Complex behavior from simple molecular systems

Peter Schuster

Institut für Theoretische Chemie, Universität Wien, Austria and The Santa Fe Institute, Santa Fe, New Mexico, USA



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Review article:

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ENCODE stands for **ENC**yclopedia Of **DNA** Elements.

ENCODE Project Consortium. Identification and analysis of functional elements in 1% of the human genome by the ENCODE pilot project. *Nature* 447:799-816, 2007

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Author Information Reprints and permissions information is available at www.nature.com/reprints. The authors declare no competing financial interests. The list of individual authors is divided among the six main analysis groups and five organizational groups. Correspondence and requests for materials should be addressed to the co-chairs of the ENCODE analysis groups (listed in the Analysis Coordination group). E Birney (birney@eblac.uk); J. A. Stamatoyannopoulos (jstam@u.washington.edu). A. Duta(add@gwijnia.edu). R. Guigo (rguigo@imim.es); T. R. Gingeras (Torm, Gingeras@affymetrix.com); E. H. Margulies (elliot@mkpir.inib.gov); Z. Weng (chiping@bucdu); M. Snyder (michael.snyder@yale.edu). E. T. Dermitzakis (mdd@sanger.ac.uk) or collectively (encode_chairs@eblac.uk).

The ENCODE Project Consortium

Analysis Coordination Ewan Birney¹, John A. Stamatoyannopoulos², Anindya Dutta³, Roderic Guigó^{4,5}, Thomas R. Gingeras⁶, Elliot H. Margulies⁴, Zhiping Weng^{8,6}, Michael Snyde^{10,11} & Emmanouil T. Dermitzakis¹²

Chromatin and Replication John A. Stamatoyannoppulos², Robert E. Thurman^{2,13}, Michael S. Kuehn^{2,13}, Christopher M. Taylor², Shane Neph², Christoph M. Koch¹², Saurabh Asthan^{2,4}, Ankit Malhotra³, Ivan Adzhubel⁴¹, Jason A. Greenbaum⁷, Robert M. Andrews¹⁰, Paul Flicek¹, Patrick J. Boyle¹, Hua Cao¹³, Nigel P. Carter², Gayle K. Clelland³, Sean Davis¹⁰, Nathan Day², Pavandeep Dham¹³, Shane C. Dillon², Michael O. Dorschner², Heike Flegler¹², Paul G. Giresi¹⁷, Jeff Goldy⁴, Michael Hawrylvc2¹⁰, Andrew Haydock², Richard Humbert², Keith D. James¹⁰, Brett E. Johnson¹¹, Ericka M, Johnson¹³, Tristan T. Frum¹³, Elizabeth R. Rosenzweig¹¹, Nereja Karnan¹³, Kristen Lee⁷, Gregory C. Lefebvre¹⁰, Patrick A. Navas³, Fidencio Ner¹³, Stephen C. Janks¹⁰, Sandsr¹⁰, Sarah Wilcox¹⁰, Man Yu¹³, Francis S. Collins⁷, Job Dekker¹⁹, Jason D. Lieb¹⁷, Thomas D. Tullius¹⁶, Gregory E. Crawford¹⁰, Shamil Sunyaev¹⁸, William S. Noble², Ian Dunham¹⁰ & Anindva Dutta³

ARTICLES

ARTICLES

Genes and Transcripts Roderic Guigo^{4, 5}, France Denoeud⁵, Alexandre Reymond^{21,22} Philipp Kapranov⁶, Joel Rozowsky¹¹, Deyou Zheng¹¹, Robert Castelo⁵, Adam Frankish¹² Jennifer Harrow¹², Srinka Ghosh⁶, Albin Sandelin²³, Ivo L. Hofacker²⁴, Robert Baertsch^{25,26}, Damian Keefe¹, Paul Flicek¹, Sujit Dike⁶, Jill Cheng⁶, Heather A. Hirsch²⁷ Edward A. Sekinger²⁷, Julien Lagarde⁵, Josep F. Abril^{5,28}, Atif Shahab²⁹, Christoph Flamm^{24,30}, Claudia Fried³⁰, Jörg Hackermüller³², Jana Hertel³⁰, Mania Lindemever³⁰, Kristin Missal^{20,31}, Andrea Tanzer^{24,30}, Stefan Washietl²⁴, Jan Korbel¹¹, Olof Emanuelsson¹¹, Jakob S. Pedersen²⁶, Nancy Holroyd¹², Ruth Taylor¹², David Swarbreck¹², Nicholas Matthews¹², Mark C. Dickson³³, Daryl J. Thomas^{25,26}, Matthew Swatterek, "Netrauch²⁵, James Gilbert¹², Jorg Drenkow⁶, Ian Bell⁶, XiaoDong Zhao¹⁴, K.G. 7. Neirauch²⁵, James Gilbert¹², Jorg Drenkow⁶, Ian Bell⁶, XiaoDong Zhao¹⁴, K.G. 7. Tyler Alioto⁴, Michael Brent³⁵, Lior Pachter¹⁶, Michael L. Tress³⁷, Alfonso Valencia³¹ Siew Woh Choo34, Chiou Yu Choo34, Catherine Ucla22, Caroline Manzano22, Carine Wyss²², Evelyn Cheung⁶, Taane G. Clark³⁸, James B. Brown³⁹, Madhavan Ganesh⁶ Sandeep Patel⁹, Hari Tammana⁶, Jacqueline Chrast²¹, Charlotte N. Henrichsen²¹, Chikatoshi Kai²³, Jun Kawai^{23,40}, Ugrappa Nagalakshmi¹⁰, Jiaqian Wu¹⁰, Zheng Lian⁴¹ Jin Lian⁴¹, Peter Newburger⁴², Xueqing Zhang⁴², Peter Bickel⁴³, John S. Mattick⁴⁴, Piero Carrinci⁴⁰, Yoshihide Hayashizaki^{23,40}, Sherman Weissman⁴¹, Emmanouil T, Dermitzakis¹⁷, Elliott H. Margules⁷, Tim Hubbard¹⁷, Richard M. Myers³³, Jane Rogers¹², Peter F. Stadler^{24,30,45}, Todd M. Lowe³⁵, Chia-Lin Wei³⁴, Yijun Ruan³⁴, Michael Snyder^{10,11}, Ewan Birney¹, Kevin Struhl²⁷, Mark Gerstein^{11,46,47}, Stylianos E. Antonarakis²² & Thomas R. Gingeras⁶

Integrated Analysis and Manuscript Preparation James B. Brown³⁹, Paul Flicek¹, Yutos Fu^{*}, Damian Keefe¹, Ewan Birney¹, France Denoeud⁴, Mark Gerstill^{114,6,47}, Erich D. Green^{7,48}, Philipp Kapranov¹, Ulas Karalo², Richard M. Myers¹³, William S. Noble², Alexandre Reymond^{12,02}, Joel Rozowsky¹¹, Kevin Struhl²⁷, Adam Siepel^{25, 26}4, John A. Stamatoyannopoulos², Christopher M. Taylor¹, James Taylor^{49,50}, Robert E. Thurman^{21,13}, Thomas D. Tullius⁵, Stefan Washiel²⁴ & Gevoo Lehen¹¹

Management Group Laura A. Liefer⁵¹, Kris A. Wetterstrand⁵¹, Peter J. Good⁵¹, Elise A. Feingold⁵³, Mark S. Guyer⁵¹ & Francis S. Collins⁵²

Multi-species Sequence Analysis Elliott H. Margules', Gregory M. Cooper³⁴; Gorcg Asimenos³⁵. Dary J. Thomas^{25,45}. Colin N. Devery⁴⁵, Adam Siegel^{25,46}; F. Wan Birney¹, Damian Keele¹, Minmel Hou^{49,50}, James Taylor^{49,50}, Sergey Nikolaev²⁵, Juan I. Mottoya-Burgos²⁵, Ari Löytynoja¹, Simon Whetan¹, Fabio Pardi¹¹, Tim Massingham¹, James B. Brown²⁹, Haiyan Huang⁴⁵, Nancy R. Zhang^{45,56}, Peter Bickel⁴³, Ian Holmes³⁷, James C. Mullikin^{16,46}, Kate Rosenbolom²⁰, W. James Kent^{15,56}, Pieter Bickel⁴³, Ian Holmes³⁷, James C. Mullikin^{16,46}, Kate Rosenbolom²⁰, W. James Kent^{15,56}, Fick A. Stone³⁸, NISC Comparative Sequencing Program², Baylor College of Medicine Human Genome Sequencing Center³, Washing Markon University Genome Sequencing Center³, Broad Institute⁴, Children's Hospital Dakland Research Institute⁴, Mark Gerstein^{15,46,40}, David Haussler^{25,26,60}, Webb Miller^{49,50,61}, Lior Pachter³⁶, Eric D. Green^{7,48} & Arend Sidow^{31,42}

