

Lecture 17:

Data-driven Animation

FUNDAMENTALS OF COMPUTER GRAPHICS
Animation & Simulation
Stanford CS248B

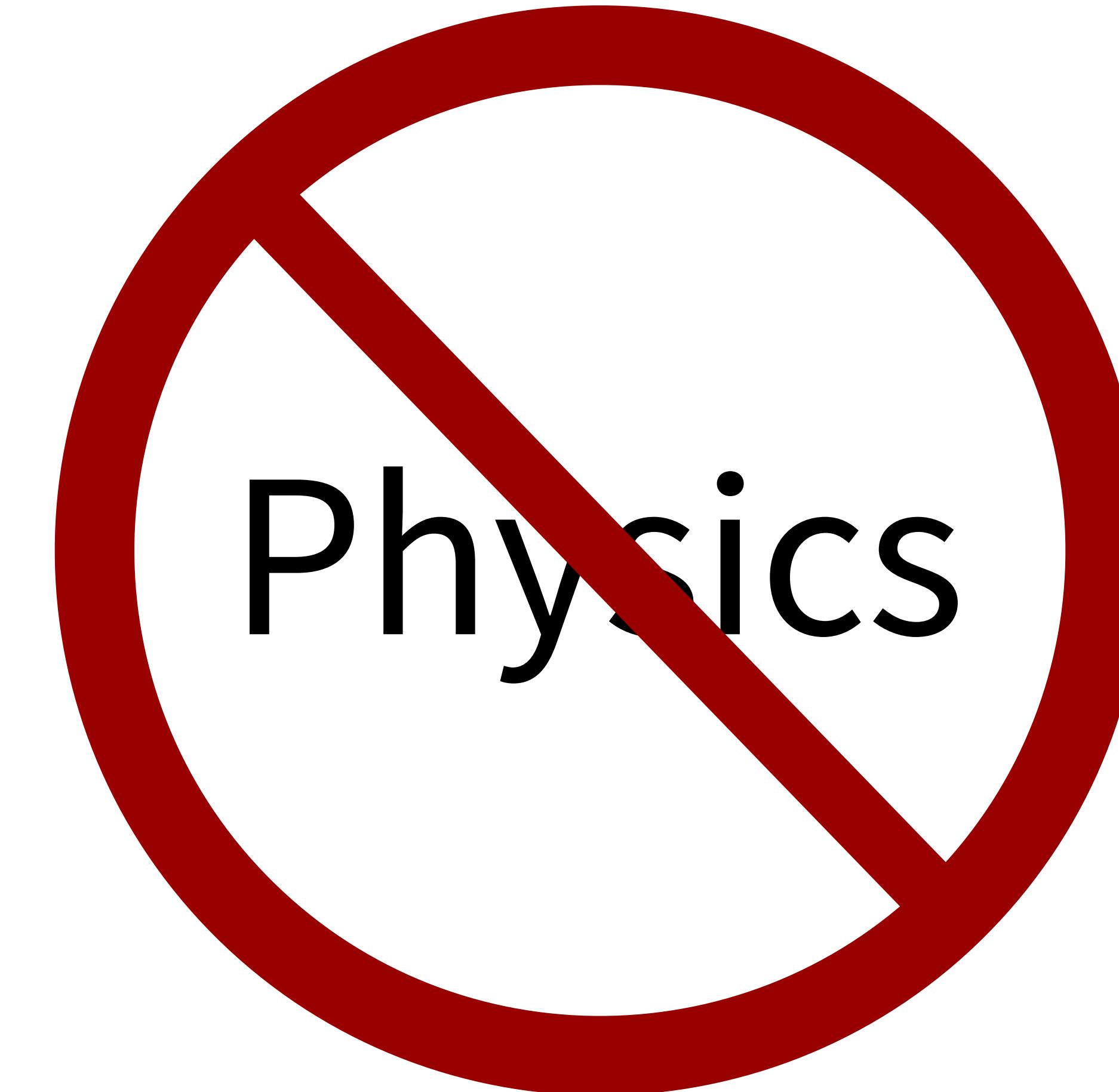
Character Animation

Kinematics-only

Physics-based

Character Animation

Kinematics-only



Physics-based

How to get data?

Optical systems

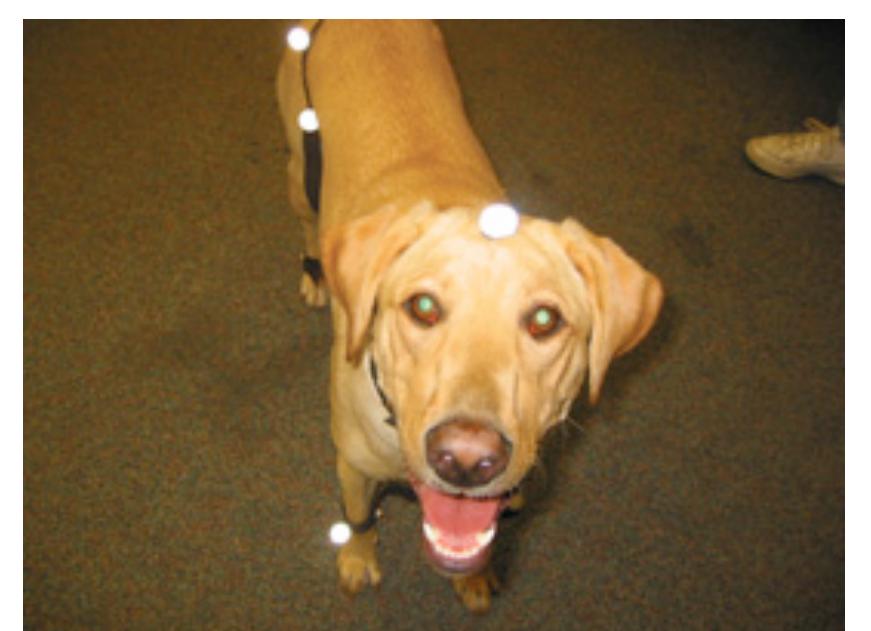
■ Cameras

- High temporal resolution (120+ fps)
- Detect the locations of reflective markers
- In principle, two cameras are sufficient to reconstruct the 3D location of a marker. In practice, more cameras can reduce occlusion and increase precision

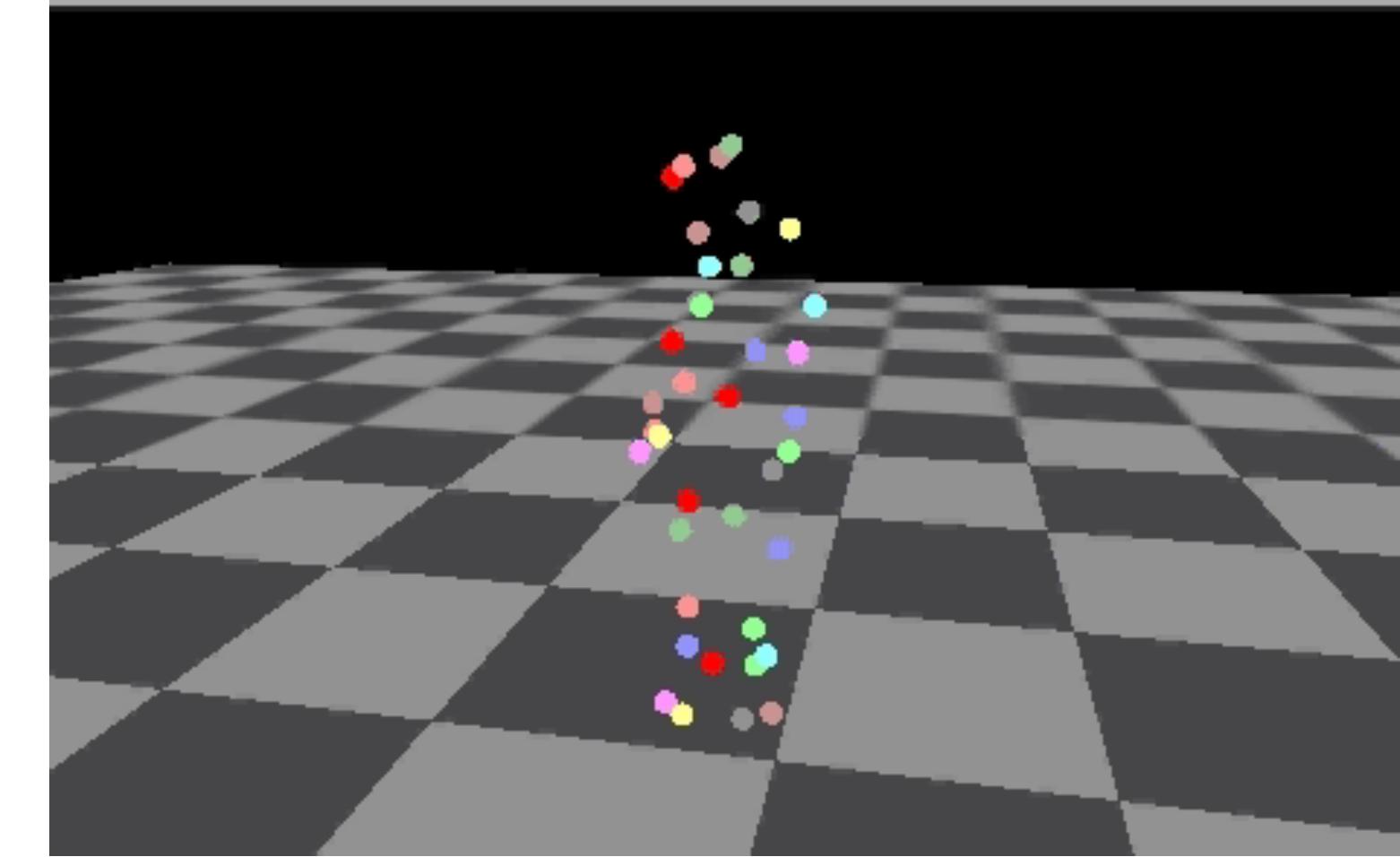
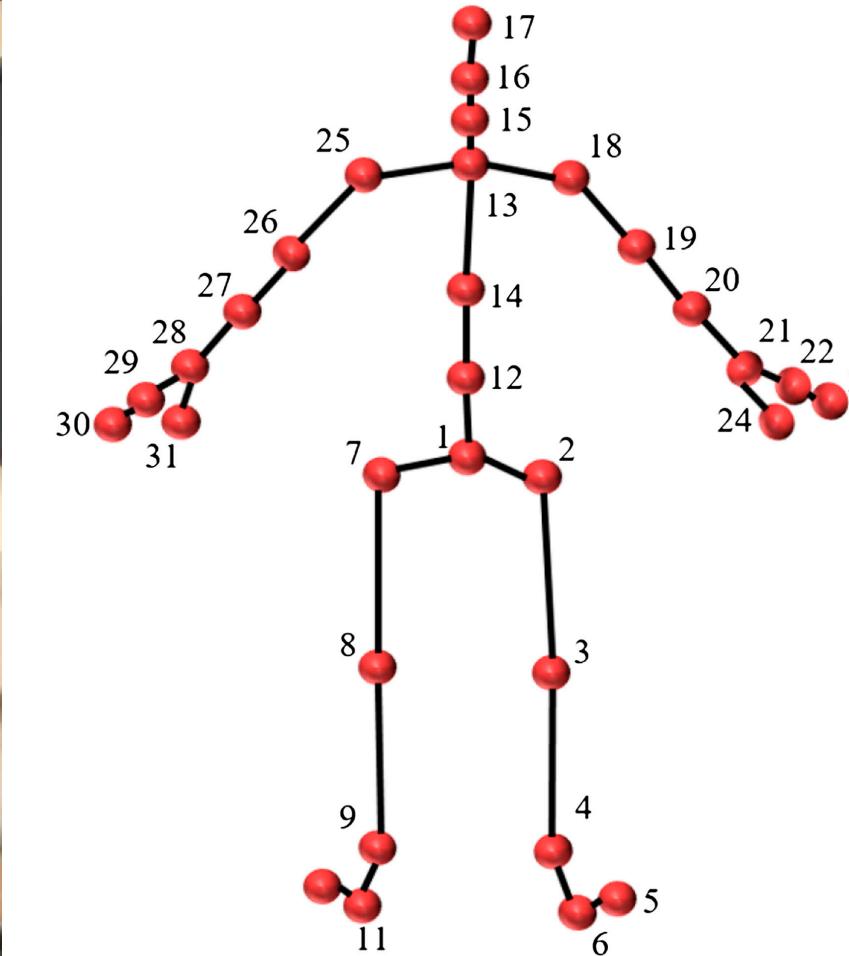
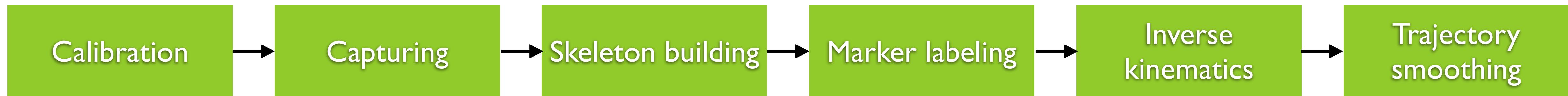


■ Markers:

- passive: sensitive to infrared
- active: emit LED light



Motion capture pipeline



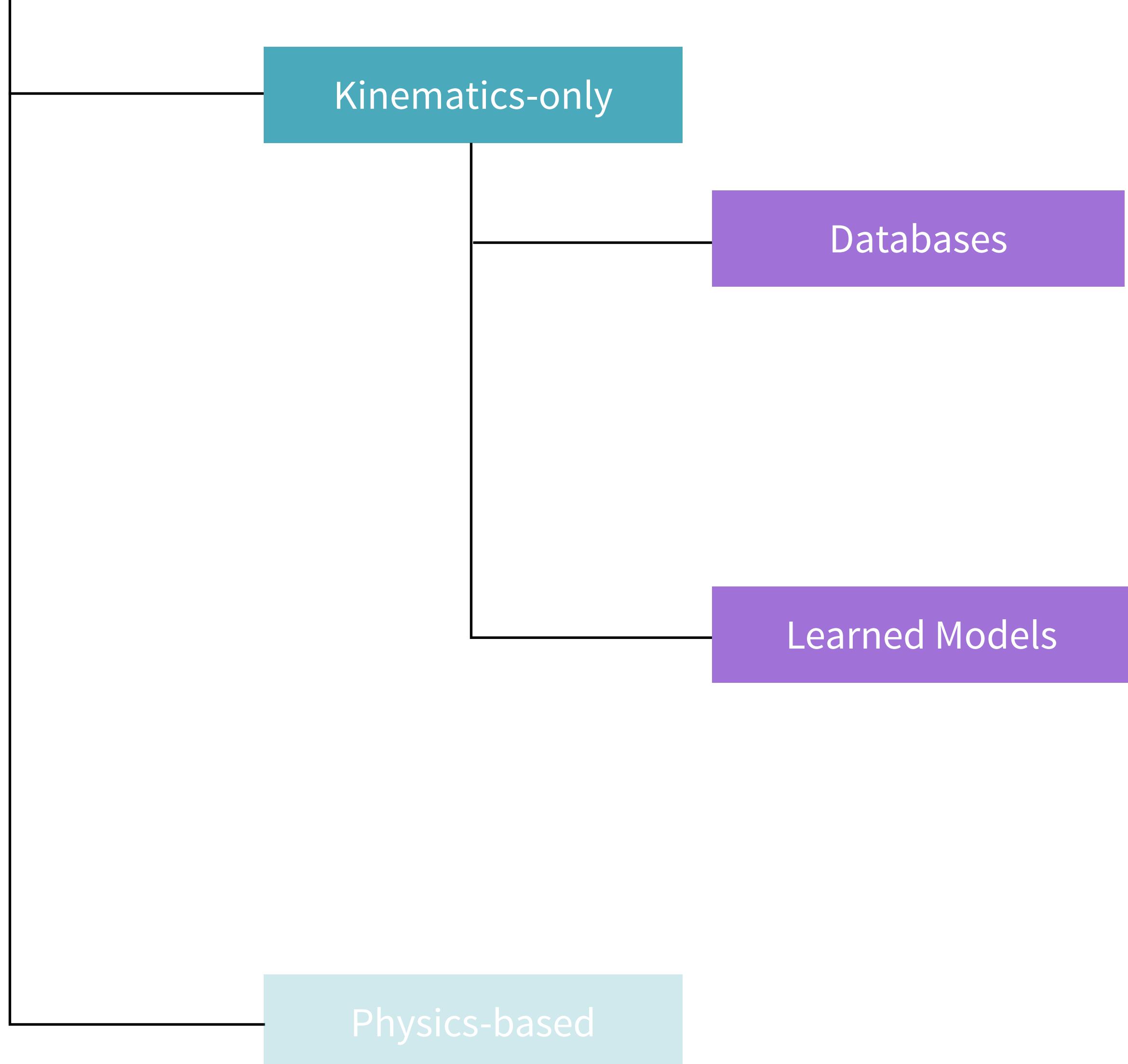
Motion databases

- A motion database consists of a collection of motion sequences with different motion types and lengths, but for the same character model parameterization.
- Existing motion databases, such as AMASS mocap database, provide motions for a wide variety of human activities.

