Estimating mutual information for high-dimensional sparse relationships

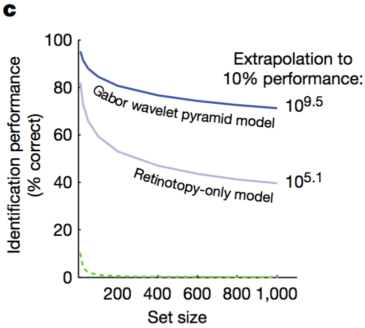
Charles Zheng

Stanford University

January 24, 2017

(Joint work with Yuval Benjamini, Hebrew University.)

Introduction



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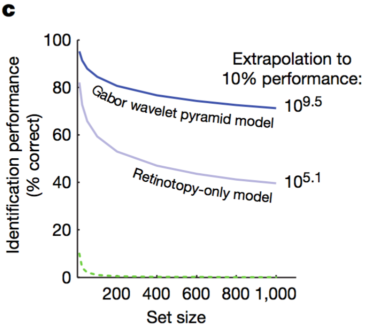

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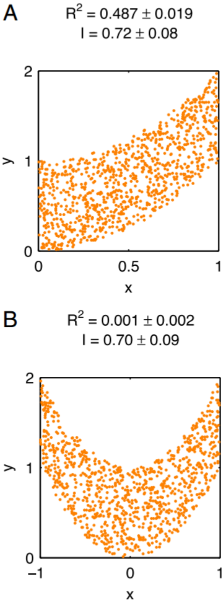
- E.g.: Extrapolating classification accuracy curves (Z., Achanta, and Benjamini 2016)

This talk



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

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

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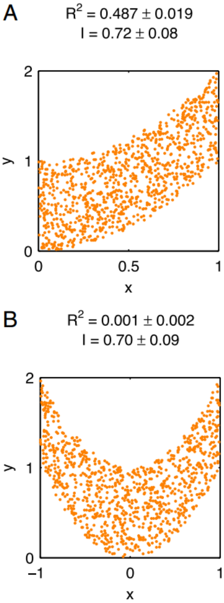

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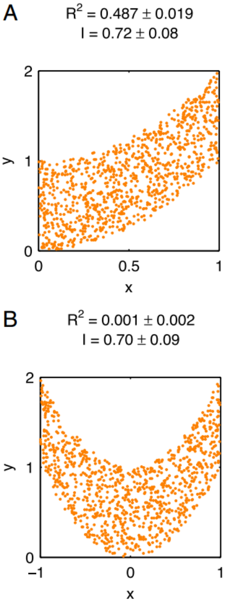

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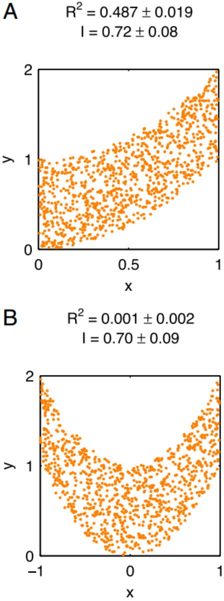

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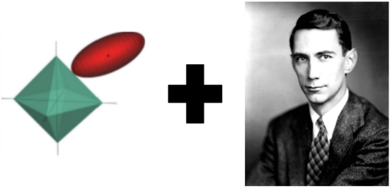
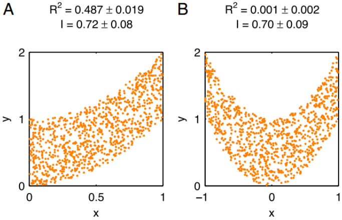
We combine *machine learning* (sparse estimation) with *information theory* to obtain better estimates of $I(\vec{X};\vec{Y})$



Mutual information $I(X; Y)$



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

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

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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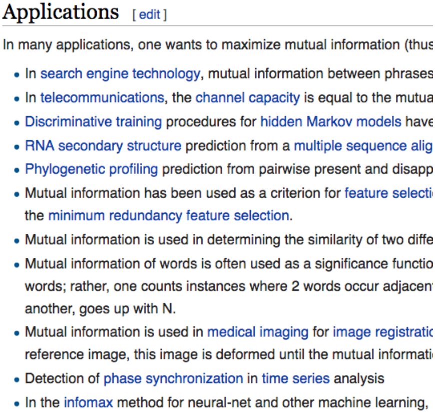


