

# Stability and Aggregation of Experimental Results

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10 August 2017 ICML workshop on Computational Biology

# What is machine learning?



### Machine learning is about prediction

Examples/features	$x_1,\ldots,x_n\sim\mathfrak{X}$
Labels/annotations	$y_1, \ldots, y_n \sim \mathcal{Y}$
	$f_{\mathbf{w}}(x): \mathfrak{X} \to \mathfrak{Y}$

### Estimate best predictor = training

Given data  $(x_1, y_1), \ldots, (x_n, y_n)$ , find a predictor  $f_{\mathbf{w}}(\cdot)$ .

- No mechanistic model of the phenomenon
- $\checkmark$  There is relatively large amounts of data (examples, x usually  $\mathbb{R}^d$ )
- $\checkmark$  The outcomes (labels, y usually binary) are well defined

### $\textbf{Prediction} \neq \textbf{understanding}$

How can we use prediction to help with scientific research?

# What are good features?



## $f_{\mathbf{w}}(x): \mathbf{\mathfrak{X}} \to \mathbf{\mathfrak{Y}}$

## What to measure?



# $f_{\mathbf{w}}(x): \mathfrak{X} \to \mathcal{Y}$

# This talk ...



#### Use predictive model ...

 $f_{\mathbf{w}}(x): \mathfrak{X} \to \mathfrak{Y}$ 

### ... to discover good biomarkers

$$f_{\mathbf{w}}(x): \mathbf{X} \to \mathbf{Y}$$

- Spearman's Correlation
- Stability and Aggregation

# **Genome wide association study**



#### **Case-control studies**

A cohort of sick individuals (cases) and healthy individuals (controls) are genotyped and their corresponding binary phenotype are recorded.

#### We use the framework of hypothesis testing

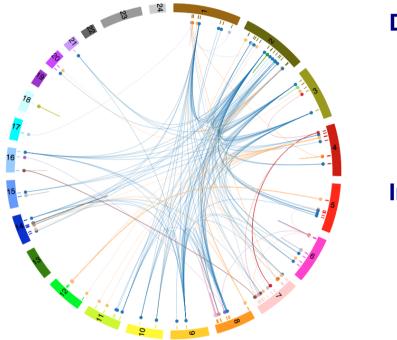
Hypothesis testing Given a case control study, test whether a particular SNP is associated with the phenotype.

#### **Epistatic Interactions**

- WTCCC data
- Need to tabulate 125 billion contingency tables
- Consider specificity and sensitivity
- Gain over univariate ROC
- **●** CPU ( $\approx$  days) and GPU ( $\approx$  hours)
- Store the top 1 million pairs

# **Interacting with results**





Cristovao Freitas Iglesias Junior, Stefan Sevelda github.com/chengsoon.ong/rede

#### D3.js

- Circular plot
- Linear plot
- Manhattan plot
- 🍠 Heat map

#### Interaction

- Filter
- 🍠 Zoom
- 🗩 Drill down
- 🍠 Call out

# p-values



### Interpreting p-values

Is  $10^{-10}$  probability of association very significant?

### Quote

... but a reliable method of procedure. In relation to the test of significance, we may say that a phenomenon is experimentally demonstrable when we know how to conduct an experiment which will rarely fail to give us a statistically significant result.

Fisher, The Design of Experiments, 1947, p. 14

### Stability of scoring

We consider p-values as a score of association.

- How stable is this score if we repeat the experiment?
- How do we combine scores?

### Challenges

- Scores available for only the top-k examples
- Scores from different sources not calibrated

# Outline



#### Use predictive model ...

 $f_{\mathbf{w}}(x): \mathfrak{X} \to \mathfrak{Y}$ 

#### ... to discover good biomarkers

$$f_{\mathbf{w}}(x): \mathbf{\mathcal{X}} \to \mathbf{\mathcal{Y}}$$

#### Stability of feature selection

How to measure overlap?

#### **Rank aggregation**

How to combine different sources of information?

