Willy Xiao and Kevin Eskici
STAT 221
Pset 3
Oct 22, 2014

question 1. Show:

(a)

$$
\begin{aligned}
E\left[\nabla l(\theta; y)\right] &= 0 \text{ at } \theta^* \\
\nabla l(\theta; y) &= \frac{(y - b'(x^T\theta^*)) * x}{\phi} \\
E\left[\frac{y_n - b'(x^T\theta^*)}{\phi}\right] &= \frac{E(Y) - b'(x^T\theta^*)}{\phi} = 0 \\
E(Y) &= b'(x^T\theta^*)
\end{aligned}
$$

(b)

$$
\begin{aligned}
\text{We know that } -E\left[\nabla\nabla l(\theta; y)\right] &= E\left[\nabla l(\theta; y)\right]^2 \\
\nabla\nabla l(\theta; y) &= \frac{-b''(x^T\theta^*)}{\phi} \\
E\left[\frac{Y - b'(\lambda)}{\phi}\right]^2 &= \frac{E(Y - E(Y))^2}{\phi^2} = \frac{Var(Y)}{\phi^2} \\
\phi b''(\lambda_n) = \phi h'(\lambda_n) &= var(y_n|\lambda_n)
\end{aligned}
$$

(c)

$$
\begin{aligned}
l(\theta; y) &= \frac{\lambda_n y_n - b(\lambda_n)}{\phi} + \log y_n, \phi \\
\nabla l(\theta, y) &= \frac{1}{\phi} * (y_n - b'(x^T\theta))x_n \\
&= \frac{1}{\phi} * (y_n - h(x^T\theta))x_n
\end{aligned}
$$

(d) This is the fisher's information:

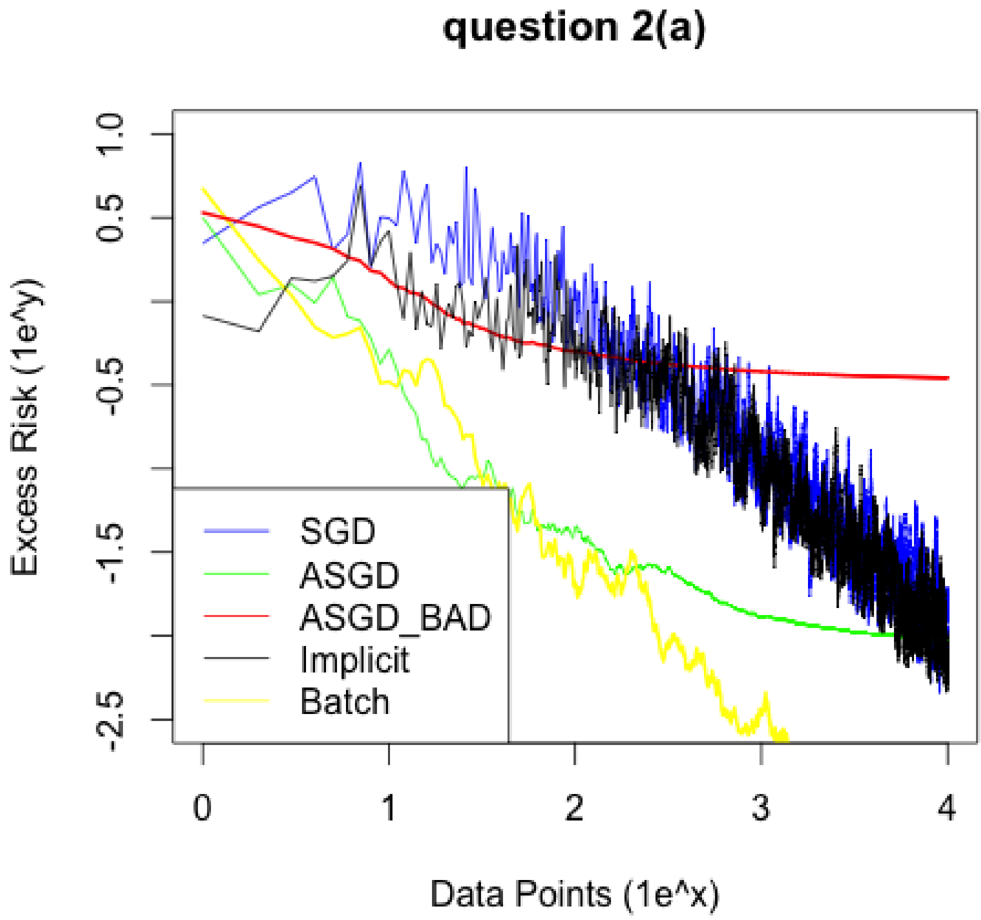
$$
\begin{aligned}
-\nabla\frac{1}{\phi} * (y_n - h(x^T\theta))x_n &= \nabla\frac{1}{\phi} * h(x^T\theta)x_n \\
I(\theta) &= \frac{1}{\phi}E(h'(x^T\theta)x_n x_n^T)
\end{aligned}
$$

