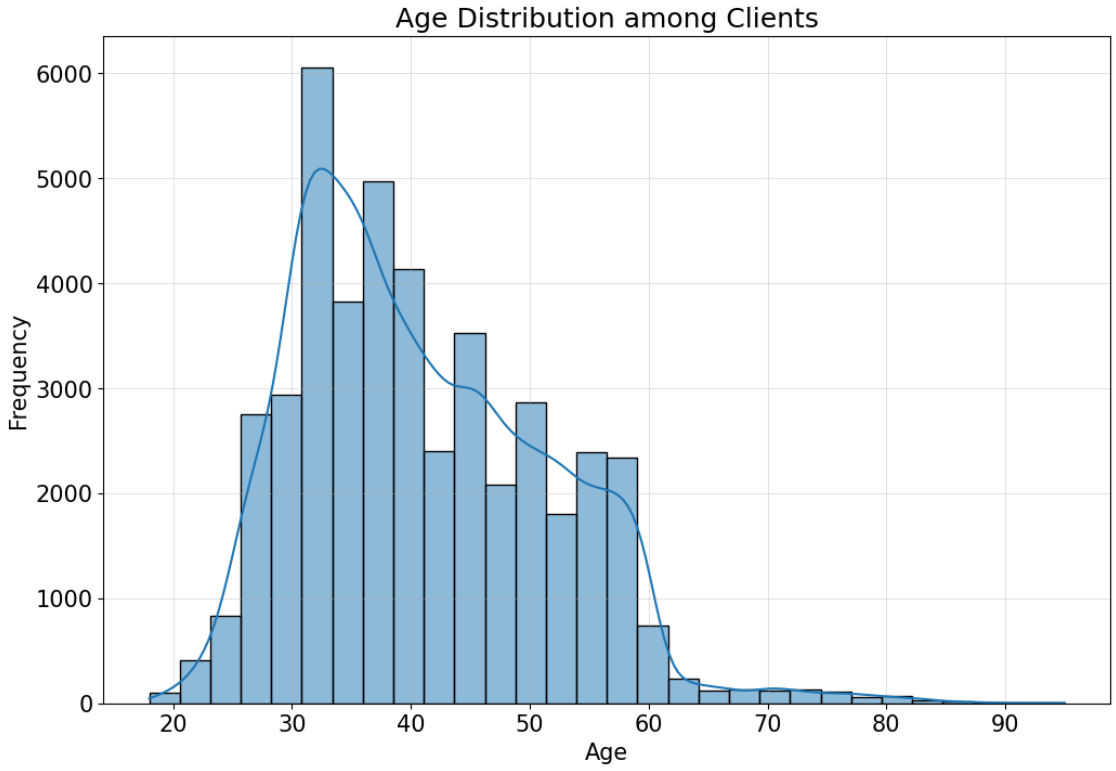
3 Exploratory Data Analysis

3.1 What is the distribution of age among the clients?

Conclusion:

- Minimum age is 18 yrs and maximum age is 95 yrs
- A significant number of clients are in their late 30s to early 40s
- Mean age is approximately 41 yrs
- Median age is 39 yrs

[35]:
```
plt.figure(figsize=(12,8))
sns.histplot(df1['age'],bins=30,kde=True)
plt.title('Age Distribution among Clients')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.grid(True,linewidth=0.5, alpha=0.5)
plt.show()
```



[36]:
```
df1['age'].describe()
```

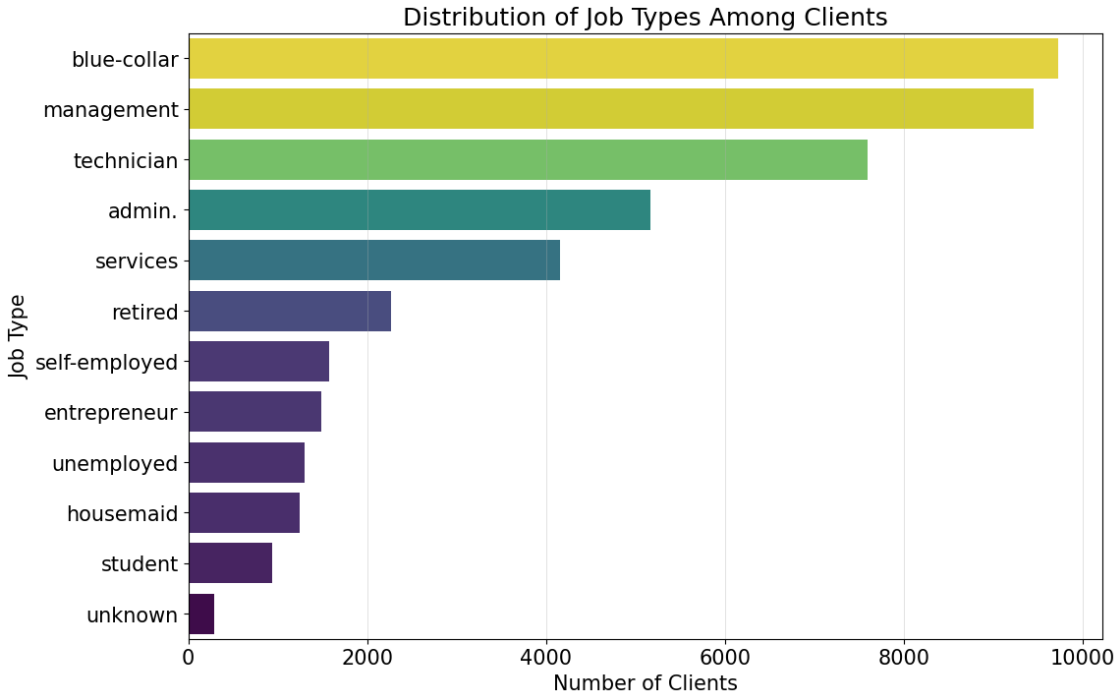
[36]:
```
count    45211.000000
mean        40.936210
std         10.618762
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64
```

3.2 How does the job type vary among the clients?

Conclusion:

- blue-collar workers, management, and technicians are the top three job categories among clients
- Students represent the smallest client group

[37]:
```
job_df = df1['job'].value_counts().reset_index().sort_values(by='count',␣
 ↪ascending=False)
plt.figure(figsize=(12, 8))
sns.barplot(x='count', y='job',data=job_df,hue='count',legend=False,␣
 ↪palette="viridis",order=job_df['job'])
plt.title('Distribution of Job Types Among Clients')
plt.xlabel('Number of Clients')
plt.ylabel('Job Type')
plt.grid(axis='x',linewidth=0.5, alpha=0.5)
plt.show()
```

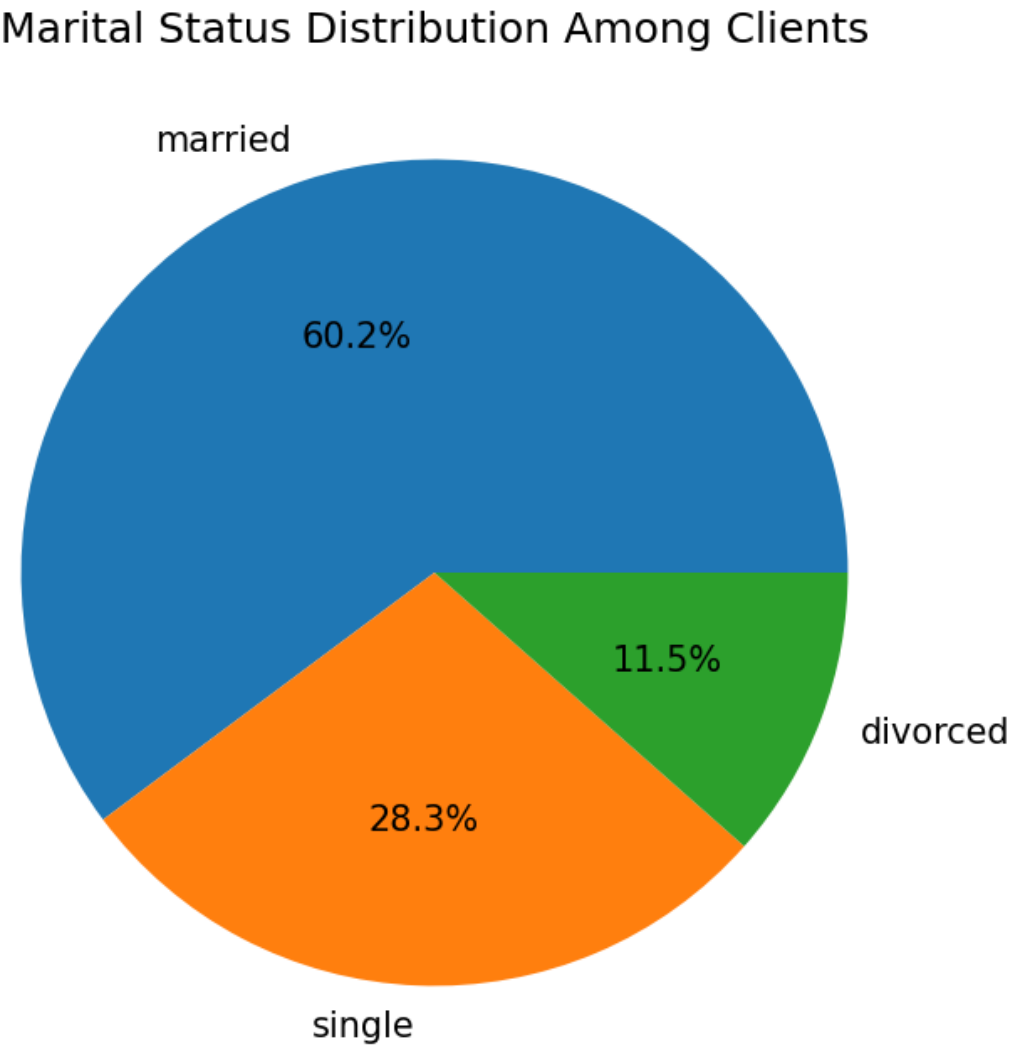


3.3 What is the marital status distribution of the clients?

Conclusion:

- Around 60% clients are married, 10% are divorced, 30% are single

[38]:
```
marital_df = df1['marital'].value_counts().reset_index().
  ↪sort_values(by='count', ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(marital_df['count'],labels=marital_df['marital'], autopct='%0.1f%%')
plt.title('Marital Status Distribution Among Clients')
plt.show()
```



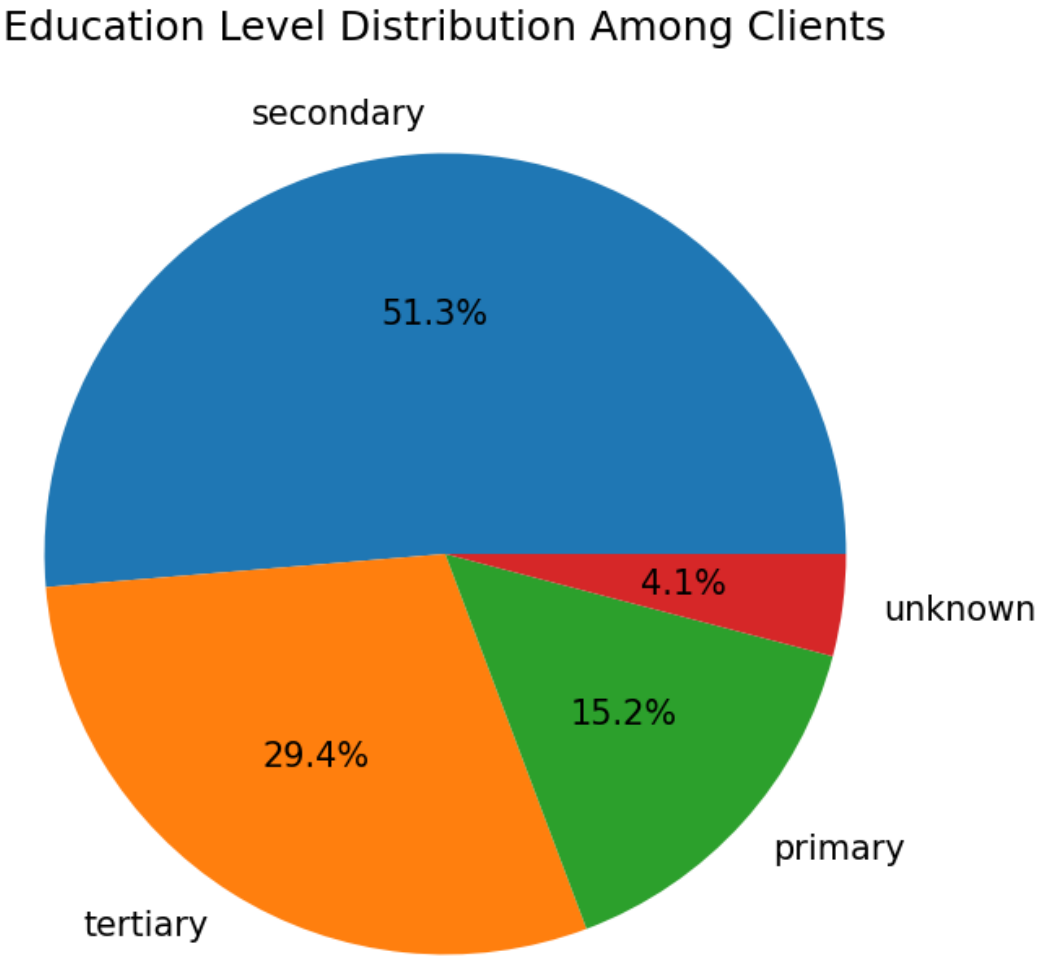
3.4 What is the level of education among the clients?

