Security and Privacy - Assignment 4

Privacy-Preserving Data Publishing

Diogo Cordeiro (201705417) Hugo Sales (201704178)

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Attribute classification

We classified the attributes as follows:

Table 1: Attribute classifications

Attribute	Classification
`age`	QID
`workclass`	Insensitive
`fnlwgt`	Insensitive
`education`	QID
`education-num`	QID
`marital-status`	QID
`occupation`	QID
`relationship`	QID
`race`	QID
`sex`	QID
`capital-gain`	Sensitive
`capital-loss`	Sensitive
`hours-per-week`	QID
`native-country`	Insensitive
`prediction`	Insensitive

Justifications

The vast majority of attributes present low values of distinction. This is consistent with the nature of the dataset, considering that `fnlwgt` should indicate the quantity of individuals that present the same set of attributes.

`age`

According to HIPPA recommendations, and together with it's very high separation value (99.87%), we classify this attribute as a QID.

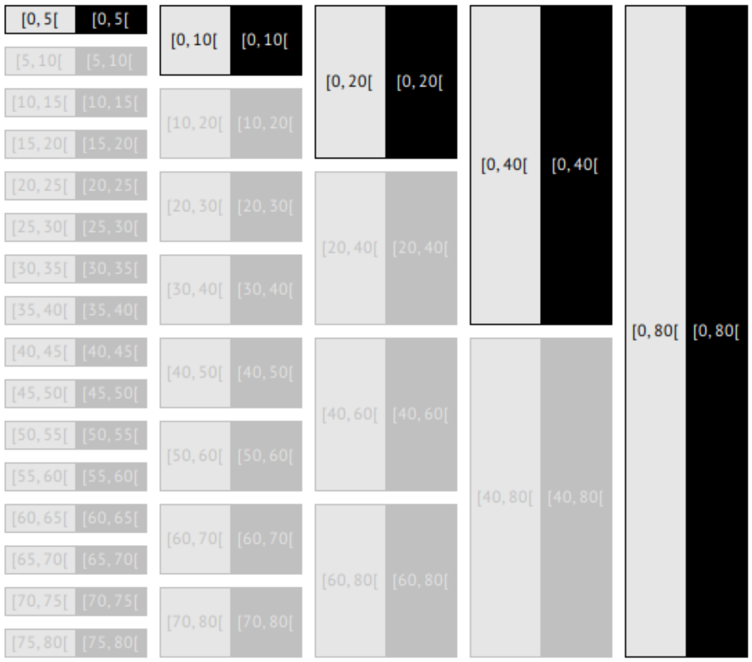


Figure 1: Hierarchy for attribute `age`

`workclass`

This attribute presents a relatively low separation value (49.71%), and given how generic it is, it's deemed Insensitive.

`fnlwgt`

Despite high values of distinction (66.48%) and separation (99.99%) the `fnlwgt` column is not a QID because it represents a weight, not a count of individuals in the same equivalence class in the original dataset. This can be seen with the results below. Additionally, it's not easily connected to other auxiliary datasets.

```
$ tail -n '+2' adult_data.csv | awk -F',' '{count[$10] += $3;} \
    END {for(sex in count){print sex, count[sex]}}'
```

Resulting in:

Table 2: Sum of `fnlwgt` for each `sex`

Sex	Sum
Female	2000673518
Male	4178699874

The sum of these values is 6,179,373,392. This value is much larger than the population of the U.S.A., the origin of the dataset, which implies this attribute is not a count, as stated.

We also note there are substantially more Male than Female records, being that the sum of `fnlwgt` for Male is more than double that of Female, as well as that the number of rows with Female is 10771 and for Male is 21790.

`education`

This attribute presents a separation of 80.96%, which is quite high, thus we classified it as a QID.

