Learning and Prediction over Light-Weight Spatio-Temporal Data

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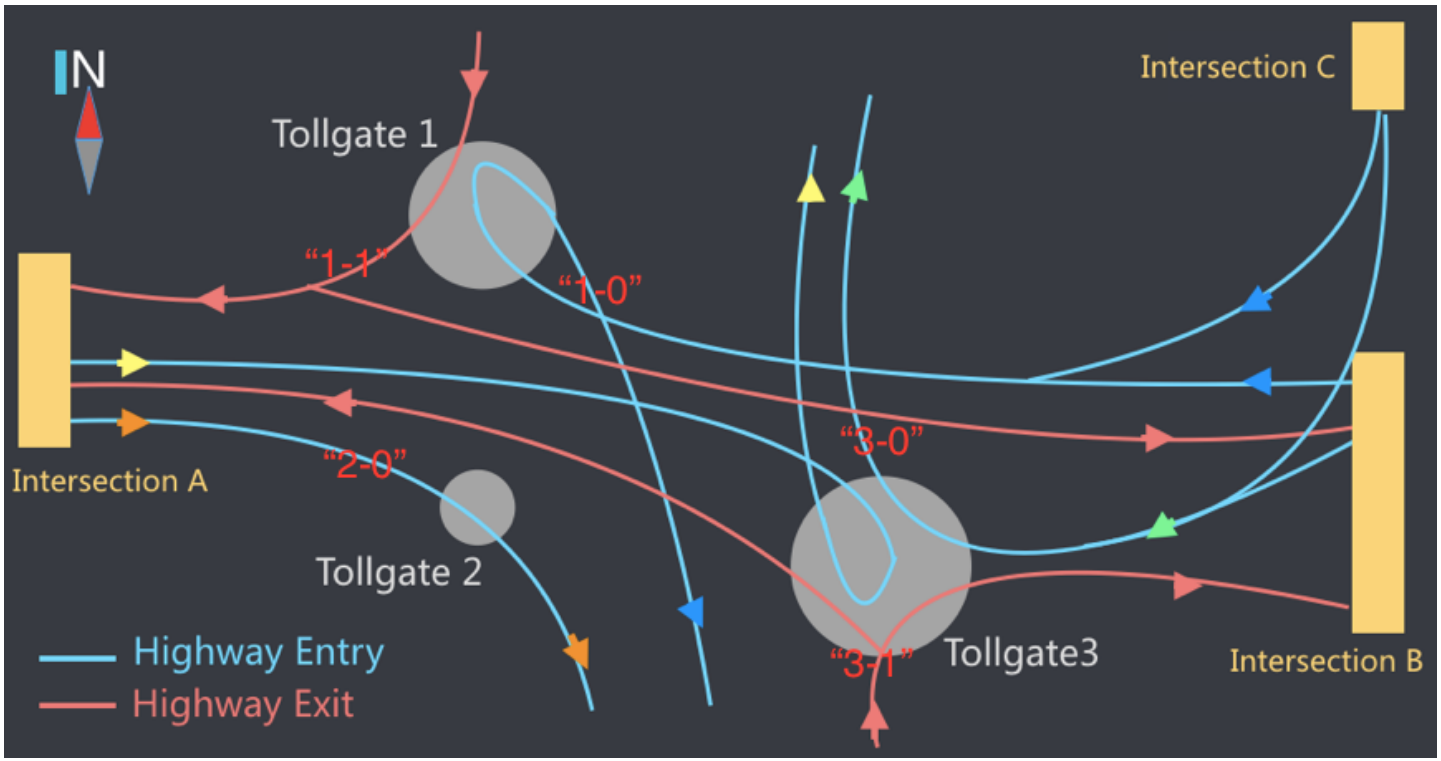
Motivation

- Help authorities do better decision making.
- Expedite the toll collection process.
- Streamline future traffic flow and reduce congestion.



Directions: entry:0; exit:1

Task Formulation

Task: Given 5 tollgate-direction pairs and previous two-hour vehicle records, predict the traffic volume of every 20-minute time window for the next 2 hours.

Data

- Testing days: previous 2-hour vehicle records.
- Training days: vehicle records of all days (24 hours).
- Weather: humidity, precipitation, wind....

time	tollgate_id	direction	vehicle_model	has_etc
2016-09-21 05:47:44	1	0	2	0
2016-09-21 05:52:19	1	0	1	0
2016-09-21 05:53:27	1	0	1	0
2016-09-21 05:54:46	1	0	2	0
2016-09-21 05:55:26	1	0	1	0
2016-09-21 10:09:31	1	0	1	0
2016-09-21 10:09:33	1	0	1	1
2016-09-21 10:10:53	1	0	1	0
2016-09-21 10:11:13	1	0	1	0
2016-09-21 10:11:55	1	0	1	0

Directions: entry:0; exit:1

Note: the traffic volume for a given tollgate-direction pair is the total volume of all vehicles that enter/exit the tollgate in that time window. Each 20-minute time window is defined as a right half-open interval, e.g., [2016-09-21 8:00:00, 2016-09-21 8:20:00).

Task Formulation

Basic ML approach:Use previous 6 20-minute time-window volume points to predict the next 6 points.

$$X = \begin{array}{c} \begin{array}{cccccc} \textit{Lag1} & \textit{Lag2} & \dots & \textit{Lag6} & \textit{tsDistance} & \textit{otherFeatures} \end{array} \\ \begin{bmatrix} V_{[7:40,8:00]} & V_{[7:20,7:40]} & \cdots & V_{[6:00,6:20]} & 20 & \cdots \\ V_{[7:40,8:00]} & V_{[7:20,7:40]} & \cdots & V_{[6:00,6:20]} & 40 & \cdots \\ V_{[7:40,8:00]} & V_{[7:20,7:40]} & \cdots & V_{[6:00,6:20]} & 60 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ V_{[7:40,8:00]} & V_{[7:20,7:40]} & \cdots & V_{[6:00,6:20]} & 120 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \end{array}, \quad Y = \begin{array}{c} \textit{Labels} \\ \begin{bmatrix} V_{[8:00,8:20]} \\ V_{[8:20,8:40]} \\ V_{[8:40,9:00]} \\ \cdots \\ V_{[9:40,10:00]} \\ \cdots \end{bmatrix} \end{array}$$

Objective: minimize the MAPE($\hat{Y}$, Y): $\frac{1}{n}\sum_{t=1}^{n}|\frac{y-\hat{y}}{y}|$. Works to do:

- Feature engineering: transfer raw data into features better represent the problem (Refer GIT for details).
- Modeling: design model framework/policy given the specific problem (**focused in this talk**).

