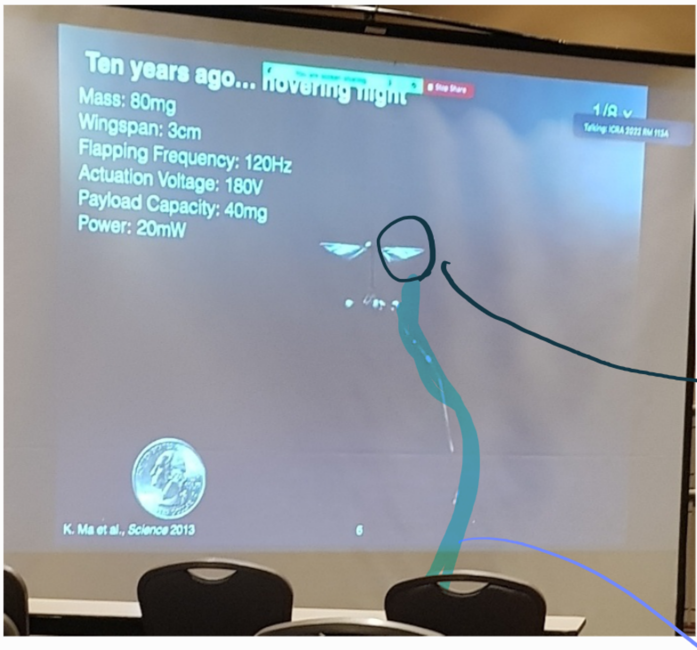
Mon 09:00 Workshop (SoRo)

* Bioinspiration 잠자리 로봇

★ Microrobots (still constrained in Lab environments)

↳ autonomous platform needed.



← 요런 잠자리로봇을 만든 분이심.

* mesoscale manufacturing

* piezoelectric bimorphs

날개 한땀한땀...

↳ locomotion generation

"control strategy"

tethered system !!!

★ Power ★ 에 관해서.

actuation signals / mass & payload 문제.

⇒ voltage amplifier

★ high voltage & time-varying signal

회로 power amp를 위한 과정

⇒ PV 태양전지를 사용

* mass 줄이기

\+ force 효율 높이기

계속 mass를 줄여나가는 과정

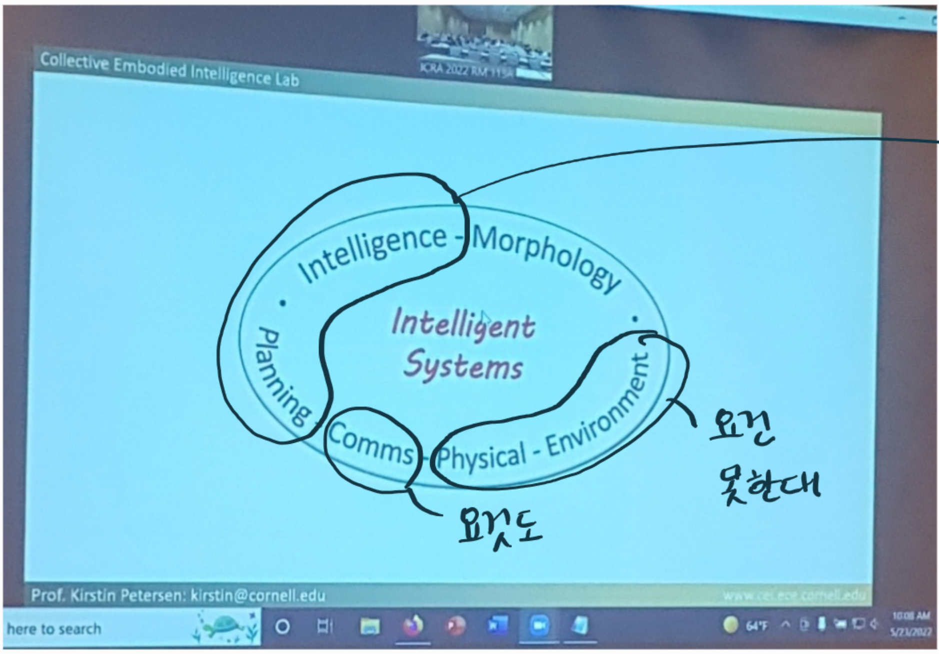
FLYING SOLO

★ 1회성 연구로 끝나는게 아쉬운

나 연구들...?

