Finite Model Theory Lecture 14: Weisfeiler-Leman and Logic

Spring 2025

Announcement

- HW4 (the last one!!) to be posted this week.
- Topic for today: WL, Logics, connection to GNNs. Lecture based on [Morris et al., 2023, Grohe, 2021, Morris et al., 2019, Grohe, 2020]
- Next week: descriptive complexity.

This and the previous lecture are based on [Morris et al., 2023, Grohe, 2021, Morris et al., 2019, Grohe, 2020]

Review

Finite Model Theory

Review: Color Refinement

Iterative process that assigns a "color" to each node.

• Initially all nodes have the same color:

$$\operatorname{cr}^{0}(v) \stackrel{\mathrm{def}}{=} ()$$

• For $t \ge 0$, assign colors based on the neighbors's colors:¹

$$\operatorname{cr}^{t+1}(v) \stackrel{\text{def}}{=} (\operatorname{cr}^t(v), \{\!\!\{\operatorname{cr}^t(w) \mid w \in N(v)\}\!\!\})$$

• The stable coloring is $cr^{\infty} \stackrel{\text{def}}{=} cr^{t}$ where t is s.t. $cr^{t+1} = cr^{t}$.

¹{...} is a bag, as in {
$$\{a, a, b, c, c, c\}$$
}.

Color Refinement for Isomorphism Test

Input: G, G'

Take their disjoint union $G \cup G'$ and compute its stable color cr^{∞} .

If for any color, the two graphs a have different number of nodes of that color, then they are not isomorphic.

Other, we need to run an expensive isomorphism test.

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Review: Color Refinement is Insufficient to Identify a Graph



All nodes have the same color, yet they are not isomorphic.

Color refinement fails to differentiate any two nodes in a regular graph.

Review: k-WL

Initially, each vector $\mathbf{v} \in V(G)^k$ is colored with $\operatorname{atp}_k(\mathbf{v})$.

At step t + 1, the tuple **v** is colored with:

$$\operatorname{wl}_k^{t+1}(\mathbf{v}) \stackrel{\text{def}}{=} (\operatorname{wl}_k^t(\mathbf{v}), M(\mathbf{v}))$$

where M is:

 $M(\mathbf{v}) \stackrel{\text{def}}{=} \{\!\!\{(\operatorname{atp}_{k+1}(\mathbf{v}w), \operatorname{wl}_k^t(\mathbf{v}[w/v_1]), \dots, \operatorname{wl}_k^t(\mathbf{v}[w/v_k])) \mid w \in V(G)\}\!\!\}$

note that $atp_{k+1}(\mathbf{v}w)$ considers all colors of wl_k^t (no need)

Fact

Color refinement and 1-WL coincide: $\forall t \ge 0$, $cr^t(v) = wl_1^t(v)$.

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 $\begin{aligned} \mathbf{cr}^{t+1}(v) &= \\ (\mathbf{cr}^{t}(v), \{\!\!\{\mathbf{cr}^{t}(w) \mid w \in N(v)\}\!\!\}) & & & \\ & & \\ M(v) \stackrel{\text{def}}{=} (\!\{\mathbf{ul}_{1}^{t}(v), M(v)), & & \\ & & \\ M(v) \stackrel{\text{def}}{=} \{\!\!\{\mathbf{ul}_{2}^{t}(vw), \mathbf{ul}_{1}^{t}(w)\} \mid w \in V(G)\}\!\!\} \end{aligned}$

Fact

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Color refinement counts the colors of the neighbors.

1-WL counts both neighbors and non-neighbors. Same thing!

- Color refinement (or 1-WL) provides a canonical labeling of the nodes of a random graph, with high probability. But fails completely on regular graphs.
- 2-WL differentiates two random regular graph with high probability. But fails completely on strongly regular graphs.
- Cai, Führer, Immerman [Cai et al., 1992] described a sequence of pairs of graphs G_k , H_k such that, for all k:
 - G_k, H_k are not isomorphic,
 - G_k, H_k are not distinguished by k-WL,
 - G_k, H_k are distinguished by k + 1-WL.
- They also described the strong connection to logics. Next.