GIT:https://github.com/12190143/Black-Swan

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Challenges

Challenge-1 The vehicle volume of a route varies a lot depending on.

- Time of day.
- Day of the week.
- Holidays vs normal days.

Challenge-2 Small dataset: Only 29 (36 for stage 2) days' data of 5 tollgate-direction pairs is provided. And it's very noisy.

Challenge-3 Evaluation metrics (MAPE): Most regression loss functions do not minimize APE(Absolute percentage error) directly.

- MSE (Gaussian distribution): $loss = \frac{1}{2}(y - \hat{y})^2$.
- MAE (Laplace/Quantile distribution): $loss = |y - \hat{y}|$.

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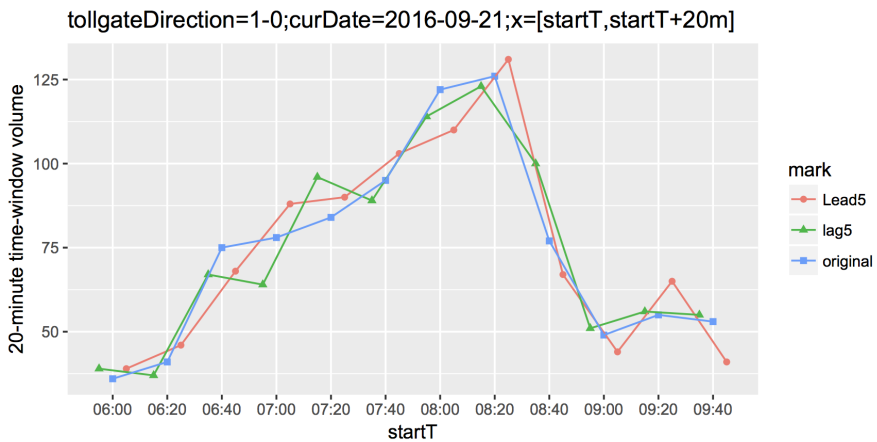
Strategy

Data-Augmentation: Augment the data by sliding time windows from $w(t)$ to $w(t+\pi)$.

	previous-2-hour	to-be-predicted
original	[6:00,6:20], [6:20,6:40],..., [7:40,8:00]	[8:00,8:20], [8:20,8:40],...,[9:40,10:00]
$\pi = 5$	[6:05,6:25], [6:25,6:45],..., [7:45,8:05]	[8:05,8:25], [8:25,8:45],...,[9:45,10:05]
$\pi = -5$	[5:55,6:15], [6:15,6:35],..., [7:35,7:55]	[7:55,8:15], [8:15,8:35],...,[9:35,9:55]
...	...	...

Regression-Objective: We consider two ways of approximating the evaluation objective.

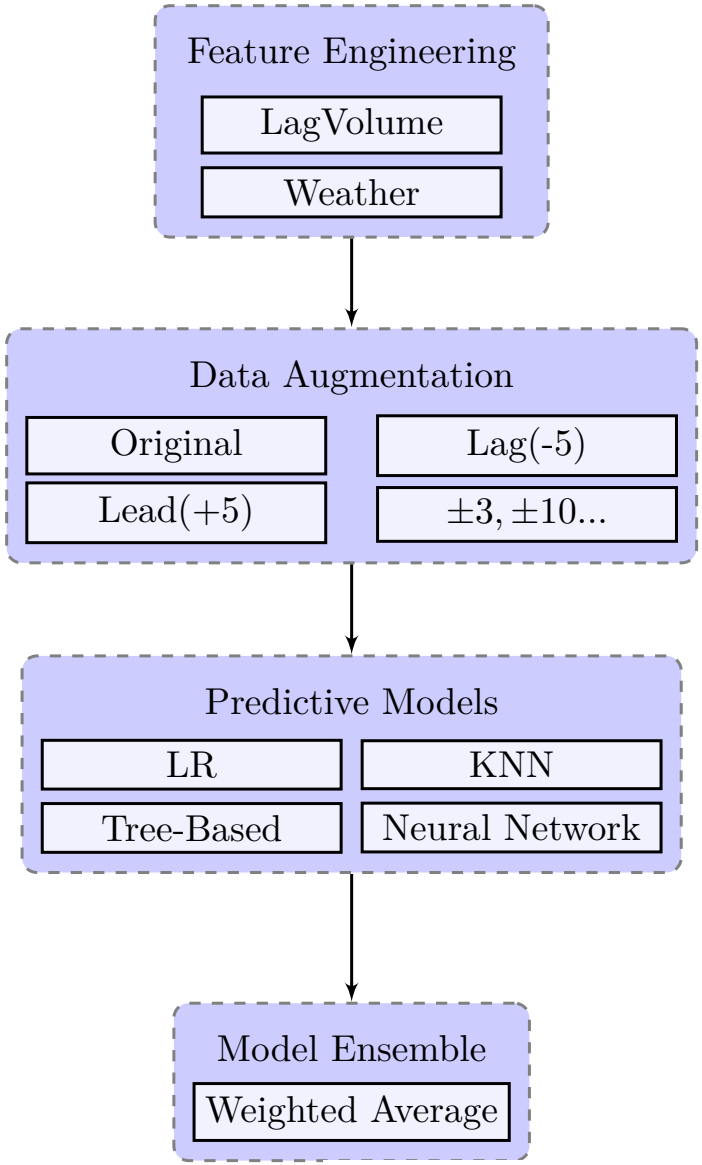
- Logarithm-Transform: $|log\hat{y} - logy| = |log\frac{\hat{y}}{y}| = |log(1 + \frac{\hat{y}-y}{y})| \approx |\frac{\hat{y}-y}{y}|$ (APE).
- Quantile-Regression: Minimize $|y - \hat{y}|$, a quantile point a little smaller than 0.5 (prediction a little small than median).



