# Expected Number of Distinct Subsequences in Randomly Generated Strings 

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- This could be of biological relevance in the case of two DNA strings.
- Subadditivity arguments are easy to apply to prove that $L=\lim _{n \rightarrow \infty} \frac{E\left(L_{n}\right)}{n}$ exists.


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- But even here, calculation of the expected value was non-trivial.
- The combined results of Vershik and Kerov; Logan and Shepp from the 1970's gave

$$
\lim \frac{E L_{n}}{\sqrt{n}}=2
$$

## Tracy Widom Distribution

This was followed by concentration results-due to Bollobas and Janson; Kim; and Frieze among others-that revealed that the standard deviation of the size of the longest monotone subsequence (LMS) is of order $\Theta\left(n^{1 / 6}\right)$, and culminated with the work of Baik, Deift and Johansson that exhibited the limiting law of a normalized version of the LMS. This is often cited as one of the crowning achievements of Probability/Analysis of the 20th Century. An AMS Notices article of Aldous and Diaconis gives a great summary.

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- The string 10110 contains the subsequences $0,1,01,10,11$, 00, 100, 101, 110, 111, 011, 010, 1011, 1010, 1110, 0110, and 10110 .


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- The string 10110 contains the subsequences $0,1,01,10,11$, 00, 100, 101, 110, 111, 011, 010, 1011, 1010, 1110, 0110, and 10110.
- What is the average case behavior?


## Existence

In our submitted paper, we proved
Theorem
Let $s_{1}, s_{2}, \ldots$ be a sequence of independent and identically distributed random variables with
$\operatorname{Pr}\left(s_{1}=j\right)=\alpha_{j}, j=1,2, \ldots, d, \sum_{j} \alpha_{j}=1$. Set $\alpha=\left(\alpha_{1}, \ldots, \alpha_{d}\right)$.
Let $\phi\left(S_{n}\right)$ be the number of distinct subsequences in
$S_{n}=\left(s_{1}, \ldots, s_{n}\right)$. Let $\psi(n)=E\left(\phi\left(S_{n}\right)\right)$. Then there exists
$c=c_{d, \alpha} \geq 1$ such that

$$
\psi(n)^{1 / n} \rightarrow c ; n \rightarrow \infty
$$

where $c=1$ iff $d \geq 1$ and $\max _{j} \alpha_{j}=1$.

## Discussion

- The above theorem is hardly surprising, but raises other questions, namely as to whether the "true" numbers contain, additionally, polynomial factors as do several Stanley-Wilf limits in the theory of pattern avoidance (note that there are no polynomial factors in our next result with $d=2$ ) Also, in general the existence of limits is not automatic, as seen by the following example:


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- Assume that $n$ balls are independently thrown into an infinite array of boxes so that box $j$ is hit with probability $1 / 2^{j}$ for $j=1,2, \ldots$. Let $\pi_{n}$ be the probability that the largest occupied box has a single ball in it. Then, as proved by several people in the 1990's, $\lim _{n \rightarrow \infty} \pi_{n}$ does not exist, and $\lim \sup _{n \rightarrow \infty} \pi_{n}$ and $\lim \inf _{n \rightarrow \infty} \pi_{n}$ differ in the fourth decimal place! Such behavior does not however occur in our context, as the theorem states.


## The case of $d=2$

Theorem
Suppose $\operatorname{Pr}\left[s_{i}=1\right]=\alpha \in[0,1]$ for all $1 \leq i \leq n$, and $\operatorname{Pr}\left[s_{i}=0\right]=1-\alpha, \alpha \neq 0,1$. Then we have

$$
\phi\left(S_{n}\right)=\frac{A+B}{2 \sqrt{\alpha(1-\alpha)}},
$$

where

$$
A=(1-2 \sqrt{\alpha(1-\alpha)})\left(1-(1-\sqrt{\alpha(1-\alpha)})^{n}\right)
$$

and

$$
B=(1+2 \sqrt{\alpha(1-\alpha)})\left((1+\sqrt{\alpha(1-\alpha)})^{n}-1\right)
$$

