IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Location Analytics Prototype For Business Expansion Analysis

[1]Prof. Neeraj Bhargava, [2]Dr. Ritu Bhargava, [3]Dr. Vaibhav Khanna
[1]Professor, [2]Associate Professor, [3]Associate Professor
[1]Department of Computer Science, MDS University Ajmer
[2] Department of Computer Science, Sophia Girls' College (Autonomous), Ajmer
[3]Department of Computer Science, Dezyne E'Cole College, Ajmer

Abstract: Every decision is made in a specific context to the location and location analytics adds decision supporting context to the "why" "when" and "how much" questions associated to every dataset. This paper outlines a prototype that we developed to be followed for systematically conducting this type of analysis. For demonstrating the usage of the prototype, we have used the laundry business expansion dataset in Michigan and the associated maps and demographic data layers.

One of the most important activities when planning a business expansion is to analyse the existing businesses for identifying the Geographic attributes and Critical success factors for the business. Research results in this paper first analysed a set of best-performing similar businesses to identify critical success factors. These are applied along with other known demographic criteria to identify the most suitable market for the expansion of the business.

***Index Terms* - Location analytics, Business expansion Spatial Data Mining, Business Intelligence, Locational Intelligence.**

Introduction

We live in an age of data and the intelligence and insights derived out of that data. It's a 21st century dilemma that getting data has never been easier but understanding it and analyzing it for insights has never been more challenging. The best solution to this situation is "map it, analyze it as layers of information and visualize it." (Ain, Vaia, DeLone, & Waheed, 2019) Literally when data is put on a map, it becomes much easier to analyze it and the patterns get clearer. The relationships between data elements become more obvious and questions get answered through spatial mining of related information. This called location analytics and it provides answers about the "where"' component of data.

Every decision is made in a specific context to the location and location analytics adds decision supporting context to the "why" "when" and "how much" questions associated to every dataset. Whenever there is a computing problem we look for a solution through data analytics as to what do about it. Irrespective of the source data there's a right way to start analysing the data by observing the patterns and converting it into layers of information. (Anselin, A Local Indicator of Multivariate Spatial Association: Extending Geary's c, 2019) Businesses traditionally are good at seeing where things are but not necessarily understanding why they are there. For example, businesses use maps to visualize locations where the product is selling more as the stage one of business intelligence. This is the stage of descriptive analytics in which we monitor what is happening and add a where component to it in the form of location of event. (Anselin & Williams, Digital neighborhoods, 2016)

The next stage of "spatial data mining for location analytics" is very powerful because after seeing data in the map, we look for patterns to start getting an idea about "why" something is happening somewhere.

To compute this analytics we need to model the characteristics that demonstrates why the business is performing well in that particular location. (Dastjerdi, McArdle, Matthews, & Keenan , 2020) So locational intelligence starts with how to make a data driven map and visualizing data maps and moves further to analyzing data using maps. (Huang, Pei, & Xiong, 2006)

I. Review of Related Works

Location analytics organize features in a database about geography and store them as a series of spatial relationships not simply graphic representations. (Newgrove, 2017) This is important because certain things that we want to do with data like queries that are complicated, that need to see interrelationships across space or through different layers. (ESRI White Paper, 2017) This complex structure of layers can support all kind of queries and provide the basis for decision support. (Huang, Pei, & Xiong, 2006)

One of the principles of GIS databases is that we organize data formally to the data models and that data model should be should be able to accommodate all kinds of explicit relationships, spatial as well as non spatial. (Jiang, Sainju, Li, Shekhar, & Knight, 2019) The second one is that it has minimum redundancy you don't store a lot of different graphic views in the database we generate graphic views as we had want them using software to associate symbology to these features. (Keenan, 2020) Environmental Systems Research Institute, ESRI was one of the first companies founded specifically to provide Location software tools. ESRI's ArcGIS software is now a widely used commercial software package and is considered the industry leader for Spatial Data analytics. Spatial data analytics is the superset of Location Analytics and spatial data mining. (ESRI White Paper, 2017)

