# Discovering Communities in MetaFilter

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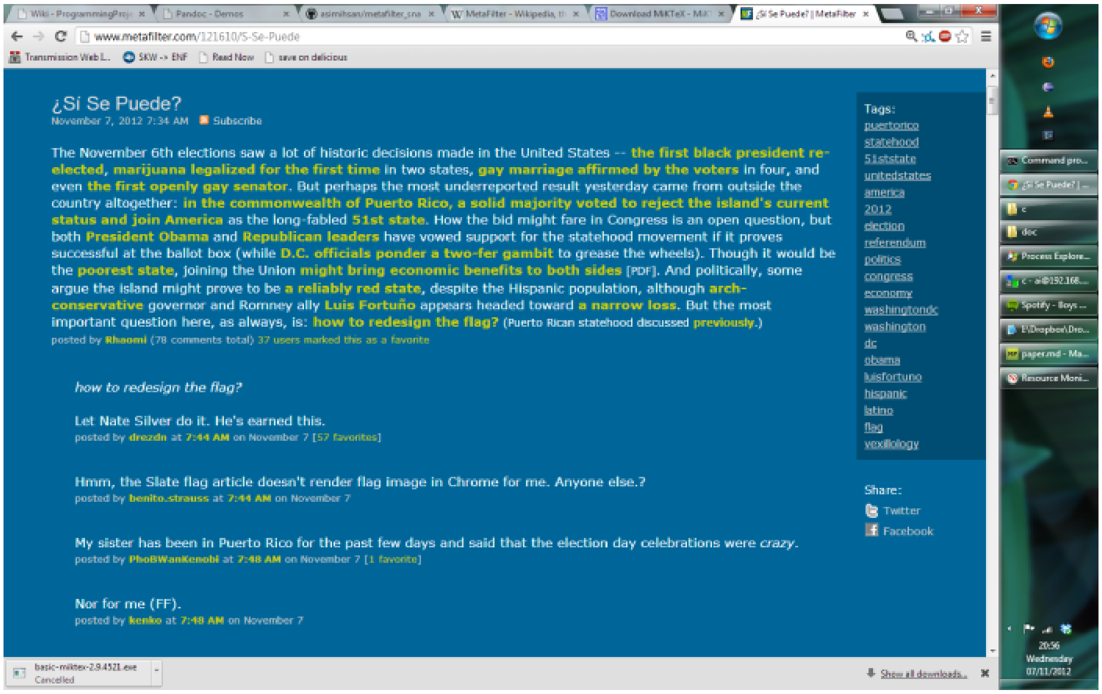
## 1. Abstract

MetaFilter is an active and exciting online forum that discusses a wide variety of topics. Running since 1994, it allows members to post topics onto a front page, comment on the topics, and mark both posts and comments as "favorites". In this paper I discuss several hypotheses surrounding these participation mechanisms, how I collected data to investigate these hypotheses, and what methods I used to test my hypotheses. My conclusion is that there is clear evidence that several small-world communities are present on MetaFilter, and that the strength of such communities is correlated to the amount of effort required when participating.

Section 2 clarifies what parts of MetaFilter I am seeking to analyse, what hypotheses I wish to test, and why I think these hypotheses are interesting. Section 3 explores the gathered data with several metrics, compares them to Erdős–Rényi graphs of a similar size, and draws conclusions. Section 4 addresses limitations of my approach and suggested areas for future work.

## 2. MetaFilter, hypotheses, and data collection

### MetaFilter



¿Si Se Puede?
November 7, 2012 7:34 AM Subscribe

The November 6th elections saw a lot of historic decisions made in the United States -- **the first black president re-elected**, **marijuana legalized for the first time** in two states, **gay marriage affirmed by the voters** in four, and even **the first openly gay senator**. But perhaps the most underreported result yesterday came from outside the country altogether: **in the commonwealth of Puerto Rico, a solid majority voted to reject the island's current status and join America** as the long-fabled **51st state**. How the bid might fare in Congress is an open question, but both **President Obama** and **Republican leaders** have vowed support for the statehood movement if it proves successful at the ballot box (while **D.C. officials ponder a two-fer gambit** to grease the wheels). Though it would be the **poorest state**, joining the Union **might bring economic benefits to both sides** [PDF]. And politically, some argue the island might prove to be **a reliably red state**, despite the Hispanic population, although **arch-conservative** governor and Romney ally **Luis Fortuño** appears headed toward **a narrow loss**. But the most important question here, as always, is: **how to redesign the flag?** (Puerto Rican statehood discussed previously.)
posted by Rhaomi (78 comments total) 37 users marked this as a favorite

