KDD CUP 2017 Travel Time Prediction
Predicting Travel Time – The Winning Solution of KDD CUP 2017

Team: Convolution

Ke Hu

Bing Ads, Microsoft

Pan Huang

Bing Ads, Microsoft

Huan Chen

Beihang University(Master Candidate, CS)

Peng Yan

Meituan-Dianping

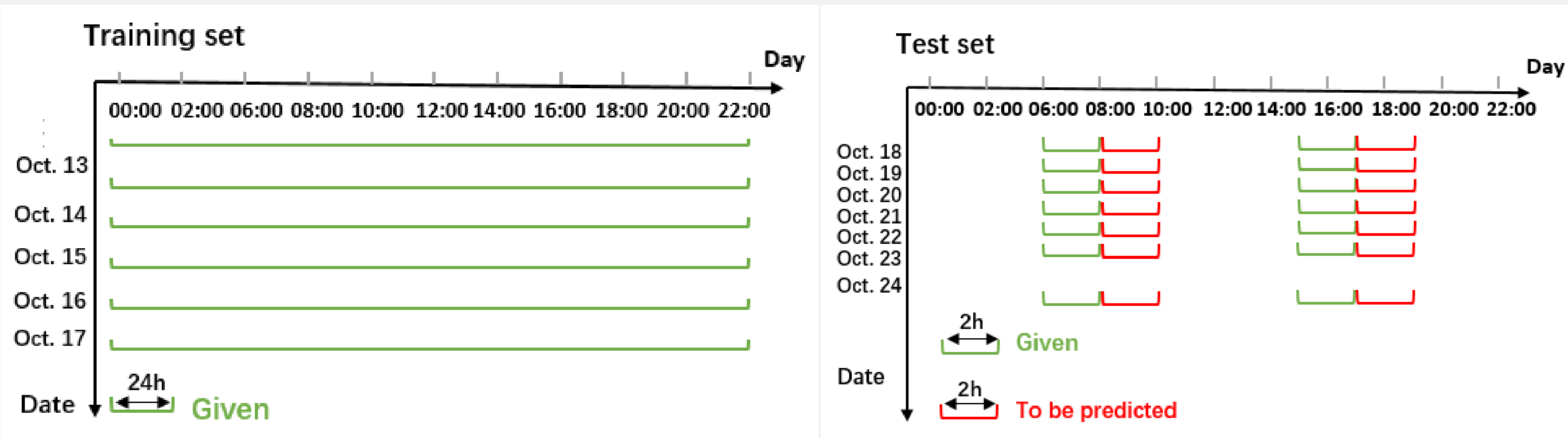
Outline

- Task understanding
- Features
- Models
- Summary

Task Understanding

Problem Definition

Task	To estimate the average travel time from designated intersections to tollgates
Metrics	$MAPE = \frac{1}{R}\sum_{r=1}^{R}\left(\frac{1}{T}\sum_{t=1}^{T}\left\lvert\frac{d_{rt}-p_{rt}}{d_{rt}}\right\rvert\right)$
Data	• Vehicle trajectories along routes • Weather data in the target area • Road topology



