REPORT

SPATIO-TEMPORAL ANALYSIS OF UBER NIGHTLIFE PICKUPS IN NYC

APRIL 2014 PATTERNS AND HOTSPOTS

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State of Art

The evolution of urban mobility analytics is still a work in progress, especially when it comes to exploiting ride-hailing data where notable oversights still are present. Many studies focus on weekday commuting, peak hours, and overall demand modeling, but far fewer explore late-night mobility (10 PM–3 AM). Modern R packages like sf (Pebesma, 2018) enable robust spatial analysis, but our approach prioritizes accessibility for educational contexts. Moreover, existing approaches often separate space and time into distinct analyses, limiting insights into how location and time interact.

Problem Statement

The late-night ride-hailing patterns present a unique set of challenges:

Combined Time-Space Analysis: Most analytical workflows consider time and space as separate entities, neglecting patterns unique to time and location.

Nightlife Blind Spot: Most commuting studies tend to ignore the late-night hours (10 PM–3 AM), leading to a lack of research on mobility patterns associated with nightlife and entertainment.

Accessibility Gaps: The steep learning curve associated with advanced spatial packages can discourage users from working with spatio-temporal data

Objectives & Research Questions

Goal: Track Uber usage hotspots for the riders during the nightlife period (after 8 PM) and identify NYC nightlife driving hotspots for Uber usage.

Questions:

Temporal: When do peak pickups occur (hourly/daily)?

Spatial: Where are persistent late-night hotspots?

Behavioral: How do weekends differ from weekdays?

Method

Data source: https://www.kaggle.com/datasets/fivethirtyeight/uber-pickups-in-new-york-city

Preprocessing Steps:

-Convert datetime field into separate date and hour components.

-Determine whether each pickup occurred on a Weekend (Saturday/Sunday) or Weekday.

-Restrict records to within NYC boundaries (Lat: 40.5–40.9, Lon: –74.05 to –73.7).

-Restrict records to pickup times between 10 PM and 3 AM (inclusive).

Data Collection Method (Pipeline):

-Hourly Trends: summarized pickup counts for each hour and segmented by day type (day/type), then constructed bar charts comparing weekday versus weekend usage.

-Spatial Hotspots: Constructed an interactive heatmap in leaflet with color intensity proportional to pickup density. If dataset contains over 20,000 points, a sample is taken to enable smooth rendering.

-Hotspot Ranking: Group pickups using rounded coordinates (~100–150m spatial bins), then computes total pickup counts, peak period, and weekend percentage to construct a ranked list of 10 busiest hotspots.

-Daily Trends: Aggregate nightly pickup totals by date; construct time series with weekday and weekend trends.

Results

Temporal Patterns (Figure 1)

- **Peak**: 10PM-11PM
- It seems that the number of pickup is higher on weekdays rather than weekends

