Bank Marketing Dataset - Data Dictionary

Dataset Information

Title: Bank Marketing (with social/economic context)

Source: UCI Machine Learning Repository **Created by:** Sérgio Moro (ISCTE-IUL), Paulo Cortez (Univ. Minho) and Paulo Rita (ISCTE-IUL) @ 2014

Citation

If you use this dataset, please include the following citation:

> [Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, In press, http://dx.doi.org/10.1016/j.dss.2014.03.001

Dataset Overview

- **Number of Instances:** 41,188 (bank-additional-full.csv)
- **Number of Features:** 20 input variables + 1 output variable
- **Time Period:** May 2008 to November 2010
- **Target Variable:** Binary classification - predict if the client will subscribe a bank term deposit

Feature Descriptions

Bank Client Data

Variable	Type	Description	Values
`age`	Numeric	Age of the client	Integer values
`job`	Categorical	Type of job	"admin.", "blue-collar", "entrepreneur", "housemaid", "management", "retired", "self-employed", "services", "student", "technician", "unemployed", "unknown"
`marital`	Categorical	Marital status	"divorced", "married", "single", "unknown" *Note: "divorced" includes divorced or widowed*
`education`	Categorical	Education level	"basic.4y", "basic.6y", "basic.9y", "high.school", "illiterate", "professional.course", "university.degree", "unknown"
`default`	Categorical	Has credit in default?	"no", "yes", "unknown"
`housing`	Categorical	Has housing loan?	"no", "yes", "unknown"
`loan`	Categorical	Has personal loan?	"no", "yes", "unknown"

Last Contact Information (Current Campaign)

Variable	Type	Description	Values
`contact`	Categorical	Contact communication type	"cellular", "telephone"
`month`	Categorical	Last contact month of year	"jan", "feb", "mar", "apr", "may", "jun", "jul", "aug", "sep", "oct", "nov", "dec"
`day_of_week`	Categorical	Last contact day of the week	"mon", "tue", "wed", "thu", "fri"
`duration`	Numeric	Last contact duration (seconds)	Integer values ⚠️ **Important: See note below**

Campaign Information

Variable	Type	Description	Values
`campaign`	Numeric	Number of contacts performed during this campaign for this client	Integer (includes last contact)
`pdays`	Numeric	Days since client was last contacted from a previous campaign	Integer (999 = not previously contacted)
`previous`	Numeric	Number of contacts performed before this campaign for this client	Integer
`poutcome`	Categorical	Outcome of the previous marketing campaign	"failure", "nonexistent", "success"

Social and Economic Context Attributes

Variable	Type	Description	Indicator Type
`emp.var.rate`	Numeric	Employment variation rate	Quarterly indicator
`cons.price.idx`	Numeric	Consumer price index	Monthly indicator
`cons.conf.idx`	Numeric	Consumer confidence index	Monthly indicator
`euribor3m`	Numeric	Euribor 3 month rate	Daily indicator
`nr.employed`	Numeric	Number of employees	Quarterly indicator

Target Variable

Variable	Type	Description	Values
`y`	Binary	Has the client subscribed a term deposit?	"yes", "no"

Important Notes

Duration Variable Warning

⚠️ **Critical Note about `duration` variable:**

- This attribute highly affects the output target (if duration=0 then y="no")
- Duration is not known before a call is performed
- After the call ends, the outcome (y) is obviously known
- **Recommendation:** This variable should only be included for benchmark purposes and should be **discarded** if the intention is to have a realistic predictive model

Missing Values

- Several categorical attributes contain missing values
- All missing values are coded with the label **"unknown"**
- These can be treated as:
  - A possible class label
  - Handled using deletion techniques
  - Handled using imputation techniques

Dataset Versions

The dataset comes in two versions:

1. **bank-additional-full.csv**: Full dataset with 41,188 examples (ordered by date)
2. **bank-additional.csv**: 10% sample with 4,119 examples (randomly selected)
   - Provided for testing computationally demanding algorithms (e.g., SVM)

