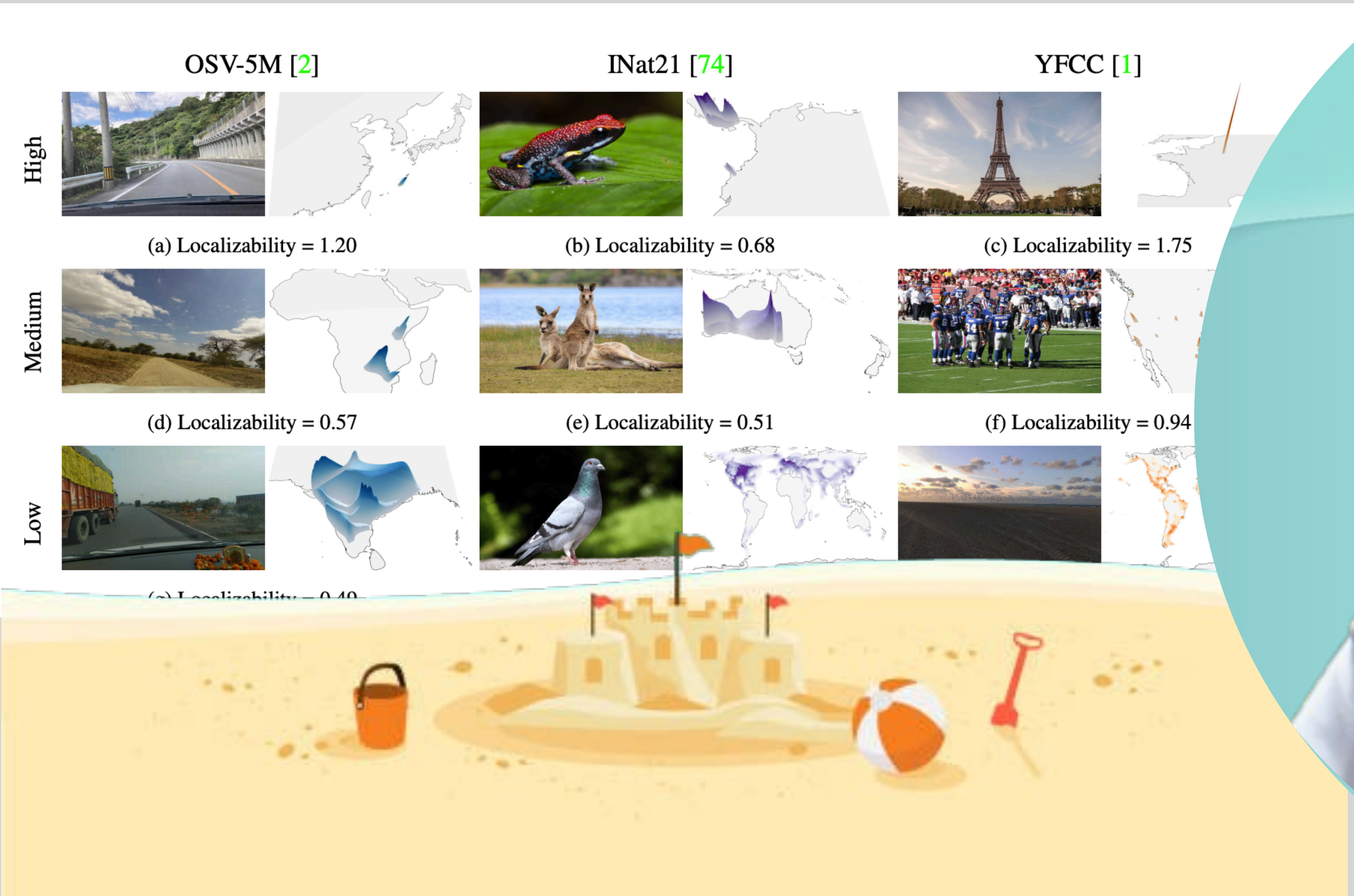
Flow Matching from dummies

Sometimes you gotta go with the flow…

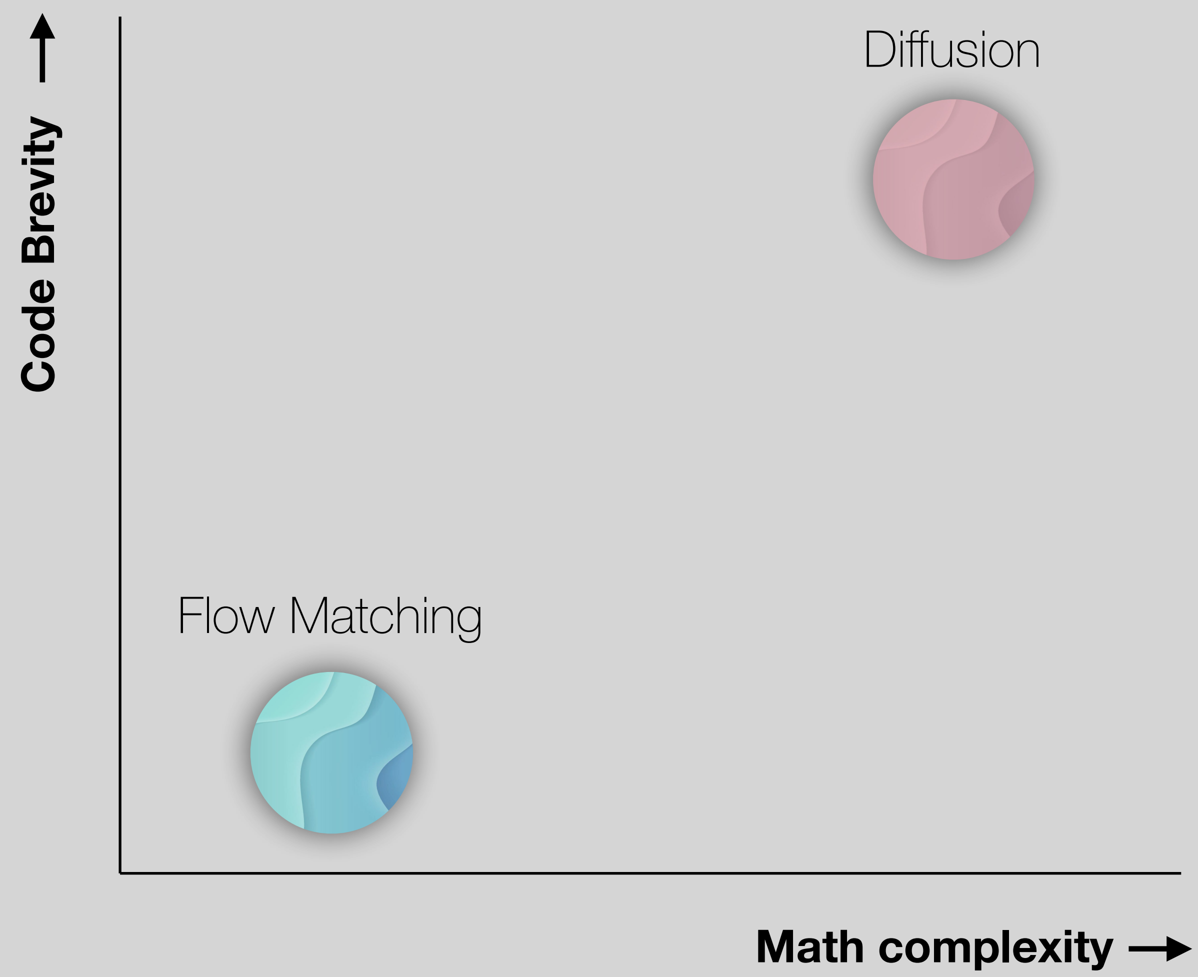
!!! Disclaimer: This presentation contains memes. OMG!

Why do Flow Matching 101…



Dufour, Nicolas, et al. "Around the world in 80 timesteps: A generative approach to global visual geolocation." CVPR 2025.

Why do Flow Matching 102…



Join the Flow Matching Cult

Source: Yaron Lipman

Flow Matching

1

2

Flow Matching

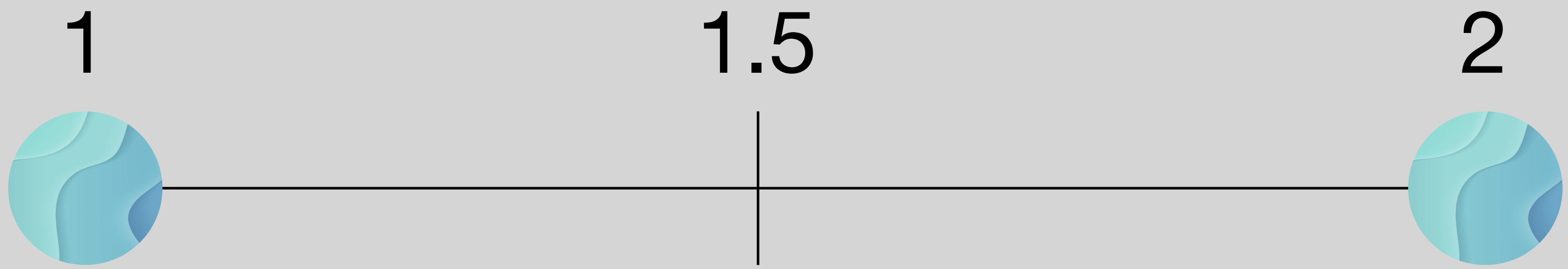
1

3 numbers

2

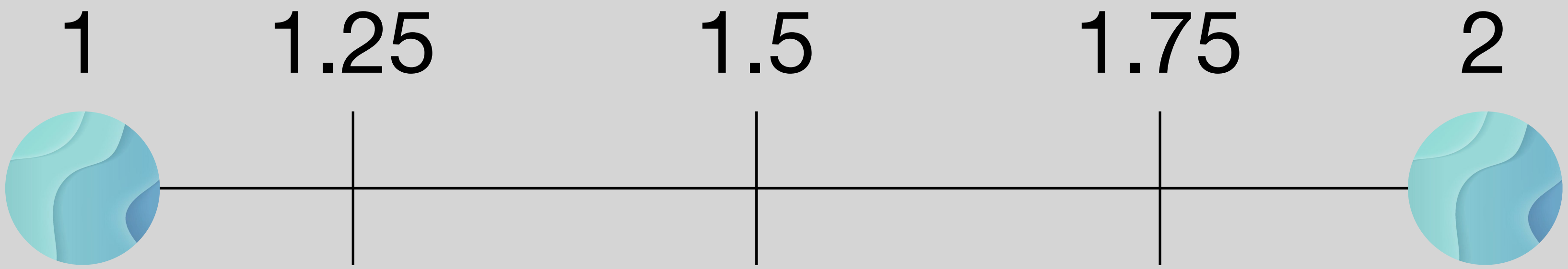
Flow Matching

Flow Matching



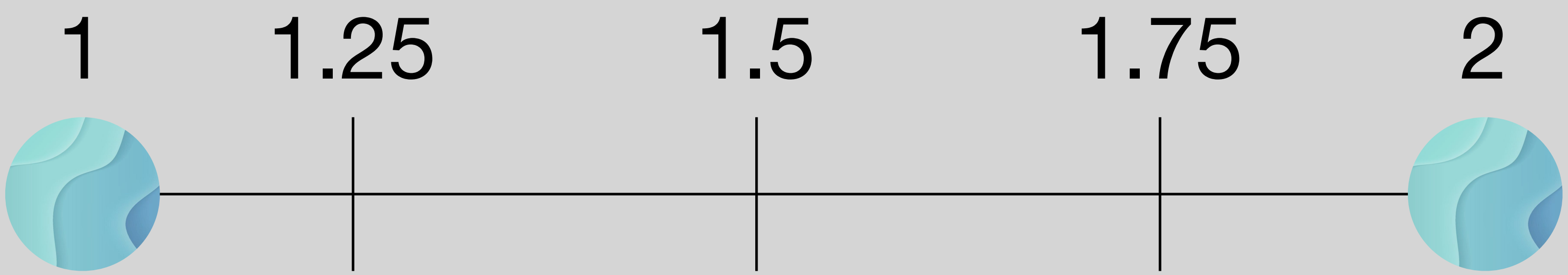
Flow Matching

Flow Matching



Here are the 3 numbers

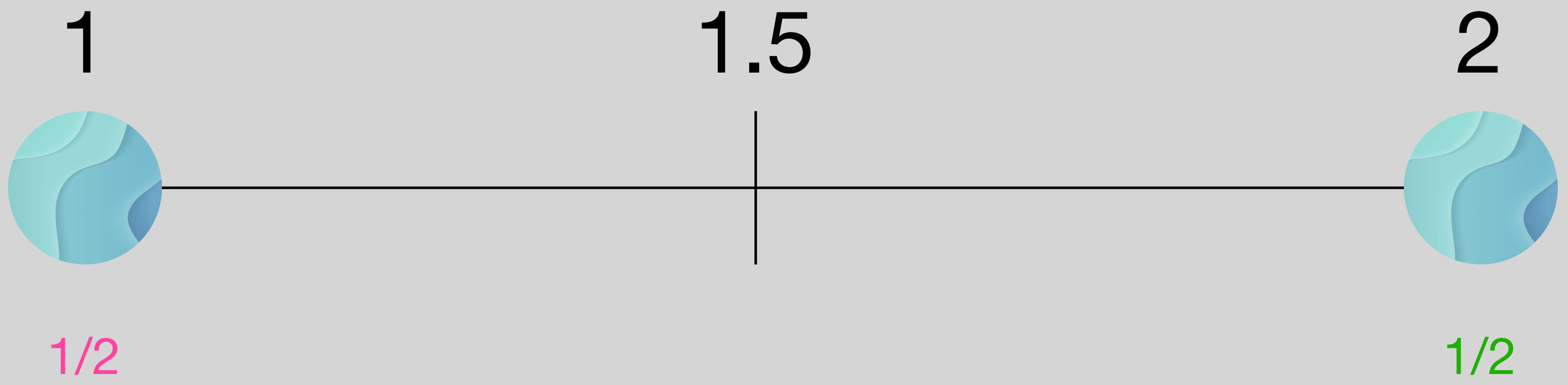
Flow Matching



How do you get them?

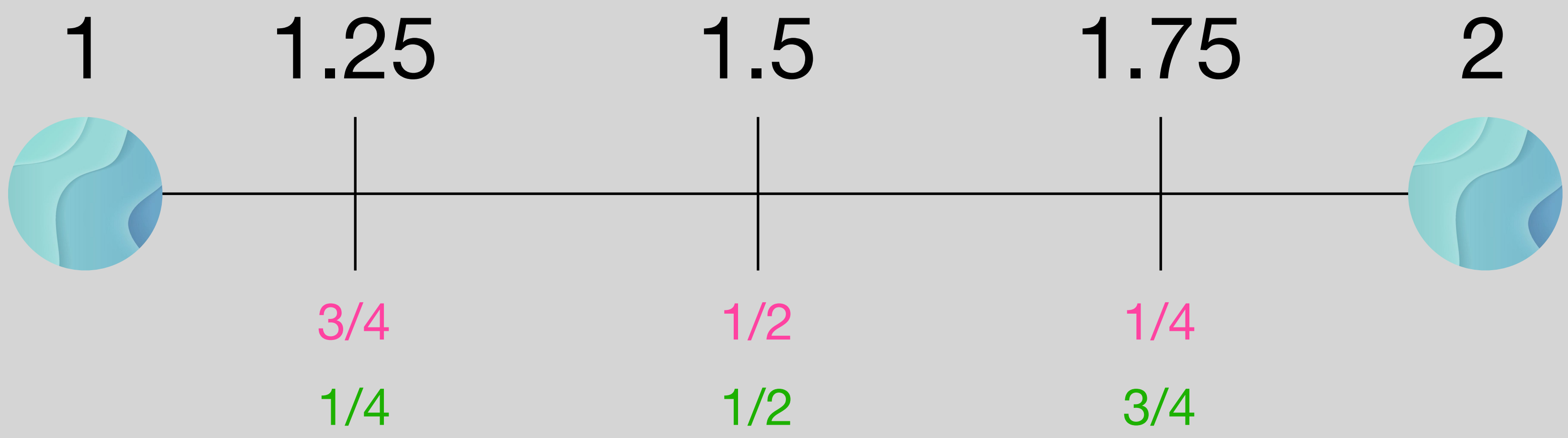
Flow Matching

Flow Matching

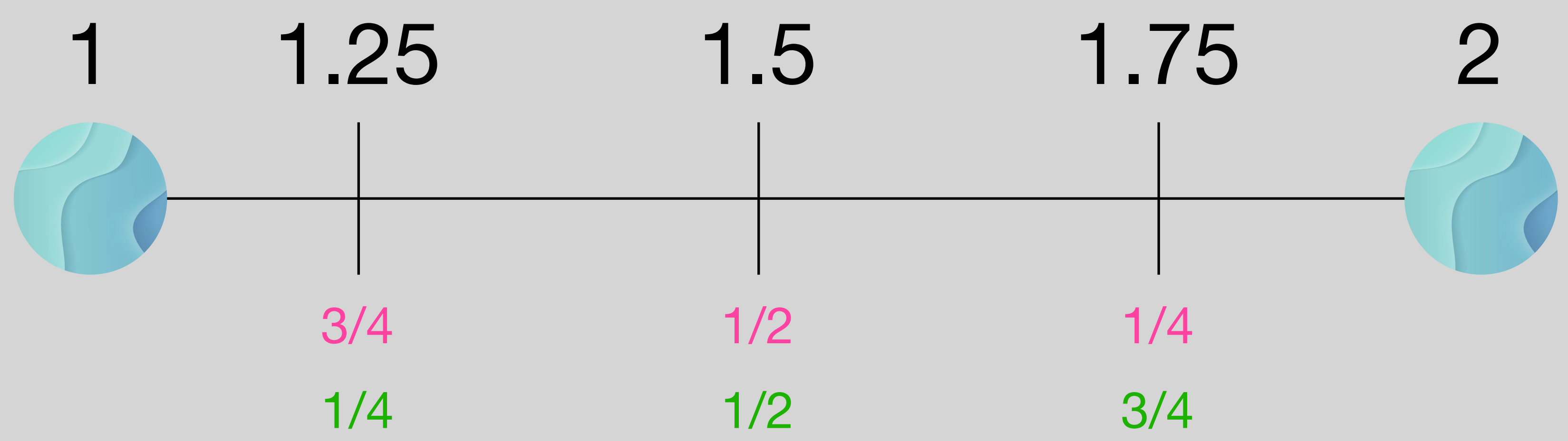


Flow Matching

Flow Matching

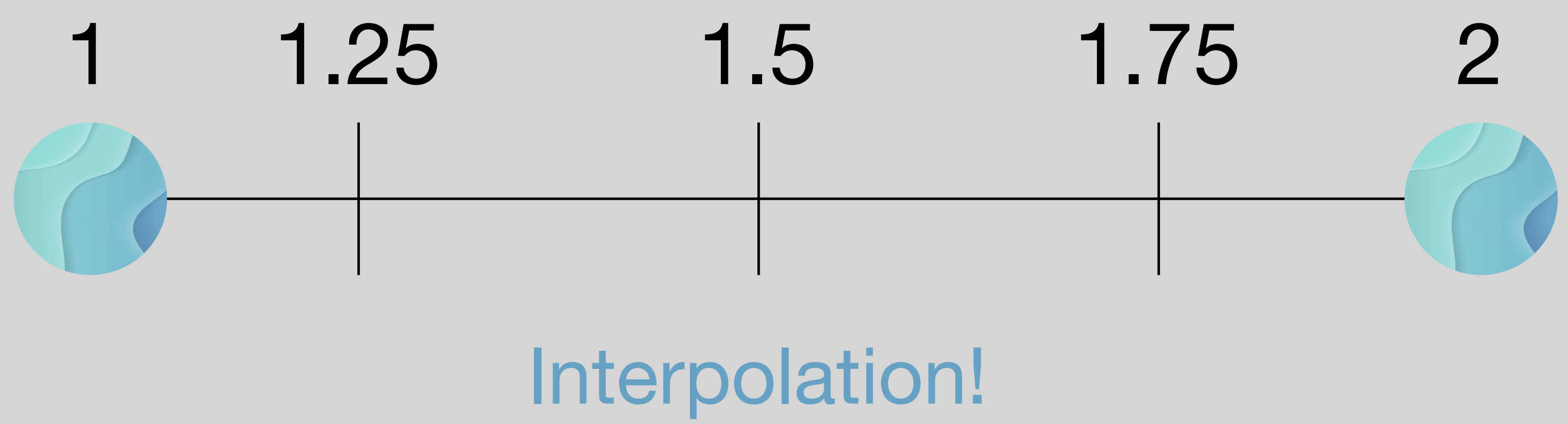


Flow Matching



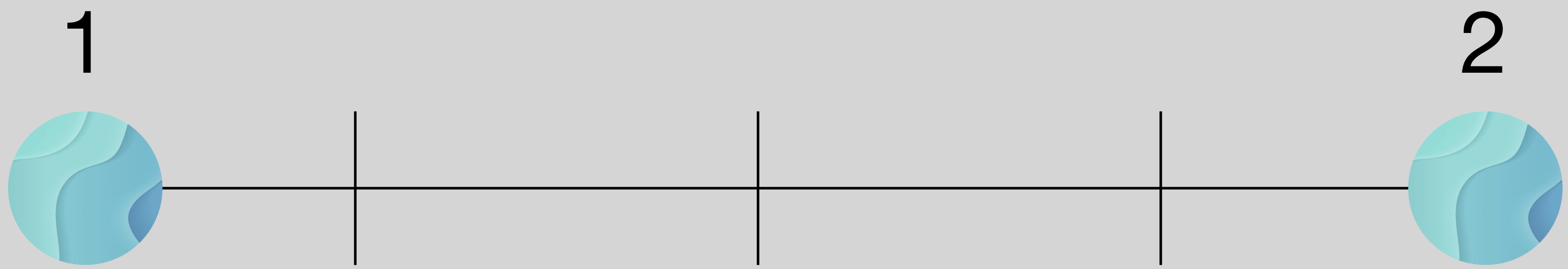
$$\pi_t = t \cdot \pi_1 + (1 - t) \cdot \pi_0$$

Flow Matching



Flow Matching

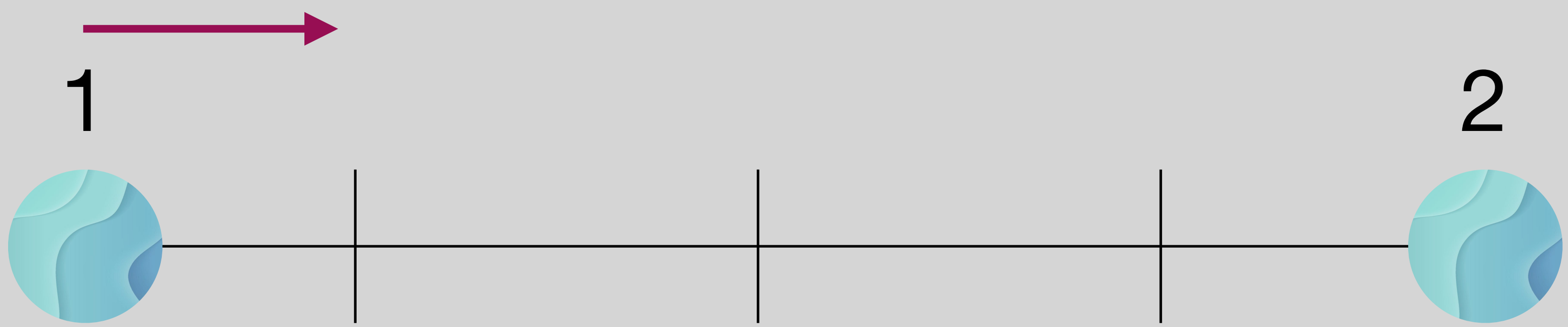
One more way!



