**Portfolio Project-Module Eight: Option One**

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**Abstract**

The following paper reviews the use of data analytics and data visualization to assist Feeding America, a non-profit U.S. Organization dedicated to eradicating hunger in the U.S., with allocating both their financial and non-financial resources based on information provided by the U.S Census Bureau dataset, 2021 Annual Social and Economic Supplement (ASEC), which provides labor force data and additional information regarding work experience, income, non-cash benefits and geogaphic data for regions and by states, including 260 selected core-based statistical areas (U.S. Census Bureau, 2022). The project seeks to answer whether the data analysis can provide the ability for Feeding America to allocate 100% of their financial and non-financial resources based on greatest need, whether there are non-cash benefits that certain geographical areas are not accessing, and whether there are strong correlations between variables within the dataset that can help Feeding America with future resource allocation. The data analysis and visualizations will be conducted utilizing SAS and Tableau. SAS will provide the descriptive and predictive statistics for the dataset, and Tableau will provide additional data visualizations using geographical, income, and demographic data. This research will show whether the non-profit organization Feeding America can provide better resource allocation with the use of data analytics and data visualization, thus better fulfilling their mission of eradicating hunger in the U.S..

*Keywords:* Feeding America, U.S. Census Bureau, data analytics, data visualizations

**Data Analytics and Visualization for Feeding America Resource Allocation**

Feeding America is a non-profit organization dedication to eradicating hunger in the United States (Feeding America, 2022). Founded over 40 years ago in 1979 by John Van Hengal as a national food bank network called Second Harvest, it is now called Feeding America and based in Chicago, IL., providing food pantries, meal programs, and assistance services for those in need (Bloomberg, 2022: Feeding America, 2022). According to Feeding America (2022) John Van Hengal developed the idea of food banking while volunteering at a food kitchen in Phoenix, AZ. He was talking to a mother who needed assistance, who said that she would regularly search behind grocery stores and mentioned that unused food should be stored in one location so people could pick up food if necessary, leading to the idea of a food “bank” (Feeding America, 2022). The first food bank, named St. Mary’s Food Bank, opened by Van Hengal, distributed almost 300,000 pounds of food in its first year (Feeding America, 2022). Because of its success distributing food, by 1977 - 18 other cities established their own food banks (Feeding America, 2022). Today, Feeding America runs a network of 200 food banks and 60,000 food pantries around the United States, and last year distributed 6.6 billion meals, serving 1 in 7 Americans (Feeding America, 2022).

**Objectives**

Feeding America’s core mission is to eradicate hunger in the United States. Using current publicly available information such as the 2021 Annual Social and Economic Supplement (ASEC) provided by the U.S. Census Bureau, and data analytics tools such as SAS and Tableau for data analysis and data visualization, Feeding America could more effectively allocate financial and non-financial resources to these specific areas and people, and they could be provided with data to help in expanding their food bank and food pantry networks. Because hunger and poverty does not impact everyone equally, using U.S. Census Bureau data can help target communities in need. While data analytics and data visualization will not provide a silver bullet to eradicating hunger it can provide Feeding America with the tools necessary to gain better insight into the food insecurity issues that are so prevalent in the United States.

**Overview of Study**

Hypotheses for the Capstone were derived by identifying business questions that may be relevant to Feeding America through the population survey from the U.S. Census Bureau named the 2021 Annual Social and Economic Supplement (ASEC). It is an annual estimate of measures of income and poverty levels based on the responses from more than 75,000 households (U.S. Census Bureau, 2022).

