SPARCS: a web server to analyze (un)structured regions in coding RNA sequences

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ABSTRACT

More than a simple carrier of the genetic information, mRNA coding regions can also harbour functional elements that evolved to control different post-transcriptional processes, such as mRNA splicing, localization and translation. Functional elements in RNA molecules are often encoded by secondary structure elements. In this paper, we introduce SPARCS (Structural Profile Assignment of RNA Coding Sequences), an efficient method to analyze the (secondary) structure profile of protein coding regions in mRNAs. First, we develop a novel algorithm that enables us to sample uniformly the sequence landscape preserving the dinucleotide frequency and the encoded amino acid sequence of the input mRNA. Then, we use this algorithm to generate a set of artificial sequences that is used to estimate the Z-score of classical structural metrics such as the sum of base pair probabilities and the base pair entropy. Finally, we use these metrics to predict structured and unstructured regions in the input mRNA. We applied our methods to study the structural profile of the ASH1 genes, and recovered key structural elements. A web server implementing this discovery pipeline is available at http://csb.cs.mcgill.ca/nasp together with the source code of the sampling algorithm.

INTRODUCTION

Sequence analysis in the post-genomic era has revealed the multiplicity of selective pressures applied on the genetic code and therefore a frequent overlap of functional elements. Recent studies suggested that coding regions of messenger RNAs can often include secondary structure elements involved in post-transcriptional regulatory processes (1, 2, 3). While many programs have been developed to analyze folding properties of large non-coding RNAs (4) or untranslated regions of mRNAs (5), these tools cannot be directly applied to study the structural properties in coding regions. Indeed, the sequence of codons that specify the amino acid chain might bias the thermodynamic folding properties of the polynucleotide, thus preventing accurate estimate of the statistical significance of local structural motifs. Similar issues are encountered in the context of large scale studies and techniques aiming at defining RNA structure characteristics on a genome-wide scale (6, 7). Actually, assessing the statistical significance of observed phenomena or patterns requires the definition of a reliable and expressive background model (a.k.a. the null hypothesis). In particular, any sequence property that is a natural consequence of a well-understood mechanism should be captured by the background model, so that it will generically appear in random sequences. Including these features in the background model will lead to an increased statistical significance for novel phenomena.

A classic exploratory approach starts with a random generation of sequences that share similar properties as a reference set of sequences. Various metrics can then be evaluated, possibly leading to diverging distributions of values within the random and reference sets. The significance of such an observation can be empirically assessed using classic statistical tools (Z-score, P-value . . . ) . To implement such an approach in the context of mRNAs, one must restrict random sequences to synonymous sequences (i.e. the set of sequences that encode the same amino acid sequence). Such sequences can trivially be generated, uniformly at random, by simply choosing, for each amino acid, one of its alternate codons. Another constraint, essential when analyzing structural properties of RNA molecules, is the preservation of the overall dinucleotide frequencies (DF). Such a constraint has been popular in the field of RNA bioinformatics following the study of Workman and Krogh (8), and builds on the rationale that preserving the DF maintains the feasibility of stacking base pairs, arguably the main contributor to RNA stability. Efficient methods have been proposed for such a model, drawing an analogy with the random generation of a Euler path in a De Bruijn-like graph, whose edges represent the dinucleotides (9, 10).

When attempting to infer an evolutionary pressure from the observation of structural features within mRNA sequences,
both constraints should ideally be satisfied. Unfortunately, the algorithms used to capture these two constraints rely on radically different principles, and cannot be easily combined into an algorithm that would, at the same time, preserve the dinucleotide frequency and an amino acid sequence. For this reason, Katz and Burge proposed DiCodonShuffle (11), a heuristic algorithm based on a swapping procedure, which repeatedly exchanges codons while preserving the DF. As shown by Shabal in et al (12), such a model preserves the periodic pattern of base-pair frequencies observed within coding regions of mRNAs. However, this method is only asymptotically uniform, and a bias towards certain sequences may be anticipated in samples produced in finite time (depending on the initial sequence and the number of swaps). Furthermore, as noted by the authors, the codon/DF preserving swaps may disconnect the underlying Markov chain, causing some legit sequences to be completely inaccessible by the sampling procedure. The impact of such limitations turned out to be more than purely theoretical, and we observed (see Figure 1) that the diversity (indicated by the sequence entropy) of generated sequences was much lower for DiCodonShuffle than for our truly uniform procedure, indicating a substantial bias in the method.

