URL for Demo Video on YouTube:

URL for Systems: https://siddydutta.github.io/Multiview-Visualisation-Systems/

Information Visualisation Group Project
Multiview Visualisation

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Chapter 1 Design and Implementation

1.1 The Data

The chosen dataset, the World Weather Repository, provides daily weather information for capital cities around the world, including features such as temperature, humidity, wind, and precipitation.

Link to source data: https://www.kaggle.com/datasets/nelgiriyewithana/global-weather-repository/data (retrieved on 2025-02-22)

The dataset is a table type, with rows representing data items with different metric measurements across locations and columns representing weather-related features. It also contains latitude and longitude columns, which provide a spatial component. While the original dataset is updated daily, making data availability dynamic, the filtered subset used below is static.

With 41 features covering 248 unique cities, this dataset is comprehensive, containing 54,763 data items. The dataset was filtered [1] to include only specific cities and weather features from 2024-05-16 to 2025-02-16, reducing the number of data items to 7,943 and the feature set to 7 attributes, as described below.

1. **location_name**: A categorical attribute representing the capital cities of 27 countries of the European Union and the United Kingdom.
2. **latitude**: A quantitative attribute providing a spatial location. As the filtered dataset only contains countries from the northern hemisphere, all values are positive.
3. **longitude**: A quantitative attribute providing a spatial location. The dataset includes values both east and west of the prime meridian.
4. **last_updated_epoch**: A quantitative attribute with sequential ordering representing the Unix timestamp of when the measurement for the data item was recorded.
5. **temperature_celsius**: A quantitative attribute with diverging ordering with values both above and below 0° Celsius.
6. **humidity**: A quantitative attribute with sequential ordering represented as a percentage.
7. **condition**: A categorical attribute representing the weather condition as a textual category, for example, "Clear/Sunny".

Furthermore, some attributes were derived from existing columns to simplify visualisation and filtering tasks:

8. **date**: A quantitative attribute with sequential ordering transforming the *last_updated_epoch* timestamp into a yyyy-mm-dd format.
9. **day**: A quantitative attribute with cyclic ordering extracted from the *date* representing the day of the month, which ranges from 1 to 30 / 31 across ten months.
10. **month**: A quantitative attribute with sequential ordering extracted from the *date* representing the month, which ranges from May 2024 to February 2025.

11. **year**: A quantitative attribute with sequential ordering extracted from the *date* representing the year, which is either 2024 or 2025 in the filtered dataset.
12. **season**: A categorical attribute derived from the *latitude* and *month*, mapping each data item to a value - Summer, Autumn, Winter, or Spring.

1.2 The Tasks

Users can perform several key actions while exploring the "World Weather Repository" dataset through the three visualisation systems. The selected tasks are exploratory in nature, requiring users to extract specific insights and compare historical weather patterns [2]. This may be particularly relevant for types of users such as climate researchers, journalists, or policy analysts.

The actions required by the tasks in this section primarily involve high-level "Consume" and "Discover" actions as defined by the terminology in the "Analyze" section of Munzner's "Why" framework [3] for task abstraction.

1.2.1 Task 1: Lookup

Determine the week # when the first occurrence of a "Snowy" weather condition took place.

The task requires users to query specific data items from the dataset by filtering on a categorical attribute and then identifying the first occurrence among the filtered data items. The target is the specific week number when the "Snowy" weather condition first occurred.

1.2.2 Task 2: Search

Find three cities that had humidity levels between 40% and 50% in week 28.

The task involves a search action where the location in terms of the humidity levels and the week number are known, while the user must browse to find the target, i.e. the three cities. This requires users to filter the dataset based on a quantitative range and a temporal constraint by performing a query action followed by identifying three data items from the filtered data.

1.2.3 Task 3: Derive

Find the date when London recorded its highest temperature, and determine the lowest temperature recorded across Europe on the same day.

The task involves multiple actions through querying and comparison steps. First, users must query the dataset to identify the highest value of a quantitative attribute, i.e. temperature for a specific location. Then, using the associated temporal value, they perform a derive action to extract the values of the same quantitative attribute for a different set of data items. Finally, they identify the lowest value among these extracted data points.

1.2.4 Task 4: Compare

Rank the cities - Luxembourg, London, and Brussels based on the number of "Fog / Mist" days experienced in November 2024.

The task requires users to query the dataset to retrieve the number of days with a specific categorical attribute for each location in the dataset over a defined temporal range. Users then perform a comparison action by ranking the cities based on the aggregated counts of the categorical attribute.

1.3 The Core Systems

1.3.1 System A

- Zip File: SystemA.zip
- System: https://siddydutta.github.io/Multiview-Visualisation-Systems/SystemA.html
- Code: https://github.com/siddydutta/Multiview-Visualisation-Systems/blob/main/SystemA.ipynb

1.3.2 System B

- Zip File: SystemB.zip
- System: https://siddydutta.github.io/Multiview-Visualisation-Systems/SystemB.html
- Code: https://github.com/siddydutta/Multiview-Visualisation-Systems/blob/main/SystemB.ipynb

1.3.3 System C

- Zip File: SystemC.zip
- System: https://siddydutta.github.io/Multiview-Visualisation-Systems/SystemC.html
- Code: https://github.com/siddydutta/Multiview-Visualisation-Systems/blob/main/SystemC.ipynb

1.4 Generalised Selection

System B extends the core functionality by enabling generalised selection through interactive query relaxation. Users can select data items in the scatter plot and expand their selections dynamically via query relaxation techniques. This requires a well-defined semantic structure and traversal policy to guide query expansion [4].

1.4.1 Semantic Structure

Given the dataset's time-series nature, a hierarchical date structure can be defined that supports progressive generalisation. This hierarchy is derived from the *date* column and consists of:

1. Day: The finest level of abstraction as individual dates (e.g., 2024-09-16).
2. Week #: Groups of seven days indexed sequentially (e.g., week 20).

3. Month: Data grouped by month (e.g., September).
4. Season: The highest level of abstraction as broad seasonal categories (e.g., Autumn).

This structure enables multi-level query generalisation, allowing users to explore data at different granularities.

1.4.2 Traversal Policy

Query relaxation is performed by traversing the semantic hierarchy. With each relaxation step, the relaxer moves one level higher in the hierarchy and generates a query that selects all values in the current sub-hierarchy, expanding the selection to a broader level.

