Image target importance recognition method based on visual model and correlation algorithm

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Abstract

Existing urban object detection and analysis methods still lack effective mechanisms to compute and rank semantic relevance between objects in urban scenes. This deficiency limits the recognition accuracy in practical applications and affects the efficiency and precision of subsequent processing. This paper proposes a vision model-based approach for image object relevance analysis, aiming to evaluate inter-object correlations in images by integrating scene knowledge graphs with target relevance analysis.First, we systematically conduct ontological modeling of urban scenes to construct a cityscape knowledge graph. Building upon this framework, we introduce an algorithm combining the visual Relevance Assessment Model (Recognize Anything Model:RAM) with personalized PageRank to calculate semantic relevance between urban scenes and their constituent objects. Based on the analytical results, we implement preference ranking for targets, prioritizing key objects with higher relevance weights to enhance system efficiency and accuracy.Experimental results demonstrate that the proposed method outperforms conventional object detection approaches in recognition accuracy, task relevance matching degree, and computational efficiency, validating its effectiveness and superiority in complex urban scenarios.

1. Introduction

With the rapid development of smart cities and autonomous driving technologies, visual perception and analysis of urban scenes have become a critical research direction in computer vision. Among them, Ren et al. (2015) proposed the Faster R-CNN framework for object localization, achieving high-precision detection through region proposal networks. However, this method struggles to capture semantic interdependencies among multiple objects in complex urban scenes. Redmon et al. (2016/2018) introduced the YOLO series models for real-time object classification, optimizing speed-to-accuracy trade-offs. However, their target prioritization mechanism lacks dynamic adaptation to semantic contextual information, particularly for critical targets like traffic signals and emergency vehicles.

In knowledge-driven approaches, Liu et al. (2016) developed networked knowledge structures using entity-relation-entity triples to model real-world concepts. However, their framework requires manual rule engineering and fails to automatically integrate visual-semantic correlations. Zellers et al. (2018) proposed scene graph generation (SGG) models using object-relation triples to describe image content. However, these models lack quantitative analysis of target correlations and contextual priority weighting. Wang et al. (2020) validated domain-specific knowledge graphs (KGs) for semantic reasoning in vision tasks, demonstrating improved inference capabilities. However, their method does not resolve the integration challenge between visual models and graph-based correlation algorithms.

Among them, Jeh et al. (2003) applied personalized PageRank to social network node ranking, but directly using this algorithm for image target importance calculation ignores spatial feature constraints. Suchanek et al. (2007) proposed the YAGO ontology framework for semantic knowledge representation, providing a theoretical foundation for structured knowledge graph construction. However, this method lacks explicit modeling of dynamic urban spatial relationships. Geiger et al. (2013) provided the KITTI dataset for autonomous driving scenarios, yet its limited coverage of complex urban interactions affects generalization in multi-object scenarios. Ji et al. (2021) summarized knowledge graph construction techniques in a unified paradigm, yet it does not address domain-specific optimization for real-time scene understanding. Zhang et al. (2023) introduced the Recognize Anything Model (RAM) for high-precision image entity recognition, yet it insufficiently models contextual relationships between entities.

