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# Teaching Case Analyzing Disney World Wait Time Data: A Lesson in Visualization Using Tableau 

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#### Abstract

We present a case study to teach data visualization with Tableau in an introductory business analytics course. The case uses publicly available data sets from touringplans.com that record wait times for various attractions at Disney World in Orlando, Florida. In the case study, students use Tableau to clean, organize, and analyze wait time data, and to create data visualizations to illustrate how wait times are affected by several variables. Ultimately, students use their results to inform the client, a Disney travel agent, about when wait times are the shortest and longest. The case was piloted in a business analytics course; students reported finding the case study useful and interesting and were largely observed to meet the learning goals of the exercise.


Keywords: Data analytics, Data visualization, Tableau, Data mining, Descriptive statistics

## 1. CASE SUMMARY

In June 2018, Touringplans.com (Testa, 2018) announced the release to the public of several large data sets containing wait times for multiple attractions at Disney World. Due to the size and complexity of the data sets, a data mining and visualization approach is an appropriate way to summarize and analyze the data sets. In this case study, Tableau (Tableau Software, 2020) is used to link, visualize, and interpret the data to summarize how wait times for the various rides are affected by other variables such as month, day, season, time of day, weather, and special park events. This information can be used by travel agents and visitors to plan itineraries in addition to being informative for managing business operations.

## 2. BACKGROUND

Walt Disney World theme parks are a huge business, with 156 million visitors worldwide (Smith, 2020) and over $\$ 26$ billion in revenue in 2019 (Bilbao, 2019). The four parks comprising Walt Disney World in Orlando, Florida recorded 58.8 million visitors in 2019 (Rubin, 2019). Many visitors consult with authorized Disney travel planners and/or travel agencies
"Earmarked" by Disney. These agents and agencies have special training at the College of Disney Knowledge to gain advanced knowledge of the parks and access to special deals. These services are paid for by the suppliers and offered at no cost to travelers. One such agency is Key to the World Travel, which has over 450 travel agents in the United States, including Terre Pohlar, our client.

When Terre learned of the Touringplans data, she was curious to see how she could use this information to help make the best choices for her travelers. She indicated that if she knew when wait times were shortest and longest for various rides, she could better advise her customers regarding when to plan their vacation, which parks to visit on certain days, and what time of day to ride their favorite attractions. Terre has hired your team as data analysis consultants. She would like to know how wait times for the various Disney World attractions are affected by season, month, holidays, days of the week, time of the day, and other factors.

As consultants that specialize in data insights, you will be using a data visualization approach and Tableau software to present and summarize patterns in the wait times data. You will present and communicate your results to Terre using graphs in
an easy-to-understand format so that she can easily translate the results into recommendations for her customers.

## 3. DATA DESCRIPTION

The data used for this case study involve wait times for several attractions at Disney World and were downloaded from Touringplans.com, which updates wait-time data periodically (Disney World Ride Wait Time Datasets, 2018). In the initial data release in 2018, there were wait times available from nine attractions in all four parks of Disney World. As of August 2019, wait times from five additional attractions had been made available, bringing the total to 14 attractions across the Disney World campus (see Table 1).

| Magic <br> Kingdom | Epcot | Disney's <br> Hollywood <br> Studios | Disney's <br> Animal <br> Kingdom |
| :--- | :--- | :--- | :--- |
| Pirates of <br> the <br> Caribbean | Soarin' | Rock 'n' <br> Roller <br> Coaster | DINOSAUR |
| Splash <br> Mountain | Spaceship <br> Earth | Toy Story <br> Mania | Expedition <br> Everest |
| Seven <br> Dwarfs <br> Mine Train |  | Alien <br> Swirling <br> Saucers | Kilimanjaro <br> Safaris |
|  |  | Slinky Dog <br> Dash | Avatar Flight <br> of Passage |
|  |  | Na'vi River <br> Journey |  |

Table 1. Attractions Used in the Initial Case Study

### 3.1 Ride Data

As of July 2020, data for each attraction include Actual (SACTMIN) and Posted (SPOSTMIN) wait times measured multiple times per day for each day starting on January 1, 2015, or the date the ride first opened, through the end of 2019. The actual time is measured by the time a single rider takes from entering the queue until boarding the ride. The posted time is the time shown at the attraction's entrance as the estimated wait time. The first several rows of the Toy Story Mania data set are shown in Table 2 for illustration.

As of July 2020, there were approximately 200,000250,000 recorded observations for the older rides, and about 70,000-125,000 rows for the newer rides (Disney World Ride Wait Time Datasets, 2018).

| Date | datetime | SACTMIN | SPOSTMIN |
| :--- | :--- | :--- | :--- |
| $1 / 1 / 2015$ | $1 / 1 / 20157: 51$ |  | 20 |
| $1 / 1 / 2015$ | $1 / 1 / 20157: 53$ |  | 20 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 04$ |  | 30 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 11$ |  | 30 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 12$ |  | 40 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 18$ |  | 55 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 25$ |  | 65 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 31$ |  | 65 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 39$ |  | 70 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 46$ |  | 70 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 53$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20158: 55$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 04$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 06$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 06$ | 55 |  |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 11$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 18$ |  | 60 |
| $1 / 1 / 2015$ | $1 / 1 / 20159: 25$ |  | 80 |

Table 2. Sample Data from Toy Story Mania

### 3.2 Metadata

In addition to individual ride data, a Metadata file is also available (Disney World Ride Wait Time Datasets, 2018). The Metadata contains one row for each day specifying information about that day, including season, open and close times, high and low temps, if the day was a holiday, any special events taking place, the percentage of schools in session in various regions, and capacity lost due to downed rides, among other data. As of July 2020, the Metadata file included 2133 rows, one for each day between January 1, 2015, and December 30, 2019 (Disney World Ride Wait Time Datasets, 2018). See Table 3 for an excerpt from the Metadata file.

