

AAMAS 2024, Auckland, New Zealand

# Forecasting and Mitigating Disruptions in Public Bus Transit Services

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**PennState**

College of Information  
Sciences and Technology

# Background



1. Infrastructure and  
Demand Imbalance

2. Congestion and  
Commute Delays

3. Need for  
Proactive Strategies

# Background

## **Trips**

A single journey along a designated route at a designated time  
e.g., For Route 7 on January Mondays at 4am

## **Disruptions**

Unplanned cancellation or suspension of service  
e.g., Mechanical problems, Accidents, etc.

# Objectives

## 1 **Forecasting Problem**

Predict disruptions in space and time

## 2 **Stationing Problem**

Optimize the stationing of substitute buses to promptly respond to disruptions

# Data

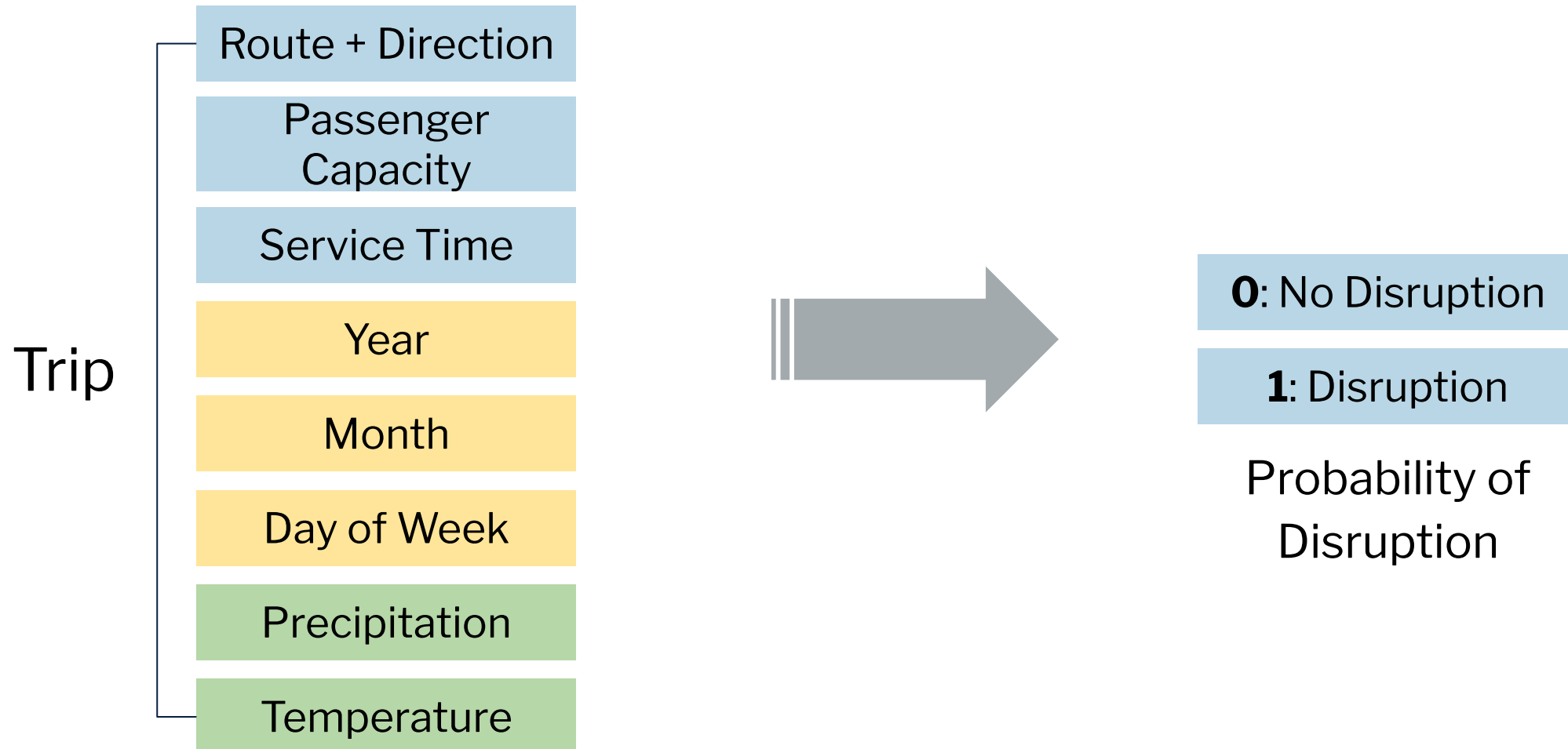
Dataset	Features	Date
General Transit Feed Specification (GTFS)	33 Routes, 1619 Stops	2020-2023
Automated Passenger Count (APC)	Ridership, Stops	2020-2023
Disruption	Location, Datetime, Stops	2020-2023
Weather	Location, Temperature, Precipitation	2020-2023

