Rebuttal Response

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1. Comparison Table of Stochastic Bilevel Optimization Algorithms

Table 1. Comparison of stochastic bilevel optimization algorithms in the nonconvex-strongly-convex setting under different smoothness assumptions on f and g. The oracle complexity stands for the number of oracle calls to stochastic gradients and stochastic Hessian/Jacobian-vector products to find an ϵ-stationary point. $\mathcal{C}_L^{a,k}$ denotes a-times differentiability with Lipschitz k-th order derivatives. "SC" means "strongly-convex". $\widetilde{O}(\cdot)$ compresses logarithmic factors of $1/\epsilon$ and $1/\delta$, where $\delta \in (0,1)$ denotes the failure probability.

Method [1]	Loop Style	Stochastic Setting	Oracle Complexity	Upper-Level f	Lower-Level g	Batch Size
BSA (Ghadimi & Wang, 2018)	Double	General expectation	$\widetilde{O}(\epsilon^{-6})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$\widetilde{O}(1)$
StocBio (Ji et al., 2021)	Double	General expectation	$\widetilde{O}(\epsilon^{-4})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$\widetilde{O}(\epsilon^{-2})$
AmIGO (Arbel & Mairal, 2021)	Double	General expectation	$\widetilde{O}(\epsilon^{-4})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$O(\epsilon^{-2})$
ALSET (Chen et al., 2021)	Double / Single [2]	General expectation	$O(\epsilon^{-4})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$O(1)$
TTSA (Hong et al., 2023)	Single	General expectation	$\widetilde{O}(\epsilon^{-5})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$\widetilde{O}(1)$
F^{2}SA (Kwon et al., 2023)	Single	General expectation	$O(\epsilon^{-7})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$O(1)$
SOBA (Dagréou et al., 2022)	Single	Finite sum	$O(\epsilon^{-4})$	$\mathcal{C}_L^{2,2}$	SC and $\mathcal{C}_L^{3,3}$	$O(1)$
SABA (Dagréou et al., 2022)	Single	Finite sum	$O(N^{4/3}\epsilon^{-2})$ [3]	$\mathcal{C}_L^{2,2}$	SC and $\mathcal{C}_L^{3,3}$	$O(1)$
MA-SOBA (Chen et al., 2023)	Single	General expectation	$O(\epsilon^{-4})$	$\mathcal{C}_L^{1,1}$	SC and $\mathcal{C}_L^{2,2}$	$O(1)$
BO-REP (Hao et al., 2024)	Double	General expectation	$\widetilde{O}(\epsilon^{-4})$	$(L_{x,0}, L_{x,1}, L_{y,0}, L_{y,1})$-smooth	SC and $\mathcal{C}_L^{2,2}$	$O(1)$
SLIP (This work)	Single	General expectation	$\widetilde{O}(\epsilon^{-4})$	$(L_{x,0}, L_{x,1}, L_{y,0}, L_{y,1})$-smooth	SC and $\mathcal{C}_L^{2,2}$	$O(1)$

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[1]We omit the comparison with variance reduction-based methods (except for SABA (Dagréou et al., 2022)) that may achieve $\widetilde{O}(\epsilon^{-3})$ complexity under additional mean-squared smoothness assumptions on both upper-level and lower-level problems, e.g., VRBO, MRBO (Yang et al., 2021); SUSTAIN (Khanduri et al., 2021); SVRB (Guo et al., 2021); or under the finite sum setting, e.g., SRBA (Dagréou et al., 2023).

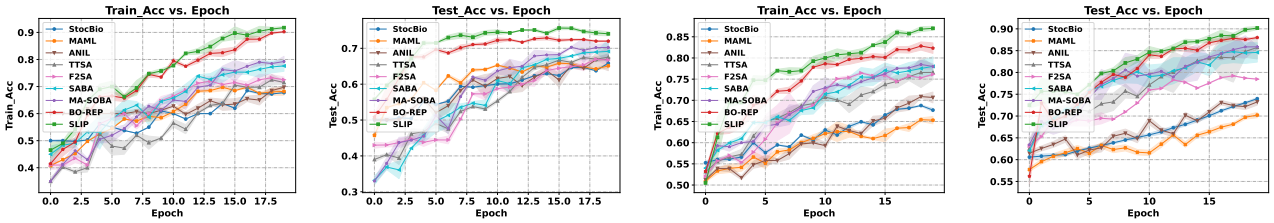
[2]ALSET can converge without the need for double loops, but at the cost of a worse dependence on $\kappa := l_{g,1}/\mu$ in oracle complexity.

