Flow-Based Conformal Predictive Distributions

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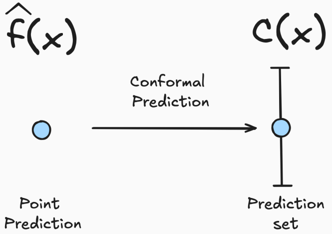
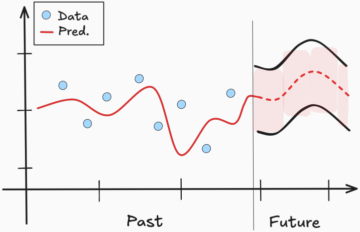
Conformal Prediction and Prediction Sets

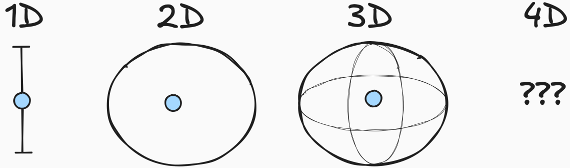




- General framework for uncertainty quantification in predictive models.
- Constructs post-hoc **prediction sets** $C_\alpha(x)$ that contain the target with probability $1 - \alpha$.
- No asymptotics (finite sample valid), priors, or modification to the training procedure. No model assumptions. Distribution free.
- Requires data (x, y) to be exchangeable.

Conformal Prediction - Implicit Sets

- Conformal prediction based on **nonconformity scores**:
  - $S(x, y)$ is a nonconformity score – e.g. $S(x, y) = \|f_\theta(x) - y\|_2$
  - Measures accuracy of predictions
- Defined implicitly via the score: $C_\alpha(x) = \{y : S(x, y) \leq \tau_\alpha\}$
  - τ_α is an empirical threshold.
  - Guarantees $P(y \in C_\alpha(x)) \geq 1 - \alpha$.
- What to do with $C_\alpha(x)$? Need a usable uncertainty object.
- Fine in 1D; okay in 2D/3D (if simple); problematic in higher D



Conformal Prediction in High Dimensions

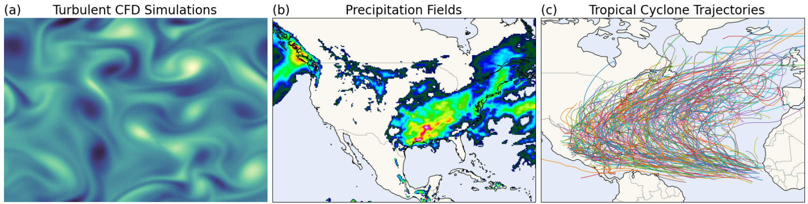


Figure 1: What do prediction sets look like for CFD simulations? Precipitation patterns? Tropical Cyclones? How do we operationalize sets in these spaces?

- What if the data are significantly more complex? structured? non Euclidean? multi-modal? What if the score is too?
- CP sets well-defined:

$$C_\alpha(x) = \{\, y \in \mathcal{Y} : \ S(x, y) \leq \tau_\alpha \,\} \tag{1}$$

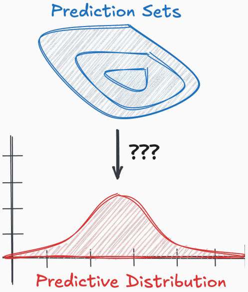
1. How can we *interact* with $C_\alpha(x)$?
2. Can we even *compute* anything useful from a set?

Conformal Prediction... Distributions?

- **Problem:** We have prediction sets, but no distribution
  - Universally applicable (big ML models), distribution free, exact calibration.
  - Hard to represent, hard to sample from or visualize, not easily usable for downstream tasks.

- Sets alone are inadequate UQ objects for many tasks.

- What if we had a distribution instead?
  1. Representation - Sample at fixed α. Explore prediction sets.
  2. Computation – Expectations, Risk, probabilistic forecasting, etc.



- **Question:** Can we invert prediction sets into a predictive distribution?