Transcriptional Regulatory Elements Zhiping Weng^{8,9}, Nathan D. Trinklein³³†, Yutao Fu⁸, Zhengdong D. Zhang¹¹, Ulaş Karaöz⁸, Leah Barrera⁶⁸, Rhona Stuart⁶⁸, Deyou Zheng¹¹, Srinka Ghosh⁶, Paul Flicek¹, David C. King^{50, 59}, James Taylor^{49, 50}, Adam Ameur⁶⁹, Stefan Enroth⁶⁹, Mark C. Bieda⁷⁰, Christoph M. Koch¹², Heather A. Hirsch²⁷ Chia-Lin Wei³⁴, Jill Cheng⁶, Jonghwan Kim⁷¹, Akshay A. Bhinge⁷¹, Paul G. Giresi¹⁷, Nan Jiang⁷², Jun Liu³⁴, Fei Yao³⁴, Wing-Kin Sung¹⁴, Kuo Ping Chiu³⁴, Vinsensius B. Vega³⁴, Charlie W.H. Lee³⁴, Patrick Ng³⁴, Atif Shahab²⁹, Edward A. Sekinger²⁷, Annie Yang²⁷ Zarmik Moqtaderi27, Zhou Zhu27, Xiaoqin Xu70, Sharon Squazzo7 ⁷⁰, Matthew J Oberley⁷³, David Inman⁷³, Michael A. Singer⁷², Todd A. Richmond⁷², Kyle J. Munn^{72,74} Alvaro Rada-Iglesias⁷⁴, Ola Wallerman⁷⁴, Jan Komorowski⁶⁹, Gayle K. Clelland¹² Sarah Wilcox¹², Shane C. Dillon¹², Robert M. Andrews¹², Joanna C. Fowler¹², Phillippe Couttet¹², Keith D. James¹², Gregory C. Lefebyre¹², Alexander W. Bruce¹², Oliver M Dovey¹², Peter D. Ellis¹², Pawandeep Dhami¹², Cordelia F. Langford¹², Nigel P. Carter¹⁵ David Vetrie¹² Philipp Kapranov⁶ David A. Nix⁶ Jan Bell⁶ Sandeep Patel⁶ Joel Rozowsky¹¹, Ghia Euskirchen¹⁰, Stephen Hartman¹⁰, Jin Lian⁴¹, Jiagian Wu¹⁰, Alexander E. Urban¹⁰, Peter Kraus¹⁰, Sara Van Calcar⁶⁸, Nate Heintzman⁶⁸, Tae Hoon Kim⁶⁸, Kun Wang⁶⁸, Chunxu Qu⁶⁸, Gary Hon⁶⁸, Rosa Luna⁷⁵, Christopher K. Glass⁷⁵, M. Geoff Rosenfeld⁷⁵, Shelley Force Aldred³³, Sara J. Cooper³³, Anason Halees⁸, Jane M. Lin⁹ Hennady P. Shulha⁶, Xiaoling Zhang⁸, Mousheng Xu⁸, Jaafar N. S. Haidar⁹, Yong Yu⁵ Ewan Birney*1, Sherman Weissman41, Yijun Ruan34, Jason D. Lieb17, Vishwanath R. Iyer71, Roland D. Green72, Thomas R. Gingeras6, Claes Wadelius74, Ian Dunham12 Kevin Struhl²⁷, Ross C. Hardison^{50,59}, Mark Gerstein^{11,46,47}, Peggy J. Farnham⁷⁰ Richard M. Myers³³ Bing Ren⁶⁸ & Michael Snyder^{10,11}

UCSC Genome Browser Daryl. J. Thomay^{53,20}, Kate Rosenbloom²⁶, Rachel A. Harte²⁶, Angie S. Hinichs²⁶, Heather Trumbower²⁶, Hiram Clawson⁴⁶, Jennifer Hilman-Jackson²⁹, Ann S. Zweig²⁶, Kayla Smith³⁰, Archana Thakkapallayil²⁶, Galt Barber^{15,26}, Robert M. Kuhn³⁶, Donna Karolchik²⁶, David Haussler^{25,26,66} & W. James Kent^{25,26} Variation Emmanouil T. Dermitzakis¹², Lluis Armengol¹⁶, Christine P. Bird¹², Taane G. Clark¹⁸, Gregory M. Cooper³³, Paul I. W. de Bakker⁷⁷, Andrew D. Kem³⁵, Nuria Loper-Bigas², Joel D. Matrin⁵⁵, Barbara E. Stranger¹², Danyi I. Thomas²⁵, Jolipi and Woodrolfe⁷⁸, Serafim Batzoglou⁵³, Eugene Davydov⁵³, Antigone Dimas¹⁹, Eduardo Eyras², Ingilel B. Hallgrimsdditir²⁷, Ross C. Hardison^{65,99}, Julian Huppert¹², Arend Sidow^{33,62}, James Taylor^{45,69}, Heather Trumbower¹⁰, Michael C. Zody⁷⁷, Roderic Guigód^{5,6}, James C. Mullikin⁷, Gonçalo R. Abecasis¹⁸, Xavier Estivill^{10,60,68} & Ewan Birneu¹

*NISC Comparative Sequencing Program Gerard G. Bouffard⁷⁻⁴⁹, Xiaobin Guan⁴⁸, Nancy F. Hansen⁴⁹, Jacqueyn R. Idol, 'Valerie V.B. Maduro,' Baishail Masker⁴⁹, Jannifer C. McDowell⁴⁹, Morgan Park⁴⁹, Pamela J. Thomas⁴⁰, Alice C. Young⁴⁰ & Robert W. Blakesley^{1,44} Baylor College of Medicine, Human Genome Sequencing Center Donna M. Margu⁴⁰, Erics Sodergren⁴⁰, David A. Wheele⁴⁷, Kim C. Worley⁴⁷, Hualyang Jiang⁴⁰, George M. Weinstock⁴⁰ & Richard A. Gibbs⁴⁰, Washington University Genome Sequencing Center Tina Graves⁴⁴, Rober Hulton⁴⁴, Elsine R. Mardis⁴⁴ & Richard K. Wilson⁴⁶ Broad Institute Michele Clamp⁴⁰, James Cuff⁴⁰, Sante Gnerre⁴⁰, David B. Jaffe⁴⁰, Jean L. Chang⁴⁷, Kerstin Lindblad⁴ Toh⁴⁷ & Eric S. Mikhail Nefedov⁴⁶, Kazutoyo Osoegawa⁴⁰, Yuko Yoshinaga⁴⁰, Baoli Zhu⁵⁷ & Pieter J. de Jone⁵⁵.

Affiliations for participants: ¹EMBL-European Bioinformatics Institute, Wellcome Trust Genome Campus, Hinxton, Cambridge, CB10 1SD, UK. ²Department of Genome Sciences 1705 NE Pacific Street, Box 357730, University of Washington, Seattle, Washington 98195, USA. ³Department of Biochemistry and Molecular Genetics, Jordan 1240. Box 800733, 1300 Jefferson Park Ave, University of Virginia School of Medicine, Charlottesville, Virginia 22908, USA. ⁴Genomic Bioinformatics Program, Center for Genomic Regulation. ⁵Research Group in Biomedical Informatics, Institut Municipal d'Investigació Médica/Universitat Pompeu Fabra, c/o Dr. Aiguader 88, Barcelona Biomedical Research Park Building, 08003 Barcelona, Catalonia, Spain. ⁶Affymetrix, Inc., Santa Clara, California 95051, USA. 7Genome Technology Branch, National Human Genome Research Institute, National Institutes of Health, Bethesda, Maryland 20892. USA. [®]Bioinformatics Program, Boston University, 24 Cummington St., Boston, Massachusetts 02215, USA. ⁹Biomedical Engineering Department, Boston University, 44 Cummington St., Boston, Massachusetts 02215, USA. 10 Department of Molecular, Cellular, and Developmental Biology, Yale University, New Haven, Connecticut 06520, LISA. ¹¹Department of Molecular Biophysics and Biochemistry, Yale University, PO Box 208114, New Haven, Connecticut 06520, USA. 12 The Wellcome Trust Sanger Institute, Wellcome Trust Genome Campus, Hinxton, Cambridge, CB10 1SA, UK. ¹³Division of Medical Genetics, 1705 NE Pacific Street, Box 357720, University of Washington, Seattle, Washington 98195, USA. ¹⁴Division of Genetics, Brigham and Women's Hospital and Harvard Medical School, 77 Avenue Louis Pasteur, Boston, Massachusetts 02115, USA. ¹⁶Department of Chemistry and Program in Bioinformatics, Boston University, 590 Commonwealth Avenue, Boston, Massachusetts 02215, USA. ¹⁶Genetics Branch, Center for Cancer Research, National Cancer Institute, National Institutes of Health. Bethesda. Maryland 20892, USA. 17 Department of Biology and Carolina Center for Genome Sciences, CB# 3280, 202 Fordham Hall, The University of North Carolina at Chapel Hill, Chapel Hill, North Carolina 27599, USA. ¹⁸Allen Institute for Brain Sciences, 551 North 34th Street, Seattle, Washington 98103, USA. ¹⁹Program in Gene Function and Expression and Department of Biochemistry and Molecular Pharmacology, University of Massachusetts Medical School, 364 Plantation Street, Worcester, Massachusetts 01605, USA. 20 Institute for Genome Sciences & Policy and Department of Pediatrics, 101 Science Drive, Duke University, Durham, North Carolina 27708, USA. ²¹Center for Integrative Genomics, University of Lausanne, Genopode building, 1015 Lausanne, Switzerland. 22 Department of Genetic Medicine and Development, University of Geneva Medical School, 1211 Geneva, Switzerland. 23 Genome Exploration Research Group, RIKEN Genomic Sciences Center (GSC), RIKEN Yokohama Institute, 1-7-22, Suehiro-cho, Tsurumi-ku, Yokohama, Kanagawa, 230-0045, Japan. 24 Institute for Theoretical Chemistry, University of Vienna, Währingerstraße 17, A-1090 Wien, Austria. ²⁵Department of Biomolecular Engineering, University of California, Santa Cruz, 1156 High Street, Santa Cruz, California 95064, USA. 26 Center for Biomolecular Science and Engineering, Engineering 2, Suite 501, Mail Stop CBSE/ITI, University of California, Santa Cruz, California 95064, USA. 27 Department of Biological Chemistry & Molecular Pharmacology, Harvard Medical School, 240 Longwood Avenue, Boston, Massachusetts 02115, USA. 28 Department of Genetics, Facultat de Biologia, Universitat de Barcelona, Av Diagonal, 645, 08028, Barcelona, Catalonia, Spain. 29 Bioinformatics Institute, 30 Biopolis Street, #07-01 Matrix, Singapore, 138671, Singapore. ³⁰Bioinformatics Group, Department of Computer Science, ³¹Interdisciplinary Center of Bioinformatics, University of Leipzig, Härtelstraße 16-18, D-04107 Leipzig, Germany. 32 Fraunhofer Institut für Zelltherapie und Immunologie - IZI, Deutscher Platz 5e, D-04103 Leipzig. Germany. 33 Department of Genetics, Stanford University School of Medicine, Stanford, NATURE Vol 447 14 June 2007

