Data Science for Design Group Report

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Politics, twitter and bots

Twitter has been evolved from personal microblog into an event following medium (Weller, Bruns, Burgess, Mahrt & Puschmann, 2014). It provides an alternative route for people to discuss political events.

In Mexico, traditional media stopped to report drug cartels issues from being killed ("Award-winning Mexican reporter shot dead", 2017). In contrast, Twitter users act as informal correspondents to spread information about the drug war ("In Mexico, Tweeting on Drug War to Fill the Void of Traditional Media | YaleGlobal Online", 2013). Another example is Egyptian revolution in 2011, protesters use twitter to express their opinions and organise events that was not possible otherwise (as the media is controlled by the authorities) (Schonfeld, 2011).

However, lots of news and literature have reported that Twitter can be manipulated by political bots (Ratkiewicz, Conover, Meiss & Menczer, 2011, Ehrenberg, 2012, Forelle, Howard, Monroy-Hernandez & Savage, 2015, Hern, 2017). Political bots are program operated accounts that post, or retweet contents to support certain political opinions. They are powerful for influencing human's decisions, for example, in 2010 U.S. midterm elections, social bots were employed to support some candidates and smear their opponents, injecting thousands of tweets pointing to websites with fake news (Ratkiewicz, Conover, Meiss & Menczer, 2011). It leads to abnormal changes in the number of followers of candidates' twitter account, and affect candidates' likelihood of winning the House races (Roarty, 2013).
It has been reported that during 2016 British EU referendum, @ivoteLeave and @ivotestay were the most active accounts of each side of the debate, but their behaviour was mechanical: they do not generate any new contents, but rather, periodically retweets content from their side of debate (Howard & Kollanyi, 2016). These bots were act as amplifiers to amplify the voice of certain groups.

Since the literature have reported that bots exist in the referendum, we are interested in the degree of authenticity of the data we have. Were humans actually debating on twitter or it is just an illusion created by computers and algorithms.

Background of the data

The dataset we had was collected from Twitter on 21/06/2016, which is two day before the referendum. Although we did not know how the data was collected, we assumed it was collected by web crawler which capture referendum-related tweets.

There were 710637 tweets, and all of them were stored in a uniform JSON format, which has over 50 fields for each tweet, such as, \`text\`, \`hashtags\`, \`retweeted count\`, \`create time\`, \`retweeted original tweets\`, \`user's created time\`, \`users' location\` etc.

Data exploration

To distinguish bots from human, a rule-based classifier was defined at first and it was mainly based on the comparison between the user's tweet number on 21/06/2016 and its average tweet number per day. A user will be judged as "overactive user" (i.e. bot) if at least one of the following rules is met (rule is based on "Bots and Automation over Twitter during the U.S. Election — Oxford Internet Institute", 2016):

1. The user's tweet number on 21/06/2016 is 20 greater than its average tweet number per day.
2. The user's tweet number on 21/06/2016 is greater than 35.
3. The user's average tweet number per day is greater than 50.

Compared with other classifiers, a rule-based classifier is much more easier to setup and faster to apply, although not so accurate. However, in our case (we have tested it manually to a small sub-data set), the classifier did cover the majority of bots-like users (based on the content they were sending (auto-generate or retweet)) and only include few human users.

According to the bots and human data we derived from the classifier, we found that 225,532 (95.98%) human users sent 480,027 (67.55%) tweets while 9,445 (4.02%) bots sent 230,610 (32.45%) tweets in the dataset.

Hypothesis

Based on the user's behaviour, we are certain that bots exist in our dataset. However, the contents of bots should be further analysed. We hypothesis that the contents of bots should differ from contents of humans, as bots have more specific political purpose.

Analysis and Core Findings

Based on our hypotheses, we went deeper into the contents and sentiments. We used hashtag and bigram frequencies to analyse content of tweets, and we used a rule based sentiment analysis algorithm (Hutto & Gilbert, 2014) to analyse sentiments (because it is faster and do not need training).

First, we split our dataset into two sub-groups **based on the human-bot classification rule**. Then, we selected top 50 most common hashtags from each group, and manually decide which opinion-class (support levave, support remain, or neutral) that these tags should belong to. Interestingly, we also found that both human and bots have around 20 neutral hashtags. However, human have more remain hashtags than leave hashtags (16 vs 14) but the difference is not that many, while bots have many more leave hashtags than remain hashtags (21 vs 12). This means bots trend to send more kind of “leave-supporting” messages.