# Data

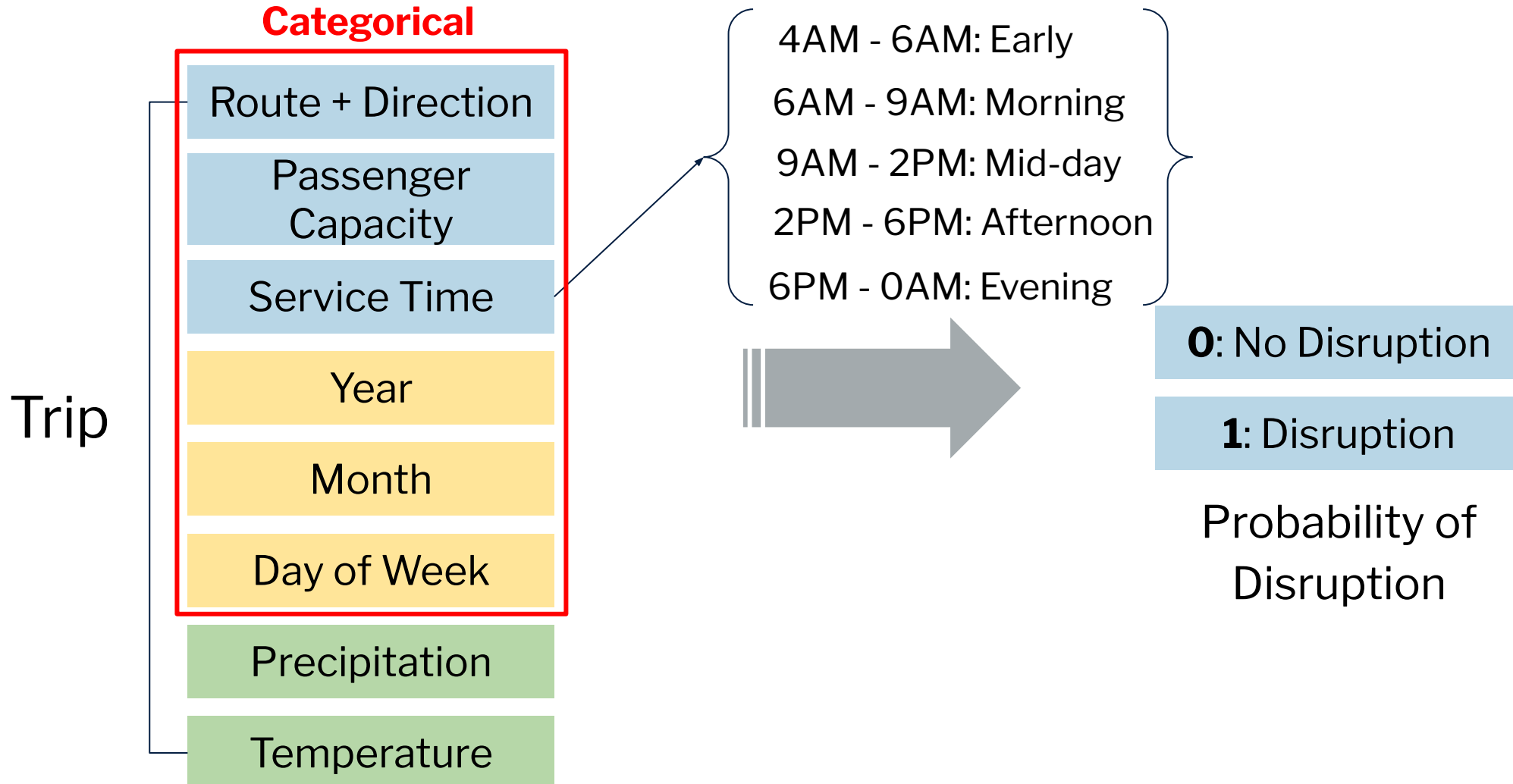
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5096 disruptions out of about 90,000 trips  
=> Imbalance in data

