

Estimating mutual information for high-dimensional sparse relationships

Charles Zheng

Stanford University

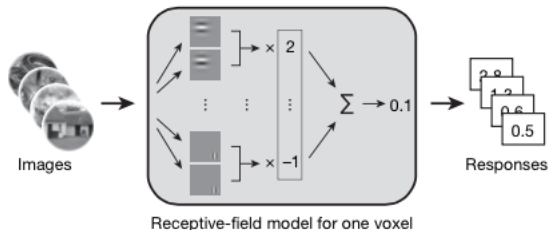
January 23, 2017

(Joint work with Yuval Benjamini, Hebrew University.)

Introduction

Stage 1: model estimation

Estimate a receptive-field model for each voxel

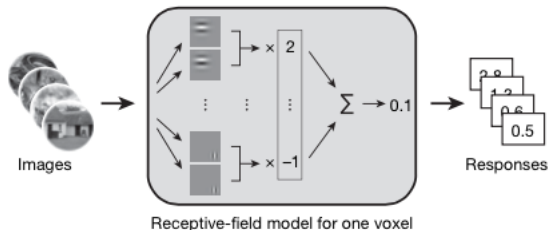


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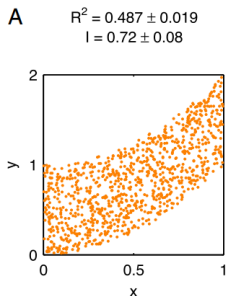
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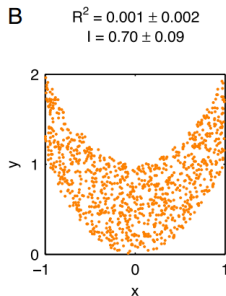
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- E.g.: Extrapolating classification accuracy curves (Z., Achanta, and Benjamini 2016)

This talk

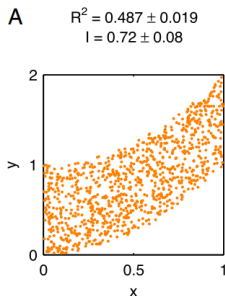


Mutual information $I(\vec{X}; \vec{Y})$

- measures dependence between two random vectors, \vec{X} and \vec{Y}

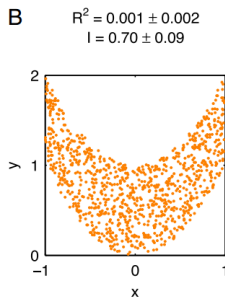


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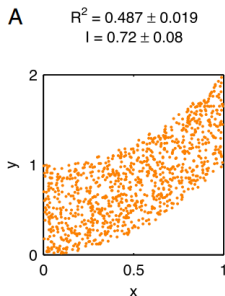


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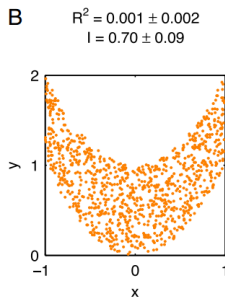


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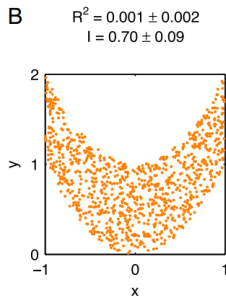
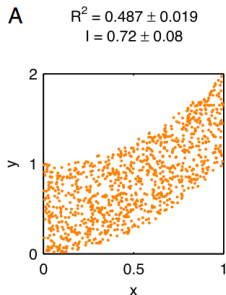


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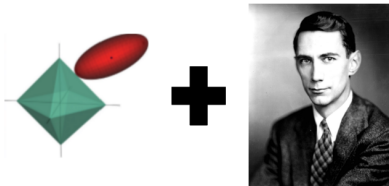
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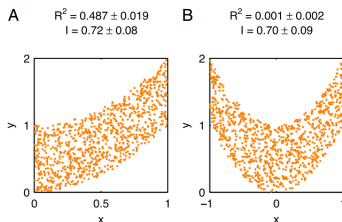
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We combine *machine learning* (sparse estimation) with *information theory* to obtain better estimates of $I(\vec{X}; \vec{Y})$



Mutual information $I(X; Y)$



Introduced in Shannon's 1948 paper, "A mathematical theory of communication"

$$I(X; Y) = \int \log \left(\frac{p(x, y)}{p(x)p(y)} \right) p(x, y) dx dy$$

Image credit Kinney et al. 2014.

