Neural SDEs Made Easy: SDEs are Infinite-Dimensional GANs

SUMMARY

SDEs are a map from noise (Brownian motion) to a solution distribution. They may be sampled from via numerical SDE solvers, but they do not admit a notion of probability density.

We observe that this is exactly the same as the generator of a GAN. By adding a discriminator, we train arbitrary neural SDEs as continuous-time generative models for time series; e.g. to model financial stocks.

BACKGROUND: SDEs

Consider an SDE of the form

 $X_0 \sim \mu$, $dX_t = f(t, X_t) dt + g(t, X_t) \circ dW_t$.

Here:

- μ is the initial distribution.
- *f* is the drift, *g* is the diffusion.
- W is Brownian motion.

The (strong) solution to an SDE is the unique map F such that $F(\mu, W) =$ X. It is a map from noise distributions to a target distribution. It can be sampled from via SDE solvers; it does not have a probability density.

BACKGROUND: GANS

Given some noise distribution μ , and a target distribution ν , then the generator G_{θ} of a GAN is trained such that $G_{\theta}(\mu) = \nu$.

It is a map from a noise distribution to a target distribution. It can be sampled from, but its probability density is impossible to compute.

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Method

We see that SDEs and GANs have a lot in common. It goes further: SDEs are usually trained by matching specific statistics (e.g. option prices). Meanwhile GANs are trained by matching a learnt scalar statistic: the discriminator.

Thus by using a neural SDE as a generator—and a neural CDE as the discriminator—we can train a general neural SDE as a model for time series.

	Initial	Hidden
Noise	$V \sim \mathcal{N}(0, I_v)$	$W_t = Browni$
Concrator	$\mathbf{V}_{2} = \mathbf{\zeta}_{2}(\mathbf{V})$	$\mathbf{A}\mathbf{X}_{i} = \mathbf{U}_{i}(t \mathbf{X}_{i}) \mathbf{A}t$
Generator	$\Delta 0 - \zeta \theta(V)$	$u x_t - \mu \theta(t, x_t) u t$
Discriminator	$H_0 = \xi_{\phi}(Y_0) \longrightarrow$	$\mathrm{d}H_t = f_\phi(t,H_t)\mathrm{d}t$
JISCHIMATOR	110 - 90(10)	$\mathbf{u}_{t} - j\phi(\mathbf{r},\mathbf{n}_{t})\mathbf{u}$

Results

Dataset	Performance Metric	Neural SDE	CTFP	Latent ODE
Financial	Classification	0.357 ± 0.045	0.165 ± 0.087	0.000239 ± 0.000086
Stocks	Prediction	$\textbf{0.144} \pm \textbf{0.045}$	0.725 ± 0.233	46.2 ± 12.3
	MMD	$\boldsymbol{1.92\pm0.09}$	2.70 ± 0.47	60.4 ± 35.8
CNN Training	g Classification	0.507 ± 0.019	$\textbf{0.676} \pm \textbf{0.014}$	0.0112 ± 0.0025
Weights	Prediction	0.00843 ± 0.00759	0.0808 ± 0.0514	0.127 ± 0.152
	MMD	$\textbf{5.28} \pm \textbf{1.27}$	12.0 ± 0.5	23.2 ± 11.8
Beijing Air	Classification	0.589 ± 0.051	$\textbf{0.764} \pm \textbf{0.064}$	0.392 ± 0.011
Quality	Prediction	0.395 ± 0.056	0.810 ± 0.083	0.456 ± 0.095
	MMD	0.000160 ± 0.000029	0.00198 ± 0.00001	0.000242 ± 0.000002

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