Full story를 만들기 위한 과정 ★

(10:00 Talk)



→ 자기 lab 학생들 대부분이 매우 잘함

"modular soft robot"

↑ robot collectives?

* "distributed" sensor & actuator network. ☆

Deformable robot collectives — planning (A* 부터 복잡한 것까지)

↑ leveraging

"Gap filling" (소프트 로봇만이 할수있음)

↑ simulation-based ☆ ⇒ hardware-level 상에서 먼저!!

(genetic algorithm 등)

* 문제이긴 함.

Mon (13:30) Workshop (RL for Robotics)

* safe-control-gym (safe-learning-based control)
  - model-based control designs
  - hand-tuned control parameters.
  - large prior uncertainties,
  - active decision making

COMPLEXITY (design, environment)

12:30-13:30	Lunch Break
13:30-14:30	safe-control-gym: a Unified Benchmark Suite for Safe Learning-based Control and Reinforcement Learning
14:30-15:15	Automatic Hyperparameter Optimization
15:15-16:00	Hyperparameter Tuning with Optuna
16:00-16:15	Break

- 더이상 modeling + validation은 힘들다.

BUT ① prior knowledge availability
- data 얻는게 effort 필요.

② disturbances & noises

③ safety & constraint satisfaction.

* SAFE robot learning.

(Safe learning in Robotics: From L-B control to safe RL)

① system model
② cost function describes task
③ constraints
- soft constraints (encourage safety)
- probabilistic " (no violations w/ high prob)
- hard " (no violations)

{Prior, Data} → π_k

pure control ↑ ↖ pure RL

* safely learning uncertain dynamics
* RL encouraging safety & robustness
* safety certificate & filter

* GAP b.w. learning-based vs control theorists.
↖ 요걸 줄이기 위한 노력들 많이 한다.

* 정형화된 "metric"을 정의하는 것이 좋은가?

$\boxed{\text{YES}}$ 정량적인 평가 자료가 되므로.

$\boxed{\text{NO}}$ 그 task의 SOTA에 맞추기 위한 무의미한 시간 소요.

* Automatic Hyperparameter tuning

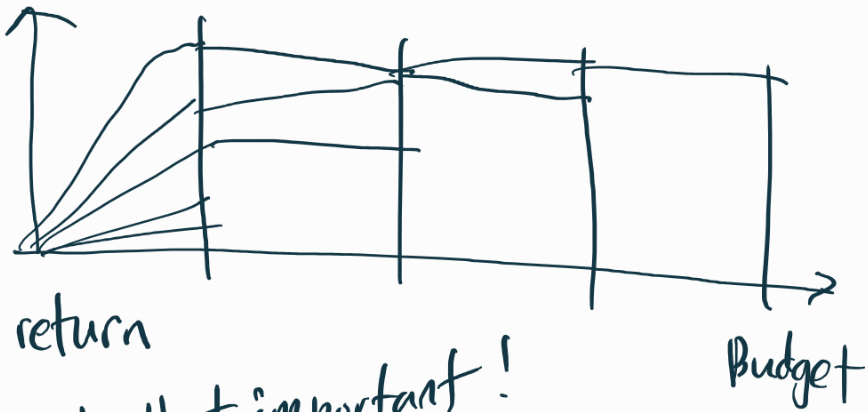
fair comparison w/ baselines

- n vs B/n tradeoff
- samplers (search algo.)
- schedulers (pruner)

