Machine Learning Approach for Dynamic Bus Arrival Time Prediction

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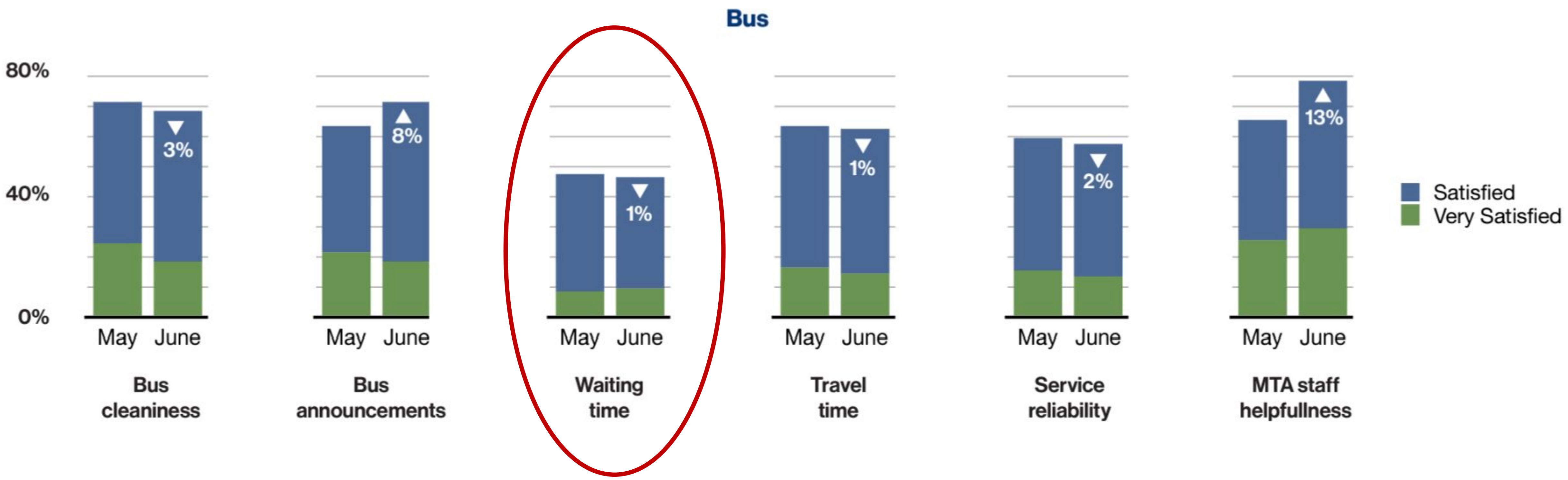
Accurate bus arrival time predictions

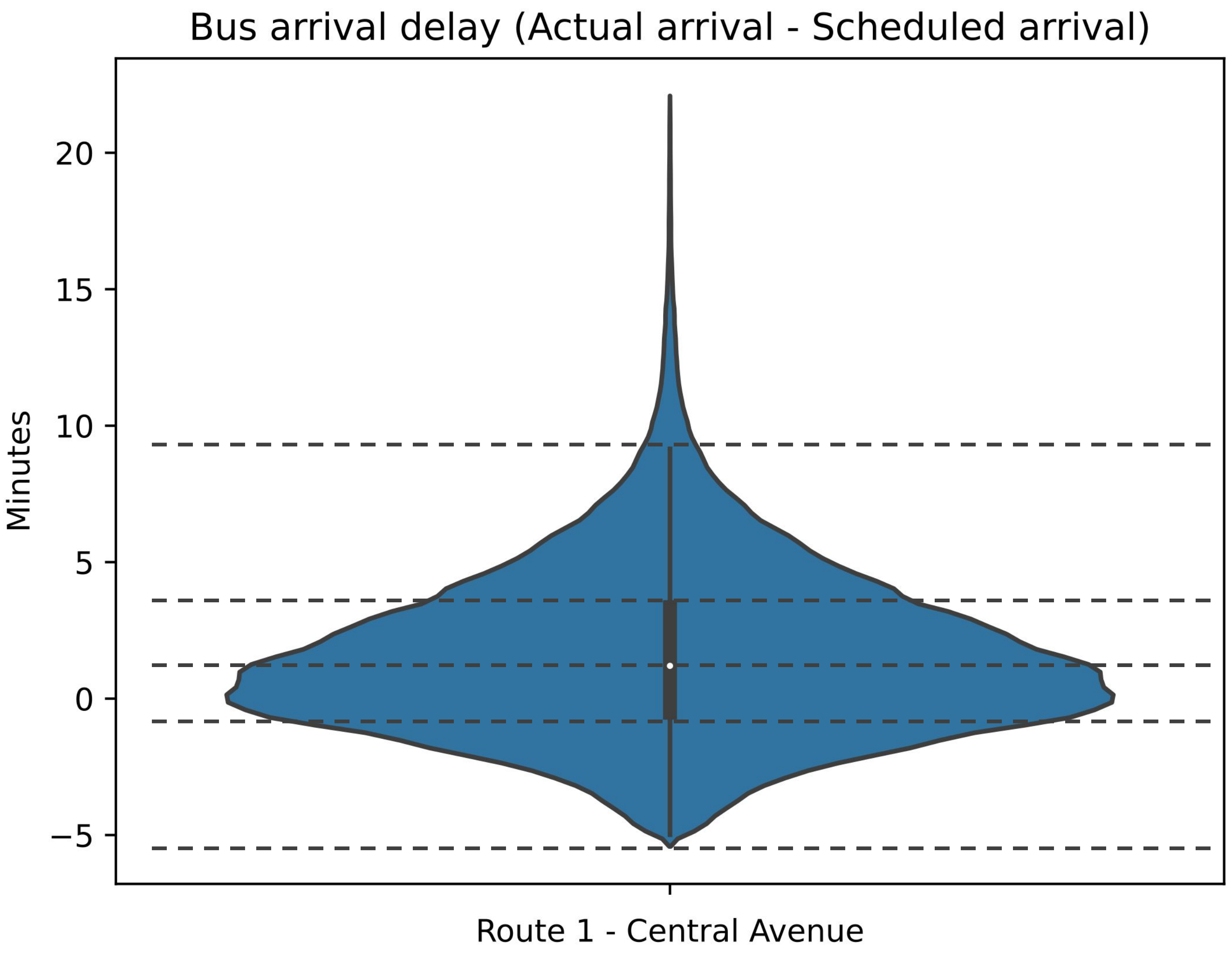
- Enhanced passenger experience
- Time management and productivity
- Improved accessibility
- Increased ridership
- Efficient resource allocation
- Enhancing traffic management and urban planning
- Intelligent decision making

