How to Optimize Online Ordering at Wegmans: An Approach to Enhance the Item Selection for the FastPick Section

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***Abstract*—This project involved the descriptive analysis and modeling of the Wegmans Woodmore, Maryland store sales data for identifying the best one thousand items for the FastPick section. The FastPick section or zone is a smaller section of the store only accessible to Wegmans employees and Instacart shoppers who gather items for online orders. This section is meant to decrease the amount of time it takes for Wegmans employees and Instacart shoppers to collect items for an online order. Optimally, the majority of an online order can be filled in the FastPick section, so that the shopper does not have to navigate the store looking for other items. With decreased time spent searching for items to fill online orders, more orders can be scheduled and fulfilled within a block of time. Currently, the Woodmore store is the only Wegmans with a FastPick section, and our goal was to improve FastPick item selection to increase online order efficiency. Using sales data to find the items most frequently ordered online, we were able to increase the average percentage each online transaction is filled by FastPick items from 36.72% to 46.3% and the percentage of online orders completely filled by FastPick items from an average of 1.3% to 3.05%.**

I. INTRODUCTION AND PROBLEM STATEMENT

Wegmans is a well-known grocery store chain in the North-eastern Region of the United States, located in New York, Pennsylvania, New Jersey, Virginia, Maryland, Massachusetts, North Carolina, Delaware, and Washington, D.C. It's one of the larger private companies in the US with 52,000 employees and annual sales of almost 12 billion dollars. Customer care, products, and service quality have been Wegmans' main focus and philosophy since 1916, the year the company was founded. This project focuses on a pilot program to increase the number of online orders that Wegmans stores can process and fulfill. Specifically, we are aiming to improve the selection of items grouped as FastPick items and available only to shoppers for online orders, Wegmans employees, and Instacart shoppers, in the Woodmore store. In order to make recommendations for this single store location, we are analyzing the sales, pricing, and item data only from the Wegmans Woodmore, Maryland store. The goal is to allocate the best combinations of items that reduce the time spent filling online orders at the store by identifying the top 1000 items that fill the largest number of orders. This project optimizing the FastPick section, as illustrated in Fig. 1, of the Woodmore store, is an example of one of the projects that distinguish Wegmans' research to provide a better experience for Wegmans customers. [1]

Fig. 1. FastPick Conceptual Idea

II. DATA

The data-set provided by Wegmans is composed of seven different files as shown in Fig. 2 recording historical sales by week and month, a file describing the relation between fiscal and calendar year, an item dictionary, a description of all the store locations, and a pricing record file of the items across time.

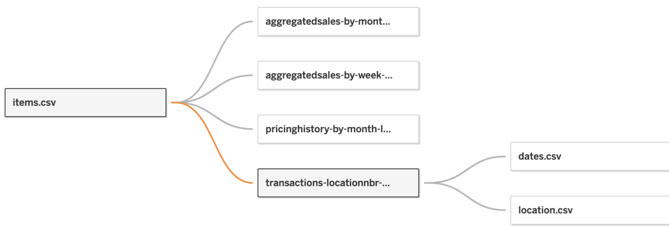

Fig. 2. Structure of the Dataset.

A. DATASET DESCRIPTION

The aggregated sales data has 384543 entries for the monthly records and 1257513 entries for the weekly records. It records information on the total and ecommerce units and dollars sold in a week or month period by item. Included in the aggregated sales data, both monthly and weekly, are the fiscal year number, fiscal month number and name, item number, and location number.

The dates file has 364 records with information on the relationship between the natural year and fiscal year at Wegmans. Features for the dates data are logical date key (yyyymmdd), display date (m/d/yyyy), fiscal week, week start and end dates (m/d/yyyy), fiscal month number and name, fiscal year quarter, and fiscal year number.

The items file stores 155059 entries with information on the item number, brand name, item description, sub-brand name, department name and number, category name and number, class name and number, item size, unit of measurement, and status (new, store active, seasonally suspended) at the Woodmore store. Lastly, four Boolean records on whether an item has internet availability, is organic, is a club pack, if the item is currently in the Woodmore store FastPick, and whether an item is included in the nature marketplace. The Boolean values are always 1 for yes/true and 0 for no/false.

Data from the location file has 5 different store locations. The features are location number and full name, street address, city, state, and zip code.

The pricing file stores 34246 entries for each item with information on the average retail price and the average Instacart dollar markup. Both types of price records are from May 2021 to September 2022. The item number and location number are included to match the pricing data to the correct store's items.

All flag and indicator (0,1) features in this dataset use 1 as yes/true and 0 as no/false. There is relevant data that was not included because it was either private or not captured. Though whether an item in an online transaction was the original item or a substitution is included as a feature, the item originally ordered is unavailable if the item was substituted out. No time efficiency data related to how long it takes to fill online orders were available, either.

III. EXPLORATORY DATA ANALYSIS

A first look at the data showed us that we were working with an imbalanced dataset and with an unsupervised machine learning problem. So, our EDA approaches were aimed at getting valuable information for feature engineering and target labeling purposes. At the time that our dataset was generated by the sponsor, only 0.6 percent of the available items in the store were marked as FastPick (Fig. 3), which confirms the target, with a goal of having only 1000 items in the FastPick section, is imbalanced.

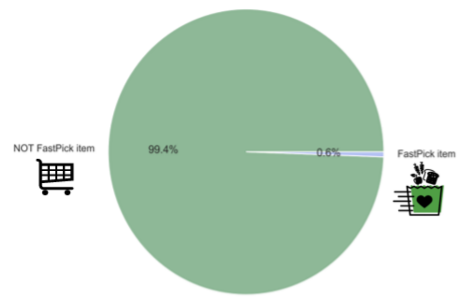

Fig. 3. Dataset Distribution

In dealing with an imbalanced dataset, it is vital to exclude or include certain features. An example of this issue are the "Total Sales" and "Online sales" (Table I) features. As seen in the table, the online sales are a much smaller portion of the total sales with fewer than half as many items sold online monthly (213,705) than overall (565,724). Even the top-selling 250 and 1000 online items are only a fraction of the highest total sales, with a maximum of 2,353 online units sold versus 28,149 total units sold. In the top 250 online items sold, the 250th best-selling only sold 24 units in one month. While the online sales do not make up a majority of the revenue for the Woodmore store, these data are invaluable for this project to be able to predict which items occur most frequently in online transactions and can fill the most orders.