- Day: Includes all the data items from the initially selected day across all locations.
- Day → Week: This expands to include all data items with the same week number.
- Week → Month: Extends the selection to cover all data items in the same month.
- Month → Season: The broadest selection, grouping data by the mapped season.

This systematic relaxation ensures flexible selection while preserving meaningful structure.

1.4.3 Implementation

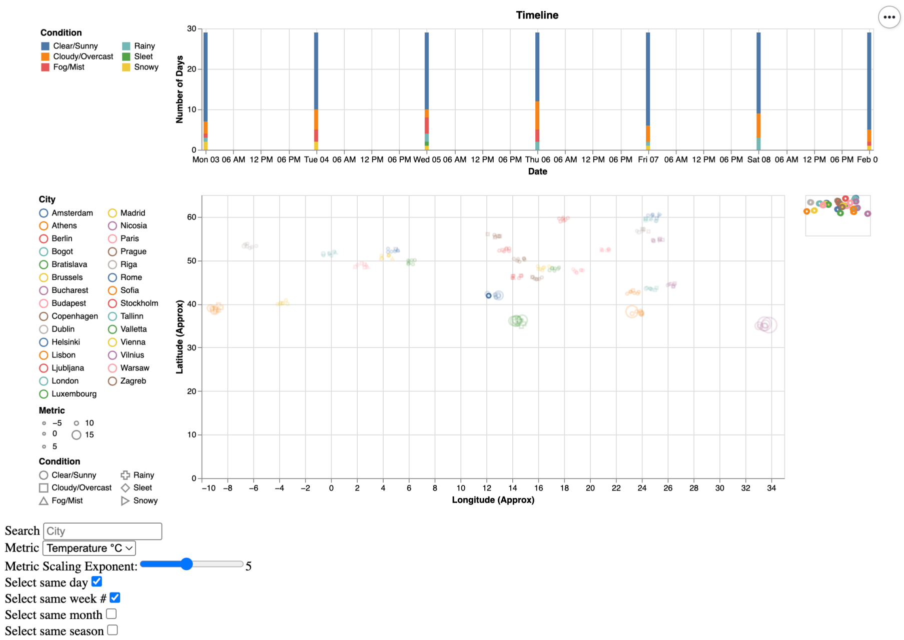

Figure 1: Query Relaxation to Select Data Items of the Same Week

The system enables generalised selection via interactive query relaxation using Altair selection predicates. Users can first select a particular data item and then use checkboxes to expand the selections across the hierarchical levels. The query relaxation logic below is implemented using Boolean expressions and ensures that selections are dynamically updated based on the user input via checkboxes.

```
selection_boolean = (~day_checkbox & ~week_checkbox &
~month_checkbox & ~season_checkbox)| \
(day_checkbox & day_matches) |       \
(week_checkbox & week_matches) |     \
(month_checkbox & month_matches) |   \
(season_checkbox & season_matches)
```

The default view with no checkboxes selected allows the user to select a specific data item, which is highlighted using opacity. The checkbox-based selection mechanism then allows the users to traverse the semantic hierarchy, selecting broader time intervals step by step. Additionally, the selection persists across the linked views in the bar chart and mini-map visualisations.

1.5 Demo Video

URL for Demo Video on YouTube:

1.6 Design Comparison

1.6.1 Weather Conditions Encoding

In the dataset, the weather condition is a categorical attribute with seven distinct values. This attribute is encoded using the shape channel on point marks in a line chart in system A, the colour hue channel in a stacked bar chart in system B, and the colour hue channel in a pie chart in system C.

Both shape and colour hue are effective visual variables for categorical data as they allow distinct values to be perceptually distinguished. The first task requires the user to identify the first occurrence of a particular weather condition, which is best supported by system B's colour hues, requiring minimal interaction, thus enabling pre-attentive processing.

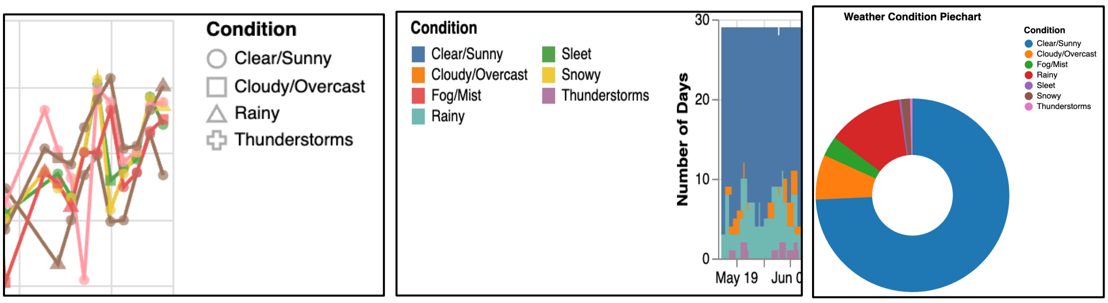

Figure 2: Shape & Colour Hues for Weather Condition (Systems A, B, C)

The shape encoding in system A proves to be weaker due to the large number of categories, which makes it difficult to differentiate between squares and circles or triangles with different directions, especially at small sizes. While system C also uses the colour hue visual variable, it presents the data as a pie chart, focussing on proportions rather than temporal trends, necessitating an interactive exploration to complete the task, hence making it less effective.

1.6.2 Geo Spatial Encoding

The dataset contains geographic attributes - latitude and longitude representing spatial locations for cities. These attributes are encoded using the position channel through different visual idioms - a scatter plot, bubble plot and heatmap in systems A, B and C, respectively.

As tasks 2, 3 and 4 require spatial assistance, the effectiveness principle [3] was invoked where the most important attribute, location, is encoded by the most effective visual channel, leveraging human spatial reasoning. System A's scatter plot overlaid on a map layer is the most effective representation, as each location is represented by a single mark, facilitating easy identification and selection. In contrast, System B violates the expressiveness principle by overplotting data points, obscuring values at higher zoom levels. System C further limits spatial representation by encoding locations along the Y-axis of a heatmap rather than using geographic positioning.

