Using Mobile Social Media to Understand the Dynamics of Cities

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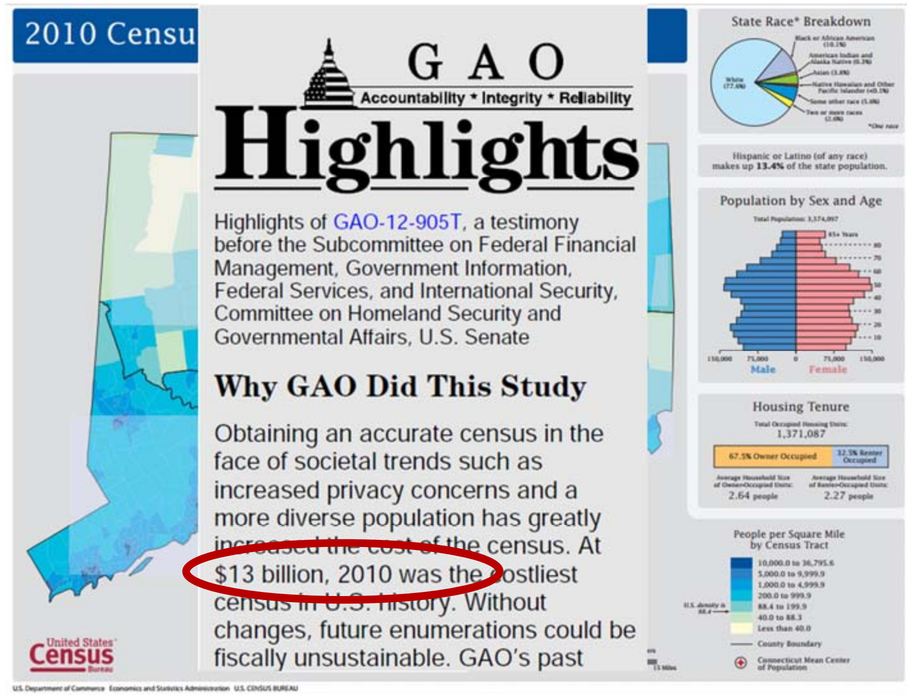
mobile commerce lab

Outline

- Leveraging the wisdom of crowds in mobile and social contexts
- Combining the power of crowd sourcing and machine learning
- Two contexts:
  - Understanding the dynamics of cities
  - Time permitting, we will also discuss work on enhancing app quality in a mobile app store

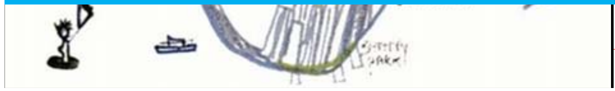
Have you ever wondered…

- Where people who attend a football game on Sunday go after the game is over
- Where people who come to a mall on Saturday afternoon were in the morning
- What are the neighborhoods most at risk if a given individual is found to be infected with a new strand of the flu virus
- How the construction of a new highway in a given neighborhood might impact people's activities
- What people in a given area of town are most likely to be doing on a given day and at a given time
- How you might want to modulate public bus schedules to accommodate shifting traffic demands over time



Taken together, these mental maps

They also provide unique insights into the social fabric of a city



Could social media help us?

