



Taxonomy of Daily Travel and Time Use Patterns Using Sequence Analysis to Explore Schedule Fragmentation and Gender Roles

WEBINAR PRESENTER: KONSTADINOS (KOSTAS) G. GOULIAS (UCSB)

SEPTEMBER 24, 2020

Based on work with Elizabeth C. Mcbride (UCSB), Adam W. Davis (UCDavis), Rongxiang Su (UCSB), and Jingyi Xiao (UCSB)



Sponsored METRAS, PSR and by TRB Standing Committees

Women and Gender in Transportation (AME20)



Traveler Behavior and Values (AEP30)

Typical fragmented schedule

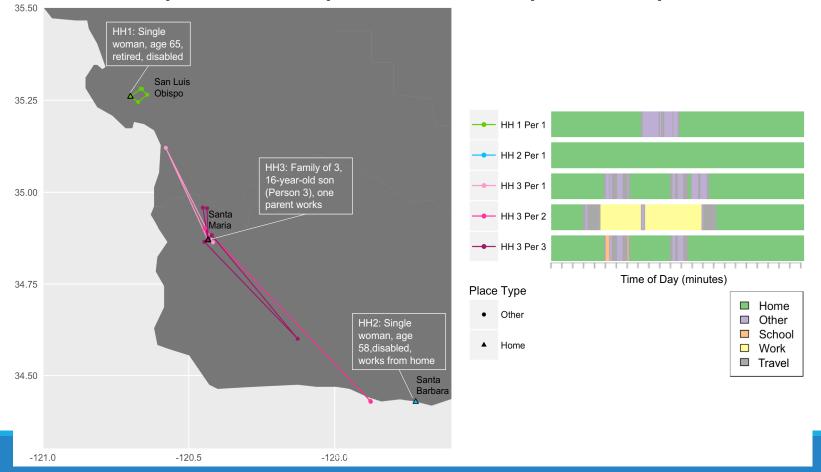
escorting children to schools—go to work—eat meal with colleagues—run errand—go back to work—go to a social event—go back to work—pick up children from schools—go shopping—return home—escort a child to soccer practice—do some work using mobile technologies—escort child back home—work at home

Fragmentation

Low fragmentation = indicator of possible social exclusion Disabilities, poverty, unemployment

High fragmentation = indicator of time poverty
Obligations -> little time for personal leisure

An example of spatiotemporal patterns



Patterns of Sequences & Durations

Person Daily Pattern: H-T-W-T-H

The person was at home (H) in the morning, traveled (T) to work (W), and after work traveled (T) back home (H)

If we include duration at each location (Location, Duration)

(H,830)-(T,10)-(W,320)-(T,10)-(H,270)

Another person with the same pattern but different durations

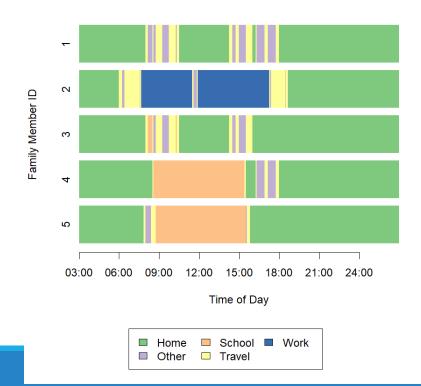
(H,345)-(T,15)-(W,615)-(T,20)-(H,445)

Sequence analysis distinguishes between these persons

It also accounts for activity locations, travel, and respective durations

Example of a day in the life of a family

Sequence Index Plot

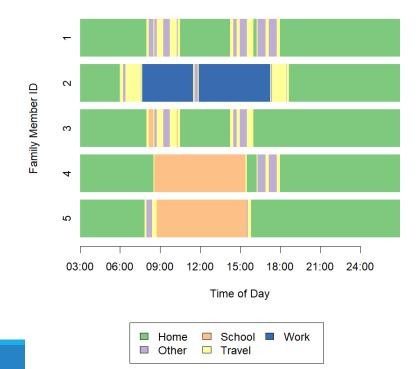


Person 1 Pattern

6

Example of a day in the life of a family

Sequence Index Plot



Person 5 Pattern

H-T-O-T-S-T-O-T-H

(H,290)-(T,10)-(O,25)-(T,20)-(S,405)-(T,1)-(O,4)-(T,15)-(H,670)

ENTROPY

$$h(x) = h(\pi_1, ... \pi_s) = -\sum_{i=1}^{s} \pi_i \log(\pi_i)$$

Where x is the sequence, s is number of potential states and π_i is proportion of occurrences of the *i*th state in the considered sequence.

High entropy means a person spends a lot of time in multiple different activities.

Zero entropy means the person stayed at the same location all day.

Sequences and subsequences

Consider the pattern H-T-W-T-H

This is a sequence of "states" and contains **subsequences**:

An empty sequence;

The full sequence itself;

Subsequences of the type T-W-T-H, W-T-H, and T-W-T;

Discontinuous subsequences like T-T-H (which skips the work activity); and

Single activities/locations H, T, and W.

Enumerating all these subsequences yields ($\phi(x) = 27$) possible combinations that respect the precedence of activities in the H-T-W-T-H sequence

TURBULENCE

$$T(x) = \log_2\left(\phi(x) \frac{s_{t,max}^2(x)+1}{s_t^2(x)+1}\right)$$

x represents the sequence of activities and travel episodes in one person's diary;

 $\phi(x)$ is the number of distinct subsequences in sequence x;

 t_i is duration in each distinct state and is used to compute the mean consecutive time and variance below (i=1,..., number of distinct episodes);

 s_t^2 is variance of the state-duration for the x sequence;

 $s_{t,max}^2$ is the maximum value that the variance can take given the total duration of the sequence x

The number of subsequences and variance within the pattern of durations drives this measure

NUMERICAL EXAMPLES

	(Activity/Place, Duration in minutes)	Pattern	Number of Subsequences	Entropy h(x)	Turbulence T(x)
	(H,1440)	Н	2	0.000	1.00
	(H,830)-(T,10)-(W,320)-(T,10)-(H,270)	H-T-W-T-H	27	0.372	6.63
	(H,345)-(T,15)-(W,615)-(T,20)-(H,445)	H-T-W-T-H	27	0.487	7.31
	(H,300)-(T,10)-(O,20)-(T,5)-(O,10)-(T,30)- (O,30)-(T,30)-(O,5)-(T,10)-(H,225)-(T,15)- (O,15)-(T,15)-(O,30)-(T,30)-(H,15)-(T,5)-(O,35)- (T,15)-(O,35)-(T,15)-(H,540)	H-T-O-T-O-T- O-T-O-T-H-T- O-T-O-T-H	496578	0.457	21.37
	(H,180)-(T,15)-(O,10)-(T,70)-(O,1)-(T,5)- (W,229)-(T,5)-(O,15)-(T,5)-(W,320)-(T,5)-(O,5)- (T,65)-(O,1)-(T,9)-(H,500)	H-T-O-T-O-T- W-T-O-T-W-T- O-T-O-T-H	25183	0.662	17.17
Not	e: H= home, W=work, S= school, O=other, T=travel	TADINOS G GOULIAS			11

COMPLEXITY

$$C(s) = \sqrt{\frac{nt(s)}{(l(s)-1)} \frac{h(s)}{h_{max}}}$$

- function of the Entropy
- number of transitions (nt(s) = l(s) 1) in a sequence s,
- normalized by the maximum theoretical entropy (hmax) and the length of the sequence (l(s)).

