Feeding America Eastern Wisconsin – Agency Optimizer

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Business Need and Importance

Feeding America Eastern Wisconsin (FAEW) works with over 300 food pantries servicing 35 counties across the Eastern part of the state. In 2021 alone, FAEW spent over **$102M** on program services and much of those funds are allocated directly to the agencies in which they serve. Currently, resource allocation is generally equally split or often on a 'first come first serve' basis, but there is no *clear* process that efficiently targets the areas of improvement for each location through funding. This means that the annual funding on program services, such as the $102M last year, *could* have been more strategically spent to target these improvement areas for agencies who would benefit most. The amount spent each year by FAEW also could have been too much and was not efficiently utilized to maximize the return in helping food-insecure people in Wisconsin. In order to allocate funds and resources more effectively, one must know where food pantries are deficient and why some locations are performing better or are rated higher than others. In 2017, nearly 70% of FAEW agencies completed a survey that allowed the FAEW team to collect data surrounding the current equipment, storage capacity, processes, and other metrics of the food pantries in their network. The purpose of this project was to leverage the FAEW survey data containing agency features to provide a data-driven approach to understanding what makes a 'top' and 'underperforming' agency and how FAEW can allocate future program resources more effectively to upgrade locations. Additionally, combining survey data and historical food distribution data with public metrics such as food insecure persons (FIP), FAEW can see the direct impact current infrastructure/equipment has on food distribution and how future funding to improve shortcomings can serve more food-insecure people in each county.

Statistical Methodology

There were two main goals associated with this project, each requiring their own supervised data mining technique. The first goal was to leverage the 90+ question survey data consisting of features for each agency, such as having a forklift or the number of volunteers, to determine what type of partner each location was *(visionary, humanitarian, community or program partner)* **and** identify the most important features of the best agencies (*visionary*). After significant data cleaning and management, there were close to 150 final features (variables) for each of the 135 agencies that completed the 2017 survey, consisting of numerical and categorical values. Since the outcome variable of interest here was categorical and the input values were a mix, the first method deployed was a classification tree. All categorical variables were converted into factors, along with the outcome variable *partnerType*. This method was also selected due to the simplicity of illustrating the impact of meeting or not meeting a given feature (yes/no), which is much easier to interpret, regardless of the data science background of the viewer (in this case the

Figure 1: *Sample agency survey data*

expand_freezer_storage	hasRefrigerator	numHouseholdFridge
We have no need to expand our program's freezer storage.	0	None
Yes, and we would like to.	1	4 or 5
Not sure.	1	None
Yes, and we would like to.	1	4 or 5
No, we cannot.	1	2 or 3

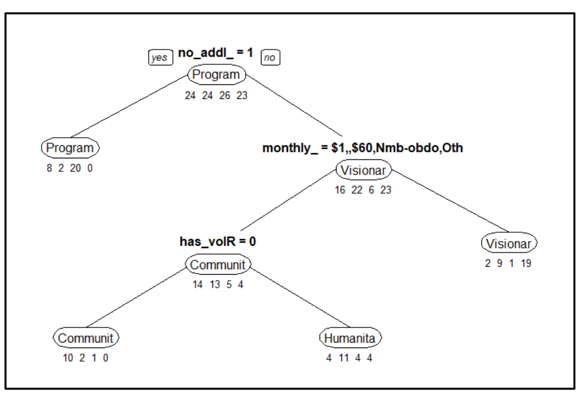
FAEW operations team). It was also able to visually identify the most important features within the dataset as it pertains to classifying the type of agency. The process was run with various training/validation splits (70/30, 80/20, 90/10) and yielded different accuracy values for the model itself. The accuracy of the models were compared based on their area-under-the-curve values.

A regression tree was the other method deployed, which was used since the outcome value of interest changed from *partnerType* (categorical) to pounds of food per food-insecure persons in the country (**PFIP**), which is numeric. This was the optimal supervised data mining technique to predict PFIP while **quantifying** the weight/importance of each feature of the agency as it pertains to the outcome. This was vital to include so that FAEW could easily see the impact of funding a given location's project, such as purchasing a forklift, and how it could be directly translated to PFIP. Since regression trees require numeric inputs, and the original cleaned data was a mix of categorical and numeric, additional data management needed to be done. The historical food distribution data provided by FAEW was for 2017 and 2021 for each location and normally would be fairly similar for each location within a 5-year period. However, due to the global pandemic that started in late 2019 (COVID-19), food distribution/demand looked significantly different between the two options, with the 2021 food-pound-totals *(13,648,306)* for the 135 agencies increasing by almost **42%** compared to 2017 *(9,639,818).* Thus, the 2021 figures were chosen to better reflect current and future demand for Eastern Wisconsin food-insecure people. All TRUE/FALSE values were converted into 1s and 0s, respectively, which accounted for roughly half of the variables. The remaining variables were all categorical and were first factorized and then assigned an integer value based on the alphabetical order of the unique values for each column (i.e. a = 1, b = 2, c = 3…). The accuracy of the created regression trees were assessed and compared by the lowest root mean square error (RMSE) values.