*how to redesign the flag?*

Let Nate Silver do it. He's earned this.
posted by drezdn at 7:44 AM on November 7 [57 favorites]

Hmm, the Slate flag article doesn't render flag image in Chrome for me. Anyone else.?
posted by benito.strauss at 7:44 AM on November 7

My sister has been in Puerto Rico for the past few days and said that the election day celebrations were *crazy*.
posted by PhoBWanKenobi at 7:48 AM on November 7 [1 favorite]

Nor for me (FF).
posted by kenko at 7:48 AM on November 7

MetaFilter is an online forum where members are free to post on whatever they want. You'll notice in the screenshot above two important points:

- Users can **mark a post as a favorite**. Using this mechanism means that the post is explicitly marked as a user's favorite in their profile page.
- Users can **post comments** and have those comments themselves marked as favourites.

### Hypotheses

Although users have their own particular motivations for participating in online forums I believe that they do so in a context that largely reinforces their own beliefs, values, and finite interests. MetaFilter regularly hosts an astonishingly wide variety of topics, however I want to test to what extent people segregate their time and attention to particular subtopics, if at all.

Hence, the hypotheses I wish to test are:

- **H1**: Users will tend to both favorite and comment on posts with particular subsets of the total set of users.
- **H2**: Users are less likely to focus their favorites as they are their comments.

Intuitively, H1 is likely to be true because users each have their own interests and these are likely to intersect with strict subsets of other users. Attention and time are so finite that we're likely to behave like this. Given how broad the topic variation is on MetaFilter it'd be interesting to see what these topic clusters are.

H2 is a bit more obscure but perhaps more interesting. I believe there is a significantly lower threshold to ticking a single link marking a post as a favorite, perhaps marking it for later reading or reference, than there is to actively commenting on a post. The latter is so much more involved and time consuming that users, perhaps, will restrict such an action to those topics which they are particularly interested in.

### Data collection

In short, the code I've written uses Python to launch a small number of workers to scrape posts off of MetaFilter. They output a SQLite database with a single table, "posts", with the raw HTML required for subsequent analysis.

You may find the code that I've used to collect and parse the data in the following GitHub repository:

https://github.com/asimihsan/metafilter_sna

Here are some basic instructions on setting up your computer to execute this code. These instructions are intended for Mac OS X but equivalent Linux instructions (i.e. using `yum` or `apt`) should work.

Please note that these instructions are very rough and are untested. If you encounter any difficulties please feel free to contact me via GitHub for help, I'm happy to assist.

- Mac OS X
  - Install Homebrew (http://mxcl.github.com/homebrew/)
  - Install RabbitMQ using Homebrew (http://www.rabbitmq.com/install-homebrew.html)
  - Install Python 2.7 and virtualenv using Homebrew (https://gist.github.com/1208841)
  - Install lxml dependencies: `brew install libxslt libxml2`
  - Checkout the code from the git repository above.
  - Create a new virtulenv for this code:

    ```
    mkvirtualenv metafilter_sna
    ```

  - Install the dependencies for the repository:

    ```
    pip install -r requirements.txt
    ```

  - In one terminal window execute the celery workers:

```
cd metafilter_sna/src/01_scrape/
./launch_celeryd.sh
```

- In a second terminal window execute the following to monitor the celery workers to confirm that they are working:

```
cd metafilter_sna/src/01_scrape/
celeryev -A tasks
```

- In a third terminal window execute the trigger script that starts the scraping:

```
cd metafilter_sna/src/01_scrape/
./main.py
```

- On executing `main.py` you should notice both the first two terminal windows outputting a lot of logs. If not something is wrong!
- After gathering a sufficient amount of data you can execute the following in order to convert the SQLite database into the pair of GML graph files:

```
cd metafilter_sna/src/02_parse
./database_to_gml.py
```

- The above script will output GML files into the "data" subdirectory.

