

Verifying Graph Neural Networks

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LORI 2025 - Xi'an

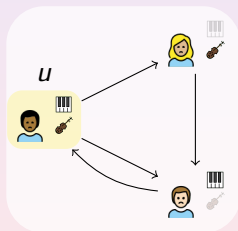
Lecture notes



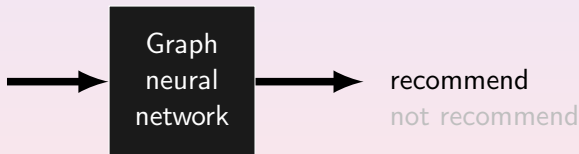
<https://arxiv.org/abs/2510.11617>

Motivation

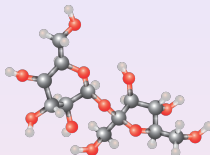
A GNN = a machine learning model for classifying graphs/vertices



labeled pointed graph



Applications



- Toxicity of a molecule [Reiser et al. 2022]
- Drug discovery [Xiong et al., 2021]
- Recommendation in social network [Salamat et al., 2021]
- Voice segmentation in music scores
[Karystinaios et al., IJCAI 2023]
- Link prediction etc. in knowledge graphs [Ye et al. 2022]
- Heuristics in epistemic planning [Briglia et al. 2025]

GNNs = Blackboxes

We need:

- 🗨️ Explanations on decisions made
- 💡 Make GNNs more interpretable
- ✓ Guarantees

⇒ research on the interaction $\text{logic} \leftrightarrow \text{GNNs}$



Some references

- GNNs and Weisfeiler-Leman tests: [Grohe LICS 2021]
 - GNNs and graded modal logic [Barceló et al. ICLR 2020]
 - Verification [Nunn et al. 2023] [Nunn et al. IJCAI 2024]
[Benedikt et al. ICALP 2024] [Sälzer et al. IJCAI 2025]
 - Explosion of connections logic $\leftrightarrow$ GNNs:
 - mu-calculus and recurrent GNNs [Ahvonen et al. NeurIPS 2024]
 - standard modal logic and mean-GNNs [Schönherr et al. 2025]
 - datalog and max-GNNs [Cucala et al. KR 2024]
- etc.

Outline

- 1 Graph neural networks
 - Definition
 - Activation function
 - GNN as expressions
- 2 Link with graded modal logic
- 3 Verification of Truncated-ReLU GNNs
- 4 Discussions
- 5 Conclusion

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Labelled graphs

Definition

A *labelled graph* is (V, E, ℓ) where:

- V is a set of vertices;
- E is a set of edges;
- $\ell : V \rightarrow \mathbb{Q}^d$ is a labelling function.

$\mathbb{Q}$ = set of rational numbers
 d = dimension of vectors

$$\begin{pmatrix} 2 \\ 0 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ 1 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

Definition of a graph neural network

A GNN is an algorithm $\mathcal{A}$ of the form:

```
input: a labelled pointed graph  $(G, u, \ell_0)$ 
output: yes/no
function  $\mathcal{A}(G, u, \ell_0)$ 
|    $\ell_1 := \text{layer}_1(G, \ell_0)$ 
|    $\vdots$ 
|    $\ell_L := \text{layer}_L(G, \ell_{L-1})$ 
|   return yes if  $w^t \ell_L(u) + b \geq 0$  else no
```

Example of a GNN layer

Previous labelling: $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$ ————— $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ ————— $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$

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Multiply the current vector by 2

Example of a GNN layer

Previous labelling: $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$ ————— $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ ————— $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$



Multiply the current vector by 2

$\begin{pmatrix} 4 \\ 0 \end{pmatrix}$ ————— $\begin{pmatrix} 2 \\ 2 \end{pmatrix}$ ————— $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$

Example of a GNN layer

Previous labelling: $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$ — $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ — $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$

↓ Multiply the current vector by 2

$\begin{pmatrix} 4 \\ 0 \end{pmatrix}$ — $\begin{pmatrix} 2 \\ 2 \end{pmatrix}$ — $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$

