

Probabilistic Graph Homomorphism

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Probabilistic Graph

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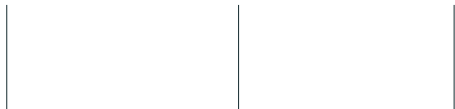
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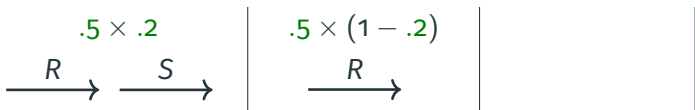
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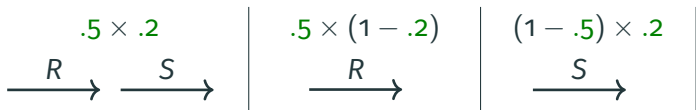
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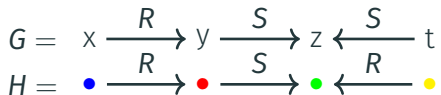
- $(x, y) \in E_G \implies (h(x), h(y)) \in E_H$
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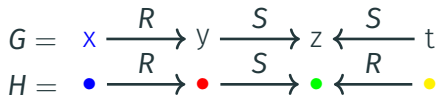


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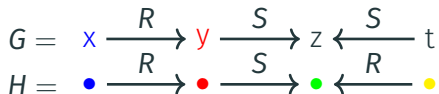


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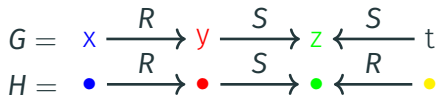


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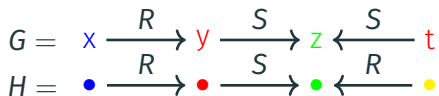


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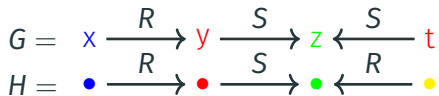


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We write $G \rightsquigarrow H$ if there exists a homomorphism from G to H

Probabilistic Graph Homomorphism (PHom)

Let us fix:

- Finite set of labels Σ
- Class \mathcal{G} of **query graphs** on Σ (e.g., paths, trees)
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Probabilistic Graph Homomorphism (PHom) problem for \mathcal{G} and \mathcal{H} :

- Given a query graph $G \in \mathcal{G}$
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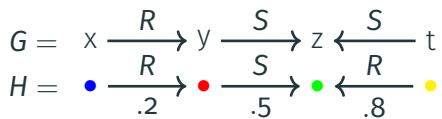
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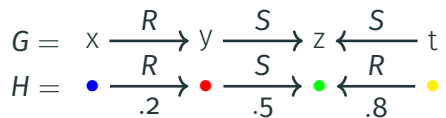
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$$\rightarrow \Pr(G \rightsquigarrow H) = \sum_{J \subseteq H, G \rightsquigarrow J} \Pr(J)$$

Example



Example



$$\Pr(G \rightsquigarrow H) = .2 \times .5$$

Complexity of Probabilistic Graph Homomorphism

Question: what is the **complexity** of PHom depending on the class \mathcal{G} of **query graphs** and class \mathcal{H} of **instance graphs**?

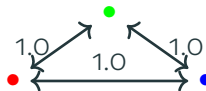
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Like **CSP** but with probabilities!

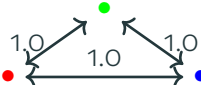

Fix one side

- Fix the instance graph $H =$





NP-hard

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- Fix the query graph $G =$  #P-hard

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- Fix the instance graph $H =$  **NP-hard**
- Fix the query graph $G =$  **#P-hard**

To make PHom **tractable**, we must restrict both sides

Restrict instance graphs to trees

\mathcal{G} = one-way paths (1WP), \mathcal{H} = polytrees (PT)

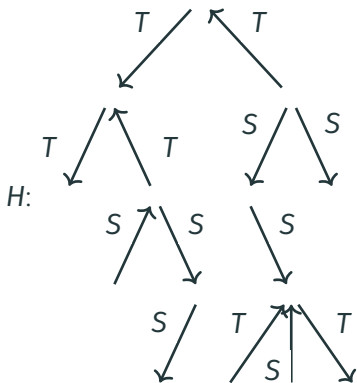
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G : $\xrightarrow{T} \xrightarrow{S} \xrightarrow{S} \xrightarrow{S} \xrightarrow{T}$

