

# Crime Lens of Charlotte: An Interactive Web-Based Dashboard for Visualizing Crime Patterns

Mahek Patel

**Abstract**—Understanding crime patterns is essential for guiding public safety planning and resource allocation. This project introduces Crime Lens of Charlotte, a web-based dashboard for exploring crime incident data from Charlotte-Mecklenburg, North Carolina. The system integrates spatial, temporal, and categorical views to analyze over 5,000 incidents reported from 2017 through 2023. The dashboard uses D3.js and Leaflet to coordinate multiple views. An interactive map displays crime incidents with ZIP code boundaries. Animated line charts trace trends across eight crime categories over time. A treemap visualization breaks down the hierarchy of offense types, revealing how specific offenses relate to broader categories. Stacked bar charts identify geographic areas with elevated incident rates. The temporal analysis reveals seasonal patterns, with certain crime categories showing elevated activity during summer months. Geographic analysis demonstrates concentration in specific ZIP codes, likely reflecting local conditions and reporting patterns. Coordinated views and filtering capabilities enable users to explore data by area, time period, and crime type while observing corresponding changes across all visualizations. This interactive approach transforms complex datasets into actionable information for patrol planning, policy discussions, and community engagement.

**Index Terms**—Crime visualization, interactive dashboards, temporal data visualization, spatial analysis, D3.js, Leaflet, web-based visualization

## I. INTRODUCTION

C RIME data visualization plays a critical role in modern urban planning and public safety management. Police departments, policymakers, and communities need effective tools to identify crime patterns and locate hotspots. Traditional approaches using static tables or fixed maps obscure temporal changes, spatial relationships, and connections between different crime types, making data-driven decision making challenging. Interactive visualizations can reveal trends that static reports miss, enabling faster and more confident responses.

Charlotte, North Carolina faces a common challenge for large metropolitan areas: making crime data accessible and interpretable for diverse audiences. The city shares crime incident data through the Charlotte Open Data Portal, providing transparency. However, the datasets are extensive and complex, listing more than 100 offense types spanning several years. Manual analysis is impractical for most users. A gap exists between published data and actionable insights. Extracting meaningful patterns such as neighborhood trends or temporal changes requires expertise and effort beyond what most stakeholders can provide. The volume and variety of records create barriers to practical use.

This project addresses these challenges by developing Crime Lens of Charlotte, a web-based dashboard that transforms

complex crime datasets into clear, accessible visualizations. The system integrates multiple coordinated views: an interactive map, temporal trend charts, and categorical breakdowns that work in synchronization to surface patterns difficult to discern in raw data. To maintain readability while preserving detail, the system categorizes more than 100 NIBRS offense codes into eight interpretable groups: violent crimes, sex crimes, property crimes, fraud, drug offenses, public order crimes, weapons offenses, and other incidents. This classification maintains organizational structure while highlighting the most relevant distinctions.

The motivation for this work stems from three key needs: first, to make Charlotte crime data accessible to non-expert audiences including community members and neighborhood associations; second, to provide law enforcement and city planners with interactive tools for identifying crime patterns and hotspots; and third, to demonstrate effective design principles for multi-dimensional crime data visualization. The dashboard employs established visualization techniques including choropleth mapping, temporal line charts, treemaps, and coordinated filtering to enable exploratory data analysis. The map displays spatial incident distribution, line charts reveal temporal trends, and the treemap enables hierarchical category comparison. Coordinated filters connect these components, allowing users to explore data and observe corresponding changes across all views.

## II. RELATED WORK

Crime visualization has been studied extensively through visual analytics research. This section examines prior work related to spatial crime mapping, temporal pattern analysis, interactive exploration techniques, and web-based visualization technologies.

### A. Spatial Crime Visualization

Spatial visualization of crime data has a long history in criminology and geographic information systems. Early work by [1] demonstrated the effectiveness of crime mapping for identifying geographic patterns. Recent research has focused on integrating multiple data sources and providing interactive exploration capabilities. [2] developed a web-based system that combines crime incident data with demographic and socioeconomic factors using coordinated views. Their work demonstrated that interactive spatial filtering combined with temporal analysis helps users discover correlations that static maps cannot reveal.