This indicator will have a value between 0 and 1, with zero corresponding to Entropy zero and no transitions

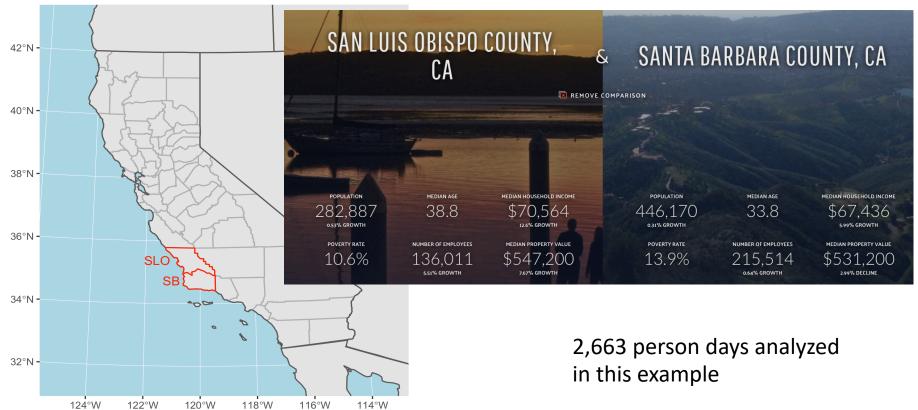
	(Activity/Place, Duration in minutes)	Pattern	Entropy h(x)	Complexity C(x)
Person 1	(H,1440)	Н	0.000	0.00
Person 2	(H,830)-(T,10)-(W,320)-(T,10)-(H,270)	H-T-W-T-H	0.372	0.0322
Person 3	(H,255)-(T,45)-(O,120)-(T,30)-(H,990)	Н-Т-О-Т-Н	0.302	0.0290
Person 4	(H,600)-(T,15)-(O,60)-(T,10)-(O,20)- (T,10)-(H,725)	Н-Т-О-Т-О-Т-Н	0.203	0.0291
Person 5	(H,485)-(T,5)-(W,169)-(T,2)-(H,10)- (T,14)-(O,70)-(T,10)-(O,25)-(T,15)- (H,125)-(T,15)-(W,321)-(T,14)-(H,160)	H-T-W-T-H-T- O-T-O-T-H-T- W-T-H	0.641	0.0790

Examples using CHTS

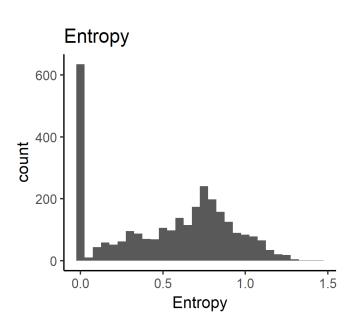
California Household Travel Survey

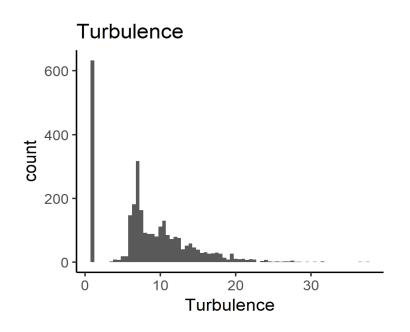
- One day place-based diary
- Spans a year February 2012 to February 2013
- 114,639 persons in 45,362 households
- Every location in the dary has also the top three activities at the location
- Combination of paper and pencil, computer aided telephone interview, and online
- Has other components but not important in this analysis (long distance travel, GPS tracking, On board diagnostics etc).





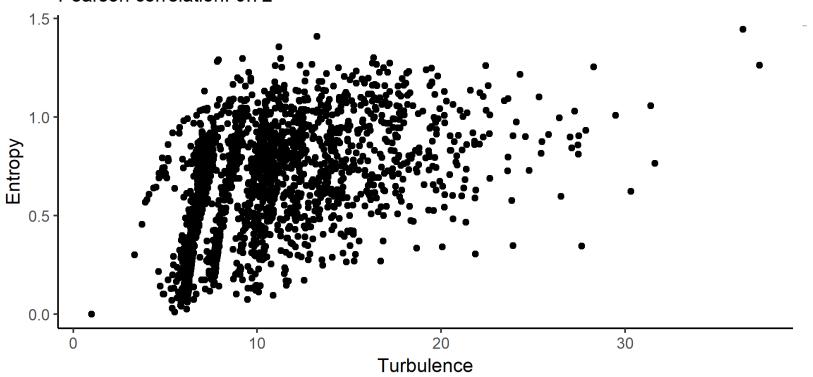
HISTOGRAMS OF VALUES





Entropy vs. Turbulence

Pearson correlation: 0.72



RESEARCH QUESTIONS

- WHO IS MORE LIKELY TO HAVE COMPLEX DAILY PATTERNS?
- WHERE DO WE FIND MORE COMPLEX PATTERNS (CITY VS SUBURBS?)
- ARE THESE DIFFERENT ACROSS THE DAYS OF A WEEK?
- ARE MEN AND WOMEN DIFFERENT IN PATTERN COMPLEXITY?
- WHAT ROLE DO CHILDREN IN THE HOUSEHOLD PLAY?
- DOES DISABILITY IMPACT PATTERN COMPLEXITY?

Analysis

Use Tobit Regression to account for the large concentration of observations at a value (0 in Entropy and 1 in Turbulence)

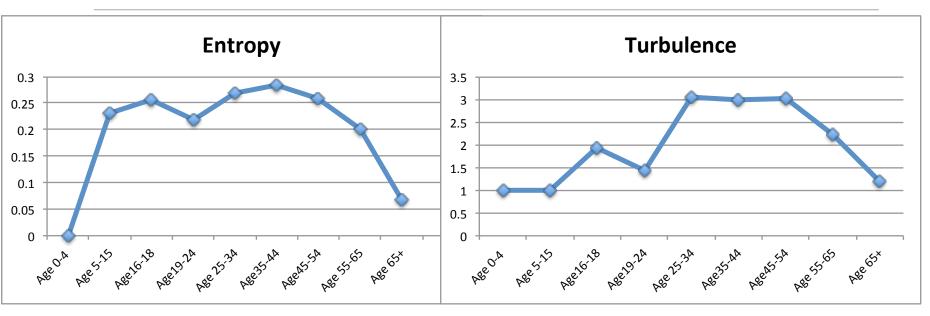
Include social and demographic variables to explain variation

Include an indicator of residential character (urban, suburban, exurban, rural)