Dataset	Field of origin	License	Participants	Lower body kinematics	Upper body kinematics	GRF	EMG	
CMU	Graphics	Free to use + Redistribute	96	Yes	Yes	No	No	No
ACCAD	Graphics	CCv3.0	20	Yes	Yes	No	No	No
BMLmovi	Graphics	Free to redistribute	67	Yes	Yes	No	No	No
KIT	Graphics	Redistribute with citation	226	Yes	Yes	No	No	Yes
Eyes Japan	Graphics	CCv2.1	37	Yes	Yes	No	No	No
MPI HDM05	Graphics	CCv3.0	4	Yes	Yes	No	No	No
SFU	Graphics	Free for research purpose	7	Yes	Yes	No	No	No
TotalCapture	Graphics	Free for research purpose	5	Yes	Yes	No	No	Yes
Carmago et al	Biomechanics	Redistribute with citation	25	Yes	No	Yes	Yes	Yes
Fukuchi et al	Biomechanics	Redistribute with citation	49	Yes	Yes	Yes	No	No
Moore et al	Biomechanics	Redistribute with citation	15	Yes	Yes	Yes	No	No
Macaluso et al	Biomechanics	Redistribute with citation	10	Yes	No	Yes	Yes	No
Embry et al	Biomechanics	Redistribute with citation	10	Yes	No	Yes	Yes	No
Tiziana et al	Biomechanics	Redistribute with citation	50	Yes	Yes	Yes	Yes	No
Collins lab data	Unpublished	???	???	Yes	Yes	Yes	No	Yes

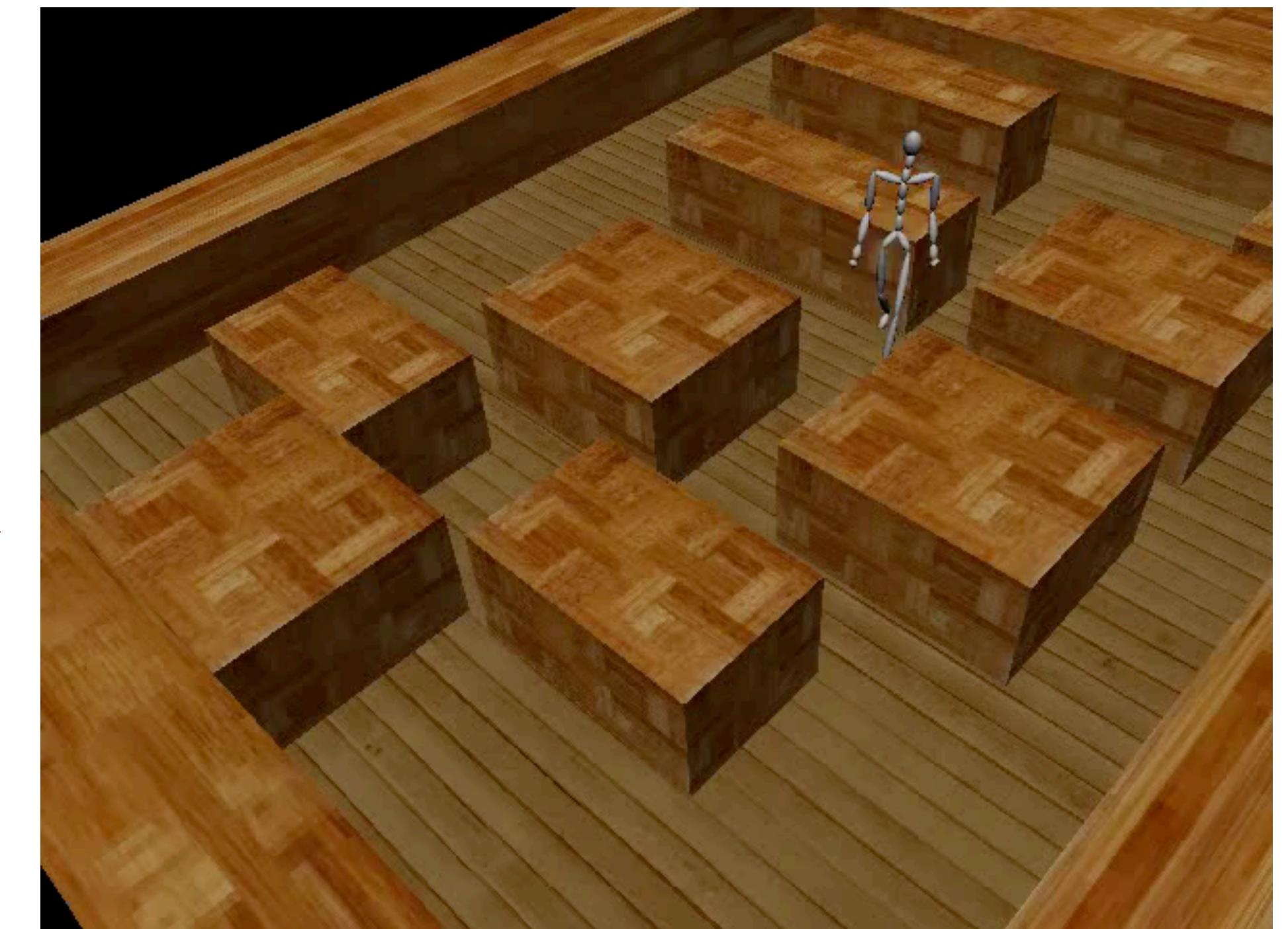
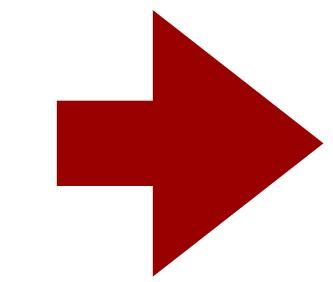
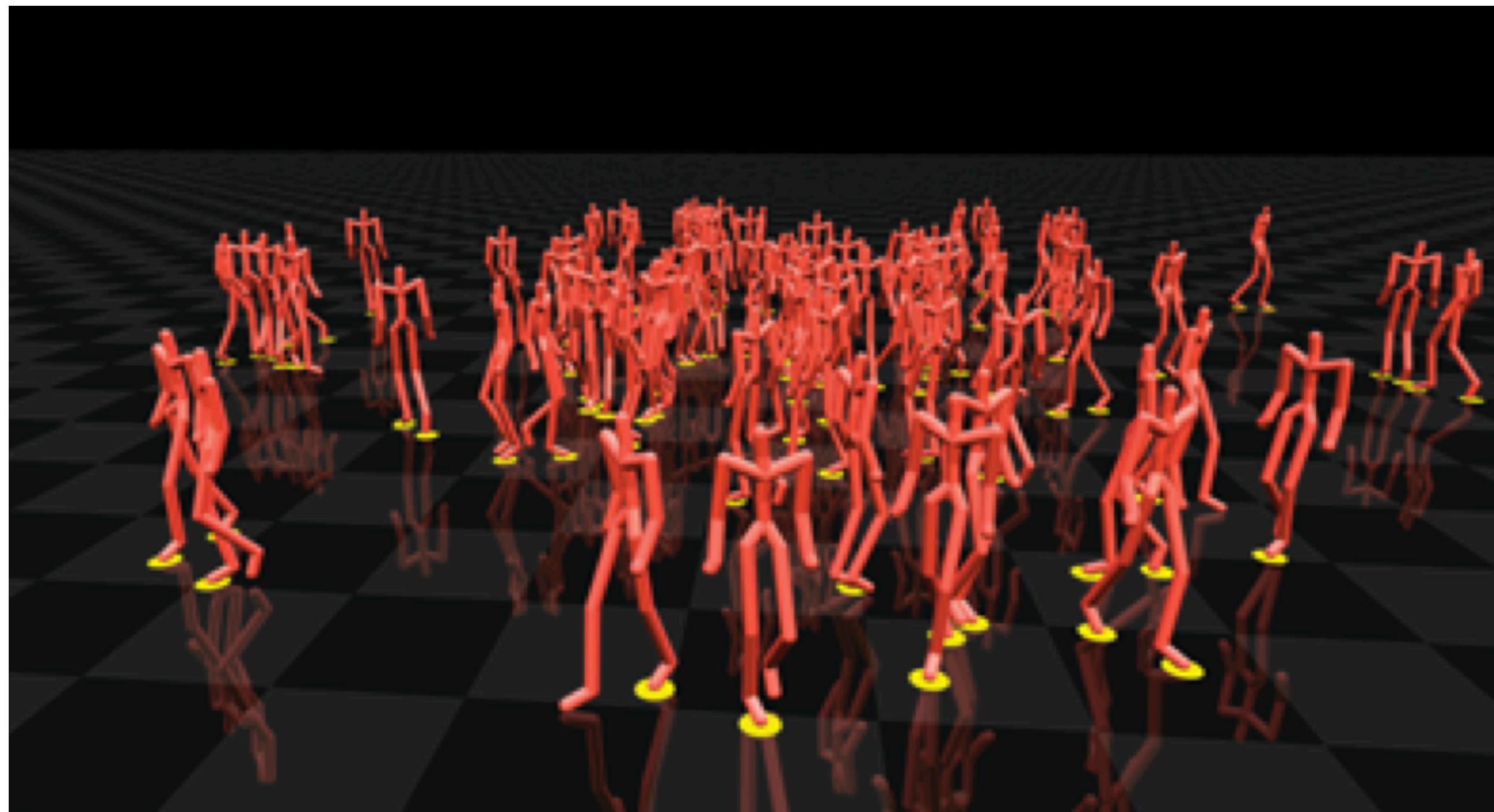
How to use data?

Character Animation

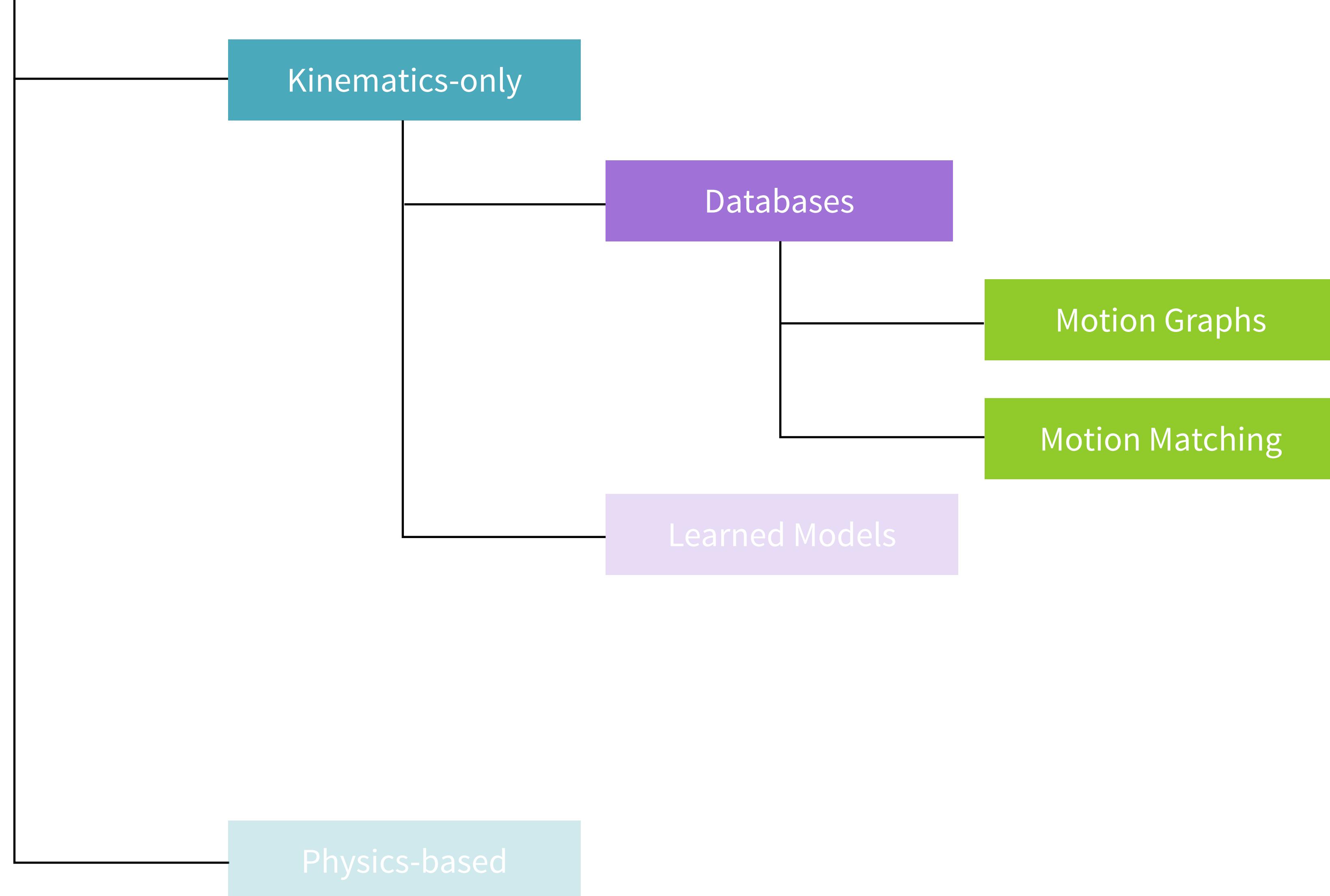


Synthesize animation from a motion database

- Which frame to play next, given the current frame and user constraints?
- How to make transitions smooth?