Applications of $I(X; Y)$

Mutual information has since been applied to many areas outside of information theory

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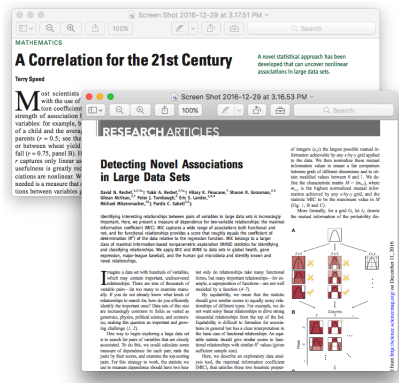
Applications [\[edit \]](#)

In many applications, one wants to maximize mutual information (thus

- In [search engine technology](#), mutual information between phrases
- In [telecommunications](#), the [channel capacity](#) is equal to the mutual information
- [Discriminative training](#) procedures for [hidden Markov models](#) have
- [RNA secondary structure](#) prediction from a [multiple sequence alignment](#)
- [Phylogenetic profiling](#) prediction from pairwise presence and absence
- Mutual information has been used as a criterion for [feature selection](#) the [minimum redundancy feature selection](#).
- Mutual information is used in determining the similarity of two documents
- Mutual information of words is often used as a significance function for word pairs; rather, one counts instances where 2 words occur adjacent to each other, goes up with N.
- Mutual information is used in [medical imaging](#) for [image registration](#) reference image, this image is deformed until the mutual information is maximized
- Detection of [phase synchronization](#) in [time series](#) analysis
- In the [infomax](#) method for neural-net and other machine learning,

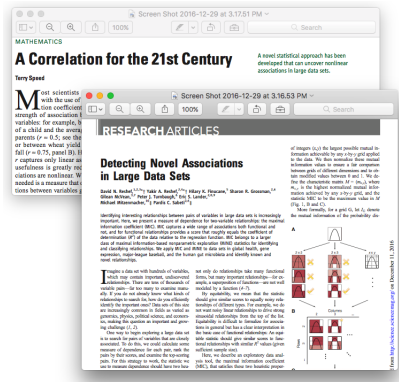
Engineering, biology, computer science, physics, medicine

Comparing $I(X; Y)$ with Pearson correlation



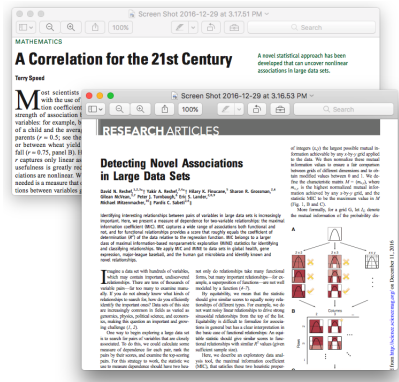
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How to estimate $I(X; Y)$

Suppose we observe pairs $(X_i, Y_i)_{i=1}^n$ iid from density $p(x, y)$

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$$I(X; Y) = \int \log \left(\frac{p(x, y)}{p(x)p(y)} \right) p(x, y) dx dy$$

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- Kernel density estimate approaches estimate $p(x, y)$ (Beirlant et al. 2001, Ivanov and Rozhkova 1981)
- Nearest neighbor estimators rely on distance-based computations (Mnatsakanov et al. 2008, Gorja et al. 2005, Singh et al. 2003)

How to estimate $I(X; Y)$

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- **Plug-in estimate:**

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Problems in high dimensions

- Density estimation is known to have *exponential complexity* with respect to dimensionality.
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- Many applications with high-dimensional X, Y .
 - Gene expression time series
 - Functional magnetic resonance imaging