Spatial data is the building block of spatial data analysis and mining. (Li, Wang, & Yuan, 2016) Understanding the concept of spatial data requires a understanding of the major distinction between three types of things that happen in space and that we will record observe as spatial data. (McKinsey Global Institute, 2019)

Events are things that happen in a particular location for example the addresses of the people or locations of the stores, or the addresses where the crime happened. Those are locations of events that happened at a particular location. (Eftelioglu, Shekhar, Kang, & Farah, 2016) This means that the first set of recorded transactions are generally for the observed events. That will affect what we can say and how much we can say in the analysis. (Anselin, A Local Indicator of Multivariate Spatial Association: Extending Geary's c, 2019) In real world the analysis needs to analyze the existing data as well as interpolate data that does not exist. (Oracle Corporation, 2019)

This would be saying that when we study people demographics and city income, we are analyzing whether there's convergence or divergence of the income between cities or states. (Yilmaz, Elbasi, & Ferhatosmanoglu, 2017) Similarly, we have a spatial pattern of cities, districts, states, countries, regions or zones of similar data patterns. Another example would be an analysis for creating a prized surface in real estate analysis. If we create an interpolated price surface out of the discrete observations of sales at particular points, the analysis will construct the surface of prices. (Yap, Ho, & Ting, 2019)

II. Experimental Analysis Process

Businesses need to plan their expansion meticulously and methodically to new business areas. This can be done using "Location Analytics" as expansion decision is costly and critical for the success of the business.

This paper outlines a prototype that we developed to be followed for systematically conducting this type of analysis. For demonstrating the usage of the prototype we have used the laundry business expansion dataset in Michigan and the associated maps and demographic data layers.

A framework for the Location Analytics Business Expansion Prototype can be outlined as given below:

- Identify Critical Success factors for the business category
- Analyze successful business in potential markets
- Plan potential candidate-markets for expansion
- Analyze geographic attributes of customer derived trade zones
- Analyze existing sales dataset for sale-based zoning
- Identify contributing demographic variables

- Add color coded demographic layers.
- Generate Market Suitability Analysis
- Generate Sub-market suitability analysis layers
- Generate and Rank candidate sites
- Create analysis based on variable criterion
- Adjust Criterion weights for multi criterion analysis
- Create reports and infographics to generate insights.

3.1 Identifying Critical Success Factors

One of the most important activities when planning a business expansion is to analyze the existing businesses for identifying the Geographic attributes and Critical success factors for the business. This can be done by analyzing the location attributes of existing successful businesses and existing markets.

3.2 Analyze successful business in potential markets

We can use locational Analytics to understand what makes a successful business. Using this we can identify the information criteria based on which the market is to be analyzed and then point high potential submarkets and candidate sites.

Location analytics has a built-in Toolbox for geo database analysis. In this current project we analyze the geo database for business expansion of laundry services in Michigan. The ArcGIS dataset used is ExpansionStudies.ppkx.

3.3 Analyze customer attributes for trade area analysis / zones

There are several layers of information that we analyzed especially the customer layer, gym and movie theaters layer, and also the geographic features related to laundry drop service. There is also a layer for competitor attribute analysis. This kind of analysis is called the trade area analysis and we can add a new map layer showing the existing customer trade area zones to the existing map layers. (Kedron, Li, Fotheringham, & Goodchild, 2020)

