Stylized Subjects and the Limits of Photographic Identity Metrics

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Abstract

Stylization can preserve a recognizable character while changing the visual properties expected by a photographic identity metric. This article proposes evaluating that boundary through separately defined subject, style, and instruction judgments. ARGUS motivates the use of structured references, but no stylized clips or embeddings are analyzed. The study design emphasizes independent evidence and uncertainty when a metric leaves its validated population. It explains why a convenient numerical similarity should not silently decide what preservation means after a deliberate change in visual representation.

1. A transformation can change the evidence of identity

Moving from a photograph to a stylized depiction can alter texture, proportions, and the relationship between local features. A viewer may still recognize a subject through a combination of cues, but the relevant cues need not match those used by a photographic scoring system. The evaluation problem is therefore partly definitional. It must specify what should remain recognizable and how much variation the requested style is supposed to permit.

ARGUS addresses subject preservation with multi-view identity information (Meng et al., 2026b). That setting motivates a question about the boundary of its evaluation rather than an assumption that any reference-based metric extends to every style. This article develops a conceptual protocol for stylized outputs. It reports no stylization performance, no identity similarities, and no test of ARGUS under altered rendering. The focus is how a future study could make a valid preservation claim when the observation process intentionally changes.

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.

Discriminative identity representations address a different question from the design of the test population. FaceNet learns an embedding for verification and related recognition tasks (Schroff et al., 2015). ArcFace (Deng et al., 2018) and CosFace (Wang et al., 2018) develop margin-based approaches to discriminative face learning. These methods do not determine which reference views should be supplied to a generator. Dataset choices also alter the challenge: VGGFace2 emphasizes pose and age variation (Cao et al., 2017), MegaFace increases the scale of recognition distractors (Kemelmacher-Shlizerman et al., 2015), and FairFace studies representation across annotated demographic groups (Kärkkäinen and Joo, 2019). Their relevance is to separate distinct kinds of coverage. Many comparisons of a small reference set cannot replace missing pose variation or a different population of people. A study should state which identity

measurement it uses, how thresholds are selected, and what the represented cases actually cover. Strong performance on one protocol does not establish universal validity of the embedding across generated or stylized subjects.

2. Defining the style task and reference access

A proposed comparison would specify the target style through instructions and examples selected before final assessment. It should also state which properties are permitted to change. Leaving that boundary implicit can make one method appear better simply because it applies a weaker transformation. A preservation score must therefore be accompanied by evidence that the requested style was carried out. Identity and style outcomes should remain separate even when the application eventually combines them.

Reference access should be documented for both generators and evaluators. Observers given a photographic reference and a stylized output face a different task from observers also given a stylized reference. The latter may provide useful information, but it changes the information budget. If additional references are introduced only for difficult cases, the procedure should record that adaptation and avoid pooling its results with fixed-reference assessments as though the viewing conditions were identical.

The evaluation would include independently judged examples across the intended range of transformations. An automated metric could be examined against those judgments, with uncertain cases preserved. Its photographic calibration could be reported as background, while its stylized operating characteristics would need direct observations. A failure to detect or score a stylized face belongs in the coverage record; silently excluding such cases would narrow the population without making the limitation visible to readers.

The choice of statistical unit should precede the choice of a standard error. A dataset can contain many rows but relatively few independently acquired histories. Heteroskedasticity-consistent covariance protects an otherwise specified regression against unequal residual variances (White, 1980). It does not automatically accommodate observations sharing an environment, subject, or recording. Cluster-robust inference makes that dependence part of the variance calculation (Cameron and Miller, 2015). The grouping must follow the observation process and the claim being made; an identifier that is convenient to store is not necessarily the relevant independent unit. For a descriptive analysis, preserving the groups also allows readers to recalculate a different population average. An uncertainty interval remains conditional on the observations and assumptions actually available.

Describing a contrast accurately can be more valuable than giving it an unjustified mechanistic name. A causal interpretation needs assumptions about how exposure and outcome arose, including selection into the analyzed sample. Causal diagrams provide a language for those assumptions (Greenland et al., 1999). If several alternative metrics or partitions are examined, the investigator should also account for the freedom to select whichever result appears strongest. False-discovery control is relevant to explicit collections of statistical tests (Benjamini and Hochberg, 1995), while a descriptive sensitivity analysis should be presented as such. A model can fit the observed rows well and still leave the principal explanation unresolved. Reporting that boundary preserves the value of the observation without overstating what adjustment or a significance threshold has established.

