

# Weighted Random Sampling over Data Streams

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**Abstract.** In this work, we present a comprehensive treatment of weighted random sampling (WRS) over data streams. More precisely, we examine two natural interpretations of the item weights, describe an existing algorithm for each case ([3,8]), discuss sampling with and without replacement and show adaptations of the algorithms for several WRS problems and evolving data streams.

## 1 Introduction

The problem of random sampling calls for the selection of  $m$  random items out of a population of size  $n$ . If all items have the same probability to be selected, the problem is known as uniform random sampling. If each item has an associated weight and the probability of each item to be selected is determined by these item weights, then the problem is called weighted random sampling (WRS).

Weighted random sampling, and random sampling in general, is a fundamental problem with applications in several fields of computer science including databases, data streams, data mining and randomized algorithms. Moreover, random sampling is important in many practical problems, like market surveys, quality control in manufacturing, statistics and on-line advertising.

There are several factors that have to be taken into account, when facing a WRS problem. It has to be defined if the sampling procedure is with or without replacement, whether the sampling procedure has to be executed over data streams, and what the semantics of the item weights are. In this work, we present a comprehensive treatment of WRS over data streams. In particular, we examine the above problem parameters and describe efficient solutions for different WRS problems that arise in each case.

- **Weights.** In WRS the probability of each item to be selected is determined by its weight with respect to the weights of the other items. However, for random sampling schemes without replacement there are at least two natural ways to interpret the item weights. In the first case, the relative weight of each item determines the probability that the item is in the final sample. In the second, the weight of each item determines the probability that the item is selected in each of the explicit or implicit item selections of the sampling procedure. Both cases will become clear in the sequel.

- **Replacement.** Like other sampling procedures, the WRS procedures can be with replacement or without replacement. In WRS with replacement, each selected item is replaced in the main lot with an identical item, whereas in WRS without replacement each selected item is simply removed from the population.
- **Data Streams.** Random sampling is often applied to very large datasets and in particular to data streams. In this case, the random sample has to be generated in one pass over an initially unknown population. An elegant and efficient approach to generate random samples from data streams is the use of a reservoir of size  $m$ , where  $m$  is the sample size. The reservoir-based sampling algorithms maintain the invariant that, at each step of the sampling process, the contents of the reservoir are a valid random sample for the set of items that have been processed up to that point. There are many random sampling algorithms that make use of a reservoir to generate uniform random samples over data streams [17].
- **Feasibility of WRS.** When considering the problem of generating a weighted random sample in one pass over an unknown population one may doubt that this is possible. In [1], the question whether reservoir maintenance can be achieved in one pass with arbitrary bias functions, is stated as an open problem. In this work, we bring to the fore two algorithms [3,8] for the two, probably most important, flavors of the problem. In our view, the above results, and especially the older one, should become more known to the databases and algorithms communities.
- **A Standard Class Implementation.** Finally, we believe that the algorithms for WRS over data streams can and should be part of standard class libraries at the disposal of the contemporary algorithm or software engineer. To this end, we design an abstract class for WRS and provide prototype implementations of the presented algorithms in Java.

**Contribution and Related Work.** Random sampling is a classic, well studied field, and the volume of the corresponding literature is enormous. See for example [11,16,17,14,12] and the references therein. These results concern uniform random sampling, random sampling with a reservoir (which can be used on data streams), and weighted random sampling but not over data streams. An efficient algorithm for weighted random sampling with a reservoir which can support data streams is presented in [8]. Another weighted random sampling algorithm, which is less known to the computer science community and which uses a different interpretation for the item weights, is presented in [3]. This algorithm, too, is efficient and can be applied to data streams.

Random sampling is still an active research field and new sampling schemes are studied in various contexts; some indicative examples are sampling from sliding windows [13], from distributed data streams [4,15,5], from streams with time decay [6], independent range sampling [10], sampling on very large file systems [9], and stratified reservoir sampling [2]. In light of the above results (which are mainly from the data streams field), we consider the algorithms of [3]

and [8] as fundamental sampling schemes for general purpose weighted random sampling over data streams.

