The Social Planet: A Visualization tool for Social Networks across the globe

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***Abstract*— Social media is a very important part of everyone's life and it is an effective tool for influencing and advertising. Our project aims to analyze the effect of location on the network between people from all over the world by targeting the travel history of social media users and their connections. The users would be able to see how the network changes according to the user's location and travel patterns of people. We visualize the network on The Magic Planet, a spherical globe for digital display. Our visualizations would be useful for users like social media analysts, influencer agencies, and companies who want to maximize their social media reach.**

***Keywords*— Network, social media, magic planet, web scraping, visualization.**

I. Introduction

All of us are a part of a network. Each person is connected to some other person across the world. We want to visualize how this network expands all over the world. In today's life, the best way to network is through social media, where we can communicate with anyone. Many social media platforms today include Facebook, Instagram, Twitter, etc., and according to [1] there are a total of more than 3 billion people using social media. This network analysis can be helpful in social media analytics and influencer strategy to understand how the network expands, optimal targeting, and how to advertise their campaigns to maximize reach. Cigna Corp., wanted to become a global organization by breaking down its geographic barriers. To accomplish that, [2] surveyed and analyzed the social network to find effective influencers.

The Magic Planet [6] is a spherical-shaped globe that acts as a digital display. It utilizes a simple projector and lens arrangement to allow interaction and customizability when employing the globe. This globe makes understanding geographic relations and positions remarkably easy, as a globe is about as natural and accurate as it gets. We use [7] Processing, a visualization-oriented java-based language, to construct the primary network visualization. Section III will explain our use of Processing in greater depth.

In visualization, analysis of the design is an important step. There are four nested levels of design. We have validated the domain, data abstraction, and algorithm levels. In our system, at the domain situation level, we read related work and other articles to understand what uses our globe could have for viewing a social network and, most importantly, if our project effectively used the globe to display this data. We validated the data abstraction by comparing the different datasets and their transformation for visualizing the network and checking if it satisfied our goal of what must be shown. A successful project would use the globe to convey information that could otherwise not be effectively conveyed on a classic two-dimensional screen. 2-D would distort the length between the nodes and misrepresent the actual connection, as some projection, such as the Mercator projection, would be needed to flatten the map. At the algorithmic level, we checked the time complexity to ensure that our project is sufficiently responsive to user interaction.

In the sections to come, we discuss the following: Section II presents the literature survey related to our study, Section III elaborates on our Implementation, Section IV mentions our results, and Section V concludes our paper by discussing the future scope.

II. Related Work

Kasim, H. et al. [8] research investigates how people use social media to help determine travel plans and how social media influences people's spending behaviors. This paper helped us understand the impact of social media on the public and the use of social media to reach a select audience. Unlike our method of scraping data, this article used a questionnaire to gather information. This research showed that social media has an extremely significant contribution and it cannot be ignored. So it inspired us to create a visualization of the social media network to help the social media companies and marketing agencies.

Tidy, Joe [9] gives insight into how we can obtain data for the project by scraping data from various social media accounts. It also shows how this same data can often be used maliciously. It shows the risks of web scraping and how people exploit it. We learned about the various methods to scrape the data and implemented one of the methods using Instragrapi to scrape the data.

McKitrick, M et al. [10] shows that location based social media data (LBSMD) can serve as a versatile spatial data resource due to its high volumes, large variety, and low cost, in contrast to spatial data from traditional sources, which usually have significant costs associated with access and production. This research mentions two ways of accessing data on social media platforms: by gathering the data from the front-end of a platform, or by using an application-program interface (API). We used the second method of using an api to scrape the data. We also used the similar method of cartographic representation (mapping) of the social media accounts to visualize our network as mentioned in the article.

