# Machine Learning II

## Aplicar un modelo de regresion logistica haciendo previamente un masajeo de datos con imputación

### - Importación del archivo de uso

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

os.chdir('E:\WORK IN PROGRESS\Data Analytics course\parte 2 python\week 26')

# Se usa la funcion read_csv para leer el archivo . csv
# Tener en cuenta que esta vez el archivo tenia separadores el ;

df = pd.read_csv('bank-additional-full.csv',sep=';')
```

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

Out[ ]:

| | age | job | marital | education | default | housing | loan | contact | month | day_of_week | ... | campaign | pdays | previous | poutcome | emp.var.r |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | housemaid | married | basic.4y | no | no | no | telephone | may | mon | ... | 1 | 999 | 0 | nonexistent | |
| **1** | 57 | services | married | high.school | unknown | no | no | telephone | may | mon | ... | 1 | 999 | 0 | nonexistent | |
| **2** | 37 | services | married | high.school | no | yes | no | telephone | may | mon | ... | 1 | 999 | 0 | nonexistent | |
| **3** | 40 | admin. | married | basic.6y | no | no | no | telephone | may | mon | ... | 1 | 999 | 0 | nonexistent | |
| **4** | 56 | services | married | high.school | no | no | yes | telephone | may | mon | ... | 1 | 999 | 0 | nonexistent | |

5 rows × 21 columns

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             41188 non-null  object 
 2   marital         41188 non-null  object 
 3   education       41188 non-null  object 
 4   default         41188 non-null  object 
 5   housing         41188 non-null  object 
 6   loan            41188 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

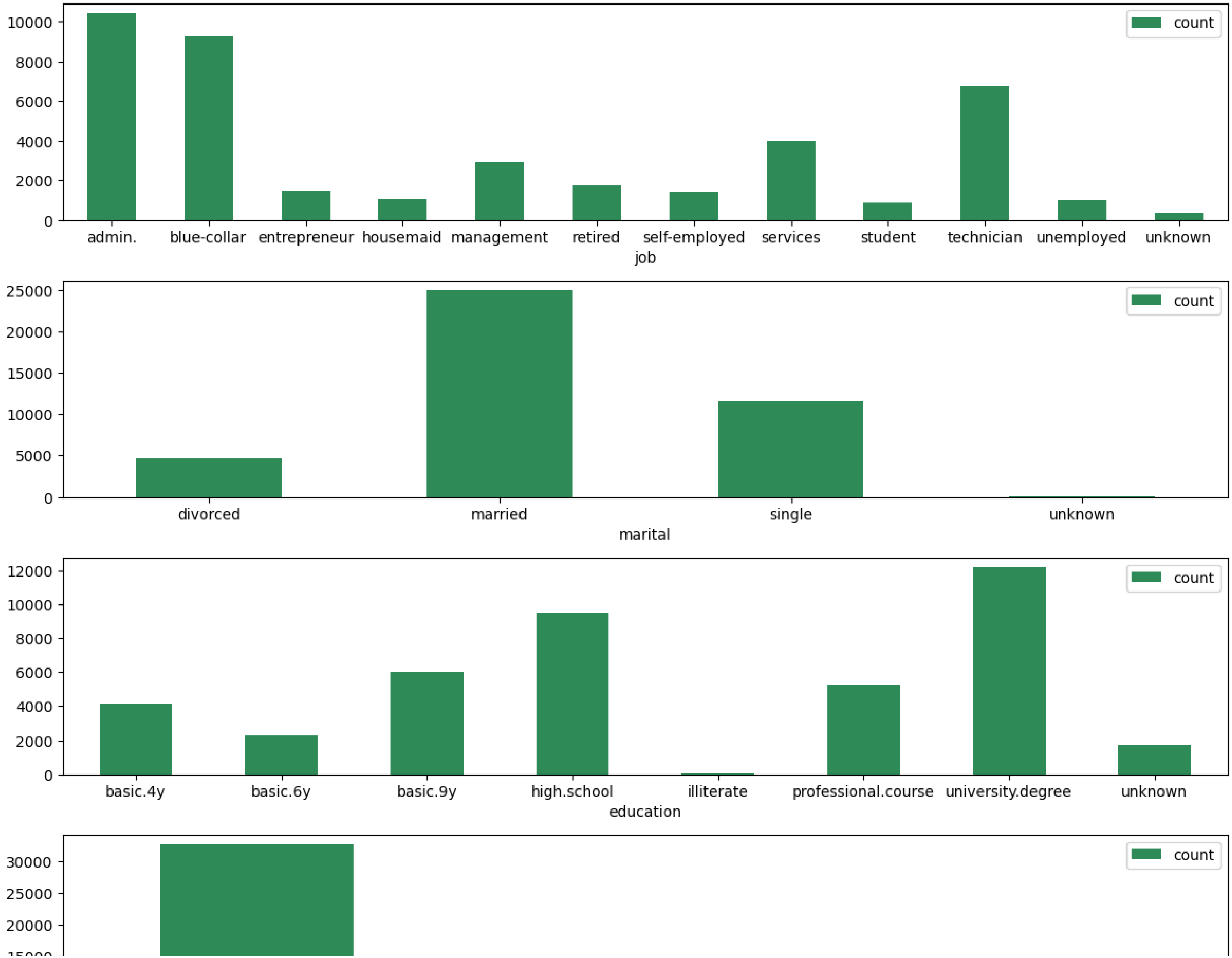
In [ ]:
```
# Del ejercicio anterior se vio que las siguientes son las columnas que tienen valores desconocidos.
# Solo que dichos valores no aparecen como nulos porque se les fue asignado el nombre 'unknown'
# Como se vera en el siguiente grafico.

