Parallel shortest-path route planning on real-world road networks: SP over graph processing and GNN based SP
Motivation

- Fast shortest-path computations on real-world road networks are evermore necessary

- Use in routing for autonomous vehicles, large-scale vehicle scheduling, etc

- Unpredictable conditions require fast rerouting
Parallel SP

- Spark (parallel computing) + GraphX (graph processing) can execute SP on large graphs efficiently \cite{1}

- Can be extended to be used on real-world road networks (as these can be modelled as graphs)

- With parallel execution, SP on large real-world graphs has been shown to be fast
GNN based SP

- Advantage: generalises to unseen graphs whereas traditional SP solves for a single graph

- SP using GNNs is fast once trained [2]

- Don’t need to retrain for each path plan
Aim of Work

- Integrating real-world road network data from Open Street Map into:
  - Parallel SP: Spark + GraphX
  - GNN based SP: DeepMind’s GNN library Graph Nets [3] which uses TensorFlow

- Evaluate systems by comparing performance on a variety of paths of different lengths and on different networks:
  - Time taken to plan route
  - Accuracy/length of route: shortest?
  - Novel route found?
  - Computational complexity
Questions to answer

- Is it overkill to use GNN since the traditional SP graph algorithms already perform well?
- How does the training time of the GNN change with different networks or routes?
- Does GNN increase planning speed on unseen graphs once trained?
- Do both methods find the same route?
- Are there certain networks or routes where one performs better than the other?
Project Plan

- Research phase & finding GNN SP implementation
- Download Spark, GraphX, Graph Nets
- Experiment with toy example graphs
- Download OSM data
- Process data into appropriate graph format
- Integrate data into GraphX and Graph Nets
- Test running SP on different networks and route sizes
- Collect data and evaluate performance
- Write report (notes throughout)