

変遷し続ける世界に うなずきを与える



Katsumi Inoue 



▶ researchmap

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機械学習と記号推論の融合



1. Translate program P into a Program Matrix D^P

P $p :- \text{not } q.$
 $q :- \text{not } p.$

Program

D^P p q \bar{p} \bar{q}
 q $\begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$

Program Matrix

x p $\begin{pmatrix} 0 \\ 0 \end{pmatrix}$
 q

Interpretation vector

2. Define Loss function w.r.t. continuous interpretation

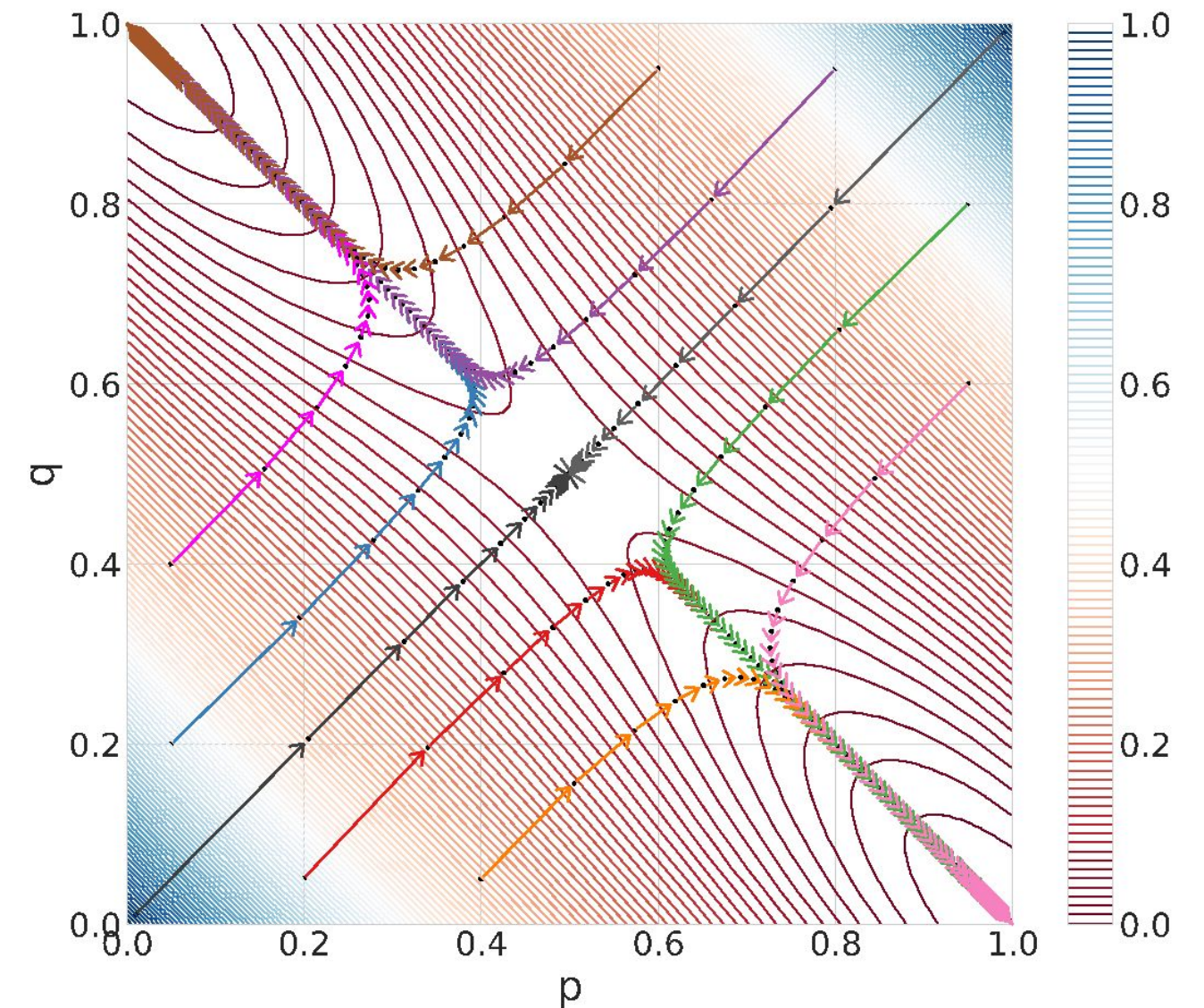
$$L(x)$$

Loss function w.r.t. x

$$\frac{\partial L(x)}{\partial x}$$

Gradient of $L(x)$ w.r.t. x

3. Minimize the loss with gradient descent

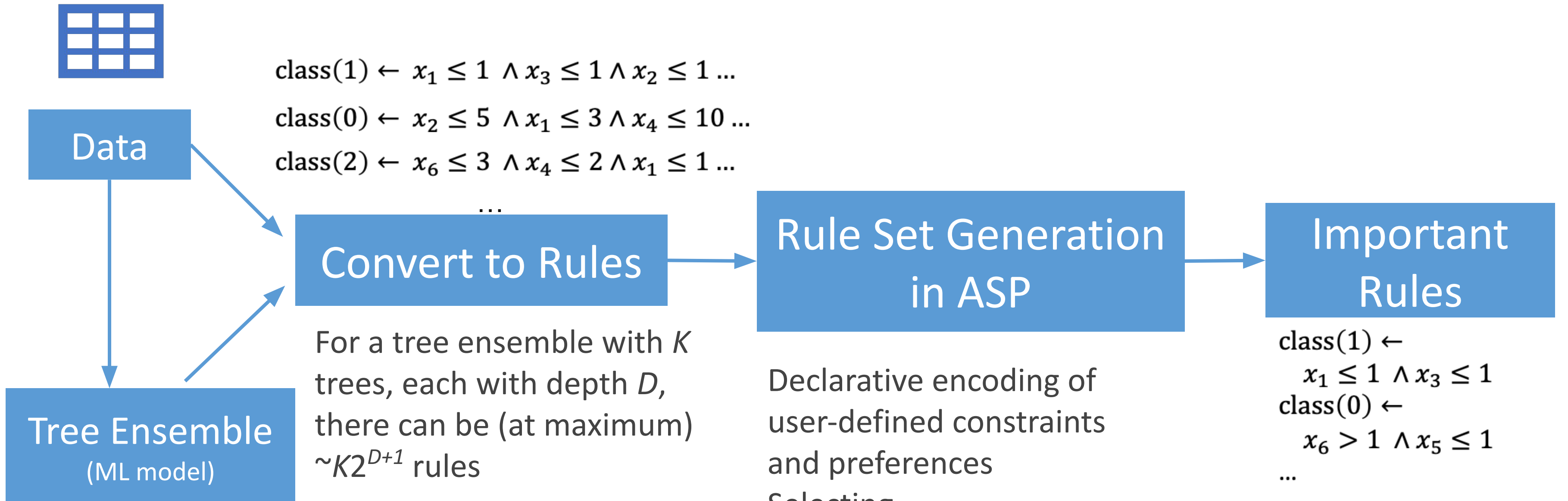


Rule Set Generation from Tree Ensembles with ASP

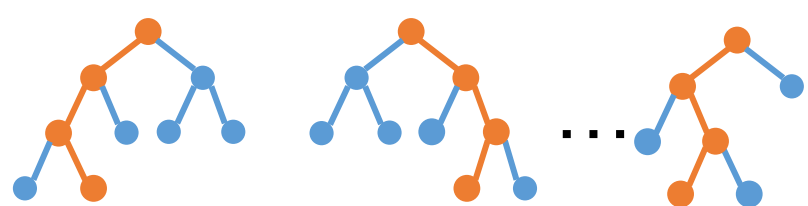


Akihiro Takemura
(Doctoral student)

Google Scholar



No. rules can be controlled
 Performance metrics can be taken into consideration in encoding



Bridging Logic and Matrix



Taisuke Sato

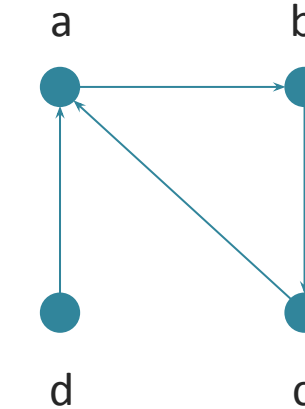
(Professor by Special Appointment)

