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You Are What Apps You Use: Demographic Prediction Based on User's Apps

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Abstract

Understanding the demographics of app users is crucial, for example, for app developers, who wish to target their advertisements more effectively. Our work addresses this need by studying the predictability of user demographics based on the list of a user's apps which is readily available to many app developers. We extend previous work on the problem on three frontiers: (1) We predict new demographics (age, race, and income) and analyze the most informative apps for four demographic attributes included in our analysis. The most predictable attribute is gender (82.3 % accuracy), whereas the hardest to predict is income (60.3 % accuracy). (2) We compare several dimensionality reduction methods for high-dimensional app data, finding out that an unsupervised method yields superior results compared to aggregating the apps at the app category level, but the best results are obtained simply by the raw list of apps. (3) We look into the effect of the training set size and the number of apps on the predictability and show that both of these factors have a large impact on the prediction accuracy. The predictability increases, or in other words, a user's privacy decreases, the more apps the user has used, but somewhat surprisingly, after 100 apps, the prediction accuracy starts to decrease.

Introduction

In 2014, 60 % of internet traffic was estimated to come from mobile devices[1], of which 51 % was attributed to apps.[2] As the importance of mobile apps continues to rise, some have even declared that "apps are the new Web"[3]. Though claims of the Web's demise are probably exaggerated, the number of available mobile apps continues to increase and with it, one would expect, the importance of apps for the wider Web ecosystem.

At the same time, most academic studies looking at "online users" still concentrate on website visits with, by comparison, much fewer attention being given to mobile apps. In this paper, we study the predictability of six demographic attributes based on the list of used apps.

The most apparent applications of demographic prediction methods are in marketing. For instance, an app developer might be interested in understanding which user segments are underrepresented when designing new ad campaigns for the app. On the other hand, computational social scientists, studying the behavior of people as observed through an app, like Twitter, need to understand how representative users of the app are as a sample of the whole population.

Studying the predictability of demographics also points out privacy implications of users allowing apps to access their list of installed apps. Many users undoubtedly do not carefully review the permissions that the apps they install require, and even less, understand the scope of the information that can be inferred from the data accessible by the apps.

The only previous studies on demographic prediction based on lists of apps, we are aware of, are (Seneviratne et al. 2014; 2015). In the latter work, only gender prediction is studied and the dataset comprises of 218 users. We have obtained a dataset of 3 760 users, which allows us to perform more fine-grained analyses, e.g., looking into the effect of app count on the predictability, and to obtain statistically more reliable results.

Material

Our dataset contains the demographic attributes and a list of apps for 3 760 Android users. While (Seneviratne et al. 2015) analyze the lists of *installed* apps, we are studying the lists of apps *used at least once* within a period of one month in 2015. Some very rarely used apps are probably missing from the latter list, but nevertheless, the lists can be expected to be highly correlated.

The average number of apps per user is 82.6 and the number of unique apps is 8 840. Apps with less than ten users have been discarded to remove all personally identifiable information. The dataset is from Verto Analytics who have provided us a subsample of their media-measurement panel from the US. The panelists were recruited with the target of getting a representative sample of the US population. Each panelist has installed a meter app which tracks their app usage, and in return, the user is paid for providing the data.

[1]http://smallbiztrends.com/2014/07/online-traffic-report-mobile.html

[2]Another 2015 report by Morgan Stanley put this fraction closer to 33 % though, with mobile web browsing dominating mobile traffic http://tinyurl.com/jstkty7.

[3]http://tinyurl.com/3a3ru2o

Table 1: Demographic prediction accuracy based on a user's apps. Classes have been binarized and balanced. AUC (Web) column shows the prediction performance based on visited websites from (Goel, Hofman, and Sirer 2012).

Attribute	Classes	Accuracy	AUC	AUC (Web)
Gender	Male vs. Female	82.3 %	0.901	0.84
Age	18–32 vs. 33–100	77.1 %	0.850	0.85*
Race	White vs. Non-white	72.7 %	0.801	0.83
Married	Married vs. Single	72.5 %	0.792	NA
Children	0 vs. ≥ 1 children	63.5 %	0.688	NA
Income	$\leq$ \$40K vs. $>$ \$40K	60.3 %	0.645	0.75*

Methods

When choosing a suitable prediction method, it is important to consider the following characteristics of the dataset: (1) feature vectors (bags–of–apps) are binary and very sparse, (2) the number of features, 8 840, is larger than the number of datapoints, 3 760, and (3) the dependent variables (user demographics) can be treated categorical.

