Data Visualization and Voter Arrival Behavior Analytics

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Abstract

In voting, maps are traditionally used to indicate voter turnout and/or election results with respect to political parties. This paper explores the use of geospatial choropleth maps to analyze voter arrival patterns through a case study of using logs from electronic poll books (EPB) across the State of Rhode Island and Providence Plantations (RI). The EPB transaction logs record various metrics, such as the precinct number, location, and timestamp for every voter that checks in on Election Day. Geographically referenced jurisdiction datasets were plotted in ArcGIS and combined with the EPB transaction log data for the entire state's 2018 Midterm elections to create the choropleth maps. The choropleth maps were shaded based on the percentage of total check-ins observed during selected time windows throughout the day.

Analyses were undertaken to assess the visual representation of arrival densities for both the state and its major metropolitan area. Arrival observations statewide were highlighted and expanded in conjunction with known jurisdiction profiles. At the town/city level arrival patterns were identified based urban/suburban and rural areas. A precinct level analysis was performed in the metropolitan area and revealed differing arrival patterns within the City of Providence. General observations are provided based on visual inspection. Identifying specific precinct groups with similar overarching trends of community voting behavior will require computationally based clustering methods. Future considerations of how data visualization of arrival patterns via EPBs are discussed.

Introduction

The passage of the Help Americans Vote Act (HAVA) by Congress in 2002 has enabled Election Administration officials across the United States to update and upgrade the equipment and procedures within their voting systems. Electronic-based technologies for voter check-ins, ballot marking, and ballot casting are increasingly popular. These technologies offer enhanced usability and security features compared to traditional paper/mechanical based methods. Unfortunately, these new technologies can be very expensive and are often a scarce resource in many jurisdictions. In addition, the HAVA equipment certification mandates make it increasingly difficult to change resource allocation decisions as Election Day draws near. As a result, it is essential for Election Administrators to use accurate, efficient resource allocation and capacity planning methods to meet the 30 minute Vote Time benchmark set forth by the Election Assistance Commission (eac.gov).

One challenging aspect of election preparation is knowing how to utilize and understand election data generated from previous years. As these updated voting technologies are in use, an increasing amount of unused data accumulates in election databases. As it currently stands, there are few resources at the disposal of election officials to assist in the data analysis and interpretation process aside from equipment vendors or in-house data analysts. There is a desperate need for tools that can be used by the average Election Official to easily understand and assess election data while generating value for election reporting and election preparation. Graphical data visualization methods propose a robust medium on which to present a broad audience with information and decision making. Good data visualizations allow viewers to

understand a concept/data purely through general observation, while also providing the scientific community with enough information to assess critically.

While there are many aspects of elections that must be understood and estimated to perform successful election preparation, one of the most important is voter turnout. Voter turnout is generally referred to as an aggregate value of the total percent or number of voters on Election Day, although hourly turnout/arrival rates provide further insight with respect to resource allocation planning. There are no such methods for understanding, let alone estimating, how voter turnout to polling locations aside from speculation, simulation, and rules of thumb. As election systems and election equipment evolve over time, the methods by which election preparation occur must adapt in parallel. In this work, a methodology for assessing and understanding voter arrival patterns is proposed in a graphical, geospatial format. The proposed methodology is applied to statewide data generated from the 2018 Midterm elections and is discussed at two levels of granularity (i.e., at the state-wide and precinct-wide levels).

Literature Review

Election-related research has been conducted extensively for as long as elections have been held. The use of spatial and geographical maps has been present in election research since 1913 and in nearly every election since (Forest, 2018). Election map research has three predominant areas of focus: (i) methods for making election maps (i.e., Rutchick, Smyth, & Konrath, 2009; Stoffel, Janetzko, & Mansmann, 2012; Ondrejka, 2016; Ourednik, 2017), (ii) investigating voter behavior (i.e., election results and party affiliation) (i.e., Calvo & Escolar, 2003; Ghitza &

Gelman, 2013; Kinsella, 2018; Simiyu, 2008; Kohfeld & Sprague, 2002; Lai et al., 2010; Power & Rodrigues-Silveira, 2019; Seabrook, 2009; Vandermotten & Lockhart, 2000; Zhang, 2018), and (iii) investigating voter turnout (i.e., Althaus & Trautman, 2008; Bellettini, Ceroni, & Monfardini, 2016; Calvo & Escolar, 2003; Ghitza & Gelman, 2013; Kavanagh, Mills, & Sinnott, 2004; Persson, Sundell, & Öhrvall, 2014; Wuffle, Brians, & Coulter, 2012; Yandri, 2016).

