Detecting Communities of Commuters: Graph Based Techniques vs Generative Models

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Motivation

Card Number	In-Timestamp	Out-timestamp	In-ID	Out-ID
c530524	yyyy-dd-mm;07:22:49.0	yyyy-dd-mm;07:28:50.0	2383	1467
c530545	yyyy-dd-mm;12:09:40.0	yyyy-dd-mm;12:29:40.0	1464	8
c630568	yyyy-dd-mm;13:10:30.0	yyyy-dd-mm;13:40:50.0	2413	99
c534554	yyyy-dd-mm;20:08:12.0	yyyy-dd-mm;20:28:07.0	2384	2
c837483	yyyy-dd-mm;16:02:10.0	yyyy-dd-mm;16:34:33.0	1467	185
c254234	yyyy-dd-mm;09:09:43.0	yyyy-dd-mm;09:19:23.0	1899	99

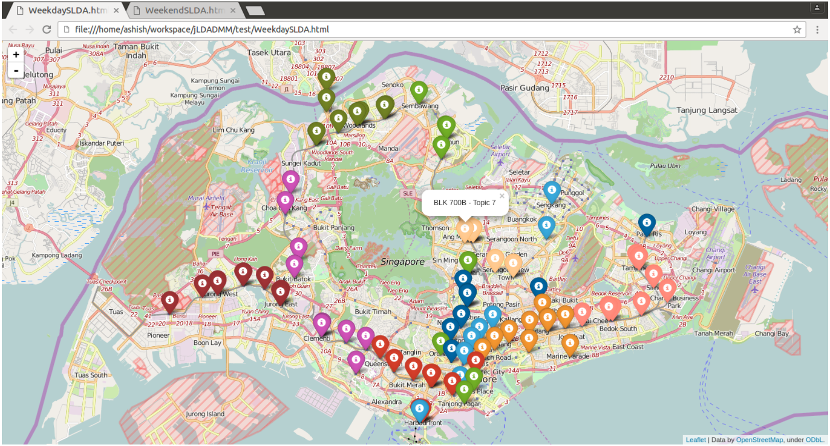
...

...

...

Millions of such records!

Motivation



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Introduction

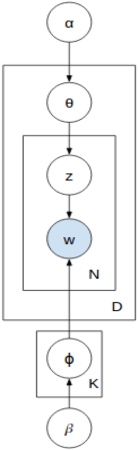
- Community detection by using overlaps in mobility
- Exisiting Techniques
  - Traditional Data Mining Techniques
  - Graph based techniques
- Generative Model
  - Statistical modelling
  - Bayesian approach
  - Generative process

Problem - Are generative models more effective than graph based techniques?

Related Work

- Urban Computing [19]
  - Reducing waiting time of commuters [5]
  - Travelling behaviour analysis [12, 11, 13]
  - Identifying tourists from daily commuters [16]
- Graph based techniques [6]
  - Divisive algorithm [7]
  - Modularity optimization [2, 4]
- Generative Models
  - Finding communities in LBSN data using LDA [14, 10, 3]
  - Extending LDA to handle geolocations [15, 9]
  - Extending LDA to handle spatio-temporal events [17, 18]

Latent Dirichlet Allocation - LDA[1]



Notation

- N : Vocabulary size
- D : Total number of Documents
- K : Total number of Topics

Intuition

- Bag of Words assumption
- A document is a distribution over topics
  - $\bar{\theta}_m \rightarrow K$-dim vector; $m \in [1...D]$
- A topic is a distribution over words
  - $\bar{\phi}_k \rightarrow N$-dim vector; $k \in [1...K]$

Adopting LDA to Spatio-Temporal Data

What does LDA require?

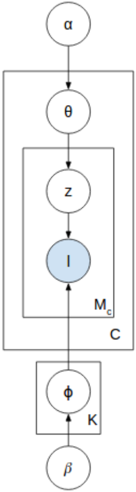
Bags of words!

