Neural Net-Based and Safety-Oriented Visual Analytics for Time-Spatial Data

Zhenghao Chen, Jianlong Zhou*, Xiuying Wang*, Jeremy Swanson, Fang Chen, and Dagan Feng

***Abstract*— Safety-oriented visualization is one of significant approaches to gain insights from time-spatial data while neural net currently serves as a decent way to perform machine learning in data mining industry. This paper proposes a visual analytics pipeline for trajectory data enabling better understanding movements pattern of people using Neural Network as back-end and other visualization techniques as front-end for gaining information of preferences of attractions, similarities of groups, popularities of attractions and pattern of movement flow. Such understandings help to address the management issue by extracting the outstanding features to detect abnormal pattern such as detection of crime and predicting overall movements, and so on. Successfully dealing with those issues would have significant improvements of entire management of public facility such as parks and transportation.**

***Index Terms*— Time-spatial, Visual Analytics, Self-organizing Map, Recurrent Neural Net, Crime Detection, Prediction.**

I. INTRODUCTION

With the advance of positioning technologies such as sensors and GPS, vast amounts of time-spatial data are being generated every second every day from various domains, such as traffic, mobile phones, public transportation, etc. Visual analytics is one of promising techniques widely used to extract knowledge and support better reasoning and understanding of data for planning and decision making in society and business. Taken the people movement data as an example, using visual analytics to understand movement of visitors is crucial for better management of transportation, big events with large number of people, and others involving people movement. Such analytics also help to address the safety issue, specifically avoid occurring of crime, and improve the traffic condition. To deal with those data, traditional methods[2], [3] and systems [7] often put much effort in constructing a sorted database as the back-end and building user interface as the front-end to enable users inspect every single visitor trajectory pattern or aggregate them by certain queries [1] - [4] for visualization. However, these approaches cannot effectively address the analytics of large amount of data. Firstly, they only plot the data with various visualizations, but such visualizations cannot be used in an integrated way to help improve the understanding data and get insights from data. Users still need to summarize the visualizations and infer possible causes and results. Secondly, the visualization of single trajectory is not practical especially when the data comes even larger. Recently more advanced approaches such as flow map[5], [6], aggregation [21] and trajectory clustering[4], [3], [12] are proposed to analyze time-spatial data. In trajectory clustering, most existing techniques focus on clustering the actual trajectory with classical clustering methodologies[4]. Aggregation of the trajectory takes visitors in group in more specific way that study group movement rather than individual behavior. Flow map typically uses arrow symbol to represent the number of objects moving between the places and with clear directions encoding some other information like number of items to represent the movement pattern and trajectories. Those approaches are straightforward and essentially suitable for movement pattern visualization which is relatively simple and regular. However, when trajectory pattern becomes complicated and irregular, and especially movements of huge number of people get massively cluttered, the legibility of flow map would be significantly decreased while clustering such irregular trajectories would also be difficult.

Recently, neural network achieves much success and serves as an effective methodology to address massive data issue using its comprehensive model and computation. Deep Learning, an extension of Neural Net[20] is also widely used with massive data and has a high performance requirement. In this paper, we propose a visual analytics approach based on neural net using the combination of people movement data and communication data for understanding movement patterns. Our aim is to mine movement patterns under different conditions and figure out peoples motivation of behaviors with information from multimodalities. Various features such as visiting frequency of a site are extracted from time-spatial information. Based on visiting features we extract, advanced neural net Self-Organizing Map (SOM)[8] is utilized to cluster movement patterns which provides the better resolution to find out group within cluster as well as helps users to detect anomalous such as unusual patterns of movement group like crime group. Furthermore, such unusual patterns of movement are verified with the use of associated visual techniques including space-time cube, heat map, dynamic flow and another modality of data such as communications between people. Besides, a Deep Leaning method Recurrent Neural Network (RNN) [22] is utilized for predicting the movement flow timely for integrated movement in the park to help manage the security by understanding which spatial spot would likely be hot-spot in next timestamp. Other methods including hot-spot scan statistics[23] to verify the abnormal

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spatial temporal behavior, Dynamic Time Warping (DTW) [15] for comparing the similarity of real-time trajectory and communication signal of group. The main contributions of this paper can be summarized as :

- Incorporate both movement data and communication data into the visual analytics pipeline to understand people movement behavior and test hypotheses.
- Propose a neural net based visual analytics methodology by utilizing SOM for clustering and visualizing patterns of movement while RNN for predicting the flow associated other visual techniques.
- Set up a pipeline to successfully detect unusual patterns in the time-spatial data by neural net and associated visual analytics.

II. Related Work

Previous research works can be summarized as four parts: clustering, prediction, aggregation and visualization.