Among the research investigating methods of using maps for election information, Rutchick, Smyth, & Konrath (2009) investigate the difference between displaying the proportion of votes per party rather than displaying the winning party for a specific region. The study indicates that participants viewed the nation as more politically divided when election results are presented based on the winning political party. The findings by Stoffel, Janetzko, & Mansmann (2012), who also investigate the use of bipolar map coloring and proportionate result presentation, support the findings of Rutchick, Smyth, & Konrath (2009) and go a step further in order to accommodate multi-party election systems. Stoffel, Janetzko, & Mansmann (2012) propose a map development method to implement color gradients and polygon manipulation techniques to better represent election results from multi-party elections, as well as two-party elections. The method by Stoffel, Janetzko, & Mansmann (2012) is later adapted to fit a 2012 Slovic election by Ondrejka (2016) with minor alterations. The author proposes a method of including both the proportion of votes for each political party as well as the proportion of voter abstention using a color striping method as opposed to the color gradient technique. Ourednik (2017) also utilizes the color gradient technique to represent proportional election results similar to that proposed by Rutchick, Smyth, & Konrath (2009) and Stoffel, Janetzko, & Mansmann (2012), although the core of their work investigates the use of the third dimension to indicate voter density. The

authors employ the 2016 Austrian presidential election results and a Swiss referendum from 1992 as examples to apply the three-dimensional mapping of the proportion of votes for each presidential candidate/referendum choice in a given region, as well as the number of voters living in that region. The methods discussed focus on the use of color and color gradients to accurately present election results, although, with respect to election maps, this is a narrow focus. The remaining area indicates a lack in the literature.

Tufte (1990) demonstrates that all graphics have the ability to be used in a variety of ways to represent or reinforce essentially anything. This implies that there are many aspects of elections, whether regarding voter behavior, voter turnout, or other region-based statistics that would benefit from geographic and choropleth mapping. Some specific gaps include frameworks for plotting statistics throughout an Election Day from a variety of regions (the focus of this paper), mapping how voters vote (i.e., what types of election technology are in use), or presenting time to vote or wait times in different geographic areas.

The second area of focus on election mapping research consists of displaying voter behavior and election results. Within this research topic, the authors explore how political preference and election results differ by geographic region (Vandermotten & Lockhart, 2000; Calvo & Escolar, 2003; Seabrook, 2009; Simiyu, 2008), investigate how voter demographics impact election results and voter behavior (Kohfeld & Sprague, 2002; Zhang, 2018; Power & Rodrigues-Silveira, 2019; Lai et al., 2010), and study how a combination of geographic information and voter demographic information impact election results (Ghitza & Gelman, 2013; Kinsella, 2018).

In research that primarily considers geographical and spatial factors, maps are used to identify voting behavior clusters and patterns by area (Calvo & Escolar, 2003; Seabrook, 2009; Simiyu, 2008). Calvo & Escolar (2003) use choropleth maps to demonstrate the results of different modeling approaches for predicting voter behavior. Seabrook (2009), on the other hand, uses choropleth maps to assess the clusters of geographic areas comparing voting behavior patterns between the 2004 and 2008 United States (U.S.) Presidential elections. Similar to the work by Seabrook (2009), Simiyu (2008) uses choropleth maps to investigate how regions and regional factors affect the number of votes cast for different candidates in the 1992, 1997, and 2000 elections in Kenya. Taking a more general approach, Vandermotten & Lockhart (2000) explore how regions vote in western European countries. Their work compares how various regions identify with respect to political affiliation.

An investigation into voter demographics and election results by Zhang (2018) and Power & Rodrigues-Silveira (2019) use maps to spatially display election results and political affiliation for different geographic regions. In addition to their analysis of the maps, Zhang (2018) and Power & Rodrigues-Silveira (2019) perform additional analyses that investigate the impacts of voter specific factors for each region on voter behavior and election results. Kohfeld & Sprague (2002) utilize the geographical maps further, not only displaying election results but also displaying how the voter demographic factors considered in their analysis vary across their region of interest. The work by Lai et al. (2010) investigates how specific voter demographics (e.g., marital status, age, education) influence political affiliation in Hong Kong elections, using choropleth maps to demonstrate their projections of political support across the region and the distribution of voter demographic metrics throughout Hong Kong.

Within research investigating the effect of both geographical factors and voter demographics, authors either use explicit factors to identify geographical and voter demographic metrics (Kinsella, 2018; Ghitza & Gelman, 2013) or use implicit metrics for geographical regions (Lai et al., 2010). Kinsella (2018) and Ghitza & Gelman (2013) investigate the effect of voter demographics and specific regions impact election results. These works utilize geographic, choropleth maps to demonstrate the election results for the regions investigated. Ghitza & Gelman (2013) use several maps to compare how voting behavior changes for different locations by displaying results for different age groups and different levels of income.

While these works investigate a variety of election types from a variety of geographic locations, their implementation of choropleth maps follow a traditional method, providing end of the election, stationary election results. Although Ghitza & Gelman (2013) take a creative approach, mapping election results in a matrix with age and income varying. Regardless of this work, there are few articles that investigate time-varying statistics using choropleth maps. The current use of time-varying statistics implements an election cycle scale [i.e., every two years in the case of Power & Rodrigues-Silveira (2019)]. There are also a variety of voter behaviors (e.g., decision-making methods, level of risk aversion, understanding of ballot question topics, comfort with election systems) that have little research and are prime candidates for choropleth and heat mapping.