Results and Interpretation

The most important feature when determining the partner-level of a FAEW agency was whether additional services outside of the food program were available *(job training, drug rehab, nutritional class, etc.).* There were 14 possible 'additional services' options on the original survey and agencies that answered "yes" to ***not*** having any additional services at their program (i.e. *no_addl_services = 1*) were more than likely be "program partners", the lowest level of a partnership within FAEW. The simplest/shortest decision tree to interpret used a 70/30 training and validation split (Figure 2) and had an area under the curve (AUC) value of nearly 60% (57.78%), which was similar to other models with different split values (Table 1). This means that the 70/30 split for this classification

Figure 2: *Pruned Classification Tree for Determining FAEW Partner Type*

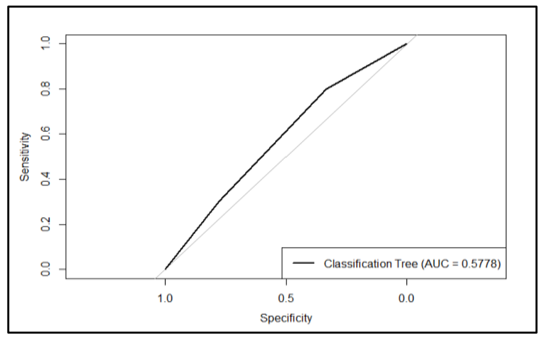


model was successfully able to correctly classify “visionary partners” 57.78% of the time. The second most important factor/feature for agency classification was the “monthly budget”. If an agency’s budget was one of the following: $600-1000, $1001-2000, no monthly budget/donations only OR other, they were more likely to be a “community partner”. All other selections (such as $401-600, $2001-3000, over $3k...) were more likely to be “visionary partners”, the highest level of agency partner. Finally, the third most important feature was having a “volunteer recruitment plan” in place, for situations when additional help is needed. Those that did *not* have a plan in place were likely to be “Community” partners. The FAEW team can begin to work with agencies that do not offer ***any*** additional services outside of their food program, by assisting in the creation/funding of other services that can be beneficial for the community members are already visit their site. It should be noted that when models were run with different seed values, which determines the selected data values for the training/validation set, the AUC and tree node values differed. This suggests that there is variability and the data is highly sensitive to subtle changes. This can be expected with a small dataset (135 agencies/observations), so model accuracy and results can more than likely benefit from additional data being collected, such as getting survey responses from *100%* of partner agencies, rather than 70%, or expanding this onto a national scale for additional data to train the model with.

Training/Validation Data Split *(seed = 1)*	Area Under the Curve (AUC) Value	Number of Tree Nodes
70/30	0.5778	3
80/20	0.5883	11
90/10	0.5000	2

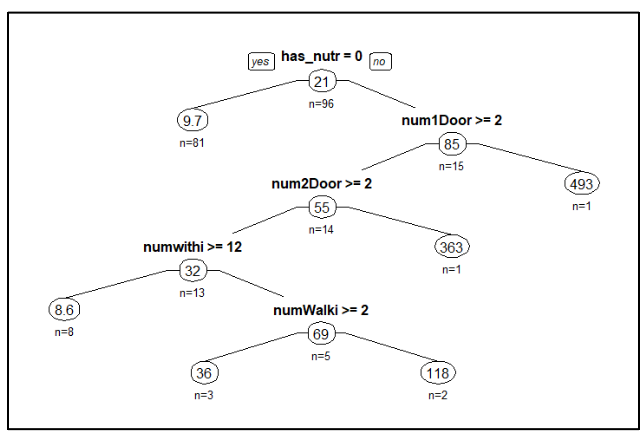
Table 1: *Summary of training and validation split values and their AUC/accuracy values*

