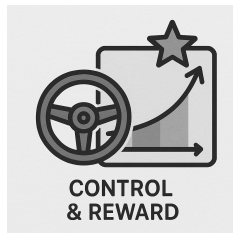


Reward Alignment

Are you doing `Rectify(Align( $\{X_t\}$ ))` or `Align(Rectify( $\{X_t\}$ ))`?

Reward Alignment

- Given a reward function $r(x)$, how to modify the flow/diffusion model to favor r ?
- Applications:
 - Classifier free/classifier guidance
 - Reward alignment
 - Control, editing
 - Sampling from density + data
 - Constrained domains
 - Reinforcement learning



Tilted Distributions and Processes

- Let $r(x)$ be a non-negative reward
- $X_1^r \sim \pi^r$ is the **r -tilted distribution** of $X_1 \sim \pi_r$ if

$$\pi_1^r(x) = \frac{\pi_1(x) \times r(x)}{A_r}, \quad A_r = \mathbb{E}_{\pi_1}[r(x)].$$

- $\{X_t^r\} \sim P^r$ is the **r -tilted process** of $\{X_t\} \sim P^r$ if

$$P^r(\{x_t\}) = \frac{P(\{x_t\}) \times r(x_1)}{A_r}.$$

Reweight paths based on the reward $r(x_1)$ at the end point.

- Yields a variational representation:

$$\min_Q \text{KL}(Q \parallel P) - \mathbb{E}_Q[\log r(X_1)].$$

Two Approaches

Tilt the interpolation process,
then derive rectified flow

$\text{Rectify}(\text{Tilt}(\{X_t\}))$

Leveraging special properties of
rectified flow

Examples: DPS [CKM⁺22],
RewardSDS [CYB25], Importance
Weighted Score Matching
[WZC⁺25], ORW-CFM-W2
[FSC⁺25]

Nice recent reviews on RL/alignment of diffusion: [UZBL24], [UZW⁺25].

Tilt or steer the learned ODE/SDE.

$\text{Tilt}(\text{Rectify}(\{X_t\}))$

Yields generic control and RL prob-
lems of ODE/SDE.

Examples: Readout Guidance
[LDW⁺24], Universal Guidance
[BCS⁺23], Autoguidance [KAK⁺24],
Diffusion Policy Optimization
(DRWR) [RLA⁺24]

Tilted Rectified Flow: General Case

- Define $\{Z_t^r\}$ be the rectified flow induced from the titled interpolation process:

$$\{Z_t^r\} = \text{Rectify}(\{X_t^r\}), \quad \{X_t^r\} = r\text{-tilt}(X).$$

- Velocity field of v_t^r :** reward-weighted average of the original slope $\dot{X}_t$.

$$v_t^r(x) = \frac{\mathbb{E}[r(X_1)\dot{X}_t \mid X_t = x]}{\mathbb{E}[r(X_1) \mid X_t = x]}$$

- Can be estimated by reward-weighted mean square:

$$\min_{\mu} \mathbb{E}_{(X_0, X_1, t)} [r(X_1) \|\dot{X}_t - v(X_t)\|^2]$$

- Initial Distribution:** For an independent coupling (X_0, X_1) , the initial distribution is unchanged: $\rho_0^r = \rho_0$.

Titled Rectified Flow: Score Functions

- **Marginal Distribution** $X_t^r \sim \rho_t^r$:

$$\rho_t^r(x) = \rho_t(x) \frac{\mathbb{E}[r(X_1) | X_t = x]}{\mathbb{E}[r(X_1)]}$$

- **Score Function:**

$$\nabla \log \rho_t^r(x) = \nabla \log \rho_t(x) + \nabla \log \mathbb{E}[r(X_1) | X_t = x]$$

- For independent Gaussian noise X_0 , we have affine relation:

$$v^r(x) - v_t(x) = \frac{1-t}{t} (\nabla \log \rho_t^r(x) - \nabla \log \rho_t(x)).$$

This yields

$$v_t^r(x) = v_t(x) + \frac{1-t}{t} \nabla_x \log \mathbb{E}[r(X_1) | X_t = x].$$

Tilted Rectified Flow: Independent Gaussian Noise

When $X_0|X_1 \sim \text{Normal}(0, I)$, velocity of tilted RF is

$$v_t^r(x) = v_t(x) + \frac{1-t}{t} \nabla_x \log \mathbb{E}[r(X_1) | X_t = x].$$

- Using Taylor Approximation ($\mathbb{E}[r(X_1)|X_t] \approx r(\mathbb{E}[X_1|X_t])$):

$$v_t^r(x) = v_t(x) + \frac{1-t}{t} \nabla_x \log r(\mu_{1,t}(x)).$$

where $\mu_{1,t}(x)$ is the expected prediction of the target X_1 :

$$\mu_{1,t}(x) = \mathbb{E}[X_1 | X_t = x] = x + (1-t)v_t(x).$$

- Examples: Classifier Guidance [DN21], DPS [CKM⁺22], RF-inversion [RCR⁺24], etc.

Reward Tilting: Variational Approaches

Variational Approach: π_1^r is the solution of

$$\min_{\varrho_1} \text{KL}(\varrho_1 \parallel \rho_1) - \mathbb{E}_{\varrho_1}[r(X_1)]$$

- With independent Gaussian noise, using KL-velocity formula:

$$\min_v \int \frac{t}{1-t} \mathbb{E} \left[\|\mu_t(X_t^r) - v_t(X_t^r)\|^2 - \log r(X_1^r) \right].$$

- Same as Variational Score Distillation but with a reward. Examples: Diff-Instruct++ [Luo24], Reward-Instruct [LHL⁺25], etc.

Takeaways

`Rectify(Tilt( $\{X_t\}$ ))`

Leveraging special properties of rectified flow: General, score function, variational forms.

`Tilt(Rectify( $\{X_t\}$ ))`

General control/RL tools: policy gradient, preference optimization, Q-learning, optimal control, Doob's h -transform, etc.