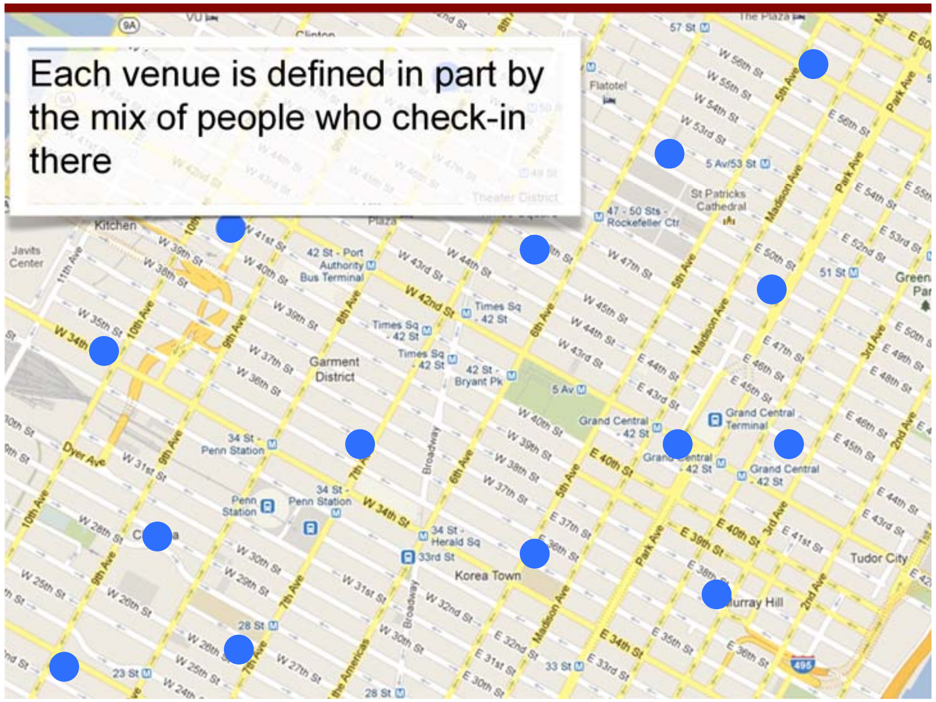
The Livehoods Project

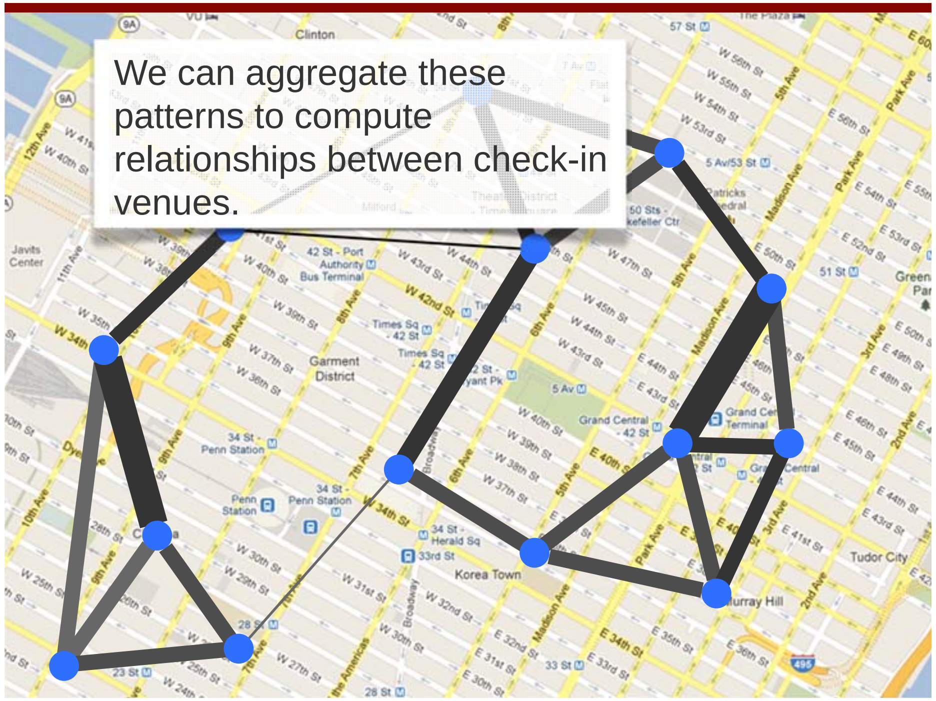
18 million foursquare check-ins that people shared publicly on their Twitter feeds

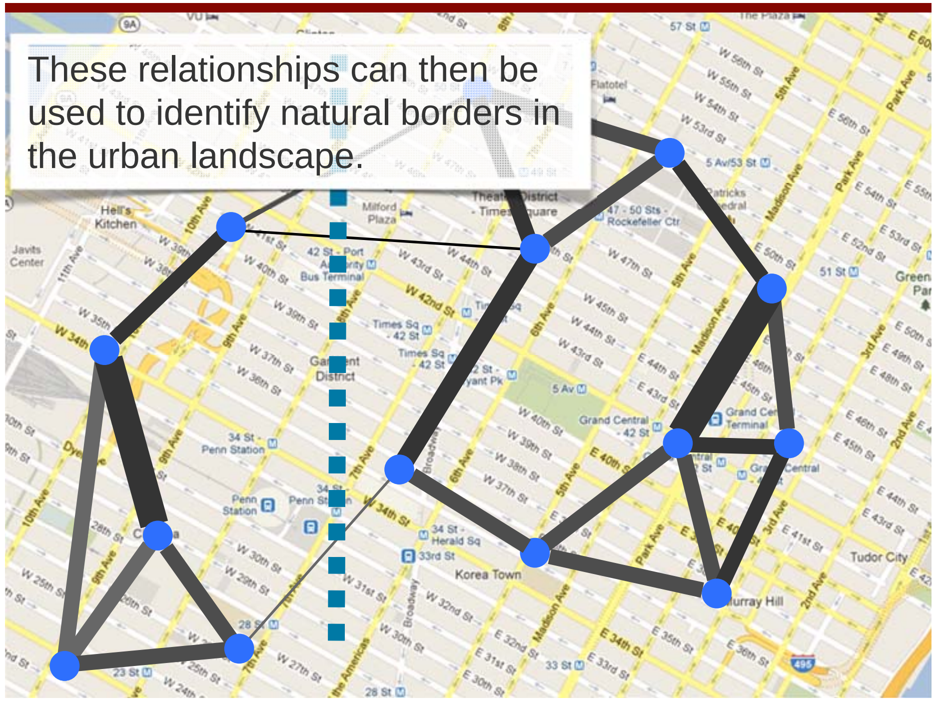
(patent pending)

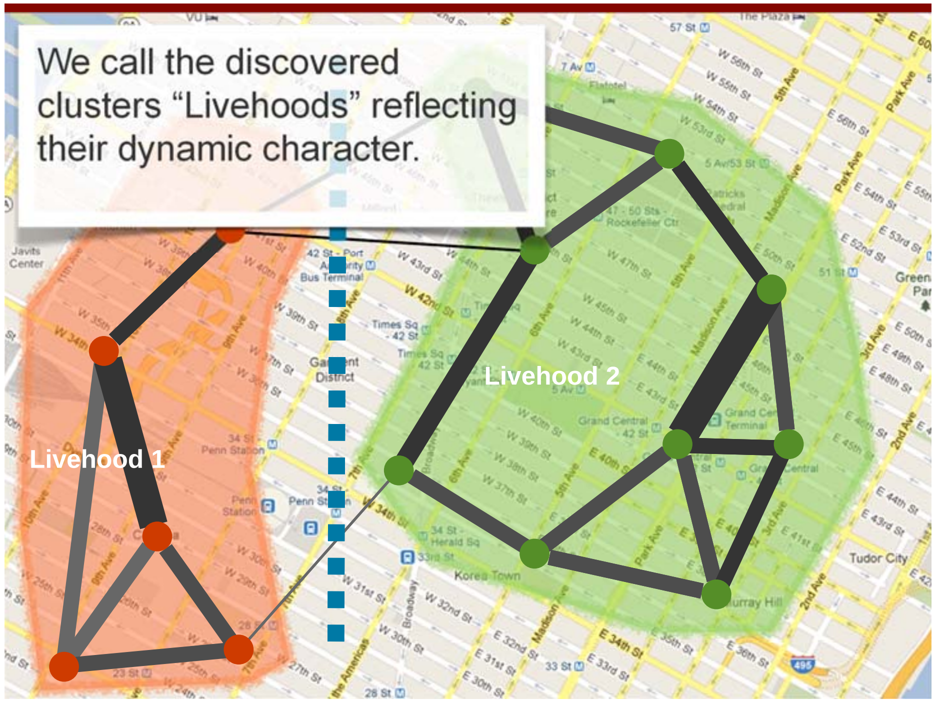
"J. Cranshaw, R. Schwartz, J. Hong, N. Sadeh, "The Livehoods Project: Utilizing Social Media to Understand the Dynamics of a City", in Proc. of the 6th International AAAI Conference on Weblogs and Social Media (ICWSM-12), Dublin, Ireland, June 2012 – *best paper award*