Additional Resources

- Original Paper
- UCI Repository
- Banco de Portugal Statistics

Data Dictionary 📊

Variable Name	Role	Type	Description
age	Feature	Numeric 🔢	Client's age.
job	Feature	Categorical 🏷️	Type of job: "admin.", "unknown", "unemployed", "management", "housemaid", "entrepreneur", "student", "blue-collar", "self-employed", "retired", "technician", "services".
marital	Feature	Categorical 🏷️	Marital status: "married", "divorced", "single". Note: "divorced" includes widowed. 💔
education	Feature	Categorical 🏷️	Education level: "unknown", "secondary", "primary", "tertiary". 🎓
default	Feature	Binary ✅❌	Has credit in default?: "yes" or "no". ⚠️
balance	Feature	Numeric 🔢	Average yearly balance. 💰

Variable Name	Role	Type	Description
housing	Feature	Binary ✅❌	Has a housing loan?: "yes" or "no". 🏠
loan	Feature	Binary ✅❌	Has a personal loan?: "yes" or "no". 💳
contact	Feature	Categorical 🏷️	Contact communication type: "unknown", "telephone", "cellular". 📞📱
day	Feature	Numeric 🔢	Last contact day of the month. 🗓️
month	Feature	Categorical 🏷️	Last contact month of the year: "jan", "feb", "mar", ..., "nov", "dec". 🗓️
duration	Feature	Numeric 🔢	Last contact duration. ⏱️
campaign	Feature	Numeric 🔢	Number of contacts performed during this campaign for this client. 📢
pdays	Feature	Numeric 🔢	Days since client was last contacted from a previous campaign (-1 means not previously contacted). 🗓️
previous	Feature	Numeric 🔢	Number of contacts performed before this campaign for this client. 🔁
poutcome	Feature	Categorical 🏷️	Outcome of the previous marketing campaign: "unknown", "other", "failure", "success". 📈📉
y	Target	Binary ✅❌	Has the client subscribed to a term deposit?: "yes" or "no". 🎯

Legend 📝

- 🔢 **Numeric**: Continuous or discrete numerical values
- 🏷️ **Categorical**: Discrete categories or labels
- ✅❌ **Binary**: Yes/No or True/False values
- 🎯 **Target**: The variable we want to predict
- ⚠️ **Important**: Credit default status - critical risk indicator
- 💰 **Financial**: Money-related variable
- 📞📱 **Communication**: Contact method indicators
- ⏱️ **Time**: Duration or time-related measurements

In [1]:
```
import pandas as pd
from tools import *
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

# Set pandas display options for better readability
pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)
pd.set_option('display.max_colwidth', 50)
```

```
# Configuración de visualización
plt.style.use('default')
sns.set_palette("husl")
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 12


plt.style.use('seaborn-v0_8')
```

In [2]:
```
print("Step 1: Loading and preprocessing data...")
df = load_and_preprocess_data('data/bank-additional-full.csv')
basic_info = get_basic_info(df)
```

```
Step 1: Loading and preprocessing data...
```

In [3]:
```
# Step 2: Data quality analysis
print("Step 2: Analyzing data quality...")
quality_analysis = analyze_data_quality(df)
var_types = identify_variable_types(df)
```

```
Step 2: Analyzing data quality...
```

In [4]:
```
# Step 3: Target variable analysis
print("Step 3: Analyzing target variable...")
target_analysis = analyze_target_variable(df)
```

```
Step 3: Analyzing target variable...
```

In [5]:
```
# Step 4: Numeric variables analysis
print("Step 4: Analyzing numeric variables...")
numeric_analysis_general = analyze_numeric_variables(df, var_types['numeric'])
```

```
Step 4: Analyzing numeric variables...
```

In [6]:
```
# Step 5: Categorical variables analysis
print("Step 5: Analyzing categorical variables...")
categorical_analysis_general = analyze_categorical_variables(df, var_types['categorical'])
```

```
Step 5: Analyzing categorical variables...
```

In [7]:
```
selected_numeric='duration'
selected_categorical='job'
```

In [8]:
```
# Step 6: Focused bivariate analysis
print("Step 6: Performing bivariate analysis...")
numeric_bivariate = analyze_numeric_vs_target(df, selected_numeric)
categorical_bivariate = analyze_categorical_vs_target(df, selected_categorical)
```

```
Step 6: Performing bivariate analysis...
```

