Maxim A Ziatdinov

List of Publications by Year
in descending order

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111 papers	2,329 citations	218592 26 h-index	243529 44 g-index
116 all docs	116 docs citations	116 times ranked	2327 citing authors

#	Article	IF	Citations
1	Deep Learning of Atomically Resolved Scanning Transmission Electron Microscopy Images: Chemical Identification and Tracking Local Transformations. ACS Nano, 2017, 11, 12742-12752.	7.3	282
2	Deep learning analysis of defect and phase evolution during electron beam-induced transformations in WS2. Npj Computational Materials, 2019, 5, .	3.5	113
3	Materials science in the artificial intelligence age: high-throughput library generation, machine learning, and a pathway from correlations to the underpinning physics. MRS Communications, 2019, 9, 821-838.	0.8	109
4	Learning surface molecular structures via machine vision. Npj Computational Materials, 2017, 3, .	3.5	79
5	Atom-by-atom fabrication with electron beams. Nature Reviews Materials, 2019, 4, 497-507.	23.3	73
6	Building and exploring libraries of atomic defects in graphene: Scanning transmission electron and scanning tunneling microscopy study. Science Advances, 2019, 5, eaaw8989.	4.7	70
7	Atomic-scale observation of structural and electronic orders in the layered compound Î±-RuCl3. Nature Communications, 2016, 7, 13774.	5.8	66
8	Chemical Robotics Enabled Exploration of Stability in Multicomponent Lead Halide Perovskites via Machine Learning. ACS Energy Letters, 2020, 5, 3426-3436.	8.8	66
9	Machine learning in scanning transmission electron microscopy. Nature Reviews Methods Primers, 2022, 2, .	11.8	59
10	Role of edge geometry and chemistry in the electronic properties of graphene nanostructures. Faraday Discussions, 2014, 173, 173-199.	1.6	58
11	Automated and Autonomous Experiments in Electron and Scanning Probe Microscopy. ACS Nano, 2021, 15, 12604-12627.	7.3	49
12	Deep data analysis via physically constrained linear unmixing: universal framework, domain examples, and a community-wide platform. Advanced Structural and Chemical Imaging, 2018, 4, 6.	4.0	45
13	Direct imaging of monovacancy-hydrogen complexes in a single graphitic layer. Physical Review B, 2014, 89, .	1.1	44
14	Bowl Inversion and Electronic Switching of Buckybowls on Gold. Journal of the American Chemical Society, 2016, 138, 12142-12149.	6.6	44
15	Machine learning for high-throughput experimental exploration of metal halide perovskites. Joule, 2021, 5, 2797-2822.	11.7	44
16	Visualization of electronic states on atomically smooth graphitic edges with different types of hydrogen termination. Physical Review B, 2013, 87, .	1.1	41
17	Phases and Interfaces from Real Space Atomically Resolved Data: Physics-Based Deep Data Image Analysis. Nano Letters, 2016, 16, 5574-5581.	4.5	40
18	Exploring order parameters and dynamic processes in disordered systems via variational autoencoders. Science Advances, 2021, 7, .	4.7	38

