Correction


The authors note that Snehal Gaikwad should be added to the author list between Alex Limpaecher and Sungroh Yoon. Snehal Gaikwad should be credited with designing research and performing research. The corrected author line, affiliation line, and author contributions appear below. The online version has been corrected.

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RNA design rules from a massive open laboratory

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Self-assembling RNA molecules present compelling substrates for the rational interrogation and control of living systems. However, imperfect in silico models—even at the secondary structure level—hinder the design of new RNAs that function properly when synthesized. Here, we present a unique and potentially general approach to such empirical problems: the Massive Open Laboratory. The EteRNA project connects 37,000 enthusiasts to RNA design puzzles through an online interface. Uniquely, EteRNA participants not only manipulate simulated molecules but also control a remote experimental pipeline for high-throughput RNA synthesis and structure mapping. We show herein that the EteRNA community leveraged dozens of cycles of continuous wet laboratory feedback to learn strategies for solving in vitro RNA design problems on which automated methods fail. The top strategies—including several previously unrecognized negative design rules—were distilled by machine learning into an algorithm, EteRNABot. Over a rigorous 1-y testing phase, both the EteRNA community and EteRNABot significantly outperformed prior algorithms in a dozen RNA secondary structure design tests, including the creation of dendrimer-like structures and scaffolds for small molecule sensors. These results show that an online community can carry out large-scale experiments, hypothesis generation, and algorithm design to create practical advances in empirical science.

RNA folding | citizen science | high-throughput experiments | crowdsourcing

Structured RNA molecules play critical roles in biological processes from genetic regulation to viral replication; the characterization, detection, and reengineering of these RNAs are major goals of modern molecular biology and bioengineering (1–7). Recent years have witnessed the emergence of elegant RNA folding models that accurately capture secondary structure formation of loops and simple helices (8–12). However, more complex motifs, such as multiloops, remain challenging to model (1), and thus, algorithmically designed RNAs frequently misfold in vitro. Practitioners must often fall back on trial-and-error refinement or problem-specific selection methods (1–7).

High-throughput synthesis and biochemical interrogation offer the prospect of developing better folding models. Nevertheless, a small group of professional scientists must interpret this torrent of empirical data, a challenging task even with modern machine learning and visualization tools. The results of such big data science often lack the parsimony, elegance, and predictive power of handcrafed models. This paper presents an alternative approach, a Massive Open Laboratory, that combines the parallelism of high-throughput experimental biochemistry with the advantages of detailed human-guided experimental design and analysis.

The 37,000-member EteRNA project has now generated many hundreds of designs probed at single nucleotide resolution, resulting in a database of nearly 100,000 data points. Instead of outpacing human curation, this unprecedented dataset of designs has been created concomitantly with detailed handicrafted hypotheses advanced by the community, most of which were previously unexplored in the RNA modeling literature. Sifting and automating these hypotheses by machine learning has resulted in an automated algorithm, EteRNABot, which parsimoniously describes a unique optimization function for RNA design. A gauntlet of additional design targets tested this algorithm, including previously unseen RNA secondary structures as well as complex scaffolds for small molecule sensors, with binding that provided independent readouts of folding accuracy. These tests confirmed that both EteRNABot-designed RNAs and handcrafted RNAs by the community outperform existing state of the art algorithms. Although previous internet-scale communities have solved difficult problems in silico (13–16), the results herein are unique in showing that such a community can collectively generate and test hypotheses through actual experiments, which are required for advancing empirical science.

Results

EteRNA combines an interactive interface for modeling biomolecules with a remote wet laboratory experimental pipeline (Materials and Methods and Fig. 1). A web-based interface challenges participants to design and rank sequences that will fold into a target structure when synthesized in vitro (SI Appendix, Fig. S1 and Table S1) and develop design rules that explain the community’s experimental results. High-throughput synthesis and structure mapping measurements [selective 2′-hydroxyl acylation with primer extension (SHAPE)] (17) (Materials and Methods and Fig. 1C) assess nucleotide pairing of eight community-selected designs per week. EteRNA returns these experimental results to participants through visualization of the data at single nucleotide resolution (Fig. 1D) as well as an overall structure mapping score on a scale of 0–100 (Materials and Methods), indicating the percentage of nucleotides giving reactivities consistent with the target structure (experimental

Significance

Self-assembling RNA molecules play critical roles throughout biology and bioengineering. To accelerate progress in RNA design, we present EteRNA, the first internet-scale citizen science “game” scored by high-throughput experiments. A community of 37,000 nonexperts leveraged continuous remote laboratory feedback to learn new design rules that substantially improve the experimental accuracy of RNA structure designs. These rules, distilled by machine learning into a new automated algorithm EteRNABot, also significantly outperform prior algorithms in a gauntlet of independent tests. These results show that an online community can carry out large-scale experiments, hypothesis generation, and algorithm design to create practical advances in empirical science.