# Disruption Forecasting



# Disruption Forecasting





# Disruption Forecasting

Route + Direction

Passenger  
Capacity

Service Time

Year

Month

Day of Week

Precipitation

Temperature

VS

Negative Log  
Likelihood

**Categorical**

Route + Direction

~~Passenger  
Capacity~~

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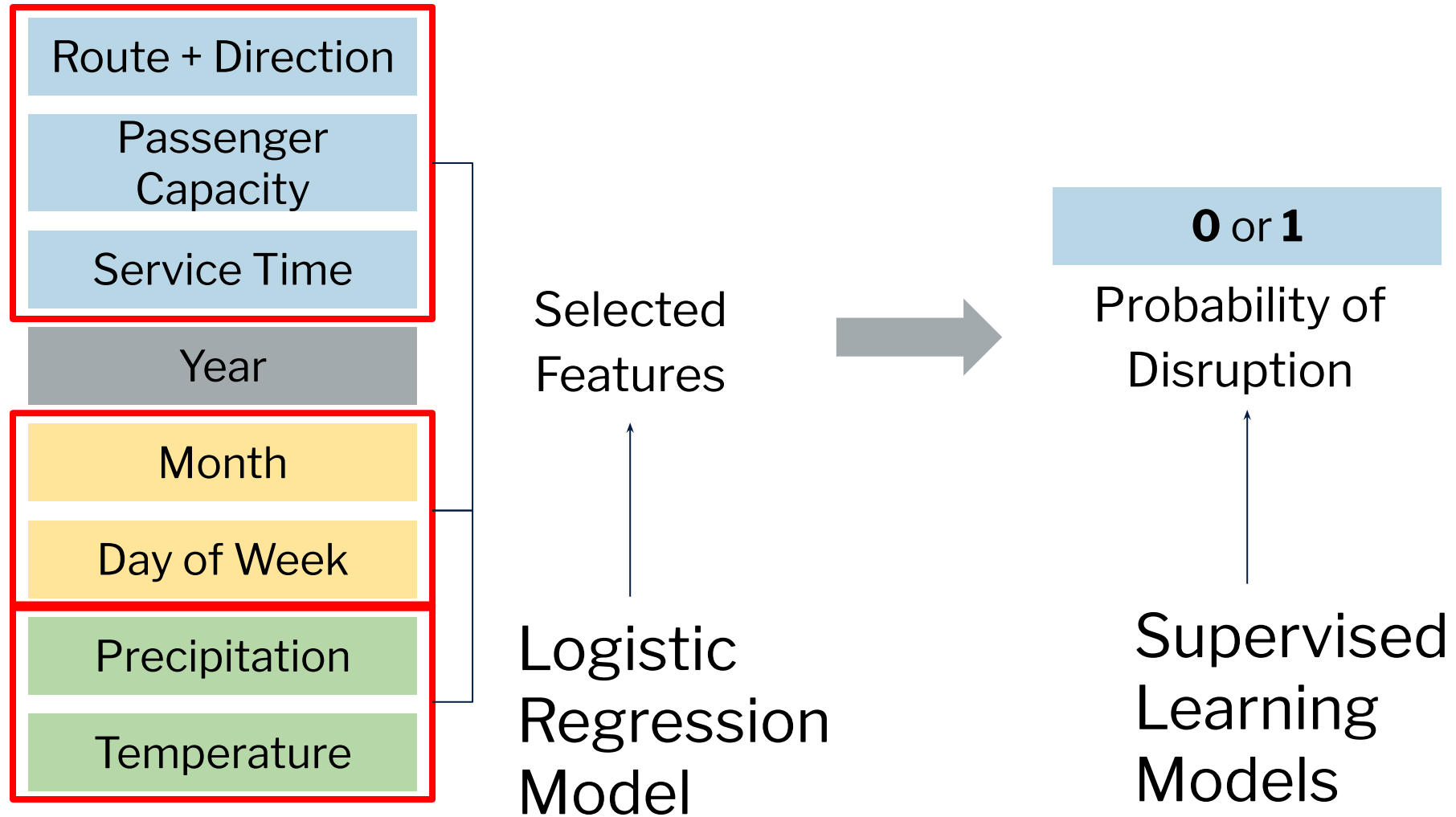
~~Month~~

