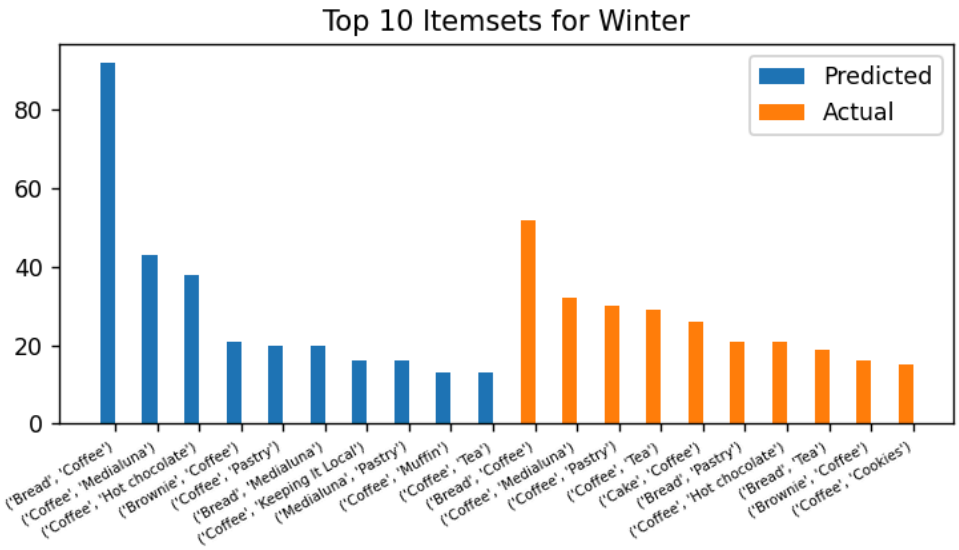
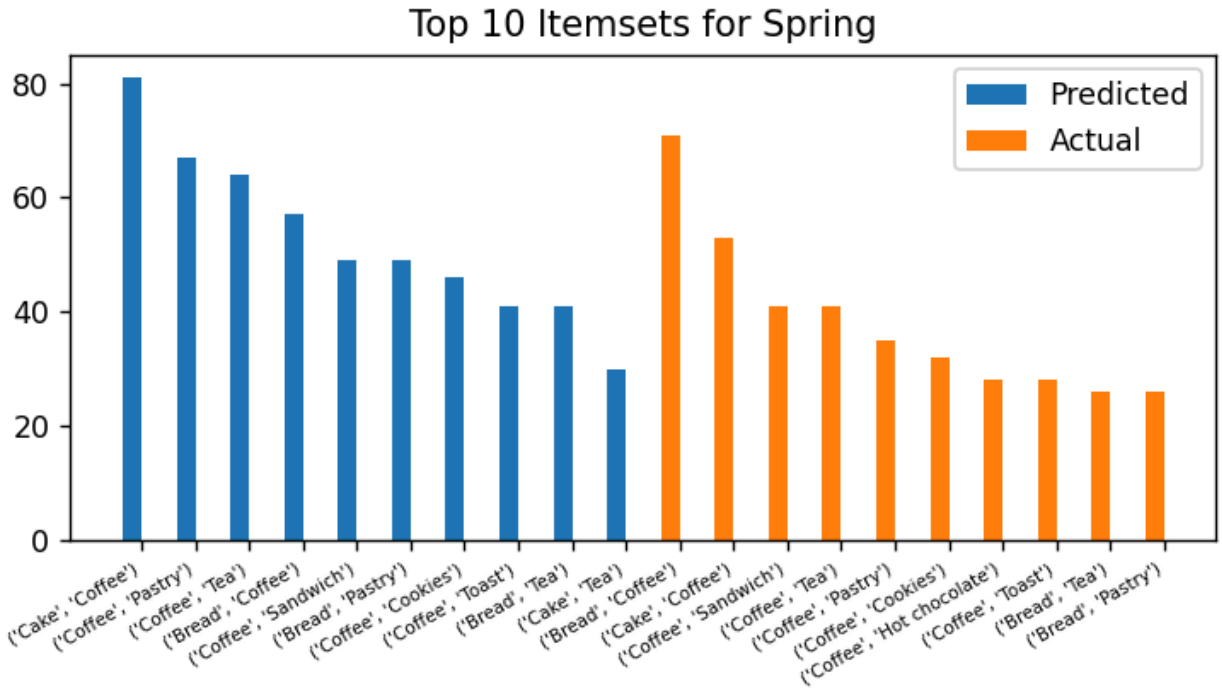
To further illustrate the importance of sales data analysis in bakery settings and the impact of the ebbs and flows of business throughout the year, our examination also focused on the intrarelatedness of different items within single transactions in order to optimize seasonal performance. The ability to algorithmically predict item pairings that are frequently purchased together offers bakeries a modern avenue to optimize profitability and streamline their operations. By leveraging these insights, bakeries can implement targeted promotions and sales strategies aimed at items that are frequently bought in the same transaction. For instance, identifying that cakes and coffee are frequently purchased together could prompt the bakery to offer a bundled discount on these items, enticing customers who might be initially coming in with the intent of only purchasing a prer-ordered cake to make a complementary purchase and boost overall sales revenue.

