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BATCH : 3:30 - 5

PROJECT

DATE : 13/03/2024

PREDICTING CUSTOMER SATISFACTION

SISPLINT : 121020345

0.0 Imports

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

from IPython.core.display       import HTML
from IPython.display            import Image

from scipy                      import stats     as ss
from sklearn                    import metrics   as m

from sklearn.impute             import SimpleImputer
from sklearn.preprocessing      import StandardScaler, OneHotEncoder
from sklearn.compose            import ColumnTransformer, make_column_transformer, mak
from imblearn.over_sampling     import SMOTE
from imblearn.pipeline          import Pipeline


from sklearn.linear_model       import LogisticRegression
```

```
from sklearn.neighbors         import KNeighborsClassifier
from sklearn.tree              import DecisionTreeClassifier
from sklearn.ensemble          import RandomForestClassifier
from xgboost                   import XGBClassifier
from sklearn.svm               import SVC


from sklearn.model_selection import train_test_split, cross_val_score, ShuffleSplit
from sklearn.metrics           import accuracy_score, roc_curve, confusion_matrix, cl
```

0.1 Helper Functions

In [ ]:
```
def personal_settings():

    # notbook
    display(HTML('<style>.container{width:98% !important;}</style>'))
    np.set_printoptions(suppress=True)
    pd.options.display.float_format = '{:.2f}'.format

    # seaborn settings
    sns.set(rc={'figure.figsize':(22,10)})
    sns.set_theme(style = 'darkgrid', font_scale = 1.2)
    sns.set_palette('RdBu_r')

    return None


def cramer_v( x, y ):
    cm = pd.crosstab( x, y ).to_numpy()
    n = cm.sum()
    r, k = cm.shape

    chi2 = ss.chi2_contingency( cm )[0]
    chi2corr = max( 0, chi2 - (k-1)*(r-1)/(n-1))

    kcorr = k - (k-1)**2/(n-1)
    rcorr = r - (r-1)**2/(n-1)

    return np.sqrt((chi2corr/n) / (min( kcorr-1, rcorr-1 )))


def cf_matrix_labels(cf_matrix):

    group_names = ['True Negatives','False Positives','False Negatives','True Posit
    group_counts = ['{0:0.0f}'.format(value) for value in cf_matrix.flatten()]
    group_percentages = ['{0:.2%}'.format(value) for value in cf_matrix.flatten()/r
    labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in zip(group_names,group_counts,gr
    labels = np.asarray(labels).reshape(2,2)

    return labels
```

In [ ]:
```
personal_settings()
```

0.2 Loading Data

In [ ]:
```
directory = 'datasets/olist/'

orders                 = pd.read_csv(directory + 'olist_orders_dataset.csv')
order_items            = pd.read_csv(directory + 'olist_order_items_dataset.csv')
```

```
order_payments      = pd.read_csv(directory + 'olist_order_payments_dataset.csv')
order_reviews       = pd.read_csv(directory + 'olist_order_reviews_dataset.csv')
customer            = pd.read_csv(directory + 'olist_customers_dataset.csv')
products            = pd.read_csv(directory + 'olist_products_dataset.csv')
product_translation = pd.read_csv(directory + 'product_category_name_translation.cs
sellers             = pd.read_csv(directory + 'olist_sellers_dataset.csv')
```

In [ ]:
```
# merge all datasets that related to the customer
m1 = pd.merge(orders, order_reviews, on='order_id')
m2 = pd.merge(m1, order_payments, on='order_id')
customer = pd.merge(m2, customer, on='customer_id')
```

In [ ]:
```
# merge all datasets related to the seller
m1 = pd.merge(order_items, products, on='product_id')
m2 = pd.merge(m1, sellers, on='seller_id')
seller = pd.merge(m2, product_translation, on='product_category_name')
```

In [ ]:
```
# merge customer and seller datasets
df_raw = pd.merge(customer, seller, on ='order_id')
```

1.0 Data Description

In [ ]:
```
# filtering useful columns
df1 = df_raw[['order_id', 'order_item_id', 'order_status', 'payment_value', 'price'
              'order_delivered_customer_date', 'order_estimated_delivery_date','pay
              'product_category_name_english', 'product_name_lenght','product_descr
```

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

Out[ ]:

	order_id	order_item_id	order_status	payment_value	price	freight_
0	e481f51cbdc54678b7cc49136f2d6af7	1	delivered	18.12	29.99	
1	e481f51cbdc54678b7cc49136f2d6af7	1	delivered	2.00	29.99	
2	e481f51cbdc54678b7cc49136f2d6af7	1	delivered	18.59	29.99	
3	53cdb2fc8bc7dce0b6741e2150273451	1	delivered	141.46	118.70	
4	47770eb9100c2d0c44946d9cf07ec65d	1	delivered	179.12	159.90	

5 rows × 21 columns

1.1 Rename Columns

In [ ]:
```
df1 = df1.rename(columns={'product_category_name_english': 'product_category'})
```

1.2 Data Dimensions

In [ ]:
```
print(df1.shape[0], 'rows')
print(df1.shape[1], 'columns')
```

```
115609 rows
21 columns
```

1.3 Data Types

In [ ]:
```
description = []
for i in df1.columns:
    description.append([
        i,
        df1[i].dtypes,
        df1[i].nunique(),
        df1[i].drop_duplicates().sample(2).values
    ])

pd.DataFrame(data=description, columns=['attributes','dtypes', 'nunique','sample'])
```

Out[ ]:

	attributes	dtypes	nunique	sample
0	order_id	object	96516	[3f1a7cead33aa1b0af3f491ed618c946, 236909a5eec...
1	order_item_id	int64	21	[19, 1]
2	order_status	object	7	[shipped, delivered]
3	payment_value	float64	28657	[71.42, 16.54]
4	price	float64	5879	[2.9, 998.9]
5	freight_value	float64	6954	[3.34, 339.59]
6	customer_state	object	27	[RR, PR]
7	seller_state	object	23	[RJ, DF]
8	order_purchase_timestamp	object	95989	[2018-05-03 16:21:45, 2017-09-03 16:44:56]
9	order_approved_at	object	88332	[2017-05-28 20:10:17, 2018-02-12 20:30:22]
10	order_delivered_customer_date	object	93702	[2017-01-30 13:24:40, 2018-08-03 18:12:57]
11	order_estimated_delivery_date	object	449	[2017-10-02 00:00:00, 2017-05-25 00:00:00]
12	payment_sequential	int64	29	[29, 23]
13	payment_type	object	4	[boleto, voucher]
14	payment_installments	int64	24	[18, 7]
15	product_category	object	71	[home_comfort_2, fashion_male_clothing]
16	product_name_lenght	float64	66	[39.0, 58.0]
17	product_description_lenght	float64	2958	[1682.0, 3120.0]
18	product_photos_qty	float64	19	[18.0, 8.0]
19	product_weight_g	float64	2197	[2320.0, 517.0]
20	review_score	int64	5	[4, 1]

1.4 Check NA

In [ ]:
```
description = []
for i in df1.columns:
    description.append([
        i,
        df1[i].isna().sum(),
        round((df1[i].isna().sum()/len(df1))*100)
    ])

pd.DataFrame(data=description, columns=['attributes','null', '%null'])
```

Out[ ]:

	attributes	null	%null
0	order_id	0	0
1	order_item_id	0	0
2	order_status	0	0
3	payment_value	0	0
4	price	0	0
5	freight_value	0	0
6	customer_state	0	0
7	seller_state	0	0
8	order_purchase_timestamp	0	0
9	order_approved_at	14	0
10	order_delivered_customer_date	2400	2
11	order_estimated_delivery_date	0	0
12	payment_sequential	0	0
13	payment_type	0	0
14	payment_installments	0	0
15	product_category	0	0
16	product_name_lenght	0	0
17	product_description_lenght	0	0
18	product_photos_qty	0	0
19	product_weight_g	1	0
20	review_score	0	0

The null rows represent less than 3% of the dataset. Removing these rows will not have much impact on the analysis.

1.5 Remove NA

In [ ]:
```
df1.dropna(how='any', inplace=True)

print(df1.shape[0], 'rows')
print(df1.shape[1], 'columns')
```

```
113194 rows
21 columns
```

1.6 Change Data Types

In [ ]:
```
cols = ['order_purchase_timestamp', 'order_approved_at', 'order_estimated_delivery_

for col in cols:
    df1[col] = pd.to_datetime(df1[col]).dt.date

df1[['order_purchase_timestamp', 'order_approved_at', 'order_estimated_delivery_dat
```

Out[ ]:

	order_purchase_timestamp	order_approved_at	order_estimated_delivery_date	order_delivered_cu
0	2017-10-02	2017-10-02	2017-10-18	
1	2017-10-02	2017-10-02	2017-10-18	
2	2017-10-02	2017-10-02	2017-10-18	
3	2018-07-24	2018-07-26	2018-08-13	
4	2018-08-08	2018-08-08	2018-09-04	

1.7 Descriptive Statistical

In [ ]:
```
num_attributes = df1[['payment_sequential', 'payment_installments', 'payment_value'
                      'product_description_lenght', 'product_photos_qty', 'product

cat_attributes = df1[['order_status', 'order_id', 'order_item_id', 'order_purchase_
                      'payment_type', 'product_category', 'customer_state', 'selle
```

Numerical Attributes

In [ ]:
```
num_attributes.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
payment_sequential	113194.00	1.09	0.69	1.00	1.00	1.00	1.00	26.00
payment_installments	113194.00	2.94	2.78	0.00	1.00	2.00	4.00	24.00
payment_value	113194.00	171.56	264.20	0.00	60.85	107.97	189.16	13664.08
price	113194.00	119.85	181.08	0.85	39.90	74.90	132.98	6735.00
freight_value	113194.00	20.00	15.71	0.00	13.08	16.32	21.19	409.68
product_name_lenght	113194.00	48.80	10.02	5.00	42.00	52.00	57.00	76.00
product_description_lenght	113194.00	784.73	650.33	4.00	346.00	600.00	982.00	3992.00
product_photos_qty	113194.00	2.21	1.72	1.00	1.00	1.00	3.00	20.00
product_weight_g	113194.00	2106.28	3765.22	0.00	300.00	700.00	1800.00	40425.00

