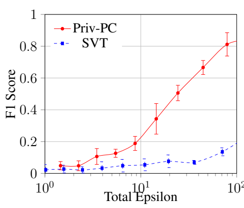
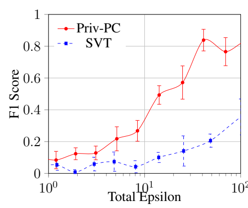
We thank reviewers for their constructive comments, please see below for our response.

Reviewer#1-1-Why only discrete data? Priv-PC can only deal with discrete data because PC algorithm itself can only deal with discrete data. We will make this clear in the revised version.

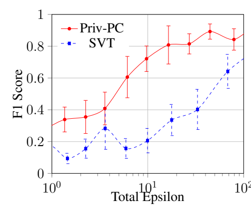
Reviewer#1-2-Performance on larger graphs. Thanks for the constructive feedback! Following the advice, we evaluated Priv-PC on three larger causal graphs: (1) Alarm with 37 nodes and 46 edges (Figure 1a); (2) Child with 20 nodes and 25 edges (Figure 1b); (3) Sachs with 11 nodes and 17 edges (Figure 1c). We use standard PC algorithm as the baseline (*i.e.* F1 score equaling 1 means the same performance as standard PC) and the results are consistent with the evaluation on small graphs in the paper. We are also running EM-PC on these datasets but have not been able to collect the results due to its long running time (about 10 hours per datapoint). We will include the new results in the revision.



(a) Alarm.



(b) Child.



(c) Sachs.

#idp tests	Priv-PC	EM-PC
Asia	95	216
Cancer	37	57
Earthquake	40	61
Survey	29	38
Alarm	1843	12979
Child	1162	7393
Sachs	165	1224

(d) The number of independence tests in Priv-PC and EM-PC.

Reviewer#2-1-Why SVT suffers from low accuracy. We refer to [4] as an explanation for the low accuracy of SVT.

Reviewer#2-2-Influence of greedy search on the privacy proof. Thanks for the review but there seems to be a misunderstanding about the statement due to our insufficient elaboration. Given the greedy search compromise, EM-PC's original privacy guarantee might not hold because the sensitivity of the utility score calculated with greedy search is not necessarily the same as the one used in the privacy proof. To validate the concern, we use greedy search to calculate the utility scores on neighboring datasets and observe a difference of 3, larger than the claimed sensitivity 1 used in the proof. We will make the statement more clear in the revision.

Reviewer#2-3-Is improvement due to relaxation of privacy? We appreciate the reviewer's feedback but there seems to be a misunderstanding about EM-PC due to our insufficient elaboration. EM-PC is (ϵ, δ)-differentially private because it is composed of multiple EMs with advanced composition [3]. The composition process makes EM-PC (ϵ, δ)-differentially private although exponential mechanism itself follows ϵ-differential privacy. Thus in our evaluation, EM-PC and Priv-PC are compared under exactly the same privacy guarantee. We will make it more clear in the revision.

Reviewer#2-4-Performance in the high privacy region. We agree that smaller privacy budget (≤ 1) provides stronger privacy guarantee, but we argue that in many data-intense tasks such as deep learning, privacy budget larger than 1 is acceptable and even a common case. For example, in Abadi et al.'s pioneering work [1], they use $\epsilon = 2, 4, 8$ in their experiments for a neural network with one hidden layer. Other examples of large ϵ can be found in many well-cited papers. Due to space limitation, we list two here [2, 5]. Priv-PC typically outperforms EM-PC somewhere between 2 and 8, which is an acceptable and practical privacy regime in many real-world applications.

Reviewer#3-1-Record the number of independence tests in EM-PC and Priv-PC. Thanks for the advice! As suggested, we have recorded the number of independence tests needed in Priv-PC and EM-PC on the 4 original datasets and the 3 new datasets as shown in Table 1d. The results show that Priv-PC saves 24%∼56% independence tests on small graphs and 94%∼97% on larger graphs compared to EM-PC. We will include the new results in the revision.

Reviewer#3-2-Compatibility with different independence tests. We admit that Priv-PC can only accommodate Kendall's τ and Spearman's ρ currently and the reconciling of other independence tests is an interesting future direction. On the other hand, although theoretically EM-PC can leverage any independence test, the only known way to obtain the accurate utility score is brutal-force search with exponential complexity, which is almost impossible to implement. Thus, we view Priv-PC as a step forward compared to EM-PC since it is implementable.

Reviewer#4-1-Is speed a big issue? We entirely agree that for most DP algorithms, the privacy-utility trade-off is the biggest challenge. We emphasize the speedup of Priv-PC because the only prior work, EM-PC, suffers from extremely slow computation. The slowing down stems from the privacy augmentation, which cannot be fully addressed by traditional methods developed for PC algorithm. Thus, we would like to find a way to achieve an elegant balance between speed, utility and privacy guarantee.

[1] M. Abadi, A. Chu, I. Goodfellow, H. B. McMahan, I. Mironov, K. Talwar, and L. Zhang. Deep learning with differential privacy.
[2] N. Agarwal, A. T. Suresh, F. X. X. Yu, S. Kumar, and B. McMahan. cpsgd: Communication-efficient and differentially-private distributed sgd.
[3] C. Dwork, G. N. Rothblum, and S. Vadhan. Boosting and differential privacy.
[4] M. Lyu, D. Su, and N. Li. Understanding the sparse vector technique for differential privacy.
[5] Y.-X. Wang, B. Balle, and S. P. Kasiviswanathan. Subsampled rényi differential privacy and analytical moments accountant.