columns_unknownvalues=['job', 'marital', 'education', 'default', 'housing', 'loan']
```

In [ ]:
```
fig, axes = plt.subplots(nrows=6,ncols=1, figsize=(12,16))
fig.tight_layout(pad=2.0)
for i, column in enumerate (columns_unknownvalues):

    df_helper= df.groupby(column)[column].count().rename('count').reset_index()
```

```
    df_helper.plot.bar(x=column,ax=axes[i],color='seagreen')
    axes[i].tick_params(labelrotation=360)
```


count
10000
8000
6000
4000
2000
0
admin.
blue-collar
entrepreneur
housemaid
management
retired
self-employed
services
student
technician
unemployed
unknown
job
count
25000
20000
15000
10000
5000
0
divorced
married
single
unknown
marital
count
12000
10000
8000
6000
4000
2000
0
basic.4y
basic.6y
basic.9y
high.school
illiterate
professional.course
university.degree
unknown
education
count
30000
25000
20000

In [ ]:
```
# La variable default es la que tiene el mayor tipo de valores desconocidos.
# En el ejercicio anterior lo que hice fue simplemente eliminar las columnas con valores desconocidos
# Ahora voy a utilizar el metoddo knn imputation para llevar a cabo la imputacion de los datos nulos.
```

## Field Engineering

### Hacer que los valores nulos se muestren como nulos:

In [ ]:
```
df.replace('unknown',np.nan,inplace=True)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   age             41188 non-null  int64  
 1   job             40858 non-null  object 
 2   marital         41108 non-null  object 
 3   education       39457 non-null  object 
 4   default         32591 non-null  object 
 5   housing         40198 non-null  object 
 6   loan            40198 non-null  object 
 7   contact         41188 non-null  object 
 8   month           41188 non-null  object 
 9   day_of_week     41188 non-null  object 
 10  duration        41188 non-null  int64  
 11  campaign        41188 non-null  int64  
 12  pdays           41188 non-null  int64  
 13  previous        41188 non-null  int64  
 14  poutcome        41188 non-null  object 
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object 
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

In [ ]:
```
missing_values_count = df.isnull().sum()

missing_values_count
```

Out[ ]:
```
age                  0
job                330
marital             80
education         1731
default           8597
housing            990
loan               990
contact              0
month                0
day_of_week          0
duration             0
campaign             0
pdays                0
previous             0
poutcome             0
emp.var.rate         0
cons.price.idx       0
cons.conf.idx        0
euribor3m            0
nr.employed          0
y                    0
dtype: int64
```

In [ ]:
```
# Se realiza una copia del dataset original para empezar a realizar el masajeo de datos
df1=df.copy()
```

In [ ]:
```
df1.nunique().sort_values(ascending=False)
```

Out[ ]:
```
duration          1544
euribor3m          316
age                 78
campaign            42
pdays               27
cons.conf.idx       26
cons.price.idx      26
nr.employed         11
job                 11
month               10
emp.var.rate        10
previous             8
education            7
day_of_week          5
poutcome             3
marital              3
default              2
contact              2
loan                 2
housing              2
y                    2
dtype: int64
```

# Cambiar el formato de las variables 'job', 'marital','education','month','day_of_week','poutcome' de object a categorical.

In [ ]:
```
df1['job']= df1['job'].astype('category')
df1['marital']= df1['marital'].astype('category')
df1['education']= df1['education'].astype('category')
df1['month']= df1['month'].astype('category')
df1['day_of_week']= df1['day_of_week'].astype('category')
df1['poutcome']= df1['poutcome'].astype('category')
```

### Cambiar el formato de las variables housing, loan, default, contact, y, de object a binary (int64).

In [ ]:
```
df1.loc[df1["housing"] == "no", "housing"] = 0
df1.loc[df1["housing"] == "yes", "housing"] = 1
df1.loc[df1["loan"] == "no", "loan"] = 0
df1.loc[df1["loan"] == "yes", "loan"] = 1
df1.loc[df1["y"] == "no", "y"] = 0
df1.loc[df1["y"] == "yes", "y"] = 1
```

```
df1.loc[df1["default"] == "no", "default"] = 0
df1.loc[df1["default"] == "yes", "default"] = 1
df1.loc[df1["contact"] == "telephone", "contact"] = 0
df1.loc[df1["contact"] == "cellular", "contact"] = 1
```

In [ ]:

```
df1['housing']= df1['housing'].astype('float')
df1['loan']= df1['loan'].astype('float')
df1['y']= df1['y'].astype('float')
df1['default']= df1['default'].astype('float')
df1['contact']= df1['contact'].astype('float')
```

In [ ]:

```
df1.info()
# Ahora el dataframe no tien mas columnas de tipo object.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             40858 non-null  category
 2   marital         41108 non-null  category
 3   education       39457 non-null  category
 4   default         32591 non-null  float64
 5   housing         40198 non-null  float64
 6   loan            40198 non-null  float64
 7   contact         41188 non-null  float64
 8   month           41188 non-null  category
 9   day_of_week     41188 non-null  category
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  category
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  float64
dtypes: category(6), float64(10), int64(5)
memory usage: 5.0 MB
```

In [ ]:
```
# Ya no se tienen variables tipo objeto
```

## Correlación

In [ ]:
```
df1.corr().style.background_gradient(cmap='Greens')\
          .set_properties(**{'font-size':'10px'})
```

```
C:\Users\oscah\AppData\Local\Temp\ipykernel_5288\2296899345.py:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.
  df1.corr().style.background_gradient(cmap='Greens')\
```

Out[ ]:

| | age | default | housing | loan | contact | duration | campaign | pdays | previous | emp.var.rate | cons.price.idx | cons.conf.idx | euribor3m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **age** | 1.000000 | 0.002924 | -0.001636 | -0.007375 | -0.007021 | -0.000866 | 0.004594 | -0.034369 | 0.024365 | -0.000371 | 0.000857 | 0.129372 | 0.01076 |
| **default** | 0.002924 | 1.000000 | -0.004042 | -0.004180 | 0.006760 | -0.005752 | -0.004207 | 0.002071 | 0.002419 | 0.005825 | -0.002657 | 0.004990 | 0.00670 |
| **housing** | -0.001636 | -0.004042 | 1.000000 | 0.046462 | 0.083022 | -0.007806 | -0.011168 | -0.010649 | 0.021656 | -0.060917 | -0.081396 | -0.034167 | -0.05997 |
| **loan** | -0.007375 | -0.004180 | 0.046462 | 1.000000 | 0.012078 | -0.000207 | 0.005353 | 0.000050 | -0.001924 | 0.001422 | -0.004934 | -0.013379 | -0.00030 |
| **contact** | -0.007021 | 0.006760 | 0.083022 | 0.012078 | 1.000000 | 0.026657 | -0.077368 | -0.117970 | 0.212848 | -0.393584 | -0.591474 | -0.251614 | -0.39977 |
| **duration** | -0.000866 | -0.005752 | -0.007806 | -0.000207 | 0.026657 | 1.000000 | -0.071699 | -0.047577 | 0.020640 | -0.027968 | 0.005312 | -0.008173 | -0.03289 |
| **campaign** | 0.004594 | -0.004207 | -0.011168 | 0.005353 | -0.077368 | -0.071699 | 1.000000 | 0.052584 | -0.079141 | 0.150754 | 0.127836 | -0.013733 | 0.13513 |
| **pdays** | -0.034369 | 0.002071 | -0.010649 | 0.000050 | -0.117970 | -0.047577 | 0.052584 | 1.000000 | -0.587514 | 0.271004 | 0.078889 | -0.091342 | 0.29689 |
| **previous** | 0.024365 | 0.002419 | 0.021656 | -0.001924 | 0.212848 | 0.020640 | -0.079141 | -0.587514 | 1.000000 | -0.420489 | -0.203130 | -0.050936 | -0.45449 |
| **emp.var.rate** | -0.000371 | 0.005825 | -0.060917 | 0.001422 | -0.393584 | -0.027968 | 0.150754 | 0.271004 | -0.420489 | 1.000000 | 0.775334 | 0.196041 | 0.97224 |
| **cons.price.idx** | 0.000857 | -0.002657 | -0.081396 | -0.004934 | -0.591474 | 0.005312 | 0.127836 | 0.078889 | -0.203130 | 0.775334 | 1.000000 | 0.058986 | 0.68823 |
| **cons.conf.idx** | 0.129372 | 0.004990 | -0.034167 | -0.013379 | -0.251614 | -0.008173 | -0.013733 | -0.091342 | -0.050936 | 0.196041 | 0.058986 | 1.000000 | 0.27768 |
| **euribor3m** | 0.010767 | 0.006700 | -0.059978 | -0.000300 | -0.399773 | -0.032897 | 0.135133 | 0.296899 | -0.454494 | 0.972245 | 0.688230 | 0.277686 | 1.00000 |
| **nr.employed** | -0.017725 | 0.007258 | -0.046455 | 0.004183 | -0.269155 | -0.044703 | 0.144095 | 0.372605 | -0.501333 | 0.906970 | 0.522034 | 0.100513 | 0.94515 |
| **y** | 0.030399 | -0.003689 | 0.011662 | -0.004682 | 0.144773 | 0.405274 | -0.066357 | -0.324914 | 0.230181 | -0.298334 | -0.136211 | 0.054878 | -0.30777 |

## Se eliminan las variables con alto coeficiente de correlacion

In [ ]:
```
df1.drop(['emp.var.rate','euribor3m','duration'],axis=1,inplace=True)

# La variable duracion la eliminé por sugerencia del administración del dataset
```

In [ ]:
```
df1.head()
```

Out[ ]:

| | age | job | marital | education | default | housing | loan | contact | month | day_of_week | campaign | pdays | previous | poutcome | cons.price.idx |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | housemaid | married | basic.4y | 0.00 | 0.00 | 0.00 | 0.00 | may | mon | 1 | 999 | 0 | nonexistent | 93.99 |
| **1** | 57 | services | married | high.school | NaN | 0.00 | 0.00 | 0.00 | may | mon | 1 | 999 | 0 | nonexistent | 93.99 |
| **2** | 37 | services | married | high.school | 0.00 | 1.00 | 0.00 | 0.00 | may | mon | 1 | 999 | 0 | nonexistent | 93.99 |
| **3** | 40 | admin. | married | basic.6y | 0.00 | 0.00 | 0.00 | 0.00 | may | mon | 1 | 999 | 0 | nonexistent | 93.99 |
| **4** | 56 | services | married | high.school | 0.00 | 0.00 | 1.00 | 0.00 | may | mon | 1 | 999 | 0 | nonexistent | 93.99 |

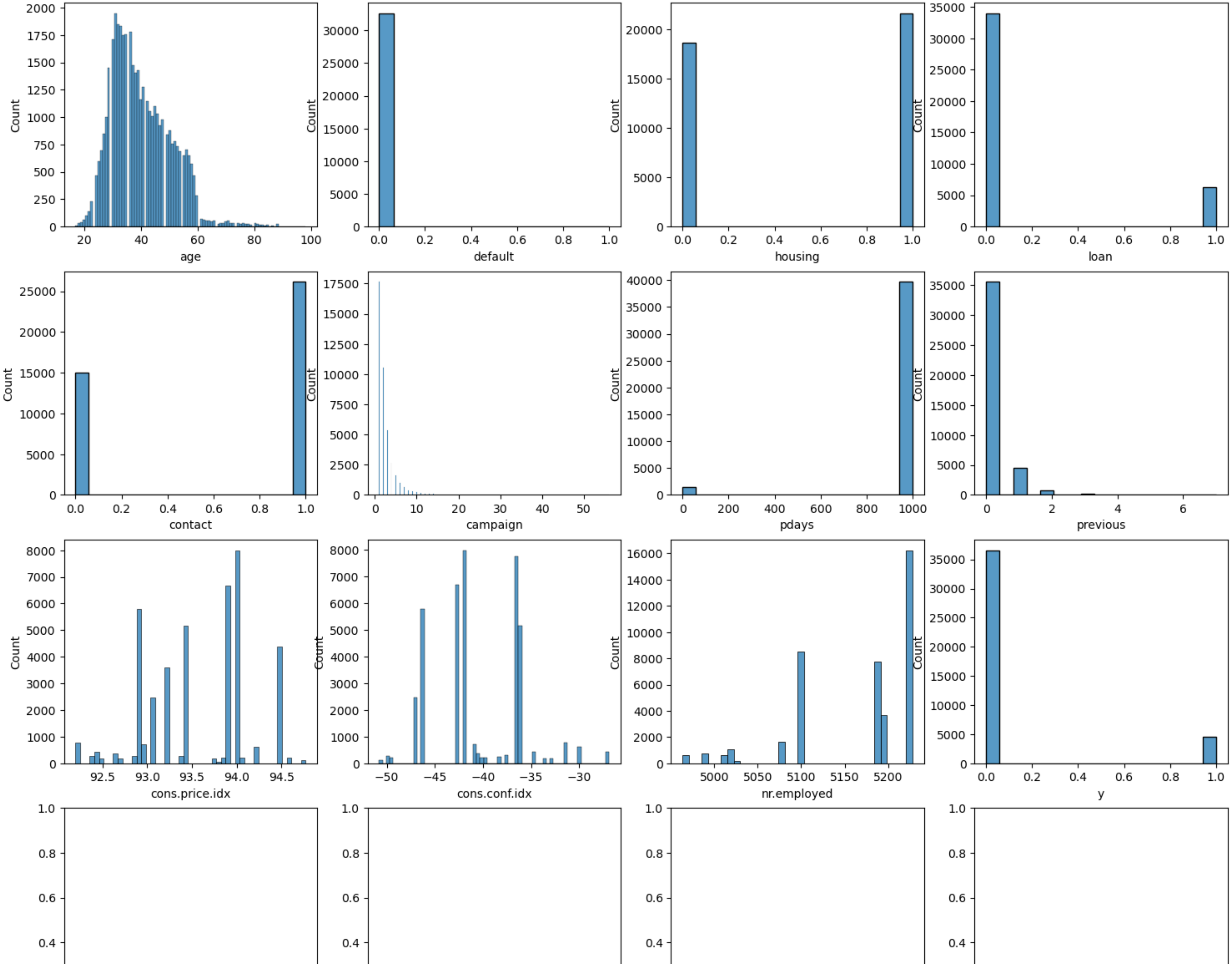
## Se buscan variables numéricas con un alto sesgo