In this paper, we introduce SPARCS (Structural Profile Assignment of RNA Coding Sequences) a web server that predicts structured, unstructured and disorder regions in coding RNA sequences. Building on recent algorithmic advances (13, 14), we developed a novel sampling algorithm that enables us to sample uniformly random sequences preserving the encoded protein sequence as well as the dinucleotide frequencies. Combined with multiple classical metrics (e.g. base pair probabilities and base pairing entropy), this sampling algorithm enables the calculation of Z-scores Z-scores and the prediction of strongly and weakly structured regions, along with disordered regions in exons – an insight that could not be fully achieved using previously existing sampling techniques.

SPARCS takes as input the coding region of an mRNA and proceeds in two steps. First, it generates a set of random sequences preserving the encoded amino acid sequence and the dinucleotide frequency of the input sequence. Next, it uses RNAplfold (4) to compute thermodynamic properties of the input sequence and all random sequences generated.

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**Multivariate Boltzmann sampling of protein-coding sequences under dinucleotide frequency constraint**

Our approach builds on a multivariate Boltzmann sampling scheme, initially introduced in the context of enumerative combinatorics (13), and previously applied to control the GC-content of sampled RNA sequences within the RNAmutants software (14). This approach initially relaxes the goal of preserving the DF, and draws sequences that strictly preserve the amino acid sequence while only achieving, on the average, the prescribed DF. A further rejection of unsuitable sequences, whose DF differ too much from the targeted DF, filters the generated sequences, reestablishing the uniformity within the selected subset. The produced sequences therefore feature both correct DF and coding capacity while being generated with uniform probability.

Namely, let $S$ be an amino acid sequence, and $\mathbf{dc}' = (dc'_{AA}, dc'_{AC}, dc'_{AG}, \ldots)$ be the vector of targeted dinucleotide frequencies, the algorithm repeats the following steps until the desired number of samples is reached:

1. Draw a set of structures encoding $S$, with respect to a weighted distribution;

2. Estimate expected DF from sample;

3. Collect suitable sequences;

4. Update weights to match expected DF with target.

**Weighted distribution.** We associate a weight $\pi_{XY}$ to each dinucleotide $XY$. This weight is inherited multiplicatively by any RNA sequence in rna($S$), the set of sequences compatible with a targeted amino acid sequence $S$. This implicitly defines a probability distribution over rna($S$) where any RNA sequence $w \in \text{rna}(S)$ has probability

$$\mathbb{P}(w) = \frac{\pi(w)}{\sum_{w' \in \text{rna}(S)} \pi(w')}$$

with $\pi(w) = \prod_{i=1}^{w-1} \pi_{w_i, w_{i+1}}$.

Quite importantly, it should be noted that any pair of sequences having an equal DF will also have equal relative probability. Therefore, generating a set of sequences, and
retaining only the sequences that do feature the targeted DF, gives an unbiased set of sequences. This property also holds for sequences generated using different weights, therefore they can be gathered across different iterations of the adaptive sampling without introducing a bias.

**Self-adaptive calibration of weights.** The weighting scheme may be used to shift the expected number of occurrences of each dinucleotide, as illustrated by Figure 2. Let us denote by $V_{XY}$ the number of copies of $XY$ in a random sequence generated in the weighted model. For instance, setting $\pi_{GU}$ to 0 will cancel the probability of any sequence featuring any occurrence of $GU$, and the expected number of $GU$ will therefore drop to 0. Conversely, setting $\pi_{GU} \to +\infty$ will only grant positive probability to sequences that maximize the number of copies of $GU$.

To find a weight that matches the expected DF with the targeted one, we use a heuristic strategy to figure out weights that achieve, on the average, the targeted DF. To that purpose, we initially set $\pi(XY):=d_{XY}/V_{XY}$ and, after each iteration of the adaptive sampling, we update each weight to $\pi(XY)\cdot d_{XY}/\mu_{XY}$, where $\mu_{XY}$ is the expected value for $V_{XY}$ estimated from the sample. The process typically converges after a few iterations, leading to a good approximation of the best weight set.

**Random generation.** To draw a sequence of rna$(S)$ within the weighted distribution, one needs to choose a compatible codon for each of the $n$ amino acid in $S$. Such choices cannot be made independently, since the overlap between consecutive codons contributes to an additional dinucleotide, ultimately impacting the weight of a generated sequence.