We also analysed bigrams of the actual tweet contents to see if any missing information that was not captured by hashtags. The reason of using co-occurrence words is that the meaning of a single word is usually ambiguous (e.g. “don’t” - don’t leave or don’t stay). Figure 1 and Figure 2 reveals the 10 most common bigrams, after the removal of stop words, used by humans and bots respectively.

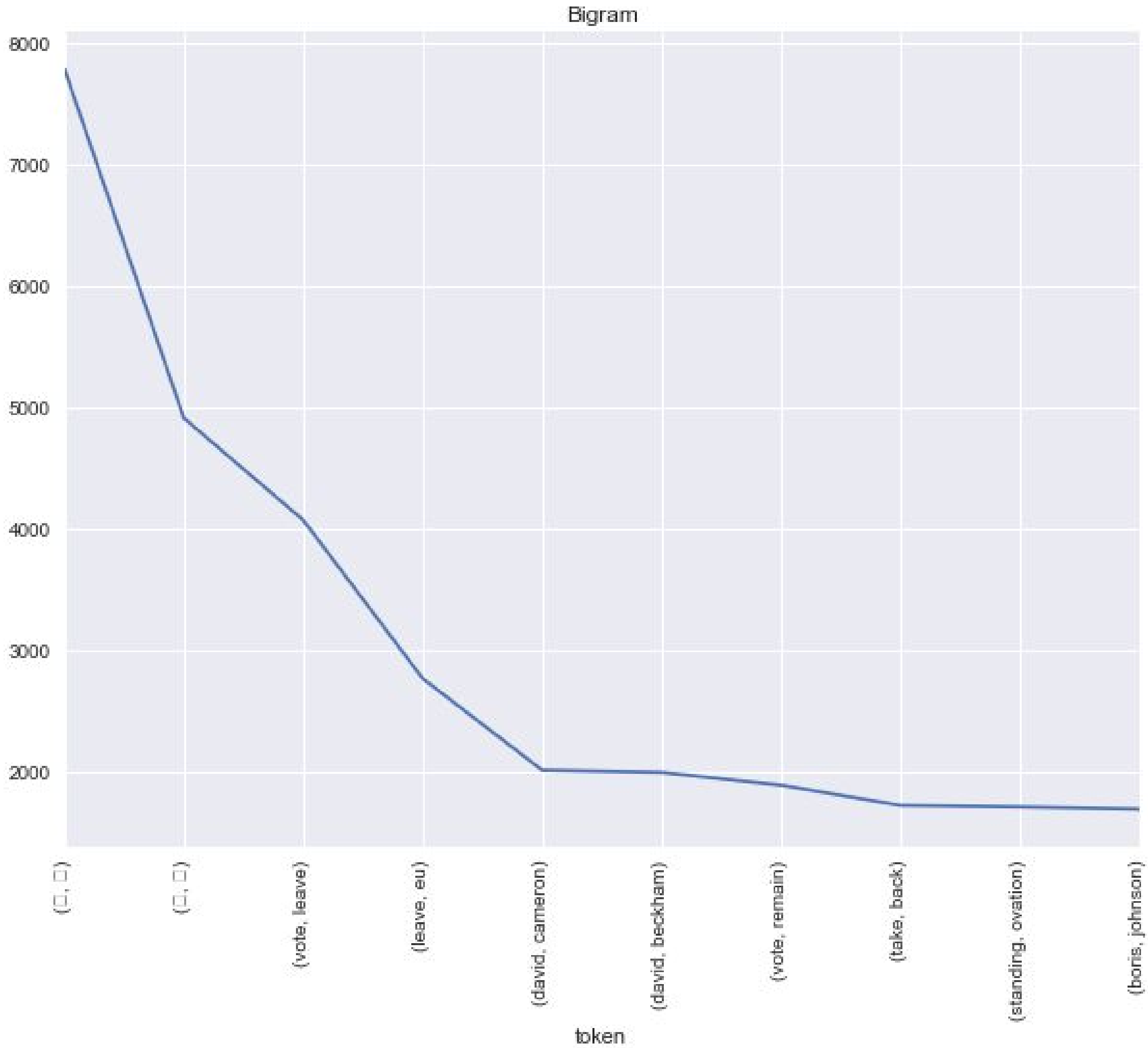

Figure 1: Distributions of bigrams from bots

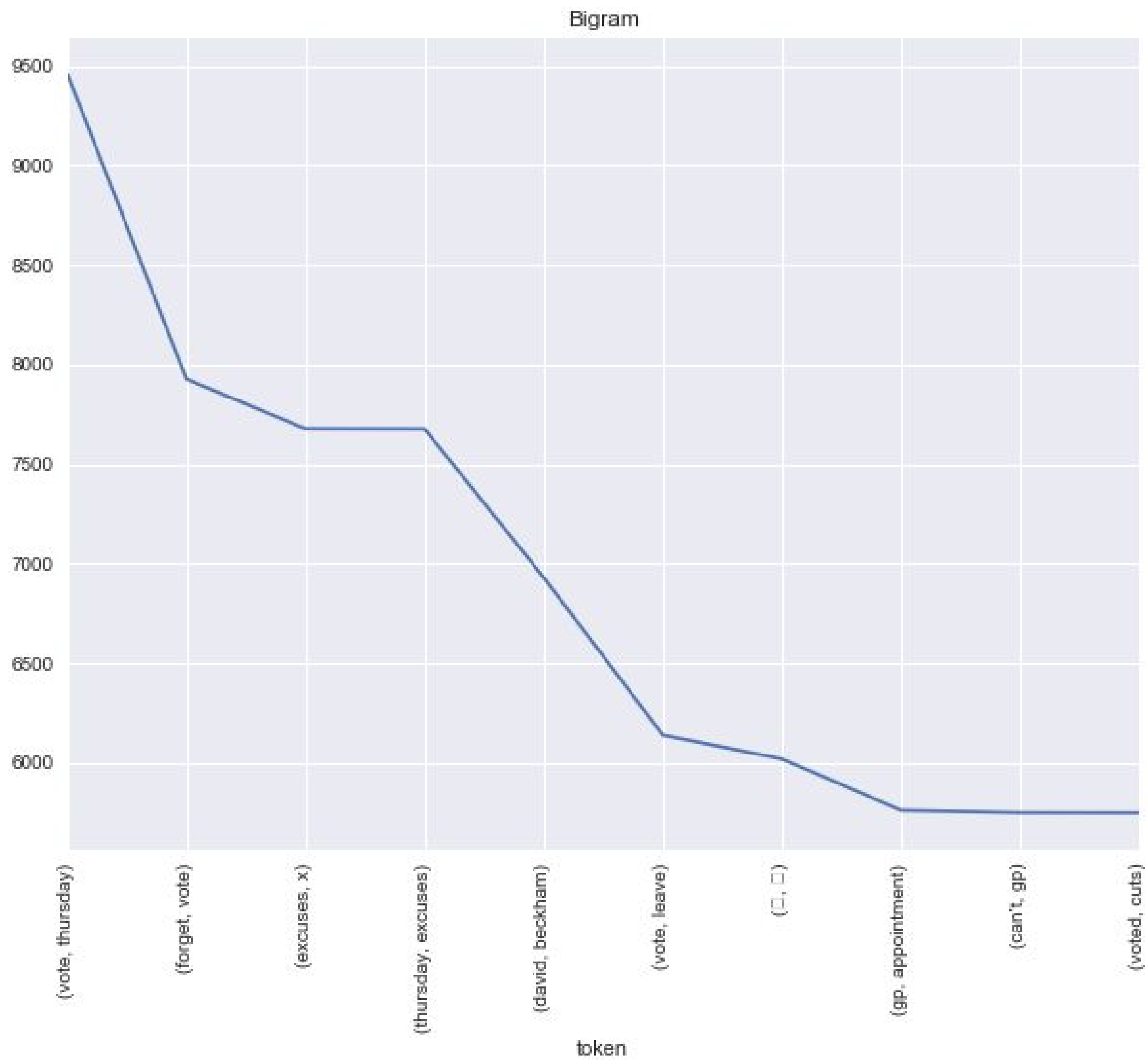

Figure 2: Distributions of bigrams from humans

Comparing figure 1 and 2, bots send more of “leave” messages than “remain” (e.g. (vote, leave), (leave, EU) were more than (david, beckham) and (vote, remain)). In contrast, human send more neutral messages, and more “remain” messages than “leave” (e.g. (excuses, x), (david, beckham) were more than (vote, leave) and (can’t, GP)). The results of bigrams between humans and bots accord with the results of hashtags analysis.

Since bigrams were accord the results of hashtags, we used hashtags to identify opinion of the tweets on referendum (i.e. supported leave, remain, or neutral). We found there were 163183 tweets supported leave and 90323 tweets supported remain (approximately 13:8). In contrast, bots sent 112138 tweets supported leave and 26639 tweets supported remain (approximately 7:2).