Interpolation!

Flow Matching

One more way!



Interpolation!

Flow Matching

One more way!

$$v = \frac{dy}{dt} = 1$$

Interpolation!

Flow Matching

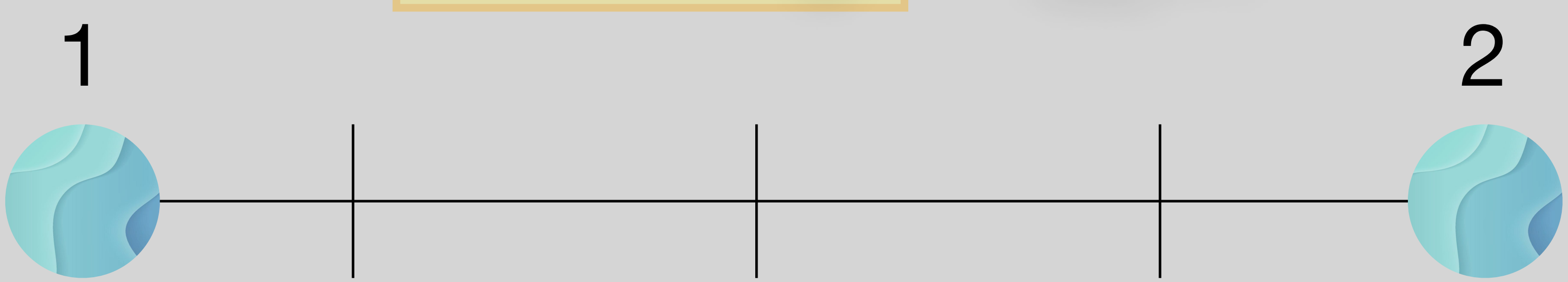
One more way!

Euler's Method

$$y_{new} = y_{old} + h \cdot \frac{dy}{dt}$$

$$\frac{dy}{dt} = 1$$

$$y_{initial} = 1$$



Interpolation!

Flow Matching

One more way!

Initial Value Problem

Unique Solution

Euler's Method

$$y_{new} = y_{old} + h \cdot \frac{dy}{dt}$$

$$\frac{dy}{dt} = 1$$

$$y_{initial} = 1$$

Interpolation!

Source: Picard–Lindelöf theorem

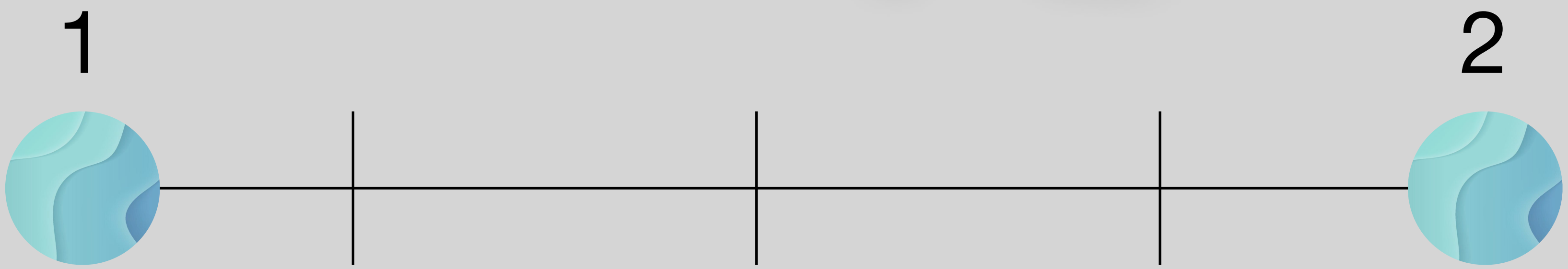
Flow Matching

One more way!

$$\frac{dy}{dt} = 1$$

$$y_1 = y_{initial} + 0.25 \cdot \frac{dy}{dt}$$

$$y_{initial} = 1$$



Interpolation!

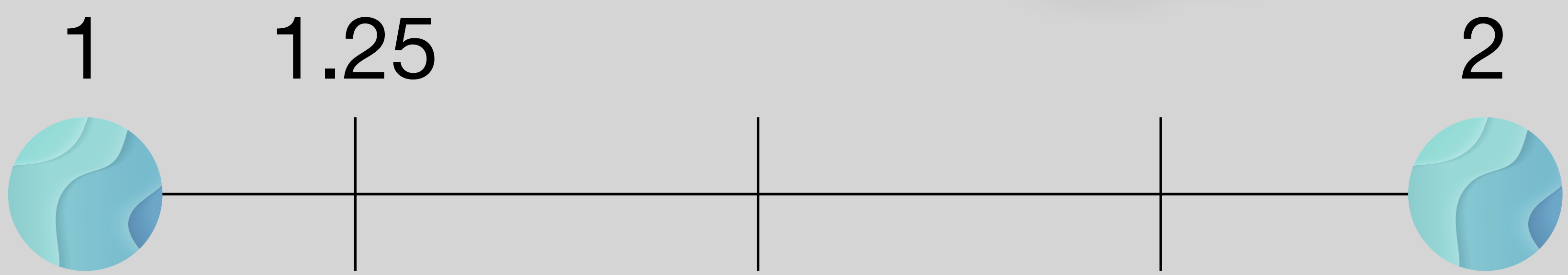
Flow Matching

One more way!

$$y_1 = 1 + 0.25 \cdot 1 = 1.25$$

$$\frac{dy}{dt} = 1$$

$$y_{initial} = 1$$

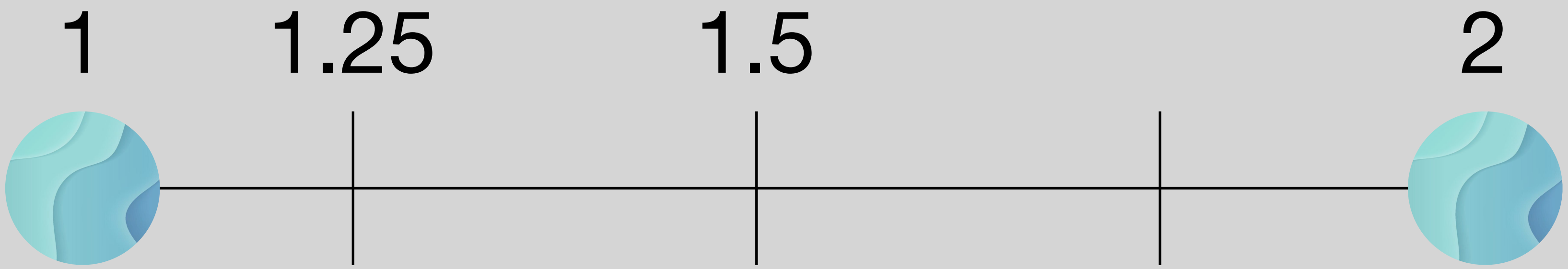


Interpolation!

Flow Matching

One more way!

$$y_2 = 1.25 + 0.25 \cdot 1 = 1.5$$

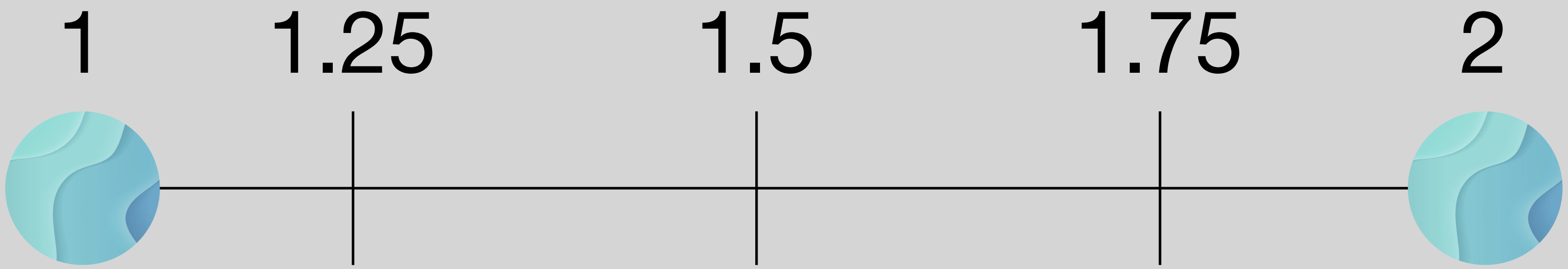


Interpolation!

Flow Matching

One more way!

$$y_3 = 1.5 + 0.25 \cdot 1 = 1.75$$

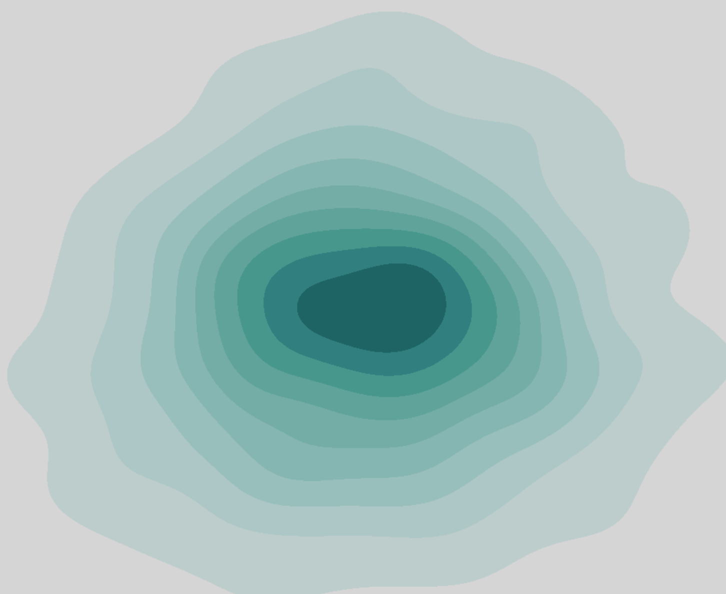


Interpolation!

Flow Matching is literally Interpolation

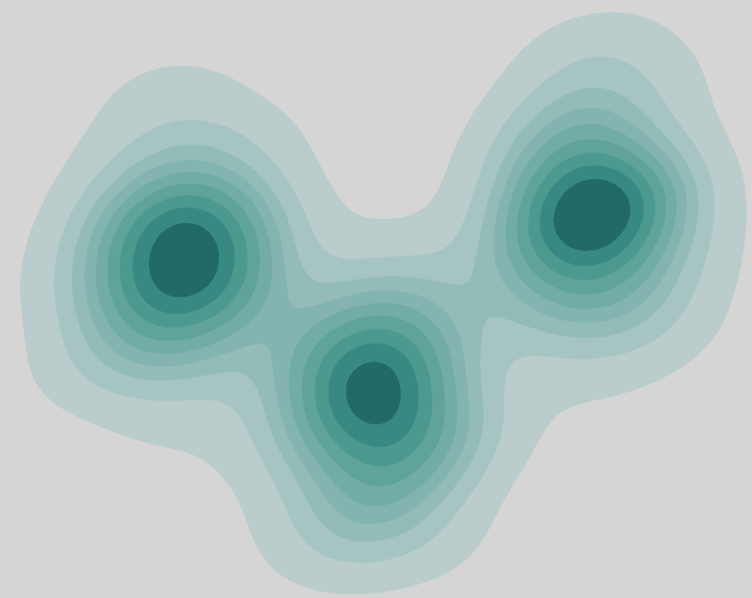
Source: memegenerator.org

Flow Matching is literally Interpolation



Source Distribution

π_0

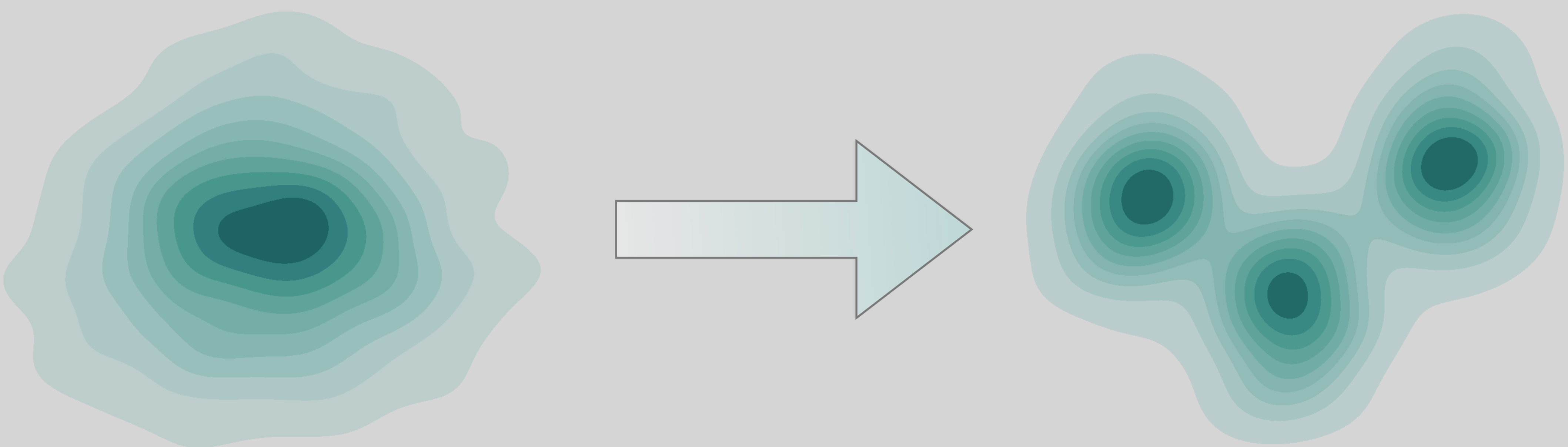


Target Distribution

π_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Flow Matching is literally Interpolation



Source Distribution π_0

Target Distribution π_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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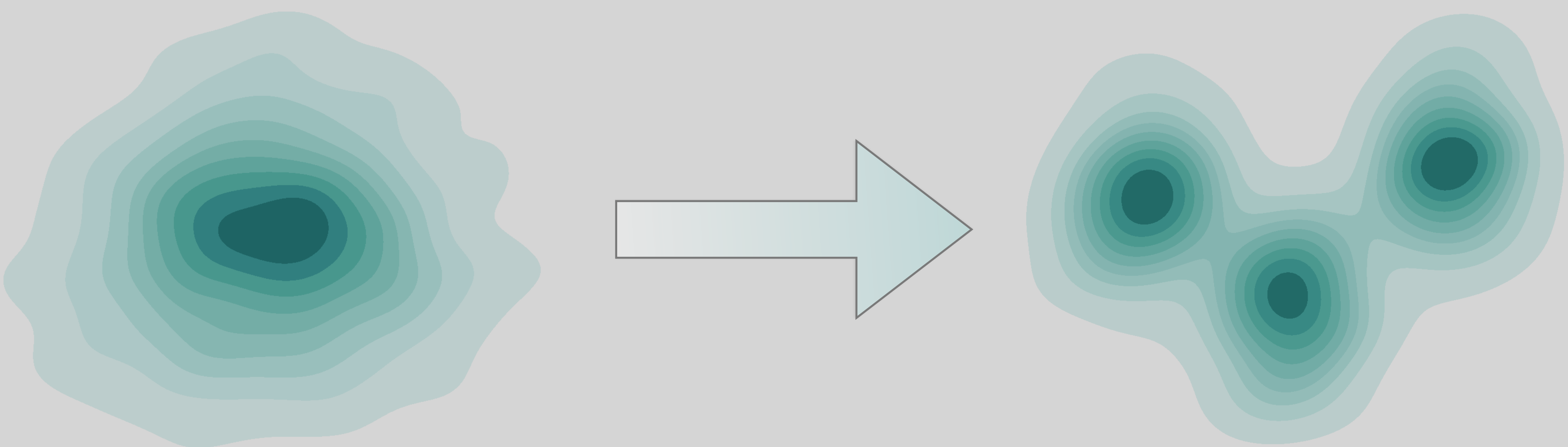
Flow Matching is literally Interpolation



Source Distribution π_0

Target Distribution π_1

$$\pi_t = t \cdot \pi_1 + (1 - t) \cdot \pi_0$$

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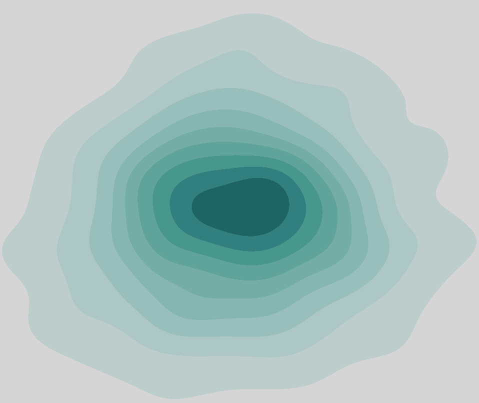
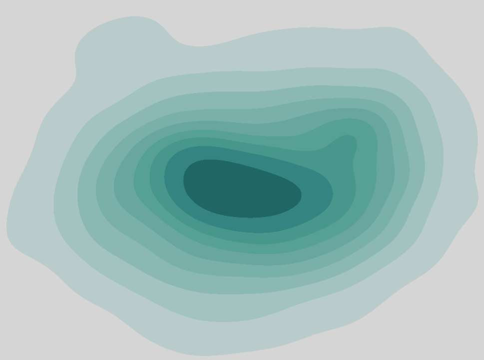
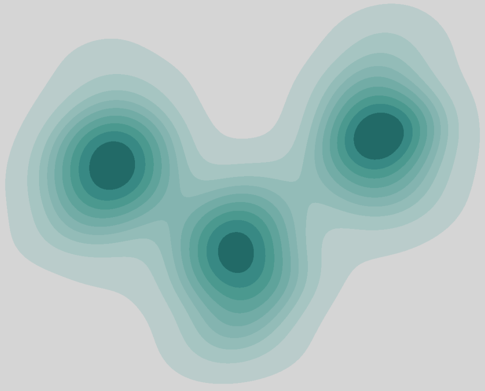
Flow Matching is literally Interpolation

Source Distribution

Target Distribution

$$\pi_t = \frac{1}{4} \cdot \pi_1 + \frac{3}{4} \cdot \pi_0$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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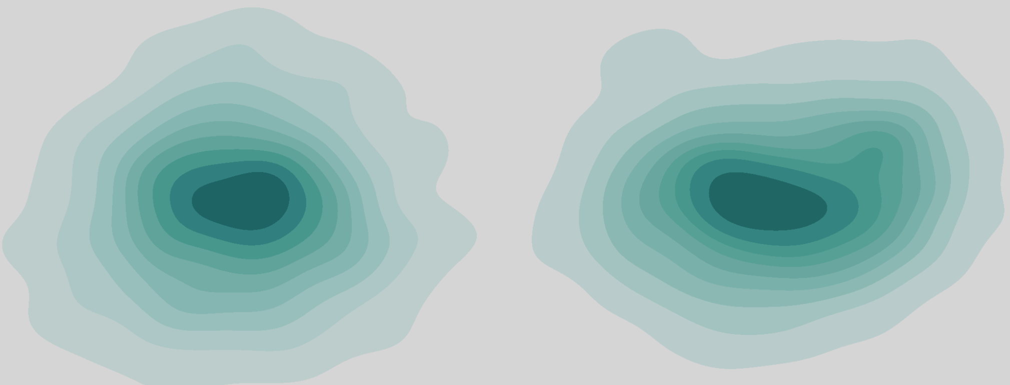
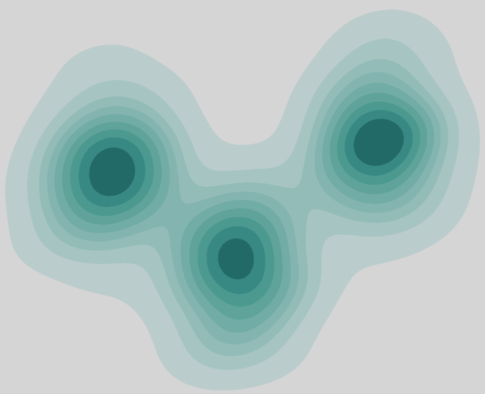
Flow Matching is literally Interpolation



