Social Classes Shape Our Trajectories in Both Online and Offline Space

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ABSTRACT

The social classes of people have important impact on our behaviors in both the virtual world and physical space. Nowadays, digital media provides a new lens for researchers to investigate people's allocation of attention in the virtual world and their mobility in the physical space. Using a smartphone dataset of 100， 000 people, we tried to study how social class influences our moving behaviors in both online and offline space.

We find a significant correlation between the social class an individual belongs to and his or her online and offline trajectories. Compared with the people of lower social class, the people of upper social class are more likely to surf between high conventional combinations of applications, yet to visit a low conventional combinations of locations in the physical space.

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INTRODUCTION

The social classes have important impact on our behaviors in both online and offline space. The online space means the attention flow in the virtual world, whereas the offline space represents the mobility behaviors in the physical space.

The smartphone dataset for this study is from the log file of 1×10^5 users randomly selected in a major city of China. The dataset consists of two parts. The first part is the user profile information including mobile terminal price, fees and house price (home is inferred from the observed frequency of recorded locations). We use the first part information to match the social status a person belongs to. The second is the user behavior information, which contains call detailed records (CDR) and data detailed records (DDR). We use this part information to match the moving trajectories in the attention and mobility network.

METHODS

We use the Z score method to evaluate the weight between any pair of nodes. To measure the observed frequency of any pair of nodes, we take the sequence of mobile phone applications and the sequence of base stations for a given person, and count the frequency for all pairwise combinations. Repeating this step for all the users, we can get the population level. To remove the link between two pair of nodes which is observed purely by chance, we randomly shuffle the bipartite network, which ensures that the number of mobile applications or base stations visited by a user in the observed network will be the same in the randomized network. Then, we can calculate the Z score for each observed pair relative to what was expected by chance, Zscore = (W_{ij} - E(W_{ij})) / SD(W_{ij}).

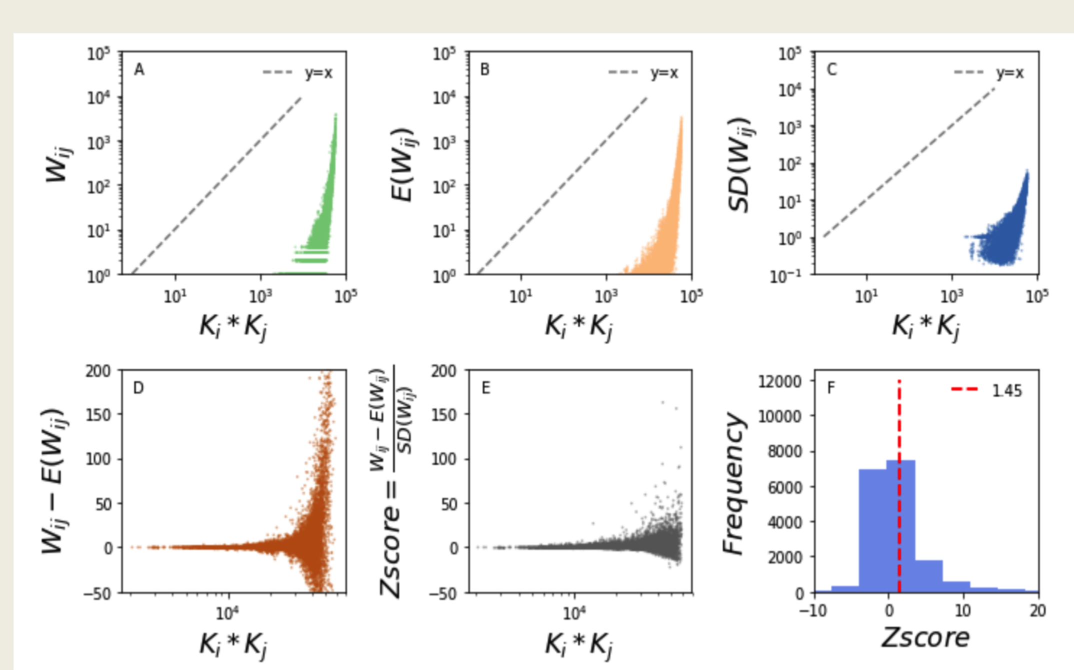

Figure 1. The process of calculating Zscore in the attention network

RESULTS

Figure 2A presents the cumulative distribution frequency of Z scores for a given user. We use two dashed lines to mark the median value. As a statistic, median can measure an individual's trajectory. Figure 2B shows cumulative distribution frequency of median Z score for all users.

In figure 3A, social class is measured by judging whether he or she is in the top 20% users who live in the most expensive house or not. It suggests users with high conventional combinations of mobile applications and low conventional combination of locations visited in the physical space has the highest probability of being in the upper class (*P = 23%*). Figure 3B indicates the same finding as figure 3A, where social class is measured by terminal prices and fees. Upper-class users with top 20% highest terminal price and fees displays a highest probability in "attention-high convention" and "mobility-low convention", nearly 1.5 times of the probability in "attention-low convention" and "mobility-high convention". It also indicates the upper-class people are more likely to visit more common and popular app combinations in the attention network, whereas in the mobility network, the upper-class people stay in the less common and public location combinations.