In [ ]:
```
cols_num=[col for col in df1.columns if (df1[col].dtypes=='float64') | (df1[col].dtypes=='int64')]
cols_num
```

Out[ ]:
```
['age',
 'default',
 'housing',
 'loan',
 'contact',
 'campaign',
 'pdays',
 'previous',
 'cons.price.idx',
 'cons.conf.idx',
 'nr.employed',
 'y']
```

In [ ]:
```
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(18,16))
for i, column in enumerate (cols_num):
```

```
    sns.histplot(df1[column],ax=axes[i//4,i%4],kde=False)
```


Count
age
default
housing
loan
contact
campaign
pdays
previous
cons.price.idx
cons.conf.idx
nr.employed
y

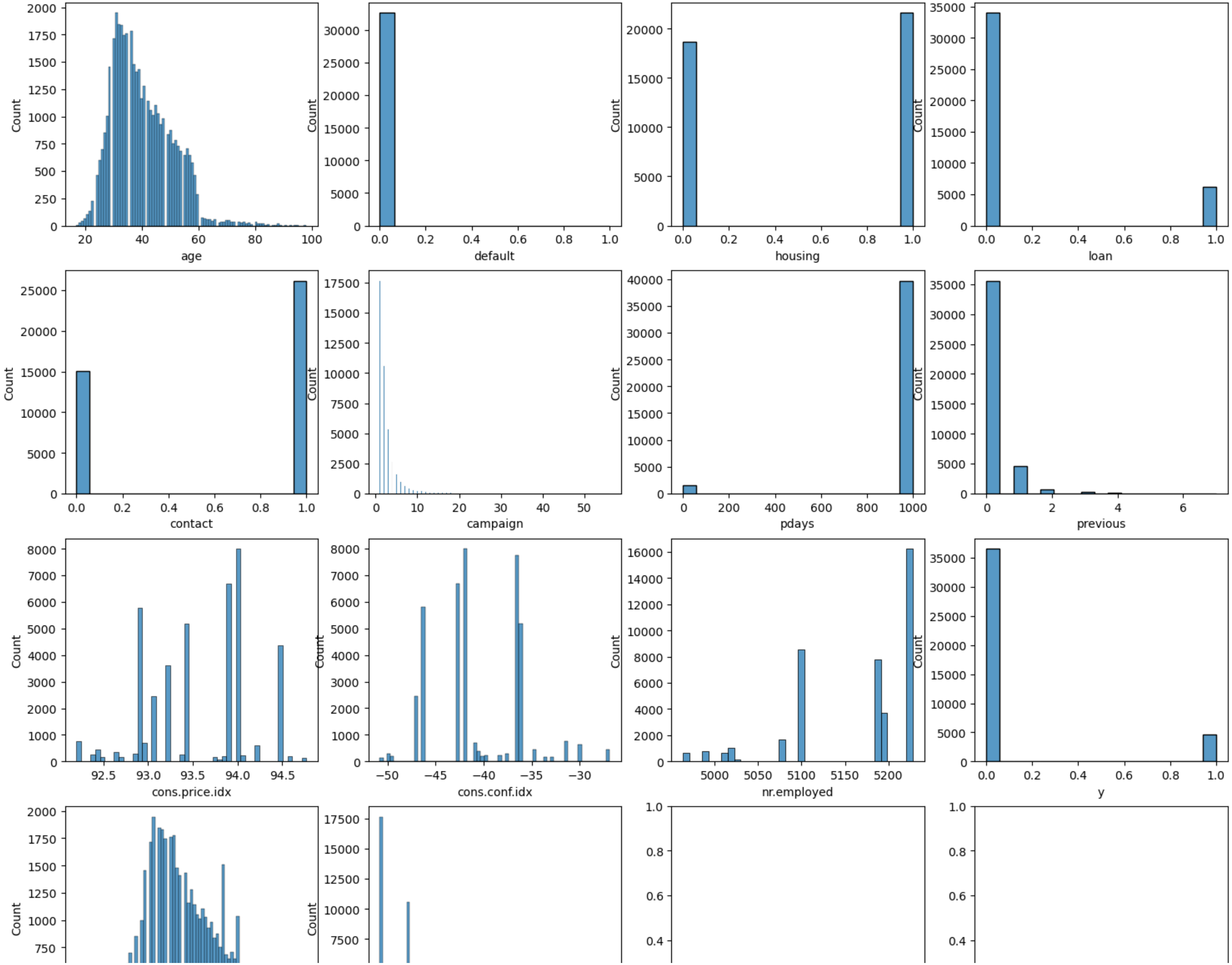
In [ ]:
```
# Las variables age y campaign tienen un sesgo significativo hacia la derecha por lo cual
# es pertinente usar logaritmo.
```

In [ ]:
```
df1['age-log']=np.log(df1['age']+1)
df1['campaign-log']=np.log(df1['campaign']+1)
```

In [ ]:
```
cols_num=[col for col in df1.columns if (df1[col].dtypes=='float64') | (df1[col].dtypes=='int64')]
cols_num
```

Out[ ]:
```
['age',
 'default',
 'housing',
 'loan',
 'contact',
 'campaign',
 'pdays',
 'previous',
 'cons.price.idx',
 'cons.conf.idx',
 'nr.employed',
 'y',
 'age-log',
 'campaign-log']
```

In [ ]:
```
fig, axes = plt.subplots(nrows=4, ncols=4, figsize=(18,16))
for i, column in enumerate (cols_num):
    sns.histplot(df1[column],ax=axes[i//4,i%4],kde=False)
```


Count
age
default
housing
loan
contact
campaign
pdays
previous
cons.price.idx
cons.conf.idx
nr.employed
y

