A1 Data Availability

Trajectory data:
https://www.microsoft.com/en-us/research/publication/t-drive-trajectory-data-sample/
OpenStreetMap file:
https://download.openstreetmap.fr/extracts/asia/china/beijing.osm.pbf
Code: https://github.com/huangs001/UFN

A2 Questionnaire

We design a questionnaire and collect the result from 147 people that drive to commute. The questionnaire has eight questions, asking the maximum acceptable percentage of time increase, regarding the improvement percentage of safety/comfort (four questions each) in 20%, 40%, 60%, and 80%, respectively. Each question has 10 options, corresponding to 10 ranges in 0%∼100% of the maximum acceptable percentage of time increase.

The results are shown in Fig. A1. There is a trend that with the increase in safety/comfort rate, the drivers accept more travel time along the route. This indicates that safety and comfort are important for the drivers, which is consistent with our design.

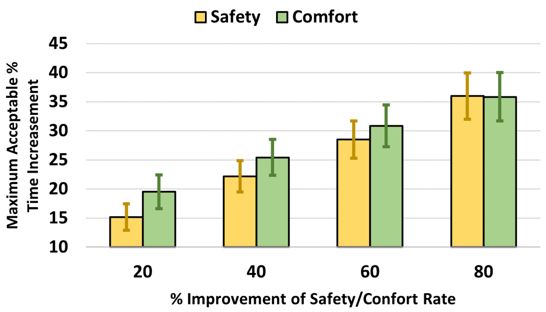

Fig. A1: Questionnaire results about the maximum acceptable percentage of time increase for safety/comfort improvement.

Algorithm A1 UFN

Input: HT data; Origin ori and destination des.
Output: Driver friendly route r.

//Calculation of DUR, SP, CP for each trajectory
for each trajectory τ from trajectory data **do**
    Calculate DUR, SP and CP of τ with equations (1) and (2);
end for
//Calculation of DUR, SP, CP for each road
$\mathcal{G} \leftarrow$ traffic graph from HT data;
$T_s \leftarrow$ time of starting frame from HT data;
$T_e \leftarrow$ time of ending frame from HT data;
Map trajectories to $\mathcal{G}$;
for $t = T_s$ to T_e **do**
    for each road e of $\mathcal{G}$ **do**
        Calculate DUR, SP and CP of e at time t;
        $(d_e, s_e, c_e) \mapsto \mathcal{G}$ at time t;
    end for
end for
//DSC correlation matrix construction
//Long periodic running
for f_1, f_2 in {DUR, SP, CP} **do**
    for two roads e_1, e_2 of $\mathcal{G}$ **do**
        Calculate $W_{f_1 \to f_2}(e_1, e_2)$ with C-DTW;
    end for
    Construct $M^0_{f_1 \to f_2}$ using the $W_{f_1 \to f_2}(e_1, e_2)$;
    Construct $M_{f_1 \to f_2}$ using the $M^0_{f_1 \to f_2}$;
end for
for f in {DUR, SP, CP} **do**
    for time interval δt in $\{\delta h, \delta d, \delta w\}$ **do**
        for e of $\mathcal{G}$ **do**
            Calculate $K^{\delta t}_f(e)$ with equations (3) and (4);
        end for
        Construct $M^{\delta t}_f$ using the $K^{\delta t}_f(e)$;
    end for
    Construct M_f using the $M^{\delta t}_f$;
end for
Construct DSC correlation matrix;
//Traffic forecasting with the DSC correlation matrix
$N \leftarrow$ number of roads of $\mathcal{G}$;
$\hat{t} \leftarrow$ current time;
for f in {DUR, SP, CP} **do**
    for δt in $\{0, \delta h, \delta d, \delta w\}$ **do**
        Embed all roads' f from $\mathcal{G}$ at $\hat{t} - \delta t$ into a $1 \times N$ vector;
    end for
    Concatenate four $1 \times N$ vectors into a $1 \times 4N$ vector;
end for
Concatenate three $1 \times 4N$ vectors into a $1 \times 12N$ vector;
Input the $1 \times 12N$ vector into GCN to predict DUR, SP and CP;
//Route planning with the predicted DUR, SP and CP
Path set $P' \leftarrow ori$;
$found \leftarrow$ False;
while not $found$ **do**
    for each path p in P' **do**
        if p contains des **then**
            $r \leftarrow p$;
            $found \leftarrow$ True;
        end if
    end for
    Update P' using simplified constraints (1) and (2);
end while
return r;

