

Probit Regression for Large Data Sets via Coresets

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December 18, 2021

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- with n labels: $y_1, \dots, y_n \in \{-1, 1\}$

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- y_1, \dots, y_n are realizations of Y_1, \dots, Y_n
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- $\Phi(\cdot)$ is cdf of standard normal distribution

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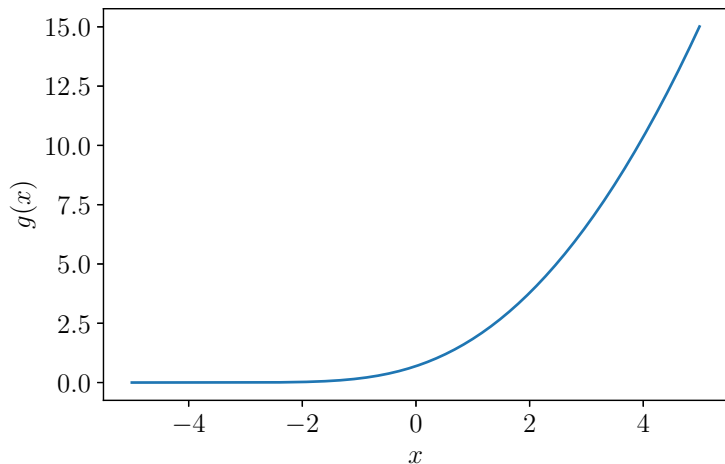
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Loss function (negative log-likelihood):

$$f(\beta) = \sum_{i=1}^n \ln \left(\frac{1}{\Phi(y_i x_i^T \beta)} \right)$$

The Probit Loss



$$g(x) = \ln \left(\frac{1}{\Phi(-x)} \right)$$

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- Internet logs
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¹see e.g. [Feldman et al., 2020]

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Conventional optimization algorithms become inefficient!

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⇒ Otherwise useless!

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Main Goal: Develop efficient coreset construction algorithms!

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(1) ...approximate the data well:

- Let $f(\beta)$ be the original loss and $\tilde{f}(\beta)$ be the loss on the coreset
- Then for $\epsilon > 0$ and for all $\beta \in \mathbb{R}^d$ we want:

$$(1 - \epsilon)f(\beta) \leq \tilde{f}(\beta) \leq (1 + \epsilon)f(\beta)$$

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(2) ...are significantly smaller than our data:

- Coreset sizes logarithmic in n would be a great success
- Given a dataset with $n = 1,000,000,000$ observations, $\log(n) \leq 21$
- Even better: Independent of n !

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\Rightarrow Need to restrict the class of data sets under study!

- Slightly adapt the concept of μ -complexity from [Munteanu et al., 2018] to probit regression

μ -Complexity

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μ is a useful parameter introduced by [Munteanu et al., 2018]:

$$\mu = \sup_{\beta \in \mathbb{R}^d \setminus \{0\}} \frac{\sum_{y_i x_i^T \beta > 0} (x_i^T \beta)^2}{\sum_{y_i x_i^T \beta < 0} (x_i^T \beta)^2}$$

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We show how μ can be used to find small coresets!

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- ⇒ We need to give "important" observations a higher priority

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Our approach: Use importance sampling based on the sensitivity² of each observation!

²see [Langberg and Schulman, 2010]

The Sensitivity Framework

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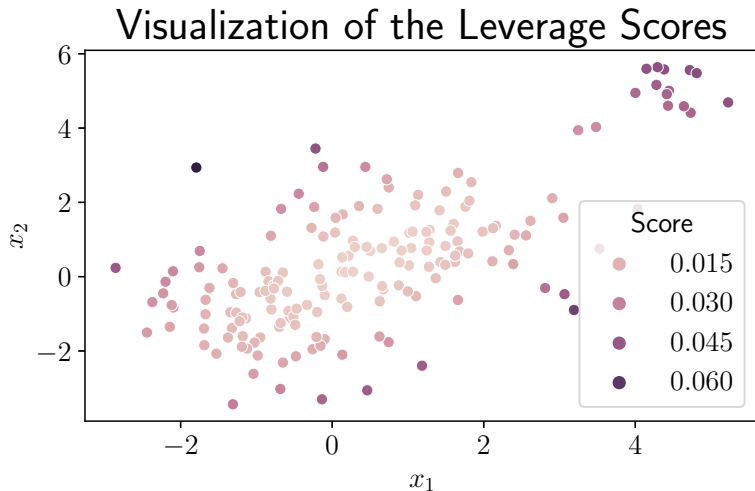
- Well known algorithmic framework for coresets construction via importance sampling introduced by [Feldman and Langberg, 2011].
 - The sensitivity is the worst-case importance of an observation
 - Sampling proportionally to upper bounds on the sensitivities can lead to small coresets
- ⇒ Need to derive tight upper bounds!

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We show that the statistical leverage scores can be used to bound the sensitivities of high-loss points!

Statistical Leverage Scores



First Algorithm: Fast Leverage Score Sampling

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First pass: Approximate the leverage scores

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Coreset size: $O\left(\frac{\mu d^2}{\epsilon^2}\right)$, independent of n !