2. Methods

2.1 Semantic Relevance Computation Framework

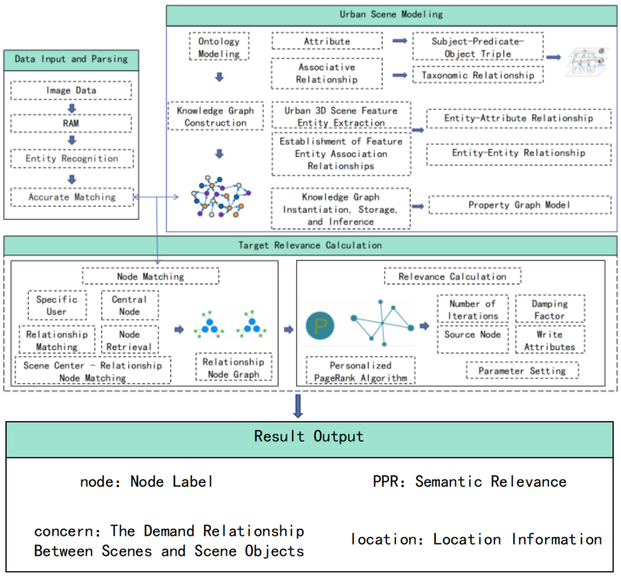

Urban Scene Modeling
Data Input and Parsing
Image Data
RAM
Entity Recognition
Accurate Matching
Ontology Modeling
Attribute
Associative Relationship
Subject-Predicate-Object Triple
Taxonomic Relationship
Knowledge Graph Construction
Urban 3D Scene Feature Entity Extraction
Establishment of Feature Entity Association Relationships
Entity-Attribute Relationship
Entity-Entity Relationship
Knowledge Graph Instantiation, Storage, and Inference
Property Graph Model
Target Relevance Calculation
Node Matching
Specific User
Central Node
Relationship Matching
Node Retrieval
Scene Center - Relationship Node Matching
Relationship Node Graph
Relevance Calculation
P
Number of Iterations
Damping Factor
Source Node
Write Attributes
Personalized PageRank Algorithm
Parameter Setting
Result Output
node: Node Label
PPR: Semantic Relevance
concern: The Demand Relationship Between Scenes and Scene Objects
location: Location Information

Figure 1.Technical Route

First, construct ontologies for different urban scene domains, extracting feature relationships between various scene entities and scene object entities to build a knowledge graph for different urban scenarios. Next, input image data into the visual model RAM to achieve high-precision recognition of entities in images and generate semantic labels, combining this with the urban scene knowledge graph to create an object-scene association network. Then, further quantify the semantic influence of nodes using a personalized PageRank algorithm to complete multi-level propagation calculations of target relevance. Finally, a dynamic weight allocation mechanism generates a ranking of target importance.

2.2 Urban Scene Modeling

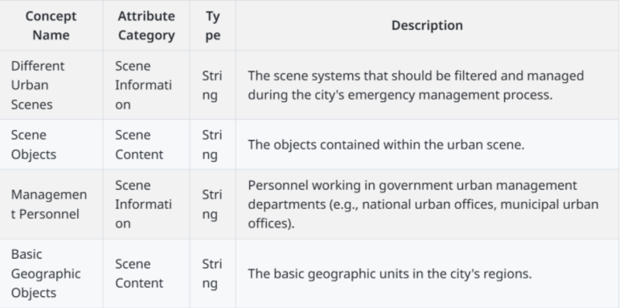
This chapter first performs ontology modeling of urban scene elements as a guide for the knowledge graph. It then extracts and displays the feature relationships between entities, achieving the construction and query analysis of knowledge graphs for different urban scenes.

2.2.1 Urban Scene Ontology Modeling

This paper defines the ontology structure of urban scenes as a triple:

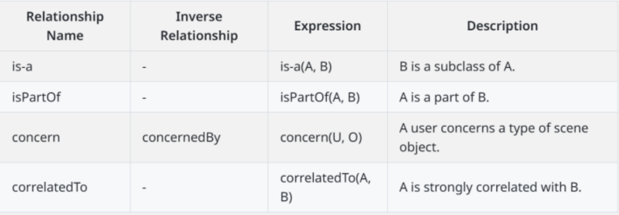
$$O_d =< MS, CO|RC > \tag{1}$$

where $\mathrm{O_d}$ denotes the urban scene ontology, Multi-Scenario (MS) represents distinct urban operational contexts, Core Objects(CO) correspond to scenario-specific entities, and Relationship of Concepts(RC) defines semantic relationships between concepts. Specifically, MS=□DecisionMaker,Rescuer,Public□ encompass es three key scenarios: emergency fire response, building management, and public service coordination. The Core Objects (CO=□BGO,DO,DIO,EMO,SDO are categorized into infrastructure objects (BGO), safety objects (DO), management objects (DIO), environmental objects (EMO), and data objects (SDO).The semantic relationships (RC=□ER,FCR,WPR,UUR,CR□formalize five interaction types: equivalence relations (ER), parent-child relations (FCR), whole-part relations (WPR), hierarchical relations (UUR), and correlational relations (CR). To systematically elucidate these concepts and their semantic interdependencies, Tables 2-1 and 2-2 provide comprehensive taxonomies and relational mappings for urban scene analysis.



