Deadline: Fr. July 5 (online) or Mo. July 8, 10:00 AM (hand-in)

Drop your printed or legible handwritten submissions into the boxes at Samelson platz, or upload a <code>.pdf</code> file via LearnWeb.

Remark 1. This is the last hand in tutorial for this semester. For each 20 points you earned, you will get 0.5 bonus points in the exam. (capped at 4)

1 Proximal Gradients

A. [10p] Apply SPARSA (ISTA with homotopy) to solve the LASSO problem

minimize $f(\theta) = L(\theta) + \lambda R(\theta)$ $L(\theta) = \frac{1}{2} \|y - X\theta\|_2^2$ $R(\theta) = \|\theta\|_1$

on the dataset from Table 1 below. Use the parameters s = 0.5 and $\lambda = 0.1$ and the acceptance criterion $f(\theta) < f(\theta_{\text{old}})$ (called monotone criterion).

Hint:	The algorithm	should	terminate	after	4 outer	loops
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Algorithm 1: SPARSA algorithm (ISTA with homotopy) for LASSO	
input : parameters $\lambda \ge 0, s \in (0, 1)$	

 $\begin{array}{l} \mathbf{output} : \mathbf{A} \text{ partition of the bitmap} \\ \mathbf{init} \quad : \theta = 0, \ \alpha = 1, \ \lambda_0 = \infty \\ \mathbf{while} \ \lambda_t \neq \lambda \ \mathbf{do} \\ \\ \mathbf{\lambda}_t = \max(s \| \nabla L(\theta) \|_{\infty}, \lambda) \\ \mathbf{repeat} \\ \\ \left| \begin{array}{c} \theta_{\text{old}} = \theta \\ g = \nabla L(\theta) \\ u = \theta - \frac{1}{\alpha}g \\ \theta = \operatorname{soft}(u, \frac{\lambda_t}{\alpha}) \\ \alpha = \operatorname{BB}(\theta, \theta_{\text{old}}) \\ \mathbf{until} \ \theta \ satisfies \ acceptance \ criterion \\ \mathbf{end} \\ \mathbf{return} : \theta \end{array} \right. \end{array}$

Table 1						
x_1	x_2	x_3	y			
0	1	0	1			
0.5	0.5	1	0.75			
1	0	0	0.5			

2 Laplace Priors

Hint: Let X be a Random Variable (RV) with density function f(x). Then $Y = X^{-1}$ has the density function $\frac{1}{y^2}f(\frac{1}{y})$.

A. [2p] Explain the role of the prior $p(\beta)$ in Bayesian Linear Regression

B. [4p] Given $p(\beta_i \mid \tau_i^2) = \mathcal{N}(\beta_i \mid 0, \tau_i^2)$ and $p(\tau_i^2) = \text{Exp}(\tau_i^2 \mid \frac{1}{2}\lambda^2)$, show that $z_i = \frac{1}{\tau_i^2}$ has the conditional distribution

$$p(z_i \mid \beta_i) = \text{InvGauss}\left(z \mid \sqrt{\frac{\lambda^2}{\beta_i^2}}, \lambda^2\right)$$
(1)

C. [2p] Given that $p(y \mid X, \beta, \sigma^2) = \mathcal{N}(y \mid X\beta, \sigma^2 I)$ and $p(\sigma^2) = \text{IG}(\sigma^2 \mid a, b)$, show that σ^2 has the conditional distribution

$$p(\sigma^2 \mid X, y, \beta, \tau^2) = \mathrm{IG}(\sigma^2, a', b')$$

with $a' = a + \frac{1}{2}N$ and $b' = b + \frac{1}{2}||y - X\beta||_2^2$.

(10 points)

(10 points)

$L(0) = L(0) + D(0) = L(0) = \frac{1}{2} L(0) = \frac{1}{2$

D. [2p] Show that in general $\mathbb{E}[X] \neq \mathbb{E}[X^{-1}]^{-1}$ by providing an example.