Counting Logic

Finite Model Theory

Finite Variable Logic

Recall: FO^k is FO restricted to k variables x_1, \ldots, x_k

The crux is that we can reuse variables, e.g. check if there exists a path of length 100 in FO^2 .

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 FO^k related to k-WL, but there is a catch:

- With 1-WL we can distinguish two nodes that have 100 and 101 neighbors.
- But in FO we need 101 variables.

Finite Variable Logic

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- With 1-WL we can distinguish two nodes that have 100 and 101 neighbors.
- But in FO we need 101 variables.

Better: extend FO with counting quantifiers

Finite Variable Counting Logic

The logic C extends FO with a counting quantifier:

$$\exists^{\geq n} x(\varphi(x))$$

It means "there are at least *n* values *x* s.t. $\varphi(x)$ is true"

The logic C^k is C restricted to k variables.

Example:
$$\exists^{\geq 3} x(\neg \exists^{\geq 2} y(E(x,y)))$$

"There are at least 3 nodes with at most 1 neighbor"

Example: $\exists^{\geq 3}x(\neg\exists^{\geq 2}y(E(x,y)))$ "There are at least 3 nodes with at most 1 neighbor"

C as expressive as FO, but C^k is more expressive than FO^k:

Example: $\exists^{\geq 3} x(\varphi(x))$ becomes $\exists x_1 \exists x_2 \exists x_3(x_1 \neq x_2) \land (x_1 \neq x_3) \land (x_2 \neq x_3) \land \varphi(x_1) \land \varphi(x_2) \land \varphi(x_3)$

Example: $\exists^{\geq 3}x(\neg\exists^{\geq 2}y(E(x,y)))$ "There are at least 3 nodes with at most 1 neighbor"

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Notice that, if $\varphi \in C^k$, then so are $\exists^{=n}(\varphi)$ and $\exists^{\leq n}(\varphi)$. $\exists^{=n}(\varphi) = \exists^{\geq n}(\varphi) \land \neg \exists^{\geq n+1}(\varphi)$

Graph Kernels, GNNs

Examples

Which of the following C^2 sentences are true?

 $\forall x (\exists y (E(x,y) \land \exists x (\neg E(y,x))))$

 $\forall x (\exists^{\geq 2} y (E(x, y) \land \exists x (\neg E(y, x))))$

 $\forall x (\exists y (E(x,y) \land \exists^{\geq 2} x (\neg E(y,x))))$



Fig. 1. An Undirected Graph

From [Cai et al., 1992]

 $\forall x (\exists^{\geq 2} y (E(x, y) \land \exists^{\geq 2} x (\neg E(y, x))))$

Graph Kernels, GNNs

Examples

Which of the following C^2 sentences are true?

```
\forall x (\exists y (E(x, y) \land \exists x (\neg E(y, x))))
TRUE
\forall x (\exists^{\geq 2} y (E(x, y) \land \exists x (\neg E(y, x))))
```

$$\forall x (\exists y (E(x,y) \land \exists^{\geq 2} x (\neg E(y,x))))$$



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TRUE

\forall x (\exists^{\geq 2} y (E(x, y) \land \exists x (\neg E(y, x))))

FALSE

\forall x (\exists y (E(x, y) \land \exists^{\geq 2} x (\neg E(y, x))))
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Theorem ([Cai et al., 1992])

Two graphs are C^{k+1} -equivalent iff they cannot be distinguished by k-WL.

Color refinement cannot distinguish two graphs that are C^2 -equivalent.

Example



They cannot be distinguished by C^2 . But they can be distinguished by C^3 . What φ distinguishes G, G'??? Example



They cannot be distinguished by C². But they can be distinguished by C³. What φ distinguishes G, G'???

 $\exists x \exists y \exists z (E(xy) \land E(yz) \land \neg E(xz))$

• As stated, the equivalence between *k*-WL and C^{*k*+1} is only about properties of graphs.

• By looking closer at the details we can characterize their equivalence in terms of what properties of nodes they express.

• But first let's talk about applications to ML.

Graph Kernels and Graph Neural Networks

Graph Kernels

From [Grohe, 2020]

We are processing a large collection of graphs, denoted χ , and need to compare the similarity/distance of two graphs in χ .