Fan, C. et al. [11] utilized social media posts to help map out various natural disasters. The study is demonstrated using the data set collected from Twitter during the 2017 Hurricane Harvey in Houston. It shows that the detection of location and finer-grained event information significantly improves the utility, credibility, and interpretability of social media data for situation awareness. They used cartographic maps to represent the natural disasters. Social media platforms enable public users to report events and share personal experiences and reactions to disasters. Hence, the data generated on social media provides a unique opportunity to capture disaster situations with a relatively high temporal and spatial resolution to map different events across various locations. They scraped the data from Twitter to find and map natural disasters in real time. This study showed how location based social media data can serve various purposes.

S. Majeed, M. Uzair, U. Qamar, and A. Farooq [12] analyzed and compared the various tools available for Social Network Analysis (SNA) of large-scale datasets, based on different measures of SNA like Betweenness, Centrality, Closeness, Cohesion, etc. It also addresses the various problems researchers face in SNA and how these tools help overcome them. The tools compared are Node XL, GEPHI, PAJEK, UCINET, and MuxViz. This paper helps us understand the different problems and approaches of SNA, and how we could use a few techniques mentioned in the paper in our project to validate our results.

L. Belcastro [13] used Geotagged data gathered from social media to discover places of interest (PoIs) that have attracted many visitors. It defined an area, called region-of-interest (RoI), represented by the boundaries of a PoI. The main goal of this study was to discover RoIs from PoIs using spatial data mining techniques. It proposed a new parallel method for extracting RoIs from social media datasets. The first step extracts keywords identifying the PoIs; these are then used to group social media items according to the places they refer to. The second step uses a Parallel Clustering Approach (ParCA) of a spatial dataset to identify RoIs. ParCA was implemented using the MapReduce model. The experiments showed that the approach used was highly scalable and reached an accuracy of 79% in detecting RoIs. This paper gave us an idea of how to use the clustering approach to find the most interesting places from the given data.

HL Chuan, I. Kulkumjon, and S.Dangi [14] have three distinct approaches to visualize the dataset addressing two goals. First, arriving at a time-based region-specific recommendation logic for different types of users classified by the places they frequent, and second, analyzing the behaviors of users that check-in in groups of two or more people. The study revealed that distinct patterns exist for people that are residents of the city and for people who are short-term visitors to the city. The frequency of visits, however, is dependent on the time of the day and the urban area itself (e.g. eateries, offices, and local attractions). The check-in date is visualized with overlays of geographical maps in Tableau and presented with time-based distributions to map the pattern of group check-ins over a period of time. This made us understand the approach for visualizing users based on the region.

F Hruby, A Riedl [15] discusses the usage of maps and globes over the last few thousand years, how they have changed, and reasons to use one over an alternative visualization method. The article examines how approximately 2,000 years ago maps were favored over globes due to how maps are more portable, easier to make and duplicate, and easier to draw on. The article moves on to discuss how all maps are distorted in some manner. Finally, the article reviews how maps allow users to see the entire world at once, while globes allow users to see only a more focused, single hemisphere at a time. After reading and understanding the pros and cons of globes and maps, we decided to use the globe in our project as we would like to select no distortion over not seeing the entire world at once.

III. Implementation

A. Data Collection

i) Alpha Release

The main source for our data set is Instagram. With Instagram, the connection we are trying to extract is to see how different location placement of people can affect their social network and reach. To collect the data desired for our visualization, we created an Instagram web scraper. The web scrapers first downloaded a list of recent posts which used a specific hashtag. For our first run we used #Travel, and collected 250 posts. The next step of the scraper was to go through each one of the 250 posts going to the account who posted it and download their 50 most recent posts. Some of these 250 accounts got skipped, to avoid extremely small accounts and potential bot accounts. During the scraping process we converted instagram geotags to longitude and latitude. Finally all data was exported to a CSV. We imported our CSV and cleaned our data. Using the R package Tidyverse we created a map and overalayed our data points using the posts and their longitudes and latitudes collected.

ii) Beta and Final Release

Originally our plan for data collection was to use selenium to scrape instagram but due to the time constraints we had this was not feasible. Following is our explanation for how we would have collected instagram data, given the time.

