Who tweets (and where) ? Social, political and environmental determinants of Twitter use in France

Data Science in the Alps Workshop Grenoble, March 20th 2018

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The Problem

The promised land and the sociologist's nightmare



What we know (the promised land)

- Total Number of Monthly Active Twitter Users (worldwide Jan. 2018) : 330 M
- Total Number of Tweets sent per Day(worldwide Dec. 2017) : 500 M
- Percentage of Twitter users who tweet on Mobile : 80%
- Number of Monthly Active users in France : 21.8 M

What we know (the promised land)

Le Top 30 des Marques*

Rang	arques B Visiteurs uniques par m		
1	Google	34 517 000	
2	Facebook	32 673 000	
3	YouTube	24 779 000	
4	Twitter.com	12 140 000	
5	Apple	12 021 000	
6	Orange	11 222 000	
7	Leboncoin.fr	11 029 000	
8	Amazon	10 383 000	
9	Instagram	9 786 000	
10	LinkedIn	9 616 000	
11	PagesJaunes	8 936 000	
12	Wikipedia	8 713 000	
13	SFR	8 297 000	
14	Snapchat	8 025 000	
15	King	7 620 000	
16	Tele Loisirs	7 248 000	
17	Le Monde	7 074 000	
18	AccuWeather.com	6 839 000	
19	Shazam	6 817 000	
20	France Televisions	6 596 000	
21	Waze	6 087 000	
22	L Equipe	5 968 000	
23	20minutes.fr	5 852 000	
24	Le Figaro	5 782 000	
25	AlloCine	5 632 000	
26	Dailymotion	5 629 000	
27	WhatsApp	5 533 000	
28	Yahoo	5 504 000	
29	Skype	5 463 000	
30	vente-privee	5 454 000	

Figure 2: Twitter monthly users on mobile devices in France - March 2016

What we know (the sociologist's nigtmare)

- 44% of Twitter users never sent a Tweet. Only 8% of users have sent more than 50 tweets.
- Some biases are known (Twitter data & Mediametrie 2016) :
- A gender bias
- 2 Young users are over-represented
- 34 % of users are CSP+ (29% of the web users / 25% of the population)



Figure 3: Twitter users in France : some well known biases

The users attributes inference literature (1)

- Profile information, tweeting behavior, linguistic content of tweets, social network information (RT)
- Used to infer gender (Rao et. al., 2010, Liu & Ruths, 2013), age (Schler et. al., 2006; Al Zamal et. al., 2011), occupation and social class (Sloan et. al., 2014; Preotiuc-Pietro et. al., 2015; Mac Kim et. al., 2016), location (Jones et. al., 2007), political orientation (Thomas et. al., 2006; Rao et. al., 2010), ethnicity (Pennacchiotti & Popescu, 2011; Rao et. al., 2011)
- Supervised Machine Learning

The users attributes inference literature (2)

- Using twitter accounts lists to infer profession (Ke et. al., 2016)
- Using external data such as websites visitors demographics (Goel et. al., 2012; Culotta et. al., 2015)
- Using geotagged tweet to retrieve localized demographics from census data : US County data (Mislove et. al., 2011)

Why it Matters

Why it Matters

- Twitter based research has to be aware (and control) biases at the user level : tweets are sent by a very biased part of the overall population
- It has also to know more about tweeting behavior as a social behavior
 : people do not tweet randomly during the day or wherever they are
- Mapping tweets geographically can help us better understand issues such as how connected the virtual public sphere is to actual physical environments (equipments, urban segregation, political participation...)

Understanding the social, political and environmental determinants of Twitter use in France using geolocalised tweets

The Data

- 32.8 M Tweets sent from France between 2014 and 2017 with GPS geolocalisation
- Every Tweet was attributed to the IRIS zone it was sent from (+/-2.500 inhabitants)
- Census (and other) data were collected to describe every IRIS
- A dataset with 47.484 IRIS counting at least one tweet between 2014 and 2017
- Some information being only available at the town level (e.g. political participation) another dataset was created with 33.881 towns (most of them being small/very small towns that count only one IRIS)

Geotagging : a bias ?

