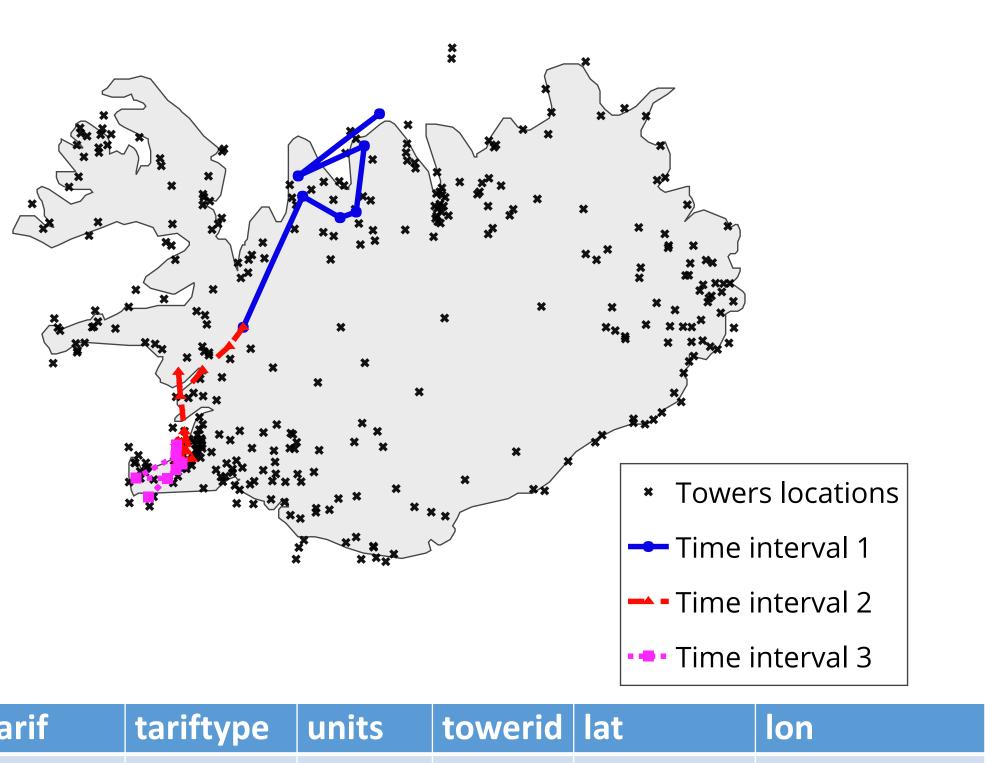


The Data

• A large mobile network operator supplied their billing data for October 2008 to 2012. We focus on the 2009-2010 records during the H1N1 outbreak. • The Centre for Health Security and Communicable Disease Control (CHS-CDC) in Iceland provided the date of diagnosis for a patient who displayed symptoms of influenza.

 Data Protection Authority (Personuvernd) approved the anonymizing process.

\frown



subject	object	time	In	call	tarif	tariftype	units	towerid	lat	lon
98937	52674	2010-09-17 10:34:46	t	f		PREP	0	719	65.679166	-18.092559
4197	89504	2010-05-06 16:07:24	t	t	GIN	PREP	7	287	66.152133	-18.903783
51993	607	2010-09-29 01:47:50	f	t	GGSM7	POST	25	617	65.66145	-18.10765

