**Transportation network perimeter identification**

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**Abstract**

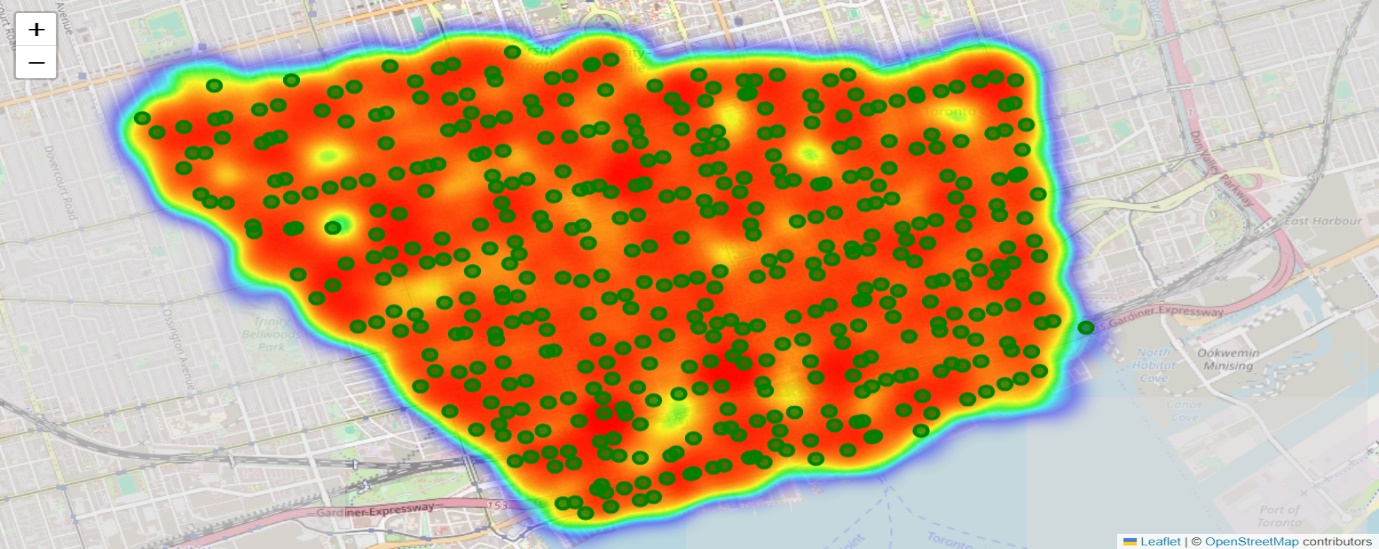
This project identifies high-interest zones within urban environments to improve traffic flow and optimize urban infrastructure planning. Our approach combines advanced heatmap analysis with K-Means clustering to outpoint activity hotspots and employes reinforcement learning to optimize computational efficiency.  
Preliminary results demonstrate efficient clustering of interesting and accurate identification of critical zones, providing actionable insights for urban planning. This framework has the potential to transform urban planning processes, offering a scalable and dynamic solution for managing rapidly evolving city landscapes.

**Introduction**

With the rapid growth of urban areas, identifying key zones of activity within cities has become essential for optimizing infrastructure, managing traffic, and creating safer, more vibrant environments. As of 2023, more than 56% of the global population resides in urban areas, a figure expected to reach 68% by 2050. This rapid urbanization presents significant challenges, including traffic congestion, increased pollution, and inefficient infrastructure use. Identifying high-interest zones within cities is critical to addressing these issues effectively and enabling sustainable urban development.  
To address these challenges, this project develops a dynamic framework for identifying and visualizing high-interest zones in urban environments. By leveraging geospatial traffic data from TomTom, a leading provider of navigation and traffic information, the framework integrates advanced heatmap analysis, K-Means clustering, and reinforcement learning techniques. The TomTom dataset, which provides precise data on GPS coordinates (latitude and longitude) , speed limit and average speed, forms the foundation for generating actionable insights and optimizing computational resources.  
The framework begins by generating geospatial heatmaps to visualize activity intensity. K-Means clustering is employed to group critical intersections, while reinforcement learning, powered by a neural network and the DQN algorithm, enhances computational efficiency and improves clustering accuracy. The DQN algorithm, a deep reinforcement learning technique, allows the framework to make adaptive and data-driven decisions by learning optimal policies for intersection clustering. Unlike traditional methods that rely on static traffic simulations or isolated heatmap analyses, this project introduces a dynamic, AI-driven approach that adapts to urban complexities.  
The insights generated by this framework have applications beyond traffic optimization. Urban planners can use these findings to enhance public transportation routes, improve pedestrian safety in high-density areas, and develop data-driven strategies for emergency response. By integrating neural networks and reinforcement learning into the analysis process, the framework provides a scalable and intelligent solution for managing dynamic city landscapes.  
This paper outlines the methodology, tools, and findings of the project. It begins with a discussion of data acquisition from TomTom and its processing into heatmaps. Subsequent sections present the analysis and findings, including heatmap visualizations, clustering results, and the role of the DQN algorithm in optimizing these processes. Finally, the paper explores the broader implications of this framework and highlights directions for future work.