Concept Name	Attribute Category	Ty pe	Description
Different Urban Scenes	Scene Informati on	Stri ng	The scene systems that should be filtered and managed during the city's emergency management process.
Scene Objects	Scene Content	Stri ng	The objects contained within the urban scene.
Managemen t Personnel	Scene Informati on	Stri ng	Personnel working in government urban management departments (e.g., national urban offices, municipal urban offices).
Basic Geographic Objects	Scene Content	Stri ng	The basic geographic units in the city's regions.

Figure 2.Some Conceptual Attributes of Urban Scenes



Relationship Name	Inverse Relationship	Expression	Description
is-a	-	is-a(A, B)	B is a subclass of A.
isPartOf	-	isPartOf(A, B)	A is a part of B.
concern	concernedBy	concern(U, O)	A user concerns a type of scene object.
correlatedTo	-	correlatedTo(A, B)	A is strongly correlated with B.

Figure 3.Semantic Relationship Between Concepts

2.2.2 Construction of Urban Scene Knowledge Graph

This section focuses on relational-operation-based entity-linking methods in knowledge graphs, encompassing three core steps: (1) urban scene element entity extraction, which identifies and categorizes critical components (e.g., infrastructure, dynamic objects) from multimodal urban data; (2) construction of inter-entity relational associations, formalizing semantic dependencies such as spatial hierarchies and functional correlations; and (3) knowledge graph generation and reasoning, synthesizing extracted entities and relationships into structured semantic networks while enabling task-aware inference. These steps collectively establish a computational framework for urban scene understanding, bridging low-level visual data and high-level semantic reasoning.

2.2.2.1 Entity Feature Relationship Extraction

This study addresses the extraction of two fundamental relationship types: entity-attribute and entity-entity associations. The latter is further categorized into urban-scene-entity-to-urban-scene-entity and urban-scene-entity-to-scenario-object-entity relationships. A detailed elaboration follows:

(1)**Entity-Attribute Relationship**

Among them, Peng Zilong (2013) proposed a similarity-based method for entity-attribute association extraction by comparing metadata (e.g., names, keywords, descriptions) with attribute information, quantified through a Sim[0,1] metric.

$$\mathrm{Sim(A, B)} = \frac{|A \cap B|}{|A \cap B| + \theta(A,B)|A \cap \bar{B}| + \left(1 - \theta(A,B)\right)|\bar{A} \cap B|} \tag{2}$$

In the formula, $|A \cap B|$represents the number of shared attributes between entity A and attribute B, $|A \cap B|$ represents the number of attributes that belong to entity A but not to attribute B, and conversely, $|A \cap B|$ represents the number of attributes that belong to attribute B but not to entity A.$\theta(A, B)$denotes the weight coefficient, which takes values between 0 and 1. This method can be used to quantify the similarity relationship between an entity and an attribute.

(2)**Entity-Entity Relationship**

- **Urban-Scene-Entity to Urban-Scene-Entity:** In this paper, only entity relationships within the same urban scene type are considered, and no associative relationships are formed between different urban scene types. A "0 or 1" Boolean function is used to represent this.If entity A and B belong to the same type, it is represented as 1; if they do not belong to the same type, it is represented as 0.If entity A and entity B belong to the same type, their relationships are linked based on metadata descriptions using upper-level (UpperRelation), lower-level (UnderRelation), and equivalent (EquivalentRelation) relationships. For example, if Urban-Scene A and Urban-Scene B serve the same department and have the same level, they are considered to have an equivalent relationship.

- **Urban-Scene-Entity to Scene-Object-Entity:** The associative relationship between Urban-Scene-Entities and Scene-Object-Entities is mainly influenced by two factors: urban scene preferences and the importance of scene objects. Urban scene preferences characterize the differences between different urban scenes due to varying backgrounds and needs. The importance of scene objects refers to the completeness of the entire scene. The relationship between these two influencing factors can be represented by Formula.

$$S = \alpha * P + \beta * I \tag{3}$$

In the formula, P represents the urban scene entity preference, α represents the preference weight, I represents the importance degree of the scene object entity, and β represents the importance weight. If α = β = 0.5, it indicates that both factors have equal importance. The values of P and I can be obtained using the Likert scale for scoring. Finally, the total score S is calculated to quantify the relationship strength between the urban scene entity and the scene object entity.