In this work, we present a comprehensive treatment of general purpose weighted random sampling (WRS) over data streams. More precisely, we identify and examine two natural interpretations of the item weights, describe an existing algorithm for each case ([3,8]), discuss sampling with and without replacement and show adaptations of the algorithms for several WRS problems and evolving data streams. Moreover, we bring to the fore the sampling algorithm of Chao and show how to apply the jumps technique on it. Finally, we propose an abstract class definition for weighted random sampling over data streams and present a prototype implementation for this class.

**Outline.** The rest of this work is organized as follows: Notation and definitions for WRS problems are presented in Section 2. Core algorithms for WRS are described in 3. The treatment of representative WRS problems is described in 4. In Section 5, a prototype implementation and experimental results are presented. Finally, the role of item weights is examined in 6 and an overall conclusion of this work is given in 7.

## 2 Weighted Random Sampling (WRS)

Given an instance of a WRS problem, let  $V$  denote the population of all items and  $n = |V|$  the size of the population. In general, the size  $n$  will not be known to the WRS algorithms. Each item  $v_i \in V$ , for  $i = 1, 2, \dots, n$ , of the population has an associated weight  $w_i$ . The weight  $w_i$  is a strictly positive real number  $w_i > 0$  and the weights of all items are initially considered unknown. The WRS algorithms will generate a weighted random sample of size  $m$ . If the sampling procedure is without replacement then it must hold that  $m \leq n$ . All items of the population are assumed to be discrete, in the sense that they are distinguishable but not necessarily different. The distinguishability can be trivially achieved by assigning an increasing ID number to each item in the population, including the replaced items (for WRS with replacement). We define the following notation to represent the various WRS problems:

$$WRS - \langle \text{rep} \rangle - \langle \text{role} \rangle, \quad (1)$$

where the first parameter specifies the replacement policy and the second parameter the role of the item weights.

- **Parameter **rep**:** This parameter determines if and how many times a selected item can be replaced in the population. A value of “N” means that each selected item is not replaced and thus it can appear in the final sample at most once, i.e., sampling without replacement. A value of “R” means that the sampling procedure is with replacement and, finally, an arithmetic value  $k$ , where  $1 \leq k \leq m$ , defines that each item is replaced at most  $k - 1$  times, i.e., it can appear in the final sample at most  $k$  times.

- **Parameter *role*:** This parameter defines the role of the item weights in the sampling scheme. As already noted, we consider two natural ways to interpret item weights. In the first case, when the role has value P, the probability of an item to be in the random sample is proportional to its relative weight. In the second case, the role is equal to W and the relative weight determines the probability of each item selection, if the items would be selected sequentially.

Moreover, WRS-P will denote the whole class of WRS problems where the item weights directly determine the selection probabilities of each item, and WRS-W the class of WRS problems where the items weights determine the selection probability of each item in a supposed<sup>1</sup> sequential sampling procedure. A summary of the notation for different WRS problems is given in Table 1.

WRS Problem		Notation
With Replacement		WRS-R
Without Replacement	Probabilities	WRS-N-P
	Weights	WRS-N-W
With $k - 1$ Replacements		WRS-k-W

Table 1: Notation for WRS problems.

**Definition 1.** *Problem WRS-R (Weighted Random Sampling with Replacement).*

*Input:* A population of  $n$  weighted items and a size  $m$  for the random sample.

*Output:* A weighted random sample of size  $m$ . The probability of each item to occupy each slot in the random sample is proportional to the relative weight of the item, i.e., the weight of the item with respect to the total weight of all items.

**Definition 2.** *Problem WRS-N-P (Weighted Random Sampling without Replacement, with defined Probabilities).*

*Input:* A population of  $n$  weighted items and a size  $m$  for the random sample.

*Output:* A weighted random sample of size  $m$ . The probability of each item to be included in the random sample is proportional to its relative weight.

