A Additional Experimental Results

This section provides additional experimental results of Section 5.

Figure 4 and 5 try to explain the reason why our algorithms have much better performance than the other algorithms in super heavy-tailed linear bandit problems. For every algorithm from MoM, CRT, MENU, TOFU, SupBMM and SupBTC, we transform it into an efficient algorithm for super heavy-tailed linear bandits by Algorithm 1. The counterpart is named as the original name with suffix "_mom", which represents our mean of medians estimator. Figure 4 considers Student's t-noise with df $= 3$ while Figure 5 focuses on more heavy-tailed case, where df $= 1.02$. We notice that in Figure 4, when df $= 3$, all algorithms make an accurate estimation of θ^*, thus perform well. However, in Figure 5, when df $= 1.02$, the estimation error of other algorithms seems to vary more and even not converge. While the counterparts by our algorithmic framework have estimation error approaching 0 stably. In this way, no matter how heavy-tailed the noise is, as long as we choose $\widetilde{n}$ large enough according to Theorem 4.1, our algorithms will have comparably good performance.

What's more, we notice that in Figure 5, performance improvement varies with different algorithms. For example, if we take TOFU and MENU as input algorithm $\mathcal{A}$ in Algorithm 1 respectively, the performance of TOFU_mom is not as good as MENU_mom, even TOFU and MENU have comparable performance. In this way, we only adopt SupBMM_mom and SupBTC_mom for comparisons in Figure 2 for better performance.

B The Selection of Parameter ε

In this section, we further illustrate the selection of parameter ε.

First we discuss the choice of ε with respect to α. In order to approximate the optimal value of ε, according to Theorem 4.1, we let $\left(16\log(2T/\delta)\right)^{1/\varepsilon} = (2\cdot 4^{2/\alpha}\log(4/\delta))^{\frac{1}{1-\varepsilon}}$. Figure 6 shows the relationship between ε and α, where we set $\delta = 0.01$ and $T = 10000$.

Then we concern about how sensitive our mom-algorithms are to the choice of $\varepsilon \in (0, 1)$. Figure 7 demonstrates the mean regret of 100 independent paths under Student's t-noise with df $= 1(\alpha = 1)$, which corresponds to the setting of Figure 3(a) in our paper. Each sample path contains 10000 iterations. We choose $\varepsilon \in [0.3, 0.8]$ to avoid extreme situation, i.e. we can't choose ε close to 0 or 1.

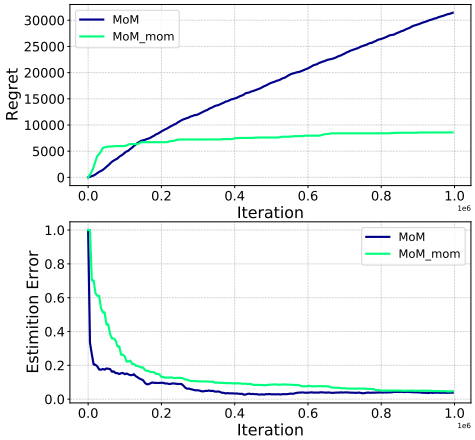
We observe that the optimal ε is between 0.5 and 0.6, which is consistent with the result in Figure 6.

C The Selection of Parameter v

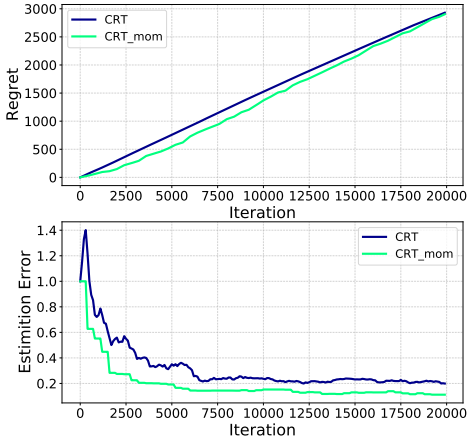
In the experiments, for the noise processed by our mean of medians estimator, we choose to tune the bound parameter v satisfying $\mathbb{E}[|\eta_{\text{mom}}|^2] \leq v$ to ensure performance. In this section, we show that our algorithms are not sensitive to v according to the plots.