One possibility is to compute an embedding of each graph in \mathbb{R}^d , then use the similarity/distance in \mathbb{R}^d .

Some machine learning algorithm do not need to ever compute the embedding, but only compute similarity: this is motivation behind a kernel

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Graph Kernels

Fix a set of objects $\chi \text{, e.g.}$ the set of all graphs.

A kernel function is $K : \chi \times \chi \rightarrow \mathbb{R}$ that is:

• Symmetric:
$$K(x, y) = K(y, x)$$

 Positive semidefinite: for any finite set x₁,..., x_n, the matrix M_{ij} = K(x_i, x_j) is positive semidefinite. Recall, this means: z^TMz ≥ 0 for all z ∈ ℝⁿ.

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Graph Kernels

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• Positive semidefinite: for any finite set x_1, \ldots, x_n , the matrix $M_{ij} = K(x_i, x_j)$ is positive semidefinite. Recall, this means: $z^T M z \ge 0$ for all $z \in \mathbb{R}^n$.

Canonical example: given an embedding $f : \chi \to \mathbb{R}^d$, then the function $\mathcal{K}(x, y) \stackrel{\text{def}}{=} \langle f(x), f(y) \rangle$ is a kernel function.

A form of converse also holds (replace \mathbb{R}^d with a Hilbert space).

Review: Colors as Tree Unfoldings

One can view the set of colors at round t as the set of all trees of depths t. Example from [Grohe, 2020]:



Figure 5: Viewing colours of WL as trees

Weisfeiler-Leman Graph Kernels

Let C_t be the set of trees of depth t.

Infinite!

For any "color" $c \in C_t$: $\mathfrak{wl}(c, G) \stackrel{\text{def}}{=}$ number of $v \in V(G)$ colored with c

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Weisfeiler-Leman Graph Kernels

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The *t*-round WL-kernel is:

$$K_{WL}^t(G,H) = \sum_{i=0,t} \sum_{c \in C_t} \operatorname{wl}(c,G) \cdot \operatorname{wl}(c,H)$$

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Although C_t is infinite, there are only finitely many non-zero terms.

A variant is:

$$\sum_{i=0,t} \frac{1}{2^i} \sum_{c \in C_t} \operatorname{wl}(c,G) \cdot \operatorname{wl}(c,H)$$

Graph Neural Networks

From [Grohe, 2020]

Given a fixed graph, the goal is to compute a node embedding that maps each node v to $x_v \in \mathbb{R}^d$ such that the distance/similarity between two nodes u, v is approximated by the distance/similarity between x_u, x_v .

Graph Neural Networks

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GNNs are a method that uses deep learning techniques, while being independent of the graph size, and isomorphism invariant.

We will discuss only a very simple form of GNN

Graph Neural Networks

Each node $v \in V(G)$ has a state $\mathbf{x}_v \in \mathbb{R}^d$.

A GNN is defined by two matrices W_{AGG} , W_{UP} and a function σ . The computation of the GNN is:

Assume the initial configuration $(\mathbf{x}_{v}^{0})_{v \in V(G)}$ is the same at all nodes.

We stop at some fixed iteration t.

GNNs and Color Refinement

Theorem

If $cr^{\infty}(u) = cr^{\infty}(v)$ then for any GNN parameters, $\mathbf{x}_{u}^{t} = \mathbf{x}_{v}^{t}$.

Thus, a GNN cannot distinguish more than color refinement.

Some converse statement is possible.

GNNs as Classifiers

Add classification function, $C : \mathbb{R}^d \to \{0,1\}; \quad GNN(G,v) \stackrel{\text{def}}{=} C(\boldsymbol{x}_v^t).$

The GNN distinguishes (G, v) and (G', v') if $GNN(G, v) \neq GNN(G', v')$.

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The GNN distinguishes (G, v) and (G', v') if $GNN(G, v) \neq GNN(G', v')$.

Fact

If (G, v), (G', v') are C^2 equivalent, they are indistinguishable by GNN.

The converse fails, e.g. $\varphi(x) = \exists^{\geq 2} y(y = y)$. A GNN cannot distinguish between a graph with 1 node and a graph with 2 nodes and no edges.

