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I Open at the Close: A Deep Reinforcement Learning Evaluation of Open Streets Initiatives

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Open Streets

Close streets to vehicles, **open streets** to people

Benefits:
- Public space in urban environments
- Cultural programming
- Special events
- Community building
- Cost effective

NYC DOT Open Streets

Open Streets Access

Often, open streets initiatives use an application process, biasing the streets to communities that know about it.

Question: Is there a more objective way to choose streets?

NYC DOT Open Streets

Full Closure

Full Closure: Schools

Limited Local Access

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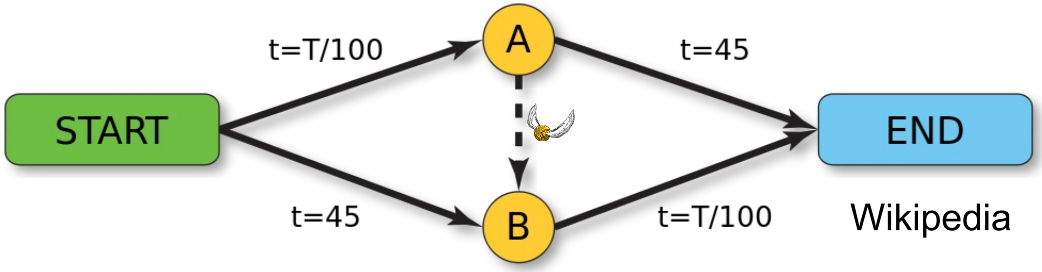
Braess's Paradox

Removing edges in a network can sometimes **reduce** traffic.



Wikipedia

Question: Can we choose streets which, when "opened", reduce traffic?

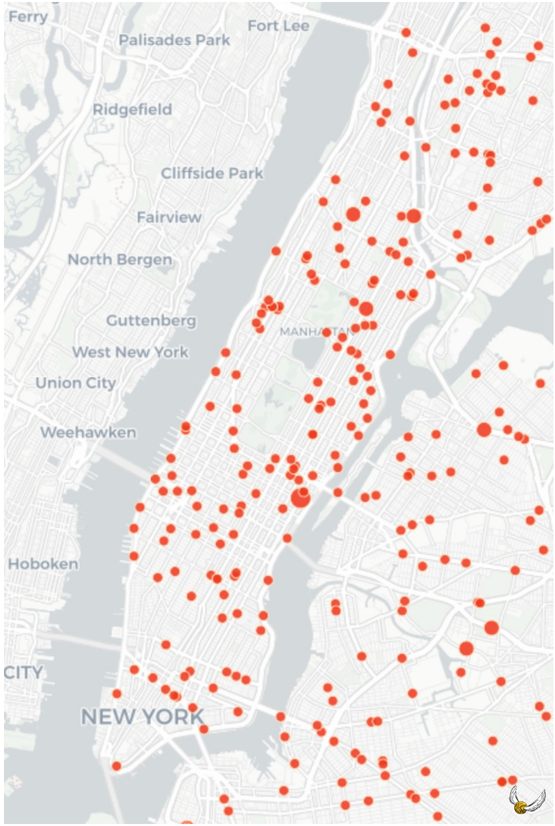
Modeling: Empirical taxi trips. Easy to reroute cars when streets are "opened".

Collisions

Some intersections are more dangerous than others.

