Decoupling the Unfairness Propagation Chain in Crowd Sensing and Learning Systems for Spatio-temporal Urban Monitoring

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ABSTRACT

In smart cities, urban monitoring systems rely on advanced mobile sensing and learning technologies to track large-scale urban systems and provide efficient urban services in real time. However, the fidelity and amount of sensors deployed at different geo-communities are closely related to their socioeconomic conditions, demographics, and entrenched geographic patterns, causing inequal sensing opportunities across communities. The biased sensing data contain distorted spatio-temporal patterns of undersensed community, inducing unfairness in subsequent algorithmic prediction and decision-making. This work characterize this unfairness propagation chain of sensing - learning - decision-making process. We introduce the first formal mathematical definitions to quantify and decouple community-level unfairness induced by joint cascading effects of sensing inequality and algorithmic bias. Our real-world experiments with vehicular crowdsensing system in Cangzhou, China verifies that sensing inequality, especially community-level gap of sensor fidelity, result in large fairness gap in spatio-temporal data imputation task. Our preliminary results show that sensing inequality amplifies the algorithmic bias. This work is a critical first step in formally defining and understanding unfairness propagation in intelligent spatio-temporal urban monitoring system.

CCS CONCEPTS

• **Information systems** → *Spatial-temporal systems.*

KEYWORDS

Fairness, Crowdsensing Systems, Urban Monitoring

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1 INTRODUCTION

In smart cities, urban monitoring integrates sensing systems and learning algorithms to estimate, infer, and forecast spatio-temporal urban dynamics, such as air quality, traffic conditions, infrastructure health [10]. The emerging sensing paradigms, such as mobile crowd-sensing systems, provides low-cost and flexible solutions leveraging individual device mobility to acquire real-time data [4, 10]. These data are input to learning algorithms, such as spatio-temporal data imputation methods [3], to reconstruct high-resolution urban states.

However, a major challenge associated with these large-scale urban sensing systems is sensing inequality. Sensor fidelity, amount, and degradation rates are closely related to socio-economic status and technology-awareness of device carriers. For example, sensors in aging and low-income communities may have lower quality than other communities [6]. Consequently, those data-driven algorithms, extracting spatio-temporal correlations from data, might ignore the patterns these underrepresented communities and results in lower estimation performance for these communities. Community-level unfairness in estimation performance finally leads to discrimination or inefficiency in decision-making process of urban planning and operations, such as discriminatory housing law and policy [8] or biased risk assessment instruments and risk assessment instruments [5]. We denote it as **unfairness propagation chain** along with sensing-learning-decision making process in spatio-temporal urban monitoring systems, as shown in Figure 1. Most past research focused on population-based unfairness in large-scale spatio-temporal urban services, such as surveillance [2] and transportation [11]. It is still unclear how to quantitatively track where the unfairness come from and how they are propagated along sensing - learning - decision-making process.

In this paper, we introduce a systematical way to understand and quantify the impacts of multiple types of sensing inequality and algorithmic bias on community-level fairness of urban dynamics estimation. The major challenges lie in the coupled impacts of spatio-temporal sensing inequality and algorithmic bias. We define three factors measuring sensing inequality, including sensing fidelity gap, sensor heterogeneity gap, and imbalance level of spatial sensing distribution across communities. We also defined community-level algorithmic bias (*CAB*) and overall fairness gap (*OFG*) is formulated to quantify the community-level estimation fairness of integrated urban monitoring systems. We characterize spatio-temporal patterns of how sensing inequality impact algorithmic bias, and their coupled impacts on estimation unfairness using data from a real-world crowdsensing system.

2 COMMUNITY-LEVEL SENSING INEQUALITY AND ALGORITHMIC BIAS

We define multiple metrics to quantify community-level sensing inequality and algorithmic bias, which are coupled to induce unfairness in decision-making for urban monitoring and management.

