

Linear Algebraic Characterization of Logic Programs

Chiaki Sakama (Wakayama Univ., Japan)

Katsumi Inoue (NII, Japan)

Taisuke Sato (AIST, Japan)

Why LP in LA?

- Linear algebra is at the core of many applications of scientific computation, and **integrating linear algebraic and symbolic computation** is a challenging topic in AI.
- Linear algebraic computation has potential to cope with **Web scale symbolic data**, and several studies develop scalable techniques to process **huge relational knowledge bases**.
- The next challenge is applying LA to relational facts with **rules**, which would enable us to use **efficient (parallel) algorithms** of numerical linear algebra for computing LP.

Logical Reasoning in LA

- Grefenstette (2013) introduces tensor-based predicate calculus.
 - Yang, *et al.* (2015) mine Horn clauses from relational facts in a vector space.
 - Serafini, *et al.* (2016) integrate deductive reasoning and relational learning in logic tensor networks.
 - Sato (2017) formalizes FOL in vector spaces and realizes efficient computation of Datalog.
- !** These studies do not target at computing LP semantics.

Contribution

1. A propositional Herbrand base is represented in a **vector space** and if-then rules in a logic program are encoded in a **matrix**.
2. The least model of a (propositional) Horn logic program is computed using **matrix products**.
3. Disjunctive logic programs are represented in **3rd-order tensors** and their minimal models are computed by algebraic manipulation of tensors.
4. Normal logic programs are represented by **3rd-order tensors** in terms of disjunctive LPs, and stable models are computed using **tensor products**.

Tensor Logic Programming

- A **Horn program** is a finite set of **rules** of the form

$$h \leftarrow b_1 \wedge \cdots \wedge b_m \quad (m \geq 0)$$

where h and b_i are propositional variables.

- Given a rule r of the above form, $head(r)=h$ and $body(r)=\{ b_1, \dots, b_m \}$.
- A rule $h \leftarrow \top$ is a **fact** where \top represents **true**.
- A rule $\perp \leftarrow b_1 \wedge \cdots \wedge b_m$ is a **constraint** where \perp represents **false**.
- The set of all propositional variables appearing in a program P is the **Herbrand base** of P (written B_P).

T_P Operator

- Given an interpretation I s.t. $\{\top\} \subseteq I \subseteq B_P$, a **mapping** $T_P : 2^{B_P} \rightarrow 2^{B_P}$ is defined as
$$T_P(I) = \{ h \mid h \leftarrow b_1 \wedge \cdots \wedge b_m \in P \text{ and } \{b_1, \dots, b_m\} \subseteq I \}$$
if $\perp \notin I$; otherwise, $T_P(I) = B_P$
- The **powers** of T_P are defined as
$$T_P^{k+1}(I) = T_P(T_P^k(I)) \quad (k \geq 0) \text{ and } T_P^0(I) = I$$
- Given $\{\top\} \subseteq I \subseteq B_P$ there is a **fixpoint** $T_P^{n+1}(I) = T_P^n(I)$ ($n \geq 0$).
- For a definite program, the fixpoint $T_P^n(\{\top\})$ coincides with the **least model** of P .

Multiple Definitions (MD) Condition

- We assume a Horn program satisfying the condition:
*for any two rules r_1 and r_2 in P , $\text{head}(r_1)=\text{head}(r_2)$
implies $|\text{body}(r_1)| \leq 1$ and $|\text{body}(r_2)| \leq 1$*
i.e., if two different rules have the same head,
those rules contain at most one atom in their bodies.
- Every Horn program P is transformed to a semantically equivalent program P' that satisfies the MD condition.

Example

- $P = \{ p \leftarrow q \wedge r, p \leftarrow r \wedge s, p \leftarrow t, r \leftarrow t, s \leftarrow, t \leftarrow \}$

is transformed to

$$P' = \{ p1 \leftarrow q \wedge r, p2 \leftarrow r \wedge s, p \leftarrow t, r \leftarrow t, s \leftarrow, t \leftarrow, \\ p \leftarrow p1, p \leftarrow p2 \}$$

where $p1$ and $p2$ are new propositional variables.

