

# Learning Fast-Inference Bayesian Networks



P. R. Vaidyanathan · Stefan Szeider

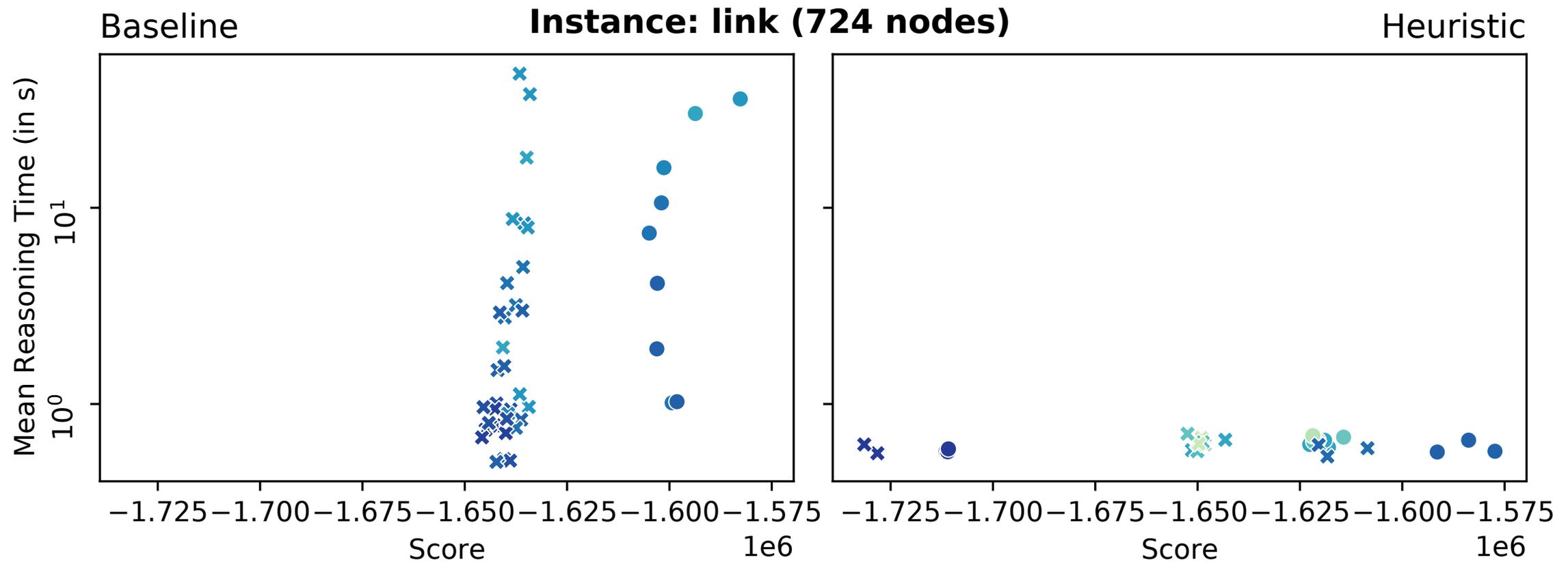
December 14, 2021 · Neural Information Processing Systems