Conflict of interest statement: The editor, David Baker, is a recent coauthor with R.D. having published a paper with him in 2013. This article is a PNAS Direct Submission. Freely available online through the PNAS open access option.

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2A complete list of the EteRNA Group can be found in Dataset S1.

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Fig. 1. EteRNA workflow. Each week, participants (A) design sequences that can fold into a target RNA structure in the sequence design interface and (B) review and vote for the best designs with the voting interface. (C) At the end of the round, the eight top-voted sequences are synthesized and verified by single nucleotide resolution chemical reactivity measurements. (D) The experimental results are published online and available for review in the results viewer. Participants then create new hypotheses and (A) start the next experimental cycle or (E) submit design rules learned from the results (text that are codified and automatically ranked based on scores obtained to date (numbers).

error ±5) (SI Appendix, Fig. S2). As participants intuited features of experimentally successful designs, they can submit heuristics to a design rule collection (Fig. 1E). Additional descriptions of the platform design (SI Appendix, Fig. S3), training of participants, reward structure, visualization, participant distributions (SI Appendix, Fig. S4), and experimental reproducibility (SI Appendix, Fig. S2) are given in Materials and Methods and SI Appendix.

The initial 6-mo training period, called phase I, saw the EteRNA community engaging in six RNA design problems containing increasing numbers of nonhelical elements (bulges and multihelix junctions) and more complex topologies (Fig. 2), mimicking components of known functional RNAs (1, 5, 6, 18); 189 community-chosen sequences were synthesized along with 65 sequences from RNAInverse (11) and NUPACK (12) algorithms for comparison. Initially, the community was inexperienced, and their designs depended solely on computational folding models (11). These designs fared poorly: during the first laboratory competition (the three-helix finger) (Fig. 2A), many participants’ designs gave structure mapping scores lower than the maximum scores, with top participant designs achieving scores indistinguishable from perfect designs given experimental error (>95). In contrast, the increasing structural complexity (measured in stems and junctions) led to declining performances for RNAInverse and NUPACK (Fig. 2). First round designs from EteRNA participants were significantly better than designs from RNAInverse and NUPACK in the last three puzzles, with P values of 2.9 × 10−4 against both algorithms (Fig. 2, structure mapping data and SI Appendix, Table S3B). We independently confirmed these results from the EteRNA training period by additional tests based on several additional design challenges (SI Appendix, Fig. S5), automated SHAPE-directed secondary structure inference (SI Appendix, Fig. S6), a different chemical mapping method based on dimethyl sulfate alkylation (19) (SI Appendix, Fig. S7), 2D chemical mapping with the more information-rich mutate-and-map technique (20) (which suggests structural heterogeneity in failed designs; SI Appendix, Supporting Results and Fig. S8), and replicates by separate experimenters and with alternative techniques (next generation sequencing) (SI Appendix, Fig. S2). SI Appendix, Supporting Results gives a complete description of these results and structure models.

During the training challenges, the community-submitted collection of design rules grew to 40 contributions (Fig. 3 and SI Appendix, Table S4), most of which encoded unique insights into successful RNA designs. On one hand, some of these rules involved features previously discussed in the RNA design literature [e.g., G-C content (SI Appendix, Table S4, A Basic Test), the ensemble defect (8, 12) (SI Appendix, Supporting Results and Table S4, Clean Dot Plot), and sequence symmetry minimization (21) (SI Appendix, Table S4, Repetition)]. Some features were similar to patterns highlighted in bioinformatic analyses of naturally structured RNAs, such as the prevalence of G-C closing pairs at multiloop junctions (SI Appendix, Table S4, GC Pairs in Junctions) or the general prevalence of adenosines outside stems (SI Appendix, Table S4, Only As in the Loops) (18). On the other hand, EteRNA participants developed many design rules unique in the RNA folding and design field, including prescriptions for the identities of unpaired nucleotides adjacent to stems (SI Appendix, Table S4, No Blue Nucleotides in Hook Area), C-G vs. G-C edge base pairs in different contexts (SI Appendix, Table S4, Direction of GC Pairs in Multiloops + Neck Area), and placement of Gs within loops (SI Appendix, Table S4, Gs in Place of the Last As on the Righthand Side of Any End Loop).

Few of these rules have been previously encoded into energetic models or automated RNA design methods or confirmed experimentally, and it remained unclear if the participants’ proposed rules accounted for their outperformance of prior design methods. We, therefore, sought to evaluate the rules independently from EteRNA participants through their integration into a single score function. Sparse machine learning regression (22) with cross-validation selected five rules (Fig. 3), which we tested by incorporation into a unique automated Monte Carlo algorithm called EteRNABot and rigorous experimental tests. Materials and Methods and SI Appendix, Supporting Results provide additional discussion on this algorithm, a less parsimonious algorithm EteRNABot-alt reweighting all 40 rules, and a variant algorithm using only features preexisting in the project interface.