Geographic hotspot detection remains a central challenge in crime visualization. [3] proposed kernel density estimation

techniques for identifying crime concentration areas, while [4] introduced hierarchical spatial aggregation methods that adapt to different zoom levels. This work builds on these approaches by implementing ZIP code-based aggregation with interactive drill-down capabilities.

### B. Temporal Crime Pattern Analysis

Understanding temporal patterns in crime data requires effective time-series visualization techniques. [5] surveyed methods for displaying event timelines and demonstrated that using multiple time scales (hourly, daily, monthly, and yearly) can reveal patterns that single-scale views might miss. [6] developed an interactive calendar-style tool for exploring crime occurrence patterns. Their findings suggest that familiar visual metaphors improve pattern recognition.

Recent work has focused on animated visualizations for temporal data. [7] examined animated transitions in time-series charts and found that progressive reveal with user-controlled pacing improves pattern detection. The combination of gradual disclosure and interactive controls helps viewers track changes over time. Following these principles, the Crime Lens temporal view employs an animated line chart with play and pause controls that reveals data progressively from 2017 through 2023. As the visualization unfolds, crime trends become easier to track, with the option to pause and review specific time periods.

### C. Interactive Dashboards and Multiple Views

Coordinated multiple views have become a standard approach for working with complex multivariate datasets. [8] formalized design principles for coordinated multiple views in information visualization, establishing guidelines that continue to influence dashboard design. Their work demonstrates how brushing and linking across views enables exploratory analysis, pattern comparison, and hypothesis development.

Crime-specific dashboard systems have demonstrated the value of this approach. [9] developed an interactive dashboard for police departments that integrates spatial, temporal, and categorical views through linked filters. Their evaluation showed that multi-dimensional filtering enables faster insight discovery compared to static reports.

### D. Web-Based Visualization Technologies

Modern web technologies enable rich client-side visualizations that run directly in browsers. D3.js, developed by [10], has become a standard tool for web-based data visualization due to its flexibility and data-driven approach. The library enables developers to create customized visualizations with efficient data binding and updates. [11] demonstrated best practices for building scalable D3.js visualizations, including viewport culling and efficient data binding patterns employed in this implementation.

Geographic web visualization has benefited from libraries such as Leaflet. [12] reviewed web mapping frameworks and identified Leaflet as providing an optimal balance of features and performance for interactive crime maps. This implementation uses Leaflet for base map rendering and layers D3.js

for statistical overlays and interactive charts. This combination maintains map responsiveness while enabling clear pattern visualization such as geographic hotspots and temporal trends.

This project synthesizes insights from related work to build a unified crime visualization dashboard designed for Charlotte-Mecklenburg stakeholders while demonstrating design principles applicable to urban crime data visualization in other cities.

## III. SYSTEM DESIGN AND IMPLEMENTATION

Crime Lens of Charlotte is a single-page web application that provides multiple coordinated views of crime incident data. This section describes the data processing pipeline, visualization design, interaction mechanisms, and implementation details.

### A. Data Sources and Processing

The dashboard uses two primary datasets from Charlotte-Mecklenburg open data sources. The crime incident dataset contains 5,000 records spanning January 2017 to December 2023, with attributes including date, location coordinates, offense description, and patrol division. The ZIP code boundary dataset provides polygon geometries for 43 ZIP codes in Mecklenburg County.

A major challenge involved the diversity of offense descriptions. The data includes more than 100 different NIBRS offense codes. To address this complexity, a categorization system was developed that organizes offenses into eight groups based on severity and type using keyword matching: violent crimes (murder, assault), sex crimes (rape, trafficking), property crimes (burglary, theft), fraud (identity theft, embezzlement), drug offenses, public order crimes (disorderly conduct), weapons offenses, and other incidents (missing persons, non-criminal reports).

