# On the Biased Partial Word Collector Problem 

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## Coupon collector



The classical coupon collector problem is the following:

- There are $n$ different pictures
- Each chocolate bar contains one picture, uniformly at random


## Coupon collector

How many chocolate bars are required to complete the collection?
Answer: in expectation, around $n \log n$ chocolate bars are needed.

## Birthday paradox



The classical birthday paradox problem is the following (assuming that all birthdays are uniformly random (365 possibilities)):

## Birthday problem

In a room with $m$ people, what is the probability that at least two people have the same birthday?

Answer: for $m=23$, the probability is just above $50 \%$

## Birthday problem



The birthday problem is the following:
Birthday problem
How many chocolate bars until the first duplicate?
Answer: in expectation it is $\sim \sqrt{\frac{\pi n}{2}}$

## biased partial word collector problem

## aabacba



## Our problem

(1) Draw $N$ random words of length $L$, independently
(2) Remove duplicates
(3) Select a word uniformly at random

The words are generated using a memoryless source $\mathcal{S}$ :
Each letter is chosen independently following a fixed probability on the alphabet. For instance $p_{a}=\frac{1}{3}$ and $p_{b}=\frac{2}{3}$ and the probability of aabba is $\left(\frac{1}{3}\right)^{3}\left(\frac{2}{3}\right)^{2}=\frac{4}{243}$

## biased partial word collector problem

## aabacba



## Our problem

(1) Draw $N$ random words of length $L$, independently (partial)
(2) Remove duplicates (collector problem)
(3) Select a word uniformly at random

The words are generated using a memoryless source $\mathcal{S}$ :
Each letter is chosen independently following a fixed probability on the alphabet. For instance $p_{a}=\frac{1}{3}$ and $p_{b}=\frac{2}{3}$ and the probability of aabba is $\left(\frac{1}{3}\right)^{3}\left(\frac{2}{3}\right)^{2}=\frac{4}{243}$ (biased)

## Related works and motivations

\# Birthday paradox, coupon collectors, caching algorithms and self-organizing search. Ph. Flajolet, D. Gardy, and L. Thimonier (DAM'92)
$\geqslant$ The weighted words collector. J. Du Boisberranger, D. Gardy, and Y. Ponty (AofA'12)
E On Correlation Polynomials and Subword Complexity.
I. Gheorghiciuc and M. D. Ward (AofA'07)
$\rightleftharpoons$ The number of distinct subpalindromes in random words.
M. Rubinchik and A. M. Shur. (Fundam. Inform. 16)

## Subword complexity

It is the number of distinct factors (of a given length or not) in a string.
In our settings: $N \approx|u|$ and $L \approx \mid$ factor $\mid$, not completely independent.

## Getting started

## Our problem

(1) Draw $N$ random words of length $L$, independently using $\mathcal{S}$
(2) Remove duplicates
(3) Select a word uniformly at random

Some remarks:

- There are $|A|^{L}$ distinct words
- If $\mathcal{S}$ is uniform, then the output is a uniform random word
- If $N$ is small, the output looks like a word generated by $\mathcal{S}$
- If $N$ is large, the output looks like a uniform random word

By looks like we mean that the number of occurrences of the letters are approximatively the same.

## Full statement

- The alphabet is $A=\left\{a_{1}, \ldots, a_{k}\right\}$
- The probabilities for $\mathcal{S}$ are $\mathbf{p}=\left(p_{1}, \ldots, p_{k}\right)$, with $p_{i}=p\left(a_{i}\right)$
- The random variable $U_{N, L}$ denote the output of our process
- $H(\mathbf{x})=-\sum_{i} x_{i} \log x_{i}$ is the classical entropy function
- $\operatorname{Freq}(u)=\left(f_{1}, \ldots, f_{k}\right)$ is the frequency vector of $u$ with $f_{i}=\frac{|u|_{i}}{|u|}$.


## Theorem [Duchon \& N., LATIN'18]

Let $\ell_{0}=\frac{-k}{\sum \log p_{i}}$ and $\ell_{1}=\frac{1}{H(\mathbf{p})}$. For $L$ sufficiently large and for any $N \geq 2$, there are three different behaviors depending on $\ell=\frac{L}{\log N}$ :
(a) If $\ell \leq \ell_{0}$, then $\operatorname{Freq}\left(U_{N, L}\right) \approx\left(\frac{1}{k}, \ldots, \frac{1}{k}\right)$
(b) If $\ell_{0} \leq \ell \leq \ell_{1}$, then $\operatorname{Freq}\left(U_{N, L}\right) \approx \mathbf{x}_{\ell}$, for some fully caracterized $\mathbf{x}_{\ell}$
(c) If $\ell_{1} \leq \ell$, then $\operatorname{Freq}\left(U_{N, L}\right) \approx \mathbf{p}$
$\operatorname{Freq}\left(U_{N, L}\right) \approx \mathbf{y}$ means $\mathbb{P}\left(\left\|\operatorname{Freq}\left(U_{N, L}\right)-\mathbf{y}\right\|_{2} \geq \frac{\log L}{\sqrt{L}}\right) \leq L^{-\lambda \log L}$

## Simplified statement

- The probabilities for $\mathcal{S}$ are $\mathbf{p}=\left(p_{1}, \ldots, p_{k}\right)$, with $p_{i}=p\left(a_{i}\right)$
- The random variable $U_{N, L}$ denote the output of our process
- $\operatorname{Freq}(u)=\left(f_{1}, \ldots, f_{k}\right)$ is the frequency vector of $u$ with $f_{i}=\frac{|u|_{i}}{|u|}$.