Level-0	Level-1	Level-2	Level-3
Preschool	{Preschool, 1st-4th, 5th-6th}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
1st-4th	{Preschool, 1st-4th, 5th-6th}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
5th-6th	{Preschool, 1st-4th, 5th-6th}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
7th-8th	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
9th	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
10th	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
11th	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
12th	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
HS-grad	{7th-8th, 9th, 10th, 11th, 12th, HS-grad}	{Preschool, 1st-4th, 5th-6th, 7th-8th, 9th, 10th, 11th, 12th, HS-grad}	*
Some-college	{Some-college, Assoc-voc, Assoc-acdm}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Assoc-voc	{Some-college, Assoc-voc, Assoc-acdm}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Assoc-acdm	{Some-college, Assoc-voc, Assoc-acdm}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Bachelors	{Bachelors, Masters}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Masters	{Bachelors, Masters}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Prof-school	{Prof-school, Doctorate}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*
Doctorate	{Prof-school, Doctorate}	{Some-college, Assoc-voc, Assoc-acdm, Bachelors, Masters, Prof-school, Doctorate}	*

Figure 2: Hierarchy for attribute `education`

`education-num`

We used the following command to verify there weren't any discrepencies between the `education` and `education-num` columns:

```
$ cat adult_data.csv | awk -F',' '{print $5, $4}' | sort -un
```

Since there was a one-to-one mapping, we confirmed this was just a representation of the `education` attribute. As such, this attribute recieves the same classification, which is backed by the equally high separation value of 80.96%, so it's classified as a QID.

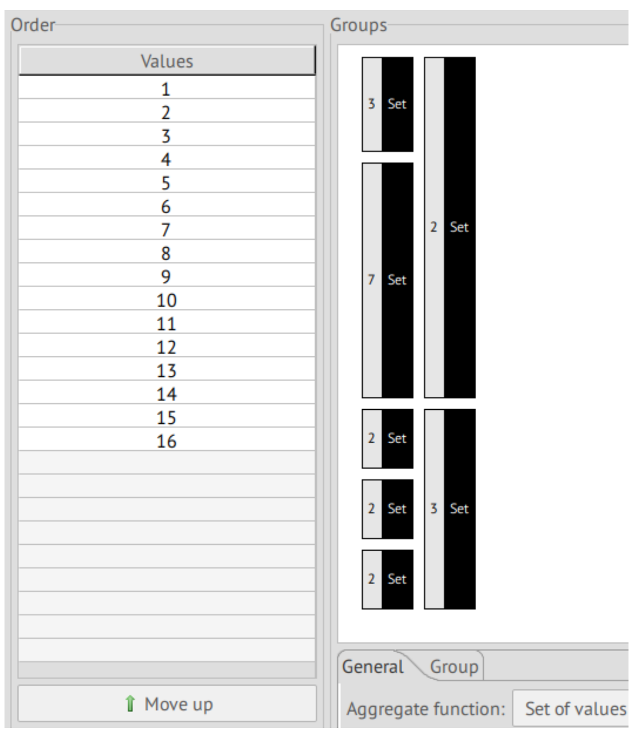


Figure 3: Hierarchy for attribute `education-num`

`marital-status`

With a relatively high separation value of 66.01%, together with the fact that it could be cross referenced with other available datasets, we classify this attribute as a QID.

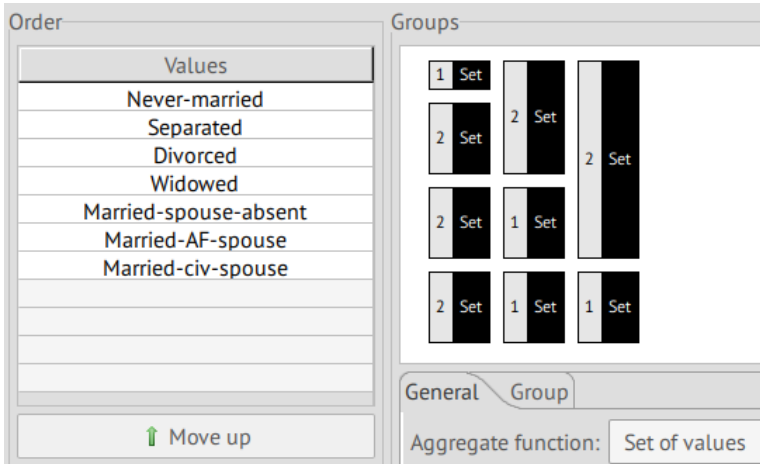


Figure 4: Hierarchy for attribute `marital-status`

`occupation`

With a separation of 90.02%, this attribute is classified as a QID.

