Weighted random generation of context-free languages: Analysis of collisions in random urn occupancy models

Danièle Gardy Yann Ponty

PRISM - Université de Versailles St-Quentin en Yvelines - France LIX - Polytechnique/CNRS/INRIA AMIB - France Three¹ levels of representation:

UUAGGCGGCCACAGC GGUGGGUUGCCUCC CGUACCAUCCCGAA CACGGAAGAUAAGCC CACCAGCGUUCCGGG GAGUACUGGAGUGCG CGAGCCUCUGGGAAA CCCGGUUCGCCGCCA CC June Can

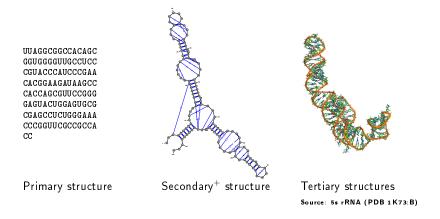
Primary structure

Secondary structure

Tertiary structures Source: 55 rRNA (PDB 1K73:B)

¹Well, almost...

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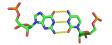


¹Well, almost...

Collisions in random generation of weighted languages

• Non-canonical base-pairs

Any basepair other than {(A-U), (C-G), (G-U)} Or interacting using a non-standard edge/orientation (WC/WC-Cis) [LW01].





C/G canonical pair (WC/WC-Cis)

CG non-canonical pair (Sugar/WC-Trans)

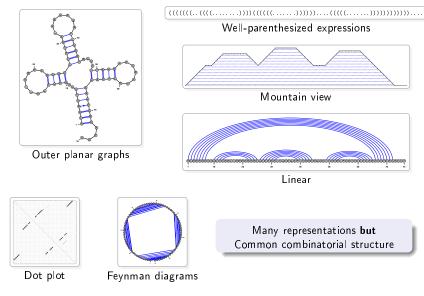
• Pseudoknots



Pseudoknots within a group I Ribozyme (PDBID: 1Y0Q:A)

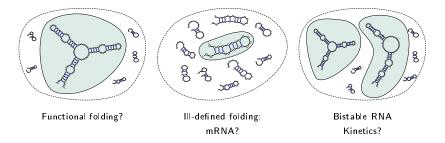
More expressive model, but *ab initio* folding with pseudoknots: ⇒ NP-Complete [LP00]... yet polynomial for restricted classes [CDR⁺04].

Secondary structures



Secondary structures = Motzkin words avoiding *plateaux* (•···•) of width $< \theta$.

Driving hypothesis for the RNA folding community assumes a Boltzmann distribution $e^{\frac{-\varepsilon}{RT}}$ based on free-energy on secondary structures compatible with base-pairing constraints.



Gold standard method: To build a consensus based on a representative sample of the Boltzmann ensemble of low-energy. \Rightarrow (Weighted)-random generation of 1000 structures and clustering.

Initial question: Is this magic number sufficient? (What is *sufficient*?)

Generalization: Drop base-pairing compatibility constraint... Secondary structures → Context-free language Boltzmann factor → Multiplicative weight

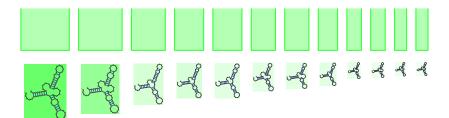
Starting point: (Weighted-)Random generation yields (huge) redundancy Remark #1: Redundancy does not teach us anything. Remark #2: Some structures/features might be obfuscated by heaviest structures.

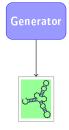
Natural questions:

- Q1 How many generations are required before some word is drawn twice?
- **Q2** How many words must be sampled before each word is encountered at least once?
- Q3 How many distinct words are there after sampling k objects?
- Q4 What is the cumulated non-redundant probability after k generations?

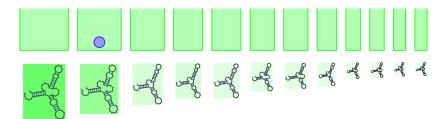
Generator

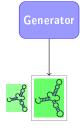
- Expected time of first collision
- #Distinct words after k generations
- Coverage after k generations
- Expected time of full collection



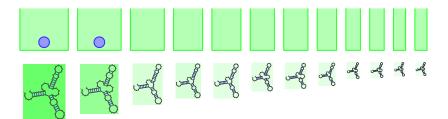


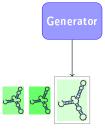
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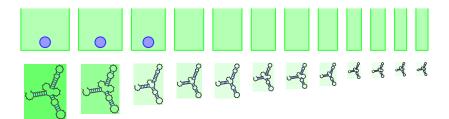


