From individual behavior to social process: using human traces for social good

Esteban Moro





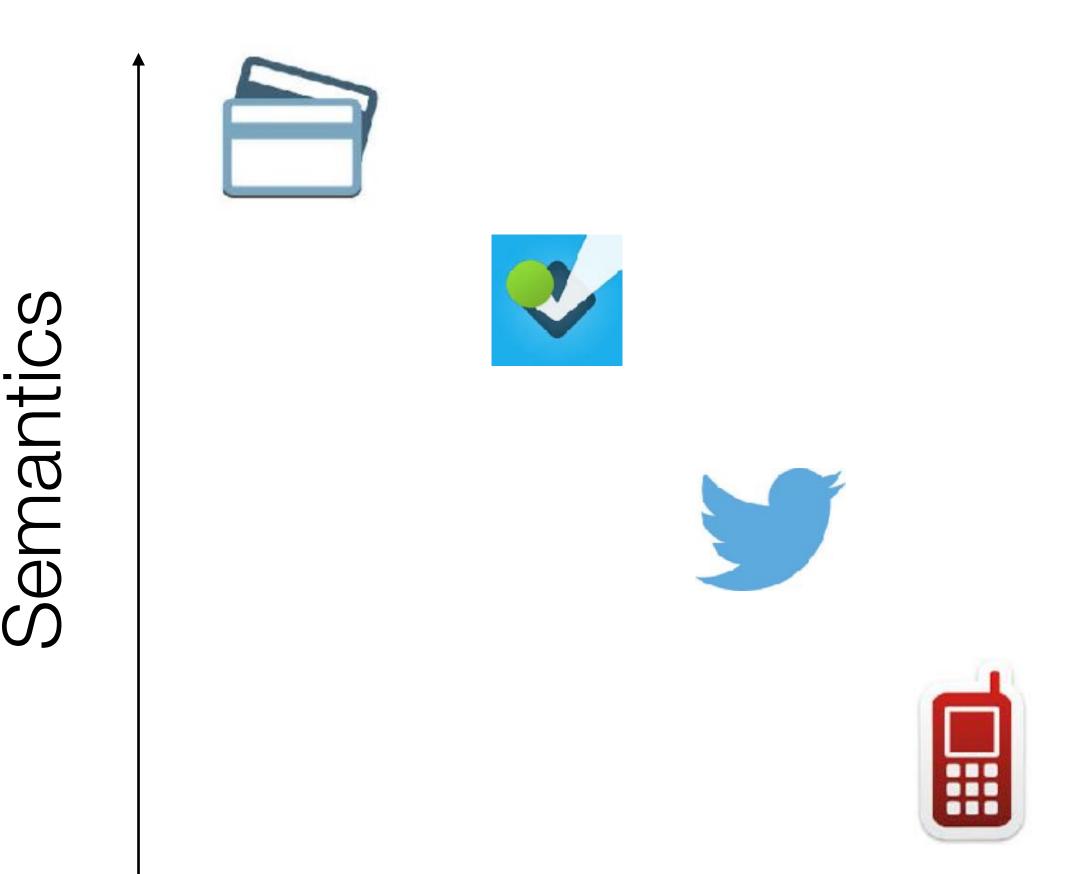
Sources of human traces

- Social networks:
 - Twitter, Facebook, Foursquare, etc.
- Financial data
 - Transfers
 - Credit card transactions
- Mobile phone:
 - CDRs (calls/SMS), network events, etc.
 - Phone sensors
 - Apps
- Satellite data





Frequency



Why alternative data?

- Better spatial-temporal resolution
- Faster answers
- Cheaper
- Availability

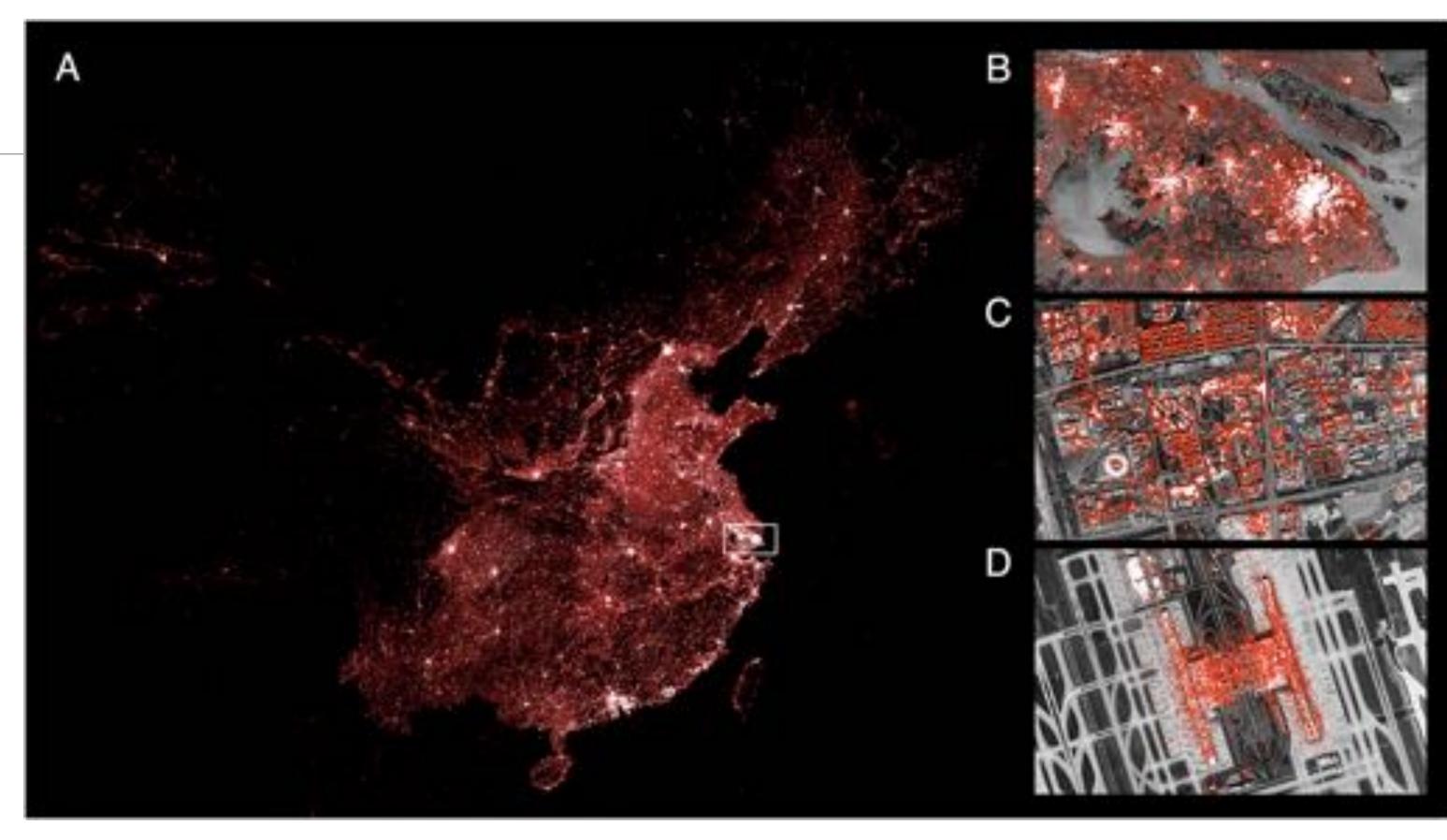


Figure 1 Spatial-temporal big data reflects human activity at different scales. (A) At the national level: Data points depict the fact that most of China's population is concentrated in large cities in the east. As the brightness of the spot increases, the aggregation of the data points (population) increases. (B) At the regional level: This figure shows urban clusters in the Yangtze River Delta. (C) At the zone level: Zhangjiang Hi-tech Park in Shanghai. (D) At the building level: Pudong Airport in Shanghai. Maps were created using C and Datamaps (https://github.com/ericfischer/datamaps), and the remote sensing images were derived from Baidu Maps.







Dong, L., Chen, S., Cheng, Y., Wu, Z., Li, C., & Wu, H. (2017). Measuring economic activity in China with mobile big data



Why alternative data?

- Better spatial-temporal resolution
- Faster answers
- Cheaper
- Availability
- Different questions



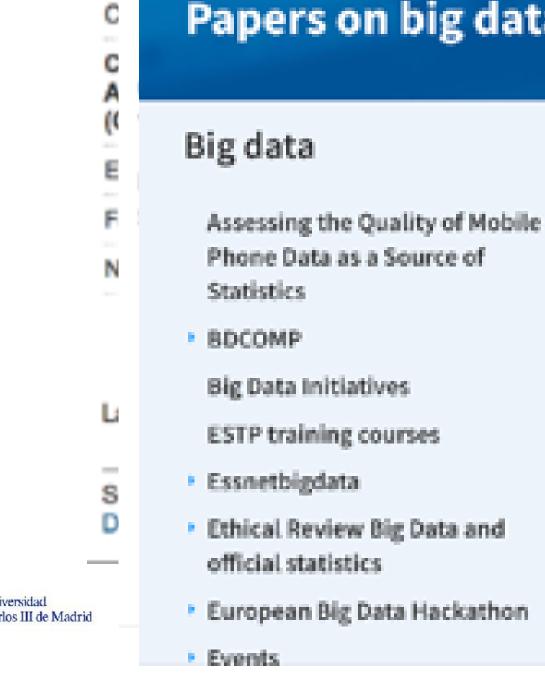




Deville, P, et al. (2014). Dynamic population mapping using mobile phone data. PNAS 111(45), 15888-15893. http://doi.org/10.1073/pnas.1408439111

Why alternative data?

 Complements official data



С

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Buropean Commission







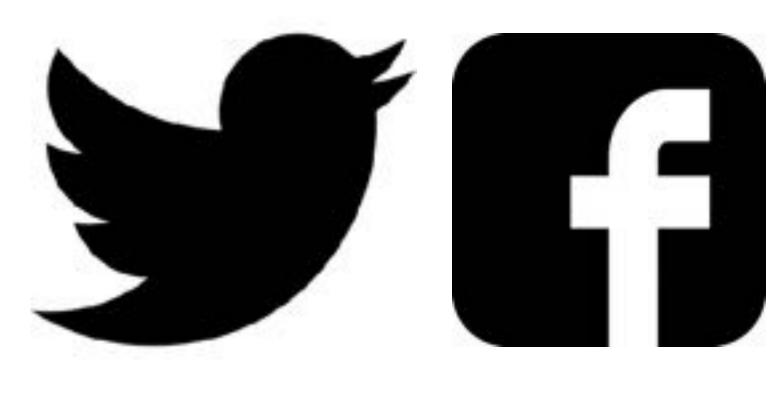


Below, please find some interesting papers on big data with relevance to official statistics:

Beresewicz, M. (2016) Internet data sources for real estate market statistics

- ESS Big Data Action Plan and Roadmap 1.0
- Business Case Vision Implementing Project Big Data
- Structuring risks and solutions in the use of big data sources for producing official statistics Analysis based on a rir. framework
- Analysis of methodologies for using the Internet for the collection of information society and other statistics.
- Estimating Population Density Distribution from Network-based Mobile Phone Data
- Improving prediction of unemployment statistics with Google trends: preliminary experiments
- Methods for treating selectivity in big data sources.
- Use of web activity evidence to increase timeliness (IAOS2014)







Human Development

Gender Gap



- ~20 Million Geolocalized tweets
- Use mobility to find "efficient economic zones"
- Fingerprints of unemployment:
 - Twitter penetration
 - Social interactions between zones
 - Mobility between zones
 - Daily patterns of activity
 - Tweets' content in each zone