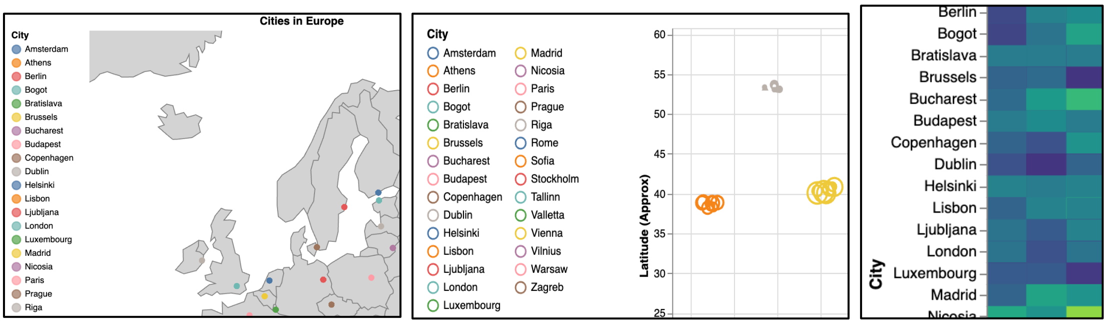

Figure 3: Using the Position Channel for Spatial Encodings (Systems A, B, C)

A choropleth map, often used for geospatial data encoding values using the colour hue or colour saturation channel on area fills, was not used. Since weather data is highly localised, such a visual idiom could obscure detailed spatial variations within large areas.

1.6.3 Temporal Filtering

The dataset includes a date attribute representing the temporal dimension. System A encodes time using the position channel on the X-axis of a line chart, allowing users to filter data by zooming and panning. While line charts effectively reveal trends in time-series data, the interaction introduces overhead, requiring iterative adjustments to refine the view.

System B enables brushing over a bar chart, where time is also mapped to the position channel using bar marks. This approach allows users to select a date range while maintaining an overview of trends. As a result, System B effectively supports tasks 2 and 3, which require selecting specific dates, and task 4, which involves filtering by a date range.

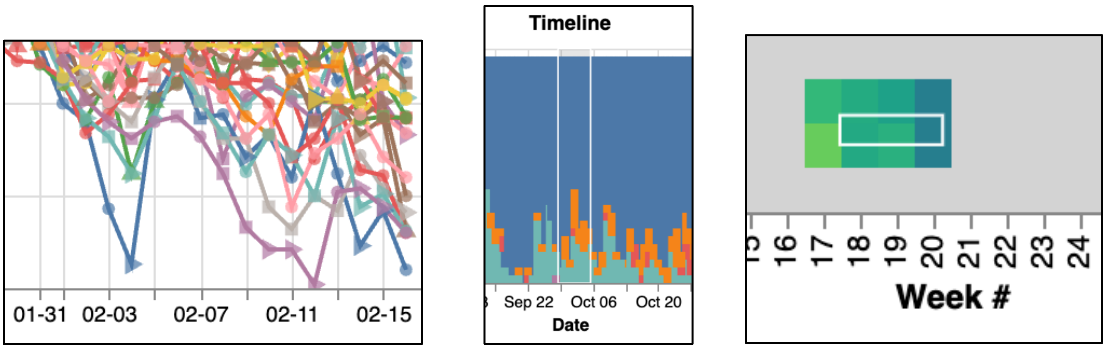

Figure 4: Zooming and Panning (System A) & Brushing Along the X-Axis (Systems B, C)

System C facilitates brushing over a heatmap, selecting weeks along the X-axis. The heatmap uses area marks, with time encoded in the position channel and a quantitative attribute mapped to the colour channel using a sequential colormap. Explicit controls such as range sliders were not employed in any system, as zooming, panning and brushing seemed more intuitive for the temporal filtering required to perform the tasks.

1.6.4 Quantitative Metrics Encoding

The dataset includes two key quantitative attributes - temperature and humidity. In System A, these attributes are encoded using line marks in two separate line charts, mapping the quantitative values on the Y-axis. This leverages the high precision of the position channel, enabling users to detect extreme values as required in Task 2.

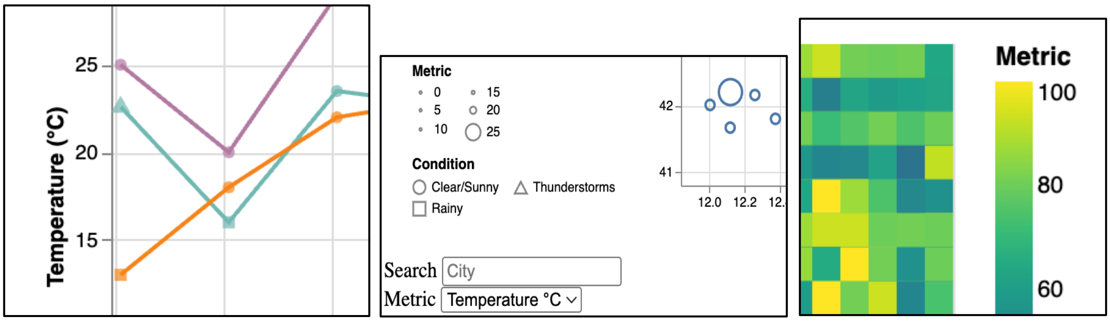

Figure 5: Position, Size & Colour Value for Quantitative Attributes (Systems A, B, C)

In System B, both metrics are encoded in a bubble plot, with the size channel representing quantitative values. This encoding allows users to easily identify fluctuations but sacrifices precision due to the inherent difficulty of accurately comparing sizes of bubbles.

System C employs a heatmap, where the colour saturation channel encodes the chosen metric, aggregated by week. Additionally, stacked bar charts are used to represent the contribution of each location to a given day's metric. The dual approach allows for both high-level comparisons and detailed breakdowns at the cost of an interaction and memory burden, as users must explore multiple views to extract precise values.

Alternative approaches, such as dual-axis line charts, were not implemented due to the dataset size, which led to visual clutter and interpretation challenges.

1.6.5 User Selection & Filtering

As the dataset contains multiple categorical, quantitative, temporal and spatial attributes, effective filtering mechanisms are essential for supporting the tasks. System A allows filtering by city (legend), spatial region (map brushing), and date (zooming / panning on the line chart) and condition (legend). While effective for fine-grained exploration, such as for tasks 1 and 3, it requires iterative adjustments.