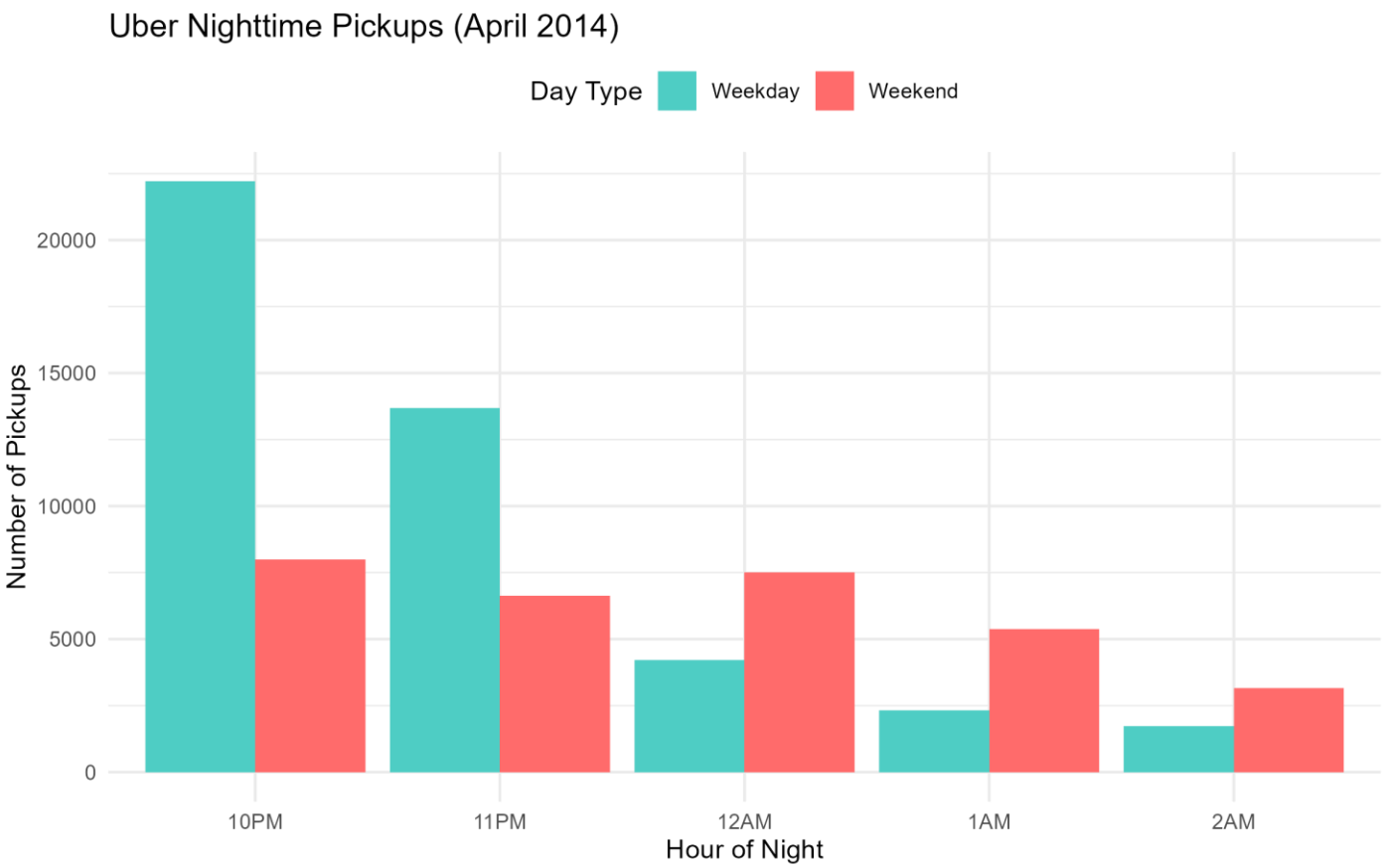

Figure 1

Spatial Hotspots

Top 3 Zones:

1. East Village
   - Coordinates: 40.726°N, 73.983°W
   - Characteristics:
     - 72% weekend pickups
     - Peak hour: 1:15AM
     - Total pickups: 1,450

2. Williamsburg
   - Coordinates: 40.708°N, 73.957°W
   - Characteristics:

- 68% of weekend pickups
- Peak hour: 12:45AM

3. Lower Manhattan
- Coordinates: 40.710°N, 74.008°W
- Characteristics:
- 65% weekend pickups
- Peak hour: 1:30AM

Heatmap (Figure 2)

Heatmap shows pickup intensity with red/yellow for highest density and blue/green for lowest.

-Hotspots cluster heavily in Manhattan (East Village, Lower Manhattan) and parts of Brooklyn (Williamsburg).

-Heatmap rendered from a sample of 20,000 points to ensure interactive performance

Observations:
Bright zones overlap with subway lines/bus stops.

