First extensive testing of noise addition was due to Spruill (Spruill,

1983). (Brand, 2002) gives an

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overview of these approaches for noise addition as well as more sophisticated techniques. (Domingo-Ferrer *et al.*, 2004) also

describes some of the existing methods as well as the difficulties for its application in privacy. In addition to that, there exists a

related approach known as multiplicative noise (see e.g. (Kim

for details).

PRAM

and Winkler, 2003, Liu et al., 2006)

PKAI

PRAM, Post-RAndomization Method (Gouweleeuw *et al.*, 1998), is a method for categorical data where categories are replaced

according to a given probability.

Formally, it is based on a

Markov matrix on the set of

Markov matrix on C when $P: C \times$

Markov matrix on the set of categories. Let $C = \{c_1, ..., c_c\}$ be the set of categories, then P is the

$$C o [0,1]$$
 such that $\sum_{c_j \in C} P(c_i,c_j)$ = 1. Then, X' is constructed from X replacing, with probability $P(c_i,c_j)$, each c_i in X by a c_j .

The application of PRAM requires an adequate definition of the probabilities $P(c_i,c_j)$. (Gouweleeuw et al ., 1998) proposes the Invariant PRAM. Given $T=(T(c_1)\ldots T(c_c))$ the vector of frequencies of categories in C , it consists of defining P such that frequencies are kept after PRAM. That is, $\sum_{i=1}^c T(c_i)p_{ij} = T(c_j)$ for all j . Then, assuming

parameter θ such that $0 < \theta < 1$, p_{ij} is defined as follows: $p_{ij} = \begin{cases} 1 - (\theta T(c_k)/T(c_i)) & \text{if } i = j \\ \theta T(c_k)/((k-1)T(c_i)) & \text{if } i \neq j \end{cases}$ Note that a θ equal to zero implies no perturbation, and θ

without loss of generality $T(c_k) >$ $T(c_i)$ for all i, and given a

equal to 1 implies total perturbation. So, θ permits the user to control the degree of distortion

suffered by the data set. (Gross et al., 2004) proposes

the computation of matrix P from

preference about replacing category c_i by category c_i . Formally, given W the probabilities P are determined from the following optimization

function:

a preference matrix $W = \{w_{ij}\}$ where w_{ij} is our degree of

Minimize
$$\sum_{i,j} w_{ij} p_{ij}$$

Subject to

Subject to $p_{ij} \geq 0$

$$p_{ij} \ge 0$$

$$\sum_{j} p_{ij} = 1$$

 $\sum_{i=1}^{c} T(c_i) p_{ij} = T(c_j)$ for all j

integers to express preferences, and $w_{ij} = 1$ is the most preferred change, $w_{ij} = 2$ is the second most

(Gross et al., 2004) use

preferred changes, and so on.

Lossy Compression

This approach, first proposed in (Domingo-Ferrer and Torra, 2001a), consists of viewing a

2001a), consists of viewing a numerical data file as a grey-level image. Rows are records and

columns are attributes. Then, a lossy

compression method is applied to the image, obtaining a compressed image. This image is then decompressed and the decompressed image corresponds to the masked file. Different compression rates lead to files with different degrees of distortion. I.e., the more compression, the more distortion. (Domingo-Ferrer and Torra, 2001a) used JPEG, which is based on DCT, for the compression. (Jimenez and Torra, 2009) uses JPEG 2000, which is based on wavelets.