

Zipf's power law in activity schedules and the effect of aggregation

Wim Ectors^a Bruno Kochan^a Davy Janssens^a Tom Bellemans^a
Geert Wets^a

^aHasselt University, Transportation Research Institute (IMOB), Agoralaan, 3590 Diepenbeek, Belgium

18-05-2017



ANT 2017



Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding
- 4 Aggregation of Individual Data
 - Study Area Level
 - Subsets of Study Area
 - The Individual Level
- 5 Conclusion



Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding
- 4 Aggregation of Individual Data
- 5 Conclusion



Intro: Zipf's law?

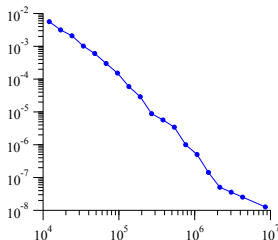
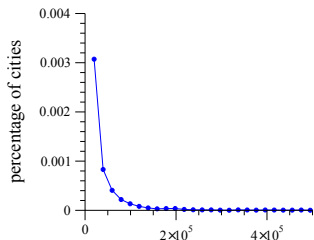
Complex observations, but simple empirical distribution

- Power-law distribution

$$p(x) = Cx^{-\alpha}$$

- Rank-size interpretation

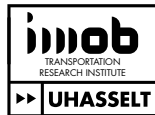
$$f(r_i) = \frac{f(r_1)}{r_i}$$



(Newman, 2005)

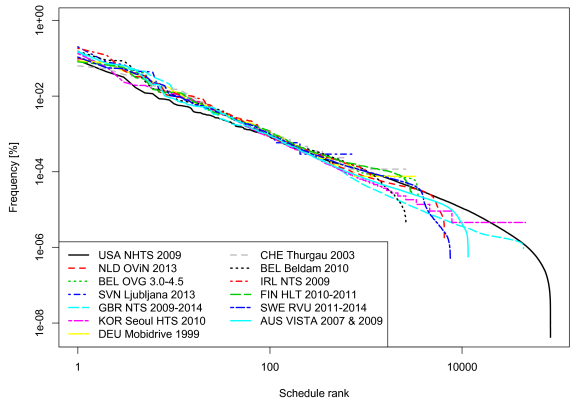


- Observed in many fields (Newman, 2005; Okuyama et al., 1999; Zipf, 1949)
 - Word frequency
 - City size
 - Earthquake magnitude
 - Annual company income
 - Solar flares
 - Number of citations of papers
 - ...
- Traffic demand models
 - Extremely complex, multidimensional processes
 - AB-models
 - (non-)mandatory activity schedulers
 - TOD models
 - re-schedulers
 - interaction with others
 - ...
- *Yet, day-long schedules obey a simple power law*



In a previous research:

- Universal power law governs schedule data (13 HTSs from across the world)



This research:

- Aggregation of Zipf's law in activity schedules?
 - Dimension 1: activity type encoding
 - Dimension 2: aggregation of individual data



Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding
- 4 Aggregation of Individual Data
- 5 Conclusion



Data & Estimation Procedure

4 data sets:

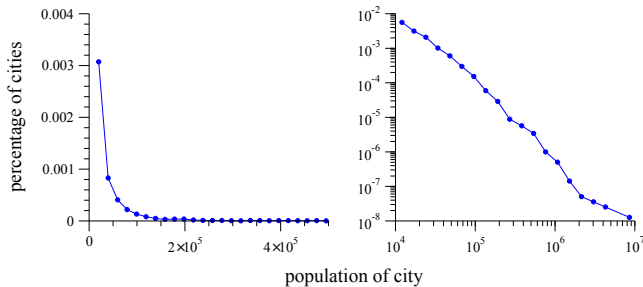
- USA NHTS 2009 (1-day HTS; 258k schedules)
- DEU MobiDrive 1999 (6-week HTS; 13k schedules)
- CHE Thurgau 2003 (6-week HTS; 9k schedules)
- Donated trip data of one individual (24 weeks)
 - Moves app; enriched with trip purposes (10 classes)

Out-of-home activity schedules created by concatenating trip purposes into a sequence

- *“home-work-shopping-home-sport-home”*



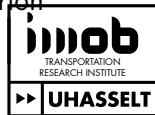
Data & Estimation Procedure



(Newman, 2005)

Fitting a power law?