↓ Add $-1 \times$ the sum of its neighbor vectors

Example of a GNN layer

Previous labelling: $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$ — $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$ — $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$

↓ Multiply the current vector by 2

$\begin{pmatrix} 4 \\ 0 \end{pmatrix}$ — $\begin{pmatrix} 2 \\ 2 \end{pmatrix}$ — $\begin{pmatrix} 2 \\ 0 \end{pmatrix}$

↓ Add $-1 \times$ the sum of its neighbor vectors

$\begin{pmatrix} 3 \\ -1 \end{pmatrix}$ — $\begin{pmatrix} -1 \\ 2 \end{pmatrix}$ — $\begin{pmatrix} 1 \\ -1 \end{pmatrix}$

Example of a GNN layer

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↓ Replace negative values by 0

Example of a GNN layer

Previous labelling: $\begin{pmatrix} 2 \\ 0 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ 1 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

↓ Multiply the current vector by 2

$\begin{pmatrix} 4 \\ 0 \end{pmatrix} \text{ ————— } \begin{pmatrix} 2 \\ 2 \end{pmatrix} \text{ ————— } \begin{pmatrix} 2 \\ 0 \end{pmatrix}$

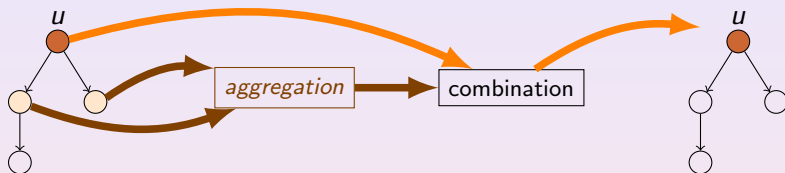
↓ Add $-1 \times$ the sum of its neighbor vectors

$\begin{pmatrix} 3 \\ -1 \end{pmatrix} \text{ ————— } \begin{pmatrix} -1 \\ 2 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ -1 \end{pmatrix}$

↓ Replace negative values by 0

New labelling: $\begin{pmatrix} 3 \\ 0 \end{pmatrix} \text{ ————— } \begin{pmatrix} 0 \\ 2 \end{pmatrix} \text{ ————— } \begin{pmatrix} 1 \\ 0 \end{pmatrix}$

Each layer



```

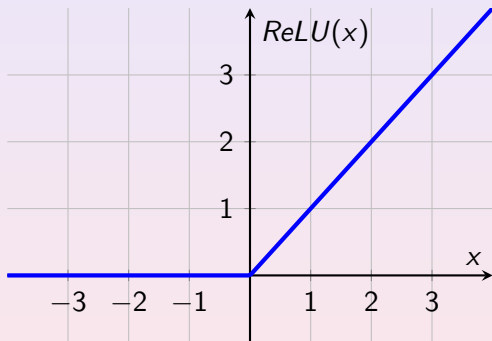
function layeri( $V, E, \ell$ )
     $\ell' := \text{new labelling } V \rightarrow \mathbb{Q}^d$ 
    for vertices  $u \in V$  do
        aggregation  $:= \sum \{\ell[v] \mid v \in E(u)\}$ 
         $\ell'[u] := \vec{\sigma}(A_i \times \ell[u] + B_i \times \textit{aggregation} + b_i)$ 
    return  $\ell'$ 
    
```

where $A_i, B_i \in \mathbb{Q}^{d \times d}$ and $b_i \in \mathbb{Q}^d$.