Additional plots are provided here for further illustration. Under the same setting of Section 5, multiple independent paths are generated by algorithm SupBTC_mom and SupBTC_mom respectively. Figures 8 and 9 shows the mean and median regret of 500 independent paths under Student's t-noise with df $= 0.5$. Each sample path contains 10000 iterations. And three values of parameter v are selected over a suitably large range. Figure 8 is for algorithm SupBMM_mom and Figure 9 is for SupBTC_mom.

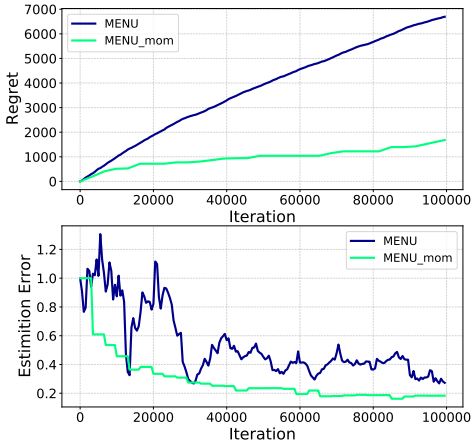
Figure 4: Comparison of our algorithms versus MoM, CRT, MENU, TOFU, SupBMM and SupBTC under Student's t-Noise with df $= 3$. The figures at the bottom of each subfigure represent estimation error $\|\widehat{\theta}_t - \theta^*\|_2 / \|\theta^*\|_2$, except for SupBMM and SupBTC since $\widehat{\theta}_t$ is not available.