Include presence of children in household

Analyze partial derivative of dependent variables wrt explanatory variable

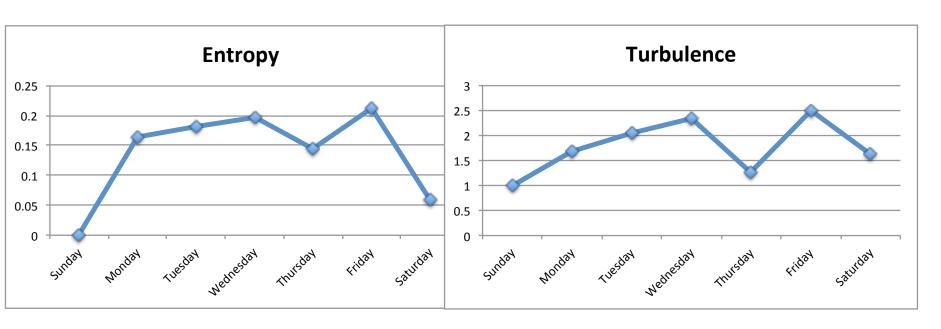
Age Effect



High school age kids and middle aged adults both have high entropy: they spend a lot of time at school/work and have other activities

Adults have higher turbulence, since their other activity duration is from multiple short events / errands.

Day of the Week Effect



Sunday is the resting day. All days are different (but also different persons)

Summary of Select Findings Part 1

- Children in the age groups Age 5 to 15 and Age 16 to 18 show almost as high Entropy and Turbulence as their parents age groups (Age 25-34, Age 35-44, Age 45-54)
 - These groups not only visit multiple places in a day but also switch between long and short durations of activities
- Days of the week indicate substantial dissimilarity in ordering and duration of activities across the days of a week.
 - Friday is the day of the week with the most within-sequence variety, indicating substantial mixing of types of places and activities.
- Turbulence is significantly higher for the urbanites and suburbanites, indicating the higher complexity of their activity sequences than their counterpart exurbanites and rural residents – but no differences in entropy.

Summary of Select Findings Part 2

- Men and Women differ only for Entropy in SLO/SBA but ...
- **Disability** inhibits pattern complexity (recall the first examples= either stay home all day or have a simple pattern)
- US-born and Hispanic have higher Entropy and Turbulence than other groups
- Poverty plays a major role in inhibiting complexity in daily patterns
- The presence of very young children in household (< 3 years old) inhibit complexity
- The presence of **children 4 to 15 years** old have a large, significant, and positive impact on a person's variety and complexity of daily patterns
 - Note this includes impact on their siblings

What are the daily patterns looking like?

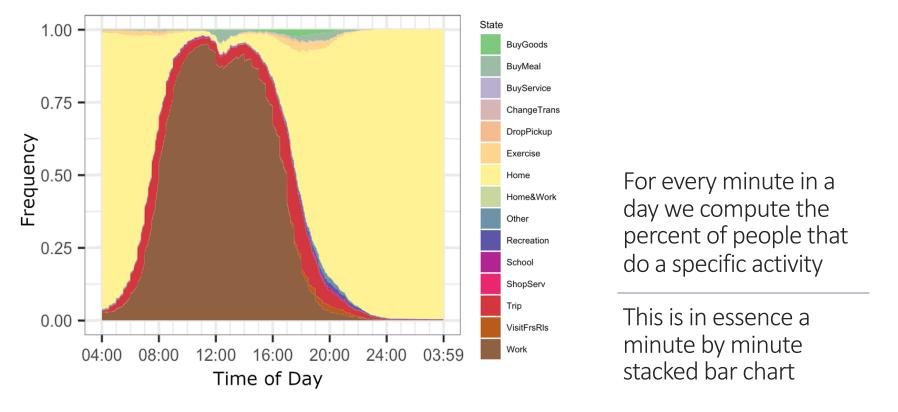
Method

- 1. Consider every sequence of 1440 minutes with each minute classified as Home, Work, School, Other place, Travel
- 2. Compare all sequences with each other and compute pairwise dissimilarity indicators
- 3. Apply a clustering technique that groups sequences by similar dissimilarity scores -> low dissimilarity sequences are grouped together
- 4. Decide on the number of clusters that is optimally representing the data using a criterion of within group similarity and across groups dissimilarity

