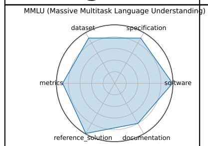
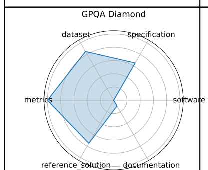
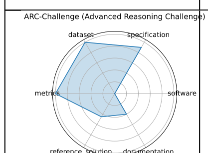
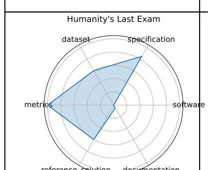
1 Benchmark Overview Table

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	MMLU (Massive Multitask Language Understanding)	Multidomain	Academic knowledge and reasoning across 57 subjects	multitask, multiple-choice, zero-shot, few-shot, knowledge probing	Multiple choice	General reasoning, subject-matter understanding	Accuracy	GPT-4o, Gemini 1.5 Pro, o1, DeepSeek-R1	[1]⇒
	GPQA Diamond	Science	Graduate-level scientific reasoning	Google-proof, graduate-level, science QA, chemistry, physics	Multiple choice, Multi-step QA	Scientific reasoning, deep knowledge	Accuracy	o1, DeepSeek-R1	[2]⇒
	ARC-Challenge (Advanced Reasoning Challenge)	Science	Grade-school science with reasoning emphasis	grade-school, science QA, challenge set, reasoning	Multiple choice	Commonsense and scientific reasoning	Accuracy	GPT-4, Claude	[3]⇒
	Humanity's Last Exam	Multidomain	Broad cross-domain academic reasoning	cross-domain, academic exam, multiple-choice, multidisciplinary	Multiple choice	Cross-domain academic reasoning	Accuracy	unkown	[4]⇒

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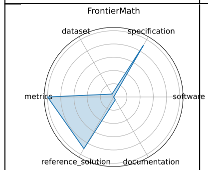
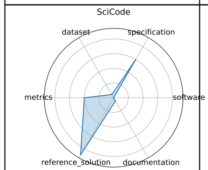
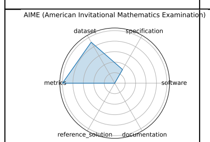
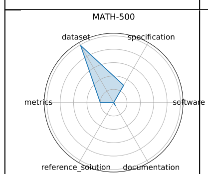
	FrontierMath	Mathematics	Challenging advanced mathematical reasoning	symbolic reasoning, number theory, algebraic geometry, category theory	Problem solving	Symbolic and abstract mathematical reasoning	Accuracy	unkown	[5]⇒
	SciCode	Scientific Programming	Scientific code generation and problem solving	code synthesis, scientific computing, programming benchmark	Coding	Program synthesis, scientific computing	Solve rate (%)	Claude3.5-Sonnet	[6]⇒
	AIME (American Invitational Mathematics Examination)	Mathematics	Pre-college advanced problem solving	algebra, combinatorics, number theory, geometry	Problem solving	Mathematical problem-solving and reasoning	Accuracy	unkown	[7]⇒
	MATH-500	Mathematics	Math reasoning generalization	calculus, algebra, number theory, geometry	Problem solving	Math reasoning and generalization	Accuracy	unkown	[8]⇒

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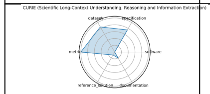
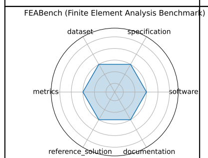
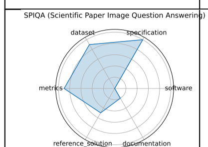
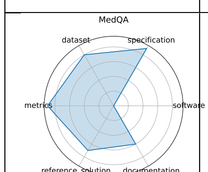
	CURIE (Scientific Long-Context Understanding, Reasoning and Information Extraction)	Multidomain Science	Long-context scientific reasoning	long-context, information extraction, multimodal	Information extraction, Reasoning, Concept tracking, Aggregation, Algebraic manipulation, Multimodal comprehension	Long-context understanding and scientific reasoning	Accuracy	unkown	[9]⇒
	FEABench (Finite Element Analysis Benchmark)	Computational Engineering	FEA simulation accuracy and performance	finite element, simulation, PDE	Simulation, Performance evaluation	Numerical simulation accuracy and efficiency	Solve time, Error norm	FEniCS, deal.II	⇒
	SPIQA (Scientific Paper Image Question Answering)	Computer Science	Multimodal QA on scientific figures	multimodal QA, figure understanding, table comprehension, chain-of-thought	Question answering, Multimodal QA, Chain-of-Thought evaluation	Visual-textual reasoning in scientific contexts	Accuracy, F1 score	Chain-of-Thought models, Multimodal QA systems	[10]⇒
	MedQA	Medical Question Answering	Medical board exam QA	USMLE, diagnostic QA, medical knowledge, multilingual	Multiple choice	Medical diagnosis and knowledge retrieval	Accuracy	Neural reader, Retrieval-based QA systems	[11]⇒

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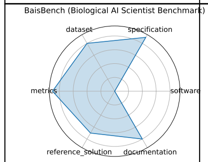
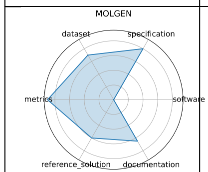
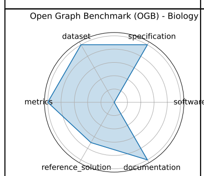
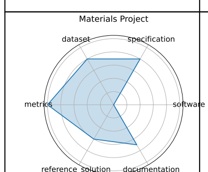
	BaisBench (Biological AI Scientist Benchmark)	Computational Biology	Omics-driven AI research tasks	single-cell annotation, biological QA, autonomous discovery	Cell type annotation, Multiple choice	Autonomous biological research capabilities	Annotation accuracy, QA accuracy	LLM-based AI scientist agents	[12]⇒
	MOLGEN	Computational Chemistry	Molecular generation and optimization	SELFIES, GAN, property optimization	Distribution learning, Goal-oriented generation	Generation of valid and optimized molecular structures	Validity%, Novelty%, QED, Docking score	MolGen	[13]⇒
	Open Graph Benchmark (OGB) - Biology	Graph ML	Biological graph property prediction	node prediction, link prediction, graph classification	Node property prediction, Link property prediction, Graph property prediction	Scalability and generalization in graph ML for biology	Accuracy, ROC-AUC	GCN, GraphSAGE, GAT	[14]⇒
	Materials Project	Materials Science	DFT-based property prediction	DFT, materials genome, high-throughput	Property prediction	Prediction of inorganic material properties	MAE, R^2	Automatminer, Crystal Graph Neural Networks	[15]⇒

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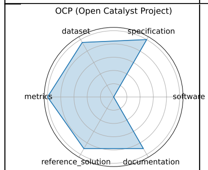
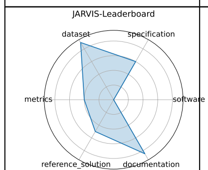
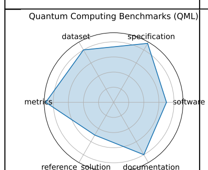
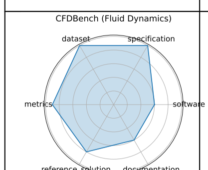
	OCP (Open Catalyst Project)	Chemistry; Materials Science	Catalyst adsorption energy prediction	DFT relaxations, adsorption energy, graph neural networks	Energy prediction, Force prediction	Prediction of adsorption energies and forces	MAE (energy), MAE (force)	CGCNN, SchNet, DimeNet++, GemNet-OC	[16]–[19]⇒
	JARVIS-Leaderboard	Materials Science; Benchmarking	Comparative evaluation of materials design methods	leaderboards, materials methods, simulation	Method benchmarking, Leaderboard ranking	Performance comparison across diverse materials design methods	MAE, RMSE, Accuracy	unkown	[20]⇒
	Quantum Computing Benchmarks (QML)	Quantum Computing	Quantum algorithm performance evaluation	quantum circuits, state preparation, error correction	Circuit benchmarking, State classification	Quantum algorithm performance and fidelity	Fidelity, Success probability	IBM Q, IonQ, AQT@LBNL	[21]⇒
	CFDBench (Fluid Dynamics)	Fluid Dynamics; Scientific ML	Neural operator surrogate modeling	neural operators, CFD, FNO, DeepONet	Surrogate modeling	Generalization of neural operators for PDEs	L2 error, MAE	FNO, DeepONet, U-Net	[22]⇒

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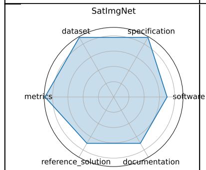
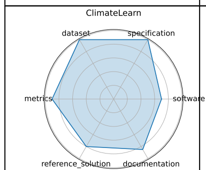
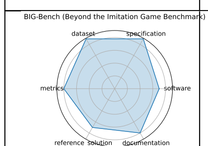
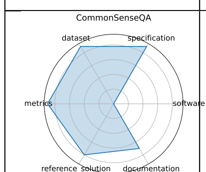
	SatImgNet	Remote Sensing	Satellite imagery classification	land-use, zero-shot, multi-task	Image classification	Zero-shot land-use classification	Accuracy	CLIP, BLIP, ALBEF	[23]⇒
	ClimateLearn	Climate Science; Forecasting	ML for weather and climate modeling	medium-range forecasting, ERA5, data-driven	Forecasting	Global weather prediction (3-5 days)	RMSE, Anomaly correlation	CNN baselines, ResNet variants	[24]⇒
	BIG-Bench (Beyond the Imitation Game Benchmark)	NLP; AI Evaluation	Diverse reasoning and generalization tasks	few-shot, multi-task, bias analysis	Few-shot evaluation, Multi-task evaluation	Reasoning and generalization across diverse tasks	Accuracy, Task-specific metrics	GPT-3, Dense Transformers, Sparse Transformers	[25]⇒
	CommonSenseQA	NLP; Commonsense	Commonsense question answering	ConceptNet, multiple-choice, adversarial	Multiple choice	Commonsense reasoning and knowledge integration	Accuracy	BERT-large, RoBERTa, GPT-3	[26]⇒

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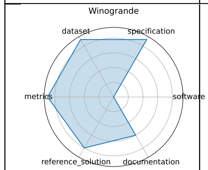
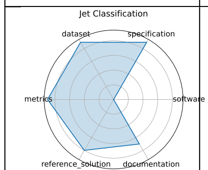
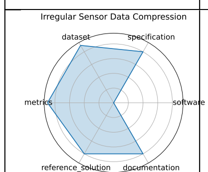
	Winogrande	NLP; Commonsense	Winograd Schema-style pronoun resolution	adversarial, pronoun resolution	Pronoun resolution	Robust commonsense reasoning	Accuracy, AUC	RoBERTa, BERT, GPT-2	[27]⇒
	Jet Classification	Particle Physics	Real-time classification of particle jets using HL-LHC simulation features	classification, real-time ML, jet tagging, QKeras	Classification	Real-time inference, model compression performance	Accuracy, AUC	Keras DNN, QKeras quantized DNN	[28]⇒
	Irregular Sensor Data Compression	Particle Physics	Real-time compression of sparse sensor data with autoencoders	compression, autoencoder, sparse data, irregular sampling	Compression	Reconstruction quality, compression efficiency	MSE, Compression ratio	Autoencoder, Quantized autoencoder	[29]⇒

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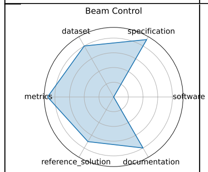
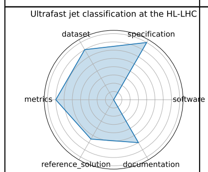
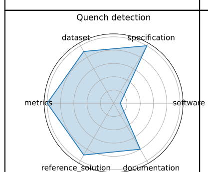
	Beam Control	Accelerators and Magnets	Reinforcement learning control of accelerator beam position	RL, beam stabilization, control systems, simulation	Control	Policy performance in simulated accelerator control	Stability, Control loss	DDPG, PPO (planned)	[29], [30]⇒
	Ultrafast jet classification at the HL-LHC	Particle Physics	FPGA-optimized real-time jet origin classification at the HL-LHC	jet classification, FPGA, quantization-aware training, Deep Sets, Interaction Networks	Classification	Real-time inference under FPGA constraints	Accuracy, Latency, Resource utilization	MLP, Deep Sets, Interaction Network	[31]⇒
	Quench detection	Accelerators and Magnets	Real-time detection of superconducting magnet quenches using ML	quench detection, autoencoder, anomaly detection, real-time	Anomaly detection, Quench localization	Real-time anomaly detection with multi-modal sensors	ROC-AUC, Detection latency	Autoencoder, RL agents (in development)	[32]⇒

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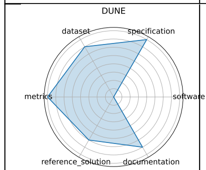
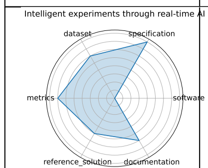
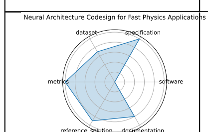
	DUNE	Particle Physics	Real-time ML for DUNE DAQ time-series data	DUNE, time-series, real-time, trigger	Trigger selection, Time-series anomaly detection	Low-latency event detection	Detection efficiency, Latency	CNN, LSTM (planned)	[33]⇒
	Intelligent experiments through real-time AI	Instrumentation and Detectors; Nuclear Physics; Particle Physics	Real-time FPGA-based triggering and detector control for sPHENIX and future EIC	FPGA, Graph Neural Network, hls4ml, real-time inference, detector control	Trigger classification, Detector control, Real-time inference	Low-latency GNN inference on FPGA	Accuracy (charm and beauty detection), Latency (micros), Resource utilization (LUT/FF/BRAM/DSP)	Bipartite Graph Network with Set Transformers (BGN-ST), GarNet (edge-classifier)	[34]⇒
	Neural Architecture Codesign for Fast Physics Applications	Physics; Materials Science; Particle Physics	Automated neural architecture search and hardware-efficient model codesign for fast physics applications	neural architecture search, FPGA deployment, quantization, pruning, hls4ml	Classification, Peak finding	Hardware-aware model optimization; low-latency inference	Accuracy, Latency, Resource utilization	NAC-based BraggNN, NAC-optimized Deep Sets (jet)	[35]⇒

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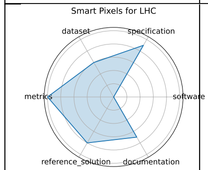
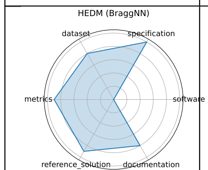
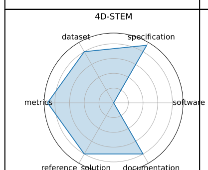
	Smart Pixels for LHC	Particle Physics; Instrumentation and Detectors	On-sensor, in-pixel ML filtering for high-rate LHC pixel detectors	smart pixel, on-sensor inference, data reduction, trigger	Image Classification, Data filtering	On-chip, low-power inference; data reduction	Data rejection rate, Power per pixel	2-layer pixel NN	[36]⇒
	HEDM (BraggNN)	Material Science	Fast Bragg peak analysis using deep learning in diffraction microscopy	BraggNN, diffraction, peak finding, HEDM	Peak detection	High-throughput peak localization	Localization accuracy, Inference time	BraggNN	[37]⇒
	4D-STEM	Material Science	Real-time ML for scanning transmission electron microscopy	4D-STEM, electron microscopy, real-time, image processing	Image Classification, Streamed data inference	Real-time large-scale microscopy inference	Classification accuracy, Throughput	CNN models (prototype)	[38]⇒

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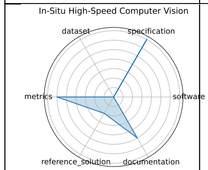
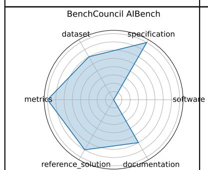
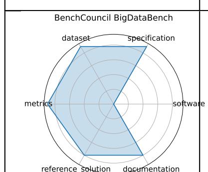
	In-Situ High-Speed Computer Vision	Fusion/Plasma	Real-time image classification for in-situ plasma diagnostics	plasma, in-situ vision, real-time ML	Image Classification	Real-time diagnostic inference	Accuracy, FPS	CNN	[39]⇒
	BenchCouncil AIBench	General	End-to-end AI benchmarking across micro, component, and application levels	benchmarking, AI systems, application-level evaluation	Training, Inference, End-to-end AI workloads	System-level AI workload performance	Throughput, Latency, Accuracy	ResNet, BERT, GANs, Recommendation systems	[40]⇒
	BenchCouncil BigDataBench	General	Big data and AI benchmarking across structured, semi-structured, and unstructured data workloads	big data, AI benchmarking, data analytics	Data preprocessing, Inference, End-to-end data pipelines	Data processing and AI model inference performance at scale	Data throughput, Latency, Accuracy	CNN, LSTM, SVM, XGBoost	[41]⇒

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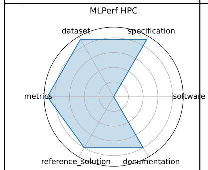
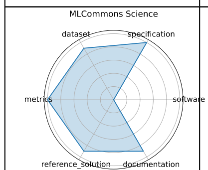
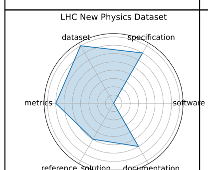
	MLPerf HPC	Cosmology, Climate, Protein Structure, Catalysis	Scientific ML training and inference on HPC systems	HPC, training, inference, scientific ML	Training, Inference	Scaling efficiency, training time, model accuracy on HPC	Training time, Accuracy, GPU utilization	CosmoFlow, DeepCAM, OpenCatalyst	[42]⇒
	MLCommons Science	Earthquake, Satellite Image, Drug Discovery, Electron Microscope, CFD	AI benchmarks for scientific applications including time-series, imaging, and simulation	science AI, benchmark, MLCommons, HPC	Time-series analysis, Image classification, Simulation surrogate modeling	Inference accuracy, simulation speed-up, generalization	MAE, Accuracy, Speedup vs simulation	CNN, GNN, Transformer	[43]⇒
	LHC New Physics Dataset	Particle Physics; Real-time Triggering	Real-time LHC event filtering for anomaly detection using proton collision data	anomaly detection, proton collision, real-time inference, event filtering, unsupervised ML	Anomaly detection, Event classification	Unsupervised signal detection under latency and bandwidth constraints	ROC-AUC, Detection efficiency	Autoencoder, Variational autoencoder, Isolation forest	[44]⇒

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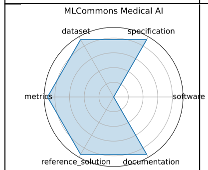
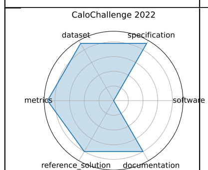
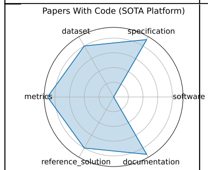
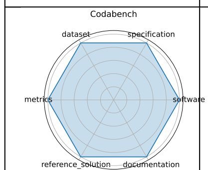
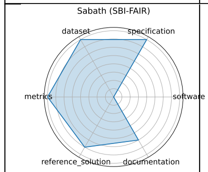
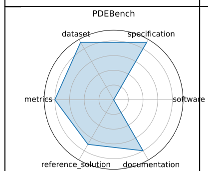
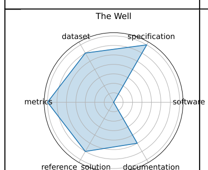
Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	MLCommons Medical AI	Healthcare; Medical AI	Federated benchmarking and evaluation of medical AI models across diverse real-world clinical data	medical AI, federated evaluation, privacy-preserving, fairness, healthcare benchmarks	Federated evaluation, Model validation	Clinical accuracy, fairness, generalizability, privacy compliance	ROC AUC, Accuracy, Fairness metrics	MedPerf-validated CNNs, GaNDLF workflows	[45]⇒
	CaloChallenge 2022	LHC Calorimeter; Particle Physics	Fast generative-model-based calorimeter shower simulation evaluation	calorimeter simulation, generative models, surrogate modeling, LHC, fast simulation	Surrogate modeling	Simulation fidelity, speed, efficiency	Histogram similarity, Classifier AUC, Generation latency	VAE variants, GAN variants, Normalizing flows, Diffusion models	[46]⇒

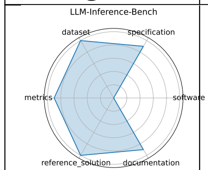
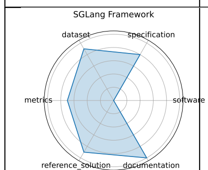
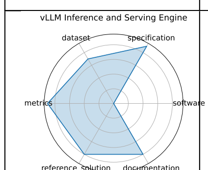
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	Papers With Code (SOTA Platform)	General ML; All domains	Open platform tracking state-of-the-art results, benchmarks, and implementations across ML tasks and papers	leaderboard, benchmarking, reproducibility, open-source	Multiple (Classification, Detection, NLP, etc.)	Model performance across tasks (accuracy, F1, BLEU, etc.)	Task-specific (Accuracy, F1, BLEU, etc.)	All published models with code	[47]⇒
	Codabench	General ML; Multiple	Open-source platform for organizing reproducible AI benchmarks and competitions	benchmark platform, code submission, competitions, meta-benchmark	Multiple	Model reproducibility, performance across datasets	Submission count, Leaderboard ranking, Task-specific metrics	Arbitrary code submissions	[48]⇒

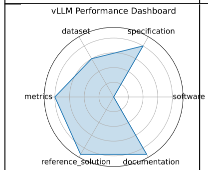
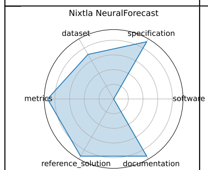
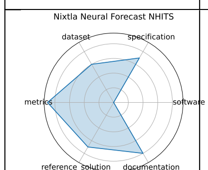
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	Sabath (SBI-FAIR)	Systems; Metadata	FAIR metadata framework for ML-driven surrogate workflows in HPC systems	meta-benchmark, metadata, HPC, surrogate modeling	Systems benchmarking	Metadata tracking, reproducible HPC workflows	Metadata completeness, FAIR compliance	NA	[49]⇒
	PDEBench	CFD; Weather Modeling	Benchmark suite for ML-based surrogates solving time-dependent PDEs	PDEs, CFD, scientific ML, surrogate modeling, NeurIPS	Supervised Learning	Time-dependent PDE modeling; physical accuracy	RMSE, boundary RMSE, Fourier RMSE	FNO, U-Net, PINN, Gradient-Based inverse methods	[50]⇒
	The Well	biological systems, fluid dynamics, acoustic scattering, astrophysical MHD	Foundation model + surrogate dataset spanning 16 physical simulation domains	surrogate modeling, foundation model, physics simulations, spatiotemporal dynamics	Supervised Learning	Surrogate modeling, physics-based prediction	Dataset size, Domain breadth	FNO baselines, U-Net baselines	[51]⇒

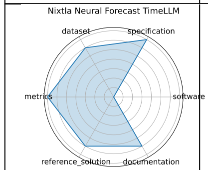
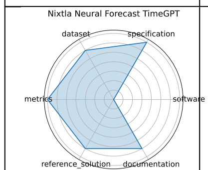
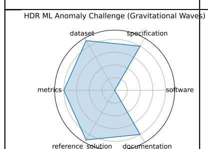
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	LLM-Inference-Bench	LLM; HPC/inference	Hardware performance benchmarking of LLMs on AI accelerators	LLM, inference benchmarking, GPU, accelerator, throughput	Inference Benchmarking	Inference throughput, latency, hardware utilization	Token throughput (tok/s), Latency, Framework-hardware mix performance	LLaMA-2-7B, LLaMA-2-70B, Mistral-7B, Qwen-7B	[52]⇒
	SGLang Framework	LLM Vision	Fast serving framework for LLMs and vision-language models	LLM serving, vision-language, RadixAttention, performance, JSON decoding	Model serving framework	Serving throughput, JSON/task-specific latency	Tokens/sec, Time-to-first-token, Throughput gain vs baseline	LLaVA, DeepSeek, Llama	[53]⇒
	vLLM Inference and Serving Engine	LLM; HPC/inference	High-throughput, memory-efficient inference and serving engine for LLMs	LLM inference, PagedAttention, CUDA graph, streaming API, quantization	Inference Benchmarking	Throughput, latency, memory efficiency	Tokens/sec, Time to First Token (TTFT), Memory footprint	LLaMA, Mixtral, FlashAttention-based models	[54]⇒