Conformal Predictive Distributions

- Several approaches for lifting prediction sets into predictive distributions.
- Conformal Predictive Systems
  - [Vovk et al. (2017, 2018); Vovk (2019)]
  - Empirical CDFs whose quantile regions match conformal prediction sets.
  - Limited to univariate targets.
- Generative Models:
  - [Wang et al. (2022); Teneggi et al. (2023); Zheng and Zhu (2024)]
  - Approximate with generative model (diffusion). Rejection sampling.
  - Computationally heavy, limited data, adds structure (likelihood), inefficient.
- Optimal Transport
  - [Ndiaye (2025)]
  - Optimal transport to define vector-ranks and conformal quantile regions
  - OT scales poorly in dimension

Our Contribution

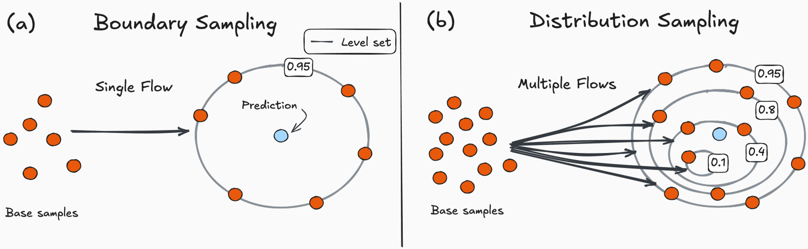


Figure 2: Score + confidence level determines a flow. Score + sequence of confidence levels determines a sequence of flows.

- **Key result:** differentiable scores induce **flows** to CP **boundaries**
    1. Boundary samples ⇒ usable uncertainty objects (a)
    2. Mix over boundaries ⇒ calibrated predictive distributions (b)
- Why? Yields an exact and highly scalable solution. Not cursed by dimensionality.

Background – Conformal Algorithm

- Given $f_\theta : \mathcal{X} \mapsto \mathcal{Y}$ and $\alpha \in (0,1)$, Construct $C_\alpha(x) \subset \mathcal{Y}$ s.t.

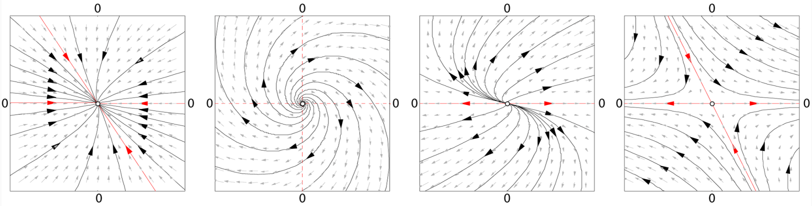
$$P\big(y \in C_\alpha(x)\big) \;\geq\; 1-\alpha, \tag{2}$$

- Train model on $D_{train} = \{(x_j, y_j)\}_{j=1}^m$, construct sets on disjoint calibration data $D_{cal} = \{(x_i, y_i)\}_{i=1}^n$.

- **Split conformal Alg.**:
  1. Nonconformity score $S : \mathcal{X} \times \mathcal{Y} \mapsto \mathbb{R}$, e.g $S(x,y) = ||y - f_\theta(x)||_2$
  2. Calibration scores: $S_1 = S(x_1, y_1), \ldots, S_n = S(x_n, y_n)$
  3. Order: $S_{(1)} \leq \cdots \leq S_{(n)}$
  4. Conformal threshold is $\tau_\alpha = S_{(k)}$ where $k = \lceil (1-\alpha)(n+1) \rceil$
  5. Return the prediction set:

$$C_\alpha(x) \;=\; \big\{\, y \in \mathcal{Y} : \; S(x,y) \leq \tau_\alpha \,\big\}, \tag{3}$$

Background – Dynamical Systems and Flows



- A **Flow** is a map describing how initial points $y_0 \in \mathcal{Y}$ move over "time".

$$\Phi(t, \cdot) : \mathcal{Y} \mapsto \mathcal{Y} \quad t \geq 0$$

- Flows can be defined as solutions to ODEs:

$$\frac{d}{dt} y(t) := y'(t) = v(y(t))$$

  where $v : \mathcal{Y} \mapsto \mathcal{Y}$ is a vector field.
- The corresponding flow **trajectory** is defined as:

$$y(t) := \Phi(t, y_0) = y_0 + \int_0^t v(y(t)) dt$$

Background – Attractors

- Attractor — region $A \subset \mathcal{Y}$ that $\Phi(t, \cdot)$ moves toward and never leaves
- Defn: $A \subset \mathcal{Y}$ such that:
  - $\Phi(t, A) = A$ for all $t \geq 0$ (invariance)
  - $\lim_{t \to \infty} \text{dist}(\Phi(t, U), A) = 0$ (attraction)
  - open subset $U \subset \mathcal{Y}$ is the basin of attraction.