- P' has the least model $M' = \{ p, p2, r, s, t \}$ and $M' \cap B_p = \{ p, r, s, t \}$ is the least model of P .
- We consider programs satisfying the MD condition without loss of generality.

Vector Representation of Interpretations

- Let $B_p = \{p_1, \dots, p_n\}$ be the Herbrand base.
An interpretation I ($\{\top\} \subseteq I \subseteq B_p$) of a program P is represented by a column vector $\mathbf{v} = (a_1, \dots, a_n)^T \in \mathbf{R}^n$ where each a_i represents the truth value of the proposition p_i such that
 - $a_i = 1$ if $p_i \in I$ ($1 \leq i \leq n$)
 - $a_i = 0$ otherwise
- The vector representing $I = \{\top\}$ is written by \mathbf{v}_0
- We write $row_i(\mathbf{v}) = p_i$

Matrix Representation of Horn Programs

- Let P be a Horn program and $B_p = \{ p_1, \dots, p_n \}$.
 P is represented by a matrix $\mathbf{M}_p \in \mathbf{R}^{n \times n}$ s.t.
for each element a_{ij} ($1 \leq i, j \leq n$) in \mathbf{M}_p ,
 - $a_{ij} = 1$ if $p_i = \top$ or $p_j = \perp$
 - $a_{ij_k} = 1/m$ ($1 \leq k \leq m$; $1 \leq i, j_k \leq n$)
if $p_i \leftarrow p_{j_1} \wedge \dots \wedge p_{j_m}$ is in P
 - otherwise $a_{ij} = 0$
- We write $row_i(\mathbf{M}_p) = p_i$ and $col_j(\mathbf{M}_p) = p_j$

Example

- $P = \{ p \leftarrow q, p \leftarrow r, q \leftarrow r \wedge s, r \leftarrow \top, \perp \leftarrow q \}$ with $B_p = \{ p, q, r, s, \top, \perp \}$ is represented by $M_p \in \mathbf{R}^{6 \times 6}$:

		body						
		p	q	r	s	\top	\perp	
head	p	0	1	1	0	0	1	$p \leftarrow q, p \leftarrow r, p \leftarrow \perp (\equiv \top)$
	q	0	0	$\frac{1}{2}$	$\frac{1}{2}$	0	1	$q \leftarrow r \wedge s, q \leftarrow \perp (\equiv \top)$
	r	0	0	0	0	1	1	$r \leftarrow \top (\equiv r \leftarrow), r \leftarrow \perp (\equiv \top)$
	s	0	0	0	0	0	1	$s \leftarrow \perp (\equiv \top)$
	\top	1	1	1	1	1	1	$\top \leftarrow p (\equiv \top), \top \leftarrow q, \dots, \top \leftarrow \perp$
	\perp	0	1	0	0	0	1	$\perp \leftarrow q (\equiv \leftarrow q), \perp \leftarrow \perp (\equiv \top)$

- $row_1(M_p) = p$ and $col_2(M_p) = q$

Need of MD-condition

- $P_1 = \{ p \leftarrow q \wedge r, p \leftarrow s \wedge t \}$ is represented by

$$\begin{array}{c} p \\ q \\ r \\ s \\ t \end{array} \begin{array}{ccccc} p & q & r & s & t \\ \left(\begin{array}{ccccc} 0 & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{array} \right)
 \end{array}$$

- The matrix representation does not distinguish P_1 , $P_2 = \{ p \leftarrow q \wedge s, p \leftarrow r \wedge t \}$ and $P_3 = \{ p \leftarrow q \wedge t, p \leftarrow r \wedge s \}$.