Following the general principle of the recursive approach for random generation (15, 16), we precompute the total weight $Z_{b,i}$ of every sequence accessible upon choosing some codon ending with a base $b\in\{A,U,C,G\}$ at the $i$-th position. Such weights can be efficiently computed using dynamic programming based on

$$Z_{b,n+1} = 1 \quad \text{and} \quad Z_{b,i} = \sum_{c\in\text{cod}(S_i)} \pi(b,c)\cdot Z_{c-1,i+1}$$

where $\text{cod}(S_i)$ is the set of codons compatible with the $i$-th amino acid in $S$, and $c_1$ is the last nucleotide of $c$. Since the first amino acid ($i=1$) is not preceded by any nucleotide, it must be treated slightly differently by setting $b:=\varnothing$ and $\pi(\varnothing,c) := 1$.

During the random generation, these precomputations are used to assign probabilities to each of the possible codons, such that each sequence is generated which respect to the weighted distribution. Namely, one picks a codon $c\in\text{cod}(S_i)$ for the $i$-th amino acid, in the context of a previous nucleotide $b$, with probability

$$p_{b,c,i} = \frac{\pi(b,c)\cdot Z_{c-1,i+1}}{Z_{b,i}}.$$ 

The sampling algorithm starts on the first codon ($i:=1$ and $b:=\varnothing$), and iterates over the amino acid sequence $S$ in increasing order, picking a codon with the above probabilities, and updating $b$ to the last nucleotide in the elected codon. After picking the last codon, it can be shown that the generated sequence is indeed in rna$(S)$, and has probability which is proportional to its weight (cf supp. mat.). The complexity of the algorithm is in $\Theta(k\cdot n)$ time and space for sampling $k$ sequences, each consisting of $n$ codons.

**Overall time and space requirement.** We empirically observed, and could formally prove using Drmota
theorem (17) for non-degenerate cases, that \( V_{XY} \) asymptotically follows a Normal law of mean in \( \Theta(n) \) and standard deviation \( \sigma_{XY} \) in \( \Theta(\sqrt{n}) \). Furthermore, the covariances between numbers for different dinucleotides remains provably limited, and the joint distribution of the \( V_{XY} \) for every dinucleotide \( XY \) asymptotically follows a 16-variate Normal law. Consequently, the probability of generating a sequence having expected DF scales like \( \Theta(n^{-1/2}) \) and it takes, on the average, \( \Theta(n^3) \) attempts to obtain such a sequence. The average-case complexity of a rejection procedure for the uniform sampling is in \( \Theta(k \cdot n^3) \) time, after a linear time and space preprocessing.

Such a large time complexity may be impractical for real-life applications. However, if a small relative tolerance \( \varepsilon \in \Theta(1/\sqrt{n}) \) is allowed on every targeted dinucleotide count, leading any sequence \( w \) to be accepted if its dinucleotide counts are such that

\[
(1-\varepsilon) \cdot dc^\varepsilon_{XY} \leq dc_{XY}(w) \leq (1+\varepsilon) \cdot dc^\varepsilon_{XY},
\]

for every dinucleotide \( XY \). Under this setting, the probability of acceptance only decreases like \( o(1/n) \) for every dinucleotide \( XY \), leading any sequence \( w \) to be accepted if its dinucleotide counts are such that

\[
\varepsilon = 3 \cdot \max_{XY} (\sigma_{XY}/n) \in \Theta(1/\sqrt{n}) \quad \text{(The 3 std.-dev. rule),}
\]

then the probability of acceptance becomes greater than 0.99\(^{16} \approx 85\% \), and the average-case complexity of the method becomes asymptotically equivalent to \( \Theta(k \cdot n) \), at the cost of loss of uniformity which is typically negligible, and can be efficiently corrected through a post-processing step (13).

### Secondary structure prediction

The secondary structures of both the input mRNA sequence and random sequences are predicted using the RNAplfold software, distributed within the Vienna RNA package (18). RNAplfold considers all possible locally stable secondary structures for an input RNA sequence, and calculates base pair probabilities, assuming a Boltzmann equilibrium. As recommended by Lange et al. (19), we use a window size of \( W + 50 \) nucleotides (\( W = 150 \) by default), and retain only those base pairs separated by at most \( W \) positions, and set a base pair probability cut off threshold to 0.1.

