

CrimeVis: Visualizing Vancouver Crime

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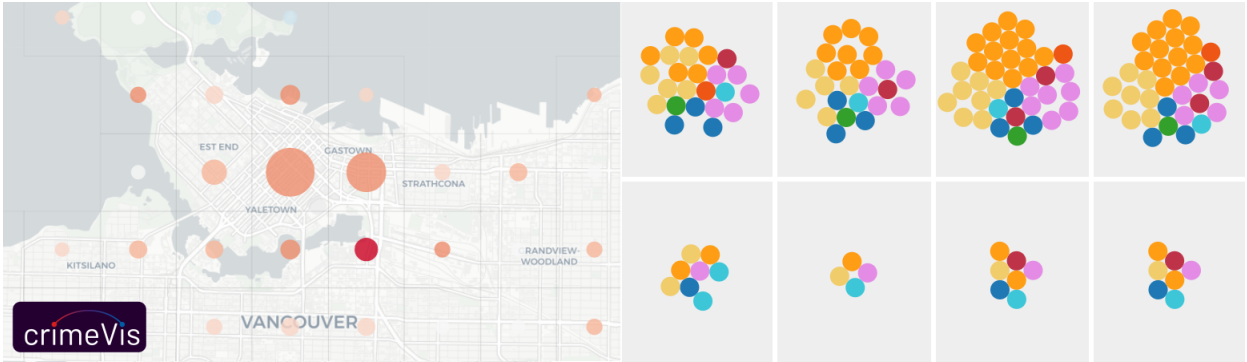


Fig. 1. Screenshot of CrimeVis, available at <https://kimalser.github.io/crimevis>

Abstract—Discovering and analyzing patterns in crime data is an important but nontrivial task. In this work, we present two methods of processing the data and visualizing it to the end user to allow for a faster pattern discovery. We utilize isotype plots for a comparative analysis of crime volumes per each neighbourhood of the city of Vancouver, as well as a grid map showing percentage change of the crime rates over time per each grid cell.

Index Terms—Spatiotemporal data, isotype plot, visual analysis, interactive visualization.

1 INTRODUCTION

The Vancouver Police Department (VPD) releases crime reports on a weekly basis. In order to discover various patterns in crime distribution and location, it is important to visualize this data for analysis by human experts or regular users who are interested in discovering trends. Both visualizations available at the time are limited in expressive power and granularity, limiting the analysis that could be done. We propose a new tool, CrimeVis, that shows a more detailed analysis of trends in the data, as well as providing flexible granularity for visualizing the data.

We hope that the tool would be of interest to data analysts who are looking for suspicious patterns in data, historians interested in the past trends or general public who perhaps wonder what the most frequent crime in their neighbourhood is and how the crime rates compare to the other parts of the city.

The following sections of the paper are going to be organized as follows. Section 2 will give an overview of the previous projects that visualize crimes in Vancouver, as well as some related works and methods in the same or similar domain. Section 3.1 will introduce the dataset that we are working with and introduce the scenarios that we envision when designing our tool. Sections 4 and 5 discuss the proposed solutions and their implementations in more detail. Section 6 introduces our final visualization and walks the readers through usage scenarios. The future work is discussed in 7 and section 8 concludes our paper with final remarks.

2 RELATED WORK

To the best of our knowledge, only two visualizations exist for crime data in the city of Vancouver. The first vis, GeoDash, is offered by the VPD [21]. The tool provides basic functionality of viewing the geographic distribution of crimes. It is only possible, however, to see locations of crimes occurred in the past week. Crime locations are

denoted with icons, where the icon specifies the type of crime. The drawbacks of this vis implementation are many:

1. it is only possible to see the data for the past week, meaning it is outright impossible to examine trends at a greater time scale;
2. there is heavy occlusion due to bulky crime icons on the map;
3. there is no aggregation of data;
4. doing any kind of detailed analysis would require a lot of manual labour, since trends in the data are not shown and data is represented by individual points on the map.

The second visualization is provided by Rex Chang, 2015 [8]. It improves over the VPD visualization in a number of ways, notably enabling users to choose time period of interest and using color to encode the number of crimes per region, providing some aggregated results to assist a user with analysis. However:

1. it is not possible to view data at a finer granularity than months;
2. it is very difficult to compare geographical visualizations across different time periods, since only one map view can be shown at a time;
3. the two plots showing crime rates changing over time aggregate all crime types and either show only one neighbourhood alone or sum over all neighbourhoods, losing the ability to compare trends between crime type and region over time.