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$$\begin{matrix} r_1(a,b), r_1(b,c) \\ r_1(c,d), r_1(d,a) \end{matrix}$$

$$\mathbf{R}_1 = \begin{pmatrix} a & b & c & d \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

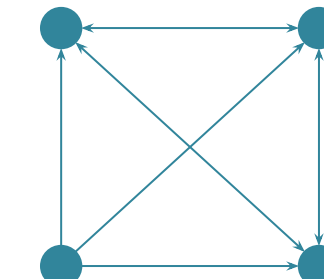


$$\|\mathbf{R}_1\|_\infty = \max\{1, 1, 1, 1\} = 1$$

$$\epsilon = (1 + \|\mathbf{R}_1\|_\infty)^{-1} = 1/2$$

$$\begin{aligned} \tilde{\mathbf{R}}_2 &= (\mathbf{I} - \epsilon\mathbf{R}_1)^{-1}\epsilon\mathbf{R}_1 \\ &= \left(\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} - \begin{pmatrix} 0 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 0 \\ 1/2 & 0 & 0 & 0 \\ 1/2 & 0 & 0 & 0 \end{pmatrix} \right)^{-1} \begin{pmatrix} 0 & 1/2 & 0 & 0 \\ 0 & 0 & 1/2 & 0 \\ 1/2 & 0 & 0 & 0 \\ 1/2 & 0 & 0 & 0 \end{pmatrix} \\ &= \begin{pmatrix} 0.1428 & 0.5714 & 0.2857 & 0.0000 \\ 0.2857 & 0.1428 & 0.5714 & 0.0000 \\ 0.5714 & 0.2857 & 0.1428 & 0.0000 \\ 0.5714 & 0.2857 & 0.1428 & 0.0000 \end{pmatrix} \end{aligned}$$

$$\mathbf{R}_2 = \begin{pmatrix} 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 \end{pmatrix}$$