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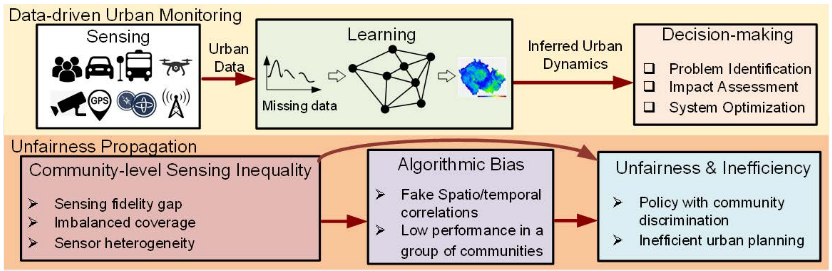

Figure 1: Overview of data-driven spatio-temporal urban monitoring systems and associated unfairness propagation chain.

We use algorithms for spatio-temporal data imputation – a common task in urban monitoring to reconstruct missing values in some locations/time [3]. The definition for spatio-temporal data imputation algorithmic bias is generalizable to other estimation tasks such as forecasting.

2.1 Community-level Sensing Inequality

Urban systems are often large-scale and complex physical systems. One major challenge associated with urban systems is sensing inequality. Due to different socio-technical awareness and socio-economic status, sensor fidelity, sensing coverage, and sensor consistency may differ over communities. However, sensor spatial distribution is dominated by human mobility pattern, resulting in unequal sensing opportunities. The sensing opportunities reflect which people and places are represented and legitimised in the decision-making efforts of smart city. In this section, we quantify sensing inequality for characterizing the unfairness propagation chain in spatio-temporal urban monitoring system.

Given a multi-community target sensing area, we denote several mathematical representations here. We divide the target sensing areas into multiple geo-communities. (i, j) refers to geo-locations, where $i \in [Longitude_1, Longitude_2]$, $j \in [Latitude_1, Latitude_2]$, during a sensing period $[t_1, t_2)$. The sensed data value, e.g., air quality index, at location (i, j) at time point $t \in [t_1, t_2)$ as $\hat{S}_{i,j,t}$, and corresponding ground truth value as $S_{i,j,t}$. We define a sensor k's longitude as r_k and latitude as c_k.

Sensing fidelity inequality across communities: Crowdsensing systems use existing mobile devices to measure physical phenomenon of urban systems. It is inevitable that these sensors/devices have distinct fidelity, including measurement accuracy, signal-to-noise ratio, signal distortion, communication failure rate, and etc. We define sensing fidelity as inverse of its expected absolute percentage error between sensed data and ground truth values, i.e., $f(k) = 1/\mathbb{E}_{i,j,t}[|S_{i,j,t} - \hat{S}_{i,j,t}(k)|/S_{i,j,t}]$. $f(k)$ describes overall data fidelity provided by a sensor k that are determined by the quality of sensor itself. Given a community (i, j), its sensing fidelity at time point t takes average over the fidelity of all sensors in it,

$$f(i, j, t) = \frac{\sum_{k \in K_t} f(k) I(r_k = i, c_k = j)}{\sum_{k \in K_t} I(r_k = i, c_k = j)}, \tag{1}$$

where K_t refers to the mobile sensors that collect and upload data at t, r_k^t, c_k^t refer to the longitude and latitude of sensor k at t. $I(r_k^t = i, c_k^t = j)$ is an indicator function which equals to 1 if $r_k^t = i, c_k^t = j$ is true. Therefore, we define the overall sensing fidelity gap as the upper bound of sensing fidelity difference across communities defined by spatial location:

$$F = sup_{(m,n),(u,v)}[|\mathbb{E}_t f(m, n, t) - \mathbb{E}_t f(u, v, t)|], \tag{2}$$

where (m, n), (u, v) are longitude and latitude of community.

Distinct levels of sensor heterogeneity across communities: Sensor heterogeneity mainly describes the variance levels of sensing fidelity in each community. For example, business areas where people have more diverse socio-economic status might have larger sensor heterogeneity than a residential community. It depicts how consistent the values measured by different sensors at the same location and time point are. We denote $V_{i,j}(t)$ as the distribution of sensing fidelity variance at (i, j) and time t, where$V_{i,j}(t) = Var[f(k)I(r_k^t = i, c_k^t = j)]$.To understand the community-level sensor heterogeneity of a crowdsensing system, we define the index H based on the total variation of the temporal distribution of sensing fidelity variance as follows:

$$H = sup_{(m,n),(u,v),t}|V_{m,n}(t) - V_{u,v}(t)|, \tag{3}$$

where (m, n), (u, v) are longitude and latitude of any two communities in the target sensing area.