Conclusion:

- More than 50% clients have completed secondary education
- Approx. 30% clients have completed tertiary education and 15% have completed primary education
- Education level of a few clients is unknown

[39]:
```
edu_df = df1['education'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(edu_df['count'],labels=edu_df['education'], autopct='%0.1f%%')
```

```
plt.title("Education Level Distribution Among Clients")
plt.show()
```



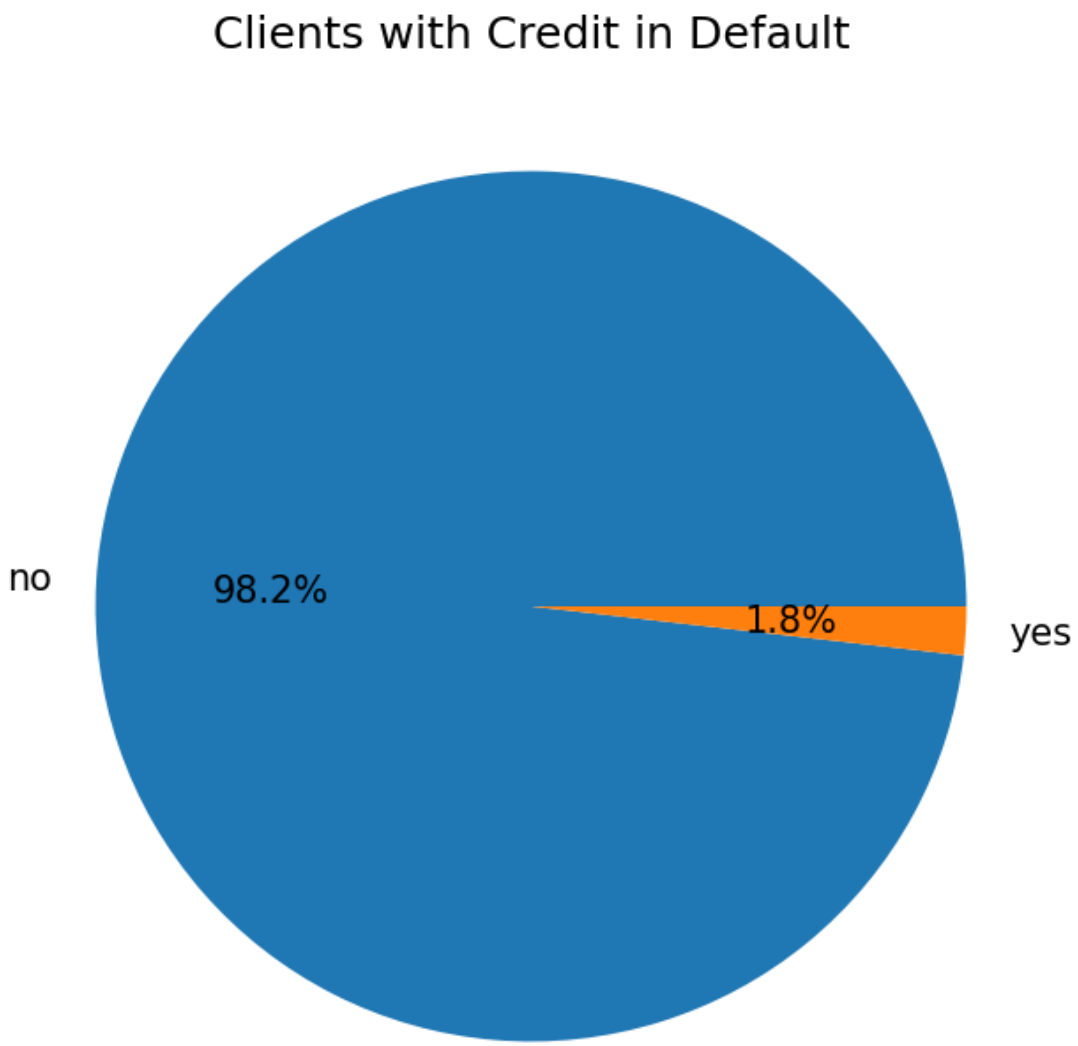
3.5 What proportion of clients have credit in default?

Conclusion:

- Approximately 98.2% of clients do not have credit in default, while about 1.8% of clients do have credit in default

[40]:
```
def_df = df1['default'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(def_df['count'],labels=def_df['default'], autopct='%0.1f%%')
plt.title("Clients with Credit in Default")
```

```
plt.show()
```



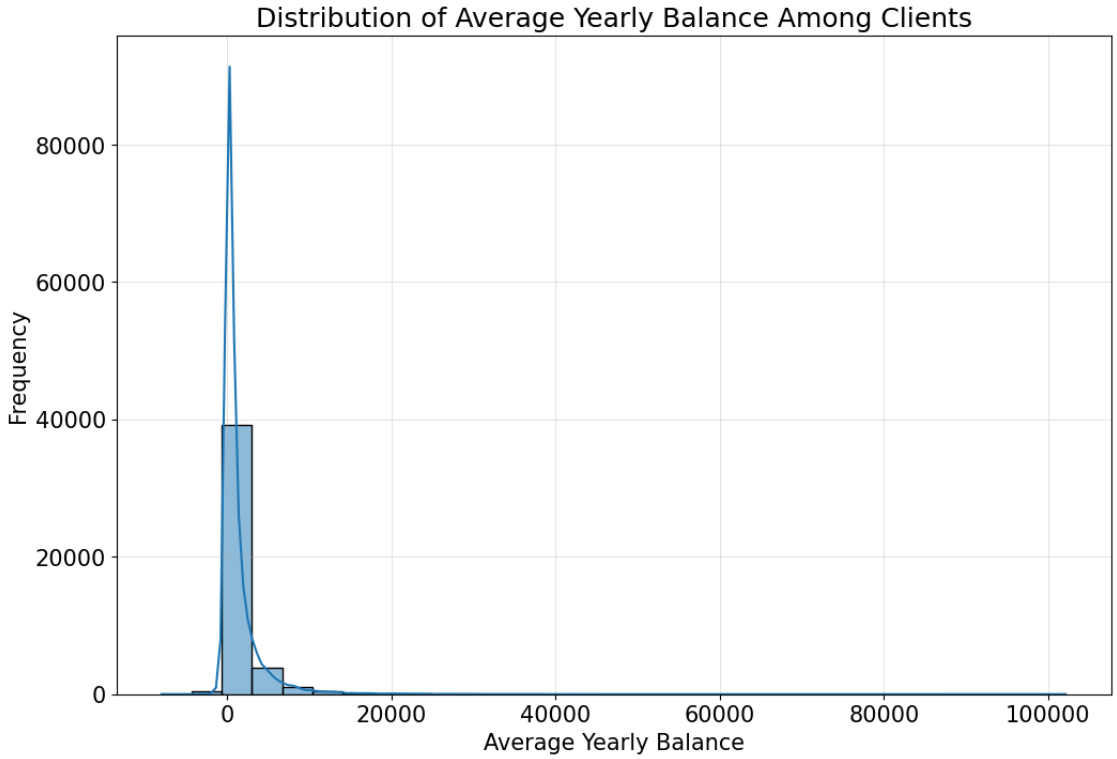
3.6 What is the distribution of average yearly balance among the clients?

Conclusion:

- Mean Average Balance: Approximately €1,362
- Median Average Balance: Approximately €448.5
- Minimum Balance: -€8,019, suggesting some clients have an overdrawn account
- Maximum Balance: €1,02,127, showing that some clients have very high balances

- The distribution of balances is highly positively skewed, with a majority of clients having relatively low balances, and a small number of clients having very high balances

[41]:
```
plt.figure(figsize=(12,8))
sns.histplot(df1['balance'],bins=30,kde=True)
plt.title('Distribution of Average Yearly Balance Among Clients')
plt.xlabel('Average Yearly Balance')
plt.ylabel('Frequency')
plt.grid(True,linewidth=0.5, alpha=0.5)
plt.show()
```



[42]:
```
df['balance'].describe()
```

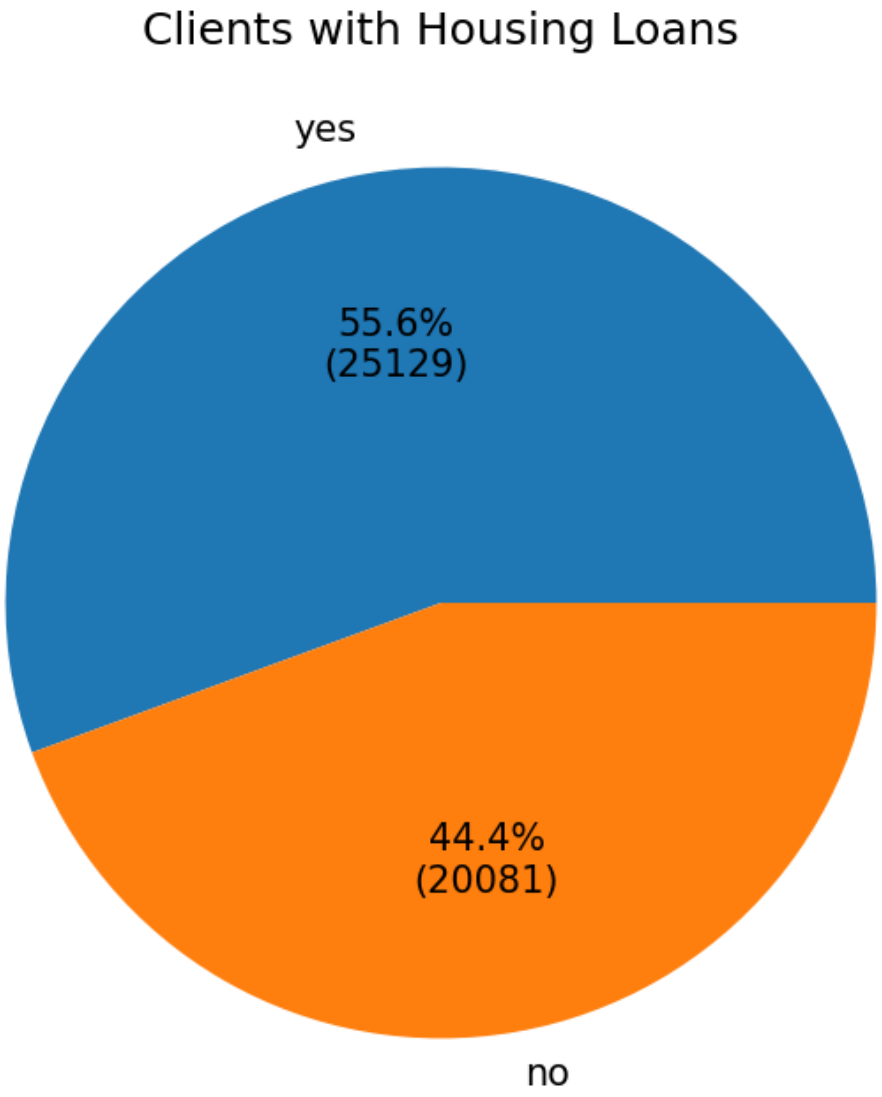
[42]:
```
count     45216.000000
mean       1362.277844
std        3044.609674
min       -8019.000000
25%          72.000000
50%         448.500000
75%        1428.000000
max      102127.000000
Name: balance, dtype: float64
```

3.7 How many clients have housing loans?

Conclusion:

- 25129 clients have housing loans(55.6%)
- 20081 clients do not have housing loans(44.4%)

[43]:
```
house_df = df1['housing'].value_counts().reset_index().sort_values(by='count',␣
 ↪ascending=False)
#Function to display values in pie chart
def func(pct, allvals):
    absolute = int(pct/100.*np.sum(allvals))
    return "{:.1f}%\n({:d})".format(pct, absolute)
plt.figure(figsize=(12, 8))
plt.pie(house_df['count'],labels=house_df['housing'], autopct=lambda pct:␣
 ↪func(pct, house_df['count']))
plt.title('Clients with Housing Loans')
plt.show()
```



