Telling Causal from Confounded

David Kaltenpoth
Jilles Vreeken

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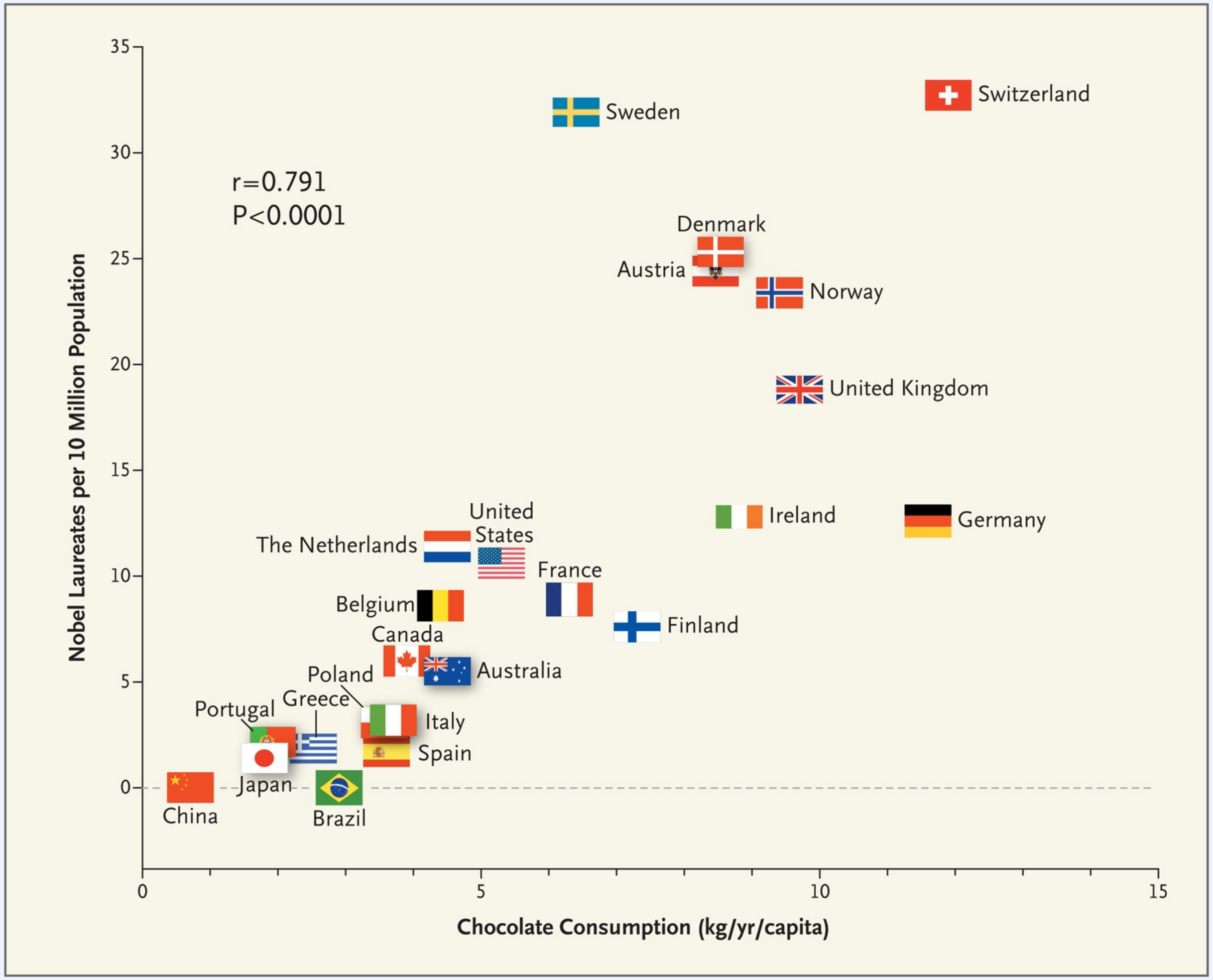
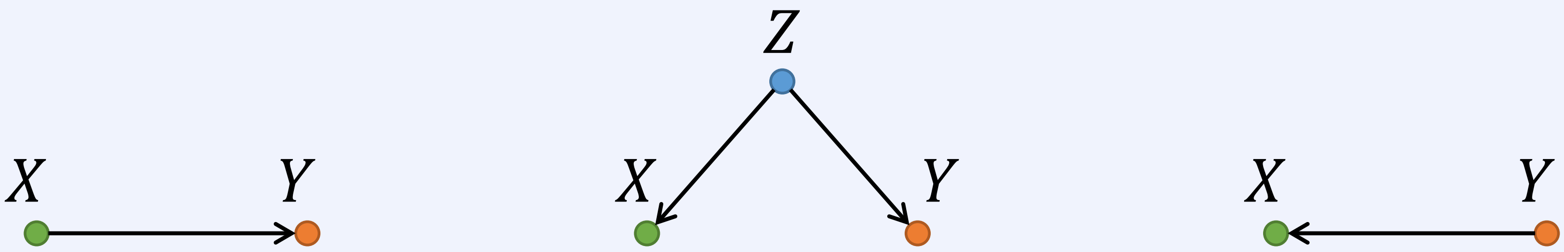
UNIVERSITÄT DES SAARLANDES
max planck institut informatik
CISPA HELMHOLTZ CENTER FOR INFORMATION SECURITY