Source Distribution



Target Distribution

$$\pi_{\frac{1}{4}} = \frac{1}{4} \cdot \pi_1 + \frac{3}{4} \cdot \pi_0$$

$$\pi_{\frac{1}{4}} = \pi_0 + \frac{1}{4} \cdot \nabla \pi_t$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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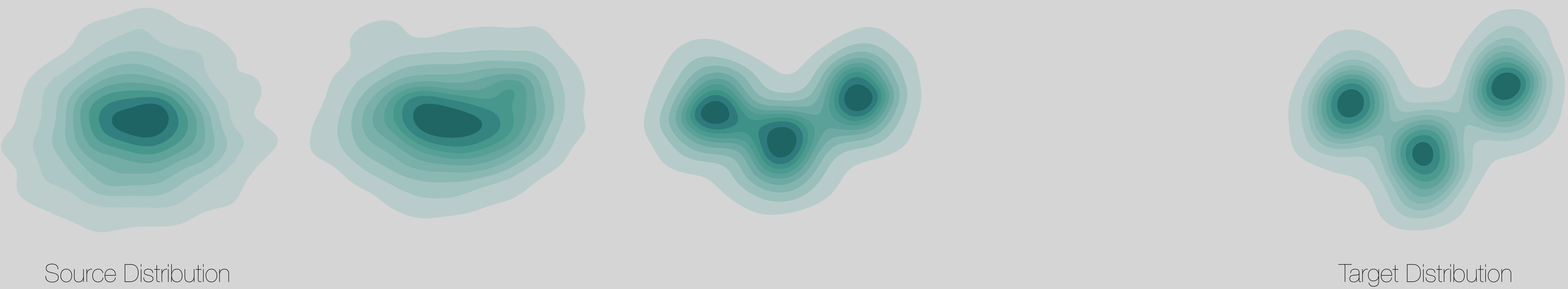
Flow Matching is literally Interpolation



$$\pi_{\frac{1}{4}} = \frac{1}{2} \cdot \pi_1 + \frac{1}{2} \cdot \pi_0$$

$$\pi_{\frac{1}{2}} = \pi_{\frac{1}{4}} + \frac{1}{4} \cdot \nabla \pi_t$$

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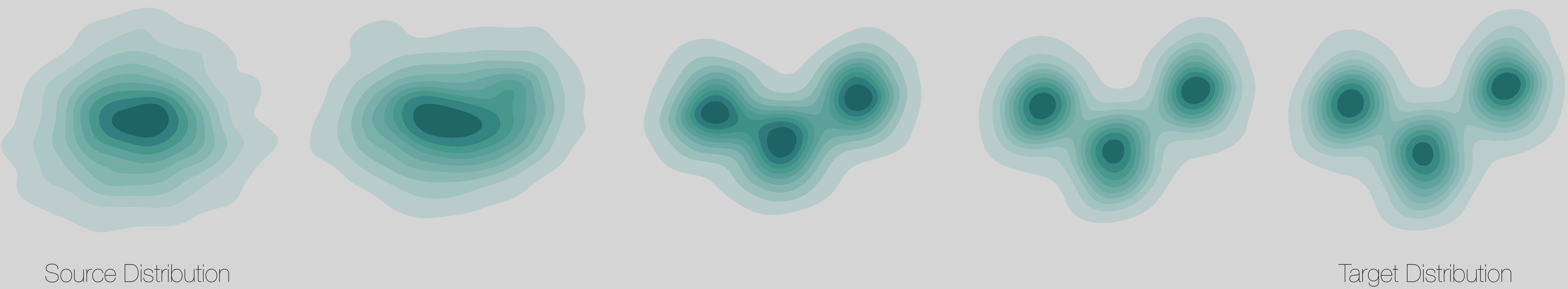
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Flow Matching is literally Interpolation



$$\pi_{\frac{3}{4}} = \frac{3}{4} \cdot \pi_1 + \frac{1}{4} \cdot \pi_0$$

$$\pi_{\frac{3}{4}} = \pi_{\frac{1}{2}} + \frac{1}{4} \cdot \nabla \pi_t$$

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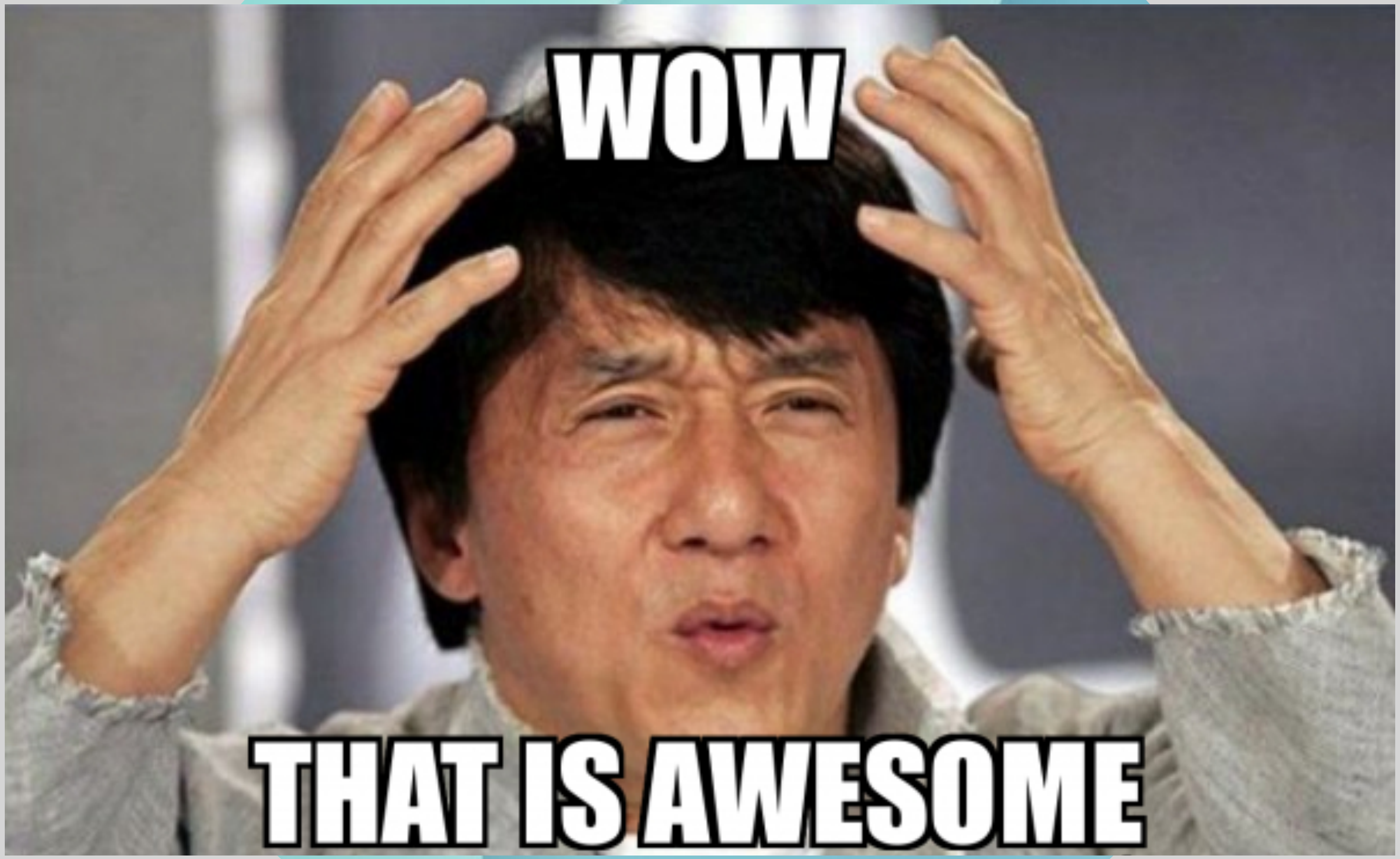
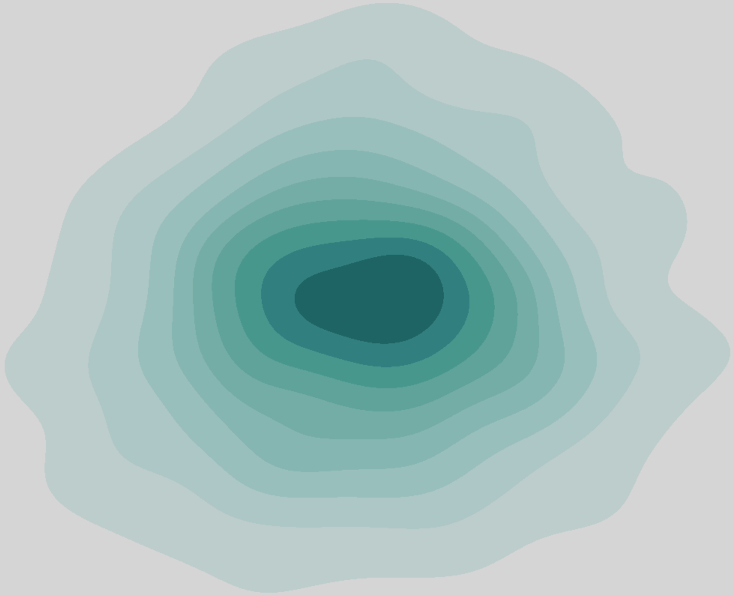
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Flow Matching is So Simple!

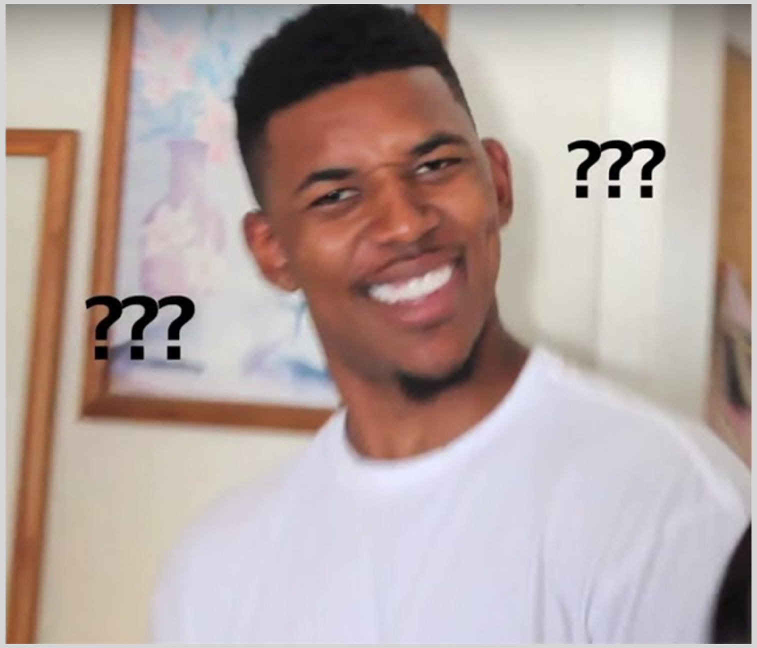


Source: makeameme.org

However…



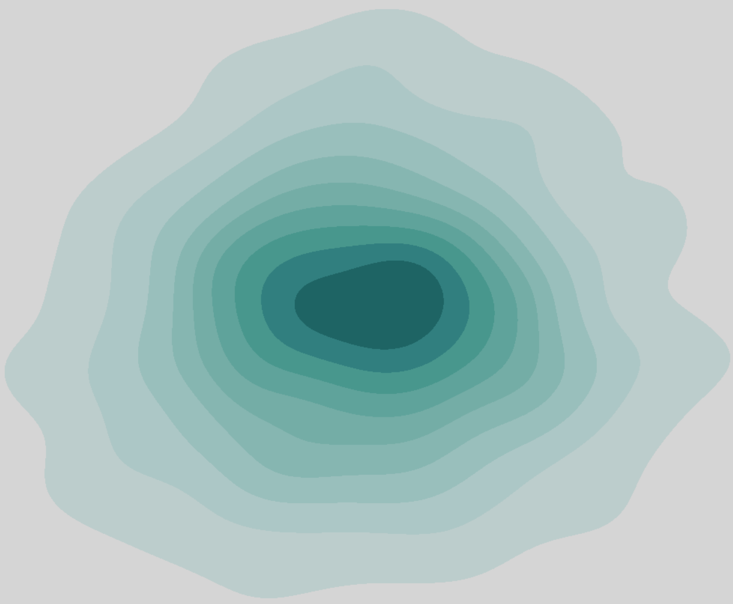
Source Distribution



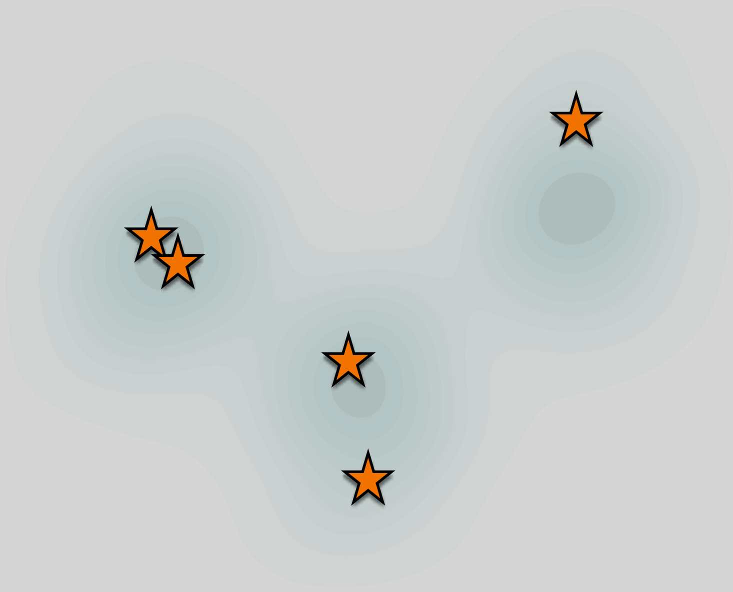
Target Distribution???

Source: Cassy Athena's YouTube episode with Nick Young

However…

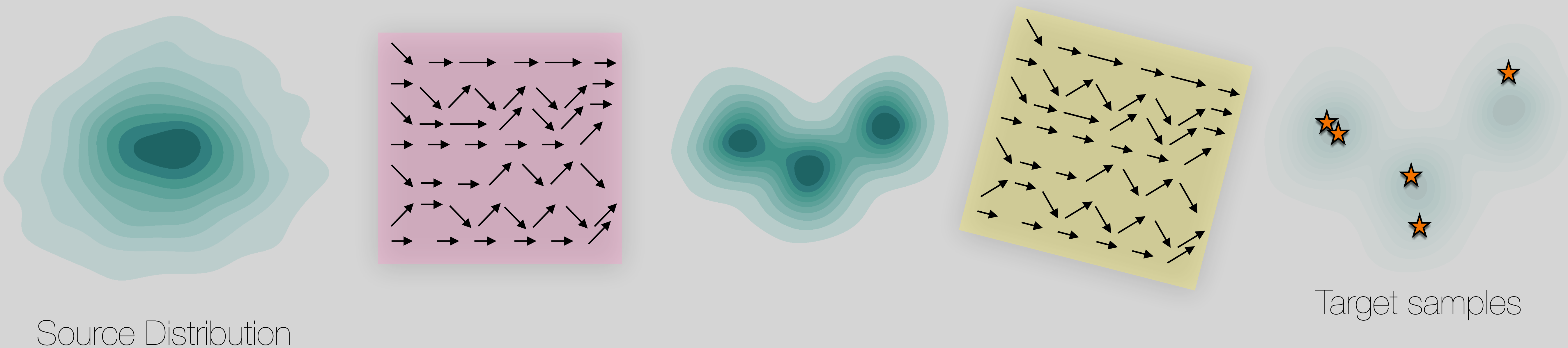


Source Distribution



Target samples

Can we get the velocity to get to intermediates?



Solution 101 : Random coupling

Source Samples

Target samples

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Solution 101 : Random coupling

Source Samples

Target samples

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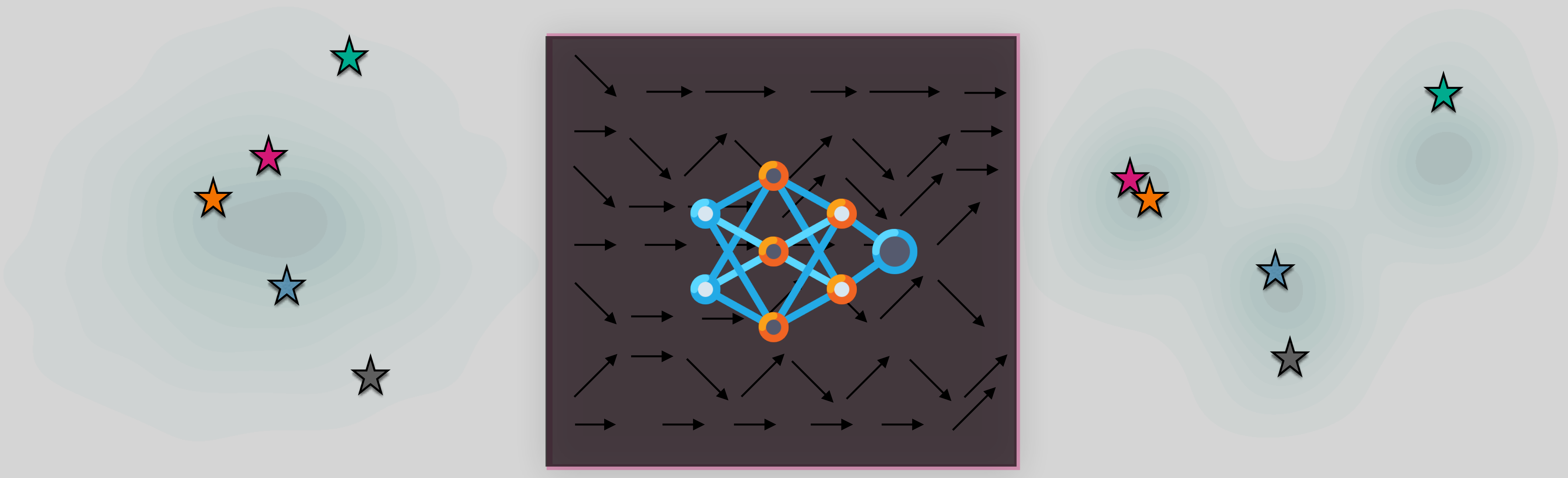
Solution 101 : Intermediate gradient/ velocity

What are the velocities to make the intermediates?



Source Samples

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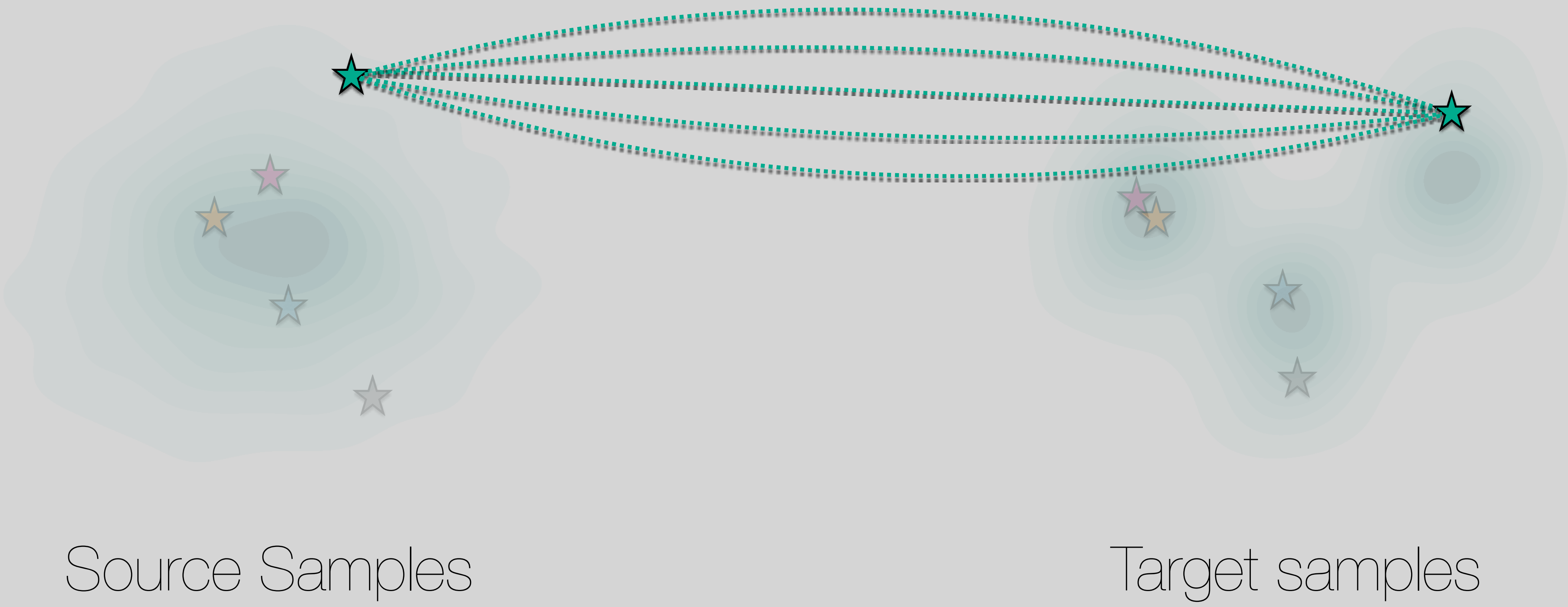
!!! Velocity depends on Interpolation paths

Which one to pick?



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Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Solution 101 : Go linear

Source Samples

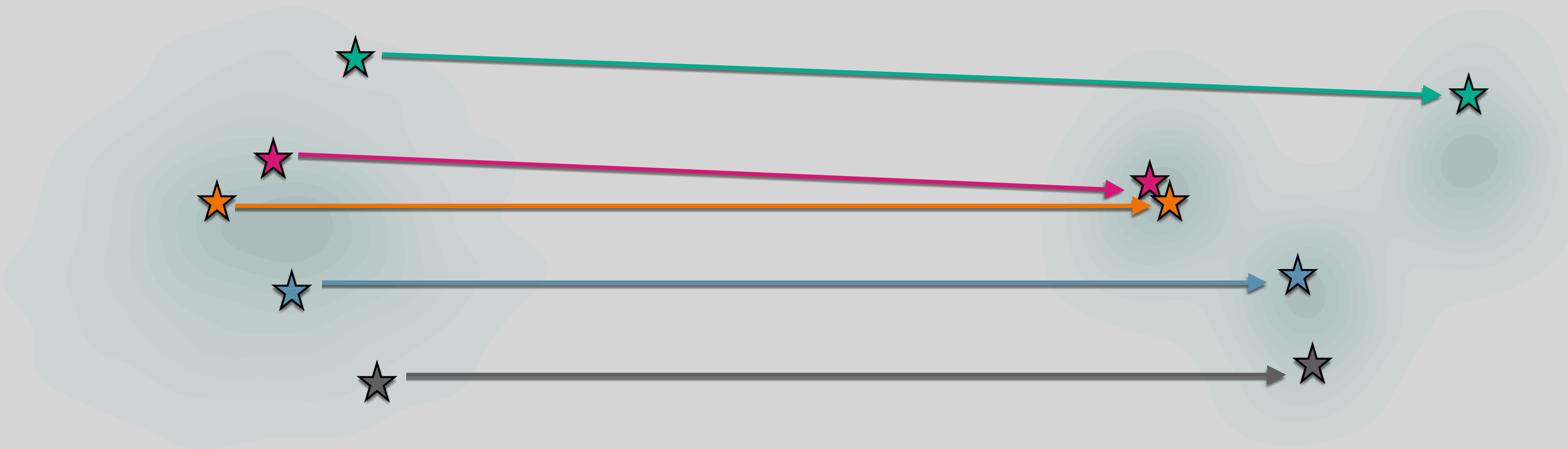
Target samples

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Source: Superman Comics

Solution 101 : Gradients

Model prediction

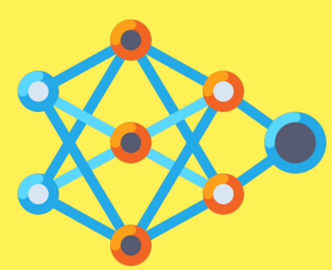


Source Samples

X_0

Target samples

X_1



$$\nabla X_t = X_1 - X_0$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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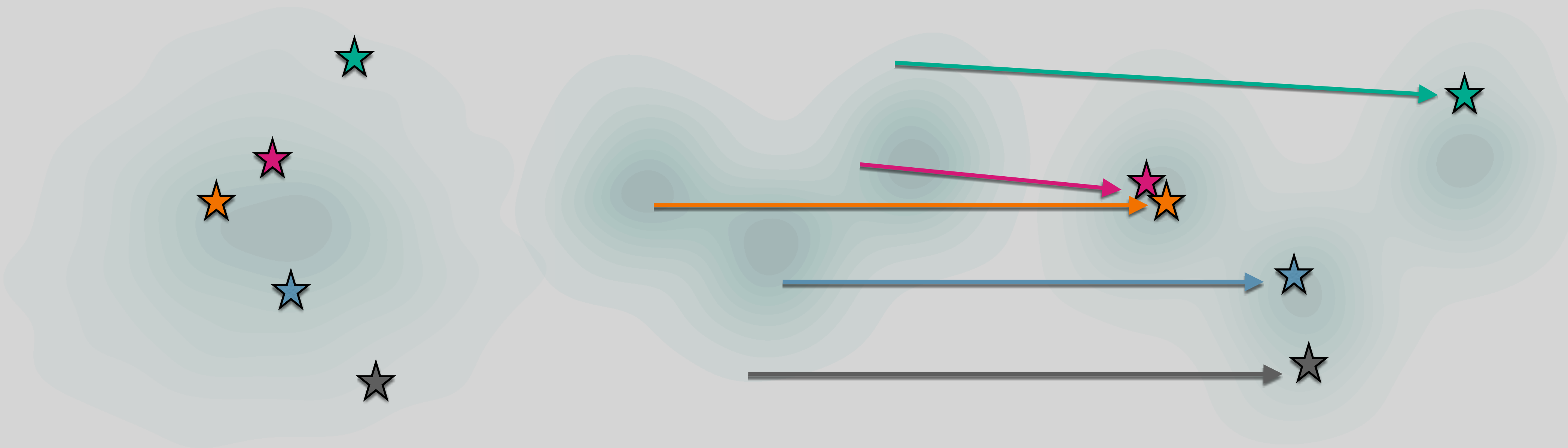
Solution 101 : Gradients

Model prediction

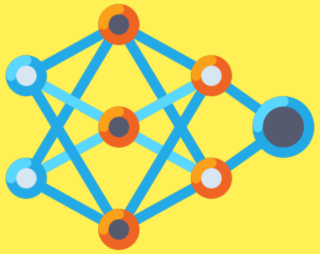


Source Samples

X_0

Target samples

X_1



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Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.

