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Supply-Demand Prediction for Online Car-hailing Services using Deep Neural Network

- **Objective**
  - Predict the gap between the car-hailing supply and demand in a certain area in the next 10 minutes.[1]
- *This problem is from [Di-tech Algorithm Competition 2016]*
- **Motivation**
  - Balance the supply-demand by scheduling the drivers in advance
  - Adjust the price dynamically

Definitions

Car-hailing order   valid (invalid)

1. Date   2. Timeslot   3. Passenger ID
4. Star area ID   5. Destination area ID

Environment data:

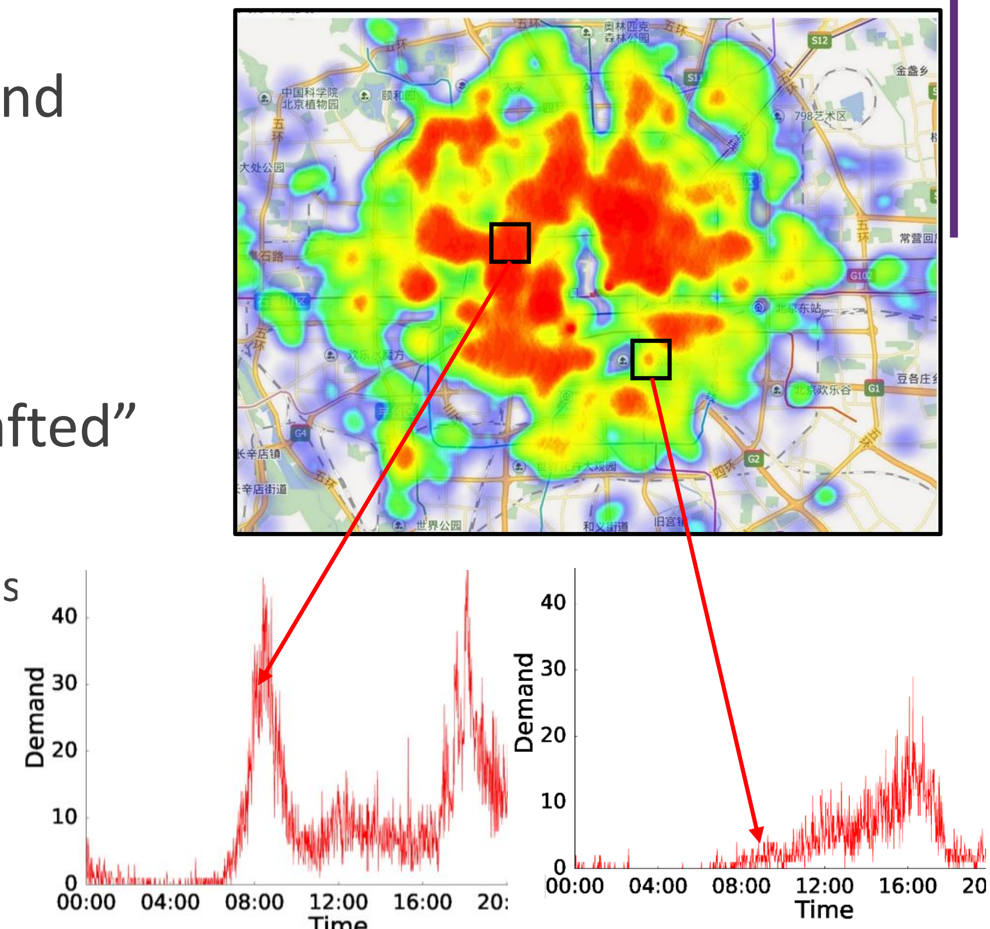
1. weather   2. traffic condition

Objective

Predict the supply-demand gap (e.g., the number of invalid orders) of a certain area, in the next 10 minutes.

Challenges

- The car-hailing supply-demand varies dynamically
  - geographic locations
  - time intervals.
- Standard models +“hand-crafted” features
- Logistic regression, SVM, random fores gradient boosting
- Various data types
  - Order, date, weather, traffic
- Various data sources