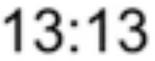




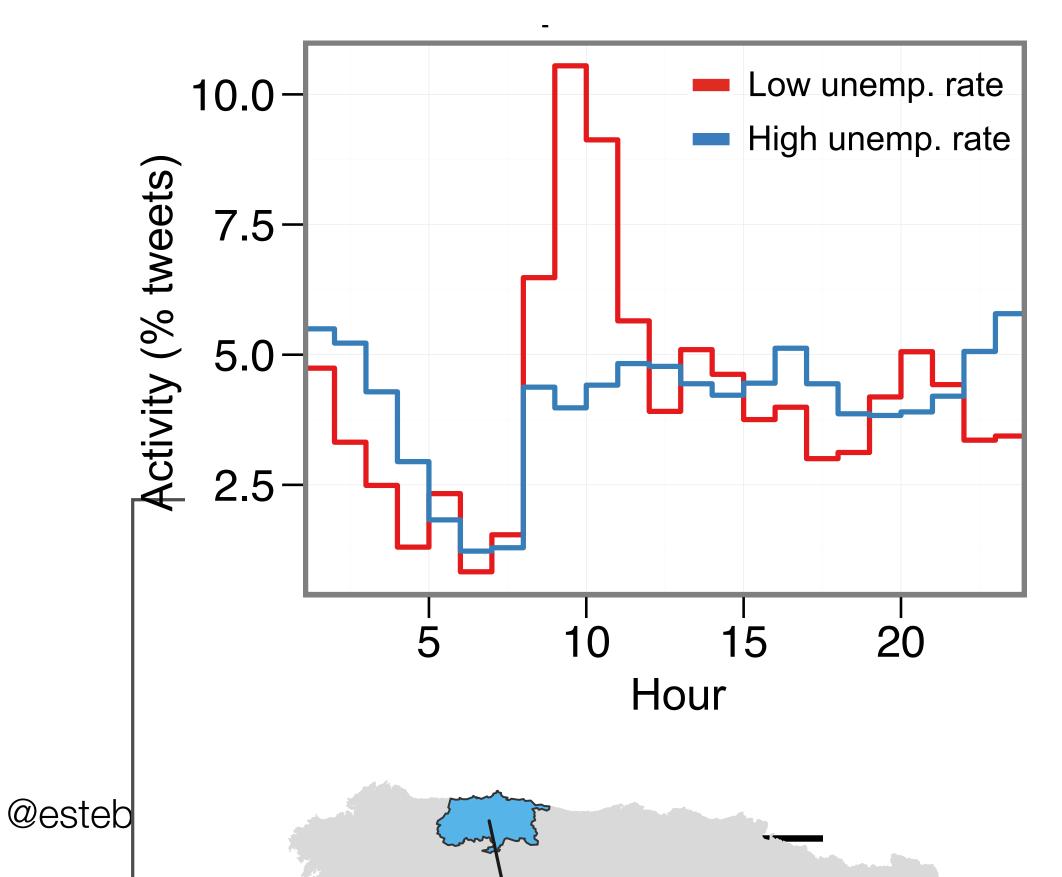


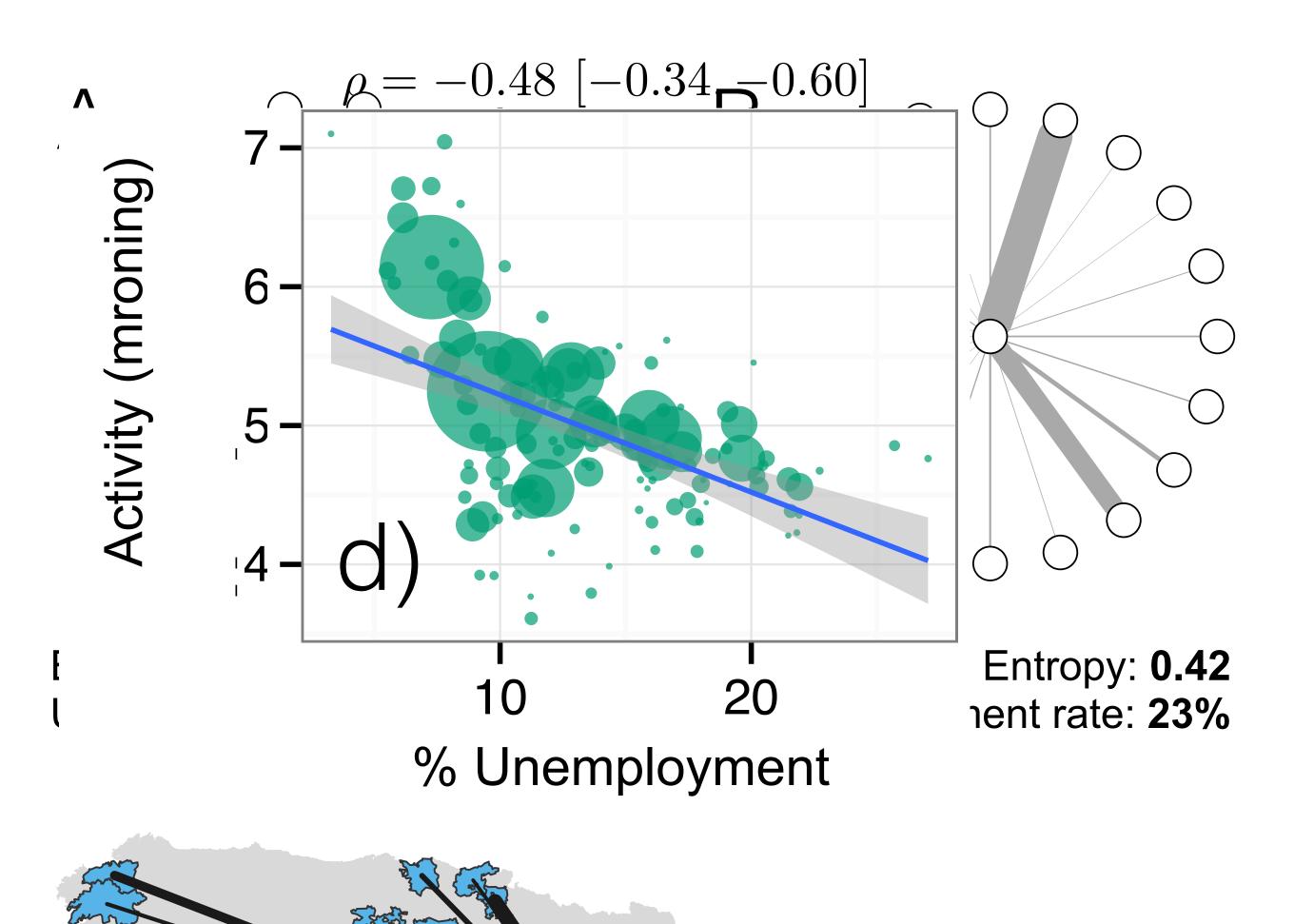
Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment. PLoS ONE, 10(5), e0128692. <u>http://doi.org/10.1371/journal.pone.0128692</u>





- Daily patterns of activity:
 - Early morning activity is correlated with unemployment





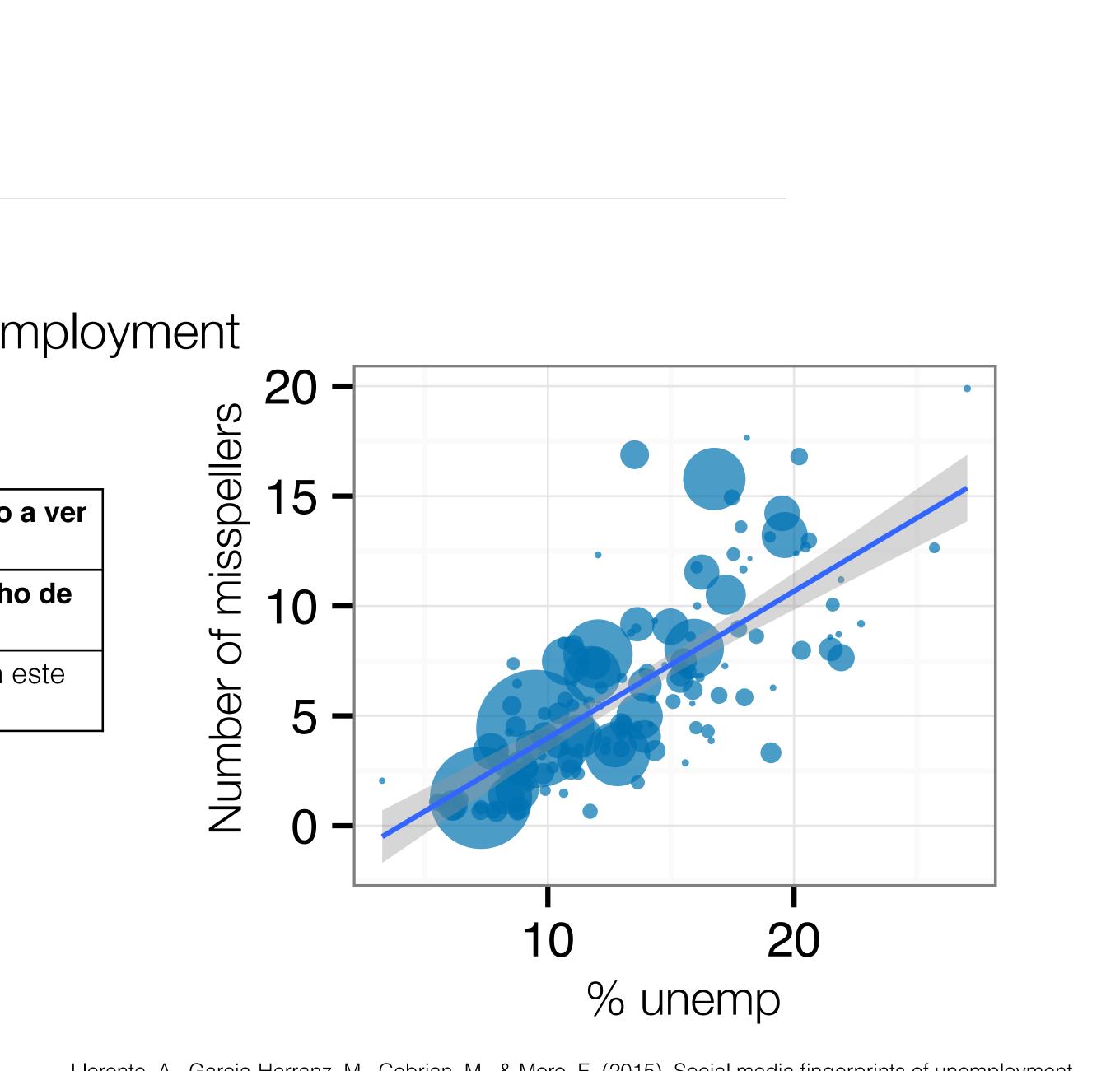
- Tweet's content:
 - Misspelling is highly correlated with unemployment

Tweet	Correct spelling	
Alguien se viene con migo aver la vida de PI??	Alguien se viene conmigo la vida de PI??	
La quiero mucho y la hecho de	La quiero mucho y la ech	
menos	menos	
Yo llendo a trabajar con este	Yo yendo a trabajar con	
tiempo	tiempo	

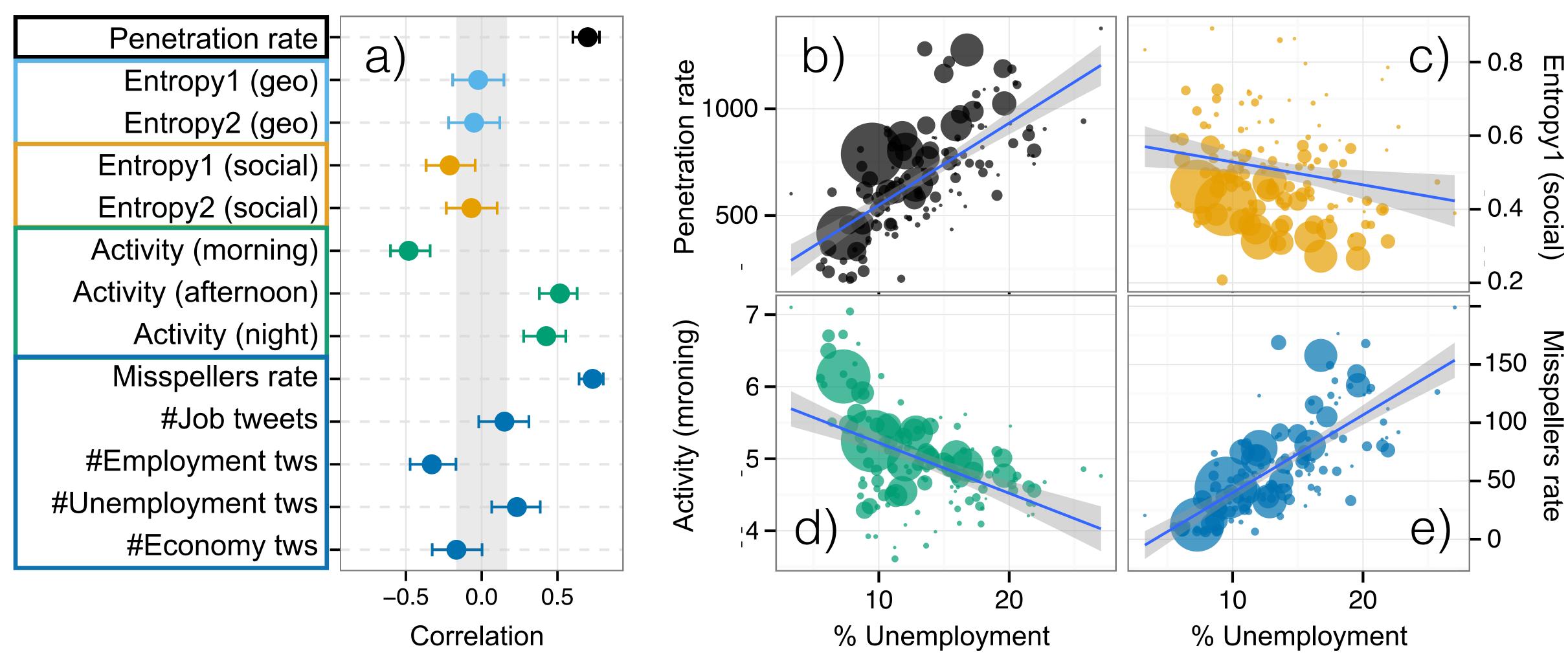








Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment. PLoS ONE, 10(5), e0128692. <u>http://doi.org/10.1371/journal.pone.0128692</u>