Voter turnout is another statistic often displayed using choropleth and heat mapping techniques. Among the research in this area, the authors investigate how voter turnout is impacted by weather (Persson, Sundell, & Öhrvall, 2014; Wuffle, Brians, & Coulter, 2012), television market size (Althaus & Trautman, 2008), geographical factors (Calvo & Escolar, 2003; Kavanagh,

Mills, & Sinnott, 2004; Yandri, 2016; Bellettini, Ceroni, & Monfardini, 2016), and voter demographics (Ghitza & Gelman, 2013). Persson, Sundell, & Öhrvall (2014) investigate how Election Day weather impacted turnout in Swedish elections between 1976 and 2010. Using choropleth maps, the turnout and rainfall in Sweden are compared for the 1985 election, assisting in visualization of their results indicating that rain had no significant effect on turnout in the observed elections (Persson, Sundell, & Öhrvall, 2014, p. 340-341). Wuffle, Brians, & Coulter (2012) investigate the impact of temperature on turnout in the U.S. Similar to Persson, Sundell, & Öhrvall (2014), the authors present a choropleth map to visually display the weather statistics (i.e., temperature) and turnout across the U.S. Through a bivariate regression analysis, the authors identify that temperature does play some role in election turnout (Wuffle, Brians, & Coulter, 2012, p. 79).

An investigation into information accessibility is presented by Althaus & Trautman (2008) who explores the relationship between television market size and election turnout to estimate the impact of media on Election Day participation. The authors use choropleth maps to identify the size of television markets and their boundaries as well as to present turnout statistics across New York (Althaus & Trautman, 2008, p. 839).

With respect to geographic analyses, the authors investigate how spatial- and location-specific characteristics (e.g., neighborhood boundaries, regional borders, population statistics) impact election turnout. In the works by Calvo & Escolar (2003), Kavanagh, Mills, & Sinnott (2004), Yandri (2016), and Bellettini, Ceroni, & Monfardini (2016) choropleth maps are used to emphasize the regional patterns with respect to turnout, using color and color gradients to differentiate regions and display turnout rates. As previously referenced, Ghitza & Gelman

(2013) utilize choropleth maps to demonstrate how variations in voter demographics (i.e., age and income). Within the same work, the authors also compare voter turnout rates based on voter age groups and ethnicity, utilizing additional maps to emphasize their findings (Ghitza & Gelman, 2013, p. 774). In the literature regarding voter turnout choropleth mapping, researchers apply choropleth maps to display total turnout rates among various geographic regions, although this is a narrow use of the spatial and graphical tool. While authors such as Ghitza & Gelman (2013) use choropleth maps to show change across voter demographics, limited works show change over time on a scale less than an election cycle.

With the increased technological capabilities of voting equipment, obtaining real-time voter turnout is no difficult task. Despite this, the data containing these granular statistics are aggregated prior to their presentation. Choropleth maps have a promising future in the realm of voter turnout, with potential adaptation to show any number of factors and their effect on political participation. This paper seeks to fill the gap in the literature by presenting a method of Election Day data visualization, using choropleth maps and graphic design techniques on a granular voter turnout dataset. Using check-in timestamps to determine voter turnout per hour, a pseudo arrival pattern of voters by region is established.

The rest of the paper is organized as follows. First, a brief overview is given for each of the data sources used in this work. The procedures used to transform the raw data into useable input data tables are defined and then joined with geospatial datasets in ArcGIS. Following this, a description of the data visualization techniques used to motivate various design decisions is provided. These methods are first applied statewide for RI using aggregated EPB transaction log data. The three visualizations are then used to determine an appropriate shading scheme for

serval choropleth maps showing the percentage of total check-ins observed during different time intervals throughout Election Day. Next, general observations are given for the statewide choropleth maps. This process is then repeated at the precinct level for the city of Providence. Speculations about potential underlying factors driving the observed arrival patterns are addressed in the discussion section. The current limitations and ongoing/future work are described in the final section.

Overview of Data Sources

Geographically Referenced Data:

The Rhode Island Geographic Information System (RIGIS) provided the basic geospatial data used to create all maps. The "Municipalities (1997)" dataset is used to define boundary lines for RI cities and towns. This dataset contains attribute information such as name, county, physical area, and municipality code number. In RI, a two-digit Municipality Code is assigned alphabetically to each city and town. The first municipality code, "01" is assigned to the town of Barrington with the last municipality code, "39" is given to the City of Woonsocket. Municipal codes are indexed when joining arrival data with geographically referenced data tables in ArcGIS.The "voting_precinct16" dataset defines voter precinct boundaries for the City of Providence. The Precinct Name attribute will be indexed when importing data tables into Providence only maps.

Voter Arrival Data:

The primary source of data used to analyze arrival behavior patterns comes from the transaction logs of knowInk EPBs used in all RI polling places during the Midterm Elections on November 7th, 2018. This file contains a “Check-In ID”, “Timestamp”, “Precinct Number”, and “Poll Pad ID” for approx. 350,000 voters across Rhode Island’s 420 precincts. The first two digits of each Precinct Number, representing an alphabetically assigned municipal code, allows the poll pad transaction log data to easily be aggregated for each city or town.