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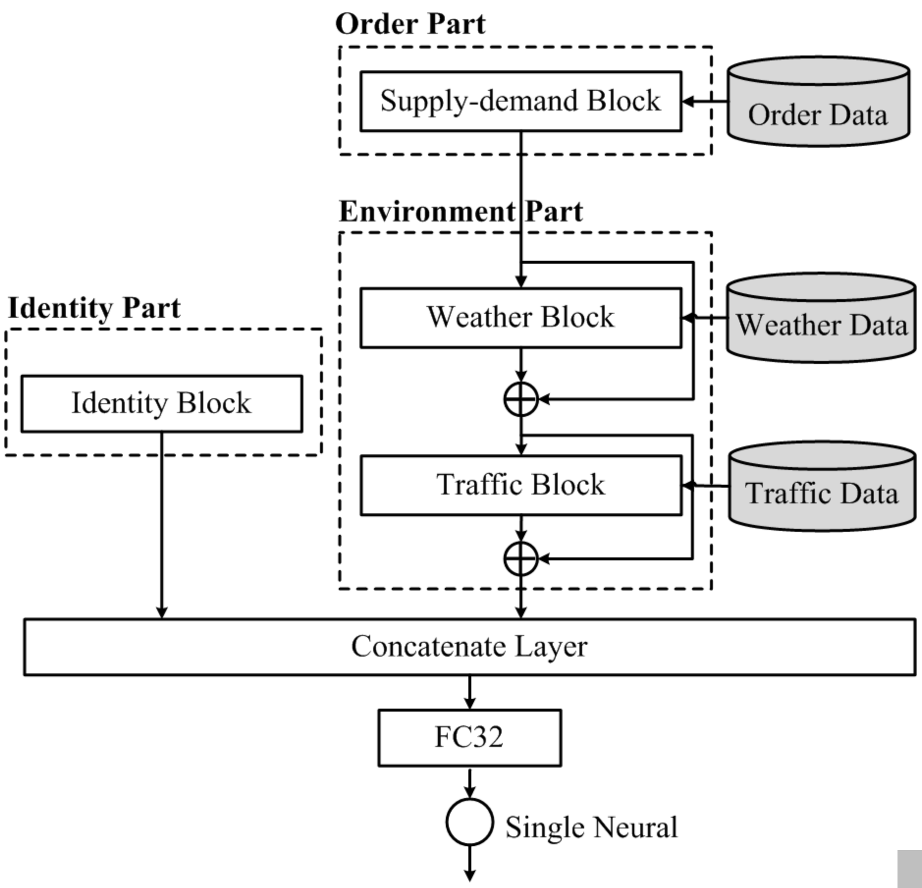
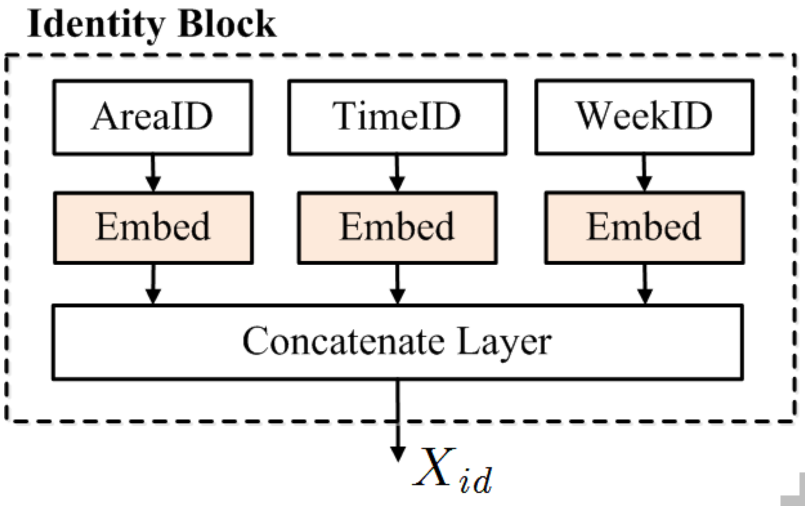
Framework

1. General blocks
2. Using embedding to "cluster" similar areas and timeslots
3. Learning the useful feature vector from the order data
4. Connecting different blocks with residual link
5. End-to-end model



Identity Part

- Different areas at different time can share similar supply-demand patterns.
- Prior work clusters the similar data :
  - Manually design the distance measure
  - Build several sub-models (business area, residential area, etc.)