Intuitively, the basic principle of WRS-N-P can be shown with the following example. Assume any two items  $v_i$  and  $v_j$  of the population with weights  $w_i$  and  $w_j$ , respectively. Let  $c = w_i/w_j$ . Then the probability  $p_i$  that  $v_i$  is in the random sample is equal to  $cp_j$ , where  $p_j$  is the probability that  $v_j$  is in the random sample. For heavy items with relative weight larger than  $1/m$  we say that the respective items are “infeasible” or “overweight”. If the inclusion probability of

<sup>1</sup> We say “supposed” because even though WRS is best described with a sequential sampling procedure, it is not inherently sequential. Algorithm A-ES [8] which we will use to solve WRS-W problems can be executed on sequential, parallel and distributed settings.

an overweight item would be proportional to its weight, then this probability would become larger than 1, which of course is not possible. As shown in Section 3.1, the overweight items are handled in a special way that guarantees that they are selected with probability exactly 1.

**Definition 3.** *Problem WRS-N-W (Weighted Random Sampling without Replacement, with defined Weights).*

*Input: A population of  $n$  weighted items and a size  $m$  for the random sample.*

*Output: A weighted random sample of size  $m$ . In each round, the probability of every unselected item to be selected in that round is proportional to the relative item weight with respect to the weights of all unselected items.*

The definition of problem WRS-N-W is essentially the following sampling procedure. Let  $S$  be the current random sample. Initially,  $S$  is empty. The  $m$  items of the random sample are selected in  $m$  rounds. In each round, the probability for each item in  $V - S$  to be selected is  $p_i(k) = \frac{w_i}{\sum_{s_j \in V-S} w_j}$ . Using the probabilities  $p_i(k)$ , an item  $v_k$  is randomly selected from  $V - S$  and inserted into  $S$ . We use two simple examples to illustrate the above defined WRS problems.

*Example 1.* Assume that we want to select a weighted random sample of size  $m = 2$  from a population of  $n = 4$  items with weights 1, 1, 1 and 2, respectively. For problem WRS-N-P the probability of items 1, 2 and 3 to be in the random sample is 0.4, whereas the probability of item 4 is 0.8. For WRS-N-W the probability of items 1, 2 and 3 to be in the random sample is 0.433, while the probability of item 4 is 0.7.

*Example 2.* Assume now that we want to select  $m = 2$  items from a population of 4 items with weights 1, 1, 1, and 4, respectively. For WRS-N-W the probability of items 1, 2 and 3 to be in the random sample is 0.381, while the probability of item 4 is 0.857. For WRS-N-P, however, the weights are infeasible because the weight of item 4 is infeasible. In particular, the product  $m$  times the relative weight of item 4 is  $2 \cdot (4/7)$  which is larger than 1 and cannot be used as a probability. This case is handled by assigning with probability 1 a position of the reservoir to item 4 and filling the other position of the reservoir randomly with one of the remaining (feasible) items. Note that if the sampling procedure is applied on a data stream and a fifth item, for example with weight 3, arrives, then the instance becomes feasible with probabilities 0.2 for items 1, 2 and 3, 0.8 for item 4 and 0.6 for item 5. The possibility for infeasible problem instances or temporary infeasible evolving problem instances over data streams is an inherent complication of the WRS-N-P problem that has to be handled in the respective sampling algorithms.

### 3 The Two Core Algorithms

The two core algorithms that we use for the WRS problems of this work are the *General Purpose Unequal Probability Sampling Plan* of Chao [3] and the

*Weighted Random Sampling with a Reservoir* algorithm of Efraimidis and Spirakis [8]. We provide a short description of each algorithm while more details can be found in the respective papers.

### 3.1 A-Chao

The sampling plan of Chao [3], which we will call A-Chao, is a reservoir-based sampling algorithm that processes sequentially an initially unknown population  $V$  of weighted items.

A typical step of algorithm A-Chao is presented in Figure 1. When a new item is examined, its relative weight is calculated and used to randomly decide if the item will be inserted into the reservoir. If the item is selected, then one of the existing items of the reservoir is uniformly selected and replaced with the new item. The trick here is that, if the probabilities of all items in the reservoir are already proportional to their weights, then by selecting uniformly which item to replace, the probabilities of all items remain proportional to their weight after the replacement.