Data Visualization Methods for Exploratory Analysis

Two different graphical representations were created to visualize the relative distribution of arrival percentage rates per time interval. These graphs are used to determine quantity and boundary locations of the discrete intervals used for the initial shading of all six choropleth maps. Choosing an appropriate shading schema is not an arbitrary task and can significantly impact the quality of information communicated by the maps. An appropriate shading schema is able to clearly and consistently display the variation between jurisdictions for each interval while also making intensity changes over time to be readily apparent (Rutchick, Smyth, & Konrath, 2009; Stoffel, Janetzko, & Mansmann, 2012). Adjustments to the shading schema are made iteratively until information communicated by the choropleth maps is consistent with the data visualizations described below.

The first data visualization graphic is comprised of multiple histograms. In the left half of Figure 1 the arrival percentages are plotted separately for each time interval. On the right, a layered histogram is used to combine the individual histograms into a single chart. The axis parameters, such as scale and domain, are identically defined for all histograms to facilitate direct comparisons between the different time intervals.

The second data visualization graphic, Figure 2, features boxplots for the six-time intervals. The interquartile range illustrated by blue box sections is useful when determining an appropriate interval size to use for the shading schema. The lines shown on both sides of the blue box, called whiskers, extend out to mark the 10th and 90th percentiles. The blue circles beyond the whiskers denote marginal outliers, values that fall within the 5th and 95th percentiles. Outliers values exceeding this range are not shown. The relative overlap of the box and whisker sections of the various boxplots are an important consideration when deciding the number of intervals that will be used to shade the maps.

Rhode Island Cities and Towns

For the first analysis, arrival behavior observations are broken down in the six-time intervals defined in Table 1.

Table 1. Arrival Time Intervals

Interval	Time Range
1	7:00 am – 10:00 am
2	10:00 am – 12:00 pm
3	12:00 pm – 2:00 pm
4	2:00 pm – 4:00 pm
5	4:00 pm – 6:00 pm
6	6:00 pm – 8:00 pm

The percentage of check-ins occurring during each time interval was computed for Cities and Towns using the EPB Transaction Logs' data. The arrival percentage values were used to create histograms. The individual histograms found on the left side of Figure 1 shows that the greatest variability occurs during the first (i.e., 7:00 am - 10:00 am) and last (i.e., 6:00 pm - 8:00 pm) time intervals. The first and last time intervals also have the highest and lowest mean percentage values, respectively. The 12:00 pm - 2:00 pm and 2:00 pm - 4:00 pm time intervals show the lowest variability with respect to percent turnout and also appear to have similar means. While both intervals have moderate variability and a similar range, it is interestingly noted that the second (i.e., 10:00 am - 12:00 pm) and fifth (i.e., 4:00 pm - 6:00 pm) intervals appear to be skewed in opposite directions relative to their mode values.

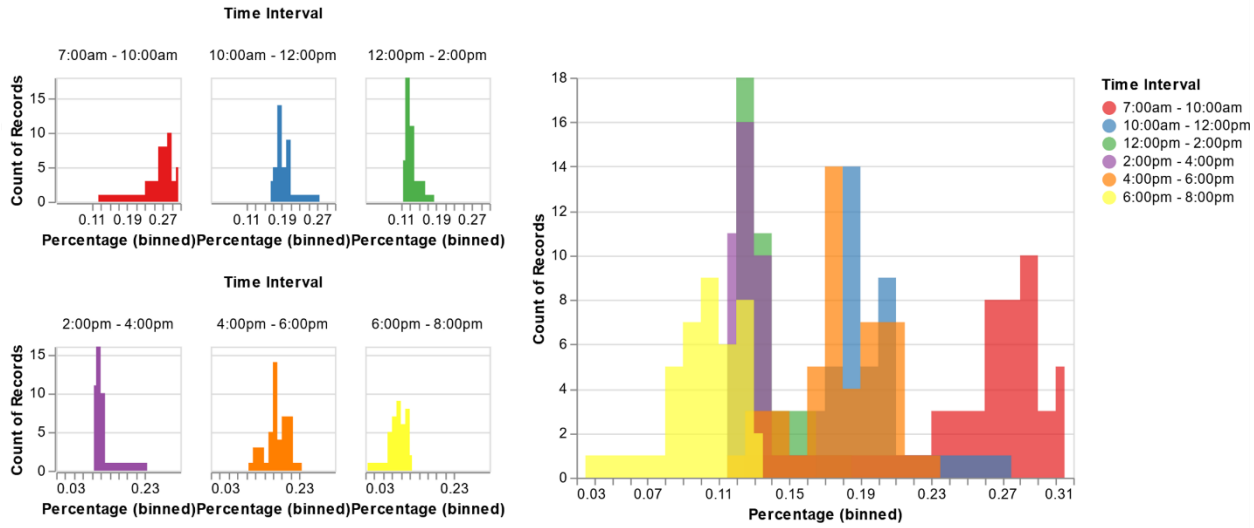

Figure 1. Histograms of voter arrival percentage by time interval for the 2018 Midterm elections in Rhode Island