The main source for our data set in these phases was also Instagram. In this phase we wanted to visualize how the social network tree of someone living in Japan looks compared to someone who lives in America? We wanted to mainly look at the follower count and how spreaded the network is depending on the location of an Instagram account. To accomplish this, we select a random account from a location of interest, and collect a list of random followers of that person along with their location, and keep doing the same for those followers. For now, we are collecting up to a depth of 5 (depth = number of edges from the root node[the originally selected person]to the last node [last person]). We also put some constraints when selecting the random accounts:

1. The account must have less than 2500 thousand followers (Unless we are trying to target public figures/content creators).
2. The account must be public - since we can not collect data on private accounts.
3. The account must have a post with a location tag.

For the protection of the privacy of users, almost all social media platforms have removed their API access for collecting data from their websites/apps. We use web scraping to collect such data, which is not readily available due to social media platforms shutting down their APIs. This data collected is unstructured and needs to be cleaned and processed to become useful. [3] Web scraping has two parts, crawler, and scraper. The crawler is an algorithm that follows the links to get to the required search destination. The scraper then scrapes the data from the page. [4] Selenium, our scraper of choice, is a python library and tool which performs the task. It is easy to use and has options for UI or programming elements to command the steps. An alternative library for scraping Instagram is [5] Instagrapi which is faster than selenium and supports multiple programming languages, though it is far less reliable.

We format the dataset for use in the visualization in a CSV, with columns of account, followers, post count, post link, location, longitude and latitude, likes, description, time, following. This way all pertinent data can be efficiently stored for use at runtime, and connections can easily be rendered.

We transitioned to using R along with a list of cities from around the world to generate a data set. The first step is to generate a list of random cities with a given length, each city is going to be a node. Then loop through the generated list and use a random number generator creating attributes such as follower count and post count.

Following this we loop through the list of nodes and generate connections. A number, x, is generated which will represent the number of accounts followed is generated, then a list of length x is generated where all numbers contained in the list are less than the number of total accounts, this list represents the accounts followed. From here we move on to use the first account as a starting node and calculate distance to each other account from the starting node, this is calculated using each edge as a jump, adding one to the distance. The starting node is given a distance of 0.

851	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	207 likes	#ru_goldenscapes_22	2022-10-09T19:13:18.000Z
852	angfame	183	Kalimarmaro, The Birth Place Of Tl	_	_	43 likes	#ig_athens #in_athens #ig_	2022-10-09T19:05:38.000Z
853	angfame	183	Athens, Greece	23.7283052	37.9839412	41 likes	Day 9: Scapes	2022-10-09T10:15:00.000Z
854	angfame	183	Athens, Greece	23.7283052	37.9839412	27 likes	#wu_greece#ig_greece #kir	2022-10-08T07:41:41.000Z
855	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	162 likes	#ru_pink_22	2022-10-05T01:03:06.000Z
856	angfame	183	Athens, Greece	23.7283052	37.9839412	53 likes	Day 3: Street Art	2022-10-03T08:48:39.000Z
857	angfame	183	Athens, Greece	23.7283052	37.9839412	19 likes	#wu_greece#ig_greece #kir	2022-10-03T06:42:37.000Z
858	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	178 likes	#ru_cityscapes_22	2022-10-02T19:02:53.000Z
859	angfame	183	Stockport, Manchester	-2.160243	53.407901	47 likes	Day 1: Sky	2022-10-01T13:49:10.000Z
860	angfame	183	Levenshulme, Manchester, United	-2.1931527	53.4443366	52 likes	Day 30: Colors	2022-09-30T10:15:09.000Z
861	angfame	183	Peak District, National Trust	_	_	18 likes	#rebel_colors	2022-09-30T09:38:37.000Z
862	angfame	183	Stockport, Manchester	-2.160243	53.407901	24 likes	#bikespoetry#bikes	2022-09-29T12:37:03.000Z
863	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	200 likes	#ru_story_22	2022-09-28T01:03:29.000Z
864	angfame	183	Levenshulme, Manchester, United	-2.1931527	53.4443366	51 likes	Day 27: Harvest Colors	2022-09-27T12:44:20.000Z
865	angfame	183	Greek Orthodox Church Manchest	-71.42136679	42.9716997	34 likes	Day 26 : Behind (car park)	2022-09-26T16:35:04.000Z
866	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	258 likes	#ru_shadesofwhite_22	2022-09-25T19:03:23.000Z
867	angfame	183	Levenshulme, Manchester, United	-2.1931527	53.4443366	57 likes	Day 25: Long Exposure	2022-09-25T16:00:36.000Z
868	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	105 likes	#raw_snap_yellow1	2022-09-24T19:57:09.000Z
869	angfame	183	The Levenshulme Antiques Village	-2.188960085	53.44141875	45 likes	Day 24: Opposites. Large	2022-09-24T10:59:03.000Z
870	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	64 likes	Day 23: Sunflower Sunset	2022-09-23T09:39:18.000Z
871	angfame	183	Little Underbank, Stockport, Uk	-2.1579174	53.4111242	40 likes	#underbanks	2022-09-22T21:43:58.000Z
872	angfame	183	Fletcher Moss Park	-2.233145655	53.40924285	49 likes	Day 21: Nature	2022-09-21T09:48:32.000Z
873	angfame	183	Manchester, United Kingdom	-2.2451148	53.4794892	63 likes	#ru_colorsplash_22	2022-09-21T02:13:59.000Z