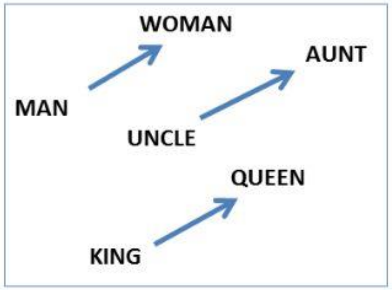
Embedding

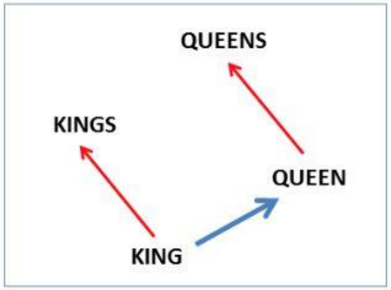
- Categorical value -> real vector

$$y_t = x_t \cdot W$$

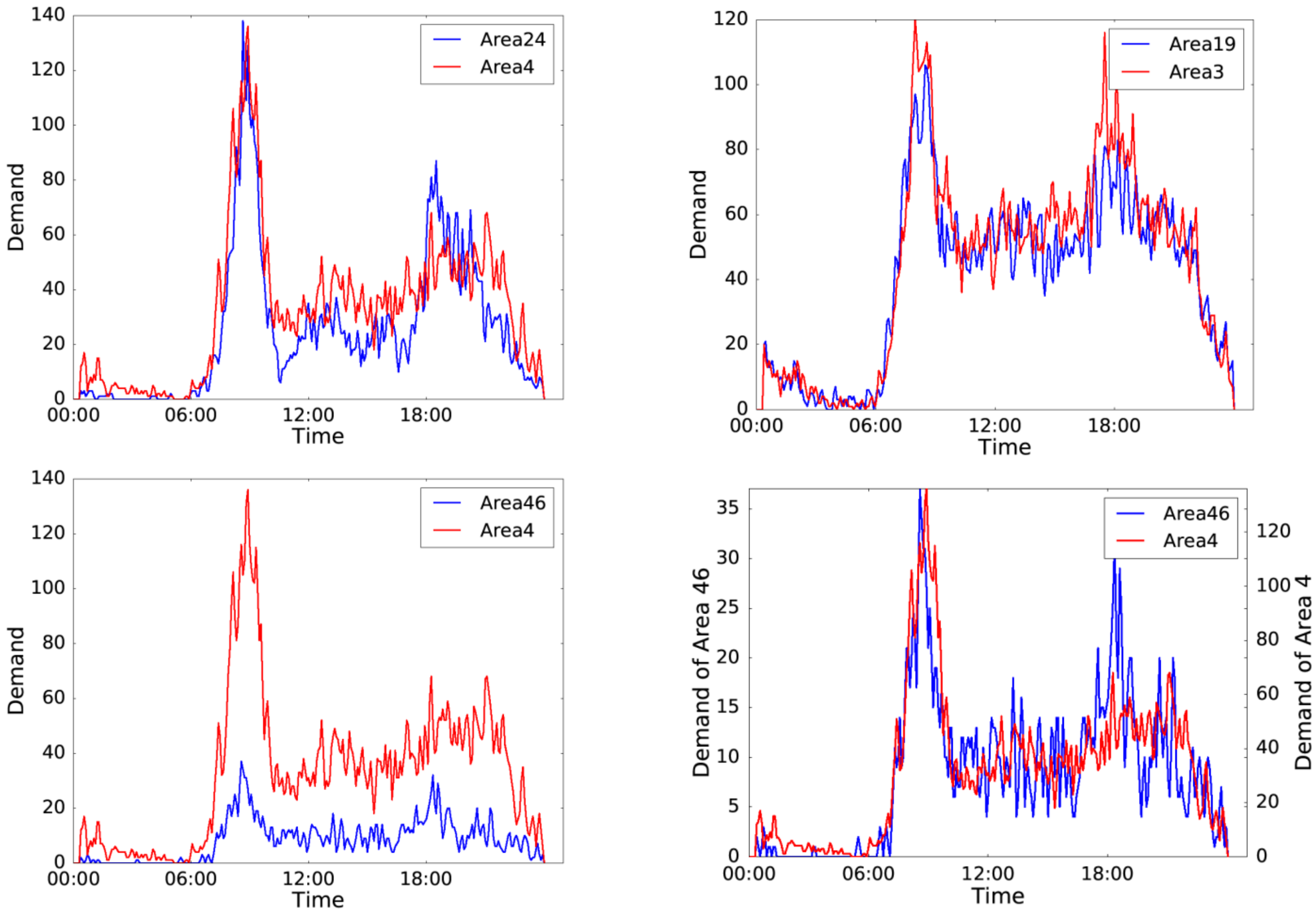
$$y_t = (-0.2, 0.4, 0.1) \qquad x_t = (0, 0, 1, 0, 0)$$

