Using Multi-demension Built Environment Features and Machine Learning to Identify Potential Traffic Black Spots

-- Taking Camden in London as An Example

Abstract

Road traffic accidents have long-term been the main safety threat to urban residents. Concentration areas of traffic accidents on the road are regared as the traffic black spots.

The study outlines an attempt to train random forest classification models to identify the potential traffic black spots based on the junctions built environment features, including street view information, urban activities, junciton structure and facilities, and road network configurations.

Around the accident risk of junctions, the trained models present a high overall accuracy of 0.66 in classifying safe, low-risk and high risk juncitons, and the recall scores of for safe and high-risk junctions are 0.8 and 0.71, respectively.

In terms of the feature importance, whether the junction is formed based on only minor roads and the multi-scales road network configuration features, play most important roles in the classification model. The street view information of the road junctions, though tested effective in identifying traffic black spots in previous studies, have relatively poor performance in predicting and classify juncitons with different risk levels.

In general，

Keywords: Road Accidents , Road Junction, Random Forest Classifier, Street View, Space Syntax

# Introduction

Road traffic accidents have long-term been the main safety threat to urban residents. According to the statistics of the World Health Organization (WHO), an estimate of 1.35 million people dies in road traffic accidents every year and in high-income countries the average death rate is 8.3 per 100,000 population(World Health Organization, 2018). Due to the huge hazard of traffic accidents, the prediction and prevention of accident risks are of great significance.

The study outlines an attempt to train random forest classification models to identify the potential traffic black spots based on the junctions’ built environment features, including visual information from street view images, urban activities and funcitons, shape and configuration of juncitons and the street network.

# Literature Review

## Definition and Identification of Traffic Black Spot

Generally, the traffic black spots refer to concentration areas of traffic accidents on the road (Dereli & Erdogan, 2017). However, the specific criteria and identification methods of traffic black spots can vary greatly, according to the differences in urban form and social characteristics. Objects considered as traffic black spots can be road intersections, short road sections or mid-mid-blocks (Kowtanapanich, Tanaboriboon, & Chadbunchachai, 2006). Common defining elements of traffic black spots may include the frequency of accidents in a specific spatial and temporal range, the severity of accidents, and the proportion of accident numbers to the traffic volume (Aziz & Ram, 2022). For example, China defines urban road black spots as: road sections within 500 meters or intersections within 150 meters that have at least three casualty accidents every year (Yuan, Zeng & Shi, 2020); In Thailand, the black spot is the place where at least 3 serious accidents or 5 injury accidents have been recorded within 100m within three years (Tanprasert, T. et al., 2020). In addition, some studies do not adopt fixed threshold standards, but identify the clustering structure of collision accidents as traffic black spots. Modified clustering algorithm of K-Means (Zhang, Shu & Yan, 2019), Firefly (Yuan, Zeng & Shi, 2020) and DBSCAN(Ye et al., 2010) have been tested to improve the accuracy of identitfying traffic black spots from large accident datasets. However, in sparse datasets the application of clustering methods is relatively limited.

## Built Environment and Traffic Black Spots

Numerous studies have explored and examined the built-environment triggers for traffic accidents. Most studies focus on road crashes dominated by vehicle traffic, and the types of accidents include vehicle-to-vehicle (Asadi et al., 2022), vehicle-to-pedestrian (Ukkusuri et al., 2012), and vehicle-to-bicycle (Osama & Sayed, 2017), and small geographic areas such as census tracts or travel analysis areas are common study units. The corresponding built environment variables may include population and employment density(Fischer et al., Sternfeld & Melnick, 2013), land use and diversity(Yang & Loo, 2016; Osama & Sayed, 2017), street network configuration(Marshall & Garrick, 2011; Choi & Ewing, 2021), road grade and intersection density( Chen & Zhou, 2016), characteristics of transportation and public services(Osama & Sayed, 2017).