original vs new

Solution Framework

- **Original data**: 573140 vehicle records of 5 tollgate-direction pairs from Sep 19 to Oct 24.
- **Data augmentation**: Sliding time-window with different timestamps.
- **Feature engineering**: Vehicle records aggregation, weather data preprocessing;reformulate the data for ML training.
- **Model training**: Train different models with absolute-loss or log-transform.
- **Model ensemble**: Weighted average of multiple model results.



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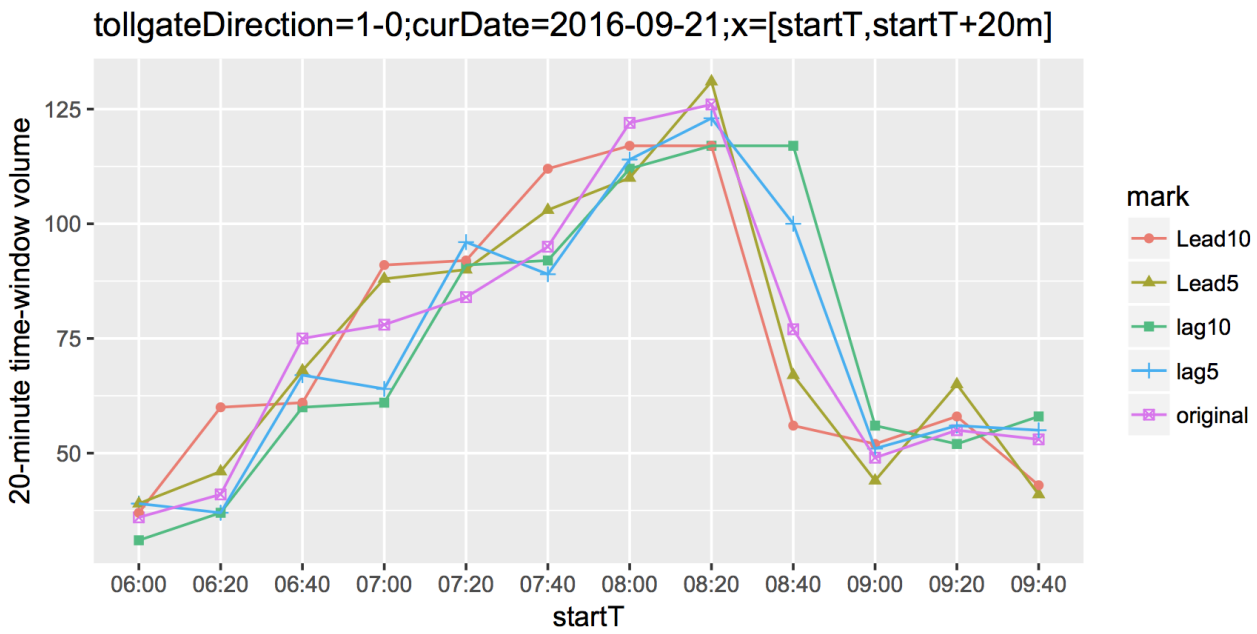
Experiment: Data Augmentation



π(Lead)	mean	sd	aveCor	π(Lag)	mean	sd	aveCor
...	...	...	...	...	...	...	...
3	0.157	5.53	0.954	-3	-0.199	5.61	0.954
5	0.224	7.39	0.915	-5	-0.327	7.41	0.919
10	0.358	11.18	0.812	-10	-0.693	11.51	0.838
15	0.562	14.67	0.717	-15	-1.079	14.45	0.737
20	0.714	17.89	0.621	-20	-1.47	17.42	0.638
...	...	...	...	...	...	...	...

Experiment

Experiment:Take last 7 days (Oct 18 to Oct 24) as test data (leaderboard), the remains as training data.

Model	Data	Approach	MAPE
LR	original	Log-Trans	0.146
KNN	original	Abs-Dist	0.140
GBDT	original	Gaussian	0.147
LightGBM	original	Log-Trans	0.133
LightGBM	original, ±1, ±5, ±10	Log-Trans	0.1222
NN	original, ±3, ±5	Quantile	0.1219
Ensemble		Weighted Average	0.1150

Experiment

Performance of Neural Network:

- Laplace/Quantile regression for absolute loss $|\hat{y} - y|$.
- Two NN Model results, eg, "with-dropout" A and "without-dropout" B.
- $\alpha \cdot min(A, B) + (1 - \alpha) \cdot max(A, B)$ $(\alpha \in [0.5, 0.7])$.
- Apply cross-validation to find the best α $(\alpha \in seq(0.5, 0.7, by = 0.05))$.
- Train with "adadelta" for adaptive learning rate.