Non-uniform spatial coverage across communities: Imbalanced sensing coverage is another major cause of community-level sensing inequality. For example, there are more moving vehicles in the business areas than rural areas in the daytime. Here we measure the unevenness of spatial sensing coverage using Wasserstein distance between spatial distribution of crowdsensing systems and uniform distribution. Wasserstein distance is more accurate than traditional distance by estimating optimal way of morphing the mass of one distribution into target distribution, preserving the underlying geodesic structure of data distribution. Denote P_t is the empirical spatial distribution of crowdsensing systems at time point t. The empirical probability of a sensor appear at location (i, j) is $P(i, j) = \frac{\sum_{k \in K_t} I(r_k = i, c_k = j)}{K_t}$, where K_t is the amount of sensors. Denote Q_t as the empirical distribution of the target distribution, i.e., uniform spatial distribution. Then the distance is:

$$W = \mathbb{E}_t[(\sum_{i,j} ||P(i, j, t) - Q(i, j, t)||^p)^{1/p}]. \tag{4}$$

2.2 Algorithmic Bias of Spatio-temporal Data Imputation

Given the crowdsensed data from sensors at different locations, machine learning algorithms, such as spatio-temporal data imputation, are employed to generate estimations for target communities. These algorithms estimate values, e.g., air quality index, for under-sensed communities using spatio-temporal correlations. Mathematically, given sensed data $\hat{S}$, a data imputation model would learn a function $\mathcal{G}$ to generate estimation $\hat{Y}_{(i,j,t)}$ at location (i, j) and time point t as $\{\hat{Y}_{(i,j,t)}\}_{\forall i,j,t} = \mathcal{G}[\{\hat{S}_{(i,j,t)}(k)\}_{\forall i,j,t,k}]$.

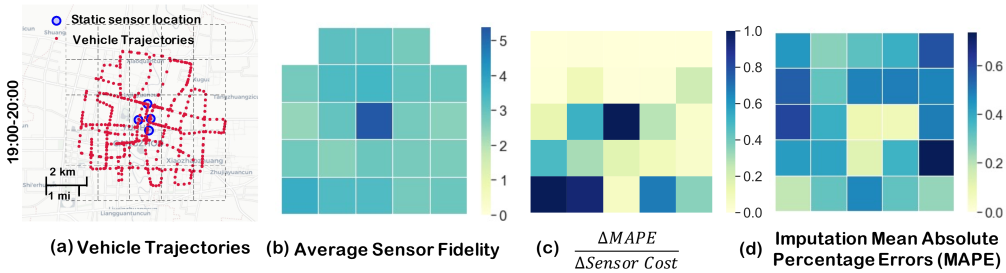

Figure 2: Spatial distributions of (a) vehicle trajectories, (b) sensor fidelity, (c) error reduction by imputation algorithm per sensor cost unit, and (d) mean absolute percentage error of the data imputation (Data: 19:00~20:00 01/01/2019, Cangzhou).

These data imputation algorithms leverage the spatio-temporal correlations among urban systems to improve accuracy. However, communities often have different feature distributions and spatio-temporal correlations determined by their demographic and geolocations. As a result, if we train a community-blind imputer to minimise overall error, or the model capacity constrains its ability to fit highly-nonlinear patterns from some communities, it will fit communities with majority or less-complex spatio-temporal correlations. This might leads to (potentially) higher distribution of errors in the underrepresented community. We introduce Community-level Algorithmic Bias (*CAB*) to describe the community-level unfairness of the algorithms, regardless of sensing inequality. We define *CAB* between two communities (m, n) and (u, v) over time $t \in [t_1, t_2)$ as error reduction per sensor cost to decouple the impacts of sensing elements:

$$\mathbb{E}_t\left[\frac{\Delta T(m,n,t)}{\Delta \sum_{k\in K_t} g(f_k) I(r_k = m, c_k = n)} - \frac{\Delta T(u,v,t)}{\Delta \sum_{k\in K_t} g(f_k) I(r_k = u, c_k = v)}\right].$$

