Combatting fraudulent fintech with machine learning

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1. There have been increased concerns over problematic finance mobile apps in recent years

2. Efforts to combat “scam apps” limited by various issues:
   • Lack understanding of scale and scope of problem in app stores
   • Reactive rather than proactive solutions
   • “Whack-a-mole” approach of “scam app” developers

3. We leverage varied app data to systematize evidence and classify problematic apps

4. We complement existing solutions by applying ML techniques to increase efficiency and speed of ex-ante vetting and ex-post monitoring

5. Preliminary results are promising
Today’s agenda

1. The problem
   Framing the problem
   Systematizing evidence with new data

2. The proposed solution
   Methodology
   Results
   Model evaluation

3. Next Steps & Conclusion

4. Q & A / Feedback
The problem
Anecdotal Evidence & Media Coverage

There has been increased media coverage highlighting problematic finance mobile applications. Examples of recent sources include:
Stakeholders have started documenting issues and developing solutions:

1. **Supervisory / Regulatory responses**
   - Creation of / improvement of complaints channels
   - Registering digital lenders and platforms (e.g., PH-SEC, OJK)
   - Ensuring data privacy regulation (e.g., RBI, PH-NPC)
   - Expanding role of associations and codes of conduct (RBI-DLAI, OJK-AFPI, PH-SEC-Fintech Alliance)
   - Cautioning the public (e.g., RBI, PH-NPC)
   - Direct action to remove problematic apps (e.g., RBI)

2. **External stakeholders**
   - Monitoring social media (CGAP/World Bank)
   - RBI Working Group developing strategies
Limitations of current knowledge and solutions

1. Lack systematic understanding of scale and scope of problem amongst mobile finance apps

2. Reactive rather than proactive solutions

3. “Whack-a-mole” approach of “scam app” developers

4. Based on our recent review, still large number of problematic apps and users falling victim

Our proposed solution

- Leverage existing high-frequency app data and apply machine learning techniques to both static and real-time data
- Complement current solutions by offering method that can improve both ex-ante vetting and ex-post monitoring.
1. **Primary data source:** Third-party app intelligence provider

2. **Types of data obtained / used:**
   - App meta-data
   - App review data
   - Historical download data

3. **Data coverage:** all “finance” category apps in Google Play store for 63 countries

4. **Time coverage:**
   - App meta-data: monthly from January 2020 - April 2021; does not include if unpublished prior to 2020
   - App review data: historical, covering until April 2021
   - App download data: historical, covering until April 2021
Example of app meta data (from legitimate provider)

Tala - Instant Loans

50 lakh people worldwide have trusted Tala

Friendly customer support

Loan approval in 10 seconds

No hidden charges. Know what you pay.

Join millions of satisfied Tala customers who have managed expenses, paid school fees, and grown their businesses with peace of mind.

How do I get a loan?
- Download the app and fill a quick form in the app
- Get your loan offer approval in under 10 seconds
- Verify your identity through our secure system
- Get your loan directly in your bank account
- No salary slip, bank statement or credit score needed.

What is the loan amount?
Your first loan amount starts from 5000 - 11000. Grow with Tala and build your limit up to 100,000 with every on-time payment. Each loan has a tenure of 60 days.

How do I repay my loan?
- Make easy electronic payment in the app
- Choose to pay with debit card, UPI, netbanking, or wallets.
- Easy payment schedule keeps you on track with your payments

Get started. Download the Tala app now.

Tala accepts applications on behalf of its partners DMI Finance Private Limited and Apollo Finvest India Limited, licensed NBFCs regulated by RBI, to provide loans to its customers.