Bus Service Performance Metrics



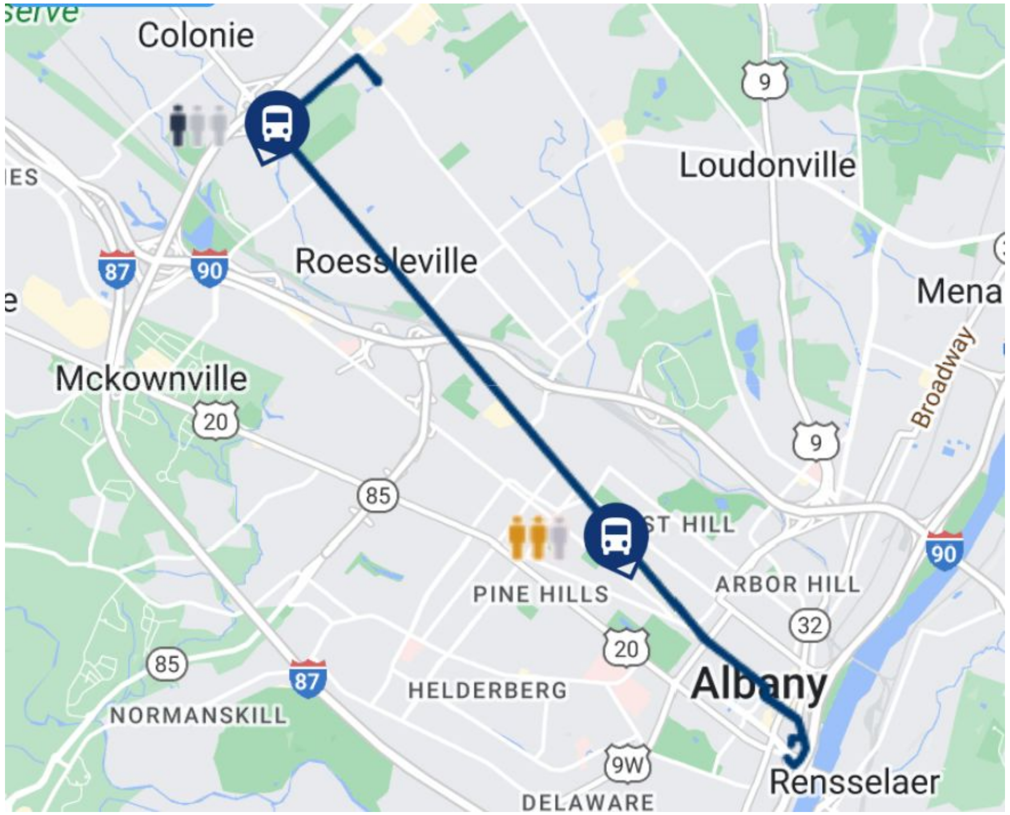
Source: NEW YORK CITY TRANSIT & BUS KEY PERFORMANCE METRICS, MTA (July 2022)

