Graph Neural Network for Predicting Flight Delays

Cameron Ferrarini and Maahee Abdus Sabur

Background

Airline delays have substantial economic and operational impacts, and every delay propagates across the network due the interconnectedness of the airline network. Traditional classifiers like Random Forest models treat flights as independent samples. We believe that by applying a Graph Neural Network to the airline network, we can better capture dependencies between them and develop a better model to predict flight delays.

Direct cost of air transportation delay in 2007

Cost Component	Cost (in billions)
Costs to Airlines	$8.3
Costs to Passengers	$16.7
Costs from Lost Demand	$3.9
Total Direct Cost	$28.9
Impact on GDP	$4.0
Total Cost	**$32.9**

Source: Research UC Berkeley, "Flight delays cost $32.9 billion, passengers foot half the bill," Ann Brody Guy, Institute of Transportation Studies, October 18 2010. https://vcresearch.berkeley.edu/news/flight-delays-cost-329-billion-passengers-foot-half-bill

Model and Methodology

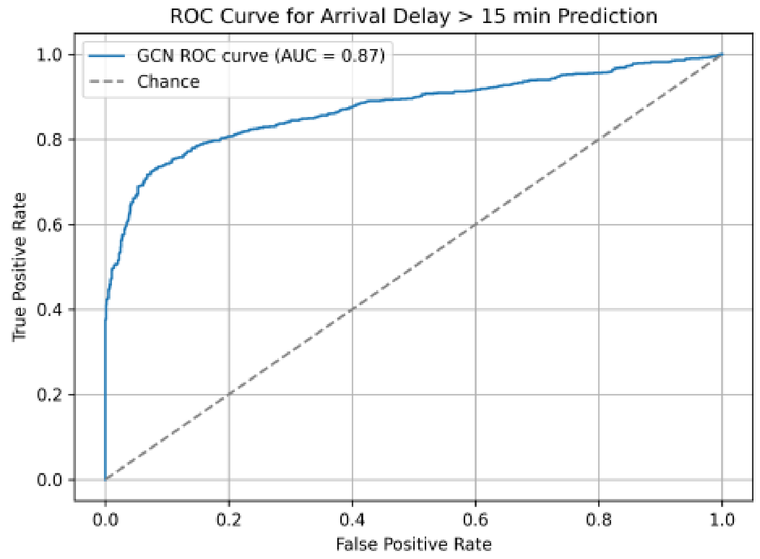
- **Graph Construction**
  - Nodes – Each flight in the dataset. Each node was encoded with information about the flight, such as its route, carrier, and departure time.
  - Edges – Edges were built to capture the following relationships between flights
    - Flights on the same aircraft on the same day
    - Flights departing from the same airport within 6 hours of each other
    - Flights on the same route
    - Flights with the same flight number on the same day
  - K-Nearest Neighbors was used to capture relationships not necessarily captured in the other edges
- **Model**
  - We implemented a GCN to perform binary classification, predicting if the arrival delay would exceed 15 minutes.

Key Results

- After training the GCN model on a balanced dataset of 10k flights where half were delayed and half weren't, we achieved the prediction accuracy shown in the table for delayed and on-time flights. Our average F1-Score of 0.82 and AUC of 0.87 on the ROC Curve show that our model is excellent at determining if a flight will be delayed.

- We also trained a Random Forest model on our same dataset of flights - it achieved an F1-Score of 0.77, performing worse than our graph-based model.

Class	Precision	Recall	F1-Score	Support
Not Delayed	0.77	0.91	0.83	984
Delayed	0.90	0.73	0.81	1016



Analysis and Future Work

- The GCN model outperforms the random forest baseline which demonstrates the value of incorporating networked features into the predictive model
- One major limitation is that due to computational constraints, our work was limited to a network of 10,000 flights instead of capturing the whole breadth of the US airline network. Future work could expand this network to better capture how delays propagate between flights
- Another way for the model to improve would be to integrate actual weather data into each flight to better capture one of the biggest causes of flight delays
- Finally, future work could involve deploying the model on future flight data for real-time delay forecasting and decision making