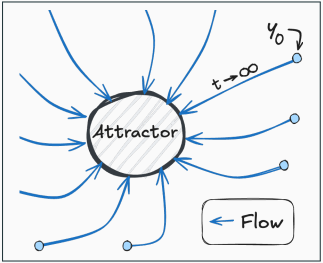


Figure 3: Trajectories are drawn into the attractor

- If $U = \mathcal{Y}$, then A is a global attractor of $\Phi(t, \cdot)$. All trajectories eventually land in A (Figure 3)
- Idea: is there a flow $\Phi_\alpha(t, \cdot)$ such that $C_\alpha(x)$ is the global attractor?

Method – Nonconformity Flows

- Fix $x \in \mathcal{X}$ and confidence level $\alpha \in (0,1)$. Write $S(x,y) = S(y)$.

- Construct a nonconformity flow $\Phi_\alpha(t,\cdot)$ through a system of ODEs
  1. State ODE — describes how $y(t)$ evolves by vector field $v(\cdot)$:
  $$y'(t) = v(y(t)), \qquad y(0) = y_0$$
  2. Score ODE — describes how the *score along the trajectory* evolves:
  $$S'(y(t)) = -\lambda\big(S(y(t)) - \tau_\alpha\big),$$
  with $\lambda > 0$. Note: $S'(y(t)) = \nabla S^T v$

- Intuition: the score ODE will drive $S(y(t)) \to \tau_\alpha$ as $t \to \infty$, hence
$$y(t) = \Phi_\alpha(t,\cdot) \to \partial C_\alpha(x) = \{y \in \mathcal{Y} : S(y) = \tau_\alpha\}$$

.

Method – Nonconformity Velocity Field

- The velocity field has an exact, deterministic, minimum norm solution:

$$v_\alpha(y(t)) = -\lambda(S(y(t)) - \tau_\alpha)\frac{\nabla S(y(t))}{\|\nabla S(y(t))\|_2^2}, \tag{4}$$

  where $\nabla S(y(t))$ is the gradient with respect to y.

- $v_\alpha(\cdot)$ is entirely computable from known quantities!
  - No training, generative models, transport maps, etc. No estimation!
  - Only depends on the score $S(\cdot)$, which is **known**.
  - Score gradients computational efficient with automatic differentiation (JAX / Pytorch). Runs on GPUs.

- λ can be set automatically to ensure finite-time convergence

Method – Induced Flow

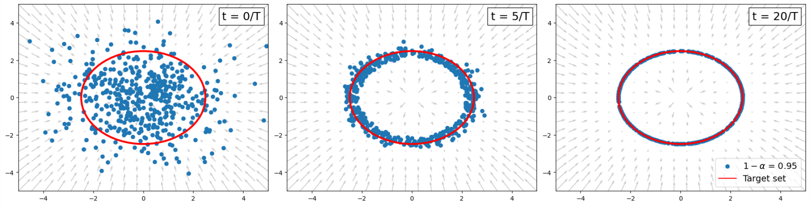


Figure 4: The nonconformity flow globally attract towards the target level set.

- Nonconformity velocity:

$$v_\alpha(y(t)) = -\lambda(S(y(t)) - \tau_\alpha)\frac{\nabla S(y(t))}{\|\nabla S(y(t))\|_2^2},$$

- Defines a nonconformity flow:

$$\Phi_\alpha(t, y_0) = y_0 + \int_0^t v_\alpha(y(s))ds, \tag{5}$$

- Integrate with Euler, RK, etc. Fast and stable ($\approx$ 5-20 steps).

Method – Sample diversity

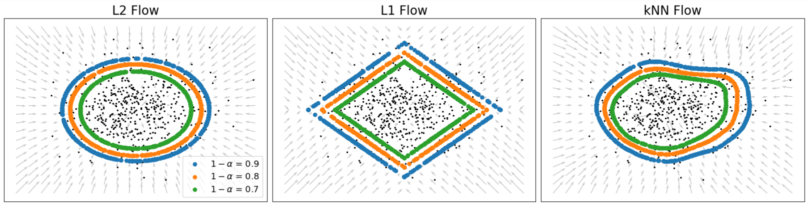


Figure 5: Same data. Different scores results in different flows and prediction sets.