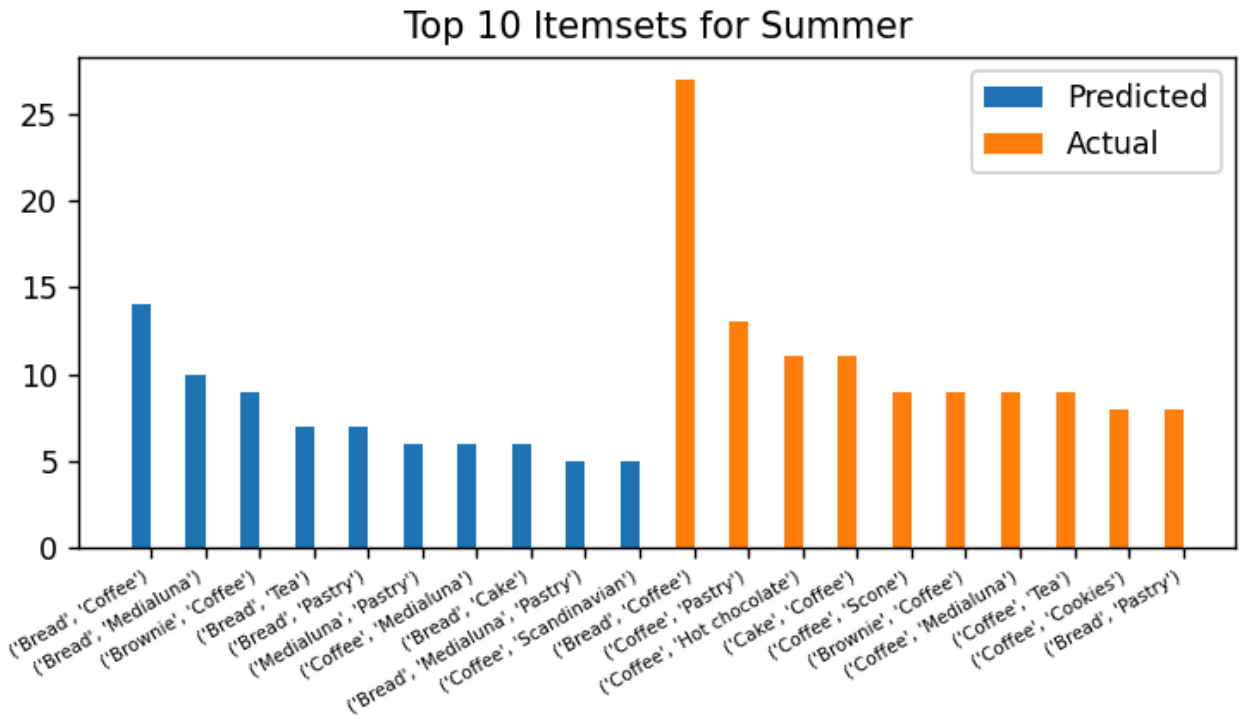
Additionally, understanding the seasonal dynamics of popular item pairings enables bakeries to make informed decisions about inventory management. By anticipating which materials are in high demand during specific seasons or promotional periods, bakeries can optimize their ingredient purchasing habits, minimizing overstocking and reducing potential losses due to excess inventory.

