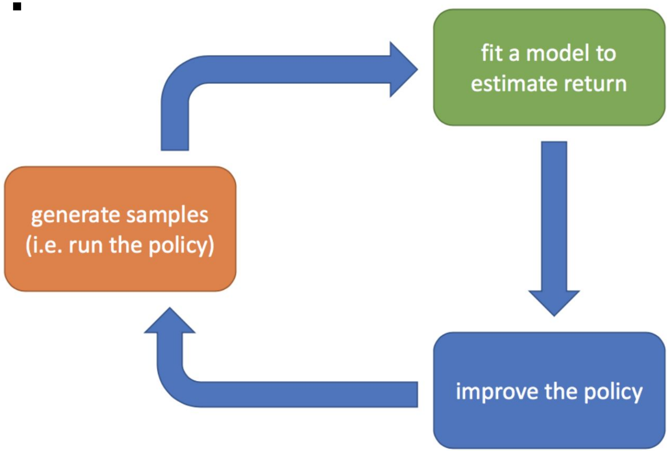
Generative and Predictive Models of Videos for Understanding the World

Oleh Rybkin

(some slides taken from Drew Jaegle, Karl Pertsch)

Can predictive objectives be useful for semantic understanding?



- Objects?
- Events?
- Affordances?

Credits: (left) Francis Vachon, found in a Chelsea Finn presentation, (right) Sergey Levine

Learning what you can do before doing anything

Oleh Rybkin*, Karl Pertsch*,
Konstantinos G. Derpanis, Kostas Daniilidis, Andrew Jaegle

ICLR 2019

Penn Engineering
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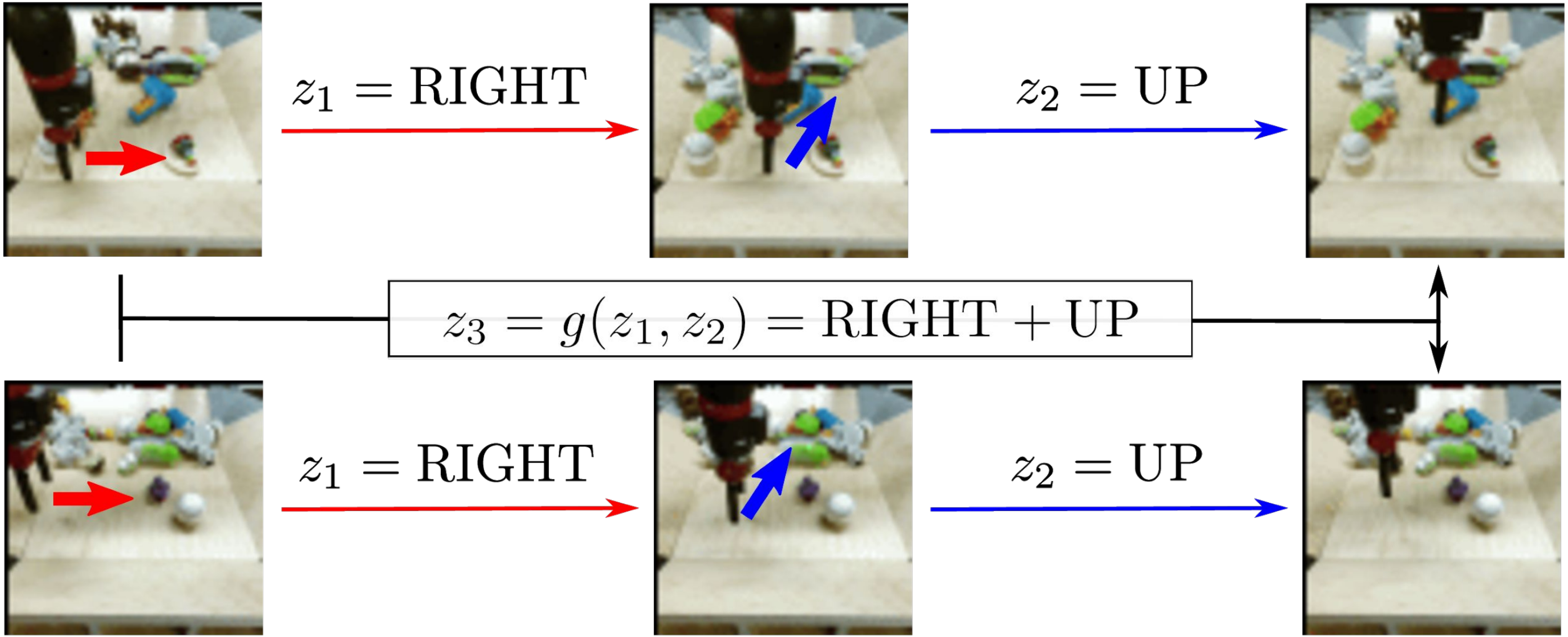
Understanding actions

Credit: found via Nando De Freitas tweets

Understanding actions



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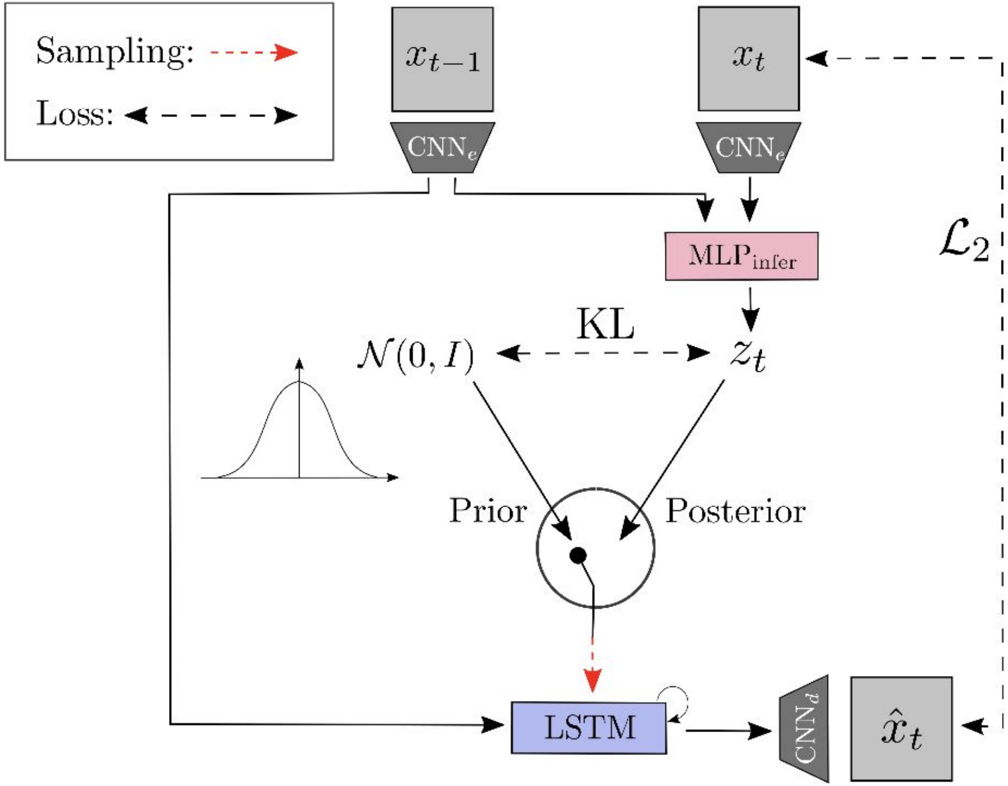
Variational Video Prediction



Denton & Fergus, 2018; Lee et al., 2018. Chung et al., 2015

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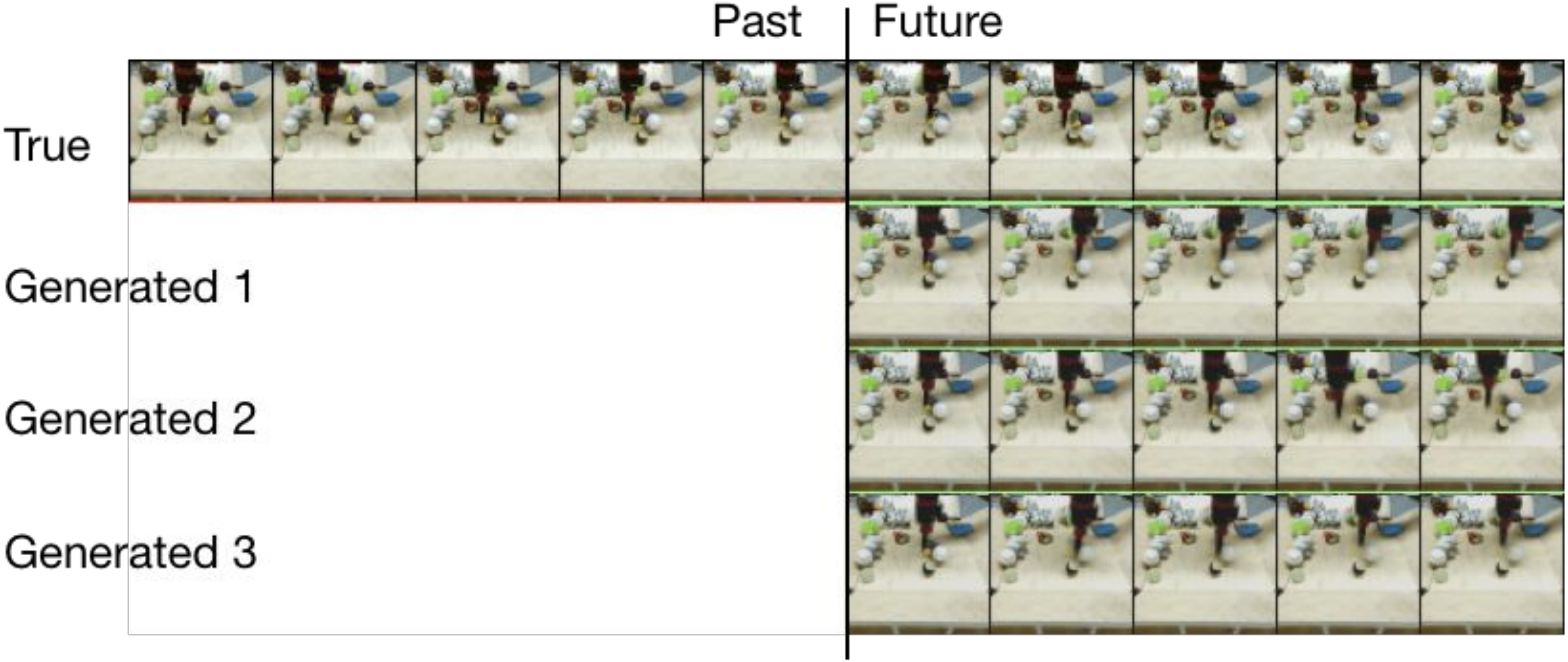
Variational Video Prediction