In the subsequent testing period, called phase II, nine unique targets challenged EteRNA participants, the EteRNABot method, and prior algorithms (Fig. 4 and SI Appendix, Fig. S9). The first five targets (Fig. 4 A–E) were multijunction structures distinct from each other and the phase I structures in topology. We evaluated only one round of participant designs per target, thus testing whether community knowledge was generalizable across target structures. We again observed superior performance of the participant designs compared with RNAInverse and NUPACK, (P = 1.5 × 10−4 and 2.9 × 10−4, respectively) (SI Appendix, Table S3C). Furthermore, in three of five cases (Fig. 4 B, D, and E), automated designs from the unique EteRNABot algorithm achieved maximum scores within ±1.5 of the participant designs and median scores within ±5.5. In the two remaining cases
(Fig. 4 A and C), EteRNA Bot modestly underperformed participants, a gap that may close as more experimental data and design rules are collected. Importantly, EteRNA Bot outperformed RNAInverse and NUPACK (\( \text{P} = 3.0 \times 10^{-4} \) and \( 1.2 \times 10^{-3} \), respectively) (SI Appendix, Table S3C), with higher maximum scores in all cases (Fig. 4 F–I and SI Appendix, Table S3D). Furthermore, these designs’ association constants for FMN binding offered stringent tests of folding accuracy that were fully independent of the structure mapping scores (Fig. 4 K–N and SI Appendix, Supporting Results and Fig. S11). Here again, both EteRNA participants and EteRNA Bot outperformed RNAInverse and NUPACK in both best and median association constants (\( \text{P} < 0.05 \) in all pairwise comparisons) (Fig. 4N and SI Appendix, Table S3E). These small molecule binding measurements
in any reasonable energetic model. Such features may not be captured in prior RNA design algorithms, which may uncover designs that stabilize the target structure compared with misfolds by overoptimizing idiosyncrasies of a particular energetic model. The emergence of energy-function-independent negative design rules in the EteRNA project underscores the importance of actual experimental falsification/validation in developing RNA design methods.

Beyond its implications for RNA engineering, our method represents a successful attempt to generate and experimentally test hypotheses through crowdsourcing. As the data throughput of experimental approaches continues to grow, this approach offers several benefits. Currently, small sets of professional scientists attempt to resolve the complexity of designing and analyzing high-throughput experiments and enumerate a space of folding hypotheses for computational analysis of these data. Instead, the approach herein enables a vastly larger number of participants to design and execute remote experiments in parallel, while machine learning algorithms sift through the community's catalog of hypotheses. This Massive Open Laboratory template could be generalized to a broad class of biomolecule design problems, including mechanistic dissection of current design rules (26), modeling of pseudoknots, engineering of RNA switches for cellular control (5, 6), and 3D modeling and design, all assessed by high-throughput mapping (1, 7, 16, 20, 29, 30). Other fields, such as taxonomy (31), astronomy (13), and neural mapping (32), are making pioneering efforts in internet-scale scientific discovery games. Our Massive Open Laboratory results suggest that integrating timely player-proposed experiments as part of the standard game play will be worthwhile challenges for such projects.

Materials and Methods

Online Interface. EteRNA is an online Flash (Adobe Systems Inc.) application that can be accessed within any web browser. EteRNA presents the RNA design problem as a set of puzzles; participants use an interactive sequence design interface to design RNA sequences that fold into target secondary structures. The interface visualizes each nucleotide with yellow, blue, red, and green circular symbols representing adenine, uracil, guanine, and cytosine, respectively. Symbols are laid out using the NAView drawing algorithm (33). The secondary structure display updates in real time with the minimum free energy pseudoknot-free solution predicted by the ViennaRNA package (11) (compiled into Flash). The interface also gives access to predicted melting curves and dot plots of alternative base pairings (11). Additional descriptions of the individual components of the EteRNA online interface are presented in SI Appendix, Supporting Methods and Fig. S3.