Level-0	Level-1	Level-2
?	{?}	*
Adm-clerical	Other	*
Armed-Forces	Military	*
Craft-repair	Technical	*
Exec-managerial	Non-Technical	*
Farming-fishing	Agriculture	*
Handlers-cleaners	Non-Technical	*
Machine-op-inspct	Technical	*
Other-service	Other	*
Priv-house-serv	Other	*
Prof-specialty	Technical	*
Protective-serv	Other	*
Sales	Non-Technical	*
Tech-support	Technical	*
Transport-moving	Other	*

Figure 5: Hierarchy for attribute `occupation`

`relationship`

Given it's separation value of 73.21%, this attribute is classified as a QID.

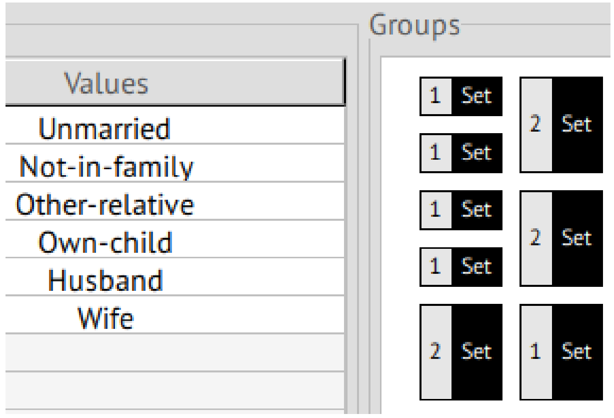
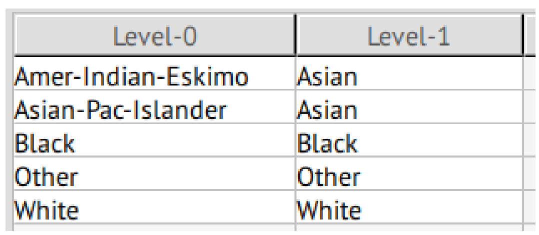


Figure 6: Hierarchy for attribute `relationship`

`race`

This collumn presents some weirdly specific values (Amer-Indian-Eskimo), but has a separation of 25.98%; given the fact that this attribute could be cross referenced with other datases, it is classified as a QID, so it may be transformed into more generic values.



Level-0	Level-1
Amer-Indian-Eskimo	Asian
Asian-Pac-Islander	Asian
Black	Black
Other	Other
White	White

Figure 7: Hierarchy for attribute `race`

`sex`

Despite the low separation value of 44.27%, this attribute is canonically classified as a QID, since it can be easily cross referenced with other datasets.

We noted this dataset seems to have more males than females. See Table 2 and the following table

Table 3: Number of records with each `education` for each `sex`

`education`	Female	Male
Preschool	16	35
1st-4th	46	122
5th-6th	84	249
7th-8th	160	486
9th	144	370
10th	295	638
11th	432	743
12th	144	289
HS-grad	3390	7111
Some-college	2806	4485
Assoc-voc	500	882

education	Female	Male
Assoc-acdm	421	646
Bachelors	1619	3736
Masters	536	1187
Prof-school	92	484
Doctorate	86	327

Level-0	Level-1
Female	{Female, Male}
Male	{Female, Male}

Figure 8: Hierarchy for attribute `sex`

`capital-gain` & `capital-loss`

With a separation of 15.93% and 9.15% respectively, these attributes are not QIDs. They're qualified as Sensitive, as the individuals may not want their capital gains and losses publicly known.