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19	Fast Scanning Probe Microscopy via Machine Learning: Nonâ€Rectangular Scans with Compressed Sensing and Gaussian Process Optimization. Small, 2020, 16, e2002878.	5.2	37
20	Experimental discovery of structureâ€"property relationships in ferroelectric materials via active learning. Nature Machine Intelligence, 2022, 4, 341-350.	8.3	37
21	High-Throughput Study of Antisolvents on the Stability of Multicomponent Metal Halide Perovskites through Robotics-Based Synthesis and Machine Learning Approaches. Journal of the American Chemical Society, 2021, 143, 19945-19955.	6.6	35
22	Toward Electrochemical Studies on the Nanometer and Atomic Scales: Progress, Challenges, and Opportunities. ACS Nano, 2019, 13, 9735-9780.	7.3	32
23	Mapping mesoscopic phase evolution during E-beam induced transformations via deep learning of atomically resolved images. Npj Computational Materials, 2018, 4, .	3.5	31
24	Exploration of Electrochemical Reactions at Organicâ€"Inorganic Halide Perovskite Interfaces via Machine Learning in In Situ Timeâ€ofâ€Flight Secondary Ion Mass Spectrometry. Advanced Functional Materials, 2020, 30, 2001995.	7.8	30
25	Hypothesis Learning in Automated Experiment: Application to Combinatorial Materials Libraries. Advanced Materials, 2022, 34, e2201345.	11.1	30
26	Data mining for better material synthesis: The case of pulsed laser deposition of complex oxides. Journal of Applied Physics, 2018, 123, .	1.1	29
27	Off-the-shelf deep learning is not enough, and requires parsimony, Bayesianity, and causality. Npj Computational Materials, 2021, 7, .	3.5	28
28	Ensemble learning-iterative training machine learning for uncertainty quantification and automated experiment in atom-resolved microscopy. Npj Computational Materials, 2021, 7, .	3.5	26
29	Atomic Mechanisms for the Si Atom Dynamics in Graphene: Chemical Transformations at the Edge and in the Bulk. Advanced Functional Materials, 2019, 29, 1904480.	7.8	25
30	Lab on a beamâ€"Big data and artificial intelligence in scanning transmission electron microscopy. MRS Bulletin, 2019, 44, 565-575.	1.7	24
31	Learning from Imperfections: Predicting Structure and Thermodynamics from Atomic Imaging of Fluctuations. ACS Nano, 2019, 13, 718-727.	7.3	24
32	Autonomous Experiments in Scanning Probe Microscopy and Spectroscopy: Choosing Where to Explore Polarization Dynamics in Ferroelectrics. ACS Nano, 2021, 15, 11253-11262.	7.3	23
33	Automated Experiment in 4D-STEM: Exploring Emergent Physics and Structural Behaviors. ACS Nano, 2022, 16, 7605-7614.	7.3	23
34	Toward Decoding the Relationship between Domain Structure and Functionality in Ferroelectrics via Hidden Latent Variables. ACS Applied Materials & Interfaces, 2021, 13, 1693-1703.	4.0	22
35	Deep data mining in a real space: separation of intertwined electronic responses in a lightly doped BaFe₂As₂. Nanotechnology, 2016, 27, 475706.	1.3	21
36	Causal analysis of competing atomistic mechanisms in ferroelectric materials from high-resolution scanning transmission electron microscopy data. Npj Computational Materials, 2020, 6, .	3.5	21

