

# Maximizing Revenue for NYC Taxi Drivers

A Statistical Analysis of  
Payment Methods and Fare Pricing

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## PROJECT SCOPE:

Statistical Hypothesis Testing

Python / Pandas / Scipy

Method: Independent T-Test & EDA

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# “The Analytical Journey: From Raw Data to Revenue Strategy



**The Problem.**  
Driver revenue optimization.

**The Data.**  
6.4M row NYC  
Taxi dataset.

**The Cleanup.**  
Filtering noise & Feature Engineering

**The Proof.**  
Hypothesis Testing (T-Test) & EDA.

**The Strategy.**  
Actionable recommendations

# In a low-margin industry, every trip counts

**GOAL:** Maximize revenue streams for drivers.



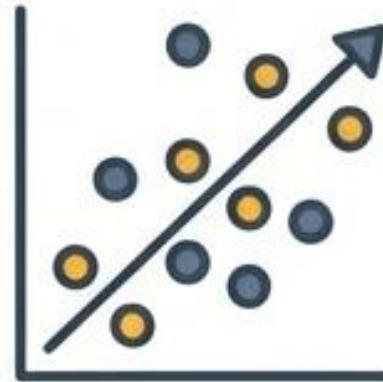
## The Problem Statement

In the fast-paced taxi booking sector, long-term success requires data-driven insights. Drivers operate on thin margins and time efficiency.

We aim to determine if specific payment behaviors correlate with higher fare pricing.

Primary Variable: `Payment Type` vs `Fare Amount`

# Two Key Questions Drive This Analysis



## 1. The Correlation

Is there a statistically significant relationship between the total fare amount and the payment type chosen by the passenger?



## 2. The Behavior

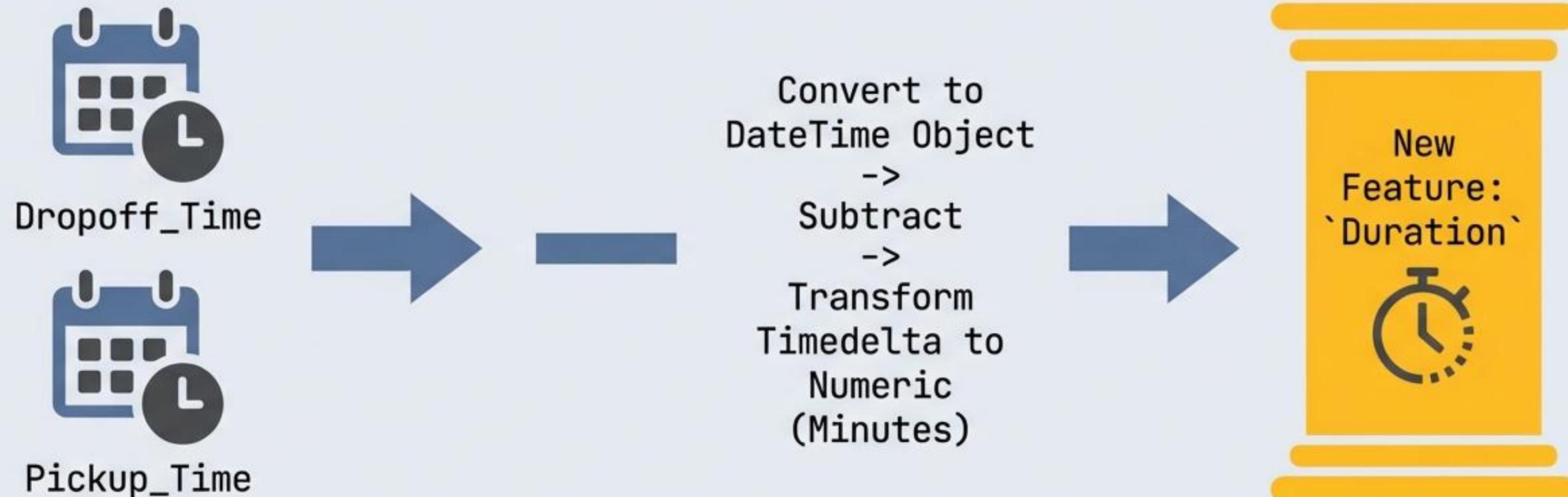
Can we nudge customers toward payment methods that generate higher revenue without negatively impacting their experience?

# The Source Material: NYC Taxi Trip Records

VendorID	Pickup_DateTime	Dropoff_DateTime	Passenger_Count	Trip_Distance	Payment_Type	Fare_Amount
Creative Mobile	2023-01-01 12:00:00	2023-01-01 12:15:00	1	2.5 miles	Card	\$15.50
VeriFone Inc	2023-01-01 12:30:00	2023-01-01 12:55:00	2	4.8 miles	Cash	\$24.00
Creative Mobile	2023-01-01 13:10:00	2023-01-01 13:22:00	1	1.7 miles	Card	\$11.50
VeriFone Inc	2023-01-01 13:45:00	2023-01-01 14:05:00	1	3.2 miles	Cash	\$18.00

