How did covid19 change our communities? A compared analysis of meetup communities before and after the pandemic

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Abstract

The year 2020 has been characterized by the outbreak of covid19. The spread of the disease has had a severe impact in many aspects of our lives that go beyond our health. From economical to psychological or social contexts, covid19 caused a halt in our daily activities and forced us to adapt or develop new habits. The following study uses data retrieved from 800 groups in the platform meetup.com to study and compare the impact of the coronavirus in the social life of two vibrant but culturally different cities such as Washington DC and Barcelona. Results suggest that though groups have been able to maintain their activity, mostly through complementing offline with online events, communities have become more fragmented in 2020. The results also suggest that the halt in activity along with the fragmentation has been higher in Barcelona where a very strict lockdown policy was implemented and that Washington DC has been more able to effectively switch to online events after the outbreak of the pandemic.

Keywords: Covid19, meetup, social network analysis, social life, social habits

1 Introduction

As humans we are social beings, we fully realize as individuals by integrating ourselves into the society. The rapid development and implementation of internet communication technologies allowed the creation of digital tools aimed

towards facilitating social integration to a large degree. Social networking software or SNS such as Facebook or Instagram has been used extensively to support online integration's between preexisting ties [1] as well as to form new connections between strangers with related interests. Specific social network sites have focused their efforts towards the creation of offline activity through communities of members organizing events, being the site meetup.com one of the networks of reference [1] [2]. The site meetup.com allows its users to start or join groups of interest that gravitate towards specific activities such as sports, gastronomy, language exchange, nightlife or board games among many others. Those groups set up events on a regular basis and the users of the network may browse through the site and join the activities they like. This site is widely used and growing in popularity in most of the western major cities, where thousands of individuals attend to a variety of events every week [3]. Certain kinds of individuals such as temporary international workers or "expats" and overall newcomers in town may even base a large part of their social life on events on the platform [4]. Thus, because of its massive implementation and the variety of individuals that use it, meetup is an ideal platform to measure and study the social life of a city, that is the social interaction habits of its citizens, community structure and overall the geography of social its activities [5] [6].

The year 2020 was characterized by the appearance and spread of covid19, a severe disease that has had disastrous implications on health, economic, political and overall social systems all around the world which its effects persist to this day. Covid19 first appeared in the city of Wuhan, China by the end of 2019 and from then quickly spread to the rest of the world. In Europe, the first cases of the disease appeared in Italy by January the 31st and rapidly grew till February where the Italian government declared quarantine lock downs all around the territory. The disease spread in a similar way in other European countries such as Spain where severe lock downs were promoted, completely halting the social life in major cities. The pandemic affected other societies such as the American similarly though lock downs and stay-home mandates developed differently in the USA depending more on the particular state and in general terms were less restrictive than in Europe [7]. The effects of both the pandemic itself and the health related measures been taken proved to have severely affected the mental health of a remarkable amount of the population [8] as well as the social life of a very large portion of society. Lock downs and stay-home recommendations paralyzed the social life in western cities [9] and health related measures such as social distancing, mask use as well as the intrinsic risk of contagion in social events influenced a change in the habits of many individuals, causing an overall decrease in social activity in many cities [10]. The rise of tele-work and new forms of online interactions in social networks derived from the periods of confinement and health risks also contributed to the change of social habits and may have long lasting effects [11] [12] though there is still a lack of empirical studies specifically looking at

how the pandemic affected local communities and human relations in cities.

Due to its massive implementation and technical possibilities, meetup is an ideal online social network to measure and study social life.

In this work, I studied how communities in meetup.com changed from the year 2019 to 2020 to explore the effects of covid19 and its health related measures on the shape and social activity of communities in Barcelona a Mediterranean city where lockdown measures were severe and strictly enforced and Washington DC an Atlantic city where they were less severe. The results obtained indicate an overall decrease in offline participation as well as a major fragmentation of the communities in 2020.

2 Background

I start by reviewing the usage of online social networks for social interaction, specifically in the context of online to offline interaction in meet ups in the aforementioned platform. I follow to discuss the properties of meetup.com and its affordances to study social life in a city. Then I describe the covid19 impact and health measures in both Washington DC and Barcelona and present the research.

2.1 Online social networks

An online social network is an internet community that is presented in the form of a web or mobile based application where individuals interact, often through profiles that represent their public persona and their networks of connections to others [13]. Social network sites provide a public forum that enables the exchange of digital information, such as pictures, videos, text, blogs and hyperlinks between users with common interests such as hobbies, work, school, family and friendship [14]. According to the Pew Research Center the vast majority of adult individuals in the United States uses at least one kind of social network on a regular basis [15]. That makes online social networks a great tool for analyzing public opinion as well as social patterns especially in developed countries.

2.2 Event-based Social Networks

Event-based social networks (EBSNs) are a particular kind of online social networks that focus their activity towards the celebration of offline events. Usually they would allow users to filter for events by categories of interest such as sports or cultural activities along with their particular location. Users can also use them to adhere to a variety of interest groups thus allowing the creation of local communities that would hold events on a regular basis. These platforms are widely used in major western cities, especially by young people, tech professionals and the expat community. Among EBSNs one of the most popular if not the main one is meetup.com. Meetup allows users to create groups based

on different interests and use them to create events where other users can join. [3] [16]. Events in the platform usually include descriptions, the place address, the list of attendees and offer the possibility of posting comments, often used as a way to ask questions about the activity or cheer up the organizers. Thus, due to its massive implementation and the kind of features it offers, the volume and shape of the social activity in the platform may serve as an indicator of the overall activity in the city where it is implemented.