California 94305, USA. ³⁴Genome Institute of Singapore, 60 Biopolis Street, Singapore 138672, Singapore. 35 Laboratory for Computational Genomics, Washington University. Campus Box 1045, Saint Louis, Missouri 63130, USA. ³⁶Department of Mathematics and Computer Science, University of California, Berkeley, California 94720, USA. 37Spanish National Cancer Research Centre, CNIO, Madrid, E-28029, Spain. 38Department of Epidemiology and Public Health, Imperial College, St Mary's Campus, Norfolk Place, London W2 IPG, UK. 39 Department of Applied Science & Technology, University of California, Berkeley, California 94720, USA. 40 Genome Science Laboratory, Discovery and Research Institute, RIKEN Wako Institute, 2-1 Hirosawa, Wako, Saitama, 351-0198, Japan. 41Department of Genetics, Yale University School of Medicine, 333 Cedar Street, New Haven, Connecticut 06510, USA. 42Department of Pediatrics, University of Massachusetts Medical School, 55 Lake Avenue, North Worcester, Massachusetts 01605, USA, 43Department of Statistics, University of California, Berkeley, California 94720, USA, 44 Institute for Molecular Bioscience, University of Queensland, St. Lucia, OLD 4072, Australia. 45 The Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, New Mexico 87501, USA, ⁴⁶Department of Computer Science, Yale University, PO Box 208114, New Haven, Connecticut 06520-8114, USA. 47Program in Computational Biology & Bioinformatics, Yale University, PO Box 208114, New Haven, Connecticut 06520-8114, USA, 48NIH Intramural Sequencing Center, National Human Genome Research Institute, National Institutes of Health, Bethesda, Maryland 20892, USA. 49 Department of Computer Science and Engineering, The Pennsylvania State University, University Park, Pennsylvania 16802, USA. 50 Center for Comparative Genomics and Bioinformatics, Huck Institutes for Life Sciences, The Pennsylvania State University, University Park, Pennsylvania 16802, USA. ⁵¹Division of Extramural Research, National Human Genome Research Institute, National Institute of Health, 5635 Fishers Lane, Suite 4076, Bethesda, Maryland 20892-9305, USA. 52Office of the Director, National Human Genome Research Institute, National Institute of Health, 31 Center Drive, Suite 4809, Bathesda, Maryland 20892-2152, USA, 53Department of Computer Science, Stanford University, Stanford, California 94305, USA. 54 Department of Biostatistics and Medical Informatics, University of Wisconsin-Madison, 6720 MSC, 1300 University Ave, Madison, Wisconsin 53706, USA. 55 Department of Zoology and Animal Biology, Faculty of Sciences, University of Geneva, 1205 Geneva, Switzerland. 56 Department of Statistics, Stanford University, Stanford, California 94305, USA. 57 Department of Bioengineering, University of California, Berkeley, California 94720-1762, USA. 58 National Center for Biotechnology Information, National Institutes of Health, Bethesda, Maryland 20894, USA. 59 Department of Biochemistry and Molecular Biology, Huck Institutes of Life Sciences, The Pennsylvania State University, University Park, Pennsylvania 16802, USA. ⁰Howard Hughes Medical Institute, University of California, Santa Cruz, California 95064, USA. ⁶¹Department of Biology, The Pennsylvania State University, University Park, Pennsylvania 16802, USA, 62 Department of Pathology, Stanford University School of Medicine, Stanford, California 94305, USA. 63 Human Genome Sequencing Center and Department of Molecular and Human Genetics, Baylor College of Medicine, Houston, Texas 77030, USA. 64 Genome Sequencing Center, Washington University School of Medicine, Campus Box 8501, 4444 Forest Park Avenue, Saint Louis, Missouri 63108, USA. 65 Broad Institute of Harvard University and Massachusetts Institute of Technology, 320 Charles Street, Cambridge, Massachusetts 02141, USA. 66 Whitehead Institute for Biomedical Research, 9 Cambridge Center, Cambridge, Massachusetts 02142, USA. 67 Children's Hospital Oakland Research Institute, BACPAC Resources, 747 52nd Street, Oakland, California 94609, USA. 68 Ludwig Institute for Cancer Research, 9500 Gilman Drive, La Jolla, California 92093-0653, USA. 69 The Linnaeus Centre for Bioinformatics, Uppsala University, BMC, Box 598, SE-75124 Uppsala, Sweden. 70 Department of Pharmacology and the Genome Center, University of California, Davis, California 95616, USA. 71Institute for Cellular & Molecular Biology, The University of Texas at Austin, 1 University Station A4800, Austin, Texas 78712, USA. 72NimbleGen Systems, Inc., 1 Science Court, Madison, Wisconsin 53711, USA. 73 University of Wisconsin Medical School, Madison, Wisconsin 53706, USA. 74Department of Genetics and Pathology, Rudbeck Laboratory, Uppsala University, SE-75185 Uppsala, Sweden. 75University of California, San Diego School of Medicine, 9500 Gilman Drive, La Jolla, California 92093, USA. ⁷⁶Genes and Disease Program, Center for Genomic Regulation, c/o Dr. Aiguader 88, Barcelona Biomedical Research Park Building, 08003 Barcelona, Catalonia, Spain. ⁷Broad Institute of MIT and Harvard, 7 Cambridge Center, Cambridge, Massachusetts 02142, USA. 78Center for Statistical Genetics, Department of Biostatistics, SPH II, 1420 Washington Heights, Ann Arbor, Michigan 48109-2029, USA. 79Department of Statistics, University of Oxford, Oxford OX1 3TG, UK. 80 Universitat Pompeu Fabra, c/o Dr. Aiguader 88, Barcelona Biomedical Research Park Building, 08003 Barcelona, Catalonia, Spain. †Present addresses: Department of Genome Sciences. University of Washington School of Medicine, Seattle, Washington 98195, USA (G.M.C.); Department of Biological Statistics & Computational Biology, Cornell University, Ithaca, New York 14853, USA (A.S.); Faculty of Life Sciences, University of Manchester, Michael Smith Building, Oxford Road, Manchester, M13 9PT, UK (S.W.); SwitchGear Genomics, 1455 Adams Drive, Suite 2015, Menlo Park, California 94025, USA (N.D.T.; S.F.A.).

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- 1. Minimum free energy structures of RNA
- 2. Suboptimal structures of RNA
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5' - end

N₁



A symbolic notation of RNA secondary structure that is equivalent to the conventional graphs

sequence
$$\xrightarrow{S_{\cdot} = \Psi(X_{\cdot})}$$
 structure $\xrightarrow{f_{\cdot} = \Phi(S_{\cdot})}$ function

The paradigm of structural biology

What is neutrality?

Selective neutrality =

= several genotypes having the same fitness.

Structural neutrality = = several sequences forming molecules with the same structure.

RNA sequence GUAUCGAAAUACGUAGCGUAUGGGGAUGCUGGACGGUCCCAUCGGUACUCCA



Structural biology, spectroscopy of biomolecules, understanding molecular function

Biophysical chemistry: thermodynamics and kinetics **Empirical parameters RNA structure** of minimal free energy

Sequence, structure, and design



The minimum free energy structures on a discrete space of conformations



Minimum free energy structure

Extension of the notion of structure

RNA sequence GUAUCGAAAUACGUAGCGUAUGGGGAUGCUGGACGGUCCCAUCGGUACUCCA

RNA folding:

Structural biology, spectroscopy of biomolecules, understanding molecular function Iterative determination of a sequence for the given secondary structure

> Inverse Folding Algorithm

Inverse folding of RNA:

Biotechnology, design of biomolecules with predefined structures and functions

RNA structure of minimal free energy

Sequence, structure, and design



Space of genotypes: $Q = \{X_1, X_2, X_3, X_4, \dots, X_N\}$; Hamming metric Space of phenotypes: $S = \{S_1, S_2, S_3, S_4, \dots, S_M\}$; metric (not required)

N >> M

 $\psi(X_j) = S_k$

$$\mathbf{G}_{\mathbf{k}} = \boldsymbol{\psi}^{-1}(S_{\mathbf{k}}) \doteq \left\{ X_{\mathbf{j}} \mid \boldsymbol{\psi}(X_{\mathbf{j}}) = S_{\mathbf{k}} \right\}$$