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37	Building ferroelectric from the bottom up: The machine learning analysis of the atomic-scale ferroelectric distortions. Applied Physics Letters, 2019, 115, .	1.5	20
38	Imaging mechanism for hyperspectral scanning probe microscopy via Gaussian process modelling. Npj Computational Materials, 2020, 6, .	3.5	19
39	Disentangling Rotational Dynamics and Ordering Transitions in a System of Self-Organizing Protein Nanorods <i>via</i> Rotationally Invariant Latent Representations. ACS Nano, 2021, 15, 6471-6480.	7.3	19
40	Data mining graphene: correlative analysis of structure and electronic degrees of freedom in graphenic monolayers with defects. Nanotechnology, 2016, 27, 495703.	1.3	18
41	167-PFlops Deep Learning for Electron Microscopy: From Learning Physics to Atomic Manipulation. , 2018, , .		18
42	Exploring physics of ferroelectric domain walls via Bayesian analysis of atomically resolved STEM data. Nature Communications, 2020, 11, 6361.	5.8	17
43	Quantifying the Dynamics of Protein Self-Organization Using Deep Learning Analysis of Atomic Force Microscopy Data. Nano Letters, 2021, 21, 158-165.	4.5	17
44	Predictability of Localized Plasmonic Responses in Nanoparticle Assemblies. Small, 2021, 17, e2100181.	5.2	17
45	Disentangling Ferroelectric Wall Dynamics and Identification of Pinning Mechanisms via Deep Learning. Advanced Materials, 2021, 33, e2103680.	11.1	17
46	Deep data analytics for genetic engineering of diatoms linking genotype to phenotype via machine learning. Npj Computational Materials, 2019, 5, .	3.5	16
47	Computational scanning tunneling microscope image database. Scientific Data, 2021, 8, 57.	2.4	15
48	Probing atomic-scale symmetry breaking by rotationally invariant machine learning of multidimensional electron scattering. Npj Computational Materials, 2021, 7, .	3.5	15
49	Multi-objective Bayesian optimization of ferroelectric materials with interfacial control for memory and energy storage applications. Journal of Applied Physics, 2021, 130, .	1.1	15
50	Deep Bayesian local crystallography. Npj Computational Materials, 2021, 7, .	3.5	15
51	Identifying local structural states in atomic imaging by computer vision. Advanced Structural and Chemical Imaging, 2016, 2, 14.	4.0	14
52	Disentangling ferroelectric domain wall geometries and pathways in dynamic piezoresponse force microscopy via unsupervised machine learning. Nanotechnology, 2022, 33, 055707.	1.3	14
53	Physics makes the difference: Bayesian optimization and active learning via augmented Gaussian process. Machine Learning: Science and Technology, 2022, 3, 015003.	2.4	14
54	Separating Physically Distinct Mechanisms in Complex Infrared Plasmonic Nanostructures via Machine Learning Enhanced Electron Energy Loss Spectroscopy. Advanced Optical Materials, 2021, 9, 2001808.	3.6	13

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55	Revealing the Chemical Bonding in Adatom Arrays via Machine Learning of Hyperspectral Scanning Tunneling Spectroscopy Data. ACS Nano, 2021, 15, 11806-11816.	7.3	13
56	Chemically induced topological zero mode at graphene armchair edges. Physical Chemistry Chemical Physics, 2017, 19, 5145-5154.	1.3	12
57	Exploring Causal Physical Mechanisms via Non-Gaussian Linear Models and Deep Kernel Learning: Applications for Ferroelectric Domain Structures. ACS Nano, 2022, 16, 1250-1259.	7.3	12
58	Towards automating structural discovery in scanning transmission electron microscopy [*]. Machine Learning: Science and Technology, 2022, 3, 015024.	2.4	11
59	Tracking atomic structure evolution during directed electron beam induced Si-atom motion in graphene via deep machine learning. Nanotechnology, 2021, 32, 035703.	1.3	10
60	Bridging microscopy with molecular dynamics and quantum simulations: an atomAI based pipeline. Npj Computational Materials, 2022, 8, .	3.5	10
61	Guided search for desired functional responses via Bayesian optimization of generative model: Hysteresis loop shape engineering in ferroelectrics. Journal of Applied Physics, 2020, 128, .	1.1	9
62	Analysis of citation networks as a new tool for scientific research. MRS Bulletin, 2016, 41, 1009-1016.	1.7	8
63	Bayesian Learning of Adatom Interactions from Atomically Resolved Imaging Data. ACS Nano, 2021, 15, 9649-9657.	7.3	8
64	Exploration of lattice Hamiltonians for functional and structural discovery via Gaussian process-based explorationâ€“exploitation. Journal of Applied Physics, 2020, 128, 164304.	1.1	8
65	Predictability as a probe of manifest and latent physics: The case of atomic scale structural, chemical, and polarization behaviors in multiferroic Sm-doped BiFeO3. Applied Physics Reviews, 2021, 8, .	5.5	7
66	Investigating phase transitions from local crystallographic analysis based on statistical learning of atomic environments in 2D MoS2-ReS2. Applied Physics Reviews, 2021, 8, 011409.	5.5	7
67	Latent Mechanisms of Polarization Switching from In Situ Electron Microscopy Observations. Advanced Functional Materials, 2022, 32, .	7.8	7
68	Super-resolution and signal separation in contact Kelvin probe force microscopy of electrochemically active ferroelectric materials. Journal of Applied Physics, 2020, 128, 055101.	1.1	6
69	Gaussian process analysis of electron energy loss spectroscopy data: multivariate reconstruction and kernel control. Npj Computational Materials, 2021, 7, .	3.5	6
70	Identification and correction of temporal and spatial distortions in scanning transmission electron microscopy. Ultramicroscopy, 2021, 229, 113337.	0.8	6
71	Deep learning of interface structures from simulated 4D STEM data: cation intermixing vs. roughening ^{^{âˆ—}}. Machine Learning: Science and Technology, 2020, 1, 04LT01.	2.4	6
72	Deep Learning for Atomically Resolved Imaging. Microscopy and Microanalysis, 2018, 24, 60-61.	0.2	5