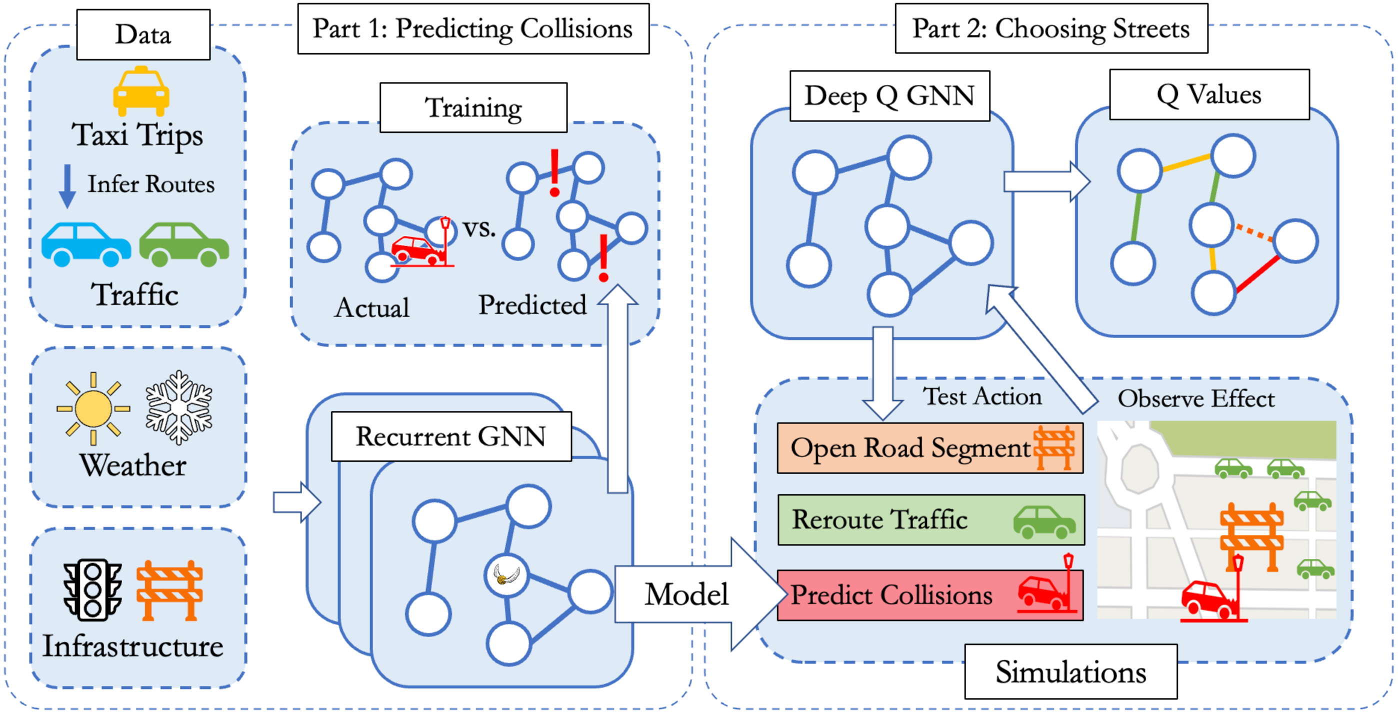
Question: Can we choose streets which, when “opened”, reduce collisions?

Modeling: Empirical collisions. Not obvious how collisions change when streets are “opened”.



Collision fatalities from 2013-2016
NYC Crash Mapper

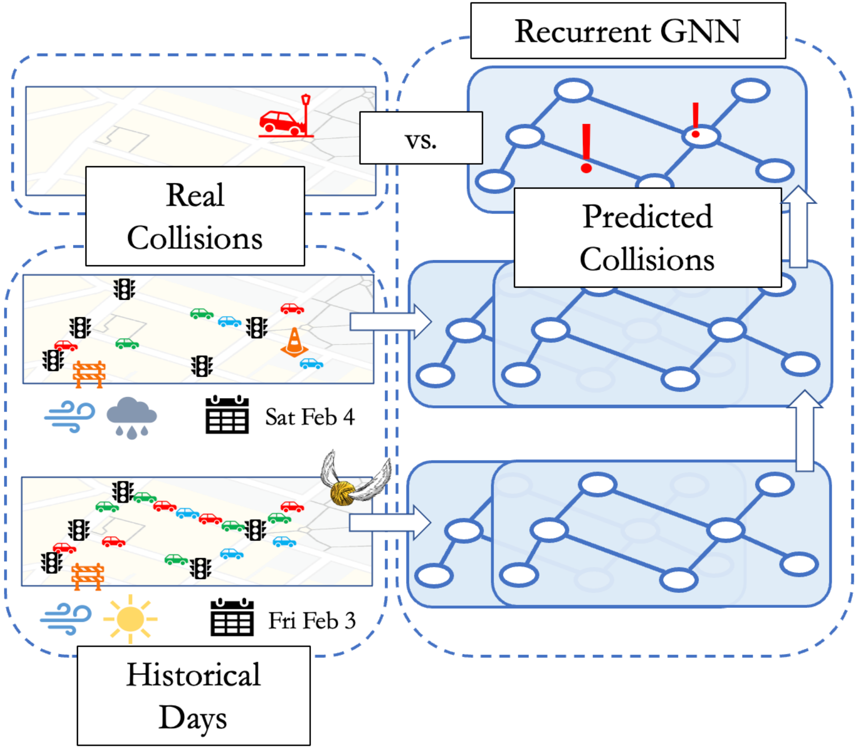
Our Approach



Part I: Predicting Collisions

Data Sources:
- NYC Collisions
- NYC LION Infrastructure
- NOAA Daily Weather
- NYC Taxi Trips

Recurrent Graph Neural Network:
- Spatial dependency
(e.g., speed changes)
- Temporal dependency
(e.g., wet roads)