A mapping ψ and its inversion

	$\mathbf{G}_{\mathbf{k}} = \boldsymbol{\psi}^{-1}(\mathbf{S}_{\mathbf{k}}) \doteq \left\{ \mathbf{I}_{j} \mid \boldsymbol{\psi} \right\}$ $\boldsymbol{\Sigma} \boldsymbol{\lambda} \cdot (\mathbf{k})$	$r(I_j) = S$	5 _k }	
	$\overline{\lambda}_k = \frac{\sum_{j \in G_k } \mathcal{N}_j(\mathbf{R})}{ G_k }$			
			Alphabet	size ĸ:
		к	λ_{cr}	
		2	0.5	AU,GC,DU
$\lambda_{j} = 12 / 27 = 0.444$		3	0.423	AUG , UGC
_		4	0.370	AUGC

 $\bar{\lambda}_k > \lambda_{cr} \dots$ network \mathbf{G}_k is connected

 $\bar{\lambda}_k < \lambda_{cr} \dots$ network G_k is **not** connected

Connectivity threshold: $\lambda_{cr} = 1 - \kappa^{-1/(\kappa-1)}$

Degree of neutrality of neutral networks and the connectivity threshold



A multi-component neutral network formed by a rare structure: $\lambda < \lambda_{cr}$



A connected neutral network formed by a common structure: $\lambda > \lambda_{cr}$

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG



GGCUAUCGUACGUUUACCCGAAAGUCUACGUUGGACCCAGGCAUUGGACG

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG





GGCUAUCGUACGUUUACCCGAAAGUCUACGUUGGACCCAGGCAUUGGACG

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG





GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGG^UCCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCC<mark>G</mark>AAAGUCUACGUUGGACCCAGGCAUUGGACG

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCAGGCAUUGGACG







GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGUCCCAGGCAUUGGACG

GGCUAUCGUACGUUUACCCGAAAGUCUACGUUGGACCCAGGCAUUGGACG

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG



GGCUAUCGUAUGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACUCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGCUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCCAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUGUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCUGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCUGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCACUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG GGCUAUCGUACGUUUACCCCAAAAGUCUACGUUGGACCCAGGCAUUGGACG

PAN

	Number	Mean Value	Variance	Std.Dev.	
Total Hamming Distance:	150000	11.647973	23.140715	4.810480	
Nonzero Hamming Distance:	99875	16.949991	30.757651	5.545958	
Degree of Neutrality:	50125	0.334167	0.006961	0.083434	
Number of Structures:	1000	52.31	85.30	9.24	
1 ((((((((((()))))).))).))	50125	0.334167	
2(((((())))))).)))	2856	0.019040	
3 (((((((((((((())))))))).))	2799	0.018660	
4 (((((.(((()))))))).))).))	2417	0.016113	
5 (((((.((((.())).)))).))).))	2265	0.015100	
6 (((((((((((().))))))))).))	2233	0.014887	
7 (((((((()))))))			1442	0 009613	
8 ((((((((((()))))))))))	1081	0.009013	
9 (((((((((())) • •)))))))))	1025	0.007207	
10 (((((((((((((((((((((((((((((((((((()))))	1003	0.006687	
11 (((((((((((((((((((((((((((((((((())))	963	0.006420	
12 ((((((((((((((((((((((((((((((((((((860	0.005733	
13 ((((((((((((((((((((((((((((((((((((800	0.005333	
14 (((((((((((((((((((((((((((((((((((()),)),,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	548	0.003653	
15 ((((((((()))) .))).))	362	0.002413	AGGU
16 ((.((((((((((((((((((((())))))))))))))))))) .))))	337	0.002247	
17 (.(((.(((())))))))))).)	241	0.001607	~ č
18 (((((((((((((())))))))))))))))))))))))))))))))))))))))).))	231	0.001540	A A
19 ((((((((()))))	.))))	225	0.001500	CAG CAG
20 (()))))))))	202	0.001347	LLA GA
20 (())))))))))	202	0.001347	u A G ^{GA}
				GC A A	
~				AUGGUE	
Shadow – Surrounding of an RN.	A structure i	n shape space:	ç		
AUGC alphabet, chain length n=	50		¢	A	

Results from RNA minimun free energy structures:

• RNA minimum free energy structures show neutrality: Many sequences fold into the same (secondary) structure.

• The single base mutation neighborhood contains structures from neutral sequences **and** a great variety of other structures: Biopolymer landscapes are **rugged**.

1. Minimum free energy structures of RNA

- 2. Suboptimal structures of RNA
- 3. Kinetic folding and RNA switches
- 4. Chemistry of Darwinian evolution
- 5. Consequences of neutrality
- 6. Evolutionary optimization of RNA structure



Minimum free energy structure

Extension of the notion of structure



Minimum free energy structure

Suboptimal structures

Extension of the notion of structure

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCA**U**UGGACG

GGCUAUCGUACGUUUACACAAAAGUCUACGUUGGACCCAGGCAUUGGACG

•	(((((•	•	()	((((. ((•	•	•	•))	•	•)]))))	•))		•	•	•)))							 •	-6.	50
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•	(((((()	((((. ((•))	•	•)))))))		•	•)))	•							-6.	00

GGCUAUCGUACGUUUACCCAAAAGUCUACGUUGGACCCAGGCAAUGGACG

(((((((((((((((((((((((((((((((((((((((7.30
(((((()))))))((()))).	7.20
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At equilibrium and temperature *T* the conformations form a Boltzmann ensemble that contains S_j with the Boltzmann weight $\gamma_j(T) = g_j \exp(-(\varepsilon_j - \varepsilon_0)/RT)/Q(T)$, where *R* is the Boltzmann constant for 1 mole, $R = N_L \cdot k_B$, and Q(T) is the partition function

$$Q(T) = \sum_{i} g_{i} \exp\left(-(\varepsilon_{i} - \varepsilon_{0})/RT\right).$$

$$\gamma_{j}(T) = g_{j} \exp\left(-(\varepsilon_{j} - \varepsilon_{0})/RT\right)/Q(T)$$

$$P(X, T) = \sum_{k} \gamma_{k}(T) A(S_{k}) \text{ or } p_{ij}(X, T) = \sum_{k} \gamma_{k}(T) a_{ij}(S_{k})$$

$$A(S_{k}) \dots \text{ adjacency matrix of structure } S_{k}$$

$$p_{ij}(X, T) \dots \text{ base pairing probability}$$

$$X \dots \text{ sequence}$$

Usage of the partition function to analyze the spectrum of suboptimal states



CGUCCCGUCUCUUCCGAGCGCCAGGA

(((((((((,,))))))))))))))))))))))))))	-4.50
(((((((()))).)).)))	-3.70
$\dots (((((((((((((((((((((((((((((((((((($	-3.60
(((()))))	-3.00
\dots ((.((((()))).)).)).)).	-2.80
(((.(.((())))))))))))))))))))))))	-2.60
(.(((.(()))))))))))))))))))))))))	-2.50



Suboptimal structures and partition function of a small RNA molecule: n = 26



CGGCCGGAGCGGAUAUGCCUAAAGGU

..((((((((((...))))))...))) -3.70

•	•	(((•	•	•	(((•	•	•	•)))	•	•	•	•	•)))	-3.	60
•	•	(((•	(•	(((•	•	•	•)))	•)	•	•	•)))	-3.	50
•	•	(((•	•	((((•	•	•	•)))	•)	•	•	•)))	-3.	30
•	•	(((•	•	((((•	•	•	•))	•))	•	•	•)))	-3.	30
•	•	(((•	(•	(((•	•	•	•))))	•	•	•	•)))	-3.	10
(•	((•	•	•	•))	•)	•	•	•	•	(((•	•	•	•)))	-2.	90
•	•	(((•	•	•	•	•	((•	•	•	•	•))	•	•	•	•)))	-2.	90
•	•	•	(((•	•	•)))	•	•	•	•	(((•	•	•	•)))	-2.	90
•	•	(((((•	((•	•	•	•	•	•))))	•	•	•)))	-2.	70
•	•	(((•	•	•	((•	•	•	•	•	•))	•	•	•	•	•)))	-2.	60
•	•	•	((•	•	•	•	•))	•	•	•	•	(((•	•	•	•)))	-2.	60
•	•	(((•	(•	((•	•	•	•	•	•))	•)	•	•	•)))	-2.	50
•	•	(((•	•	((•	(•	•	•	•	•	•)))	•	•	•)))	-2.	50
•	(((•	•	•	•	•	•	•	•	•	•	•	•)))	•	•	•	•	•	•	•	-2.	30
•	•	(((•	•	(((•	•	•	•	•	•))	•)	•	•	•)))	-2.	30
•	•	(((•	•	(((•	•	•	•	•	•)	•))	•	•	•)))	-2.	30
•	•	•	•	•	((•	(((•	•	•	•)))))	•	•	•	•	•	•	-2.	20



Suboptimal structures and partition function of a small RNA molecule: n = 26


UUUGGUGCUCAUAUCUGACAGAUCCA

..((((((((((...))))))...))) -1.10

•	•	(((•	•	•	(((•	•	•	•)))	•	•	•	•	•)))	-1.00
•	•	•	((((•	(((•	•	•	•)))))	•	•	•))	•	-1.00
•	•	•	((•	•	•	(((•	•	•	•)))	•	•	•	•	•))	•	-0.90
•	•	(((((•	((•	•	•	•	•	•))))	•	•	•)))	-0.70
•	•	(((•	•	•	((•	•	•	•	•	•))	•	•	•	•	•)))	-0.60
•	•	•	((((•	((•	•	•	•	•	•))))	•	•	•))	•	-0.60
•	•	•	((•	•	•	((•	•	•	•	•	•))	•	•	•	•	•))	•	-0.50
•	•	•	•	•	((•	(((•	•	•	•)))))	•	•	•	•	•	•	-0.20
•	•	(((•	(•	(((•	•	•	•))))	•	•	•	•)))	-0.10
•	•	(((•	•	((((•	•	•	•)))	•	•)	•	•)))	-0.10
((((•	•	•	(•	•	•	•	•	•	•	•)	•))))	•	•	•	•	0.00
•	•	•	((•	(•	(((•	•	•	•))))	•	•	•	•))	•	0.00
•	•	•	((•	•	((((•	•	•	•)))	•	•)	•	•))	•	0.00
•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	•	0.00



Suboptimal structures and partition function of a small RNA molecule: n = 26



The intersection of two compatible sets is always non empty: $\mathbf{C}_0 \cap \mathbf{C}_1 \notin \emptyset$



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GENERIC PROPERTIES OF COMBINATORY MAPS: NEUTRAL NETWORKS OF RNA SECONDARY STRUCTURES¹

 CHRISTIAN REIDYS*,†, PETER F. STADLER*,‡ and PETER SCHUSTER*,‡, §,²
 *Santa Fe Institute, Santa Fe, NM 87501, U.S.A.