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Solution: Online approximation of the leverage scores

- Use approximation techniques by [Chhaya et al., 2020]
- Increases coreset size by a factor of $\log(\sigma_{max})$
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Requires only one pass over the data set!

Experiments

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Goal: Compare our algorithms to uniform random sampling

- Show that coresets construction is worth the effort

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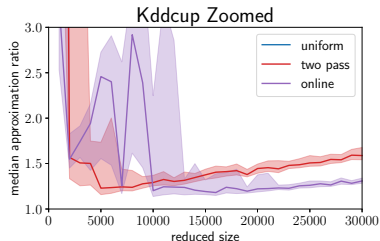
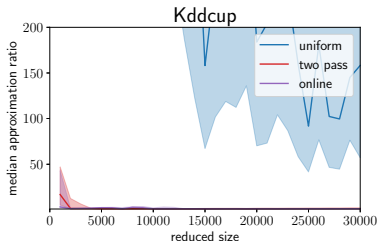
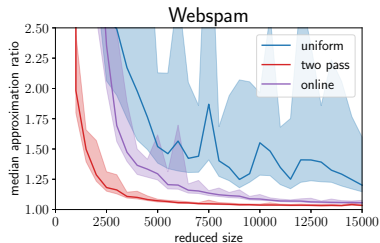
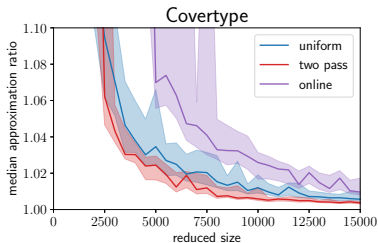
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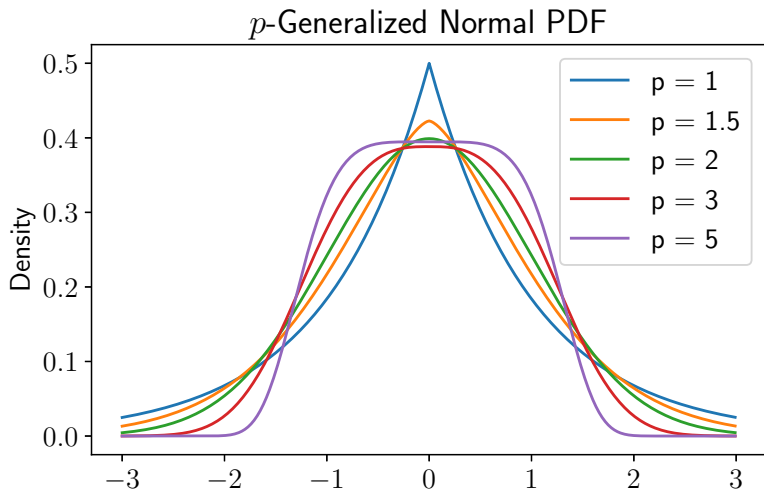
Use approximation ratio for evaluation:

- Let $\tilde{f}(\beta)$ be the loss function on the coresets and let $f(\beta)$ be the original loss
- Let β^{opt} be the solution of the original problem
- Optimize $\tilde{f}(\beta)$ to find solution $\tilde{\beta}$ of the reduced problem
- Compute ratio $\frac{f(\tilde{\beta})}{f(\beta^{opt})}$

Experiments

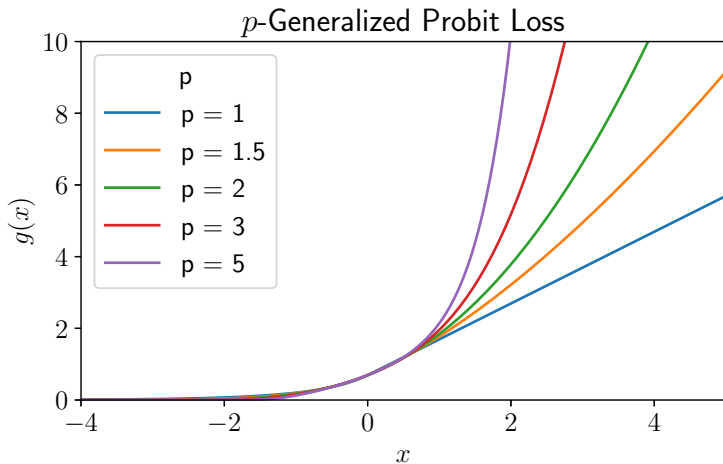


Extensions – p -Generalized Probit Model³



³See [Kalke and Richter, 2013] for a definition of the p -generalized normal distribution

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Extensions – p -Generalized Probit Model

Three adaptations are required:

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$$\text{Coreset size: } \begin{cases} O\left(\frac{\mu d^p}{\epsilon^2}\right), & \text{for } p \in [1, 2) \\ O\left(\frac{\mu d^{2p}}{\epsilon^2}\right), & \text{for } p \in (2, \infty) \end{cases}$$

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- Based on fast coresets construction algorithms and modern sketching techniques

(2) Demonstrated that our methods outperform standard uniform sampling

- By conducting experiments on well known real-world datasets

(3) Introduced the p -generalized probit model as a flexible framework for modeling binary data

- Enables you to control the tail behavior of the distribution

Literature I



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