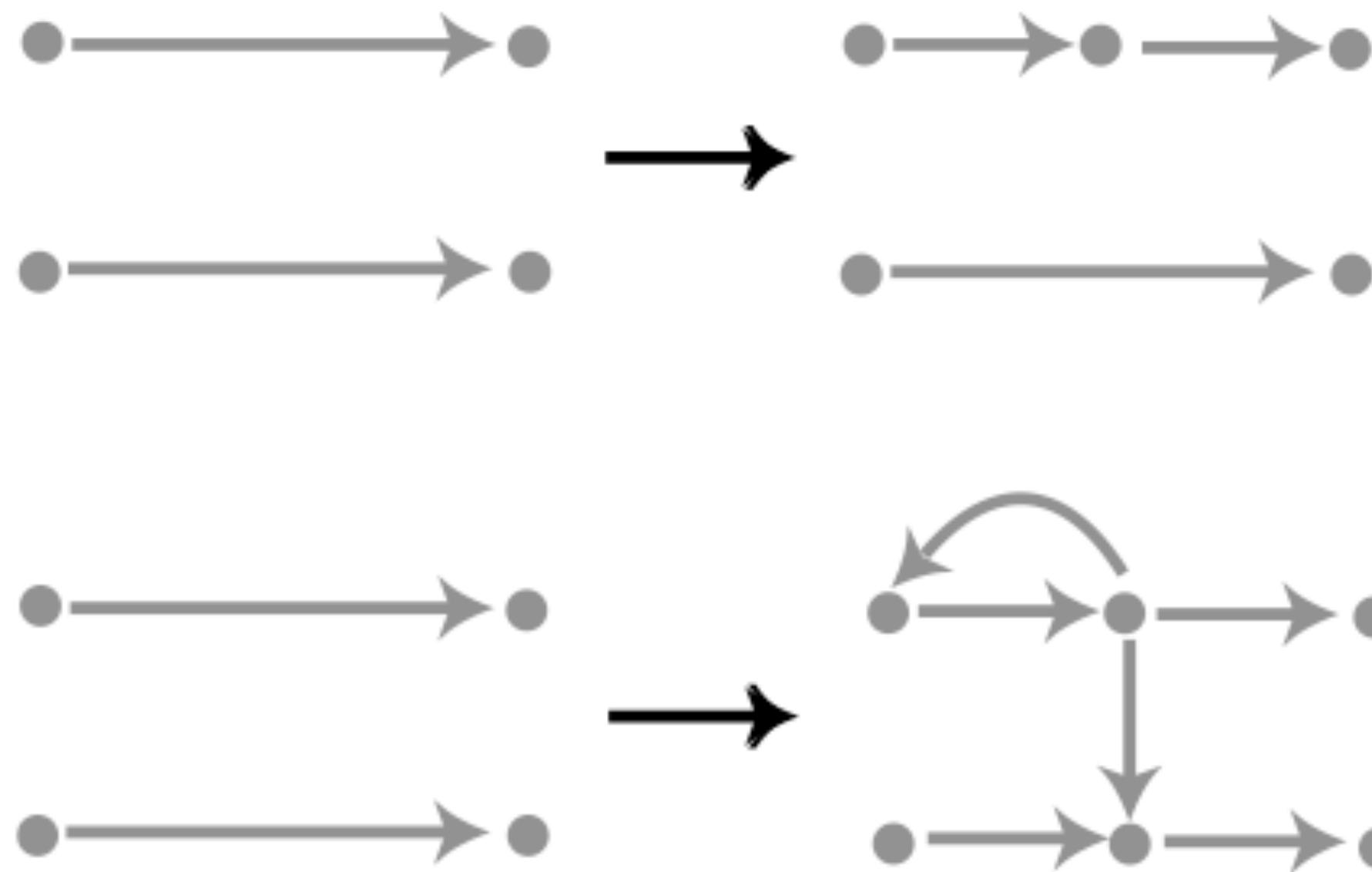


Character Animation



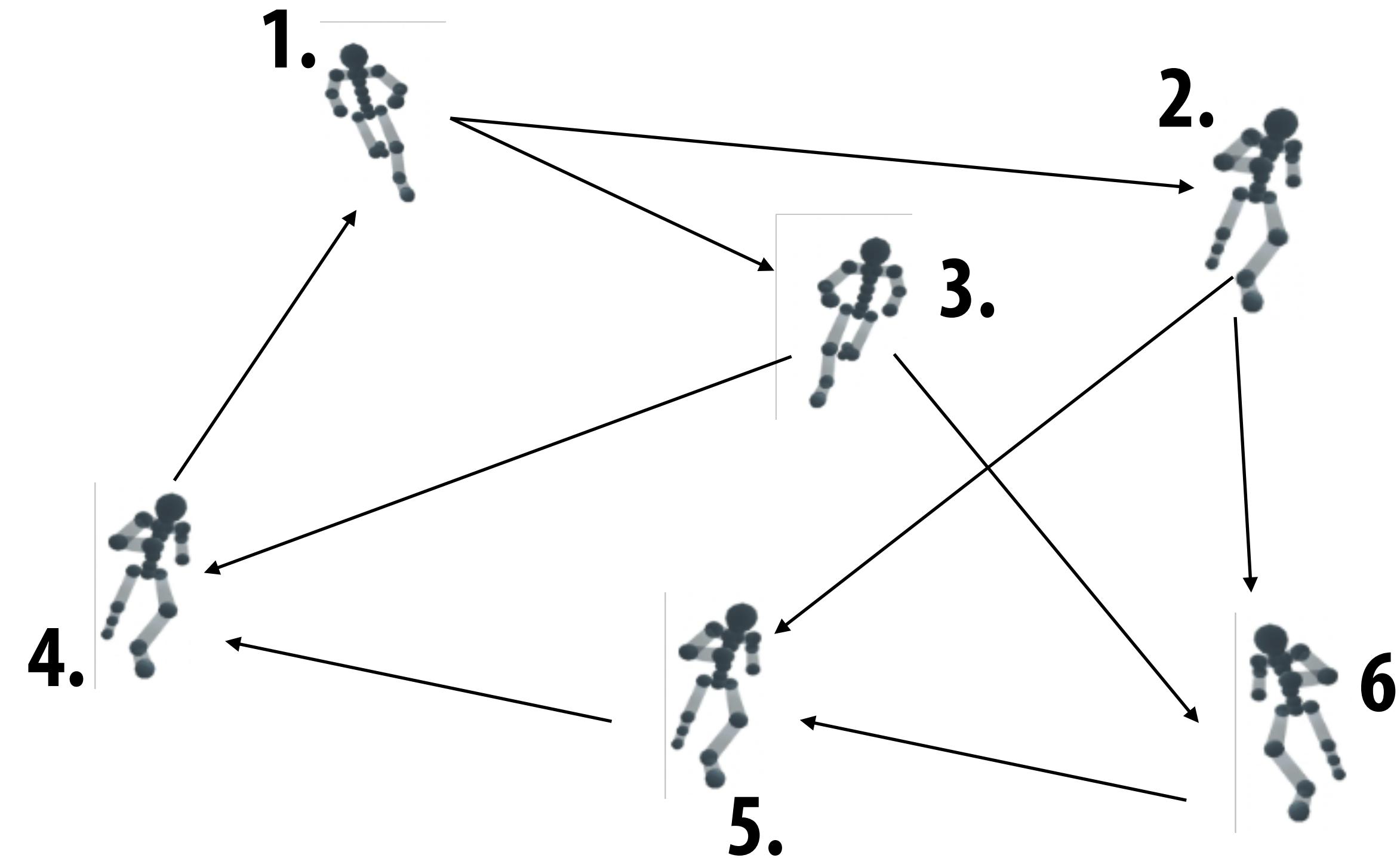
Motion graphs

- Each edge corresponds to a motion clip
- Each node corresponds to a choice point connecting motion clips



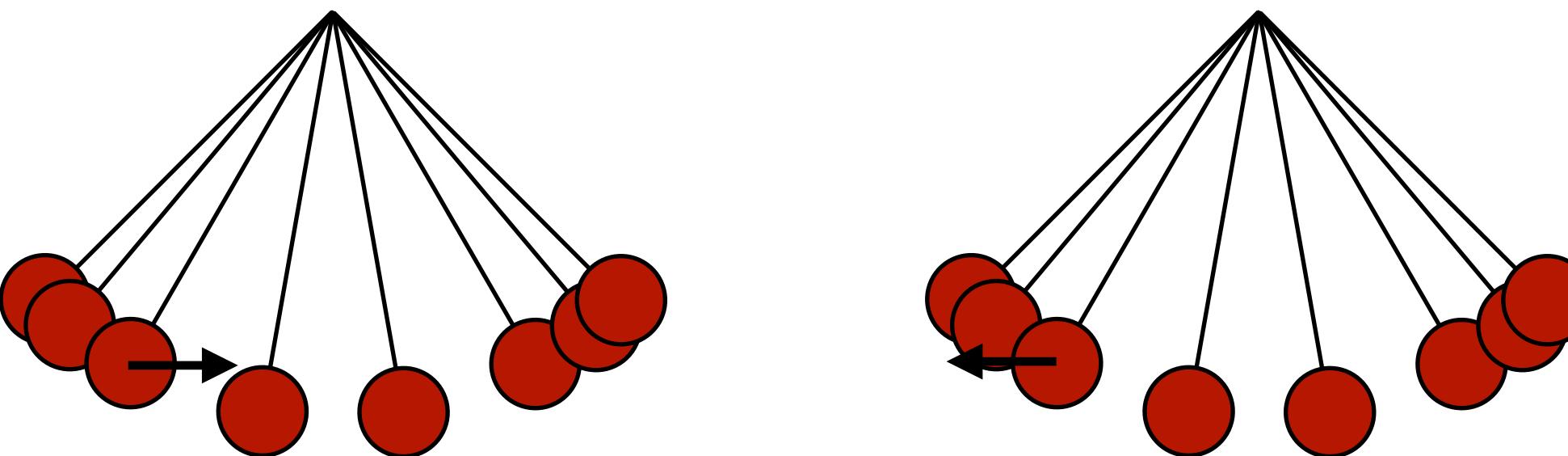
Motion graphs

- Each node corresponds to a motion clip
- Each edge means a smooth transition between clips



Similarity metrics

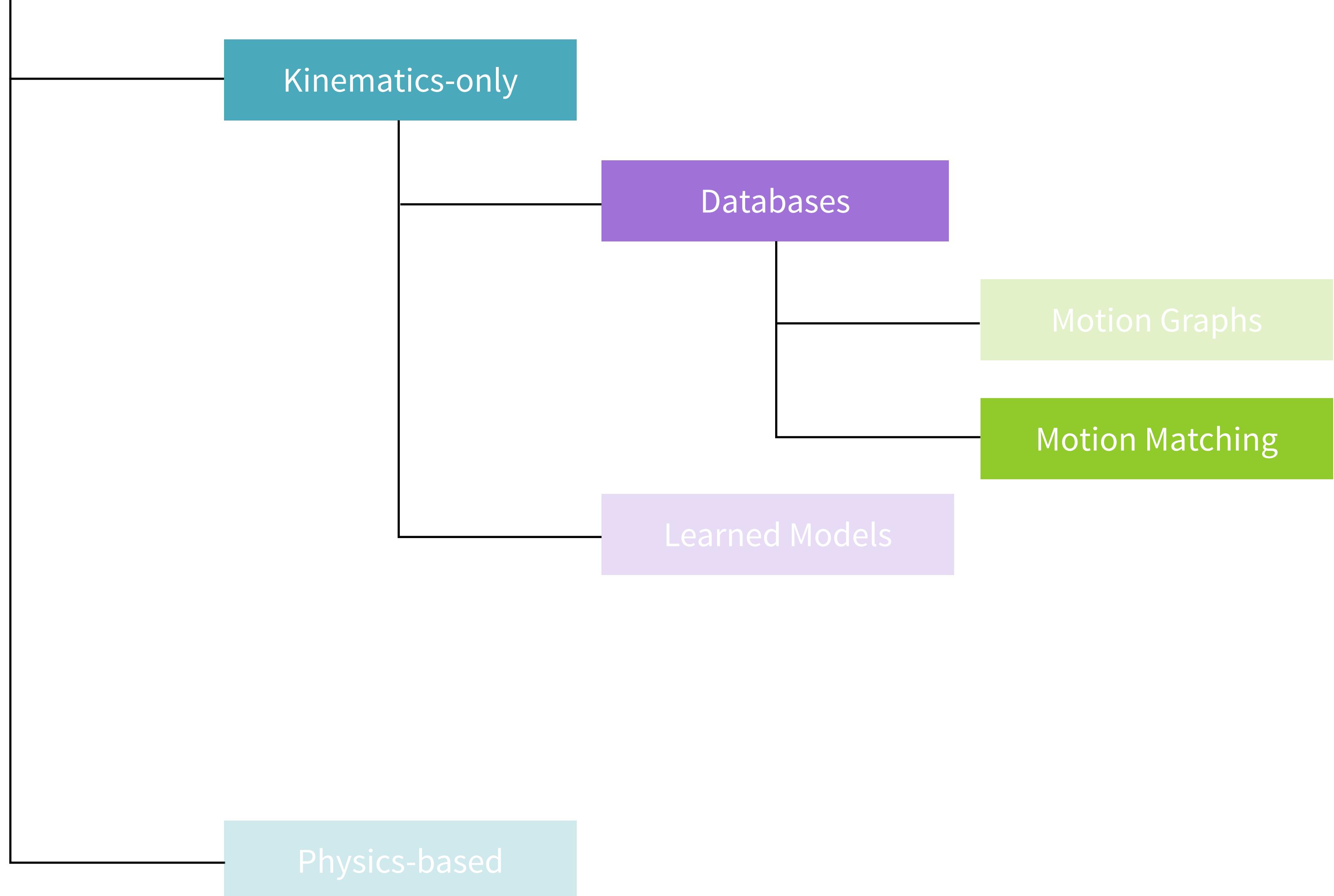
- Transition is allowed when two motions are very similar
 - Naive similarity metric: $\|\mathbf{q}_i - \mathbf{q}_j\|_2$
- Parameters have different overall effects on the character
 - Position and orientation are in different units: ($\mathbf{x}, \mathbf{R}, \theta, \phi, \sigma, \dots$)
- Velocity also needs to be considered: $\|\dot{\mathbf{q}}_i - \dot{\mathbf{q}}_j\|_2$



Search on motion graphs

- Given constraints/goals at specific time instances on the graph, use a search algorithm to find paths connecting the constraints

Character Animation



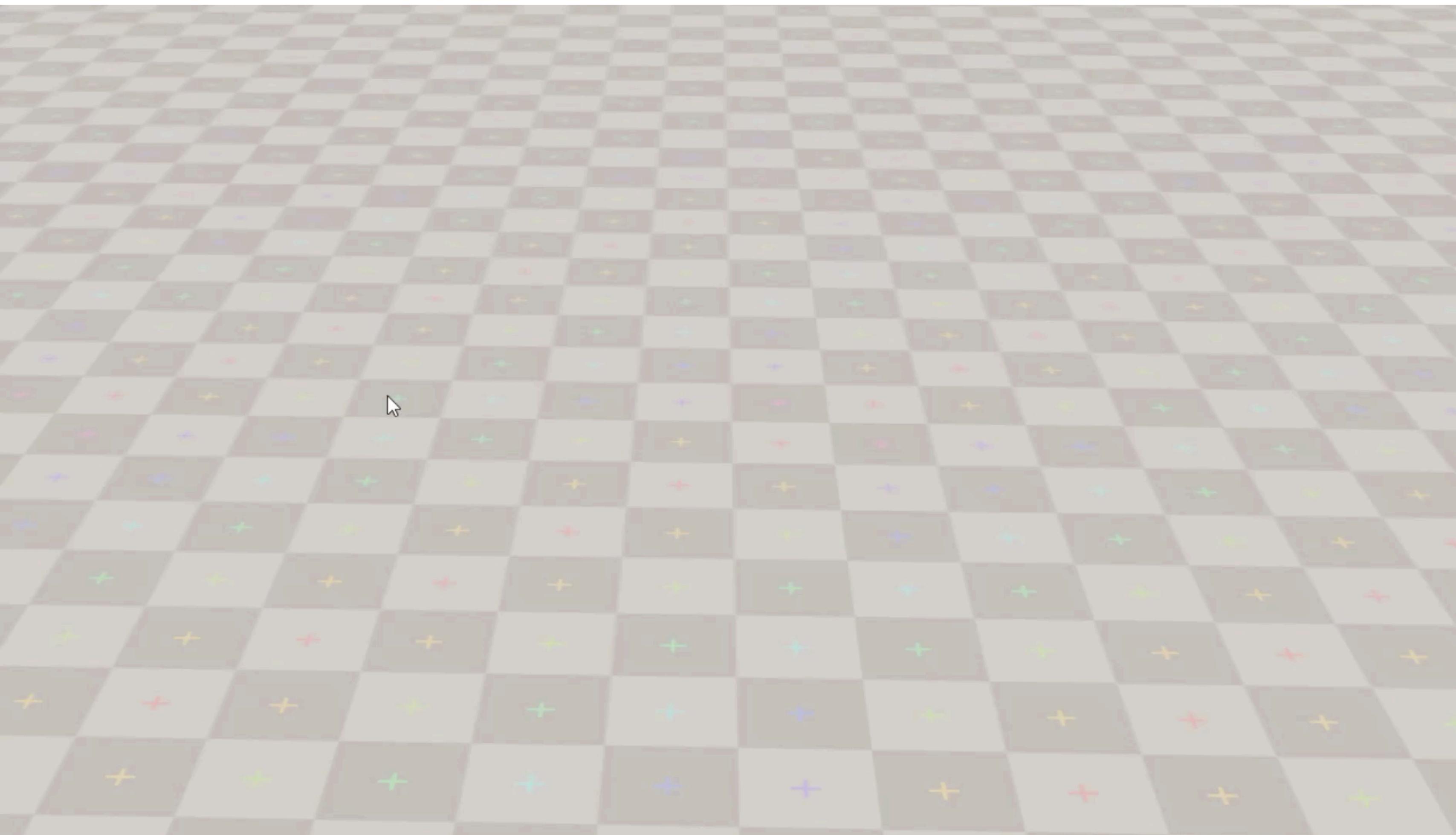
Motion matching

- Which frame to play next, given the current frame and user constraints?
- How to make transitions smooth?