Day of Week

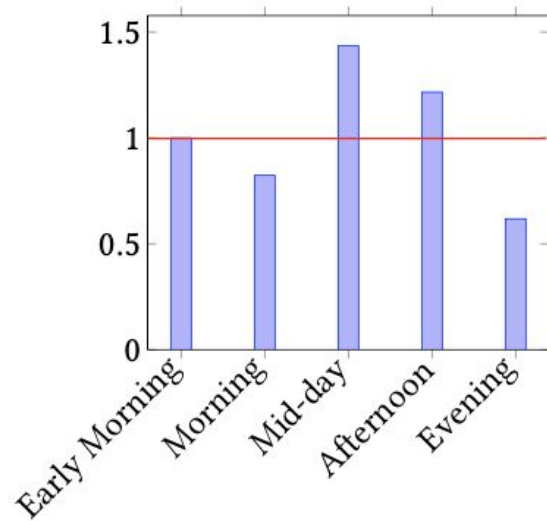
Precipitation

Temperature

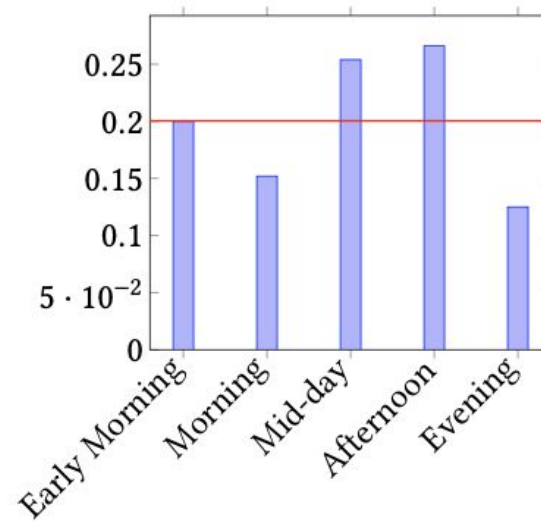
# Disruption Forecasting



# Disruption Forecasting



(a) Log-Odds



(b) Probability



**0 or 1**

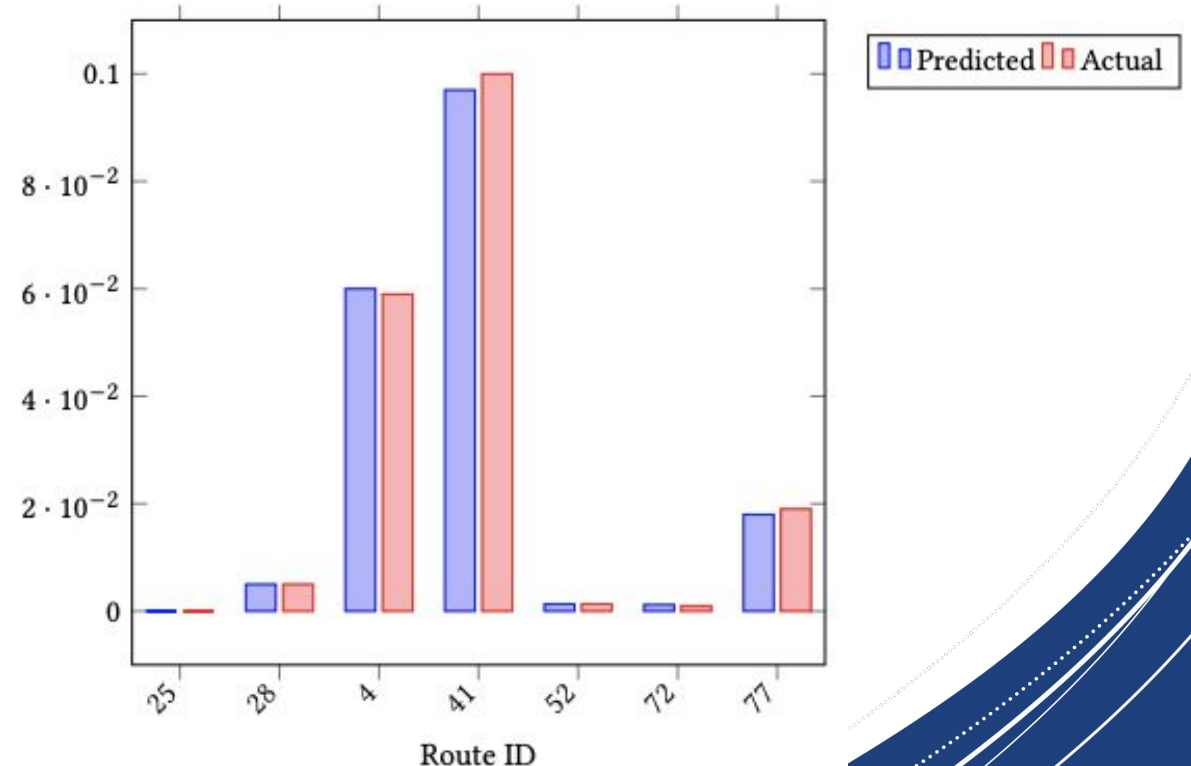
Probability of  
Disruption

# Disruption Forecasting

## Calibration

Transform classifier scores into class probabilities  
i.e., probabilities of trips having disruptions or not

Model	Test Cross Entropy
Logistic Regression	0.0903
XGBoost	0.0872
XGBoost + Calibration	0.0870



# Vehicle Stationing

## Regular Buses

Normal buses start and end from main depot

## Substitute Buses

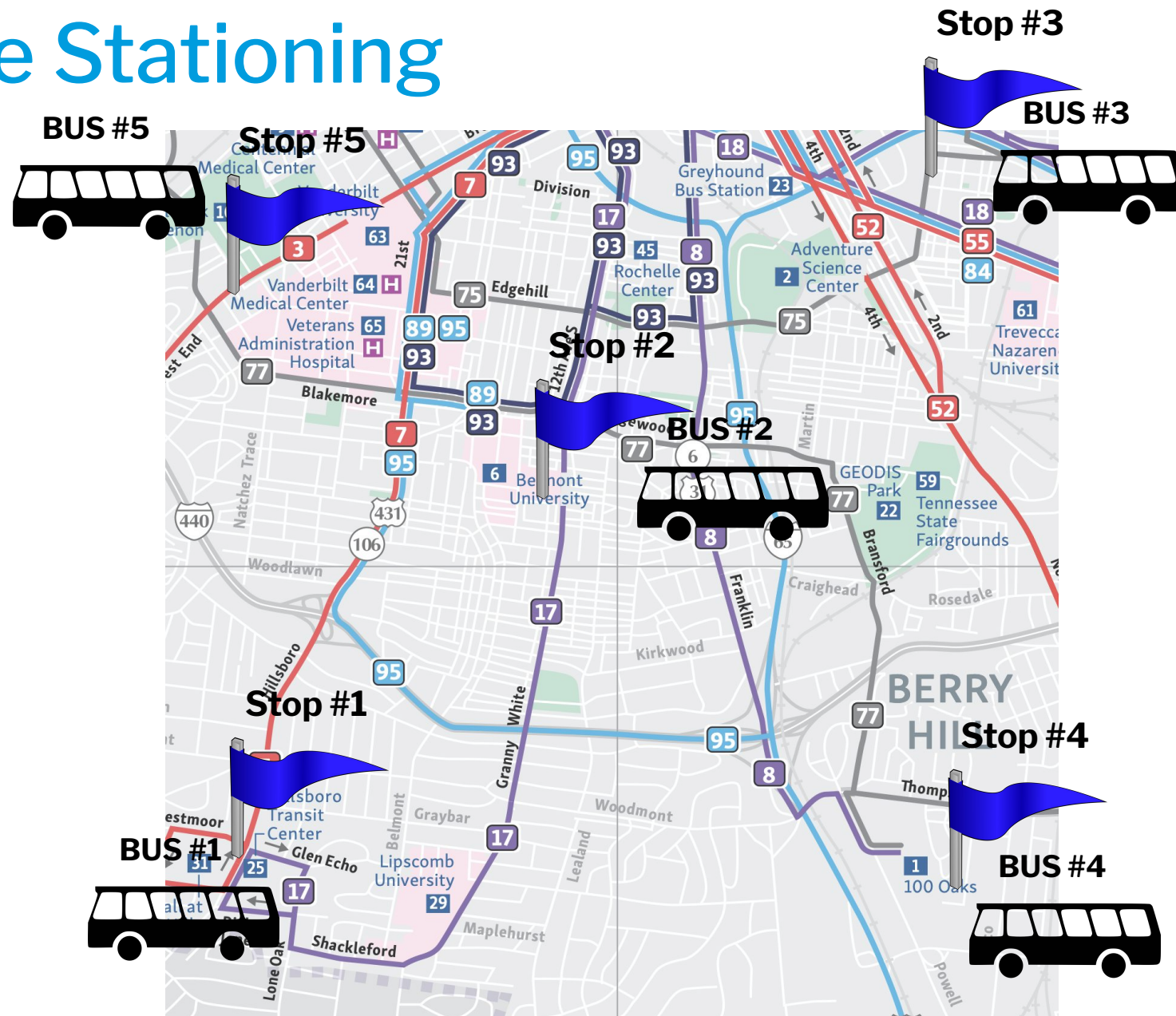
Extra buses waiting at predetermined stop for when regular buses are overcrowded or face disruptions

