SAPIENZA
UNIVERSITÀ DI ROMA

...

TELCO CUSTOMER CHURN DATASET

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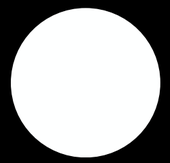
IL PROBLEMA

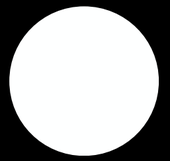
Classificazione

Input



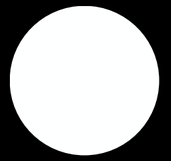
DATI ETEROGENEI (FINANZIARI, TECNICI, DEMOGRAFICI).

Task



CLASSIFICAZIONE BINARIA (YES/NO).

Vincolo



CLASSI SBILANCIATE (DATA IMBALANCE)

IL DATASET

Telco Customer Churn

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

Gruppo demografico

Gruppo tecnico

Gruppo finanziario

PRE PROCESSING E FEATURE ENGINEERING

Parte 1

PULIZIA DEL DATASET

```
# 1. La feature "customerID"
if "customerID" in data.columns: data.drop(columns=["customerID"], inplace=True)

# 2. La feature "TotalCharges" è il prodotto di "MonthlyCharges" e "tenure"
if "TotalCharges" in data.columns: data.drop(columns=["TotalCharges"], inplace=True)
```

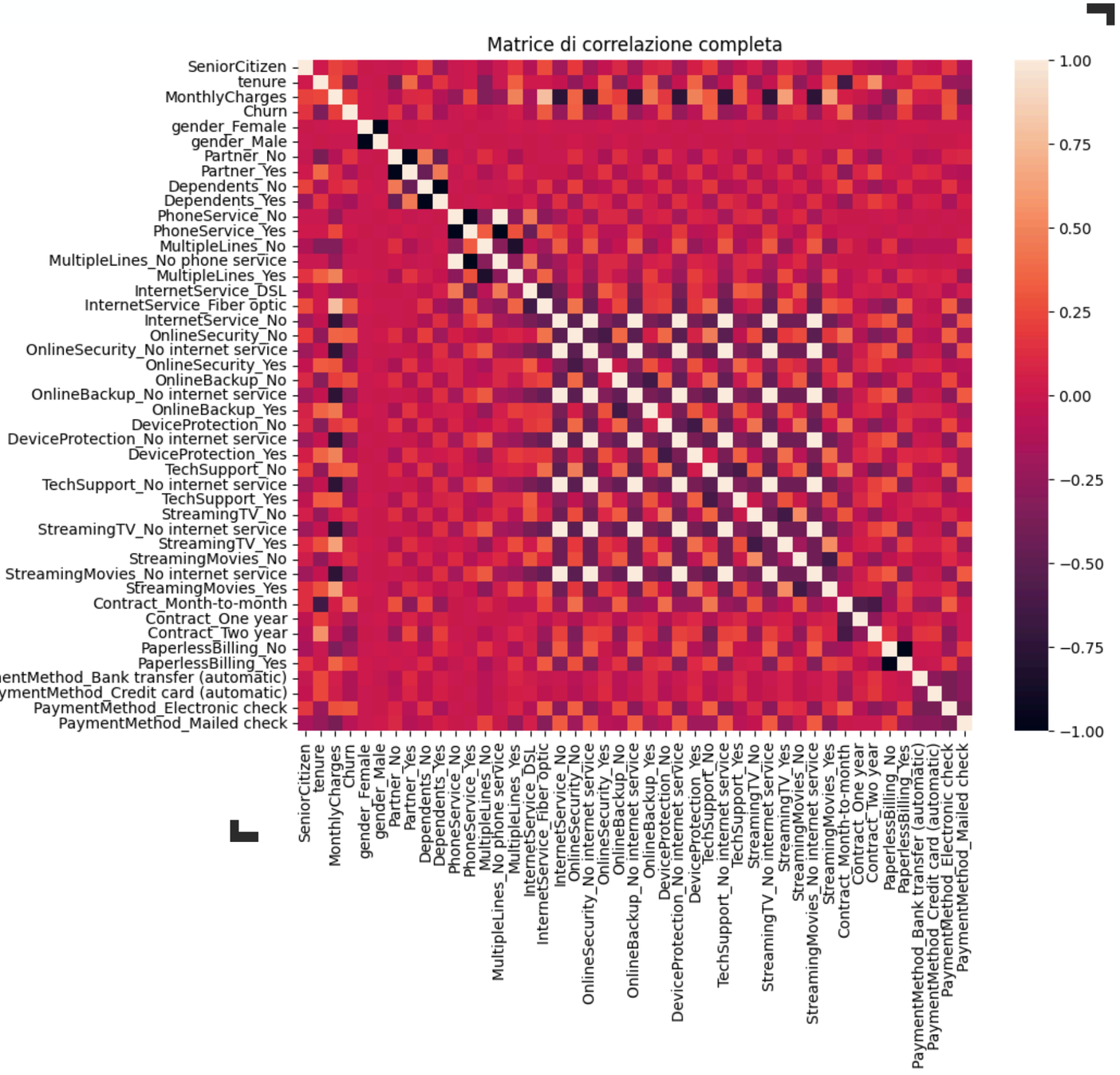
- Eliminazione delle variabili superflue
- Verifica dei valori nulli
- Operazione di One-hot encoding

```
valori_nulli = ["", "none", "n/a", "na", "null", "?"]
print("RICERCA VALORI NULLI - dtype object:")
print(data.select_dtypes(include="object").apply(lambda x:
x.astype(str).str.strip().str.lower().isin(valori_nulli).sum()))
print("\n")
print("RICERCA VALORI NULLI - dtype numerico:")
print(data.isna().sum())
```

```
data_dummy_provv = pd.get_dummies(data, drop_first=False, dtype=int)
```