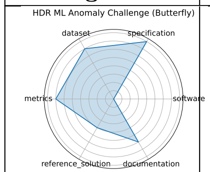
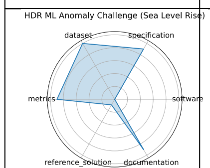
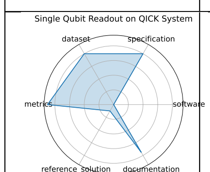
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	vLLM Performance Dashboard	LLM; HPC/inference	Interactive dashboard showing inference performance of vLLM	Dashboard, Throughput visualization, Latency analysis, Metric tracking	Performance visualization	Throughput, latency, hardware utilization	Tokens/sec, TTFT, Memory usage	LLaMA-2, Mistral, Qwen	[55]⇒
	Nixtla NeuralForecast	Time-series forecasting; General ML	High-performance neural forecasting library with >30 models	time-series, neural forecasting, NBEATS, NHITS, TFT, probabilistic forecasting, usability	Time-series forecasting	Forecast accuracy, interpretability, speed	RMSE, MAPE, CRPS	NBEATS, NHITS, TFT, DeepAR	[56]⇒
	Nixtla Neural Forecast NHITS	Time-series; General ML	Official NHITS implementation for long-horizon time series forecasting	NHITS, long-horizon forecasting, neural interpolation, time-series	Time-series forecasting	Accuracy, compute efficiency for long series	RMSE, MAPE	NHITS	[57]⇒

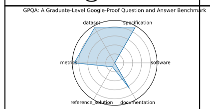
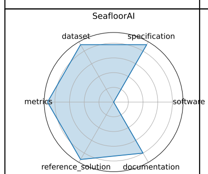
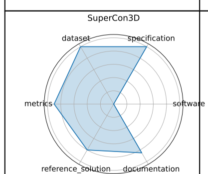
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	Nixtla Neural Forecast TimeLLM	Time-series; General ML	Reprogramming LLMs for time series forecasting	Time-LLM, language model, time-series, reprogramming	Time-series forecasting	Model reuse via LLM, few-shot forecasting	RMSE, MAPE	Time-LLM	[58]⇒
	Nixtla Neural Forecast TimeGPT	Time-series; General ML	Time-series foundation model "TimeGPT" for forecasting and anomaly detection	TimeGPT, foundation model, time-series, generative model	Time-series forecasting, Anomaly detection	Zero-shot forecasting, anomaly detection	RMSE, Anomaly detection metrics	TimeGPT	[59]⇒
	HDR ML Anomaly Challenge (Gravitational Waves)	Astrophysics; Time-series	Detecting anomalous gravitational-wave signals from LIGO/Virgo datasets	anomaly detection, gravitational waves, astrophysics, time-series	Anomaly detection	Novel event detection in physical signals	ROC-AUC, Precision/Recall	Deep latent CNNs, Autoencoders	[60]⇒

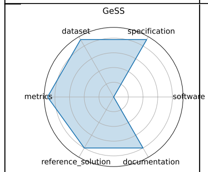
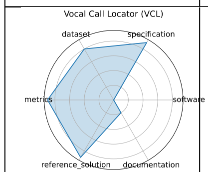
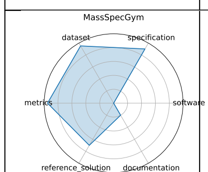
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	HDR ML Anomaly Challenge (Butterfly)	Genomics; Image/CV	Detecting hybrid butterflies via image anomaly detection in genomic-informed dataset	anomaly detection, computer vision, genomics, butterfly hybrids	Anomaly detection	Hybrid detection in biological systems	Classification accuracy, F1 score	CNN-based detectors	[60]⇒
	HDR ML Anomaly Challenge (Sea Level Rise)	Climate Science; Time-series, Image/CV	Detecting anomalous sea-level rise and flooding events via time-series and satellite imagery	anomaly detection, climate science, sea-level rise, time-series, remote sensing	Anomaly detection	Detection of environmental anomalies	ROC-AUC, Precision/Recall	CNNs, RNNs, Transformers	[60]⇒
	Single Qubit Readout on QICK System	Quantum Computing	Real-time single-qubit state classification using FPGA firmware	qubit readout, hls4ml, FPGA, QICK	Classification	Single-shot fidelity, inference latency	Accuracy, Latency	hls4ml quantized NN	[61]⇒

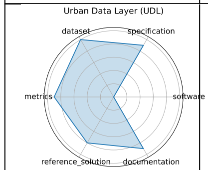
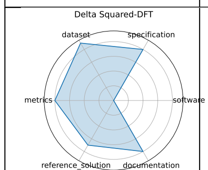
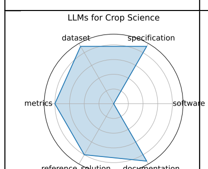
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark	Science (Biology, Physics, Chemistry)	Graduate-level, expert-validated multiple-choice questions hard even with web access	Google-proof, multiple-choice, expert reasoning, science QA	Multiple choice	Scientific reasoning, knowledge probing	Accuracy	GPT-4 baseline	[2]⇒
	SeafloorAI	Marine Science; Vision-Language	Large-scale vision-language dataset for seafloor mapping and geological classification	sonar imagery, vision-language, seafloor mapping, segmentation, QA	Image segmentation, Vision-language QA	Geospatial understanding, multimodal reasoning	Segmentation pixel accuracy, QA accuracy	SegFormer, ViLT-style multimodal models	[62]⇒
	SuperCon3D	Materials Science; Superconductivity	Dataset and models for predicting and generating high-Tc superconductors using 3D crystal structures	superconductivity, crystal structures, equivariant GNN, generative models	Regression (Tc prediction), Generative modeling	Structure-to-property prediction, structure generation	MAE (Tc), Validity of generated structures	SODNet, DiffCSP-SC	[63]⇒

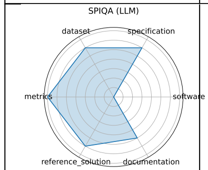
Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	GeSS	Scientific ML; Geometric Deep Learning	Benchmark suite evaluating geometric deep learning models under real-world distribution shifts	geometric deep learning, distribution shift, OOD robustness, scientific applications	Classification, Regression	OOD performance in scientific settings	Accuracy, RMSE, OOD robustness delta	GCN, EGNN, DimeNet++	[64]⇒
	Vocal Call Locator (VCL)	Neuroscience; Bioacoustics	Benchmarking sound-source localization of rodent vocalizations from multi-channel audio	source localization, bioacoustics, time-series, SSL	Sound source localization	Source localization accuracy in bioacoustic settings	Localization error (cm), Recall/Precision	CNN-based SSL models	[65]⇒
	MassSpecGym	Cheminformatics; Molecular Discovery	Benchmark suite for discovery and identification of molecules via MS/MS	mass spectrometry, molecular structure, de novo generation, retrieval, dataset	De novo generation, Retrieval, Simulation	Molecular identification and generation from spectral data	Structure accuracy, Retrieval precision, Simulation MSE	Graph-based generative models, Retrieval baselines	[66]⇒

Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	Urban Data Layer (UDL)	Urban Computing; Data Engineering	Unified data pipeline for multi-modal urban science research	data pipeline, urban science, multi-modal, benchmark	Prediction, Classification	Multi-modal urban inference, standardization	Task-specific accuracy or RMSE	Baseline regression/classification pipelines	[67]⇒
	Delta Squared-DFT	Computational Chemistry; Materials Science	Benchmarking machine-learning corrections to DFT using Delta Squared-trained models for reaction energies	density functional theory, Delta Squared-ML correction, reaction energetics, quantum chemistry	Regression	High-accuracy energy prediction, DFT correction	Mean Absolute Error (eV), Energy ranking accuracy	Delta Squared-ML correction networks, Kernel ridge regression	[68]⇒
	LLMs for Crop Science	Agricultural Science; NLP	Evaluating LLMs on crop trait QA and textual inference tasks with domain-specific prompts	crop science, prompt engineering, domain adaptation, question answering	Question Answering, Inference	Scientific knowledge, crop reasoning	Accuracy, F1 score	GPT-4, LLaMA-2-13B, T5-XXL	[69]⇒

Continued on next page

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	SPIQA (LLM)	Multimodal Scientific QA; Computer Vision	Evaluating LLMs on image-based scientific paper figure QA tasks (LLM Adapter performance)	multimodal QA, scientific figures, image+text, chain-of-thought prompting	Multimodal QA	Visual reasoning, scientific figure understanding	Accuracy, F1 score	LLaVA, MiniGPT-4, Owl-LLM adapter variants	[70]⇒

2 Radar Chart Table

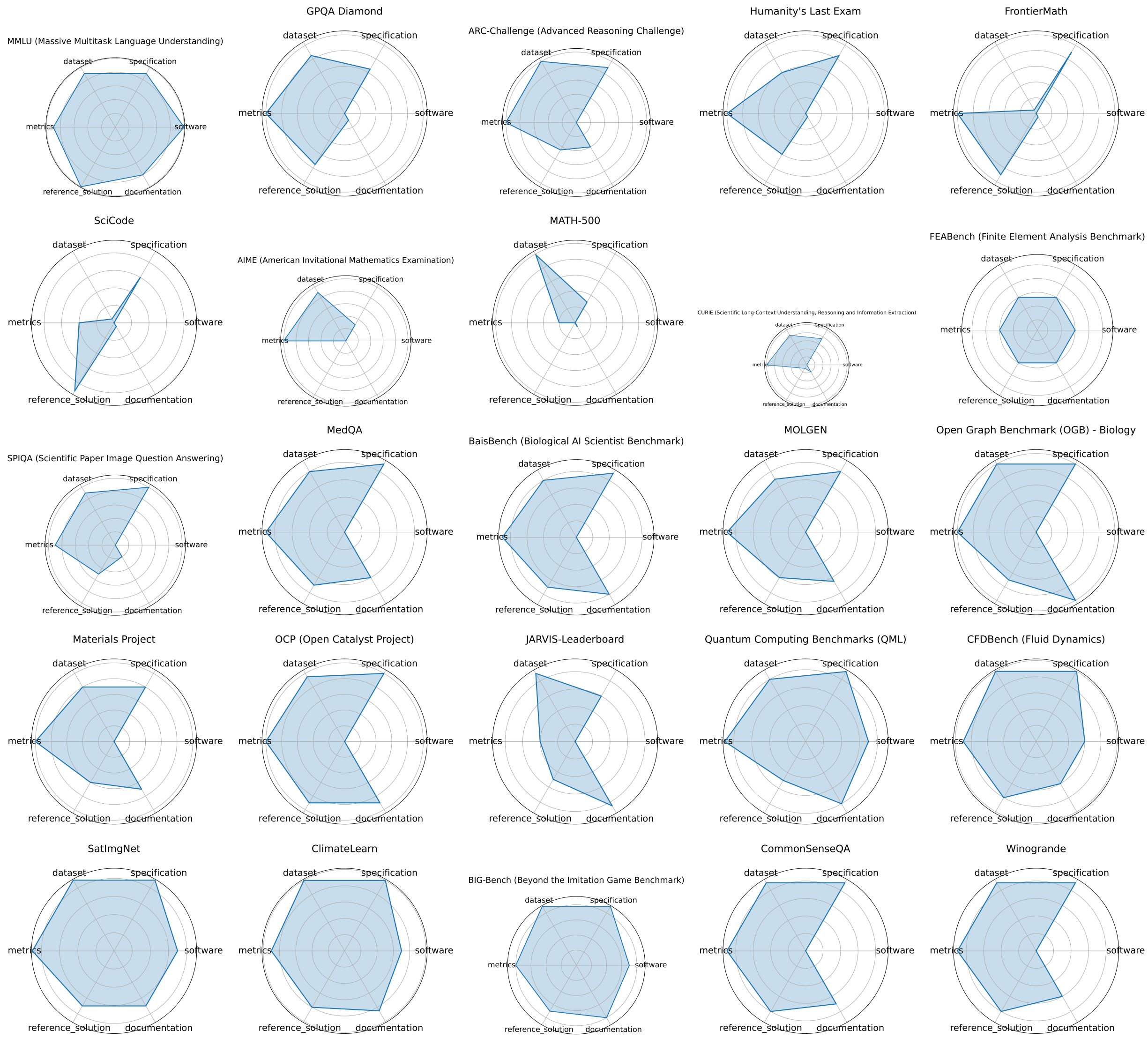


Figure 1: Radar chart overview (page 1)

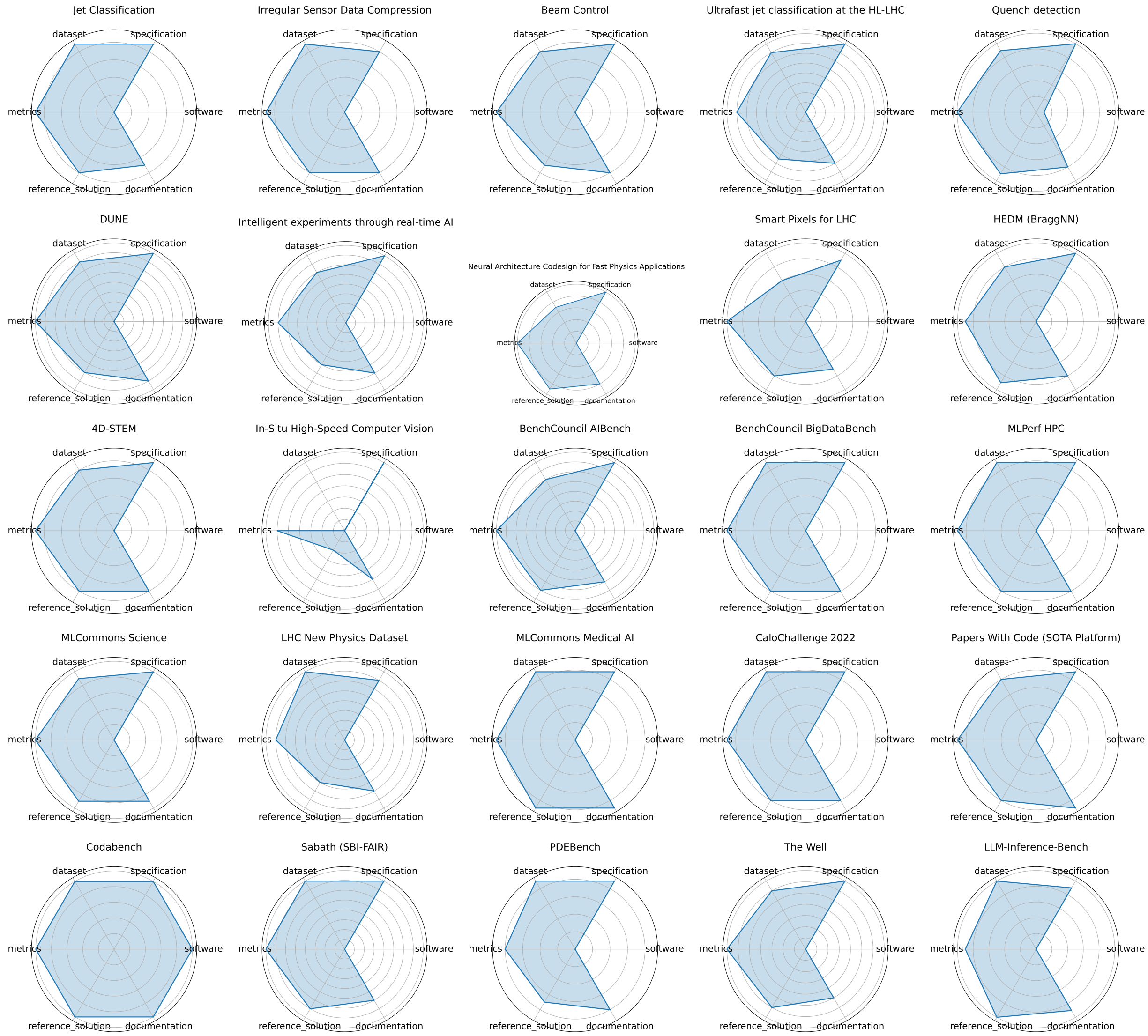


Figure 2: Radar chart overview (page 2)

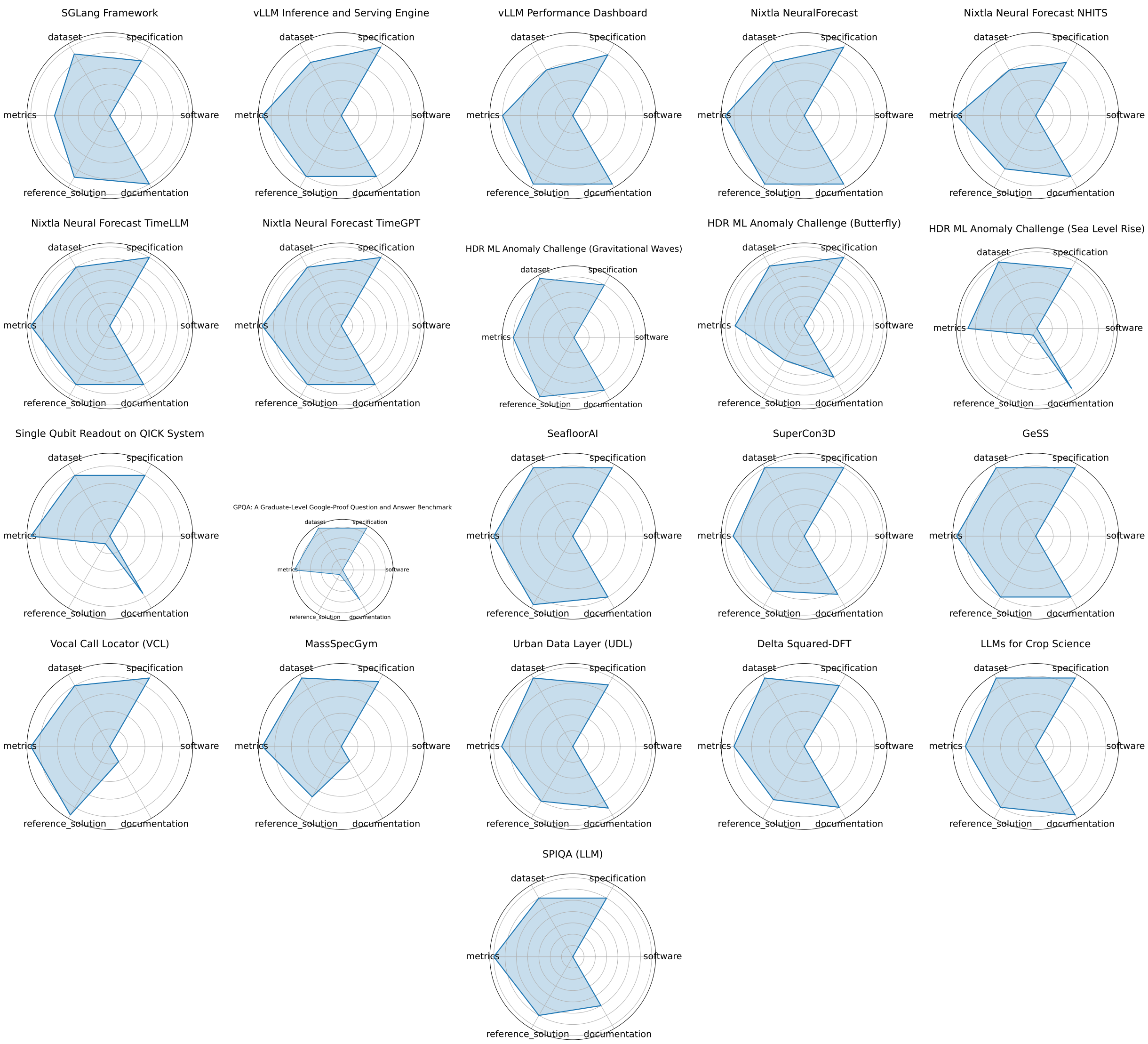


Figure 3: Radar chart overview (page 3)

3 Benchmark Details

4 MMLU (Massive Multitask Language Understanding)

date: 2020-09-07

version: 1

last_updated: 2020-09-07

expired: false

valid: yes

valid_date: 2025-07-28

url: https://paperswithcode.com/dataset/mmlu

doi: 10.48550/arXiv.2009.03300

domain: Multidomain

focus: Academic knowledge and reasoning across 57 subjects

keywords: - multitask - multiple-choice - zero-shot - few-shot - knowledge probing

summary: Measuring Massive Multitask Language Understanding (MMLU) is a benchmark of 57 multiple-choice tasks covering elementary mathematics, US history, computer science, law, and more, designed to evaluate a model's breadth and depth of knowledge in zero-shot and few-shot settings.

licensing: MIT License

task_types: - Multiple choice

ai_capability_measured: - General reasoning, subject-matter understanding

metrics: - Accuracy

models: - GPT-4o - Gemini 1.5 Pro - o1 - DeepSeek-R1

ml_motif: - General knowledge

type: Benchmark

ml_task: - Supervised Learning

solutions: 1

notes: Good

contact.name: Dan Hendrycks

contact.email: dan (at) safe.ai

datasets.links.name: Papers with Code datasets

datasets.links.url: https://github.com/paperswithcode/paperswithcode-data

results.links.name: Chinchilla

results.links.url: https://arxiv.org/abs/2203.15556

fair.reproducible: True

fair.benchmark_ready: True

ratings.software.rating: 10

ratings.software.reason: Well documented Github, instructions and dataset easy to download

ratings.specification.rating: 9

ratings.specification.reason: Clearly defined method of giving inputs, although it lacks hardware specifications.

ratings.dataset.rating: 9

ratings.dataset.reason: Contains predefined few-shot development, validation, and testing set. Easy to access and download, but not versioned.

ratings.metrics.rating: 9

ratings.metrics.reason: Clearly defined primary metric of number of multiple-choice questions answered correctly. Secondary metric of confidence requires models to self-report.

ratings.reference_solution.rating: 10

ratings.reference_solution.reason: Performance and links to several top models linked on the Github.