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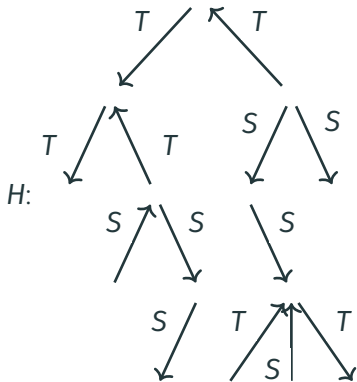


+ prob. for each edge

PHom of 1WP on PT is **#P-hard!**

$\mathcal{G} = \text{one-way paths}$, $\mathcal{H} = \text{polytrees, without labels}$

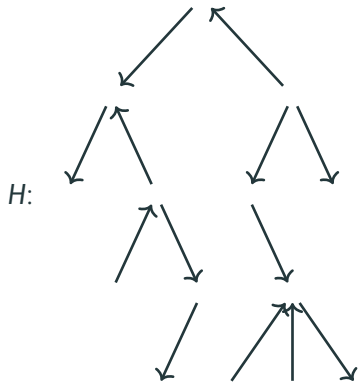
- What if we **do not have labels**?



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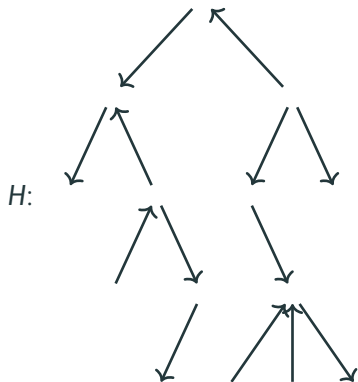
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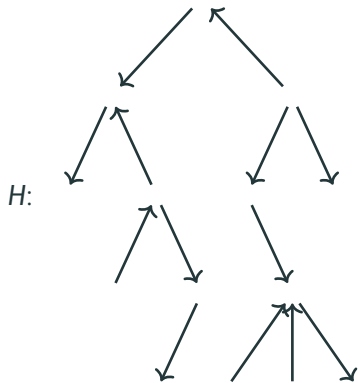
- What if we **do not have labels**?
- Probability that the instance graph has a path of length $|G|$



+ prob. for each edge

\mathcal{G} = two-way paths, \mathcal{H} = polytrees, without labels

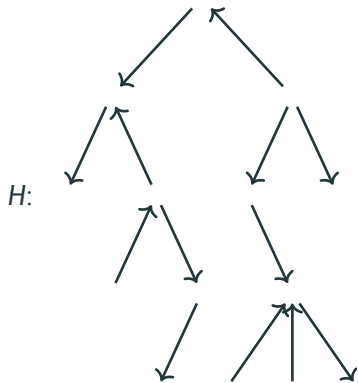
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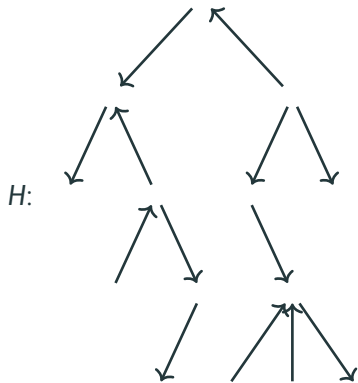
- \mathcal{G} = **two-way paths** (2WP), \mathcal{H} = **polytrees** (PT)



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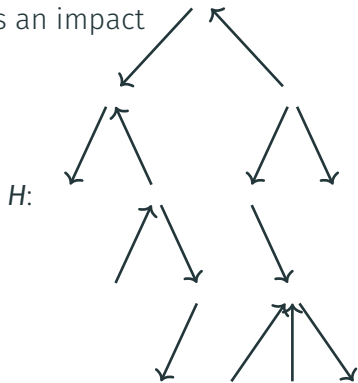
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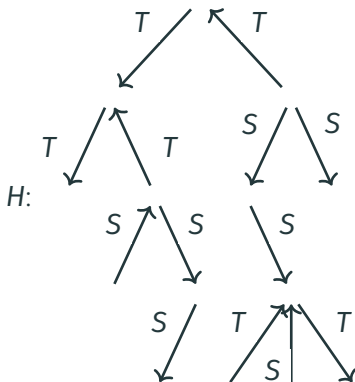
- \mathcal{G} = **two-way paths** (2WP), \mathcal{H} = **polytrees** (PT)
- **#P-hard**
- **Global orientation** of the **query** has an impact



