A Novel Approach on the Joint De-Identification of Textual and Relational Data with a Modified Mondrian Algorithm

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ABSTRACT

Traditional approaches for data anonymization consider relational data and textual data independently. We propose rx-anon, an anonymization approach for heterogeneous semi-structured documents composed of relational and textual attributes. We map sensitive terms extracted from the text to the structured data. This allows us to use concepts like k -anonymity to generate a joint, privacy-preserved version of the heterogeneous data input. We introduce the concept of redundant sensitive information to consistently anonymize the heterogeneous data. To control the influence of anonymization over unstructured textual data versus structured data attributes, we introduce a modified, parameterized Mondrian algorithm. We evaluate our approach with two real-world datasets using a Normalized Certainty Penalty score, adapted to the problem of jointly anonymizing relational and textual data. The results show that our approach is capable of reducing information loss by using the tuning parameter to control the Mondrian partitioning while guaranteeing k -anonymity. As rx-anon is a framework approach, it can be reused and extended by other anonymization algorithms, privacy models, and textual similarity metrics.

CCS CONCEPTS

• Security and privacy → Data anonymization and sanitization; • Computing methodologies → Information extraction.

KEYWORDS

data anonymization, heterogeneous data, k -anonymity

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Supplementary Materials

A EXTENDED EXPERIMENTAL RESULTS

The following sections contain extended experiment results. In particular, we provide numbers of distinct entities, give information about the performance of our framework, share statistics relevant for partitioning, and present details on information loss.

A.1 Distinct Terms

Table 1 provides an overview of the number of distinct terms appearing in textual attributes. In general, the texts of the Blog Authorship Corpus contain significantly more distinct entities.

Table 1: Numbers of distinct terms per entity type. The Blog Authorship Corpus contains one textual attribute *text*. The Hotel Reviews Dataset contains two textual attributes, namely *negative review* and *positive review*.

entity type	Blog Authorship Corpus text	Hotel Reviews Dataset	
		negative review	positive review
DATE	83,972	2,672	1,993
EVENT	13,883	161	244
FAC	32,864	3,452	14,070
GPE	34,639	1,058	2,512
LANGUAGE	761	30	30
LAW	5,153	12	3
LOC	13,635	480	1,370
MAIL	3,225	0	0
MONEY	16,050	2,089	625
NORP	9,676	293	344
ORG	162,555	3,887	9,444
PERCENT	4,104	30	25
PERSON	245,667	2,273	5,728
PHONE	442	1	0
POSTCODE	739	7	8
PRODUCT	48,207	842	892
TIME	61,669	4,311	2,366
URL	29,297	0	0
WORK_OF_ART	145,421	290	349

A.2 Performance

Table 2 provides valuable insights in execution times of the experiments. Each experiment was executed on a single CPU core and did not require to analyze the texts, since the processed Natural Language Processing (NLP) state is read from cached results. In the case of experiments run on the Blog Authorship Corpus, execution times were significantly higher compared to the Hotel Reviews dataset. One observation is that if only relational attributes are considered (Mondrian, $\lambda = 1$), execution times come down to a fraction of experiments where sensitive terms are considered during the partitioning phase.

Considering memory consumption, running a single experiment on the Blog Authorship Corpus required 25.2 GB for all entities and 13.4 GB in the case of just considering GPE entities (locations). In the case of the Hotel Review dataset, 5.4 GB and 4.2 GB were required respectively.

Table 2: Execution times of experiments in hh:mm:ss.

	λ	Blog Authorship Corpus		Hotel Reviews Dataset	
		all	GPE	all	GPE
GDF	-	10:25:12	03:50:13	00:12:55	00:10:26
	0	15:19:31	02:46:14	00:29:26	00:11:44
Mondrian	0.1	15:01:34	01:32:25	00:29:56	00:13:16
	0.2	14:43:37	01:30:11	00:29:44	00:12:58
	0.3	14:32:23	01:24:31	00:29:17	00:12:49
	0.4	13:59:02	01:15:58	00:27:59	00:12:44
	0.5	11:03:43	01:04:59	00:25:13	00:12:18
	0.6	11:05:29	01:05:04	00:25:12	00:12:20
	0.7	11:06:26	01:04:47	00:25:14	00:12:20
	0.8	11:03:33	01:04:50	00:25:01	00:12:23
	0.9	11:02:57	01:04:32	00:25:12	00:12:19
	1	01:48:41	00:47:22	00:12:48	00:11:17

A.3 Partitions

In our experiments, we evaluate statistics on partition splits to gain insights how λ influences splitting decisions of Mondrian partitioning. Moreover, we also share statistics on resulting partitions.