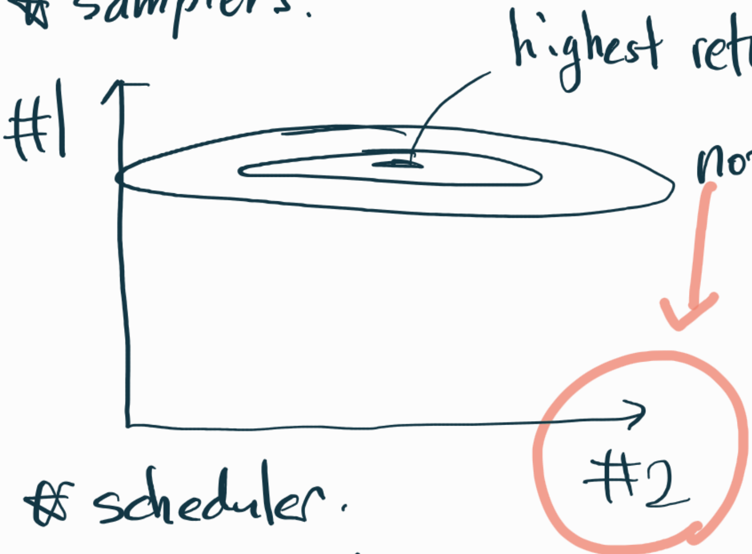
☆ n vs B/n tradeoff

\# configuration

Budget per config.



☆ samplers.



not that important!

- Grid search 안좋음
- random search 은따라
- Bayesian Optimization

☆ scheduler.

* Hyperband * ⇒ successive halving

median pruner

☆ OPTUNA ☆

① define search space

② define objective fcn.

③ sampler & pruner

import optuna

RL Zoo

Mon 16:00 Workshop : Real-World Robot

RealTime Robotics Inc

\# Robotics in Academia vs practicality (real life)

↳ open-loop

no sensors (용접로봇)

☆ Industrial Robots

\# Horizontal vs Vertical

경쟁, 신절

components (ex. processor)

완제품

\# Know Your Market (= Reviewers)

☆ Automation Costs

= operation cost + acquisition cost

☆ Customer // Integrators integrate

☆ Product means Reliability ☆ Innovation

" Intellectual property " 가 중요? Industrial 에서 (controvertial)

☆ technology readiness level (TRL)

Tue Plenary

"Humans" have cognitive bias w.r.t. intelligent agents.

"Support the needs" (bias trust)

$\underline{\text{CAN}}$ robot manipulate human behavior?

「When a Robot Tells You It Can Lie」

* 거북 / 어색하지만 acceptable (robot interact with human)

「Embodiment Conditions」

Howard. 「Intelligent Agent Deception …」

Robots improve our life.

$\boxed{\text{BUT}}$ Implications for healthcare, bias, data privacy

<u>Biases</u> { race, gender, age }

☆ Addressing BIAS in ML Algorithms

Robot <u>gender</u>?

성별 주어지지 않았을때 대부분 실험 참가자들은 로봇을 male로 간주.

$\boxed{\text{BUT}}$ 로봇에 gender를 부여하든 말든 상관없음 //

여자 참가자가 남자 이미지의 표정을 구별하는 task를 부여받을때 로봇 recommendation에 더 많이 의존 (여자 이미지 구별과 비교했을때)

「Diversity in AI: The invisible men and women」 (2020)

Tue Morning Technical Program

* Sensor fusion *

⇒ Lie Group 상에서 Gaussian Kernel의 중첩 model을 사용하는 방법

⇒ Graph Attention Network-based localization.

☆ Data ☆ 를 얻는 과정과 valuability를 중요 문제로 삼았음.

Tue Afternoon Technical Program

* Representation Learning, SLAM & Exploration *

⇓

"latent representation"

NN 안쪽을 살펴보고 최적화

* Robot communication "

+ interaction

* 간단한 예제

→ 복잡하게 확장.

☆ "Particle"

↖ 이게 많이씀.

"kernel herding"

(

⇓

Graph optimization 기반 방법이 많음

⇒ Task-specific Applications 많음.

뭔가 breakthrough 필요...?

* ensemble KF (recursive Bayesian filter)

-LiDAR-

⇑

* Camera error

(굴절 등으로 인한 reconstruction error) 보정을 위한

"알고리즘" 위주.

* Point cloud에 대한 연구 많음

* "Global 기준"이 없다.

"RKHS (samples mapping)"

Wed. Plenary Human-Machine Partnerships. (Julie Shah)

Robot이 직업을 뺏어갈 것인가??

NO 오히려 creating new works.

Era 로봇작업공간 접근불가 (No enter)

→ 사람과 공간 공유 but 길 터줘야함 (out of way)

→ ???

① 로봇 작업공간 들어가면 아예 멈추는 방법

② sensing + interacting.