For sentiment analysis, we fed the tweets’ content from humans and bots to the algorithm respectively. We found that the sentiment of bots (Figure 3) fluctuate more than sentiment of humans (Figure 4) across the day. The standard deviation of the humans sentiment and bots sentiment are 0.21 vs 0.29.

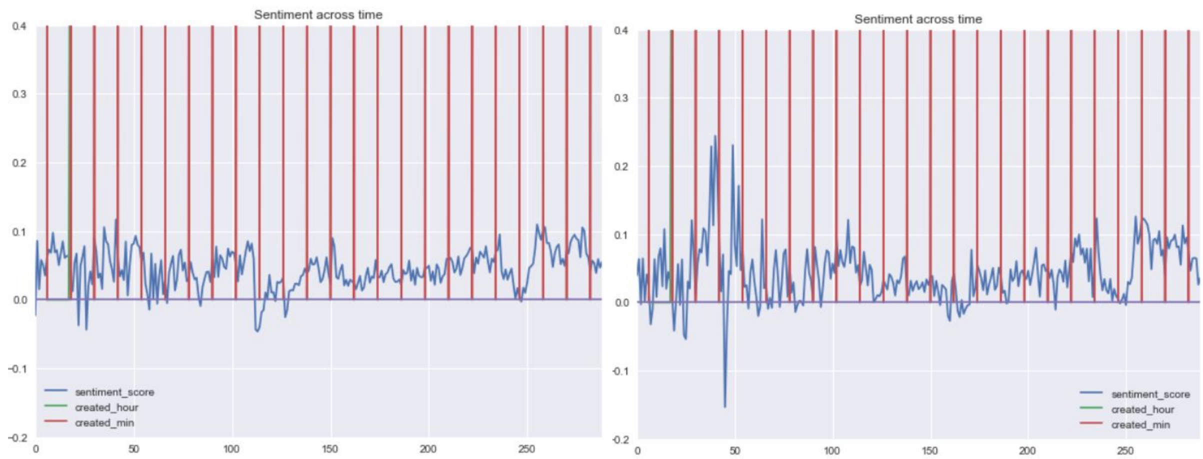

Figure 3 & 4: humans sentiment and bots sentiment across the day

This means that of the contents from bots were more sentimental, i.e. bots voiced their opinions stronger than human did and they urgently wanted other people to follow them.

Visualization process and design decision

We decided to use various facts and graphs as our storyline. Firstly, we showed the “outliers” that we found in data exploration. Then, we compare the content (i.e. hashtags) that human and bots were sending. We decided to use treemaps because it is a common visualisation to represent word frequencies (as frequency map to areas). We also changed the hue of the treemap, where red represents the remain-related hashtags and the blue represents the leave-related hashtags, in order to let viewer quickly differentiates the polarised standpoints.

