

Generalized Linear Rule Models

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Generalized Linear Models + Rules

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- Linear regression
 - Logistic regression
 - Poisson regression
 - ...
- Conjunctions of conditions on individual features



- Can capture nonlinearities and interactions

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Problem Formulation

$$\min_{\beta} \underbrace{\frac{1}{n} \sum_{i=1}^n \text{Loss} \left(\sum_{k \in \mathcal{K}} a_{ik} \beta_k, y_i \right)}_{\text{performance}} + \underbrace{\sum_{k \in \mathcal{K}} \lambda_k |\beta_k|}_{\text{complexity}}$$

conjunction values coefficients conjunction complexity

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Challenge: Set of conjunctions \mathcal{K} is exponentially large

- e.g. age alone, age AND blood pressure, age AND blood pressure AND body mass index, ...

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We avoid limitations of existing methods

- Pre-select (large) subset e.g. [Friedman & Popescu, 2008]
- Boost but do not revise rules e.g. [Cohen & Singer, 1999; Dembczynski et al., 2010]

Column Generation

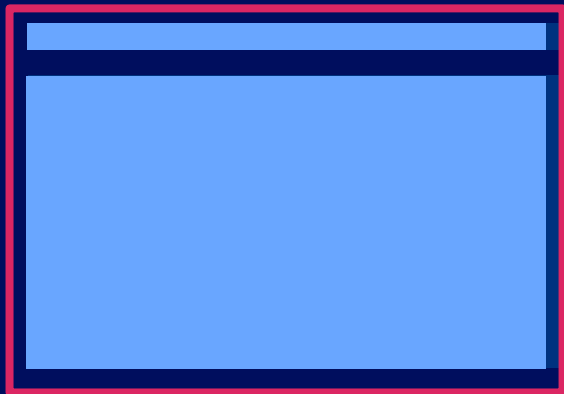
conjunction complexities λ

conjunction matrix A

Column Generation

$$\min_{\beta} \frac{1}{n} \sum_{i=1}^n \text{Loss} \left(\sum_{k \in \mathcal{S}} a_{ik} \beta_k, y_i \right) + \sum_{k \in \mathcal{S}} \lambda_k |\beta_k|$$

Solve over small subsets \mathcal{S}



conjunction complexities λ

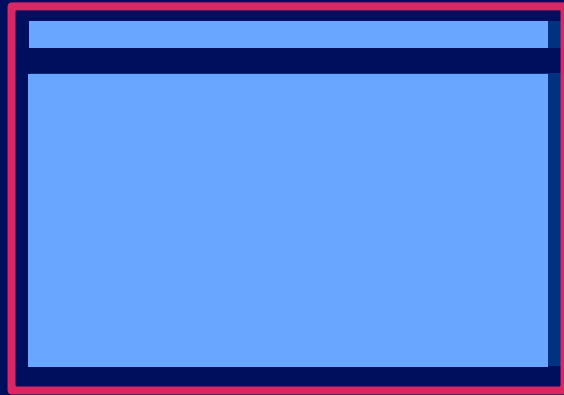
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Restricted GLM

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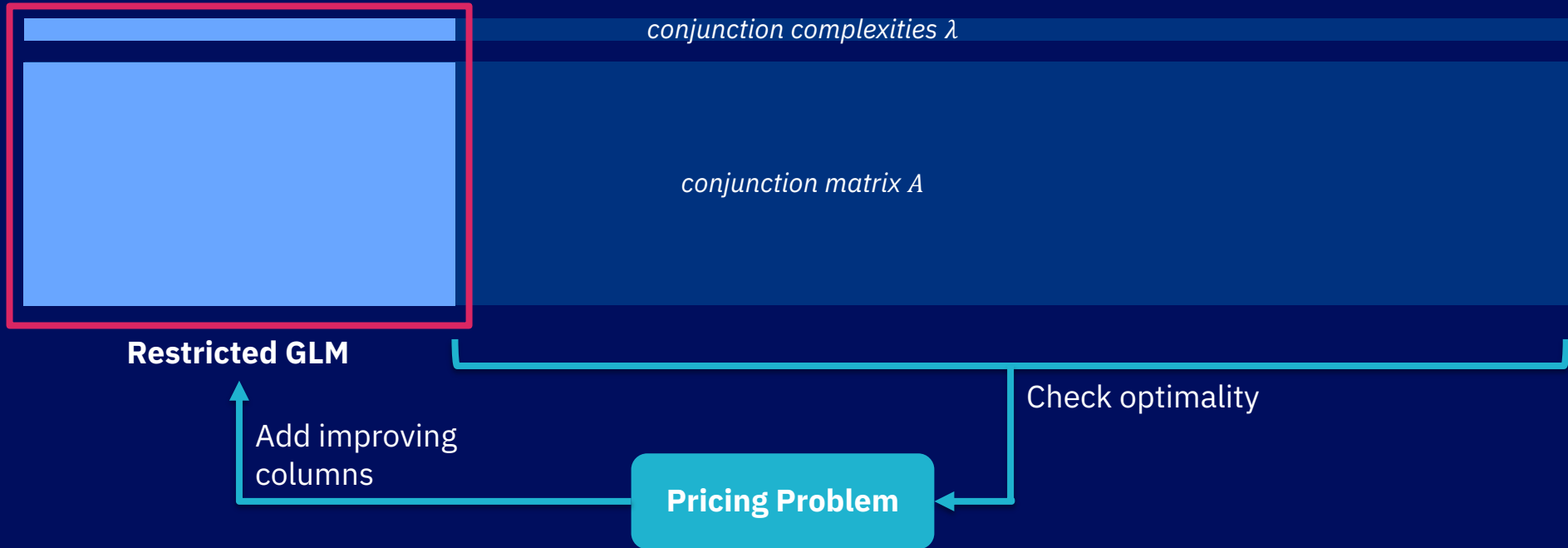
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Check optimality

