

A Benchmark for Bivariate Causal Discovery Methods

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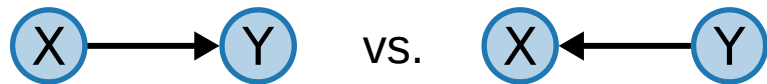
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Problem and Motivation

- Discovering underlying causal structures from observational data is a fundamental problem.
- We consider the generic case where we know that two variables are **dependent** (e.g. from causal discovery algorithms), but we do not know the **causal direction**.
Thus, we want to distinguish:



- The Causal direction is not **identifiable** without further **assumptions** (e.g. [Janzing, 2019]).
- A plethora of approaches has been proposed to tackle this problem.

Our Approach

- We utilize available benchmarks that include **real-world data**.
- Additionally, we propose our own **synthetic data** where we can control conditions in detail.
- We are working toward an overview including state-of-the-art methods and various datasets.
- We want to evaluate methods when their underlying assumptions are met or violated.



Utilized Existing Benchmarks

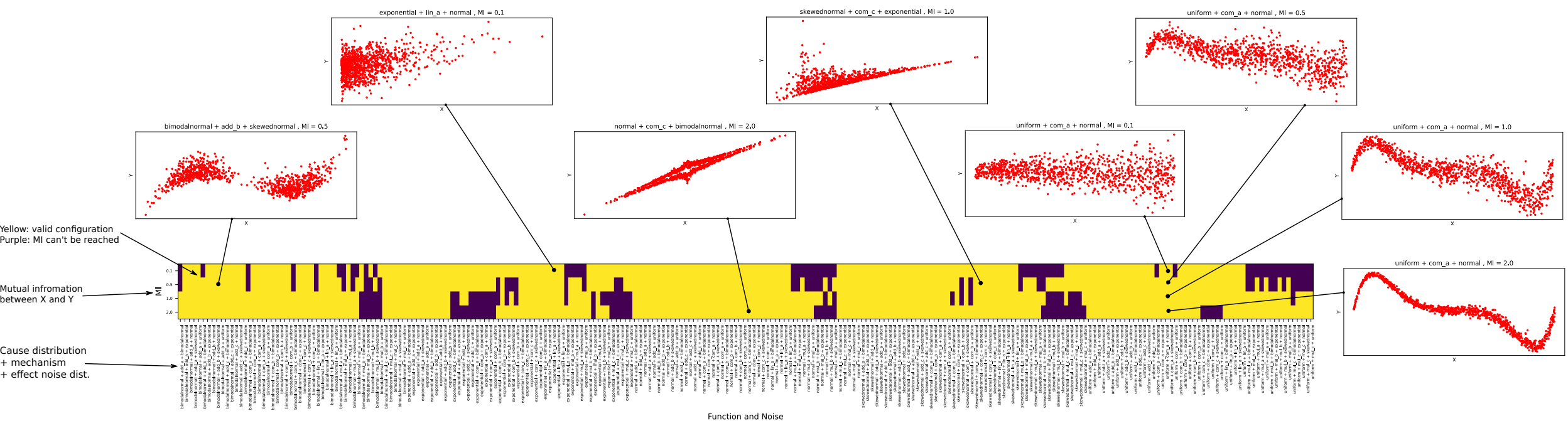
- Tübingen Cause Effect Pairs (TCEP) [Mooij et al., 2016]
 - 95 datasets with 94 to 16.382 samples, weighted and un-weighted results
- Cause Effect Pairs Challenge (CEC) [Guyon, 2013]
 - 1584 datasets with 53 to 7995 samples, only real-valued data (+ binary treated as real-valued)
- Cause Effect Benchmark [Goudet et al., 2018]
 - 300 datasets with 1500 samples each per type, three types used: CE-Gauss, CE-Net, CE-Multi