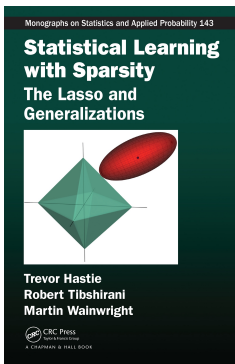
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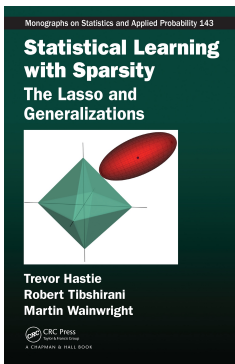
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- One approach is to assume joint multivariate normality of X, Y , but this reduces mutual information to a linear statistic.
- Other approaches: binning (Bialek et al. 1991, Paninski 2003), confusion matrix of a classifier (Treves 1997, Quiroga et al. 2009)

First idea: Use sparsity!



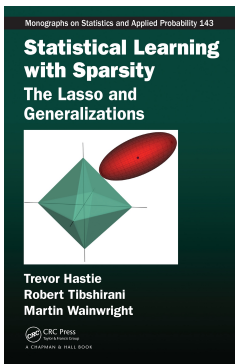
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- *Sparsity* refers to existence of low-dimensional structure hidden in high-dimensional data.
- E.g. suppose X is 100-dimensional but Y is only a function of (X_5, X_9) .
- Can we exploit sparsity to obtain a good estimate of $I(X; Y)$ even under low sample sizes?

Our proposal

Suppose we observe pairs $(X_i, Y_i)_{i=1}^n$ iid from density $p(x, y)$.

- 1 Estimate a (sparse) regression model for $\mathbf{E}[\vec{Y}|\vec{X}]$.
- 2 Assess the *prediction accuracy* of the model using *identification risk*
- 3 Use the identification risk to obtain a lower bound for the mutual information $I(X; Y)$

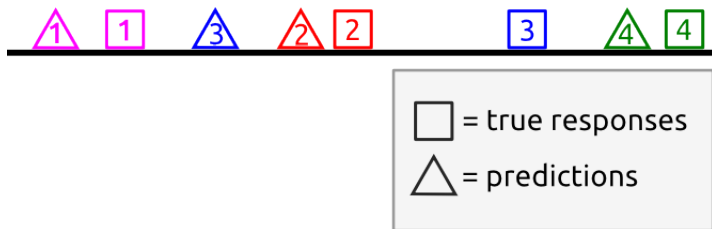
Multiple-response regression

- Pairs $(x_i, y_i)_{i=1}^n$, where X is p -dimensional and Y is q -dimensional.
- Data matrices $\mathbf{X}_{n \times p}$, $\mathbf{Y}_{n \times q}$.
- For each column of Y , fit sparse model $Y^{(i)} \approx X^T \beta^{(i)} + \epsilon$, e.g. by using elastic net (Zou 2008),

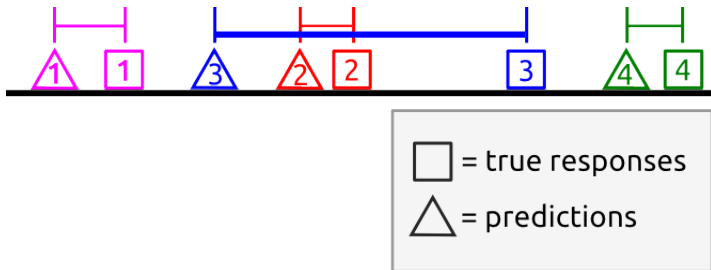
$$\hat{\beta}^{(i)} = \operatorname{argmin}_{\beta} \|\mathbf{X}^T \beta^{(i)} - Y^{(i)}\|^2 + \lambda_2 \|\beta^{(i)}\|_2^2 + \lambda_1 \|\beta^{(i)}\|_1$$

- Or, fit a *random forest* model for each column of Y (Breiman 2001)