The function $g(\cdot)$ is the utility function mapping from single sensor fidelity to corresponding sensor cost. $T(i, j, t) = |Y_{(i,j,t)} - \hat{Y}_{(i,j,t)}|/Y_{(i,j,t)}$ refers to error of final imputation. We also quantify overall community-level estimation unfairness of urban monitoring, which is final fairness impacted by both sensing inequality and algorithmic bias. Define Overall Fairness Gap (*OFG*) as:

$$OFG = \mathbb{E}_{\substack{m\neq u,\\ n\neq v, t}}\left[|T(m,n,t) - T(u,v,t)|\right].$$

This gap measures unfairness induced by bias of sensing (sensing inequality) and flaws of algorithms (algorithmic bias).

2.3 Comparison with Previous Fairness Metrics

Existing works on measuring unfairness in urban systems, such as Region-based Fairness Gap (RFG) [11], Individual-based Fairness Gap (IFG) [11], and Hybrid notions of fairness [1], focus on population-based unfairness by assuming different groups should share same urban service quality (e.g., mobility demand), but overlook the community-level variations of demands or system status (e.g., air quality). Our metrics are based on the expected relative percentage error between predicted values and true values over a time span and thus eliminate the impacts of such variations in true demands/system status. Besides, the incorporation of relative percentage error makes our metrics comparable in the temporal domain and across sensing systems with different configurations.

3 CHARACTERIZATION OF UNFAIRNESS PROPAGATION: A CASE STUDY

In this section, we quantitatively decouple the unfairness propagation chain from three types of sensing inequality, through algorithmic bias, to the final unfairness of estimations. We characterize these impacts with experiments using a deployed real-world vehicular crowdsensing system for urban air quality monitoring.

3.1 Overview of System

A real-world vehicular crowdsensing system for urban air quality monitoring: We deploy a real-world vehicular crowdsensing system on taxis in Cangzhou, China. Sensing modules are mounted on taxis, including GPS and air pollutant sensors to record concentrations of Particle Matters (PM2.5). Measurement error ranges from 10% to 80%. We select 30 taxis moving in a $50km^2$ area, covering different types of communities.

Spatio-temporal Data Imputation Algorithms: The emerging approaches of spatio-temporal data imputation focus on uncovering or reconstructing spatio-temporal urban dynamics map using large-scale, high-dimensional, and incomplete urban sensing data. This paper focuses on the fairness of general spatio-temporal imputation algorithms instead of proposing new learning algorithms. Therefore, we study three state-of-the-art methods: Bayesian Probabilistic Matrix Factorization (BPMF) [7], Bayesian Gaussian CP decomposition (BGCP) [3], and Bayesian Probabilistic Tensor Factorization (BPTF) [3]. They have been validated to achieve the best performance in multiple spatio-temporal urban monitoring tasks, e.g. traffic speed data imputation and passenger flow data imputation [3, 9]. They achieve the best imputation performance with a constrained running time on our data.

3.2 Fairness Gap Reasoning and Analysis

Though past studies resolve each type of sensing inequality, it is unclear how they quantitatively change the final community-level fairness gap with coupled impacts. In Figure 2, average sensor fidelity achieves the highest in the center area (Figure 2b), demonstrating sensing inequality across communities. But the algorithm apparently favor areas of southwestern corner (Figure 2d), showing different bias from the sensing system. Figure 2 (c) show the spatial distribution of $\Delta MAPE/\Delta Sensor\ Cost$, referring to by paying one cost unit, how much error reduction one community achieves. It shows data imputation method favors the communities locating at the Southwestern and Central areas, providing more effective estimations with the same sensor cost compared to the Northern areas. Based on our vehicular crowdsensing systems, we characterize these impacts to provide the first quantitative analysis between sensing inequality and community-level urban estimation fairness. Figure 3(a), (b), and (c) presented pairwise analysis of how final imputation error changes with sensing fidelity gap, heterogeneity gap, and spatial coverage imbalance level. For each pair of factors, we collect data by fixing the third impact factor, and conduct data