Transitive closure program for r_1 :

$$r_2(x,z) \leftarrow r_1(x,z)$$

$$r_2(x,z) \leftarrow r_1(x,y) \ \& \ r_2(y,z)$$



$$r_2(x,z) \Leftrightarrow r_1(x,z) \vee \exists y(r_1(x,y) \wedge r_2(y,z))$$



$$\mathbf{R}_2 = \min_1(\mathbf{R}_1 + \mathbf{R}_1\mathbf{R}_2)$$

least solution

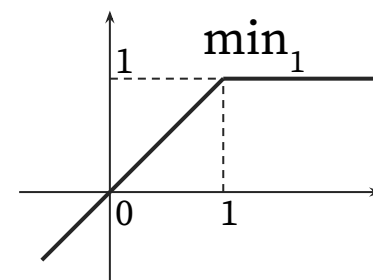
$$\hat{\mathbf{R}}_2 = \epsilon(\mathbf{R}_1 + \mathbf{R}_1\hat{\mathbf{R}}_2)$$

$$= (\mathbf{I} - \epsilon\mathbf{R}_1)^{-1}\epsilon\mathbf{R}_1$$



$$\mathbf{R}_2 = \hat{\mathbf{R}}_2 > 0$$

(positive entry \rightarrow 1, else 0)