Does Chocolate Consumption cause Nobel Prizes?



Reichenbach

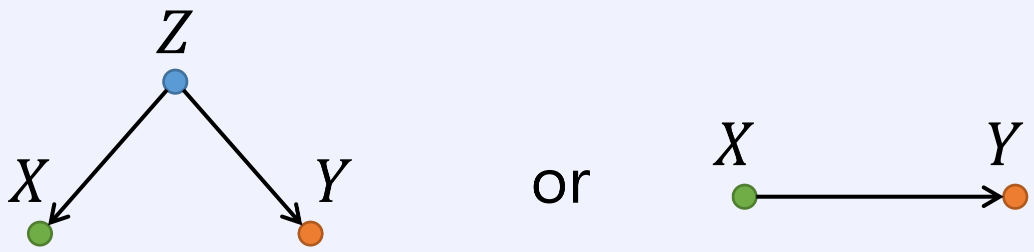
If X and Y are statistically dependent then either



How can we distinguish these cases?

Conditional Independence Tests

If we have measured everything relevant
then testing $X \perp\!\!\!\perp Y \mid Z$ for all possible Z
lets us decide whether



Problem: It's impossible to measure everything relevant

Why not just find a confounder?

We would like to be able to infer a $\hat{Z}$ such that

$$X \perp\!\!\!\perp Y \mid \hat{Z}$$

if and only if X and Y are actually confounded

Problem: Finding such a $\hat{Z}$ is **too easy**

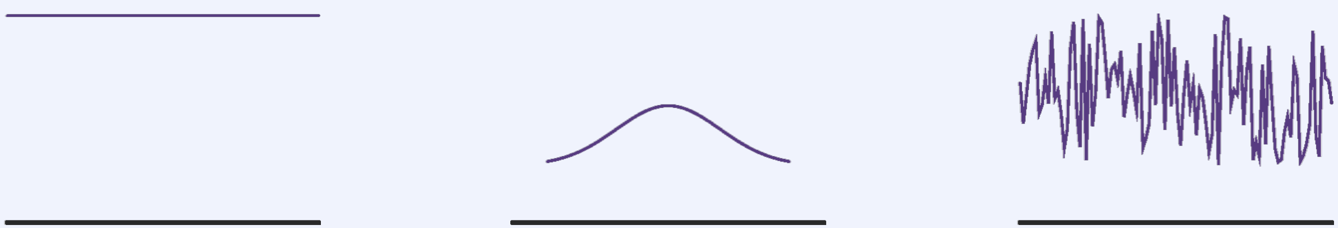
$\hat{Z} = X$ always works

Kolmogorov Complexity

$K(P)$ is the length of the shortest program computing P

$$K(P) = \min_{p} \left\{ |p| : p \in \{0,1\}^*, |\mathcal{U}(p, x, q) - P(x)| < \frac{1}{q} \right\}$$

