# Part 1 ‐ Exploratory data analysis

### Important Features of the Demand

1. **Daily Cycles**:
   * **Peak Times**: They're distinct peak times in login activities unknowingly. The primary peak occurs lately in the evening around midnight, which might suggest significant activities during leisure hours, winding down their days. A secondary peak is observed in the late evening, potentially indicating increased activities when persons is finishing their work or daily activities.
   * **Low Activity**: The lowest activities is consistently found in early morning hours, particularly around 6 AM, which could be used for performing maintenance or updates when it least disrupting users.
2. **Intraday Variability**:
   * The demand isn't consistent thru the day, but showing significant fluctuations, which highlights the needs for dynamic resources allocations by time of day to efficiently managed system load.

### Visualization Insights

* The average daily cycle plot reveals times with highest and lowest demands, useful for strategic plannings in operations and customer services.
* Visualizing the first week provided a clear representation of intraday variations, illuminate the consistency of peak and low times across days.

### Data Quality Issues

Upon initial inspections, there appears to be no evident data quality issues like missing values, incorrect timestamps? or anomalies in data formatting. The timestamps are consistently formatted and appropriately parsed as datetime objects, there were no errors or inconsistencies observed during the data aggregation, process which suggest data quality concerns!

The provided login data is robust for analyzing daily user login patterns, and it show clear cycles of demand that could informs various operational strategy include staffing, system resource allocation, and timing for Maintenance. The lack of data quality issue is suggesting that the dataset is well-prepared for this type of temporal analysis.

# Part 2 ‐ Experiment and metrics design

## PRIME Measure of Successfulness

The prime measure for success of this experiment must directly shine a light on the objective of getting more cross-city road trips between Gotham and Metropolis, Like so:

* **Lift in the count of cross-city road trips**: to be seen as the percentage hike in trips beginning in one city and wrapping in the other- This metric be really important for it straight up gauges the switch in driver conducts, which is like, the main point of repaying toll costs!

We go for this metric for it:

* Is touching base with the experiment's goal.
* Can be counted and tracked without much fuss.
* Lends a hand in understanding the shift in traffic flows owing to the policy switch-up.

## Lay outing the Experiment

### a) Putting the Experiment in Action

* **Groups to Control & Treat**:
  + **Control Group**: The drivers not getting back toll costs.
  + **Treatment Group**: Ones who do get back toll money, yippee!
* **Time Slot**: Ought to be long enough for gathering good data and see behavior changes that really mean something, a couple months maybe.
* **Data Gathering**: Like, we need to keep tabs on how many trips drivers in both groups are doodling, paying special mind to trips between cities. Also, got to record when these trips happen (day vs. night) and how it affects the drivers' wallets (shifts in earnings).

### b) Statistical Tests to Confirm the Big Deal

* **Testing Theories**:
  + **Base Theory (H0)**: No diff in the count of city-crossing trips betwixt the control and treatment set.
  + **Other Theory (H1)**: The treating group (drivers getting toll money back) sees more city-hopping compared to the control lot.
* **Stats Test**:
  + Use a **Two-ratio Z-test** if enough data that's nicely distributed, which should be, because, context!
* **Mark of Significance**:
  + Mostly, a 5% mark of significance (α = 0.05) is fixed into use.

**c) Making Sense of Outcomes and Giving Suggestions**

* **Reading the Results**:
  + If Z-test p-value is under 0.05, we turn down the base hypothesis, and say "yes!" the tolls paid back did bump up city-crossing trips!
  + But, if the p-value goes over 0.05! We hold back on dismissing the base hypothesis, suggests toll payback’s proving nugatory on driver swings.
* **What to Advise**:
  + If the trials show a great up in city trips, advise keeping this up! Maybe even think to spread out toll paybacks!
  + Maybe try extra help, like promo actions or bonuses during less busy times, to even out needs across cities.
* **Words of Caution**:
  + Keep an eye on the economic hit to drivers as more cross-city voyages might not mean more money.
  + Watch for unintended side effects, like more traffic bunch-ups or longer waits for riders.

The real win of the experiment leans on strong data gathers and sharp analysis! By tuning into how drivers trek and using reliably solid methods to interpret what comes out, the Ultimate crew can smartly call shots on future city runnings and the tolls payback.

# Part 3: Discussion and Suggestions

Given the model's insights, Ultimate can consider the following strategies to improve long-term rider retention:

Target iPhone Users: Since iPhone users have higher retention rates, Ultimate might explore optimizing their app's experience on Android to match or exceed the experience provided on iOS.

Promote Ultimate Black Service: Users of Ultimate Black are more likely to be retained. Offering promotions or trials could encourage more users to try and continue using this premium service.

Engagement in First 30 Days: Users active in the first 30 days are more likely to stay with the service. Implementing strategies to encourage new users to use the service more during this initial period could be beneficial.

Surge Pricing Impact: Lower surge multipliers are associated with higher retention. Reviewing and possibly adjusting surge pricing strategies to be more competitive or user-friendly could help retain users sensitive to price changes.

These suggestions are based on patterns observed in the data, and implementing changes based on these insights could help Ultimate drive higher retention rates among their users. Further experiments and analysis could refine these strategies, especially by exploring user feedback and deeper dive into user behavior segments.