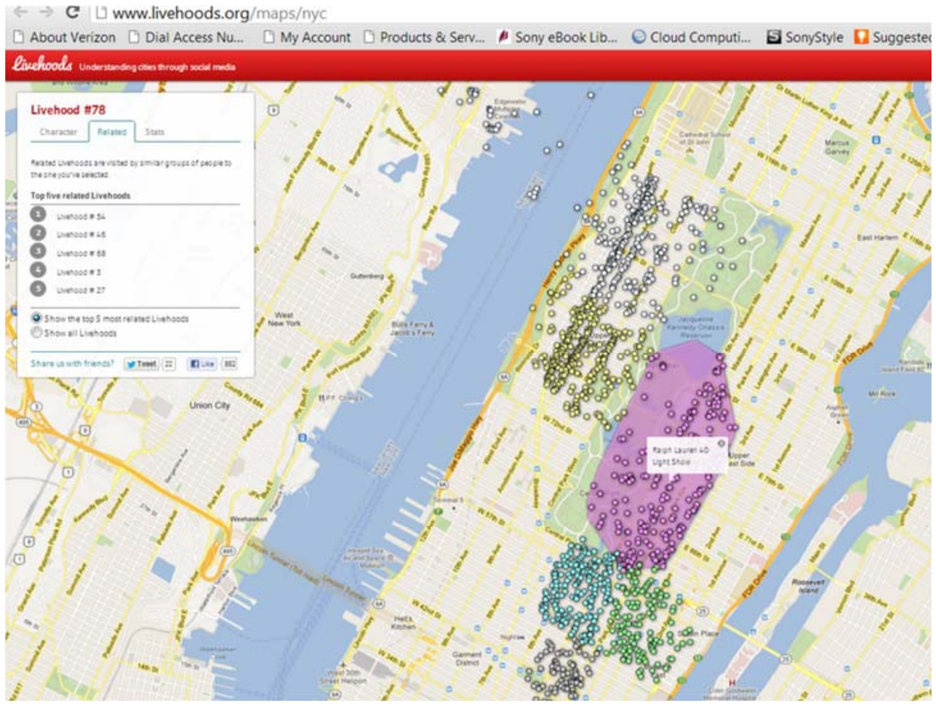
www.livehoods.org
info@livehoods.org




We can aggregate these patterns to compute relationships between check-in venues.

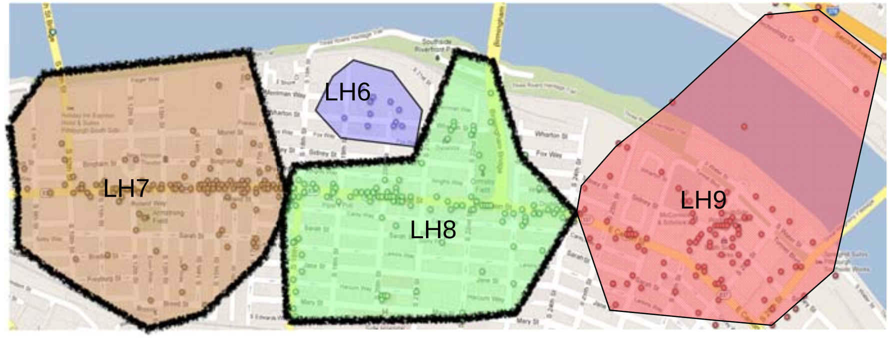

These relationships can then be used to identify natural borders in the urban landscape.


We call the discovered clusters "Livehoods" reflecting their dynamic character.
Livehood 1
Livehood 2


www.livehoods.org/maps/nyc
About Verizon
Dial Access Nu...
My Account
Products & Serv...
Sony eBook Lib...
Cloud Computi...
SonyStyle
Suggested
Livehoods
Livehood #78

The South Side "Flats" (Pittsburgh)

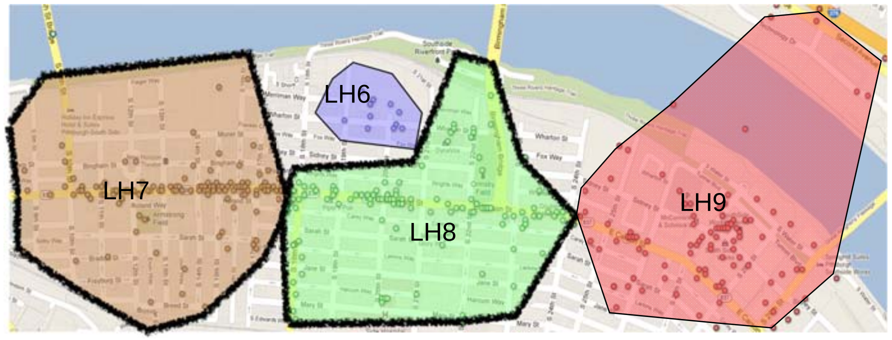
The South Side "Flats" (Pittsburgh)



Safety

"Whenever I was living down on 15th Street [LH7] I had to worry about drunk people following me home, but on 23rd [LH8] I need to worry about people trying to mug you... so it's different. It's not something I had anticipated, but there is a distinct difference between the two areas of the South Side."

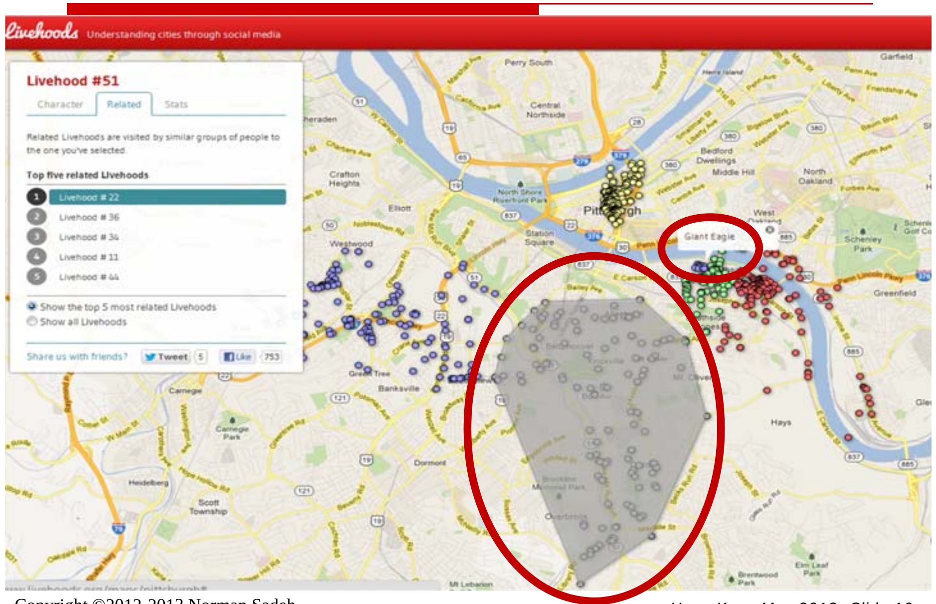
The South Side "Flats" (Pittsburgh)



