

Vol. 10, Issue 5, May 2021 DOI 10.17148/IJARCCE.2021.105120

# Enhanced COVID-19 Analysis Using Viewer-Friendly Data Visualization Techniques and Improvised Methodologies

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**Abstract:** The coronavirus disease (COVID-19) is a global pandemic that was discovered by a Chinese physician in Wuhan, the capital city of Hubei province in mainland China, in December 2019. Visualization techniques have been front-and-center in the efforts to communicate the science around COVID-19 to the very broad audience of policy makers, scientists, healthcare providers, and the general public. In particular, the project is focused on visualizing live COVID-19 trends. In this paper, the authors develop a data visualization module that specializes in improvising current COVID-19 Data Visualization Techniques and providing methodologies which enhance viewer-friendliness and boost visual clarity. The module uses authentic sources of data, like the John Hopkins University Covid GitHub Repository, to develop accurate, real-time visualizations which erase discrepancies in visualizations due to inaccurate and irregular streams of data. The authors suggest alternative data visualization techniques to represent data which has the potential of being visualized better than it currently is. Various data visualization libraries such as Plotly, Matplotlib, Seaborn, Ggplot2, GeoPlotlib, etc. have been used to create a variety of visualizations such as scatterplots, bubble charts, histograms, boxplots, distplots, heatmaps, choropleth maps, etc.

Keywords - Coronavirus, COVID-19, Data Science, Data Visualization, Modeling, Pandemic, Simulation, Statistics

# I. INTRODUCTION

Data visualization has arguably been the star of the coronavirus pandemic coverage. From early graphics urging us to flatten the curve, to John Burn-Murdoch's Financial Times charts, to regularly updated dashboards like the Johns Hopkins COVID-19 dashboard, the world has been inundated with visual interpretations of the pandemic data. Data visualization is one of the fastest and most efficient ways to make sense out of large amounts of data. Usually the data is quantitative, and the goal is to show it graphically. One of the main ways that data viz creates insight is by creating comparability between data. As people go through a very challenging global health crisis, they crave narratives and information to help them understand what is happening. This is why we see the popularity of graphs that compare COVID-19 data from different countries. Beyond communicating, data visualization also plays a role in helping convince people to change their behavior. Once a virus spreads, public health officials need to make critical decisions about how much to communicate and at what point. One of the most important aspects of containing an outbreak is all about convincing people to change their behavior when it's not immediately clear they should do something yet. Data visualization has been very important in communicating and convincing people. Some of the early graphics that became widely shared and influential during the initial stages of the pandemic in North America and Europe urged people to do their part by succinctly explaining the concept of 'flattening the curve'.

A lot of people who have not studied data visualization do not know how methodologies are read into. They see an official looking chart and take it as a hard fact. Herein lies the risk for both data visualization creators and consumers. People misrepresent data, sometimes intentionally or sometimes unintentionally due to lack of experience. We have known for a long time how easily statistics and charts can mislead. The risk lies in incorrect labelling, titling and annotations and misleading axes. When the stakes are so high as informing public opinion and action during a global pandemic, designers have a big responsibility for the graphics they create. Data visualization is interdisciplinary, and requires an understanding of the data as well as design. We have to think about the end person who will be consuming the visualization we create, using it to equip and educate them. In this research work, the authors revise existing data visualization techniques used to communicate COVID-19 trends across the globe. They propose improvements in plotting and charting data to make it more viewer-friendly and suggest alternatives to make data representation as lucid and error-free as possible. They aim to underline the importance of adding the essence of data story-telling to data visualization so as to make it more appealing



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#### DOI 10.17148/IJARCCE.2021.105120

and convincing to the masses, contrary to mere communication of statistics. This work highlights major pitfalls in the existing graphing system with the help of strong examples to support the claim of the authors.

#### **II. BACKGROUND**

As Jones et al. (2016) argued, technical communication as a field has long been committed to social justice. Melonçon and Warner (2017) suggested that technical and professional communication (TPC) scholars can make an impact in the end products of data visualization with their expertise in user experience and audience analysis. Wolfe (2015) emphasized the importance of selecting and manipulating data before visualizations are created, arguing that selecting data to report without the appropriate context is unethical and, even if the data is accurate, misleading. Given how powerful data-driven arguments can be, we must ensure that when we create data visualizations or teach them to our students, we attend to their potential for advocacy and firmly root data stories in context (Loukissas, 2019).