Outline

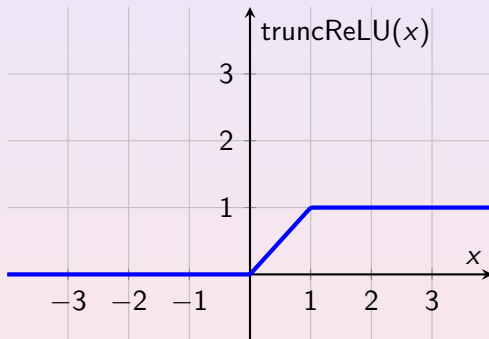
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ReLU activation function



$$ReLU(x) = \max(0, x)$$

TruncReLU activation function



$$\text{truncReLU}(x) = \max(0, \min(1, x))$$

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Syntax and semantics

Syntax of GNN expressions [Sälzer et al., IJCAI 2025]

$$\vartheta ::= c \mid x_i \mid \sigma(\vartheta) \mid \text{agg}(\vartheta) \mid \vartheta + \vartheta \mid c \times \vartheta$$

Semantics

$$\begin{aligned} \llbracket c \rrbracket_{G,u} &= c, \\ \llbracket x_i \rrbracket_{G,u} &= \ell(u)_i, \\ \llbracket \vartheta + \vartheta' \rrbracket_{G,u} &= \llbracket \vartheta \rrbracket_{G,u} + \llbracket \vartheta' \rrbracket_{G,u}, \\ \llbracket c \times \vartheta \rrbracket_{G,u} &= c \times \llbracket \vartheta \rrbracket_{G,u}, \\ \llbracket \sigma(\vartheta) \rrbracket_{G,u} &= \llbracket \sigma \rrbracket(\llbracket \vartheta \rrbracket_{G,u}), \\ \llbracket \text{agg}(\vartheta) \rrbracket_{G,u} &= \Sigma_{v \mid uEv} \llbracket \vartheta \rrbracket_{G,v}, \end{aligned}$$

GNN expressions capture GNNs!

Proposition

Given a GNN $\mathcal{A}$, there exists an expression ϑ such that

$$(G, u) \in \llbracket \mathcal{A} \rrbracket \quad \text{iff} \quad \llbracket \vartheta \geq 1 \rrbracket_{G,u} = \text{true}.$$

Example

- $\mathcal{A}^{(0)}(G, u) = \ell_0(G, u);$
- $\mathcal{A}^{(1)}(G, u) = \vec{\sigma} \left(\begin{pmatrix} 2 & 1 \\ -1 & 4 \end{pmatrix} \times \mathcal{A}^{(0)}(G, u) + \begin{pmatrix} 5 & 3 \\ 2 & 6 \end{pmatrix} \times \sum \llbracket \mathcal{A}^{(0)}(G, v) \mid v \in E(u) \rrbracket + \begin{pmatrix} 1 \\ -2 \end{pmatrix} \right)$
- $\mathcal{A}^{(2)}(G, u) = \vec{\sigma} \left(\begin{pmatrix} 3 & 0 \\ -2 & 0 \end{pmatrix} \times \mathcal{A}^{(1)}(G, u) + \begin{pmatrix} -1 & 0 \\ 0 & 5 \end{pmatrix} \times \sum \llbracket \mathcal{A}^{(1)}(G, v) \mid v \in E(u) \rrbracket + \begin{pmatrix} 0 \\ 0 \end{pmatrix} \right)$

$$\psi_1 = \sigma(2x_1 + x_2 + 5\text{agg}(x_1) - 3\text{agg}(x_2) + 1),$$

$$\psi_2 := \sigma(-x_1 + 4x_2 + 2\text{agg}(x_1) + 6\text{agg}(x_2) - 2),$$

$$\chi_1 := \sigma(3\psi_1 - \text{agg}(\psi_1),$$

$$\chi_2 := \sigma(-2\psi_1 + 5(\text{agg}(\psi_2))),$$

$$\varphi_{\mathcal{A}} := 2(\chi_1) - \chi_2 \geq 1.$$

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 - Via expressivity
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Modal logic and Graded modal logic

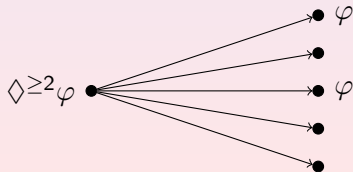
Modal logic

$\Diamond\varphi$: φ holds in at least one successor

Graded Modal logic

$\Diamond^{\geq k}\varphi$: φ holds in at least k successors

$G, u \models \Diamond^{\geq k}\varphi$ if there are $v_1, \dots, v_k \in E(u)$ all distinct such that
 $G, v_i \models \varphi$ for all $i = 1..k$.