③ human motion prediction & planning

★LfD: task-level info 필요하다.

direct

Domain Expert ⇄ Robot

coding engineer (logic controller)

이거 해줄사람?

flexibility

task-specific reactions!!

"temporal logic limitation

learning plan-satisficing motion policies from demonstration"

(3rd) programming for collaboration

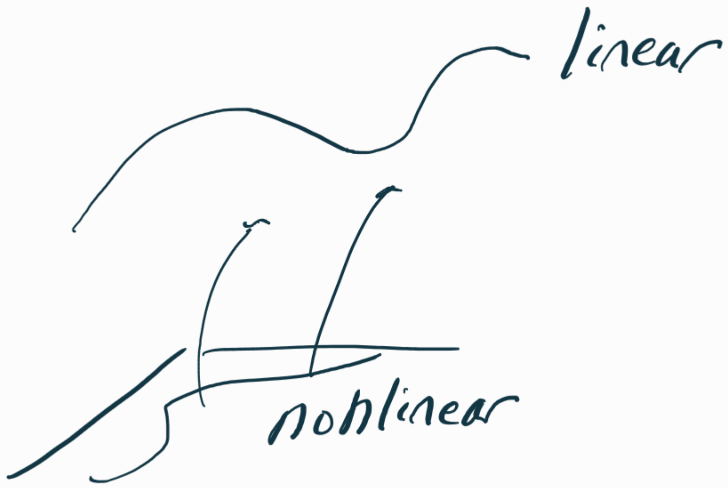
* A quality diversity approach to automatically ... ☆

☆ RoCUS 논문

Fri. Workshop -- Harry Asada Prof, MIT

— Koopman Operator and Lifting Linearization —

* Augmenting / Lifting the input space.



$$\frac{dz}{dt} = Az$$

$$\uparrow$$

$$\frac{dx}{dt} = f(x)$$

(example)

$$\begin{pmatrix} \dot{x}_1 \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} a x_1 \\ b(x_2 - x_1^2) \end{pmatrix} \Rightarrow z_1 = x_1 \quad z_3 = x_1^2$$

$$z_2 = x_2$$

then
$$\begin{pmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \end{pmatrix} = \begin{pmatrix} a z_1 \\ b(z_2 - z_3) \\ 2a z_3 \end{pmatrix}$$

* no approximation needed.

* Hamiltonian systems & transformations in hilbert space *

* General nonlinear dynamical systems cannot be exact linear eqn' of finite order, BUT as inf. order of systems.

$$\boxed{K_f \varphi = \varphi \circ f}$$

* orthonormal functions $\int_a^b \varphi_i(x) \varphi_j(x) w(x)\, dx = \delta_{ij}$

* Hilbert space : complete inner-product space
① ②

$\{x_n\}_{n=1}^{\infty}$ are orthonormal in H, then

$$x = \sum_{n=1}^{\infty} \langle x, x_n \rangle x_n \, , \quad \forall x \in H.$$

$$\text{also } \|x\|^2 = \sum_{n=1}^{\infty} \|\langle x, x_n \rangle\|^2.$$

* if f is a function in H, then

$f = \sum_{k=1}^{\infty} \langle f, \psi_k \rangle \psi_k$ where ψ are orthonormal bases.

L2 $\boxed{K_f \varphi = \varphi \circ f}$

$$\left[\begin{array}{l} x_{t+1} = F(x_t) \\ y_t = \underbrace{g(x_t)}_{\text{observable}} \end{array}\right\} \quad g(x_{t+1}) = \underbrace{g[F(x_t)]}_{g\circ F = g(F(x))}$$

basis $\{\varphi_1, \varphi_2, \cdots, \varphi_k\} \in \mathcal{H}$.

$g \in \mathcal{H}$ is $\quad g(x) = \sum_{k=1}^{\infty} a_k \varphi_k(x).$

$$a_k = \langle g, \varphi \rangle = \int_X g(x) \overline{\varphi_k}(x)\, dx.$$

$$g \circ F = g(F(x))$$

$$= \left(\sum_{k=1}^{\infty} \langle g, \varphi_k \rangle \varphi_k \right) \circ F$$

$$= \sum_{k=1}^{\infty} \langle g, \varphi_k \rangle (\varphi_k \circ F)$$

$$= \sum_{k=1}^{\infty} \int_X g(\xi) \overline{\varphi_k}(\xi)\, d\xi \; (\varphi_k \circ F)$$