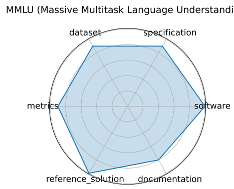
ratings.documentation.rating: 8

ratings.documentation.reason: Code and datasets provided and easy to find, but no environment setup instructions given.

id: mmlu_massive_multitask_language_understanding

Citations: [1]

Ratings:

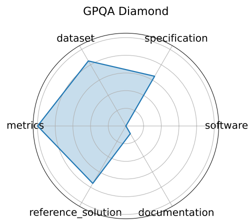


MMLU (Massive Multitask Language Understanding)
dataset
specification
metrics
software
reference_solution
documentation

5 GPQA Diamond

date: 2023-11-20
version: 1
last_updated: 2023-11-20
expired: false
valid: yes
valid_date: 2023-11-20
url: https://arxiv.org/abs/2311.12022
doi: 10.48550/arXiv.2311.12022
domain: Science
focus: Graduate-level scientific reasoning
keywords: - Google-proof - graduate-level - science QA - chemistry - physics
summary: GPQA is a dataset of 448 challenging, multiple-choice questions in biology, physics, and chemistry, written by domain experts. It is Google-proof - experts score 65% (74% after error correction) while skilled non-experts with web access score only 34%. State-of-the-art LLMs like GPT-4 reach around 39% accuracy.
licensing: unknown
task_types: - Multiple choice - Multi-step QA
ai_capability_measured: - Scientific reasoning, deep knowledge
metrics: - Accuracy
models: - o1 - DeepSeek-R1
ml_motif: - Science and STEM fields
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Good
contact.name: Julian Michael
contact.email: julianjm@nyu.edu
datasets.links.name: unknown
datasets.links.url: unknown
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet rated
ratings.specification.rating: 6.5
ratings.specification.reason: Good description of how the problems are received, but little specification on how the models are tested
ratings.dataset.rating: 8.5
ratings.dataset.reason: Easily able to access dataset. No labels or train/test/valid split
ratings.metrics.rating: 10
ratings.metrics.reason: Each question has a correct answer
ratings.reference_solution.rating: 7.5
ratings.reference_solution.reason: Common models such as GPT-3.5 were compared. Reproducibility of results unknown
ratings.documentation.rating: 1
ratings.documentation.reason: No reference solution, platform for reproduction, or procedure for replication
id: gpqa_diamond
Citations: [2]

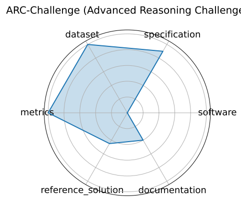
Ratings:


GPQA Diamond
dataset
specification
metrics
software
reference_solution
documentation

6 ARC-Challenge (Advanced Reasoning Challenge)

date: 2018-03-14
version: 1
last_updated: 2018-03-14
expired: false
valid: yes
valid_date: 2018-03-14
url: https://allenai.org/data/arc
doi: NA
domain: Science
focus: Grade-school science with reasoning emphasis
keywords: - grade-school - science QA - challenge set - reasoning
summary: The AI2 Reasoning Challenge (ARC) Challenge set comprises 7,787 natural, grade-school science questions that retrieval-based and word co-occurrence algorithms both fail, requiring advanced reasoning over a 14-million-sentence corpus.
licensing: Apache 2.0 License
task_types: - Multiple choice
ai_capability_measured: - Commonsense and scientific reasoning
metrics: - Accuracy
models: - GPT-4 - Claude
ml_motif: - Elementary science
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Good
contact.name: unknown
contact.email: unknown
datasets.links.name: Hugging Face
datasets.links.url: https://huggingface.co/datasets/allenai/ai2_arc
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet rated
ratings.specification.rating: 9
ratings.specification.reason: Exact format of data, questions, and answers are specified. No HW constraints
ratings.dataset.rating: 10
ratings.dataset.reason: Data accessible, offers instructions on how to download the data via CLI tools
ratings.metrics.rating: 10
ratings.metrics.reason: (by default) All questions in the dataset are multiple choice, all have a correct answer
ratings.reference_solution.rating: 4.5
ratings.reference_solution.reason: There are over 300 models listed, but very few, if any, show performance on the dataset
ratings.documentation.rating: 4
ratings.documentation.reason: There are easy ways to download the dataset. Documentation quantity and clarity depends on authors of tested models
id: arc-challenge_advanced_reasoning_challenge
Citations: [3]

Ratings:

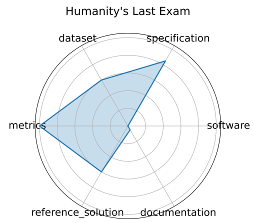


ARC-Challenge (Advanced Reasoning Challenge)
dataset
specification
metrics
software
reference_solution
documentation

7 Humanity's Last Exam

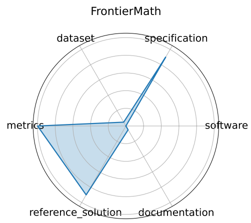
date: 2025-01-24
version: 1
last_updated: 2025-01-24
expired: false
valid: yes
valid_date: 2025-01-24
url: https://arxiv.org/abs/2501.14249
doi: 10.48550/arXiv.2501.14249
domain: Multidomain
focus: Broad cross-domain academic reasoning
keywords: - cross-domain - academic exam - multiple-choice - multidisciplinary
summary: Humanity's Last Exam is a multi-domain, multiple-choice benchmark containing 2,000 questions across diverse academic disciplines, designed to evaluate LLMs' ability to reason across domains without external resources.
licensing: MIT License
task_types: - Multiple choice
ai_capability_measured: - Cross-domain academic reasoning
metrics: - Accuracy
models: - unkown
ml_motif: - Multi-domain
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Good
contact.name: HLE team
contact.email: agibenchmark@safe.ai
datasets.links.name: Hugging Face
datasets.links.url: https://huggingface.co/datasets/cais/hle
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 8.5
ratings.specification.reason: Format of inputs (natural language) and outputs (multiple choice or natural language) specified. No HW constraints specified
ratings.dataset.rating: 6
ratings.dataset.reason: Data accessible through Hugging Face, but requires giving contact information to access
ratings.metrics.rating: 10
ratings.metrics.reason: (by default) All questions in the dataset are multiple choice, all have a correct answer
ratings.reference_solution.rating: 6
ratings.reference_solution.reason: Performance for cutting-edge models listed, but does not specify exact version of the models or how to reproduce the result
ratings.documentation.rating: 0.5
ratings.documentation.reason: No specified way to reproduce the reference solution
id: humanitys_last_exam
Citations: [4]

Ratings:


Humanity's Last Exam
dataset
specification
metrics
software
reference_solution
documentation

8 FrontierMath

date: 2024-11-07
version: 1
last_updated: 2024-11-07
expired: false
valid: yes
valid_date: 2024-11-07
url: https://arxiv.org/abs/2411.04872
doi: 10.48550/arXiv.2411.04872
domain: Mathematics
focus: Challenging advanced mathematical reasoning
keywords: - symbolic reasoning - number theory - algebraic geometry - category theory
summary: FrontierMath is a benchmark of hundreds of expert-vetted mathematics problems spanning number theory, real analysis, algebraic geometry, and category theory, measuring LLMs ability to solve problems requiring deep abstract reasoning.
licensing: unknown
task_types: - Problem solving
ai_capability_measured: - Symbolic and abstract mathematical reasoning
metrics: - Accuracy
models: - unkown
ml_motif: - Math problem solving
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Good
contact.name: FrontierMath team
contact.email: math_evals@epochai.org
datasets.links.name: unknown
datasets.links.url: unknown
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 9
ratings.specification.reason: Well-specified process for asking questions and receiving answers. No HW constraints
ratings.dataset.rating: 0.5
ratings.dataset.reason: Paper and website had no link to any dataset. It may still exist somewhere
ratings.metrics.rating: 10
ratings.metrics.reason: (by default) All questions in the dataset are multiple choice, all have a correct answer
ratings.reference_solution.rating: 9
ratings.reference_solution.reason: Displays result of leading models on the benchmark
ratings.documentation.rating: 0.5
ratings.documentation.reason: No specified way to reproduce the reference solution
id: frontiermath
Citations: [5]

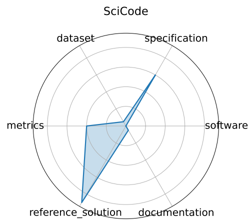

FrontierMath
dataset
specification
metrics
software
reference_solution
documentation

Ratings:

9 SciCode

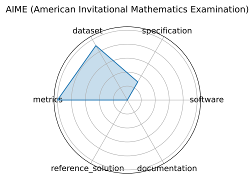
date: 2024-07-18
version: 1
last_updated: 2024-07-18
expired: false
valid: yes
valid_date: 2024-07-18
url: https://arxiv.org/abs/2407.13168
doi: 10.48550/arXiv.2407.13168
domain: Scientific Programming
focus: Scientific code generation and problem solving
keywords: - code synthesis - scientific computing - programming benchmark
summary: SciCode is a scientist-curated coding benchmark with 338 subproblems derived from 80 real research tasks across 16 scientific subfields, evaluating models on knowledge recall, reasoning, and code synthesis for scientific computing tasks.
licensing: unknown
task_types: - Coding
ai_capability_measured: - Program synthesis, scientific computing
metrics: - Solve rate (%)
models: - Claude3.5-Sonnet
ml_motif: - Coding
type: Benchmark
ml_task: - Supervised Learning
solutions: unknown
notes: Good
contact.name: Minyang Tian
contact.email: mtian8@illinois.edu
datasets.links.name: unknown
datasets.links.url: unknown
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 6
ratings.specification.reason: Expected outputs and broad types of inputs stated. Few details on output grading. No HW constraints.
ratings.dataset.rating: 0.5
ratings.dataset.reason: Paper and website had no link to any dataset. It may still exist somewhere
ratings.metrics.rating: 4
ratings.metrics.reason: Metrics stated, but not specified in detail
ratings.reference_solution.rating: 9
ratings.reference_solution.reason: Models presented with scores
ratings.documentation.rating: 0.5
ratings.documentation.reason: No specified way to reproduce the reference solution
id: scicode
Citations: [6]

Ratings:


SciCode
dataset
specification
metrics
software
reference_solution
documentation

10 AIME (American Invitational Mathematics Examination)

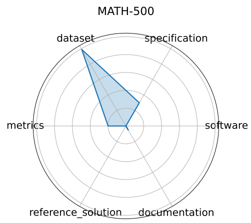
date: 2025-03-13
version: 1
last_updated: 2025-03-13
expired: false
valid: yes
valid_date: 2025-03-13
url: https://artofproblemsolving.com/wiki/index.php/AIME_Problems_and_Solutions
doi: NA
domain: Mathematics
focus: Pre-college advanced problem solving
keywords: - algebra - combinatorics - number theory - geometry
summary: The AIME is a 15-question, 3-hour exam for high-school students featuring challenging short-answer math problems in algebra, number theory, geometry, and combinatorics, assessing depth of problem-solving ability.
licensing: unknown
task_types: - Problem solving
ai_capability_measured: - Mathematical problem-solving and reasoning
metrics: - Accuracy
models: - unkown
ml_motif: - Math problem solving
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Designed for human test-takers
contact.name: unknown
contact.email: unknown
datasets.links.name: AoPS website
datasets.links.url: https://artofproblemsolving.com/wiki/index.php/AIME_Problems_and_Solutions
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 3
ratings.specification.reason: Obvious what the problems are, but not specified how to administer them to AI models. No HW constraints
ratings.dataset.rating: 9
ratings.dataset.reason: Easily accessible data with problems and solutions
ratings.metrics.rating: 10
ratings.metrics.reason: (by default) Answer is correct or it's not
ratings.reference_solution.rating: 0
ratings.reference_solution.reason: Not given. Human performance stats exist, but no mentions of AI performance
ratings.documentation.rating: 0
ratings.documentation.reason: Not given
id: aime_american_invitational_mathematics_examination
Citations: [7]

Ratings: 
AIME (American Invitational Mathematics Examination)
dataset
specification
metrics
software
reference_solution
documentation

11 MATH-500

date: 2025-02-15
version: 1
last_updated: 2025-02-15
expired: false
valid: yes
valid_date: 2025-02-15
url: https://huggingface.co/datasets/HuggingFaceH4/MATH-500
doi: unknown
domain: Mathematics
focus: Math reasoning generalization
keywords: - calculus - algebra - number theory - geometry
summary: MATH-500 is a curated subset of 500 problems from the OpenAI MATH dataset, spanning high-school to advanced levels, designed to evaluate LLMs mathematical reasoning and generalization.
licensing: MIT License
task_types: - Problem solving
ai_capability_measured: - Math reasoning and generalization
metrics: - Accuracy
models: - unkown
ml_motif: - Math problem solving
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Dataset hosted on Hugging Face. Data comes from a subset of OpenAI's dataset
contact.name: unknown
contact.email: unknown
datasets.links.name: Hugging Face
datasets.links.url: https://huggingface.co/datasets/HuggingFaceH4/MATH-500
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 3
ratings.specification.reason: Known what the problems are, but method of presentation and evaluation is not stated. No HW constraints
ratings.dataset.rating: 9.9
ratings.dataset.reason: Problems and solutions are easily downloaded. Could not find a way to download the data
ratings.metrics.rating: 2
ratings.metrics.reason: Problem spec states that all of the AI reasoning steps are subject to grading, but no specified way to evaluate the steps
ratings.reference_solution.rating: 0
ratings.reference_solution.reason: Not given
ratings.documentation.rating: 0.5
ratings.documentation.reason: Not given. Implicit instructions to download dataset.
id: math-
Citations: [8]

Ratings:


MATH-500
dataset
specification
metrics
software
reference_solution
documentation

12 CURIE (Scientific Long-Context Understanding, Reasoning and Information Extraction)

date: 2024-04-02

version: 1

last_updated: 2024-04-02

expired: false

valid: yes

valid_date: 2024-04-02

url: https://arxiv.org/abs/2503.13517

doi: 10.48550/arXiv.2503.13517

domain: Multidomain Science

focus: Long-context scientific reasoning

keywords: - long-context - information extraction - multimodal

summary: CURIE is a benchmark of 580 problems across six scientific disciplines-materials science, quantum computing, biology, chemistry, climate science, and astrophysics- designed to evaluate LLMs on long-context understanding, reasoning, and information extraction in realistic scientific workflows.

licensing: Apache 2.0 License

task_types: - Information extraction - Reasoning - Concept tracking - Aggregation - Algebraic manipulation - Multimodal comprehension

ai_capability_measured: - Long-context understanding and scientific reasoning

metrics: - Accuracy

models: - unkown

ml_motif: - Scientific problem solving

type: Benchmark

ml_task: - Supervised Learning

solutions: 0

notes: Good

contact.name: Subhashini Venugopalan

contact.email: vsubhashini@google.com

datasets.links.name: unknown

datasets.links.url: unknown

results.links.name: unknown

results.links.url: unknown

fair.reproducible: True

fair.benchmark_ready: True

ratings.software.rating: 0

ratings.software.reason: Not yet evaluated

ratings.specification.rating: 7.5

ratings.specification.reason: Explains types of problems in detail, but does not state exactly how to administer them.

ratings.dataset.rating: 8.5

ratings.dataset.reason: Dataset is available via Github, but hard to find

ratings.metrics.rating: 10

ratings.metrics.reason: Quantitiative metrics such as ROUGE-L and F1 used. Metrics are tailored to the specific problem.

ratings.reference_solution.rating: 1

ratings.reference_solution.reason: Does not exist

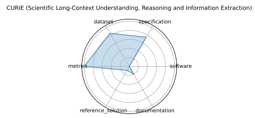
ratings.documentation.rating: 2

ratings.documentation.reason: Provides very little information, if at all, on how to install and run the programs.

id: curie_scientific_long-context_understanding_reasoning_and_information_extraction

Citations: [9]

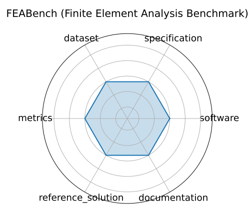
Ratings:


CURIE (Scientific Long-Context Understanding, Reasoning and Information Extraction)
dataset
specification
metrics
software
reference_solution
documentation

13 FEABench (Finite Element Analysis Benchmark)

date: 2023-01-26
version: 1
last_updated: 2023-01-26
expired: false
valid: no
valid_date: 2023-01-26
url: https://github.com/alleninstitute/feabench
doi: unknown
domain: Computational Engineering
focus: FEA simulation accuracy and performance
keywords: - finite element - simulation - PDE
summary: Does not exist
licensing: unknown
task_types: - Simulation - Performance evaluation
ai_capability_measured: - Numerical simulation accuracy and efficiency
metrics: - Solve time - Error norm
models: - FEniCS - deal.II
ml_motif: - unknown
type: Benchmark
ml_task: - Supervised Learning
solutions: unknown
notes: Google search for "FEABench" gave https://arxiv.org/abs/2503.06680, which relates to coding instead of math
contact.name: unknown
contact.email: unknown
datasets.links.name: unknown
datasets.links.url: unknown
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 0
ratings.specification.reason: Using the link results in a 404 Not Found error
ratings.dataset.rating: 0
ratings.dataset.reason: Using the link results in a 404 Not Found error
ratings.metrics.rating: 0
ratings.metrics.reason: Using the link results in a 404 Not Found error
ratings.reference_solution.rating: 0
ratings.reference_solution.reason: Using the link results in a 404 Not Found error
ratings.documentation.rating: 0
ratings.documentation.reason: Using the link results in a 404 Not Found error
id: feabench_finite_element_analysis_benchmark
Citations: **<unknown>**

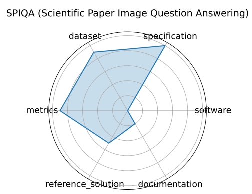
Ratings:


FEABench (Finite Element Analysis Benchmark)
dataset
specification
metrics
software
reference_solution
documentation

14 SPIQA (Scientific Paper Image Question Answering)

date: 2024-07-12
version: 1
last_updated: 2024-07-12
expired: false
valid: yes
valid_date: 2024-07-12
url: https://arxiv.org/abs/2407.09413
doi: 10.48550/arXiv.2407.09413
domain: Computer Science
focus: Multimodal QA on scientific figures
keywords: - multimodal QA - figure understanding - table comprehension - chain-of-thought
summary: SPIQA assesses AI models' ability to interpret and answer questions about figures and tables in scientific papers by integrating visual and textual modalities with chain-of-thought reasoning.
licensing: Apache 2.0 License
task_types: - Question answering - Multimodal QA - Chain-of-Thought evaluation
ai_capability_measured: - Visual-textual reasoning in scientific contexts
metrics: - Accuracy - F1 score
models: - Chain-of-Thought models - Multimodal QA systems
ml_motif: - Scientific paper reading
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Good
contact.name: Subhashini Venugopalan
contact.email: vsubhashini@google.com
datasets.links.name: Hugging Face
datasets.links.url: https://huggingface.co/datasets/google/spiqa
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 10
ratings.specification.reason: Task administration clearly defined; prompt instructions explicitly given, no ambiguity in format or scope.
ratings.dataset.rating: 9
ratings.dataset.reason: Dataset is available (via paper/appendix), includes train/test/valid split. FAIR-compliant with minor gaps in versioning or access standardization.
ratings.metrics.rating: 9
ratings.metrics.reason: Uses quantitative metrics (Accuracy, F1) aligned with the task. Well-suited for benchmarking multimodal reasoning.
ratings.reference_solution.rating: 5
ratings.reference_solution.reason: Multiple model results (e.g., GPT-4V, Gemini) reported; baselines exist, but full runnable code not confirmed for all.
ratings.documentation.rating: 2
ratings.documentation.reason: Dataset and benchmark description provided; code/software mentioned; however, full step-by-step setup or containerized environment not stated.
id: spiqa_scientific_paper_image_question_answering
Citations: [10]

Ratings:


SPIQA (Scientific Paper Image Question Answering)
dataset
specification
metrics
software
reference_solution
documentation

15 MedQA

date: 2020-09-28

version: 1

last_updated: 2020-09-28

expired: false

valid: yes

valid_date: 2020-09-28

url: https://arxiv.org/abs/2009.13081

doi: 10.48550/arXiv.2009.13081

domain: Medical Question Answering

focus: Medical board exam QA

keywords: - USMLE - diagnostic QA - medical knowledge - multilingual

summary: MedQA is a large-scale multiple-choice dataset drawn from professional medical board exams (e.g., USMLE), testing AI systems on diagnostic and medical knowledge questions in English and Chinese.

licensing: Under Association for the Advancement of Artificial Intelligence

task_types: - Multiple choice

ai_capability_measured: - Medical diagnosis and knowledge retrieval

metrics: - Accuracy

models: - Neural reader - Retrieval-based QA systems

ml_motif: - Medical diagnosis

type: Benchmark

ml_task: - Supervised Learning

solutions: 0

notes: Multilingual (English, Simplified and Traditional Chinese)

contact.name: Di Jin

contact.email: jindi15@mit.edu

datasets.links.name: Github

datasets.links.url: https://github.com/jind11/MedQA

results.links.name: unknown

results.links.url: unknown

fair.reproducible: True

fair.benchmark_ready: True

ratings.software.rating: 0

ratings.software.reason: Not yet evaluated

ratings.specification.rating: 9

ratings.specification.reason: Task is clearly defined as multiple-choice QA for medical board exams; input and output formats are explicit; task scope is rigorous and structured. System constraints not specified.

ratings.dataset.rating: 8

ratings.dataset.reason: Dataset is publicly available (GitHub, paper, Hugging Face), well-structured. However, versioning and metadata could be more standardized to fully meet FAIR criteria.

ratings.metrics.rating: 9

ratings.metrics.reason: Uses clear, quantitative metric (accuracy), standard for multiple-choice benchmarks; easily comparable across models.

ratings.reference_solution.rating: 7

ratings.reference_solution.reason: Model results reported (GPT-4, Med-PaLM, etc.); implementations discussed in papers, but runnable baselines not fully packaged or documented.

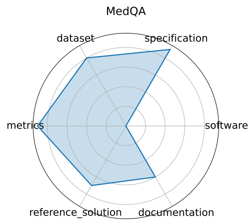
ratings.documentation.rating: 6

ratings.documentation.reason: Dataset and paper are accessible; instructions on how to use the source code available, but environment setup or full reproducibility workflow is not packaged.

id: medqa

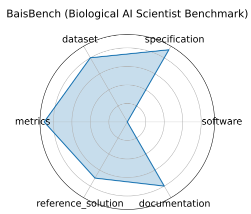
Citations: [11]

Ratings:


MedQA
dataset
specification
metrics
software
reference_solution
documentation

16 BaisBench (Biological AI Scientist Benchmark)

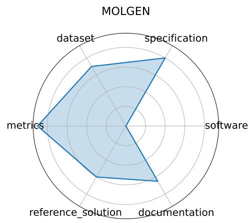
date: 2025-05-13
version: 1
last_updated: 2025-05-13
expired: false
valid: yes
valid_date: 2025-05-13
url: https://arxiv.org/abs/2505.08341
doi: 10.48550/arXiv.2505.08341
domain: Computational Biology
focus: Omics-driven AI research tasks
keywords: - single-cell annotation - biological QA - autonomous discovery
summary: BaisBench evaluates AI scientists' ability to perform data-driven biological research by annotating cell types in single-cell datasets and answering MCQs derived from biological study insights, measuring autonomous scientific discovery.
licensing: MIT License
task_types: - Cell type annotation - Multiple choice
ai_capability_measured: - Autonomous biological research capabilities
metrics: - Annotation accuracy - QA accuracy
models: - LLM-based AI scientist agents
ml_motif: - Scientific research
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Underperforms human experts; aims to advance AI-driven discovery
contact.name: Xuegong Zhang
contact.email: zhangxg@mail.tsinghua.edu.cn
datasets.links.name: Github
datasets.links.url: https://github.com/EperLuo/BaisBench
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 9
ratings.specification.reason: Task clearly defined-cell type annotation and biological QA; input/output formats are well-described; system constraints are not deeply quantified.
ratings.dataset.rating: 8
ratings.dataset.reason: Uses public scRNA-seq datasets linked in paper appendix; structured and accessible, though versioning and full metadata not formalized per FAIR standards.
ratings.metrics.rating: 9
ratings.metrics.reason: Includes precise and interpretable metrics (annotation and QA accuracy); directly aligned with task outputs and benchmarking goals.
ratings.reference_solution.rating: 7
ratings.reference_solution.reason: Model evaluations and LLM agent results discussed; however, no fully packaged, runnable baseline with training/eval pipeline confirmed yet.
ratings.documentation.rating: 8
ratings.documentation.reason: Dataset and paper accessible; IPYNB files for setup are available on the github repo; further instructions are minimal.
id: baisbench_biological_ai_scientist_benchmark
Citations: [12]

Ratings: 
BaisBench (Biological AI Scientist Benchmark)
dataset
specification
metrics
software
reference_solution
documentation

17 MOLGEN

date: 2023-01-26
version: 1
last_updated: 2023-01-26
expired: false
valid: yes
valid_date: 2023-01-26
url: https://github.com/zjunlp/MolGen
doi: 10.48550/arXiv.2301.11259
domain: Computational Chemistry
focus: Molecular generation and optimization
keywords: - SELFIES - GAN - property optimization
summary: MolGen is a pre-trained molecular language model that generates chemically valid molecules using SELFIES and reinforcement learning, guided by chemical feedback to optimize properties such as logP, QED, and docking score.
licensing: MIT License
task_types: - Distribution learning - Goal-oriented generation
ai_capability_measured: - Generation of valid and optimized molecular structures
metrics: - Validity% - Novelty% - QED - Docking score
models: - MolGen
ml_motif: - Chemical generation
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: This is a model, not a benchmark
contact.name: unknown
contact.email: unknown
datasets.links.name: unknown
datasets.links.url: unknown
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 8
ratings.specification.reason: The molecular generation task is well-defined, with input/output via SELFIES and chemical properties
ratings.dataset.rating: 7
ratings.dataset.reason: Uses standard datasets (ZINC, MOSES, QM9); accessible and widely used, but FAIR metadata, versioning, and splits are not detailed within this specific repo.
ratings.metrics.rating: 9
ratings.metrics.reason: Metrics like Validity%, Novelty%, QED, and Docking Score are quantitative, supporting clear model evaluation.
ratings.reference_solution.rating: 6
ratings.reference_solution.reason: Model is released and functional; some training/evaluation code exists, but it's not framed as a reusable baseline in a benchmark context.
ratings.documentation.rating: 6.5
ratings.documentation.reason: Code is available and usable; instructions exist, though setup may require domain knowledge or adaptation for different datasets/environments.
id: molgen
Citations: [13]