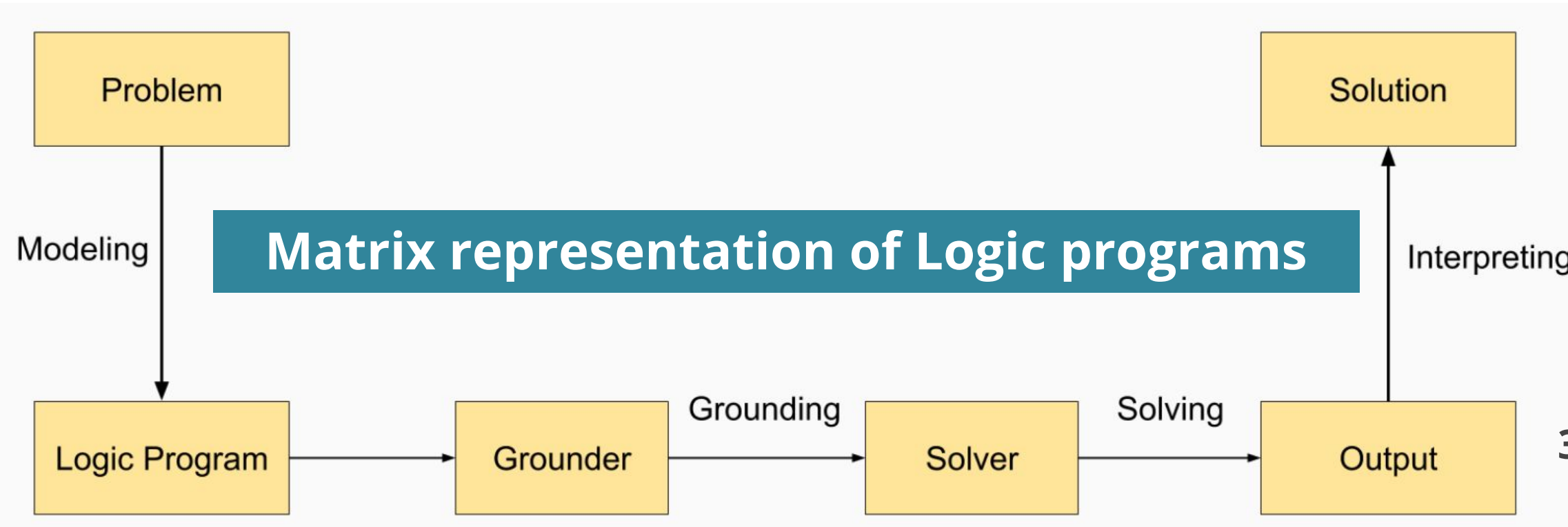
$$\min_1(x) = \min(x, 1)$$

$$r_2(d,c) = 1$$

On Linear Algebraic Computation for Logic Programming



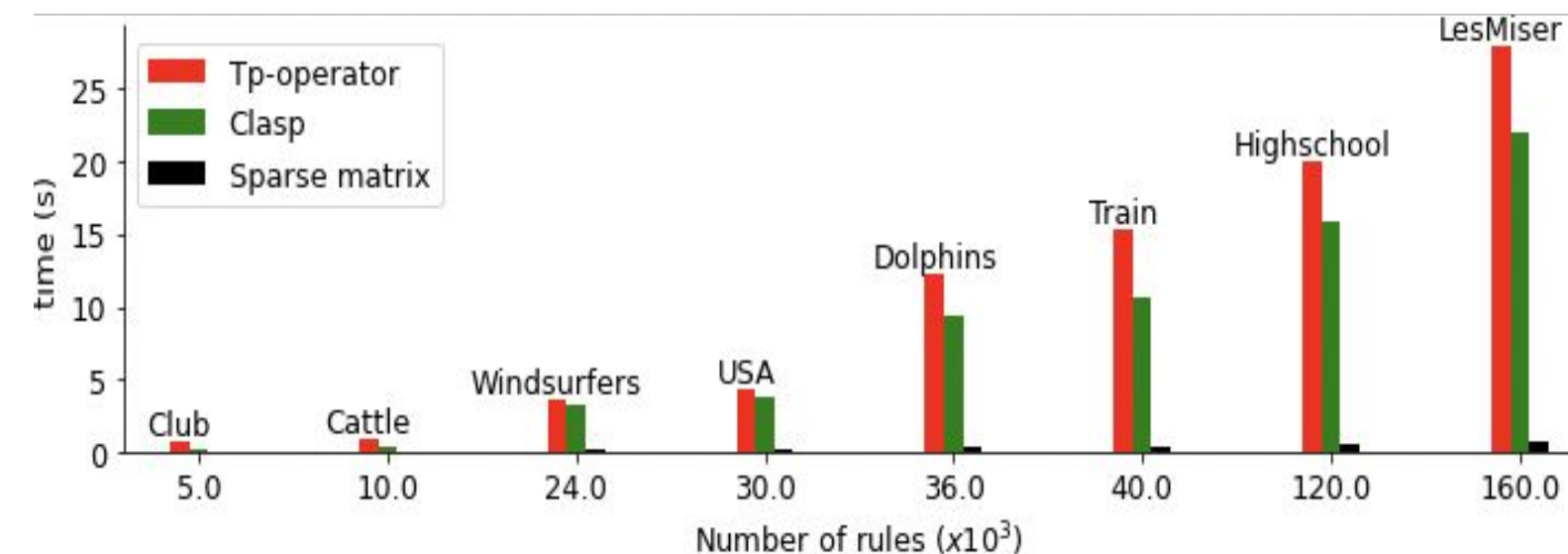
Tuan Nguyen Quoc
(Doctoral student)



- 否定を含む一般論理プログラムの安定モデルを線形代数手法で解く。
- 論理プログラムを行列表現。そのスパース性を活用する。
- 大規模論理プログラムをGPU代数計算により高速に解く。

3. Analyzing the use of matrix in different aspects

- Sparsity
- Differentiability
- Using complex numbers



2. Perform logic reasoning in vector spaces:

- Deduction $\frac{P \rightarrow Q}{P} Q$
- Abduction $\frac{P \rightarrow Q}{P} Q$
- Induction $\frac{P \rightarrow Q}{P} Q$

$$\begin{matrix}
 & p & q & s & t & \neg t & u & v \\
 p & 0 & 1/2 & 1/2 & 0 & 0 & 0 & 0 \\
 q & 1/2 & 0 & 0 & 1/2 & 0 & 0 & 0 \\
 s & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 t & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
 \neg t & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
 u & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
 v & 0 & 0 & 0 & 0 & 0 & 0 & 0
 \end{matrix}$$

Program matrix

$$P = \{p \leftarrow q \wedge s, q \leftarrow p \wedge t, s \leftarrow \neg t, t \leftarrow, u \leftarrow v\}$$

1. Encode logic programs into matrices

- Scalability
- Robustness
- Integrability e.g., ANN



Differentiable SAT Solver in Vector Spaces

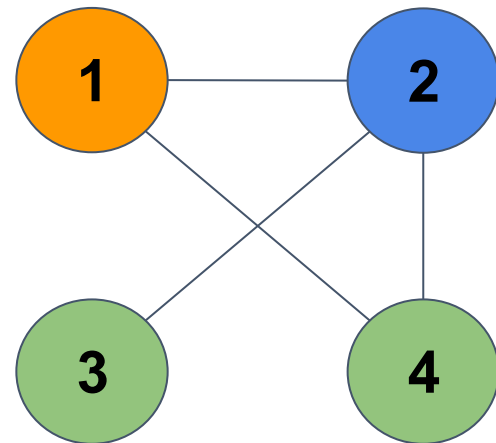


Koji Watanabe
(5-Year Doctoral Student)