(e) Because we know the fisher's information must be positive (it's a variance) and we know that $x_n x_n^T$ is positive-definite, then that means $h'(x^T\theta)$ must also be positive. If this is true then it means $h(\cdot)$ is non-decreasing.

question 2. Experiment:

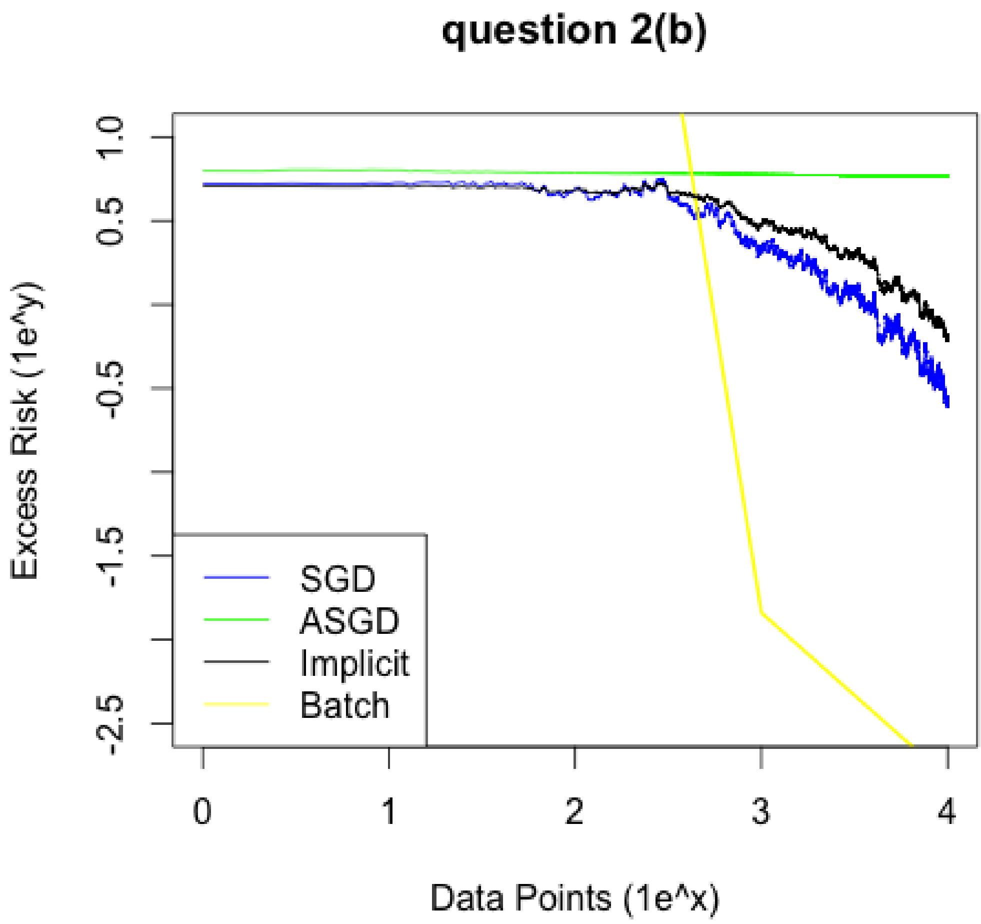
(a)

$$\text{SGD: } \theta_{t+1} = \theta_t + (1 + .02 * t)^{-1} * (\Sigma^{-1} * (\vec{x_t} - \vec{\theta_t}))$$
$$\text{ASGD: } \overline{\theta}_{t+1} = (1 - 1/t) * \overline{\theta}_t + (1/t) * \theta_{t+1}$$
$$\text{where } \theta_{t+1} = \theta_t + (1 + .02 * t)^{-2/3} * (\Sigma^{-1} * (\vec{x_t} - \vec{\theta_t}))$$
$$\text{ASGD\_BAD: Same as ASGD, but with learning rate } (1 + t)^{-1}$$
$$\text{Implicit: } \theta_{t+1} = (1 + \gamma_t)^{-1} * (\theta_t + \gamma_t * \vec{x_t}), \text{ where } \gamma_t = (1 + .02 * t)^{-1}$$