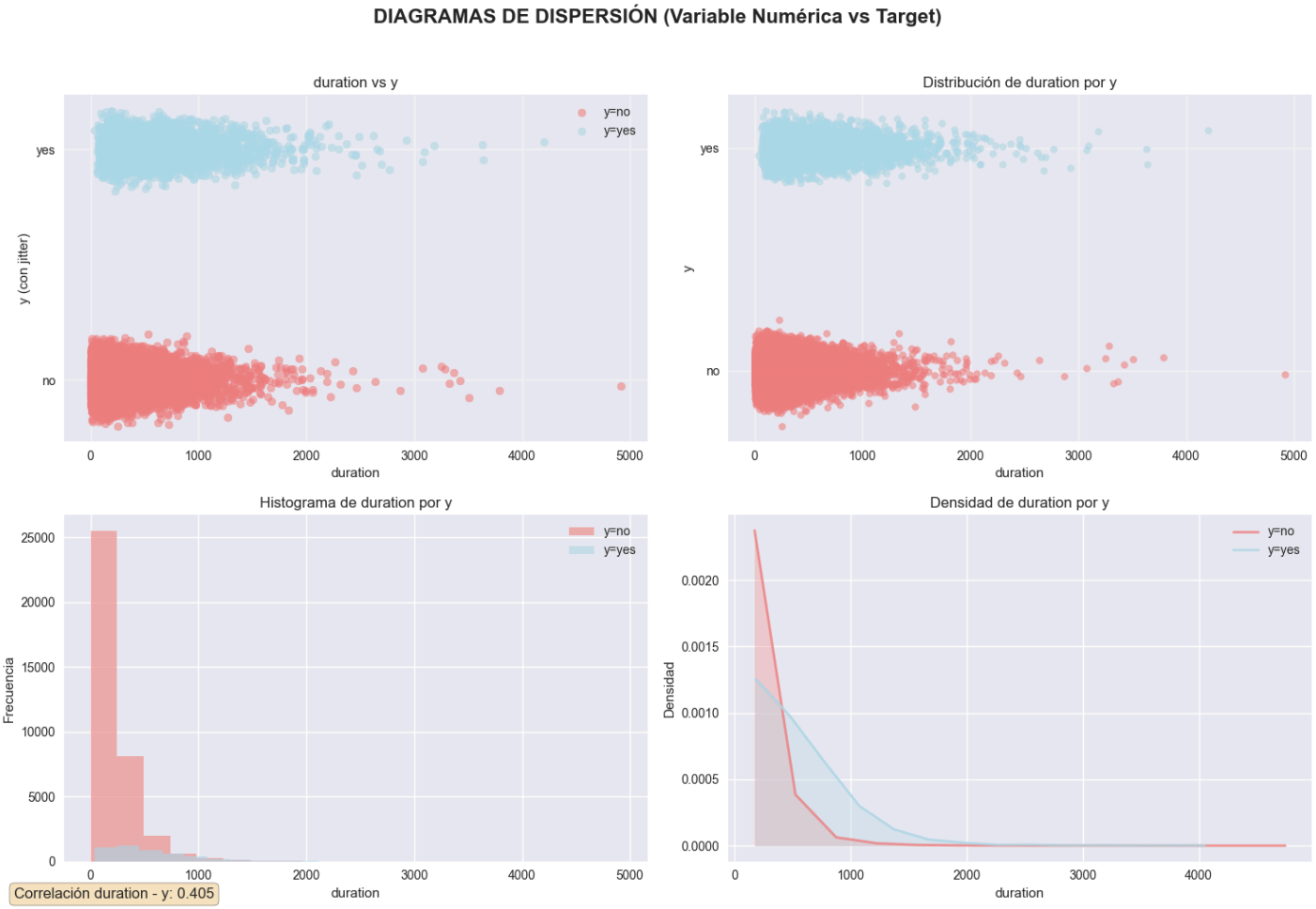
In [9]:
```
# Step 7: Correlation analysis
print("Step 7: Computing correlations...")
correlation_analysis = calculate_correlations(df, var_types['numeric'])
```