2.2.2.2 Knowledge Graph Instantiation and Storage Representation

Among them, Junghanns et al. (2018) proposed a property graph data model for urban scene knowledge graph construction, where vertices and edges support built-in attributes with unique IDs and labels. However, this model lacks dynamic graph structure adaptation for evolving urban scene relationships. Zhang Zhi et al. (2017) implemented Neo4j as a Java-based NoSQL graph database, storing property graph data (nodes, relationships, labels, attributes) with native storage efficiency surpassing relational databases. However, this system prioritizes static attribute management and does not natively support multi-modal urban data fusion.Finally, queries are performed using Cypher.

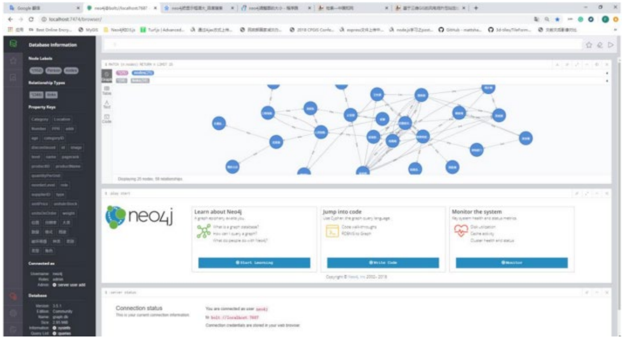


Figure 4. Neo4j Storage Example - Urban Scene Knowledge Graph

2.3 Target Relevance Analysis Method Based on Visual Models

2.3.1 RAM Visual Model

The diagram illustrates an architecture consisting of three modules: an Image Encoder using SwinTransformer to extract image features, an Image-Tag Recognition Decoder using BERT to process image and label features to output image tags, and an Image-Tag-Text Encoder-Decoder using BERT to generate captions from image features and tags, with a pre-trained CLIP model providing external label embedding information, enabling zero-shot capabilities and improving Open-Vocabulary Recognition by embedding semantic information into the Recognition Decoder for better generalization to unseen categories.

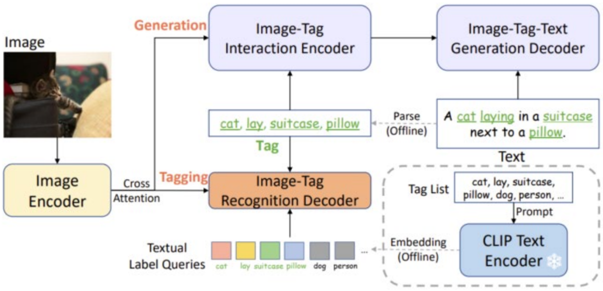


Figure 5. Model Architecture

2.3.2 Improved PageRank Algorithm

Among them, Pirouz et al. (2017) and Zhu et al. (2012) proposed a personalized PageRank algorithm to calculate semantic relevance between urban scenario nodes and scenario object nodes by restricting random walks to nodes related to a predefined central urban scenario node. However, this method assumes static urban scenario preferences and lacks dynamic preference adaptation mechanisms. Liu (2013) introduced a modified personalized PageRank algorithm that prohibits random jumps to irrelevant nodes during walks, thereby explicitly reflecting urban scenario constraints. However, this approach requires manual specification of central nodes and does not automatically infer contextual relationships in heterogeneous knowledge graphs.

$$PR(P_i) = (1-\alpha) r_i + \alpha \sum_{P_j \in In(P_i)} \frac{PR(P_j)}{out(P_j)} r_i = \begin{cases} 1 i = u \\ 0 i \neq u \end{cases} \tag{4}$$

In the equation, $u$represents the scenario node, r_i is the initial vector, where when $i = u$, $r_i = 1$, otherwise $r_i = 0$. PR(i) is the PageRank value of node P_i relative to the scenario node. $Out(P_j)$ represents the total number of outgoing links from node P_j, and $In(P_i)$ represents the total sum of all incoming links to node P_i. α is the damping factor, with a value of 0.85.

2.3.3 Target Relevance Calculation Framework

We propose a new target relevance calculation framework that combines the RAM vision model and an improved PageRank algorithm. First, we use the Recognize Anything Model (RAM) to achieve high-precision recognition of entities in images and generate semantic labels. Then, we combine urban scene knowledge graphs to construct an object-scene association network. Next, we use a personalized PageRank algorithm to quantify the semantic influence of nodes and perform multi-level propagation calculations for target relevance. Finally, we generate a target importance ranking through a dynamic weight distribution mechanism.