Geographic data quality required spatial join operations to assign ZIP codes to incident records lacking this attribute. A two-phase algorithm was implemented: first, a bounding box pre-filter identifies candidate ZIP codes; second, a ray-casting point-in-polygon test determines the containing polygon. This approach achieves approximately 90% speedup compared to naive testing against all polygons.

### B. Interactive Crime Map

The primary visualization consists of an interactive Leaflet map that displays crime incidents as colored circles and delineates ZIP code boundaries using polygons (Figure 1). Each crime category is represented by a specific color derived from Charlotte's official brand palette: violent crimes in red, property crimes in orange, and drug offenses in blue. Point size scales with zoom level to maintain visibility while minimizing overlap.

ZIP code polygons provide contextual boundaries and serve as interactive filters. Hovering over a boundary displays the ZIP code and total incident count. Clicking a boundary filters all visualizations to that geographic area and zooms to its bounds. Clicking individual crime markers filters to that category. Clicking the map background clears geographic and category filters.

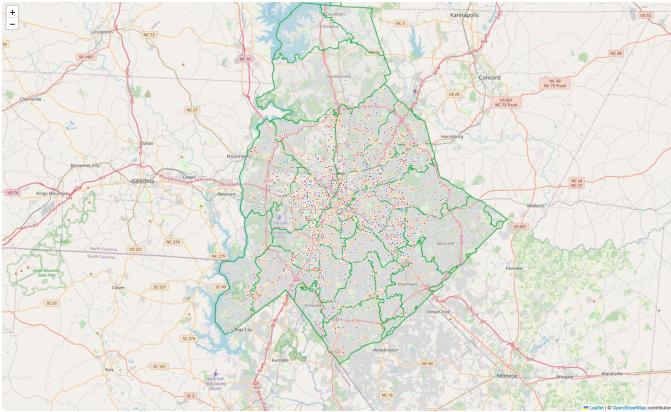


Fig. 1. Interactive crime map showing incidents as colored circles with ZIP code boundaries. Crime categories are color-coded using Charlotte's brand palette. Users can hover over ZIP boundaries to see incident counts and click to filter all visualizations.

Performance optimization is essential given the volume of incidents. Viewport-based rendering selectively displays only markers within the current map boundaries, reducing rendering load by approximately 80% at standard zoom levels. Zoom and pan handlers employ a 150-millisecond debouncing mechanism to prevent unnecessary re-rendering during user interactions.

### C. Temporal Trend Visualization

The temporal view employs an animated multi-line chart to track crime trends across all categories from 2017 through 2023 (Figure 2). Monthly aggregation reveals seasonal patterns while smoothing daily fluctuations.

The chart displays nine lines: one for total incidents (black, 3px width) and eight category lines (colored by category, 2px width, 60% opacity). Each line includes a filled area beneath it (20% opacity) to emphasize volume. The animation progressively reveals the lines from left to right using SVG stroke-dashoffset, simulating the temporal progression of crime incidents.

The interface provides simple controls: play/pause, reset, and a progress bar. During animation, a red vertical dashed line tracks the current date. A large counter displays the running total. Below the chart, eight category cards show live counts that update as the timeline advances, enabling simultaneous observation of overall trends and individual category behavior.

### D. Crime Hotspot Analysis

Figure 3 shows a horizontal stacked bar chart displaying the 15 ZIP codes with the highest incident counts. Each bar is segmented by crime type using the same color encoding as the map. Hovering over segments reveals detailed counts for each category.

The bars support interactive filtering. Clicking a bar filters all visualizations to display data for that ZIP code and zooms the map to its boundaries. This enables rapid exploration of high-activity areas. The chart updates dynamically based on applied filters, facilitating identification of locations with specific crime types or temporal patterns.