ANALISI ESPLORATIVA DEI DATI

EDA

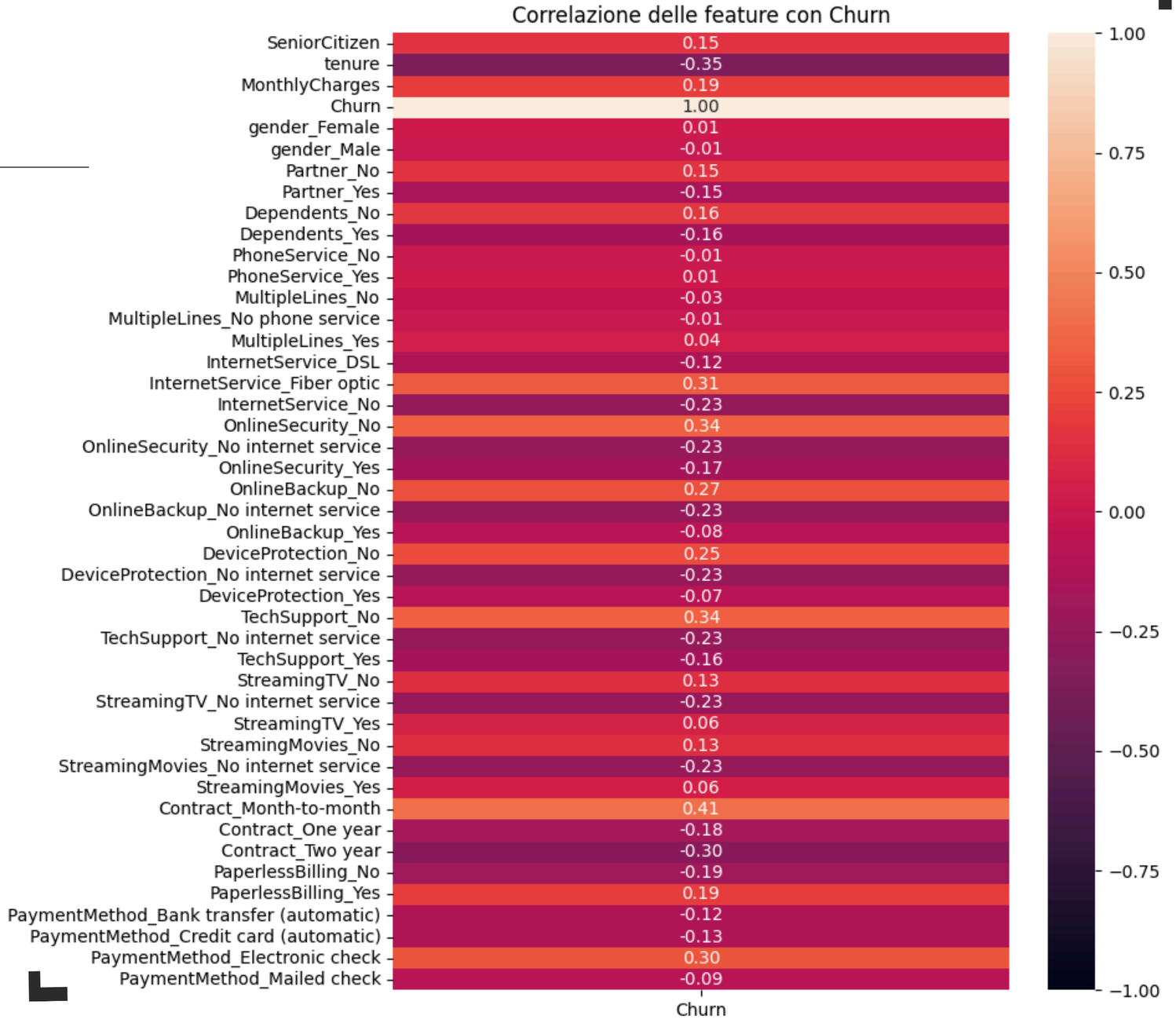


Heatmap completa

Osservazioni

- Mantenere “PhoneService_Yes” e “MultipleLines_No phone service” è ridondante.
- Mantenere tutti i valori che si concludono con "[...]_No internet service" è ridondante.

