Super-know-you Mall

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Face Alignment	Bowen, Chen; Yunxia, Shi
Face Identification Complement	Bowen, Chen
Training Result Test & Optimization	Xue, Luo; Zimin, Shen
Data Analysis	Zimin, Shen; Yunxia, Shi
Data Visualization & Demo	Xue, Luo； Juelin, Ye

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1 Pain points & Our solution

1.1 Pain points

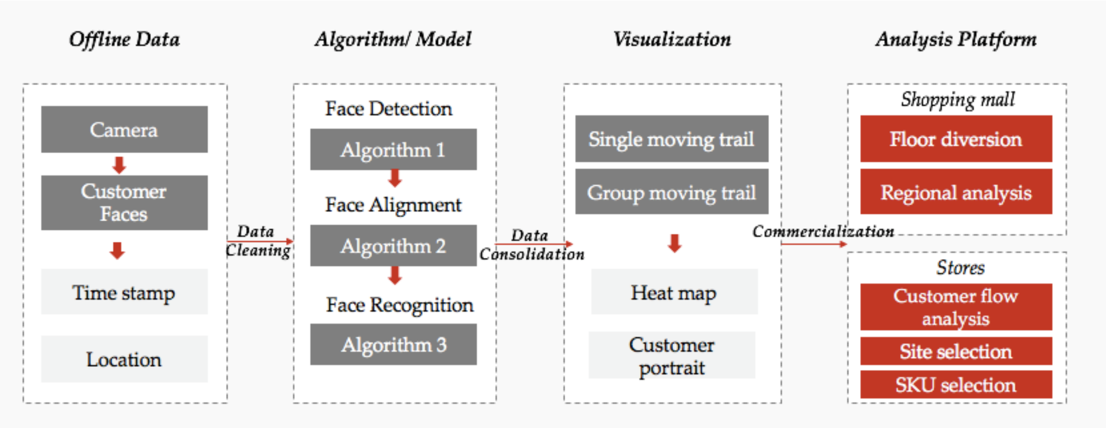
According to the China Industry Association, in 2018, 400 shopping malls have been closed due to poor earnings, and the highest vacancy rate of shopping centers has reached 35%. In addition, Chinese business centers are estimated to have an average 20% vacancy rate in next 3-5 years.

The key cause of this phenomenon is the lack of offline customer data. For stores, they used to have inefficient site selection and unreasonable SKU selection. Hence, they failed to recognize customers' needs and had poor interaction of discount activities. For stores, they also had unreasonable store layout and low sales conversion of customer flow. In this way, they failed to activate member repurchase and had poor customer stickiness and interaction.

Because of the above reasons, consumers consumed less online during 2013 to 2018, inducing offline channel sales share drops by 20%. Meanwhile, low sales and high costs causing more stores' moving out instead of moving in the shopping centers in core business district in the 1st tier cities. Besides, the vacancy rate of business centers in first tier cities continues to rise.

1.2 Our Solution

Therefore, our group tried to come up with a big data solution to solve pain points (as follows).



2 Face Identification Algorithm

There are three steps in face identification. Face detection is to find all the face positions in the image, usually marked with a rectangular box. Face alignment is to find the eyes, mouth and nose on a face. Face identification is to match the face with the identity.

2.1 Dataset

We used an annotated face dataset from Chinese Academy of Science with 70% for training and 30% for testing. The features of this dataset are shown as follow.

	Features
Number	2,2404 images, 7,1711 labeled faces
Multi-face	An average of 3.2 faces/images.
Skin Color	Yellow, white
Specification	Rectangular and elliptical box
Appearance	Rich facial expressions and poses, multi-angle (frontal or side faces)
Gender	59% are tagged as female, 41% are tagged as male
Age	5 years old ~ 79 years old
Background	Indoors and outdoors
Image Color	81% color images and 19% grayscale images
Resolution	100 x 100 pixels ~ 4480 x 2560 pixels

2.2 Algorithm

There are three parts in Algorithm including Face Detection, Face Alignment and Face Identification.