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Variational Video Prediction with Information Bottleneck

The (beta-)VAE objective for stochastic video prediction is:

$$\sum_t \left[\mathbb{E}_{q(z_t|x_{t-1:t})} \log p(x_t|Z_t, x_{t-1}) - \beta \mathrm{KL}[q(Z_t|x_{t-1:t}), p(Z)]\right]$$

Which is equivalent to the VIB lower bound of the following:

$$\max I((z_t, x_{t-1}); x_t) \text{ s.t. } I(z_t; x_{t-1:t}) \leq I_c.$$

Alemi et al., 2017, 2018

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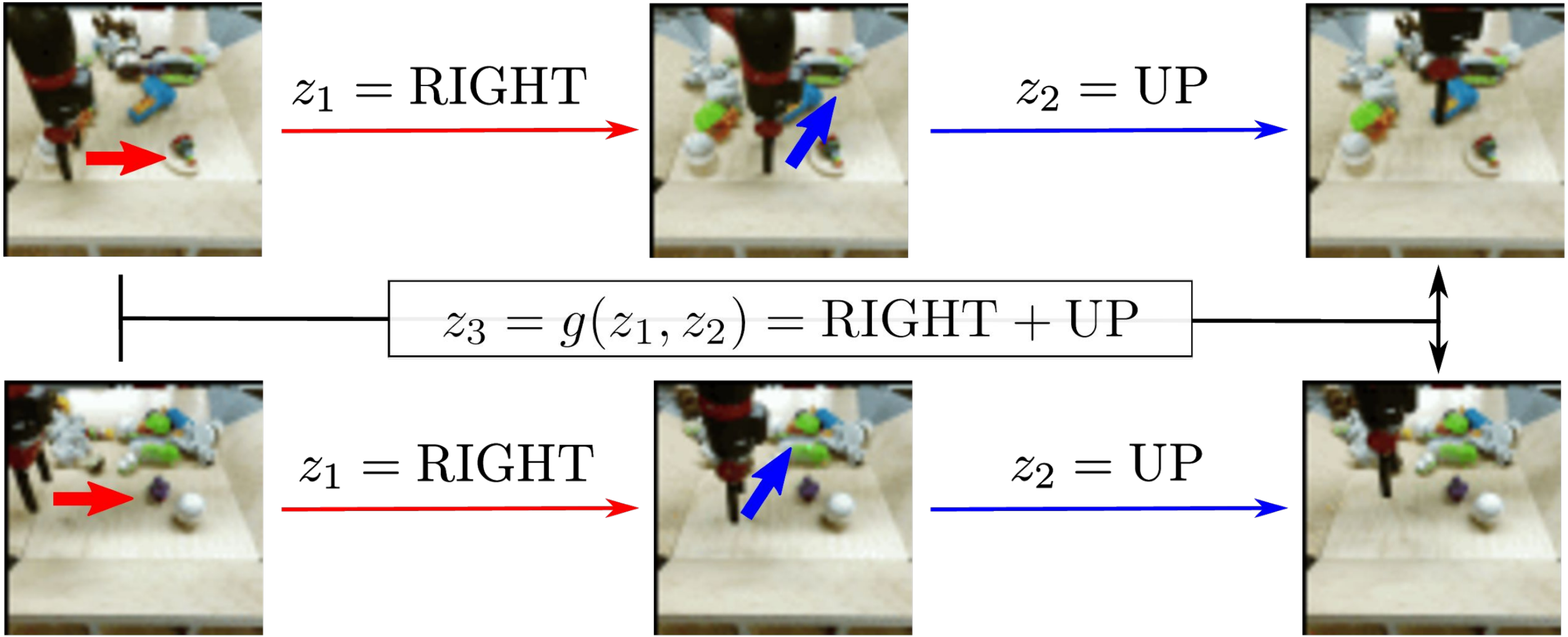
Enforcing structure with composability



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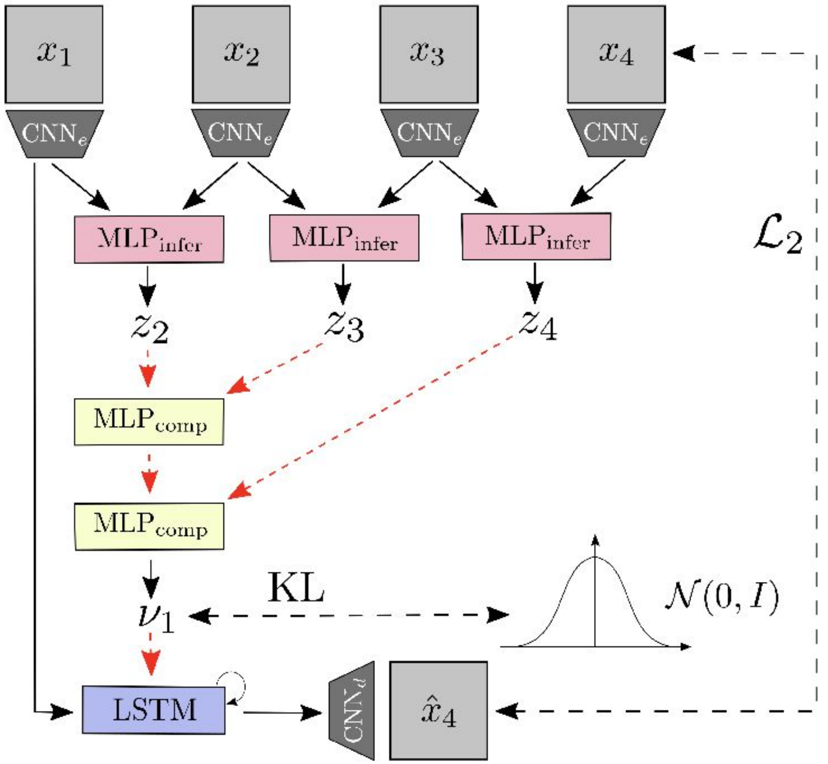
CLASP: Enforcing structure with composability



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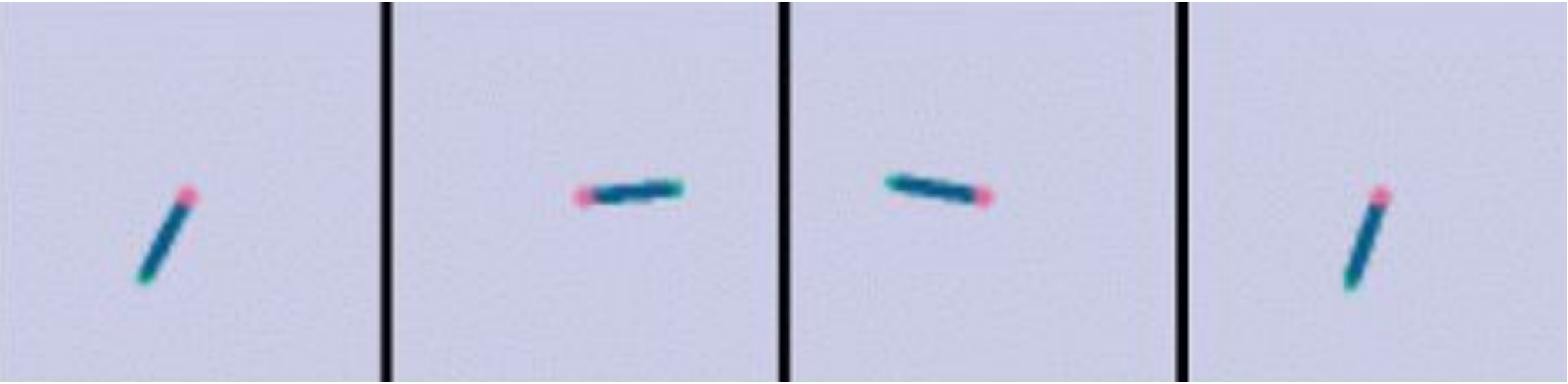
Reacher environment



