

**PRIVACY PRESERVING DATA PUBLISHING  
FRAMEWORK FOR UNSTRUCTURED TEXTUAL  
SOCIAL MEDIA DATA**

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## DECLARATION

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## **Abstract**

Privacy has become an essential part of data science and analytics due to the potential of personal data misuse. As a result of privacy breaches reported in various analytical studies privacy preservation has become a legal responsibility rather than a simple social responsibility. Preserving privacy of unstructured data is more challenging compared to structured data. Social media has become largely popular over the past couple of decades and they are pumping a huge amount of data at a high velocity into analytical systems. Social media profiles contain a wealth of personal and sensitive information, creating enormous opportunities for third parties to analyze them with different algorithms, draw conclusions and use in disinformation campaigns and micro targeting based dark advertising. The primary goal of this study is to provide a mitigation mechanism for privacy breaches happening via disinformation campaigns that are done based on the insights extracted from personal/sensitive data analysis. Specifically, this research is aimed at building a privacy preserving data publishing framework for unstructured and textual social media data without compromising the true analytical value of those data. A novel way is proposed to apply traditional structured privacy preserving techniques on unstructured data. Creating a comprehensive twitter corpus annotated with privacy attributes is another objective of this research, especially because the research community is lacking one.

An easily extensible framework that can be adopted by many domains is implemented here, integrating different concepts from the literature. A comprehensive set of experiments are also performed in order to assess the capabilities of the machine learning models, algorithms as well as to simulate some real-world privacy preserving data publishing use cases.

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## **LIST OF ABBREVIATIONS**

API	Application Programming Interface
EU	European Union
EEA	European Economic Area
BDSG	Bundesdatenschutzgesetz
GDPR	General Data Protection Regulation
PPDP	Privacy Preserving Data Publishing
GSR	Global Science Research
PPDM	Privacy Preserving Data Mining
MinGen	Minimum Generalization Algorithm
PPDC	Privacy Preserving Data Collection
GPS	Global Positioning System
LM	Loss Metric
DM	Discernibility Metrics
IoT	Internet of Things
UK DA	United Kingdom Data Archive
KL Distance	Kullback-Leibler Distance