2.3 Covid19 lockdowns and stay-home policies across Spain and the USA

The first cases of covid19 appeared in Spain during the month of February and rapidly grew till march. A state of alarm was declared in Spain at March the 15Th at 00:00 and lasted until June the 21Th. A strict lockdown was enforced in Spain by the central government during the state of the alarm where non essential workers were forced to remain home all day unless they had to buy basic products, go to the hospital or attend to other emergencies alike. After June, covid19 measures were relaxed and can be summarized in: the enforcement of face masks inside of buildings, a limited forty per cent occupation of services such as cinemas, bars or restaurants, the closing of nightclubs and a curfew that lasted from October the 25Th to June the 4Th [17] [7].

In Washington DC the first cases appeared during the first week of March. During the following weeks most of the universities and public places such as museums or places related to sport started to close and if possible to move their activities online. The stay-at-home order was issued at a local level by Mayor Bowser on March 30 and went into effect on April the 1st. The order acted in a similar way as in Spain, residents were only allowed to go outside for essential activities such as acquiring basic goods or going to the hospital. The stay-at-home order took effect on April the first and lasted till June, where the order switched to a mandatory use of face-masks along with social distancing and disinfecting measures. Though lockdown orders were similar in Barcelona and Washington DC, they lasted more and were by far more strict and strictly enforced in Spain. As in Washington DC several leisure outdoor activities such as hiking, dog walking, tennis, golf or skateboarding among others were specifically allowed whenever the participants were able to comply with social distancing [18].

3 Research approach

While it is clear that covid19 has had an effect in social life we don't know whether it has been the same in different societies such as the North American and the Spanish Mediterranean. We also don't know if those effects have had a sufficient impact to affect the whole year.

3.1 Group selection

To better comprehend the form and degree of the impact covid19 has had on the social life of those cities I developed a program to automatically browse through the site meetup.com for the areas of Washington DC and Barcelona and randomly select 400 groups. The selected groups met the condition that they must have been active all along two years, that is, they held at least one event per month in 2019 and in 2020.

3.2 Data collection

Having the lists of selected groups, for each of them in both cities I then proceeded to download the information about all of the events in 2019 and 2020, including the event location, the description, the list of attendees and the list of comments.

3.3 Research questions

To better comprehend the form and degree of the impact of the pandemic in social life on those cities I focused on the number of events, its location and the attendance patterns on the networks of the selected cities. That can be summarized in the following research questions:

- *RQ1: Did covid19 cause a halt in the number of offline events?*
- *RQ2: Did most of the events move online after covid19?*
- *RQ3: Did the user participation increase or decrease after covid19?*
- *RQ4: Did events remained in the same locations after covid19? Or did they move to periphery?*
- *RQ5: Did covid19 change the shape of the social networks?*
- *RQ6: Do people diversify their events more or less after covid19?*
- *RQ7: Which city is more worried about covid19?*

From the research questions we can assume that there will be a halt in events after covid19, that is:

H1: The number of offline events per group per month on average will decrease in 2020.

and:

H2: The number of online events per group per month on average will increase in 2020.

It is also reasonable to assume the same regarding to the attendees. We should expect less unique attendees in offline events, that is:

H3: The number of unique attendees in offline events per group per month on average will decrease in 2020. and more in online events, that is:

H4: The number of unique attendees in online events per group per month on average will increase in 2020.

When it comes to the comment activity we should assume a large number of comments per event per group on average as a result of a rise in preoccupations and overall worries regarding to the health situation. For the same reasons we should also assume a decrease in the positive and an increase in negative feelings in comments. Thus we can set:

H5: The number of comments per event per group will increase in 2020, H6: The number of comments with a positive feeling will decrease and the number of comments with negative feeling will increase in 2020.

Regarding to the event geographic properties we could also assume that events will move further from the city centre, as the city centre will be associated with crowded closed areas and the participants will prefer to spend time in open spaces in far away from the cities. We can set:

H7: The average distance from the event location to the city centre per event per group will be higher in 2020. We can also assume that this will be accentuated in cities that suffered very strict lock down's.

We may also believe that communities will be more fragmented in 2020 as people will limit to less groups and prefer to minimize the diversity of social contacts for health reasons, that is:

H8: The number of communities per month of the social network formed by the events and attendances should grow in 2020.

3.4 Dataset

The main features of the dataset that has been generated can be summarized in the following table:

	Barcelona	Washington DC
Total number of events	85943	74290
Number of offline events	78517	60255
Number of online events	7426	14035
Number of attendees	504237	654914
Number of unique attendees	68355	97559
Number of references to covid19 in text's	951	1532

Summary of the basic information on 800 groups in Washington DC and Barcelona

This dataset is strictly meant for academic research uses and because of that it won't be available for download. Any researcher interested in using it for legitimate purposes feel free to reach the IRG-UAM group at pau.munnoz@estudiante.uam.es exposing the research goal of the project.

4 Results

The data has been evaluated grouping the values by meetup group and by month, to allow a comparison of the same group in different months. Shapiro test was used to check for normality and Wilcoxon test was used to compare means whenever normality was not found, otherwise t-test was the choice.