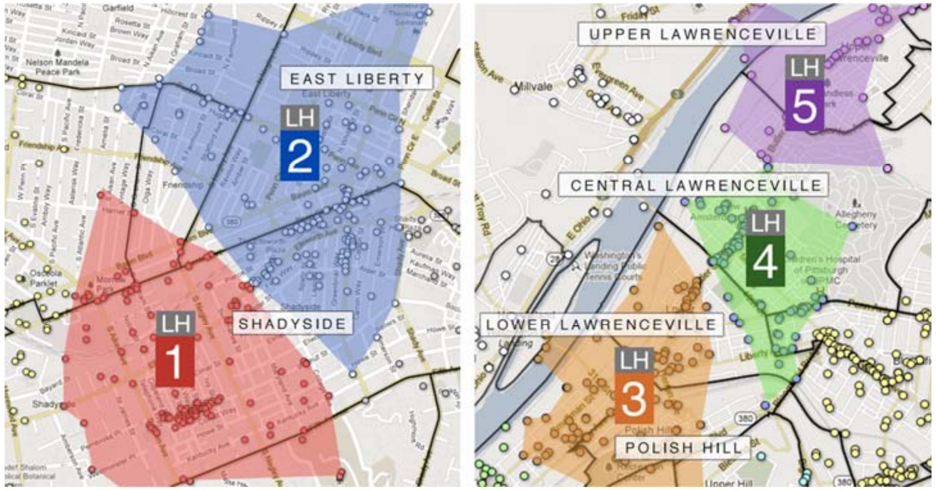
Architecture & Urban Design

"from an urban standpoint it is a lot tighter on the western part once you get west of 17th or 18th [LH7]."

"They came from up the hill..."



Beyond Municipal Boundaries



Some Limitations

Foursquare data is skewed

…but the methodology can be applied to other data sets

Typology of a City

- Can we identify canonical city neighborhoods – across different cities?
  - Shopping areas
  - University neighborhoods
  - Entertainment districts

Topic Modeling Applied to Venues

Topic 3 *Rail Travel*	**Topic 4** *Medical*	**Topic 6** *Air Travel*	**Topic 8** *Shopping*	**Topic 11** *University*	**Topic 12** *Coastal*	**Topic 14** *Outdoors*	**Topic 15** *Korea Town*	**Topic 19** *China Town*	**Topic 20** *Sporting Events*
Train	Hospital	Airport Gate	Clothing Store	College Academic Bldng.	Apartment / Condo	Park	Korean Restnt.	Chinese Restnt.	Baseball Stadium
Train Station	Doctor's Office	Plane	Office	College Residence Hall	Harbor / Marina	Hiking Trail	Karaoke Bar	Mexican Restnt.	Bar
Office	Medical School	Airport Terminal	Boutique	University	Boat or Ferry	Great Outdoors	Asian Restnt.	Vietnamese Restnt.	Entertainment
Train Platform	Medical Center	Airport	Women's Store	College Admin. Bldng.	Bldng.	Music Venue	Bar	Bakery	Sports Bar
Coffee Shop	Coffee Shop	Travel	Shoe Store	College Library	Bus Station	Entertainment	Coffee Shop	Entertainment	Beer Garden
Bar	Mexican Restnt.	Airport Lounge	American Restnt.	Coffee Shop	Beach	Scenic Lookout	Cafe	Dim Sum Restnt.	Baseball Field
American Restnt.	American Restnt.	Coffee Shop	Cosmetics Shop	College Arts Bldng.	Park	Zoo	Mexican Restnt.	Grocery Store	Parking
Bakery	Park	Parking	Coffee Shop	College / University	Bus Line	Harbor / Marina	Bakery	Park	American Restnt.
Pizza Place	Emergency Room	American Restnt.	Bar	Student Center	Great Outdoors	Lake	Church	Plaza	Strip Club
Bus Line	Sandwich Place	Bus Line	Italian Restnt.	College Science Bldng.	Office	Sculpture Garden	Japanese Restnt.	Tea Room	Music Venue
Deli / Bodega	Office	Pizza Place	Art Gallery	College Quad	Scenic Lookout	American Restnt.	Office	Gift Shop	Apartment / Condo
Light Rail	Fast Food Restnt.	Bar	Salon / Barbershop	Apartment / Condo	Gym	Art Museum	Grocery Store	Building	Clothing Store
Bldng.	Gas Station / Garage	Fast Food Restnt.	Hotel	Fraternity House	American Restnt.	Cafe	Chinese Restnt.	Asian Restaurant	Sandwich Place
Entertainment	Bus Line	Rental Car Location	Men's Store	Bar	Event Space	Apartment / Condo	Hotel	Music Venue	Sporting Goods Shop
Bus Station	School	Mexican Restnt.	Sandwich Place	College Cafeteria	Entertainment	Monument	Bldng.	Church	Nightlife

Table 2. Here we highlight 10 topics discovered by posterior inference on our model. The 15 most probable categories from each topic are shown. Topic names are supplied by us to capture what we felt each collection of veneus represents.