Table A1: List of symbols.

Symbol	Description	Section
$\mathcal{G}$	Traffic graph	3
$\mathcal{D}_\tau$	DUR of trajectory τ	4.1.1
$\mathcal{S}_\tau$	SP of trajectory τ	4.1.1
$\mathcal{C}_\tau$	CP of trajectory τ	4.1.1
M	DSC correlation matrix	4.1.2
$M_{f_1 \to f_2}$	Matrix constructed from $M^0_{f_1 \to f_2}$ as diagonal blocks	4.1.3
$M^0_{f_1 \to f_2}$	Matrix storing correlation from f_1 to f_2 for any two roads	4.1.3
$W_{f_1 \to f_2}$	Similarity value from f_1 to f_2 for two roads	4.1.3
δt	Time interval	4.1.4
M_f	Matrix constructed from $M_f^{\delta t}$	4.1.4
$M_f^{\delta t}$	Matrix storing δt periodic correlation of f for any road	4.1.4
$K_f^{\delta t}$	Periodic correlation value of δt of f for each road	4.1.4
$J_f^{t,t+\delta t}$	Periodic correlation value between t and $t + \delta t$ of f for each road	4.1.4
b_p	Weight of path p	4.2.1
D'_p	DUR of path p	4.2.1
S_p	SP of path p	4.2.1
C_p	CP of path p	4.2.1
d'_e	Fuzzy duration of road e	4.2.1
s_e	SP of road e	4.2.1
c_e	CP of road e	4.2.1
Q	A set of origin and destination pairs	5.3

Table A2: MAE, MAPE (%) and RMSE of predicted DUR.

		HA	VAR	DCRNN	STGCN	ASTGCN	STSGCN	STFGNN	UFN
HD	MAE	0.36	0.31	0.23	0.24	0.20	0.18	0.19	0.18
	MAPE (%)	21.95	13.02	7.77	7.84	8.94	7.81	7.76	7.63
	RMSE	1.88	1.21	1.25	1.21	1.18	1.17	1.17	1.17
MD	MAE	0.36	0.34	0.34	0.24	0.25	0.23	0.23	0.22
	MAPE (%)	22.99	21.36	12.59	12.26	12.65	10.65	10.59	10.06
	RMSE	2.15	1.39	1.44	1.15	1.27	1.28	1.29	1.28
LD	MAE	0.98	0.70	0.57	0.52	0.43	0.42	0.42	0.42
	MAPE (%)	49.29	36.50	17.36	17.66	17.48	15.10	14.84	14.54
	RMSE	4.30	2.75	2.81	2.90	2.72	2.75	2.74	2.75

Table A3: MAE, MAPE (%) and RMSE of predicted SP.

		HA	VAR	DCRNN	STGCN	ASTGCN	STSGCN	STFGNN	UFN
HD	MAE	0.67	0.65	0.55	0.58	0.61	0.52	0.58	0.52
	MAPE (%)	34.25	39.29	32.36	32.45	33.91	30.90	29.71	29.10
	RMSE	0.93	0.89	0.92	0.9	0.85	0.89	0.84	0.85
MD	MAE	0.37	0.45	0.41	0.40	0.34	0.34	0.36	0.34
	MAPE (%)	34.03	27.86	21.91	22.41	22.55	20.20	20.50	18.62
	RMSE	0.61	0.61	0.64	0.57	0.58	0.58	0.59	0.59
LD	MAE	0.71	0.60	0.50	0.47	0.49	0.45	0.43	0.39
	MAPE (%)	37.59	38.46	26.60	25.99	26.77	26.69	26.36	25.40
	RMSE	1.07	0.80	0.74	0.75	0.68	0.69	0.71	0.68

Table A4: MAE, MAPE (%) and RMSE of predicted CP.