**Research Hypotheses**

**Table 1**

*Business Questions. Null and Alternate Hypothesis*

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| Business Question One – Using publicly available income, supplemental income, and geographical data from the 2021 Annual Social and Economic (ASEC) Supplement, and tools such as SAS and Tableau, can Feeding America allocate 100% of their monetary or food-based resources based on greatest need?  H0 - Null Hypothesis – Feeding America will not be able to use targeted resource allocation based on income, supplemental income, and geographical data from the 2021 Annual Social and Economic (ASEC) Supplement, and tools such as SAS and Tableau, to allocate 100% of their monetary or food-based resources based on greatest need?  Ha - Alternate Hypothesis –Feeding America will be able to use targeted resource allocation based on income, supplemental income, and geographical data from the 2021 Annual Social and Economic (ASEC) Supplement, and tools such as SAS and Tableau, to allocate 100% of their monetary or food-based resources based on greatest need |
| Why? The answer to this question could give Feeding America insight into whether the annual population survey would better help them allocate resources to those in need by analyzing and visualizing household data by geographical area. |
| Business Question Two – Using data from the 2021 Annual Social and Economic (ASEC) Supplement, are there any strong correlations (> .75 Correlation Coefficient) between variables in the dataset, which can help Feeding America in predicting where future resource allocations will need to be made?  H0 - Null Hypothesis –There are strong correlations (>.75 Correlation Coefficient) between variables in the dataset that will help Feeding America in predicting where future resources will need to be allocated.  Ha - Alternate Hypothesis – There are no strong correlations (>.75 Correlation Coefficient) between variables in the dataset that will help Feeding America in predicting where future resources will need to be allocated. |
| Why? By finding strong correlations in the dataset, Feeding America may be able to make predictive resource allocations for future years. |

*Note*. Business questions related to Feeding America and the 2021 Annual Social and Economic (ASEC) Supplement, adapted from "Hypothesis Testing" by StatisticsHowTo.com, 2022. Copyright 2022 by Statistics How To.

**Literature Review**

According to Feeding America (2022), over 38 million people, including 12 million children, live with food insecurity. Non-profit organizations such as Feeding America have played an increasingly important role in serving the underprovided (Erete et al., 2016). As of 2010, 2.3 million non-profit organizations serve in the United States, contributing 5.5% of GDP or close to $805 billion to the U.S. economy (Blackwood et al., 2012). Non-profit organizational success is measured by resources taken in, what resources are output, the efficiency of redirecting those resources, and stakeholder satisfaction (Sarikaya & Buhl, 2021).   
 West (2019) states that decision making based on data analytics was a new concept for many non-profit organizations. As their effectiveness was measured more on fulfilling their mission and not on economic terms such as profit. For these organizations being able to properly allocate resources meant having a heavy reliance on relationships with field experts for their data needs, so that data consumption for non-profit organizations was both labor and cost intensive (Erete et al., 2016).

For some time, data related to food security mean dealing with missing values that could render the data less reliable (Caccavale & Giuffrida, 2019). Today, quality data is available and easily accessible to organizations to help transform the way they operate. So then why the slow adoption of data analytics to non-profit decision making? According to West (2019), the primary reasons for the slow adoption of data-analytics in non-profit decision making was that it was considered to be an expensive administrative cost for the infrastructure involved. Much of a non-profit organization’s resource allocation deals with balancing the delivery of resources with the cost of fundraising and marketing (Sarikaya & Buhl, 2021). With watchdog organizations and funders constantly focusing on the non-profit organization’s bottom line, it was believed that technology was too expensive, and that better data was needed for decision making (West, 2019). So why change now? As previously stated, quality data is readily available and more easily accessible, storage costs are being lowered, and processing power has increased such that a large investment may not be necessary (West, 2019: Wu & Dull, 2021). The use of data-analytics in decision making is seen as an objective decision-making process which can lead to consistency and standardization, rather than a subjective haphazard approach (West, 2019). It’s use can also provide a more predictive, evidence-based strategy for organizations with little margin, and high scrutiny (West, 2019). While the use of data visualization additionally provides a tool to correlate data from surveys and census organizations for better targeting of assistance (Hwang & Smith, 2010).

