

A decision-making rule to detect insufficient data quality

an application of statistical learning techniques to the non-performing loans banking data

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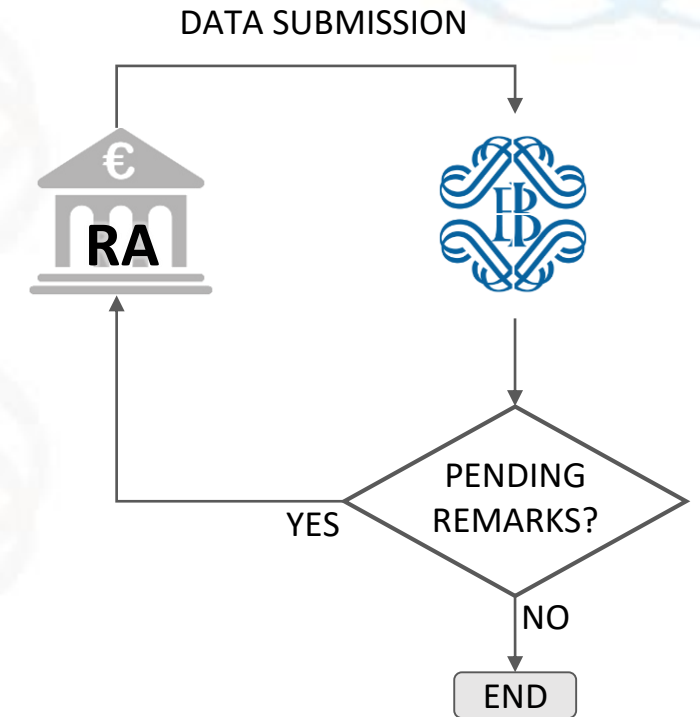
Banca d'Italia

Motivation

- ▶ It is key to count on **an efficient and effective monitoring of the quality level of the data** transmitted by Reporting Agents (RAs) in order **to provide users with high-reliable data to carry out thorough and robust analyses.**
- ▶ **Data Quality Level (DQL) generally follows a positive trend** thanks to subsequent corrections submitted by RAs; however, **a data quality worsening may occur** especially when data production is affected by exogenous and unpredictable events, such as **RAs' IT malfunctions, changes in the reporting requirements or operative tensions and staff shortage** (also as seen during the pandemic).
- ▶ The aim of the study is to define a decision-making rule:
 - to speed up the **detection of DQL worsening;**
 - to provide a **synthetic measure of the DQL.**

Data quality cycle in Banca d'Italia

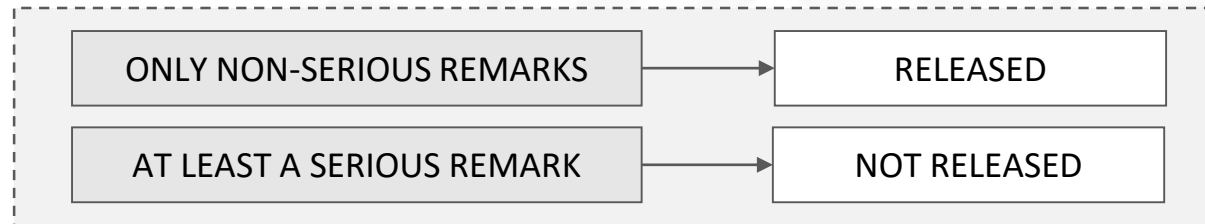
- ▶ At each data submission, the reliability of the data is assessed upon arrival by the Banca d'Italia by using a **set of automatic Data Quality Checks (DQCs)**.
- ▶ A severity level from 0 to 10 is assigned to each DQC.
- ▶ When a DQC detects plausible errors (outliers) or deterministic errors, **remarks** are sent to the RA to request for:
 - **corrections** of erroneous data by sending a new data submission
 - or
 - **confirmations** of the data. These can be, in turn, accepted or refused by the Data Manager