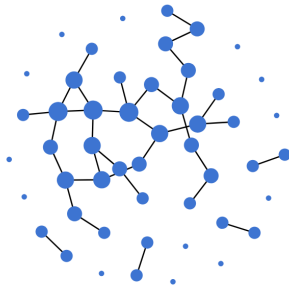


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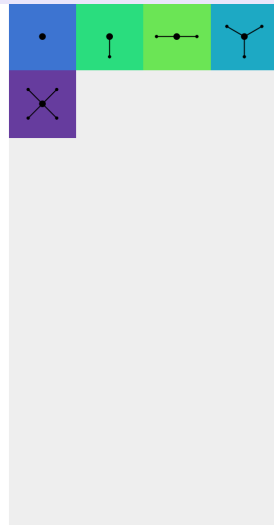
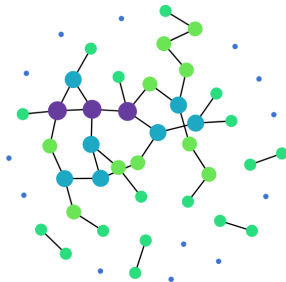
Color Refinement

Round $\langle 0 \rangle$ of 4



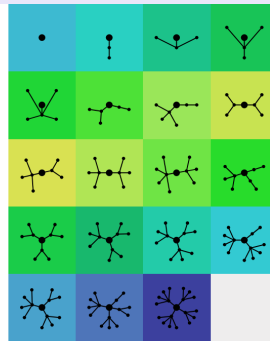
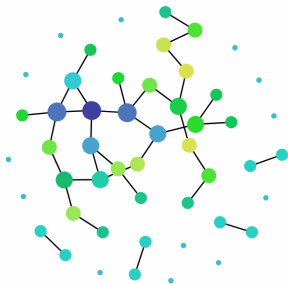
Color Refinement

Round < 1 > of 4



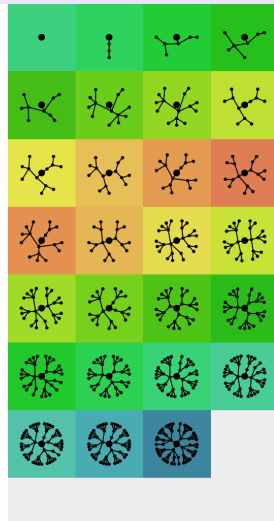
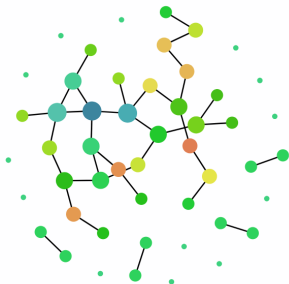
Color Refinement

Round < 2 > of 4



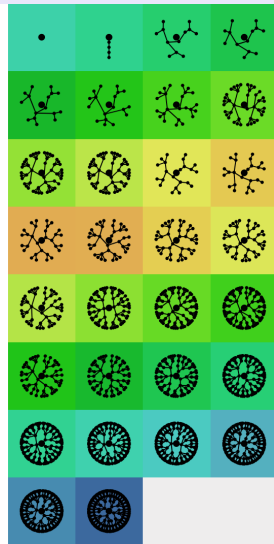
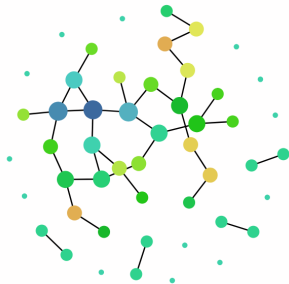
Color Refinement

Round < 3 > of 4



Color Refinement

Round < 4 > of 4



by [Holger Dell](#) (2020). Source code on [github](#).

