

**Ai DAY** RISING TO  
**2020** THE CHALLENGES

# Predictive Coding for Locally Linear Control

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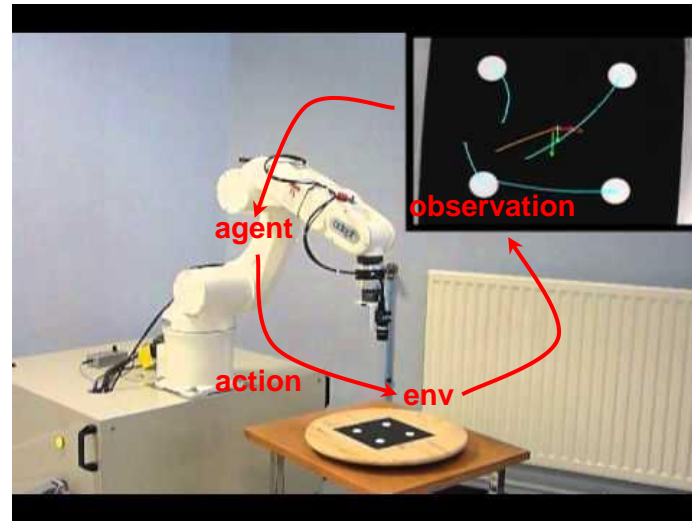
SPEAKER:

**Tung Nguyen – VinAI Resident**



# Motivation

Decision making from high-dimensional observations



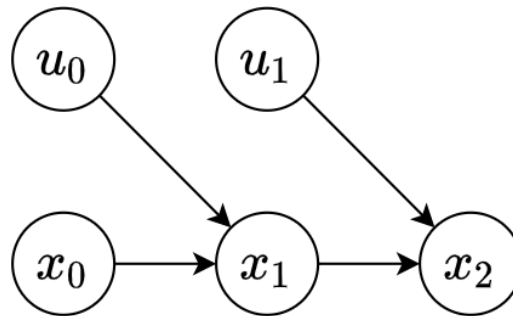
Example: Robot arm manipulation from visual inputs



# Problem Formulation

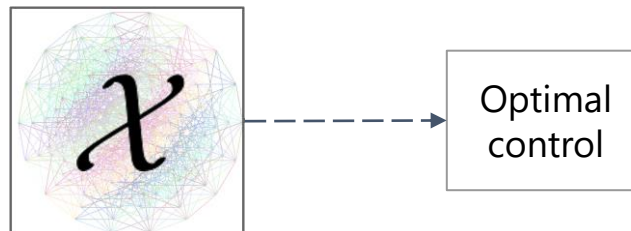
Control a high-dimensional Markov Decision Process

