Novelty Assessment Report

Paper: Pareto Variational Autoencoder
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Abstract

Incorporating robustness in generative modeling has enticed many researchers of the field. To this end, we introduce a new class of multivariate power-law distributions---the symmetric Pareto (symPareto) distribution---which can be viewed as an ℓ_1-norm-based counterpart of the multivariate T distribution. The symPareto distribution possesses many attractive information-geometric properties with respect to the γ-power divergence that naturally populates power-law families. Leveraging on the joint minimization view of variational inference, we propose the ParetoVAE, a probabilistic autoencoder that minimizes the γ-power divergence between two statistical manifolds. ParetoVAE employs the symPareto distribution for both prior and encoder, with flexible decoder options including Student's T and symPareto distributions. Empirical evidences demonstrate ParetoVAE's effectiveness across multiple domains through varying the types of the decoder. The T decoder achieves superior performance in sparse, heavy-tailed data reconstruction and word frequency analysis; the symPareto decoder enables robust high-dimensional denoising.

Core Task Landscape

This paper addresses: **robust generative modeling with heavy-tailed distributions**

A total of **50 papers** were analyzed and organized into a taxonomy with **14 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Generative Model Architectures for Heavy-Tailed Data**
- **Robust Inference and Estimation Under Heavy-Tailed Noise**
- **Statistical Theory and Estimation for Heavy-Tailed Distributions**
- **Applications and Domain-Specific Methods**

Complete Taxonomy Tree

- robust generative modeling with heavy-tailed distributions Survey Taxonomy
- Generative Model Architectures for Heavy-Tailed Data
  - Variational Autoencoders with Heavy-Tailed Priors and Posteriors ★ (2 papers)
  - [0] Pareto Variational Autoencoder (Anon et al., 2026) View paper
  - [18] -Variational Autoencoder: Learning Heavy-tailed Data with Student's t and Power Divergence (J Kim, 2023) View paper
  - Adversarial and Flow-Based Generative Models (6 papers)
  - [8] Learning to simulate from heavy-tailed distribution via diffusion model (Haoyu Liu, 2024) View paper
  - [10] Cauchy Diffusion: A Heavy-tailed Denoising Diffusion Probabilistic Model for Speech Synthesis (Qi Lian, 2025) View paper
  - [12] Mirror Flow Matching with Heavy-Tailed Priors for Generative Modeling on Convex Domains (Balasubramanian, 2025) View paper
  - [14] Stock Price Prediction with Heavy-Tailed Distribution Time-Series Generation Based on WGAN-BiLSTM (Ming Kang, 2025) View paper
  - [27] Improving skin cancer classification using heavy-tailed Student t-distribution in generative adversarial networks (TED-GAN) (Bilal Ahmad, 2021) View paper
  - [37] Heavy-tailed denoising score matching (Deasy, 2021) View paper
  - Multivariate Extreme and Tail Dependence Modeling (4 papers)
  - [6] Deep generative modeling of multivariate dependent extremes (Girard, 2024) View paper
  - [20] Comet flows: Towards generative modeling of multivariate extremes and tail dependence (McDonald, 2022) View paper
  - [33] Nonlinear 3D cosmic web simulation with heavy-tailed generative adversarial networks (Richard M. Feder, 2020) View paper
  - [47] Generative models of simultaneously heavy-tailed distributions of inter-event times on nodes and edges (Reis, 2022) View paper
  - Divergence and Objective Function Design (2 papers)
  - [5] Robust generative learning with Lipschitz-regularized Î±-divergences allows minimal assumptions on target distributions (Ziyu Chen, 2024) View paper
  - [31] Robust Training of Implicit Generative Models for Multivariate and Heavy-Tailed Distributions with an Invariant Statistical Loss (JosÃ© Manuel de Frutos, 2025) View paper
- Robust Inference and Estimation Under Heavy-Tailed Noise
  - Kalman Filtering and State-Space Models (7 papers)
  - [11] A Robust Kalman Filter for Heavy-Tailed Measurement Noise Based on Gamma Pearson VII Mixture Distribution (Shen Liang, 2025) View paper
  - [13] Robust Adaptive Filters and Smoothers for Linear Systems With Heavy-Tailed Multiplicative/Additive Noises (Xingkai Yu, 2024) View paper