A.3.1 Partition Splits. Figure 1 provides an overview of the distribution of splitting decisions between relational and textual attributes for experiments run on the Blog Authorship Corpus for all values of k . The left column includes experiments considering all entities, while the right column presents results for experiments run only considering location (GPE) entities.

A noteworthy observation is that for a fixed λ , the number of splits on textual attributes decreases if k increases. Since we are only considering valid splits, sensitive terms have to appear at least $2k$ times within a partition to be split on. Therefore, in case of $k = 50$, sensitive terms are required to appear 100 times, which is less likely due to heterogeneity of blog post texts.

If only locations, i. e., entities of type GPE, are considered, λ is not in all cases able to control the share of splits between relational and textual attributes, since low values for λ do not result in more splits on textual attributes. This effect is caused by the lack of multi-dimensionality. Since only one category of sensitive entity types is considered, Mondrian has only one option (namely split on sensitive terms with type GPE) to split on textual attributes. If splits on GPE terms fail (e. g., if there are none), Mondrian will ultimately continue to split on a relational attribute.

Similarly, Figure 2 highlights the impact of λ on partition splits for experiments run on the Hotel Reviews Dataset for all values of k .

A.3.2 Partition Count and Size. We present the results regarding partition statistics. Table 3 provides valuable insights on the number of partitions as well as the size and standard deviation regarding partition sizes for the experiments on the Blog Authorship Corpus considering all entities. Similarly, Table 4 provides an overview of the same metrics for the Blog Authorship Corpus only considering GPE entities (locations). Tables 5 and 6 share insights on partition statistics for the Hotel Reviews dataset.

A.4 Information Loss

In addition to evaluating resulting partitions, we are also interested in the actual information loss which is introduced by anonymizing a given dataset. Figure 3 provides an overview of information loss for experiments run on the Blog Authorship Corpus. In particular, Figure 3a visualizes relational and Figure 3b textual information loss for experiments considering all entity types. Similarly, Figure 3c and Figure 3d provide an overview of information loss if only GPE entities are considered. Figure 6 provides the same statistics for the Hotel Reviews Dataset.

Moreover, Figures 4 and 5 provide a zoomed version of Figure 3b and Figure 3d showing textual information loss for experiments on the Blog Authorship Corpus. Similarly, we visualize zoomed textual information loss for the Hotel Reviews Dataset in Figure 7 and Figure 8.

In addition to high-level charts on information loss, Figure 9 provides a detailed analysis of information loss per entity type for the attribute *text* in the Blog Authorship Corpus. Additionally, Figure 10 and Figure 11 visualize the textual information loss per entity type for the attributes *negative review* and *positive review* respectively.

B EXTENDED RELATED WORK

We present related work for anonymization of other types of data.

B.1 Research in Data Anonymization for Audio, Images, and Video

Even though this work only focuses on structured data and free text, recent work on anonymization of other forms of data is worth mentioning. For de-identification of images showing faces, Gross et al. [4] highlighted that pixelation and blurring offers poor privacy and suggested a model-based approach to protect privacy while preserving data utility. In contrast, recent work by Hukkelås et al. [5] applied methods from machine learning by implementing

a simple Generative Adversarial Network (GAN) to generate new faces to preserve privacy while retaining original data distribution.

For audio data, recent work focused either on anonymization of the speaker's identity or the speech content. Justin et al. [6] suggested a framework which automatically transfers speech into a de-identified version using different acoustical models for recognition and synthesis. Moreover, Cohn et al. [2] investigated the task of de-identifying spoken text by first using Automatic Speech Recognition (ASR) to transcribe texts, then extracting entities using Named Entity Recognition (NER), and finally aligning text elements to the audio and suppressing audio segments which should be de-identified.

Additionally, recent work by Agrawal and Narayanan [1] showed that de-identification of people can also be applied to whole bodies within videos whereas Gafni et al. [3] focused on live de-identification of faces in video streams.

Finally, McDonald et al. [7] developed a framework for obfuscating writing styles which can be used by authors to prevent stylometry attacks to retrieve their identities. When it comes to unstructured text, their approach anonymizes writing styles in text

documents by analyzing stylistic properties, determining features to be changed, ranking those features with respect to their clusters, and suggesting those changes to the user.

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Figure 1: Splitting statistics for the Blog Authorship Corpus. Left plots are results for experiments run considering all entities. Right plots represent statistics for experiments run only considering GPE entities.

Figure 2: Splitting statistics for Hotel Reviews Dataset. Left plots are results for experiments run considering all entities. Right plots represent statistics for experiments run only considering GPE entities.

Table 3: Statistics on resulting partitions for Blog Authorship Corpus considering all entity types.

