

Final Project: New York City Case Study using CRSIP-DM

Report 2: Association rule mining

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DATA 475: Advanced Concepts in Data Analytics

Data Preparation & modelling

For an APRIORI analysis, the dataset needs to be shortened to include just the required attributes. A “police force” data frame was processed without positive results. A “reason for search” data frame didn’t give accurate information as well. So the following data frame was prepared for a APRIORI model:

```
selected_attributes = ['arstmade', 'frisked', 'sex', 'race']
apr = crimes[selected_attributes]
df_encoded = pd.get_dummies(apr)
print(df_encoded)

te = TransactionEncoder ()
te_ary = te.fit (apr).transform(apr)
df_apriori = pd.DataFrame(te_ary, columns=te.columns_)
print (df_apriori)

# # min_support = 0.001 : algorithm will consider itemsets that appear in 0.1% of the transactions.
frequent_itemsets = apriori(df_encoded, min_support=0.1, use_colnames=True)
rules = association_rules(frequent_itemsets, metric='confidence', min_threshold=0.5)
```

The dummy variables dataset has the following shape.

```
[531653 rows x 13 columns]
```

Data evaluation

Frequent Itemsets

The most frequent itemsets are:

- (arstmade_N) with a support of 0.939301
- (frisked_N) with a support of 0.442108
- (frisked_Y) with a support of 0.557892
- (sex_M) with a support of 0.914021
- (race_B) with a support of 0.533239

Association Rules

A selection of rules includes:

- **Rule:** (frisked_N) -> (arstmade_N), with support 0.432408, confidence 0.978060, lift 1.041264
- **Rule:** (sex_M) -> (arstmade_N), with support 0.860093, confidence 0.940999, lift 1.001808
- **Rule:** (arstmade_N) -> (frisked_Y), with support 0.506893, confidence 0.539649, lift 0.967300
- **Rule:** (race_B, frisked_Y) -> (arstmade_N), with support 0.306420, confidence 0.544455, lift 1.022259

