

# 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 (I)

- 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

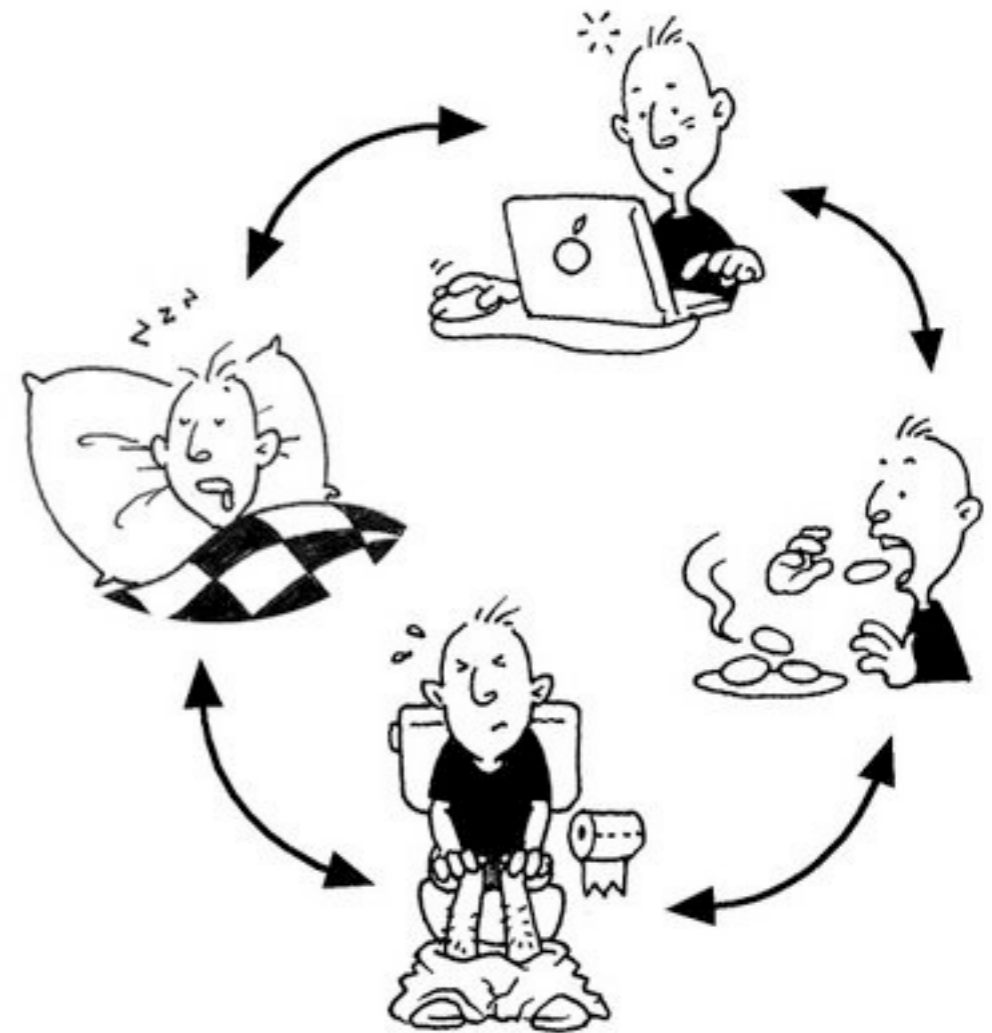
# Data Collection (3)

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

# Contributions (I)

Routines and family life

40 %





# Contributions (2)

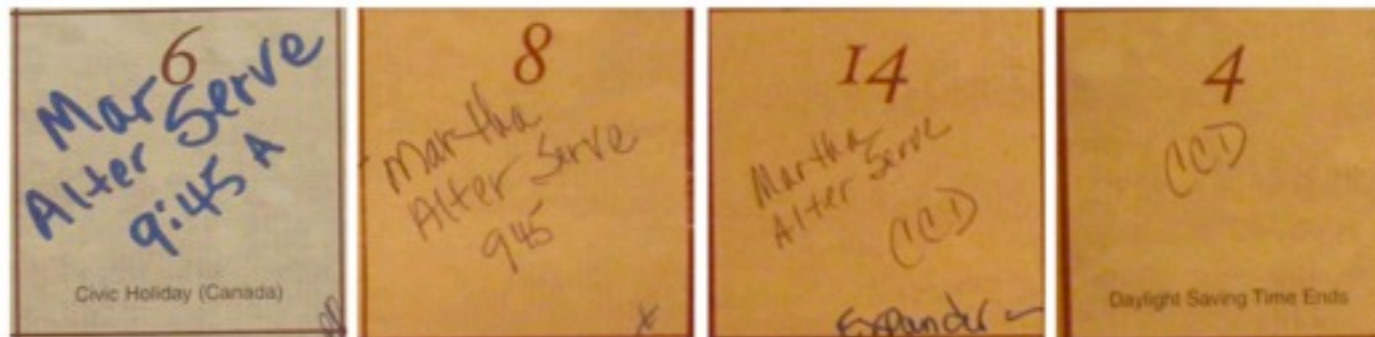
Routine knowledge of others is **incomplete**  
or **inaccurate**



