Mining Human Trajectory Data: A Study on Check-in Sequences

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Check-in data

What information these check-in data contain?

User ID
Location ID
Check-in time
Category label/name
GPS information
Check-in data

What information these check-in data contain?

User ID
Location ID
Check-in time
Category label/name
GPS information

An example

UID25821
Burger King@BH Point
2015-01-13/1:30pm
Restaurant
A Sequential Way to Model the Data

- Given a user $u$, a trajectory is a sequence of check-in records related to $u$

<table>
<thead>
<tr>
<th>User ID</th>
<th>Location ID</th>
<th>Check-in Timestamp</th>
</tr>
</thead>
<tbody>
<tr>
<td>u1</td>
<td>l181</td>
<td>2016-08-26 9:26am</td>
</tr>
<tr>
<td>u1</td>
<td>l32</td>
<td>2016-08-26 10:26am</td>
</tr>
<tr>
<td>u1</td>
<td>l323</td>
<td>2016-08-26 11:26am</td>
</tr>
<tr>
<td>u1</td>
<td>l32323</td>
<td>2016-08-26 1:26pm</td>
</tr>
<tr>
<td>u2</td>
<td>l345</td>
<td>2016-08-26 9:16am</td>
</tr>
<tr>
<td>u2</td>
<td>l13</td>
<td>2016-08-26 10:36am</td>
</tr>
</tbody>
</table>
A Sequential Way to Model the Data

• Given a user $u$, a trajectory is a sequence of check-in records related to $u$

<table>
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<th>Location ID</th>
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<td>l323</td>
<td>2016-08-26 11:26am</td>
</tr>
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</tr>
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</tr>
<tr>
<td>u2</td>
<td>l13</td>
<td>2016-08-26 10:36am</td>
</tr>
</tbody>
</table>

u1:  l181 → l32 → l323 → l32323
u2:  l345 → l13
What we want to do with trajectory sequences

• **Check-in Sequences → Patterns & Characteristics**
  – A Probabilistic Lifestyle-based Trajectory Model for Social Strength Inference from Human Trajectory Data. To appear in ACM TOIS.

• **Check-in Sequences → Representations**
  – A General Multi-Context Embedding Model For Mining Human Trajectory Data. To appear in IEEE TKDE.
What we want to do with trajectory sequences

- Check-in Sequences $\rightarrow$ Patterns & Characteristics

- Check-in Sequences $\rightarrow$ Representations

A Probabilistic Lifestyle-based Trajectory Model for Social Strength Inference from Human Trajectory Data. To appear in ACM TOIS.
Motivation

• Home → Traffic → ?
Motivation

• Home ➔ Traffic ➔ ?
  – Company, if u=worker and time=weekday
  – Plaza, if u=worker and time=weekend
  – Library, if u=student and time=weekday
  – Plaza, if u=student and time=weekend

Finding I: Different users are likely to have different moving patterns
Finding II: A user may have different moving patterns in different contexts
Finding III: Different users may share similar moving patterns
Our goal

• Discover interesting trajectory-based patterns

u1: l181 → l32 → l323 → l32323
u2: l345 → l13
Elementary Components

• Grouping locations into coherent topics by functionality

(a) Functionality Topic.
Elementary Components

- Computing transition probability between different topics

(b) Functionality Dependency.
Put two components together

- It is really like Hidden Markov Models

```python
states = ('Rainy', 'Sunny')

observations = ('walk', 'shop', 'clean')

start_probability = {'Rainy': 0.6, 'Sunny': 0.4}

transition_probability = {
    'Rainy': {'Rainy': 0.7, 'Sunny': 0.3},
    'Sunny': {'Rainy': 0.4, 'Sunny': 0.6},
}

emission_probability = {
    'Rainy': {'walk': 0.1, 'shop': 0.4, 'clean': 0.5},
    'Sunny': {'walk': 0.5, 'shop': 0.3, 'clean': 0.1},
}
```
But it doesn’t work

- An individual user will have different transition patterns under different contexts

A single transition matrix will not work
Our ideas

• Set multiple transition matrices
  – Each corresponds to a lifestyle

![Transition Matrices]

(c) Lifestyle.