Current decision rule to release data to users

- ▶ Based on the severity level of the DQC, the generated **remarks** are classified as “serious” and “non-serious”. If at least 1 serious remark is generated, the data submitted are kept on hold to be examined by the Data Manger (hence not immediately released to the users)

AT EACH DATA SUBMISSION



- ▶ Considering 2 subsequent data submissions sent by an RA for a specific reference date, the possible cases are as follows:

		$(k+1)^{th}$ submission	
		Not-released	Released
k^{th} submission	Not-released	D	C
	Released	A	B

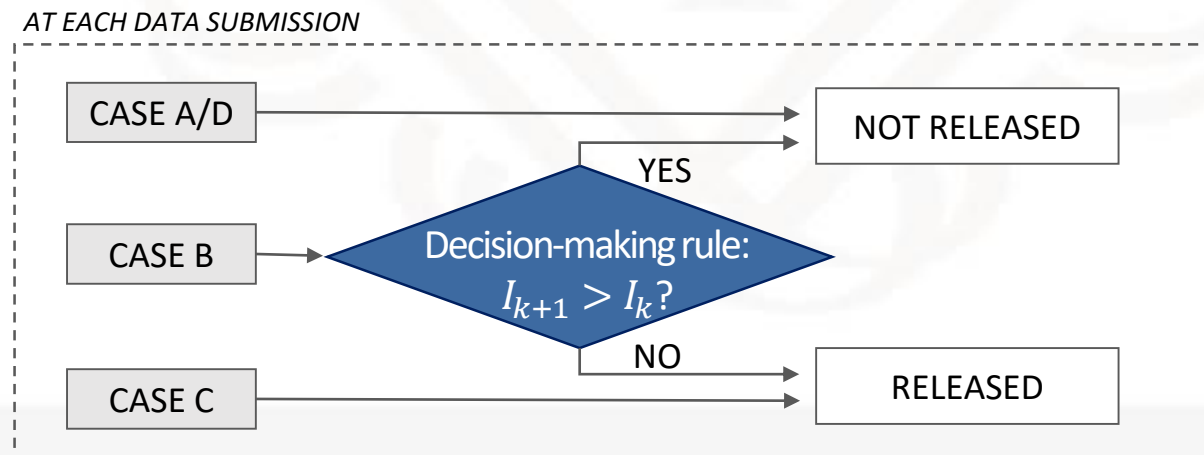
- ▶ In cases A, C and D, the Data Manager’s decision is **straightforward**; in case B the $(k+1)^{th}$ submission may worsen the DQL.
- ▶ The proposed decision-making rule is applied to case B to detect the unexpected worsening of the DQL.

Definition of the proposed decision-making rule

- ▶ The proposed rule is based on a synthetic data quality indicator computed through past evidence from the Data Quality Management (DQM) activity:
 - **number of remarks (R)** generated by the **DQC c**
 - **severity level (τ)**
 - **number of confirmations (Conf)**
- ▶ Definition of a **synthetic data quality indicator I_k** for the k^{th} data submission sent by an RA for a specific reference date:

$$I_k = \sum_c \tau_c \cdot (R_{c,k} - Conf_{c,k})$$

- ▶ If the DQC detects deterministic errors precisely (non-confirmable DQCs), $Conf_{c,k}$ is by construction equal to 0.
- ▶ **The higher the value of I_k , the lower the DQL of the k^{th} data submission.**
- ▶ The proposed decision-making rule is defined as follows:



What quantities are available for the calculation of I_k and I_{k+1} ?