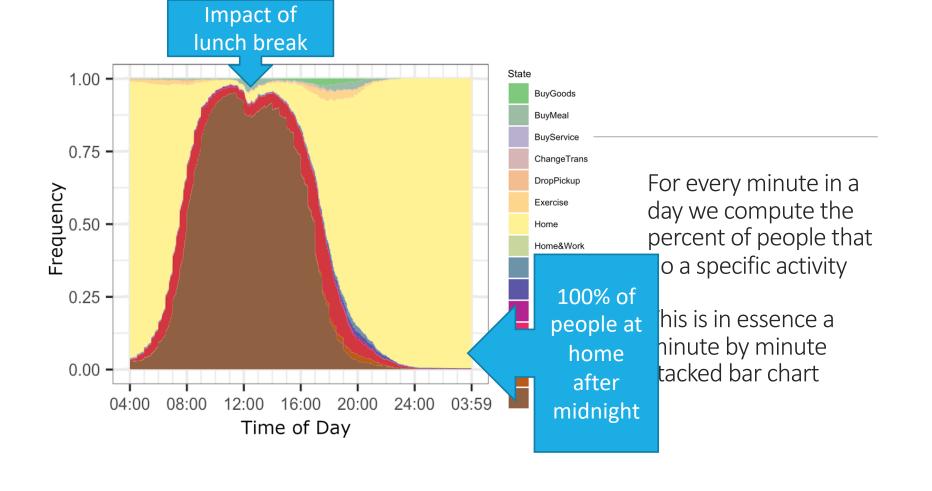
Example of sequence dissimilarities

_	±	±	±	±	<u> </u>	±	±	±	±	±	±	±	±	±	±	±	±	±
1	0.0000	469.2242	876.7258	1327.5763	1139.3562	825.9358	1265.0995	708.4956	894.4847	987.9549	1198.8168	1147.8225	1098.5412	989.3488	1558.4081	678.2299	1198.3754	1138.47205
2	469.2242	0.0000	617.8528	1278.4485	1139.5484	817.4141	1255.7072	249.2713	1294.9221	988.3830	1199.2450	1228.7448	1028.7278	959.5484	1558.6003	728.1899	1238.4692	1138.90018
3	876.7258	617.8528	0.0000	1478.1607	1089.6148	1116.1224	1509.2552	447.1709	943.8837	1097.6224	1338.4463	1227.9482	1097.6767	1078.8529	1538.3440	1037.9494	1337.6666	1248.05138
4	1327.5763	1278.4485	1478.1607	0.0000	1559.4106	1147.6902	174.9477	1448.3623	1655.9535	1018.0411	688.6713	1338.2866	1737.9032	1538.8105	1638.5177	769.0933	1628.2431	838.44237
5	1139.3562	1139.5484	1089.6148	1559.4106	0.0000	1288.5671	1586.4282	1139.4417	1287.9826	1139.3135	1349.4098	1459.3023	1529.0223	219.5698	458.6216	1139.3135	1478.9582	1259.12986
6	825.9358	817.4141	1116.1224	1147.6902	1288.5671	0.0000	1124.9489	1026.9831	1183.3229	1166.7096	1198.2936	1597.7142	1666.8326	1178.6173	1507.2175	827.5959	1626.5370	1128.26762
7	1265.0995	1255.7072	1509.2552	174.9477	1586.4282	1124.9489	0.0000	1465.2762	1702.3921	991.4388	662.0690	1335.0329	1734.6494	1496.3454	1604.3123	759.8021	1651.4864	811.84013
8	708.4956	249.2713	447.1709	1448.3623	1139.4417	1026.9831	1465.2762	0.0000	1184.4563	1077.6780	1318.7407	1218.6270	1028.4899	999.1970	1558.4935	937.7589	1238.2313	1228.34574
9	894.4847	1294.9221	943.8837	1655.9535	1287.9826	1183.3229	1702.3921	1184.4563	0.0000	1186.7495	1466.0178	1246.0743	1405.2071	1287.3192	1596.7879	1254.9984	1466.1334	1346.29055
10	987.9549	988.3830	1097.6224	1018.0411	1139.3135	1166.7096	991.4388	1077.6780	1186.7495	0.0000	369.0071	1008.4899	1268.0500	1029.2390	1558.3654	547.8597	817.9073	268.91198
11	1198.8168	1199.2450	1338.4463	688.6713	1349.4098	1198.2936	662.0690	1318.7407	1466.0178	369.0071	0.0000	1198.9904	1448.6842	1279.4484	1558.3497	758.7217	1048.6148	199.10226
12	1147.8225	1228.7448	1227.9482	1338.2866	1459.3023	1597.7142	1335.0329	1218.6270	1246.0743	1008.4899	1198.9904	0.0000	618.6969	1389.1633	1498.1072	1007.6907	878.4810	1128.97743
13	1098.5412	1028.7278	1097.6767	1737.9032	1529.0223	1666.8326	1734.6494	1028.4899	1405.2071	1268.0500	1448.6842	618.6969	0.0000	1458.8833	1567.8272	1368.0136	928.0203	1388.45131
14	989.3488	959.5484	1078.8529	1538.8105	219.5698	1178.6173	1496.3454	999.1970	1287.3192	1029.2390	1279.4484	1389.1633	1458.8833	0.0000	638.6216	989.3949	1408.9969	1189.16849
15	1558.4081	1558.6003	1538.3440	1638.5177	458.6216	1507.2175	1604.3123	1558.4935	1596.7879	1558.3654	1558.3497	1498.1072	1567.8272	638.6216	0.0000	1558.3654	1838.1646	1557.91926
16	678.2299	728.1899	1037.9494	769.0933	1139.3135	827.5959	759.8021	937.7589	1254.9984	547.8597	758.7217	1007.6907	1368.0136	989.3949	1558.3654	0.0000	1058.0232	698.37691
17	1198.3754	1238.4692	1337.6666	1628.2431	1478.9582	1626.5370	1651.4864	1238.2313	1466.1334	817.9073	1048.6148	878.4810	928.0203	1408.9969	1838.1646	1058.0232	0.0000	938.30860
18	1138.4721	1138.9002	1248.0514	838.4424	1259.1299	1128.2676	811.8401	1228.3457	1346.2905	268.9120	199.1023	1128.9774	1388.4513	1189.1685	1557.9193	698.3769	938.3086	0.00000

One outcome of this analysis is a summary daily schedule for each cluster of person-days

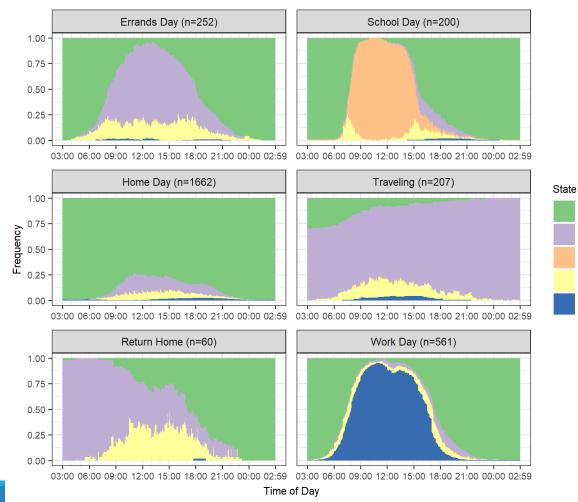


This example is using NHTS data we will review later



Central Coast of CA

First application with a small sample



I Expected to find: Home Day, Errands Day, Work Day, and School Day

Home

Other

School

Travel

Work

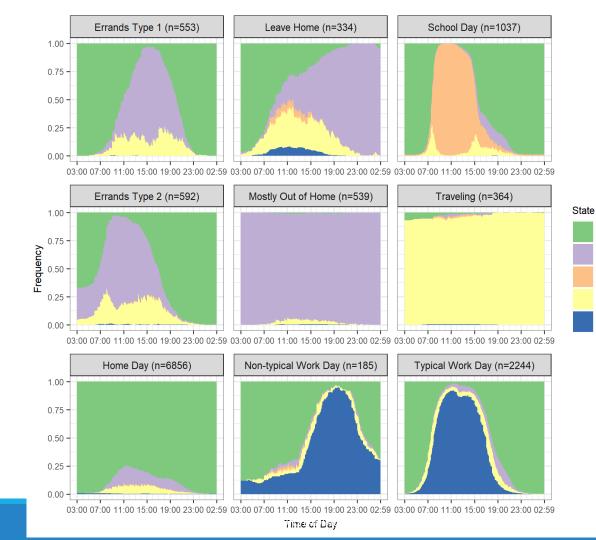
New patterns: Traveling outside residence & Return home from a long distance trip

Expanding the Analysis to the Entire State of California

POPULATION ABOUT 39 MILLION, 14.6 MILLION WORKERS, ALMOST 1 MILLION BUSINESS ESTABLISHMENTS, DENSITY ABOUT 239.1 PERSONS/SQ MILE

This is a richer taxonomy of daily schedules

Sample = 5,000 households (containing 12,704 persons).