The arrival rate percentages were then used to create a boxplot for each of the six-time intervals (Figure 2). The interquartile range is relatively similar for all but the middle two intervals (i.e., 12:00 pm - 2:00 pm and 2:00 pm - 4:00 pm). The distance between the whiskers' ends for the 12:00 pm - 2:00 pm and 2:00 pm - 4:00 pm intervals both appear to be less than 5%, indicating a relatively consistent arrival rate for all precincts during those time intervals. The values in the 12:00 pm - 2:00 pm interval appear to be evenly distributed across the arrival rate percentages, whereas the 2:00 pm - 4:00 pm interval's values appear to be heavily skewed toward lower percentage rates.

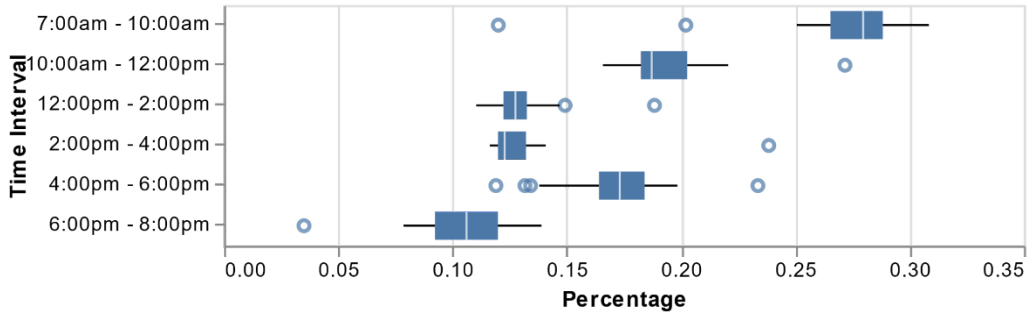

Figure 2. Box Plots of voter turnout percentage by time interval for the 2018 Midterm elections in Rhode Island

The initial observations from the data visualization graphics, Figures 1 and 2, were taken into consideration when testing different shading schemas. Slight adjustments were made over several iterations before arriving at the final shading schema used to create the series choropleth maps shown in Figure 3. The use of color was avoided as to not unintentionally imply that the maps display party affiliation information as well as to make them accessible to those who have difficulty interpreting certain color gradients.