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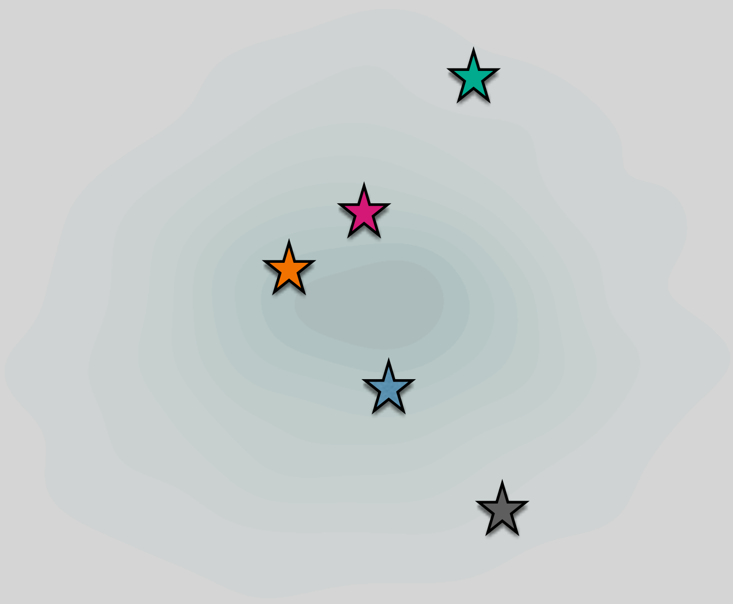
Overall Training

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

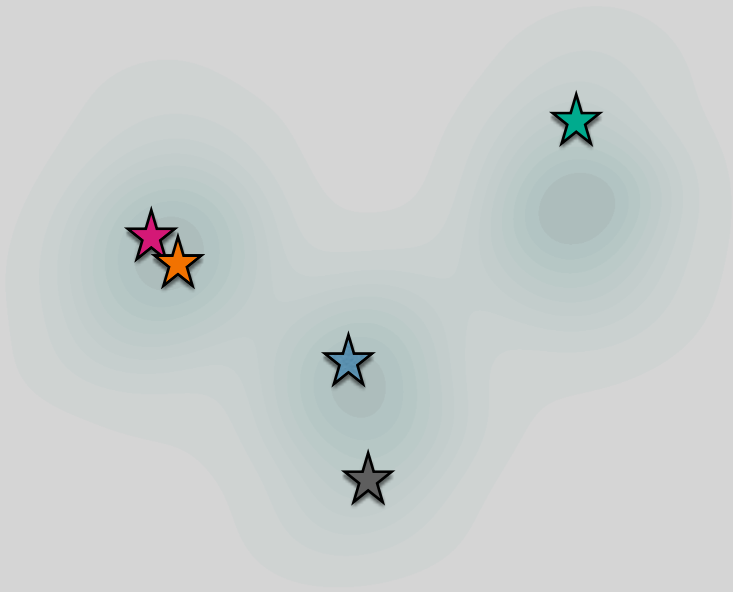
Overall Training

(1) Random Coupling



Source Samples

X_0



Target samples

X_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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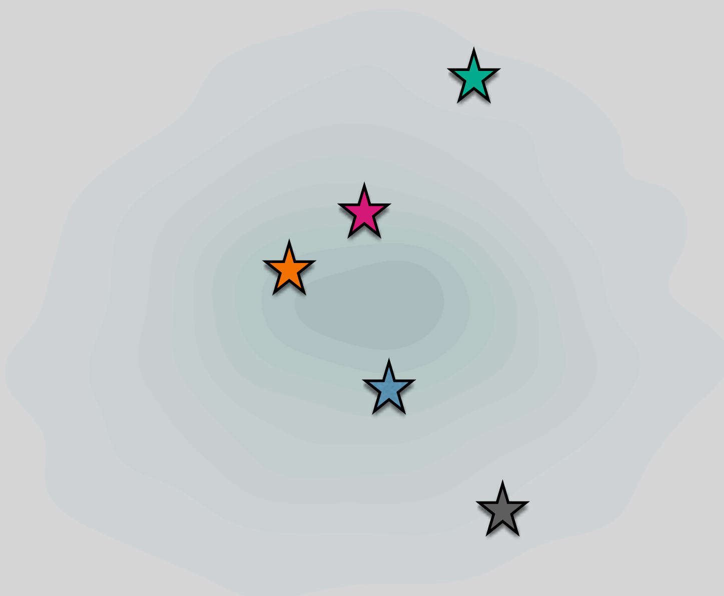
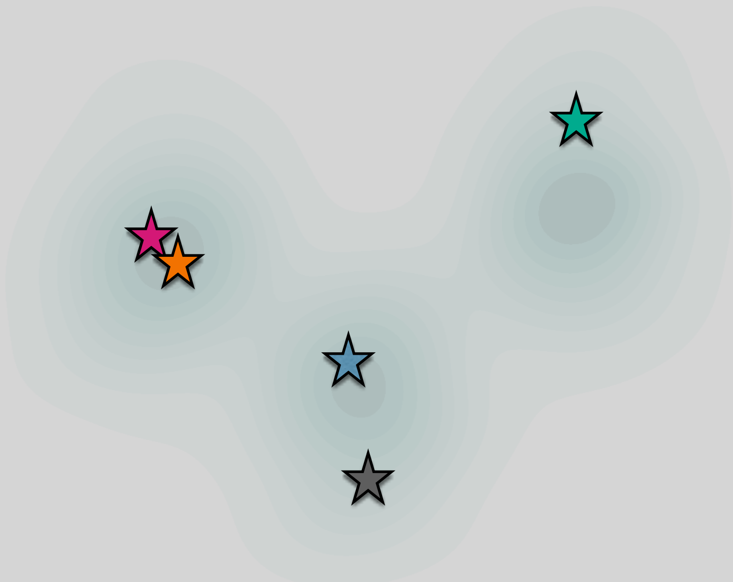
Overall Training

(2) Randomly sample t in [0,1)



Source Samples

X_0



Target samples

X_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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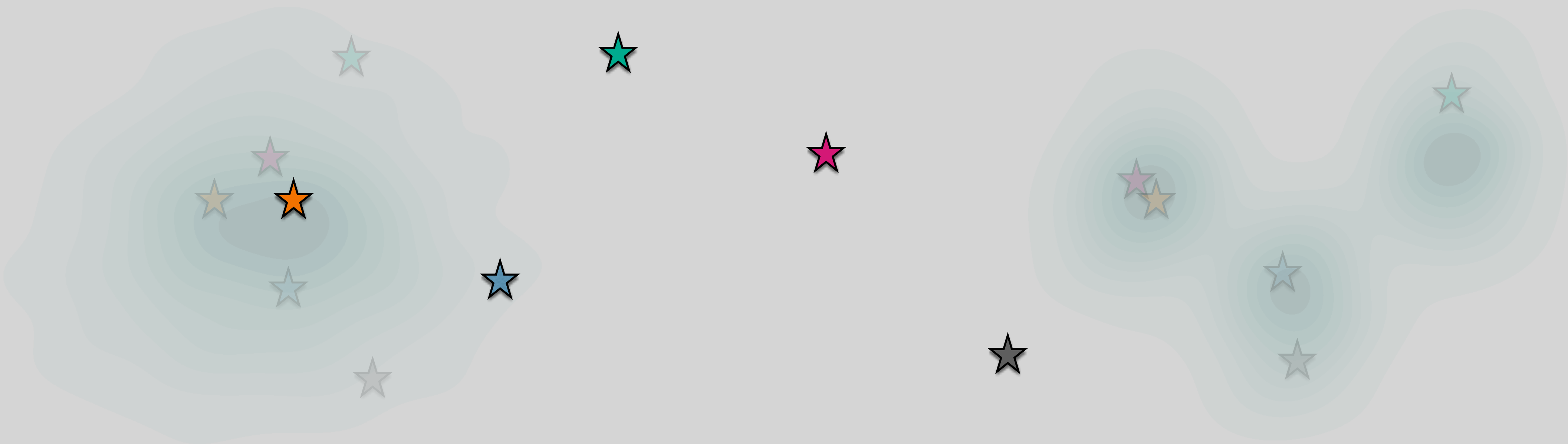
Overall Training

(3) Linear interpolation (model input)



Source Samples

X_0

Target samples

X_1

$$X_t = t \cdot X_1 + (1 - t) \cdot X_0$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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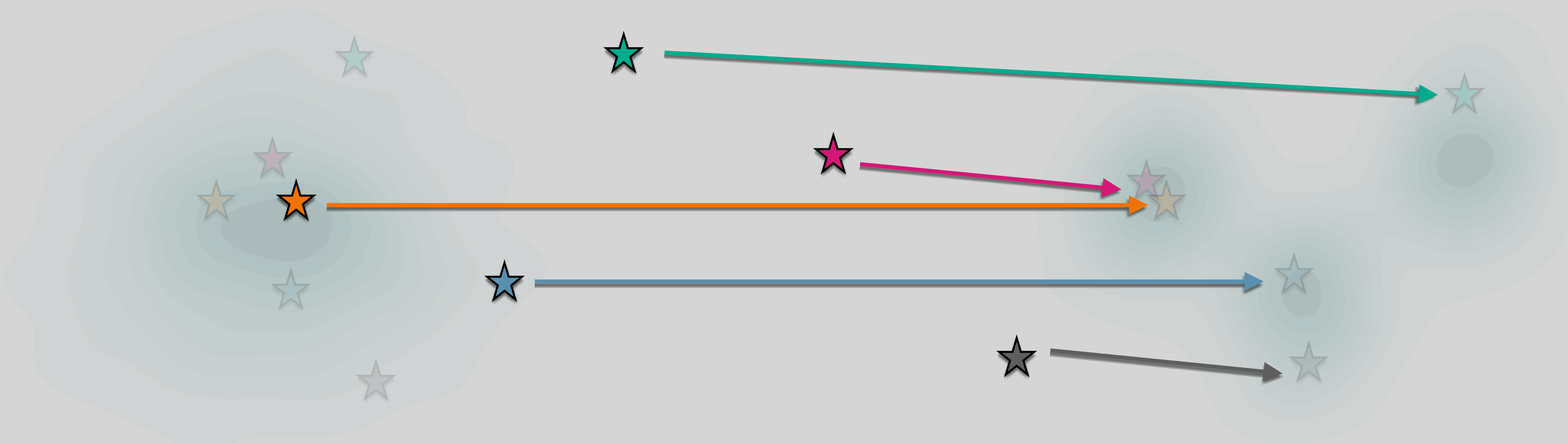
Overall Training

(4) Predict Velocity (model output)

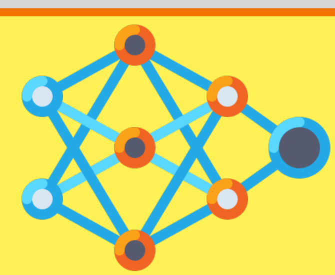


Source Samples

X_0

Target samples

X_1



$= \nabla X_t$

$u_\theta(t)$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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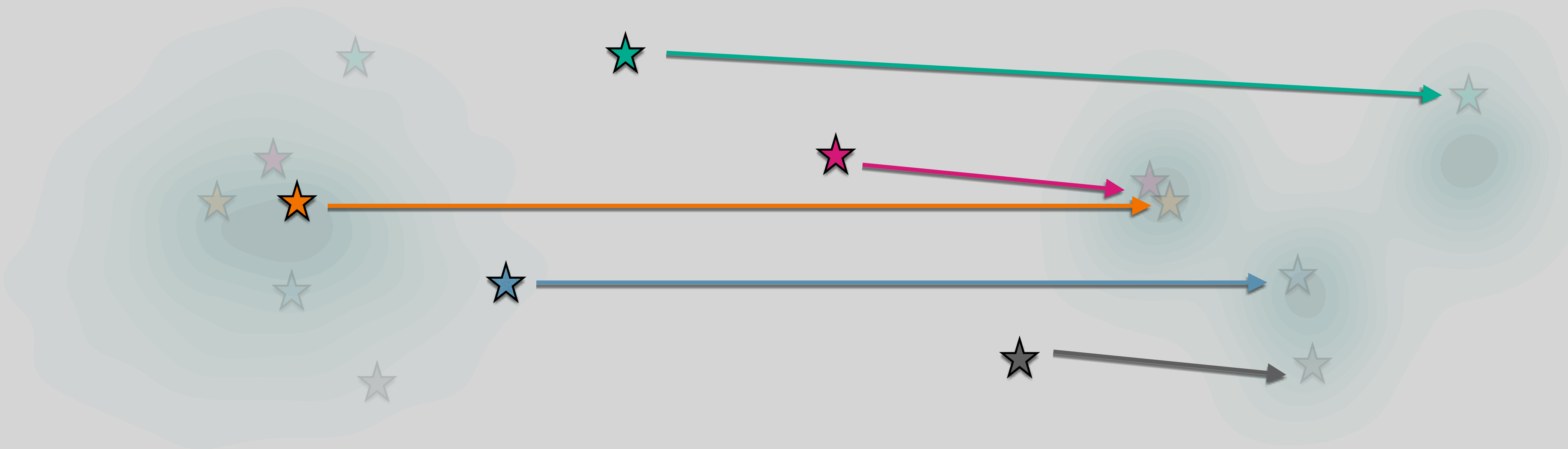
Overall Training

(5) Optimize



Source Samples

X_0

Target samples

X_1

$$\mathbb{E}[\,||u_\theta(t) - (X_1 - X_0)||^2\,]$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Sampling

Euler's Method

$$x_{next} = x_{old} + \frac{1}{num\_steps} \cdot u_\theta(t)$$

$$x_{initial} \sim \mathcal{N}(0, I)$$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Code 101...

```python
## Setting up the flow matching pipeline ##
class FlowMatchingPipeline:
  """Implements the Flow Matching pipeline"""

  def __init__(self):
    """Constructor"""
    self.model = model()
    self.optim = torch.optim.AdamW(self.model.parameters(), lr=1e-4)
    self.loss = nn.MSELoss()
```

Code 101...

```python
def interpolate(self, x1, t):
  """Interpolate x1 data from x0 data."""

  x0 = torch.randn(*x1.shape, device=x1.device, dtype=x1.dtype)

  xt = t * x1 + (1 - t) * x0

  vel = x1 - x0

  return xt, vel
```

Code 101...

```python
def training_step(self, data):
  """Implements one single training step for the model"""

  data = data.to(self.device)

  t = torch.rand(
      data.shape[0],
      dtype=data.dtype,
      device=self.device
  ).view(-1,1)

  xt, true_vt = self.interpolate(data, t)

  self.optim.zero_grad()

  vt = self.model(xt, t)

  loss = self.loss(true_vt, vt)
  loss_val = loss.clone().detach().cpu().item()

  loss.backward()

  self.optim.step()

  return loss_val
```

Code 101…

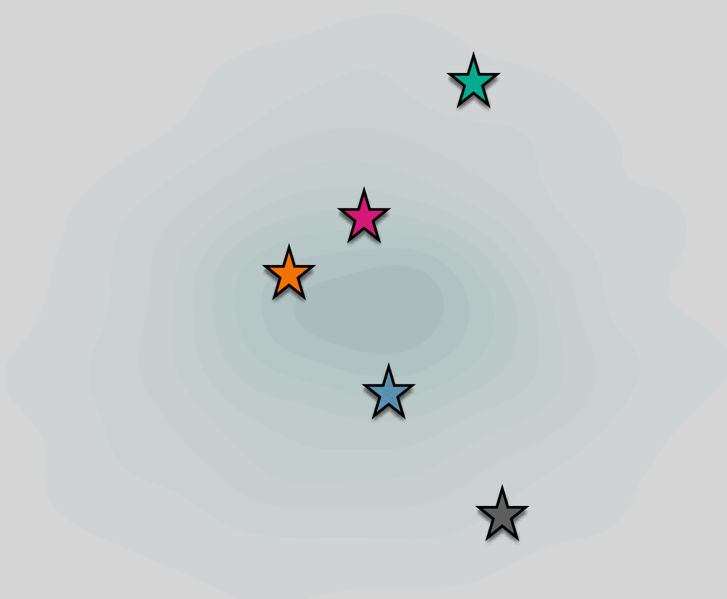
```python
@torch.no_grad()
def sample(self, num_steps, init_val):
  """Samples using euler steps using the model"""

  step_size = 1 / num_steps
  xt = init_val

  for step in range(1, num_steps):
    t = torch.tensor(
        [step / num_steps] * init_val.shape[0],
        dtype=xt.dtype,
        device=self.device
    ).view(-1,1)
    vt = self.model(xt, t)
    xt = xt + step_size * vt

  return xt
```

Gimme the Theory…

Source: https://tapas.io/series/grumpy-codes

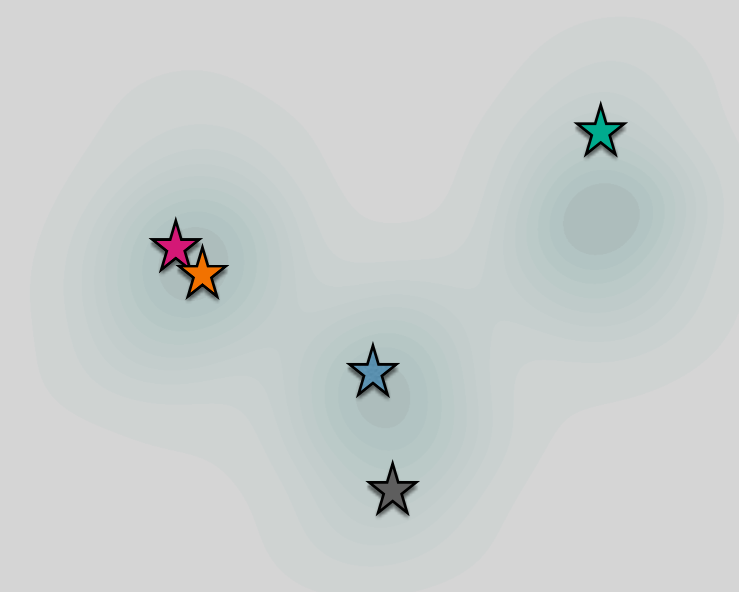
Theory of Flow Matching 101…

Recap: Random Coupling



Source Samples

X_0



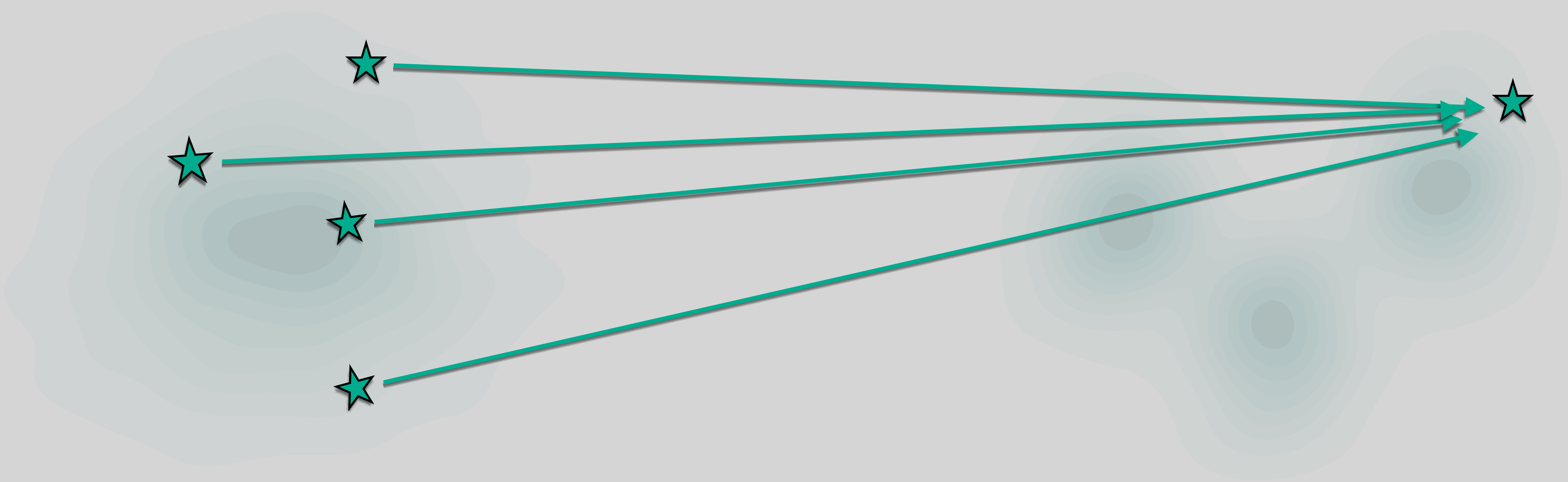
Target samples

X_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Theory of Flow Matching 101…

Recap: Random Coupling



Source Samples

X_0

Target samples

X_1

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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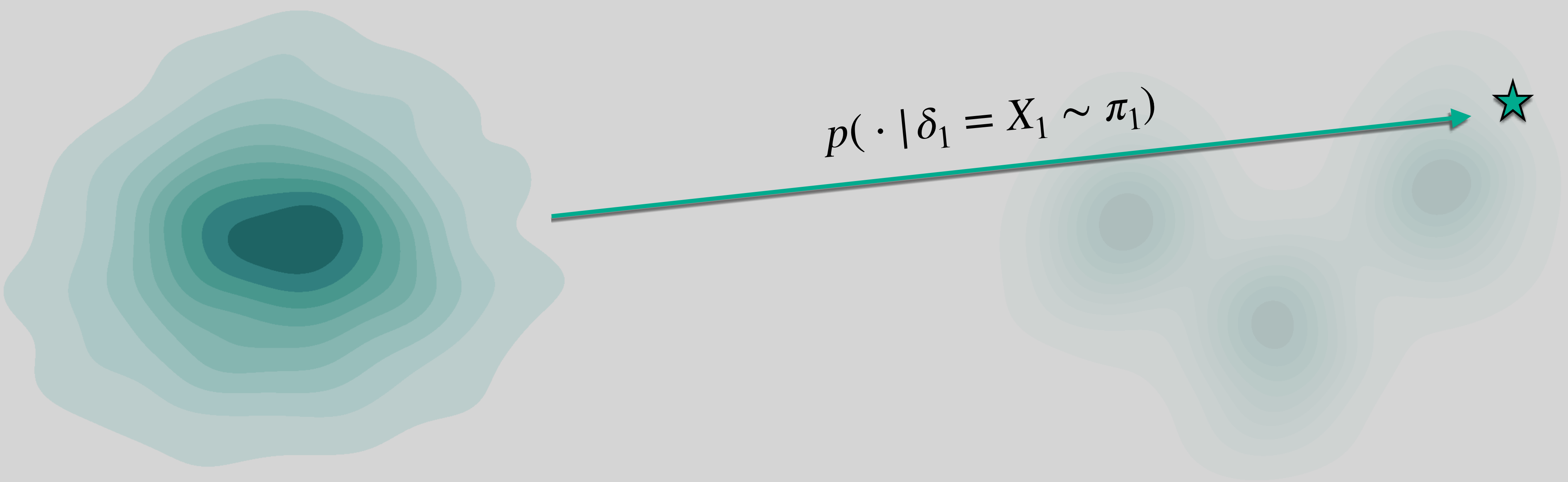
Theory of Flow Matching 101…