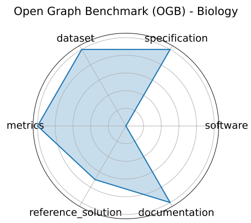
Ratings:


MOLGEN
dataset
specification
metrics
software
reference_solution
documentation

18 Open Graph Benchmark (OGB) - Biology

date: 2020-05-02
version: 1
last_updated: 2020-05-02
expired: false
valid: yes
valid_date: 2020-05-02
url: https://ogb.stanford.edu/docs/home/
doi: 10.48550/arXiv.2005.00687
domain: Graph ML
focus: Biological graph property prediction
keywords: - node prediction - link prediction - graph classification
summary: OGB-Biology is a suite of large-scale biological network datasets (protein-protein interaction, drug-target, etc.) with standardized splits and evaluation protocols for node, link, and graph property prediction tasks.
licensing: MIT License
task_types: - Node property prediction - Link property prediction - Graph property prediction
ai_capability_measured: - Scalability and generalization in graph ML for biology
metrics: - Accuracy - ROC-AUC
models: - GCN - GraphSAGE - GAT
ml_motif: - Chemical biology
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Community-driven updates
contact.name: OGB Team
contact.email: ogb@cs.stanford.edu
datasets.links.name: OGB Webpage
datasets.links.url: https://ogb.stanford.edu/docs/dataset_overview/
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 10
ratings.specification.reason: Tasks (node/link/graph property prediction) are clearly specified with input/output formats and standardized protocols; constraints (e.g., splits) are well-defined.
ratings.dataset.rating: 10
ratings.dataset.reason: Fully FAIR- datasets are versioned, split, and accessible via a standardized API; extensive metadata and documentation are included.
ratings.metrics.rating: 10
ratings.metrics.reason: Reproducible, quantitative metrics (e.g., ROC-AUC, accuracy) that are tightly aligned with the tasks.
ratings.reference_solution.rating: 7
ratings.reference_solution.reason: Multiple baselines implemented and documented (GCN, GAT, GraphSAGE), though most are provided by 3rd parties.
ratings.documentation.rating: 10
ratings.documentation.reason: Full codebase available via GitHub, with documented installation and usage instructions.
id: open_graph_benchmark_ogb_-_biology
Citations: [14]

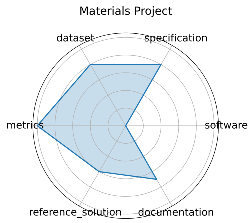
Ratings:


Open Graph Benchmark (OGB) - Biology
dataset
specification
metrics
software
reference_solution
documentation

19 Materials Project

date: 2011-10-01
version: 1
last_updated: 2011-10-01
expired: false
valid: yes
valid_date: 2011-10-01
url: https://materialsproject.org/
doi: unknown
domain: Materials Science
focus: DFT-based property prediction
keywords: - DFT - materials genome - high-throughput
summary: The Materials Project provides an open-access database of computed properties for inorganic materials via high-throughput density functional theory (DFT), accelerating materials discovery.
licensing: https://next-gen.materialsproject.org/about/terms
task_types: - Property prediction
ai_capability_measured: - Prediction of inorganic material properties
metrics: - MAE - R^2
models: - Automatminer - Crystal Graph Neural Networks
ml_motif: - Material properties
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Core component of the Materials Genome Initiative
contact.name: unknown
contact.email: unknown
datasets.links.name: Materials Project Catalysis Explorer
datasets.links.url: https://next-gen.materialsproject.org/catalysis
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 8
ratings.specification.reason: The platform offers a wide range of material property prediction tasks, but task framing and I/O formats vary by API use and are not always standardized across use cases.
ratings.dataset.rating: 8
ratings.dataset.reason: Data is versioned, accessible through both UI and API, with rich metadata and citations; widely reused. API key required to access data.
ratings.metrics.rating: 10
ratings.metrics.reason: Uses numerical metrics like MAE and R^2
ratings.reference_solution.rating: 6
ratings.reference_solution.reason: Numerous models (e.g., Automatminer, CGCNN) trained on the database, but no single canonical baseline is tightly integrated into the platform.
ratings.documentation.rating: 7
ratings.documentation.reason: Extensive API, code repositories, and user guides exist, but end-to-end benchmarking workflows require additional setup by users. 'Documentation' link did not work.
id: materials_project
Citations: [15]

Ratings:

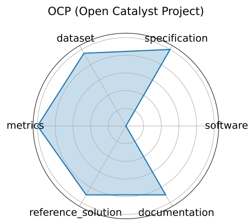


Materials Project
dataset
specification
metrics
software
reference_solution
documentation

20 OCP (Open Catalyst Project)

date: 2020-10-20
version: 1
last_updated: 2020-10-20
expired: false
valid: yes
valid_date: 2020-10-20
url: https://opencatalystproject.org/
doi: unknown
domain: Chemistry; Materials Science
focus: Catalyst adsorption energy prediction
keywords: - DFT relaxations - adsorption energy - graph neural networks
summary: The Open Catalyst Project (OC20 and OC22) provides DFT-calculated catalyst-adsorbate relaxation datasets, challenging ML models to predict energies and forces for renewable energy applications.
licensing: OCP Terms of Use
task_types: - Energy prediction - Force prediction
ai_capability_measured: - Prediction of adsorption energies and forces
metrics: - MAE (energy) - MAE (force)
models: - CGCNN - SchNet - DimeNet++ - GemNet-OC
ml_motif: - Chemistry
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: Public leaderboards; active community development
contact.name: unknown
contact.email: unknown
datasets.links.name: OCP Dataset
datasets.links.url: https://fair-chem.github.io/catalysts/datasets/summary
results.links.name: OCP Pretrained Models
results.links.url: https://fair-chem.github.io/catalysts/models.html
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 10
ratings.specification.reason: Tasks (energy and force prediction) are clearly defined with explicit I/O specifications, constraints, and physical relevance for renewable energy.
ratings.dataset.rating: 9.5
ratings.dataset.reason: Fully FAIR- OC20, per-adsorbate trajectories, and OC22 are versioned; datasets come with standardized splits, metadata, and are downloadable.
ratings.metrics.rating: 10
ratings.metrics.reason: MAE (energy and force) are standard and reproducible.
ratings.reference_solution.rating: 9
ratings.reference_solution.reason: Multiple baselines (GemNet-OC, DimeNet++, etc.) implemented and evaluated; highly cited with documented performance.
ratings.documentation.rating: 9
ratings.documentation.reason: Code, data loaders, usage instructions, and leaderboard available; minor setup effort may still be required for full reproduction.
id: ocp_open_catalyst_project
Citations: [16], [17], [18], [19]

Ratings:

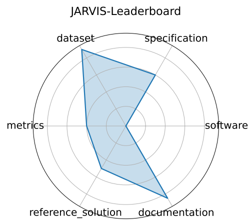


OCP (Open Catalyst Project)
dataset
specification
metrics
software
reference_solution
documentation

21 JARVIS-Leaderboard

date: 2023-06-20
version: 1
last_updated: 2023-06-20
expired: false
valid: yes
valid_date: 2023-06-20
url: https://arxiv.org/abs/2306.11688
doi: 10.48550/arXiv.2306.11688
domain: Materials Science; Benchmarking
focus: Comparative evaluation of materials design methods
keywords: - leaderboards - materials methods - simulation
summary: JARVIS-Leaderboard is a community-driven platform benchmarking AI, electronic structure, force-fields, quantum computing, and experimental methods across hundreds of materials science tasks.
licensing: NIST
task_types: - Method benchmarking - Leaderboard ranking
ai_capability_measured: - Performance comparison across diverse materials design methods
metrics: - MAE - RMSE - Accuracy
models: - unkown
ml_motif: - Material science
type: Benchmark
ml_task: - Supervised Learning
solutions: 0
notes: 1281 contributions across 274 benchmarks
contact.name: Kamal Choudhary
contact.email: kamal.choudhary@nist.gov
datasets.links.name: AI model specific benchmarks
datasets.links.url: https://pages.nist.gov/jarvis_leaderboard/AI/
results.links.name: unknown
results.links.url: unknown
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not yet evaluated
ratings.specification.rating: 6
ratings.specification.reason: Tasks are clearly defined; heterogeneity in benchmarks slightly reduces uniformity; I/O format is not specified
ratings.dataset.rating: 9
ratings.dataset.reason: Data is versioned, public, and adheres to FAIR principles across the NIST-hosted infrastructure; however, metadata completeness varies slightly across benchmarks.
ratings.metrics.rating: 4
ratings.metrics.reason: Overall goal is stated, but the exact metric evaluated is not listed
ratings.reference_solution.rating: 5
ratings.reference_solution.reason: Many baselines across tasks (CGCNN, ALIGNN, M3GNet, etc.); documentation is good, but baselines may be hard to find or not available for every individual task.
ratings.documentation.rating: 8.5
ratings.documentation.reason: JARVIS-Tools and leaderboard APIs are well-documented and actively maintained; minimal setup burden, though some task-specific workflows may require additional guidance.
id: jarvis-leaderboard
Citations: [20]

Ratings:

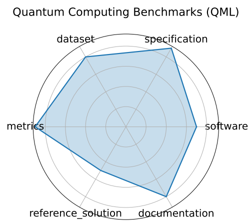


JARVIS-Leaderboard
dataset
specification
metrics
software
reference_solution
documentation

22 Quantum Computing Benchmarks (QML)

date: 2022-02-22
version: 1
last_updated: 2022-02-22
expired: false
valid: yes
valid_date: 2022-02-22
url: https://github.com/XanaduAI/qml-benchmarks
doi: 10.48550/arXiv.2307.03901
domain: Quantum Computing
focus: Quantum algorithm performance evaluation
keywords: - quantum circuits - state preparation - error correction
summary: A suite of benchmarks evaluating quantum hardware and algorithms on tasks such as state preparation, circuit optimization, and error correction across multiple platforms.
licensing: Apache-2.0
task_types: - Circuit benchmarking - State classification
ai_capability_measured: - Quantum algorithm performance and fidelity
metrics: - Fidelity - Success probability
models: - IBM Q - IonQ - AQT@LBNL
ml_motif: - Performance Evaluation
type: Benchmark
ml_task: - Supervised Learning
solutions: Varies per benchmark
notes: Hardware-agnostic, application-level metrics. The citation may not be correct.
contact.name: Xanadu AI
contact.email: support@xanadu.ai
datasets.links.name: PennyLane QML Benchmarks Datasets
datasets.links.url: https://pennylane.ai/datasets/collection/qml-benchmarks
results.links.name: QML Benchmarks GitHub Repository (Results section)
results.links.url: https://github.com/XanaduAI/qml-benchmarks#results-and-leaderboards
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 7.0
ratings.software.reason: The benchmarks are primarily implemented within the PennyLane ecosystem, offering runnable code and integration with various quantum hardware backends. While not a standalone software package, it provides a functional framework for executing and evaluating benchmarks.
ratings.specification.rating: 9
ratings.specification.reason: Tasks like fidelity estimation, state preparation, and runtime benchmarking are clearly defined; I/O formats vary slightly across hardware but are consistently framed in PennyLane/Qiskit ecosystems.
ratings.dataset.rating: 8
ratings.dataset.reason: Datasets are accessible, structured, and interoperable via PennyLane; however, not all are versioned or richly annotated in conventional ML metadata standards.
ratings.metrics.rating: 9
ratings.metrics.reason: Quantitative and well-motivated metrics (e.g., fidelity, success probability) are used, though reproducibility can depend on hardware noise profiles.
ratings.reference_solution.rating: 5
ratings.reference_solution.reason: Reference implementations exist and are integrated into tools like PennyLane, but performance varies per backend; not all benchmarks include reproducible reference runs.
ratings.documentation.rating: 8
ratings.documentation.reason: Strong integration with PennyLane and QML ecosystem; guides and code provided, but advanced hardware setup may pose reproducibility hurdles for newcomers.
id: quantum_computing_benchmarks_qml

Citations: [21]



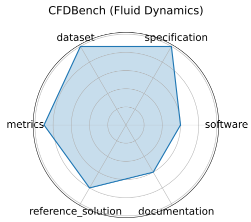
Ratings:

23 CFDBench (Fluid Dynamics)

date: 2024-10-01
version: 1
last_updated: 2024-10-01
expired: false
valid: yes
valid_date: 2024-10-01
url: https://arxiv.org/abs/2310.05963
doi: 10.48550/arXiv.2310.05963
domain: Fluid Dynamics; Scientific ML
focus: Neural operator surrogate modeling
keywords: - neural operators - CFD - FNO - DeepONet
summary: CFDBench provides large-scale CFD data for four canonical fluid flow problems, assessing neural operators' ability to generalize to unseen PDE parameters and domains.
licensing: CC-BY-4.0
task_types: - Surrogate modeling
ai_capability_measured: - Generalization of neural operators for PDEs
metrics: - L2 error - MAE
models: - FNO - DeepONet - U-Net
ml_motif: - Generalization
type: Benchmark
ml_task: - Supervised Learning
solutions: Numerous, as it's a benchmark for ML models
notes: 302K frames across 739 cases
contact.name: Yining Luo
contact.email: yining.luo@mail.utoronto.ca
datasets.links.name: CFDBench on Zenodo
datasets.links.url: https://zenodo.org/record/8410294
results.links.name: Results in the CFDBench paper
results.links.url: https://arxiv.org/abs/2310.05963
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 6.0
ratings.software.reason: The benchmark provides Python scripts for data loading, preprocessing, and model training/evaluation, primarily using PyTorch. While not a standalone software, it offers sufficient code for reproducing experiments and building upon the benchmark.
ratings.specification.rating: 10
ratings.specification.reason: Tasks are clearly framed (PDE regression, surrogate modeling), with explicit details on the four canonical CFD problems, input/output structure, and generalization goals.
ratings.dataset.rating: 10
ratings.dataset.reason: Publicly available on Zenodo, versioned, with metadata and splits; covers thousands of simulations with proper documentation.
ratings.metrics.rating: 9
ratings.metrics.reason: Quantitative metrics (L2 error, MAE, relative error) are clearly defined and align with regression task objectives.
ratings.reference_solution.rating: 8
ratings.reference_solution.reason: Baseline models like FNO and DeepONet are implemented, but full reproduction pipelines or eval scripts may require additional user configuration.
ratings.documentation.rating: 6
ratings.documentation.reason: GitHub and Zenodo provide data and code, but setup for evaluating across all 739 cases requires moderate user effort and technical fluency with PyTorch-based frameworks. Reproducibility depends on full implementation details.

id: cfdbench_fluid_dynamics

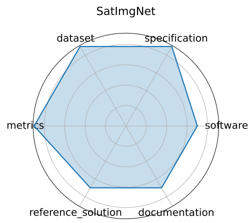
Citations: [22]

Ratings: 

24 SatImgNet

date: 2023-04-23
version: 1
last_updated: 2023-04-23
expired: false
valid: yes
valid_date: 2023-04-23
url: https://huggingface.co/datasets/saral-ai/satimagnet
doi: 10.48550/arXiv.2304.11619
domain: Remote Sensing
focus: Satellite imagery classification
keywords: - land-use - zero-shot - multi-task
summary: SATIN (sometimes referred to as SatImgNet) is a multi-task metadataset of 27 satellite imagery classification datasets evaluating zero-shot transfer of vision-language models across diverse remote sensing tasks.
licensing: CC-BY-4.0
task_types: - Image classification
ai_capability_measured: - Zero-shot land-use classification
metrics: - Accuracy
models: - CLIP - BLIP - ALBEF
ml_motif: - Transfer Learning
type: Benchmark
ml_task: - Supervised Learning
solutions: Numerous, evaluated via leaderboard
notes: Public leaderboard available
contact.name: Jonathan Roberts
contact.email: j.roberts@cs.ox.ac.uk
datasets.links.name: SatImgNet on Hugging Face
datasets.links.url: https://huggingface.co/datasets/saral-ai/satimagnet
results.links.name: SatImgNet Leaderboard
results.links.url: https://huggingface.co/spaces/saral-ai/satin-leaderboard
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 7.0
ratings.software.reason: The metadataset is well-integrated with Hugging Face, providing easy access and tools for data loading. While not a full software package, it offers essential components and scripts for model evaluation.
ratings.specification.rating: 9
ratings.specification.reason: Tasks (image classification across 27 satellite datasets) are clearly defined with multi-task and zero-shot framing; input/output structure is mostly standard but some task-specific nuances require interpretation.
ratings.dataset.rating: 9
ratings.dataset.reason: Hosted on Hugging Face, versioned, FAIR-compliant with rich metadata; covers many well-known remote sensing datasets unified under one metadataset, though documentation depth varies slightly across tasks.
ratings.metrics.rating: 9
ratings.metrics.reason: Standard quantitative metrics (Accuracy, Top-1 Accuracy) aligned with classification tasks; consistent across models, with leaderboard results available.
ratings.reference_solution.rating: 7
ratings.reference_solution.reason: Baselines like CLIP, BLIP, ALBEF evaluated in the paper; full inference pipelines or training code may need reconstruction from paper or GitHub references.
ratings.documentation.rating: 7
ratings.documentation.reason: Good usage guidance via Hugging Face and paper; example scripts and evaluation tools exist, but end-to-end reproducibility may require manual integration of model checkpoints and preprocessing.
id: satimgnet
Citations: [23]

Ratings:



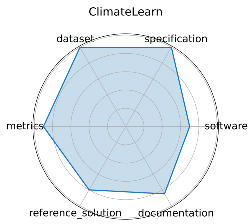
SatImgNet
dataset
specification
metrics
software
reference_solution
documentation

25 ClimateLearn

date: 2023-07-19
version: 1
last_updated: 2023-07-19
expired: false
valid: yes
valid_date: 2023-07-19
url: https://arxiv.org/abs/2307.01909
doi: 10.48550/arXiv.2307.01909
domain: Climate Science; Forecasting
focus: ML for weather and climate modeling
keywords: - medium-range forecasting - ERA5 - data-driven
summary: ClimateLearn provides standardized datasets and evaluation protocols for machine learning models in medium-range weather and climate forecasting using ERA5 reanalysis.
licensing: CC-BY-4.0
task_types: - Forecasting
ai_capability_measured: - Global weather prediction (3-5 days)
metrics: - RMSE - Anomaly correlation
models: - CNN baselines - ResNet variants
ml_motif: - Forecasting - Benchmarking
type: Benchmark
ml_task: - Supervised Learning
solutions: Multiple baseline models provided
notes: Includes physical and ML baselines.
contact.name: Jason Jewik
contact.email: jason.jewik@ucla.edu
datasets.links.name: ClimateLearn GitHub Repository (data loaders and processing)
datasets.links.url: https://github.com/aditya-grover/climate-learn
results.links.name: ClimateLearn Paper (results section)
results.links.url: https://arxiv.org/abs/2307.01909
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 7.0
ratings.software.reason: ClimateLearn is an open-source PyTorch library that simplifies data processing, model implementation, and evaluation for climate science. It provides holistic pipelines and is actively maintained, facilitating reproducible research.
ratings.specification.rating: 10
ratings.specification.reason: Task framing (medium-range climate forecasting), input/output formats, and evaluation windows are clearly defined; benchmark supports both physical and learned models with detailed constraints.
ratings.dataset.rating: 10
ratings.dataset.reason: Provides standardized access to ERA5 and other reanalysis datasets, with ML-ready splits, metadata, and Xarray-compatible formats; versioned and fully FAIR-compliant.
ratings.metrics.rating: 9
ratings.metrics.reason: ACC and RMSE are standard, quantitative, and appropriate for climate forecasting; well-integrated into the benchmark, though interpretation across domains may vary.
ratings.reference_solution.rating: 8
ratings.reference_solution.reason: Multiple baselines (e.g., FourCastNet, ClimaX) are provided and evaluated; implementations are available but may require tuning or GPU-specific configuration.
ratings.documentation.rating: 8.5
ratings.documentation.reason: Comprehensive setup via GitHub, including data loaders, training scripts, config files, and reproducibility protocols; minor complexity in large-scale data preprocessing.
id: climatelearn

Citations: [24]

Ratings:



26 BIG-Bench (Beyond the Imitation Game Benchmark)

date: 2022-06-09

version: 1

last_updated: 2022-06-09

expired: false

valid: yes

valid_date: 2022-06-09

url: https://github.com/google/BIG-bench

doi: 10.48550/arXiv.2206.04615

domain: NLP; AI Evaluation

focus: Diverse reasoning and generalization tasks

keywords: - few-shot - multi-task - bias analysis

summary: BIG-Bench is a collaborative suite of 204 tasks designed to probe LLMs' reasoning, knowledge, and bias across diverse domains and difficulty levels beyond simple imitation.

licensing: Apache-2.0

task_types: - Few-shot evaluation - Multi-task evaluation

ai_capability_measured: - Reasoning and generalization across diverse tasks

metrics: - Accuracy - Task-specific metrics

models: - GPT-3 - Dense Transformers - Sparse Transformers

ml_motif: - LLM evaluation

type: Benchmark

ml_task: - Supervised Learning

solutions: Multiple, including human baselines

notes: Human baselines included

contact.name: Aarohi Srivastava et al.

contact.email: bigbench@googlegroups.com

datasets.links.name: BIG-Bench GitHub Repository (contains tasks and data)

datasets.links.url: https://github.com/google/BIG-bench/tree/main/bigbench/benchmark_tasks

results.links.name: BIG-Bench GitHub Repository (results in papers and code)

results.links.url: https://github.com/google/BIG-bench

fair.reproducible: True

fair.benchmark_ready: True

ratings.software.rating: 7.0

ratings.software.reason: BIG-Bench provides a well-structured framework for task definitions and evaluation scripts, allowing users to run and contribute new tasks. While it requires some setup, the modular design facilitates extending and evaluating language models.

ratings.specification.rating: 9.0

ratings.specification.reason: Tasks are diverse and clearly described; input/output formats are usually defined but vary widely, and system constraints are not standardized.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Public, versioned, and well-documented; FAIR overall, though consistency and metadata completeness vary across tasks.

ratings.metrics.rating: 8.0

ratings.metrics.reason: Many tasks use standard quantitative metrics (accuracy, BLEU, F1), but others involve subjective ratings (e.g., Likert), which reduces cross-task comparability.

ratings.reference_solution.rating: 7.0

ratings.reference_solution.reason: Human baselines and LLM performance results are included; however, runnable reference solutions are limited and setup is not fully turnkey.

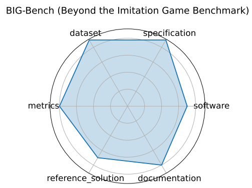
ratings.documentation.rating: 8.0

ratings.documentation.reason: Excellent GitHub documentation with usage examples, task templates, and tooling; task diversity may require manual task-by-task execution setup.

id: big-bench_beyond_the_imitation_game_benchmark

Citations: [25]

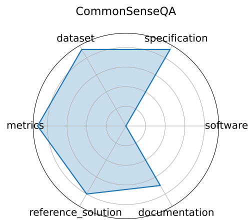
Ratings:



27 CommonSenseQA

date: 2019-11-20
version: 1
last_updated: 2019-11-20
expired: false
valid: yes
valid_date: 2019-11-20
url: https://paperswithcode.com/paper/commonsenseqa-a-question-answering-challenge
doi: 10.48550/arXiv.1811.00937
domain: NLP; Commonsense
focus: Commonsense question answering
keywords: - ConceptNet - multiple-choice - adversarial
summary: CommonsenseQA is a challenging multiple-choice QA dataset built from ConceptNet, requiring models to apply commonsense knowledge to select the correct answer among five choices.
licensing: MIT
task_types: - Multiple choice
ai_capability_measured: - Commonsense reasoning and knowledge integration
metrics: - Accuracy
models: - BERT-large - RoBERTa - GPT-3
ml_motif: - Commonsense question answering
type: Benchmark
ml_task: - Supervised Learning
solutions: 2
notes: Baseline 56%, human 89%
contact.name: Alon Talmor, Jonathan Herzig, Nicholas Lourie, Jonathan Berant
contact.email: Unknown
datasets.links.name: CommonsenseQA Dataset (Hugging Face)
datasets.links.url: https://huggingface.co/datasets/commonsense_qa
results.links.name: Papers With Code Leaderboard for CommonsenseQA
results.links.url: https://paperswithcode.com/dataset/commonsenseqa
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not rated
ratings.specification.rating: 9.0
ratings.specification.reason: Task and format (multiple-choice QA with 5 options) are clearly defined; grounded in ConceptNet with consistent structure, though no hardware/system constraints are specified.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Public, versioned, and FAIR-compliant; includes metadata, splits, and licensing; well-integrated with HuggingFace and other ML libraries.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Accuracy is a simple, reproducible metric aligned with task goals; no ambiguity in evaluation.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Several baseline models (e.g., BERT, RoBERTa) are reported with scores; implementations exist in public repos, but not bundled as an official starter kit.
ratings.documentation.rating: 7.0
ratings.documentation.reason: Clear paper, GitHub repo, and integration with HuggingFace Datasets; full reproducibility requires manually connecting models to dataset.
id: commonsenseqa
Citations: [26]

Ratings:



CommonSenseQA
dataset
specification
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software
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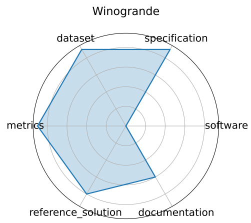
documentation

28 Winogrande

date: 2019-07-24
version: 1
last_updated: 2019-07-24
expired: false
valid: yes
valid_date: 2019-07-24
url: https://leaderboard.allenai.org/winogrande/submissions/public
doi: 10.48550/arXiv.1907.10641
domain: NLP; Commonsense
focus: Winograd Schema-style pronoun resolution
keywords: - adversarial - pronoun resolution
summary: WinoGrande is a large-scale adversarial dataset of 44,000 Winograd Schema-style questions with reduced bias using AFLite, serving as both a benchmark and transfer learning resource.
licensing: CC-BY
task_types: - Pronoun resolution
ai_capability_measured: - Robust commonsense reasoning
metrics: - Accuracy - AUC
models: - RoBERTa - BERT - GPT-2
ml_motif: - Commonsense reasoning
type: Benchmark
ml_task: - Supervised Learning
solutions: 2
notes: Human ~94%
contact.name: Keisuke Sakaguchi
contact.email: keisukes@allenai.org
datasets.links.name: Hugging Face / AllenAI
datasets.links.url: https://huggingface.co/datasets/allenai/winogrande
results.links.name: Papers With Code leaderboard
results.links.url: https://paperswithcode.com/dataset/winogrande
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0.0
ratings.software.reason: Not Rated
ratings.specification.rating: 9.0
ratings.specification.reason: Task (pronoun/coreference resolution) is clearly defined in Winograd Schema style, with consistent input/output format; no system constraints included.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Public, versioned, and FAIR-compliant with AFLite-generated splits to reduce annotation artifacts; hosted by AllenAI with good metadata.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Accuracy and AUC are quantitative and well-aligned with disambiguation goals; standardized across evaluations.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Baseline results for BERT, RoBERTa, GPT-2, etc., are published, but official runnable baselines require setup via AllenNLP or other frameworks.
ratings.documentation.rating: 6.0
ratings.documentation.reason: Dataset page and paper provide sufficient detail; usage with HuggingFace is smooth, but full reproducibility for training requires configuration effort.
id: winogrande
Citations: [27]

Ratings:


Winogrande
dataset
specification
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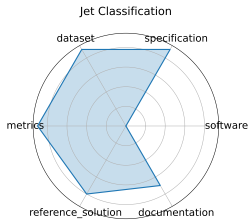
29 Jet Classification

date: 2024-05-01
version: v0.2.0
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: 2024-05-01
url: https://github.com/fastmachinelearning/fastml-science/tree/main/jet-classify
doi: 10.48550/arXiv.2207.07958
domain: Particle Physics
focus: Real-time classification of particle jets using HL-LHC simulation features
keywords: - classification - real-time ML - jet tagging - QKeras
summary: This benchmark evaluates ML models for real-time classification of particle jets using high-level features derived from simulated LHC data. It includes both full-precision and quantized models optimized for FPGA deployment.
licensing: Apache License 2.0
task_types: - Classification
ai_capability_measured: - Real-time inference - model compression performance
metrics: - Accuracy - AUC
models: - Keras DNN - QKeras quantized DNN
ml_motif: - Real-time
type: Benchmark
ml_task: - Supervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Includes both float and quantized models using QKeras
contact.name: Jules Muhizi
contact.email: unknown
datasets.links.name: JetClass
datasets.links.url: https://zenodo.org/record/6619768
results.links.name: ChatGPT LLM
results.links.url: https://docs.google.com/document/d/1runrcij-eoH3_lgGZ8wm2z1YbL1Qf5cSNbVbHyWFDs4
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Task and format (multiple-choice QA with 5 options) are clearly defined; grounded in ConceptNet with consistent structure, though no hardware/system constraints are specified.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Public, versioned, and FAIR-compliant; includes metadata, splits, and licensing; well-integrated with HuggingFace and other ML libraries.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Accuracy is a simple, reproducible metric aligned with task goals; no ambiguity in evaluation.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Several baseline models (e.g., BERT, RoBERTa) are reported with scores; implementations exist in public repos, but not bundled as an official starter kit.
ratings.documentation.rating: 7.0
ratings.documentation.reason: Clear paper, GitHub repo, and integration with HuggingFace Datasets; full reproducibility requires manually connecting models to dataset.
id: jet_classification
Citations: [28]

Ratings:



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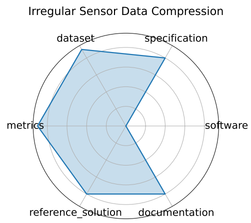
30 Irregular Sensor Data Compression

date: 2024-05-01
version: v0.2.0
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: 2024-05-01
url: https://github.com/fastmachinelearning/fastml-science/tree/main/sensor-data-compression
doi: 10.48550/arXiv.2207.07958
domain: Particle Physics
focus: Real-time compression of sparse sensor data with autoencoders
keywords: - compression - autoencoder - sparse data - irregular sampling
summary: This benchmark addresses lossy compression of irregularly sampled sensor data from particle detectors using real-time autoencoder architectures, targeting latency-critical applications in physics experiments.
licensing: Apache License 2.0
task_types: - Compression
ai_capability_measured: - Reconstruction quality - compression efficiency
metrics: - MSE - Compression ratio
models: - Autoencoder - Quantized autoencoder
ml_motif: - Real-time, Image/CV
type: Benchmark
ml_task: - Unsupervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Based on synthetic but realistic physics sensor data
contact.name: Ben Hawks, Nhan Tran
contact.email: unknown
datasets.links.name: Custom synthetic irregular sensor dataset
datasets.links.url: https://github.com/fastmachinelearning/fastml-science/tree/main/sensor-data-compression
results.links.name: ChatGPT LLM
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Classification is clearly defined for real-time inference on simulated LHC jets. Input features (HLFs) are documented, though exact latency or resource constraints are not numerically specified.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Two datasets (OpenML and Zenodo) are public, well-formatted, and documented; FAIR principles are followed, though richer metadata would raise confidence to a 10.
ratings.metrics.rating: 9.0
ratings.metrics.reason: AUC and Accuracy are standard, quantitative, and well-aligned with goals of jet tagging and inference efficiency.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Float and quantized Keras/QKeras models are provided with results. Reproducibility is good, though full automation and documentation could be improved.
ratings.documentation.rating: 8.0
ratings.documentation.reason: GitHub contains baseline code, data loaders, and references, but setup for deployment (e.g., FPGA pipeline) requires familiarity with the tooling.
id: irregular_sensor_data_compression
Citations: [29]

Ratings:



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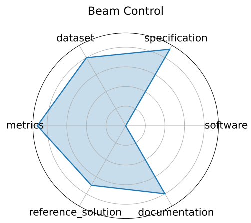
31 Beam Control

date: 2024-05-01
version: v0.2.0
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: 2024-05-01
url: https://github.com/fastmachinelearning/fastml-science/tree/main/beam-control
doi: 10.48550/arXiv.2207.07958
domain: Accelerators and Magnets
focus: Reinforcement learning control of accelerator beam position
keywords: - RL - beam stabilization - control systems - simulation
summary: Beam Control explores real-time reinforcement learning strategies for maintaining stable beam trajectories in particle accelerators. The benchmark is based on the BOOSTR environment for accelerator simulation.
licensing: Apache License 2.0
task_types: - Control
ai_capability_measured: - Policy performance in simulated accelerator control
metrics: - Stability - Control loss
models: - DDPG - PPO (planned)
ml_motif: - Real-time, RL
type: Benchmark
ml_task: - Reinforcement Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Environment defined, baseline RL implementation is in progress
contact.name: Ben Hawks, Nhan Tran
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: in progress
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Task is well defined (real-time compression of sparse, irregular sensor data using autoencoders); latency constraints are implied but not fully quantified.
ratings.dataset.rating: 8.0
ratings.dataset.reason: Dataset is custom and synthetic but described well; FAIR-compliance is partial (reusable and accessible, but not externally versioned with rich metadata).
ratings.metrics.rating: 9.0
ratings.metrics.reason: Uses standard quantitative metrics (MSE, compression ratio) clearly aligned with compression and reconstruction goals.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: Baseline (autoencoder and quantized variant) is provided, but training/inference pipeline is minimally documented and needs user setup.
ratings.documentation.rating: 8.0
ratings.documentation.reason: GitHub repo contains core components, but more structured setup instructions and pretrained weights would improve usability.
id: beam_control
Citations: [29], [30]

Ratings:


Beam Control
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32 Ultrafast jet classification at the HL-LHC

date: 2024-07-08

version: v1.0

last_updated: 2024-07

expired: unknown

valid: yes

valid_date: 2024-07-08

url: https://arxiv.org/pdf/2402.01876

doi: 10.48550/arXiv.2402.01876

domain: Particle Physics

focus: FPGA-optimized real-time jet origin classification at the HL-LHC

keywords: - jet classification - FPGA - quantization-aware training - Deep Sets - Interaction Networks

summary: Demonstrates three ML models (MLP, Deep Sets, Interaction Networks) optimized for FPGA deployment with O(100 ns) inference using quantized models and hls4ml, targeting real-time jet tagging in the L1 trigger environment at the high-luminosity LHC. Data is available on Zenodo DOI:10.5281/zenodo.3602260. :contentReference[oaicite:1]{index=1}

licensing: CC-BY

task_types: - Classification

ai_capability_measured: - Real-time inference under FPGA constraints

metrics: - Accuracy - Latency - Resource utilization

models: - MLP - Deep Sets - Interaction Network

ml_motif: - Real-time

type: Model

ml_task: - Supervised Learning

solutions: Solution details are described in the referenced paper or repository.

notes: Uses quantization-aware training; hardware synthesis evaluated via hls4ml

contact.name: Patrick Odagiu

contact.email: podagiu@ethz.ch

datasets.links.name: Zenodo dataset

datasets.links.url: https://zenodo.org/records/3602260

results.links.name: ChatGPT LLM

results.links.url: https://docs.google.com/document/d/1gDf1CIYtfmfZ9urv1jCRZMYz_3WwEETkugUC65OZBdw

fair.reproducible: True

fair.benchmark_ready: False

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 8.0

ratings.specification.reason: Task is clear (RL control of beam stability), with BOOSTR-based simulator; control objectives are well motivated, but system constraints and reward structure are still under refinement.

ratings.dataset.rating: 7.0

ratings.dataset.reason: BOOSTR dataset exists and is cited, but integration into the benchmark is in early stages; metadata and FAIR structure are limited.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Stability and control loss are mentioned, but metrics are not yet formalized with clear definitions or baselines.

ratings.reference_solution.rating: 5.5

ratings.reference_solution.reason: DDPG baseline mentioned; PPO planned; implementation is still in progress with no reproducible results available yet.

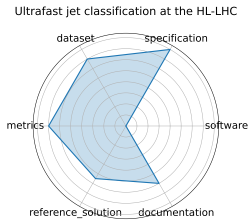
ratings.documentation.rating: 6.0

ratings.documentation.reason: GitHub has a defined structure but is incomplete; setup and execution instructions for training/evaluation are not fully established.

id: ultrafast_jet_classification_at_the_hl-lhc

Citations: [31]

Ratings:


Ultrafast jet classification at the HL-LHC
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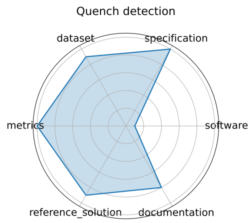
33 Quench detection

date: 2024-10-15
version: v1.0
last_updated: 2024-10
expired: no
valid: yes
valid_date: 2024-10-15
url: https://indico.cern.ch/event/1387540/contributions/6153618/attachments/2948441/5182077/fast_ml_magnets_2024_final.pdf
doi: NA
domain: Accelerators and Magnets
focus: Real-time detection of superconducting magnet quenches using ML
keywords: - quench detection - autoencoder - anomaly detection - real-time
summary: Exploration of real-time quench detection using unsupervised and RL approaches, combining multi-modal sensor data (BPM, power supply, acoustic), operating on kHz-MHz streams with anomaly detection and frequency-domain features.
licensing: Via Fermilab
task_types: - Anomaly detection - Quench localization
ai_capability_measured: - Real-time anomaly detection with multi-modal sensors
metrics: - ROC-AUC - Detection latency
models: - Autoencoder - RL agents (in development)
ml_motif: - Real-time, RL
type: Benchmark
ml_task: - Reinforcement + Unsupervised Learning
solutions: 0
notes: Precursor detection in progress; multi-modal and dynamic weighting methods
contact.name: Maira Khan
contact.email: unknown
datasets.links.name: BPM and power supply data from BNL
results.links.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: False
ratings.software.rating: 1
ratings.software.reason: Not provided.
ratings.specification.rating: 10.0
ratings.specification.reason: Real-time jet origin classification under FPGA constraints is clearly defined, with explicit latency targets (~100 ns) and I/O formats.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Data available on Zenodo with DOI, includes constituent-level jets; accessible and well-documented, though not deeply versioned with full FAIR metadata.
ratings.metrics.rating: 10.0
ratings.metrics.reason: Accuracy, latency, and hardware resource usage (LUTs, DSPs) are rigorously measured and aligned with real-time goals.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Includes models (MLP, Deep Sets, Interaction Networks) with quantization-aware training and synthesis results via hls4ml; reproducible but tightly coupled with specific toolchains.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Paper and code (via hls4ml) are sufficient, but a centralized, standalone repo for reproducing all models would enhance accessibility.
id: quench_detection
Citations: [32]

Ratings:



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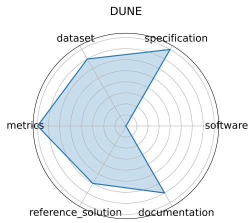
34 DUNE

date: 2024-10-15
version: v1.0
last_updated: 2024-10
expired: unknown
valid: yes
valid_date: 2024-10-15
url: https://indico.fnal.gov/event/66520/contributions/301423/attachments/182439/250508/fast_ml_dunedaq_sonic_10_15_24.pdf
doi: 10.48550/arXiv.2103.13910
domain: Particle Physics
focus: Real-time ML for DUNE DAQ time-series data
keywords: - DUNE - time-series - real-time - trigger
summary: Applying real-time ML methods to time-series data from DUNE detectors, exploring trigger-level anomaly detection and event selection with low latency constraints.
licensing: Via Fermilab
task_types: - Trigger selection - Time-series anomaly detection
ai_capability_measured: - Low-latency event detection
metrics: - Detection efficiency - Latency
models: - CNN - LSTM (planned)
ml_motif: - Real-time, Time-series
type: Benchmark (in progress)
ml_task: - Supervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Prototype models demonstrated on SONIC platform
contact.name: Andrew J. Morgan
contact.email: unknown
datasets.links.name: DUNE SONIC data
results.links.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: False
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Task (quench detection via anomaly detection) is clearly described; multi-modal sensors, streaming rates, and objective are provided, but constraints (latency thresholds) are qualitative.
ratings.dataset.rating: 7.0
ratings.dataset.reason: Custom dataset using real data from BNL; HDF5 formatted and structured, but access may be internal or limited, and not versioned for public FAIR use.
ratings.metrics.rating: 8.0
ratings.metrics.reason: ROC-AUC and detection latency are defined; relevant and quantitative but not yet paired with benchmark baselines.
ratings.reference_solution.rating: 6.0
ratings.reference_solution.reason: Autoencoder prototype exists; RL methods are in development; no fully reproducible pipeline is available yet.
ratings.documentation.rating: 7.0
ratings.documentation.reason: Slides and GDocs outline results; implementation is in progress with limited setup/code release.
id: dune
Citations: [33]

Ratings:



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35 Intelligent experiments through real-time AI

date: 2025-01-08

version: v1.0

last_updated: 2025-01

expired: unknown

valid: yes

valid_date: 2025-01-08

url: https://arxiv.org/pdf/2501.04845

doi: 10.48550/arXiv.2501.04845

domain: Instrumentation and Detectors; Nuclear Physics; Particle Physics

focus: Real-time FPGA-based triggering and detector control for sPHENIX and future EIC

keywords: - FPGA - Graph Neural Network - hls4ml - real-time inference - detector control

summary: Research and Development demonstrator for real-time processing of high-rate tracking data from the sPHENIX detector (RHIC) and future EIC systems. Uses GNNs with hls4ml for FPGA-based trigger generation to identify rare events (heavy flavor, DIS electrons) within 10 micros latency. Demonstrated improved accuracy and latency on Alveo/FELIX platforms.

licensing: CC BY-NC-ND 4.0

task_types: - Trigger classification - Detector control - Real-time inference

ai_capability_measured: - Low-latency GNN inference on FPGA

metrics: - Accuracy (charm and beauty detection) - Latency (micros) - Resource utilization (LUT/FF/BRAM/DSP)

models: - Bipartite Graph Network with Set Transformers (BGN-ST) - GarNet (edge-classifier)

ml_motif: - Real-time

type: Model

ml_task: - Supervised Learning

solutions: Solution details are described in the referenced paper or repository.

notes: Achieved ~97.4% accuracy for beauty decay triggers; sub-10 micros latency on Alveo U280; hit-based FPGA design via hls4ml and FlowGNN.

contact.name: Jakub Kvapil

contact.email: Jakub.Kvapil@lanl.gov

datasets.links.name: Internal simulated tracking data (sPHENIX and EIC DIS-electron tagger)

results.links.name: ChatGPT LLM

fair.reproducible: True

fair.benchmark_ready: False

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 8.0

ratings.specification.reason: Task (trigger-level anomaly detection) is clearly defined for low-latency streaming input, but the problem framing lacks complete architectural/system specs.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Internal DUNE SONIC data; not publicly released and no formal FAIR support; replicability is institutionally gated.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Metrics include detection efficiency and latency, which are relevant, but only lightly supported by baselines or formal eval scripts.

ratings.reference_solution.rating: 5.0

ratings.reference_solution.reason: One CNN prototype demonstrated; LSTM planned. No public implementation or ready-to-run example yet.

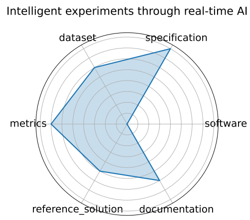
ratings.documentation.rating: 6.0

ratings.documentation.reason: Slides and some internal documentation exist, but no full pipeline or public GitHub repo yet.

id: intelligent_experiments_through_real-time_ai

Citations: [34]

Ratings:


Intelligent experiments through real-time AI
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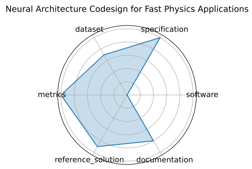
36 Neural Architecture Codesign for Fast Physics Applications

date: 2025-01-09
version: v1.0
last_updated: 2025-01
expired: unknown
valid: yes
valid_date: 2025-01-09
url: https://arxiv.org/abs/2501.05515
doi: 10.48550/arXiv.2501.05515
domain: Physics; Materials Science; Particle Physics
focus: Automated neural architecture search and hardware-efficient model codesign for fast physics applications
keywords: - neural architecture search - FPGA deployment - quantization - pruning - hls4ml
summary: Introduces a two-stage neural architecture codesign (NAC) pipeline combining global and local search, quantization-aware training, and pruning to design efficient models for fast Bragg peak finding and jet classification, synthesized for FPGA deployment with hls4ml. Achieves >30x reduction in BOPs and sub-100 ns inference latency on FPGA.
licensing: Via Fermilab
task_types: - Classification - Peak finding
ai_capability_measured: - Hardware-aware model optimization; low-latency inference
metrics: - Accuracy - Latency - Resource utilization
models: - NAC-based BraggNN - NAC-optimized Deep Sets (jet)
ml_motif: - Real-time, Image/CV
type: Framework
ml_task: - Supervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Demonstrated two case studies (materials science, HEP); pipeline and code open-sourced.
contact.name: Jason Weitz (UCSD), Nhan Tran (FNAL)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes (nac-opt, hls4ml)
fair.benchmark_ready: False
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 10.0
ratings.specification.reason: Task is clearly defined (triggering on rare events with sub-10 micros latency); architecture, constraints, and system context (FPGA, Alveo) are well detailed.
ratings.dataset.rating: 7.0
ratings.dataset.reason: Simulated tracking data from sPHENIX and EIC; internally structured but not yet released in a public FAIR-compliant format.
ratings.metrics.rating: 10.0
ratings.metrics.reason: Accuracy, latency, and hardware resource utilization (LUTs, DSPs) are clearly defined and used in evaluation.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Graph-based models (BGN-ST, GarNet) are implemented and tested on real hardware; reproducibility possible with hls4ml but full scripts not bundled.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Paper is detailed and tool usage (FlowGNN, hls4ml) is described, but repo release and dataset access remain in progress.
id: neural_architecture_codesign_for_fast_physics_applications
Citations: [35]

Ratings: 
Neural Architecture Codesign for Fast Physics Applications
dataset
specification
metrics
software
reference_solution
documentation

37 Smart Pixels for LHC

date: 2024-06-24

version: v1.0

last_updated: 2024-06

expired: unknown

valid: yes

valid_date: 2024-06-24

url: https://arxiv.org/abs/2406.14860

doi: 10.48550/arXiv.2406.14860

domain: Particle Physics; Instrumentation and Detectors

focus: On-sensor, in-pixel ML filtering for high-rate LHC pixel detectors

keywords: - smart pixel - on-sensor inference - data reduction - trigger

summary: Presents a 256x256-pixel ROIC in 28 nm CMOS with embedded 2-layer NN for cluster filtering at 25 ns, achieving 54-75% data reduction while maintaining noise and latency constraints. Prototype consumes ~300 microW/pixel and operates in combinatorial digital logic.

licensing: Via Fermilab

task_types: - Image Classification - Data filtering

ai_capability_measured: - On-chip - low-power inference; data reduction

metrics: - Data rejection rate - Power per pixel

models: - 2-layer pixel NN

ml_motif: - Real-time, Image/CV

type: Benchmark

ml_task: - Image Classification

solutions: Solution details are described in the referenced paper or repository.

notes: Prototype in CMOS 28 nm; proof-of-concept for Phase III pixel upgrades.

contact.name: Lindsey Gray; Jennet Dickinson

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: True

fair.benchmark_ready: Yes (Zenodo:7331128)

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Task (automated neural architecture search for real-time physics) is well formulated with clear latency, model compression, and deployment goals.

ratings.dataset.rating: 6.0

ratings.dataset.reason: Internal Bragg and jet datasets used; not publicly hosted or FAIR-compliant, though mentioned in the paper.

ratings.metrics.rating: 10.0

ratings.metrics.reason: BOP reduction, latency, and accuracy are all quantitatively evaluated.

ratings.reference_solution.rating: 8.0

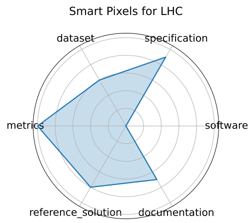
ratings.reference_solution.reason: NAC-generated models for Bragg peak and jet classification are described, but pipeline requires integration of several tools and is not fully packaged.

ratings.documentation.rating: 7.0

ratings.documentation.reason: NAC pipeline, hls4ml usage, and results are discussed; code (e.g., nac-opt) referenced, but replication requires stitching together toolchain and data.

id: smart_pixels_for_lhc

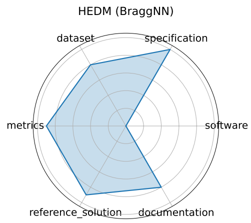
Citations: [36]

Ratings: 
Smart Pixels for LHC
dataset
specification
metrics
software
reference_solution
documentation