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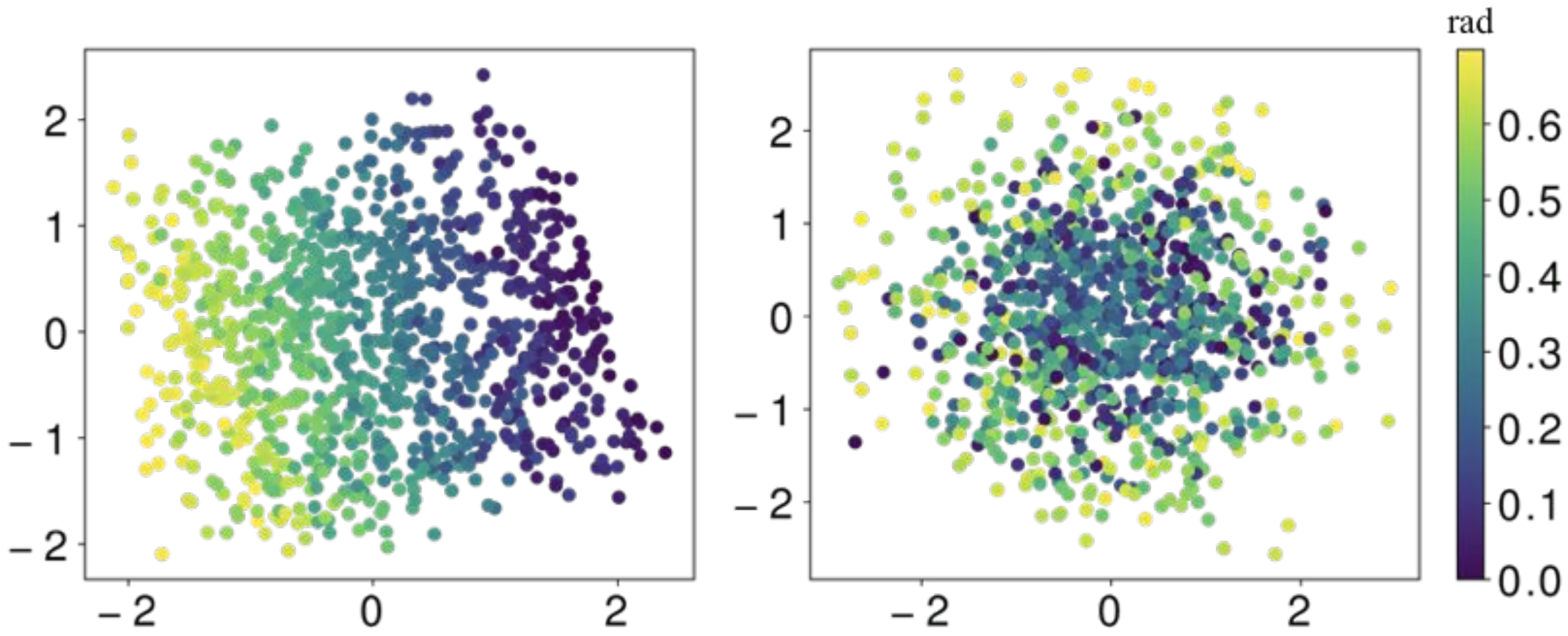
Understanding actions



a) CLASP (Ours) **b)** Denton & Fergus (2018)

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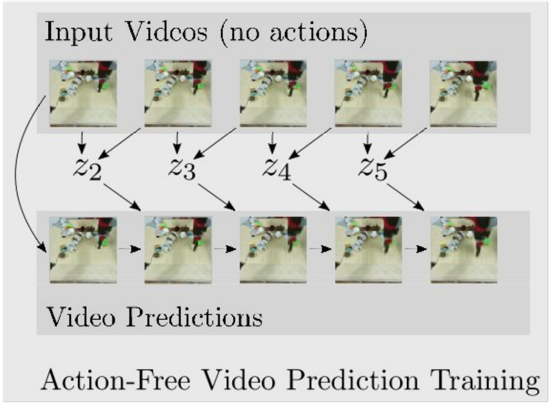
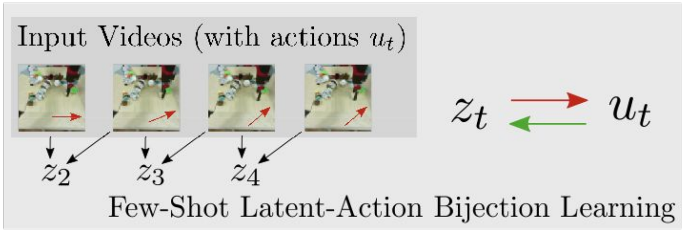
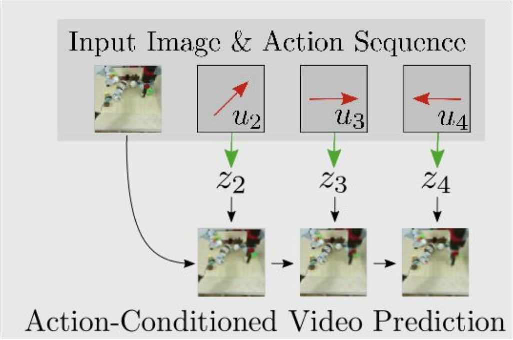
Applications of CLASP

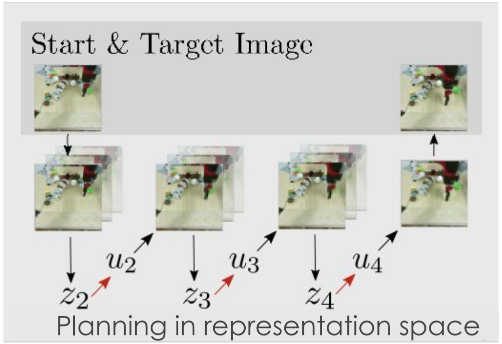
Passive learning



Active learning







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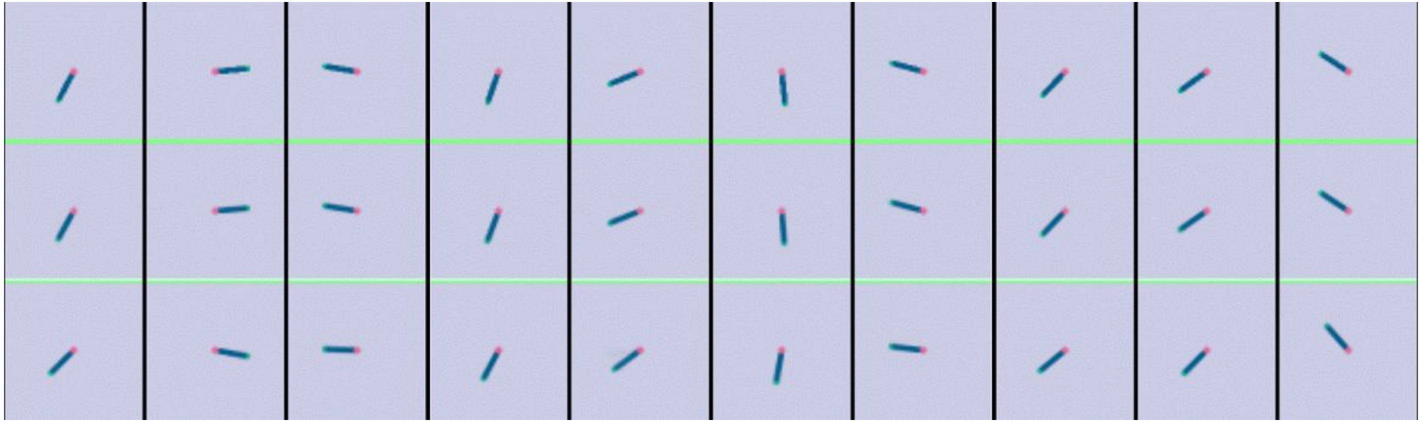
Action-conditioned prediction

Ground Truth:

CLASP (ours):

Denton & Fergus:



	Reacher	BAIR
Method	Error [deg]	Error [px]
Random	26.6 ± 21.5	-
Baseline	22.6 ± 17.7	3.6 ± 4.0
Ours	$\mathbf{2.9 \pm 2.1}$	$\mathbf{3.0 \pm 2.1}$
Supervised	2.6 ± 1.8	2.0 ± 1.3

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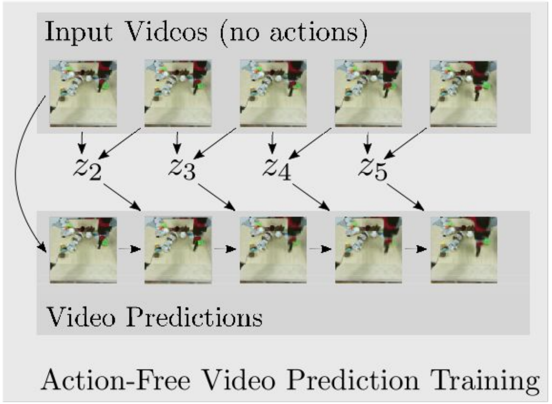
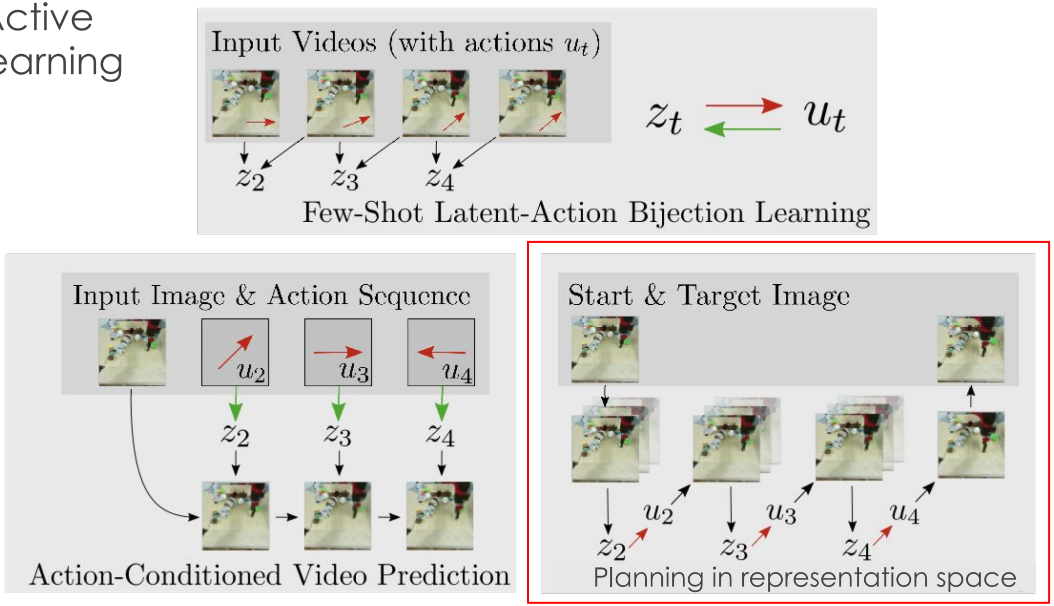
Applications of CLASP