## balance de clases

In [ ]:
```
pd.options.display.float_format='{:.2f}'.format
```

### se revisa el porcentaje de cada variable con respesto al total para cada columna categorica

In [ ]:
```
categ_columns=['job','marital','education','month','day_of_week','poutcome']
for column in categ_columns:
    helper = df1.groupby(column)[column].count().rename('total').reset_index()

    helper['percent']=(helper['total']/helper['total'].sum())*100
    print('\n' + column)
    print(helper)
```

```
job
              job  total  percent
0          admin.  10422    25.51
1     blue-collar   9254    22.65
2    entrepreneur   1456     3.56
3       housemaid   1060     2.59
4      management   2924     7.16
5         retired   1720     4.21
6   self-employed   1421     3.48
7        services   3969     9.71
8         student    875     2.14
9      technician   6743    16.50
10     unemployed   1014     2.48

marital
    marital  total  percent
0  divorced   4612    11.22
1   married  24928    60.64
2    single  11568    28.14

education
             education  total  percent
0             basic.4y   4176    10.58
1             basic.6y   2292     5.81
2             basic.9y   6045    15.32
3          high.school   9515    24.11
4           illiterate     18     0.05
5  professional.course   5243    13.29
6    university.degree  12168    30.84

month
  month  total  percent
0   apr   2632     6.39
1   aug   6178    15.00
2   dec    182     0.44
3   jul   7174    17.42
4   jun   5318    12.91
5   mar    546     1.33
6   may  13769    33.43
7   nov   4101     9.96
8   oct    718     1.74
9   sep    570     1.38

day_of_week
```

```
  day_of_week  total  percent
0         fri   7827    19.00
1         mon   8514    20.67
2         thu   8623    20.94
3         tue   8090    19.64
4         wed   8134    19.75

poutcome
      poutcome  total  percent
0      failure   4252    10.32
1  nonexistent  35563    86.34
2      success   1373     3.33
```

## job

```
- Se ponen juntas aquellas opciones que tienen un valor menor al 5% en la categoria 'other'
```

In [ ]:
```
df1['job'].replace({'entrepreneur':'other','housemaid':'other','retired':'other','self-employed':'other','student':'other','unem
```

## education

```
- Se elimina la oocion illiterate
```

In [ ]:
```
df1['education']= df1['education'].astype('object')
df1.drop(df1[df1['education']=='illiterate'].index,inplace=True)
df1['education']= df1['education'].astype('category')
```

## month

```
- Se agrupan los meses en tres grupos (1,2,3)
```

In [ ]:
```
df1['month'].replace({'apr':1,'aug':2,'dec':3,'jul':2,'jun':2,'mar':1,'may':2,'nov':3,'oct':3,'sep':3}, inplace=True)
```

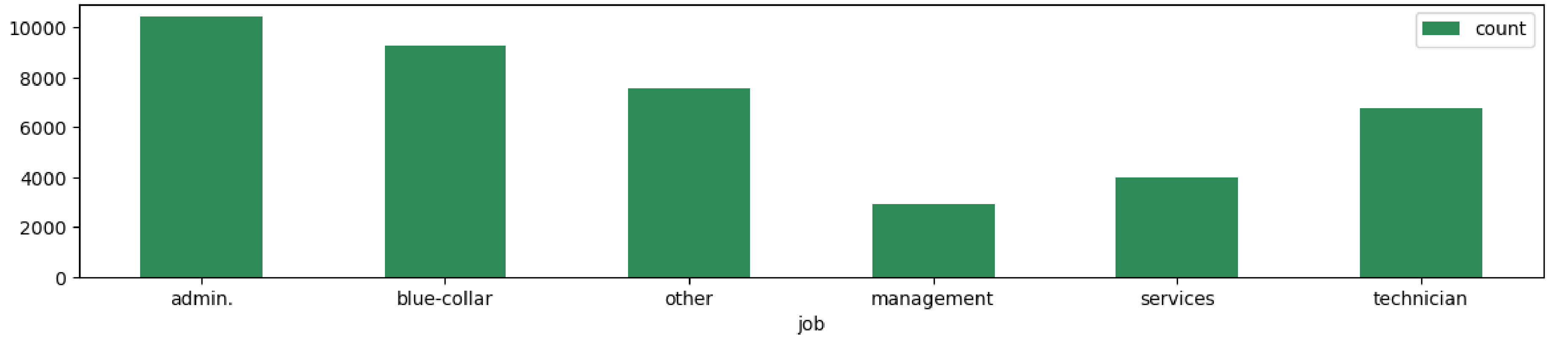
## Marital y Poutcome

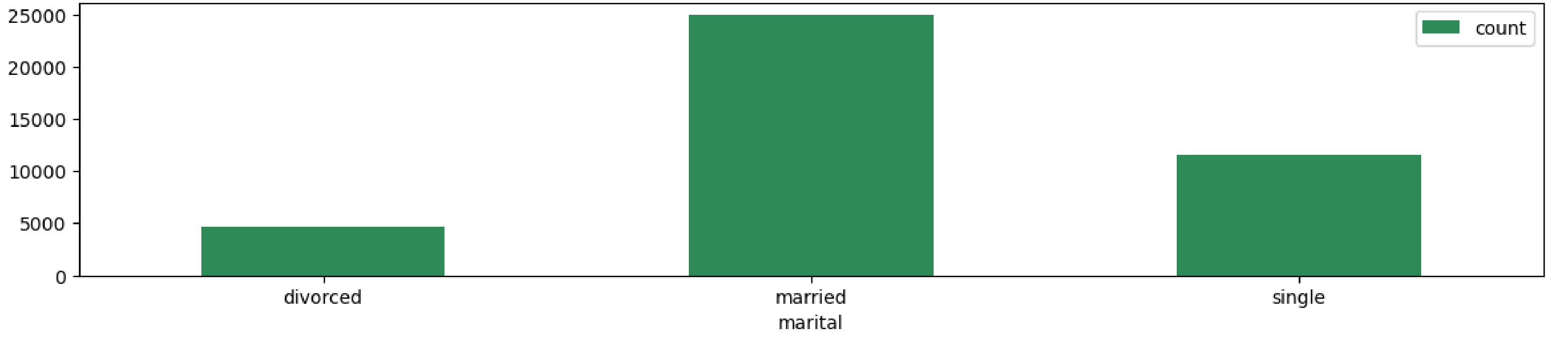
```
- No se le realiza ningun cambio
```