- Discover semantic similarity

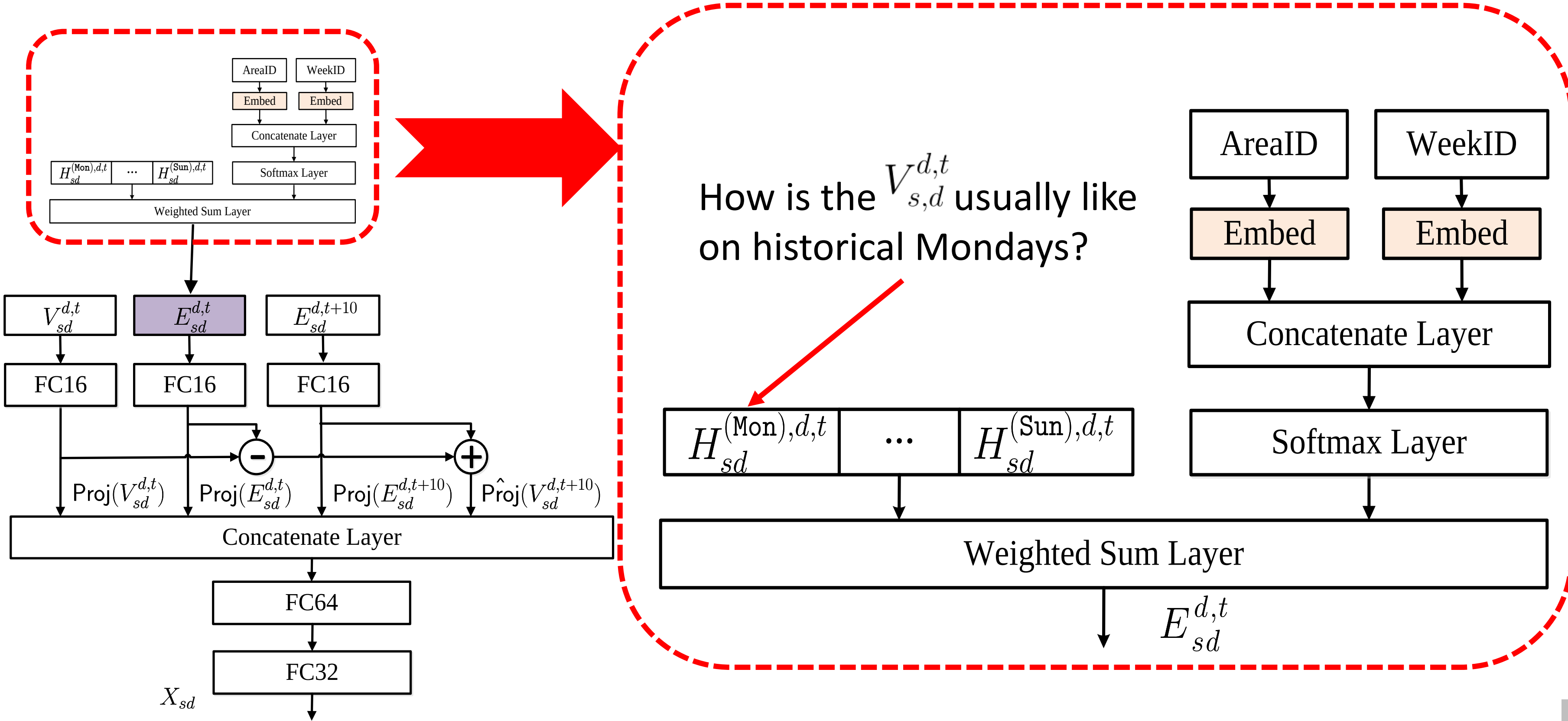




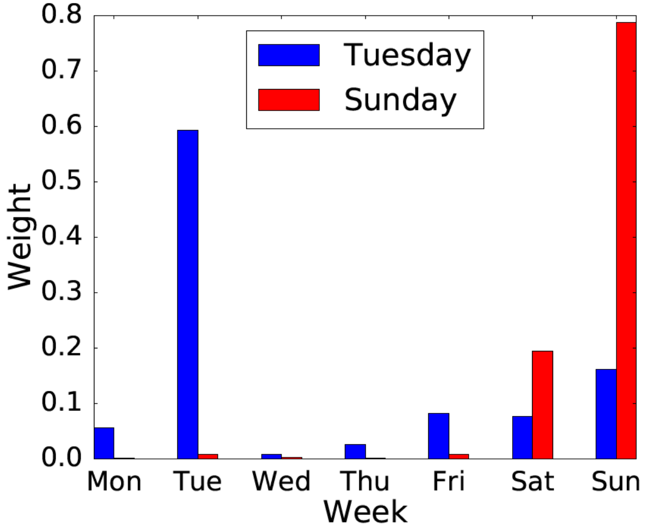
Effects of Embedding



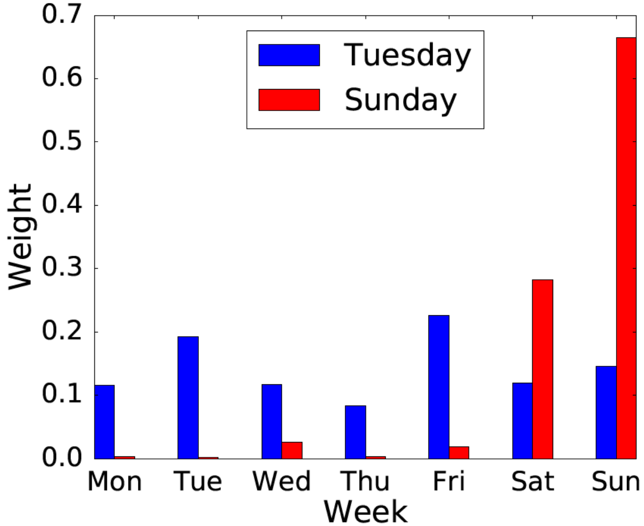
Order Part


AreaID
WeekID
Embed
Embed
Concatenate Layer
Softmax Layer
$H_{sd}^{(\text{Mon}),d,t}$
...
$H_{sd}^{(\text{Sun}),d,t}$
Weighted Sum Layer
How is the $V_{s,d}^{d,t}$ usually like on historical Mondays?