Passive learning



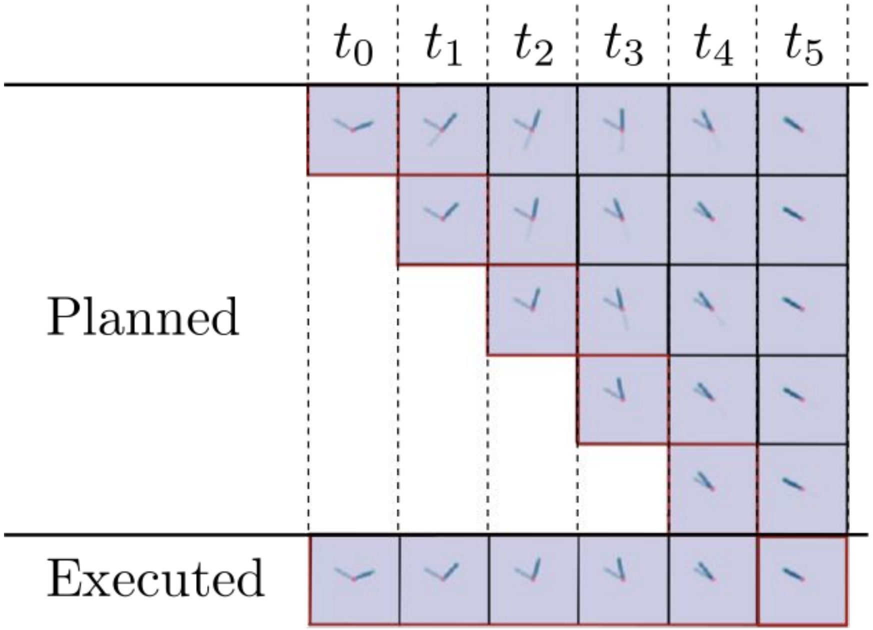
Active learning

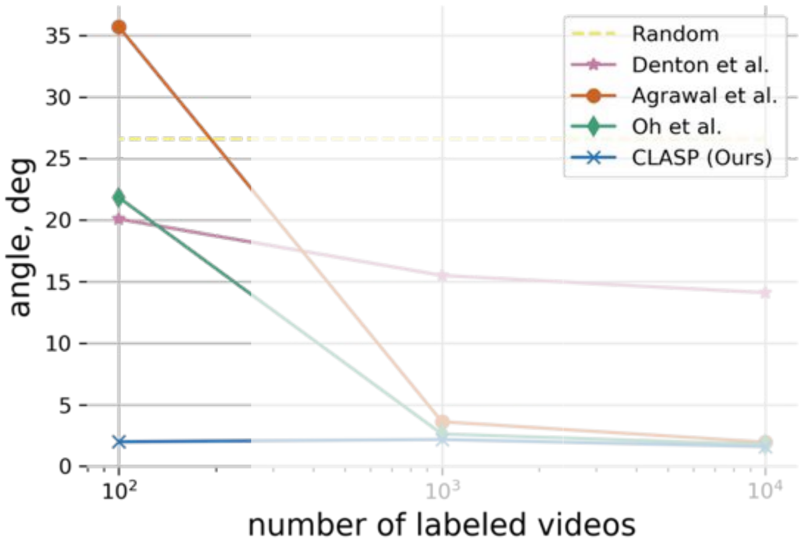


Ebert et Finn et al., 2018

Learning what you can do before doing anything. ICLR 2019.

Planning in learned latent space





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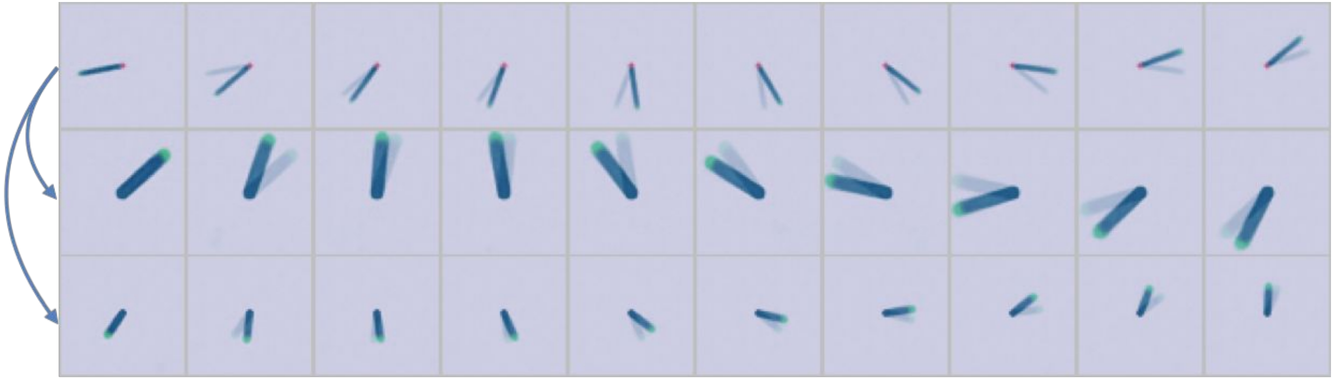
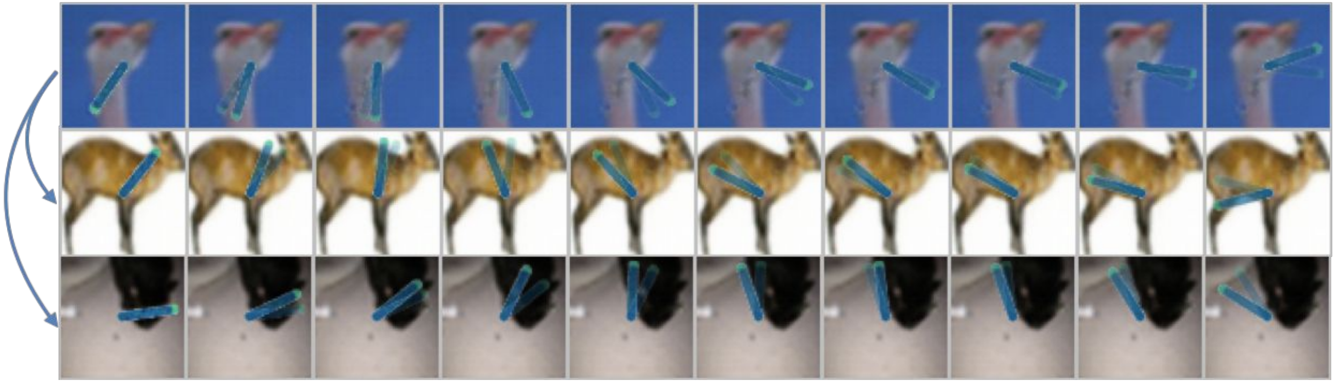
Varying visual characteristics

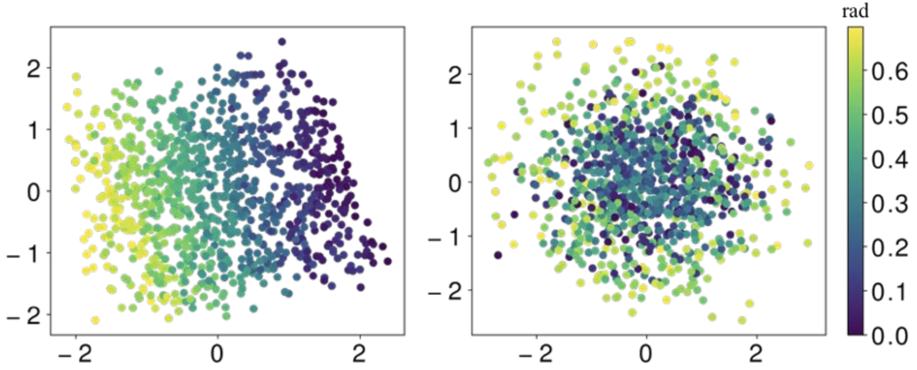




Learning what you can do before doing anything. ICLR 2019.

Learning what you can do before doing anything

1. The *inductive biases* of minimality and composability provide sufficient constraints for learning action representations just from visual observations
2. The learned representation is *disentangled* from the static scene content and visual characteristics of the environment.
3. The representation to be used for *planning* and *action-conditioned prediction* while requiring orders of magnitude less action-labeled videos.



a) CLASP (Ours) **b)** Denton & Fergus (2018)

Karl Pertsch*

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Learning what you can do before doing anything. ICLR 2019.

