# Enhancing User's Income Estimation with Super-App Alternative Data

Gabriel Suárez[1], Juan Raful[1], Maria A. Luque[1], Carlos F. Valencia[2], and
Alejandro Correa-Bahnsen[1]

[1] Rappi, Cl. 93 #19-58, Bogotá, Colombia.
[2] Industrial Engineering, University of Los Andes, Cra 1 Este 19-40, Bogota,
Colombia

**Abstract.** This paper presents the advantages of alternative data from
Super-Apps to enhance user's income estimation models. It compares
the performance of these alternative data sources with the performance
of industry-accepted bureau income estimators that takes into account
only financial system information; successfully showing that the alterna-
tive data manage to capture information that bureau income estimators
does not. By implementing the TreeSHAP method for Stochastic Gra-
dient Boosting Interpretation, this paper highlights which of the cus-
tomer's behavioral and transactional patterns within a Super-App have
a stronger predictive power when estimating user's income. Ultimately,
this paper shows how alternative data benefit financial institutions from
a credit risk perspective.

**Keywords:** Fintech · Income Estimate · Alternative Data · Credit Risk.

## 1   Introduction

Technology-based companies are disrupting traditional business lines while they
show an unprecedented ability to capture, manage, and analyze large volumes
of customer data, previously unavailable to the organizations that traditionally
operated in such lines, and therefore becoming increasingly competitive within
them [9,28,19]. Given this, the business model of Super-Apps has emerged. Those
are, mobile applications that seek to satisfy a various number of customer's daily
needs, all within the same marketplace-based application. Whereas tradition-
ally, users could only found those different services and solutions in a mobile
application specifically designed for providing each one of them, like Uber for
transportation and Uber Eats for delivery services.

One of the traditional sectors Super-Apps is venturing into is the financial
sector, and so, it is logical then to raise the question on whether this Super-
App data adds value within this field. This publication will explore how this
alternative data might help financial institutions address one of the fundamental
questions in credit risk management; that is, how much it should be lent to a
customer, by building the most accurate user income estimate. This paper will
then try to determine the following research questions:

1. Is there a significant improvement in income estimation statistical performance when using alternative data sources, retrieved from a Super-App, compared to industry-accepted Income Estimates?
2. What behaviors these Super-App features reveal, and how do they differ from traditional financial information resources?
3. Which of these behaviors appear to offer more predictive power?

## 2    Credit Risk and Income Estimation

Financial Institutions have to effectively manage credit risk to lend money to their customers, being this the potential that their counter party will fail to meet its obligations under agreed terms [3]. Hence, the challenge for these companies relies on the fact that each customer has a different probability of failing his particular obligations (PD) (as this is the reflection of each customer individual psychological characteristics [31] together with its financial knowledge, demographic characteristics and situational factors [21]) , as well as an individualized credit loss amount if the debtor of the loan defaults or so called loss given default (LGD) [31,21,3,27]. Therefore, financial institutions have to answer two fundamental questions for their accurate credit risk management, being one to which customers should these institutions lend money to and the second one, how much money should they lend to them. To address the second question, it is necessary for financial institutions to estimate each of its customers' payment capability. Properly calculating the amount of money they should lend to its customers allows financial institutions to accurately estimate their exposure at default (EAD) [3], which ultimately leads to organizations to operate within their desired expected loss (EL) in correspondence with their risk appetite. $EL = PD * LGD * EAD$.

Traditionally, financial institutions take user's income as a starting point to answer this second question. Nevertheless, the willingness of consumers to provide this information is relatively low, as user's income, being part of the user's financial information, is the most sensitive data to provide from their personal identifiable information [22]. This, leads financial institutions to try estimate user's income from their available financial information, and in some cases having to require it from third party institutions that gather this type of data. This estimate is, for some organizations, the best proxy for knowing this relevant user feature. However, having an income estimator that relies absolutely on financial information marginalizes the opportunity to have a complete profile of those users who do not have information within the financial system.

## 3    Users Interactions with Super-Apps

Alternative Data sourced from a Super-App can be retrieved from the various ways users of the Super-App interact and navigate through it. Moreover,

each transaction carried out within them different solutions (Delivery of restaurants/groceries/goods, transportation, travel, e-commerce and many more) generates different types of data. The features that can be collected then variate in their values in unique ways for each user as they reflect their individual behavioral and consumption patterns, and can be grouped into four categories:

**Personal Information:** The identifiable demographic attributes of the user such as age, place of residence, the brand of cell phone as well as personally identifiable information such as wealth estimators or address from where the orders where placed.

**Consumption Patterns:** User's consumption patterns are retrieved from the delivery vertical within the Super-App, which are all the services and solutions related to the purchase and delivery of groceries, food, clothing, technology, pharmaceutical products, and others.

**Payment Information:** This is the information that can be retrieved from all of the transactions the user makes in the Super-App. The features that can be extracted from this type of interaction allow identifying user's favorite payment method, tendencies of installments when paying regular orders versus more expensive orders, number of times a credit card is declined and even the number of credit cards the user has available to pay within the app and the level of them.

**Financial services:** This last set of features comes from the fintech functionality within the Super-App. These features collect users' behavior towards the financial services or products delivered via technology ranging from e-wallets and digital cards to loan services, on- and offline payments, and money transfers [24].