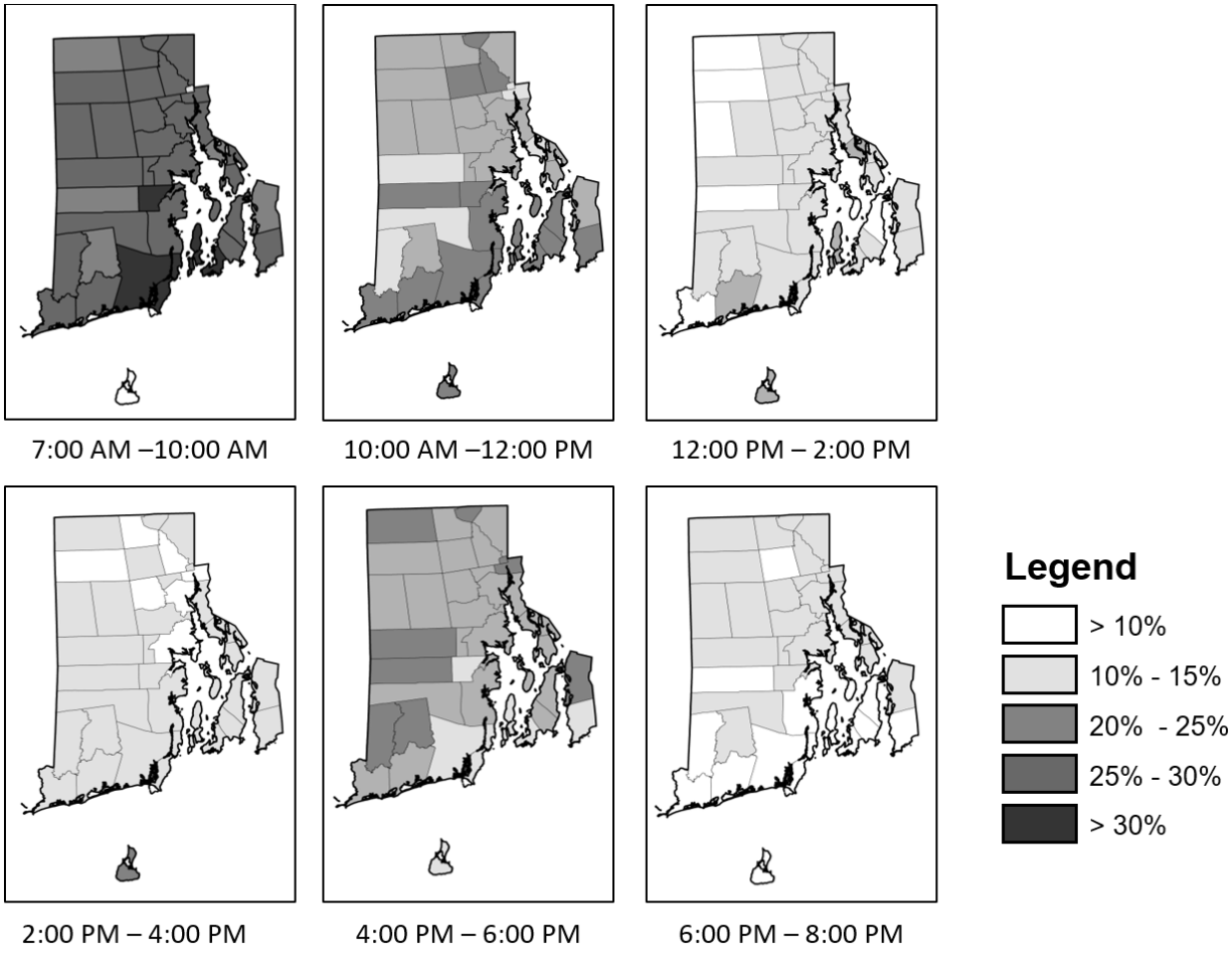

Figure 3. Choropleth maps of percent voter turnout by time interval during the 2018 Midterm elections in Rhode Island

Interpreting the Map

A visual inspection of the choropleth maps in Figure 3 immediately reveals several valuable insights about the arrival behavior of voters in RI's cities and towns. The choropleth maps confirm the survey-based research finding of Stewart (2015) who identify that peak arrival rates generally occurred early in the morning and steadily decline throughout the afternoon. The

second uptick in arrivals in the evening characterized by Stewart (2015) can also be seen. However, the timing and duration of increased arrival rate periods varies between cities and towns. In general, the towns along the southern coast peak earlier in the day and steadily decline into the evening, experiencing less than 10% of total voter arrivals between 6:00 pm and 8:00 pm. Although a slight uptick in arrival intensity occurs between 4:00 pm and 6:00 pm for some towns, the arrival rate in the second half of the day is lower, relative to the rest of the state. For the more rural towns in the western half of the state, arrivals are lower between 12:00 pm and 2:00 pm and higher between 4:00 pm and 6:00 pm relative to the rest of the state. The urban/suburban areas in the eastern part of RI appear to follow the general arrival trend defined by Stewart (2015). The magnitude of peak arrival intensity periods appears to be moderate for the eastern towns and cities. Speculation about the underlying factors potentially driving these observed are described in the discussion section.

Polling Precincts in Providence, Rhode Island

The second analysis is performed at the precinct level and focuses on the city of Providence. Providence is RI's largest city with a population of approximately 179,335 residents ("Providence, Rhode Island Population," 2019). with a land area of 18.4mi^2 the cities population density sits around 9,746 persons/mi^2. Of this population, there are 124,775 residents considered to be eligible voters according to the RI Board of Elections. In order to accommodate 69.6% of the population who are potential voters, Providence alone contains nearly 20% of all polling locations in the state (i.e., 80 of 420). Due to its large population and its public recognition as RI's capital city, Providence is chosen for precinct-level analysis. Another interesting property of

Providence is the commuting infrastructure, in which the eastern part of the city is densely populated with highways and freeways, while the western area has predominantly local roads. This may allow insight into commuter patterns throughout the city and its effect on voting behavior.

The precinct level analysis was performed following an identical procedure to the first analysis. The percentage of check-ins occurring during each time interval was computed for each precinct using EPB transaction logs. The arrival percentage rates were then used to create a data visualization graphic with multiple histograms displayed in Figure 4. When broken down into its 80 precincts the range of percentage values across Providence nearly doubled in comparison to the aggregated averages used in the state level analysis. The percentage values for a majority of the intervals do not appear to be unimodal. Several different bin sizes were tested but did not produce any trends that were immediately recognizable.