$$x_{t+1} = f_{\chi}(x_t, u_t) + w$$

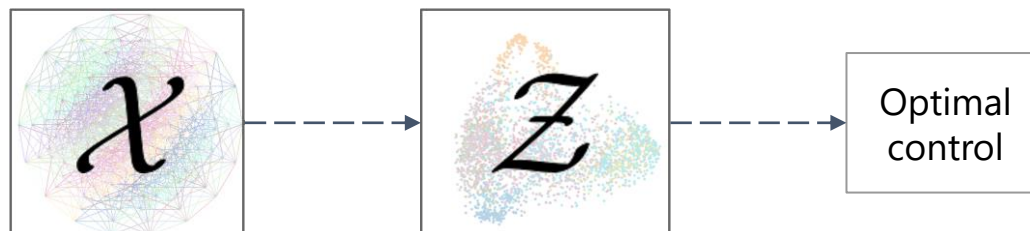


# High-Dimensional Control is Challenging

Attempt optimal control in the observation space



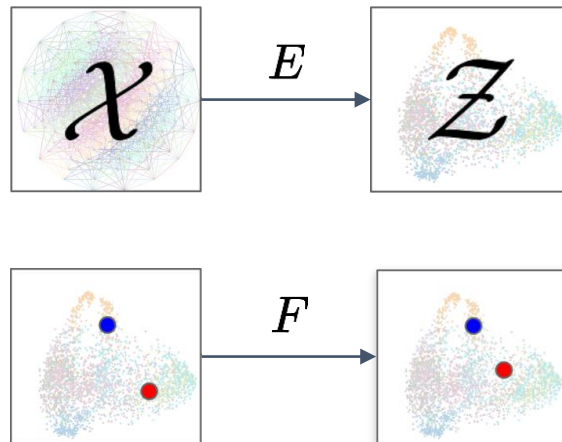
Embed then control



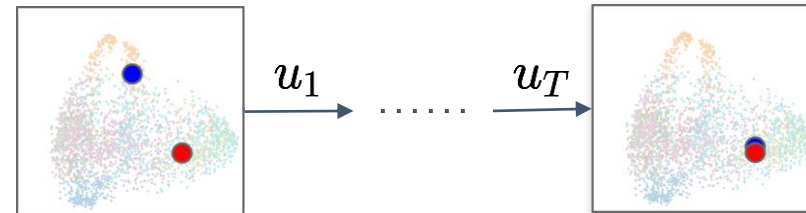
# General approach

## Learning Controllable Embedding (LCE): A two-step framework

Learn the embedding and latent dynamics

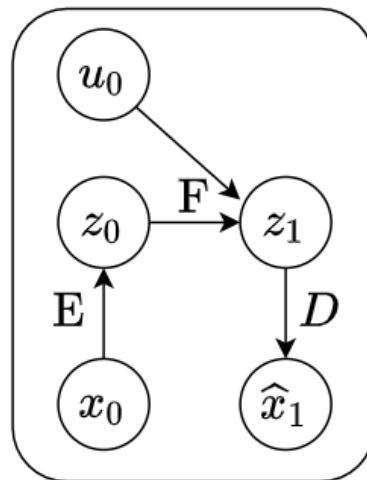


Control in the latent space



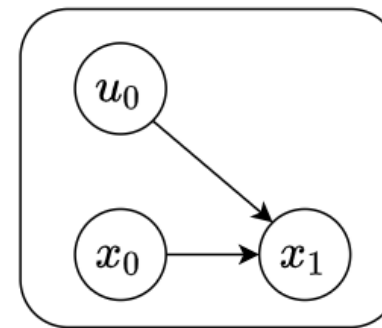
# Existing LCE Models Use Explicit Prediction