Model	Data	Approach	MAPE
3-Layers	original	gaussian	0.144
3-Layers	original	new	0.138
3-Layers	original, ± 3, ± 5	...	0.133
2-Layers	original, ± 3, ± 5	...	0.1277
1-Layer	original, ± 3, ± 5	...	0.1219

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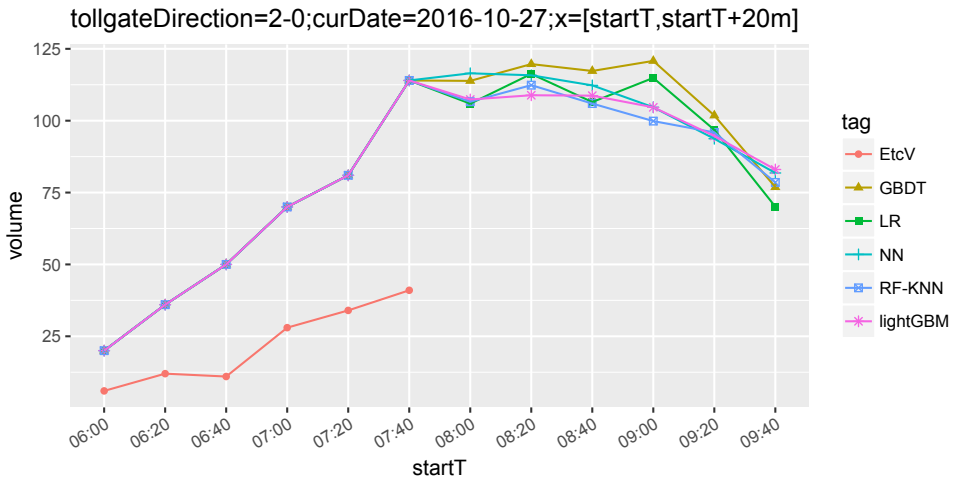
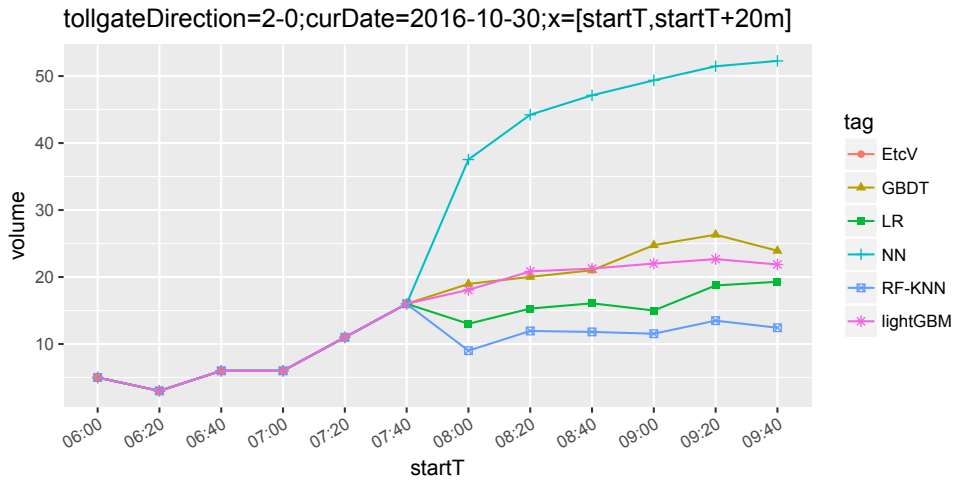
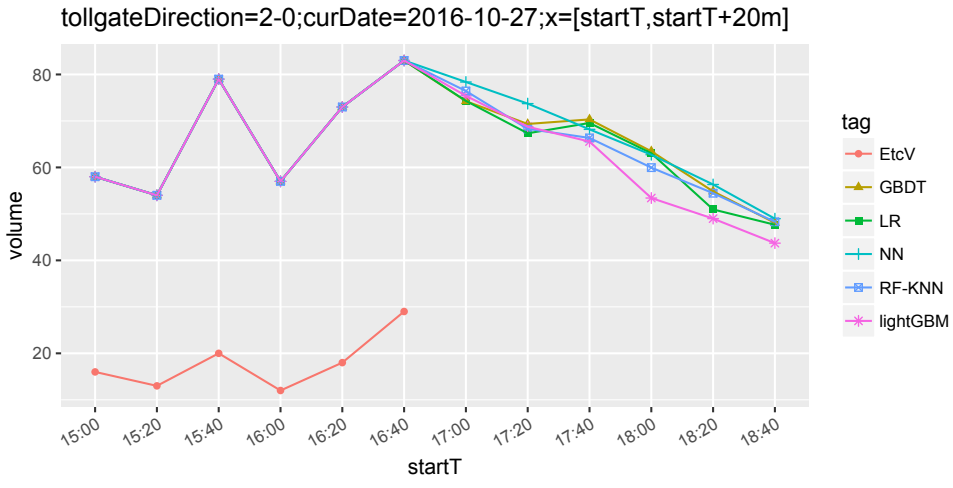
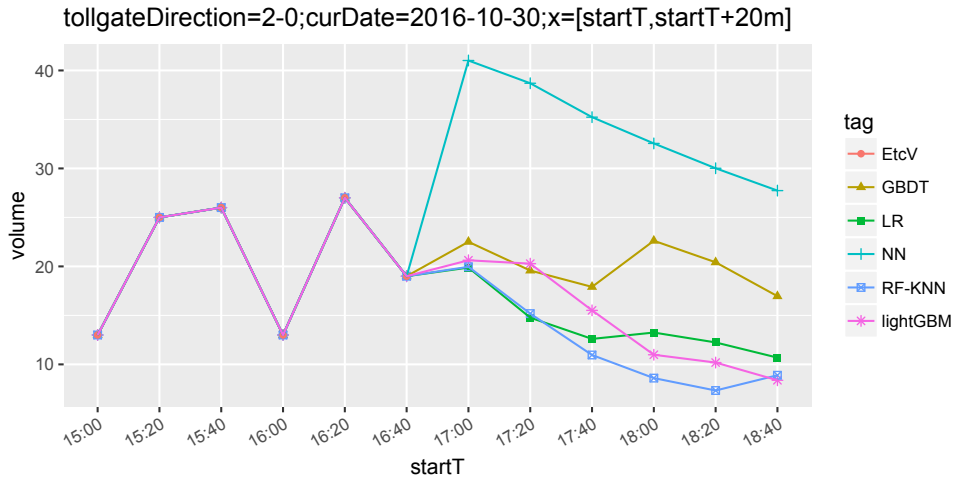
Decision Making: which models can we trust?