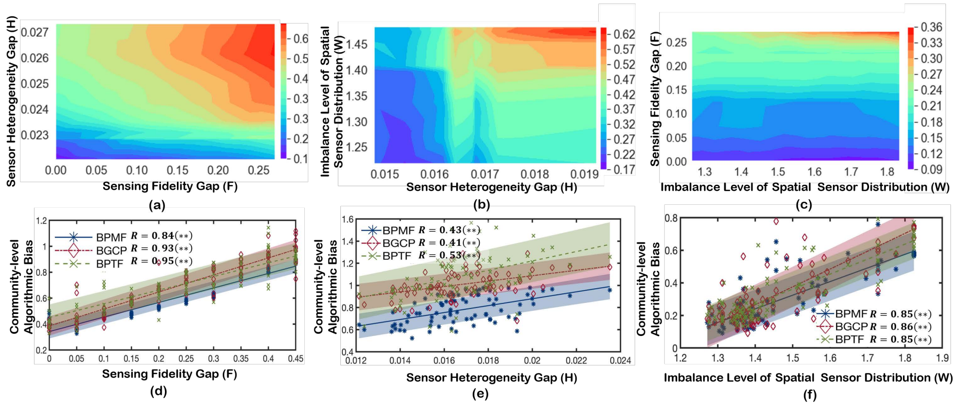

Figure 3: (a) - (c) present how the overall fairness gap is impacted by joint effects of sensing fidelity gap across communities (F), heterogeneity gap across communities (H), and unevenness of sensing spatial distribution (measured by W). (d) - (f) characterize correlations between sensing inequality and algorithmic bias of three spatio-temporal data imputation algorithms.

imputation using BPMF to obtain the overall estimation fairness gap (OFG). The larger the gap, the more unfair the system.

The overall fairness gap (OFG) increases as sensing fidelity gap increases, imbalance level of spatial distribution increases, and sensor heterogeneity gap increases. Figure 3(a), (b), and (c) show that the coupled impacts between different pairs of sensing inequality factors present distinct patterns. We further explore how sensing inequality changes the impacts of community-level algorithmic bias to understand the algorithms' robustness over sensing inequality. Figure 3(d), (e) and (f) presents the correlation between sensing fidelity gap, sensor heterogeneity gap, and imbalance level of spatial sensor distribution with community-level algorithmic bias (CAB) of three state-of-the-art spatio-temporal data imputation algorithms. For all three algorithms, the increasing sensing fidelity gap and imbalance spatial sensing distribution level amplify the community-level algorithmic bias significantly with correlation coefficients ranging between $0.85 \sim 0.95$. The strength of this amplification effects varies across algorithms – BPMF is relatively more robust to the impacts of sensing inequality compared to the other two. Besides, increasing the time span of data collection and spatio-temporal imputation may not ensure the improvement of fairness of the systems. The improvement of final system fairness is determined by the variations of sensing data qualities across communities, which may not be improved with a longer data collection time. For example, our evaluation shows that the sensing fidelity gap is amplified from 0.238 to 0.250 when extending the time window from 0-11am to 0-12pm. Mobile devices are concentrating towards central areas from 11:00 to 12:00 and hence increases the difference of sensing fidelity between the central community and others.

4 DISCUSSION AND CONCLUSION

We introduce a systematical way to characterize the unfairness propagation in spatio-temporal urban monitoring system, by decoupling sensing inequality and algorithmic bias on community-level fairness. We found that (1) different sensing inequality factors would amplify or reduce each other's impacts on final system unfairness ; (2) besides directly inducing imbalance in the dataset, sensing inequality amplifies the community-level algorithmic bias through distorting spatio-temporal correlations captured by data. Meanwhile, different algorithms have different amplification effects, indicating their distinct levels of robustness to sensing inequality.

We note that this work is a first step to quantitatively understand unfairness chain in the loop of sensing-learning-decision making which commonly exists in existing large-scale spatio-temporal urban monitoring. More importantly, our novel metrics will benefit to resolving the unfairness in sensing and learning stages as well as the unfairness propagation problem. The introduced three sensing inequality metrics could be integrated to guide the configurations, deployments, or incentivizing of existing urban sensing systems for improving their sensing fairness. Meanwhile, these sensing inequality metrics could be further incorporated into the loss function design of spatio-temporal data imputation algorithms, together with algorithmic bias measurements, and yield fairness-aware algorithms that are more robust to coupled impacts of sensing data bias and algorithmic bias while ensuring their imputation accuracy.

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