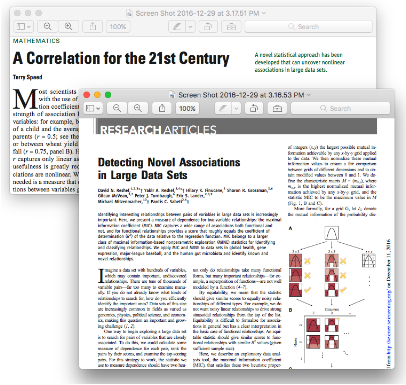
Applications [edit]

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 mutua
- Discriminative training procedures for hidden Markov models have
- RNA secondary structure prediction from a multiple sequence alig
- Phylogenetic profiling prediction from pairwise present and disapp
- Mutual information has been used as a criterion for feature selecti the minimum redundancy feature selection.
- Mutual information is used in determining the similarity of two diffe
- Mutual information of words is often used as a significance functio words; rather, one counts instances where 2 words occur adjacen another, goes up with N.
- Mutual information is used in medical imaging for image registratic reference image, this image is deformed until the mutual informati
- 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



MATHEMATICS

A Correlation for the 21st Century

Terry Speed

A novel statistical approach has been developed that can uncover nonlinear associations in large data sets.

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RESEARCH ARTICLES

Detecting Novel Associations in Large Data Sets

David N. Reshef,[1,2,3*†] Yakir A. Reshef,[2,4*†] Hilary K. Finucane,[5] Sharon R. Grossman,[2,6] Gilean McVean,[3,7] Peter J. Turnbaugh,[6] Eric S. Lander,[2,8,9] Michael Mitzenmacher,[10‡] Pardis C. Sabeti[2,6‡]

Identifying interesting relationships between pairs of variables in large data sets is increasingly important. Here, we present a measure of dependence for two-variable relationships: the maximal information coefficient (MIC). MIC captures a wide range of associations both functional and not, and for functional relationships provides a score that roughly equals the coefficient of determination (R^2) of the data relative to the regression function. MIC belongs to a larger class of maximal information-based nonparametric exploration (MINE) statistics for identifying and classifying relationships. We apply MIC and MINE to data sets in global health, gene expression, major-league baseball, and the human gut microbiota and identify known and novel relationships.

Imagine a data set with hundreds of variables, which may contain important, undiscovered relationships. There are tens of thousands of variable pairs—far too many to examine manually. If you do not already know what kinds of relationships to search for, how do you efficiently identify the important ones? Data sets of this size are increasingly common in fields as varied as genomics, physics, political science, and economics, making this question an important and growing challenge (*1*, *2*).

One way to begin exploring a large data set is to search for pairs of variables that are closely associated. To do this, we could calculate some measure of dependence for each pair, rank the pairs by their scores, and examine the top-scoring pairs. For this strategy to work, the statistic we use to measure dependence should have two heu- not only do relationships take many functional forms, but many important relationships—for example, a superposition of functions—are not well modeled by a function (*4*–*7*).

By equitability, we mean that the statistic should give similar scores to equally noisy relationships of different types. For example, we do not want noisy linear relationships to drive strong sinusoidal relationships from the top of the list. Equitability is difficult to formalize for associations in general but has a clear interpretation in the basic case of functional relationships: An equitable statistic should give similar scores to functional relationships with similar R^2 values (given sufficient sample size).

Here, we describe an exploratory data analysis tool, the maximal information coefficient (MIC), that satisfies these two heuristic proper-

of integers (x,y) the largest possible mutual information achievable by any x-by-y grid applied to the data. We then normalize these mutual information values to ensure a fair comparison between grids of different dimensions and to obtain modified values between 0 and 1. We define the characteristic matrix $M = (m_{x,y})$, where $m_{x,y}$ is the highest normalized mutual information achieved by any x-by-y grid, and the statistic MIC to be the maximum value in M (Fig. 1, B and C).

