Population Level Behavior Analysis in Smart

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Future Work

Overview

Formal modeling and analysis of human behavior can properly

advance disciplines ranging from psychology to economics.

Formal Models of Human Indoor Routine Patterns

→ Heavy tailed distributions, the Pareto distribution

→ Bed to toilet transitions reflect mobility difficulties

· Predict subgroup classifications from inter-arrival times

→ Bivariate or multivariate Pareto distributions

Construct Markov models for activities and locations.

interactions and time spent in locations) (future)

→ Selected orders of Markov model for indoor behavior

· Build up a model combine more elements (e.g. social

Datasets

Description

→ Different order of MC and a resident's health status

Analyze the inter-arrival times of activities (e.g. Eat, Cook)

· Investigate the relationship between formal models and a

→ 81.4% prediction accuracy from Work inter-arrival times

Investigate interdependencies of certain activities both at 99

WASHINGTON STATE

I INIVERSITY

resident health status

Smart Home Dataset

A fixed-size sliding window

11:42:50.57

11:42:51.15

11:42:51.57

11:42:51.99

11-42-53.01

11:42:54.82

11:42:55.74

11:42:56.95

11:42:57.18

11:42:58.15

11:42:59.78

11:43:00 0

11:43:08.2

11:43:09.47

2017-02-22

2017-02-22

2017-02-22 2017-02-22

2017-02-22

2017-02-22

2017-02-22

2017-02-22

2017-02-22

2017-02-2

2017-02-22

2017-02-22

smart homes and among subgroups

Hypothesis

Modeling Fitting

Inter-Arrival Times of Each Activity



8 10 12 14 16 18 the Pareto shape parameters 1.1 SUBGROUP H SUBGROUP NH

Inter-Arrival Times of Sequences of Activities



Interdependencies of certain activities

 $F_{subgroupNH}(x_{washDishes}, x_{eat}) = (1 + \frac{x_{washDishes} + 1.31}{1.22} + \frac{x_{eat} + 1.17}{1.22})^{-1.08}$

Markov Models of both Sequences of Activities and

Loc	Selected Order for Different Datasets							
	Group #	Groups	# of homes	activities with CPD	activities without CPD	locations	clusters with start/end	clusters w/o start/end
	1	All	99	N/A	1	N/A	1	1
	2	All Young	14	2	1	4	1	1
	3	All Middle Aged	6	1	1	3	1	1
	4	Middle Aged Single	4	1	1	3	1	1
	5	Middle Aged Double	2	1	1	3	1	1
	6	Middle Aged Not Healthy	1	1	1	2	1	1
	7	Middle Aged Healthy	5	2	1	3	1	1
	8	Middle and Old	3	1	1	3	1	1
	9	All Old	53	3	1	4	1	1
	10	Old Single	41	2	1	4	1	1
	11	Old Double	12	2	1	3	1	1
	12	Old Single Healthy	16	2	1	4	1	1
	13	Old Single Not Healthy	17	2	1	4	1	1

Hidden Markov Model



Our routine model generates a particular routine from a resident R_k by first generating a sequence of locations, l_1 , are hidden states s_0 , s_1 , ... according to a included in distinct Markov model. Each state s_i then states and routines generates a list of activities a_{0i} , progress through the $a_{1,i}$... according learning from stages in a fixed history data.

 l_2 State transitions for routine models. Activities, a_i , and

A Model Combines Other Elements

Social interactions:

- Seniors whether or not keep the doors open
- Compare their health status

Time Spent in Locations:

- Duration models including parametric models, semiparametric models, nonparametric models

Conclusions

These findings will help researchers

- Understand indoor activity routine patterns
- Develop more sophisticated models of predicting routine behaviors and their timings
- Automate diagnoses
- Design customized behavioral interventions - Provide activity-anticipatory services that
- will benefit both caregivers and patients.

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Hour of day for current event Seconds since the start of the day for the current event Window duration Seconds since previous event Most frequent event sensor in the previous window Most frequent event sensor in the window before that Current event sensor Extraction Most recent location sensor Number of events in the window for each sensor Time since last fired for each sensor Maximum value of sensor Complexity of events in window Number of motion events in window

Kitchen **Residents' Information Dataset**

FrontDoor

Entry

Hall

Entry

Entry

Entry Entry

Entry

Hall

Hall

Kitchen

FrontDo



education level # of residents age(s)

 $F_{entire}(x_{work}, x_{eat}) = (1 + \frac{x_{relax} + 1.14}{1.14} + \frac{x_{eat} + 1.61}{1.61})^{-1.17}$

 $F_{subgroupH}(x_{PH}, x_{relax}, x_{cook}, x_{eat}) = (1 + \frac{x_{PH} + 1.66}{1.70} + \frac{x_{relax} + 2.96}{2.97} + \frac{x_{cook} + 1.66}{1.66} + \frac{x_{eat} + 1.33}{1.33})^{-1.11}$

nal Hygiene – Relax – Cook – Eat – Slee

Stage 1 Stage 2 a_1 a_2 l_1

order.