Fig. 1(a). Dataset used in the Alpha phase

B. Data Processing

The data is imported directly into Processing 4. Using an image derived from the Blue Marble [16] picture set, a map is rendered on which the data nodes are displayed. The nodes represent the most recent location of a user, which we find from the location data attributed to their recent posts. Our design implements a network, displaying the relationship among many users. The edges encode a binary attribute that represents follower status. The connections between the nodes are directional and indicate the account that a given node follows. As the most intensive tasks are performed upon loading a dataset, the algorithm for display is extremely simple and runs quickly on a wide range of hardware.

index	location	follower_c	following_	long	lat	post_count
1	Antsirabe	819	9	47.0333	-19.8667	94
2	Az Zarqa'	565	13	36.1	32.0833	43
3	Dessau-Rosslau	579	6	12.2333	51.8333	2
4	Brzesko	413	10	20.6167	49.9667	70
5	Koszeg	63	5	16.5519	47.3817	92
6	Sariyer	389	9	29.0094	41.1911	41
7	Oregon	851	8	-89.3892	42.9253	39
8	Tympaki	485	11	24.7683	35.0719	62
9	Bariri	156	5	-48.7403	-22.0744	36
10	Kaora Abdou	937	5	5.6604	14.4525	48
11	Yinajia	290	11	105.695	26.8239	61
12	Bloomfield	638	14	-72.7406	41.8426	64
13	Burkhardtsdorf	92	8	12.9219	50.7347	44
14	Ceadir-Lunga	368	8	28.8303	46.055	18
15	Lake Barcroft	545	14	-77.1579	38.8514	30
16	Lithgow	830	13	150.15	-33.4833	14
17	Milngavie	914	15	-4.3137	55.9421	18
18	Westlock	478	8	-113.851	54.1522	9

Fig. 1(b). Dataset used in the Beta and Final phases

C. Data Visualization

i) Alpha Release

In the alpha release, the marks we used were points to represent nodes of the network, and each point corresponded to a post. We decided to use size to represent the number of followers accounts had, a channel corresponding to a quantitative attribute. We used color to show the account that posted it, a channel using a categorical attribute. We removed both axes and the legend, in order to give the projection a cleaner look, and saved the photo. The photo is shown in fig. 1. This photo was then opened in Processing 4 using a program professor Don Engel gave us to work from. From here the program distorted the image and mapped it to The Magic Planet which is called data warping and is shown in fig. 2. How data warping works while fig. 3. Shows the visualization of the globe.

ii) Beta Release

The visualization displayed the network of users and the relations between their followers. After loading the data and the given longitude and latitude values, the program converted them to screen space coordinates. We rendered the points on top of the map dynamically, then applied a shader to allow the visualization to display on the globe. The interaction mechanism allowed using rotation and the zoom function. The zoom functionality allowed the users to zoom in and out of the network. The zoom interactivity is carried out using the keyboard '+' and '-' keys. When zoom is used, the selected area is stretched and the remaining areas are compressed for focus and context using the fisheye lens idiom. This keeps the far edge of the globe clean.