Definition of Colour refinement

Tool: <https://holgerdell.github.io/color-refinement/>

Definition (Morgan, 1965)

- Initially, $\text{color}^{(0)}(G, u) = \text{label at } u \text{ in } G$;
- $\text{color}^{(t+1)}(G, u) = \left(\text{color}^{(t)}(G, u), \{ \text{color}^{(t)}(G, v) \mid uEv \} \right)$.

When it stabilizes, we get $\text{color}(G, u)$ for all $u \in V$.

$\text{color}(G, u)$ = the information used in the computation of a GNN.

Link between GML, colour refinement and GNNs

Theorem

Let $\mathcal{A}$ be a GNN.

$color(G, u) = color(G, v)$ implies $\mathcal{A}(G, u) = \mathcal{A}(G, v)$.

Theorem (folklore, see Grohe LICS 2021)

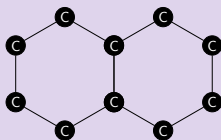
$color(G, u) = color(G, v)$ iff both u and v satisfy the same GML-formulas.

Colour refinement: a partial test for isomorphism

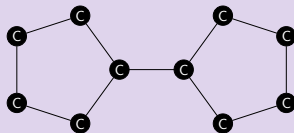
Proposition

$$G \equiv_{iso} G' \implies \{\{color(G, u) \mid u \in V\}\} = \{\{color(G', u') \mid u' \in V'\}\}.$$

⚠ The converse $\Leftarrow$ fails e.g. on regular graphs:



Decalin



Bicyclopentyl

↪ GNNs have been generalized to 2-WL, 3-WL, etc.

[Morris et al., AAAI 2019]

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Expressivity of GNNs

Theorem (Barc  lo et al. 2020)

For all GML-formulas φ , there is a GNN $\mathcal{A}$ such that $\llbracket \mathcal{A} \rrbracket = \llbracket \varphi \rrbracket$.

Theorem (Barc  lo et al. 2020)

FO-expressible

For all $\underbrace{\hspace{1cm}}$ GNNs $\mathcal{A}$, there is a GML-formula φ such that $\llbracket \mathcal{A} \rrbracket = \llbracket \varphi \rrbracket$.

In the theorems, the activation function is TruncReLU.

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Verification problems

$[[\mathcal{A}]] :=$ set of *pointed graphs* recommended by the GNN $\mathcal{A}$

$[[\varphi]] =$ set of *pointed graphs* satisfying the property φ
e.g. *having a violinist friend*

$$[[\mathcal{A}]] \subseteq [[\varphi]]?$$

Do all recommended persons
have a violinist friend?

$$[[\varphi]] \subseteq [[\mathcal{A}]]?$$

Are all persons *having a violinist friend* recommended?

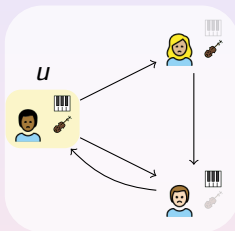
$$[[\mathcal{A}]] \cap [[\varphi]] \neq \emptyset?$$

Is it possible to recommend
a person *having a violinist friend*

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Example of a formula of $K^\#$



$$pianist \wedge (\#violinist + 2 \times \#pianist \leq 3)$$

$$\text{👤 is pianist} \quad \text{and} \quad \left(\begin{array}{c} \text{the number of 👤's friends} \\ \text{that are violinist} \end{array} + 2 \times \begin{array}{c} \text{the number of 👤's friends} \\ \text{that are pianist} \end{array} \leq 3 \right)$$

$K^\#$ syntax

- $K^\#$ -formulas φ are Boolean combinations of atomic propositions and inequalities.
- Expressions ξ in inequalities are linear over:
 - 1_φ which 1 if φ holds, 0 otherwise;
 - $\#\varphi$, equals to the number of φ -successors.