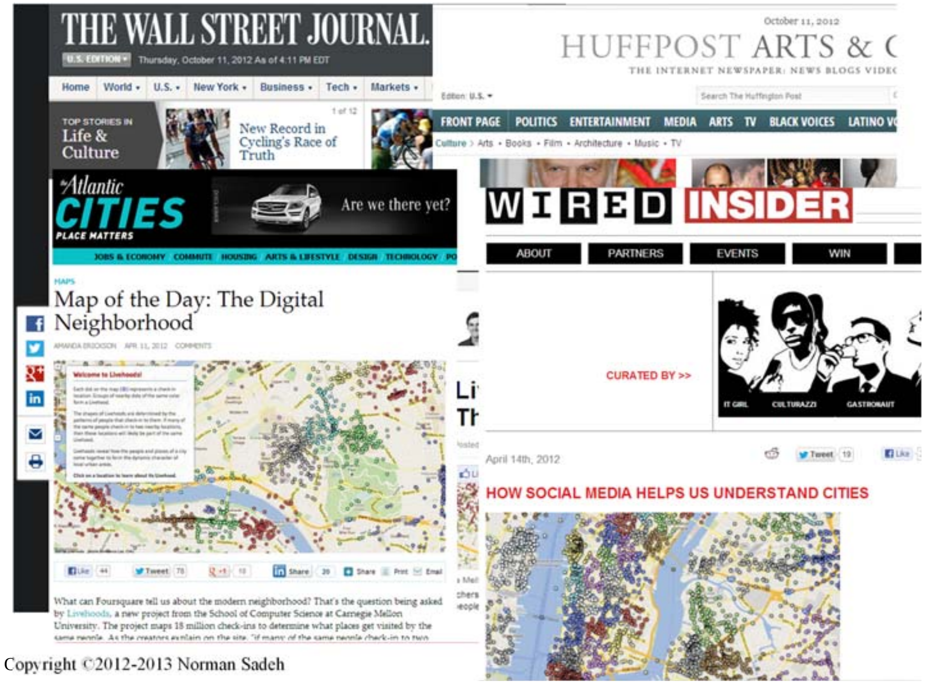
(patent pending)

J. Cranshaw and N. Sadeh, "The Latent City: Discovering City Neighborhood Typologies Using Spatial Topic Modeling", Proc. of the 15th ACM International Conference on Ubiquitous Computing (Ubicomp2013), Zurich, Switzerland, Sept. 2013 – pending final acceptance

Examples: College Neighborhoods

Or Shopping Areas in Lower Manhattan

SoHo, NoLIta, Union Square (and Madison Square), Harold Square, and the Meat Packing District



Imagine the Possibilities

- Urban Planning
- Transportation
- Personal Recommendations
- Real Estate
- Public Health
- Travel & Tourism
- Public Safety
- Marketing

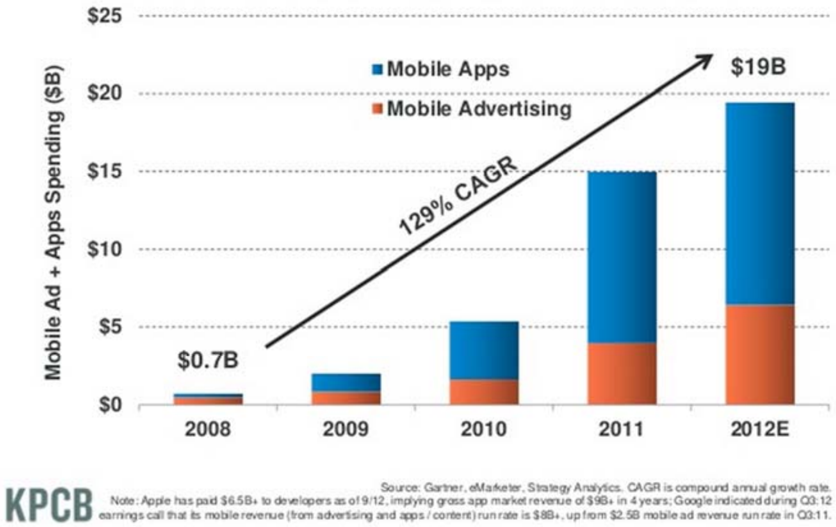
The WisCom Project

13 million mobile app reviews

171,000 Android Apps

"Why People Hate Your App: Making Sense of User Feedback in a Mobile App Store", Bin Fu, Jialiu Lin, Lei Li, Jason I. Hong, Christos Faloutsos, Norman Sadeh – to appear KDD 2013

Gobal Mobile App & Mobile Ad Markets



Life Before the App Store

The App Store is about addressing fundamental trust and usability issues

scheme to get your credit card credentials

Lots of Bad Apps

- From malware

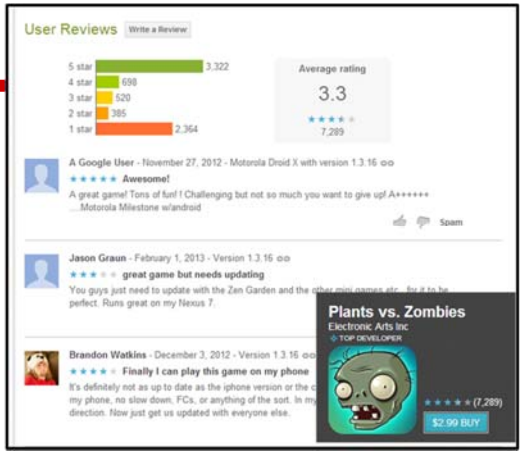
Could App stores leverage user comments to automatically take down bad apps and help developers fix their apps?

- ...and more...

"Why People Hate Your App: Making Sense of User Feedback in a Mobile App Store", Bin Fu, Jialiu Lin, Lei Li, Jason I. Hong, Christos Faloutsos, Norman Sadeh – to appear KDD 2013

Distinct Features of App Reviews

(in contrast to other product reviews)

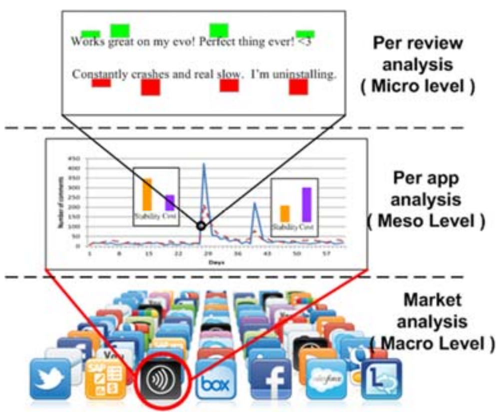


- ❑ Shorter in length
- ❑ More typos, slang, ill-structured sentences
- ❑ Reviews of the same app can refer to different versions