（1） Face Detection

Multi-view face detection in open environment is a challenging task due to diverse variations of face appearances and shapes. Most multi-view face detectors depend on multiple models and organize them in parallel, pyramid or tree structure, which compromise between the accuracy and time-cost. Aiming at a more favorable multi-view face detector, we propose a novel funnel-structured cascade (FuSt) detection framework. In a coarse-to-fine flavor, our FuSt consists of:

①Multiple view-specfic fast LAB cascade for extremely quick face proposal. Although the LAB feature is quite computationally efficient, it is less expressive and has difficulty modeling the complicated variations of multi-view faces for a high recall of face windows. Therefore, we adopt a divide-and-conquer strategy by dividing the difficult multi-view face detection problem into multiple easier single-view face detection problems.

②Multiple coarse MLP cascade for further candidate window verification. SURF features are more expressive than LAB features, but are computationally efficient benefited from the integral image trick. So face windows can be better differentiated from non-face windows with low time cost.

③A unified fine MLP cascade with shape-indexed features for accurate face detection.

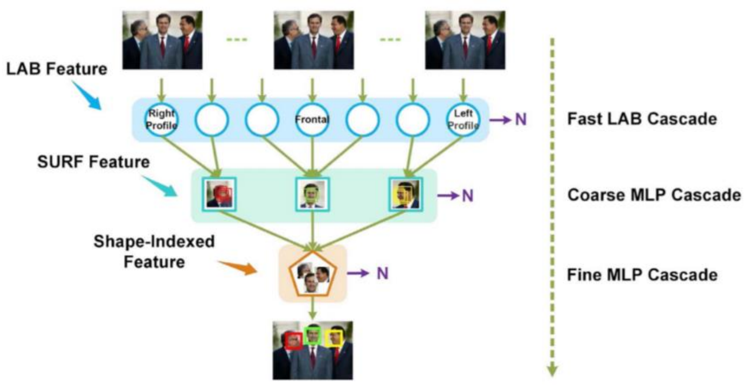


Figure 1 Face Detection Method Introduction

(2) Face Alignment

We propose a Coarse-to-Fine Auto-encoder Networks (CFAN) approach, which cascades a few successive Stacked Auto-encoder Networks (SANs). Specifically, the first SAN predicts the landmarks quickly but accurately enough as a preliminary, by taking as input a low-resolution version of the detected face holistically. The following SANs then progressively refine the landmark by taking as input the local features extracted around the current landmarks (output of the previous SAN) with higher and higher resolution.

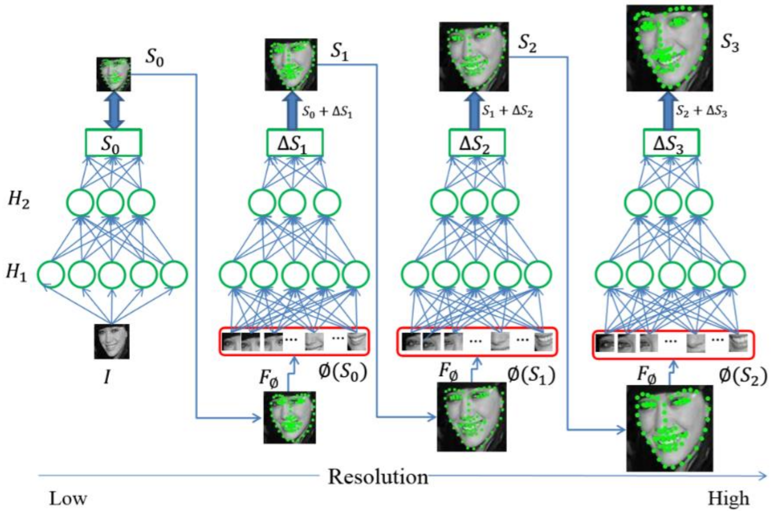


Figure 2 Face Alignment Method

(3) Face Identification

We proposed VIPLFaceNet to achieve Face Identification. Considering the success and efficiency of AlexNet, our network is designed by adapting AlexNet to incorporate some recent new findings. 1) We use 9×9 size for the first convolutional layer. 2) We remove all local response normalization layers. 3) We decompose the second 5×5 convolutional layer of AlexNet to two 3×3 layers.