**Background**

Urban Analysis: Urban analysis is the study of city structures, dynamics, and interactions to better understand how urban areas function and evolve. By leveraging data from sources like TomTom, urban analysis helps uncover patterns in mobility, population density, and infrastructure usage. This understanding enables city planners, policymakers, and businesses to optimize resources, improve traffic flow, and enhance urban livability. Modern urban analysis often relies on advanced tools like heatmaps, clustering algorithms, and machine learning to visualize and process complex data, making it a critical component in shaping smarter and more sustainable cities.  
Urban analysis tools, such as geospatial mapping and clustering algorithms, are instrumental in identifying traffic bottlenecks, improving public transport networks, and planning pedestrian-friendly zones. This project extends these capabilities by integrating advanced heatmap visualizations and machine learning techniques to derive actionable insights.

Heatmap: A heatmap is a powerful visualization tool that represents the density or intensity of data over a geographical area using a gradient of colors. Warmer colors (such as red, orange, and yellow) typically indicate regions with higher activity, while cooler colors (like blue or green) signify lower levels of activity. In this project, the heatmap serves as a key component for analyzing urban environments by visualizing areas of high-interest activity based on traffic data.  
The heatmap in this work is generated using geospatial traffic data from TomTom, which includes traffic flow (speed limit and average speed), and intersection density across a specific urban area. Each point of interest, such as intersections or road segments, contributes to the overall activity level in a particular region. The heatmap highlights these high-activity zones, enabling the identification of traffic congestion areas or critical hotspots that require further analysis.   
In summary, the heatmap plays a crucial role in identifying high-activity zones by transforming complex geospatial traffic data into an intuitive, visual format. It provides a foundation for deeper analysis using clustering techniques and machine learning, ultimately supporting urban planning decisions that aim to optimize traffic flow and infrastructure usage.  
Clustering algorithm: Clustering algorithms are unsupervised machine learning techniques used to group data points based on their similarity or proximity. In the context of this project, clustering algorithms, specifically K-Means, are employed to group high-activity intersections identified on the heatmap. These algorithms analyze geospatial traffic data, such as vehicle density or intersection activity, and partition the data into clusters that represent regions with similar activity patterns.  
In this project, K-Means helps to reduce computational complexity by grouping closely related intersections or traffic points into clusters.   
This enables more efficient analysis of critical areas, as the algorithm focuses on meaningful regions rather than individual data points. By integrating clustering with heatmap visualization, the project identifies zones of high interest, optimizes urban infrastructure planning, and provides actionable insights for managing traffic congestion effectively.

Neural Network: A Neural Network is a machine learning model inspired by the human brain, designed to recognize patterns and relationships within data. It consists of an input layer that receives data, hidden layers that process it using weights and activation functions, and an output layer that provides predictions. In this project, a Convolutional Neural Network (CNN) processes geospatial traffic data, leveraging convolutional layers to extract spatial features from heatmaps. The network is trained via backpropagation to optimize decision-making in tasks such as clustering and traffic analysis.

Reinforcement Learning: Reinforcement Learning is a type of machine learning where an agent learns to make decisions by interacting with an environment to achieve a specific goal. The agent takes actions in the environment, observes the outcomes, and receives rewards based on how effective its actions are. Over time, the agent learns an optimal policy, a strategy for selecting actions that maximize cumulative rewards. In this project, RL is implemented using the DQN algorithm, which combines reinforcement learning with deep neural networks. By integrating RL, the project enhances the computational efficiency and accuracy of clustering processes, ensuring more intelligent and adaptive urban planning solutions.  
  
Deep Q-Network (DQN): The DQN is a reinforcement learning algorithm that combines Q-Learning with deep neural networks to solve decision-making problems in high-dimensional spaces. It is particularly effective for tasks where the environment is complex, and the state space or the possible conditions is too large to handle with traditional Q-Learning.

**Convolutional Neural Network**

A Convolutional Neural Network (CNN) is a type of neural network designed to process spatially structured data, such as images and geospatial traffic heatmaps. CNNs are especially effective at recognizing patterns and extracting features from structured inputs by learning spatial relationships within the data.  
Structure of a CNN:  
A typical CNN consists of many types of layers:

1. Input Layer: Receives structured input data, such as traffic heatmaps represented as multi-dimensional arrays. Each feature map encodes specific spatial attributes of the data.
2. Convolutional Layers: These layers apply filters (kernels) that scan across the input data to extract local features like edges, textures, and high-activity regions. Convolution operations preserve the spatial structure of the data.
3. Pooling Layers (optional): Reduce the spatial dimensions of the feature maps, retaining important features while improving computational efficiency
4. Fully Connected Layers: Process the extracted features to make predictions, such as Q-values for decision-making tasks in reinforcement learning.
5. Output Layer: Produces the final predictions, such as classification probabilities or clustering decisions.