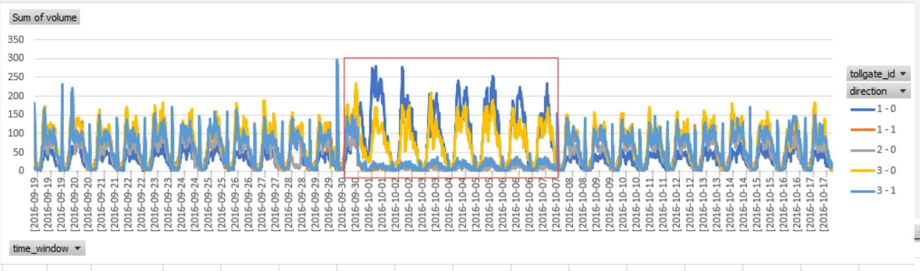
Task Understanding

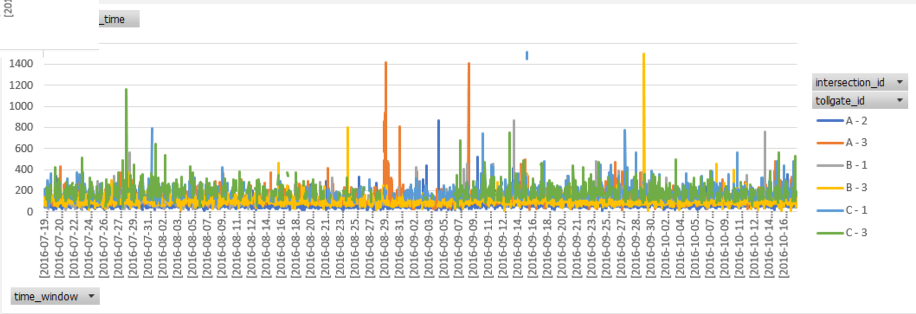
Challenges

- Data is **noisy and sparse**, easy to overfit to specific validation data
  - Hard to conduct offline experiments

- **Small abnormal values** have big impact on final metrics, especially considering MAPE evaluation

- Time sequence is hard to predict, especially the following pattern of the next six windows

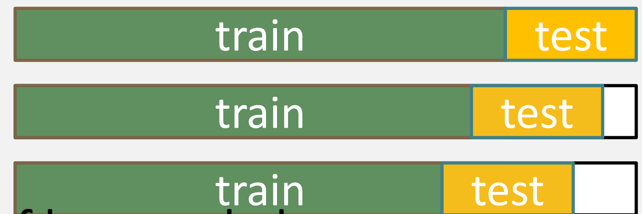




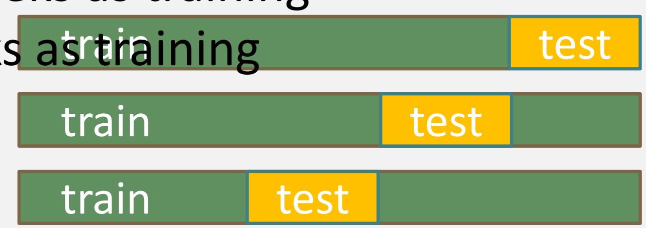
Task Understanding

More Effective Validation Methods

- Moving window based CV split
  - Use Last 2-8 days as validation, last 9-98 days as training
  - Use Last 3-9 days as validation, last 10-98 days as training