4.1 Number of events

The number of meetup events is useful for studying the effects of the pandemic in the overall social activity of a city. By studying it we answer RQ1 and RQ2. To calculate how the pandemic affected the volume of activity in the selected cities I listed and counted the number of events per group per month in both cities, then I averaged the number of events per group for every month to be able to group them per year.

The number of events per month per group can be summarized in the following tables for Washington DC and Barcelona.

Month	Online events	Offline events	Total events
2019-01	8	3263	3271
2019-02	18	3070	3088
2019-03	20	2505	2525
2019-04	21	3204	3225
2019-05	15	2492	2507
2019-06	33	2836	2869
2019-07	30	2891	2921
2019-08	30	2510	2540
2019-09	15	2756	2771
2019-10	23	3086	3109
2019-11	29	2384	2413
2019-12	18	3144	3162
2020-01	24	3163	3187
2020-02	30	2714	2744
2020-03	277	2708	2985
2020-04	1071	1762	2833
2020-05	1343	1640	2983
2020-06	1431	1694	3125
2020-07	1460	1891	3351
2020-08	1578	2032	3610
2020-09	1706	2171	3877
2020-10	1959	2968	4927
2020-11	1476	1778	3254
2020-12	1420	1593	3013

Summary of the number of events by month in Washington DC

Month	Online events	Offline events	Total events
2019-01	20	2769	2789
2019-02	22	2689	2711
2019-03	25	3172	3197
2019-04	21	3075	3096
2019-05	21	3405	3426
2019-06	32	3779	3811
2019-07	28	3442	3470
2019-08	14	3345	3359
2019-09	23	3571	3594
2019-10	34	3415	3449
2019-11	29	3874	3903
2019-12	31	2849	2880
2020-01	34	3387	3421
2020-02	40	3692	3732
2020-03	254	3543	3797
2020-04	944	2901	3845
2020-05	945	3629	4574
2020-06	763	3345	4108
2020-07	659	3677	4336
2020-08	483	2426	2909
2020-09	618	3966	4584
2020-10	741	2306	3047
2020-11	867	3051	3918
2020-12	778	3209	3987

Summary of the number of events by month in Barcelona

An initial inspection on the tables along with a visual analysis of the time series gives us an initial idea of how both cities adapted their social life to the safety restrictions imposed by the pandemic, showing that Washington DC quickly adapted and moved its activities online while Barcelona done it in a partial way:

Fig. 1 Number of online and offline events in Washington DC, 2019-2020

Fig. 2 Number of online and offline events in Barcelona, 2019-2020

The average number of offline events per month per group in Washington DC before covid19 is 1.135 and after covid19 is 1.105. Wilcoxon test offers a p value < 0.05 so we can reject the null hypothesis and accept that offline events per group per month slightly decreased in Washington DC in 2020. When it comes to online events the mean before covid19 is of 0.132 events per group per month whereas after covid it moved to 0.742 events per month, Wilcoxon test offers a p-value < 0.05 so we can also accept that online events per group per month increased in 2020.

In Barcelona, when it comes to offline events the mean before covid is of 1.209 and in 2020 is of 1.203 events per group per month. Wilcoxon test offers a p-value > 0.05 so can't reject the null hypothesis and accept that there has

been a change. Regarding to online events the average in 2019 is of 0.08 and in 2020 it moved to 0.613. Wilcoxon test offers a p-value < 0.05 so we can believe that the number of online events per group per month increased in 2020.

According to the p-values we can confirm H2 for both Washington DC and Barcelona though accept H1 only in Washington DC.

4.2 Number of attendees

After the number of events, the number of unique attendees also serves as a good indicator for studying overall social activity in a city as well. To analyze the user participation and answer RQ3. I counted the unique individuals that interacted with each of the groups per month in each city, that can be summarized in the following table

Month	Online attendees	Offline attendees	Total attendees
2019-01	48	11939	11957
2019-02	170	11531	11577
2019-03	129	13707	13758
2019-04	152	12713	12772
2019-05	96	12993	13024
2019-06	322	13753	13918
2019-07	261	13182	13299
2019-08	269	14520	14639
2019-09	131	14768	14826
2019-10	182	13723	13792
2019-11	374	12955	13169
2019-12	113	10838	10887
2020-01	196	12931	13017
2020-02	383	14338	14489
2020-03	2809	9384	11166
2020-04	7201	2796	9183
2020-05	8332	2429	9935
2020-06	8880	3122	11316
2020-07	8056	3684	10942
2020-08	9366	4081	12605
2020-09	9700	4463	13231
2020-10	8231	4479	12086
2020-11	7500	3547	10503
2020-12	7433	2793	9594

Total number of unique attendees per month per kind of event in Washington DC

Month	Online attendees	Offline attendees	Total attendees
2019-01	136	7782	7858
2019-02	79	7977	8016
2019-03	308	8640	8841
2019-04	72	8130	8174
2019-05	140	8847	8925
2019-06	331	9151	9300
2019-07	177	8381	8461
2019-08	94	8405	8444
2019-09	181	10328	10398
2019-10	162	9368	9445
2019-11	94	9330	9354
2019-12	76	7799	7833
2020-01	171	8851	8906
2020-02	73	9648	9672
2020-03	1126	7041	7600
2020-04	3026	937	3723
2020-05	2232	1388	3359
2020-06	2513	4975	6968
2020-07	1584	6274	7431
2020-08	722	6109	6627
2020-09	1781	7416	8833
2020-10	2251	6245	8212
2020-11	2119	3874	5729
2020-12	1739	3934	5407

Total number of unique attendees per month per kind of event in Barcelona

Visually, we can see that, during the first days of the massive spread of covid in both cities the number of unique attendees belonging to the studied groups drastically dropped just to recover along with the end of lockdown policies and stay-home recommendations. From data listed on the tables we clearly see what we confirmed in the previous section that is, though offline events still hold, most of the activity is moved online after the outbreak of covid19.