†Los Alamos National Laboratory, Los Alamos, NM 87545, U.S.A.

‡Institut für Theoretische Chemie der Universität Wien, A-1090 Wien, Austria

§Institut für Molekulare Biotechnologie, D-07708 Jena, Germany

(E.mail: pks@tbi.univie.ac.at)

Random graph theory is used to model and analyse the relationships between sequences and secondary structures of RNA molecules, which are understood as mappings from sequence space into shape space. These maps are non-invertible since there are always many orders of magnitude more sequences than structures. Sequences folding into identical structures form neutral networks. A neutral network is embedded in the set of sequences that are compatible with the given structure. Networks are modeled as graphs and constructed by random choice of vertices from the space of compatible sequences. The theory characterizes neutral networks by the mean fraction of neutral neighbors (λ). The networks are connected and percolate sequence space if the fraction of neutral nearest neighbors exceeds a threshold value $(\lambda > \lambda^*)$. Below threshold $(\lambda < \lambda^*)$, the networks are partitioned into a largest "giant" component and several smaller components. Structures are classified as "common" or "rare" according to the sizes of their pre-images, i.e. according to the fractions of sequences folding into them. The neutral networks of any pair of two different common structures almost touch each other, and, as expressed by the conjecture of shape space covering sequences folding into almost all common structures, can be found in a small ball of an arbitrary location in sequence space. The results from random graph theory are compared to data obtained by folding large samples of RNA sequences. Differences are explained in terms of specific features of RNA molecular structures. © 1997 Society for Mathematical Biology

THEOREM 5. INTERSECTION-THEOREM. Let s and s' be arbitrary secondary structures and C[s], C[s'] their corresponding compatible sequences. Then,

$C[s] \cap C[s'] \neq \emptyset.$

Proof. Suppose that the alphabet admits only the complementary base pair [XY] and we ask for a sequence x compatible to both s and s'. Then $j(s, s') \cong D_m$ operates on the set of all positions $\{x_1, \ldots, x_n\}$. Since we have the operation of a dihedral group, the orbits are either cycles or chains and the cycles have even order. A constraint for the sequence compatible to both structures appears only in the cycles where the choice of bases is not independent. It remains to be shown that there is a valid choice of bases for each cycle, which is obvious since these have even order. Therefore, it suffices to choose an alternating sequence of the pairing partners X and Y. Thus, there are at least two different choices for the first base in the orbit.

Remark. A generalization of the statement of theorem 5 to three different structures is false.

Reference for the definition of the intersection and the proof of the **intersection theorem**

Results from RNA suboptimal structures:

• Neutral RNA sequences differ with respect to their spectra of suboptimal structures.

• Suboptimal RNA structures with low free energies contribute substantially to the partition function.

• Nature selects for stable structures in the sense that the contribution of the mfe structure to the partition function is large.

• For every pair of structures it is possible to find a sequence that can form both. This is not (always) true for three structures.

- 1. Minimum free energy structures of RNA
- 2. Suboptimal structures of RNA
- 3. Kinetic folding and RNA switches
- 4. Chemistry of Darwinian evolution
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Minimum free energy structure

Suboptimal structures

Extension of the notion of structure



Extension of the notion of structure

The Folding Algorithm

A sequence I specifies an energy ordered set of compatible structures ⓒ(I):

 $\mathfrak{S}(\mathbf{I}) = \{\mathbf{S}_0, \mathbf{S}_1, \dots, \mathbf{S}_m, \mathbf{O}\}$

A trajectory $\mathfrak{T}_k(\mathbf{I})$ is a time ordered series of structures in $\mathfrak{S}(\mathbf{I})$. A folding trajectory is defined by starting with the open chain \mathbf{O} and ending with the global minimum free energy structure \mathbf{S}_0 or a metastable structure \mathbf{S}_k which represents a local energy minimum:

$$\begin{aligned} \boldsymbol{\mathfrak{T}_{0}(I)} &= \{ \mathbf{O}, \mathbf{S}(1), \dots, \mathbf{S}(t-1), \mathbf{S}(t), \\ & \mathbf{S}(t+1), \dots, \mathbf{S}_{0} \} \\ \boldsymbol{\mathfrak{T}_{k}(I)} &= \{ \mathbf{O}, \mathbf{S}(1), \dots, \mathbf{S}(t-1), \mathbf{S}(t), \\ & \mathbf{S}(t+1), \dots, \mathbf{S}_{k} \} \end{aligned}$$

$$\frac{dP_k}{dt} = \sum_{i=0}^{m+1} \left(P_{ik}(t) - P_{ki}(t) \right) = \sum_{i=0}^{m+1} k_{ik} P_i - P_k \sum_{i=0}^{m+1} k_{ki} k_{ik} P_i - P_k \sum_{i=0}^{m+1} k_{ik} k_{ik} P_i - P_k \sum_{i=0}^{m+1} k_{$$

10

Transition probabilities $P_{ij}(t) = \operatorname{Prob}\{S_i \rightarrow S_j\}$ are defined by

$$P_{ij}(t) = P_i(t) k_{ij} = P_i(t) \exp(-\Delta G_{ij}/2RT) / \Sigma_i$$

$$P_{ji}(t) = P_{j}(t) k_{ji} = P_{j}(t) \exp(-\Delta G_{ji}/2RT) / \Sigma_{j}$$
$$\Sigma_{k} = \sum_{k=1, k \neq i}^{m+2} \exp(-\Delta G_{ki}/2RT)$$

The symmetric rule for transition rate parameters is due to Kawasaki (K. Kawasaki, *Diffusion constants near the critical point for time dependent Ising models*. Phys.Rev. **145**:224-230, 1966).

Formulation of kinetic RNA folding as a stochastic process

Master equation



Definition of a ,barrier tree'



Structural parameters affecting the kinetic competition of RNA hairpin formation. *Nucleic Acids Res.* **34**:3568-3576 (2006)



J1LH barrier tree

A ribozyme switch

E.A.Schultes, D.B.Bartel, Science **289** (2000), 448-452

minus the background levels observed in the HSP in the control (Sar1-GDP-containing) incubation that prevents COPII vesicle formation. In the microsome control, the level of p115-SNARE associations was less than 0.1%.

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50. GST-SNARE proteins were expressed in bacteria and purified on glutathione-Sepharose beads using standard methods. Immobilized GST-SNARE protein (0.5 μM) was incubated with rat liver cytosol (20 mg) or purified recombinant p115 (0.5 μM) in 1 ml of NS buffer containing 1% BSA for 2 hours at 4°C with rotation. Beads were briefly spun (3000 rpm for 10.s) and sequentially washed three times with NS buffer and three times with NS buffer supplemented with 150 ml NaCL Bound proteins were eluted three times in 50 μJ of 50 ml tris-HCI (pH 8.5), 50 ml reduced glutathione. 150 ml NaCL and 0.1% Tirtion 0.1% Tirtion M NaCL and 0.1% Tirtion M 10.1% Tirtion

REPORTS

X-100 for 15 min at 4°C with intermittent mixing, and elutes were pooled. Proteins were precipitated by MeOH/CH₃Cl and separated by SDS-polyacrylamide gel electrophoresis (PAGE) followed by immunoblotting using p115 mAb 13F12.

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One Sequence, Two Ribozymes: Implications for the Emergence of New Ribozyme Folds

Erik A. Schultes and David P. Bartel*

We describe a single RNA sequence that can assume either of two ribozyme folds and catalyze the two respective reactions. The two ribozyme folds share no evolutionary history and are completely different, with no base pairs (and probably no hydrogen bonds) in common. Minor variants of this sequence are highly active for one or the other reaction, and can be accessed from prototype ribozymes through a series of neutral mutations. Thus, in the course of evolution, new RNA folds could arise from preexisting folds, without the need to carry inactive intermediate sequences. This raises the possibility that biological RNAs having no structural or functional similarity might share a common ancestry. Furthermore, functional and structural divergence might, in some cases, precede rather than follow gene duplication.