ALGORITHMS AND  
COMPLEXITY GROUP

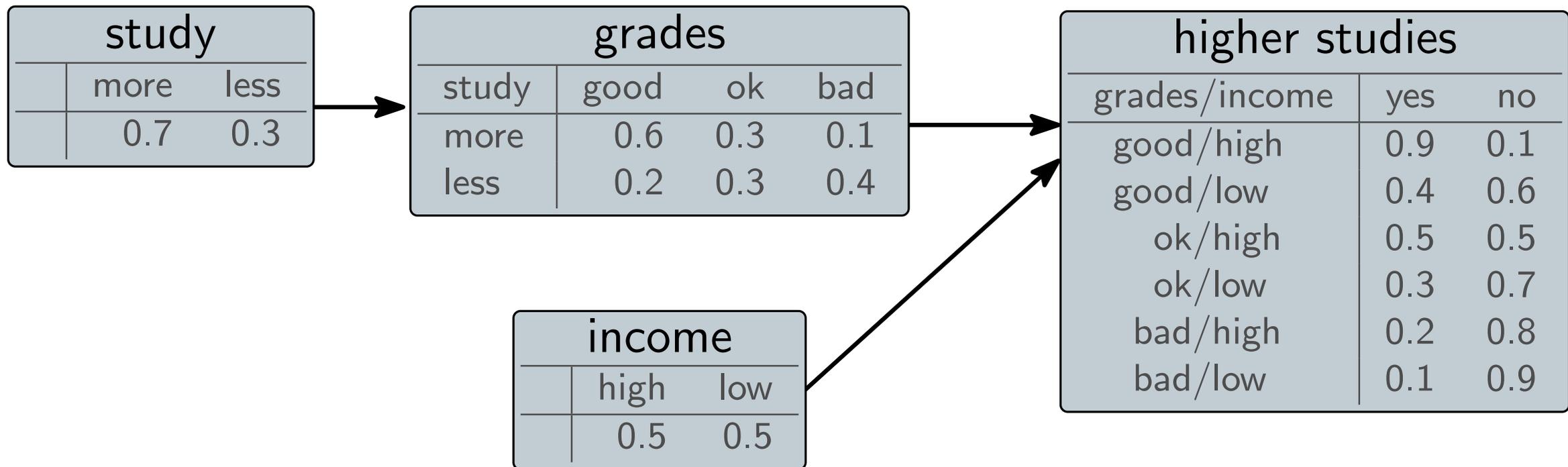
New approach to learn Bayesian Networks

- with *reliably low* reasoning times
- not compromising on the *quality*



# Bayesian Network Basics

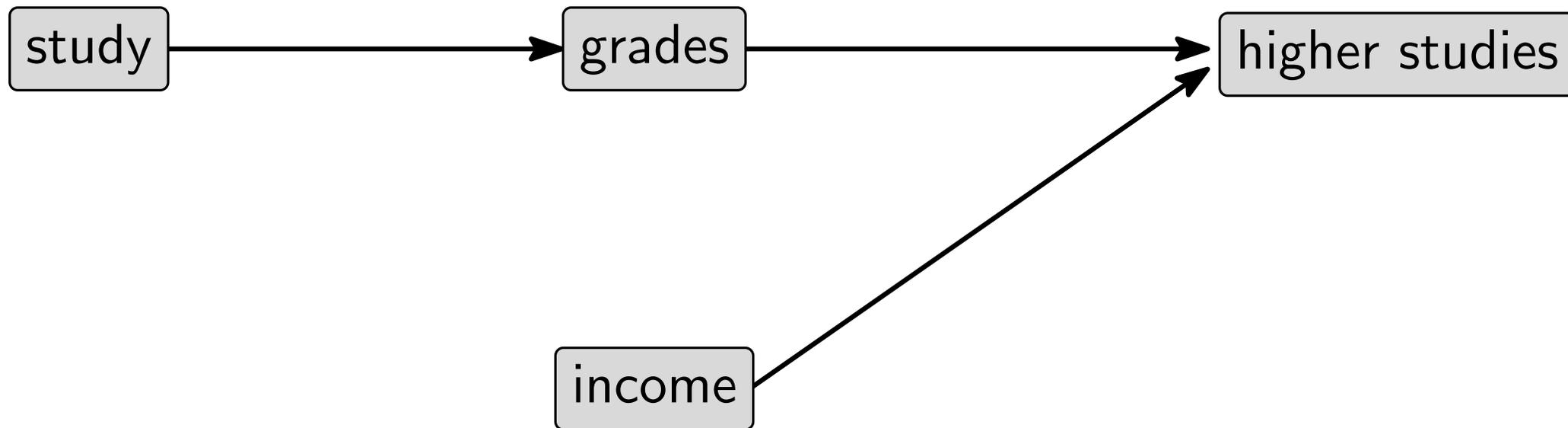
- A Bayesian Network (BN) is a DAG  $D$ , with random variables  $X$  as vertices along with probability distribution tables for each variable
- Arc  $X_p \rightarrow X_q$  indicates  $q$  depends on  $p$



Bayesian Network  $\mathcal{B}$

# Bayesian Network Basics

- A Bayesian Network (BN) is a DAG  $D$ , with random variables  $X$  as vertices along with probability distribution tables for each variable
- Arc  $X_p \rightarrow X_q$  indicates  $q$  depends on  $p$

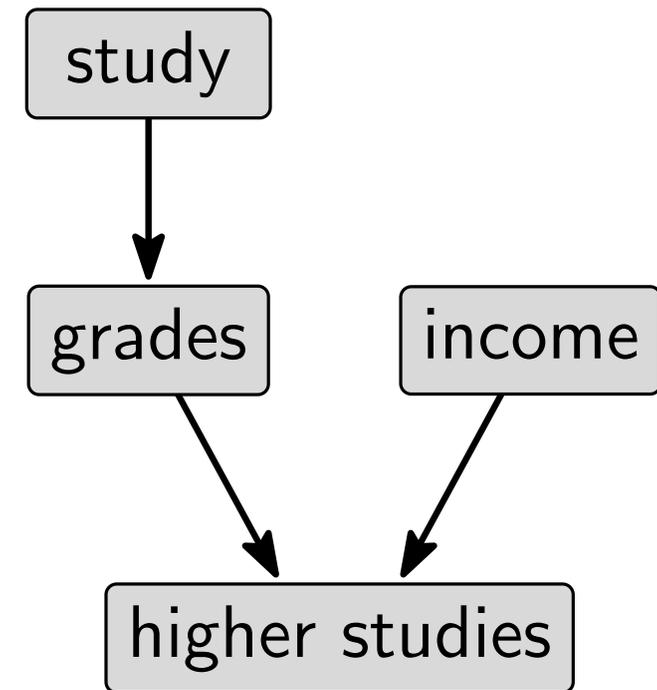


Structure of  $\mathcal{B}$

## Bayesian Network Structure Learning (BNSL)

study	grade	income	higher studies
less	good	high	no
more	ok	low	yes
less	ok	high	yes
less	good	high	yes
⋮	⋮	⋮	⋮
more	bad	high	no
less	bad	high	no
more	bad	high	no

