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Interpretable machine learning models for crime prediction

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ABSTRACT

The relationship between crime patterns and associated variables has drawn a lot of attention. These variables play a critical role in crime prediction. While traditional regression models are capable of revealing the contribution of the variables, they are not optimal for crime prediction. In contrast, machine learning models are more effective for crime prediction, but most of them cannot estimate the contribution of each individual variable. This study aims to overcome this limitation by taking advantage of the interpretability of advanced machine learning models. Based on the routine activity theory and crime pattern theory, this study selects 17 variables for the crime prediction. The XGBoost algorithm is adopted to train the prediction model. A post-hoc interpretable method, Shapley additive explanation (SHAP), is used to discern the contribution of individual variables. A variable with a higher SHAP value has a higher contribution to the crime prediction model. In addition to the global model for the entire area, a local model is calibrated at each study unit, revealing the spatial variation of the variables' unique contributions. Among all 17 variables used in this model, the proportion of the non-local population and the ambient population aged 25–44 contribute more than other variables in predicting crime. The more the ambient population aged 25–44 in the area, the more the public thefts. Additionally, local SHAP values are mapped to demonstrate each variable's contribution to the crime prediction model across the study area. The results of the local models can help the police tackle the most important factors at each location, while the global model identifies the important factors for the entire region.

1. Introduction

Machine learning technology has achieved great success in many fields and has been widely applied to some important practical tasks, such as face recognition (Taigman, Yang, Ranzato, & Wolf, 2014; Sun, Wang, & Tang, 2014), speech recognition (Deng, Hinton, & Kingsbury, 2013), automatic driving (Hoermann, Bach, & Dietmayer, 2018), intelligent medical analysis (Choy et al., 2018), etc. While machine learning outperforms other models in many tasks, this method generally lacks transparency and interpretability. Thus machine learning is typically regarded as a "black box" approach, and it is difficult to explain what happened in the "black box" (Apicella, Isgrò, Prevete, & Tamburrini, 2020).

Interpretability of machine learning has drawn attention from both social sciences and artificial intelligence fields (Miller, 2019). However, the interpretability and transparency of machine learning based crime prediction models remain questionable (Alves, Ribeiro, & Rodrigues, 2018; Rummens, Hardyns, & Pauwels, 2017; Wang, Ge, Li, & Chang, 2020; Zhang, Liu, Xiao, & Ji, 2020). Because of this, practitioners tend to distrust the results of such models. Therefore, there is an urgent need for an interpretable and transparent crime prediction model, so that practitioners would know the calculation logic and factors they need to pay attention to. Also, spatial variations of each variable in the machine learning model shall receive special attention as they influence crime opportunities (Lan, Liu, & Eck, 2021; Wilcox & Eck, 2011).

Before machine learning is introduced to crime prediction, traditional crime prediction models solely use historical crime data with the assumption that crime events are near-repeated in space and time. That is to say, spatiotemporal information of historical crime events is used to predict the distribution of criminal activities in a later time (Farrell & Pease, 1993; Sherman, Gartin, & Buerger, 1989). Some examples are: near-repeat prediction model (Townsley, 2003) and density estimation model (Chainey & Ratcliffe, 2013; Kalinic & Krisp, 2018). Such models are suitable for crime risk prediction in large spatial and temporal scales

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可解释的机学习模式的犯罪预测

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[d] 司法部科学、大学Findlay,Findlay，美国R T I C L E I N F O关键词：犯罪预测学习机
XGBoost模型的解释性十八值

A B S T R A C T之间关系的犯罪模式和相关的变量已经制定了很多的关注。 这些变量方面发挥关键作用，在犯罪预测。 虽然传统的回归模型能够显露出贡献的变量，它们不是最佳的犯罪的预测。 相比之下，机学习模型更有效的犯罪预测，但他们大多无法估计的贡献的每一个变量。 这项研究的目的是为了克服这种限制通过利用解释性的，先进的机械学习的模型。 根据日常活动的理论和犯罪问题的模式的理论，这项研究的选择17变量为犯罪的预测。 该XGBoost算法是通过训练的预测模型。 事后可解释的方法，沙普利添加剂的解释(十八)，用于辨别贡献的独立的变量。 一个变量有一个更高的十八值有更高的贡献犯罪预测模型。 除了全球模型对于整个区域，一个当地模型的校准每一个学习单元，揭示的空间变化的变量的独特贡献。 在所有17个变量使用这一模式，这一比例的非当地居民和环境的人口年龄在25至44岁的贡献超过其他变量预测的犯罪。 更多的环境人口年龄在25至44岁的区域，更多的公共盗窃。 此外，当地十八值映射，以证明每个变量的贡献犯罪预测模型研究领域。 结果当地模型可以帮助警察处理的最重要因素，在每个位置，同时将全球模型标识的重要因素对整个区域。

1. 介绍机学习技术已经取得了巨大的成功在许多领域，并已被广泛应用于一些重要的实际任务，例如面部识别(Taigman、杨,Ranzato,&狼，2014年的太阳，王&唐2014年)、语音识别(邓Hinton,&Kingsbury,2013年)、自动驾驶(Hoermann，巴赫，&Dietmayer，2018年)、智能化的医疗分析(蔡et al., 2018年)，等等。 时机的学习优于其他模式中的许多任务，这种方法通常缺乏透明度和解释性. 因此学习机会是通常被视为"黑箱"办法，而这是难以解释发生了什么"黑箱"(磊亚皮赛拉,Isgr'o,Prevete,&Tamburrini，2020年). 解释性的学习机已提请注意从两个社会科学及人工智能领域(Miller,2019年). 然而，解释性和透明度的机学习为基础的犯罪预测模型仍然有疑问的(*阿尔维斯，Ribeiro,&罗德里格斯前的机学习引入到犯罪预测，传统的犯罪预测模型仅仅使用历史犯罪数据的假设是，犯罪事件是近重复在空间和时间。 这就是说，时空信息的历史犯罪活动是用来预测分布的犯罪活动，在稍后的时间(Farrell&皮斯，1993年；谢尔曼，Gartin,&伯格,1989年)。 一些例子是：近重复预测模型(Townsley，2003年)，密度估计模型(Chainey&Ratcliffe2013年Kalinic&Krisp，2018年). 这种模型适用于犯罪的风险预测在很大的空间和时间尺度*应提交人的在于：中心的地理信息对公共安全、学校的地理科学、广州大学，中国广州市。

2018年;Rummens,Hardyns,&鲍,2017;Wang,Ge,Li,&张，2020年；张,Liu,小,&Ji，2020年). 因此，从业人员往往不信任的结果，这样的模型。 因此，迫切需要一个解释的和透明的犯罪的预测模型，以便从业者会知道计算的逻辑和因素，他们需要注意。 此外，空间变化每个可变的机学习模式应当得到特别的关注，因为它们影响犯罪的机会(局域网、刘&埃克,2021;Wilcox&埃克,2011年)。

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when environmental details and subject behavior information are insufficient. However, their prediction accuracy cannot be guaranteed at fine spatial and temporal scales.

As various environmental factors are found to influence crime opportunities, fine-scale crime predictions incorporating such factors become possible. Since the middle of the 20th century, with the cross integration and gradual development of criminology and geography, basic theories of criminal geography have emerged. Some examples are crime opportunity theory (Cohen, 1981), routine activity theory (Cohen & Felson, 1979), rational choice theory (Cornish & Clarke, 1987), and crime pattern theory (Brantingham & Brantingham, 1993a). Crime opportunity theory emphasizes that the distribution of people's daily activities and crime opportunities have an important impact on the spatial pattern of crime (Cohen, 1981; Weisburd, Lawton, & Ready, 2012). Crime opportunity is the key to influencing the offenders' choice to commit crimes or not (Cornish & Clarke, 1987). Routine activity theory argues that the convergence of motivated offenders, suitable targets/victims, and the absence of capable guardians at time and space is needed for a crime event to happen. People's routines may provide such convergences (Cohen & Felson, 1979). The rational choice theory also suggests the potential influence of built environment factors on offenders' rational thinking process (Stummvoll, 2009). Crime pattern theory focuses on places and opportunities, and especially emphasizes the overlap of consciousness space of offenders and victims. Offenders always tend to choose the places they are familiar with when searching for potential targets (Brantingham & Brantingham, 1993b). These places can be very small areas or facilities that reflect and affect the activities of their users and may impact a specific criminal event (Loukaitou-Sideris, Liggett, Iseki, & Thurlow, 2001). The places may present two types of attractiveness to criminals: target attractiveness and spatial attractiveness(Rhodes & Conly, 2017). Target attractiveness refers to the presence of a certain level of victims at the places. Spatial attractiveness refers to the physical features of the places and their nearby environments that may facilitate crimes to occur unnoticed. Many empirical studies have proved that many business or public facilities people routinely visit can be crime attractors or generators, which provide more potential crime opportunities and increase crime in their vicinity, such as restaurants (Bernasco, Block, Rengert, Groff, & Eck, 2011), convenience stores (Askey, Taylor, Groff, & Fingerhut, 2018), department stores (Carroll & Weaver, 2017), neighborhood parks (Groff & McCord, 2012), stadiums (Kurland, Johnson, & Tilley, 2014), alcohol outlets (Day, Breetzke, Kingham, & Campbell, 2012) and so forth. For example, schools are generally found to have a significant positive correlation with crime incidents at block-level studies (Weisburd, Ready, & Lawton, 2012). In addition, scholars found an association between bus stops and street robberies (Liu, Lan, Eck, & Kang, 2020), and a correlation between road networks densities and property crime (Du & Law, 2016). In terms of theft crime, some scholars also found that motor vehicle theft was concentrated on facilities on commercial land (Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008). Song et al. (2018) used official crime data from a large Chinese city to verify that theft rates were related to the presence of retail facilities that shape daily activities from the opportunity perspective (Song et al., 2018).

In the recent decades, researchers start to consider environmental factors when modeling crime, for example, risk terrain modeling (RTM) (Caplan & Kennedy, 2010), Bayesian model (Hu, Zhu, Duan, & Guo, 2018; Law, Quick, & Chan, 2014), and discrete choice model (Bernasco, 2010; Picasso & Cohen, 2019). Among them, RTM receives more attention. RTM tries to identify features in the environment which attract crime, and model how the existence of these features may create more crime opportunities. It starts by selecting and weighing environmental features that are spatially related to crime incidents in cross-section. Then a statistical model is used to calculate and plot places that have higher statistical possibilities of crime (so-called risk terrains) (Kennedy, Caplan, & Piza, 2011; Wheeler & Steenbeek, 2021). While RTM captures individual influence from each environmental feature, it fails to consider interactive effect among these features. In addition, the prediction accuracy of RTM may be low because it normally fails to consider temporal influences.

Unlike traditional crime prediction models and RTM, which need specific algorithms set by researchers, machine learning crime prediction models solely rely on computers' automotive analyses. Variables including historic crime events, various environmental features, and even time can all be incorporated in machine learning models. Users do not need to specify a particular algorithm, and the computer will decide the most suitable function to train itself. Thus, machine learning models tend to have better model fits than traditional regression models (Liu, Liu, Liao, et al., 2018; Yi, Yu, Zhuang, & Guo, 2019). With the rapid development of artificial intelligence (AI) technology in recent years, various machine learning crime prediction models emerge. The representative ones are: neural network model (Rummens et al., 2017), random forest model (Alves et al., 2018), and graph convolution model (Wang, Zheng, Yang, & Wang, 2020). However, even though they may improve prediction accuracy, none of them have systematically considered the spatiotemporal environment variables, nor did they explain the prediction process in a transparent manner.

In order to improve the transparency and interpretability in machine learning, two different methods are proposed: ante-hoc and post-hoc (Molnar, Casalicchio, & Bischl, 2020). The ante-hoc method uses a simple and interpretable structure to train the models (Alvarez-Melis & Jaakkola, 2018); while the post-hoc method, conversely, allows models to be trained as they normally would, and then consider models' interpretability after the training. Additionally, interpretability in the post-hoc method can be subdivided into global interpretability and local interpretability. Global interpretability aims to help the audience understand the overall logic and mechanism behind complex models (Guidotti et al., 2019); and local interpretability aims to explain the decision-making process and the basis of the machine learning model for each input sample (Baehrens et al., 2009).

The interpretability of the machine learning model is very important for crime prediction. it is important for researchers to know the machine learns in the right way. Model interpretation can help us understand why a machine learning model makes such a decision and what variable plays the most important role in the learning and decision process. At the same time, being able to interpret the machine learning model helps improve the credibility of the model and the transparency of the prediction results. It is certainly not practical for the police department to rely on the "black box" model to direct crime prevention and crime control strategies. Thus, interpreting the machine learning models can help researchers and practitioners check the unique contribution (positive or negative, significant or not) of each variable.

As stated earlier, an interpretable approach is needed to let the audience know what is going on in the "black box", so that the state-of-the-art performance can earn trust from stakeholders and practitioners. However, understanding how the machine makes the decision is a challenge. Many complex models with high accuracy (e.g., deep learning model) do not make transparent decisions. While simple regression models usually cannot achieve a comparable prediction accuracy. This conflict forces a trade-off between accuracy and interpretability. Thus, to reduce the unexpected deviation and improve transparency, we need both a reliable crime prediction model and a transparent procedure that is understandable by scholars, practitioners, and stakeholders. Guided by environmental criminology theories, our study uses the XGBoost machine learning method with necessary crime and environment variables to predict crime, and then interpret predictions with the SHAP method. XGBoost predicts future crime with historical crime data and environmental factors. Then SHAP serves as a machine learning interpreter and interprets the prediction from both global and local perspectives to reveal the contribution of each variable. The combination of an accurate machine learning method and efficient interpreter is the unique contribution of this study to the literature.

