Temporal Appearance Change and the Scope of an Identity Claim

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Abstract

Reference photographs can document the same person at different times without providing interchangeable appearance evidence. This conceptual analysis separates variation across capture occasions from the stronger claim of preserving a subject through a requested temporal change. It proposes recording reference dates or independently supplied occasion labels where available, while avoiding inferred age labels from faces. ARGUS motivates the reference-selection question. No personal attributes are estimated and no new video is generated. The argument is that an identity claim should identify which temporal appearances it actually observes rather than imply an unlimited appearance trajectory from a finite reference set.

1. A reference set has a temporal boundary

A subject's appearance can differ across recording occasions because of hairstyle, clothing, lighting, expression, image quality, and longer-term changes. A collection of references may mix these factors without indicating which one explains a particular difference. Calling the collection temporally diverse does not establish that every relevant appearance change is represented. An evaluation should state which occasions are documented and which temporal interpretation depends only on speculation.

ARGUS selects and organizes identity observations for subject-preserving generation (Meng et al., 2026b). That motivates examining whether reference selection favors one familiar appearance or covers the variation relevant to the requested output. The present article does not estimate ages, infer sensitive personal characteristics, or diagnose a failure in ARGUS. It develops a conceptual study of documented temporal reference coverage. Its purpose is to identify the evidence required for a bounded identity claim across appearance change, without pretending that a finite image set records an entire personal history.

Identity evidence has a sampling structure before any recognition score is calculated. LFW defines a particular pair-verification protocol (Huang et al., 2008), and the documented scikit-learn loader makes its prescribed files accessible through a reproducible software interface (Pedregosa et al., 2011). Neither source turns a pair count into a count of independent subjects or images. Dataset documentation should identify how references, identities, comparisons, and splits were assembled (Gebru et al., 2021). For generated video, the analogous record should distinguish a new person from another reference photograph, another trajectory, or another frame. Each adds evidence along a different dimension. A transparent report should preserve those links rather than flattening every observation into one score table. The resulting metadata can support a useful audit even when no images or generated clips are available. Such an audit describes coverage and organization; it does not itself establish recognition accuracy, demographic representativeness, or identity preservation in an unobserved video.

Precision and identification are separate properties of a result. A narrow interval can surround an association whose scientific target is unclear. Robust covariance calculations allow particular departures from simple error assumptions, including unequal variance (White, 1980) and dependence within declared clusters (Cameron and Miller, 2015). Their role is to improve uncertainty calculations under those assumptions. They do not establish a causal assignment, guarantee a correct measurement, or expand coverage to conditions missing from the data. The analyst should therefore explain both the averaging population and the source of replication. An evaluation repeated many times on one history may provide

information about stochastic variability while supplying little evidence about transfer to another history. Those two sources of uncertainty should remain distinguishable in the final interpretation.

2. Recording occasions without inventing labels

A proposed dataset could retain verified capture dates, source-provided occasion identifiers, or another independently documented temporal grouping. The origin and reliability of those fields should be preserved. If such information is unavailable, the study should not replace it with confident assumptions from a face's appearance. A visually older-looking image can differ for many reasons, and using that impression as ground truth would entangle the evaluation with an unvalidated attribute inference.

The reference protocol should then define the task. Generating a new scene using several documented appearances is different from requesting a specific appearance change not contained in the references. The first tests selection and preservation given available evidence. The second requires a stronger transformation claim. A comparison should report which observations each method receives and whether any adaptation or manual selection occurs. Differences in access can be scientifically important even when both outputs are described as videos of the same subject.

The endpoint should keep identity and temporal appearance separate. An output can resemble a documented occasion closely without preserving the intended person, or preserve recognizability while failing a requested appearance instruction. A meaningful test would ask both questions using independent criteria and include ambiguous cases explicitly. It should not infer successful temporal transformation from a generic image match or interpret every reduced match to one reference as an identity error.

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 phrase generalization needs an object: another observation of the same source, another source within the same collection, or a different acquisition process. Each requires a different assessment boundary. Structured validation makes explicit how correlated observations are assigned across training and evaluation (Roberts et al., 2017). Selection bias can still arise if the final boundary is repeatedly consulted

while choosing a method (Varma and Simon, 2006). Publishing the split identifiers and the information permitted during each stage allows the claimed transfer to be checked. When a study proposes a new architecture but performs only a data audit, it should state that difference directly. Useful evidence about data coverage does not require pretending that a prediction system has already been trained and externally validated.

3. Generalization across appearances and measurement procedures

A held-out appearance assessment would need to state what is unfamiliar: the capture occasion, the image source, the viewing condition, or the subject itself. Those boundaries support different transfer claims. If reference selection is tuned using the final held-out appearance, that appearance is no longer independent assessment information. The record should distinguish automatic selection, human curation, and any additional subject knowledge available during development.

Measurement instruments can also have appearance-specific behavior. A face embedding trained on one photographic distribution may respond differently to changes in image quality or style. A human judge may need several verified references to recognize continuity across occasions. The study should examine those conditions rather than treat the identity instrument as a universal arbiter. Where a judgment cannot be made confidently, the observation should remain an assessment limitation instead of becoming an assumed generator failure or disappearing from the denominator.

The practical goal is not to demand unlimited invariance. An application can legitimately target one documented reference appearance or a limited collection of occasions. It should state that scope and evaluate the transformations it actually supports. A broader claim would require further observations and an appropriate account of how the intended appearance is defined. This prevents a useful but narrow generation capability from acquiring an unsupported interpretation about all possible appearances of the person.

A subject-generation pipeline can succeed at using a reference without succeeding at every identity requirement. DreamBooth's model adaptation (Ruiz et al., 2022) and IP-Adapter's image prompting (Ye et al., 2023) offer examples of reference use with different costs and information access. CLIP (Radford et al., 2021) and DINO (Caron et al., 2021) provide further visual representations whose similarity scores may emphasize other aspects of content. The evaluation should therefore define its target before choosing a convenient feature. If the intended target is a recognizable moving person, that target needs appropriate observations across the relevant views and expressions. A high generic image similarity can instead reflect scene layout or texture. Matching reference budgets and documenting the evaluator's representation permit those explanations to be compared. The objective is to connect a claimed conditioning advantage to the particular identity evidence the resulting output actually preserves.

A substitute measurement needs evidence about its relationship to the intended judgment. Two scores may correlate strongly while differing systematically in particular conditions. Method-comparison analysis distinguishes association from agreement (Bland and Altman, 1986). When a system additionally reports confidence, calibration asks whether those probabilities correspond to observed outcome frequencies (Guo et al., 2017). These are separate properties: a metric can rank examples usefully while having a distorted numerical scale or unreliable confidence. An evaluation should therefore retain the original target observations when possible, describe the scale of each endpoint, and examine disagreements instead of averaging them away. A convenient automated score becomes more credible when its limitations are measured in the conditions that motivate its use.

4. Scope, uncertainty, and independent assessment

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.

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.

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

Temporal reference coverage should be documented through independent source information rather than inferred confidently from faces. The proposed design separates identity preservation, appearance selection, and a requested temporal transformation. It also makes the assessment boundary explicit. No new attribute inference or generation result is reported here. A credible subject-preservation claim can remain valuable within a finite set of documented appearances, provided that boundary is retained when the result is described and compared.

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