$E_{sd}^{d,t}$
$V_{sd}^{d,t}$
$E_{sd}^{d,t+10}$
FC16
FC16
FC16
Proj$(V_{sd}^{d,t})$
Proj$(E_{sd}^{d,t})$
Proj$(E_{sd}^{d,t+10})$
$\hat{\text{Proj}}(V_{sd}^{d,t+10})$
Concatenate Layer
FC64
FC32
X_{sd}

Effects of Embedding



Area 1

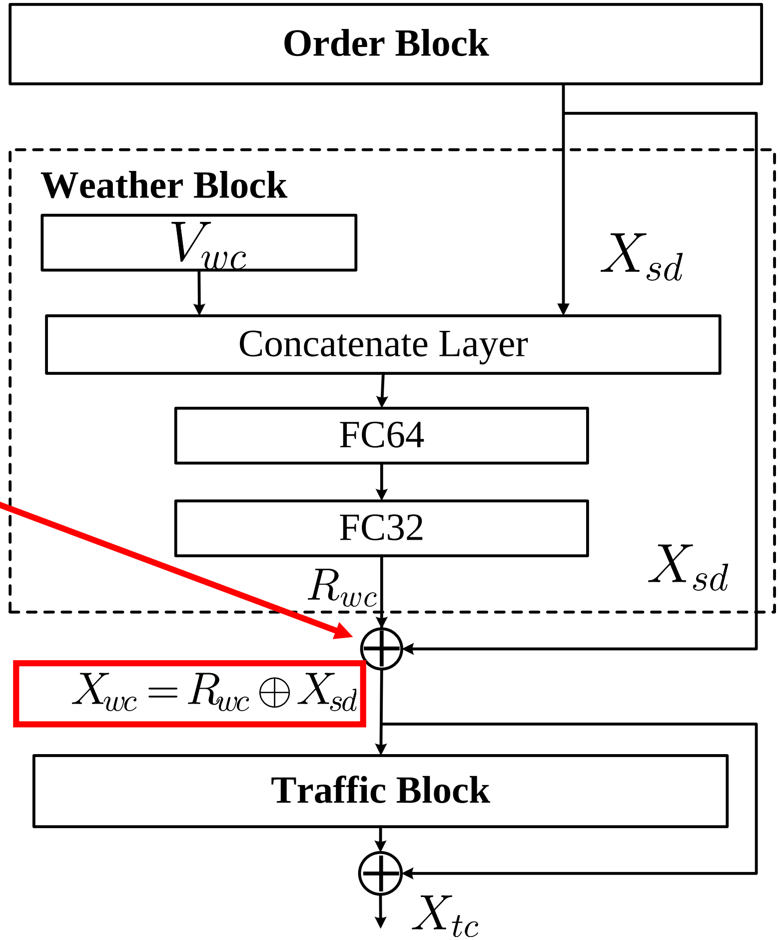


Area 26

We visualize the weight vectors in two different areas at Tuesday and Sunday.