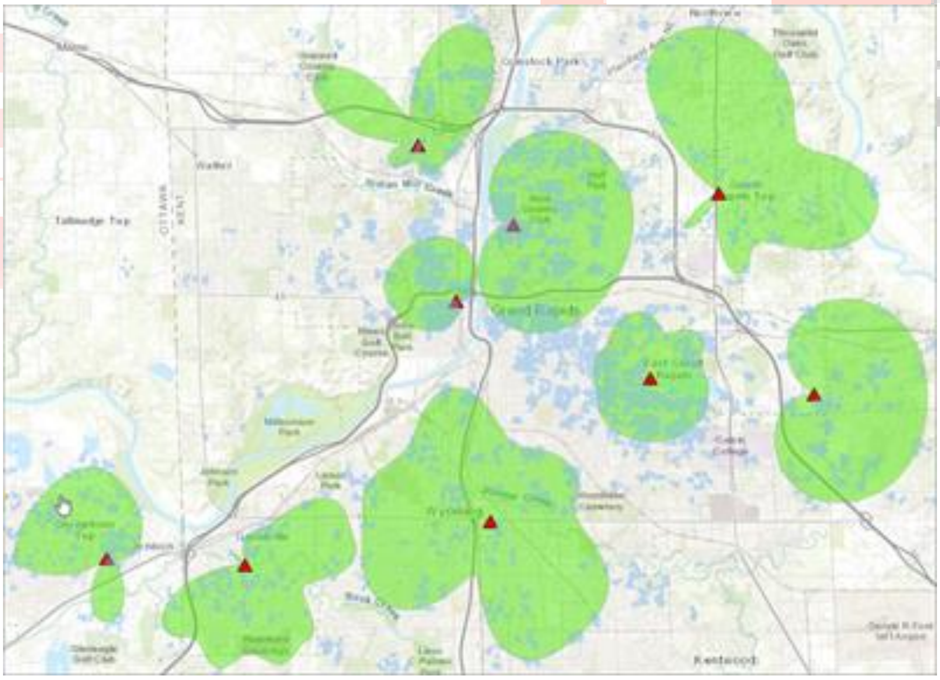

Figure 1: Trade area analysis

3.4 Analyze existing sales dataset for sale-based zoning

If we conduct sales data analysis for these customer trade zones using scripts, we can create trade areas by sales. The trade areas by sales can be overlaid on the customer trade zones to understand the distribution of customers and the distribution of sales at business store level. (Talen, Anselin, Lee, & Koschinsky, 2016)

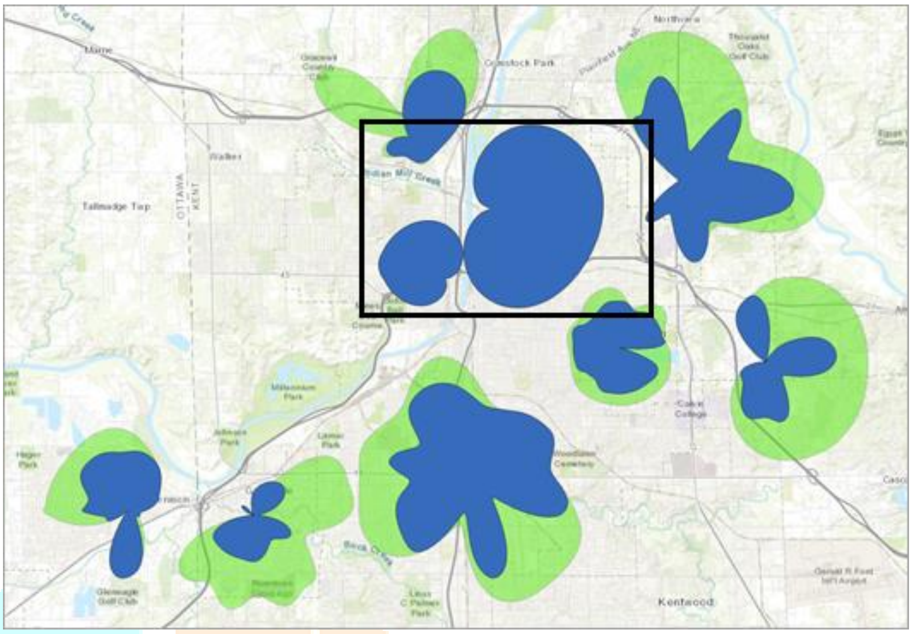

Figure 2: Overlay map for Sale based zoning

From this we can identify the business locations that can generate the highest sales.

