

Optimal Subsampling Design for Big Data Regression

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Summary

While modern information technology allows for collecting large amounts of data (X_i, Y_i) , i = 1..., N, limitations in terms of statistical methods and costs for acquiring such data may make it desirable to perform statistical analysis on a subsample only. We construct *D*-optimal subsample designs, based on the density of the independent variables and on the regression model.

Optimal Bounded Design Measures

Consider the general regression model

$$Y_i = \mu(X_i, \beta) + \varepsilon_i, \quad i = 1, \dots, N.$$

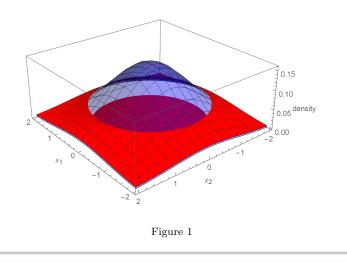
- N is very large.
- The X_i follow a given distribution with density f_X .
- The response function μ is known except for β .

We want to find a subsampling design ξ^* that

- has density g^* with total mass $\alpha < 1$, which is the percentage of the full data we want to sample.
- g^* is bounded from above by f_X .
- minimizes the *D*-criterion, which aims at minimizing the volume of the asymptotic confidence ellipsoid for the parameter β .

Figure 1 shows the density function g^* (red) of such a *D*-optimal design in multilinear regression,

 $Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \varepsilon_i$, given standard normal twodimensional data X_i with density f_X (blue).



Easy Implementation

- Regions where $g^*(x) = f_X(x) \to \text{accept all } \mathbf{x}$
- Regions where $g^*(x) = 0 \rightarrow$ reject all x

Subsample Design in Quadratic Regression

Consider quadratic regression, i.e. $Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i$ and assume $\mathbb{E}[X_i^4] < \infty$. We determine an optimal subsampling design ξ^* with density g^* by doing the following.

- Determine the directional derivative F(ξ*, x) of the D-criterion from ξ* in the direction of a single-point measure at point x.
- Determine the threshold c such that $P(F(\xi^*, X_i) \le c) = \alpha$. Then $g^*(x) = f_X(x)$ when $F(\xi^*, x) \le c$ and $g^*(x) = 0$ otherwise.

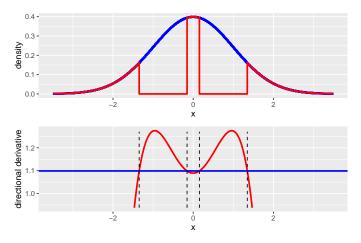


Figure 2: upper panel: *D*-optimal subsample density g^* (red) and full sample density f_X (blue, standard normal), lower panel: directional derivative (red) and threshold *c* (blue).

Discussion

So far: Subsample designs in various linear regression models.

Next step: Extend to generalized linear models, e.g.

- Poisson regression.
- Logistic regression.

Challenge: Optimal design is dependent on the unknown β . Locally optimal designs have to be obtained first before sequential or multi-stage algorithms can be developed.

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