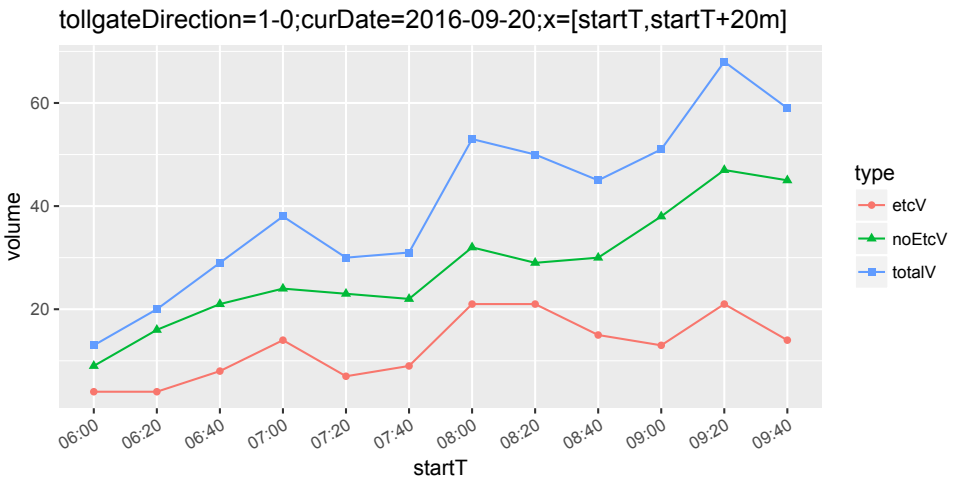


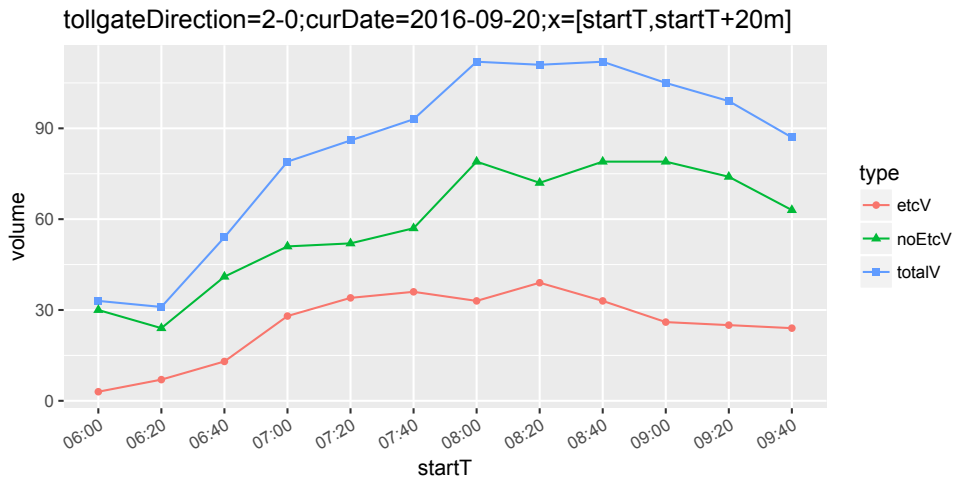


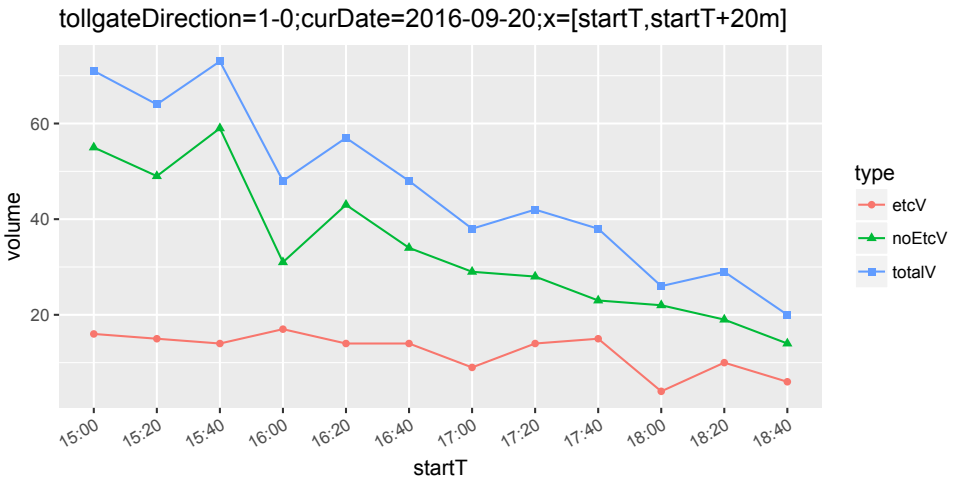
Normal model results.