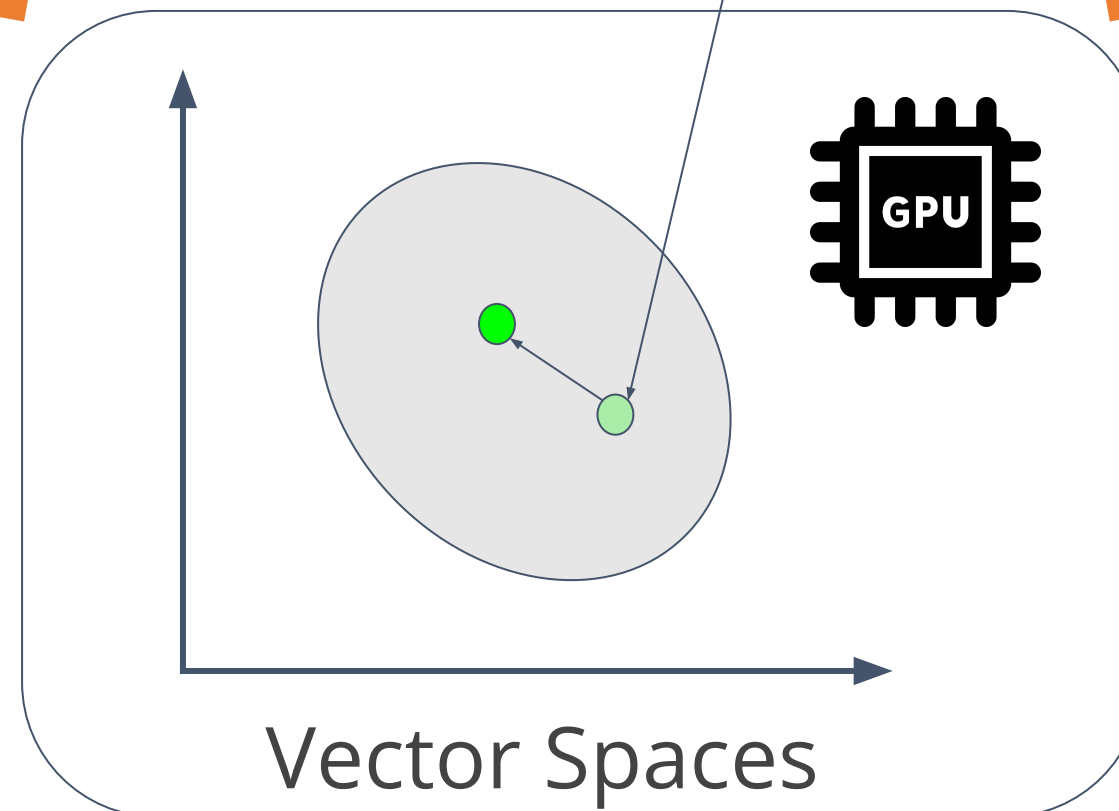
Real World

| | | | | | | |
|---|---|---|---|---|---|---|
| 5 | 3 | | 7 | | | |
| 6 | | 1 | 9 | 5 | | |
| | 9 | 8 | | | | 6 |
| 8 | | | 6 | | | 3 |
| 4 | | 8 | 3 | | | 1 |
| 7 | | | 2 | | | 6 |
| | 6 | | | | 2 | 8 |
| | | 4 | 1 | 9 | | 5 |
| | | | 8 | | 7 | 9 |



Symbolic Spaces

$$\begin{aligned}
 S = & (x_1 \vee x_2, \vee \neg x_3 \dots \vee x_n) \\
 & \wedge (x_1 \vee x_2, \vee x_3 \dots \vee \neg x_n) \\
 & \vdots \\
 & \wedge (\neg x_1 \vee x_2, \vee x_3 \dots \vee x_n)
 \end{aligned}$$




Finding a solution that satisfies a logical equation is called **SAT problem**, and the software for solving the SAT problem is called **SAT solver**. This study proposes a **new differentiable SAT solver** that maps the symbolic problem SAT to a vector space and finds the solution minimizing a cost function. Replacing symbolic representations with **vector and tensor representations**, we aim to improve the **speed and scalability** by using hardware specialized for parallel computing such as GPUs.



Plan & Goal Recognition in Real Time Strategy Games



Guillaume Lorthioir 
(Doctoral student)