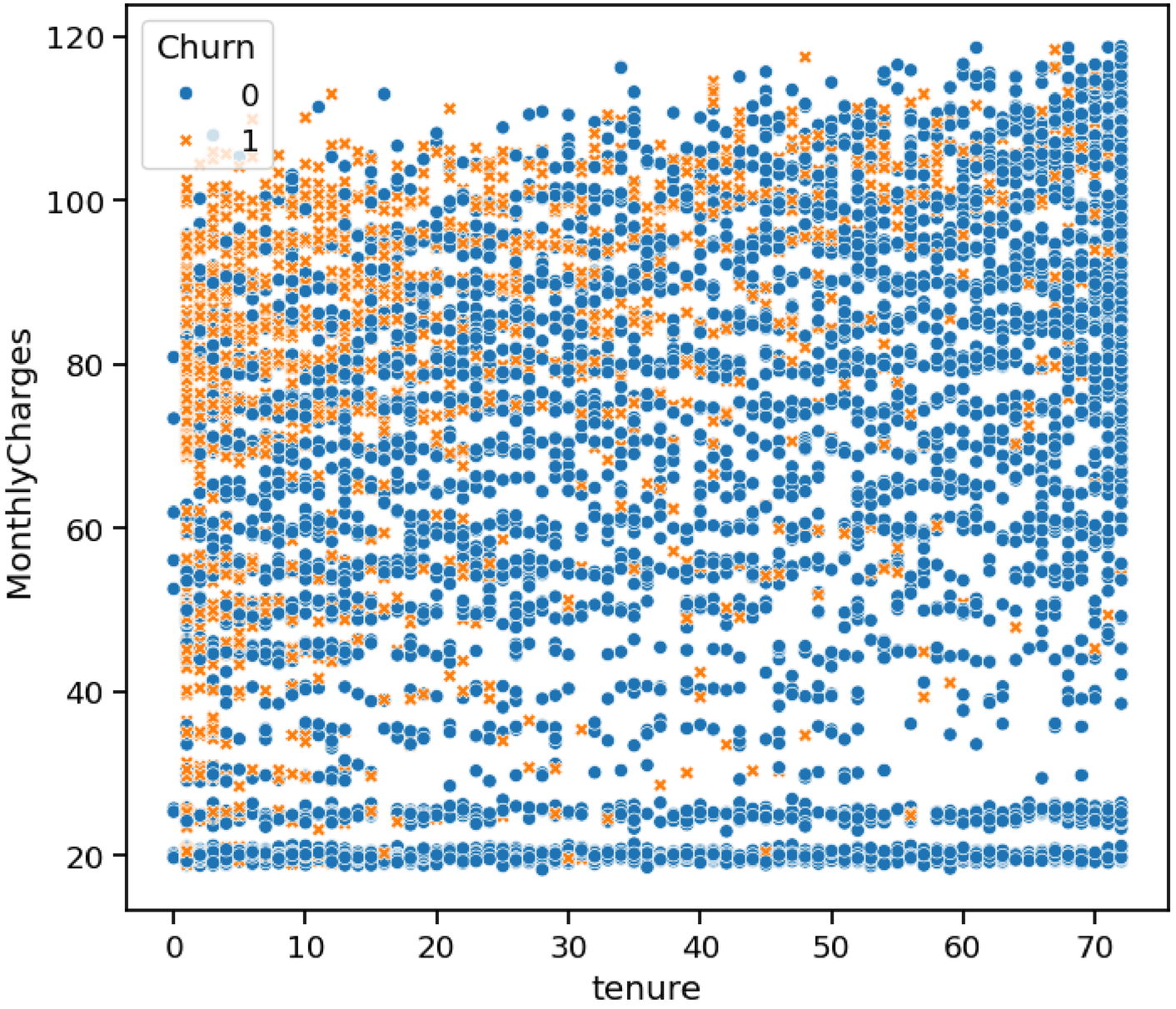
Heatmap della variabile target



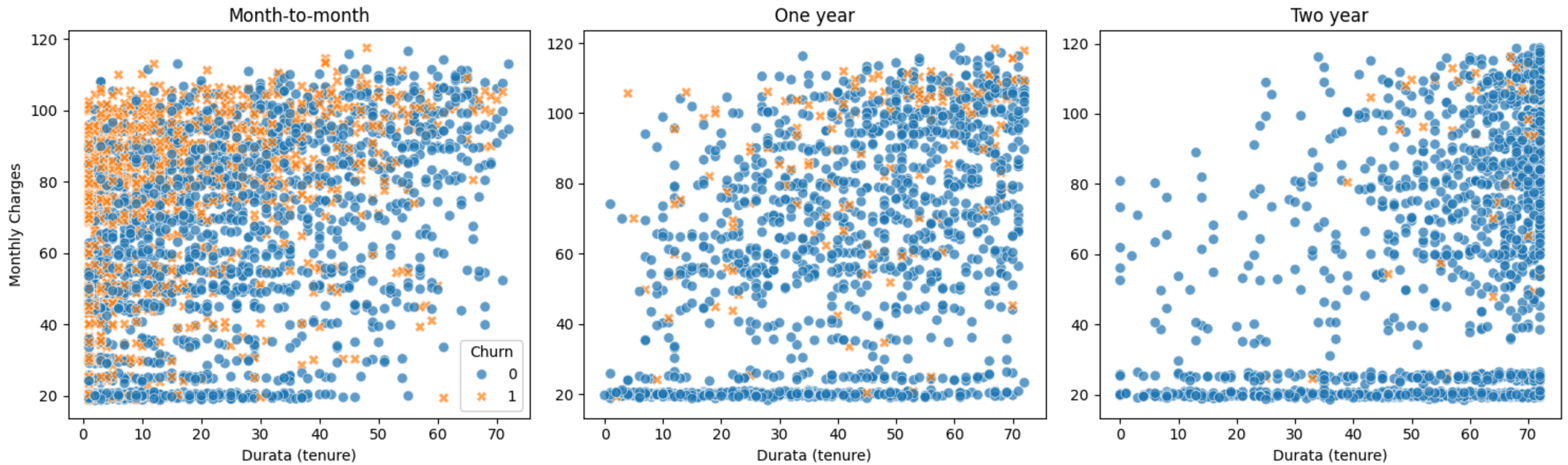
Scatter plot

Relazione tra tenure e Monthly charges rispetto alla variabile target

Relazione tra tenure e Monthly charges rispetto alla variabile target in correlazione con il tipo di contratto

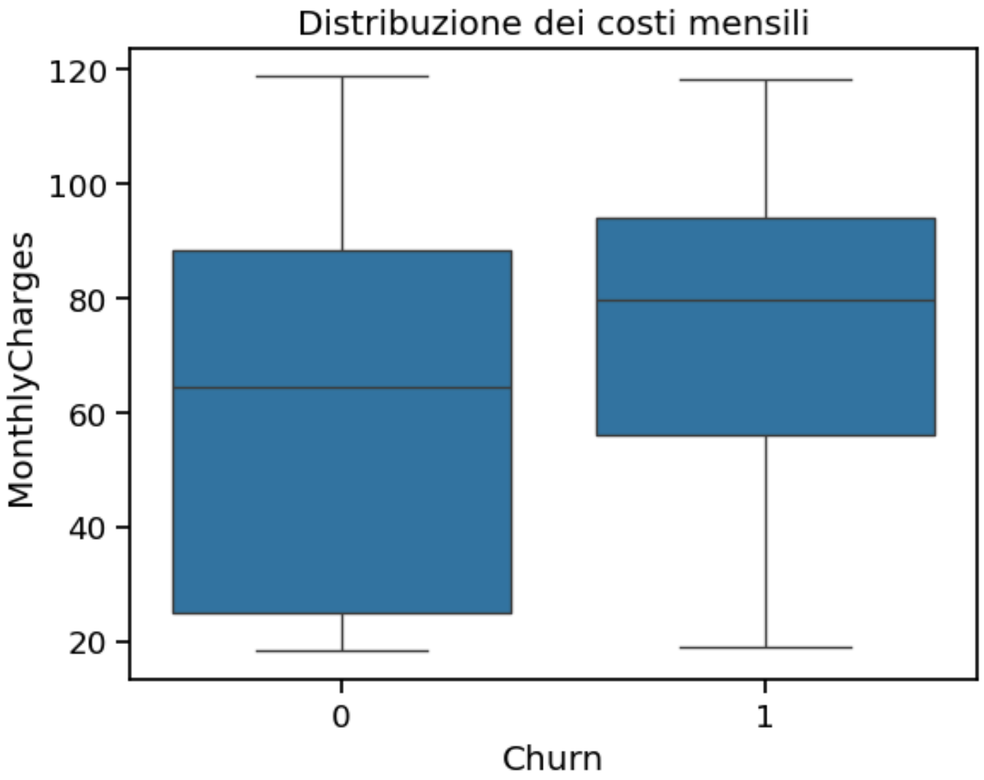

Churn
0
1
MonthlyCharges
120
100
80
60
40
20
0
10
20
30
40
50
60
70
tenure

```python
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

for i, contract_type in enumerate(data["Contract"].unique()):
    contract_data = data[data["Contract"] == contract_type]
    sns.scatterplot(data=contract_data, x="tenure", y="MonthlyCharges", hue="Churn", style="Churn",
    axes[i].set_title(contract_type)
    axes[i].set_xlabel("Durata (tenure)")

    if i == 0:
        axes[i].set_ylabel("Monthly Charges")
    else:
        axes[i].set_ylabel("")

    if i > 0:
        axes[i].get_legend().remove()

plt.suptitle("La durata del contratto impatta sulla permanenza del cliente?", y=1.05, fontsize=14)
plt.tight_layout()
plt.subplots_adjust(top=0.85)
plt.show()
```