Analogy

- LBSN: Users and their checkins
- Taxi: Taxis and their GPS positions
- Public Transport Data: Commuters and bus/train stops

SLDA - Spatial LDA

- Document → Commuter
- Words → Spatial mobility of a commuter
- Topics → Spatial mobility patterns

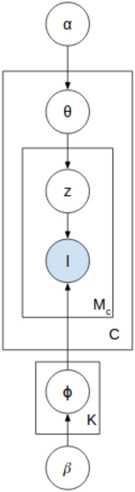


SLDA

SLDA - Spatial LDA

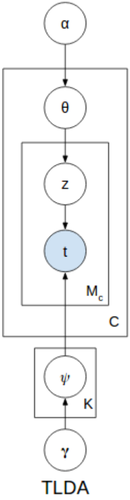
- Document → Commuter
- Words → Spatial mobility of a commuter
- Topics → Spatial mobility patterns

What about time?



SLDA

TLDA - Temporal LDA



- Document → Commuter
- Words → Temporal mobility of a commuter
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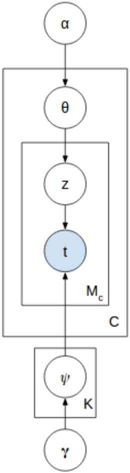
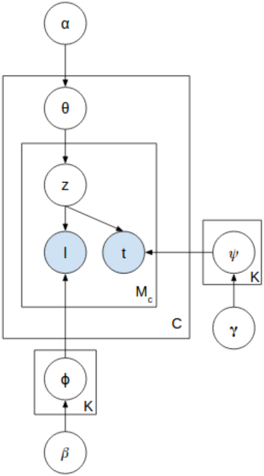
TLDA - Temporal LDA



- Document → Commuter
- Words → Temporal mobility of a commuter
- Topics → Temporal mobility patterns

Can we consider both space and time simultaneously?

STLDA - Spatio-Temporal LDA



- Document → Commuter
- Words → Spatio-temporal events
- Topics → Spatial and temporal mobility patterns

Inference

Inference[8]

Algorithm 1 Gibbs Sampling Interation

for all commuters $c \in \mathcal{C}$ **do**
    for all visits $v \in \mathcal{M}$ **do**
        $K \leftarrow$ topic assigned to v
        Decrement counts $\phi_{k,v}, \theta_k$
        $Z \leftarrow$ sample new topic
        Increment counts $\phi_{z,v}, \theta_z$
    end for
end for

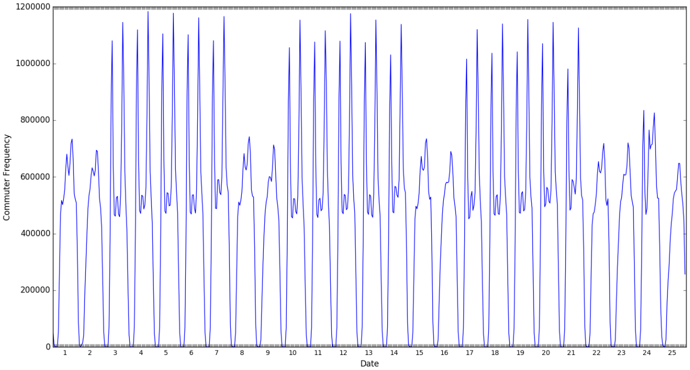
Experiments

EZ-link Data

Field	Description
Card_Number_E	ID of the EZ-link card
Transport_Mode	Bus, MRT or LRT
Entry_Date	Date of the tap-in
Entry_Time	Time of the tap-in
Exit_Date	Date of the tap-out
Exit_Time	Time of the tap-out
Payment_Mode	Mode of the payment
Commuter_Category	Category of the card
Origin_Location_ID	Location ID of the tap-in
Destination_Location_ID	Location ID of the tap-out