Bus On-Time Arrival Statistics

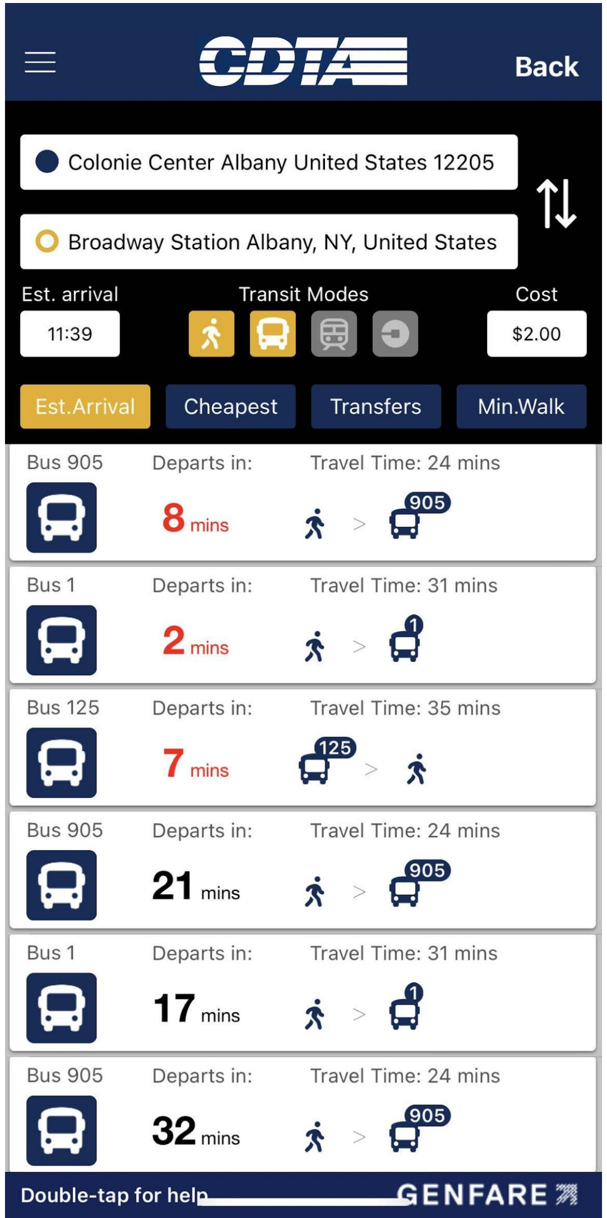


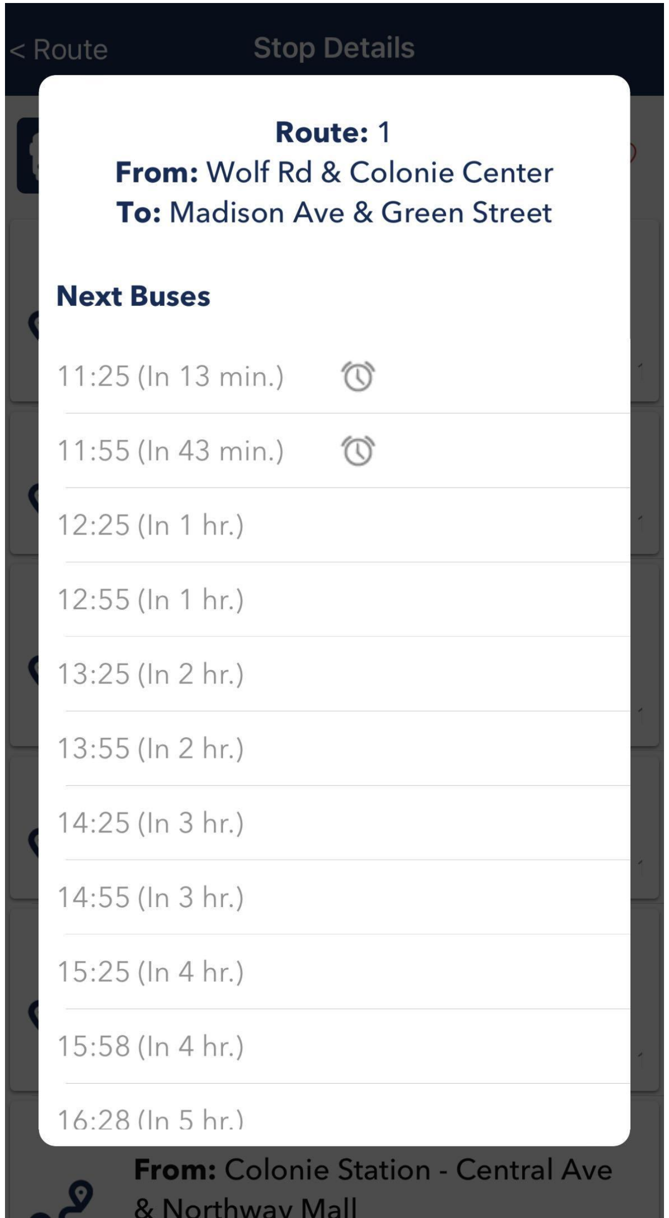
[-1,5]: 68%

- CDTA Data (09/2022 – 03/2023)
  - 630K stop arrival data
  - Workdays
- Route 1 – Central Ave



Bus Arrival Time Information





- **Travelers' convenience**
  - plan their trips and minimize waiting times
- **Operational efficiency**
  - optimize schedules, reduce operational costs
- **Equity**
  - disproportionately affect low-income and marginalized communities
- **Transit ridership**
  - environmental benefits

Challenges in Accurate Bus Arrival Time Prediction

Bus Operations	Environment
Route specific factors	*Traffic variability*
Passenger demand	*Weather conditions*
Accommodation for special needs	*Dynamic events*
Dwell time	*Traffic management decisions*

- **Influencing factors are uncertain and highly dynamic**
- **Accurate predictions rely on massive high-quality and reliable data**
- **Requires sophisticated algorithms and techniques**

Machine Learning Based on Markov Process

Markov property: In the evolution of a Markov process, the current state depends only on the previous state and does not depend on the past

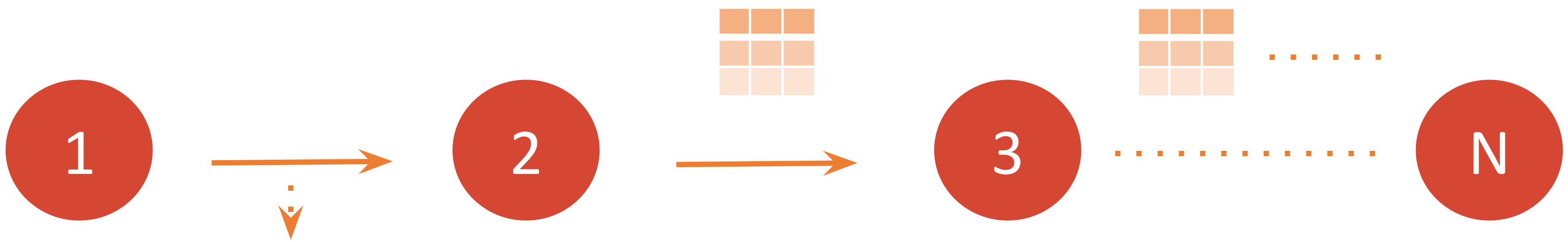
Markov Process	Bus Arrival Process
Current state	Arrival time at current stop
Previous state	Arrival time at previous stop
Uncertainties in the environment	Uncertainties in: a. Traffic condition; b. Bus travel demand(dwelling time)

Pattern to be learned by ML

Learn the pattern!

Bus Arrivals as a Markov Process

State:



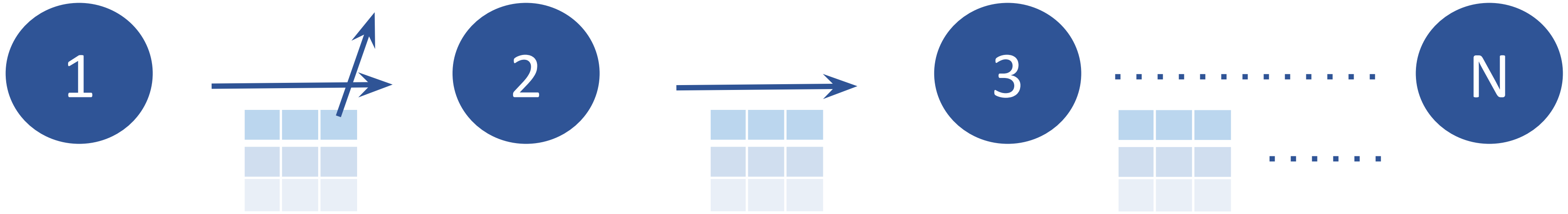
Transition matrix:

	S_2^d	S_2^e	S_2^m
S_1^a	0.1	0.7	0.2
S_1^b	0.4	0.5	0.1
S_1^c	0.5	0.2	0.3

Given state S_1^a at node 1, the probability of S_2^m happening at node 2

Given arrival time T_1^a at stop 1, the probability of arriving at time T_2^m at stop 2

Bus stop:



Illustrative Example

Arrival time at stop 2

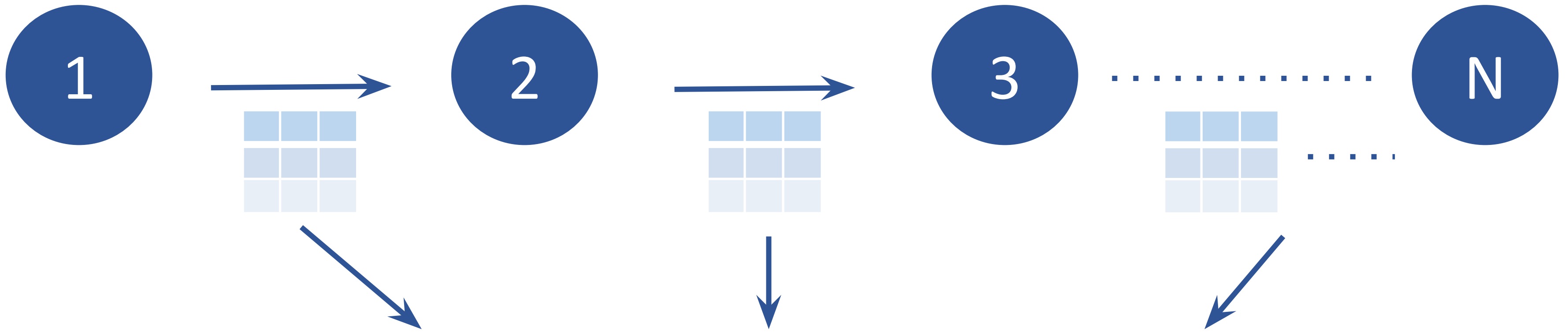
Arrival time at stop 1	10:14	10:15	10:16
10:09	0.8	0.1	0.1
10:10	0.2	0.7	0.1
10:11	0	0.1	0.9