#### Algorithm A-Chao (sketch)

**Input :** Item  $v_k$  for  $m < k \leq n$

**Output :** A WRS-N-P sample of size  $m$

- 1 : Calculate the probability  $p_k = w_k / (\sum_{i=1}^k w_i)$  for item  $v_k$
- 2 : Decide randomly if  $v_k$  will be inserted into the reservoir
- 3 :     if No, do nothing. Simply increase the total weight
- 4 :     if Yes, choose uniformly a random item from the  
reservoir and replace it with  $v_k$

Fig. 1: A sketch of Algorithm A-Chao. We assume that all the positions of the reservoir are already occupied and that all item weights are feasible.

The main approach of A-Chao is simple, flexible and effective. There are however some complications inherent to problem WRS-N-P that have to be addressed. As shown in Example 2, an instance of WRS-N-P may temporarily not be feasible, in case of data streams, or may not be feasible at all. This happens when the (current) population contains one or more overweight items, i.e., items each of which has a relative weight greater than  $1/m$ . The main idea to handle this case, is to sample each overweight item with probability 1. Thus, each overweight item automatically occupies a position in the reservoir. The remaining positions are assigned with the normal procedure to the feasible items. In case of sampling over a data stream, an initially infeasible (overweight) item may later become feasible as more items arrive. Thus, with each new item arrival the relative weights of the infeasible items are updated and if an infeasible item becomes feasible it is treated as such. Appropriate procedures to initialize the reservoir and to handle the overweight items are described in [3].

### 3.2 A-ES

The algorithm of Efraimidis and Spirakis [8], which we call A-ES, is a sampling scheme for problem WRS-N-W. In A-ES, each item  $v_i$  of the population  $V$  independently generates a uniform random number  $u_i \in (0, 1)$  and calculates a key  $k_i = u_i^{1/w_i}$ . The items that possess the  $m$  largest keys form a weighted random sample. We will use the reservoir-based version of A-ES, where the algorithm maintains a reservoir of size  $m$  with the items with  $m$  largest keys.

The basic principle underlying algorithm A-ES is the remark that a uniform random variable can be “amplified” as desired by raising it to an appropriate power (Remark 1). A high level description of algorithm A-ES is shown in Figure 2.

*Remark 1.* ([8]) Let  $U_1$  and  $U_2$  be independent random variables with uniform distributions in  $[0, 1]$ . If  $X_1 = (U_1)^{1/w_1}$  and  $X_2 = (U_2)^{1/w_2}$ , for  $w_1, w_2 > 0$ , then  $P[X_1 \leq X_2] = \frac{w_2}{w_1 + w_2}$ .

#### **Algorithm A-ES (High Level Description)**

**Input :** A population  $V$  of  $n$  weighted items

**Output :** A WRS-N-W sample of size  $m$

- 1: For each  $v_i \in V$ ,  $u_i = \text{random}(0, 1)$  and  $k_i = u_i^{\frac{1}{w_i}}$
- 2: Select the  $m$  items with the largest keys  $k_i$

Fig. 2: A high level description of Algorithm A-ES.

### 3.3 Algorithm A-Chao with Jumps

A common technique to improve certain reservoir-based sampling algorithms is to change the random experiment used in the sampling procedure. In normal reservoir-based sampling algorithms, a random experiment is performed for each new item to decide if it is inserted into the reservoir. In random sampling with jumps instead, a single random experiment is used to directly decide which will be the next item that will enter the reservoir. Since each item that is processed will be inserted with some probability into the reservoir, the number of items that will be skipped until the next item is selected for the reservoir, is a random variable. In uniform random sampling it is possible to generate an exponential jump that identifies the next item of the population that will enter the reservoir [7], while in [8] it is shown that exponential jumps can be used for WRS with algorithm A-ES.

In this work, we show that a jumps approach can be used for algorithm A-Chao too, albeit in a slightly more complicated way than for algorithm A-ES. The reason is that in WRS-N-W the probability that an item will be the next

item that will enter the reservoir can be directly obtained from its weight and the total weight of the items preceding it, while in WRS-N-P the respective probabilities have to be computed.

