AAAI

DeepETA: A Spatial-temporal Sequential Neural Network Model for Estimating Time of Arrival in Package Delivery System

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Background

- Over 100 million packages are delivered each day in China
- Importance of estimating time of arrival (ETA) of packages
  - reducing the anxiety of customers
  - improving the customer experience
  - measuring the service ability and quality of couriers

Delivering time

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Arrival time - Depature time

Depature

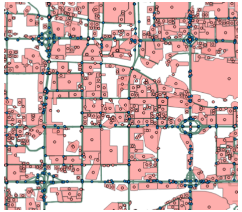
Arrival

Challenges

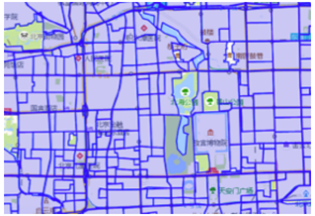
- Multiple destinations
  - All undelivered packages should be predicted at any time
  - The delivery time of different locations may vary due to the delivery sequence and the locations of the packages
- Time-variant delivery status
  - the sequence of the latest route, the regularity of the de-livery pattern and the sequence of packages to be delivered is hard to model
- Time-invariant delivery features
  - The geographical locations of the packages
  - the inherent properties of packages such as the weight or size

Problem Description

- Locations in delivery route
  - Packages are clustered into areas like communities or blocks
  - Utilizing an optimized partition method based on road network and areas of interest (AOI)



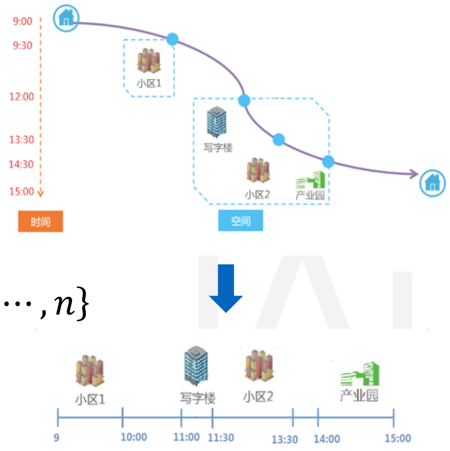
Road and AOI



Partition result

- Delivery route
  - Predicting the delivery time of a set of locations, namely $Set = \{a_i \mid i = 0, \cdots, n\}$
  - the delivery sequence at time t_i in day d

$$Route^{d}_{a_c,t_i} = \{node_{a_s,t_0} \rightarrow node_{a_1,t_1} \rightarrow \cdots \rightarrow node_{a_c,t_i}\}$$