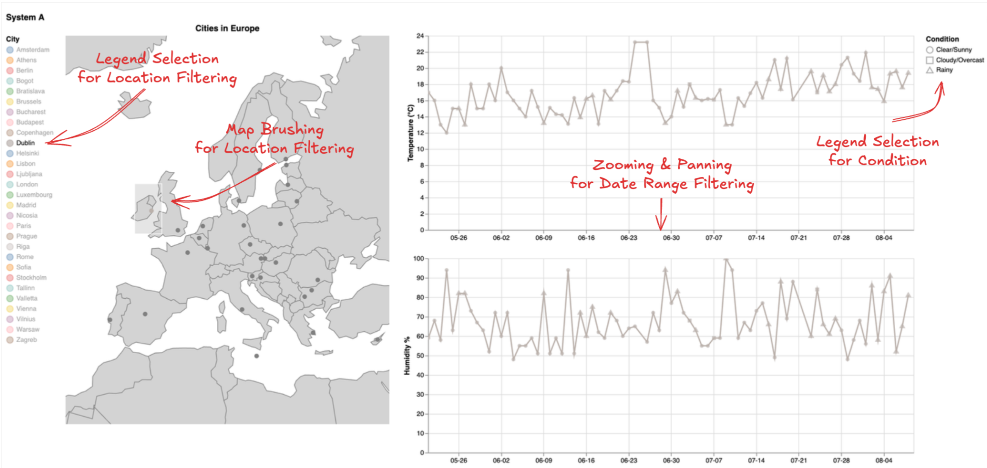

Figure 6: Brushing, Panning and Legend Selection (System A)

System B supports weather condition filtering (legend) and scatterplot selection, with an option to generalise by time granularity (day, week, month, season) via checkboxes. Additional min-max slider filters are provided to filter quantitative attributes based on a range, making it highly effective for task 2. Additionally, a search box allows location filtering.

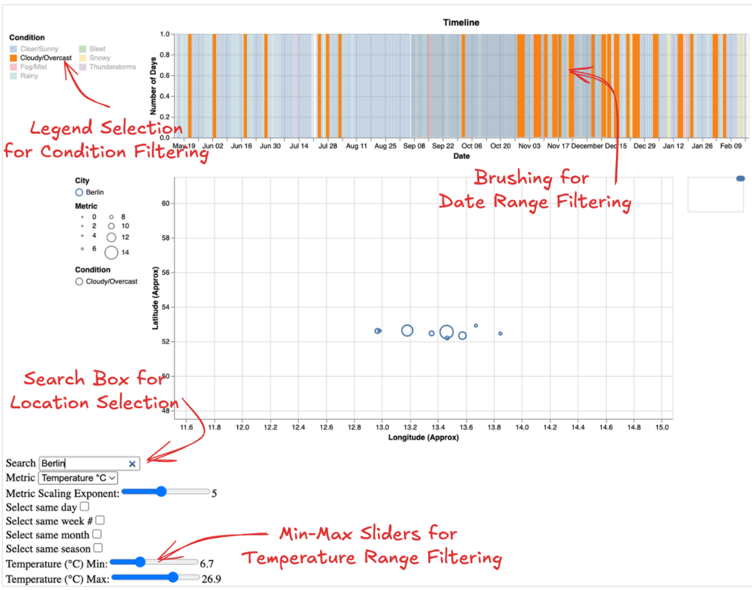

Figure 7: Brushing, Legend Selection and Slider Filtering (System B)

System C offers the most flexible filtering via heatmap brushing (date & location), city and condition legends and zooming/panning. While powerful, this increases interaction overhead and cognitive load, requiring users to remember selections - especially in task 4, which involves tracking aggregate counts over time.

Figure 8: Panning, Brushing and Selection (System C)

External bindings such as dropdown menus were not implemented to prioritise more direct manipulations.

1.6.6 Multiview Linking & Interaction

Coordinating multiple views in visualisation systems allows users to explore different facets of the dataset across spatial, temporal, and categorical dimensions, following the overview first, zoom and filter, then details-on-demand principle [8]. In system A, interactive selections on the map or legend highlight corresponding cities in the line chart, and vice versa. This bi-directional linking helps in task 2, where users query city specific data.

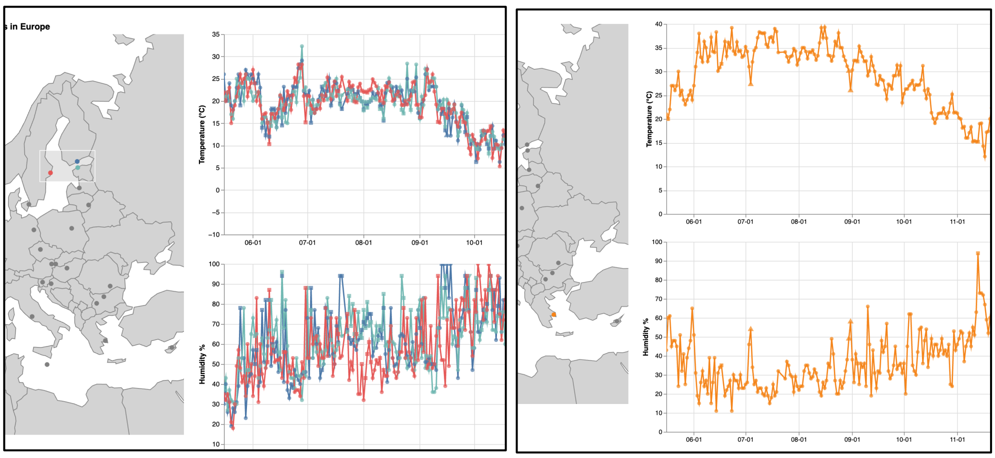

Figure 9: Bi-directional Linking (System A)

System B also supports bi-directional linking: filtering a time range in the stacked bar chart reflects on the scatterplot, and general selections on the scatterplot update the bar chart. Selecting a weather condition from the legend filters both views, useful for task 1. A linked minimap aids navigation while zooming.