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Part I: Model Performance

Goal: Performance on negative and positive instances

Model	F1-score	Recall (Negative)	Recall (Positive)	**Recall (Macro Average)**
Gaussian NB	0.97±0.0001	0.95±0.0001	0.15±0.0001	0.55±0.0001
LightGBM	0.78±0.0005	0.64±0.0006	0.80±0.0003	0.72±0.0002
XGBoost	0.80±0.0001	0.67±0.0001	0.81±0.0001	0.74±0.0001
DSTGCN (Yu et al. 2021)	0.67±0.2600	0.56±0.2701	0.59±0.1070	0.57±0.0401
Graph WaveNet (Wu et al. 2019)	0.75±0.0121	0.61±0.0160	0.68±0.0006	0.64±0.0080
Recurrent GNN (Lite)	0.86±0.0130	0.77±0.0200	0.68±0.0215	0.73±0.0043
Recurrent GNN	0.87±0.0064	0.78±0.0102	0.74±0.0157	**0.76±0.0040**

Table 1: Results of collision prediction models. Overall support in the test set was 1,803,363 observations: 1,789,838 negative and 13,525 positive examples. The ± denotes standard deviation 10 random seeds. Since the F1-score ignores the imbalanced nature of our data, we use the macro average recall to select the best model.

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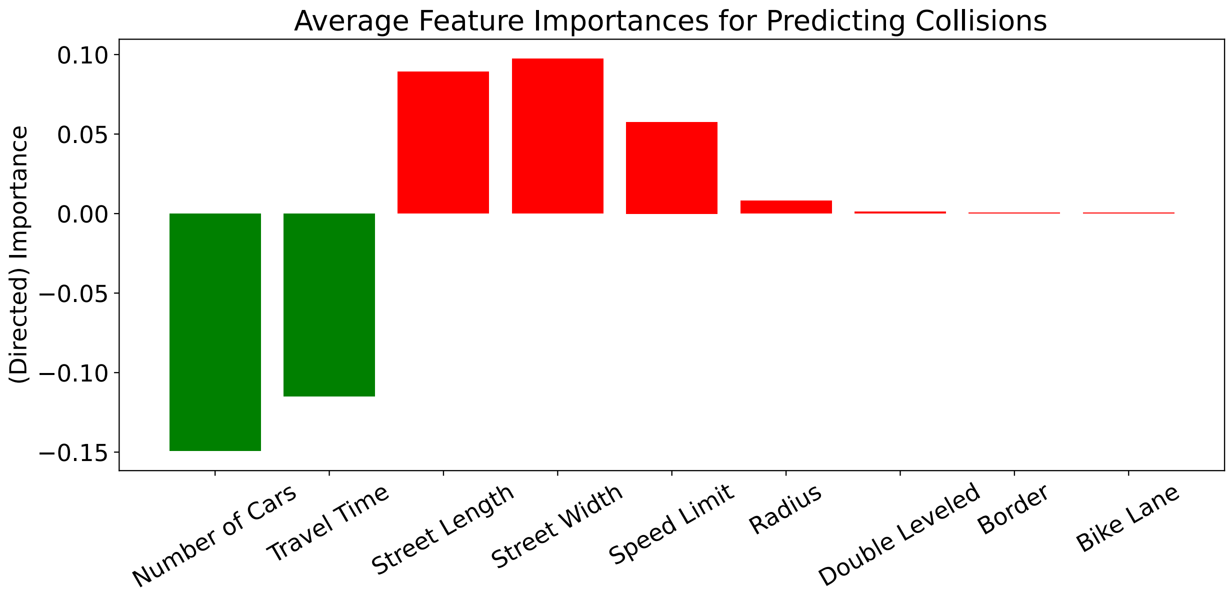
Part I: Feature Importance

Directed importance using the integrated gradients approach on the model with the highest macro recall.



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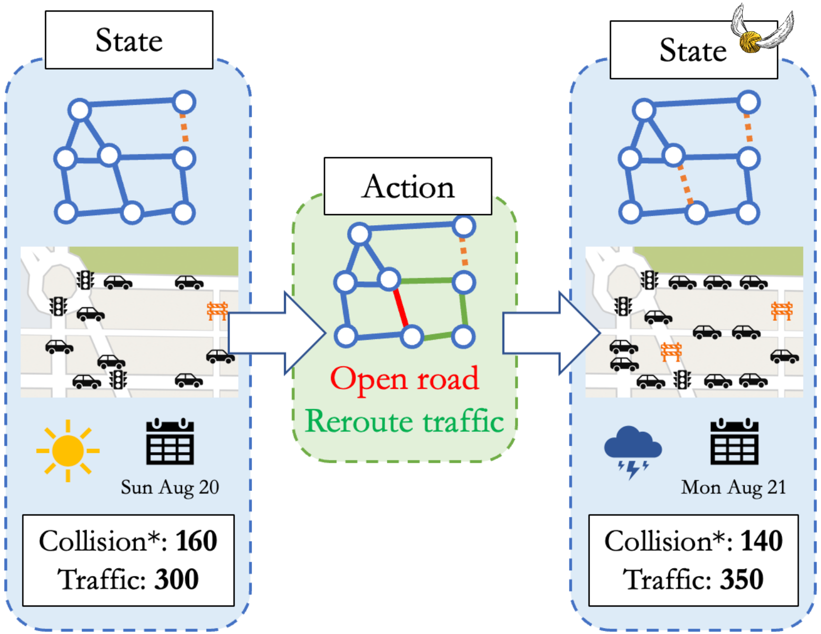
Part II: Reinforcement Learning



*collision risk from Recurrent GNN

State: Real historical day with some streets opened.

