How Routine Learners can Support Family Coordination

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Overview

• How Routine Learners can Support Family Coordination

• Learning Patterns of Pick-ups and Drop-offs to Support Busy Family Coordination

• Unremarkable Computing
How Routine Learners can Support Family Coordination
Intention

• Discussion of conceptual feasibility

• Roadmap

• 1. Analyze what families would find valuable
   2. Come up with a solution
Data Collection (1)

• 6 dual-income families

• 6 months
Data Collection (2)

- Quantitative
- Six month of field observation
  - Four families completed
  - 528 unique interview sessions
  - 2112 person days
Data Collection (3)

- Qualitative
  - Evaluation of knowledge of others routines (Activity interviews)
  - Identification of routine or non-routine
Contributions (I)

Routines and family life

40 %
Contributions (2)

Routine knowledge of others is incomplete or inaccurate
Contributions (3)

Calendars hold deviations not routine

90 %
Contributions (4)

Small information *gaps* lead to stressful situations
Future Potential

• Access to routine
• Augmented calendars
• Augmented reminders
• Use of more sensors
• Better routine detection algorithms
Reviews (I)

• Rating: 2 (accept)
• Positive
  • Extensive data collection
  • Base for applications supporting family coordination
  • Interesting to read with many examples
Reviews (2)

- Negative
  - No technical aspects
  - Only GPS location
  - Children and mobile phones
Learning Patterns of Pick-ups and Drop-offs to Support Busy Family Coordination
Setup

- Dual-income families
- GPS location data (once per minute)
- Data from first paper
Intention

• Pick-ups and drop-offs
  • Detect pick-ups and drop-offs
  • Predict driver
• Infer if child will be forgotten
Recognizing Rides (1)

- States

\[ States = \{ L_n, T \mid CoT, else \} \]

- People

\[ People = \{ P, C \} \]
Recognizing Rides (2)

- Pick-up

\[(t_1, P, \neg CoT) \land (t_1, C, L_n) \land (t_2, P, L_n) \land (t_2, C, L_n) \land (t_3, P, CoT) \land (t_3, C, CoT)\]

- Drop-off

\[(t_1, P, CoT) \land (t_1, C, CoT) \land (t_2, P, L_n) \land (t_2, C, L_n) \land (t_3, P, \neg CoT) \land (t_3, C, L_n)\]
Recognizing Rides (3)

• Precision 90.1 %

• Recall 95.5 %
Predicting Drivers (I)

- Feature Vector

<table>
<thead>
<tr>
<th>Name</th>
<th>Meaning</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_n$</td>
<td>Location of pick-up or drop-off</td>
<td>Place ID</td>
</tr>
<tr>
<td>$RT_{ype}$</td>
<td>Ride type</td>
<td>Pick-up, Drop-off</td>
</tr>
<tr>
<td>$DoW$</td>
<td>Day of week</td>
<td>0,1,2,3,4,5,6</td>
</tr>
<tr>
<td>$ToD$</td>
<td>Discretized time of day (15 min)</td>
<td>1,2,3…96</td>
</tr>
<tr>
<td>$driver_{t,j}$</td>
<td>Driver for the last 5 rides to $L_n$</td>
<td>Mom, Dad</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Driver distribution model</td>
<td>[0,1]</td>
</tr>
</tbody>
</table>

- Labeling and weighting

- Weighted decision tree (LWDT)
Predicting Drivers (2)

- Accuracy
- Sliding window
  - 1 week: 72.1%
  - 4 weeks: 87.7%
Forgetting Children (I)

• 10 minutes late

• Features

<table>
<thead>
<tr>
<th>Name</th>
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<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R$</td>
<td>Whether the parent remembers</td>
<td>True, False</td>
</tr>
<tr>
<td>$J$</td>
<td>Driver prediction model</td>
<td>Mom, Dad</td>
</tr>
<tr>
<td>$T$</td>
<td>If the parent is traveling</td>
<td>True, False</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Empirical cumulative distribution (ecdf) of on-time arrivals to $L_{child}$ at time $T_{now}T_{ideal}$</td>
<td>[0,1]</td>
</tr>
<tr>
<td>$L_{child}$</td>
<td>Location of the child</td>
<td>Place ID</td>
</tr>
<tr>
<td>$L_{start}$</td>
<td>Starting location of a parent</td>
<td>Place ID</td>
</tr>
<tr>
<td>$L_{curr}$</td>
<td>Ending location of a parent</td>
<td>Place ID</td>
</tr>
<tr>
<td>$D$</td>
<td>Destination of a parent</td>
<td>Place ID</td>
</tr>
</tbody>
</table>
Forgetting Children (2)

Bayesian Network
Forgetting Children (3)

ROC (Receiver Operating Characteristic)
Optimizations

• Increase GPS rates
• Other modes of transport
  • other than one parent, one child, one car
• Better driver prediction model
  • “only“ 70 - 85 %
Future Potential

- Awareness Systems
- Calendars
- Reminder Systems
Unremarkable Computing
Intention

• Analyze home / domestic life routines

• Make technology “invisible in use”
Scenarios

• Door as a means of communication
  • Knocking, opening, context dependent
• Alarm clock becomes routine
  • Failure would be noted
• Routines are unknown to yourself
  • Can be noted by others
Conclusions (1)

Invisibility in use
≠
perceptual invisibility
Conclusions (2)

Augment the action not artifacts per se
Conclusions (3)

Support the **doing** without description of activities
Thanks for your attention
Questions / Discussion

• Use of more sensors?

• Potential of routine detection algorithms?
  • T-Patterns
  • Eigenbehaviors
  • Topic Models

• Data collection and children?