Jeff Clune

List of Publications by Citations

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The third column is the impact factor (IF) of the journal, and the fourth column is the number of citations of the article.

51 papers	3,331 citations	23 h-index	54 g-index
54 ext. papers	4,511 ext. citations	8.5 avg, IF	5.92 L-index

#	Paper	IF	Citations
51	Deep neural networks are easily fooled: High confidence predictions for unrecognizable images **2015**,		811
50	Robots that can adapt like animals. *Nature*, **2015**, 521, 503-7	50.4	417
49	Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences of the United States of America*, **2018**, 115, E5716-E5725	11.5	345
48	The evolutionary origins of modularity. *Proceedings of the Royal Society B: Biological Sciences*, **2013**, 280, 20122863	4.4	337
47	Designing neural networks through neuroevolution. *Nature Machine Intelligence*, **2019**, 1, 24-35	22.5	227
46	Machine learning to classify animal species in camera trap images: Applications in ecology. *Methods in Ecology and Evolution*, **2019**, 10, 585-590	7.7	130
45	Unshackling evolution **2013**,		99
44	On the Performance of Indirect Encoding Across the Continuum of Regularity. *IEEE Transactions on Evolutionary Computation*, **2011**, 15, 346-367	15.6	82
43	Neural modularity helps organisms evolve to learn new skills without forgetting old skills. *PLoS Computational Biology*, **2015**, 11, e1004128	5	75
42	Natural selection fails to optimize mutation rates for long-term adaptation on rugged fitness landscapes. *PLoS Computational Biology*, **2008**, 4, e1000187	5	70
41	The Evolutionary Origins of Hierarchy. *PLoS Computational Biology*, **2016**, 12, e1004829	5	69
40	Evolving coordinated quadruped gaits with the HyperNEAT generative encoding **2009**,		61
39	How evolution learns to generalise: Using the principles of learning theory to understand the evolution of developmental organisation. *PLoS Computational Biology*, **2017**, 13, e1005358	5	46
38	Unshackling evolution. *ACM SIGEVOlution*, **2014**, 7, 11-23	0.1	36
37	Evolving 3D objects with a generative encoding inspired by developmental biology. *ACM SIGEVOlution*, **2011**, 5, 2-12	0.1	35
36	Innovation Engines **2015**,		34
35	The Surprising Creativity of Digital Evolution: A Collection of Anecdotes from the Evolutionary Computation and Artificial Life Research Communities. *Artificial Life*, **2020**, 26, 274-306	1.4	31

34	A deep active learning system for species identification and counting in camera trap images. *Methods in Ecology and Evolution*, **2021**, 12, 150-161	7.7	28
33	Evolving neural networks that are both modular and regular **2014**,		26
32	The sensitivity of HyperNEAT to different geometric representations of a problem **2009**,		25
31	Investigating whether hyperNEAT produces modular neural networks **2010**,		24
30	Evolved Electrophysiological Soft Robots		24
29	The Surprising Creativity of Digital Evolution **2018**,		24
28	First return, then explore. *Nature*, **2021**, 590, 580-586	50.4	23
27	Diffusion-based neuromodulation can eliminate catastrophic forgetting in simple neural networks. *PLoS ONE*, **2017**, 12, e0187736	3.7	22
26	How do Different Encodings Influence the Performance of the MAP-Elites Algorithm? **2016**,		21
25	Safe mutations for deep and recurrent neural networks through output gradients **2018**,		19
24	Investigations in meta-GAs **2005**,		19
23	Evolving Gaits for Physical Robots with the HyperNEAT Generative Encoding: The Benefits of Simulation. *Lecture Notes in Computer Science*, **2013**, 540-549	0.9	18
22	Selective pressures for accurate altruism targeting: evidence from digital evolution for difficult-to-test aspects of inclusive fitness theory. *Proceedings of the Royal Society B: Biological Sciences*, **2011**, 278, 666-74	4.4	16
21	Ontogeny tends to recapitulate phylogeny in digital organisms. *American Naturalist*, **2012**, 180, E54-63	3.7	14
20	How a Generative Encoding Fares as Problem-Regularity Decreases. *Lecture Notes in Computer Science*, **2008**, 358-367	0.9	14
19	ES is more than just a traditional finite-difference approximator **2018**,		14
18	Novelty search creates robots with general skills for exploration **2014**,		13
17	POET **2019**,		10

16	Curiosity Search: Producing Generalists by Encouraging Individuals to Continually Explore and Acquire Skills throughout Their Lifetime. *PLoS ONE*, **2016**, 11, e0162235	3.7	8
15	Evolvability Search **2016**,		7
14	Does Aligning Phenotypic and Genotypic Modularity Improve the Evolution of Neural Networks? **2016**,		6
13	Upload any object and evolve it: Injecting complex geometric patterns into CPPNS for further evolution **2013**,		6
12	HybrID: A Hybridization of Indirect and Direct Encodings for Evolutionary Computation. *Lecture Notes in Computer Science*, **2011**, 134-141	0.9	6
11	Improving the accessibility and transferability of machine learning algorithms for identification of animals in camera trap images: MLWIC2. *Ecology and Evolution*, **2020**, 10, 10374-10383	2.8	6
10	Neuromodulation Improves the Evolution of Forward Models **2016**,		5
9	Improving HybrID: How to best combine indirect and direct encoding in evolutionary algorithms. *PLoS ONE*, **2017**, 12, e0174635	3.7	5
8	Improving the accessibility and transferability of machine learning algorithms for identification of animals in camera trap images: MLWIC2		4
7	Machine learning to classify animal species in camera trap images: applications in ecology		4
6	The Emergence of Canalization and Evolvability in an Open-Ended, Interactive Evolutionary System. *Artificial Life*, **2018**, 24, 157-181	1.4	4
5	Encouraging creative thinking in robots improves their ability to solve challenging problems **2014**,		3
4	WebAL Comes of Age: A Review of the First 21 Years of Artificial Life on the Web. *Artificial Life*, **2016**, 22, 364-407	1.4	3
3	Identifying Core Functional Networks and Functional Modules within Artificial Neural Networks via Subsets Regression **2016**,		2
2	Automated generation of environments to test the general learning capabilities of AI agents **2014**,		1
1	Biological underpinnings for lifelong learning machines. *Nature Machine Intelligence*, **2022**, 4, 196-210	22.5	1