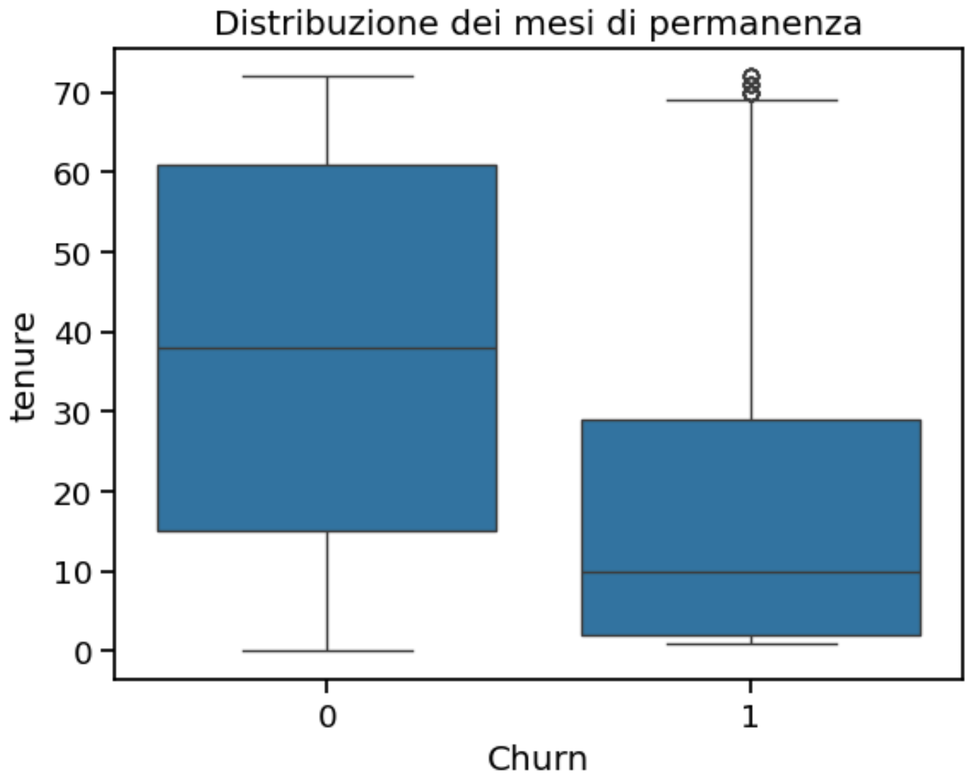


Boxplot

```
#### 1. MonthlyCharges
sns.boxplot(x='Churn', y='MonthlyCharges', data=data_dummy)
plt.title('Distribuzione dei costi mensili')
plt.show()
print("\n\n")
```




```
#### 2. tenure
sns.boxplot(x='Churn', y='tenure', data=data_dummy)
plt.title('Distribuzione dei mesi di permanenza')
plt.show()
```



PRE PROCESSING E FEATURE ENGINEERING

Parte 2

Verifica del bilanciamento delle classi

```
data.describe()[["Churn"]]
```

	Churn
count	7043.000000
mean	0.265370
std	0.441561
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

```
print("Distribuzione Variabile Target [Churn]:")
print((data["Churn"].value_counts()/len(data_dummy)) * 100)
```

```
Distribuzione Variabile Target [Churn]:
Churn
0    73.463013
1    26.536987
Name: count, dtype: float64
```

```
# Divisione del dataset training set e test set
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size = 0.2,
                 random_state = 42, stratify = y)
```

Normalizzazione

STATISTICHE

	tenure	MonthlyCharges	SeniorCitizen	Churn
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	32.371149	64.761692	0.162147	0.265370
std	24.559481	30.090047	0.368612	0.441561
min	0.000000	18.250000	0.000000	0.000000
25%	9.000000	35.500000	0.000000	0.000000
50%	29.000000	70.350000	0.000000	0.000000
75%	55.000000	89.850000	0.000000	1.000000
max	72.000000	118.750000	1.000000	1.000000

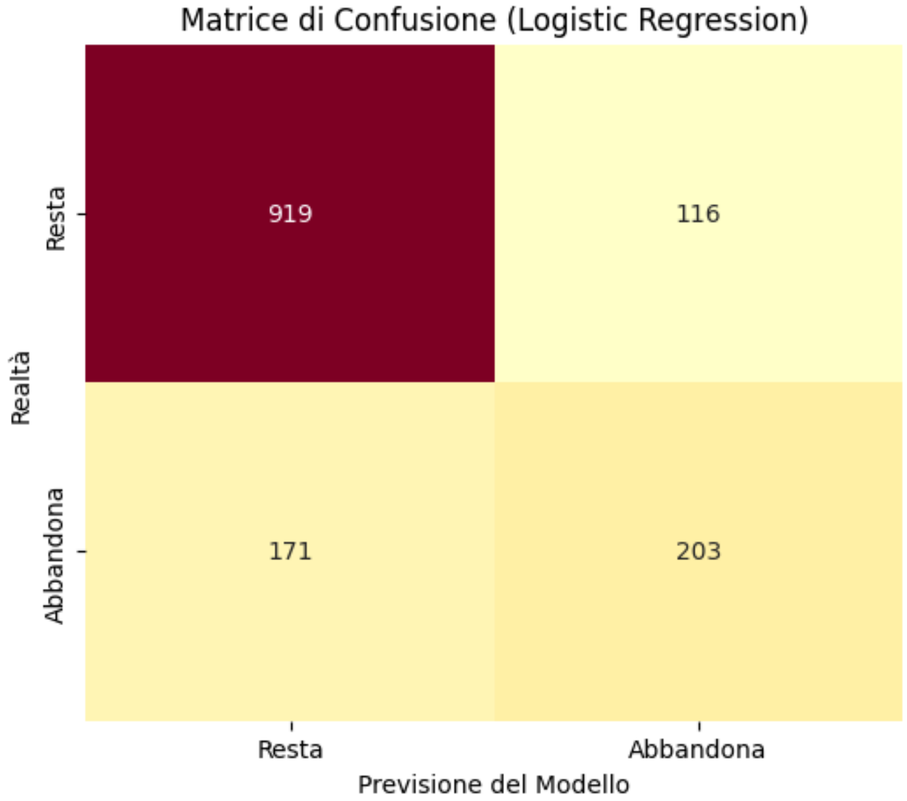
```
features_numeriche = ["tenure", "MonthlyCharges"]
scaler = MinMaxScaler()
X_train[features_numeriche] = scaler.fit_transform(X_train[features_numeriche])
X_test[features_numeriche] = scaler.transform(X_test[features_numeriche])
```