If the bus arrives at **stop 1** at 10:09, the probability of arriving at **stop 2** at 10:12 is 0.1

Matrix size and discrete time interval are flexible to be adjusted

Uncertainties to be Learned

Bus stop:



Transition matrix will be learned from historical bus arrival data

- Identifications of the trip, stop, schedule
- Arrival time at **previous stop**

Input → Machine learning model → Output

The probability distribution of arrival times at the stop (transition matrix)

Using historical bus arrival data

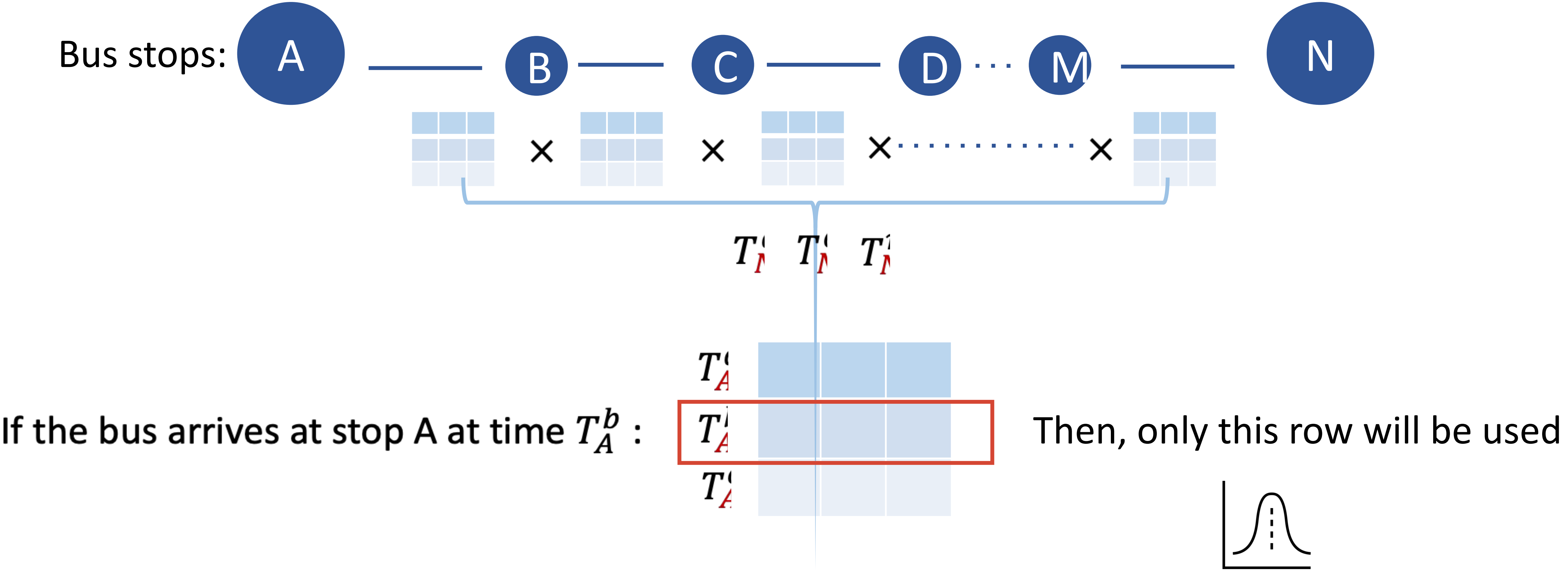
Machine Learning Approach

- Supervised machine learning problem
  - Label: the frequency of different arrival time intervals
- XGBoost is used in the case study of this research
  - Extreme Gradient Boosting
  - A scalable, distributed gradient-boosted decision tree (GBDT)
- Loss function: Mean Square Error (MSE)

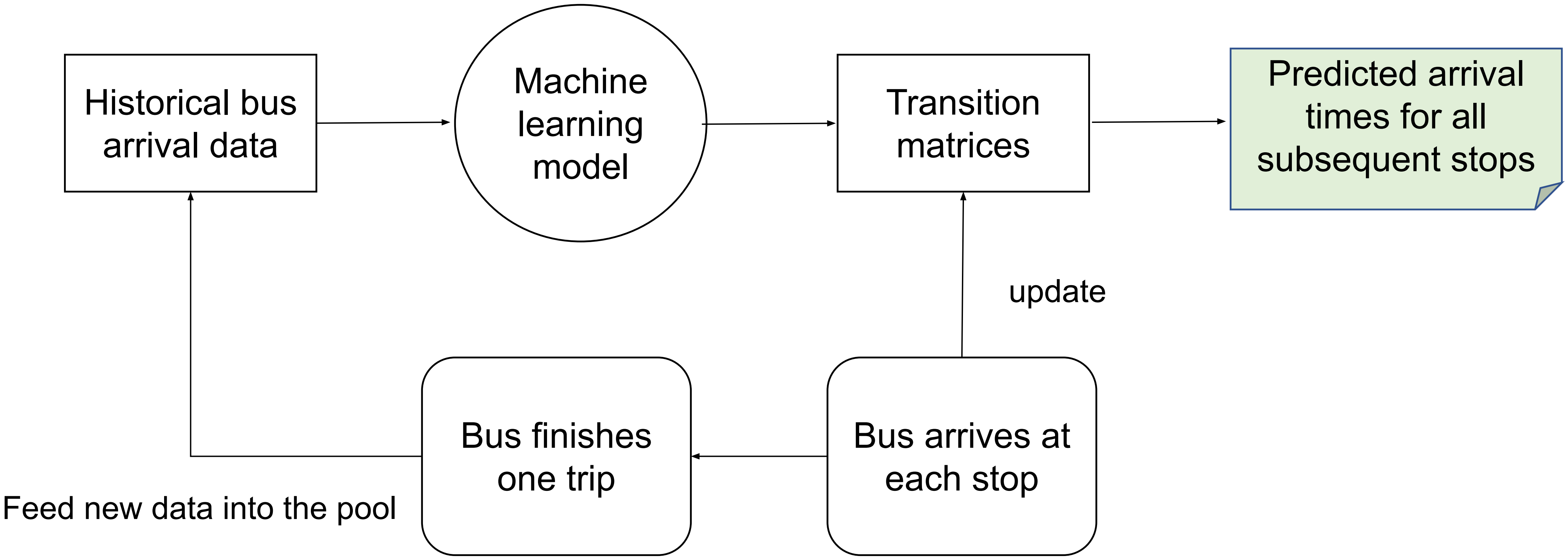
Learning input	Learning output
▪ *Stop ID* ▪ *Type of trip* ▪ *Scheduled arrival time* ▪ *Actual arrival time at previous stop*	▪ The probabilities of arrival times at the stop • One row in the transition matrix represented the probability mass function