### Modeling using Spearman's correlation

# How to represent ranks?





Multiple ways to represent ranks

- **D** Ordered list of n objects selected from  $\Omega$
- $\checkmark$  List of values  $[1, \ldots, n]$  (the ranks of the object)
- **Permutation mapping**  $R: \Omega \rightarrow (0, 1)$

# **Measuring Overlap**

### **Motivation**

Given a set of replicated experiments, how do we measure overlap?

### Examples

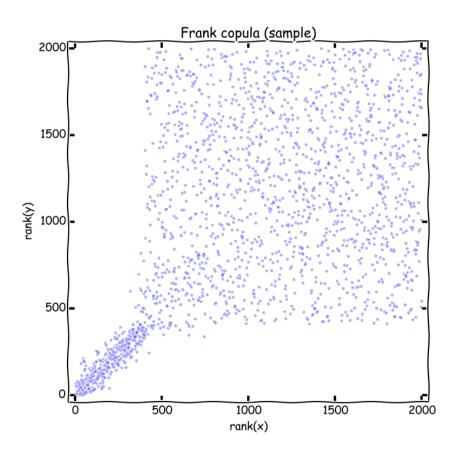
- Perform repeated splits of the data
- Experiments on different cohorts
- Multiple sources of information

### Challenges

- Scores available for only the top-k examples
- Scores from different sources not calibrated

# **Signal and Noise**





# Set based overlap



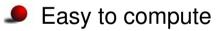
#### **Running example (6 objects)**

$$A = [a, b, c, d, e, f]$$
$$B = [a, b, e, f, c, d]$$

**Jaccard Index** 

$$\mathsf{overlap} = \frac{|A \cap B|}{|A \cup B|}$$

### **Measuring stability**



Works for top-k lists Consider the top-3 lists from above:

Jaccard index = 
$$\frac{|\{a, b\}|}{|\{a, b, c, e\}|} = \frac{1}{2}$$



# Spearman's $\rho$



Similar to Pearson's correlation for the measure of dependence Spearman's  $\rho$  is a correlation measure between ranked lists

$$\rho(A,B) := \frac{\sum_{i} (r_A^{(i)} - \bar{r}_A) (r_B^{(i)} - \bar{r}_B)}{\sqrt{\sum_{i} (r_A^{(i)} - \bar{r}_A)^2 \sum_{i} (r_B^{(i)} - \bar{r}_B)^2}},$$

Running example:

$$\rho([a,b,c,d,e,f],[a,b,e,f,c,d]) = 0.543$$

(Jaccard index = 1)

Need the same elements in A and B

 $\rho([a,b,c],[a,b,e])$  ?

# Spearman's $\rho$ on top k lists



#### Our idea

Define Spearman's  $\rho$  for top k lists

#### **Key observation**

Any elements in list A that do not appear in list B must have a rank higher than the number of elements in B

### Running example (top-3)

 $A = [a, b, c, d, e, f] \quad \text{and} \quad B = [a, b, e, f, c, d]$  $A_3 = [a, b, c] \quad \text{and} \quad B_3 = [a, b, e]$  $A_3 \stackrel{B_3}{\rightarrow} = [a, b, c, e] \quad \text{and} \quad B_3 \stackrel{A_3}{\rightarrow} = [a, b, e, c]$ 

Spearman's 
$$\rho = \rho(A_3 \stackrel{B_3}{\rightarrow}, B_3 \stackrel{A_3}{\rightarrow}) = 0.8$$

# **Spearman's** $\rho$ **on top** k **lists**

### **Extend the list**



We expand lists *A* and *B* to complete rankings over the same set of elements, denoting them as  $A \xrightarrow{B}$  and  $B \xrightarrow{A}$  respectively.