[3]SABA (Dagréou et al., 2022) studies finite-sum problem and adapts variance reduction technique SAGA (Defazio et al., 2014), here $N = m + n$ denotes the total number of samples.

2. Experiments with Multiple Runs

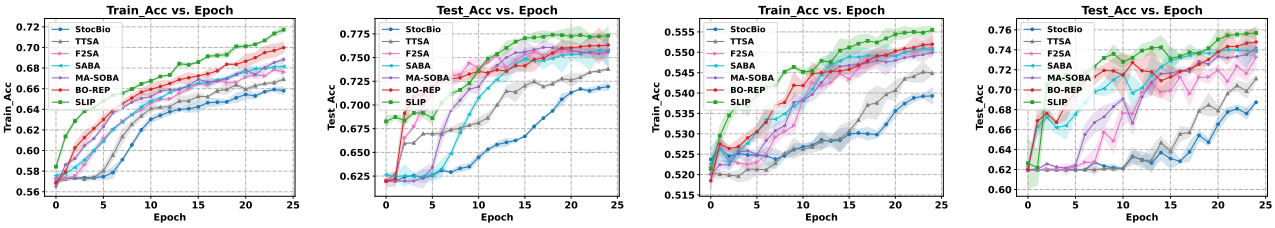
In this section, we rerun all experiments for multiple times and present the average accuracy and running time results. The results show that SLIP consistently exhibits low standard deviation and outperforms other baselines significantly.

2.1. Hyper-representation Learning and Data Hyper-cleaning



(a) Training accuracy on SNLI (b) Test accuracy on SNLI (c) Training accuracy on ARD (d) Test accuracy on ARD

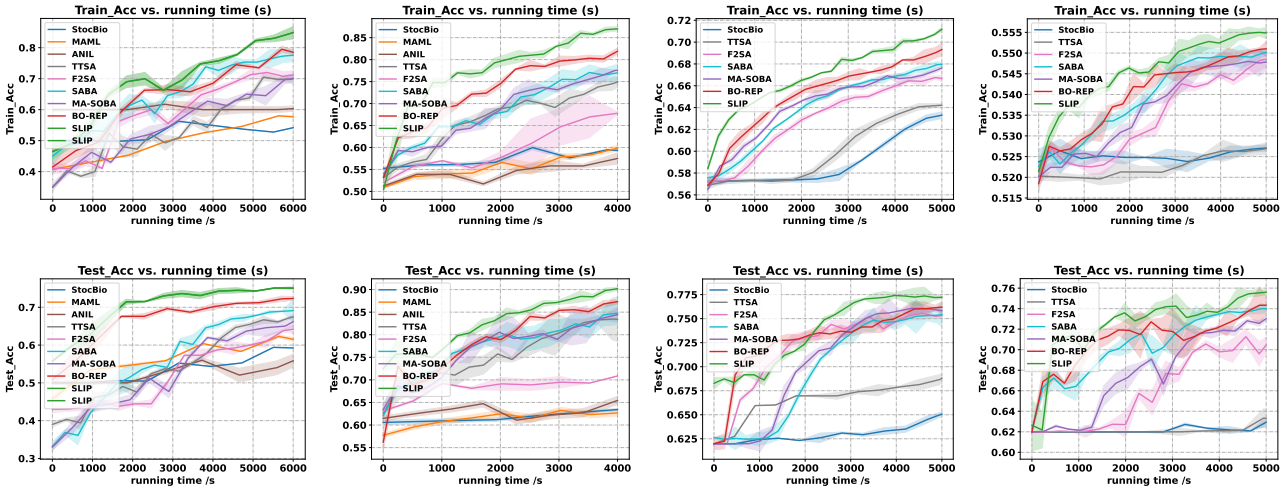
Figure 1. Comparison with bilevel optimization baselines on Hyper-representation. Figure (a) and (b) are the results in the SNLI dataset. Figures (c) and (d) are the results of the Amazon Review Dataset (ARD).