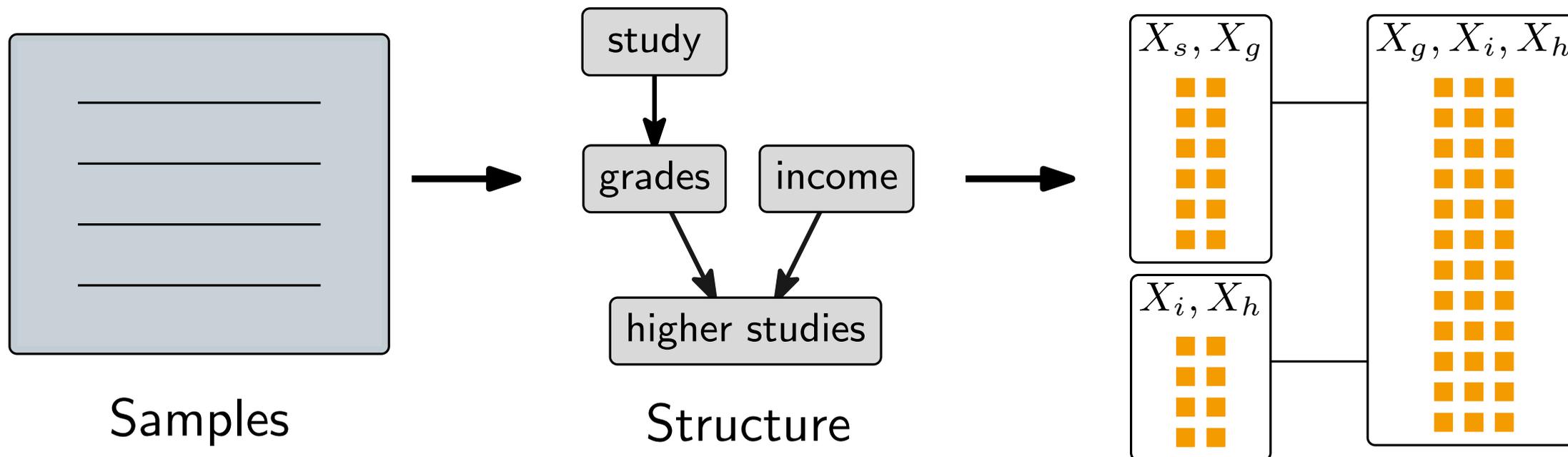
Samples



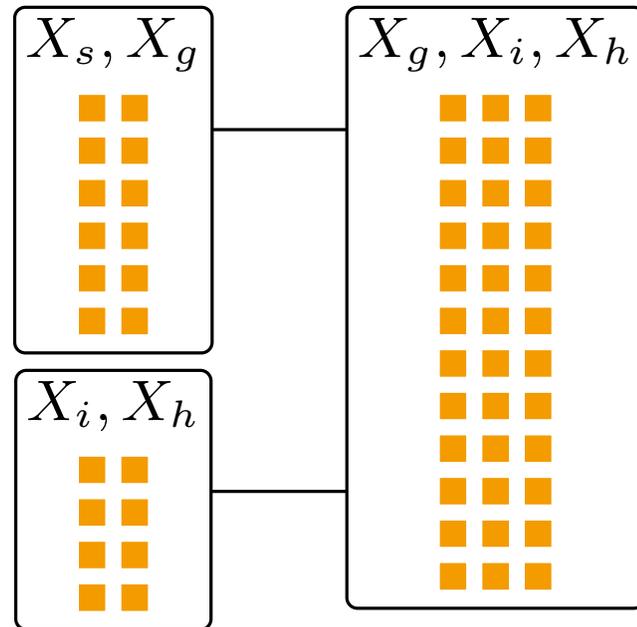
Structure

# Inference on BNs

- Once learned, BNs can be used to make predictions (inference)
- Inference is **exponential** in general
- For special classes of graphs, inference can be polytime
- Most popular special class: graphs with bounded **treewidth**

