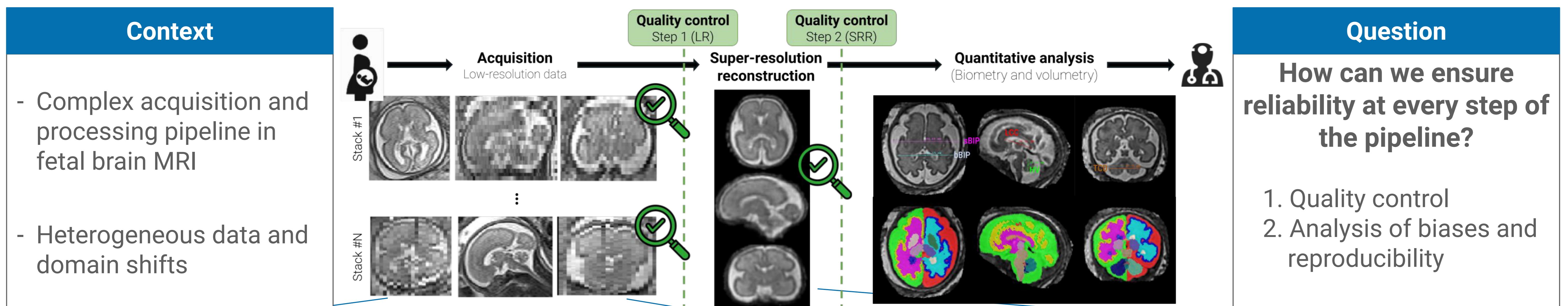


Improving reliability in fetal brain MRI analysis

Thomas Sanchez^{1,2}, Oscar Esteban², Angeline Mihailov³, Yvan Gomez^{4,5}, Alexandre Pron³, Gerard Martí Juan⁶, Mériam Koob², Vincent Dunet², Nadine Girard^{3,7}, Andras Jakab^{8,9,10}, Elisenda Eixarch^{5,11}, Guillaume Auzias³, Meritxell Bach Cuadra^{1,2}

¹CIBM – Center for Biomedical Imaging
²Department of Diagnostic and Interventional Radiology, CHUV-UNIL
³Aix-Marseille Université, CNRS, Institut de Neurosciences de La Timone, Marseilles
⁴Department Woman-Mother-Child, CHUV
⁵BCNatal Fetal Medicine Research Center (Hospital Clínic and Hospital Sant Joan de Déu), Universitat de Barcelona
⁶Universitat Pompeu Fabra, Barcelona

⁷Service de Neuroradiologie Diagnostique et Interventionnelle, Hôpital Timone, AP-HM, Marseilles
⁸Center for MR Research, University Children's Hospital Zurich, University of Zurich
⁹Neuroscience Center Zurich, University of Zurich
¹⁰Research Priority Project Adaptive Brain Circuits in Development and Learning (AdaBD), University of Zürich
¹¹IDIBAPS and CIBERER, Barcelona



Tackling domain shifts with FetMRQC [2]

The problem. Heterogeneity across scanners and sites → Machine learning models fail to generalize [1].