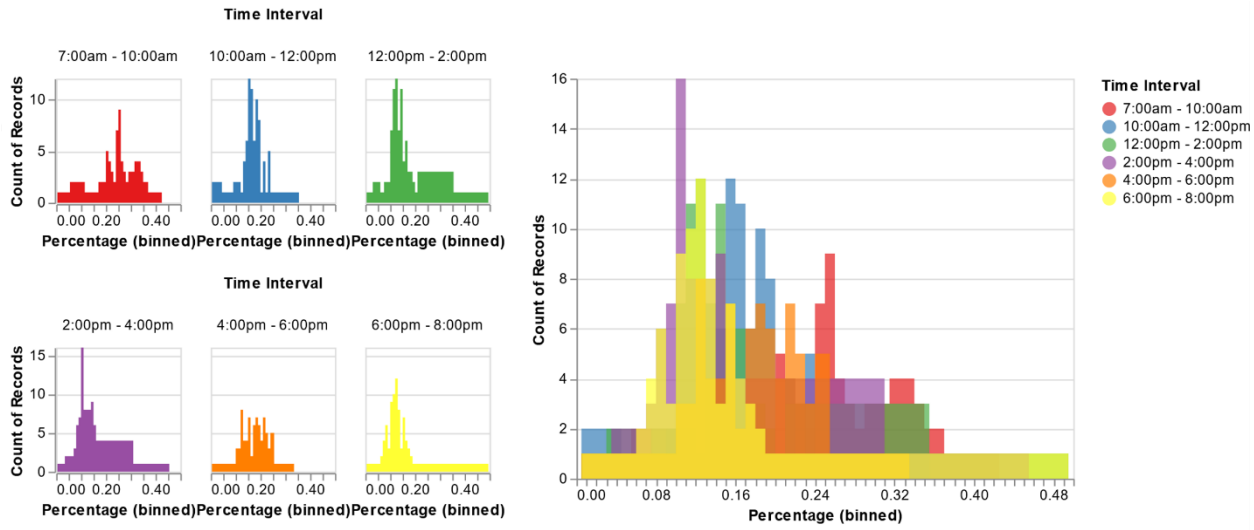

Figure 4. Histograms of voter arrival percentage by time interval for the 2018 Midterm elections in the City of Providence, Rhode Island

When the arrival percentage data are presented in box plots an interesting relationship between the mean and variance is observed (Figure 5). The width of the box and whisker sections appears to increase and decrease in the same direction as the median percentage value.

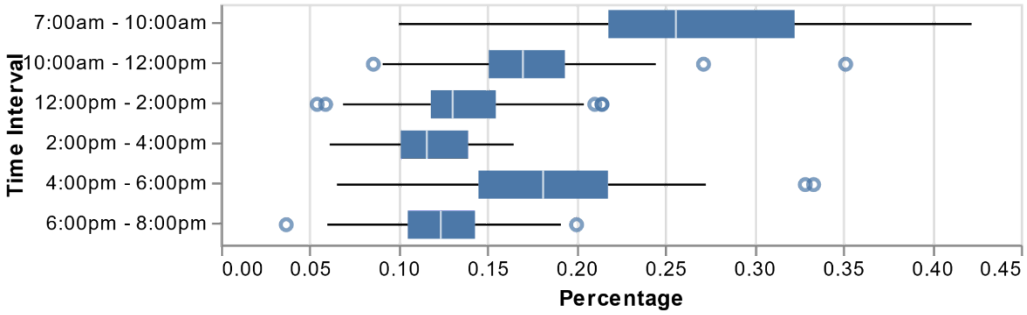

Figure 5. Box Plots of voter turnout percentage by time interval for the 2018 Midterm elections in the City of Providence, Rhode Island

Observations from Figures 4 and 5 were used to assist with shading schema design for creating the choropleth maps shown in Figure 6. The larger variance and range motivated the decision to use a 10% step size between shading intervals. Again, the use of color was avoided as to not unintentionally imply that the maps display party affiliation information as well as to make them accessible to those who have difficulty interpreting certain color gradients.

