Quality checks on granular banking data: an experimental approach based on machine learning

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Outline

- Context and Motivations
- Data
- The Algorithm
- Results
- Conclusions and Future Work
Central Banks collect, process and disseminate a wide set of statistical data: **Data Quality Management** (DQM) is crucial to support decision making.

- **DQM in Bank of Italy:** automated checks to verify **pre-determined relationships** in the data (e.g. accounting, logical and mathematical relationships).

- When deterministic relationships are **weak** DQM entails **plausibility checks** (trend-based) that rely on “acceptance regions” to isolate outliers.
Context and Motivations (2)

- Shortcomings of plausibility checks:
  - Calibration not straightforward,
  - Periodical revision and update needed,
  - Large number of acceptance thresholds.

- Complex and time-consuming system with highly granular data and heterogeneous reporting patterns.

**Aim**: employ ML to improve plausibility checks in granular databases.

- Approach: a supervised learning algorithm (Quantile Regression Forests) employed to detect potential outliers.
Findings

- Application to payment services data reported by banks. Outliers cross-checked with reporting agents.

- Empirical findings:
  - **New outliers** detected (not identified by the current DQM system).
  - **High accuracy** (77% precision; reduced “false positives”).

- Improvements:
  - Thresholds tailored to the characteristics of banks and to the degree of granularity of the data.
  - **Dynamic** thresholds that are automatically updated as new data are reported. Reduced involvement of analysts.
Focus on debit cards issued:

- **Unit of analysis** = n. of cards issued by bank \( (i) \), at the end of the semester \( (t) \), for a given province \( (p) \).
- Data extracted from DWH. Period: Dec-2014 to Jun-2018.

Additional data on bank features:

- n. of customers by province of the counterparty,
- type of customer accounts,
- other payment services offered (business model).

Final sample: **18,000 observations** corresponding to **213** banks.
The Algorithm (1)

- Analysis of the empirical distribution of the n. of debit cards (\(Y\)) conditional on bank characteristics (\(X_s\)).

- Estimation of quantile functions \(q_\tau (Y|X)\):
  \[
  \text{Prob}(Y < q_\tau (X)) = F(q_\tau (X)) = \tau
  \]

- Quantile functions combined to form **prediction intervals** (acceptance thresholds) associated with a given probability (\(\alpha\)):
  \[
  PI(X) = [q_\frac{\alpha}{2}(X), q_{1-\frac{\alpha}{2}}(X)]
  \]

- **Outliers**: values outside the intervals; unlikely to occur (too high/too low) given the reporting context.
The Algorithm (2)

- **Sampling:**
  - **Train** set to estimate quantile functions $q_\tau(x)$ for different $\tau$s.
  - **Test** set to compute intervals $[\hat{q}_{\tau_1}(x), \hat{q}_{\tau_2}(x)]$ and detect outliers.

- **Training:**
  - Algorithms: Quantile Regression Forest, Linear Quantile Model, Linear Quantile Model with Fixed-Effects.
  - Model selection with 10-folds cross validation.

- **Testing:**
  - Rolling window with two snapshots of data. Last two semesters in each snapshot as test set.
  - Outliers communicated to banks for cross-check.
The Algorithm (3)

- Model:
  \[ q_t(x_{ipt}) = \beta_0 + \beta_1 depositors_{ipt} + \beta_2 perc_ca_{ipt} + \beta_3 size_{it} + \beta_4 iss_acq_ratio_{it} + \beta_5 trend + \beta_6 sem + \alpha_i + \mu_p \]

- Predictors:
  - \( depositors_{ipt} \) = N. of depositors (of a bank in a given province)
  - \( perc_ca_{ipt} \) = % of depositors with current accounts
  - \( size_{it} \) = Total transacted amounts (as an issuer and as an acquirer)
  - \( iss_acq_ratio_{it} \) = Balance between issuing and acquiring services
  - \( sem \) = Semester dummy
  - \( t \) = N. of semesters starting from the first period in the dataset
  - \( \alpha_i \) = Bank fixed effects
  - \( \mu_p \) = Province fixed effects
The Algorithm (4)

- Estimated acceptance thresholds:

\[ PI_1(x) = [q_{0.01}(x), q_{0.99}(x)] \]

\[ PI_2(x) = [q_{0.025}(x), q_{0.975}(x)] \]

\[ PI_3(x) = [q_{0.25}(x) - 1.5 \cdot (q_{0.75}(x) - q_{0.25}(x)), q_{0.75}(x) + 1.5 \cdot (q_{0.75}(x) - q_{0.25}(x))] \]

- Observations falling outside **any** of the intervals flagged as potential outliers.
Cross check of outliers with banks

<table>
<thead>
<tr>
<th>Prediction intervals:</th>
<th>PI1</th>
<th>PI2</th>
<th>PI3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$[q_{0.01}, q_{0.99}]$</td>
<td>$[q_{0.025}, q_{0.975}]$</td>
<td>Inter-quartile range</td>
</tr>
<tr>
<td>a-Total number of potential outliers</td>
<td>373</td>
<td>489</td>
<td>457</td>
</tr>
<tr>
<td>b-Anomalies detected and revised (“true positives”)</td>
<td>289</td>
<td>312</td>
<td>292</td>
</tr>
<tr>
<td>c-Confirmed observations (“false positives”)</td>
<td>84</td>
<td>177</td>
<td>165</td>
</tr>
<tr>
<td>d-Precision b/a (%)</td>
<td>77.5%</td>
<td>63.8%</td>
<td>63.9%</td>
</tr>
</tbody>
</table>
Concluding Remarks

- Potential to improve DQM: more precise quality checks to detect outliers at a fine grained level with reasonable level of accuracy.

- Maintenance of DQM system: dynamic thresholds and periodical training of the algorithm vs manual update of acceptance thresholds.

- Additional challenges:
  - New processes and IT solutions for the production phase.
  - Communication of anomalies to banks becomes more complex.
Future Work

- **Extensions:**
  - Application to other payment services data (e.g. credit cards).
  - Analysis of data at the collection stage (i.e. before delivery to the DWH).
  - Classification algorithms (exploiting variations to reported data).
  - Unsupervised algorithms for outlier detection.

- **In perspective:** extend the ML approach to other granular data collections (in particular when current checks are weak).
Thank you for your attention!

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