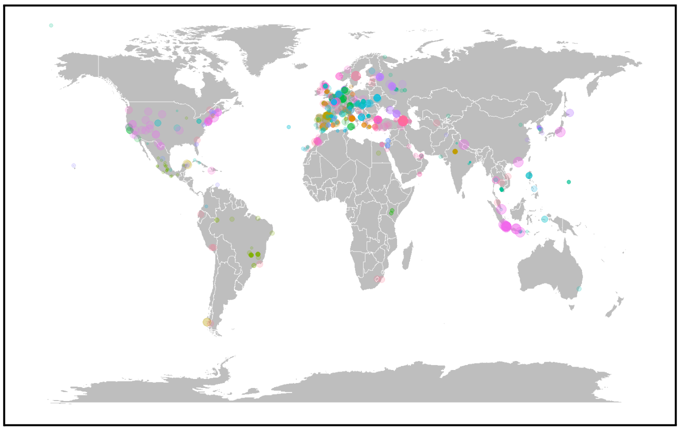

Fig. 2(a). Alpha Release Visualization marks and channel.

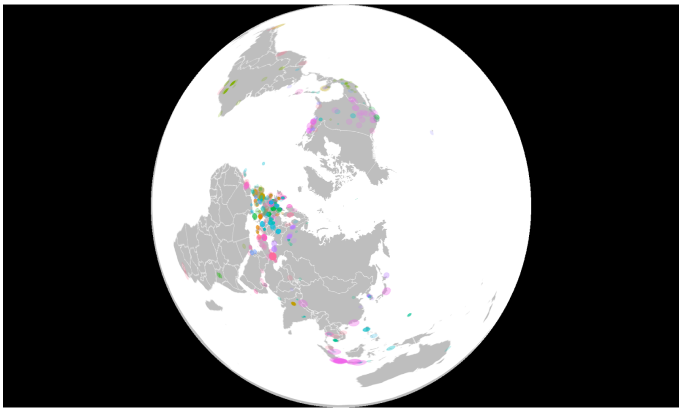

Fig 2(b). Alpha release visualization on the magic planet.

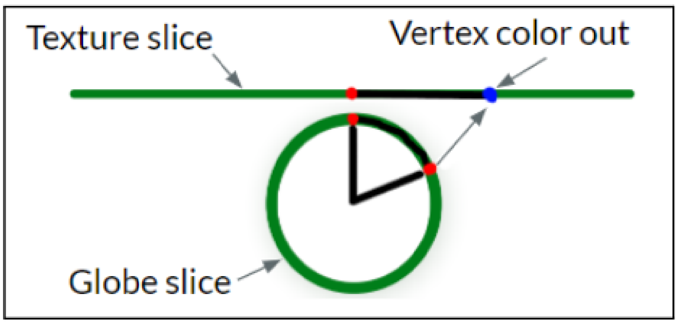

Fig. 3. Data Warping Process

Our visualization used color, size, and the spatial region as the visual channels. The color represented different user profiles, a channel that corresponded to categorical attributes. The size that is the area of the nodes represents the number of followers a person has, which is a channel that corresponds to quantitative attributes. The mark used is node and connection for the network. Fig 4 (a) shows a 2D view of our visualization which is using the dataset from our alpha but now in Processing 4. Figure 4 (b) shows the same figure but is now projected onto the magic planet.