KeyIn: Discovering Subgoal Structure with Keyframe-based Video Prediction

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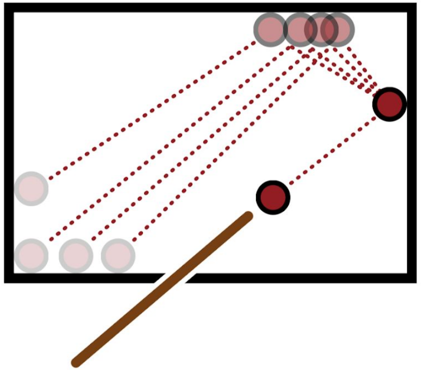
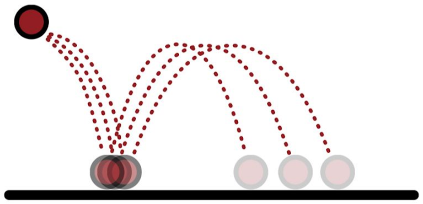
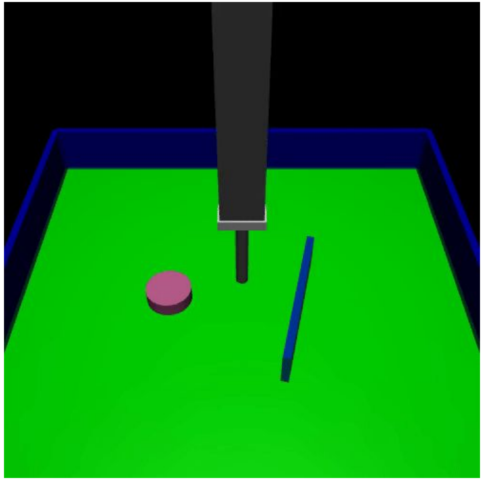
Keyframes in natural sequences



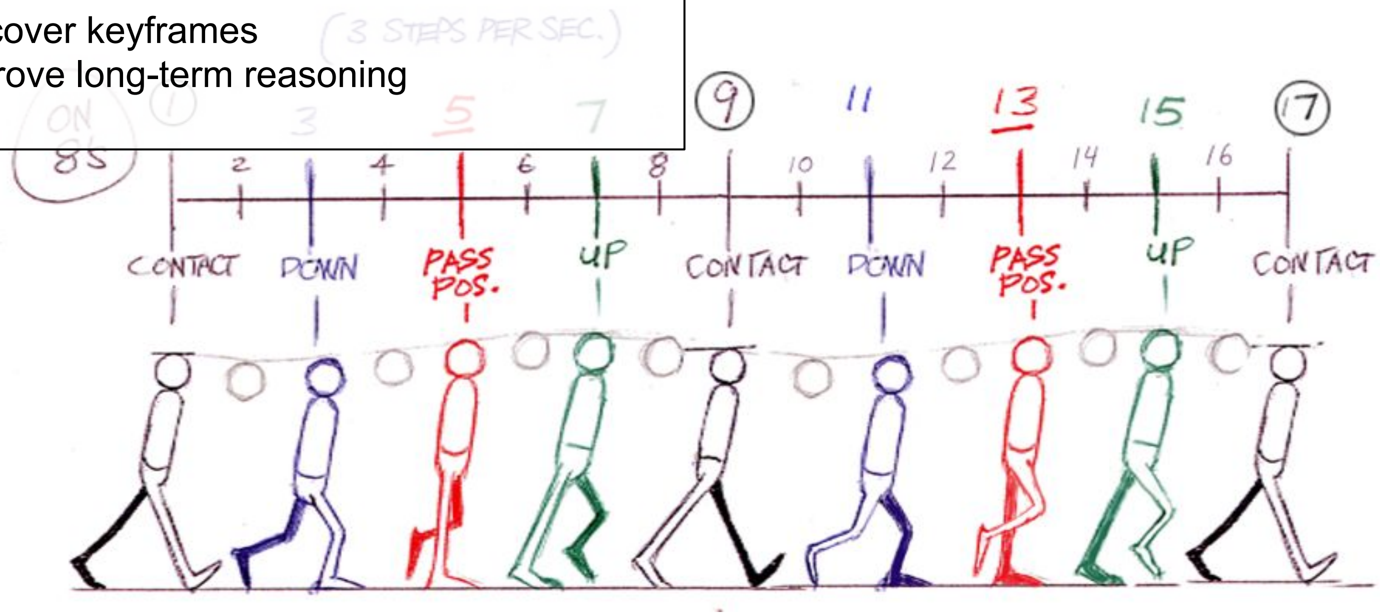




- Dynamics in complex scenes are stochastic. But not uniformly so!
- How can we exploit this structure to improve long-term reasoning?
- **Keyframes**: capture interesting structure in time, but also allow reconstruction of the full dynamics.

Keyframing

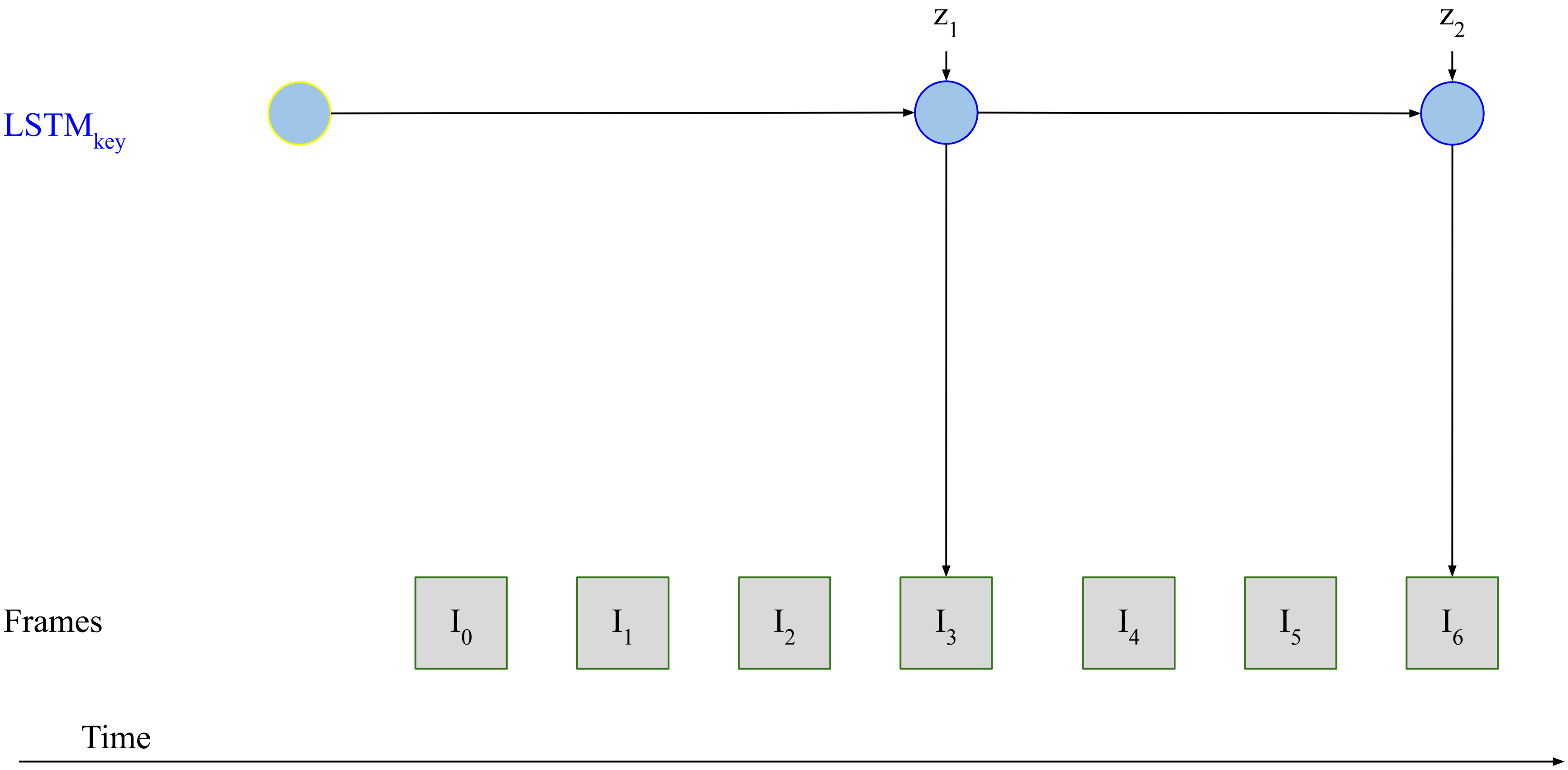
- Discover keyframes
- Improve long-term reasoning