In our project, we will improve on these two visualizations. First, we want to be able to do a high-level comparison of crime rates over all neighbourhoods of Vancouver per each crime type in the selected period of time.

A visualization aiming to solve a similar problem of crime visualization was presented by Roth et al. in their project where they visualize a map of violent crimes in the District of Columbia [17]. Instead of showing how data might have evolved, however, the task is designing

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CrimeVis (2017) is a project for CPSC 547: Information Visualization.

Table 1. Categorical attributes in the crime dataset.

Name	Description	# of Categories	Example
TYPE	Type of crime	11	Mischief
HUNDRED_BLOCK	Offset location of crime	21321 + 1 blank	85XX STANLEY PARK DR
NEIGHBOURHOOD	Vancouver neighbourhood	24 + 1 blank	Mount Pleasant

Table 2. Numerical attributes in the crime dataset.

Name	Description	Min value	Max value	Median value
YEAR	Year of crime occurred	2003	2017	-
MONTH	Month of crime occurred	1	12	-
DAY	Day of crime occurred	1	31	-
HOURL	Hour of crime occurred	0	23	-
MINUTE	Minute of crime occurred	0	59	-
X	UTM Zone 10 X coordinate of the crime	0	511303	491505.5
Y	UTM Zone 10 Y coordinate of the crime	0	5512579	5456845.31

an interactive tool for exploration of historical crime records. The solution is a map with marks for each occurred crime and a stacked bar chart showing total number of crimes per time window per type of crime, combined with a playback feature, as well as the feature of choosing flexible time periods to visualize the data over.

Heatmaps were used in the work by Tabangin et al. to display crime hotspots when trying to determine the relationship between the environment and crime occurrences in the city of Baguio, Philippines [19].

A different approach has been taken by Lodha et al. in the similar problem of spatiotemporal visualization of crimes where they use 3D height bars to show the total number of crimes aggregated per map grid cell [13].

A good overview of general terms and techniques of mapping crimes are described in the work by Eck et al. on understanding hot spots with maps, where they explain clustering, kernel density estimation (KDE), heatmaps and different types of plots as related to the task of visualizing crime hot spots [10].

3 DATA AND TASK ABSTRACTIONS

3.1 Data

Our dataset comes from the city of Vancouver’s open data catalogue, provided by the Vancouver Police Department [16].

As of Dec 15, the provided `crime.csv.all_years.csv` file has 546759 rows (~50MB), where each row represents a single instance of crime. Each crime item consists of a categorical *crime type*, as well as spatiotemporal data relating to the time and location of the crime. The time of the crime occurrence is reported up to minute precision. Spatial data includes a categorical *neighbourhood* based on Vancouver census tracts, as well as more precise UTM Zone 10 *XY coordinates* and a *hundred block* address. The more precise spatial attributes are desensitized by a random offset within several blocks, and to an intersection [16].

Crimes of type “Offence Against a Person” and “Homicide” are considered sensitive. For privacy reasons, these crime items only have *year*, *month*, and *day* attributes, omitting values for *hour*, *minute*, and *neighbourhood*. As well, default values “X NK.LOC ST” and (0, 0) are provided for *hundred block* and X, Y attributes for these rows.

Categorical and numerical attributes are outlined in Tables 1 and 2 respectively. The statistics provided in these tables are inexact, as the data is updated weekly on Sunday mornings. Items in the raw dataset are roughly ordered sequentially by time - they are ordered by *year*, but without any apparent order within years.

Although the dataset is updated publicly once a week to include new crimes, this slow rate of data streaming, as well as the permanence of older crimes, suggest little demand for designing for dynamic streams. This would be a greater concern for internal analysts in the police department, for whom the crime data is streaming on a case-by-case, minute-by-minute basis.

3.2 Task

When analyzing design tasks, first consider the use case of a police investigator looking to track down a repeat offender. These specific internal needs by the police department are met by richer and more sensitive crime data, whereas our public data describes each crime incident only by a broad type, time, and imprecise location. Due to the desensitized nature of the public-facing data, we aim to address higher-level tasks involving aggregate data and trends as opposed to drilling down to individual crimes. For instance, *community needs may be interested in the prevalence of bicycle thefts*, asking questions such as “What neighbourhood has the most bicycle thefts, and how has this changed historically?” We can also imagine future homeowners looking for safe areas to live in, with low crime rates. An analyst might look at the bigger picture to find patterns of crime changing over long time spans, look for outliers, compare across crime type, times, geography, or neighbourhoods, and project trends to the future.