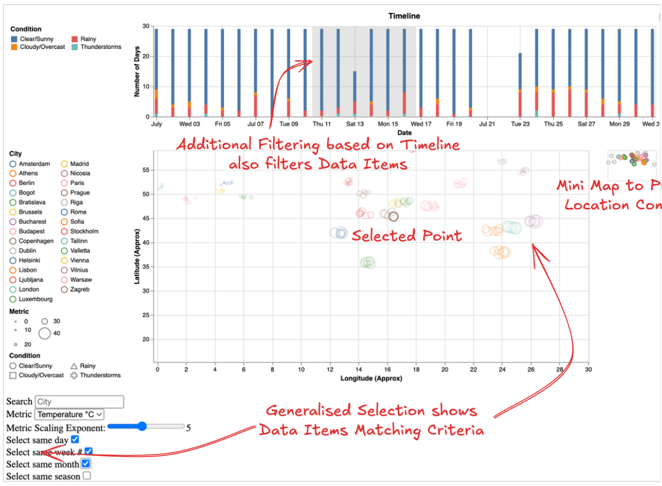

Figure 10: Filtering Persists Across Linked Views (System B)

System C introduces tri-directional linking, where selections from zooming and panning the bar chart, brushing the heatmap, or choosing a pie chart slice update all three views simultaneously. Using various charts and providing a linking integration across them helps users perform multiple steps like identify, compare and summarise without needing much memory such as for tasks 3 and 4.

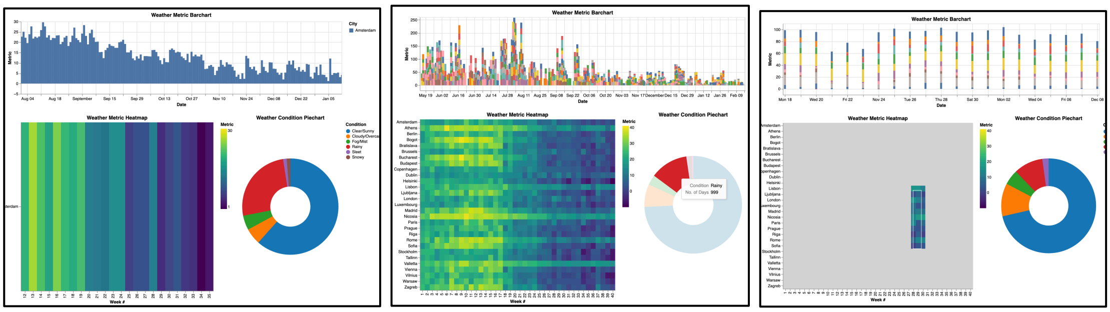

Figure 11: Tri-Directional Linking (System C)

Chapter 2 Evaluation

2.1 User Evaluation Method

In this study, we adopt an assessment-based user-centred evaluation protocol for assessing the proposed information visualisation systems' efficacy, efficiency, and user experience [5] [6]. The objective is to comprehensively evaluate and compare the systems A, B, and C by five users across four different tasks. The assessment strategy follows systematic data recordings based on task completion, user interactions, system performance, and subjective preferences. We have recorded answers to ordinal/ranking-based measures, as well as to open-ended questions through user feedback/comments (see Appendix A) through an observation and interview process [7].

2.1.1 Participant Information

First, we record the demographic and contextual information related to the participating users. It includes - Name, Age, Email, Domain, Average Daily Hours on a Computer and Method of Input (Mouse/Trackpad). This ensures that the evaluation accounts for diversity in user profiles, enabling better generalisation of findings. These attributes also serve as the control variables in this experiment, reflecting real-world variability.

2.1.2 Task Performance Recording

It is essential to gather information about how individual users interact with the respective systems to perform different tasks. Here, we record the user's experience based on Completion Time (in seconds), Difficulty Rating (on a scale of 1 easy to 5 difficult), User Answer, Artefact produced, and the Score obtained by the user. It is pertinent to note that the following answers were expected corresponding to each task, based on which the scores were calculated.
Task 1: Week **#18**
Task 2: **Athens, Bogot, Bucharest, Nicosia, Rome, Vienna** (any three)
Task 3: **2024-08-12, 15.6**
Task 4: **Luxembourg, London, Brussels**
The user-to-task execution strategy across systems is randomised via a Latin squares approach. These findings help capture subjective user experience regarding task complexity and the efficacy of a system.

2.1.3 System Preference

Participants indicated their preference for Best System (A/B/C) for Task Completion and Overall System (A/B/C) Preference based on usability. This enables us to not only identify which system performs best for specific tasks but also captures the user's holistic perception of each system's functionality.

2.1.4 User Feedback

Shneiderman's visual information seeking principle [8] suggests that qualitative analysis is crucial. In this user-centred evaluation method, it is imperative to record qualitative user feedback regarding Overall Aesthetics (Scale of 1 bad to 5 good), Cognitive Load Assessment (Scale of 1 heavy to 5 light), Comments on User-Friendly Nature (Navigation/Accessibility) and Overall Feedback about specific systems. For visualisation systems, it is important to qualitatively evaluate their visually pleasing attributes as they contribute to engagement. Also, perception and cognition-based assessment is critical to determine the mental effort and cognitive pressure required to interpret and interact with the systems [9].

2.2 User Evaluation Analysis

Post the user evaluation data collection step, we analyse the recorded data to interpret multifarious properties associated with the proposed systems. We aim to combine the recorded objective and qualitative metrics, ensuring a robust evaluation that highlights both measurable outcomes and user perceptions.

2.2.1 Analysis Based on Task Performance

Here, we use the User Task Performance data to analyse and interpret the efficiency and accuracy in task execution across the systems. Figure 12 illustrates the cumulative task execution time for all users across the three systems for each task. We observe that system A exhibits high efficiency across most tasks, particularly excelling in tasks 1, 3, and 4. System B, however, consistently exhibits higher completion times across all tasks, suggesting inefficiency compared to the other systems. System C performs best for task 2 and competes closely with system A for task 3. We can conclude that system A shows overall superior performance in terms of task completion time, making it potentially the most efficient system, while system C performs moderately well but struggles in certain tasks compared to system A. Furthermore, system B consistently underperforms, indicating potential usability or design issues.