Motivations for Analyzing User Reviews

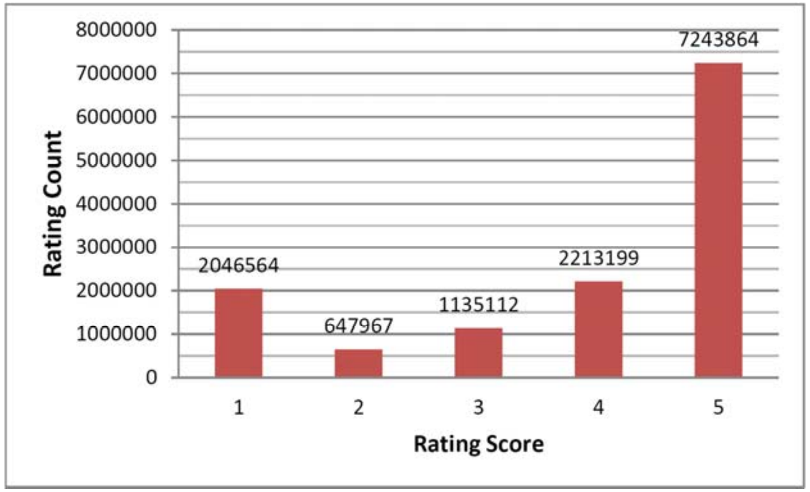
- **App store**: Manual inspection of hundreds of thousands of apps is impractical. Maintaining **user trust** & **prevent manipulation**
- **End-user:** Develop **summary** of what others think about an app
- **App developer**: Help identify & **diagnose** problems associated with user complaints
- Analyze overall market & **spot trends**
  - **What are those issues that matter most to users in different app categories**

WisCom: A Multi-level Review Summarization System



- **Per Review Analysis:** Sentiment analysis on each review, identify inconsistent reviews
- **Per App Analysis:** Topic modeling on aggregated reviews, detect major releases and identify major sources of complaints
- **Market Analysis:** analyze market segments & spot trends, incl. user preferences. Can also help develop/refine app development guidelines

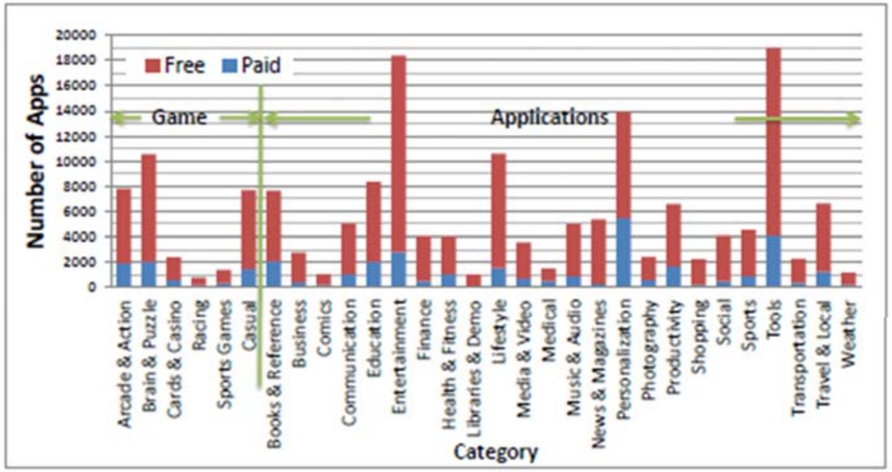
Dataset: 13 million Android App Reviews



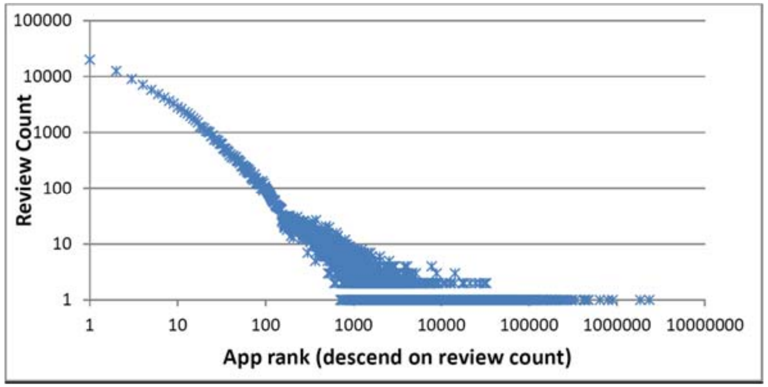
-Crawled Google Play – Looked at 171,000 Android apps(Nov. 2012)

- Info about the identity of the reviewer is not available

Apps by Categories

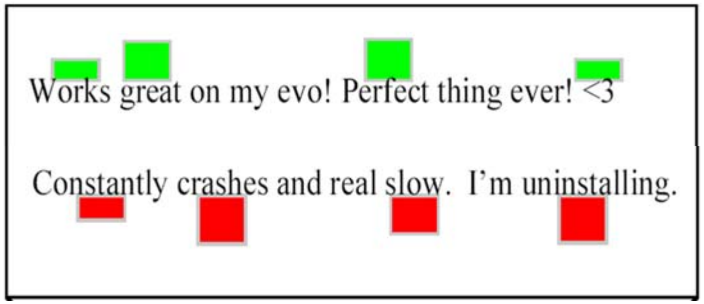


Dataset



- The number of comments follows a heavy tailed distribution.
- Average number of comments = 101.90, STD = 460.25, median=8

PER REVIEW ANALYSIS



Used 3 as threshold between “positive review” and “negative review”

-Avg rating is 3.9 and 54% of apps are rated 5 stars.

Preprocessing

- Sample 8% of the comments (1 million reviews)
- Remove HTML tags and delete non-English reviews
- Segment comments into words
- Remove rarely used words.
- Yield 19K distinct words, from 988K comments.