Further, data is often communicated in visualizations that are crafted to tell a specific story, and context is often lost in the process of simplifying the data; similarly, data is often touted as objective, inherently factual information, untouched by human interference ("raw" data). As Gitelman (2013) reminded us, however, data is never "raw," or free from interpretation and explanation, on any level; human actors always play a part in how data is created and communicated. As a result, rather than acting as an objective third party, data reifies those actors' existing power structures and inequalities.

Data visualization in health communication is no exception. While data already shows that COVID-19 disproportionately affects Black people (Garg et al., 2020), as of April 14 data from the Centers for Disease Control and Prevention (CDC, 2020a) lists race as "missing/unspecified" in 78% of cases. Almost all of the tools created to help citizens track the virus's magnitude, spread, and impact focus specifically on cases and deaths broken down by county, state, and country; the Johns Hopkins University dashboard (2020) is a particularly good example of this. Most of these tools allow users to look at the data on a map over time or to focus on a particular area, but almost all the available data does not show demographic information. Such incomplete demographic data obscures the virus's full impact on marginalized communities.

In this study, the authors analyze various data visualization techniques being used in current times to communicate Covid-19 pandemic statistics and growth. They explain shortcomings of these models and suggest more efficient techniques and methodologies to make them more viewer-friendly and storytelling type. They focus more on the concept of making analytics and visualizations "more humane" so that it does not require one to be a data scientist to understand said plots and analytics.

# **II.1 DATASETS**

This module primarily uses the official government websites of various countries and as one authentic global data source it uses the Covid-19 Data Repository by The Center for Systems Science and Engineering (CSSE) at Johns Hopkins University

# **III. METHODOLOGIES**

# III.1 ANALYZING CURRENT DATA VISUALIZATION PRACTICES

The first COVID-19 chart that came across news feeds prompted questions many couldn't answer. The charts were doubledigit case counts from Singapore with active, recovered, and fatal cases displayed on individual graphs that were simpler than what we see on the tracker charts of cases and deaths from COVID-19, from dozens of countries and still trending up in December.



Figure I : From Our World In Data, downloaded 15 December 2020 at 8:32PM EST

Charts, maps, and graphs are powerful tools for communicating information about current events like the COVID-19 crisis, and the world has seeked visualizations for answers. Ben Schneiderman, a leader in the data visualization field, called this "data visualization's breakthrough moment." Simple is often effective, with many small multiple tables and line charts packed with data. But all of that simplicity can mask complexity.

Discussed below are a few repetitive glitches occurring in most of the published works the authors reviewed for this paper. Unreliable Datasets

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# International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 5, May 2021

DOI 10.17148/IJARCCE.2021.105120

	World Health Organization	John Hopkins University	Our World in Data	Belgian government
March 1	1	2	1	2
March 2	1	8	1	8
March 3	8	13	8	13
March 4	8	23	8	23
March 5	23	50	23	50
March 6	50	109	50	109
March 7	109	169	109	169
March 8	169	200	169	200
March 9	200	239	200	239
March 10	239	267	239	267
March 11	267	314	267	314
March 12	314	314	314	399
March 13	314	559	314	559
March 14	599	689	599	689
March 15	689	886	689	886
March 16	1 085	1 058	1 085	1 058
March 17	1 085	1 243	1 085	1 243
March 18	1 486	1 486		1 486
March 19				1 795

Figure II. Comparison between different data sources of the reported total number of confirmed COVID-19 cases in Belgium between March 1 and March 19, 2020.