In abstracting the task domain, our goals are to *allow analysis, search, and query* over our data. Particularly, our design allows users to *discover* trends, outliers, and features over crime data over flexible time and space domains. We address three search actions: *explore, locate, and browse*. *Lookup* is not a well-suited task for our spatiotemporal data, since there are few attributes beyond a known target’s location and time. All query actions are important in the design of CrimeVis: users should be able to *identify* outliers, *compare* distributions, trends, and features across type, time, and space, as well as *summarize* these patterns over fine and coarse-grained spatiotemporal scope.

4 SOLUTION

We treat the data as a static file due to the slow rate of data streaming, as mentioned in Section 3.1. The work required to reprocess new data once a week is marginal and not particularly relevant to our design focus, given that there is already fifteen years of data, so we disregard the dynamic streaming aspect of the dataset.

In both visualizations, the specific time periods of interest can be changed by *dragging the time slider*. The visualizations will update automatically to reflect the changes according to the newly selected time periods.

4.1 Isotype Plot

The first design proposed by CrimeVis is an *isotype plot*. An isotype chart, or a pictograph, is a simple visualization that *shows figures pictorially* [5, 12]. They are often used when users need to perform a comparison task since it is easy to see and compare relative volumes of two or more entities with these charts. We use isotype plots to visualize the relative crime rates per city neighbourhood per selected time window.

The vis is presented with a table where ordinal blocks of time lie on the x-axis and neighbourhoods of the city lie on the categorical y-axis. Since we would also like to show distribution of crimes for different

types of crime in our chart, we will use color to encode crime type. Each dot represents a fixed but adjustable number of crime occurrences, so that the number of dots in each cell reflects the number of crimes of a particular type committed in the corresponding region.

Interactive manipulation of the view is key: users can zoom and pan the time window and select relevant neighbourhoods. Since we allow the user to select the time period of interest; our chart should automatically quantize the horizontal axis into a suitable number of bins (e.g. each bin represents days / weeks / months / years). This requires a balance between keeping the time granularity fine-grained while ensuring a dense enough dotplot in bins to maximize screen space and be useful in pattern recognition. As an extension, we will also enable the user to manually adjust the time granularity within reason.

With the isotype charts, the users will be enabled to compare the crime progression throughout the neighborhoods they are interested in, see how the rates compare to other neighbourhoods and visually see the crime type distribution as they will be colored differently. Filtering by crime type is a useful extension; hovering over a particular coloured dot desaturates dots of other colours to grey to allow an easier comparison of the crime type the user could be interested in.

The chart uses density as a channel to encode the crime count, which is easily scalable by dynamically altering the number of crimes a single dot represents. This way, we can always maximize the use of screen space. Since we have 9 crime types, colour is a suitable encoding at this scale.

4.2 Grid Map

Since isotype charts aggregate crimes per neighbourhood, they discard the more granular geographical information available in the dataset. To help us see the crime rates throughout the city without cluttering the map with individual marks for each crime, a heatmap would be an appropriate way of showing the crime distribution. However, while heatmaps are good for displaying static data (i.e. a state at a point in time), we would mainly like to enable users to see trends and change in data which is why a diverging map showing change per unit of area would be desirable.

Similar to [6], we will split the city area into a grid and encode descriptive information per each grid cell. We will let a user choose two time periods to compare, and show the percent change in total crime rates from the first selected time period to the second one, per each grid cell. A diverging color gradient will be used to represent increases and decreases in crime at a particular geographical location. This not only addresses the relative nature of the derived crime intensities, but also normalizes these values. It is not unexpected to find high crime rates downtown, for instance, since there is a higher population density in downtown. By representing the *percentage change* in crime at each grid cell, we essentially normalize the absolute crime intensity at each cell at the current time period by the crime intensities at the earlier time period to which we compare to.

While the diverging color scheme encodes the percent increase or decrease, the saturation of the color will encode the amount of change. Note, that the percent change doesn't convey any information about the scale of the crime rates, e.g. the percent change is the same in the case where the number of crimes increases from 2 to 3, and from 400 to 600. This is important because an event is especially "surprising" when it is both of a significant scale and has a noticeable percent change. To encode the scale, or the difference in crime rates between two time windows, we will use the channel of size; figures of a larger size mean a larger absolute difference in crime numbers, than the figures of smaller sizes.

