Modelagem Preditiva

A Modelagem Preditiva envolve a criação de um modelo estatístico ou de aprendizado de máquina para prever um evento ou resultado futuro. No contexto do desafio de e-commerce com o dataset da Olist, a tarefa é criar um modelo de regressão logística para prever a probabilidade de conversão dos clientes (se um pedido será entregue ou não).

Instalação de bibliotecas

In [2]:
```
%pip install pandas matplotlib seaborn scikit-learn
```

```
Requirement already satisfied: pandas in c:\python312\lib\site-packages (2.2.2)
Requirement already satisfied: matplotlib in c:\python312\lib\site-packages (3.9.
2)
Requirement already satisfied: seaborn in c:\python312\lib\site-packages (0.13.2)
Requirement already satisfied: scikit-learn in c:\python312\lib\site-packages (1.
5.1)
Requirement already satisfied: numpy>=1.26.0 in c:\python312\lib\site-packages (f
rom pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\python312\lib\site-pa
ckages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\python312\lib\site-packages (fr
om pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\python312\lib\site-packages
(from pandas) (2024.1)
Requirement already satisfied: contourpy>=1.0.1 in c:\python312\lib\site-packages
(from matplotlib) (1.3.0)
Requirement already satisfied: cycler>=0.10 in c:\python312\lib\site-packages (fr
om matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\python312\lib\site-package
s (from matplotlib) (4.53.1)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\python312\lib\site-package
s (from matplotlib) (1.4.7)
Requirement already satisfied: packaging>=20.0 in c:\users\salom\appdata\roaming
\python\python312\site-packages (from matplotlib) (24.0)
Requirement already satisfied: pillow>=8 in c:\python312\lib\site-packages (from
matplotlib) (10.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\python312\lib\site-packages
(from matplotlib) (3.1.4)
Requirement already satisfied: scipy>=1.6.0 in c:\python312\lib\site-packages (fr
om scikit-learn) (1.14.1)
Requirement already satisfied: joblib>=1.2.0 in c:\python312\lib\site-packages (f
rom scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\python312\lib\site-pack
ages (from scikit-learn) (3.5.0)
Requirement already satisfied: six>=1.5 in c:\python312\lib\site-packages (from p
ython-dateutil>=2.8.2->pandas) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
[notice] A new release of pip is available: 24.0 -> 24.3.1
[notice] To update, run: python.exe -m pip install --upgrade pip
```

Preparação dos Dados

In [4]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_auc_score, roc_curve
import matplotlib.pyplot as plt
import seaborn as sns


# Carregar os datasets
customers = pd.read_csv("olist_customers_dataset.csv")
geolocation = pd.read_csv("olist_geolocation_dataset.csv")
order_items = pd.read_csv("olist_order_items_dataset.csv")
order_payments = pd.read_csv("olist_order_payments_dataset.csv")
order_reviews = pd.read_csv("olist_order_reviews_dataset.csv")
orders = pd.read_csv("olist_orders_dataset.csv")
products = pd.read_csv("olist_products_dataset.csv")
sellers = pd.read_csv("olist_sellers_dataset.csv")
product_category_translation = pd.read_csv("product_category_name_translation.cs

# Merge para obter payment_value, payment_installments:
orders = pd.merge(orders, order_payments[['order_id', 'payment_value', 'payment_

# Merge para obter review_score:
orders = pd.merge(orders, order_reviews[['order_id', 'review_score']], on='order

# Merge para freight_value (requer dois merges):
# Merge order_items com orders para customer_id:
order_items_merged = pd.merge(order_items, orders[['order_id', 'customer_id']],

# Calcule o frete médio por pedido
frete_medio = order_items_merged.groupby('order_id')['freight_value'].mean().res

# Merge com orders
orders = pd.merge(orders, frete_medio, on='order_id', how='left')

# Crie a variável alvo (conversão)
orders['converted'] = orders['order_status'].apply(lambda x: 1 if x == 'delivere

# Selecione as features para o modelo.  Exemplos:
features = ['payment_value', 'freight_value', 'payment_installments', 'review_sc
X = orders[features]

# Preencha valores ausentes (se houver) na variável 'review_score'
X['review_score'] = X['review_score'].fillna(X['review_score'].median())  # Ou o

y = orders['converted']
```

```
C:\Users\salom\AppData\Local\Temp\ipykernel_19300\2122939727.py:44: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  X['review_score'] = X['review_score'].fillna(X['review_score'].median())  # Ou
outra estratégia
```

Divisão Treino/Teste

In [ ]:
```
print("Valores NaN em X:\n", X.isna().sum())
print("\nValores NaN em y:\n", y.isna().sum())