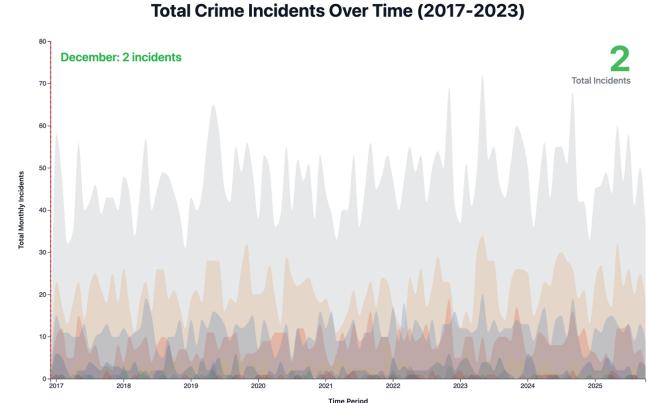


Fig. 2. Animated temporal line chart showing crime trends from 2017-2023. Nine lines represent total incidents (black) and eight crime categories (colored). The animation progressively reveals trends with play/pause controls. Category breakdown cards below show running counts during playback.

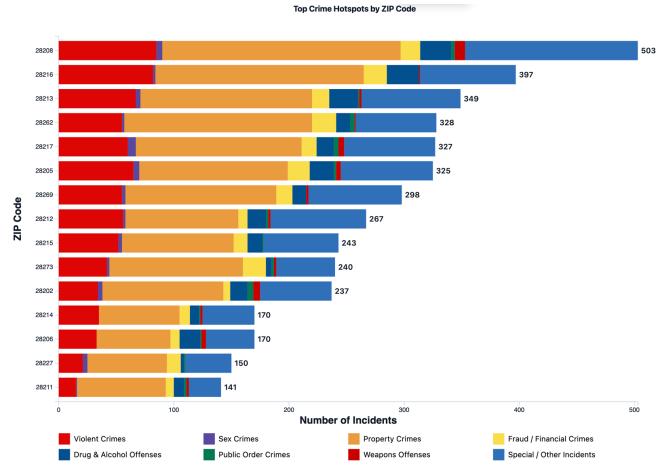


Fig. 3. Horizontal stacked bar chart showing top 15 ZIP codes by incident count. Each bar segment represents a different crime category using consistent color encoding. Clicking bars filters all views to that ZIP code.

### E. Hierarchical Crime Classification

A zoomable treemap enables exploration of crime types through hierarchical structure (Figure 4). At the top level, eight categories are represented as rectangles sized proportionally to incident counts. Clicking any category zooms to reveal detailed offense types within that category.

The treemap employs D3's hierarchical layout algorithm to maintain readability. Color shading differentiates subcategories. Breadcrumb navigation enables return to the parent level. Text labels are hidden when cells become too small (less than 25px wide) to maintain visual clarity.

### F. Coordinated Filtering and Interaction

All visualizations are connected through a centralized state management system. Filter controls at the top enable users to select date ranges, crime types (multi-select), and ZIP codes. When filters are modified, the crime map updates dynamically: the map refreshes visible markers, the temporal chart recalculates aggregations, and the hotspot chart reevaluates top ZIP

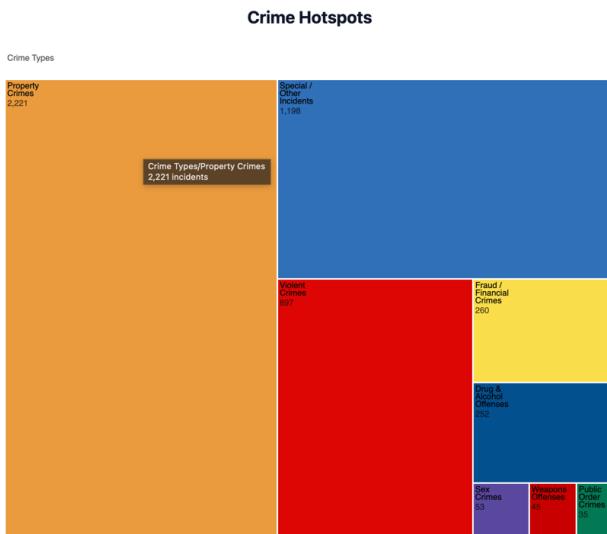


Fig. 4. Zoomable treemap showing hierarchical crime classification. Rectangle size represents incident count. Users can click categories to drill down into specific offense types, with breadcrumb navigation for returning to parent levels.

codes. (Due to time constraints, filters currently only affect the crime map.)