Fig. 3 Number of unique users attending events in Washington DC, 2019-2020

Fig. 4 Number of unique users attending events in Barcelona, 2019-2020

In Washington DC, the number of unique attendees in offline events in 2019 is 17.468 while in 2020 is of 16.341 unique attendees per group per month. The Wilcoxon test applied to the data set offered a $p\text{-value} < 0.05$ so we can reject the null hypothesis and accept that less people got involved in offline events on average in 2020. For online events, the average unique attendees per group per month in 2019 is 1.904 while in 2020 it is of 14.243 unique attendees per group per month. The $p\text{-value}$ obtained in the Wilcoxon test < 0.05 so we can accept that unique attendees rise in online events in 2020 in Washington DC.

The average number of unique attendees in offline events in 2019 in Barcelona is of 12.262 individuals per group per month while in 2020 it is of

10.538. The Wilcoxon test offers a p-value < 0.05 so we reject the null hypothesis and accept that unique attendees decreased in 2020 for offline events. When it comes to online events the number in 2019 is of 2.165 and in 2020 it is of 6.587 unique individuals per group per month. Here the Wilcoxon tests returns a p-value < 0.05 so we can reject the null hypothesis as well and accept an increase in online unique individual participation in Barcelona.

The results in these analyses confirm H3 and H4 for both Washington DC and Barcelona.

4.3 User comment activity

User comments, in contrast with the attendance data, can serve as an indicator of the user involvement in the platform, they can be used data to analyze the preoccupations and worries of the users which is of interest as we can guess that an external catastrophic event such as the spread of a pandemic may alter the patterns of activity and feelings of the users in the platform. To better comprehend this and continue to answer RQ3 in an online perspective, all of the comments for all of the events recovered have been analyzed using state of the art deep learning models for sentiment analysis. In the case of English comments the Roberta model [19] has been used. For Spanish comments the choice has been the Beto model, another bert-based state of the art model [20].

The comment data is summarized in the following table:

Month	Number of positive comments	Number of negative comments
2019-01	1709	891
2019-02	1724	858
2019-03	2082	988
2019-04	2037	985
2019-05	2065	1009
2019-06	2292	1086
2019-07	2226	1038
2019-08	2353	962
2019-09	2314	970
2019-10	1968	944
2019-11	2056	924
2019-12	1773	779
2020-01	1909	956
2020-02	2133	936
2020-03	1430	948
2020-04	953	679
2020-05	1103	563
2020-06	1221	683
2020-07	1515	781
2020-08	1889	958
2020-09	2037	972
2020-10	2615	1239
2020-11	2061	829
2020-12	1717	784

Summary of comment data in Washington DC

Month	Number of positive comments	Number of negative comments
2019-01	1882	221
2019-02	1972	215
2019-03	2498	280
2019-04	2282	319
2019-05	2149	264
2019-06	2329	275
2019-07	2322	337
2019-08	2513	348
2019-09	2365	363
2019-10	1926	292
2019-11	2186	308
2019-12	1801	225
2020-01	2032	249
2020-02	2206	248
2020-03	1561	358
2020-04	705	122
2020-05	552	87
2020-06	1483	268
2020-07	1774	267
2020-08	1607	264
2020-09	1832	316
2020-10	2008	405
2020-11	858	284
2020-12	784	127

Summary of comment data in Barcelona The following figures 5 and 6 serve as an indicator of overall comment activity in both places.

Fig. 5 Number of positive and negative comments in event pages in Washington DC, 2019-2020

Fig. 6 Number of positive and negative comments in event pages in Barcelona, 2019-2020

In Washington DC, the average score of positive sentiment per event per group in 2019 is of 0.455 and in 2020 of 0.422. The p-value returned by the Wilcoxon test is of < 0.05 so we can accept a decrease in positive sentiment. The score of negative sentiment in 2019 is of 0.255 and in 2020 of 0.292. The Wilcoxon test also returned a p-value < 0.05 thus we can accept that negative sentiment increased in 2020. The average number of comments per event per group in 2019 is of 1.879 and of 2.046 in 2020 though the p-value returned by the Wilcoxon test is of > 0.05 so we can't believe there was an increase of comment activity.

The average score of positive sentiment per event per group in 2019 in Barcelona is of 0.673 and in 2020 of 0.619. The Wilcoxon test returns a p-value of < 0.05 in this case, so we can believe that positive sentiment decreased for the studied groups in 2020. When it comes to the negative sentiment, the average in 2019 is of 0.111 and in 2020 of 0.122. In this case the Wilcoxon test returned a p-value of > 0.05 so we can't reject the null hypothesis and consider an increase. When it comes to the number of comments the average per event per group in 2019 is of 2.238 and in 2020 of 2.001 comments per event per group. The Wilcoxon test returned a p-value < 0.05 so we can accept a decrease in the number of comment activity in 2020 in Barcelona.

The analyses fail to confirm H5 for Washington DC and reject it for Barcelona though confirm H6 for Washington DC and fail to fully confirm it for Barcelona.