Nearest substitute bus provides service

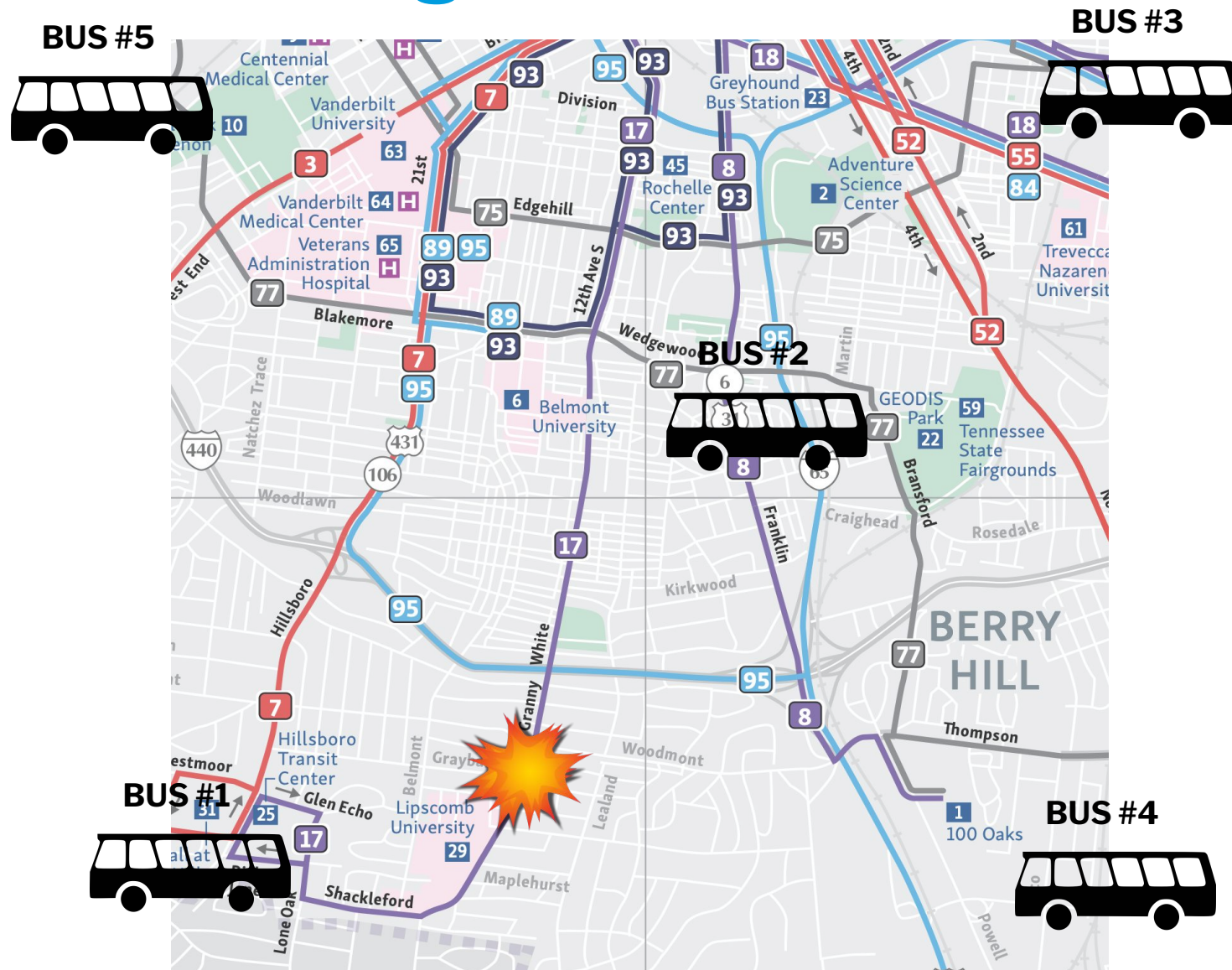
## Passengers



# Vehicle Stationing

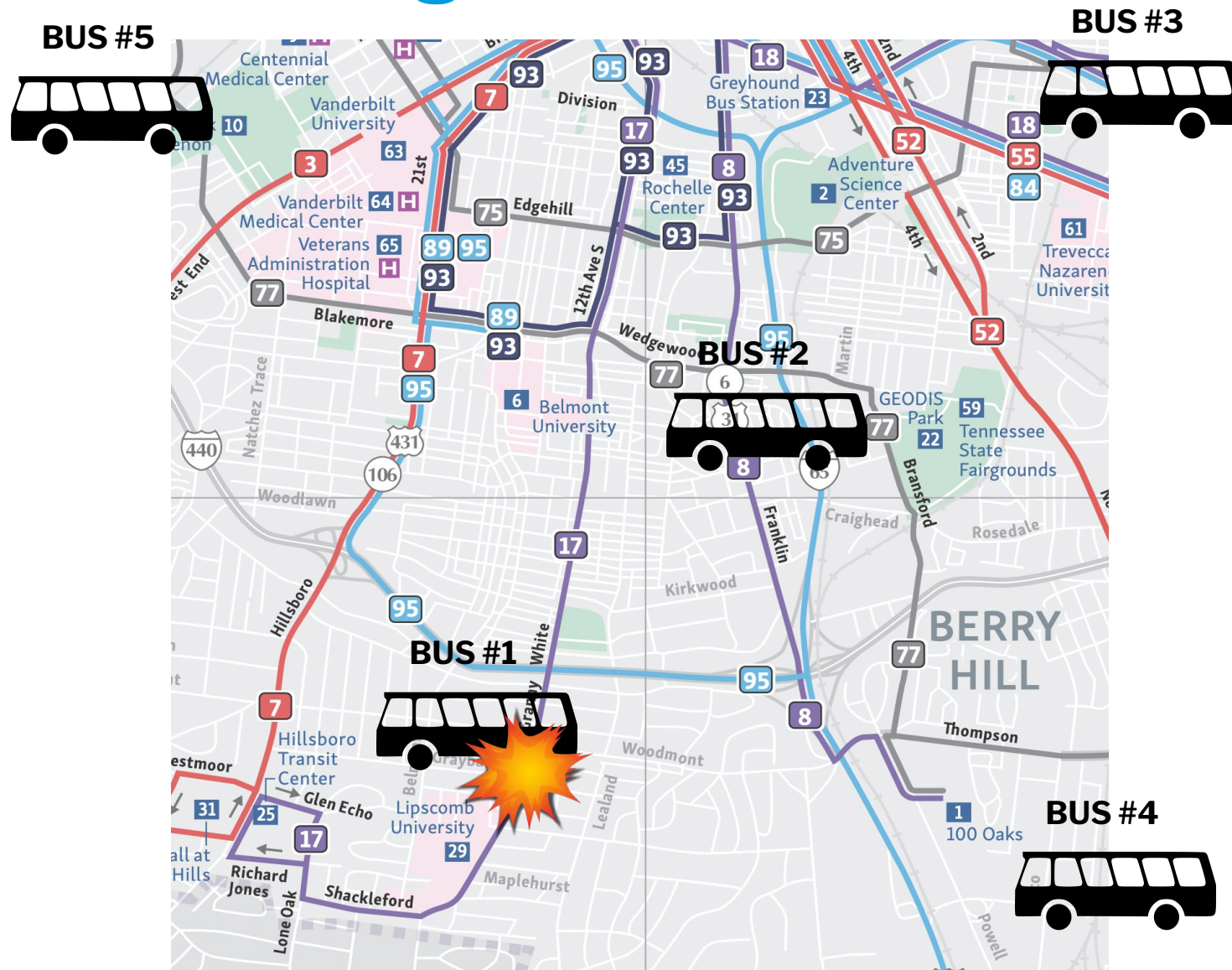