Logistic regression is a natural choice for this type of a problem. We also tested support vector machines with different kernels and random forests, but both the results and the running times were inferior. While logistic regression can be adapted to multi-class problems, we instead binarize the demographic variables and balance the classes. This allows us to compare the predictability of different demographic variables.

Results

Next, we show results related to three different aspects of demographic prediction, namely, (1) the predictability of different demographics, (2) the effects of the training set size and the number of user's apps, and (3) the effect of various dimensionality reduction methods.

How Much is Revealed by Which Apps?

Classification accuracies for six different demographic attributes are shown in Table 1. They are computed based on a ten-fold cross-validation, and the most predictable attribute is *gender*, whereas the *household income* of a user is the most difficult to tell based on the list of user's apps. The results are surprisingly similar to the AUC scores reported by (Goel, Hofman, and Sirer 2012) who employed visited websites as the features instead of apps. In their work, the attributes marked with '*' had a slightly different binarization threshold compared to us. The receiver operating characteristic for gender, given in Figure 1a, shows that for half of the users, the gender can be predicted with a 97 % accuracy.

By studying the coefficients of the logistic model, we can analyze the contribution of individual apps to the predictions. The coefficients with the largest absolute values are the most predictive ones. In Table 2, we have listed these apps for four different demographics along with the coefficients, the shares and the numbers of users who have used the app[4]. Many of the results are not surprising; for instance, period tracking apps are good predictors for gender, whereas dating apps are more informative about the marital status.

How Much Does the Size Matter?

We also study the gender prediction accuracy as a function of the training set size in Figure 1b. An absolute improvement of more than ten percents can be obtained by increasing the training set size from 100 users to 2 300 users. Error bars show the standard deviations of the accuracies over 100 balanced random subsamples per given number of train users.

(Seneviratne et al. 2015) report an accuracy of 69.8 % for a dataset of 174 users, 50 % of which are used for training (their original dataset is 218 users but they undersample the majority class to balance the classes). To be able to benchmark against this result, we take 300 balanced random subsamples of 174 users and run 2-fold cross-validation for these samples. We obtain a comparable average accuracy of (68$\pm$5)% even though we are not using content-based features derived from app descriptions nor numeric features as done in (Seneviratne et al. 2015). This suggests that the bag–of–apps features alone can provide a competitive performance. Furthermore, these features can be extracted more easily, without having an access to an API for scraping the Google Play store.

A user who has installed a hundred apps probably reveals more of herself than a user with five apps. Thus it is relevant to ask, how quickly is privacy lost when the number of apps increases. In Figure 1c, we tackle this question by binning the users according to the number of apps they have used and showing the prediction accuracy averaged over all demographic attributes of all users in a bin. The standard errors are given by $\sqrt{p(1-p)/n}$. The results show that the accuracy increases by about ten percents going from 20 apps to 100 apps but after that, somewhat surprisingly, the accuracy starts to decrease. To test whether the decrease is statistically significant, we perform an independent two-sample t test with the following null hypothesis: "The overall demographic prediction accuracy is not higher for the users with 50-150 apps compared to the users with more than 150 apps." We can reject the null hypothesis ($p = 0.014$), which shows that using a lot of apps at least once per month actually increases privacy.

Dimensionality Reduction

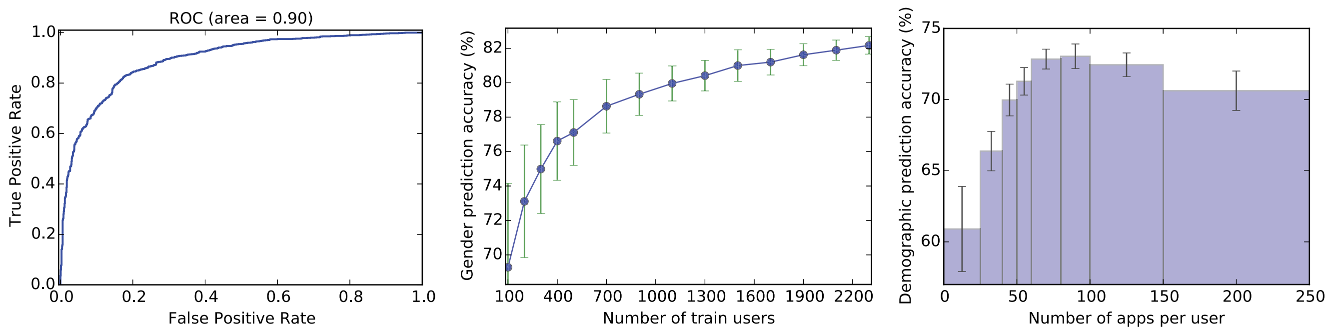
Due to the high dimensionality of feature vectors (8 840 unique apps) we study three different dimensionality reduction approaches.