Visitor Clustering and Anomaly Detection: Classical clustering algorithms of K-means is widely used for clustering trajectory data in the early research, and has been proved to be an efficient way [2] - [10] for regular and irregular movement patterns. The main trade-off of K-means is that K needs to be predefined for but finding an optimal K value is a non-trivial work that can be another big research and cause expensive experiment. Also it is sensitive to noise especially for massive cluttered time-spatial information and irregular movement patterns which might increase the error rate. The attempt of new method Self-Organizing Map has been used in this area recently in the work done by researchers [24], [25] which shows the excellent performance with Self Organizing Map in such data. Previous researches attempted to apply SOM clustering on time-oriented information such as visiting pattern of people and display clustering map as result. The only issue is that even though SOM is able to cluster complicated trajectories and render the consequence maps but there are no any deep studies and interprets based on those clustering result [24] though the decode and interpret of those information are essential for analytic. Different from those traditional way, in our research, we do not only illustrate the clustering result, but also further decode the information for the SOM result using other visual analytic tool like heat map and animation. Based on those visualization, we can further infer what kind of visitors they are. Using clustering technique for abnormal behavior detection is also quite widely used, some of research has used neural net for this purpose. Particularly SOM has good usability [12], [26] to perform the job. To explore the crime pattern, the data type in those study are mostly socio-economic and environmental data which might have more obvious feature to study. However in most cases those data are hard to obtained, for instance, in our study except the pure time-series movement data, we would not use other data like gender, background, age and so forth of users. Therefore data processing before clustering are required in order to extract the feature like preference of visitors.

Movement Prediction: To accurate and timely predict the flow, a lot of methodologies have been developed [27], [28], [29]. Due to the stochastic and non-linear nature of sequence data set, the researchers have paid much attention to the classical machine classification methodologies. Comparing with several methodologies, K-Nearest Neighborhood, Random Forest and Support Vector Machine are considered to be good ways for resolving such problem [27]. Different from the problems addressed by majority popular techniques, this paper requires to solve the multi-trajectory problem that we do not just predict the flow of individual trajectory, instead, this issue covers all movements of vistors in the same time stamp that is we try to predict and visualize in certain time that how all the customer moves. This complicated problem essentially combines a number of individual predictions, therefore it is trivial for multi-trajectroy problem assuming we address the single traffic flow prediction issue.

Aggregation of Trajectory[3], [4], [9], [21]: After grouping instead of investigating single movement, visual analytics approaches analyze movement based on aggregation of users. Groups are usually defined as two types, for one, Groups which have the same or similar type of trajectories. Clustering results are usually defined as groups in this case [6], [10]. For another, only people who visit sites together having exactly the same spatial trajectory can be defined in a group such as family, couple or friends[2], [4]. In order to find these groups, we normally need to compare every individual trajectory data. Therefore we need to scan entire trajectory database to calculate the spatial temporal difference of one individual trajectory to every other single trajectories. This method is much more accurate than the first type of grouping but is very time-consuming $(O(n^2))$. We use the second definition in our paper, but to reduce the work, we detect groups based on clustering results. That is only visitors within the same clusters can potentially be in the same group which narrows the search space.

Trajectory Visualization Analysis: 2D map-based approach and 3D time-spatial cubes [2] - [6], [7] are two the most popular ways. In 2D map-based visualization, classical approach based on 2D map visualization named spatial flow [5], [6], [12] is recognized as a useful way to visualize the movement pattern by showing the flow magnitudes. Furthermore, real time trajectory can be further represented by revealing those movement(flow) using animations [2], [3], [5], [7] which can demonstrate the order of locations that visitors travel as well as other information such as speed changes in real time. From each frame of an animation, we can see how movement occurs during certain intervals. For 3D visualization, spatial-time cube [13] is an approach widely used to display massive trajectory data. However, these approaches cannot perfectly present trajectories when trajectories come cluttered. In this paper, both 2D-map based visualization and spatial-time cube are used to visualize aggregation trajectories. Those methodologies serve as essential information display to help user better understand the analysis result of neural network. Besides those, the similarity of trajectories is also important in movement visual analytics. Various approaches are used to compute difference between trajectories including Leven-Shtein distance[1], Euclidean distance, and Dynamic Time Warping (DTW) [9], [14]. This paper mainly uses DTW [15], [16] in trajectory comparison.

III. Approach

This section covers the pipeline of approach and how we implement and adjust the methodology for our system. Our system mainly covers 3 main parts that firstly the overall visualization for whole data in our system and hot-spot statistics that is used to visualize the visiting pattern in certain attraction which we define as hot-spot. Secondly, a SOM based cluster would be used for clustering. Finally we predict the movement flow timely use RNN approach.