A lifestyle typically reflects an individual’s attitudes, way of life, values or world view [Veal 1993].

We focus on moving behaviors.
Definition. **Lifestyle.** A lifestyle refers to a specific group of patterns in the transitions over the functionality topics. Let $a$ denote a lifestyle, its corresponding transition probabilities from a topic $c_1$ to the next topic is modeled as a multinomial distribution over the set of all the possible topics, $\pi^{a,c_1}$. Furthermore, $\pi^{a,c_1}_{c_2}$ denotes the transition probability from topic $c_1$ to $c_2$ in lifestyle $a$.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Office</td>
<td>0.5</td>
<td>0.2</td>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>Transportation</td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dining</td>
<td>0.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entertainment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Office</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transportation</td>
<td></td>
<td>0.3</td>
<td>0.3</td>
<td></td>
</tr>
<tr>
<td>Dining</td>
<td></td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Entertainment</td>
<td></td>
<td>0.3</td>
<td>0.2</td>
<td>0.4</td>
</tr>
</tbody>
</table>

(c) Lifestyle.
**User Preference**

*Definition.* **User lifestyle preference.** Given a set of lifestyles, the lifestyle preference of user $u$ is modeled as a multinomial distribution $\theta^u$ over the set of lifestyles.

(d) User Preference.
A Global View of the Ideas

(a) Functionality Topic.

(b) Functionality Dependency.

(c) Lifestyle.

(d) User Preference.
Generative Model
Generative Model

- For each user \( u \)
  - For each trajectory \( s \)
    - draw lifestyle \( z_{u,s} \sim \text{Multi}(\theta^u) \);
    - For each location \( n = 1, 2, ..., N_{u,s} \)
      - draw topic \( y_{u,s,n} \sim \text{Multi}(\pi_{z_{u,s},y_{u,s,n}}) \);
      - draw location \( l_{u,s,n} \sim \text{Multi}(\phi_{y_{u,s,n}}) \);
      - draw time interval \( \Delta_{u,s,n} \sim \text{Exp}(\psi_{y_{u,s,n}}) \);
## Results