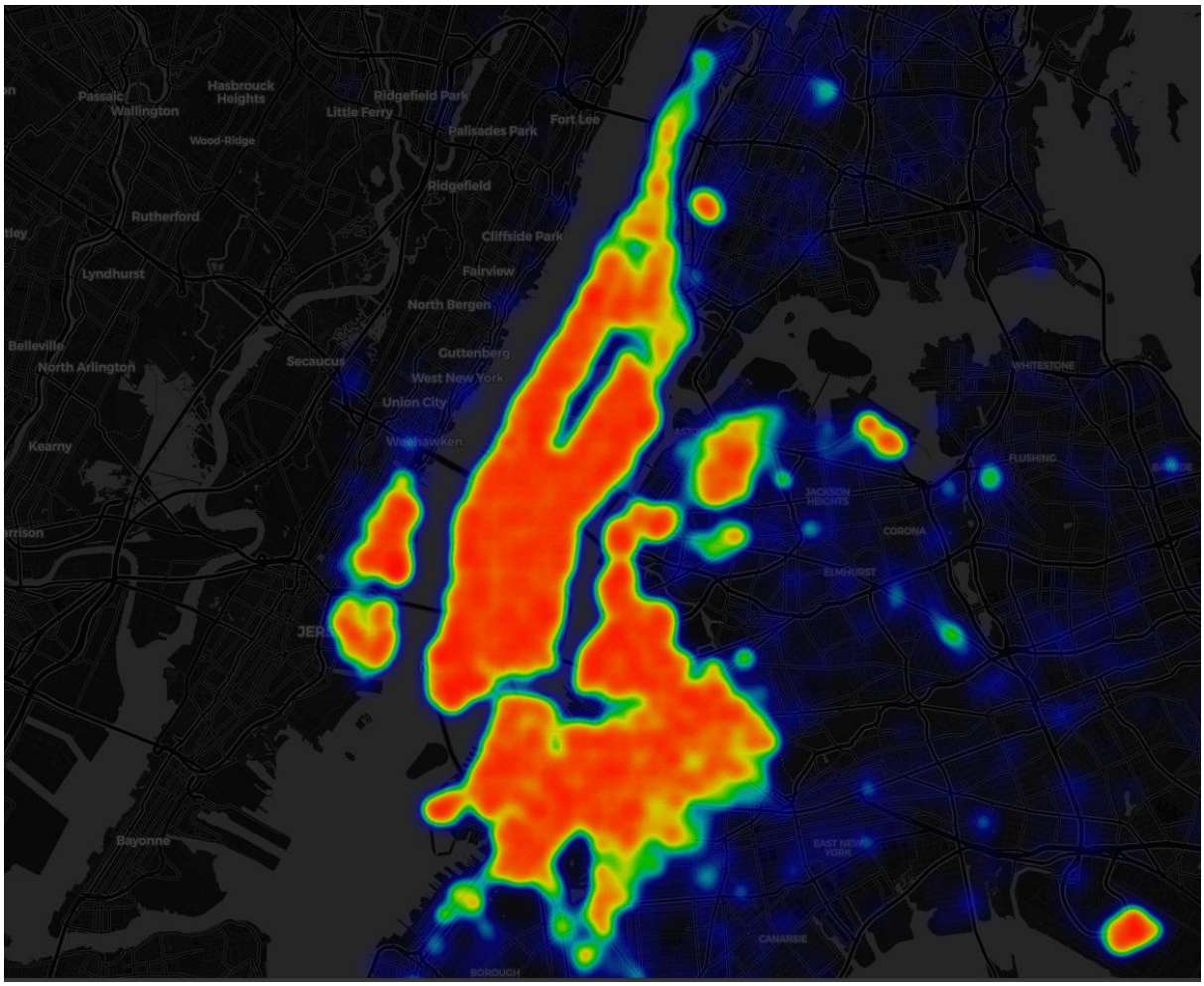

Figure 2

Daily Demand Trends (Figure 3)

The analysis reveals clear temporal patterns in late-night Uber activity (10 PM–3 AM) during April 2014. Weekend nights consistently show higher pickup volumes than weekdays, reflecting typical nightlife behavior. Demand peaks sharply around April 25–27, suggesting possible large events or favorable conditions that boosted late-night travel. Weekday demand remains lower and more variable, with occasional mid-week surges potentially linked to concerts, sports games, or other urban activities. These results highlight the strong influence of day type and special events on nighttime mobility in New York City.