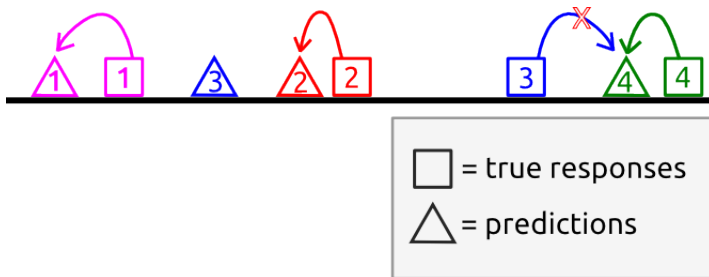
Regression vs Identification loss



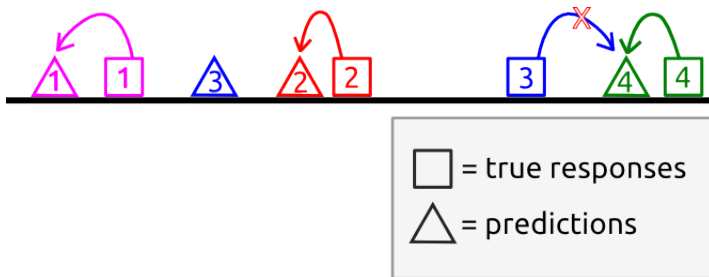
Mean-squared error



Identification loss

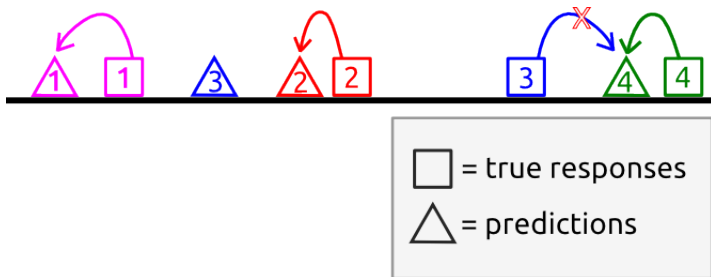


Identification loss



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- We are the first to explore theoretical properties of the loss (e.g. connection to mutual information)

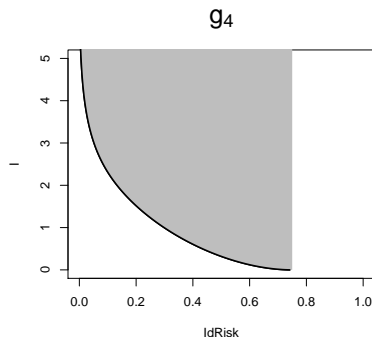
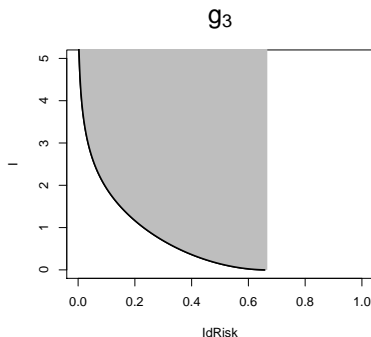
Identification loss and mutual information

- Define the identification risk as the expected identification loss

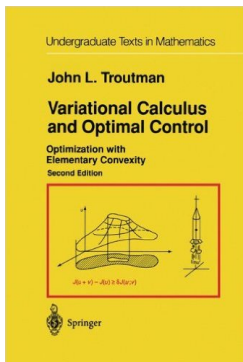
$$\text{IdRisk}_k = \mathbf{E}[\text{IdLoss}_k]$$

- Theorem.** (Z., Benjamini 2017) There exists a function g_k such that

$$I(X; Y) \geq g_k(\text{IdRisk}_k).$$

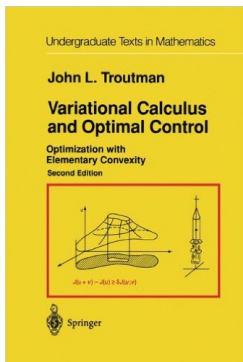


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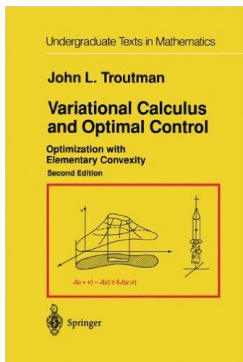