Introduce an additional decoder  $D$  and learns to predict the next observation



**Latent Variable Model**

$\approx$



**True environment dynamics**

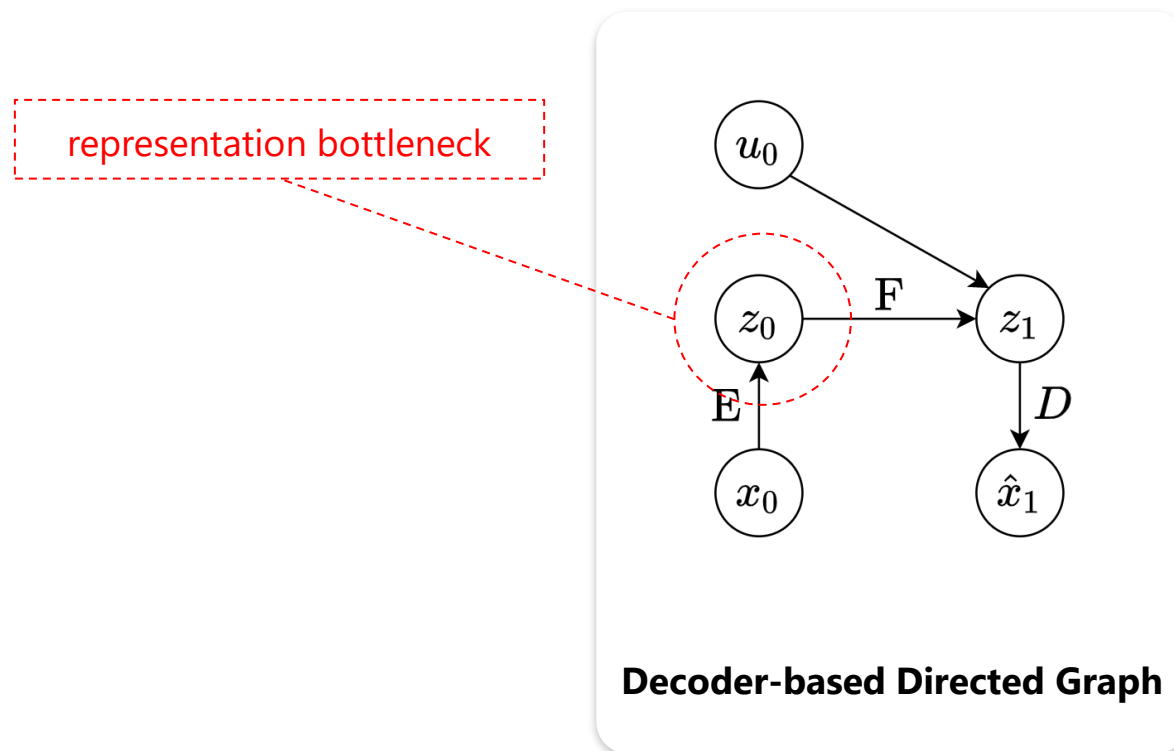
## Contributions

**Propose a decoder-free LCE-based model**

**Provide theoretical analysis for the learned embedding**

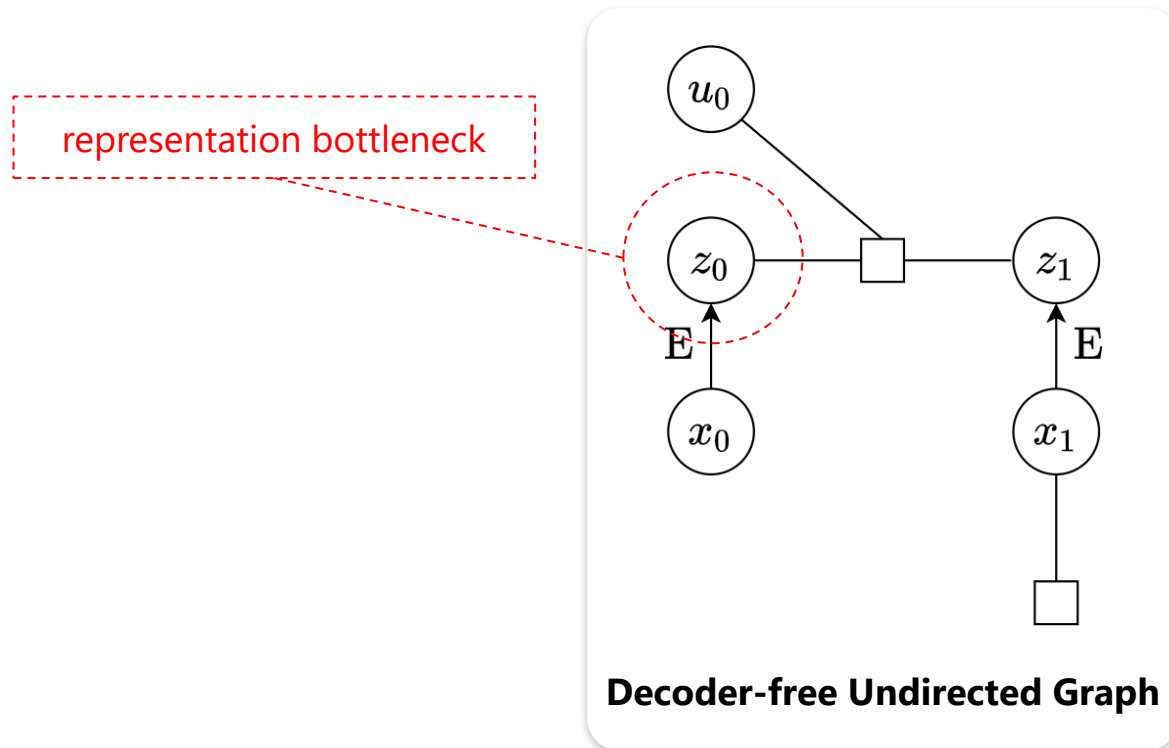
**Conduct extensive experiments**

# Learning an Embedding That is Good for Prediction





# Learning an Embedding That is Good for Prediction



## Predictive suboptimality of a representation:

The *best possible* prediction loss achievable by such this model family for a fixed choice of representation

# Learning an Embedding That is Good for Prediction

**Lemma 1:** Predictive suboptimality is upper bounded by the mutual information gap:

$$I(x_{t+1}; x_t, u_t) - I(z_{t+1}; z_t, u_t)$$

Information of  
observation data