I MODELLI

Modello base

Modello base

```
RLogistica = LogisticRegression()
```

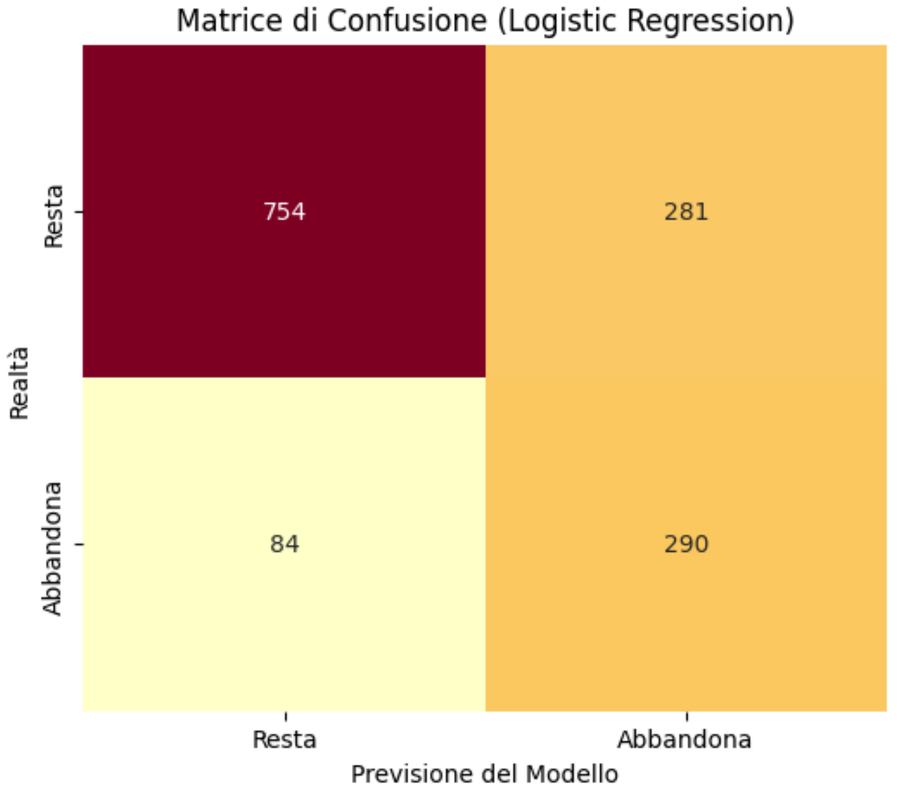


RIEPILOGO

	precision	recall	f1-score	support
0	0.84	0.89	0.86	1035
1	0.64	0.54	0.59	374
accuracy			0.80	1409
macro avg	0.74	0.72	0.73	1409
weighted avg	0.79	0.80	0.79	1409

Modello base bilanciato

```
RLogistica2 = LogisticRegression(class_weight='balanced', random_state=42)
```



RIEPILOGO

	precision	recall	f1-score	support
0	0.90	0.73	0.81	1035
1	0.51	0.78	0.61	374
accuracy			0.74	1409
macro avg	0.70	0.75	0.71	1409
weighted avg	0.80	0.74	0.75	1409

MODELLO CON SOGLIA OTTIMALE

1. CREIAMO IL TERZO MODELLO

```
RLOGISTICA3 = LOGISTICREGRESSION(CLASS_WEIGHT="BALANCED",
RANDOM_STATE=42)
```

2. RICORRIAMO ALLA CROSS-VALIDATION PER NON CALCOLARE LA SOGLIA INCLUDENDO IL TEST SET E CAUSANDO UNA DATA LEAKAGE

```
Y_PROB_CV = CROSS_VAL_PREDICT(RLOGISTICA3, X_TRAIN,
Y_TRAIN, CV=5, METHOD='PREDICT_PROBA')[:, 1]
```