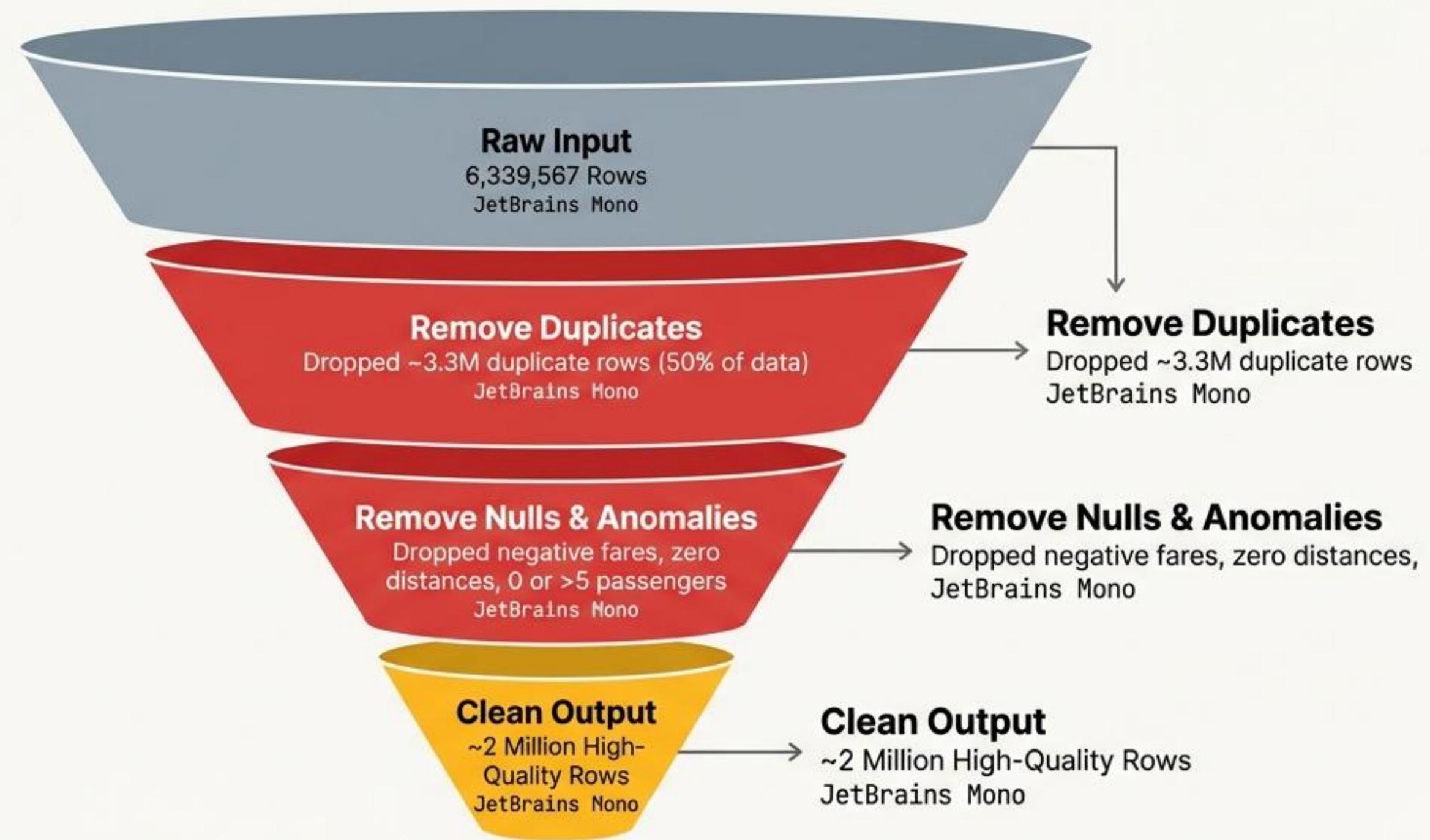
Initial Dataset Size:  
~6.4 Million Rows

# Engineering Value from Raw Timestamps



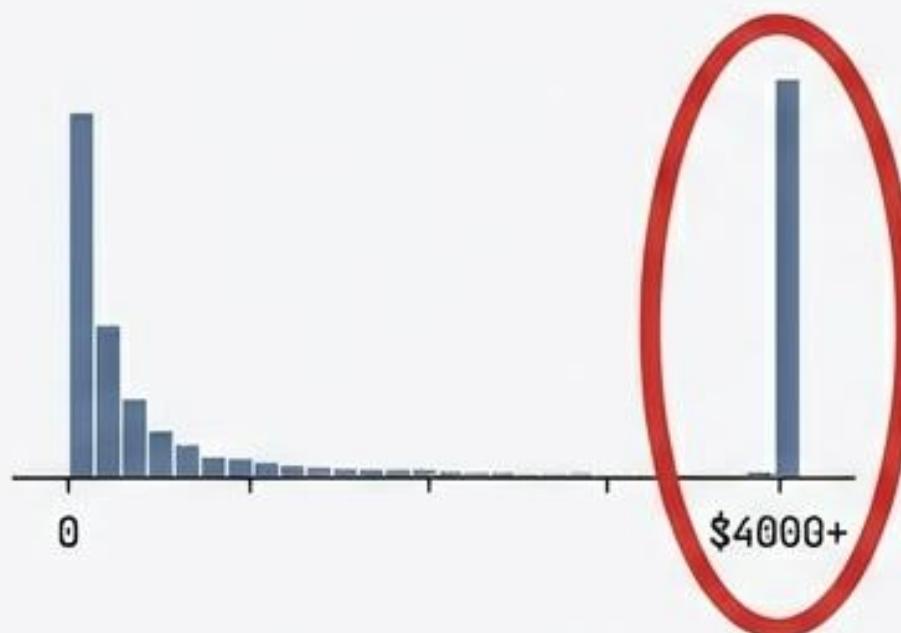
Insight: This derived feature allows us to analyze trip efficiency alongside distance and fare.