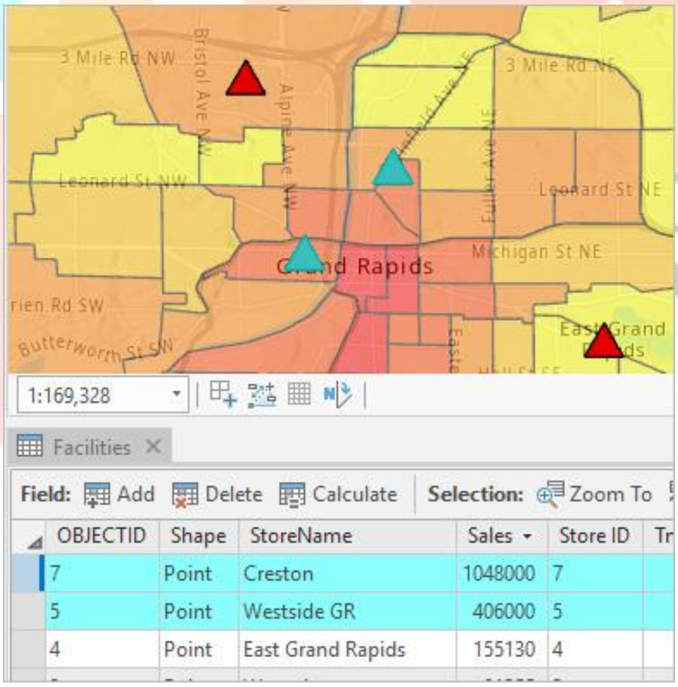

Figure 3: Color Coded Choropleth map for multi factor location analytics

3.5 Add color coded demographic layers for market suitability analysis

Next we can add the demographic variable layers and give them colour codes. The colour coded choropleth layer is very useful for evaluating the market-based opportunities depend on specific variables. The first variable is generally the classification variable that can be used for data enrichment using demographic information. (Tan, Ting, & Ho, 2020) These locations are highlighted in the maps as well as the attribute tables.

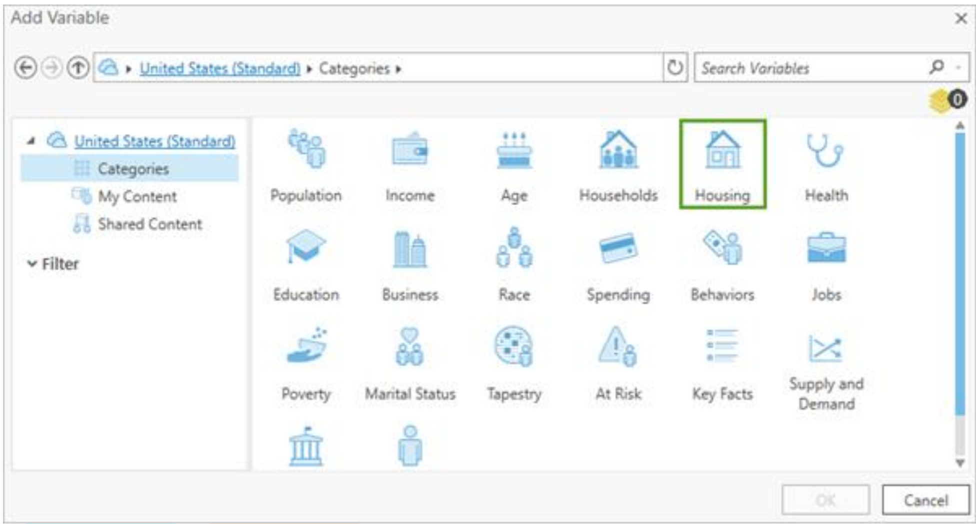

Figure 4: Multifactor Demographic Analysis Layers

3.6 Generate Market Suitability Analysis

We have to analyse several dimensions for market suitability analysis. For example, the housing-units-occupied data in terms of percentage of housing units occupied can give a fair idea of the people living in specific locations.

Similarly, the day time density of population present in a given location during the business as another criteria that can be useful for business analysis. (Ting, Ho, Yee, & Matsah, 2018)

Another parameter can be the workers of age 20 and above that walked to the work and the traffic generated through these workers. To this we can add the layer of workers using public transportation for going to the workplace. The scripts can convert this information to infographics for ready analysis.

Additional attribute can be the propensity of the people to spend money for buying a service and the average spending of a representative customer. (Yee, Ting, & Ho, 2018) This is generally expressed as an index. Through this we get the potential markets for expansion of the business through market suitability analysis.

