Streaming Feature Selection

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Plan

Motivating applications Predictive models

Sequential testing Alpha investing Robust standard errors Sandwich estimator

- Auction framework
- Collaborators Dean Foster Dongyu Lin



Applications



Modeling Challenges

<u>Rare Events</u> bankruptcy random forest Function Estimation smoothing wavelets/Dantzig

<u>Linguistics, Text Mining</u> cloze TF-IDF

<u>Spatiotemporal Models</u> disease MRF + MCMC

TF-IDF: term frequency-inverse document frequency frequency in document relative to frequency in corpos

MRF: Markov random fields

Text Mining

- Variety of applications...
 - <u>Word disambiguation</u>
 Does "Georgia" refer to a person, US state, or
 - perhaps to a Nation?
 - <u>Tagging</u> parts of speech Identifying noun, verb, adjective...
 - <u>Cloze</u> (predicting the next word)
 - "...in the midst of modern life the greatest, ____"
- Huge corpus of data from various sources ×,000,000 cases
 - novels, news feeds, web pages
 - downloaded the entire text of Wikipedia for testing disambiguation methods



Challenges in Text

Cloze

- Is the next word "the" or "her"?
- "...in the midst of modern life the greatest, _____
- Balanced training data with 50/50 rate
- Possible predictors
 - Word frequencies (bag of words)
 - Neighboring sentences/words
 - Parts of speech, tree banks, stem words, synonyms
- Over-fitting?
 - Transfer learning
 - Do predictors in the context of one source (Washington Post) carry over to models for another (NY Times)?



Spatial Temporal Models

- Questions
 - Predict default rates in mortgages, credit cards
 - Spatial time series
 - 3,000 counties in US, quarterly since 1997
 - vec(data) gives n = 210,000 (next individuals!)
 - Possible predictors
 - Macroeconomic factors, at some geographic unit
 - Personal payment history
 - Local trends
 - Modeling issues
 - All sorts of dependence (spatial, temporal)
 - Heterogeneity among observations (counties)
 - Population drift



Goals

- "Turnkey" predictive model that is Competitive with best in each domain Fast
- Stepwise regression (gradient descent)
 Question is which features (direction)
 Leverage extensive domain knowledge
 Regression benefits: well-understood, diagnostics, etc
 Tolerate complex error structure
 Variety of sources of dependence
 - Heterogeneity of variation
- Avoid over-fitting, "expensive" cross-validation.





TF-IDF: term frequency-inverse document frequency frequency in document relative to frequency in corpos

MRF: Markov random fields

Methods



Lessons from Prior Modeling

- Bankruptcy: n=500,000, p=60,000+, 450 events
 - "Breadth-first" search causes problems
 - Slow, memory hog

1

0.8

0.6

0.4

0.2

- Severe penalty on largest z-score, sqrt(2 log p)
- If tested features are mostly interactions, then selected features are mostly interactions
 - Example

 $\mu \gg 0$ and β_1 , $\beta_2 \neq 0$, then $X_1^* X_2 \Rightarrow c + \beta_1 X_1 + \beta_2 X_2$

Outliers cause problems even with large n



Reaction to Lessons

Breadth-first becomes streaming selection

- Test a sequence of possible features
- Examining each is very fast
- Over-fitting? Multiplicity adjustments?

Equal significance levels replaced by levels that vary with the type of the variable
Simple Bonferroni procedure
Divide α level equally between linear & interactions
p linear: test each at level α/(2p)
p² interactions: test at level α/(2p²)

Rather than trust model to obtain standard errors, use a more robust estimate.



Methods Summary

Supercharged stepwise regression

Auction

Explore more expansive feature space

- Robust standard errors (ultimately p-values) Allow for dependence and heterogeneity
- Alpha investing Control over-fitting adaptively





Experts

Expert

Strategy for creating list of features. Experts embody domain knowledge, science of application.

Source experts

- A collection of measurements (eg, synonyms, clusters)
- Components of a subspace basis (PCA, RKHS)
- Lags of a time series

Parasitic experts

- Interactions
- among features accepted into model
- among features rejected by model
- between those accepted with those rejected
- Transformations
- segmenting, as in scatterplot smoothing
- polynomial transformations



Winning Experts

- Expert is rewarded if correct
 - Experts have alpha-wealth
 - If recommended feature is accepted in the model, expert earns $\boldsymbol{\omega}$ additional wealth
 - If recommended feature is refused, expert loses bid
- As auction proceeds, it ...
 - Rewards experts that offer useful features. These then can win later bids and recommend more X's
 - Eliminates experts whose features are not accepted.
- Taxes fund parasitic experts
 - Ensure that continue to control overall FDR
- Critical
 - control multiplicity in a sequence of hypotheses
 - p-values determine useful features