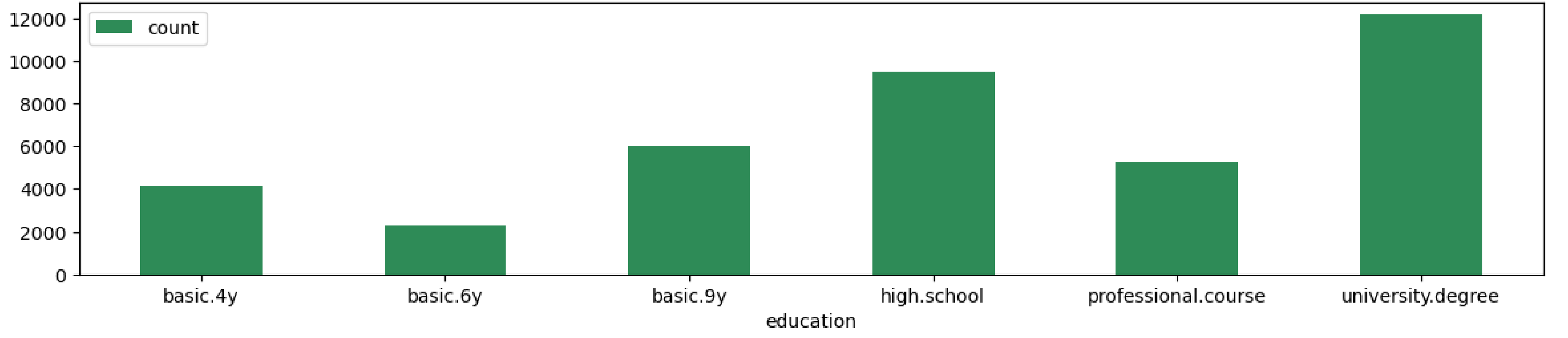
In [ ]:
```
categ_columns=['job','marital','education','month','day_of_week','poutcome']

fig, axes = plt.subplots(nrows=6,ncols=1, figsize=(12,16))
fig.tight_layout(pad=2.0)
for i, column in enumerate (categ_columns):

    df_helper= df1.groupby(column)[column].count().rename('count').reset_index()
    df_helper.plot.bar(x=column,ax=axes[i],color='seagreen')
    axes[i].tick_params(labelrotation=360)
```


count
10000
8000
6000
4000
2000
0
admin.
blue-collar
other
management
services
technician
job


count
25000
20000
15000
10000
5000
0
divorced
married
single
marital


count
12000
10000
8000
6000
4000
2000
0
basic.4y
basic.6y
basic.9y
high.school
professional.course
university.degree
education


count
30000
25000
20000

In [ ]:
```
for column in categ_columns:
    helper = df1.groupby(column)[column].count().rename('total').reset_index()

    helper['percent']=(helper['total']/helper['total'].sum())*100
    print('\n' + column)
    print(helper)
```

```
job
           job  total  percent
0       admin.  10421    25.52
1  blue-collar   9246    22.64
2        other   7537    18.45
3   management   2924     7.16
4     services   3969     9.72
5   technician   6743    16.51

marital
    marital  total  percent
0  divorced   4610    11.22
1   married  24913    60.63
2    single  11567    28.15

education
             education  total  percent
0             basic.4y   4176    10.59
1             basic.6y   2292     5.81
2             basic.9y   6045    15.33
3          high.school   9515    24.13
4  professional.course   5243    13.29
5    university.degree  12168    30.85

month
  month  total  percent
0     1   3176     7.71
1     2  32426    78.76
2     3   5568    13.52

day_of_week
  day_of_week  total  percent
0         fri   7823    19.00
1         mon   8513    20.68
2         thu   8617    20.93
3         tue   8085    19.64
4         wed   8132    19.75

poutcome
      poutcome  total  percent
0      failure   4251    10.33
1  nonexistent  35547    86.34
2      success   1372     3.33
```

- Solo un valor quedó menor al 5% (3.33% success in putcome)

In [ ]:
```
df2=df1.copy()
```

In [ ]:
```
categ_columns=['job','marital','education','month','day_of_week','poutcome']
categ_variables = df2[categ_columns]
categ_dummies = pd.get_dummies(categ_variables, drop_first=True)
categ_dummies.head()
```

Out[ ]:

| | job_blue-collar | job_other | job_management | job_services | job_technician | marital_married | marital_single | education_basic.6y | education_basic.9y | education_ |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | |
| **1** | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |
| **2** | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |
| **3** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | |
| **4** | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | |

In [ ]:
```
df2 = df2.drop(categ_columns, axis=1)
df2 = pd.concat([df2, categ_dummies], axis=1)
df2.head()
```

Out[ ]:

| | age | default | housing | loan | contact | campaign | pdays | previous | cons.price.idx | cons.conf.idx | ... | education_professional.course | education_university |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56 | 0.00 | 0.00 | 0.00 | 0.00 | 1 | 999 | 0 | 93.99 | -36.40 | ... | 0 | |
| **1** | 57 | NaN | 0.00 | 0.00 | 0.00 | 1 | 999 | 0 | 93.99 | -36.40 | ... | 0 | |
| **2** | 37 | 0.00 | 1.00 | 0.00 | 0.00 | 1 | 999 | 0 | 93.99 | -36.40 | ... | 0 | |
| **3** | 40 | 0.00 | 0.00 | 0.00 | 0.00 | 1 | 999 | 0 | 93.99 | -36.40 | ... | 0 | |
| **4** | 56 | 0.00 | 0.00 | 1.00 | 0.00 | 1 | 999 | 0 | 93.99 | -36.40 | ... | 0 | |

5 rows × 34 columns

## Se usa la funcion Iterative Imputer para imputar los valores nulos

In [ ]:

```
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

impute_it = IterativeImputer()
df_to_test=pd.DataFrame(impute_it.fit_transform(df2),columns=df2.columns)

df_to_test.head()
```

Out[ ]:

| | age | default | housing | loan | contact | campaign | pdays | previous | cons.price.idx | cons.conf.idx | ... | education_professional.course | education_universi |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 56.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |
| **1** | 57.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |
| **2** | 37.00 | 0.00 | 1.00 | 0.00 | 0.00 | 1.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |
| **3** | 40.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |
| **4** | 56.00 | 0.00 | 0.00 | 1.00 | 0.00 | 1.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |

5 rows × 34 columns

In [ ]:

```
missing_values_count= df_to_test.isnull().sum().sum()
```

```
print("hay ", missing_values_count, "valores nulos en este dataset")
```

```
hay  0 valores nulos en este dataset
```