## Result was Previously Known for $\alpha=0.5$

It was shown in a 2004 EJC paper of Flaxman et al.that when $\operatorname{Pr}\left[s_{i}=1\right]=.5$ then $E\left[\phi\left(S_{n}\right)\right] \sim k\left(\frac{3}{2}\right)^{n}$ for a constant $k$. Later, Collins improved this result by finding that $E\left[\phi\left(S_{n}\right)\right]=2\left(\frac{3}{2}\right)^{n}-1$. We generalized this in the previous theorem to non-uniform letter generation. Moreover, our method for finding this formula is very different from that used by Collins. We defined a new property of a string - the number of new distinct subsequences - and then use these numbers as the entries in a binary tree. Our formula is then given as a weighted sum of the entries in this tree. This procedure is a modification of a 2008 method due to Elzinga, Rahmann, and Wang.

## Arbitrary $d$ and Two-state Markov Chains

We are done with strings on a binary alphabet generated by a random process in which the probability that any given element was 1 was fixed at $\alpha$. In the paper, we generalized this in two ways. First, we considered strings on the alphabet $\{1,2, \ldots, d\}=[d]$ where each letter is independently $j$ with probability $\alpha_{j}$ for all $j \in[d]$. After that, we returned to binary strings, but those generated according to a two-state Markov chain; in particular, if a letter follows a 1 , then it is 1 with probability $\alpha$, but if it follows a 0 , then it is 1 with probability $\beta$. In both these cases, we found recurrences for the expected new weight contributed by the $n^{\text {th }}$ letter, which led to explicit matrix equations for that expected new weight. Unfortunately, we have not yet been able able to find a closed-form formula for the total expected number of subsequences like we did for $d=2$ (independent case). But we know that in the first of these two generalizations, the limit exists!

## Open Problem 1

One of the central questions in the Permutation Patterns community is that of packing patterns and words in larger ensembles; see, e.g., a paper by Burstein et al. In a similar vein, we have the question of superpatterns, i.e., strings that contain all the patterns or words of a smaller size; see, e.g., the same paper. A distinguished question in this area is the one posed by Alon, who conjectured that a random permutation on $[n]=\left[\frac{k^{2}}{4}(1+o(1))\right]$ contains all the permutations of length $k$ with probability asymptotic to 1 as $n \rightarrow \infty$. In the present context, a similar question might be: What is the largest $k$ so that each element of $\{0,1\}^{k}$ appears as a subsequence of a binary random string with high probability?
Also, the basic question studied in this paper appears to not have been considered in the context of permutations; i.e., one might ask: What is the expected number of patterns present in a random permutation on [ $n$ ]?

## Open Question 2

In the baseline case of binary equiprobable letter generation, we have that $E\left(\phi\left(S_{n}\right)\right) \sim 2(1.5)^{n}$, which implies that the average number of occurrence of a subsequence is $\frac{1}{2} 2^{n} /(1.5)^{n}=\frac{1}{2}(4 / 3)^{n}$. Now a subsequence such as 1 occurs "just" around $n / 2$ times, and the sequence $11 \ldots 1$ with $n / 2$ ones occurs an average of $\binom{n}{n / 2} \cdot \frac{1}{2^{n / 2}}$ times, which simplifies, via Stirling's formula, to around $\sqrt{2}^{n}$, ignoring constants and polynomial factors. The same is true of any sequence of length $n / 2$; it is, on average, over-represented. We might ask, however, what length sequences occur more-or-less an average number (1.33) ${ }^{n}$ of times. We can parametrize by setting $k=x n$ and equating the expected number of occurrences of a $k$-long sequence to $(1.33)^{n}$. We seek, in other words, the solution to the equation

$$
\binom{n}{x n} \frac{1}{2^{x n}}=(1.33)^{n}
$$

Ignoring non-exponential terms and employing Stirling's approximation, the above reduces to

$$
2^{x} x^{x}(1-x)^{1-x}=0.75
$$

which, via Wolfram Alpha, yields the solutions $x=.123 \ldots$ and $x=.570 \ldots$.