Robust Standard Errors

- p-values are critical, but...
 - Error structure often heteroscedastic
 - Observations frequently dependent
 - Dependence
 - "Observations"
 - Spatial time series at multiple locations
 - Documents from various news feeds
 - Transfer learning problem
 - When train on observations from selected
 - regions or document sources, what can you infer to others?
- What are the right degrees of freedom? Tukey story



Sandwich Estimator

Usual OLS estimate of variance

Assume your model is true

$$var(b) = (X'X)^{-1}X'E(ee')X(X'X)^{-1} = \sigma^{2}(X'X)^{-1}(X'X) (X'X)^{-1} = \sigma^{2}(X'X)^{-1}$$

Sandwich estimators

 Robust to deviations from assumptions
 heteroscedasticity
 dependence

 var(b) = (X'X)⁻¹X'E(ee')X(X'X)⁻¹
 var(b) = (X'X)⁻¹X'E(ee')X(X'X)⁻¹
 e (X'X)⁻¹ X'D²X (X'X)⁻¹
 diagonal
 block diagonal



18

Flashback...

1

0.8

0.4

Heteroscedastic error

- Estimate standard error with outlier
- Sandwich estimator allowing heteroscedastic error variances gives a t-stat ≈ 1, not 10.
- Dependent error
 - Even more important need for accurate SE
 - Netflix example Bonferroni (or hard thresholding) overfits due to dependence in responses.
 - Credit modeling
 - Everything seems significant unless incorporate dependence into the calculation of the SE



Alpha Investing

- Situation
 - Test possibly infinite sequence of m hypotheses H1, H2, H3, ... Hm ...
 - obtaining the p-values p_1 , p_2 , ...
 - Order of tests may depend prior outcomes
- Procedure
 - Start with an initial alpha wealth $W_0 = \alpha$
 - Invest wealth 0 ≤ αj ≤ Wj in the test of Hj
 - Change in wealth depends on test outcome
 - $\omega \leq \alpha$ denotes the payout earned by rejecting

$$w \text{ if } p_j \leq \alpha_j$$

$$W_j - W_{j-1} = -\alpha_j / (1 - \alpha_j) \text{ if } p_j \leq \alpha_j$$



Properties of Alpha Investing

- Provides <u>uniform</u> control of the expected false discovery rate. At any stopping time during testing, martigale argument shows $\sup_{\theta} \frac{E(\# false \ rejects)}{E(\# rejects)+1} \leq \alpha$
- Flexibility in choice of how to invest alphawealth in test of each hypothesis
 - Example. Invest more when just reject if suspect that significant results cluster.
 - Universal strategies
- Avoids need to compute p-values in advance



Connections

Bonferroni test of H₁,...,H_m Set $W_0 = \alpha$ and reward $\omega = 0$ Bid $\alpha_i = \alpha/m$ Step-down test of Benjamini & Hochberg Set $W_0 = \alpha$ and reward $\omega = \alpha$ Test all m at level α/m If none are significant, done If one is significant, earn α back

Test remaining m–1 conditional on $p_j > \alpha/m$



Benefits of Knowledge



Example Results



Examples

- On-line prototype used in classroom
 - Limited experts
 - www-stat.wharton.upenn.edu/~foster
- Data
 - Supply a csv file or use one provided
 - Graphical summary
 - all expert bids and winning bid
 - p-value of result
 - accepted variable names
 - CVSS



Boston Housing



arton

Department of Statistics

Baseball

AUCTIONS: STREAMING FEATURE SELECTION (by Robert Stine and Dean Foster)



Wharton Department of Statistics

Next Steps

- Very much a work in progress
- Improved experts
 - Identify common expert classes that appear in various situations (eg, cluster detection)
 - Neighborhood structure
 - geographical
 - temporal
 - Better software
 - Front end
 - Back end



Discussion

- Expert bidding
 - Aggressive vs Passive
 - "Stacking the deck"
- Anonymous vs attributed variables
 - Stat traditionally models X1, X2, ...
 - Right emphasis?
 - Standard errors are only part of the path to
 - a good p-value
 - Other bounds often useful (Bennett type)



References

- Feature auction
 - www-stat.wharton.upenn.edu/~stine
- Alpha investing
 - " α -investing: a procedure for sequential control of expected false discoveries", JRSSB, 2006
- Early improved stepwise regression "Variable selection in data mining: Building a predictive model for bankruptcy", JASA, 2004
- Robust standard errors
 - "Variable selection in models with blockwise dependence", Lin and Foster.

Thanks!