- Then P_1 is transformed to

$P_1' = \{ p1 \leftarrow q \wedge r, p2 \leftarrow s \wedge t, p \leftarrow p1, p \leftarrow p2 \}$ which is represented by

$$\begin{array}{c} p \\ p1 \\ p2 \\ q \\ r \\ s \\ t \end{array} \begin{array}{cccccc} p & p1 & p2 & q & r & s & t \\ \left(\begin{array}{cccccc} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ & & & & & & \\ & & & & & & \\ & & & & & & \\ & & & & & & \mathbf{0} \end{array} \right)
 \end{array}$$

Product

- Given a matrix $\mathbf{M}_p \in \mathbf{R}^{n \times n}$ representing a program and a vector $\mathbf{v} \in \mathbf{R}^n$ representing an interpretation $I \subseteq B_p$, the product $\mathbf{M}_p \bullet \mathbf{v} = (a_1, \dots, a_n)^\top$ is computed.
- Transform $\mathbf{M}_p \bullet \mathbf{v}$ to a vector $\mathbf{w} = (a'_1, \dots, a'_n)^\top$ where $a'_i = 1$ ($1 \leq i \leq n$) if $a_{ij} \geq 1$; otherwise, $a'_i = 0$
- We write $\mathbf{w} = \mathbf{M}_p \underline{\bullet} \mathbf{v}$

Example (cont.)

- $P = \{ p \leftarrow q, p \leftarrow r, q \leftarrow r \wedge s, r \leftarrow, \leftarrow q \}$
- Given $\mathbf{v} = (0, 1, 1, 0, 1, 0)^T$ representing $I = \{q, r, \top\}$,

$$\mathbf{M}_P \bullet \mathbf{v} = \begin{matrix} & \mathbf{p} & \mathbf{q} & \mathbf{r} & \mathbf{s} & \top & \perp \\ \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \end{pmatrix} & \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} & = & \begin{pmatrix} 2 \\ \frac{1}{2} \\ 1 \\ 0 \\ 3 \\ 1 \end{pmatrix} & \begin{matrix} \mathbf{p} \\ \mathbf{q} \\ \mathbf{r} \\ \mathbf{s} \\ \top \\ \perp \end{matrix}
 \end{matrix}$$

- Then $\mathbf{w} = \mathbf{M}_P \bullet \mathbf{v} = (1, 0, 1, 0, 1, 1)^T$ represents $J = \{p, r, \top, \perp\}$

Deduction by Matrix Product

- **Proposition** Let P be a Horn program and $M_p \in \mathbf{R}^{n \times n}$ its matrix representation. Let $v \in \mathbf{R}^n$ be a vector representing $I \subseteq B_p$. Then $w \in \mathbf{R}^n$ is a vector representing $J = T_p(I)$ iff $w = M_p \bullet v$

Fixpoint Computation

- Given a matrix $M_p \in \mathbf{R}^{n \times n}$ and a vector $v \in \mathbf{R}^n$, define

$$M_p \bullet^{k+1} v = M_p \bullet (M_p \bullet^k v) \text{ and } M_p \bullet^1 v = M_p \bullet v \text{ (} k \geq 1 \text{)}$$

- When $M_p \bullet^{k+1} v = M_p \bullet^k v$ for some $k \geq 1$, write $\mathbf{FP}(M_p \bullet v) = M_p \bullet^k v$

Computing Least Model by Matrix Product

- **Theorem** Let P be a Horn program and $M_P \in \mathbf{R}^{n \times n}$ its matrix representation. Then $m \in \mathbf{R}^n$ is a vector representing the least model of P iff $m = \mathbf{FP}(M_P \bullet v_0)$ and $a_i = 1$ implies $row_i(m) \neq \perp$ for any element a_i in m
- **Corollary** P is inconsistent iff a vector $w = M_P^k \bullet v_0$ ($k \geq 1$) has an element $a_i = 1$ ($1 \leq i \leq n$) such that $row_i(w) = \perp$

Example (cont.)