Conditional Probability Path



Source Distribution

π_0

Sample Distribution

$X_1 = \delta_1$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
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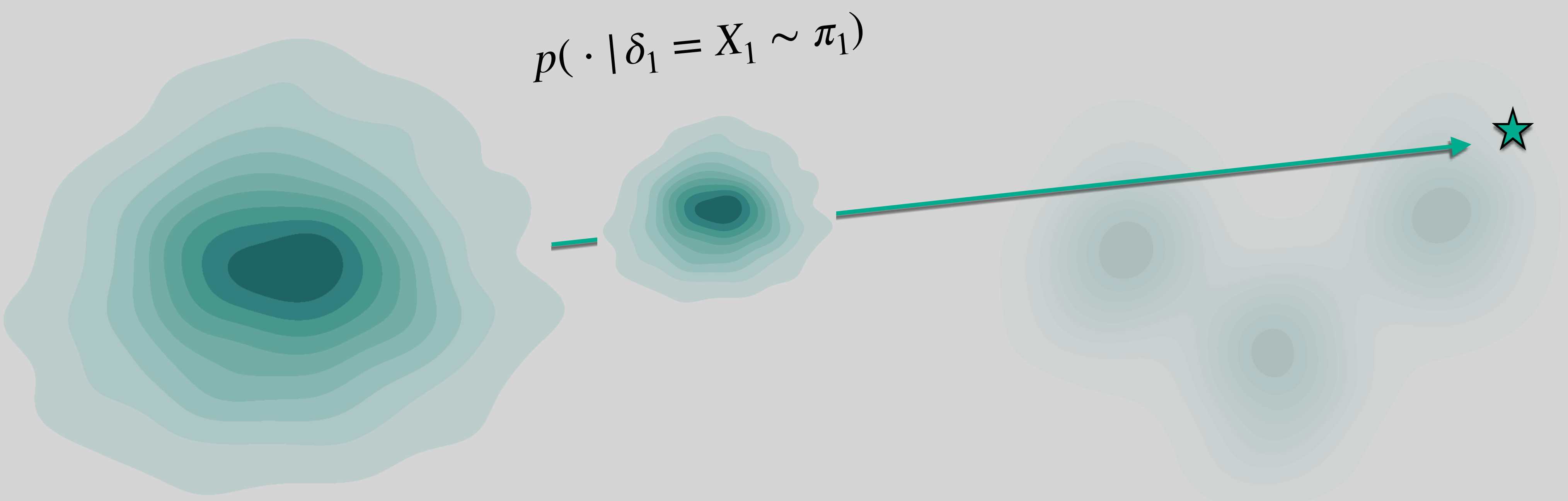
Theory of Flow Matching 101…

Conditional Probability Path



Source Distribution

π_0

Sample Distribution

$X_1 = \delta_1$

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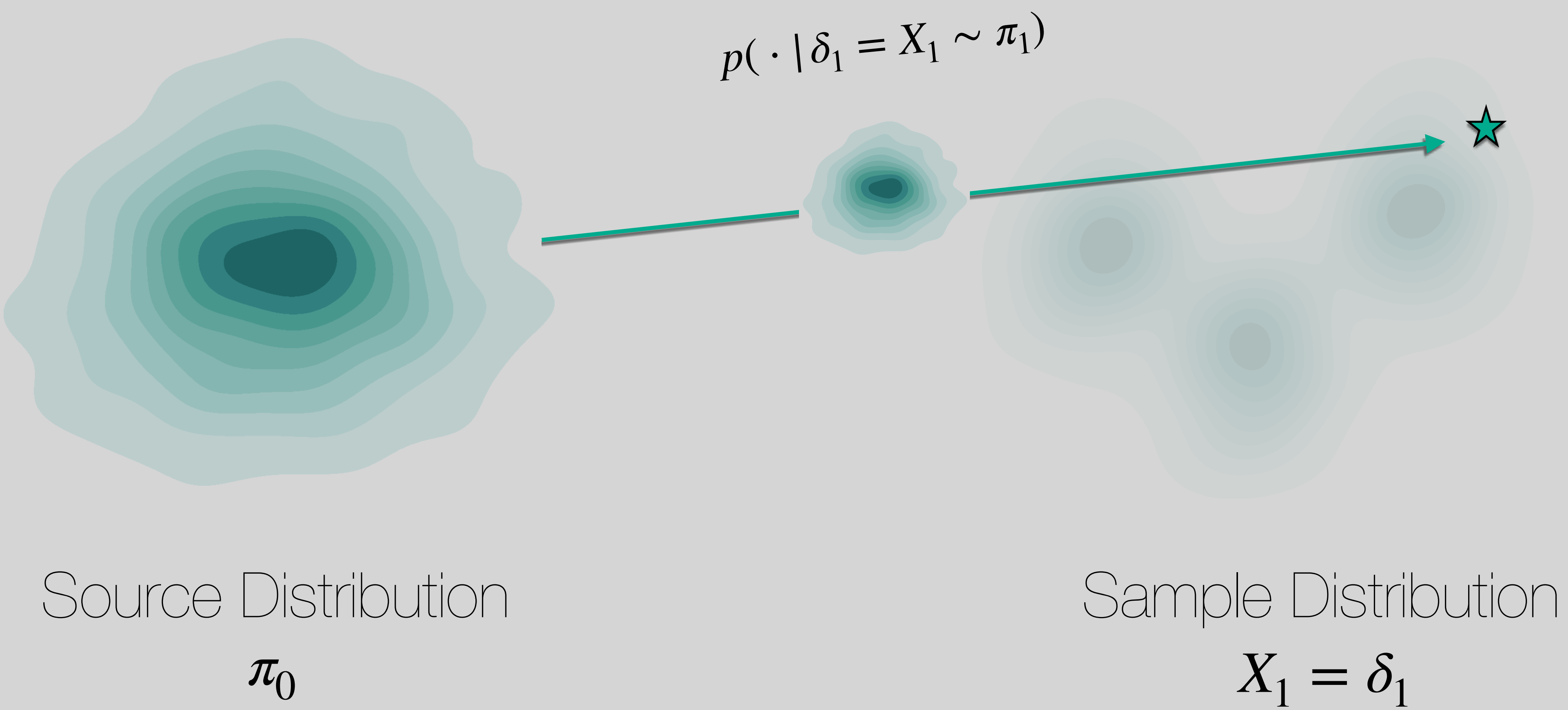
Theory of Flow Matching 101…

Conditional Probability Path



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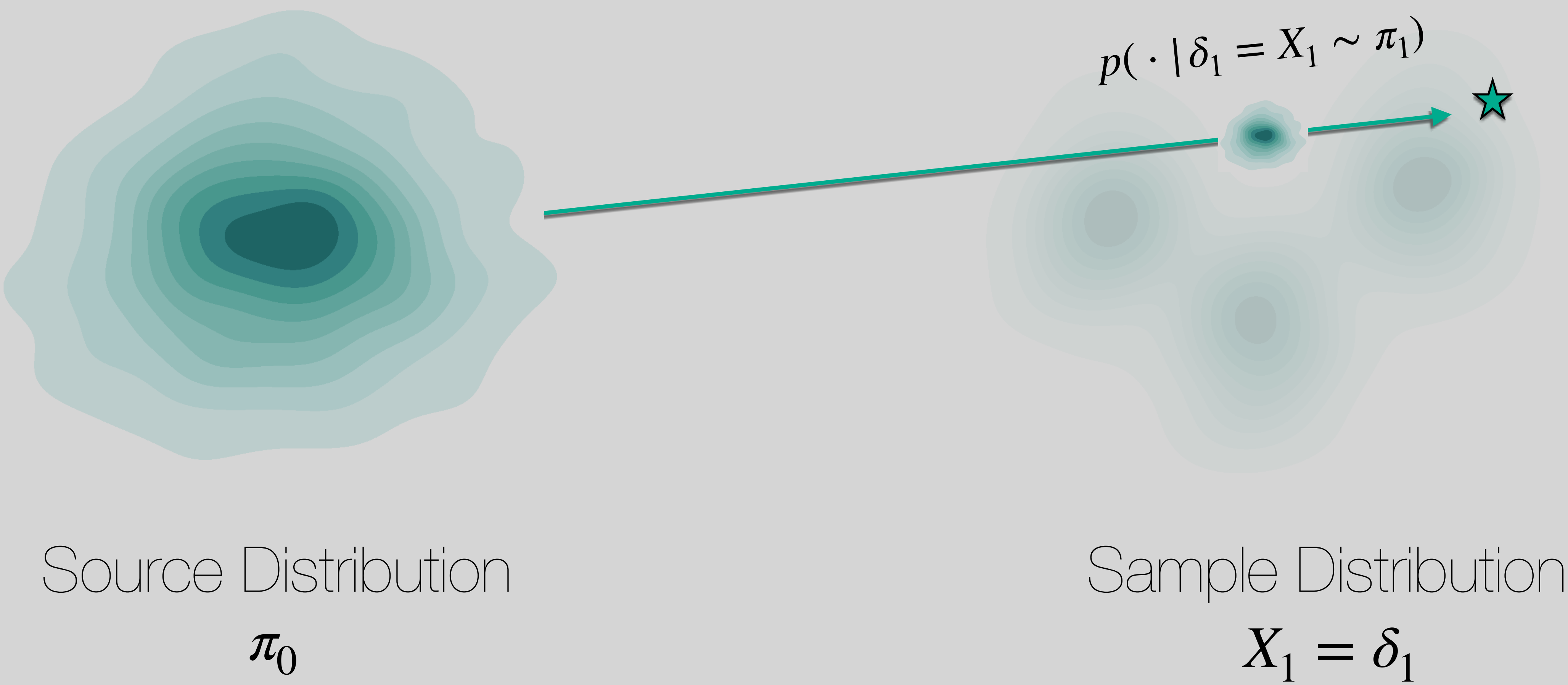
Theory of Flow Matching 101…

Conditional Probability Path



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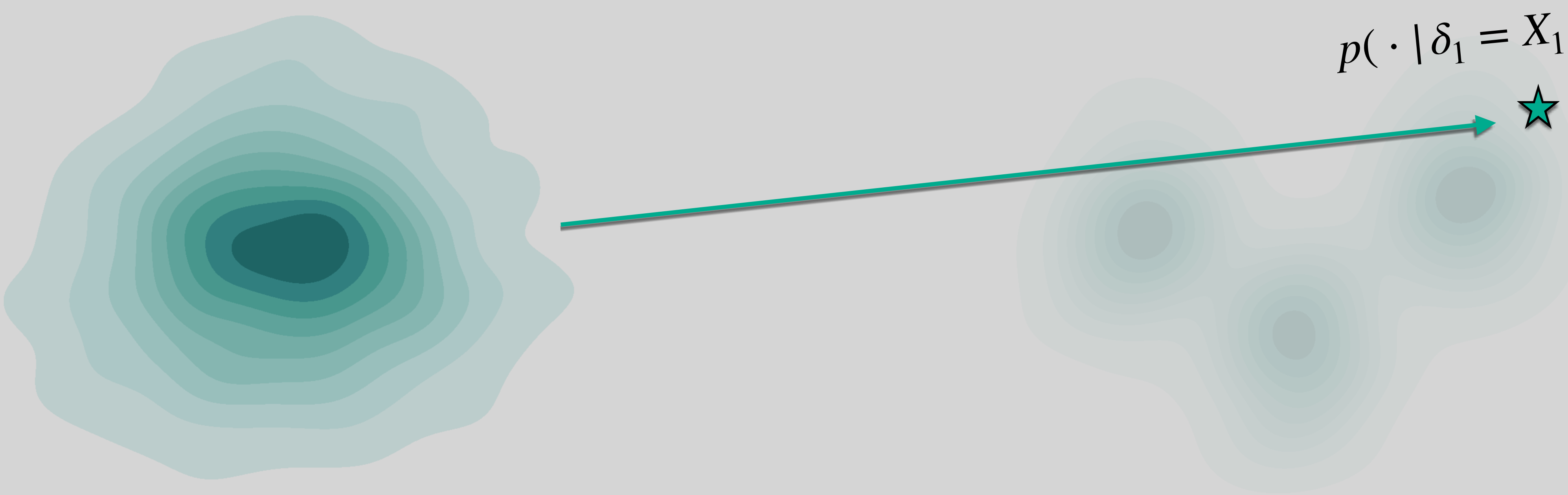
Theory of Flow Matching 101…

Conditional Probability Path



Source Distribution

π_0

Sample Distribution

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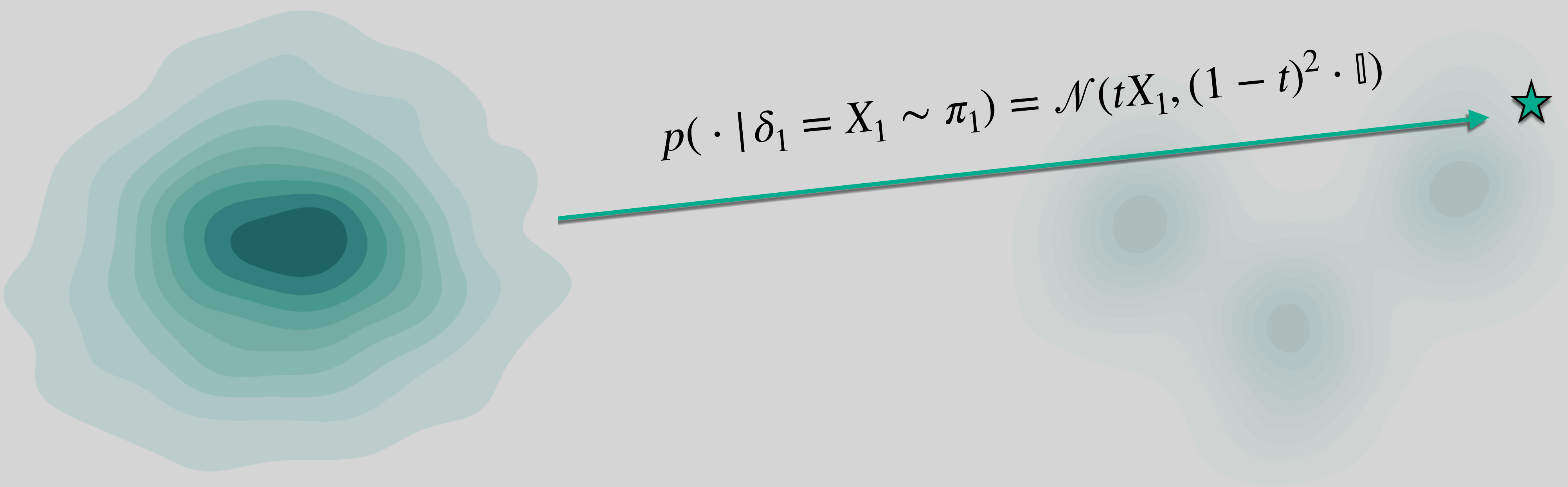
Theory of Flow Matching 101…

Conditional Probability Path



Source Distribution

π_0

Sample Distribution

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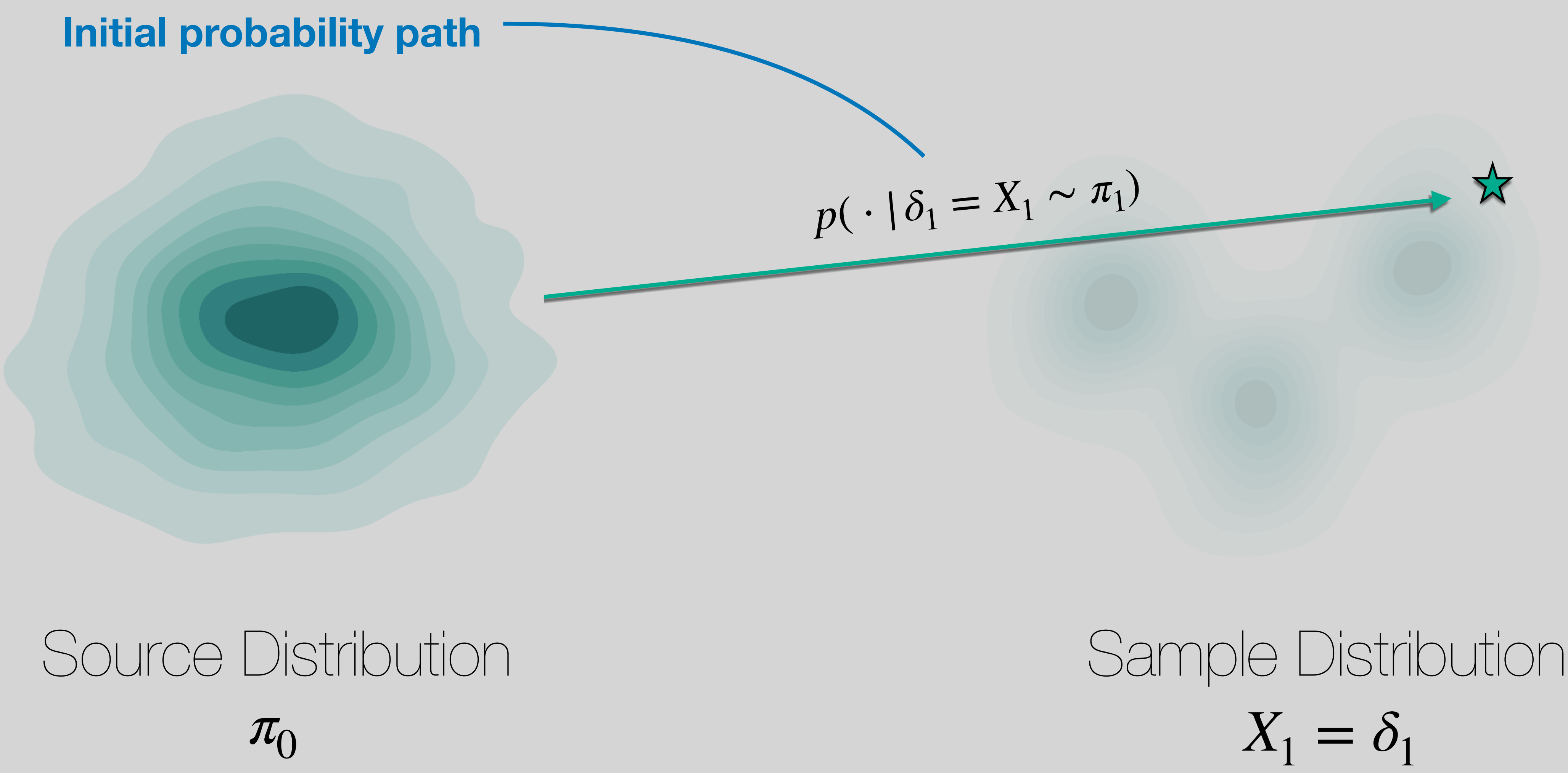
Theory of Flow Matching 101…

Conditional Probability Path



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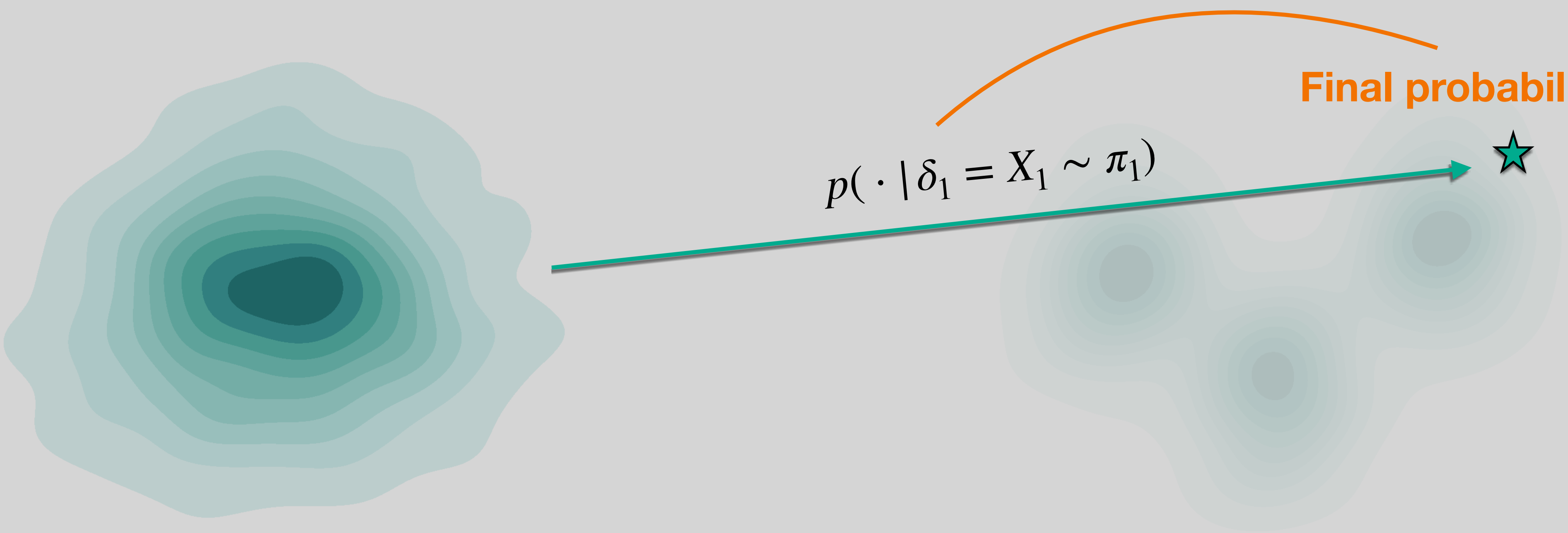
Theory of Flow Matching 101…

Conditional Probability Path



Source Distribution

π_0

Sample Distribution

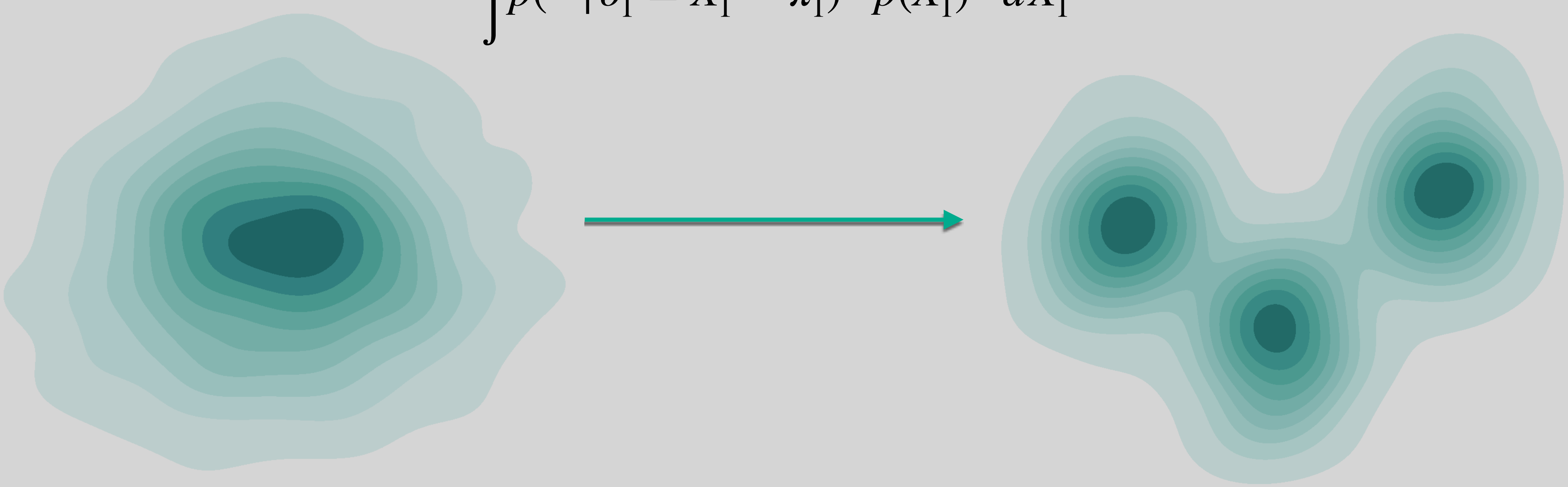
$X_1 = \delta_1$

Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Theory of Flow Matching 101…