The first method, adopted by (Seneviratne et al. 2015), considers only the apps installed by at least 10 % of the users (125 apps in total). With this approach the gender prediction accuracy drops from 82.3 % to 73.6 %, and even with the dataset of 174 users, the accuracy is decreased from 68 % to 65 %. It is important to use the full list of apps since some of the apps might be reliable predictors even though they are rare (think, for example, of a rare *period tracking* app).

[4]Note that for a given app, the number of users, n, might vary over demographics as some users have been removed when balancing the classes.

Table 2: The most predictive apps for different demographic attributes along with the logistic regression coefficients (Coef), the fractions of app users with the demographic attribute (Share), and the numbers of app users (n).

Gender (Male)				**Age (33–100)**				**Married (Married)**				**Income ($\geq$ \$50K)**			
Coef	Share	n	App name	Coef	Share	n	App name	Coef	Share	n	App name	Coef	Share	n	App name
0.81	85 %	150	ESPN	0.53	80 %	42	Great Clips Online Check-in	0.55	67 %	200	Zillow Real Estate & Rentals	0.58	75 %	141	Fitbit
0.73	80 %	142	Geek - Smarter Shopping	0.48	53 %	1687	Email	0.44	67 %	622	Walmart	0.45	66 %	205	LinkedIn
0.63	78 %	277	Tinder	0.46	58 %	318	New Words With Friends	0.44	60 %	823	Pinterest	0.41	65 %	41	com.ws.dm
0.59	80 %	172	Fallout Shelter	0.44	80 %	65	BINGO Blitz	0.44	74 %	39	Gospel Library	0.37	52 %	141	LG Android QuickMemo+
0.56	86 %	106	WatchESPN	0.43	60 %	380	iHeartRadio - Music & Radio	0.40	59 %	91	USAA Mobile	0.37	58 %	191	Redbox
0.52	72 %	190	Clash of Clans	0.41	54 %	197	Field Agent	0.40	80 %	63	ClassDojo	0.36	72 %	22	Like Parent
0.52	97 %	41	Grindr - Gay chat, meet & date	0.40	55 %	690	Lookout Security & Antivirus	0.38	60 %	123	ESPN	0.34	66 %	63	Peel Smart Remote
0.49	84 %	96	Yahoo Fantasy Football & More	0.40	92 %	41	DoubleUCasino	0.37	82 %	28	Deer Hunter 2014	0.34	61 %	220	Yelp
Gender (Female)				**Age (18–32)**				**Married (Single)**				**Income ($\leq$ \$40K)**			
-1.03	76 %	736	Pinterest	-1.17	78 %	1066	Snapchat	-0.89	70 %	810	Snapchat	-0.43	66 %	136	Job Search
-0.73	84 %	182	Etsy	-0.52	59 %	113	Perk Word Search	-0.78	89 %	114	POF Free Dating App	-0.43	63 %	97	Security policy updates
-0.61	97 %	79	Period Tracker	-0.49	64 %	88	Summoners War	-0.73	85 %	219	Tinder	-0.37	78 %	23	Solitaire
-0.54	96 %	58	Period Calendar / Tracker	-0.46	59 %	98	Clash of Kings	-0.66	98 %	69	OkCupid Dating	-0.35	67 %	79	Prize Claw 2
-0.50	76 %	346	Cartwheel by Target	-0.45	86 %	90	iFunny :)	-0.48	72 %	269	Tumblr	-0.34	72 %	51	ScreenPay- Get Paid to Unlock
-0.49	66 %	258	Wish - Shopping Made Fun	-0.45	81 %	158	GroupMe	-0.42	72 %	205	SoundCloud - Music & Audio	-0.33	78 %	56	MeetMe
-0.49	74 %	325	Checkout 51 - Grocery Coupons	-0.42	80 %	68	GIPHY for Messenger	-0.41	65 %	331	Uber	-0.33	62 %	77	Foursquare
-0.45	74 %	178	Photo Grid - Collage Maker	-0.42	80 %	183	Vine	-0.41	89 %	69	MeetMe	-0.32	56 %	73	Microsoft Word



(a) ROC curve for gender prediction. 'Male' is treated as the positive class.

(b) Effect of training set size on gender prediction.