4.4 Event location

Event location is useful for analyzing the effects of the pandemic and specifically the safety measures assumed and or enforced after the outbreak. To study the spread of events on average by group by months and answer RQ4 I calculated the distance between the location of each of the events to the city centre

in meters. For Washington DC I assumed a latitude of: 38.897957 and a longitude of: -77.036560. For Barcelona I assumed a latitude of 41.390205 and a longitude of: 2.154007.

The following tables summarizes the location data per group per month in both cities:

Month	Average event distance to city centre (meters)
2019-01	3.609703e+06
2019-02	3.612517e+06
2019-03	3.610924e+06
2019-04	3.611136e+06
2019-05	3.606897e+06
2019-06	3.623684e+06
2019-07	3.625642e+06
2019-08	3.637558e+06
2019-09	3.629460e+06
2019-10	3.643253e+06
2019-11	3.611840e+06
2019-12	3.611349e+06
2020-01	3.619378e+06
2020-02	3.637916e+06
2020-03	3.648315e+06
2020-04	3.594442e+06
2020-05	3.557645e+06
2020-06	3.680746e+06
2020-07	3.583385e+06
2020-08	3.587197e+06
2020-09	3.595806e+06
2020-10	3.551769e+06
2020-11	3.597614e+06
2020-12	3.602637e+06

Average distance to city centre for events in Washington DC

Month	Average event distance to city centre (meters)
2019-01	4086.225129
2019-02	7179.607681
2019-03	10533.333348
2019-04	5060.029379
2019-05	6984.942967
2019-06	15005.341322
2019-07	7413.985041
2019-08	8258.065184
2019-09	8423.330191
2019-10	10235.254976
2019-11	12865.737664
2019-12	52012.451112
2020-01	36768.680641
2020-02	17229.917945
2020-03	35156.220418
2020-04	10151.162292
2020-05	4652.200549
2020-06	10544.711740
2020-07	5559.371334
2020-08	12267.226019
2020-09	6684.653650
2020-10	16071.693804
2020-11	6140.928132
2020-12	5719.660222

Average distance to city centre for events in Barcelona

In Washington DC, the spread of offline events in 2019 and 2020 can be observed in figures 7 and 8. We can observe less intensity in the number of events an increase in the spread of events.

Fig. 7 Heatmap representing the number of events and its location in Washington DC in 2019

Fig. 8 Heatmap representing the number of events and its location in Washington DC in 2020

A similar pattern can be observed in Barcelona's offline events distribution.

Fig. 9 Heatmap representing the number of events and its location in Barcelona in 2019

Fig. 10 Heatmap representing the number of events and its location in Barcelona in 2020

In Washington DC the average distance per event per group in 2019 is of $2.406e+06$ meters and in 2020 of $2.507e+06$. The Wilcoxon test returned a p -value > 0.05 so we cannot reject the null hypothesis and we should assume the events did not significantly change in distance. In Barcelona the average distance per event is of 74915.329 meters in 2019 while of 58809.746 meters in 2020 in this case the Wilcoxon test returned a p -value < 0.05 so we can assume that events moved closer to the city centre in 2020 in Barcelona.

As a result of the tests, we can't accept $H7$ in Washington DC and we should explicitly reject $H7$ for Barcelona as on average the events moved closer to the city centre.

4.5 Structure of communities

To study and compare the structure of the social life in the platform in 2019 and 2020 and answer RQ5 and RQ6 I decided to use network modularity and density, to measure how well on average a user was integrated on the events in town as well as how fragmented the network has been in both years.

Network modularity is a popular and very practical metric for community detection and analysis in graphs. It is a measure of the structure of networks or graphs which measures the strength of division of a network into modules also known as clusters, groups or communities. Networks that score high in modularity have dense connections between the nodes within the communities but sparse connections between nodes in different communities [21].

According to Newman's original work [22] [21], network modularity can be defined as:

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \gamma \frac{k_i k_j}{2m} \right) \delta(c_i, c_j) \quad (1)$$

Which can be reduced to:

$$Q = \sum_{c=1}^n \left[\frac{L_c}{m} - \gamma \left(\frac{k_c}{2m} \right)^2 \right] \quad (2)$$

Where m is the number of edges, A is the adjacency matrix of the graph and k_i is the degree of i . $\delta(c_i, c_j)$ is a function that returns 1 if i and j are in the same community and 0 if they are not. L_c is the number of links between nodes in the same community for c and k_c is the sum of degrees of the nodes in community c and γ is the resolution parameter, that sets an arbitrary trade-off between intra-group and inter-group edges. Though gamma may come very useful for advanced analyses and overall community pattern discovery, it is very common to set its value at 1 [23]. The **greedy modularity maximization algorithm**, as defined in [24] splits the network in a set of communities that maximize the modularity. The algorithm begins by setting each of the nodes in its own community and proceeds by joining pairs of communities in a way that maximize the modularity of the resulting network. The process repeats in a greedy way until no single improvement is met. Due to its ease of use and speed when working with large networks [24] this has been the algorithm of choice for detecting algorithms in this work.

On the other hand, **network density** refers to a measure of dyadic linkage or direct tie within a social network. It describes the portion of potential connections in a network that are actual connections. Network density can be defined as follows:

$$d = \frac{2m}{n(n-1)}, \quad (3)$$

Where n is the number of nodes and m is the number of edges in the graph.

For each city, the overall group activity graph has been built with nodes representing individual users and groups and the edges representing the attendance relationships. That is, if a user g has attended to at least one event belonging to group g an edge between them is set on the graph.