A. Data Pre-processing

Regular GPS-tracked time-series data include id, timestamp, x and y position and can be processed in following way.

Check-in Frequency Data: Each person is represented as a vector recording their visiting type, and each dimension of a vector specifically set up for each place(attraction, station, etc). The value of each dimension represents the check-in frequency of this visitor.

Time Spend Data: Similar as check-in frequency data, a vector for each visitor represents how long they spend in each place per day.

Composite of Location Data: Tree data structure is used to store place and their position information as branches rooted by categories they belong to. This hierarchy is useful for making composition of each place. For instance, a big station may contain several sub-station.

Index: Movement data are indexed in two ways: visitor and location. This indexing allows to easily query information when we analyse trajectory, visit pattern and popularity of places as well as other features.

Other Data: System should also set up separate database to store other associated data for instance communication data and visitor information.

B. Integrated Scan and Hot-Spot Scan

Overall visualization of the movement is used to give an overview of the entire movement and visiting patterns of all movement objects (people, cars etc) in the entire area. This study visualizes the staying time and overall movement to understand the movement behavior. Specifically, visualization of staying time helps to understand how long visitors mostly spent in the same location before they move to next location. The point is to find our some customers spent irregularly longer time and it is important to why they spent longer time than others for safety issue.

Besides the overall scan, hot-spot statistics also serves as a crucial part. It takes spatio-temporal scan statistics [26] for certain location. In our definition, there are two types of hot-spots. For one, the explicit location or attraction. For instance, the location holding certain events or where crime happens can be considered as hot spot. For another, a composition of locations is identified as hot spot. Thanks to using Tree Structure (Composite Design Pattern), we are able to store a bunch of sub-locations to a big type. In real case, it could be a big state holds several cites or a comprehensive category has couple of attraction [4]. There are 2 particularly issues we particular concern about the hot-spot, the number of visitors they check in this hot spot as well as duration they stay in this hot spot. Our main aim is to find out the outliers. The purpose is to evaluate the attendance among each sub-locations by using each graph figuring out that which location is most popular one in certain category or which sub-station is the busiest one in different timestamp.

C. Self-Organizing Map Based Clustering

As data has been processed to be frequency check-in and time spent formatted matrix we are able to use Self-Organizing Map to perform the clustering. Furthermore, we decode the information from the unified distance Matrix(U-Matrix) to visualize the explicit visiting pattern of visitors as well as detect the group in each cluster.

Algorithm 1 SOM Cluster and Visual Analytic

$data \leftarrow$ Original Data
$t \leftarrow$ training time
$map \leftarrow$ **Initialization**
repeat
  for t_i **in** $(0, t)$: **do**
    $BMUs \leftarrow$ **Competition**
    for b **in** $BMUs$ **do**
      $b_{NeighborCircle} \leftarrow$ **Cooperation**
      for n **in** map **do**
        if n in $C_{NeighborCircle}$ **then Adaption**
        end if
      end for
    end for
  end for
until t_i reach t
$U_{matrix} \leftarrow map$
for $O_{outstandingcluser}$ **in** U_{matrix} **do**
  $T_{trajectory} \leftarrow data + O_{outstandingcluser}$
  $V_{pattern} \leftarrow data + O_{outstandingcluser}$
  for $O_{otherCluster}$ **in** U_{matrix} **do**
    $D_{distance} \leftarrow DTW(O_{otherCluster}, O_{outstandingcluser})$
  end for
  Output $T_{trajectory}$, $V_{pattern}$ and $D_{distance}$
end for

Initialization creates a 2D-array map with nodes in the lattice and each node with arbitrary value in its dimensions.

Competition uses Euclidean distance as Equation 1 to calculate the weight distance D between every node W and input vector V in a 2D map. It then defines a node with minimum weight difference as Best-Matching Unit (BMU).

$$D = \left\| \sum_{i=0}^{i=n} (V_i - W_i) \right\|_2^2 \tag{1}$$

Cooperation: Cooperation uses radius decay function to locate the neighborhoods of BMU in each iteration. There are three sub-steps in this stage. The first step is to compute the distance between the node and the BMU with Equation 2.

$$D_{bmu} = \left\| (X_{bmu} - X_{node_n})^2 - (Y_{bmu} - Y_{node_n})^2 \right\|_2 \tag{2}$$

The second step computes a decay radius of neighborhood circle which takes the BMU as the center. In Equation 3, σ_t is the decay radius of neighborhood, σ_0 is the initial radius of circle which is equal to the map width, t is the iteration time and λ is a constant number for learning rate. The last step is to compare every node to see whether they are inside their neighborhood circles, that is $D_{bmu} < \sigma_t$, they are defined as neighbors of related BMU.

