in the presence of heteroscedastic noise



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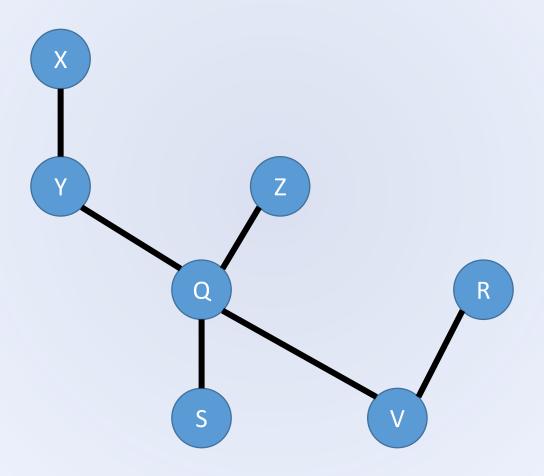


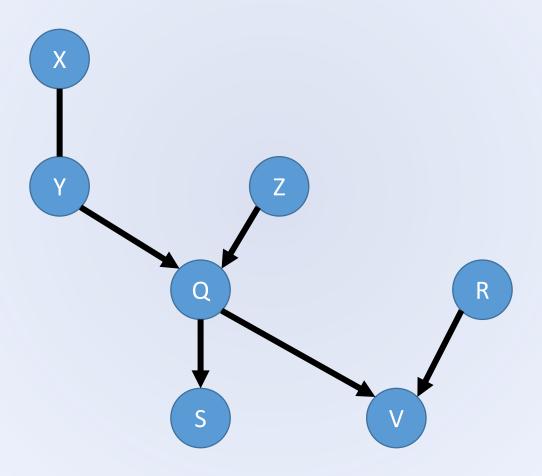


### Question of the day



How can we distinguish cause from effect under realistic noise assumptions?





Bi-variate causal inference

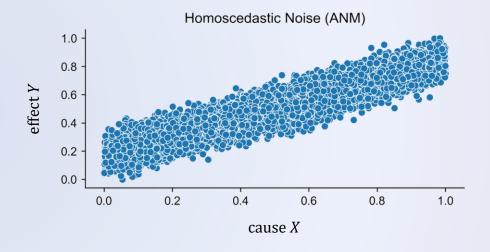
#### Causal Model

We consider **continuous valued** cause *X*, Gaussian noise *N* and effect *Y* 

$$Y = f(X) + s(X) * N$$

where we use a scaling function s(x) to model heteroscedastic noise

Very general causal model



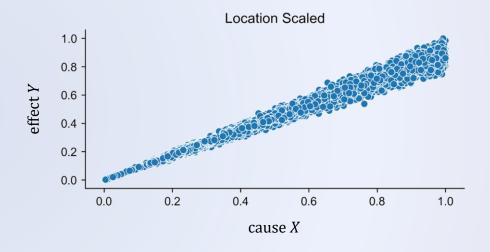
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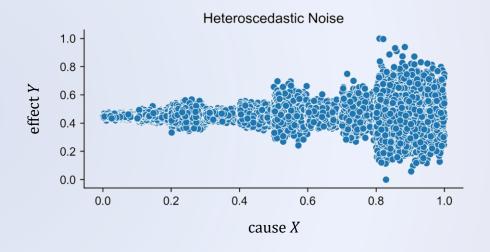
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#### Identifiability

Linear functions, heteroscedastic noise

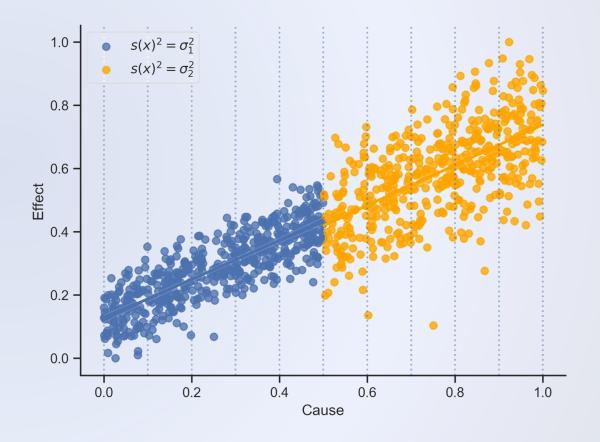
$$\int p_X(x)log(Var(Y|X=x))dx$$

$$\leq \int p_Y(y)log(Var(X|Y=y))dy$$

Non-linear, homoscedastic noise

$$E[\log(Var(Y|X))] < E[\log(Var(X|Y))]$$

We can identify cause from effect by comparing log-likelihood!