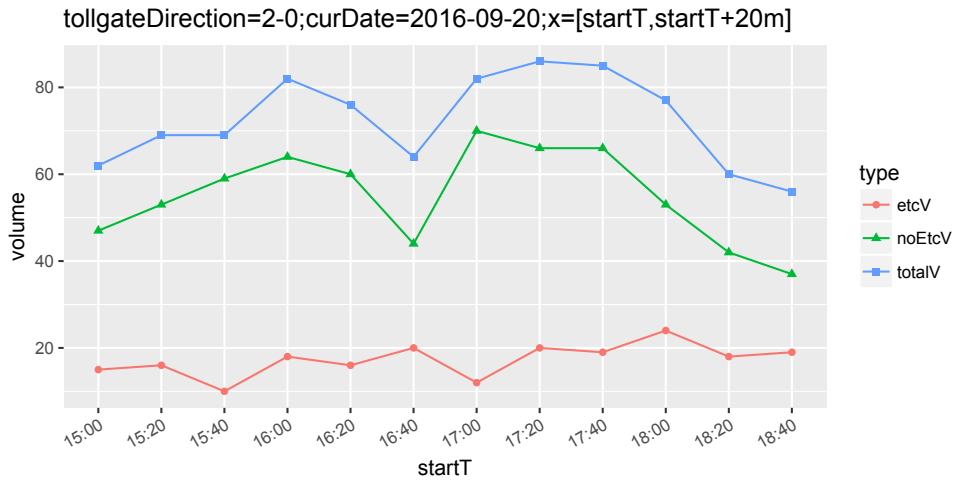
Huge differences among model results

Observation: Normal days







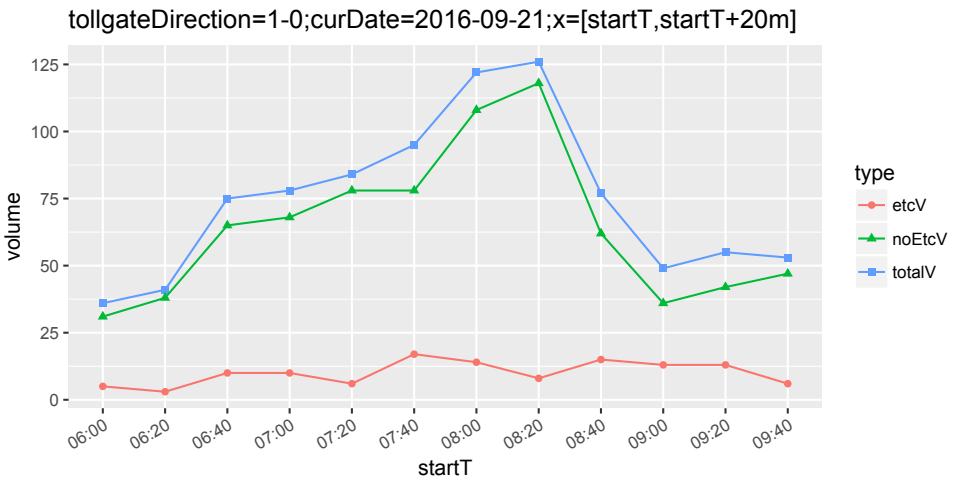


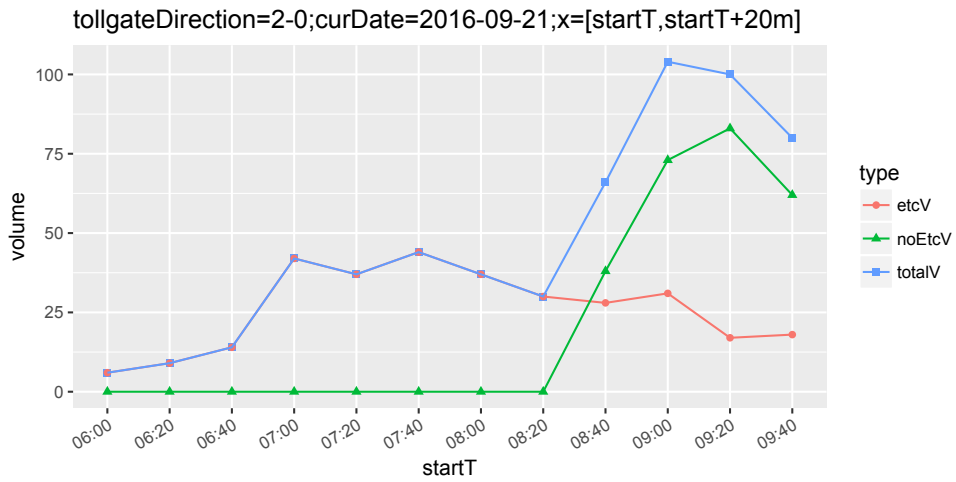
ETC introduction guide

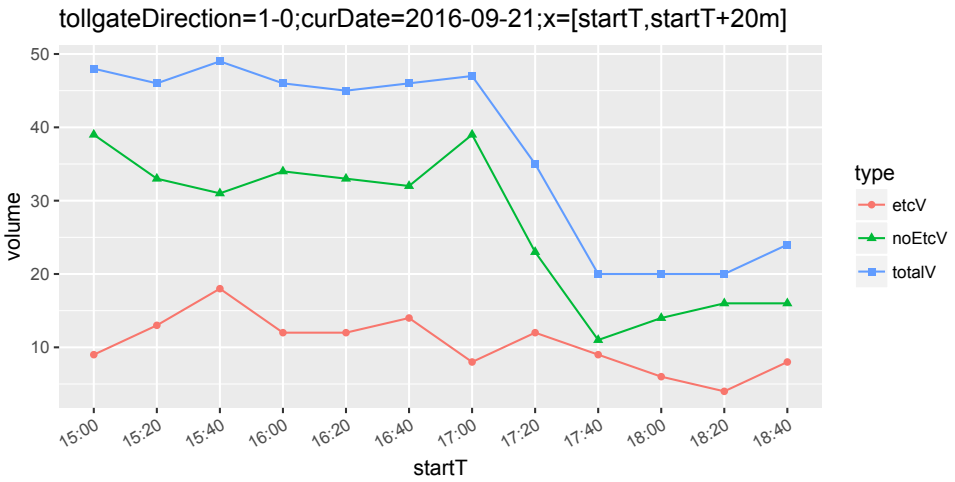
The ETC in-vehicle device

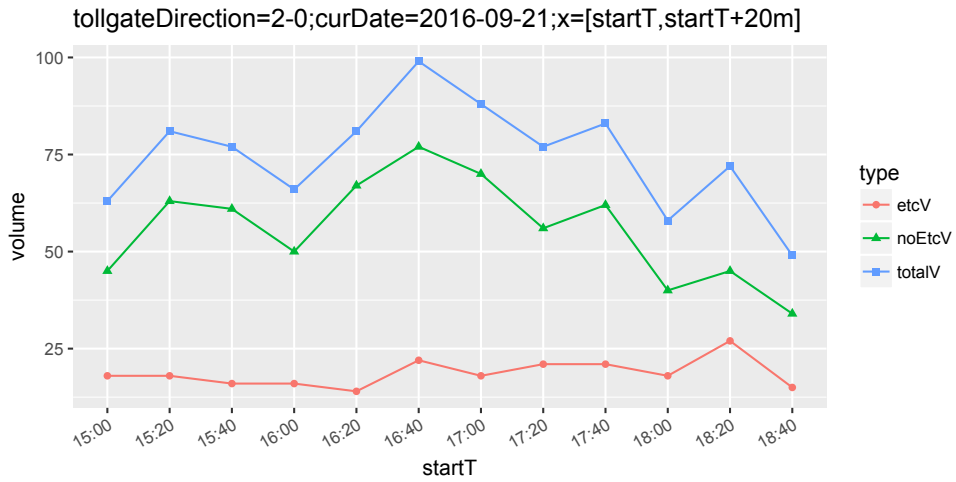
ETC systems can be used simply by inserting the ETC card into the in-vehicle device. The ETC in-vehicle device is equipped with