Energy consumption for Travel Optimisation

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Problem Statement

What are we trying to optimize?

- The pathfinding algorithm for electric vehicle (EV) travel, incorporating energy consumption statistics, congestion fees, and real-time traffic data.

Applications

- In contrast to conventional navigation software, we want to offer accurate insights on energy-efficient travel while accounting for urban constraints.
- Calculate concrete figures to represent energy consumption over routes.

Success Metrics & Limitations

How we gauge success:

- Comparison to baseline models
- Accuracy of energy-efficient routing
- Performance vs. Google Maps & proprietary software

Key limitations:

- Real-time data access issues
- Computational efficiency challenges
- Trade-off between speed & energy efficiency
- Problem breadth

Data Requirements & Challenges

Key Data Sources

- IEEE dataset
- Traffic Congestion Dataset
- EV consumption dataset

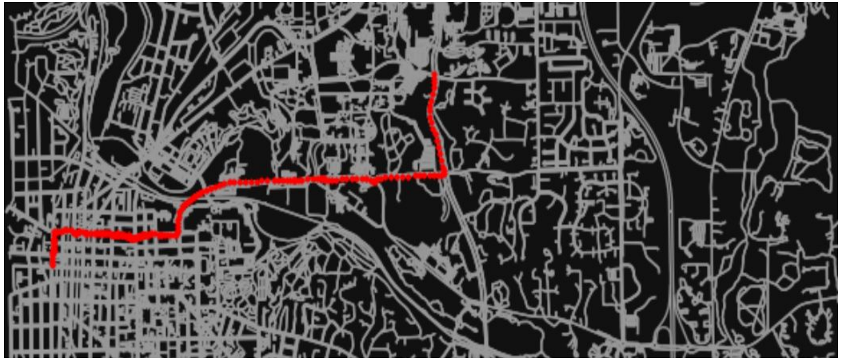
Graph Representation

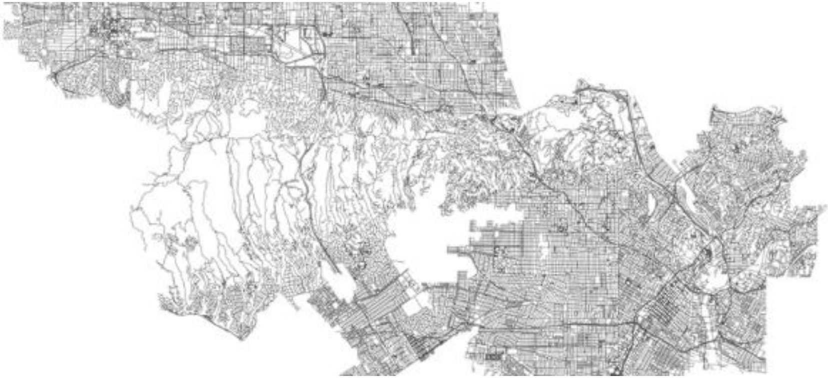
- Data Source: OpenStreetMap (via OSMnx package)
    - Nodes = Intersections ; Edges = Roads ; Features : Congestion, energy consumption, speed limits

Challenges

- Resolving very large datasets into small workable instances.
- Dataset Synchronization between different cities.