A. Descriptive Statistics

We explore the sales data by exhibiting descriptive statistics. Table I shows a summary of the total, minimum, and maximum online sales compared to total sales. To clarify, total sales referred to the online plus the in-store sales.

TABLE I
STATISTICAL ANALYSIS

Measure	Total Sales	Online Sales	Top 250 online items	Top 1000 online items
Total items/month	565,724	213,705	4,500	18,000
Min units/month	15 Units $18,515	0 Units $0	24 Units $10.92	9 Units $3.19
Max units/month	28,149 Units $114,073	2,353 Units $3,865.7	2,353 Units $3,865	2,353 Units $3,865.7

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B. Insights from Dataset

Inferences and observations derived from the dataset are explained in this section. First, let's explore the top-selling online items according to units sold and dollars sold as shown in Figure 4. Top-selling items online can be ranked by two different measures (1) units sold and (2) dollars sold. We have identified that bananas are always ranked as the top-selling item online by having the largest number of units sold. However, organic chicken is the top-selling item according to dollars sold online. Since we are looking for the items that will fill the most orders and not the items that will earn the most money, bananas would make a more significant contribution to the FastPick section. We have found that the top-selling online items are very consistent for the entire time frame for which we have data. Across aggregated sales for all months, the top 250 items sold online by units have only 604 unique items. So, the same small group of items is regularly selling the most units.

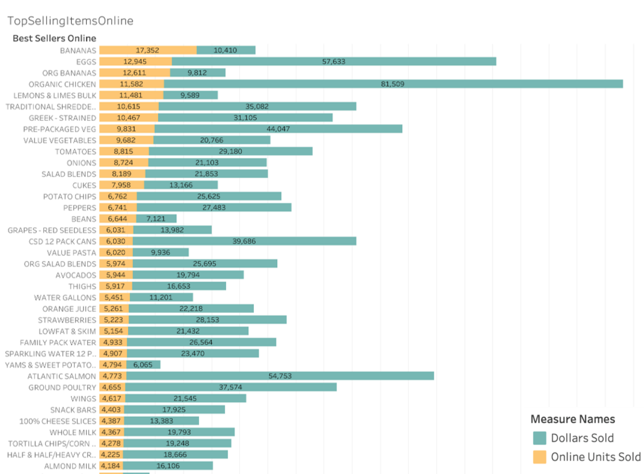

Fig. 4. Top Selling Items Online According to Units and Dollars Sold

We can see the behavior of the two features: online and total sales in Figures 5 and 6. These two features are extremely important in forming a target variable for whether or not an item should be in the FastPick section. But they might be concerning in order to avoid overfitting our models (due to their magnitude) compared to other item features included in our modeling processes.

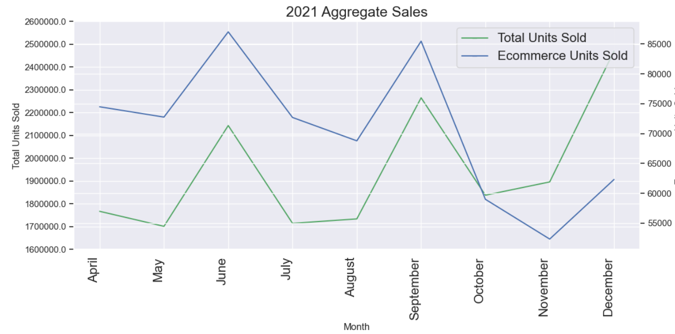

Fig. 5. Aggregated Sales Across Months by Ecommerce Units Sold and Total Units Sold, 2021

Looking at the comparison of total and online units sold by month shows notable trends in the data over time. The difference in scale of online sales compared to total sales by units is clear when observing this data. Total unit sales peak in June (roughly 2.1 million in 2021 and 2022), September (approximately 2.2 million), December (almost 2.5 million), and March (almost 2.3 million) as shown in Figures 5 and 6. Online units sold also peak in June (about 90,000 in 2021, well over 120,000 in 2022) and September (85,000 in 2021), but they take a dip in the winter months from about October to February, with fewer than 65,000 online units sold in each of those months. We expected that customers might want to order online during the frigid months to avoid going out in the cold. However, the contrasting fall in winter sales and peaks during the summer seem to contradict that assumption.

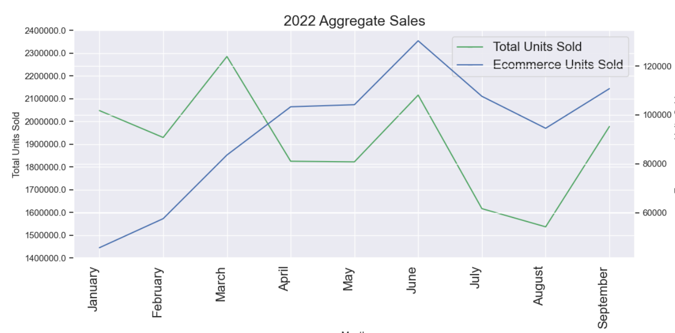

Fig. 6. Aggregated Sales Across Months by Ecommerce Units Sold and Total Units Sold, 2022

Right away, we notice the importance of Departments: items in the data are grouped in Categories, and Categories are grouped in Departments. As seen in Fig. 7, the top-selling items online are most frequently from the following departments: Grocery, Produce, Dairy, Frozen Food, Meat, and Cultured Dairy. Grocery and Produce are by far the most popular departments across the months for which we have data and even look to contribute a majority of all online sales between the two of them. It is also interesting to see the online sales balloon from March to July Fig. 7. These groupings played a key role in feature engineering and for the EDA.