Input: set of possible goals

Output: most likely goal and plan

REPEAT

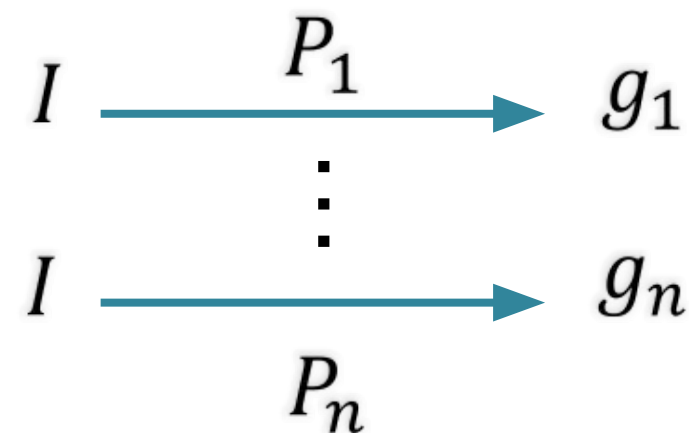
New observation O_i

Pruning

Online planner

Set of possible goals

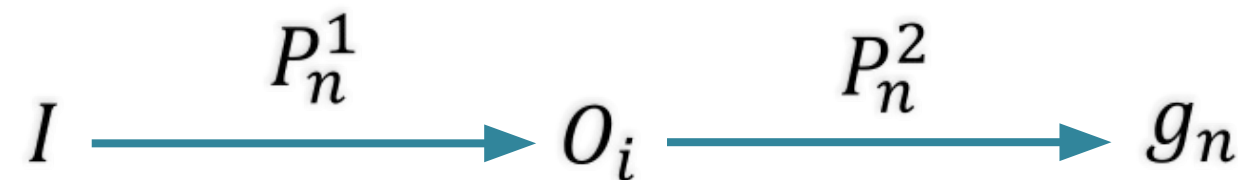
$\{ \{ g_1, \dots, g_n \} \}$



P_1 satisfies the observation:
nothing is done

⋮

P_n does not satisfy the
observation: $P_n =$



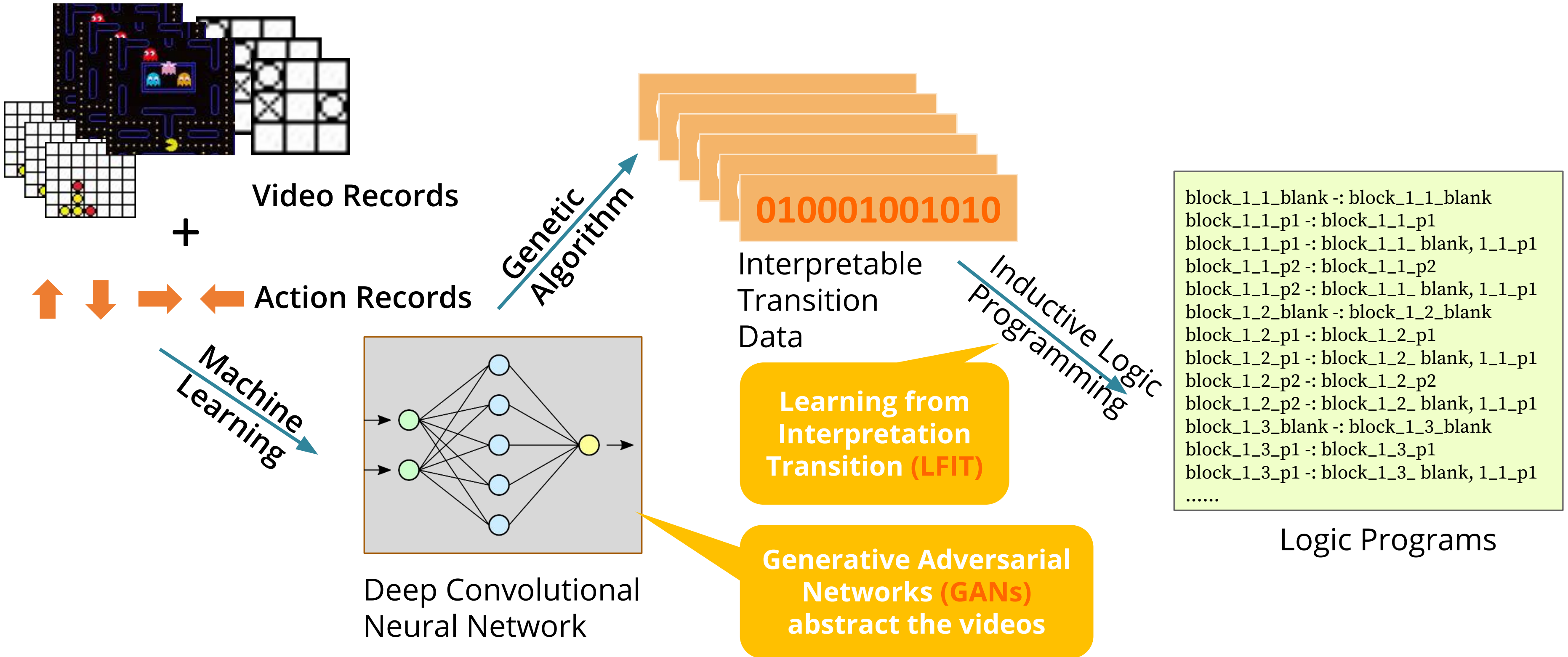
P_1 does not satisfy
pruning criteria, we
keep P_1 and g_1

⋮

P_n satisfies pruning
criteria, we remove
 P_n and g_n

Trying to **predict the plan and goal of the opponent player** in a game of StarCraft in real-time. For each possible goal for the player, we design one plan to achieve it, we modify these plans according to **partial observations of the player's action**, and then we estimate the most likely plan and goal.

Extract Game Rules from Game Video Records



Understand games, **Explain** games, **Learn** from games.

