Urban Rideshare Passenger Demand Prediction

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Problem

- Ridesharing apps don't tell drivers where to wait effectively. Drivers must travel to where they think demand will be greatest.
- There are no live accurate models for rideshare passenger demand in use [1, 2].
- Thus, drivers & passengers both must wait longer to reach one another.

Methods

Data

- Rideshare trips (location, duration, time) in Chicago from 6/30/19-9/30/19 taken from Chicago Data Portal [3].

Recurrent Neural Networks (RNNs)

- 2-layer Sequential LSTM to predict ride demand for next unseen 15-min time interval based on the past 8 hours of data.
- One RNN cell per location block (83 blocks total). Used Mean Absolute Error (MAE) as the loss function for training.
- Trained RNN on data from feature vectors consisting of block request frequencies from 6/30/19-9/30/19.
- Input Layer: 32 units | Hidden Layer: 16 units | Dense: 1 output.

Markov Decision Processes (MDPs)

- Given a driver at a location and time, we determine if and where they should move for getting a rider.

Start State: driver starting location and time.

End State: driver location at ending time.

States: location [192 distinct blocks/spaces of Chicago] and time [15-minute periods throughout day (00-15-30-45)]

Transition Matrix: the number of rides that transition into every other state is counted and normalized for each states.

Actions- move [up | down | left | right] or stay/not move.

Reward- With Rider: (duration in minutes * 100) as reward. 800 bonus if ride completed during same 15-minute state. Without Rider: transition to new location/time, -1500 reward.

- Value iteration was ran with start/end states in the middle of Chicago, between 7-9AM on a Monday.

Results

RNN for Ride Demand Prediction

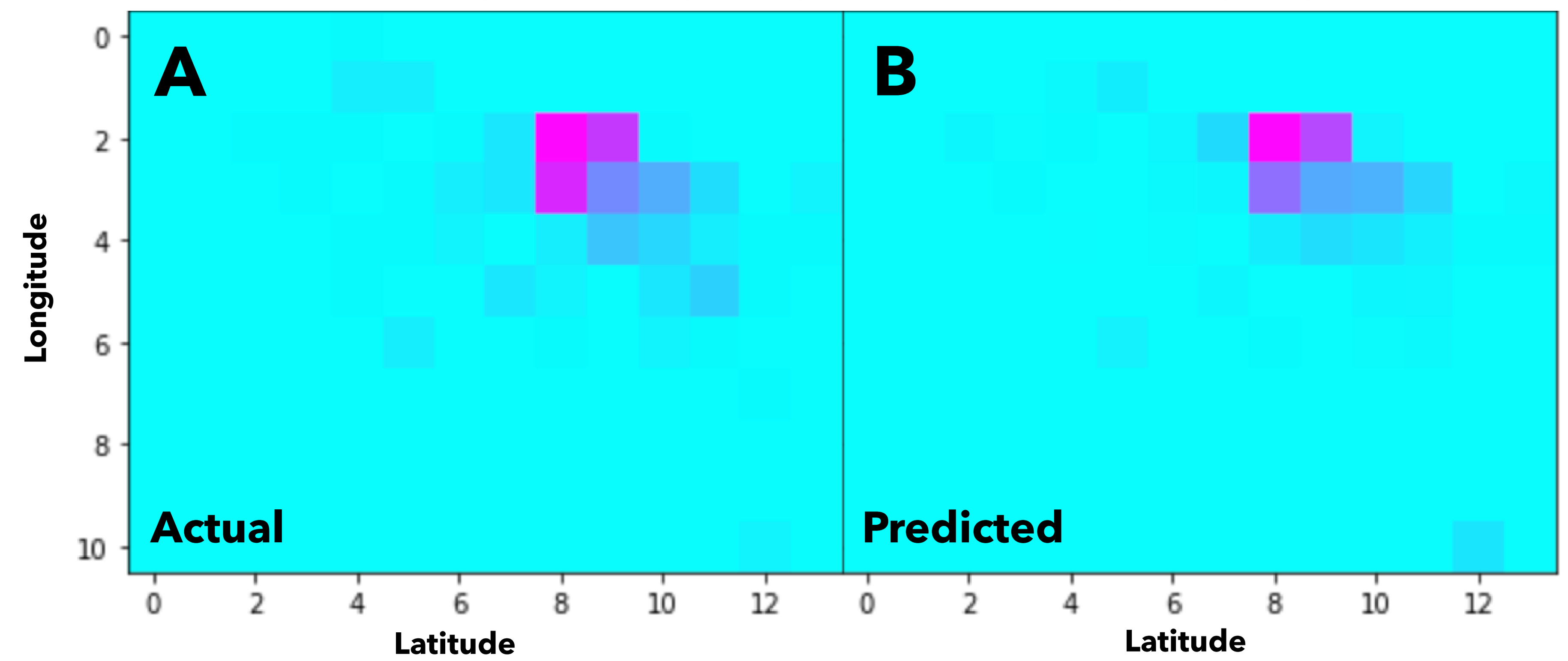

Figure 1. Ride demand heatmap at 12:00AM on 9/12/19. Fig. 1A: actual heatmap from data. Fig. 1B: aggregated output of RNN prediction.

- L2 norm of difference between matrices: 16.239 (Fig. 1).

