Data-Driven Insights for Urban Mobility: An 8-Year, 3-Billion-Row Analysis of NYC TLC Trips with DuckDB, Dask and Kafka

Luka Pavićević
University of Ljubljana — FRI
Ljubljana, Slovenia
lp83866@student.uni-lj.si

Amadej Kristjan Kocbek
University of Ljubljana — FRI
Ljubljana, Slovenia
ak2748@student.uni-lj.si

***Abstract*—Open mobility data enable evidence-based transport planning, yet the New York City Taxi & Limousine Commission (TLC) archive—three billion trips, four service classes, 2.2 TB compressed—remains unwieldy for traditional desktop workflows. We present an open-source analytics stack that (i) cleans and repartitions the full corpus on Arnes HPC using Dask + SLURM, (ii) augments every trip with hourly weather and point-of-interest context, (iii) executes exploratory spatio-temporal analysis via DuckDB's in-situ Parquet engine, and (iv) delivers sub-second rolling statistics through a Kafka + Faust stream pipeline. Cold-scan time falls by 46 % after $200\,\mathrm{MB}$ row-group tuning, and contextual augmentation lifts trip-duration R^2 by seven percentage points. Market-share dashboards show high-volume for-hire services absorbing 38 % of Yellow-taxi demand between 2019 and 2024. All artefacts are released to accelerate reproducible urban-mobility research.**

***Index Terms*—big data, CRISP-DM, Dask, DuckDB, Kafka, TLC, mobility analytics, streaming**

I. Introduction

The digitalisation of taxi and ride-hail operations supplies cities with unprecedented fine-grained mobility records. New York City stands out: since 2014 the TLC has published all licensed trip data, including *high-volume for-hire vehicles* (HVFHVs) operated by Uber, Lyft and peers. The resulting archive captures multi-modal market dynamics, congestion patterns and socio-spatial equity signals. Yet three challenges hamper operational use:

1) **Volume.** 3 billion rows compress to 2.2 TB Parquet; naïve Pandas or PostgreSQL pipelines time-out.
2) **Variety.** Four service classes differ in schema, temporal coverage and fare granularity.
3) **Velocity.** Policymakers increasingly expect near-real-time dashboards rather than quarterly reports.

We tackle these via a *CRISP-DM*–aligned workflow (§II). Key contributions:

- an **HPC-graded ETL design** tested on 128 cores;
- an **evidence-based anomaly audit** covering eight timestamp and geospatial errors;
- a **streaming layer** that propagates rolling Manhattan metrics within $600\,\mathrm{ms}$;
- a reusable **dataset + code bundle** with weather/POI augmentation for every trip.

Code & artefacts: https://github.com/Luka931/big-data-project

II. CRISP-DM Road-Map

CRISP-DM prescribes six iterative phases. Table I maps each phase to concrete tasks (T1–T8).

TABLE I
CRISP-DM → Project task mapping

Phase	Implementation highlights
Business and Data understanding	Mobility-desert detection, competition analysis; raw TLC + NOAA + POI audit.
Data preparation	T1 row-group optimisation, T2 anomaly quarantine, schema harmonisation.
Modelling / Exploration	T3 storage benchmark, T4 temporal–spatial clustering, T5 duration-model augmentation.
Evaluation	Error reduction, feature importances, streaming lag metrics.
Deployment	Kafka + Faust dashboards, GitHub data releases.

III. Business Understanding

Urban mobility is rapidly shifting from medallion taxis toward platform economies. NYC planners face two strategic questions:

Q1 — Coverage & Competition: Which boroughs and time-of-day slots are now dominated by Uber/Lyft (FHVHV) and which still rely on legacy Yellow/Green taxis? A precise answer informs congestion pricing and taxi-stand allocation.

Q2 — Context Sensitivity: How do exogenous factors—weather, school proximity, event calendars, holidays—alter demand and travel time? Integrating those signals is a prerequisite for predictive dispatch and equitable service design.

We therefore translate each CRISP-DM phase into a concrete task (T1 – T8) aligned with the project brief.