+ prob. for each edge

$\mathcal{G} = \text{one-way paths}$, $\mathcal{H} = \text{downwards trees}$

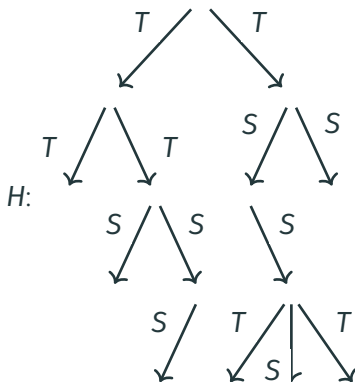
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+ prob. for each edge 10/13

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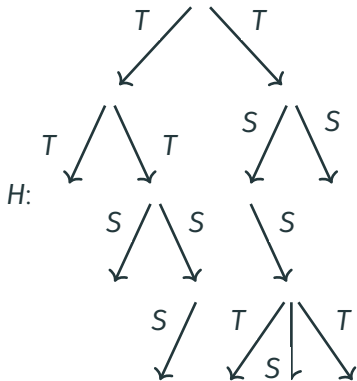
- $\mathcal{G} = \text{one-way paths}$ (1WP), $\mathcal{H} = \text{downwards trees}$ (DWT)



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\mathcal{G} = downwards trees, \mathcal{H} = downwards trees, with labels

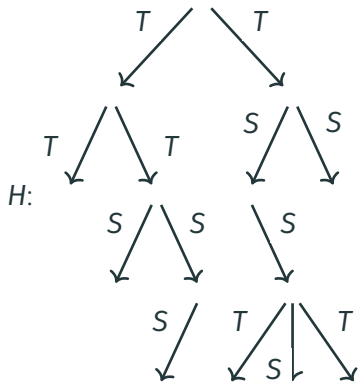
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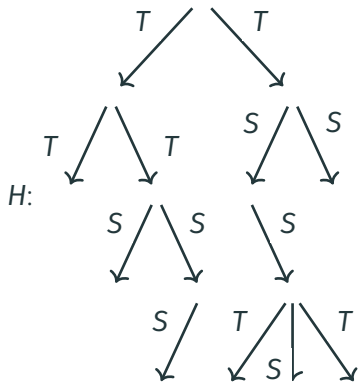
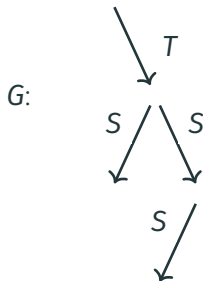
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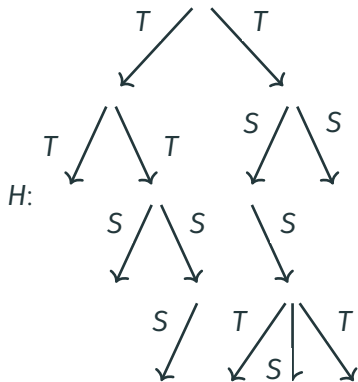
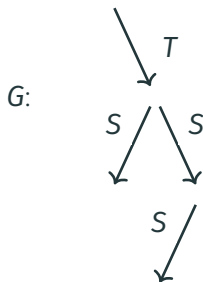
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- \mathcal{G} = **downwards trees** (DWT), \mathcal{H} = **downwards trees**
- **#P-hard**
- **Branching** has an impact!



+ prob. for each edge

Results

$\downarrow G$	$H \rightarrow$	1WP	2WP	DWT	PT	Connected	
1WP							≥ 2 labels
2WP							
DWT			PTIME				
PT						#P-hard	
Connected							
$\downarrow G$	$H \rightarrow$	1WP	2WP	DWT	PT	Connected	
1WP							No labels
2WP							
DWT			PTIME				
PT						#P-hard	
Connected							

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