Datasets





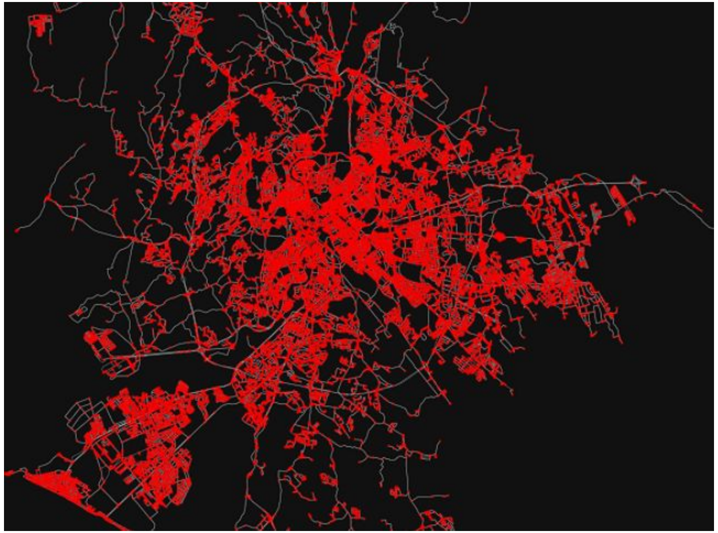
Vehicle Energy Dataset

- Coordinates
- Fuel Consumption
- Speed

OSmnx

- Road Network

Datasets



Traffic Congestion US

- Coordinates
- Timestamp
- Speed

Challenges

- Independent datasets were not aligned for measuring coordinates.
    - Solution: We latch eVED datapoints to nearest intersection in osmnx

- Data is exclusively related through coordinates which can’t directly be used for energy calculations
    - Solution: We use Haversine conversion to map to 2d distances

- Critical metrics not readily available
    - Solution: Query Google Maps API for information such as elevation

- Optimality of A* is challenged by dropping the Euclidean distance heuristic
    - Solution: ??

Technical Approach:

- We used graph based deep learning with probabilistic decision making to find a an optimal route from a source to destination for EVs considering factors such as energy consumption and traffic congestion
- Pass nodes through a NN which then outputs the following predictions for each node: energy_score, congestion_score
- Calculated a combined score using these predictions with weights for each node, convert this final score for each node into a probability (higher score = higher probability), and probabilistically sample a subset of nodes select the best route from this subset

Algorithm choices:

- **Baseline**: Dijkstra's Algorithm
- **Enhancements**: A*, ML-based models, Loss Optimisation from basic consumption formulation
- **Deep Learning**: Graph Neural Networks (GNNs) via PyTorch

Mathematical Formulation

- We define the output as an edge weight to be used for A*
    - Assuming α, β, and γ are weights reflecting the relative importance of energy consumption, fees, and travel time.

$$c(e) = \alpha\, E_e + \beta\, C_e + \gamma\, T_e$$

- The overall goal is to find the path P from a start node sss to a destination t that minimizes the total cost:

$$\min_{P \in \mathcal{P}(s,t)} \sum_{e \in P} c(e) = \min_{P \in \mathcal{P}(s,t)} \sum_{e \in P} (\alpha\, E_e + \beta\, C_e + \gamma\, T_e)$$

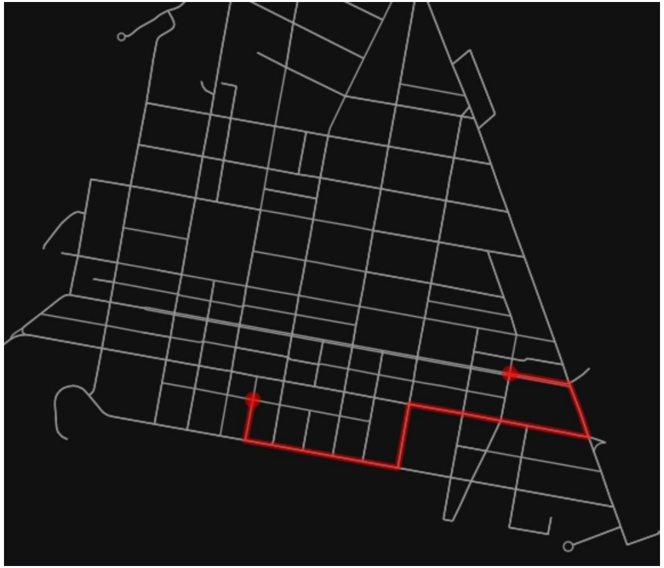
Pathfinding Progress

- Use an A* base algorithm to be able to provide a heuristic direction bias.