## Data Split

In [ ]:
```
from sklearn.model_selection import train_test_split

X = df_to_test.drop('y',axis=1) #El array x (atributos) no va a contener la respuesta (num columnas x m)
y = df_to_test['y'] # Clase a predecir
#Se divide a X y Y en un ratio 70:30

# Convert categorical variables to dummy variables
# This will generate 467 additional columns

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=1)
```

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

Out[ ]:

| | age | default | housing | loan | contact | campaign | pdays | previous | cons.price.idx | cons.conf.idx | ... | education_professional.course | education_uni |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **4895** | 46.00 | 0.00 | 1.00 | 0.00 | 0.00 | 4.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |
| **17063** | 56.00 | 0.00 | 1.00 | 0.00 | 1.00 | 4.00 | 999.00 | 0.00 | 93.92 | -42.70 | ... | 1.00 | |
| **7305** | 37.00 | -0.00 | 1.00 | 1.00 | 0.00 | 3.00 | 999.00 | 0.00 | 93.99 | -36.40 | ... | 0.00 | |

3 rows × 33 columns

In [ ]:
```
print('{0:0.2f}% data is in training set'.format((len(X_train)/len(df_to_test.index))*100))
print('{0:0.2f}% data is in test set'.format((len(X_test)/len(df_to_test.index))*100))
```

```
70.00% data is in training set
30.00% data is in test set
```

In [ ]:
```
# Validacion de la estructura de los datasets
# En este caso la variable "Response" tiene 15/85 en cuanto a 1/0 y deberia perdurar en el Original, training y testing
# Esa es justamente la idea de hacer el split
print('Original Personal Loan True Values : {0} ({1:0.2f}%)'.format(len(df_to_test.loc[df_to_test['y']==1]),(len(df_to_test.loc[(
print('Original Personal Loan False Values : {0} ({1:0.2f}%)'.format(len(df_to_test.loc[df_to_test['y']==0]),(len(df_to_test.loc
print('')
```

```
print('Original Personal Loan True Values : {0} ({1:0.2f}%)'.format(len(y_train[y_train[:]==1]),(len(y_train[y_train[:]==1])/len
print('Original Personal Loan False Values : {0} ({1:0.2f}%)'.format(len(y_train[y_train[:]==0]),(len(y_train[y_train[:]==0])/le
print('')
print('Original Personal Loan True Values : {0} ({1:0.2f}%)'.format(len(y_test[y_test[:]==1]),(len(y_test[y_test[:]==1])/len(y_t
print('Original Personal Loan False Values : {0} ({1:0.2f}%)'.format(len(y_test[y_test[:]==0]),(len(y_test[y_test[:]==0])/len(y_
```

```
Original Personal Loan True Values : 4636 (11.26%)
Original Personal Loan False Values : 36534 (88.74%)

Original Personal Loan True Values : 3248 (11.27%)
Original Personal Loan False Values : 25571 (88.73%)

Original Personal Loan True Values : 1388 (11.24%)
Original Personal Loan False Values : 10963 (88.76%)
```

## Regresion logistica

In [ ]:

```
from sklearn import metrics
from sklearn.linear_model import LogisticRegression

# Adapta el modelo a los x_train y y_train (Entrenamiento)

model= LogisticRegression(class_weight={0:0.11,1:0.89}, solver="liblinear")
model.fit(X_train, y_train)

# Hace la prediccion en x_test y la guarda en y_predict

y_predict = model.predict(X_test)
```

In [ ]:

```
# La prediccion no es mas que un conjunto de 0s y 1s que se aplican al mismo dataset
y_predict[0:100]
```

Out[ ]:

```
array([1., 0., 1., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 1., 0., 0.,
       1., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       1., 0., 1., 0., 1., 0., 0., 0., 1., 1., 0., 0., 0., 1., 1., 0., 0.,
       0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0.])
```

In [ ]:

```
# Construye un dataset con el valor original y la prediccion

z= X_test.copy()
z['Response real']=y_test
```

```
z['Response prediccion']=y_predict
z[['Response real','Response prediccion']].head(10)
```

Out[ ]:

| | Response real | Response prediccion |
|---|---|---|
| **37604** | 0.00 | 1.00 |
| **30687** | 0.00 | 0.00 |
| **36985** | 0.00 | 1.00 |
| **29143** | 1.00 | 0.00 |
| **32278** | 0.00 | 0.00 |
| **838** | 0.00 | 0.00 |
| **17132** | 0.00 | 0.00 |
| **6897** | 0.00 | 0.00 |
| **28953** | 0.00 | 1.00 |
| **9427** | 0.00 | 0.00 |

In [ ]:

```
# Genera los coeficientes de la ecuacion
coef_df = pd.DataFrame(model.coef_)
coef_df.columns = X.columns
# Incluye el intercept
coef_df['intercept']=model.intercept_
coef_df.T.sort_values(by=0)
```

Out[ ]:

| | 0 |
|---|---|
| **age-log** | -1.47 |
| **month_2** | -0.80 |
| **month_3** | -0.67 |
| **job_services** | -0.21 |
| **job_blue-collar** | -0.21 |
| **previous** | -0.17 |
| **day_of_week_mon** | -0.12 |
| **campaign** | -0.07 |
| **loan** | -0.05 |
| **housing** | -0.05 |
| **job_technician** | -0.04 |
| **default** | -0.03 |
| **day_of_week_tue** | -0.03 |
| **day_of_week_thu** | -0.02 |
| **nr.employed** | -0.01 |
| **pdays** | -0.00 |
| **job_management** | 0.01 |
| **age** | 0.03 |
| **cons.conf.idx** | 0.05 |
| **education_basic.9y** | 0.05 |
| **education_high.school** | 0.05 |
| **education_professional.course** | 0.06 |
| **marital_married** | 0.08 |
| **job_other** | 0.08 |

| | 0 |
|---|---|
| **day_of_week_wed** | 0.13 |
| **campaign-log** | 0.13 |
| **education_university.degree** | 0.17 |
| **marital_single** | 0.21 |
| **education_basic.6y** | 0.22 |
| **poutcome_nonexistent** | 0.30 |
| **poutcome_success** | 0.38 |
| **cons.price.idx** | 0.64 |
| **intercept** | 0.67 |
| **contact** | 0.96 |