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73	Deep Convolutional Neural Networks for Symmetry Detection. Microscopy and Microanalysis, 2018, 24, 112-113.	0.2	5
74	Probing potential energy landscapes via electron-beam-induced single atom dynamics. Acta Materialia, 2021, 203, 116508.	3.8	5
75	Deep learning ferroelectric polarization distributions from STEM data via with and without atom finding. Npj Computational Materials, 2021, 7, .	3.5	5
76	Decoding the shift-invariant data: applications for band-excitation scanning probe microscopy [*]. Machine Learning: Science and Technology, 2021, 2, 045028.	2.4	5
77	Probing polarization dynamics at specific domain configurations: Computer-vision based automated experiment in piezoresponse force microscopy. Applied Physics Letters, 2021, 119, .	1.5	5
78	Reconstruction of effective potential from statistical analysis of dynamic trajectories. AIP Advances, 2020, 10, .	0.6	4
79	Alignment of Au nanorods along <i>de novo</i> designed protein nanofibers studied with automated image analysis. Soft Matter, 2021, 17, 6109-6115.	1.2	4
80	Exploring electron beam induced atomic assembly via reinforcement learning in a molecular dynamics environment. Nanotechnology, 2021, , .	1.3	4
81	Deep Data Analytics in Structural and Functional Imaging of Nanoscale Materials. Springer Series in Materials Science, 2018, , 103-128.	0.4	3
82	Statistical Physics-based Framework and Bayesian Inference for Model Selection and Uncertainty Quantification. Microscopy and Microanalysis, 2019, 25, 130-131.	0.2	3
83	Exploring Responses of Contact Kelvin Probe Force Microscopy in Triple-Cation Double-Halide Perovskites. Journal of Physical Chemistry C, 2021, 125, 12355-12365.	1.5	3
84	AtomAI: Open-source software for applications of deep learning to microscopy data. Microscopy and Microanalysis, 2021, 27, 3000-3002.	0.2	3
85	Beyond NMF: Advanced Signal Processing and Machine Learning Methodologies for Hyperspectral Analysis in EELS. Microscopy and Microanalysis, 2021, 27, 322-324.	0.2	3
86	Reconstruction of the interatomic forces from dynamic scanning transmission electron microscopy data. Journal of Applied Physics, 2020, 127, 224301.	1.1	2
87	Building an edge computing infrastructure for rapid multi-dimensional electron microscopy. Microscopy and Microanalysis, 2021, 27, 56-57.	0.2	2
88	Denoising STEM Electron Energy Loss Spectra using Convolutional Autoencoders. Microscopy and Microanalysis, 2021, 27, 1180-1182.	0.2	2
89	Reconstruction and uncertainty quantification of lattice Hamiltonian model parameters from observations of microscopic degrees of freedom. Journal of Applied Physics, 2020, 128, 214103.	1.1	2
90	Nanoscale interlayer defects in iron arsenides. Journal of Solid State Chemistry, 2019, 277, 422-426.	1.4	1