Design Rule Selection Method and EteRNABot. EteRNABot is a unique algorithm for design of pseudoknot-free secondary structures that optimize a function to predict structure mapping scores (see below) generated from participant-submitted design rules. To create the score predictor, each participant-submitted rule was coded into a scoring function. When a rule contained nondiscrete numeric parameters (given as numbers in brackets in Fig. 3B and SI Appendix, Table S4), its scoring function was optimized over the parameters using the downhill simplex algorithm (34) to minimize the average squared error between the predicted and actual structure mapping scores for the training set (results from phase I and the four follow-up puzzles before phase II). SI Appendix, Table S4 lists all design rules and corresponding scoring functions; SI Appendix, Table S5 gives a glossary of frequently used terms in design rules. The EteRNABot score is a linear combination of five scoring functions selected from 40 submitted rules using least angle regression (22) and cross-validation from analyses leaving out data for each target shape (Fig. 3B). SI Appendix, Supporting Results and Fig. S10 report the predictive power of EteRNABot scores for structure mapping scores. To design a unique secondary structure, EteRNABot runs a loop of randomized nucleotide mutations to find a sequence that accepts a mutation if it increases the sequence's predicted score or decreases a base pair distance between the predicted minimum free energy structure [calculated with ViennaRNA (11)] and the target structure; its speed is nearly the same as RNAInverse. The search ends when the sequence's predicted score is over 90 and the base pair distance is less than 0.1 times the sequence length. The EteRNABot algorithm and its training data are freely available as a server at http://eternabot.org. We also report experimental results of an alternate EteRNABot that uses all 40 submitted rules in SI Appendix, Supporting Results, Fig. S10, and Tables S2 and S3.
Fig. 4. Phase II puzzles and results, including the EteRNABot algorithm, in order of puzzle posting date. (A–E) Multijunction target structures distinct from each other and the phase I structures in topology. (F–I) Puzzles giving the binding site for FMN as a fixed sequence that must be displayed as an internal loop (boxed in the target structure; J shows the sequence) within a complex structure. The coloring scheme is identical to the coloring scheme used in Fig. 2, with EteRNABot shown in magenta. (K–N) FMN association constants for all designs synthesized for the last four puzzles measured by dimethyl sulfate chemical mapping as a function of FMN concentration. Measurements on a simple construct displaying FMN binding (green dashed line) give the best possible association constant, which is achievable only with correct secondary structure folding. The down arrows in K–N mark RNAInverse designs that gave no observable FMN binding, setting the upper bounds on the association constants.
RNA Synthesis and Structure Mapping. RNA sequences were prepared by in vitro transcription with T7 RNA polymerase from DNA templates encoding the sequence designs and probed with structure mapping based on Nmethylisothiourea (SHAPE chemistry (17)) using 96-well protocols described previously (35). All RNAs contained a shared primer binding site (AAAGAAAGAAAAACACAAACAC) at their 3’ end, which was included as a fixed sequence in EteRNA puzzles. Measurements included SHAPE reactions (final concentration of Nmethyl isothiourea of 6 mM with 20% DMSO (vol/vol)) or dimethyl sulfate reactions (final concentration of 0.25% at 24 °C with 60 mM NaCl) in two solution conditions (10 mM MgCl2 and 1 M NaCl) with 50 mM Na-Hepes (pH 8.0), control measurements without SHAPE agent, and control measurements using 2′-3′-deoxyisothymidine triphosphate in primer extension to generate reference ladders at adenosine residues. All data were aligned and quantified with the HITRACE software (36), corrected for attenuation of long reverse transcription products, and background-subtracted as described in ref. 35. SHAPE-directed secondary structure models and confidence estimates were obtained with data-derived pseudoenergy terms and nonparametric bootstrapping (35). Binding titrations to FMM were monitored with dimethyl sulfate alklylation (19), which gave a strong protection signal on FMM binding to the aptamer (SI Appendix, Fig. S11 A–C). Titrations were analyzed with likelihood-based fits and error estimation (SI Appendix, Fig. S11 C and D) (37). Finally, for 30 sequences, we also carried out the SHAPE experiments as a read out by illumina sequencing, which was analogous to the L1 norm scores used in prior work (41). A nucleotide was assigned a point if its reactivity exceeded 0.25 (if designed to be unpaired) or was less than 0.50 (if designed to be paired). The threshold for unpaired nucleotides was less stringent to allow for the possibility that the nucleotide could have received reactivity from nearby nucleotides by interactions and set based on calibration data on natural structured RNAs (35). The baseline and normalization of each dataset were determined using linear programming to optimize the total score. Scores were given as the percentage of nucleotides with points (0–100). An additional scoring system based on the ratio of likelihoods for the data given the target secondary structure and the best possible unpaired/paired status at each nucleotide was also tested using likelihood distributions derived from a benchmark of natural RNAs (35). The likelihood-based scheme gave ranking consistent with the point-based scheme and took into account experimental error; we chose to use the point-based scheme to calculate the EteRNA structure mapping score because of its simplicity.

Availability
EteRNA platform and all synthesis data used in this paper are available at http://eternagame.org. EteRNABot and its training data are available at http://eternabot.org. Please see Dataset SI for a complete listing of the EteRNA participants.

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