Fig. 4 (a) Beta Release Social Network Visualized on the World Map

Fig. 4 (b) Beta Release Social Network Visualized on the Magic Planet

iii) Final Release

In the final release, we are now using generated networks. A distance metric is defined. Distance from the root node is measured by the minimum number of levels between the root node and any other node. The root node right now is selected randomly but can be selected using the node that has a minimum distance from other nodes. We have also used a new color scheme. The nodes with the same distance from the root node have the same color. Red is used for the root node and blue is used for the furthest nodes. We have also removed the linkage between the globe rotation axis, that is the x and y axis, which makes it possible to rotate in any direction.

During the testing and development phase for the final release we tested out a zoom function. It was implemented with a simple fish eye distortion. As seen in Fig 5(c), the zoom functionality was more confusing and distorting than helpful. We ended up removing it for the final, but it is an interesting feature that could be further developed in the future.

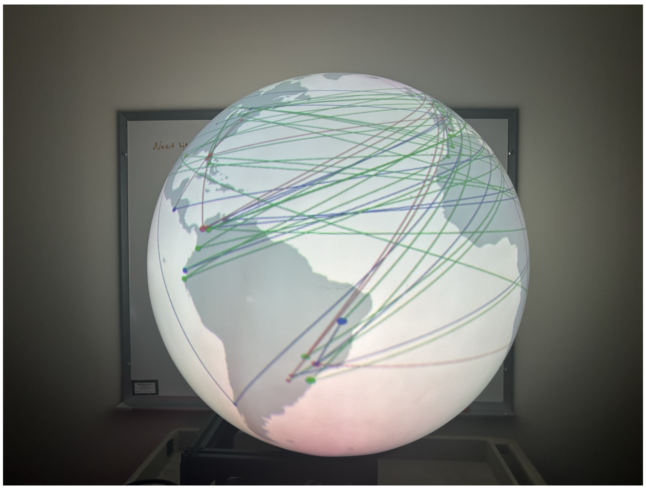

Fig. 5 (a) Final Release Social Network Visualized on the World Map

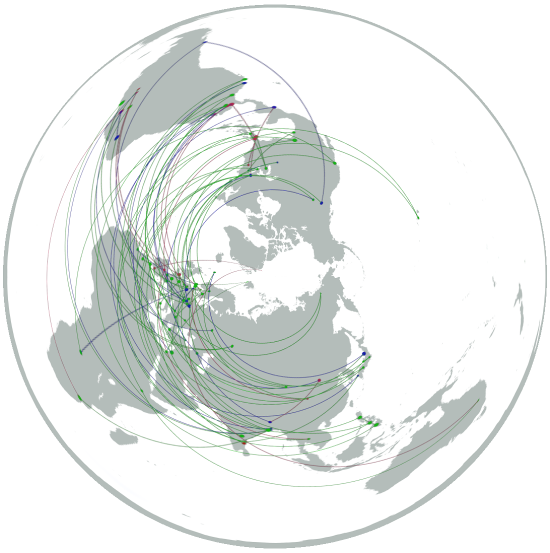

Fig 5 (b) Final Release visualization of generated social networks projected onto the magic planet.

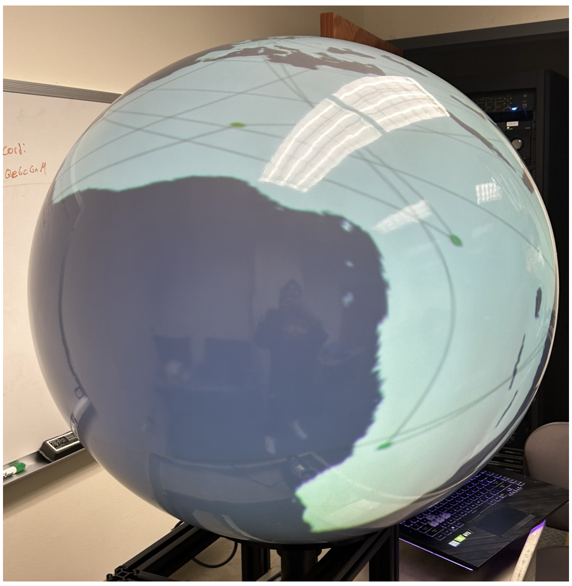

Fig 5 (c) Visualization of world map with social network with fisheye distortion applied

IV. Results

For the final release, we have included several visual channels in our design. These include the position, color, and size of the nodes and connections in the network. The nodes represent individuals from all over the world, while the connections between them show the relationships between these individuals.