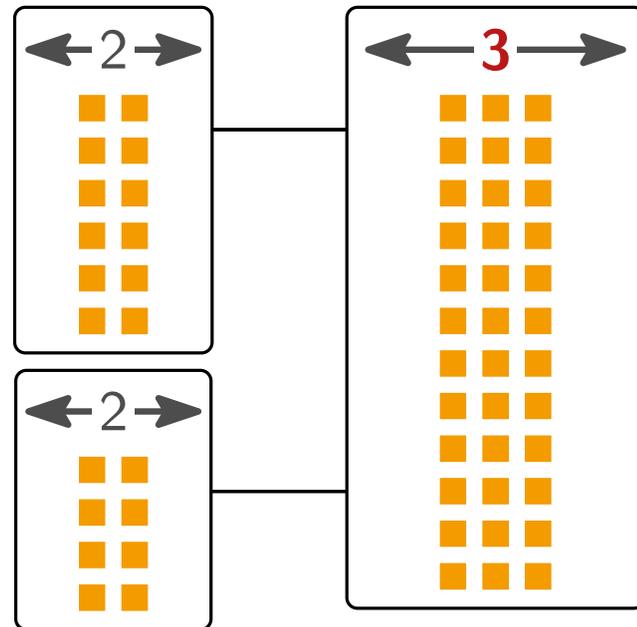


# Inference on BNs



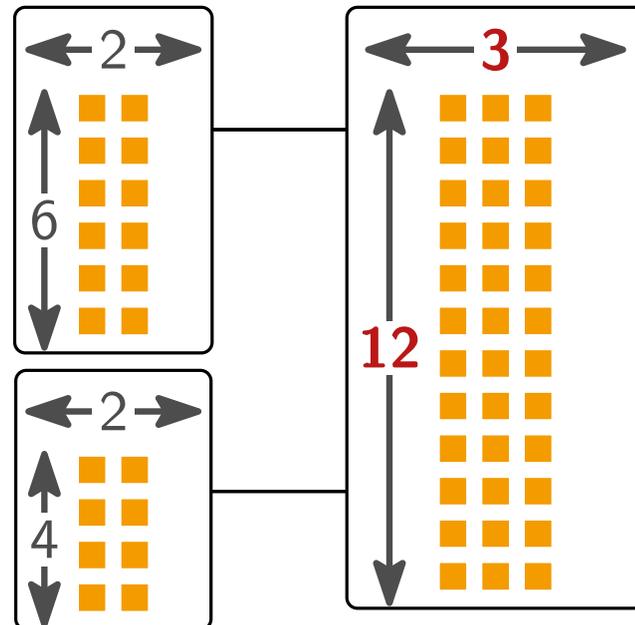
# Inference on BNs

- Treewidth bounds maximum number of columns



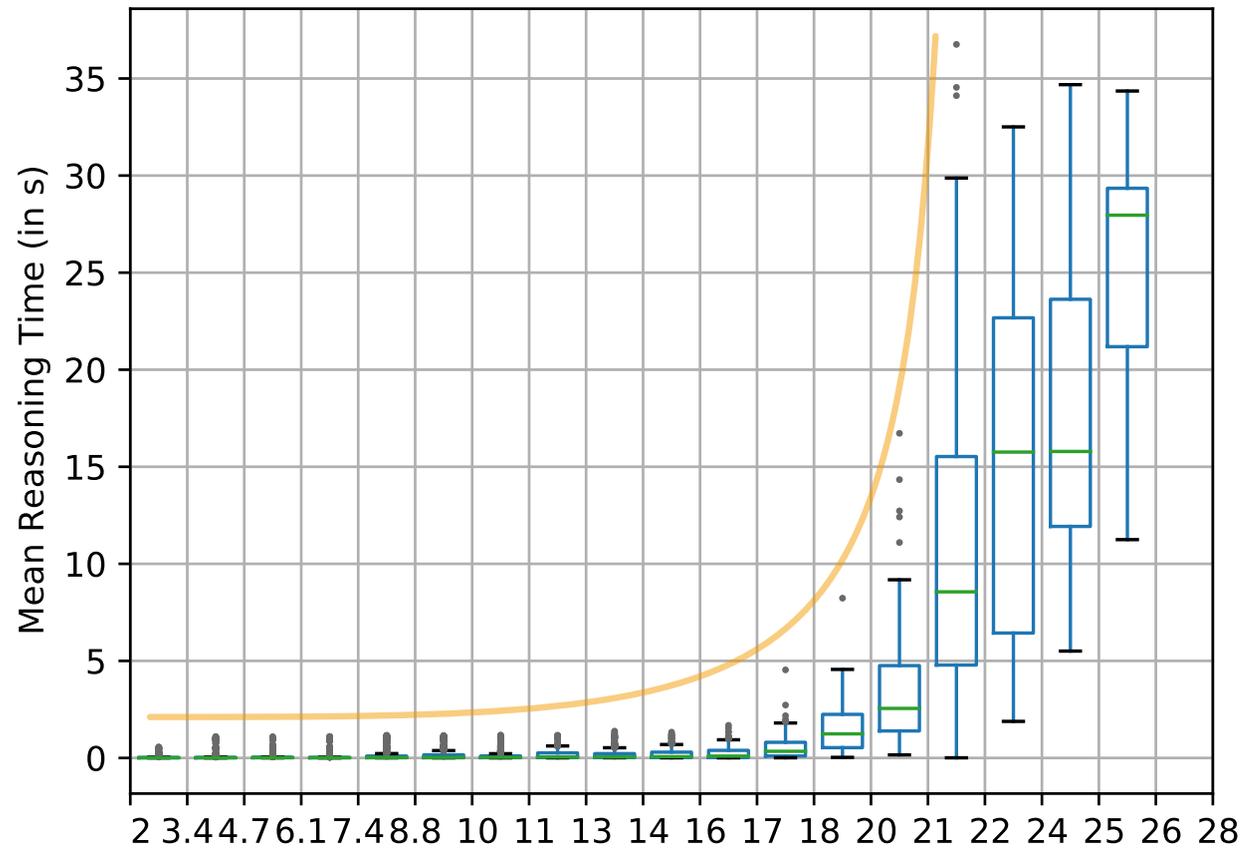
# Inference on BNs

- Treewidth bounds maximum number of columns
- Many real-world datasets contain non-binary variables
- We propose to use **maximum state space size**(msss) in place of treewidth
- More fine-grained than treewidth