# 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 (I)

- States

$$States = \{L_n, T \mid CoT, else\}$$

- People

$$People = \{P, C\}$$

# Recognizing Rides (2)

- Pick-up

$$(t_1, P, \neg CoT) \wedge (t_1, C, L_n) \wedge$$
$$(t_2, P, L_n) \wedge (t_2, C, L_n) \wedge$$
$$(t_3, P, CoT) \wedge (t_3, C, CoT)$$

- Drop-off

$$(t_1, P, CoT) \wedge (t_1, C, CoT) \wedge$$
$$(t_2, P, L_n) \wedge (t_2, C, L_n) \wedge$$
$$(t_3, P, \neg CoT) \wedge (t_3, C, L_n)$$

# Recognizing Rides (3)

- Precision **90.1 %**
- Recall **95.5 %**

# Predicting Drivers (I)

- Feature Vector

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

- Labeling and weighting
- Weighted decision tree (LWDT)

# Predicting Drivers (2)

- Accuracy
- Sliding window
  - 1 week: 72.1 %
  - 4 weeks: **87.7 %**

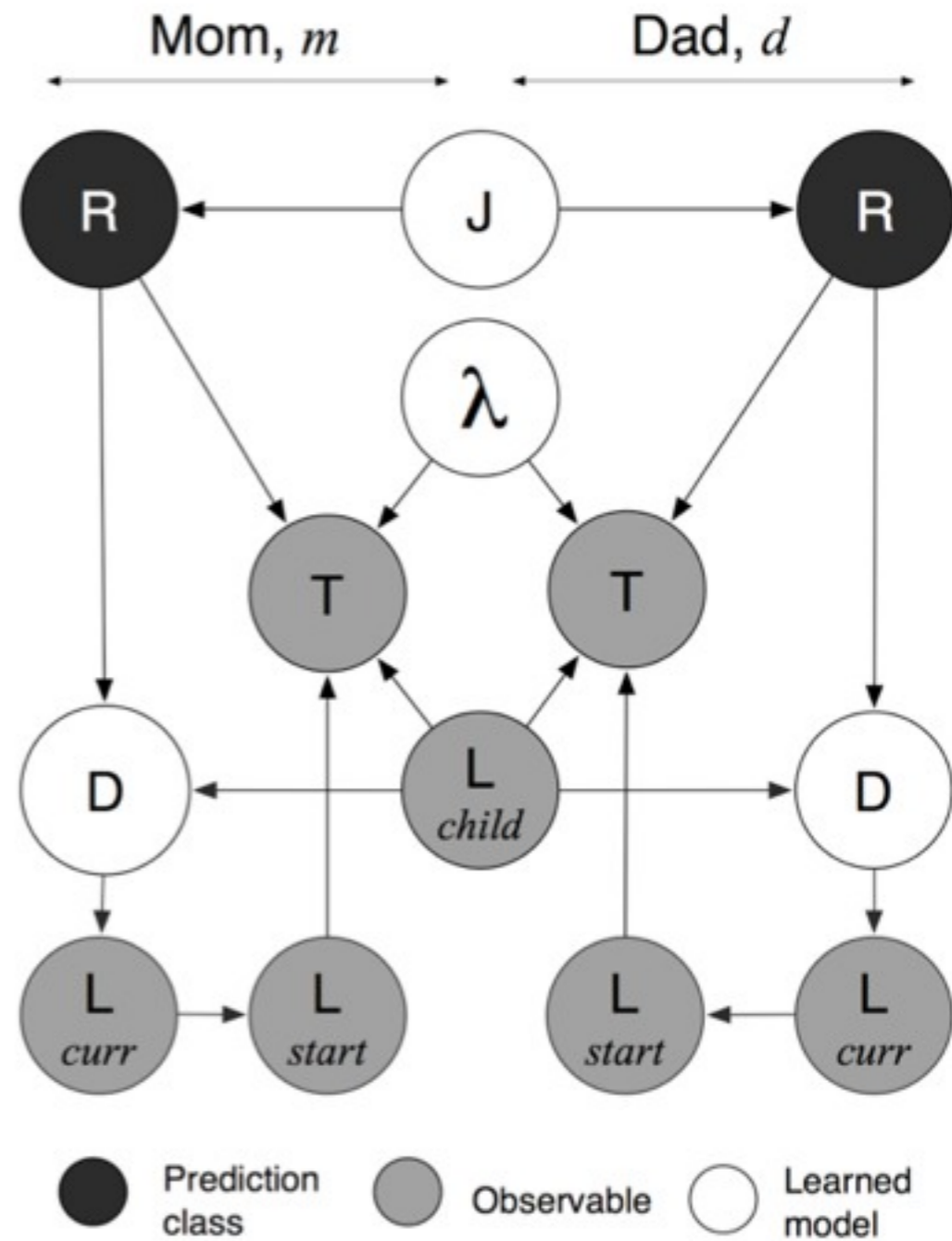
# Forgetting Children (I)