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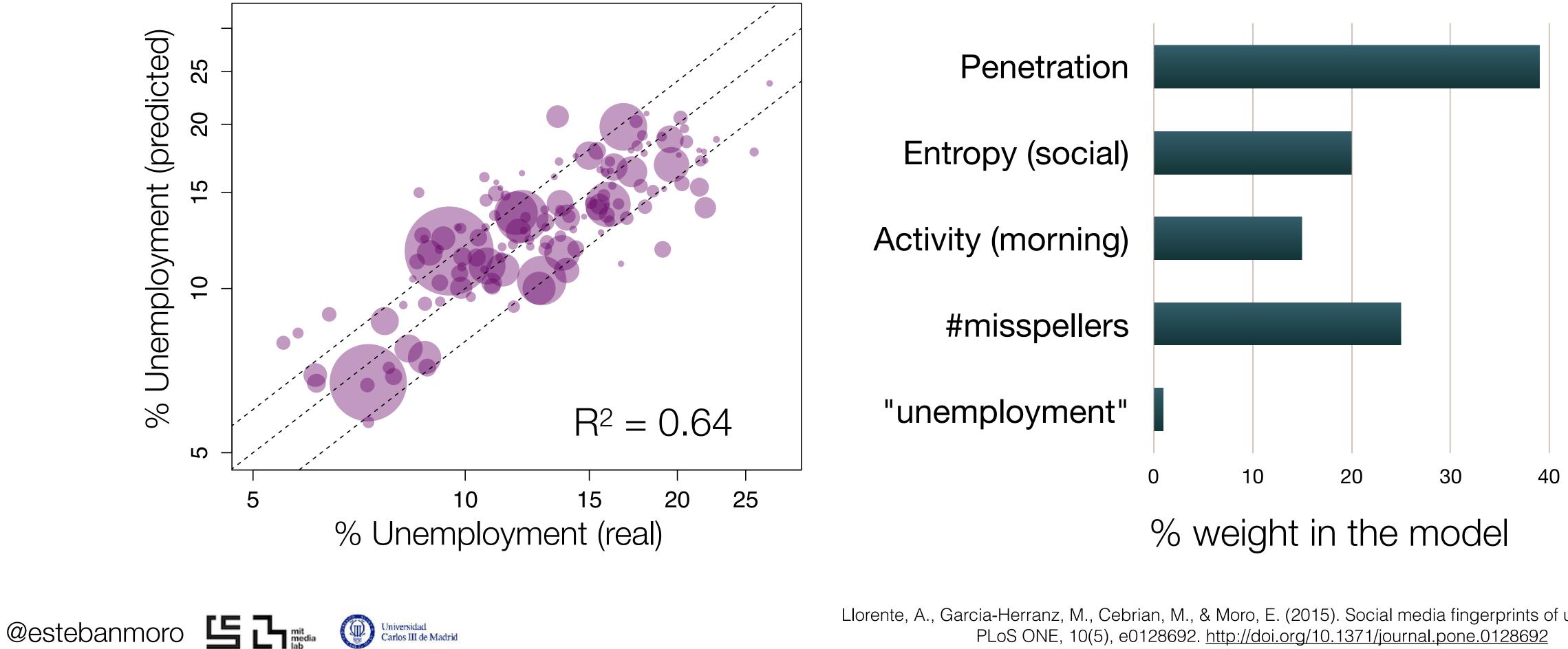


Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment. PLoS ONE, 10(5), e0128692. <u>http://doi.org/10.1371/journal.pone.0128692</u>



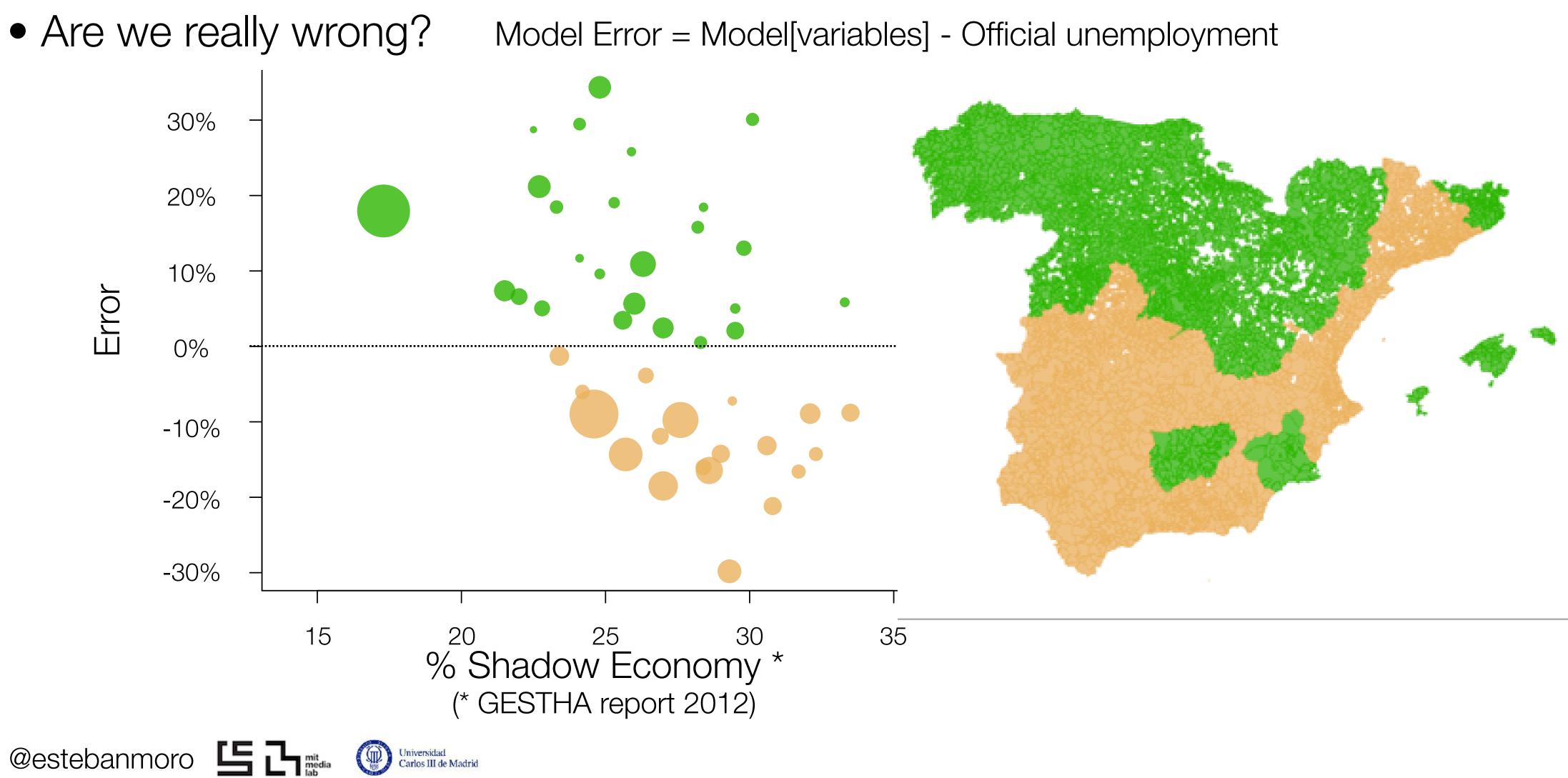
• Explanatory power of the social media fingerprints

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Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment. PLoS ONE, 10(5), e0128692. <u>http://doi.org/10.1371/journal.pone.0128692</u>