Our Synthetic Data

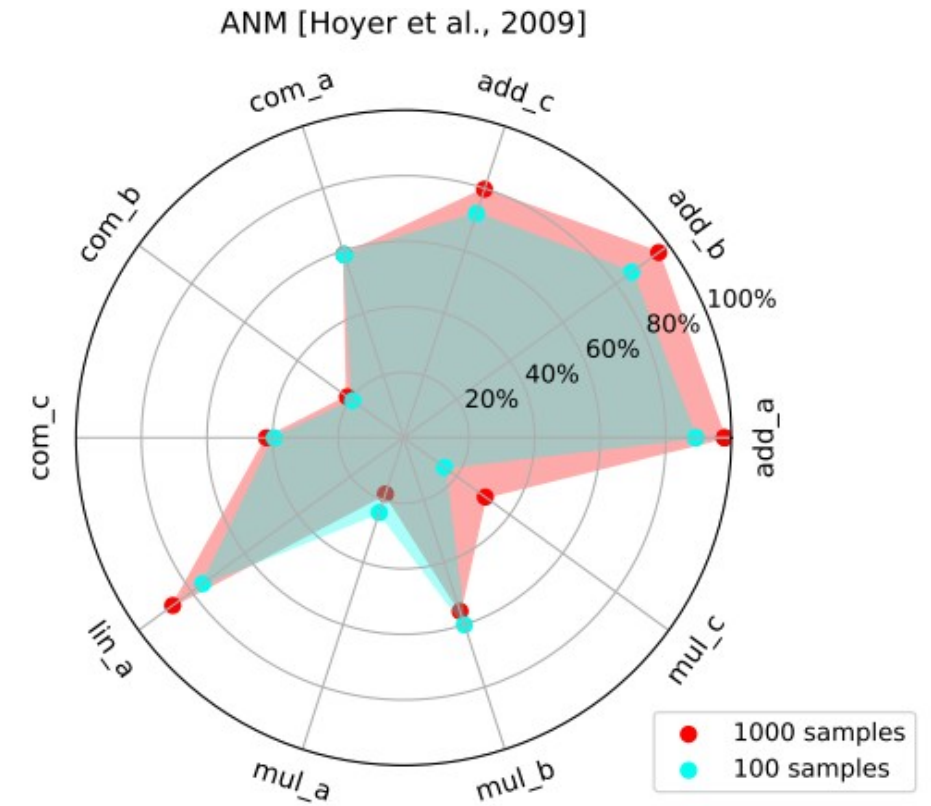
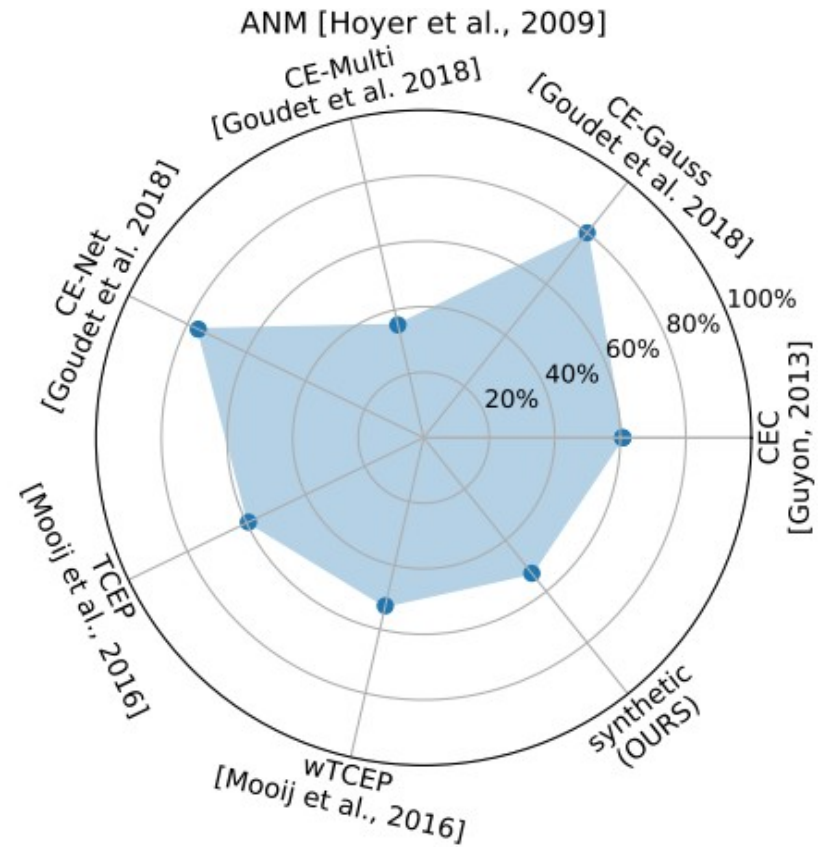
- four types of causal mechanisms:
 - linear, additive, multiplicative, complex
- three example functions per type (except for linear only one)
- five distribution types for cause and effect noise:
 - bimodal normal, exponential, normal, skewed normal, uniform
- four levels of dependence between cause and effect (measured by mutual information)
- 828 configurations are valid
 - valid: desired MI could be reached by adjusting cause and effect noise distributions
- different sample sizes per configuration
- 1000 realizations for every combination of configuration and sample size