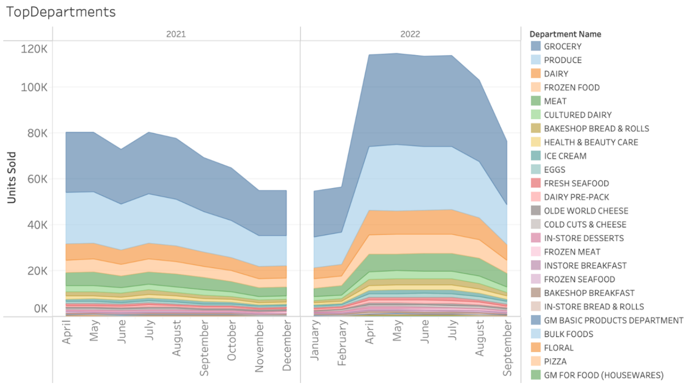

Fig. 7. Top Departments by Units Sold

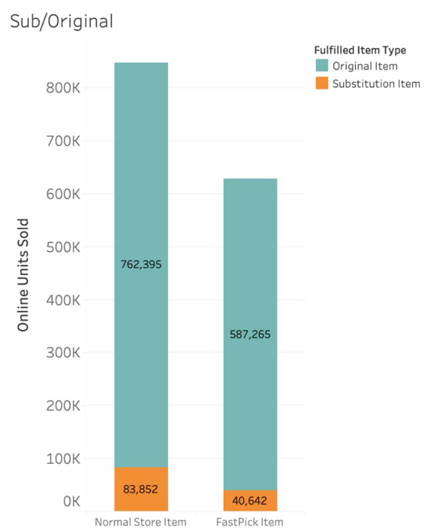

Fig. 9. Percentage of Substitute and Original Items

Analyzing the top-selling brands for the normal Wegmans store compared to the FastPick area, there is not much variation based on the brands. The distribution of the brands also looks similar for the two classes. Therefore, we decided not to depend on this predictor in our modeling. We also identified that *Wegmans* brand is the top brand for online and in-store sales as illustrated in Fig. 8.

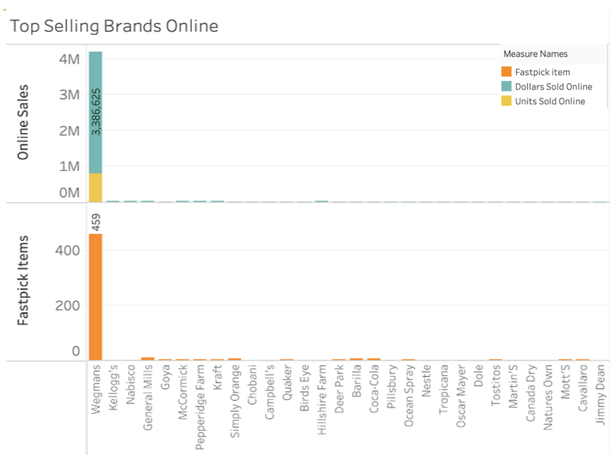

Fig. 8. Top Brands by Units Sold for FastPick Zone vs Normal Wegmans Store.

If an item a substituted item is frequently appearing in transactions, then it is a good choice to add to the FastPick area. Substituted items repeatedly showing up in online orders could mean that the original item ordered is similar, and it could indicate that the item originally ordered is hard to locate in-store or often out of stock. Fig. 9 shows the distribution of substitute and original items in the online orders and the normal Wegmans store. Obviously, transactions are more likely to include original items (majority class) than substitute items (minority class) because substitute items are always a replacement for the original item ordered if the original is for some reason unavailable.

The last piece of exploratory data analysis refers to Figures 27 and 28, due to visualization purposes both have been included at the end of the document. Both of them display a graph that shows the connections among items either in the entire store or in the fast-pick section. The process followed for generating the graphs is the same for Figure 27 and Figure 28 - run the Apriori algorithm with a 0.02 support and a minimum lift threshold support of 2. After, create a graph based on the number of connections among items and calculate the most important nodes based on the page rank algorithm and classify them with the Louvain algorithm.

In figure 27 the most important items are "SALAD VEGETABLES", "SALAD AND SALAD KITS", "BERRIES", "COOKING VEGETABLES", "PASTA SAUCE AND PASTA". In figure 28 the most important items are "SALAD LEAF", "SALAD VEGETABLES", "BERRIES", "COOKING VEGETABLES", "BANANAS" and "SALAD AND SALAD KITS". We are also able to recognize some communities in the entire store like: "GROUND BEEF", "PASTA", "SHREDDED CHEESE or BACON" AND "EGGS" or in the case of the FastPick section: "TROPICAL", "CITRUS", "BANANAS", "APPLES/PEARS" AND "BERRIES"

IV. FEATURE ENGINEERING

To create our target variable, we used the transactions file data. Each time an item was purchased in an online order, regardless of how many units, it was counted. These counts for how many times an item appeared in orders were compiled for each month. By month, the top 1000 most frequently appearing items in online orders were given a flag feature marking them as "is top 1000 frequency." While we attempted to use other data from our market basket analysis and exploratory data analysis, this top 1000 frequency flag is the best-performing target variable we were able to generate.

Depending on the month, at least one of the top 1000 most frequent items appears in roughly 90-94% of transactions. In Figure 10, we can see that the average percentage of orders covered (at least one item in a transaction) by the target variable is 92.28%. The average percentage of each transaction filled by the target is 42.36%, 47.15% if we only look at transactions with at least one of these top 1000 frequency items in them. The average percentage of transactions completely filled by the top 1000 most frequent items is 2.12%.

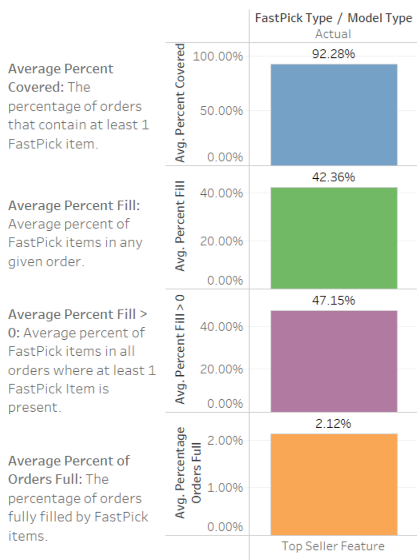

Fig. 10. Target Variable Average Coverage and Fill of Orders

For our feature engineering, we manipulated the categorical features we believed would be influential to modeling - department, category, class, and item - as well as combining some numerical data from features. The items, monthly aggregated sales, transactions, pricing, and engineered target variable files were merged to create a dataset for modeling. At the end of engineering new features, we have twenty features in our engineered dataset (ranked from most to least important): (1) Original Ordered Count, (2) Ecommerce Units Sold (aggregate by month),(3) Online Units Sold (aggregate by year), (4) Total Units Sold (aggregate by month), (5) Aggregate Units Sold (aggregate by year), (6) the flag indicating whether an item is currently in the Woodmore FastPick section, (7) Substitution Ordered Count, (8) Item Sales Percent in Department, (9) Department Sales Rank, (10) Fiscal Month Number, (11) Average Percent Markup (for the year), (12) Store Brand Indicator, (13) Item Size Percent, (14) Category Sales Percent, (15) Class Sales Percent, (16) Department Sales Percent, (17) Club Pack Indicator, (18) Organic Indicator, (19) Seasonal Flag, (20) Internet Item Indicator.