- $P = \{ p \leftarrow q, p \leftarrow r, q \leftarrow r \wedge s, r \leftarrow, \leftarrow q \}$

$$M_P \bullet v_0 = \begin{matrix} p \\ q \\ r \\ s \\ \top \\ \perp \end{matrix} \begin{pmatrix} p & q & r & s & \top & \perp \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} = M_P \underline{\bullet}^1 v_0$$

$$M_P \bullet (M_P \underline{\bullet}^1 v_0) = \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 1 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} = \begin{pmatrix} 1 \\ \frac{1}{2} \\ 1 \\ 0 \\ 2 \\ 0 \end{pmatrix} \quad M_P \underline{\bullet}^2 v_0 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 0 \\ 1 \\ 0 \end{pmatrix} \\ = \text{FP}(M_P \bullet v_0)$$

- $\text{FP}(M_P \bullet v_0) = (1, 0, 1, 0, 1, 0)^\top$ represents the least model $\{p, r, \top\}$ of P .

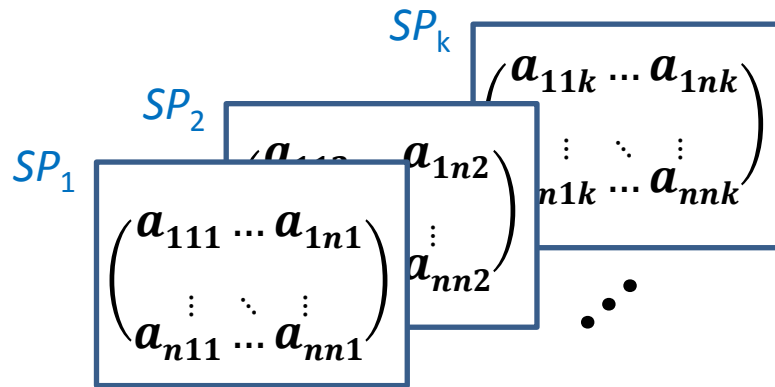
Computing Disjunctive Logic Programs by 3rd-Order Tensor

1. Split a disjunctive program into Horn programs.

ex. $P = \{ p \vee r \leftarrow s, q \vee r \leftarrow \}$ is split into

$$SP_1 = \{ p \leftarrow s, q \leftarrow \}, \quad SP_2 = \{ p \leftarrow s, r \leftarrow \}, \\ SP_3 = \{ r \leftarrow s, q \leftarrow \}, \quad SP_4 = \{ r \leftarrow s, r \leftarrow \}.$$

2. Represent split programs by a 3rd-order tensor.



3. Compute least models of split programs by tensor product and select minimal models among them.

Computing Normal Logic Programs by 3rd-Order Tensor

- Transform a normal program to a semantically equivalent disjunctive program (Fernandez, *et al.*, 1993).

$$h \leftarrow b_1 \wedge \cdots \wedge b_m \wedge \neg b_{m+1} \wedge \cdots \wedge \neg b_n$$



$$h \vee \varepsilon b_{m+1} \vee \cdots \vee \varepsilon b_n \leftarrow b_1 \wedge \cdots \wedge b_m$$

and $\varepsilon p \leftarrow p$ for $p \in B_p \setminus \{\top, \perp\}$

+ integrity constraints $\varepsilon p \Rightarrow p$ for $p \in B_p \setminus \{\top, \perp\}$

where εp is a new atom associated with p .

- Compute stable models via minimal models of the transformed disjunctive program.

Complexity

- The least model of a Horn program is computed in $O(N)$ time and space where N is the size of the program (Dowling & Gallier, 1984).
- The proposed method requires $O(n^2)$ space and $O(n^4)$ time in the worst case where n is the number of propositional variables in B_p
- Since the size of a matrix is independent of the size of a program, LA computation would be advantageous in a large knowledge base on a fixed language.

Conclusion

- Linear algebraic characterization of logic programs bridges symbolic and linear algebraic approaches, which would contribute to a step for realizing logical inference in huge scale of knowledge bases.
- We are now implementing/evaluating the algorithm and also plan to use parallel computing on GPU.