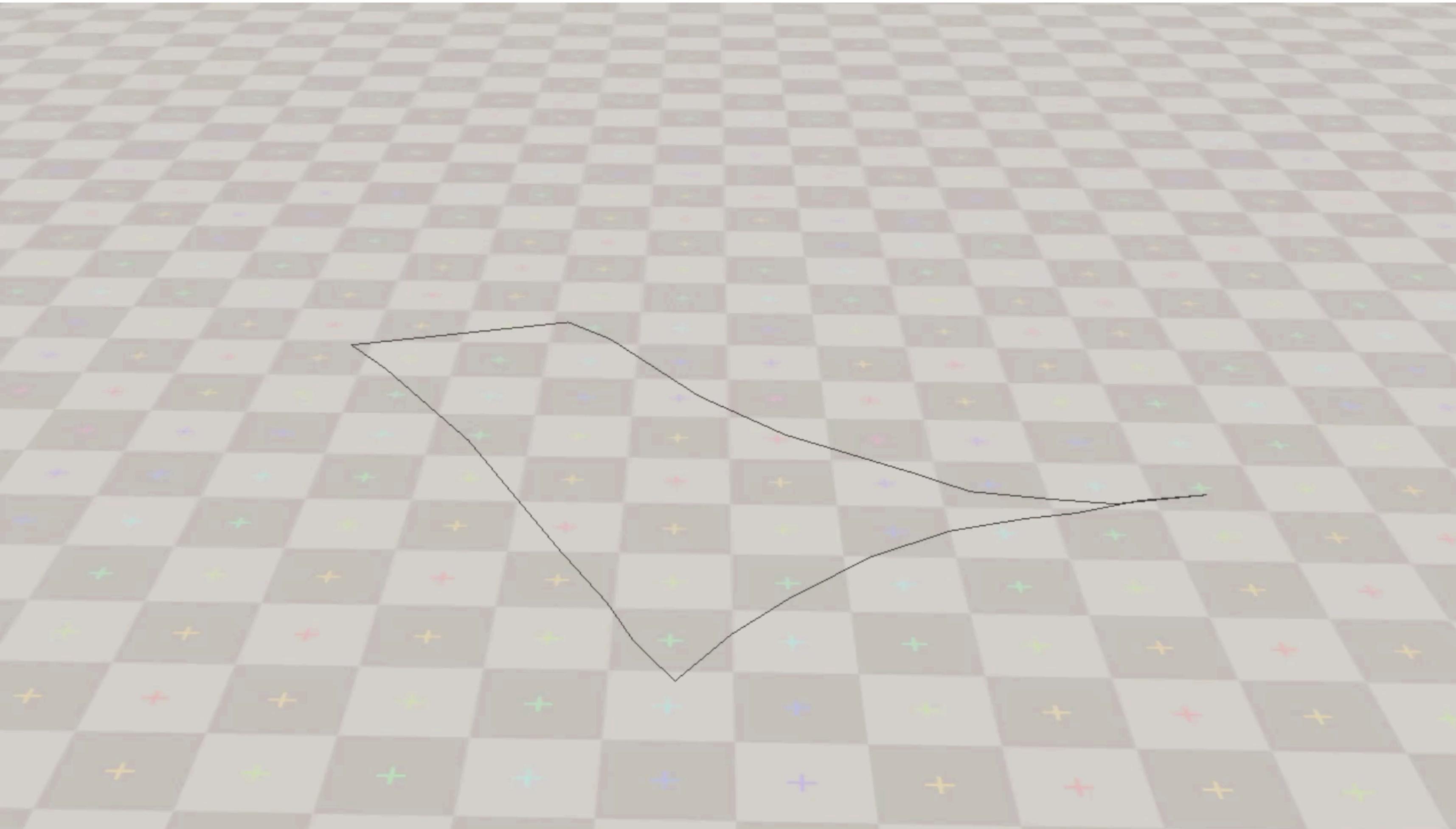
Motion Matching works best with lots of motion capture data.

Path following



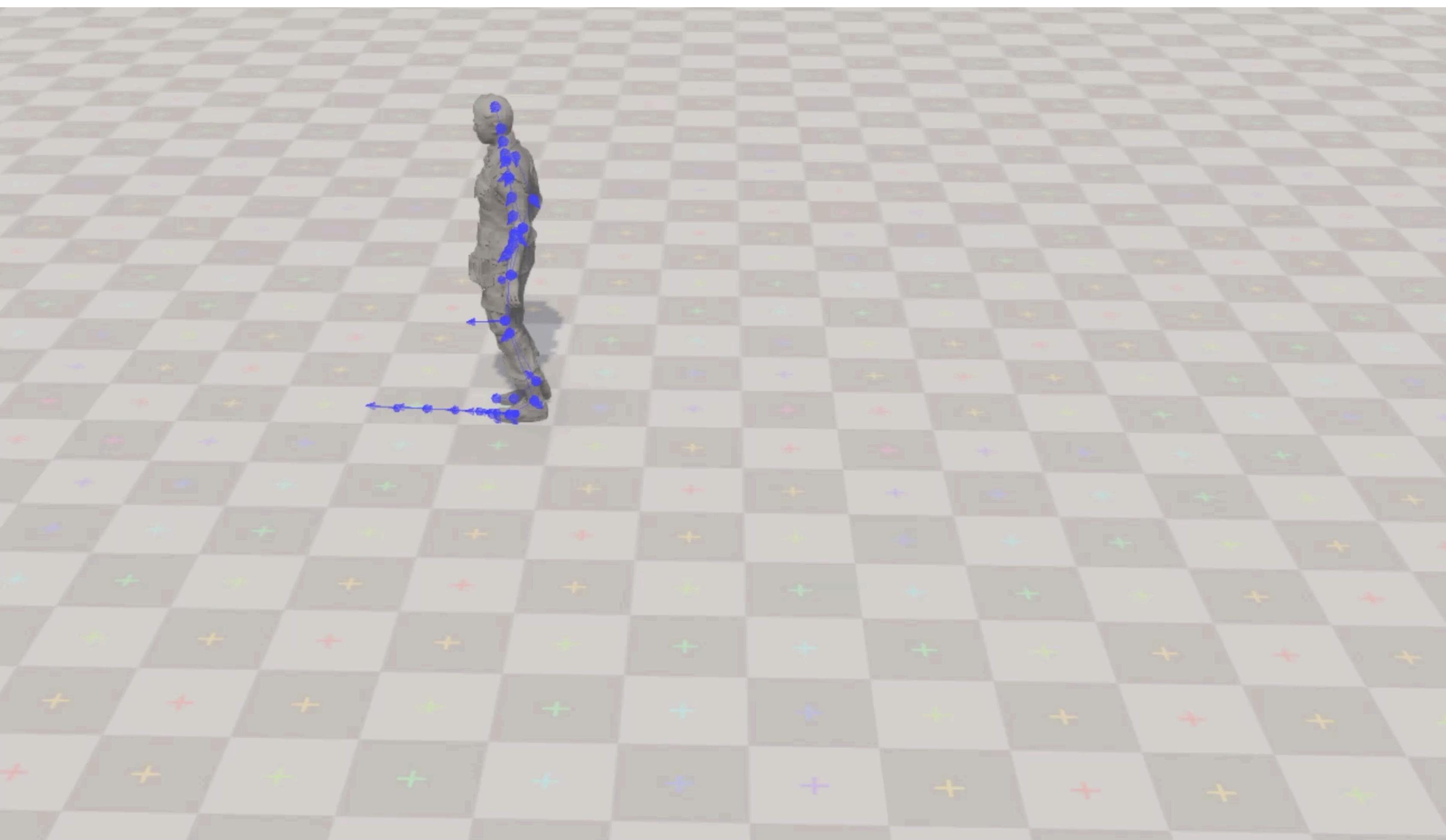
How to animate a character
to make it follow this new
path?

Patch motion clips



Repeatedly searching the dataset for a clip that, if played from the current location, would do a better job of keeping the character on the path than the current clip.

When to switch?



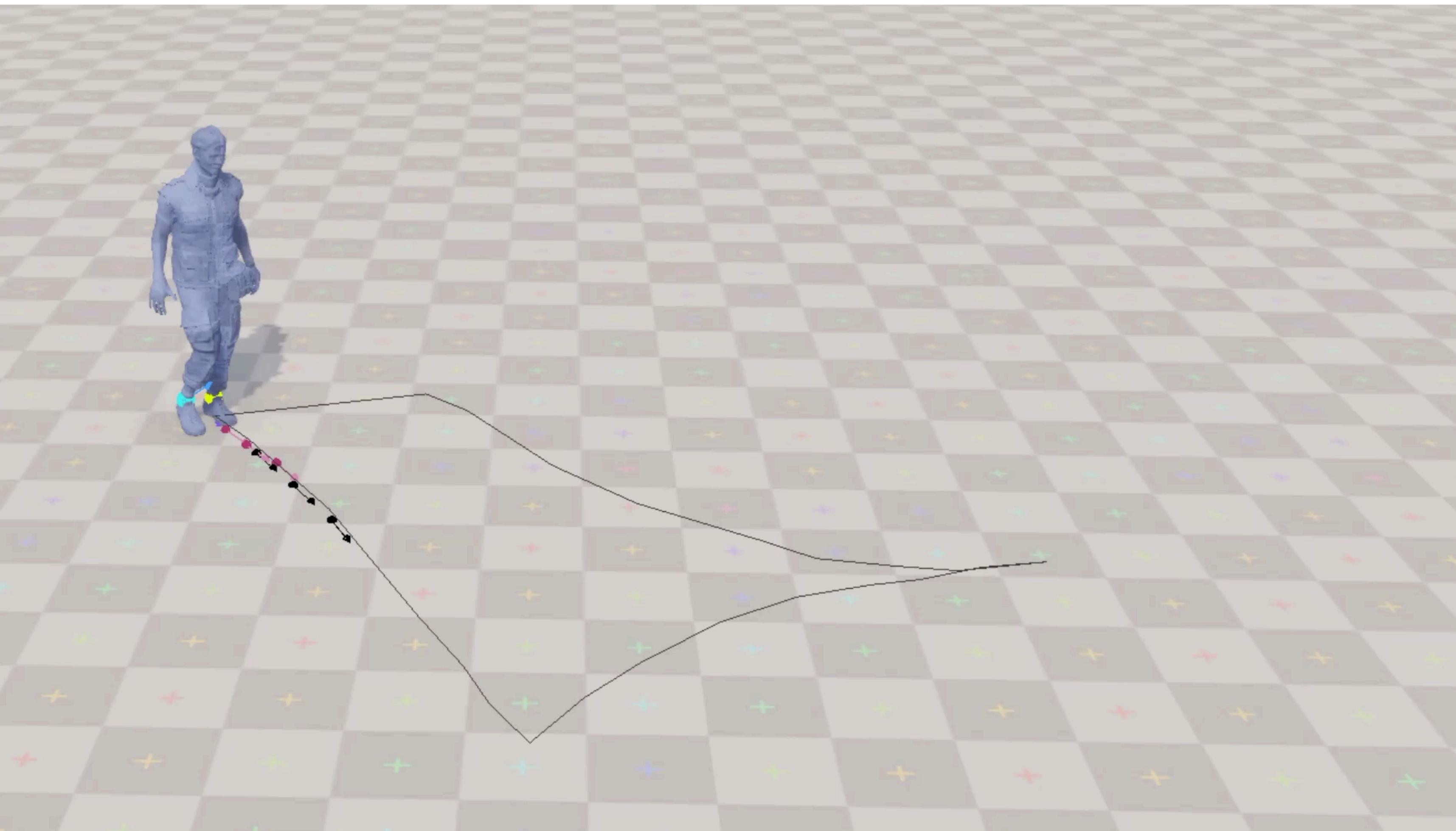
A single frame of animation contains a lot of information – and some of the information might not be useful for this decision.

Feature selection

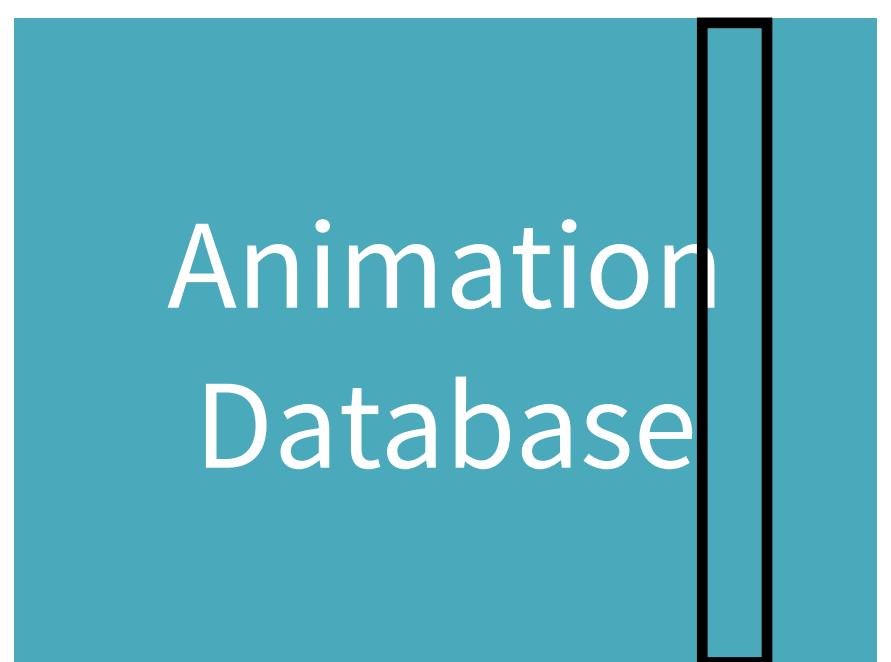
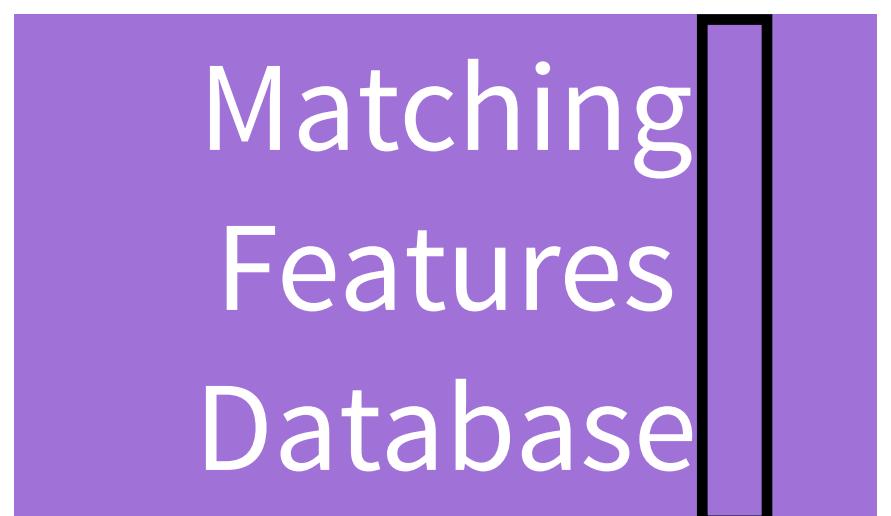


For this task, feet positions, velocities, the character root's velocity, and a couple of snapshots from the future trajectory position and direction are the only features we need.

