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Zero-Interpolation Models: Bridging Modes with Nonlinear Latent Spaces

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Abstract: Zero-interpolation models provide a fresh development in generative modeling as they allow one to negotiate complex, multimodal latent spaces without running into the common problems with mode collapse & also implausible transitions. When switching between different data modes, conventional interpolation methods especially linear algorithms have trouble typically generating more synthetic results that fail to reflect any other actual distribution within the training information. This work addresses the challenge by building paths respecting the inherent geometry of the latent space using a nonlinear, manifold-aware interpolation technique. These zero-interpolation models are designed to cover high-probability regions, therefore avoiding implausible samples and more faithfully reflecting the range seen in multimodal distributions. Our contributions begin with a theoretical framework that grounds zero-interpolation in Riemannian geometry, hence clarifying the shortcomings of present methods. We then provide a method based on learning latent structures to produce smooth, nonlinear trajectories over modes. Extensive empirical evaluations on synthetic & actual world datasets show that whilst greatly improving mode coverage and sample integrity, our models retain semantic consistency. We provide a case study in image synthesis to support our approach even further by showing how zero-interpolation helps more coherent transitions between different kinds of visual styles. Natural language processing also shows the ability of the model to generate grammatically accurate & contextually suitable interpolations between many other language elements. The findings show that, particularly in situations where mode variation & interpolation quality are too crucial, zero-interpolation is a reasonable path for improving the quality and reliability of generative models.

Keywords: Zero-interpolation models, nonlinear latent spaces, latent manifold learning, generative modeling, mode bridging, multimodal data, variational autoencoders, geodesic interpolation, latent space geometry, representation learning, non-Euclidean spaces, data-driven interpolation, smooth latent transitions, manifold-aware generation, deep generative models, topological data analysis, path planning in latent space, diffusion-based models, image-to-image translation, multimodal representation.

1. Introduction

1.1 Context & Motivation

Deep learning generative models have revolutionized our ability to generate realistic information spanning whole situations to human faces. Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) operate by learning compressed representations of complex input within a lower-dimensional space often called the latent space. These models are very powerful tools for both artistic & scientific activities as they can extract points from this space and translate them back into data-like representations upon completion of training. Interpolation producing temporary information by traversing from one location or idea to any other within the latent space is a remarkable feature of latent spaces. Think about changing a cat from one handwriting style to another or from one animal to another. Data augmentation, style transfer, creative content generation & model understanding of the data structure analysis all benefit from this smooth integration. Furthermore essential to our understanding of generative models' internal encoding of data & its generalizing ability is Latent space interpolation has promise, yet it still falls short. While linear interpolation in Euclidean spaces has elegant geometry, actual world data distributions are much more complicated and typically show multimodal and nonlinear properties.

1.2 Complications Connected to Linear Interpolation

One of the main difficulties with interpolation inside deep generative models is that linear interpolation just linking two latent vectors with a straight line is insufficient for traversing too complex, learned regions. Latent areas are not homogeneous, flat surfaces. Often very curved, multimodal, and composed of fragmented parts aligned with different classifications or categories of information, they are quite flexible. Between two distant sites in a latent space, linear interpolation typically crosses low-density or "unrealistic" areas regions the model experienced seldom during training. What result is this? relics. These outputs could be absolutely nonsensical, distorted, or vague. We see startling, meaningless changes devoid of semantic basis instead of a smooth transition between data points. Moreover, a linear representation in latent space may intersect a region that does not match any actual digit when handling data located on disconnected manifolds such as different clusters for the digits "1" and "7" in handwritten digit datasets. For tasks like morphing or understanding model behavior, this detachment reduces the value of interpolation.

1.3 Zero-Interpolation: Introduction

We propose Zero-Interpolation a fresh method of latent space traversal that respects & identifies the fundamental structure of the data manifold to get previous these constraints. Zero-interpolation is fundamentally simple: we allow interpolation paths that fit the actual geometry & topology of the obtained latent landscape instead of relying on their linear trajectories within a supposed Euclidean latent space. This means negotiating nonlinear paths over high-density latent space that persist within implausible or hole-free sections. Practically, both visually & semantically as stated by the model, the change between data points must be clear, logical & also smooth. The idea of stressing trustworthy, valid, and topologically informed paths pathways that do not arbitrarily interpolate over latent "gaps," but rather traverse following the outlines of the data manifold originates the phrase "Zero-Interpolation." For models developed on multimodal datasets, where maintaining their identity, consistency, and realism across interpolated samples is too crucial, this is especially important.