Use twitter to estimate the Human **Development Index (HDI)**







NIGERIA



POLAND



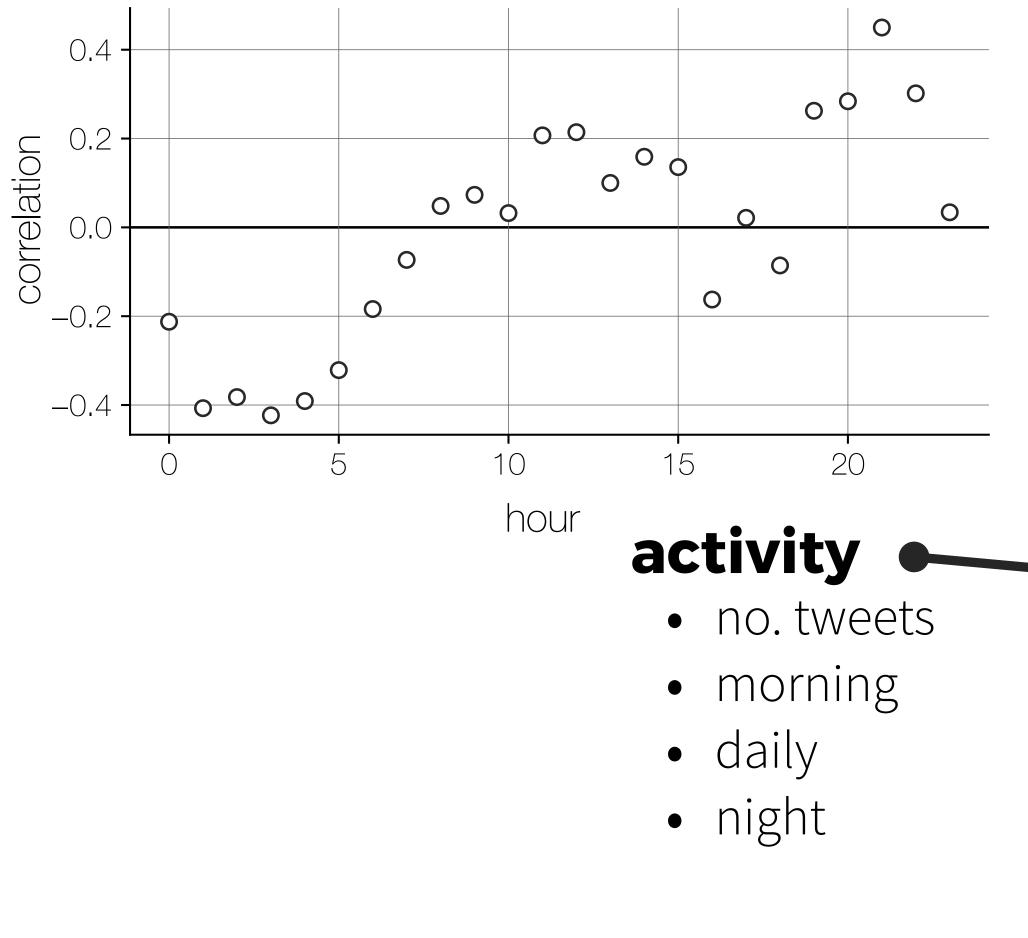


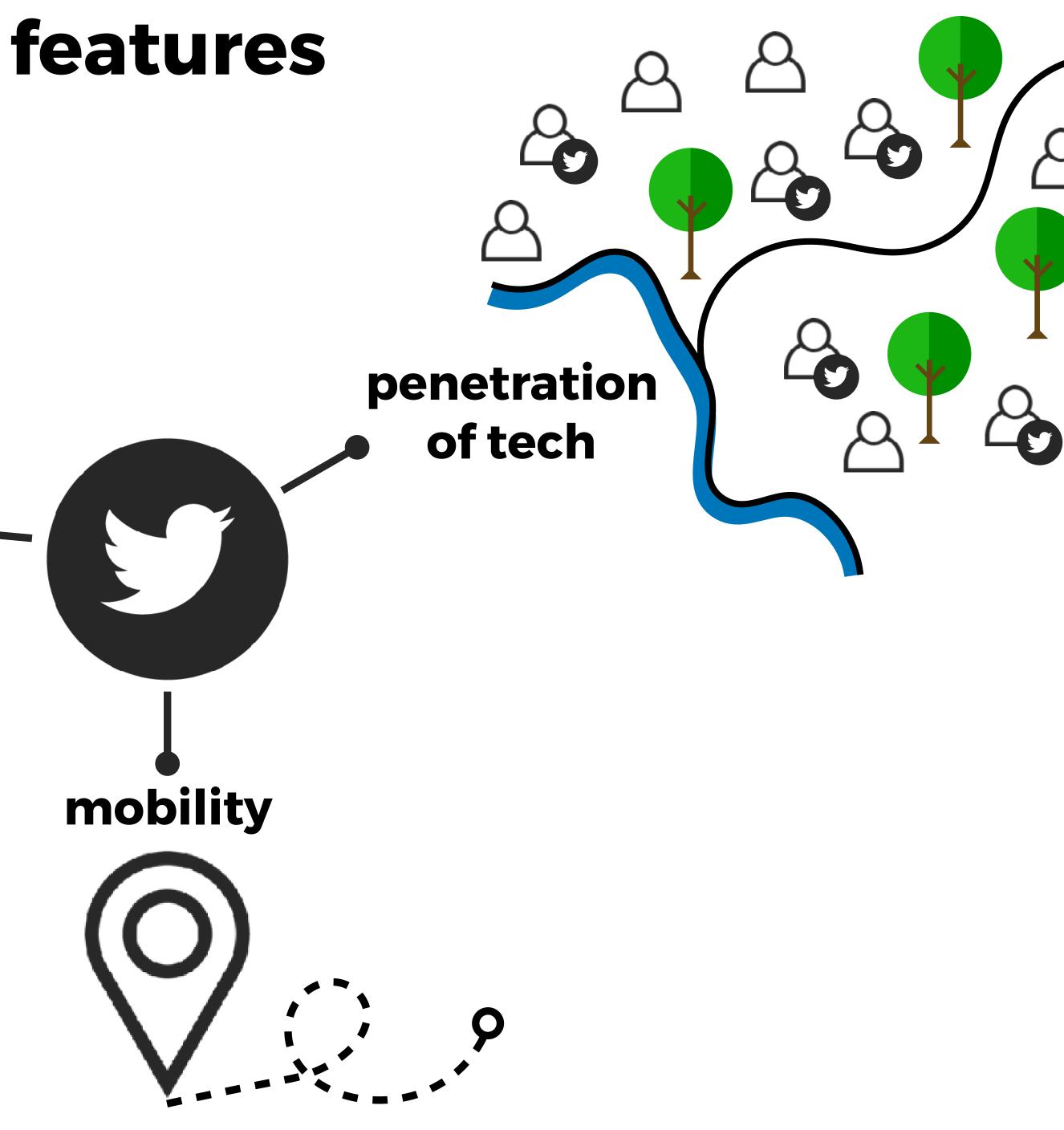


Use twitter to estimate HDI on sub-national levels

Admin 0 Country



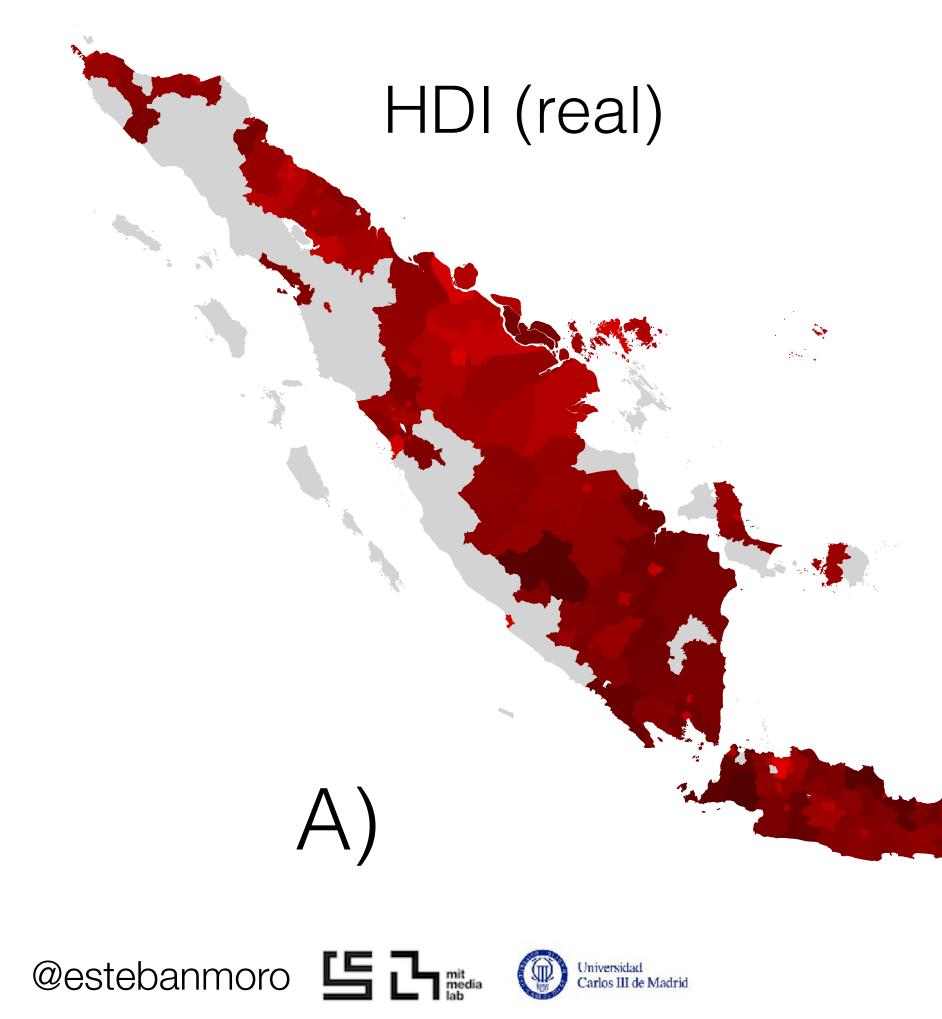


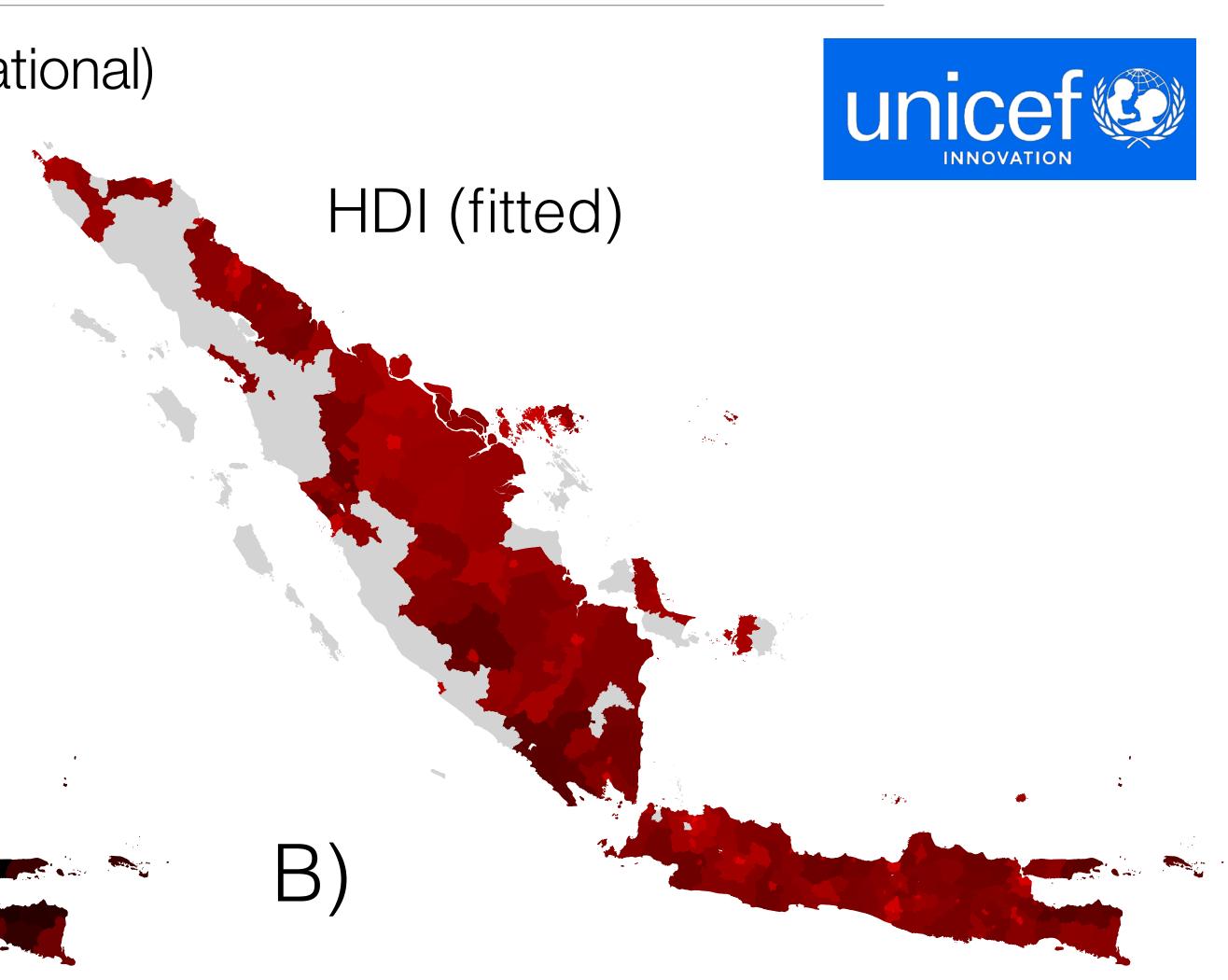




Human development

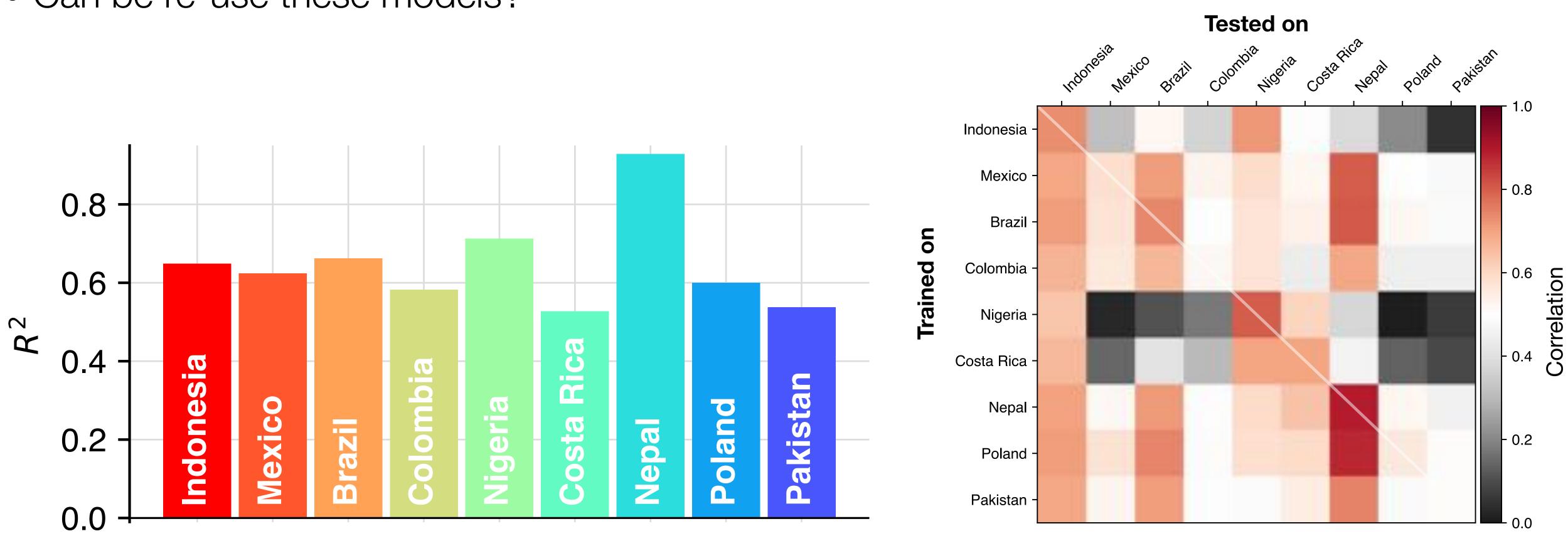
• HDI = Human Development index (sub-national)





Human development

• Can be re-use these models?