By applying publicly available data, such as the U.S. Census Bureau ASEC dataset, to readily available and inexpensive tools such as SAS and Tableau, the non-profit organization Feeding America can align their goals with business analytics methodology of problem structuring, business model mapping, leveraging analytics analysis and implementation of analytics (Hindle & Vidgen, 2018).

**Research Design**

The research design used for the Module Eight Capstone will be in the quantitative tradition. Research projects that use a quantitative approach use statistical methods to analyze numbers in the search for knowledge. The quantitative approach is based on the idea that the world can be defined by numbers, and that using deductive logic and reasoning and the scientific method and testing of hypothesis, that the results will lead to accurate knowledge of the world all around us (O’Leary, 2021). The research approach methods include generating a theory, from this theory generate hypotheses, gather quantitative data, analyze the data using statistical methods, and conclude whether the defined hypotheses were correct (O'Leary, 2021).

**Methodology**

The quantitative method uses experimental or population research design methods to produce knowledge from either existing or gathered data (O'Leary, 2021). This research project will use the quantitative research approach using population design and existing data from the U.S Census Bureau in the 2021 Annual Social and Economic (ASEC) Supplement to analyze income and poverty levels across the United States to help Feeding America in allocating their resources.

**Methods**

Analysis of the U.S Census Bureau dataset, 2021 Annual Social and Economic Supplement (ASEC), will be performed using two distinct tools. The first is SAS Studio which is a web-based SAS development environment for descriptive and predictive analytics. The second tool is Tableau Desktop for additional analytics and data visualization.

SAS Studio will be used to generate descriptive and predictive statistics for the dataset. Tools such as Proc Means, and Proc Univariate will generate descriptive statistic (SAS, 2022). Proc Means can analyze the mean, standard deviation, minimums, and maximums of quantitative data. Proc Univariate can go a step further and generate descriptive statistics, distribution graphs for each of the variables, as well as skew information for variables (SAS, 2022). Proc Frequency may be used to generate frequency tables and analyze multiple pairs of variables to discover relationships prior to the use of predictive analytics (SAS, 2022). For predictive analytics tools such as Proc Corr and Proc Logistic will be analyzed to examine the strength of relationships between variables (SAS, 2022). These tools will produce data that may allow Feeding America to focus their resources on certain areas of the country or on certain services that would be beneficial in their mission to eradicate hunger.

Tableau can also analyze the data using functions such as table calculations and predictive modeling functions, its focus however will be to tell the story of the data using visualizations. Tableau allows for highly customizable data views, including maps and geographical data that can be used to show regions of the U.S where Feeding America’s resources and services can be of most use (Tableau, 2022). A dashboard may also be created for Feeding America to use for additional data analytics from this dataset and for future potential analysis of new datasets (Tableau, 2022).

**Limitations**

Constraints or limitations of the data analysis may be seen due to privacy limitations. By analyzing only household data, and not family or personal data, the precision with which Feeding America is able to allocate its resources may be limited. However, limiting the scope of the data analysis to this broader view will help to alleviate any ethical, privacy and security challenges. Another limitation of this approach is that Feeding America is dependent on annual U.S. Census Bureau data for its information, and any lapse in survey coverage may impact Feeding America operations. Finding more real time or near-real time data may also be beneficial to Feeding America’s mission.

**Ethical Considerations**

Ethics as it relates to data analytics has to do with the moral obligations in collection, storage and use of sensitive information and what impacts this has on individuals and organizations (Cote, 2021). Feeding America will only utilize the household dataset, rather than the family or household dataset for its analysis which will minimize privacy issues. Access to the analysis will be restricted to those granted access on a need-to-know basis, and authentication will need to be provided to access the system. Any communication outside of the company will be encrypted for security.

The challenges of security, privacy and ethics in data analysis extends to the dissemination of insights (Cote, 2021). Data analytics and associated visualizations are used to inform decisions for organizations and governments both big and small. Because analytics can have such a far-reaching impact, these findings should be conveyed accurately and in an unbiased manner, should not reveal any sensitive information to audiences that are not cleared to receive it, and should be protected from deletion and corruption (Haferl, 2019).