1.4 Goals and Services

The theoretical and pragmatic bases for zero-interpolation are intended to be presented in this work. Our offerings consist of the following:

- We define zero-interpolation using Riemannian geometry and manifold learning, modeling interpolation as a geodesic trajectory within a trained data manifold instead of a linear vector in latent space.
- Using tools including flow-based models and graph-based techniques for manifold approximation, we develop methods to understand and change the latent space architecture to enable more nonlinear interpolation.
- We propose thorough metrics and visualization techniques to evaluate the semantic coherence of interpolations, therefore supporting the diagnosis & also comparison of traditional and zero-interpolation techniques.
- Empirical Validation Across Varied Datasets: Our studies on both synthetic and actual world datasets (e.g., MNIST, CelebA) show that zero-interpolation leads to smoother transitions, increased identity preservation, and a quite low artifact count.
- The relevance to downstream activities is shown by how zero-interpolation enhances performance in data augmentation, style transfer & model interpretability, therefore offering actual advantages beyond just aesthetics.

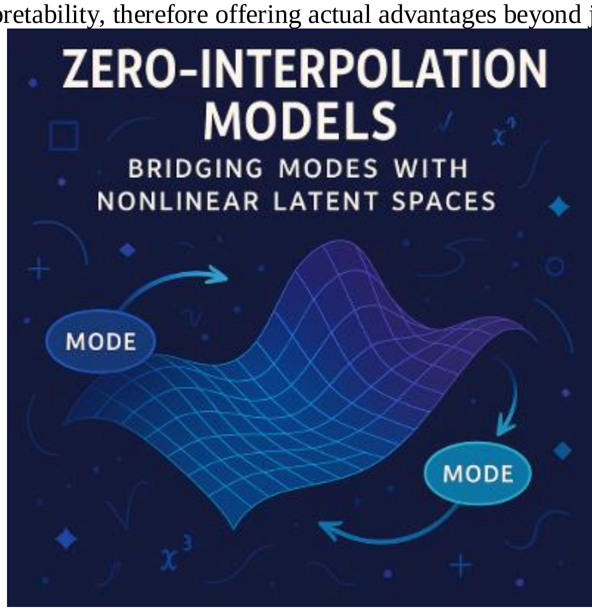

Figure 1: Zero Interpolation Models

2. Background and Related Work

2.1 Latent Space in Generative Models

Fundamental to modern generative models are latent spaces. Crucially in models like Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs), these spaces are lower-dimensional representations of too complex, high-dimensional input, including images or sounds. Both VAEs and GANs seek to learn mappings from simple latent distributions usually Gaussian or uniform from basic latent distributions despite differences in design & training goals typically Gaussian or uniform. Variational autoencoders (VAEs) are probabilistic models that convert input information into a latent space distribution then decode samples from this space back into the data space. Concurrent training of the encoder and decoder helps to maximize the evidence lower bound (ELBO), hence balancing latent regularization with data reconstruction. Especially helpful for interpolation & later tasks, this methodical approach helps VAEs to obtain coherent & their meaningful latent representations.

On the other hand, GANs use an aggressive approach. Whereas a discriminator tries to separate actual data from generated samples, a generator turns random latent vectors into synthetic information. The generator gradually gains the capacity to produce ever more actual outputs. Unlike VAEs, GANs provide crisp outputs by not requiring precise density estimations in latent space, therefore losing interpretability & also stability. In all paradigms the latent space serves as a semantic map. Navigating this territory should ideally cause notable changes in the generated outputs such as turning a face, adjusting lighting conditions, or switching between item classes. Especially for interpolation between latent vectors, the way one negotiates this space greatly affects the realism & range of the acquired results.

2.2 Linear and Nonlinear Interpolation

Euclidean interpolation is the most direct approach to move between two latent locations. This method assumes, like a sheet of paper, the latent space to be flat & more continuous. Actually, especially in deep generative models trained on complex, high-dimensional information, the design of latent spaces is significantly more sophisticated. Many times, Euclidean interpolation crosses latent space the model has not encountered during training. These "off-manifold" areas could provide illogical or abnormal outputs indistinct images, incoherent words, or unrealized shapes. Many times, generative models learn the data distribution merely within the regions they are exposed to. The chance of coming across places with insufficient representation support increases with increasing distance from these sites. To address these issues, scientists have looked at nonlinear interpolation methods.