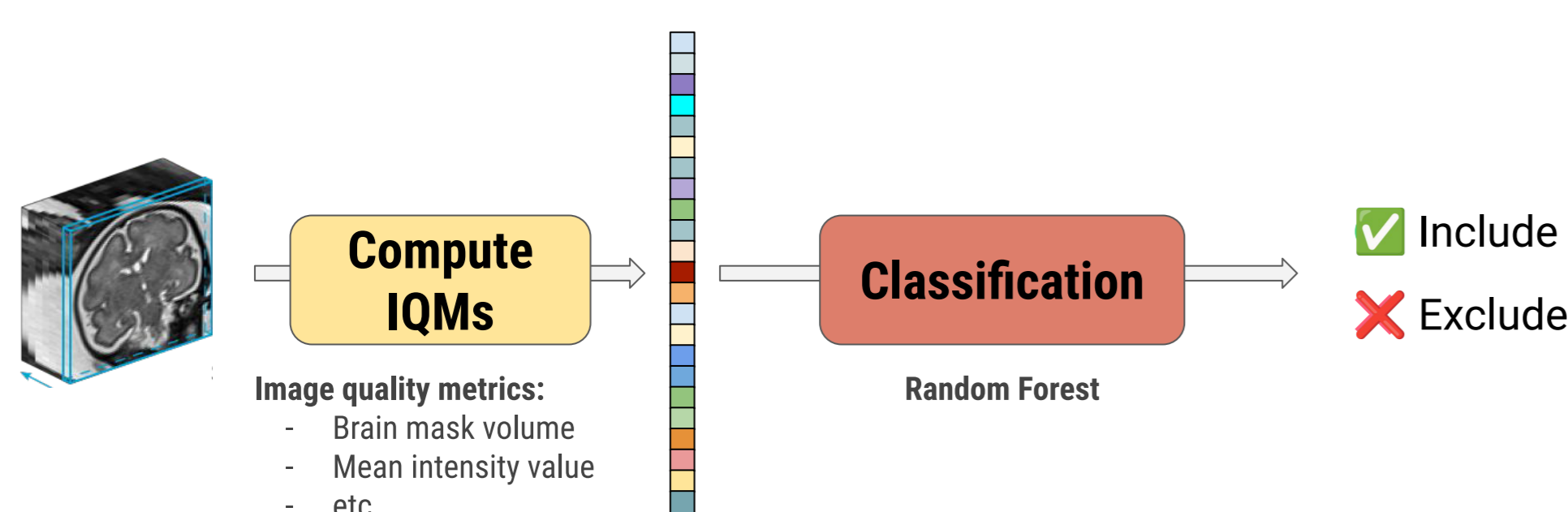
Our solution

Step 1. Standardized ratings.

Annotation interface and multiple raters [3]
Result. Two experts annotated more than 1600 LR T2w scans from 13 scanners across 4 hospitals.

Step 2. Automated prediction of quality.

Insight. Use a simple model. More complex models using nested cross validation and more sophisticated predictors failed to generalize out-of-domain.