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91	Thermodynamics of order and randomness in dopant distributions inferred from atomically resolved imaging. Npj Computational Materials, 2021, 7, .	3.5	1
92	Automated Experiment in SPM: Bayesian Optimization for efficient searching of parameter space to maximize functional response. Microscopy and Microanalysis, 2021, 27, 470-471.	0.2	1
93	Probing atomic-scale symmetry breaking by rotationally invariant machine learning of 4D-STEM Data.. Microscopy and Microanalysis, 2021, 27, 2200-2201.	0.2	1
94	Bayesian Inference for Materials Physics from STEM Data: The Probability Distribution of Physical Parameters from Ferroelectric Domain Wall Observations. Microscopy and Microanalysis, 2021, 27, 1212-1214.	0.2	1
95	Deep Data Mining in a Real Space: Application to Scanning Probe Microscopy Studies on a â€œParentâ€• State of a High Temperature Superconductor. Microscopy and Microanalysis, 2016, 22, 1418-1419.	0.2	0
96	Phase determination from atomically resolved images: physics-constrained deep data analysis through an unmixing approach. Microscopy and Microanalysis, 2016, 22, 1452-1453.	0.2	0
97	Atomic Level Structure-Property Relationship in a Spin-Orbit Mott insulator: Scanning Transmission Electron and Scanning Tunneling Microscopy Studies. Microscopy and Microanalysis, 2016, 22, 908-909.	0.2	0
98	Leveraging Single Atom Dynamics to Measure the Electron-Beam-Induced Force and Atomic Potentials. Microscopy and Microanalysis, 2018, 24, 96-97.	0.2	0
99	Machine Learning for the Dynamic Scanning Transmission Electron Microscopy Experiment on Solid State Transformations. Microscopy and Microanalysis, 2018, 24, 1600-1601.	0.2	0
100	FerroNet: Machine Learning Flow for Analysis of Ferroelectric and Ferroelastic Materials. Microscopy and Microanalysis, 2019, 25, 170-171.	0.2	0
101	Towards Atomic Scale Quantum Structure Fabrication in 2D Materials. Microscopy and Microanalysis, 2019, 25, 940-941.	0.2	0
102	Causal Learning from Structural and Spectral Electron Microscopy Data. Microscopy and Microanalysis, 2020, 26, 6-6.	0.2	0
103	Mapping the Distortion Function via Multivariate Analysis of Atomically Resolved Images. Microscopy and Microanalysis, 2020, 26, 2134-2135.	0.2	0
104	Towards Automating Structural Discovery in Scanning Transmission Electron Microscopy. Microscopy and Microanalysis, 2021, 27, 2770-2772.	0.2	0
105	Deep Learningâ€"Based Workflow for Analyzing Helium Bubbles in Transmission Electron Microscopy Images. Microscopy and Microanalysis, 2021, 27, 2132-2133.	0.2	0
106	Causal Analysis of Parameterized Atomic HAADF-STEM Across a Doped Ferroelectric Phase Boundary. Microscopy and Microanalysis, 2021, 27, 2762-2764.	0.2	0
107	Direct mapping of polarization fields from STEM images: A Deep Learning based exploration of ferroelectrics. Microscopy and Microanalysis, 2021, 27, 2990-2992.	0.2	0
108	Predicting local plasmon resonances and geometries using autoencoder networks in complex nanoparticle assemblies. Microscopy and Microanalysis, 2021, 27, 2766-2768.	0.2	0

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109	Deep Machine Learning in Electron and Scanning Probe Microscopy. , 2020, , 363-395.		0
110	Big and Deep Data Methods in Scanning Probe Microscopy and Spectroscopy. , 2020, , 301-362.		0
111	Strain-Induced asymmetry and on-site dynamics of silicon defects in graphene. Carbon Trends, 2022, 9, 100189.	1.4	0