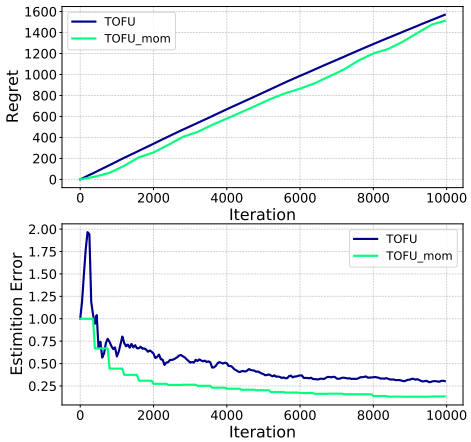
(a) MoM



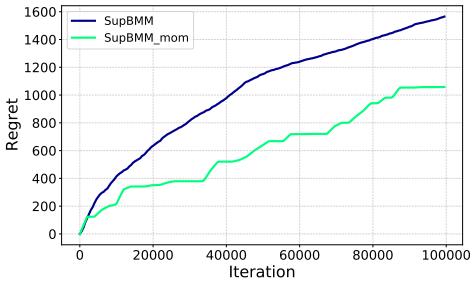
(b) CRT



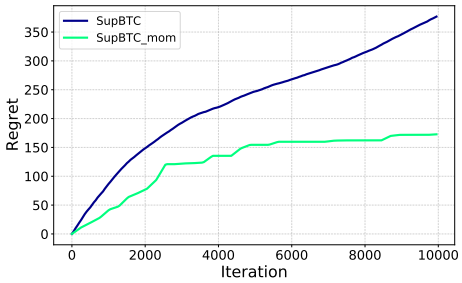
(c) MENU



(d) TOFU

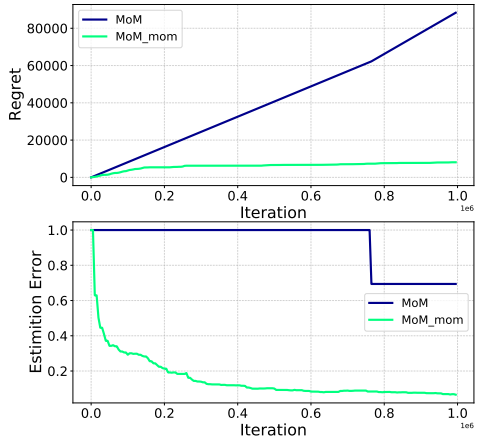


(e) SupBMM

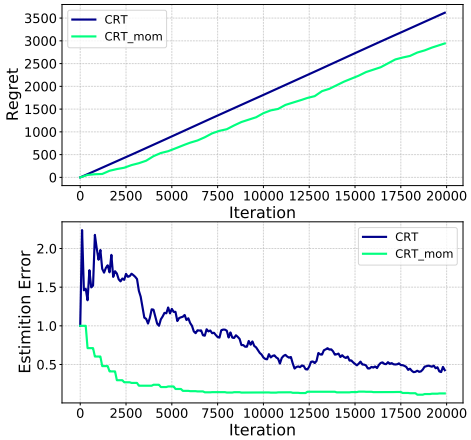


(f) SupBTC

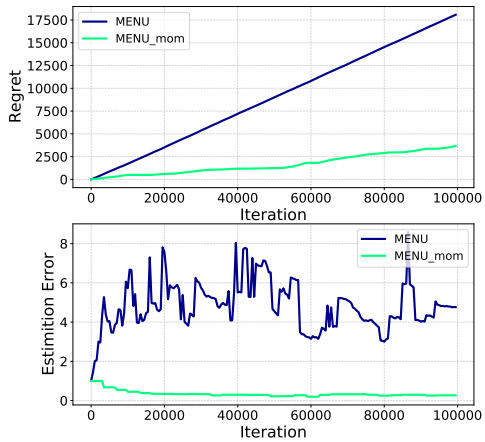
Figure 5: Comparison of our algorithms versus MoM, CRT, MENU, TOFU, SupBMM and SupBTC under Student's t-Noise with df $= 1.02$. The figures at the bottom of each subfigure represent estimation error $\|\widehat{\theta}_t - \theta^*\|_2 / \|\theta^*\|_2$, except for SupBMM and SupBTC since $\widehat{\theta}_t$ is not available.



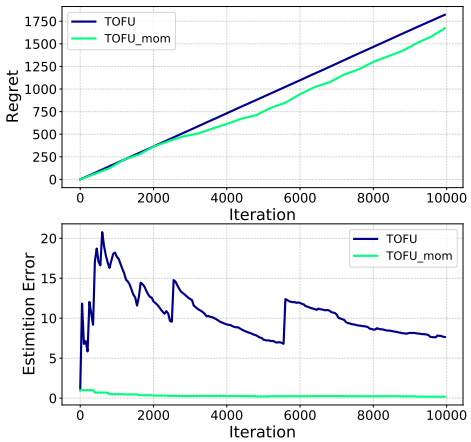
(a) MoM



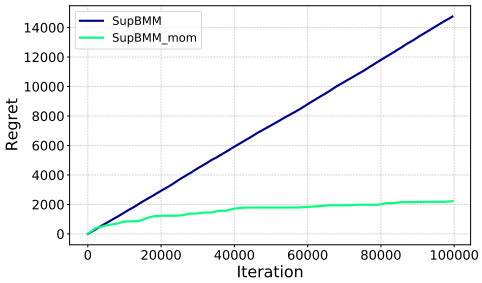
(b) CRT



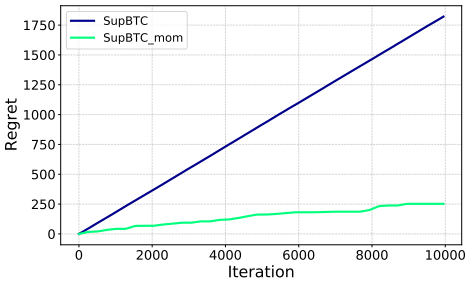
(c) MENU



(d) TOFU



(e) SupBMM



(f) SupBTC

Figure 6: Optimal ε with respect to α.

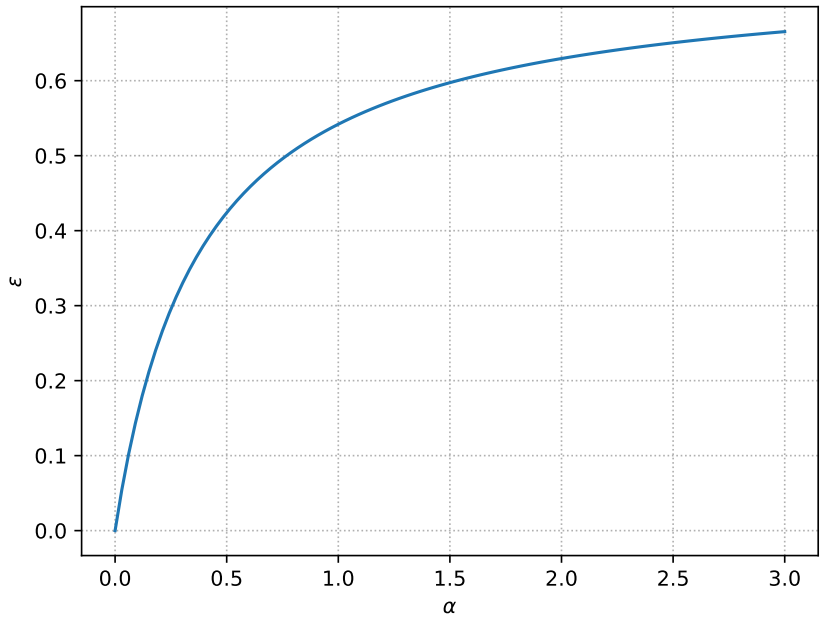


Figure 7: Mean regret of 100 independent paths under Student's t-noise with df $= 1$ by algorithm SupBTC_mom.