In this particular case we can see it as the actual relationships between users and groups in the form of event participation versus the total number of available groups. So the maximum of density is reached when each of the users is participating in events from all of the groups. When analyzing the network structure on event based social networks such as the ones in meetup.com we should expect them to score low in density and relatively high in modularity due to the locality of the social interactions they allow [25].

The following tables summarize the network metrics obtained for each of the months in the two cities:

Month	Communities	Modularity	Density	Users/community
2019-01	79	0.831072	0.000204	154.594937
2019-02	80	0.844726	0.000204	147.962500
2019-03	81	0.837846	0.000177	173.234568
2019-04	82	0.842761	0.000187	159.109756
2019-05	79	0.846379	0.000181	168.341772
2019-06	79	0.830452	0.000176	179.721519
2019-07	78	0.844847	0.000178	174.000000
2019-08	79	0.837114	0.000164	188.822785
2019-09	75	0.836794	0.000162	201.560000
2019-10	81	0.845576	0.000172	173.925926
2019-11	85	0.836536	0.000182	158.494118
2019-12	95	0.843193	0.000216	117.610526
2020-01	75	0.840197	0.000185	177.400000
2020-02	86	0.833133	0.000168	172.023256
2020-03	89	0.866213	0.000207	128.764045
2020-04	96	0.872277	0.000251	98.447917
2020-05	91	0.856382	0.000236	112.175824
2020-06	80	0.868908	0.000204	145.062500
2020-07	85	0.859263	0.000214	132.247059
2020-08	84	0.865128	0.000185	153.726190
2020-09	77	0.861803	0.000176	175.792208
2020-10	74	0.870317	0.000185	167.040541
2020-11	69	0.862889	0.000210	155.681159
2020-12	71	0.848274	0.000233	138.295775

Summary of network metrics by month in Washington DC

Month	Communities	Modularity	Density	Users/community
2019-01	58	0.758899	0.000328	138.931034
2019-02	57	0.754968	0.000325	144.263158
2019-03	59	0.746264	0.000299	153.491525
2019-04	51	0.746883	0.000323	164.411765
2019-05	55	0.768229	0.000288	166.418182
2019-06	62	0.741201	0.000287	153.774194
2019-07	53	0.747178	0.000315	163.886792
2019-08	49	0.719897	0.000325	176.102041
2019-09	46	0.743485	0.000262	231.086957
2019-10	59	0.771608	0.000274	164.271186
2019-11	60	0.747453	0.000284	160.016667
2019-12	68	0.758355	0.000332	118.691176
2020-01	61	0.762042	0.000294	149.918033
2020-02	61	0.778181	0.000266	162.836066
2020-03	81	0.805799	0.000320	96.864198
2020-04	111	0.844599	0.000576	35.432432
2020-05	99	0.852778	0.000644	35.909091
2020-06	74	0.786193	0.000369	97.391892
2020-07	71	0.755736	0.000359	108.098592
2020-08	70	0.740569	0.000403	97.757143
2020-09	68	0.776661	0.000298	133.558824
2020-10	76	0.792606	0.000303	111.539474
2020-11	77	0.827761	0.000411	77.324675
2020-12	83	0.814067	0.000433	68.012048

Summary of network metrics by month in Barcelona

The nodes in the following figures 11,12,13,14 are colored according to the community they belong as detected by the greedy modularity maximization algorithm. That allows us to visually analyze and compare the structure of social activity in both 2019 and 2020 in Washington DC and Barcelona.

Fig. 11 Structure of the meetup.com network for the selected groups in Washington DC in 2019

Fig. 12 Structure of the meetup.com network for the selected groups in Washington DC in 2020

Fig. 13 Structure of the meetup.com network for the selected groups in Barcelona in 2019

Fig. 14 Structure of the meetup.com network for the selected groups in Barcelona in 2020

In Washington DC, the mean of individuals per community in 2019 is of 166.448 and in 2020 is of 146.388. Both of the data series present normality, passing the Shapiro test, so t-test for related measures was selected in this case. The p-value returned by the test is of < 0.05 so we can accept a decrease of individuals per community in 2020. Regarding to the number of communities, the number per month on average in 2019 is of 81.083 and in 2020 is of 81.4166. The data series does not present normality, so the Wilcoxon test is selected again. This time we fail to reject the null hypothesis as the returned p-value is of > 0.05 . Network modularity on average per month in 2019 is of 0.839 and in 2020 is of 0.858. The p-value returned by the test is of < 0.05 so we can accept a slightly increase in modularity in 2020 in Washington DC. The density of the retrieved network on average per month is of 0.0001 in 2019 and of 0.0002 in 2020, presenting the data series in both years normality the t-test was again used. The returned p-value is of < 0.05 so we can accept an increase in network density in 2020.

In Barcelona, on average, the number of individuals per community in 2019 is of 161.278 individuals per community, in 2020 is of 97.886. Wilcoxon test returned a p-value < 0.05 so we can believe that the number of individuals per community decreased in 2020. When it comes to the number of communities, we have 56.416 communities per month on average in 2019 and 77.666 in 2020. Both the data in 2019 and 2020 presents normality passing the Shapiro test, so the t-test for related samples is used here. The p-value returned by the t-test is of < 0.05 so we can also assume that the number of communities per month

increased in 2020. The modularity of the network resulting of all interactions between users in groups on average per month is of 0.750 in 2019 and of 0.794 in 2020. This time the data also presents normality so the t-test for related samples was selected as well. The returned p-value is of < 0.05 so we can also assume that modularity per month increased in Barcelona as well. Finally, the density of the resulting networks per month in 2019 on average is of 0.000303 and in 2020 of 0.000389. Due to the lack of normality of the data, this time the Wilcoxon test was again used. The p-value returned by the test is of < 0.05 so we can assume a slight increase in network density per month on average though density is remains low in general.