(c) Effect of user's app count averaged over all demographics.

Figure 1: Demographic prediction results.

The second method, also adopted by (Seneviratne et al. 2015), aggregates the installed apps to category level based on Google Play categorization. In our dataset, there are apps from 48 categories. We take the number of apps in each category as the features, which yields an accuracy of 74.6 %.

The third method employs the Truncated Singular Value Decomposition (TSVD). (Hu et al. 2007) also employ TSVD, but instead of using the SVD components directly as features for predicting the demographics of web users, they adopt a recommender system approach. Setting the number of dimensions to 48, we obtain a gender prediction accuracy of 76.9 %. This shows that rather than using the Google Play categories of the apps, it is better to use the same number of SVD components learned in an unsupervised manner. However, the performance is clearly worse compared to not using any dimensionality reduction, and even by increasing the number of SVD components, we were unable to exceed the performance of the logistic regression with all features, although with 500 components, the accuracy is already 81.8 %.

In conclusion, none of the explored dimensionality reduction methods helped us to improve the gender prediction accuracy. We should also note that although TSVD can help to reduce the data dimensionality to about one-tenth of the original without losing much in accuracy, this still does not necessarily help with the space complexity of the method. The reason is that unlike the SVD components, the original bag–of–apps features are very sparse and the logistic regression implementation we use[5] supports sparse matrices.

Related Work

Characterizing the demographics of Twitter users has been studied by (Mislove et al. 2011) who infer geography, gender, and race of the users based on self-reported locations and the names of the users. They find large deviances from the demographic distribution of the overall population. (Duggan et al. 2015) provide a more extensive demographic comparison of five social media platforms based on telephone interviews. (Goel, Hofman, and Sirer 2012) look into the demographics and behavior of web users, whereas (Weber and Jaimes 2011) study the same for search-engine users.

The demographic prediction based on user's apps has been previously studied by (Seneviratne et al. 2015) who predict the users' gender. In their previous work (Seneviratne et al. 2014), they also predict language, country, relationship status, and whether the user is a parent, but in-

[5]http://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

stead of predicting these attributes directly, they first predict which apps are associated with the attributes and then check whether a user has apps corresponding to a given demographic attribute. We extend these works by studying new demographics (age, race, and income), showing that increasing the training dataset size drastically improves the prediction accuracy, and comparing various dimensionality reduction methods for the app data.

Others have studied demographic prediction, e.g., based on website visits (Hu et al. 2007; Goel, Hofman, and Sirer 2012), social network features (Brea et al. 2014; Al Zamal, Liu, and Ruths 2012), call patterns (Sarraute, Blanc, and Burroni 2014), Twitter followers (Culotta, Ravi, and Cutler 2015) and profiles (Chen et al. 2015), and location data (Riederer et al. 2015). Related to demographic prediction, (Chittaranjan, Blom, and Gatica-Perez 2013) investigate the predictability of personality traits based on apps and other smartphone usage features. There also was an app for predicting personality based on installed apps[6].

Conclusions and Discussion

We studied the demographic prediction problem based on the list of used apps. Large differences in the predictability were observed between the six demographic attributes studied in this work, gender being the most predictable and income being the hardest to predict. The apps contributing the most to the predictions were identified for each attribute, revealing some expected patterns: dating apps are used, although not exclusively, by single people, and high-income people are more likely to use *LinkedIn*, whereas lower-income people prefer an app called *Job Search*.

We also studied various dimensionality reduction methods for high-dimensional app data (8 840 unique apps), finding out that SVD yields superior results compared to aggregating the apps on app category level, but the best results are obtained simply by the raw list of apps. Finally, we looked into the effect of the training set size and the number of apps on the predictability and showed that both of these factors can have an impact of over 10 % on the prediction accuracy. Interestingly, the predictability increases the more apps the user has used, but after 100 apps, the prediction accuracy starts to decrease. The accuracy drop from users with 50-150 apps to users with more than 150 apps was found to be statistically significant.

Several interesting questions are left for future work. First, we note that demographic attributes are most likely not independent, and therefore, predicting the attributes simultaneously, employing multi-label prediction techniques, could improve the performance. Second, we plan to study the demographics of various popular apps to understand potential biases in their userbases compared to the whole population. Third, it would be interesting to study the usage patterns of different demographic groups (as done previously in the context of web search (Weber and Castillo 2010)) to better understand the effects of demographic biases.

[6]http://www.idigitaltimes.com/what-do-your -apps-say-about-you-new-app-iphone-here -tell-you-410883

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