X.dropna(inplace=True) # Remove linhas com NaN em qualquer coluna de X. ATENÇÃO:
y = y[X.index] #garante a correspondencia entre as bases

print("Valores NaN em X:\n", X.isna().sum())
print("\nValores NaN em y:\n", y.isna().sum())

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random
```

```
Valores NaN em X:
 payment_value              1
freight_value            833
payment_installments       1
review_score               0
dtype: int64

Valores NaN em y:
 0
Valores NaN em X:
 payment_value            0
freight_value            0
payment_installments     0
review_score             0
dtype: int64

Valores NaN em y:
 0
```

```
C:\Users\salom\AppData\Local\Temp\ipykernel_19300\3255796987.py:4: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  X.dropna(inplace=True) # Remove linhas com NaN em qualquer coluna de X. ATENÇÃ
O: certifique-se de que o y seja consistente com X
```

Treinamento do Modelo

In [9]:
```
model = LogisticRegression(random_state=42)  # Você pode ajustar os hiperparâmet
model.fit(X_train, y_train)
```

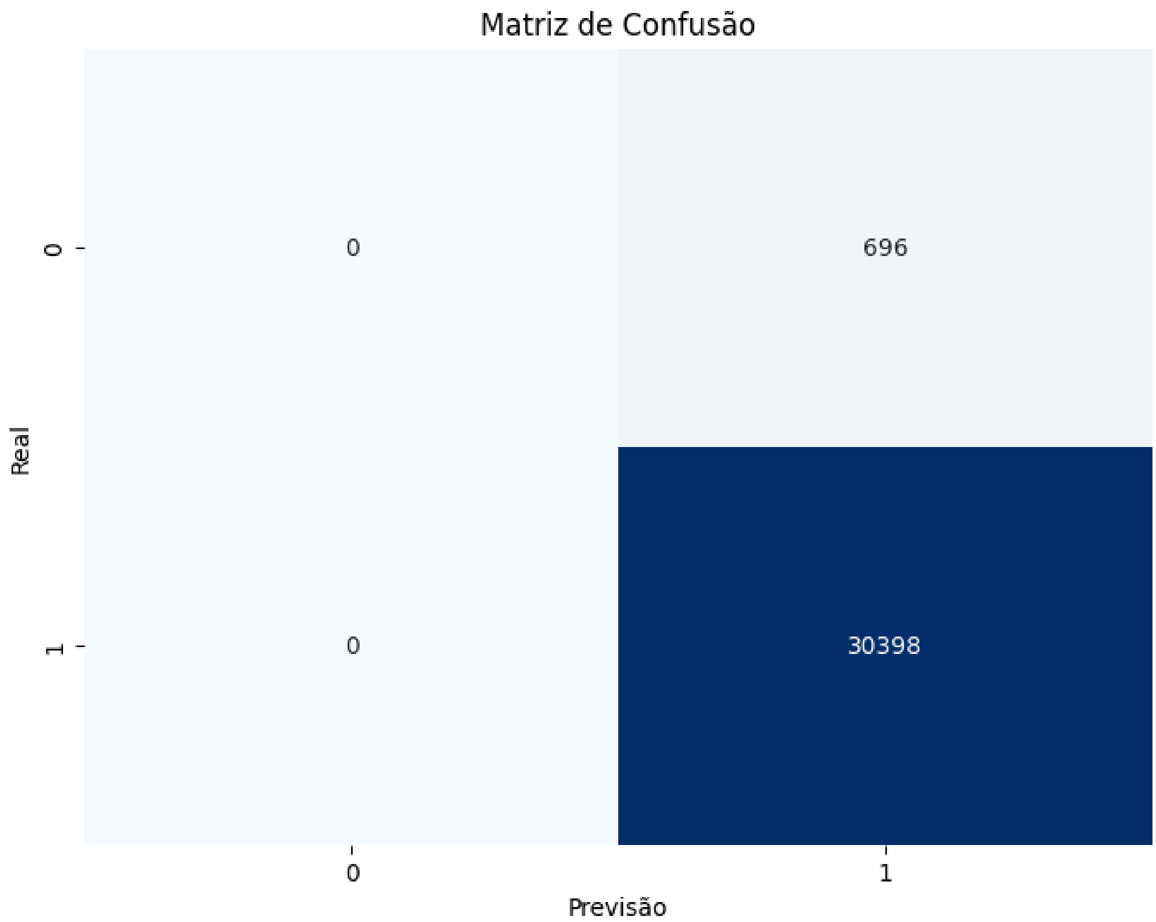
Out[9]:
```
LogisticRegression(random_state=42)
```

Avaliação do Modelo

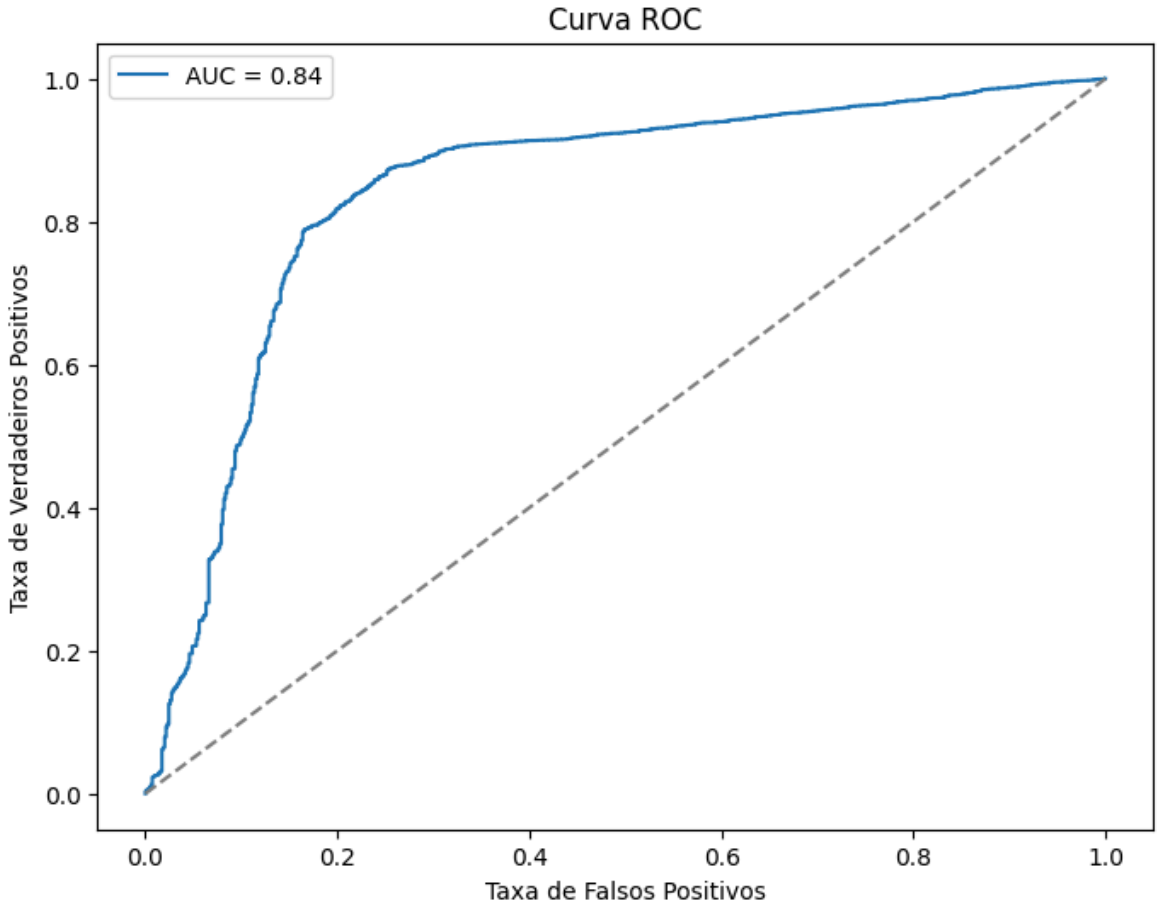
In [10]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, r

y_pred = model.predict(X_test)

print("Acurácia:", accuracy_score(y_test, y_pred))
print("Precisão:", precision_score(y_test, y_pred))
```