Results of the performed network analyses proof H8 for both cities.

4.6 References to covid19

The study of the times an event makes a reference on covid19 can serve as a valid indication on how the event organizers are showing worrisome towards the disease and are prone to take and enforce safety measures in their events. To study I first selected a set of words containing references to the virus in the form of the following terms: "covid", "covid19", "coronavirus", "ncov", "pandemic", "pandemia", "health measures", "social distancing", "disantciamiento social", "gel", "reduced groups", "grupos reducidos", "ventilation" and "ventilación". Then for each of the retrieved events I marked them as covid19 related if they included at least one of the presented terms.

The following table summarizes the number of mentions to covid19 on average per month per group by the number of users in both cities:

Month	Barcelona	Washington
2020-01	0.003446	0.000226
2020-02	0.007003	0.001533
2020-03	0.013927	0.055288
2020-04	0.031752	0.089963
2020-05	0.038279	0.083026
2020-06	0.045964	0.064584
2020-07	0.040210	0.061102
2020-08	0.043592	0.052610
2020-09	0.046416	0.067773
2020-10	0.050976	0.069723
2020-11	0.046743	0.066112
2020-12	0.028874	0.066072

Summary of references to covid19 by month in Washington DC and Barcelona

The average references per event per user, per group per month in Barcelona is of 0.330 and 0.056 in Washington DC. Due to the lack of normality of the data series, the Wilcoxon test was used to compare the means. The p-value

returned by the test is of < 0.05 so we can accept that more references to covid19 per user have been done in Washington DC than in Barcelona.

5 Discussion

While this study has shed light into the potential effects of covid19 on the social habits in the American and Spanish societies, it still faces some limitations mainly related to the retrieved dataset. The gathered data corresponds only to a couple of cities though they are different, more general patterns and cases of interest can be found in a wider analysis, especially if considering cities with no lockdown/stay-at-home measures at all. On the other hand this study is limited to the years 2019 and 2020 a deeper analysis may come very useful as well to detect the degree to which the pandemic and related phenomena affected a trend or any particular time-pattern. Finally, it is important to remark that to this date, covid19 is still very present in our societies. As successive vaccination campaigns are being taken in different countries at different speeds we should expect a return to the situation before the pandemic, at least to some degree. Then new analyses should be performed to discover to what extent this phenomenon affected our social habits.

6 Conclusions and future work

The present study sheds light on how our social habits changed after the outbreak of the covid19 pandemic. Results show that social activity in the form of new events changed significantly in 2020. Though the number of offline events remained stable in Barcelona, and slightly decreased in Washington DC, the number of online events increased in both cities, specially in Washington DC where they quickly generated a similar volume as with offline events. References to covid19 proved to be higher in Washington DC as well which can be interpreted as a sign that the population on the city is more worried and alert regarding the disease (and thus maybe willing to take more measures). We also have reasons to believe that the pandemic affected the participation in meetups and the shape of the communities. The number of unique attendees in offline events decreased in 2020 while increased for online events in both cities. Online activity in the platform did not significantly change in 2020 in Barcelona. In Washington DC we can perceive a slightly switch in the feelings of interactions that is, an overall less positive feeling along with an increase in comments with negative feelings, that may be interpreted as a sign of worry by the users. Regarding to the geographic location of the events, we can't say that they moved further from the city centre, conversely they moved closer to it in Barcelona. More research should be done in this direction to study the effects of the end of lockdown's and the rush for returning to normal life vs the fears of contagion and its relationship with the concentration of events near the city centres. Finally, regarding to the structure of the communities we see

that they have become more fragmented in both cities as the average individual is connected with less groups, especially in Barcelona, where covid19 lockdown policies were more strict and lasted for more time.

The outcomes of this study should be carefully examined and considered before implementing measures that potentially restrict social activity, as they might have long lasting effects on the structure of the social life in the city.

Future work should include larger datasets composed of larger time periods on more countries. Analyses correlating specific policies and or the number of covid19 cases with the volume of social activity through meet-up's might also lead to a clearer understanding on the effects of the pandemic.