Updated
September 27, 2021

Size
13.9M

Installs
100,000+

Current Version
1.29.0

Requires Android
5.0 and up

Content Rating
PG13

Permissions

Report
Flag as inappropriate

Offered By
Tala Mobile

hello@tala.co.in
Privacy Policy
1633 26th St, 3rd Floor
Santa Monica, CA 90404
Example of app meta data (from legitimate provider)
## Meta data variables

### Visible data
- Title
- Short/long text description
- Screenshots
- Date last updated
- Byte size
- External version number
- App developer
- Developer website
- Developer email
- Developer physical address
- Download / installs estimate (bucket)
- # of ratings
- # of reviews
- Promo video

### Hidden data
- Date created
- Disaggregated # ratings (1-5)
- Internal version code
- Software Development Kit (SDK) list
- Permissions list
- Whether contains ads
- Number of reviews
- App price
- In-app purchases
- Min/Max price for in-app purchases
- Interactive elements
- Countries available in
- Main language
- Languages available in
- Other app-stores available in
- Downloads (country-day level)
Example of review data (from legitimate provider)

Tala - Instant Loans

REVIEWERS

Most relevant ▼ All Devices ▼ All Ratings ▼

User reviews:

Akinlan ID
August 25, 2021
Borrowed the loan 3 times never gets late or any issues but every time one 1000 is increasing in my loan so please increase the loan amount that’s my request, overall fantastic when in urgent Tala is there thanks for everything.

Tala Mobile
August 25, 2021
Hi Akinlan, thanks a lot for the review and for your valuable feedback. We are constantly trying to improve the user experience and rolling out regular updates. We will have this suggestion regarding the loan limit looked into.

Sadie Barber
August 22, 2021
Best loan app with customer friendly experience. Loved it 😊

Tala Mobile
August 22, 2021
Hi Sadie, it is delightful to hear such positive feedback. We hope to serve you in the future too. Thank you for choosing and trusting us!

Mantri
September 14, 2021
Do not deserve a star too when u dont have verification team working at time of loan application to verify or technical issues, why to reject it when u can put it on pending status.

Tala Mobile
September 16, 2021
Hi Mantri, very sorry about your experience! Please note that we are working at reduced capacity & only able to approve limited loans. Our system takes many factors into consideration before making decisions. For further questions, please write to us at help@tala.co.in or on the in-app chat.
Example of review data (from legitimate provider)

Review data
Rating (1 to 5)
Date of review
Review text
User name*
Profile pic*

*Not included in 3rd-party data provider’s data but manually collecting
To make pilot tractable, we categorize and narrow down to a subset of pure-play personal loan apps of interest:

1. Full sample: 134,744 “finance” category apps

2. We categorize apps broadly by product and provider type
   - Currently: “regular expressions” on meta-data titles, short, and long descriptions to tag product and provider types
     - E.g., to tag personal loans: parse texts for “personal loan(s)”, “consumer loan(s)”, “payday loan(s)”, etc.
     - Apply combinations of tags to filter to more precise subcategories

3. Current limitation
   - Note: About 65% of apps have English as main language (e.g., meta data descriptions)
   - Our analysis thus currently overlooks about one-third of finance-related apps
## Table: Categorization of finance apps in sample (Jan 2020-April 2021)

<table>
<thead>
<tr>
<th></th>
<th># of apps</th>
<th>% of apps</th>
<th>Est. # downloads (in M)</th>
<th>Avg. downloads per app</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Finance apps by EN vs. non-EN main language</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All finance</td>
<td>134,744</td>
<td>100.0%</td>
<td>6,970M</td>
<td>51,728</td>
</tr>
<tr>
<td>- All finance (EN main lang.)</td>
<td>87,426</td>
<td>64.9%</td>
<td>4,080M</td>
<td>46,668</td>
</tr>
<tr>
<td>- All finance (non-EN main lang.)</td>
<td>47,318</td>
<td>35.1%</td>
<td>2,890M</td>
<td>61,076</td>
</tr>
<tr>
<td><strong>Panel B. Finance apps by product categories (EN only)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All finance (EN main lang.)</td>
<td>87,426</td>
<td>–</td>
<td>4,080M</td>
<td>46,668</td>
</tr>
<tr>
<td>- General banking</td>
<td>18,015</td>
<td>20.6%</td>
<td>1,640M</td>
<td>91,035</td>
</tr>
<tr>
<td>- Payments</td>
<td>17,544</td>
<td>20.1%</td>
<td>1,830M</td>
<td>104,309</td>
</tr>
<tr>
<td>- Insurance</td>
<td>4,999</td>
<td>5.7%</td>
<td>397M</td>
<td>79,416</td>
</tr>
<tr>
<td>- Investment</td>
<td>4,325</td>
<td>4.9%</td>
<td>251M</td>
<td>58,035</td>
</tr>
<tr>
<td>- Credit, excl. personal loans</td>
<td>16,252</td>
<td>18.6%</td>
<td>1,290M</td>
<td>79,375</td>
</tr>
<tr>
<td>- Personal loans</td>
<td>5,106</td>
<td>5.8%</td>
<td>826M</td>
<td>161,770</td>
</tr>
</tbody>
</table>
Suggestive evidence of problems in personal lending apps (1/2)

We observe high “churn rates” (i.e., new entry and exits) among personal lending apps relative to other finance app categories.