The Johns Hopkins University data follows the government data most closely, with an exception on March 12 where for some reason the number was not updated. The two other datasets (WHO and Our World in Data) appear to lag behind by one day up until March 16, possibly because WHO Situation reports are published at specific timings which don't match accurately with government reporting timings. Also, these datasets miss the same update as the Johns Hopkins numbers (from 314 to 399 cases), they were not updated on March 17, and they appear to have a typing error in them (1.085 cases on March 16, while the official government number was 1.058). Finally, Our World in Data temporarily stopped updating beyond March 17 because WHO shifted their reporting window: up until Situation report 57 the observed 24-hour time window ended at 10 a.m. CET, since then it ends at midnight. This causes a small overlap making it difficult to accurately compare data and analyze trends. In summary, Johns Hopkins University data most closely matches official government numbers (for Belgium).

**Reducing usefulness of Logarithmic Charts** 



Figure III: Number of confirmed coronavirus cases per country, on a linear-logarithmic scale.

As the infection continuous to spread, a growing fraction of the population will become either already infected, or immune when they have been infected in the past but survived. Also, vaccines can be developed, or increasingly strict measures of social distancing and quarantine can be enforced. In practice, this means the effective reproduction number will drop, the exponential growth will start to decelerate and the number of infections will reach a peak and start dropping again. When this happens, the usefulness of logarithmic scales has reached its end.

# **Confusion between Relative and Absolute Numbers**

Comparing the number of COVID-19 tests performed by country in absolute and relative numbers reveals some interesting insights:



Figure IV: Number of tests performed per country and per 1.000 inhabitants. (Source: Our World in Data)

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#### DOI 10.17148/IJARCCE.2021.105120

While the bars indicating Absolute numbers promise a good overall picture into the progression in tests performed, the ones indicating Relative (per 1000) numbers do not put forth as promising a picture. Such confusion can mislead viewers as they are not usually aware enough about miniature statistic details such as the one explained above.

# **Mapping Issues**

One of the most common issues encountered when creating data maps is the impact of population and population density. If we simply color a map according to the presence of a certain parameter, we can easily mask the fact that we are actually looking at a map of an underlying different parameter, such as population density. Many of the maps published during this coronavirus crisis suffer from a similar problem. Take for example this map by ABC News showing the countries where COVID-19 cases have been confirmed:



Figure V: Countries and territories with confirmed cases on March 10, 2020 (ABC News)

**Bubble maps,** such as the ones by the Washington Post shown above, avoid this trap because each nation gets its own bubble, independent of area, population, or population density. This is what makes this kind of chart so successful to map a wide range of values in a wide range of countries around the globe.

There is only one minor downside: bubbles can start overlapping each other when two neighbouring regions have very large values (or one of them has a large value while the other only a small one). Then your bubble chart might start looking like this:



Figure VI: Bubble map on the nCoV-2019 Data Working Group dashboard.

# **Misleading Tables**

Tables can also be used to misinform, or at least to distort information or present data in a way that suits you best. For a while, the following table was popular on social media in the Netherlands, showing how the country was following the exact same pace as Italy, with only a few weeks of delay.

NETHERLANDS			ITALY		
Date	Cases	Deaths	Date	Cases	Deaths
Mar 16	1 413	24	Feb 29	1 049	29
Mar 17	1 705	43	Mar 1	1 577	41
Mar 18	2 051	58	Mar 2	1 835	52
Mar 19	2 460	76	Mar 3	2 263	79
Mar 20	2 994	106	Mar 4	2 706	107
Mar 21			Mar 5	3 296	148
Mar 22			Mar 6	3 916	197
Mar 23			Mar 7	5 061	233
Mar 24		***	Mar 8	6 387	366
Mar 25			Mar 9	7 985	463

Figure VII: Table comparing the number of infections and deaths between the Netherlands and Italy.



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#### DOI 10.17148/IJARCCE.2021.105120

Also, differences in age distribution among the population have an impact on the death rate, so it's rarely a good idea to blindly start comparing different columns or rows with each other, without thinking things through.

# Flattening the Curve

The "flattening the curve" chart is no different to being claimed by researchers, to be a simplified tool for understanding a complex reality. Embedded within the most common versions of the chart are a few simplifying assumptions: 1) That the number of people infected over time will be roughly similar if the curve is flat or spiky, 2) That the severity of illness, the amount of burden people who are sick will put on the health care system will remain roughly similar over time, and 3) That the capacity of the health care system will remain roughly similar for the duration of the pandemic. It has been observed in research works that up to a certain date the bars' height corresponded to the numbers, thereon the scaling of bars became inconsistent with the numerical differences. For an increase of x new cases, the graphs went up by x/2 units only, all in the bid to flatten the curve. Cases keep growing exponentially, and it is a bad sign. This error occurred numerous researches.