# Filtering the Noise to Find the Signal



# Statistical Cleaning: Handling Extreme Outliers

## The Issue

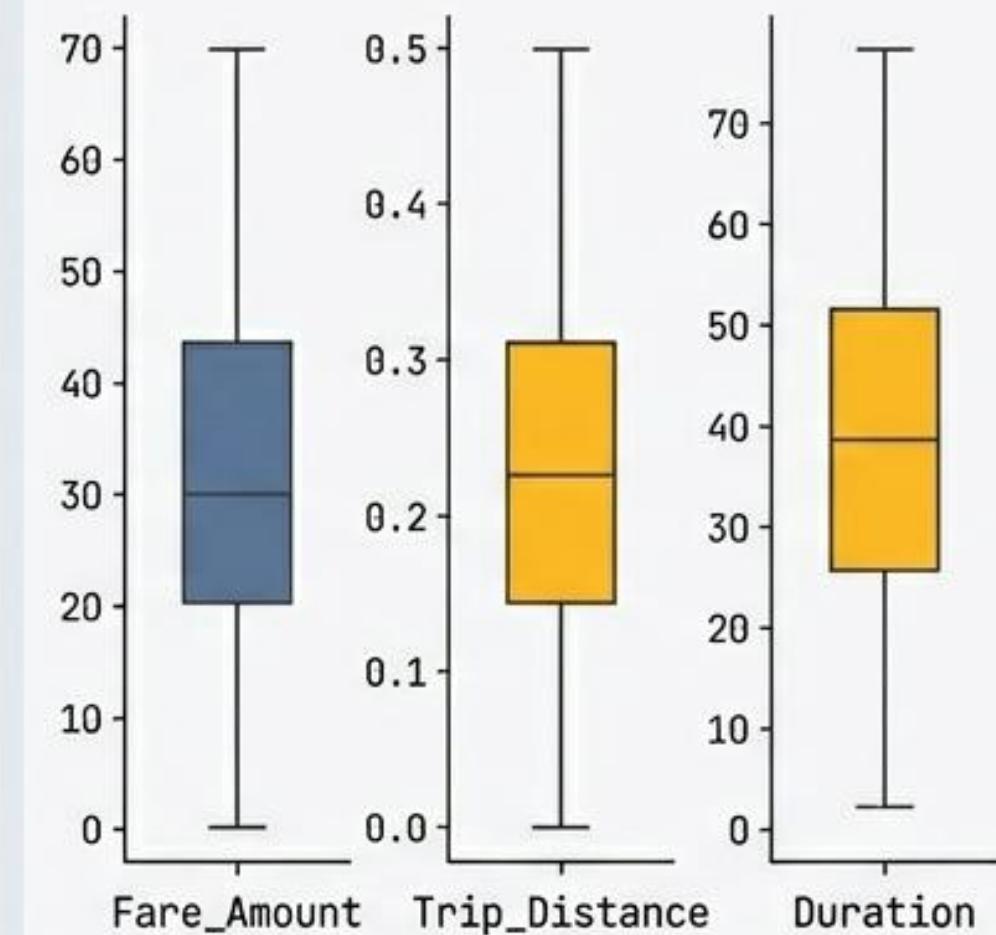


Extreme skew caused  
by data errors.

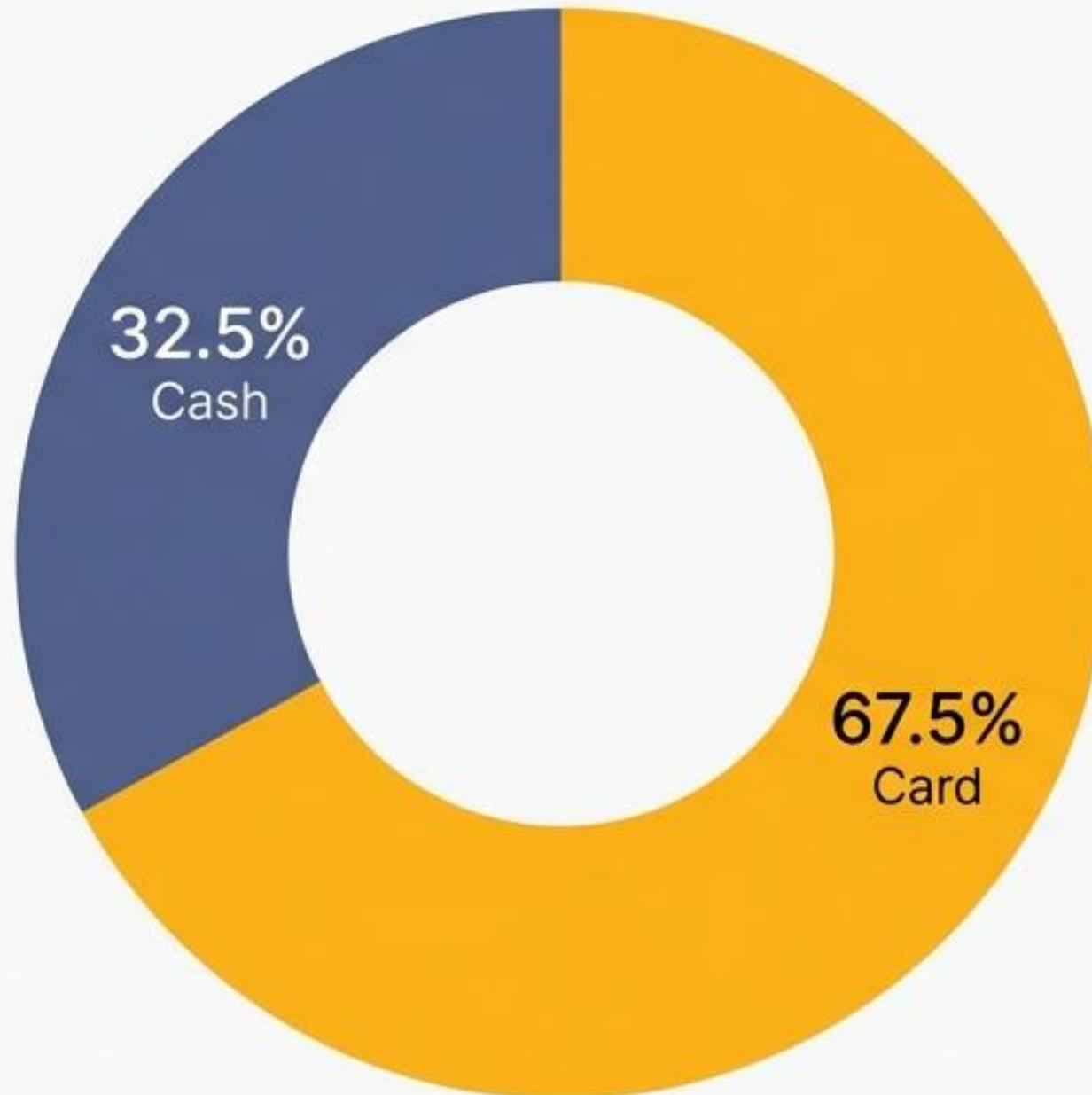
## The Method

$$\text{Lower} = Q1 - 1.5 * \text{IQR}$$
$$\text{Upper} = Q3 + 1.5 * \text{IQR}$$