$$\sigma_t = \sigma_0 e^{(-\dfrac{t}{\lambda})} \quad t = 1, 2, 3, ... \tag{3}$$

Adaptation: Adaptation trains all the nodes inside the neighborhood circle whose center is BMU using neighborhood function to update their weight W as in Equation 4.

$$W_{t+1} = W_t + \Theta_t L_t (V_t - W_t) \tag{4}$$

where Θ_t is used to consider neighborhood in the weight adaptation, L_t is the learning decay, for computing the learning rate in each training iteration. The factors that affect L_t are the current iteration time and the initial learning rate L_0. L_t is calculated with Equation 5.

$$L(t) = L_0 e^{(-\dfrac{t}{\lambda})} \quad t = 1, 2, 3, ... \tag{5}$$

The effect of neighborhood on the weight of nodes is the function of the distance between the current node and BMU, the radius of neighborhood circle, and the current training iteration time as shown in Equation 6.

$$\Theta(t) = e^{(-\dfrac{D^2}{2\sigma_t^2})} \quad t = 1, 2, 3, ... \tag{6}$$

After iterative update of all nodes, the map is self-organized and all nodes save their trained weights and the information of the nodes can be encoded and rendered using U-matrix.

Visualize the visiting pattern For those distinct group in the U-matrix. Such nodes(data) have high potential to be outliers and abnormal patterns. In our analysis, heat map will be used to present the frequency they check in specific location and duration they spend as well as bar chart to see the check-in information of big hot-spot(big station etc).

Detect groups and visualize the real time trajectory. Being in the same cluster indicates that those visitors have very similar visiting pattern and potentially travel in the group (family, couple etc). We compare trajectory of one visitor to trajectories of all other visitors in one cluster. Trajectories firstly need to be resampled to have the same resolution. For example, visitor A may have the movement record slightly different from visitor B. We resample both of them to make sure that in every time step they have the position data(x_i, y_i). The Euclidean distance between every time point of two visitors is computed and summed to get the trajectory distance of two visitors as shown in Equation 7. Where D is the trajectory distance between two visitors of A and B, n is the number of time points in a trajectory.

$$D = \left\| \sum_{i=0}^{i=n} ((X_{Ai} - X_{Bi})^2 - (Y_{Ai} - Y_{Bi}))^2 \right\|_2 \tag{7}$$

Threshold will be set up, once D is less than that, we assume A and B is in the same group. After groups are detected, a 3D spatio-temporal visualization will show the entire trajectory of group while an animation will be used to dynamically reveal how this group move and speed change.

Compare the difference among groups using DTW that is one of most popular method to compute the similarity of two set of time series data. We input the real trajectory signal of every two groups and compute the difference. There are two keys to ensure the usability in this stage. For one, SOM is able to outline the cluster by U-matrix. For another, our system is able to inspect corresponding input visiting pattern by selecting those BMUs in the user interface.

D. Recurrent Neural Network Based Flow Prediction

In this part, we predict the travel flow of objects moving among each location. We take individual traveling pattern as sequence data similar to natural language processing. Specifically, we convert the trajectory from continues geometrical position using (x, y) 2D coordinators into discrete label data by given hot spot labels [27]. For instance, a vector of an individual traveling could be like $(2, 3, 41, 5)$ which means this person visit attraction 2, 3, 41 and 5 and we need to predict what is the next location this person would be most likely to attend. We ignore the time stamp, and take the data as pure one-dimensional sequence vector for training and take the prediction result which is the attraction label as the vector label. For instance, we have training sequence vector $(2, 3, 41, 5)$ which we can take vector $(2, 3, 41)$ as training set while 5 as target label or $(2, 3)$ as training set while 41 as label. As RNN provides a dynamic training framework for neural nets. The feature of RNN is that the network contains feed-back connection, therefore activation can flow round in a loop which makes it able to do the temporal processing and learn sequences. Such features guarantee that RNN can have excellent performance in time series data. In this task, we utilize 3 hidden layers for RNN and each hidden layer manages loops that can achieve dynamic updated and training based on timestamp t_i.