当环境细节和主题的行为的信息是不够的。 然而，它们的预测的准确性无法保证在现有空间和时间尺度。 正如各种环境因素可影响犯罪的机会，现规模犯罪的预测结合这些因素成为可能。 由于20世纪中叶，与跨越一体化和逐步发展犯罪学和地理学、基本理论的刑事地理已经出现。 一些例子都是犯罪理论的机会(科恩，1981年)、日常活动的理论(Cohen&Felson,1979)，合理选择理论(康沃尔&克拉，1987年)，犯罪的模式的理论(Brantingham&Brantingham，1993年a). 犯罪理论的机会强调，所分配的人们的日常活动和犯罪问题的机会产生重要影响的空间模式的犯罪(Cohen,1981年；Weisburd,劳顿，和准备2012年)。 犯罪机会的关键是影响犯罪分子选择犯罪或不(康沃尔&克拉克，1987年)。 日常活动的理论认为，汇聚的动机罪犯，适当的指标/受害人，并且没有监护人能够在时间和空间，是需要一个犯罪事件发生。 人们的程序可能提供这样的共识(Cohen&Felson,1979). 合理选择理论还表明的潜在影响建筑环境因素对犯罪者的理性思维过程(Stummvoll，2009年)。 犯罪模式的理论侧重于地方和机会，并特别强调重叠的意识的空间，罪犯和受害者。 罪犯总是倾向于选择的地方，他们熟悉当搜寻潜在的目标(Brantingham&Brantingham,1993b). 这些地方可以以非常小的区域或设施，这反映和影响的活动，他们的用户与可能影响一个特定的刑事事件(Loukaitou-西达尼斯,Liggett,I,&瑟罗，2001年)。 地方可能存在两种类型的吸引到罪犯：目标吸引力和空间吸引力(罗德&Conly,2017年). 目标吸引力是指存在一定水平的受害者所在的地方。 空间吸引力是指身体特征的地方，他们附近的环境中，可能便利犯罪发生被忽视。 许多经验的研究已经证明，许多企业或公共设施的人经常访问可能犯罪的吸引器或发电机，提供更多的潜在犯罪的机会和增加犯罪在其附近，例如餐馆(Bernasco，块，Rengert,Groff,&之角，2011年)、便利店(旭，泰勒，格罗夫,&费，2018年)，百货公司(Carroll&织,2017年)，附近的公园(Groff&麦、2012年)，体育场馆(库兰，约翰逊，&Tilley2014年), 酒精口(日，Breetzke,金汉,&坎贝尔，2012年)等等。 例如，学校一般都发现有显着的正相关犯罪事件在块级研究(Weisburd，准备好了，&劳顿，2012年)。 此外，学者发现的一个协会之间的巴士站及街头抢劫(刘、局域网、埃克,&康、2020年)，和一个相关之间的公路网络的密度和财产的犯罪(Du&法、2016年). 在盗窃犯罪，一些学者还发现，机动车盗窃物浓缩设施的商业土地(肯尼Brantingham,Wuschke，柯克，&Brantingham，2008年)。 歌曲等。 (2018年)中使用官方的犯罪数据，从中国一家大型城市验证盗窃率存在相关的零售设施，形状的日常活动从机会的角度(歌et al., 2018年). 在最近几十年来，研究人员开始考虑环境因素的建模时犯罪，例如，风险地形模型(题)(Caplan&肯尼迪，2010)、贝叶斯模型(胡朱段&郭2018年；法律，快，&陈2014年)，以及离散的选择模型(Bernasco2010年毕加索&Cohen,2019年). 其中，题收到更多的关注。 题试图识别特征的环境中吸引的犯罪，并示范如何存在这些特征可以创造更多的犯罪的机会。 它开始通过选择和权衡环境的特点是空间有关的犯罪事件在截面. 然后一个统计模型用于计算和绘制的地方，具有更高的统计可能性犯罪(所谓的风险的地形)(肯尼迪，Caplan,&Piza2011年轮&Steenbeek,2021). 同时，题捕的个人的影响，从每个环境要素它未能考虑的交互影响之间的这些特征。 此外，预测准确度题可能较低，因为它通常未能考虑时间的影响。

不同于传统的犯罪预测模型及题，这需要具体算法的组由研究人员、学习机犯罪的预测模型仅仅依赖于计算机的汽车分析。 变量，包括历史悠久的犯罪活动、各种环境功能，甚至时间都可以纳入机学习模型。 用户不需要指定一个特定的算法，计算机将确定最合适的功能培训本身。 因此，机学习模式往往有更好的模型适合于传统的回归模型(Liu,Liu,廖,et al., 2018；Yi,Yu庄，&郭2019年). 随着快速的人工智能的发展(AI)技术近年来，各种学习机犯罪的预测模型的出现。 代表的是：神经网络模型(Rummens et al., 2017年)，随机的型森林(阿尔维斯et al., 2018年)，以及图的卷积模型(Wang,Zheng,Yang,&王2020年). 然而，即使他们可以提高预测的准确性，他们都没有系统地考虑环境的时空变量，他们也没有解释预测过程中以透明的方式进行。

为了提高透明度和解释性在学习机、两个不同的方法提出：安组织和后织(Molnar,卡萨,&Bischl，2020年). 赌注织法采用一个简单的和解释的结构，以培训模式(阿尔瓦雷斯-梅利斯&先生，2018年)；同时员额的特设方法，相反，可以允许的模式接受培训，因为他们通常会，然后考虑的模型的解释性后的培训。 此外，解释性在it方法可以细分为全球可解释性和地方的解释性. 全球的解释性目的在于帮助受众的了解的总体逻辑和机构背后的复杂模型(基多悌et al., 2019年)；以及当地的解释性目的在于解释的决策过程和基础机学习模式，用于每一个样品输入(Baehrens et al., 2009年)。

该解释性的机学习模式是非常重要的犯罪预测。 重要的是研究人员知道的机会学习在正确的方式。 模型的解释可以帮助我们理解为什么一个机学习模式，使得这样的决定和什么变量发挥的最重要的作用在学习和决策过程。 同时，能够解释该机学习模式有助于提高可信度的模型和透明度的预测结果。 这肯定是不实用的警察部门依赖的"黑箱"的模式，以直接预防犯罪和犯罪控制战略。 因此，解释该机学习模式，可以帮助研究人员和从业人员检查所作出的独特贡献(正或负，明显或不)中的每一个变量。 正如早些时候所说，一个解释的方法是必要的，让观众知道什么是"黑匣子"，使得先进的性能可以赢得信任，从利益攸关者和从业人员。 但是，了解如何在机使得决定是一个挑战。 许多复杂的模型具有高精确度(例如，深入学习的模型)不使透明的决定。 而简单的回归模型，通常不能达到一个可比的预测的准确性。 这场冲突的部队的一个贸易之间的准确性和可解释性. 因此，减少意想不到的偏差和提高透明度，我们需要一个可靠的犯罪预测模型和一个透明的程序，是可以理解的，由学者、从业者和利益攸关方。 指导由环境犯罪学理论，我们的研究使用XGBoost机学习方法与必要的犯罪和环境变量预测的罪行，然后解释预测的十八方法。 XGBoost预测未来犯罪与犯罪历史数据和环境因素。 然后形作为一个学习机器翻译和解释预测全球和地方观点，揭示出贡献的每一个变量。 该组合的一个精确的机学习方法和高效率的解释是独特的贡献，这项研究的文献。

2. Methods

2.1. XGBoost

To achieve high prediction accuracy and high interpretability, we select the XGBoost model to predict crime. XGBoost is a widely recognized tree machine learning model which balances accuracy, scalability, and efficiency well (Mousa, Bakhit, Osman, & Ishak, 2018). According to the decision rules in this tree model, the given samples are categorized, and the prediction is made by calculating the scores in the leaves after the cumulative classification (Chen & Guestrin, 2016). Supposing the model has k decision trees, the model's equation is:

$$\widehat{y}_i = \sum_{i=1}^{k} f_k(x_i), f_k \in \mathscr{F} \tag{1}$$

The objective function is as following:

$$obj(t) = \sum_{i=1}^{n} l(y_i, \widehat{y}_i) + \Omega(f(t)) \tag{2}$$

where $\Omega(f(t)) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2$

For Eq. (2), $l(y_i, \widehat{y}_i)$ is the loss function with the target $y_i$and prediction $\widehat{y}_i$. $\Omega(f(t))$ is the complexity of the entire tree and it is a regular term of the objective function. T is the total number of leaf nodes. γ is the penalty coefficient to control the number of leaf nodes to prevent overfitting. λ is the regularization coefficient. ω_j is the weight of leaf nodes. The number of leaf nodes (T) and the vector norm of weight (ω_j) jointly determine the size of the regularization term.

When a new decision tree is generated, the residual of the previous prediction needs to be fitted , f_t is added to minimize the loss function. $\widehat{y}_i^{\,t}$ is the prediction of the i$^{\text{th}}$ instance at the t$^{\text{th}}$ iteration.

$$\widehat{y}_i^{\,t} = \widehat{y}_i^{\,t-1} + f_t(x_i) \tag{3}$$

Then the objective function can be expressed as:

$$Obj(t) = \sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^{\,t-1} + f_t(x_i)\right) + \Omega f(t) \tag{4}$$

After applying Taylor series expansion to the objective function, the final objective function can be obtained:

$$obj(t) \cong \sum_{j=1}^{t} \left[G_j \omega_j + \frac{1}{2}(H_j + \lambda)\omega_j^2 \right] + \gamma T + constant \tag{5}$$

Where $G_j = \sum_{i \in I_j} g_i$, $H_j = \sum_{i \in I_j} h_i$.

Here g_i is the first derivative of the objective function, h_i is the second derivative of the objective function, and I_j is defined as the set of samples on each leaf $I_j = \{i | q(x_i) = j_i\}$.

XGBoost is a second-order Taylor expansion of the loss function and adds a regular term to the loss function. It can calculate the optimal solution for the whole model, measure the decline of the loss function and the complexity of the model, avoid overfitting, and improve the solution efficiency of the model (Mousa et al., 2018). Additionally, XGBoost is not affected by multicollinearity, so we can keep all influential factors in the model, though some of them may correlate with each other (Parsa, Movahedi, Taghipour, Derrible, & Mohammadian, 2020).

2.2. Shapley additive explanation (SHAP)

The interpretability of the tree ensemble method is rather important but can be hard to achieve. In some machine learning methods, when the weight of one influential factor increases, the importance of this factor would decrease, which is confusing (Lundberg et al., 2018). Shapley additive explanation (SHAP), as a machine learning interpreter, can address such problems (Lundberg & Lee, 2017). SHAP was proposed by Shapley based on Game Theory in 1953 (Shapley, 1953). The goal of SHAP is to provide a measure of the importance of features in machine learning models. Its working principle is shown in the following equation. In a model , $\varnothing_i(v)$ represents the attribute value for each feature i:

$$\varnothing_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!} (v(S \cup \{i\}) - v(s)) \tag{6}$$

Here, S is a subset of the features used in the model, N is the vector of feature values, and n is the number of features. $v(s)$ is the prediction for feature values in the set S. $\sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!}$ represents the weight, and ($v(S \cup \{i\}) - v(s)$) indicates the change value before and after adding the new feature i. By comparing the attribute value of each feature, the importance of the feature can be sorted. The contribution of each feature to the model output is assigned according to its marginal contribution in comparison to other features measured in SHAP values.

Lundberg and Lee have developed a practical Python package to calculate the SHAP of tree models such as GBoost, CatBoost, and XGBoost (Lundberg & Lee, 2017). SHAP has received recognition from many researchers in the field of transportation, traffic control, and energy demand management (Mihaita, Liu, Cai, & Rizoiu, 2019; Movahedi & Derrible, 2020; Molnar et al., 2020).

3. Study area and data

The study area is the XT Paichusuo of ZG City, a coastal city in Southeast China that has more than 10 million population and ranks at the top for economic development. Public theft is one of the most common crime types in this city and especially in the study area. The total area of XT Paichusuo is 7.42 km2, with a population of 400,000. Of the total population, 177,000 are registered residents with Hukou, while the rest are non-residents (domestic migrant workers). A Paichusuo is a basic unit for policing in China. Each can devise and carry out the optimal policing strategy for its jurisdiction. Therefore, Paichusuo is an ideal unit for crime research in China. The XT Paichusuo has one of the highest crime rates in the city, so the selection of XT Paichusuo as the study area has significant implications for policing and crime prevention. We retrieve public theft data with precise spatiotemporal information in our study area that happened during 2017–2020 from the Public Security Bureau of ZG City. In addition, we also collect the spatial locations of the surveillance cameras, police stations, and police substations in the study area from the police department. The unit of analysis is the 150 m × 150 m grid, and the entire study area is divided into 371 grids. The resolution of 150 m is based on the previous studies and the police's practical knowledge (Leigh, Jackson, & Dunnett, 2016; Block, 2000; Santitissadeekorn, Short and Lloyd, 2018). If the grid is too small, incidents will concentrate on only several grids, while the larger grid will reduce the spatial resolution (Rummens & Hardyns, 2021). Besides, 150x150 m^2 is typically regarded as the largest foot patrol area that a single police officer can cover in one petrol session, and targeted foot patrol can increase visibility and accessibility to audiences(Williams, 2016). Visible policing can both reduce fear of crime and increase public confidence (Ariel, Weinborn, & Sherman, 2016).