Information captured  
in latent space

**Predictive suboptimality can be minimized in a decoder-free and information-theoretic manner**

# Learning an Embedding via Predictive Coding

Predictive coding maximizes a lower bound of  $I(z_{t+1}; z_t, u_t)$

$$\ell_{\text{cpc}} = \mathbb{E} \frac{1}{K} \sum_i \ln \frac{\overset{\text{critic}}{F}(E(x_{t+1}^{(i)}) | E(x_t^{(i)}), u_t^{(i)})}{\frac{1}{K} \sum_j F(E(x_{t+1}^{(i)}) | E(x_t^{(j)}), u_t^{(j)})}$$

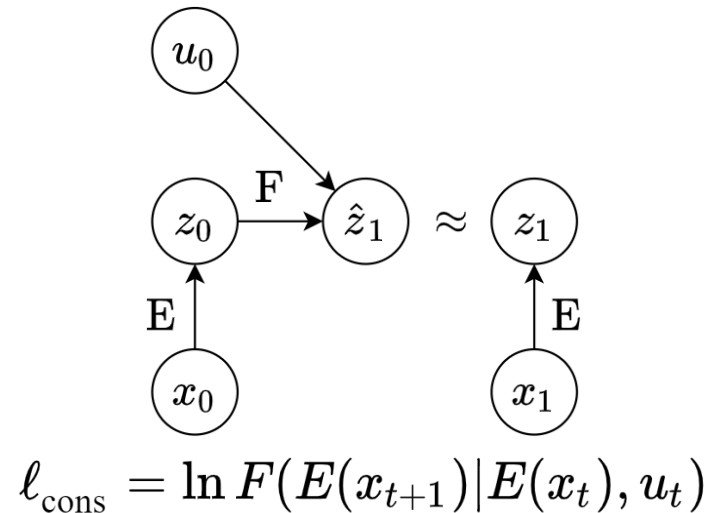
For a fixed choice of  $E$ , if  $F$  is the true latent dynamics, the CPC objective is maximized

# Estimating the Latent Dynamics via Consistency

Choosing  $F$  to be the true latent dynamics maximizes the CPC objective

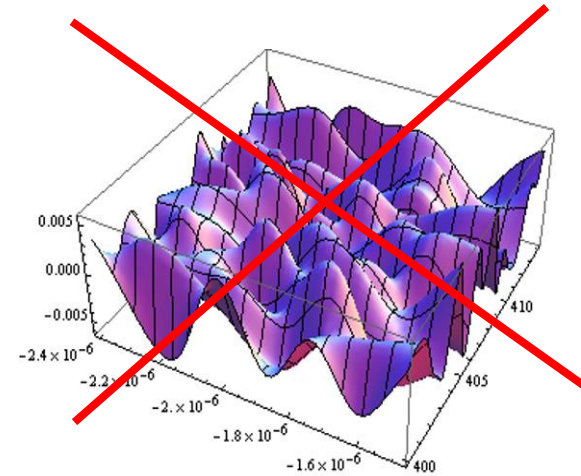
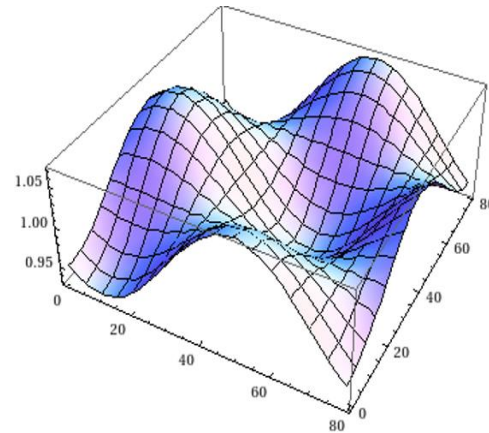
Choosing an  $F$  that maximizes the CPC objective does not imply  $F$  is the true latent dynamics model

