
Supplementary Material for An Efficient Semismooth Newton based Algorithm for Convex Clustering

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Proof of Lemma 1

Lemma 1 For any $t > 0$, the proximal mapping $\text{Prox}_{t\|\cdot\|_2}$ is strongly semismooth.

Proof. From the definition of $\text{Prox}_{t\|\cdot\|_2}(\cdot)$ and the fact that the projection of any vector onto the second order cone, i.e., the epigraph of the ℓ_2 norm function, is strongly semismooth (Chen et al., 2003) [Proposition 4.3]. Then, we can obtain the conclusion directly from (Meng et al., 2005) [Theorem 4].

Proof of Theorem 2

Proof. From Lemma 1, we know that $\text{Prox}_{t\|\cdot\|_2}$ is strongly semismooth for any $t > 0$, together with the Moreau identity $\text{Prox}_{tp}(x) + t\text{Prox}_{p^*/t}(x/t) = x$, we know that

$$\nabla\phi(X) = X - A + \mathcal{B}^*(\text{Prox}_{\sigma p^*}(\sigma\mathcal{B}(X) + \tilde{Z}))$$

is strongly semismooth. By (Zhao et al., 2010) [Proposition 3.3], we know that d^j obtained in SSNCG is a descent direction, which guarantees the Algorithm SSNCG is well defined.

From (Zhao et al., 2010) [Theorem 3.4, 3.5], we can get the desired results in this theorem.

More Numerical Results on Unbalanced Gaussian Dataset

In this section, we show detailed time comparison experiment results between SSNAL and AMA on Unbalanced Gaussian dataset. We summarize our results in Table 1. We can see that AMA almost cannot solve the problem within 100000 iterations.

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References

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Supplementary Material

Table 1. Numerical Results on Unbalanced Gaussian Dataset. $k = 10$, $\phi = 0.5$. $Gap = P_{AMA} - P_{Ssnal}$

γ	0.2	0.4	0.6	0.8	1.0
$t_{AMA}(S)$	264.54	256.21	260.06	262.16	263.27
$t_{Ssnal}(S)$	1.15	0.57	0.67	0.66	0.86
$Iter_{AMA}$	100000	97560	97333	100000	100000
$Iter_{Ssnal}$	23	21	24	24	27
P_{AMA}	0.784611	0.990282	1.184049	1.365560	1.535217
P_{Ssnal}	0.783797	0.990281	1.184048	1.365554	1.535209
Gap	0.000814	1E-6	1E-6	6E-6	8E-6
γ	1.2	1.4	1.6	1.8	2.0
$t_{AMA}(S)$	270.88	264.12	264.58	271.85	264.84
$t_{Ssnal}(S)$	0.97	1.03	1.03	1.05	1.04
$Iter_{AMA}$	100000	100000	100000	100000	100000
$Iter_{Ssnal}$	28	28	27	27	26
P_{AMA}	1.693393	1.840384	1.976499	2.101939	2.216956
P_{Ssnal}	1.693375	1.840369	1.976470	2.101920	2.216925
Gap	0.000018	0.000015	0.000028	2E-5	3E-5