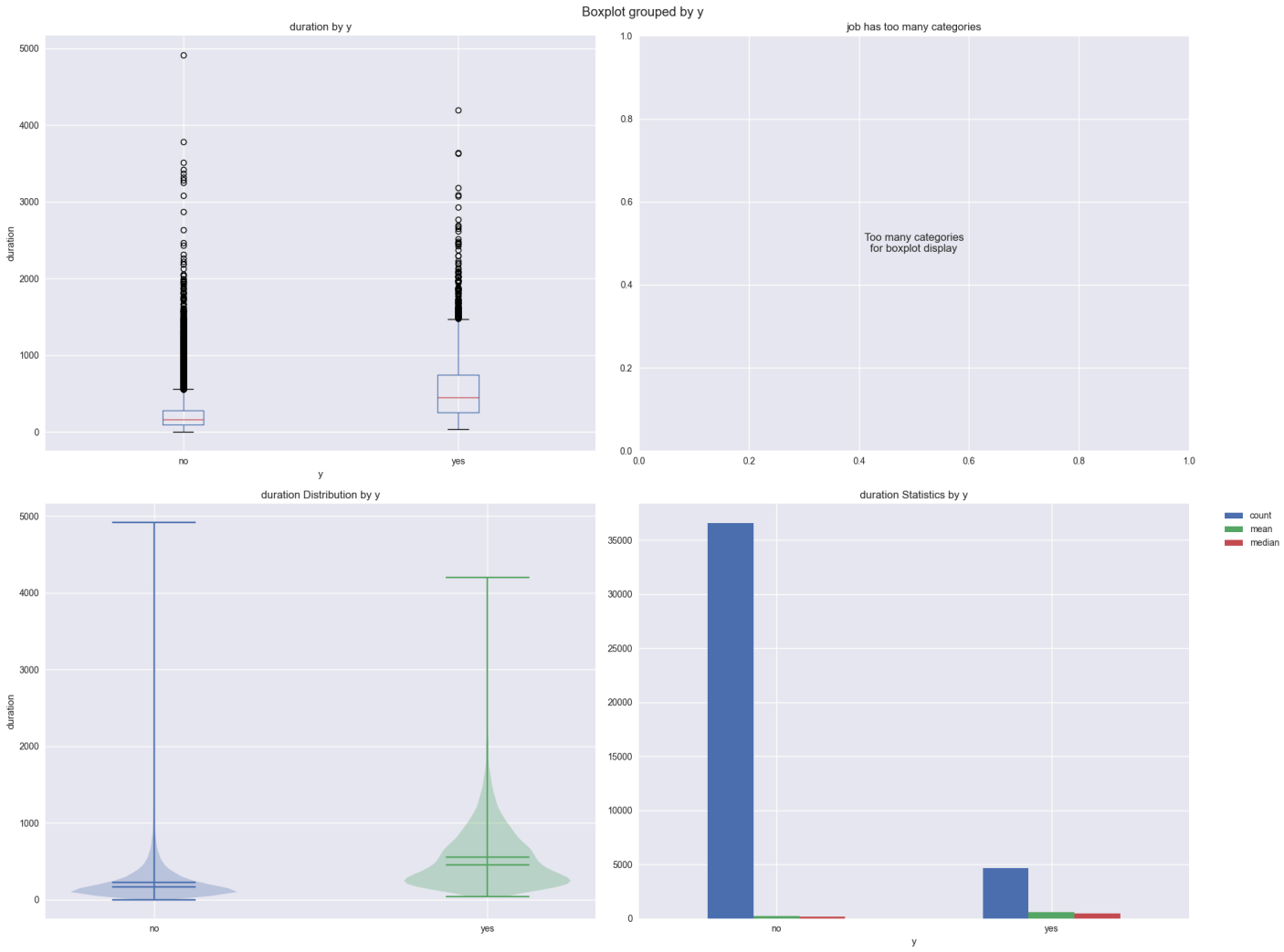
```
Step 7: Computing correlations...
```

In [10]:
```
# Step 8: Generate visualizations
print("Step 8: Creating all required visualization types...")

print("  → Generando Diagramas de Dispersión (variables numéricas)...")
fig1 = create_scatter_plots_numeric(df, selected_numeric)
```