Table: Dataset Schema

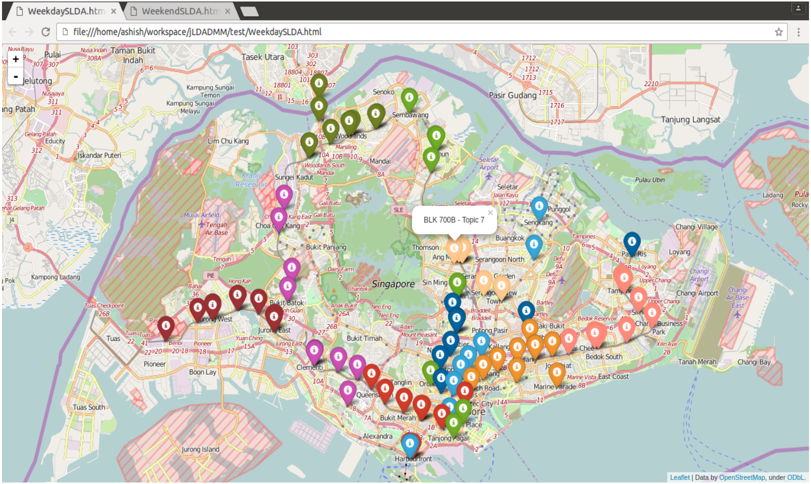
EZ-link Data


Commuter Frequency
1200000
1000000
800000
600000
400000
200000
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
Date

EZ-link Data

- Filtered two weekdays and two weekends
- Sampled 40,000 regular commuters

EZ-link Data: Weekday Topics (SLDA)



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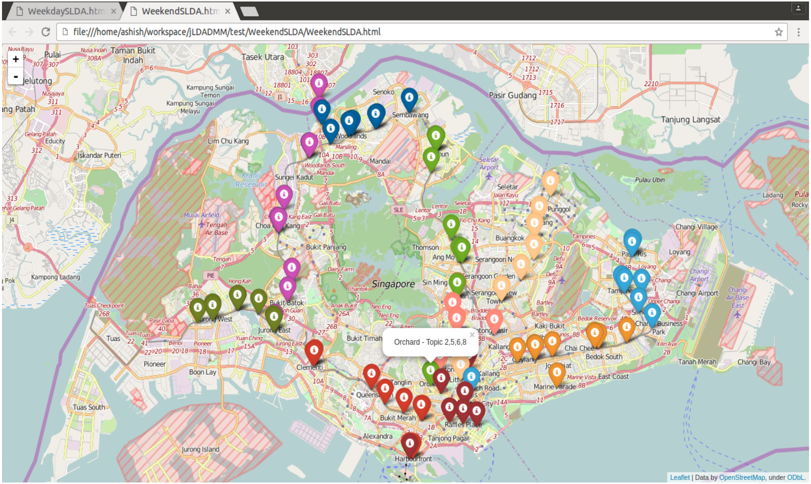
EZ-link Data: Weekend Topics (SLDA)



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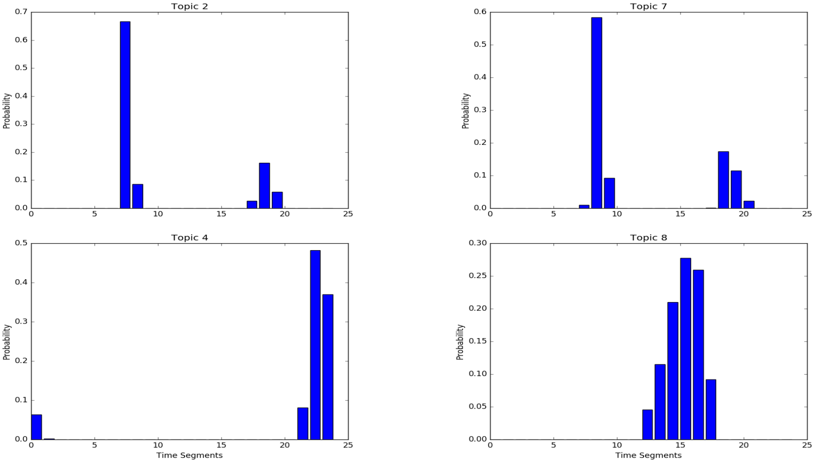
EZ-link Data: Weekday Clusters (TLDA)