Prediction Using the Learned Transition Matrices

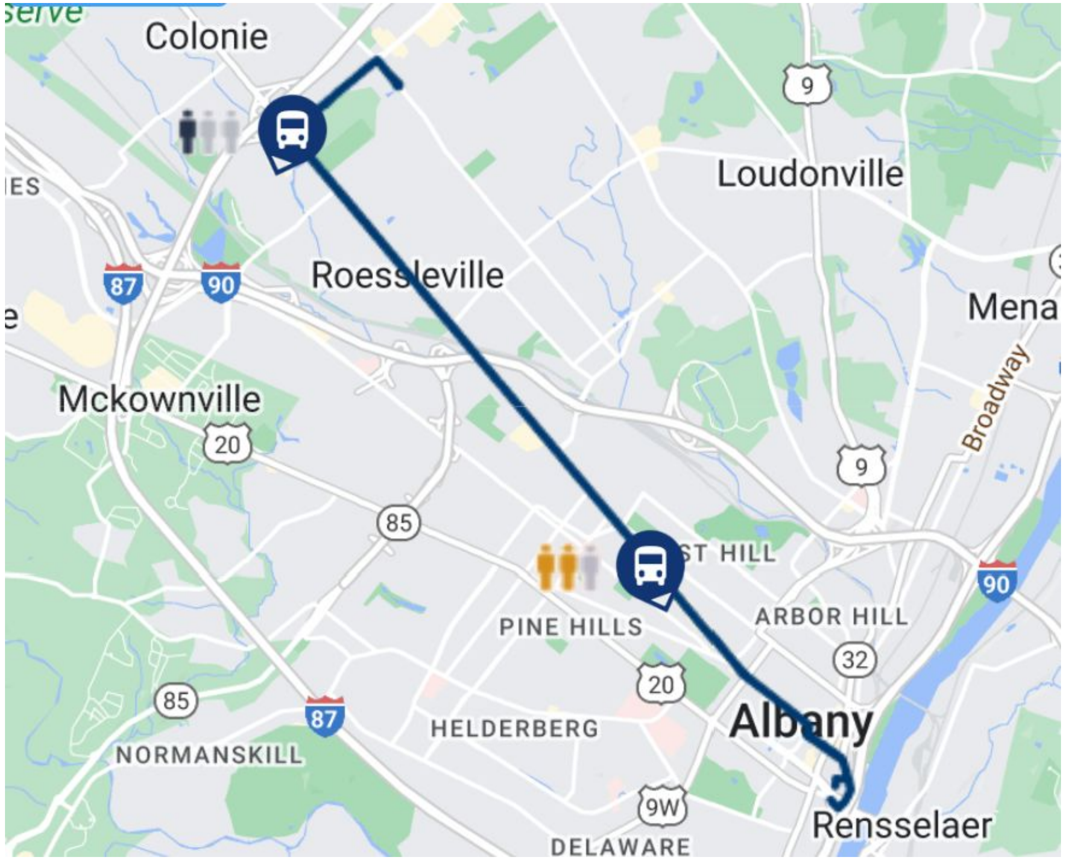
To predict the arrival time of **any stop N** from stop A, we multiply all transition matrices between stop A and stop N. **Note**: The result is a **distribution**



Framework


Historical bus arrival data
Machine learning model
Transition matrices
Predicted arrival times for all subsequent stops
update
Bus finishes one trip
Bus arrives at each stop
Feed new data into the pool

Case Study on Route 1



Directions:

East: Colonie Center to Downtown Albany
West: Downtown Albany to Colonie Center

Data:

09/2022 – 03/2023, workdays

Features: stop, direction, schedule arrival time, actual arrival time, date

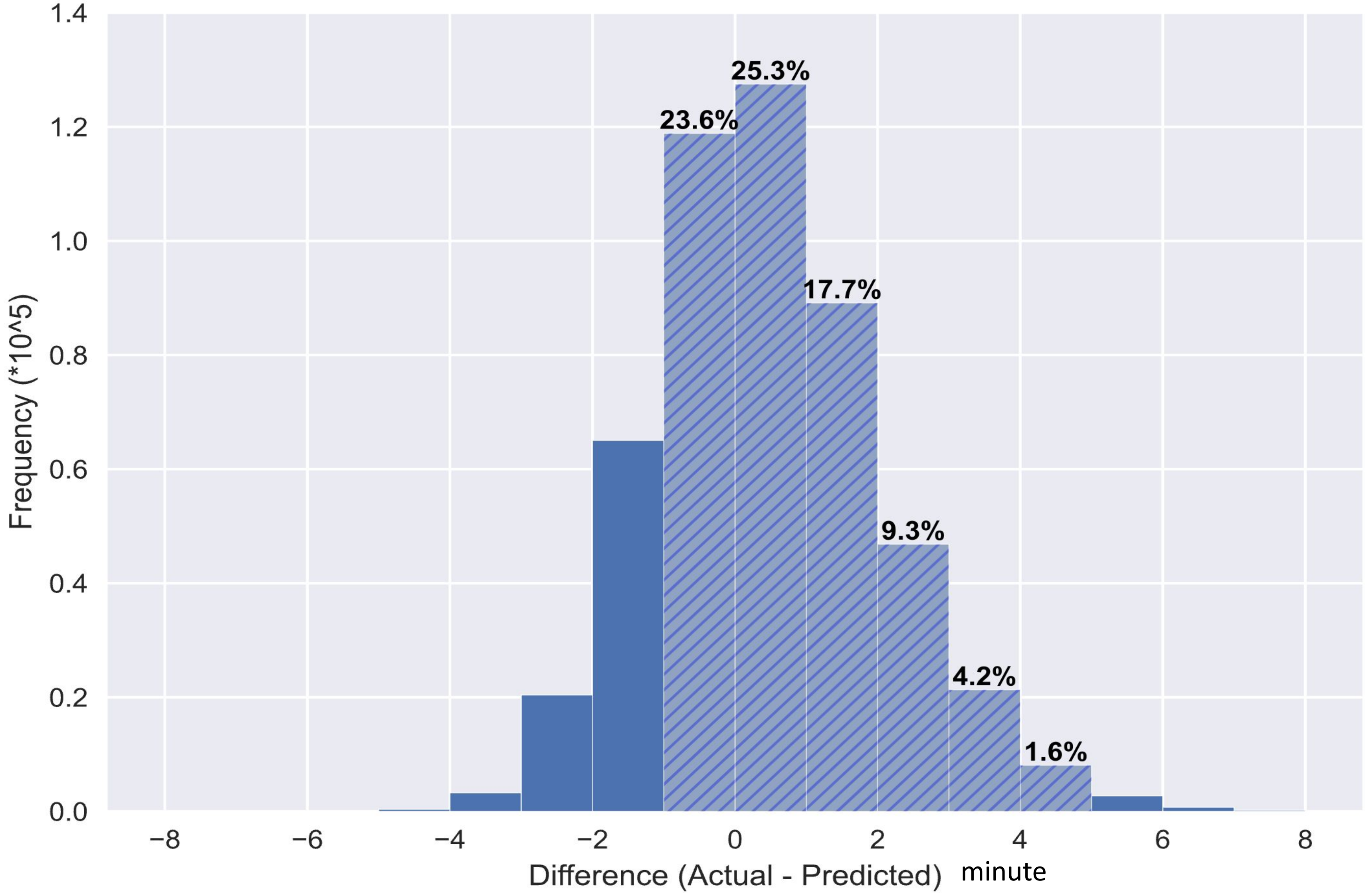
Discrete time interval:

1 minute

Settings

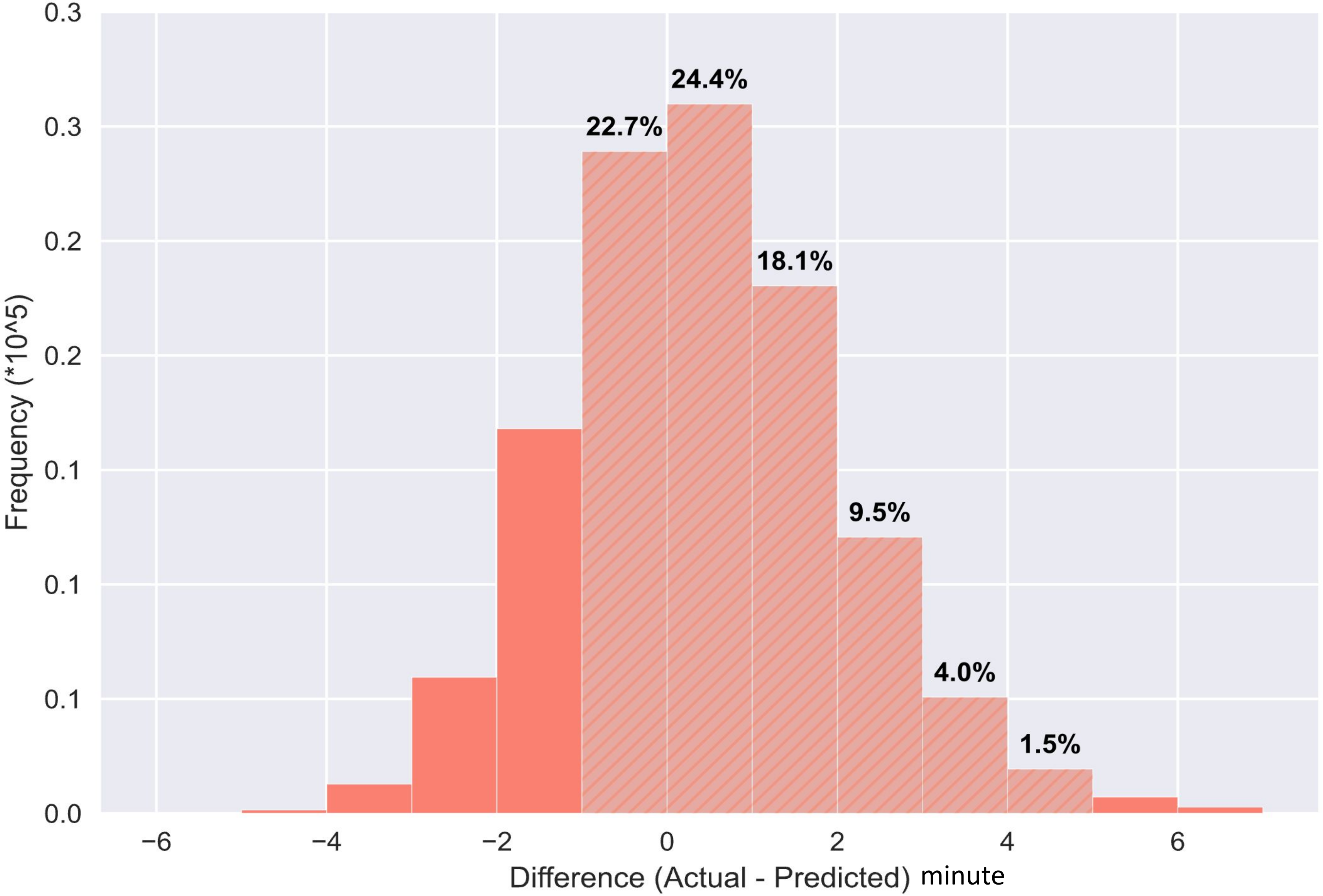
- Stops
  - 37(long trip) / 30(short trip) for eastbound
  - 29(long trip) / 28(short trip) for westbound
- Schedules
  - 36(long trip) / 73(short trip) for eastbound
  - 36(long trip) / 75(short trip) for westbound
- Discrete time interval: 1 minute
- Transition matrix
  - Size 27*27
  - The rows and columns represent the arrival times that deviate the scheduled arrival time from -5 to 22 (actual – scheduled, minute)
  - 1296(long trip) / 2117(short trip) transition matrices for eastbound
  - 1008(long trip) / 2025(short trip) transition matrices for westbound
- 630,000 stop arrival data for Route 1: 80% for training; 20% for testing

