

An evaluation of machine learning and traditional statistical methods for discovery in large-scale data

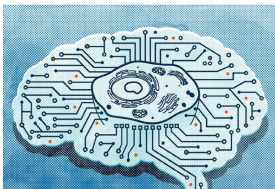
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THIS MONTH

POINTS OF SIGNIFICANCE

Statistics versus machine learning

Statistics draws population inferences from a sample, and machine learning finds generalizable predictive patterns.

Two major goals in the study of biological systems are inference and prediction. Inference creates a mathematical model of the data-generating process to formulate understanding or test a hypothesis about how the system behaves. Prediction aims at forecasting unobserved outcomes or future behavior, such as whether a mouse with a given gene expression pattern has a disease. Prediction makes it possible to identify best courses of action (e.g., treatment choice) without requiring understanding of the underlying mechanisms. In a typical research project, both inference and prediction can be of value—we want to know how biological processes work and what will happen next. For example, we might want to select which biological processes are associated with the dysregulation of a gene in a disease, as well as detect whether a subject has the disease and predict the best therapy.

Many methods from statistics and machine learning (ML) may,

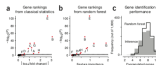


Figure 2 | Analysis of gene ranking by classical inference and ML. (a) Unadjusted log-scaled P values from statistical differential expression analysis as a function of effect size, measured by fold change in expression. (b) Log-scaled P values from a machine learning model of gene importance from modern forest classification. In a and b, red circles identify the top differentially expressed genes from Figure 1; the remaining genes are indicated by gray circles. (c) Distribution of the number of dysregulated genes correctly identified in 1,000 simulations by inference (gray) and modern forest (black) (see text).

number of subjects, is contrast to 'big data', where the number of subjects is greater than that of input variables. ML makes minimal assumptions about the data-generating systems; they can be effective even when the data are gathered without a carefully controlled experimental design and in the presence of complicated nonlinear interactions. However, despite convincing prediction results, the lack of an explicit model can make ML solutions difficult to directly relate to existing biological knowledge.

- Recent paper in *Nature Methods* on statistical discovery in large-scale data
- Concluded random forests outperformed Benjamini-Hochberg p -value based approaches
- Based on simulations of dysregulated genes in expression data
- Not all approaches were given the same a priori information

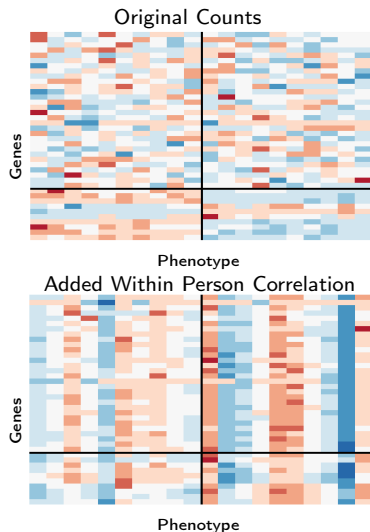
→ Paper received much press and substantial twitter discussion

Objectives:

- ① Examine claims using unbiased and fair comparisons
- ② Estimate accuracy of machine learning and “traditional” methods
- ③ Identify methods with the best performance characteristics

Methods

Simulated Gene Expression Data



- 40 genes ; 20 people
- 10 phenotype positive ; 10 negative
- 25% (10) of genes are “dysregulated” across phenotype
- Computed pseudo-counts = normalized counts (Robinson and Smyth, 2008)
- *Allowed within person correlation across genes (new)*

Methods

Discovery Methods

Traditional	Machine Learning
Nominal p -values	Random Forest importance levels
Bonferroni adjusted p -values	Neural Net prediction weights
Benjamini-Hochberg Emp FDRs	Penalized Regression (forthcoming)
Second-generation p -values	

- 1 5% significance level / FWER / FDR
- 2 Top 10 ranked genes by ML criteria
- 3 *Top 10 ranked genes by Traditional criteria (new)*

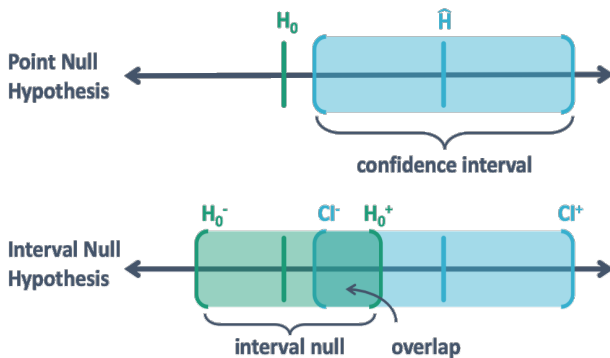
Second Generation p -values

Overview

- SGPV is in $[0, 1]$ and denoted by p_δ
- δ indicates dependence on (pre-specified) interval null hypothesis
- SGPV reports the fraction of data-supported effect sizes that are null or trivial
- Adjustment for multiple comparisons is automatic
- **Cases:**
 - 1 $p_\delta = 0$ when data incompatible with null region
 - 2 $p_\delta = 1$ when data compatible with null region
 - 3 $0 < p_\delta < 1$ when data are inconclusive