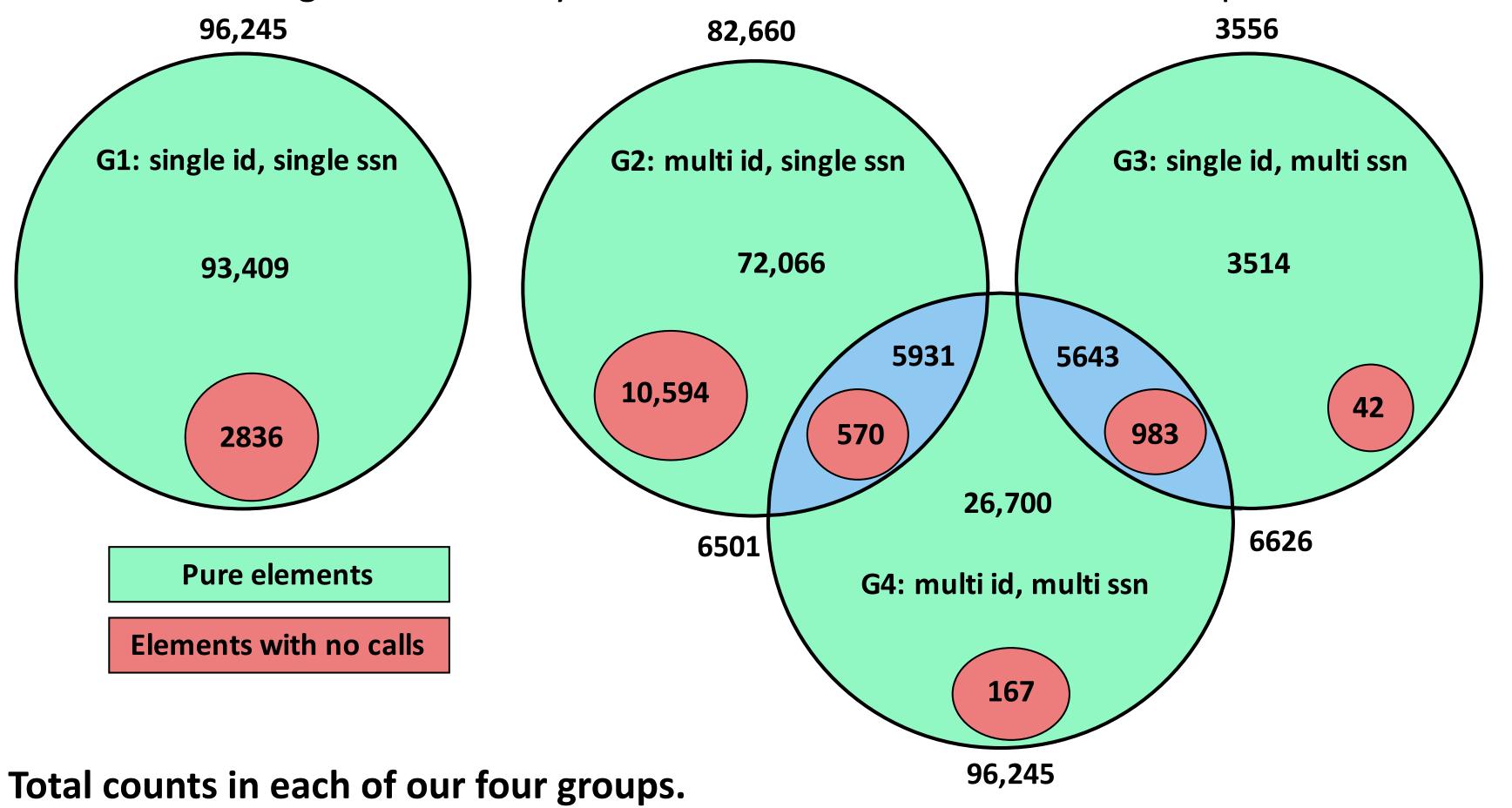
Calls table. Each line represents information related to the phone id labeled subject.

ssn_no	famely_no	in_nat_reg	cust_type	first_record	illness
41486	41486	1	Person	2009-10-04	Influenza
2732	24003	1	Person	2009-10-28	Influenza
749	40780	1	Person	2009-05-25	Influenza

Health table. Each line represents one diagnosis.

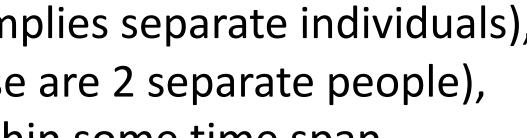
Quantifying the Groups

- Not every phone or ssn represents one individual (families, people with a company phone, etc.)
- Data split into four groups based on (id,ssn) pairs. Groups 3 and 4 are primarily companies.
- Group 2: How many people exist here?
- Determine distinct people based on:
- Sequential use of a phone (disjoint sequential use implies separate individuals),
- Phones calling each other within a ssn (assume those are 2 separate people),
- Phones calling from distinctly different locations within some time span. 96,245 82,660



Tracking Behavioral Alterations via Mobile Phone Data Derek Onken¹, Thorgeir Karlsson², Atli Einarsson², Congzeng Song¹, Leon Danon³, Ymir Vigfusson¹ ¹Math & Computer Science, Emory University ² Reykjavik University