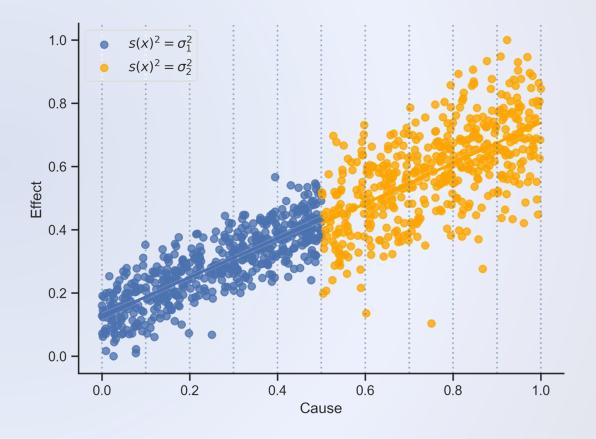
### The Algorithm: HECI

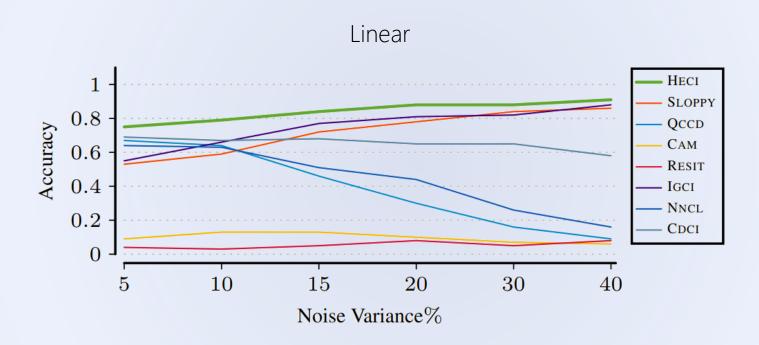
Partition domain of the presumed cause into bins with constant noise variance

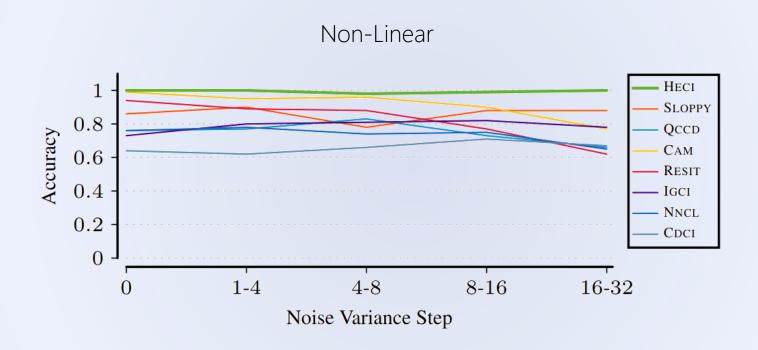
Determine number of bins using the Bayesian Information Criterion (*BIC*)

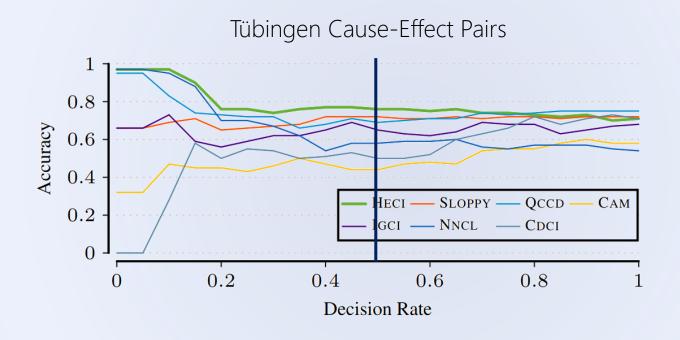
Determine the optimal binning using dynamic programming

optimal model is found in O(b²n)









HECI performs on par with SOTA when noise is stationary and better on heteroscedastic noise

#### Conclusion



#### Causal model

$$Y = f(X) + s(X) * N$$

#### Identifiable

- linear with heteroscedastic noise
- non-linear with homoscedastic noise

#### Inference

- HECI for discovering optimal models
- accurately infers cause and effect in the presence of heteroscedastic noise