$$\varphi ::= p \mid \neg\varphi \mid \varphi \vee \varphi \mid \xi \geq 0$$

$$\xi ::= c \mid 1_\varphi \mid \#\varphi \mid \xi + \xi \mid c \times \xi$$

$K^\#$ semantics

$$\begin{aligned}
 (G, u) \models p & \quad \text{if} \quad \ell(u)(p) = 1, \\
 (G, u) \models \neg\varphi & \quad \text{if} \quad \text{it is not the case that } (G, u) \models \varphi, \\
 (G, u) \models \varphi \wedge \psi & \quad \text{if} \quad (G, u) \models \varphi \text{ and } (G, u) \models \psi, \\
 (G, u) \models \xi \geq 0 & \quad \text{if} \quad [[\xi]]_{G,u} \geq 0,
 \end{aligned}$$

$$\begin{aligned}
 [[c]]_{G,u} & = c, \\
 [[\xi_1 + \xi_2]]_{G,u} & = [[\xi_1]]_{G,u} + [[\xi_2]]_{G,u}, \\
 [[c \times \xi]]_{G,u} & = c \times [[\xi]]_{G,u}, \\
 [[1_\varphi]]_{G,u} & = \begin{cases} 1 & \text{if } (G, u) \models \varphi \\ 0 & \text{else,} \end{cases} \\
 [[\#\varphi]]_{G,u} & = |\{v \in V \mid (u, v) \in E \text{ and } (G, v) \models \varphi\}|.
 \end{aligned}$$

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From $K^\#$ to GNNs

Inspired from [Barcélo et al. 2020], [Nunn et al., 2023, IJCAI 2024], [Benedikt et al. ICALP 2024]

Theorem

For all $K^\#$ -formulas φ , there is a GNN $tr(\varphi)$ sth. $\llbracket tr(\varphi) \rrbracket = \llbracket \varphi \rrbracket$.

$$tr(x_i = 1) = x_i \text{ provided } x_i \text{ takes its value in } \{0, 1\}$$

$$tr(\neg\varphi) = 1 - \text{truncReLU}(tr(\varphi))$$

$$tr(\varphi \wedge \psi) = \text{truncReLU}(tr(\varphi) + tr(\psi) - 1)$$

$$tr(\vartheta \geq 1) = \text{truncReLU}(\tau(\vartheta))$$

$$\tau(\#\varphi) = \text{agg}(tr(\varphi))$$

$$\tau(\vartheta + \vartheta') = \tau(\vartheta) + \tau(\vartheta')$$

$$\tau(1_\varphi) = tr(\varphi)$$

$$\tau(c) = c$$

From GNNs to $K^\#$

Theorem

For all GNNs $\mathcal{A}$, there is a $K^\#$ -formula $tr'(\mathcal{A})$ sth. $\llbracket tr'(\mathcal{A}) \rrbracket = \llbracket \varphi \rrbracket$.

Proof idea for integer weights:

$$tr'(x_i) = x_i$$

$$tr'(c) = c$$

$$tr'(c\vartheta) = c \times tr'(\vartheta)$$

$$tr'(\vartheta + \vartheta') = tr'(\vartheta) + tr'(\vartheta')$$

$$tr'(\text{truncReLU}(\vartheta)) = 1_{tr'(\vartheta) \geq 1}$$

$$tr'(\text{agg}(\vartheta)) = \#(tr'(\vartheta) \geq 1) \text{ provided } \vartheta \text{ is of the form } \text{truncReLU}(\cdot)$$

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Satisfiability of $K^\#$

Theorem

Satisfiability of $K^\#$ is decidable and is in PSPACE.