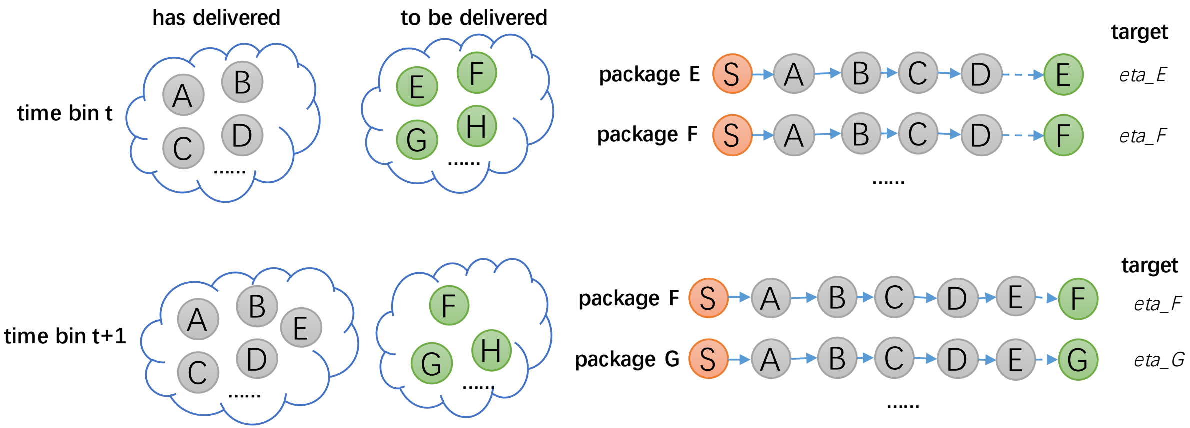


Delivery route

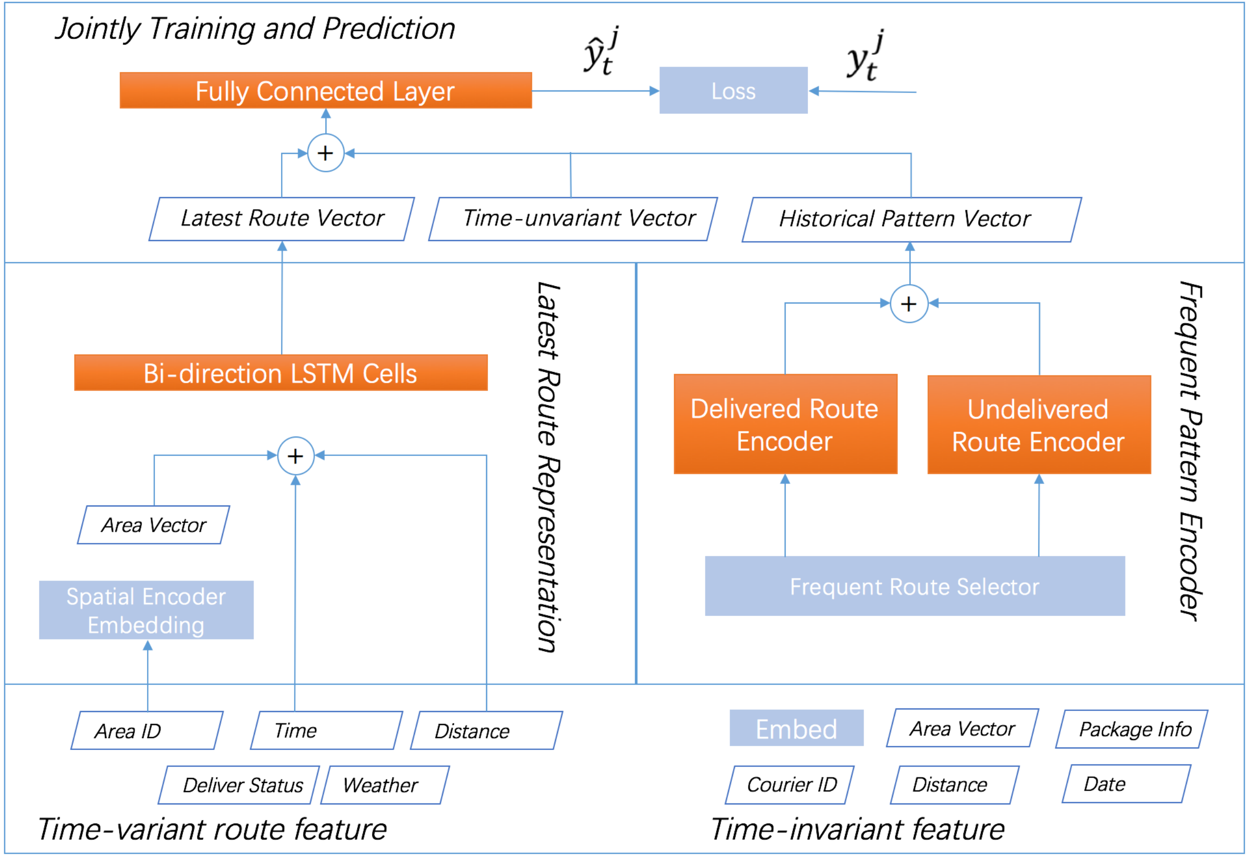
Problem Description

- Problem definition
  - The latest route $Route^{d}_{a_s,a_c}$ and the predicted location a_i
  - Relative routes from history that are similar with the current route symbolized as $\mathcal{H}_{route}$
  - Undelivered location set $Set^{d}_{t_i,}$ and all similar sets from history marked as $\mathcal{F}_{set}$
  - Find the most possible delivery time dt_{a_i} from historical relative routes:

$$dt_{a_i} = f(\mathcal{H}_{route}, \mathcal{F}_{set})$$



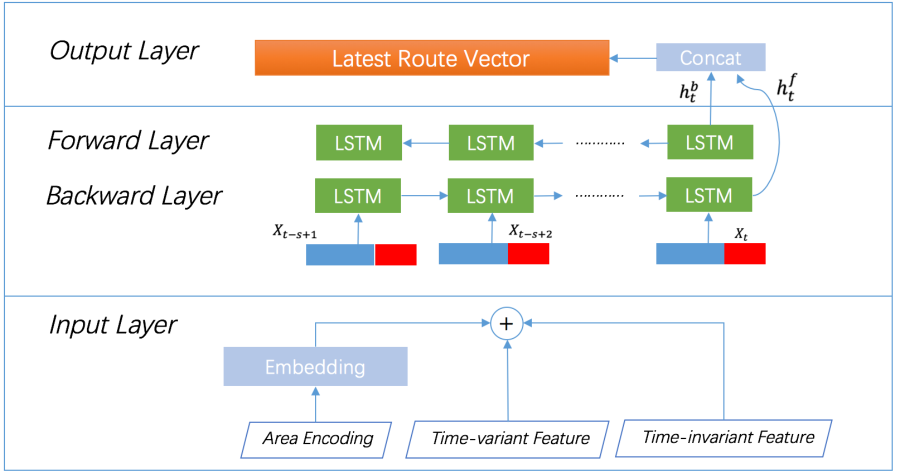
Proposed DeepETA Framework



- End to end structure
- Latest route encoder
- The frequent pattern encoder
- The prediction module

Model Structure

- Latest Route Encoder
  - To capture the complicated sequential information that influences the delivery time
  - Consists of the spatial encoder and the BiLSTM cells



- Spatial encoder
  - Location a_i is transformed into Geohash encoding of 40 digits, namely G_{a_i}

$$V_{a_i} = f\left(W_a G_{a_i} + b_a\right)$$

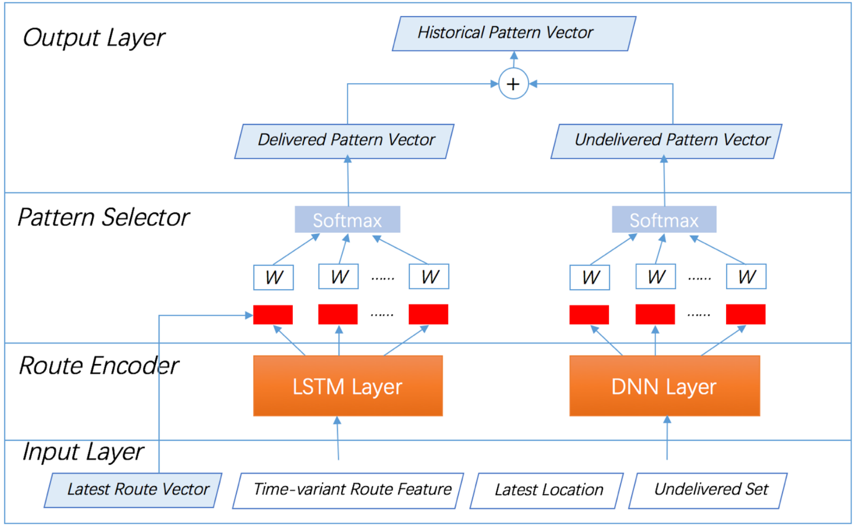
- BiLSTM
  - Spatial encoder V_{a_i}, time-variant features V_{tv} and time-invariant features V_{ti} as $X_t = [V_{a_i}, V_{tv}, V_{ti}]$

$$h_t = LSTM(h_{t-1}, X_t)$$

  - Combine the back and forward vectors $h_t = [h_t^b, h_t^f]$

Model Structure

- Frequent Pattern Encoder
  - To capture the frequent mobility patterns
  - Consists of the route encoder and the pattern selector



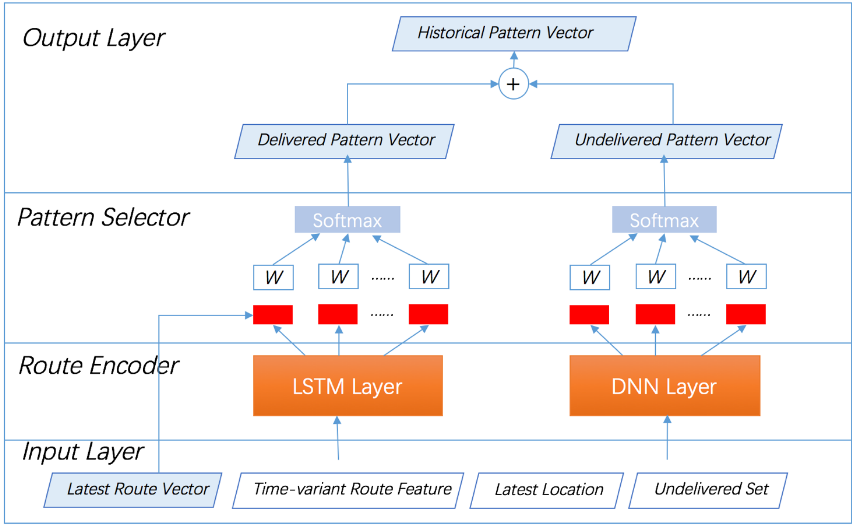
- Route encoder
  - Extracts only the relative frequent patterns
  - Delivered route pattern