$$= \int_X \sum_{k=1}^{\infty} \varphi_k[F(x)] \overline{\varphi_k}(\xi) g(\xi)\, d\xi$$

$$= \int_X \underbrace{K(x,\xi)}_{\text{type of kernel}} g(\xi)\, d\xi$$

Prop 1 $g \in \mathcal{H}$, $g \circ F = \int_X K(x,\xi)\, g(\xi)\, d\xi$,

$$K(x,\xi) = \sum_{k=1}^{\infty} \varphi_k[F(x)]\, \overline{\varphi_k}(\xi)$$

"Linearity" between g & $g \circ F$

kernel "encodes" the state transition $F(x)$ using basis φ.

☆ Kernel matrix

$\int_X K(x,\xi)\, g(\xi)\, d\xi$ as

$K_F \simeq \{K(x^i, \xi^j)\}\Delta\xi$ points x^i, ξ^j

$$g_F = K_F\, g$$

$$g_i \circ F = \int_X K(x,\xi)\, g_i(\xi)\, d\xi, \quad g_i \in H.$$

$$[g_1 \circ F \;\; g_2 \circ F \;\cdots] = \int_X K(x,\xi)\, [g_1(\xi) \;\; g_2(\xi) \;\cdots]\, d\xi$$

↳ g are the observables

$$\begin{bmatrix} g_1[f(x^1)] & g_2[f(x^1)] & \cdots \\ g_1[f(x^2)] & & \cdots \\ \vdots & & \end{bmatrix} = K_F \begin{bmatrix} g_1(x^1) & g_2(x^1) & \cdots \\ g_1(x^2) & & \\ \vdots & & \end{bmatrix}$$

$$= \begin{bmatrix} g_1(x^1_{t+1}) & g_2(x^1_{t+1}) & \cdots \\ g_1(x^2_{t+1}) & & \\ \vdots & & \end{bmatrix}$$

different viewpoints

$Y = K_F X$

time evolution.

revolution transformation

요걸 알아야해

* viewing from "different g" (다른점에서 본 것들 모음)

$$\left.\begin{aligned} X^T K_F^T &= A X^T \\ A &= X^T K_F^T (X^T)^+ \end{aligned}\right) \quad \text{Approximated}$$

$$\chi[F(x)] = A\chi(x)$$

* A is given by

$\chi = \begin{bmatrix} g_1(x_t) \\ g_2(x_t) \\ \vdots \end{bmatrix}$ is lifting

$$A = \sum_{j=1}^{\infty} \begin{bmatrix} \langle g_1, \varphi_j \rangle \\ \langle g_2, \varphi_j \rangle \\ \vdots \end{bmatrix} [\langle \varphi_j \circ F, g_1 \rangle, \langle \varphi_j \circ F, g_2 \rangle, \cdots]$$

$$\begin{bmatrix} g_1[f(x)] \\ g_2[f(x)] \\ \vdots \end{bmatrix} = [A] \begin{bmatrix} g_1 \\ g_2 \\ \vdots \end{bmatrix}$$

어떻게??

$\boxed{\text{by } \varphi_i \circ F \in H}$

* if we use $g = \varphi$, then

$$\bar{A} = \begin{bmatrix} \langle \varphi_1 \circ F, \varphi_1 \rangle & \langle \varphi_1 \circ F, \varphi_2 \rangle & \cdots \\ \langle \varphi_2 \circ F, \varphi_1 \rangle & \langle \varphi_2 \circ F, \varphi_2 \rangle & \cdots \\ \vdots & \vdots & \end{bmatrix}$$

$$\because \langle g_i, \varphi_j \rangle = \langle \varphi_i, \varphi_j \rangle$$

☆ $g_1, g_2, \cdots$ must be orthonormal.