References

- [1] Ricken, S., Barkhuus, L., Jones, Q.: Going online to meet offline: Organizational practices of social activities through meetup. Association for Computing Machinery, New York, NY, USA (2017)
- [2] Liu, X., He, Q., Tian, Y., Lee, W.-C., McPherson, J., Han, J.: Event-based social networks: Linking the online and offline social worlds. Association for Computing Machinery, New York, NY, USA (2012)
- [3] Torres, E.N.: Online-to-offline interactions and online community life cycles: A longitudinal study of shared leisure activities. *Leisure Sciences* **42**(1), 32–50 (2020)
- [4]
- [5] Shen, C., Cage, C.: Exodus to the real world? assessing the impact of offline meetups on community participation and social capital. *New Media & Society* **17**(3), 394–414 (2015)
- [6] Ajmi, S., Hentati, S., Masmoudi, R., Sellami, R., Baati, I., Feki, I., Masmoudi, J.: Anxiety on the lockdown resolution. *EUROPEAN PSYCHIATRY* **64**(1, SI), 282–283 (2021)
- [7] Plümper, T., Neumayer, E.: Lockdown policies and the dynamics of the first wave of the sars-cov-2 pandemic in europe. *Journal of European Public Policy* **0**(0), 1–21 (2020)
- [8] Rubin, G.J., Wessely, S.: The psychological effects of quarantining a city. *BMJ* **368** (2020)
- [9] Ammar, A., Chtourou, H., Boukhris, O., Trabelsi, K., Masmoudi, L., Brach, M., Bouaziz, B., Bentlage, E., How, D., Ahmed, M., Mueller, P., Mueller, N., Hsouna, H., Aloui, A., Hammouda, O., Paineiras-Domingos, L.L., Braakman-Jansen, A., Wrede, C., Bastoni, S., Pernambuco, C.S., Mataruna-Dos-Santos, L.J., Taheri, M., Irandoust, K., Khacharem, A.,

- Bragazzi, N.L., Strahler, J., Washif, J.A., Andreeva, A., khoshnami, S.C., Samara, E., Zisi, V., Sankar, P., Ahmed, W.N., Romdhani, M., Delhey, J., Bailey, S.J., Bott, N.T., Gargouri, F., Chaari, L., Batatia, H., Ali, G.M., Abdelkarim, O., Jaraya, M., Abed, K.E., Souissi, N., Gemert-Pijnen, L.V., Riemann, B.L., Riemann, L., Moalla, W., Gómez-Raja, J., Epstein, M., Sanderman, R., Schulz, S., Jerg, A., Al-Horani, R., Mansi, T., Jmail, M., Barbosa, F., Ferreira-Santos, F., Šimunič, B., Pišot, R., Pišot, S., Gaggioli, A., Zmijewski, P., Apfelbacher, C., Steinacker, J., Saad, H.B., Glenn, J.M., Chamari, K., Driss, T., Hoekelmann, A., on behalf of the ECLB-COVID19 Consortium: Covid-19 home confinement negatively impacts social participation and life satisfaction: A worldwide multicenter study. *International Journal of Environmental Research and Public Health* **17**(17) (2020)
- [10] Caroppo, E., Mazza, M., Sannella, A., Marano, G., Avallone, C., Claro, A.E., Janiri, D., Moccia, L., Janiri, L., Sani, G.: Will nothing be the same again?: Changes in lifestyle during covid-19 pandemic and consequences on mental health. *International Journal of Environmental Research and Public Health* **18**(16) (2021)
- [11] Conway, M.W., Salon, D., da Silva, D.C., Mirtich, L.: How will the covid-19 pandemic affect the future of urban life? early evidence from highly-educated respondents in the united states. *Urban Science* **4**(4) (2020)
- [12] Kaufmann, K., Straganz, C., Bork-Hüffer, T.: City-life no more? young adults' disrupted urban experiences and their digital mediation under covid-19. *Urban Planning* **5**(4) (2020)
- [13] Acquisti, A., Gross, R.: Imagined communities: Awareness, information sharing, and privacy on the facebook. In: Danezis, G., Golle, P. (eds.) *Privacy Enhancing Technologies*, pp. 36–58. Springer, Berlin, Heidelberg (2006)
- [14] Sledgianowski, D., Kulviwat, S.: Using social network sites: The effects of playfulness, critical mass and trust in a hedonic context. *Journal of Computer Information Systems* **49**, 74–83 (2009)
- [15] Social Media Use in 2021. <https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/>. Accessed: 2021-09-01
- [16] Ingram, C., Drachen, A.: How software practitioners use informal local meetups to share software engineering knowledge. Association for Computing Machinery, New York, NY, USA (2020)
- [17] State of alarm decree, Barcelona. <https://boe.es/buscar/pdf/2020/BOE-A-2020-3692-consolidado.pdf>. Accessed: 2021-09-01

- [18] Stay-at-home order, Washington DC. https://mayor.dc.gov/sites/default/files/dc/sites/coronavirus/release_content/attachments/Mayor%27s%20Order%202020-054%20Stay%20at%20Home.pdf. Accessed: 2021-09-01
- [19] Heitmann, M., Siebert, C., Hartmann, J., Schamp, C.: More than a feeling: Benchmarks for sentiment analysis accuracy. Available at SSRN 3489963 (2020)
- [20] Pérez, J.M., Giudici, J.C., Luque, F.: pysentimiento: A Python Toolkit for Sentiment Analysis and SocialNLP tasks (2021)
- [21] Newman, M.: Newman mej.. modularity and community structure in networks. *proc natl acad sci usa* 103: 8577-8582. *Proceedings of the National Academy of Sciences of the United States of America* **103**, 8577–82 (2006)
- [22] Newman, M., Girvan, M.: Finding and evaluating community structure in networks. *Physical review. E, Statistical, nonlinear, and soft matter physics* **69**, 026113 (2004)
- [23] Newman, M.E.J.: Equivalence between modularity optimization and maximum likelihood methods for community detection. *Phys. Rev. E* **94**, 052315 (2016)
- [24] Clauset, A., Newman, M.E.J., Moore, C.: Finding community structure in very large networks. *Phys. Rev. E* **70**, 066111 (2004)
- [25] Liu, X., He, Q., Tian, Y., Lee, W.-C., Mcpherson, J., Han, J.: Event-based social networks: linking the online and offline social worlds (2012)