Marginal Probability Path

$$\int p(\,\cdot \mid \delta_1 = X_1 \sim \pi_1) \cdot p(X_1) \cdot dX_1$$



Source Distribution

π_0

Target Distribution

π_1

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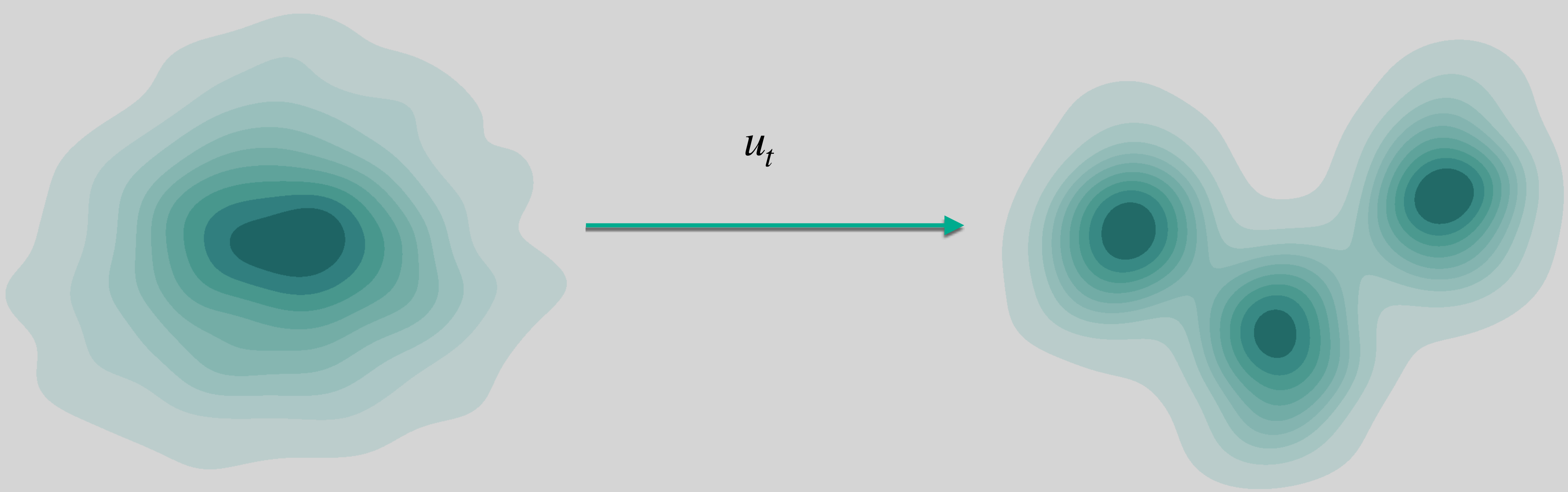
Theory of Flow Matching 101…

Marginal Velocity Field



Source Distribution

π_0

Target Distribution

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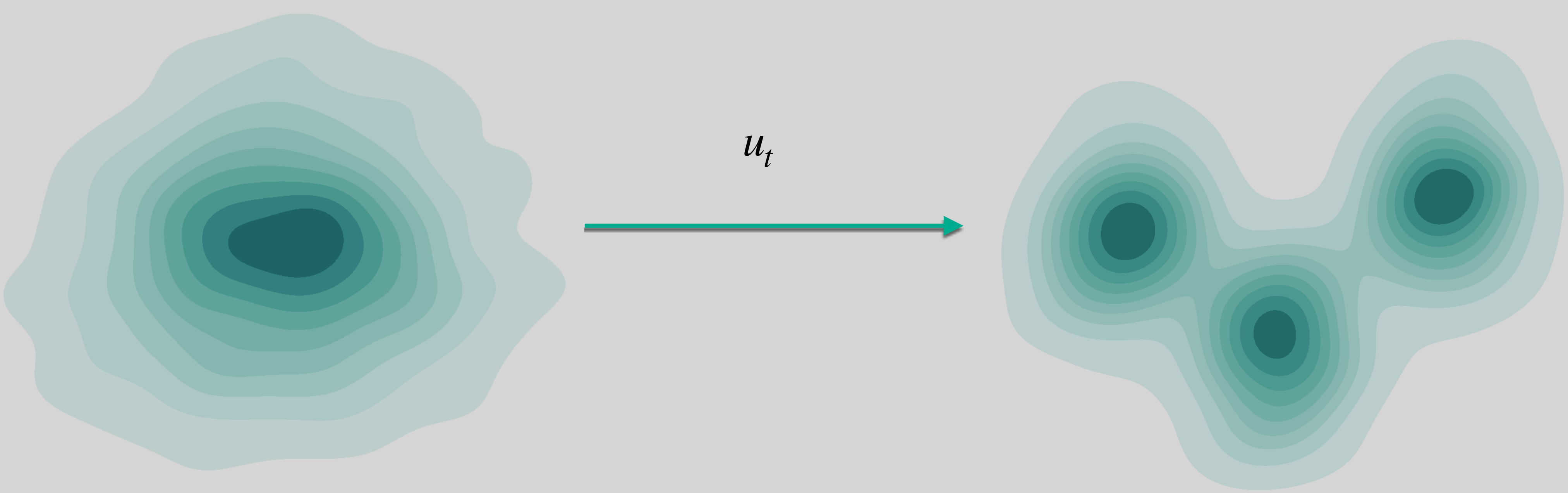
Theory of Flow Matching 101…

Marginal Velocity Field : Follows marginal probability path



Source Distribution

π_0

Target Distribution

π_1

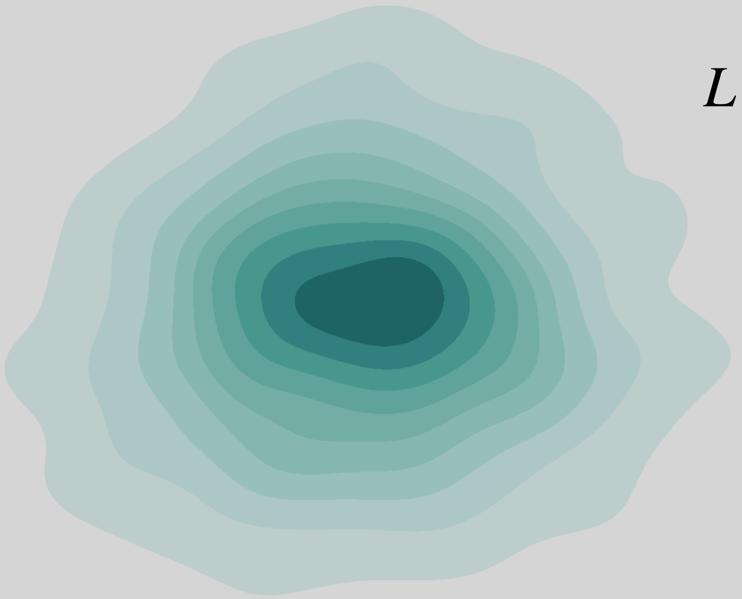
Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Theory of Flow Matching 101…

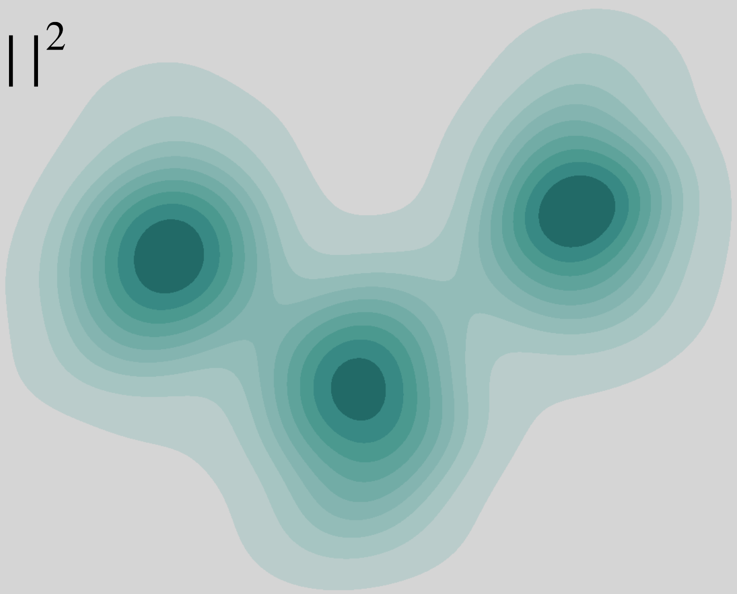
Marginal Velocity Field : Minimize

$$L = || u_t^{\theta}(X_t) - u_t^{target}(X_t) ||^2$$



Source Distribution

π_0



Target Distribution

π_1

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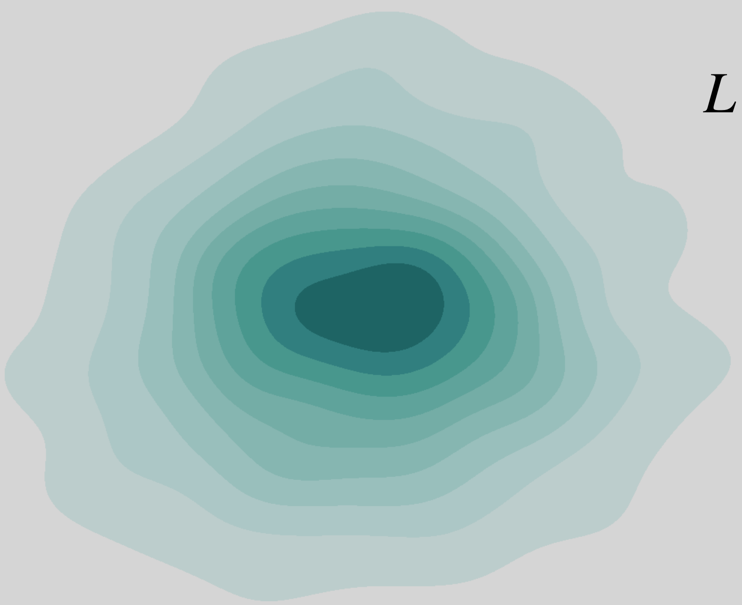
Theory of Flow Matching 101…

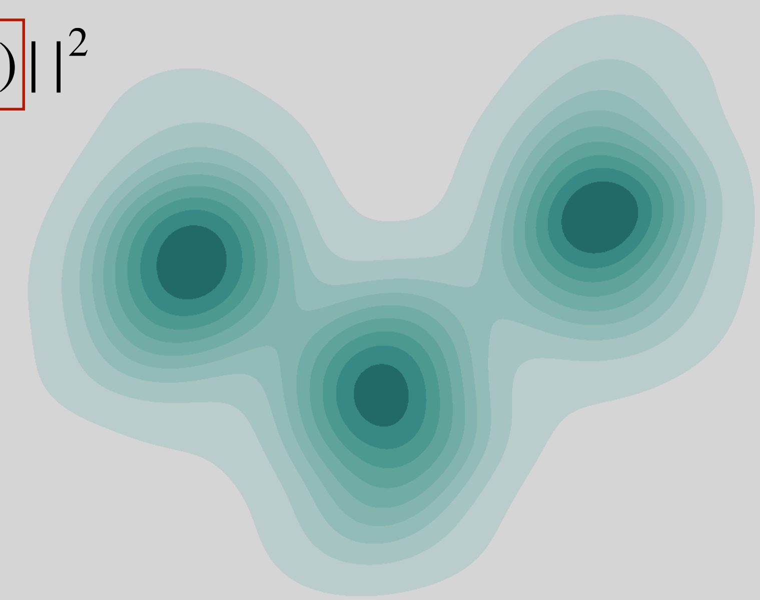
Marginal Velocity Field

$$L = ||u_t^\theta(X_t) - \boxed{u_t^{target}(X_t)}||^2$$



Source Distribution

π_0



Target Distribution

π_1

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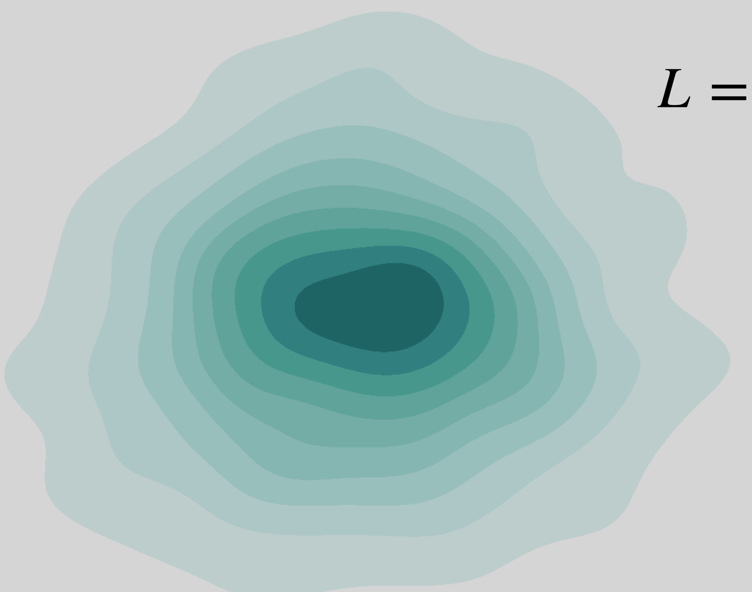
Theory of Flow Matching 101…

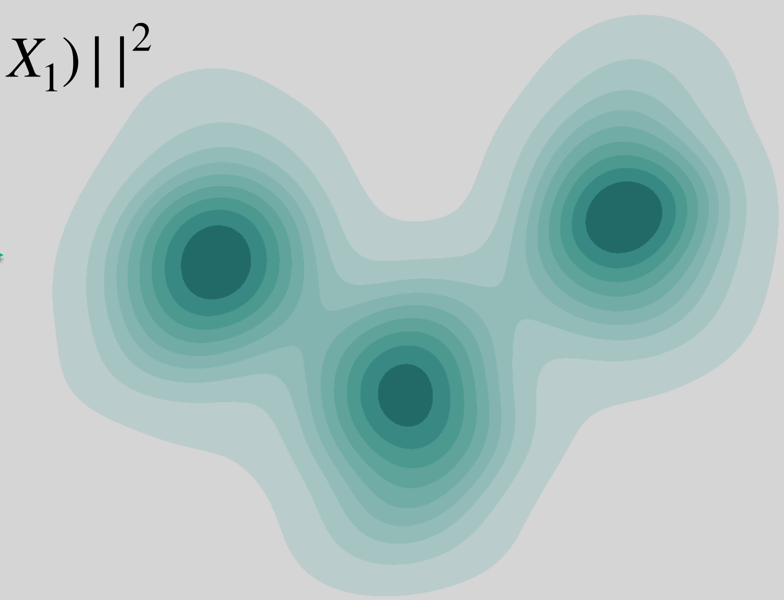
Conditional Velocity Field

$$L = ||u_t^{\theta}(X_t) - u_t^{target}(X_t | X_1)||^2$$



Source Distribution

π_0



Target Distribution

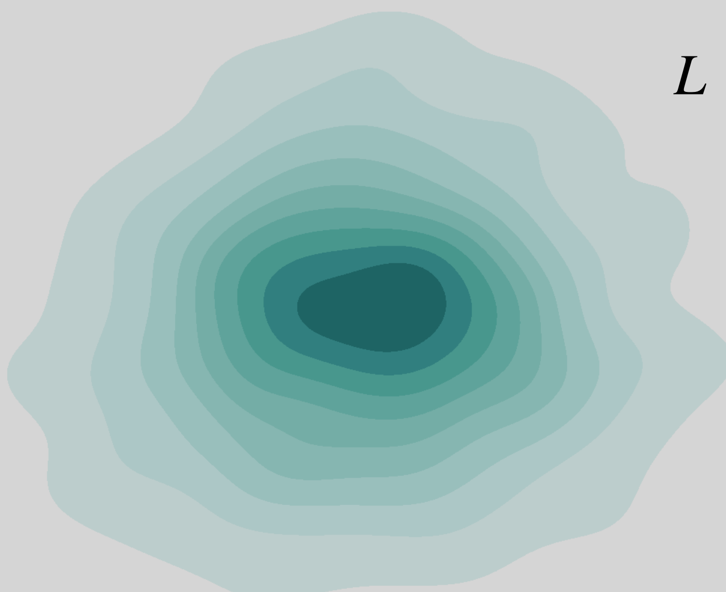
π_1

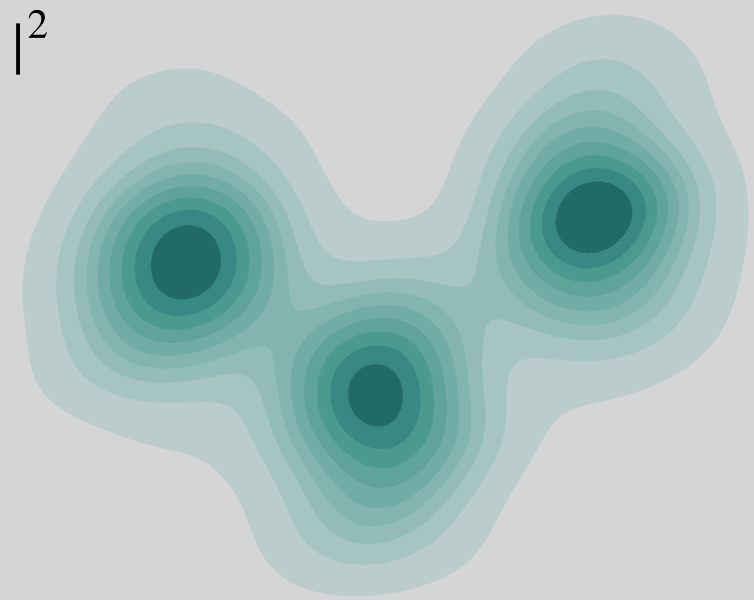
Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Theory of Flow Matching 101…

Conditional Velocity Field for optimal transport path

$$L = ||u_t^{\theta}(X_t) - (X_1 - X_0)||^2$$





Source Distribution
π_0

Target Distribution
π_1

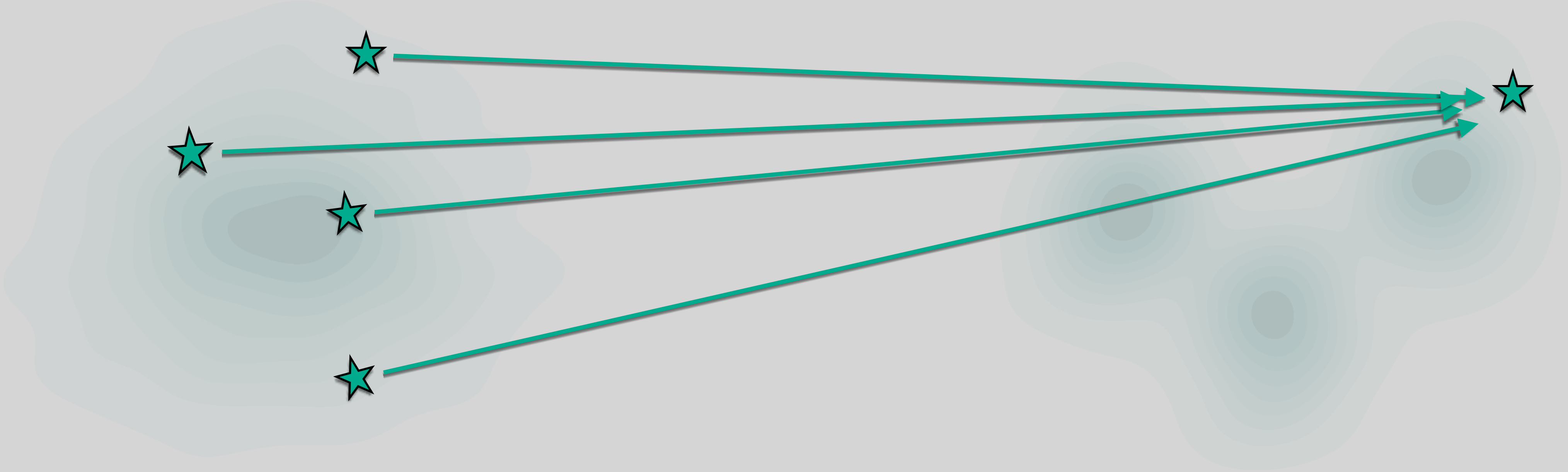
Lipman, Yaron, et al. "Flow Matching for Generative Modeling.." ICLR 2023.
Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Recap: Random Coupling