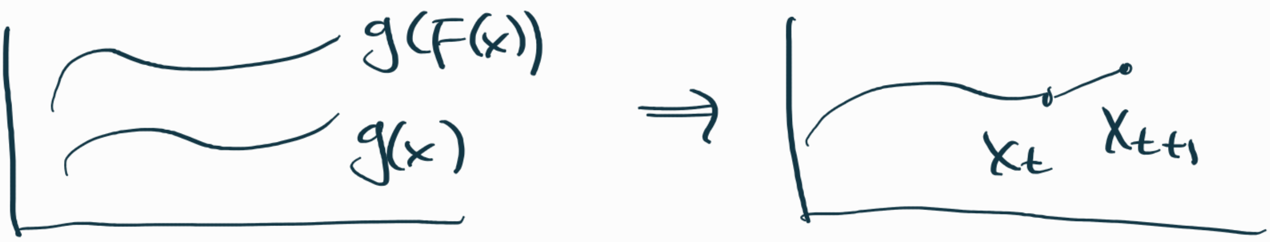
Let $\{g_1, g_2, \cdots\}$ independent

just set $g_i = \sum \langle g_i, \varphi_k \rangle \varphi_k$.

Nonlinear Autonomous

$$\begin{cases} x_{t+1} = F(x_t) \\ y_t = g(x_t) \end{cases} \Longrightarrow x_{t+1} = A x_t$$

Exact Linearization.



* continuous-time systems.

* Data-driven methods available.

L3 DMD

* $g_i(f(x)) = K_N\, g_i(x)$ for each observable

Cm.

$$
\begin{pmatrix}
g_1(1) & g_2(1) & \cdots & g_m(1) \\
g_1(2) & g_2(2) & \cdots & g_m(2) \\
\vdots & \vdots & \ddots & \vdots \\
g_1(m) & g_2(m) & \cdots & g_m(m)
\end{pmatrix}
=
\begin{pmatrix}
0 & 1 & \cdots & 0 & 0 \\
0 & 0 & 1 \cdots & 0 & 0 \\
 & & \ddots & & \\
 & & \cdots & 0 & 1 \\
c_1 & c_2 & \cdots & & c_m
\end{pmatrix}
\begin{pmatrix}
g_1(0) & g_2(0) & \cdots & g_m(0) \\
\vdots & & \ddots & \vdots \\
g_1(m-1) & & \cdots & g_m(m-1)
\end{pmatrix}
$$

$$g_i(m) = \sum_{j=0}^{m-1} c_j\, g_i(j) + r_i \Rightarrow \text{least-squares.}$$

n, m

* DMD.

$Y = [y_0, y_1, \ldots, y_m]$ let $Y_- = [y_0, \ldots, y_{m-1}] \in \mathbb{R}^{n\times m}$

$Y_+ = [y_1, \ldots, y_m] \in \mathbb{R}^{n\times m}$

Goal: $Y_+ = AY_-$

$$A^* = \underset{A}{\operatorname{argmin}} \| Y_+ - AY_- \|^2.$$

$$A^* = Y_+ Y_-^{\dagger}$$

$$\underset{n\times n}{\bar{U}}\;\underset{n\times m}{\bar{D}}\;\underset{m\times m}{\bar{V}^T} = Y_-$$

$r = \text{rank}(Y_-)$

$$\Rightarrow Y_- = \underset{n\times r}{U}\;\underset{r\times r}{D}\;\underset{r\times m}{V^T}$$

then $Y_-^{+} = V D^{-1} U^T$

then $A = Y_+ Y_-^{+} = Y_+ V D^{-1} U^T$

$\tilde{y} = U^T y \in \mathbb{R}^r$ where $y = U\tilde{y} \in \mathbb{R}^n$. $n \gg r$.

$\tilde{A} = U^T A U = U^T Y_+ V D^{-1}$ where $\tilde{Y} = U^T Y$.

where $\tilde{Y}_+ = \tilde{A}\tilde{Y}_-$ (reduced space)

$\tilde{A} w = \lambda w \Rightarrow \phi = U w$

$$x(t) \doteq \sum_{i=1}^{r} \phi_i \exp(\omega_i t)\, b_i$$

initial

temporal

spatial

ex) Gait Analysis *

Data: human gaits from MoCAP

whole-body measurement.

$\boxed{\text{CAN}}$ response to perturbation/recovery from sudden loss of balance ex) Passive dynamic walker

* Koopman eigenvalues & eigenfunctions.

$$\boxed{K\varphi_j(x) = \lambda_j \varphi_j(x)}$$

"need a systematic method"

* depending on an observables

accuracy varies!!

