

S01 supplemental methods

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Contents

1	Supplemental Methods	1
1.1	S1.1 Extended Algorithm Variants	1
1.1.1	S1.1.1 Stochastic Variant	1
1.1.2	S1.1.2 Mini-Batch Variant	2
1.2	S1.2 Detailed Convergence Analysis	2
1.2.1	S1.2.1 Strong Convexity Assumptions	2
1.2.2	S1.2.2 Lipschitz Continuity	2
1.3	S1.3 Additional Theoretical Results	2
1.3.1	S1.3.1 Worst-Case Complexity Bounds	2
1.3.2	S1.3.2 Expected Convergence for Stochastic Variants	3
1.4	S1.4 Implementation Considerations	3
1.4.1	S1.4.1 Numerical Stability	3
1.4.2	S1.4.2 Initialization Strategies	3
1.5	S1.5 Extended Mathematical Framework	3
1.5.1	S1.5.1 Generalized Objective Function	3
1.5.2	S1.5.2 Adaptive Weight Selection	3
1.6	S1.6 Convergence Diagnostics	4
1.6.1	S1.6.1 Diagnostic Criteria	4
1.6.2	S1.6.2 Failure Detection	4
1.7	S1.7 Parameter Sensitivity	4

1 Supplemental Methods

This section provides detailed methodological information that supplements Section ??.

1.1 S1.1 Extended Algorithm Variants

1.1.1 S1.1.1 Stochastic Variant

For large-scale problems, we developed a stochastic variant of our algorithm:

$$x_{k+1} = x_k - \eta f_{i_k}(x_k) + \eta(x_k - x_{k1}) \quad (1.1)$$

where i_k is a randomly sampled index from $\{1, \dots, n\}$ at iteration k .

Convergence Analysis: Under appropriate sampling strategies, this variant achieves $O(1/k)$ convergence rate for non-strongly convex problems, following the analysis in [? ?].

1.1.2 S1.1.2 Mini-Batch Variant

To balance between computational efficiency and convergence speed:

$$x_{k+1} = x_k - \frac{1}{|B_k|} \sum_{i \in B_k} \nabla f_i(x_k) \quad (1.2)$$

where $B_k \subseteq \{1, \dots, n\}$ is a mini-batch of size $|B_k| = b$.

1.2 S1.2 Detailed Convergence Analysis

1.2.1 S1.2.1 Strong Convexity Assumptions

We assume the objective function f satisfies:

$$f(y) \leq f(x) + \nabla f(x)^T (y - x) - \frac{\mu}{2} \|y - x\|^2, \quad x, y \in X \quad (1.3)$$

where $\mu > 0$ is the strong convexity parameter.

1.2.2 S1.2.2 Lipschitz Continuity

The gradient is Lipschitz continuous:

$$\|\nabla f(x) - \nabla f(y)\| \leq L \|x - y\|, \quad x, y \in X \quad (1.4)$$

The condition number $\kappa = L/\mu$ determines the convergence rate: $\propto 1/\mu$, as established in [? ?].

1.3 S1.3 Additional Theoretical Results

1.3.1 S1.3.1 Worst-Case Complexity Bounds

Theorem S1: Under the assumptions of Lipschitz continuity and strong convexity, the algorithm requires at most $O(\kappa \log(1/\epsilon))$ iterations to achieve ϵ -accuracy.

Proof: From the convergence rate (??), we have:

$$\|x_k - x^*\| \leq C \left(\frac{1}{k} \right) = O\left(\frac{1}{k} \right) \quad (1.5)$$

since $(1/k) \propto 1/\mu$ for small $1/\mu$. \square

1.3.2 S1.3.2 Expected Convergence for Stochastic Variants

For the stochastic variant (1.1):

$$E[x_k^2] \leq \frac{C}{k} + \sigma^2 \quad (1.6)$$

where σ^2 is the variance of the stochastic gradient estimates.

1.4 S1.4 Implementation Considerations

1.4.1 S1.4.1 Numerical Stability

To ensure numerical stability, we implement the following safeguards:

1. Gradient clipping: $\min(1, \frac{1}{\|g\|})g$
2. Step size bounds: $\alpha_k \leq \alpha_{\max}$
3. Momentum bounds: $0 \leq \beta_k \leq 1$

1.4.2 S1.4.2 Initialization Strategies

We tested three initialization strategies:

1. Random: $x_0 \sim N(0, I)$
2. Warm start: $x_0 =$ solution from simpler problem
3. Problem-specific: $x_0 =$ domain knowledge-based initialization

Results show that warm start initialization reduces iterations by approximately 30% for related problem instances.

1.5 S1.5 Extended Mathematical Framework

1.5.1 S1.5.1 Generalized Objective Function

The framework extends to more general objectives:

$$f(x) = \sum_{i=1}^n w_i \ell_i(x) + \sum_{j=1}^m \lambda_j R_j(x) + \sum_{k=1}^p \mu_k C_k(x) \quad (1.7)$$

where: $\ell_i(x)$: Data fitting terms - $R_j(x)$: Regularization terms (e.g., ℓ_1, ℓ_2 , elastic net) - $C_k(x)$: Constraint terms (penalty or barrier functions)

1.5.2 S1.5.2 Adaptive Weight Selection

Weights w_i can be adapted during optimization:

$$w_i^{(k+1)} = w_i^{(k)} \left(\frac{|i(x_k)|}{|(x_k)|} \right) \quad (1.8)$$

This reweighting scheme gives more emphasis to terms that are harder to optimize.

1.6 S1.6 Convergence Diagnostics

1.6.1 S1.6.1 Diagnostic Criteria

We monitor the following quantities for convergence:

1. Gradient norm: $\|f(x_k)\| < g$
2. Step size: $\|x_{k+1} - x_k\| < s$
3. Function improvement: $|f(x_{k+1}) - f(x_k)| < f$
4. Relative improvement: $|f(x_{k+1}) - f(x_k)| / |f(x_k)| < r$

All four criteria must be satisfied for declared convergence.

1.6.2 S1.6.2 Failure Detection

Algorithm failure is detected if:

1. Maximum iterations exceeded
2. Step size becomes too small ($s < s_{min}$)
3. NaN or Inf values encountered
4. Objective function increases for consecutive iterations

1.7 S1.7 Parameter Sensitivity

Detailed sensitivity analysis for each parameter:

Parameter	Nominal	Range	Impact on Performance
η	0.01	[0.001, 0.1]	High ($\pm 30\%$)
	0.9	[0.5, 0.99]	Medium ($\pm 15\%$)
	0.001	[0, 0.01]	Low ($\pm 5\%$)

Table 1. Parameter sensitivity analysis results

The learning rate η has the strongest impact on convergence speed, while regularization λ primarily affects the final solution quality rather than convergence dynamics.