Neural-Symbolic Learning and Reasoning



Yin Jun Phua
(Doctoral Student)



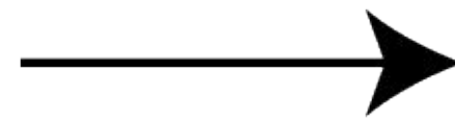
Semantic Scholar



∂ LFIT+

Input: Time series data

$ab \rightarrow a \rightarrow b \rightarrow \dots$



Output: NLP Encoded Matrix

| | | Rule body | | | | | | | | | |
|-----------|-----|-----------|---------|---------|--------------|--------------|------------|-----------------|-----------------|----------------------|--|
| | | $\{\}$ | $\{a\}$ | $\{b\}$ | $\{\neg a\}$ | $\{\neg b\}$ | $\{a, b\}$ | $\{\neg a, b\}$ | $\{a, \neg b\}$ | $\{\neg a, \neg b\}$ | |
| Rule head | a | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | |
| | b | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | |

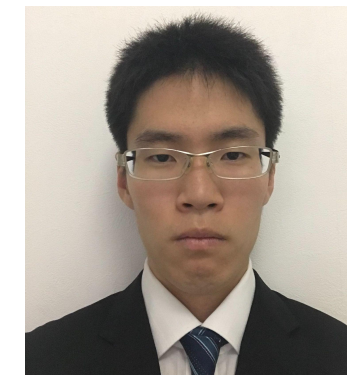
We interact with various **complex dynamic systems** everyday. These systems with composed of components evolve over time. Understanding the influences between these components provide valuable insights. **LFIT** is an unsupervised learning algorithm which learns the dynamics just by observing state transitions. LFIT has been mostly implemented in symbolic methods that utilize logical operations to induce logic programs. In our work, **we combine neural network with this previously symbolic algorithm.** We proposed a general model **∂ LFIT** that learns to predict logic programs that explain the underlying observations. However, this model suffered from a combinatorial explosion problem. To solve the scalability issue, we propose a new model **∂ LFIT+** that is capable of learning systems that are larger than previously possible.

Learning Logic Programs from Noisy State Transition Data [Phua *et al.*, ILP 2019]

▼ [Link to research article](#)



Towards Learning Live-cell Dynamics

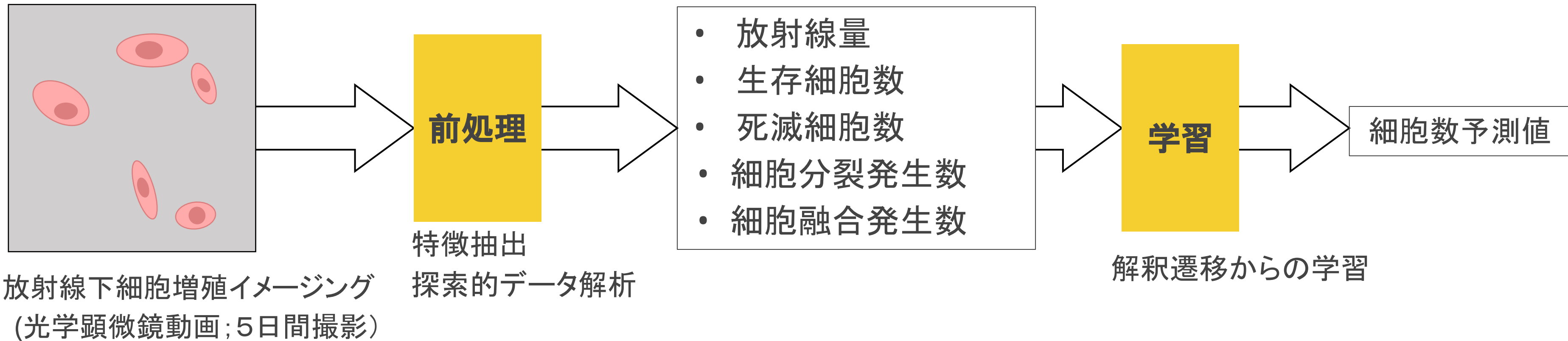


Ryota Yakushiji
(Master Student)



放射線下における細胞挙動の理解に向けた、
機械学習による細胞増殖過程の予測モデル構築

がん治療などへの応用可能性



解釈遷移からの学習 (Learning from Interpretation Transition; LFIT) [Inoue *et al.*, MLJ 2014]
観測時系列から動的システムの背後に潜む法則を学習。標準論理プログラムで表現。

▼ [Link to research article](#)

Equation Discovery in SARS-CoV-2 Network Dynamics



Mitsuhiro Odaka
(5-Year Doctoral Student)