- Takes into account domain sizes of variables

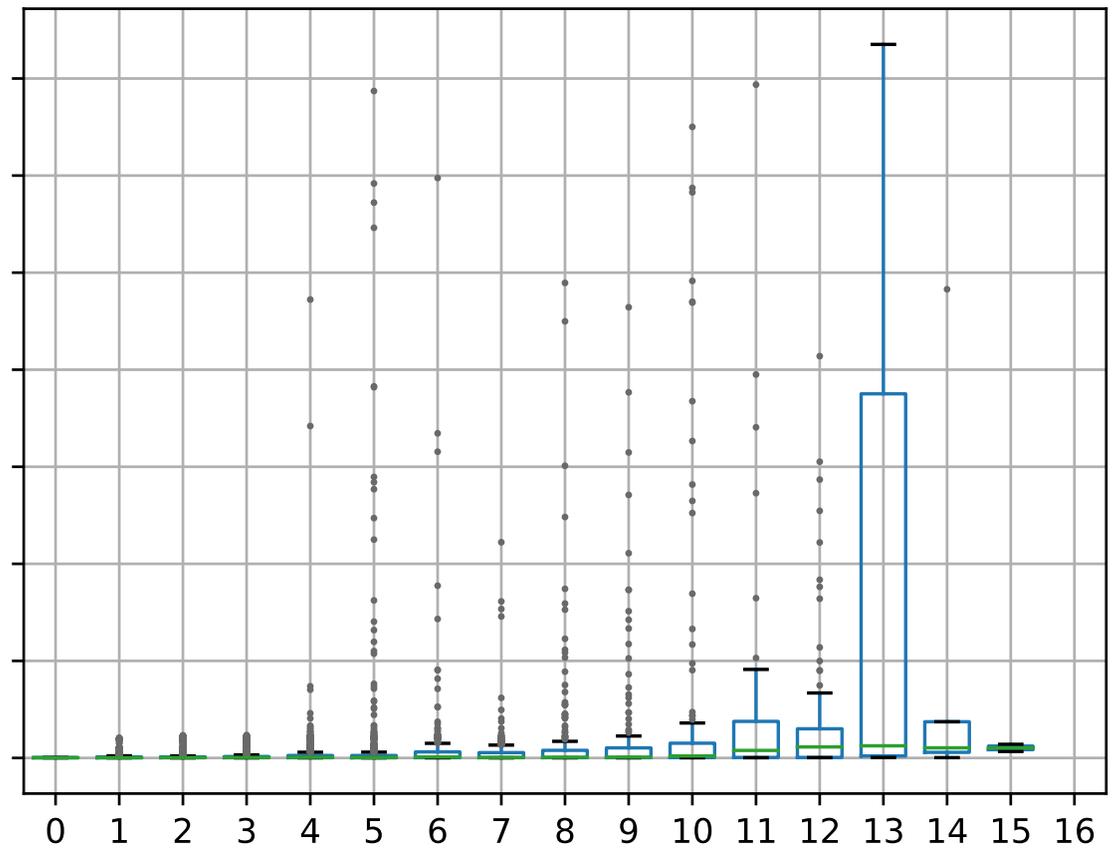


# Correlation with Reasoning times

$\log_2(\text{max state space size})$



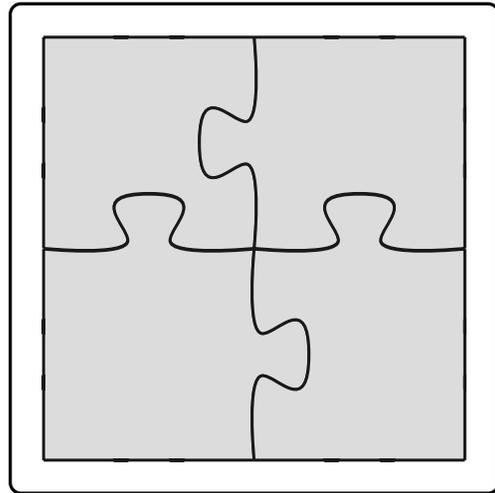
treewidth



tighter correlation  $\implies$  more control over reasoning time

# Learning such Networks

- How to learn networks with bounded max state space size?
- Build on top of 'SLIM' approach used for learning bounded treewidth BNs