In [ ]:
```
# Armar los valores de cada prediccion
```

## Matriz de Confusion

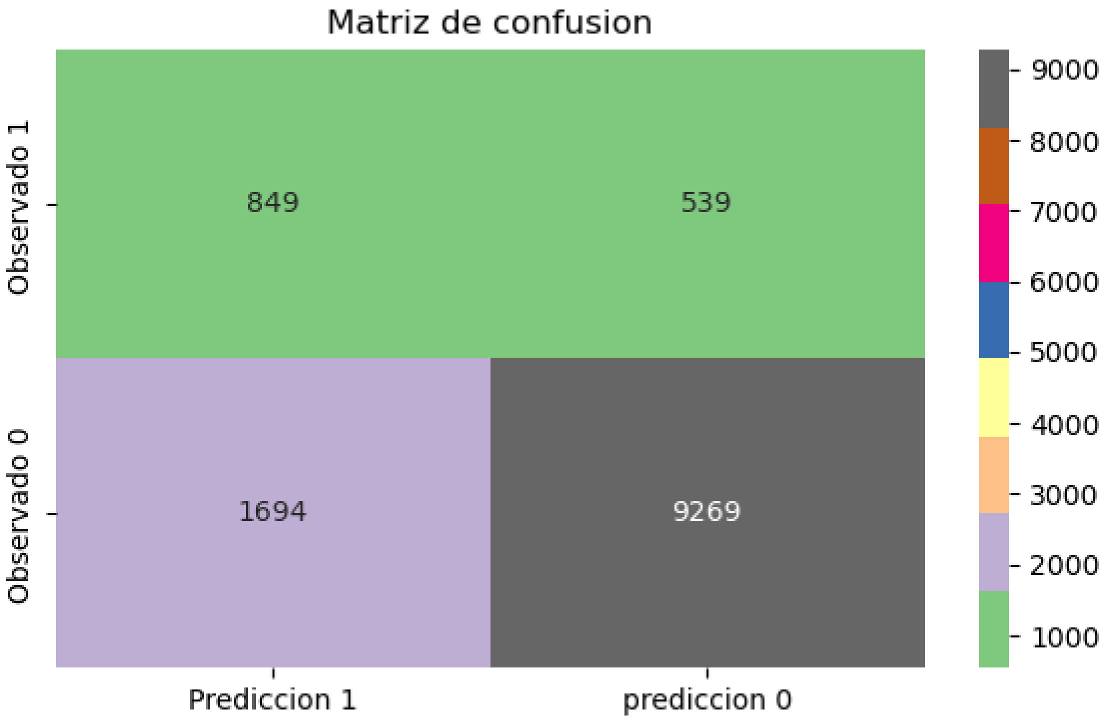
- Entender Falsos positivos, Falsos negativos
- Medidas de precision de modelos

In [ ]:
```
cm=metrics.confusion_matrix(y_test, y_predict, labels=[1,0])

df_cm= pd.DataFrame(cm,index=[i for i in['Observado 1','Observado 0']],
                    columns = [i for i in['Prediccion 1','prediccion 0']])

plt.figure(figsize=(7,4))
sns.heatmap(df_cm,annot=True, cmap='Accent',fmt='d').set_title('Matriz de confusion')
```

Out[ ]:
```
Text(0.5, 1.0, 'Matriz de confusion')
```




In [ ]:

```
df_cm
```

Out[ ]:

| | Prediccion 1 | prediccion 0 |
|---|---|---|
| **Observado 1** | 849 | 539 |
| **Observado 0** | 1694 | 9269 |

In [ ]:

```
# Un TP es un valor que fue observado y predicho como positivo
# Un TN es un valor que fue observado y predicho como negativo
# Un FP es un valor que fue observado como negarivo pero predicho como positivo
# Un FN es un valor que fue observado como positivo pero predicho como negativo


TP= df_cm.iloc[0][0]
FP= df_cm.iloc[0][1]
FN= df_cm.iloc[1][0]
TN= df_cm.iloc[1][1]
```

```
print('TP =',TP,'FP =',FP,'FN =',FN,'TN =',TN)
```

```
TP = 849 FP = 539 FN = 1694 TN = 9269
```

In [ ]:
```
# Medidas del Modelo
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, roc_auc_score, classification_report, confu

y_pred = model.predict(X_test)
model_score = accuracy_score(y_test,y_pred)
recall_score = recall_score(y_test,y_pred)
precision_score = precision_score(y_test,y_pred)
f1_score=f1_score(y_test,y_pred)

print('Medidas del Modelo')
print('________')
print('Accuracy = {0:0.2f}'.format(model_score))
print('Precision = {0:0.2f}'.format(precision_score))
print('Recall = {0:0.2f}'.format(recall_score))
print('F1 Score = {0:0.2f}'.format(f1_score))
print('Roc Auc Score = {0:0.2f}'.format(roc_auc_score(y_test,y_predict)))
```

```
Medidas del Modelo
________
Accuracy = 0.82
Precision = 0.33
Recall = 0.61
F1 Score = 0.43
Roc Auc Score = 0.73
```

- La exactitud (acuracy) de este modelo representa el porcentaje de predicciones correctas frente al total. Para este caso laexactitud fue del 82%
- la presición del modelo es mucho más baja (0.33) y se refiere a lo cerca que esta el modelo de predecir un valor verdadero.
- La sensibilidad (recall) es la proporcion entre los casos positivos bien clasificados por el modelo, respecto al total de positivos. para nuestro modelo esto equivale al 61% de lo que se podría decir que nuestro algoritmo de clasificación es medianamente sensible.

In [ ]:
```
# Create a dataframe with the predicion, y_hats
y_hats = pd.DataFrame(y_pred)

# Resets index fory_test
df_out = y_test.reset_index()
```

```
df_out['Actual']=y_test.reset_index()['y']
df_out['Prediction']=y_hats.reset_index()[0]
df_out.drop('index', axis=1, inplace=True)

df_out = df_out[df_out['Actual']!=df_out['Prediction']]
print(len(df_out),'registros donde lo observado <> predicho')
```

```
2233 registros donde lo observado <> predicho
```

In [ ]:

```
df_out
```

Out[ ]:

| | y | Actual | Prediction |
|---|---|---|---|
| **0** | 0.00 | 0.00 | 1.00 |
| **2** | 0.00 | 0.00 | 1.00 |
| **3** | 1.00 | 1.00 | 0.00 |
| **8** | 0.00 | 0.00 | 1.00 |
| **12** | 1.00 | 1.00 | 0.00 |
| **...** | ... | ... | ... |
| **12304** | 0.00 | 0.00 | 1.00 |
| **12318** | 0.00 | 0.00 | 1.00 |
| **12320** | 0.00 | 0.00 | 1.00 |
| **12322** | 0.00 | 0.00 | 1.00 |
| **12332** | 1.00 | 1.00 | 0.00 |

2233 rows × 3 columns