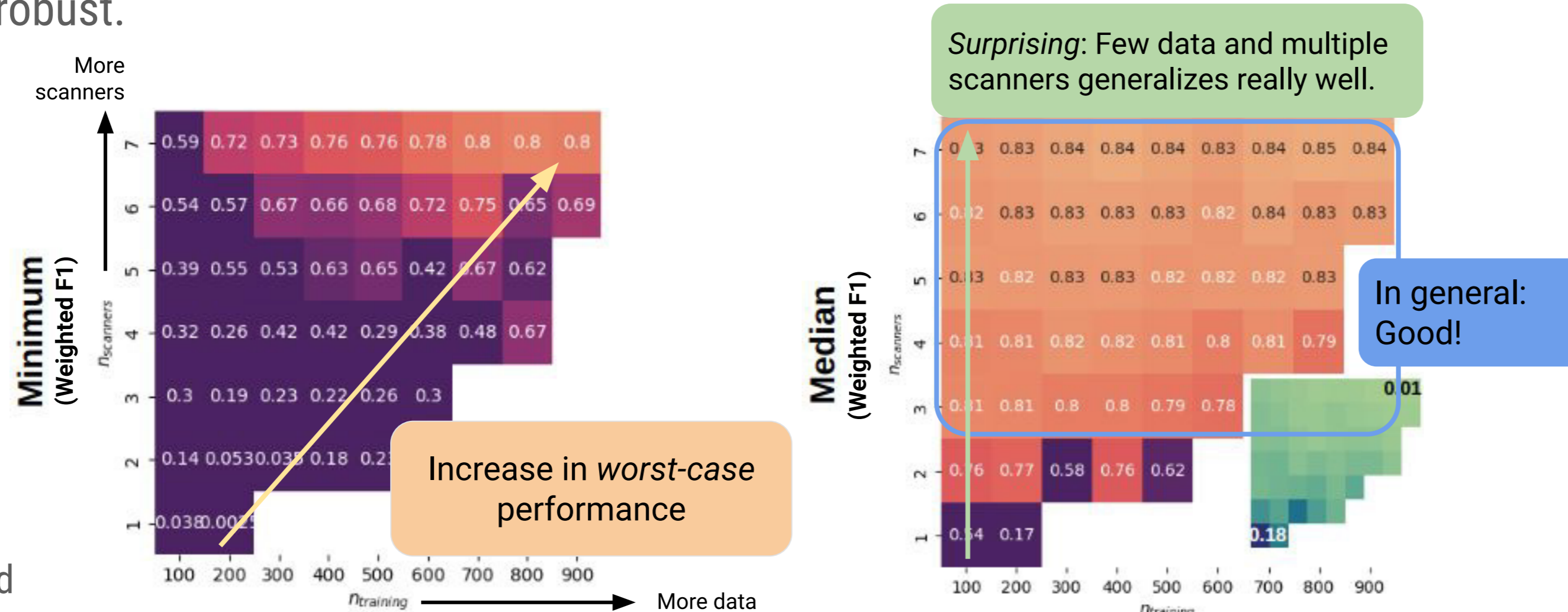


Step 3. Robust evaluation.

Use leave-one-site-out cross-validation and report worst-split performance with multiple metrics.

Experiment. How well can we expect to generalize given limited # of scanners and # of training data?

Insight. Heterogeneous data in training are key to a strong *median* generalization ability. More data helps make the model more robust.



More details and results in the paper

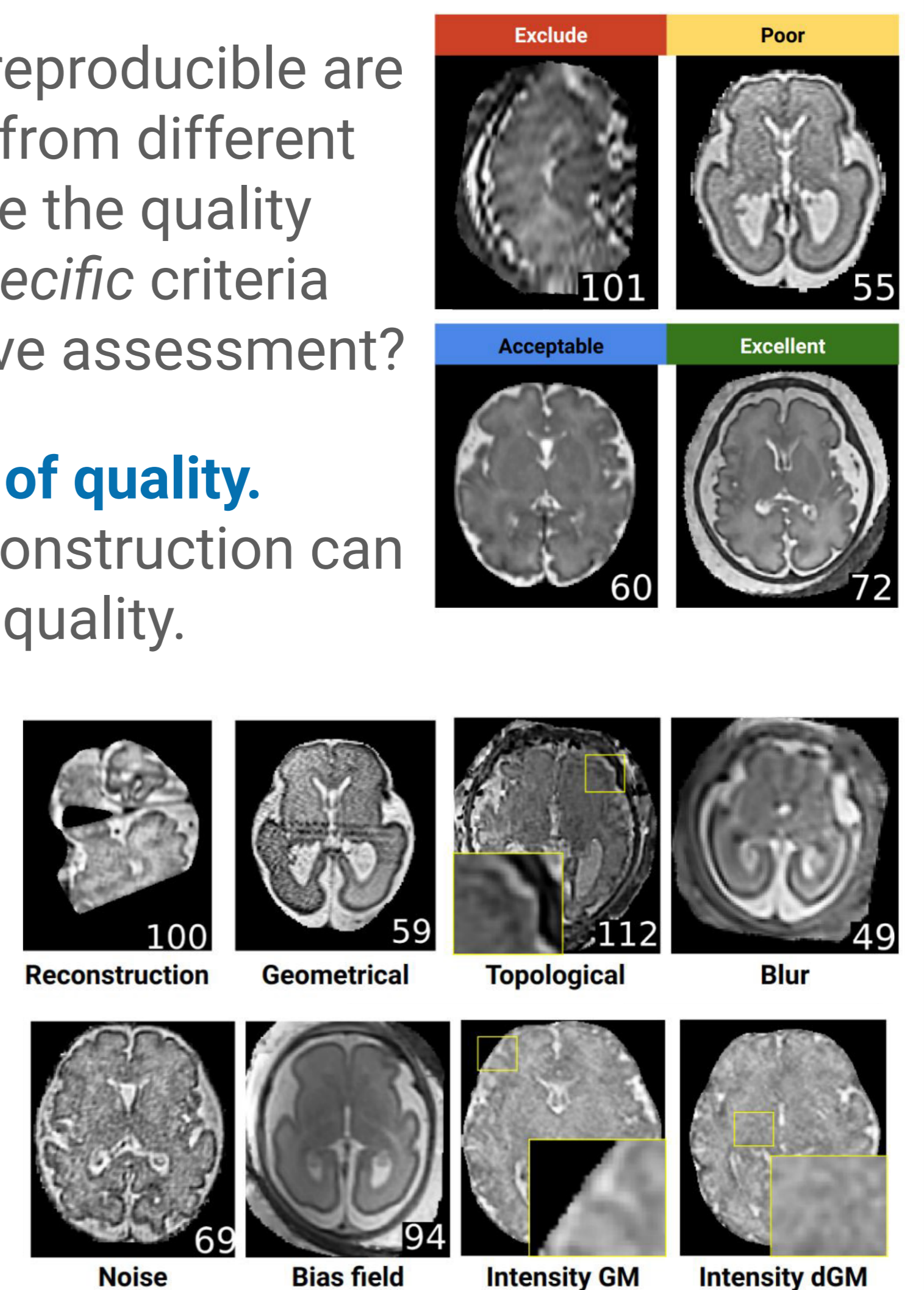
Towards more reproducible quality control [4]