**Findings**

Prior to analysis of the 2021 Annual Social and Economic Supplement (ASEC) from the U.S. Census Bureau, the data required transformation. The data, which consisted of 130+ variables and 90,000+ rows of information required constructive, destructive, aesthetic, and structural transformations (Stitch, 2022). To begin, destructive measures were taken to remove data from the dataset. There were exactly 26,313 non-respondents to the survey. These rows were removed as they skewed the results of the analysis. The variables were then reduced from a total of 130+ to 16 total variables. This removed unnecessary variables and all variables that could be used to identify any of the recipients to reduce any ethic, security or privacy concerns.

Once destructive techniques were complete, aesthetic, and structural transformations were employed. Aesthetic transformation included transforming multiple columns from ternary format to binary format which was possible as the format of ten of the columns/questions included three responses: not in universe - 0, yes – 1, and no - 2. As “not in universe” and “no” were both negative responses, the “no” responses were converted to zero to obtain a binary format. Structural transformation was used and each of the 16 variables were renamed for easy identification of variables during the study. Analysis began in SAS OnDemand for Academics, but it was immediately clear that additional information would be needed to continue with analysis. It was at this point that constructive transformation took place, and additional data from the U.S. Census Bureau was acquired. An additional data source, Poverty Thresholds for 2020 (U.S. Census Bureau, 2020) was extracted, and used to create an additional variable in the dataset called Poverty. Using the variable Numberinhousehold, a poverty threshold was set against the TotalIncome variable to identify whether a zero would be entered for non-poverty status, or a one would be entered for poverty status.

**SAS OnDemand for Academics**

Once transformation was complete, analysis could begin. In SAS OnDemand PROC MEANS was used to generate simple descriptive statistics for variables from the transformed dataset. As seen below, some general information about the data can be observed. The descriptive statistics show that there are 62,850 rows of information in the dataset, 17 variables-including the new Poverty variable. The mean for variables Poverty (10.8%), Foodstamps (11.4%) and Lunch (free/reduced lunch-11.7%) are close percentages of each other. Other statistics of interest include that the average household size is 2.6 individuals, and the mean for total income is $97,134 with a range of -$31,941 to $2,990,301.

**Figure 1**

*PROC MEANS Descriptive Statistics*

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Additional analysis was done with descriptive statistics using PROC UNIVARIATE. This analysis as seen in figures 2 and 3 (below) show that while all responses could be traced to a specific state, not all responses could be traced to one of 49,740 Metropolitan Statistical Areas (MSA) areas around the country, denoted by the Metro Variable, meaning that potentially over 15,000 of the responses are in rural parts of a state not identified.

**Figure 2**

*Distribution Plot for State using PROC UNIVARIATE*

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**Figure 3**

*Distribution Plot for Metro areas using PROC UNIVARIATE.*

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Additional information of interest from PROC UNIVARIATE output is total income distribution. This plot, shown below in Figure 4 shows income of respondents with a positive skewness (6.08) which trends towards lower income figures. Negative income figures and high-income figures encompass only a small percentage of responses. 75% percentile income shows as $123,004, 50% percentile as $68,002, 25% percentile as $33,309.

**Figure 4**

*TotalIncome distribution plot – PROC UNIVARIATE.*

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PROC FREQ was used for frequency plots which resulted in interesting cross tabulation tables that provide count data analysis for the dataset. For example, specifying a cross tabulation table between Poverty and States, and ordering by frequency produced the below table which shows a state-by-state count of respondents and whether based on their total income they are considered below the poverty line. California shows the most respondents with 5571, of which 583 are in poverty, accounting for 8.56% of the total. If the dataset is weighted to correctly represent population, then these figures could be used to determine a state-by-state allocation of resources. For further breakdown of allocation of resources by MAS area within a state, frequency tables can be used to show distribution of poverty as shown in Figure 6. This however highlights responses of 0 -no metropolitan statistical areas, which means that there exist a large number of potential recipients of resources from Feeding America that are either rural or failed to accurately list their MAS.