2 types of errands days
2 types of working days
1 new totally out of home
Pattern mostly traveling

Н

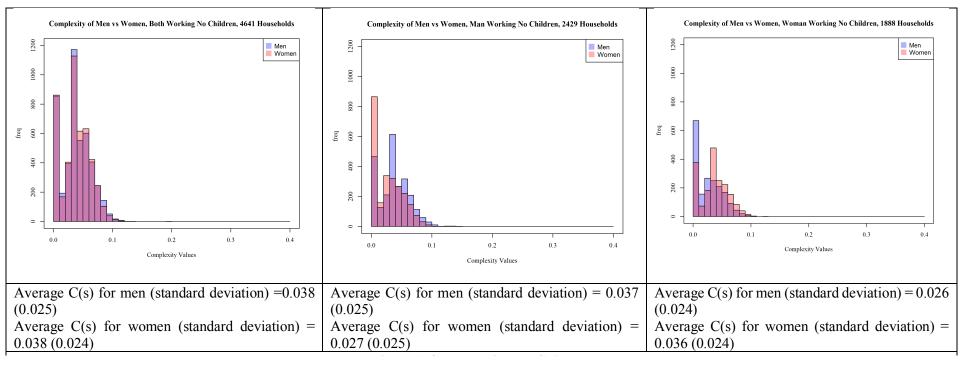
	Home Day	School Day	Typical Work Day	Errands Type 1	Mostly Out of Home	Errands Type 2	Non- typical Work Day	Leave Home	Traveling
By-Cluster Complexit	ty								
Mean C(s)	0.024	0.045	0.052	0.054	0.007	0.049	0.041	0.049	0.003
Std. Dev C(s)	0.024	0.015	0.017	0.016	0.014	0.018	0.02	0.022	0.009
Travel Time Ratio									
Mean TTR	0.368	0.1	0.136	0.257	0.019	0.253	0.113	0.22	0.984
Std.Dev TTR	0.213	0.07	0.081	0.14	0.048	0.208	0.08	0.159	0.06
Modal Split (Private I	Motorized)								
Driving alone	37.38%	7.26%	61.44%	26.83%	20.67%	39.33%	64.59%	30.83%	27.48%
Driving others	21.87%	2.44%	13.39%	24.69%	29.92%	17.17%	7.94%	22.28%	17.90%
Passenger in car	23.45%	61.00%	6.26%	33.28%	30.51%	23.84%	9.33%	31.88%	31.04%
Pass. in other	0.71%	2.22%	1.83%	0.72%	4.53%	1.34%	1.21%	1.95%	2.46%
Total	83.41%	72.91%	82.92%	85.52%	85.63%	81.68%	83.07%	86.95%	78.88%
Modal Split (All Othe	ers)								
Biking	1.63%	2.33%	2.07%	1.07%	1.38%	1.15%	2.42%	1.20%	2.97%
Walking	12.11%	16.43%	11.05%	9.52%	11.22%	11.46%	10.71%	7.80%	13.06%
Transit	2.36%	8.03%	3.88%	3.83%	0.59%	4.91%	3.80%	2.93%	3.82%
Other non- motor	0.50%	0.30%	0.04%	0.07%	0.39%	0.15%	0.00%	0.00%	0.17%
All Other	0.00%	0.00%	0.03%	0.00%	0.79%	0.65%	0.00%	1.13%	1.10%
Total	16.59%	27.09%	17.08%	14.48%	14.37%	18.32%	16.93%	13.05%	21.12%
Trips/Person	2.76	3.52	4.24	5.24	1.52	4.41	3.13	3.99	3.24
Note: Compare colors horizontally/row-wise									

	Home Day	School Day	Typical Work Day	Errands Type 1	Mostly Out of Home	Errands Type 2	Non- typical Work Day	Leave Home	Traveling	
By-Cluster Complexit	y									
Mean C(s)	0.024	0.045	0.052	0.054	0.007	0.049	0.041	0.049	0.003	
Std. Dev C(s)	0.024	0.015	0.017	0.016	0.014	0.018	0.02	0.022	0.009	
Travel Time Ratio										
Mean TTR	0.368	0.1	0.136	0.257	0.019	0.253	0.113	0.22	0.984	
Std.Dev TTR	0.213	0.07	0.081	0.14	0.048	0.208	0.08	0.159	0.06	
Modal Split (Private N	Motorized)									
Driving alone	37.38%	7.26%	61.44%	26.83%	20.67%	39.33%	64.59%	30.83%	27.48%	
Driving others	21.87%	2.44%	13/9%	24.69%	29.92%	17.17%	7.50%	22.28%	17.90%	
Passenger in car	23.45%	61.00%		33.28%	30.51%	23.84%		31.88%	31.04%	
Pass. in other	0.71%	2.22%	ó	0.72%	4.53%	1.34%	,	1.95%	2.46%	
Total	83.41%	72.910		52%	85.63%	81.6		5%	78.88%	
Modal Split (All Othe	rs)						Commun	to		
Biking	1.63%	2.3	Commut	le _{)7%}	1.38%	1.1	Commu	0%	2.97%	
Walking	12.11%	16.4	driving	52%	11.22%	11.4	driving	0%	13.06%	
Transit	2.36%	8.0	alone	33%	0.59%	4.9	alone	3%	3.82%	
Other non- motor	0.50%	0.3	alone)7%	0.39%	0.1	alone	0%	0.17%	
All Other	0.00%	0.00%	0.03%	0.00%	0.79%	0.65%	0.00%	1.13%	1.10%	
Total	16.59%	27.09%	17.08%	14.48%	14.37%	18.32%	16.93%	13.05%	21.12%	
Trips/Person	2.76	3.52	4.24	5.24	1.52	4.41	3.13	3.99	3.24	
Note: Compare colors horizontally/row-wise										

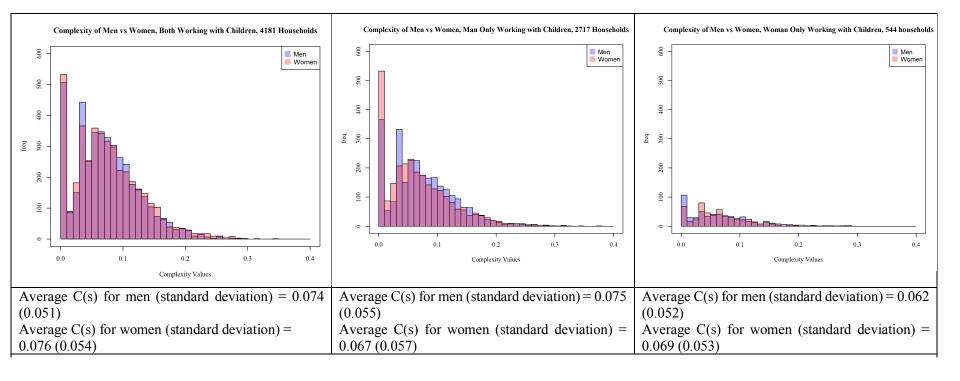
	Home Day	School Day	Typical Work Day	Errands Type 1	Mostly Out of Home	Errands Type 2	Non- typical Work Day	Leave Home	Traveling
By-Cluster Complexit	ty								
Mean C(s)	0.024	0.045	0.052	0.054	0.007	0.049	0.041	0.049	0.003
Std. Dev C(s)	0.024	0.015	0.017	0.016	0.014	0.018	0.02	0.022	0.009
Travel Time Ratio									
Mean TTR	0.368	0.1	0.136	0.257	0.019	0.253	0.113	0.22	0.984
Std.Dev TTR	0.213	0.07	0.081	0.14	0.048	0.208	0.08	0.159	0.06
Modal Split (Private I	Motorized)								
Driving alone	37.38%	7.26%	61.44%	26.83%	20.67%	39.33%	64.59%	30.83%	27.48%
Driving others	21.87%	2.44%	13.39%	24.69%	29.92%	17.17%	7.94%	22.28%	17.90%
Passenger in car	23.45%	61.00%	6.26%	33.28%	30.51%	23.84%	9.33%	31.88%	31.04%
Pass. in other	0.71%	2/2%	1.83%	0.72%	4.53%	1.34%	1.21%	1.95%	2.46%
Total	83.41%		82.92%	85.52%	85.63%	81.68%	83.07%	86.95%	78.88%
Modal Split (All Othe	ers)								
Biking	1.620/	/	 07%	1.07%	1.38%	1.15%	2.42%	1.20%	2.97%
Walking	12.)5%	9.52%	11.22%	11.46%	10.71%	7.80%	13.06%
Transit	2.3	Parents	38%	3.83%	0.59%	4.91%	3.80%	2.93%	3.82%
Other non- motor	0	rive kid	7470	0.07%	0.39%	0.15%	0.00%	0.00%	0.17%
All Other	0.(t	o schoo)3%	0.00%	0.79%	0.65%	0.00%	1.13%	1.10%
Total	16.5)8%	14.48%	14.37%	18.32%	16.93%	13.05%	21.12%
Trips/Person	2.76	3.52	4.24	5.24	1.52	4.41	3.13	3.99	3.24
Note: Compare colors	s horizontall	y/row-wise							