*we have an algorithm using a
polynomial amount of space.
~ "implementable"*

Alternative proofs:

- [Nunn et al. 2024]
By poly-time reduction to a logic in [Demri and Lugiez 2010]
- [Lecture notes]

Tableau method + oracle to QFBAPA-sat
(close to [Baader, 2017])

Quantifier-free Boolean algebra and Presburger arithmetics

[Kuncak et al. 2007]

Example (of a QFBAPA formula)

$$|pianist \cap student| + x \geq 5 \quad \wedge \quad (|pianist| \leq 10 \vee |student| \leq 10)$$

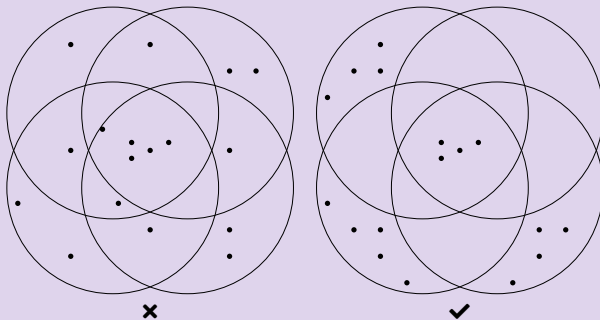
- Integer variables: x , etc.
- Set variables: *pianist*, *student*, etc.
- Cardinality of some sets expressed with Boolean algebras
- Linear inequalities involving integer variables and cardinality

Quantifier-free Boolean algebra and Presburger arithmetics

Theorem (Kuncak et al. 2007)

QFBAPA-satisfiability is in NP.

Proof.



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Global readout

```
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   $\ell' := \text{new labelling } V \rightarrow \mathbb{Q}^d$   
  for vertices  $u \in V$  do  
    aggregation  $:= \sum \{\ell[v] \mid v \in E(u)\}$   
    globalreadoutaggregation  $:= \sum \{\ell[v] \mid v \in V\}$   
     $\ell'[u] := \vec{\sigma} \begin{pmatrix} A_i \times \ell[u] \\ + B_i \times \textit{aggregation} \\ + C_i \times \textit{globalreadoutaggregation} \\ + b_i \end{pmatrix}$   
  return  $\ell'$ 
```

Global readout

$K^{\#, \#^g}$ extends $K^{\#}$ with global counting modality $\#^g \varphi$:

$$\llbracket \#^g \varphi \rrbracket_{G,u} = \text{number of } \varphi\text{-vertices in } G.$$

Proposition

Globalreadout-truncReLU-GNNs and $K^{\#, \#^g}$ are equivalent.

Theorem

$K^{\#, \#^g}$ -satisfiability is:

- *NEXPTIME-complete for directed graphs;*
[Chernobrovkin et al. 2025]
- *undecidable if undirected graphs.* [Benedikt et al. 2024]

Outline

- 1 Graph neural networks
- 2 Link with graded modal logic
- 3 Verification of Truncated-ReLU GNNs
- 4 Discussions**
 - Global readout
 - ReLU GNNs**
 - Quantized GNNs
- 5 Conclusion

ReLU GNNs

Theorem (Benedikt et al. 2024)

The satisfiability of ReLU-GNNs is:

- *NEXPTIME-complete for directed graphs;*
- *undecidable if undirected graphs or global readout.*

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Idealistic GNN vs Quantized GNN

Idealistic GNN

- Arbitrary big integers
35467487612987698761230
- Arbitrary large rationals
4238761289293/123876298375
- Real numbers

$\sqrt{2}$

π

e

Quantized GNN

0	0	1	0	1	1	0	1
---	---	---	---	---	---	---	---

- 32-bit floating-point arithmetics
- 16-bit fixed-point arithmetics
- 8-bit signed integers

[Gholami et al. 2021] [Zhu et al. ICLR 2023]

Verification of quantized GNNs

Theorem (Sälzer et al. IJCAI 2025)

The verification problems are in PSPACE.