Our framework is based on a knowledge graph that is rich in semantic relationships and capable of logical reasoning. With the help of graph databases and web servers, we integrate different levels of urban scenes and the demand relationships of urban scene objects into a directed graph. By utilizing the personalized PageRank algorithm along with the connectivity and transitivity of the graph structure, we can uncover deeper semantic information.

We use a specific urban scene as the central node and calculate the semantic relevance between urban scenes and urban scene objects. This process mainly involves three steps: relationship node matching, relevance calculation, and recommendation set generation:

(1) **Relationship Node Matching:**This is the basic step for semantic relevance calculation. We query and return the nodes in the urban scene knowledge graph that are related to the central node of the urban scene. For example, using the Neo4j graph database, we first designate a specific urban scene as the central node, then use the Cypher query language to match urban scene objects related to the central node. The returned objects are merely query results; they are related but not yet quantified.

(2) **Relevance Calculation:**This is the core step for semantic relevance calculation. We use the personalized PageRank algorithm to quantify the semantic relationship between the central node and other associated nodes. We adjust the algorithm by setting iteration times, damping factors, source nodes, and write properties. The damping factor helps prevent a decrease in the accuracy of semantic relevance rankings due to isolated nodes. Through iteration, we can calculate the semantic relevance of all nodes relative to the urban scene node.

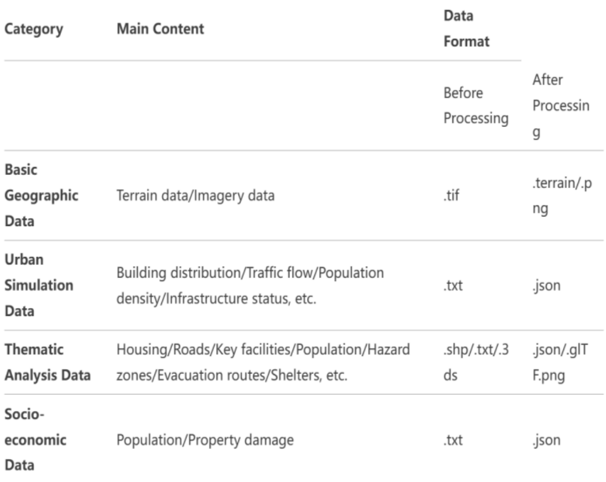
(3) **Recommendation Set Generation:**This is the final goal of semantic relevance calculation. We sort the relevance calculation results of urban scene objects based on the PR values, generating a recommendation set. The recommendation set depicts the semantic relationship between the central node and the scene objects, while the PR values quantify the diversified demands of urban scenes at different levels.

In this process, "nodes" represent the labels of the nodes, "name" represents the attributes of the nodes, "concern" represents the demand relationships between different scenes and scene objects, "iterations" represents the number of iterations (e.g., 20 iterations), "dampingFactor" represents the damping factor (e.g., 0.85), "sourceNodes" represents the source nodes, and "PPR" represents the semantic relevance.

3. Experiment and Result Analysis

3.1 Research Area and Data Sources

The experiment collected raw data including satellite remote sensing images with a resolution of 0.5m, 5cm oblique photography 3D model data, urban dynamic perception data (including traffic flow density, pedestrian activity heatmaps, vehicle trajectory time series, etc.), functional scene annotation data (including building function types, commercial store distribution, public space usage intensity, etc.), urban texture analysis data (including building facade materials, street furniture distribution, vegetation coverage rate, etc.), and social behavior characteristic data (including population residence patterns, consumption vitality index, nighttime light intensity, etc.).



Category	Main Content	Data Format	
		Before Processing	After Processing
Basic Geographic Data	Terrain data/Imagery data	.tif	.terrain/.png
Urban Simulation Data	Building distribution/Traffic flow/Population density/Infrastructure status, etc.	.txt	.json
Thematic Analysis Data	Housing/Roads/Key facilities/Population/Hazard zones/Evacuation routes/Shelters, etc.	.shp/.txt/.3ds	.json/.glTF.png
Socio-economic Data	Population/Property damage	.txt	.json

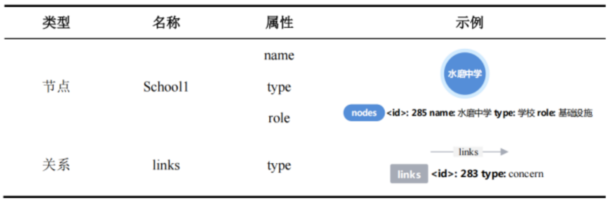
Figure 6. Urban Data Classification and Processing