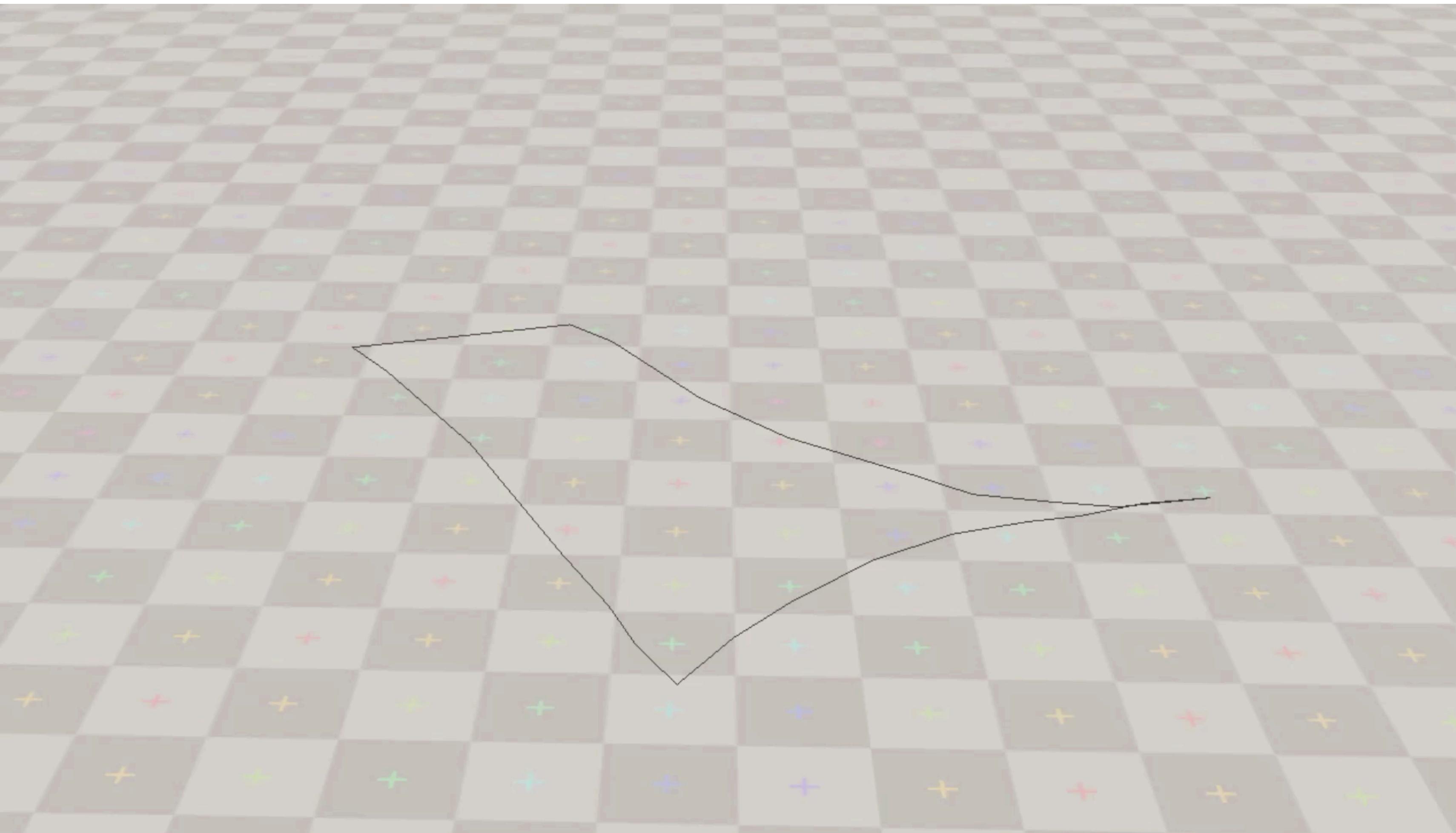
Feature matching



query feature vector



Post processing

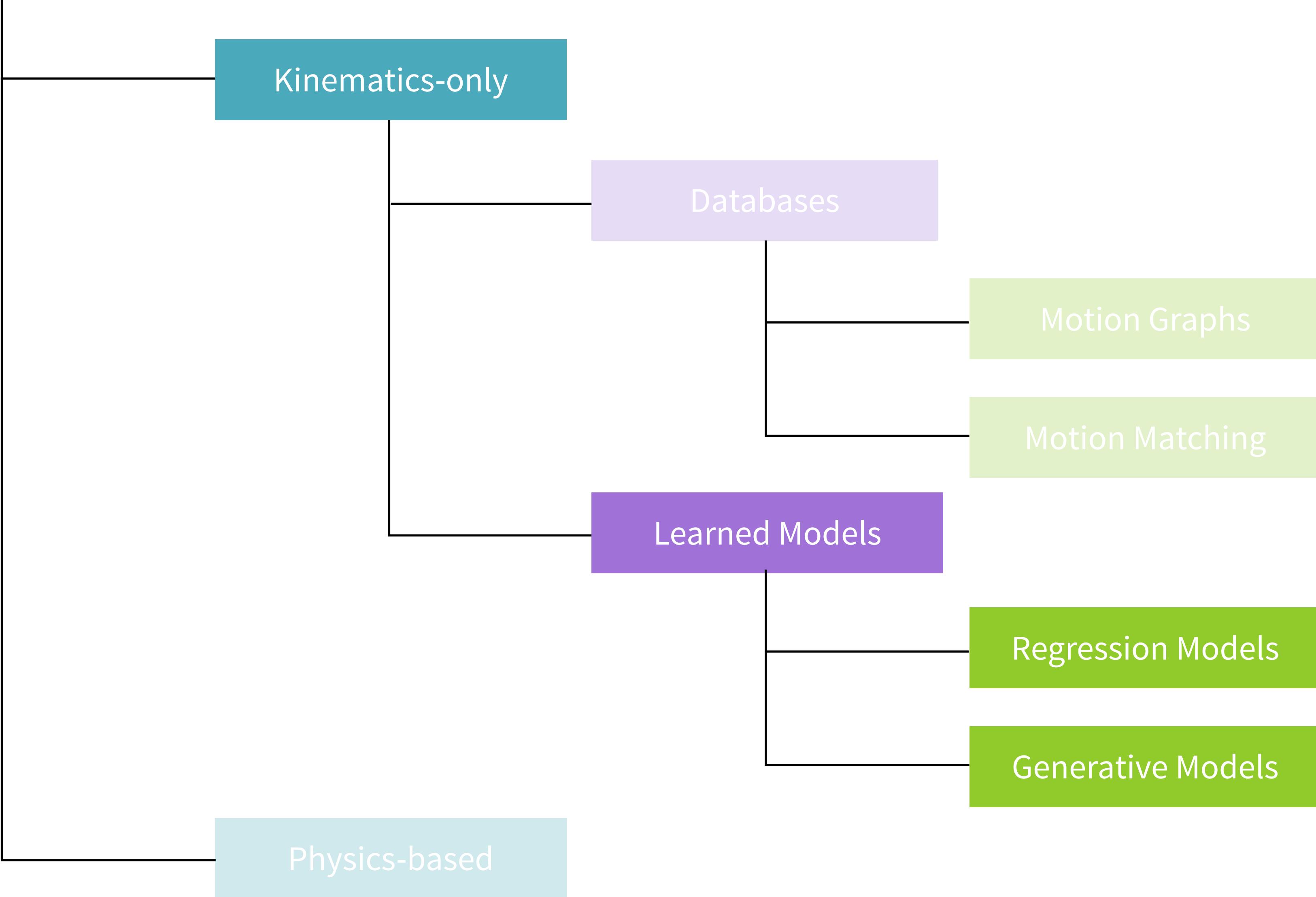


If the change in pose is not too large, this discontinuity can be easily removed using common techniques.





Character Animation



Predicting the next frame

- Given sequences of human poses, $\mathbf{q}_0, \mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_T$, can we learn a transition model from data in a supervised fashion?
- Given a pose \mathbf{q}_t , there are many plausible next pose \mathbf{q}_{t+1} — the model needs information more than just the current pose.
- Define a control/intent vector \mathbf{u}_t to capture additional information necessary to disambiguate the next frame.



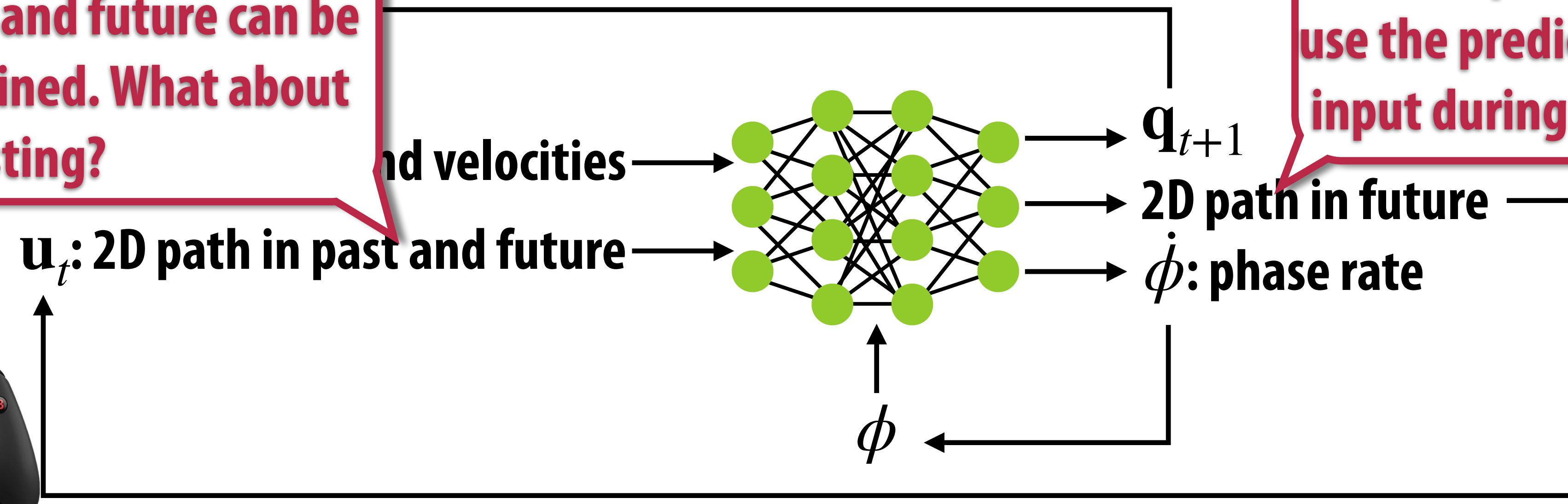
Predicting the next frame

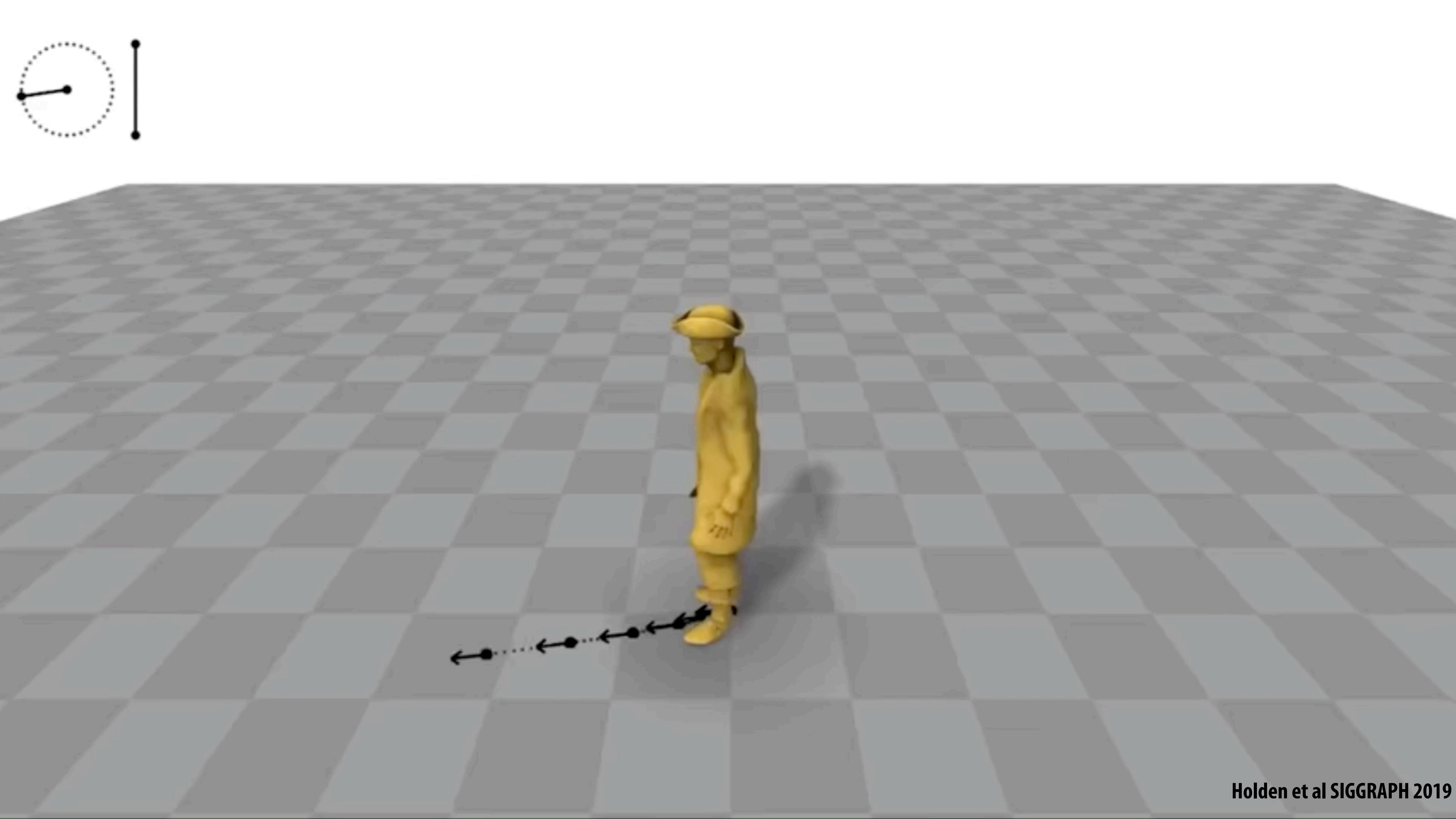
- Use a neural network to represent the model
- Define q : 3D joint positions and velocities
- Secret sauce

- Define u as 2D path in past and future and learn to predict future path
- Regulate the motion phase



During training, 2D path in the past and future can be easily obtained. What about during testing?