## The Result



# Card Payments Dominate the Market Share

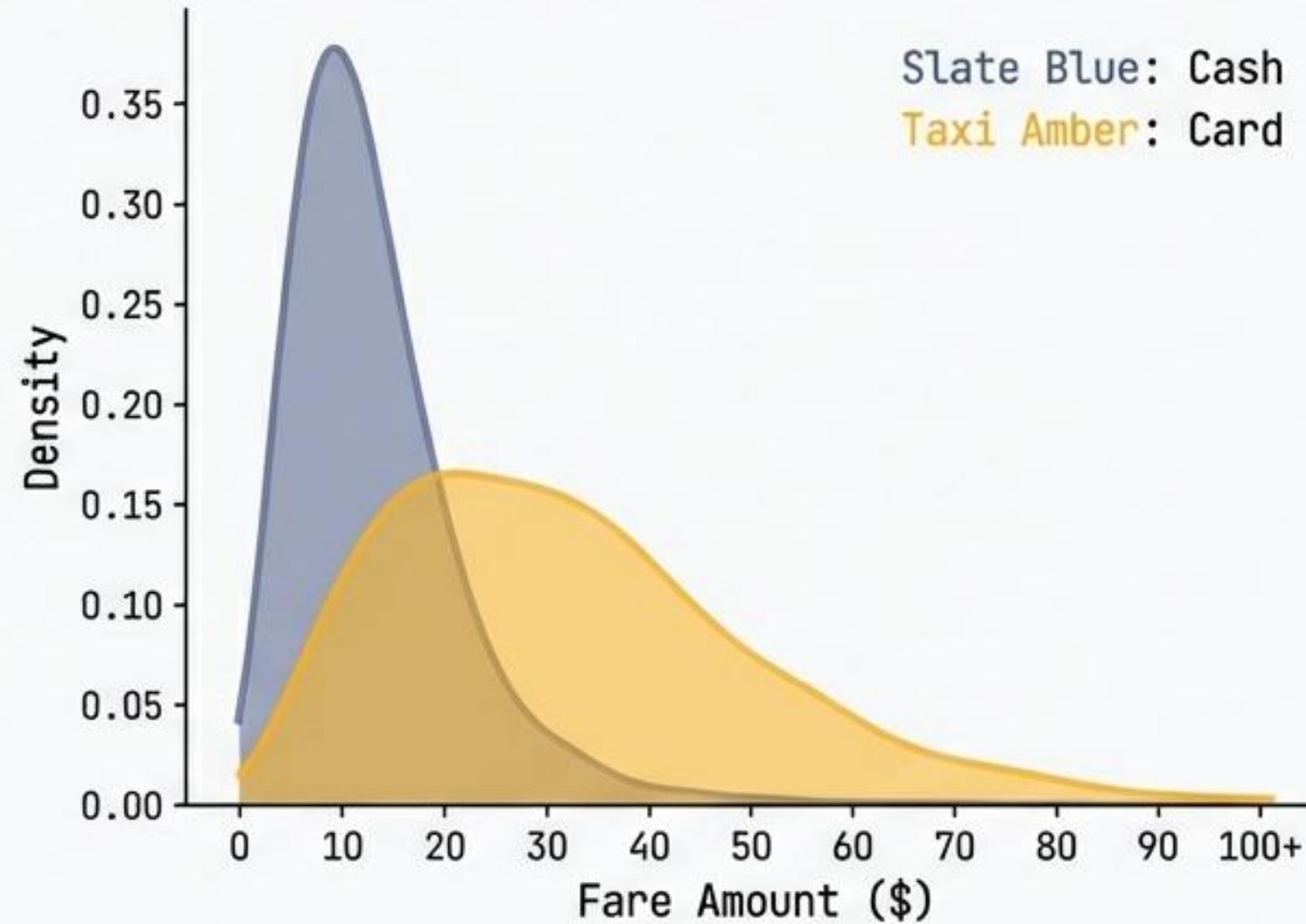


**2/3rds of all transactions are already digital.**

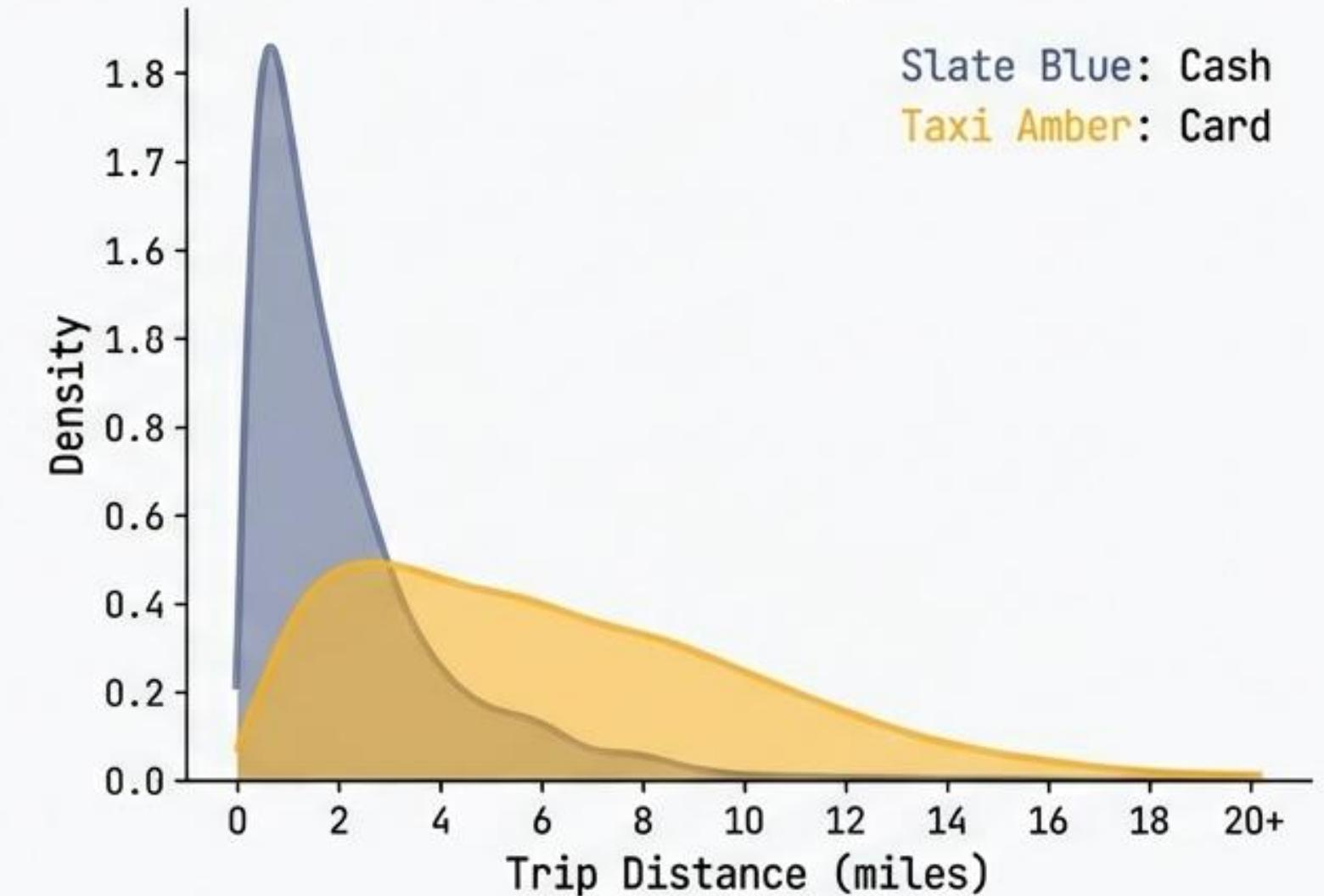
While cards are dominant, cash remains a significant 32% of the market—representing a major conversion opportunity.

# Card Users Take Longer Trips and Pay Higher Fares

## Distribution of Fare Amount

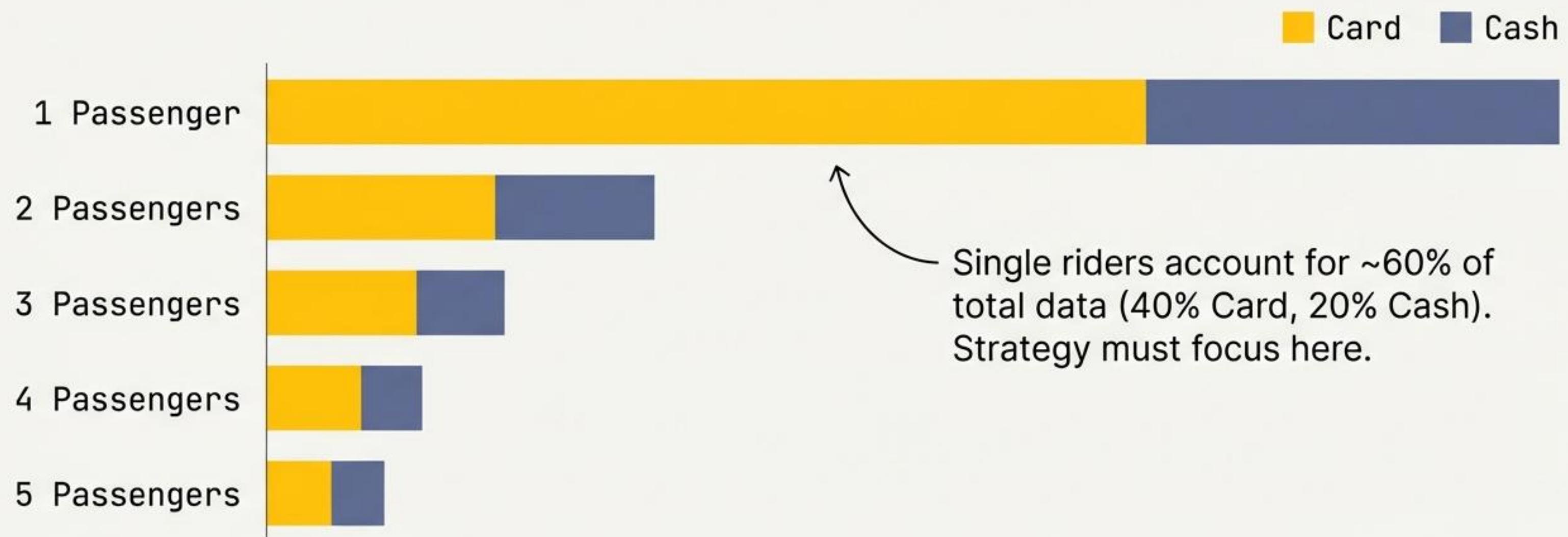


## Distribution of Trip Distance



Visual evidence suggests a correlation between higher value trips and card usage.

# Single Passengers Drive the Majority of Revenue



# The Raw Numbers: A Clear Value Gap

Payment Type	Mean Fare (\$)	Mean Distance (Miles)	Standard Deviation	
Card	\$ 14.50	6.8 Miles	High SD	 The Revenue Gap
Cash	\$ 11.00	3.2 Miles	Low SD	

# Putting the Observation to the Test

Null Hypothesis ( $H_0$ )

There is NO difference in average fare between Card and Cash users.