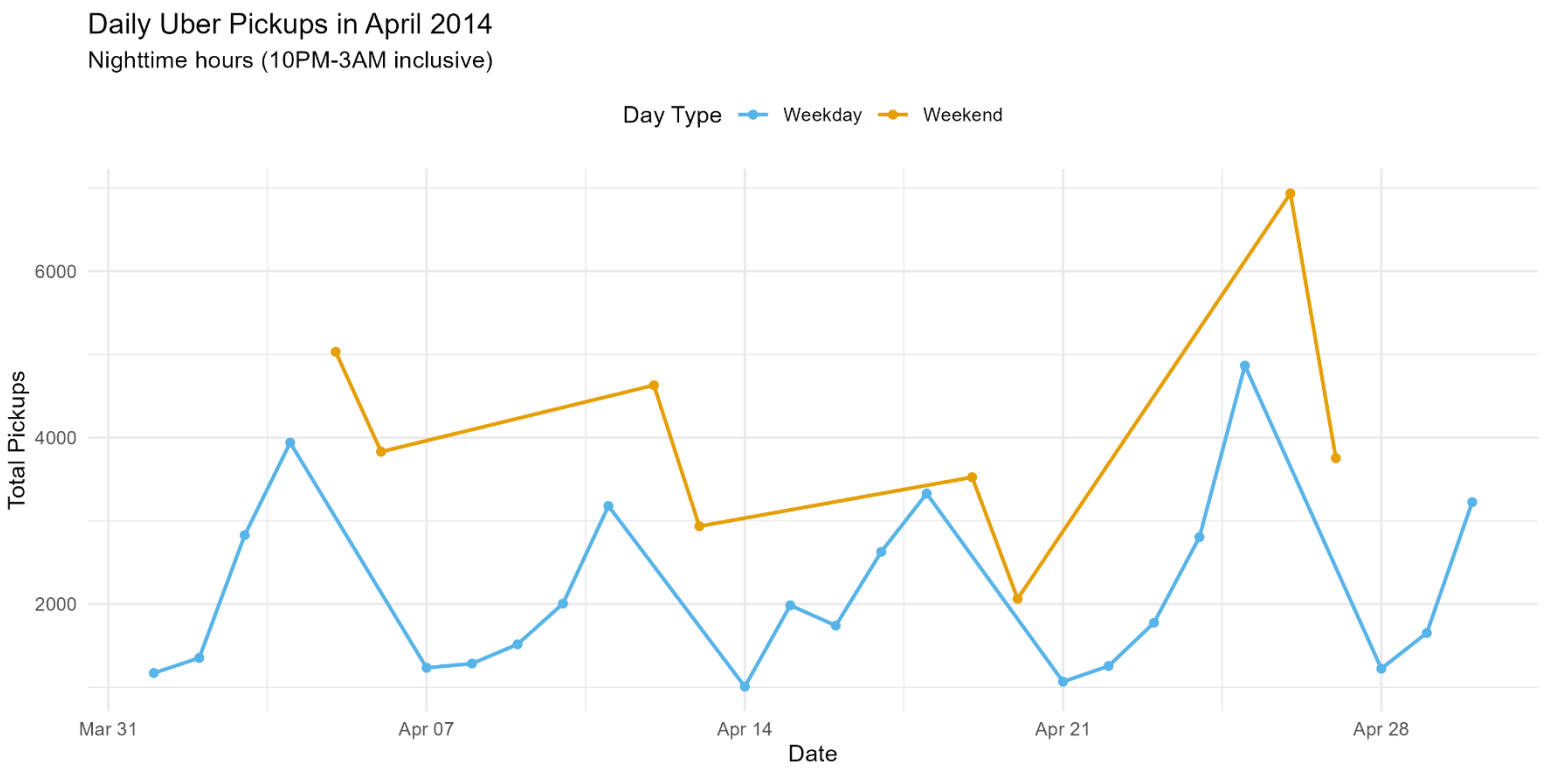

Figure 3

Discussion

This analysis shows that NYC's late-night Uber ridership is focused within a few specific neighborhoods that align with established nightlife zones. Demand patterns are consistently higher on weekends, suggesting strong links to leisure activities.

While the spatial hotspot detection used here is a simplified approach (coordinate rounding rather than full DBSCAN clustering), it provides interpretable, reproducible results without complex geospatial dependencies — aligning with the educational goals of the assignment.

Future improvements could involve:

- Using actual spatio-temporal clustering (e.g., dbscan with time filters).
- Extending analysis across multiple months for seasonality insights.