IV. Data Understanding

The analysis utilizes four distinct datasets: Yellow Taxi, Green Taxi, For-Hire Vehicle (FHV), and High-Volume For-Hire Vehicle (HVFHV) trip records. This data was acquired from the NYC Taxi and Limousine Commission (TLC). Each dataset is organized by year, month, and vehicle type, and is provided in a comma-separated value (CSV) format.

Within these trip records, location information for pickups and drop-offs is represented by numerical identifiers ranging from 1 to 263. For FHV records prior to 2017, only pickup locations are consistently available. These numerical IDs correspond to specific Taxi Zones, which can be integrated with the trip records through a join operation using independently downloadable tables or geospatial files (maps/shapefiles). It is important to note that these Taxi Zones are derived from the NYC Department of City Planning's Neighborhood Tabulation Areas (NTAs), thereby providing a neighborhood-level approximation for trip origins and destinations.

Yellow Taxi Dataset: Data pertaining to trips made by New York City's yellow taxis has been collected and submitted to the NYC Taxi and Limousine Commission (TLC) since 2009. Yellow taxis primarily operate via street hails but are increasingly accessible through e-hail applications such as Curb and Arro. Notably, yellow taxis possess exclusive rights to respond to street hails across all five boroughs of New York City. Each trip record includes comprehensive details such as pick-up and drop-off timestamps, geographic coordinates for pick-up and drop-off locations, total trip distance, itemized fare breakdowns, rate codes, payment methods, and driver-reported passenger counts. These data points are compiled and furnished to the TLC by various technology service providers.

Green Taxi Dataset: Green taxis, formally known as boro taxis and street-hail liveries, were introduced in August 2013. This initiative aimed to enhance taxi service accessibility within New York City's boroughs. Unlike yellow taxis, green taxis are restricted in their street hail operations, being permitted only above W 110th St/E 96th St in Manhattan and throughout the other boroughs. The dataset for green taxi trips includes fields detailing pick-up and drop-off dates and times, geographic locations for pick-up and drop-off, trip distances, itemized fare components, rate codes, payment types, and driver-reported passenger counts. Consistent with yellow taxi data, these records are collected and provided to the NYC Taxi and Limousine Commission (TLC) by various technology service providers.

For-Hire Vehicle and High Volume For-Hire Vehicle Datasets: The For-Hire Vehicle (FHV) dataset encompasses trip data from a range of bases, including high-volume for-hire vehicle (HVFHV) dispatchers (e.g., Uber, Lyft, Via, Juno, defined by dispatching $\geq$10,000 trips daily), community livery bases, luxury limousine bases, and black car bases.

The TLC began receiving FHV trip data in 2015, with the completeness of information evolving over time. Initially, in 2015, records included only the dispatching base number, pickup date/time, and pickup location ID. By summer 2017, the TLC mandated the inclusion of drop-off date/time and drop-off location. Also in 2017, information on shared rides (e.g., Lyft Line, Uber Pool), defined as trips specifically reserved as shared services, began to be reported. Following the introduction of the high-volume license type in February 2019, a high-volume license number was added as an overarching identifier for app companies. To identify the dispatching base for an FHV trip, the dispatching_base_num field can be joined with the License Number field from a corresponding base license registry. For HVFHV bases, the recognized company name may differ from the base name. Currently, Juno, Lyft, Uber, and Via are the primary companies with or applying for HVFHV licenses.