Original and Substitution Ordered Count: To calculate these two features, each time an item was marked as originally ordered and each time an item was substituted in a transaction was counted. These counts were added for each item, any items without these counts had the missing value replaced with a zero.

Online Units Sold and Aggregate Units Sold: for each item took the Ecommerce Units Sold and Total Units Sold from the monthly aggregate sales data and summed the total for each category (Ecommerce and total) over the year. Any items missing sales received a zero in place of 'NAN'.

All sales percent and rank features: were constructed by combining the item and monthly aggregate sales data, referred to as "item sales data" from this point in the feature engineering section.

Item Sales Percent in Department: An item sales data was grouped by item number, and the total units sold were summed by year. That summed value of sales was then ranked by the percentage of sales per item for the year to create Item Sales Percent in Department.

Department Sales Rank: It was calculated by grouping item sales data by item number and department, then ranking the departments based on total units sold monthly. Using the pricing data provided by the sponsor, we combined all monthly average percentage markup values for items by fiscal year to create the Average Percent Markup feature.

local store brand: From the items data, if an item's brand name is Wegmans, that item receives a "1" (true), and if the brand name is not Wegmans, the item receives a "0" (false) in the Store Brand Indicator engineered feature.

Item Size Percent: we grouped items based on the Item Unit of Measurement feature and summed the Item Size to get the Total Unit Size or total units for each unit of measurement. Then, each item's size was taken as a percent of the Total Unit Size for that item's unit of measurement (Item Size divided by Total Unit Size).

Category Sales Percent: the Category Name for items was taken as a value count based on item sales data and normalized, items without a Category Sales Percent had the missing values replaced with zero.

Class Sales Percent and Department Sales Percent: were engineered in the same way as Category Sales Percent but by Class Name and Department Name, respectively, instead of Category Name.

Seasonal Indicator: To convert the Item Status Description referring to the item's seasonal status into a numeric value, we added a "0" if the item's status is 'Store Active' or 'New' and added "1" (true for seasonal) if the item is 'Seasonally Suspended' as a Seasonal Indicator column. The other remaining features from the above list of twenty features in the engineered dataset.

After performing feature ranking and PCA, the Club Pack Indicator, Organic Indicator, Seasonal Flag, and Internet Item Indicator were removed from the engineered dataset because their relative importance compared to the other features was near zero, as seen in Fig 11. Ecommerce Units Sold and Total Units Sold were also removed from the engineered dataset to be used in modeling because we believed they were causing overfitting due to our Decision Trees hinging their results on those features. Neither Fiscal Month Number nor the flag for current Woodmore FastPick items were used in the x-variables for modeling, but they were important for comparing modeling predictions and results.

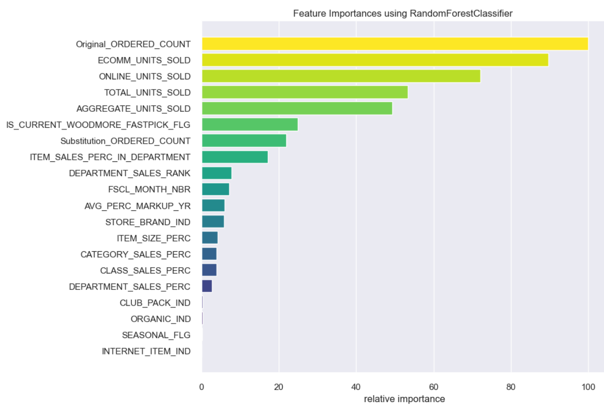

Fig. 11. Chart of Features Based on Importance

In Figure 12, we display our pipeline from the point where we are merging files in our dataset for feature engineering through exporting our results. We begin the pipeline by merging Transactions, Aggregate Sales (monthly), Pricing, Items, and the Target Variable (top 1000 most frequent items by month) to engineer our modeling dataset. That modeling dataset is upsampled so that we have the same number of items marked as our FastPick target (top 1000 most frequent items by month) as our non-FastPick items. Then, our x-features are reduced based on feature importance. That resulting dataset is run through Decision Tree, Logistic Regression, and XGBoost modeling by month, quarter, and year time frames across our full time-series of data. The results and predictions of modeling are saved and exported to review.

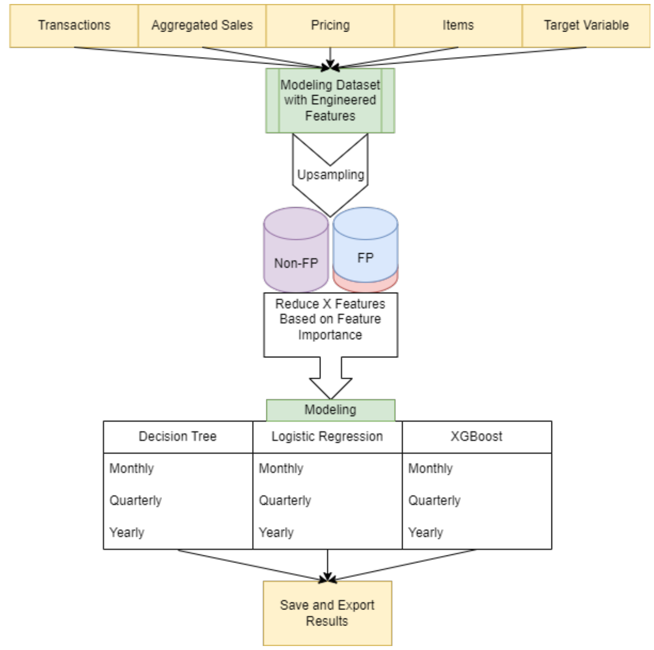

Fig. 12. Flowchart for the Pipeline from Feature Engineering to Modeling

The training and prediction automation on each of the three time frames is visualized in Fig. 13. Monthly trains on one month and predicts on the next. Quarterly takes a sequential group of three months (a quarter-year) for training and predicts on the next three-month sequence. Yearly trains on one month and predicts on the same month in the following year.