Algorithm 2 RNN Predict and Flow Generation

$T_x \leftarrow$ Time Stamp for prediction
$SM \leftarrow$ Visit Sequence Matrix processed by Original Data

$SM_x \leftarrow$ sequence matrix before T_x
$SM_{x+1} \leftarrow$ sequence vector before T_{x+1}
$T_x \leftarrow$ Training Label Vector obtain by SM_{x+1} - SM_x
$M \leftarrow RNN(SM_x, T_x)$

$ST_x \leftarrow$ New Visit Sequence Matrix before T_x
for $S_{squencevector}$ **in** ST_x **do**
  $T_{NextLocation} \leftarrow M(S_{squencevector})$
  $T_{PreviousLocation} \leftarrow$ last Location of $S_{squencevector}$
  Output $DrawFlow(T_{PreviousLocation}, T_{NextLocation})$
end for

Training in RNN includes Forward Activation and Back Propagation. **Forward Activation** in RNN is a dynamic feed-forward process that the result output from neural depends on the sequence of data ordering with t_0 to t_i

$$h_t = \theta\phi(h_{t-1}) + \theta_x x_t \tag{8}$$

$$y_t = \theta_y \phi(h_t) \tag{9}$$

where θ represent for the weights associated and ϕ the **Tanh** forward activation is taken as our activation function ϕ in our method. Also **Back-Propagation** in RNN takes the time with essential parameters and we called it **Back-Propagation through time**, the formula of it can be presented as follow:

$$E_{total}(t_0, t_1) = \sigma E_{sse/ce}(t) \tag{10}$$

$$\Delta w_{ij} = -\eta\sigma - \frac{\delta E_{sse/ce}(t)}{\delta w_{ij}} \tag{11}$$

To solve the vanishing gradient problem. Specifically, time steps and each layer of architecture relates to each other through multiplication, derivatives would have potentially vanished. **Long Short-Term Memory (LSTM)** [30] is utilized, which is set up with the output gating, output squashing, memorizing and forgetting, input gating and squashing to perform the training. We input the sequence data for training and obtain model. Such model would be used to predict traffic flow for the next timestamp.

For every visitors, after the location that visitor will attend is predicted, we draw the flow map for visualization, the start of flow will be place visited in last timestamp and point to the predicted attraction. It is crucial to understand where people is likely to move in a big place containing couple of sub-location. By knowing which location that majority of people is about to move in the next timestamp, more safety management can be done with corresponding hot spot for instance sending more security guards to that location in case people get injury because of over-crowed.

IV. EXPERIMENT - PARK MANAGEMENT

In this section we demonstrate how this approach is utilized to detect a real crime group in a park as well as to predict the customers movement to ensure the the safety and security.

A. Data Set

The data the people movement at a crowed park in the VAST 2015 Grand Challenge [1]. This data set is on the movement of visitors in a modest-size amusement park, DinoFun World, sitting around 215 hectares with 81 different attractions that can be classified by 7 main categories with Rides, Show & Entertainment, Information & Assistant, shopping, Beer Gardens, Restrooms and Food, where Rides can be further distinguished by Thrill Rides Kiddie Rides and Rides for everyone. All attractions are numbered, named and connected by a visitor pathway throughout the park. Each visitor was tracked by a mobile device that records his/her positions in real time and his/her behaviors and communications. For protecting the privacy of users, devices only recorded two behaviors of customers: movement and check-in. This park hosts thousands of visitors every day. Especially, there were 3357, 6411, and 7569 visitors on 6, 7, and 8 June 2014 respectively as an event Scott Jones Weekend was held for celebrating the coming of local star Scott Jones. On Sunday, 8 June 2014, a crime happened in this park and rapidly solved by officials. Specifically, all his personal honors including an Olympic medal were occurred at Creighton Pavilion (Attraction 32) during the time there was a crime group vandalized the exhibiting, breaking into the place.

B. Crime Detection

We assume that visiting pattern of a crime group is usually different from the regular visitors. Regular visitors normally have random distribution on the time spend and check-in in attractions in the park, while crime person may spend particularly longer time and higher frequency of check-in in certain places which is mostly the attraction that crime occurred and in this case we define crime location as hot-spot. The trajectories of crime groups may also be different from normal visitors, for instance, when the show in Creighton Pavilion is temporarily closed and ready for the next show, normal visitors probably leave the place traveling to another place while crime people more likely still stay there during that time as it is good time to commit crime as no many visitors around there. From these assumptions, our visual analytics firstly conducts the clustering of data in the morning on Sunday using SOM, then visualize the visiting pattern of outstanding clusters, and figure out their trajectory.