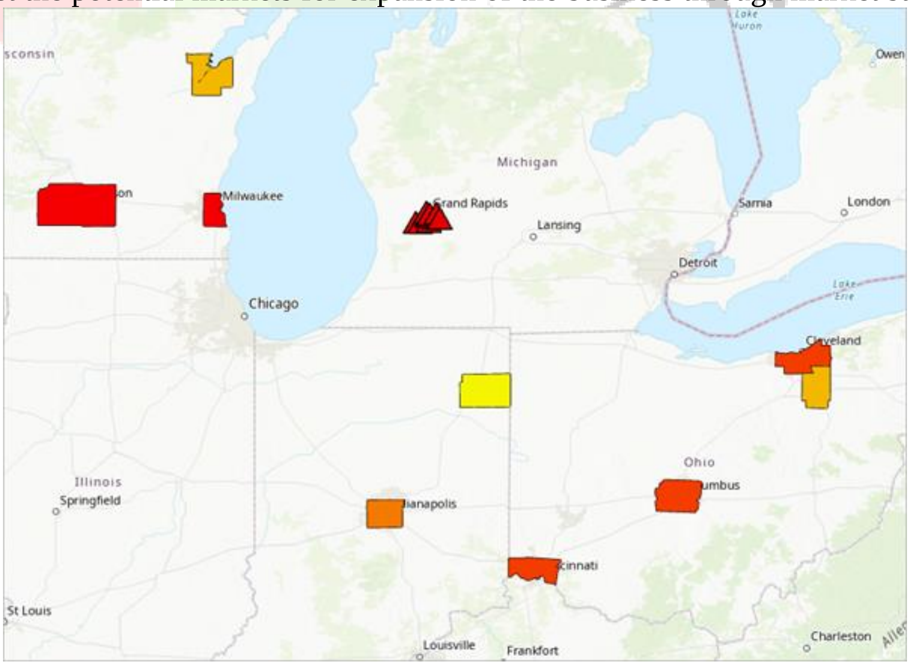

Figure 5: Market suitability Analysis

3.7 Generate and Rank candidate sites

For discovering the most potential sites among the group of candidate sites we conduct suitability analysis. The objective function is to determine the best offered site from a set of alternatives generated as candidate sites.

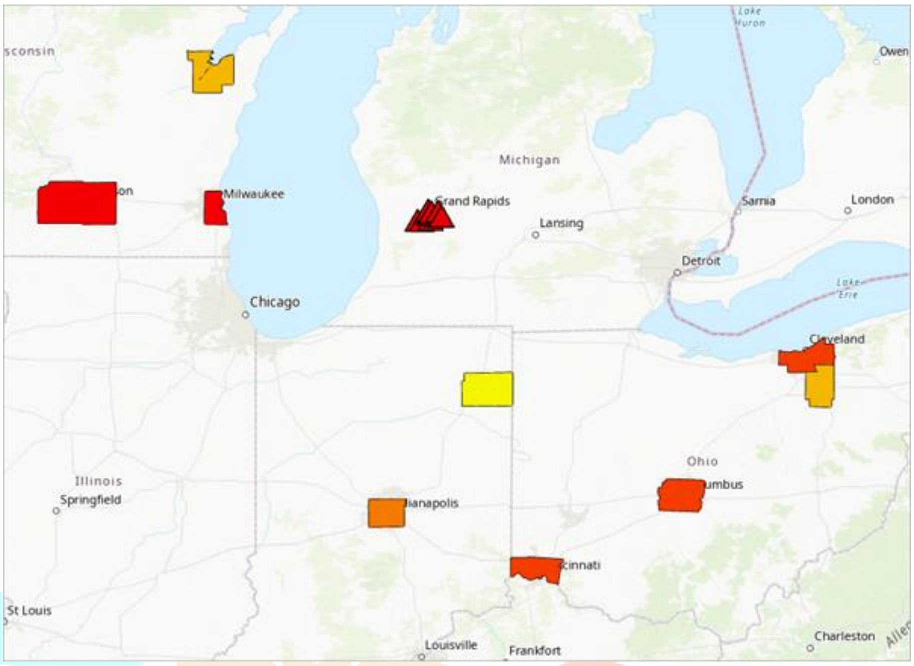

Figure 6: Generate and rank candidate sites

3.8 Adjust Criterion weights for multi criterion analysis

Using scrips for adding weights we can change the relative level of impact of these suitability analysis factors.