A t-closeness privacy model was chosen for these attributes, with a value of t of 0.2. This reasoning is discussed in Applying anonymization models > k-Anonymity > Effect of parameters

`hours-per-week`

This attribute has a relatively high separation (76.24%) and since it had really unique values, it could be cross referenced with another dataset to help identify individuals, so it's classified as QID.

`native-country`

While this attribute might be regarded as a QID, it presents really low separation values (19.65%) in this dataset, so it's qualified as Insensitive.

`prediction`

This is the target attribute, the attribute the other attributes predict, and is therefore Insensitive.

Privacy risks in the original dataset

In the original dataset, nearly 40% of records have a more than 50% risk of re-identification by a prosecutor. In general, we see a stepped distribution of the record risk, which indicates some privacy model was already applied to the dataset, however to a different standard than what we intend.

All records had really high uniqueness percentage even for small sampling factors, according to the Zayatz, Pitman and Dankar methods. Only SNB indicated a low uniquess percentage for sampling factors under 90%. What this means, is that with a fraction of the original dataset, a very significant number of records was sufficiently unique that it could be distinguished among the rest, which means it's potentially easier to re-identify the individuals in question.

All attacker models show a success rate of more than 50%, which is not acceptable.

Applying anonymization models

k-Anonymity

We opted for 8-anonymity, for it's tradeoff between maximal risk and suppression.

t-closeness was chosen for `capital-gain` and `capital-loss` (sensitive attributes).

Re-identification risk

The average re-identification risk dropped to nearly 0%, whereas the maximal risk dropped to 12.5%. The success rate for all attacker models was reduced drastically, to 1.3%.

Utility

Definitions

Precision Measures data distortion, equated to the Generalization Intensity (Gen. Intensity) of attribute values. [1]

Information Loss Measures the extent to which values are generalized. It summarizes the degree to which transformed attribute values cover the original domain of an attribute. It is equated to the converse of Granularity.

We checked [2], as mentioned in ARX's help, but no useful definition of granularity was provided therein.

Classification Performance Measures how well the attributes predict the target variable (`prediction`, in this case).

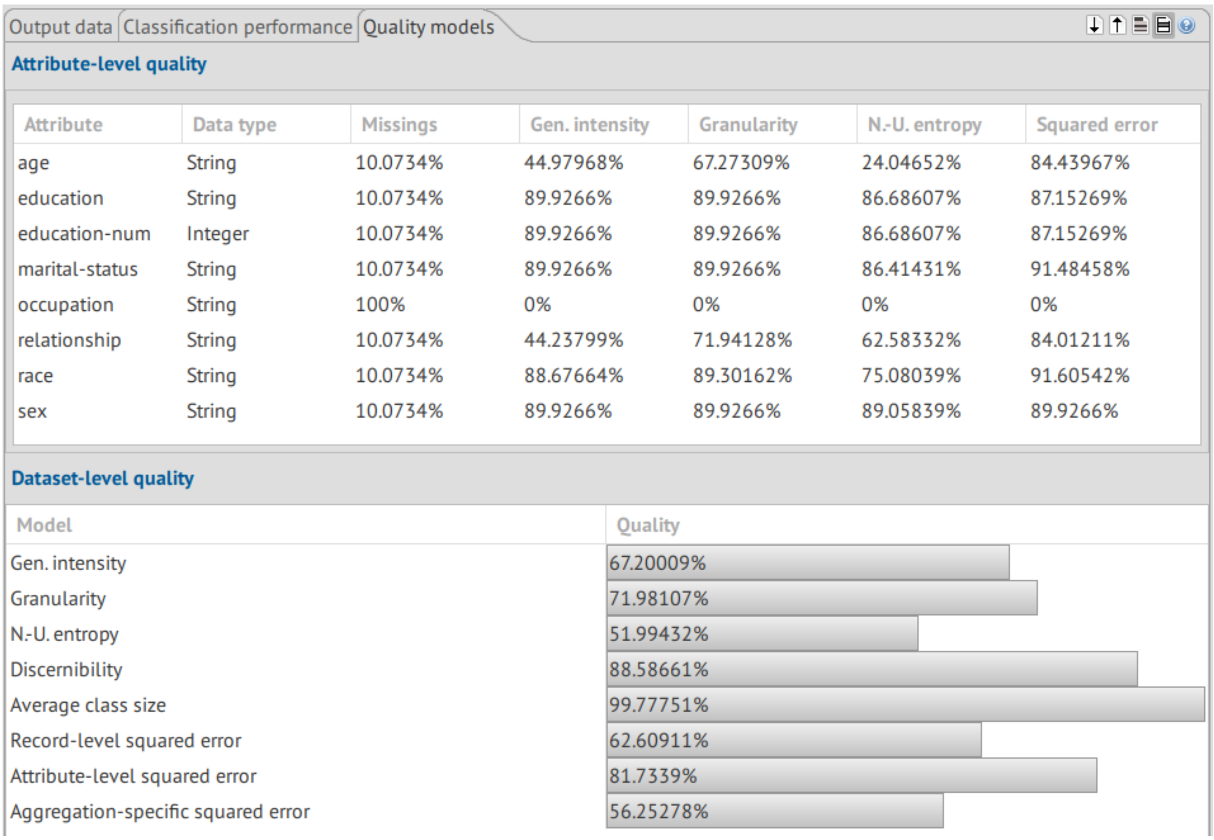
Discernibility Measures the size of groups of indistinguishable records and with a penalty for records which have been completely suppressed. [3]