Men and Women in Same Household

SAMF HOUSEHOLD - ENTIRE CALIFORNIA STATE



Complexity of Couples with **No Children**The **Worker** has always higher schedule complexity!
Look at the flipping of C(s)



Complexity of Couples with Children
Women have always higher than men schedule complexity!

RESEARCH QUESTIONS

- WHO IS MORE LIKELY TO HAVE COMPLEX DAILY PATTERNS? Workers with kids and especially women = time poverty
- WHERE DO WE FIND MORE COMPLEX PATTERNS (CITY VS SUBURBS?) urban and suburban environments = possible market for autonomous and ride hailing services
- ARE THESE DIFFERENT ACROSS THE DAYS OF A WEEK? Yes! All days of the week are different!
- ARE MEN AND WOMEN DIFFERENT IN PATTERN COMPLEXITY? Yes, women more complex patterns
- WHAT ROLE DO CHILDREN IN THE HOUSEHOLD PLAY? very young inhibit complexity and older children increase complexity of schedules but when they get a driver's license and a car things change
- DOES DISABILITY IMPACT PATTERN COMPLEXITY? Yes, lower complexity but also stay home all day = possible social exclusion

Household Responsibility Hypothesis

- Early evidence from Professor Niemeier (@UCDavis and now in Maryland) showed that women take care of work, kids, and household chores
- Evidence from our own research shows this to be clearly demonstrated when we ask a question such as for whom an activity is done
- In this research we see working women having the most fragmented schedules and dedicating substantial amounts of time in multiple activities and trips == TIME POVERTY
- So, social exclusion happens in two ways-> stay at home with little access to opportunities or be super-active for the benefit of others with no personal time

Lessons learned in Part 1

- This type of analysis can take very long computational time but converges to interpretable outcomes (time of day of schedules).
- Correlation with personal characteristics such as life cycle stages leads to powerful explanation of daily dynamics
- Day of the week analysis shows the variety of schedules people follow and challenges the "typical day" used in regional models to assess emissions, conformity, impact of SB 375, and sustainable community strategies
- -Just using location classification of Home, Work, School, Other is too limited and needs to expand
- The California Household Travel Survey is becoming dated (2012-2013)

Taxonomy in the 2017 California Component of National Household Travel Survey

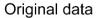
WITH MOTIFS AND EXPANDED ACTIVITY TYPES

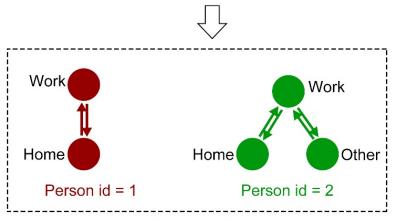
NHTS - CA

- One-day travel diary.
- Between April 24th, 2016 and April 24th, 2017
- Assigned day attempts to provide a uniform assignment throughout a complete year
- Diary day for each household can be any weekday, weekend day, or holiday
- We use data just from work days in this analysis (i.e., exclude state/federal holidays, Saturdays, and Sundays)

Household Id	Person Id	Origin	Destination	Origin type	Destination type
30000328	1	10000	100	Home	Work
30000328	1	100	10000	Work	Home
30000328	2	10000	100	Home	Work
30000328	2	100	20001	Work	Other
30000328	2	20001	100	Other	Work
30000328	2	100	10000	Work	Home

We add the idea of motifs to the daily patterns

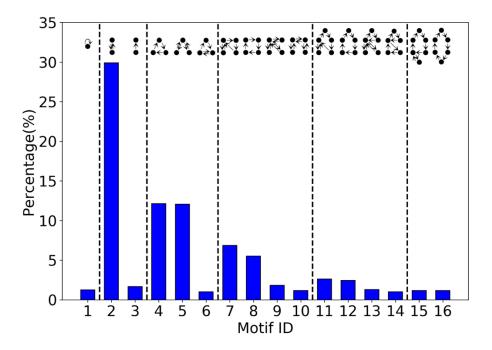




Motif representations

In this way we identify unique places visited in a day





Each motif ID has different membership in terms of social and demographic characteristics and different average time allocation to activities Home with unspecified activity (*Home*);

Work from home as in telecommuting and home stay combined (Home&Work);

Engage in recreational activities such as visit parks, movies, bars, museums (Recreation);

Work at a workplace (Work);

Education at the school location (School);

Drop off or Pick up someone (*DropPickup*);

Change type of transportation (*ChangeTrans*);

Purchase goods such as groceries, clothes, appliances, gas (BuyGoods);

Purchase services such as dry cleaners, banking, service a car, pet care (BuyService);

Go out for a meal, snack, carry-out (*BuyMeal*);

Run other general errands such as post office (ShopServ);

Exercise in a gym (Exercise);

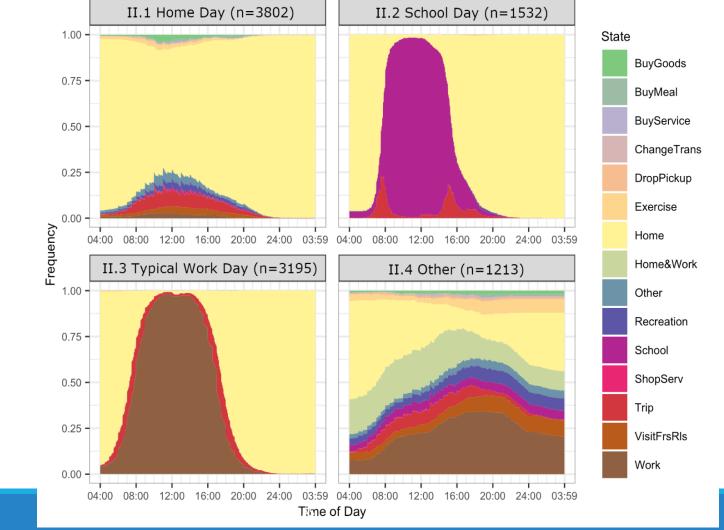
Visit friends and/or relatives (VisitFrsRls);