Explicitly encourage  $F$  to estimate the true latent dynamics via a *consistency objective*



# Enforcing Smooth Latent Dynamics via Curvature

We use locally-linear controllers (LLC), so a low-curvature dynamics is preferable



$$\ell_{\text{curv}} = \mathbb{E}_{\eta \sim \mathcal{N}(0, \delta I)} [\|f_Z(\bar{z}, \bar{u}) - (\nabla_z f_Z(\bar{z}, \bar{u})\eta_z + \nabla_u f_Z(\bar{z}, \bar{u})\eta_u) - f_Z(z, u)\|_2^2]$$



# Predictive Coding, Consistency, Curvature (PC3)

$$\ell_{\text{cpc}} = \mathbb{E} \frac{1}{K} \sum_i \ln \frac{F(E(x_{t+1}^{(i)}) | E(x_t^{(i)}), u_t^{(i)})}{\frac{1}{K} \sum_j F(E(x_{t+1}^{(i)}) | E(x_t^{(j)}), u_t^{(j)})}$$

$$\ell_{\text{cons}} = \ln F(E(x_{t+1}) | E(x_t), u_t)$$

$$\ell_{\text{curv}} = \mathbb{E}_{\eta \sim \mathcal{N}(0, \delta I)} [\|f_Z(\bar{z}, \bar{u}) - (\nabla_z f_Z(\bar{z}, \bar{u})\eta_z + \nabla_u f_Z(\bar{z}, \bar{u})\eta_u) - f_Z(z, u)\|_2^2]$$

$$\lambda_1 \ell_{\text{cpc}} + \lambda_2 \ell_{\text{cons}} + \lambda_3 \ell_{\text{cur}}$$

**Maximize CPC**

**Maximize Consistency**

**Minimize curvature**

**Learn good embedding  $E$**

**Learn good dynamics  $F$**

**$F$  is suitable for LLC**

## PCC vs PC3

### Baseline

	<u>PC3</u>	PCC
Predictive Coding	✓	✗
Prediction	✗	✓
Consistency	✓	✓
Curvature	✓	✓
iLQR Controller	✓	✓

**PC3 is contrastive analog of PCC**

## PCC vs PC3

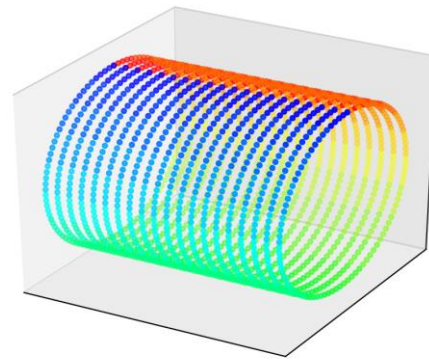
### Control performance

Train 10 models, run 10 subtasks for each model (total 100 trials/method)