GNNs as Classifiers

The guarded fragment of C^k restricts all quantifiers to range over neighbors:

 $\exists^{\geq n} y(E(x,y) \wedge \psi)$

Theorem

GNNs and the guarded fragment of C^2 the same expressive power.

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• Connection between WL, GNN, and logics has been extensively researched in the last few years.

• GNNs gain more power by using a random initialization function, instead of a constant function.

• Many other variations of GNNs exists, and their connection to logics has also been explored.

A Detailed Look

Overview

Recall: two graphs are C^{k+1} -equivalent iff they cannot be distinguished by k-WL.

The quantifier depth of C^{k+1} does not correspond 1-to-1 to the step of the k-WL

Instead, the quantifier depth corresponds 1-to-1 to the step of a slight variant, called the oblivious WL.

Folklore v.s. Oblivious k-WL

What we discussed until now is called Folklore WL:

$$\begin{aligned} & \texttt{fwl}_k^{t+1}(\boldsymbol{v}) \stackrel{\text{def}}{=} (\texttt{fwl}_k^t(\boldsymbol{v}), M(\boldsymbol{v})) \\ & M(\boldsymbol{v}) \stackrel{\text{def}}{=} \{\!\!\{(\texttt{atp}_{k+1}(\boldsymbol{v}w), \texttt{fwl}_k^t(\boldsymbol{v}[w/v_1]), \dots, \texttt{fwl}_k^t(\boldsymbol{v}[w/v_k])) \mid w \in V(G)\}\!\!\} \end{aligned}$$

Folklore v.s. Oblivious *k*-WL

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The following variant is called Oblivious WL:

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Note: owl_k makes sense only for $k \ge 2$: For k = 1 it doesn't check whether the edge v_1w exists.

Connection Between Folklore and Oblivious WL

Theorem

(1) If G, G' are distinguished by fwl_k^t then they are distinguished by owl_{k+1}^t (2) If G, G' are distinguished by owl_{k+1}^t then they are distinguished by fwl_k^{t+1}

Intuitively: the stable coloring fwl_k^{∞} is the same as owl_{k+1}^{∞} .

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Theorem

(1) If G, G' are distinguished by fwl_k^t then they are distinguished by owl_{k+1}^t (2) If G, G' are distinguished by owl_{k+1}^t then they are distinguished by fwl_k^{t+1}

Intuitively: the stable coloring fwl_k^{∞} is the same as owl_{k+1}^{∞} .

The proof in [Grohe, 2021] establishes the following equivalence:

•
$$\operatorname{owl}_{k+1}^t(G, \mathbf{v}) = \operatorname{owl}_{k+1}^t(G', \mathbf{v}')$$

•
$$\operatorname{atp}_{k+1}(G, \mathbf{v}) = \operatorname{atp}_{k+1}(G', \mathbf{v}')$$
 and for all $i = 1, k + 1$:
 $\operatorname{fwl}_k^t(G, v_1, \dots, v_{i-1}, v_{i+1}, \dots, v_{k+1}) = \operatorname{fwl}_k^t(G', v'_1, \dots, v'_{i-1}, v'_{i+1}, \dots, v'_{k+1})$

 $C^{k}[q]$ = quantifier depth $\leq q$. Fix vectors $\boldsymbol{v} \in V(G)^{k}, \boldsymbol{v}' \in (V(G'))^{k}$.

Theorem

$$owl_k^q(G, \mathbf{v}) = owl_k^q(G', \mathbf{v}') \quad \iff \quad \left(\forall \varphi \in C^k[q] : G \vDash \varphi[\mathbf{v}] \text{ iff } G' \vDash \varphi[\mathbf{v}'] \right)$$

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Proof Induction on q: When q = 0 both sides hold iff $atp_k(G, \mathbf{v}) = atp_k(G', \mathbf{v}')$.

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Assume it holds for q, we prove for q + 1.

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Assume it holds for q, we prove for q + 1.

The \Rightarrow direction. Let $\varphi \in C^{k}[q+1]$; assume w.l.o.g. $\varphi = \exists x_{i}\psi(x_{1},...,x_{k})$.