- ℓ_2 v.s. ℓ_1 v.s. kNN ℓ_2 score.
- Across $\alpha \in \{0.1, 0.2, 0.3\}$ boundaries
- Non differentiable, non convex, multi-modal? No* problem.
- Does it always work?

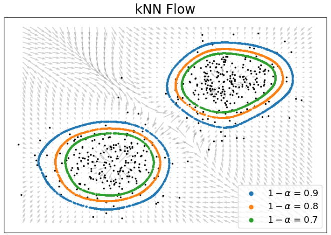


Figure 6: Bi-modal data.

Theory – Score Convergence and Global Attraction

- **Proposition (Convergence)** Define the score error along a trajectory by

$$\varepsilon(t) := S(y(t)) - \tau_\alpha.$$

Under the nonconformity flow,

$$\varepsilon'(t) = -\lambda\varepsilon(t) \quad \Rightarrow \quad \varepsilon(t) = \varepsilon(0)\, e^{-\lambda t}$$

- Therefore:
  - The score converges exponentially fast:

$$S(y(t)) \longrightarrow \tau_\alpha \quad \text{as } t \to \infty.$$

  - Every accumulation point of the trajectory lies on the boundary

$$\partial C_\alpha(x) = \{y : S(x, y) = \tau_\alpha\}.$$

  - Once a trajectory reaches the boundary, the velocity vanishes:

$$v_\alpha(y) = -\lambda(S(y) - \tau_\alpha)\frac{\nabla S(y)}{\|\nabla S(y)\|_2^2} = 0 \quad \text{for } y \in \partial C_\alpha(x)$$

$\Rightarrow$ Nonconformity flows are globally attracted to the conformal boundary

Theory – Pointwise Convergence

- **Proposition (Convergence)** Assume there exist $m > 0$ and a neighborhood U of $\partial C_\alpha(x)$ such that

$$\|\nabla S(y)\|_2 \geq m \quad \text{for all } y \in U.$$

Then, for any initial condition y_0, the trajectory $y(t) = \Phi_\alpha(t, y_0)$ converges to a *unique* limit point $y_\infty \in \partial C_\alpha(x)$, and

$$\|y(t) - y_\infty\|_2 \;\leq\; \frac{1}{m}\,|S(y_0) - \tau_\alpha|\,e^{-\lambda t} \quad \text{for sufficiently large } t.$$

- This implies:
  - Each initial point is mapped to a single boundary point.
  - Convergence is exponentially fast and dimension-free.
  - No oscillations, cycles, chaos, or pathological behavior.

$\Rightarrow$ Each trajectory converges to a single, well-defined boundary point

Theory – Finite-Time Near Convergence

- **Corollary (Hitting time)** Define the first ε-hitting time

$$T_\varepsilon(y_0) = \inf\{t \geq 0 : |S(\Phi_\alpha(t, y_0)) - \tau_\alpha| \leq \varepsilon\}.$$

  Solving the score dynamics ($\varepsilon(t) = \varepsilon(0)\, e^{-\lambda t}$) yields

$$T_\varepsilon(y_0) = \frac{1}{\lambda} \log \frac{|S(y_0) - \tau_\alpha|}{\varepsilon}.$$

- Consequently:
  - The flow reaches an ε-neighborhood of the boundary in finite time.
  - The convergence time is explicitly controllable via λ.
  - In practice, we fix $t = 1$ and $\varepsilon = 10^{-6}$ and choose

$$\lambda = \log \frac{|S(y_0) - \tau_\alpha|}{\varepsilon},$$

    which guarantees near convergence in a fixed time window ($t = 0 \to 1$)

$\Rightarrow$ Flows are fast, stable, and deterministic boundary samplers suitable for high-dimensional settings.

From Boundary Samples to Distributions

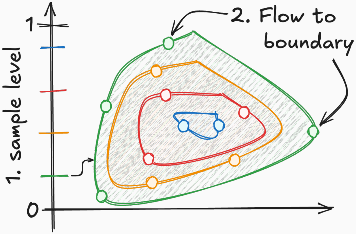
- For any confidence level α, we can efficiently sample from the conformal boundary

$$\partial C_\alpha(x) = \{y \in \mathcal{Y} : S(x, y) = \tau_\alpha\}.$$

- Conformal prediction provides a *nested family* of sets:

$$C_{\alpha_1}(x) \subset C_{\alpha_2}(x) \quad \text{for } \alpha_1 \geq \alpha_2.$$

- **Goal:** Assemble these boundary samples into a *single predictive distribution*.
- **Soln:** Randomize over α, then sample on the corresponding boundary.