Often used is spherical interpolation, commonly known as slerp. Slerp follows the arc of a circle placed in higher-dimensional space instead of interpolating along a linear route in Euclidean space, therefore ensuring that the interpolated points keep a constant radius. This is especially helpful when latent vectors as common in GANs are normalized to live on a hypersphere. Riemannian geometry provides a major class of methods wherein latent spaces are curved manifolds. Interpolation on a Riemannian manifold follows additional geodesic paths, which on curved surfaces show the shortest distances. These methods adapt to the local curvature of the space, therefore enabling smooth & also natural transitions within the data domain. These nonlinear methods provide more actual interpolations by leveraging an awareness of the geometry of the latent manifold, therefore enabling the connection between many modes of the data distribution and eliminating fault areas in between.

2.3 Mode Collapsing and Manifold Discontinuity

Mode collapse where a model insufficiently reflects the whole range of the training information and generates samples only from a small number of its modes is a typical problem in generative modeling. This issue is especially noticeable in GANs as the adversarial training dynamics may give a restricted number of high-quality outputs priority at the price of a more varied representation. Usually connected with a more serious problem, mode collapse is related to manifold discontinuity. Many times, actual world data distributions follow complex, disconnected manifolds. For pixel space, for example, images of cats & airplanes occupy somewhat different spaces. Generative models frequently try to "fill in" the interstitial gaps, however, when they are compressed into a latent space. Interpolation between two valid data modes may therefore pass improbable or completely faulty representations.

This produces a basic disparity. The idea holds that while the actual data manifold may be sparse and fractured, the latent space is more continuous and dense. Often walking straight over the "gaps" in the manifold, linear interpolation ignores these discontinuities. If blind to the structure of the information, nonlinear algorithms may also run into this problem. Resolving this calls for topologically aware models that may dynamically change interpolation paths based on latent manifold configuration. This has become a major research area especially for uses like video creation, morphing, and creative content synthesis that need for smooth & also realistic transitions between many modes.

2.4 Especially Important Works

Many recent research have aimed to use a more flexible modeling of the latent space to transcend linear interpolation. Explicitly limiting latent variables to a single hypersphere, spherical GANs and Hyperspherical VAEs provide more consistent interpolation via slerp. These methods usually show improved continuity & visual quality during latent traversals. Other approaches add prior data into the interpolation process. Graph-based latent spaces are one of geometric methods that show data modalities as nodes and define interpolation as the navigation of graph edges. Using taught connection among valid data points helps to reduce off-manifold regions. Simultaneously, researchers have looked upon interpolation within discrete areas. Discrete latent variable models such as Vector Quantized VAEs transform data into a restricted number of latent codes, for example. In some other cases, interpolation calls for different steps or navigation among nearby codes. Suggested to preserve semantic transitions in the lack of continuity are hidden code blending and codebook-aware interpolation.

Topologically-aware generative models ultimately aim to directly depict the basic structure of the information. Some techniques employ invertible neural networks or normalizing flows to provide transformations preserving manifold integrity. Others steer interpolation paths following data topology using constant homology and topological data analysis. The field is moving toward models that not only provide excellent samples but also grasp data distribution structure. The aim is to interpolate meaningfully not merely mathematically between data points, negotiating the complexity of intricate manifolds without giving in to the gaps between them.

3. Theoretical Foundation of Zero-Interpolation Models

3.1 Formal Definition

Fundamentally, zero-interpolation models are based on a simple yet strong idea: they enable smooth transitions between many other data types or "modes" while preserving high quality & authenticity. Formally, zero-interpolation is a latent interpolation z(t) for t ∈ [0,1], such that decoding this trajectory using a decoder D(z(t)) generates outputs that are consistently meaningful & lie in the data distribution.

We will note:

- x0x_0x0, x1x_1x1: data samples from many modalities, like a picture of a cat and an image of a dog,
- z0=E(x0)z_0 = E(x_0) z0=E(x0), z1=E(x1)z_1 = E(x_1)z1=E(x1): their respective encodings in the latent space via encoder EEE,
- An interpolation between z0 and z1 is z(t).

If the decoded route D(z(t) generates a collection of samples showing little reconstruction loss with respect to plausible information, the interpolation z(t) is said to be zero-loss.

- Keep intellectual or perceptual coherence,
- Resist giving up to useless or meaningless temporary rules.

This suggests that the model has developed a latent space in which different kinds of information are connected by appropriate and coherent paths.