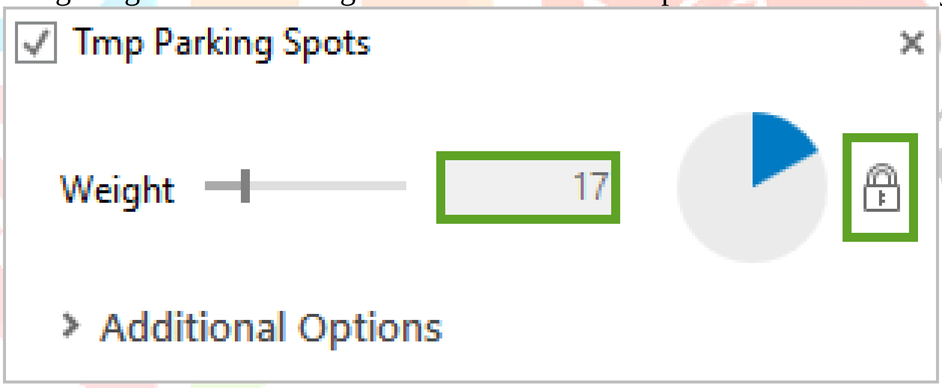

Figure 7: Adjust criterion weights for analysis refinement

III. Outcome Analysis and discussion

In this experimental dataset we have systematically funneled the search for a suitable business location from a set of potential candidate markets and suitable sites. We conducted the neighborhoods analysis to identify the most suitable market, and then analyzed further to discover the best and most potential location for business expansion.