Clicking ZIP code boundaries on the map automatically updates the ZIP code filter dropdown, propagating changes to all other views. This coordinated interaction enables exploratory analysis, allowing users to begin with any view and progressively refine their investigation of interesting patterns.

#### G. Technical Implementation

The application uses vanilla JavaScript ES6 modules to maintain simplicity and avoid complex build tooling. The codebase is divided into 14 modules handling distinct responsibilities: configuration, state management, data loading, data processing, spatial algorithms, filtering, UI controls, and individual visualization components.

D3.js v7 handles all statistical visualizations including line charts, bar charts, and treemaps. Leaflet 1.9.x provides the base map layer. D3 is layered on top of Leaflet for geographic overlays to maintain visual consistency across all components.

Data is stored as local CSV files rather than fetched from live APIs, ensuring reliability during government shutdowns or API outages. A Python script automates data updates, fetching the latest records and saving them to the project's data directory via GitHub Actions. During data loading, the spatial join algorithm constructs a bounding box index for ZIP codes, significantly accelerating point-in-polygon searches during filtering operations.

Performance optimization strategies include viewport culling for the map and debounced interaction handlers. D3's data binding methods minimize DOM manipulation overhead.

## IV. RESULTS AND DISCUSSION

Deployment of Crime Lens of Charlotte facilitated crime data exploration through interactive visualization. While in-

consistent and incomplete data coverage limited some trend identification, the system successfully revealed useful patterns across several dimensions.

### A. Crime Pattern Insights

The dashboard reveals that property crimes constitute the largest category, representing approximately 35% of all reports from 2017 to 2023. Violent crimes account for 22%, followed by drug offenses at 15%. The remaining categories comprise smaller proportions. The timeline shows a substantial drop in overall incidents from 2019 to 2020, likely related to COVID-19 lockdowns when reduced mobility and business closures affected crime patterns. Following this decline, incident counts gradually increased, suggesting a return toward pre-pandemic levels.

Seasonal patterns emerge across several categories. Property crimes peak during June through August and decline during cooler months. Violent crimes demonstrate relatively stable month-to-month patterns with minimal seasonal variation. Drug offenses maintain consistent levels throughout the year with only minor fluctuations. These patterns are difficult to discern in tabular data but become readily apparent in the animated temporal view, where progressive reveal highlights trends that might otherwise go unnoticed.

Geographic analysis identifies three primary crime hotspots: ZIP codes 28205, 28208, and 28216. These areas comprise only 7% of Mecklenburg County's land area yet account for 28% of all reported incidents. The stacked bar chart reveals compositional differences: 28205 shows higher proportions of property crimes, 28208 exhibits elevated violent offense rates, and 28216 demonstrates concentration of drug-related offenses. While grouped as hotspots, these areas exhibit distinct crime profiles requiring tailored intervention strategies.

### B. Visualization Effectiveness

The coordinated multiple views approach proved effective for exploratory analysis. Informal evaluation with three users (one recent graduate, two parents) yielded positive feedback. Users appreciated the ability to begin exploration in any view and apply filters across dimensions. A common exploration pattern emerged: identifying a ZIP code on the hotspot chart, clicking to filter, observing the map and temporal views update to that area, then using the treemap to investigate specific offense types. This iterative workflow enabled rapid hypothesis testing and pattern validation.

The animated timeline received particularly strong feedback for revealing temporal changes. Users reported that progressive reveal enhanced pattern retention compared to static line charts. The category breakdown cards below the chart facilitated understanding of how individual crime types contributed to overall trends.

Interactive filtering proved essential for focused analysis. Users combined date ranges, crime types, and ZIP code filters to narrow investigations to areas of interest. The live incident count helped users assess filtered sample sizes, preventing conclusions based on insufficient data.