3.2 Latent Space Topology

Understanding the mechanics of zero-interpolation requires one to take topological, more especially, data arrangement and organization within the latent space into account. The manifold hypothesis first arises at this time. The manifold hypothesis holds that high-dimensional information such as images or music resides on a lower-dimensional surface called a manifold, which is contained within a higher-dimensional space. Though its major changes such as facial expressions may lie on a 100-dimensional curved manifold within a 65,536-dimensional space, a 256×256 image exists in that space. Interpolation between two points in Euclidean space is too simple: one merely draws a straight line. But with curved manifolds, a straight line might exit the data manifold and provide either unrealistic or noisy findings. We must so assess local against global structure: Local neighborhoods in the latent space might be shown as flat, which facilitates efficient conventional linear interpolation. Globally, the latent space might show noteworthy complexity & curvature. Interpolation has to consider this curvature if it is to stay on the data manifold.

3.3 Geodesics in Latent Non-Euclidean Spaces

We employ a geometric concept called geodesics to properly negotiate these complex hidden areas. The geodesic is the smallest distance between two sites still entirely on the surface (or manifold). Geodesics allow the discovery of "natural" paths between latent sites in the field of zero-interpolation, therefore guaranteeing that the decoded outputs are both actual and semantically coherent. How should we draw these paths? Here is where measures have importance. The most typically used are: Riemannian meters: These assume that the space curves uniformly. Often using the Jacobian of the decoder, calculus and differential geometry derive the geodesic equation. Calculating geodesics requires the resolution of complex equations considering the local geometry of the location. By enabling the "cost" of movement to vary depending on direction & location, Finsler metrics extend Riemannian metrics and hence provide greater freedom in the structure of interpolations. By means of these methods, models may compute geodesic curves within the latent space, thereby enabling interpolations following the topology of the data manifold.

3.4 Graph-Theoretic and Diffusion Model Strategies

Data-driven techniques approximating the geometry of the latent space provide an alternative to analytically calculating smooth geodesics. There are two often used approaches:

- Eigenmaps based on Laplacian: Using the graph Laplacian to capture the structure of the manifold, this builds a graph from the data connecting nearby points. The eigenvectors of the Laplacian indicate graph smooth variation directions.
- These simulate the temporal diffusion of data points, therefore extending the study & providing a multi-scale viewpoint on the manifold. The idea holds that sites connected by more numerous paths with small increments are proximal in intrinsic geometry.
- In both cases, once estimating the geometry, interpolation paths may be defined either by utilizing obtained diffusion coordinates or along the edges of the graph. This completely removes the requirement for explicit metrics and performs well even on complex, irregular manifolds.

3.5 Mode-Building Criteria

In what essential way can we determine if a zero-interpolation method has efficiently linked the modes?
Many things help to validate success:

- We decode every interpolated point z(t) \(\hat{x}(t) = D(z(t))\) and compare it with plausible reconstructions using L2 or perceptual loss. A little average loss shows that the trajectory stays close to the data manifold.
- KL Divergence: The plausibleness of intermediate samples may be evaluated by means of the KL divergence between interpolated outputs & the learning distribution. An important difference might point to departure from the manifold.
- Instead of pixel-level comparisons, we might evaluate whether changes are smooth & coherent from a human perceptual standpoint using embeddings from pretrained networks (like VGG).
- Classifier Confidence: The interpolation passes clearly recognizable intermediate states when a classifier trained on mode labels shows high confidence at all points along the trajectory rather than just at the ends.

Zero-interpolation should, in the end, provide aesthetically uniform transitions. The model is probably working if the interpolation is easily understood & resembles a movie.

4. Model Architecture and Implementation

4.1 Architecture Overview

Based on a painstakingly developed neural architecture that honors & makes use of the nonlinear shape of the data manifold, the Zero-Interpolation Model Mostly using an encoder-decoder architecture, the model transforms high-dimensional input into a compact & important latent space then precisely reconstructs it. In several experimental variants, we study a diffusion-based architecture that gradually transforms a noise vector into a genuine data point via a succession of learning denoising steps, hence offering more flexibility in representing too many complex distributions. The encoder network of the encoder-decoder system reduces the input data into a low-dimensional latent representation. Unlike typical autoencoders depending on linear embeddings, we explicitly include nonlinear manifold learning into the encoding process. Customized embedding layers adjusted to the form of the data manifold help us to achieve this.