MDP for Driver Policy Determination

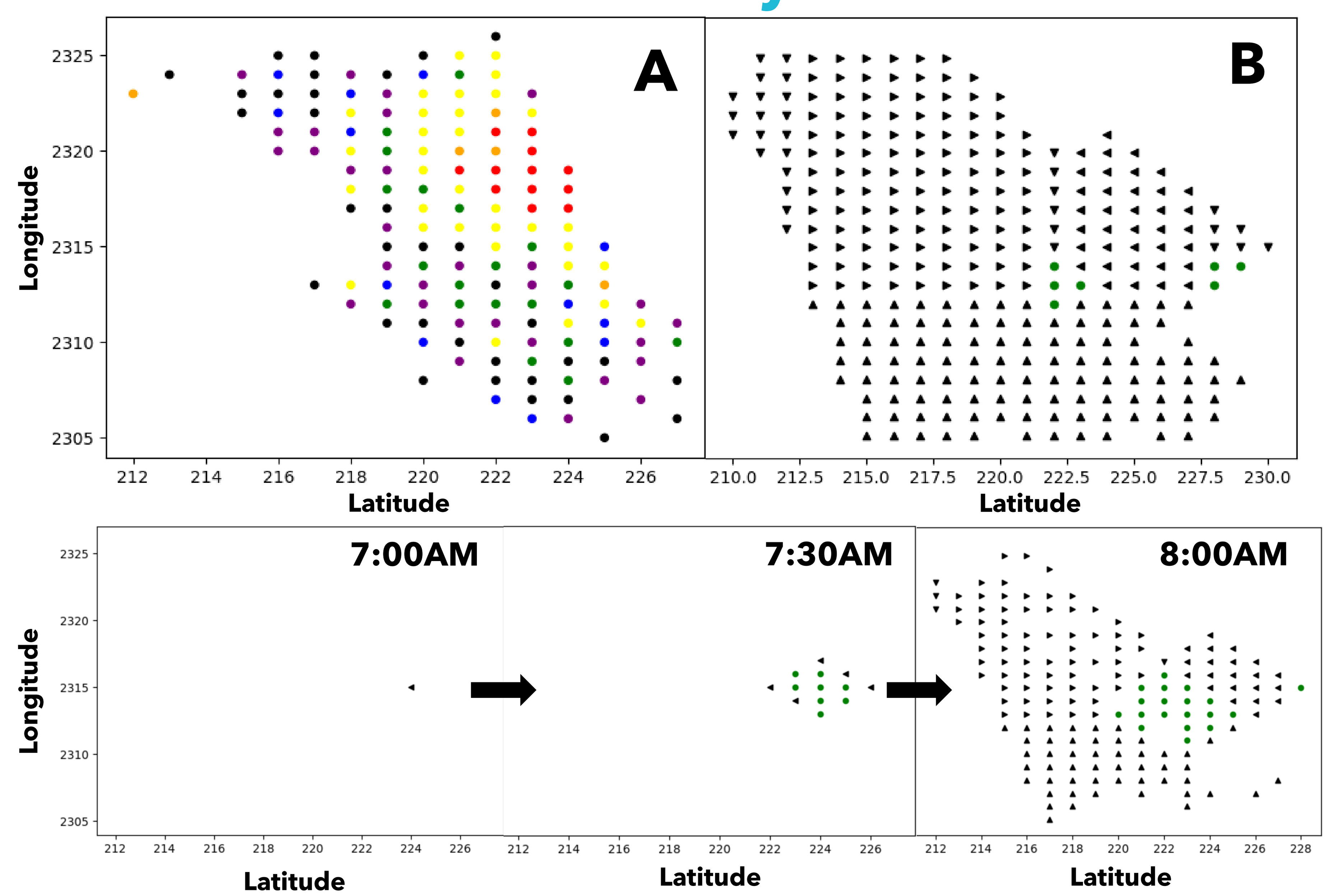

Figure 2. Driver optimal policy from 7:00AM-8:30AM. Fig. 2A: Ride demand heatmap at 8:30AM. Fig. 2B: Optimal driver policy at 8:30AM. Arrows represent direction to move towards and green circles denote to not move.

- Optimal policy promotes movement towards high rideshare demand areas (Fig. 2A/2B).
- Stay actions in driver policy biases towards set end location (Fig. 2).

Discussion

RNN for Ride Demand Prediction

- 8 hours of data (32 time intervals) was demonstrated to be a sufficient amount of data to preserve location-based demand information from the input matrix (Fig. 1).
- RNN cells were found to be significantly more accurate at predicting demand when trained to predict one specific location block rather than entire heat map (Fig. 1).

MDP for Driver Policy Determination

- Conservative policy demonstrated in MDP as the policy favors staying near the driver's desired end location (Fig. 2).
- Driver almost always chooses to drive closer to end location, and policy grows more conservative as the driver approaches its desired end time (Fig. 2).

Conclusion

- Rideshare passenger demand can be accurately predicted with RNNs and MDPs to optimize both driver earnings and passenger wait times.
- Just a spatiotemporal view of rideshare demand already enables significant prediction ability.

Future Work

- Incorporation of other relevant features (fare, wait-time, trip duration) and relevant non-trip factors (ex: weather, holidays, special events).
- Leverage other AI/ML techniques (CNNs, SVMs) to further explore rideshare demand prediction.

References

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