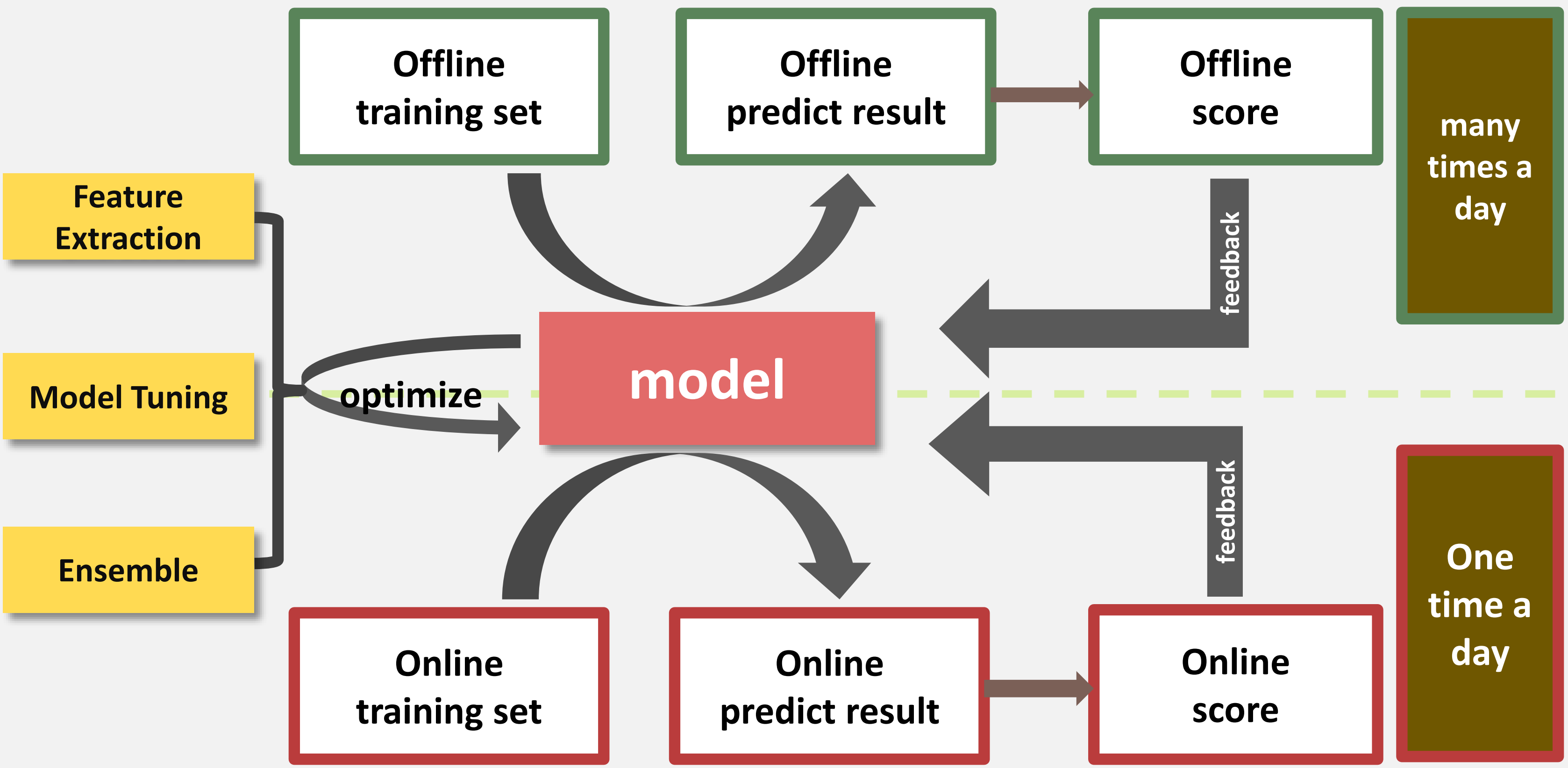
- Interval K-fold based CV split (know the impact of last week data for train)
  - Use second week as validation, other weeks as training
  - Use third week as validation, other weeks as training



- Use online leaderboard feedback to determine the weight of validation sets
  - totally 13 CV sets used, much more consistent with online feedback