Categorical Attributes

In [ ]:
```
cat_summary = cat_attributes.astype('category').describe().T
cat_summary
```

Out[ ]:

	count	unique	top	freq
order_status	113194	2	delivered	113187
order_id	113194	94472	895ab968e7bb0d5659d16cd74cd1650c	63
order_item_id	113194	21	1	99172
order_purchase_timestamp	113194	611	2017-11-24	1379
order_approved_at	113194	608	2018-04-24	1134
order_delivered_customer_date	113194	642	2018-05-21	523
order_estimated_delivery_date	113194	444	2017-12-20	640
payment_type	113194	4	credit_card	83535
product_category	113194	71	bed_bath_table	11684
customer_state	113194	27	SP	47813
seller_state	113194	22	SP	80728
review_score	113194	5	5	65146

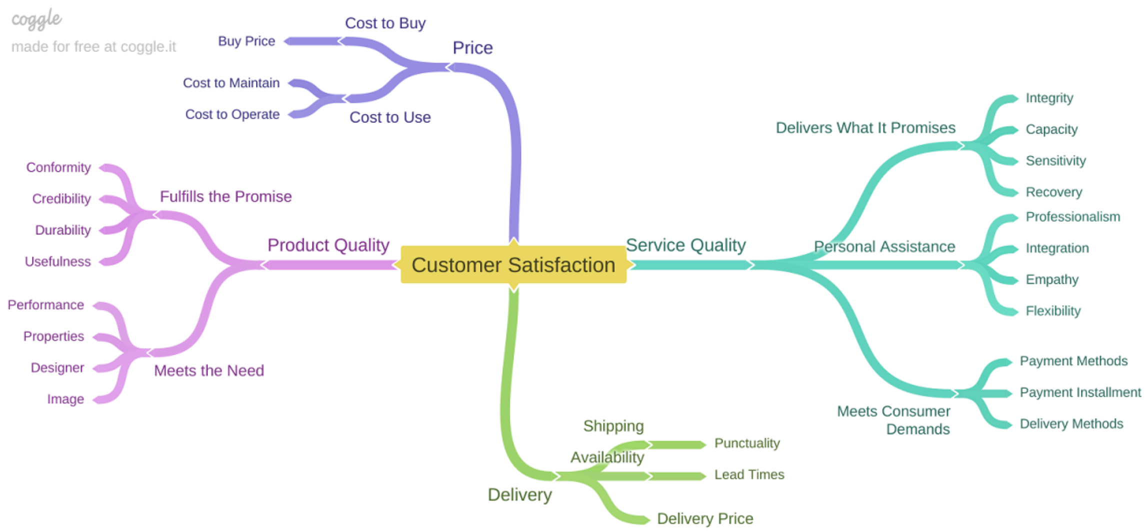
2.0 Feature Engineering

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

2.1 Mind Map

In [ ]:
```
Image('images/mind_map.png')
```

Out[ ]:



2.2 Hypotesis

1. Customers who pay in more installments tend to give a negative review score. These customers will have been paying for the product for a long time, so they probably expect more.

2. Customers who spend more tend to give a negative review score. If a customer spends more, that customer is likely to expect more.

3. Customers are not satisfied when the delivery of days exceeds the estimated days for delivery, which make them to give a negative review score.

4. Customers are satisfied when the delivery of days are shorter than the estimated delivery dyas, which makes them give positive review scores.

5. Negative review scores have the highest average freight value. In addition to customers not liking to pay for freight, more expensive freight can mean more days for delivery.

2.3 Features Engineering

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

# extracting days from date columns
df2['estimated_delivery_days']  = df2['order_estimated_delivery_date'] - df2['order
df2['delivery_days']            = df2['order_delivered_customer_date'] - df2['order

cols = ['estimated_delivery_days', 'delivery_days']
for col in cols:
    df2[col] = df2[col].apply(lambda x: x.days)

# whether the product arrived on time(1) or not(0)
df2['arrival_on_time'] = df2['estimated_delivery_days'] - df2['delivery_days']
df2['arrival_on_time'] = df2['arrival_on_time'].apply(lambda x: 1 if x >= 1 else 0)

# order status binary transformation -- delivered(1), canceled(0)
df2['order_status'] = df2['order_status'].replace(['canceled','delivered'], [0,1])

# review score binary transformation -- positive review(1), negative review(0)
df2['review_score'] = df2['review_score'].apply(lambda x: 1 if x > 3 else 0)

# remove the timestamps from the dataset, order_id and order_items, since we have c
df2.drop(['order_purchase_timestamp', 'order_approved_at', 'order_estimated_deliver
```

2.5 Split Into Training and Test

In [ ]:
```
df_train, df_test = train_test_split(df2, test_size=0.2, random_state=42)
```

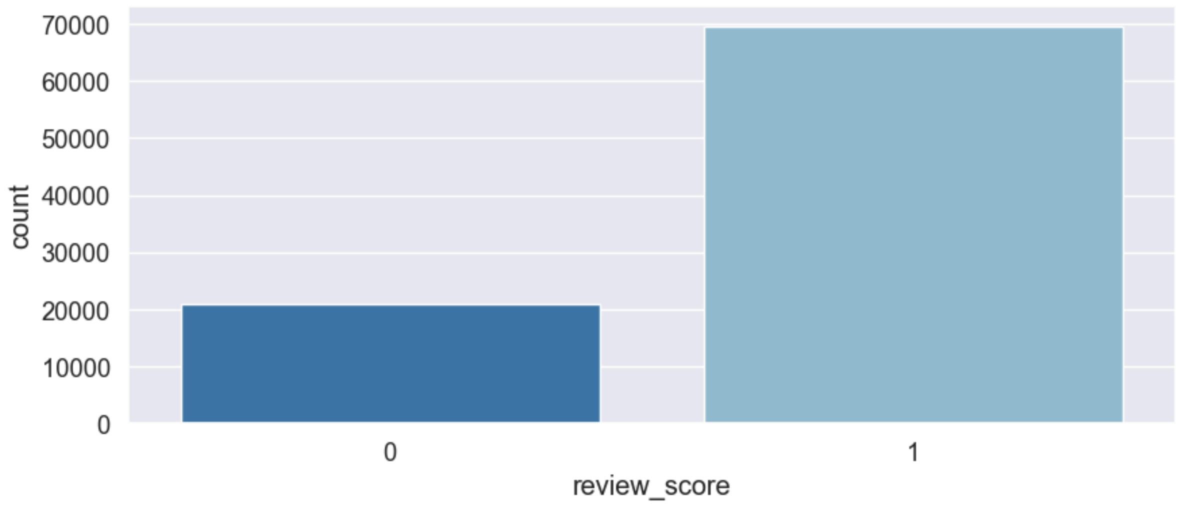
3.0 Exploratory Data Analysis

In [ ]:
```
num_attributes = df_train[['payment_value', 'price', 'freight_value', 'payment_sequ
                           'product_photos_qty', 'product_weight_g', 'estimated_del