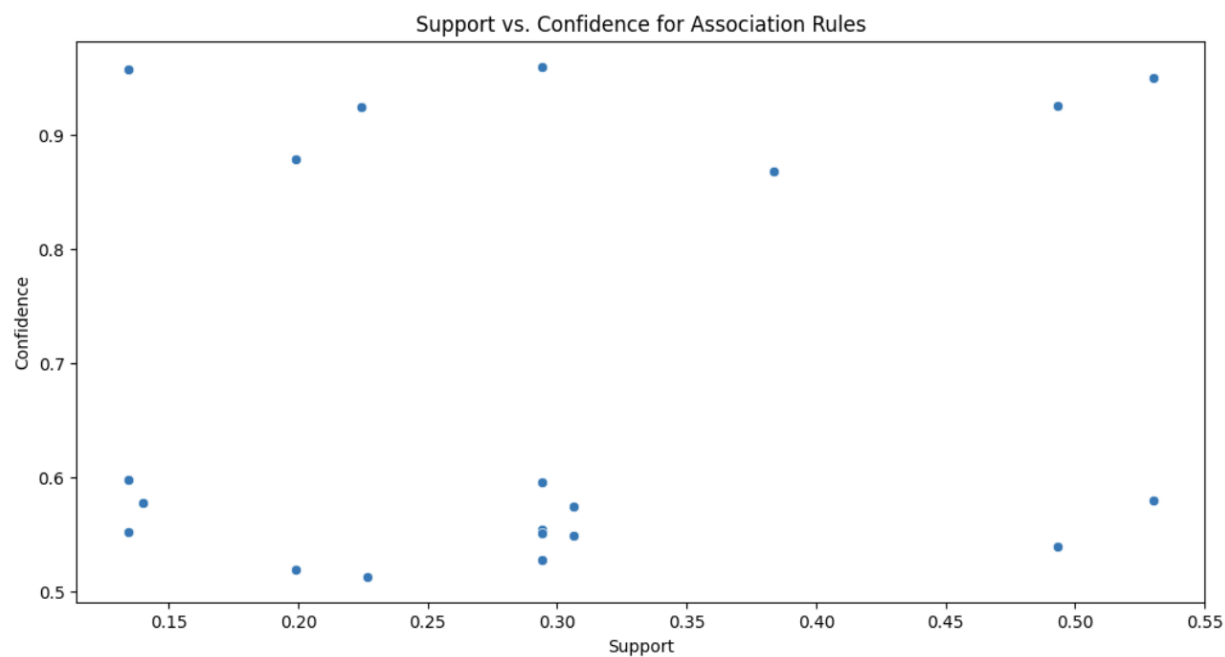
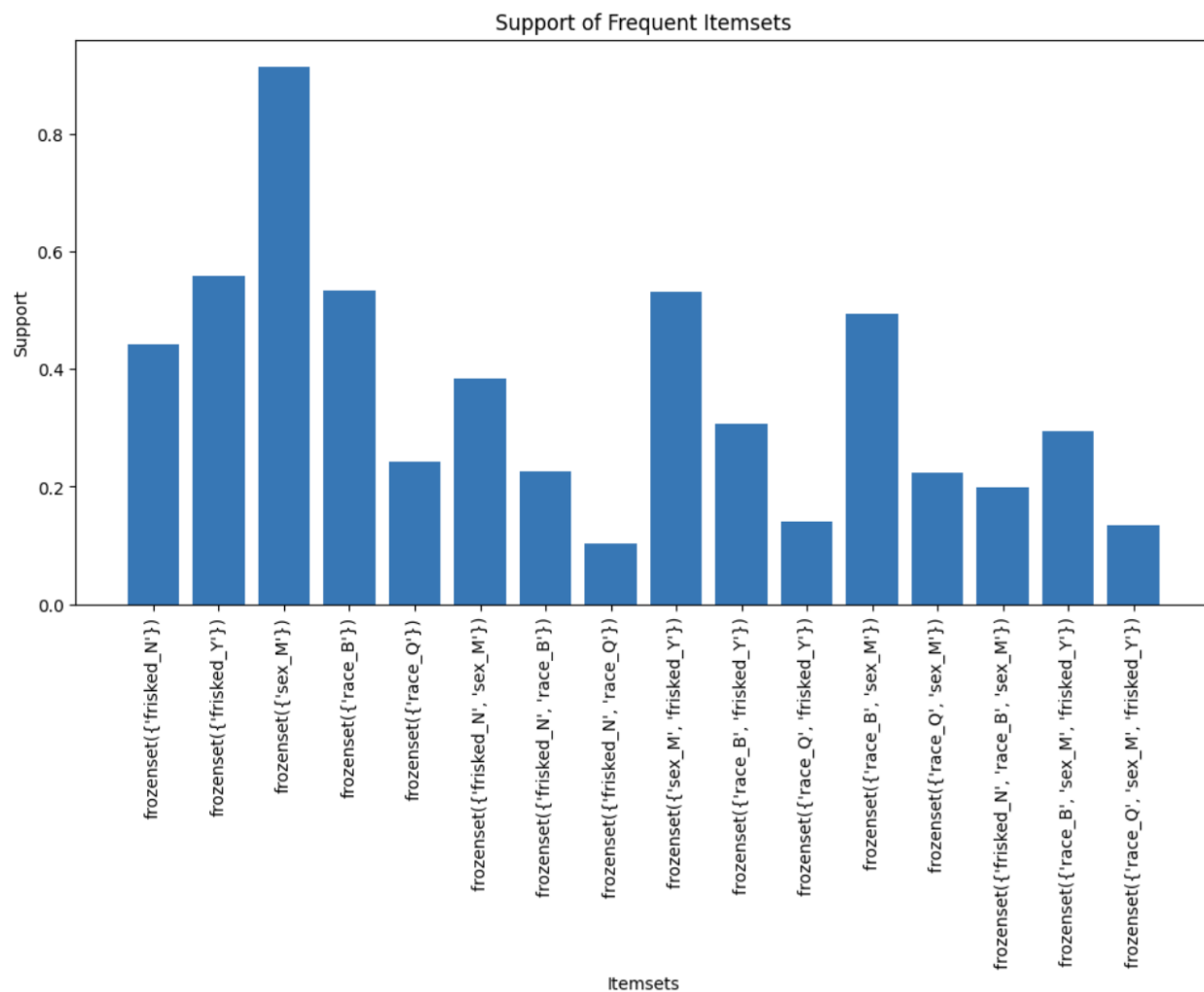
Key Metrics

- **Support:** Frequency of itemsets/rules in the dataset.
- **Confidence:** Probability of the consequent given the antecedent.
- **Lift:** How much more likely the consequent is given the antecedent compared to random chance.
- **Leverage:** The difference between the observed frequency and expected frequency.
- **Conviction:** Measures the degree of implication of the antecedent on the consequent.
- **Zhang's Metric:** A variant of lift, indicating the strength of association.

The following charts will give a visual insight for the model:

```
# Plotting support values for itemsets
plt.figure(figsize=(12, 6))
plt.bar(range(len(frequent_itemsets)), frequent_itemsets['support'])
plt.xticks(range(len(frequent_itemsets)), frequent_itemsets['itemsets'], rotation=90)
plt.xlabel('Itemsets')
plt.ylabel('Support')
plt.title('Support of Frequent Itemsets')
plt.show()

# Scatter plot of confidence vs. support for the rules
plt.figure(figsize=(12, 6))
sns.scatterplot(x='support', y='confidence', data=rules)
plt.xlabel('Support')
plt.ylabel('Confidence')
plt.title('Support vs. Confidence for Association Rules')
plt.show()
```



Furthermore, if we analyze frisked_Y and races we get the following results:

