Data Visualization E-25

Dashboard Project

Group 1

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Contents

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Abstract

This report introduces an interactive dashboard that visualizes global earthquake data from a Kaggle dataset covering 2023 to 2024, comprising 1,137 events with attributes such as magnitude, depth, location, and timestamps. The dashboard incorporates nine visualizations, including an interactive map with tectonic plate overlays, animated time-series charts, scatter plots, heatmaps, seasonal distributions, and outlier infographics. These visualizations reveal spatial patterns along plate boundaries, a predominance of shallow low-to-medium magnitude events, an unexpected clustering of events during summer attributed to dataset bias, and notable outliers such as a 640 km deep earthquake and another event felt by 184,000 people.

1. Background and Motivation

For our data visualization project, we chose to work with the *Global Earthquake* dataset[1] found on Kaggle. This dataset contains global earthquake event records from across the world. The data consist of things like time, geographic coordinates, depth, magnitude and other seismic-related attributes, making it well-suited for visual analysis and storytelling through data.

Our motivations for selecting this topic and dataset stem from a combination of personal and research interests.

1.1. Relevance to Real-world Problems

Earthquakes are one of the most impactful natural disasters. It destroys social infrastructure, communities and peoples way of life every time a substantial earthquake occurs, causing both human and economic losses.

Visualizing the geographical patterns can help communicate risk to the average person, and understanding the seismic activity can help prepare emergency responders and disaster prevention organizations to reduce losses and help with planning relief.

1.2. Suitability for Data Visualization Techniques

Earthquake data consists of spatial, temporal and multidimensional attributes, which makes it useful for a variety of data visualization techniques. This makes it possible to create a plethora of visual stories through things like map, clustering and time-based visualization to identify patterns.

Interest in how map visualization can be utilized has been the biggest motivation in choosing earthquakes as a topic. Seeing what kind of and how many attributes can be visualized in a map at one time, and how much this can tell about earthquake evolution and their trajectories over time.

1.3. Personal Interest

We live in an area with no significant seismic activity. So having never actually felt an earthquake, curiosity around how and where they happen has grown. Natural disasters like earthquakes have huge consequences on communities we have never been a part of, so understanding the severities of them is something we are interested in. Visualizing the data of earthquakes gives us a better understanding of the scale, and makes it easier to compare the geographical differences in regions that are more affected than others. This can also help us discover patterns and trends that are not immediately obvious through raw data, and help us understand the relationship between geological factors and seismic activity.

2. Project Objectives

Since our project has the goal of visualizing data about earthquakes, our objectives should revolve around their patterns, relationships and gaining an overall insight on earthquakes, which visualizations can reveal far better than raw table data.

Based on this reasoning we have developed a list of questions which we plan to answer with our visualization:

1. Where and when do earthquakes occur most frequently?
   - Does specific regions have more seismic activity than others?
   - How frequent are earthquakes (yearly, monthly, seasonal)?
   - Are clusters and hotspots identifiable?
2. How strong are the earthquakes?
   - What is the distribution of earthquake magnitudes?
   - Are high-magnitude earthquakes concentrated?
   - How often does high-magnitude (magnitude > 6) earthquakes occur?
3. What is the relationship between earthquake depth and magnitude?
   - Does depth relate to other attributes of earthquakes?
   - Are shallow earthquakes more common, and in which regions?
   - Is there a pattern to depth distribution over time?
4. How are earthquakes distributed geographically?
   - Do they relate to tectonic plate boundaries?
   - Are there patterns comparing continental vs. oceanic regions?
   - Is there specific bands of latitude/longitude where activity is higher?
5. How are earthquake patterns and trends developing over time?
   - Is earthquake frequency increasing, decreasing or stable over time?
   - Are there noticeable anomalies in specific years?
6. Can we easily identify extreme events?
   - Which earthquakes are outliers in magnitude or depth?
   - Are there extreme deviation in specific earthquake events?
7. What correlation of multiple variables are most common?
   - Does magnitude correlate with depth, location, time or any other attribute?
   - Are certain combination of attributes most common (e.g. shallow + high magnitude)?

With these questions we have set up sizeable goals we wish to accomplish with our visualizations and storytelling throughout or dashboard that we will create. These will be used to quality check and verify our project as a whole, but also the need of individual visualizations in our project. The ultimate goal is to have all these questions answered and how they are answered in our *Results from Story* chapter.

3. Data

3.1. From Where

This project utilizes the "Global Earthquake Data" dataset from Kaggle [1], uploaded by user shreyasur965 on September 18, 2024. The dataset compiles 1,137 global earthquake records sourced from the Earthquake API via RapidAPI, providing granular attributes like magnitude, location, depth, and timestamps for reliable seismological analysis.

3.2. Description

The Recent earthquakes dataset contains records for 1137 distinct earthquake events, each described by 43 variables. Every record corresponds to a unique event, capturing a wide range of details that collectively offer a perspective on the earthquake's context. Among the most important attributes are a unique identifier for each event, the exact date and time of the earthquake, and the magnitude, which quantifies the energy released during the event and is most often measured on widely recognized scales such as the Richter magnitude scale. The dataset also specifies the depth at which each earthquake originated beneath the Earth's surface, recorded in km, which is an essential parameter for assessing the surface impact and potential for damage.

Geographical information in the dataset is provided at multiple levels of specificity, enabling a detailed understanding of where each event occurred. Each record documents the continent, country, subnational region, city, locality, and postal code associated with the earthquake's epicenter, along with a full address or descriptive location field. Latitude and longitude coordinates give precise geo-spatial positioning for each event, enabling accurate mapping and deeper analysis. The place, distance from the nearest populated area, and timezone further enrich the dataset's locational context, while additional details about the event's location are captured in dedicated fields. The Shake intensity measured in the dataset, such as the Modified Mercalli Intensity (MMI), provides valuable insight into how events are felt by people and the potential for structural damage in affected areas. The measurements are used to assess how strongly an earthquake is felt at the surface, reflecting reports from individuals as well as instrumental data. In addition to intensity, the dataset includes information on tsunami triggers, indicating whether an earthquake has the potential to generate a tsunami and thus pose additional risks to coastal regions. The classification of event types, distinguishing between natural earthquakes and other seismic occurrences such as explosions, further enriches the contextual understanding of each record.

3.3. Data Processing

To prepare our data we had to process the dataset to make it useful for our dashboard implementation.

The first thing was to remove unnecessary entries. This included entries that was duplicates, and entries with no values in important columns:

```py
# Filter out rows with missing values in key columns
earthquakes = earthquakes.dropna(subset=['magnitude', 'depth', 'latitude', 'longitude'])
earthquakes = earthquakes.reset_index(drop=True) # Reset index after filtering

# Delete duplicate rows based on 'id' column
earthquakes = earthquakes.drop_duplicates(subset=['id'])
```

Furthermore we removed columns that was not needed. The criteria for being an unnecessary data column, was based on different reasons; if the data was completely or partly present in other columns, was in a format not suitable for data visualization (e.g. multiple values in one field), or data that was not interesting or needed for our visualizations:

```py
# Remove unnecessary columns
columns_to_drop = ["type", "updated", "url", "detailUrl", "status", "code", "sources", "types", "rms", "geometryType", "placeOnly", "location", "locality", "postcode", "what3words", "locationDetails"]
earthquakes = earthquakes.drop(columns=columns_to_drop)
```

The temporal attributes was set in UNIX time, so changing them to a read-able format was better:

```py
# Convert time to datetime (time is in milliseconds since epoch)
earthquakes['datetime'] = pd.to_datetime(earthquakes['time'], unit='ms')
```

Further categorization of the data could be useful. For things like earthquake distribution, time-based categorization; categorizing the month and season to make a more simple and straight forward time-series distribution visualization:

```py
# Make new columns for month and season
earthquakes['month'] = earthquakes['datetime'].dt.month
earthquakes['season'] = earthquakes['month'] % 12 // 3 + 1
season_mapping = {1: 'Winter', 2: 'Spring', 3: 'Summer', 4: 'Fall'}
earthquakes['season'] = earthquakes['season'].map(season_mapping)
```

To find correlation and categorize seismic attributes, we chose to put earthquake records in to simple size categories for both their magnitude (small, medium, large) and depth (shallow, intermediate, deep). This approach helps the viewer understand what constitutes a deep or strong earthquake, which they otherwise might not based on numerical values:

```py
# Categoerize magnitude to small, medium, large in new column
earthquakes['magnitude_category'] = pd.cut(
    earthquakes['magnitude'],
    bins=[-float('inf'), 4.0, 6.0, float('inf')],
    labels=['Small', 'Medium', 'Large'])

# Categorize depth to shallow, intermediate, deep in new column
earthquakes['depth_category'] = pd.cut(
    earthquakes['depth'],
    bins=[-float('inf'), 70.0, 300.0, float('inf')],
    labels=['Shallow', 'Intermediate', 'Deep'])
```

Other interesting columns were present in the data set as well. The dataset consisted of records from several places, so there could be multiple records of the same event. This was put to relations through the `ids` column, which could then be used for de-duplication, to only get records of unique seismic events. Though after considerations, was decided not to be done, since we then would have too small of an amount of data samples to use for our data visualizations.

4. Visualization of Dashboard

4.1. Design

In this sub-chapter, we will explore the design choices and the basis for these choices. Design can be considered in several different directions. Most importantly the choice of visual encoding for every specific use case, story and type of visualization technique we want to use in our project.

For our design we also have to consider the complexity of our design, should it be simple and straightforward for the user, or should we go for a complex design to show more detailed data and visualizations.

4.1.1. Visual Encoding

We use visual encoding to translate our data attributes into visual properties through several different data visualization techniques. Our overall goal with our visualizations is to make the readability and patterns of the charts as accessible for our general intended user demographic.

But not all visual channels are equal. Some visual channels are more perceptually accurate than others. Things like using a position on a common sacle and 1-dimensional lengths are considered highly effective compared to others. This also takes effect when considering categorizations, which our project will use as well, where color hues usually is poor for ordered data, but excels when used for categorical distinctions [2, Ch. 5.4].

Following Munzner's principle of *"matching the importance of data to the effectiveness of channels"* [2, Ch. 5.6], the most critical attributes in a visualization should be encoded using the most perceptually accurate visual channels. Secondary or other contextual attributes can then be assigned to less precise channels (e.g. using color hue or shapes). Using this theoretical approach, we can make ensure that the viewers perceive the most important and meaningful aspects of a visualization first.

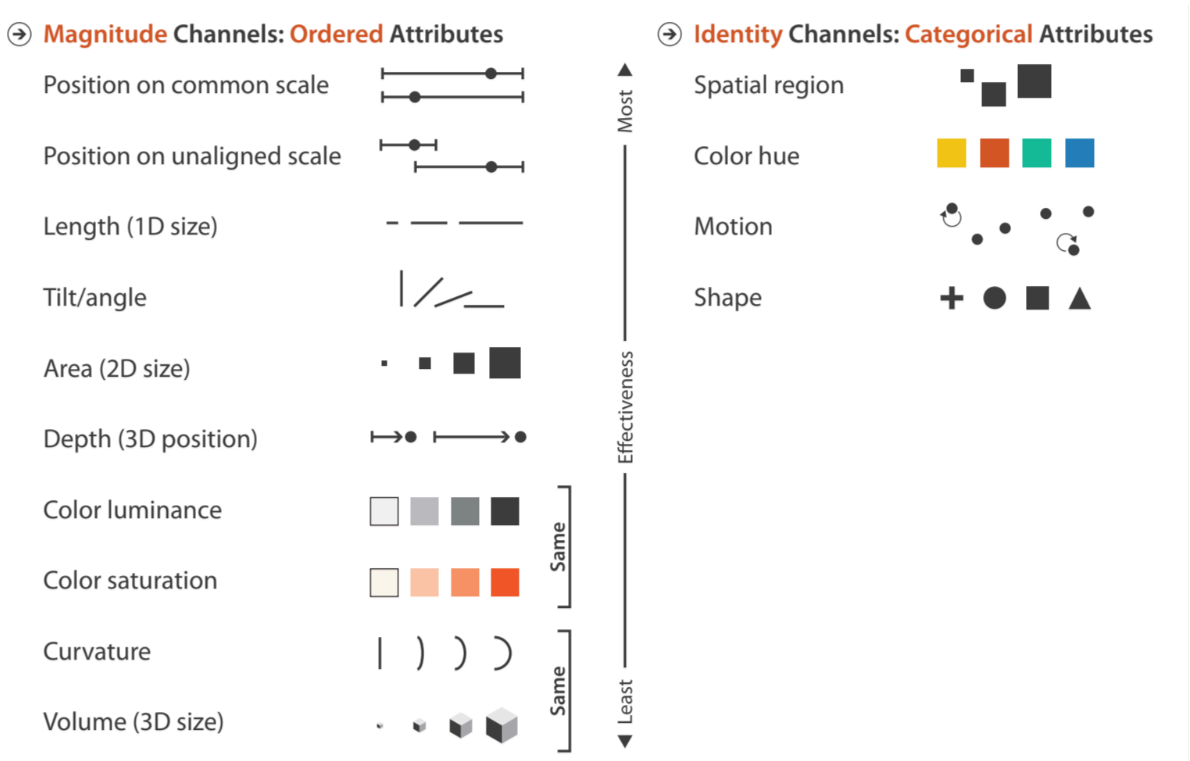

Figure 1: Visual Encoding Channel Rankings [2, Fig. 5.6]

Using the rankings (See Figure 1) we can then map our data attributes from our dataset [1] based on their importance. Some of the most critical attributes are the spatial position, magnitude, depth and temporal attributes that each require different visual encodings. Each design choice made for our visualizations are based on the approach described.

4.1.2. Choice of complexity

Deciding on the complexity of our visualizations are important; going too simple will have the risk of losing important information, but going too complex can risk overwhelming the viewer. Therefore we need to find a fine line choosing the complexity, keeping it simple enough for viewers, but without going too simple.

This approach is backed up by Jambor, who emphasizes that effective scientific figures should prioritize clarity and reduce unnecessary clutter, ensuring complex data remains interpretable without overwhelming the viewer [3].

To simplify our design, we should decide on simplifying things where possible. Keeping a clean color pallette throughout every visualization, and removing chart junk to keep it simple. But we can't go too simple, we still need to make sure we retain necessary complexity, this is prioritized by not simplifying aspects that consist of critical data attributes (e.g. magnitude, depth, time and spatial location) to prevent hiding their important patterns. Overall the project has the goal of adopting a "simple-but-not-simplistic" design philosophy, focusing on clarity and effective communication.

4.2. Must-Have Features

ID	Feature
F1	Must have at least 3 types of graphs (i.e barchart, timeseries plot or boxplots)
F2	Must have at least one animated graph
F3	Must have an AI-generated graph with description on how (platform and prompt used)
F4	Must have at least 9 graphs
F5	Must have an option to download the report as a manual from the dashboard
F6	Must have a map that visualizes the location of earthquakes and their depth and magnitude

5. Results from Story

5.1. Implementation of the Visualizations

Our earthquake dashboard supports five types of visualizations, each chosen for its ability to explore specific features of the earthquake data. The first type is "Interactive Geographic Map," implemented in map.py, which supports a scatter mapbox visualization layer to display earthquake points with overlaid tectonic plate boundaries. The dominant encoding features in this type of visualization involve location or geographic position (latitude and longitude) variables displayed through size variables that illustrate magnitude, with greater size representing stronger earthquakes, and colors (using a Viridis channel) that represent earthquake depth variables and enable users to conveniently identify shallow versus deep earthquakes through visual inspection. In this image, the color is from the Viridis scale and is appropriate because it supports ordered data like earthquake depth variables. Tectonic plate boundaries can also be superimposed in red in this image. The rationale behind this feature is that geographic position is a natural channel for geographic or location-based visualizations, size is practical for illustrating magnitude variables because it is perceived preattentively, and a color channel is appropriate for illustrating ordered variables like earthquake depth.

The second visualization is a Scatter Plot (scatterplot.py), where the relationship between magnitude and depth is analyzed, with an optional color scheme for categories. In this scatter plot, the magnitude is plotted using the x-coordinate, and the depth, graphed with an inverted y-coordinate to place deeper earthquakes below others, occupies the rest of the coordinate space. The inclusion of an optional coloring scheme enables the use of categories such as magnitude type or network in the scatter plot, where position is the most accurate way to perceive quantitative differences, with an inverted y-coordinate to provide an "underground" metaphor.

The third visualization is an Animated Time Series implemented using timeseries.py. It is an animated bar chart with a red linear regression trendline that shows earthquake characteristics over time. The x-axis marks time aggregated at a daily, weekly, or monthly basis, while the bars correspond to an aggregated value for a certain time series point, which is an average value for magnitude, a maximum value for magnitude, or a count of occurrences. It is highly suitable for comparing discrete time periods; adding an animated aspect highlights the story elements of time-series data analysis.

The fourth is a Seasonal Distribution Chart in seasonal.py; it combines a grouped bar chart and a donut chart. The x-coordinate is categorized by months from January to December, and each bar represents the number of earthquakes that occurred in a particular month. The color of every bar is based on seasons: blue for winter, green for spring, orange for summer, and red for Autumn. Additionally, a donut chart is used to represent the number of occurrences for each season: blue for winter, green for spring, orange for summer, and red for Autumn.

The fifth visualization is Outliers Infographic, which is created using the outliers.py file. The infographic uses a card design to showcase the three most powerful earthquakes among the data sources. This is achieved through sizes and center positioning, with the most important one being the largest and most prominent. The use of a green to red color gradation indicates the level (from lowest to highest), while magnitudes are emphasized through bold font sizes to draw the audience's attention to the most intriguing values, while semantic icons (such as a calendar icon, a push-pin symbol, or a tsunami mark) ensure quick identification and awareness among the target group. A number of crucial design elements make up a dashboard. Filtering tools, such as magnitude and range sliders, help analyze data effectively. Color schemes throughout the dashboard emphasize meanings, such as red for large or warning values. Coordinated views automatically update all graphs when a selection is made from a reactive data source. Progressive Disclosure keeps the dashboard clutter-free by tucking complex settings into popovers for better usability.

The sixth visualization in the dashboard is a heatmap, implemented in heatmap.py. This visualization highlights correlations among earthquake variables, including magnitude, depth, latitude, and longitude. The heatmap employs a two-dimensional grid where both axes represent the same set of variables, enabling users to assess relationships and dependencies between these attributes.

The seventh visualization is a scatterplot matrix, developed in scatter_matrixc.py, which offers a multivariate overview of earthquake attributes within a single, compact display. The matrix comprises multiple scatterplots arranged in a grid, with each cell representing a pairwise comparison of variables.

5.2. Story of the Dashboard

Using the data visualizations presented on the dashboard, we strive to narrate a unified story about the earthquakes contained within our dataset. The project objectives (as detailed in Project Objectives) define the questions we seek to answer, and the dashboard functions as the platform for exploring these inquiries.

Starting with the value boxes at the top, we get a statistical snapshot: the total earthquake count, the average magnitude, and the average depth. These numbers offer a foundational understanding of the dataset, setting the stage before exploring more complex visualizations.

Next, we examine the evolution of earthquake activity over time through an animated time-series graph. This visualization displays the variations and development in both the frequency and magnitude of earthquakes throughout the time period. Though due to the dataset's limited scope of two years, it is challenging to discern any significant long-term trends.

A key component of our dashboard is the interactive geographic map. By encoding magnitude using point size and depth using color hue, the map gives a clear overview of where earthquakes occur. When tectonic plate boundaries are added to the visualization, the spatial pattern becomes immediately apparent: earthquakes overwhelmingly align with these boundaries. The map also reveals a few location outlier events occurring farther from plate boundaries than typical.

Because outliers can be particularly meaningful, we also examine them more closely. While the map hints at spatial outliers, we wanted to explore outliers across other attributes as well. This is visualized using infographic cards highlighting the strongest earthquake, the deepest earthquake, and the event that was felt by the most people. The strongest earthquake is not an extreme outlier compared to the rest of the dataset, as similar magnitudes appear elsewhere. However, the deepest event (640 km) and the event felt by nearly 184,000 people are clear anomalies, lying far outside the normal range. The infographics alone do not show how these compare to typical values, so we explore these patterns further in subsequent plots.

To investigate attribute relationships and compare outliers to the rest of the dataset, we use a scatterplot of magnitude versus depth. This visualization shows that deeper earthquakes are more likely to have higher magnitudes, although a small number of very strong but shallow earthquakes form notable exceptions. The scatterplot also helps highlight both weak and strong outliers.

To clarify density patterns that may not be immediately obvious in the scatterplot, we use a heatmap categorizing events by depth and magnitude. This makes it clear that most earthquakes are shallow and fall within the low-to-medium magnitude range.

Earthquakes also have societal impact, so we further examined the relationship between magnitude, depth, and the number of people who reported feeling the event. Using a scatterplot matrix, we see that the earthquake with the highest number of felt reports is a significant outlier: in the magnitude–felt and depth–felt comparisons, it stands alone and is not clustered near the axes like the others.

To uncover broader temporal patterns, we analyze the distribution of earthquakes by month and by season. A bar chart shows the number of events each month, using seasonal color coding to reinforce the grouping. This visualization reveals a strong pattern: the summer months (June–September) account for nearly half of all events in the dataset.

Taken together, the dashboard provides a comprehensive visual story of the earthquake data. Each visualization highlights different aspects of the dataset's patterns, trends, relationships, and outliers.

5.3. Expectations to Results

Before building our dashboard and visualizing our data, we formed some expectations about what the data would show. We expected typical magnitudes between 3-6 and that the earthquakes would occur mostly near tectonic plates (general knowledge). We thought that the depth of the earthquake would correlate to the magnitude, the deeper the stronger, and expected the earthquakes to have no temporal trends in terms of seasonal and monthly. We expected the felt reports to scale with magnitude, the stronger the bigger societal awareness, and expected there to be some outliers, but not extremely rare.

These expectations was based on our general assumptions from our general knowledge and logical intuition which we had yet to support by data. This section will go through and verify whether our expectations was correct, and if not, how the result changed that.

Through general knowledge about how earthquakes happen we were almost certain that earthquakes almost exclusively occurred along tectonic plates. Through the visualizations we confirmed this assumption, and saw that the spatial pattern was stronger and more concentrated along tectonic plates than we initially expected.

For magnitude patterns we expected most earthquakes to be moderate and usually between 3-6, with rare ones exceeding 6+ magnitude. This was also confirmed through our visualizations and storytelling, easily perceived that small to medium magnitude earthquakes was the most common, and that stronger events still occurred, but did not dominate the dataset.

Our initial expectation was that depth patterns correlated to strength, making stronger earthquakes occur at deeper depths. But through our result based on our visualizations, this was partially contradicted. The deepest earthquakes were not the strongest, and several strong earthquakes were actually very shallow in depth. The overall depth distribution was more skewed toward the shallow depth category than we expected, concluding that depth to magnitude is not a simple and straight relationship.

We expected that there was no seasonal and monthly variation to earthquake frequencies, and that our time-series plots would show this with random fluctuations. But after visualizing this, we instead confirmed something completely different from our expectations. There was a clear seasonal pattern, where June-September had almost half of all events, clustering most earthquakes to the summer season. This was a surprise to us, and with further research found this conclusion to be not true on a global scale, searching further, to find a possible explanation. The explanation we found was, that the dataset only represents a small sample of earthquakes in a short time span of 2 years, creating a clear bias that created the seasonal concentration.

For the outliers, we expected few outliers in both magnitude, depth and felt reports. The result showed this to be the case, but even more extreme than expected. We found one event, felt by 184.000 people, that was a massive outlier. And found another outlier, with 640 km depth, having a extreme variation in only its depth.

Another expectation was that the magnitude correlated with felt reports, which was disproven. Some moderate earthquakes affected huge populations and the strong earthquakes was positioned far from populated areas, impacting the felt counts. Learning that the impact of earthquakes on humans is not purely physical, but a geographical and demographic dependent attribute.

To summarize, most of our expectations was partly or fully backed by the visualizations we created. What surprised us was the unexpected seasonal clustering, uneven felt reports, that strong earthquakes can be shallow, and that outliers are more extreme than predicted. Comparing our expectations with the results revealed that earthquakes follow geographical rules, but behave far less predictably across depth, impact, and temporal patterns than we expected. Using our visualizations allowed us to uncover patterns that our simple assumptions could not predict.

5.4. Objectives Accomplished

In the start of the project we set out to explore some questions we wanted answered through our visualizations (See *Project Objectives*). Now we want to verify whether these questions have been answered.

The dashboard successfully answered all our seven main project objectives. It shows where and when earthquakes occur most often, identifies regional hotspots and whether strong earthquakes cluster through. It clearly reveals the seasonal and monthly patterns, and describes how strong earthquakes typically are and how often large events happen. Through scatterplots, heatmaps and pairwise comparisons, we explain the relationships between our key attributes, and show that shallow, low to medium magnitude strength earthquakes dominate. The geographic map clearly visualizes that earthquakes follow tectonic plate boundaries. Outlier cards and different plots are used to identify extreme events in magnitude, depth, and societal impact through felt reports, and a combination of visuals show which multi-attribute patterns are most common, clarifying the weak and strong relationships between attributes.

Problems with the limited temporal scope of the dataset works against a defined conclusion of some of our objectives. This could be further investigated through acquiring more entries for more coverage, so we do not rely on data that only spans from a two-year period.

6. Discussion and Conclusion

We developed an earthquake data visualization dashboard that fulfills all project requirements. The final dashboard includes nine visualizations, meeting the minimum specification. These visualizations comprise an interactive geographic map displaying earthquake locations and tectonic plate boundaries, where marker size encodes magnitude and color represents depth. An animated time-series bar chart with a trend line illustrates the evolution of earthquake activity (F2). Additional visualizations consist of a magnitude-versus-depth scatter plot, a monthly distribution bar chart colored by season, a seasonal donut chart, a magnitude-depth heatmap indicating event density, a scatterplot matrix showing relationships among magnitude, depth, and felt reports, and infographic cards highlighting the strongest and deepest events. The dashboard also presents the most felt earthquakes (f3 AI-generated) and three value boxes displaying total events, average magnitude, and average depth. A filtering system enables users to explore data by magnitude range, depth range, and magnitude type, with all visualizations updating dynamically in response to filter changes. A raw data viewer with column selection is also included, allowing users to access the dataset for independent analysis.

In addition to meeting the specified requirements, our dashboard addresses all seven questions outlined in the Project Objectives section. Our analysis identified tectonic plates, examined the magnitude distribution, demonstrating that most events are in the small-to-medium range, and explored depth-magnitude relationships, revealing that most earthquakes are shallow.

6.1. future work

Given additional time, we would pursue several enhancements to improve the dashboard's functionality. Currently, our dashboard uses a static dataset from Kaggle covering 2023-2024. With further development, we would implement direct integration with the USGS earthquake API or other seismic data sources to enable real-time earthquake monitoring. This enhancement would transform the dashboard from a historical analysis tool to a live monitoring system that updates automatically as new earthquakes occur. We would also add WebSocket support, such as socket.io, to ensure the dashboard updates instantly when new data is received. Although the dashboard's user interface and user experience are functional, several improvements could enhance usability. For example, enabling users to bookmark notable earthquakes for later reference and create personal collections of events for comparison.

7. Appendix

7.1. GenAI

- Grammarly - For grammar

7.2. Contribution

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7.3. Code Contribution

Throughout the project we have developed our dashboard utilizing the pair-programming software development practice. For most of the code implementation one of us has written the code, and another sitting “over-the-shoulder”, giving pointers, feedback and solutions. These roles were swapped depending on the code tasks, giving us as much individual insight to the code and how it works as possible. Some of the code has been developed while alone, in this case we ensured that everything written alone was still comprehensively reviewed by the non-author, making sure the code quality and understanding was held.

Bibliography

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