Considering that the impact of the same built environment element on collision accidents may be ambiguous or contradictory in some studies, due to regional differences or incomplete selection of variables, some scholars have attempted to summarise the roles of different environmental characteristics in the accident process. Hakkert and Braimaster (2002) divided the occurrence of collision accidents into three parts: exposure, collision risks and injury probability. On this basis, Guerra and Dumbaugh (2020) argued that users' exposure and collision risks as primary mediums are affected by the built environment factors, thereby increasing or reducing the probability of traffic accidents. The variables associated with exposure may include traffic volume and the number of potential traffic participants (population and employment density); Variables associated with risk include vehicle speed and number of intersections. Land use, street configuration and facilities may have mixed or unconfirmed effects.

In the face of smaller-scale research scenarios, the visual information from Street View imagery is believed to be useful for simulating and reflecting features of the built environment in the perception of drivers ,cyclists or pedestriansm. 快速发展的计算机视觉技术为精确，高效的提取和分析街景图片信息提供了可能，并推动了一系列探索街景信息与街道事故，安全关联性的研究。街景与犯罪，街景与可骑行性，街景与交通黑点等。

# Research Question

# Objectes and Data

## Research Objects

The research takes London Borough of Camden as the research objects.

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|  |  |
| Figure 1 Junciton Location | Figure 2 Mapping of Road network(with road class) |

## Data Collection

The research is mainly based on the ‘Road Collision Attendants In Camden’ dataset provided by Transport for London(TfL). The dataset contains 4555 road collisions in Camden during 2015-2019, recording the time, location, road type, speed limit, junction detail and other external environment details about the accidents and the severity class(fatal,serious,slight) and casualty number of accidents. Table 1 provide the definition of severity class by Department of Transportation in the UK.

|  |  |
| --- | --- |
| Table 1. The Definition of Accident Severity | |
| Severity | Definition |
| Fatal Accident | An accident in which at least one person is killed; other casualties (if any) may have serious or slightly injuries. |
| Serious Accident | One in which at least one person is seriously injured but no person is killed. |
| Slight Accident | One in which at least one person is slightly injured but no person is killed or seriously injured. |

Besides, the research also apply the road central line data from Ordnance Survey (OS), the Point of Interest(POI) data from OpenStreetMap(OSM) and the administrative boundary data of Camden town. An image segmentation model is trained based on the Cambridge-driving Labelled Video Database(CamVid)，and street view images of road junctions are collected from Google Street View Static API.

# Methods

## Research Framework

## Measurement

### Road Junctions’ Risk as Traffic Black Spots

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|  |
| Figure 2 |

### Road Junciton Features

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Group** | **Indicators** | **Data Source** | **Spatial Scale** | **Measure Scale** |
| **Junction Structure and Facility** | Minimum distance to nearest junctions | OS | Local/Global | 0-1(Min-Max) |
| Count of roads connected | OS | Local | 0-1(Min-Max) |
| Maximum maxspeed of roads connected | OSM | Local | 0-1(Min-Max) |
| Level of roads connected | OS | Local/Global | 0-ALL minor road  1-Major&minor road  2-All\_Major road |
| Presence of crossing | OSM | Local | 0-True, 1-False |
| Presence of traffic light | OSM | Local | 0-True, 1-False |
| **Street View** | Perception of building pixels | SVI | Local | 0-1 |
| Perception of sky pixels | SVI | Local | 0-1 |
| Perception of mix-vegetation pixels | SVI | Local | 0-1 |
| Perception of tree pixels | SVI | Local | 0-1 |
| Perception of road pixels | SVI | Local | 0-1 |
| Perception of road shoulder pixels | SVI | Local | 0-1 |
| Perception of sidewalk pixels | SVI | Local | 0-1 |
| Perception of fence pixels | SVI | Local | 0-1 |
| Perception of wall pixels | SVI | Local | 0-1 |
| Perception of road shoulder pixels | SVI | Local | 0-1 |
| **Comercial and Public Activities** | Number of cultural POI in 50m | OSM | Local/Global | 0-1(Min-Max) |
| Number of food & drink POI in 50m | OSM | Local/Global | 0-1(Min-Max) |
| Number of hotels in 50m | OSM | Local/Global | 0-1(Min-Max) |
| Number of schools in 50m | OSM | Local/Global | 0-1(Min-Max) |
| Number of shops & malls in 50m | OSM | Local/Global | 0-1(Min-Max) |
| Number of pub & bar POI in 50m | OSM | Local/Global | 0-1(Min-Max) |
| **Road Network** | Normalized Angular Choice R800m | OS | Local | 0-1(Min-Max) |
| Normalized Angular Choice R1600m | OS | Global | 0-1(Min-Max) |
| Normalized Angular Choice R3200m | OS | Global | 0-1(Min-Max) |
| Normalized Angular Integration R800m | OS | Local | 0-1(Min-Max) |
| Normalized Angular Integration R1600m | OS | Global | 0-1(Min-Max) |
| Normalized Angular Integration R3200m | OS | Global | 0-1(Min-Max) |