3. CALCOLO SOGLIA OTTIMA

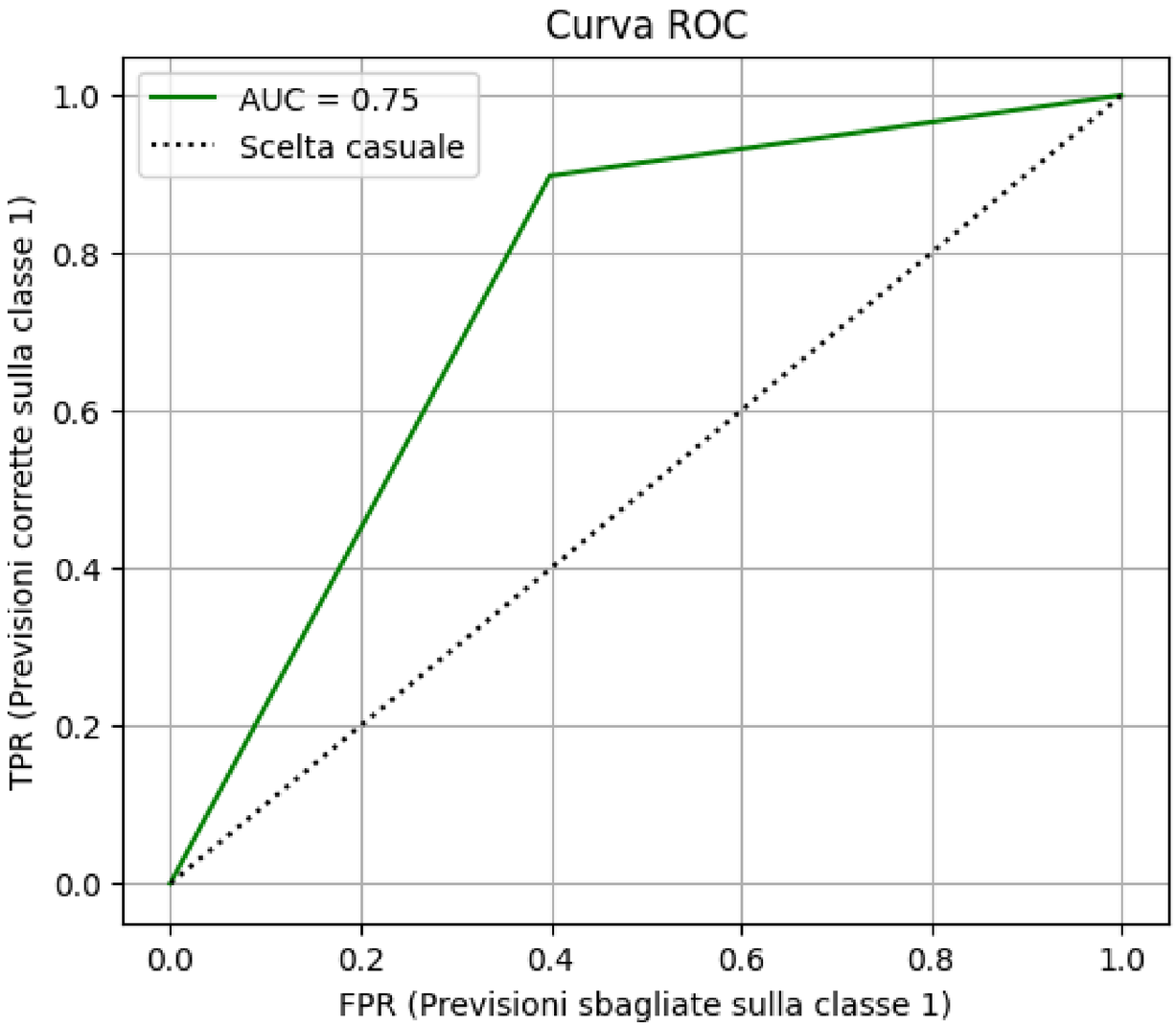
```
SOGLIE = NP.LINSPACE(0, 1, 100)
F2_SCORES = [FBETA_SCORE(Y_TRAIN, (Y_PROB_CV >= S).ASTYPE(INT),
BETA=2) FOR S IN SOGLIE]
SOGLIA_OTTIMA_1 = SOGLIE[NP.ARGMAX(F2_SCORES)]
```

4. FIT MODELLO

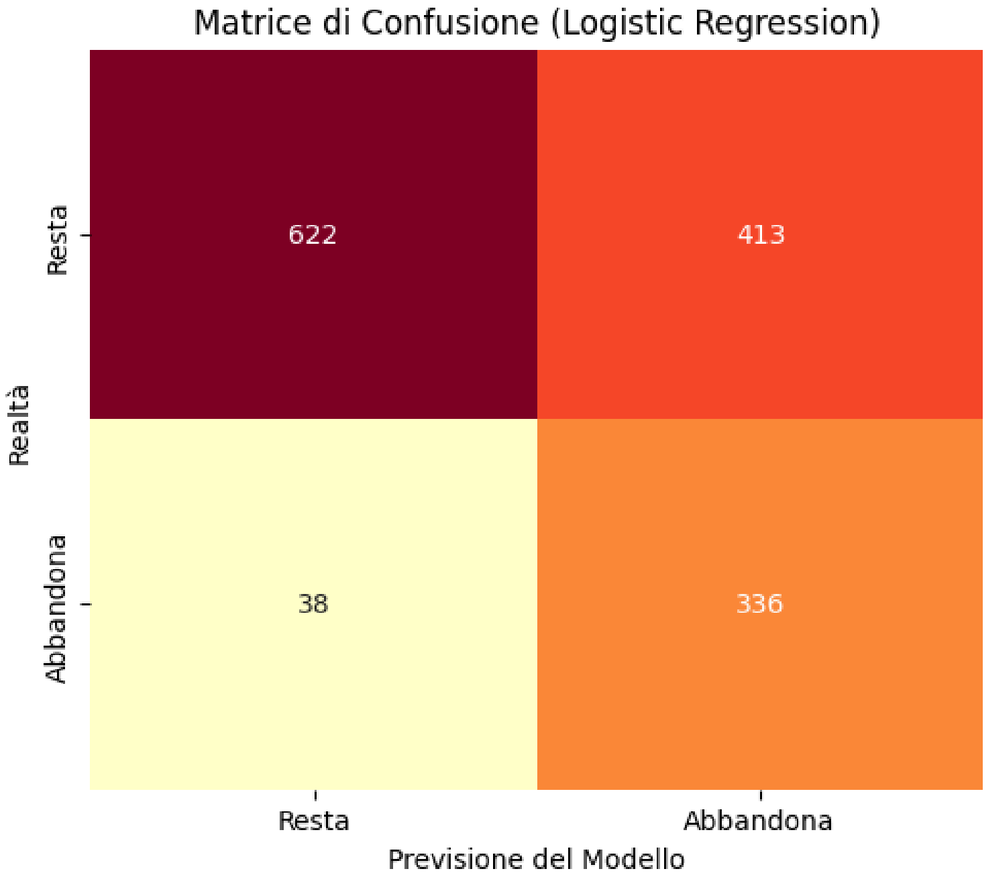
```
RLOGISTICA3.FIT(X_TRAIN, Y_TRAIN)
```

5. PREDIZIONE SUL TEST SET

```
Y_PROB = RLOGISTICA3.PREDICT_PROBA(X_TEST)[:, 1]
Y_SOGLIA = (Y_PROB >= SOGLIA_OTTIMA_1).ASTYPE(INT)
```