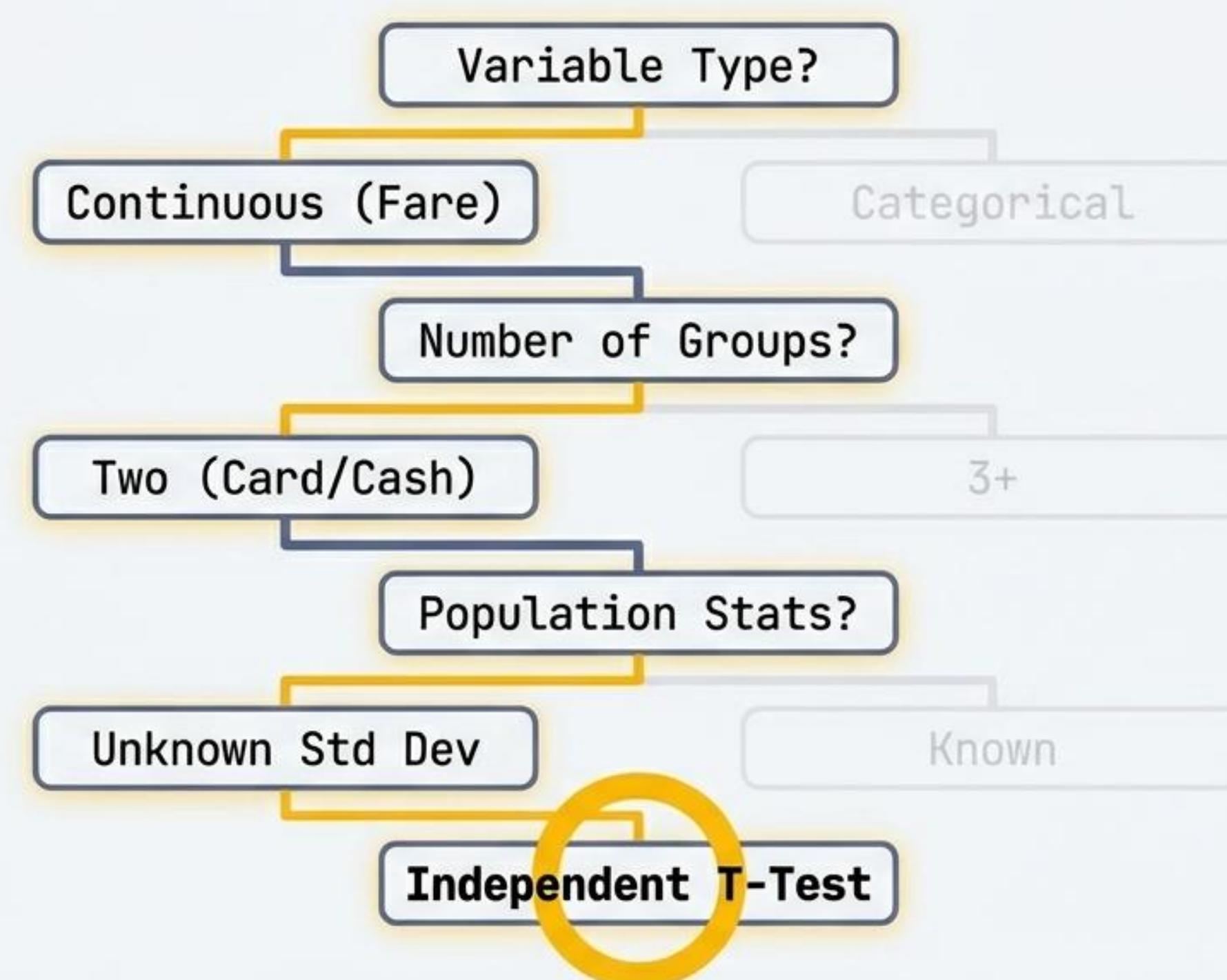


Alternate Hypothesis ( $H_1$ )