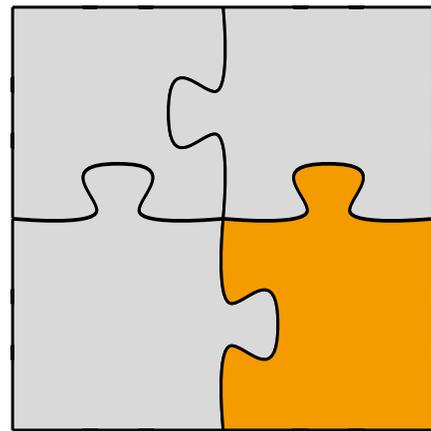


Global solution

SAT-based Local Improvement Method (SLIM)

# Learning such Networks

- How to learn networks with bounded max state space size?
- Build on top of 'SLIM' approach used for learning bounded treewidth BNs

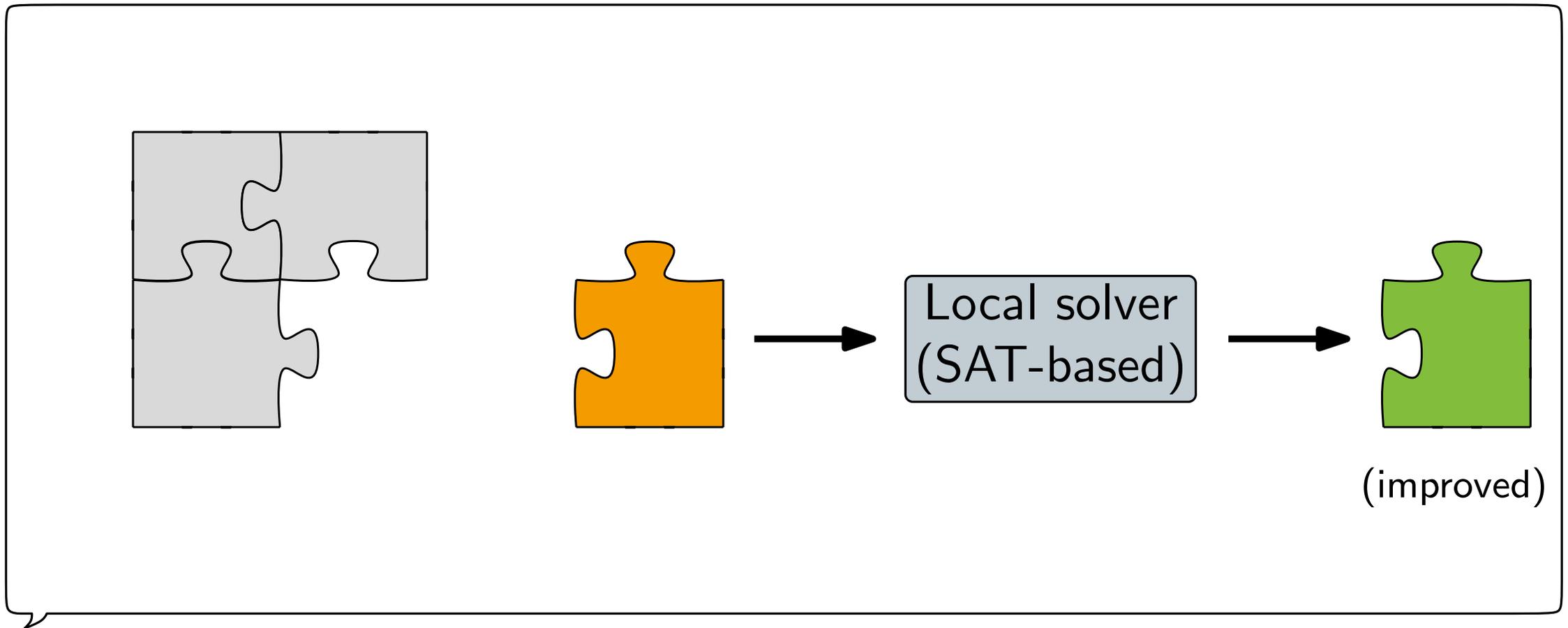


Local subinstance

SAT-based Local Improvement Method (SLIM)

# Learning such Networks

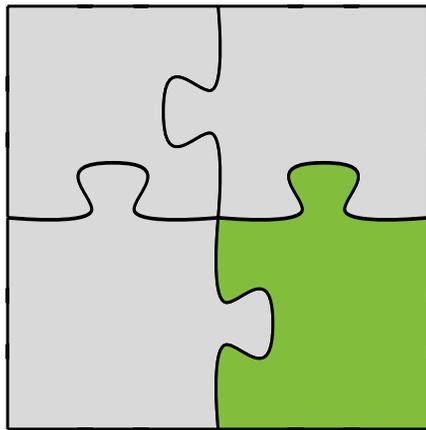
- How to learn networks with bounded max state space size?
- Build on top of 'SLIM' approach used for learning bounded treewidth BNs



