Maintaining Comparable Identity Evaluation across Model Releases

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Abstract

A new model release can change generated appearance, output format, and the reliability of an identity evaluator. A higher benchmark score may therefore mix genuine improvement with changes in measurement or task conditions. This article develops a versioned comparison plan for subject-preserving video, motivated by ARGUS. No releases are run or ranked. The design preserves a stable assessment boundary while documenting necessary updates, so that later evaluations can distinguish a model change from an altered benchmark, reference set, or scoring procedure.

1. A release comparison is also a measurement comparison

Models evolve through changes in weights, interfaces, sampling defaults, and preprocessing. Evaluators also evolve, sometimes with revised detectors, embeddings, thresholds, or aggregation rules. If both change between reported results, the observed difference does not identify the contribution of either. A release comparison therefore needs version records for the full evaluation path, not merely the generator's public name. Without them, an apparently continuous score history can contain several incompatible scientific tasks.

ARGUS provides a motivating subject-preserving generation setting with structured identity references (Meng et al., 2026b). This article proposes a longitudinal evaluation design rather than assessing current or future ARGUS releases. It reports no measured improvement. The question is how to retain comparable evidence when the generator and its surrounding measurement tools change, and how to document revisions that improve the study without pretending that every historical number remains directly interchangeable.

A reference collection can grow in several ways: more identities, more images of existing identities, or more comparisons among the same images. The LFW protocol makes these units distinguishable (Huang et al., 2008), while its official loader documentation preserves the difference among development and assessment files (Pedregosa et al., 2011). Datasheets provide a framework for explaining why those objects were collected and which uses they support (Gebru et al., 2021). A subject-generation study should apply the same discipline to reference mosaics and output trajectories. The number of reference tiles is not automatically the number of independent observations, and the number of scored frames is not automatically the number of subjects. Recording the hierarchy permits appropriate weighting and uncertainty calculations later. Where a study uses only a public pair list, its conclusions should remain about that list and its protocol. They cannot supply observations of appearance, motion, or recognition errors that were never processed.

A large collection of measurements does not guarantee a large collection of independent cases. Repeated observations can share unrecorded acquisition conditions or a common source, making row-level uncertainty misleading. White's covariance estimator addresses heteroskedasticity within a specified regression (White, 1980), while cluster methods address a declared form of grouped dependence (Cameron and Miller, 2015). Neither approach repairs a poorly defined outcome or establishes representativeness of the observed sample. A report should identify the number of groups, their relative sizes, and the reason for selecting the grouping level. When only a few independent groups are available, apparently precise numerical intervals warrant particular caution. This is a limitation of the evidence structure, rather than a reason to count correlated measurements as fresh observations.

2. Preserving a stable comparison boundary

A proposed benchmark would version its subjects, reference observations, instructions, output requirements, sampling settings, and assessment rules. A reserved comparison set could support release-to-release contrasts under a common protocol. Its independence would weaken if it were repeatedly used for detailed tuning, so development monitoring should remain separate where feasible. The report should describe that use history rather than treating a long-familiar test set as indefinitely untouched evidence of generalization.

Each release would be evaluated under recorded software and hardware conditions, with failed requests and unavailable scores retained. If an interface no longer supports an old condition, the study should document the mismatch. A common subset can support a restricted comparison, while new tasks can assess new capability. These results answer different questions and should not be collapsed into a single trend whose denominator changes invisibly whenever a model's interface or output range changes.

Evaluator updates need their own bridge study. Where retained outputs are available, old and new scoring procedures can assess the same clips. This reveals measurement changes without requiring a new generation result. It does not establish that either scorer is more valid unless independent evidence supports that conclusion. A threshold recalibration should be reported separately from a generator improvement, particularly when the new release produces styles or visibility conditions outside the original evaluator's assessed population.

A face embedding is an instrument whose output needs a defined task. FaceNet supports verification and recognition through a learned metric space (Schroff et al., 2015), while ArcFace (Deng et al., 2018) and CosFace (Wang et al., 2018) pursue discriminative margins through different formulations. The scientific population is supplied by the benchmark, not by those objectives. VGGFace2's within-person variation (Cao et al., 2017), MegaFace's distractor scale (Kemelmacher-Shlizerman et al., 2015), and FairFace's representation emphasis (Kärkkäinen and Joo, 2019) show why populations can differ materially. For subject-preserving video, reference access and output conditions should therefore be documented alongside the identity score. An automated evaluator may be accurate on its original photographic population yet behave differently on generated motion, unusual lighting, or stylization. Establishing the relevant transfer requires observations in those settings. Architectural sophistication in the identity instrument cannot replace a direct assessment of the claim the generator is making.

A proposed explanation should be distinguishable from alternative explanations using observations the study can actually collect. Diagramming the relationships among selection, exposure, measurement, and outcome makes that requirement explicit (Greenland et al., 1999). The diagram does not establish its own correctness, but it prevents adjustment choices from remaining invisible. The same transparency is needed when investigators inspect many endpoints before choosing a narrative. Controlling false discovery concerns the behavior of a specified testing family (Benjamini and Hochberg, 1995); it is not a general certificate of scientific validity. Primary endpoints, secondary descriptions, and future mechanism tests should be named separately. Readers can then assess whether an attractive pattern was predicted, explored, or merely noticed after the available comparisons were examined.