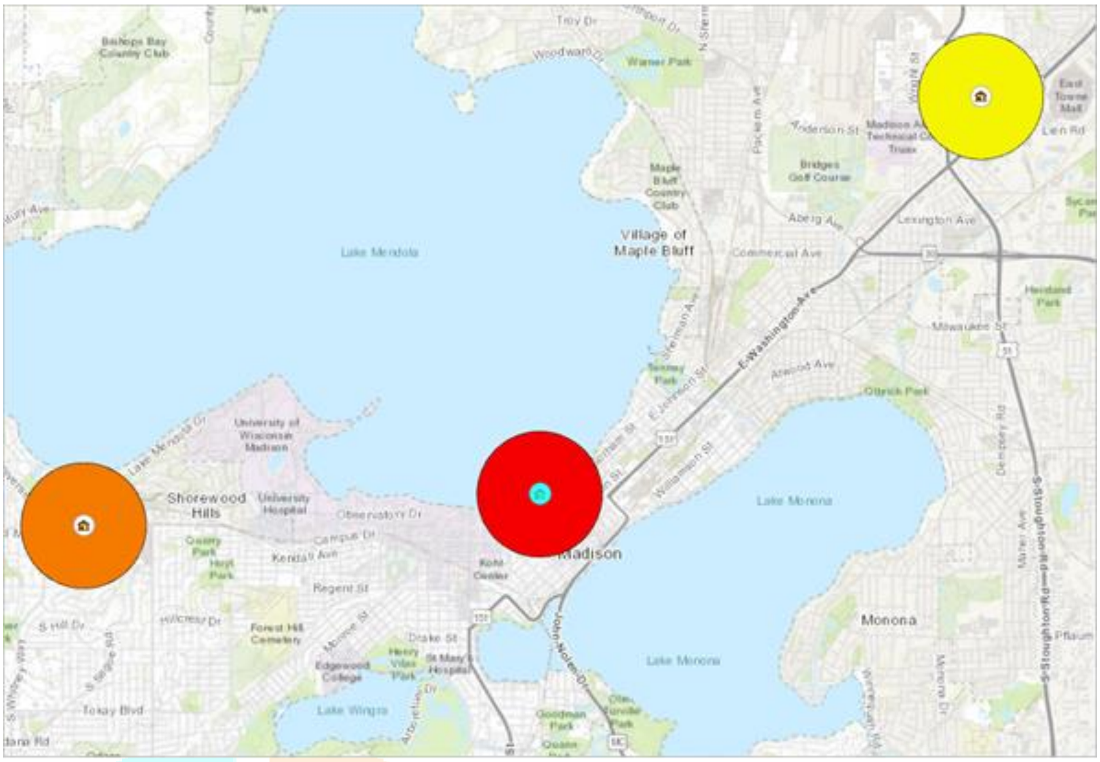

Figure 8: Trade area Rings for identified locations.

We generate infographics and summary analysis reports on the selected location for business expansion. This validates our analysis and makes it more useful by better data visualization. Using these infographics we will generate and view Key Customer Facts, Nearby Business Places and Transportation to Work type of summary reports and infographics.

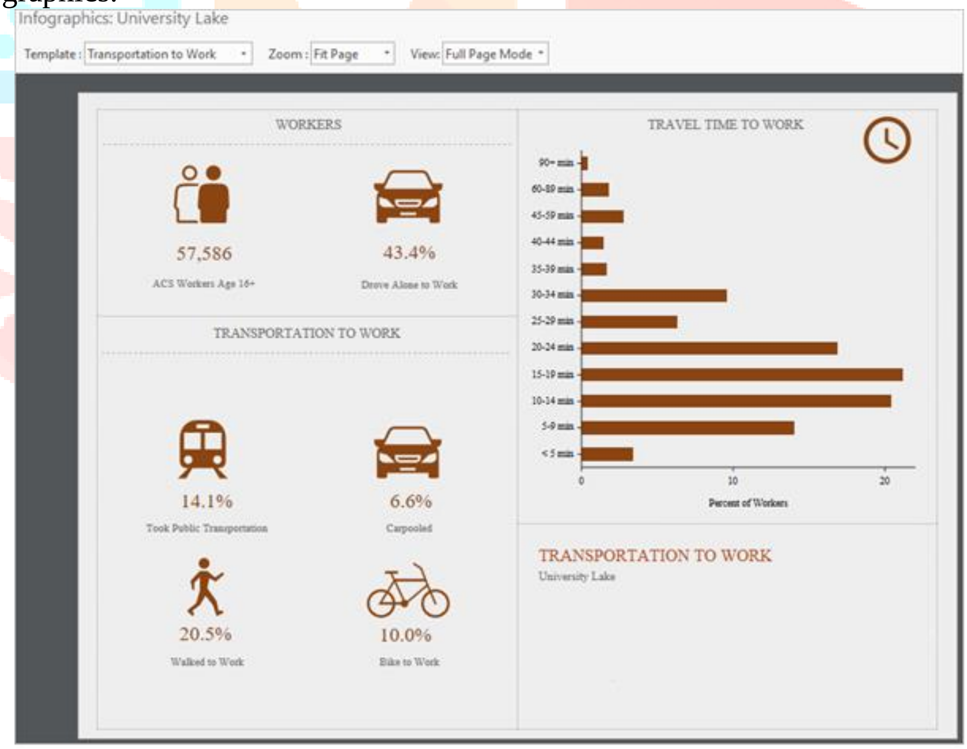

Figure 9: Sample Infographic for better visualization of data

IV. Conclusion

Research results in this paper first analyzed a set of best-performing similar businesses to identify critical success factors and characteristics to be used in business expansion analysis. Once the Critical factors are identified these are applied along with other known demographic criteria to identify the most suitable market for the expansion of the business. Furter refinement may be done by creating submarkets within the market identified in the suitability analysis. We further narrow down and funnel this search to the most suitable zones and add a layer of available commercial business locations available in the most suitable zone. From this set of alternative candidate sits we have to detect the best location for business expansion. Finally, we embellished the analysis by adding summary reports and infographics.

REFERENCES

[1] Ain, N., Vaia, G., DeLone, W. H., & Waheed, M. (2019). Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review. Decision Support Systems, Volume 125, pp 113113.