Components of a CNN:

* Filters and Feature Maps: Filters in convolutional layers detect specific patterns in the input, creating feature maps that highlight these patterns.
* Activation Functions: Non-linear functions like ReLU (Rectified Linear Unit) are applied to introduce non-linearity, enabling the network to model complex relationships.
* Weights and Biases: Each filter has trainable weights and biases, which are adjusted during training to optimize the feature extraction process.

Training a Neural Network:  
CNNs are trained through forward propagation and backpropagation:

1. Forward Propagation: Input data passes through the layers, with filters extracting features and producing intermediate outputs
2. Loss Function: The difference between the predicted output and the true output is calculated using a loss function, such as Mean Squared Error (MSE) or Cross-Entropy Loss.
3. Backpropagation: Gradients of the loss function with respect to each filter's weights are calculated and used to update the weights, optimizing the network’s performance.
4. Optimization**:** Techniques like Adam or Stochastic Gradient Descent (SGD) are used to iteratively adjust weights and biases, minimizing the loss.

Advantages of Neural Network:  
Neural Networks are powerful because they can:

* Spatial Feature Extraction: Convolutional layers automatically detect patterns and relationships in structured data.
* Scalability: CNNs handle high-dimensional inputs effectively, such as heatmaps.
* Adaptability**:** CNNs generalize well across different datasets, making them ideal for dynamic urban planning and traffic analysis tasks.

**Reinforcement Learning with DQN**

Reinforcement Learning (RL) is a branch of machine learning where an agent learns to make decisions by interacting with an environment. The agent takes actions in the environment, observes the outcomes, and receives rewards based on the effectiveness of those actions. The goal of the agent is to learn an optimal policy, a strategy that maximizes the cumulative rewards over time.  
The RL process can be described as a Markov Decision Process (MDP), which includes:

1. States : The current condition or situation of the environment.
2. Actions : The decisions or moves the agent can take in each state.
3. Rewards : A numerical value indicating the outcome of an action.
4. Policy 𝞹: A mapping from states to actions
5. Transition Dynamics : The probability of moving from one state to another after taking a particular action.
6. Discount Factor γ: A value between 0 and 1 that determines the importance of future rewards.

Q-Learning is a value-based RL algorithm that learns the Q-value for each (state, action) pair where:

* represents the expected cumulative reward of taking action in state and following the optimal policy thereafter.  
  The Q-values are updated iteratively using the Bellman Equation:
* α is the learning rate
* is the reward received after taking action
* γ is the discount factor.
* is the maximum value of the next state .

Limitation of Q-Learning:  
When the state space is very large (e.g., urban traffic networks), Q-values cannot be stored in a table because the number of states and actions becomes impractically large. This is where DQN comes in.  
Overview:  
DQN combines Q-Learning with deep neural networks to approximate the Q-values. Instead of maintaining a Q-table, DQN uses a neural network to predict the Q-values for all possible actions in each state.  
How DQN Works:

1. Neural Network as a Q-Function Approximator:

* A deep neural network takes the current state as input and outputs the Q-values for all possible actions.
* The network approximates the mapping

1. Replay Buffer:

* DQN uses a replay buffer which is a memory bank to store past experiences as tuples
* During training, batches of these experiences are sampled randomly to break the correlation between consecutive experiences, leading to more stable learning.

1. Target Network:

* DQN uses two networks:   
  Main Q-Network: Learns the current Q-values.  
  Target Q-Network: Provides stable target Q-values during training
* The target network is updated periodically with the weights of the main Q-network to stabilize training.

1. Loss Function:

* The DQN algorithm minimizes the difference between the predicted Q-value and the target Q-value:
* is the Q-value predicted by the main network.
* is the Q-value from the target network

1. Epsilon-Greedy Exploration:

* To balance exploration and exploitation using known optimal actions, DQN uses an epsilon-greedy policy:  
  with probability ϵ take a random action.  
  with probability , take the action with the highest Q-value.

1. Training Process:

* The agent interacts with the environment and stores experiences in the replay buffer.
* A batch of experiences is sampled from the buffer.
* The Q-values are updated using the neural network and the target network.
* This process repeats until the agent learns an optimal policy.

Advantages of DQN:  
Scalability- DQN can handle large state spaces where traditional Q-Learning fails.  
Stability- The use of replay buffers and target networks improves the stability of training.  
Generalization- The neural network enables the agent to generalize learning across similar states.