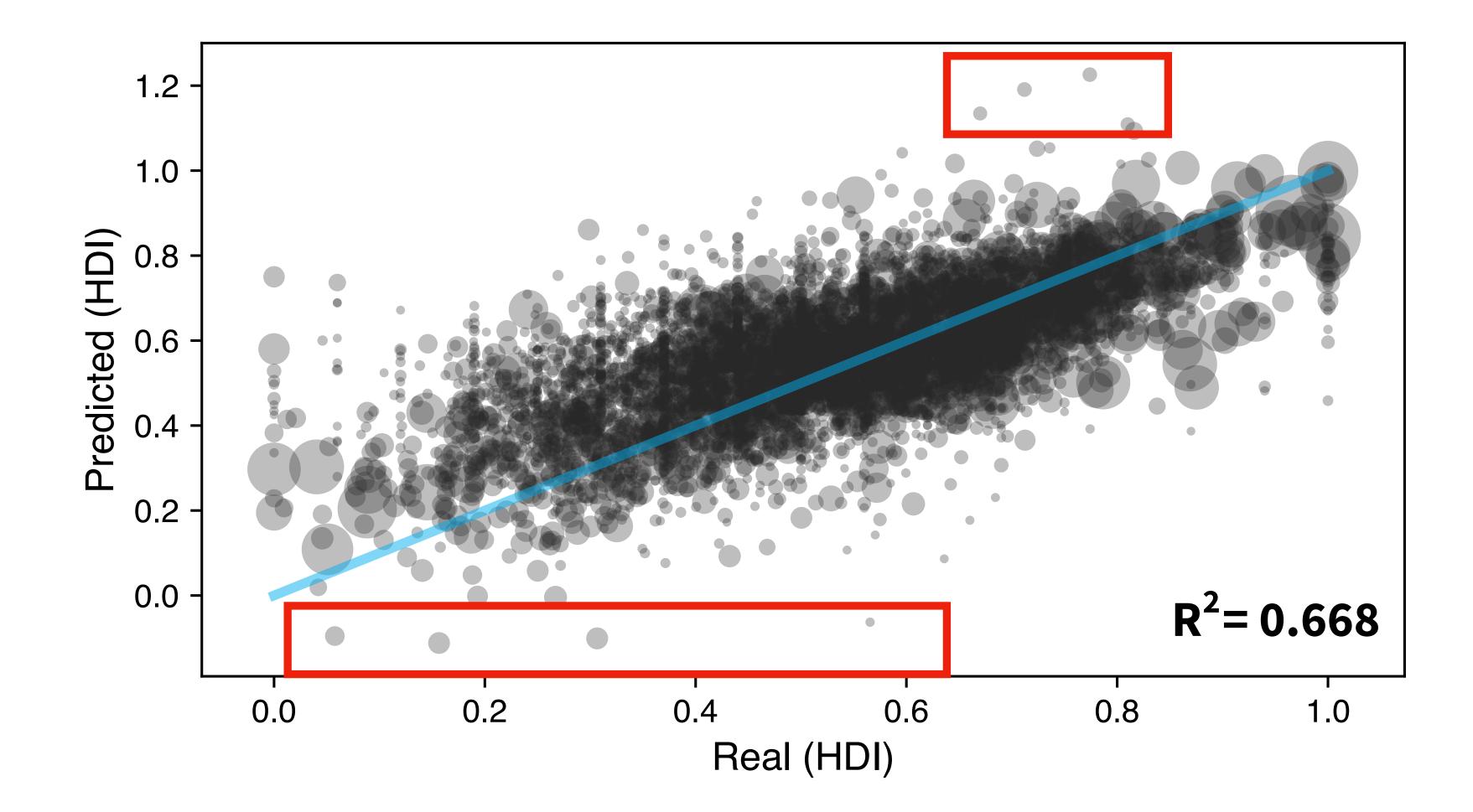


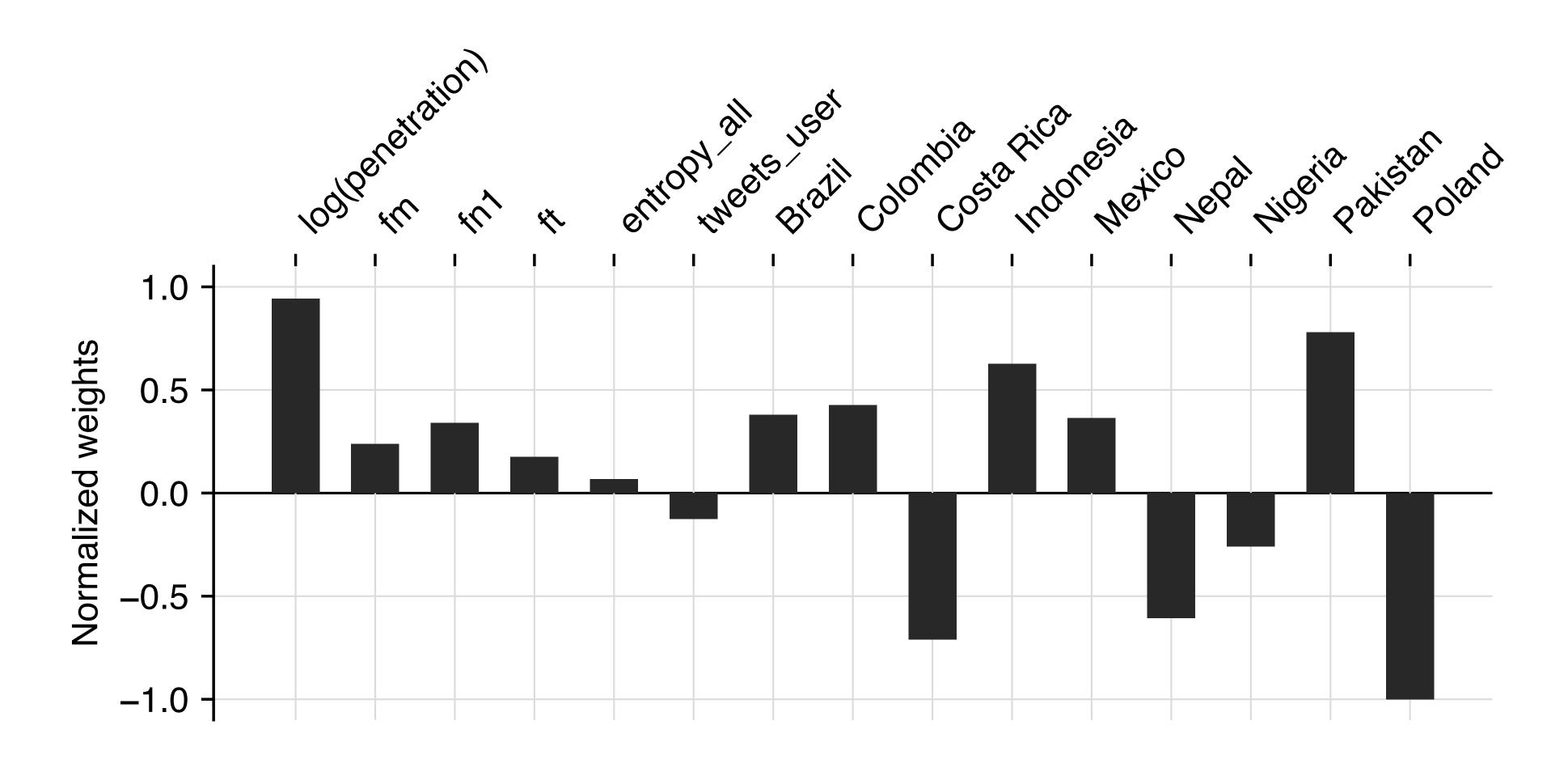






Über model Building one model for all countries

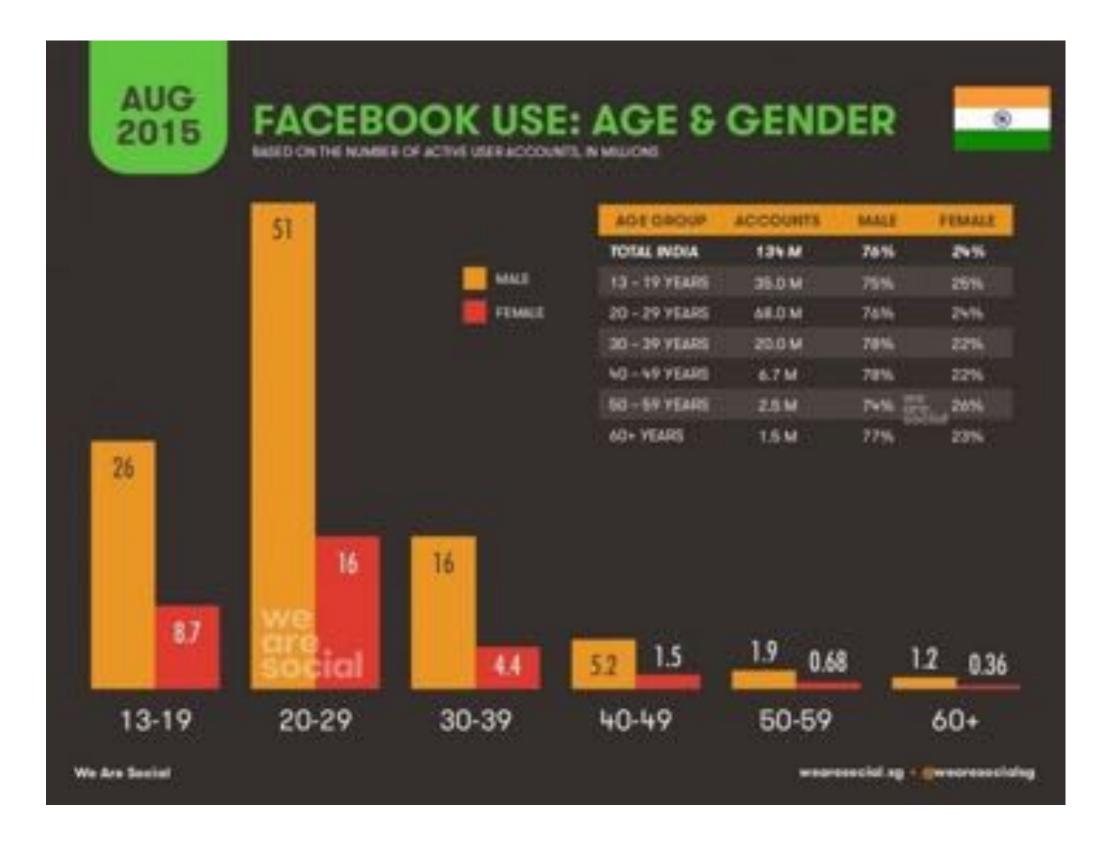




Sekara, Lee, Luengo, Obradovich, García-Herranz and EM, 2018



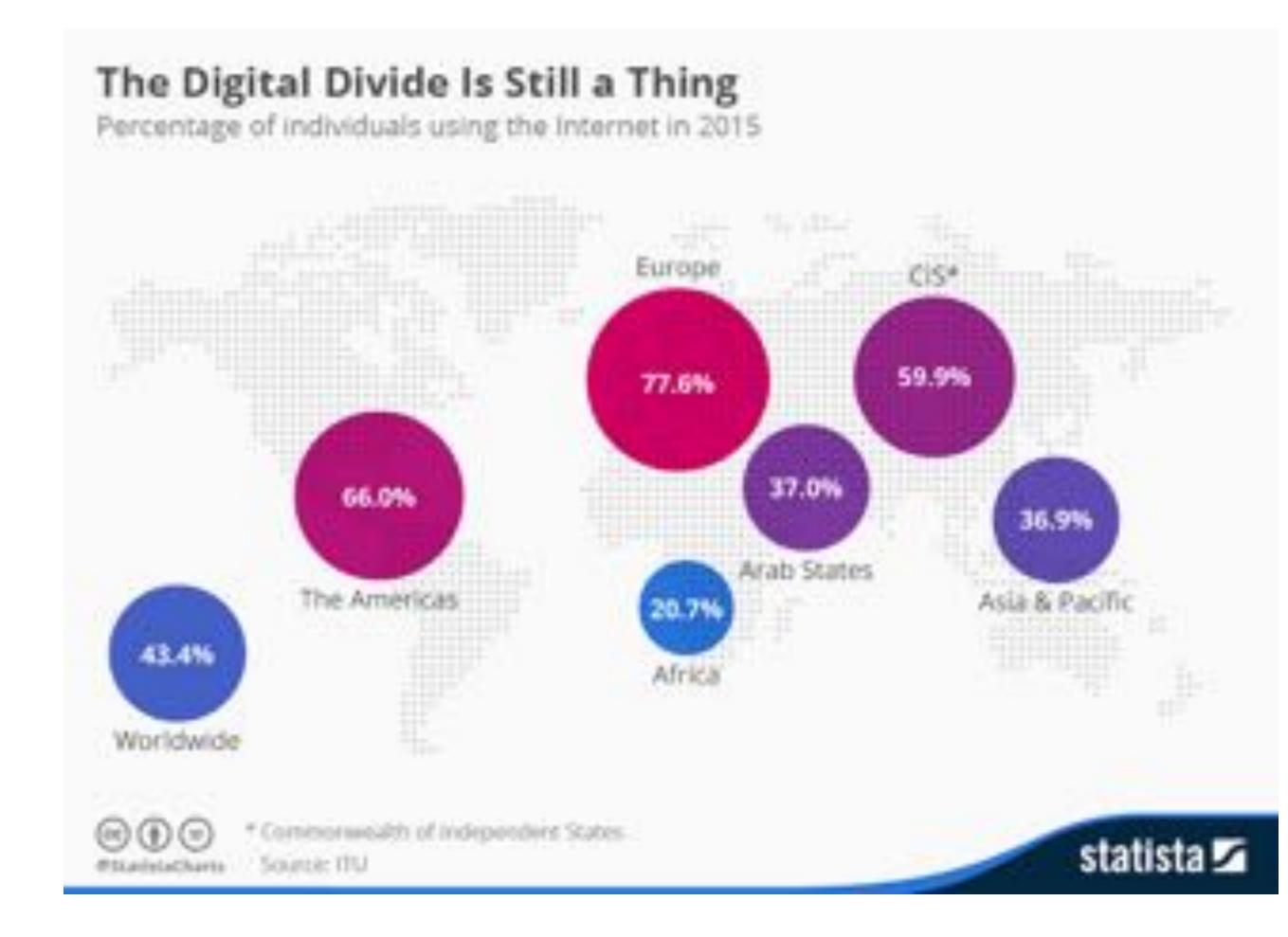
Can we understand gender digital divide in the whole world?