Cellphone towers and movement inference



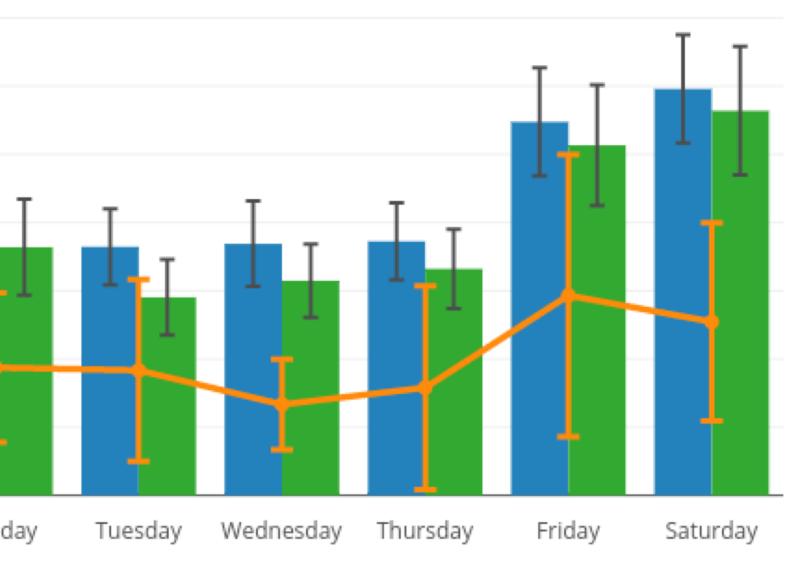
• For our baseline model, we applied naïve linear regression to the single id, single ssn group. features with a label of sick or not into our regression. the full data (black curve) because some individuals lack density of phone-use data. • We use the output of the model on the training set to define a correctional transform. • We apply the transform to the smoothing it with Hodrick-Prescott.



³ University of Exeter

iltered Train Set: Number of Individuals Sick Per Date — actual (from DOD offsets -1 to 2 - actual (from labels) - predicted • We pass week-long sequences of Jan 2010 Mar 2010 • Our input (blue curve) is less than Nov 2009 Test Set Model Prediction: Individuals Sick Per Date actual (input into model) HP filter on predicted Jul 2009 output of the model on testing set,

Summary of 66 users with same onset date Analyzing the Features Summary of 71 users with same onset date Number of new location visited (Not visited in the last month)

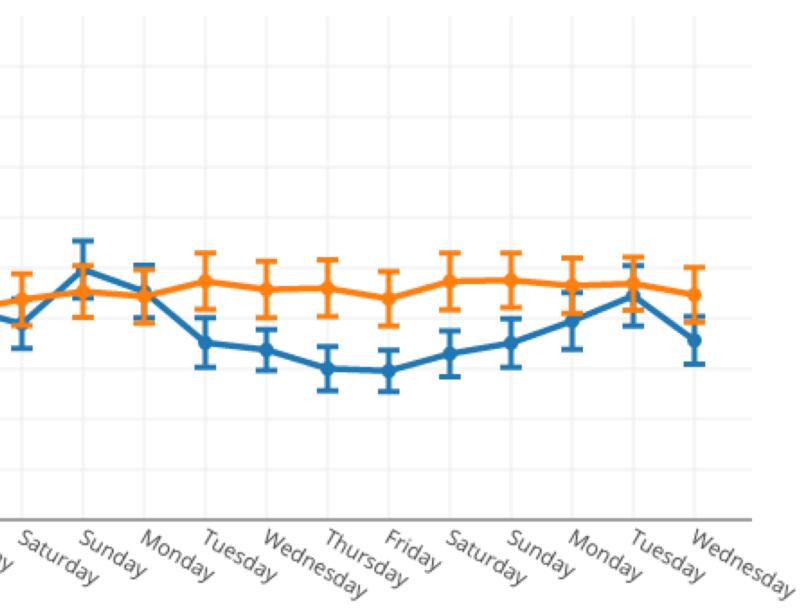


Days around onset (Wednesday, 14. October 2009)

Week of onset (DoD middle)