Average class size Measures the average size of groups of indistinguishable records. [4]

Analysis

The original Classification Performance, was 83.24% and it remained at 82.45%.

10.07% of attributes are missing from the anonymized dataset. This value being equal across all atributes suggests entire rows were removed, rather than select values from separate rows. The only exception is the `occupation` attribute, which was entirely removed.



Output data | Classification performance | Quality models

Attribute-level quality

Attribute	Data type	Missings	Gen. intensity	Granularity	N.-U. entropy	Squared error
age	String	10.0734%	44.97968%	67.27309%	24.04652%	84.43967%
education	String	10.0734%	89.9266%	89.9266%	86.68607%	87.15269%
education-num	Integer	10.0734%	89.9266%	89.9266%	86.68607%	87.15269%
marital-status	String	10.0734%	89.9266%	89.9266%	86.41431%	91.48458%
occupation	String	100%	0%	0%	0%	0%
relationship	String	10.0734%	44.23799%	71.94128%	62.58332%	84.01211%
race	String	10.0734%	88.67664%	89.30162%	75.08039%	91.60542%
sex	String	10.0734%	89.9266%	89.9266%	89.05839%	89.9266%

Dataset-level quality

Model	Quality
Gen. intensity	67.20009%
Granularity	71.98107%
N.-U. entropy	51.99432%
Discernibility	88.58661%
Average class size	99.77751%
Record-level squared error	62.60911%
Attribute-level squared error	81.7339%
Aggregation-specific squared error	56.25278%

Figure 9: Quality models

The high values for Generalization Intensity and Granularity suggest a moderate ammount of information loss and a loss of precision.

The values for Discernibility and Average Equivalence Class Size are also high. And in general, all the quality models (both attribute-level and dataset-level) are high.

However, given the classification performance is maintained, this was deemed acceptable.

Effect of parameters

At a suppression limit of 0%, the same accuracy is maintained, but the vast majority of QIDs are entirely removed.

At a suppression limit of 5%, roughly the same prediction accuracy is maintained, with around 4.5% of values missing, however with really high Generalization Intensity values for some attributes (e.g. 95.42% for `sex`, 93.87% for `race` and 91.47% for `education` and `education-num`). `occupation` was entirely removed.

At a suppression limit of 10%, the prediction accuracy is maintained, with around 9.8% of values missing. However, the Gen. Intensity drops to around 90%.

At a suppression limit of 20%, accuracy is maintained, once again, with around 10% of values missing, indicating this would be the optimal settings, as the same results are achieved with a limit of 100%.