- 😊 in PSPACE for *many* activation and aggregation functions
- 😊 We can check GML-formulas...
- 😞 ...for all modalities $\Diamond^{\geq k} \varphi$, number k should be representable with n bits

Tableau method

$$\begin{aligned}
 (\vee) & \frac{(w \varphi \vee \psi)}{(w \varphi) \mid (w \psi)} \\
 (\neg\vee) & \frac{(w \neg(\varphi \vee \psi))}{(w \neg\varphi), (w \neg\psi)} \\
 (\wedge) & \frac{(w \varphi \wedge \psi)}{(w \varphi), (w \psi)} \\
 (\neg\wedge) & \frac{(w \neg(\varphi \wedge \psi))}{(w \neg\varphi) \mid (w \neg\psi)} \\
 (\neg\neg) & \frac{(w \neg\neg\varphi)}{(w \varphi)} \\
 (\neg\geq) & \frac{(w \neg(\vartheta \geq k))}{(w \vartheta = k') \text{ for some } k' \in \mathbb{K}_n \text{ with } k' <_{\mathbb{K}_n} k} \\
 (+) & \frac{(w \vartheta_1 + \vartheta_2 = k)}{(w \vartheta_1 = k_1), (w \vartheta_2 = k_2) \text{ for some } k_1, k_2 \in \mathbb{K}_n, \text{ with } k_1 +_{\mathbb{K}_n} k_2 = k} \\
 (\text{degree}) & \frac{(w \varphi) \text{ and no term } (w \text{ degree} = \dots)}{(w \text{ degree} = \delta') \text{ for some } \delta' \leq \delta}
 \end{aligned}$$

$$\begin{aligned}
 (\text{clash}_c) & \frac{(w c = k) \text{ if } c \neq k}{\text{fail}} \\
 (\text{clash}_=) & \frac{(w x_i = k), (w x_i = k') \text{ if } k \neq k'}{\text{fail}} \\
 (\sigma) & \frac{(w \sigma(\vartheta) = k)}{(w \vartheta = k') \text{ for some } k' \in \mathbb{K}_n \text{ with } \llbracket \sigma \rrbracket(k') = k} \\
 (\geq) & \frac{(w \vartheta \geq k)}{(w \vartheta = k') \text{ for some } k' \in \mathbb{K}_n \text{ with } k' \geq_{\mathbb{K}_n} k} \\
 (\times) & \frac{(w c\vartheta = k)}{(w \vartheta = k') \text{ for some } k' \in \mathbb{K}_n \text{ with } c \times_{\mathbb{K}_n} k' = k} \\
 (\text{agg}) & \frac{(w \text{agg}(\vartheta) = k) \quad (w \text{degree} = \delta')}{(w 1 \vartheta = k_1), \dots, (w \delta' \vartheta = k_{\delta'}) \text{ for some } (k_u)_{u=1..\delta'}, \text{ with } k_1 +_{\mathbb{K}_n} \dots +_{\mathbb{K}_n} k_{\delta'} = k}
 \end{aligned}$$

where $\mathbb{K}_n$ is the set of quantized numbers over n bits

Implementations for quantized GNNs

- Tableau method:

`https://github.com/francoisschwarzentruer/
ijcai2025-verifquantgnn`

- Bounded verification, also with global readout:

`https://github.com/francoisschwarzentruer/gnn_
verification`

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Perspectives

-  Other ML models: GNN with attention, etc.
-  Efficient implementation
-  Applications
-  Define new verification tasks
-  Design interpretable GNNs

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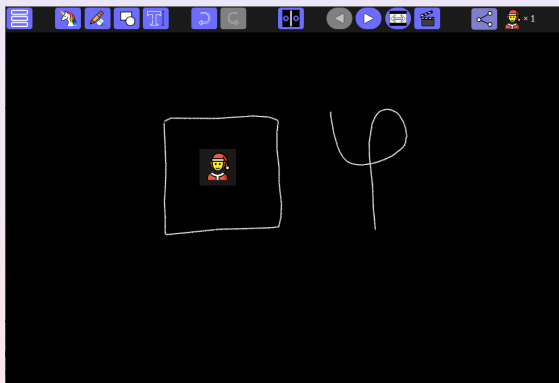


Lecture notes



<https://arxiv.org/abs/2510.11617>

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