# Vehicle Stationing





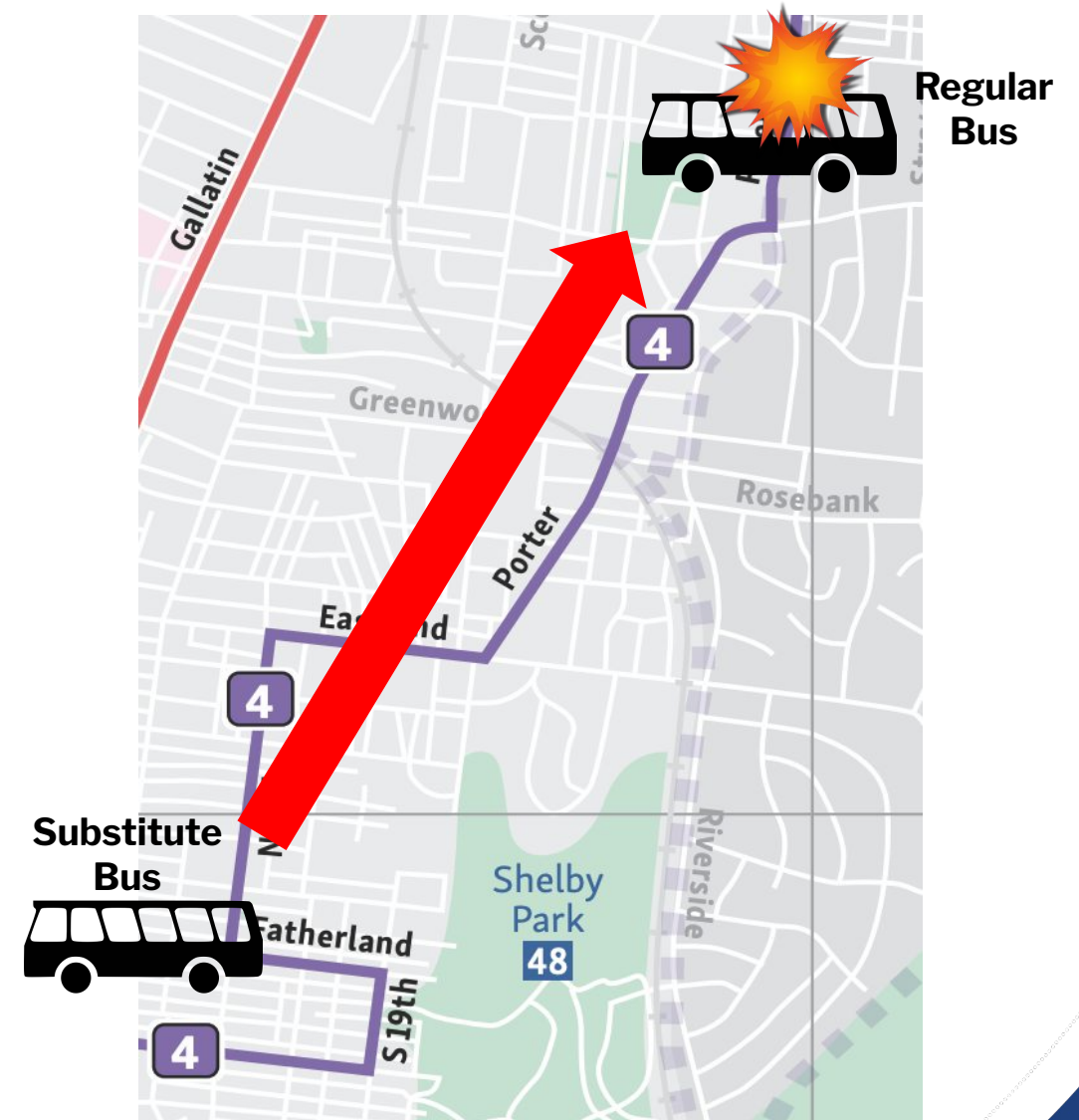
# Vehicle Stationing



# Vehicle Stationing

## Objectives

- 1 How far? (Deadhead Miles)
- 2 How long it takes? (Deadhead Times)