- **Location topics**

<table>
<thead>
<tr>
<th>Transportation</th>
<th>Resort</th>
<th>Dining</th>
<th>Shop</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stockholms centralstation</td>
<td>Disney’s Polynesian Resort</td>
<td>Stubb’s Bar-B-Q</td>
<td>Urban Outfitters</td>
</tr>
<tr>
<td>New York Penn Station</td>
<td>Lilla Essingen</td>
<td>Fogo de Chao</td>
<td>Victoria’s Secret</td>
</tr>
<tr>
<td>Grand Central Terminal</td>
<td>Great Wolf Lodge</td>
<td>home Slice Pizza</td>
<td>Mellow Johnny’s</td>
</tr>
<tr>
<td>Lund Centralstation</td>
<td>Hilton Hawaiian Village</td>
<td>Uncle Billy’s Brew &amp; Que</td>
<td>Santa Monica Pier</td>
</tr>
<tr>
<td>Waterloo Station</td>
<td>Garcia Home</td>
<td>Grill</td>
<td>Apple Store</td>
</tr>
<tr>
<td>Hauptbahnhof Berlin</td>
<td>Waikiki Beach</td>
<td>Iron Works</td>
<td>Hermans</td>
</tr>
<tr>
<td>Statin Amsterdam Centraal</td>
<td>Social Media Clubhouse</td>
<td>Salt Lick</td>
<td>REI flagship</td>
</tr>
<tr>
<td>Station Utrecht Centraal</td>
<td>Delta Crown Room</td>
<td>Ranch 616</td>
<td>Quincy Market</td>
</tr>
<tr>
<td>Caltrain Depot - 4th and King</td>
<td>Hyatt Regency Lost Pines</td>
<td>Pontus By The Sea</td>
<td>Equinox</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Entertainment</th>
<th>Office/Univ.</th>
<th>Sports</th>
<th>Apartment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Studio Movie Grill</td>
<td>Gowalla Incorporated</td>
<td>Equinox</td>
<td>Mickey Mouse’s House</td>
</tr>
<tr>
<td>Sony Plaza Public Arcade</td>
<td>Apple HQ</td>
<td>REI</td>
<td>My House</td>
</tr>
<tr>
<td>Kista Galleria</td>
<td>Academy of Art University</td>
<td>Cabela’s</td>
<td>Minnie Mouse’s House</td>
</tr>
<tr>
<td>KGSR Blue On The Green</td>
<td>Viget Labs</td>
<td>Academy Sports</td>
<td>Home</td>
</tr>
<tr>
<td>Paramount Theatre</td>
<td>Austin Convention Center</td>
<td>Ericsson Globe</td>
<td>Beacon Park</td>
</tr>
<tr>
<td>Austin Children’s Museum</td>
<td>Twitter HQ</td>
<td>Wrigley Field</td>
<td>Sherwood Court Apartments</td>
</tr>
<tr>
<td>Frank Erwin Center</td>
<td>Google World</td>
<td>Konserthuset</td>
<td>Gill Residence</td>
</tr>
<tr>
<td>Central Park Carousel</td>
<td>Yelp HQ</td>
<td>Safeco Field</td>
<td>Stone Creek at Druid Hills</td>
</tr>
<tr>
<td>Navy Pier</td>
<td>Facebook HQ</td>
<td>Dallas Cowboys Stadium</td>
<td>Floyd Manor</td>
</tr>
</tbody>
</table>
Results

• Lifestyle-based transitions
Results

- Impact of home location

Table VII: Top lifestyles and transitions for the users from three sample home locations. The latitude and longitude information is also given.

<table>
<thead>
<tr>
<th>Home Locations</th>
<th>Top Lifestyles</th>
<th>Top Transitions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Near Austin Downtown</strong></td>
<td>Office Life</td>
<td>Office → Apartment</td>
</tr>
<tr>
<td>(30.26, -97.75)</td>
<td>Offduty</td>
<td>Office → Transportation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Office → Shop</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Dining → Entertainment</td>
</tr>
<tr>
<td><strong>Near San Francisco Bay Area</strong></td>
<td>Office Life</td>
<td>Office → Office</td>
</tr>
<tr>
<td>(37.77, -122.39)</td>
<td>Weekend</td>
<td>Office → Dining</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Apartment → Sports</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Apartment → Shop</td>
</tr>
<tr>
<td><strong>Near Germany University</strong></td>
<td>College Life</td>
<td>Office/Univ. → Dining</td>
</tr>
<tr>
<td>(51.48, 11.94)</td>
<td>Weekend</td>
<td>Office/Univ. → Sports</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Apartment → Entertainment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Shop → Apartment</td>
</tr>
</tbody>
</table>
What we want to do with trajectory sequences

• Check-in Sequences → Patterns & Characteristics

• Check-in Sequences → Representations

A General Multi-Context Embedding Model For Mining Human Trajectory Data. To appear in IEEE TKDE.
We are always interested in the **representations** of informational entities.