We followed routine activity theory and crime pattern theory to select variables, so all variables in our crime prediction model are theory-driven (Table 1). Ambient population can be used as an indicator of potential victims as one of the three elements of the routine activity theory (Malleson & Andresen, 2016). In addition to the residential population, the ambient population also contributes to crime within an area (Andresen, 2011). Different types of population data such as Landscan data, travel survey data, social media data, et al. have been used to measure the ambient population in previous studies of crime models (Felson & Boivin, 2015; He et al., 2020; Kurland et al., 2014; Malleson & Andresen, 2015). The ambient population data used in this

2. 方法

2.1. XGBoost实现高预测的准确性和高可解释性，我们选择XGBoost模型预测的犯罪。 XGBoost是一个广泛公认的树机学习模式，其结余的准确性，可扩展性，

和效率以及(Mousa,巴希特，奥斯曼,&Ishak，2018年). 根据该决定的规则，在这种树的模式，给予样品进行分类，并预测是通过计算的成绩，在离开后的累计分类(陈&格斯特林，到2016年). 假设的模型的有k决策树、模型的公式是：y=∑

f(x)、f∈F(1)

i-1

目标函数如下：

obj(t)= ∑ l(y,y)+Ω(f(t))(2)

其中Ω(f(t))=yT+ λ ∑ jω2j

为均衡。 (2)、l y,y)损失的功能与目标yand预测y

. Ω(f(t))的复杂性，整个的树，它是一个正常任期内的目标的功能。 T总数的叶子中的节点。 γ刑罚系数控制数量的叶节点，以防止过度匹配。 λ为正规化的系数。 wis重叶节点。 数叶节点(T)和矢量规范的重量(ω)共同确定尺寸的正规化术语。 当一个新的决定树产生，剩余的先前预测的需要装配的金融机构加入，以尽量减少损失的功能。 y

t 是预测的我 th 实例在t th 迭代。

y=y+f(x)(3)然后目标功能，可以表示为：

Obj(t)= ∑ i l y,y+f(x)) +单位ωf(t)(4)

之后，施泰勒系列扩张的目标功能，最终目标功能，可以获得：obj(t)≅∑

[G ω +12H - j+1) ω] +yT+恒(5)

j=1

其中G= ∑ i∈I gH= ∑i∈I h

这里gis第一个衍生物的目标功能，他的第二衍生物的目标功能，并Iis定义为集的样本上每一片叶子我

={i|q(x) = j }.

XGBoost是第二阶泰勒膨胀的损失功能，并增加了一个定期的损失的功能。 它可以计算出的最佳解决方案的整个模型，测量下降的损失功能和模型的复杂性，避免过度匹配，并提高方案效率的模型(Mousa et al., 2018年). 此外，XGBoost不是受到多重共线性，因此，我们可以让所有有影响力的因素模型中，虽然一些人可能互相关联(帕尔萨,Movahedi,Taghipour,Derrible,&Mohammadian，2020年). 2.2. 沙普利添加剂的解释(十八)的解释性的树团种方法是相当重要，但可能难以实现。 在一些机学习方法，当量的一个有影响的因素的增加，这一因素的重要性将会减少，这是令人困惑(Lundberg et al., 2018年). 沙普利添加剂的解释(十八)，作为一个学习机器翻译

可以解决这些问题(Lundberg&Lee,2017年). 十八提议由沙普利的基础上游戏的理论在1953年(沙普利，1953年). 我们的目标的十八的是提供一个衡量的重要性的特点，在机学习模型。 它的工作原理是以下所示的方程式。 在一个模型，ø

i (v)表示的特性的价值为每一个特征，我：

ø(v)= ∑ S⊆N\{i} |S|!(n|S|1)! / n! (v(S∪{我})v(s))(6个)

在这里，S是一个子集的功能，使用在模型中，N为矢量特征数值，n为特征。 v(s)是预测为特点的价值观的集S∑Snrepresents的重量，以及(v(S∪{我})v(s))的指示改变的价值之前和之后添加新的功能。 通过比较特性值的每个要素的重要性的特征可以进行排序。 所作的贡献的每个要素的模型输出分配给根据其边际的贡献比其他特征测定于十八值。

伦德伯格和李已经开发出一个实用的蟒蛇揽子计算十八树模式，如受CatBoost，并XGBoost(Lundberg&Lee,2017年). 十八已经获得认可，从许多领域的研究人员的交通、业务控制以及能源需求管理(Mihaita,Liu,Cai,&Rizoiu，2019年;Movahedi&Derrible，2020年;莫尔纳et al., 2020年). 3. 研究区域和数据的研究领域是XT Paichusuo的ZG城市，一个沿海城市在中国东南部，有超过10亿人口，排名在顶部对于经济发展。 公共盗窃是一种最常见的犯罪类型在这个城市，特别是在研究领域。 总面积的XT Paichusuo是7.42平方公里2，人口为400 000名. 总人口中，177,000人是注册的居民户口的，而其余的都是非居民(国内移徙工人). 一Paichusuo是一个基本单元，用于维持治安在中国。 每个可以制定和执行最佳的警务战略用于其管辖权。 因此，Paichusuo是一个理想的单元，用于犯罪的研究在中国。 XT Paichusuo有一个最高的犯罪率在城市，所以选择的XT Paichusuo作为研究区域具有显着影响到维持治安和预防犯罪。 我们取回盗窃公共数据的精确的时空信息在我们研究区域发生在2017年至2020年如从公共安全局的ZG城市。 此外，我们还收集的空间位置的监控摄像机、警察站和警察分站在研究区域警察部门。 该单元的分析是150米×150米格，并将整个研究区域划分为371网。 该决议的150米是基于以前的研究和警察的实用知识(Leigh，杰克逊，&Dunnett2016年；块，2000年；Santitissadeekorn，短期和劳埃德，2018年). 如果网太小，事件将集中在仅仅几个电网，而较大电网将减少空间分辨率(Rummens&Hardyns,2021). 此外，150×150误通常被视为最大的徒步巡逻的区域，一个单一的警务人员可以涵盖在一个加油届会议，和有针对性的徒步巡逻队可以增加可见性和无障碍的受众(Williams,2016年). 可见的维持治安可以降低对犯罪的恐惧和增加公众的信心(Ariel Weinborn,&谢尔曼，2016年).

我们随后是常规活动的理论和犯罪问题的模式的理论选择的变量，因此，所有的变量在我们的犯罪预测模型是理论驱动的(表1)。 环境人口可以用作指示潜在的受害者的三大要素之一的例行活动的理论(Malleson&安德烈2016年). 除了住宅的人口，环境，人口也有助于犯罪的一个区域内(安德烈2011年)。 不同类型的人口数据，如Landscan数据，旅行的调查数据，社会媒体的数据，et al. 已被用于测量环境的人口在以前的研究的犯罪模型(Felson&洛2015年；他et al., 2020年;库兰et al., 2014年Malleson&安德烈2015年)。 环境的人口数据的使用在这

Table 1
Independent variable descriptions.

Variable category	Variable name	Source and meaning
1	Ambient population (16–24)	Population size at corresponding age groups in each grid
2	Ambient population (25–44)	
3	Ambient population (45–59)	
4	Ambient population (60–69)	
5	Camera	Number of Skynet cameras in each grid
6	Dist_Police	The distance from the grid's centroid to the nearest police station or police sub-station
7	Restaurant	The numbers of different Points of interest (POIs). The data is from the navigation data of Daodaotong Map company.
8	Bus station	
9	Department store	
10	Internet café	
11	Entertainment venue	
12	School	
13	Bank	
14	Hotel	
15	Convenience store	
16	Richness	Affluence index of each grid from Smart Steps data of China Unicom
17	Road_Lengh	Length of all road segments within the grid

paper come from China Unicom, which is one of the three telecom operators in China and has 300 million active users every day. As each user conducts user-BS (user and base station) communication every 7 min on average, the user's location data is recorded in the same time interval (Wu et al., 2020). According to the age classification of WHO, young is 25–44, middle age is 45–59, and old age is 60 and above (Dyussenbayev, 2017). Since the minimum age of theft offenders eligible for criminal punishment is 16 years in China, we also added a youth population variable of 16–24 years old. We extracted the four age groups from this dataset: 16–24, 25–44, 45–59, and 60–69 respectively. This dataset also provides the richness index, which shows the user's aggregated movement insights and can show society's overall wealth level by evaluating their property value, cell phone value, phone bill, and so forth. The company uses its patented algorithm to score each user on a scale of 1–8 based on their behavioral profile attributes, and then calculates the average of this score for users within a grid to create an index of affluence of that grid. According to Unicom, the behavioral characteristics attributes include the price of housing in the subscriber's neighborhood, the price of cell phone terminal, the number of places to stay for entertainment, the amount of travel in foreign cities, the mode of travel, phone bills and other multi-source data indicators. This richness index ranges from 1 to 8, and a higher value indicates more assets. The accessibility variable is measured as the total length of the road segments in each grid. The numbers of restaurants, bus stations, department stores, Internet cafés, entertainment venues, schools, banks, hotels, and convenience stores are also included as they may act as crime attractors/generators and influence crime opportunities (Brantingham & Brantingham, 1993a; Lan et al., 2021).

The crime type studied in this paper is public theft, which refers to theft that happened in public places. Pickpocketing, thefts from malls and convenience stores, theft of electric vehicles, bicycles, and motorcycles are all considered as public theft (Liu et al., 2017). From 2017 to 2020, in our study area, public theft accounted for more than 40% of all crime incidents. Our dependent variable data is binary, showing the presence or not of public theft in the grid. This is because more than 90% of grids have no cases in the two-week statistical cycle, and no grid has more than 9 thefts. The time scale used in this paper is two weeks, which is recommended by local police officers. This is a practical time slot that police officers would use to adjust their strategies.

4. Results

4.1. *The result of the* crime prediction model

In total, 371 grids (150 m × 150 m) are used for crime prediction models. We divide historical public thefts into biweekly cycles and receive 78 cycles during 2017–2019, so the sample size of the data set is 28,938 (371 × 78 = 28,938). In our study area, public thefts are concentrated, more than 93% (27,005/28,938) grids have no theft problem. We use Python to conduct crime prediction with the XGBoost machine learning algorithm. First, we divide all samples into the training group (75% of all samples) and the verification group (25% of all samples). Then, the XGBoost model is fit, and the grid search method is used to adjust the parameters of the model as an optimization (Putatunda & Rama, 2018). Finally, the best model is automatically decided based on the evaluation index by computer. Cross-validation is used to evaluate the performance of various combinations of parameters, and the best combination is selected as the model parameters.

The accuracy of the training model is 0.91, suggesting that 91% of the grids are correctly predicted. The accuracy of the verification set is 0.89, and the ROC (Receiver Operating Characteristic)score is 0.586. In addition, we also compare the XGBoost model with other popular machine learning models such as logistic regression, decision tree, and random forest; and the XGBoost model clearly shows the best model fit (Fig. 1).

4.2. *Global interpretability*

SHAP tree explainer is used to explain the model both globally and locally. The SHAP value of a feature (variable) shows its contribution to the output, and such a value is weighted and summed over all possible feature value combinations. Global interpretability refers to the ability to interpret model decisions based on conditional interactions between dependent and independent features in the entire dataset. It shows the overall influence of model features and how each algorithm component (e.g., weight, structure, and other parameters) help machine make decisions. The SHAP value, $\varnothing_i(f,x)$, is an allocation of credit among the various features in the feature set to explain a prediction f(x). In our crime prediction model, f is the XGBoost model results and x is the variable. The mean value of all absolute SHAP values ($\varnothing\_i\,\widehat{(f,x)}$) shows the global interpretability of the crime prediction model.