- The share of users who enable location services (at least once) = 41 % of worldwide users
- the share of tweets with geographic information = 2.5 % of tweets
- The share of geotagged tweets (latitude / longitude) has been estimated at 0.85 % of all tweets (Sloan et al. 2013)
- The share of users who ever geotagged a tweet at 3.1% (Sloan & Morgan, 2015)
- no clear sociological bias among those users (gender, Age, Class)
- but a linguistic/national bias (interface language matters : 8.8 % of Turkish users geotagged tweets ; 2.6 % of French ones ans 0.3 % of Korean ones)
- Changes in the Twitter settings have reduced the number of geotagged tweets (users have to opt in)
- Using the API and Bounding Boxes limitations is very efficient to gather all geotagged tweets in France (2.5%*3% = 0.075%)

The geographical structure of Tweeting



Figure 4:



Figure 5:

Modeling tweeting behavior (1)



Figure 6: Distribution of tweet_num

Modeling tweeting behavior (2)

- A subset containing only towns with more than 1.000 inhabitants
- A log-linear regression model explaining log(tweet_num) by the following predictors :
- 1 urban environment (number of inhabitants ; density)
- tourism (hotels/pop ; tourism information points / pop ; airports/pop ; museums/pop)
- 3 demographics (men/pop ; young people/pop ; foreigner/pop)
- 4 social classes (white collars/pop ; highly educated / pop)
- 6 wealth (income ; unemployment)
- 6 activity (high schools/pop ; shops/pop ; businesses/pop)
- political participation (participation rate at the 2014 local elections)

Modeling tweeting behavior (3)

Call:

$$\label{eq:linear} \begin{split} &\ln(formula = sqrt(tweet_num) \sim pop2014 + densite + hotel + tourisme + \\ &depl1 + p1529 + pH + etr + pcs3 + dipl3 + chom + tcom + musee + \\ &gare + aerop + lycee + entcom + gdesent + revenu + participation, \\ &data = commune.big) \end{split}$$

Residuals:

Min	1Q	Median	3Q	Max
-313.59	-10.41	-3.18	6.98	507.48

Coefficients:

	Estimate	Std. Error	t value	Pr(>ltl)		
(Intercept)	4.502e+01	8.698e+00	5.176	2.32e-07	***	
pop2014	1.562e-03	1.995e-05	78.308	< Ze-16	***	
densite	3.682e-03	1.954e-04	18.844	< Ze-16	***	
hotel	-4.274e-03	3.235e-02	-0.132	0.894897		
tourisme	-2.266e-01	8.749e-02	-2.590	0.009600	••	
depl1	-3.997e-02	2.297e-02	-1.740	0.081828		
p1529	1.202e+00	9.550e-02	12.583	< 2e-16	***	
pH	-8.414e-01	1.556e-01	-5.407	6.57e-08	***	
etr	1.734e-01	7.432e-02	2.333	0.019683	•	
pcs3	-2.538e-01	1.147e-01	-2.212	0.027013	*	
dipl3	7.836e-02	7.937e-02	0.987	0.323584		
chom	4.384e-01	7.493e-02	5.851	5.05e-09	***	
tcom	1.308e+00	4.649e-02	28.127	< 2e-16	***	
musee	-2.775e-01	2.624e-01	-1.057	0.290420		
gare	-5.266e-01	1.180e-01	-4.461	8.27e-06	***	
aerop	4.042e-01	8.018e-01	0.504	0.614208		
lycee	5.848e-01	2.411e-01	2.425	0.015308	•	
entcom	1.921e-02	1.049e-03	18.303	< Ze-16	***	
gdesent	3.655e-03	6.796e-03	0.538	0.590679		
revenu	-5.501e-04	1.477e-04	-3.725	0.000196	•••	
participation	-1.474e-01	2.873e-02	-5.131	2.93e-07	•••	
Signif. codes:	: 0 '***' (0.001 '**' (0.01 '*'	0.05 '.'	0.1 ' ' 1	
Residual standard error: 21.13 on 9442 degrees of freedom						
(290 observations deleted due to missingness)						
Multiple R-squared: 0.7877, Adjusted R-squared: 0.7873						
E-statistic: 1752 on 20 and 9442 DE. p-value: < 2.2e-16						

Figure 7:

Modeling tweeting behavior (4)

1

Call:

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Figure 8:



Figure 9: A surprise



Figure 10:



Figure 11:



Figure 12:



Figure 13:



Figure 14: A surprise

What's Next ?

What's Next ?

- We need to address the ecological fallacy risks, notably identify and isolate tweets that are sent by tourists and commuting people
- We need to look at the content of the tweets to expand the scope of the questions we will be able to ask (such as : is there a relation between the content of the tweets posted in a specific town and participation levels ?)