38 HEDM (BraggNN)

date: 2023-10-03
version: v1.0
last_updated: 2023-10
expired: unknown
valid: yes
valid_date: 2023-10-03
url: https://arxiv.org/abs/2008.08198
doi: 10.48550/arXiv.2008.08198
domain: Material Science
focus: Fast Bragg peak analysis using deep learning in diffraction microscopy
keywords: - BraggNN - diffraction - peak finding - HEDM
summary: Uses BraggNN, a deep neural network, for rapid Bragg peak localization in high-energy diffraction microscopy, achieving about 13x speedup compared to Voigt-based methods while maintaining sub-pixel accuracy.
licensing: DOE Public Access Plan
task_types: - Peak detection
ai_capability_measured: - High-throughput peak localization
metrics: - Localization accuracy - Inference time
models: - BraggNN
ml_motif: - Real-time, Image/CV
type: Framework
ml_task: - Peak finding
solutions: Solution details are described in the referenced paper or repository.
notes: Enables real-time HEDM workflows; basis for NAC case study.
contact.name: Jason Weitz (UCSD)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: True
fair.benchmark_ready: True
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 10.0
ratings.specification.reason: Fully specified: describes task (data filtering/classification, system design (on-sensor inference), latency (25 ns), and power constraints.
ratings.dataset.rating: 8.0
ratings.dataset.reason: In-pixel charge cluster data used, but dataset release info is minimal; FAIR metadata/versioning limited.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Data rejection rate and power per pixel are clearly defined and directly tied to hardware goals.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: 2-layer NN implementation is evaluated in hardware; reproducible via hls4ml flow with results in paper.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Paper is clear; Zenodo asset is referenced, but additional GitHub or setup repo would improve reproducibility.
id: hedm_braggnn
Citations: [37]

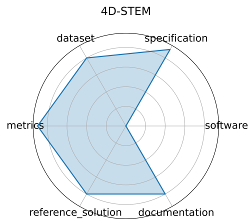
Ratings:


HEDM (BraggNN)
dataset
specification
metrics
software
reference_solution
documentation

39 4D-STEM

date: 2023-12-03
version: v1.0
last_updated: 2023-12
expired: unknown
valid: yes
valid_date: 2023-12-03
url: https://openreview.net/pdf?id=7yt3N0o0W9
doi: unknown
domain: Material Science
focus: Real-time ML for scanning transmission electron microscopy
keywords: - 4D-STEM - electron microscopy - real-time - image processing
summary: Proposes ML methods for real-time analysis of 4D scanning transmission electron microscopy datasets; framework details in progress.
licensing: unknown
task_types: - Image Classification - Streamed data inference
ai_capability_measured: - Real-time large-scale microscopy inference
metrics: - Classification accuracy - Throughput
models: - CNN models (prototype)
ml_motif: - Real-time, Image/CV
type: Model
ml_task: - Image Classification
solutions: 0
notes: In-progress; model design under development.
contact.name: Shuyu Qin
contact.email: shq219@lehigh.edu
results.links.name: ChatGPT LLM
fair.reproducible: in progress
fair.benchmark_ready: False
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Peak localization task is well-defined for diffraction images; input/output described clearly, but no system constraints.
ratings.dataset.rating: 8.0
ratings.dataset.reason: Simulated diffraction images provided; reusable and downloadable, but not externally versioned or FAIR-structured.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Inference speed and localization accuracy are standard and quantitatively reported.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: BraggNN model and training pipeline exist, but need stitching from separate repositories.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Paper and codebase are available and usable, though not fully turnkey.
id: d-stem
Citations: [38]

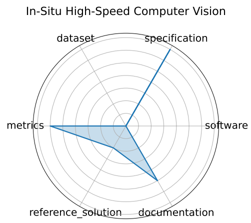
Ratings:


4D-STEM
dataset
specification
metrics
software
reference_solution
documentation

40 In-Situ High-Speed Computer Vision

date: 2023-12-05
version: v1.0
last_updated: 2023-12
expired: unknown
valid: yes
valid_date: 2023-12-05
url: https://arxiv.org/abs/2312.00128
doi: 10.48550/arXiv.2312.00128
domain: Fusion/Plasma
focus: Real-time image classification for in-situ plasma diagnostics
keywords: - plasma - in-situ vision - real-time ML
summary: Applies low-latency CNN models for image classification of plasma diagnostics streams; supports deployment on embedded platforms.
licensing: Via Fermilab
task_types: - Image Classification
ai_capability_measured: - Real-time diagnostic inference
metrics: - Accuracy - FPS
models: - CNN
ml_motif: - Real-time, Image/CV
type: Model
ml_task: - Image Classification
solutions: Solution details are described in the referenced paper or repository.
notes: Embedded/deployment details in progress.
contact.name: unknown
contact.email: unknown
results.links.name: ChatGPT LLM
results.links.url: https://docs.google.com/document/d/1EqkRHuQs1yQqMvZs_L6p9JAy2vKX5OCTubzttFBuRoQ/edit?usp=sharing
fair.reproducible: in progress
fair.benchmark_ready: False
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 7.0
ratings.specification.reason: General task defined (real-time microscopy inference), but no standardized I/O format, latency constraint, or complete problem framing yet.
ratings.dataset.rating: 0.0
ratings.dataset.reason: Dataset not provided or described in any formal way.
ratings.metrics.rating: 6.0
ratings.metrics.reason: Mentions throughput and accuracy, but metrics are not formally defined or benchmarked.
ratings.reference_solution.rating: 2.0
ratings.reference_solution.reason: Prototype CNNs described; no baseline or implementation released.
ratings.documentation.rating: 5.0
ratings.documentation.reason: OpenReview paper and Gemini doc give some insight, but no working code, environment, or example.
id: in-situ_high-speed_computer_vision
Citations: [39]

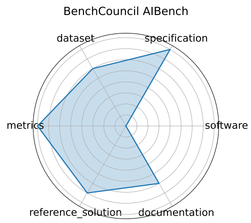
Ratings:


In-Situ High-Speed Computer Vision
dataset
specification
metrics
software
reference_solution
documentation

41 BenchCouncil AIBench

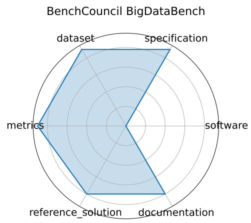
date: 2020-01-01
version: v1.0
last_updated: 2020-01
expired: unknown
valid: yes
valid_date: 2020-01-01
url: https://www.benchcouncil.org/AIBench/
doi: 10.48550/arXiv.1908.08998
domain: General
focus: End-to-end AI benchmarking across micro, component, and application levels
keywords: - benchmarking - AI systems - application-level evaluation
summary: AIBench is a comprehensive benchmark suite that evaluates AI workloads at different levels (micro, component, application) across hardware systems-covering image generation, object detection, translation, recommendation, video prediction, etc.
licensing: Apache License 2.0
task_types: - Training - Inference - End-to-end AI workloads
ai_capability_measured: - System-level AI workload performance
metrics: - Throughput - Latency - Accuracy
models: - ResNet - BERT - GANs - Recommendation systems
ml_motif: - General
type: Benchmark
ml_task: - NA
solutions: Solution details are described in the referenced paper or repository.
notes: Covers scenario-distilling, micro, component, and end-to-end benchmarks.
contact.name: Wanling Gao (BenchCouncil)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Task (plasma diagnostic classification) and real-time deployment described; system specs (FPS targets) implied but not fully quantified.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Dataset is sensor stream-based but not shared or FAIR-documented.
ratings.metrics.rating: 8.0
ratings.metrics.reason: FPS and classification accuracy reported and relevant.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: CNN model described and evaluated, but public implementation and benchmarks are not available yet.
ratings.documentation.rating: 6.0
ratings.documentation.reason: Paper and Gemini doc exist, but full setup instructions and tools are still in progress.
id: benchcouncil_aibench
Citations: [40]

Ratings:


BenchCouncil AIBench
dataset
specification
metrics
software
reference_solution
documentation

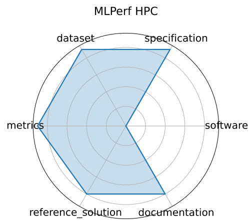
42 BenchCouncil BigDataBench

date: 2020-01-01
version: v1.0
last_updated: 2020-01
expired: unknown
valid: yes
valid_date: 2020-01-01
url: https://www.benchcouncil.org/BigDataBench/
doi: 10.48550/arXiv.1802.08254
domain: General
focus: Big data and AI benchmarking across structured, semi-structured, and unstructured data workloads
keywords: - big data - AI benchmarking - data analytics
summary: BigDataBench provides benchmarks for evaluating big data and AI workloads with realistic datasets (13 sources) and pipelines across analytics, graph, warehouse, NoSQL, streaming, and AI.
licensing: Apache License 2.0
task_types: - Data preprocessing - Inference - End-to-end data pipelines
ai_capability_measured: - Data processing and AI model inference performance at scale
metrics: - Data throughput - Latency - Accuracy
models: - CNN - LSTM - SVM - XGBoost
ml_motif: - General
type: Benchmark
ml_task: - NA
solutions: Solution details are described in the referenced paper or repository.
notes: Built on eight data motifs; provides Hadoop, Spark, Flink, MPI implementations.
contact.name: Jianfeng Zhan (BenchCouncil)
contact.email: unknown
results.links.name: ChatGPT LLM
results.links.url: https://docs.google.com/document/d/1VFRxhR2G5A83S8PqKBrP99LLVgcCGvX2WW4vTtwxmQ4/edit?usp=sharing
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Evaluates AI at multiple levels (micro to end-to-end); tasks and workloads are clearly defined, though specific I/O formats and constraints vary.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Realistic datasets across diverse domains; FAIR structure for many components, but individual datasets may not all be versioned or richly annotated.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Latency, throughput, and accuracy clearly defined for end-to-end tasks; consistent across models and setups.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Reference implementations for several tasks exist, but setup across all tasks is complex and not fully streamlined.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Central documentation exists, with detailed component breakdowns; environment setup across platforms (e.g., hardware variations) can require manual adjustment.
id: benchcouncil_bigdatabench
Citations: [41]

Ratings: 
BenchCouncil BigDataBench
dataset
specification
metrics
software
reference_solution
documentation

43 MLPerf HPC

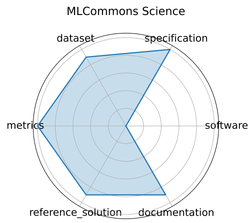
date: 2021-10-20
version: v1.0
last_updated: 2021-10
expired: unknown
valid: yes
valid_date: 2021-10-20
url: https://github.com/mlcommons/hpc
doi: 10.48550/arXiv.2110.11466
domain: Cosmology, Climate, Protein Structure, Catalysis
focus: Scientific ML training and inference on HPC systems
keywords: - HPC - training - inference - scientific ML
summary: MLPerf HPC introduces scientific model benchmarks (e.g., CosmoFlow, DeepCAM) aimed at large-scale HPC evaluation with >10x performance scaling through system-level optimizations.
licensing: Apache License 2.0
task_types: - Training - Inference
ai_capability_measured: - Scaling efficiency - training time - model accuracy on HPC
metrics: - Training time - Accuracy - GPU utilization
models: - CosmoFlow - DeepCAM - OpenCatalyst
ml_motif: - HPC/inference, HPC/training
type: Framework
ml_task: - NA
solutions: Solution details are described in the referenced paper or repository.
notes: Shared framework with MLCommons Science; reference implementations included.
contact.name: Steven Farrell (MLCommons)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Focused on structured/unstructured data pipelines; clearly defined tasks spanning analytics to AI; some scenarios lack hardware constraint modeling.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Built from 13 real-world sources; structured for realistic big data scenarios; partially FAIR-compliant with documented data motifs.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Covers data throughput, latency, and accuracy; quantitative and benchmark-ready.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Many pipeline and model examples provided using Hadoop/Spark/Flink; setup effort varies by task and platform.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Strong documentation with examples and task specifications; centralized support exists, but task-specific tuning may require domain expertise.
id: mlperf_hpc
Citations: [42]

Ratings: 
MLPerf HPC
dataset
specification
metrics
software
reference_solution
documentation

44 MLCommons Science

date: 2023-06-01
version: v1.0
last_updated: 2023-06
expired: unknown
valid: yes
valid_date: 2023-06-01
url: https://github.com/mlcommons/science
doi: unknown
domain: Earthquake, Satellite Image, Drug Discovery, Electron Microscope, CFD
focus: AI benchmarks for scientific applications including time-series, imaging, and simulation
keywords: - science AI - benchmark - MLCommons - HPC
summary: MLCommons Science assembles benchmark tasks with datasets, targets, and implementations across earthquake forecasting, satellite imagery, drug screening, electron microscopy, and CFD to drive scientific ML reproducibility.
licensing: Apache License 2.0
task_types: - Time-series analysis - Image classification - Simulation surrogate modeling
ai_capability_measured: - Inference accuracy - simulation speed-up - generalization
metrics: - MAE - Accuracy - Speedup vs simulation
models: - CNN - GNN - Transformer
ml_motif: - Time-series, Image/CV, HPC/inference
type: Framework
ml_task: - NA
solutions: 0
notes: Joint national-lab effort under Apache-2.0 license.
contact.name: MLCommons Science Working Group
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 10.0
ratings.specification.reason: Scientific ML tasks (e.g., CosmoFlow, DeepCAM) are clearly defined with HPC system-level constraints and targets.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Public scientific datasets (e.g., cosmology, weather); used consistently, though FAIR-compliance of individual datasets varies slightly.
ratings.metrics.rating: 10.0
ratings.metrics.reason: Training time, GPU utilization, and accuracy are all directly measured and benchmarked across HPC systems.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Reference implementations available and actively maintained; HPC setup may require domain-specific environment.
ratings.documentation.rating: 9.0
ratings.documentation.reason: GitHub repo and papers provide detailed instructions; reproducibility supported across multiple institutions.
id: mlcommons_science
Citations: [43]

Ratings:


MLCommons Science
dataset
specification
metrics
software
reference_solution
documentation

45 LHC New Physics Dataset

date: 2021-07-05

version: v1.0

last_updated: 2021-07

expired: unknown

valid: yes

valid_date: 2021-07-05

url: https://arxiv.org/pdf/2107.02157

doi: unknown

domain: Particle Physics; Real-time Triggering

focus: Real-time LHC event filtering for anomaly detection using proton collision data

keywords: - anomaly detection - proton collision - real-time inference - event filtering - unsupervised ML

summary: A dataset of proton-proton collision events emulating a 40 MHz real-time data stream from LHC detectors, pre-filtered on electron or muon presence. Designed for unsupervised new-physics detection algorithms under latency/bandwidth constraints.

licensing: unknown

task_types: - Anomaly detection - Event classification

ai_capability_measured: - Unsupervised signal detection under latency and bandwidth constraints

metrics: - ROC-AUC - Detection efficiency

models: - Autoencoder - Variational autoencoder - Isolation forest

ml_motif: - Multiple

type: Framework

ml_task: - NA

solutions: 0

notes: Includes electron/muon-filtered background and black-box signal benchmarks; 1M events per black box.

contact.name: Ema Puljak (ema.puljak@cern.ch)

contact.email: unknown

datasets.links.name: Zenodo stores, background + 3 black-box signal sets. 1M events each

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analysed.

ratings.specification.rating: 7.0

ratings.specification.reason: The problem (anomaly detection for new physics at LHC) is clearly described with goals and background, but lacks a formal task specification or constraints.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Large-scale, public dataset derived from LHC simulations; well-documented and available via Zenodo.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Provides AUROC, accuracy, and anomaly detection metrics but lacks standardized evaluation script.

ratings.reference_solution.rating: 5.0

ratings.reference_solution.reason: Baseline models (autoencoders, GANs) are described in associated papers, but implementations vary across papers.

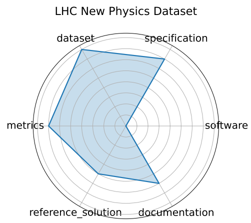
ratings.documentation.rating: 6.0

ratings.documentation.reason: Publicly available papers and datasets with descriptions, but no unified README or training setup.

id: lhc_new_physics_dataset

Citations: [44]

Ratings:



LHC New Physics Dataset
dataset
specification
metrics
software
reference_solution
documentation

46 MLCommons Medical AI

date: 2023-07-17

version: v1.0

last_updated: 2023-07

expired: unknown

valid: yes

valid_date: 2023-07-17

url: https://github.com/mlcommons/medical

doi: unknown

domain: Healthcare; Medical AI

focus: Federated benchmarking and evaluation of medical AI models across diverse real-world clinical data

keywords: - medical AI - federated evaluation - privacy-preserving - fairness - healthcare benchmarks

summary: The MLCommons Medical AI working group develops benchmarks, best practices, and platforms (MedPerf, GaNDLF, COFE) to accelerate robust, privacy-preserving AI development for healthcare. MedPerf enables federated testing of clinical models on diverse datasets, improving generalizability and equity while keeping data onsite :contentReference[oaicite:1]{index=1}.

licensing: Apache License 2.0

task_types: - Federated evaluation - Model validation

ai_capability_measured: - Clinical accuracy - fairness - generalizability - privacy compliance

metrics: - ROC AUC - Accuracy - Fairness metrics

models: - MedPerf-validated CNNs - GaNDLF workflows

ml_motif: - Multiple

type: Platform

ml_task: - NA

solutions: 0

notes: Open-source platform under Apache-2.0; used across 20+ institutions and hospitals :contentReference[oaicite:2]{index=2}.

contact.name: Alex Karargyris (MLCommons Medical AI)

contact.email: unknown

datasets.links.name: Multi-institutional clinical datasets, radiology

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Diverse scientific tasks (earthquake, CFD, microscopy) with detailed problem statements and goals; system constraints not uniformly applied.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Domain-specific datasets (e.g., microscopy, climate); mostly public and structured, but FAIR annotations are not always explicit.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Task-specific metrics (MAE, speedup, accuracy) are clear and reproducible.

ratings.reference_solution.rating: 9.0

ratings.reference_solution.reason: Reference models (CNN, GNN, Transformer) provided with training/evaluation pipelines.

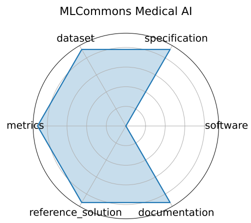
ratings.documentation.rating: 9.0

ratings.documentation.reason: Well-documented, open-sourced, and maintained with examples; strong community support and reproducibility focus.

id: mlcommons_medical_ai

Citations: [45]

Ratings:


MLCommons Medical AI
dataset
specification
metrics
software
reference_solution
documentation

47 CaloChallenge 2022

date: 2024-10-28

version: v1.0

last_updated: 2024-10

expired: unknown

valid: yes

valid_date: 2024-10-28

url: http://arxiv.org/abs/2410.21611

doi: 10.48550/arXiv.2410.21611

domain: LHC Calorimeter; Particle Physics

focus: Fast generative-model-based calorimeter shower simulation evaluation

keywords: - calorimeter simulation - generative models - surrogate modeling - LHC - fast simulation

summary: The Fast Calorimeter Simulation Challenge 2022 assessed 31 generative-model submissions (VAEs, GANs, Flows, Diffusion) on four calorimeter shower datasets; benchmarking shower quality, generation speed, and model complexity :contentReference[oaicite:3]{index=3}.

licensing: Via Fermilab

task_types: - Surrogate modeling

ai_capability_measured: - Simulation fidelity - speed - efficiency

metrics: - Histogram similarity - Classifier AUC - Generation latency

models: - VAE variants - GAN variants - Normalizing flows - Diffusion models

ml_motif: - Surrogate

type: Dataset

ml_task: - Surrogate Modeling

solutions: Solution details are described in the referenced paper or repository.

notes: The most comprehensive survey to date on ML-based calorimeter simulation; 31 submissions over different dataset sizes.

contact.name: Claudius Krause (CaloChallenge Lead)

contact.email: unknown

datasets.links.name: Four LHC calorimeter shower datasets

datasets.links.url: various voxel resolutions

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Task is clearly defined: real-time anomaly detection from high-rate LHC collisions. Latency and bandwidth constraints are mentioned, though not numerically enforced.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Publicly available via Zenodo, with structured signal/background splits, and rich metadata; nearly fully FAIR.

ratings.metrics.rating: 9.0

ratings.metrics.reason: ROC-AUC and detection efficiency are clearly defined and appropriate for unsupervised anomaly detection.

ratings.reference_solution.rating: 8.0

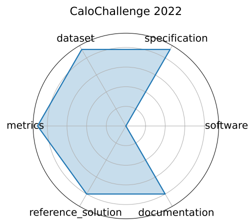
ratings.reference_solution.reason: Several baseline methods (autoencoder, VAE, isolation forest) are evaluated; runnable versions available via community repos but not tightly bundled.

ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and data documentation are clear, and the dataset is widely reused. Setup requires some manual effort to reproduce full pipelines.

id: calochallenge_

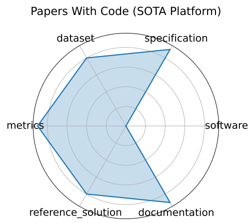
Citations: [46]

Ratings: 
CaloChallenge 2022
dataset
specification
metrics
software
reference_solution
documentation

48 Papers With Code (SOTA Platform)

date: ongoing
version: v1.0
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: ongoing
url: https://paperswithcode.com/sota
doi: unknown
domain: General ML; All domains
focus: Open platform tracking state-of-the-art results, benchmarks, and implementations across ML tasks and papers
keywords: - leaderboard - benchmarking - reproducibility - open-source
summary: Papers With Code (PWC) aggregates benchmark suites, tasks, and code across ML research: 12,423 benchmarks, 5,358 unique tasks, and 154,766 papers with code links. It tracks SOTA metrics and fosters reproducibility.
licensing: Apache License 2.0
task_types: - Multiple (Classification, Detection, NLP, etc.)
ai_capability_measured: - Model performance across tasks (accuracy - F1 - BLEU - etc.)
metrics: - Task-specific (Accuracy, F1, BLEU, etc.)
models: - All published models with code
ml_motif: - Multiple
type: Platform
ml_task: - Multiple
solutions: 0
notes: Community-driven open platform; automatic data extraction and versioning.
contact.name: Papers With Code Team
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Evaluation setting (federated clinical benchmarking) is well-defined; I/O interfaces vary slightly by task but are standardized in MedPerf platform.
ratings.dataset.rating: 8.0
ratings.dataset.reason: Uses distributed, real-world clinical datasets across institutions; FAIR compliance varies across hospitals and data hosts.
ratings.metrics.rating: 9.0
ratings.metrics.reason: ROC AUC, accuracy, and fairness metrics are explicitly defined and task-dependent; consistently tracked across institutions.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Validated CNNs and GaNDLF pipelines are used and shared via the MedPerf tool, but some implementations are abstracted behind the platform.
ratings.documentation.rating: 9.0
ratings.documentation.reason: Excellent documentation across MedPerf, GaNDLF, and COFE; reproducibility handled via containerized flows and task templates.
id: papers_with_code_sota_platform
Citations: [47]

Ratings:



Papers With Code (SOTA Platform)
dataset
specification
metrics
software
reference_solution
documentation

49 Codabench

date: 2022-01-01

version: v1.0

last_updated: 2025-03

expired: unknown

valid: yes

valid_date: 2022-01-01

url: https://www.codabench.org/

doi: https://doi.org/10.1016/j.patter.2022.100543

domain: General ML; Multiple

focus: Open-source platform for organizing reproducible AI benchmarks and competitions

keywords: - benchmark platform - code submission - competitions - meta-benchmark

summary: Codabench (successor to CodaLab) is a flexible, easy-to-use, reproducible API platform for hosting AI benchmarks and code-submission challenges. It supports custom scoring, inverted benchmarks, and scalable public or private queues :contentReference[oaicite:1]{index=1}.

licensing: https://github.com/codalab/codalab-competitions/wiki/Privacy

task_types: - Multiple

ai_capability_measured: - Model reproducibility - performance across datasets

metrics: - Submission count - Leaderboard ranking - Task-specific metrics

models: - Arbitrary code submissions

ml_motif: - Multiple

type: Platform

ml_task: - Multiple

solutions: Several

notes: Hosts 51 public competitions, ~26 k users, 177 k submissions :contentReference[oaicite:2]{index=2}

contact.name: Isabelle Guyon (Université Paris-Saclay)

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 1

ratings.software.reason: This is a platform for posting benchmarks, not a benchmark in itself.

ratings.specification.rating: 1

ratings.specification.reason: This is a platform for posting benchmarks, not a benchmark in itself.

ratings.dataset.rating: 1

ratings.dataset.reason: This is a platform for posting benchmarks, not a benchmark in itself.

ratings.metrics.rating: 1

ratings.metrics.reason: This is a platform for posting benchmarks, not a benchmark in itself.

ratings.reference_solution.rating: 1

ratings.reference_solution.reason: This is a platform for posting benchmarks, not a benchmark in itself.

