Learning to Generate Maps from Trajectories

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Increasing Demands of Accurate & Updated Maps

Navigation

Route Planning & Real-time Scheduling
Traditional Map Data Collecting Methods

On-field Study

Low Spatial Coverage

Dynamic Traffic Status
Crowdsourcing GPS Trajectories
Challenges

- Ground Truth Map
- Positioning Error (~15 meters)
- Difficult to Distinguish Spatially Close Roads
- Low Sampling Rate (30s/pt)
- Ambiguous Underlying Traversing Routes
Framework of DeepMG

Training
- Feature Extraction
- T2RNet
- Trajectory

Inference
- Feature Extraction
- Trained Model
- Centerline

Geometry Translation
- predictions

Topology Construction
- Graph Extraction
- Link Generation
- Map
- Map Refinement
Geometry Translation (1/2)

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

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

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

- Point, Line, Speed, Direction (8 channels)
- Each grid cell has an incoming and an outgoing matrix.

(a) Transitions S/E at c. (b) Local Incoming Matrix. (c) Local 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]
    \[ L_{Dice}(\hat{Y}, Y) = 1 - \frac{2 \sum_i \sum_j \hat{Y}_{ij} Y_{ij} + \epsilon}{\sum_i \sum_j \hat{Y}_{ij} + \sum_i \sum_j Y_{ij} + \epsilon} \]
  - Multi-task Loss
    \[ L(\theta) = (1 - \lambda)L_{Dice}(\hat{Y}_c, Y_c) + \lambda L_{Dice}(\hat{Y}_r, Y_r) \]

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

\[
dist(P) = \sum_{e_i \in P} \omega(e_i) \cdot \text{len}(e_i)
\]

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

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>

• 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

| Dataset       | TaxiBJ | TaxiJN |
|---------------|--------|--------|
| #Days         | 30     | 30     |
| #Vehicles     | 500    | 70     |
| Sampling Rate | ~30s   | ~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) |

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

• Quantitative Comparison

TaxiBJ (32.3% improvement)

TaxiJN (6.5% improvement)

• Visual Comparison
Practice in JD.COM: Resident Area Map Generation from JD Couriers’ Trajectories
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 iCity

JD Urban Spatio-Temporal Data Engine (JUST)

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