5 IMPLEMENTATION

CrimeVis is a web app built with HTML, CSS and Javascript. We use Javascript libraries D3 [3] for visualization, as well as Leaflet [1] for mapping. Python 3 and Javascript is used for data preprocessing.

The breakdown of work between the participants of the project is roughly as shown in table 3.

Table 3. Work distribution breakdown.

Task	Alexandra	Amon
preprocessing	70%	30%
parallelization	20%	80%
grid map	60%	40%
isotype plot	40%	60%
UI design	60%	40%

5.1 Preprocessing

We first exclude the sensitive crime types "Offence Against a Person" and "Homicide", since they lack specific temporal and geographical information to visualize (see Section 3.1). We then converted UTM XY coordinates to latitude-longitude coordinates using an online Javascript library [20], and converted all temporal attributes into one ISO 8601 text field. All crimes were then sorted and binned in two ways:

1. by each unique *neighbourhood* \times *crime type*, for the isotype plot (see Section 4.1), and
2. by *location*, that is, each geographical grid cell for the map (see Section 4.2).

All crimes in each bin were exported to a separate .csv file for fast parallelized loading. To count the number of crimes in each bin, we use D3's asynchronous task library (d3-queue) to send workers for each bin. Each worker runs binary search on the start and end times of the time window(s) of interest on their assigned bin, returning the number of rows within each continuous time window. The entire parallel queue completes in under one second on our local machines, allowing for highly interactive navigation.

5.2 Isotype Plot

Our isotype plot uses D3's ordinal scales to create a table with neighbourhoods on the y-axis and time bins on the x-axis. We use D3's force layout library (d3-force) to cluster dots together within the same neighbourhood and time bin. Since this library was originally intended for dynamic graph visualizations, we create links between dots of the same crime type (encoded by color) to encourage grouping. After realizing crimes across different types still mixed together unpredictably in the same cell, we initiated each crime type's dots at a slightly offset location around the center of the bin, which produced much better results. Please refer to Fig. 2 for a visual explanation.

The following are the three forces used for dot clustering in our isotype plot:

1. a force pulling all dots in the same bin towards the center location of the bin,
2. a force pushing individual dots from each other, to prevent collision and occlusion, and
3. a force pulling dots within the same crime type towards one another.

Our UI for user interactivity includes a map of Vancouver's neighbourhoods (A in Fig. 3), a time slider (B, C in Fig. 3) with a dropdown box (D in Fig. 3) for the width of the time bin (years/months/weeks/days), a crime type legend indicating what each color encodes (E in Fig. 3), as well as an isotype legend indicating how many crimes a single dot represents (F in Fig. 3). Although we created these ourselves with D3, HTML, and CSS, here are sources we built off of:

1. The neighbourhood map uses local area boundaries provided by Vancouver's Open Data Catalogue [9], adapted by Chang [8] to .json format.
2. The dropdown time bin width selector's CSS was modified from an open source Codepen by Barrera [2]
3. Linked highlighting for force layout nodes was inspired by a visualization project with beeswarm plots by Haber [11]

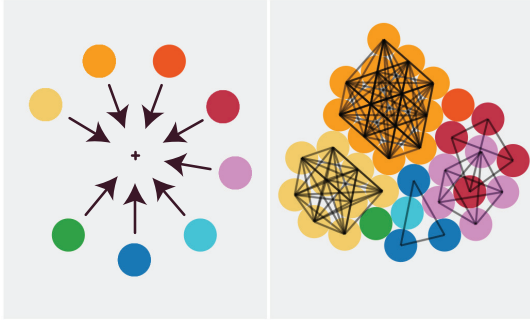


Fig. 2. Isotype dots in a single table cell. (left) Initial dot positions, arrows represent forces attracting dots towards the center of the cell (+). (right) Settled dot positions, hidden links attracting dots sharing the same crime type are shown.

5.3 Grid Map

The grid map uses Javascript **Leaflet library [1]** as the underlying map, as well as its **built-in polygon, circle marks and pop-ups**.