Fig. 2 ranks the mean absolute SHAP value of each variable from high to low. Variables are sorted according to their impact, and the

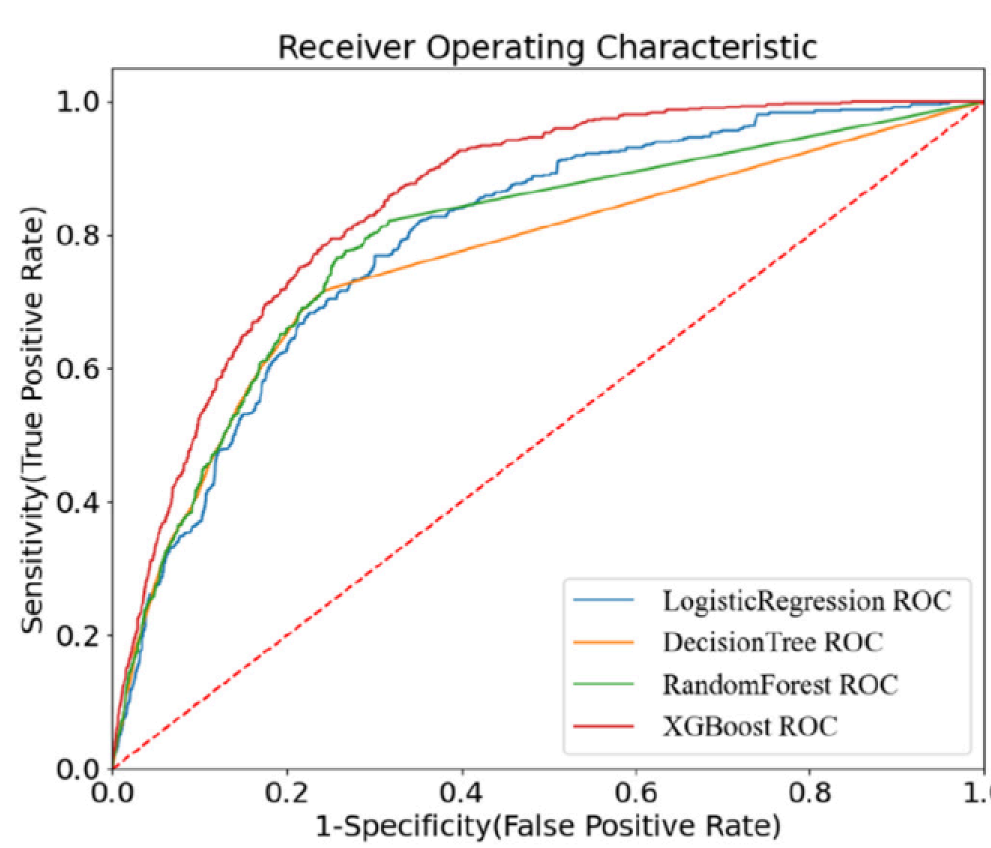


Fig. 1. Comparison of ROC curves of different models.

表1独立的变量的描述。 变量分类的变量名来源和含义

1环境的人口(16至24)人口规模相对应的年龄组中的每个网格

2环境的人口(25至44岁)
环境人口(为45-59)
3

4环境的人口(60-69)

5照相机数天网摄像机在每个网格

6Dist_Police距离电网的心到最近的警察站或警察子站7餐厅的数量不同的兴趣点(景点). 数据是从导航数据的Daodaotong地图的公司。 8巴士站

9百货商店
10互联网咖啡馆
11娱乐
场地
12所学校
13银行

14酒店15便利店

16丰富的富裕指数的每个格从智能的步骤，数据的中国联通

17Road_Lengh长的所有时段内格

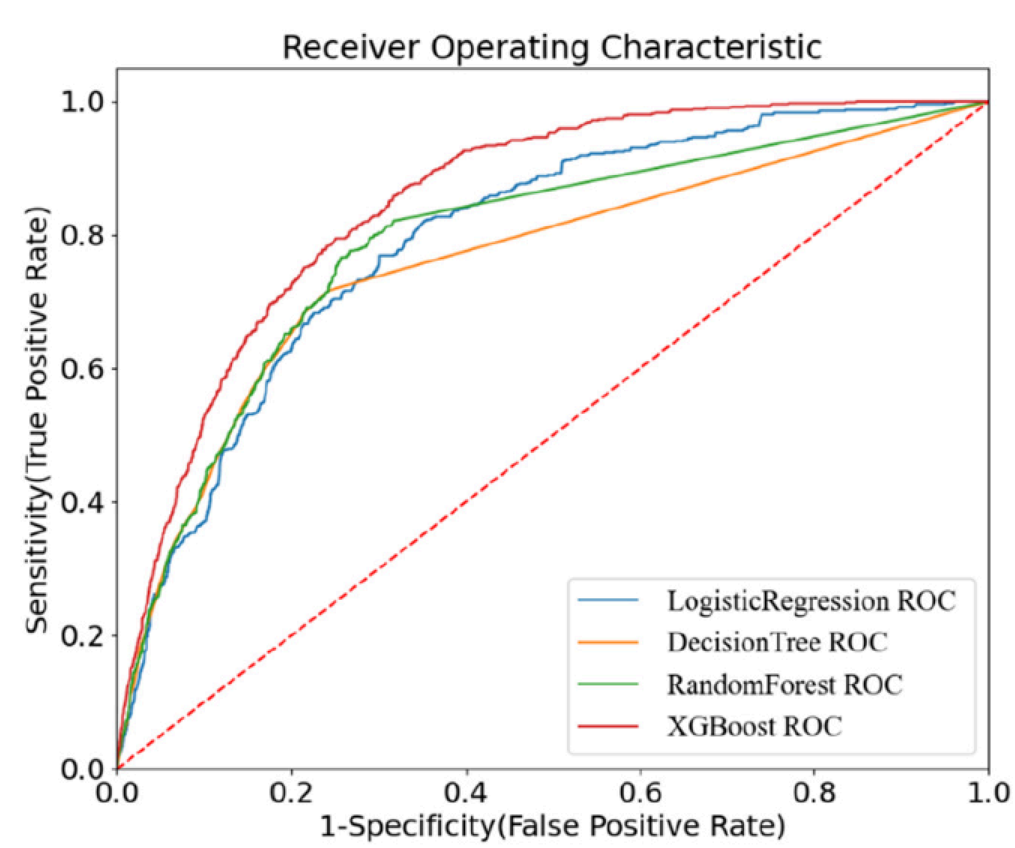
纸来自中国联通，这是一个电信运营商在中国和有300万名积极用户的每一天。 作为每个用户举办的用户-BS(用户和基站)通信每次7分钟的平均而言，用户的位置的数据是记录在同一时间间隔(吴et al., 2020年). 根据年龄分类的人，年轻的是25–44、中间年龄为45-59，与老年龄是60和上述(Dyussenbayev,2017年). 由于最低年龄的盗窃罪犯获刑16年，在中国，我们还增加了一个青年人口变量的16至24岁。 我们中提取的四个年龄组从这一数据集：16至24,25至44岁,为45-59，并60-69分别。 这个数据集还提供了丰富指数，显示了使用者的总体运动的见解，并可以显示社会的整体财富水平，通过评估他们的财产价值、手机的价值，电话账单等。 该公司使用其专利算法，这是你的每个用户规模的1-8中基于其行为的个人档案属性，然后计算的平均水平的这个分数的用户在网，以建立一个索引富裕的网格。 根据联通的，该行为特征属性，包括住房价格在用户附近，价格的手机终端、数量的地方留下来娱乐、数量的旅行在外的城市，该模式的旅行、电话帐单和其他多种来源的数据指标。 这种丰富性指数的范围从1至8和更高的价值表示了更多的资产。 性变量测定的总长度的时段在每一个电网。 数字餐厅、汽车站、百货店、网络咖啡馆、娱乐场所、学校、银行、酒店、便利店也包括在内，因为它们可能作为犯罪吸引/发电机和影响犯罪的机会(Brantingham&Brantingham，1993年a;局域网et al., 2021). 犯罪类型研究在本文件是公开的盗窃，它指的是偷窃发生在公共场所。 扒窃、盗窃，从商场和便利商店、盗窃的电动汽车、自行车、摩托车都被认为是为公共盗窃(刘et al., 2017年). 从2017年至2020年，在我们研究区域、公共盗窃占40%以上的所有犯罪事件。 我们依赖的变量的数据是二进制的，表示存在或不公共盗窃的网格。 这是因为超过90%的电网没有情况下在两个星期的统计周期，并且没有栅格已超过9盗窃。 时间标度中使用的本文件是两个星期，这是建议通过当地警官。 这是一个实用的时隙，警官会用来调整自己的战略。

4. 结果4.1. 结果，犯罪预测模型，在总共371网(150米×150m)用于犯罪预测模型。 我们分裂历史的公共盗窃到两周一次的周期和会收到78周期在2017年至2019年，这样的样本大小的数据集是28,938(371×78=28,938). 在我们研究区域、公共盗窃案都集中，超过93%(27,005/28,938)电网没有盗窃问题。 我们使用Python进行犯罪的预测与XGBoost机学习算法。 第一，我们把所有样品进入培训小组(75%的所有样品)，并核查团(25%的所有样品)。 然后，XGBoost模式是合适的，而网搜索的方法是用来调整参数模型作为一种优化方式(Putatunda&拉玛，2018年). 最后，最好的模型自动决定，根据评价指数通过计算机。 交叉验证是用来评价绩效的各种组合参数，并最佳组合是选择作为模型参数。

准确性的培训模式为0.91，这表明，91%的网格是否正确预测的。 准确性的核查设置为0.89，中华民国(接收操作的特征)分是0.586. 此外，我们也比较XGBoost模型与其他流行机学习模式，例如逻辑回归，决定树，并随机的森林；以及XGBoost模式清楚地显示了更好的模型配合(图。 1). 4.2. 全球的解释性十八树讲解员是用于解释模型在全球和

在本地。 第十八值的一个要素(变量)显示了其贡献的输出，这样一个数值是加权，并总结了所有可能的功能价值的组合。 全球的解释性是指能够解释模型的基础上决定的条件之间的相互依赖性和独立特性在整个数据集。 它显示了整体的影响的模式的特点和每个算法的成分(例如，重量、结构、和其他参数)有助机作出决定。 第十八值，ø(f、x)是一个信贷分配之间的各种特征，在特定解释的预测f(x)。 在我们的犯罪预测模型、f是XGBoost模型的结果和x变量。 这意味着价值的所有绝对十八值(ø日(f、x))显示了全球的解释性犯罪的预测模型。

图。 2排名平均绝对十八值的每个变量从高到低。 变量都按照他们的影响，



图。 1. 比较的中华民国的曲线的不同的模型。

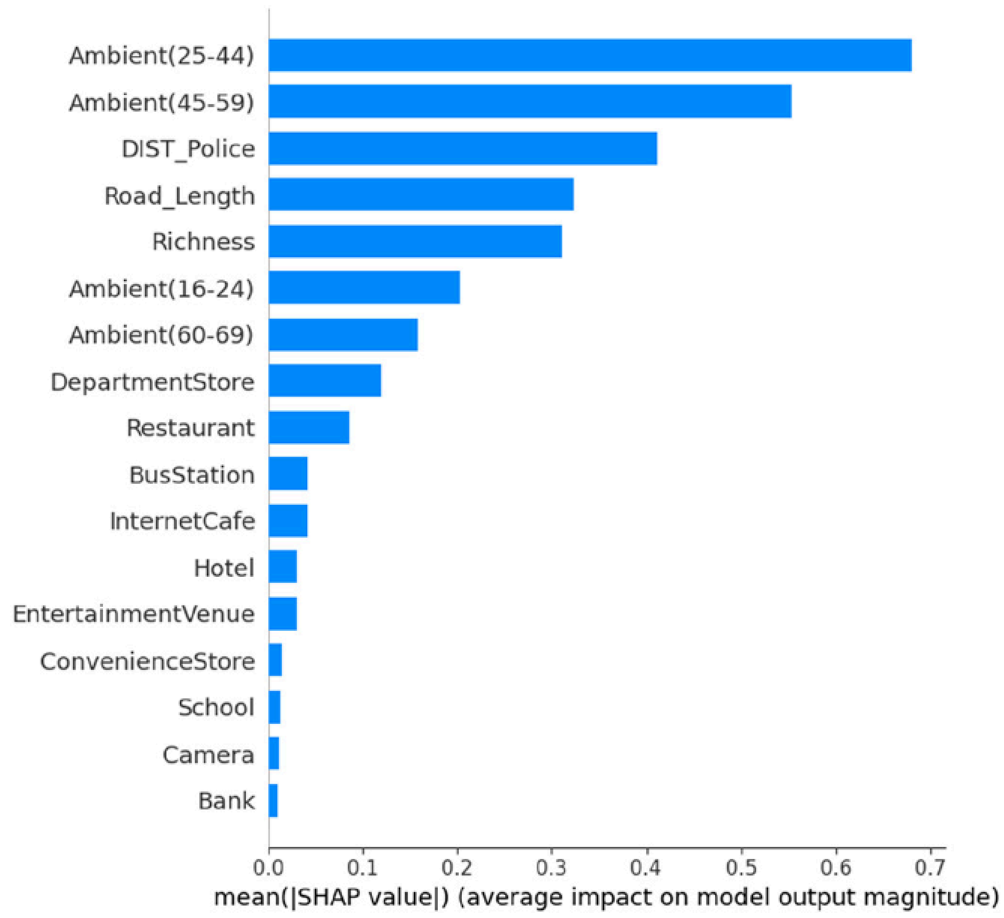


Fig. 2. Ranking of the absolute value of SHAP value of all features.

variables at the top have the greatest impact. The top two variables are *ambient (25–44)* and *ambient (45–59)*. This means the ambient population at ages of 25–59 and 45–59 have the best global interpretability to the crime prediction in the study area.