Figure VIII: Flattening the curve visual from the Information is Beautiful COVID-19 #Coronavirus Data Pack.

# **IV. PROPOSED SOLUTIONS**

# Finding Reliable Data

Excellent graphics consist of complex ideas communicated with clarity, precision, and efficiency. At the core of a good data visual, therefore, lies accurate data. There are currently four important places where one can obtain reliable and relatively complete aggregate data about the Coronavirus epidemic:

# 1) World Health Organization

**The World Health Organization publishes** daily Situation reports detailing the number of confirmed cases and deaths per country. They also provide a Situation dashboard which is updated three times per day.

# 2) Johns Hopkins University

**Researchers at Johns Hopkins University also maintain** a dashboard providing an overview of the current number of cases, deaths and recoveries on a per country basis. The underlying data is made freely available through GitHub.



Figure IX: Johns Hopkins University Coronavirus Dashboard

# **Improvising Current Techniques**

# Transparent Bubble Charts

Transparent bubbles erase the uncertainty cause by opacity of the bubbles as showcased above and make visualization clearer and more interactive.

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Fig. X: Map showing the global spread of the coronavirus on March 27, 2020

These are examples of **proportional symbol maps**, or **bubble maps**. Altering the opacity of the bubbles, clever bubble outlines can make the result both beautiful and effective:

# Creative Tabling

Colors have been used to add optimism to this table that demonstrates a particularly pessimistic subject matter.

region	▼ current confirmed cases	deaths	recovered	Currently, one in people is confirmed to have the virus
World	115,113	8,248	82,091	67,000
() Italy	26,052	2,503	2,941	2,000
Other countries	24,723	300	1,233	229,000
Spain 3	12,205	623	1,081	3,000
🗣 Iran	10,837	1,135	5,389	7,000
Germany	9,982	27	73	8,000
Hubei Province in Chine	7,751	3,122	56,927	7,000
D France	7,501	148	12	8,000
Couth Korea	6,789	84	1,540	7,000
Curited States	6,404	115	0	51,000
United Kingdom	2,503	72	67	27,000
China without Hubel	255	119	12.828	3 889 000

# Fig. XI: Colour-Coded Columns

Here, the columns are colored based on the moods associated with the values they represent. Green for recovered cases gives a sense of progress and hope. This is an effective way of humanizing a visualization as it connects with people on a psychological level.

# The A-R-E Process

Everyone can create some one-liner scatterplot and call it data visualization. It takes a passionate and skilled data scientist, however, to transform basic visualizations into a story, that your target audience will not only understand, but be excited about and inspired

An example of a basic plot is this



Figure 1 — Our basic plot

There's a lot of things wrong with this plot. We improve it in these three steps:

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1. Add Information

2. Reduce Information

**3.** Emphasize Information

We improve the signal/noise ratio by adding useful information, but also by removing useless information. In an ideal visualization, all of the important information is present and emphasized while everything that does not add any real value is removed.

# Step 1— Add Information

We add: a title, axis labels, ticks and tick labels for the y-axis, a way to read single values for different age groups directly from the lines.



# Step 2— Reduce Information

Reducing information doesn't always mean actually deleting information like labels, legends or ticks. Sometimes, it just means reducing the extent to which the information is an obstacle to the reader. Here are some ideas on what to do with this plot:

We can: remove ticks, remove spines, remove the big legend and write the labels on each line directly, leave only 4 ticks on the y axis, remove the x and y labels and indicate them on the last tick directly

Step 3 — Emphasize Information

Now that we have added all the relevant information and removed everything that is not, we can still optimize our visualization. Here is a couple of ideas for this specific plot: Change font, font size, and weight of the title, Emphasize the continuous quality of the data. To change the title font, we can create a font\_dict and call it in the ax.set\_title() function. We could also go the other route and emphasize the categorical features of our data.