Fig 1 shows the SOM framework of clusters to detect crime groups. U-Matrix (Fig1(a)) shows six distinct clusters. By further analyzing these six clusters, we found that among six clusters, two of them have the highest probability to be relevant with each other. We name these clusters as group 1 and group 2. By visualizing visiting patterns (see (Fig1(b))) of these two groups we found that group 1 spent the most

[1] http://vacommunity.org/VAST+Challenge+2015

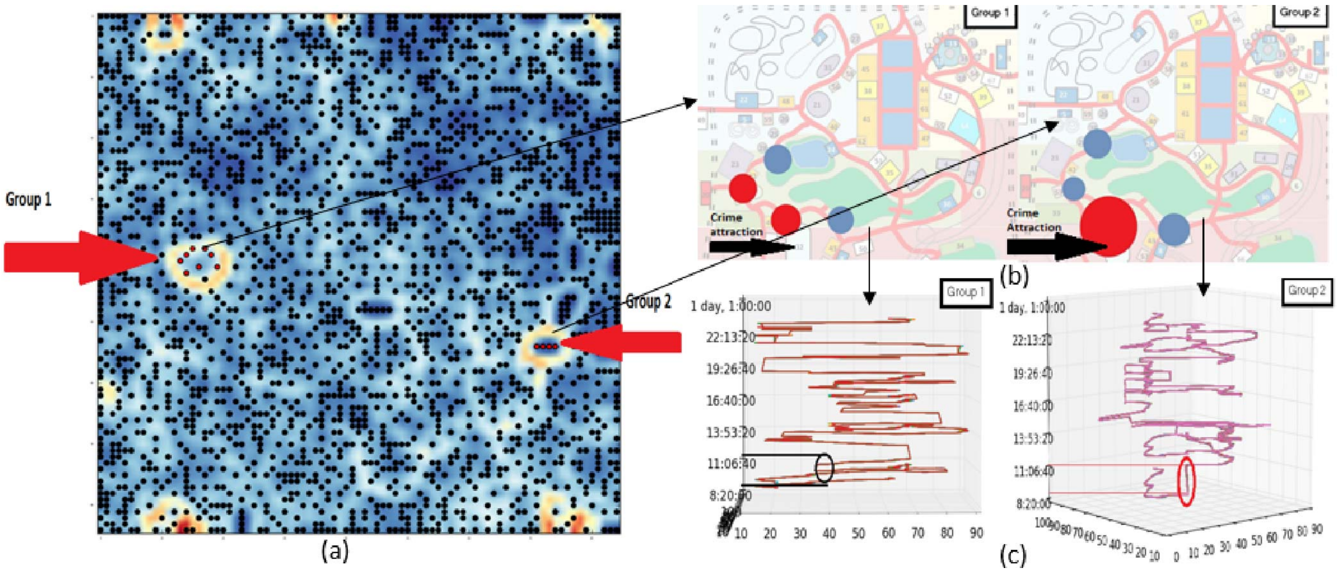

Fig. 1. Visualization Framework SOM based Cluster shows that Group 1 and group 2 are suspected to be crime relevant, heat map illustrates both these 2 groups has high check-in frequency in the crime hot spot while time-spatial cube indicates that both 2 groups checked in crime attraction in crime time.

of their morning at two attractions of Attraction 53 Smoky Wood BBQ and Attraction 32 Creighton Pavilion, while group 2 spent almost the whole morning at Attraction 32 Creighton Pavilion. As both of groups spent quite a lot of time at the Attraction 32 which is the crime location(hot spot), we suspect these two groups committed a crime in Attraction 32 because of longer time spent at that attraction. By analyzing their movement in spatial-time cube visualization (see (Fig1(c))), we found that from 9:30 am to 11:30 am, group 1 did check-in at crime attraction and stayed there until 11:00am, and then moved to Attraction 53. While group 2 spent all the time from about 9:30 am to 11:30 am at Attraction 32 without any further movement.

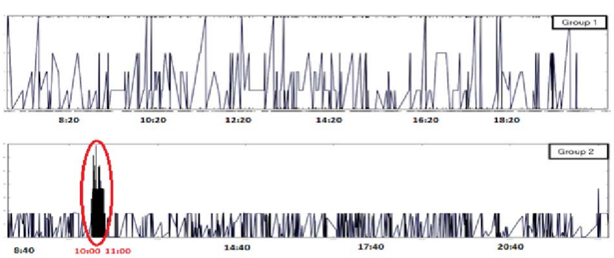

Fig. 2. communication within group1 & group 2, group 2 has abnormally communication pattern in the crime time from 10-11am

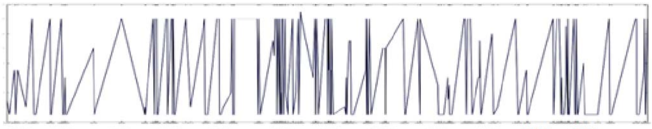

Fig. 3. communication between group1 & 2 shows 2 groups keep in touch

Besides the pure trajectory data, this challenge also provided communication data of visitors which record different

