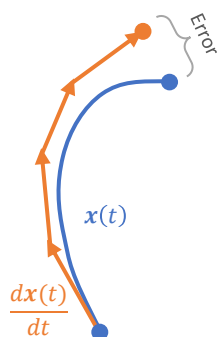


## TL;DR

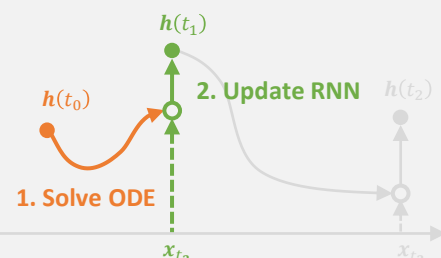
- ❖ We **directly model** the neural ODE **solutions** with neural flows
- ❖ This is **much faster**, since we avoid using expensive numerical solvers
- ❖ We achieve **better results** on time series and density estimation applications

## Neural ordinary differential equations

- Describe the instantaneous change in the system  $\frac{dx(t)}{dt} = f(t, x(t))$ ,  $f$  is a neural network
- Given initial condition  $x(t_0)$ , want to evaluate the solution **curve**  $x(t)$  – usually solved numerically
- Trade-off between speed and precision

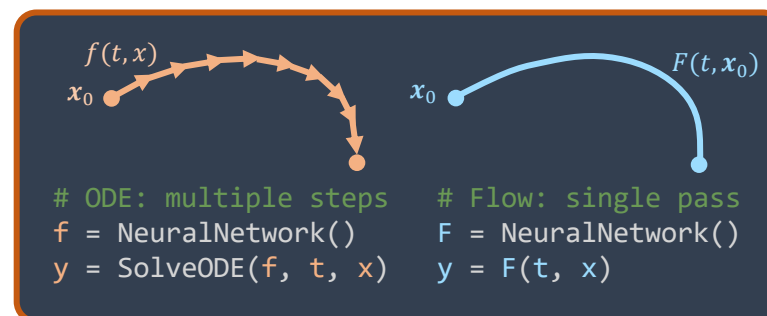


Example: Irregular time series



## Neural flows

- Model the solution curve directly!
- Function  $F(t, x_0)$  is the solution to some ODE with the initial condition  $x_0$  iff:
  - $F(0, x_0) = x_0$  (initial condition)
  - $F(t, \cdot)$  is invertible,  $\forall t$  (unique solution)



## Implementation

- Neural networks need to satisfy conditions 1. and 2.
- Models: **ResNet flow**, **GRU flow**, **coupling flow**

```
# ResNet flow
F(t, x) = x + phi(t) * g(t, x)
spectral_norm(g) # Lip(g) < 1
```

```
# Coupling flow
F(t, xa) = xa * u(t, xb) + v(t, xb)
```

## Irregularly-sampled time series

- Previous works: evolve the RNN state in between observations with **neural ODE** – we use **neural flows**
- Experiments: smoothing, filtering, temporal point process
- Neural flows outperform neural ODEs** across different experimental setups at a fraction of the computation cost

## Density estimation in continuous time

- Density changes with time, e.g. modeling spatial data
- Previous works: **continuous normalizing flow** (ODE-based)
- We use **coupling flow** that provides closed-form density
- Coupling flow outperforms CNF** on spatio-temporal data

## Speed comparison

- How much time it takes to run one training epoch?
- With similar number of parameters (same hyperparam)