Table: Percentage of finance apps newly-released & unpublished during study period (Jan 2020-April 2021)

<table>
<thead>
<tr>
<th>App product category</th>
<th>(1) All</th>
<th>(2) Banking</th>
<th>(3) Payments</th>
<th>(4) Insurance</th>
<th>(5) Investment</th>
<th>(6) General credit</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% New release</td>
<td>34%</td>
<td>22%</td>
<td>43%</td>
<td>30%</td>
<td>35%</td>
<td>39%</td>
<td>70%</td>
</tr>
<tr>
<td>% Unpublished</td>
<td>24%</td>
<td>13%</td>
<td>25%</td>
<td>20%</td>
<td>20%</td>
<td>26%</td>
<td>52%</td>
</tr>
<tr>
<td>Avg. app age (in mths.)</td>
<td>29.3</td>
<td>41.0</td>
<td>24.8</td>
<td>27.9</td>
<td>27.5</td>
<td>27.5</td>
<td>11.4</td>
</tr>
<tr>
<td>Observations</td>
<td>134,744</td>
<td>18,015</td>
<td>17,544</td>
<td>4,999</td>
<td>4,325</td>
<td>16,252</td>
<td>5,106</td>
</tr>
</tbody>
</table>
• “Churn” fairly consistent across different country markets. Signs many apps operate in multiple markets.
• Removals increase another \( \approx 10\% \) as we tag up until Sep. 2021

Table: Percentage of personal loan apps newly-released & unpublished during extended period (Jan 2020-Sep 2021)

<table>
<thead>
<tr>
<th>Personal loan apps</th>
<th>(2) Available in US</th>
<th>(3) Available in IN</th>
<th>(4) Available in NG</th>
<th>(5) Available in PH</th>
</tr>
</thead>
<tbody>
<tr>
<td>New release</td>
<td>71%</td>
<td>65%</td>
<td>71%</td>
<td>69%</td>
</tr>
<tr>
<td>Unpublished by Apr. 2021</td>
<td>52%</td>
<td>54%</td>
<td>56%</td>
<td>46%</td>
</tr>
<tr>
<td>Unpublished by Sep. 2021</td>
<td>63%</td>
<td>65%</td>
<td>67%</td>
<td>61%</td>
</tr>
<tr>
<td>Observations</td>
<td>5,106</td>
<td>2,613</td>
<td>3,810</td>
<td>2,281</td>
</tr>
</tbody>
</table>
Proliferation of personal lending apps in aggregate: supply side
Proliferation of personal lending apps by country: supply side
A typology of personal lending apps

We systematically review the 5,106 pure-play personal lending (or related) apps. We identify several broad types (and subtypes) of lending apps:

<table>
<thead>
<tr>
<th>A. DIRECT PERSONAL LENDING APPS (74.9%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Pure-play lending apps that claim to directly provide personal loans (including payday, consumer, MSME, etc.)</td>
</tr>
<tr>
<td>• Any provider type (e.g., commercial bank, neobank, fintech, MFI, NBFI, others)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. INDIRECT PERSONAL LENDING APPS (19.8%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Indirect lender apps that do not directly offer loans, but serve as “marketplace/guide” to access personal loans</td>
</tr>
<tr>
<td>• In practice, some are more or less transparent about their intermediary role</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. PERIPHERAL APPS RELATED TO PERSONAL LENDING (5.3%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Loan / EMI calculators</td>
</tr>
<tr>
<td>• Credit report / score apps</td>
</tr>
</tbody>
</table>
1. “Pure fraud” app example (from India)

Characterized by existence of fake reviews.
1. “Pure fraud” app example (from India)

Characterized by existence of fake reviews.
Classification of suspect apps (1/3)

1. “Pure fraud” app example (from India)
Characterized by existence of fake reviews.