cat_attributes = df_train[['order_status', 'customer_state', 'seller_state', 'payme
```

3.1 Univariate Analysis

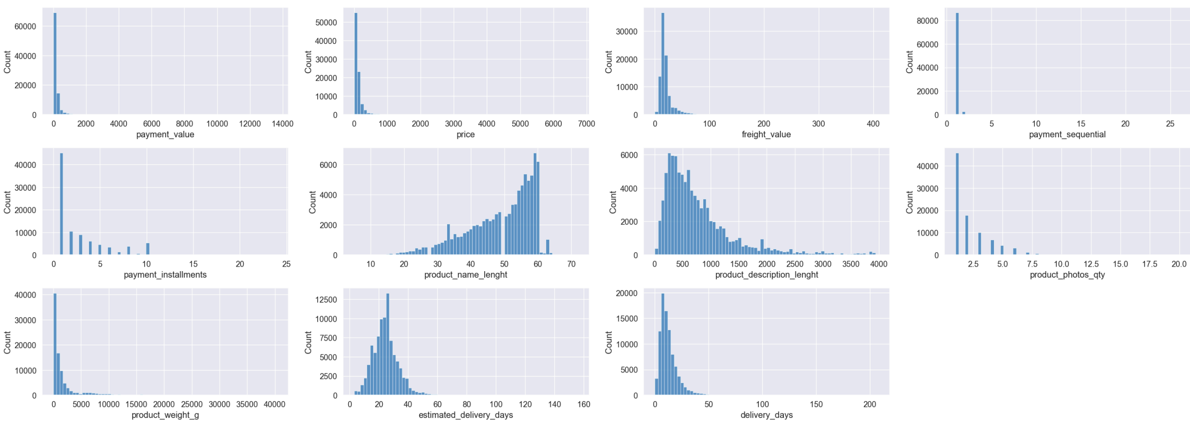
Response Variable

In [ ]:
```
plt.figure(figsize=(10, 4))
sns.countplot(x='review_score', data=df_train);
```



Numerical Variables

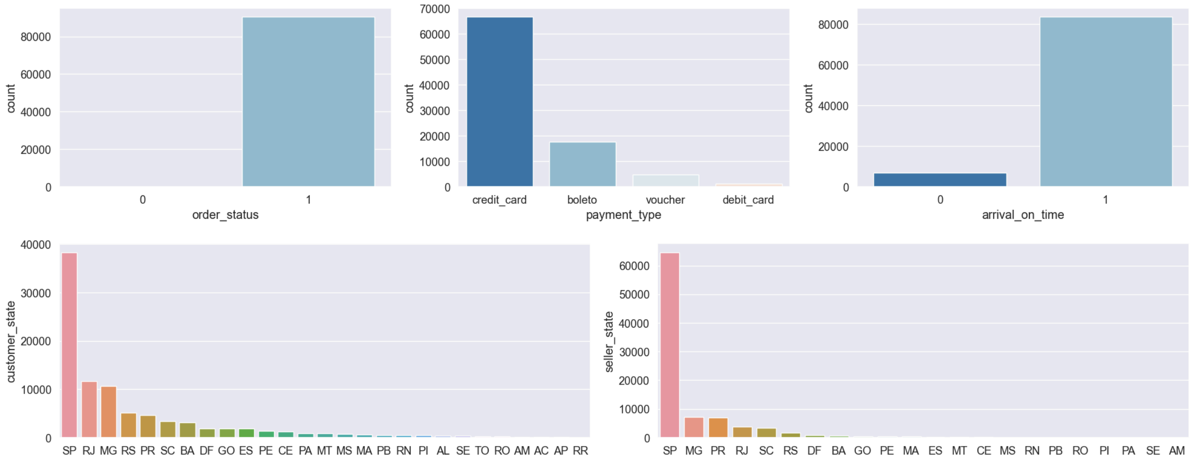
In [ ]:
```
cols = 4
rows = 3
num_cols = num_attributes

fig = plt.figure(figsize= (28, 10))
for i, col in enumerate(num_cols):
    ax=fig.add_subplot( rows, cols, i+1)
    sns.histplot(x=num_attributes[col], bins=70, ax=ax)

fig.tight_layout()
plt.show()
```



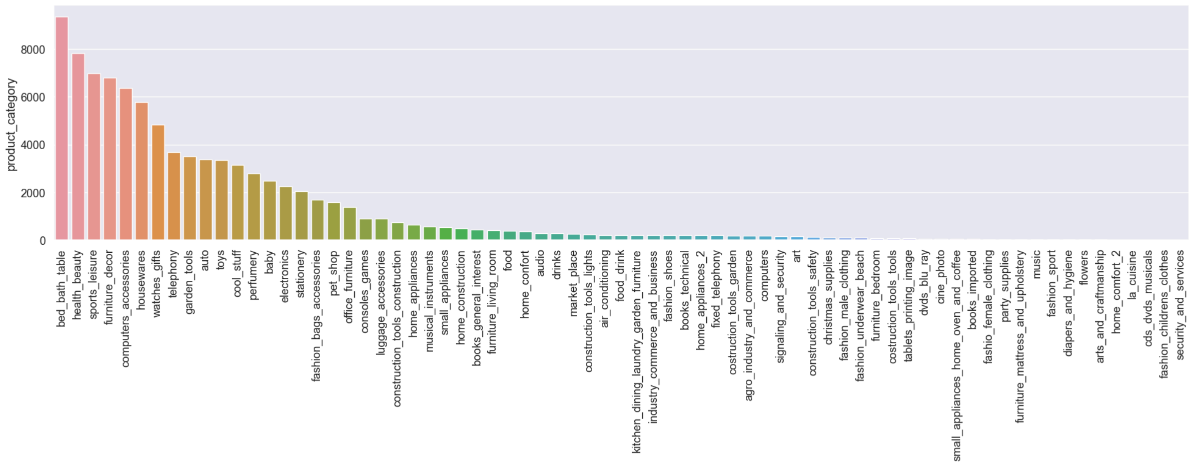
Categorical Variables

In [ ]:
```
cols = 3
rows = 1
num_cols = cat_attributes[['order_status', 'payment_type', 'arrival_on_time']]

fig = plt.figure(figsize= (20, 4))
for i, col in enumerate(num_cols):
    ax=fig.add_subplot( rows, cols, i+1)
    sns.countplot(x=cat_attributes[col], ax=ax)

fig.tight_layout()
plt.show()
```

```
cols = 2
rows = 1
num_cols = cat_attributes[['customer_state', 'seller_state']]

fig = plt.figure(figsize= (20, 4))
for i, col in enumerate(num_cols):
    ax=fig.add_subplot( rows, cols, i+1)
    sns.barplot(x=cat_attributes[col].value_counts().index,
                y=cat_attributes[col].value_counts(), ax=ax)

fig.tight_layout()
plt.show()
```



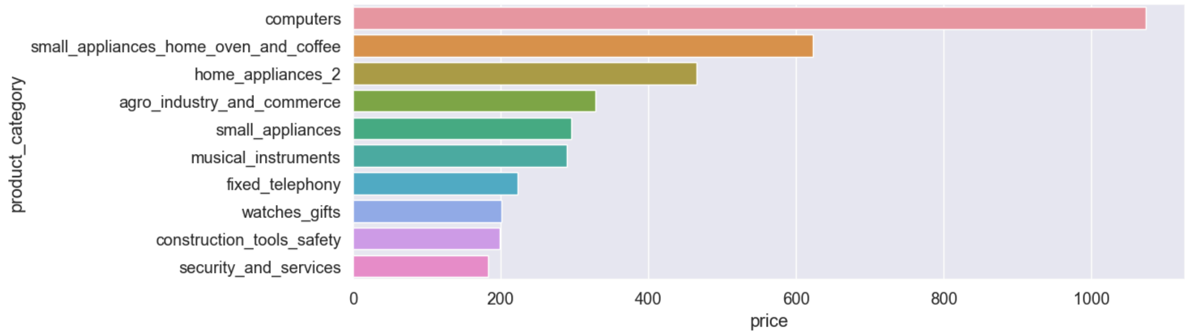
In [ ]:
```
plt.figure(figsize= (24, 5))
sns.barplot(x=cat_attributes['product_category'].value_counts().index,
            y=cat_attributes['product_category'].value_counts())
plt.xticks(rotation=90);
```



3.2 Multivariate Analysis

Top 10 highest price categories

In [ ]:
```
aux = df_train[['product_category', 'price']].groupby('product_category').mean().sc
plt.figure(figsize=(12, 4))
sns.barplot(y='product_category', x='price', data=aux);
```



When we check the price by product category, we can see that the average cost of a product is the highest for items belonging to the 'computers' category. The average price is 1100. The second highest category has an average price of 750.

Payment type based on payment value

In [ ]:
```
plt.figure(figsize=(12, 4))
sns.barplot(x = 'payment_type', y = 'payment_value', hue='review_score', data=df_tr
```

Credit cards have the highest payment value, followed by boleto, debit cards, and vouchers. The type of payment doesn't seem to influence the review score.

In [ ]:
```
aux = df_train[['payment_type', 'payment_value']].groupby('payment_type').count().s
aux['cumu%'] = (aux['payment_value'].cumsum()/aux['payment_value'].sum())*100
aux.head()
```

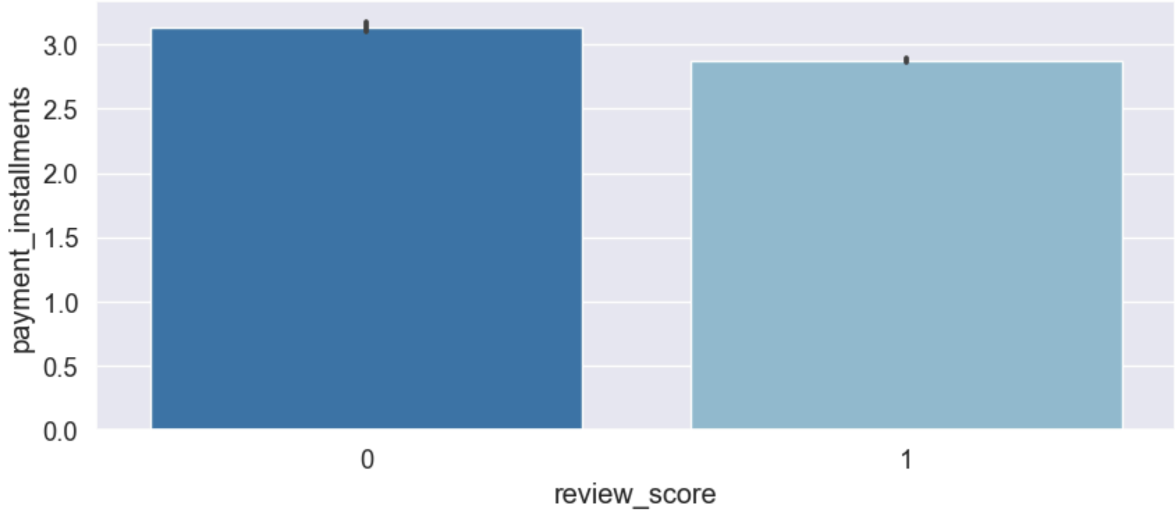
Out[ ]:

	payment_type	payment_value	cumu%
0	credit_card	66738	73.70
1	boleto	17697	93.24
2	voucher	4844	98.59
3	debit_card	1276	100.00

More than 70% of values payments, were made with credit cards.

Review score based on payment installments

In [ ]:
```
plt.figure(figsize=(10, 4))
sns.barplot(y='payment_installments', x='review_score', data=df_train);
```



In [ ]:

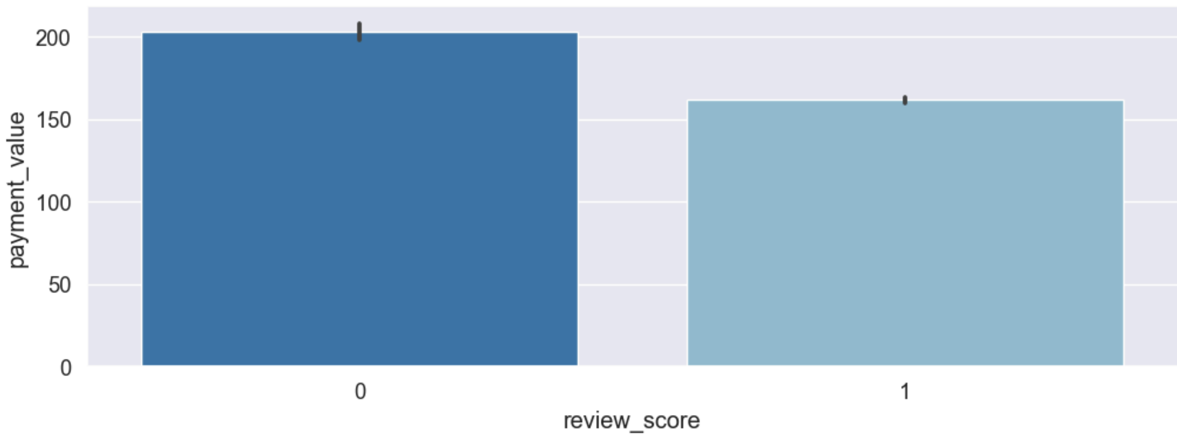
```
aux = df_train[['review_score', 'payment_installments']].groupby('review_score').me
print(aux)