We also exploit a fast normalization layer in our VIPLFaceNet before the ReLU layer to speed up the convergence and improve the generalization.

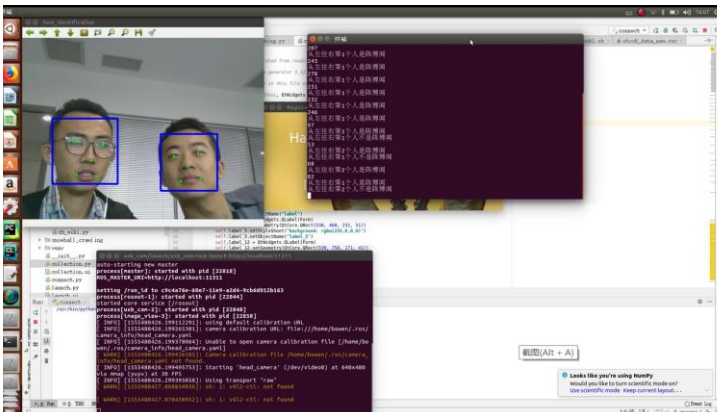


Figure 3 The Result of Face Identification

3 Big Data Analysis

3.1 Data Structure

There are mainly two type of data we collect. **Personal information table** is mainly personal information of users from store's membership database. It includes user id, name, sex, age, register time and membership level. Through it, we can get more features of the customer.

Customer flow data table includes the output user behavior data from our face identification algorithm. It mainly has three dimensions. For time information, each camera takes a picture every second and the shooting time is recorded as a timestamp. For location information, each camera has a unique location number. For user name, we use face identification algorithm to identify the user at current location. For a new customer, we can give him a user id and add it to our personal information table.

3.2 Big Data Value

In the previous section, we have explained our algorithm and the data that the algorithm can output. Next, we will explain that the data we collect is of practical value and can provide many valuable suggestions for business operations.

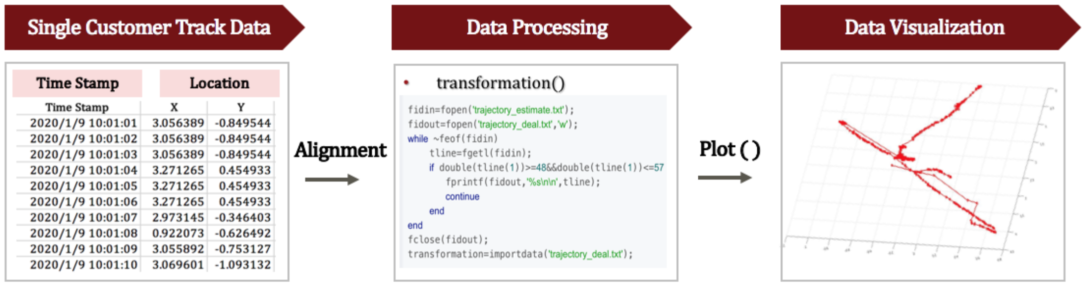
First, we can connect the collected shopping behavior data of users with the mall's order transaction database and mall member information database according to the user id to obtain a more comprehensive data table. Then, we can analyze the data we collected from the mall dimension, store dimension, user dimension, and path dimension to draw some useful suggestions.

From the perspective of the total amount of the mall, we aggregate all the data to get the overall performance of the mall. Malls can dynamically adjust the price of advertising according to the flow of people to maximize revenue and determine business hours and promotion plans based on order volume. From the store dimension, we can judge the preference of user consumption in different working days, and launch different products on different dates in a targeted manner. From the user dimension perspective, we score each user in five dimensions to obtain a more accurate customer portrait. Based on user portraits, we can conduct more targeted and accurate marketing for users, such as pushing hot dishes to customers who love food, recommending new beauty products to girls who love beauty, recommending luxury information to the rich, and so on.