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The \Rightarrow direction. Let $\varphi \in C^{k}[q+1]$; assume w.l.o.g. $\varphi = \exists x_{i}\psi(x_{1},...,x_{k})$.

If $G \vDash \varphi[\mathbf{v}]$ then $\exists w \in V(G)$ such that

$$G \vDash \psi[\mathbf{v}[\mathbf{v}_i/w]]$$

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The \Rightarrow direction. Let $\varphi \in C^k[q+1]$; assume w.l.o.g. $\varphi = \exists x_i \psi(x_1, \dots, x_k)$.

If $G \vDash \varphi[\mathbf{v}]$ then $\exists w \in V(G)$ such that

$$G \vDash \psi[\mathbf{v}[\mathbf{v}_i/\mathbf{w}]]$$

 $\operatorname{owl}_{k}^{q+1}(\boldsymbol{v}) = \operatorname{owl}_{k}^{q+1}(\boldsymbol{v}') \text{ implies } \exists w' \in V(G'), \operatorname{owl}_{k}^{q}(\boldsymbol{v}[w/v_{i}]) = \operatorname{owl}_{k}^{q}(\boldsymbol{v}'[w'/v_{i}'])$

 $C^{k}[q]$ = quantifier depth $\leq q$. Fix vectors $\boldsymbol{v} \in V(G)^{k}, \boldsymbol{v}' \in (V(G'))^{k}$.

Theorem

$$owl_k^q(G, \mathbf{v}) = owl_k^q(G', \mathbf{v}') \quad \iff \quad \left(\forall \varphi \in C^k[q] : G \vDash \varphi[\mathbf{v}] \text{ iff } G' \vDash \varphi[\mathbf{v}'] \right)$$

Assume it holds for q, we prove for q + 1. The \Rightarrow direction. Let $\varphi \in C^k[q+1]$; assume w.l.o.g. $\varphi = \exists x_i \psi(x_1, \dots, x_k)$. If $G \models \varphi[\mathbf{v}]$ then $\exists w \in V(G)$ such that $\boxed{G \models \psi[\mathbf{v}[v_i/w]]}$ owl $_k^{q+1}(\mathbf{v}) = owl_k^{q+1}(\mathbf{v}')$ implies $\exists w' \in V(G'), owl_k^q(\mathbf{v}[w/v_i]) = owl_k^q(\mathbf{v}'[w'/v_i'])$ By induction on q: $\boxed{G' \models \psi[\mathbf{v}'[v_i'/w']]}$ which implies $G' \models \exists x_i(\psi[\mathbf{v}'])$

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 $C^{k}[q]$ = quantifier depth $\leq q$. Fix vectors $\boldsymbol{v} \in V(G)^{k}, \boldsymbol{v}' \in (V(G'))^{k}$.

Theorem

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The \leftarrow direction.

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The \Leftarrow direction. To prove $\operatorname{owl}_{k}^{q+1}(\mathbf{v}) = \operatorname{owl}_{k}^{q+1}(\mathbf{v}')$ we need to check:

•
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•
$$\{\{ \mathsf{owl}_k^q(\mathbf{v}[w/v_i]) \mid w \in V(G)\}\} = \{\{ \mathsf{owl}_k^q(\mathbf{v}'[w'/v_i']) \mid w' \in V(G')\}\}, i = 1, k.$$

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 Fix a color c on the left, and let n_c be the number of its occurrences.

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 Let ψ_c(x₁,...,x_k) ^{def} = the q, k-type (in C) of tuples v[w/v_i] colored c.

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 Fix a color c on the left, and let n_c be the number of its occurrences.
 Let ψ_c(x₁,...,x_k) ^{def} = the q, k-type (in C) of tuples v[w/v_i] colored c.
 Then G ⊨ (∃^{=n_c}x_iψ_c(x₁,...,x_k))[v], thus G' ⊨ (∃^{=n_c}x_iψ_c(x₁,...,x_k))[v'].

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- Color refinement was discovered multiple times in the past.
- Weisfeiler and Leman introduced 2-WL.
- Cai, Führer, Immerman established connection between k-WL, C^k , and certain EF-games. They also described the graphs G_k , H_k .
- There is a connection between GNNs, WL, C^k, however the exact/rigorous statement requires a careful examination of the details.

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