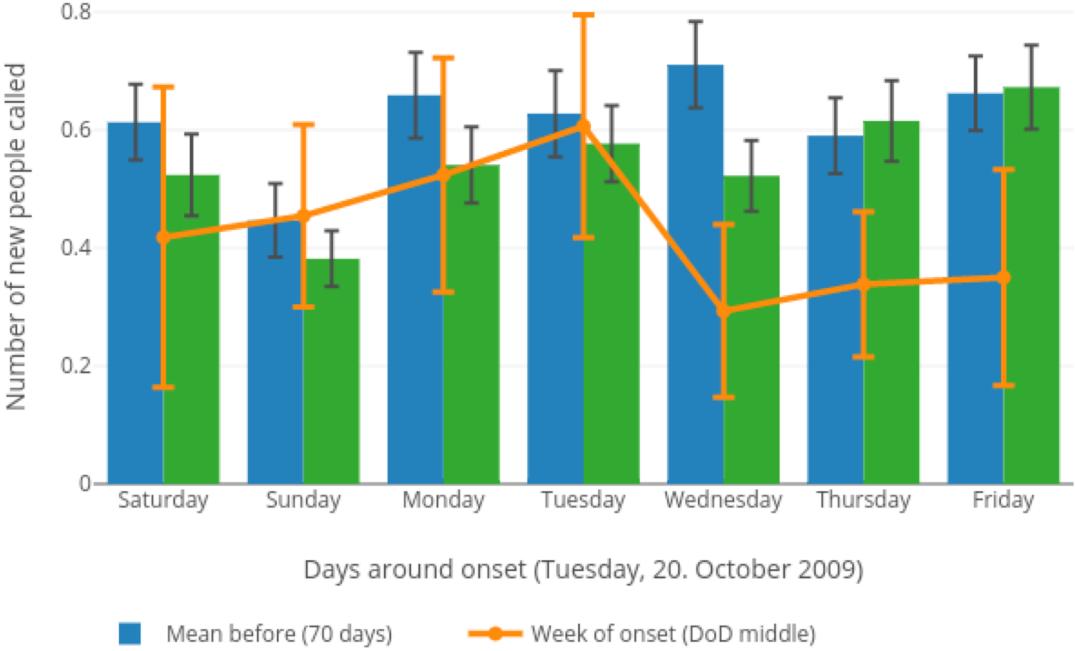
Summary of 70 users with same onset date Distance traveled per weekday



Days around onset (Wednesday, 14. October 2009) Sick (70 users) Sick (844 users)

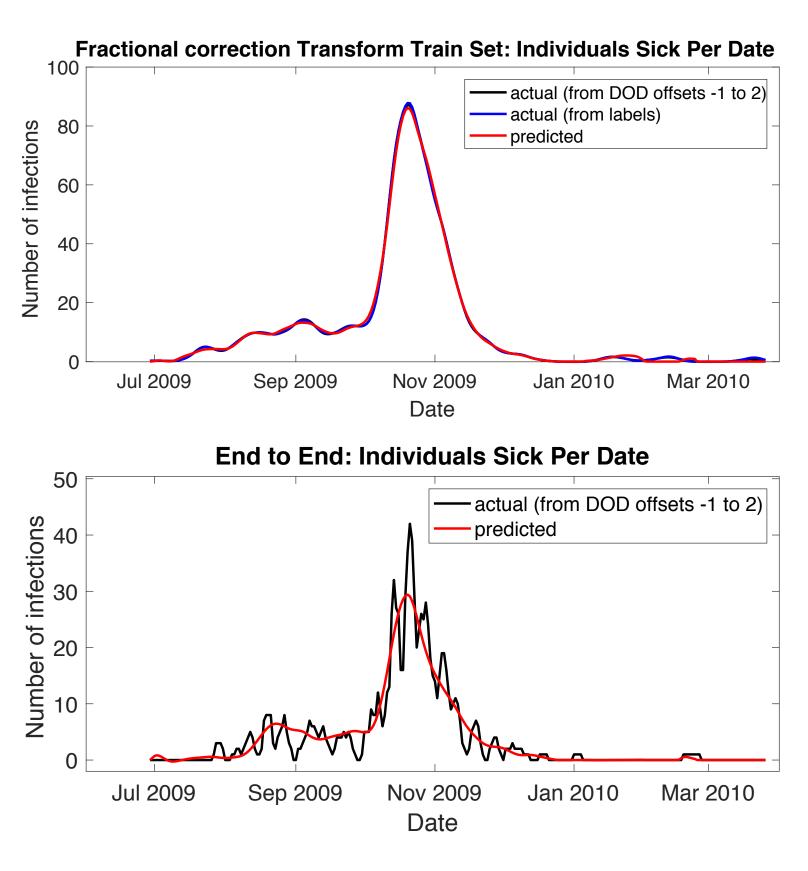
Sick individuals move around less than when healthy

Baseline Model



and weekends.





Plotting our model's output of the epidemic curve vs. our "ground truth"

Number of new people called, outgoing (Not called in the last month)

Mean after (70 days)

Sick individuals call new/weaker contacts less

• Differences in behavior occur between weekdays

• To account for this, we compare sick individuals to other sick individuals diagnosed on the same date. • Compare mean of feature in the ten weeks before, the ten weeks after, and the week of illness.

• Do this for every feature. Some plots of the features with most clear distinction are displayed here.

 This is only on the training and validation sets of the single id-single ssn group.