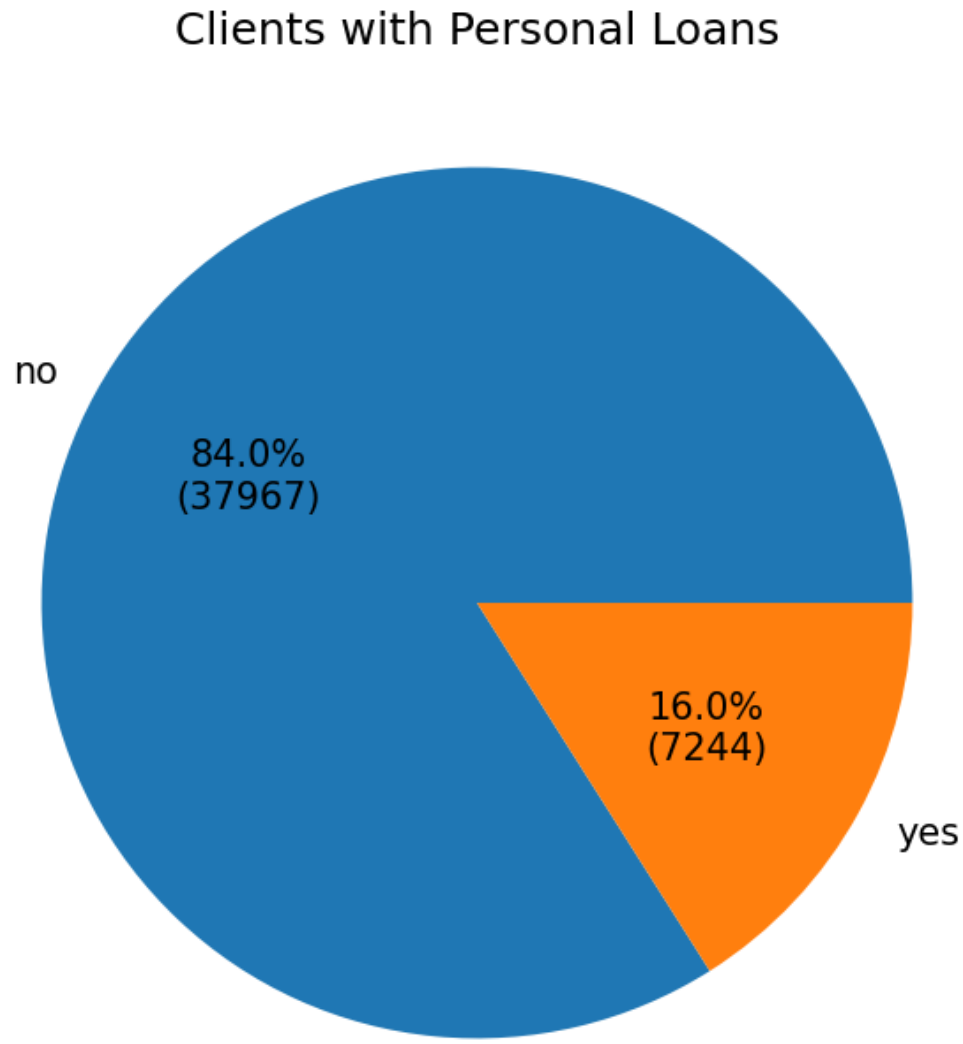
3.8 How many clients have personal loans?

Conclusion:

- 7244 clients have personal loans(16%)
- 37967 clients do not have personal loans(84%)

[44]:
```
personal_df = df1['loan'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(personal_df['count'],labels=personal_df['loan'], autopct=lambda pct:␣
↪func(pct, house_df['count']))
```

```
plt.title('Clients with Personal Loans')
plt.show()
```

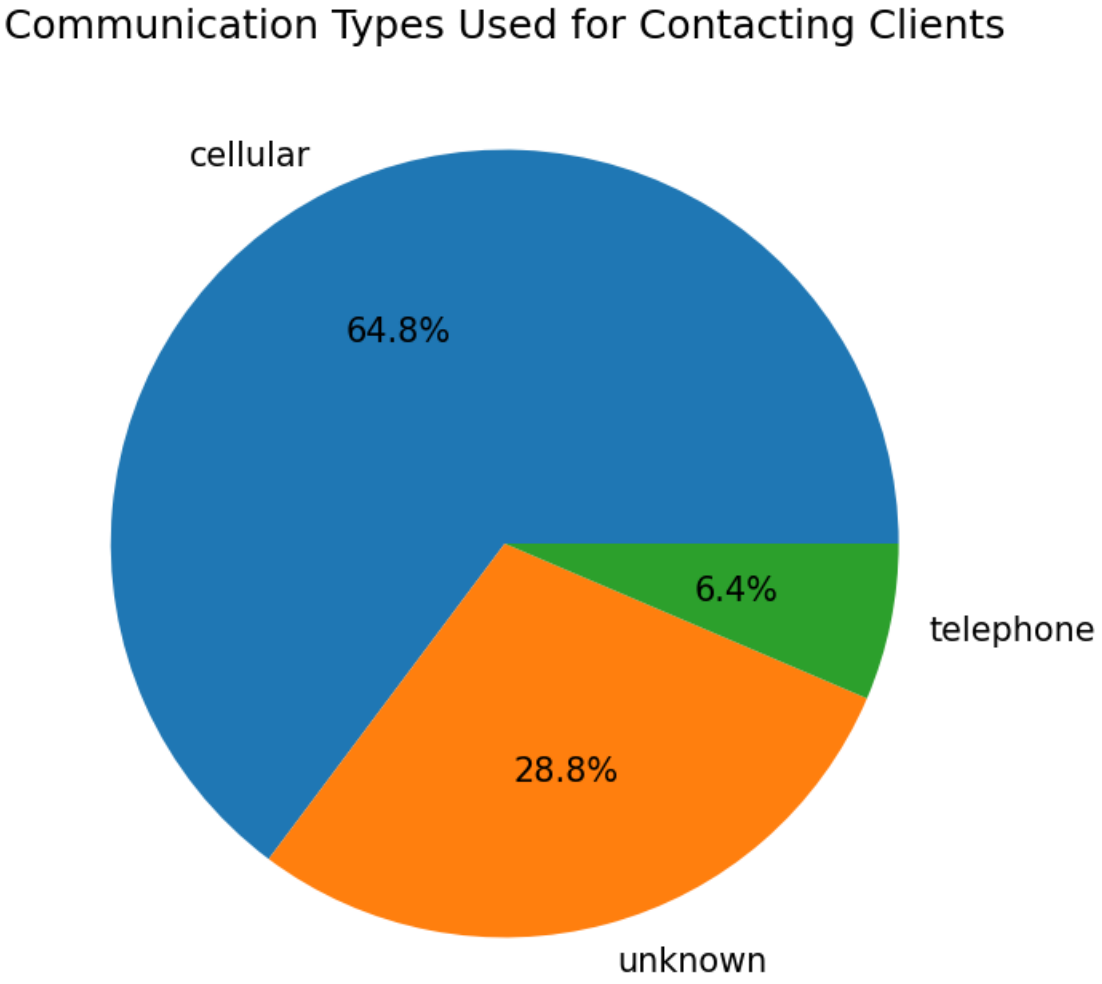


3.9 What are the communication types used for contacting clients during the campaign?

`Conclusion:`

- Cellular phones were the most frequently used communication method, followed by instances where the communication type was not specified ('unknown'), and telephone calls were the least used method

[45]:
```
comm_df = df1['contact'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(comm_df['count'],labels=comm_df['contact'], autopct='%1.1f%%')
plt.title('Communication Types Used for Contacting Clients')
plt.show()
```

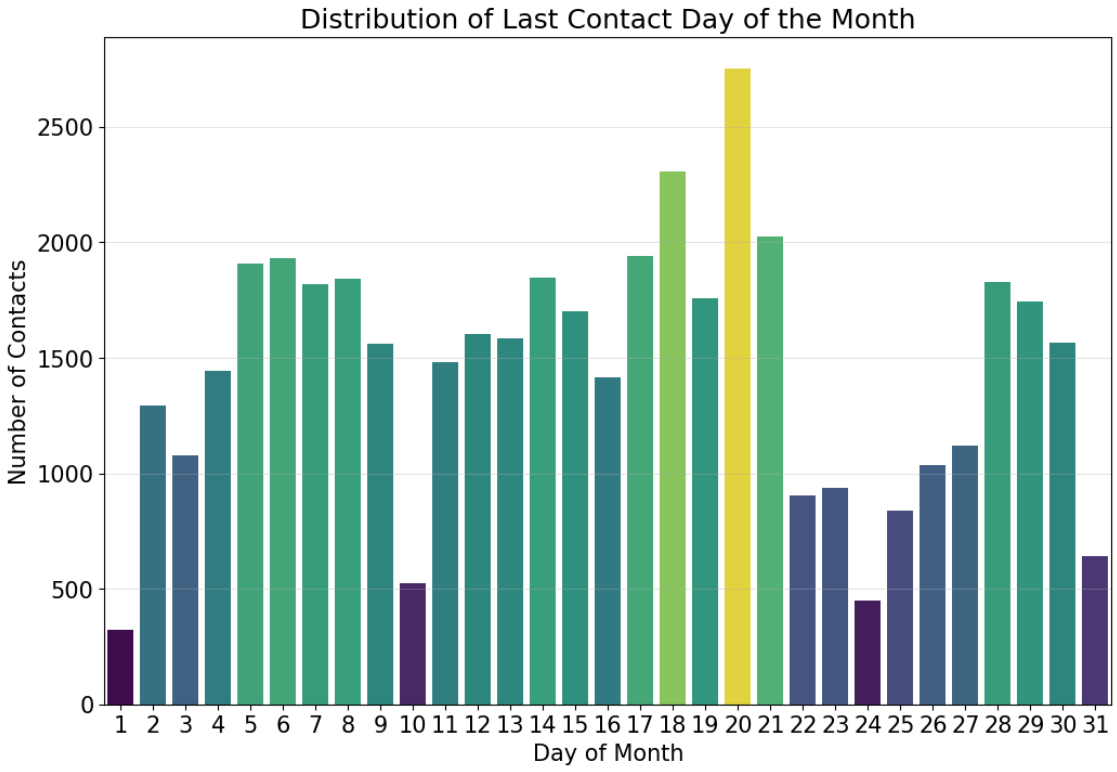


3.10 What is the distribution of the last contact day of the month?

Conclusion:

- The 20th of the month stands out as having the highest number of contacts, followed by the 18th and the 21st
- Month start and end have relatively lower number of contacts

[46]:
```
date_df = df1['date'].apply(lambda x : x.day).value_counts().reset_index()
plt.figure(figsize=(12, 8))
sns.barplot(x='date', y='count',data=date_df,hue='count',palette=sns.
 ↪color_palette("viridis", as_cmap=True),legend=False)
plt.title('Distribution of Last Contact Day of the Month')
plt.xlabel('Day of Month')
plt.ylabel('Number of Contacts')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



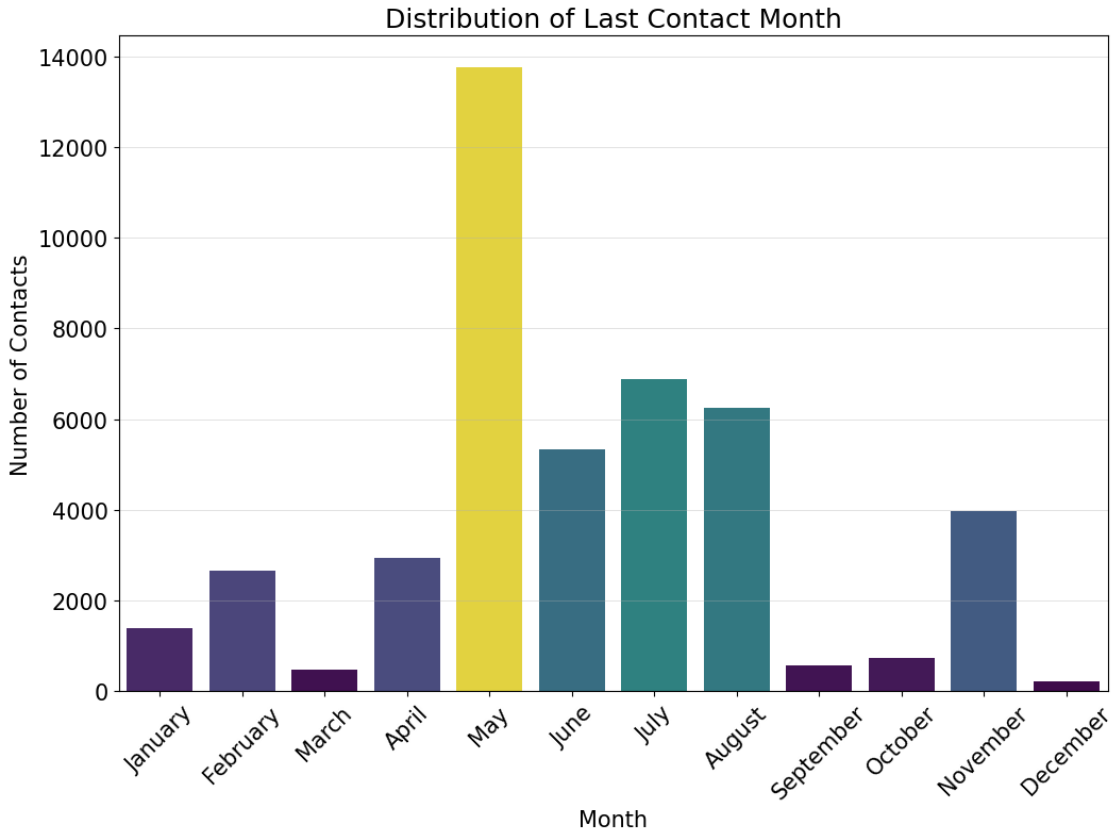
3.11 How does the last contact month vary among the clients?

Conclusion:

- May was the month with the highest number of client contacts during the campaign, followed by July and August
- Least number of client contacts during the campaign were in December

[47]:
```
date_df = df1['date'].dt.month_name().value_counts()
order =␣
 ↪['January','February','March','April','May','June','July','August','September','October','N
date_df = date_df.reindex(order,axis=0).reset_index()
```