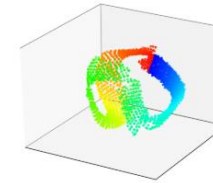
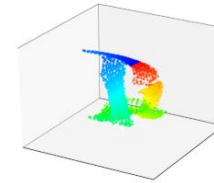
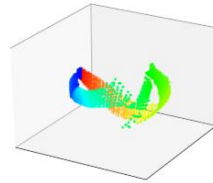
Task	PC3 (all)	PCC (all)	PC3 (top 1)	PCC (top 1)
Planar	<b>74.35 ± 0.76</b>	56.6 ± 3.15	<b>75.5 ± 0.32</b>	<b>75.5 ± 0.32</b>
Balance	<b>99.12 ± 0.66</b>	91.9 ± 1.72	<b>100 ± 0</b>	<b>100 ± 0</b>
Swing Up	<b>58.4 ± 3.53</b>	26.41 ± 2.64	<b>84 ± 0</b>	66.9 ± 3.8
Cartpole	<b>96.26 ± 0.95</b>	94.44 ± 1.34	<b>97.8 ± 1.4</b>	<b>97.8 ± 1.4</b>
3-link	<b>42.4 ± 3.23</b>	14.17 ± 2.2	<b>78 ± 1.04</b>	45.8 ± 6.4

# PCC vs PC3

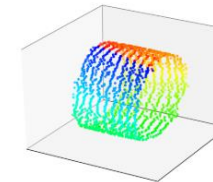
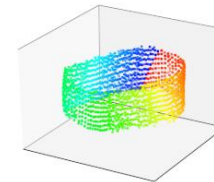
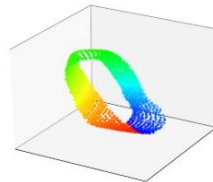
## Latent maps



True state space



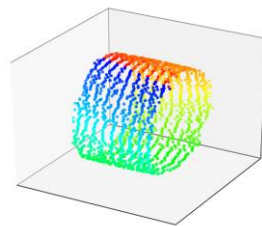
PCC



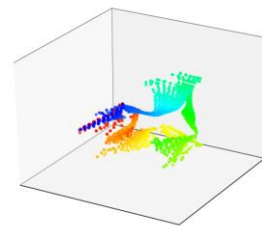
PC3

# Ablation Analysis

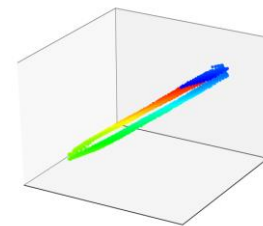
Setting	$\ell_{\text{cpc}}$	$\ell_{\text{cons}}$	$\ell_{\text{cur}}$	Control
PC3	4.58	2.13	0.03	$58.4 \pm 3.53$
w/o $\ell_{\text{cons}}$	5.03	-4.87	0.0025	$7.46 \pm 1.32$
w/o $\ell_{\text{cur}}$	4.8	2.34	0.56	$21.69 \pm 2.73$



PC3



Without  $\ell_{\text{cons}}$

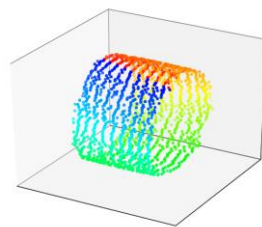


Without  $\ell_{\text{cur}}$

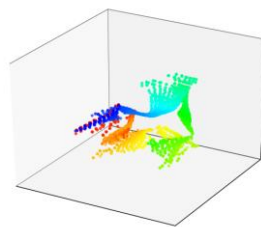


## Ablation Analysis

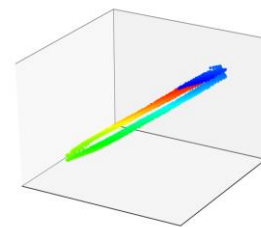
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PC3



Without  $\ell_{\text{cons}}$



Without  $\ell_{\text{cur}}$

# Conclusion

- ❑ Predictive Coding-Consistency-Curvature (PC3) outperforms existing LCE-based models
- ❑ Promising information-theoretic extension of the LCE framework
- ❑ Future work
  - ❑ Scale to more complicated domains
  - ❑ Predictive coding in conjunction with other control algorithms

# Thank you for listening!



Paper Link



[www.vinai.io](http://www.vinai.io)