MATH1298 Chapter 5: Model Selection and Evaluation

Addtional material: Feature selection under presence of interaction terms - a very brief coverage

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Background

- A motivating example: do gene interactions help predict cancer type?
- How to determine interactions in high dimensions optimally?
- Focus on pairwise interaction terms (no quadratic terms)
- Given *p* features with 2-way pairwise interaction terms, the number of possible features is

$$p + \binom{p}{2} = \frac{p(p+1)}{2}$$

- Side question: what is the number of possible features if we include quadratic terms?
- Not in examination

Notations and terminology

- Y: response feature
- X_j : explanatory feature j for j = 1, 2, ...p
- Model formulation:

$$g(Y) = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \sum_{i < j} \beta_{i:j} X_j X_i$$

• A precise definition [Lim and Hastie, 2018, p.1]:

"When a function $f(x_1, x_2)$ cannot be expressed as $h_1(x_1) + h_2(x_2)$ for some functions h_1 and h_2 , we say that there is an interaction in f between x_1 and x_2 ."

Introduction of "hierarchy"

Terminology: hierarchy

Lim and Hastie [2018] define:

Hierarchy	Description
Strong	Interactions are only among pairs of
	nonzero main effects
Weak	Each interaction has only one of its main
	effects present
Anti-hierarchical	Interactions are only among pairs of main
	effects that are not present
Pure interaction	No main effects present; only interactions

Terminology: an example of hierarchy

Consider three explanatory features: $\mathbf{X} = \{X_1, X_2, X_3\}$

- Strong hierarchy: $\{X_1, X_2, X_1X_2\}$
- ② Weak hierarchy: $\{X_1, X_1X_2, X_1X_3\}$
- **3** Anti-hierarchical: $\{X_2, X_1X_3\}$
- **9** Pure interaction: $\{X_2X_3, X_1X_3, X_1X_2\}$

In practice, how do we know? How can we detect?

Main methods to identify pairwise interaction terms

- Statistical hypothesis test [Cox, 1984]
- Regularisation, e.g. LASSO
- Wrapper Feature Selection [Kohavi and John, 1997]

Statistical hypothesis test: an example

Considers two models:

1
$$g(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

Run hypothesis on test on $\beta_{1:2} = 0$.

Regularisation: glinternet

- Let $I(y_i; \beta)$ be the **negative** log-likelihood contribution
- Elastic-net [Friedman et al., 2010]

$$\arg\min_{\beta} \frac{1}{n} \sum_{i=i}^{n} I(y_i; \beta) + \lambda [(1-\alpha) \parallel \beta \parallel_2^2 / 2 + \alpha \parallel \beta \parallel_1]$$

- glinternet [Lim and Hastie, 2018]: group-based LASSO ($\alpha=1$) by imposing additional constraints on $\beta_{k:i}$ and β_{i}
- glinternet package is available in R

Wrapper feature selection

Extending feature selection by including interaction terms

- SFFS: Sequential (Floating) Forward Selection [Pudil et al., 1994]
- SFBS: Sequential (Floating) Backward Selection[1994]
- **3** SP-FSR [2016]

SP-FSR algorithm

- Introduced by Aksakalli and Malekipirbazari [2016]
- Based on Simultaneous Perturbation Stochastic Approximation [Spall, 1992]
- Refined by Yenice et al. [2018]
- Pseudo gradient descent method on the loss function
- spFSR package is available in R [Aksakalli et al., 2018]

SP-FSR algorithm to identify interactions

- Assume a strong hierarchy
- Simplified version of **two-step SP-FSR** algorithm:
- Identify the optimal set of k main effects using SP-FSR
- 2 Search k', number of interactions from k main effects with SP-FSR
 - ullet k and k' can be determined via grid search or automatically
- GitHub link: https://github.com/yongkai17/n-way-spFSR

Limitations

Both algorithms

- Only two-way interaction terms under strong hierarchy
- Both incorporate cross-validation. Why is this a limitation?

glinternet

- Applicable to regression and logistic classification problems only.
- Not available for log-log and probit regression models.

SP-FSR algorithm

- Not available for Poisson regression which is not available in mlr
- Implementation in R hence slow
- Not experiment with other binary models yet.

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