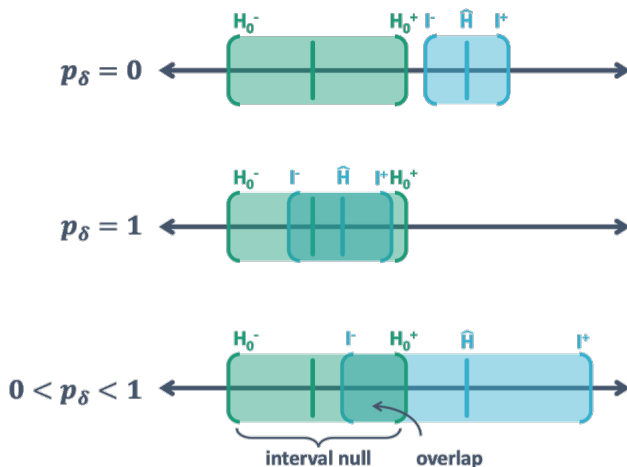
Second Generation p -values

Illustration 1



Second Generation p -values

Illustration 2

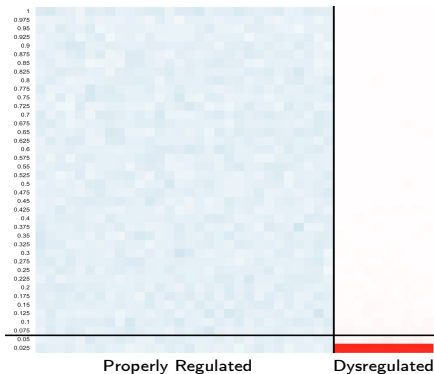


Results

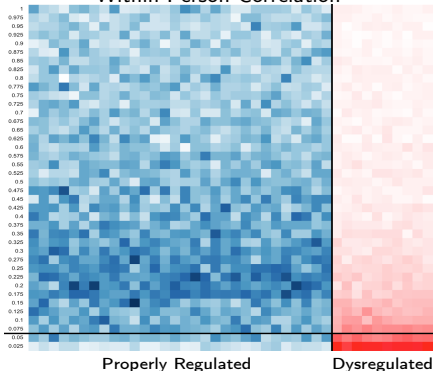
Heatmaps of p -values

- Heatmap of discovery p -values by nominal p -values
- Values below horizontal line less than 0.05

Nominal p -values



Nominal p -values with
Within Person Correlation

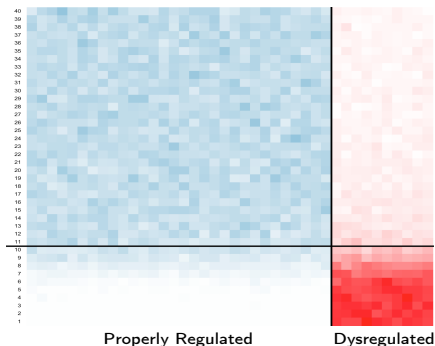


Results

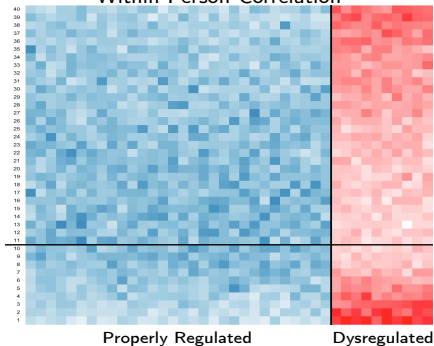
Heatmaps of Rankings

- Heatmap of gene rankings by FDR (Benjamini-Hochberg)
- Top 10 rankings below horizontal line