  - [15] Variational robust filter with a heavy-tailed mixture model for GNSS/INS tightly coupled integration (Baoyu Guo, 2024) View paper
  - [26] Robust and Flexible Maritime ISAR Tracking Algorithm for Multiple Maneuvering Extended Vessels in Heavy-Tailed Clutter Using Skewed Multiple Model MB-Sub-RMM-TBD Filter (Mohamed Barbary, 2024) View paper
  - [28] Robust Bayesian Recursive Ensemble Kalman Filter Under the Nonstationary Heavy-Tailed Noise (Li Wang, 2025) View paper
  - [38] A robust distributed interaction multiple model filter for jump Markov systems with heavy-tailed measurement noise (Shun Tong, 2024) View paper
  - [44] Robust Kalman Filter for Systems With Colored Heavy-Tailed Process and Measurement Noises (Guoqing Wang, 2023) View paper
  - Regression and Supervised Learning (7 papers)
  - [1] Robust SCN for Data-Driven Modeling Based on Heavy-Tailed Noise Distribution (Xin Liu, 2025) View paper
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  - [24] Robust change point detection for highâ□□dimensional linear models with tolerance for outliers and heavy tails (Zhi Yang, 2025) View paper
  - [30] Robust Gradient Descent Estimation for Tensor Models under Heavy-Tailed Distributions (Zhang Xiao-yu, 2024) View paper
  - [34] Bayesian robust symmetric regression for medical data with heavy-tailed errors and censoring. (Ali, 2025) View paper
  - [45] Robust Inference for High-dimensional Linear Models with Heavy-tailed Errors via Partial Gini Covariance (Zhang Yilin, 2024) View paper
  - Bayesian Inference with Heavy-Tailed Priors and Likelihoods (3 papers)
  - [25] Gamma shape mixtures for heavy-tailed distributions (Sergio Venturini, 2022) View paper
  - [29] BayeSMM: Robust Deep Combined Computing Tackling Heavy-Tailed Distribution in Medical Images (Yuanye Liu, 2025) View paper
  - [41] Simple proof of robustness for Bayesian heavy-tailed linear regression models (Gagnon, 2025) View paper
- Statistical Theory and Estimation for Heavy-Tailed Distributions
  - Extreme Value and Tail Quantile Estimation (2 papers)
  - [4] Estimation of extreme quantiles from heavy-tailed distributions with neural networks (Michael Allouche, 2024) View paper
  - [39] Estimating flexible, fat-tailed asset return distributions (Craig Friedman, 2012) View paper
  - Distribution Families and Parametric Modeling (4 papers)
  - [16] Transformed-Arimax Model for Heavy Tailed Distributions (K. I. Ekerikevwe, 2025) View paper
  - [17] A useful family of fat-tailed distributions (Baker, 2022) View paper
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  - [40] A General Framework for Generating Three-Components Heavy-Tailed Distributions with Application (P. Osatohanmwen, 2024) View paper
  - Robust Estimation Algorithms and Convergence Analysis (7 papers)
  - [7] Outlier-Robust Sparse Mean Estimation for Heavy-Tailed Distributions (Diakonikolas, 2022) View paper
  - [22] Outlier-Robust Linear System Identification Under Heavy-tailed Noise (Mitra, 2024) View paper
  - [23] On learning mixtures of heavy-tailed distributions (A. Dasgupta, 2005) View paper
  - [32] On the statistical rate of nonlinear recovery in generative models with heavy-tailed data (Xiaohan Wei, 2019) View paper
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  - [50] Efficient Estimators for Heavy-Tailed Machine Learning (Vishwak Srinivasan, 2021) View paper
- Applications and Domain-Specific Methods
  - Financial and Economic Modeling (3 papers)
  - [36] On the robustness of the fat-tailed distribution of firm growth rates: a global sensitivity analysis (Dosi, 2018) View paper
  - [46] Parsimonious Generative Machine Learning for Non-Gaussian Tail Modeling and Risk-Neutral Distribution Extraction (Wu Qi, 2024) View paper
  - [48] Distribution-free expectation operators for robust pricing and stocking with heavy-tailed demand (Kleer, 2024) View paper
  - Medical Imaging and Healthcare Data (1 papers)
  - [43] Robust Hybrid Data-Level Approach for Handling Skewed Fat-Tailed Distributed Datasets and Diverse Features in Financial Credit Risk (Keith R. Musara, 2025) View paper
  - Reinforcement Learning and Curriculum Design (2 papers)
  - [2] Risk-aware curriculum generation for heavy-tailed task distributions (Cevahir Koprulu, 2023) View paper
  - [49] Robust Offline Reinforcement learning with Heavy-Tailed Rewards (Zhu Jin, 2023) View paper
  - Rare Event and Extreme Phenomenon Simulation (1 papers)
  - [21] Beyond the Norm: A Survey of Synthetic Data Generation for Rare Events (Gu, 2025) View paper