negative = aux.iloc[0,1]
positive = aux.iloc[1,1]

percentage = abs(((negative - positive) / positive)*100)
percentage
print(f'\n Negative review scores have {percentage:.2f}% more payment installments
```

```
   review_score  payment_installments
0             0                  3.14
1             1                  2.88

 Negative review scores have 9.06% more payment installments than positive review
scores.
```

Review score based on payment value

In [ ]:

```
plt.figure(figsize=(12, 4))
sns.barplot(x = 'review_score', y = 'payment_value', data=df_train);
```



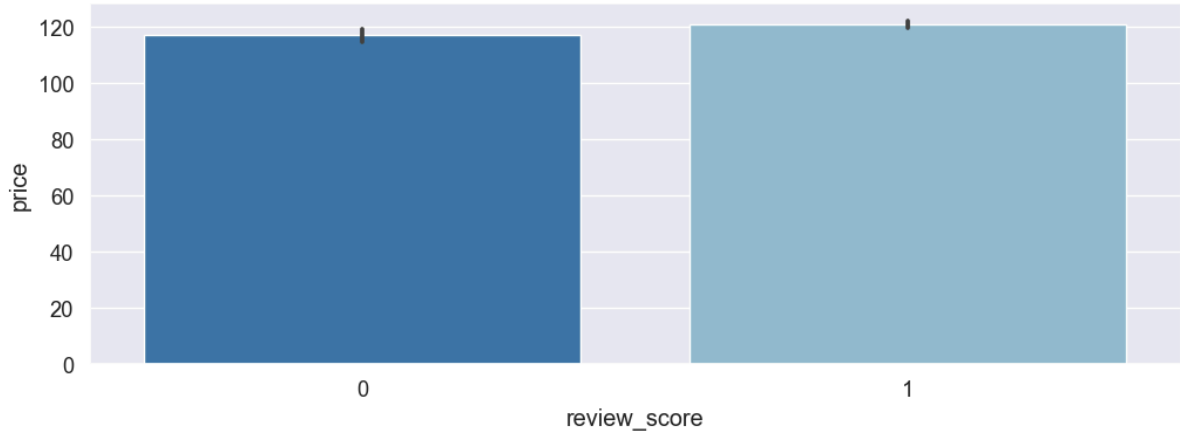
In [ ]:

```
aux = df_train[['review_score', 'payment_value']].groupby('review_score').mean().re
print(aux)

negative = aux.iloc[0,1]
positive = aux.iloc[1,1]

percentage = abs(((negative - positive) / positive)*100)
print(f'\n Negative review scores have a payment value {percentage:.2f}% higher tha
```

```
   review_score  payment_value
0             0         202.98
1             1         161.38

 Negative review scores have a payment value 25.78% higher than positive review sc
ores.
```

Review score based on product price

In [ ]:
```
plt.figure(figsize=(12, 4))
sns.barplot(x = 'review_score', y = 'price', data=df_train);
```

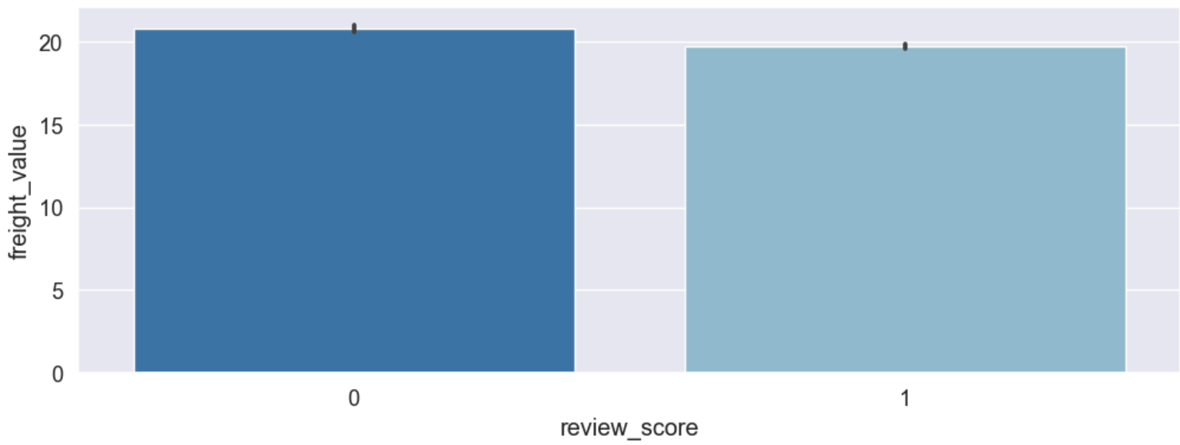


In [ ]:
```
aux = df_train[['review_score', 'price']].groupby('review_score').mean().reset_inde
print(aux)

negative = aux.iloc[0,1]
positive = aux.iloc[1,1]

percentage = abs(((positive - negative) / negative)*100)
print(f'\n Negative scores have a product price {percentage:.2f}% higher than posit
```