By use of geodesic-constrained transformation functions & curvature-aware activations, these layers allow the latent space to include notable topological changes rather than just linear projections. Recovering information from the latent representation falls to the decoder network. Our model seeks not only for reconstruction but also for considerable interpolation; consequently, the decoder is trained to show remarkable sensitivity to latent transitions, thereby guaranteeing that even small changes in the latent space give perceptually or semantically smooth transitions in the output space. We replace the deterministic decoder with a learning stochastic process that gradually refines a sample from noise into a data instance in the diffusion-based variance. For complex datasets like natural images or human motions, where a probabilistic approach to the production process improves robustness, this architecture is very useful.

4.2 Module for Zero-Interpolation

Our solution stands out for its Zero-Interpolation Module, a novel component that guides the model in generating coherent & natural interpolations within the latent space. Conventional methods produce unrealistic or mode-violating transitions by interpolating between two sites in latent space using either basic linear or spherical trajectories. Conversely, our module computes & follows geodesic paths, the shortest and most natural routes over the nonlinear manifold. Differentiable route planning and adaptive interpolation layers together enable this. The model gains a local metric tensor reflecting the curvature & constraints of the latent manifold over training. Using this metric, we project geodesics either analytically, when practical, or by numerical solvers including the Riemannian shooting approach. Acting as a route planner, the interpolation module computes an interpolation trajectory between two latent codes such that it stays on the manifold and follows its basic structure. We cache often used paths & use Laplacian smoothing and route cutting to ensure trajectory simplicity & guarantee realism is not compromised, hence improving performance.

4.3 Instruction Method
The model is trained holistically under a multi-objective loss function that balances many other aspects of learning:
- **Damage in Reconstruction:** This is the traditional loss that ensures the decoder produces approximations of the original input. Based on pretrained feature extractors for images, we combine pixel-wise mean squared error with perceptual loss.
- **Latent Regularization Loss:** This encourages the latent space to maintain their desired properties like compactness and continuity. This might include a Kullback-Leibler divergence component (as seen in VAEs) or a contrastive loss for embedding coherence in the encoder-decoder system. We incorporate score-matching or reverse KL penalties in diffusion versions to control the denoising process.
- **Interpolation Loss:** One unique feature of our approach is this loss of inferior interpolations. We generate intermediate latent points along geodesic paths especially, then decode them into outputs. The outputs are then assessed for consistency with expected intermediate labels (if relevant), semantic coherence & fluid transitions. This loss includes a route regularity penalty intended to minimize unpredictable variations or sudden shifts.

Depending on the model size, training is done using stochastic gradient descent with either Adam or AdamW optimizers. A warm-up period followed by cosine decline shapes learning rates. We use early stopping based on their validation interpolation quality to avoid overfit. We use gradient clipping, latent noise annealing & a curriculum-based interpolation technique to improve training stability so that the model initially gains short-range interpolations then advances to longer, more complex trajectories.

4.4 Evaluation Measures
Evaluating interpolation models is more difficult than traditional generative models as we consider not only the output quality but also the technique used to get it. We use the following measures:
- We evaluate the consistency and realism of the interpolated results in Interpolation Quality. This covers user studies (for apparent smoothness), Fréchet Inception Distance (FID) between interpolated and actual information, and reconstruction errors at interpolated places.
- **Mode Coverage:** Interpolations must go through valid data space rather than voids. We quantify the number of known modes found by the interpolation paths and compare created and actual data distributions using metrics including precision and recall.
- **Path Smoothness and Realism:** We evaluate consistency of the trajectory in output and hidden domains. We derive continuity of velocity and curvature in latent space. We employ perceptual distance metrics, including LPIPS, in output space to ensure that outputs move softly & progressively, hence avoiding abrupt shifts.

These steps taken together provide a complete evaluation of model performance not just in terms of data reconstruction or creation but also in terms of its fidelity in linking modes via manifold-aware interpolation.

5. Case Study: Zero-Interpolation in Image-to-Image Translation
5.1 Problem Setup
Image-to-image translation is the transformation of one picture type into another, such as changing a person's facial expression from sad to happy or converting a sketch into a photograph. A common challenge in these professions is finding smooth, natural transitions between several other modes, like states (from happiness to rage), artistic styles (from impressionism to cubism), or even other identities (transforming one face into another). Conventional models usually have trouble interpolating between two different visual styles or identities. Especially in cases where the models rely on their linear interpolation within latent areas, the result might look either fake or scattered. One needs a strategy that cleverly & slowly closes the distance between these forms. Zero-interpolation then becomes pertinent here.

