

Statistics in the age of data science, issues you can and can not ignore

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Session: <http://conf.datofair.com/speakers/dr-john-mount/>
These slides, all data and code: <http://winvector.github.io/DS/>



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This talk

- Our most important data science tools are our theories and methods.
Let us look a bit at their fundamentals.
- Large data gives the apparent luxury of wishing away some common model evaluation biases (instead of needing to apply the traditional statistical corrections).
- Conversely, to work agilely data scientists must act as if a few naive axioms of statistical inference were true (though they are not).
- I will point out some common statistical issues that do and do not remain critical problems when you are data rich.
- I will concentrate on the simple case of supervised learning.

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Outline

- (quick) What is data science?
- How can that work?
- An example critical task that gets easier when you have more data.
- What are some of the folk axioms of data science?
- How to design bad data.

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What is Data Science: my position

- Data science is the continuation of data engineering and predictive analytics.
- More data allows domain *naive* models to perform well.
 - See: "The Unreasonable Effectiveness of Data", Alon Halevy, Peter Norvig, and Fernando Pereira, IEEE Intelligent Systems, 2009, pp. 1541-1672.
- Emphasis on prediction over harder statistical problems such as coefficient inference.
- Strong preference for easy procedures that become more statistically reliable as you accumulate more data.
- Reliance on strong black-box tools.

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<http://static.googleusercontent.com/media/research.google.com/en/us/pubs/archive/35179.pdf>

Why does data science work at all?

Complicated domain theory doesn't always preclude easily observable statistical signals

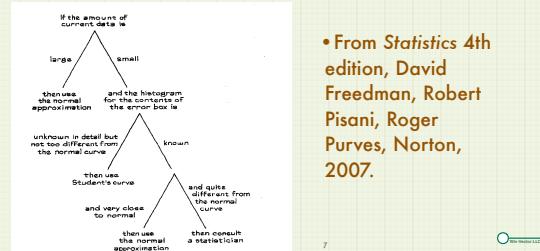
"Maybe the molecule didn't go to graduate school."



(Will Welch defending the success of his approximate molecular screening algorithm, given he is a computer scientist and not a chemist.)

Example approximate docking (in this case using ISIDE approximation, not Welch et al.'s Homology Screening).
"Optimized Screening for HIV Protein-Ligand: The Influence of Binding-Site Conformation and Representation on Ligand Selectivity," Valer Shulman, David Welch, and Michael J. Sanner. In: Eighth International Conference on Intelligent Systems for Molecular Biology, Pages 245-251, AAAI Press, 1999.

A lot of deep statistics is about how to work correctly with small data sets



Clearly we are ignoring some important domain science issues and statistical science issues, so how does data science work?

<http://www.aaai.org/Papers/ISMB/1999/ISMB99-028.pdf>

You may not get the whole story, but you may not miss the whole story.

Ch. 26 page 493. Statistical efficiency is a huge worry when you don't have a lot of data.

What is a good example of a critical task that becomes easier when you have more data?

Model assessment

- Estimating the performance of your predictive model on future instances
- A critical task
- Gets easier when you have more data:
 - Don't need to rely on statistical adjustments
 - Can reserve a single sample of data as a held-out test set (see "The Elements of Statistical Learning" 2nd edition section 7.2)
 - Computationally cheaper than:
 - leave k-out cross validation
 - k-fold cross validation

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"The Elements of Statistical Learning" 2nd edition section 7.2 page 222.
[https://en.wikipedia.org/wiki/Cross-validation_\(statistics\)](https://en.wikipedia.org/wiki/Cross-validation_(statistics))

Let's review these terms

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Statistical Adjustments

- Attempt to estimate the value of a statistic or the performance of a model on new data using only training data.
- Examples:
 - Sample size adjustment for variance: writing $\sum_{i=1}^n (x_i - \bar{\mu})^2 / (n - 1)$ instead of $\sum_{i=1}^n (x_i - \bar{\mu})^2 / n$
 - "adjusted R-squared", in-sample p-values, "AIC", "BIC", ...
- Pointless to adjust in training sample quantities when you have enough data to try and estimate out of sample quantities directly (cross validation methods, train/test methods, or bootstrap methods).