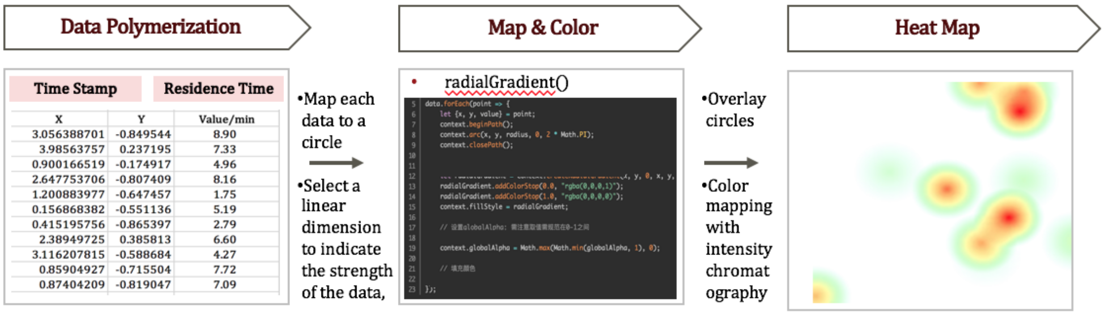
4 Data Visualization & Product Demo

4.1 Data Visualization

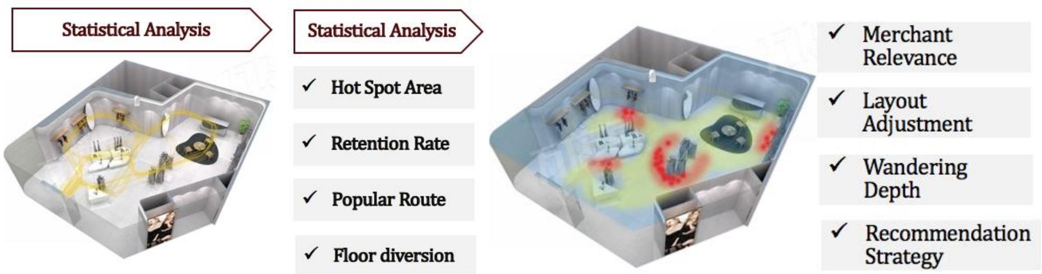
For single customer shopping track, we can aggregate the time stamp and location data of a certain customer. Next, print these dots on the canvas, and thus, we can know the shopping track of a certain customer – what is his preferred shopping route and his shopping preferences and taste. The process can be seen below:



For the heat map of single customer, we can aggregate the location data of a user and then calculate the time of this user staying in a store. And set the stay time as the value of a pair of (x,y), and then we draw the heat map of the single customer shopping track.



For multi customer shopping track, we can also do the same data polymerization and data visualization. As we can see here, we can clearly know what is the popular shopping area, popular shopping route, which will greatly help the shopping mall to improve its operation efficiency.