The missing values in the extension are given the average rank. Running example (top-4)

 $A_4 = [a, b, c, d] \quad \text{and} \quad B_4 = [a, b, e, f]$  $A_4 \stackrel{B_4}{\rightarrow} = [1, 2, 3, 4, 5.5, 5.5] \quad \text{and} \quad B_4 \stackrel{A_4}{\rightarrow} = [1, 2, 5.5, 5.5, 3, 4]$ 

Makes no assumption about the order of the unranked objects

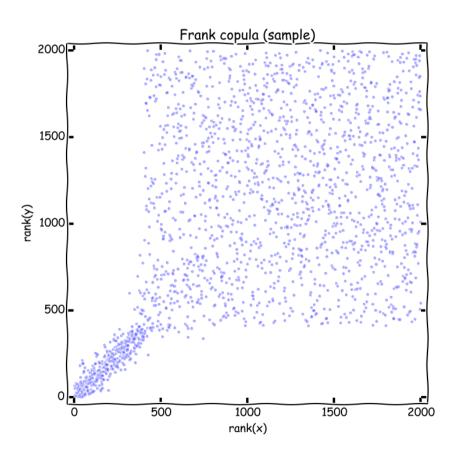
### Other possible imputation approaches

- Optimistic
- Worst case

Bedő, Rawlinson, Goudey, Ong, PLoS ONE, 2014

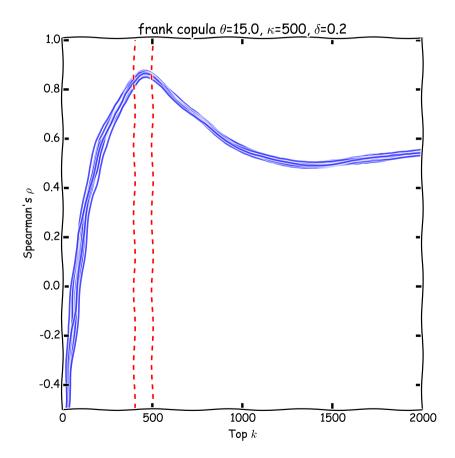
# **Signal and Noise**



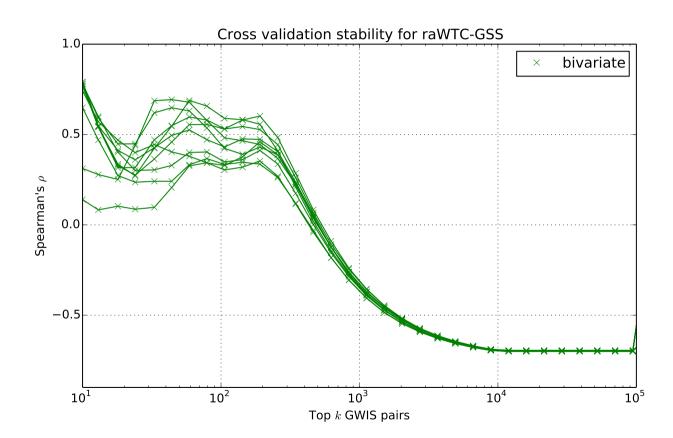


# Spearman's $\rho$





# Simulate two cohorts by splitting



Bedő, Rawlinson, Goudey, Ong, PLoS ONE, 2014

Cheng Soon Ong: Finding Good Scientific Experiments with Machine Learning, Page 19

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# **Measuring Overlap**

### **Motivation**

Given a set of replicated experiments, how do we measure overlap?

### Challenges

- Scores available for only the top-k examples
- Scores from different sources not calibrated

### Model

- Ranked list Instead of just using set intersection, we can use the scores from GWIS to order the results
- top k Traditional methods (Spearman's ρ) requires ranks for the whole list. We have incomplete information, but we know our ranks are the top ones.
- Multivariate Textbook Spearman's  $\rho$  is for computing correlation between two ranks. We want to compute the correlation between multiple ranked lists.