Rankings of Original Counts



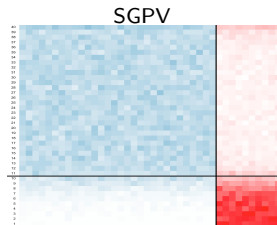
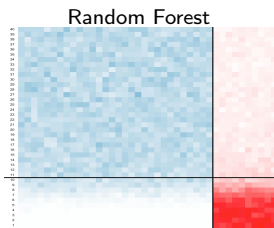
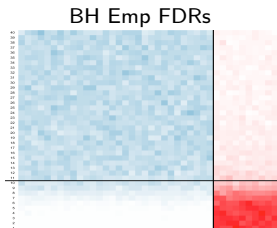
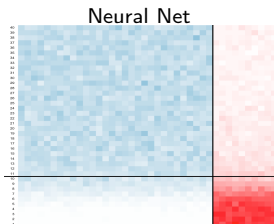
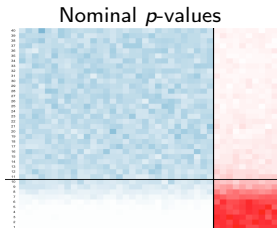
Rankings of Counts with Within Person Correlation



Results

Heatmaps of Rankings

- Heatmaps of rankings of the original gene expression counts



Results

Comparisons

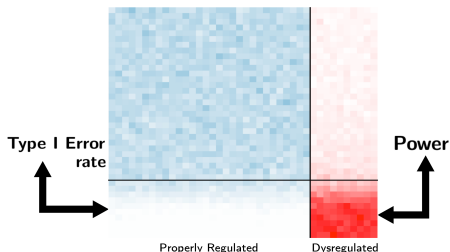
Accuracy statistics:

- **Power**

→ Proportion of “dysregulated” genes identified as “dysregulated”

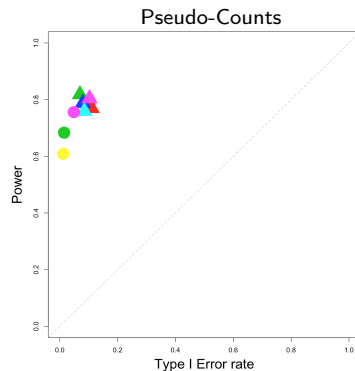
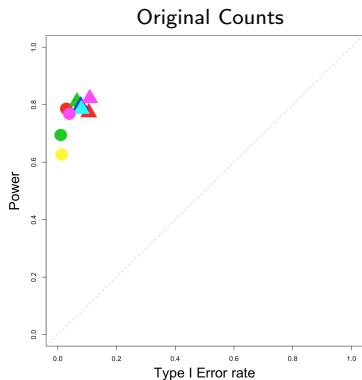
- **Type I Error rate**

→ Proportion of “properly regulated” genes identified as “dysregulated”



Results

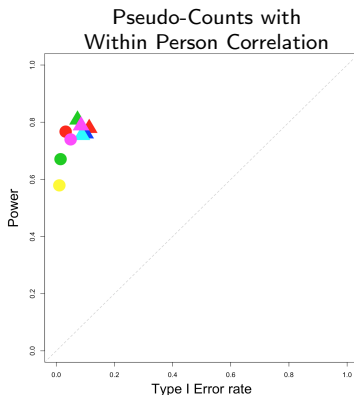
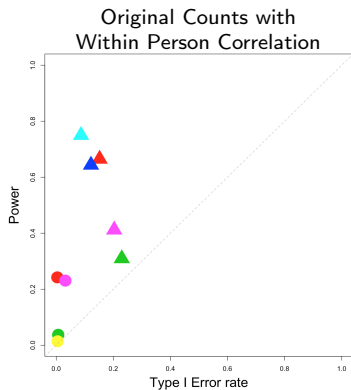
Comparisons



- Nominal P-value
- Benjamini-Hochberg
- Second Generation P-value
- ▲ Nominal P-value(rank)
- ▲ Benjamini-Hochberg(rank)
- ▲ Second Generation P-value(rank)
- Bonferroni
- ▲ Random Forest(rank)
- ▲ Neural Net(rank)

Results

Comparisons



- Nominal P-value
- Benjamini-Hochberg
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Conclusions

- Normalizing step is critical for some methods
- Methods perform identically when properly compared (by rankings)
- Comparing ranking vs threshold discovery gives *false* impression of differential statistical accuracy (ie, *Nature Methods*)

	Traditional Methods	Machine Learning
Pros	<ul style="list-style-type: none">• Significance level criterion• Can be ranked• Interpretable coefficients	<ul style="list-style-type: none">• Handles complexity with ease• Variety of flexible algorithms
Cons	<ul style="list-style-type: none">• Complexity poses challenges• Significance criterion not universal• Models can be simplistic	<ul style="list-style-type: none">• Must pre-specify number of findings• No threshold criterion• Coefficients hard to interpret

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- Valerie Welty

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