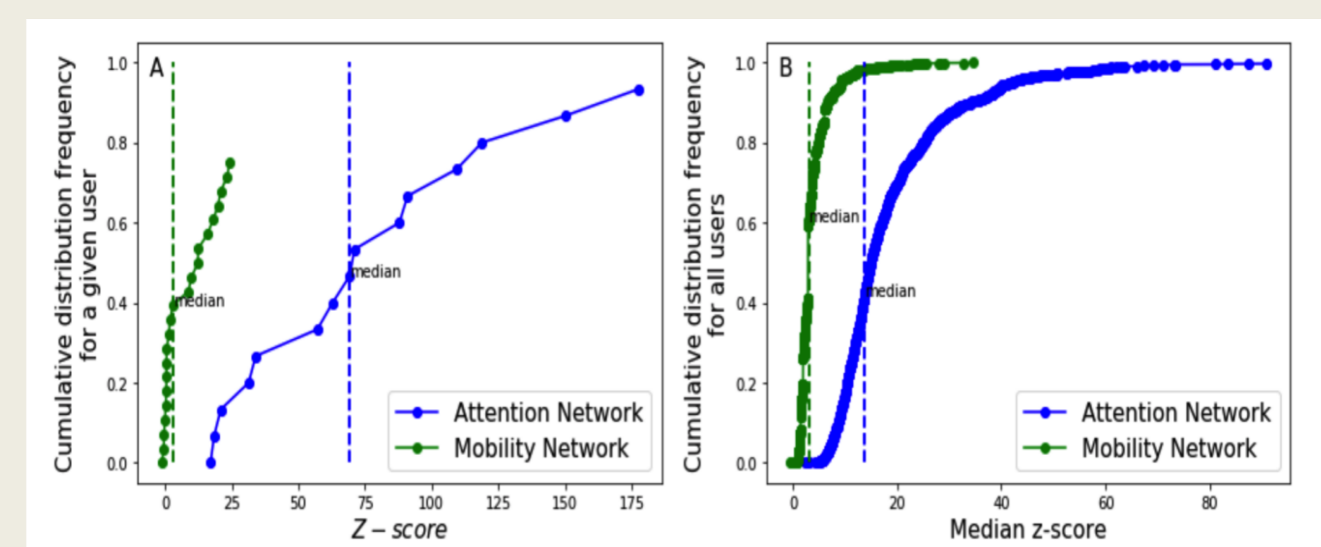

Figure 2. CDF for a given user and for all users

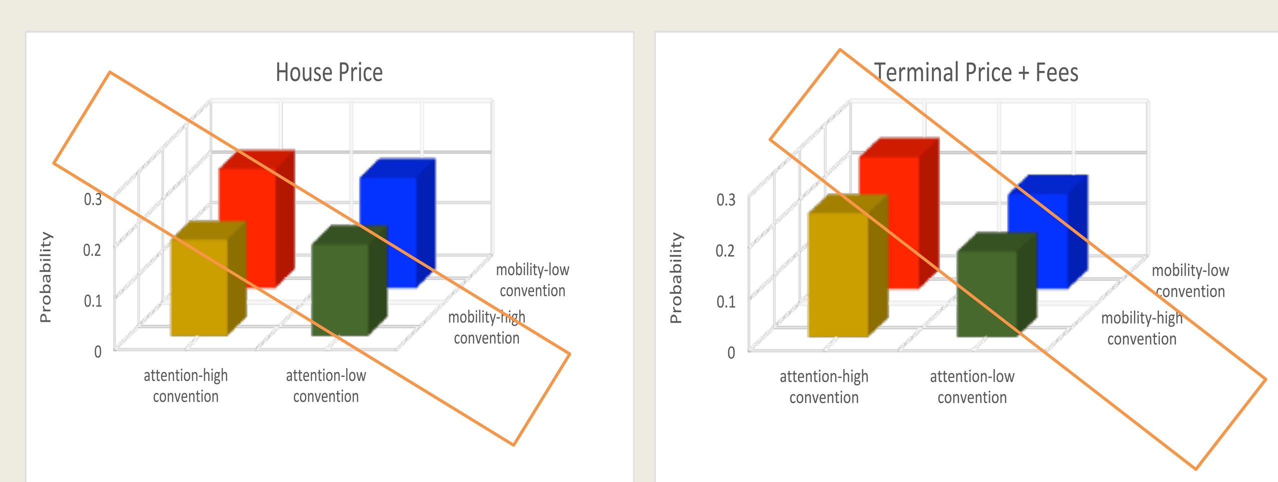

Figure 3. Social class and 2*2 categorizations

DISCUSSION

As to the question how social classes influence trajectory, we explore four reasons.

1. Schedule

We can divide the time intervals into two - work time (from 7 am to 8 pm) and break time. We can see that during the break time, the rich use app significantly less than the poor but more than the poor when they work. So the rich have a more regular schedule.

2. Lifestyle

We use each type of apps to represent one part of lifestyle. The poor use the video, navigation type more frequently whereas the rich listen to music and read news more often.

3. Demand

We find that upper-class people have more communication, music, news, shopping and video types of application, indicating that the upper social class tends to have wider needs in these types even though they do not necessarily use them frequently.

4. Access to location

Regardless of the time, the rich walked more than the poor. The more variance for the rich indicates that they have more access to different locations.

CONCLUSIONS

Self-management of limited attention and energy is an important standard for class division.

The upper-class people save the energy to go to less common and public places, pay attention to more popular and social applications and have a regular schedule.

With the popularity of digital media, the attention of people in the lower class are more fragmented. And the inherent class limits their exploration in the mobility space.

The significant difference in the patterns of schedule, lifestyle and demand and access to locations suggests the solidification of social stratification.

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