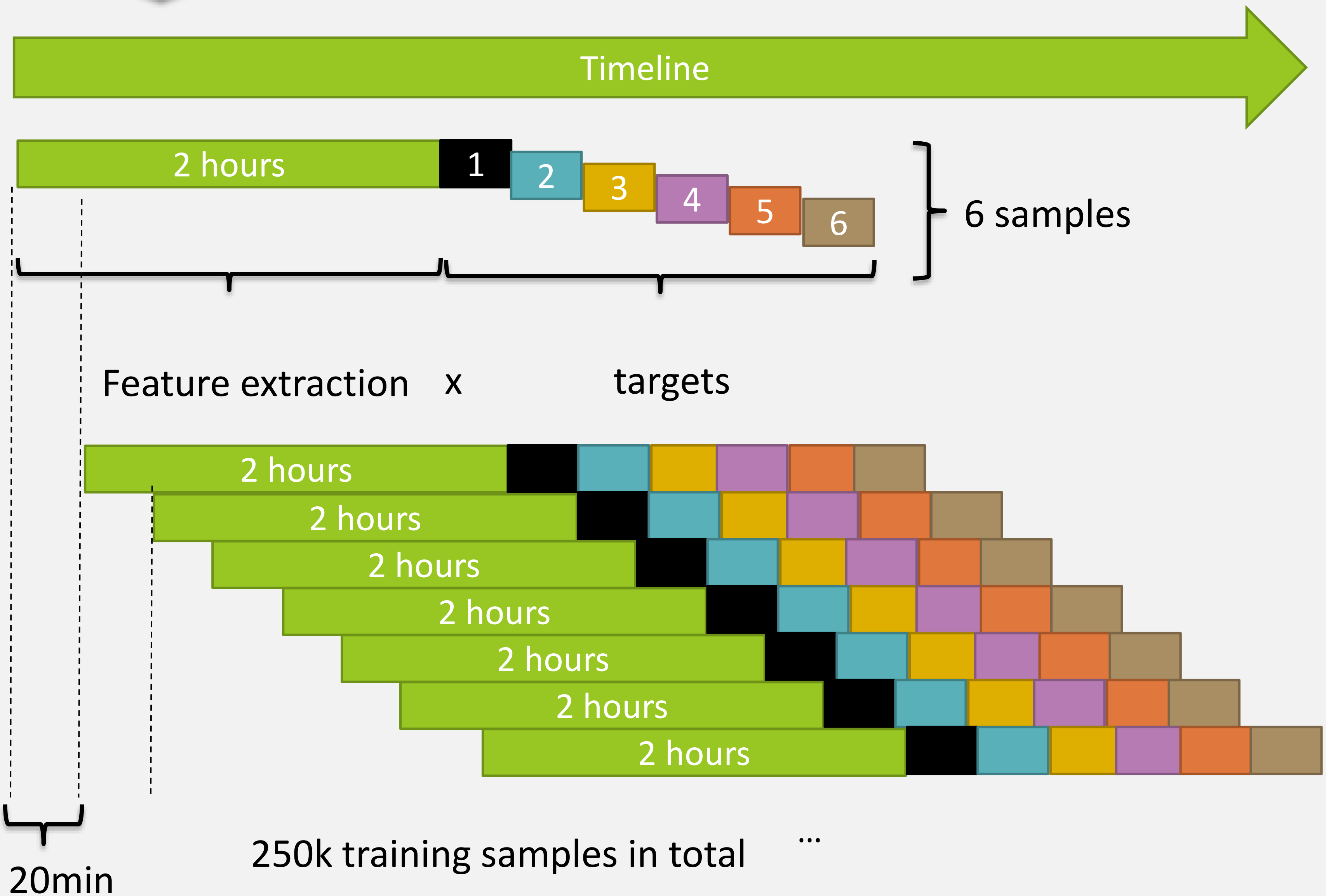
Task Understanding

Workflow



Features

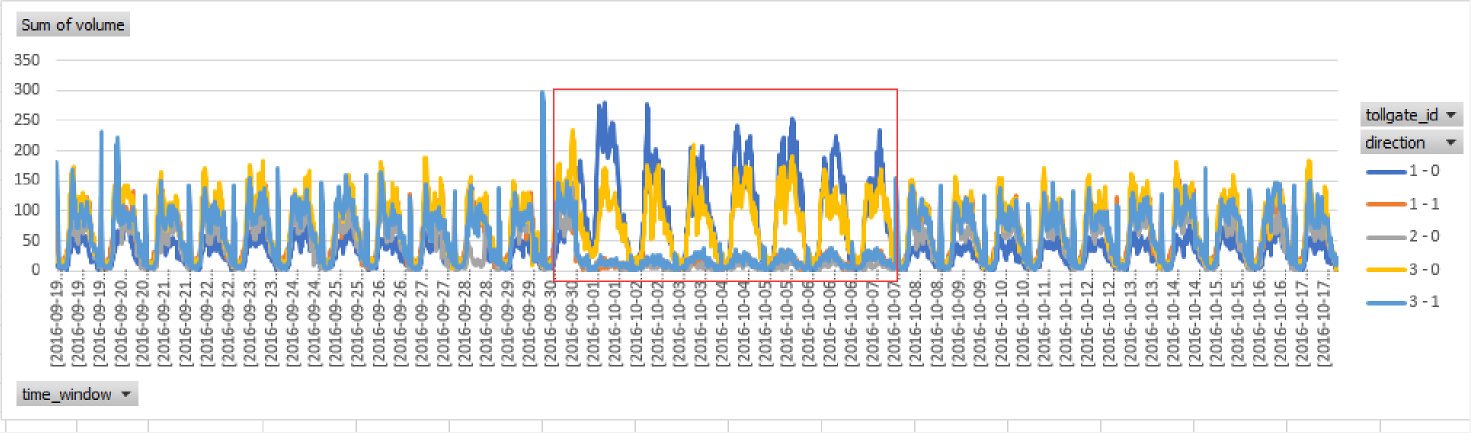
Data Augmentation



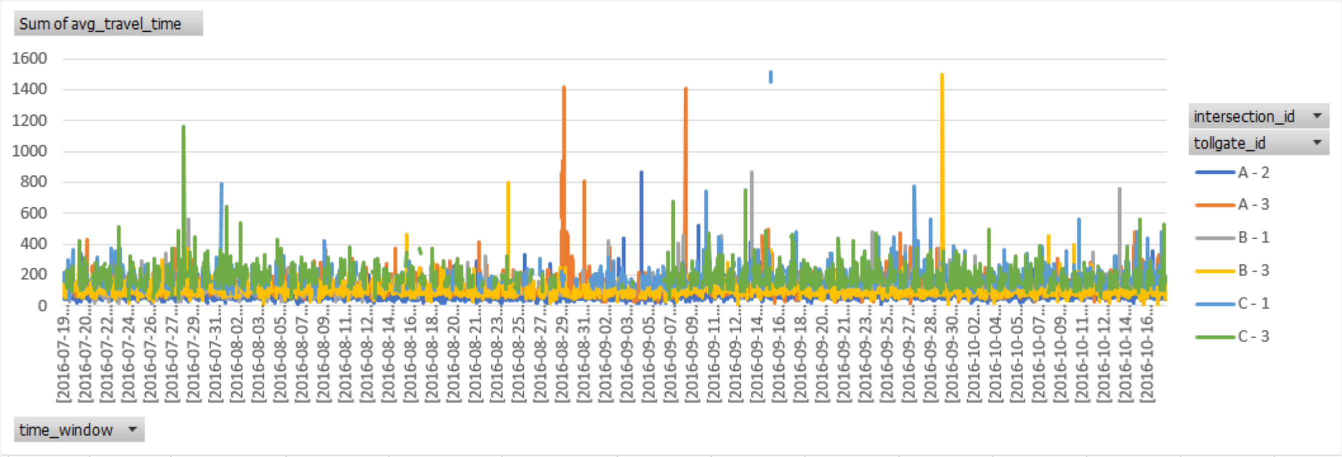
Features

Data Preprocessing