Effective representations for trajectory data can be useful in many tasks:
- POI recommendation
- Social link prediction
- Etc.
Distributional semantics

• Target word = “stars”

He curtains open and the stars shining in on the barely ars and the cold, close stars " . And neither of the w rough the night with the stars shining so brightly, it made in the light of the stars. It all boils down, wr surely under the bright stars, thrilled by ice-white sun, the seasons of the stars? Home, alone, Jay pla m is dazzling snow, the stars have risen full and cold un and the temple of the stars, driving out of the hug in the dark and now the stars rise, full and amber a bird on the shape of the stars over the trees in front But I could n’t see the stars or the moon, only the they love the sun, the stars and the stars. None of r the light of the shiny stars. Theplash of flowing w man ‘s first look at the stars; various exhibits, aer rief information on both stars and constellations, inc
Distributional semantics

• Collect the contextual words for “stars”

<table>
<thead>
<tr>
<th>Construct vector representations</th>
<th>shining</th>
<th>bright</th>
<th>trees</th>
<th>dark</th>
<th>look</th>
</tr>
</thead>
<tbody>
<tr>
<td>stars</td>
<td>38</td>
<td>45</td>
<td>2</td>
<td>27</td>
<td>12</td>
</tr>
</tbody>
</table>

Similarity in meaning as vector similarity

- cucumber
- stars
- sun
Word2Vec

• Input: a sequence of word tokens from a vocabulary $V$

• Output: a fixed-length vector for each term in the vocabulary

  – $v_w$

It implements the idea of distributional semantics using a shallow neural network model.
Architecture 1

- **CBOW** predicts the current word using surrounding contexts
  
  \[ Pr(w | \text{context}(w)) \]
  
  - Window size 2c
  - \( \text{context}(w) = [w(t-c), \ldots, w(t+c)] \)

  - \( v_w \): a \( K \)-dimensional vector
  
  - \( v_{\text{context}} = \text{Average}_{w' \text{ in context}(w)} (v_{w'}) \)

  \[
P(w | \text{w}_{\text{context}}) = P(v_w | v_{\text{context}}) = \frac{\exp(v_w^T \cdot v_{\text{context}})}{\sum_{w'} \exp(v_{w'}^T \cdot v_{\text{context}})}
  \]
Architecture 2

- **Skip-gram** predicts surrounding words using the current word

  \[ Pr(\text{context}(w) \mid w) \]

  - Window size 2c
  - \( \text{context}(w) = [w(t-c), \ldots, w(t+c)] \)

\[
P(\text{context}(w) \mid w) = \prod_{w \in \text{context}(w)} P(v_{w'} \mid v_w)
\]

\[
P(v_{w'} \mid v_w) = \frac{\exp(v_w^T \cdot v_{w'})}{\sum_{w''} \exp(v_w^T \cdot v_{w''})}
\]
Key idea learnt from word embedding

• Contexts are important
  – Using contextual information to capture the semantics of a “word”

• Other types of sequences can be modeled in a similar way
  – Check-in record

  \begin{align*}
  \text{u1:} & \quad l181 & \rightarrow & \rightarrow & \rightarrow & \rightarrow & l32323 \\
  \text{u2:} & \quad l345 & \rightarrow & \rightarrow & & l13
  \end{align*}
Revisiting Check-in Data

Definition 1 (Check-in record). When a user $u$ checks in a location $\ell$ with a category label $c$ at the timestamp $s$, the check-in record can be modeled as a quadruple $\langle u, \ell, c, s \rangle$.

UID25821, Burger King@BH Point, Restaurant, 2015-01-13/1:30pm

Definition 2 (Trajectory). Given a user $u$, a trajectory $t$ is a sequence of chronologically ordered check-in records related to $u$: $\langle u, \ell_1, c_1, s_1 \rangle, \ldots, \langle u, \ell_i, c_i, s_i \rangle, \ldots, \langle u, \ell_N, c_N, s_N \rangle$, where $N$ is the sequence length and $s_i < s_{i+1}$ for $i \leq N - 1$.