- **X** linear regression (least squares) to log-transformed variables
- **✓** MLE with Kolmogorov-Smirnov (KS) gof as cutoff criterion
- R package PowerLaw (Gillespie, 2015)
 - bootstrapping procedure evaluates parameter estimation uncertainty



Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding**
- 4 Aggregation of Individual Data
- 5 Conclusion

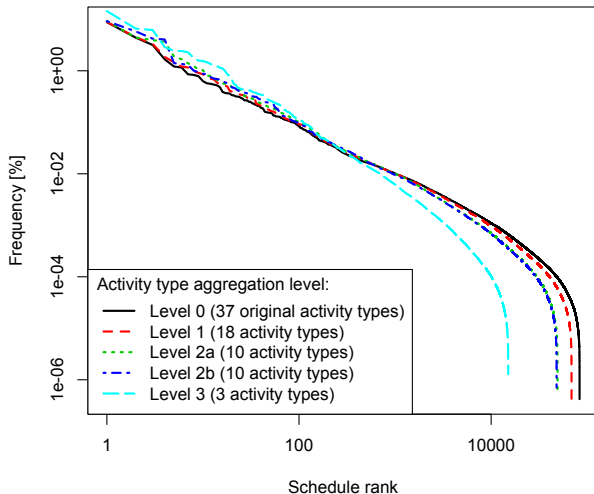


Aggregation of Activity Type Encoding

- USA NHTS 2009 data
- Originally 37 distinct trip purposes
Aggregated to:
 - 18 act. type
 - 10 act. types (2x)
 - 3 act. types
- Still power-law distributed? (with the same exponent?)



Aggregation of Activity Type Encoding



Aggregation or subset	powerLaw estimations (MLE + KS)			Bootstrapping uncertainty evaluation		
	α	x_{\min}	Cum. pct rejected	AM(α)	SD(α)	P-value
Level 0 (37 original activity types)	2.003	36809977	55%	2.006	0.070	0.255
Level 1 (18 activity types)	1.967	36837451	50%	1.972	0.065	0.166
Level 2a (10 activity types)	1.934	46135634	43%	1.939	0.065	0.998
Level 2b (10 activity types)	1.892	60781076	45%	1.899	0.071	0.741
Level 3 (3 activity types)	1.890	109512566	28%	1.891	0.084	0.835

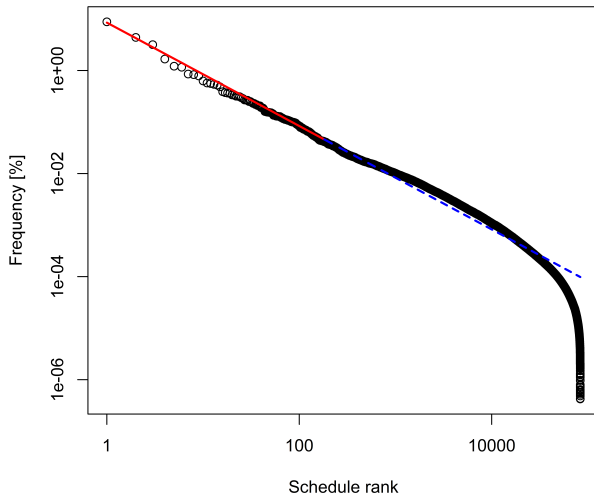
Data: USA NHTS 2009.

Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding
- 4 Aggregation of Individual Data**
 - Study Area Level
 - Subsets of Study Area
 - The Individual Level
- 5 Conclusion



Study Area Level



Aggregation of Individual Data

Dataset	powerRlaw estimations (MLE + KS)			Bootstrapping uncertainty evaluation		
	α	x_{\min}	Cum. pct rejected	AM(α)	SD(α)	P-value
USA NHTS 2009	2.003	36809977	55%	2.006	0.070	0.255
DEU Mobidrive 1999	2.053	23	52%	2.002	0.133	0.714
CHE Thurgau 2003	1.929	16	49%	2.009	0.113	0.317

Note: the different scales of x_{\min} are caused by different weight variables.

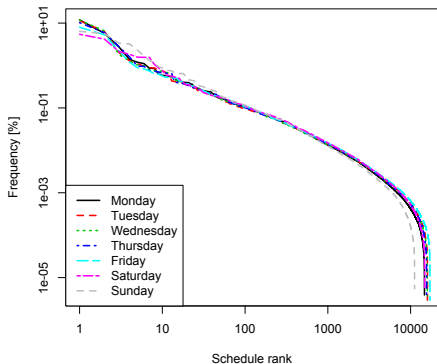


Subsets of Study Area

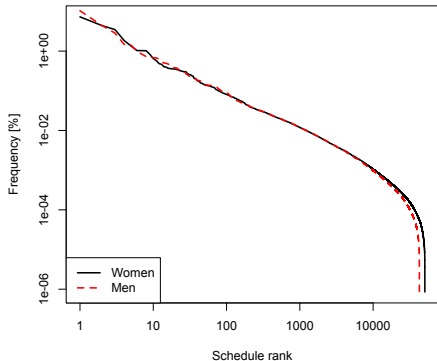
- USA NHTS 2009 data
 - sufficiently large
- Subsets based on
 - DOW
 - Gender



Subsets of Study Area



Day of the week



Gender

Aggregation of Individual Data

Aggregation or subset	powerLaw estimations (MLE + KS)			Bootstrapping uncertainty evaluation		
	α	x_{\min}	Cum. pct rejected	$AM(\alpha)$	$SD(\alpha)$	P-value
All individuals aggregated	2.003	36809977	55%	2.006	0.070	0.255
Monday*	2.290	46616705	67%	2.270	0.359	0.831
Tuesday*	2.161	35581917	67%	2.182	0.236	0.820
Wednesday*	2.152	45646004	68%	2.172	0.267	0.679
Thursday*	2.088	48120314	71%	2.140	0.282	0.221
Friday*	2.279	34509610	72%	2.284	0.250	0.901
Saturday*	2.182	61045896	76%	2.176	0.288	0.134
Sunday*	2.091	52160661	66%	2.060	0.200	0.982
Women	2.104	37421218	61%	2.115	0.114	0.551
Men	2.157	36416801	58%	2.165	0.116	0.783

Data: USA NHTS 2009.



The Individual Level

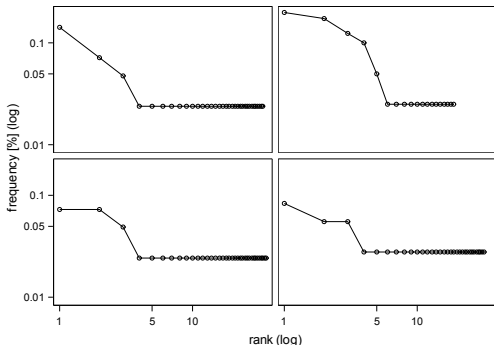
- Challenging...
- DEU MobiDrive 1999 (6 weeks)
- CHE Thurgau 2003 (6 weeks)
- Donated trip data of one individual (24 weeks)

Do the schedules of each individual exhibit a power law distribution?

- KS goodness-of-fit test



The Individual Level



Examples of distributions rejecting H_0 : power law is a good fit

- MobiDrive & Thurgau
- Only 12% do not reject H_0 of a power law distribution
- → results do **not** support Zipf's law
- However, *insufficient* data?