		HA	VAR	DCRNN	STGCN	ASTGCN	STSGCN	STFGNN	UFN
HD	MAE	2.08	2.04	1.89	1.86	1.92	1.81	1.82	1.85
	MAPE (%)	49.05	44.85	23.67	23.23	24.87	22.5	22.15	20.89
	RMSE	11.88	11.06	11.19	11.81	11.28	10.99	11.02	11.09
MD	MAE	1.59	1.61	1.42	1.53	1.39	0.34	1.36	1.34
	MAPE (%)	55.43	42.22	19.01	18.72	20.14	17.93	17.3	15.53
	RMSE	11.32	11.52	11.38	12.75	11.68	11.33	11.2	11.23
LD	MAE	2.10	2.13	1.94	1.86	1.9	1.86	1.83	1.93
	MAPE (%)	57.15	49.53	19.80	20.99	23.18	22.84	21.53	19.76
	RMSE	13.92	14.03	14.19	13.95	14.22	13.76	13.76	13.82

Table A5: UFN's improvement over other traffic forecasting methods in high/medium/low-density areas.

		FR1 (%)	FR2 (%)	SR1 (%)	SR2 (%)	CR1 (%)	CR2 (%)	UR1 (%)	UR2 (%)
HD	HA	7.94	0.16	5.81	5.64	9.49	4.88	11.79	5.11
	VAR	7.93	0.15	5.72	5.49	9.37	4.78	11.64	5.00
	DCRNN	6.71	0.13	4.05	3.40	7.46	3.00	9.59	3.00
	STGCN	6.69	0.13	3.80	3.31	7.10	2.96	9.27	2.95
	ASTGCN	6.32	0.12	3.83	3.09	6.77	2.60	8.97	2.59
	STSGCN	2.26	0.03	2.02	1.67	3.91	1.28	5.61	1.23
	STFGNN	2.25	0.04	1.74	1.39	3.40	1.06	5.03	1.00
MD	HA	9.81	0.29	2.45	1.02	18.85	7.62	19.71	4.70
	VAR	8.47	0.23	2.40	1.04	18.60	7.57	19.42	4.68
	DCRNN	8.21	0.22	1.44	0.56	11.81	3.91	12.38	2.56
	STGCN	5.99	0.15	1.21	0.55	11.26	3.68	11.87	2.26
	ASTGCN	5.98	0.14	1.19	0.47	11.11	3.60	11.71	2.23
	STSGCN	6.02	0.15	0.68	0.33	6.22	1.75	6.33	1.20
	STFGNN	0.57	0.01	0.53	0.28	5.46	1.49	5.45	0.88
LD	HA	20.62	0.17	21.60	1.65	10.91	6.29	18.58	4.47
	VAR	20.52	0.16	21.28	1.60	10.57	6.13	18.11	4.31
	DCRNN	18.60	0.13	16.98	0.73	8.29	4.47	14.83	3.21
	STGCN	18.60	0.12	18.19	0.86	8.47	4.57	15.38	3.40
	ASTGCN	18.14	0.12	15.46	0.56	7.76	4.19	14.10	2.98
	STSGCN	15.62	0.09	12.09	0.32	5.58	2.72	10.85	1.96
	STFGNN	13.89	0.07	9.49	0.27	4.76	2.16	9.55	1.64

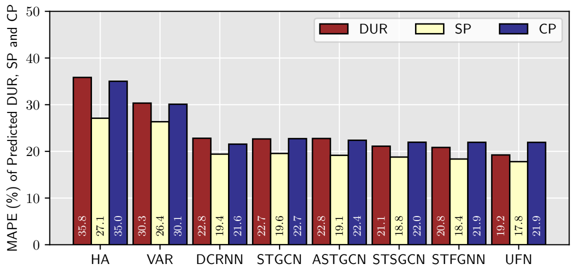

Fig. A2: MAPE of predicted features for Bloomington dataset.

