Estimating Socioeconomic Attributes from Location Information

Shohei Doi (NII)
Takayuki Mizuno (NII/Univ. Of Tokyo)
Naoya Fujiwara (Univ. of Tohoku/Univ. Of Tokyo)
Motivation

- Location-based service has been used for administrative and marketing purposes (Hammer et al., 2017; Huan et al., 2017).
- In particular, the distribution of socioeconomic attributes of individuals are crucial.
  - However, due to privacy security like GDPR, it is hard to obtain personal data associated with location information.
- To overcome this limitation, Lamanna et al. (2018) estimate office of a twitter user by geo-tagged tweets actively posted in the daytime while Lenormand et al. (2016) infer a user’s house by tweets at night.
  - Personal attributes: mobile phone behavior (Ying et al., 2012; Al-Zuabi et al., 2019), SNS (Cesare et al., 2018; Kosinski et al., 2013; Aletras and Chamberlain, 2018), photo (Lewenberg et al., 2016)
  - Distribution of attributes: content of talk via phone (Blumenstock et al., 2015), tweet (Montasser and Kifer, 2017), restaurant info (Dong, 2019)
- In this study, we collect survey data including location information and predict personal socioeconomic attributes.
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   - Future Work: GPS Log

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Rakuten Insight Survey Data

58 Personal Attributes

Hobby

Preference

Family, Income
## Frequency of Visiting 52 places

<table>
<thead>
<tr>
<th>Place</th>
<th>Frequency of Visiting</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Convenience store (n=3960)</td>
<td>44.9 (1/2) 9.1 14.5 16.2 6.6 4.0 3.9</td>
</tr>
<tr>
<td>2. Supermarket (n=3960)</td>
<td>3.8 5.0 9.8 24.6 40.5 12.6</td>
</tr>
<tr>
<td>3. Appliance store (n=3960)</td>
<td>11.2 11.5 15.3 32.9 18.8 7.7</td>
</tr>
<tr>
<td>4. Outdoor equipment/sports equipment store (n=3960)</td>
<td>48.6 13.8 12.0 15.6 6.7 2.5</td>
</tr>
<tr>
<td>5. Interior decoration store (n=3960)</td>
<td>31.1 22.5 15.8 20.1 7.5 2.4</td>
</tr>
<tr>
<td>6. Home center (n=3960)</td>
<td>21.2 11.4 12.6 23.9 18.5 8.9 2.8</td>
</tr>
<tr>
<td>7. Discount shop (n=3960)</td>
<td>28.8 9.4 9.1 19.1 16.0 10.3 4.6 2.3</td>
</tr>
<tr>
<td>8. Department store (n=3960)</td>
<td>22.3 10.9 11.4 22.5 18.1 9.7 3.7</td>
</tr>
<tr>
<td>9. Shopping mall (n=3960)</td>
<td>23.2 9.7 10.6 21.2 17.6 11.7 4.1</td>
</tr>
</tbody>
</table>
Representative Population?

![Bar chart showing the comparison between two datasets for different social media platforms: Facebook, Twitter, Instagram, YouTube, LINE, LinkedIn, and TikTok. The chart indicates the percentage of users for each platform based on the administrative data and the survey data.](image)
Future Work: GPS Log

GPS log -> stop detection -> apply our classifier

Stop is detected if
20 > minutes
0.2 < km

GPS log for one month and
Personal attributes of
100 individuals in Tokyo
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      ◆ SVM
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Logistic regression with L1 regularization

-> shrinking coefficients

-> avoiding over-fitting & selecting important features
Naive Bayes (Gaussian)

According to Bayes rule, the probability of personal attribute, \( y \), conditional on location information, \( x \):

\[
p(y|x) = \frac{p(y)p(x|y)}{p(x)}
\]

Elements of location history, \((x_1, \ldots, x_n)\), are independent:

\[
p(x|y) = \prod p(x_i|y)
\]

Each location, \( x_i \), is normally distributed:

\[
p(x_i|y) = \phi(x_i|\mu_y, \sigma_y)
\]
Random Forest, XGBoost, LightGBM

Prediction by many weak decision trees

In boosting, weak trees are generated based on previous failures.
**Support Vector Machine (RBF)**

SVM finds (hyper)plane separating sample into positive and negative ones. Kernel trick expand the dimension of feature space to improve prediction.
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**ROC AUC, PR AUC, MCC**

Confusion Matrix

<table>
<thead>
<tr>
<th>Predicted Positive (1)</th>
<th>Actually Positive (1)</th>
<th>Actually Negative (0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Positives (TPs)</td>
<td></td>
<td>False Positives (FPs)</td>
</tr>
<tr>
<td>False Negatives (FNs)</td>
<td></td>
<td>True Negatives (TNs)</td>
</tr>
</tbody>
</table>

Imbalanced data --> Accuracy is unreliable

Matthews coefficient: correlation of confusion matrix
Cross-validation, SMOTE

5-fold CV to evaluate performance

Up-sampling by SMOTE
Gender

XG-Boost
Train: 3000 in Tokyo
Test: 400 in Miyagi
400 in Hiroshima
160 in Nagasaki
Important Features for predicting gender
XG-Boost
Train: 3000 in Tokyo
Test: 400 in Miyagi
400 in Hiroshima
160 in Nagasaki
Important Features for Predicting Age

- Clinic
- Barber shop
- Dental office
- Supermarket
- Museum
- Hospital
- Golf course
- Automotive store
- Culture center
- Shrines Temples
- Luxury hotel
- Soccer ground (playing), Futsal court
- Beauty salon
- Furniture store
- Amusement park
- Baseball park (playing), Batting cage
- Beach
- Shopping mall
- Nursery, Kindergarten
- Wedding Hall
- Pub, Bar
- Karaoke, Internet cafe
- Penny arcade
- School
Overall Performance
Conclusion

acional socioeconomic attributes from location information.

Gender is predicted as accurately as existing studies using other information (accuracy is around 85%).

Hobbies which requires specific facilities are well predicted.

Whether they have infants and children or not is predictable while whether they live with adults and elderly people is not.

Other attributes not explicitly related to location, like income, use of web apps and indoor activities are hard to estimate.

In a future work, we apply the classifiers developed in this study to actual GPS log data to estimate personal attributes.