Linear Regression Model

$$L(W) = \Sigma_{i=1}^{m}(Y_i - (w_0 + \Sigma_{j=1}^{n} X_{ij} w_j))^2 + \gamma P(W)$$

Where m=988K, n=19K, Y: reported ratings

Xij is frequency of *j*-th word in *i*-th comment

Wj is the weight of j-th word in vocabulary

$$P(W) = \Sigma_{i=1}^{n}((1-\alpha)w_i^2 + \alpha|w_i|)$$

Normal Tikhonov regularization to reduce overfitting,

L1 norm, penalty of complexity of model – forces a number of zero weights for words that don't matter

Most Positive and Negative Words

(a)			(b)		
Word	Weight	Freq	Word	Weight	Freq
awsome	0.67	4893	sucks	-1.24	13178
excellent	0.67	31971	lame	-1.16	2701
awesome	0.63	63257	rubbish	-1.12	2127
fault	0.61	1027	worthless	-1.03	1628
sweet	0.60	3572	poor	-1.02	6307
superb	0.58	3694	boring	-0.99	3529
brilliant	0.58	6384	useless	-0.98	8075
yay	0.57	1134	horrible	-0.96	4428
greatest	0.56	1148	crap	-0.95	7515
amazing	0.56	18753	garbage	-0.93	2217

Examples of Negative Words that Imply Problems

Word	Weight	Freq	Word	Weight	Freq
bloatware	-0.89	1778	slow	-0.44	9939
misleading	-0.84	465	confusing	-0.38	1300
crashes	-0.71	9081	expensive	-0.26	1538
spam	-0.62	1601	permission	-0.18	1409
freezes	-0.54	3960	privacy	-0.10	962

Some negative words are particularly informative and hint to the source of a user's complaint

Detect Inconsistent Reviews

- 0.9% of the reviews are inconsistent with their ratings.
- Might be attributed to carelessness or could be sign of intentional manipulation
- Inconsistent reviews were removed for later analysis

PER APP ANALYSIS

Can we monitor apps and, based on reviews, identify and help diagnose problems associated with complaints?

Topic Analysis

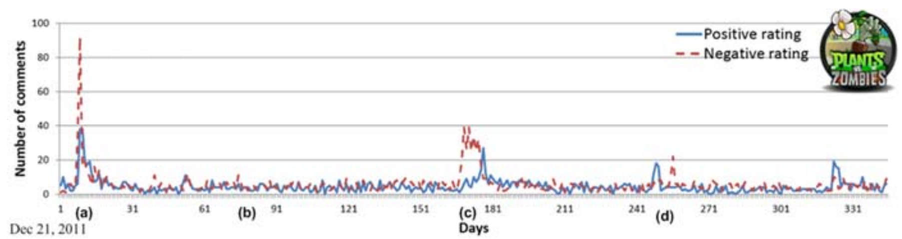
- Preprocessing:
  - Only on negative reviews, and negative words → avg. 71 characters, median length is 47 characters.
    - Removed inconsistent comments
    - Only negative comments associated with 1-star and 2-star ratings
    - Removed words with non-negative weights
  - Concatenate comments from the same app as documents (otherwise too short)
  - Remove apps with too few comments: This left us with >52K apps to analyze
- Latent Dirichlet Allocation model (LDA)
  - Identify 10 topics

Top 10 Root Causes

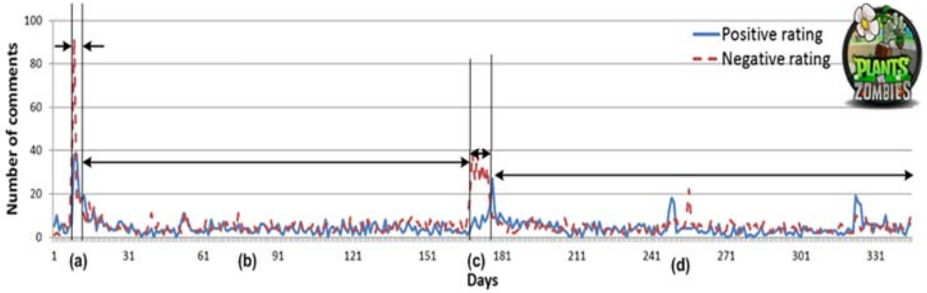
Table 5: The most frequent words from top 10 causes found by WisCom–topic model.

cause	*Attract-iveness*	*Stability*	*Accuracy*	*Compati-bility*	*Connec-tivity*	*Cost*	*Telephony*	*Picture*	*Media*	*Spam*
Words	boring	closes	find	galaxy	log	free	uninstall	pictures	video	ads
	bad	close	location	battery	error	money	want	picture	sound	notification
	stupid	load	search	support	account	buy	need	pics	watch	spam
	waste	every	info	off	connect	pay	send	camera	videos	bar
	dont	crashes	useless	droid	login	paid	messages	save	songs	notifications
	hard	keeps	data	nexus	connection	refund	delete	wallpaper	audio	adds
	make	won	way	compatible	sign	want	let	see	sounds	annoying
	way	start	list	install	let	back	contacts	photos	hear	many
	graphics	please	sync	samsung	slow	bought	calls	upload	record	pop
	controls	closing	wrong	worked	website	waste	off	pic	anything	push
%	18%	13%	13%	11%	10%	9%	8%	8%	5%	5%
Example app	Stardunk	Opera	Kindle	App 2 SD	Zedge	Sygic	LINE	Pho.to Lab	IMDB	Brightest Flashlight
	Blast Monkeys	Bible	Kobo	Solar Charger	Dropbox	Cut the Rope	WhatsApp	Retro	Tuner	Shoot the Apple

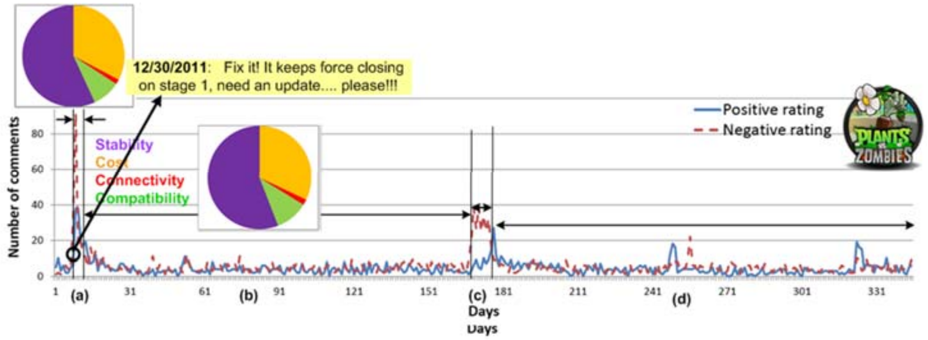
Dynamic View: Life Story of App (I)