Narrative

Core task: robust generative modeling with heavy-tailed distributions. The field addresses the challenge of learning generative models when data exhibit extreme values, outliers, or distributional properties that deviate from standard Gaussian assumptions. The taxonomy organizes research into four main branches. Generative Model Architectures for Heavy-Tailed Data explores how to design neural generative frameworks—such as variational autoencoders, diffusion models, and GANs—that explicitly incorporate heavy-tailed priors or likelihoods; representative works include Heavy-Tailed Diffusion[8], Cauchy Diffusion[10], and Variational Autoencoder Student[18]. Robust Inference and Estimation Under Heavy-Tailed Noise focuses on algorithmic techniques for parameter estimation and filtering when measurements are corrupted by non-Gaussian noise, exemplified by Robust SCN Heavy-Tailed[1] and Gamma Pearson Kalman[11]. Statistical Theory and Estimation for Heavy-Tailed Distributions develops foundational methods for learning mixture models, extreme quantiles, and tail indices, with contributions such as Extreme Quantiles Neural[4] and Learning Heavy-Tailed Mixtures[23]. Applications and Domain-Specific Methods translate these ideas into finance, signal processing, and other domains where tail behavior is critical, as seen in Stock Price WGAN[14] and GNSS INS Robust[15].

A particularly active line of work centers on variational autoencoders that replace Gaussian assumptions with heavy-tailed distributions to improve robustness and capture outlier-prone latent structures. Pareto VAE[0] introduces Pareto-distributed priors and posteriors within the VAE framework, offering a principled way to model power-law tails in latent space. This approach contrasts with Variational Autoencoder Student[18], which employs Student-t distributions to achieve similar robustness but with different tail decay properties. Meanwhile, diffusion-based generative models are exploring heavy-tailed score matching and noise schedules, as in Heavy-Tailed

Diffusion[8] and Cauchy Diffusion[10], raising questions about the trade-offs between tail flexibility and training stability. Pareto VAE[0] sits squarely within the VAE branch, sharing conceptual ground with Variational Autoencoder Student[18] but distinguished by its use of Pareto rather than Student-t distributions, which may offer advantages in modeling extremely sparse or skewed data. Across these branches, open questions remain about scalability, theoretical guarantees, and the interplay between architectural choices and the statistical properties of heavy-tailed noise.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. -Variational Autoencoder: Learning Heavy-tailed Data with Student's t and Power Divergence

Authors: J Kim, J Kwon, M Cho, H Lee, JH Won | **Year/Venue**: 2023 | **URL**: View paper

Abstract

â¦ 2013) is a popular probabilistic generative model for learning â¦ exhibits outlier-heavy or heavy-tailed behavior which is better â¦ been studied before in the robust statistics literature. Some â¦

Relationship Analysis

Both papers belong to the same taxonomy category of VAE frameworks incorporating heavy-tailed distributions, specifically focusing on Student's t distributions and power divergence methods for robust generative modeling. They overlap in their use of heavy-tailed priors/posteriors and information-geometric divergence measures (γ-power divergence) to handle outlier-heavy data. The key difference is that the original paper (Pareto VAE) introduces symmetric Pareto distributions with $\ell 1$-norm structure and explores both Student's t and symPareto decoders, while the candidate paper appears to focus primarily on Student's t distributions throughout the VAE architecture.