Source Samples

X_0

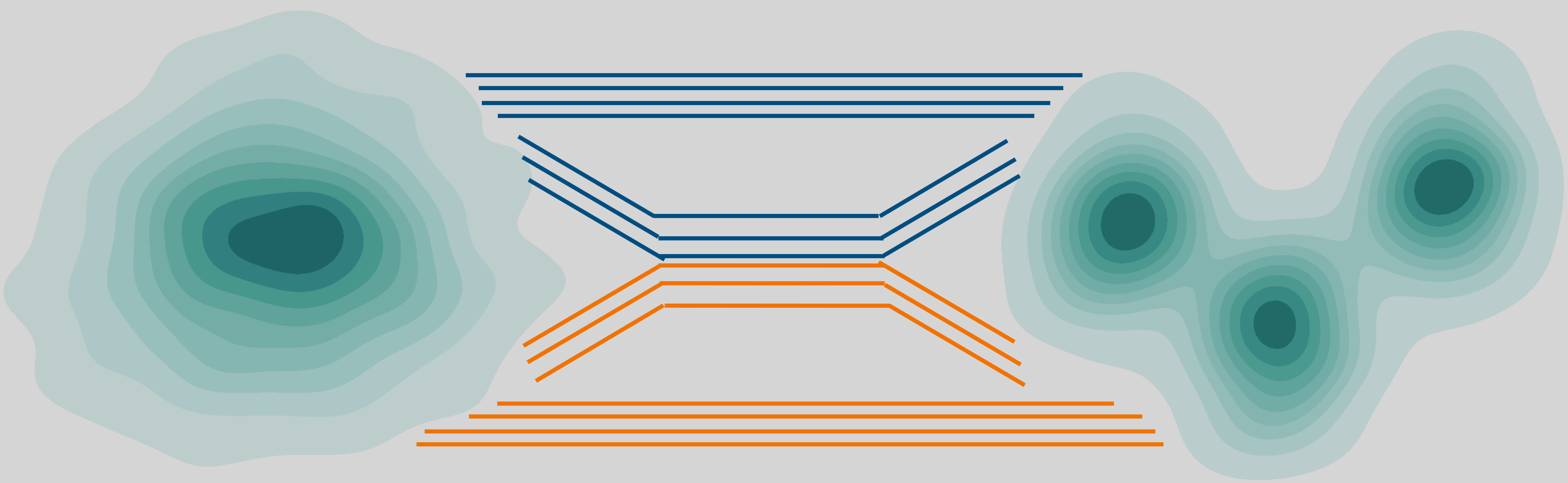
Target samples

X_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Learnt Vector Fields



Source Distribution

π_0

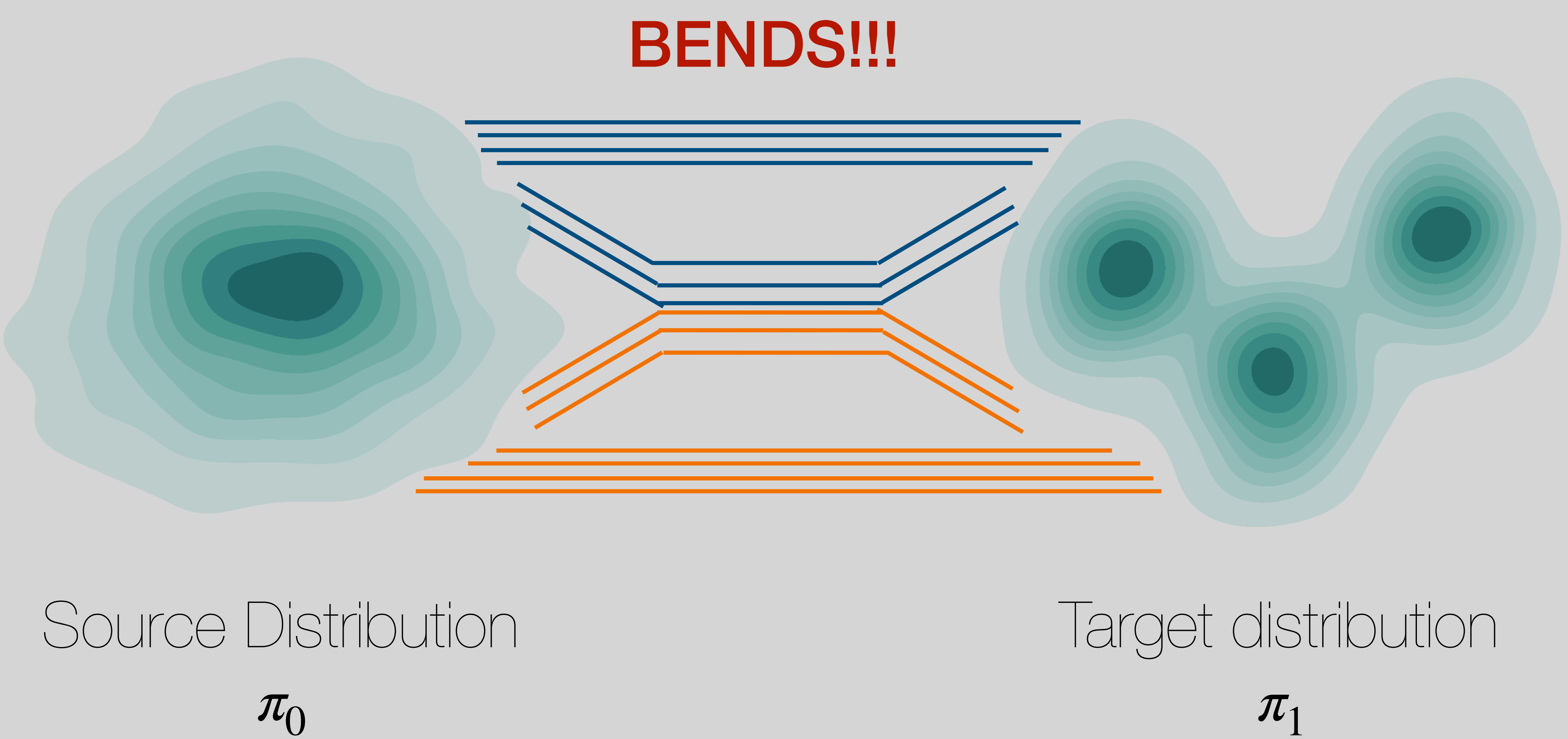
Target distribution

π_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Learnt Vector Fields

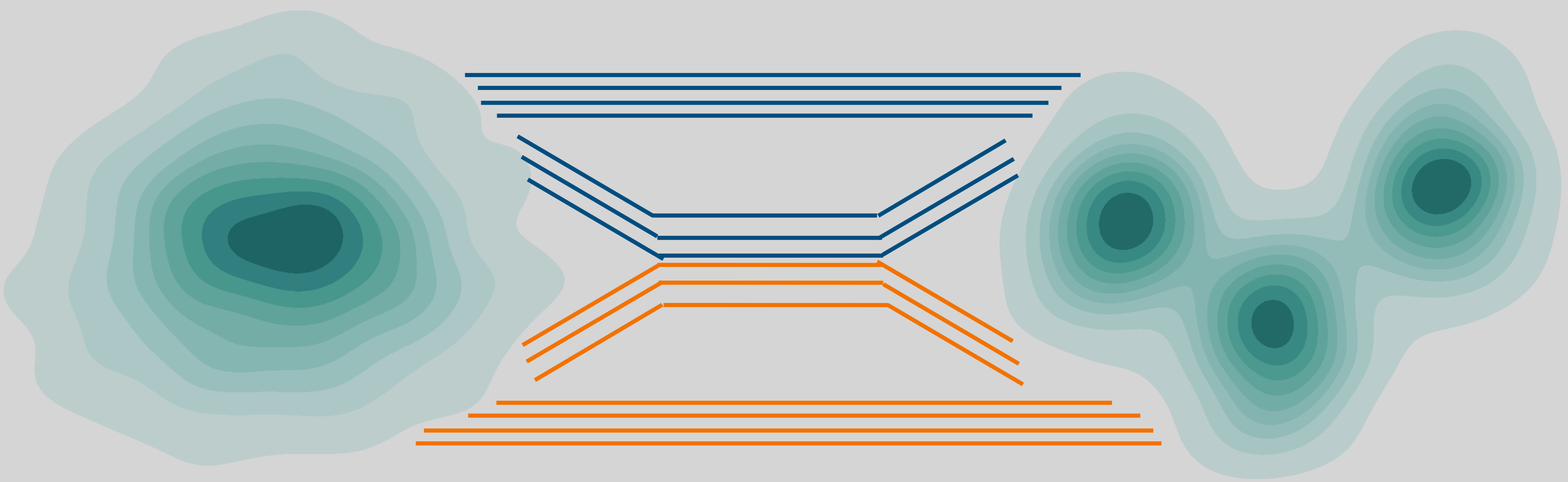


Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Learnt Vector Fields

Requires more Sampling steps



Source Distribution

π_0

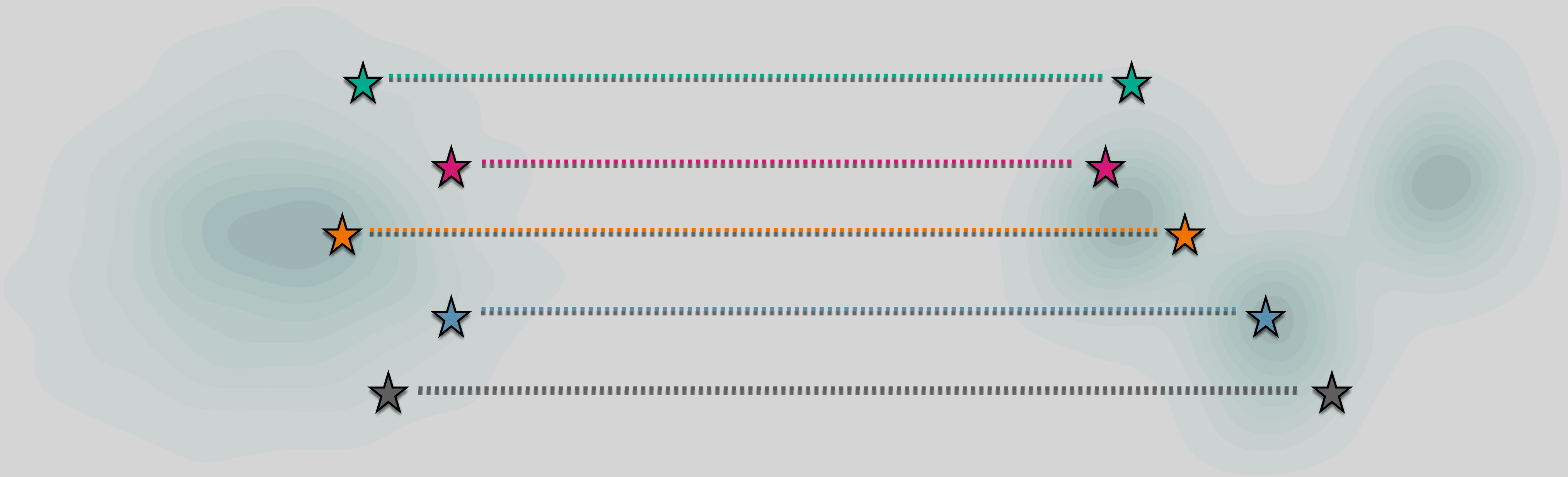
Target distribution

π_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Distill with straight pairs



Source Samples

X_0

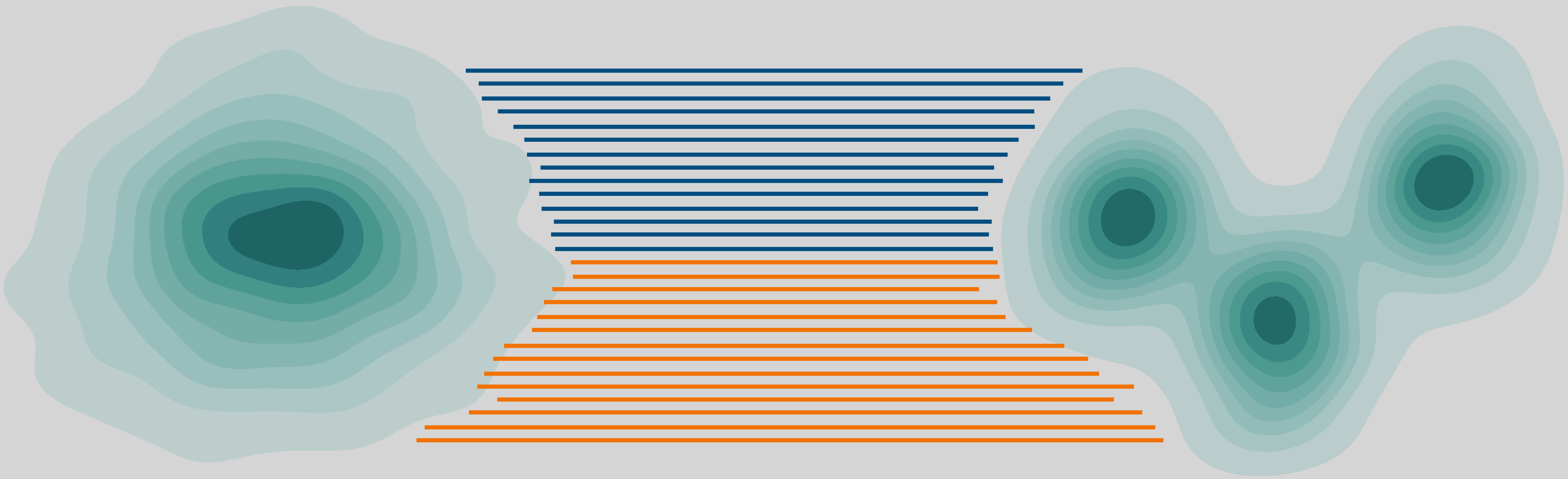
Target samples

X_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Learnt Vector Fields



Source Distribution

π_0

Target distribution

π_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 101: ReFlow

Learnt Vector Fields

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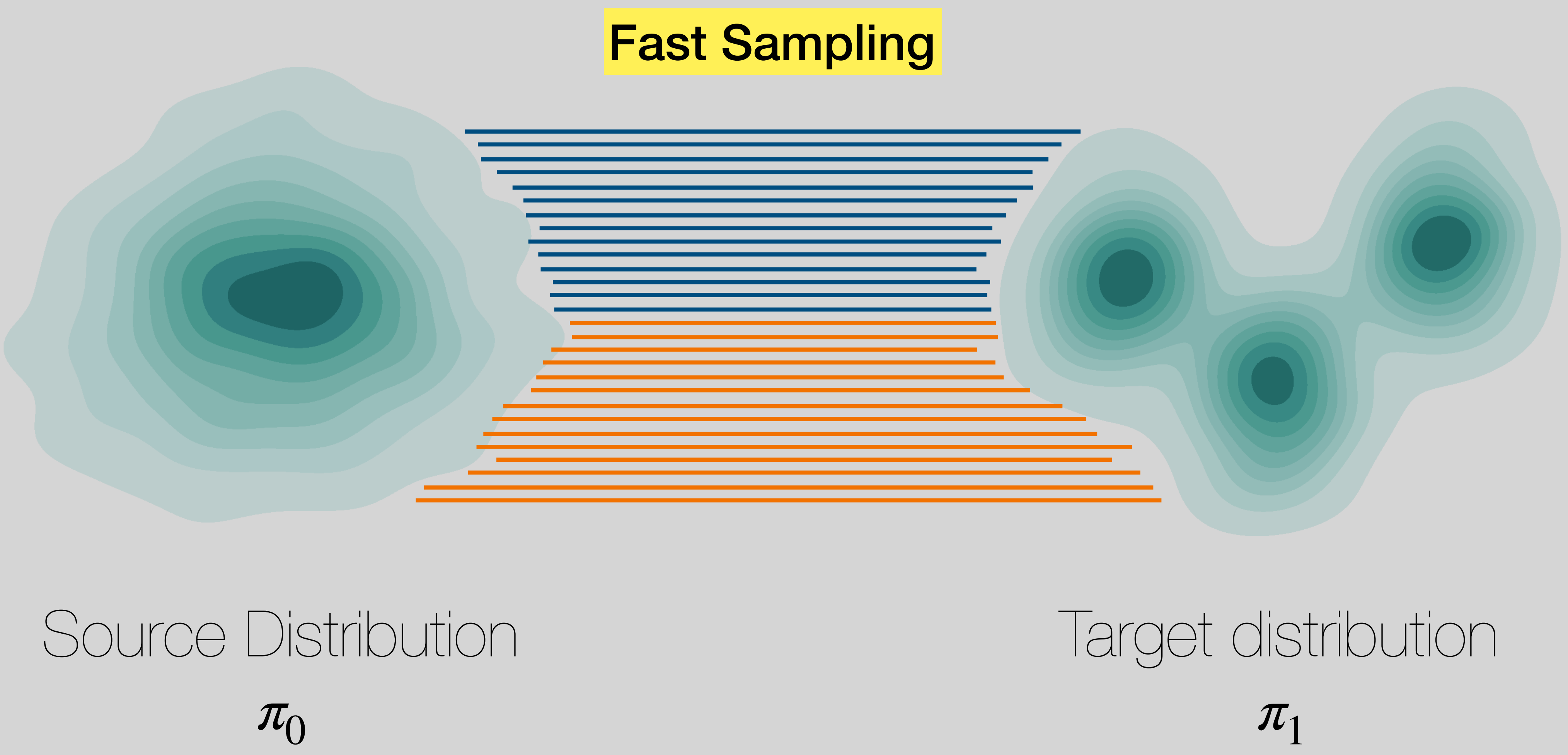
Update 101: ReFlow

Learnt Vector Fields



Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 102: Better ODE Solvers

Recap: Sampling

Euler's Method

$$x_{next} = x_{old} + \frac{1}{num\_steps} \cdot u_\theta(t)$$

$x_{initial} \sim \mathcal{N}(0, I)$

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 102: Better ODE Solvers

Why not use better ones?

Heun Method

RK Method

Ma, Nanye, et al. "SiT: Exploring Flow and Diffusion-based Generative Models with Scalable Interpolant Transformers." ECCV 2024.

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 103: Non-uniform timestep sampling

Recap: Randomly sample t in [0,1)

Source Samples

X_0

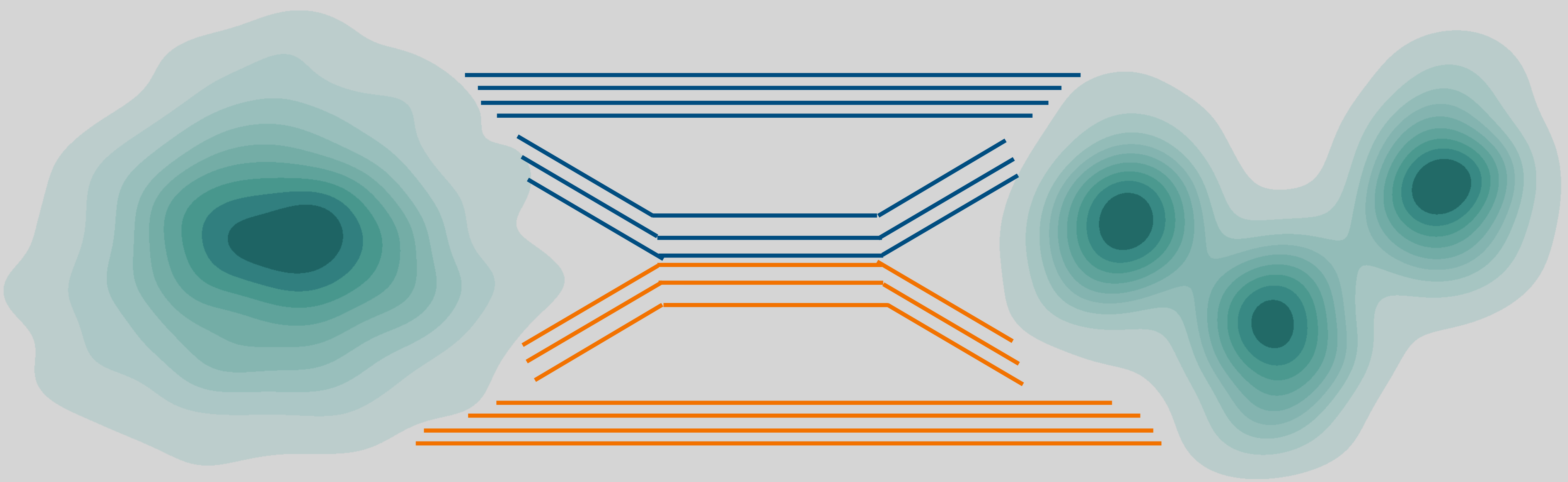
Target samples

X_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 103: Non-uniform timestep sampling

Recap: Learnt Vector Fields



Source Distribution

π_0

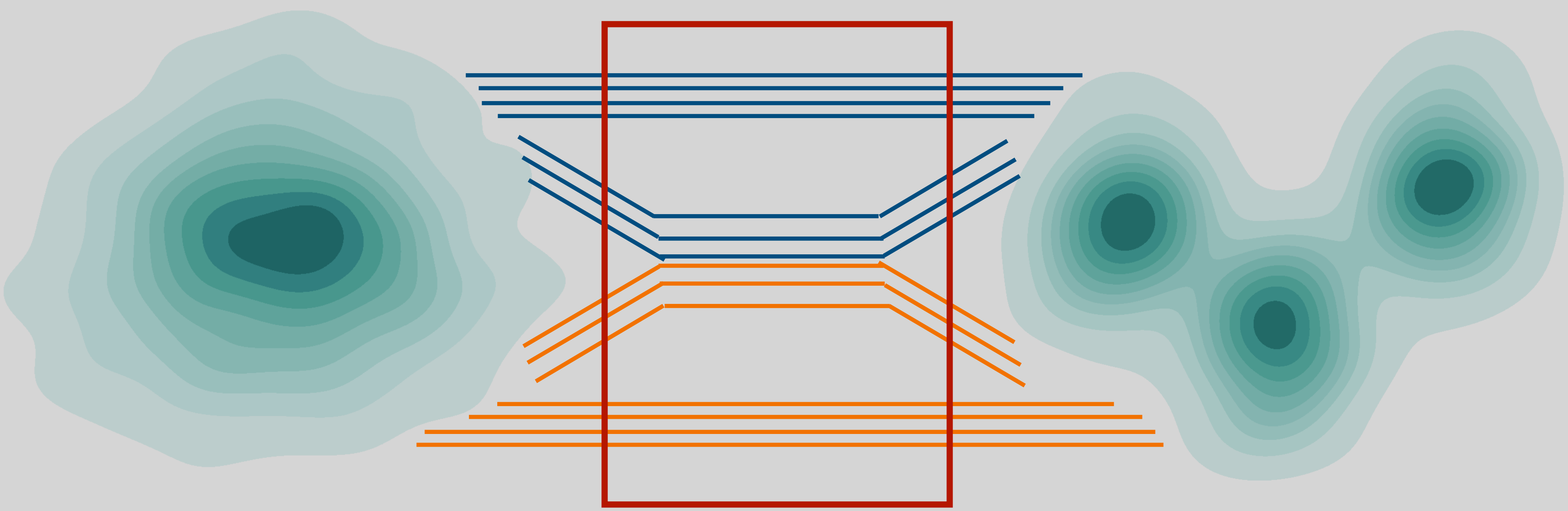
Target distribution

π_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 103: Non-uniform timestep sampling

Change in single path mostly in the middle



Source Distribution

π_0

Target distribution

π_1

Liu, Xingchao, et al. "Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow." ICLR 2023.

Update 103: Non-uniform timestep sampling

Logit-Normal Sampling

$$t = \frac{1}{1 + \exp(u)}$$

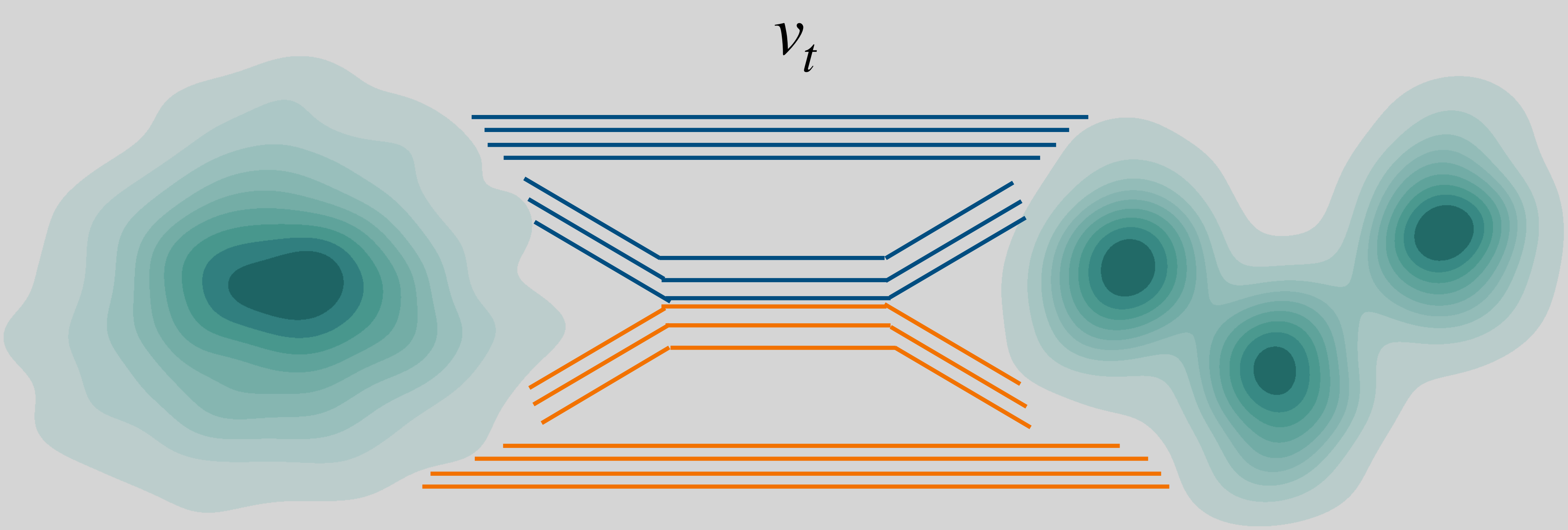
$$u \sim \mathcal{N}(0,1)$$

Esser, Patrick, et al. "Scaling Rectified Flow Transformers for High-Resolution Image Synthesis." ICML 2024.