# Copulas

#### Intuition

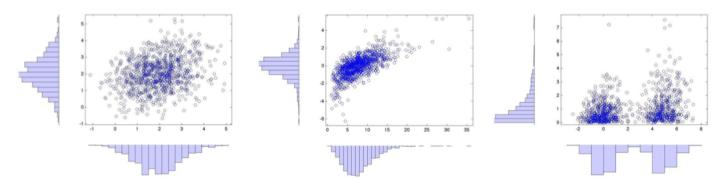
For continuous random variables, copulas model the dependence component after discounting for univariate marginal effects

### **Probabilistic definition**

Let  $U_1, \ldots, U_d$  be real random variables  $\sim U([0, 1])$ . A copula function  $C : [0, 1]^d \longrightarrow [0, 1]$  is a joint distribution

$$C_{\theta}(u_1,\ldots,u_d) = P(U_1 \leqslant u_1,\ldots,U_d \leqslant u_d)$$

#### The same Gaussian copula function



# **Copulas and Spearman's** $\rho$

 $\rho($ 



#### Spearman's $\rho$ can be expressed in terms of the copula

$$\rho(A,B) = 12 \int_{[0,1]^2} C(u,v) du dv - 3$$

Proof

$$\begin{split} A,B) &= \frac{\sum_{i} (r_{A}^{(i)} - \bar{r}_{A}) (r_{B}^{(i)} - \bar{r}_{B})}{\sqrt{\sum_{i} (r_{A}^{(i)} - \bar{r}_{A})^{2} \sum_{i} (r_{B}^{(i)} - \bar{r}_{B})^{2}}} \\ &= \frac{\mathbb{E}[F(X)G(Y)] - \mathbb{E}[F(X)]\mathbb{E}[G(Y)]}{\mathrm{STD}[F(X)]\mathrm{STD}[G(Y)]} \\ &= \frac{\mathbb{E}[F(X)G(Y)] - \frac{1}{2}^{2}}{\frac{1}{12}} \\ &= 12\mathbb{E}[F(X)G(Y)] - 3 \\ &= 12\int\int\int uvC(u,v) - 3 \\ &= 12\int_{[0,1]^{2}} C(u,v) dudv - 3 \end{split}$$

# **Copulas and Spearman's** $\rho$



#### Spearman's $\rho$ can be expressed in terms of the copula

$$\rho(A,B) = 12 \int_{[0,1]^2} C(u,v) du dv - 3$$

**Empirical copula** 

$$C_n(u,v) = \frac{1}{|\Omega|} \sum_{x \in \Omega} \mathbf{1} \left( R(x) \leqslant u, S(x) \leqslant v \right)$$

#### Why do the math?

- Unclear how to extend formula for Spearman's correlation.
- Multivariate distributions  $\Rightarrow$  multivariate copula.

# Multivariate Spearman's $\rho$



#### A multivariate extension of Spearman's $\rho$

For a *d* dimensional set of random variables  $\mathbf{u}$ , the multivariate Spearman's  $\rho$  is given by

$$\rho(R_1,\ldots,R_d) = Q(C,\pi) = h(d) \left( 2^d \int_{[0,1]^d} \pi(\mathbf{u}) \, \mathrm{d}C(\mathbf{u}) - 1 \right),$$

where

$$h(d) = \frac{d+1}{2^d - (d+1)}$$

**Empirical multivariate Spearman's corelation** 

$$\rho_n(R_1, \dots, R_d) = h(d) \left[ \frac{2^d}{n} \sum_x \prod_{j=1}^d R_j(x) - 1 \right].$$

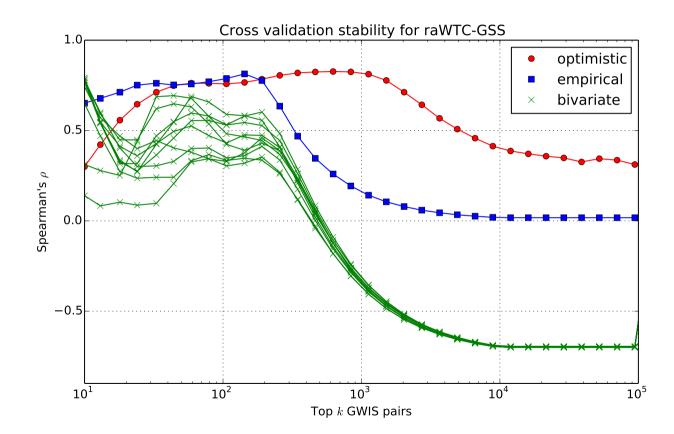
#### **Empirical multivariate Spearman's corelation**

$$\rho_n(R_1, \dots, R_d) = h(d) \left[ \frac{2^d}{n} \sum_x \prod_{j=1}^d R_j(x) - 1 \right]$$

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# **Multiple replicates**





# Wait... there's more



Modeling using Spearman's correlation

Use predictive model ...