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$$I[p(x, y)] = \mathbf{E} \left[\log \frac{p(X, Y)}{p(X)p(Y)} \right].$$

- Identification risk is *lower-bounded* by another functional—the *Bayes risk*.

$$\text{BayesRisk}_k[p(x, y)] = 1 - \mathbf{E}[\max_{i=1}^k p(Y|X_i)].$$



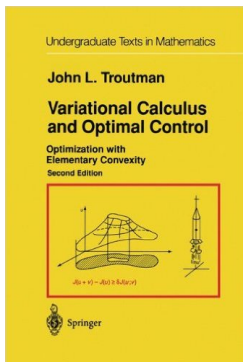
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$$\text{BayesRisk}_k[p(x, y)] = 1 - \mathbf{E}[\max_{i=1}^k p(Y|X_i)].$$

- $g_k(u)$ obtained by minimizing $I[p(x, y)]$ subject to $\text{BayesRisk}_k[p(x, y)] \leq u$.



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Suppose we observe pairs $(X_i, Y_i)_{i=1}^n$ iid from density $p(x, y)$.

- 1 Estimate a (sparse) regression model for $\mathbf{E}[\vec{Y}|\vec{X}]$.
- 2 Compute *identification loss*, IdLoss_k , using *leave-k-out*.
- 3 Estimate mutual information using

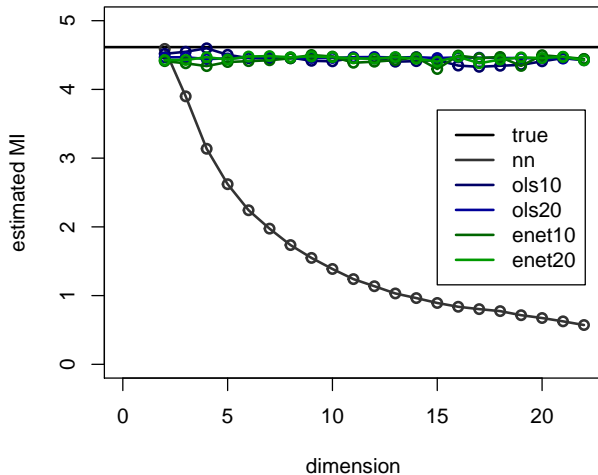
$$\hat{I}_{\text{IdLoss}}(X; Y) = g_k(\text{IdLoss}_k).$$

Section 2

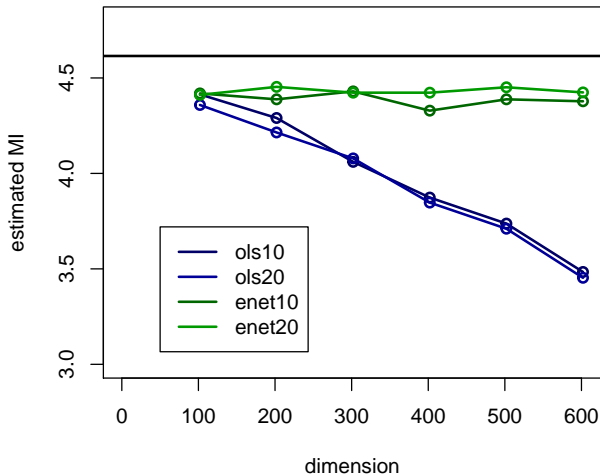
Applications

- Generate data: $(Y_1, Y_2) = (X_1, X_2)^T B + \epsilon$ where B is a randomly generated coefficient matrix.
- Add extra noise dimensions X_3, X_4, \dots
- $n = 1000$.
- Compare Nearest-Neighbor estimator (Mnatsakov et al, 2008, implemented in FNN) with our method using OLS and elastic net (sparse).