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.

3. Avoiding a false choice between style and identity

A strong reference resemblance can be achieved by retaining photographic features that the requested style should change. A strong style resemblance can instead erase distinctions needed to recognize the subject. These are substantive tradeoffs rather than mere scoring noise. A proposed report would show the joint outcomes and relevant examples under controlled presentation. It should avoid selecting a weighted total after observing which tradeoff favors a preferred method.

Human judgments also require a task boundary. Recognizing a familiar public figure may rely on memory outside the supplied references, whereas recognizing an unfamiliar subject depends more directly on those references. Reviewers may also recognize a character through clothing or context rather than face structure. These interpretations should be elicited through explicit questions or documented follow-up procedures, not inferred from a single preference response. Uncertainty remains appropriate where the available evidence cannot support the intended distinction.

The final study should identify the styles, subjects, and output conditions actually tested. A successful comparison within one stylization family does not establish validity for all nonphotographic images. Future revisions can add styles and evaluate whether the measurement relationship changes. Those revisions need stable version records and independent assessment data. Otherwise repeated adaptation to the same examples can make an apparent improvement in generalization reflect increasingly specific familiarity with the benchmark's limited visual vocabulary.

A validation split defines which form of transfer has been observed. Related observations can share subjects, scenes, prompts, or acquisition conditions, so randomly splitting rows may leave important information on both sides of the boundary. Structured cross-validation addresses these dependencies (Roberts et al., 2017). Model selection introduces another boundary: choosing a representation, threshold, or tuning parameter using the final assessment data makes the resulting error estimate optimistic (Varma and Simon, 2006). The appropriate held-out unit follows the intended future use. Generalization to a new frame, a new trajectory, and a new subject are not equivalent claims. A study should record those units before fitting or choosing a scoring rule, and preserve an assessment set that has not become part of iterative development.

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

Subject preservation is one dimension of a larger video-generation task. VBench explicitly motivates separating evaluation dimensions (Huang et al., 2023), and the visual literature offers structural (Wang et al., 2004), perceptual (Zhang et al., 2018), and temporal-distribution measurements (Unterthiner et al., 2018). A study should choose among them according to the claim and available reference information. When identity, motion, and visual quality move in different directions, the disagreement should be analyzed rather than automatically resolved by a weighted total. The weighting itself expresses a preference that may differ across applications. Preserving per-frame and per-clip records allows alternative interpretations to be evaluated later. It also makes coverage visible when some poses or occlusions prevent valid scoring. A generator can demonstrate a useful, limited preservation capability without having established universal reliability across all subjects, durations, and visual conditions.

Coverage should be reported whenever the system or its evaluator can avoid difficult cases. An abstention policy changes the population on which an accuracy or fidelity score is calculated. Selective classification formalizes the joint reporting of coverage and conditional performance (Geifman and El-Yaniv, 2017). Distribution-shift research adds that estimated uncertainty can behave differently outside the development population (Ovadia et al., 2019). A benchmark should therefore retain which observations were eligible, accepted, rejected, or unavailable. A result on a carefully limited subset can be useful, provided the subset is visible. The challenge is to prevent a narrow success claim from becoming a broad capability claim through omission of the denominator or the circumstances in which the system declines to operate.

The unit of provenance should be fine enough to reconstruct an important disagreement. Reusable identifiers can connect a reported score to its input evidence and the relevant model and evaluator versions (Wilkinson et al., 2016). Pipeline dependencies should be treated as part of the experiment because apparently minor changes can alter output eligibility or metric behavior (Sculley et al., 2015). A report that preserves only aggregate numbers prevents this reconstruction. Keeping per-case results and documented transformations enables alternative weighting and error analysis without repeating expensive generation. Such a record also helps identify whether two papers compare the same scientific objects or merely use similar names for different releases. Versioned evidence makes progress easier to assess across successive evaluations.

5. Conclusion

Stylized identity evaluation needs an explicit account of permitted change and recognizable persistence. The proposed protocol separates style execution, subject recognition, metric coverage, and reference access. It has not been implemented. Its contribution is a principled way to test photographic identity instruments on a changed observation population, allowing useful numerical evidence without letting the instrument alone define whether a deliberate visual transformation preserved the intended subject.

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