##### Junction Structure and Function Measurement

Camden borough范围内不同交叉口的结构和功能特征存在差异。对于结构特征，连接在各个交叉口的道路数量决定了交叉口的基本形态；而所连接道路的等级组合，如主路和主路，主路和次要路，次要路和次要路，可能影响交叉口的尺寸。

此外，研究尝试从交叉口的交通设施构成和交叉口所连接road segment的长度和速度限制中，提取交叉口的功能特征。这些变量具体表征为：交叉口是否有交通灯，交叉口是否设置了crossing, 交叉口所连接道路中的最大限速的最大值，和交叉口所连接道路段的最小长度。

本研究中假设，健全的交通设施可以提高交叉口的安全性；而交叉口所连接道路的较高的限速值和两个相邻交叉口间过近的距离，可能使交叉口的交通环境变得复杂，从而提升事故发生的风险。

##### Street View Measurement

从道路网络中提取了xxx个道路端点，

##### Activities Measurement

##### Road Network Measurement

基于空间句法和自然运动理论，城市道路网络的组构特征在一定程度上可以用于反映和描述城市空间中活动的聚集特性。空间句法理论开发了一系列网络度量指标揭示空间组构和城市活动的内在联系。其中，标准化角度整合度（NAIN），作为网络分析中centrality的变体，用于反映不同道路段在特定空间尺度下对城市活动的吸引力；标准化角度选择度，作为betweeness的变体，侧重于反映车流在道路网络中不同路段的潜在分布特征。研究尝试分别以800m，1600m，3600m为分析半径，计算Camden道路网络中每个路段在不同空间尺度下的NAIN以及NACH;在此基础上，为Camden每个交叉口汇总所连接到路段的NAIN和NACH的算数平均值，以此反映道路交叉口在网络中对城市活动的潜在吸引力以及潜在繁忙程度。

## Random Forest Classifier

研究首先利用四类建成环境变量，基于默认参数分别独立拟合随机森林分类器，预测交叉口的风险等级；通过比较不同分类器的表现，了解不同大类的环境变量对交叉口风险的解释性的整体差异。在此基础上，研究尝试利用全部四类建成环境变量拟合随机森林分类器，利用GridSearchCV方法，基于不同的参数组合，以accuracy为scoring进行模型调试；对每一组参数组合进行，研究采用kfold方法对训练数据集重新划分为训练集和校验集以进行交叉检验。最后，研究通过SHAP特征重要性分析方法，识别对交叉口风险具有潜在更强解释性的具体建成环境变量。

围绕交通黑点的分类，此前的研究中也有基于随机森林分类器的研究实践。

Tanprasert and his colleagues have explored the method to recognize and classify traffic black spots in Thailand based on street view images(Tanprasert et al., 2020).