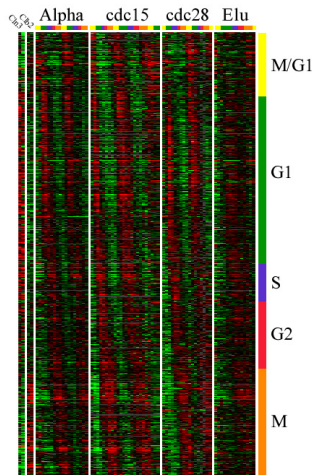
Simulation Results - I. low dimension



Simulation Results - III. high dimension



Application to gene expression time series



- Data from Spellman et al. 1998
- Expression levels of 6178 yeast genes during cell cycle
- Total 73 time points per gene

Groups of genes

Group	No. genes
unknown	396
cell cycle	27
DNA replication	27
transport	19
cytoskeleton	17
chromatin structure	16

Total 145 different categories (only top 6 shown).

Canonical correlations between time series

Top canonical correlation (Hotelling 1936)

	CC	DR	Tr	Cy	CS
CC		1	1	1	1
DR			1	0.99	0.99
Tr				0.99	0.98
Cy					0.98
CS					

CC = cell cycle, DR = DNA replication, Tr = transport,
Cy = cytoskeleton, CS = chromatin structure

Sparse canonical correlations between time series

Using sparse CCA* (Witten and Tibshirani 2009).

	CC	DR	Tr	Cy	CS
CC		0.96	0.87	0.92	0.94
DR			0.83	0.88	0.95
Tr				0.83	0.78
Cy					0.90
CS					

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*: using CCApermute in R package PMA

Information correlations between time series

Taking the max of $\hat{I}(X; Y)$ and $\hat{I}(Y; X)$.

	CC	DR	Tr	Cy	CS
CC		0.93	0.78	0.98	0.83
DR			0.85	0.91	0.92
Tr				0.72	0.71
Cy					0.93
CS					

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- Transform data from each group with random rotation...

$$\tilde{\mathbf{X}} = \mathbf{X}E$$

$$\tilde{\mathbf{Y}} = \mathbf{X}F$$

with $E^T E = I$, $F^T F = I$.

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$$\text{CCA}(\mathbf{X}, \mathbf{Y}) = \text{CCA}(\tilde{\mathbf{X}}, \tilde{\mathbf{Y}})$$

Invariance properties

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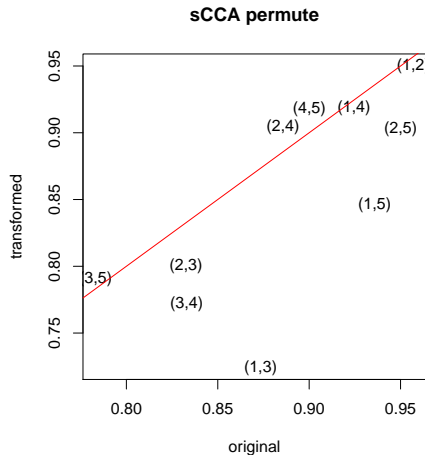
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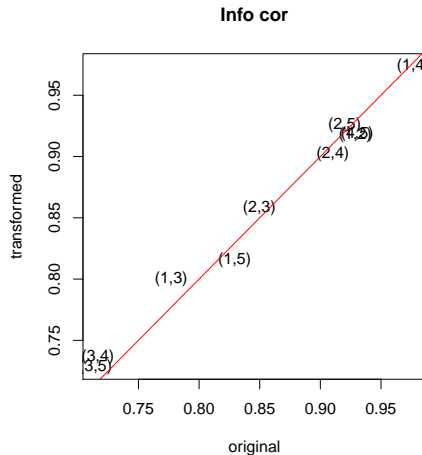
Invariance properties

However, sparse CCA is not invariant.



Invariance properties

Our method, on the other hand, is *robust* to rotation.



Conclusions

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- Example application: measure of joint information between two tables which is robust to transformations.

Related work and future directions

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- Estimating quantities related to mutual information, such as *transfer information*, *stimulus-specific information* and *redundancy* (Borst and Theunissen 1999)
- Inferring resting-state brain networks.

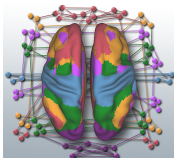


Image credit Simons Foundation

Section 3

The End

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