```
   review_score  price
0             0 116.89
1             1 120.70

 Negative scores have a product price 3.26% higher than positive review scores.
```

Review score based on freight value

In [ ]:
```
plt.figure(figsize=(12, 4))
sns.barplot(x = 'review_score', y = 'freight_value', data=df_train);
```

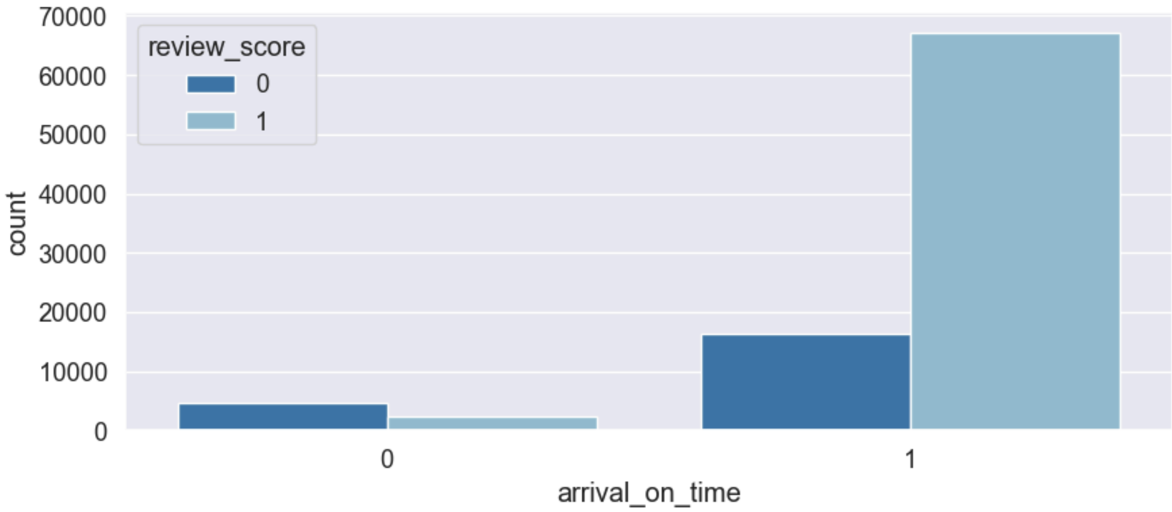


In [ ]:
```
aux = df_train[['review_score', 'freight_value']].groupby('review_score').mean().re
print(aux)

negative = aux.iloc[0,1]
positive = aux.iloc[1,1]

percentage = abs(((negative - positive) / positive)*100)
percentage
print(f'\n Negative review scores have a freight value {percentage:.2f}% more exper
```

```
   review_score  freight_value
0             0          20.80
1             1          19.71

 Negative review scores have a freight value 5.52% more expensive than positive re
view scores.
```

The number of orders that arrived on time or not by review score type

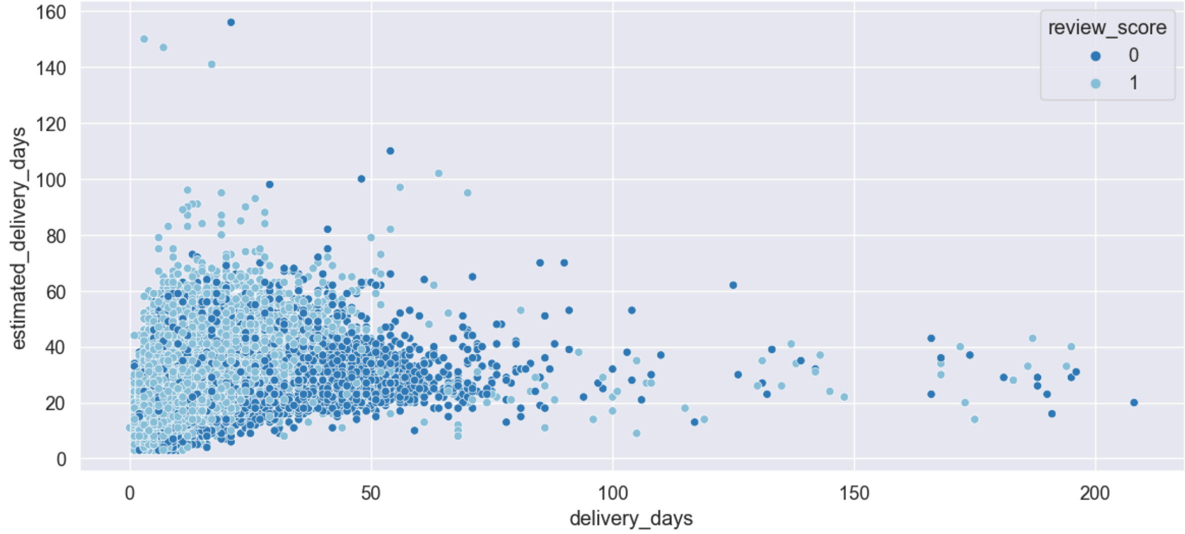
In [ ]:
```
plt.figure(figsize=(10, 4))
sns.countplot(x = 'arrival_on_time', hue='review_score', data=df_train);
```



Orders that arrive on time have a far more positive review score while orders that don't arrive on time have more negative reviews.

Correlation between estimated delivery and delivery days

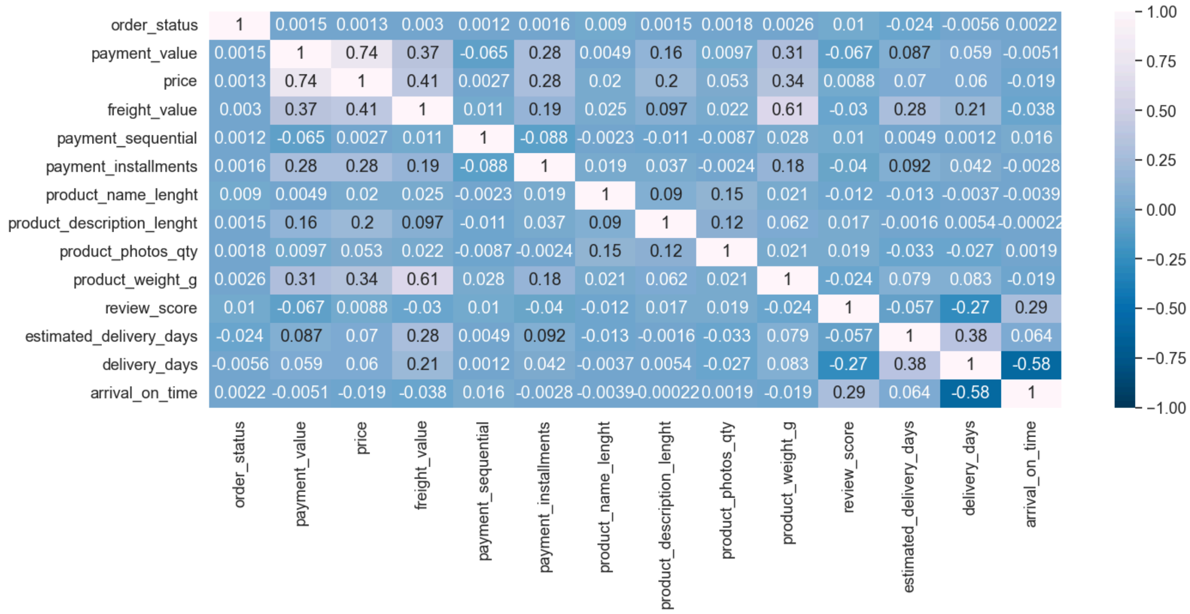
In [ ]:
```
plt.figure(figsize=(14, 6))
sns.scatterplot(x='delivery_days', y='estimated_delivery_days', hue='review_score',
```



- Most positive reviews have long estimated delivery days, but the actual delivery days are before or on schedule.
- Most negative review scores have short estimated delivery days, but the actual delivery days of the product are longer than the expected time.

Correlation matrix between the numerical variables in the dataset

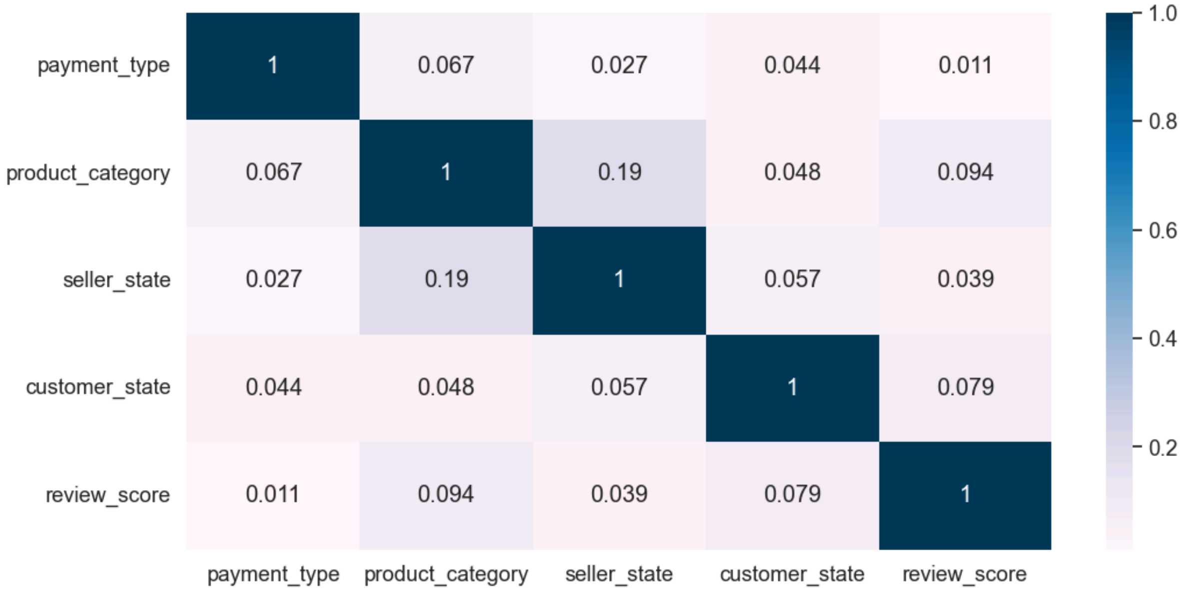
In [ ]:
```
corr = df_train.corr(method='pearson')

plt.figure(figsize=(16, 6))
sns.heatmap(corr, cmap='PuBu_r', vmin=-1, vmax=1, annot=True);
```



- The freight value has a positive correlation with the estimated days. It makes sense, the more days to delivery, the higher the freight (further away).
- Delivery days have a negative correlation with the customer review score. It makes sense, the longer it takes for the customer to receive the order, the worse the customer review score will be.

Correlation matrix between the categorical variables in the dataset

In [ ]:
```
a = df_train[['payment_type', 'product_category','seller_state', 'customer_state',