a function which wirelessly communicates with the antenna set up at the toll booths to send and receive vehicle information necessary for paying the appropriate toll fare.

Observation: Abnormal days









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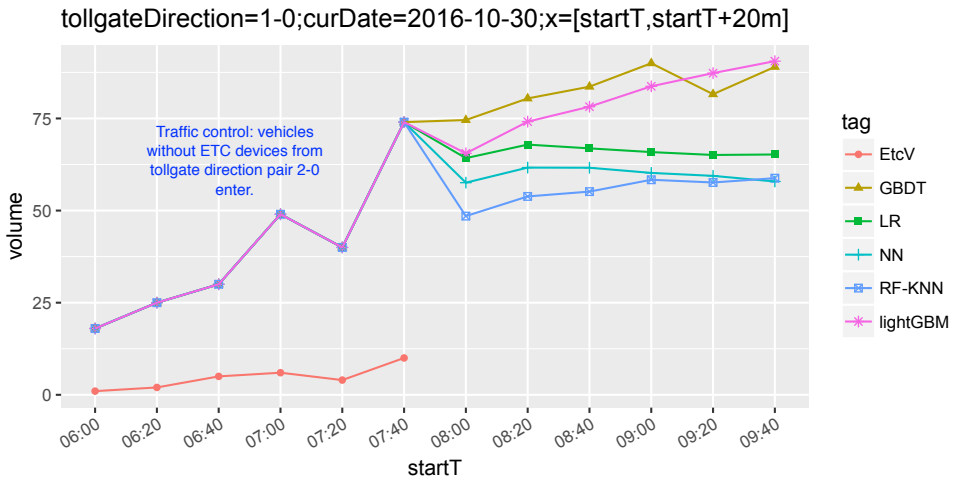
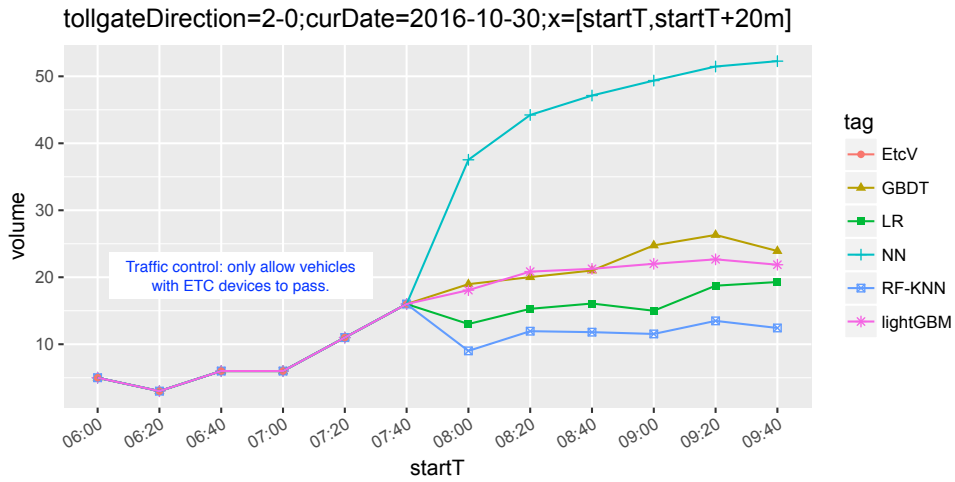
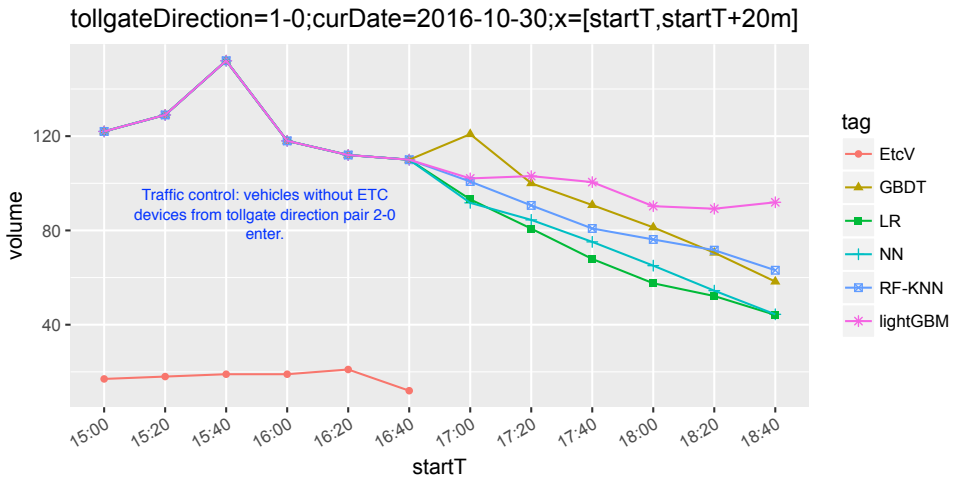
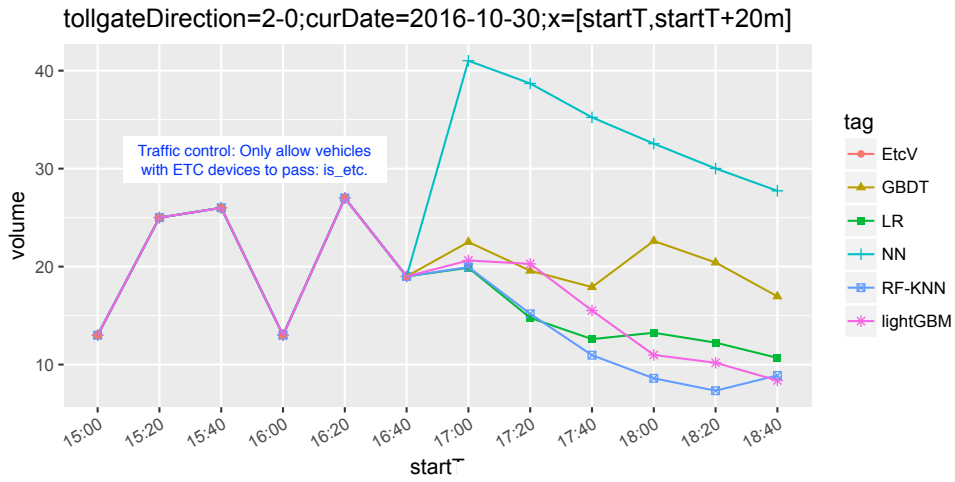
Analysis and Inference









