We appreciate reviewers' comments. Below are our responses to each reviewer.

Reviewer 1 1) About the motivation of Equation (4). Consider the case of exact updates of two canonical variables $\mathbf{\Phi}$ and $\mathbf{\Psi}$ in Equation (3), i.e., $\xi_t = \eta_t = \mathbf{0}$. In the second line of Equation (3), it is easy to see that if $\mathbf{\Phi}_t$ is equal to the canonical subspace $\mathbf{\Phi}^\star = \mathbf{C}_{xx}^{-1/2}\mathbf{U}$ (i.e., ground truth) then $\tilde{\mathbf{\Phi}}_{t+1} = \mathbf{C}_{yy}^{-1/2}\mathbf{V}\mathbf{\Sigma}$ will span the canonical subspace $\mathbf{\Psi}^\star = \mathbf{C}_{yy}^{-1/2}\mathbf{V}$. This basically means that if $\mathbf{\Phi}_t$ is closer to the ground truth, $\mathbf{\Psi}_{t+1}$ will be closer to its ground truth as well. This in turn suggests that replacing $\mathbf{\Phi}_t$ with $\mathbf{\Phi}_{t+1}$ in the second line of Equation (3) may improve the convergence, because $\mathbf{\Phi}_{t+1}$ is supposed to be closer to the ground truth than $\mathbf{\Phi}_t$. This replacement makes Equation (3) have deviated from the standard power iteration from which Equation (3) is derived. Thus it is no longer necessary for us to stick to the joint orthogonalization of two canonical variables. Instead, sperate orthogonalizations are used. The proof of Theorem 3.1 justifies this change. We then can arrive at Equation (4) in the inexact case.

2) About the lack of convergence analysis. We guess the reviewer referred to the tight convergence analysis of FastTALS, as TALS is globally convergent and the analysis is tight (i.e., rate matching the method) as stated in Theorem 3.1. FastTALS is locally convergent and the analysis is not tight as stated in Theorem 4.1. First, the global convergence actually is not an issue, because one can use our globally convergent TALS algorithm to warm start FastTALS so that two canonical variables are sufficiently close to the ground truth. On the tight analysis, this is indeed difficult. We tried to follow the work of accelerated stochastic power method by Xu et al., 2018. for a tight analysis. However, their analysis only considered the vector case $k = 1$ in the stochastic setting where there are special structures, e.g., the quantity inside the trace in Problem (1) is a scalar, that can be sufficiently utilized. In our case, this quantity is a matrix and many analysis tricks fail to be applied. The extensions from vector to block are often difficult for this class of problems. More difficulties arise in our case due to the coupling of update equations as well as approximation errors. We thus leave it to our future work at the current stage.

3) We will follow the suggestion to improve the readability and move the description of the datasets back.

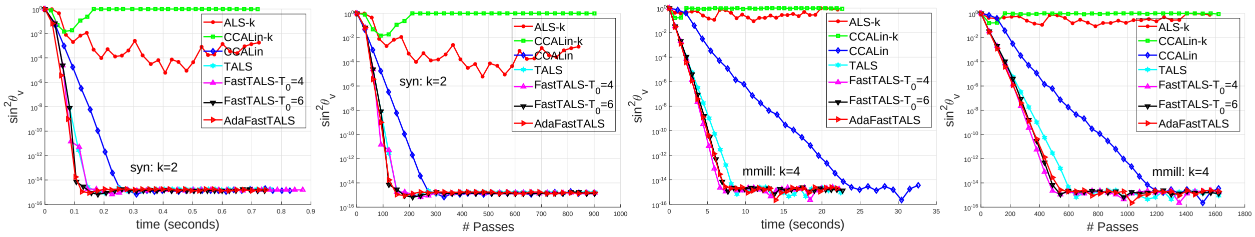
Reviewer 2 1) View on the difference of performance. First, algorithms ALS-k (using block size k and adapted from ALS for vector setting $k = 1$) and CCALin-k (using block size k and adapted from CCALin for block setting) are introduced to show the necessity of using block size $2k$ in order for them to recover top-k canonical subspaces. Throughout our experiments, they indeed fail to learn anything because their ground truth do not cover the top-k canonical subspaces. Second, the reason why CCALin is worse than our algorithms (TALS, FastTALS, and AdaFastTALS) is that CCALin needs to use block size $2k$ and a post-processing step that randomly projects the resulting $2k$-dimensional subspaces onto k-dimensional subspaces.

2) View as to whether the proposed algorithm would work in all cases or a set of them. One premise of our algorithms is that they work in the offline setting, i.e., the data pair $(\mathbf{X}, \mathbf{Y})$ is ready. This means that our algorithms may not work in streaming/online setting directly. However, following the idea of GenOja (Kush Bhatia et al. NeurIPS 2018), we may use one step of stochastic gradient descent as the least-squares solver. This might give rise to new algorithms, i.e., truly streaming versions of our algorithms, and is well worth investigating. We may also consider our algorithms in robust settings for future work.

3) Applications to downstream tasks. This is a good suggestion for the extension of the present work.

Reviewer 3 1) Simulation study. We initially planned simulation study. However, we soon found that there is no simple way to generate the simulated data $(\mathbf{X}, \mathbf{Y})$ using $\mathbf{U}$ and $\mathbf{V}$. This is because we can only use the singular value decomposition $(\frac{1}{n}\mathbf{X}\mathbf{X}^\top)^{-1/2}\frac{1}{n}\mathbf{X}\mathbf{Y}^\top(\frac{1}{n}\mathbf{Y}\mathbf{Y}^\top)^{-1/2} = \mathbf{C}_{xx}^{-1/2}\mathbf{C}_{xy}\mathbf{C}_{yy}^{-1/2} = \mathbf{C} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top$ to generate $\mathbf{C}$ from random matrices $\mathbf{U}$, $\mathbf{\Sigma}$, and $\mathbf{V}$, but cannot recover $\mathbf{X}$ and $\mathbf{Y}$ from $\mathbf{C}$. This may be the reason why there are no previous CCA works that did experiments on such simulated data (to the best of our knowledge). Nonetheless, we did experiments on a randomly generated data pair $(\mathbf{X}, \mathbf{Y})$ (the first two plots in the figure) for which the ground truth is obtained by matlab's function svds. Contrastingly, the performance improvements of our algorithms on real data are more prominent.

2) Convergence of competing methods. As mentioned in the first item of our response to Reviewer 2, ALS-k and CCALin-k fail to recover top-k canonical subspaces for CCA. Given sufficient running time, CCALin indeed can recover top-k canonical subspaces, as shown in the last two plots of the figure.


ALS-k
CCALin-k
CCALin
TALS
FastTALS-T_0=4
FastTALS-T_0=6
AdaFastTALS
$\sin^2\theta_v$
10^0
10^{-2}
10^{-4}
10^{-6}
10^{-8}
10^{-10}
10^{-12}
10^{-14}
10^{-16}
syn: k=2
time (seconds)
syn: k=2
# Passes
mmill: k=4
time (seconds)
mmill: k=4
# Passes