Residual links

- Weather Block
- Residual link
  - Take the output of weather block as the “residual”
  - Makes the model more flexible to incorporate new data



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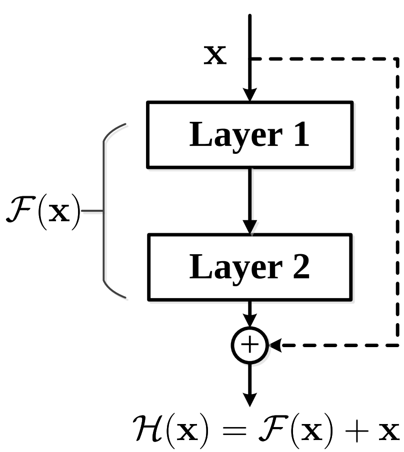
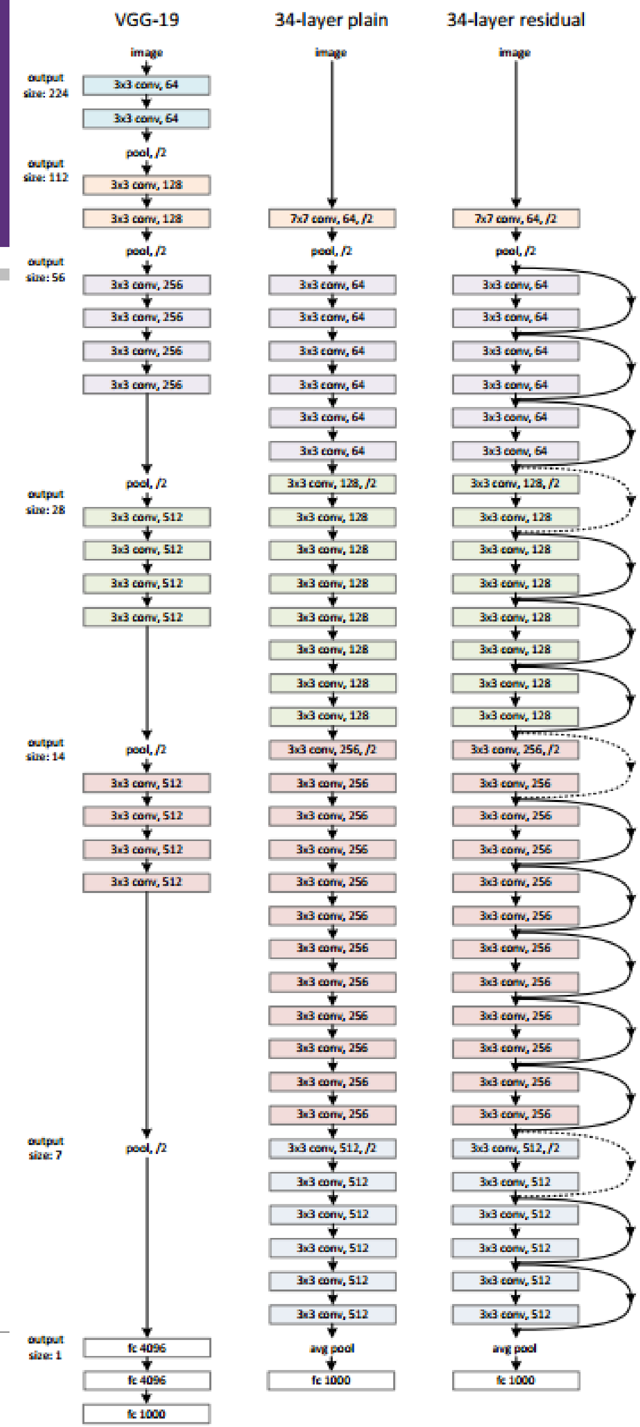
Deep Residual Networks[1]

- Train very deep neural network
  - Gradient vanishing/exploding problem
- Add connections between layers