This shortest program p^* is the best compression of P



From the Markov…

An admissible causal network for $X_1, \ldots, X_m$ is G satisfying

$$P(X_1, \ldots, X_m) = \prod_{i=1}^{m} P(X_i \mid PA_i)$$

Problem: How do we find a simple factorization?

…to the Algorithmic Markov Condition

The simplest causal network for $X_1, \dots, X_m$ is G^* satisfying

$$K(P(X_1, \dots, X_m)) = \sum_{i=1}^{m} K(P(X_i \mid PA_i^*))$$

Postulate: G^* corresponds to the true generating process

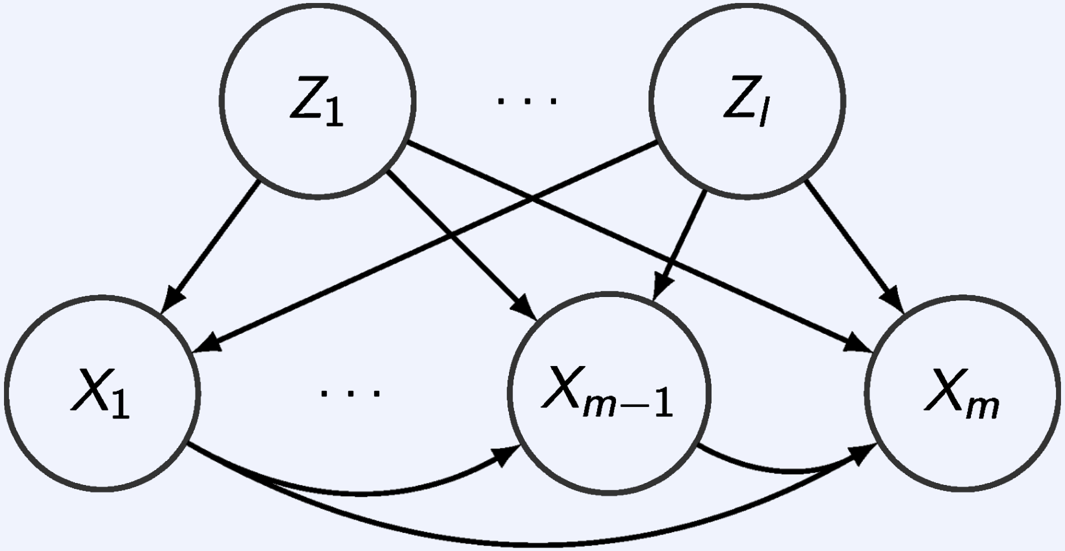
(Janzing & Schölkopf, 2010)

AMC with Confounding

We can also include latent variables

$$K\big(P(\boldsymbol{X},\boldsymbol{Z})\big) = \sum_{i=1}^{m} K\big(P(X_i \mid PA_i')\big) + \sum_{j=1}^{l} K\Big(P\big(Z_j\big)\Big)$$

We don't know $P(\cdot)$



$$P(\boldsymbol{X},\boldsymbol{Z}) = P(\boldsymbol{Z})\prod_{i=1}^{m} P(X_i \mid \boldsymbol{Z})$$

In particular, we will use probabilistic PCA

Kolmogorov is not computable

For data X, the **Minimum Description Length** principle identifies the best model $M \in \mathcal{M}$ by minimizing

$$L(X, M) = L(M) + L(X \mid M)$$

which provides a **computable** and **statistically sound approximation** to K

(Grünwald 2007)