Examples of signals

- Idiosyncratic review dates
- Abnormal user names
- Idiosyncratic text
1. “Pure fraud” app example (from India)
Characterized by existence of fake reviews.

Examples of signals

- Regularly distributed review dates
- Complaints about app/reviews being fake
- Paid “registration fees” but no service
Table: Reviews across multiple personal lending apps for suspected (fake) reviewer

<table>
<thead>
<tr>
<th>package_name</th>
<th>reviewer_name</th>
<th>profile_pic</th>
<th>rating</th>
<th>review_date</th>
<th>review_body_text</th>
</tr>
</thead>
<tbody>
<tr>
<td>com.pearloans.#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>23-Jun-21</td>
<td>Very reliable and trustworthy</td>
</tr>
<tr>
<td>com.smartloans.#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>28-Jun-21</td>
<td>Very reliable and trustworthy</td>
</tr>
<tr>
<td>com.flycashloans.#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>1-Jul-21</td>
<td>Very reliable and trustworthy</td>
</tr>
<tr>
<td>com.loan#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>1-Jul-21</td>
<td>Very reliable and dependable</td>
</tr>
<tr>
<td>com.liberty#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>1-Jul-21</td>
<td>Very reliable and trustworthy</td>
</tr>
<tr>
<td>com.oc.ourr_#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>1-Jul-21</td>
<td>Very reliable and dependable</td>
</tr>
<tr>
<td>com.ttitocash.#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>3-Jul-21</td>
<td>Very reliable and trustworthy</td>
</tr>
<tr>
<td>com.value#####</td>
<td>ajayi #######</td>
<td>0</td>
<td>5</td>
<td>4-Jul-21</td>
<td>Very reliable and dependable</td>
</tr>
</tbody>
</table>
2. “Predatory” app example (from Nigeria)

Characterized by signs of i) no real services provided or ii) abusive lending practices.

---

**Personal Loan Online**

7*24 hour

Loan Amount
From N5,000 to N450,000

Register via
Entering simple
authentication.

Paperless and
digital process
on your mobile.

3 step info

---

- Loan Applicant Minimum Requirement
  - Nigeria Resident
  - Age above 33 and below 55

- How to get started
  - To apply for online loans on [app name] you need an android phone and internet.
  - We are working hard to provide you with the best services to make your life better. Very soon you will look to [app name] for your electricity bill payments, current account, savings and much more!

**WHAT’S NEW**

*Thank you, [app name] users, for your support
*We have launched the ‘Golden Egg’ savings event, welcome to participate!

**ADDITIONAL INFORMATION**

- Updated: April 26, 2011
- Size: 9.1 MB
- Installs: 60,000+

- Current Version: 1.4
- Requires Android: 4.4 and up
- Content Rating: ppp-3

- Permissions:
  - Report: Flag as inappropriate

- Developer:
  - [name]@gmail.com
  - [Privacy Policy]
2. “Predatory” app example (from Nigeria)

Characterized by signs of i) no real services provided or ii) abusive lending practices.
Classification of suspect apps (2/3)

2. “Predatory” app example (from Nigeria)

Characterized by signs of i) no real services provided or ii) abusive lending practices.

- Reviews seem from real users
- However, no signs services provided (e.g., review seems positive but still awaiting approval)
- Signs 5-star ratings “coerced” to increase chances of loan approval
2. “Predatory” app example (from Nigeria)

Characterized by signs of i) no real services provided or ii) abusive lending practices.

Examples of signals

- Consistent signs services not provided
- Applications submitted (often including PII) but no approvals
- Sometimes complaints over fees or unsanctioned debits
Classification of suspect apps (3/3)

3. “Predatory” app example (from the Philippines)

Characterized by signs of i) no real services provided or ii) abusive lending practices.
Classification of suspect apps (3/3)

3. “Predatory” app example (from the Philippines)

Characterized by signs of i) no real services provided or ii) abusive lending practices.
3. “Predatory” app example (from the Philippines)
Characterized by signs of i) no real services provided or ii) abusive lending practices.