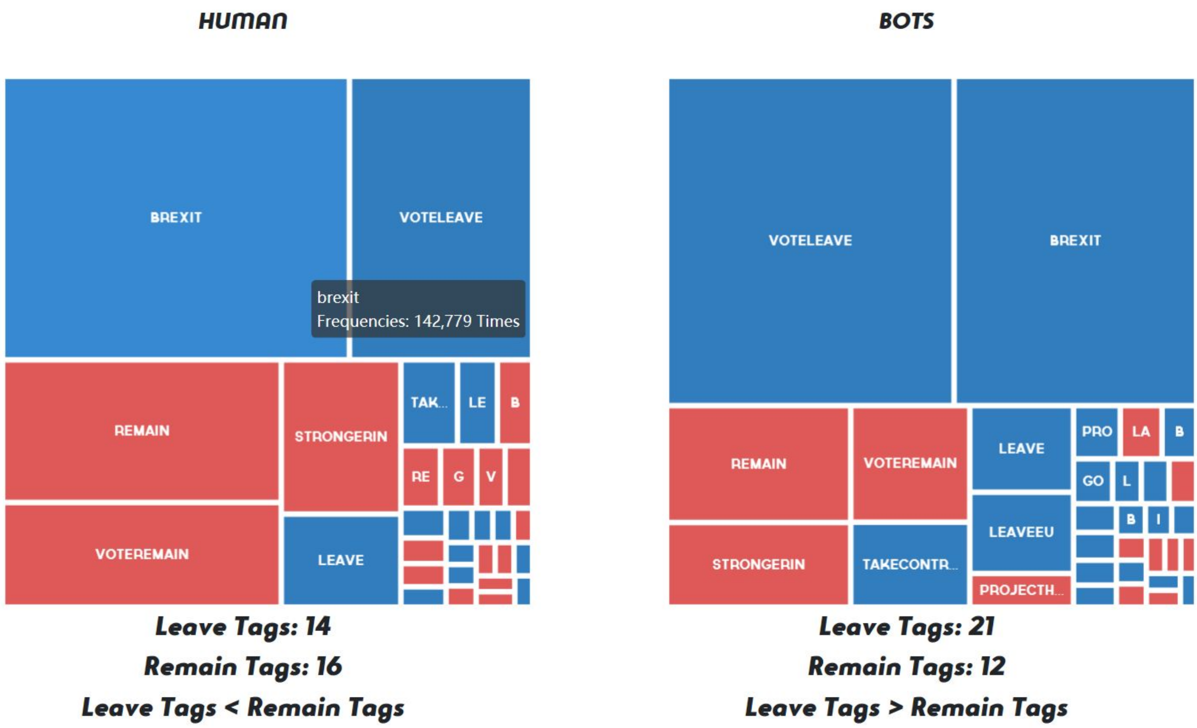

Figure 5 the treemaps of hashtags that humans sent (left) and bots sent (right)

Secondly, we use a line plot to show the average variation of human' and bots' sentiment across the day. The reason to use line plot is that it is clear to see how sentiments fluctuate with time. In addition, the zoom-in and zoom-out bar under the graph enable user to customise the time resolution, which make the sentiment variations more clearer.

