Visualization of *What-If* Forecasts for Proactive Crowd Control

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1 Introduction

Crowd control at large-scale events such as sporting events, music concerts and festivals is essential for the safety of the public. Inadequate control can lead to overcrowding which may result in a catastrophe. The event organizers retain overall responsibility for ensuring the safety of visiting crowd. They want to know what will happen next and what should they do. *What* will occur *if* they take some kind of control strategy (e.g., real-time schedule adjustment, rearrangement of security guards, route guidance and information dissemination) and *what* will happen *if* they don't. In order to grasp what's going to happen and what the organizers should do to avoid getting into an unsafe situation, interactive and real-time spatiotemporal visualization is a crucial component. It can support intuitive and comprehensive understanding of such multiple *What-If* forecasts corresponding with possible control strategies, each of which has multidimensional structure.

Therefore, we propose a technique for forecasting crowd densities of hypothesized future states and visualizing the forecasting results. First, we produce multiple What-If forecasts with respect to a pre-defined set of control strategy scenarios. We utilized a multivariate regression technique, multivariate Gaussian Process (GP) [2]. Although it is not a prime goal of the multivariate GP models, it can be used for What-If forecast by incorporating each control strategy scenario as external variable (e.g., the event program and the number of security guards per area). Upon creating the multiple forecasts, we visualize their spatial and temporal aspects in real-time through the interactive, coordinated multiple views of crowd density maps and polyline-based time series graphs (see Figure 1).

Several works have suggested interactive and real-time visualization method for spatiotemporal data such as trajectories [1, 6, 3, 7], criminal incidents [5], and so on. We extended the idea of these method to provide further information about the effectiveness of the possible control strategies by adding one feature, What-If forecast. The proposed method features include: What-If forecast, interactive and real-time spatiotemporal visualization and application of these technique to the issue of crowd control.

In this poster, we demonstrate visualization of multiple What-If forecasts as use cases using experimentally collected real crowd data. The visualization enables users to quickly grasp the effect of making different strategy scenarios and helps them in taking the right decisions.

2 Visualization of *What-If* Forecasts

Our technique consists of two phases: What-If forecasting and forecast visualization.

2.1 *What-If* Forecasts

We produce multiple What-If forecasts with respect to a pre-defined set of control strategy scenarios by using a multivariate regression technique. The general purpose of the multiple regression models is to learn the interrelationship between two or more variables and then to use the model to forecast values of one variable based on values of a collection of the other variables given the observations of multiple variables. It can be used to produce a range of different What-If forecast by incorporating each control strategy scenario as external variable. We utilized a multivariate regression technique, multivariate GP to make What-If forecast, which is an extended GP model [4] for accommodating multiple data sets. The multivariate GP has several advantages over the other multivariate models in that (i) it is consistent with the properties of the data: be able to handle multiple data measured at different sample intervals, and (ii) it satisfies the complexity requirement: be capable of real-time parameter estimation. Furthermore, (iii) it is consistent with prior knowledge: assumes that the sample points which are close together in space or time tend to have the similar values.

Suppose that we have multiple observations on the target variable and the the external variables. For example, we might observe the crowd density (the target variable) and get the values of the external variables which have an affect on crowd density (e.g, the event program and the number of security guards per area) simultaneously. The data consists of the tuples of the form *(location, time, value)*,*(location, time, ex-value)* where *location* is the x-y coordinates of the place where the observation took place, *time* is when the observation took place, *value* is the observed target value and *ex-value* is the value of the external variables. We must choose the external variables such that can be controlled and measured/accessed. In learning phase, we estimate the parameters which represent the spatiotemporal interdependence among each observation and serial dependence between the variables (*value* and *ex-value*) by using marginal maximum likelihood via gradient descent, a standard optimization method for GP. And then, in inference phase, multiple forecasts on different future values of external variables (*ex-value*) according to possible strategies can be made. The forecast model returns an estimated *value* with the different scenarios for all locations at the forecasting time period.

2.2 Visualization

Our tool outputs interactive coordinated multiple-view visualizations. Figure 1 shows the user interface of our tool implemented in

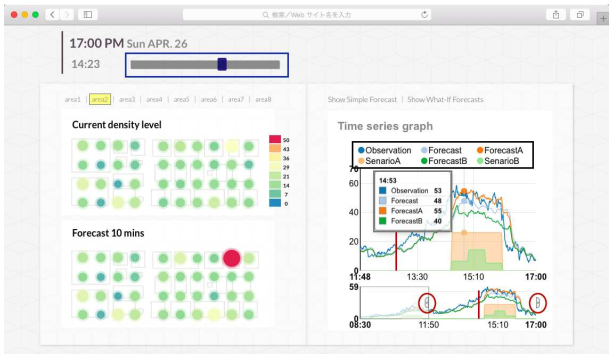

Figure 1: The user interface of our tool: (left) spatial display (the crowd density map) (right) temporal display (the time series graph)

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HTML5 and D3.js, which consists of two components: the crowd density map (spatial display) and the time series graph (temporal display). The spatial display features the heat intensity map showing crowd density. Dot size indicates crowd density. The temporal display features multiple forecasts, each of which is conditioned on a pre-defined scenario. Each line is corresponding to the forecast based on different scenario assumptions (e.g., the case if the organizers take some control strategies and the case if they don't). The displays are updated in real-time at fixed intervals.