**Methodology**

**Data Acquisition**

Efficient data acquisition forms the foundation of the project, enabling accurate identification and analysis of high-interest zones within urban environments. The primary goal is to gather, preprocess, and structure geospatial traffic data for generating heatmaps and applying clustering techniques. The data acquisition process is tailored to ensure high-quality inputs for machine learning models and reinforcement learning algorithms.  
  
Sources of Data:

We used the source TomTom, its precision and comprehensiveness make it an ideal choice for traffic analysis. Geospatial Traffic Data from TomTom, Includes:  
GPS coordinates of road segments and intersections.  
Traffic flow and density data  
Speed limits and average speed measurements

Preprocessing Steps:

1. Data Cleaning
2. Filtering for Relevance
3. Feature Engineering
4. Spatial Data Transformation

Data Pipeline Automation:  
The data acquisition pipeline is automated to streamline the process using custom Python scripts:  
Extract JSON Data: Processes raw traffic data, cleans it, and generates an analysis-ready CSV (as implemented in extractJsonnData.py)​.  
Filter Relevant Data: Ensures only useful traffic points are passed into subsequent analysis stages.

Conclusion:  
The data acquisition process is a critical first step in creating a reliable framework for traffic analysis. By ensuring data quality and consistency, the project lays a strong foundation for generating accurate heatmaps, clustering intersections, and deriving actionable insights for urban planning.

**Heatmap Generation**

Heatmaps are a vital visualization tool in this project, enabling the identification of high-interest zones by transforming complex geospatial traffic data into an intuitive, color-coded representation. The heatmap highlights traffic intensity across urban environments, with warmer colors (e.g., red) indicating areas of high activity and cooler colors (e.g., green or blue) representing lower activity levels.

This step bridges the raw data collected during the Data Acquisition phase with the analytical insights provided by clustering and reinforcement learning, laying the foundation for actionable urban planning decisions.  
  
Methodology:

1. Input Data  
   Geospatial traffic data includes:  
   Latitude and Longitude: To map intersections and road segments.  
   Inverted Speed Ratios: Derived from speed limits and average speed, emphasizing congestion levels.
2. Heatmap Metrics  
   Intensity -   
   The degree of activity or congestion at each point, calculated using:

Points with higher inverted ratios indicate areas of congestion.

Weighting -  
Assign weights to traffic points based on their importance, such as traffic density or proximity to intersections.

1. Heatmap Creation  
   A Python-based pipeline is used to generate heatmaps:

Data preprocessing ensures all traffic points are relevant (speed > 0)  
Geospatial points are plotted using Folium and the HeatMap plugin​​.  
A color gradient visualizes intensity, from blue (low activity) to red (high activity).

1. Dynamic Heatmap Updates  
   The pipeline is designed to support dynamic updates for real-time traffic analysis  
   By integrating streaming traffic data, the heatmap reflects current urban activity.

Implementation Details:

* Data Filtering:  
  Traffic data with invalid or missing fields (e.g., zero-speed segments) is removed.  
  Only high-activity points are retained, improving the clarity of the heatmap.
* Visualization Setup:  
  Folium Library:  
  A Python library used to create geospatial maps.  
  Heatmap Layer:   
  Represents traffic intensity over the area of interest, with adjustable parameters such as:  
  Radius: Controls the size of heatmap influence for each point  
  Blur: Smoothens the heatmap for better visual clarity.
* Integration with Clustering:  
  The generated heatmap is overlaid with clustered intersection points, helping identify zones that require deeper analysis.  
  Cluster centroids are visually represented as markers on the heatmap​.

Output and Interpretation:

* Visualizations:  
  Heatmaps are saved as interactive HTML files, allowing urban planners to explore traffic activity zones dynamically.  
  Combined maps (heatmaps + clustering markers) provide a holistic view of urban activity hotspots.
* Interpretation:  
  High-intensity areas (red zones) identify traffic bottlenecks or zones requiring infrastructure improvement.  
  Low-intensity areas (blue zones) suggest smooth traffic flow or less critical regions.

Conclusion:  
Heatmap generation transforms raw traffic data into actionable visual insights, enabling the identification of urban activity zones that demand intervention. By integrating heatmaps with clustering and reinforcement learning, the project provides a scalable and dynamic tool for optimizing urban infrastructure and managing traffic flows effectively.

**Clustering with K-Means Algorithm**

Clustering is a vital technique in this project to group high-activity regions or intersections within urban environments. By reducing the complexity of large geospatial datasets, clustering simplifies the identification of critical zones, aiding in traffic management and infrastructure planning.

The project employs a hybrid approach:

* K-Means Clustering for grouping intersections based on geospatial proximity and traffic intensity.
* Reinforcement Learning (DQN) to dynamically optimize clustering parameters for real-time, adaptive analysis.

This combined method ensures high computational efficiency while maintaining accuracy in identifying zones of interest.