### Nodes, edges, weights

In this paper we will create **weighted, undirected** graphs where nodes are **users**. We will use the data collected above to create two graphs:

- **Favorites**: a graph where an edge exists between two users if they have favorited the same post. The weight of the edge is $ln(x+1)$, where $x$ is the number of posts co-favorited.
- **Comments**: a graph where an edge exists between two users if they have commented on the same post. The weight of the edge is $ln(x+1)$, where $x$ is the number of posts co-commented.

## 3. Data analysis and conclusions

For this paper I will consider the last 1,386 posts on MetaFilter, covering a time period of approximately one and a half months. Both the SQLite database of raw HTML, discussed in section 2, and the Graph Markup Language (GML) files of the corresponding weighted undirected graphs are available in the following compressed 7-Zip file here:

`http://files.asimihsan.com/metafilter_sna_data.7z`

Table 1 summarises metrics for the favorites graph, described in section 2, in comparison to an Erdős–Rényi graph with the same number of nodes and a similar number of edges:

| Metric | Favorites graph | Erdős–Rényi graph |
|---|---|---|
| Nodes | 3,693 | 3,693 |
| Edges | 329,288 | 329,576 |
| Average clustering coefficient | 0.315 | 0.0482 |
| Diameter | 4 | 3 |
| Average shortest path length | 2.00 | 1.95 |
| Number of communities via greedy optimization of modularity | 13 | 5 |
| Largest community via greedy optimization of modularity | 1831 | 1429 |
| Number of communities via walktrap | 43 | 9 |
| Largest community via walktrap | 2304 | 723 |
| Assortativity based on degree | -0.158 | -0.00213 |

The following is interesting about the above:

- Compared to a similar ER graph, i.e. a graph with a similar number of edges and nodes where edges connect at random, the favorites graph has a higher average clustering coefficient. This means that, on average, each node in the favorites graph is closer to becoming a *clique*, i.e. a complete subgraph, than a random graph. This suggests that clustering is more common than random in the favorites graph.
- Compared to a similar ER graph the favorites graph has a similar average shortest path length. The combination of a relatively high average clustering coefficient and similar average shortest path length suggests the favorites graph is exhibiting *small-world* behavior, i.e. that there are tightly-bound and very connected subgraphs, and the subgraphs are sparsely connected to other subgraphs.
- Using two methods for approximating the number of communities in the graph, either by maximizing modularity or using random walks (i.e. walktrap), we see that there are more communities present than random and that the largest community is larger than random.
- The diameter, i.e. the length of the longest path, is remarkably similar between the favorites graph and the ER graph. This confirms the conclusion with respect to the similar average shortest path length discussed above, i.e. there are small-world networks in effect.
- Assortativity based on degree is positive if vertices with similar degrees tend to connect with one another, and negative if vertices with dissimilar degrees connect with one another. In the ER graph it is almost 0, indicating no bias, whereas for the favorites graph it is more strongly negative, suggesting that nodes preferentially attach to high-degree nodes, i.e. hubs.

Table 2 summarises metrics for the comments graph, described in section 2, in comparison to an Erdős–Rényi graph with the same number of nodes and a similar number of edges:

| Metric | Comments graph | Erdős–Rényi graph |
|---|---|---|
| Nodes | 4,348 | 4,348 |
| Edges | 749,313 | 748,481 |
| Average clustering coefficient | 0.468 | 0.0792 |
| Diameter | 4 | 2 |
| Average shortest path length | 1.97 | 1.92 |
| Number of communities via greedy optimization of modularity | 11 | 3 |
| Largest community via greedy optimization of modularity | 3460 | 1926 |
| Number of communities via walktrap | 16 | 10 |
| Largest community via walktrap | 3405 | 758 |
| Assortativity based on degree | -0.143 | -0.00243 |

The differences in the metrics between the comments graph and an equivalent ER graph are similar to the difference in the metrics between the favorites graph and its equivalent ER graph. Hence please refer to the analysis above as it also applies here.