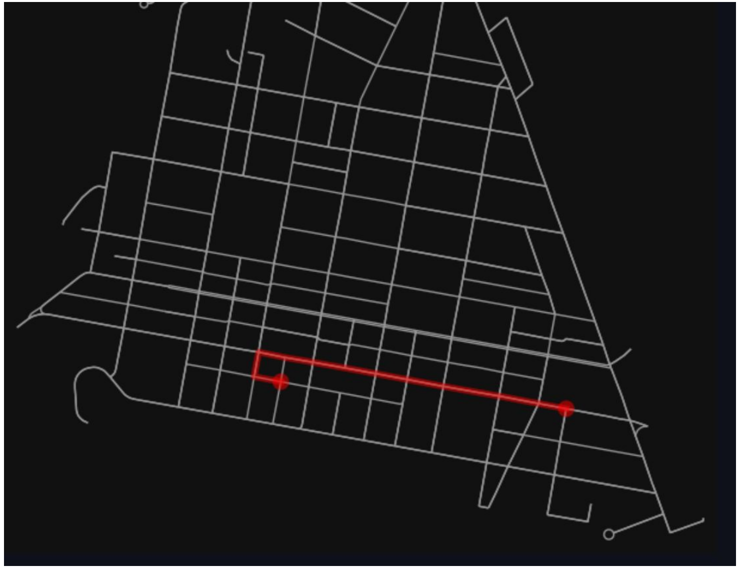
- Use a basic deterministic energy-based cost function that aggregates energy estimates from the dataset
  - derived from factors such as speed limits, road gradients, and elevation.

- Moving to potentially generating a path using a Neural Network/Bert transformer model

Progress



Base Djikstras



A* with cost function

Progress

What's done so far:

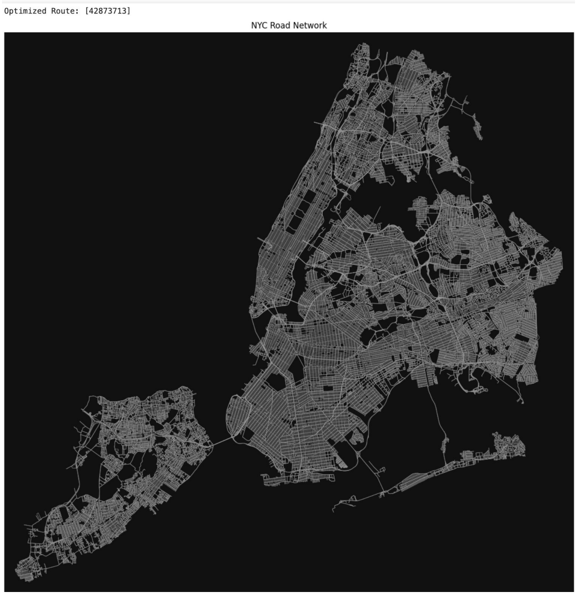
- Pathfinding with A* and Djikstras
- Dataset fine-tuning
- Improved Heuristic calculation through GNN
- Basic energy modeling
- GNN with embeddings and multiple features

Preliminary results:

- Correct path calculation in small NYC road sections
- A* with simple heuristics also delivers viable results
- GNN Structure developed

Graph Neural Network Feature Engineering

- Node Features
  - Intersection Degree
  - PageRank Score (importance of an intersection within the graph)
  - Elevation
- Edge Features
  - Road length
  - Speed limit
  - Congestion level



Performance Metrics & Findings

Key performance indicators:

- Execution time efficiency
- Accuracy of EV energy estimation
- Portability to regular fuel usage estimations

Limitations observed:

- Lack of real-time updates
- Need for improved energy consumption modeling
- No available data to incorporate differences between various EV models

Next Steps & Improvements

Short-term goals:

- Extending NN input set to include incoming edge data.
- Incorporate real-time congestion data
- Transform problem into Graph Neural Network

Long-term goals:

- Implement machine learning-based dynamic routing
- Scale model for larger road networks

Areas to explore

- **Machine Learning & RL:** Adaptive route prediction
- **Urban Constraints:** Road closures, pedestrian zones
- **Optimized Algorithms:** Localizing existing pathfinding methods
- **Alternative Data:** Satellite imagery for traffic prediction