```
plt.figure(figsize=(12, 8))
sns.barplot(x='date',␣
 ↪y='count',data=date_df,hue='count',legend=False,palette=sns.
 ↪color_palette("viridis", as_cmap=True))
plt.title('Distribution of Last Contact Month')
plt.xlabel('Month')
plt.ylabel('Number of Contacts')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.xticks(rotation=45)
plt.show()
```

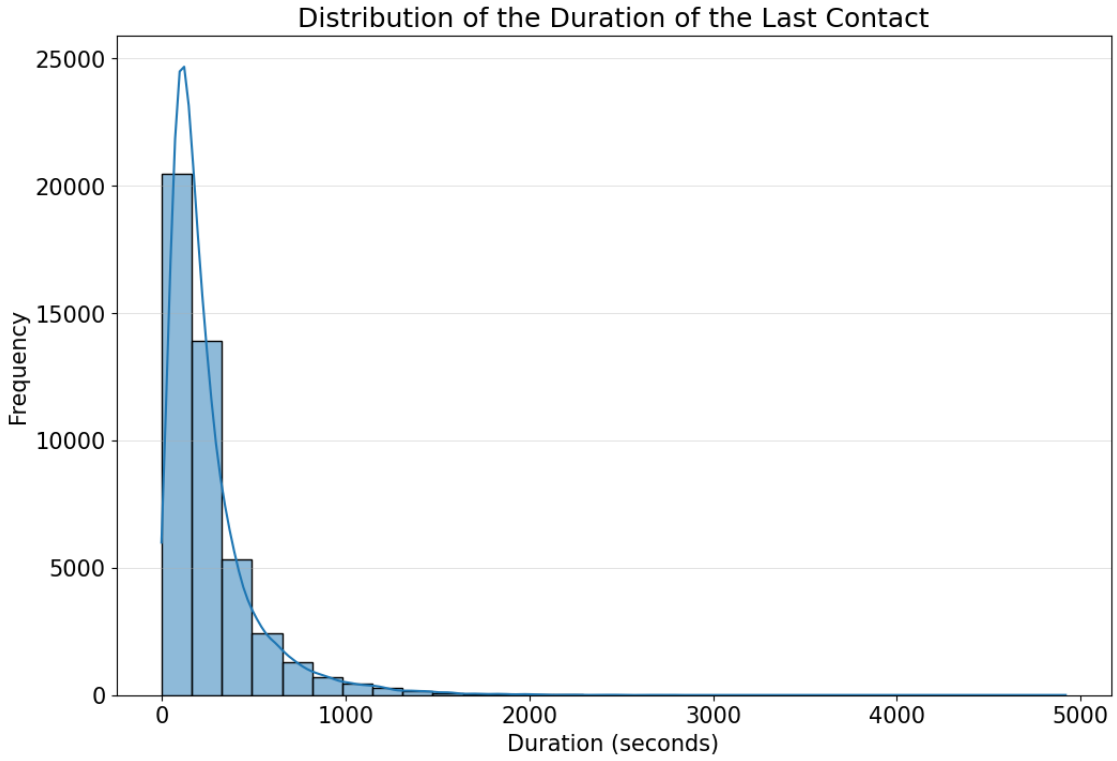


3.12 What is the distribution of the duration of the last contact?

Conclusion:

- Mean duration of last contact is approximately 258 seconds
- Median duration of last contact is 180 seconds
- Minimum duration is 0 seconds while maximum duration is 4918 seconds
- The distribution of last contact duration is highly positively skewed, with a majority of clients having relatively low duration, and a small number of clients having very high duration

[48]:
```
plt.figure(figsize=(12, 8))
sns.histplot(df1['duration'], bins=30, kde=True)
plt.title('Distribution of the Duration of the Last Contact')
plt.xlabel('Duration (seconds)')
plt.ylabel('Frequency')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



[49]:
```
df1['duration'].describe()
```

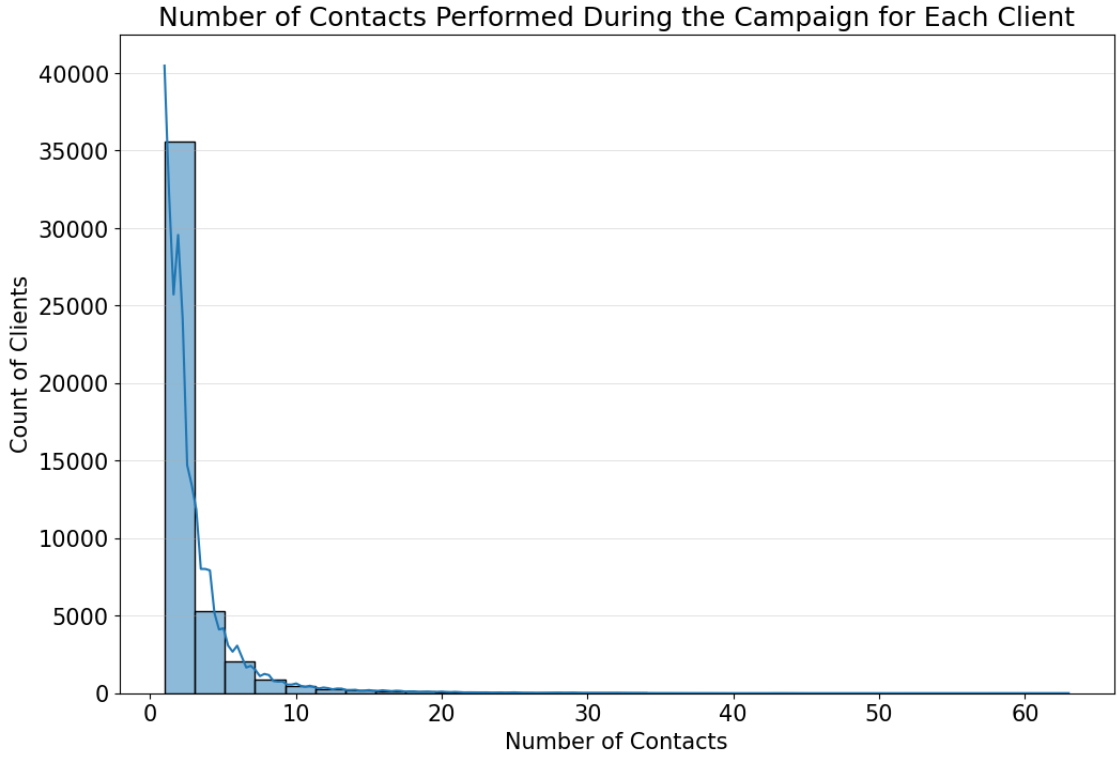
[49]:
```
count    45211.000000
mean       258.163080
std        257.527812
min          0.000000
25%        103.000000
50%        180.000000
75%        319.000000
max       4918.000000
Name: duration, dtype: float64
```

3.13 How many contacts were performed during the campaign for each client?

Conclusion:

- Mean contacts performed for a client is approximately 2.8
- Median contacts performed for a client is 2
- Minimum contacts is 1 while maximum contacts are 63
- The distribution of contacts performed is highly positively skewed, with a majority of clients having relatively low contacts, and a small number of clients having very high contacts

[50]:
```
plt.figure(figsize=(12, 8))
sns.histplot(df1['campaign'], bins=30, kde=True)
plt.title('Number of Contacts Performed During the Campaign for Each Client')
plt.xlabel('Number of Contacts')
plt.ylabel('Count of Clients')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



[51]:
```
df1['campaign'].describe()
```

[51]:
```
count    45211.000000
mean         2.763841
std          3.098021
min          1.000000
25%          1.000000
```

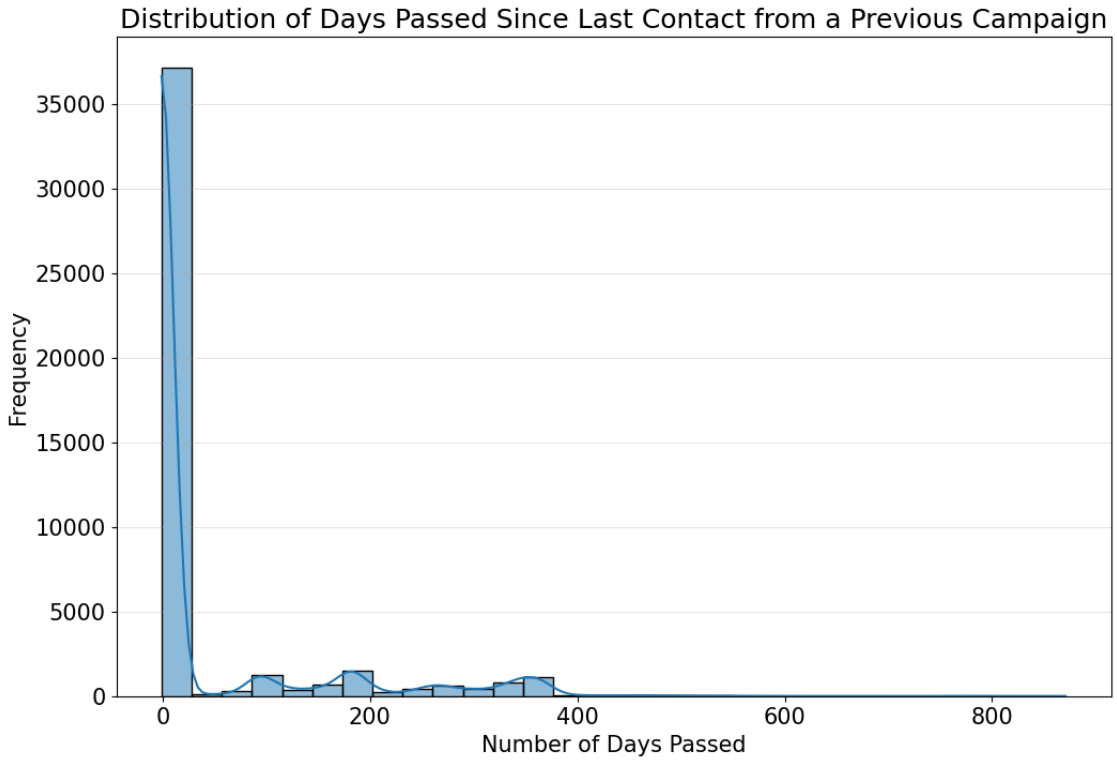
```
50%          2.000000
75%          3.000000
max         63.000000
Name: campaign, dtype: float64
```

3.14 What is the distribution of the number of days passed since the client was last contacted from a previous campaign?

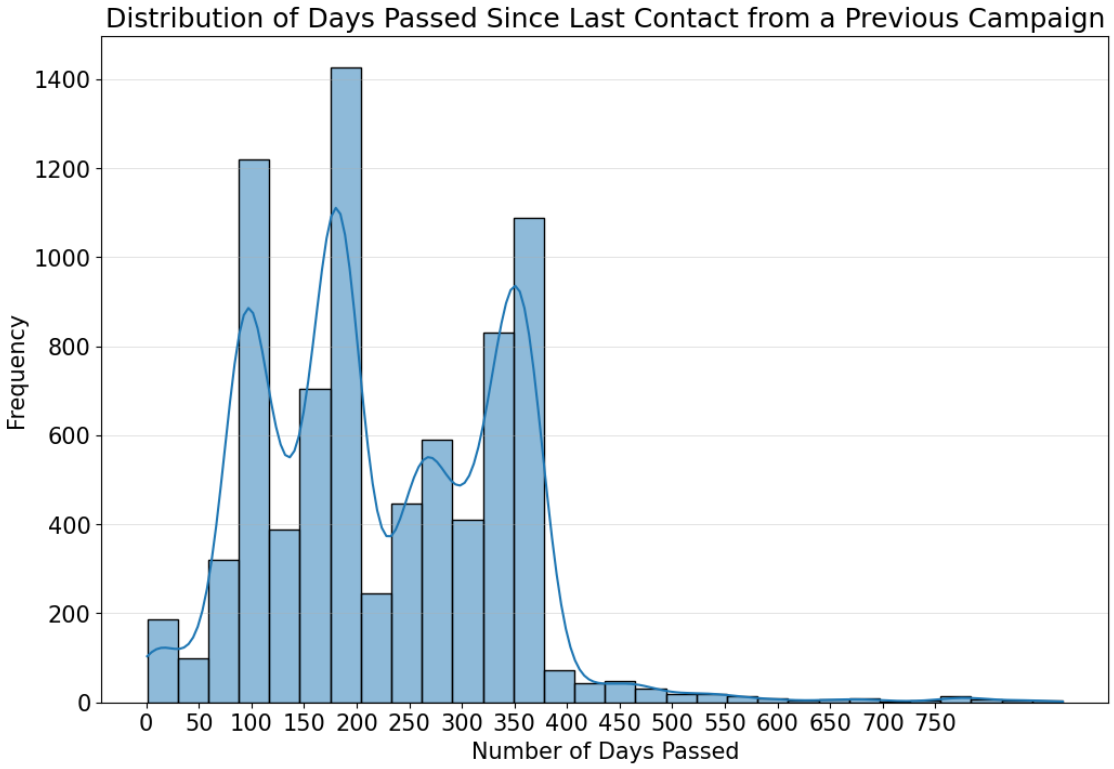
Conclusion:

- There is an extremely high peak at -1, which implies that the majority of clients had not been contacted before the current campaign
- Mean days passed since last contact are approximately 40
- Median days passed since last contact are -1
- Minimum days passed since last contact are -1 while maximum days passed are 871
- Peaks occur roughly every 50 to 100 days, indicating systematic follow-up intervals in the campaign strategy

[52]:
```
plt.figure(figsize=(12, 8))
sns.histplot(df1['pdays'], bins=30, kde=True)
plt.title('Distribution of Days Passed Since Last Contact from a Previous␣
 ↪Campaign')
plt.xlabel('Number of Days Passed')
plt.ylabel('Frequency')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