Conformal Predictive Distributions (CPDs)

- Let π be a probability measure on $(0, 1)$. Mixing distribution.
- For each α, let $\nu_{x,\alpha}$ be a probability measure on $\partial C_\alpha(x)$.
- **Definition (CPD):** The conformal predictive distribution is

$$P_x^{\mathrm{CPD}}(A) = \int_0^1 \nu_{x,\alpha}(A)\, d\pi(\alpha), \qquad A \in \mathcal{B}(\mathcal{Y}).$$

- Interpretation:
  - π controls *which quantile region* is selected
  - $\nu_{x,\alpha}$ controls *where on that region* mass is placed
- Nonparametric and model-free: only $S(\cdot)$ and π are required. Not shape constrained.

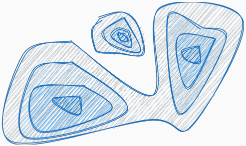


Figure 7: CPDs are mixtures of level sets

Admissibility and Calibration

- **Proposition (Calibration):** Every CPD satisfies

$$P_x^{\mathrm{CPD}}\big(C_\alpha(x)\big) = \pi([\alpha, 1)),$$

  regardless of the choice of boundary measures $\{\nu_{x,\alpha}\}$.

- Special case:

$$\pi = \mathrm{Unif}(0,1) \quad \Rightarrow \quad P_x^{\mathrm{CPD}}(C_\alpha(x)) = 1 - \alpha.$$

  then the CPD is exactly conformally calibrated.

- Calibration is automatic and independent of boundary measure

- Non-uniform π measures are still useful, e.g. oversampling rare events by overweighting small α values.

Boundary Measures via Nonconformity Flows

- Let μ_x be any base distribution on $\mathcal{Y}$. Define boundary projection map:

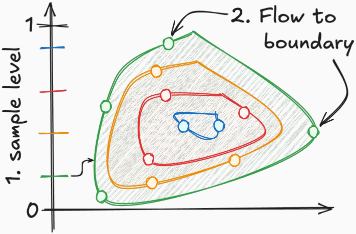
$$\Pi_{x,\alpha}(y_0) = \lim_{t \to \infty} \Phi_\alpha(t, y_0),$$

  since $\Phi_\alpha(t, \cdot)$ is globally attracted to the boundary $\partial C_\alpha(x)$.
- The induced boundary measure is the pushforward

$$\nu_{x,\alpha} = (\Pi_{x,\alpha})_{\#}\mu_x.$$

- **CPD Sampling Alg:**
  1. Sample $\alpha \sim \pi$.
  2. Sample a base point $y_0 \sim \mu_x$.
  3. Flow to the boundary:

$$y = \lim_{t \to \infty} \Phi_\alpha(t, y_0)$$



- Generalized inverse CDF sampling to implicit, high-dimensional settings.

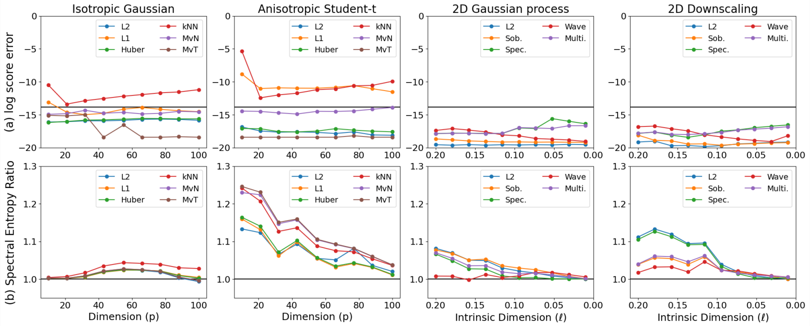
Numerical Experiments

- We evaluate the proposed framework in two stages.
- **Part 1:** empirical behavior of the nonconformity flow
  - convergence to the conformal boundary,
  - stability across dimension and score choice,
  - diversity of boundary samples.
- **Part 2:** empirical performance of the CPDs on regression tasks
  - Compare against probabilistic methods
  - global, local, and spectral fidelity
- Application to hurricane trajectory forecasting, illustrating targeted sampling and score dependence.