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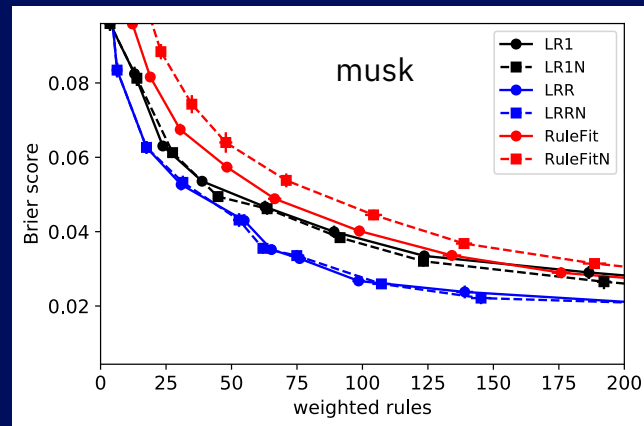
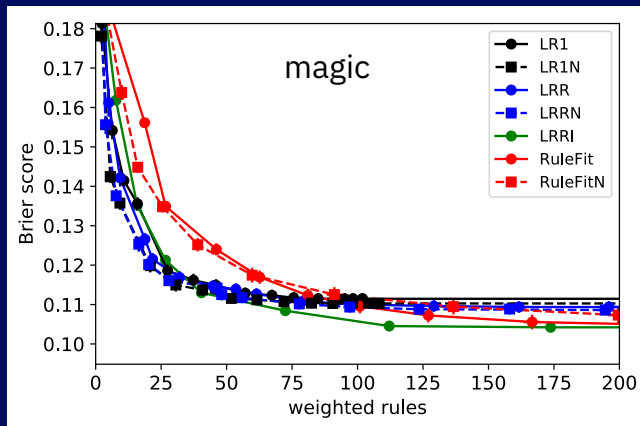
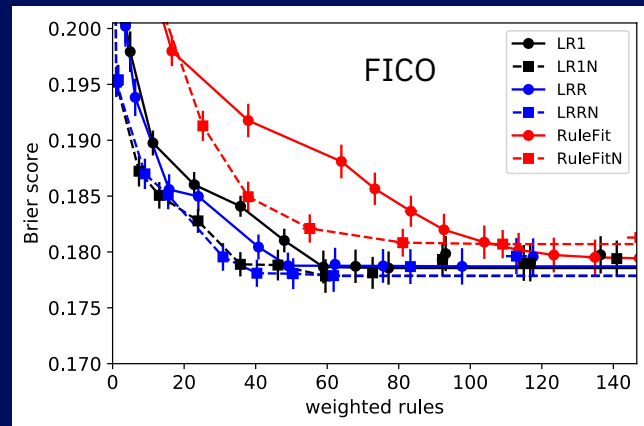
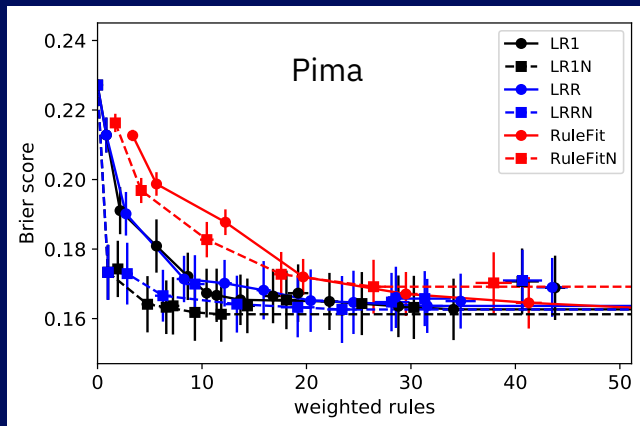


Integer program (solved using CPLEX) gives optimality guarantee
Heuristic also effective and more practical

Performance-Complexity Trade-Offs

Logistic and linear regression experiments

Logistic Rule Regression with CG (**LRR, LRRN**) obtains better trade-offs than (**RuleFit, RuleFitN**) on most of 16 classification datasets



Performance Maximization

Logistic/Linear Rule Regression with CG (LRR, LRRN) is highly competitive when tuned to maximize performance

method	LRR	LRRN	RuleFit	RuleFitN	GBM	SVM
logistic regression mean rank	4.1	3.6	4.8	3.6	5.3	4.0
linear regression mean rank	4.9	3.0	4.5	3.5	3.4	5.0

and uses 2-4 times fewer rules than RuleFit [[Friedman & Popescu, 2008](#)]

GLRM: Generalized Linear Models + Rules

Flexible and interpretable models

Probabilistic classification and regression

Column generation to efficiently search space of rules without restrictions

Poster #264, today 6:30-9:00 PM