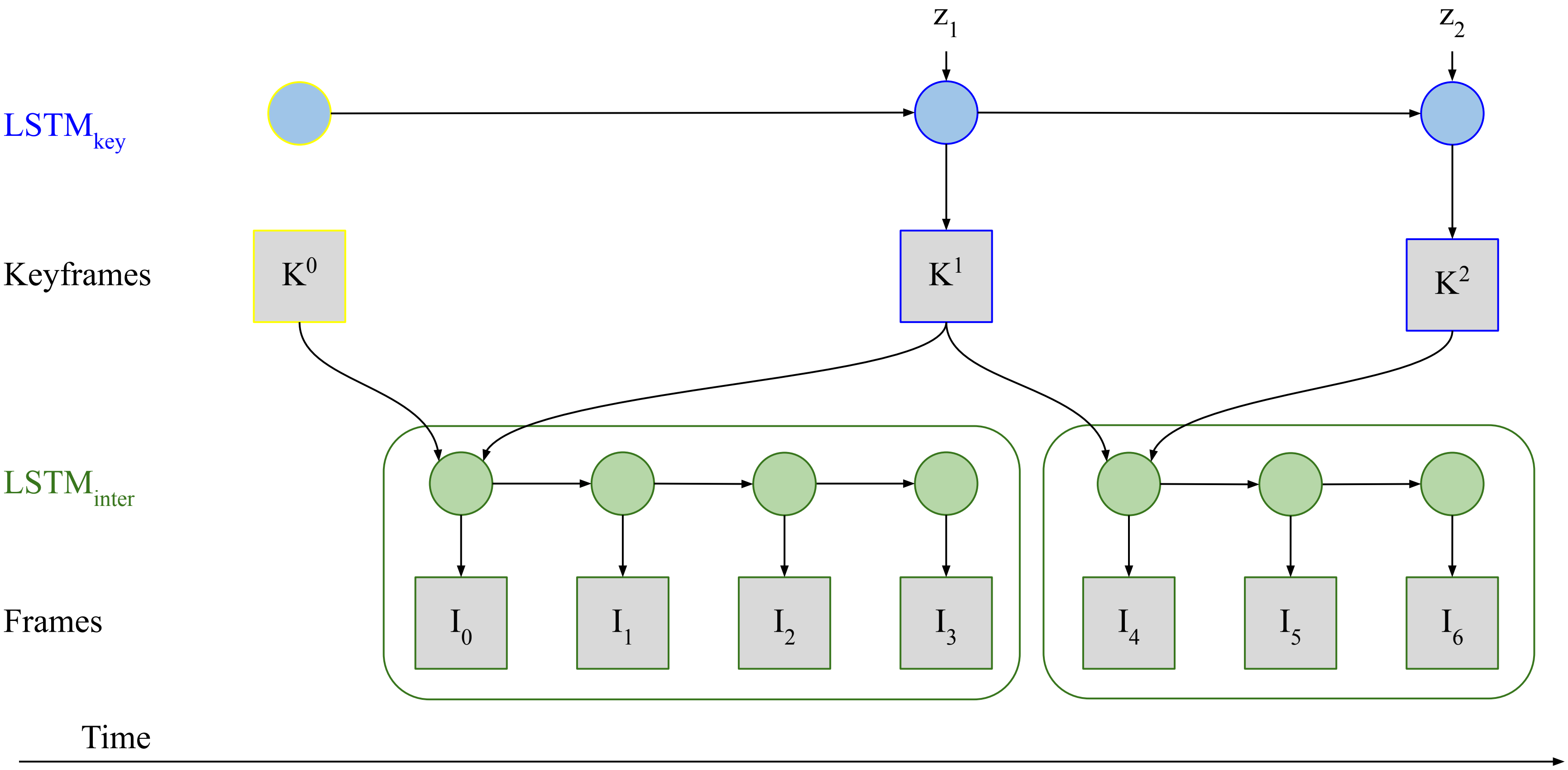
1. Draw the start and end points of all motions: define the stochastic long-term sequence dynamics (*lead animator*).
2. Interpolate between the start and end points: make the local, deterministic dynamics explicit (*inbetweener*).

Image credit: Emily Wakefield (source)