Since we are using maps to visualize the network, the default position channel is occupied by the geographic attribute, which shows the location of each individual on the map. However, we also wanted to show other information about the individuals in the network, so we used the color and size channels to encode additional data.

The color channel is used to encode the distance between individuals in the network. This makes it easy to compare the distances between different individuals at a glance. In contrast, the size channel is used to encode the number of followers that each individual has on their profile. This allows us to show a quantitative attribute, namely the popularity of each individual, in a visually striking way.

Overall, our use of multiple visual channels allows us to show a rich and detailed network of individuals from all over the world, and to provide useful information about each individual in the network.

In our system, we have implemented interactivity to allow users to easily explore and navigate the network of individuals. Specifically, users can rotate the globe to view the network from different angles, which can be useful for gaining a better understanding of the relationships between individuals in the network.

We initially considered adding additional interactivity, such as the ability to zoom in on specific areas of the network, but we were unable to implement this feature to our satisfaction. As a result, our system currently only allows users to rotate the globe as a way of focusing their attention on different parts of the network.

In terms of scalability, our system is currently designed to handle networks of up to 1000 individuals. However, if the network grows beyond this size, the data will become cluttered and difficult to understand. In this case, we may need to implement additional filters or other tools to help users more easily navigate and understand the network. Overall, our system provides a useful way of visualizing small to medium-sized networks, but may not be suitable for very large networks without additional features to support them.

V. Future Directions

For future work, it would be great to have a larger and proper dataset because dataset creation was a big and difficult task. One potential future improvement for a data visualization project that shows the social interaction and networks of people on a map would be to incorporate real-time data. This could allow the visualization to show not only the current state of the social networks but also how they are changing and evolving over time. This could provide a more dynamic and detailed picture of the social interactions and networks of people on the map.

Another potential improvement would be to incorporate additional data sources, such as other social media data or location data from mobile devices. This could provide a more comprehensive view of social networks, and it could allow the visualization to show not only the connections between people but also the places where they interact and the activities they engage in.

In terms of potential use cases, this type of data visualization could be used to study the spread of social networks and the ways in which they evolve over time. For example, it could be used to study how social networks form and change in response to events like natural disasters or political upheaval. It could also be used to study the ways in which social networks are influenced by factors like geography, demographics, or social norms.

Additionally, this type of data visualization could be used to study the ways in which social networks impact individual behavior and decision-making. For example, it could be used to study the ways in which social networks influence the spread of ideas, the adoption of new technologies, or the formation of social norms. It could also be used to study the ways in which social networks impact individual health and well-being, and to identify potential interventions that could improve social connections and support social cohesion.

Overall, there are many potential future improvements and use cases for such data visualization projects that show the social interaction and networks of people on a map. These improvements and use cases could help to deepen our understanding of the ways in which social networks form and evolve, and they could provide valuable insights into the ways in which social networks impact individual behavior and decision-making.

We can also add interactivity to our project. We tried doing the zoom function but it didn’t work very well and made the visualization more distorted. So, it would be a future goal to add a more controlled zoom function. We can also try to add animations to show the flow of edges in the network.

VI. Conclusion

Social networks play such an important role in society, especially during this generation of social media. A toolset such as the social planet, allows for an easy and accurate visualization of network data which is tied to geographical locations. Using the magic planet allows for an accurate representation of geographical data and the reach an influence has. As travel becomes cheaper and more frequent, people will be more likely to travel on whims, frequently inspired by social media. Following and tracking the trends of this travel data will be a very valuable tool for any tourism related industry as well as many other related companies. With the proper improvements this analysis tool would be very valuable to a multitude of companies, as well as to future researchers.

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