Table 3 compares metrics between the comments and favorites graphs:

| Metric | Comments graph | Favorites graph |
|---|---|---|
| Nodes | 4,348 | 3,693 |
| Edges | 749,313 | 329,288 |
| Average clustering coefficient | 0.468 | 0.315 |
| Diameter | 4 | 4 |
| Average shortest path length | 1.97 | 2.00 |
| Number of communities via greedy optimization of modularity | 11 | 13 |
| Largest community via greedy optimization of modularity | 3460 | 1831 |
| Number of communities via walktrap | 16 | 43 |
| Largest community via walktrap | 3405 | 2304 |
| Assortativity based on degree | -0.143 | -0.158 |

In comparing the comments and favorites graphs note that the comments graph is not only more clustered but also has fewer communities, and that the largest community is greater than that of the favorites graph.

### Calculation

Before stepping into the interpretation and conclusions I'd like to go over how the above metrics were calculated.

I used R and the igraph package to calculate all of the above metrics. Here is a script that calculates all of the above:

```
library(igraph)
library(ggplot2)

g = read.graph("I:\\Programming\\metafilter_sna\\data\\comments.gml", format="gml")
```

```
# Number of nodes and edges.
summary(g)

# Average clustering coefficient.
transitivity(as.undirected(g))

# Diameter.
diameter(g)

# Average shortest path.
average.path.length(as.undirected(g))

# Community finding using greedy optimization of modularity.
fc = fastgreedy.community(as.undirected(g))
fc_sizes = sizes(fc)
max(fc_sizes)

# Community finding using greedy optimization of modularity.
wt = walktrap.community(as.undirected(g))
wt_sizes = sizes(wt)
max(wt_sizes)

# Assortativity based on degree
assortativity.degree(g)
```

In order to derive the equivalent random graph metrics you can generate an Erdős–Rényi graph with the same number of nodes and then calculate an appropriate edge probability $p$ such that:

$\frac{N(N-1)}{2} \times p = E$

Where N is the number of nodes, E is the number of edges. Generating the graph is as simple as substituting the `g` line above with:

```
g <- erdos.renyi.game(N, p)
```

### Interpretation and conclusions

(Please note that I have not provided a visualization of my data because I was unable to find a suitable layout algorithm that displayed anything useful!)

I believe that the above results confirm hypothesis H1, i.e. that users tend to both favorite posts and comment on posts wuth particular subsets of other users, i.e. in clusters. Both the average clustering coefficients and the community finding algorithms confirm this. Moreover, and even more interesting, with the average shortest paths the same between both the favorites and comments graphs and their equivalent ER graphs, it's clear that there is small-world structure in effect.

I also belive that the results confirm hypothesis H2, i.e. that users are more discriminative and clustered on high-effort participation methods. However, to what degree is difficult to say. Is an average clustering coefficient $0.468 > 0.315$ sufficient to say that comments graphs are "more clustered" than favorites graphs? If so then to what extent? This is very difficult to say. However I think that, in combination with the larger community sizes, the comments graph seems to be "more community-like" than the favorites graph.

The assortativity coefficient metrics also suggest that there may be hubs in both graphs, but without a usable visualization it's difficult to explore this conclusion.

## 4. Limitations and suggestions for future work

There are a wide variety of limitations to the above that should be mentioned:

- The weighting of the edges is rather arbitrary. Why $ln(x+1)$? Simply because I did not want users who have co-favorited 2 posts to be twice as important as those who have co-favorited 1 post. I think a logarithmic weighting is appropriate and that the constant factor is negligible, but this is an assumption.

- I did not collect that much data. 1,300 posts are not enough. However, I've set up my scraping scripts to be very slow in order to be polite to the MetaFilter system administrators; more data could yield a more clear confirmation of e.g. hypothesis H2.

- An overlapping community detection algorithm seems quite ideal here, and should be applied in future studies.

- Given that community-finding algorithms suggest there are communities present it'd be worthwhile developing a simple recommendation service that would suggest posts for users to read based on which communities they're in, and whether other community members have commented or favorited posts. This would give some useful subjective feedback on the community structure.