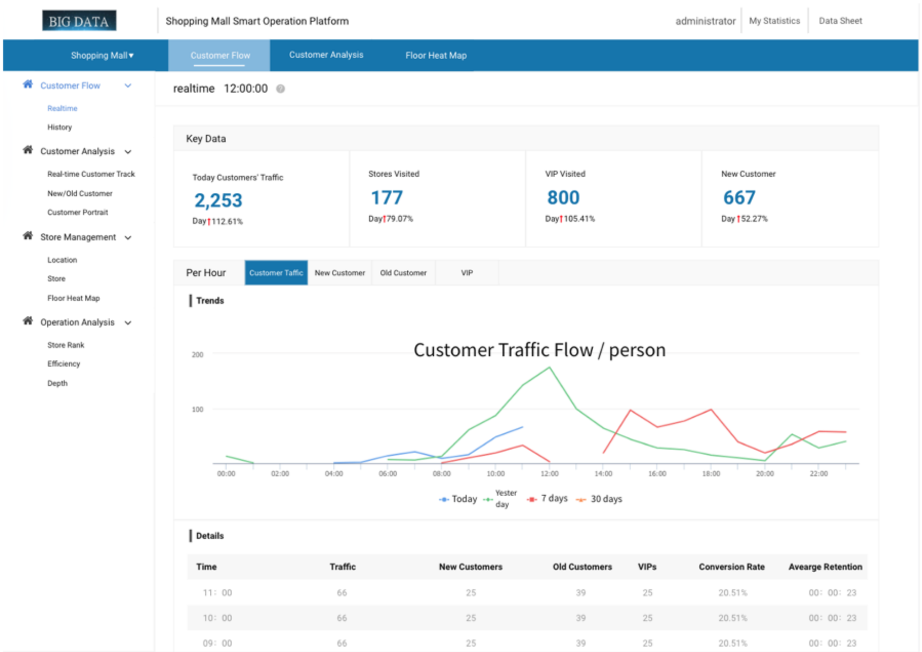
4.2 Product Demo

When shopping malls Master more offline shopping data of customer, which means it knows customers deeper, and then it can select and recommend the suitable products to the right customers, and make accurate advertising on their preferred shopping path. We have 2 platforms product demo for shopping malls and shops, which can be seen in the Appendix.