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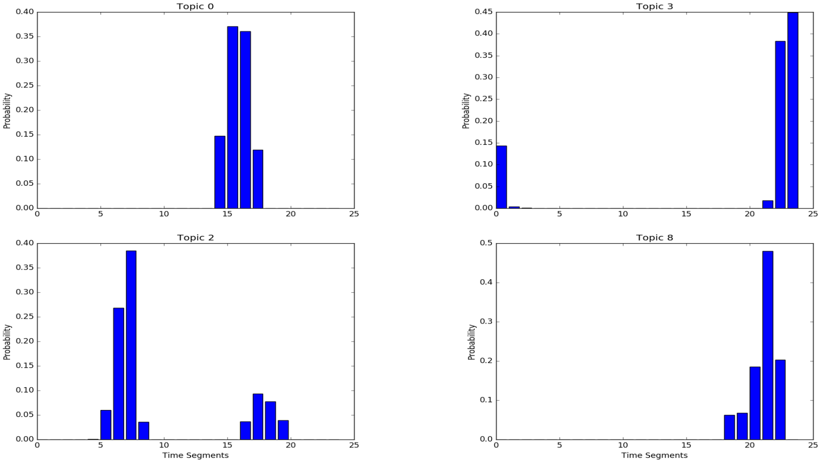
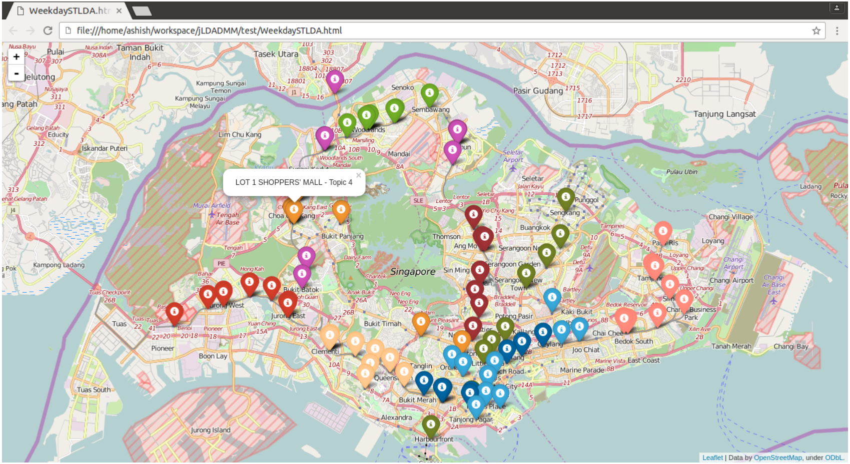
EZ-link Data: Weekend Clusters (TLDA)

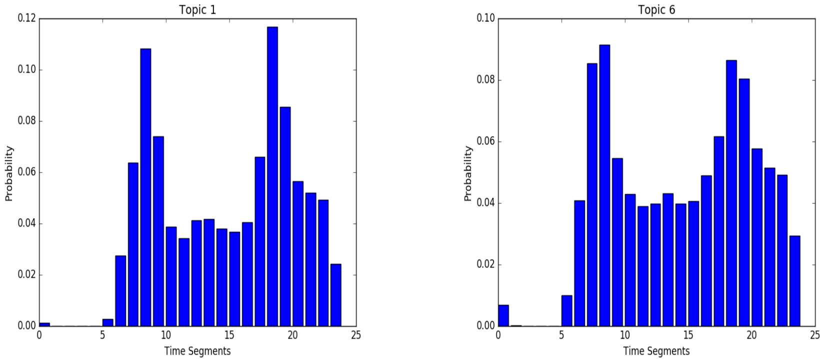


EZ-link Data: Weekday Topics (STLDA)



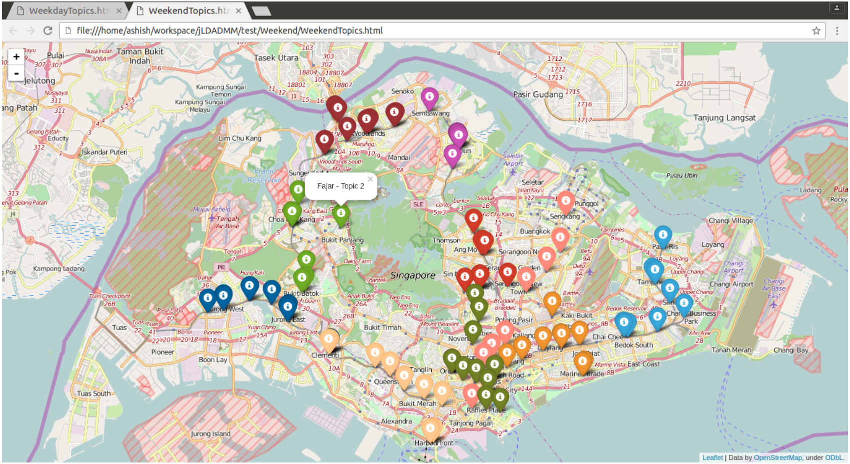
Spatial Part

EZ-link Data: Weekday Clusters (STLDA)