# **Alternative Visualizations**

# Curve alternatives

There are some great curve alternatives to the by now overused visual. Rather than showing the same old curves, **simulate** the effects of protective measures and social distancing, and show the impact through a series of animations.

Using these simulations, the effect of doing nothing, enforcing quarantine, or enforcing moderate or extensive social distancing are convincingly shown:



Simulation results showing the differences between different suppression strategies on the number of sick (brown), healthy (blue) and recovered (pink) people.

# **Future Work**

An important challenge for future developers of information visualization tools for public health is to focus not only on individual user needs and comprehension of graphics, but also to plan and develop these tools in the broader contexts of available data, existing algorithms/services, team collaboration, and inter-organizational and interdisciplinary needs. Too many software projects are developed as new information silos, resulting in redundancy of effort, failure to integrate data and tools, and challenges to training and adoption. Further, many existing systems are access-restricted, limiting their use in infectious disease epidemiology, and may not have completed (or shared) evaluations of their visualization features.

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Vol. 10, Issue 5, May 2021

#### DOI 10.17148/IJARCCE.2021.105120

Visualization tools of the future should be developed to be compatible with existing data formats and standards, and interoperable with each other. Future tools should also adapt to the increasing pressure to be open-access, allowing users from low-resource settings, academia, and industry to capitalize on the advances in surveillance and visualization technology. This level of interoperability could support more advanced features such as phylogeographic (the study of genetic variation across geographic space), inference of person-to-person contact from molecular epidemiology, statistical cluster detection based on joint spatiotemporal and genomic data, integration of remote sensing and environmental data, and other tasks as users become increasingly savvy in their use of advanced analytical and visualization tools for public health. Data Visualization for Covid-19 can be upgraded in near future by introducing Scientific charts, Artificial Intelligence and Machine Learning Charts, Augmented Reality Visualization Modules and 3D displays to offer multi-dimensional and multi-variable views to the target audience for a unique and thorough analysis.

#### CONCLUSION

The issue is around trusting data because of the ease with which it can be manipulated or misrepresented. The very best visualizations are the ones which force us to reflect upon the human side of things. Data Visualization is one more way for us to make sense of the complex, nuanced and uncertain crisis that we all are living through. It comes with its own pitfalls, benefits and complexities. There is no more important time for health organizations to use all of the data available to them than in a health crisis. The data can help health officials stay informed, but it can also help inform a response – where and how to intervene. As a result, the care that is being provided can improve and lives can be saved. The way that data is presented can also make a difference. Many different organizations are using visualizations of the current coronavirus that allow the data be viewed and understood more easily in order to improve the response. In this review, the authors assessed the inconsistencies with the current landscape of visualization tools developed for infectious disease epidemiology. The richness of the information offered by these data for communication and decision making are counterbalanced by difficulties in displaying, interpreting, and trusting these data sources. Several themes and challenges emerged pertaining to both individual stages as well as broader topics. Despite the different scholarly approaches of the included articles, the following themes emerged: (1) importance of knowledge regarding user needs and preferences; (2) importance of user training; integration of the tool into routine work practices; (3) complications associated with understanding and use of visualizations; and (4) the role of user trust and organizational support in the ultimate usability and uptake of these tools. A lot of people who don't practice data visualization won't know the nuances into the methodologies. They will see an official looking chart and take it as a hard fact. Herein lies the risk for both data visualization creators and consumers. The issue is around trusting data and how it can be manipulated or misrepresented. The very best visualization are the ones that force you to think about the human side of things. Data visualization is one more way for us to try to make sense of the complex, nuanced, and uncertain crisis that we are all living through. It comes with its own pitfalls, benefits and complexities.

#### ACKNOWLEDGEMENT

The authors express sincere gratitude to their guide Prof. Rucha Joshi who administered every step of this research and reviewed the article for final scripting.

# **Declaration of Conflicting Interests**

The Authors declare that there is no conflict of interest.

# Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

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#### International Journal of Advanced Research in Computer and Communication Engineering

Vol. 10, Issue 5, May 2021

#### DOI 10.17148/IJARCCE.2021.105120

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