- 3 How many passengers are left behind?



# Vehicle Stationing

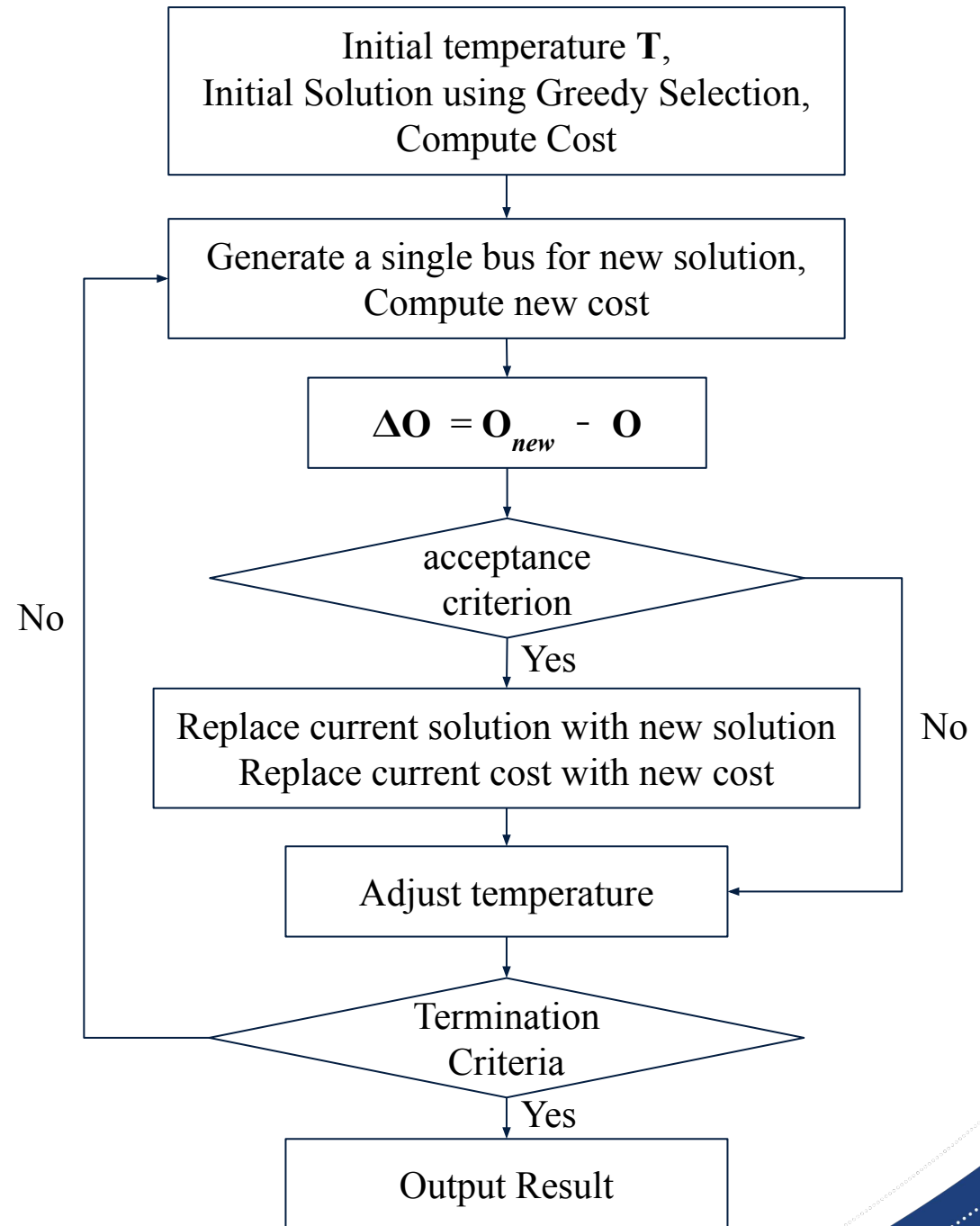
- 1 Deadhead Miles
- 2 Deadhead Times
- 3 Left behind passengers