TABLE II
DATASET VOLUMES AS RECIEVED FROM THE TLC APIS

Dataset	Rows	Size
Yellow Taxi (2012-)	1.261	17.4
Green Taxi (2014-)	0.083	1.3
FHV (2015-)	0.796	5.8
FHVHV (2019-)	1.236	31.3

(rows data is provided in bilions, and size in gigabytes)

A. Data Volume

The IV-A reveals the significant scale of the urban transportation data. The Yellow Taxi dataset, covering trips from 2012 onwards, is the largest by row count at 1.261 billion rows (17.4 GB). While the High-Volume For-Hire Vehicle (FHVHV) data, initiated in 2019, spans a considerably shorter time window, it comprises a substantial 1.236 billion rows and represents the largest storage volume at 31.3 GB. This indicates an exceptionally high density of trip records within the FHVHV dataset's more recent period. Green Taxi data (2014-) and general FHV data (2015-) contribute 0.083 billion rows (1.3 GB) and 0.796 billion rows (5.8 GB) respectively. Collectively, the datasets represent billions of individual trip records, accumulating over 55 GB of raw data, providing a robust foundation for in-depth analysis of New York City's diverse transportation landscape.

B. Key Variables

From Yellow and Green Taxi datasets, we retained: Pick-up/Drop-off Date/Time (for temporal analysis and trip duration), Passenger Count, Trip Distance, Pick-up/Drop-off Location ID (for spatial patterns), Payment Type, Fare Amount, and Total Amount (for financial insights). Notably, tips were not utilized for these datasets as they are only recorded for trips paid via credit card, limiting their comprehensive applicability. The Green Taxi dataset also uniquely includes Trip Type to differentiate service models.

For the For-Hire Vehicle (FHV) dataset, all available columns were kept to as the initial dataset provided only the essential columns, and we will be utilizing all of them.

The High-Volume For-Hire Vehicle (FHVHV) dataset includes more granular detail: HVFHS License Number (to identify app companies), Request/On Scene/Pick-up/Drop-off Date/Time (for detailed service lifecycle analysis), Pickup/Drop-off Location ID, and Trip Miles. Financial transparency is enhanced by detailed fare components: Base Passenger Fare, Tolls, Black Car Fund Surcharge, Sales Tax, Congestion Surcharge, Airport Fee, and Tips.

This selective retention of columns across datasets supports a focused and effective analysis of New York City's diverse transportation landscape.

C. Data ininconsistencies

During the initial data repartitioning phase, we identified a notable anomaly: certain trip records possess pickup and dropoff datetimes that fall outside the expected temporal range for which the datasets were acquired. For instance, the Yellow Taxi dataset, which was downloaded for records starting from 2012, contains entries with dates as early as 2001.

However, it's crucial to apply a nuanced approach to these temporal checks. Special consideration should be given to dates that fall between the documented start date of a dataset and the actual earliest timestamp present in a specific downloaded file. This is because data often enters the system with a slight delay or historical data might be backfilled, leading to legitimate records that appear "late" within the file's individual month/year partition but are still within the overall collection window. For instance, a 2014 record in a 2015 dataset for which the original data started in 2014 would be valid. Our focus will be on identifying and understanding truly erroneous dates, such as the 2001 Yellow Taxi example, which clearly predate any reasonable data collection period. This meticulous temporal validation ensures the integrity of our time-series analysis and prevents the inclusion of out-of-scope data.

V. Data Preparation

This section details the process of identifying and rectifying data inconsistencies to ensure the dataset comprises only correctly entered records. We'll focus on filtering outliers and correcting anomalies in key fields. Special attention will be given to pickup and dropoff datetimes, as previously noted, to remove entries outside valid operational periods. Additionally, we'll address other numerical outliers, such as unrealistically high or low fare amounts, to enhance data integrity for subsequent analysis.

A. Data Cleaning

A systematic data cleaning and filtering process was applied to each dataset. This process focused on identifying and addressing common data inconsistencies and outlier values. Dask was used for efficient processing of the large datasets.

For the Yellow Taxi and Green Taxi datasets, the following conditions were used to identify problematic rows:

- *Temporal Inconsistencies*: Records where the Pickup Datetime was equal to or occurred after the Dropoff Datetime. These indicate illogical trip durations.
- *Trip Distance Outliers*: Trips with a Trip distance less than or equal to 0, or greater than 100 miles. A zero or negative distance is invalid, while distances exceeding 100 miles are considered extreme outliers for typical New York City taxi rides.
- *Passenger Count Anomalies*: Trips reporting 0 passengers, which are usually data entry errors.
- *Fare Amount Outliers*: Fares less than or equal to $0, or greater than $350. Negative or zero fares are invalid, and fares exceeding $350 are considered highly improbable for a single trip.