Numerical - Nonconformity Flows (Part 1)

- Data Generating Mechanisms:
  1. Isotropic Gaussian ($p = 10...100$) – baseline
  2. Anisotropic Student-t ($p = 10...100$) – heavy tails
  3. 2D Gaussian processes (64x64 grid, $\ell = 0.2...0.01$) – correlation
  4. 2D GP $8\times$ upscaling (64x64 grid, $\ell = 0.2...0.01$) – nonlinear error
- Prediction Models
  - Vectors: 3 layer Multilayer Perceptron (MLP).
  - Operators: 4 layer 2D Fourier Neural Operator. [Li et al. (2020)].
- Nonconformity scores
  - Vectors: 1. ℓ_2 score, 2. ℓ_1 score, 3. Huber score, 4. kNN score, 5. Gaussian NLL score, 6. Student-t NLL score.
  - Operators: 1. ℓ_2 score, 2. Sobolev (gradient) score, 3. Spectral score, 4. Wavelet score, 5. composite score (Sob + Spec.)
- Evaluation metrics
  1. log convergence error (distance to target) ($\searrow 0$)
  2. spectral entropy ratio (sample diversity) ($1 \nearrow$) [Friedman and Dieng (2022)]

Numerical - Nonconformity Flows (Part 1)



- Convergence in all cases. iid vs correlated, isotropic vs anisotropic, linear vs nonlinear error. All* nonconformity scores. Dimension free. (Panel a)
- High sample diversity. Spectral entropy ratio ≥ 1, samples are as, or more, random than actual data. No subspace collapse (Panel b).

Numerical - CPDs (Part 2)

- Data Generating Mechanisms:
  1. 2D Gaussian processes – Predict GP's (64x64, $\ell = 0.08$)
  2. Elliptic PDE Inv. – Predict forcing field from noisy solution (32x32)
  3. Navier-Stokes – Predict NS soln. at $t = 2$ under unknown forcing (64x64)
  4. Precip. downscale – Upample NA precip. by $8\times$. (64x128)
  5. Climate debias – Predict reanalysis from model (t2m) (64x128)
- Prediction Models
  - Operators: 4 layer 2D Fourier Neural Operator. [Li et al. (2020)].
- Nonconformity flows
  1. **CPD-G**: global ℓ_2 residual scores
  2. **CPD-L**: localized composite score for spatial fields
- Evaluation metrics
  1. energy distance (ED) (overall distribution) ($\searrow 0$)
  2. log spectral distance (LSD) (spatial patterns) ($\searrow 0$)
  3. patch-wise maximum mean discrepancy (MMD) (local detail) ($\searrow 0$)

Numerical - CPDs (Part 2)

- Baseline UQ methods (all use 4 layer FNO):
  1. **MC Dropout (Drop)**: Dropout rate 0.1 applied at test time; 20 stochastic forward passes.
  2. **Deep Ensembles (D. Ens)**: 5 independently initialized models; identical architecture and training procedure.
  3. **Implicit Quantile Networks (IQN)**: trained to predict quantiles uniformly over $\tau \in (0, 1)$; samples obtained by random quantile draws.
  4. **Conditional Flow Matching (Flow)**: conditional generative flow trained on (x, y); sampling via learned transport map.
  5. **Mixture Density Networks (MDN)**: Gaussian mixture output with fixed number of components $(\mathsf{K} = 5)$; trained by likelihood maximization.
  6. **Mean–Variance Networks (MVE)**: Gaussian likelihood with learned mean and diagonal variance; trained by maximum likelihood.
- All methods given roughly equal computational budget.

Numerical - CPDs (Part 2)

Table 1: CPDs vs baselines across a range of tasks.