Decisions, decisions

If

$$L(\boldsymbol{X}, Y, \mid \mathcal{M}_{co}) < L(\boldsymbol{X}, Y \mid \mathcal{M}_{ca})$$

then we consider $\boldsymbol{X}, Y$ to be confounded

Decisions, decisions

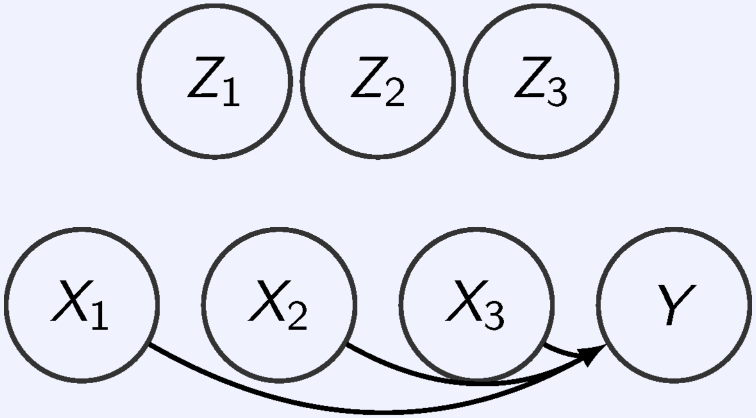
If

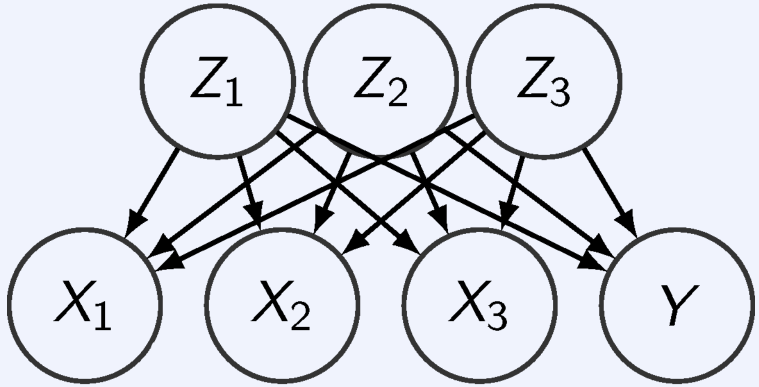
$$L(\boldsymbol{X}, Y, \mid \mathcal{M}_{co}) > L(\boldsymbol{X}, Y \mid \mathcal{M}_{ca})$$