Contributions Analysis

Overall novelty summary. The paper introduces a symmetric Pareto distribution and the ParetoVAE framework, which employs this distribution in both encoder and prior while offering flexible decoder options. Within the taxonomy, it resides in the 'Variational Autoencoders with Heavy-Tailed Priors and Posteriors' leaf, which contains only two papers total. This leaf sits under 'Generative Model Architectures for Heavy-Tailed Data', a branch with four sub-areas encompassing VAEs, adversarial models, multivariate extremes, and divergence design. The sparse population of this specific leaf suggests that VAE-based heavy-tailed generative modeling remains relatively underexplored compared to adjacent directions.

The taxonomy reveals neighboring research in adversarial and flow-based models (six papers on diffusion and GANs with heavy-tailed noise), multivariate extreme modeling (four papers on tail dependence structures), and divergence design (two papers on alpha-divergences and Lipschitz regularization). The paper's use of γ-power divergence connects it to the divergence design subtopic, while its focus on multivariate distributions relates to the extreme dependence modeling branch. However, the VAE-specific architecture distinguishes it from flow-based methods, and the symmetric Pareto choice differs from copula-based approaches in the multivariate extremes leaf.

Among seven candidates examined across three contributions, the ParetoVAE framework shows one refutable candidate from five examined, while the symmetric Pareto distribution itself has no refutations among two candidates. The upper bound contribution was not examined against prior work. The single sibling paper in the same taxonomy leaf—Variational Autoencoder Student—uses Student-t distributions rather than Pareto, suggesting architectural overlap but distributional differentiation. The limited search scope (seven candidates total) means these statistics reflect top semantic matches rather than exhaustive coverage, and the sparse leaf population indicates fewer direct comparisons are available in the literature.

Based on the top-seven semantic matches examined, the work appears to occupy a relatively sparse research direction within VAE-based heavy-tailed modeling. The symmetric Pareto distribution contribution shows no overlap in the limited candidate set, while the ParetoVAE framework has one potential precedent among five examined. The taxonomy structure confirms that this specific combination—VAE architecture with Pareto-family distributions—has minimal prior exploration, though related ideas exist in adjacent branches using different architectures or distributional families.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Multivariate symmetric Pareto distribution

Description: The authors introduce the symmetric Pareto (symPareto) distribution as a new multivariate power-law distribution family. This distribution serves as an l1-norm-based analogue to the multivariate t distribution and possesses attractive information-geometric properties with respect to the γ-power divergence.

This contribution was assessed against **2 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Hardware-Software Co-design of Efficient and Scalable Deep Learning

URL: View paper

Brief Assessment

Hardware-Software Co-design[51] focuses on efficient deep learning implementation and hardware optimization. The candidate's brief mentions of power-law distributions and regularization techniques are unrelated to the statistical distribution theory presented in the original paper.

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2. The Law of Large Numbers Under Fat Tails

URL: View paper

Brief Assessment

Fat Tails Law[52] focuses on sample size requirements and convergence properties under fat-tailed distributions for statistical inference, not on introducing multivariate power-law distributions as l1-norm analogues of t distributions or their information-geometric properties.

Contribution 2: ParetoVAE framework

Description: The authors propose ParetoVAE, a probabilistic autoencoder framework that employs symPareto distributions for both prior and encoder, with flexible decoder options. The framework minimizes the γ-power divergence between statistical manifolds using a joint minimization view of variational inference.

This contribution was assessed against **5 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Î-VAE: Curvature regularized variational autoencoders for uncovering emergent low dimensional geometric structure in high dimensional data

URL: View paper

Brief Assessment

Gamma-VAE[53] focuses on curvature regularization of VAE manifolds for biological data analysis, not on γ-power divergence minimization between statistical manifolds using symPareto distributions as in the original paper.

2. Conditional-t^3VAE: Equitable Latent Space Allocation for Fair Generation

URL: View paper

Brief Assessment

Conditional-t3VAE[56] focuses on enforcing equitable latent space allocation across classes for fair generation on imbalanced datasets, using per-class Student's t priors. It does not propose a ParetoVAE framework with symPareto distributions or address the general γ-power divergence minimization between statistical manifolds that characterizes the original contribution.