A distance-aware image segmentation model was developed to extract information of objects surrounding the road and a fully-connected neural networks was trained to identify the black points. The model has shown an accuracy of 69.91% in classifying black and safe spots in Thailand where recall of black points is 75.86%. The combination of street view information and the classification task of traffic black spots is proved to have sufficient potential.

# Results

## Descriptive Results

In this section, preliminary exploratory analysis is conducted to investigate the accident, junction, POI info and street view info datasets.

### Collision Accidents around Road Junctions

##### Count and severity of Accidents around Road Juncitons

According to the accident records, for each year during 2015-2019 about 70% accidents happened near a road junciton(Figure 2). The significantly high proportion indicates a potential high risk of road junction as traffic black points. The section also presents the distribution of severity class of collision accidents(Figure 3). It is found that for each year most of the accidents belong to the 'slight' type, and 'serious' type account to about 1/6 of the slight type. Few accidents can be labeled as 'fatal'.

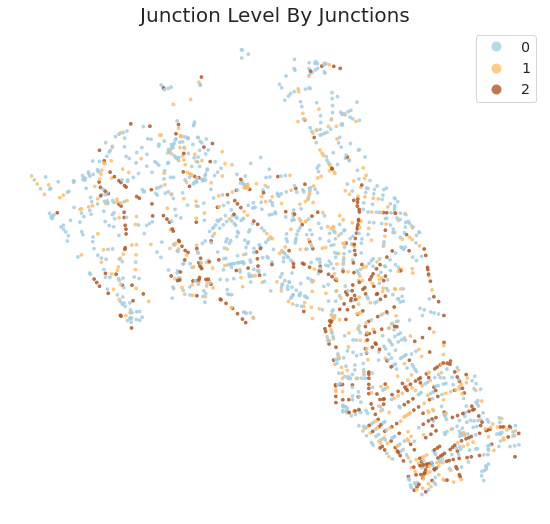
Figure 4 then plots all the road junctions and highlight their difference in accident count. The accident count follows an exponential distribution, where most of the junctions have no accident. Besides, it is found that most of the accidents happened on the junctions near local commercial centres or high streets in the southern area of Camden, which indicates a possible relation between commercial activities and accidents.

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|  |  |
| Figure 2 | Figure 3 |
|  | |
| Figure 4 | |

##### Risk Classification of Road Junctions

基于5.2.1 所建立的交叉口风险分类框架和现有的交叉口事故数据，对Camden Borough内交叉口的分类如图所示。在2015-2019年间，在1877个交叉口中，有1008交叉口范围没有发生过碰撞事故，被分类为安全；有445交叉口存在不超过2起的轻微事故，被分类为低风险；有424交叉口存在3起及以上轻微事故，或存在至少一起严重或致死事故，被分类为高风险。

在空间分布上，可以看到高风险的交叉口多数连续分布在主要交通干路上。考虑到交通干路上通常相比次要道路和社区道路都有较为庞大的车流量，可以假设交通风险与车流量的潜在联系。这种关联已经受到许多证据支持。尽管如此，高风险交叉口在整个Camden Borough, 乃至同一交通干路上的分布并不均匀。更多的高风险交叉口集中于Camden 中部的Camden town以及南部的Kings cross, Holborn等地。这表明，除了车流量，还有其他因素也可能对交叉口的安全风险带来影响，例如交叉口的建成环境特征，而这将是本文讨论的重点。



### Built Environment Features around Juncitons

本节重点讨论了道路交叉口几类不同的建成环境特征在Camden范围内的空间分布。

##### Junction Structure and function

本节展示了Camden borough范围内不同交叉口的结构和功能特征差异。 在结构特征上，多数交叉口为4道路交叉口，5道路交叉口也占据相当的比例，三岔口和多于5条道路相交的交叉口的数量较少；由于camden borough的高等级道路密度较低，多数交叉口属于次要路-次要路和次要路-主要路交叉口，主要路-主要路交叉口的数量有限。