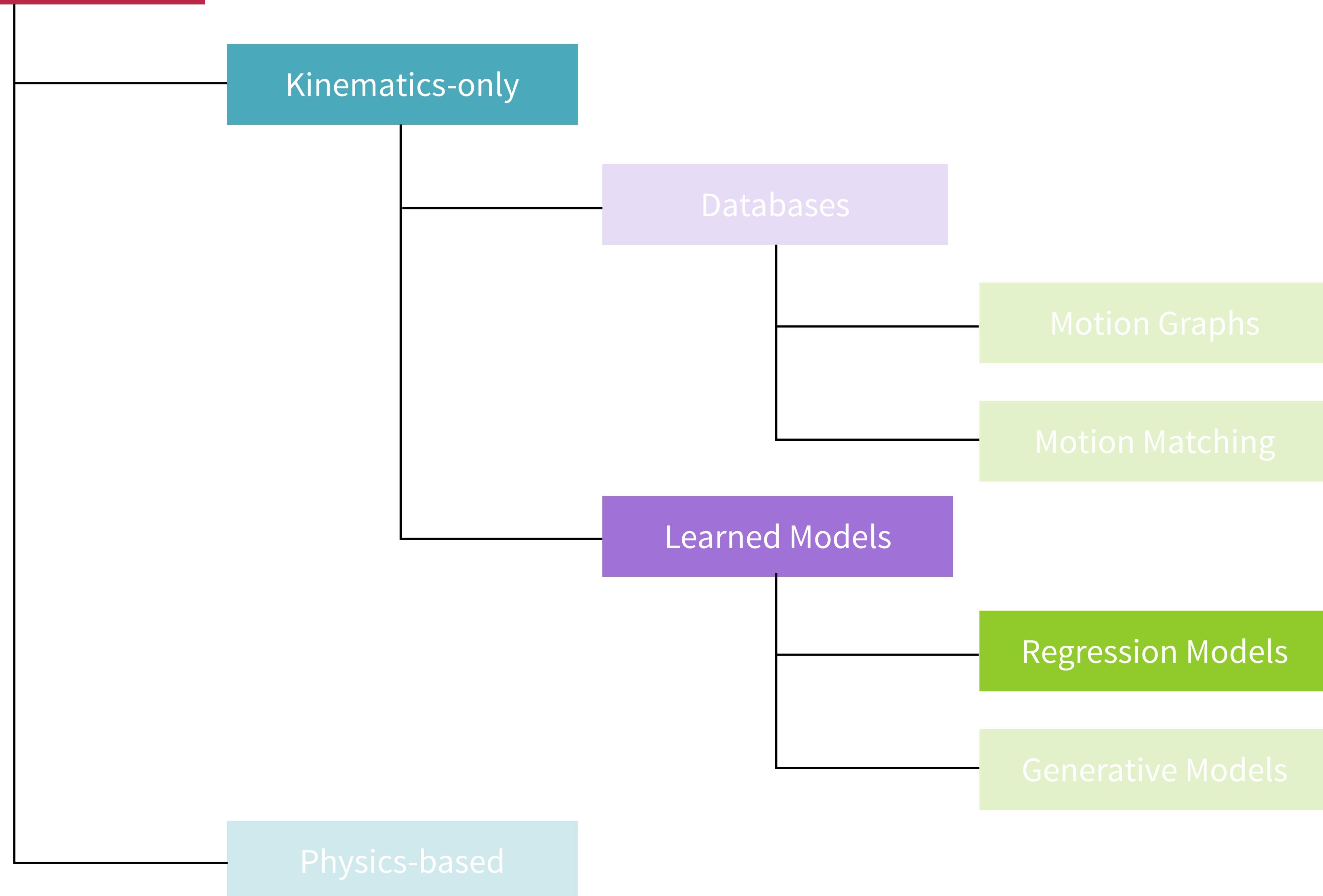


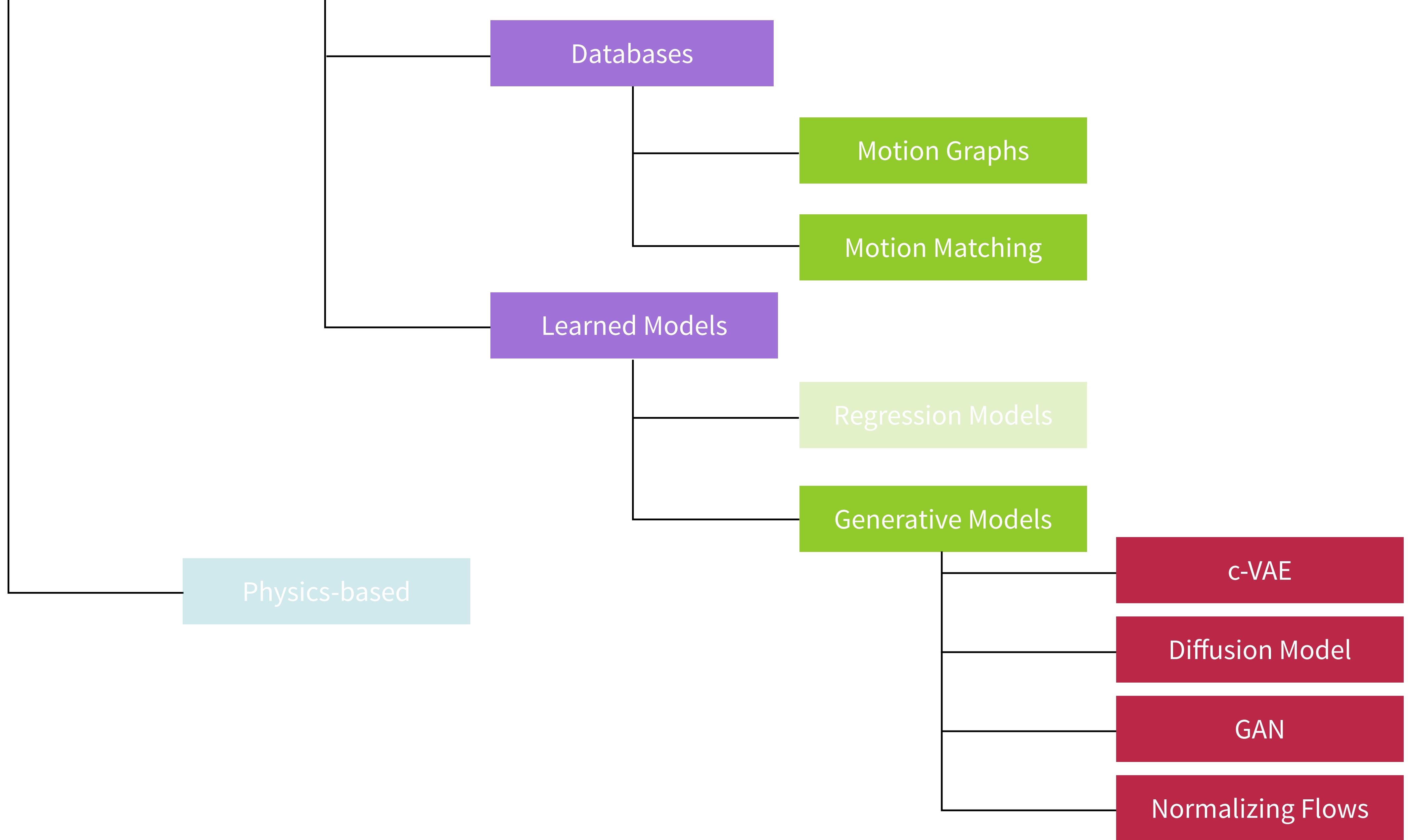
Neural motion synthesizer



Starke et al SIGGRAPH Asia 2019

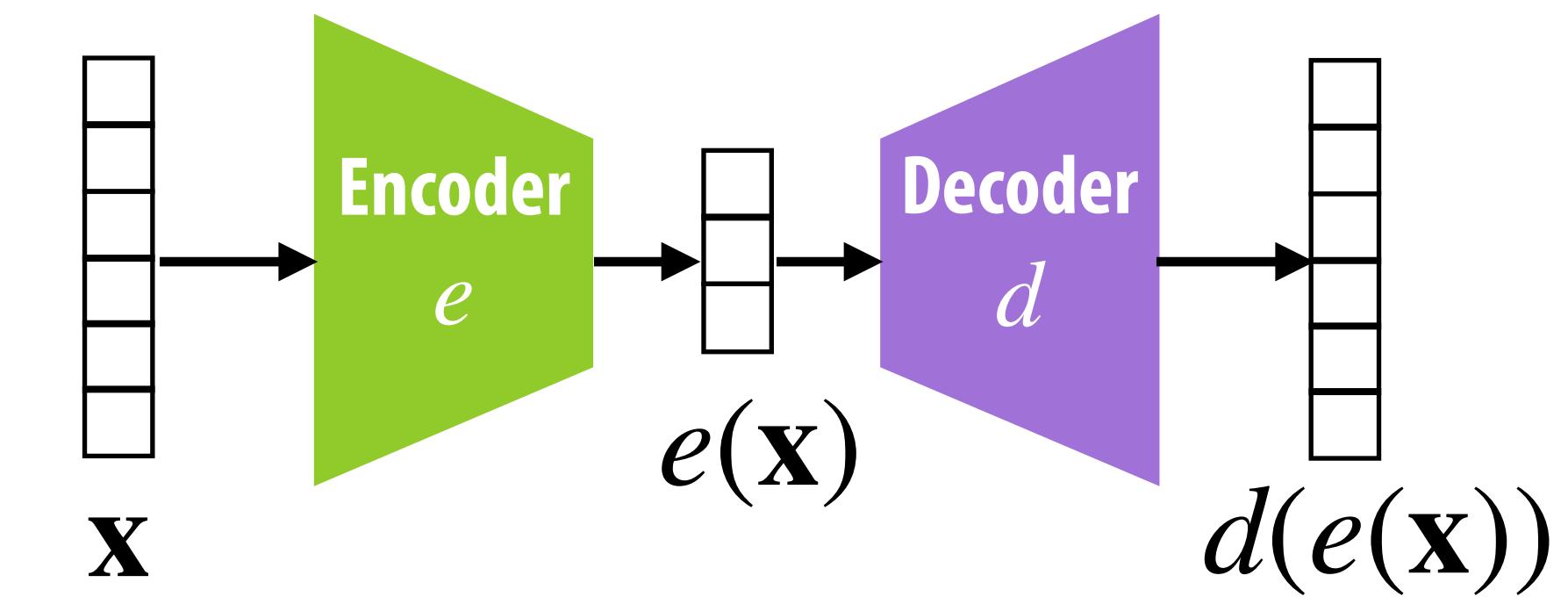
Character Animation





Generative models for human motion

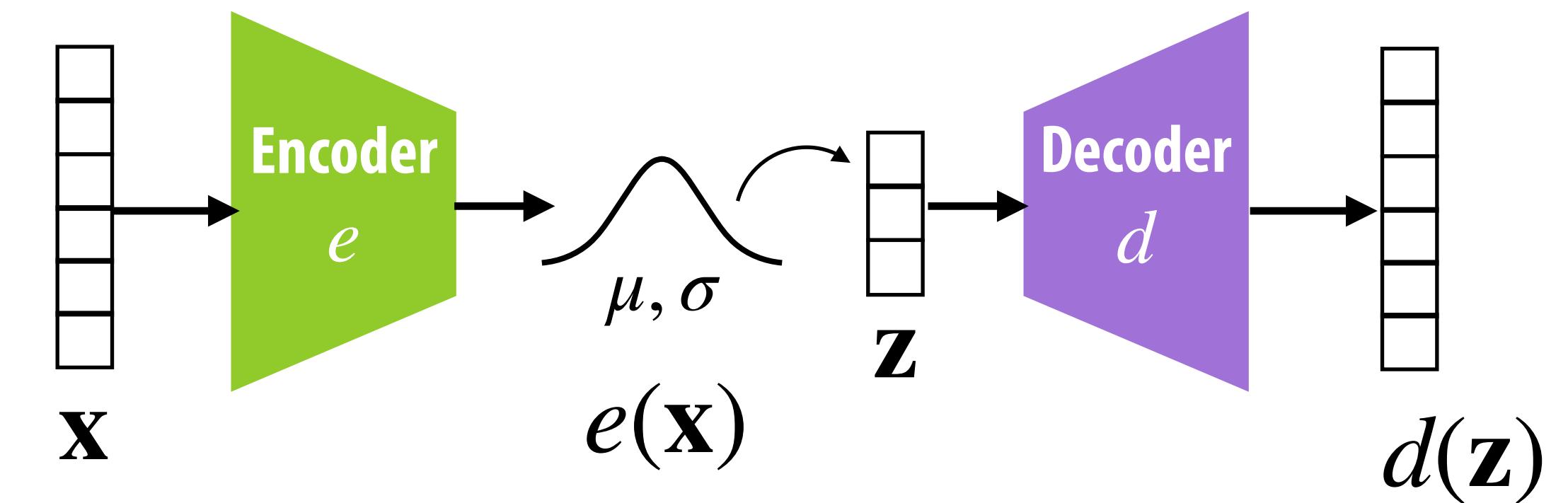
■ What is an Autoencoder?



$$\text{loss} = \|\mathbf{x} - d(e(\mathbf{x}))\|^2$$

Generative models for human motion

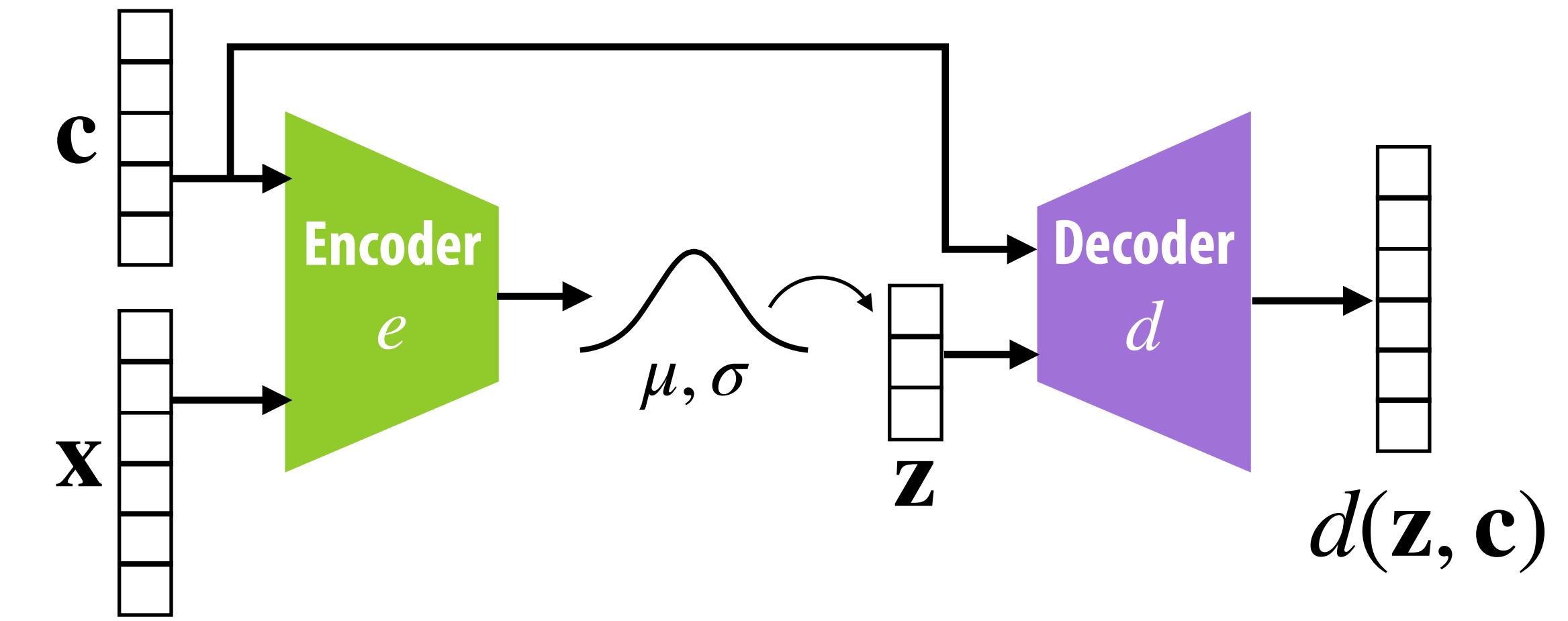
- What is an Autoencoder?
- What is a Variational Autoencoder?



$$\text{loss} = \|\mathbf{x} - d(\mathbf{z})\|^2 + KL(N(\mu, \sigma), N(0, \mathbf{I}))$$

Generative models for human motion

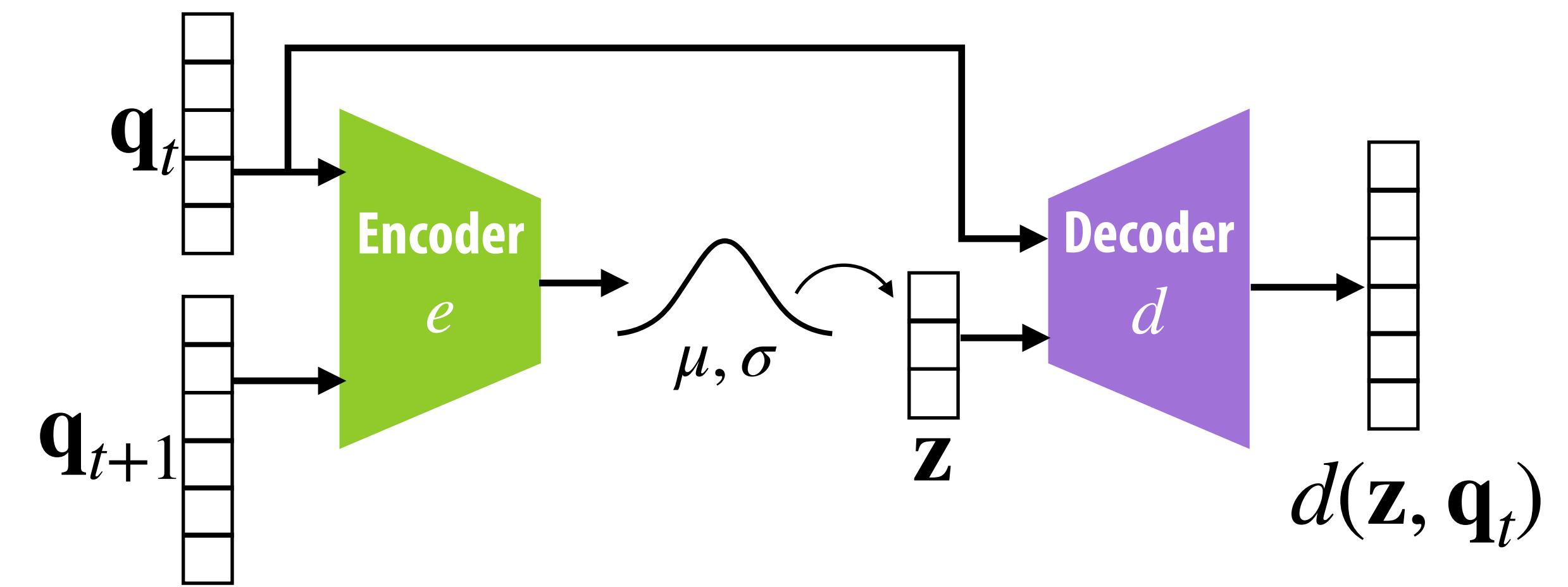
- What is an Autoencoder?
- What is a Variational Autoencoder (VAE)?
- What is a Conditional Variational Autoencoder (CVAE)?