- Use the Marketing Application Programming Interface to collect:
 - Number of Facebook users by age and gender in each 217 countries
 - Calculate the "Facebook gender divide" metric

$$FGD_{c} = \log\left(\frac{R_{Male,c}}{R_{Female,c}}\right),$$

• Find the main explanatory variables for that divide



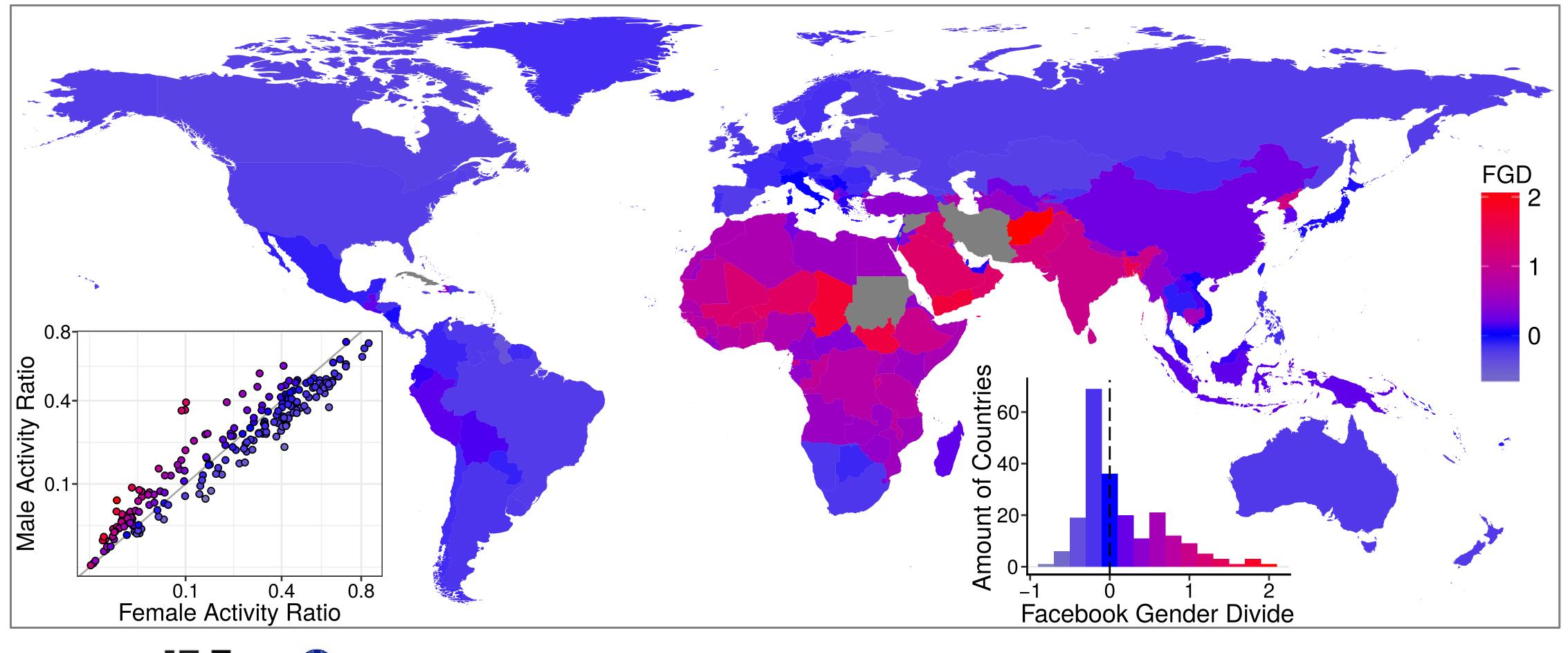




Location	United States *	Targeting By default, Pscobauk to 18 and older mithe defi
	O By State/Province	Theo can change any targ people and can be an easy from the people reformation a sear 's location. May any first and based and bases list in their Processes such as Actuations, Passes Dates Maximum, etc.
Age	O By Dby 2448	
Sec	IF Hale IF Female	
Reywords	Marketing #	
Educations	Al College Grad	
	O In Callege O In High School	
Workplaces	limer a company, organization or other workplace.	
Relationship:	□ Single □ In a Relationship □ Engaged □ Harried	
Interested Inc	("Meil ("Wanen	
Languagest	timer tanguage	



• 217 countries, around 1.4 billion users



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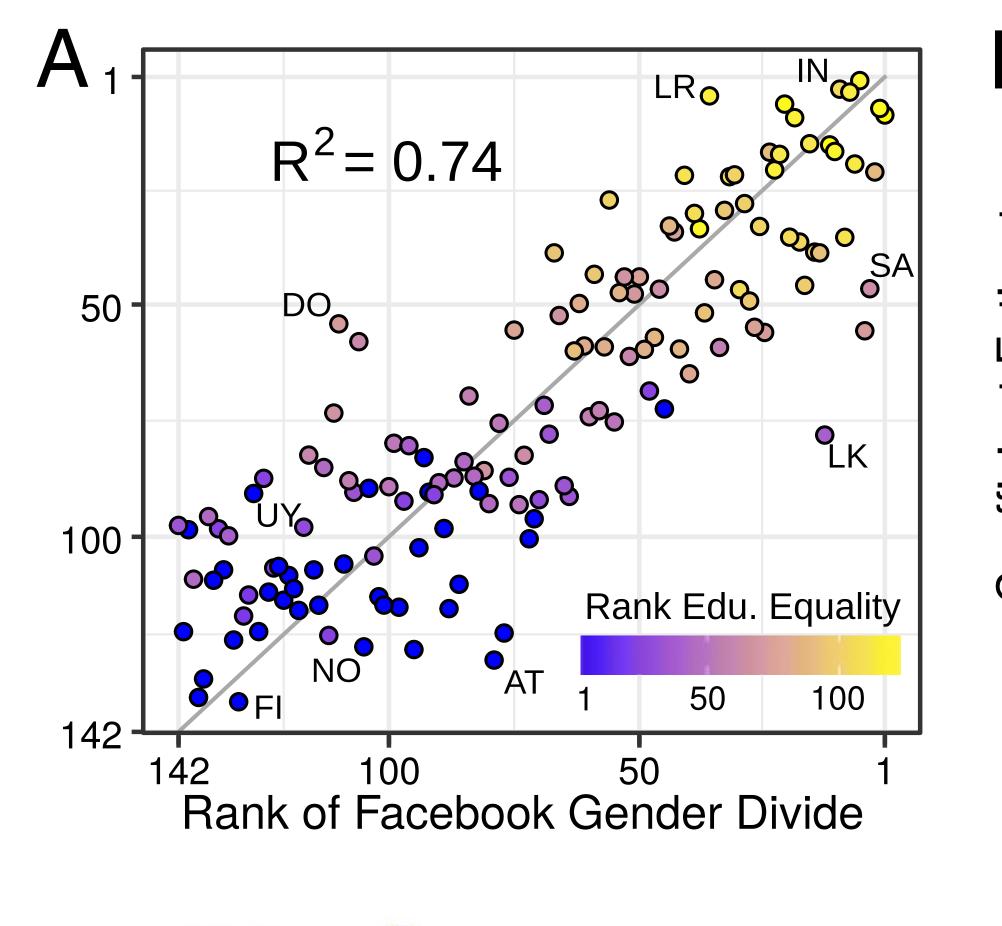




Garcia, D., Kassa, Y. M., Cuevas, A., Cebrian, M., Moro, E., Rahwan, I., & Cuevas, R. (2018). PNAS



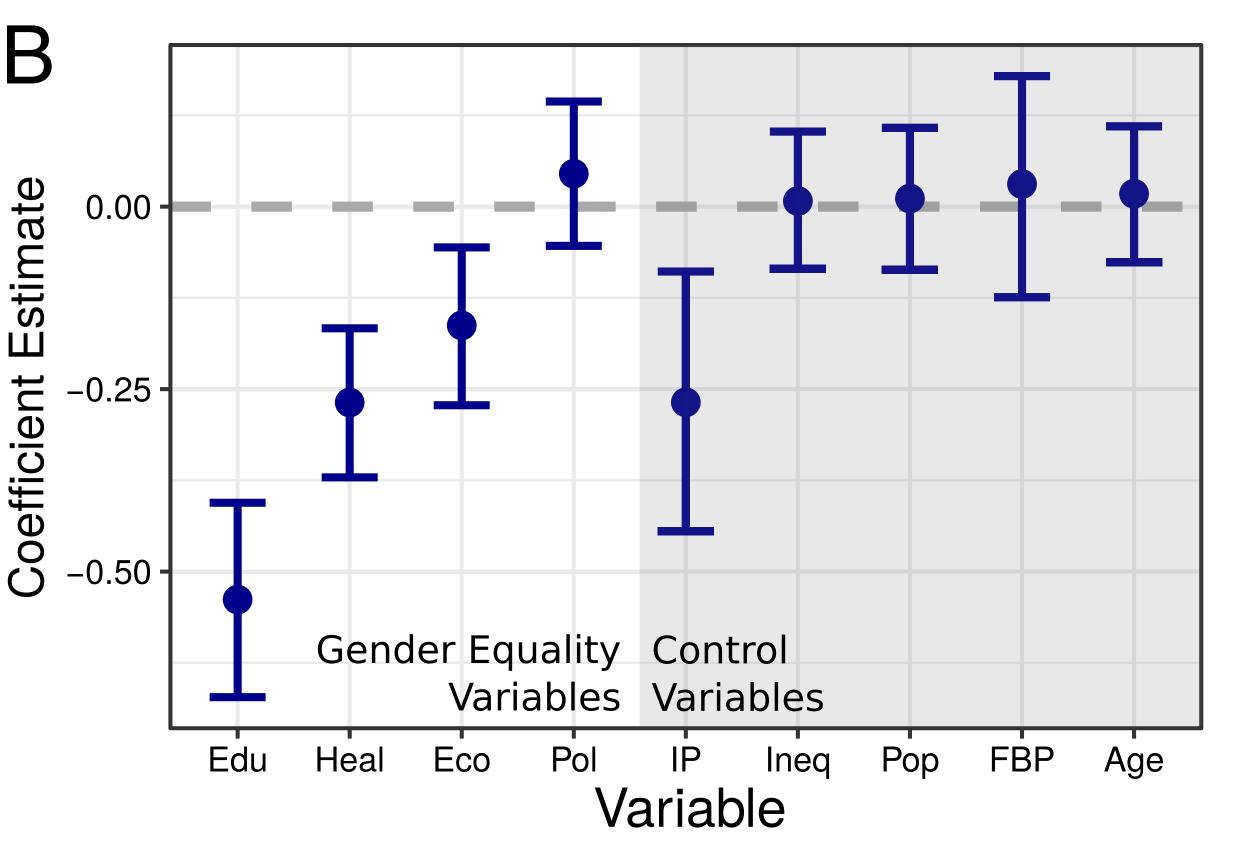
What are the explanatory variables for the Facebook gender divide?



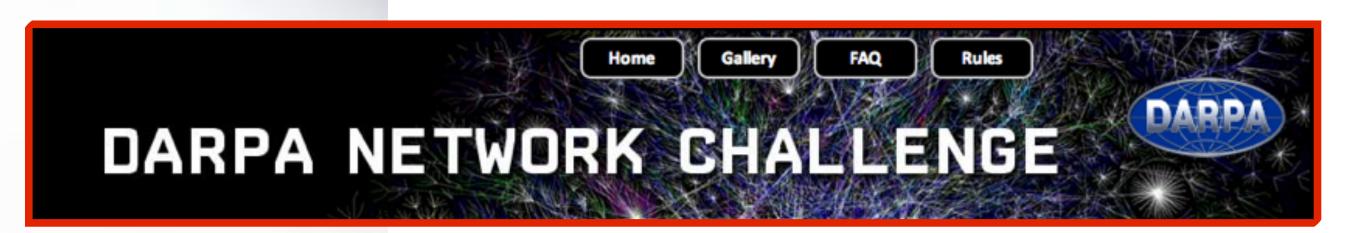








Can we use networks to mobilize people?





• Yes, information travels very fast in social networks, but can we use it to mobilize people?

"Impossible by conventional intelligence"

Can we use networks to mobilize people? mit media lah





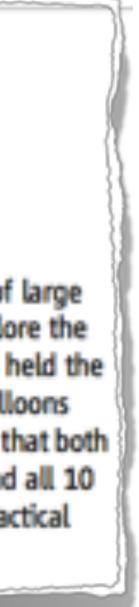






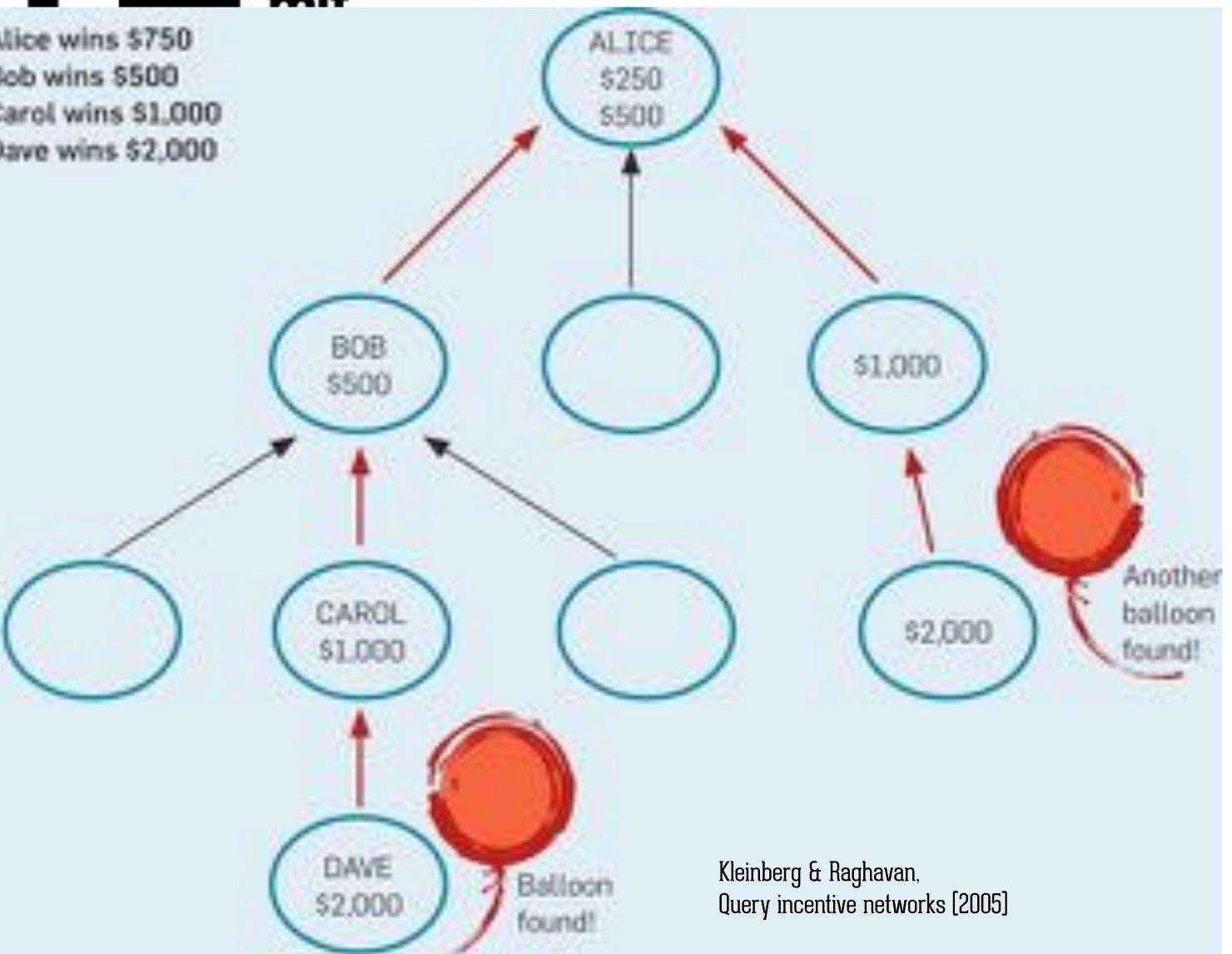
Galen Pickard, 1,2* Wei Pan, 1* Iyad Rahwan, 1,3* Manuel Cebrian, 1* Riley Crane, 1 Anmol Madan,¹ Alex Pentland¹[†]