As described in Section 5.1, for each grid cell we have a corresponding .csv file containing the times of all crimes occurred within the given cell. When initializing or updating, the time window intervals are passed to the asynchronous workers that return the number of crimes that happened during the given time window at each cell. This is done for both time windows that the user is comparing. Then the relative change is calculated as follows:

$$\delta_t = \frac{n_{t_j} - n_{t_i}}{n_{t_i} + \alpha},$$

where t_i and t_j denote the two time windows, n_{t_i} and n_{t_j} are the number of crimes in each time window, and α is an additive smoothing parameter, set to 1.¹

For coloring, we further clamp δ_t between $[-1, 1]$ and map it to our diverging color scheme. To calculate the radius of each circle mark, we first give rough estimations of minimum and maximum numbers of crimes per given time period; the minimum is set to 1 and the maximum is defined as $210 * monthNum$ if we are comparing months of data, or $7 * dayNum$ if our granularity is in days. Then we map the obtained amount in respect to the min and max estimated crime numbers to a range of circle radii of $[100, 500]$ (in the scale that Leaflet.js uses). The radius of each grid cell is calculated as follows:

$$minR + \frac{maxR - minR}{maxN - minN} * (|n_{t_j} - n_{t_i}| - minN),$$

where $minR$ and $maxR$ are the range bounds of a circle radius, and $minN$ and $maxN$ are the estimated minimum and maximum numbers of crimes for the given time window.

Then, for each grid, a circle with the calculated radius and color is drawn. The borders of each grid cell are also shown on the map for a reference.

6 RESULTS

We present CrimeVis and walk through sample usage scenarios for each visualization.

6.1 Isotype Plot

Fig. 4.1 shows the isotype plot in CrimeVis. Below are two possible use cases for a novice and an expert analyst.

¹This is equivalent to adding 1 crime to each time window, preventing an infinite increase in crime when $n_{t_i} = 0$.

6.1.1 Querying the safest neighbourhood

A new graduate student is planning to move to Vancouver, and is looking for the safest neighbourhood to live in. She drags the time slider (C in Fig. 3) to pan the time window right to the year 2017. Dots in the main visualization (G in Fig. 3) are dynamically updated to reflect the change. She then clicks on selected pink neighbourhoods in the map (A in Fig. 3) with a large density of dots, such as Central Business District, to hide them from the plot. She then clicks unselected grey neighbourhoods in the map to view them in the plot. She can manually adjust the number of crimes a single dot represents by typing in the isotype legend's numerical field (F in Fig. 3). She lowers this number to get more precision as she finds safer neighbourhoods, and quickly finds that the safest neighbourhoods are Arbutus Ridge and South Cambie.

6.1.2 Discovering Trends and outliers

An analyst is interested in exploring trends and outliers throughout the dataset. Highlighting over a crime type color in the legend (E in Fig. 3) desaturates all dots in the plot to grey, revealing the pattern of higher bicycle theft in summer months and lower theft in winter months (see Fig. 4). She wants to examine long term trends, and drags the ends of the time slider to increase the time window over several years. As she does this, the number of crimes that each dot represents in the isotype legend is automatically adjusted up to fit the increased number of bins. There are too many month bins to look at fine grained data, so she adjusts the time bin to aggregate over years with the dropdown box (D in Fig. 3). Again, the number of crimes that each dot represents is lowered drastically to fit the screen automatically. Panning her window along the time scale (B in Fig. 3), she notices that crime rates have been decreasing slowly since the late 2000s, but has slightly picked up again in the past two years or so.

She then rescales her time window to a few months, changes her bin size to months, and pans the time slider slowly over the years, and notices an abnormal amount of pink and dark blue dots in June 2011. She consults the crime type legend to find that these crimes are Mischief and Break and Enter Commercial. She adjusts her time window smaller still, and changes her bin size to weeks, then days, to find that all these anomalous crimes occurred on June 15, 2011. An internet search informs (or reminds) her that this was the night of the Vancouver Stanley Cup riot, where many cars were set on fire and businesses were looted [7].

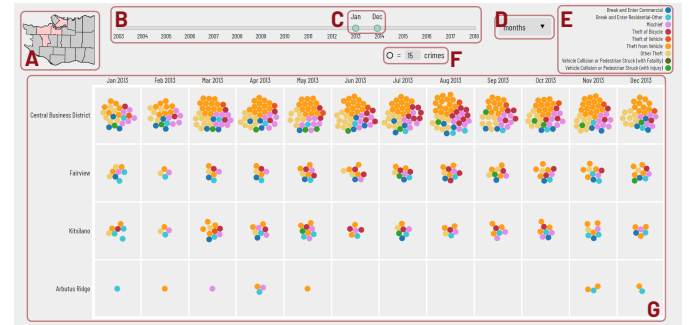


Fig. 3. The isotype plot in CrimeVis. (A) The neighbourhood selection map. (B) The time scale, over the entire domain of the data. (C) The time window slider. (D) The time bin selection dropdown. (E) The crime type color legend. (F) The isotype legend, showing the number of crimes a single dot represents.