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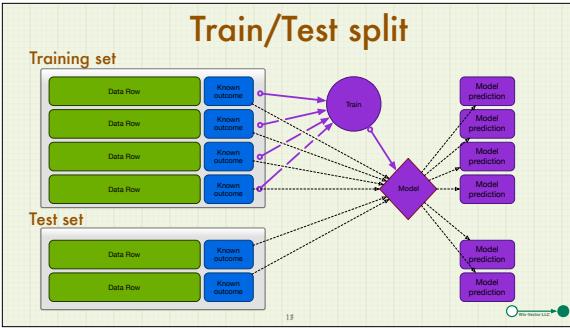
Does not matter when n is large. Can actually be quite complicated and require a lot of background to apply correctly. Prefer tools like the PRESS statistics to adjusted R-squared. Can use training mean against out of sample instances and so on.

Leave k-out, k-way, and k-fold scoring

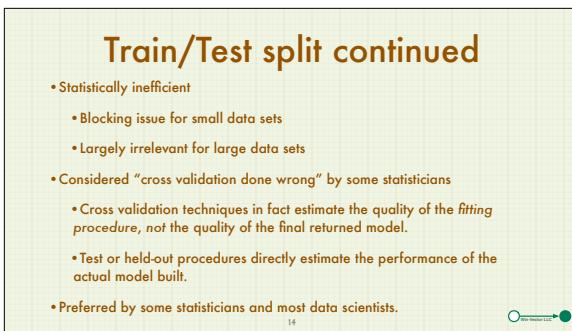
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k-X cross validation methods are a procedural alternative. Shown: 3-fold cross validation. We try to simulate the performance of a model on new data by never applying a model to any data used to construct it. Which cross validation scheme you are using determines pattern of arrows. Common to all schemes: there are many throw away models. The larger the models the more like training on all of the available data they behave.



Test/Train split is an easier alternative that is less statistically efficient and depends on having good tools (that themselves cross-validate) during the training phase. Test set is held secret during model construction, tuning, and even early evaluation. Scoring in Train subset may in fact itself use both cross-validation and train/test subsplit methods. Actual model produced is scored on test set (though some data scientists re-train on the entire data set as a final “model polish” step).



Splitting your available data into train and test is a way to try and *simulate* the arrival of future data. Like any simulation- it may fail. Controlled experiments are prospective designs that are somewhat more expensive and somewhat more powerful than this.



Data science is a bit looser than traditional statistical practice and moves a bit faster; what does that look like?



We have to admit:
data scientists are a flourishing species

- Must be something to be learned from that.
- What axioms (true or false) would be needed to explain their success?



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Data science axiom wish list

- Just a few:
 - Wish more data was always better.
 - Wish more variables were always better.
 - Wish you can retain some fraction of training performance on future model application.



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Is more data always better?



- In theory: yes (you could always simulate having less data by throwing some away).
- In practice: almost always yes.
- Absolutely for every algorithm every time? no.

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More data can be bad for a fixed procedure
(artificial example)

- Statistics / machine learning algorithms that depend on re-sampling to supply diversity can degrade in the presence of extra data.
- Case in point: random forest over shallow trees can lose tree diversity (especially when there are duplicate or near-duplicate variables).

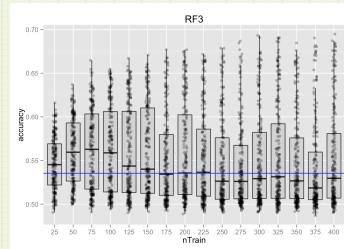
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Axioms that are true are true in the extreme.

Random forest example

- A data set where a random forest over shallow trees shows lower median accuracy on test data as we increase training data set size.
- (synthetic data set designed to hurt random forest, logistic model passes 0.85 accuracy)
- All code/data: <http://winvector.github.io/DS/>



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Are more variables always better?

- In theory: yes.
- Consequence of the non-negativity of mutual information.
- Only true for training set performance, *not* performance on future instances.
- In practice: often.
- In fact: ridiculously easy to break:
 - Noise variables
 - Collinear variables
 - Near constant variables
 - Overfit



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Note: collinear variables while damaging to prediction are nowhere near as large a hazard to prediction as they are to coefficient inference. And classic “x alone” methods of dealing with them become problematic in so called “wide data” situations.