More formally, for a grid G, let I_G denote the mutual information of the probability dis-

d from http://science.sciencemag.org/ on December 11, 2016

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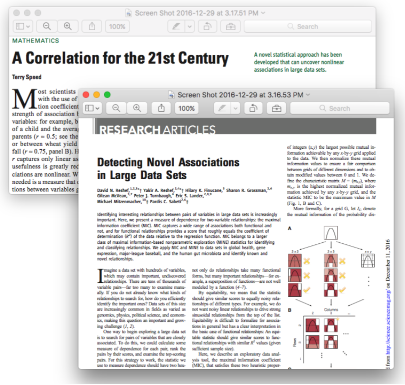
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- Only mutual information (and derived quantities) measures dependence directly.

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- **Plug-in estimate**:

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Problems in high dimensions

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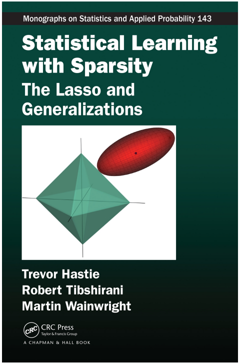
- Other approaches: binning (Bialek et al. 1991, Paninski 2003), confusion matrix of a classifier (Treves 1997, Quiroga et al. 2009)

New idea: Use sparsity!



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The Lasso and Generalizations

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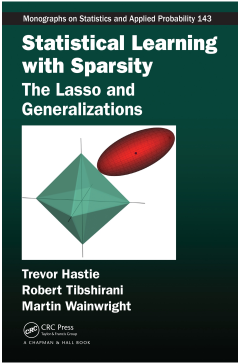

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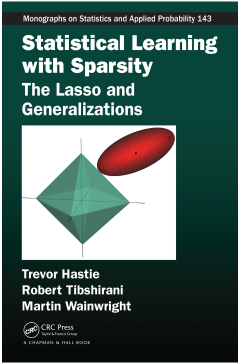

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- *Sparsity* refers to existence of low-dimensional structure hidden in high-dimensional data.
- E.g. suppose X is 100-dimensional but Y is only a function of (X_5, X_9).
- Can we exploit sparsity to obtain a good estimate of $I(X;Y)$ even under low 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 loss* (Kay et al. 2008)
3. Use the identification loss to obtain a lower bound for the mutual information $I(X; Y)$

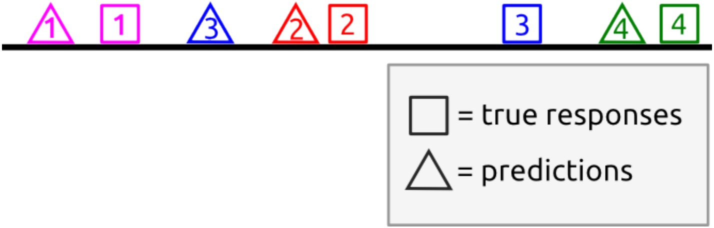
Multiple-response regression

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

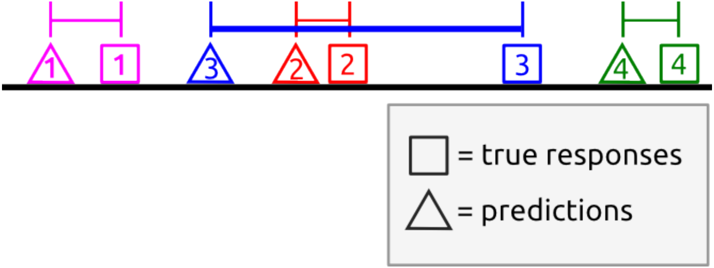
$$\hat{\beta}^{(i)} = \text{argmin}_\beta ||\boldsymbol{X}^T \beta^{(i)} - Y^{(i)}||^2 + \lambda_2 ||\beta^{(i)}||_2^2 + \lambda_1 ||\beta^{(i)}||_1$$