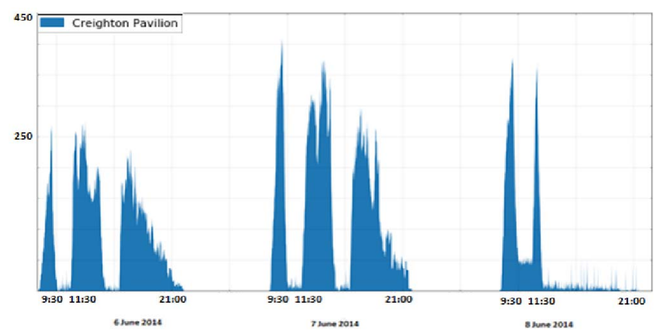

Fig. 4. Crime Location Attendance Scan indicates that the shows took places 3 times each day with 2 breaks

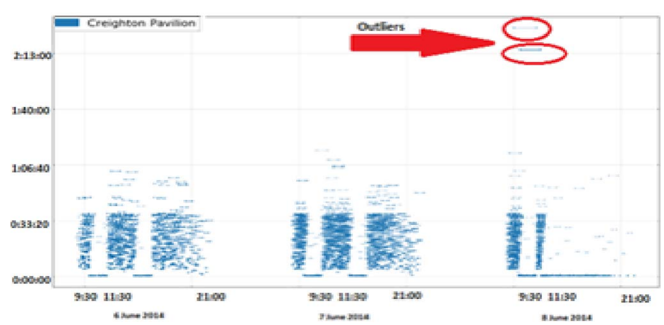

Fig. 5. Crime Location Stay-time Scan shows there 2 outliers groups having unusually high stay time in the crime attraction and their check-in time is in the break of show

timestamp, one calling another visitor in the format (id, time, x, y, callid). By processing this data we can visualize the communication pattern of groups. Fig 2 illustrates the communication pattern of group 1 and group 2. We found that the communication frequency of group 2 was much higher and sharper during the period from 10:00 am to 11:00 am than the other time period. Therefore, we can assume that the time period from 10:00 am to 11:00 am was highly possibly the crime time. Based on these observations, we can conclude that group 2 committed crime while we still cannot exclude the suspects of group 1. We further visualize the communication pattern between group 1 and group 2 as shown in Fig 3, the result shows that group 1 and group 2 kept in touch during the whole day of 8 June 2014, which means that group 1 and group 2 were not independent groups and they knew each other. Therefore, our conclusion is that group 2 committed crime at Attraction 32 while group 1 guarded Attraction 32 and Attraction 53 to help group 2 to commit the crime from about 10:00 am to 11:00 am.

Hot-spot scan and statistics are further analyzed to confirm our conclusions. Fig 4 shows that there are three large attendance periods on each of three days, which means that Scott Jones Shows took place during these three time periods on each day. In addition, we found that from around 9:30am to 11:30am every day, there was a sharp decrease followed by a very small number of check-in of visitors and then increased again. From this pattern, we can infer that from 9:30am to 11:30am this attraction was shortly closed until the next shows ready after 11:30am. Normally during this time period visitors most likely left this attraction as the show temporarily closed. However from the time spent on Attraction 32 shown in Fig 5, there were two groups of visitors staying in this place from 9:30 am to 11:30 m. Also the time they spent at Creighton Pavilion are clearly outliers as normal visitors spent less than one hour there but they spent more than two hours in this place. Therefore, we can assume that these visitors are relevant to the crime.

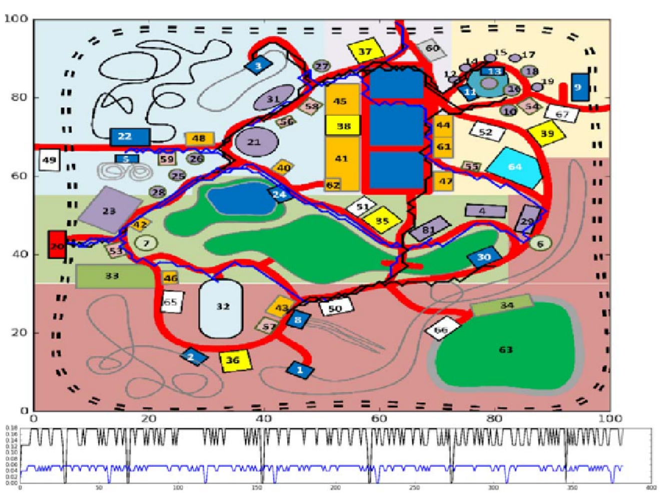

Fig. 6. Whole crime story can be revealed using animation

In summary, based on these visual analytics, whole crime story can be described as follows: Scott Jones Shows took place three times every day from Friday to Sunday. After the first show ending at about 9:30am, the attraction was closed until 11:30am. During this time period on Sunday, the crime people were divided into two groups: the first group mainly acted as assistance group and the second group committed the actual crime in Creighton Pavilion. The first group traveled around Attraction 32 to guard the crime. At around 10:00am, the second group started working on breaking into exhibition and stolen. Therefore the communication in the second group was increased a lot. Two groups also kept in touch frequently during the whole crime committing period.The entire crime story can be illustrated and revealed by using real-time animation after selected cluster from U-matrix shown in Fig. 6 .