		λ	k	2	3	4	5	10	20	50
GDF	-		count	5810	2479	1512	1078	352	92	7
			size	3.33	7.79	12.78	17.92	54.88	209.99	2759.86
			std	26.78	103.95	199.22	292.95	726.15	1742.66	7146.68
Mondrian	0		count	8219	5162	3795	2971	1412	692	278
			size	2.35	3.74	5.09	6.50	13.68	27.92	69.49
			std	0.76	1.15	1.48	1.91	3.56	6.76	18.28
	0.1		count	8277	5226	3841	3028	1471	710	286
			size	2.33	3.70	5.03	6.38	13.13	27.21	67.55
			std	0.47	0.78	1.06	1.35	2.74	5.77	14.40
	0.2		count	8243	5234	3829	3031	1460	715	283
			size	2.34	3.69	5.05	6.37	13.23	27.02	68.27
			std	0.47	0.79	1.06	1.36	2.79	5.67	14.64
	0.3		count	8302	5236	3841	3023	1462	707	280
			size	2.33	3.69	5.03	6.39	13.21	27.33	69.00
			std	0.47	0.78	1.06	1.34	2.82	5.81	14.47
	0.4		count	8307	5238	3855	3024	1466	720	283
			size	2.33	3.69	5.01	6.39	13.18	26.83	68.27
			std	0.47	0.78	1.06	1.36	2.77	5.57	14.50
	0.5		count	8186	5198	3800	2979	1441	711	278
			size	2.36	3.72	5.08	6.49	13.41	27.17	69.49
			std	0.48	0.77	1.07	1.34	2.76	5.68	14.59
	0.6 - 0.9		count	8168	5180	3781	2987	1441	711	276
			size	2.37	3.73	5.11	6.47	13.41	27.17	70.00
			std	0.48	0.77	1.07	1.35	2.76	5.69	14.43
	1		count	8080	5128	3749	2964	1431	703	273
			size	2.39	3.77	5.15	6.52	13.50	27.48	70.77
			std	0.51	0.80	1.10	1.38	2.80	5.78	14.63

Table 4: Statistics on resulting partitions for Blog Authorship Corpus considering only GPE entities

λ	k	2	3	4	5	10	20	50
GDF	-	count	2140	737	301	129	2	1
		size	9.03	26.21	64.18	149.76	9659.50	19319
		std	575.34	1016.03	1629.78	13645.04	0	0
Mondrian	0	count	1447	1164	828	703	392	242
		size	13.35	16.60	23.33	27.48	49.28	79.83
		std	113.84	126.77	150.14	162.72	217.34	275.39
	0.1	count	8137	5265	3790	3019	1460	704
		size	2.37	3.67	5.10	6.40	13.23	27.44
		std	0.49	0.77	1.09	1.36	2.83	5.82
	0.2	count	8186	5227	3801	3016	1451	709
		size	2.36	3.70	5.08	6.41	13.31	27.25
		std	0.48	0.79	1.08	1.37	2.85	5.87
	0.3	count	8167	5248	3780	2994	1443	700
		size	2.37	3.68	5.11	6.45	13.39	27.60
		std	0.48	0.78	1.09	1.34	2.86	6.08
	0.4	count	8153	5200	3780	3022	1473	707
		size	2.37	3.72	5.11	6.39	13.12	27.33
		std	0.48	0.79	1.08	1.35	2.74	5.88
	0.5	count	8153	5154	3762	2970	1433	703
		size	2.37	3.75	5.14	6.50	13.48	27.48
		std	0.49	0.79	1.09	1.37	2.79	5.82
	0.6 - 0.9	count	8146	5153	3761	2970	1433	703
		size	2.37	3.75	5.14	6.50	13.48	27.48
		std	0.49	0.79	1.09	1.37	2.79	5.78
	1	count	8080	5128	3749	2964	1431	703
		size	2.39	3.77	5.15	6.52	13.50	27.48
		std	0.51	0.80	1.10	1.38	2.80	5.78

Table 5: Statistics on resulting partitions for Hotel Reviews Dataset considering all entity types.

