Learning to Generate Maps from Trajectories

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Increasing Demands of Accurate & Updated Maps





Route Planning & Real-time Scheduling

Navigation

Traditional Map Data Collecting Methods



On-field Study



Low Spatial Coverage



Dynamic Traffic Status





Crowdsourcing GPS Trajectories



Massive Moving Objects

GPS Devices Real-time City-wide Map Information



Framework of DeepMG



Geometry Translation (1/2)

- Feature Extraction
 - For each $I \times J$ Region Tile

Spatial View ($\mathbb{R}^{11 \times I \times J}$)



Transition View ($\mathbb{Z}_2^{2 \times T \times T \times I \times J}$)



(a) Transitions S/E at c. (b) Local Incoming Matrix. (c) Local Outgoing Matrix.

Point, Line, Speed, Direction (8 channels)

Each grid cell has an incoming and an outgoing matrix

Geometry Translation (2/2)

- T2RNet
 - Transition Embedding
 - Shared Encoder
 - Road Region Decoder
 - Road Centerline Decoder
- Optimization
 - Dice Loss [Milletari F, et al. 2016]

 $\mathcal{L}_{Dice}(\hat{\mathbf{Y}}, \mathbf{Y}) = 1 - \frac{2\sum_{i}^{I} \sum_{j}^{J} \hat{Y}_{ij} Y_{ij} + \epsilon}{\sum_{i}^{I} \sum_{j}^{J} \hat{Y}_{ij} + \sum_{i}^{I} \sum_{j}^{J} Y_{ij} + \epsilon}$

• Multi-task Loss

$$\mathcal{L}(\boldsymbol{\theta}) = (1 - \lambda) \mathcal{L}_{Dice}(\hat{\mathbf{Y}}_{c}, \mathbf{Y}_{c}) + \lambda \mathcal{L}_{Dice}(\hat{\mathbf{Y}}_{r}, \mathbf{Y}_{r})$$



Milletari F, et al. "V-net: Fully convolutional neural networks for volumetric medical image segmentation". 3DV. 2016.

Topology Construction (1/2)

- Graph Extraction
 - Merge predicted tiles
 - Extract road segments
- Link Generation
 - For each dead end





- Case 1: intersects another edge on the extension
- Case 2: has smooth transition to the closest dead end of another edge



Topology Construction (2/2)

- Map Refinement
 - Perform trajectory map matching on the linked map [Yuan J, et al. 2010]
 - Remove edges and links with low support

If the map matching is directly applied...

Proposed solution



$$dist(P) = \sum_{e_i \in P} \omega(e_i) \cdot len(e_i)$$

 $\omega(e_i) = \begin{cases} \alpha, & e_i \text{ is a generated link } \alpha > 1 \\ 1, & e_i \text{ is a predicted edge} \end{cases}$

Yuan J, et al. "An Interactive Voting-based Map Matching Algorithm". MDM. 2010.

Evaluation

• Datasets

- Trajectory
 - <oid, timestamp, latitude, longitude>
- Map
 - Node: <latitude, longitude>
 - Edge: <start_node, end_node>

| Dataset | TaxiBJ | TaxiJN |
|-------------------------|----------------------|----------------|
| #Days | 30 | 30 |
| #Vehicles | 500 | 70 |
| Sampling Rate | $\sim 30 \mathrm{s}$ | $\sim 3s$ |
| Size (km ²) | 16×16 (5×5) | 16×26 (5×5) |
| #Points | 3.1M (304K) | 5.7M (322K) |
| #Trajectories | 66,124 (13,462) | 29,556 (3,954) |
| Roads (km) | 2,772 (284) | 2,048 (123) |

Evaluation Metrics

- Topological F1 [Biagioni, et al. 2012]
 - Repeat N times
 - a. Select a random starting location
 - b. Find reachable area within a maximum radius
 - c. Compare generated map with GT using F1
 - Report the average F1 score



Biagioni J, Eriksson J. "Inferring road maps from global positioning system traces: Survey and comparative evaluation". Transportation research record. 2012.

Results

• Quantitative Comparison

ullet



♥ 物流轨迹地图修复 地图修复 场景模拟



Conclusion

- A valuable but challenging task
 - Position errors
 - Low sampling rate
- Our method
 - Geometry translation (T2RNet)
 - Convolutional network: learns the structure of the road network
 - Auxiliary task: helps the centerline inference
 - Topology construction (Link + Prune)
 - Trajectories as transition evidences
- Results
 - Superior than traditional methods
 - More effective on low-sampling rate datasets





Thanks!



JD Urban Spatio-Temporal Data Engine (JUST)



Ruan S., et al. "Learning to Generate Maps from Trajectories". AAAI. 2020.