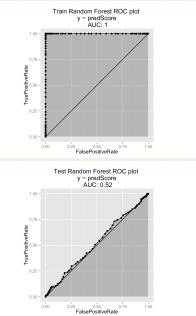
To benefit from more variables

- Need at least a few of the following:
 - Enough additional data to falsify additional columns.
 - Regularization terms / useful inductive biases.
 - Variance reduction / bagging schemes.
 - Dependent variable aware pre-processing (variable selection, partial least squares, word2vec, and not principal components projection).

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Can't we keep at least some of our training performance?

- Common situation:
 - Near perfect fit on training data.
 - Model performs like random guessing on new instances.
 - Extreme over fit.
- One often hopes some regularized, ensemble, or transformed version of such a model would have at least some use on new instances.



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Random forest is a dominant machine learning algorithm in practice. This is a problem where logistic regression gets 85% accuracy as n increases, and the concept is reachable by the random forest model.

Not the case

- For at least the following common popular machine learning algorithms we can design a simple data set where we get arbitrarily high accuracy on training even when the dependent variable is generated completely independently of all of the independent variables.

- Decision Trees
- Logistic Regression
- Elastic Net Logistic Regression
- Gradient Boosting
- Naive Bayes
- Random Forest
- Support Vector Machine

(All code/data:
<http://winvector.github.io/DSL/>)

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I.e. we see an arbitrarily good model on training, even when no model is possible.

Also have sometimes seen a reversal: the model is significantly worse than random on the test set. Being worse than random is likely a minor distribution change from training to test. The observed statistical significance is likely due to some process causing dependence between rows in a limited window (like serial correlation or bad sessionizing) and not

Lesson

- Can't just tack on cross validation late in a machine learning algorithm's design (or just use it to pick a few calibration parameters).
- Have to express model quality in terms of out of sample data throughout.
 - And must understand some fraction of the above measurements will still be chimeric and falsely optimistic (statistical significance re-enters the picture).

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Gradient boosting typically uses cross val to number of trees, zero trees being no model.

How did we design the counter examples?

- A lot of common machine learning algorithms fail in the presence of:
 - Noise variables
 - Duplicate examples
 - Serial correlation
 - Incompatible scales
- Punchline: all these things are common in typical under-curated real world data!

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Some of these problems even break test/train exchangeability, one of the major justifications of machine learning.

The analyst themselves can be a source of additional exotic "can never happen" biases

- Neighboring duplicate and near-duplicate rows (bad join/sessionizing logic).
- Features with activation patterns depending on the size of the training set (opportunistic feature generation/selection).
- Leakage of facts about evaluation set through repeated scoring (see "wacky boosting" by Moritz Hardt, which gives a reliable procedure to place high on Kaggle leaderboards without even looking at the data).

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<http://blog.mrtz.org/2015/03/09/competition.html>

Conclusions

- Data scientists, statisticians, and domain experts all see things differently.
- Data science emphasizes procedures that are conceptually easy and become more correct when scaled to large data. Procedures can seem overly ambitious and as pandering to domain/business needs.
- Statistics emphasizes procedures that are correct at all data scales, including difficult small data problems. Procedures can seem overly doctrinal and as insensitive to original domain/business needs.
- Domain experts/scientists value correctness and foundation, over implementability.
- An effective data science team must work agilely, understand statistics, and develop domain empathy.
- We need a deeper science of structured back-testing.

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It is equally arrogant to completely ignore domain science as it is to believe you can always quickly become a domain expert.

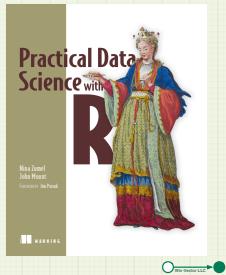
<http://www.win-vector.com/blog/2014/05/a-bit-of-the-agenda-of-practical-data-science-with-r/>

Better structured back-testing: i.e. invent procedures that obey appropriately adjusted “axioms of data science.”

Thank you

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or contact me at win-vector.com

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