Methodology:

1. Clustering with K-Means Algorithm:

* Objective:  
  We use K-Means because it is an unsupervised clustering algorithm that efficiently partitions spatial data based on proximity.
* Process:  
  Input geospatial traffic data (latitude, longitude).  
  Define k clusters (number of zones) based on traffic density.  
  Use K-Means to group data points into clusters
* Optimization:  
  Cluster centroids represent the high-interest zones, reducing the dataset size.  
  Results are saved in a simplified format for further processing (as demonstrated in generate2layersMap.py and extractIntersections.py)​​.
* Output:  
  Cluster centroids represent the most critical intersections.  
  The reduced dataset is saved in a simplified format for further processing
* Integration with Heatmap:

Clustering results are overlaid onto heatmaps generated from traffic intensity data.

The heatmap intensity (e.g., inverted speed ratios) is used to determine zones that require further analysis or clustering optimization.

1. Dynamic Optimization with Reinforcement Learning (DQN):

* Objective:  
  Traditional K-Means methods rely on static configurations and cannot adapt to real-time traffic changes.
* DQN Integration:  
  State: The current clustering of intersections and activity zones.  
  Action: Adjust clustering parameters (k) or modify existing clusters.  
  Reward: A numerical value evaluating the clustering efficiency, balancing:  
  Coverage of high-intensity zones and, Reduction of computational complexity.  
  Q-network: A neural network approximates the Q-values to optimize the clustering policy.
* Improvements in Clustering Process:  
  Adaptive clustering ensures the RL agent dynamically optimizes the number of clusters.  
  Redundant actions, such as selecting the same intersections repeatedly, are filtered through action memory mechanisms.

Evaluation:

1. Clustering Results:

Clustered intersections and high-activity zones are visualized on combined heatmap maps.  
Results demonstrate significant reduction in the number of intersections analyzed while preserving data accuracy.

1. Performance Metrics:  
   Inertia: Measures the compactness of clusters, lower values indicate better clustering.   
   Silhouette Score: Evaluates how well data points fit within their clusters.  
   Computational Efficiency: Clustering reduces the dataset size, leading to faster analysis and visualization.
2. Visualization:

Clustered points are represented as green markers on top of the heatmap, highlighting critical zones.  
Representative results are saved as HTML visualizations or images (e.g., combined\_heatmap\_intersections\_map.html).

Conclusion:  
The combination of K-Means clustering with reinforcement learning (DQN) offers a robust and adaptive solution for identifying critical zones in urban environments. This approach reduces computational overhead, dynamically adjusts to real-time traffic patterns, and provides valuable insights for urban infrastructure optimization.

**Neural Network Architecture**

The Neural Network (NN) used in the project plays a crucial role in optimizing the clustering of high-interest zones within urban environments. This network is based on the Deep Q-Network (DQN), which integrates reinforcement learning with neural networks to handle complex decision-making tasks like urban traffic clustering. Convolutional Neural Networks (CNNs) are employed within this architecture to process geospatial heatmap data, leveraging their ability to capture spatial patterns and dependencies effectively.

Layers Used in the Neural Network:  
The CNN-based neural network consists of the following layers as implemented in the Q-Network class:

1. Input Layer:  
   Receives the state representation of the environment, including processed heatmap data, convex hull masks, and dot indicators.  
   The input is a three-channel tensor representing these components:   
   where spatial relationships are preserved
2. Convolutional Layers:  
   Two convolutional layers are used to extract spatial features from the input:  
   the first convolutional layer applies 32 filters with a kernel, followed by ReLU activation.  
   the second convolutional layer applies 64 filters with a kernel, also followed by ReLU activation.  
   These layers detect spatial patterns such as high-activity zones and intersections.
3. Flattening Layer:  
   Converts the spatially structured feature maps produced by the convolutional layers into a one-dimensional vector, preparing it for fully connected layers.
4. Fully Connected Layers:  
   First Fully Connected Layer: Contains 128 neurons with ReLU activation to refine the extracted features and capture complex relationships in the data.  
   Second Fully Connected Layer: Also contains 128 neurons with ReLU activation for further feature processing.
5. Output Layer:  
   The output layer is a fully connected layer, where the number of neurons corresponds to the number of possible actions (intersections available for toggling).  
   It outputs Q-values for each action, representing the expected cumulative reward for taking that action in the current state.

Advantages of the Network Design:

* Spatial Feature Extraction: The convolutional layers allow the network to capture spatial dependencies in the input heatmaps, improving decision-making accuracy.
* Scalability: The lightweight architecture is powerful, ensuring efficient learning while handling large input sizes (21168 features)
* Action-Specific Outputs: The output layer directly maps to all possible actions, simplifying the integration with reinforcement learning algorithms.