6.2 Grid Map

Fig. 5 shows the grid map. As we described earlier, this visualization is designed to help see the trends in the data, in particular, percent change of crime rates throughout the city.

Suppose, a data analyst is intending to discover whether or not the crime rates changed in the more recent years compared to the previous years. Perhaps, she even has particular dates in mind, but for now let's

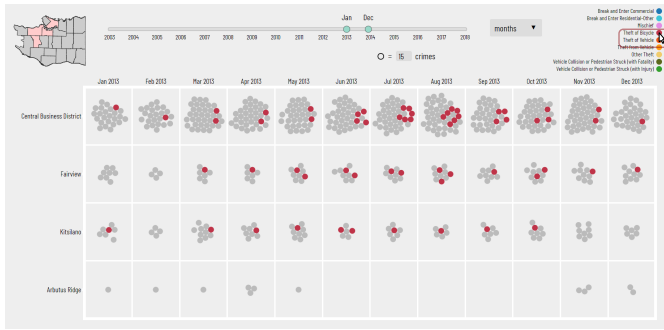


Fig. 4. Hovering over Theft of Bicycle in the crime type legend acts as a filter to highlight the hovered crime type in the isotype plot. Other crime type dots are desaturated to a uniform grey color.

assume that she mainly is interested in comparing some range of years to each other.

She chooses the time windows of interest using the slider. She slides the first window to set its start time to Jan 2011, by using the first pair of handles (coloured in green and denoted by B on fig. 5). She adjusts the width of the window so that it is equal to two years, by dragging the handles and the width of the second window updates automatically to match the width of the first window. She then uses the second pair of handles (coloured in blue and denoted by letter C), and slides them to the period of Jan 2014 to Dec 2015. The time windows that are being compared are shown in box A. Every time she makes changes to the windows, the map (denoted by letter E) updates automatically to reflect the changes. The analyst now sees that the number of crimes predominantly increased throughout most neighbourhoods in the city of Vancouver in the last years.

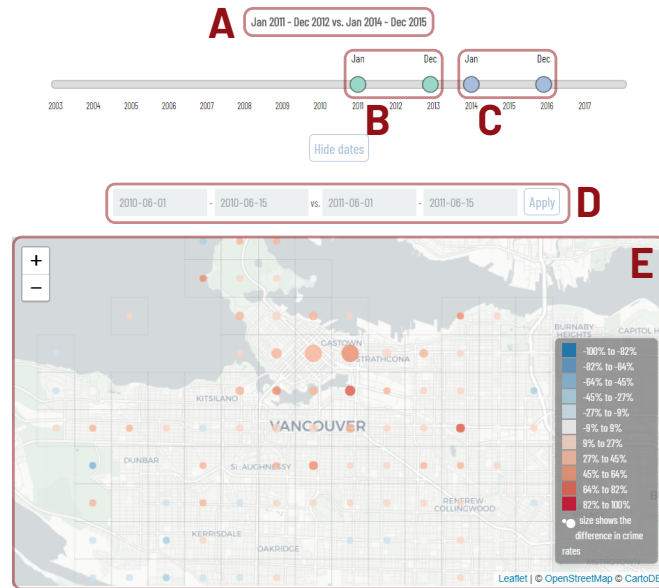


Fig. 5. The grid map.

The analyst then clicks on some grids to see the exact figures. She clicks on the grid corresponding to Downtown East Side and sees that the number of crimes increased by about 50% in the last few years (fig. 6.2). She proceeds with clicking on several grids within the area of her interest and writes down the figures for her further research.

If she is interested in looking up any particular days, she is able to do so by using the input box D.