We split the entire check-in sequences from a user into trajectories by day. A user typically generates multiple trajectory sequences.
Task

• Input: Check-in sequences

• Output: Embedding representations for users, locations and other related information
Motivations

• Trajectories are complicated
  – Much contextual information needs to be considered

• Can we borrow the ideas in the work of **word embedding**?
  – A relatively cheap way to combine contexts
  – A simple, efficient yet effective approach
Generation of a **Single Location** in a Trajectory

- **User interests:** $u$
- **Trajectory intents:** $t$
- **Surrounding locations:** $l_{j-K} : l_{j+K}, c_{j-K} : c_{j+K}$
- **Temporal contexts:** $d, h$
Model

• A CBOW based framework

\[ \frac{1}{N} \sum_{j=1}^{N} \log Pr(\ell_j | x^{(\ell_j)}) , \]

\( x^{(\ell_j)} \) is a real-valued feature vector consisting of all the contextual information for the target location \( \ell_j \)

– Coding the contextual information by using a feature vector
  • It is like the feature coding format in LibSVM
Model

• A softmax classifier

\[ Pr(\ell_j|x^{(\ell_j)}) = \frac{\exp(\bar{v}_{\ell_j} \cdot v_{\ell_j})}{\sum_{v'} \exp(\bar{v}_{\ell_j} \cdot v')} , \]

• Derive a context embedding vector

\[ \bar{v}_{\ell_j} = \frac{1}{\sum_{f} x_f^{(\ell_j)} \sum_{f} x_f^{(\ell_j)} \times v_f}. \]

– Each contextual feature corresponds to a unique embedding vector
– Using simple weighted aggregation
The general model

• Log-likelihood function

\[
\sum_{u \in U} \sum_{t \in \mathcal{T}(u)} \frac{1}{N_t} \sum_{j=1}^{N_t} \log \Pr\left( \ell_j \mid u \right),
\]

User-level context

\[
\left\{ \ell_{j-K} : \ell_{j+K}, c_{j-K} : c_{j+K}, d, h \right\},
\]

Trajectory-level context

Location-level context

Temporal context

– General contextual embedding vector

\[
\bar{v}_{\ell_j} = \frac{1}{4K+4} \left\{ \sum_{-K \leq k \leq K, k \neq 0} \left( v_{\ell_j+k} + v_{c_{j+k}} \right) + (v_u + v_i + v_d + v_h) \right\},
\]
Illustrative example
Application I: Location recommendation

• General recommendation

\[ S(u, l) \propto (v_r + v_u)^\top \cdot (v_c + v_l). \]

• Time-aware recommendation

\[ S(u, l) \propto (v_r + v_{d_t} + v_{h_j} + v_u)^\top \cdot (v_c + v_l). \]
Application II: Social Link Prediction

• Given the trajectory data from users $u$ and $v$, link prediction aims to predict whether there is a (reciprocal) link between $u$ and $v$

  – A binary-classification approach
    • A pair of users
  – Represent a user using the embedding vector
    • Hadamard product between two user embedding vectors

\[
x^{u,v} = x^u \circ x^v
\]

\[
x_{i}^{u,v} = x_{i}^{u} \times x_{i}^{v}
\]
Experiments

• Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th># Users</th>
<th># Check-ins</th>
<th># Links</th>
<th># Locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>FoursquareS</td>
<td>4,163</td>
<td>483,814</td>
<td>32,512</td>
<td>121,142</td>
</tr>
<tr>
<td>FoursquareL</td>
<td>266,909</td>
<td>33,278,683</td>
<td>—</td>
<td>3,680,126</td>
</tr>
<tr>
<td>Gowalla</td>
<td>216,734</td>
<td>12,846,151</td>
<td>736,778</td>
<td>1,421,262</td>
</tr>
</tbody>
</table>

TABLE 2
Statistics of Our Datasets
Location Recommendation

• General location recommendation

Fig. 5. Performance comparison on general location recommendation.
Location Recommendation

- Time-aware location recommendation

Fig. 6. Performance comparison on time-aware location recommendation.
Social link prediction