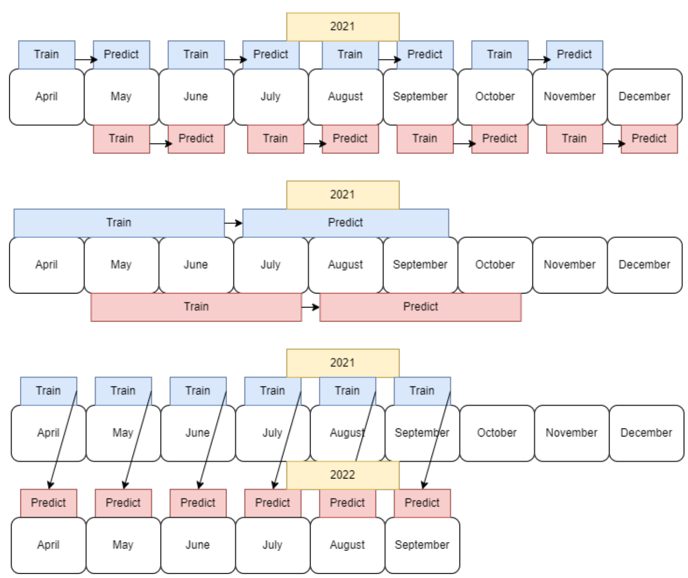

Fig. 13. Flowchart for the Pipeline from Feature Engineering to Modeling

V. MODELING AND RESULTS

As we stated earlier, we need to handle an imbalanced dataset and an unsupervised machine learning problem. One of our initial strategies for modeling was relying on the basket market analysis for understanding purchase patterns and for understanding features' importance. In Fig. 14 we can see a clustering of the orders after a PCA analysis.

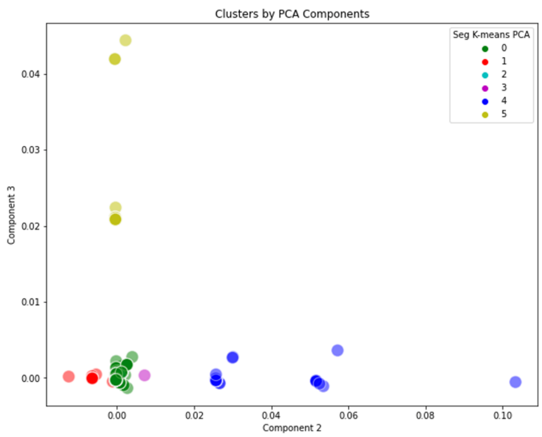

Fig. 14. Clustering Orders

Because the PCA analysis works on variance, we thought it would have been a good fit to check the variety between the orders. The PCA analysis was run on several components, the best number of components was 4 and in Fig. 14 we are showing Component 2 and Component 3, which showed the highest variance (the clusters are more spread out). Even if we have the highest variance in this picture, the clusters show orders with a really low variety between each other. The yellow and blue dots are about sixty orders out of five thousand. In general, the orders are all different, but many of them just differ for one, two or three items. The next step was understanding which departments shared more orders. We ran a correlation between departments based on order frequency in the departments and then a cosine similarity. The results were the same, the cosine similarity showed brighter and fuller colors (Fig. 15).

Fig. 15. Department Cosine Similarity

After we ran a market basket analysis from the most correlated departments to extract items for flagging them as our target for modeling. The initial results from a Decision tree model on a monthly basis were promising (Fig. 16 and Fig. 17).

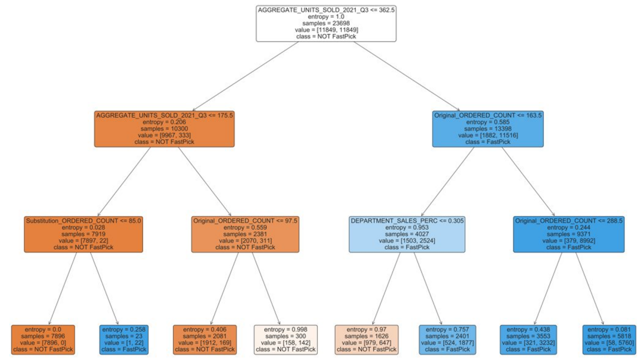

Fig. 16. Decision Tree Model.

	Accuracy	CV
April	99.55%	99.46%
May	99.58%	99.36%
June	96.98%	97.36%
July	96.85%	96.54%
August	96.71%	96.74%
September	97.22%	96.88%
October	96.62%	96.91%
November	96.53%	96.82%
December	96.71%	96.72%

Fig. 17. Accuracy and Cross-Validation Scores

We ran cross-validation with the leave-one-out technique for understanding overfitting. This technique is the most expensive in terms of time and computational power, but the most reliable in terms of results when you need to avoid overfitting. The problems we faced, in this case, are about tuning the basket market analysis and fewer data during the fall and winter months. During the cold months, we have a small drop in accuracy, which might not a big problem, but we can see a high number of false positives and false negatives. We had the same results when we tried to push more from the basket market analysis. (Fig. 18).

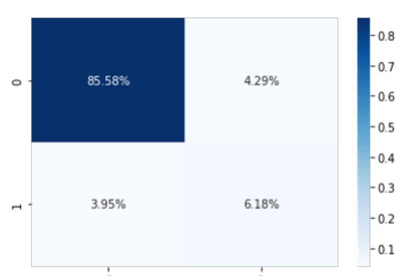

Fig. 18. Decision Tree Confusion Matrix

These results convinced us to consider a quarter basis dataset (three months) for modeling. This helped us to avoid the monthly small dataset issue and helped us for having a larger window on tuning the basket market analysis. For the quarter basis dataset and the use of the basket market analysis for labeling our target items, we considered Decision Tree, Logistic Regression, and XGBoost models. All the models performed well in terms of accuracy, cross-validation, and also on an error analysis over 20 random folds (the considered error is the mean absolute error), with the XGBoost model performing slightly better than the others. In Fig. 19, 20, and 21 the XGBoost results are shown.