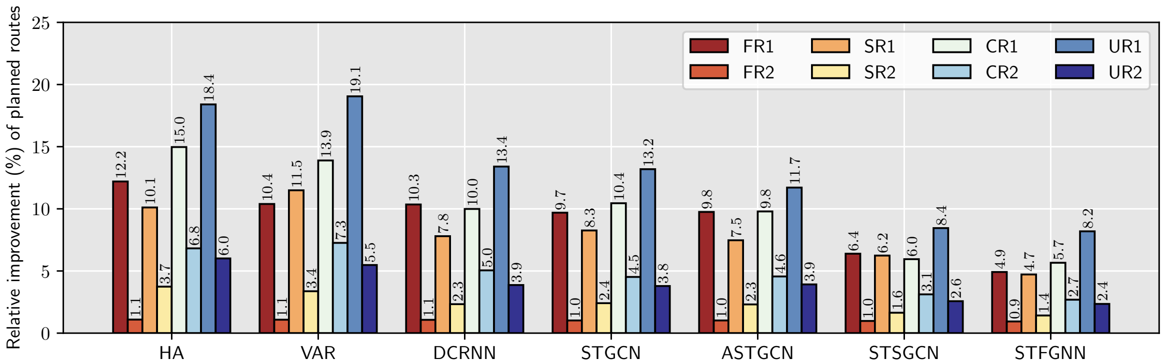

Fig. A3: UFN's improvement over other traffic forecasting methods for Bloomington dataset.

Table A6: MAE, MAPE (%) and RMSE of predicted DUR, SP and DUR for Bloomington dataset.

		HA	VAR	DCRNN	STGCN	ASTGCN	STSGCN	STFGNN	UFN
DUR	MAE	0.50	0.47	0.42	0.43	0.42	0.42	0.41	0.40
	MAPE (%)	35.84	30.34	22.81	22.66	22.76	21.14	20.84	19.23
	RMSE	1.59	1.12	1.05	1.06	1.01	0.98	0.97	0.97
SP	MAE	0.69	0.67	0.38	0.39	0.37	0.36	0.35	0.34
	MAPE (%)	27.1	26.35	19.41	19.55	19.15	18.78	18.36	17.80
	RMSE	2.43	2.30	2.15	2.14	2.11	2.08	2.10	2.20
CP	MAE	1.41	1.35	1.04	0.99	0.97	0.92	0.93	0.91
	MAPE (%)	35.02	30.10	21.55	22.73	22.38	21.96	21.94	21.93
	RMSE	13.01	13.05	12.37	10.01	9.90	9.46	9.48	9.47

Table A7: UFN's improvement over other traffic forecasting methods for Bloomington dataset.

	FR1 (%)	FR2 (%)	SR1 (%)	SR2 (%)	CR1 (%)	CR2 (%)	UR1 (%)	UR2 (%)
HA	12.20	1.09	10.11	3.74	14.97	6.82	18.40	6.01
VAR	10.39	1.08	11.49	3.37	13.89	7.26	19.05	5.48
DCRNN	10.35	1.07	7.80	2.33	9.99	5.05	13.40	3.87
STGCN	9.69	1.02	8.26	2.41	10.45	4.52	13.19	3.79
ASTGCN	9.75	1.02	7.47	2.31	9.79	4.56	11.71	3.92
SFSGCN	6.39	0.98	6.24	1.64	5.95	3.12	8.45	2.57
STFGNN	4.92	0.94	4.72	1.42	5.66	2.69	8.19	2.35