# calculate cramer V
a1  = cramer_v(a['payment_type'], a['payment_type'    ])
a2  = cramer_v(a['payment_type'], a['product_category'])
a3  = cramer_v(a['payment_type'], a['seller_state'    ])
a4  = cramer_v(a['payment_type'], a['customer_state'  ])
a5  = cramer_v(a['payment_type'], a['review_score'    ])

a6  = cramer_v(a['product_category'], a['payment_type'    ])
a7  = cramer_v(a['product_category'], a['product_category'])
a8  = cramer_v(a['product_category'], a['seller_state'    ])
a9  = cramer_v(a['product_category'], a['customer_state'  ])
a10 = cramer_v(a['product_category'], a['review_score'    ])

a11 = cramer_v(a['seller_state'], a['payment_type'    ])
a12 = cramer_v(a['seller_state'], a['product_category'])
a13 = cramer_v(a['seller_state'], a['seller_state'    ])
a14 = cramer_v(a['seller_state'], a['customer_state'  ])
a15 = cramer_v(a['seller_state'], a['review_score'    ])

a16 = cramer_v(a['customer_state'], a['payment_type'    ])
a17 = cramer_v(a['customer_state'], a['product_category'])
a18 = cramer_v(a['customer_state'], a['seller_state'    ])
a19 = cramer_v(a['customer_state'], a['customer_state'  ])
a20 = cramer_v(a['customer_state'], a['review_score'    ])

a21 = cramer_v(a['review_score'], a['payment_type'    ])
a22 = cramer_v(a['review_score'], a['product_category'])
a23 = cramer_v(a['review_score'], a['seller_state'    ])
a24 = cramer_v(a['review_score'], a['customer_state'  ])
a25 = cramer_v(a['review_score'], a['review_score'    ])

# final dataset
d = pd.DataFrame({'payment_type':     [a1,  a2,  a3,  a4,  a5  ],
                  'product_category': [a6,  a7,  a8,  a9,  a10 ],
                  'seller_state':     [a11, a12, a13, a14, a15 ],
                  'customer_state':   [a16, a17, a18, a19, a20 ],
                  'review_score':     [a21, a22, a23, a24, a25 ]})

d = d.set_index(d.columns)

plt.figure(figsize=(12, 6))
sns.heatmap(d, annot=True, cmap='PuBu');
```



4.0 ML Modeling

It is certain that there is a high class imbalance in the dataset.
A negative review score (0) is very important, since misclassifying them would cause the seller to lose customers. The false positive should be the concern here.

4.1 Data Preparation

Rescaling

In [ ]:
```
num_features = [['order_status', 'payment_value', 'price', 'freight_value', 'paymer
                 'product_description_lenght', 'product_photos_qty', 'product_weigh

num_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                                  ('scaler',  StandardScaler())])
```

Encoding

In [ ]:
```
cat_features = [['customer_state', 'seller_state', 'payment_type', 'product_categor

cat_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='most_frequent
                                  ('onehot',  OneHotEncoder(handle_unknown='ignore'
```

Transformation Pipeline

In [ ]:
```
preprocessor = ColumnTransformer(transformers=[('num', num_transformer, num_feature
                                               ('cat', cat_transformer, cat_feature

preprocessor = make_column_transformer((num_transformer, make_column_selector(dtype
                                        (cat_transformer, make_column_selector(dtype
```

In [ ]:
```
## how we can get a DataFrame out after transformation pipeline if we want
#X_train_t = preprocessor.fit_transform(X_train)
#
#X_train_t_df = pd.DataFrame(X_train_t,
```

```
#                              columns=preprocessor.get_feature_names_out(),
#                              index=X_train.index)
#
#X_train_t_df.head(2)
```

Separete Target

In [ ]:
```
df_train = df_train.replace((np.inf, -np.inf, np.nan), 0).reset_index(drop=True)

X_train  = df_train.drop("review_score", axis=1)
y_train  = df_train["review_score"].copy()

X_test = df_test.drop("review_score", axis=1)
y_test = df_test["review_score"].copy()
```

4.2 ML Evaluation

Models Baseline

In [ ]:
```
model_pipeline = []
model_pipeline.append(LogisticRegression(solver='newton-cg'))
model_pipeline.append(SVC())
model_pipeline.append(KNeighborsClassifier())
model_pipeline.append(DecisionTreeClassifier())
model_pipeline.append(RandomForestClassifier())
model_pipeline.append(XGBClassifier())
```

ML Evaluation

In [ ]:
```
model_list = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree', 'Random Forest'

acuracy_list  = []
auc_list = []
n_precision_list = []
p_precision_list = []
macro_precision_list = []
n_recall_list = []
p_recall_list  = []
macro_recall_list = []
n_fscore_list = []
p_fscore_list = []
macro_fscore_list = []
cm_list = []

for model in model_pipeline:

    # defining a global seed
    np.random.seed(7)

    # full pipeline
    preprocessor = preprocessor
    oversample   = SMOTE(random_state=14)
    model        = model

    steps = [('preprocessor', preprocessor), ('oversample', oversample), ('model',

    pipeline = Pipeline(steps=steps)
```

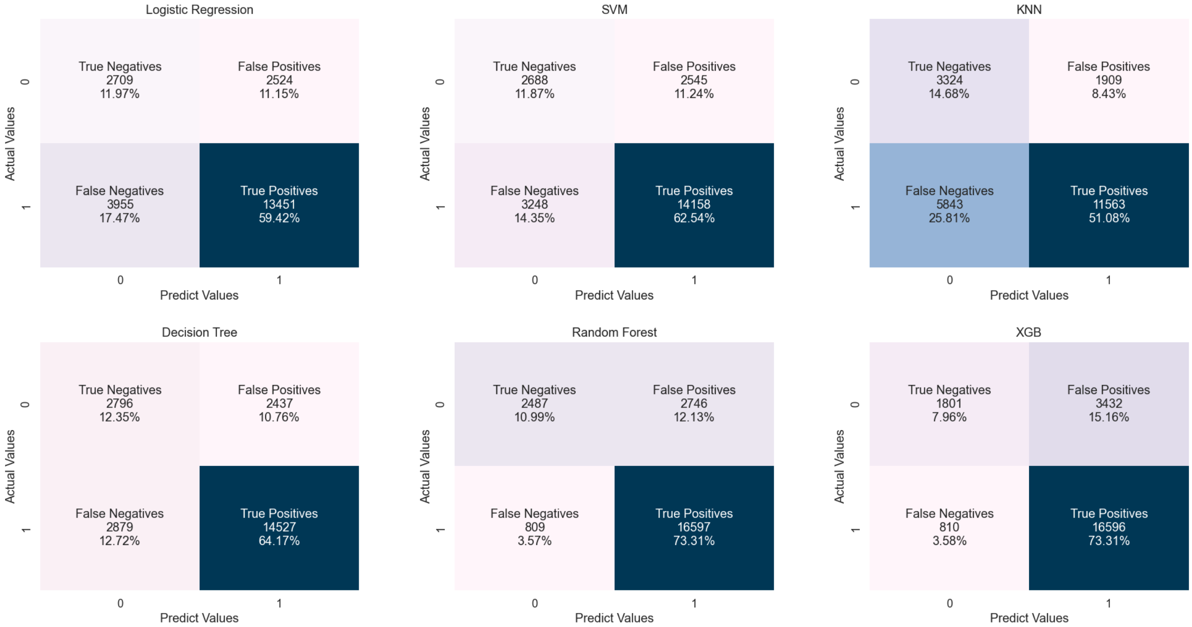
```
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    ## ml evaluation
    report = classification_report(y_test, y_pred, output_dict=True)

    # acuracy
    acuracy_list.append(report['accuracy'])

    # precision
    n_precision_list.append(report['0']['precision'])
    p_precision_list.append(report['1']['precision'])
    macro_precision_list.append(report['macro avg']['precision'])

    #recall
    n_recall_list.append(report['0']['recall'])
    p_recall_list.append(report['1']['recall'])
    macro_recall_list.append(report['macro avg']['recall'])

    # f1-score
    n_fscore_list.append(report['0']['f1-score'])
    p_fscore_list.append(report['1']['f1-score'])
    macro_fscore_list.append(report['macro avg']['f1-score'])