To better understand the impact of each variable on the model, we plot the SHAP value of each variable at each grid (Fig. 3). The x-axis shows the impact of variables on the outcome. Positive SHAP values indicate a positive relationship between the independent variable and dependent variable, while negative values indicate negative relationships.The attribute values of the samples are indicated by the colors of the dots (red color indicates high attribute value and blue color indicates low attribute value) Fig. 3 shows that the ambient population at ages of 25–44 (*ambient(25–44)*) has the greatest impact on crime. This means grids with a larger population of 25–44 are more prone to have public theft problems than other grids. The variable of the ambient population at ages of 45–59 (*ambient(45–59)*) has the second-highest impact on the model. For the variable *DIST_ Police*, the red dots are mostly on the left side of the y-axis, which indicates that when the feature value of the variable *DIST_ Police* is large, its SHAP value is negative. This means the risk of public theft is high near the location of police stations/sub-stations. This may seem controversial, but it is actually reasonable, we will explain this in detail in the later paragraph. Other variables, such as the number of department stores, restaurants, bus stations, and internet cafes, have less impact on the model. However, when their values are large, their SHAP values are positive.

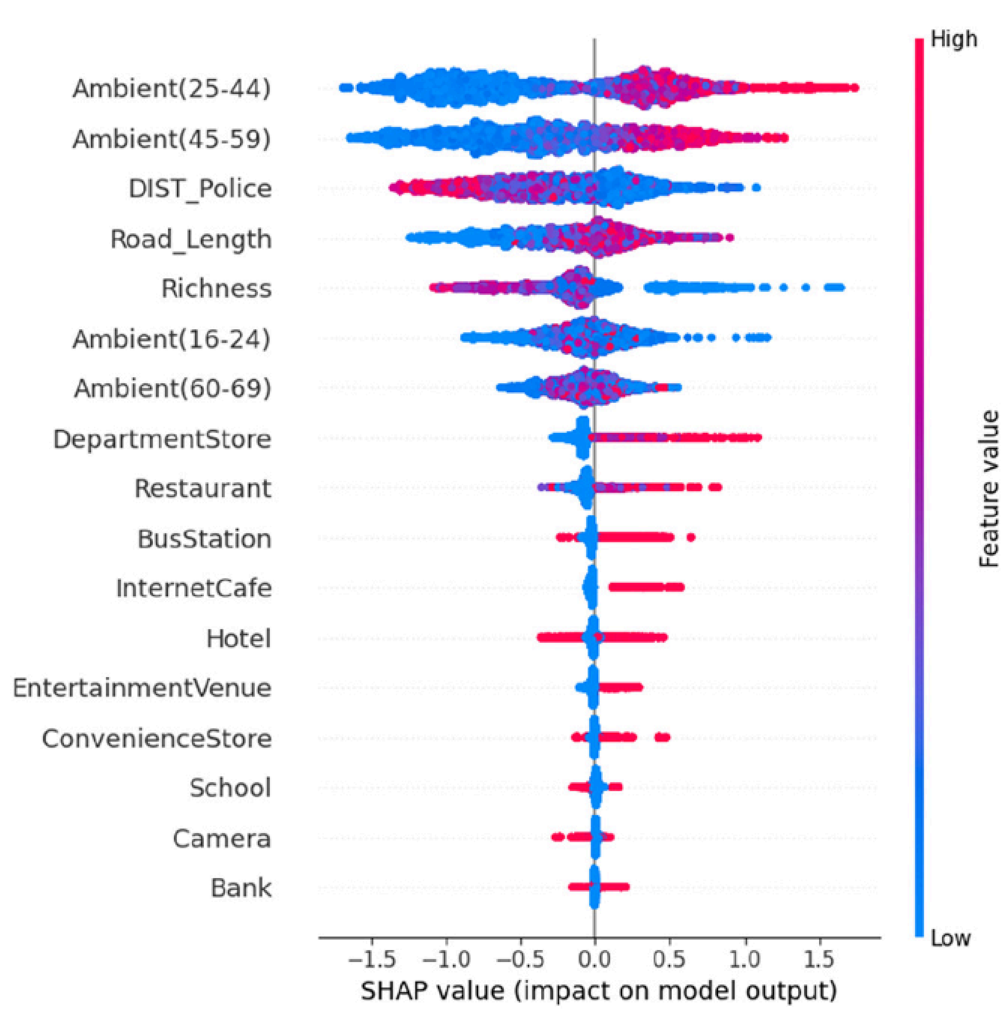


Fig. 3. Distribution of SHAP values of all samples.

To further study the interrelationships between crime and each variable, we plot variables with variable values on the x-axis and its SHAP value on the y-axis (Fig. 4). Fig. 4(a) and Fig. 4(b) illustrate the impact of the ambient population (25–44) and ambient population (45–59) on model output. Larger variable values generally relate to higher SHAP values, which indicates that they are positively correlated with public theft. Thus, those grids with a large proportion of the population of 25–59 are more likely to be the target area of public theft. These ambient populations characterize the potential victims. The increase of potential victims increases the risk of crime to a great extent. On the contrary, the value of *DIST_Police* and SHAP value are negatively related (Fig. 4(c)). This means that grids closer to the police station/sub-station tend to have a higher theft risk. This is because, in our study area, police stations and police sub-stations are generally located in an area where there are a more dynamic population and a higher crime risk. Fig. 4(d) shows that the high value of the variable of *ambient(25–44)* is concentrated in the area with a small variable value of *DIST_Police* (the red points are on the left part of the figure), which means that grids with more 25–44 aged population and closer to police stations/sub-stations tend to experience more public theft. Plots such as Fig. 4(d) helps reveal interactive effects between the different variables.

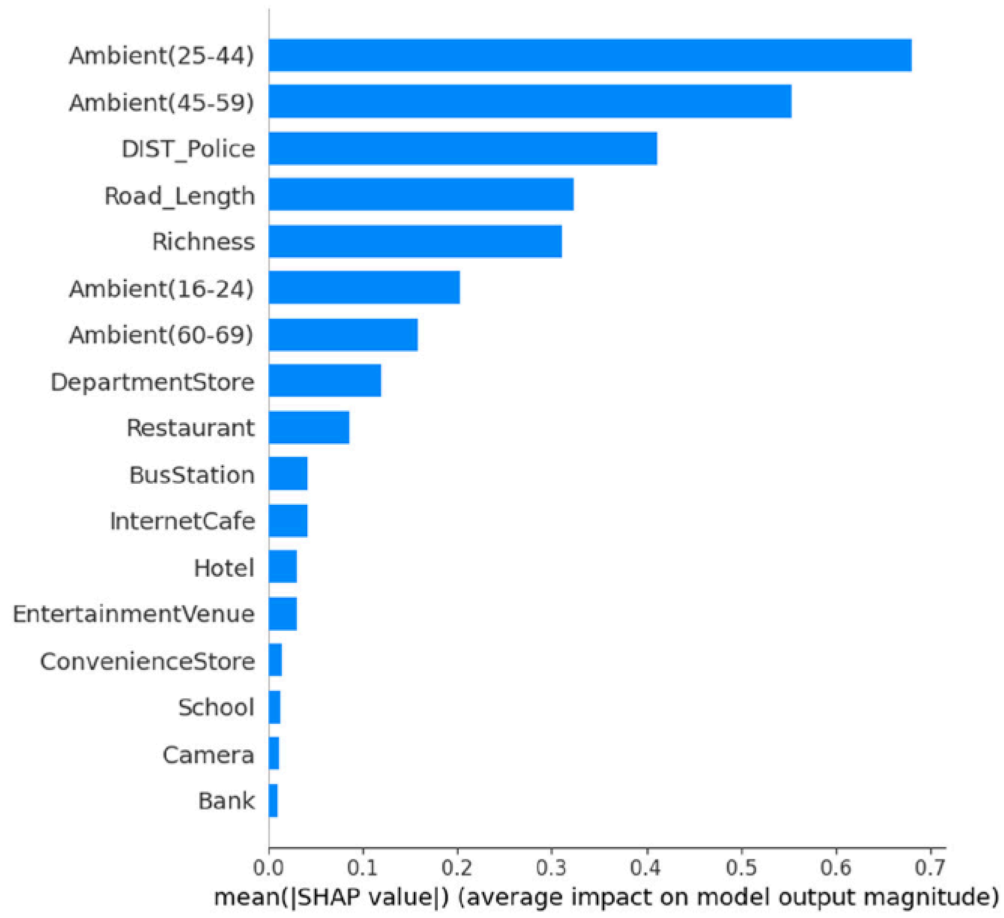
While the machine learning model does not explicitly specify the interaction between the explanatory variables, it can assess the individual contribution of a variable in comparison with the others, in a way similar to the controls used in a regular regression.

To test the consistency between the machine learning model and traditional regression model, we performed logistic regression modeling and obtained the results in Table 2. Among the statistically significant variables, *Ambient (25–44)*, *Ambient (45–59)*, *Ambient (60–69)*, *Restaurant*, *DepartmentStore*, *InternetCafe* and *ConvenienceStore*have an odds ratio greater than 1 and a z-value greater than 0 which means that these variables can increase the risk of crime. Observing Fig. 3, the SHAP model also has the same results. While *Ambient (16–24)*, *DIST_Police*, *School* and *Richness* have an odds radio less than 1 and a z-value less than 0, implying that the relationship between crime occurrence of these variables is negative. These odds ratios are consistent with those presented by the SHAP model.

4.3. Local interpretability

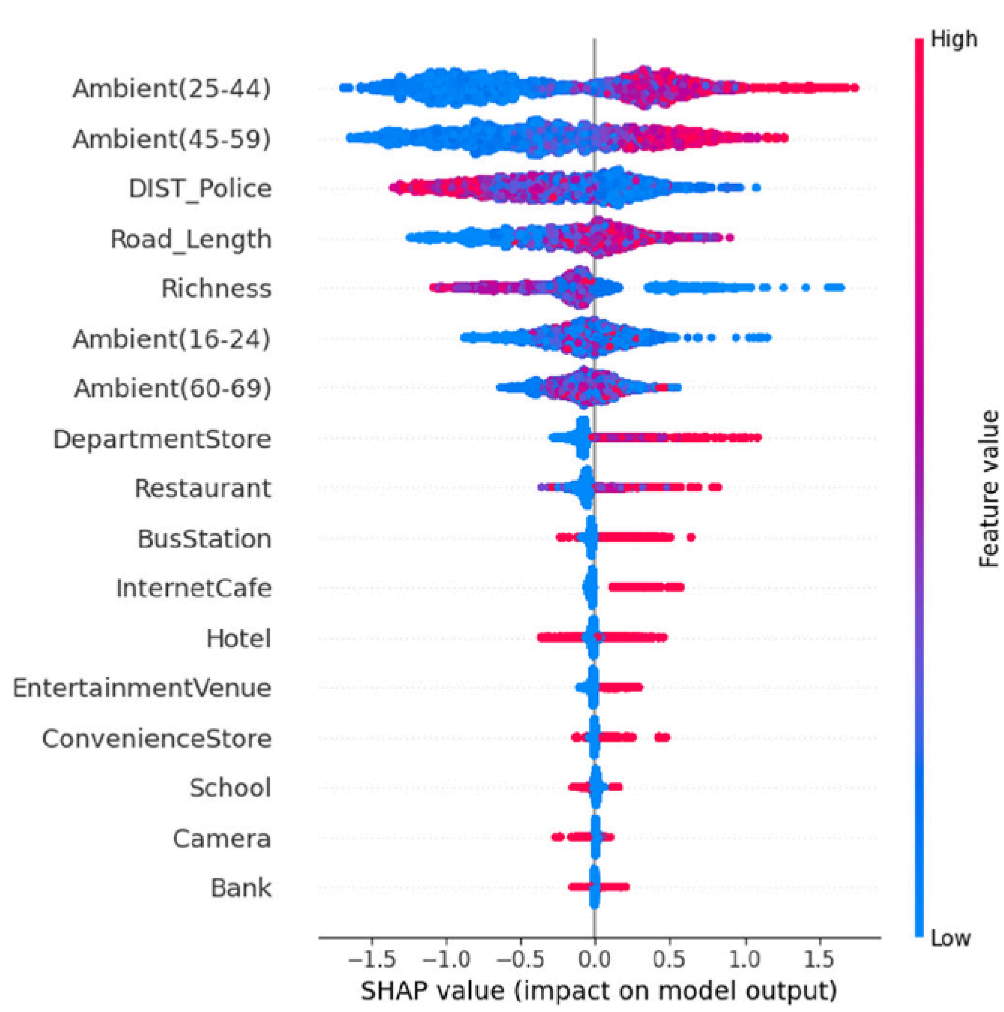
The local interpretability of the model suggests the prediction contribution of every single grid. That can be achieved by analyzing the contribution of each dimensional feature of each individual sample to the model outputs (Lundberg & Lee, 2017). Through the local variation of different feature' SHAP values, we can get a sense of the local microenvironment in each grid. The goal of SHAP value calculation is to explain the result of the machine judgment by calculating the contribution of each feature when predicting. The sum of the SHAP values of each feature in a sample plus the baseline value equals the predicted value of the sample. The local accuracy, also known as additivity, can be calculated as follows:

$$f(x) = \varnothing_0(f,x) + \sum_{i=1}^{V} \varnothing_i(f,x) \quad (7)$$



图。 2. 排名的绝对值十八值的所有特征。

变量的顶部有最大的影响。 前两个变量是环境(25至44岁)和环境(为45-59). 这意味着环境的人口年龄段的25-59和为45-59具有最佳的全球解释性犯罪预测在研究领域。 更好地了解影响的每个变量的模型上，我们绘制十八值的每个变量在每个网格(图。 3款)。 X轴表示的影响的变量的结果。 积极的。值表示的正相关关系之间对独立的变量和变量的依赖，同时负值表示的负面关系。属性值的样品表示颜色的点(红色表示高属性的价值和蓝色表示低attribute value)图。 3显示出，环境的人口年龄在25至44岁(环境(25至44岁))具有最大影响的犯罪