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

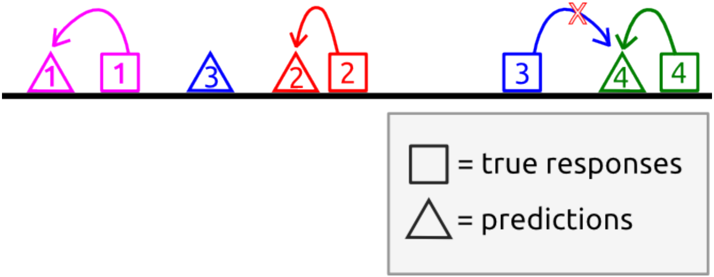
Regression vs Identification loss



Mean-squared error



Identification loss



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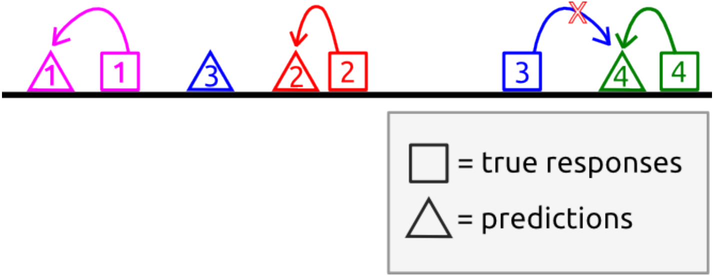

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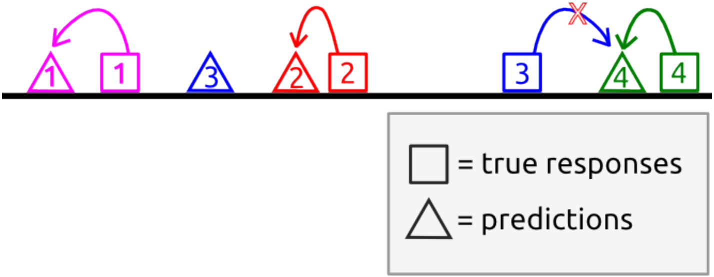
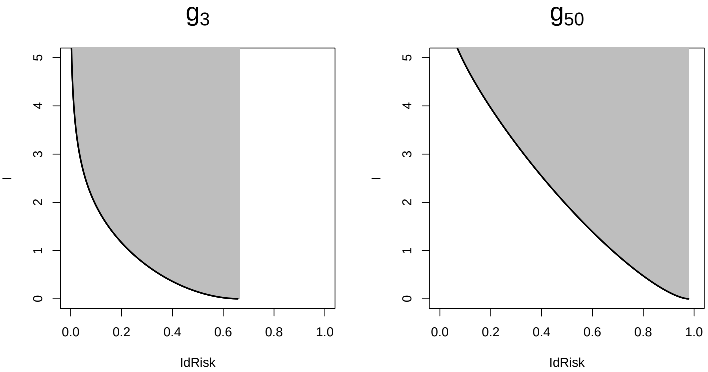


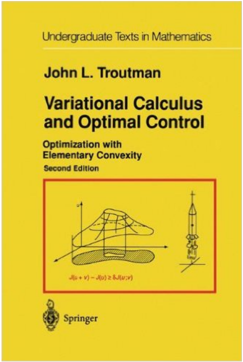
- First used by Kay et al. (2008) to compare accuracy of center-surround model of V1 versus Gabor filter model of V1.
- We are the first to explore theoretical properties of the loss (e.g. connection to mutual information)

Identification loss and mutual information

- Define the identification risk as the expected identification loss
$$\mathrm{IdRisk}_k = \mathbf{E}[\mathrm{IdLoss}_k]$$
- **Theorem.** (Z., Benjamini 2017) There exists a function g_k such that
$$I(X;Y) \geq g_k(\mathrm{IdRisk}_k).$$



Proof details



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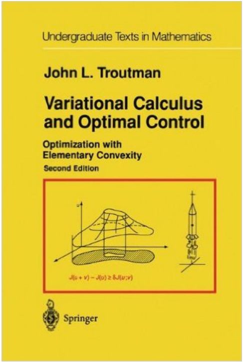

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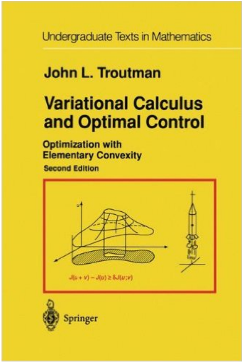

