Consumer Targeting Based on Historical path and Network Structure on Real Time

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Motivation

Smart phone usage is expected to exceed 6.1 billion users worldwide by 2020. The proliferation of mobile and sensor technologies has contributed to the rise of mobile location-based advertising. such advertising can enable business to deliver information to mobile users in real time about offers in geographical proximity to them. Recent studies using randomized field experiments have causally shown that mobile advertisements based on static location and time information can significantly increase consumers' likelihood of redeeming a geo-targeted mobile coupon.
Beyond the real-time snapshot about the static geographical location , the mobile trajectory of each individual consumer and behavior of geographically near consumers can provide richer information about consumer preferences. In particular, "trajectory" refers to the offline physical movement of each consumer. Combining the movements of all consumers, we get a dynamic network in which consumers who are geographically close might share common preferences. The ***goal*** of this project is to come up with an advertising strategy using the information of historical trajectory of each consumer and the information of geographic relationship among consumers.
Consider in a big shopping mall, say Domain, consumers are walking around to search for products they like. Consumer A is in the Sports section and wants to buy a pair of shoes. He/She has visited Nike, Adidas, Air Jordan and is now in New Balance. Consumer B is also in the sports section, and has bought a pair of shoes in Puma. In that case, for consumer A at time t, a trajectory would be Nike to Adidas, to Air Jordan, to New Balance. His/Her geographically close "neighbor", consumer B, is likely to embrace similar preference for shoes as consumer A. The question of interest is how shall we make recommendations to consumer A based on his/her own trajectory and the behavior of other consumers near by.
In the end, we would like to come up with a dynamic recommendation system, i.e., sending mobile-based coupons to consumers on real time. We decompose the problem into two tasks.

- Based on a snapshot about the static geographic location, and historical trajectory and purchasing behavior, how shall we make recommendations and design advertising strategy?
- When taking dynamics into account, how shall we make recommendations and design advertising strategy efficiently? The biggest challenge is the computational burden when there is a large number of consumers. Given that people's history changes between timestamps, how to update the previously computed recommendations to the current recommendations?

In this project we aim to implement the first task, and leave the second task as future work.

Methodology

We formulate our problem as such. Given a population of people P, a label set L, each individual in P is associated with a list of {0,1} with the size of L, where each value corresponds to a label in L. Given time span {0,1,2,3,T-1}, each individual $\in$ P is also associated with a list of size T, and the t_{th} slot in this list contain the 2-D location of this individual at time t. To simplify the setting and save memory, we fix T in our project. In other words, we only keep the last T locations of each individual. Let V^i_{label} and $V^i_{location}$ denote the first list and the second list of individual i respectively.

Suppose now we obtained the 2-D locations at time T of all individuals $\in$ P and updated their $V_{location}$, our goal is to find out those individuals whose value for label l in the V_{label} changes from zero to one at time T. If value one denotes having bought a product, and value zero denotes otherwise, this is equivalent to finding customers that have not bought this product but will buy it at time T.

There are many possible approaches to this problem. One of them is spatial smoothing. Specifically, we design a similarity measure of individuals, and perform spatial smoothing of the l label values from all individuals. Then we output those individuals who have a zero value but are smoothed to a value close to one.

One key aspect of this smoothing method is the similarity measure. Ideally this measure represents how much interest two individuals share. In our context, $V_{location}$ gives a hint about where the individual usually go and V_{label} indicates what kind of goods this individual likes. Hence we are going to incorporate the similarity of both $V_{location}$ and V_{label} into our similarity measure.

One could easily come up with a hand-crafted weighted average of the two similarities, which has the advantage of computational efficiency and implementation simplicity. We would also like to explore supervised learning methods that takes two individuals' V_{label} and $V_{location}$ as input and predict how likely two individual will have the same value for label l at time T or not. This probability can be considered a similarity measure of higher level. Also, spatial smoothing would take less time if the similarity matrix of all individuals is sparse, so our similarity measure should ensure that two very different individual have zero or close to zero similarity.

In this project, we are going to try both weighted average and supervised learning similarities, in the hope of devising a measure that is computationally inexpensive, informative and sparse. In particular, for supervised learning, we are going to try support vector machine, neural networks and random forest. To make the similarity sparse, we transform it with a sigmoid function of form:

$$s' = \frac{1}{1 + e^{-(s-a)*b}}$$

where s is the original similarity and s' is the transformed similarity. a and b are constants to be chosen such that s' is sparse.
As for spatial smoothing, we will compare fused lasso and laplacian smoothing and choose the one that performs better.

Data

Ideal data:
Ideally, we would run a field experiment in a shopping mall where free WiFi is offered. Once the consumer is connected to the WiFi, we are able to track the detailed movement of consumers. The information provides trajectory of each consumer and dynamic geographical network of all consumers in the shopping mall. Furthermore, we assume that if the time a consumer spends at the checkout exceeds a certain threshold, a purchase occurs.
Data we would use in this project:
We would like to use GPS data that is generously provided by the professor as our location data. Note that this is a snapshot static data. Therefore, we would like to address the first task for the current project.
We consider only one product and randomly assign 1 and 0 to hypothesized consumers, with 1 indicating that he/she has already purchased the product by time t, and 0 otherwise.

Expected results and contribution

We would like to see how Laplacian method and fused Lasso method perform in our context. We will compare the speed of the algorithms when changing parameters such as the number of total consumers, the percentage of consumers who have already purchased the product, and so on. This result offers a solid foundation for dynamic implementation in the future.
We contribute the extant stream of literature by incorporating consumers' own behavior (trajectory) and their "similar" consumers' behavior (trajectory + purchasing).

Schedule

We sill start working on the data once we get it. Since we plan to implement both Laplacian method and fused Lasso method. Each of us will focus on one method independently and then decide which one works better.