Integration with DQN:  
This neural network is a key component of the DQN Agent, which performs the following:

* Select Actions: The network predicts Q-values for each possible action, enabling the agent to choose the optimal action.
* Update Policy: The network is trained using the Mean Squared Error (MSE) loss to minimize the difference between predicted Q-values and target Q-values

Conclusion:  
By combining this CNN-based architecture with the reinforcement learning algorithm, the system dynamically adjusts clustering strategies for high-interest zones, ensuring computational efficiency and accuracy. The network’s ability to process spatial data makes it particularly effective for analyzing and optimizing urban traffic patterns.

**DQN Architecture**

The primary objective of the DQN implementation is to:  
Maximize the coverage of high-intensity zones (based on the heatmap).  
Minimize computational overhead by efficiently selecting intersections to form the convex hull.  
Encourage exploration of new configurations while penalizing redundant or unproductive actions.

State:   
The current clustering of intersections and activity zones derived from the heatmap, the state includes the following components:

* Heatmap Data: represents traffic intensity and critical zones visually.
* Convex Hull Mask: Encodes the current shape of the convex hull formed by selected intersections.
* Dot Indicators: Denotes the state (active or inactive) of each intersection.

Actions:  
Decisions related to toggling intersections in or out of the convex hull, each action corresponds to selecting or deselecting a specific intersection, which modifies the shape and coverage of the convex hull.

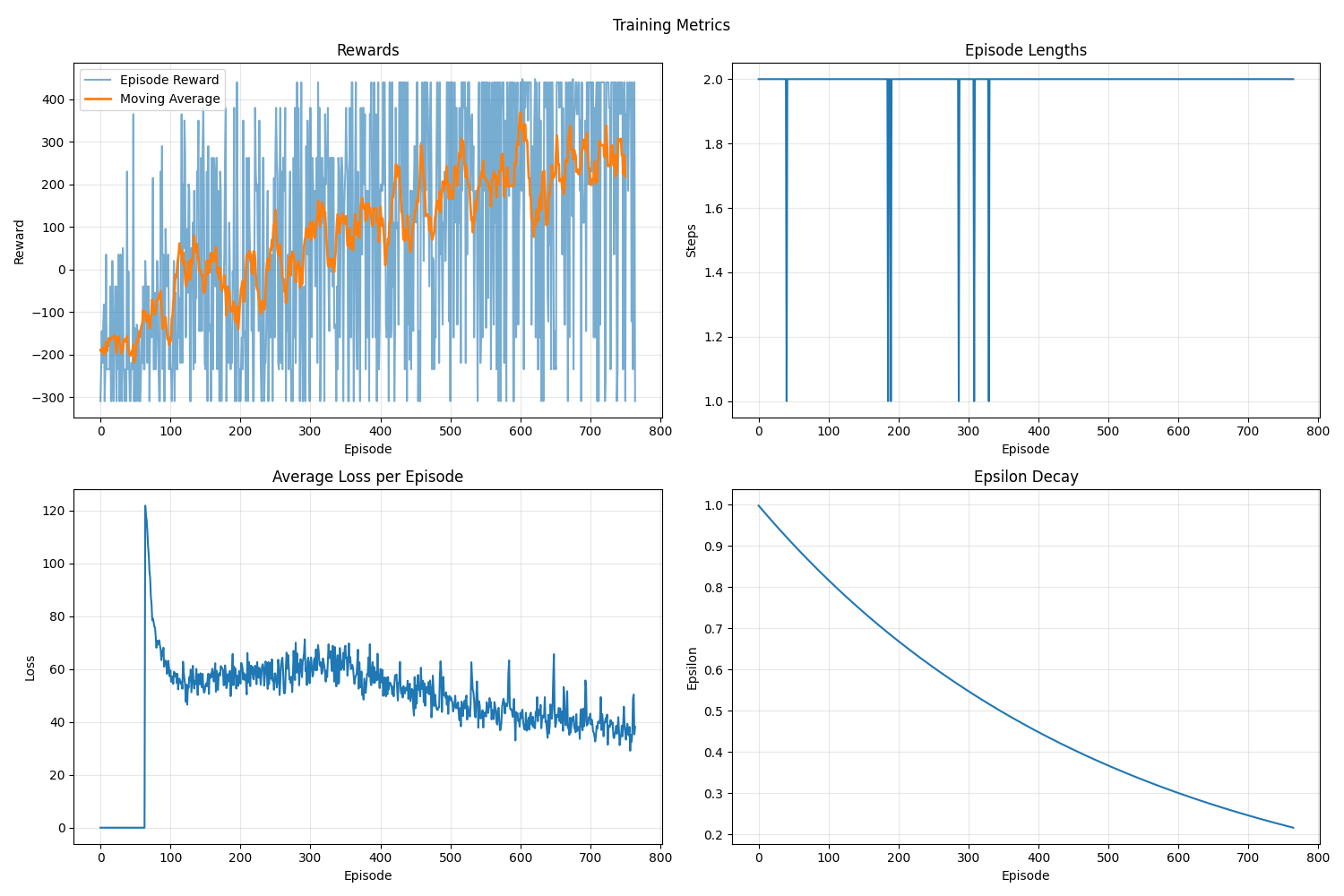
Reward:   
The reward function is designed to balance the following objectives:

1. Encouraging Area Expansion:  
   the reward is proportional to the increase in the area covered by the convex hull. A positive reward is given when the addition of an intersection significantly increases the convex hull area.
2. Penalizing Redundant Actions:  
   repeated actions on already toggled intersections incur a heavy penalty.
3. Avoiding Insignificant Changes:  
   small or negligible changes in the convex hull area are penalized to discourage unproductive actions

Summary of Workflow:

* Generate heatmaps to identify activity intensity.
* Use K-Means clustering to group intersections.
* Train the RL agent using DQN to learn optimal clustering actions:  
  explore different clustering configurations.  
  learn from rewards to optimize clustering efficiency.
* Continuously update the model to adapt to real-world changes in traffic patterns.

This integration of DQN ensures a dynamic, AI-driven framework for urban analysis, providing scalable and intelligent solutions for managing city landscapes. Over time, the system dynamically adapts to changes in traffic patterns, identifying and optimizing the most critical zones for urban infrastructure planning.

**Analysis and Findings**

**A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a point in the center

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a red and green dot

AI-generated content may be incorrect.A map with a map and a map

AI-generated content may be incorrect.A map with dots and lines

AI-generated content may be incorrect.**

Let’s analyze the heatmap visualization, as it represents the basis of our analysis:

The heatmap visualization represents the traffic intensity across Toronto’s landscape. As shown in the images above, we can see that the heatmap shows the distinct pattern of the traffic intensity, the darkest red areas represent the most intense traffic zones, and the yellow to blue areas represent slow activity of traffic. This is good for transforming the complex traffic data into a simpler, easy color-coded representation of the urban hotspots that require our focus and attention.

The generation of the heatmaps was successful in marking traffic congestion points and intersections, that provide a clear foundation for subsequent clustering and reinforcement learning methods.

As shown in the first figure, the results of our DQN agent training show a remarkable improvement in the agent’s ability to identify the high-traffic zones. The training metrics give us information on the Reward Progress through the training, the steady decrease in the Loss Average, the epsilon decay that shows the exploration-exploitation balance and episode lengths that suggested the agent’s quick ability to learn.

First, regarding the reward’s progress through the training, the average reward of the training is increased over time through the training, from having negative values at first, to having increased positive values that reached above 200 by the later episodes. This progress of the reward shows us that the agent can learn successfully to identify high-traffic zones with increasing proficiency.

Secondly, regarding the average loss shown in the first figure, after being up at first, around episode 100, the average loss value decreased and stabilized around 30-40. This shows the effective convergence of the weight parameters of the neural network.

In addition, the epsilon decay graph shows the changes from exploration to exploitation, by starting at 1.0, it gradually decreases to ~0.2 by the later episodes of the training, this allows the agent to leverage its learned knowledge increasingly.

Last, the first figure shows the graph of the episode lengths, most of the episodes were finished in 2 steps, this shows that the agent is learning fast to decide on the actions rather than having to extended sequence of modifications to make the decisive actions.

Our reward function was designed to distinguish the balance between traffic intensity and the geometric compacts, that’s why the agent is showing the ability to learn to prioritize intersections that are in high-traffic zones, while keeping a geometrically sensible convex hull.

Let’s analyze the convex hulls that are generated by our trained agent, that represent the identified traffic zones. Our reward function was designed in a way that let the agent learn to select specific high-traffic sub areas rather than selecting the entire area (larger convex hulls). This selective approach enables efficient and more targeted strategies. In addition, the convex hulls generated through training have covered areas with highest traffic data(dark red areas), this shows the agent’s ability to prioritize traffic density. Moreover, the agent learned to generate convex hulls with minimal area and maximum in traffic coverage, by seeing the small number of intersections that define each convex hull (3-5). Lastly, the agent has explored different convex hull configurations through different training runs, this indicates that the agent is learning robustly rather than insisting on a single solution.

The above patterns can be evidence that our approach of combining heatmap visualization with K-mean clustering and Deep Q-Networks reinforcement learning, our algorithm managed to learn successfully to balance between maximizing the coverage of the traffic along with minimizing geometrics complexes in order to have the best results for finding the high traffic urban areas.

**Challenges and Limitation**

During the development of this project, we encountered several challenges that shaped our final approach.   
Initially, before implementing the CNN based reinforcement learning model, we explored alternative methods to construct and analyze the urban traffic map.