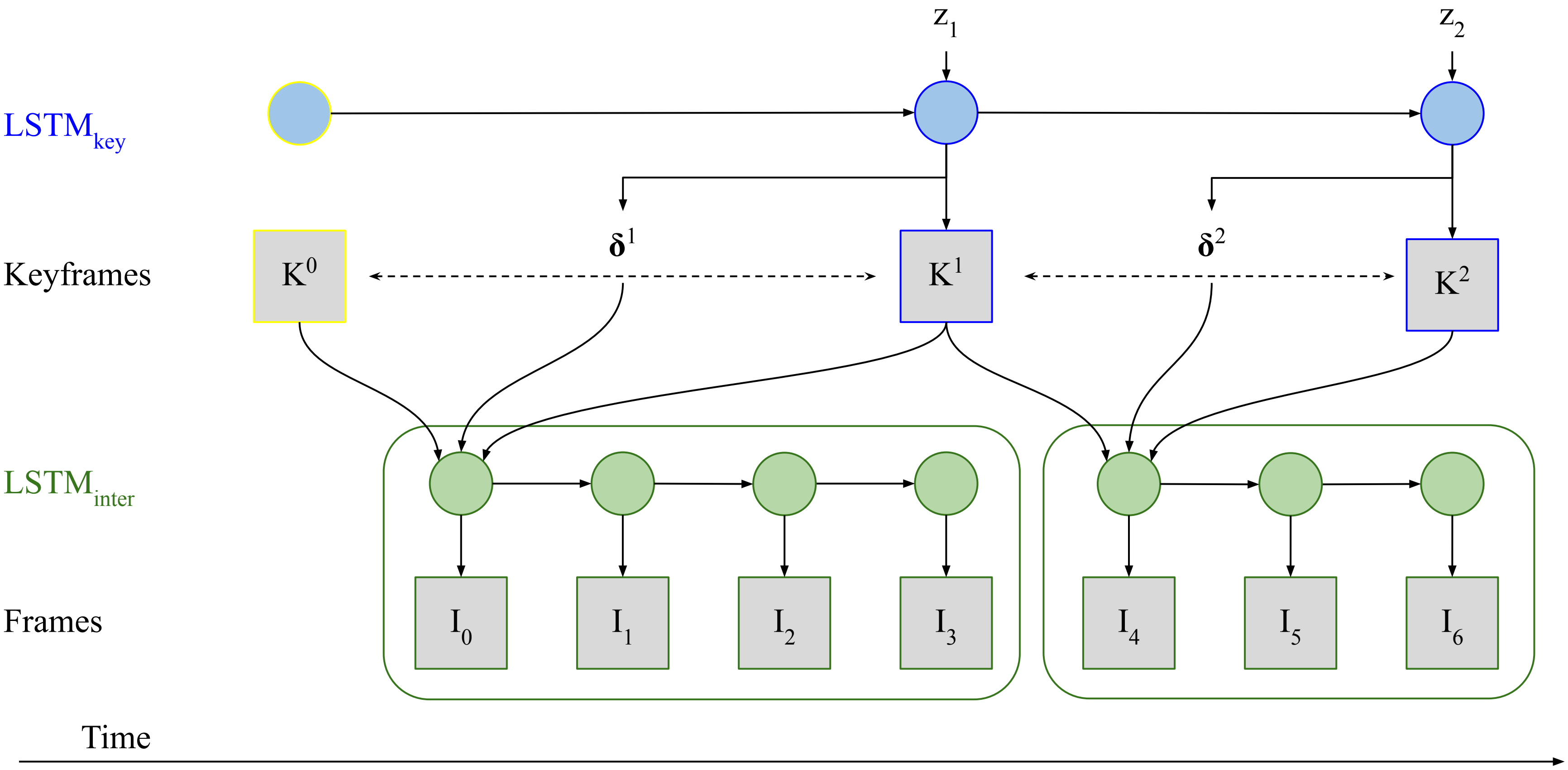
KeyIn - keyframe prediction



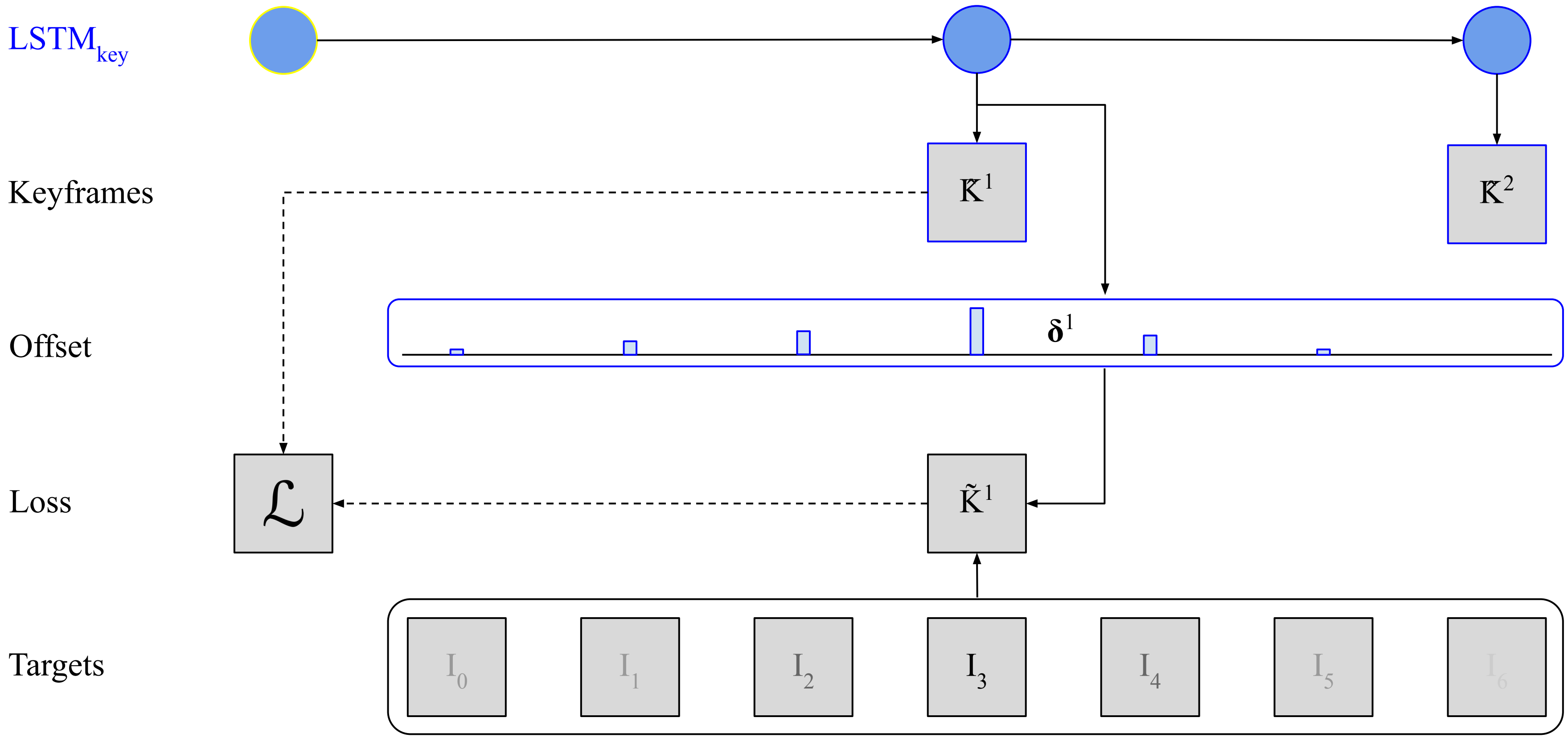
KeyIn - keyframe-based prediction



KeyIn - predicting interframe offsets



KeyIn - Continuous relaxation



KeyIn -Full loss

Soft Keyframe targets

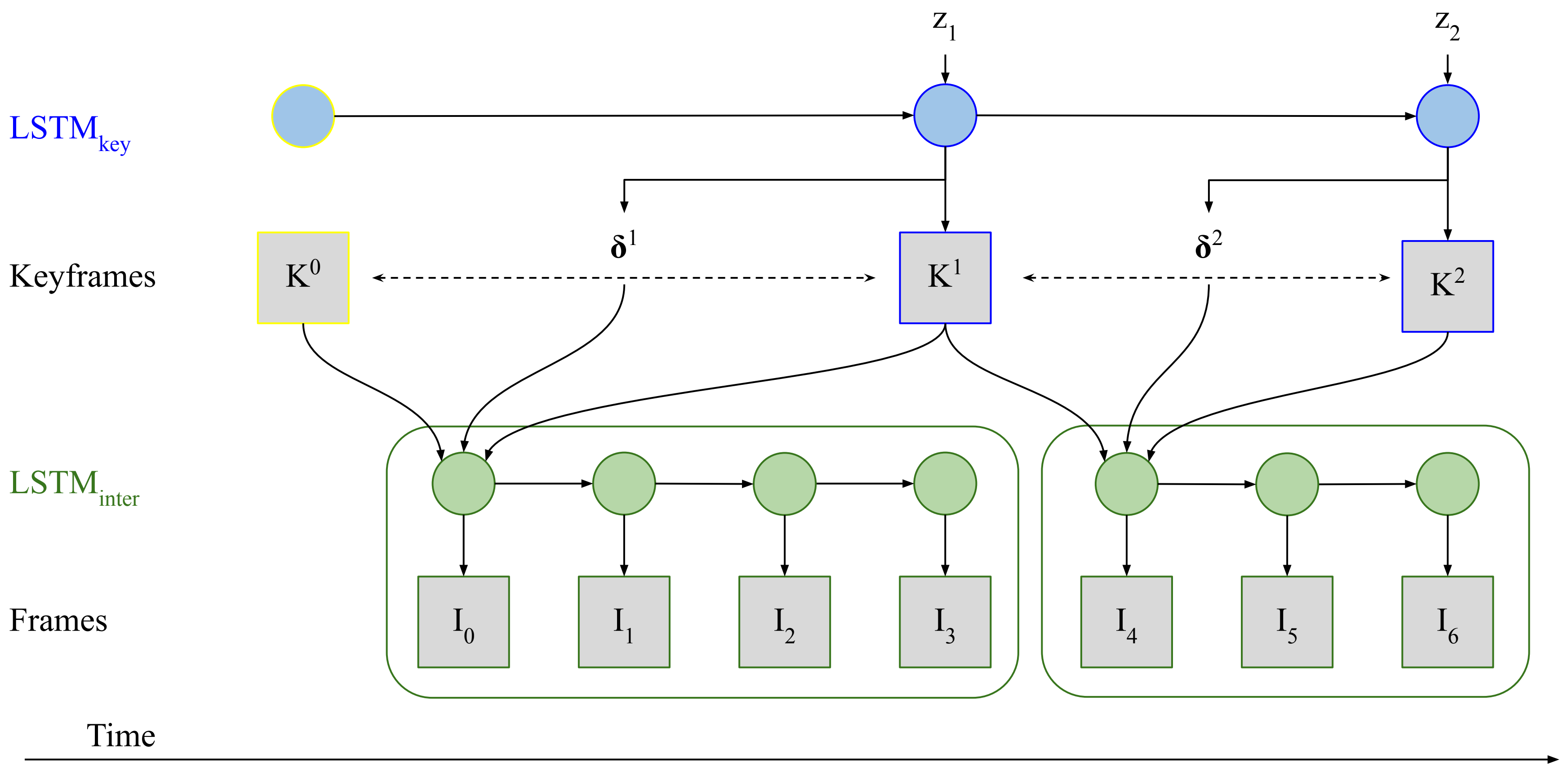
$$\mathcal{L}_{key} =(\sum_t c^t \beta_{ki} ||\hat{K}^t - \tilde{K}^t||^2$$

