2018 Predictive Analytics Symposium

Session 21: Dangers of Overfitting; Myths and Facts of Predicitive Analytics (PA)

SOA Antitrust Compliance Guidelines SOA Presentation Disclaimer





Dangers of Overfitting in Predictive Analytics

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Outline

Motivation
Overfitting

Definition

When Does Overfitting Occur?







Motivation

Power Posing

Most popular **TED** talk of all time

Power Posing

Power Posing: Brief Nonverbal Displays Affect Neuroendocrine Levels and Risk Tolerance Authors: Dana R. Carney , Amy J.C. Cuddy, and Andy J. Yap





Power Posing



Findings

Increased testosterone levels/lower cortisol levels among highpower posers

High-power posers were more likely than low-power poses to take gambling risk

RGA

Fig. 3. Mean changes in the dominance hormone testosterone following high-power and low-power poses. Changes are depicted as difference scores (Time 2 – Time 1). Error bars represent standard errors of the mean.

Eleven new studies suggest 'Power Poses' don't work



Michigan State University Today, "Eleven new studies suggest 'Power Poses' don't work," https://msutoday.msu.edu/news/2017/eleven-new-studies-suggest-power-poses-dont-work/ accessed August 18, 2018.

The Replication Crisis



Science, "Rigorous replication effort succeeds for just two of five cancer papers," http://www.sciencemag.org/news/2017/01/rigorous-replication-effort-succeeds-just-two-five-cancer-papers accessed August 18, 2018.



Motivation: Building Predictive Models



We are asked to build predictive models



We are given a fixed set of data



PROBLEM: How do we know our model will predict new data reasonably well?



Motivation: Building Predictive Models





Motivation: Building Predictive Models









Overfitting: A Definition

Overfitting: Definition

"The problem of capitalizing on the idiosyncratic characteristics of the sample at hand, also known as *overfitting*, in regression-type models.

Overfitting yields overly optimistic model results: "findings" that appear in an overfitted model don't really exist in the population and hence will not replicate." (Babyak, 2004)



Text from Babyak 2004: What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models.





Generally, overfitting occurs due to analyst oversight in two key areas:

- Researcher degrees of freedom (also known as procedural overfitting, data dredging, phacking, etc.)
- Asking too much from the data (model complexity)





Researcher Degrees of Freedom

Example:

Dataset of 1000 individuals for a weight-loss biomarker study with three time points





Researcher Degrees of Freedom

Bob performs some simple data exploration.

He first uses data visualization to investigate the average activity of all the genes across all the individuals at each of the time points, and observes that there is very little difference between time 1 and 2 and there is a large jump between time 2 and 3 in the average activity.

So **he decides** to focus on these later two time points.



Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.



Researcher Degrees of Freedom

Next, he realizes that **half of the genes** always have low activity values and decides to simply filter them out.



Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.

Researcher Degrees of Freedom

Finally, he computes the correlations

between the activity of the 1000 post-filtered genes and the weight change between time 2 and 3.

He selects the gene with the largest correlation and reports its value.



Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.



Researcher Degrees of Freedom



What did Bob do wrong?

Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.



The culprit is a construct we refer to as **researcher degrees of freedom**. In the course of collecting and analyzing data, researchers have many decisions to make:

- Should more data be collected?
- Should some observations be excluded?
- Which conditions should be combined and which ones compared?
- Which control variables should be considered?
- Should specific measures be combined or transformed or both?

-Simmons, Relson, and Simonsohn, 2011

Text from Simmons, Nelson, and Simonsohn 2011: False-Positive Psychology List format added





Researcher Degrees of Freedom

Bob performs some simple data exploration.

He first uses data visualization to investigate the average activity of all the genes across all the individuals at each of the time points, and observes that there is very little difference between time 1 and 2 and there is a large jump between time 2 and 3 in the average activity.

So **he decides** to focus on these later two time points.



Research design decisions shouldn't be contingent on observed results. Use previous experience or knowledge to guide analysis choices.

Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.



Researcher Degrees of Freedom

Next, he realizes that **half of the genes** always have low activity values and decides to simply filter them out.



What are "low" activity values? These decisions may be arbitrary. If they're determined by this dataset, it may not generalize.

Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.

Researcher Degrees of Freedom

Finally, he **computes the correlations** between the activity of the 1000 post-filtered genes and the weight change between time 2 and 3.

He selects the gene with the largest correlation and reports its value.



The resulting "largest" correlation is built upon the series of analysis choices made before it. Again, may not generalize.

Example and text from Russo and Zou 2016 How much does your data exploration overfit? Controlling bias via information usage.



Researcher Degrees of Freedom

Make research design decisions before analyzing the data

Where applicable, use subject matter knowledge to inform data aggregation (i.e., age groups)

Limit the exclusion of data

Validate your results (discussed later in the presentation)

Strategies to minimize researcher degrees of freedom



Generally, overfitting occurs due to analyst oversight in two key areas:

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- Asking too much from the data (model complexity)





"Given a certain number of observations in a data set, there is an upper limit to the complexity of the model that can be derived with any acceptable degree of uncertainty." (Babyak, 2004)

...asking too much from the data



Text from Babyak 2004: What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models.















Sample Size & Model Complexity





Which model fits this

dataset better?

Sample Size & Model Complexity





Which model fits this dataset better?

Sample Size & Model Complexity



Which model fits **new** data better?

Predict the





Sample Size & Model Complexity



We want to know which model gets us closer to learning about future outcomes and not just our historical data.

Measuring the performance of our models on new data will help us get there.









Sample Size & Model Complexity



IGA





Testing the procedure on the data that gave it birth is almost certain to overestimate performance. -Mosteller and Tukey, 1977

If the quantity we care about is how *well* our models will perform on **NEW** data...why don't we just estimate that?







Test Set Method



- Randomly select 30% of your data to be your test set
- 2. Build models on training data
- 3. Estimate future performance by estimating models on **test data**









Test Set Method

Easy to implement

The more data you use to estimate test error, the less data you have to build your model

More data used for training results in more uncertainty about the test error estimate

Less data used for training results in more uncertainty about the model







These are some additional classical ways to approach overfitting and researcher degrees of freedom:

- AIC/BIC metrics
- Bootstrapping
- Bonferroni correction (adjusts for multiple comparisons)