- ▶ Let us assume we want to compare the DQL of the $(k+1)^{th}$ data submission with the DQL of the k^{th} . Once the $(k+1)^{th}$ data submission is received, the **availability of the information for the calculation of I_k and I_{k+1}** is as follows:

	I_k	I_{k+1}
Number of remarks	✓	✓
severity level	✓	✓
Number of confirmations	✓	✗

- ▶ The **number of confirmations related to remarks, generated by the confirmable DQC c for the $(k+1)^{th}$ data submission, is estimated:**

$$\widehat{\text{Conf}}_{c,k+1} = \sum_{r=1}^{R_{c,k+1}} \widehat{\text{Conf}}_{c,k+1,r} \quad \text{where:} \quad \widehat{\text{Conf}}_{c,k+1,r} = \begin{cases} 1, & \text{if } p(\text{Conf}_{c,k+1,r}) > \text{cut-off} \\ 0, & \text{otherwise} \end{cases}$$

- ▶ **cut-off** is a threshold lying within (0, 1) assessed with a cross-validation method
- ▶ The **estimation of the probability $p(\text{Conf})$** is derived applying **machine learning techniques** to a dataset including remarks generated by confirmable DQCs actually observed in the previous reference dates.


Dataset and Model selection


- ▶ **Dataset: Banks Non-performing loans dataset (NPL)**, collected by Banca d'Italia on a biannual basis
 - over 17 million of records between 30th June 2017 and 30th June 2019
 - about 65K remarks generated, of which 5,083 by confirmable DQCs
 - 15 dummy variables for DQCs and 415 for RAs
 - numeric variables: differences among quantitative aggregates of remarks, number of records sent and reference dates
- ▶ **Model selection: the logistic regression model outperforms.**

	Model	Logistic regression	Ridge logistic classifier ($\lambda=1$)	Linear discriminant analysis	Decision tree classifier	Quadratic discriminant analysis	K-neighbors classifier	Random forest
	<i>Optimal cut-off</i>	0.41	0.69	0.50	0.52	0.49	0.53	0.71
Training set • from June 2017 to December 2018 • 4,643 remarks	Accuracy	0.83	0.83	0.73	0.73	0.73	0.73	0.50
	Recall	0.95	0.92	0.99	0.94	0.99	0.98	0.39
	Precision	0.83	0.86	0.73	0.75	0.73	0.73	0.83
	Negative predictive value	0.80	0.73	0.55	0.50	0.54	0.54	0.33
Validation set • June 2019 • 440 remarks	Accuracy	0.81	0.78	0.76	0.75	0.78	0.75	0.78
	Recall	0.94	0.85	0.97	0.90	0.99	0.94	1.00
	Precision	0.83	0.87	0.78	0.80	0.78	0.79	0.78
	Negative predictive value	0.62	0.51	0.18	0.39	0.50	0.33	NA

Application of the decision-making rule

- Considering the subsequent submissions of the case B, the decision-making rule allows the Data Manager to **automatically and promptly identify cases where the DQL decreases** and it **prevents the users to use non-fit-for-use data**.

Reference dates between years 2017 and 2018		$(k+1)^{th}$ submission				Results of the decision rule for the $(k+1)^{th}$ submissions of Case B	Percentage
k^{th} submission		Not-released	Released	Total			
	Not-released	269	407	696		Released submissions	89%
	Released	51	275 (Case B)	326		Additional Not-released submissions	11%
Total		320	682	1,002			

Reference date of June 2019		$(k+1)^{th}$ submission				Results of the decision rule for the $(k+1)^{th}$ submissions of Case B	Percentage
k^{th} submission		Not-released	Released	Total			
	Not-released	15	23	38		Released submissions	93%
	Released	1	14 (Case B)	15		Additional Not-released submissions	7%
Total		16	37	53			

Conclusions

- ▶ The proposed decision-making rule **improves the current DQL monitoring** by promptly detecting additional cases of DQL worsening.
- ▶ The synthetic data quality indicator I_k provide a **synthetic measure of the overall quality of data** transmitted by the RAs.
- ▶ **The decision-making rule is accurate.** It was assessed by comparing its results with the outcome resulting from an application of the decision-making rule based on the real status of the remarks confirmability: in 97% of cases the conclusions coincide.
- ▶ The proposed method can be **flexibly applicable to various data collections.**
- ▶ For the NPL dataset, the **implementation of the decision-making rule** in the Banca d'Italia's collection system is **ongoing.**



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Thank you for your attention!

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