- 10 minutes late
- Features

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

# Forgetting Children (2)

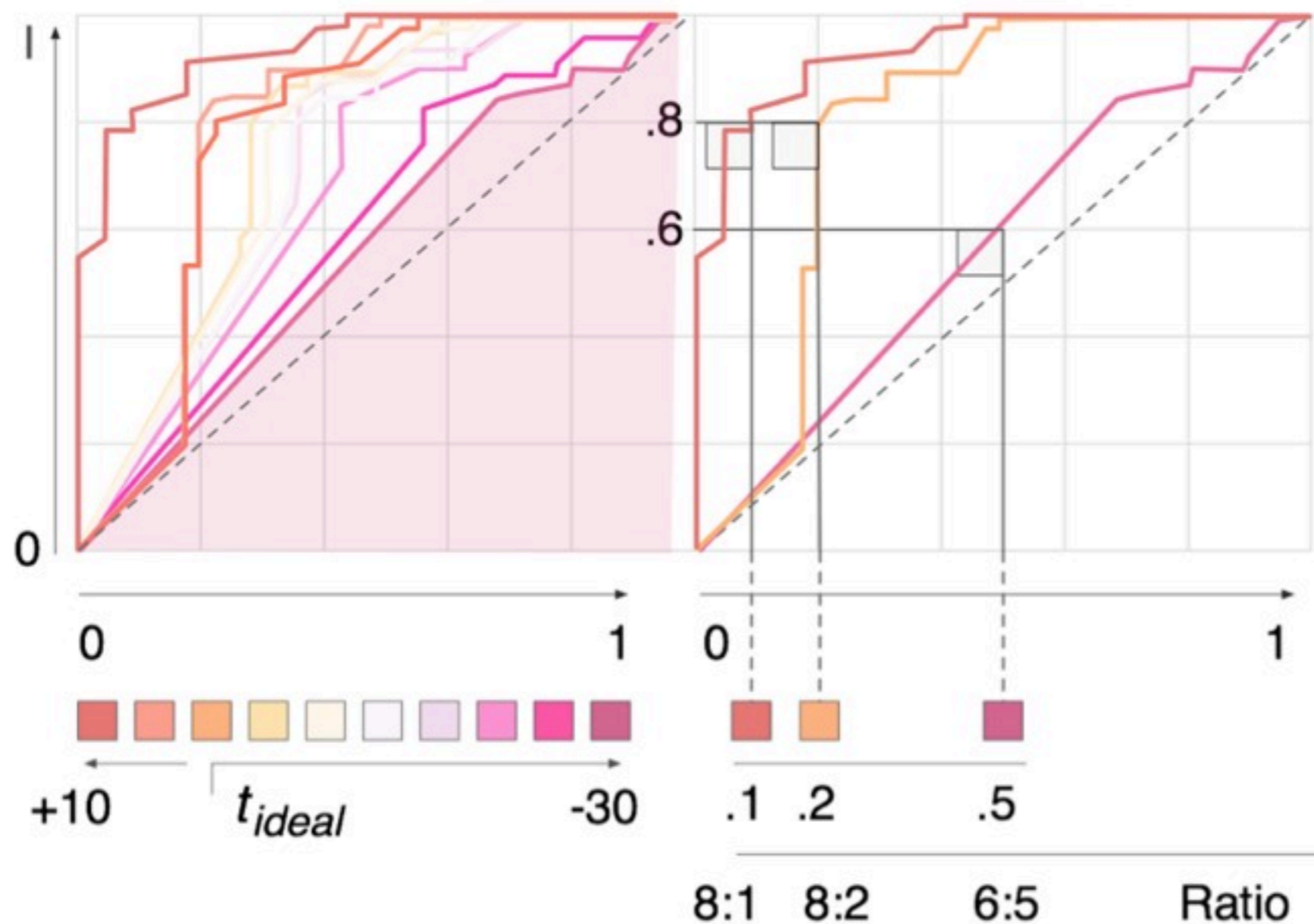
Bayesian Network





# 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 (I)

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?