    # ROC, AUC and confusion Matrix
    fpr, tpr, _thresholds = roc_curve(y_test, y_pred)
    auc_list.append(round(m.auc(fpr, tpr), 2))
    cm_list.append(confusion_matrix(y_test, y_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Confusion Matrix

In [ ]:

```
fig = plt.figure(figsize=(24, 12))
for i in range(len(cm_list)):
    cm = cm_list[i]
    model = model_list[i]

    sub = fig.add_subplot(2, 3, i+1)
    cm_plot = sns.heatmap(cm, annot=cf_matrix_labels(cm), fmt='', cmap='PuBu', cbar
    cm_plot.set_title(model)
    cm_plot.set_xlabel('Predict Values')
    cm_plot.set_ylabel('Actual Values')
    plt.subplots_adjust(wspace=0.3, hspace=0.3)
```



Evaluation Results

In [ ]:

```
df_results = pd.DataFrame({'Model'        : model_list,
                           'Accuracy'     : acuracy_list,
                           'AUC'          : auc_list,
                           'Precision (0)': n_precision_list,
                           'Precision (1)': p_precision_list,
                           'Recall (0)'   : n_recall_list,
                           'Recall (1)'   : p_recall_list,
                           'F1-Score (0)' : n_fscore_list ,
                           'F1-Score (1)' : p_fscore_list,
                           'Precision'    : macro_precision_list,
                           'Recall'       : macro_recall_list,
                           'F1-Score'     : macro_fscore_list})

df_results.style.highlight_max(subset=['Accuracy', 'AUC', 'Precision (0)', 'Precisi
                                       'F1-Score (0)','F1-Score (1)', 'Precision',
```

Out[ ]:

	Model	Accuracy	AUC	Precision (0)	Precision (1)	Recall (0)	Recall (1)	F1-Score (0)	F1-Score (1)	Pr
0	Logistic Regression	0.713812	0.650000	0.406513	0.842003	0.517676	0.772780	0.455409	0.805908	0.6
1	SVM	0.744114	0.660000	0.452830	0.847632	0.513663	0.813398	0.481332	0.830162	0.6
2	KNN	0.657582	0.650000	0.362605	0.858299	0.635200	0.664311	0.461667	0.748947	0.6
3	Decision Tree	0.765184	0.680000	0.492687	0.856343	0.534302	0.834597	0.512651	0.845330	0.6
4	Random Forest	0.842970	0.710000	0.754551	0.858036	0.475253	0.953522	0.583187	0.903263	0.8
5	XGB	0.812624	0.650000	0.689774	0.828640	0.344162	0.953464	0.459204	0.886681	0.7

We will discard Random Forest and XGB, as they had lowers recall for negative review scores. We will follow with the others to improve the algorithms' performance by making a manual selection of features considering the exploratory data analysis.

5.0 Tunnig ML Models

5.1 Data Preparation

Features Selection

Since the dataset has few variables it was possible to do some performance tests and eliminate some variables from our model manually based on the exploratory analysis, this was the final result of variables to be excluded from the model: order_status, payment_type, payment_sequential, product_name_lenght.

In [ ]:
```
X_train  = df_train.drop(["review_score", 'order_status','payment_type', 'payment_s
y_train  = df_train["review_score"].copy()

X_test = df_test.drop(["review_score", 'order_status', 'payment_type', 'payment_seq
y_test = df_test["review_score"].copy()
```

Rescaling

In [ ]:
```
num_features = [['payment_value', 'price', 'freight_value','payment_installments',
                 'product_photos_qty', 'estimated_delivery_days', 'delivery_days',

num_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='median')),
                                  ('scaler',  StandardScaler())])
```

Encoding

In [ ]:
```
cat_features = [['customer_state',  'seller_state', 'product_category']]

cat_transformer = Pipeline(steps=[('imputer', SimpleImputer(strategy='most_frequent
                                  ('onehot',  OneHotEncoder(handle_unknown='ignore'
```

Transformation Pipeline

In [ ]:
```
preprocessor  = ColumnTransformer(transformers=[('num', num_transformer, num_feature
                                               ('cat', cat_transformer, cat_feature

preprocessor  = make_column_transformer((num_transformer, make_column_selector(dtype
                                        (cat_transformer, make_column_selector(dtype
```

5.2 ML Evaluation

Models Baseline

In [ ]:
```
model_pipeline  = []
model_pipeline.append(LogisticRegression(solver='newton-cg'))
model_pipeline.append(SVC())
model_pipeline.append(KNeighborsClassifier())
model_pipeline.append(DecisionTreeClassifier())
```

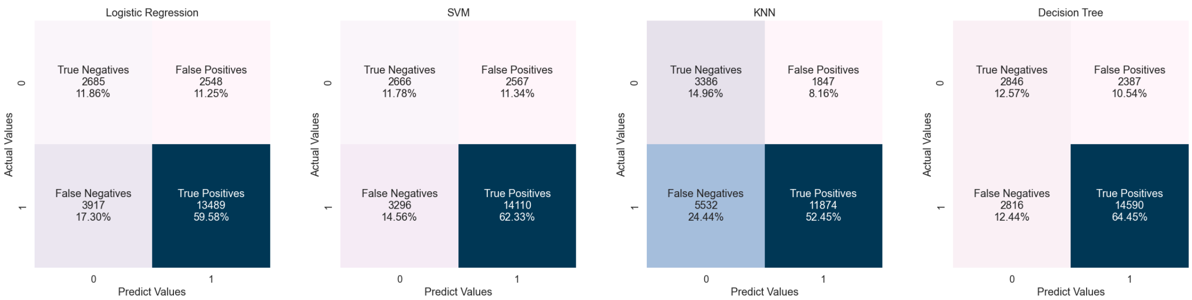
ML Evaluation

In [ ]:
```
model_list = ['Logistic Regression', 'SVM', 'KNN', 'Decision Tree']

acuracy_list  = []
auc_list = []
n_precision_list = []
p_precision_list = []
macro_precision_list = []
n_recall_list = []
p_recall_list  = []
macro_recall_list = []
n_fscore_list = []
p_fscore_list = []
macro_fscore_list = []
cm_list = []

for model in model_pipeline:

    # defining a global seed
    np.random.seed(7)

    # full pipeline
    preprocessor = preprocessor
    oversample   = SMOTE(random_state=14)
    model        = model

    steps = [('preprocessor', preprocessor), ('oversample', oversample), ('model',

    pipeline = Pipeline(steps=steps)

    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    ## ml evaluation
    report = classification_report(y_test, y_pred, output_dict=True)

    # acuracy
    acuracy_list.append(report['accuracy'])

    # precision
    n_precision_list.append(report['0']['precision'])
    p_precision_list.append(report['1']['precision'])
    macro_precision_list.append(report['macro avg']['precision'])

    #recall
    n_recall_list.append(report['0']['recall'])
    p_recall_list.append(report['1']['recall'])
    macro_recall_list.append(report['macro avg']['recall'])

    # f1-score
    n_fscore_list.append(report['0']['f1-score'])
    p_fscore_list.append(report['1']['f1-score'])
    macro_fscore_list.append(report['macro avg']['f1-score'])

    # ROC, AUC and confusion Matrix
    fpr, tpr, _thresholds = roc_curve(y_test, y_pred)
    auc_list.append(round(m.auc(fpr, tpr), 2))
    cm_list.append(confusion_matrix(y_test, y_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

Confusion Matrix

In [ ]:
```
fig = plt.figure(figsize=(28, 6))
for i in range(len(cm_list)):
    cm = cm_list[i]
    model = model_list[i]

    sub = fig.add_subplot(1, 4 , i+1)
    cm_plot = sns.heatmap(cm, annot=cf_matrix_labels(cm), fmt='', cmap='PuBu', cbar
    cm_plot.set_title(model)
    cm_plot.set_xlabel('Predict Values')
    cm_plot.set_ylabel('Actual Values')
    plt.subplots_adjust(wspace=0.3, hspace=0.3)
```



Evaluation Results

In [ ]:
```
df_results = pd.DataFrame({'Model'        : model_list,
                           'Accuracy'     : acuracy_list,
                           'AUC'          : auc_list,
                           'Precision (0)': n_precision_list,
                           'Precision (1)': p_precision_list,
                           'Recall (0)'   : n_recall_list,
                           'Recall (1)'   : p_recall_list,
                           'F1-Score (0)' : n_fscore_list ,
                           'F1-Score (1)' : p_fscore_list,
                           'Precision'    : macro_precision_list,
                           'Recall'       : macro_recall_list,
                           'F1-Score'     : macro_fscore_list})

display(df_results.style.highlight_max(subset=['Accuracy', 'AUC', 'Precision (0)',
                                      'F1-Score (0)', 'F1-Score (1)', 'Pre
```

	Model	Accuracy	AUC	Precision (0)	Precision (1)	Recall (0)	Recall (1)	F1-Score (0)	F1-Score (1)	Pr
0	Logistic Regression	0.714431	0.640000	0.406695	0.841117	0.513090	0.774963	0.453739	0.806686	0.6
1	SVM	0.741022	0.660000	0.447165	0.846075	0.509459	0.810640	0.476284	0.827979	0.6
2	KNN	0.674058	0.660000	0.379682	0.865389	0.647048	0.682179	0.478553	0.762939	0.6
3	Decision Tree	0.770175	0.690000	0.502649	0.859398	0.543856	0.838217	0.522441	0.848675	0.6

We see an improvement in the metrics across algorithms, KNN achieved a recall of 0.65 for negative review scores and a precision of 0.86 for positive review scores, following the business assumptions for negative review scores recall is more important and for positive review scores, precision is more important. But before making a decision on which algorithm to proceed with, let's cross-validate.

Cross-Validation

In [ ]:
```
scores_list = []

for model in model_pipeline:

    # defining a global seed
    np.random.seed(7)

    # ml pipeline
    preprocessor = preprocessor
    oversample   = SMOTE(random_state=14)
    model        = model

    steps = [('preprocessor', preprocessor), ('oversample', oversample), ('model', 

    pipeline = Pipeline(steps=steps)

    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=42)
    scores = cross_val_score(pipeline, X_train, y_train, cv=cv)

    scores_list.append(np.round(scores.mean(), 3).astype(str) + ' +/- ' + np.round(
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
```

In [ ]:

```
modelling_result_cv = pd.DataFrame({'Model': model_list, 'ACC CV': scores_list})
modelling_result_cv
```

Out[ ]:

	Model	ACC CV
0	Logistic Regression	0.714 +/- 0.0026
1	SVM	0.739 +/- 0.0024
2	KNN	0.664 +/- 0.0017
3	Decision Tree	0.757 +/- 0.0025

From now on I will either use the KNN algorithm, since it performs better than all the others tested in the recall for negative score reviews. I will fine tune the KNN algorithm to find the parameter combination that delivers the best possible performance for balanced accuracy.

6.0 KNN Hyperparameter Tuning

6.1 Search

In [ ]:
```
# defining a global seed
np.random.seed(7)

# ml pipeline
preprocessor = preprocessor
oversample   = SMOTE(random_state=14)
model        = KNeighborsClassifier()

steps = [('preprocessor', preprocessor), ('oversample', oversample), ('model', mode
pipeline = Pipeline(steps=steps)

param_grid  = [{'model__n_neighbors': [3, 6, 12],
                 'model__weights'   : ['uniform', 'distance']}]

grid = GridSearchCV(pipeline, param_grid, cv=10, scoring='balanced_accuracy', verbo
grid = grid.fit(X_train, y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
default behavior of `mode` typically preserves the axis it acts along. In SciPy 1.
11.0, this behavior will change: the default value of `keepdims` will become Fals
e, the `axis` over which the statistic is taken will be eliminated, and the value
None will no longer be accepted. Set `keepdims` to True or False to avoid this war
ning.
  mode, _ = stats.mode(_y[neigh_ind, k], axis=1)
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\neighbors\_classification.py:22
8: FutureWarning: Unlike other reduction functions (e.g. `skew`, `kurtosis`), the
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```

In [ ]:
```
print ('Score:', grid.best_score_)
print ('Parameters: ', grid.best_params_)
```

```
Score: 0.6859064852193247
Parameters:  {'model__n_neighbors': 6, 'model__weights': 'distance'}
```

7.0 Final Results and Conclusions

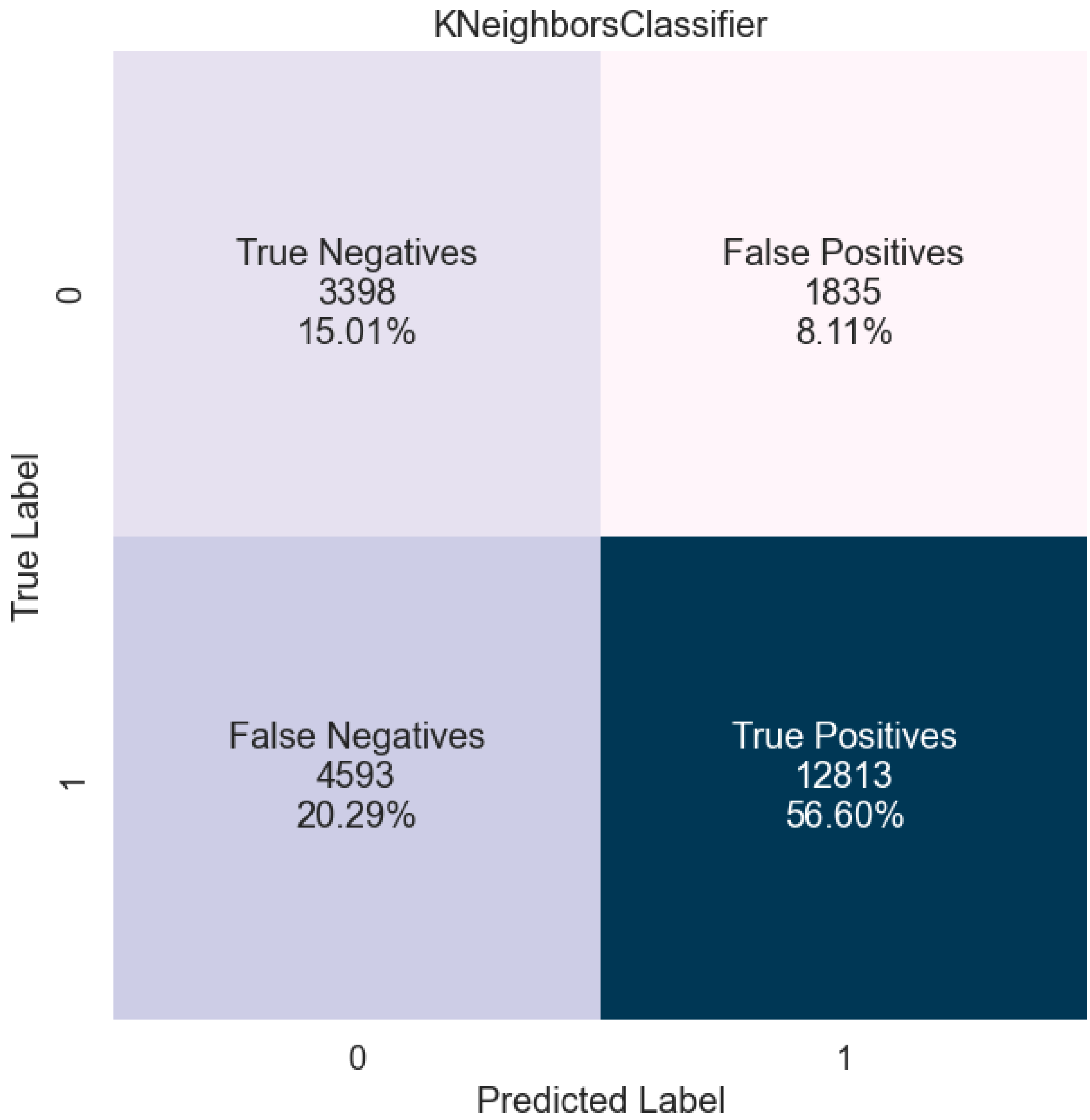
7.1 ML Evaluation

ML Model

In [ ]:
```
# defining a global seed
np.random.seed(7)

# ml pipeline
preprocessor = preprocessor
oversample   = SMOTE(random_state=14)
model        = KNeighborsClassifier(n_neighbors=6, weights='distance')

steps = [('preprocessor', preprocessor), ('oversample', oversample), ('model', mode
pipeline = Pipeline(steps=steps)

pipeline.fit(X_train, y_train)
y_pred = pipeline.predict(X_test)
```

Confusion Matrix

In [ ]:
```
fig, ax = plt.subplots(1,1, figsize=(7,7))

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=cf_matrix_labels(cm), fmt='', cmap='PuBu', ax=ax, cbar=False)
ax.set_xlabel('Predicted Label')
ax.set_ylabel('True Label')
ax.set_title('KNeighborsClassifier')

plt.subplots_adjust(hspace=0.3)
```



Classification Report

In [ ]:
```
print('KNeighborsClassifier')
print(classification_report(y_test, y_pred))
print('\n')
```

```
KNeighborsClassifier
              precision    recall  f1-score   support

           0       0.43      0.65      0.51      5233
           1       0.87      0.74      0.80     17406

    accuracy                           0.72     22639
   macro avg       0.65      0.69      0.66     22639
weighted avg       0.77      0.72      0.73     22639
```

Conclusions

By eliminating less relevant predictors and making hyperparameter adjustments we improved the overall performance of the algorithm from an accuracy of 66% to 72% and a considerable improvement in correctly identifying positive review scores from 51.07% to 56.60%. Most important for the business is the correct identification of negative review scores, by eliminating the least relevant predictors and making hyperparameter adjustments, we went from correctly identifying negative review scores from 63% to 65%.

The model still needs to be improved. Since the predictor variables have a weak relationship with the target variable, working more on feature engineering and using an algorithm for feature selection is something that might help. In any case, we already have a process, scalable and does not rely on subjective decisions, which generates time and resource savings.

In [ ]:

```

```