Results on the Training Set



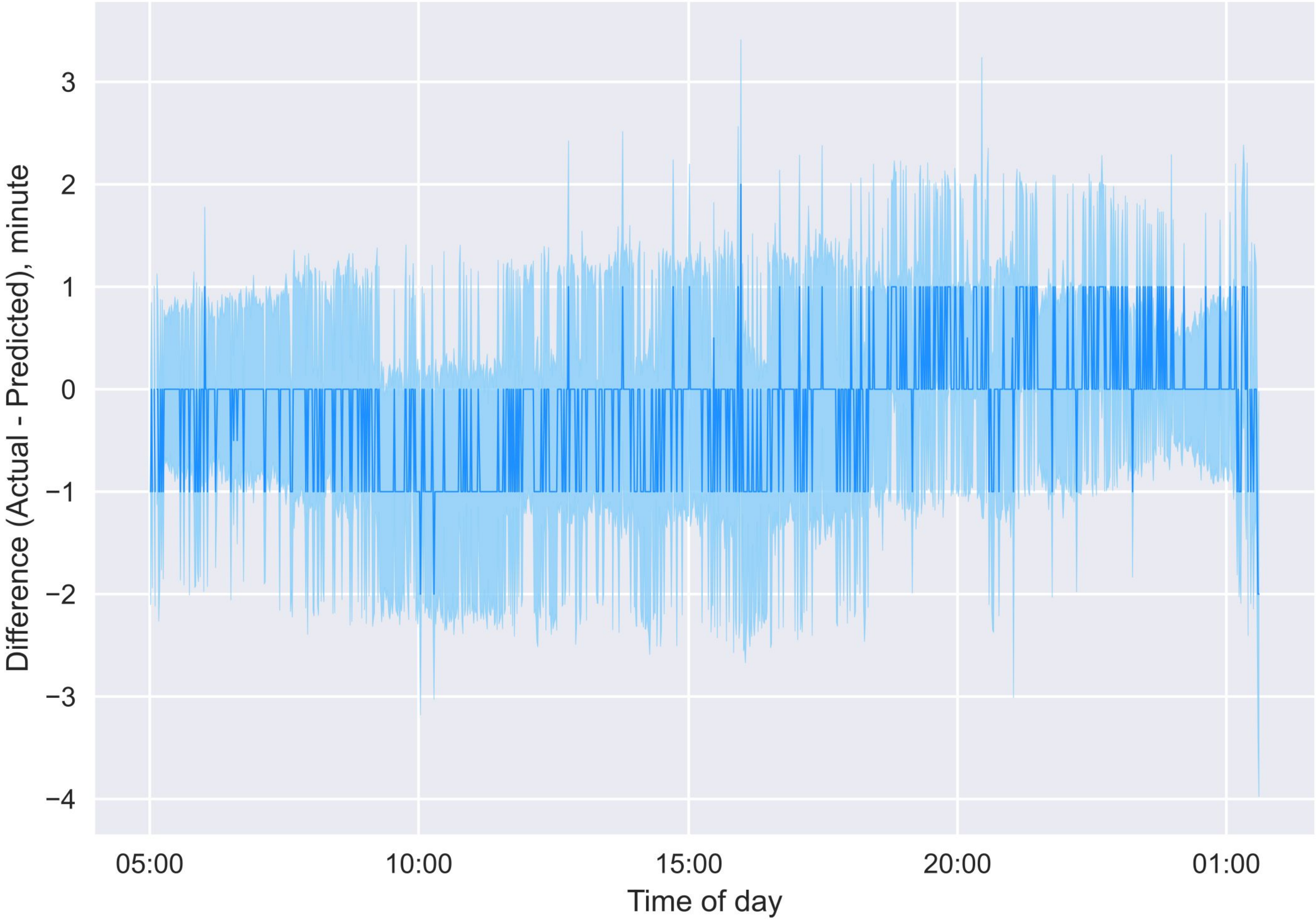
Percentage in the acceptable range [-1,5]: 81.7%

Results on the Testing Set



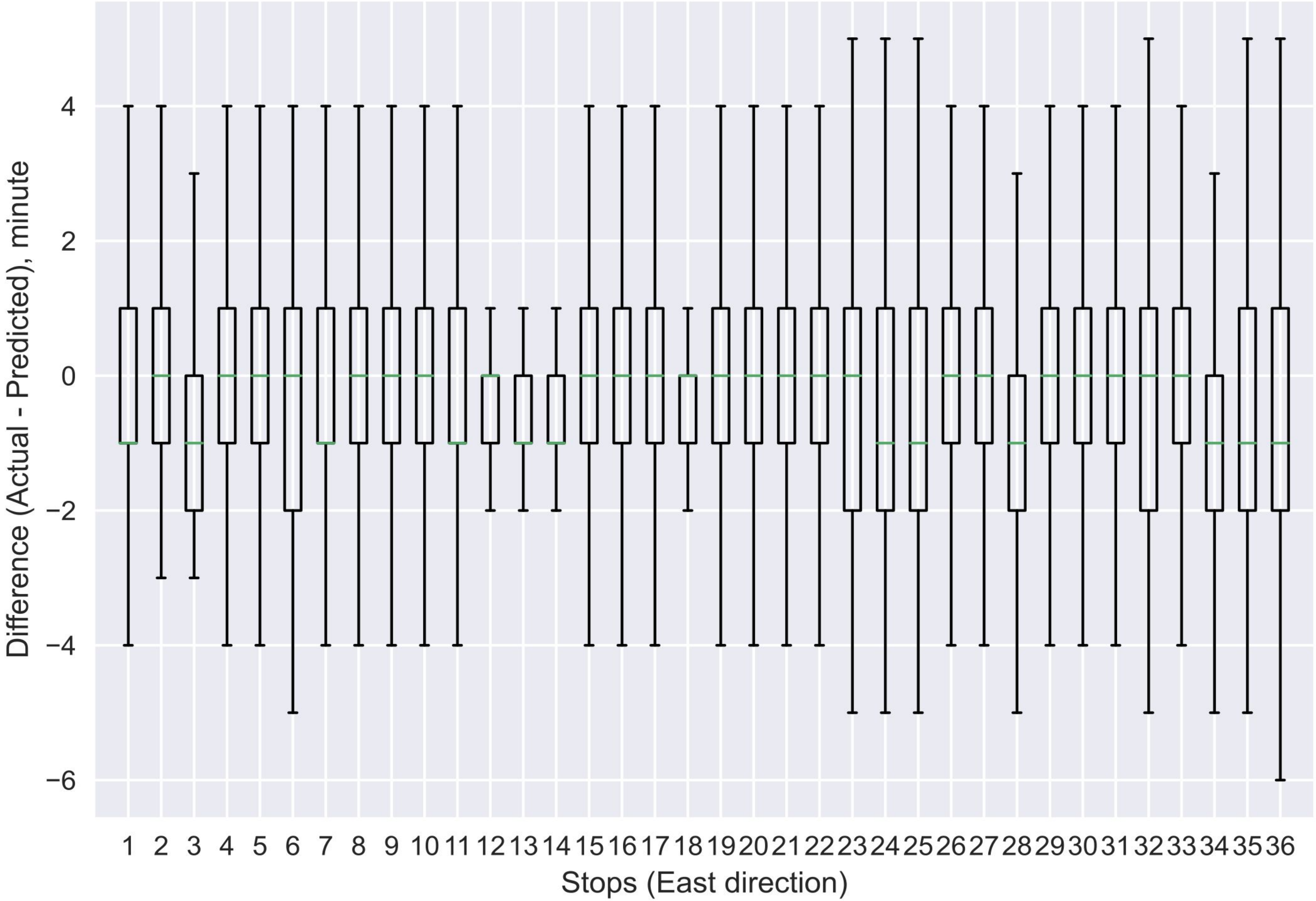
Percentage in the acceptable range [-1,5]: 80.2%

