

RaCAF ANR-15-CE40-0016-01: Dépasser les  
frontières de l'aléatoire et du calculable  
(Randomness and Computability:  
Advancing the Frontiers)

Alexander Shen,  
LIRMM CNRS & Univ. Montpellier

March 22, 2018

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- ▶ Combinatorics: randomness extractors

# Classical probability theory



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- ▶ of course, we usually speak about sequences, not individual digits

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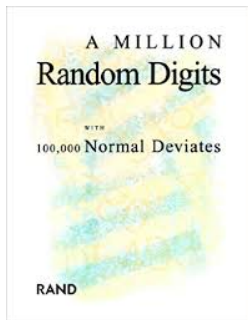


TABLE OF RANDOM DIGITS 3

00100	03991	10461	93716	16894	66083	34653	84609	58232	88618	19161
00101	38555	95554	32886	59780	08355	60860	29735	47762	71299	23853
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00103	32643	52681	63819	06821	00911	68936	76355	93779	80862	06514
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00105	24132	66591	37699	06494	14845	46672	61958	77100	90899	75754
00106	61196	30231	92962	61773	41839	55382	17267	70943	78028	70267
00107	30532	21704	10274	12202	39685	23309	10061	88829	55986	66485
00108	03788	97599	75867	20717	74416	33166	35208	33374	87339	08823
00109	48228	63379	85783	47619	53152	67433	35663	52972	16818	60311
00110	60365	84653	35075	33949	42614	29297	01918	26316	98853	73231
00111	83799	42402	56623	34442	34994	41374	70071	14736	09958	18055
00112	32960	07405	36409	83232	99385	41600	11133	07986	15917	06250
00113	18322	53845	57620	52906	66497	68646	78128	66559	19640	99413
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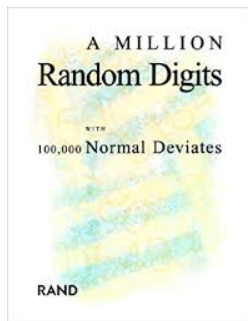


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can we complain to amazon if “non-random”?

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- ▶ (our main field of expertise)

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- ▶ why better than  $x_{n+1} = x_n + 1 \bmod 2^{32}$ ?



# Statistical tests

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- ▶ compressors as random tests: compression by  $k$  bits corresponds to  $p$ -value below  $2^{-k}$

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- ▶ conditional existence (factoring is hard, the existence of one-way functions)

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- ▶ solution attempt: “extracting randomness from weak randomness”

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- ▶ see below (and also pdf report) for more theoretical work

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- ▶ diehard uses dependent inputs when independence is required

## dieharder documentation

### speaks about “test failures”

*Many dieharder tests, despite our best efforts, are numerically unstable or have only approximately known target statistics or are straight up asymptotic results, and will eventually return a failing result even for a gold-standard generator (such as AES), or for the hypercautious the XOR generator with AES, threefish, kiss, all loaded at once and xor'd together. {...}*

*Failure with numbers of psamples within an order of magnitude of the AES thresholds should probably be considered possible test failures, not generator failures. Failures at levels significantly less than the known gold standard generator failure thresholds are, of course, probably failures of the generator.*



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- ▶ almost as sensitive as the original test

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- ▶ equally sensitive if  $R_i$  are truly random

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- ▶ some preliminary results (M.Popov, master thesis under supervision of A.Romashchenko)

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- ▶ (naive) idea of “entropy” as some kind of liquid that can be measured, kept in a pool, etc.  
similar to caloric theory

## on extracting randomness from weak random source:

*For an example of using a strong mixing function, reconsider the case of a string of 308 bits, each of which is biased 99% toward zero. The parity technique  $\langle \dots \rangle$  reduces this to one bit, with only a 1/1000 deviance from being equally likely a zero or one. But, applying the equation for information  $\langle \dots \rangle$  [Shannon entropy], this 308-bit skewed sequence contains over 5 bits of information. Thus, hashing it with SHA-1 and taking the bottom 5 bits of the result would yield 5 unbiased random bits and not the single bit given by calculating the parity of the string.*

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[Not justified: parity argument uses independence, and SHA-1 trick is not justified even in the independence case]

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- ▶ using  $B[x][y]$  where  $B$  is a balanced matrix and  $x$  and  $y$  are independent weak random sources

## Alternative ways to extract randomness

- ▶ theoretical work: randomness extractors
- ▶ two inputs: long weak random and independent short truly random
- ▶ or two long independent weak random sources
- ▶ not directly practical
- ▶ some practical approaches inspired by them
- ▶ using expander walk over weakly random edges
- ▶ using  $B[x][y]$  where  $B$  is a balanced matrix and  $x$  and  $y$  are independent weak random sources
- ▶ some preliminary experiments done



# Planned work

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- ▶ last, but not least: theoretical work to understand properties of randomness (algorithmic information theory, computability theory approach to randomness, models of computation, randomness in game-theoretic approach to probability theory, etc.)