Decision Making Continued

Business Assumption

- Total traffic volumes entering tollgate 1,2 are stable (1-0, 2-0).
- When tollgate 2 only allow is_etc vehicles to enter, those without ETC devices will turn to tollgate 1 (1-0).

Model Selection

- Build new baseline models with data:
  - 2-0: is_etc volume data.
  - 1-0: total volume + no_etc volume of 2-0.
- Bagging of selected model result(s) close to the baseline model results.

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Thank you!

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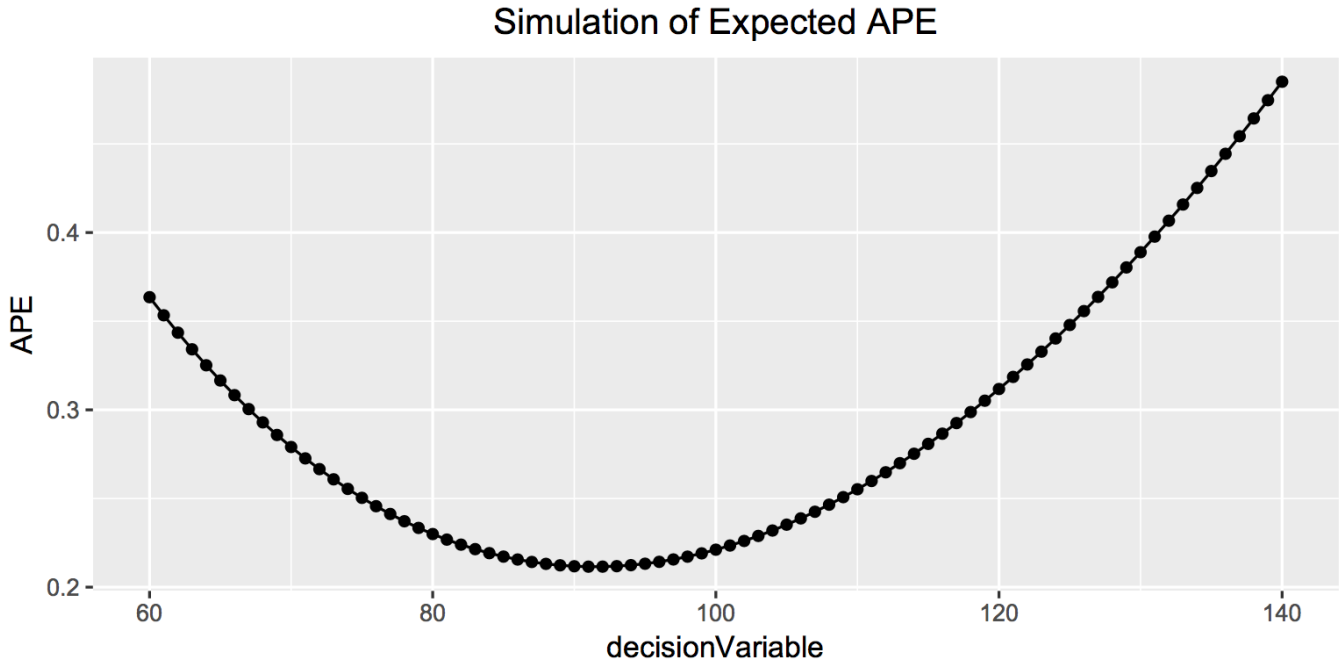
Appendix: Quantile regression approach

- We are trying to minimize the APE (absolute percentage error) $|\frac{\hat{y}-y}{y}|$ for every training sample.
- Laplace/quantile regression(with quantle_alpha=0.5) minimize the absolute error $|\hat{y}-y|$.
- Assume the true value y randomly distributed around the predicted value $\hat{y}$.
- We want to do optimal decision $\hat{y}_2$ that minimize the expected APE.
- A decision variable of $\hat{y}_2$ which is a little smaller than $\hat{y}$ achieve better(smaller) absolute percentage error.

Example: prediction value $\hat{y} = 100$, true value follows discrete uniform distribution in the interval $[60, 140]$.



Appendix: Neural network training details

- Apply randomized grid search with parameters list below.
- Bagging of blend of top-K results.

parameters	list
activation	"Rectifier","Tanh"
l1,l2 regularization	c(0, 1e-3, 1e-4, 1e-5, 1e-6, 1e-7)
input_dropout_opt	c(0,0.05,0.1,0.2)
max_w2_opt	10,20,30,40,50
adadelta-epsilon	c(1e-4,1e-6,1e-8,1e-10)
adadelta-rho	c(0.9,0.95,0.99,0.999)

grid search parameters list