[2] Anselin, L. (2019). A Local Indicator of Multivariate Spatial Association: Extending Geary's c. Geographical Analysis, 51(2), 133-150.

[3] Anselin, L., & Williams, S. (2016). Digital neighborhoods. Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 9(4), 305-328.

[4] Dastjerdi, H. R., McArdle, G., Matthews, S. A., & Keenan , P. (2020). Gap analysis in decision support systems for real-estate in the era of the digital earth. International Journal of Digital Earth, doi/abs/10.1080/17538947.2020.1808719.

[5] Eftelioglu, E., Shekhar, S., Kang, J. M., & Farah, C. C. (2016). Ring-shaped hotspot detection. IEEE Transactions on Knowledge and Data Engineering, 28(12), 3367-3381.

[6] ESRI White Paper. (2017). Location Analytics as a Service. ESRI Software as a Service, 12-27. Retrieved from http://www.esri.com/software/businessanalyst/get-started/saas

[7] Huang, Y., Pei, J., & Xiong, H. (2006). Mining co-location patterns with rare events from spatial data sets. Geoinformatica, 10(3), 239–260. .

[8] Jiang, Z., Sainju, A. M., Li, Y., Shekhar, S., & Knight, J. (2019). Spatial ensemble learning for heterogeneous geographic data with class ambiguity. ACM Transactions on Intelligent Systems and Technology (TIST), 10(4), 1-25.

[9] Kedron, P., Li, W., Fotheringham, S., & Goodchild, M. (2020). Reproducibility and replicability: opportunities and challenges for geospatial research. International Journal of Geographical Information Science, 30(1), 1-19.

[10] Keenan, P. (2020, December 3). Geographic Information Systems and Location Analytics for Business and Management. Retrieved from Oxford Research Encyclopedia of Business and Management.: https://oxfordre.com/business/view/10.1093/acrefore/9780190224851.001.0001/acrefore-9780190224851-e-200.

[11] Li, D., Wang, S., & Yuan, H. (2016). Software and applications of spatial data mining. WIREs Data Mining Knowl Discov, 6: 84–114, vol 6: 84–114.

[12] McKinsey Global Institute. (2019). The Age of Analytics: Competing In A Data-Driven World. McKinsey Global Institute Series, 35-60.

[13] Newgrove. (2017). Location Analytics in 2017: What-we-know-so-far. Newgrove Location Analytics Blog. Retrieved from https://newgrove.com/location-analytics-in-2017-what-we-know-so-far/

[14] Oracle Corporation. (2019). Value of Spatial Analytics in BI. Oracle Technetwork Whitepaper, 22-30. Retrieved from http://www.oracle.com/technetwork/middleware/bi-foundation/value-of-spatial-analytics-in-bi-ag-1-130184.pdf

[15] Talen, E., Anselin, L., Lee, S., & Koschinsky, J. (2016). Looking for logic: The zoning—land use mismatch. Landscape and Urban Planning, 152, 27-38.

[16] Tan, N. Y.-Z., Ting, C.-Y., & Ho, C. C. (2020). Location Analytics for Churn Service Type Prediction. In Computational Science and Technology (pp. 709-718). Singapore: Springer, Singapore.

[17] Ting, C.-Y., Ho, C. C., Yee, H. J., & Matsah, W. R. (2018). Geospatial analytics in retail site selection and sales prediction. Big data, 6(1), 42-52.

[18] Yap, J. Y., Ho, C. C., & Ting, C.-Y. (2019). A systematic review of the applications of multi-criteria decision-making methods in site selection problems. Built Environment Project and Asset Management, 9(4), 548-563.

[19] Yee, H. J., Ting, C. Y., & Ho, C. C. (2018). Optimal Geospatial Features for Sales Analytics. Proceedings of the 3rd International Conference on Applied Science and Technology (ICAST'18) (pp. 020152-1 - 8). Online: Published by AIP Publishing. https://doi.org/10.1063/1.5055554.

[20] Yilmaz, E., Elbasi, S., & Ferhatosmanoglu, H. (2017). Predicting optimal facility location without customer locations. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining pp 2121-2130. Singapore.