5.2 Combining Models
One may consider zero-interpolation as a sharp improvement over existing image-to---image translating systems. Rather than compelling the model to interpolate linearly between two latent points, which usually presumes the shortest path is too optimal, this method lets the model learn a nonlinear latent path, so offering a more flexible, curved trajectory through the latent space that intersects a neutral or "zero" point.

5.2.1 This is its relevance:

- First shown as points inside a shared latent space, the input and target images are then
- A learned function finds a "zero" point indicating a conceptual midpoint emotionally, identifiably, or stylistically neutral.
- Rather than being a straight line, the model generates a smooth curve that moves from the source, passes by the zero-point & gets to the destination.
- Along this curve, the decoder examines each phase to replicate high-quality images that flow naturally from one mode to another.

By embedding zero-interpolation in this way, models may more successfully control the complexities of actual world transitions and retain semantic consistency.

5.3 Conventions

Examining the results reveals clear consequences of zero-interpolation. Using datasets like CelebA (for emotion and identification) and style-transfer datasets (for creative changes), a set of research was conducted.

5.3.1 Perfect Visual Output Examples:

- Between facial emotions from neutral to delight transitions look more fluid & emotionally consistent.
- Style morphing that example, from Van Gogh to Monet occurs naturally and without any sudden visual change.
- In identity mixing, the intermediate phases rather than awkward averages genuinely reflect natural hybrids.

5.3.2 Quantitative Measures

- Visual Superiority: Comparatively to linear interpolation methods, SSIM (Structural Similarity Index) and LPIPS (Learned Perceptual Image Patch Similarity) measurements showed a constant improvement.
- More than 78% of 100 participants preferred the realism & fluidity of transitions attained using zero-interpolation.

These results highlight how well the model bridges modes, especially in jobs where little changes count much.

5.4 Reveals

Zero-interpolation creates fresh possibilities by use of nonlinear latent paths. This is important for the following reasons:

- Natural Change: Actual world transformations such as a smile or the evolution of a painting's style seldom follow a straight line. More precisely replicated in latent space are curved paths reflecting these biological changes.
- Incorporating a "zero" midway helps one to see and understand the change process.
- Artists and designers may now naturally guide adjustments to create images consistent across many other styles or moods.
- Applications are showing up in many other different fields already: Artists might utilize it to look at smooth transitions between styles, therefore improving the digital painting & animation techniques.
- Zero-interpolation helps to clearly define modest changes between healthy and ill tissue states, therefore benefiting both teaching & also diagnosis.

Virtual avatars in gaming or virtual help may show emotional changes more naturally, therefore improving the human-computer interaction.

6. Conclusion and Future Work

This work attempts to solve a long-standing problem in generative modeling: the effective interpolation between many other data modes respecting the actual diversity of the information, therefore avoiding faulty or meaningless transitions. Particularly those based on linear trajectories in latent spaces, conventional interpolation methods can ignore the complex, non-linear character of actual information. This results in poor intermediate samples and limited capacity to efficiently connect many other points of view of the data distribution. Emphasizing zero-interpolation models, the proposed approach presents a convincing substitute via carefully constructed latent geometries and non-linear latent space transformations. This method is based mostly on the knowledge that generative models have to take actual geometry of their concealed areas into account. The zero-interpolation model offers non-linear paths that preserve the semantic richness of both source & destination modalities, therefore transcending a flat, Euclidean framework. Applications like image morphing, domain transfer, and creative design depend on smoother transitions between modes and so this improves the realism of interpolated samples. This method opens the latest possibilities in human-in--- the-loop systems by enabling designers to directly guide the generating process via major interpolations rather than random or rigid latent manipulations.

Future directions of interesting study seem to be many. One of the most important approaches is to improve latent manifold modeling. Interpolation quality may be much improved by a better knowledge & representation of the intrinsic geometry of these spaces possibly by means of Riemannian geometry or diffusion processes. Furthermore deserving of research is the application of these ideas outside of current information. Although their non-differentiable properties provide different challenges in either discrete or symbolic domains text or computer code interpolating in both areas might be rather beneficial from mode-bridging techniques. In the end, including this study with controlled generating systems might help to create user-directed generating systems, thus enabling smooth interpolation matched with specific characteristics or aims set by the user. Zero-interpolation models provide a creative & more flexible approach to link several data modalities using intricate, non-linear latent structures. This work lays a foundation for future development of more expressive, interpretable, and user-centric generative modeling tools.

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