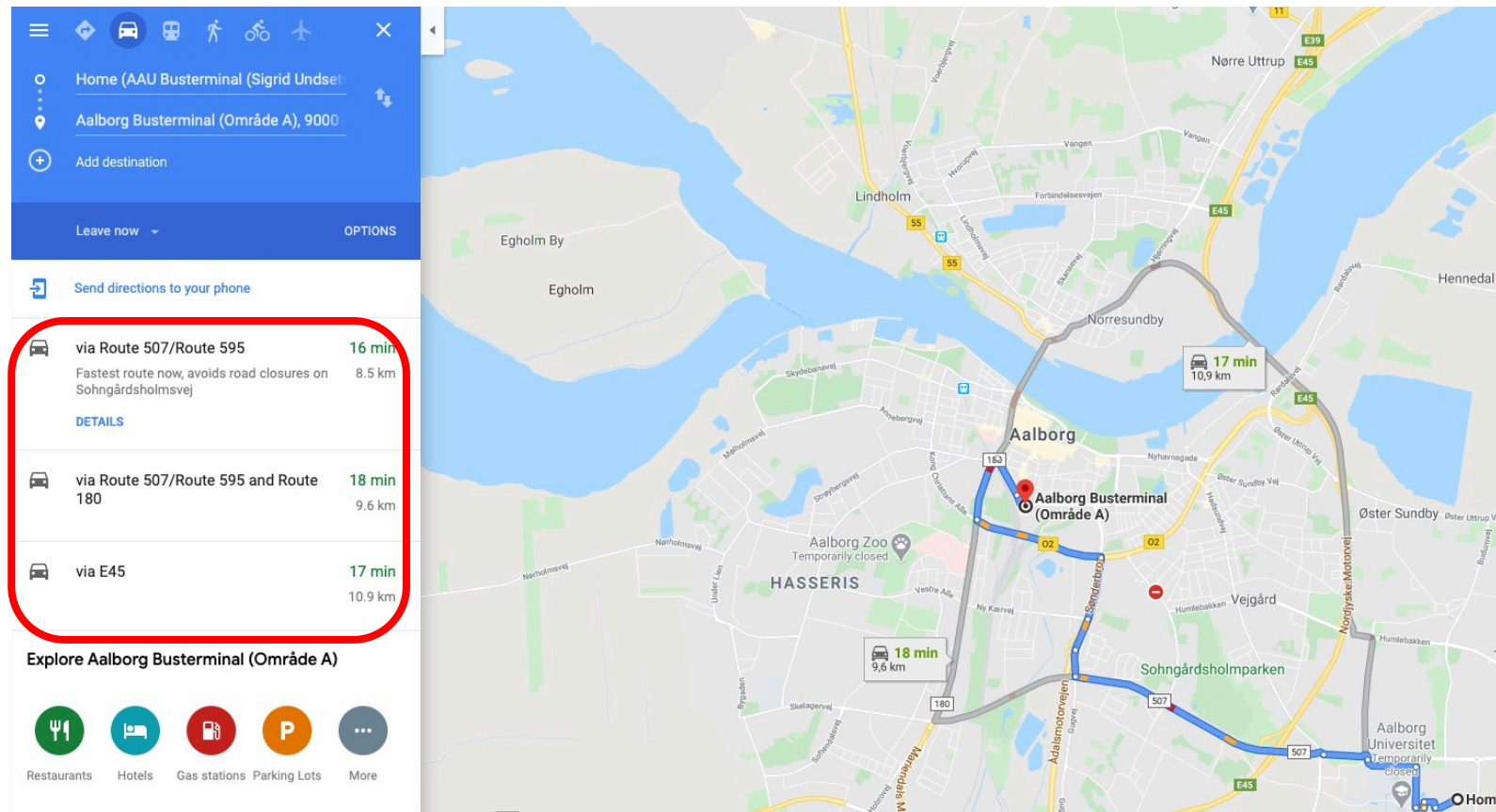


Learning to Rank Paths in Spatial Networks

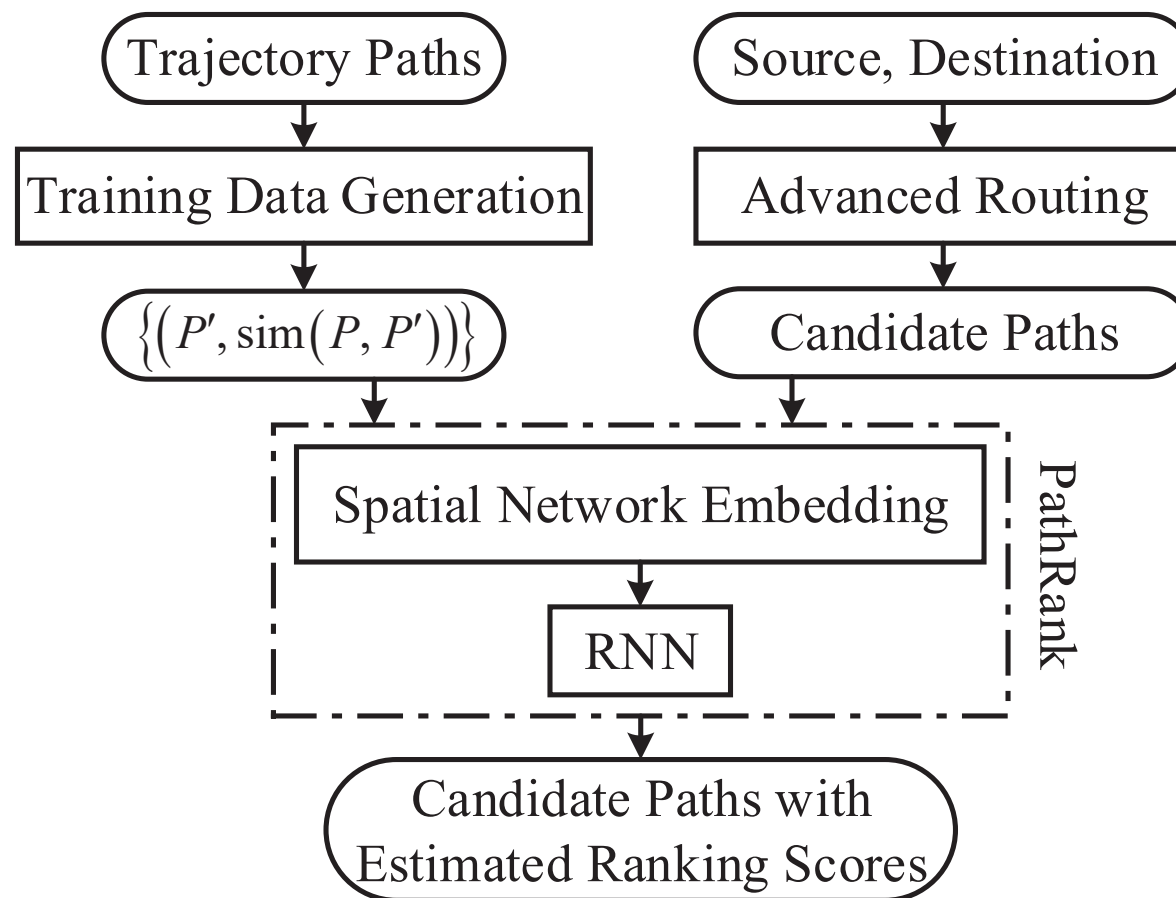
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- Local Drivers often choose path that are neither shortest nor fastest.
- Commercial navigation systems, such as Google Maps and TomTom, often follow a similar strategy by suggesting multiple candidate paths to drivers.