Data Visualization

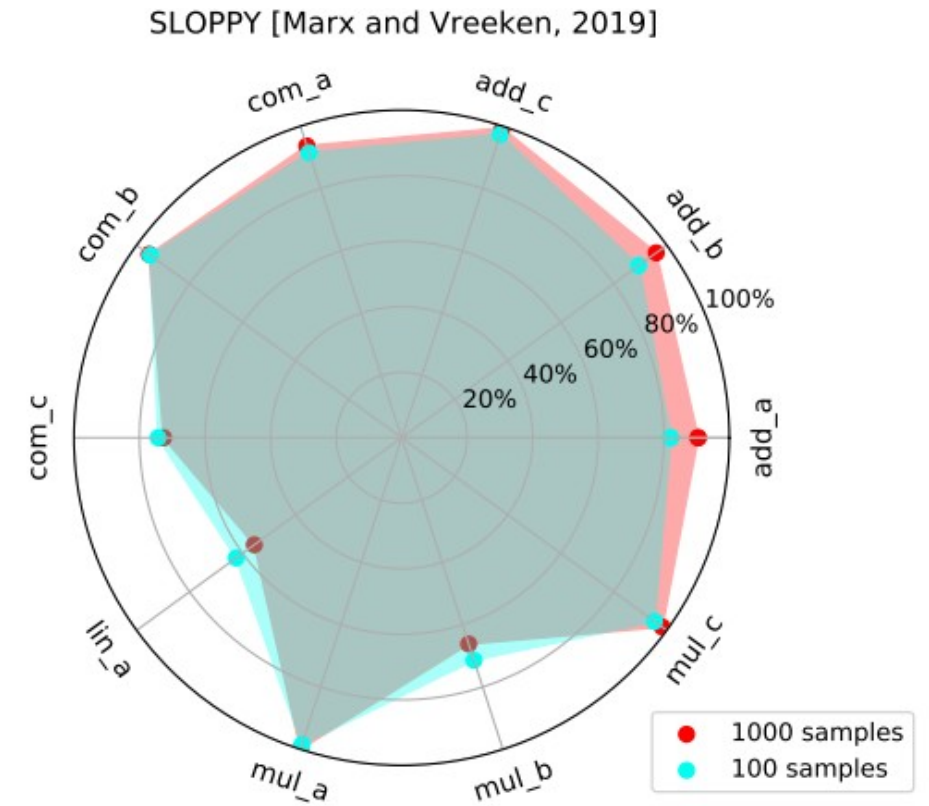
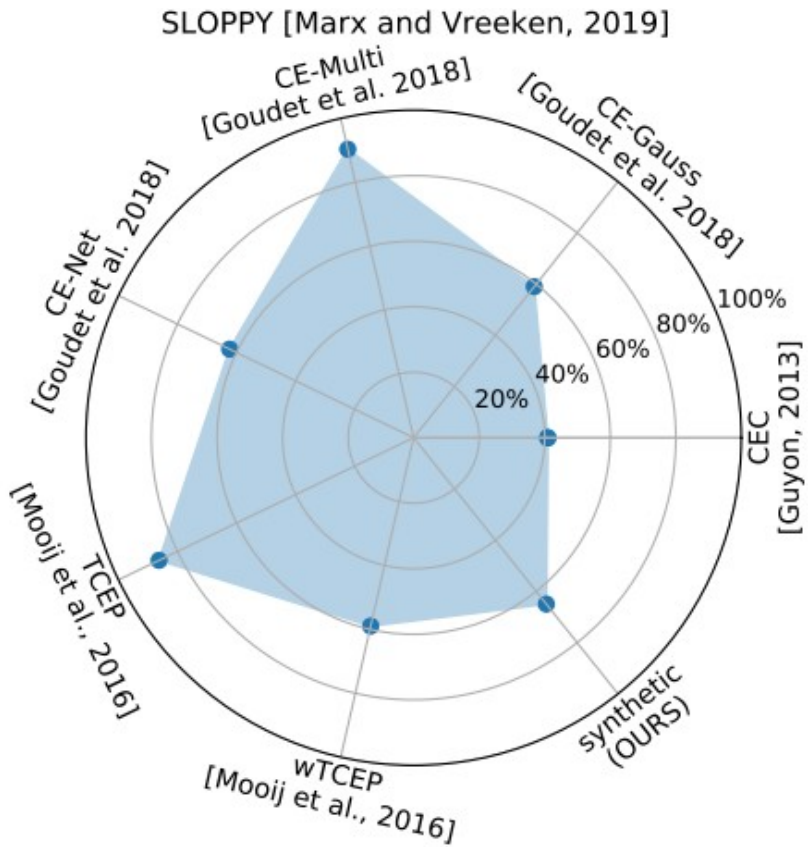


Example Results (1)



- Granularity of results can be zoomed in further

Example Results (2)



- Granularity of results can be zoomed in further

Compact Conclusion

- There is no **clear winning method** considering the whole benchmark.
- The performances are very dependent on the data conditions.
- This is an intermediate state of an ongoing investigation.

References

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