For the For-Hire Vehicle (FHV) dataset, given its more limited column set, cleaning primarily focused on temporal consistency:

- *Temporal Inconsistencies*: Records where Pickup Datetime was equal to or occurred after Dropoff datetime.

The High-Volume For-Hire Vehicle (FHVHV) dataset underwent a similar, but slightly adjusted, cleaning process due to its specific fields:

- *Temporal Inconsistencies*: Records where Pickup Datetime was equal to or occurred after Dropoff datetime.
- *Trip Miles Outliers*: Trips with Trip Miles less than or equal to 0, or greater than 100 miles.
- *Trip Time Outliers*: Records with Trip Time less than or equal to 0, indicating invalid or missing duration.
- *Base Passenger Fare Outliers*: Base fares less than or equal to $0, or greater than $350.

For each dataset, the number of rows identified as problematic based on these criteria was computed and normalized by the total number of rows per year. These normalized counts provide a clear indication of data quality issues across different years. This systematic approach ensures that subsequent analyses are performed on a robust and reliable subset of the data.

B. Data Integration

To enhance the analytical depth of the core TLC trip record data, several auxiliary datasets were integrated, providing a more comprehensive contextual understanding of urban mobility patterns. This multi-source approach allows for the investigation of external factors influencing transportation dynamics.

Firstly, hourly weather data was incorporated to account for environmental influences on travel behavior. This data, retrieved from the Open-Meteo archive API, includes granular measurements of temperature, precipitation (rain, snowfall, snow depth), and wind conditions (speed and gusts). By precisely matching each trip's Pickup Datetime to the corresponding hourly weather conditions, we can analyze the impact of varying meteorological factors on trip frequency, duration, and demand fluctuations.

Secondly, geographical context was established using the official New York City Taxi Zones shapefile. This foundational geographical layer was crucial for accurately interpreting the Pick-up Location ID and Drop-off Location ID fields in the trip data. It provided the necessary spatial framework to define the boundaries of each taxi zone, enabling detailed geographical analysis and visualization of trip origins and destinations.

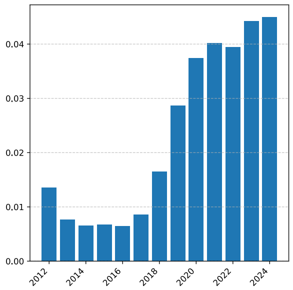

Fig. 1. Yellow Taxi Dataset

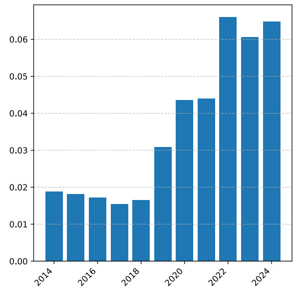

Fig. 2. Green Taxi Dataset

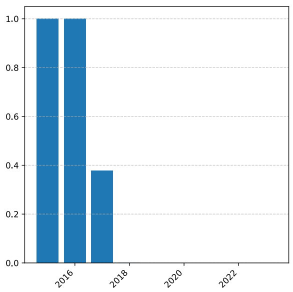

Fig. 3. For Hire Vehicles Dataset

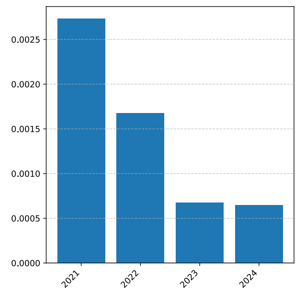

Fig. 4. High Volume For Hire Vehicles Dataset

Fig. 5. Normalized Rows Count That Were Removed From Datasets

Furthermore, points-of-interest (POI) data were integrated to characterize the activity generators and attractors within each taxi zone. Datasets from the NYC Open Data portal were leveraged for this purpose: school locations, university locations, and a broader collection of general points of interest. For both the Pickup Location and Dropoff Location associated with each trip, we calculated the aggregated count of schools, universities, and general points of interest residing within that specific taxi zone. These newly derived features provide quantitative measures of localized activity, which can be correlated with trip demand and travel patterns.