<table>
<thead>
<tr>
<th>Methods</th>
<th>Foursquare</th>
<th>Gowalla</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P</td>
<td>R</td>
</tr>
<tr>
<td>MH</td>
<td>0.71</td>
<td>0.64</td>
</tr>
<tr>
<td>EBM</td>
<td>0.78</td>
<td>0.50</td>
</tr>
<tr>
<td>TSA</td>
<td>0.61</td>
<td>0.55</td>
</tr>
<tr>
<td>HMM</td>
<td>0.22</td>
<td>0.73</td>
</tr>
<tr>
<td>PV</td>
<td>0.56</td>
<td>0.31</td>
</tr>
<tr>
<td>MC-TEM</td>
<td>0.81</td>
<td>0.75</td>
</tr>
</tbody>
</table>

TABLE 3
Performance Comparison on Link Prediction
### Qualitative examples

#### TABLE 5
Illustrative Examples for Query Context with the Corresponding Top Five Related Locations on the Foursquare Dataset, Where √ Indicates the Location was Actually Visited by the User and ✗ Otherwise

<table>
<thead>
<tr>
<th>Type</th>
<th>Query Context</th>
<th>Top five related locations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>HK Star Seafood Restaurant</td>
<td>Bo Ling’s Chinese Restaurant, Soho Restaurant, Guadalajara Grill, Flavor Del Mar, Perch</td>
</tr>
<tr>
<td>Service Category</td>
<td>Food</td>
<td>Brown Owl Coffee, Teriyaki Maki, New Ca Mau Restaurant, Espresso Roma Cafe, Ajisen Ramen</td>
</tr>
<tr>
<td></td>
<td>Museum</td>
<td>San Francisco Museum of Modern Art, San Jose Museum of Art, MOCA, The Metropolitan Museum</td>
</tr>
<tr>
<td>Time</td>
<td>7 o’clock</td>
<td>MTA Subway, California Highway Patrol, MUNI Bus Stop, Metro Bus, USA Gas Station</td>
</tr>
<tr>
<td></td>
<td>12 o’clock</td>
<td>Starbucks, McDonald’s, Denny’s, Subway, Burger King, Twitter, Inc, US Post Office, YouTube</td>
</tr>
<tr>
<td></td>
<td>Tuesday</td>
<td>First Team SnS Real Estate, Chegg HQ, Office of America, First Team SnS Real Estate Office</td>
</tr>
<tr>
<td></td>
<td>Sunday</td>
<td>Times Square, Landmark Theatres, Runyon Canyon Park, Alcatraz Island, Macy’s Recreation</td>
</tr>
<tr>
<td>City</td>
<td>Anaheim</td>
<td>Disneyland, Metrolink Anaheim Station, Anaheim Hills Medical Center, Disney California</td>
</tr>
<tr>
<td></td>
<td>San Diego</td>
<td>Adventure Park, City National Grove of Anaheim, Balboa Park, San Diego International Airport</td>
</tr>
<tr>
<td>User + Service</td>
<td>USER3584 + Food</td>
<td>KFC, Vallejo’s Restaurant, Starbucks, Roli Roti Gourmet Rotisserie, Bistro Burger</td>
</tr>
<tr>
<td>Category</td>
<td>USER 3584 + Shop</td>
<td>Walgreens, Free People, Wells Fargo - Ocean, Old Navy, Apple Store</td>
</tr>
</tbody>
</table>
Observations in text data

• King – man = Queen – woman

• What about trajectory data?
Qualitative examples

(a) Type I: City to Location
(b) Type II: Location to Location

Fig. 2. Identified examples for the pattern \( A_1 - A_2 \approx B_1 - B_2 \) using the embedding vectors learnt on the Foursquare \(_S\) [49] dataset. Each arrow line is associated with a pair of two entities. Each two corresponding entities pairs is in a ellipsoidal circle, indicating they have the approximately equal distance. For ease of visualization, PCA is used for dimensionality reduction, i.e., the first two principle components are used. See details in Section 5.4.
Conclusions

• Trajectory sequences encode human moving patterns
• How to derive effective sequential models is important to trajectory sequences
• We can borrow the models from different fields, e.g., natural language processing

Thanks!

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