C. Movement Flow Prediction

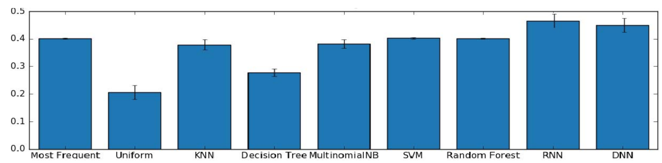

Fig. 7. RNN has highest score in Average Prediction Accuracy of Methods

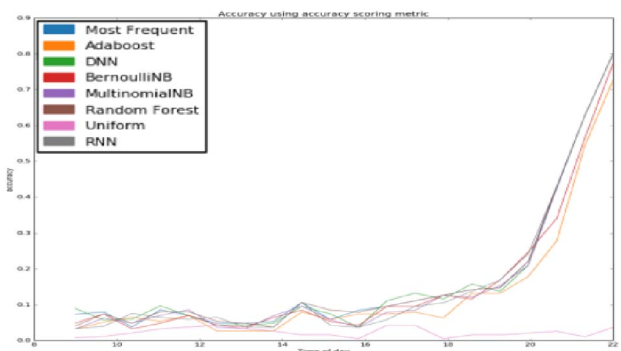

Fig. 8. Prediction Accuracy of Methods among Timestamps, RNN has almost highest score among all time and increase significantly after 20pm

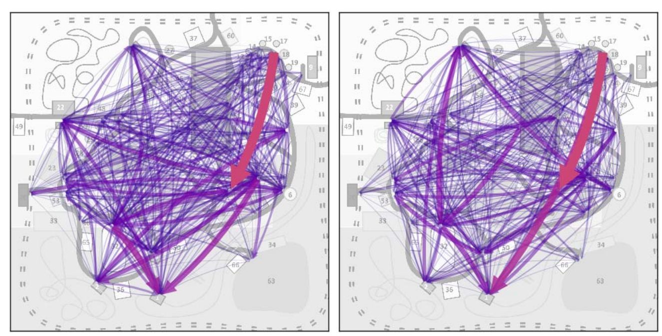

Fig. 9. Movement Prediction Visualization, RNN prediction (**right side**) is basically match the real movement(**left side**) and successfully outline the majority movement of visitors(outstanding arrows present large groups)

This section illustrates the process of predicting the movement of visitors, specifically the locations that people would visit in the next timestamp. By comparing different methods, we find the RNN is the most optimal solution. Fig. 7 shows that RNN achieves the highest average prediction accuracy with 46% while the others has the second highest score 39% achieved by 10-Nearest Neighborhood. Except the average accuracy we also analyse the prediction accuracy among different timestamps. As we utilize the movement data before certain timestamp as training set for predicting movements in this time therefore theoretically with the lager timestamp we will get larger set of training data. In other words, ideally, the accuracy will be improved with lager timestamp. Fig. 8 shows how different methods perform prediction in different time. RNN has gained almost all highest score among all the time, and increases significantly particularly after 20:00 pm.

The result of prediction visualization is shown in Fig 9 (right) with the real movement (left). It is clear that the RNN is able to predict the most movement flows and outline the movement of large group of people(outstanding flows). Prediction is essential for safety management. For instance, knowing which location will be busy and crowded in the next timestamp, we can have corresponding plan to address safety issue. Particularly in this case, prediction result shows that majority visitors is going to move to attraction 13 in the next hour therefore we would suggest the park manager to assign more security guards to attraction 13 to help visitors.

V. Conclusion

This paper proposed, for one thing, using SOM to cluster visitors into groups based on different visiting features such as time spent at attractions and visiting frequencies of attractions. The U-matrix visualization of SOM helped users detect distinct clusters of visitors. Based on these clusters, further visiting information were derived to understand visiting patterns of visitors. The proposed approach was used to detect abnormal behavior patterns such as crime detection. The results showed that the proposed approach can effectively analyze movement data and get insights for human decisions. For another, using RNN to conduct prediction of movement is another essential part, such advanced deep learning prediction models develop a better way to predict visiting patterns and safety management by incorporating both communication information and trajectory data.

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