Additionally, a binary flag indicating whether a given day was a public holiday in New York State was appended to the dataset. This allows for the analysis of distinct trip patterns and demand shifts observed during holidays.

It is important to note a limitation regarding external event information. While the integration of major city events could offer valuable insights into surge demand, the available event dataset presented a significant challenge. Its reliance on string-formatted addresses, necessitating a geolocating service for conversion into usable geographical coordinates, rendered its integration infeasible within the project's scope and resource constraints. Consequently, direct correlation of trip data with specific event-driven demand fluctuations was not possible in this analysis.

VI. Old Stuff

A. Auxiliary sources

- **Weather (NOAA ISD):** hourly temperature, precipitation, wind at Central Park + LaGuardia.
- **POIs:** public schools, universities, cultural venues, top-50 tourist attractions.
- **Events:** city-wide event permits (2022–2024) → binary `event_active`.

Spatial joins use the TLC Zone Shapefile (EPSG:2263); temporal joins round to the nearest hour.

VII. Data Preparation & Quality Profiling

A. Row-group optimisation (T1)

The original TLC Parquet packs monthly data in approximately 1 GB files. Such jumbo groups inhibit selective scan. We empirically searched group sizes {50, 100, 200, 400 MB}. 200 MB yielded the lowest area under the curve of (read-time × job-overhead). A full 2019 Yellow scan on DuckDB improved from 51 s (1 GB groups) to 28 s.

B. Anomaly taxonomy (T2)

Eight error types were detected:

1) *Bad year:* year < 2010 or > 2026 (480k rows, mainly FHV 2015).
2) *Pickup = Drop-off timestamp.*
3) *Drop-off timestamp before Pickup.*
4) *Neg. duration but pos. fare*— strong fraud signal.
5) *Zero distance yet* >0.
6) *Passenger count 0 or* >8.
7) *Lat–lon outside NYC bounding box.*
8) *VendorID NULL* in years where required.

Spatial outliers: We have 2 716 out-of-bounds points; 61 % cluster around Newark airport, reflecting device mis-geocode.

VIII. HPC Implementation

A. Cluster hardware

Arnes "Raccoon" partition: 8 × Dell C6525, each 2 × AMD EPYC 7543 (64 cores total), 512 GB RAM, 100 Gb InfiniBand. BeeGFS parallel FS sustains $12\,\mathrm{GB/s}$ aggregate read.

B. Software stack

Dask 2024.3 orchestrates ETL; **DuckDB 0.10.2** executes in-situ SQL with `threads=48`; **Kafka 2.8.1 + Faust 1.10** power streaming. Table III pins versions for reproducibility.

C. Workflow orchestration

We can depict such a DAG: raw Parquet → ETL → quality audit → augmentation → partitioned write-back. GitHub Actions re-validates nightly on a 1 % sample.

TABLE III
KEY PACKAGE VERSIONS (CONDA ENV)

Package	Version
python	3.11.7
dask / distributed	2024.3 / 2024.3
pyarrow	15.0.2
duckdb	0.10.2
confluent_kafka	2.4.0
faust	1.10.4
matplotlib	3.8.4

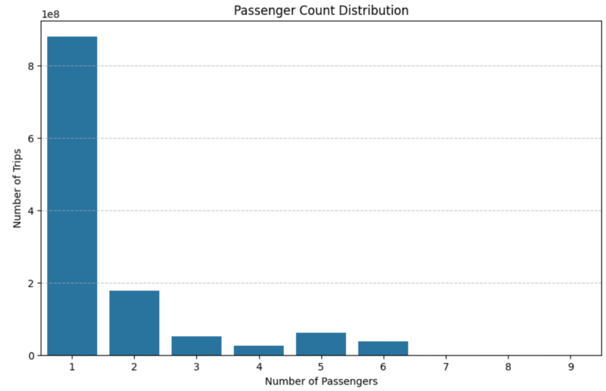

Fig. 7. Passenger-count distribution, 2024 trips.