AUC SCORE
| 0.7497 |
SOGLIA OTTIMALE
| 0.3535 |



MODELLO CON SOGLIA OTTIMALE

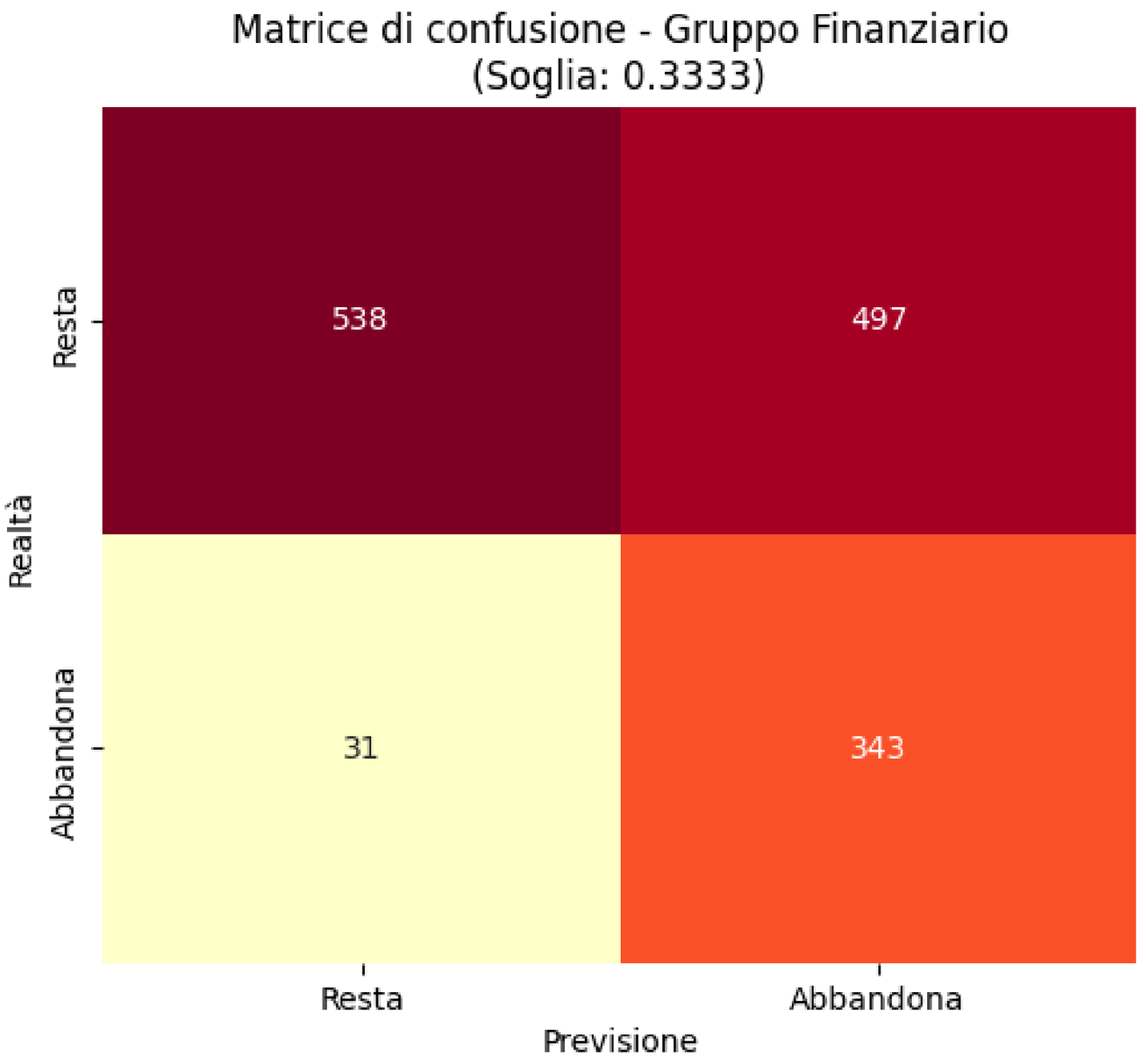
RIEPILOGO

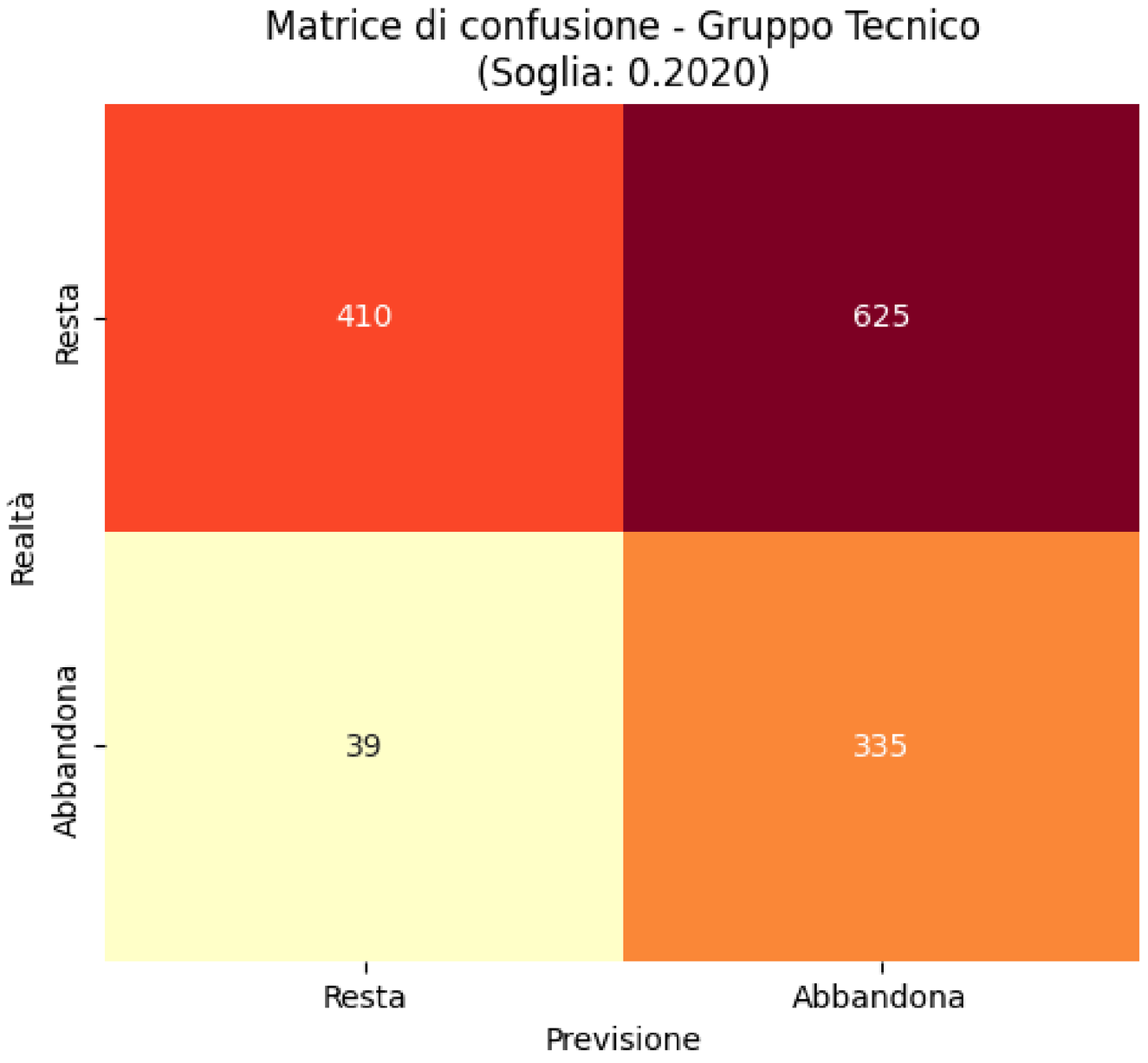
	precision	recall	f1-score	support
0	0.94	0.60	0.73	1035
1	0.45	0.90	0.60	374
accuracy			0.68	1409
macro avg	0.70	0.75	0.67	1409
weighted avg	0.81	0.68	0.70	1409