- Remove holiday days' traffic



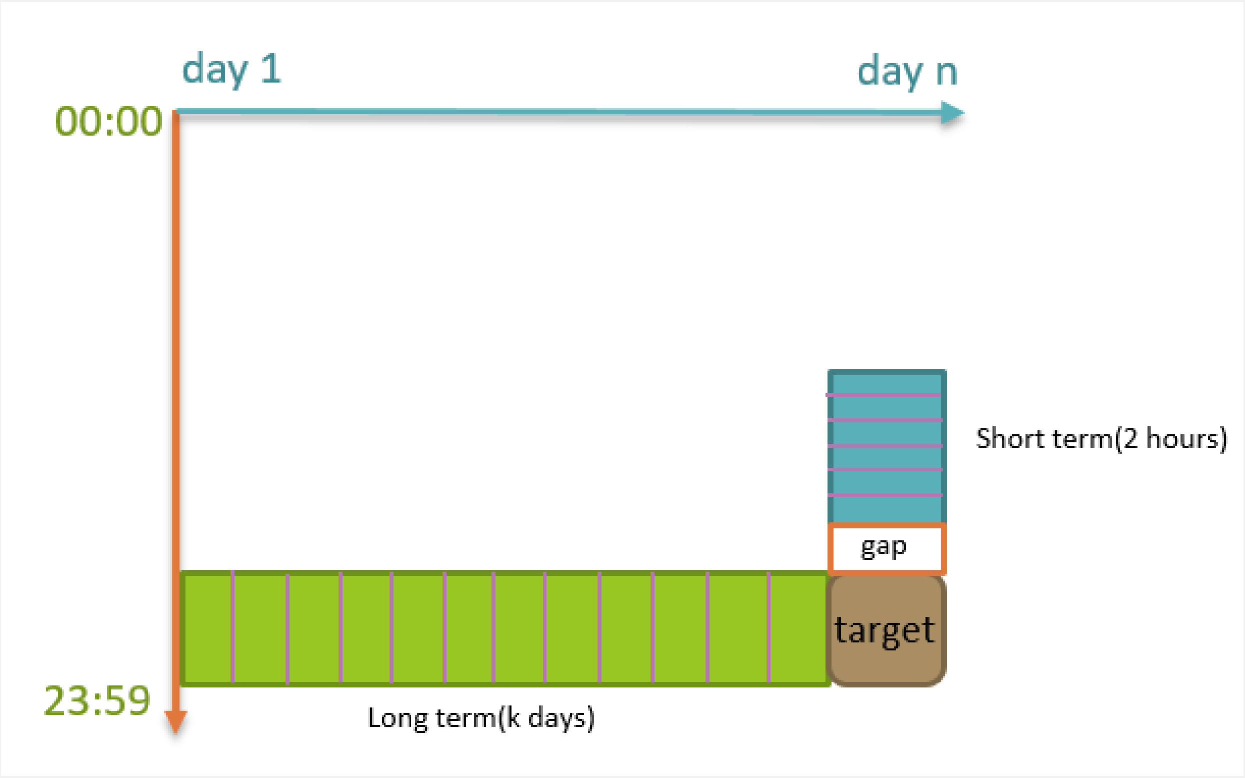
- CV based denoise



Features

Feature Extraction

Aggregate information from 2 dimensions



Basic Features

- Time
- Road

Session Level Features