The problem. How reproducible are quality annotations from different raters? Can we make the quality rating depend on *specific* criteria rather than subjective assessment?

Step 1. A taxonomy of quality.

Super-resolution reconstruction can lead to various data quality.

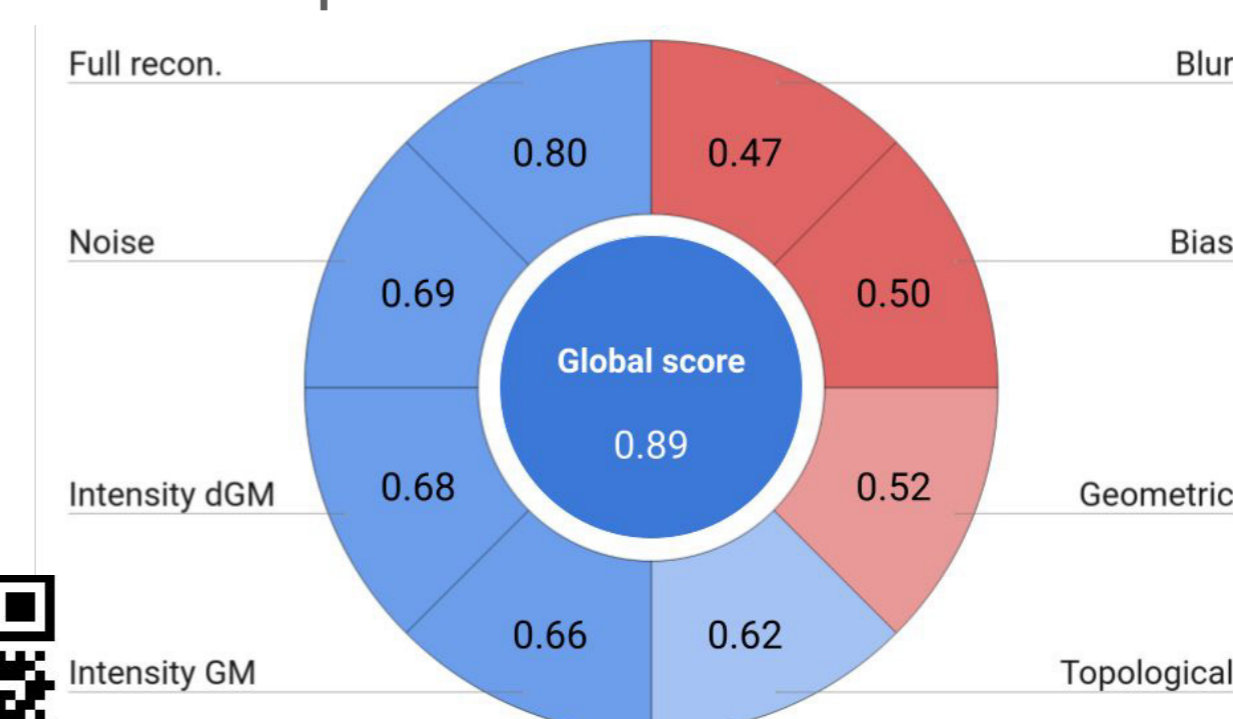
Data can feature very different artifacts.