功能特征上，Camden Borough 范围内，crossing相比交通灯在各个交叉口上更为普及。显著更多的crossing和交通灯分布于Camden中部和南部城市功能活跃区域的道路交叉口上。交叉口所连接道路的最大限速的最大值整体分布在30km/h-45km/h之间,服从于特定高通过性道路的空间分布。交叉口所连接的道路段的最短长度在空间分布上没有显著特征。

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|  | | |
|  | | |
|  | Junctions With Crossing | Junctions With Traffic Light |

##### Street View Features

本节重点分析了不同交叉路口所对应的建筑，天空，树木和道路这四种典型街景要素在Camden范围内的空间分布特征,以初步归纳不同交叉路口的景观感知特征。

天空要素和道路要素在Camden全局尺度上的分布较为均匀；个别交叉口可能作为孤立案例，拥有显著较高的的天空元素比例；不同等级的道路可能贡献了一些道路元素的局部差异。建筑要素在街景中的占比整体上相对更高，且自南向北呈递减趋势；反过来，树木要素在街景中占比自南向北呈递增趋势。

基于上述街景特征，整体而言，Camden北部的交叉口在视觉感知中可能显得更为开阔，天空和树木等自然要素的占比相对较高；南部的交叉口则显得更为紧凑，建筑，道路等人工要素的占比较高。

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|  |
| Figure 5 |

##### Activity Features

本节展示了各个交叉口50m半径范围内不同类型POI的数量。

总体上，交叉口周边，服务居民日常生活的各类商店以及café和快餐POI的出现频次较高，剧院，图书馆等文化设施和酒吧、夜店等娱乐设施次之，学校和宾馆最后。

多数POI集中在Camden 南侧的Holborn, Kingcross 以及中部的Camden Town等地。这些地段分别作为伦敦的商业中心，交通枢纽和当地高街，日常人流和车流密集。

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|  |
| Figure 6 |

##### Road Network Features

基于半径800m,半径1600m和半径3200m，对NAIN和NACH的计算结果如Figure 7所示.不同分析半径揭示了junction 在不同空间尺度下的对城市活动的吸引力和潜在的交通繁忙程度。

对于NAIN, r800的整合度分析揭示出了local/社区尺度下具有高吸引力的junction的位置。 他们中的多数与高街以及POI高频分布的区域重合。r1600和r3200的整合度则揭示出了borough 尺度下城市活动的整体空间分布差异。Camden 南部具有高整合度的路段和交叉口明显地多于北部，对应Camden 南部作为伦敦中心城区突出的商业，文化和服务功能。

对于NACH, 不同尺度下的分析结果较为相近。高NACH值的junciton 集中于较高等级的交通干道上，即多数primary road,A和B road;且随着分析半径提升，这种集中特征越明显。

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|  |
| Figure 7 |

## Traffic Black Spots Classification

### Random Forst Classifier Performance

基于分类器的默认参数[[1]](#footnote-1)，四类独立的建成环境特征以及全部特征拟合随机森林分类器的结果如图所示。总体上，交叉口周边的活动信息和交叉口的街景特征单独作为自变量所拟合的模型，对交叉口事故风险的解释能力较弱。他们在测试数据集上的精度均低于0.5. 相对的，分别由多尺度的空间句法测度以及交叉口的结构和功能所拟合的模型拥有更好表现。两个模型在测试数据集上的精度分别为0.638和0.59。此外，基于全部特征拟合的随机森林分类器拥有最佳表现。模型在训练集上的精确度可达到0.681。