then we consider $\boldsymbol{X}, Y$ to be causal

The difference can be interpreted as confidence

Confounding in Synthetic Data



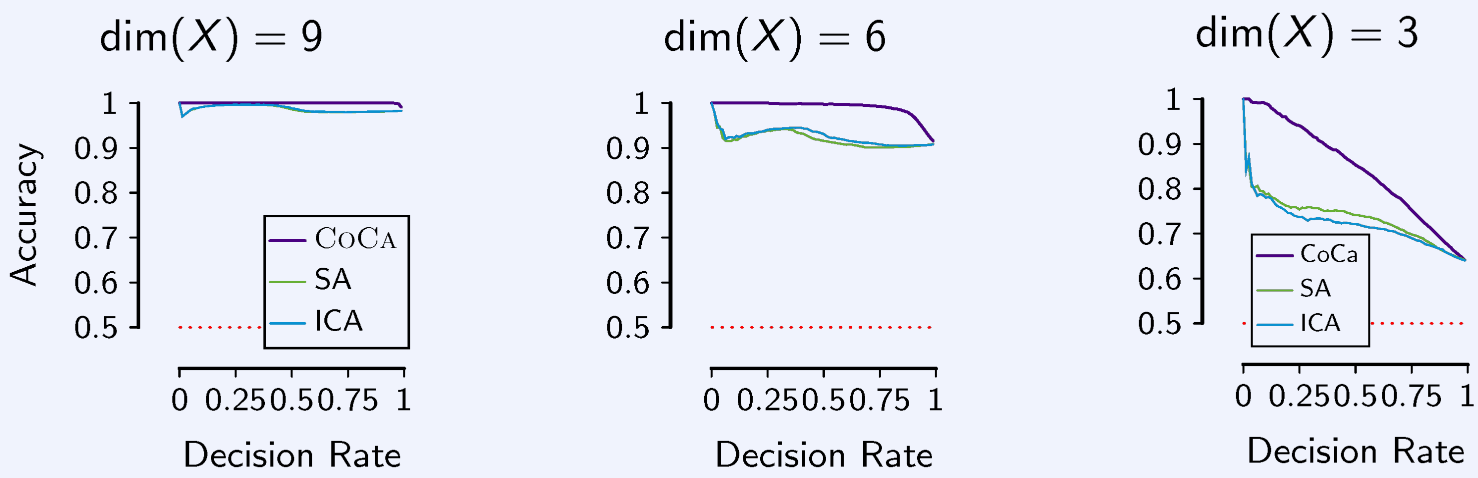


Synthetic Data: Results

There are only two other works directly related to ours

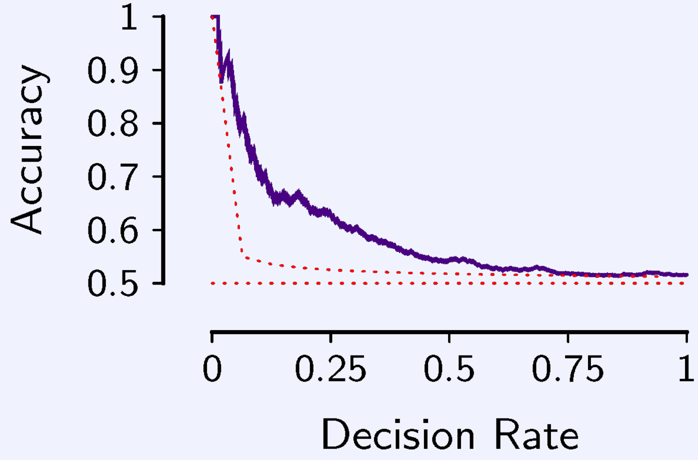
SA: Confounding strength in linear models using spectral analysis

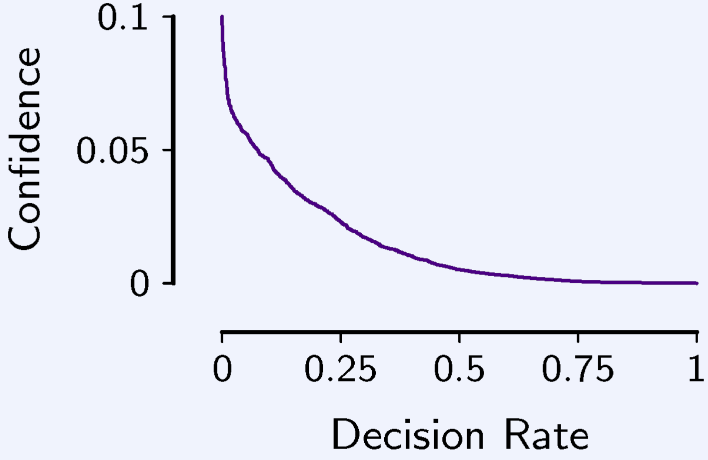
ICA: Confounding strength using independent component analysis