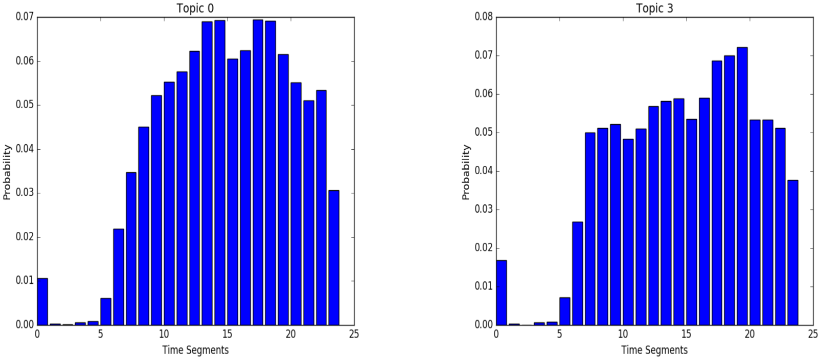
Temporal Part

EZ-link Data: Weekend Topics (STLDA)



Spatial Part

EZ-link Data: Weekend Clusters (STLDA)



Temporal Part

Comparison

Can we compare results with graph based technique?

- No groundtruth
- Multiple sparse and small communities

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Generate synthetic yet realistic data!

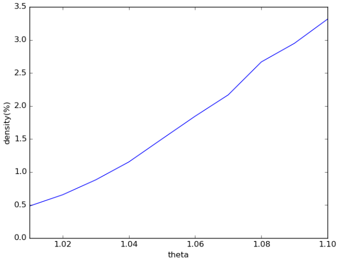
Synthetic Data: Generation

Documents Generation

- Choose distributions
  - visits per commuter $\rightarrow$ Gamma distribution
  - each community $\rightarrow$ Zipf distribution over locations
- Use generative process for the model

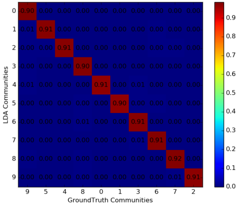
Graph Generation

- Add an edge between two commuters if mobilities have non-empty intersection
- Weigh the edge by the cardinality of overlap

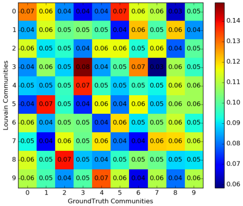


Result Analysis

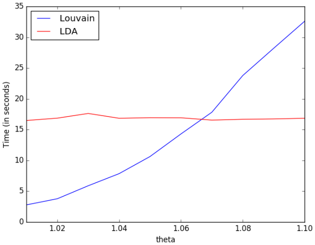
LDA vs Groundtruth



Lovain vs Groundtruth



Efficiency



Why are Graph algorithms less effective?

An Example

- Pairs of commuters A-B and C-D co-occur 5 times

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An Example

- Pairs of commuters A-B and C-D co-occur 5 times
- A-B co-occur 5 times at one place
- C-D co-occur 5 times at different places

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Why are Graph algorithms less effective?

An Example

- Pairs of commuters A-B and C-D co-occur 5 times
- A-B co-occur 5 times at one place
- C-D co-occur 5 times at different places

Loss of information in graph generation!

Conclusion

- Proposed sptio-temporal model for communitites of commuters
- Conducted experiments on real-world data
- Extended experiments to synthetic data so as to have fair quantitative comparison
- Reasoned why generative model is more effective than graph based techniques

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Thank You!

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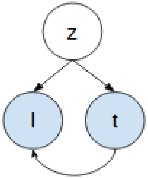
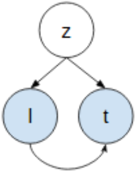
Work underway!

Space-time Interdependence





Bag of Words Assumption

How much valid is it?