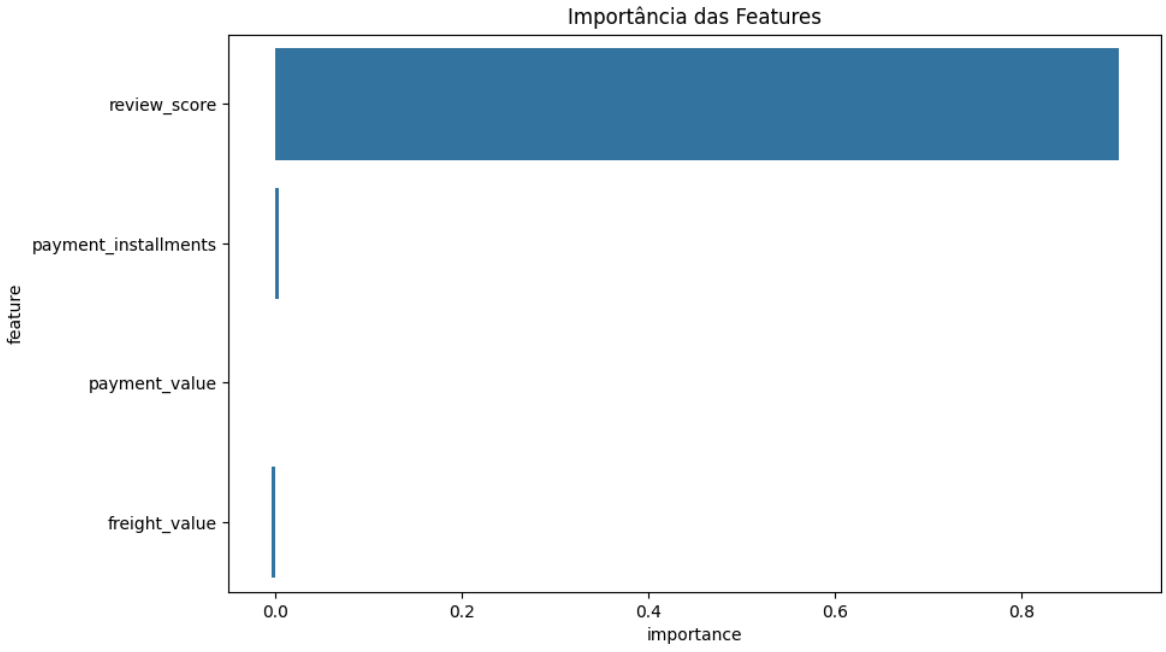
```
print("Recall:", recall_score(y_test, y_pred))
print("F1-Score:", f1_score(y_test, y_pred))

# Matriz de Confusão:
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Previsão')
plt.ylabel('Real')
plt.title('Matriz de Confusão')
plt.show()


# Previsões nas bases de treino e teste:
y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)

# Probabilidades (para a curva ROC)
y_prob = model.predict_proba(X_test)[:, 1]


# Métricas de Avaliação:
print("Relatório de Classificação (base de teste):\n", classification_report(y_t

print("AUC-ROC (base de teste):\n", roc_auc_score(y_test, y_prob))


# Curva ROC
fpr, tpr, thresholds = roc_curve(y_test, y_prob)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {roc_auc_score(y_test, y_prob):.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray') # Linha base (classificaa
plt.xlabel('Taxa de Falsos Positivos')
plt.ylabel('Taxa de Verdadeiros Positivos')
plt.title('Curva ROC')
plt.legend()
plt.show()


# Importância das Features (coeficientes da regressão logística)
feature_importance = pd.DataFrame({'feature': features, 'importance': model.coef
feature_importance = feature_importance.sort_values('importance', ascending=Fals

plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance)
plt.title('Importância das Features')
plt.show()
```

```
Acurácia: 0.977616260371776
Precisão: 0.977616260371776
Recall: 1.0
F1-Score: 0.9886814544981462
```




```
c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py:1531: Undefined
MetricWarning: Precision is ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py:1531: Undefined
MetricWarning: Precision is ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
c:\Python312\Lib\site-packages\sklearn\metrics\_classification.py:1531: Undefined
MetricWarning: Precision is ill-defined and being set to 0.0 in labels with no pr
edicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
Relatório de Classificação (base de teste):
               precision    recall  f1-score   support

           0       0.00      0.00      0.00       696
           1       0.98      1.00      0.99     30398

    accuracy                           0.98     31094
   macro avg       0.49      0.50      0.49     31094
weighted avg       0.96      0.98      0.97     31094

AUC-ROC (base de teste):
 0.8433331877550928
```


Curva ROC
AUC = 0.84
Taxa de Verdadeiros Positivos
Taxa de Falsos Positivos
0.0
0.2
0.4
0.6
0.8
1.0


Importância das Features
review_score
payment_installments
payment_value
freight_value
feature
importance
0.0
0.2
0.4
0.6
0.8