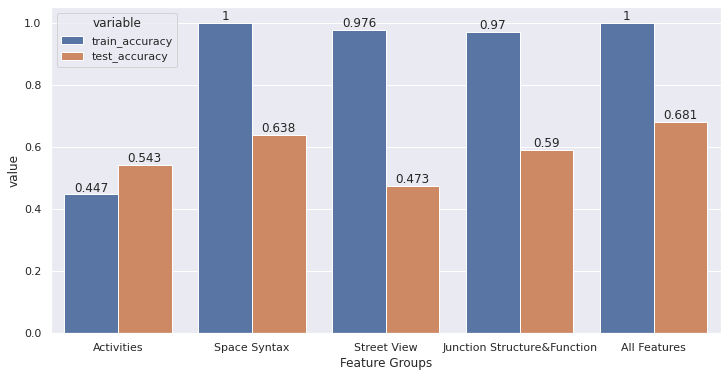


Figure 7

研究选取基于全部特征拟合的分类器，利用GridSearchCV方法，基于不同的参数组合进行模型参数调整和交叉检验。参数优化主要以分类器的 ‘max\_depth’ 和 ‘n\_estimators’为对象，参数搜索范围和获得的最佳参数如表所示。

Table

|  |  |  |
| --- | --- | --- |
|  | Searching Grid | Best Parameters |
| max\_depth | 10, 60，110，160，210，none | 60 |
| n\_estimators | 50, 100, 150, 200, 250, 300,350,400,450,500 | 350 |

基于最佳参数组合训练的分类器在测试集上的表现如表所示。分类器的总体精度约为0.665，表现出对安全交叉口和高风险交叉口的较高的识别能力。具体来说，模型对安全交叉口的分类效果最好。0.77的分类准确性和0.83的recall 表明模型在判断交叉口是安全时拥有有较高的正确性，且擅长找回所有安全交叉口的样本。模型在识别高危交叉口时的表现略弱于识别安全交叉口，主要表现在recall score 较低。模型可能会将少量高风险交叉口误识别为安全或低风险。此外，模型在识别低风险交叉口时表现较差，有一定可能模型会将安全或高风险交叉口误断为低风险交叉口。

Table

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **precision** | **recall** | **f1-score** | **support** |
| **0** | 0.77 | 0.83 | 0.80 | 100 |
| **1** | 0.24 | 0.21 | 0.22 | 39 |
| **2** | 0.72 | 0.69 | 0.71 | 49 |
| **accuracy** |  | | 0.66 | 188 |
| **macro avg** | 0.58 | 0.58 | 0.58 | 188 |
| **weighted avg** | 0.65 | 0.66 | 0.66 | 188 |

### Feature Importance

交叉口的多尺度组构特征，以及交叉口的结构和设施

图表

描述已自动生成

# Discussion and Conclusion

**在模型预测层面，**

* + 基于空间句法变量单独拟合的分类模型的预测较为充分；
  + 单独采用视觉，活动或交叉口的结构和功能信息对风险的预测能力弱。
  + 对比表现最好的单一模型(基于空间句法measurements的模型)，综合模型的表现有小但明显的提升，表明其他环境信息和要素同样对提升模型进度有所贡献。尽管其他建成环境信息可能与空间句法变量包含的信息存在重合。
  + 经历参数调整后，综合模型在检验数据集上的精确度是 0.66，对安全和高危的交叉口有良好的分类表现，但是对低风险交叉口的分类能力较弱。
  + 对低风险交叉口分类能力弱的原因可能是对于低风险交叉口的分类规则较为模糊且本研究中涵盖的低风险样本总数较少，模型对对应特征的学习不充分。
  + 考虑到，构建预测模型的重要目标是在当下的城市管理和未来的城市道路设计中识别潜在的高风险交叉口 ，减少和预防伤亡事故，尽管存在缺陷，模型整体上是有效的。