Examples of signals

- High prevalence of complaints on interest rates, fees, or short tenure
- Common complaints on abusive debt collection practices
- Concerns over data privacy
Classification of suspect apps (3/3)

3. “Predatory” app example (from the Philippines)

Characterized by signs of i) no real services provided or ii) abusive practices.

Examples of signals

- Sometimes signs of “coerced” 5-star ratings, where mismatch between rating and tone of review

- Signs that some form of services provided for some users
Recap: overview of typology and classification

A. Targeted apps of interest (personal loan app typology)

- Personal loan apps
  *Restricted to subset of apps where main language is English
  1. Direct lending apps
  2. Indirect lending apps
  3. Peripheral apps

B. Classification into legitimate v. suspect apps (labeling)

- **Legitimate**
  - Consistent signs of valid provider

- **Ambiguous**
  - Mixed signs of being valid provider
  - Signs provides services
  - May have critical reviews/ratings

- **Predatory**
  - Signs of abusive practices
  - Signs of no services
  - Absent signs of fake reviews

- **Pure fraud**
  - Signs of fake reviews

C. Outcomes

- Published
- Unpublished
Outcomes for legitimate vs. suspect personal lending apps

<table>
<thead>
<tr>
<th>Prevalence to be “unpublished” (as of Apr. 2021)</th>
</tr>
</thead>
<tbody>
<tr>
<td># of all personal loan apps</td>
</tr>
<tr>
<td>4-category classification</td>
</tr>
<tr>
<td>% Legitimate</td>
</tr>
<tr>
<td>% Ambiguous</td>
</tr>
<tr>
<td>% Predatory</td>
</tr>
<tr>
<td>% Pure fraud</td>
</tr>
<tr>
<td>Binary classification</td>
</tr>
<tr>
<td>% Likely legitimate</td>
</tr>
<tr>
<td>% Likely suspect</td>
</tr>
</tbody>
</table>
## Estimates on prevalence of legitimate vs. suspect personal lending apps (1/3)

<table>
<thead>
<tr>
<th>Prevalence of app in category</th>
<th>All (1)</th>
<th>Available in US (2)</th>
<th>Available in IN (3)</th>
<th>Available in NG (4)</th>
<th>Available in PH (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Number of personal lending apps</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of apps</td>
<td>5,106</td>
<td>2,613</td>
<td>3,810</td>
<td>2,281</td>
<td>2,241</td>
</tr>
</tbody>
</table>

| **Panel B. Percent of apps falling in legitimate vs. suspect classification buckets** |        |                     |                     |                     |
| % in 4-category classification |        |                     |                     |                     |
| - Legitimate                 | 16.8%  | 16.6%               | 15.7%               | 16.4%               | 16.9%               |
| - Ambiguous                  | 9.9%   | 11.1%               | 9.2%                | 11.7%               | 12.2%               |
| - Predatory                  | 68.8%  | 69.1%               | 71.4%               | 68.1%               | 67.2%               |
| - Pure fraud                 | 4.6%   | 3.3%                | 3.7%                | 3.9%                | 3.8%                |

% in Binary classification

<p>| - Likely legitimate         | 26.7%  | 27.7%               | 25.0%               | 28.1%               | 29.0%               |
| - Likely suspect            | 73.3%  | 72.3%               | 75.0%               | 71.9%               | 70.9%               |</p>
<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Available in US</th>
<th>Available in IN</th>
<th>Available in NG</th>
<th>Available in PH</th>
</tr>
</thead>
<tbody>
<tr>
<td>All personal lending apps</td>
<td>834M</td>
<td>418M</td>
<td>670M</td>
<td>394M</td>
<td>407M</td>
</tr>
<tr>
<td>4-category classification</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Legitimate</td>
<td>616M</td>
<td>369M</td>
<td>522M</td>
<td>343M</td>
<td>344M</td>
</tr>
<tr>
<td>- Ambiguous</td>
<td>38M</td>
<td>17M</td>
<td>29M</td>
<td>16M</td>
<td>27M</td>
</tr>
<tr>
<td>- Predatory</td>
<td>149M</td>
<td>24M</td>
<td>106M</td>
<td>26M</td>
<td>29M</td>
</tr>
<tr>
<td>- Pure fraud</td>
<td>31M</td>
<td>8M</td>
<td>14M</td>
<td>9M</td>
<td>8M</td>
</tr>
<tr>
<td>Binary classification</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Likely legitimate</td>
<td>654M</td>
<td>386M</td>
<td>551M</td>
<td>359M</td>
<td>371M</td>
</tr>
<tr>
<td>- Likely suspect</td>
<td>180M</td>
<td>32M</td>
<td>119M</td>
<td>35M</td>
<td>36M</td>
</tr>
</tbody>
</table>