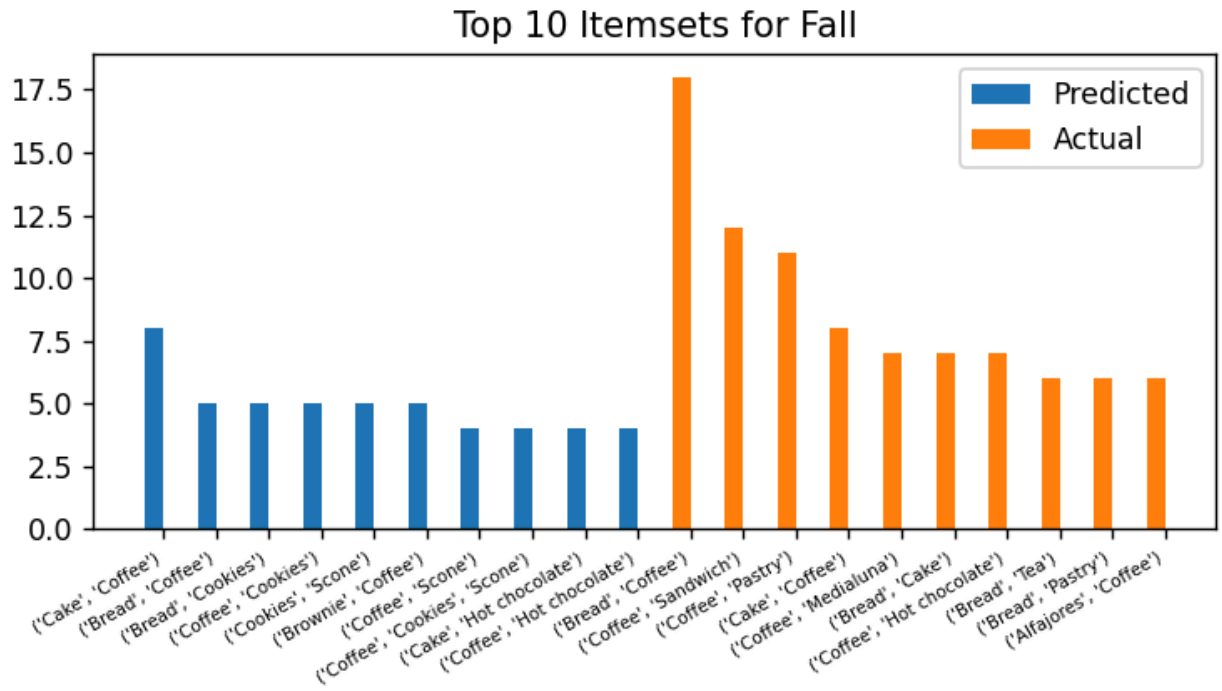
In terms of marketing, predictive insights derived from transactional data can inform strategic decisions on when and how to prioritize promotional campaigns. For instance, through predicting which item groupings are especially popular during specific seasons, bakeries can align advertising efforts to capitalize on these trends, maximizing the impact of marketing investments.

When it comes to the predictions made during this analysis, the adoption of a decision tree classifier complemented with using attributes refined through recursive feature elimination emerged as the optimal strategy. This approach excelled in uncovering and using correlations within transactional data that had ended up hindering other methods, but enabled more accurate predictions of consumer preferences based on the records of previous purchases. The following graphs show the areas where the model succeeded and where it had difficulties with data distribution before normalization:


Top 10 Itemsets for Winter
Predicted
Actual
0
20
40
60
80
('Bread', 'Coffee')
('Coffee', 'Medialuna')
('Coffee', 'Hot chocolate')
('Brownie', 'Coffee')
('Coffee', 'Pastry')
('Bread', 'Medialuna')
('Coffee', 'Keeping It Local')
('Medialuna', 'Pastry')
('Coffee', 'Muffin')
('Coffee', 'Tea')
('Bread', 'Coffee')
('Coffee', 'Medialuna')
('Coffee', 'Pastry')
('Coffee', 'Tea')
('Cake', 'Coffee')
('Bread', 'Pastry')
('Coffee', 'Hot chocolate')
('Bread', 'Tea')
('Brownie', 'Coffee')
('Coffee', 'Cookies')


Top 10 Itemsets for Spring
Predicted
Actual
0
20
40
60
80
('Cake', 'Coffee')
('Coffee', 'Pastry')
('Coffee', 'Tea')
('Bread', 'Coffee')
('Coffee', 'Sandwich')
('Bread', 'Pastry')
('Coffee', 'Cookies')
('Coffee', 'Toast')
('Bread', 'Tea')
('Cake', 'Tea')
('Bread', 'Coffee')
('Cake', 'Coffee')
('Coffee', 'Sandwich')
('Coffee', 'Tea')
('Coffee', 'Pastry')
('Coffee', 'Cookies')
('Coffee', 'Hot chocolate')
('Coffee', 'Toast')
('Bread', 'Tea')
('Bread', 'Pastry')


Top 10 Itemsets for Summer
Predicted
Actual
25
20
15
10
5
0
('Bread', 'Coffee')
('Bread', 'Medialuna')
('Brownie', 'Coffee')
('Bread', 'Tea')
('Bread', 'Pastry')
('Medialuna', 'Pastry')
('Coffee', 'Medialuna')
('Bread', 'Cake')
('Bread', 'Medialuna', 'Pastry')
('Coffee', 'Scandinavian')
('Bread', 'Coffee')
('Coffee', 'Pastry')
('Coffee', 'Hot chocolate')
('Cake', 'Coffee')
('Coffee', 'Scone')
('Brownie', 'Coffee')
('Coffee', 'Medialuna')
('Coffee', 'Tea')
('Coffee', 'Cookies')
('Bread', 'Pastry')



In contrast, the Multinomial Naive Bayes classifier faced even greater challenges in predicting the season in which transactions took place. Its reliance on the assumption of conditional independence of features likely doesn't properly represent the complex and correlated nature of customer behavior, underscoring the need for the more adaptable classification techniques of the decision tree classsifier in this context.