**Figure 5**

*Frequency table for Poverty in States using PROC FREQ.*

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**Figure 6**

*Frequency table for Poverty in Metropolitan areas using PROC FREQ.*

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PROC CORR was then used to determine correlations between variables. A broad analysis of the variables was conducted using both Pearson and Spearman correlations and mapped as seen in figure 7. Few strong correlations between variables were found. Obvious moderate negative correlative relationships existed between variables TotalIncome, Poverty, Foodstamps, and Lunch, meaning that the more income you had the less likely you were to have a positive answer for one of those three variables. Surprisingly, weak positive correlations existed between unemployment and food stamps (.064), receiving supplemental social security and receiving food stamps (.265), and receiving a free reduced price hot lunch if food stamps were received in the household (.237).

**Figure 7**

*Pearson Correlation Coefficients – PROC CORR*

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Finally, regression analysis was run on several variables within the dataset using PROC LOGISTIC. Looking for factors that influence whether a household goes into poverty. The dependent variable being Poverty, and the predictor variables being NumberinHousehold, IncomeScale, TotalIncome, and Minor. As Poverty (1), rather than non-poverty (0) is being modeled -a descending option is used so that the model is predicting the probably of being in poverty (1) based on the predictor variables. Output of the regression analysis is shown in Figure 8 and 9. The likelihood ratio chi-square of 42134.63 and a p-value of .0001 where the smaller the p-value the more significant the effect, as higher p-values denote a higher probability that the outcome is due to chance, shows that the model fits significantly better than an empty model (Kitchen, 2022: Zhu, 2016). The Analysis of Maximum Likelihood Estimates shows the three predictor variables, and the percentage increase in probability that someone will be in poverty for a one-unit increase. Income scale shows that for a one-unit movement in the income scale the log-odds of poverty increases by 2.91%, for every one-unit change in number in household the log-odds of poverty increase by 16.64 percent, and for every one-unit movement in number of minors in a household the log-odd of poverty increase by 1.68%.

**Figure 8**

*Logistic Regression output using PROC LOGISTIC.*

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**Figure 8**

*Consolidated Code used in SAS for data analytics.*

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**Tableau**

Tableau allowed for viewing the dataset in a different context. While SAS was used to for descriptive statistics, count correlation and regression analysis, Tableau will allow for data visualization. Because Feeding America is looking to use data analytics and data visualization to help in their resource allocation, visualizations showing relationships between variables and geographical mapping of data were undertaken in Tableau. Figure 9 uses a frequency count/heatmap to show distribution of poverty through states and their metropolitan areas.

**Figure 9**

*Frequency table/Heatmap for poverty in states and their associated MSA, using Tableau.*

*Chart, treemap chart

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From the image you can see the states with the largest numbers of those afflicted by poverty, and the corresponding MSA in which they live. Not surprisingly some of the largest states by population have some of the largest metropolitan areas which comprise the biggest populations of those in poverty. States down south (AL., GA., LA., and MS.) and out west (MT., NM., WY.) commonly have no MSA (0) listed for their largest frequency count, and their largest population of poverty may be scattered throughout the rural parts of the states.

The next figure provides a side-by-side comparison of those considered in poverty due to their income levels, the households that receive food stamps, free/reduced lunch, and welfare, and those on unemployment. While most of the variables in the dataset have at least a weak relationship to each other due to the nature of the survey, based on the bar chart a strong relationship exists between unemployment, receiving food stamps, receiving free/reduced lunch and poverty. Some outliers exist such as in California where the unemployment count amongst respondents is almost double the poverty number, meaning at this time those claiming unemployment may not yet be in poverty status. Otherwise, these variables are very closely related in each state, with supplementary social security recipients and disability recipients showing a bit weaker relationship to poverty, food stamps and free/reduced hot lunch. However, since discussion is of households and not individuals or families, mixed households and multigenerational families could have multiple reasons for their decline into poverty.