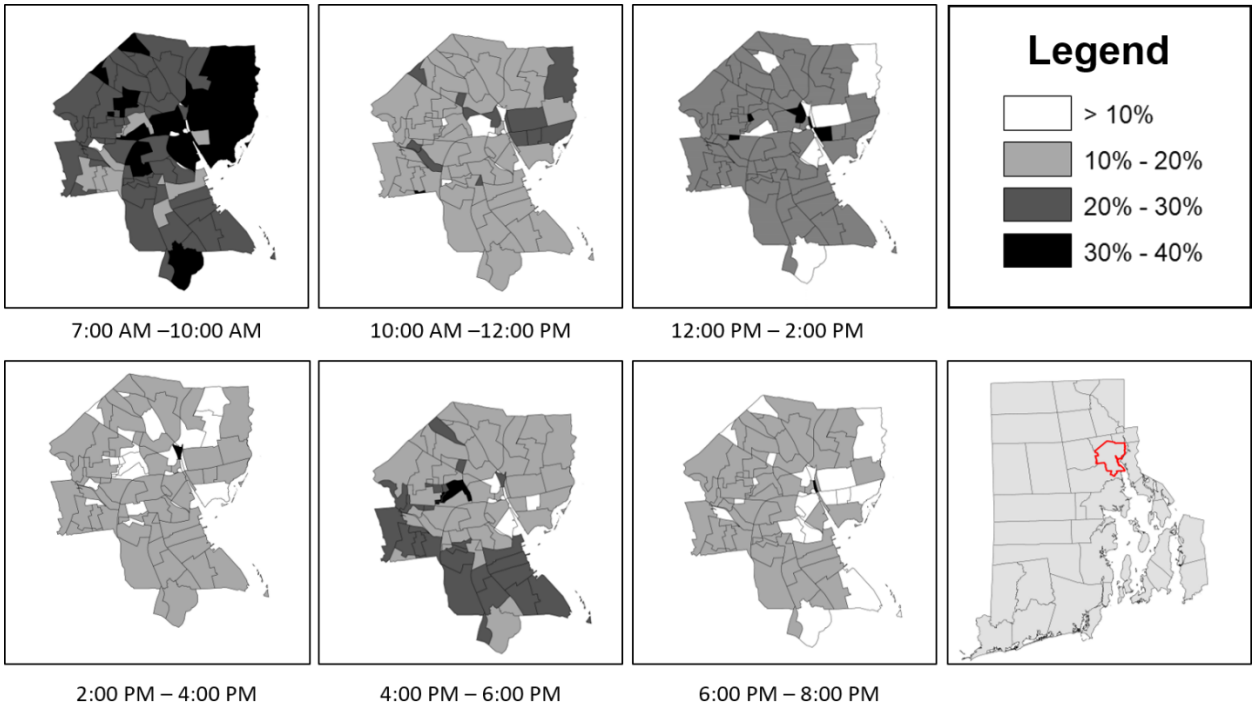

Figure 6. Choropleth maps of percent voter turnout by time interval during the 2018 Midterm elections in the City of Providence. Rhode Island

Interpreting the Map

With many precincts of varying sizes and irregularly shaped borders it becomes difficult to identify distinct arrival patterns. In general, arrival intensity was at its highest between 7:00 am and 10-am. This peak was especially strong for the precincts in the northwest portion of the city. Arrivals slowed down over the next two hours for almost all precincts. A second spike in arrivals occurred in the lunchtime hours between noon and 2:00 pm almost citywide. Many precincts in the southern section of the city experienced a third surge between 4:00 pm - 6:00 pm while arrivals to the rest of the precincts remained relatively constant. Throughout all intervals there

are precincts with relatively high or low arrival rates are scattered across the city. A geo-temporal pattern to these occurrences is cannot be inferred at this time.

Discussion and Future Work

The choropleth maps created using aggregate data by town/city identified three general areas where similar shifts in the arrival intensity occurred throughout the day. The specific factors influencing these differences in arrival behavior are not known at this time. However, the maps created in this paper, draw cause for speculation when combined with additional information about the population density in each area. In RI, the precinct boundaries within each city and town are drawn with to distribute an equal number of eligible voters. As a result, the physical size of the precinct will be inversely proportional to the population density. This could potentially mean that voters in rural areas will have to travel a further distance from their homes to the polling place in comparison to urban/suburban voters. Access to major highways for commuting to/from work is also decreased in these rural areas. These two factors could make it difficult for voters in these areas to vote during their lunch breaks and may potentially explain why turnout percentages are comparatively lower from noon to 4:00 pm and higher from 4:00 pm - 6:00 pm. Efforts to test this hypothesis are currently underway. U.S. census data pertaining to where residents work will be used to compute average travel times for each town/city. Future analysis will be conducted comparing these estimated to the statewide choropleth maps produced in this paper.

The particular series of small multiple maps of the City of Providence, Figure 6 is the first look at our analysis approach at a city or metropolitan area. The purpose of this particular paper was to explore the use of maps in understanding arrival patterns at various levels. When visually assessing Figure 4 and Figure 5 it is apparent that not a singular distribution of arrival times is evident. After mapping these arrival patterns in Figure 6, it is clearer than looking at jurisdictions require potential clustering algorithms to start sorting and assessing overarching patterns.

The transition from a statewide model to a more zoomed-in, jurisdictional model creates natural complexity that will require additional, future computational approaches. This type of hierarchical differences in system levels is not abnormal, regardless of geospatial data. Currently, in the knowledge of arrival patterns in queuing theory, most researchers summarize or operationalize data to higher levels to gain an easier to interpret a singular pattern. Although this is a traditional practice at this point, it does not establish enough knowledge to appropriately assist with decision-making behavior at the nuanced jurisdictional level (e.g., resource allocation). Hierarchical systems require knowledge at both higher and lower levels with significant communication and transmission of data between them. Therefore, there needs to be a significant amount of time and development of methodological approaches to sufficiently cull out the significant relationships at these lower levels of the hierarchical system with respect to metropolitan or larger jurisdictions.

The current precinct-level maps of Providence implicate that all jurisdictions cannot all be characterized by a single arrival pattern. Computationally based methods to identify clusters of precincts with similar arrival behavior are currently being explored. This ongoing analysis uses the EPB data to further break down arrivals into smaller intervals with piecewise constant

intensity. Time series classification methods similar to those described by (Keogh & Ratanamahatana, 2005) will be used to identify precinct clusters. Their Dynamic Time Warping methodology for identifying the optimal non-linear alignment of time series will be used as a similarity measure between jurisdictions. Overall, the methodology developed in this paper revealed new insights about voter arrival behavior. The data visualization techniques and choropleth maps facilitated the discovery of geographic patterns with relative ease for the state wide analysis. While the precinct level analysis proved to be more difficult, the choropleth maps helped to provide a deeper understanding of arrival behavior than the data visualizations alone. Geospatial mapping will continue to be used as a means of interpreting results and providing direction for future research approaches.

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