SAT-based Local Improvement Method (SLIM)

# Learning such Networks

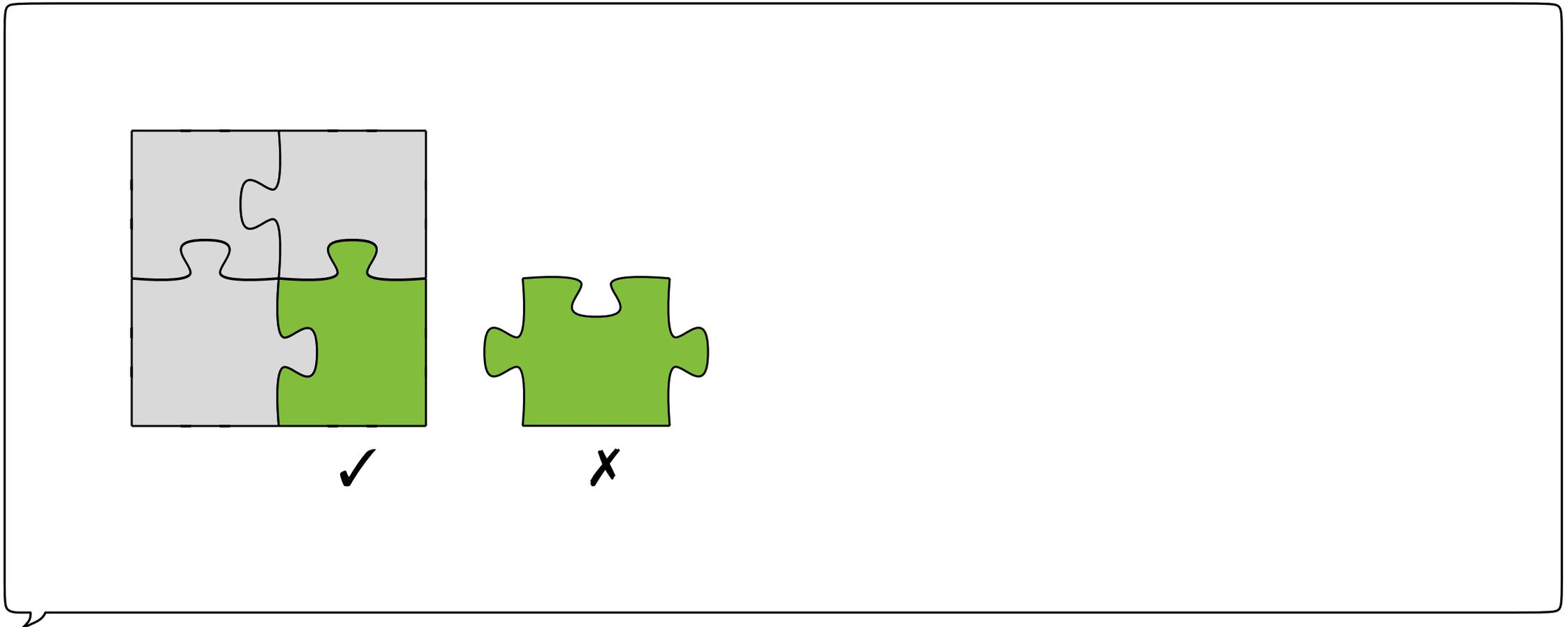
- How to learn networks with bounded max state space size?
- Build on top of 'SLIM' approach used for learning bounded treewidth BNs



SAT-based Local Improvement Method (SLIM)