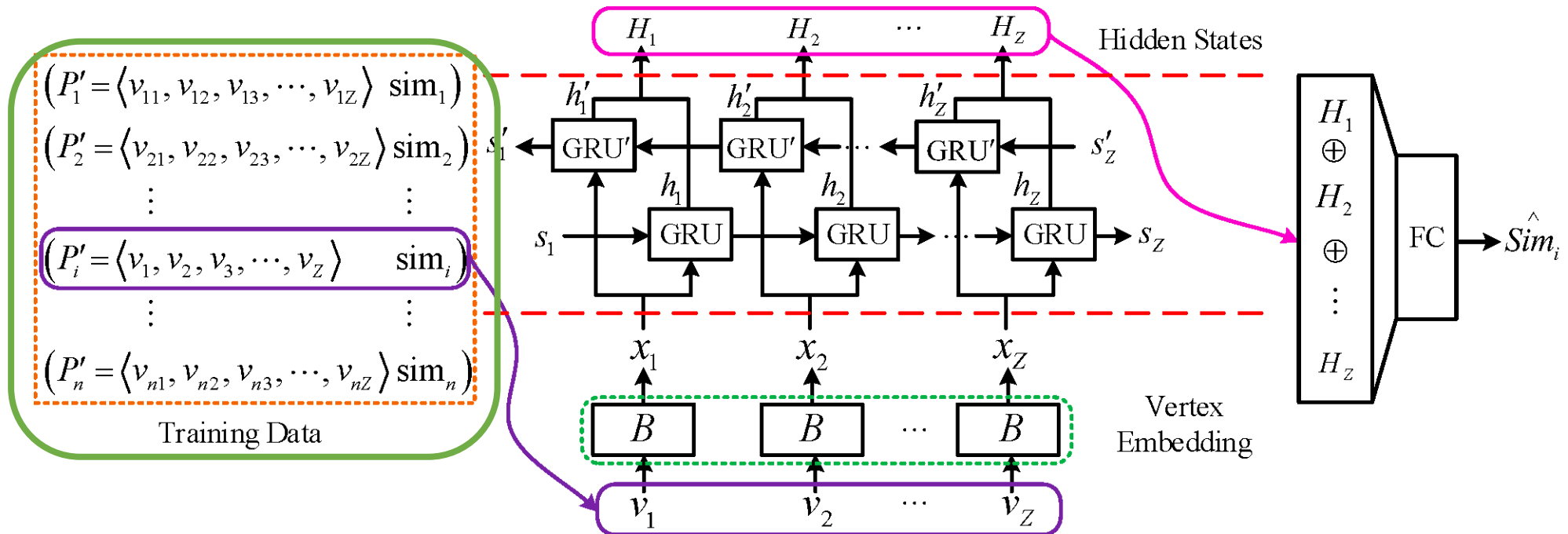


- We propose a data-driven ranking framework *PathRank*, which ranks candidate paths by taking into account the paths used by local driver in their historical trajectories.



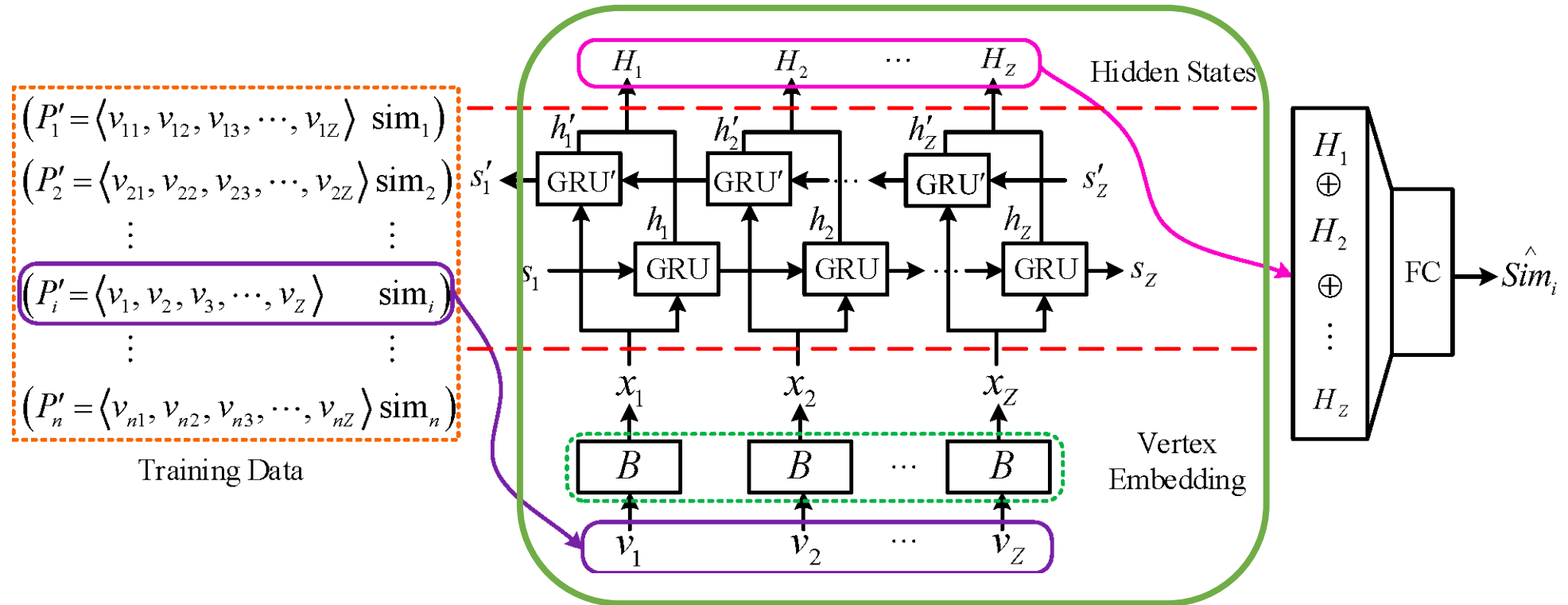
PathRank:

- Data Generation



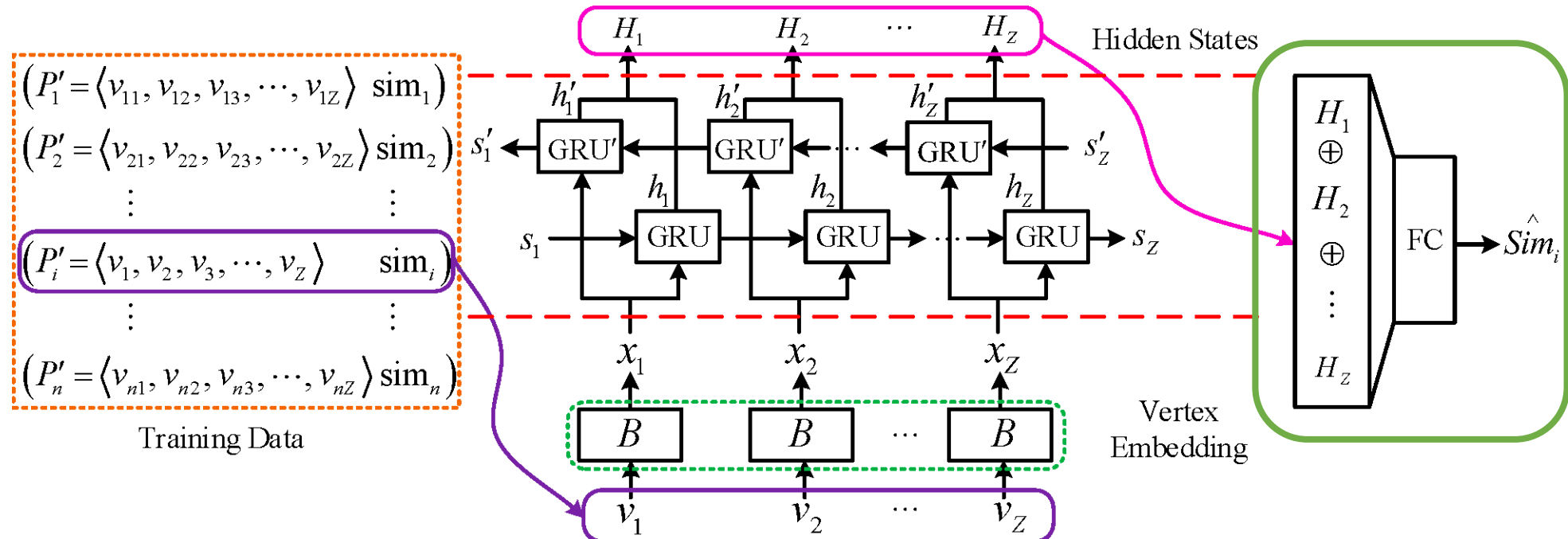
PathRank:

- Path Embedding



PathRank:

- Similarity Prediction



- Datasets
 - ✓ Aalborg, Denmark
 - 180 million GPS records
- Ground Truth Data
 - ✓ For each trajectory P_T , we generate two sets of training paths: Top-k shortest paths (TkDI), and Diversified top-k shortest paths (D-TkDI).
 - ✓ For each training path, we employ weighted Jaccard similarity (WeightedJaccard (P, P_T)) as P 's ground truth ranking score.
- Evaluation Metrics
 - ✓ Mean Absolute Error (MAE) and Mean Absolute Relative Error(MARE)
 - ✓ Kendall Rank Correlation Coefficient (τ) and Spearman's Rank Correlation Coefficient (ρ)
- Settings
 - ✓ PR-A1: Keep the graph embedding static
 - ✓ PR-A2: Keep updating the graph embedding

- Training Data Generation Strategies

Table 1 PR-A1

Strategies	M	MAE	MARE	τ	ρ
TkDI	64	0.1433	0.2300	0.6638	0.7044
	128	<u>0.1168</u>	<u>0.1875</u>	<u>0.6913</u>	<u>0.7330</u>
D-TkDI	64	0.1140	0.1830	0.6959	0.7346
	128	<u>0.0955</u>	<u>0.1533</u>	<u>0.7077</u>	<u>0.7492</u>

Table 2 PR-A2

Strategies	M	MAE	MARE	τ	ρ
TkDI	64	0.1163	0.1868	0.6835	0.7256
	128	<u>0.1130</u>	<u>0.1814</u>	<u>0.7082</u>	<u>0.7481</u>
D-TkDI	64	0.0940	0.1509	0.7144	0.7532
	128	<u>0.0855</u>	<u>0.1373</u>	<u>0.7339</u>	<u>0.7731</u>

THANK YOU