Action: Open an additional street.

Reward: Change in normalized collision risk (from model) and traffic (car density).

Goal: Capture complicated dynamics of opening street.

Part II: Comparison

Experiment: Average improvement from 30 runs of opening street simulations (a simulation lasts a month or until an opened street disconnects the network).

Comparison: Q-value approach gives consistently high improvement whereas open streets and random closures are comparable.

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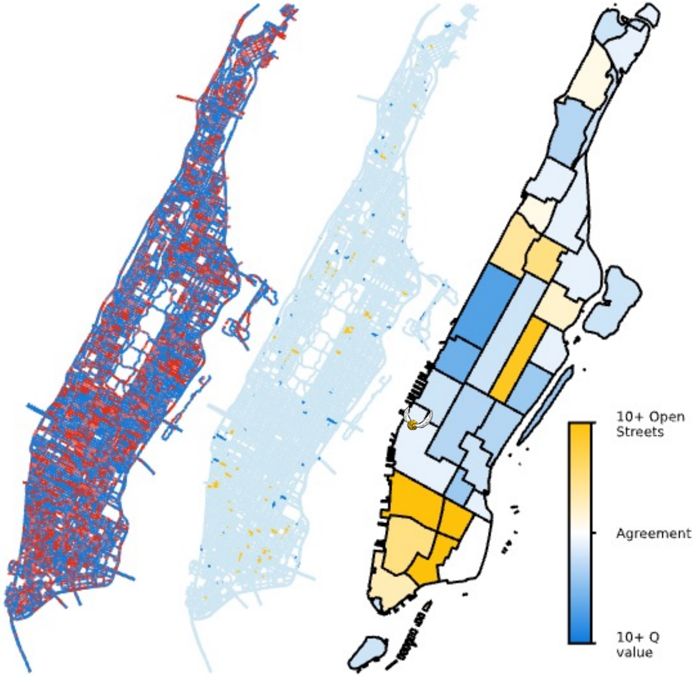
Part II: Which Streets?

Left: Q-values (blue is positive, red is negative)

Middle: 121 open streets (yellow) vs 121 q-value streets (blue)

Right: Difference in number of open vs q-value streets



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Future Work

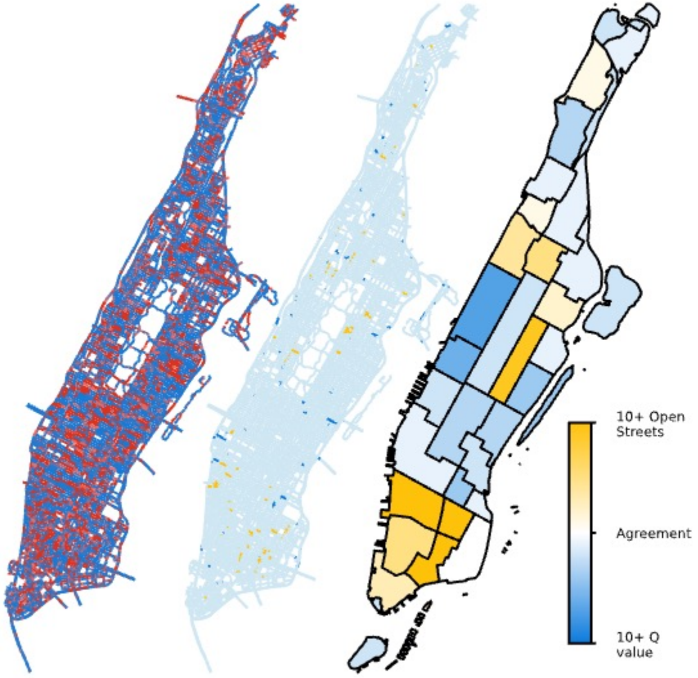
More work is needed before deployment!

Measuring traffic: We assume taxi data (and shortest path trips) are representative.

Near-collision events: Collisions are sparse but near-collision sensors are rare.

Other cities: GNN widely applicable but data sources and formats are not.

Interpretability: Our deep models are not interpretable.



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Thank you!

All our code and data are available at github.com/rtealwitter/OpenStreets

Preprint is available at arxiv.org/abs/2312.07680

Please reach out with questions or comments to rtealwitter@nyu.edu

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