The World Wide Web is commonly seen as a platform that can harness the collective abilities of large numbers of people to accomplish tasks with unprecedented speed, accuracy, and scale. To explore the Web's ability for social mobilization, the Defense Advanced Research Projects Agency (DARPA) held the DARPA Network Challenge, in which competing teams were asked to locate 10 red weather balloons placed at locations around the continental United States. Using a recursive incentive mechanism that both spread information about the task and incentivized individuals to act, our team was able to find all 10 balloons in less than 9 hours, thus winning the Challenge. We analyzed the theoretical and practical properties of this mechanism and compared it with other approaches.



Can we use networks to mobilize people?

Alice wins \$750 Bob wins \$500 Carol wins \$1,000 Dave wins \$2,000



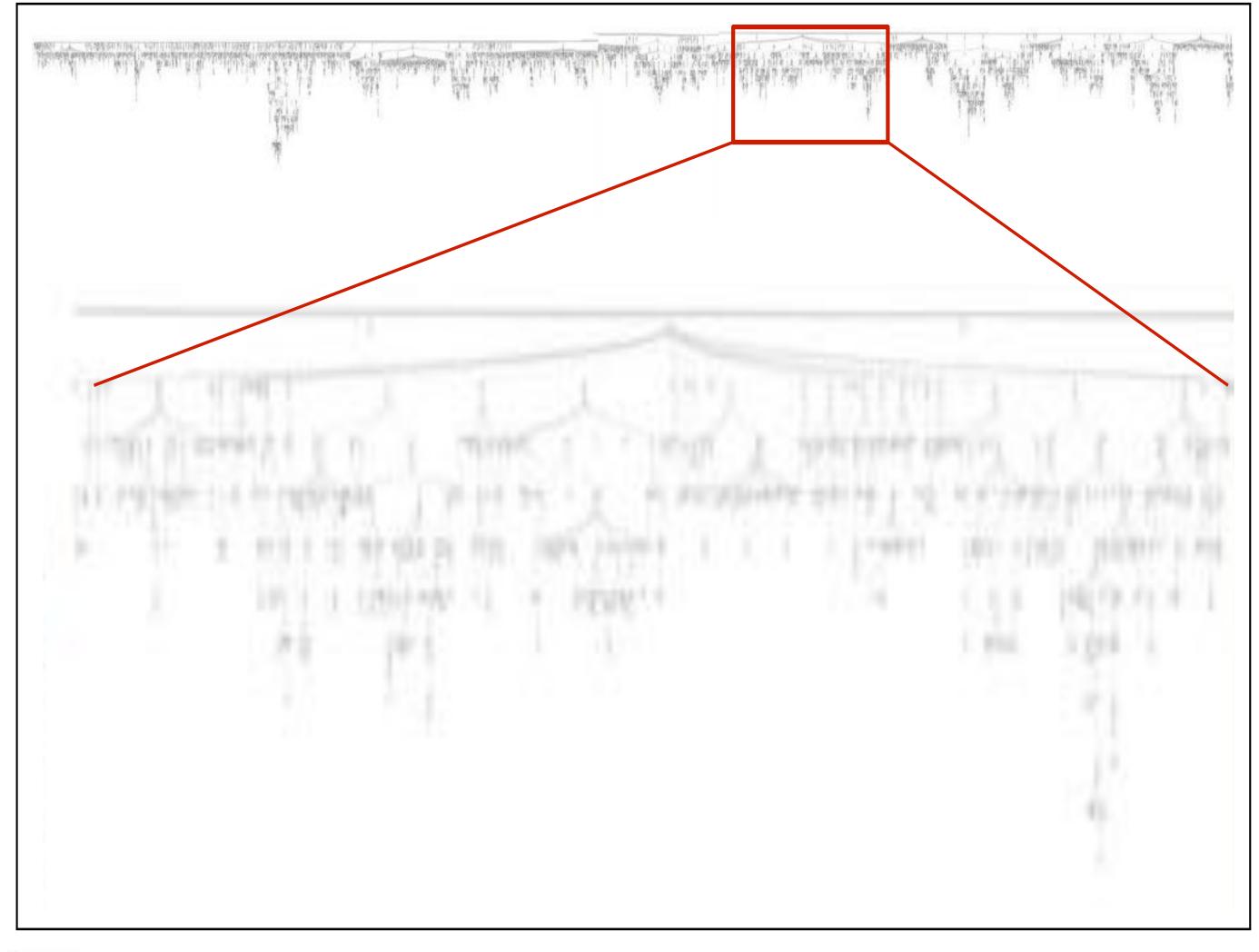








Can we use networks to mobilize people?



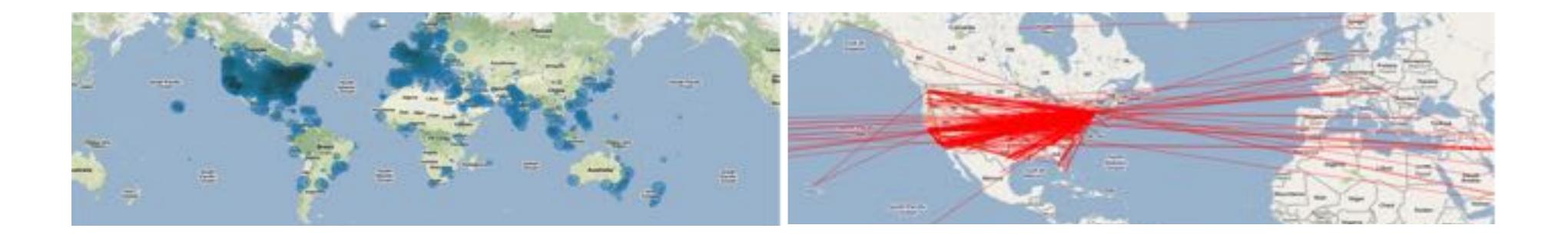






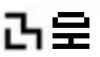
Can we use networks to mobilize people? Global reach in **36 hours**

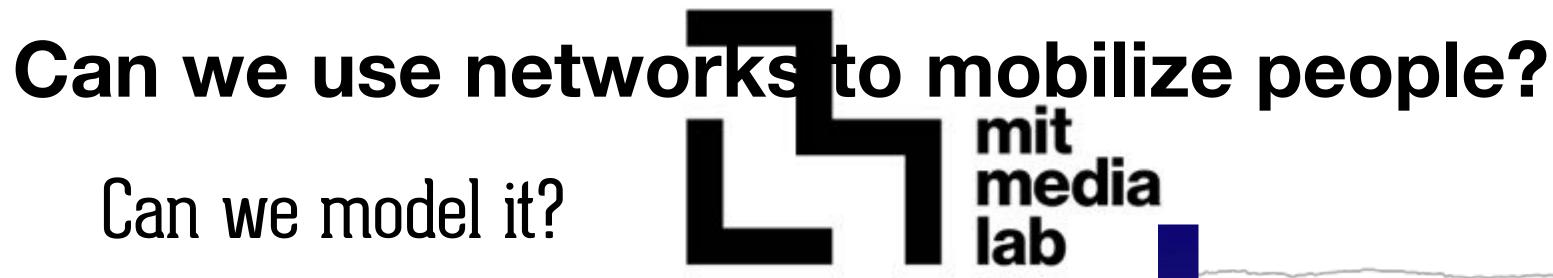




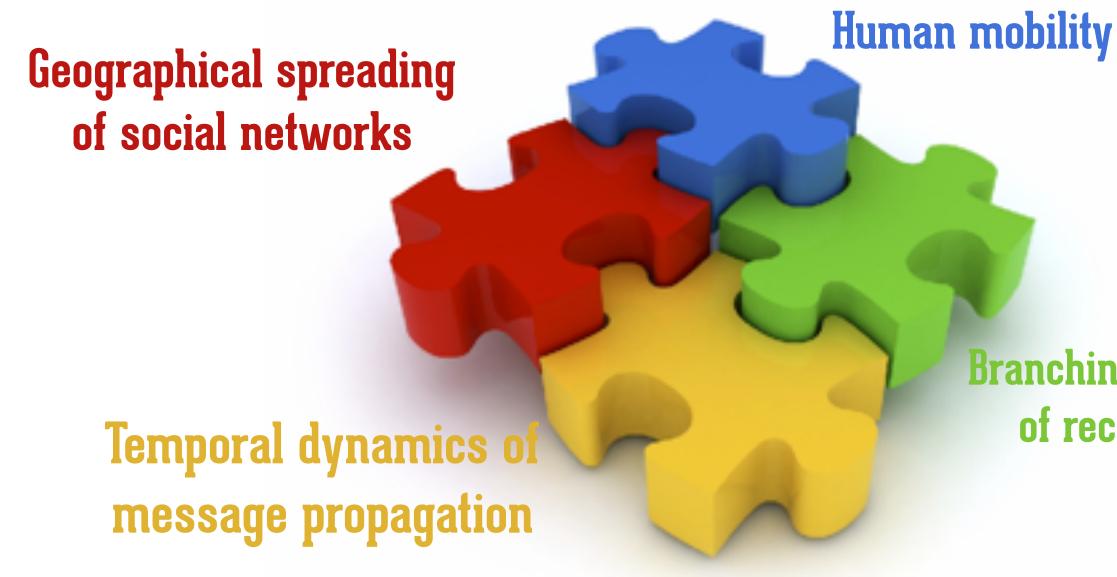








A model of social geographical mobilization











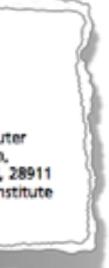
Limits of social mobilization

Alex Rutherford^a, Manuel Cebrian^{b,c}, Sohan Dsouza^a, Esteban Moro^{d,e}, Alex Pentland^f, and Iyad Rahwan^{a,g,1}

*Computing and Information Science, Masdar Institute of Science and Technology, Abu Dhabi 54224, United Arab Emirates: ^bDepartment of Computer Science and Engineering, University of California at San Diego, La Jolla, CA 92093; 'National Information and Communications Technology Australia, Melbourne, VIC 3010, Australia; ^dDepartamento de Matemáticas and Grupo Interdisciplinar de Sistemas Complejos, Universidad Carlos III de Madrid, 28911 Madrid, Spain; "Instituto de Ingeniería del Conocimiento, Universidad Autónoma de Madrid, 28049 Madrid, Spain; "Media Laboratory, Massachusetts Institute of Technology, Cambridge, MA 02139; and 9School of Informatics, University of Edinburgh, Edinburgh EH8 9AB, United Kingdom

"inhera Correll Poissanity Ithaca NY and approved March 1. 2013 (received for review-4

Branching dynamics of recruitment



Can we use networks to mobilize people?