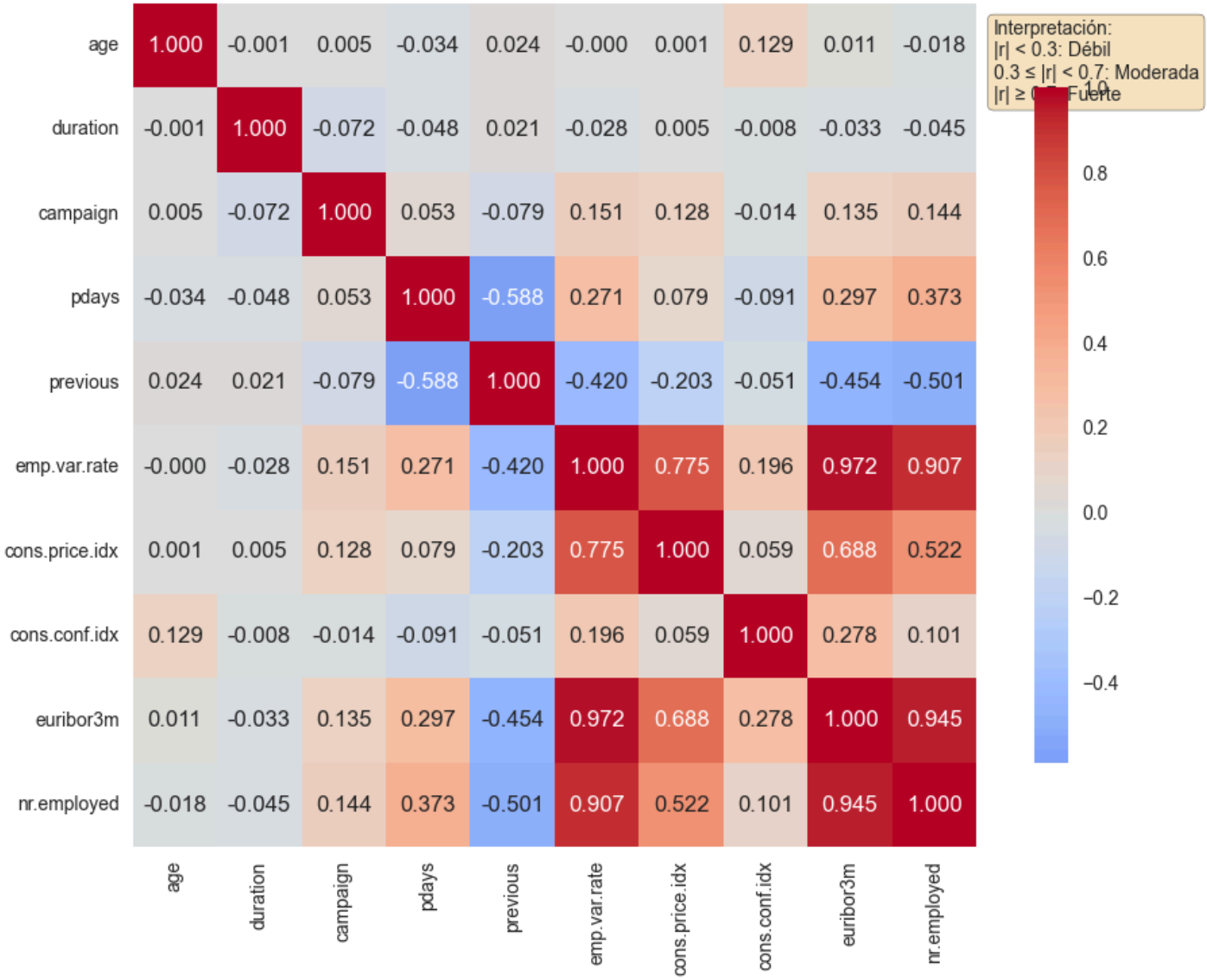
```
print("  → Generando Boxplots Comparativos (numérica vs categórica)...")

fig2 = create_comparative_boxplots(df, selected_numeric, selected_categorical)

print("  → Generando Heatmaps de Correlación (múltiples variables numéricas)...")
fig3 = create_correlation_heatmap(correlation_analysis)

print("  → Generando Gráficos de Barras y Stacked Charts (variables categóricas)...")
fig4 = create_categorical_bar_charts(df, selected_categorical)

# Additional: Target distribution for context
print("  → Generando distribución de variable objetivo...")
fig5 = create_target_distribution_plot(target_analysis)

plt.show()
```

```
Step 8: Creating all required visualization types...
  → Generando Diagramas de Dispersión (variables numéricas)...
  → Generando Boxplots Comparativos (numérica vs categórica)...
  → Generando Heatmaps de Correlación (múltiples variables numéricas)...
  → Generando Gráficos de Barras y Stacked Charts (variables categóricas)...
  → Generando distribución de variable objetivo...
```