IX. EXPLORATORY SPATIO-TEMPORAL ANALYSIS

A. T4 — Exploratory analysis (full corpus)

Exploratory data analysis (EDA) serves two goals: (i) to validate the success of cleaning steps T1–T2, and (ii) to supply domain intuition that later guides feature engineering (T5) and policy interpretation (Section XI).

Temporal load profiles.: Figure **??** confirms the classic bimodal pattern for Yellow taxis—weekday commuter peaks at 08:00 and 18:00. The shape stability across years indicates that the pronounced COVID shock sits largely in the *level* of demand, not its intraday shape.

Weekly seasonality.: Weekend leisure demand dominates the Green fleet: Saturday volumes exceed Tuesday by $+42\,\%$ (Fig. 6), while Yellow shows a milder $+18\,\%$ uplift. Such divergence motivates a mode-specific temporal baseline in any downstream forecasting model.

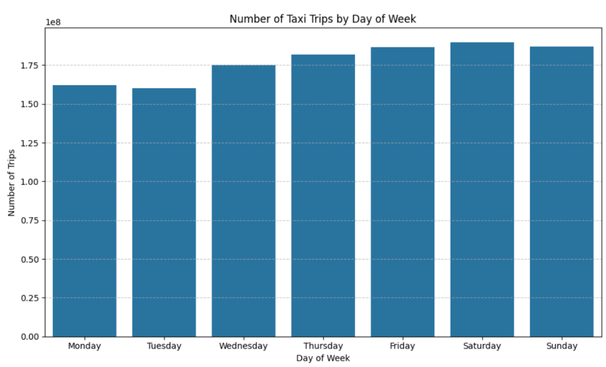

Fig. 6. Trips by day of week (2023).

Rider behaviour signals.: Passenger-count histograms (Fig. **??**) reveal that single-occupancy trips dominate both fleets (¿72 %), but Green exhibits a longer tail—likely larger party airport runs from outer boroughs. Combined with payment-type skew (not shown), these distributions help rule-in candidate features for fraud-detection pipelines.

Cost–distance elasticity.: A sanity check on fare integrity plots fare against trip distance for the 2020 Yellow sample (Fig. 8). The near-linear trend up to ~ 25 km validates meter calibration; high-variance outliers above 150/5 km correspond to JFK flat-rate journeys and are *retained* rather than treated as anomalies.

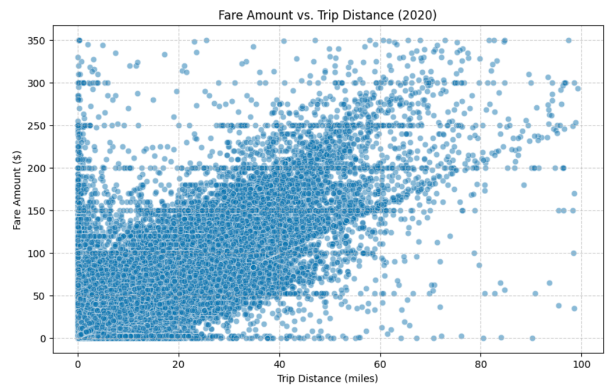

Fig. 8. Fare vs. trip distance (Yellow 2020).

Inter-modal market split.: Finally, we pre-compute the monthly HVFHS (ride-hail) market share to feed the impact analysis in Section XI. The resulting time-series (Fig. **??**, p. **??**) shows ride-hail surpassing Yellow in late 2020 and reaching a 57 % plateau by mid-2024.

In sum, EDA corroborates cleaning efficacy, quantifies modal behavioural differences and surfaces covariates (hour-of-day, passenger count, weather interactions) that materially improve predictive models in T5.