图。 3. 分布的十八值的所有样品。

这意味着电网与一个更大的人口的25至44岁更容易出现有公共盗问题比其他网。 可变的环境人口的年龄为45-59(环境(为45-59))具有第二高的影响的模型。 变量的DIST_警察、红点是主要在左侧的y-轴线，这表明当特征的变量值DIST_警察很大，其形的价值是负面的。 这意味着风险的公共盗窃是高位置附近的警察局/变电站。 这可能看起来有争议的，但它实际上是合理的，我们会解释这一详细说明，在后来的段落。 其他变量，例如数量的百货商店、餐馆、汽车站和因特网咖啡厅，有较少的影响的模型。 然而，当他们的价值很大，他们十八值是积极的。

要进一步研究之间的相互关系的犯罪以及每个变量，我们变量的绘图与变量值在x轴和其十八值在y轴线(图。 4). 图。 4(a)和图。 4(b)说明影响环境的人口(25至44岁)人口和环境(为45-59)对模型输出。 较大的变量值，通常涉及较高的十八值，这表明它们是正相关的公共盗窃。 因此，这些电网与一个大型的人口比例的25-59更有可能的目标地区的公共盗窃。 这些环境的人口特点的潜在的受害者。 增加的潜力受害者的风险增加的犯罪很大程度上。 相反，值DIST_Police和十八值产生负面相关的(图。 4(c))。 这意味着，电网接近的警察台/电站往往具有较高的盗窃的风险。 这是因为，在我们研究区域、警察站和警察分局一般是位于一个区域，那里有一个更有活力的人口和高犯罪风险。 图。 4(d)显示，高价值的变量的环境(25至44岁)集中在该地区与一个小小的变量值DIST_Police(红点是在左边的一部分，图)，这意味着格与更多的25至44岁的人口接近警察局/sub-站往往经历更多的公共盗窃。 图如图。 4(d)有助于揭示的互动效果之间不同的变量。

同时，该机学习模式并没有明确指定之间的相互作用的说明变数，它能够评估个人的贡献的一个变量比其他人，在某种程度上类似于控制使用在定期回归。

测试之间的一致性的机学习模式和传统的回归模型，我们执行逻辑回归模型和所获得的结果见表2。 在统计上显着的变量、环境(25至44岁)、环境(为45-59)、环境(为60-69)，餐厅，DepartmentStore,InternetCafe和ConvenienceStorehave赔率的比率大于1和z值大于0，这意味着，这些变量可能增加风险的犯罪。 观测图。 3的形模型也具有同样的结果。 虽然环境(16至24),DIST_Police、学校和丰富具有的赔率的无线电低于1和z值低于0，这意味着之间的关系的犯罪发生的这些变量是负面的。 这些几率比率是一致的，与那些提交了十八的模式。 4.3. 当地的解释性地解释性的模型表明预测的贡献的每一个电网。 这可以通过分析所作的贡献每个维特的每一个单独的样品的模型输出结果(Lundberg&Lee,2017年). 通过当地变化中的不同特征的'十八价值观，我们可以得到的当地环境中的每个网格。 我们的目标的十八值计算是解释的结果，机器的判断通过计算作出的贡献的每个要素时的预测。 总和十八值中的每个要素一样加上基线值等于预测值的样品。 本地的准确性，也称为累加性，可以计算如下:

$$f(x)=\phi_0(f、x)+\sum_{i=1}\phi_i(x)\quad(7)$$

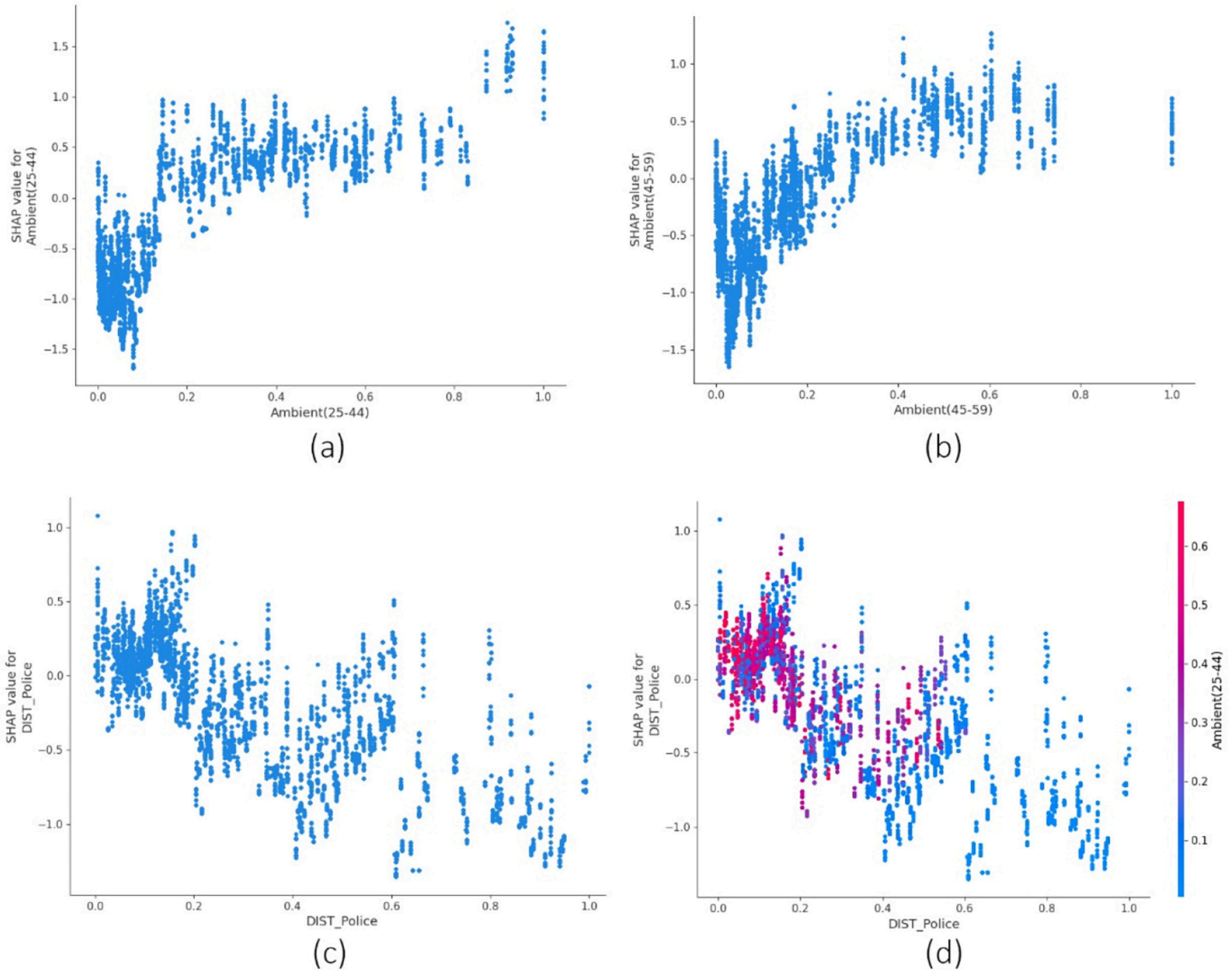


Fig. 4. Dependency plot of variables and SHAP value.

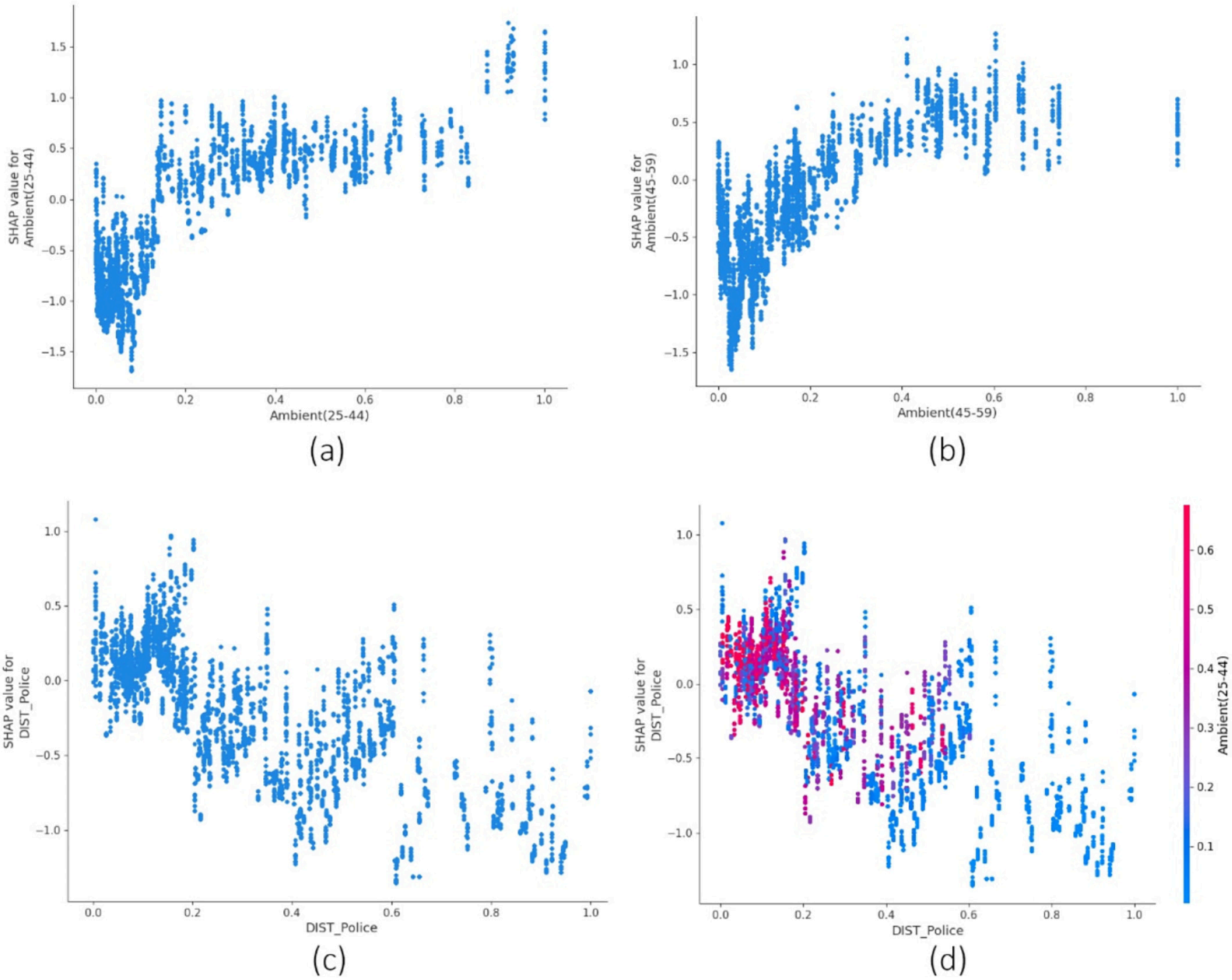
where $\varnothing_0(f,x) = E\ [f\ (\ x)]$ Represents the expected crime risk of the model over the training dataset and V is the number of inputs.

Additionally, the SHAP value has monotonicity, which is also known as consistency. Specifically, if a feature is more important in one model than other models, no matter what other features are also present in other models, the importance attributed to this very feature should also be higher (Lundberg et al., 2018). For the crime prediction model, the feature importance of one grid does not necessarily mean causality. However, such feature importance can help direct police officers when making crime prevention strategies. We randomly select two grids and show the SHAP value of each feature in Fig. 5. Fig 5(a) and 5(b) show two different grids, and they share the same base value ($\varnothing_0 = -2.41$), indicating mean value of target variable of all samples. Blue color indicates the negative influence of that feature, and red color indicates the positive influence. As shown in Fig. 5(a), features with negative SHAP values are ambient *population(24–44)*, *ambient population(45–59)*, and *ambient population(16–24)*; while variables with positive SHAP values are *Bus Station* , *DIST_ Police* and *Road_ Length*. The total SHAP value of the sample is −3.38, which is smaller than the base value. In Fig. 5(b), the variable with negative SHAP value is *Richness*, and the variables with positive SHAP values are *ambient population(45–59), ambient population (60–69), ambient population(24–44), road_ Length, DIST_ Police*, and *Entertainment Venue*, etc. These two examples show that the direction of a feature's local influence on crime can be different from that of the global model, and the local influences vary across the grids.

Fig. 6 shows the local SHAP values of four different variables in the training model by the grid. Fig. 6(a) and 6(b) show variables of the *ambient population(25–44)* and *ambient population(45–59)*, while Fig. 6 (c) and Fig. 6(d) show *department stores* and *restaurants*, which are crime attractors and generators. These graduated symbol maps can suggest crime hot spots that are dominated by that particular variable. The distributions of local SHAP values of different variables are also different, which means that different variables have different impacts on the model at different grids. These maps, which show unique contributions from every single variable, can provide meaningful information to the police to create tailored strategies for crime prevention. This is the unique contribution of this interpretable machine learning crime prediction method.