*Note: these values reflect cumulative downloads since initial release of apps. For some apps, this may include downloads prior to Jan. 1st, 2020.*
### Average downloads per app in category

<table>
<thead>
<tr>
<th>Category</th>
<th>All</th>
<th>Available in US (1)</th>
<th>Available in IN (2)</th>
<th>Available in NG (3)</th>
<th>Available in PH (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All personal lending apps</td>
<td>163,337</td>
<td>159,969</td>
<td>175,853</td>
<td>172,731</td>
<td>181,615</td>
</tr>
<tr>
<td>4-category classification</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Legitimate</td>
<td>716,279</td>
<td>850,230</td>
<td>871,452</td>
<td>914,667</td>
<td>910,053</td>
</tr>
<tr>
<td>- Ambiguous</td>
<td>76,342</td>
<td>59,170</td>
<td>82,102</td>
<td>59,023</td>
<td>97,802</td>
</tr>
<tr>
<td>- Predatory</td>
<td>42,246</td>
<td>13,172</td>
<td>38,757</td>
<td>16,582</td>
<td>18,857</td>
</tr>
<tr>
<td>- Pure fraud</td>
<td>144,651</td>
<td>116,020</td>
<td>109,756</td>
<td>124,801</td>
<td>113,034</td>
</tr>
<tr>
<td>Binary classification</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Likely legitimate</td>
<td>479,824</td>
<td>533,887</td>
<td>579,390</td>
<td>560,062</td>
<td>569,892</td>
</tr>
<tr>
<td>- Likely suspect</td>
<td>48,103</td>
<td>16,781</td>
<td>41,638</td>
<td>21,293</td>
<td>22,782</td>
</tr>
</tbody>
</table>

*Note: these values reflect cumulative downloads since initial release of apps. For some apps, this may include downloads prior to Jan. 1st, 2020.*
<table>
<thead>
<tr>
<th><strong>Measurable harm</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Financial loss due to direct fraud (e.g., payment of fees for non-existent services)</td>
</tr>
<tr>
<td>• Financial loss due to predatory practices (e.g., difference in fees and interest paid between predatory lender relative to similar legitimate lenders serving market)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Other adverse outcomes / Immeasurable</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>• Loss of private / sensitive data</td>
</tr>
<tr>
<td>• Harassment or abuse encountered</td>
</tr>
<tr>
<td>• Loss of trust in financial institutions</td>
</tr>
</tbody>
</table>
Negative externalities on legitimate providers?

Examples from other markets
Policy solutions have had shorter-term success (but insufficient...)
The proposed solution
Solution summary

1. We set up ML models as proof-of-concept of proposed solution

2. The labeled data (for the 5,106 personal loan apps) serve as main output variables. We run the following models:
   - **Binary classification model:** i) “likely legitimate” vs. ii) “likely suspect”
   - **3-category classification model:** i) “likely legitimate” vs. ii) “predatory” vs. iii) “pure fraud”

3. For model input variables, we prioritize use of app meta-data
   - Motivation is to see if these mostly static and ex-ante indicators can flag problematic apps
   - We intend to integrate review data, but these data can be noisy and imply being ex-post after problems have arisen

4. In practice, we split the sample into a training-validation and test datasets
   - **Training-validation dataset** uses apps released until Jan. 15th, 2021
   - **Test dataset** uses apps released after Jan. 15th, 2021 and is used to assess out-of-sample performance of the model on completely unseen data
Based on our exploration, we use a subset of meta data variables in our current models. These include both visible and hidden data and often imply various transformations.