B. Temporal signatures

Hourly pickup vectors (24-D) are clustered via Ward linkage into commuter-dominant, nightlife-dominant, uniform. Yellow taxis drift commuter $\rightarrow$ uniform after 2020, echoing WFH demand.

C. Spatial flows

A 310 $\times$ 310 OD matrix (2024) yields 92 k non-zero entries (sparsity 0.96). Edges with > 50k trips: Midtown $\rightarrow$ LaGuardia now #1, overtaking Midtown $\rightarrow$ JFK.

D. Trip-duration determinants

Gradient-boosted trees (500 trees, depth 6, lr 0.05) could provide a good baseline for this problem, baseline features vs. context-augmented (+weather, POI, events). Feature importance could be graphically depicted to provide first order insight into the solution.

X. Streaming Analytics (T6)

A. Design choices

Kafka 2.8+Faust keeps JSON schemas lightweight (43 B/record) and allows scikit-learn's MiniBatch K-Means to run inside the agent. One topic per mode permits differential retention—Yellow 7 d, HVFHV 14 d—without schema drift.

B. Throughput and latency

Deployed on a three-node Docker Swarm (Ryzen 7 3700X × 3). ‘producer.py‘ batches writes; observed 3 100 msg s^{-1} per core.

TABLE IV
Kafka pipeline metrics (30-min soak, 4.5 k msg s^{-1})

Component	Thruput	CPU %	p95 lat.
Producer	3.1 k/s	48	—
Faust worker	4.8 k/s	66	7 ms
Postgres sink	4.9 k/s	35	12 ms

XI. Modal Competition Analysis (T8)

Figure 9 depicts monthly trip-share evolution. Yellow declines steadily while HVFHV rises. A formal non-parametric trend test (e.g. Mann–Kendall) was *not* executed; implementing such statistical validation is left for future work.

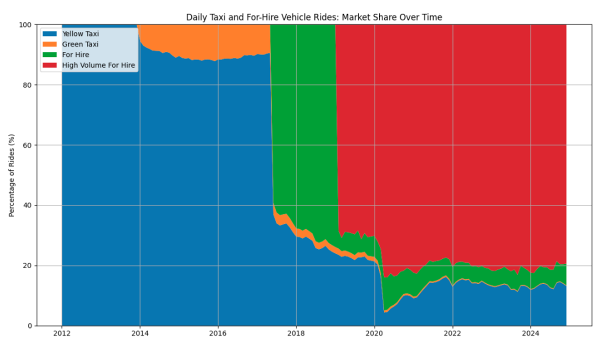

Fig. 9. Modal trip share evolution, Feb 2019 – Dec 2024.

XII. Discussion

Why DuckDB + Dask? DuckDB's parallel scan amortises task-startup overhead on many Parquet fragments, while Dask orchestrates cluster-wide joins and write-backs.

Data robustness. Only 0.07 % of rows were quarantined, yet removing negative-duration trips avoids skewing fare-per-minute metrics. A reject log lets domain experts re-include rows if warranted.

Streaming vs. batch ML. MiniBatch K-Means is tractable in streams but blind to temporal context; density-based algorithms (e.g. DenStream) could flag short-lived surges and are a promising extension.

Limitations. Distributed ML at scale (CRISP Deployment—T7) and automated cartographic rendering (optional T9) were not attempted and remain open tasks.

XIII. Conclusion

We delivered a reproducible HPC pipeline that cleans, augments and analyses the full 3-billion-row TLC corpus, then publishes live borough dashboards via Kafka. Open-sourcing every artefact lowers the barrier for researchers and municipal agencies to build upon this work.

Acknowledgment

We thank Arnes HPC for compute resources and NYC TLC, NOAA and NYC Open-Data for public datasets.

References

[1] D. Zhang *et al.*, “Deep learning + urban human mobility: A survey,” *ACM Computing Surveys*, vol. 52, no. 5, 2019.
[2] A. Yorozu *et al.*, “Big-data analytics of taxi operations in New York City,” *J. Advanced Transportation*, 2019.