## Theorem [Duchon \& N., LATIN'18]

There exist two thresholds $\ell_{0}<\ell_{1}$, which depend on $\mathbf{p}$ only, s.t. for $L$ sufficiently large and for any $N \geq 2$, there are three different behaviors depending on $\ell=\frac{L}{\log N}$ :
(a) If $\ell \leq \ell_{0}$, then $\operatorname{Freq}\left(U_{N, L}\right)$ is almost uniform
(b) If $\ell_{0} \leq \ell \leq \ell_{1}$, then $\operatorname{Freq}\left(U_{N, L}\right) \approx \mathbf{x}_{\ell}$, for some fully caracterized $\mathbf{x}_{\ell}$
(c) If $\ell_{1} \leq \ell$, then $\operatorname{Freq}\left(U_{N, L}\right)$ is almost $\mathbf{p}$

## Interpolation between the uniform distribution and p

## Theorem [Duchon \& N., LATIN'18]

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(a) If $\ell \leq \ell_{0}$, then $\operatorname{Freq}\left(U_{N, L}\right)$ is almost uniform
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(c) If $\ell_{1} \leq \ell$, then $\operatorname{Freq}\left(U_{N, L}\right)$ is almost $\mathbf{p}$

We have

$$
\mathbf{x}_{\ell}=\left(\frac{p_{1}^{c}}{\Phi(c)}, \ldots, \frac{p_{k}^{c}}{\Phi(c)}\right)
$$

Where $\Phi(t)=\sum_{i=1}^{k} p_{i}^{t}$, and $c$ is the unique solution in $[0,1]$ of

$$
\ell \Phi^{\prime}(c)+\Phi(c)=0
$$

## Interpolation between the uniform distribution and p

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\mathbf{x}_{\ell}=\left(\frac{p_{1}^{c}}{\Phi(c)}, \ldots, \frac{p_{k}^{c}}{\Phi(c)}\right)
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Where $\Phi(t)=\sum_{i=1}^{k} p_{i}^{t}$, and $c$ is the unique solution in $[0,1]$ of

$$
\ell \Phi^{\prime}(c)+\Phi(c)=0
$$

- If $\ell=\ell_{0}$ then $c=0$ and

$$
\mathbf{x}_{\ell_{0}}=\left(\frac{p_{1}^{0}}{\Phi(0)}, \ldots, \frac{p_{k}^{0}}{\Phi(0)}\right)=\left(\frac{1}{k}, \ldots, \frac{1}{k}\right)
$$

- If $\ell=\ell_{1}$ then $c=1$ and

$$
\mathbf{x}_{\ell_{1}}=\left(\frac{p_{1}^{1}}{\Phi(1)}, \ldots, \frac{p_{k}^{1}}{\Phi(1)}\right)=\mathbf{p}
$$

## Proof sketch 1/3

- Let $\mathcal{W}_{L}(\mathbf{x})$ be the words of length $L$ whose frequency vector is $\mathbf{x}$
- All the words of $\mathcal{W}_{L}(\mathbf{x})$ have the same probability $p(\mathbf{x})$ of being generated by the source $\mathcal{S}$, with $p(\mathbf{x})=\prod p_{i}^{x_{i} L}=N^{\ell \sum x_{i} \log p_{i}}$
- Hence the probability $q(\mathbf{x})$ that the set contains a given word of frequency vector $\mathbf{x}$ is $q(\mathbf{x})=1-(1-p(\mathbf{x}))^{N}$
- We approximate $q(\mathbf{x})$ with

$$
q(\mathbf{x}) \approx \min (N p(\mathbf{x}), 1)=N^{\min \left(0,1+\ell \sum x_{i} \log p_{i}\right)}
$$

- Since there are $\left({ }_{x_{1} L, \ldots, x_{k} L}\right) \approx N^{\ell H(x)}$ words in $\mathcal{W}_{L}(\mathrm{x})$, the expected number of such words in the collection is roughly

$$
N^{\ell \min \left(H(\mathbf{x}), K_{\ell}(\mathbf{x})\right)} \text {, with } K_{\ell}(\mathbf{x})=H(\mathbf{x})+\frac{1}{\ell}+\sum x_{i} \log p_{i}
$$

## Proof sketch 2/3

## Goal

Find the probability vector $\mathbf{x}$ that maximises

$$
\min \left(H(\mathbf{x}), K_{\ell}(\mathbf{x})\right), \text { with } K_{\ell}(\mathbf{x})=H(\mathbf{x})+\frac{1}{\ell}+\sum x_{i} \log p_{i}
$$

It is the minimum of two strictly concave functions. But we have to do some analysis in several variables $x_{1}, \ldots, x_{k}$

## Proof sketch 3/3

- For this proof sketch, lets consider that there is only one variable (i.e. two letters)
- Maximizing the minimum of two concave functions, two cases:

(a) The maximum of one function is smaller than the other function. It is the maximum of the min
(b) Otherwise, the maximum is on the intersection of the two curves (which can be complicated in several dimensions)
- For our problem, the function as sufficiently nice to work with explicitly and we have
- Case (a) appears for the two extremal ranges (uniform and $\mathbf{p}$ )
- Case (b) appears for the middle range (interpolation), and the maximum is found using standard analysis in several variables on the hyperplan of intersection of $H(\mathbf{x})$ and $K_{\ell}(\mathbf{x})$


## Conclusions

- There are two thresholds, fully characterized, for our problem
- A typical output word goes from uniformly random to distributed as an output of the source $\mathcal{S}$
- The interpolation between the two distributions is fully understood
- We focused on the distribution of letters, can we say more?
- More general sources (Markovian)?
- Distinct subpalindromes for memoryless sources?


## Thanks!