$$\text{loss} = \|x - d(z, c)\|^2 + KL(N(\mu, \sigma), N(0, I))$$

Generative models for human motion

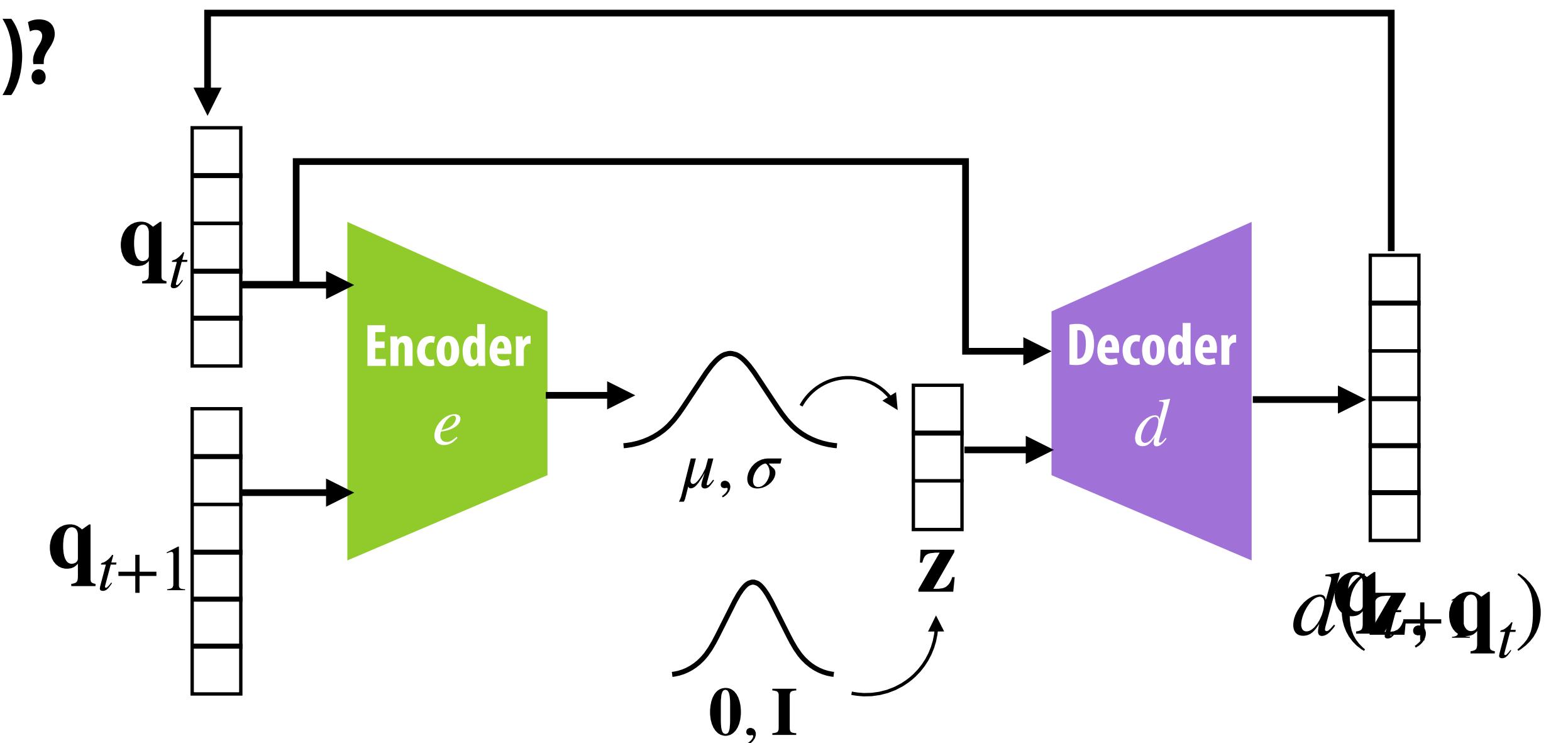
- What is an Autoencoder?
- What is a Variational Autoencoder (VAE)?
- What is a Conditional Variational Autoencoder (CVAE)?
- How to use CVAE to generate motion?
 - Define X: next pose \mathbf{q}_{t+1}
 - Define C: current pose \mathbf{q}_t

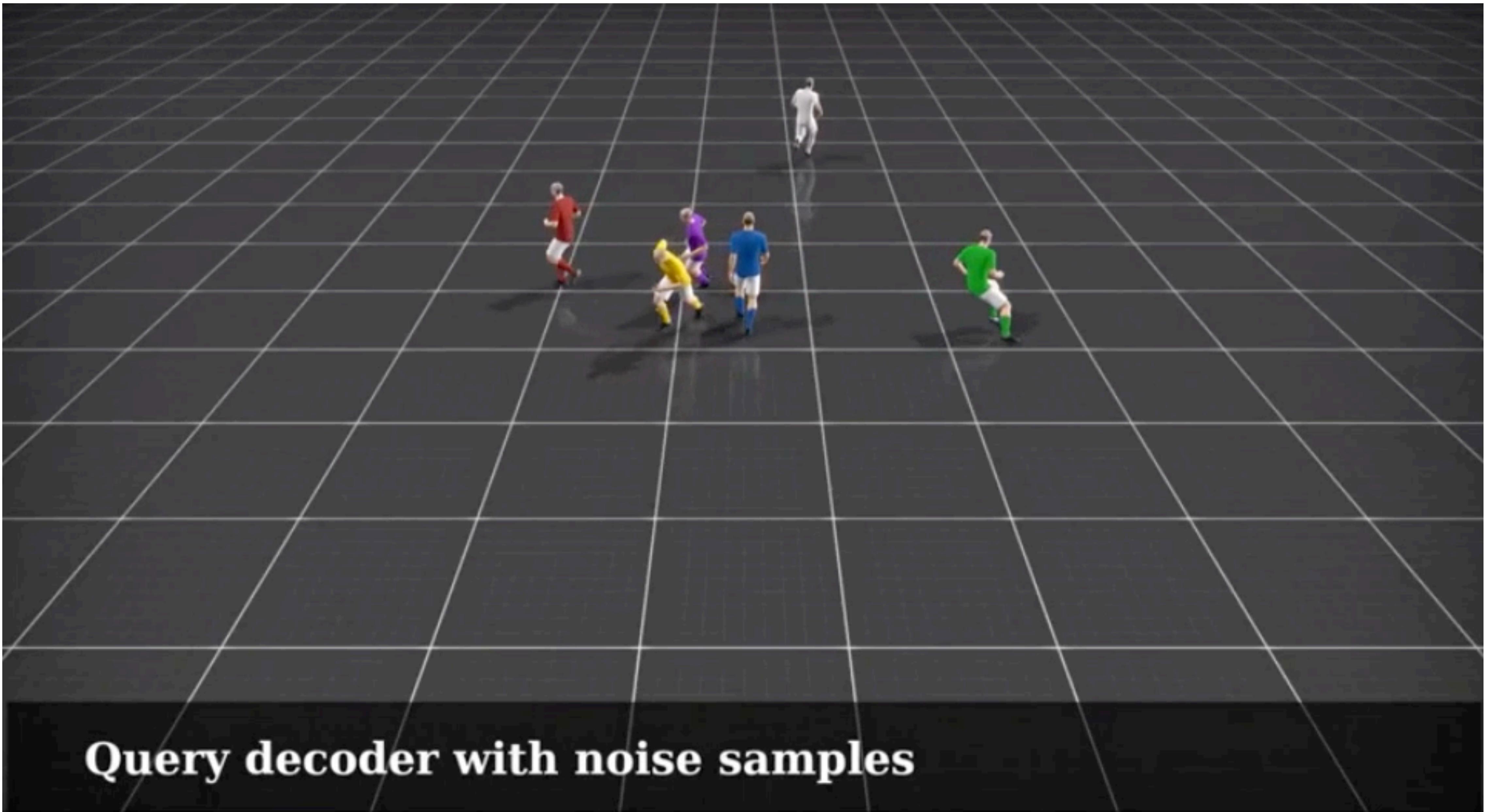


$$\text{loss} = \|\mathbf{q}_{t+1} - d(\mathbf{z}, \mathbf{q}_t)\|^2 + KL(N(\mu, \sigma), N(0, \mathbf{I}))$$

Generative models for human motion

- What is an Autoencoder?
- What is a Variational Autoencoder (VAE)?
- What is a Conditional Variational Autoencoder (CVAE)?
- How to use CVAE to generate motion?
 - Define X: next pose \mathbf{q}_{t+1}
 - Define C: current pose \mathbf{q}_t
- Once CVAE is trained, how to use it?
 - Discard the encoder and only use the decoder to generate next frame autoregressively
 - Sample z from a uniform distribution

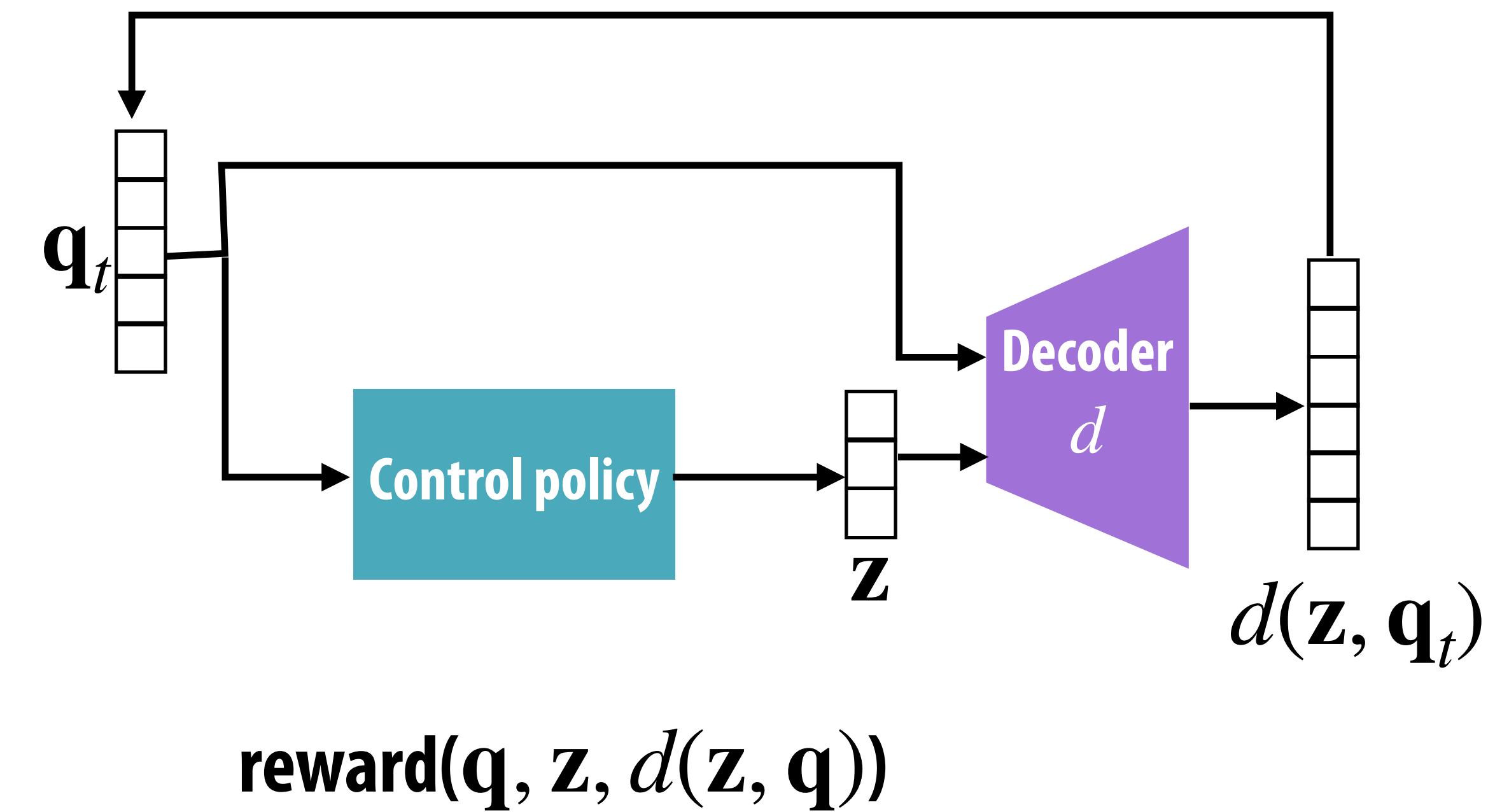




Query decoder with noise samples

Control the decoder

- The decoder can generate plausible next frames given the current frame, but it does not achieve any specific task
- Train a control policy that controls the decoder using Reinforcement Learning
 - Input state: current pose q_t
 - Output action: latent variable z





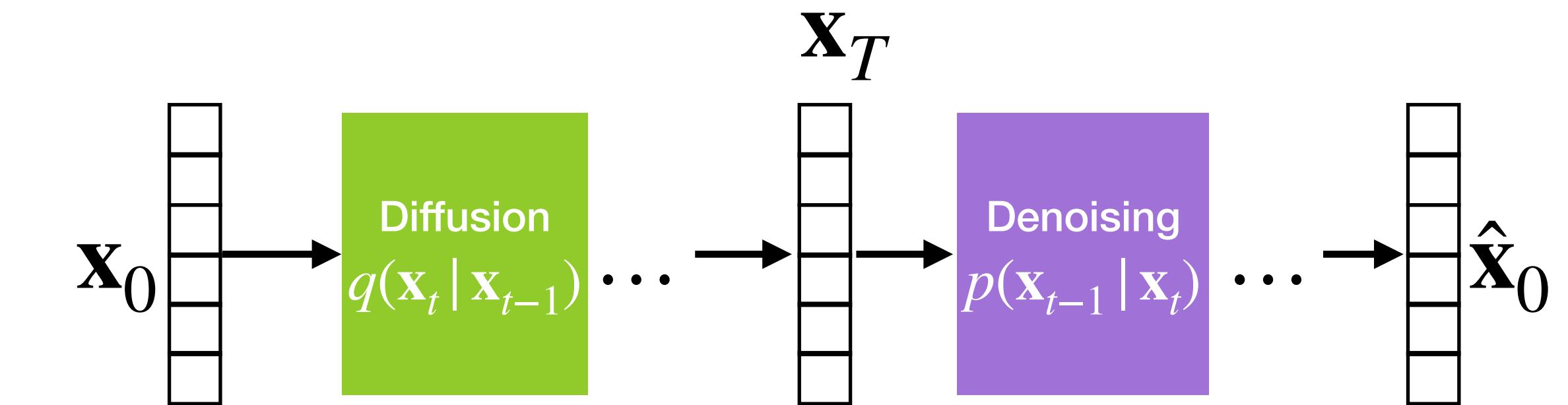
Target Runner



Maze Runner

Diffusion Model

- Diffusion process gradually adds gaussian noise to the original data; by approximating the reverse process, we can synthesize data from noise



- Diffusion process:

$$q(\mathbf{x}_t | \mathbf{x}_{t-1}) = N(\mathbf{x}_t; \boldsymbol{\mu}_t = \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \boldsymbol{\Sigma}_t = \beta_t \mathbf{I})$$

How to get \mathbf{x}_t ? Repeatedly draw samples from q conditioned on the previous sample \mathbf{x}_{t-1} .