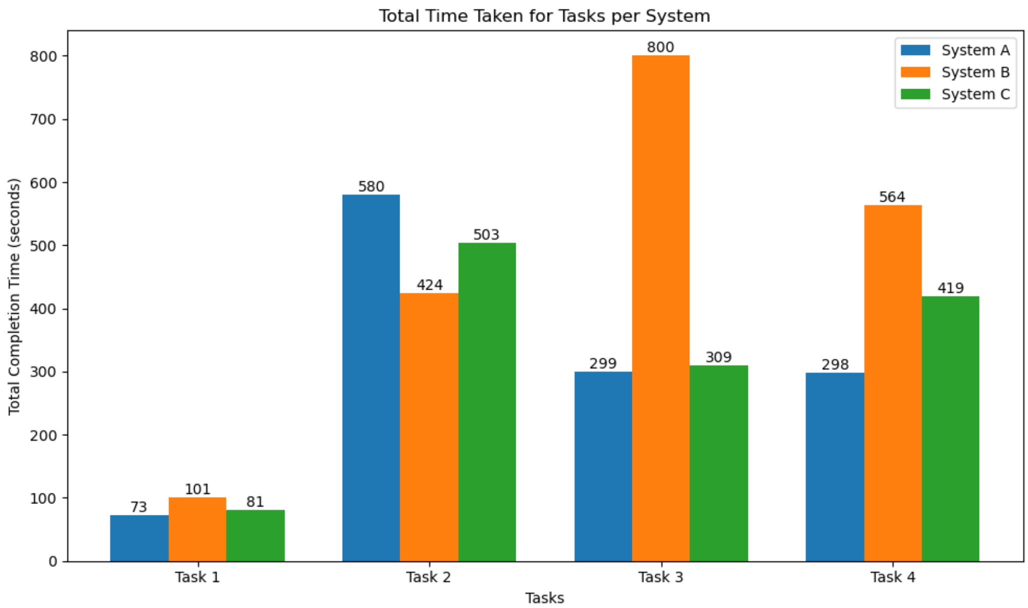

Figure 12: Total Task Execution Time by Users on Systems A, B and C

Figure 13 illustrates a grouped bar chart that analyses the performance of the systems across tasks based on accuracy. It demonstrates the percentage of correct and incorrect responses for each system per task. We observe that system A majorly outperforms systems B and C, achieving perfect scores in tasks 1 and 4. System B is superior in tasks 1 and 2, with 100 percent accuracy in task 1. System C performs reasonably for tasks 2, 3 and 4 while it performs poorly for task 1.

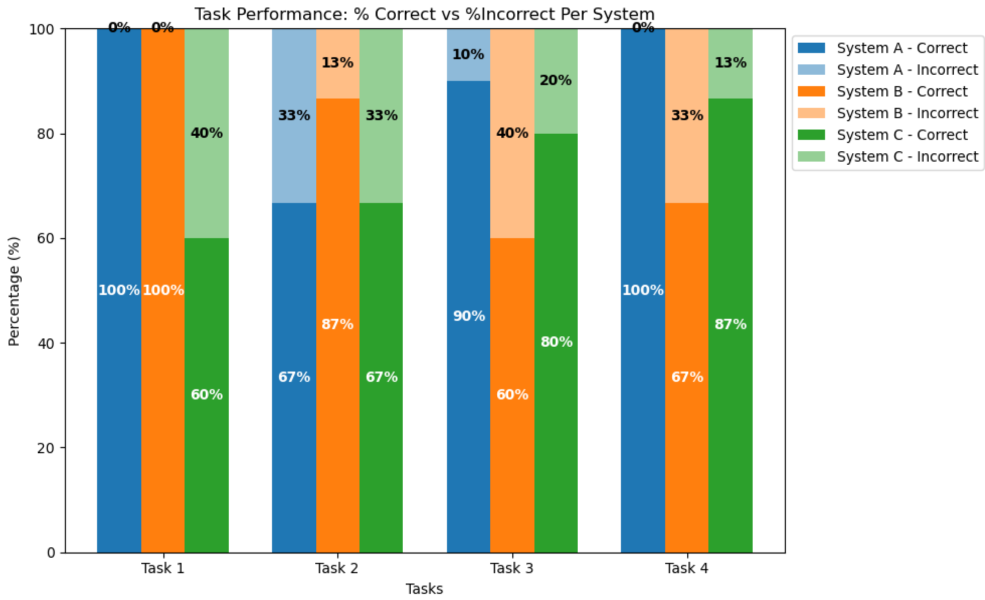

Figure 13: Percentage of Accurate and Inaccurate Task Answers across Systems A, B and C

2.2.2 Analysis Based on User Perception (Difficulty Rating)

It is important to assess user perception, highlighting the intricacy of each visualisation system in navigating through individual tasks. Figure 14 presents the total user difficulty ratings across all tasks for systems A, B and C. We observe that system B is perceived as the most intricate system across all tasks, particularly for task 3. Systems A and C appear to have more balanced and lower difficulty ratings. Task 3 is the most challenging overall, especially with system B, while task 1 is the easiest.

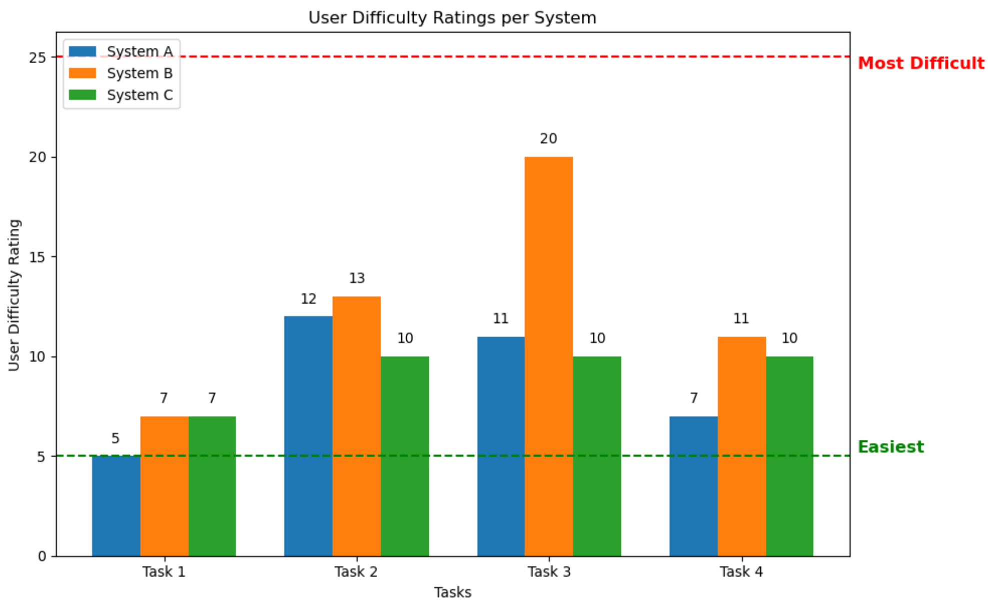

Figure 14: Total User Difficulty Ratings across Systems A, B and C

2.2.3 Analysis Based on User Preference

The crux of any visualisation system lies in its aesthetic appeal, which determines user engagement. The cogent grouping of elements within a system, their shape, size, position and colour encodings play an influential role according to Gestalt Principles [10]. Figure 15 presents a horizontal bar chart to study the user's system preference based on overall visual aesthetics and cognitive load incurred by them. We observe that system C has the highest aesthetic rating and relatively lowest cognitive load rating, suggesting it is the most visually appealing and easiest to use. System B has a moderate aesthetic appeal but is heavy on cognitive load compared to system C. Finally, system A has the lowest aesthetic rating and a relatively mediocre cognitive load.