- 1. Select a seed [@MIT]
- 2. Wait for a response time
- 3. Recruit a number of active/passive new members
- 4. Choose them on short/large distances
- 5. If ballon is in the search area of the recruit => found
- 6. Proceed to 2 with the active recruits. If none, stop



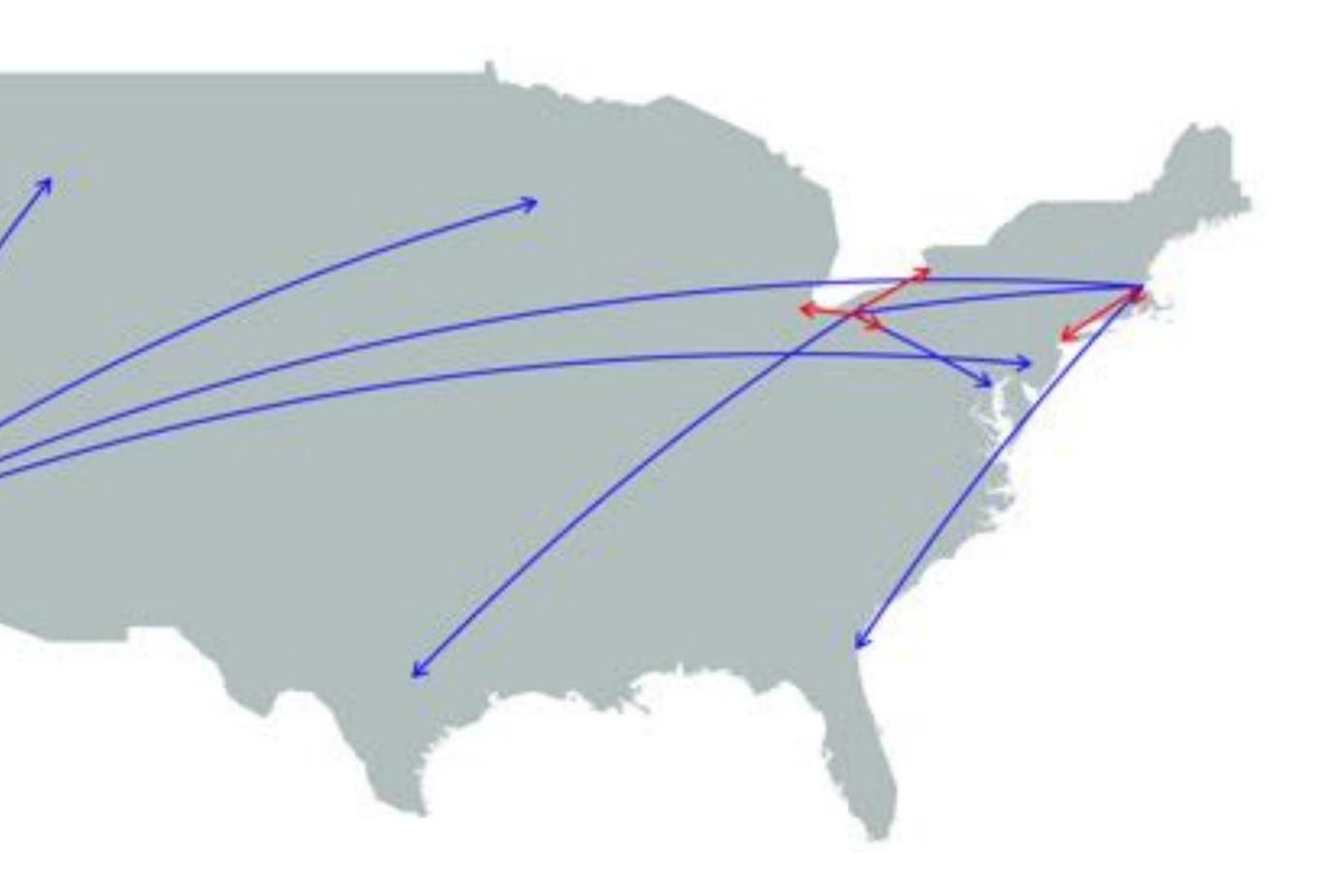


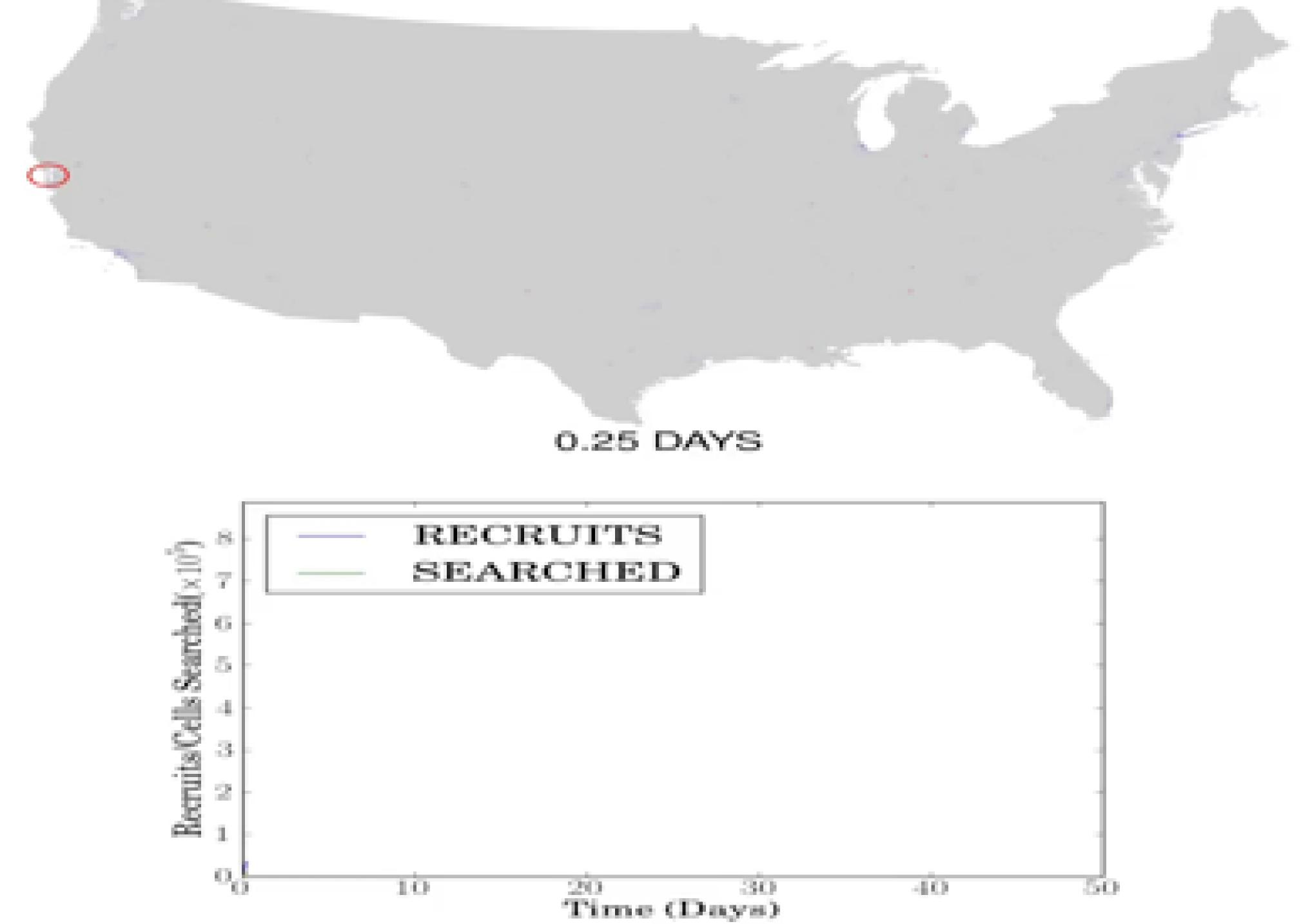




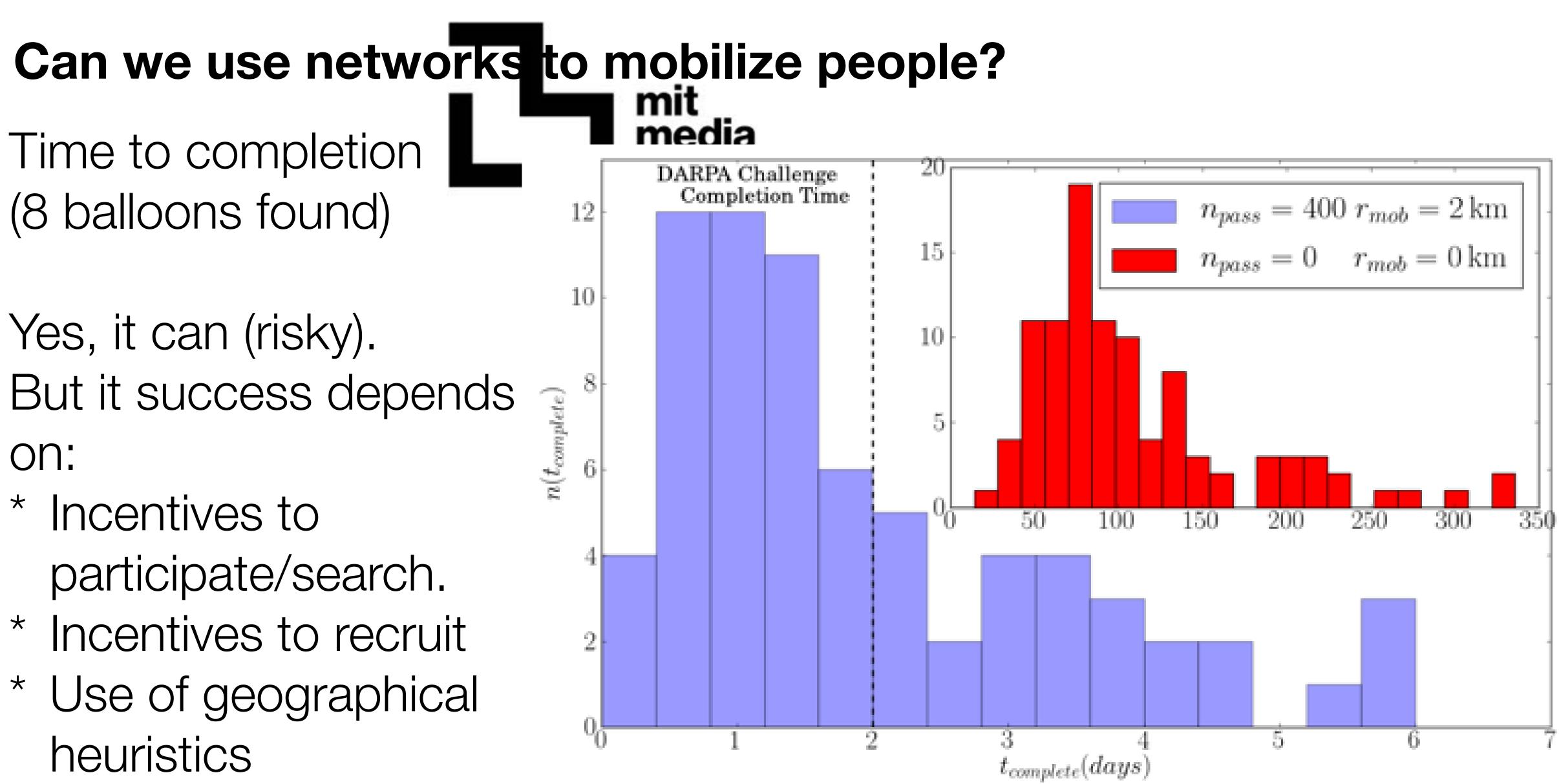
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Political research

Unemployment

Event detection

Natural disasters

Market research



Labor markets?

Consumer sentiment

NetN

Societies: Spread of diseases Social influence Privacy Product adoption Marketing

Economies:

Loan Repayment Food consumption and poverty indices Microcredit approval Labor market







Crowds:

Real time event detection in cities Estimating attendance of events



mit

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Cities:

Energy consumption Predicting crime hotspots Health catchment areas Census estimation

Mobility:

Mobility prediction Impact of Sharing Economy Optimization of public transportation





References

Facebook Gender Divide

303, 201717781. <u>http://doi.org/10.1073/pnas.1717781115</u>

Social media and extreme weather

- expressed sentiment. PLoS ONE, 13(4), e0195750. <u>http://doi.org/10.1371/journal.pone.0195750</u>
- Social media and disasters
 - e1500779. http://doi.org/10.1126/sciadv.1500779

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• Garcia, D., Kassa, Y. M., Cuevas, A., Cebrian, M., Moro, E., Rahwan, I., & Cuevas, R. (2018). Analyzing gender inequality through large-scale Facebook advertising data. Proceedings of the National Academy of Sciences,

• Baylis, P., Obradovich, N., Kryvasheyeu, Y., Chen, H., Coviello, L., Moro, E., et al. (2018). Weather impacts

 Kryvasheyeu, Y., Chen, H., Obradovich, N., Moro, E., Van Hentenryck, P., Fowler, J., & Cebrian, M. (2016). Rapid assessment of disaster damage using social media activity. Science Advances, 2(3), e1500779-

• Kryvasheyeu, Y., Chen, H., Moro, E., Van Hentenryck, P., & Cebrian, M. (2015). Performance of Social Network Sensors during Hurricane Sandy. PLoS ONE, 10(2), e0117288. <u>http://doi.org/10.1371/journal.pone.0117288</u>



References

- Social media and unemployment
 - PLoS ONE, 10(5), e0128692. <u>http://doi.org/10.1371/journal.pone.0128692</u>
- Social media and viral spreading
 - 0092413
 - 10.1371/journal.pone.0029358
- Social networks and mobilization
 - Rutherford, A., Cebrian, M., D'souza, S., Moro, E., Pentland, A., & Rahwan, I. (2013). Limits of social mobilization., 110(16), 6281–6286. <u>http://doi.org/10.1073/pnas.1216338110</u>

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• Llorente, A., Garcia-Herranz, M., Cebrian, M., & Moro, E. (2015). Social media fingerprints of unemployment.

• Garcia-Herranz, M., Moro, E., Cebrian, M., Christakis, N. A., & Fowler, J. H. (2014). Using Friends as Sensors to Detect Global-Scale Contagious Outbreaks. PLoS ONE, 9(4), e92413. http://doi.org/10.1371/journal.pone.

• Grabowicz, P. A., Ramasco, J. J., Moro, E., Pujol, J. M., & Eguiluz, V. M. (2012). Social Features of Online Networks: The Strength of Intermediary Ties in Online Social Media. PLoS ONE, 7(1), e29358. http://doi.org/