Results—Temporal Variation



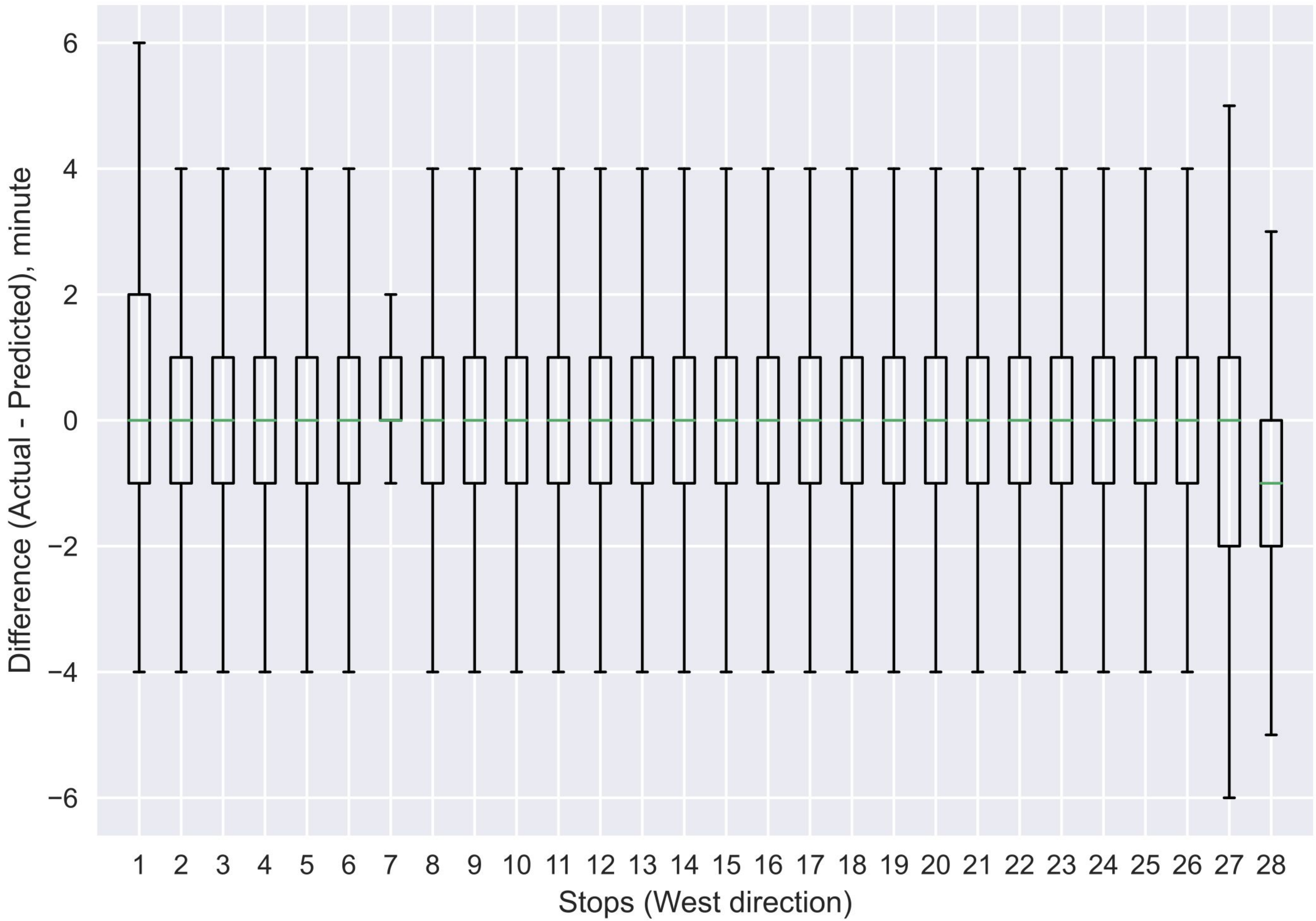
- Light blue area represents 70% trust interval
- Darker blue line: median
- Large variation during 8:00 – 19:00

Results—Spatial Variation: Eastbound



- Colonie Center to Downtown Albany
- Origin stop removed
- Larger variations for the later stops on the route
- Lowest variations at:
  - Central Ave & Osborne Rd
  - Central Ave & Yardboro Ave
  - 1010 Central Ave

Results —Spatial Variation: Westbound



- Downtown Albany to Colonie Center
- Origin stop removed
- Larger variations for the later stops on the route
- Lowest variations at:
  - Central Ave & Henry Johnson Blvd

Benefits

- Minimal data requirement: Bus arrival data only
  - Easy to transfer
- Uncertainties are well addressed by a machine learning model
  - Anticipate the environment instead of simply reacting to observations in real time
- Flexible prediction information
  - In the case study, expectation of arrival time is used for prediction
  - The maximum likelihood and trust intervals can also be provided
- Flexible modeling of transition matrices as per operational needs
  - Time intervals
  - Could be simplified as transition vectors
- High accuracy

Acknowledgements

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WHERE DISCOVERIES BEGIN

U.S. DEPARTMENT OF ENERGY

CDTA

VREF CENTER OF EXCELLENCE FOR SUSTAINABLE URBAN FREIGHT SYSTEMS

Thank you!
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