- Last K cars statistics
- Moving window statistics

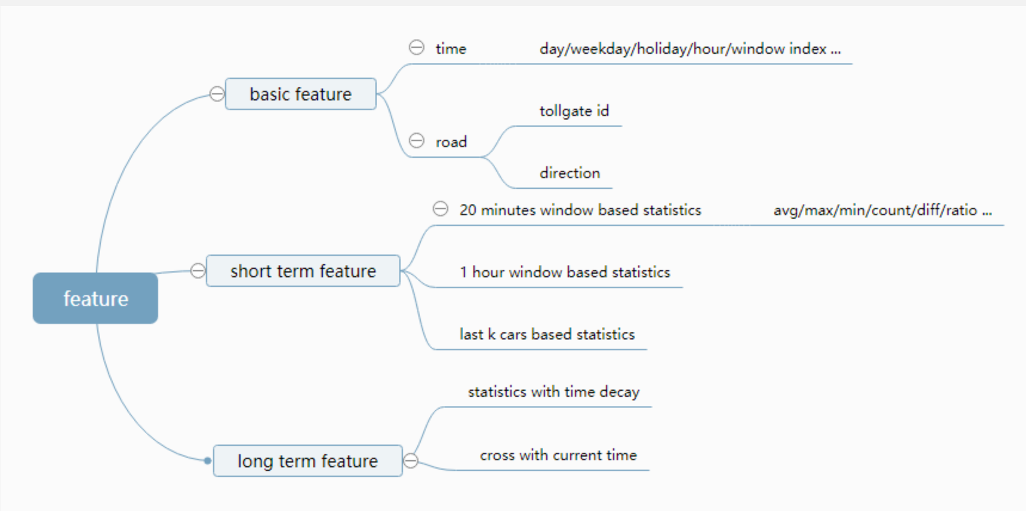
Long Term Features

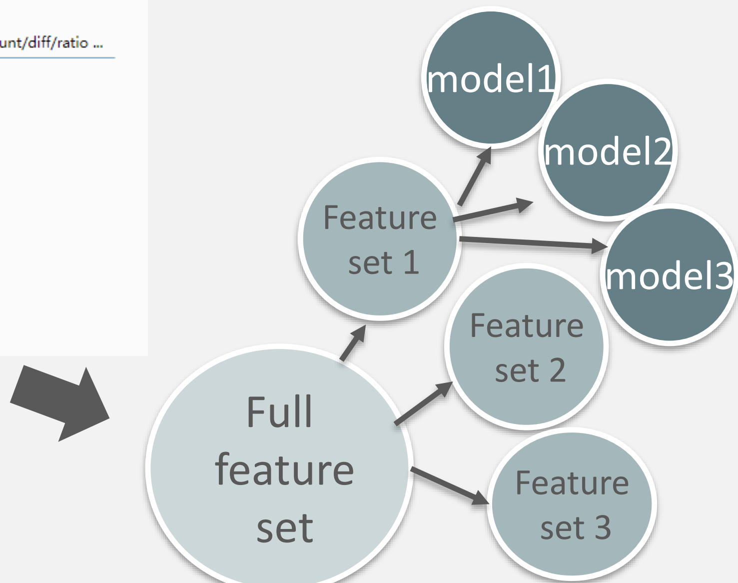
- Use exponential decay factor to conduct statistics