$$\tilde{\mathcal{H}}_t^k = \mathrm{LSTM}(\tilde{\mathcal{H}}_{t-1}^k, \mathcal{H}_{route})$$

  - To-be-delivered pattern

$$\tilde{\mathcal{F}}_t^k = DNN(\tilde{\mathcal{F}}_{t-1}^k, \mathcal{F}_{set})$$

Model Structure



- Pattern selector
  - To find which frequent pattern has the biggest impact on the current situation
  - An attention-based layer
    - the frequent pattern vectors are combined with the latest route vector through a score function

$$f\left(\widetilde{\mathcal{H}}_t^k, h_t\right) = tanh\left(\widetilde{\mathcal{H}}_t^k W_{score} h_t\right)$$

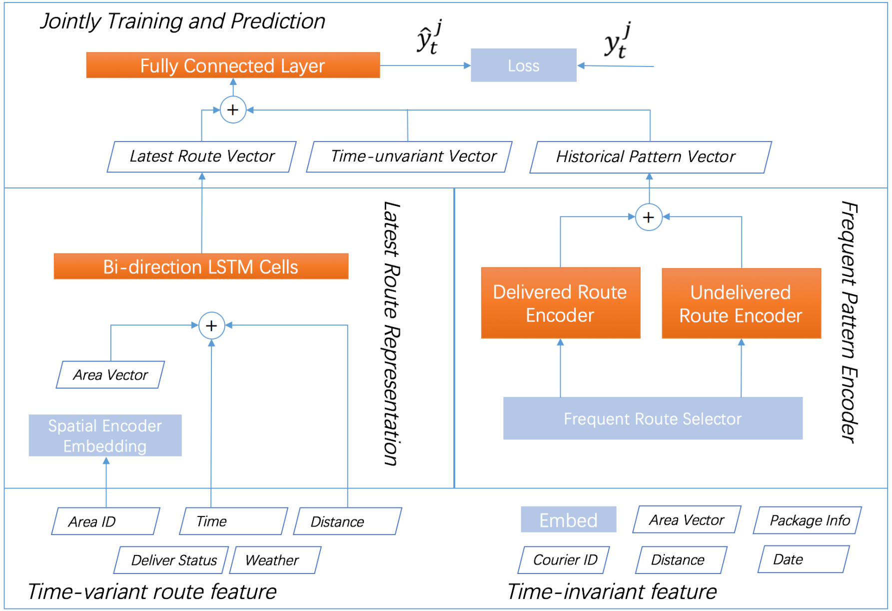
    - All scored vectors are exported to the softmax layer to calculate the weight of each vector

$$\sigma(z)_k = \frac{e^{z_k}}{\sum_{i=1}^{K} e^{z_i}}$$

    - The value of the softmax is multiply with the historical pattern vectors

$$V_{fp} = \sum\left(\sigma(z)_j \widetilde{\mathcal{H}}_t^j\right)$$

Model Structure



- Jointly Training and Prediction
  - The latest route vector h_t, the frequent pattern encoder V_{fp}, and the time-invariant features V_{ti}, as $\tilde{X}_t = [h_t, V_{fp}, V_{ti}]$
  - The fully connected layer

$$\tilde{y}_t = \sigma\left(W_{fc}\tilde{X}_t + b_{fc}\right)$$

- Loss function
  - The mean square error (MSE): *measurement of bias and variance*
  - The mean absolute percentage square error (MAPSE): *not sensitive to outliers*

$$\mathcal{L}(\theta) = \sum_{i=1}^{N}\left((\tilde{y}_t - y_t)^2 + \lambda\left(\frac{\tilde{y}_t - y_t}{y_t}\right)^2\right)$$