Assume for example a typical step of algorithm A-Chao. A new item  $v_i$  has just arrived and with probability  $p_i$  it will be inserted into the reservoir. The probability that  $v_i$  will not be selected, but the next item,  $v_{i+1}$ , is selected, is  $(1 - p_i)p_{i+1}$ . In the same way the probability that items  $v_i$  and  $v_{i+1}$  are not selected and that item  $v_{i+2}$  is selected is  $(1 - p_i)(1 - p_{i+1})p_{i+2}$ . Clearly, if the stream continues with an infinite number of items then with probability 1 some item will be the next item that will enter the reservoir. Thus, we can generate a uniform random number  $u_j$  in  $[0, 1]$  and add up the probability mass of each new item until the accumulated probability exceeds the random number  $u_j$ . The selected item is then inserted into the reservoir with the normal procedure of algorithm A-Chao.

The main advantage of using jumps in reservoir-based sampling algorithms is that, in general, the number of random number generations can be dramatically reduced. For example, if the item weights are independent random variables with a common distribution, then the number of random numbers is reduced from  $O(n)$  to  $O(m \log(n/m))$ , where  $n$  is the size of the population [8]. In contexts where the computational cost for qualitative random number generation is high, the jumps versions offer an efficient alternative for the sampling procedure. From a semantic point of view, the sampling procedures with and without jumps are identical.

## 4 Algorithms for WRS Problems

Both core algorithms, A-Chao and A-ES, are efficient and flexible and can be used to solve fundamental but also more involved random sampling problems. We start with basic WRS problems that are directly solved by A-Chao and A-ES. Then, we present sampling schemes for two WRS problems with a bound on the number of replacements and discuss the sampling problem in the presence of stream evolution.

### 4.1 Basic problems

- **Problem WRS-N-P:** The problem can be solved with algorithm P-Chao. In case no overweight items appear in the data stream, the cost to process each item is  $O(1)$  and the total cost for the whole population is  $O(n)$ . The complexity of handling overweight items is higher. For example, if a heap data structure is used to manage the current overweight items, then each overweight item costs  $O(\log m)$ . An adversary could generate a data stream where each item would be initially (at the time it is fed to the sampling algorithm) overweight and this would cause a total complexity of  $\Theta(n \log m)$  to process the complete population. However, this is a rather extreme example and in reasonable cases the total complexity is expected to be linear on  $n$ .



- **Problem WRS-N-W:** The problem can be solved with algorithm A-ES. The reservoir-based implementation of the algorithm requires  $O(1)$  computational steps for each item that is not selected and  $O(\log m)$  for each item that enters the reservoir (if, for example, the reservoir is organized as a heap). In this case too, an adversary can prepare a sequence that will require  $O(n \log m)$  computational steps. In common cases, the cost for the complete population will be  $O(n) + O(m \log(n/m))O(\log m)$ , which becomes  $O(n)$  if  $n$  is large enough with respect to  $m$ .
- **Problem WRS-R:** In WRS with replacement the population remains unaltered after each item selection. Because of this, WRS-R-P and WRS-R-W coincide and we call the problem simply WRS-R. In the data stream version, the problem can be solved by running concurrently  $m$  independent instances of WRS-N-P or WRS-N-W, each with sample size  $m' = 1$ . Both algorithms A-Chao and A-ES in both their versions, with and without jumps, can efficiently solve the problem. In most cases, the version with jumps of A-Chao or A-ES should be the most efficient approach.  
Note that sampling with replacement is not equivalent to running the experiment on a population  $V'$  with  $m$  instances of each original item of  $V$ . The sample space of the later experiment would be much larger than in the case with replacement.

## 4.2 Sampling with a bounded number of replacements

We consider weighted random sampling from populations where each item can be replaced at most a bounded number of times (Figure 3). An analogy would be to randomly select  $m$  products from an automatic selling machine with  $n$  different products and  $k$  instances of each product. The challenge is of course that the weighted random sample has to be generated in one-pass over an initially unknown population.

- **Problem WRS-k-W:** Sampling from a population of  $n$  weighted items where each item can be selected up to  $k \leq m$  times. The weights of the items are used to determine the probability that each item is selected at each step.