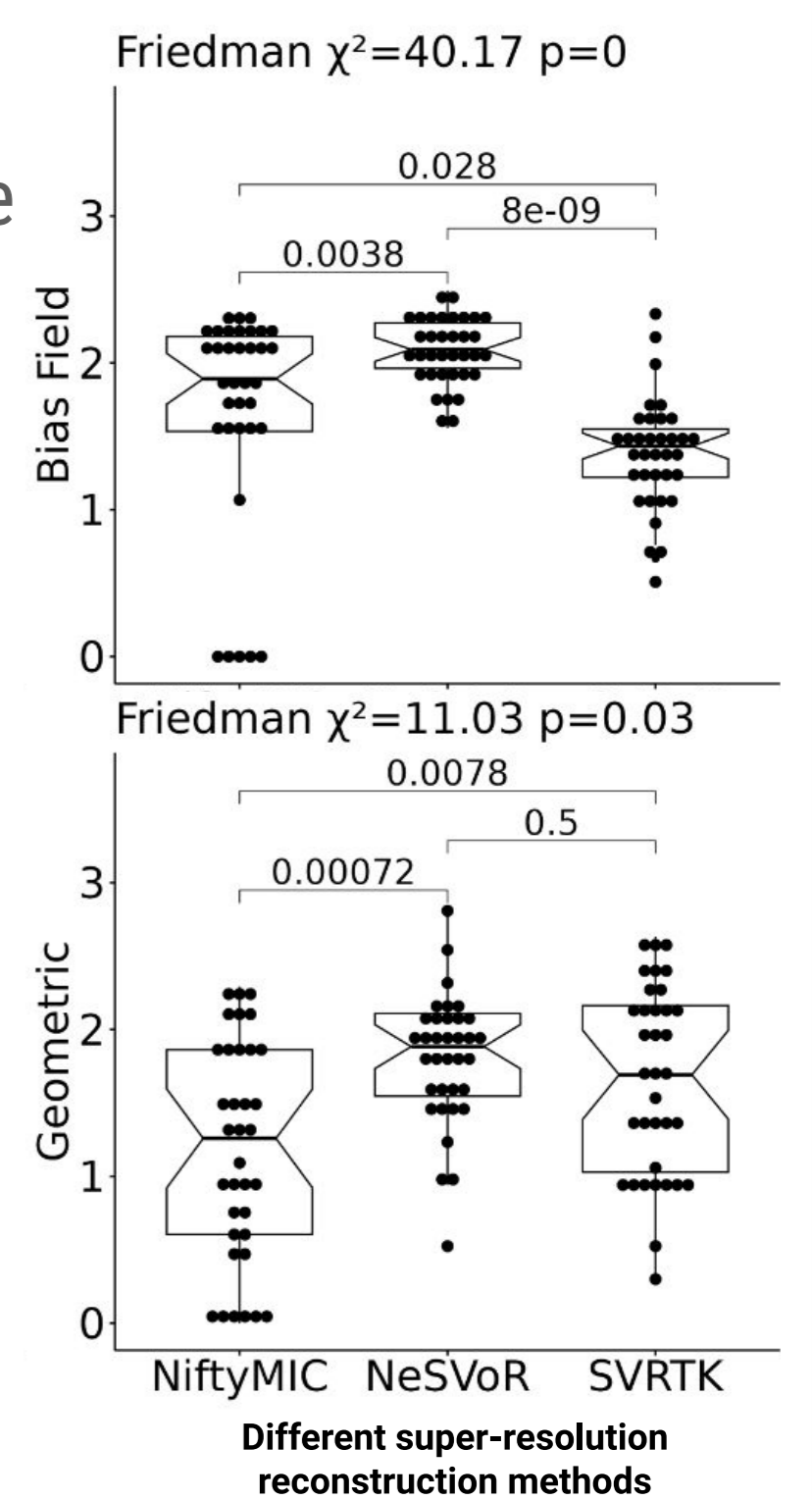
Step 2. Multi-annotator rating.

105 reconstructions annotated twice by four raters.

Result. 1. The global quality score is highly reliable. Most specific criteria can be reliably rated.
 2. The scores allow us to understand where different SRR methods underperform



More details and results in the paper



References.

- [1] Dockès J. et al. "Preventing dataset shift from breaking machine-learning biomarkers." GigaScience (2021)
- [2] Sanchez T. et al. "FetMRQC: A robust quality control system for multi-centric fetal brain MRI." Media (2024)
- [3] Esteban O. et al. "MRIQC: Advancing the automatic prediction of image quality in MRI from unseen sites." PLoS one (2017)
- [4] Sanchez T. et al. "Assessing data quality on fetal brain MRI reconstruction: a multi-site and multi-rater study." MICCAI PIPPI Workshop (2024)