**Figure 10**

*Side-by-side comparison of variables, using Tableau.*

Graphical user interface, chart

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Geographical mapping of variables poverty, state, and metro give a visual of where Feeding America resources may be needed most urgently. Figure 10 give a visual of data found previously in SAS, shown in figure 5, where total poverty percentage is given (Alaska not shown but % poverty same as Hawaii). This breakdown gives possible resource allocation by state. Figure 11 shows details by MSA within each state (The data excludes MSA of 0-rural; Alaska not shown, but all rural). This also too can be used to allocate within state, leaving the percentage attributable to MSA 0 as a rural allocation through possible delivery or funding of new food banks in strategically placed locations.

**Figure 11**

*% of Total Poverty (state allocation % for resources), from Tableau.*

Map

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**Figure 12**

*Total Poverty by MSA within state (excludes rural), from Tableau.*

Map

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**Results of Findings**

The study sought to answer two business questions. 1**.** Using publicly available income, supplemental income, and geographical data from the 2021 Annual Social and Economic (ASEC) Supplement, and tools such as SAS and Tableau, can Feeding America allocate 100% of their monetary or food-based resources based on greatest need?2. Using data from the 2021 Annual Social and Economic (ASEC) Supplement, are there any strong correlations (> .75 Correlation Coefficient) between variables in the dataset, which can help Feeding America in predicting where future resource allocations will need to be made?

For question number one the findings did not present enough evidence to support the alternate hypothesis or 100% allocation of resources based on greatest need. More information was needed to identify current resource allocation percentages per state and associated MSA’s as is information regarding rural allocation of resources as rural households who suffer from poverty and hunger may depend largely on agriculture (Dukhnytskyi, 2020). Therefore, the result of the findings is a failure to reject the null hypothesis. However, even with this result the research found substantial evidence that the information would be beneficial to Feeding America and their resource allocation management. A review of another data visual marking Poverty by MSA within states (Figure 13) and a Feeding America map showing food bank coverage by state (Figure 14), shows a very close correlation (Feeding America, 2022). In fact, figure 13 may show Feeding America where more resources may be needed. For instance, in Oregon, Montana, New Mexico, and S.W. Texas there are areas of poverty shown by the analyzed dataset that are not appearently covered by Feeding America’s network of food banks.

**Figure 13**

*Poverty by MSA within states, from Tableau*

Map

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**Figure 14**

*Feeding America’s national network of Food Banks*

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For question number two the results were similar, there was not enough evidence to support the alternate hypothesis that strong enough correlation existed between variables to predict future resource allocation needs. The findings of the Pearson and Spearman correlation coefficient tables did not show strong correlations between variables. The results of findings therefore are a failure to reject null hypothesis. However, logistic regression did find a significant correlation between number of individuals in household, minors, income scale and dependent variable poverty, but more research is needed determine usefulness of this data in predicting future allocations.

It is recommended that further analysis be done using the monthly Current Population Survey (CPS). The CPS asks a series of questions about the conditions that lead to food insecurity, and includes similar data related to poverty and income (Edwards et al., 2007). This dataset was too large for the Academic version of SAS used but could be analyzed using tools such as R or Python. It can provide Feeding America with a time series of data that may be more useful in consistently tracking resource allocation, it also provides an average over 8 months of interviews to smooth the data and is heavily used for poverty and income analysis.

**Conclusion**

Critical Thinking-Module Six: Option One, entitled, “Capstone Project Rough Draft: U.S. Organization (Instructure, 2022)” required the submission of a rough draft of the Capstone Project (Instructure, 2022). The Critical Thinking assignment presents all information from Modules 1-5, and includes research findings (Instructure, 2022). Future Critical Thinking assignments will provide an abstract and present a more through conclusion.

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