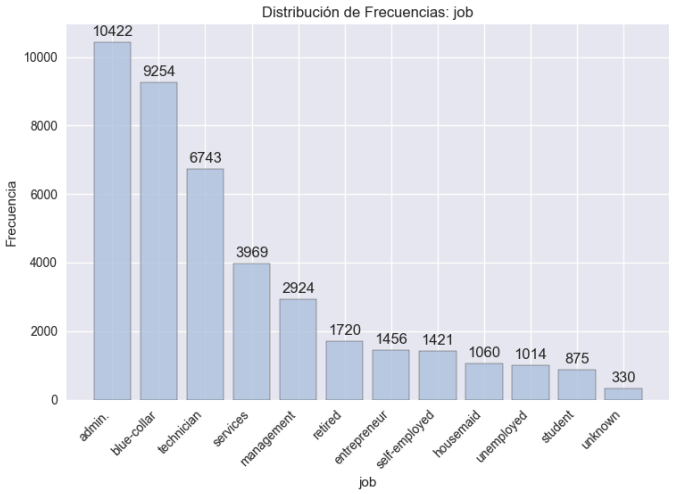


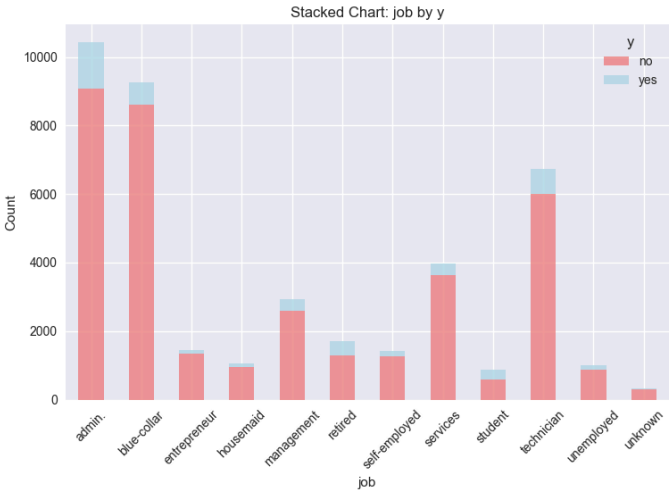

Boxplot grouped by y
duration by y
duration
y
no
yes
job has too many categories
Too many categories
for boxplot display
duration Distribution by y
duration
no
yes
duration Statistics by y
count
mean
median
y
no
yes

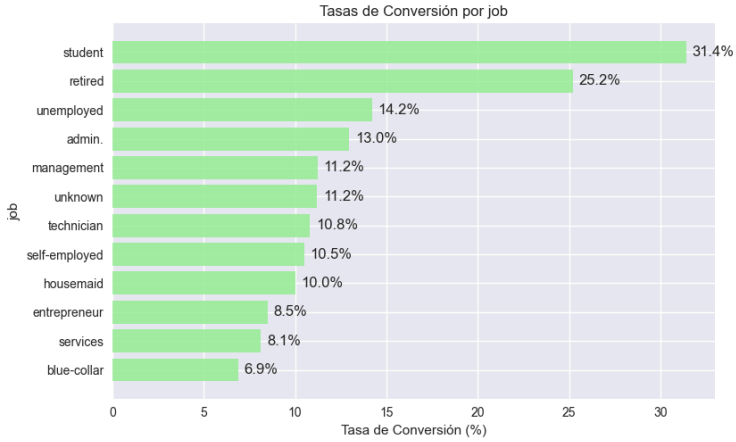
HEATMAP DE CORRELACIÓN (Variables Numéricas)