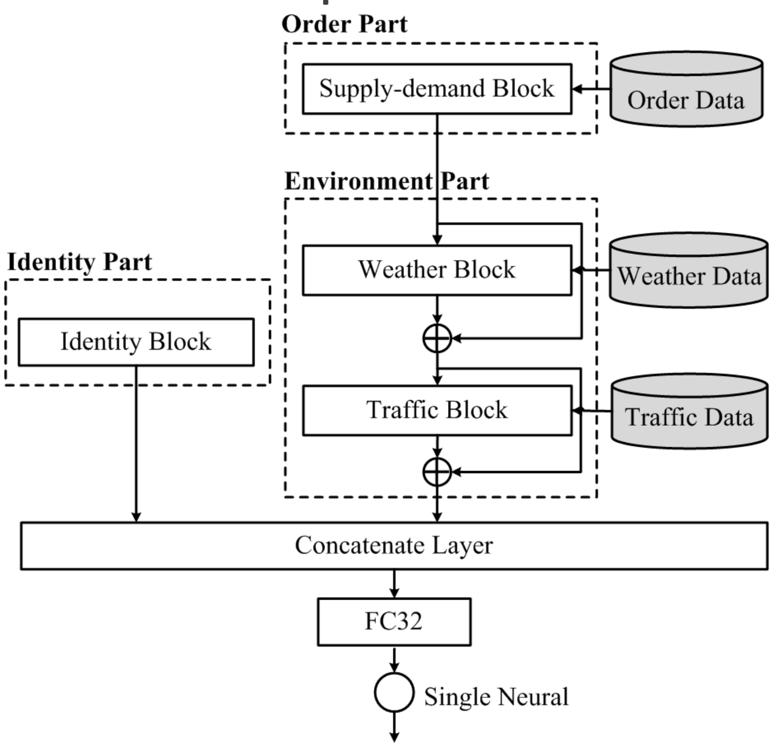


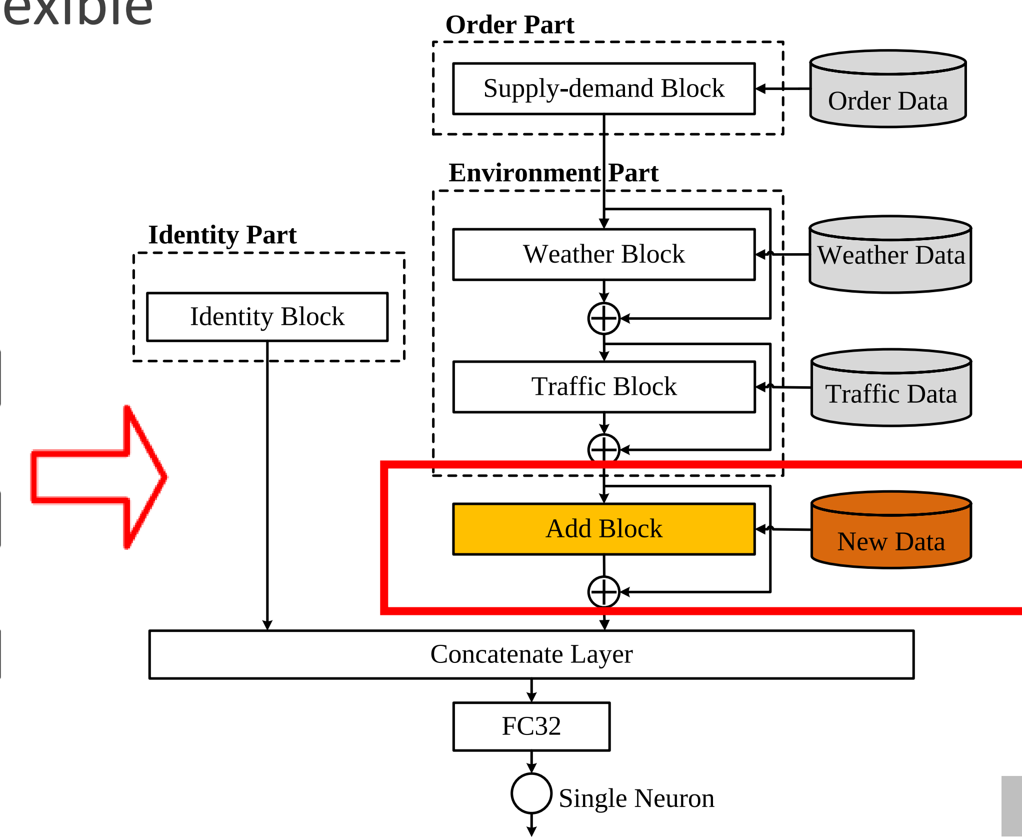


[1] He, Kaiming, et al. "Deep residual learning for image recognition." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.