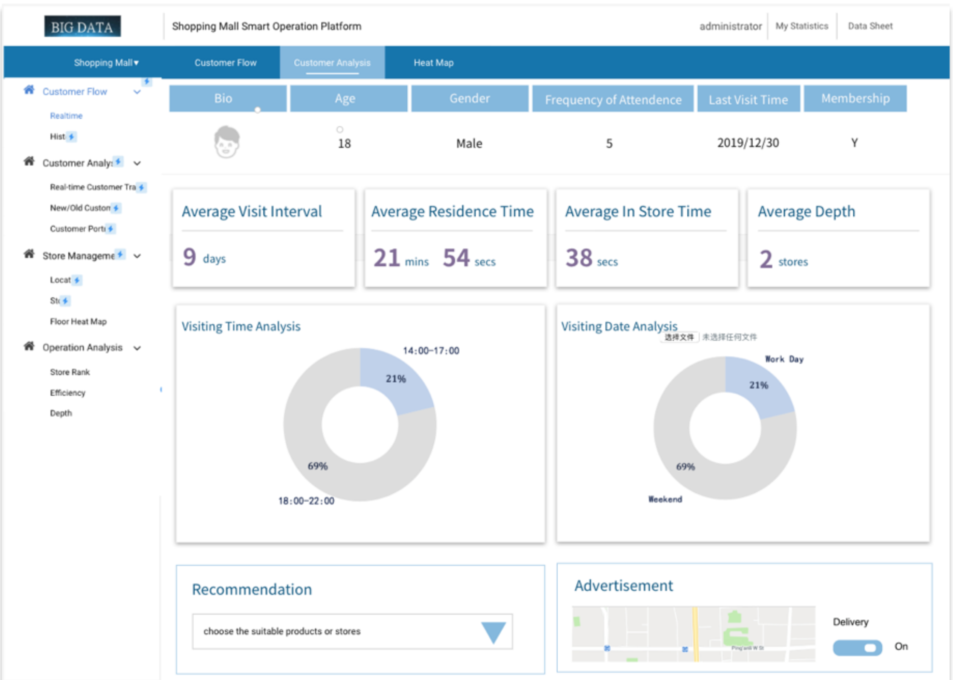
5 Appendix-Demo

- **Shopping Mall Platform**

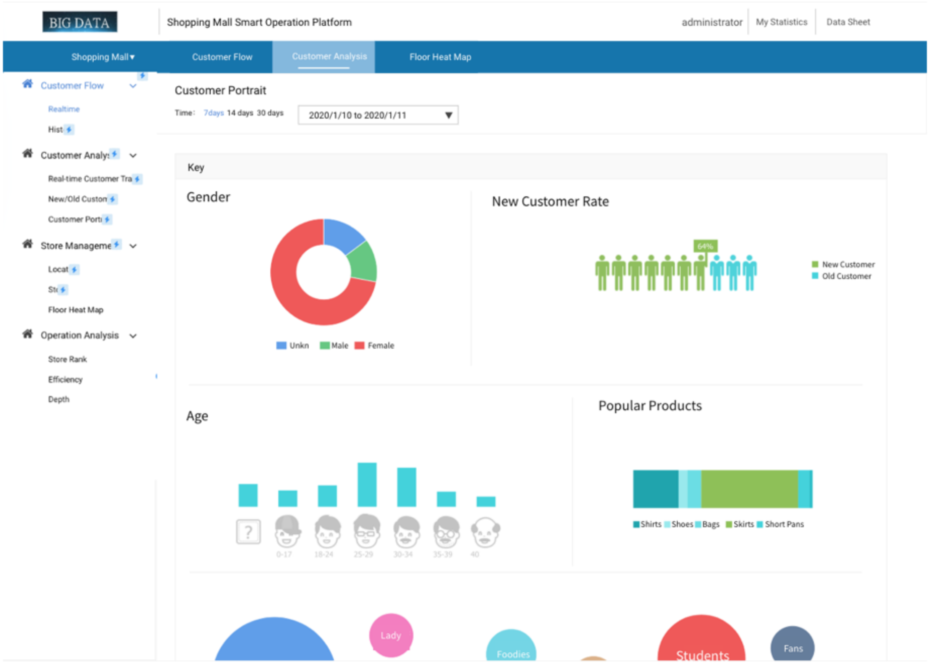
Shopping Mall Platform



Shopping Mall Platform

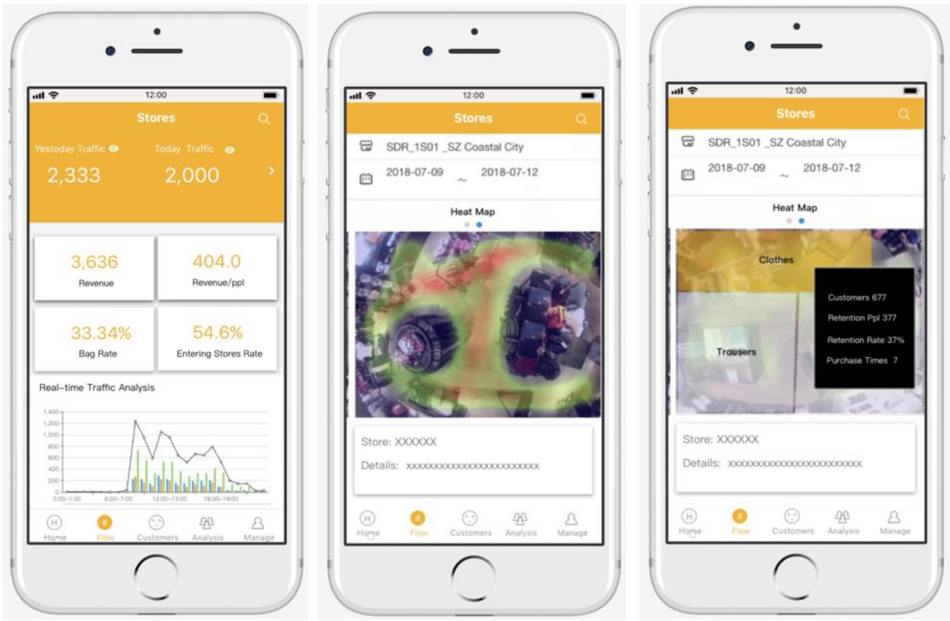


Shopping Mall Platform



- **Stores Platform**

Stores Platform



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