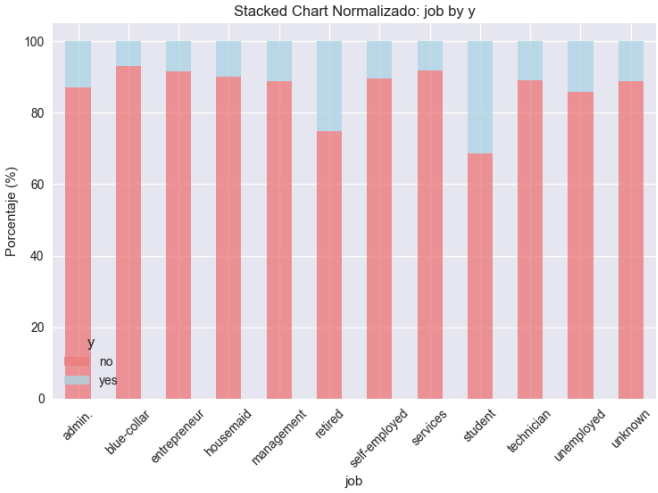


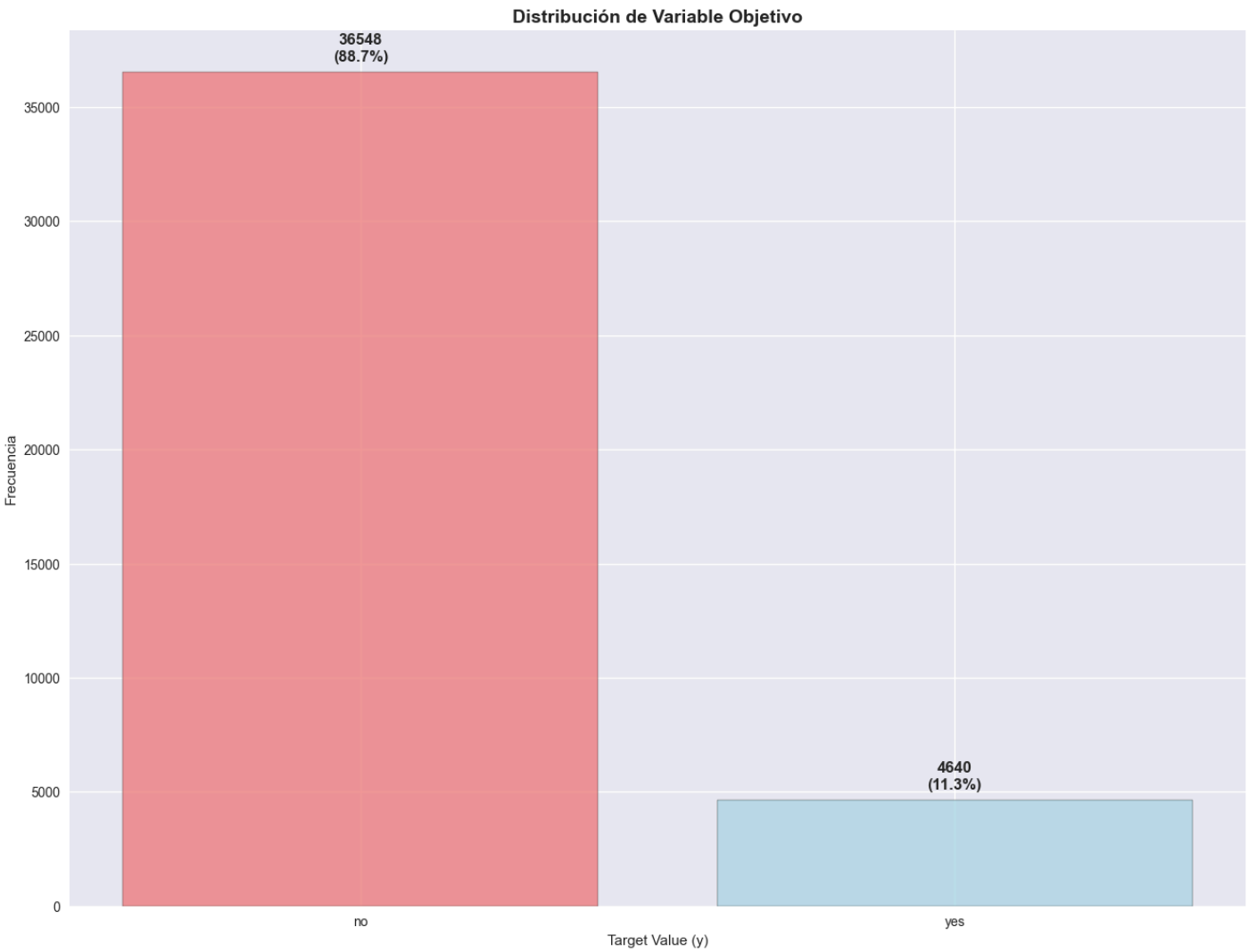
GRÁFICOS DE BARRAS Y STACKED CHARTS (Variables Categóricas)