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- ▶ mutual information and its operational characterization (A.Romashchenko, with M.Zimand, Towson University)



Chronological report about RaCAF progress, including references and texts of RaCAF-related papers,  
<http://www.lirmm.fr/~ashen/racaf.html>



M. Andreev, G. Posobin, A. Shen, Plain stopping time and conditional complexities revisited, preprint,  
<https://arxiv.org/abs/1708.08100>



O. Bournez, D.S. Gracça, A. Pouly, Polynomial Time corresponds to Solutions of Polynomial Ordinary Differential Equations of Polynomial Length, *Journal of the ACM*, Volume 64, Issue 6, November 2017, Article No. 38



O. Bournez, A. Pouly, A Universal Ordinary Differential Equation, *International Colloquium on Automata, Language and Programming*, ICALP'2017, 116:1–116:14



B. Bauwens, A. Shen, H. Takahashi, Conditional Probabilities and van Lambalgen's Theorem Revisited, *Theory of Computing Systems*, 2017, doi:10.1007/s00224-017-9789-2



M. Carl, B. Durand, G. Lafitte, S. Ouazzani, Admissible in Gaps, *CiE 2017: Unveiling Dynamics and Complexity, Proceedings, Lecture* 

Notes in Computer Science, 10307, Springer, 2017, 175–186.

[https://doi.org/10.1007/978-3-319-58741-7\\_18](https://doi.org/10.1007/978-3-319-58741-7_18)



J. Cervelle, G. Lafitte, On shift-invariant maximal filters and hormonal cellular automata, *32nd Annual ACM/IEEE Symposium on Logic in Computer Science, LICS 2017, Reykjavik, Iceland, June 20-23, 2017*, 1–10,

<https://doi.org/10.1109/LICS.2017.8005145>



O. Defrain, B. Durand, G. Lafitte, Infinite Time Busy Beavers, *CiE 2017: Unveiling Dynamics and Complexity, Proceedings*, Lecture Notes in Computer Science, 10307, Springer, 2017, 221–233.

[https://doi.org/10.1007/978-3-319-58741-7\\_22](https://doi.org/10.1007/978-3-319-58741-7_22)



B. Durand, A. Romashchenko, On the Expressive Power of Quasi-Periodic SFT, *Mathematical Foundations of Computer Science*, 2017, <https://doi.org/10.4230/LIPIcs.MFCS.2017.5>



L. Bienvenu, M. Hoyrup, A. Shen, Layerwise Computability and Image Randomness, *Theory of Computing Systems*, 2017, doi:10.1007/s00224-017-9791-8



Guilhem Marion, *Le hasard et sa production*, report de stage, LIRMM, see RaCAF diary above.



A. Milovanov, Algorithmic Statistics: Normal Objects and Universal Models, *Computer Science in Russia 2016*, Lecture Notes in Computer Science, v. 9691 (2016), 280–293.



A. Milovanov, Some Properties of Antistochastic Strings, *Theory of Computing Systems*, published online 21 June 2016, DOI 10.1007/s00224-016-9695-z.



A. Milovanov, On Algorithmic Statistics for space-bounded algorithms. In *Proceedings of 12th International Computer Science Symposium in Russia (CSR 2017)* LNCS, vol. **10304**, pp. 232–234, 2017.



A. Milovanov, N. Vereshchagin, Stochasticity in Algorithmic Statistics for Polynomial Time, *32nd Computational Complexity Conference (CCC 2017)* proceedings (Leibniz International Proceedings in Informatics, LIPIcs), doi:10.4230/LIPIcs.CCC.2017.17, 17:1–17:18



G. Novikov, Randomness Deficiencies, *CiE 2017: Unveiling Dynamics and Complexity, Proceedings*, Lecture Notes in Computer Science, 10307, Springer, 2017, 338–350. [https://link.springer.com/chapter/10.1007/978-3-319-58741-7\\_32](https://link.springer.com/chapter/10.1007/978-3-319-58741-7_32)





A. Romashchenko, *Coding in the fork network in the framework of Kolmogorov complexity*, preprint, arXiv:1602.02648.



A. Shen, Algorithmic Information Theory, book section in *The Routledge handbook of philosophy of information*, Routledge, 2016, 37–43.



A. Shen, Automatic Kolmogorov complexity and normality revisited, *FCT 2017 Conference, Bordeaux, France, Proceedings*, full version: <https://arxiv.org/pdf/1701.09060.pdf>



A. Shen, V. Uspensky, N. Vereshchagin, Kolmogorov Complexity and Algorithmic Randomness. A book accepted for publication (in 2017) by the American Mathematical Society. Draft: <http://www.lirmm.fr/~ashen/kolmbook-eng.pdf>



N. Vereshchagin, A. Shen, *Algorithmic statistics: forty years later*. Book chapter in *Computability and Complexity. Essays Dedicated to Rodney G. Downey on the Occasion of His 60th Birthday*. Lecture Notes in Computer Science, v. 10010, Springer, 2017, p. 669–737.