Features

Feature Engineering

- More than 100 features are extracted
- Feature selection based on CV experiments and online feedback
- Multiple feature combinations are used for ensemble, solving feature conflict



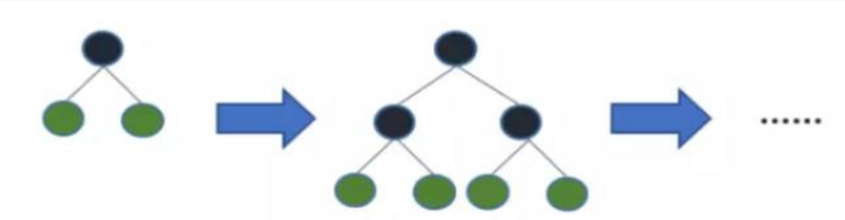


Models

Tree Based Model

XGBOOST

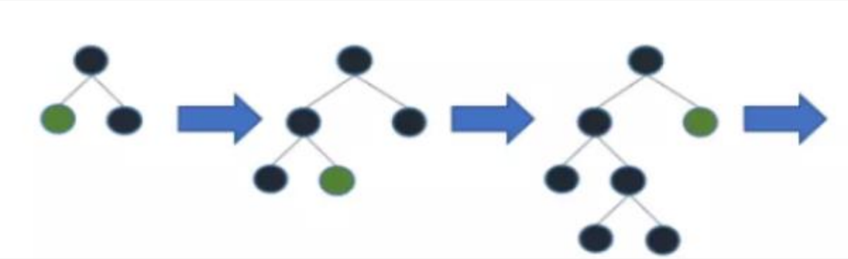
- Level-wise growth strategy
- Stable



Level-wise tree growth

LightGBM

- Leaf-wise growth strategy
- Good algo for category feature
- Very Fast



Leaf-wise tree growth

Model Tuning

- Every fold has a stop round, using CV fold weight to determine the full data stop round

Sample Weight

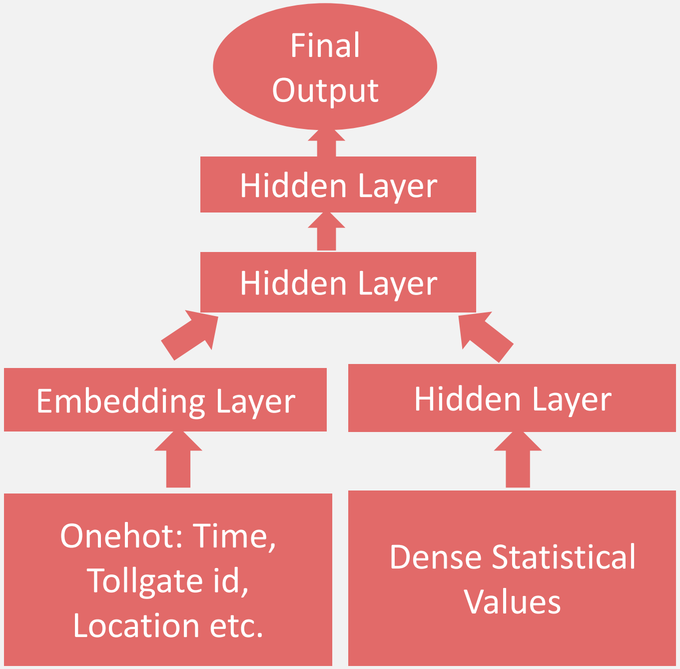
- Use 1/label as sample weight, make the little value samples learnt better

Models

Neural Network

One Hot Embedding

- Using embedding layer for basic feature
- Similar location's embedding vector is close



Early Interaction vs Later Interaction

- The balance of learning between embedding part and statistics part

MLP vs RNN

- Multiple Layer Perception: Powerful Expression Ability, Learn feature interaction
- Recurrent Neural Network: Good to model sequence relationship, but unstable for generalization

Models

Ensemble

Data Level Ensemble

- N-fold Validation model ensemble without retrain
- Global model and separate district model
- Use 2,10,20 minutes as moving window to construct samples