Soft embedding targets

Prior divergence

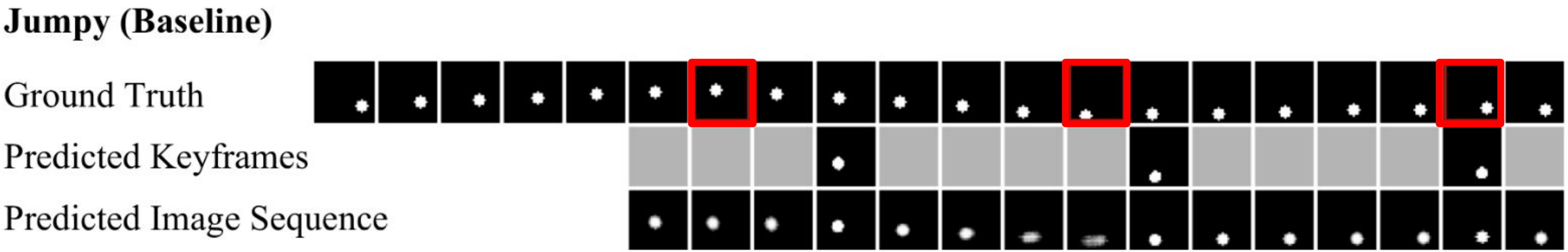
Interpolation targets

KeyIn - full method

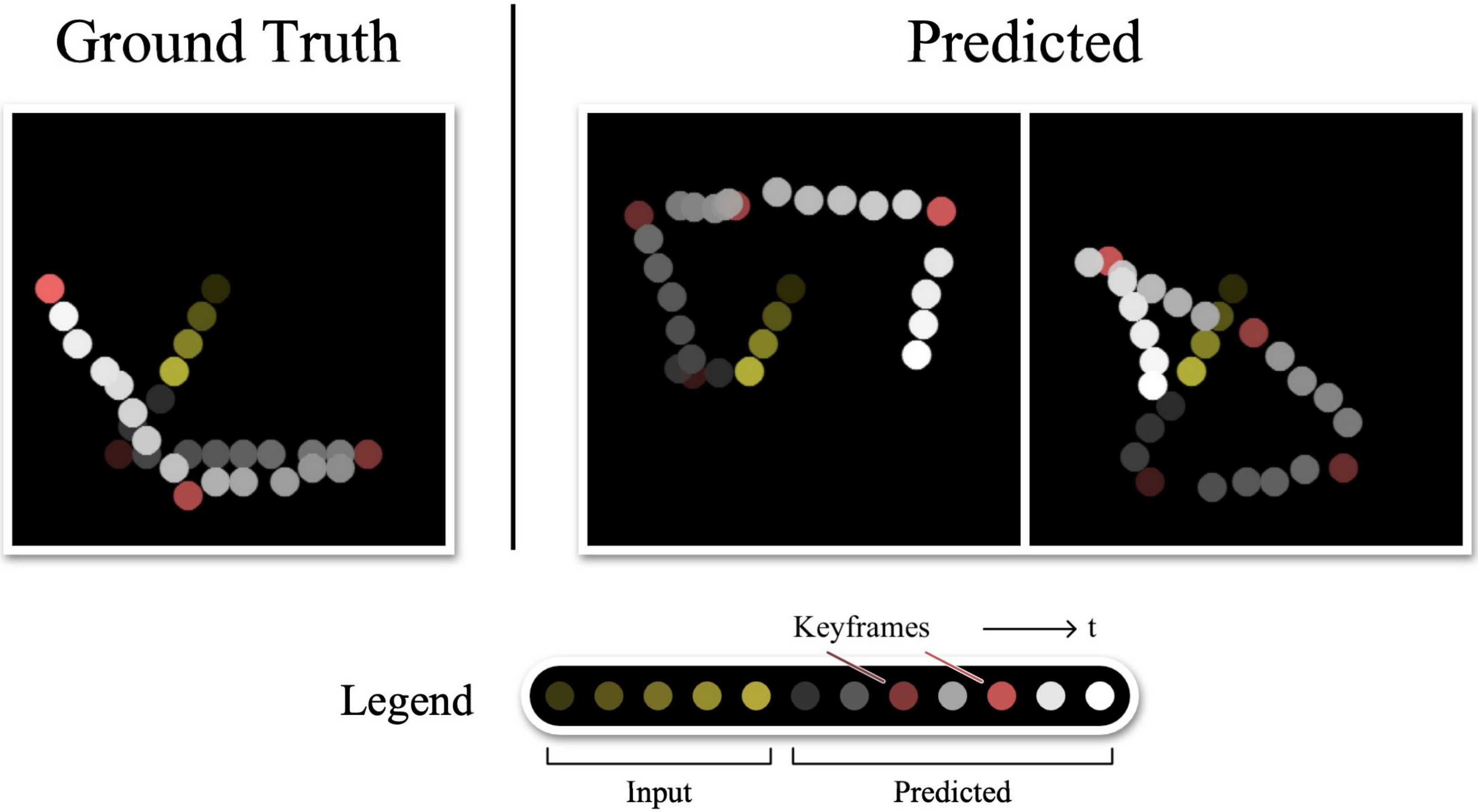


Structured Brownian motion data

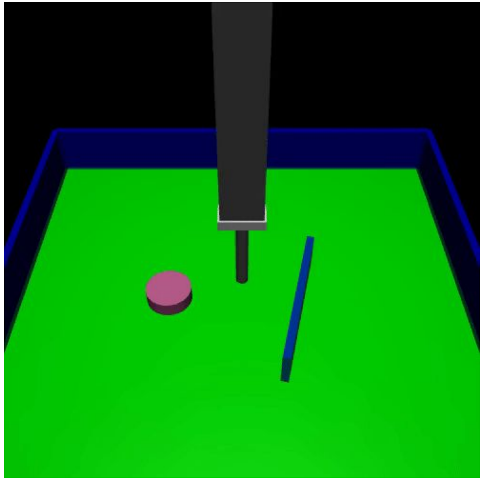
Enforcing descriptive Keyframes

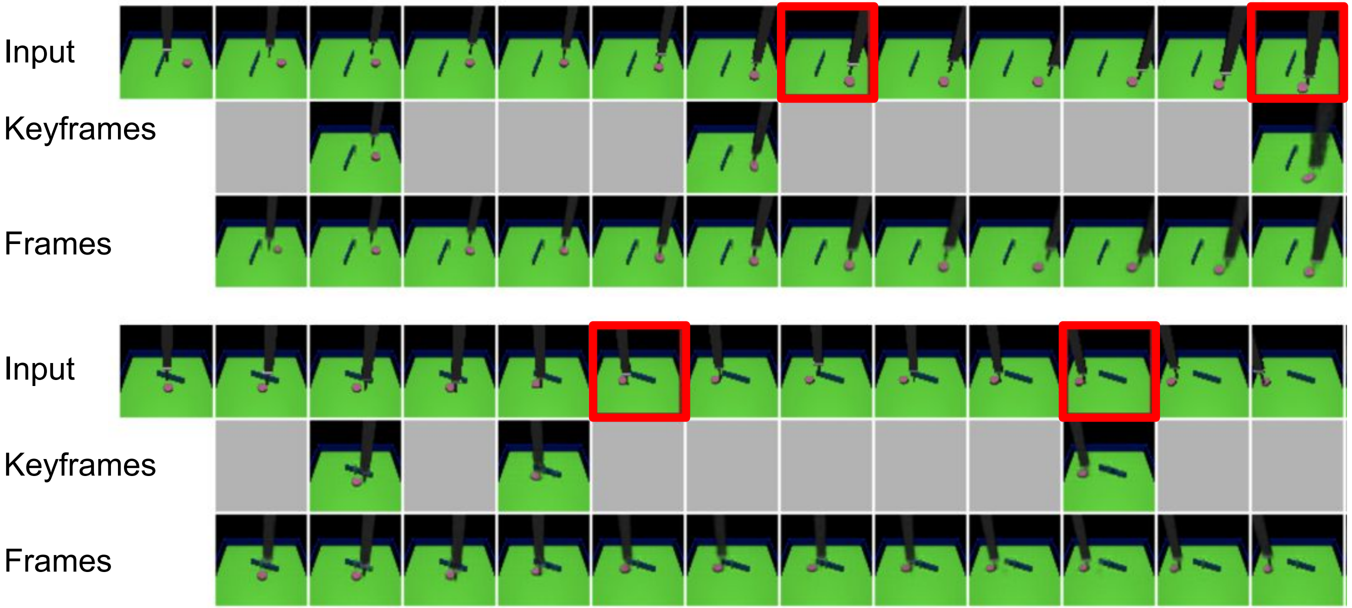


Generative model of trajectories via keyframes

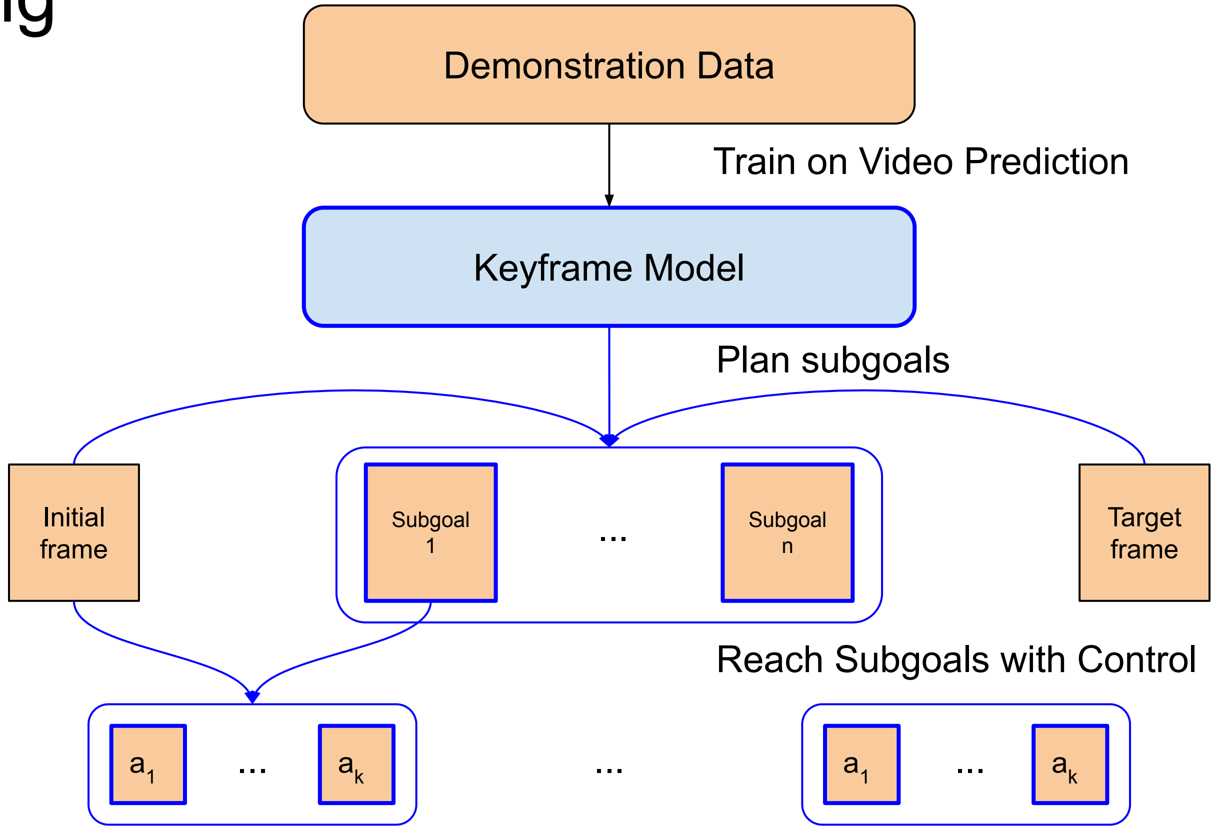


Pushing data





Planning



Ebert et Finn et al., 2018

Planning

Algorithm 1 Planning in the subgoal space.

Input: Keyframe model $\textsc{KeyIn}(.,.)$, cost function c
Input: Start and target images I_0 and I_{target}

Sample L sequences of latent variables:
$$z^{0:M} \sim \mathcal{N}(\mu_n, \sigma_n)$$
Produce subgoal plans: $\hat{K}^{0:M} = \textsc{KeyIn}(I_0, z^{0:M})$
Compute cost between produced and true target:
$$c(\hat{K}^M)$$
Choose L' best plans,

end for
Return: Best subgoal plan $K^{0:M}$

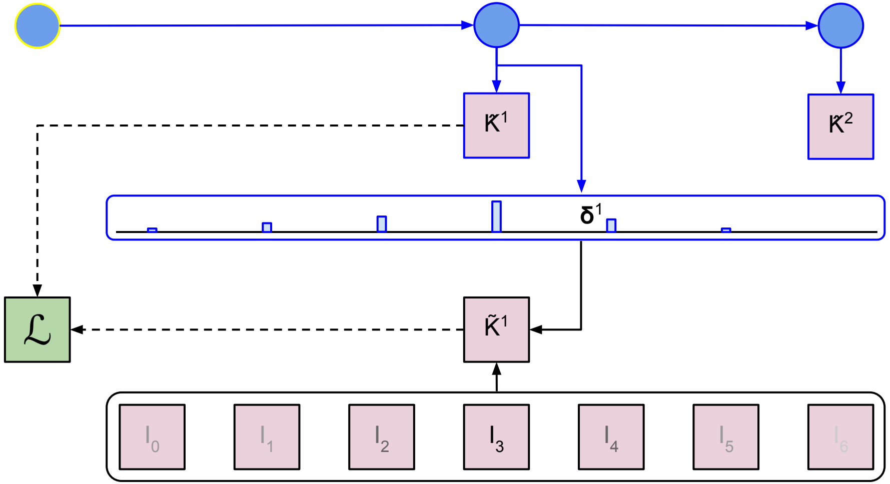
Ebert et Finn et al., 2018

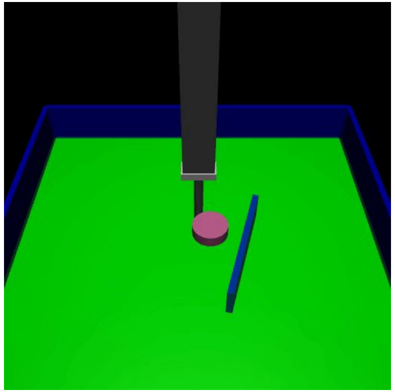
Planning on the pushing task

Method	Final position error	Success Rate
Intitial	1.32 ± 0.06	-
Random	1.32 ± 0.07	-
No subgoals	0.90 ± 0.14	$15.0\,\%$
TAP	0.80 ± 0.16	$23.3\,\%$
Jumpy	0.62 ± 0.33	$58.8\,\%$
KeyIn (Ours)	$\mathbf{0.50 \pm 0.26}$	**64.2 %**

KeyIn: Discovering Subgoal Structure with Keyframe-based Video Prediction

- The model learns to predict videos by first predicting a set of descriptive keyframes
- A differentiable loss allows to train the model to select the most descriptive keyframes
- The keyframes the model discovers are useful as subgoals for a planning task





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