Delay-allowed Differentially Private Data Stream Release

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A city transportation department monitors traffic flow to optimize signals and detect congestion.



- Vehicle Count
 Image: Count of the cou
- There are multiple streams continuously collected by sensors.

...

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• The analysts need to query the original stream for each new report.

How many vehicles are at a certain intersection during the rush hour? What is the average speed during rush hour on a certain day? When is the highest traffic flow on a certain street?

• If these streams contain sensitive personal information...

Frequent queries can increase the privacy leakage in the streams. Different types of queries require different privacy protection mechanisms. Data analysts need to interact frequently with data holders.

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It can be used to conduct all analysis without privacy concerns: How many vehicles are at a certain intersection during the rush hour? What is the average speed during rush hour on a certain day? When is the highest traffic flow on a certain street?

Differential Privacy Guarantee

We provide event-level DP protection for releasing private data stream.



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Adding noise to each data point introduces excessive noise into the data stream.

Group-based Post-Processing Framework



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data in the current group

Group-based Post-Processing Framework



start a new group from the next data

Group-based Post-Processing Framework



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The condition for accuracy improvement through post-processing is difficult to satisfy.





Merely addressing the length of the group doesn't provide much help.

Before proposing solutions, let's first consider two questions.

Is real-time release required for all data streams in practice?

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Net Load Forecasting



User Behavior Analysis



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Network Latency



Data Integration



Processing Time



Therefore, we consider a stream release setting that allows for a small delay.

Batch setting



What is the difference from processing batched data ?

The data within a batch maintains a temporal relationship.

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What is the difference from processing batched data ?

The data within a batch maintains a temporal relationship.

Sliding window setting



When processing each data, you can look ahead at the next w data points.

Batch Setting

Discontinuous Grouping



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Discontinuous Grouping









grouping/ordering results and saves the privacy budget.



Integrate all the things into a framework.



Fig. 1. Overview of the privacy-preserving and delay-allowed data releasing framework. This framework identifies the optimal strategy for the input stream, then introduces noise to comply with differential privacy (DP) standards, and finally post-processes the noised data stream before its release.

Comparisons of accuracy between the proposed methods and PeGaSus.



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Comparisons of accuracy with Methods from other privacy setting.

Methods	Unemployment			Outpatient		
	0.1	0.5	1.0	0.1	0.5	1.0
Naïve	1.0×	1.0 imes	1.0 imes	1.0 imes	1.0 imes	1.0×
DPI	$0.08 \times$	0.38×	0.76×	$0.05 \times$	$0.25 \times$	$0.48 \times$
Adapub	$1.26 \times$	$1.24 \times$	$1.26 \times$	$1.23 \times$	$1.25 \times$	$1.23 \times$
Discontin	0.41×	0.41×	0.41×	0.41×	0.41×	0.41×
CompOrder	0.19×	$0.28 \times$	$0.40 \times$	$0.20 \times$	0.39×	$0.56 \times$
BucOrder	$0.03 \times$	0.17 imes	$0.35 \times$	0.03×	$0.15 \times$	$0.29 \times$

[1] Feng, Shuya, et al. "Dpi: Ensuring strict differential privacy for infinite data streaming." 2024 IEEE Symposium on Security and Privacy (SP). IEEE, 2024.
[2] Wang, Teng, et al. "Adaptive differentially private data stream publishing in spatio-temporal monitoring of IoT." 2019 IEEE 38th International Performance Computing and Communications Conference (IPCCC). IEEE, 2019.

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The proposed methods **show accuracy advantages** over state-of-the-art solutions from **other privacy settings** with a delay of 10 timestamps.

 Feng, Shuya, et al. "Dpi: Ensuring strict differential privacy for infinite data streaming." 2024 IEEE Symposium on Security and Privacy (SP). IEEE, 2024.
Wang, Teng, et al. "Adaptive differentially private data stream publishing in spatio-temporal monitoring of IoT." 2019 IEEE 38th International Performance Computing and Communications Conference (IPCCC). IEEE, 2019. This paper developed a framework for data stream releases that allows for a delay.

Hope it inspires!

Questions are welcome 🥹!

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Paper & Artifact