## 4   Experimental Setup

### 4.1   Data

Our data set consists of 43.270 observations of the transactional historical information of users within a Super-App. This transactional information is collected directly from the orders and interactions with more than 15.000 restaurants and 2.000 grocery stores. Moreover, we had access to the certified income of the users who built the training and testing sets for the model, together with their Bureau Income Estimates.

### 4.2   Setup

It was decided to implement an XGBoost model for the scope of this research as it has proven to outperform other algorithms with regard to structured data [34,26]. Considering this research is being carried out within a business environment, evaluating statistical model performance has to come in handy in terms of interpretability. Hence, we will evaluate the proposed model performance according to the Mean Average Percentual Error (MAPE) and the performance of the features accoding to SHapley Additive exPlanations [17]. We implemented cross-validation with five splits for evaluating the model, keeping a data proportion of 80% -20% for training and testing in each iteration, respectively.

## 5    Results

### 5.1    Statistical model performance

The results obtained in this study show a significant improvement in performance in terms of the MAPE for the model that incorporates Super-App alternative data compared with the Bureau Income Estimates by themselves as can be seen in Figure 1. Moreover, an equivalent performance of the model versus the Super-App only is obtained. Hence, our results suggest that financial institutions can build better and more accurate estimates solely with this alternative data without requiring a particular bureau income estimate.
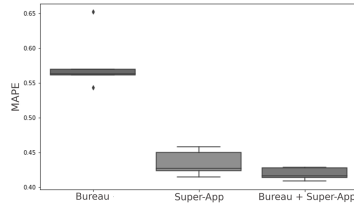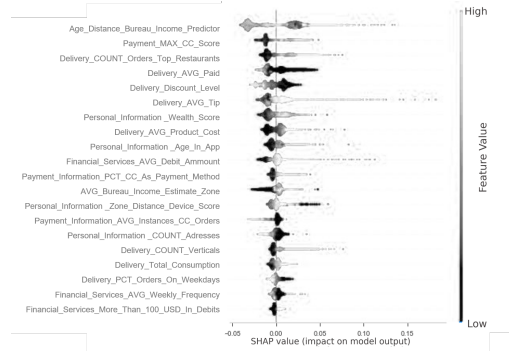


**Fig. 1.** MAPE performance by model



**Fig. 2.** Local interpretability with SHAP of Bureau + Super-App model

### 5.2    Feature Importance

In order to be able to determine which of the behavioral patterns identified have more predictive power when estimating users income, as previously mention, we implemented SHapley Additive exPlanations [17] in order to give some degree of explainability to the results of the executed XGBoost model.

Figure 2 is the visualization for the Bureau Income Estimates combined with Super-App alternative data model feature importance, where features appear from top to bottom in order of importance; Figure 2 shows that the distance of the industry-accepted Bureau Income Predictor of the user and the average of the same estimate for the users within the same age range presents the highest predictive power from the considered features. In contrast, as for alternative data features, the number of times the user has placed orders at one of the most expensive restaurants within the Super-App (Where the average plate has a value higher than the average plate of 70% of the other restaurants) has the most robust predictive value. Furthermore, Figure 2 shows each feature's impact on the combined features model. Notably, users with a taste for expensive (top)

restaurants, a higher delivery consumption, a higher amount of money debited through financial services, and users with high-level or premium credit cards registered in the app, are estimated to have a higher income. It can also be highlighted that users with a taste for discounts are predicted to have lower incomes than users who do not use discounts in their delivery orders. The tipping behavior results show that users who on average tip less in their delivery orders are estimated to have lower incomes than users that leave higher tips. Hence our results indicate that the propensity of tipping high, the taste for expensive restaurants and products, and overall a high monetary consumption and high amount of money debited through financial services are all strong positive income estimators. On the other hand, our results show that the preference to place orders with discounts is a robust negative income estimator.

## 6   Conclusions

This paper determined that the proposed Super-App alternative data have predictive power towards income estimation. Moreover, there is a significant improvement in statistical performance when taking these alternative data sources into account compared to the performance of industry-accepted Bureau Income Estimates by themselves. It was possible to identify consumption patterns, personal information, payment behavior, and engagement towards financial products from the users' interactions with the Super-App, being all this information non-available to traditional bureau estimates, that incorporate only past financial information of the user.

Finally, we presented how financial institutions that possess this kind of information could benefit from it by building more complete users' credit risk profiles. Therefore, helping them operate within a more accurate expected loss and addressing in a less biased way the fundamental credit risk question of how much money should they lend to their customers. Furthermore, this paper shows how financial institutions that manage to incorporate Super-App sourced alternative information into their credit risk profiling will be able to assess the income of customers who do not have previous financial information which should represent a benefit towards the bankarization of this population, which is outside the reach of traditional bureau income estimates.

This study's results show the incentive for financial institutions to seek to incorporate this type of information into constructing their risk profiles. Doing so will allow them to keep up with these technology-based financial institutions that, in the meantime, will have a competitive advantage if they manage to align their strategical operation with the insights of the data they can collect. Additionally, our findings should motivate further research in this field to determine what other sources of alternative information can provide value towards building complete and accurate profiles for financial institutions' users.

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