- Dataset Description
  - Real-world package delivery dataset collected by Cainiao Ltd.
    - The delivery routes of 331 couriers from Jun. 1, 2018 to Aug. 1, 2018 (60 days), in Beijing, China
    - The previous 50 days are used as training set and the last 10 days as testing set

Pkgs	Route	Nodes	Time	AvgDt
80	2	20	8h	3.5h

- Evaluation Metric
  - Mean Average Percentage Error (MAPE)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|\hat{y}_t^j - y_t^j\right|}{y_t^j}$$

  - Rooted Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_t^j - y_t^j\right)^2}$$

Experiment

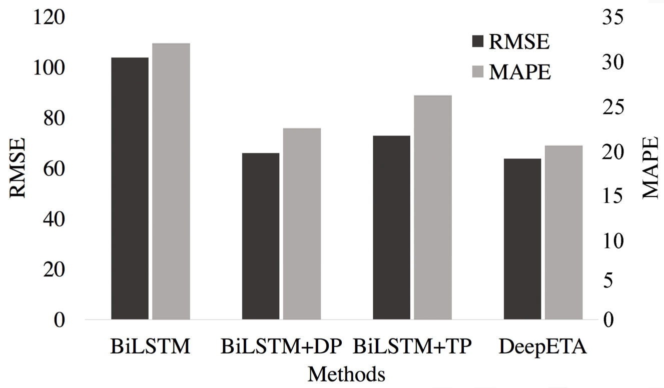
- Methods for Comparison
  - Linear regression (LR)
  - XGBoost
  - Deep neural network (DNN)
  - LSTM
  - DeepTTE
  - DeepMove
  - Latest route representation (BiLSTM)
  - Frequent pattern encoder (BiLSTM+DP and BiLSTM +TP)

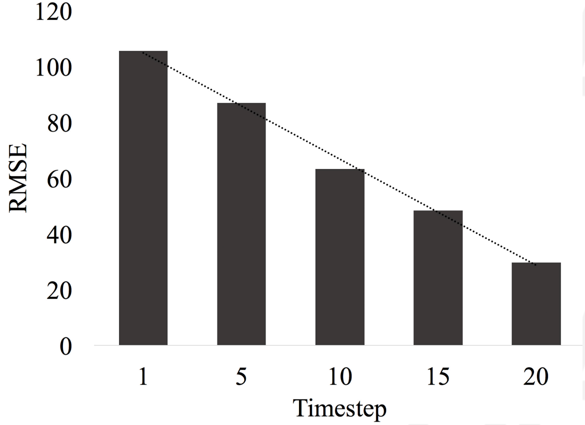
Methods	RMSE (min)	MAPE (%)
LR	144.18	43.5
DNN	127.58	37.4
XGBoost	123.66	38.2
LSTM	110.37	34.9
DeepTTE	97.85	29.7
DeepMove	72.43	24.3
DeepETA	63.58	20.6

- Model Comparison
  - DeepETA achieves the lowest RMSE (63.58 minutes) and the lowest MAPE which improves the best performance of the baseline methods by 13.8% (RMSE) and 16.5% (MAPE)
    - Attention mechanism to enhance the ability of learning long sequences
    - LSTM-based layer to extract the sequential features
    - DNN-based layer to model undelivered sets

Experiment

- Effectiveness of model components
  - An improving of 6% purely rely on the BiLSTM layer
  - The delivered pattern encoder improves 36.5%
  - The to-be-delivered pattern encoder improves 29.8%
  - The combination of all modules improves 3%
- Performance of prediction at different time
  - Re-predicting all the undelivered packages at any time
  - RMSE decrease significantly as the increasing of time step
  - More current route information can be inferred and the scope of undelivered sets can be reduced





Summary

- Propose a deep spatial-temporal sequential model for estimating the package delivery time (DeepETA)
  - The latest route encoder embeds the location of packages that remain geographical relations and BiLSTM is used to model the sequential features
  - The frequent pattern encoder selects the frequent routes from historical data and uses LSTM and DNN to represent the routes
  - An attention-based layer is developed to calculated the most similar patterns with the current route
  - Jointly training is utilized to minimize the loss function
- Experiments on real logistics dataset show that the proposed method overwhelms the start-of-art methods and the effectiveness of three modules are illustrated

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THANKS

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In the near future, codes will be released in: https://github.com/wufandm/deepeta