At a t-closeness for `capital-gain` and `capital-loss` t value of 0.001 (the default), anonymization fails, not producing any output.

At a t value of 0.01, accuracy drops to 75% and most attributes have missing values of 100%.

At a t value of 0.1, classification accuracy is nearly 81%, but missings values are around 20%.

At a t value of 0.2, the chosen value, the accuracy is 82.5% with lower Gen. Intensity values.

At a t value of 0.5, the classification accuracy goes to 82.2% with increased Generalization Intensity values.

Adjusting the coding model had no significant effects.

(ϵ, δ)-Differential Privacy

With the default ϵ value of 2 and a δ value of 10^{-6}, the performance was really good.

Re-identification risk

All indicators for risk by each attacker model were between 0.1% and 0.9%.

Utility

The original Classification Performance was 83.24% and it remained at 80.97%.

Nearly 16% of attributes are missing, with the expection of `age` and `education-num`, which are 100% missing.

Effect of parameters

An ϵ value of 3 maintained the accuracy at 80.5% with missings values rounding 32%.

An increase of δ to 10^{-5} resulted in a classification performance of 82.05% and a missings value of 21.02% for all attributes.

A further increase of δ to 10^{-4} resulted in an increased accuracy of 82.32%, but a maximal risk of 1.25%.

Results

(ϵ, δ)-Differential Privacy resulted in more missing attributes, leading to a lower precision, hence we opted for k-Anonymity, despite the higher maximal risk.

The 8-anonymity model was chosen as it resulted in a broader distribution of attribute values like `age`, whereas with Differential Privacy, they were split into only 2 categories.

Observations

We noted that the contingency between `sex` and `relationship` maintained the same distribution after anonymization, meaning that these changes don't mean `relationship` can identify an individual's `sex` any more than in the original dataset.

With the following commands, we noted some possible errors in the original dataset, where the `sex` and `relationship` attributes didn't map entirely one to one: there was one occurence of (Husband, Female) and two of (Wife, Male). It's possible this is an error in the original dataset.

```
$ cat adult_data.csv | tail -n +2 | sed -r 's/,([^ ])/\t\1/g' |
cut -d',' -f8,10 | sort | uniq -c | sort -n
```

```
      1  Husband, Female
      2  Wife, Male
    430  Other-relative, Female
    551  Other-relative, Male
    792  Unmarried, Male
```

```
   1566  Wife, Female
   2245  Own-child, Female
   2654  Unmarried, Female
   2823  Own-child, Male
   3875  Not-in-family, Female
   4430  Not-in-family, Male
  13192  Husband, Male
```

```
$ cat anonymized.csv | tail -n +2 | sed -r 's/,([^ ])/\t\1/g' |
cut -d';' -f8,10 | sort | uniq -c | sort -n | column -s ';' -t

   1295 {Husband, Wife}              Female
   2264 {Other-relative, Own-child}  Female
   2981 {Other-relative, Own-child}  Male
   3280 *                            *
   4391 {Unmarried, Not-in-family}   Male
   5713 {Unmarried, Not-in-family}   Female
  12637 {Husband, Wife}              Male
```

Since there were occurences of (Wife, Male), "({Husband, Wife}, Male)" does not undo the transformation of the `relationship` attribute.

Citations

1: Sweeney, L.: Achieving k-anonymity privacy protection using generalization and suppression. J. Uncertain. Fuzz. Knowl. Sys. 10 (5), p. 571-588 (2002

2: Iyengar, V.: Transforming data to satisfy privacy constraints. Proc. Int. Conf. Knowl. Disc. Data Mining, p. 279-288 (2002)

3: Bayardo, R., Agrawal, R.: Data privacy through optimal k-anonymization. Proc. Int. Conf. Data Engineering, p. 217-228 (2005).

4: LeFevre, K., DeWitt, D., Ramakrishnan, R.: Mondrian multidimensional k-anonymity. Proc. Int. Conf. Data Engineering (2006).