Using reparameterization trick: $\mathbf{x}_t = q(\mathbf{x}_0, t) = \bar{\alpha}_t \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}$, where $\boldsymbol{\epsilon}$ is drawn from $N(\mathbf{0}, \mathbf{I})$, and $\bar{\alpha}_t = \prod_{s=0}^t (1 - \beta_s)$

- Denoising process:

Approximate the reverse distribution: $p(\mathbf{x}_{t-1} | \mathbf{x}_t, t) = N(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$

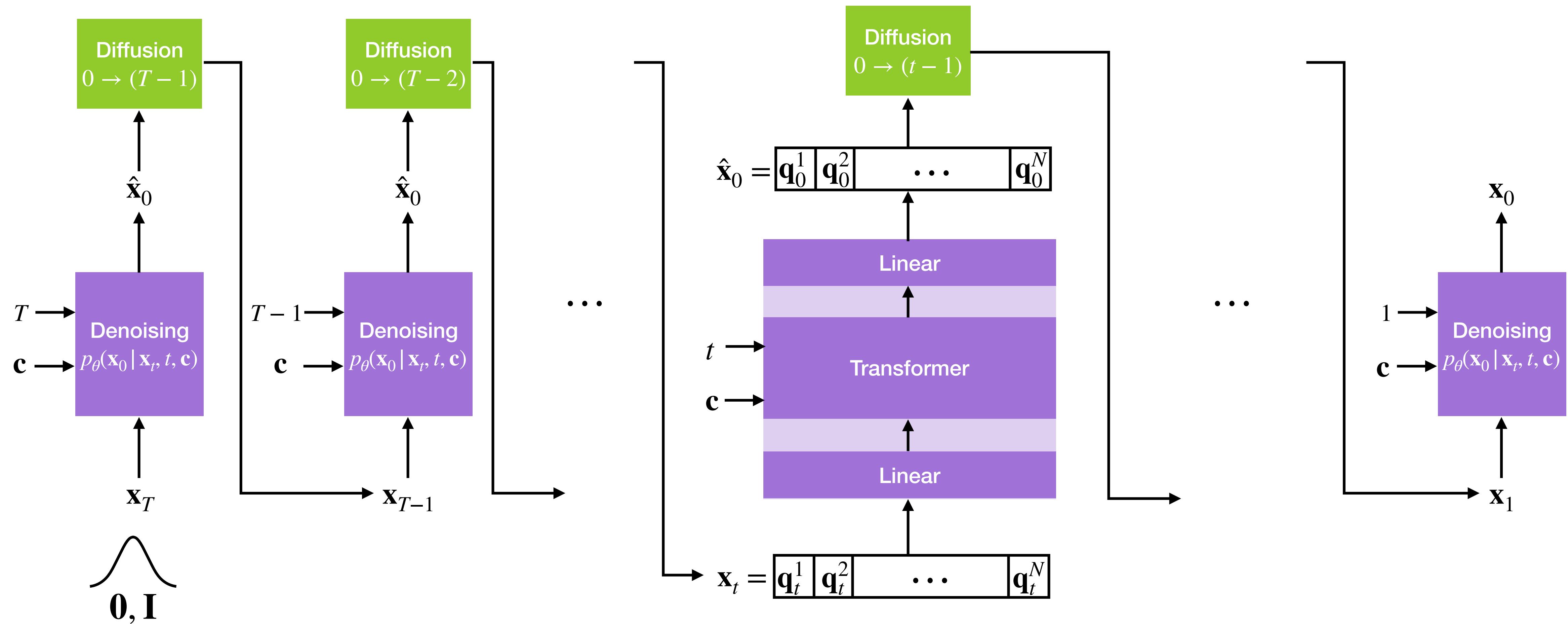
How to get \mathbf{x}_0 ? Repeatedly draw sample from p conditioned on the “next” sample \mathbf{x}_{t+1}

How to train p ? In practice, we train a neural network that predicts \mathbf{x}_0 from \mathbf{x}_t , conditioned on t , $\hat{\mathbf{x}}_0 = p_\theta(\mathbf{x}_t, t)$.

$$L_\theta = \mathbb{E}_{\mathbf{x}_0, t} [\|\mathbf{x}_0 - p_\theta(q(\mathbf{x}_0, t), t)\|]$$

diffuse a data point for t steps and denoise it back to $\hat{\mathbf{x}}_0$

Diffusion Models for Human Motion



Human Motion Diffusion Model

Guy Tevet

Sigal Raab

Brian Gordon

Yonatan Shafir

Daniel Cohen-Or

Amit H. Bermano

Tel Aviv University, Israel

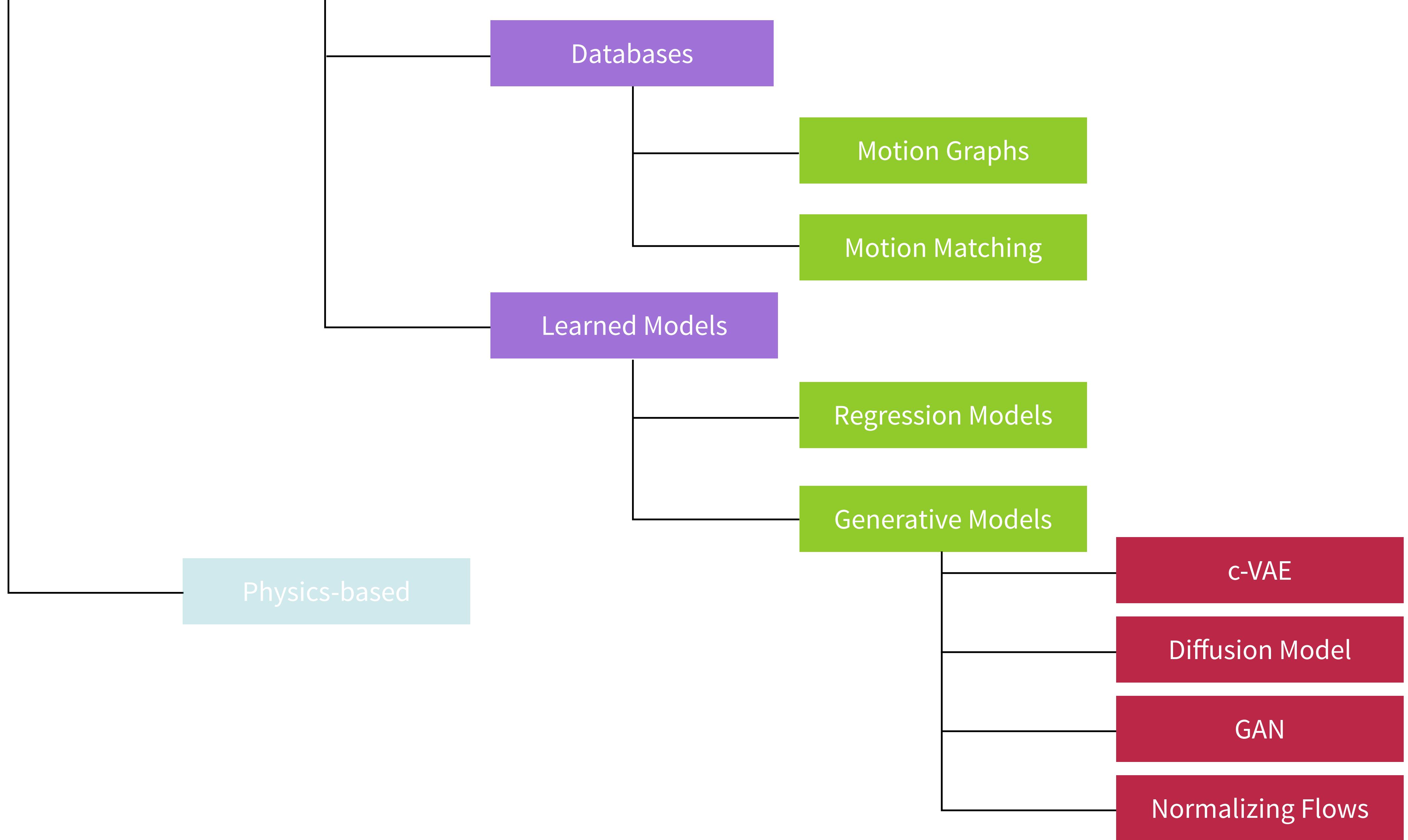
<https://github.com/andreas128/RePaint>

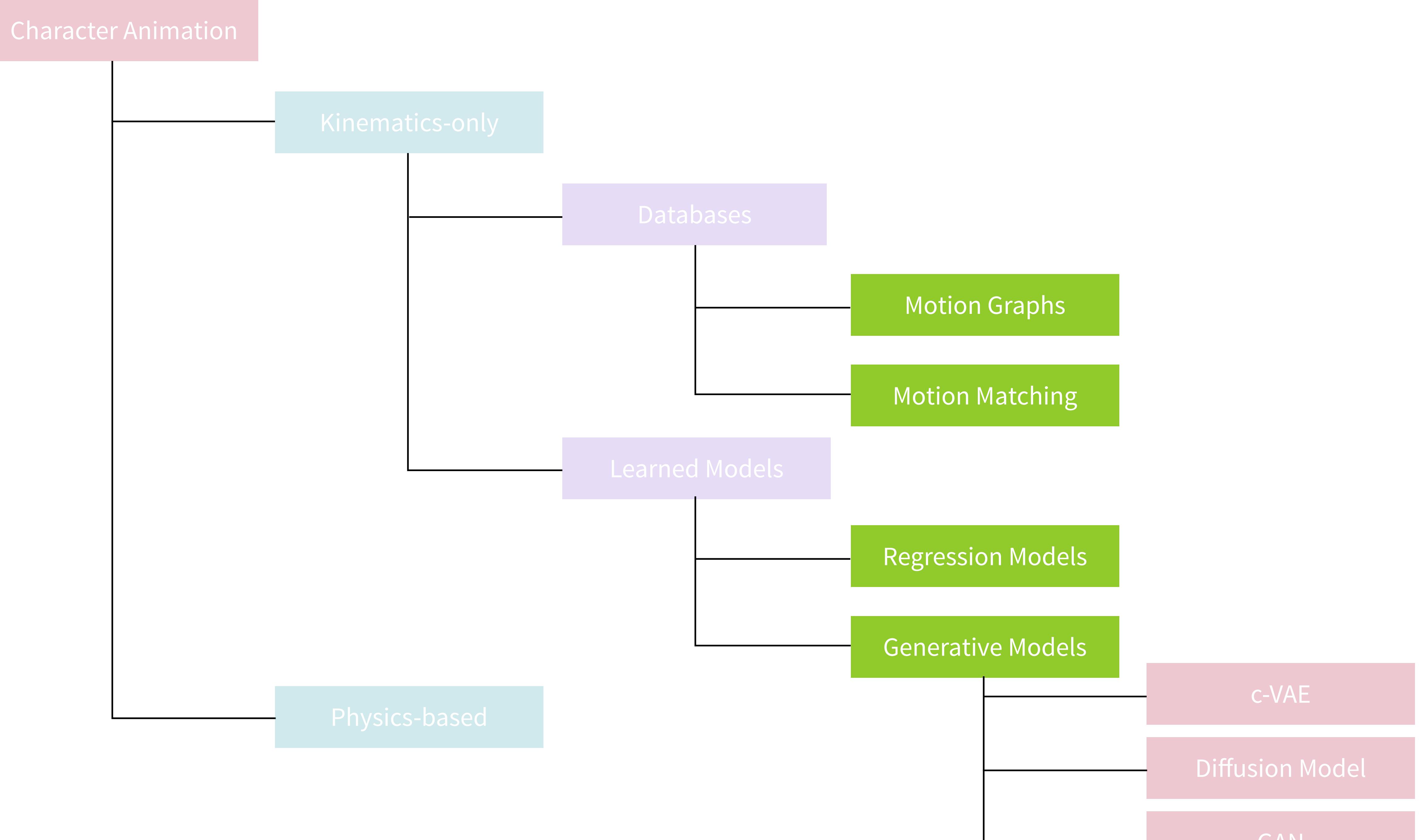


Image Diffusion

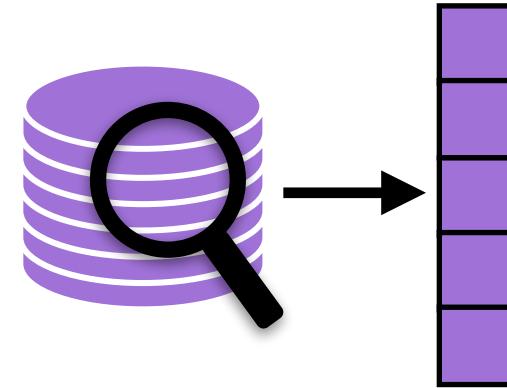


Motion Diffusion





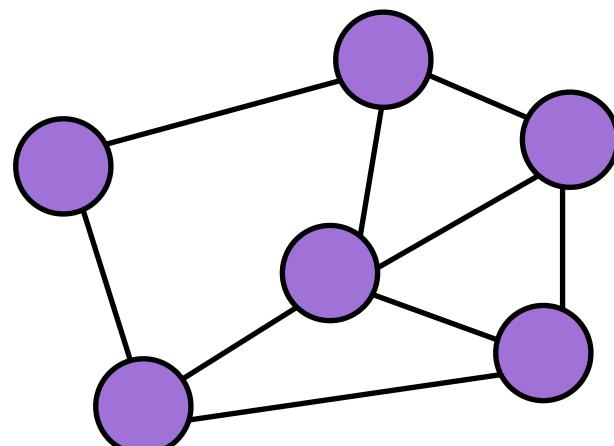
Comparisons



Motion Matching

Motion Matching vs Motion Graphs

- Both require access to motion datasets
- Motion matching computes transitions at execution time while motion graphs at construction time
- Motion matching works with short-horizon control while motion graphs allows for long-term planning

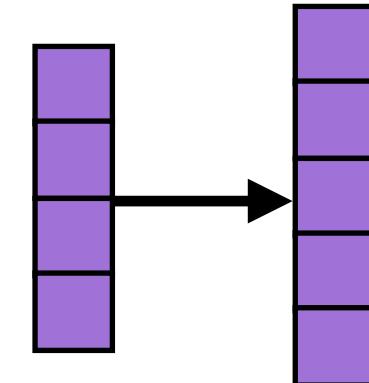


Motion Graphs

Motion Matching vs Regression

- Both require dense control signals to produce best next frame
- Motion matching explicitly selects best match while Regression learns the best match

Regression Models

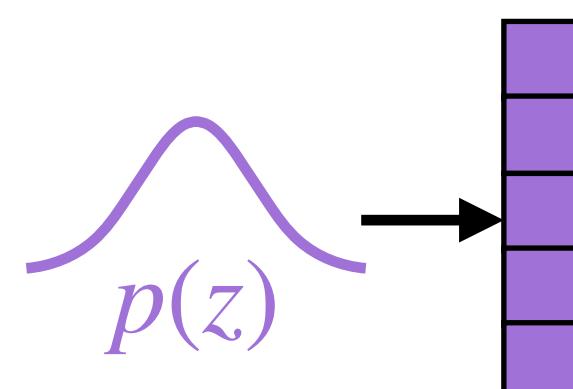


Different approaches to online motion synthesis

Motion Graphs vs Generative Models

- Both need an auxiliary planning/control algorithm for functional tasks
- Both predict multiple plausible next frames given current frame
- Generative models predict the distribution of next frame while motion graph uses graph edges to model next frames

Generative Models



Regression vs Generative Models

- Both train neural networks to produce next frame and do not need to access data once trained
- Regression models use an explicitly defined control space while generative models use a learned control space

Evaluation

- **Similarity to data**
 - **Joint position and orientation**
 - **Root position and orientation**
- **Physical plausibility**
 - **Penetration with geometry**
 - **Unrealistic foot contact**
- **Task performance**
- **User studies**