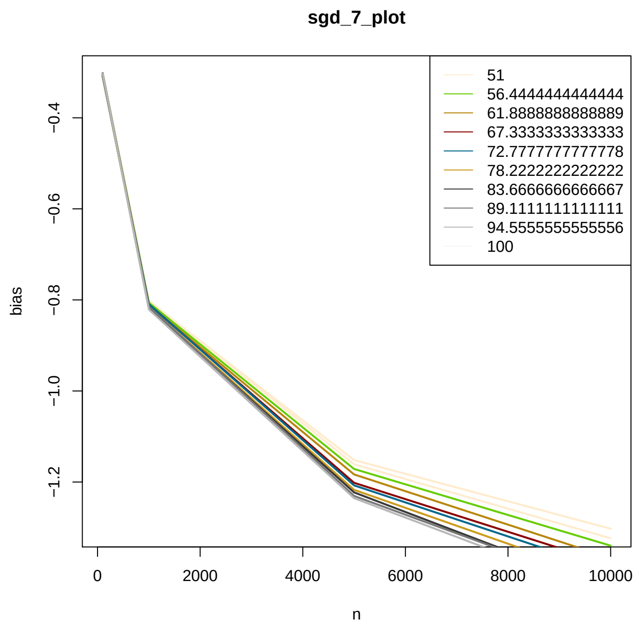
(b) For SGD and implicit, we use a learning rate a_t of $\gamma_0 * (1 + \gamma_0 \lambda_0 t)^{-1}$ and for ASGD we use $\gamma_0 * (1 + \gamma_0 \lambda_0 t)^{-2/3}$. Where $\gamma_0 = tr(A)$ and $\lambda_0 = .01$.

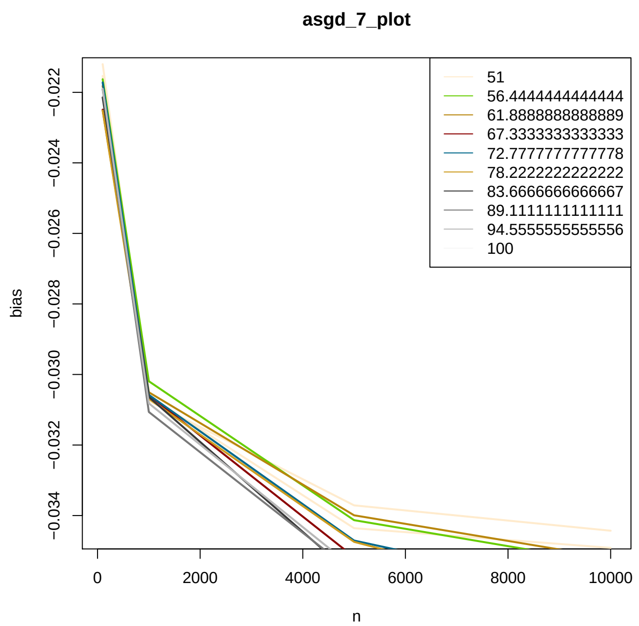
$$\begin{aligned}
\text{SGD: } \theta_{t+1} &= \theta_t - a_t * x^T \theta_t x + a_t * y * x \\
\text{ASGD: } \overline{\theta}_{t+1} &= (1 - 1/t) * \overline{\theta}_t + (1/t) * \theta_{t+1} \\
\text{Implicit: } \theta_{t+1} &= \theta_t - a_t f_t x^T \theta_t x + a_t y x - a_t^2 f_t y \Sigma(x^2) x \\
&\text{where: } f_t = 1/(1 + a_t \Sigma(x^2)) \\
&\text{Note: this is taken from Panos' distro code} \\
\text{Batch: } &\text{We ran the linear regression using R's lm(y } \sim \text{ x + 0)}
\end{aligned}$$