	Accuracy	CV
Second Quarter	99.94%	99.92%
Thrid Queater	99.97%	99.96%
Fourth Quarter	99.92%	99.83%

Fig. 19. XGBoost Accuracy and Cross-Validation Scores

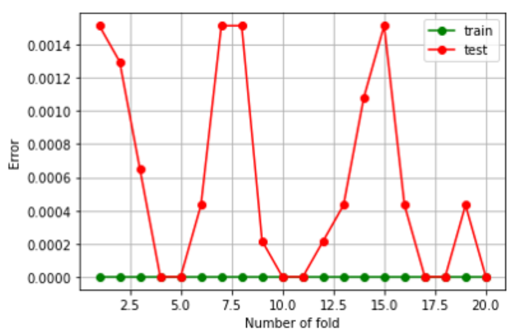

Fig. 20. XGBoost Error Based on 20 Folds

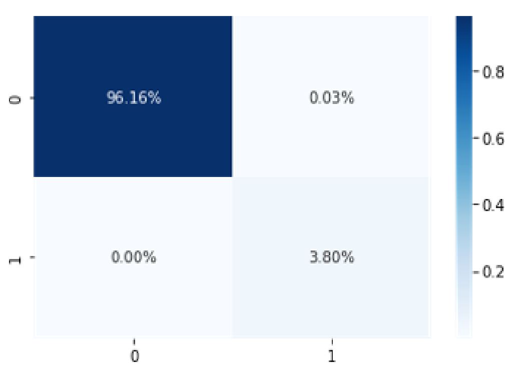

Fig. 21. XGBoost Confusion Matrix

The results were extremely promising, but the problems we encountered using the basket market analysis for labeling our target items was the amount of time needed to perform the basket market analysis several times, the necessity to find the perfect tune for the basket market analysis, and the infeasibility of the model to perform correctly with a small portion of the dataset like the monthly basis dataset. Considering this solution is not flexible for the reasons above, we examined the strategy of upsampling our dataset. This choice gave us the opportunity to have a more agile and flexible solution; we were able to obtain great results considering a monthly, quarterly, and even yearly dataset. Being a faster solution in terms of computational power, we were able to create a pipeline for the entire process, from the beginning (data cleaning, feature engineering) to the last step of the process (modeling) with the purpose to deliver a complete, effort-free package.

In our final modeling pipeline to predict which items should be considered for placement in the FastPick area of the Woodmore Wegmans store, we followed the steps shown in Fig. 12 and referenced in the Feature Engineering section. After creating the engineered dataset through our feature engineering process and reducing our features based on feature ranking using the Random Forest model (Fig. 11), we upsampled the target variable minor (FastPick) class in the dataset. So, the number of the true "1" values for the target FastPick or Top 1000 Frequent Items per month variable in the dataset were increased to match the number of items that were false "0" for that variable. Following upsampling of our target variable, modeling was performed using automation (Fig. 13) for monthly, quarterly, and yearly time frames to train and predict FastPick items with Decision Tree, Logistic Regression, and XGBoost Classifier models. With this pipeline we were able to save results for FastPick item predictions, prediction probability, and accuracy metrics (accuracy, precision, recall, and F1-score).

VI. CONCLUSIONS

Wegmans upgrades the online shopping experience for each user by utilizing advanced algorithms that decrease order prep time and drive revenue. We constructed Decision Tree, Logistic Regression, and XGBoost models to binary classify an item as either Fastpick or not FastPick class. Decision Tree, Logistic Regression, and XGBoost have average accuracies of 86.23%, 92.73%, and 91.46%, respectively, across all time frames modeled (average by model type from the Average Accuracy column of Fig. 22). Looking at all three model types, monthly average accuracy is 91.3%, quarterly accuracy is 90.15%, and yearly accuracy is 88.98% (Overall Accuracy from Fig. 22. Our Average Accuracy column in Fig. 22 also shows that each model type for each time frame had an average accuracy between 83.97% (yearly Decision Tree predictions) and 93.12% (monthly Logistic Regression predictions).

We successfully predicted itemsets of around one-thousand items recommended for the FastPick zone based on our target variable. These predicted itemsets maximize the average percentage of online orders filled and covered. Using the predicted itemsets, the average percentage of order fill, which is the average percent of FastPick items in an order divided by the unique number of items in an order, has increased from 36.72% (Current Woodmore FastPick provided by Wegmans) to 41.45-46.3%, depending on model type (Fig. 23). Excluding orders with no FastPick items, that average percentage of order fill is increased from 41.59% to 45.81-50.57%, depending on model type (Fig. 23). The average percent of order coverage, which is the percentage of orders containing at least one FastPick item, has increased from 88.33% to 90.25-91.45%, depending on model type. Most notably, the average percentage of orders completely filled by FastPick items has increased from 1.29% to 2.21-3.05%, depending on model type (Fig. 23). For the best prediction results, or average percentage of orders completely filled by FastPick is more than double the Current Woodmore FastPick section. The best results also show a 3.12% increase in average percentage of orders covered, a 9.58% increace in average percentage orders are filled by FastPick items, and 8.98% increase in average percentage orders are filled by FastPick items when at least one FastPick item is present in an order.

Model	Timeframe	Average Accuracy	Overall Accuracy
Decision Tree	Monthly	88.42%	91.30%
Logistic Regression	Monthly	93.12%	91.30%
XGBoost Classifier	Monthly	92.35%	91.30%
Decision Tree	Quarterly	86.32%	90.15%
Logistic Regression	Quarterly	92.23%	90.15%
XGBoost Classifier	Quarterly	91.88%	90.15%
Decision Tree	Yearly	83.97%	88.98%
Logistic Regression	Yearly	92.83%	88.98%
XGBoost Classifier	Yearly	90.15%	88.98%

Fig. 22. Comparison of Average Accuracy Across All Prediction Models and Time Frames