Related protein or RNA sequences with the same folded conformation can often perform very different biochemical functions, indicating that new biochemical functions can arise from preexisting folds. But what evolutionary mechanisms give rise to sequences with new macromolecular folds? When considering the origin of new folds, it is useful to picture, among all sequence possibilities, the distribution of sequences with a particular fold and function. This distribution can range very far in sequence space (1). For example, only seven nucleotides are strictly conserved among the group I selfsplicing introns, yet secondary (and presumably tertiary) structure within the core of the ribozyme is preserved (2). Because these disparate isolates have the same fold and function, it is thought that they descended from a common ancestor through a series of mutational variants that were each functional. Hence, sequence heterogeneity among divergent isolates implies the existence of paths through sequence space that have allowed neutral drift from the ancestral sequence to each isolate. The set of all possible neutral paths composes a "neutral network," connecting in sequence space those widely dispersed sequences sharing a particular fold and activity, such that any sequence on the network can potentially access very distant sequences by neutral mutations (3–5).

Theoretical analyses using algorithms for predicting RNA secondary structure have suggested that different neutral networks are interwoven and can approach each other very closely (3, 5–8). Of particular interest is whether ribozyme neutral networks approach each other so closely that they intersect. If so, a single sequence would be capable of folding into two different conformations, would M. R. Peterson, C. G. Burd, S. D. Emr, Curr. Biol. 9, 159 (1999).

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come Trust International Traveling Fellowship

20 March 2000; accepted 22 May 2000

(B.B.A.).

have two different catalytic activities, and could access by neutral drift every sequence on both networks. With intersecting networks, RNAs with novel structures and activities could arise from previously existing ribozymes, without the need to carry nonfunctional sequences as evolutionary intermediates. Here, we explore the proximity of neutral networks experimentally, at the level of RNA function. We describe a close apposition of the neutral networks for the hepatitis delta virus (HDV) self-cleaving ribozyme and the class III self-ligating ribozyme.

In choosing the two ribozymes for this investigation, an important criterion was that they share no evolutionary history that might confound the evolutionary interpretations of our results. Choosing at least one artificial ribozyme ensured independent evolutionary histories. The class III ligase is a synthetic ribozyme isolated previously from a pool of random RNA sequences (9). It joins an oligonucleotide substrate to its 5' terminus. The prototype ligase sequence (Fig. 1A) is a shortened version of the most active class III variant isolated after 10 cycles of in vitro selection and evolution. This minimal construct retains the activity of the full-length isolate (10). The HDV ribozyme carries out the site-specific self-cleavage reactions needed during the life cycle of HDV, a satellite virus of hepatitis B with a circular, single-stranded RNA genome (11). The prototype HDV construct for our study (Fig. 1B) is a shortened version of the antigenomic HDV ribozvme (12), which undergoes self-cleavage at a rate similar to that reported for other antigenomic constructs (13, 14).

The prototype class III and HDV ribozymes have no more than the 25% sequence identity expected by chance and no fortuitous structural similarities that might favor an intersection of their two neutral networks. Nevertheless, sequences can be designed that simultaneously satisfy the base-pairing requirements

Whitehead Institute for Biomedical Research and Department of Biology, Massachusetts Institute of Technology, 9 Cambridge Center, Cambridge, MA 02142, USA.

^{*}To whom correspondence should be addressed. Email: dbartel@wi.mit.edu



Two ribozymes of chain lengths n = 88 nucleotides: An artificial ligase (A) and a natural cleavage ribozyme of hepatitis- δ -virus (B)



The sequence at the *intersection*:

An RNA molecules which is 88 nucleotides long and can form both structures



Two neutral walks through sequence space with conservation of structure and catalytic activity



A natural metabolic riboswitch



The purine riboswitch

M. Mandal, B. Boese, J.E. Barrick, W.C. Winkler, and R.R. Breaker. 2003. *Molecular Cell*. **11**:1419-1420, *Cell* **113**:577-586.

ΑΑΑΑΑΙΑΑΑΑΑ	UGA	AUUA	CUC	CAU	AUAA	AUCI	JCGG	GAA	UAUG	GCC	CGGG	AGUI	UUCU	IAGC.	AGGC	CAAC	CGU.	IAAA	JGC	CUGA	ACUA	UGA	GUA	AUUU	JUGA	LAAAAU	A	
	. ((((((()	()	(. ((((••••	•))])))))	••••	(((((•••	•••)))))).	•))))))))))))	••••	•	-32.10
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The purine riboswitch: *Molecular Cell*. 2003. **11**:1419-1420.





mfe-weight: 0.1459



The thiamine-pyrophosphate riboswitch

S. Thore, M. Leibundgut, N. Ban. *Science* **312**:1208-1211, 2006.



Results from RNA folding kinetics:

• In addition to the minimum free energy structure RNA molecules can exist in one, two or more long-lived metastable structures.

• RNA switches are molecules with two or more long-lived conformations that allow for metabolic control.

- 1. Minimum free energy structures of RNA
- 2. Suboptimal structures of RNA
- 3. Kinetic folding and RNA switches
- 4. Chemistry of Darwinian evolution
- 5. Consequences of neutrality
- 6. Evolutionary optimization of RNA structure



Complementary replication is the simplest copying mechanism of RNA.

Complementarity is determined by Watson-Crick base pairs:

G≡C and A=U



 $x_{1} = \sqrt{f_{2}} \xi_{1}, \quad x_{2} = \sqrt{f_{1}} \xi_{2}, \quad \zeta = \xi_{1} + \xi_{2}, \quad \eta = \xi_{1} - \xi_{2}, \quad f = \sqrt{f_{1}f_{2}}$ $\eta(t) = \eta(0) e^{-ft}$

 $\zeta(t) = \zeta(0) e^{ft}$

Complementary replication as the simplest molecular mechanism of reproduction





Chemical kinetics of replication and mutation as parallel reactions



The error threshold in replication



A fitness landscape showing an error threshold

Biophysical Chemistry 16 (1982) 329-345 Elamier Biomedical Press

Elsevier Biomedical Press

SELF-REPLICATION WITH ERRORS

A MODEL FOR POLYNUCLEOTIDE REPLICATION **

Jörg SWETINA and Peter SCHUSTER *

Institut für Theoretische Chemie und Strahlenchemie der Universität, Währingerstraße 17, A-1090 Wien, Austria

Received 4th June 1982 Revised manuscript received 23rd August 1982 Accepted 30th August 1982

Key words: Polynucleotide replication; Quari-species; Point mutation; Mutant class; Stochastic replication

A model for polynucleotide replication is presented and analyzed by means of perturbation theory. Two basic assumptions allow handling of sequences up to a chain length of = 9 to explicitly peint matalions are retricted to a two-digit model and individual sequences are subsumed into mutant classes. Perturbation theory is in excellent agreement with the exact results for long enough sequences (*z* > 20).

1. Introduction

Eigen [8] proposed a formal kinetic equation (eq. 1) which describes self-replication under the constraint of constant total population size:

 $\frac{dx_i}{dt} = \dot{x}_i = \sum_i w_{ij} x_j - \frac{x_i}{c} \phi; i = 1, ..., n^{-1}$ (1)

By x_i , we denote the population number or concentration of the self-replicating element I_i , i.e., $x_i = [I_i]$. The total population size or total concentration $c = \sum_i x_i$, is kept constant by proper adjustment of the constraint $\phi = \phi = \sum_i \sum_{i=1}^{N} x_i$. Characteristically, this constraint $\phi = \phi = \sum_i \sum_{i=1}^{N} x_i$.

 Dedicated to the late Professor B.L. Jones who was among the first to do rigorous mathematical analysis on the problems described here.

** This paper is considered as part II of Model Studies on RNA replication. Part I is by Gassner and Schuster [14].
* All summations throughout this paper run from 1 to n unless

All summations throughout this paper run from 1 to n unless specified differently: $\Sigma_i = \sum_{j=1}^n$ and $\sum_{i,i=j} = \sum_{j=1}^{i-1} + \sum_{i=j+1}^n$, respectively.

0301-4622/82/0000-0000/\$02.75 © 1982 Elsevier Biomedical Press

 (w_{ii}) and off-diagonal $(w_{ij}, i \neq j)$ rates, as we shall see in detail in section 2, are related to the accuracy of the replication process. The specific properties of eq. 1 are essentially based on the fact that it leads to exponential growth in the absence of constraints (0 = 0) and competitors (n = 1).

110

The non-linear differential equation, eq. 1 – the non-linearity is introduced by the definition of ϕ at constant organization – shows a remarkable feature: it leads to selection of a defined ensemble of self-replicating elements above a certain accuracy threshold. This ensemble of a master and its most frequent mutants is a so-called 'quasi-species' [9]. Below this threshold, however, no selection takes place and the frequencies of the individual elements are determined exclusively by their statistical weights.