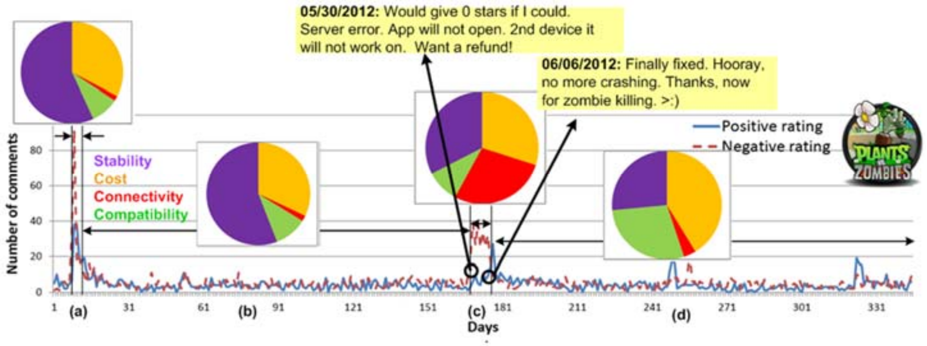
Dynamic View: Life Story of an App (II)



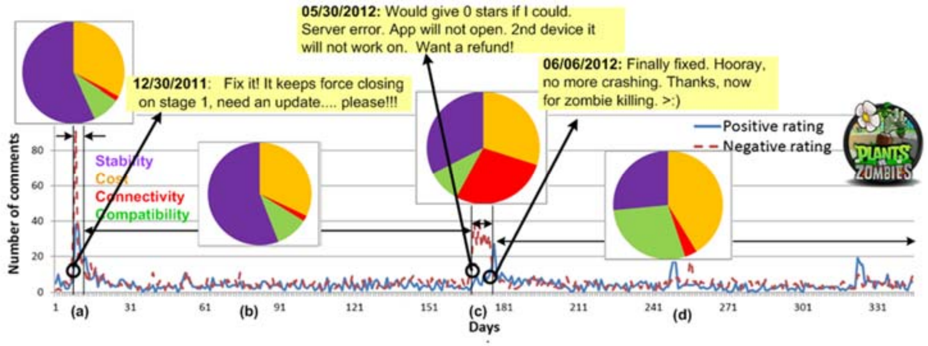
Understanding the Problem



The Life Story of an App



Dynamic View: Life Story of an App



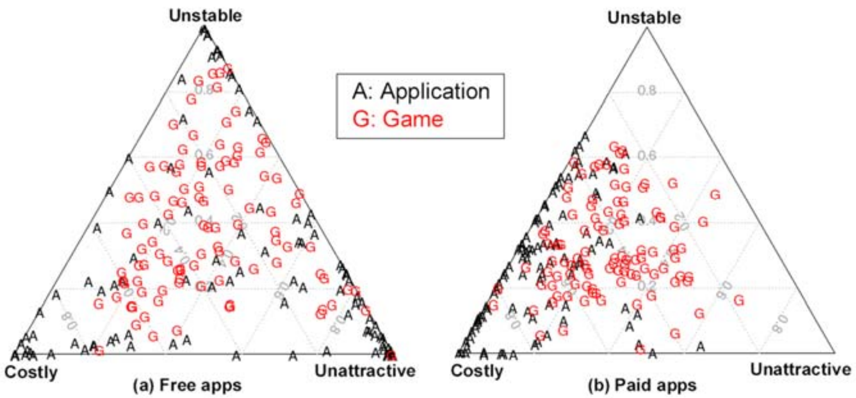
Market-Level Analysis

- Do users care about the same issues and/or exhibit the same level of tolerance for different app categories?
- Possible guidelines for developers

Outstanding Complaints in Each Category

Category	1st Complaints	2nd Complaints	3rd Complaints
Arcade & Action	Attractiveness (60%)	Stability (18%)	Cost (11%)
Brain & Puzzle	Attractiveness (49%)	Stability (18%)	Cost (8%)
Cards & Casino	Attractiveness (41%)	Cost (23%)	Stability (19%)
Racing	Attractiveness (61%)	Stability (14%)	Cost (11%)
Sports Games	Attractiveness (65%)	Stability (15%)	Cost (10%)
Casual	Attractiveness (54%)	Stability (17%)	Cost (8%)
Books & Reference	Accuracy (26%)	Phone (13%)	Connection (13%)
Business	Connection (31%)	Accuracy (22%)	Cost (15%)
Comics	Attractiveness (29%)	Picture (17%)	Connection (16%)
Communication	Phone (33%)	Connection (18%)	Compatibility (13%)
Education	Attractiveness (17%)	Accuracy (13%)	Phone (13%)
Entertainment	Attractiveness (28%)	Media (16%)	Stability (11%)
Finance	Connection (43%)	Accuracy (25%)	Cost (9%)
Health & Fitness	Accuracy (38%)	Stability (11%)	Attractiveness (10%)
Libraries & Demo	Attractiveness (21%)	Compatibility (19%)	Phone (15%)
Lifestyle	Accuracy (26%)	Stability (12%)	Connection (12%)
Media & Video	Media (28%)	Picture (15%)	Stability (12%)
Medical	Accuracy (30%)	Cost (19%)	Connection (12%)
Music & Audio	Media (32%)	Stability (17%)	Attractiveness (11%)
News & Magazines	Connection (40%)	Stability (19%)	Accuracy (12%)
Personalization	Picture (29%)	Compatibility (19%)	Spam (13%)
Photography	Picture (61%)	Stability (10%)	Cost (6%)
Productivity	Accuracy (31%)	Compatibility (16%)	Connection (15%)
Shopping	Accuracy (54%)	Connection (16%)	Stability (12%)
Social	Connection (34%)	Phone (13%)	Stability (12%)
Sports	Connection (25%)	Accuracy (21%)	Stability (16%)
Tools	Compatibility (29%)	Accuracy (16%)	Phone (13%)

Users' Reception of Free and Paid Apps



100 free/paid apps/games with the most reviews:

- **For paid apps: cost dominates**
- **For paid games: other factors matter too**

Summary

- WisCom provides analysis at 3 different levels
- WisCom can
  - Detect inconsistent reviews,
  - Identify root causes of complaints
  - Provide historical view of apps
  - Help identify market trends and develop guidelines

Concluding Remarks

- Lots of complex decisions can benefit from crowd sourcing
- Combining ML and crowd sourcing can help us:
  - Understand complex questions, automate processes, and more
  - Make crowd sourcing more efficient
- This presentation was intended to illustrate some of the research in this area at the Mobile Commerce Lab.

Q&A

mobile commerce lab

http://mcom.cs.cmu.edu