	GP Regression			Elliptic PDE Inv.			Navier Stokes			Precip. Downscale			Climate Debias		
Method	ED	LSD	MMD	ED	LSD	MMD	ED	LSD	MMD	ED	LSD	MMD	ED	LSD	MMD
CPD-G	0.313	0.069	0.023	0.068	0.103	0.006	0.233	0.252	0.043	0.395	0.067	0.019	0.107	0.003	0.024
CPD-L	0.313	0.069	0.036	0.067	0.099	0.006	0.229	0.166	0.039	0.400	0.066	0.016	0.133	0.006	0.032
Drop.	0.400	0.083	0.187	0.115	0.263	0.158	0.295	0.245	0.142	0.418	0.072	0.075	0.127	0.004	0.211
D. Ens.	0.346	0.089	0.064	0.118	0.234	0.044	0.269	0.193	0.055	0.399	0.059	0.138	0.119	0.002	0.109
IQN	0.427	0.075	0.061	0.139	0.262	0.072	0.263	0.381	0.181	0.393	0.066	0.148	0.116	0.002	0.121
Flow	0.410	0.138	0.167	0.113	0.351	0.040	0.235	0.182	0.048	0.374	0.065	0.093	0.118	0.003	0.111
MDN	0.367	0.213	0.211	0.141	0.457	0.169	0.236	0.677	0.171	0.361	0.090	0.114	0.105	0.002	0.195
MVE	0.374	0.200	0.211	0.203	6.112	0.198	0.236	0.651	0.171	0.722	0.097	0.117	0.224	0.018	0.266

- Competitive energy distance (ED). Significantly lower LSD and MMD.
- Most methods approx. distribution well. Do not get spatial patterns (LSD) or local details (MMD) correct.
- Correctly estimate high, mid, and low frequency behavior. No oversmoothing. No high-frequency noise. High sample diversity.

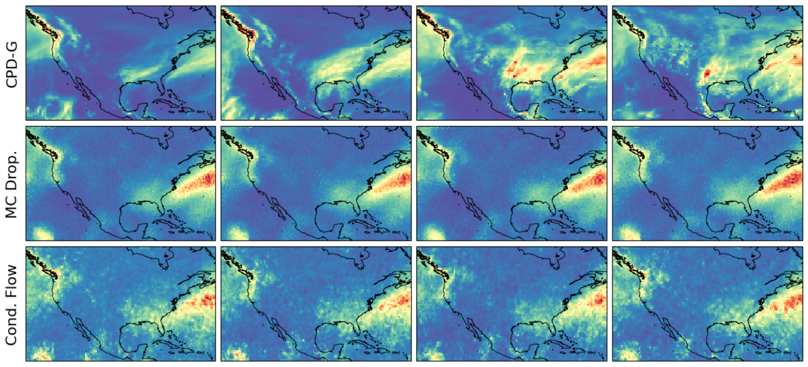


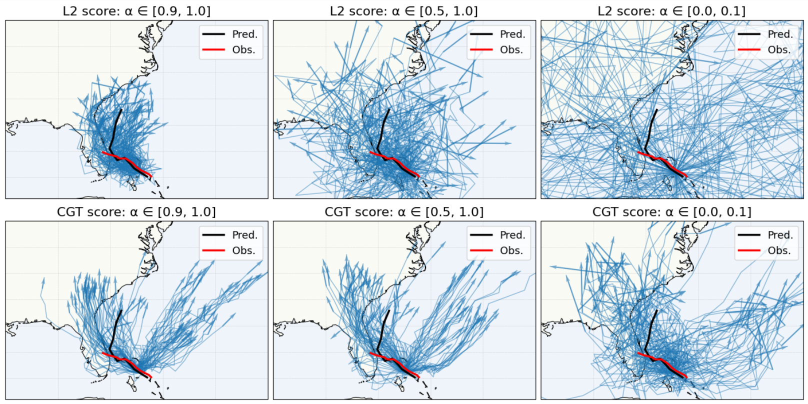
Figure 8: Sample precip. intensity from CPD-G, MC Dropout, and the Conditional. Flow. CPDs avoid oversmoothing, excessive drizzle, and exhibit realistic heterogeneity across samples.

- Realistic heterogeneity, qualitatively different (low LSD, MMD).
- Baselines underestimate structural variations (mode collapse)

Numerical - Tropical Cyclone Forecasting

- Tropical Cyclone forecasting presents a distinct challenge:
  - outputs are trajectories, not vectors or fields,
  - strong geometric constraints (smoothness, directionality),
  - rare but high-impact tail behavior.
- HURDAT2 North Atlantic hurricanes (1850–2025) – observed storm trajectories at 6-hour resolution + wind speed and sea level pressure.
- Prediction task. Given the past 24 time steps (6 days), predict the next 12 time steps (3 days) of the storm trajectory.
  - Classical conformal prediction yields valid sets.
  - CPDs allow us to sample entire trajectories.
- Two nonconformity scores:
  - ℓ_2 trajectory score — pointwise Euclidean distance
  - CGT (Conditional Geometric Trajectory) Score — composite score ℓ_2 score + velocity, curvature, length scores, conditioned trajectory direction.