In [11]:
```
# Step 9: Generate reports
print("Step 9: Generating reports...")
generate_data_quality_report(quality_analysis, var_types)
generate_target_analysis_report(target_analysis)
generate_bivariate_report(numeric_bivariate, categorical_bivariate,
                          selected_numeric, selected_categorical)
generate_summary_report(basic_info, target_analysis, correlation_analysis)
```

```
Step 9: Generating reports...

DATA QUALITY REPORT
==================
Dataset Shape: (22, 6)
Total Memory Usage: 30987.2 KB

Variable Types:
  Numeric: 10 variables
  Categorical: 11 variables

Low Variability Variables:
  default: 3 unique values
  housing: 3 unique values
  loan: 3 unique values
  contact: 2 unique values
  poutcome: 3 unique values
  y: 2 unique values

Data Quality Summary:
                  dtype  non_null  null_count  null_percentage  unique_values  \
Index               NaN       NaN         NaN              NaN            NaN
age               int64   41188.0         0.0              0.0           78.0
campaign          int64   41188.0         0.0              0.0           42.0
cons.conf.idx   float64   41188.0         0.0              0.0           26.0
cons.price.idx  float64   41188.0         0.0              0.0           26.0
contact          object   41188.0         0.0              0.0            2.0
day_of_week      object   41188.0         0.0              0.0            5.0
default          object   41188.0         0.0              0.0            3.0
duration          int64   41188.0         0.0              0.0         1544.0
education        object   41188.0         0.0              0.0            8.0
emp.var.rate    float64   41188.0         0.0              0.0           10.0
euribor3m       float64   41188.0         0.0              0.0          316.0
housing          object   41188.0         0.0              0.0            3.0
job              object   41188.0         0.0              0.0           12.0
loan             object   41188.0         0.0              0.0            3.0
marital          object   41188.0         0.0              0.0            4.0
month            object   41188.0         0.0              0.0           10.0
nr.employed     float64   41188.0         0.0              0.0           11.0
pdays             int64   41188.0         0.0              0.0           27.0
poutcome         object   41188.0         0.0              0.0            3.0
previous          int64   41188.0         0.0              0.0            8.0
y                object   41188.0         0.0              0.0            2.0

                memory_usage
Index                    128
age                   329504
campaign              329504
cons.conf.idx         329504
cons.price.idx        329504
contact              2692264
day_of_week          2471280
default              2473080
duration              329504
education            2871255
emp.var.rate          329504
euribor3m             329504
housing              2456618
job                  2716564
loan                 2441290
marital              2629076
month                2471280
```

```
nr.employed           329504
pdays                 329504
poutcome             2778284
previous              329504
y                    2434732

TARGET VARIABLE ANALYSIS
========================
Distribution:
  no: 36548 (88.73%)
  yes: 4640 (11.27%)

Dataset Balance: Imbalanced
Imbalance Ratio: 7.9:1
Minority Class: yes

BIVARIATE ANALYSIS REPORT
=========================

DURATION vs TARGET:
Group Statistics:
     count    mean  median     std  min   max
y
no   36548  220.84   163.5  207.10    0  4918
yes   4640  553.19   449.0  401.17   37  4199

Statistical Test (t-test):
  t-statistic: -89.9672
  p-value: 0.0000
  Significant: Yes


JOB vs TARGET:
Conversion Rates:
  student: 31.43%
  retired: 25.23%
  unemployed: 14.20%
  admin.: 12.97%
  management: 11.22%
  unknown: 11.21%
  technician: 10.83%
  self-employed: 10.49%
  housemaid: 10.00%
  entrepreneur: 8.52%
  services: 8.14%
  blue-collar: 6.89%

Chi-square Test:
  Chi-square: 961.2424
  p-value: 0.0000
  Significant: Yes

EXECUTIVE SUMMARY
=================
Dataset: 41188 records x 21 variables
Target Distribution: {'no': 88.73458288821988, 'yes': 11.265417111780131}
Data Quality: Good

Strong Correlations Found: 8
  pdays ↔ previous: -0.588
  previous ↔ nr.employed: -0.501
  emp.var.rate ↔ cons.price.idx: 0.775
```

```
  emp.var.rate ↔ euribor3m: 0.972
  emp.var.rate ↔ nr.employed: 0.907
  cons.price.idx ↔ euribor3m: 0.688
  cons.price.idx ↔ nr.employed: 0.522
  euribor3m ↔ nr.employed: 0.945

Limitations:
```