Rigorous mathematical analysis has been performed on eq. 17,15,24,26]. In particular, it was shown that the non-linearity of eq. 1 can be removed by an appropriate transformation. The eigenvalue problem of the linear differential equation obtained thereby may be solved approximately by the conventional perturbation technique



Stationary population or quasispecies as a function of the mutation or error rate p



Fitness landscapes showing error thresholds

Hamming distance $d_{H}(I_k, I_0)$





Error threshold: Individual sequences n = 10, $\sigma = 2$ and d = 0, 1.0, 1.85

Evolution of RNA molecules based on $Q\beta$ phage

D.R.Mills, R.L.Peterson, S.Spiegelman, *An extracellular Darwinian experiment with a self-duplicating nucleic acid molecule*. Proc.Natl.Acad.Sci.USA **58** (1967), 217-224

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F.Öhlenschlager, M.Eigen, *30 years later – A new approach to Sol Spiegelman's and Leslie Orgel's* in vitro *evolutionary studies*. Orig.Life Evol.Biosph. **27** (1997), 437-457

RNA sample



Stock solution: Qβ RNA-replicase, ATP, CTP, GTP and UTP, buffer

Anwendung der seriellen Überimpfungstechnik auf RNA-Evolution in Reagenzglas

Evolutionary design of RNA molecules

A.D. Ellington, J.W. Szostak, **In vitro** *selection of RNA molecules that bind specific ligands*. Nature **346** (1990), 818-822

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L. Jiang, A. K. Suri, R. Fiala, D. J. Patel, *Saccharide-RNA recognition in an aminoglycoside antibiotic-RNA aptamer complex*. Chemistry & Biology **4** (1997), 35-50



An example of 'artificial selection' with RNA molecules or 'breeding' of biomolecules



tobramycin

5'-GGCACGAGGUUUAGCUACACUCGUGCC-3'



Formation of secondary structure of the tobramycin binding RNA aptamer with $K_D = 9 nM$

L. Jiang, A. K. Suri, R. Fiala, D. J. Patel, *Saccharide-RNA recognition in an aminoglycoside antibiotic-RNA aptamer complex.* Chemistry & Biology **4**:35-50 (1997)


The three-dimensional structure of the tobramycin aptamer complex

L. Jiang, A. K. Suri, R. Fiala, D. J. Patel, Chemistry & Biology **4**:35-50 (1997)





Schematic overview of the principal processes, strategies, and techniques of directed evolution. Today, numerous experimental methods are available to perform the fundamental processes of true Darwinian evolution (central boxes) in the laboratory, either in vivo within microorganisms or entirely in vitro in the test tube. Arrows indicate possible routes for connecting individual evolutionary steps. Abbreviations: PCR, polymerase chain reaction; RT-PCR, reverse transcription PCR; IVC, in vitro compartmentalization; FACS, fluorescenceactivated cell sorting.

WILEY-VCH

Directed Molecular Evolution of Proteins

or How to Improve Enzymes for Biocatalysis

Edited by Susanne Brakmann and Kai Johnsson





Application of molecular evolution to problems in biotechnology

Artificial evolution in biotechnology and pharmcology

G.F. Joyce. 2004. Directed evolution of nucleic acid enzymes. *Annu.Rev.Biochem.* **73**:791-836.

C. Jäckel, P. Kast, and D. Hilvert. 2008. Protein design by directed evolution. *Annu.Rev.Biophys.* **37**:153-173.

S.J. Wrenn and P.B. Harbury. 2007. Chemical evolution as a tool for molrcular discovery. *Annu.Rev.Biochem.* **76**:331-349.

Results from replication kinetics and molecular evolution in laboratory experiments:

• Evolutionary optimization does not require cells and occurs in molecular systems too.

• *In vitro* evolution allows for production of molecules for predefined purposes and gave rise to a branch of biotechnology.

• Novel antiviral strategies were developed from known molecular mechanisms of virus evolution.

- 1. Minimum free energy structures of RNA
- 2. Suboptimal structures of RNA
- 3. Kinetic folding and RNA switches
- 4. Chemistry of Darwinian evolution
- 5. Consequences of neutrality
- 6. Evolutionary optimization of RNA structure



Fig. 3.1. Behavior of mutant genes following their appearance in a finite population. Courses of change in the frequencies of mutants destined to fixation are depicted by thick paths. N_e stands for the effective population size and v is the mutation rate.



Motoo Kimura

Is the Kimura scenario correct for frequent mutations?

Bulletin of Mathematical Biology Vol. 50, No. 6, pp. 635-660, 1988. Printed in Great Britain. 0092-8240/88\$3.00+0.00 Pergamon Press plc Society for Mathematical Biology

STATIONARY MUTANT DISTRIBUTIONS AND EVOLUTIONARY OPTIMIZATION

 PETER SCHUSTER and JÖRG SWETINA Institut für theoretische Chemie und Strahlenchemie der Universität Wien, Währingerstraße 17, A 1090 Wien, Austria

Molecular evolution is modelled by erroneous replication of binary sequences. We show how the selection of two species of equal or almost equal selective value is influenced by its nearest neighbours in sequence space. In the case of perfect neutrality and sufficiently small error rates we find that the Hamming distance between the species determines selection. As the error rate increases the fitness parameters of neighbouring species become more and more important. In the case of almost neutral sequences we observe a critical replication accuracy at which a drastic change in the "quasispecies", in the stationary mutant distribution occurs. Thus, in frequently mutating populations fitness turns out to be an ensemble property rather than an attribute of the individual.

In addition we investigate the time dependence of the mean excess production as a function of initial conditions. Although it is optimized under most conditions, cases can be found which are characterized by decrease or non-monotonous change in mean excess productions.

1. Introduction. Recent data from populations of RNA viruses provided direct evidence for vast sequence heterogeneity (Domingo *et al.*, 1987). The origin of this diversity is not yet completely known. It may be caused by the low replication accuracy of the polymerizing enzyme, commonly a virus specific, RNA dependent RNA synthetase, or it may be the result of a high degree of selective neutrality of polynucleotide sequences. Eventually, both factors contribute to the heterogeneity observed. Indeed, mutations occur much more frequently than previously assumed in microbiology. They are by no means rare events and hence, neither the methods of conventional population genetics (Ewens, 1979) nor the neutral theory (Kimura, 1983) can be applied to these virus populations. Selectively neutral variants may be close with respect to Hamming distance and then the commonly made assumption that the mutation backflow from the mutants to the wilde type is negligible does not apply.

A kinetic theory of polynucleotide evolution which was developed during the past 15 years (Eigen, 1971; 1985; Eigen and Schuster, 1979; Eigen *et al.*, 1987; Schuster, 1986); Schuster and Sigmund, 1985) treats correct replication and mutation as parallel reactions within one and the same reaction network



Neutral network

 $\lambda=0.01,\ s=367$

$$d_{\rm H} = 1$$

 $\lim_{p \to 0} x_1(p) = x_2(p) = 0.5$



Neutral network $\lim_{p \to 0} x_1(x_1)$ $\lambda = 0.01, s = 877$ $\lim_{p \to 0} x_2(x_2)$

$d_{\rm H} = 2$ $\lim_{p \to 0} x_1(p) = a$ $\lim_{p \to 0} x_2(p) = 1 - a$

d_H 3

random fixation in the sense of Motoo Kimura

Pairs of genotypes in neutral replication networks







Neutral network: Individual sequences

 $n = 10, \sigma = 1.1, d = 1.0$



Neutral network: Individual sequences

 $n = 10, \sigma = 1.1, d = 1.0$





Neutral network

 $\lambda = 0.10, s = 229$

Neutral networks with increasing λ : $\lambda = 0.10$, s = 229



Perturbation matrix W

$$\mathbf{W} = \begin{pmatrix} f & 0 & \varepsilon & 0 & 0 & 0 & 0 \\ 0 & f & \varepsilon & 0 & 0 & 0 & 0 \\ \varepsilon & \varepsilon & f & \varepsilon & 0 & 0 & 0 \\ 0 & 0 & \varepsilon & f & \varepsilon & 0 & 0 \\ 0 & 0 & 0 & \varepsilon & f & \varepsilon & \varepsilon \\ 0 & 0 & 0 & 0 & \varepsilon & f & 0 \\ 0 & 0 & 0 & 0 & \varepsilon & 0 & f \end{pmatrix}$$

Eigenvalues of W

$$\lambda_0 = f + 2\varepsilon ,$$

$$\lambda_1 = f + \sqrt{2}\varepsilon ,$$

$$\lambda_{2,3,4} = f ,$$

$$\lambda_5 = f - \sqrt{2}\varepsilon ,$$

$$\lambda_6 = f - 2\varepsilon .$$

Largest eigenvector of W

 $\xi_0 = (0.1, 0.1, 0.2, 0.2, 0.2, 0.1, 0.1) \; .$

Neutral networks with increasing λ : $\lambda = 0.10$, s = 229



Neutral networks with increasing λ : $\lambda = 0.15$, s = 229



Neutral networks with increasing λ : $\lambda = 0.20$, s = 229

Results from replication kinetics and RNA neutral networks:

• RNA sequences with Hamming distance d = 1 and d = 2 form strongly coupled replication ensembles. For d > 2 random drift in the sense of Kimura's theory occurs.

• Direct evidence that neutrality is increasing the repertoire of structures and properties in populations.

• Implication for virus replication in infected hosts.

Neutrality in evolution

Charles Darwin: "... neutrality might exist ..."

Motoo Kimura: "... neutrality is unaviodable and represents the main reason for changes in genotypes and leads to molecular phylogeny ..."

Current view: "... neutrality is essential for successful optimization on rugged landscapes ..."

Proposed view: "... neutrality provides the genetic reservoir in the rare and frequent mutation scenario ..."

- 1. Minimum free energy structures of RNA
- 2. Suboptimal structures of RNA
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- 6. Evolutionary optimization of RNA structure

random individuals. The primer pair used for genomic DNA amplification is 5'-TCTCCCTGGATTCT-CATTTA-3' (forward) and 5'-TCTTTGTCTTCTGT TCCACC-3' (reverse). Reactions were performed in 25 µl using 1 unit of Tag DNA polymerase with each primer at 0.4 µM; 200 µM each dATP, dTTP, dGTP, and dCTP; and PCR buffer [10 mM tris-HCI (pH 8.3) 50 mM KCl₂,1.5 mM MgCl₂] in a cycle condition of 94°C for 1 min and then 35 cycles of 94°C for 30 s. 55°C for 30 s, and 72°C for 30 s followed by 72°C for 6 min. PCR products were purified (Qiagen), digested with Xmn L and senarated in a 2% agarose gel.