Numerical - Tropical Cyclone Forecasting



- Controllable generation by controlling the π-mixing distribution
- Sample quality improves with better aligned scores. Score matters!
- Emergent behavior from the score geometry not present in model

Discussion

- Conformal prediction sets in high dimensions are *inert*:
    - implicit defn.
    - non-sampleable
    - non-composable with probabilistic tasks

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- Nonconformity flows — simple, training-free method to convert conformal prediction sets into calibrated predictive distributions.
- Nonconformity scores — determines structure of uncertainty; the flow exposes that structure.
- Flows converge across range of settings. CPDs competitive with fully probabilistic deep learning baselines using even simple scores.

Appendix

Application - Bands

- Boundary samples do not guarantee pointwise coverage
- Conformalized against $S(\cdot)$, not pointwise coverage.
- Reconformalize them to cover

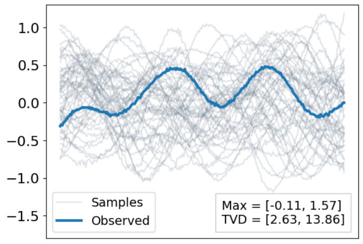

Figure 9: 1D GP samples at $\alpha = 0.1$

- Define prediction band $\mathcal{B}(x) = \{y : l(x) \leq y \leq u(x)\}$ and the pointwise risk functional (fraction outside band):

$$\ell(x, y) = \frac{1}{p} \sum_{j=1}^{p} \mathbf{1}\{y_j \notin \mathcal{B}(x)\},$$

- $\mathcal{B}_\eta$ controls risk at level (δ, α) if $P(\ell(X, Y) \leq \delta) \geq 1 - \alpha$

Application - Bands

- **Reconformalization Alg.**:
  1. Generate samples $y^{(1)}, \ldots, y^{(M)}$ in $\partial C_\alpha(x) = \{y \in \mathcal{Y} : S(x,y) = \tau_\alpha\}$.
  2. Form preliminary envelope $[\ell_0(x), u_0(x)]$ with pointwise empirical quantiles (e.g., $\alpha/2$ and $1-\alpha/2$) of samples
  3. Inflate by $\eta \geq 0$ to get
  $$\mathcal{B}_\eta(x) = \left\{y : l_0(x) - \eta \leq y \leq u_0(x) + \eta\right\}$$
  4. Find the smallest η such that
  $$P\big(\ell_\eta(X,Y) \leq \delta\big) \geq 1-\alpha$$
- Risk functional
$$\ell_\eta(x,y) = \sum_{j=1}^{p} \mathbf{1}\{y_j \notin \mathcal{B}_\eta(x)\}$$
decreases monotonically in $\eta \Rightarrow$ **Binary search**

Method - Bands

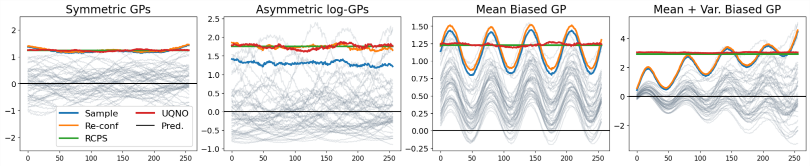

Figure 10: Sampled prediction bands (Sample), Reconformalized sampled bands (Re-conf). Samples provide the shape, reconformalization fixes the width.

- Boundary samples do not guarantee pointwise coverage
- Introduce reconformalization: ensure pointwise coverage
- Re-conf adapts to asymmetry and mean, variance bias.

	Symm.	Asym.	$\Delta\mu$	$\Delta(\mu, \sigma)$
Sample	0.894	0.646	0.828	0.876
Re-conf	0.901	0.900	0.900	0.901
RCPS	0.900	0.901	0.901	0.902
UQNO	0.901	0.902	0.906	0.907
Sample	2.443	2.032	1.145	4.269
Re-conf	2.479	2.948	1.302	4.465
RCPS	2.460	3.487	2.451	5.715
UQNO	2.467	2.982	2.348	5.772