		λ	k	2	3	4	5	10	20	50
GDF	-	count	523	272	163	127	43	16	1	
		size	2.82	5.42	9.05	11.61	34.30	92.19	1475	
		std	3.45	11.51	24.56	35.47	112.32	264.30	0	
	0	count	645	398	293	226	117	54	21	
		size	2.29	3.71	5.03	6.53	12.61	27.31	70.24	
		std	0.47	0.77	1.11	1.45	2.60	5.59	15.67	
	0.1	count	635	401	294	231	115	56	22	
		size	2.32	3.68	5.02	6.39	12.83	26.34	67.05	
		std	0.47	0.76	1.04	1.39	2.78	5.22	14.78	
Mondrian	0.2	count	641	404	295	224	112	51	20	
		size	2.30	3.65	5	6.58	13.17	28.92	73.75	
		std	0.46	0.75	1.08	1.41	2.71	5.03	15.00	
	0.3	count	645	404	285	212	106	50	24	
		size	2.29	3.65	5.18	6.96	13.92	29.50	61.46	
		std	0.45	0.79	1.03	1.41	2.43	3.65	6.47	
	0.4	count	610	406	268	209	113	48	20	
		size	2.42	3.63	5.50	7.06	13.05	30.73	73.75	
		std	0.49	0.84	0.85	1.76	2.32	6.71	6.45	
	0.5	count	558	415	256	255	128	64	20	
		size	2.64	3.55	5.76	5.78	11.52	23.05	73.75	
		std	0.48	0.84	0.70	0.72	1.19	2.22	19.13	
	0.6 - 1	count	554	417	256	255	128	64	20	
		size	2.66	3.54	5.76	5.78	11.52	23.05	73.75	
		std	0.47	0.83	0.70	0.71	1.19	2.22	19.13	

Table 6: Statistics on resulting partitions for Hotel Reviews Dataset considering only GPE entities.

		k	2	3	4	5	10	20	50
λ									
GDF	-	count	303	107	47	15	1	1	1
		size	4.87	13.79	31.38	98.33	1475	1475	1475
		std	18.59	90.92	179.98	358.71	0	0	0
Mondrian	0	count	74	49	35	32	17	13	7
		size	19.93	30.10	42.14	46.09	86.76	113.46	210.71
		std	61.71	74.77	86.30	89.59	112.62	121.77	135.59
	0.1	count	603	408	276	236	117	59	18
		size	2.45	3.62	5.34	6.25	12.61	25	81.94
		std	0.50	0.72	1.10	1.06	1.82	3.03	13.70
	0.2	count	647	380	318	201	95	45	21
		size	2.28	3.88	4.64	7.34	15.53	32.78	70.24
		std	0.45	0.70	0.89	1.45	2.70	4.46	8.09
	0.3	count	634	376	312	211	101	50	21
		size	2.33	3.92	4.73	6.99	14.60	29.50	70.24
		std	0.47	0.75	0.89	1.55	2.91	5.75	7.42
	0.4	count	657	362	327	202	99	50	21
		size	2.25	4.07	4.51	7.30	14.90	29.50	70.24
		std	0.43	0.66	0.75	1.51	2.82	5.75	7.42
	0.5 - 1	count	554	417	256	255	128	64	20
		size	2.66	3.54	5.76	5.78	11.52	23.05	73.75
		std	0.47	0.83	0.70	0.71	1.19	2.22	19.13

(a) Relational information loss NCP_A , all entity types (b) Textual information loss NCP_X , all entity types (c) Relational information loss NCP_A , only GPE entities (d) Textual information loss NCP_X , only GPE entities

Figure 3: Relational and textual information loss for experiments run on the Blog Authorship Corpus. Results for relational (a) and textual information loss (b) for experiments considering all entities. Results for relational (c) and textual information loss (d) for experiments considering only GPE entities.

Figure 4: Zoomed textual information loss for experiments run on the Blog Authorship Corpus considering all entities.

Figure 5: Zoomed textual information loss for experiments run on the Blog Authorship Corpus considering only GPE entities.

(a) Relational information loss NCP_A , all entity types (b) Textual information loss NCP_X , all entity types (c) Relational information loss NCP_A , only GPE entities (d) Textual information loss NCP_X , only GPE entities

Figure 6: Relational and textual information loss for experiments run on the Hotel Reviews Dataset. Results for relational (a) and textual information loss (b) for experiments considering all entities. Results for relational (c) and textual information loss (d) for experiments considering only GPE entities.

Figure 7: Zoomed textual information loss for experiments run on the Hotel Reviews Dataset considering all entities.

Figure 8: Zoomed textual information loss for experiments run on the Hotel Reviews Dataset considering only GPE entities.

Figure 9: Textual information loss of the attribute *text* per entity types for experiments run on the Blog Authorship Corpus. Information loss is visualized for GDF and Mondrian partitioning with varying λ .

Figure 10: Textual information loss of the attribute *negative review* per entity type for experiments run on the Hotel Reviews Dataset. Information loss is visualized for GDF and Mondrian partitioning with varying λ .

Figure 11: Textual information loss of the attribute *positive review* per entity type for experiments run on the Hotel Reviews Dataset. Information loss is visualized for GDF and Mondrian partitioning with varying λ .