[53]:
```
plt.figure(figsize=(12, 8))
sns.histplot(df1[df1['pdays']!=-1]['pdays'], bins=30, kde=True)
plt.title('Distribution of Days Passed Since Last Contact from a Previous␣
 ↪Campaign')
plt.xlabel('Number of Days Passed')
plt.ylabel('Frequency')
plt.xticks(np.arange(0,800,50))
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



[54]:
```
df1['pdays'].describe()
```

[54]:
```
count    45211.000000
mean        40.197828
std        100.128746
min         -1.000000
25%         -1.000000
50%         -1.000000
75%         -1.000000
max        871.000000
Name: pdays, dtype: float64
```

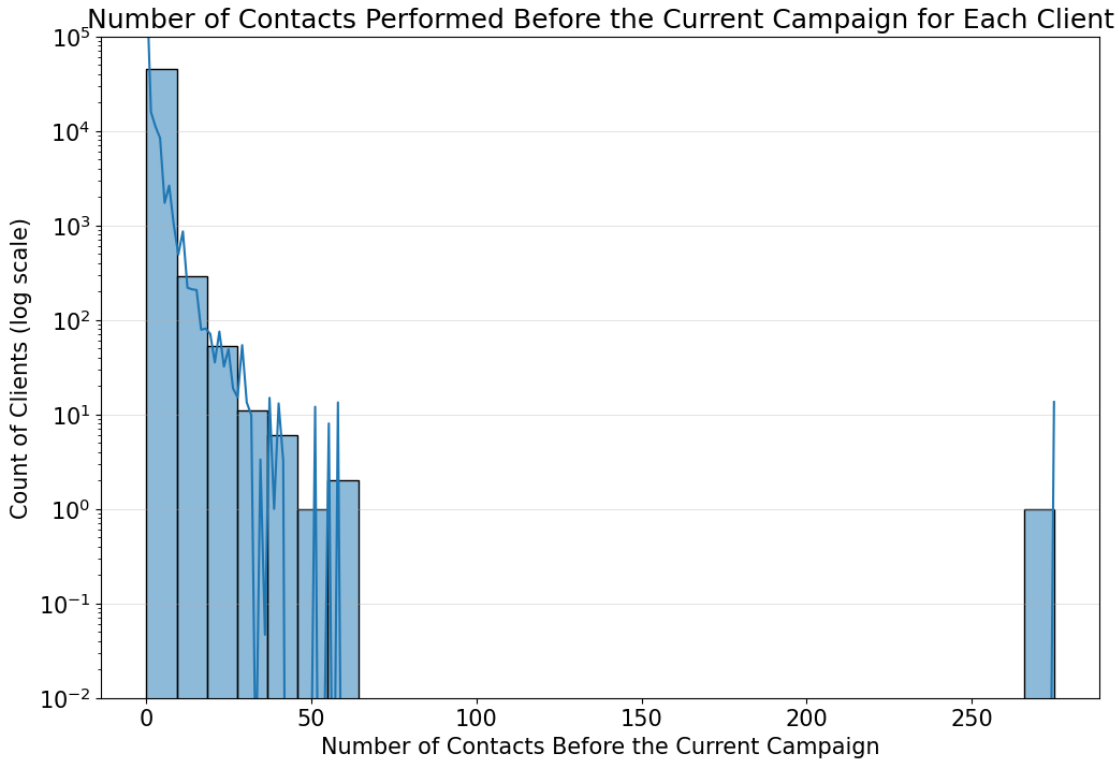
3.15 How many contacts were performed before the current campaign for each client?

Conclusion:

- A dominant peak at zero, signifying that a significant portion of clients had no prior contact before the current campaign
- Mean contacts performed before the current campaign are approximately 0.58
- Median contacts performed before the current campaign are 0

- Minimum contacts performed before the current campaign are 0 while maximum contacts performed are 275 for a client

[55]:
```
plt.figure(figsize=(12, 8))
sns.histplot(df1['previous'], bins=30, kde=True)
plt.title('Number of Contacts Performed Before the Current Campaign for Each␣
 ↪Client')
plt.xlabel('Number of Contacts Before the Current Campaign')
plt.ylabel('Count of Clients (log scale)')
plt.yscale('log')
plt.ylim(bottom=0.01,top=1e5)
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



[56]:
```
df1['previous'].describe()
```

[56]:
```
count    45211.000000
mean         0.580323
std          2.303441
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
```

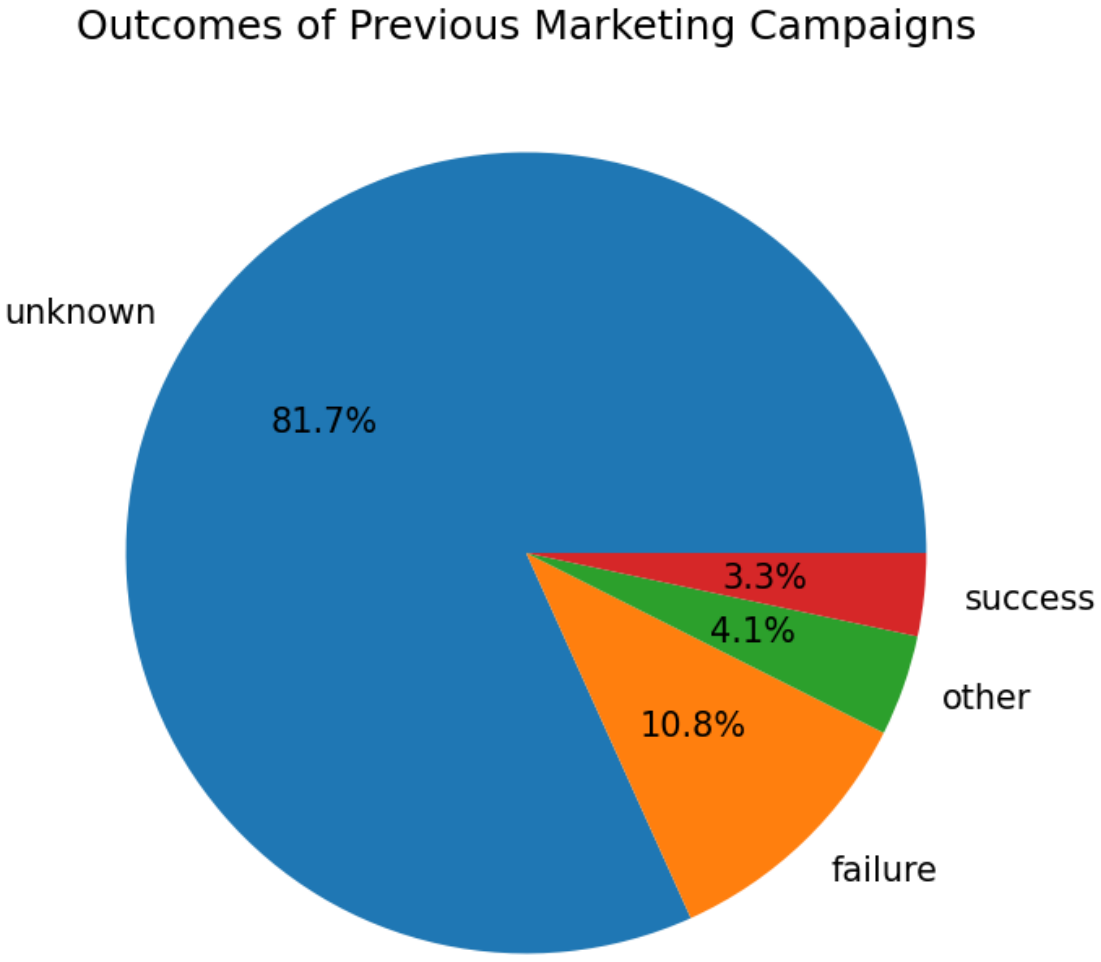
```
max         275.000000
Name: previous, dtype: float64
```

3.16 What were the outcomes of the previous marketing campaigns?

Conclusion:

- Majority of outcomes from previous marketing campaigns are unknown, making up 81.7% of the cases
- Failures constitute 10.8%, successes are 3.3%, and other outcomes account for 4.1%

[57]:
```
pout_df = df1['poutcome'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(pout_df['count'],labels=pout_df['poutcome'], autopct='%1.1f%%')
plt.title('Outcomes of Previous Marketing Campaigns')
plt.show()
```

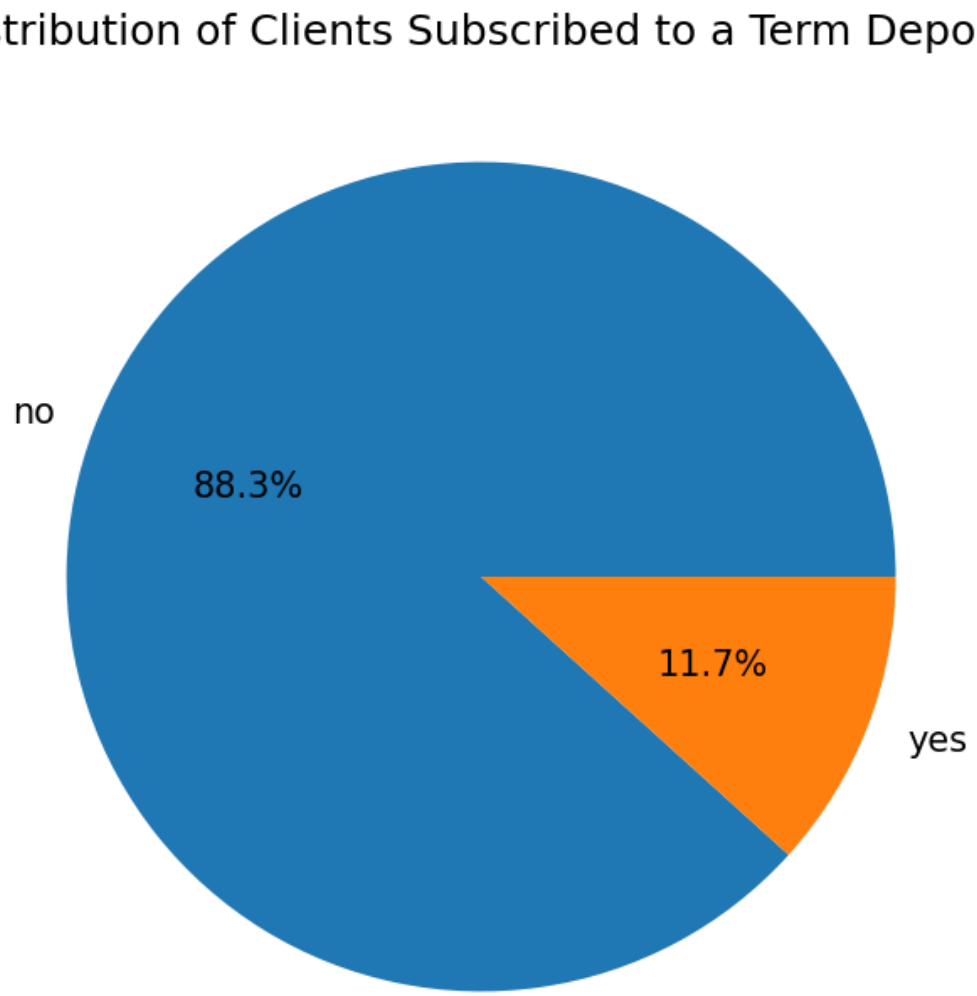


3.17 What is the distribution of clients who subscribed to a term deposit vs. those who did not?

Conclusion:

- 88.3% of clients did not subscribe to a term deposit, while 11.7% did

[58]:
```
y_df = df1['y'].value_counts().reset_index().sort_values(by='count',␣
↪ascending=False)
plt.figure(figsize=(12, 8))
plt.pie(y_df['count'],labels=y_df['y'], autopct='%1.1f%%')
plt.title('Distribution of Clients Subscribed to a Term Deposit')
plt.show()
```



3.18 Are there any correlations between different attributes and the likelihood of subscribing to a term deposit?

Overall Conclusion (in short):

- Subscriptions spike in those under 30 and over 60, but dip progressively from the 30s to the 60s.
- Students and retirees top term deposit subscriptions, while blue-collar workers and entrepreneurs lag behind.
- Singles lead in term deposit subscriptions, followed by divorced clients, with married clients trailing at the bottom.
- Individuals with higher levels of education, particularly those with tertiary education, show a higher tendency to subscribe to term deposits, as opposed to those with primary education.
- Clients without a credit default have a higher likelihood of subscribing to a term deposit compared to those who have defaulted.
- Clients with higher average account balances are more likely to subscribe to a term deposit.
- Clients without a housing loan have a higher likelihood of subscribing to a term deposit compared to those who have one.
- Clients without a personal loan have a higher likelihood of subscribing to a term deposit compared to those who have one.
- Clients contacted thorough cellular phone may have a higher chance of subscribing to term deposit.
- Clients contacted in March may prefer to subscribe to term deposits, maybe due to start of a new financial year in April (in case of India).
- Longer calls may be associated with a higher likelihood of achieving a positive outcome i.e. subscription to a term deposit.

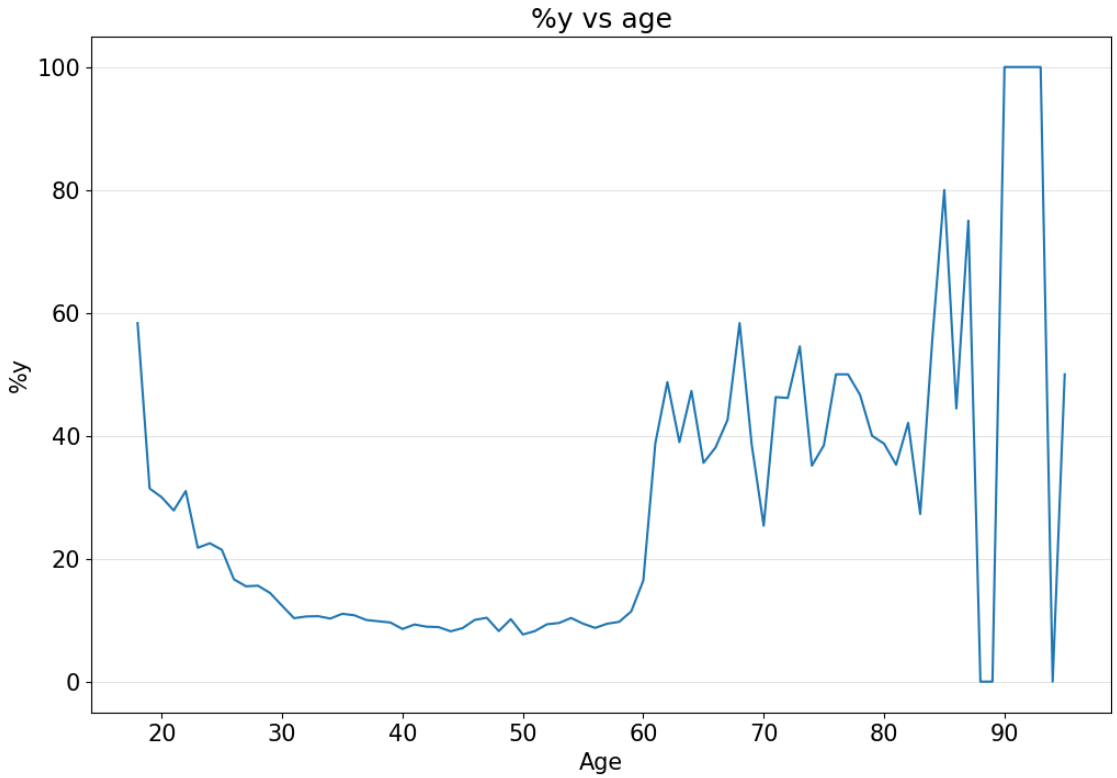
3.18.1 y vs age

Conclusion:

- There is a noticeable increase in subscriptions among the younger (<30 years) and older (>60 years) age groups
- A decline in subscription rates as age increases from the 30s to the 60s

[59]:
```
temp_df = df1[['age','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
 ↪astype(float)
temp_df = temp_df.groupby('age').mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
```

```
sns.lineplot(temp_df,x='age',y='y')
plt.title('%y vs age')
plt.xlabel('Age')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



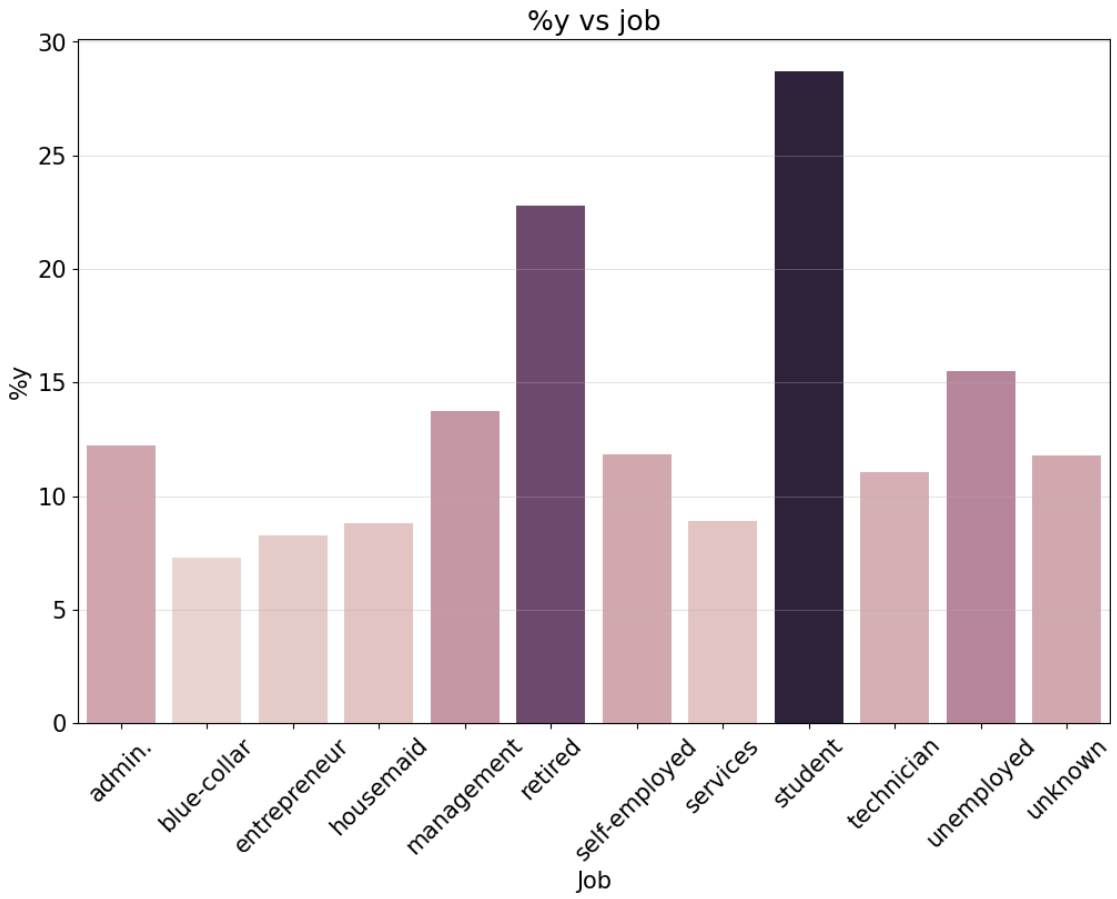
3.18.2 y vs job

Conclusion:

- Students and retired clients have the highest subscription rates to term deposits
- Blue-collar and entrepreneur job categories show lower subscription rates

[60]:
```
temp_df = df1[['job','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
↪astype(float)
temp_df = temp_df.groupby('job',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='job',y='y',hue='y',legend=False)
plt.title('%y vs job')
```

```
plt.xlabel('Job')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.xticks(rotation=45)
plt.show()
```



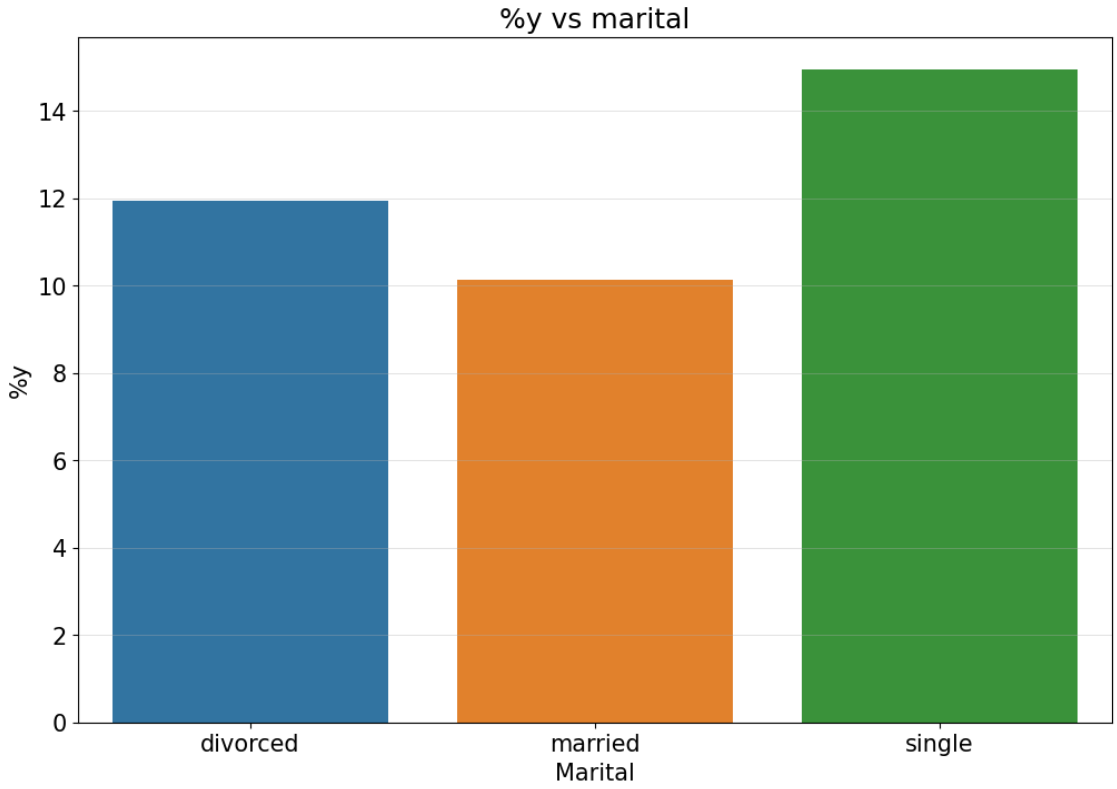
3.18.3 y vs marital

Conclusion:

- Singles have the highest likelihood of subscribing to a term deposit
- Divorced clients have a slightly lower likelihood than singles, but higher than married client
- Married clients have the lowest subscription rate to term deposits among the three categories

[61]:
```
temp_df = df1[['marital','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
↪astype(float)
temp_df = temp_df.groupby('marital',observed=True).mean().reset_index()
```

```
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='marital',y='y',hue="marital")
plt.title('%y vs marital')
plt.xlabel('Marital')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