 $f_{\mathbf{w}}(x): \mathfrak{X} \to \mathfrak{Y}$ 

### ... to discover good biomarkers

 $f_{\mathbf{w}}(x):\mathbf{\mathfrak{X}}\to\mathbf{\mathfrak{Y}}$ 

Stability of feature selection

How to measure overlap?

$$ho(R_1,\ldots,R_d)$$

#### **Rank aggregation**

How to combine different sources of information?

Macintyre, Yepes, Ong, Verspoor, PeerJ, 2014

# Optimal aggregator: geometric mean and and a second second

#### How to combine different sources of information?

We maximise multivariate correlation

$$R^* = \arg\max_R \rho(R, R_1, R_2, \dots, R_d).$$

**Theorem** The aggregator that maximises multivariate Spearman's correlation is the product of the normalised ranks.

#### Use the geometric mean

#### **NOT pairwise correlation**

Instead of decomposing the association into a combination of pairwise similarities  $\rho(R, R_1), \rho(R, R_2), \dots, \rho(R, R_d)$ .

#### Method

- 1. Divide rank by number of items
- 2. return log average

Bedő, Ong, JMLR 17(201):1-30, 2016

# **Supervised learning to rank**



#### **Problem setting**

We are given a ranking *L* of *n* objects which comprise our labels, and a set of *d* experts  $\{R_j\}$ . Find a weighting of the experts.

#### **Relaxed optimal aggregator**

We solve the least squares problem

$$\min_{\omega} \sum_{x} \left( l(x) - \sum_{j=1}^{d} \omega_j r'_j(x) \right)^2,$$

where the outer sum is over the n examples x,

l(x) is the log scaled normalised labels,

 $r'_i(x)$  is the log scaled normalised completed ranks.

#### LETOR 4.0

We (surprisingly) perform much better than state of the art

Bedő, Ong, JMLR 17(201):1-30, 2016

# Why is ML for Comp Bio hard?

### Deep data

- High dimensional low sample size data
- Finite domain (we want predictions genome wide)
- Difficult to satisfy i.i.d. assumption

### Prior knowledge

- Hard and soft constraints
- Weak constraints
- Causal systems with feedback and delays

### **Different problems/communities**

- Genomics, proteomics, medical imaging, health records
- Communication challenges

#### Keep up the great work!

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# Summary



### $\textbf{Prediction} \neq \textbf{understanding}$

How can we use prediction to help with scientific research?

Use predictive model to discover good features

### Spearman's correlation - applied to GWAS

- Stability of scoring
- Rank aggregation
- Supervised learning to rank
- Imputation from top-k lists
- Multivariate correlation using copulas

#### The dream

Facilitating scientific knowledge discovery through automated experimental design with machine learning

# **Thank You**



### $\textbf{Prediction} \neq \textbf{understanding}$

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Use predictive model to discover good features

### Spearman's correlation - applied to GWAS

- Stability of scoring
- Rank aggregation
- Supervised learning to rank
- Imputation from top-k lists
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### The dream

Facilitating scientific knowledge discovery through automated experimental design with machine learning

#### Please make your research open

machlearn.gitlab.io/fmml/

www.ong-home.my

# **Scoring candidates - ABCDE**

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### **Active Learning**

- Choose a particular example to label using heuristics
- Annotator assumed to provide ground truth

### **Bandits**

- Select a choice from a set of actions
- Simple algorithms with theoretical guarantees
- Manage uncertainty with repeated sampling

### **Choice theory**

- Aggregate set of ranks into one ordering
- Economics and social science, impossiblity theorems

### **Designing Experiments**

- Choose a set of trials to measure
- Optimisation algorithms with theoretical analysis
- Information theory, real random variables