Connection to Diffusion Models

Connection to Diffusion Models

Flow Matching: Learn a vector field



Source Distribution

π_0

Target distribution

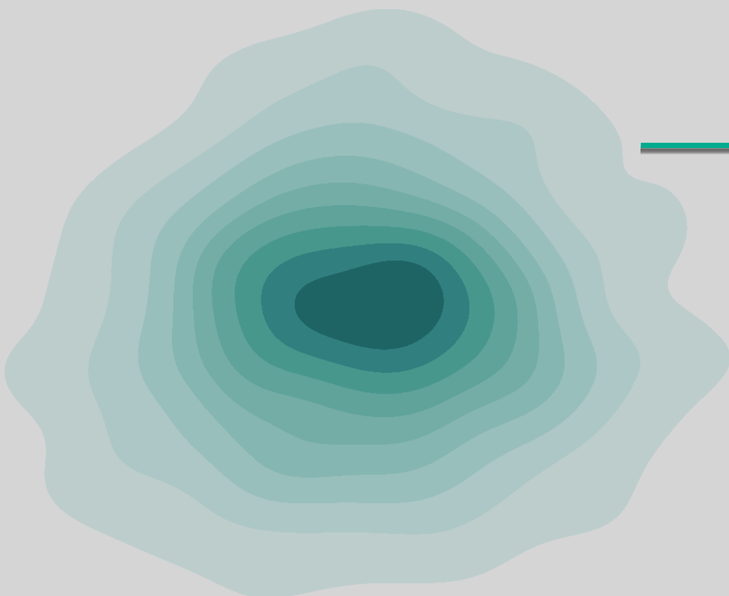
π_1

Ma, Nanye, et al. "SiT: Exploring Flow and Diffusion-based Generative Models with Scalable Interpolant Transformers." ECCV 2024.
Hu, Xixi, et al. "Flow to Diffusion: Langevin is a Guardrail." https://rectifiedflow.github.io/blog/2024/diffusion/

Connection to Diffusion Models

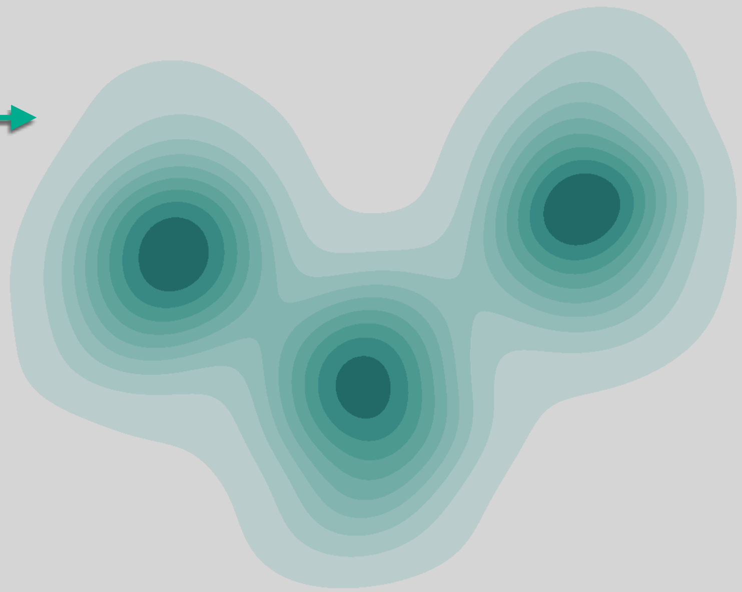
Flow Matching Sampling : Solving an ODE

$$dx = v_t \cdot dt$$



Source Distribution

π_0



Target distribution

π_1

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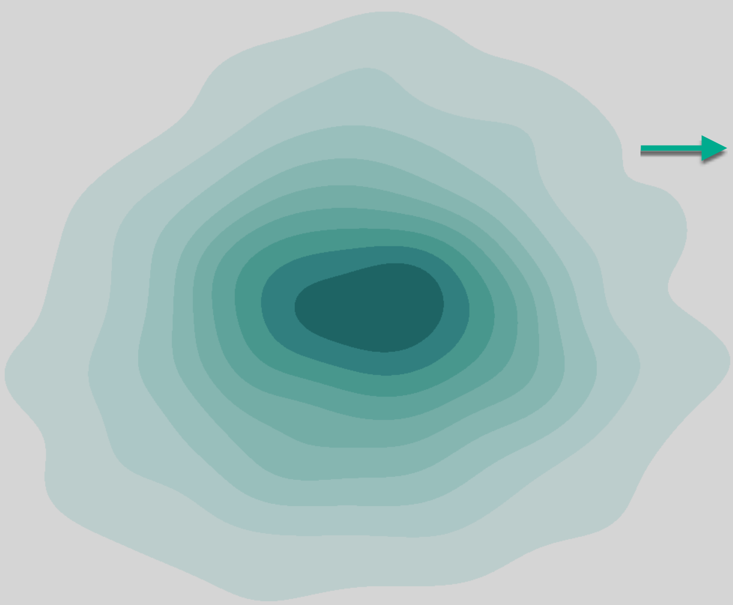
Connection to Diffusion Models

Flow Matching Sampling : Solving an ODE

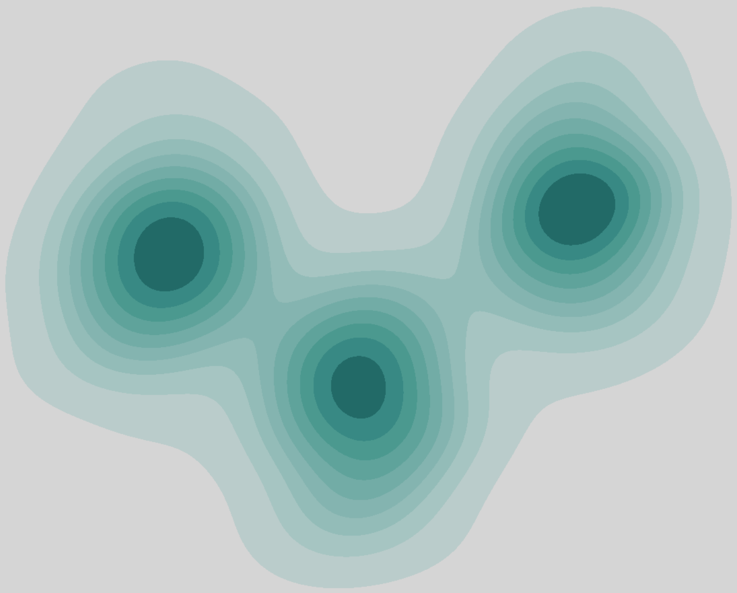
$$dx = v_t \cdot dt$$

$$x_{t+h} = x_t + h \cdot v_t$$



Source Distribution

π_0



Target distribution

π_1

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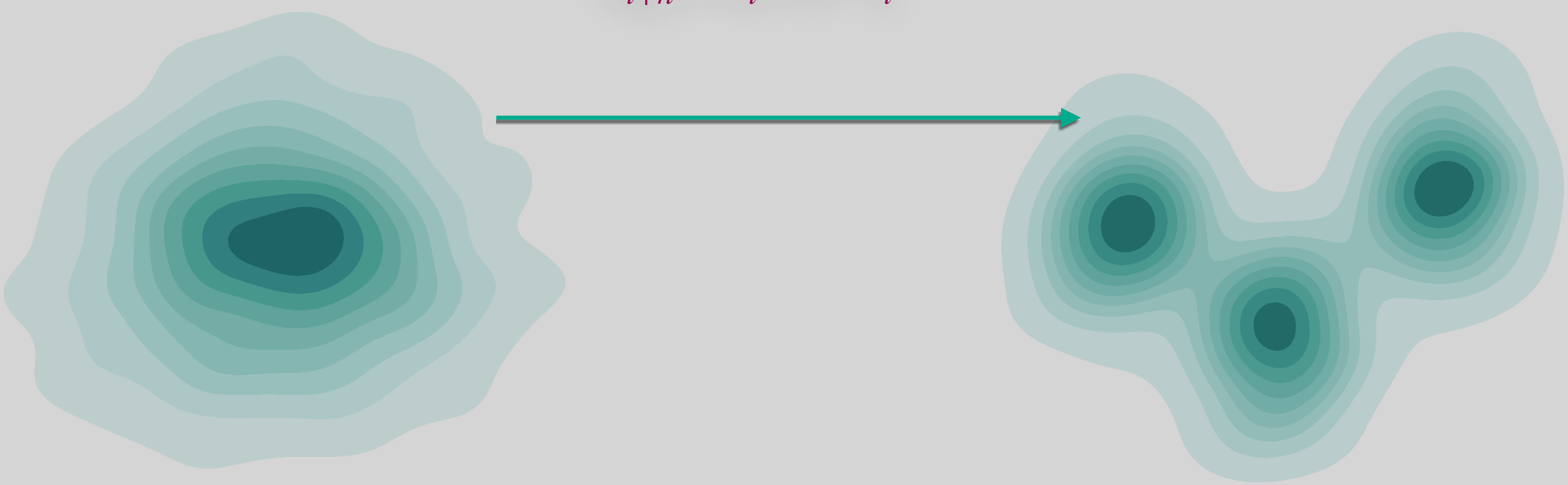
Connection to Diffusion Models

Flow Matching Sampling : Solving an ODE

$$dx = v_t \cdot dt$$

$$x_{t+h} = x_t + h \cdot v_t$$



Source Distribution

π_0

Target distribution

π_1

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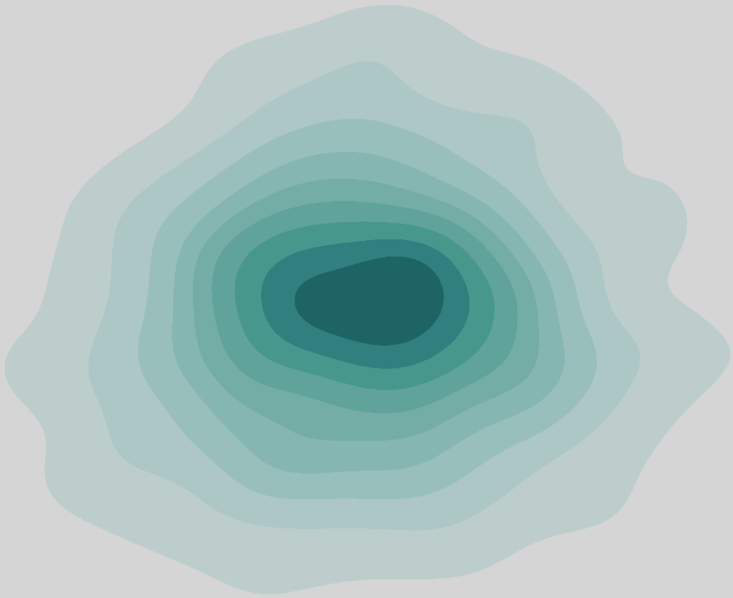
Connection to Diffusion Models

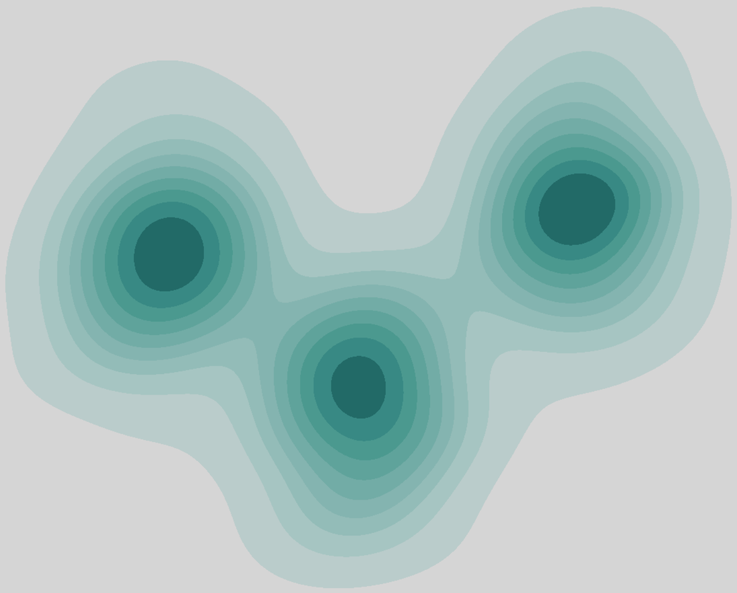
SDE and Diffusion

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$



Source Distribution

π_0



Target distribution

π_1

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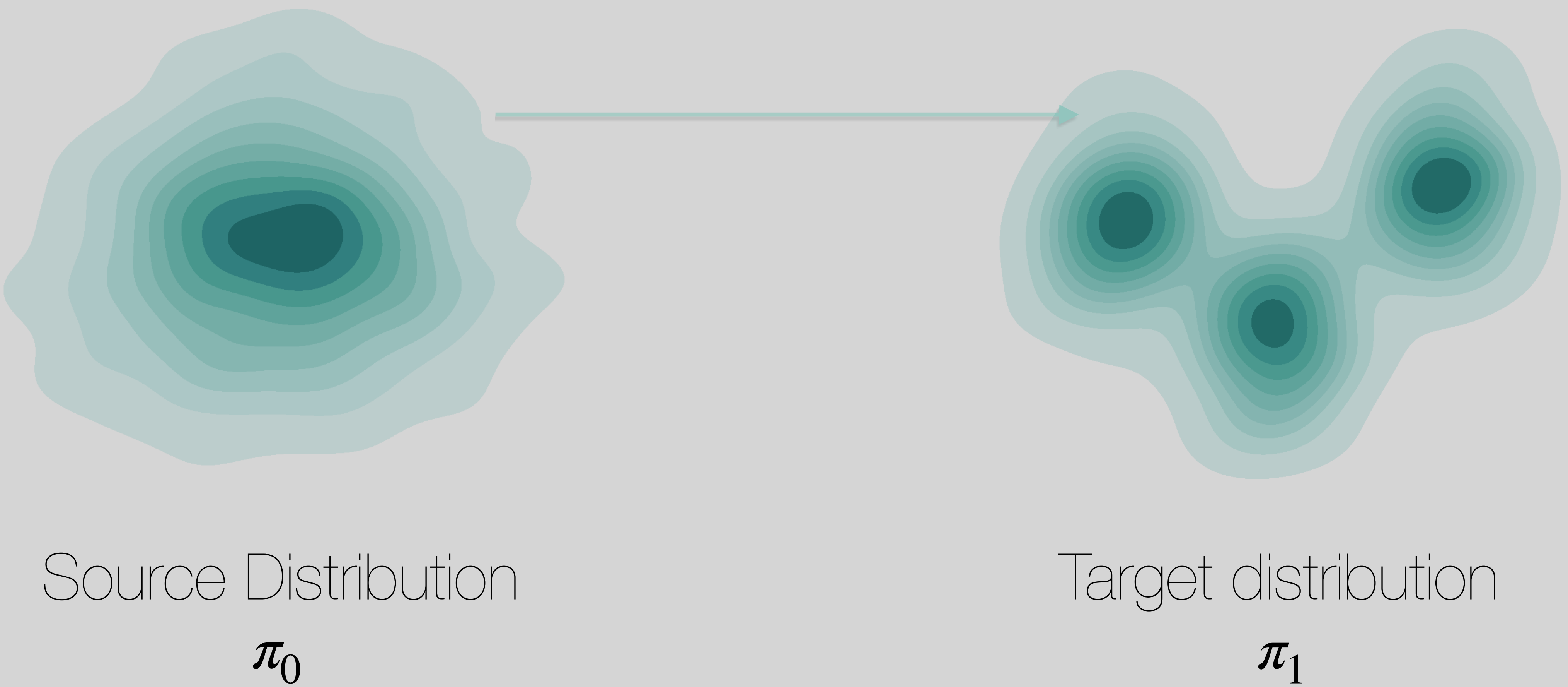
Connection to Diffusion Models

SDE and Diffusion

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$



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Hu, Xixi, et al. "Flow to Diffusion: Langevin is a Guardrail." https://rectifiedflow.github.io/blog/2024/diffusion/

Connection to Diffusion Models

SDE and Diffusion

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$

Noise

Source Distribution

π_0

Target distribution

π_1

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Connection to Diffusion Models

SDE and Diffusion

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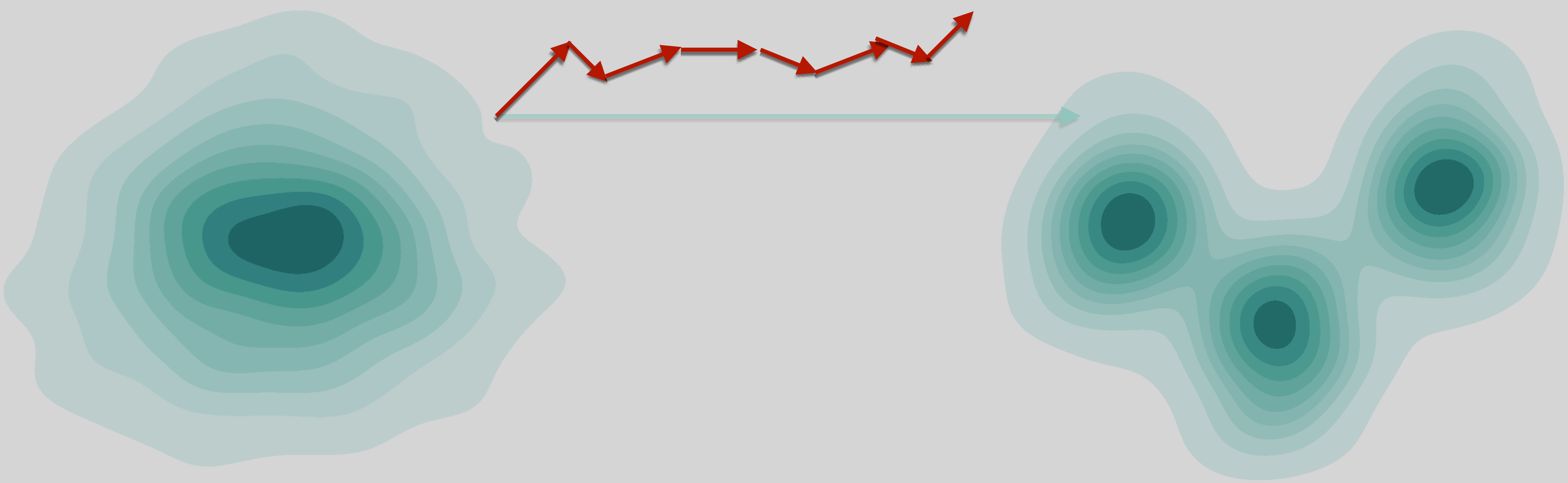
Noise



Source Distribution

π_0

Target distribution

π_1

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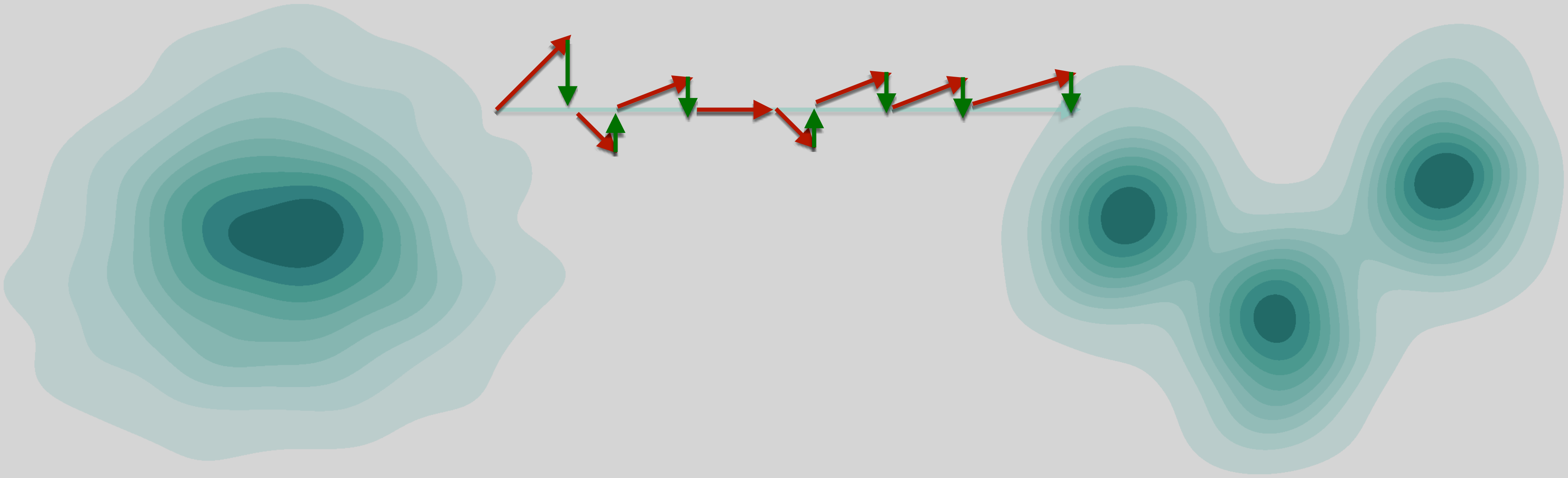
Connection to Diffusion Models

SDE and Diffusion

Correction

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$

Noise



Source Distribution

π_0

Target distribution

π_1

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Connection to Diffusion Models

Diffusion Models

Predict Score

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$

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Connection to Diffusion Models

Diffusion Models

Predict Score

$$dx = [v_t + \lambda(w_t) \cdot s_t] \cdot dt + w_t \cdot dW$$

Fun Fact: Using **Tweedie's formula**

$$v_t \leftrightarrow s_t$$

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Connection to Diffusion Models

Diffusion Models

$$x_{t+h} = x_t +$$

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Connection to Diffusion Models

Diffusion Models

$$x_{t+h} = x_t + h \cdot (s_t$$

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Connection to Diffusion Models

Diffusion Models

$$x_{t+h} = x_t + h \cdot (s_t + \frac{1}{\lambda(w_t)} \cdot v_t)$$

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Connection to Diffusion Models

Diffusion Models

DDIM Sampler

$$x_{t+h} = x_t + h \cdot (s_t + \frac{1}{\lambda(w_t)} \cdot v_t)$$

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Connection to Diffusion Models

Diffusion Models

$$x_{t+h} = x_t + h \cdot (s_t + \frac{1}{\lambda(w_t)} \cdot v_t) + w_t \cdot \epsilon$$

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Connection to Diffusion Models

Diffusion Models

DDPM Sampler

$$x_{t+h} = x_t + h \cdot (s_t + \frac{1}{\lambda(w_t)} \cdot v_t) + w_t \cdot \epsilon$$

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Thank you!

Source: Jack Black and Elmo