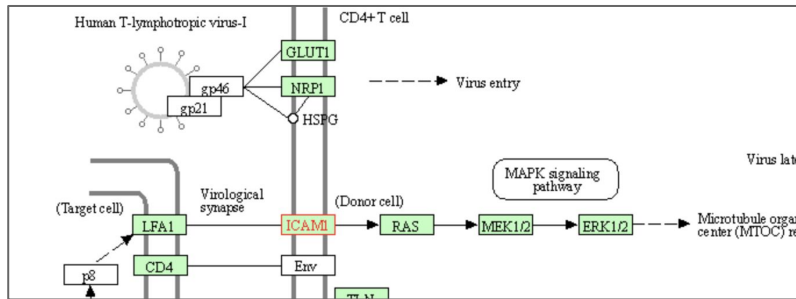
Mitsuhiro ODAKA

Google Scholar

researchmap

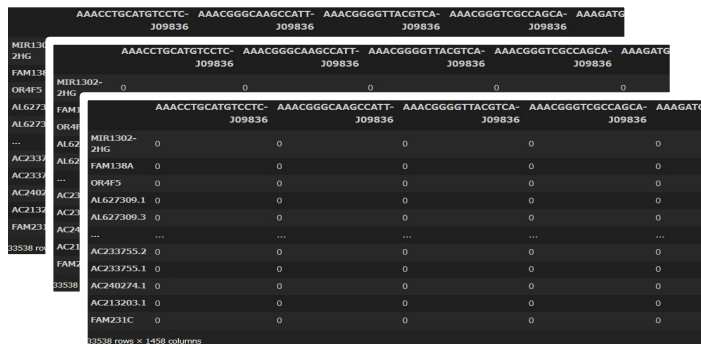
~Robust to Uncertainty, Interpretable to Causality~

SARS-CoV-2 *in vivo* dynamical systems



KEGG Pathway

Time-series scRNA-seq



Learning



SR: Symbolic regression
NA: Numerical analysis

Equations (Eqs)

(ODEs, PDEs, DAEs, S-system, ...)

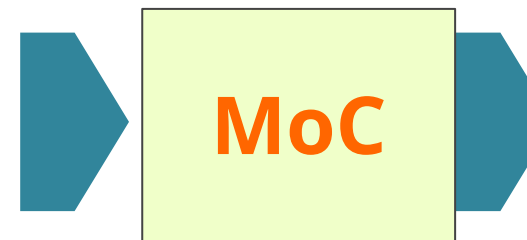
$$\frac{dX_i}{dt} = \alpha_i \prod_{j=1}^N X_j^{g_{i,j}} - \beta_i \prod_{j=1}^N X_j^{h_{i,j}} \quad (i = 1, \dots, N)$$

Logic programs (LPs)

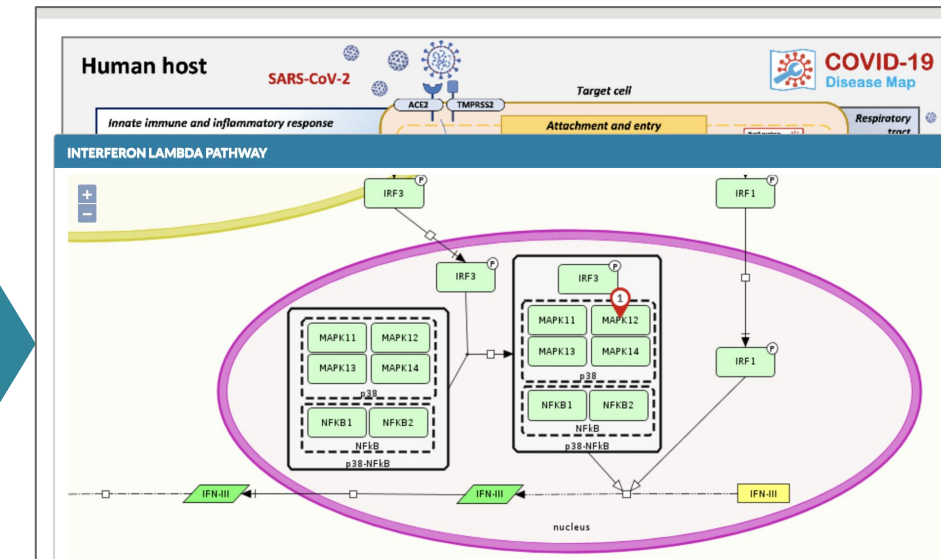
(QDEs, TCTL, ...)

- ADD(X,Y,Z)
- MULT(X,Y,Z)
- DERIV(X,Y)
- MINUS(X,Y)
- M+(X,Y)

Reasoning



MoC: Model checking



Reconstructive networks

My research attempts to build a new framework for **discovering the governing equations and hypotheses of complex system dynamics in viral infection**. This framework **combines dynamical systems theory, machine learning, and symbolic reasoning**. In other words, by organically linking differential equations, logic programs, time-series observations, and background knowledge, I aim to develop a tool for finding models **robust to uncertainty or perturbation and interpretable to causality**. One challenging task is "**multiscale modeling**," which considers the crosstalk between systems of different biological hierarchies. Applications of such frameworks could include other viruses and real-world scenarios. One particularly urgent and significant focus is the **novel coronavirus infection (COVID-19)**. While working on the proposed framework, I am currently addressing case studies such as **completion and reconstruction of the COVID-19 Disease Map**, a developing knowledge graph on the pathogenic virus (SARS-CoV-2), and **dynamic network biomarker identification**.