Figure 3: *Classification tree receiver operator curve (ROC) for chosen model*



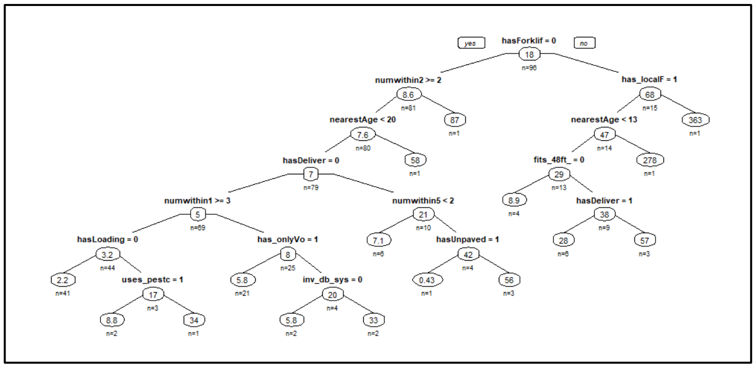
Agencies that possess a forklift had an almost **8x increase** in their pounds of food per food-insecure persons (**PFIP**) in their county than those without one (85 to 9.7). PFIP was calculated based on the agency’s 2021 food distribution totals divided by their county’s 2021 food-insecure person rate. Two regression trees were constructed to find the optimal model and visual for predicting PFIP for a given agency. The first (and inferior) model constructed included *all* variables outside of agency identifiers (such as name, location, etc.) and all data was converted into numerical values, a restriction of regression trees (140 variables). This model suggested that having nutritional classes/workshops within the agency was most important in determining the PFIP output (Figure 4). The next most important variables related to the type and quantity of refrigerators onsite at a given location, along with proximity to another food

Figure 4: *Pruned Regression Tree – using ALL features*



pantry. The second model incorporated questions that were <u>only</u> “Yes/No” responses, rather than multiple choice options. This resulted in a dataset with 45% less variables to include, but was done to investigate if a superior model could be formed with less features. Following the same process and seed value as the first model, this model found that having a forklift was the most important feature of PFIP. Unlike the classification model earlier, which can clearly by measured by an accuracy value like the AUC value, regression models are a bit more challenging to assess. Given that there is no ‘perfect’ or ‘optimal’ root mean square error (RMSE) value, the two models were compared head-to-head, with the findings summarized in Table 2. Though the second model had more nodes/variables in its pruned tree (Figure 5), it proved to be the superior model due to its smaller RMSE value of 85.55. This information can empower the FAEW team to fund the purchasing of forklifts and other key features found on the regression tree to help increase the ratio of pounds of food received per food-insecure persons in a given county.

Figure 5: *Pruned Regression Tree – using Only Yes/No Features*



	ME	RMSE	MAE	MPE	MAPE
Model 1	-20.982	116.709	46.195	-5578.276	5613.357
Model 2	11.669	85.550	34.675	-1331.513	1383.922

Table 1: *Summary of regression tree model assessment values, with the (smaller) RMSE value being the most indicative of performance*

Alternative Approaches

Several other supervised data mining techniques were considered to achieve the goals of this project, specifically Principal Component Analysis (PCA), k nearest neighbor (KNN) and random forest/ensemble trees, but each had their limitations. PCA and ensemble trees are difficult to interpret, especially for those without a data science background, and would not be as beneficial to easily hand off to the FAEW team as the other techniques that were selected. Additionally, the lack of visual outputs for the ensemble tree techniques makes for further interpretation difficulties for the FAEW team to easily digest what are the most important features of an agency to classify its type, which classification trees are great for. KNN was also seriously considered as a statistical method and is certainly beneficial as a classification option, especially given the smaller size of the data set used. However, KNN does not provide any information about the **weight or importance** of the individual predictor values (agency features) which would not provide the FAEW team with any *new* information about what areas are most influential and should be prioritized as areas for improvement.

Conclusions

Over $100M was spent on program services alone in 2021 by FAEW, which is only a subset of the entire Feeding American corporation that services over 60,000 food pantries across the country. The insights found here looking at just one branch of Feeding America on what drives the top-performing locations and what features/equipment are key for increased food distribution can be trailblazing not just for FAEW, but for the rest of the Feeding America partners. Through a data-driven approach, it is now known that additional services outside of just food programs can qualify an agency for a higher partner rating, which allows FAEW to determine its resource allocation more effectively, particularly for underperforming locations that presently do not meet these standards. Similarly, the FAEW team now knows that forklifts have the biggest impact on PFIP and can visually and computationally see the influence of funding new or upgrading existing equipment at a given site as it relates to PFIP. While the eventual goal is to *not* have food banks and food insecurity is cured, the current outlook suggests that food banks and pantries will be around for the foreseeable future. Given that, the FAEW team can leverage the insights found in this project to strategically open *new* locations within the state and predict whether a location will be a top performing partner agency ("visionary") or not ***and*** the yearly food distribution approximations given these numerous features.