Fine-Grained Urban Flow Inference via Normalizing Flow (Student Abstract)

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Abstract

Fine-grained urban flow inference (FUFI) aims to infer the coarse-grained (CG) urban flow map to the corresponding fine-grained (FG) one, which plays an important role in efficient traffic monitoring and management in smart cities. In FUFI, the CG map can be obtained with only a small number of monitoring devices, greatly reducing the overhead of deploying devices and the costs of maintenance, labor, and electricity. Existing FUFI methods are mainly based on techniques from image super-resolution (SR) models, which cannot fully consider the influence of external factors and face the ill-posed problem in SR tasks. In this paper, we propose UFI-Flow, a novel approach for addressing the FUFI problem by learning the conditional distributions of CG and FG map pairs. Given the CG map and the latent variables, the corresponding FG map is inferred by invertible transformations. In addition, an augmented distribution fusion mechanism is further proposed to constrain the urban flow distribution within the influence of external factors. We provide a new large-scale real-world FUFI dataset and show that UFI-Flow significantly outperforms the strong baselines.

Introduction

Fine-Grained Urban Flow Inference (FUFI) problem aims to use coarse-grained (CG) urban flow map which are obtained by a small number of sensors, to infer the corresponding fined-grained (FG) one. It reduced a large amount of manpower and money consumed from arranging a huge number of sensors in smart cities, and has practical implications in urban planning and traffic monitoring (Xie et al. 2020). FUFI is similar to the traditional super-resolution (SR) task, but has several intrinsic differences that pose new challenges: (1) strict structural constraints, i.e., the sum of traffic flow within a certain region (subregions) in the inferred FG map is strictly equal to the sum of traffic flow in their corresponding superregion in the original CG map; (2) the inference results are greatly affected by external factors (e.g., time and weather). Existing methods like UrbanFM (Liang et al. 2019) and FODE (Zhou et al. 2020), proposed N^2 and AN^2 mechanisms to solve the structural constraints and used sub-network to fuse external factors into their model.

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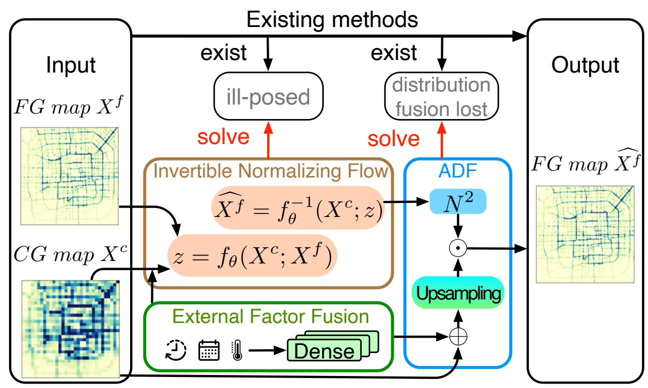

Figure 1: Overview of the proposed UFI-Flow architecture.

However, their models still have several notable shortcomings: (1) they handle the structural constraints by utilizing distributional upsampling that ensures traffic flows in superregion and subregions are equal, but the flow distribution between grids in subregions is an uncertain process, which faces the ill-posed problem; (2) lack of the consideration of external factors after the structural constraints process, which undermines the accuracy of inference.

In this paper, we propose UFI-Flow, a new approach for addressing the FUFI problem. Our method leverages an invertible normalizing flow model to compute latent variables by constructing a mapping of CG-FG pairs, and reconstructs the FG map by the learned latent variables, which makes each generated FG map deterministic by a corresponding CG map. We further propose an ADF to address the distribution fusion lost problem when aggregating external factors. The main contributions of this work are three-fold:

- We propose UFI-Flow, a new model for addressing the FUFI problem. It mitigates the ill-posed problem and distribution fusion lost problem that widely existed in prior solutions. An overview of UFI-Flow is in Figure 1.
- An augmented distribution fusion mechanism ADF is proposed to fuse the influence of external factors on the inferred flow distribution to improve performance.
- We conduct experiments on two new large-scale FUFI datasets and our model significantly outperforms *state-of-the-art* baselines.