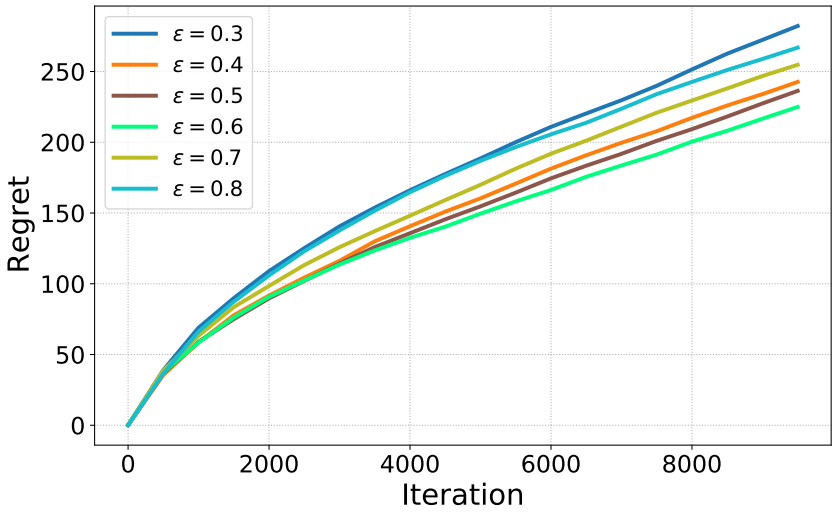
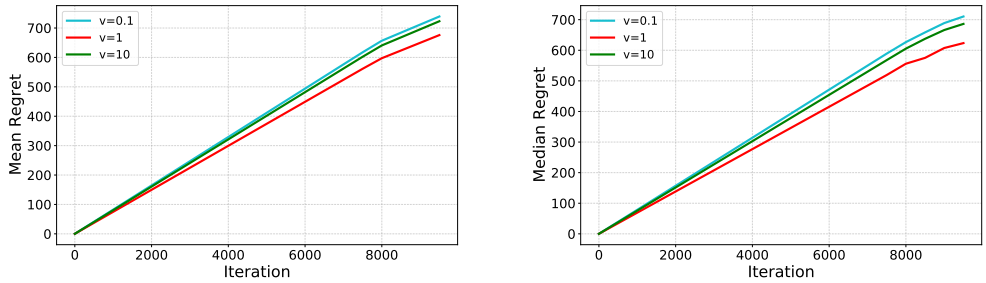
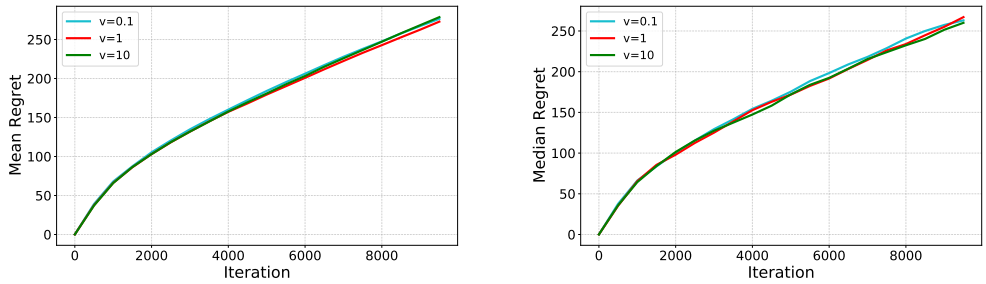


Figure 8: Mean and median regret of 500 independent paths under Student's t-noise with df $= 0.5$ by algorithm SupBMM_mom.



(a) Mean regret (b) Median regret

Figure 9: Mean and median regret of 500 independent paths under Student's t-noise with df $= 0.5$ by algorithm SupBTC_mom.



(a) Mean regret (b) Median regret