5. Discussion and conclusions

Existing crime prediction models using the machine learning method tend to act as the "black box". It is almost impossible to understand what happens in the "black box". The lack of interpretability may undermine people's confidence in these crime prediction models. This study has overcome this limitation, and the resulting models not only increased predictability but also brought interpretability, similar to those of



图。 4. 依赖情节的变量和十八值。

在ø(f、x)=E[f(x)]表示预期的犯罪风险的模型的培训数据集和V数量的投入。 此外，第十八值有单调性，这也被称为一致性。 具体地说，如果一个特征是更重要的是在一个模型比其他模型，无论有什么其他的功能还存在其他模式，重要归功于这个非常特征应该还会更高(Lundberg et al., 2018年). 对于犯罪的预测模型的功能重要性的一个网格不一定意味着因果关系。 然而，这种特征的重要性可以帮助警察人员时使预防犯罪战略。 我们随机选择的两个电网的，并显示十八值的每个特征图。 5. 图5(a)和5(b)显示两个不同的电网，和他们共享相同的基本价值(ø=2.41)，表示平均值的目标变量的所有样品。 蓝色表示的负面影响，特，红色的表示积极的影响。 如图所示。 5(a)，负十八值是环境的人口(24-44)、环境群体(为45-59)，以及环境人口(16至24)；而变量与积极十八值是巴士站，DIST_警察和Road_长。 总十八值的样品3.38，这是比较小的基值。 图。 5(b)，该变量与负十八值的丰富性和变量的积极十八值是环境的人口(为45-59)、环境群体(60-69)、环境群体(24-44),road_长，DIST_警察和娱乐场所，等等

这两个例子显示方向的一个要素是当地的影响力犯罪可以不同的全球模型，并对当地的影响各不相同的电网。

图。 6显示了当地十八值的四个不同的变量的培训模型的网格。 图。 6(a)和6(b)显示的变量的环境人口(25至44岁)人口和环境(为45-59)，同时图。 6(c)和图。 6(d)显示百货商店和餐厅，都是犯罪吸引和发电机。 这些毕业符号地图可以表明罪行的热点主要是通过特定的变量。 分布的十八当地价值观的不同的变量也各不相同，这意味着不同的变量具有不同的影响的模型在不同的网格。 这些地图，其中显示独特的捐款从每一个可变的，可以提供有意义的信息，警察建制战略对于预防犯罪。 这是独特的贡献，这可解释的学习机犯罪的预测方法。 5. 讨论和结论，现有的犯罪预测模型的使用机械学习的方法往往作为"黑箱"。 这几乎是不可能理解什么会发生在"黑箱"。 缺乏可解释性也可能破坏人们的信心，在这些犯罪的预测模型。 这项研究具有克服这种限制，并将得到模型不仅增加了可预测性，但也带来了可解释性，类似于这些的

Table 2
The result of logistic regression.

Y	Odds ratio	St.Err.	z	P > z	[95% Conf	Interval]	Sig
Ambient (16–24)	0.999	0.000	−9.53	0.000	0.998	0.999	***
Ambient (25–44)	1.002	0.000	17.13	0.000	1.002	1.003	***
Ambient (45–59)	1.009	0.001	12.16	0.000	1.008	1.011	***
Ambient (60–69)	1.015	0.004	3.43	0.001	1.006	1.024	***
Camera	1.01	0.026	0.38	0.701	0.961	1.061	
DIST_Police	0.999	0.000	−11.51	0.000	0.999	0.999	***
Restaurant	1.041	0.018	2.36	0.018	1.007	1.076	**
BusStation	1.033	0.045	0.74	0.462	0.948	1.125	
DepartmentStore	1.059	0.021	2.86	0.004	1.018	1.102	***
InternetCafe	1.748	0.152	6.42	0.000	1.474	2.074	***
EntertainmentVenue	1	0.061	−0.01	0.996	0.887	1.126	
School	0.843	0.04	−3.57	0.000	0.768	0.926	***
Bank	1.063	0.07	0.93	0.352	0.935	1.209	
Hotel	0.989	0.036	−0.31	0.756	0.92	1.063	
ConvenienceStore	1.413	0.08	6.10	0.000	1.265	1.579	***
Richness	0.866	0.013	−9.24	0.000	0.84	0.893	***
Road_Length	0.999	0.000	−1.67	0.095	0.999	1	*
Constant	0.087	0.007	−29.62	0.000	0.074	0.102	***
Mean dependent var	0.099	SD dependent var.	0.299				
Pseudo r-squared	0.162	Number of obs	28,938				
Chi-square	2798.891	Prob > chi2	0.000				
Akaike crit. (AIC)	14,510.992	Bayesian crit. (BIC)	14,658.463				

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

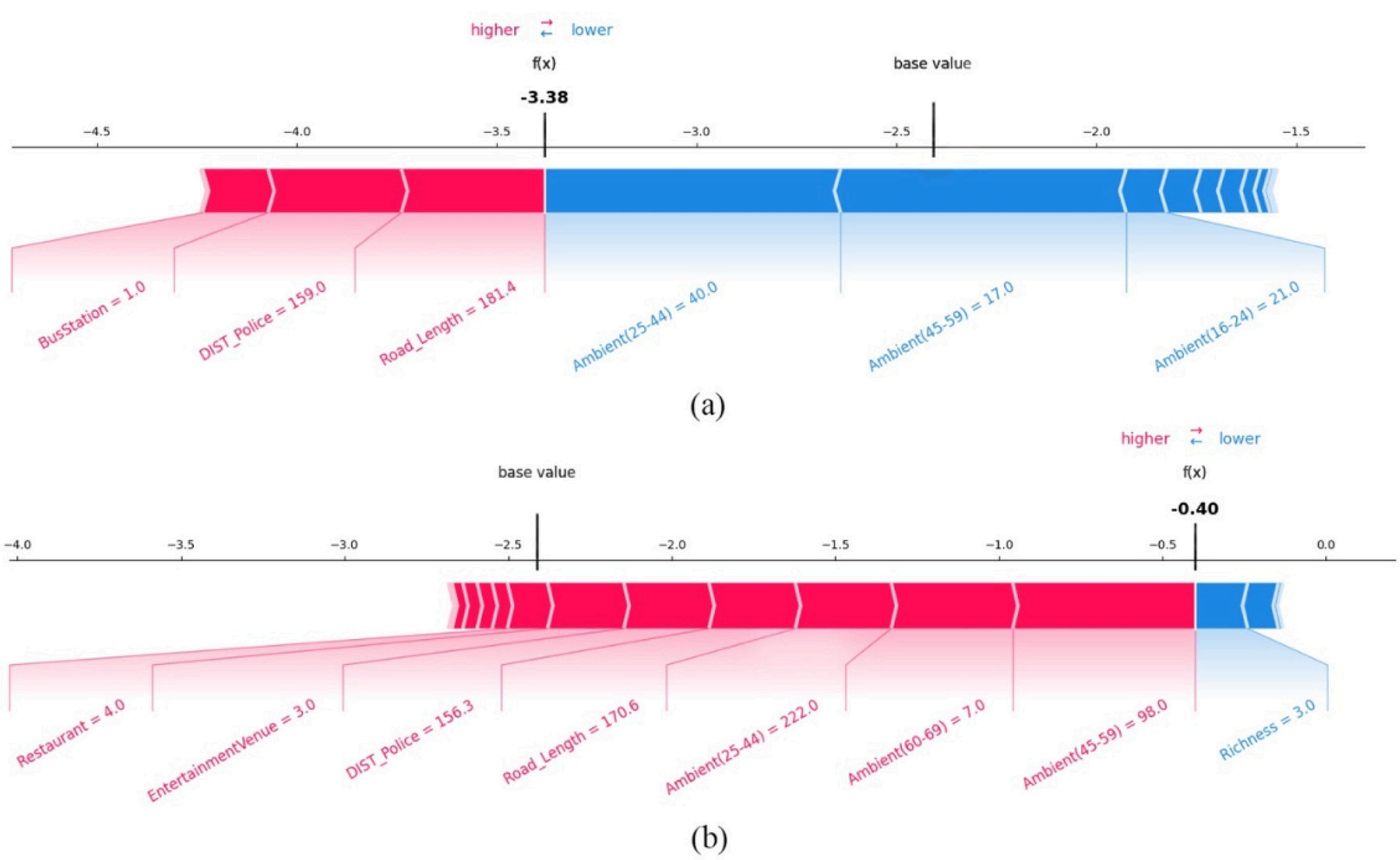
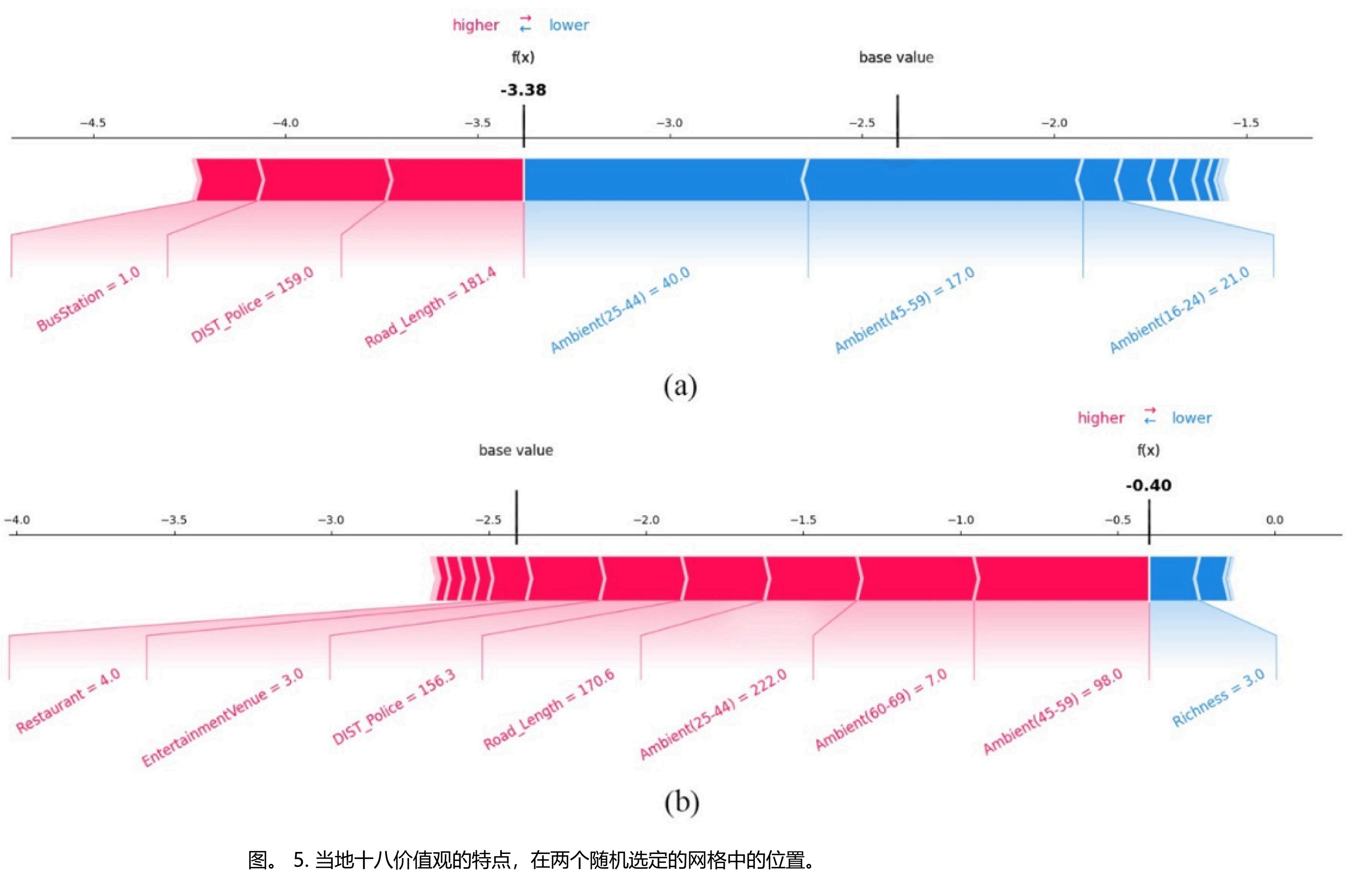


Fig. 5. Local SHAP values of the features at two randomly selected grid locations.

traditional regression models.