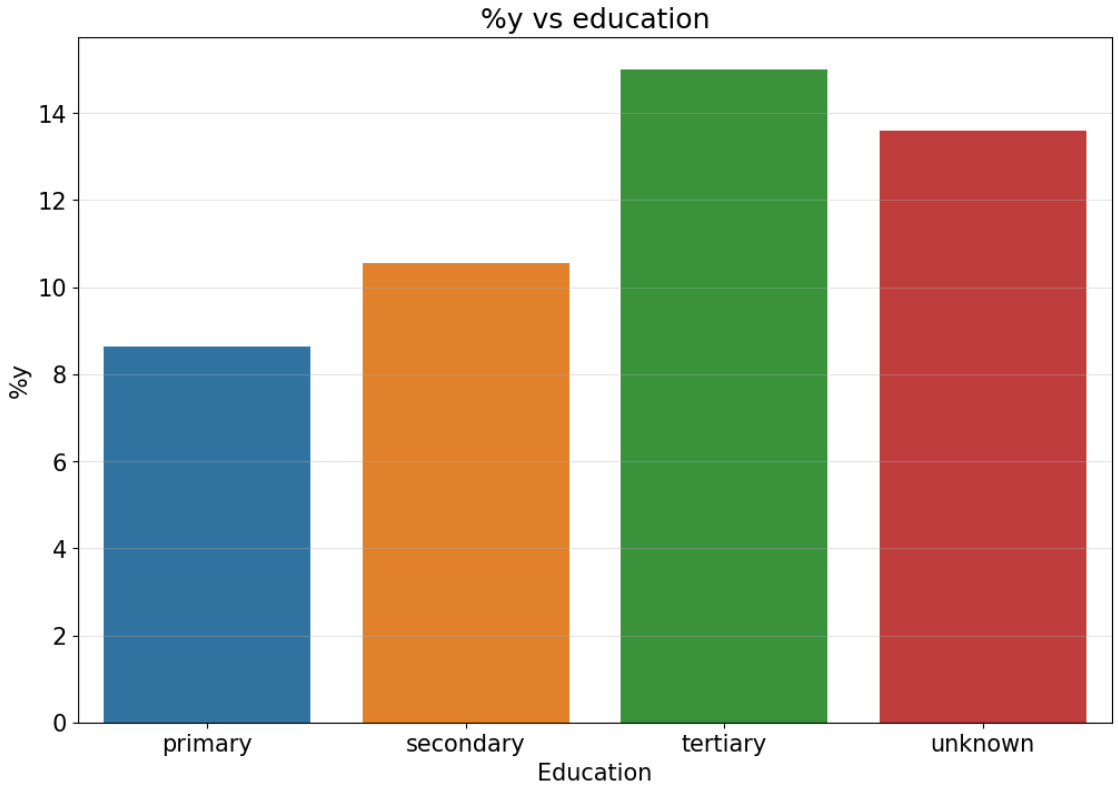
3.18.4 y vs education

Conclusion:

- Individuals with higher levels of education, particularly those with tertiary education, show a higher tendency to subscribe to term deposits, as opposed to those with primary education

[62]:
```
temp_df = df1[['education','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
↪astype(float)
temp_df = temp_df.groupby('education',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
```

```
sns.barplot(temp_df,x='education',y='y',hue='education')
plt.title('%y vs education')
plt.xlabel('Education')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



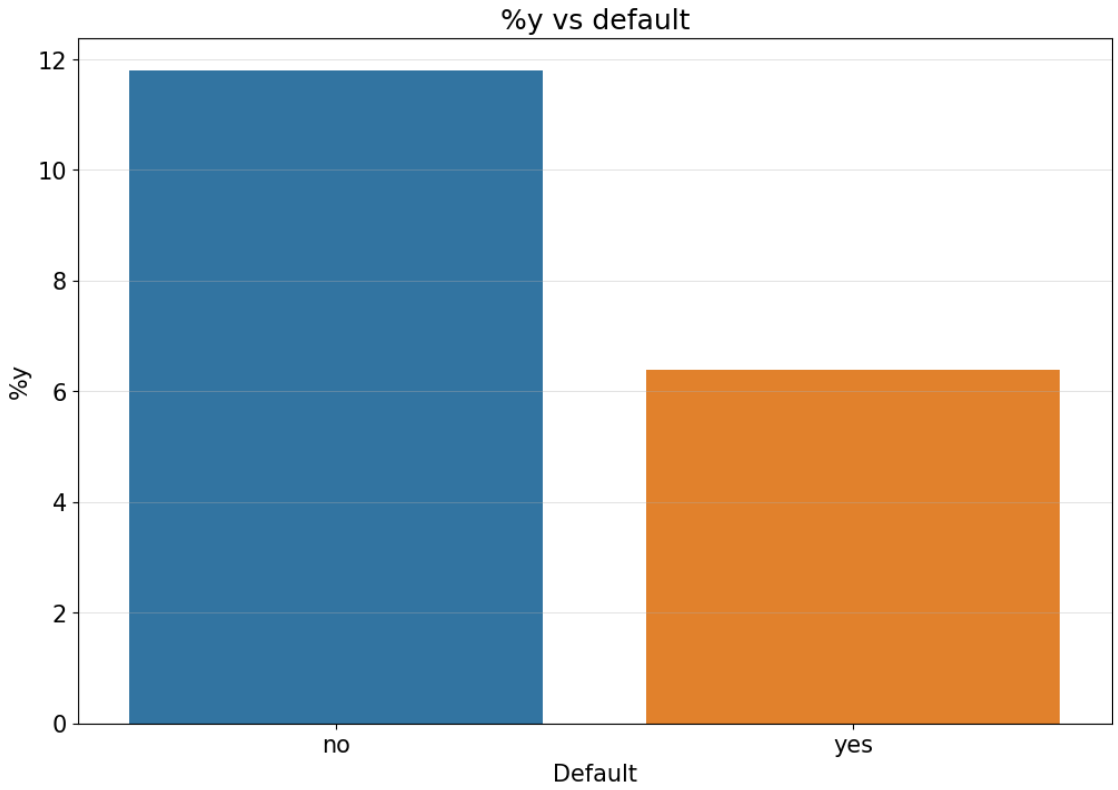
3.18.5 y vs default

Conclusion:

- Clients without a credit default have a higher likelihood of subscribing to a term deposit compared to those who have defaulted

[63]:
```
temp_df = df1[['default','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
 ↪astype(float)
temp_df = temp_df.groupby('default',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='default',y='y',hue='default')
plt.title('%y vs default')
```

```
plt.xlabel('Default')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```

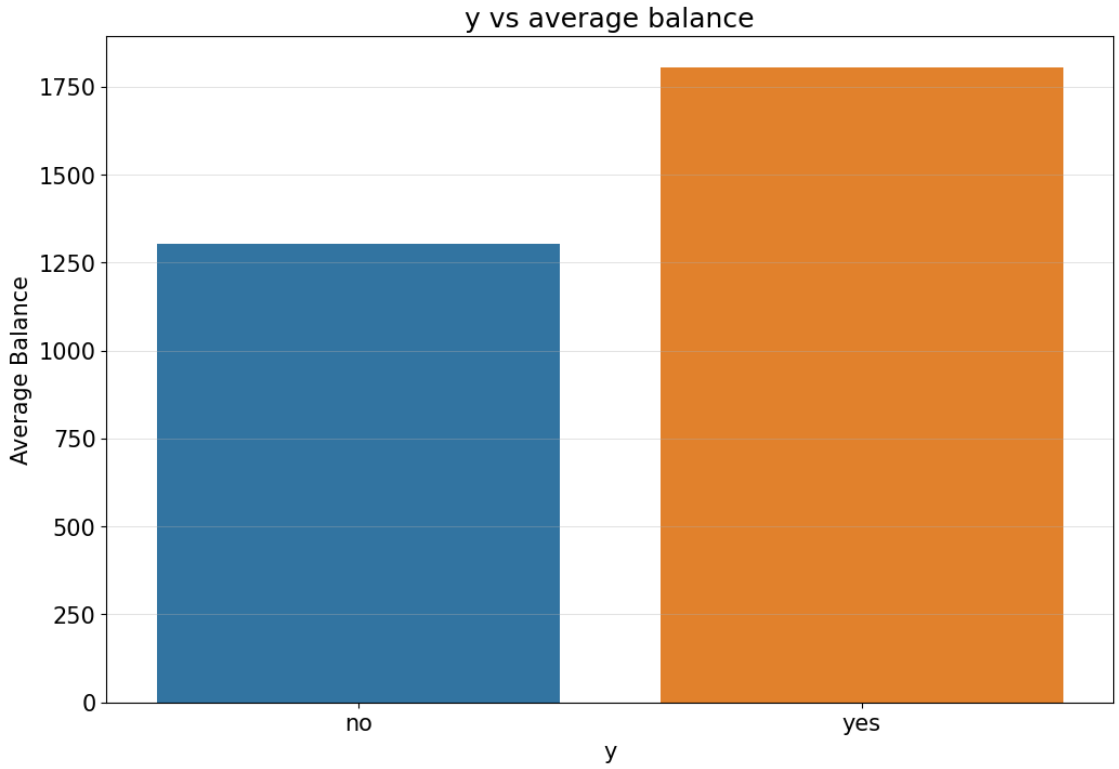


3.18.6 y vs balance

Conclusion:

- Clients with higher average account balances are more likely to subscribe to a term deposit

[64]:
```
temp_df = df1[['balance','y']]
temp_df = temp_df.groupby('y',observed=True).mean().reset_index()
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='y',y='balance',hue='y')
plt.title('y vs average balance')
plt.ylabel('Average Balance')
plt.xlabel('y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```

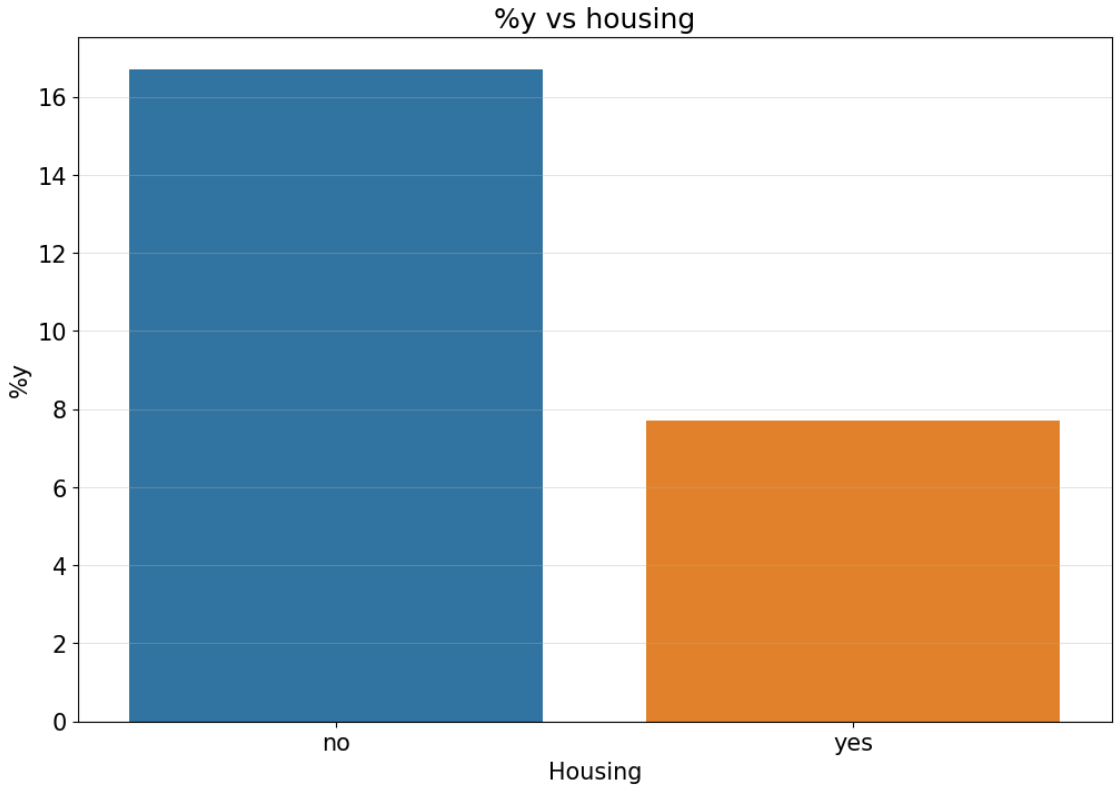


3.18.7 y vs housing

Conclusion:

- Clients without a housing loan have a higher likelihood of subscribing to a term deposit compared to those who have one

[65]:
```
temp_df = df1[['housing','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
 ↪astype(float)
temp_df = temp_df.groupby('housing',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='housing',y='y',hue='housing')
plt.title('%y vs housing')
plt.xlabel('Housing')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```