3. Conditional-VAE: Equitable Latent Space Allocation for Fair Generation

URL: View paper

Brief Assessment

Conditional-VAE[55] focuses on fairness in generative modeling through equitable latent space allocation, not on minimizing γ-power divergence between statistical manifolds using symPareto distributions as proposed in the original paper.

4. -Variational Autoencoder: Learning Heavy-tailed Data with Student's t and Power Divergence

URL: View paper

Brief Assessment

Variational Autoencoder Student[18] focuses on using Student's t distributions and power divergence for VAEs, but does not employ symPareto distributions or the specific γ-power divergence minimization framework between statistical manifolds that characterizes ParetoVAE. The candidate's limited context does not provide sufficient detail to assess overlap with the symPareto-based approach.

5. t3-Variational Autoencoder: Learning Heavy-tailed Data with Student's t and Power Divergence

URL: View paper

Prior Art Analysis

t3-VAE[54] demonstrates that prior work exists using γ-power divergence minimization between statistical manifolds in VAE frameworks. Both papers reformulate the VAE objective as joint minimization of divergence between model and data manifolds, replacing KL divergence with γ-power divergence. t3-VAE[54] explicitly states they 'derive a new objective by reformulating the evidence lower bound as joint optimization of kl divergence between two statistical manifolds and replacing with γ-power divergence,' which directly parallels the ORIGINAL paper's claimed contribution of 'minimizing the γ-power divergence between two statistical manifolds using a joint minimization view of variational inference.'

Evidence

Evidence 1 - **Rationale**: Both papers explicitly describe reformulating VAE objectives to minimize γ-power divergence between statistical manifolds, demonstrating that t3-VAE[54] already employed this approach before the ORIGINAL paper. - **Original**: leveraging on the joint minimization view of variational inference, we propose the paretov ae, a probabilistic autoencoder that minimizes theγ-power divergence between two statistical manifolds. - **Candidate**: we derive a new objective by reformulating the evidence lower bound as joint optimization of kl divergence between two statistical manifolds and replacing with γ-power divergence, a natural alternative for power families.

Evidence 2 - **Rationale**: Both papers use information geometry principles to construct joint model distributions and reformulate VAE objectives, showing t3-VAE[54] already applied these concepts to power-form distributions. - **Original**: v ae objective can be reinterpreted as a joint minimization problem between two statistical manifolds (han et al., 2020). the model distribution manifold mmodel and the data distribution manifold mdata are defined as mmodel = {pθ(x, z) = pθ(x|z)pz(z) : θ ∈ θ}, mdata = {qϕ(x, z) = pdata(x)qϕ(z|x) : ϕ... - **Candidate**: drawing upon insights from information geometry, we propose t^3vae, a modified vae framework that incorporates student's t-distributions for the prior, encoder, and decoder. this results in a joint model distribution of a power form which we argue can better fit real-world datasets.

Evidence 3 - **Rationale**: The ORIGINAL paper explicitly acknowledges that it extends t3-VAE[54]'s structure, confirming that t3-VAE[54] already established the framework of using γ-power divergence minimization between statistical manifolds for heavy-tailed VAEs. - **Original**: this work naturally extends the family of heavy-tailed variants of v aes from student'st distributions to sympareto. in particular, we generalize the t3v ae (kim et al., 2024) structure into a symparetobased formulation. - **Candidate**: drawing upon insights from information geometry, we propose t^3vae, a modified vae framework that incorporates student's t-distributions for the prior, encoder, and decoder.

Contribution 3: Upper bound for γ-power divergence between noncentral symPareto distributions

Description: The authors develop a tractable computational approach by deriving an upper bound for the γ-power divergence between noncentral symPareto distributions (Theorem 2.1). This enables efficient optimization by providing closed-form expressions that overcome the computational challenges of ELBO estimation in heavy-tailed settings.

This contribution was assessed against **0 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

Appendix: Text Similarity Detection

Textual similarity detection checked 7 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. t3-Variational Autoencoder: Learning Heavy-tailed Data with Student's t and Power Divergence

Detected in: Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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