Two coordinated views appear together with a chart container on the welcome screen. At first, the current situation is displayed. Using the time slider on the top-left screen corner (the blue rectangle in Figure 1), users can observe the crowd situation of each time period and activate a continuous animation by clicking and dragging over the time line. The vertical lines drawn within the graph on the temporal pane updates as well as the map. If the user selects a specific area on the map, the corresponding time series graph will appear in the temporal display. The time series graph shows the multiple indicators. The users can hide or show the line chart for each channel in the user interface (the black rectangle). This allows direct comparison of specific lines on the multiple line graph. They can assess the effectiveness of different strategies, each of which is written in the form of strategy scenarios, where a set of strategy scenarios are pre-prepared in What-If forecast phase. When the users hover over an area of the line chart, the pop-up appears on the graph, showing the time they are hovering over and the exact numerical values of each line at the selected time (the gray rectangle). The users also can select the temporal range through the timepicker (the red circle).

3 Experiment

3.1 Data Description

The data set was gathered at a real-world crowd event, *Niconico Chokaigi 2015 (Chokaigi)*, which is one of the biggest Japanese pop-culture events, held at Makuhari Messe located near Tokyo on Apr.25 and 26. It attracted more than 150,000 attendees over the two days. Dozens of Wi-Fi access points (AP) were installed at Chokaigi to collect data on Wi-Fi client device density (the number of Wi-Fi client devices per area) at intervals of 30 seconds to 2 minutes. Device density is, logically, approximately proportional to crowd density.

We also used the external variables (*ex-value*) about the event program which includes the start and end times and the locations for each activity, the list of the presenters and their popularity. We consider the case if the organizers are intended to make last minute program adjustments during the event. We applied the two control procedure in the scenario: the case in which a popular guest take the stage and the case in which the presenter sequence is changed.

3.2 Use cases

Figure 2 shows a Wi-Fi client device density map (crowd density map). The top pane shows the current crowd density map and the bottom pane shows a 10 minute forecast. Figure 3 shows the multiple time chart at the selected area (the red circle in Figure 2 (right)). The gray line is the simple 10 minutes forecast. The orange line and the green line show the What-If forecasts, each of which based on different scenario assumption on the event program, namely, "what if a popular guest take the stage from 14:00 to 16:00?" (scenario A shown as area chart in Figure 3) and "what if the order of the presenter is changed?" (scenario B). As expected, the crowd density increase rapidly if the popular guest take the stage (the orange line). Meanwhile, the congestion situation could be improved by adjusting the order of the presenter (the green line). The users can assess the effects of different scenarios through interactive visualization.

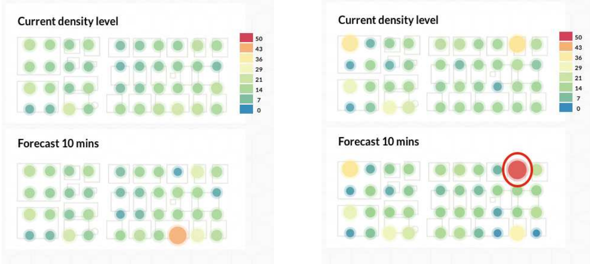

Figure 2: Spatial display: (left) 13:00 (right) 16:00 on Apr. 26

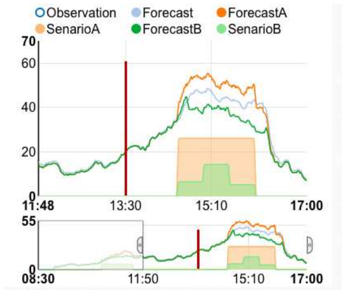

Figure 3: Temporal display (18:00 on Apr. 26)

4 Conclusion and Future work

We presented a technique for forecasting and visualizing crowd densities for given future states by using a multivariate model. This poster demonstrates a tool to automatically analyze and interactively visualize the What-If forecasts in real-time. The presented tool answers the questions: "*what* will occur *if* they take some measure (e.g., program adjustments) in real-time" and "*what* is likely to happen in the future *if* they don't?".

Future work aimed at taking into account additional real-world control scenarios such as rearrangement of security guards and real-time route guidance via mobile devices or digital signages. We are developing a web application designed for mobile devices to provide the event organizers and the attendees with forecast information. We will perform the user test at the real crowd event to evaluate the effectiveness of our tool.

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