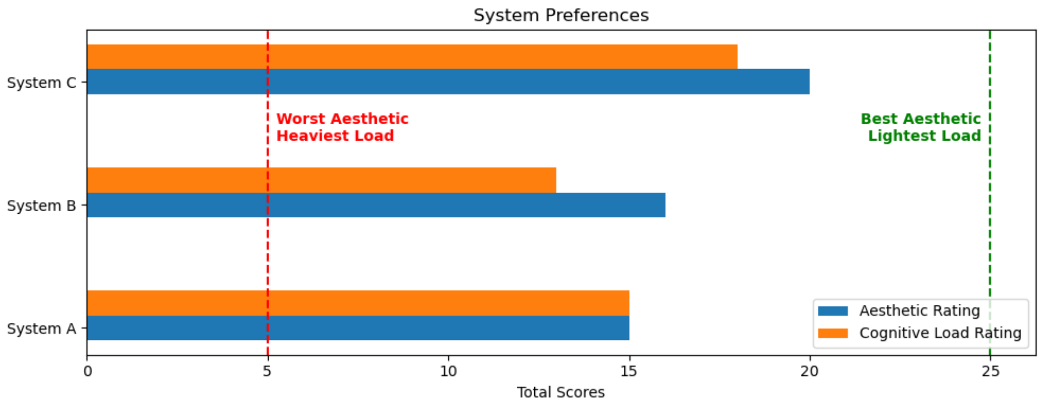

Figure 15: User System Preference based on Visual Aesthetics and Cognitive Load Assessment

Thus, based on a user evaluation with five participants, we conclude that user preference strongly favours system C, and despite its overall task accuracy being only slightly lower than system A with the highest accuracy, it can still be considered as the most effective information visualisation system.

2.3 Future Work

Based on our user evaluation, we can suggest improvements to Systems A, B, and C to address usability and performance gaps while aligning with principles of information visualisation.

For System A, tasks 1, 3, and 4 were efficient, but users noticed slowdowns with the large dataset (7,943 items). A solution for this would be to apply data aggregation techniques as suggested by Munzner [3], so the system performance will be optimised while keeping its strength in selecting multiple cities. The map shows geo-spatial data effectively, but a multi-line tooltip for line charts would help users extract insights for task 3. Zoom controls with set levels and a "reset view" button would further improve the navigation experience.

System B handled time-based filtering for tasks 1 and 2 well, but the humidity and temperature sliders were difficult to use. The date range filter confused users because the dataset begins in May 2024, which disrupts week counts. Switching to multi-select checkboxes for cities, rather than typing each one, would simplify comparisons based on the user feedback. Overplotting and dual encoding (location and weather conditions are encoded in both colour and shape) make the scatter plot visualisation less effective. Small multiples, as Heer et al. [4] recommend, would be effective multi-dimensional visualisations. Additional jittering could fix overlapping points on the map, too.

Along with multi-select functionality to city legends, users indicated that they would prefer to select the legend over the pie slice in system C. Adding y-axis encoding or text labels alongside colour would improve quantitative accuracy for the tasks, as described by Cleveland and McGill [11]. It would be crucial to address the confusing colour scheme where the same colours were used to encode both location and weather conditions, which created ambiguity in system C.

For all three systems, multi-select city filtering with day/week/month toggles would help improve visibility into trends. Further, it would exhibit inclusivity and performance by applying colourblind-oriented colour palettes and rendering methods for a particular purpose [12]. Techniques for focus + context, as seen in the Weather Dashboard [13] system, would make the overview-detail exploration that users found useful possible. In principle, combining the multi-categorical filtering of System A, the quantitative attribute filtering mechanisms of System B, and the multiple views used in System C, while addressing the identified limitations of each system by our evaluation, would lead to an ideal system.

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Appendix A Raw User Evaluation Data

P ID	Name	Email	Domain	Age	Average Daily Computer Time (Hours)	Mouse / Trackpad
1	Dibyendu Dutta	m******s@gmail.com	Management	58	4	Trackpad
2	Freyana Patel	p*************3@student.cimr.in	Management	25	8	Trackpad
3	Arshia Kaul	2******k@student.gla.ac.uk	Technical	26	11	Trackpad
4	Susmita Das	2******d@student.gla.ac.uk	Technical	30	9	Trackpad
5	Rutuja Wakchaure	2******w@student.gla.ac.uk	Healthcare	24	5	Trackpad

Table 1: Participants Data

P I D	Task ID	System ID	User Answer	Time Taken (s)	User Difficulty Rating (1 easy - 5 dificult)	Artefact
1	1	A	#18	7	1	URL
1	1	B	#18	39	3	URL
1	1	C	#25	12	1	URL
1	2	A	Bucharest,Rome,Bogot	125	3	URL
1	2	B	Bogot,Bucharest,Athens	94	4	URL
1	2	C	Bogot,Nicosia,Athens	55	2	URL
1	3	A	2024-08-12,15.6	28	2	URL
1	3	B	2024-08-12,19.5	174	5	URL
1	3	C	2024-08-12,20.2	88	2	URL
1	4	A	Luxembourg,London,Brussels	46	2	URL
1	4	B	Luxembourg,London,Brussels	55	3	URL
1	4	C	Luxembourg,London,Brussels	36	2	URL
2	2	B	Athens,Bogot,Bucharest	88	2	URL
2	2	C	Paris,Nicosia,Valletta	98	3	URL
2	2	A	Athens,Nicosia,Bogot	66	3	URL
2	1	B	#18	12	1	URL
2	1	C	#25	14	1	URL