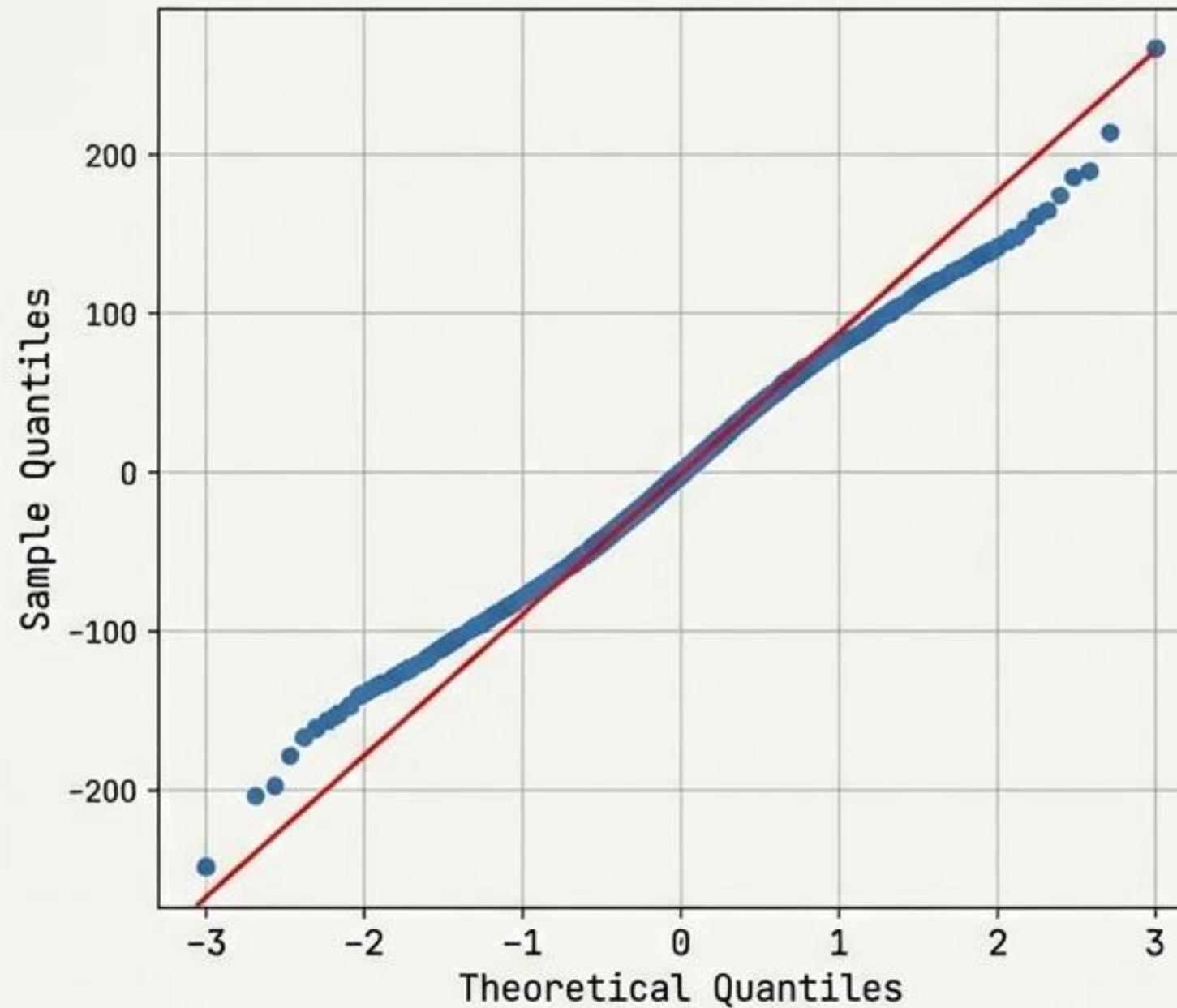
**There IS a significant difference** in average fare.

Methodology: Comparing two independent samples (Card Sample vs. Cash Sample).

# Selecting the Right Statistical Tool

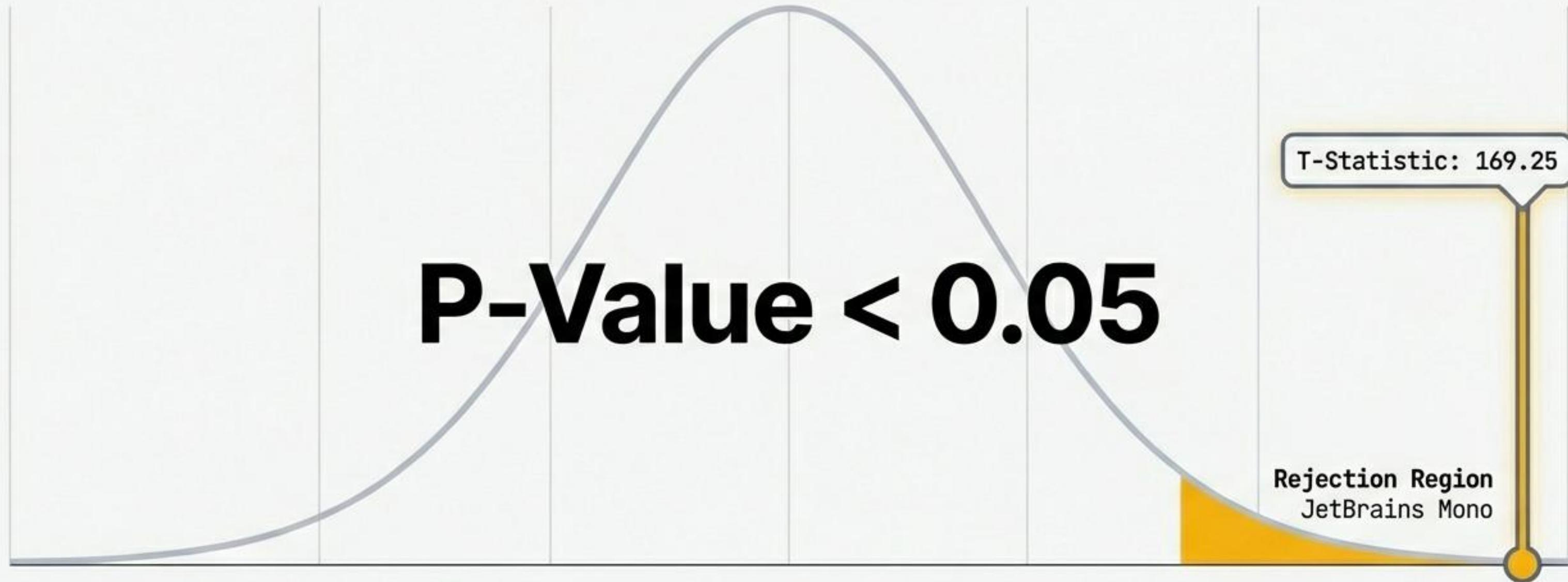


# Validating Assumptions: The Normality Check



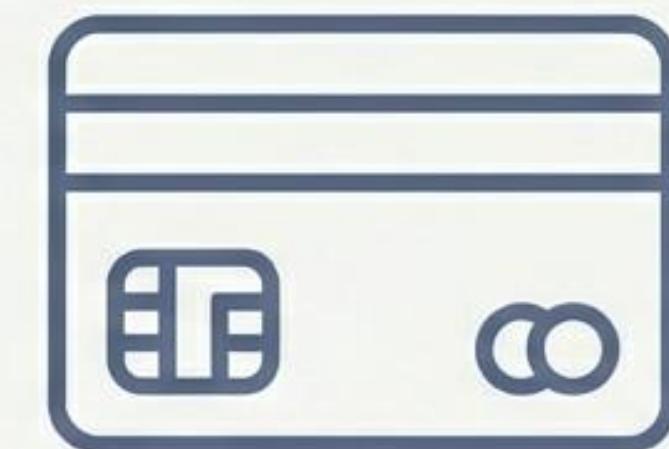
- **Observation:** Data deviates from the diagonal line -> **Not Normal.**
- **Justification:** Despite non-normality, the massive sample size (>2M rows) satisfies the Central Limit Theorem, making the **T-Test robust.**

# The Verdict: The Difference is Statistically Significant



We REJECT the Null Hypothesis. The revenue difference is not due to chance.