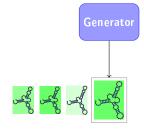
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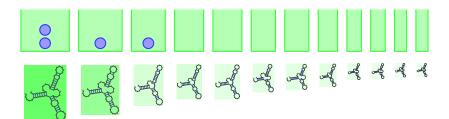
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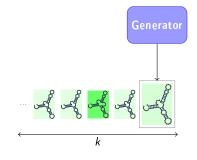




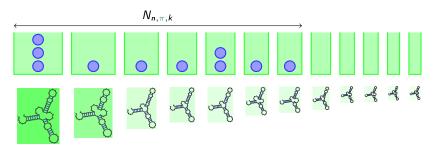
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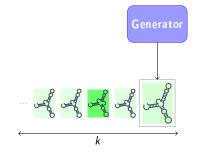
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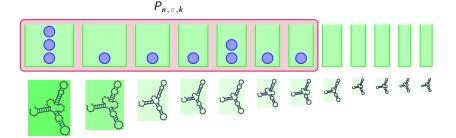


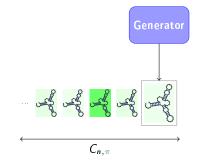
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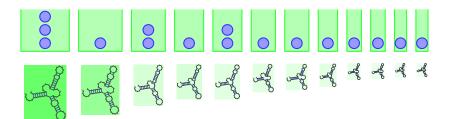


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Definition (Context-free grammar)

Context-free grammar = 4-tuple ($\Sigma, \mathcal{N}, \mathcal{P}, \mathcal{S}$):

- Σ: Alphabet.
- \mathcal{N} : Non-terminal symbols.
- \mathcal{P} : Set of production rules $N \to X \in \mathcal{N} \times \{\Sigma \cup \mathcal{N}\}^*$.
- S: Axiom, or initial non-terminal.

Alt.: Context-free grammar = admissible specification using:

- Operators {×,+}
- Finite set of atoms $\{Z_1, Z_2, \ldots, Z_k\}$
- Empty structure 1

Definition (Weighted context-free grammar [DRT00])

A weighted context-free grammar is a 5-tuple $\mathcal{G} = (\Sigma, \mathcal{N}, \mathcal{P}, \mathcal{S}, \pi)$:

- Σ , \mathcal{N} , \mathcal{P} , \mathcal{S} : Same as previously.
- π : Weight function $\pi : \Sigma \to \mathbb{R}$.

Consider the set \mathcal{L}_n of words of length *n* generated by \mathcal{G} .

Definition (Weighted probability distribution)

A WCFG G implicitly defines a weighted probability distribution over \mathcal{L}_n :

$$orall \omega \in \mathcal{L}_{n}, \ \mathbb{P}(\omega) = rac{\pi(\omega)}{\mu_{n,\pi}}.$$

where $\mu_{n,\pi} = \sum_{w \in \mathcal{L}_n} \pi(w)$ is the **total weight** of \mathcal{L}_n (partition function).

Generating k words of size n is in $\mathcal{O}(n^2 + n \log(n).k)^*$.

Furthermore, aiming at **observed** terminal frequencies:

- \Rightarrow Asymptotic weights can *sometimes* be derived analytically [DRT00]
- \Rightarrow Weights can be determined (Newton iteration)

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Definition (Weighted generating function)

A weighted generating function $L_{\pi}(z)$ can be defined as

$$L_{\pi}(z) \equiv \sum_{w \in \mathcal{L}} \pi(w) z^{|w|} = \sum_{n \ge 0} \mu_{\pi,n} z^n$$

G.f. is constructible as a solution of a weighted system of algebraic equations.

Assuming unicity of the dom. sing, the asymptotics of the total weight follow

$$[z^n] L_{\pi}(z) = \mu_{\pi,n} \sim \kappa_{\pi} \cdot \rho_{\pi}^{-n} \cdot n^{-k_{\pi}} \left(1 + \mathcal{O}\left(n^{-k'_{\pi}}\right) \right).$$

Definition (Asymptotics of total weights)

The k-th moment of a π -weighted distribution is given by

$$\alpha_{k,n} = \sum_{i=1}^{m_n} p_i^k = \frac{\sum_{w \in \mathcal{L}_n} \pi(w)^k}{\mu_{\pi,n}^k} = \frac{\mu_{\pi k,n}}{\mu_{\pi,n}^k}.$$

- **C1** Diversity: The probability $p_{n,\pi}^{\triangle}$ of the most probable word within \mathcal{L}_n decreases exponentially with n.
- C2 Log-positive weights: For each terminal symbol $t \in \Sigma$, $\pi_t > 1$. \Rightarrow No loss of generality (weighted distribution stable through rescaling)
- C3 Bounded dependency: For any rational number k > 1 and any weight vector π such that Condition C2 holds, $\rho_{\pi}{}^k < \rho_{\pi k}$ holds. (Corollary of C1)