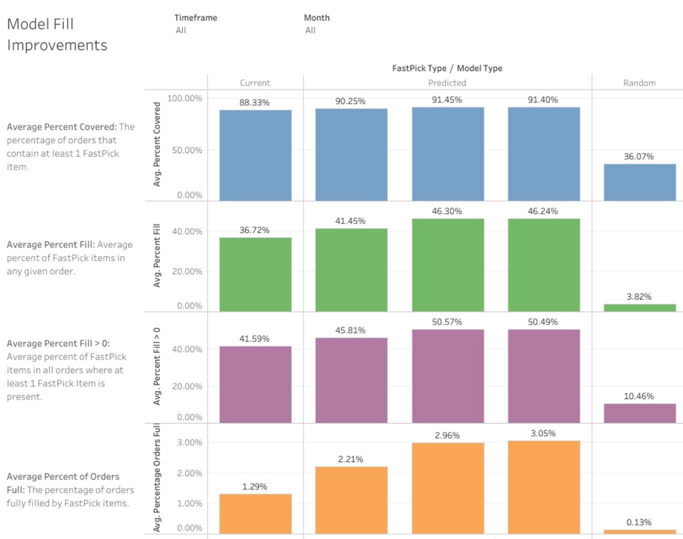

Fig. 23. Comparison of Percentage of Orders Filled with the Given Current Woodmore FastPick, Random Items, and Predicted FastPick Items Based on the Engineered Target of Top 1000 Frequently Ordered Items

In Figures 24, 25, and 26, we have a visual of how consistently items were predicted to be in the FastPick section over all model and month instances of the monthly, quarterly, and yearly time frames. The quarterly time period for modeling had the least consistent FastPick outcomes, with 33.63% of the items predicted once as FastPick items, and 10.54% of the items predicted to be in the FastPick section in 39 out of 39 of the modeling predictions. Monthly predictions were somewhat regular. Many items were only predicted as FastPick one or two times. However, 7.27% of the items were predicted as FastPick in 50 out of 51 modeling instances, and 12.45% were predicted as FastPick in all 51 instances. Yearly predictions were the most steady, with 26.35% of the items predicted as FastPick in 18 of 18 modeling predictions. Many other items were predicted to be in the FastPick section 13 or more times out of the 18 modeling instances.

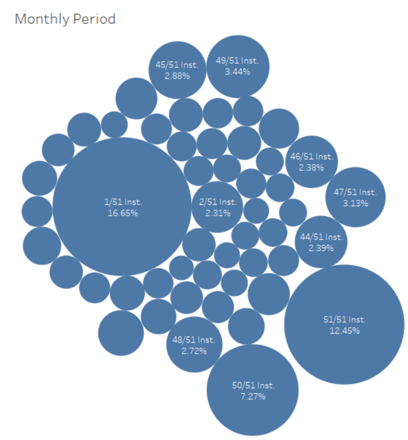

Fig. 24. Bubble Chart of Item Predicted FastPick Label Consistency Over all 51 Model and Month Instances, Monthly Time Period

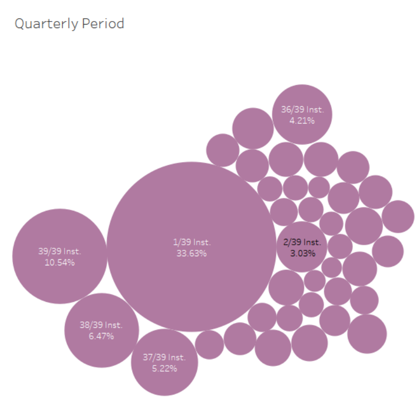

Fig. 25. Bubble Chart of Item Predicted FastPick Label Consistency Over all 39 Model and Month Instances, Quarterly Time Period

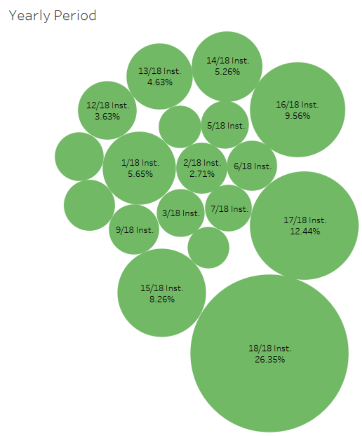

Fig. 26. Bubble Chart of Item Predicted FastPick Label Consistency Over all 18 Model and Month Instances, Yearly Time Period

Our modeling will enhance the efficiency of online order picking by helping Instacart shoppers and Wegmans employees collect an increased number of online order items in less time. This is because more of the frequently purchase online order items will be in one location. Moreover, we were able to identify the most relevant predictors that we can depend on to be useful for the FastPick section in the future: (1) Units Sold Online (2)Total Units Sold (3) Department Sales Percentage (4) Substitution Order Count (Fig. 11, in addition to the engineered outcome variable for FastPick *IS_TOP_1000_ITEMS*.

We conclude that there is some room for improvements to make on the average percentage filled for orders. We also believe Wegmans can continue making improvements on the target FastPick variable. Since it is highly reliant on item frequency in online orders, we believe there may be some combination of metrics (units sold, frequency in online orders, department features, Market Basket Analysis, etc.) that could improve the target FastPick variable. Moving forward, Wegmans can optimize the time frame used for modeling to best suit their FastPick section stocking needs, whether they choose to use our provided monthly, quarterly, or yearly modeling or some combination of the time frames. Wegmans will be able to utilize the feature engineering and modeling pipeline that we built for future months, and they can try modeling on other combinations of features if they find anything further that may influence the results.