A general solution, in the sense that each item may have its own multiplicity  $k_i \leq k$ , is to use a pipeline of  $m$  instances of a A-ES, where each instance will generate a weighted random sample of size 1. Note that either algorithm A-Chao or A-ES can be used, because for samples of size 1 the outcomes of the two algorithms are equivalent. If the first instance is at item  $\ell$ , then each other instance is one item behind the previous instance. Thus, an item of the population is first processed by instance 1, then by instance 2, etc. If at some point the item has been selected  $k_i$  times, then the item is not processed by the remaining instances and the information up to which instance the item has been processed is stored. If the item is replaced in a reservoir at a later step, then it is submitted to the next instance of A-ES. Note that in this approach, some items might be processed out of their original order. This

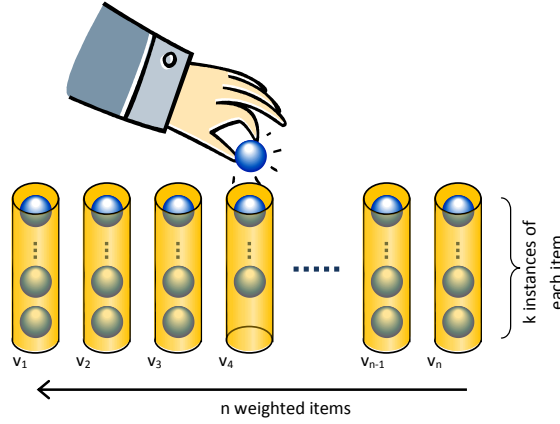


Fig. 3: WRS-k-W,  $n$  weighted items with  $k$  instances of each item.

is fine with algorithm A-ES (both A-ES and A-Chao remain semantically unaffected by any ordering of the population) but may be undesirable in certain applications.

#### 4.3 Sampling Problems in the Presence of Stream Evolution

A case of reservoir-based sampling over data streams where the more recent items are favored in the sampling process is discussed in [1]. While the items do not have weights and are uniformly treated, a temporal bias function is used to increase the probability of the more recent items to belong to the random sample. Finally, in [1], a particular biased reservoir-based sampling scheme is proposed and the problem of efficient general biased random sampling over data streams is stated as an open problem.

In this work, we have brought to the fore algorithms A-Chao and A-ES, which can efficiently solve WRS over data streams where each item can have an arbitrary weight. This should provide an affirmative answer to the open problem posed in [1]. Moreover, the particular sampling procedure presented in [1] is a special case of algorithm A-Chao.

Since algorithms A-Chao and A-ES can support arbitrary item weights, a bias favoring more recent items can be encoded into the weight of the newly arrived item or in the weights of the items already in the reservoir. Furthermore, by using algorithms A-Chao and A-ES the sampling process in the presence of stream evolution can also support weighted items. This way the bias of each item may depend on the item weight and how old the item is, or on any other factor that could be taken into account. Thus, the sampling procedure and/or the corresponding applications in [1] can be generalized to items with arbitrary weights and other, temporal or not, bias criteria.

The way to increase the selection probability of a newly arrived item is very simple for both algorithms, A-Chao and A-ES.

- **A-Chao:** By increasing the weight of the new item.
- **A-ES:** By increasing the weight of the new item or decreasing the weights of the items already in the reservoir.

## 5 An Abstract Data Structure for WRS

We designed an abstract class `StreamSampler` with the methods `feedItem()` and `getSample()`, and a set of auxiliary classes for the weighted items to capture the basic functionality for weighted random sampling over data streams (Figure 4). Then, we developed descendant classes that implement the functionality of the `StreamSampler` class for algorithms A-Chao and A-ES, both with and without jumps. The descendant classes are `StreamSamplerChao`, `StreamSamplerES`, `StreamSamplerESWithJumps` and `StreamSamplerChaoWithJumps` [18].

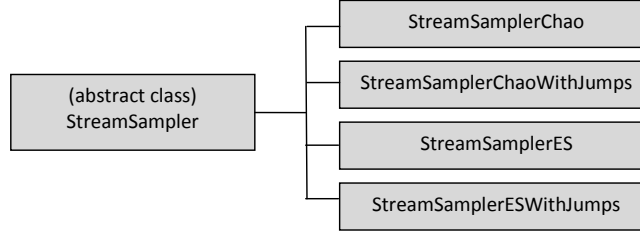


Fig. 4: The class hierarchy for sampling over data streams.