Theorem (First collision)

Under conditions C1, C2 and C3, the expected number of generations $E[B_{n,\pi}]$ before some word of \mathcal{L}_n is drawn twice is such that

$$E[B_{n,\pi}] \sim \frac{\sqrt{\pi}}{\sqrt{2\alpha_{2,n}}} = \frac{\mu_{\pi,n}\sqrt{\pi}}{\sqrt{2\mu_{\pi^2,n}}} \in \Omega(\gamma^n), \quad \gamma := \frac{\rho_{\pi}}{\sqrt{\rho_{\pi^2}}} > 1$$

$$E[B] = \int_0^{+\infty} \lambda(t) e^{-t} dt.$$

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Proof: Let $\lambda(t) = \prod_{i=1}^{m} (1 + p_i t)$, then Flajolet-Gardy-Thimonier [FGT92]

$$E[B] = \sqrt{\frac{\pi}{2\alpha_2}} \left(1 + \mathcal{O}\left(e^{-\tau^2 \alpha_2/2}\right) + \mathcal{O}\left(\alpha_3 \tau^3\right) \right) + \mathcal{O}\left(\frac{1}{\sqrt{\alpha_2}}\right)$$

for some τ chosen such that $\alpha_2 \tau^2 \to +\infty$ and $\alpha_3 \tau^3 \to 0$ (e.g. $\tau := \alpha_{5/2}$).

Theorem (Full weighted collection)

Let $W_{\pi,n}^{\nabla}$ be the weight of the least probable word in \mathcal{L}_n and $m_n = |\mathcal{L}_n|$. The waiting time $E[C_{n,\pi}]$ of the full collection is such that

$$\frac{\mu_{\pi,n}}{W_{\pi,n}^{\nabla}} \leq E[C_{n,\pi}] \leq 2 \cdot \mathcal{H}_{m_n} \cdot \frac{\mu_{\pi,n}}{W_{\pi,n}^{\nabla}}$$

which, for large values of n, adopts the equivalent

$$\frac{\kappa_{\pi} \cdot \rho_{\pi}^{-n}}{W_{\pi,n}^{\nabla} \cdot n^{k_{\pi}}} \leq E[C_{n,\pi}] \leq \frac{2 \cdot \log(1/\rho) \cdot \kappa_{\pi} \cdot \rho_{\pi}^{-n}}{W_{\pi,n}^{\nabla} \cdot n^{k_{\pi}-1}}$$

Proof: Berenbrink and Sauerwald established that waiting time obeys

$$\frac{\mathcal{U}_m}{3e \cdot \log \log m} \leq E[C_{\pi}] \leq 2\mathcal{U}_m \quad \text{with} \quad \mathcal{U}_{m_n} = \sum_{i=1}^{m_n} \frac{1}{ip_i} \leq \frac{\mu_{\pi,n}}{W_{\pi,n}^{\nabla}} \left(\sum_{i=1}^{m_n} \frac{1}{i} = \mathcal{H}_m \right)$$

where p_i is the probability of the *i*-th least probable word. Lower bound is simply the expected time for drawing least probable word. Random generation= Allocation of undistinguishable balls into distinct urns. = Sequence (urns) of sets (content) of balls.

$$\Rightarrow \Psi_{\pi}(x,y) = \sum_{j\geq 0} \sum_{k\geq 0} a_{j,k} \cdot x^j \cdot \frac{y^k}{k!} = \prod_{i=1}^m \left(1 + x\left(e^{p_i y} - 1\right)\right)$$

where $a_{j,k}$ is the probability of reaching j distinct urns upon throwing k balls.

Theorem (Distinct samples – Hwang and Janson [HJ08]) The expected number $E[N_{n,\pi,k}]$ of distinct words after k generations obeys $E[N_{n,\pi,k}] = \sum_{i=1}^{|W|} m_{i,\pi,i} \binom{1}{1-(1-\frac{W_{n,i}}{1-\frac{$

$$E[N_{n,\pi,k}] = \sum_{i=1}^{k} m_{n,i} \cdot \left(1 - \left(1 - \frac{\nu \cdot n_{n,i}}{\mu_{\pi,n}}\right)\right) = \sum_{i=1}^{k} m_{n,i} \cdot \left(1 - e^{-\frac{\nu}{\mu_{\pi,n}}\kappa}\right) + \mathcal{O}(1)$$

where \boldsymbol{W} is the set of weight classes.

Remark: Since there are at most $\mathcal{O}(n^{|\Sigma|})$ classes of distinct weights, this gives a polynomial-time algorithm for computing $E[N_{n,\pi,k}]$.