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$J(u+v) - J(u) \geq \delta J(u;v)$

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

- 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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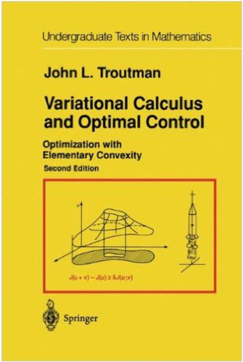

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$$\text{BayesRisk}_k[p(x,y)] = 1 - \mathbf{E}[\max_{i=1}^{k} p(Y|X_i)].$$

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

Result

Theorem. For any $\iota > 0$, there exists $\beta_\iota \geq 0$ such that defining

$$q_\beta(t) = \frac{\exp[\beta t^{k-1}]}{\int_0^1 \exp[\beta t^{k-1}]},$$

we have

$$\int_0^1 q_{\beta_\iota}(t) \log q_{\beta_\iota}(t) dt = \iota.$$

Then,

$$g_k^{-1}(\iota) = \sup_{I(X;Y)=\iota} \text{BayesAcc}_k = \int_0^1 q_{\beta_\iota}(t) t^{k-1} dt.$$

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. Compute *identification loss*, IdLoss_k, using *leave-k-out*.
3. Estimate mutual information using

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

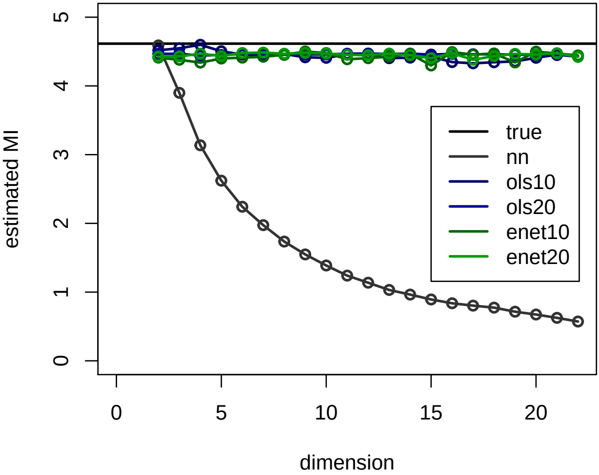
Section 2

Applications

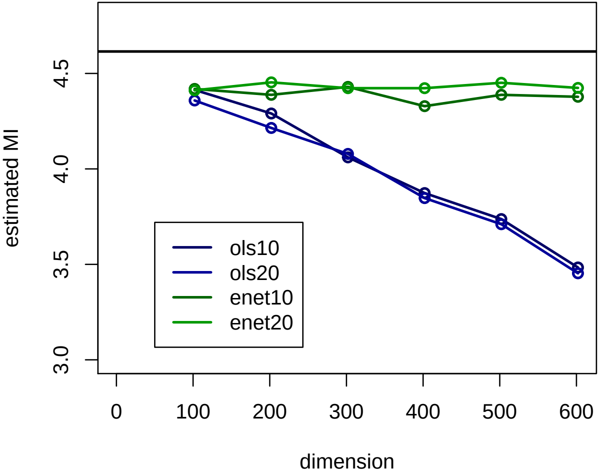
Simulation

- 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 $X_3, X_4, \ldots$.
- $n = 1000$.
- Compare Nearest-Neighbor estimator (Mnatsakov et al, 2008, implemented in `FNN`) with our method using OLS and elastic net (sparse).

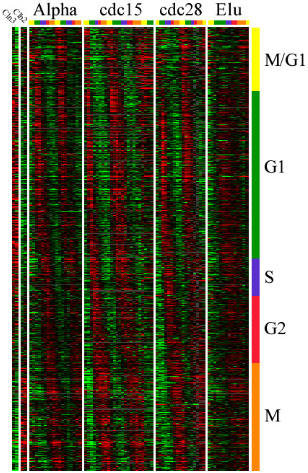
Simulation Results - I. low dimension



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 measurements 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					

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

*: 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					

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

Invariance properties

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

$$b\tilde{X} = \boldsymbol{X} E$$

$$b\tilde{Y} = \boldsymbol{X} F$$

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

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- CCA is invariant:

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

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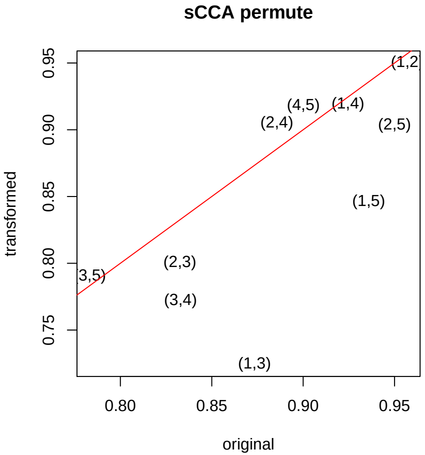
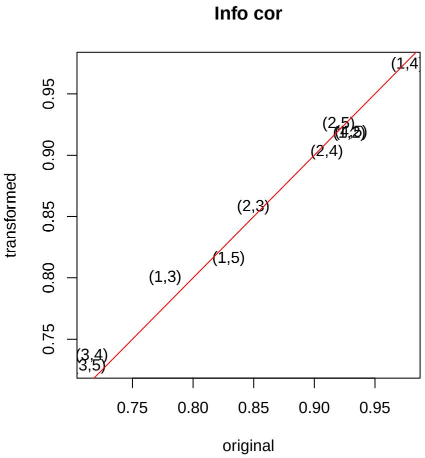
Invariance properties

However, sparse CCA is not invariant.



Invariance properties

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



Conclusions

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Conclusions

- Mutual information, and derived Cor_{Info} are useful measures of correlation, but hard to estimate.
- Our method targets high-dimensional data with sparsity.
- How to use: choose a regression model suited to the model assumptions. Our method allows you to convert the prediction accuracy of the model, IdLoss_k into an estimate of $I(\vec{X}; \vec{Y})$.
- Example application: measure of joint information between two tables which is robust to transformations.

Related work and future directions

- What if data is high-dimensional, but not sparse? We have another method based on high-dimensional asymptotics (ZB 2016).

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- Estimating quantities related to mutual information, such as *transfer information*, *stimulus-specific information* and *redundancy* (Borst and Theunissen 1999)

Related work and future directions

- What if data is high-dimensional, but not sparse? We have another method based on high-dimensional asymptotics (ZB 2016).
- Estimating quantities related to mutual information, such as *transfer information*, *stimulus-specific information* and *redundancy* (Borst and Theunissen 1999)
- Inferring resting-state brain networks.

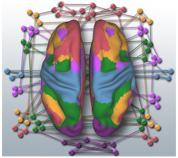

Image credit Simons Foundation

Section 3

The End

References

- Reshef et al, 2011. "Detecting Novel Associations in Large Datasets." *Science*.
- Speed, 2011. "A correlation for the 21st century." *Science*.
- Linfoot, 1957. "An informational measure of correlation." *Information and Control*.
- Kay, 2008. "Identifying natural images from human brain activity." *Nature*.
- Mnatsakanov, et al, (2008). "K-nearest neighbor estimators of entropy." *Mathematical Methods of Statistics*
- Spellman et al., (1998). "Comprehensive Identification of Cell Cycle-regulated Genes of the Yeast Saccharomyces cerevisiae by Microarray Hybridization." *Molecular Biology of the Cell*.
- Hotelling, H. (1936). "Relations Between Two Sets of Variates". *Biometrika.*
- Witten, Daniela M., and Robert J. Tibshirani. (2009). "Extensions of sparse canonical correlation analysis with applications to genomic data." *Statistical applications in genetics and molecular biology*

Result

Theorem. For any $\iota > 0$, there exists $\beta_\iota \geq 0$ such that defining

$$q_\beta(t) = \frac{\exp[\beta t^{k-1}]}{\int_0^1 \exp[\beta t^{k-1}]},$$

we have

$$\int_0^1 q_{\beta_\iota}(t) \log q_{\beta_\iota}(t) dt = \iota.$$

Then,

$$\sup_{I(X;Y)=\iota} \text{BayesAcc}_k = \int_0^1 q_{\beta_\iota}(t) t^{k-1} dt = g_k^{-1}(\iota).$$

Back to main.