- 32. A nonsense mutation may affect mRNA stability and result in degradation of the transcript [L. Maguat, Am. J. Hum. Genet. 59, 279 (1996)]
- 33. Data not shown: a dot blot with poly (A)+ RNA from 50 human tissues (The Human BNA Master Blot. 7770-1, Clontech Laboratories) was hybridized with a probe from exons 29 to 47 of MYO15 using the same condition as Northern blot analysis (13).
- 34. Smith-Magenis syndrome (SMS) is due to deletions of 17p11.2 of various sizes, the smallest of which includes MYO15 and perhaps 20 other genes ((6): K-S Chen, L. Potocki, J. R. Lupski, MRDD Res. Rev. 2 122 (1996)] MYO15 expression is easily detected in the pituitary gland (data not shown). Haploinsufficiency for MYO15 may explain a portion of the SMS

Continuity in Evolution: On the Nature of Transitions

Walter Fontana and Peter Schuster

To distinguish continuous from discontinuous evolutionary change, a relation of nearness between phenotypes is needed. Such a relation is based on the probability of one phenotype being accessible from another through changes in the genotype. This nearness relation is exemplified by calculating the shape neighborhood of a transfer RNA secondary structure and provides a characterization of discontinuous shape transformations in RNA. The simulation of replicating and mutating RNA populations under selection shows that sudden adaptive progress coincides mostly, but not always, with discontinuous shape transformations. The nature of these transformations illuminates the key role of neutral genetic drift in their realization.

A much-debated issue in evolutionary biology concerns the extent to which the history of life has proceeded gradually or has been punctuated by discontinuous transitions at the level of phenotypes (1). Our goal is to make the notion of a discontinuous transition more precise and to understand how it arises in a model of evolutionary adaptation.

We focus on the narrow domain of RNA secondary structure, which is currently the simplest computationally tractable, yet realistic phenotype (2). This choice enables the definition and exploration of concepts that may prove useful in a wider context. RNA secondary structures represent a coarse level of analysis compared with the three-dimensional structure at atomic resolution. Yet, secondary structures are empir-

Institut für Theoretische Chemie, Universität Wien, Währingerstrasse 17, A-1090 Wien, Austria, Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501, USA, and International Institute for Applied Systems Analysis (IIASA), A-2361 Laxenburg, Austria.

ically well defined and obtain their biophysical and biochemical importance from being a scaffold for the tertiary structure. For the sake of brevity, we shall refer to secondary structures as "shapes." RNA combines in a single molecule both genotype (replicatable sequence) and phenotype (selectable shape), making it ideally suited for in vitro evolution experiments (3, 4).

phenotype such as short stature. Moreover, a few

SMS natients have sensorineural hearing loss, pos-

sibly because of a point mutation in MYO15 in trans

X-7 Liu et al ihid 17 268 (1997): E Gibson et al

vrinths) obtained from human fetuses at 18 to 22

weeks of development in accordance with guidelines

established by the Human Research Committee at

the Brigham and Women's Hospital. Only samples

without evidence of degradation were pooled for

poly (A)* selection over oligo(dT) columns. First-

strand cDNA was prepared using an Advantage RT-

for-PCR kit (Clontech Laboratories). A portion of the

first-strand cDNA (4%) was amplified by PCR with

Advantage cDNA polymerase mix (Clontech Labora-

tories) using human MYO15-specific oligonucleotide

primers (forward, 5'-GCATGACCTGCCGGCTAAT

GGG-3': reverse, 5'-CTCACGGCTTCTGCATGGT-

GCTCGGCTGGC-3'). Cycling conditions were 40 s

at 94°C; 40 s at 66°C (3 cycles), 60°C (5 cycles), and

55°C (29 cycles); and 45 s at 68°C. PCB products

were visualized by ethidium bromide staining after

fractionation in a 1% agarose gel. A 688-bp PCR

Nature 374, 62 (1995): D. Weil et al. ibid. p. 60.

37. RNA was extracted from cochlea (membranous lab

36. K. B. Avraham et al., Nature Genet. 11, 369 (1995);

to the SMS 17n11.2 deletion.

35. R. A. Fridell, data not shown

To generate evolutionary histories, we used a stochastic continuous time model of an RNA population replicating and mutating in a capacity-constrained flow reactor under selection (5, 6). In the laboratory, a goal might be to find an RNA aptamer binding specifically to a molecule (4). Although in the experiment the evolutionary end product was unknown, we thought of its shape as being specified implicitly by the imposed selection criterion. Because our intent is to study evolutionary histories rather than end products, we defined a target shape in advance and assumed the replication rate of a sequence to be a function of because, in contrast to sequences, there are

product is expected from amplification of the human MYO15 cDNA. Amplification of human genomic DNA with this primer pair would result in a 2903-bp fragment

38. We are grateful to the people of Bengkala, Bali, and the two families from India. We thank J. R. Lupski and K.-S. Chen for providing the human chromosome 17 cosmid library. For technical and computational assistance, we thank N. Dietrich, M. Fergusson A Guota E Sorbello R Torkzadeh C Varner. M. Walker, G. Bouffard, and S. Beckstrom-Sternberg (National Institutes of Health Intramural Se quencing Center). We thank J. T. Hinnant, I. N. Arhya, and S. Winata for assistance in Bali, and T. Barber, S. Sullivan, E. Green, D. Drayna, and J. Battey for helpful comments on this manuscript. Supported by the National Institute on Deafness and Other Communication Disorders (NIDCD) (Z01 DC 00035-01 and Z01 DC 00038-01 to T.B.F. and E.R.W. and R01 DC 03402 to C.C.M.), the National Institute of Child Health and Human Development (R01 HD30428 to S.A.C.) and a National Science Foundation Graduate Research Fellowship to F.J.P. This paper is dedicated to J. B. Snow Jr. on his retirement as the Director of the NIDCD.

9 March 1998; accepted 17 April 1998

the similarity between its shape and the target. An actual situation may involve more than one best shape, but this does not affect our conclusions.

An instance representing in its qualitative features all the simulations we performed is shown in Fig. 1A. Starting with identical sequences folding into a random shape, the simulation was stopped when the population became dominated by the target, here a canonical tRNA shape. The black curve traces the average distance to the target (inversely related to fitness) in the population against time. Aside from a short initial phase, the entire history is dominated by steps, that is, flat periods of no apparent adaptive progress, interrupted by sudden approaches toward the target structure (7). However, the dominant shapes in the population not only change at these marked events but undergo several fitness-neutral transformations during the periods of no apparent progress. Although discontinuities in the fitness trace are evident, it is entirely unclear when and on the basis of what the series of successive phenotypes itself can be called continuous or discontinuous.

A set of entities is organized into a (topological) space by assigning to each entity a system of neighborhoods. In the present case, there are two kinds of entities: sequences and shapes, which are related by a thermodynamic folding procedure. The set of possible sequences (of fixed length) is naturally organized into a space because point mutations induce a canonical neighborhood. The neighborhood of a sequence consists of all its one-error mutants. The problem is how to organize the set of possible shapes into a space. The issue arises

Evolution *in silico*

W. Fontana, P. Schuster, Science 280 (1998), 1451-1455





Replication rate constant (Fitness): $f_k = \gamma / [\alpha + \Delta d_S^{(k)}]$ $\Delta d_{S}^{(k)} = d_{H}(S_{k},S_{\tau})$ **Selection pressure:** The population size, N =# RNA moleucles, is determined by the flux: $N(t) \approx \overline{N} \pm \sqrt{\overline{N}}$

Mutation rate:

p = 0.001 / Nucleotide × Replication

The flow reactor as a device for studying the evolution of molecules *in vitro* and *in silico*.



In silico optimization in the flow reactor: Evolutionary Trajectory

28 neutral point mutations during a long quasi-stationary epoch



entry	GGUAUGGGCGUUGAAUAGUAGGGUUUAAACCAAUCGGCCAACGAUCUCGUGUGCGCAUUUCAUAUCCCGUACAGAA
8	.(((((((((((((()))))))))((((((
exit	GGUAUGGGCGUUGAAUAAUAGGGUUUAAACCAAUCGGCCAACGAUCUCGUGUGCGCAUUUCAUAUCCCAUACAGAA
entry	GGUAUGGGCGUUGAAUAAUAGGGUUUAAACCAAUCGGCCAACGAUCUCGUGUGCGCAUUUCAUAUACCAUACAGAA
9	.((((((((((((((((((((()))))))))))))))))
exit	UGGAUGGACGUUGAAUAACAAGGUAUCGACCAAACAACCAAC
entry	UGGAUGGACGUUGAAUAACAAGGUAUCGACCAAACAACCAAC
10	((((((((((((((((((((((((((((((((((((
exit	UGGAUGGACGUUGAAUAACAAGGUAUCGACCAAACAACCAAC

Transition inducing point mutations change the molecular structure Neutral point mutations leave the molecular structure unchanged

Neutral genotype evolution during phenotypic stasis





Phenylalanyl-tRNA as target structure



A sketch of optimization on neutral networks

Results from *in silico* simulation of RNA evolution:

- Evolutionary optimization occurs on two time scales: Fast adaptive phases and random walk on neutral networks.
- Neutral networks are essential for searching sequence space.

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Prediction of RNA secondary structures: from theory to models and real molecules

Peter Schuster^{1,2}

¹Institut für Theoretische Chemie der Universität Wien, Währingerstraße 17, A-1090 Vienna, Austria ²The Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501, USA

E-mail: pks@tbi.univie.ac.at

Web-Page for further information:

http://www.tbi.univie.ac.at/~pks