# Synthesis: The 'Card Premium' is Real



**Higher Revenue.**  
Card users generate higher average fares per trip.

**Longer Trips.** Card users are significantly more likely to take longer journeys.

**Dominant Volume.** Cards already account for 67% of transactions.

# Recommendation 1: The Digital Nudge



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**Strategy:** Default the payment terminal to '**'Card'** for trips over **5 miles**.

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**Rationale:** Reduce friction. Leverage the correlation between distance and card usage by making the preferred behavior the default option.

## Recommendation 2: Incentivize the Switch



### Strategy:

Offer micro-discounts or loyalty points for card payments on high-value fares.

**Rationale:** Target “swing” users—those who have cards but pay cash out of habit. Decouple the “pain of paying” by gamifying the card experience.

# Recommendation 3: Tech & Trust Infrastructure



## — Strategy:

Deploy visible 'Secure Payment' badges and contactless NFC terminals.

## — Rationale:

Remove the barrier of trust. Many users stick to cash due to security fears.

**Visible verification encourages higher-value digital tannes-value digital transactions.**

# Future Roadmap: Beyond Descriptive Stats

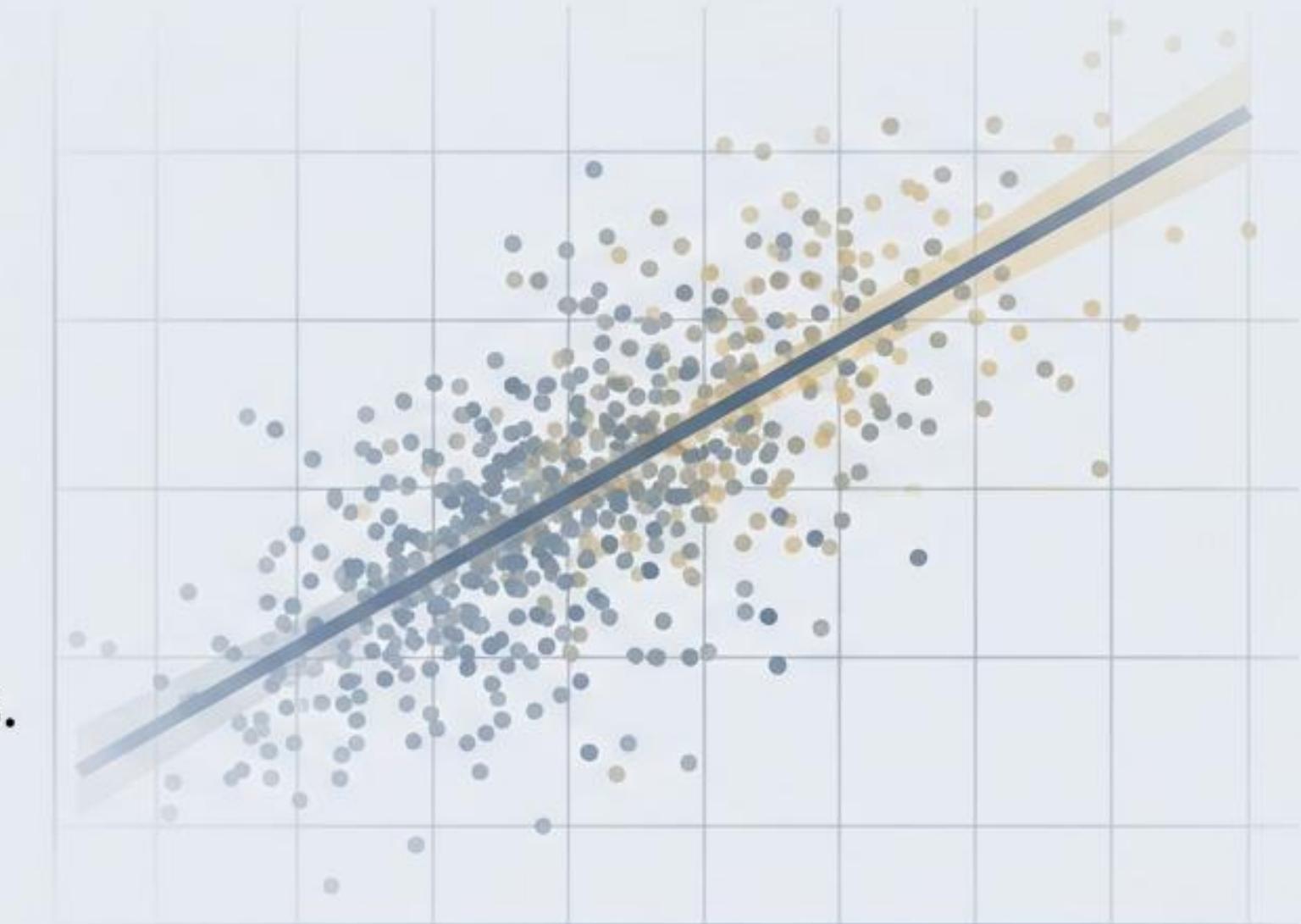
## Current State:

Correlation Proven.

## Next Step:

Regression Analysis.

Using the engineered **Duration** feature to predict exact fare amounts.



**Data + Statistics = Maximized Profitability.**