Similar analysis is performed for coverage, introducing the weight contribution

$$\Phi_{\pi}(x,y) = \sum_{j \ge 0} \sum_{k \ge 0} b_{j,k} \cdot x^{j} \cdot \frac{y^{k}}{k!} = \prod_{i=1}^{m} \left(1 + x^{W_{i}} \left(e^{p_{i}y} - 1 \right) \right)$$

where $b_{j,k}$ is now the probability of reaching distinct urns of total weight j upon throwing k balls.

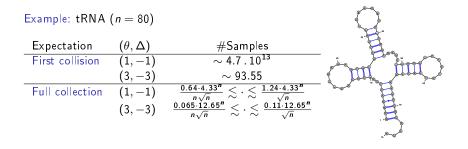
Theorem (Coverage)

In a weighted distribution, the expected cumulated probability $E[P_{n,\pi,k}] \in [0,1]$ of the set of distinct words obtained after k generations is given by

$$E[P_{n,\pi,k}] = \sum_{i=1}^{|\mathsf{W}|} m_{n,i} \cdot \frac{W_{n,i}}{\mu_{\pi,n}} \cdot \left(1 - \left(1 - \frac{W_{n,i}}{\mu_{\pi,n}}\right)^k\right)$$

$$S o (S_{\geq heta})S \mid \bullet S \mid arepsilon \qquad \qquad S_{\geq heta} o (S_{\geq heta})S \mid \bullet S_{\geq heta} \mid \bullet^{ heta}$$

Weight function: $\pi(\bigcirc) = \pi(\bigcirc) = 1$ and $\pi(\bigcirc) = e^{\frac{-\Delta}{RT}}$ with $\Delta \in \{-1, -3\}$ Remark: Every base-pair can form in this homopolymer model.



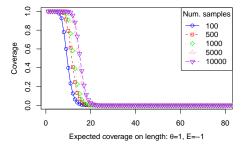
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Weight function: $\pi() = \pi(\bullet) = 1$ and $\pi(() = e^{\frac{-\Delta}{RT}}$ with $\Delta \in \{-1, -3\}$

Example:

Number $s_{n,k,i,\theta}$ of sec. str. of length n with i plateaux and $k \ge i$ bps obeys

$$s_{n,k,i,\theta} = \mathcal{N}(i,k) \binom{n-\theta k}{n-2i-\theta k} = \frac{1}{i} \binom{i}{k} \binom{i}{k-1} \binom{n-\theta k}{n-2i-\theta k}$$



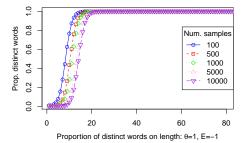
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Danièle Gardy, Yann Ponty Collisions in random generation of weighted languages

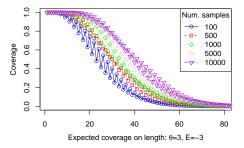
$$S o (S_{\geq heta})S \mid \bullet S \mid arepsilon \qquad \qquad S_{\geq heta} o (S_{\geq heta})S \mid \bullet S_{\geq heta} \mid \bullet^{ heta} o$$

Weight function: $\pi() = \pi(\bullet) = 1$ and $\pi(() = e^{\frac{-\Delta}{RT}} \text{ with } \Delta \in \{-1, -3\}$

Example:

Number $s_{n,k,i,\theta}$ of sec. str. of length n with i plateaux and $k \ge i$ bps obeys

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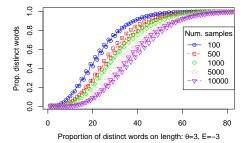
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Conclusion

We analyzed the level of redundancy within a sampled set of fixed size, and gave closed formulae/algorithms/asymptotic expansions for:

- Expected time of the first collision
- Expected time of the full collection
- Expected number of distinct samples after k generations
- Expected coverage of distinct samples

Yet certain questions remain open/partially addressed:

- Better characterization of suitable CFG languages. Which CFG satisfy the p₁ ∈ o(αⁿ), α < 1 property?
- Tighter bounds for the coupon collector $(\Theta(n) \text{ gap})$
- Perform similar analysis for non-redundant generation.
- Waiting time for d distinct samples? For a desired coverage c?
 ⇒ Determine for which k redundancy can be afforded (rejection).

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Problem: Our bounds are not tight! $\Theta(n)$ factor between upper and lower bounds.

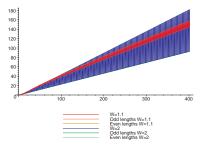


Figure: Plots of $\frac{W_{\pi,n}^{\nabla}}{\mu_{\pi,n}} \cdot \mathcal{U}_m$ for weighted Motzkin words exhibit a linear growth on *n*, suggesting that the upper bound is reached.