Methodology

Problem definition. Given a CG map X^c, a upscaling factor $N \in \mathbb{R}^Z$ and external factor E (e.g., weather and time), we aim to infer the FG map $\widehat{X^f}$:

$$\widehat{X^f} = \mathcal{F}\left(X^c | E, N; \theta\right), \quad (1)$$

where $\theta, \mathcal{F}$ represent all learnable parameters in our model. UFI-Flow consists of three parts: a flow inference backbone model, an external factor fusion block, and an augmented distribution fusion block, which are detailed in the following three paragraphs.

Backbone inference network. We use an invertible normalizing flow f_θ to infer the FG maps, which solve the ill-posed problem that widely existed in FUFI problem (Lugmayr et al. 2020). By calculating a full conditional distribution $P_{\mathbf{X}^f|\mathbf{X}^c}\left(\mathbf{X}^f|\mathbf{X}^c;\theta\right)$ of CG map, we can estimate the fine-grained urban flow distributions. First, we obtain the latent variable $z = f_\theta\left(X^c; X^f\right)$ by mapping the CG and FG map pairs. Then, we infer the reconstructed FG map $\widehat{X^f}$ based on the invertible $\widehat{X^f} = f_\theta^{-1}\left(X^c; z\right)$. Besides, we modify the loss function to make the model adapted to FUFI problem. We add a negative log-likelihood (NLL) loss to optimize the inference process for both high- and low-flow values in region, and to avoid the optimizing process dominated by mean squared error (MSE) or mean absolute error (MAE).

External factor fusion. We map the *temperature* interval to a range of [0, 1] and then fuse all the factors by overstacking fully-connected layers. Then, we treat the extracted features in both inference network and distribution fusion block to enhance the influence of factors.

Augmented distribution fusion. Prior methods address the strict structural constraint of FUFI problem by proposing distributional upsampling technique such as N^2-Normalization (Liang et al. 2019) and AN^2-Normalization (Zhou et al. 2020). However, we empirically found that A/N^2-Normalization methods neglect the influences of external factors in the inference stage. To enhance the influence of external factors on flow map inference, we propose a new fusing mechanism. First, it connects the pixel-level feature maps of external factors with CG map, and then upsampling. Finally, it infers the final FG map $\widehat{X^f}$ by fusing the structural constraint FG map and upsampling map. The inference formula is defined as follows:

$$\widehat{X^f} = \mathcal{U}(X^c \oplus E; N) \odot \mathcal{D}^f, \quad (2)$$

Where $\mathcal{U}$ represents the upsampling with scaling factor N. We name this mechanism as augmented distribution fusion (ADF).

Experiments and Results

To evaluate the effectiveness of our proposed method, we conduct experiments on a new large-scale real-world dataset: DiDi-Chengdu, where the flow maps are from a metropolis in China (Chengdu). We compare our method with the following baselines: FODE (Zhou et al. 2020), UrbanFM (Liang et al. 2019), SRResNet (Ledig et al. 2017), VDSR (Kim, Lee, and Lee 2016), and SRCNN (Dong et al. 2014). We evaluate the UFI-Flow and baselines by using three common metrics that are widely used in urban flow data: root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

Dataset	DiDi-Chengdu		
Metric	RMSE	MAE	MAPE
SRCNN (Dong et al. 2014)	5.920	3.002	1.757
VDSR (Kim, Lee, and Lee 2016)	4.959	2.372	1.320
SRResNet (Ledig et al. 2017)	4.751	2.133	1.083
UrbanFM (Liang et al. 2019)	4.275	<u>1.289</u>	<u>0.260</u>
FODE (Zhou et al. 2020)	<u>4.238</u>	1.382	0.355
UFI-Flow	**4.112**	**1.226**	**0.204**

Table 1: Performance Comparison. The best performances are in bold and the second best performances are underlined.

Table 1 shows the experimental results of all models on the real-world dataset and we have the following remarks. UFI-Flow outperforms all baselines in non-trivial margins. It achieves a significant performance improvement on DiDi-Chengdu dataset with a improvement of 2.9%, 4.8%, and 21.5% in terms of RMSE, MAE, and MAPE, respectively, compared to the best performance in baselines (underlined).

Our future work will focus on designing more powerful normalizing flow that suitable for FUFI problem.

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