Incorporate New Data

- Makes the model more flexible to incorporate new data



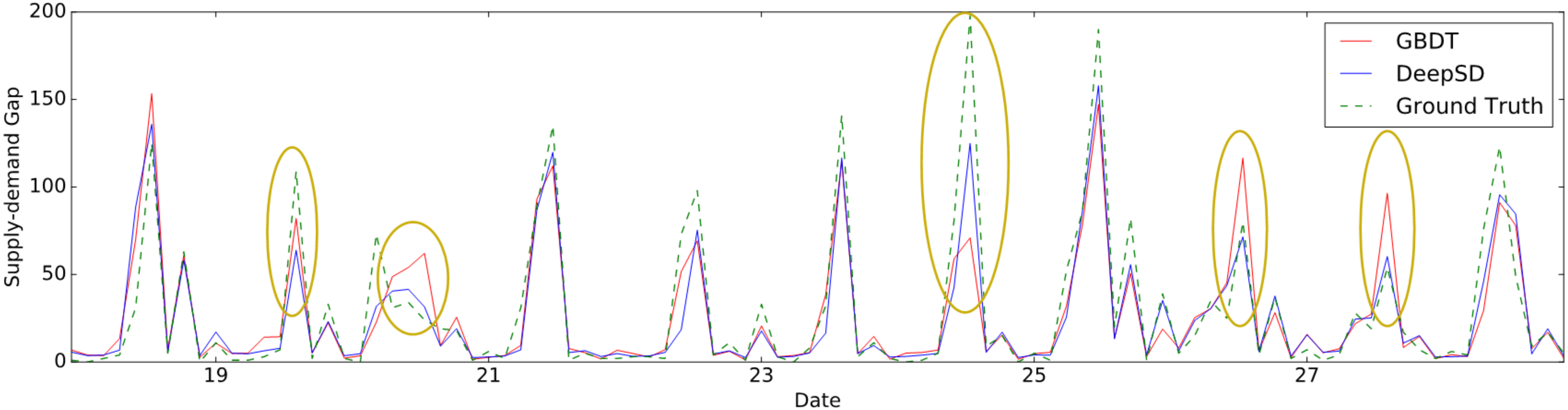


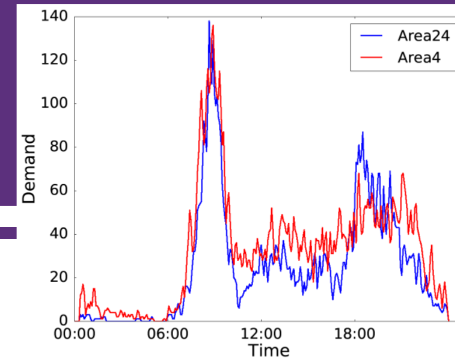
Experiment

Table: Performance Comparison

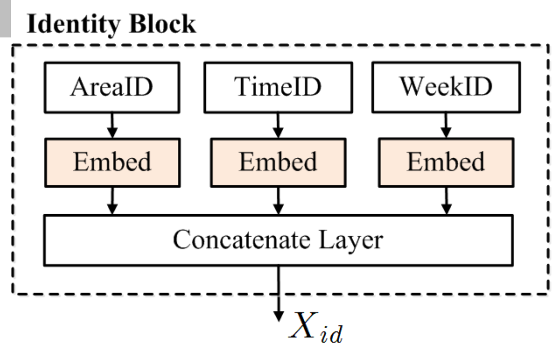
Model	Error Metrics	
	MAE	RMSE
Average	14.58	52.94
LASSO	3.82	16.29
GBDT	3.72	15.88
RF	3.92	17.18
Basic DeepSD	3.56	15.57
Advanced DeepSD	**3.30**	**13.99**

Experiment

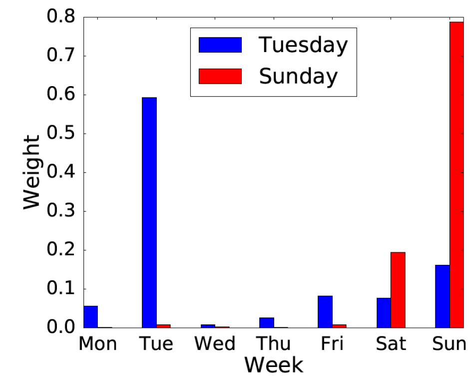

200
150
100
50
0
Supply-demand Gap
19
21
23
25
27
Date
GBDT
DeepSD
Ground Truth

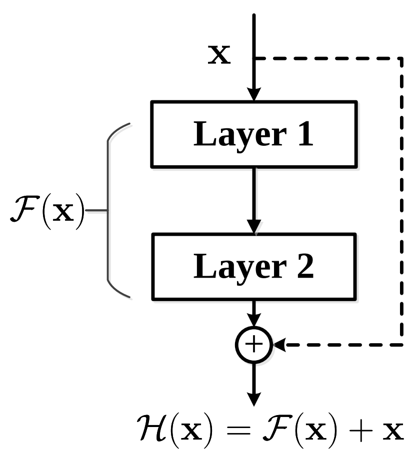


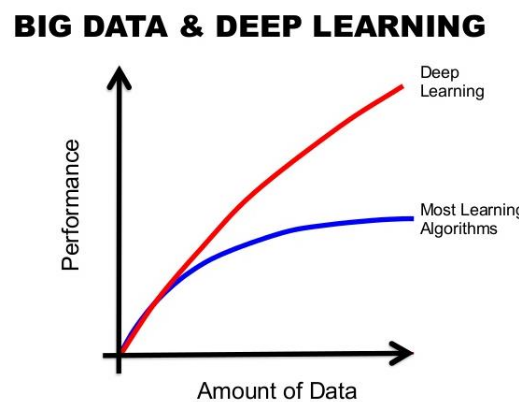
Conclusion



1. End-to-end model
2. Design a general block
3. Learn the useful feature vector from the order data
4. Involve in new external data easily
5. Great potential







Thank you