**模型解释层面**

* 交叉口是否仅基于minor road，以及交叉口的多尺度整合度和选择度特征，都在特征重要性排序中占有首要位置。其次的重要性排序整体为交叉口结构和设施特征，交叉口的视觉信息和交叉口的活动。
* 在本模型中，表征和包含大尺度或系统性空间联系的建成环境要素，如3200m为分析半径的整合度和选择度，参与构成交叉口的道路等级等，重要性整体强于仅表征局部特征的建成环境要素，如交叉口不同POI的数量，树木，墙体等视觉要素 。
* 特征重要性指向特定模型，只表征构建模型时哪些特征更有用。它们不应被解释为预测变量和目标之间的直接依赖关系。
* Shap values不同于Permutation Based Feature Importance特点的讨论

**交通风险与建成环境**

* 道路交叉口的交通风险或更应被视为一种**系统性**问题加以分析，预测和治理。可以从两个方面认知
* 其一，从本研究得到的证据看，基于单一类别建成环境变量拟合的模型中，基于多尺度道路组构特征的模型表现最好；基于全部变量的模型中，表征全局特征的变量重要性整体优于表征局部特征的。这似乎表明，变量中所捕获和表征的涉及道路和城市系统的全局信息越多，对交叉口风险的预测能力越强。
* 其二，基于Guerra and Dumbaugh (2020)的理论，交通事故的发生与建成环境中的暴露和风险两类因素有关。其中暴露相关要素，例如潜在的交通流量和人口密度，应当被视为一种系统的全局或跨尺度特征；而风险，例如限速和交叉路口，则应被视为一种局部特征。如果将基于空间句法方法的道路网络分析变量（e.g.NACH）视作长期交通流量分布或Vehicle miles traveled (VMT)（而非瞬时流量）的有限替代，可以看到代表暴露的相关特征整体在交叉口事故风险中发挥了更大作用。
* 如果我们的研究对象并非只有交叉口，那么与风险关联的要素可能会更重要，或者产生更多元的结果；在只包含交叉口的情况下，交叉口特征可能更多服务于道路系统的整体特征，一些局部建成环境的影响减弱。

**其他贡献：**

* 研究首次将空间句法方法与机器学习结合，进行道路交叉口的风险预测和分类。并在特征重要性分析中检出了基于空间句法的多尺度道路组构特征的重要作用。一方面，这开拓了空间句法方法的应用场景；另一方面，这为当前道路交叉口的管理和维护，以及未来道路网络和交叉口的设计提供了借鉴。
* 在本研究中，不同于此前Tanprasert et al（2020）的研究，由纯粹街景信息拟合的分类器在交叉口风险分类中的表现不佳。可能是由于研究： 1.仅以交叉口为研究对象，街景特征存在趋同性。2.对于交通黑点的定义和分类方法存在差异。尽管如此，在综合模型中，街景信息中road, roadshoulder, building, sky 等对于分类交叉口风险仍具有较为重要的贡献。本研究初步检验了此前研究方法和结论的可靠性，相关方法在不同场景仍有发展前景。

**局限：**

尽管本研究设置了3个交叉口风险层级，但能够实现有效分类的只有安全交叉口和高风险交叉口。这主要是由于目前的事故数据在Camden Borough范围内较为稀疏。

Table 1. Table caption

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Figures should be presented as part of the paper and should be referred to as **Figure 1** in the text. Please also save the figure as a .tiff file with a resolution of at least 300 dpi.

Figure 1 Cardiff University and city centre map

(If you want to insert a numbered formula, please use Insert -> Table -> Quick Tables -> Formula\_numbered. This will insert a three column table as below. Alternatively, you can copy and paste the table below. The number can be updated using the F9 shortcut.)

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# Acknowledgements

# References

In the draft, if you want to cite a paper, please put the paper in our shared folder in Mendeley, and then cite the paper from this folder.

If you use Mendeley, you can insert the references using the following commands in word: References -> Mendeley -> Insert Bibliography.

1. Default parameter setting for random forest classifier:

   <https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html> [↑](#footnote-ref-1)