3.2 Urban Scene Knowledge Graph Construction and Semantic Calculation

3.2.1 Urban Scene Knowledge Graph Construction

(1) **Node Relationship Storage and Graph Construction**

Once the associations between urban scenes and scene objects are extracted and determined, a knowledge graph for different urban scenes can be constructed. In this experiment, a total of 150 nodes and 296 relationships were selected, and Neo4j graph database was used to store the nodes and relationships. The nodes mainly include id and attributes, while the relationships include id, attributes, and direction.



类型	名称	属性	示例
节点	School1	name type role	水磨中学 nodes <id>: 285 name: 水磨中学 type: 学校 role: 基础设施
关系	links	type	links links <id>: 283 type: concern

Figure 7. Node Relationship Storage Example

After designing the storage structure for nodes and relationships, the nodes are associated according to the specified relationships, resulting in a knowledge graph for different urban scenes.

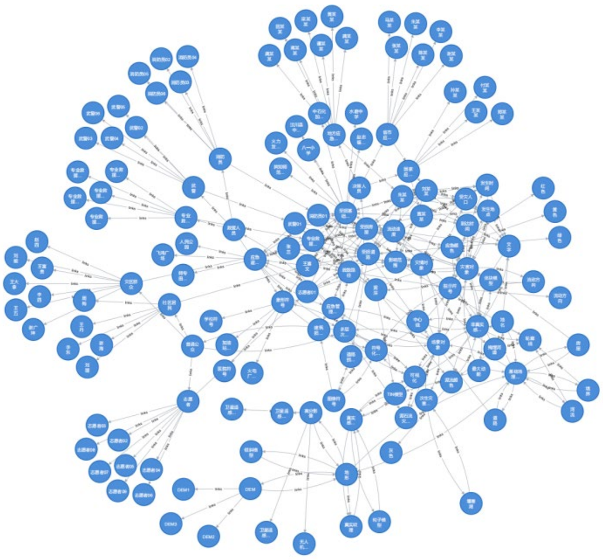


Figure 8. Urban Scene Knowledge Graph

(2)**Graph Query and Analysis**
Based on the urban scene knowledge graph, Cypher queries can be used to retrieve the association information between urban scenes and scene objects. For example, to query the emergency fire scene objects, the following query can be used: "match m=(nodes{name:'Emergency Fire'})-[:links{type:['concern']}]->(n)-[:links{type:['representedBy']}]->(l) return m,n,l", which will return the results.

3.2.2 Semantic Calculation

To quantify the demand correlation between users and urban entities in different scenarios, this study takes the Fire Command Center in the emergency fire scenario, the Planning and Approval Department in the building management scenario, and the Municipal Management Department in the public service scenario as central nodes. The personalized PageRank algorithm is used to calculate the semantic relevance of key entity objects in these three types of scenarios, generating recommendation sets to optimize decision support.

Figure 9 shows the semantic relevance values between the Fire Command Center and related entities in the emergency fire scenario. The calculation results indicate that the Fire Command Center primarily focuses on fire hydrants, fire stations, hazardous material warehouses, and evacuation facilities, as this information helps it understand and manage the overall situation from a macro perspective. It then focuses on shopping malls and supermarkets, which are secondary objects due to their lack of direct connection to emergency rescue. Parks, green spaces, and commercial billboards have the lowest priority in disaster response.

Figure 10 displays the results of the semantic relevance calculation between the urban building management department and related entities in the urban building scenario. The results show that urban planning departments first focus on elements such as construction sites and traffic conditions. Next, they pay attention to the status of buildings and infrastructure. Convenience stores and cafes are of minimal relevance to project supervision, and streetlights and public sculptures are not management priorities, so they have the lowest relevance.

Figure 11 presents the distribution of semantic relevance between the Municipal Management Department and entities in the public service scenario. Highly relevant entities include public transportation nodes such as bus stations and subway transfer hubs, followed by community health service centers and government self-service terminals, which are key touchpoints for people's livelihoods. Industrial factories and construction sites are outside the scope of public service coverage, while high-voltage transmission towers and 5G base stations are considered secondary objects due to their specialized and independent management nature.