### Characterization of the structural profile

We screen the input sequence with a sliding window of \( W \) nucleotides and evaluate the standardized score (Z-score) for each window \( w \) on two classical metrics: \( B(w) \) the sum of base pair probabilities and \( H(w) \) the base pair entropy. Let \( C \) be the set of all valid base pairs in the sliding window and \( p_{i,j} \) the probability of a base pair \( (i,j) \). We define the sum of base pair probabilities as the sum of all base pair probabilities assessed by RNAplfold within the frame, such that

\[
B(w) = \sum_{(i,j) \in C} p_{i,j}.
\]

The sum of base pair probability estimates the stability of the secondary structures in the conformational landscape and thus quantifies the structural potential of the sequence. Similarly, we define the base pair entropy as the Shannon entropy of the base pair probabilities, such that

\[
H(w) = - \sum_{(i,j) \in C} p_{i,j} \cdot \log(p_{i,j}).
\]

The base pair entropy aims to evaluate whether many alternate sub-optimal structures exist in the conformational landscape. For each nucleotide position, the Z-scores of all windows are averaged out to give the structural profile at a single nucleotide resolution.

We use these metrics to characterize a structural profile consisting in three, mutually-exclusive, types of regions, based on two user-defined thresholds \( t_\beta \) and \( t_\delta \):

- **Structured regions**: A region is said to be structured when the Z-score of the base pair probability exceeds \( t_\beta \) and the Z-score of the base pair entropy is lower than \( -t_\delta \). This configuration indicates stable structures with few competitors.

- **Unstructured regions**: A region is unstructured when the Z-score of the base pair probability and the Z-score of the base pair entropy are respectively lower than \( -t_\beta \) and \( -t_\delta \). In that case, the energy landscape is flat with no dominant structure.

- **Disordered regions**: A region is disordered when the Z-score of the base pair probability and the Z-score of the base pair entropy respectively exceed \( t_\beta \) and \( t_\delta \). This configuration suggests the presence of multiple stable and competing structures in the conformational landscape.

By default, SPARCS uses thresholds on the Z-score of 0.2 to discriminate high or low values. As illustrated in the next section, these settings aim to classify structural domains in the input sequences. Nonetheless, more stringent values can be specified, for instance if the user wishes to detect strongly (un-)structured regions.

### Analysis of Ash1 gene in yeast

We illustrate the insights brought by SPARCS on the well-studied Ash1 gene in yeast. Using mutagenesis studies and comparative sequence analysis, four functional elements have been identified in the Ash1 mRNA. Each of them has been shown to be sufficient to localize a reporter mRNA to the bud of dividing yeast cells (20). Out of the four elements, three (E1,E2A and E2B) are located within the coding region of Ash1 mRNA.
Our results show that the E1 (positions 625 to 775) match predicted disordered and structured regions. The presence of disordered region at the beginning of the element could be explained by the presence of internal loops and alternate base pairings in the predicted secondary structure (See Gonzales et al (21) and Chartrand et al (20)). Interestingly, the elements E2A (positions 1081 to 1199) and E2B (positions 1200 to 1447) are both surrounded by unstructured regions, possibly to avoid interactions between these elements. Noticeably, unlike the E2A element, the E2B element is particularly stable and structured. Outside these functional segments, we identify a large unstructured region (from 200 to 600) before the E1 element which could help to stabilize the E1 element or, hypothetically, to facilitate translation. By contrast, we identify a strongly structured regions between the E1 and E2 elements. This prediction could reveal a buffer that aims to prevent these elements interacting. Finally, our analysis also suggests a structured region at the beginning of the sequence (positions 50 to 200). To the best of our knowledge, this region has not been experimentally studied, motivating further comparative studies.

**NASP SERVER**

The SPARCS web server takes an RNA/DNA sequence or a FASTA file as input. Upon validation, a first set of 1 000 random sequences, preserving both the DF and encoded amino acid sequence of the input sequence, is generated. A second set of 1 000 random sequences, called the uniform model, is generated to preserve only the amino acid sequence. The input sequence and the 2 000 random sequences are then fed to RNAplfold to predict their base pairing properties. The Z-score is computed for a sliding window of user-specified width (defaulting to 150 nts), and all Z-scores are averaged for every position to evaluate the statistical significance of the secondary structure profile.

SPARCS finally outputs a single Z-score plot based on our metrics: sum of base pair probabilities, base pair entropy, structural potential region, unstructured potential region and
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Figure 4. Typical runtime of SPARCS for sequence lengths varying from 200 to 1000 nts.

SPARCS runs on a server hosted at University McGill, which has 8 cores and has a total of 63 GB of memory. Each core is an Intel(R) Xeon(R) CPU X5570 at 2.93GHz, with 8192 KB cache. Figure 4 shows the overall runtime on the server as a function of the mRNA length, for mRNA sequences ranging from 200 to 1000 nts, and reveals a linear trend.

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