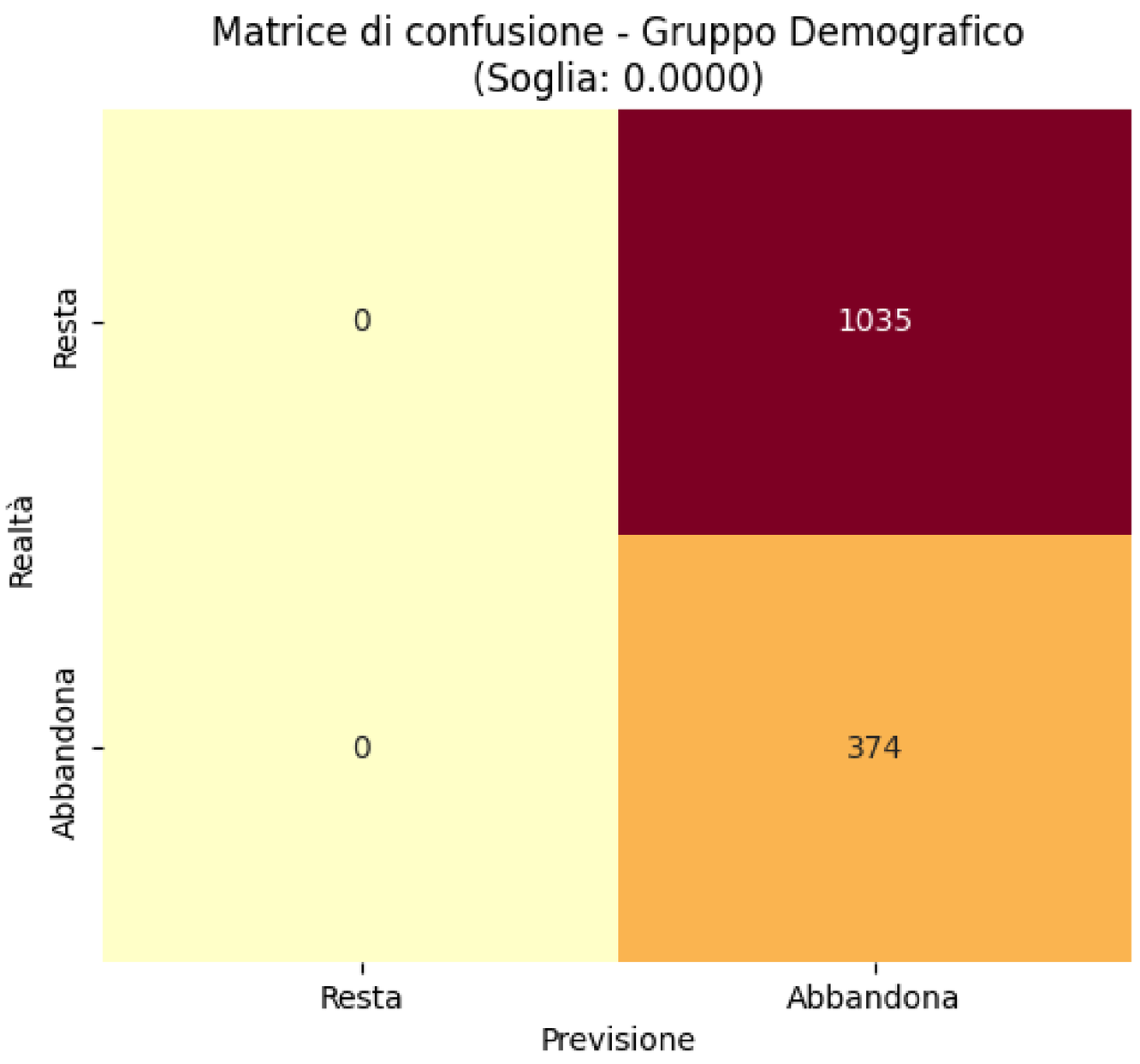
I MODELLI

Modelli tematici

GRUPPO TECNICO	["InternetService_Fiber optic", "InternetService_No", "OnlineSecurity_Yes", "TechSupport_Yes"]
GRUPPO FINANZIARIO	["MonthlyCharges", "Contract_One year", "Contract_Two year", "PaymentMethod_Electronic check", "PaperlessBilling_Yes"]
GRUPPO DEMOGRAFICO	["SeniorCitizen", "Partner_Yes", "Dependents_Yes", "gender_Male"]


Matrice di confusione - Gruppo Finanziario
(Soglia: 0.3333)
Realtà
Resta
Abbandona
538
497
31
343
Resta
Abbandona
Previsione


Matrice di confusione - Gruppo Tecnico
(Soglia: 0.2020)
Realtà
Resta
Abbandona
410
625
39
335
Resta
Abbandona
Previsione


Matrice di confusione - Gruppo Demografico
(Soglia: 0.0000)
Realtà
Resta
Abbandona
0
1035
0
374
Resta
Abbandona
Previsione

MODELLI	AUC	Recall	Precision	Soglia
Modello base non bilanciato	0.72	0.54	0.64	-
Modello base bilanciato	0.75	0.78	0.51	-
Modello base SO	0.75	0.90	0.45	0.35
Modello finanziario SO	0.79	0.92	0.41	0.33
Modello tecnico SO	0.75	0.90	0.35	0.20
Modello demografico SO	0.65	1.00	0.27	0.00

RISULTATI