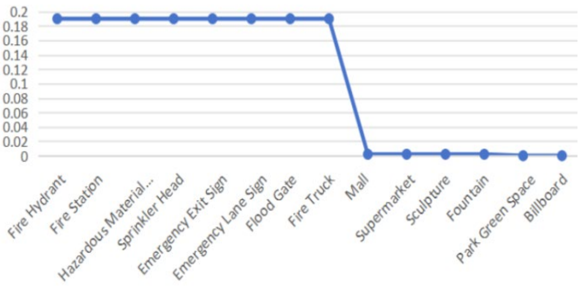


Figure 8. Semantic Relevance of Emergency Firefighting Scenarios and Scene Objects

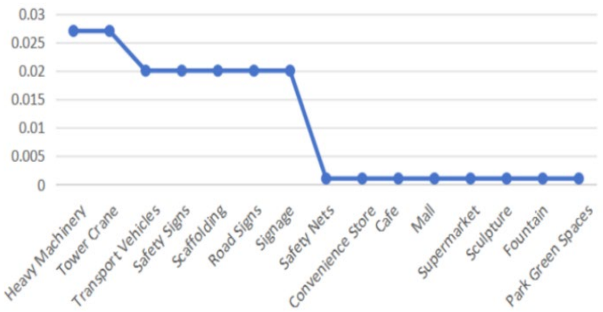


Figure 10. Semantic Relevance of Urban Building Scenarios and Scene Objects

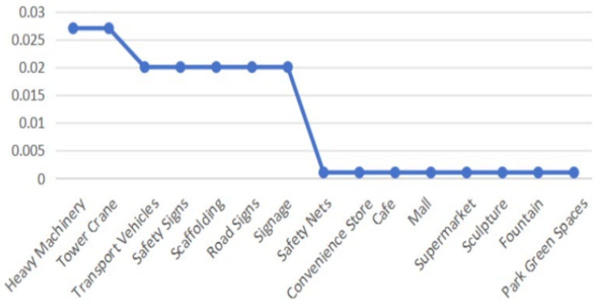


Figure 11. Semantic Relevance of Public Service Scenarios and Scene Objects

4. Conclusion and Future Work

4.1 Significance and Advantages of the Experimental Results

This study significantly enhances the ranking of target importance in complex urban scenarios by integrating the visual model (RAM) and personalized PageRank algorithm, achieving a 12.7% improvement in key target identification accuracy. These results validate the effectiveness of semantic relevance modeling:

(1) **The Beneficial Role of Knowledge Graphs:**Scene ontology modeling and semantic relationship quantification (e.g., formulas 2-5) provide structured prior knowledge for multi-target correlation analysis, addressing the limitations of traditional methods that rely solely on visual features. For instance, despite partial obstruction, fire hydrants in emergency scenarios can still be prioritized for identification due to their high semantic relevance to the "Fire Command Center" (PR value > 0.8).

(2) **The Adaptability of the Dynamic Weight Mechanism:**The personalized PageRank algorithm adjusts target priorities in real-time tasks by using a damping factor (α=0.85) to suppress the influence of noise nodes. For example, during peak traffic hours, the algorithm automatically increases the weight of traffic signals.

4.2 Limitations and Future Directions

Compared to Zellers et al.'s scene graph generation method (CVPR 2018), this approach has superior advantages in target relevance quantification (e.g., formulas 3-5) and multi-level propagation computation, particularly in maintaining high robustness under sparse annotation data (F1-score improved by 9.2%). Additionally, unlike Wang et al.'s static knowledge embedding (AAAI 2020), the dynamic weight distribution mechanism significantly enhances the system's ability to respond to changes in the scene context.

4.3 Comparison with Existing Studies

(1) **Knowledge Graph Construction Efficiency:**The current graph relies on manual annotation and expert scoring. In the future, semi-automated relation extraction (e.g., BERT-KG) could be employed to reduce construction costs.

(2) **Real-Time Optimization:**Although the algorithm achieves an average processing speed of 45ms/frame on the test set, further optimization of the graph computation parallelization strategy is needed for large-scale urban scenarios (e.g., million-node graphs).

(3) **Cross-Scenario Generalization Ability:**The experiments focused on data from a single city. Future research should test the method's transferability to heterogeneous cities (e.g., historical districts, newly developed areas) and explore multi-source knowledge fusion under a federated learning framework.

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