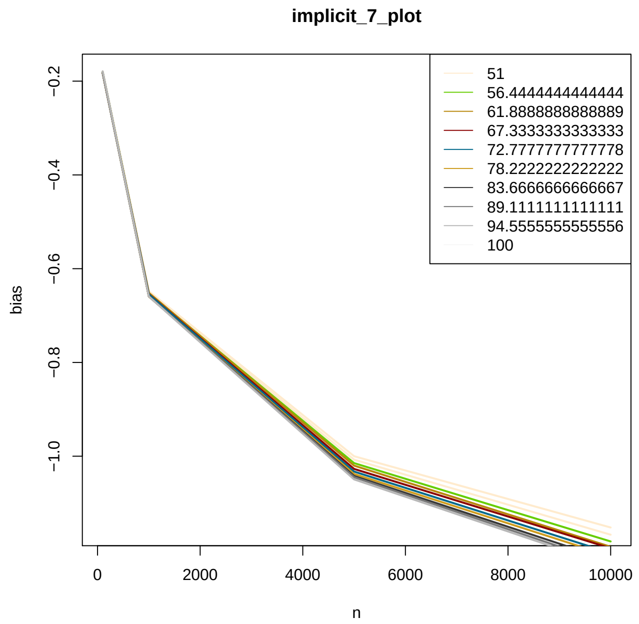


Note: After trying multiple learning rates and averaging rates for ASGD, for some reason we were still unable to produce the correct convergence rate. It may be some misunderstanding on our part or simply a bug in the code, but this will affect also 2(c).

(c) We ran our script task2c.slurm. We ran it for $n = 100, 1000, 5000, 10000$ each at 400 reps. Then we chose amin to be 51 and amax to be 100. All code for this is in task2c_runner.R. Plots below:

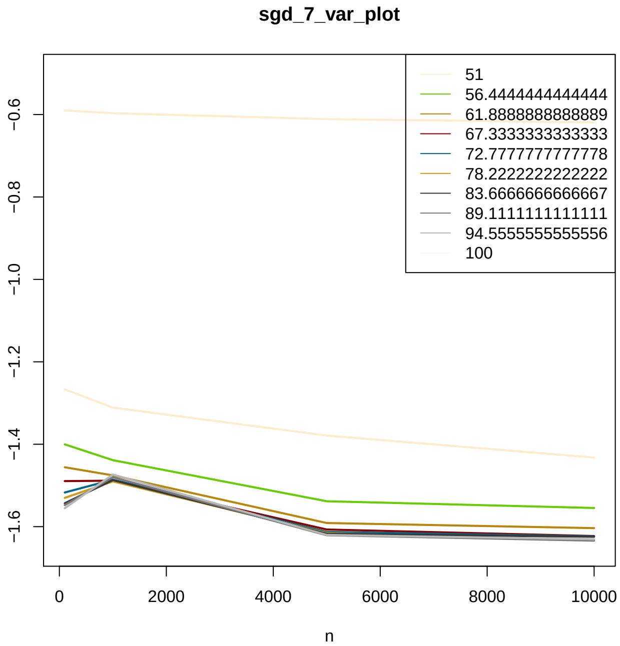


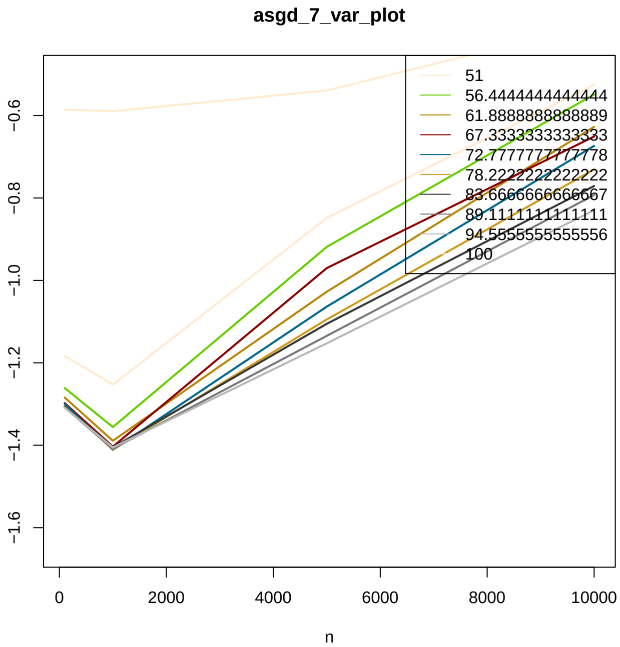


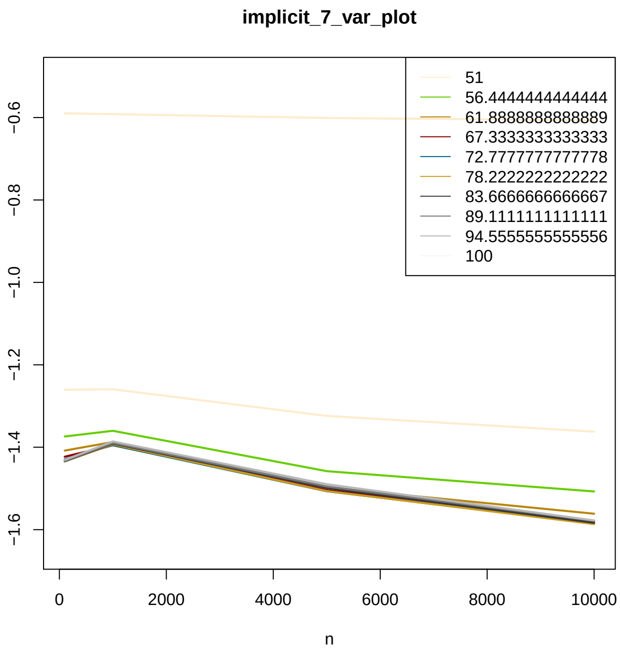


Discussion: Do note that ASGD might be a little off relatively to the other ones because of the learning rate problem we had with 2(b). Regardless, of that looking at the plots of bias over the different α values, we see that it seems that as alpha gets bigger, the bias is relatively smaller. This makes sense because as we have bigger α's we will converge faster because each jump is slightly more powerful.

(d) Trace of the empirical variance plotted on a log scale, from same data as part (c):


sgd_7_var_plot
51
56.4444444444444
61.8888888888889
67.3333333333333
72.7777777777778
78.2222222222222
83.6666666666667
89.1111111111111
94.5555555555556
100
−0.6
−0.8
−1.0
−1.2
−1.4
−1.6
0
2000
4000
6000
8000
10000
n


asgd_7_var_plot
51
56.4444444444444
61.8888888888889
67.3333333333333
72.7777777777778
78.2222222222222
83.6666666666667
89.1111111111111
94.5555555555556
100
−0.6
−0.8
−1.0
−1.2
−1.4
−1.6
0
2000
4000
6000
8000
10000
n



Discussion: Again, ASGD doesn't seem to follow the same trend as the other charts. It seems that while a small $\alpha = 51$ has a very high variance (probably because it's close to the smallest α value possible), the other values don't really follow a clear trend. For SGD and Implicit, it looks like as we get higher, the variance gets lower until some point at which it stops decreasing.

(e) Yo.

question 3. Part 3

(a.) The elastic net penalty is a compromise between ridge-regression penalty and lasso penalty, behaving more like the former for alphas close to 0 and more like the latter for alphas close to 1. The quadratic term in the regularized problem is an approximation of our log-likelihood which we get by doing a Taylor expansion about our current estimates. To take advantage of cases where the feature matrix X is sparse (like in a bag of words model), only the non-zero entries of the matrix (and their coordinates) are stored. Since it uses coordinate descent, the inner-product operations can sum over only the non-zero entries (since the other calculations would just yield 0 as the result).

(b.) Tables 1 through 6 below reproduce the Table 1 in the paper.
Note: We did the lars part before Panos said it wasn't necessary on Piazza. Additionally, Tables 11 through 16 have the corresponding MSEs from the glmnet runs so we can make adequete comparisons with SGD.

(c.)