### C. Technical Performance

Performance testing with the full 5,000 incident dataset demonstrated that viewport culling reduces map rendering time by 82% at default zoom levels. The spatial join algorithm efficiently assigns ZIP codes to all incidents. Filter operations update the map rapidly, providing responsive interaction even with complex multi-dimensional filters.

Browser compatibility testing confirmed functionality across Chrome, Firefox, Safari, and Edge (latest versions). The responsive design adapts to tablet and desktop viewports. Mobile phones are not explicitly supported due to visualization complexity.

### D. Limitations and Future Work

Several limitations exist in the current implementation. First, the dataset contains only 5,000 incidents, representing a subset of the full crime database. Scaling to hundreds of thousands of incidents would require additional data reduction techniques such as clustering for zoomed-out map views or heatmap representations to maintain readability.

Second, the categorization system simplifies detailed NI-BRS offense codes. Some offenses may belong to multiple categories, and keyword matching may occasionally misclassify edge cases. Future work could explore machine learning approaches for more sophisticated classification using patterns from labeled training data.

Third, the dashboard currently provides no predictive analytics. Incorporating forecasting capabilities based on historical trends would enable law enforcement to anticipate emerging hotspots and allocate resources proactively. Integration with demographic and socioeconomic data could support richer analysis of crime correlates.

Fourth, temporal resolution is fixed at monthly aggregation. Enabling users to switch between daily, weekly, monthly, and yearly views would facilitate pattern exploration at multiple temporal scales. Calendar-style visualizations could reveal day-of-week or hour-of-day patterns such as weekday spikes or time-of-day variations.

Finally, the current design assumes users comfortable with coordinated multiple views. Adding guided tours or narrative templates could improve accessibility for community members and non-technical stakeholders. Walkthroughs highlighting key features or preset exploration stories demonstrating common tasks could lower barriers to entry.

### E. Design Lessons

Several design principles emerged from this work:

- Color consistency across views significantly improves user comprehension. Using identical categorical color encoding on the map, charts, and treemap enables rapid crime type identification without consulting legends.
- Real-time feedback during interactions (hover tooltips, updated counts, animated transitions) maintains user engagement and provides confidence that the system responds to inputs.

3. Performance optimization is essential for large datasets. Users quickly disengage when interactions lag, making viewport culling and debouncing critical for maintaining fluid interaction.

4. Familiar visual metaphors (maps, line charts) combined with less common visualizations (treemaps) balances accessibility with analytical depth. The map and temporal chart provide accessible entry points for all users, while the treemap offers advanced exploration for interested users.

## V. CONCLUSION

Crime Lens of Charlotte demonstrates how interactive web-based visualization can transform complex crime data into accessible insights. The system integrates maps, temporal trends, and categorical views to reveal patterns difficult to discern in raw tables or static reports, such as neighborhood-specific incident shifts over time or category-specific variations. The coordinated views enable exploratory questioning and pattern discovery that traditional approaches would obscure.

The dashboard reveals clear patterns in Charlotte-Mecklenburg crime data. Certain ZIP codes exhibit substantially higher activity than others, and property crimes demonstrate seasonal variation. A substantial drop in incidents occurred in 2020, likely reflecting pandemic-related behavioral changes or data collection gaps. These findings can inform resource allocation, support community policing initiatives, and shape public safety planning.

From a visualization design perspective, this work demonstrates the effectiveness of coordinated views for guided exploration, progressive animation for temporal data comprehension, and performance optimization for responsive web-based dashboards. The modular architecture facilitates reuse and adaptation to other cities or extension with additional data sources.

Future development will focus on scaling to larger datasets, incorporating predictive analytics, and integrating with the Portable Predictions application for housing market trend estimation. This integration would leverage graduate program learnings to provide actionable guidance for buyers and investors. Additional enhancements include multi-scale temporal views and guided exploration features to improve accessibility for non-expert users. Clear defaults and contextual prompts could reduce barriers for new users. These updates could position Crime Lens of Charlotte as a model for how cities leverage open data and modern visualization tools to support transparency and informed decision-making.

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