Our study proposes an interpretable machine learning crime prediction model by using XGBoost and SHAP. By increasing the transparency and interpretability of the machine learning crime prediction model, our approach can provide practical insights to practitioners. In terms of practical application, the knowledge obtained from the interpretability analysis of the model can provide insights to help police officers formulate data-driven policies and tailored crime prevention strategies. However, we do acknowledge this model is only tested in one city. Though it shows promising results, more tests are needed to further test its general applicability for other crime types in other study areas. The interpretability analysis of other machine learning and deep learning crime prediction models may also be noteworthy to conduct. Ideally, if we had Unicom Smart Footprint data for the entire study period, we could match ambient population perfectly to the crime during the same period. However, we only have the data for seven consecutive days. The seven-day average is used to represent daily ambient population. While this is not ideal, it is still reasonably representative for our models, which are based a two-week interval, since ambient population is not expected to change significantly from one week to another. Further, the granularity of the model can be refined. The time interval of crime statistics for the grid is two weeks in this study. The effect of each variable on crime in smaller time intervals can be explored in the future. Each day can also be divided into morning,

表2的结果的逻辑回归。 Y几率比圣Err。 z P>z[95%Conf间隔]Sig环境(16-24) 0.999 0.000 9.53 0.000 0.998 0.999 *** 环境(25-44) 1.002 0.000 17.13 0.000 1.002 1.003 *** 环境(45-59) 1.009 0.001 12.16 0.000 1.008 1.011 *** 环境(60-69) 1.015 0.004 3.43 0.001 1.006 1.024 *** 摄像机1.01 0.026 0.38 0.701 0.961 1.061DIST_Police0.999 0.000 11.51 0.000 0.999 0.999 *** 餐厅1.041 0.018 2.36 0.018 1.007 1.076 ** 座公1.033 0.045 0.74 0.462 0.948 1.125DepartmentStore1.059 0.021 2.86 0.004 1.018 1.102 *** InternetCafe1.748 0.152 6.42 0.000 1.474 2.074 *** EntertainmentVenue1 0.061 0.01为0.996 0.887 1.126学校0.843 0.04 3.57 0.000 0.768 0.926 *** 银行1.063 0.07 0.93 0.352 0.935 1.209酒店0.989 0.036 0.31 0.756 0.92 1.063ConvenienceStore1.413 0.08 6.10 0.000 1.265 1.579 *** 丰富0.866 0.013 9.24 0.000 0.84 0.893 *** Road_Length0.999 0.000 1.67 0.095 0.999 1 * 恒0.087 0.007 29.62 0.000 0.074 0.102 *** 意味着依赖var0.099SD依赖var. 0.299伪r平方0.162数obs28,938卡方2798.891Prob>chi2 0.000的赤池crit. (AIC)14,510.992贝crit. (BIC)14,658.463***p < 0.01,**p < 0.05,*p < 0.1



图。 5. 当地十八价值观的特点，在两个随机选定的网格中的位置。

类似于那些传统的回归模型。 我们的研究提出了一个解释的机学习犯罪的预测模型通过使用XGBoost和十八。 通过增加透明度和可解释性的学习机犯罪的预测模型，我们的方法可以提供实际的见解到从业人员。 在条款的实际应用，获得的知识从解释性的分析模型可提供见解，以帮助警察制订数据驱动的政策，量身定制的预防犯罪战略。 然而，我们承认这一模型仅仅是测试在一个城市。 虽然它显示出有希望的结果，更多的试验都需要进一步检验它的普遍适用性的其他犯罪类型中的其他研究领域

该解释性分析的其他机学习和深入的学习犯罪的预测模型也可能值得注意的进行。 理想的情况是，如果我们有联通智能占据整个学习期间，我们可以匹配环境的人口完全到的犯罪期间相同的期间。 然而，我们仅有的数据连续七天。 七天的平均用于代表的日常环境的人口。 虽然这不是理想的，它仍然是合理的代表为我们的模型，这是基于一个为期两周的间隔，由于环境的人口预计不会有重大变化，从一个星期到另一个。 另外，粒度的模型能够完善。 的时间间隔期间的犯罪统计数据网是两个星期在这项研究。 每个变量犯罪中小时的时间间隔可以探讨的未来。 每一天也可分为上午，

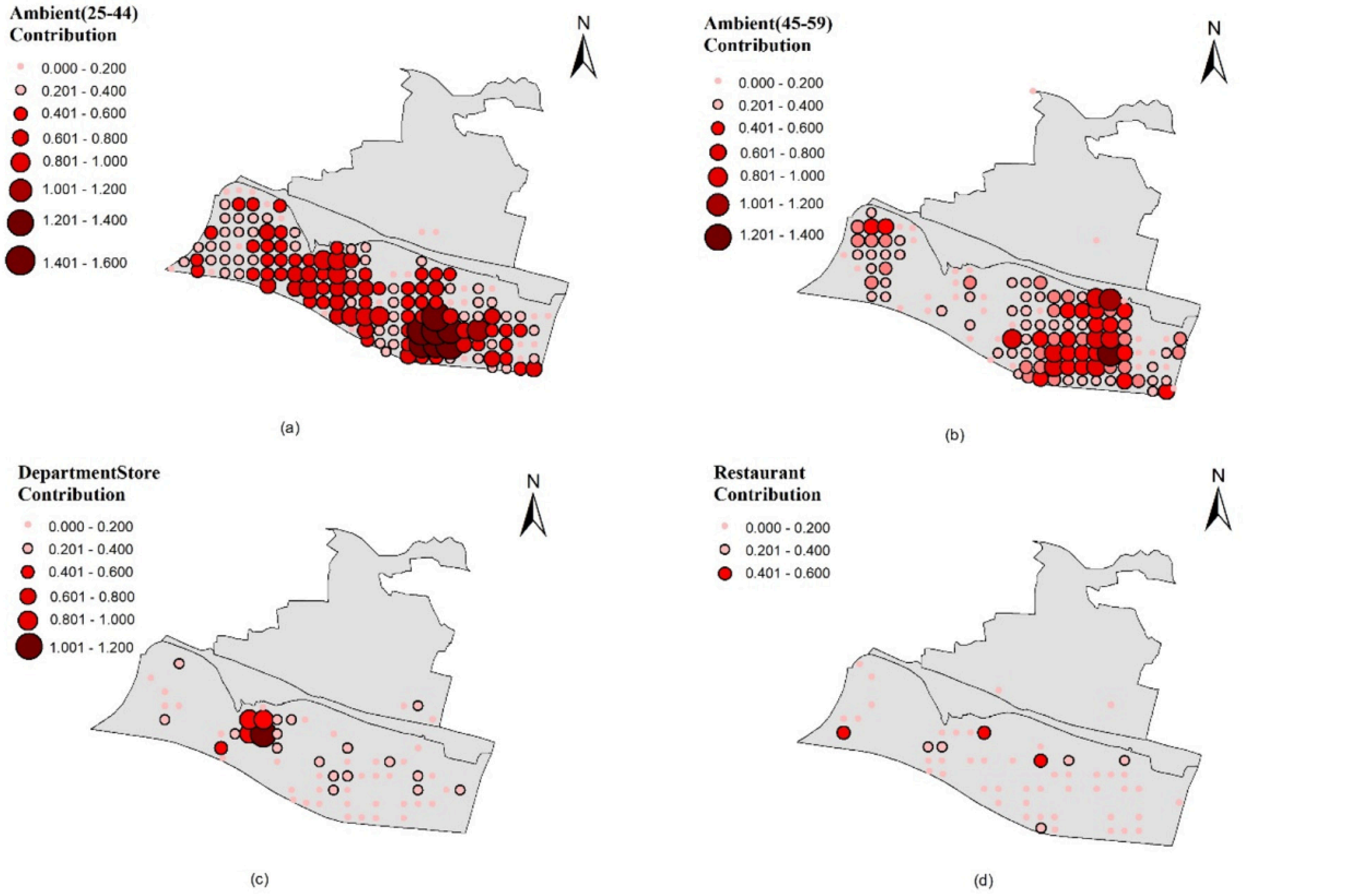


Fig. 6. Contribution of different variables in the model over space (Dec. 18 to Dec. 31, 2019).

midday and evening to explore the effect of various influencing factors on crime at different times of a day. In addition, the ambient population can be divided to more age groups, and the gender ratio and migrant population ratio of the ambient population could also be inferred.

In conclusion, our study specifically tackles machine learning models' problem of interpretability and creates a transparent and interpretable crime prediction model with machine learning methods. First, we identified the XGBoost out of several machine learning models as the best model for crime prediction. Based on the SHAP value, we ranked the contributions of all variables and found that the young population aged 25–44 contributed most to public theft in the study area. Further, we calibrated local XGBoost models and revealed the precise spatial variations of each variable in the study area. These findings help the local police force create more targeted policing strategies for crime reduction. For example, the police department can be advised to increase patrols in areas with high SHAP value of ambient population variables for the corresponding age group to enhance supervision.

Author Statement

The authors declare no conflict of interest. We sincerely appreciate anonymous reviewers for their advice to improve the quality of this study.

Data availability

The authors do not have permission to share data.

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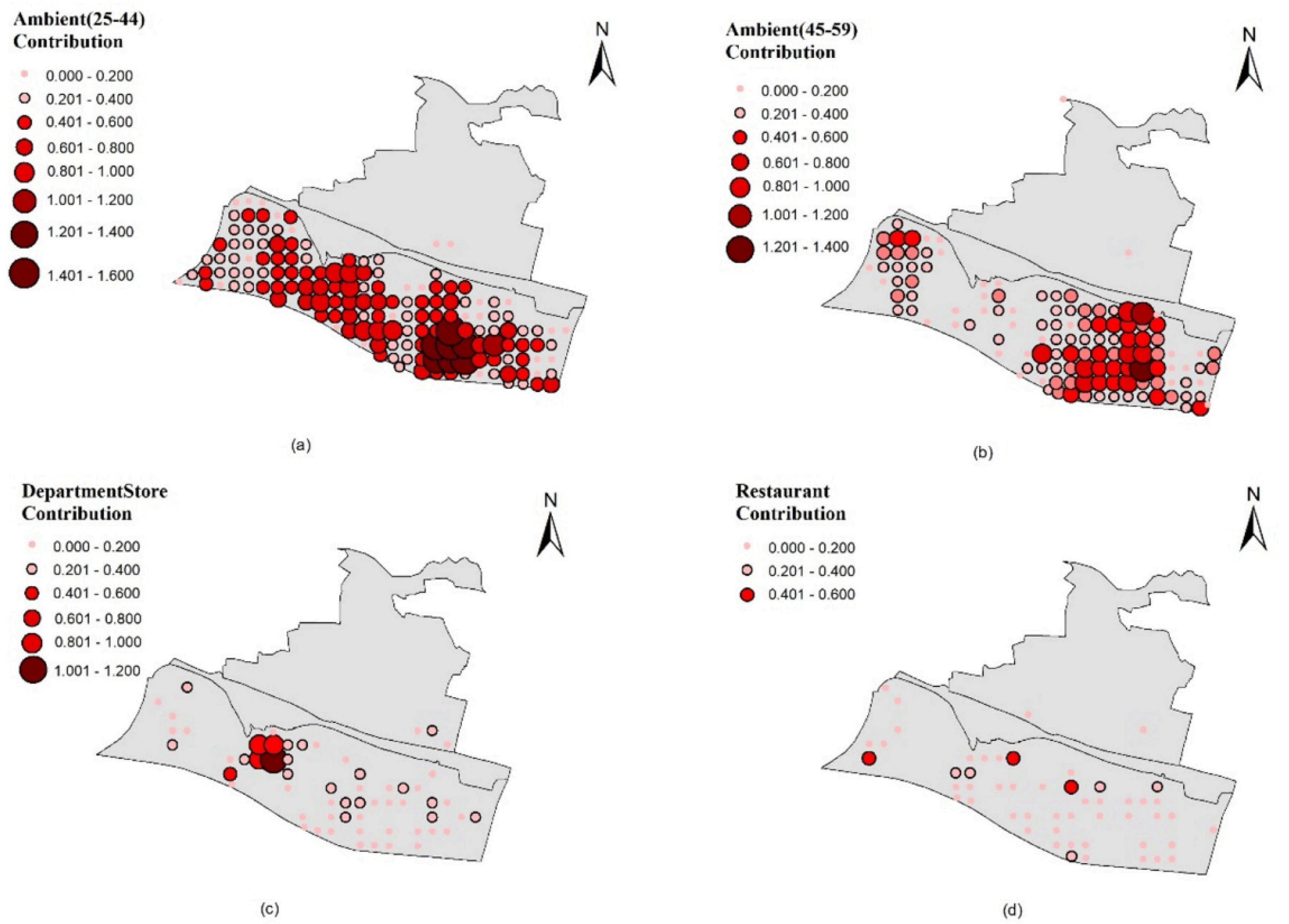

图。 6. 贡献的不同的变量的模型在空间(Dec. 18Dec. 31,2019年).

中午和晚上探索其效果的各种影响因素在犯罪中的不同时间一天。 此外，环境，人口可分为更多的年龄组和性别比率和移徙人口比率的环境人口也可能被推断出来。 最后，我们的研究具体的解决机学习模式问题的可解释性，并创建一个透明和可解释的犯罪的预测模型的有机学习方法。 第一，我们确定的XGBoost出的几个机学习模式的最佳模型，用于犯罪的预测。 基于十八价值，我们的排名的贡献的所有变量以及发现，年轻的人口年龄在25至44岁的贡献最大的公共盗在研究领域。 此外，我们进行校准地XGBoost模式，揭示了精确的空间变化中的每个变量的研究领域。 这些研究结果帮助当地警察部队的创建更有针对性的维持治安战略的犯罪的减少。 例如，警察部门可以建议以增加巡逻的地区高十八值的环境人口变量的相应的年龄组来增强监督。 提交人声明的作者声明没有利益冲突。 我们真诚地赞赏匿名评论者对于他们的建议，以提高质量这项研究。 数据提供者没有权限分享数据。

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