### 3.3 Data Dictionary

Lastly, a Data Dictionary (Disney World Ride Wait Time Datasets, 2018) file was used to explain all of the codes and variables in the data files, including:

- variables for each attraction, including definitions of SPOSTMIN and SACTMIN;
- description of each Metadata field, including variable names, variable descriptions, and formats;
- holiday codes, describing the abbreviation for each holiday. For example, "hal" is Halloween and "nyd" is New Year's Day; and
- codes for special events taking place at the parks. For example, "dah" is Disney After Hours and "mhp" is Mickey's Halloween Party.

| DATE | WDW__ <br> TICKET <br> SEASON | DAYOF <br> WEEK | $\ldots$ | SEASON | $\ldots$ | HOLIDAYN | $\ldots$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $12 / 24 / 2016$ | peak | 7 | $\ldots$ | CHRISTMAS | $\ldots$ | cme | $\ldots$ |
| $12 / 25 / 2016$ | peak | 1 | $\ldots$ | CHRISTMAS | $\ldots$ | cmd\|han | $\ldots$ |
| $12 / 26 / 2016$ | peak | 2 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $12 / 27 / 2016$ | peak | 3 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ |  | $\ldots$ |
| $12 / 28 / 2016$ | peak | 4 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ |  | $\ldots$ |
| $12 / 29 / 2016$ | peak | 5 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ |  | $\ldots$ |
| $12 / 30 / 2016$ | peak | 6 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ |  | $\ldots$ |
| $12 / 31 / 2016$ | peak | 7 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ | nye | $\ldots$ |
| $1 / 1 / 2017$ | peak | 1 | $\ldots$ | CHRISTMAS PEAK | $\ldots$ | nyd | $\ldots$ |
| $1 / 2 / 2017$ | peak | 2 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 3 / 2017$ | peak | 3 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 4 / 2017$ | regular | 4 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 5 / 2017$ | regular | 5 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 6 / 2017$ | regular | 6 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 7 / 2017$ | regular | 7 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 8 / 2017$ | regular | 1 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 9 / 2017$ | regular | 2 | $\ldots$ | CHRISTMAS | $\ldots$ |  | $\ldots$ |
| $1 / 10 / 2017$ | regular | 3 | $\ldots$ | WINTER | $\ldots$ |  | $\ldots$ |
| $1 / 11 / 2017$ | regular | 4 | $\ldots$ | WINTER | $\ldots$ |  | $\ldots$ |
| $1 / 12 / 2017$ | regular | 5 | $\ldots$ | MARTIN LUTHER KING <br> JUNIOR DAY | $\ldots$ | $\ldots$ |  |
| $1 / 13 / 2017$ | regular | 6 | $\ldots$ | MARTIN LUTHER KING <br> JUNIOR DAY | $\ldots$ |  | $\ldots$ |
| $1 / 14 / 2017$ | regular | 7 | $\ldots$ | MARTIN LUTHER KING <br> JUNIOR DAY | $\ldots$ |  | $\ldots$ |
| $1 / 15 / 2017$ | regular | 1 | $\ldots$ | MARTIN LUTHER KING <br> JUNIOR DAY | $\ldots$ |  | $\ldots$ |
| $1 / 16 / 2017$ | regular | 2 | $\ldots$ | MARTIN LUTHER KING <br> JUNIOR DAY | $\ldots$ | mlk | $\ldots$ |

Table 3. An Excerpt from the Metadata File

## 4. VISUALIZATION ASSIGNMENT

Your group will be assigned one Disney World attraction. For your assigned ride, you will address the following questions by creating visualizations.

### 4.1 The Task: Case Questions

1) How do wait times vary by season (as season is defined by Disney World in the data dictionary)? Are there seasons that are similar to each other? Which seasons have the longest and shortest wait times?
2) How do major holidays affect wait times? Are the wait times longer? By how much?
3) How do wait times vary by month? Which months give the shortest and longest wait times? Are certain months similar to each other?
4) How do wait times vary by day of the week? On which days are wait times longest? Shortest? Are there days that are similar to each other?
5) How do wait times vary throughout the day? Are there good and bad times to ride the ride?
6) How do wait times vary between "peak" ticket days, "regular" ticket days, and "value" ticket days? Why do you think Disney instituted this classification?

That is, what is the business rationale for this pricing structure?
7) How do special events at your ride's park affect wait times for your ride?
8) How does weather affect wait times for your ride?
9) How do posted wait times compare with actual wait times for your ride?
10) Optional (Advanced): How do wait times for your ride compare to wait times for another ride (or rides)?

### 4.2 Case Planning and Approach

Before beginning an in-depth analysis, you should consider and address these issues:

- What are the data types (measurements)?
- What tables will you use, i.e., ride and metadata?
- How will you join the tables? Why?
- Which independent variables from the Metadata are most appropriate to answer your questions? (see data dictionary to define variables)
- Are you doing any manipulation or cleansing of the data? For what purposes? What are you looking for?
- Consider any factors that would prompt you to exclude unusual data points from the ride's data set. For example, in 2020, the COVID-19 virus caused Disney World to shut down, and then it opened back
up with new crowd capacities and social distancing measures. Should wait times from this period be included? Why or why not?


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