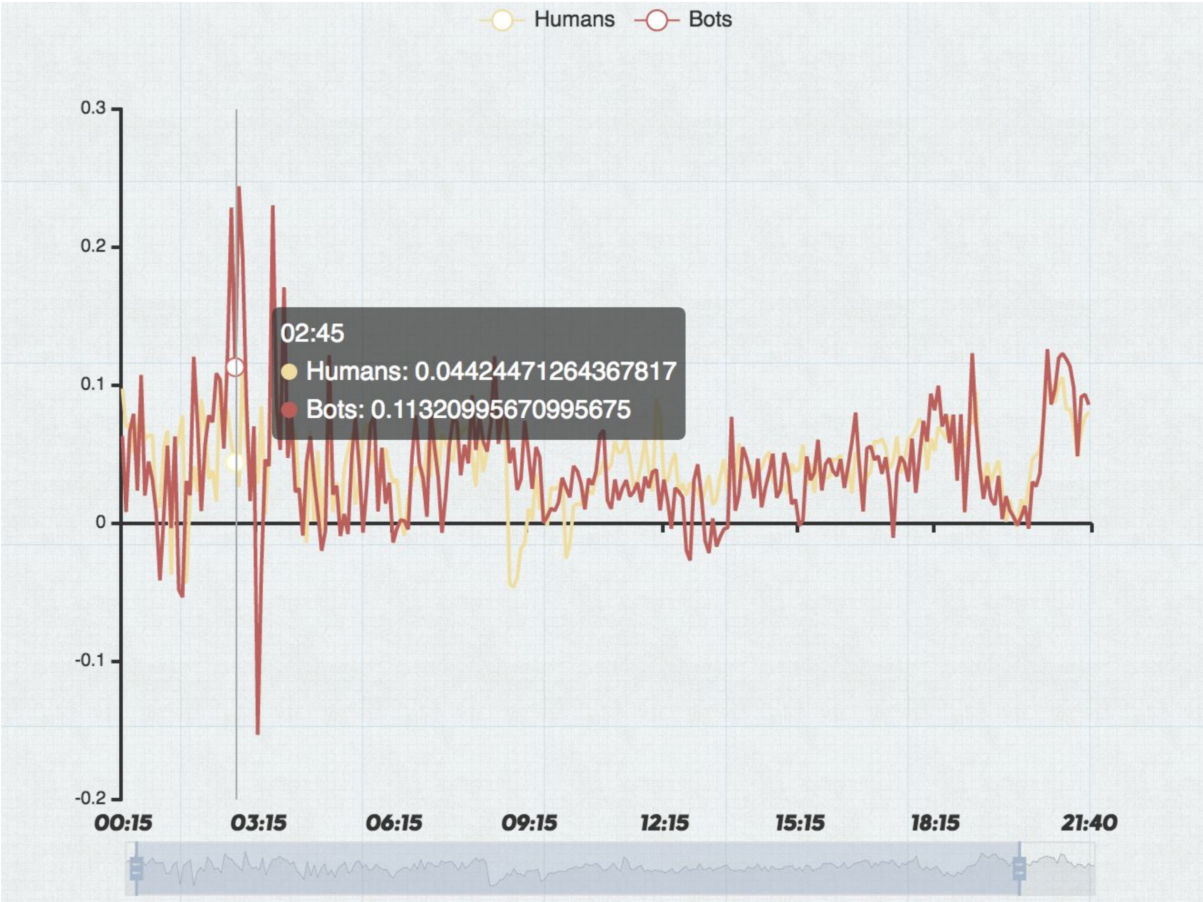

Figure 6 Time series plot of sentiment variation

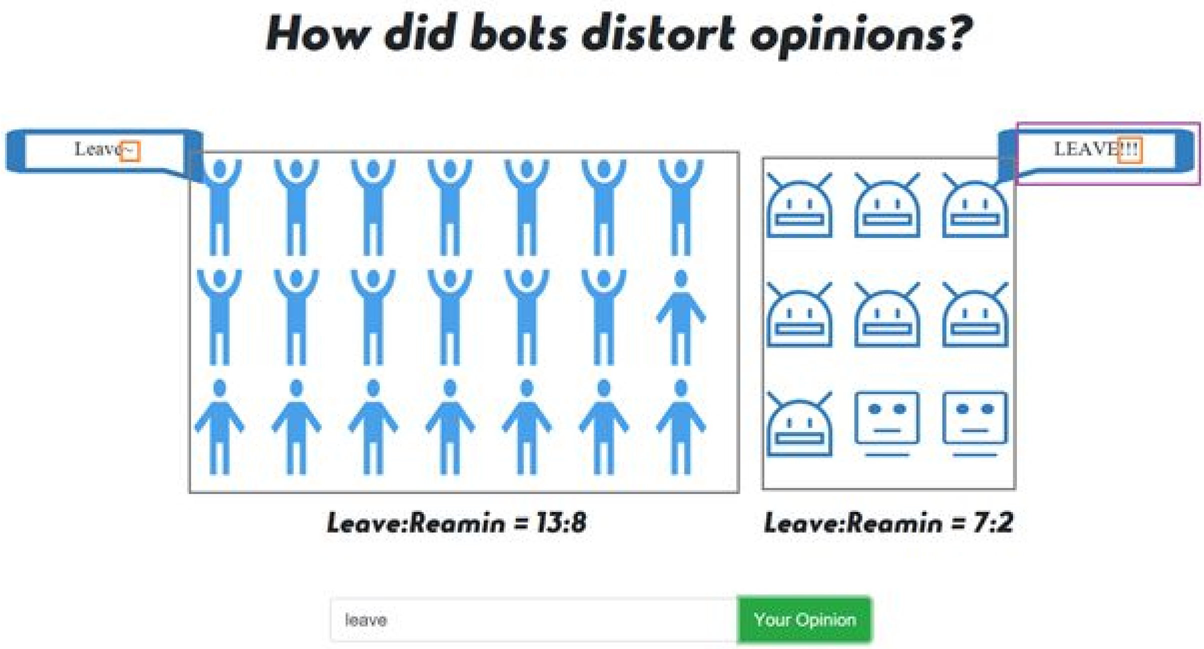

Figure 7 The interactive game

The last one is an interactive “game”. To let viewers get the genuine picture of how social media works, we build a simulation of twitter platform of what was going on during the referendum. Viewers are invited to express their opinion about referendum, “post it” on the internet, and then see how it can affect the network.

The simulation integrated the the total numbers of tweets which were sent by human and bots, and the total numbers of leave and remain messages of these two groups. These numbers are visualised by the number of human-icons and bot-icons (see the grey rectangles). Since we found that bots sent stronger messages than humans did, we visualise this by adding 3 exclamation marks (see orange rectangles) to what bot said. In addition, we found that bots rarely generate original contents, we visualise this by delaying the display of bots messages (purple rectangle) to simulate the sense of “retweet”.

Conclusion

In conclusion, we have build an interactive webpage that showed how bots distored twitter in the British-EU referendum. We are targeting at two main group of audience: Political researchers who want to use twitter data to analyse opinions on public issues. We want them to know the importance of bot filtering. Social media users. We want them to aware that trending topics could be lead / amplified by bots.

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