



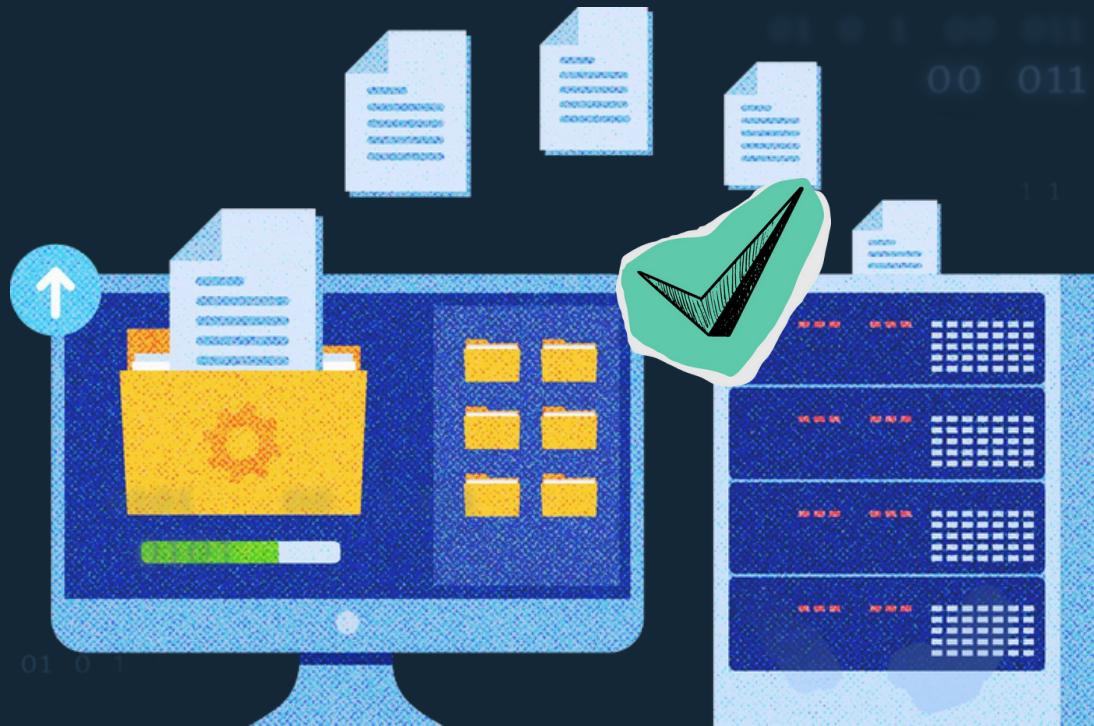
Assigning a \$ value

To NPS: An example

# Background: The Dataset

- **Approximately 6 years worth of data from holiday parks.**
- **Each row is a booking at a holiday park. It includes:**
  - Customer ID
  - NPS Score for the stay
  - \$ value of the booking
  - Nights stayed in the booking
  - Location of the booking
  - Lifetime nights stayed by the customer (till that point)
  - Lifetime \$ spent by the customer (till that point)
  - Nights stayed in the next 12 months by the customer
  - \$ spent in the next 12 months by the customer
- **Some things we know about the data/organization:**
  - The parks are each priced differently making comparing locations by \$ difficult.
  - Some customers are businesses booking accommodation for their staff.
  - Not every row has an NPS score recorded.

# Step 1: Clean the Data



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- First, we need to be confident with the data we are working with.
- Based on what we know about the business and the dataset, there are several obvious steps we need to take to prepare the data.  
We need to drop any rows without an NPS Score - they aren't useful to us.
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- We also need to remove outliers. Some of these “customers” are other businesses booking on behalf of staff. These customers will skew our commercial metrics (they appear to spend way more than other customers).
- We used a method called Interquartile Range to detect and remove outliers based on the number of nights stayed.  
We also added an NPS category column to make some calculations later in our analysis easier.

## Step 2: Is NPS correlated with commercial outcomes?



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- First, we want to see if NPS is correlated with the commercial outcomes we are interested in (nights stayed and \$ spent in the next twelve months).
- We did our data analysis using Python, and we used the ` `.corr()` functionality of Pandas to calculate the correlation between NPS and both Nights stayed in next 12 months and \$ spent in next 12 months.
- Next, we used Scipy to calculate the Pearson correlation coefficient and P-value for each pair of variables to ensure the correlations were statistically significant.

## Step 3: Detractors vs Promoters

Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

125

100

75

25

0

## Step 3: Detractors vs Promoters

- Now that we know that NPS is correlated with both nights stayed and \$ spent in the next 12 months, we need to determine if there is a statistically significant difference between Promoters and Detractors in these two metrics.
- We used a method called Tukey's honestly significant difference test to determine this, which confirmed that there is a statistically significant difference between Promoters and Detractors for both metrics.



## Step 4: Putting it all together

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- In order to get a \$ for NPS, we are going to focus on the \$ spent in next 12 months metric.
- We've proven that there is a statistically significant difference between Promoter and Detractors.
- We can use this difference together with our understanding of how NPS is calculated to calculate a \$ value for 1 point of NPS.

Let's assume:

- - the difference in the \$ spent in next 12 months metric is \$50;
  - 10,000 responded to the NPS survey; and
  - 15% of people respond to the NPS survey.
- To move NPS 1 point, we need to move  $10,000/100 = 100$  customers from Detractor to Promoter. In \$ spent in next 12 months, this would mean  $100 \times \$50 = \$5,000$ .
- If we extrapolate this number to represent everyone, not just those who respond to the survey, 1 point of NPS is worth  $\$5,000 / 0.15 = \$33,333$  of revenue in the next 12 months.