# Learning such Networks

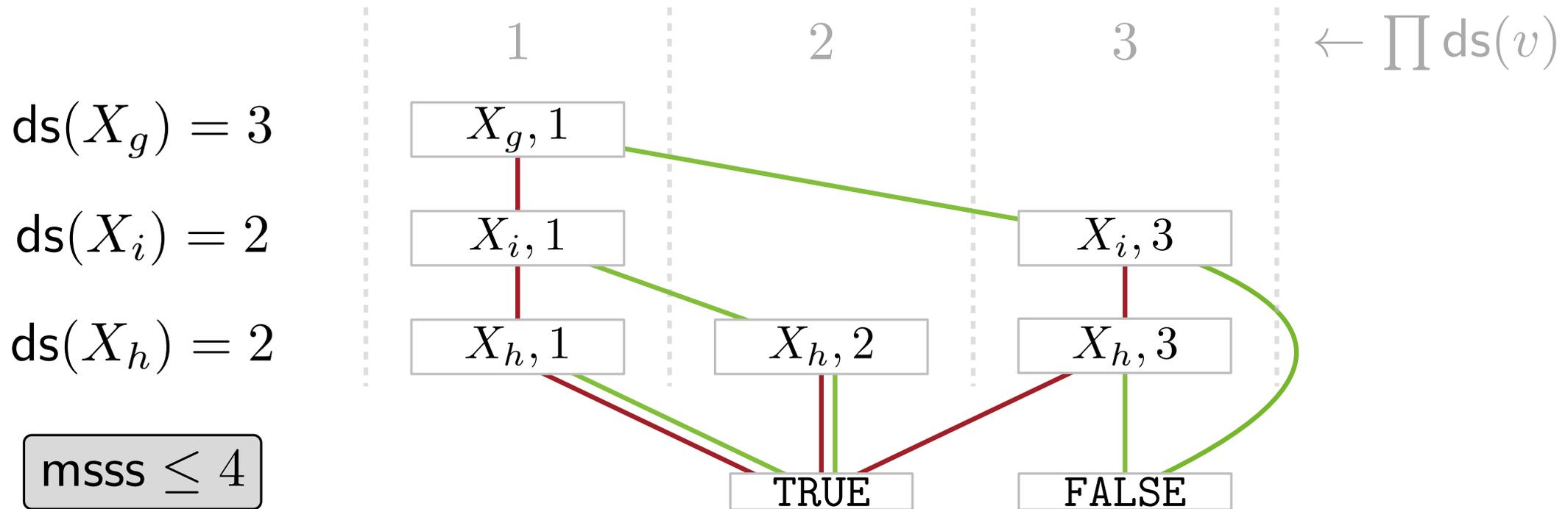
- How to learn networks with bounded max state space size?
- Build on top of 'SLIM' approach used for learning bounded treewidth BNs



SAT-based Local Improvement Method (SLIM)

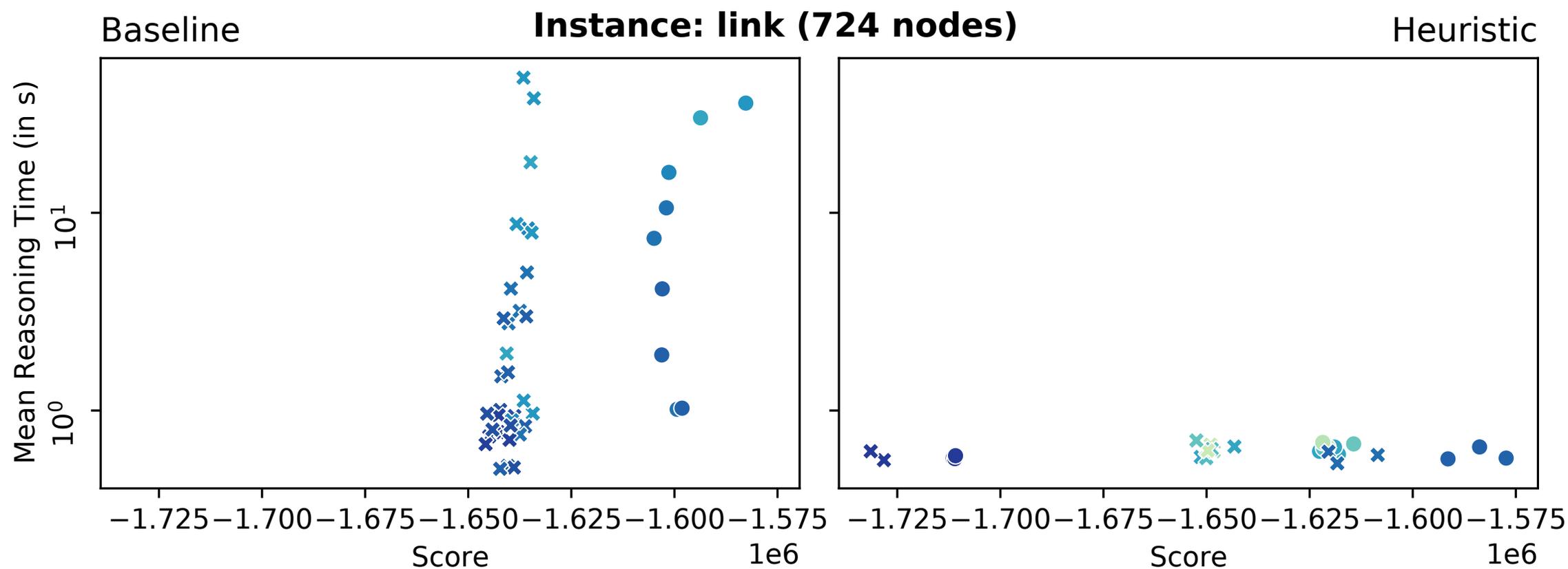
# Adapting SLIM to bounded state space

- Simple cardinality counter for treewidth
- Replaced by BDD-based counter for tracking state space size



# Experiments

- Modified existing heuristics to bound max state space size
- We compared several methods like original heuristic + SLIM, modified heuristic, modified heuristic + SLIM against the original heuristic as baseline
- Benchmark dataset from bnlearn repository, with 6-1041 random variables



- Max state space size much better indicator of inference time
- SLIM can be adapted to learn such networks (using BDDs)
- Experiments confirm inference times more reliable

Thank you!

Questions welcome