Preliminary experiments with random populations (with uniform random item weights) showed that all algorithms scale linear on the population size and at most linear on the sample size. Indicative measurements are shown in Figure 5. While there is still room for optimization of the implementations of the algorithms, the general behavior of the complexities is evident in the graphs. The experiments have been performed on the Sun Java 1.6 platform running on an Intel Core 2 Quad CPU-based PC and all measurements have been averaged over 100 (at least) executions.

## 6 The Role of Weights

The problem classes WRS-P and WRS-W differ in the way the item weights are used in the sampling procedure. In WRS-P the weights are used to directly determine the final selection probability of each item and this probability is easy to calculate. On the other hand, in WRS-W the item weights are used to determine the selection probability of each item in each step of a supposed sequential sampling procedure. In this case it is easy to study each step of the sampling procedure, but the final selection probabilities of the items seem to be hard to calculate. In the general case, a complex expression has to be evaluated

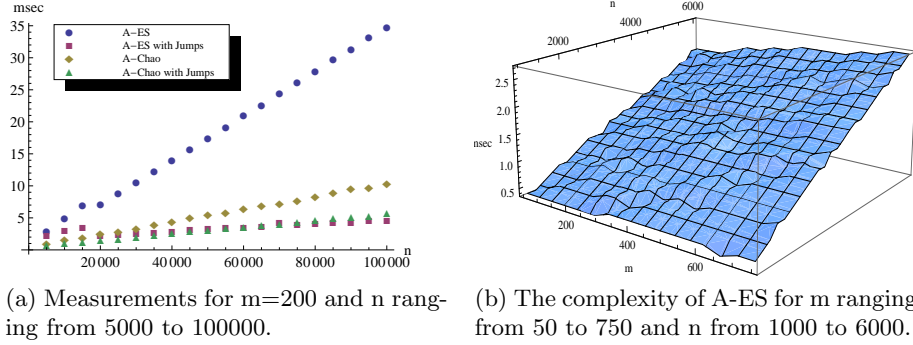


Fig. 5: Time measurements of the WRS sampling algorithms.

in order to calculate the exact inclusion probability of each item and we are not aware of an efficient procedure to calculate this expression. An interesting feature of random samples generated with WRS-W is that they support the concept of order for the sampled items. The item that is selected first or simply has the largest key (algorithm A-ES) can be assumed to take the first position, the second largest the second position etc. The concept of order can be useful in certain applications. We illustrate the two sampling approaches in the following example.

*Example 3.* On-line advertisements. A search engine shows with the results of each query a set of  $k$  sponsored links that are related to the search query. If there are  $n$  sponsored links that are relevant to a query then how should the set of  $k$  links be selected? If all sponsors have paid the same amount of money then any uniform sampling algorithm without replacement can solve the problem. If however, every sponsor has a different weight then how should the  $k$  items be selected? Assuming that the  $k$  positions are equivalent in “impact”, a sponsor who has the double weight with respect to another sponsor may expect its advertisement to appear twice as often in the results. Thus, a reasonable approach would be to use algorithm A-Chao to generate a WRS-N-P of  $k$  items. If however, the advertisement slots are ordered based on their impact, for example the first slot may have the largest impact, the second the second largest etc., then algorithm A-ES may provide the appropriate solution by generating a WRS-N-W of  $k$  items.

When the size of the population becomes large with respect to the size of the random sample, then the differences in the selection probabilities of the items in WRS-P and WRS-W become less important. The reason is that if the population is large then the change in the population because of the removed items has a small impact and the sampling procedure converges to random sampling without replacement. As noted earlier, in random sampling with replacement the two sampling approaches coincide.

## 7 Discussion

We presented a comprehensive treatment of WRS over data streams and showed that efficient sampling schemes exist for fundamental but also more specialized WRS problems. The two core algorithms, A-Chao and A-ES have been proved efficient and flexible and can be used to build more complex sampling schemes.

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