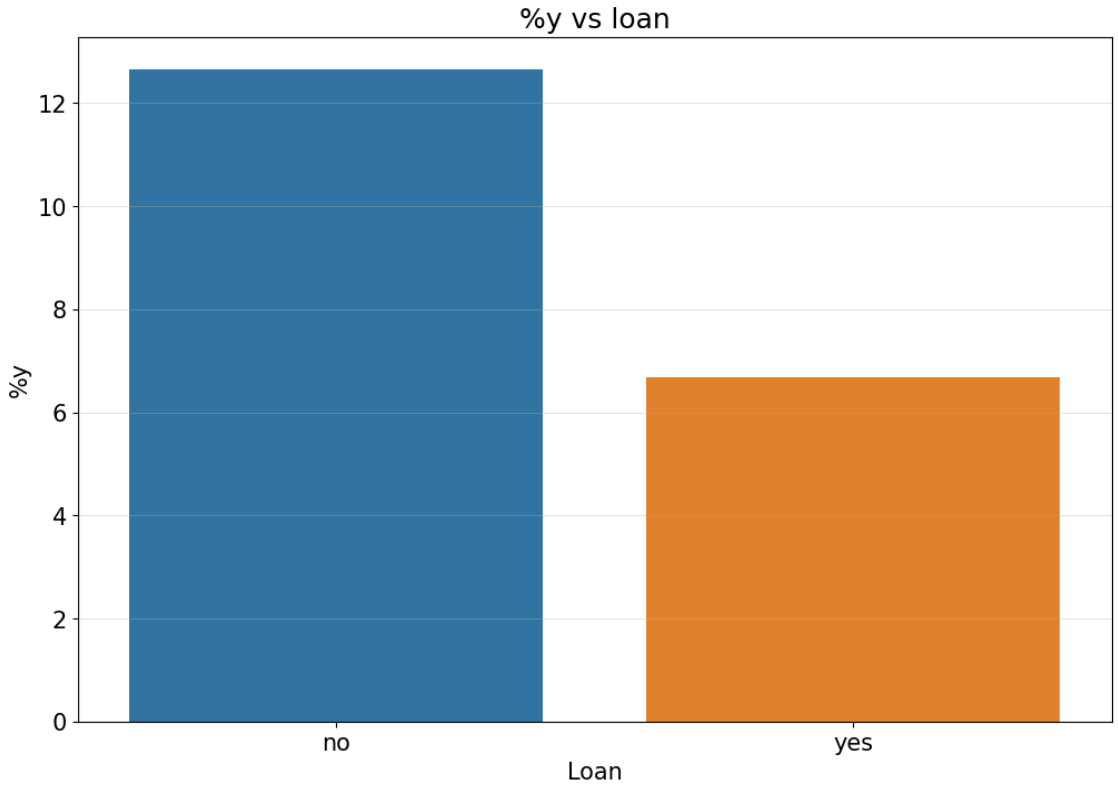


3.18.8 y vs loan

Conclusion:

- Clients without a personal loan have a higher likelihood of subscribing to a term deposit compared to those who have one

[66]:
```
temp_df = df1[['loan','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
 ↪astype(float)
temp_df = temp_df.groupby('loan',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='loan',y='y',hue='loan')
plt.title('%y vs loan')
plt.xlabel('Loan')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```

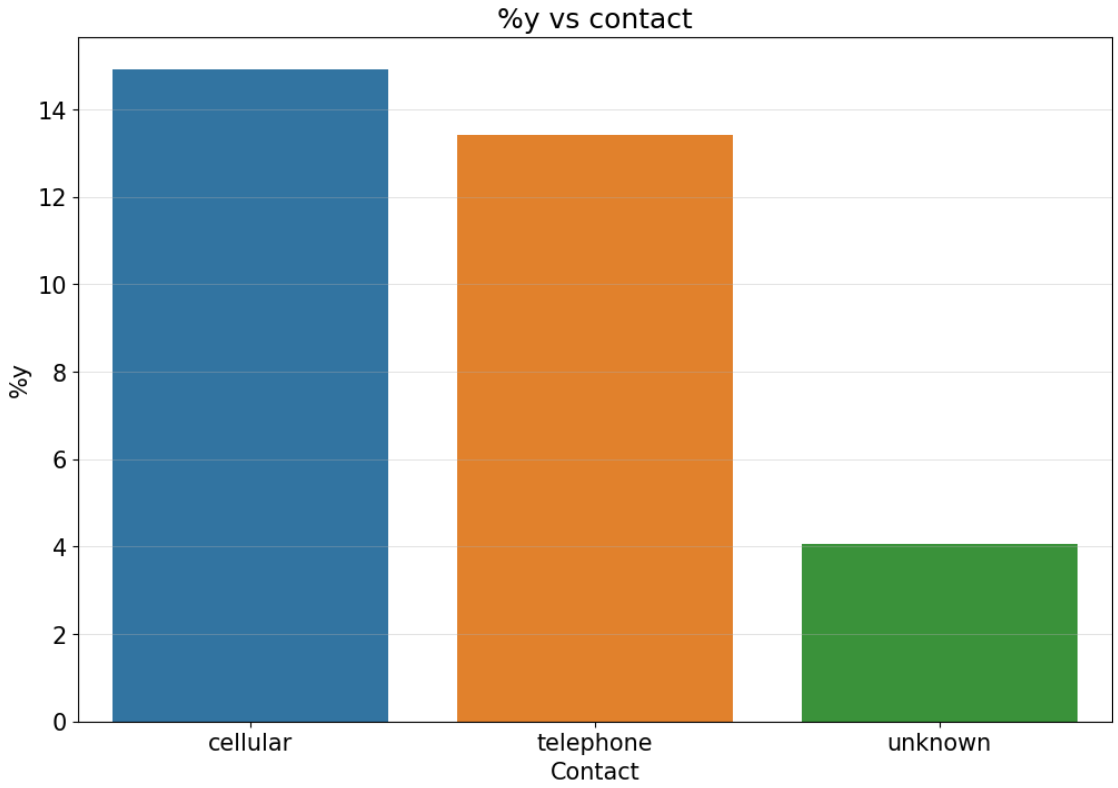


3.18.9 y vs contact

Conclusion:

- Clients contacted thorough cellular phone may have a higher chance of subscribing to term deposit

[67]:
```
temp_df = df1[['contact','y']]
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
↪astype(float)
temp_df = temp_df.groupby('contact',observed=True).mean().reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='contact',y='y',hue='contact')
plt.title('%y vs contact')
plt.xlabel('Contact')
plt.ylabel('%y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```



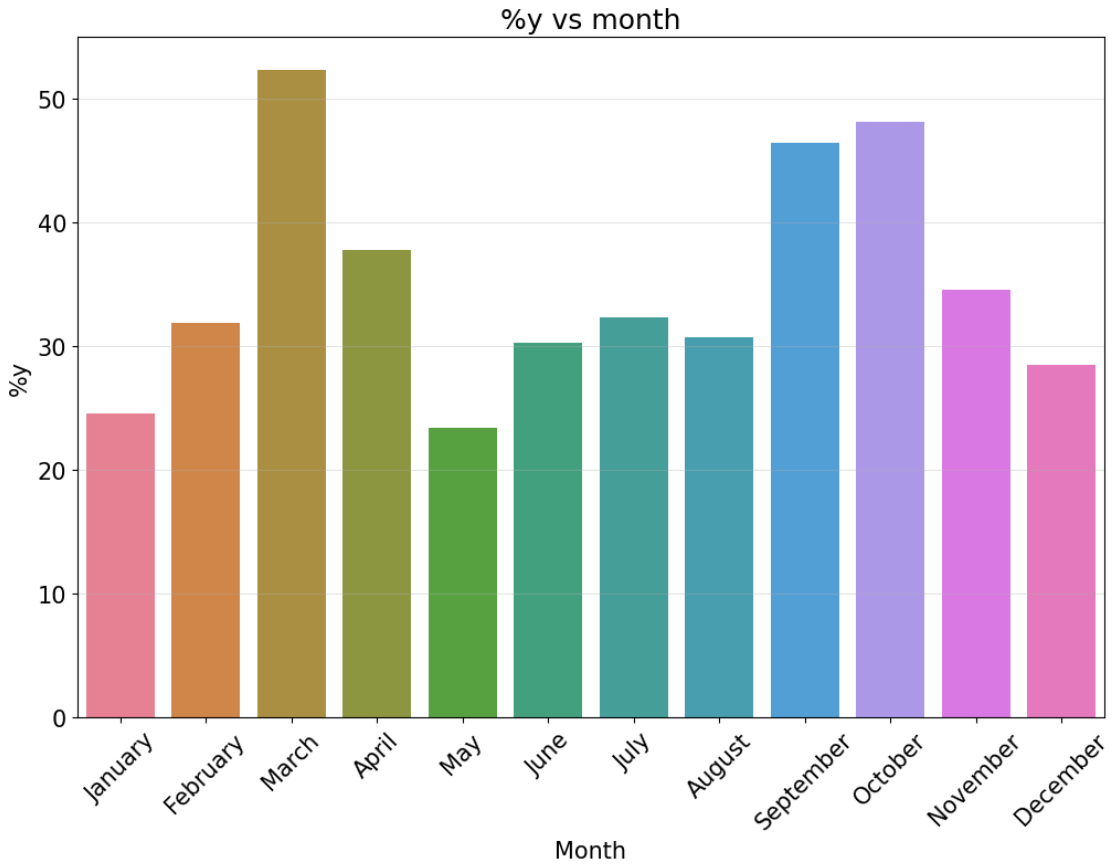
3.18.10 y vs date

Conclusion:

- Clients contacted in March may prefer to subscribe to term deposits, maybe due to start of a new financial year in April

[68]:
```
temp_df = df1[['date','y']]
order =␣
 ↪['January','February','March','April','May','June','July','August','September','October','N
temp_df.loc[:,'y'] = temp_df.loc[:,'y'].apply(lambda x: 1 if x == 'yes' else 0).
 ↪astype(float)
temp_df = temp_df.groupby(pd.Grouper(key='date', freq='ME'),observed=True).
 ↪mean().reset_index()
temp_df = temp_df.groupby(temp_df['date'].dt.month_name()).mean().
 ↪reindex(order,axis=0).drop(columns='date').reset_index()
temp_df['y'] = temp_df['y']*100
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='date',y='y',hue='date')
plt.title('%y vs month')
plt.xlabel('Month')
plt.ylabel('%y')
```

```
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.xticks(rotation=45)
plt.show()
```

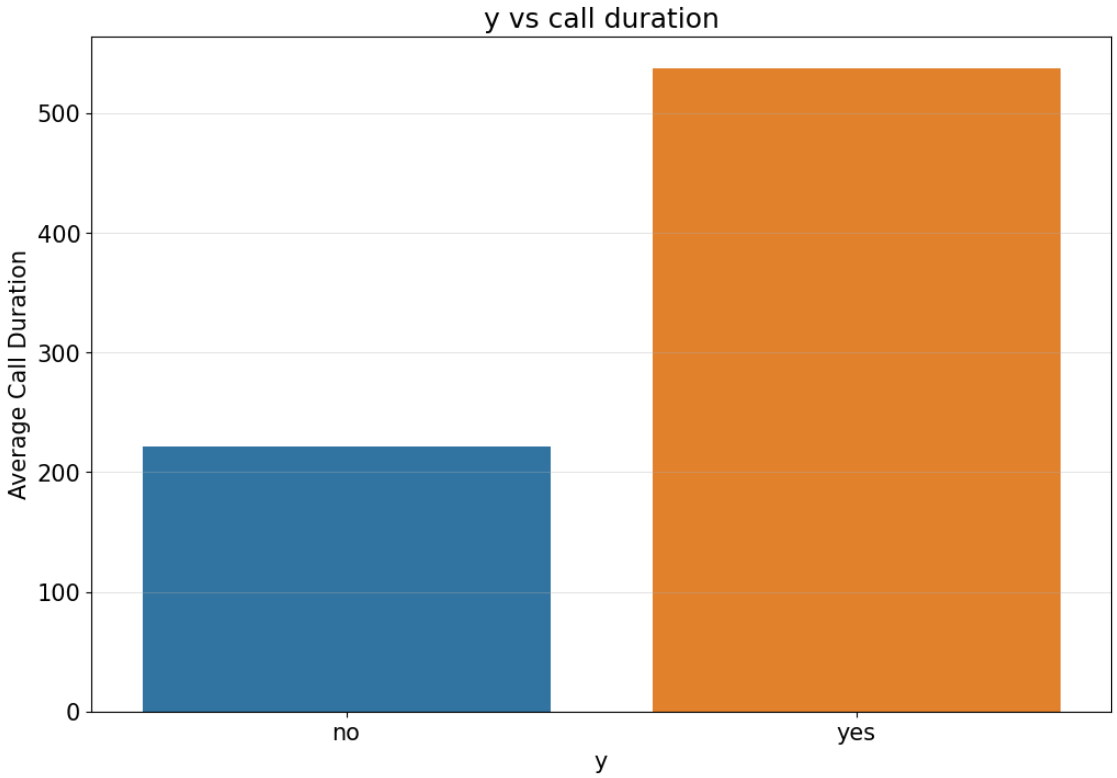


3.18.11 y vs duration

Conclusion:

- Longer calls may be associated with a higher likelihood of achieving a positive outcome i.e. subscription to a term deposit

[69]:
```
temp_df = df1[['duration','y']]
temp_df = temp_df.groupby('y',observed=True).mean().reset_index()
plt.figure(figsize=(12,8))
sns.barplot(temp_df,x='y',y='duration',hue='y')
plt.title('y vs call duration')
plt.ylabel('Average Call Duration')
plt.xlabel('y')
plt.grid(axis='y', linewidth=0.5, alpha=0.5)
plt.show()
```


y vs call duration
Average Call Duration
0
100
200
300
400
500
no
yes
y