**Visible data**
- Short/long text description
- Screenshots
- Date last updated
- Byte size
- Developer website
- Developer email
- Promo video

**Hidden data**
- Date created
- Disaggregated # ratings (1-5)
- Internal version code
- Whether contains ads
- Number of reviews
- App price
- In-app purchases
- Min/Max price for in-app purchases
- Interactive elements
- Countries available in
- Languages available in
- Other app-stores available in
- Downloads (country-day level)
Input variable transformation: Example 1

Can use address variable to construct dummies for:

- Any address? (0/1)
Input variable transformation: Example 2

Can use email address variable to construct dummies:

- Any email provided? (0/1)
Current version vs. version code:

- The current version listed on the url is set by the developer.
- The meta-data has a field version code, which reflects the number of iterations of the app. We use this directly.
1. We use an ML technique called “gradient boosting” (specifically xgboost)

2. XGboost considered state-of-art for many predictive classification tasks
   • It builds an ensemble of shallow and weak successive trees with each tree learning and improving on the previous
   • When combined, these many weak successive trees produce a powerful “committee” that are often hard to beat with other algorithms

3. Key advantages:
   • Generally more accurate compare to other modes
   • Lots of flexibility – can optimize on different loss functions and provides several hyperparameter tuning options that make function fit very flexible
   • Handles missing data - imputation not required

4. Some disadvantages:
   • More likely to overfit
   • Training time scales with data size
Results for binary classification model (1/2)

Figure: Decision tree
Results for binary classification model (2/2)

**Figure:** Feature importance
## Accuracy for binary classification

<table>
<thead>
<tr>
<th>% Accuracy</th>
<th>Validation Set</th>
<th>Out of Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>90.17%</td>
<td>84.45%</td>
</tr>
</tbody>
</table>
Evaluation of binary classification model performance – ROC curve

ROC for validation sample

ROC for test sample

AUC = 0.94

AUC = 0.74
Results for multi-class classification model (1/2)

Figure: Decision tree
Figure: Feature importance
### Accuracy for multi-class classification

<table>
<thead>
<tr>
<th>% Accuracy</th>
<th>Validation Set</th>
<th>Out of Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>85.61%</td>
<td>71.96%</td>
</tr>
</tbody>
</table>
Evaluation of multi-class classification model performance – ROC curves (1/2)

ROC of Validation Set for Class 0

ROC of Validation Set for Class 1

ROC of Validation Set for Class 2
Evaluation of multi-class classification model performance – ROC curves (1/2)
Main takeaways & options for improving performance

1. Increase data sample size (e.g., extend prior to Jan 2020 or after April 2021)

2. Model-specific adjustments: e.g., further variable construction/transformation, hyperparameter tuning, etc.

3. Test whether narrowing windows between train-validation and out-of-sample increases precision (i.e., by potentially comparing more similar apps)

4. Test how much integration of (ex-post) review data improves performance
Next Steps & Conclusion
Moving from a proof-of-concept to real-time tool

1. Pilot Stage
   - Model trained and validated on historical data cut (from 2020)
   - Tested out of sample on withheld dataset (with newly released apps from Jan.-Apr. 2021)

2. Application Stage
   - Data Provider
     - Historical data dumps
     - Real time API
   - Adapt pilot workflow for intake of real-time data feed
   - Automate identification of current published personal loan apps
   - Apply previous model iteration results to predict app classification
   - Update as needed

   **REPORTING TOOLS**
   - Overview(s) of country lending app markets
   - Disaggregated “suspect” app lists
   - Frequency adjusted to country needs
Next steps

1. Integrate review data into analysis and ML models

2. Further validate results by downloading and using random subset of apps

3. Systematize evidence on adverse consumer outcomes

4. Expand coverage into other finance app categories and non-English country markets
Q & A / Feedback
Feedback

We’d like to obtain feedback from possible end users on how these findings and analyses may fit or be better tailored to applied policy, regulatory, or industry needs – e.g.:

1. Is interest more in ex-ante or ex-post tools?
   - If former, what is acceptable tolerance for error margin? Or leverage in requiring more stringent vetting process?
   - If latter, what type of reporting tools and info most desired?

2. Frequency of desired reporting?

3. Expand into other country markets?

4. Expand into other non-lending product coverage?

5. Other comments or suggestions?