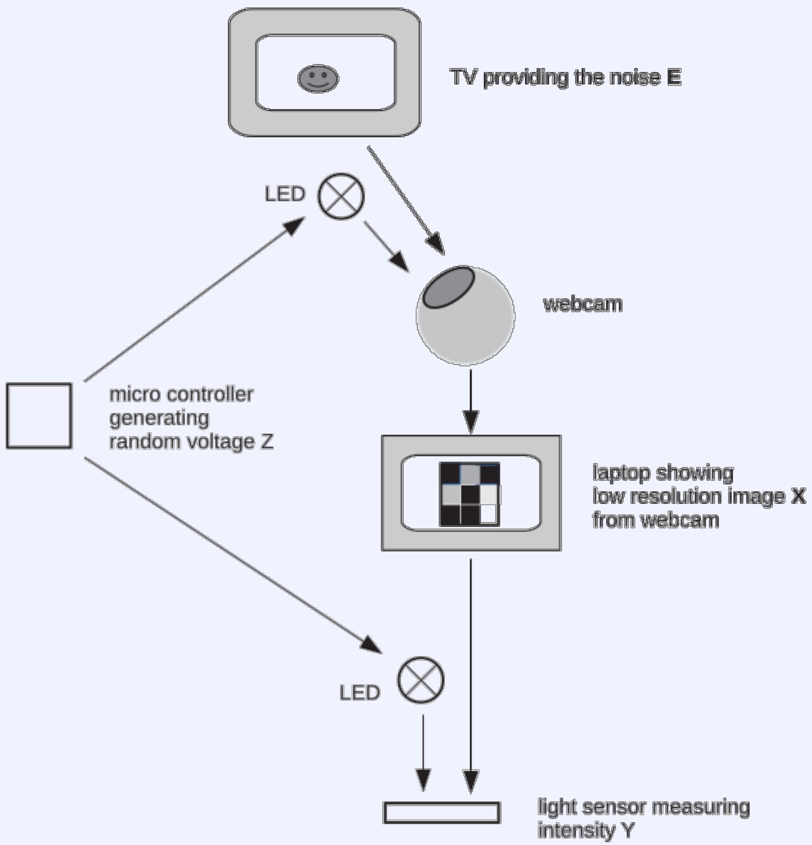
Confounding in Genetic Networks

More realistically, we consider gene regulation data



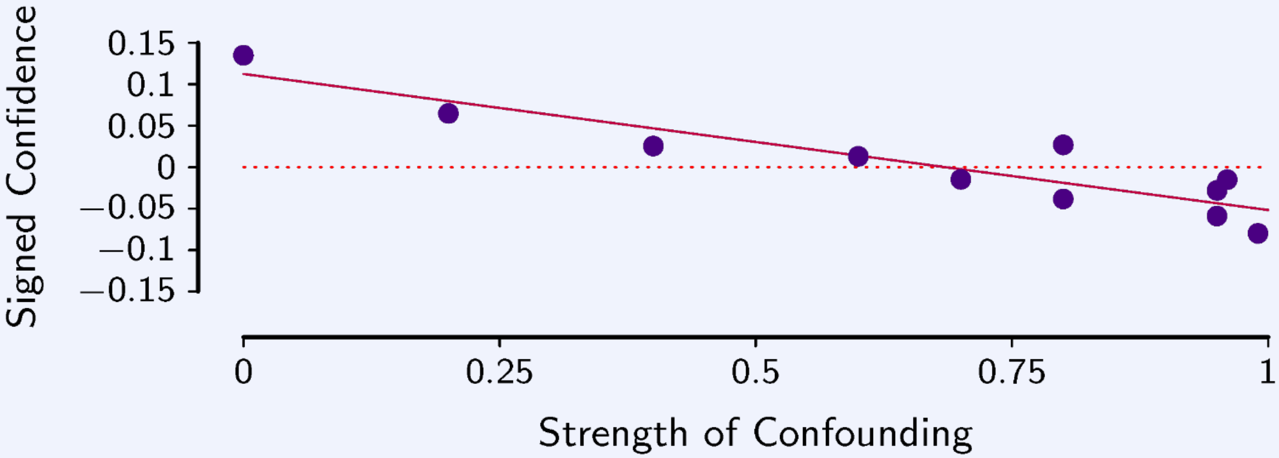


Optical Data

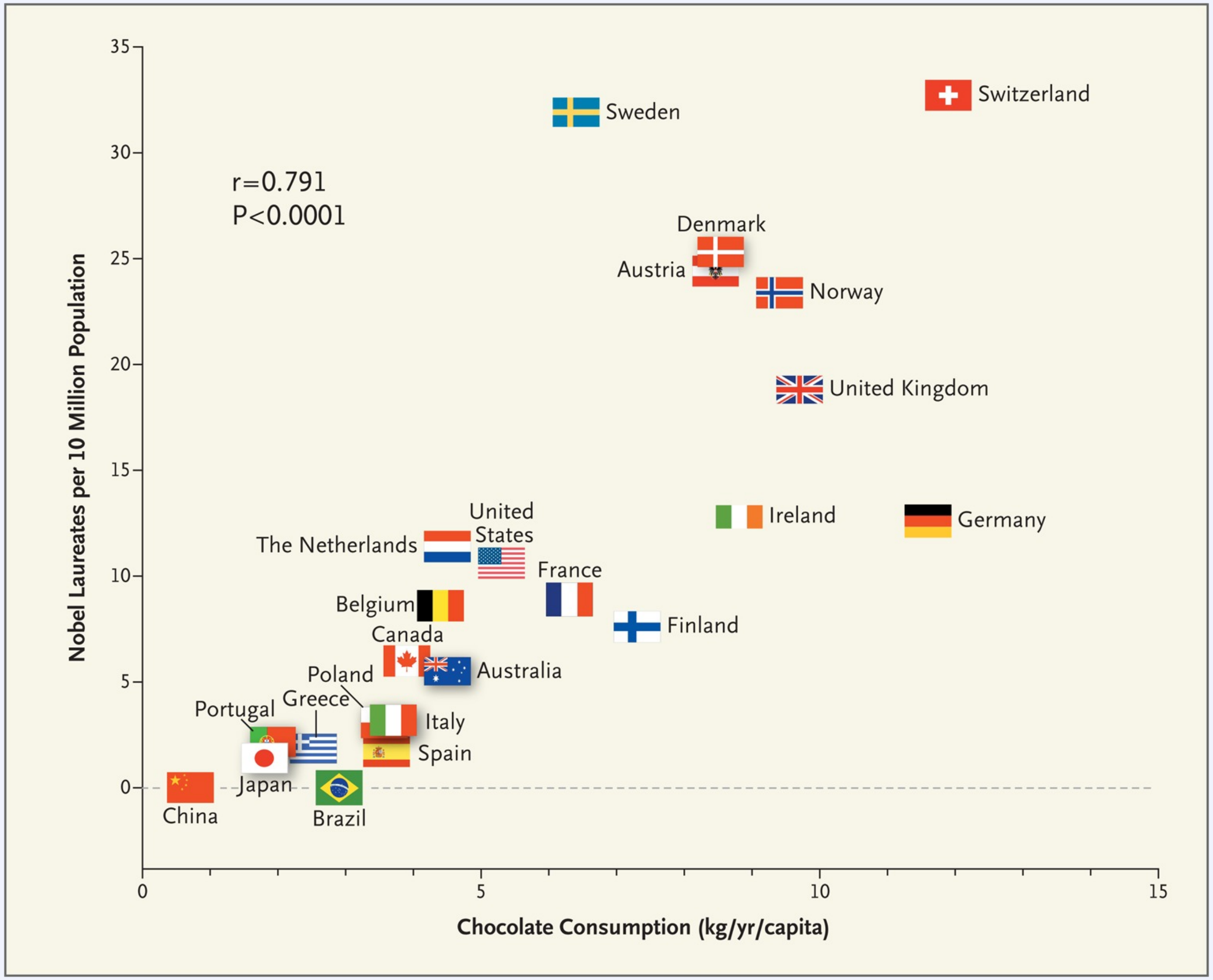


(Janzing & Schölkopf, 2017)

Optical Data



Wait! What about...



Conclusions

We looked into distinguishing causal from confounded

In particular, we

- generalized the AMC to include **latent variables**
- used a linear factor model and MDL to **instantiate** it
- showed that we obtain good results on synthetic and real data

In the future, we will

- work on a **significance test** for our score
- look into using **more complex factor models**
- apply our method to **real-world data**

Thank you!

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