PID	Task ID	System ID	User Answer	Time Taken (s)	User Difficulty Rating (1 easy - 5 dificult)	Artefact
2	1	A	#18	15	1	URL
2	4	B	Luxembourg,Brussels,London	103	2	URL
2	4	C	London,Luxembourg,Brussels	54	2	URL
2	4	A	Luxembourg,London,Brussels	44	1	URL
2	3	B	2024-08-12,NA	180	4	URL
2	3	C	2024-08-12,-6.9	46	3	URL
2	3	A	2024-08-12,15.6	78	3	URL
3	3	C	2024-08-12,15.6	50	1	URL
3	3	B	2024-08-12,19.5	180	4	URL
3	3	A	2024-08-12,16	86	3	URL
3	2	C	Nicosia,Athens,Valletta	45	1	URL
3	2	B	Rome,Bogot,Athens	48	2	URL
3	2	A	Bogot,Bucharest,Vienna	38	1	URL
3	4	C	Luxembourg,London,Brussels	64	1	URL
3	4	B	Luxembourg,London,Brussels	46	1	URL
3	4	A	Luxembourg,London,Brussels	48	1	URL
3	1	C	#18	4	1	URL
3	1	B	#18	7	1	URL
3	1	A	#18	8	1	URL
4	4	C	Luxembourg,London,Brussels	200	3	URL
4	4	A	Luxembourg,London,Brussels	120	2	URL
4	4	B	Luxembourg,London,Brussels	180	1	URL
4	2	C	Athens,Nicosia,Bogot	125	1	URL
4	2	A	NA	290	3	URL
4	2	B	Rome,Bogot,Vienna	90	1	URL
4	1	C	#18	24	2	URL
4	1	A	#18	30	1	URL
4	1	B	#18	16	1	URL
4	3	C	2024-08-12,16.8	75	2	URL
4	3	A	2024-08-12,16	42	1	URL
4	3	B	2024-08-12,19.5	165	3	URL
5	1	A	#18	13	1	URL
5	1	C	#18	27	2	NA
5	1	B	#18	27	1	URL
5	4	A	Luxembourg,London,Brussels	40	1	NA

P I D	Task ID	System ID	User Answer	Time Taken (s)	User Difficulty Rating (1 easy - 5 dificult)	Artefact
5	4	C	Luxembourg,London,Brussels	65	2	NA
5	4	B	NA	180	4	NA
5	2	A	2024-08-12,27.6	61	2	URL
5	2	C	2024-08-12,NA	180	3	NA
5	2	B	2024-08-12,29.3	104	4	NA
5	3	A	Bogot, Bucharest,Vienna	65	2	URL
5	3	C	Bogot, Bucharest,Vienna	50	2	NA
5	3	B	Bogot, Bucharest,NA	101	4	URL

Table 2: Task Performance Data

P ID	Task ID	Best System ID for Task	Overall System ID Preference
1	1	A	C
1	2	C	
1	3	C	
1	4	C	
2	2	A	A
2	1	C	
2	4	A	
2	3	C	
3	3	C	C
3	2	C	
3	4	A	
3	1	C	
4	4	A	C
4	2	B	
4	1	B	
4	3	A	
5	1	A	A
5	4	A	
5	2	A	
5	3	C	

Table 3: System Preference Data

P ID	System ID	Aesthetics (1 bad - 5 good)	Cognitive Load (1 heavy - 5 light)	Qualitative Comments	Overall Feedback
1	A	3	3	Map is redundant, very laggy, would prefer one line chart for the system.	Filters would make tasks easier, too much data,

P ID	System ID	Aesthetics (1 bad - 5 good)	Cognitive Load (1 heavy - 5 light)	Qualitative Comments	Overall Feedback
1	B	4	2	Circles are too close together, size is not easy to compare, filters are good.	zoom could have been easier.
1	C	5	5	Cannot select multiple cities, heatmap colours are not easy to distinguish.	
2	B	2	2	Typing instead of legend selection was not good, filters were good.	Very clustered, shape encodings were good.
2	C	3	3	Cannot select multiple cities, did not prefer selecting pie slice instead of legend, heatmap selection was good.	
2	A	3	3	Can select multiple cities which was good but zooming was difficult.	
3	B	4	4	Cannot select multiple cities, but identification of week was easy.	Three different charts in system C made it easy without filtering, would prefer less zooming.
3	A	2	2	Difficult to select date, too many filters, legend should be selectable, overlapping points.	
3	C	3	3	Zooming was difficult, can select multiple cities, good colour scheme.	
4	C	5	3	Multi-City Filtering Essential, Intricate to Span Timing	Aesthetically pleasing but visualisation systems must follow Tufte's rules. In addition, the researchers should address how these systems
4	A	4	4	Misleading Map, Intricate to Span Timeline, Intricate Zooming	
4	B	4	3	Easy to select range, Intricate to Span Timeline	

P ID	System ID	Aesthetics (1 bad - 5 good)	Cognitive Load (1 heavy - 5 light)	Qualitative Comments	Overall Feedback
					could be improvised for colour blind users.
5	A	2	2	I liked system A.	While system B had a lot of filters, it was confusing. User interface can be improved.
5	C	3	3	Having humidity, temperature and date filter like system B would have been more helpful.	
5	B	4	4	Difficult to work on longitude and latitude (Panning and Zooming).	

Table 4: User Feedback Data

Task	System	Total Time (s)	Total Score	Total User Rating	Task
1	A	73	5	5	A,C
1	B	101	5	7	
1	C	81	3	7	
2	A	580	10	12	C
2	B	424	13	13	
2	C	503	10	10	
3	A	299	9	11	C
3	B	800	6	20	
3	C	309	8	10	
4	A	298	15	7	A
4	B	564	10	11	
4	C	419	13	10	

Table 5: Tasks Evaluation Summary

System	Task Preference Count	Total Aesthetic Rating	Total Cognitive Load Rating
A	9	15	15
B	2	16	13
C	9	20	18

Table 6: Systems Evaluation Summary

Appendix B Team Member Contributions

NAME	STUDENT ID	CONTRIBUTION	DELTA
Ankit Das	2980596	Data, Tasks, User Evaluation	20%
Bhavisha Jatin Dholakia	3050100	User Evaluation, Future Work	20%
Dishani Sarkar	2979085	Data, Tasks, Report	20%
Rithik Sah	2980356	Tasks, Systems, User Evaluation	20%
Siddhartha Pratim Dutta	2897074	Systems, Generalised Selection, Design Comparison	20%