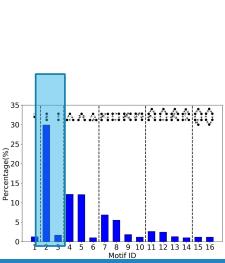
Other activity; and

Activity
Travel
Types

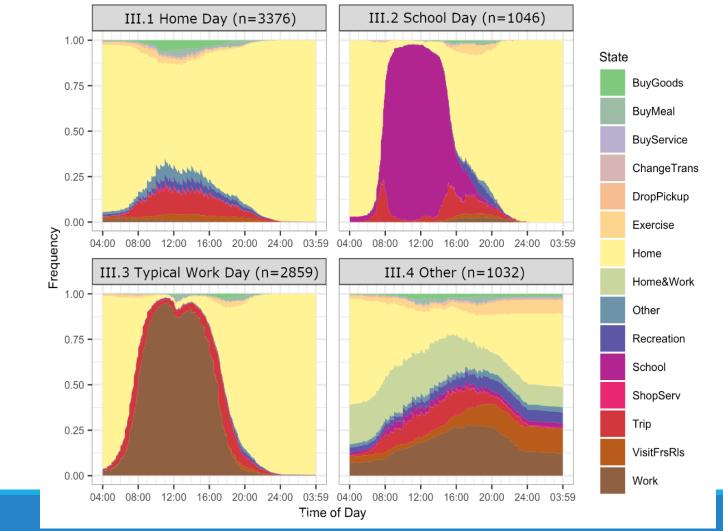
46

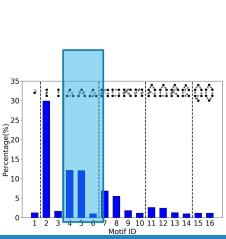
Group II



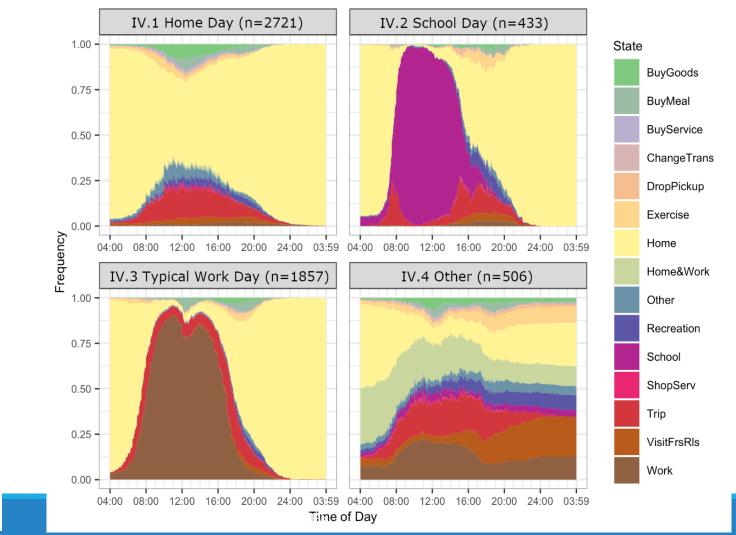


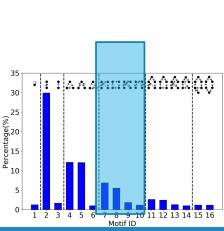
Group III



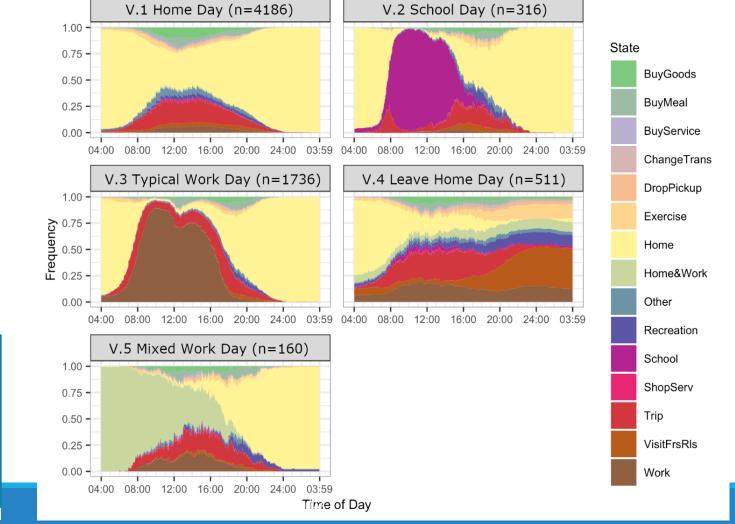


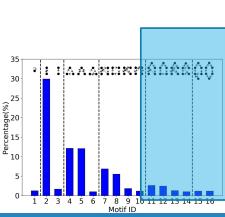
Group IV



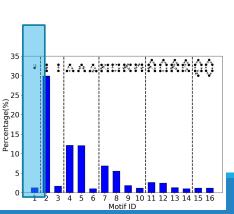


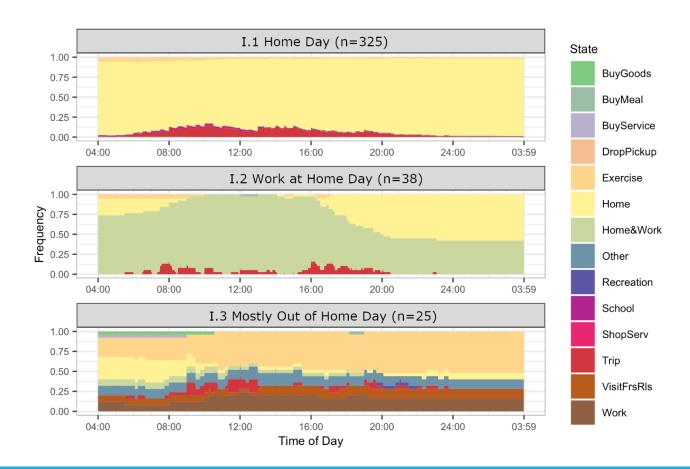
Group V





Group I





Key findings

- Home days as a pattern most popular and many regional simulation models do not pay attention to this
- Home day does not mean no travel even for the no other destination group (I)
- walk the dog, go for walk or bicycle exercise, etc. (loop trips)
- Home, Work, & School as the three anchors in daily schedules are still important
- Tremendous heterogeneity of behavior but classifiable with pattern recognition
- Patterns have strong correlation with person characteristics and day of the week
- Telecommuters do not stay at home! Instead we found them in all the groups of patterns

Some other research we did with these ideas

- Correlation between daily patterns and propensity to own and/or use an autonomous vehicle using data from the Puget Sound region (Seattle metropolis).