Table 1: N = 1000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.035	0.037	0.041	0.058	0.144	0.249
glmnet (type = ”cov”)	0.010	0.011	0.011	0.011	0.017	0.021
lars	0.210	0.207	0.216	0.214	0.210	0.213

Table 2: N = 5000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.129	0.129	0.148	0.192	0.480	0.804
glmnet (type = ”cov”)	0.033	0.034	0.032	0.035	0.038	0.039
lars	1.023	1.053	1.036	1.047	1.038	1.029

Table 3: N = 100, p = 1000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.026	0.024	0.025	0.030	0.048	0.051
glmnet (type = ”cov”)	0.047	0.045	0.051	0.070	0.151	0.136
lars	0.319	0.296	0.303	0.288	0.306	0.327

Table 4: N = 100, p = 5000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.073	0.075	0.073	0.086	0.110	0.194
glmnet (type = ”cov”)	0.237	0.257	0.256	0.312	0.655	0.679
lars	1.893	1.658	1.619	1.694	1.758	1.578

Table 5: N = 100, p = 20000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.264	0.268	0.269	0.288	0.347	0.528
glmnet (type = ”cov”)	0.981	1.034	1.069	1.267	2.348	2.777
lars	6.854	7.487	7.398	7.351	8.118	7.584

Table 6: N = 100, p = 50000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.657	0.714	0.731	0.722	0.839	1.598
glmnet (type = ”cov”)	2.566	2.666	2.536	3.227	6.326	8.347
lars	22.491	22.561	25.666	25.018	23.115	24.605

Table 7: N = 1000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
SGD Time	0.261	0.263	0.258	0.276	0.266	0.268
Implicit SGD Time	0.246	0.246	0.245	0.248	0.251	0.250
SGD MSE	0.147	0.157	0.148	0.168	0.163	0.154
Implicit SGD MSE	0.129	0.132	0.133	0.133	0.142	0.139

Table 8: N = 5000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
SGD Time	5.486	5.540	5.665	5.529	5.539	5.620
Implicit SGD Time	5.476	5.516	5.605	5.563	5.617	5.577
SGD MSE	4.421	4.342	4.275	4.133	4.150	4.187
Implicit SGD MSE	4.399	4.274	4.162	4.136	4.151	4.192

Table 9: N = 100, p = 1000

	0	0.1	0.2	0.5	0.9	0.95
SGD Time	1.643	1.607	1.623	1.617	1.617	1.631
Implicit SGD Time	1.602	1.623	1.629	1.622	1.631	1.659
SGD MSE	0.037	0.036	0.040	0.039	0.039	0.035
Implicit SGD MSE	0.035	0.037	0.043	0.040	0.040	0.035

Table 10: N = 100, p = 5000

	0	0.1	0.2	0.5	0.9	0.95
SGD Time	172.810	172.320	172.874	172.882	172.961	174.794
Implicit SGD Time	172.752	175.411	175.180	177.150	175.977	177.233
SGD MSE	0.820	0.827	0.881	0.865	0.881	0.831
Implicit SGD MSE	0.809	0.867	0.938	0.993	1.004	0.910

Table 11: MSEs: N = 1000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.045	0.045	0.045	0.048	0.057	0.080
glmnet (type = ”cov”)	0.039	0.044	0.040	0.044	0.062	0.072

Table 12: MSEs: N = 5000, p = 100

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.028	0.027	0.028	0.030	0.050	0.070
glmnet (type = ”cov”)	0.027	0.028	0.028	0.029	0.051	0.068

Table 13: MSEs: N = 100, p = 1000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.064	0.060	0.063	0.060	0.067	0.071
glmnet (type = ”cov”)	0.062	0.064	0.064	0.057	0.064	0.069

Table 14: MSEs: N = 100, p = 5000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = ”naive”)	0.033	0.031	0.032	0.031	0.030	0.032
glmnet (type = ”cov”)	0.030	0.033	0.029	0.030	0.032	0.031

Table 15: MSEs: N = 100, p = 20000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = "naive")	0.016	0.017	0.015	0.016	0.016	0.017
glmnet (type = "cov")	0.017	0.017	0.016	0.017	0.017	0.017

Table 16: MSEs: N = 100, p = 50000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = "naive")	0.010	0.011	0.011	0.011	0.011	0.010
glmnet (type = "cov")	0.010	0.010	0.010	0.011	0.011	0.010

Table 17: Times: N = 100000, p = 1000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = "naive")	14.419	14.793	15.274	16.445	41.139	60.373
glmnet (type = "cov")	50.527	50.504	50.647	50.268	50.955	49.562

Table 18: MSEs: N = 100000, p = 1000

	0	0.1	0.2	0.5	0.9	0.95
glmnet (type = "naive")	0.005	0.005	0.005	0.006	0.011	0.018
glmnet (type = "cov")	0.005	0.005	0.005	0.006	0.011	0.018