The protected assessment population should be defined before investigators inspect detailed failures. Once a collection of cases guides repeated revisions, it has become development information even if its filenames still carry an evaluation label. Cross-validation for dependent data treats the grouping of observations as a substantive design decision (Roberts et al., 2017). Research on model selection likewise shows why tuning and final error estimation should not reuse the same information (Varma and Simon, 2006). A practical record therefore distinguishes fitting data, diagnostic examples, validation data, and the

final external assessment. Where only a fixed public table is available, a descriptive analysis remains legitimate, but it should not be renamed a held-out prediction experiment without generating and assessing predictions under a protected split.

3. Reporting continuity and change together

A useful release report would show the common-protocol contrast and the expanded-capability assessment separately. Subject identity, instruction execution, temporal quality, resource use, and coverage would remain distinct outcomes. An increase in one component can coexist with a decline in another. The application may prefer the new tradeoff, but that preference should not be described as a universal improvement without stating the relevant use conditions and the weighting assigned to each outcome.

Repeated tasks and subjects provide paired evidence when the underlying observations remain comparable. The uncertainty procedure should preserve those links and state what source of variation it represents. A large number of frames cannot substitute for broader subject coverage. Similarly, a narrow interval on a stable benchmark does not establish performance on new populations. The release comparison's strength is controlled continuity; transport beyond that continuity remains a separate empirical question requiring additional observations.

Corrections should preserve earlier versions rather than silently rewriting the score history. A fixed annotation, retired reference, or revised uncertainty rule can be accompanied by a restated result with clear provenance. That practice allows readers to distinguish scientific correction from model change. It also prevents an evaluation update from being interpreted as retrospective proof that an earlier release had different capabilities than those supported by its original observations and assessment conditions.

Different reference-conditioning mechanisms can receive different amounts of information. DreamBooth adapts a generation model around a subject (Ruiz et al., 2022), while IP-Adapter offers a compatible image-conditioning route (Ye et al., 2023). A fair comparison should preserve how many views, which resolutions, and which adaptation opportunities are supplied. CLIP's language-supervised visual representation (Radford et al., 2021) and DINO's self-supervised features (Caron et al., 2021) can provide useful descriptions of outputs, but their training objectives do not establish a person-recognition standard. The endpoint should specify whether success means matching reference appearance, retaining a recognizable subject, or satisfying a requested scene. Those properties can disagree. A useful analysis would keep the disagreement visible and ask which source of evidence each method uses. The relevant advantage is a measured improvement under a declared information budget, not an unqualified increase in similarity to whatever reference happened to be available.

An automated measurement should not inherit the authority of its training labels without a direct assessment of use. The relevant checks include systematic disagreement with the intended procedure (Bland and Altman, 1986) and calibration of any probability claims (Guo et al., 2017). Ranking performance, absolute accuracy, and confidence reliability are distinct outcomes. A study can improve one while leaving the others unchanged. Keeping the measurements separate permits examination of those tradeoffs and avoids implying that one favorable statistic establishes all aspects of validity. When independent judgments are unavailable, the limitation should remain part of the result. The absence of a target observation cannot be repaired by combining several correlated proxies into a more elaborate total score.

4. Reference access and measurement reliability

A moving subject introduces quality dimensions that a still-image identity score cannot exhaust. VBench decomposes video-generation evaluation into multiple aspects (Huang et al., 2023). Structural similarity (Wang et al., 2004), learned perceptual correspondence (Zhang et al., 2018), and video-distribution metrics (Unterthiner et al., 2018) provide additional observations under their respective assumptions. They should not be treated as equivalent measurements of the same latent property. A generated clip can have coherent motion and attractive appearance while changing its subject; it can also preserve recognizable identity while containing visible temporal artifacts. Reporting separate outcomes allows those tradeoffs to be examined. The assessment should specify the frames, viewpoints, occlusion states, and durations included in each score. A difficult case that defeats the identity evaluator should remain part of the coverage record rather than disappearing silently. The resulting profile can support a bounded claim about the observed conditions without implying that every aspect of subject consistency has been solved.

Difficult cases can disappear at several stages: data eligibility, generation, measurement, and final scoring. Each exclusion changes the population represented by the reported result. Coverage-aware evaluation makes those decisions visible (Geifman and El-Yaniv, 2017). A confidence score should also be checked when the input distribution changes, because uncertainty under shift is an empirical property rather than a guarantee of the model interface (Ovadia et al., 2019). An informative record preserves failures to produce an output and failures to obtain a valid measurement. Treating either as absent data without explanation can inflate apparent reliability. A proposed method should state its unsupported conditions and test the boundary between accepted and rejected cases as carefully as the quality of its successful outputs.

Reproducibility begins with preserving which scientific objects are being linked. Stable identifiers and reusable metadata help connect inputs, reference observations, model versions, and reported outcomes (Wilkinson et al., 2016). The scoring pipeline also has dependencies that can change the interpretation of a result: preprocessing, representation checkpoints, thresholds, and aggregation code can all matter (Sculley et al., 2015). A compact release should retain those decisions rather than only the final mean. Where source data cannot be redistributed, an access description and hashes can still identify the analyzed inputs. This record allows later users to distinguish a change in the underlying system from a change in how the system was measured. Reproducibility is therefore part of interpretation, not simply a final packaging step.

5. Conclusion

Comparable release evaluation needs stable tasks, versioned evidence, and explicit bridges when measurement changes. The proposed plan reports no new model ranking. It supports a history in which common-protocol contrasts remain interpretable while new capabilities and revised instruments receive their own assessment. A favorable score change can then be connected to the observed generator behavior rather than to an undocumented shift in references, coverage, thresholds, or aggregation.

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