$S_{\text{Station}}$ : Subset of stops  
 $k$ : Budget of substitute buses  
 $D$ : Deadhead Miles  
 $T$ : Deadhead Times  
 $L$ : Left behind passengers  
 $P$ : Occurrence of disruptions

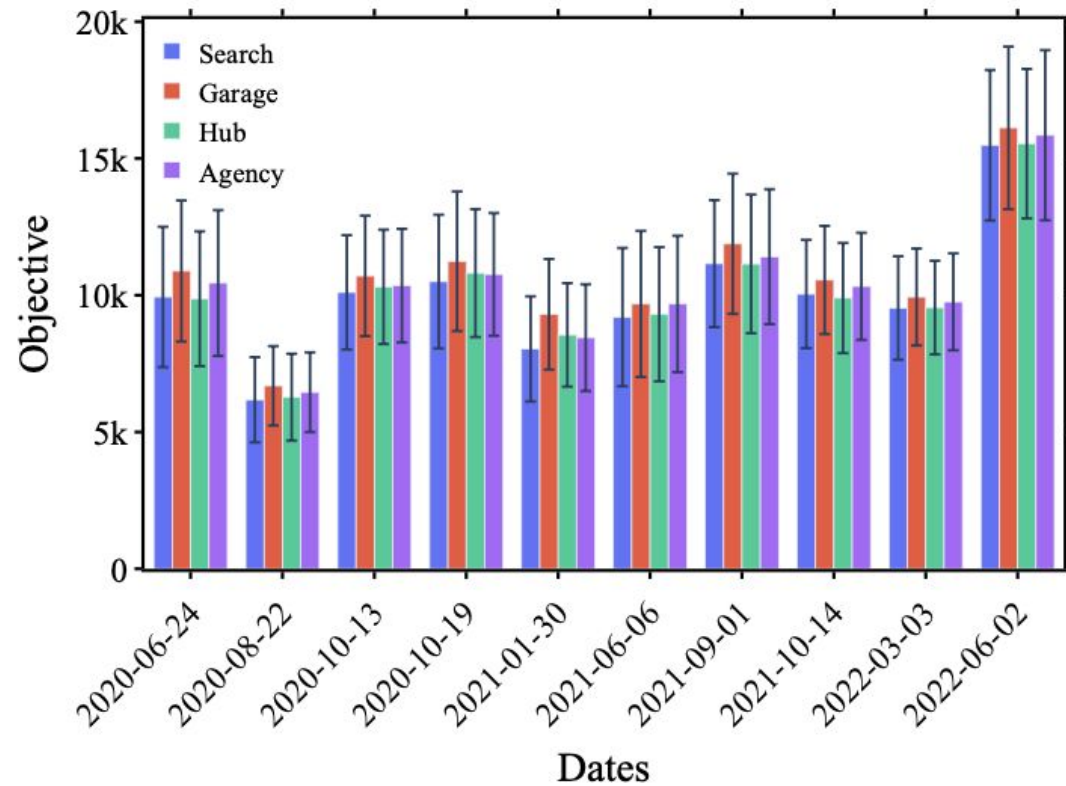
$$\operatorname{argmin}_{x \subseteq S_{\text{station}} : |x|=k} \mathbb{E}_P \left[ \overset{1}{D}(x; P) + \overset{2}{T}(x; P) + \sum_{j=1}^J \overset{3}{L}(j, x; P) \right]$$

# Vehicle Stationing

## Simulated Annealing Optimizer



# Vehicle Stationing



## Search

Our Proposed method

## Garage

When all substitute buses are waiting at garage

## Hub

When all substitute buses are waiting at hub

## Agency

When following the current agency policy

# Contribution

- 1 Predict rare incidents like disruptions
- 2 Reduce delays and crowding
- 3 Find optimal set of stops by simulation
- 4 Increase efficiency of transit operations and enhance the passenger experience



# Thank you



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