- Life Cycle stages and daily time allocated for the benefit of self and others (with time use data in Pennsylvania)

- We started correlating daily patterns to land use (we did this in CHTS and now expand to NHTS)

Publications

McBride, E. C., Davis, A. W., & Goulias, K. G. (2019). Fragmentation in Daily Schedule of Activities using Activity Sequences. *Transportation Research Record*, 2673(4), 844-854.

McBridea, E. C., Davis, A. W., & Goulias, K. G. (2019). Sequence analysis of place-travel fragmentation in California. *Mapping the Travel Behavior Genome*, 371.

Xiao, J., Su, R., McBride, E. C., & Goulias, K. G. (2020). Exploring the correlations between spatiotemporal daily activity-travel patterns and stated interest and perception of risk with self-driving cars. *AGILE: GIScience Series*, 1, 22-HASH.

McBride, E. C., Davis, A. W., & Goulias, K. G. (2020). An Exploration of Statewide Fragmentation of Activity and Travel and a Taxonomy of Daily Time Use Patterns Using Sequence Analysis in California. *Transportation Research Record (in press)*.

Su R., McBride, E.C. & Goulias K.G. (2020) Pattern recognition of daily activity patterns using human mobility motifs and sequence analysis. Transportation Research Part C (in press)

Goulias, K.G., McBride E.C., and Su R. (2020) Life Cycle Stages, Daily Contacts, and Activity-Travel Time Allocation for the Benefit of Self and Others. *Chapter 13 In Mobility and travel behaviour across the life course* (eds Scheiner J. and Rau R.), Edward Elgar Publishing.

THANK YOU & Acknowledgement

- Funding for this research was provided by
 - The University of California Santa Barbara
 - Pacific Southwest Region 9 University Transportation Center
 - CALTRANS

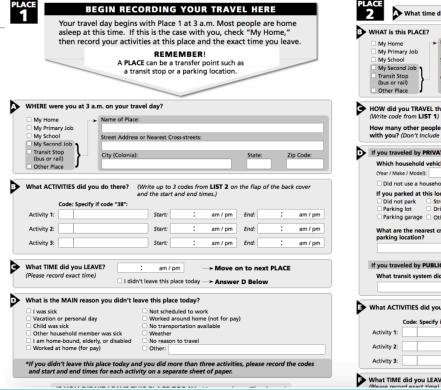






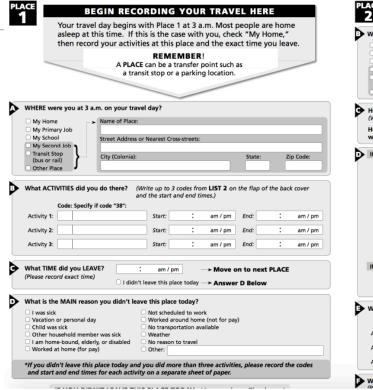


California Household Travel Survey



	his PLACE?							
☐ My Hom	ic .	Name of Place:						
☐ My Prim								
☐ My Scho		Street Address or Nea	rest Cross-st	reets:				
☐ Transit S		City (Colonia):				State:	7	ip Code:
(bus or i		city (colonia).				Jule.		p couc.
Other P	ace /							
	you TRAVEL 1				how many			
How man	y other peop	le traveled	- W	/hich ho	usehold m	embers?	DP1 □P	3 OP5
	(Don't Includ				on #s from la			4 □P6
If you tro	voled by DDIV	ATE VEHICLE:						
		icle did you use?		- How	nuch did yo	u pay te a	urb?	
	ake / Model):	nie alu you user		_		u pay to pa		
	ot use a house	oold vahida		\$	per			Did not p
	01 000 0 110 000	ocation, where did yo	u park?		did you pay		?	
□ Did no		treet	u parkr		h / credit / de			
☐ Parkin	ig lot 🗆 🗈	riveway / Personal gara	ige		paid parking ployer provid			
□ Parkin	ng garage 🗌 🕻	Other:		Oth		ed parking	pass	
What ar	e the nearest	cross-streets to this		- Our	er.			
parking	location?				nuch did yo			
]	was n	ot reimburse	d by your	employer	? 5
16	reled by Burn	IC TRANSIT						
_	veled by PUBL ansit system o			Milean	was the rou			
what tr	ansit system c	iia you user			was the rou	ite or line r	iumber c	- 46
								7.5

The diary is place-based



WHAT is this PLACE									
My Home My Primary Job My School Street Address or Nearest Cross-									
☐ My Second Job ¶									
Transit Stop (bus or rail)	City (Colonia):				State:		Zip Code:		
Other Place									
(Write code from LI: How many other p with you? (Don't In	eople traveled		Which h	old members ousehold m son #s from I	embers?		P3		
If you traveled by F	PRIVATE VEHICLE:								
Which household	vehicle did you use?		> How	much did yo	u pay to p	ark?			
(Year / Make / Model):			\$ per Did not pa						
Did not use a ho	ousehold vehicle		Нош	did you pay	for parking	n?			
	his location, where did	you park?		sh / credit / de		y:			
☐ Did not park ☐ Parking lot	☐ Street ☐ Driveway / Personal o	arage		paid parking					
Parking garage		,,.		ployer provid	ded parking	pass			
What are the nea	rest cross-streets to thi	s	Ot	her:					
parking location?				much did yo					
			was	not reimburs	ed by your	employe	r? \$		
If you traveled by F	PUBLIC TRANSIT:								
What transit syste	em did you use?		What	t was the ro	ute or line i	number (
			→				4		
What ACTIVITIES d				m LIST 2 on	the flap or	f the bac	k cover		
Code: Sp	an ecify if code "38":	d the start a	nd end tii	mes.)			(+)		
		Start:	:	am / pm	End:	:	am - pm		
Activity 1:									
Activity 1: Activity 2:		Start:	:	am / pm	End:	-:	_		

	(a) Continuous Variables										
	Variables	Description	Mean	Median	S.D.	Min	Max				
Descriptive statistics											
for 2017	Trip Count	Trip count on the survey day	4.28	4	2.45	1	39				
California-	Visited Location Count	Count of visited locations on the survey day		3	1.68	1	36				
NHTS	(b) Categorical Variables										
workday	Variables	Description					Percentage				
data	Sex	Respondent's sex									
							male:52.02%				
			Refuse to answer: 0.06%								
	Age	Respondent's age range		Under 16: 10.71%							
					16 to 17: 1.94%						
							18 to 25: 5.62% 26 to 45: 23.27%				
							65: 34.61%				
							e 65: 23.86%				
	Student		Student: 12.31%								
						Non-stud	lent: 87.69%				
	Driving license	Have driving license or not					Yes: 83.06%				
				No: 16.94%							
	Homeworker	Working from home for pay		Yes: 7.61%							
							No: 92.39%				
	Full-time or part-time	Full-time or part-time employee				Full-t	ime: 38.43%				
						Part-	time:11.71%				
							N/A: 49.86%				
	Retired	Respondent's retirement status					Yes: 25.25%				
				No: 74.75%							
	Travel day of the week	Day of the week		Monday: 16.97%							
							esday: 21.13% esday: 20.78%				
		© KONSTADINOS G GOULIAS					rsday: 21.18%				
							riday: 19 94%				