1. DMD modes
2. Neural Network / kernel methods
3. from the physics laws.

L4) Control

$x_{t+1} = F(x_t, u_t)$ $\quad x_t \in \mathbb{R}^n, \; u_t \in \mathbb{R}^p$

$z_{t+1} = \underset{m\times m}{A} z_t + \underset{m\times p}{B} u_t$ // $z = \begin{bmatrix} g_1 \\ \vdots \\ g_m \end{bmatrix} \in \mathbb{R}^m$. $m >> n$.

may be $g = g(x,u)$

$\Rightarrow$ causality problem

Assume

$z_{t+1} = Az_t + Bu_t$

$z = [g_1(x); g_2(x); \cdots]$

then, linear controls possible.

$Z_- = [z_0, \cdots, z_{N-1}]$

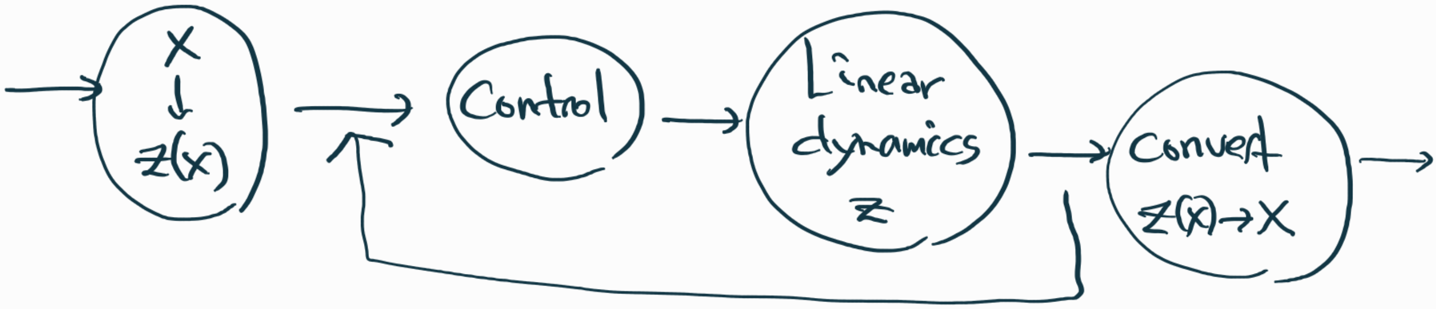
$Z_+ = [z_1, \cdots, z_N]$

$U = [u_0, \cdots, u_{N-1}]$

$Z_+ = AZ_- + BU = [A \;\; B]\begin{bmatrix} Z_- \\ U \end{bmatrix}$

find A, B from least-squares.

$[A, B] = Z_+ \begin{bmatrix} Z_- \\ U \end{bmatrix}^+$



Controllability

⇒ optimal control 사용 (CTRB 사용 X)

특히 MPC를 써본다!!!

* observable이 충분하지 않기 때문에 long-term prediction의 정확성 떨어짐. 즉 MPC를 사용해 그나마 정확한 부분을 사용한다.

Convex opt.

* Koopman + MPC의 feedback ctrl은 사실 state에 대한 nonlinear control term이 들어간다.

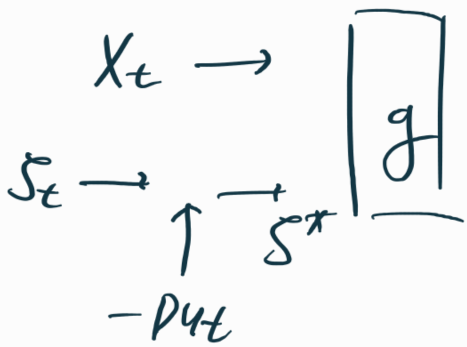
* $\boxed{\text{THEN}}$ How to find good / informative observables?

① physics : state, auxiliary states, proliferated states.

⇒ causal path analysis 이용.

② neural network : find an appropriate set of observables.

* Assume $\zeta(x,u) = \zeta^*(x) + Du$.



☆ Active learning에 대한 것 찾아보기.

☆ $p(y \mid X, z, c)$

GP model 평가보다 좋은 것을

$p(y|x)$로부터 접근 가능한가?

☆ Dynamic Mode Decomposition

각 mode 마다 ✓

✓

for each mode

need verification