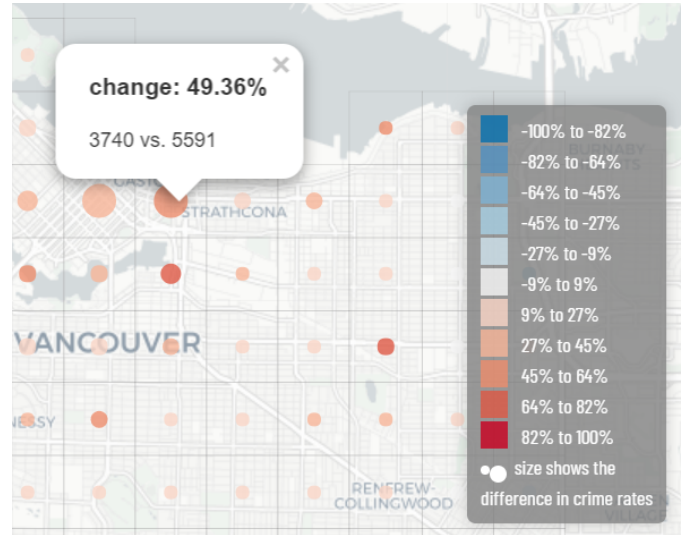


Fig. 6. The closeup of the grid map when a user clicks on one of the grid cells.

7 DISCUSSION AND FUTURE WORK

One major limitation of both our visualizations is that they each sacrifice one attribute in their choice of design. The isotype plot sacrifices geographical granularity in order to display time and neighbourhood information in a 2D table, while the comparison map discards crime type in order to aggregate all crimes with respect to their 2D spatial position in Vancouver. This means that CrimeVis users aren't able to easily find answers to more granular questions, such as "Which area within each neighbourhood has the most crime?", or "Which crime type in my block increased the most from last year to this year?"

There are many ways to address this issue without extending to three spatial dimensions (which is marred by problems [15, 18]). For instance, a simple solution starts with a crime type filter in the comparison map to only aggregate over selected crimes (similar to Chang's visualization [8]). Another, more complex solution, could stem from linking the isotype plot view with the map view on one screen, showing more granular geographic information linked with each neighbourhood's crimes.

Another problem with our design choice is that all shown data was an aggregation (unless an isotype dot was set to represent a single crime, which would require a very narrow time window). The inability to focus on individual crimes is somewhat placated by the lack of data richness mentioned in Section 3. Since each crime in the public dataset is only type, neighbourhood, and spatiotemporal information, there is not much more to glean from individual crimes. For internal analysts in the police department, different design choices need to be made for their richer data.

A promising future extension to CrimeVis arises when thinking differently about time. Although time is considered in our vis as a sequentially ordered attribute, we can also think of it as cyclic: for instance, hours repeat over days, and months repeat over years [4].

This abstraction lends itself to a new way of aggregating data - over discontinuous, but repeating, time periods. Allowing for this aggregation, for instance, over the night-time hours of every day, or the summer months of each year, would be a major future feature of CrimeVis. This feature has the most potential when using our map visualization to compare two of these time periods. From this comparison, many novel trends could arise, especially if we also retained crime type attributes. As an example, we might find that bicycle thefts are much more prevalent at night in some areas, while bicycle thefts dominate different locations during the day. An excellent example of this data aggregation is Oakland's Crimespotting project [14], which uses a radial time wheel idiom to aggregate crimes over daytime, nighttime, and even commute hours.

Since this aggregation requires counting crimes in repeated, discontinuous time windows, our parallelized binary search algorithm (see Section 5.1) would need to be reworked, as well as requiring significant UI changes; time constraints moved this feature out of this project's scope.

One more limitation arises from our preprocessing: the fixed grid size in the comparison map. Adjusting grid sizes would require preprocessing and rebinning crimes for parallelized counting, which is too costly for the live interface. Again, our data pipeline would need to be modified to allow for dynamic adjustment of grid size.

Finally, our solution could use several minor implementation improvements:

1. The stochastic nature of D3's force layout idiom is not ideal; having a more deterministic and constant reference frame for the isotype plot, as well as more consistent clustering, would be an improvement.
2. Adding tooltips and linked highlighting on the neighbourhood map would help the UI.
3. We could also enforce a limit on the number of time bins to a reasonable number on screen, or enforce the time bin width, to prevent cluttering.
4. Making categorical colors more colorblind friendly would help accessibility.
5. Building a server to update from the dataset directly and preprocess the data automatically each week would keep the vis up to date.
6. Moving from SVG to canvas would improve performance.

8 CONCLUSION

Even simple spatiotemporal crime data comes with myriad use cases and design choices. In CrimeVis, we implement an isotype plot to view crime trends over time and across neighbourhoods, and a grid map to compare absolute and relative crime rates between two time periods, allowing for easy and interactive exploration of trends and outliers.

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