Attempt with Graph based Mapping:

Our first major approach involved creating a detailed traffic map using the Graphviz and NetworkX libraries. We extracted the geographical points and connections from TomTom in a JSON dataset file, using nodes and edges to manually plot a visual representation of the street network.

The script we developed calculated distances between coordinates and connected intersections as a directed graph. We even visualized the network in hopes of accurately capturing the physical road structure and traffic relationships.

Limitations:

* Accuracy Issues: The manual graph construction based on extracted JSON data failed to accurately represent the real road geometry and traffic patterns. The raw coordinate points lacked the spatial precision required to form a reliable map.
* Incomplete Structures: Due to the limitations of the data format and the lack of full connectivity details, the graph generated often missed key connections between segments, leading to fragmented and unrealistic road networks.
* Complexity of Scaling: While this method worked on very small subsets, applying it to a full-scale urban area would dramatically increase computational cost, without guaranteeing meaningful insights.
* Time Consumption: We spent a significant amount of time refining this method processing coordinates, calculating distances, and plotting nodes only to find the result was insufficiently accurate for deeper analysis.

After extensive experimentation and evaluation of this method, we recognized that a static, manually constructed graph could not dynamically adapt to the complexity and fluidity of real urban traffic systems. These challenges motivated us to pivot toward a data-driven and adaptive approach, leading to the integration of heatmaps, K-Means clustering, and ultimately a CNN-powered DQN agent capable of learning and optimizing critical traffic zones based on actual traffic intensity.

Attempt with Google Maps API:

We then attempted to work with Google Maps. Leveraging the gmaps Python library, which provides a built-in interface to generate heatmaps using the Google Maps API. We conducted an in-depth exploration of how to create a continuous and dynamically updating heatmap with the desired color intensity.

The Goal was to ensure that the heatmap updated dynamically within the environment, reflecting real-time traffic conditions. However, despite our extensive efforts, the results were not precise enough for our needs.

Initially preferred Google Maps because of its ease of Data Manipulation, Google Maps’ API allowed for interactive and customizable visualizations, making it simple to modify the data, also because of the high Accuracy, Google Maps platform offers high resolution geographical data that is not always available in other tools.

Limitations:

* Lack of Full Control: Despite our efforts to fine-tune the output, the heatmaps generated were limited by Google's built-in visualization parameters
* Limited API Customization: Google Maps' API provided great visualization, but did not allow for the advanced level of control we needed for clustering and reinforcement learning integration.
* Performance Issues: Updating the heatmap dynamically within our RL environment proved to be inefficient, as the API calls introduced delays and performance bottlenecks.

We invested significant time and effort into this approach because we initially believed it was the best path forward. However, after multiple iterations and experiments, we realized that we needed to try a different approach, one that offered greater flexibility and control over the data processing, clustering, and AI-driven decision making.

This realization ultimately led us to explore CNN based heatmap processing combined with reinforcement learning, which provided a more structured and scalable solution for our traffic analysis.

**Conclusion**

Our project shows a successful dynamic framework for identifying high-traffic zones in the urban environments, with the use of advanced data processing, visualization and machine learning. In our project, we combined geospatial heatmap analysis with K-Means clustering and Deep Q-Network learning to identify the critical zones with precision and computational efficiency. Our main achievements of our work are effectively visualizing traffic, ability to identify zones, computational optimization and the ability to have insight on urban planning.

Our work visualizes traffic effectively, we generated heatmaps from complex traffic data to actionable visual insights, this enabled us to have clear identification of activity hotspots.

In addition, our DQN agent shows remarkable ability to identify high-traffic zones that balanced traffic density with geometric efficiency. This shows the intelligence of the agent upon zone identification.

Furthermore, in our environment we focused the analysis on critical zones rather than the entire urban networks, this significantly reduced the computational overhead but keeping a high accuracy.

Finally, this work and the findings of identifying zones can give us a good insight into how to plan urban infrastructure improvements and traffic management.

These results show the consistent improvement of the agent’s performance over training, the rewards are increasing from negative values to positive values that score above 200, with the visual results seeking that the agent is indeed identifying meaningful traffic hotspots, as we can see the convex hulls encompassing red areas on the heatmap that indicate a high-traffic area.

Our project can be extended in future work that can go in more than one direction. It can be expanded to incorporate temporal traffic patterns, exploring non-convex geometries for identifying zones, also can test the work in a diverse urban environment. Our work can be integrated into existing urban planning tools to develop their utility.

In conclusion, our work shows the potential of combining traditional urban analysis approaches with modern machine learning approaches to address urban challenges. By providing insights into traffic management and infrastructure planning, it can be useful to develop a smarter and better urban environment.

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**RESULT 1 : num of episodes 10, num of steps 300 :**

  
  
תמונה שמכילה מפה, צילום מסך, טקסט

התיאור נוצר באופן אוטומטי