The Individual Level

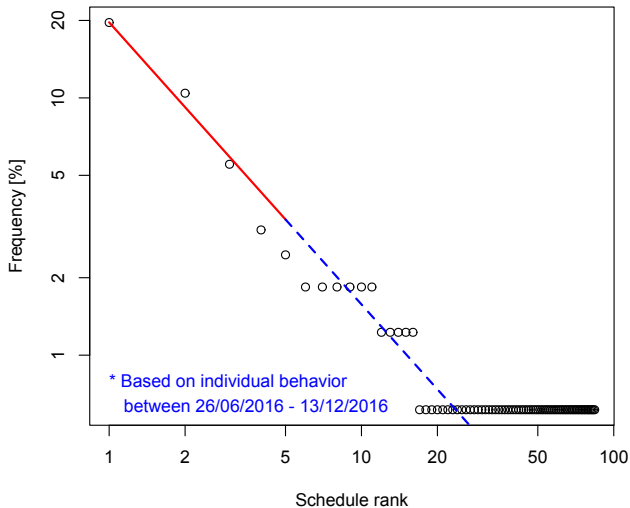


The Individual Level

- $n \gtrsim 50$ needed, but $\bar{n} = 37.625 < 50$ (Clauset et al., 2009)
- Those rejecting H_0 : transition phase
- Those not rejecting H_0 : already quite advanced evolution
- More than 6 weeks may be needed
 - Donated trip data of one individual (24 weeks)



The Individual Level



Aggregation of Individual Data

	powerLaw estimations (MLE + KS)			Bootstrapping uncertainty evaluation		
Dataset	α	x_{\min}	Cum. pct rejected	AM(α)	SD(α)	P-value
Donated schedules from an individual	2.454	4	59%	2.629	0.708	0.689



Overview

- 1 Intro: Zipf's law?
- 2 Data & Estimation Procedure
- 3 Aggregation of Activity Type Encoding
- 4 Aggregation of Individual Data
- 5 Conclusion



Conclusion

- People's behavior very complex, but schedules power law distributed
- No significant influence of activity type encoding aggregation
 - Only at extreme levels of aggregation may the power law break down more quickly
- Study area → subsets → individual data
 - Power law is found quite consistently . . .
 - On the condition that sufficient individual data is available

Further research:

- Correlate stage of evolution of power law to person characteristics
- Modeling the mechanism leading to Zipf's law



References

- Newman, M.: Power Laws, Pareto Distributions and Zipf's Law. Contemporary physics. 46, 323-351 (2005). doi:10.1080/00107510500052444
- Okuyama, K., Takayasu, M., Takayasu, H.: Zipf's law in income distribution of companies. Physica A: Statistical Mechanics and its Applications. 269, 125-131 (1999). doi:10.1016/S0378-4371(99)00086-2
- Zipf, G.K.: Human Behaviour and the Principle of Least Effort. Addison-Wesley, Reading (1949)
- Gillespie, C.S.: Fitting Heavy Tailed Distributions: The powerLaw Package. Journal of Statistical Software. 64, 1-16 (2015)
- Clauset, A., Shalizi, C.R., Newman, M.E.J.: Power-Law Distributions in Empirical Data. SIAM Review. 51, 661 (2009). doi:10.1137/070710111
- U.S. Department of Transportation, Federal Highway Administration: 2009 National Household Travel Survey, <http://nhts.ornl.gov>, (2009)
- Chalasani, V.S., Axhausen, K.W.: Mobidrive: A six week travel diary, <https://www.ethz.ch/content/dam/ethz/special-interest/baug/ivt/ivt-dam/vpl/tsms/tsms2.pdf>, (2004)
- Loechl, M.: Stability of Travel Behaviour: Thurgau 2003, <http://archiv.ivt.ethz.ch/vpl/publications/tsms/tsms16.pdf>, (2005)



Thank you!