Feature Level Ensemble

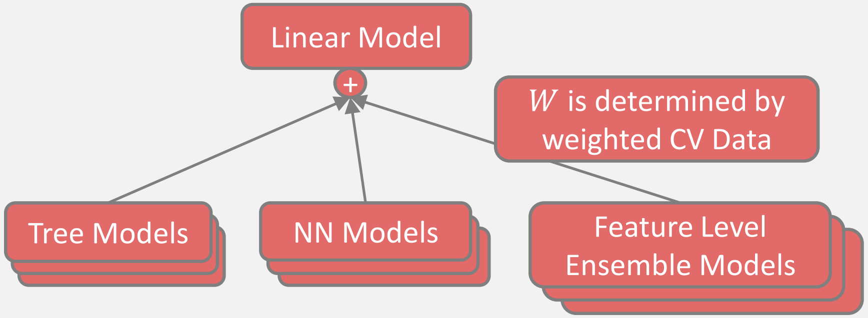
- Different Exponential decay factor or smooth factor for statistics features
- General route feature and link feature bagging
- Long term statistics and short term statistics ensemble

Models

Ensemble

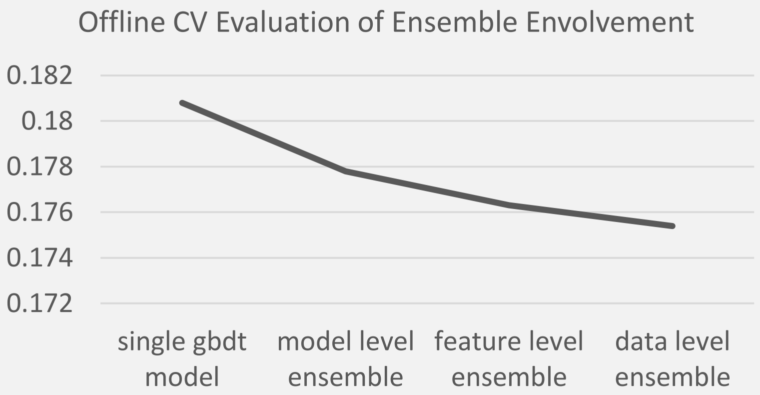
Model Level Ensemble

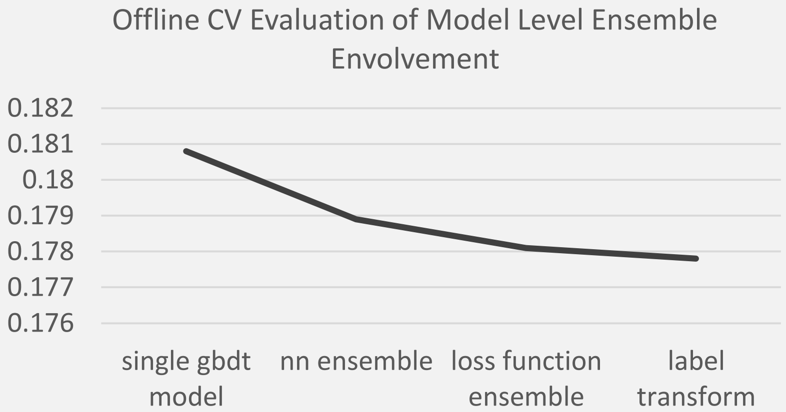
- Different ml models, including xgb, lightgbm, dnn, rnn
- Loss function changes, weighted norm-2 and fair loss to approximate norm-1 loss
- Label transform, like customized log transform, and the sample weight transform
- Model parameter, like nn structure, gbdt parameters



Result

- Choose 13 base models base on multiple weighted cv and leaderboard feedback
- Finally, we got 0.1748 mape in leaderboard





Summary

Feature	Basic Feature, Session Level Feature, Long Term Feature
Model	XGBoost, LightGBM, Multiple Layer Perception
Ensemble	Weighted CV based, Log transform, Loss function etc.

Summary

Lessons Learn

- Pay more attention to data distribution, like data changes, noisy data
- Build scientific cross validation sets is very significant, and rely on CV much more than leaderboard
- Treating error composed of bias, variance and noise, try to decrease variance if bias is hard to decrease
- Think more and fine tuning less, or it will be easy to overfit to small data
- Understand the evaluation well, and design corresponding loss function
- Separate modeling is useful if data distribution differs a lot

Thanks

Q&A