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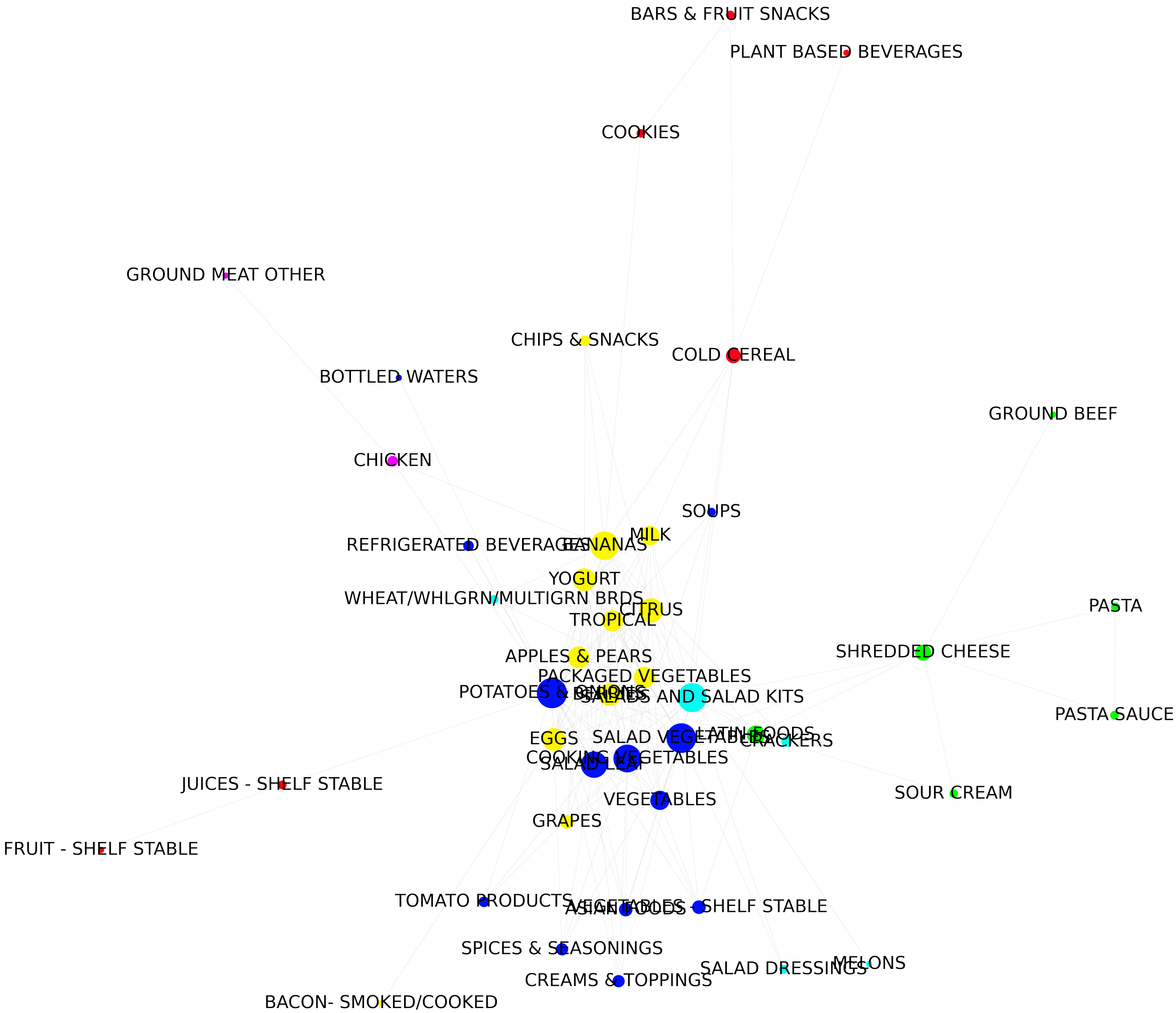

Fig. 27. Entire Store Graph Network

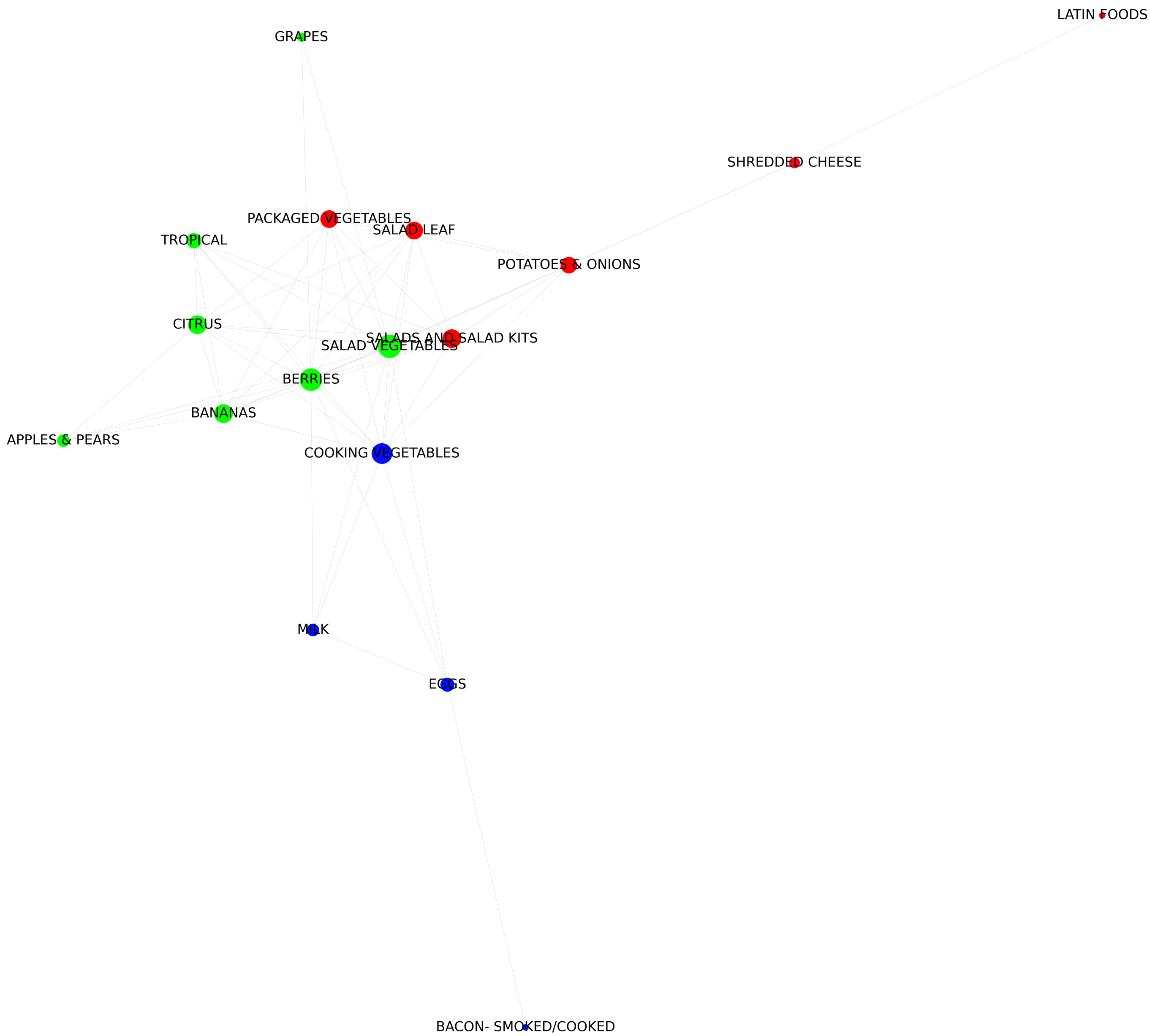

Fig. 28. Graph Network for FastPick