(a) Training acc with $p = 0.2$ (b) Test acc with $p = 0.2$ (c) Training acc with $p = 0.4$ (d) Test acc with $p = 0.4$

Figure 2. Comparison with bilevel optimization baselinses on data hyper-cleaning. Figure (a), (b) are the results with the corruption rate $p = 0.2$. Figure (c), (d) are the results with the corruption rate $p = 0.4$.

2.2. Running Time Comparison



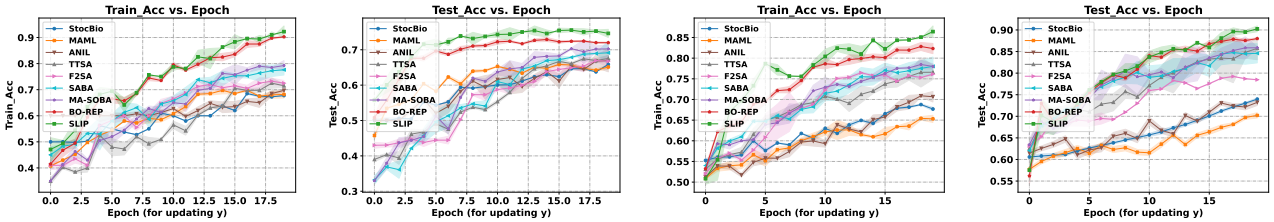
(a) Hyper-representation (SNLI) (b) Hyper-representation (ARD) (c) Data Hyper-cleaning (p=0.2) (d) Data Hyper-cleaning (p=0.4)

Figure 3. Comparision on running time. (a) Results of Hyper-representation on SNLI dataset. (b) Results of Hyper-representation on Amazon Review Dataset (ARD). (c), (d) Results of data Hyper-cleaning on Sentiment140 with corruption rate $p = 0.2$ and $p = 0.4$.

3. Experiments with Revised Epoch Definition

In this section, we clarify the notion of "epoch" in our previous experiments, where an epoch means a full pass over the validation set (for upper-level variable x update). For a more comprehensive comparison, we re-conduct experiments where an epoch means a full pass over the training set (for lower-level variable y update). In this case there are fewer x updates than the previous run due to the warm-start phase. The results show that SLIP is still empirically better than other baselines.

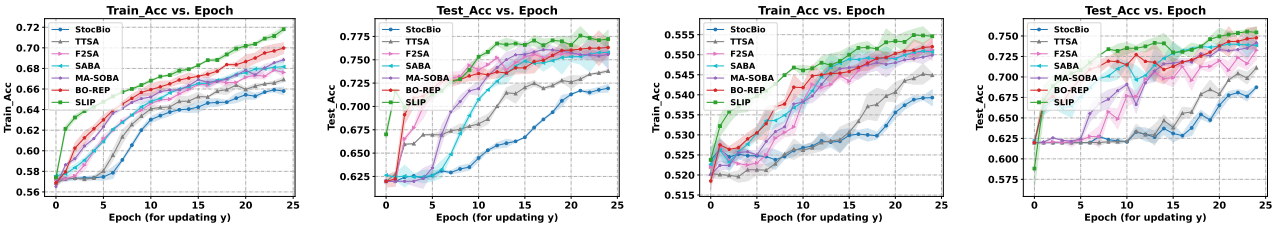
3.1. Hyper-representation Learning



(a) Training accuracy on SNLI (b) Test accuracy on SNLI (c) Training accuracy on ARD (d) Test accuracy on ARD

Figure 4. Comparison with bilevel optimization baselines on Hyper-representation. Figure (a) and (b) are the results in the SNLI dataset. Figures (c) and (d) are the results of the Amazon Review Dataset (ARD).

3.2. Data Hyper-cleaning



(a) Training acc with $p = 0.2$ (b) Test acc with $p = 0.2$ (c) Training acc with $p = 0.4$ (d) Test acc with $p = 0.4$

Figure 5. Comparison with bilevel optimization baselinses on data hyper-cleaning. Figure (a), (b) are the results with the corruption rate $p = 0.2$. Figure (c), (d) are the results with the corruption rate $p = 0.4$.

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