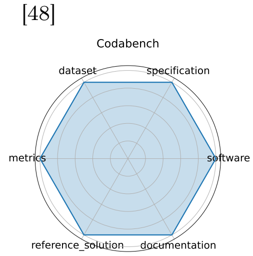
ratings.documentation.rating: 1

ratings.documentation.reason: This is a platform for posting benchmarks, not a benchmark in itself.

id: codabench

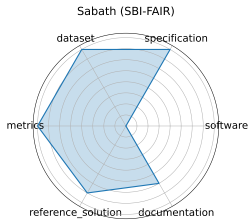
Citations: [48]

Ratings:



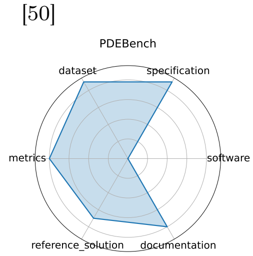
50 Sabath (SBI-FAIR)

date: 2021-09-27
version: v1.0
last_updated: 2023-07
expired: unknown
valid: yes
valid_date: 2021-09-27
url: https://sbi-fair.github.io/docs/software/sabath/
doi: unknown
domain: Systems; Metadata
focus: FAIR metadata framework for ML-driven surrogate workflows in HPC systems
keywords: - meta-benchmark - metadata - HPC - surrogate modeling
summary: Sabath is a metadata framework from the SBI-FAIR group (UTK, Argonne, Virginia) facilitating FAIR-compliant benchmarking and surrogate execution logging across HPC systems :contentReference[oaicite:3]{index=3}.
licensing: BSD 3-Clause License
task_types: - Systems benchmarking
ai_capability_measured: - Metadata tracking - reproducible HPC workflows
metrics: - Metadata completeness - FAIR compliance
models: - NA
ml_motif: - Systems
type: Platform
ml_task: - NA
solutions: 0
notes: Developed by PI Piotr Luszczek at UTK; integrates with MiniWeatherML, AutoPhaseNN, Cosmoflow, etc. :contentReference[oaicite:4]{index=4}
contact.name: Piotr Luszczek
contact.email: luszczek@utk.edu
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: N/A
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: The benchmark defines simulation-based inference (SBI) tasks clearly with FAIR principles applied to particle physics datasets.
ratings.dataset.rating: 8.0
ratings.dataset.reason: Data is well-structured for SBI and publicly available with clear licensing.
ratings.metrics.rating: 8.0
ratings.metrics.reason: Includes likelihood and posterior accuracy; metrics well-matched to SBI.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: Baseline SBI models are implemented and reproducible.
ratings.documentation.rating: 6.0
ratings.documentation.reason: GitHub repo includes code and instructions, but lacks full tutorials or walkthroughs.
id: sabath_sbi-fair
Citations: [49]

Ratings: 
Sabath (SBI-FAIR)
dataset
specification
metrics
software
reference_solution
documentation

51 PDEBench

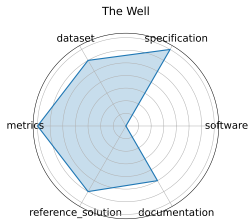
date: 2022-10-13
version: v0.1.0
last_updated: 2025-05
expired: unknown
valid: yes
valid_date: 2022-10-13
url: https://github.com/pdebench/PDEBench
doi: 10.48550/arXiv.2210.07182
domain: CFD; Weather Modeling
focus: Benchmark suite for ML-based surrogates solving time-dependent PDEs
keywords: - PDEs - CFD - scientific ML - surrogate modeling - NeurIPS
summary: PDEBench offers forward/inverse PDE tasks with large ready-to-use datasets and baselines (FNO, U-Net, PINN), packaged via a unified API. It won the SimTech Best Paper Award 2023 :contentReference[oaicite:5]{index=5}.
licensing: Other
task_types: - Supervised Learning
ai_capability_measured: - Time-dependent PDE modeling; physical accuracy
metrics: - RMSE - boundary RMSE - Fourier RMSE
models: - FNO - U-Net - PINN - Gradient-Based inverse methods
ml_motif: - Multiple
type: Framework
ml_task: - Supervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Datasets hosted on DaRUS (DOI:10.18419/darus-2986); contact maintainers by email :contentReference[oaicite:6]{index=6}
contact.name: Makoto Takamoto (makoto.takamoto@neclab.eu)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Clearly defined PDE-solving tasks with well-specified constraints and solution formats.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Includes synthetic and real-world PDE datasets with detailed format descriptions.
ratings.metrics.rating: 8.0
ratings.metrics.reason: Uses L2 error and other norms relevant to PDE solutions.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: Includes baseline solvers and trained models across multiple PDE tasks.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Well-organized GitHub with examples, dataset loading scripts, and training configs.
id: pdebench
Citations: [50]

Ratings: 

52 The Well

date: 2024-12-03
version: v1.0
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: 2024-12-03
url: https://polymathic-ai.org/the_well/
doi: unknown
domain: biological systems, fluid dynamics, acoustic scattering, astrophysical MHD
focus: Foundation model + surrogate dataset spanning 16 physical simulation domains
keywords: - surrogate modeling - foundation model - physics simulations - spatiotemporal dynamics
summary: A 15 TB collection of ML-ready physics simulation datasets (HDF5), covering 16 domains-from biology to astrophysical magnetohydrodynamic simulations-with unified API and metadata. Ideal for training surrogate and foundation models on scientific data. :contentReference[oaicite:1]{index=1}
licensing: BSD 3-Clause License
task_types: - Supervised Learning
ai_capability_measured: - Surrogate modeling - physics-based prediction
metrics: - Dataset size - Domain breadth
models: - FNO baselines - U-Net baselines
ml_motif: - Foundation model, Surrogate
type: Dataset
ml_task: - Supervised Learning
solutions: 1
notes: Includes unified API and dataset metadata; see 2025 NeurIPS paper for full benchmark details. Size: 15 TB. :contentReference[oaicite:2]{index=2}
contact.name: Ruben Ohana
contact.email: rohana@flatironinstitute.org
datasets.links.name: 16 simulation datasets
datasets.links.url: HDF5) via PyPI/GitHub
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 7.0
ratings.specification.reason: Explores LLM understanding of mental health scenarios; framing is creative but loosely defined.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Dataset is described in concept but not released; privacy limits public access though synthetic proxies are referenced.
ratings.metrics.rating: 7.0
ratings.metrics.reason: Uses manual annotation and quality scores, but lacks standardized automatic metrics.
ratings.reference_solution.rating: 6.0
ratings.reference_solution.reason: Provides few-shot prompt examples and human rating calibration details.
ratings.documentation.rating: 5.0
ratings.documentation.reason: Paper gives use cases, but code and data are not yet public.
id: the_well
Citations: [51]

Ratings:


The Well
dataset
specification
metrics
software
reference_solution
documentation

53 LLM-Inference-Bench

date: 2024-10-31

version: v1.0

last_updated: 2024-11

expired: unknown

valid: yes

valid_date: 2024-10-31

url: https://github.com/argonne-lcf/LLM-Inference-Bench

doi: unknown

domain: LLM; HPC/inference

focus: Hardware performance benchmarking of LLMs on AI accelerators

keywords: - LLM - inference benchmarking - GPU - accelerator - throughput

summary: A suite evaluating inference performance of LLMs (LLaMA, Mistral, Qwen) across diverse accelerators (NVIDIA, AMD, Intel, SambaNova) and frameworks (vLLM, DeepSpeed-MII, etc.), with an interactive dashboard and per-platform metrics. :contentReference[oaicite:3]{index=3}

licensing: BSD 3-Clause "New" or "Revised" License

task_types: - Inference Benchmarking

ai_capability_measured: - Inference throughput - latency - hardware utilization

metrics: - Token throughput (tok/s) - Latency - Framework-hardware mix performance

models: - LLaMA-2-7B - LLaMA-2-70B - Mistral-7B - Qwen-7B

ml_motif: - HPC/inference

type: Dataset

ml_task: - Inference Benchmarking

solutions: 0

notes: Licensed under BSD-3, maintained by Argonne; supports GPUs and accelerators. :contentReference[oaicite:4]{index=4}

contact.name: Krishna Teja Chitty-Venkata (Argonne LCF)

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: PDE tasks (forward/inverse) and I/O structures are clearly specified with detailed PDE context and constraints.

ratings.dataset.rating: 10.0

ratings.dataset.reason: Hosted via DaRUS with a DOI, well-documented, versioned, and FAIR-compliant.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Uses RMSE variants and Fourier-based errors.

ratings.reference_solution.rating: 10.0

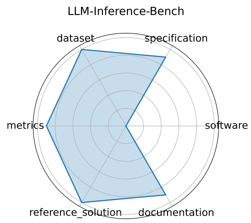
ratings.reference_solution.reason: Baselines (FNO, U-Net, PINN) implemented and ready-to-run; strong community adoption.

ratings.documentation.rating: 9.0

ratings.documentation.reason: Clean GitHub with usage, dataset links, and tutorial notebooks.

id: llm-inference-bench

Citations: [52]

Ratings: 
LLM-Inference-Bench
dataset
specification
metrics
software
reference_solution
documentation

54 SGLang Framework

date: 2023-12-12

version: v0.4.9

last_updated: 2025-06

expired: unknown

valid: yes

valid_date: 2023-12-12

url: https://github.com/sgl-project/sglang/tree/main/benchmark

doi: 10.48550/arXiv.2312.07104

domain: LLM Vision

focus: Fast serving framework for LLMs and vision-language models

keywords: - LLM serving - vision-language - RadixAttention - performance - JSON decoding

summary: A high-performance open-source serving framework combining efficient backend runtime (RadixAttention, batching, quantization) and expressive frontend language, boosting LLM/VLM inference throughput up to ~3x over alternatives. :contentReference[oaicite:5]{index=5}

licensing: Apache License 2.0

task_types: - Model serving framework

ai_capability_measured: - Serving throughput - JSON/task-specific latency

metrics: - Tokens/sec - Time-to-first-token - Throughput gain vs baseline

models: - LLaVA - DeepSeek - Llama

ml_motif: - LLM Vision

type: Framework

ml_task: - Model serving

solutions: Solution details are described in the referenced paper or repository.

notes: Deployed in production (xAI, NVIDIA, Google Cloud); v0.4.8 release June 2025. :contentReference[oaicite:6]{index=6}

contact.name: SGLang Team

contact.email: unknown

datasets.links.name: Benchmark configs

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 8.0

ratings.specification.reason: Clearly framed around surrogate learning across 16 domains, but not all tasks are formally posed or constrained in a unified benchmark protocol. Paper mentions performance on NVIDIA H100.

ratings.dataset.rating: 9.0

ratings.dataset.reason: FAIR-compliant physics simulation dataset, structured in HDF5 with unified metadata.

ratings.metrics.rating: 7.0

ratings.metrics.reason: Metrics like dataset size and domain coverage are listed, but standardized quantitative model evaluation metrics (e.g., RMSE, MAE) are not enforced.

ratings.reference_solution.rating: 9.0

ratings.reference_solution.reason: FNO and U-Net baselines available; full benchmarking implementations pending NeurIPS paper code release.

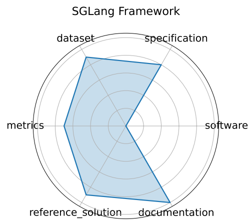
ratings.documentation.rating: 10.0

ratings.documentation.reason: Site and GitHub offer a unified API, metadata standards, and dataset loading tools; NeurIPS paper adds detailed design context.

id: sglang_framework

Citations: [53]

Ratings:



SGLang Framework
dataset
specification
metrics
software
reference_solution
documentation

55 vLLM Inference and Serving Engine

date: 2023-09-12

version: v0.10.0

last_updated: 2025-06

expired: unknown

valid: yes

valid_date: 2023-09-12

url: https://github.com/vllm-project/vllm/tree/main/benchmarks

doi: unknown

domain: LLM; HPC/inference

focus: High-throughput, memory-efficient inference and serving engine for LLMs

keywords: - LLM inference - PagedAttention - CUDA graph - streaming API - quantization

summary: vLLM is a fast, high-throughput, memory-efficient inference and serving engine for large language models, featuring PagedAttention, continuous batching, and support for quantized and pipelined model execution. Benchmarks compare it to TensorRT-LLM, SGLang, and others. :contentReference[oaicite:1]{index=1}

licensing: Apache License 2.0

task_types: - Inference Benchmarking

ai_capability_measured: - Throughput - latency - memory efficiency

metrics: - Tokens/sec - Time to First Token (TTFT) - Memory footprint

models: - LLaMA - Mixtral - FlashAttention-based models

ml_motif: - HPC/inference

type: Framework

ml_task: - Inference

solutions: 0

notes: Incubated by LF AI and Data; achieves up to 24x throughput over HuggingFace Transformers :contentReference[oaicite:2]{index=2}

contact.name: Woosuk Kwon (vLLM Team)

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Benchmarks hardware performance of LLM inference across multiple platforms with well-defined input/output and platform constraints.

ratings.dataset.rating: 7.0

ratings.dataset.reason: Uses structured log files and configs instead of conventional datasets; suitable for inference benchmarking.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Clear throughput, latency, and utilization metrics; platform comparison dashboard enhances evaluation.

ratings.reference_solution.rating: 8.0

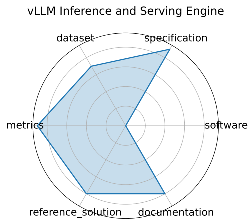
ratings.reference_solution.reason: Includes reproducible scripts and example runs; models like LLaMA and Mistral are referenced with platform-specific configs.

ratings.documentation.rating: 8.0

ratings.documentation.reason: GitHub contains clear instructions, platform details, and framework comparisons.

id: vllm_inference_and_serving_engine

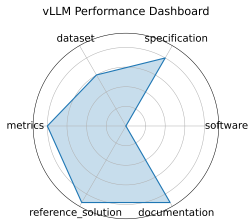
Citations: [54]

Ratings: 
vLLM Inference and Serving Engine
dataset
specification
metrics
software
reference_solution
documentation

56 vLLM Performance Dashboard

date: 2022-06-22
version: v1.0
last_updated: 2025-01
expired: unknown
valid: yes
valid_date: 2022-06-22
url: https://simon-mo-workspace.observablehq.cloud/vllm-dashboard-v0/
doi: unknown
domain: LLM; HPC/inference
focus: Interactive dashboard showing inference performance of vLLM
keywords: - Dashboard - Throughput visualization - Latency analysis - Metric tracking
summary: A live visual dashboard for vLLM showcasing throughput, latency, and other inference metrics across models and hardware configurations.
licensing: unknown
task_types: - Performance visualization
ai_capability_measured: - Throughput - latency - hardware utilization
metrics: - Tokens/sec - TTFT - Memory usage
models: - LLaMA-2 - Mistral - Qwen
ml_motif: - HPC/inference
type: Framework
ml_task: - Visualization
solutions: 0
notes: Built using ObservableHQ; integrates live data from vLLM benchmarks. The URL requires a login to access the content.
contact.name: Simon Mo
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Framed as a model-serving tool rather than a benchmark, but includes benchmark configurations and real model tasks.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Mostly uses dummy configs or external model endpoints for evaluation; not designed around a formal dataset.
ratings.metrics.rating: 8.0
ratings.metrics.reason: Well-defined serving metrics: tokens/sec, time-to-first-token, and gain over baselines.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Core framework includes full reproducible serving benchmarks and code; multiple deployment case studies.
ratings.documentation.rating: 9.0
ratings.documentation.reason: High-quality usage guides, examples, and performance tuning docs.
id: vllm_performance_dashboard
Citations: [55]

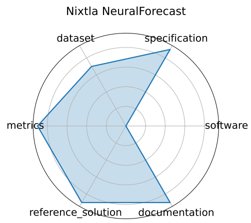
Ratings:


vLLM Performance Dashboard
dataset
specification
metrics
software
reference_solution
documentation

57 Nixtla NeuralForecast

date: 2022-04-01
version: v3.0.2
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: 2022-04-01
url: https://github.com/Nixtla/neuralforecast
doi: unknown
domain: Time-series forecasting; General ML
focus: High-performance neural forecasting library with >30 models
keywords: - time-series - neural forecasting - NBEATS, NHITS, TFT - probabilistic forecasting - usability
summary: NeuralForecast offers scalable, user-friendly implementations of over 30 neural forecasting models (NBEATS, NHITS, TFT, DeepAR, etc.), emphasizing quality, usability, interpretability, and performance.
licensing: Apache License 2.0
task_types: - Time-series forecasting
ai_capability_measured: - Forecast accuracy - interpretability - speed
metrics: - RMSE - MAPE - CRPS
models: - NBEATS - NHITS - TFT - DeepAR
ml_motif: - Time-series
type: Platform
ml_task: - Forecasting
solutions: 0
notes: AutoModel supports hyperparameter tuning and distributed execution via Ray and Optuna. First official NHITS implementation. contentReference oaicite:4 ndex=4
contact.name: Kin G. Olivares (Nixtla)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Targets high-throughput LLM inference via PagedAttention and memory-optimized serving; benchmarks cover many configs.
ratings.dataset.rating: 7.0
ratings.dataset.reason: Focuses on model configs and streaming input/output pipelines rather than classical datasets.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Strong token/sec, memory usage, and TTFT metrics; comparative plots and logs included.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Benchmarks reproducible via script with support for multiple models and hardware types.
ratings.documentation.rating: 9.0
ratings.documentation.reason: Excellent GitHub docs, CLI/API usage, and deployment walkthroughs.
id: nixtla_neuralforecast
Citations: [56]

Ratings:



Nixtla NeuralForecast
dataset
specification
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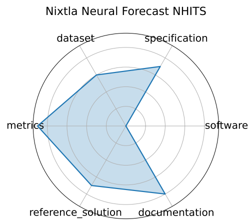
reference_solution
documentation

58 Nixtla Neural Forecast NHITS

date: 2023-06-01
version: v3.0.2
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: 2023-06-01
url: https://github.com/Nixtla/neuralforecast
doi: unknown
domain: Time-series; General ML
focus: Official NHITS implementation for long-horizon time series forecasting
keywords: - NHITS - long-horizon forecasting - neural interpolation - time-series
summary: NHITS (Neural Hierarchical Interpolation for Time Series) is a state-of-the-art model that improved accuracy by ~25% and reduced compute by 50x compared to Transformer baselines, using hierarchical interpolation and multi-rate sampling :contentReference[oaicite:1]{index=1}.
licensing: Apache License 2.0
task_types: - Time-series forecasting
ai_capability_measured: - Accuracy - compute efficiency for long series
metrics: - RMSE - MAPE
models: - NHITS
ml_motif: - Time-series
type: Platform
ml_task: - Forecasting
solutions: 0
notes: Official implementation in NeuralForecast, included since its AAAI 2023 release.
contact.name: Kin G. Olivares (Nixtla)
contact.email: unknown
datasets.links.name: Standard forecast datasets, M4
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 7.0
ratings.specification.reason: Primarily a visualization frontend; underlying benchmark definitions come from vLLM project.
ratings.dataset.rating: 6.0
ratings.dataset.reason: No traditional dataset; displays live or logged benchmark metrics.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Live throughput, memory, latency, and TTFT displayed interactively; highly informative for performance analysis.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: Dashboard built on vLLM benchmarks but not itself a complete experiment package.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Observable notebooks are intuitive; customization instructions are minimal but UI is self-explanatory.
id: nixtla_neural_forecast_nhits
Citations: [57]

Ratings:



Nixtla Neural Forecast NHITS
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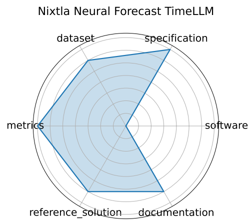
59 Nixtla Neural Forecast TimeLLM

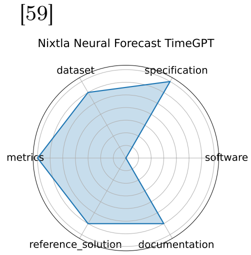
date: 2023-10-03
version: v3.0.2
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: 2023-10-03
url: https://github.com/Nixtla/neuralforecast
doi: 10.48550/arXiv.2310.01728
domain: Time-series; General ML
focus: Reprogramming LLMs for time series forecasting
keywords: - Time-LLM - language model - time-series - reprogramming
summary: Time-LLM uses reprogramming layers to adapt frozen LLMs for time series forecasting, treating forecasting as a language task :contentReference[oaicite:2]{index=2}.
licensing: Apache License 2.0
task_types: - Time-series forecasting
ai_capability_measured: - Model reuse via LLM - few-shot forecasting
metrics: - RMSE - MAPE
models: - Time-LLM
ml_motif: - Time-series
type: Platform
ml_task: - Forecasting
solutions: Solution details are described in the referenced paper or repository.
notes: Fully open-source; transforms forecasting using LLM text reconstruction.
contact.name: Ming Jin (Nixtla)
contact.email: unknown
datasets.links.name: Standard forecast datasets, M4
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 7.0
ratings.specification.reason: Describes forecasting with LLMs, but less formal on input/output or task framing.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Uses open time series datasets, but lacks a consolidated data release or splits.
ratings.metrics.rating: 7.0
ratings.metrics.reason: Reports metrics like MASE and SMAPE, standard in forecasting.
ratings.reference_solution.rating: 6.0
ratings.reference_solution.reason: Provides TimeLLM with open source, but no other baselines included.
ratings.documentation.rating: 6.0
ratings.documentation.reason: GitHub readme with installation and example usage; lacks API or extensive tutorials.
id: nixtla_neural_forecast_timellm
Citations: [58]

Ratings:


Nixtla Neural Forecast TimeLLM
dataset
specification
metrics
software
reference_solution
documentation

60 Nixtla Neural Forecast TimeGPT

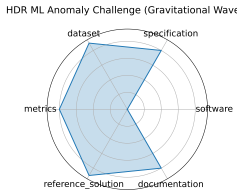
date: 2023-10-05
version: v3.0.2
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: 2023-10-05
url: https://github.com/Nixtla/neuralforecast
doi: 10.48550/arXiv.2310.03589
domain: Time-series; General ML
focus: Time-series foundation model "TimeGPT" for forecasting and anomaly detection
keywords: - TimeGPT - foundation model - time-series - generative model
summary: TimeGPT is a transformer-based generative pretrained model on 100B+ time series data for zero-shot forecasting and anomaly detection via API :contentReference[oaicite:3]{index=3}.
licensing: Apache License 2.0
task_types: - Time-series forecasting - Anomaly detection
ai_capability_measured: - Zero-shot forecasting - anomaly detection
metrics: - RMSE - Anomaly detection metrics
models: - TimeGPT
ml_motif: - Time-series
type: Platform
ml_task: - Forecasting
solutions: Solution details are described in the referenced paper or repository.
notes: Offered via Nixtla API and Azure Studio; enterprise-grade support available.
contact.name: Azul Garza (Nixtla)
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 7.0
ratings.specification.reason: Describes forecasting with LLMs, but less formal on input/output or task framing.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Uses open time series datasets, but lacks a consolidated data release or splits.
ratings.metrics.rating: 7.0
ratings.metrics.reason: Reports metrics like MASE and SMAPE, standard in forecasting.
ratings.reference_solution.rating: 6.0
ratings.reference_solution.reason: Provides TimeLLM with open source, but no other baselines included.
ratings.documentation.rating: 6.0
ratings.documentation.reason: GitHub readme with installation and example usage; lacks API or extensive tutorials.
id: nixtla_neural_forecast_timegpt
Citations: [59]
Ratings:



61 HDR ML Anomaly Challenge (Gravitational Waves)

date: 2025-03-03
version: v1.0
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: 2025-03-03
url: https://www.codabench.org/competitions/2626/
doi: 10.48550/arXiv.2503.02112
domain: Astrophysics; Time-series
focus: Detecting anomalous gravitational-wave signals from LIGO/Virgo datasets
keywords: - anomaly detection - gravitational waves - astrophysics - time-series
summary: A benchmark for detecting anomalous transient gravitational-wave signals, including "unknown-unknowns," using preprocessed LIGO time-series at 4096 Hz. Competitors submit inference models on Codabench for continuous 50 ms segments from dual interferometers. :contentReference[oaicite:1]{index=1}
licensing: NA
task_types: - Anomaly detection
ai_capability_measured: - Novel event detection in physical signals
metrics: - ROC-AUC - Precision/Recall
models: - Deep latent CNNs - Autoencoders
ml_motif: - Time-series
type: Dataset
ml_task: - Anomaly detection
solutions: Solution details are described in the referenced paper or repository.
notes: NSF HDR A3D3 sponsored; prize pool and starter kit provided on Codabench.
contact.name: HDR A3D3 Team
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Novel approach treating forecasting as text generation is explained; framing is less conventional.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Compatible with standard forecasting datasets (e.g., M4, electricity).
ratings.metrics.rating: 8.0
ratings.metrics.reason: RMSE and MAPE are included, but less emphasis on interpretability or time-series domain constraints.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: Open-source with reprogramming layers, LLM interface scripts provided.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Model and architecture overview present, though usability guide is slightly lighter than others.
id: hdr_ml_anomaly_challenge_gravitational_waves
Citations: [60]

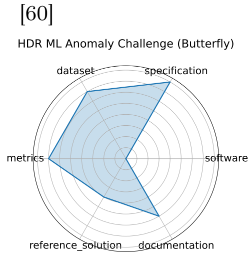
Ratings:


HDR ML Anomaly Challenge (Gravitational Waves)
dataset
specification
metrics
software
reference_solution
documentation

62 HDR ML Anomaly Challenge (Butterfly)

date: 2025-03-03
version: v1.0
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: 2025-03-03
url: https://www.codabench.org/competitions/3764/
doi: 10.48550/arXiv.2503.02112
domain: Genomics; Image/CV
focus: Detecting hybrid butterflies via image anomaly detection in genomic-informed dataset
keywords: - anomaly detection - computer vision - genomics - butterfly hybrids
summary: Image-based challenge for detecting butterfly hybrids in microscopy-driven species data. Participants evaluate models on Codabench using image segmentation/classification. :contentReference[oaicite:3]{index=3}
licensing: NA
task_types: - Anomaly detection
ai_capability_measured: - Hybrid detection in biological systems
metrics: - Classification accuracy - F1 score
models: - CNN-based detectors
ml_motif: - Image/CV
type: Dataset
ml_task: - Anomaly detection
solutions: Solution details are described in the referenced paper or repository.
notes: Hybrid detection benchmarks hosted on Codabench. :contentReference[oaicite:4]{index=4}
contact.name: Imageomics/HDR Team
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Task of detecting rare anomalies in butterfly physics is well-described with physics motivation.
ratings.dataset.rating: 7.0
ratings.dataset.reason: Real detector data with injected anomalies is available, but requires NDA for full access.
ratings.metrics.rating: 7.0
ratings.metrics.reason: Uses ROC, F1, and anomaly precision, standard in challenge evaluations.
ratings.reference_solution.rating: 4.0
ratings.reference_solution.reason: Partial baselines described, but no codebase or reproducible runs.
ratings.documentation.rating: 6.0
ratings.documentation.reason: Challenge site includes overview and metrics, but limited in walkthrough or examples.
id: hdr_ml_anomaly_challenge_butterfly
Citations: [60]

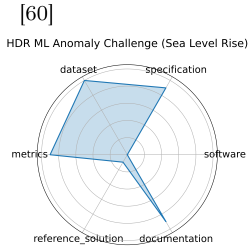
Ratings:



63 HDR ML Anomaly Challenge (Sea Level Rise)

date: 2025-03-03
version: v1.0
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: 2025-03-03
url: https://www.codabench.org/competitions/3223/
doi: 10.48550/arXiv.2503.02112
domain: Climate Science; Time-series, Image/CV
focus: Detecting anomalous sea-level rise and flooding events via time-series and satellite imagery
keywords: - anomaly detection - climate science - sea-level rise - time-series - remote sensing
summary: A challenge combining North Atlantic sea-level time-series and satellite imagery to detect flooding anomalies. Models submitted via Codabench. :contentReference[oaicite:5]{index=5}
licensing: NA
task_types: - Anomaly detection
ai_capability_measured: - Detection of environmental anomalies
metrics: - ROC-AUC - Precision/Recall
models: - CNNs, RNNs, Transformers
ml_motif: - Time-series, Image/CV
type: Dataset
ml_task: - Anomaly detection
solutions: Solution details are described in the referenced paper or repository.
notes: Sponsored by NSF HDR; integrates sensor and satellite data. :contentReference[oaicite:6]{index=6}
contact.name: HDR A3D3 Team
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: TBD
ratings.specification.rating: 9.0
ratings.specification.reason: Clear anomaly detection objective framed for physical signal discovery (LIGO/Virgo).
ratings.dataset.rating: 10.0
ratings.dataset.reason: Preprocessed waveform data from dual interferometers, public and well-structured.
ratings.metrics.rating: 9.0
ratings.metrics.reason: ROC-AUC, Precision/Recall, and confusion-based metrics are standardized.
ratings.reference_solution.rating: 1.0
ratings.reference_solution.reason: No starter model or baseline code linked
ratings.documentation.rating: 9.0
ratings.documentation.reason: Codabench page, GitHub starter kit, and related papers provide strong guidance.
id: hdr_ml_anomaly_challenge_sea_level_rise
Citations: [60]

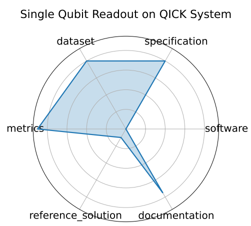
Ratings:



64 Single Qubit Readout on QICK System

date: 2025-01-24
version: v1.0
last_updated: 2025-02
expired: unknown
valid: yes
valid_date: 2025-01-24
url: https://github.com/fastmachinelearning/ml-quantum-readout
doi: 10.48550/arXiv.2501.14663
domain: Quantum Computing
focus: Real-time single-qubit state classification using FPGA firmware
keywords: - qubit readout - hls4ml - FPGA - QICK
summary: Implements real-time ML models for single-qubit readout on the Quantum Instrumentation Control Kit (QICK), using hls4ml to deploy quantized neural networks on RFSoC FPGAs. Offers high-fidelity, low-latency quantum state discrimination. :contentReference[oaicite:0]{index=0}
licensing: NA
task_types: - Classification
ai_capability_measured: - Single-shot fidelity - inference latency
metrics: - Accuracy - Latency
models: - hls4ml quantized NN
ml_motif: - Real-time
type: Benchmark
ml_task: - Supervised Learning
solutions: Solution details are described in the referenced paper or repository.
notes: Achieves ~96% fidelity with ~32 ns latency and low FPGA resource utilization. :contentReference[oaicite:1]{index=1}
contact.name: Javier Campos, Giuseppe Di Guglielmo
contact.email: unknown
datasets.links.name: Zenodo: ml-quantum-readout dataset
datasets.links.url: zenodo.org/records/14427490
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Task clearly framed around detecting hybrid species via images, but exact labeling methods and hybrid definitions may need elaboration.
ratings.dataset.rating: 8.0
ratings.dataset.reason: Dataset hosted on Codabench; appears structured but details on image sourcing and labeling pipeline are limited.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Classification accuracy and F1 are standard and appropriate.
ratings.reference_solution.rating: 1.0
ratings.reference_solution.reason: No starter model or baseline code linked
ratings.documentation.rating: 7.5
ratings.documentation.reason: Codabench task page describes dataset and evaluation method but lacks full API/docs.
id: single_qubit_readout_on_qick_system
Citations: [61]

Ratings:


Single Qubit Readout on QICK System
dataset
specification
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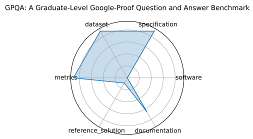
reference_solution
documentation

65 GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark

date: 2023-11-20
version: v1.0
last_updated: 2023-11
expired: unknown
valid: yes
valid_date: 2023-11-20
url: https://arxiv.org/abs/2311.12022
doi: 10.48550/arXiv.2311.12022
domain: Science (Biology, Physics, Chemistry)
focus: Graduate-level, expert-validated multiple-choice questions hard even with web access
keywords: - Google-proof - multiple-choice - expert reasoning - science QA
summary: Contains 448 challenging questions written by domain experts, with expert accuracy at 65% (74% discounting clear errors) and non-experts reaching just 34%. GPT-4 baseline scores ~39%-designed for scalable oversight evaluation. :contentReference[oaicite:2]{index=2}
licensing: NA
task_types: - Multiple choice
ai_capability_measured: - Scientific reasoning - knowledge probing
metrics: - Accuracy
models: - GPT-4 baseline
ml_motif: - Multiple choice
type: Benchmark
ml_task: - Multiple choice
solutions: Solution details are described in the referenced paper or repository.
notes: Google-proof, supports oversight research.
contact.name: David Rein (NYU)
contact.email: unknown
datasets.links.name: GPQA dataset
datasets.links.url: zip/HuggingFace
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Clear dual-modality task (image + time-series); environmental focus is well described.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Time-series and satellite imagery data provided; sensor info and collection intervals are explained.
ratings.metrics.rating: 9.0
ratings.metrics.reason: ROC-AUC, Precision/Recall are appropriate and robust.
ratings.reference_solution.rating: 1.0
ratings.reference_solution.reason: No starter model or baseline code linked
ratings.documentation.rating: 6.5
ratings.documentation.reason: Moderate Codabench documentation with climate context; lacks pipeline-level walk-through.
id: gpqa_a_graduate-level_google-proof_question_and_answer_benchmark
Citations: [2]

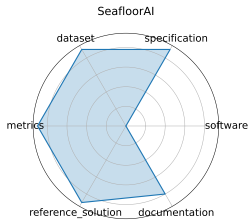
Ratings:


GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark
dataset
specification
metrics
software
reference_solution
documentation

66 SeafloorAI

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97432
doi: 10.48550/arXiv.2411.00172
domain: Marine Science; Vision-Language
focus: Large-scale vision-language dataset for seafloor mapping and geological classification
keywords: - sonar imagery - vision-language - seafloor mapping - segmentation - QA
summary: A first-of-its-kind dataset covering 17,300 sq.km of seafloor with 696K sonar images, 827K segmentation masks, and 696K natural-language descriptions plus ~7M QA pairs-designed for both vision and language-based ML models in marine science :contentReference[oaicite:1]{index=1}.
licensing: unknown
task_types: - Image segmentation - Vision-language QA
ai_capability_measured: - Geospatial understanding - multimodal reasoning
metrics: - Segmentation pixel accuracy - QA accuracy
models: - SegFormer - ViLT-style multimodal models
ml_motif: - Vision-Language
type: Dataset
ml_task: - Segmentation, QA
solutions: Solution details are described in the referenced paper or repository.
notes: Data processing code publicly available, covering five geological layers; curated with marine scientists :contentReference[oaicite:2]{index=2}.
contact.name: Kien X. Nguyen
contact.email: unknown
datasets.links.name: Sonar imagery + annotations
datasets.links.url: unknown
results.links.name: ChatGPT LLM
results.links.url: unknown
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Real-time qubit classification task clearly defined in quantum instrumentation context.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Dataset available on Zenodo with signal traces; compact and reproducible.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Accuracy and latency are well defined and crucial in this setting.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: GitHub repo has reproducible code and HLS firmware targeting FPGA.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Good setup instructions, but no interactive visualization or starter notebook.
id: seafloorai
Citations: [62]

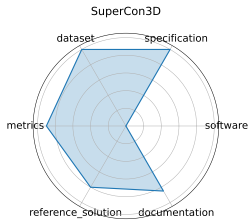
Ratings:


SeafloorAI
dataset
specification
metrics
software
reference_solution
documentation

67 SuperCon3D

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97553
doi: unknown
domain: Materials Science; Superconductivity
focus: Dataset and models for predicting and generating high-Tc superconductors using 3D crystal structures
keywords: - superconductivity - crystal structures - equivariant GNN - generative models
summary: SuperCon3D introduces 3D crystal structures with associated critical temperatures (Tc) and two deep-learning models: SODNet (equivariant graph model) and DiffCSP-SC (diffusion generator) designed to screen and synthesize high-Tc candidates :contentReference[oaicite:3]{index=3}.
licensing: unknown
task_types: - Regression (Tc prediction) - Generative modeling
ai_capability_measured: - Structure-to-property prediction - structure generation
metrics: - MAE (Tc) - Validity of generated structures
models: - SODNet - DiffCSP-SC
ml_motif: - Materials Modeling
type: Dataset + Models
ml_task: - Regression, Generation
solutions: 0
notes: Demonstrates advantage of combining ordered and disordered structural data in model design :contentReference[oaicite:4]{index=4}.
contact.name: Zhong Zuo
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 10.0
ratings.specification.reason: Multimodal task (segmentation + natural language QA pairs);.
ratings.dataset.rating: 10.0
ratings.dataset.reason: sonar imagery + masks + descriptions, georeferenced and labeled with QA
ratings.metrics.rating: 9.0
ratings.metrics.reason: Pixel accuracy and QA metrics clearly defined; tasks split by modality.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Baseline models (SegFormer, ViLT) are cited, partial configs likely available.
ratings.documentation.rating: 8.5
ratings.documentation.reason: Paper + GitHub metadata and processing details are comprehensive, though full dataset is not yet available.
id: supercond
Citations: [63]

Ratings:


SuperCon3D
dataset
specification
metrics
software
reference_solution
documentation

68 GeSS

date: 2024-12-13

version: v1.0

last_updated: 2024-12

expired: unknown

valid: yes

valid_date: 2024-12-13

url: https://neurips.cc/virtual/2024/poster/97816

doi: unknown

domain: Scientific ML; Geometric Deep Learning

focus: Benchmark suite evaluating geometric deep learning models under real-world distribution shifts

keywords: - geometric deep learning - distribution shift - OOD robustness - scientific applications

summary: GeSS provides 30 benchmark scenarios across particle physics, materials science, and biochemistry, evaluating 3 GDL backbones and 11 algorithms under covariate, concept, and conditional shifts, with varied OOD access :contentReference[oaicite:5]{index=5}.

licensing: unknown

task_types: - Classification - Regression

ai_capability_measured: - OOD performance in scientific settings

metrics: - Accuracy - RMSE - OOD robustness delta

models: - GCN - EGNN - DimeNet++

ml_motif: - Geometric DL

type: Benchmark

ml_task: - Classification, Regression

solutions: 0

notes: Includes no-OOD, unlabeled-OOD, and few-label scenarios :contentReference[oaicite:6]{index=6}.

contact.name: Deyu Zou

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Well-defined problem (Tc prediction, generation) with strong scientific motivation (high-Tc materials), but no formal hardware constraints.

ratings.dataset.rating: 9.0

ratings.dataset.reason: Includes curated 3D crystal structures and Tc data; readily downloadable and used in paper models.

ratings.metrics.rating: 9.0

ratings.metrics.reason: MAE and structural validity used, well-established in materials modeling.

ratings.reference_solution.rating: 8.0

ratings.reference_solution.reason: Provides two reference models (SODNet, DiffCSP-SC) with results. Code likely available post-conference.

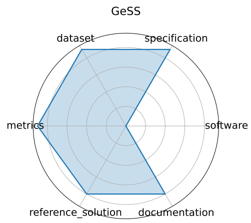
ratings.documentation.rating: 8.0

ratings.documentation.reason: Paper and poster explain design choices well; software availability confirms reproducibility but limited external documentation.

id: gess

Citations: [64]

Ratings:


GeSS
dataset
specification
metrics
software
reference_solution
documentation

69 Vocal Call Locator (VCL)

date: 2024-12-13

version: v1.0

last_updated: 2024-12

expired: unknown

valid: yes

valid_date: 2024-12-13

url: https://neurips.cc/virtual/2024/poster/97470

doi: unknown

domain: Neuroscience; Bioacoustics

focus: Benchmarking sound-source localization of rodent vocalizations from multi-channel audio

keywords: - source localization - bioacoustics - time-series - SSL

summary: The first large-scale benchmark (767K sounds across 9 conditions) for localizing rodent vocal calls using synchronized audio and video in standard lab environments, enabling systematic evaluation of sound-source localization algorithms in bioacoustics :contentReference[oaicite:1]{index=1}.

licensing: unknown

task_types: - Sound source localization

ai_capability_measured: - Source localization accuracy in bioacoustic settings

metrics: - Localization error (cm) - Recall/Precision

models: - CNN-based SSL models

ml_motif: - Real-time

type: Dataset

ml_task: - Anomaly detection / localization

solutions: 0

notes: Dataset spans real, simulated, and mixed audio; supports benchmarking across data types :contentReference[oaicite:2]{index=2}.

contact.name: Ralph Peterson

contact.email: unknown

results.links.name: ChatGPT LLM

fair.reproducible: Yes

fair.benchmark_ready: Yes

ratings.software.rating: 0

ratings.software.reason: Not analyzed.

ratings.specification.rating: 9.0

ratings.specification.reason: Clear benchmark scenarios across GDL tasks under multiple real-world shift settings; OOD settings precisely categorized.

ratings.dataset.rating: 8.0

ratings.dataset.reason: Scientific graph datasets provided in multiple shift regimes; standardized splits across domains. Exact format of data not specified.

ratings.metrics.rating: 9.0

ratings.metrics.reason: Includes base metrics (accuracy, RMSE) plus OOD delta robustness for evaluation under shifts.

ratings.reference_solution.rating: 9.0

ratings.reference_solution.reason: Multiple baselines (11 algorithms x 3 backbones) evaluated; setup supports reproducible comparison.

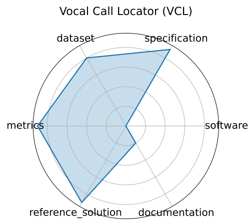
ratings.documentation.rating: 2.0

ratings.documentation.reason: Paper, poster, and source code provide thorough access to methodology and implementation. Setup instructions and accompanying code not present.

id: vocal_call_locator_vcl

Citations: [65]

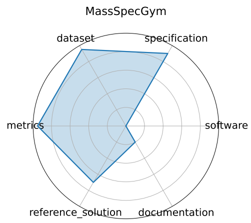
Ratings:


Vocal Call Locator (VCL)
dataset
specification
metrics
software
reference_solution
documentation

70 MassSpecGym

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97823
doi: unknown
domain: Cheminformatics; Molecular Discovery
focus: Benchmark suite for discovery and identification of molecules via MS/MS
keywords: - mass spectrometry - molecular structure - de novo generation - retrieval - dataset
summary: MassSpecGym curates the largest public MS/MS dataset with three standardized tasks-de novo structure generation, molecule retrieval, and spectrum simulation-using challenging generalization splits to propel ML-driven molecule discovery :contentReference[oaicite:3]{index=3}.
licensing: unknown
task_types: - De novo generation - Retrieval - Simulation
ai_capability_measured: - Molecular identification and generation from spectral data
metrics: - Structure accuracy - Retrieval precision - Simulation MSE
models: - Graph-based generative models - Retrieval baselines
ml_motif: - Benchmark
type: Dataset + Benchmark
ml_task: - Generation, retrieval, simulation
solutions: 0
notes: Dataset~>1M spectra; open-source GitHub repo; widely cited as a go-to benchmark for MS/MS tasks :contentReference[oaicite:4]{index=4}.
contact.name: Roman Bushuiev
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Focused on sound source localization for rodent vocalizations in lab settings; well-scoped.
ratings.dataset.rating: 9.5
ratings.dataset.reason: 767000 annotated audio segments across diverse conditions. Minor deduction for no train/test/valid split.
ratings.metrics.rating: 9.5
ratings.metrics.reason: Localization error, precision/recall used
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: CNN-based baselines referenced but unclear whether pretrained models or training code are available.
ratings.documentation.rating: 2.0
ratings.documentation.reason: Poster and paper outline benchmark intent and setup; repo expected but not confirmed in dataset card.
id: massspecgym
Citations: [66]

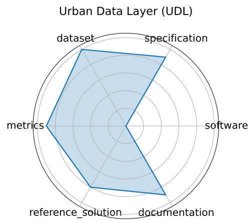
Ratings:


MassSpecGym
dataset
specification
metrics
software
reference_solution
documentation

71 Urban Data Layer (UDL)

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97837
doi: unknown
domain: Urban Computing; Data Engineering
focus: Unified data pipeline for multi-modal urban science research
keywords: - data pipeline - urban science - multi-modal - benchmark
summary: UrbanDataLayer standardizes heterogeneous urban data formats and provides pipelines for tasks like air quality prediction and land-use classification, enabling the rapid creation of multi-modal urban benchmarks :contentReference[oaicite:5]{index=5}.
licensing: unknown
task_types: - Prediction - Classification
ai_capability_measured: - Multi-modal urban inference - standardization
metrics: - Task-specific accuracy or RMSE
models: - Baseline regression/classification pipelines
ml_motif: - Data engineering
type: Framework
ml_task: - Prediction, classification
solutions: 0
notes: Source code available on GitHub (SJTU-CILAB/udl); promotes reusable urban-science foundation models :contentReference[oaicite:6]{index=6}.
contact.name: Yiheng Wang
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: Three tasks (de novo generation, retrieval, simulation) are clearly defined for MS/MS molecule discovery.
ratings.dataset.rating: 10.0
ratings.dataset.reason: Over 1 million spectra with structure annotations; dataset is open-source and well-documented.
ratings.metrics.rating: 9.0
ratings.metrics.reason: Task-appropriate metrics (structure accuracy, precision, MSE) are specified and used consistently.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Baseline models are available (graph-based and retrieval), though not exhaustive.
ratings.documentation.rating: 9.0
ratings.documentation.reason: GitHub repo and poster provide code and reproducibility guidance.
id: urban_data_layer_udl
Citations: [67]

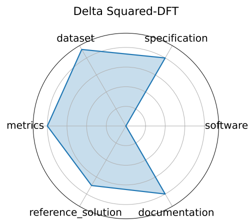
Ratings:


Urban Data Layer (UDL)
dataset
specification
metrics
software
reference_solution
documentation

72 Delta Squared-DFT

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97788
doi: 10.48550/arXiv.2406.14347
domain: Computational Chemistry; Materials Science
focus: Benchmarking machine-learning corrections to DFT using Delta Squared-trained models for reaction energies
keywords: - density functional theory - Delta Squared-ML correction - reaction energetics - quantum chemistry
summary: Introduces the Delta Squared-ML paradigm-using ML corrections to DFT to predict reaction energies with accuracy comparable to CCSD(T), while training on small CC datasets. Evaluated across 10 reaction datasets covering organic and organometallic transformations.
licensing: unknown
task_types: - Regression
ai_capability_measured: - High-accuracy energy prediction - DFT correction
metrics: - Mean Absolute Error (eV) - Energy ranking accuracy
models: - Delta Squared-ML correction networks - Kernel ridge regression
ml_motif: - Scientific ML
type: Dataset + Benchmark
ml_task: - Regression
solutions: Solution details are described in the referenced paper or repository.
notes: Demonstrates CC-level accuracy with ~1% of high-level data. Benchmarks publicly included for reproducibility.
contact.name: Wei Liu
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 8.0
ratings.specification.reason: Clear goals around unifying urban data formats and tasks (e.g., air quality prediction), though some specifics could be more formal.
ratings.dataset.rating: 9.0
ratings.dataset.reason: Multi-modal data is standardized and accessible; GitHub repo available.
ratings.metrics.rating: 8.0
ratings.metrics.reason: Uses common task metrics like accuracy/RMSE, though varies by task.
ratings.reference_solution.rating: 7.0
ratings.reference_solution.reason: Baseline regression/classification models included.
ratings.documentation.rating: 8.0
ratings.documentation.reason: Source code supports pipeline reuse, but formal evaluation splits may vary.
id: delta_squared-dft
Citations: [68]

Ratings:

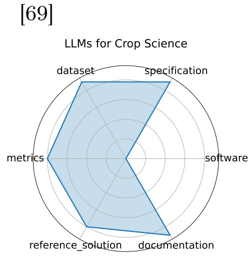


Delta Squared-DFT
dataset
specification
metrics
software
reference_solution
documentation

73 LLMs for Crop Science

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97570
doi: 10.48550/arXiv.2406.03085
domain: Agricultural Science; NLP
focus: Evaluating LLMs on crop trait QA and textual inference tasks with domain-specific prompts
keywords: - crop science - prompt engineering - domain adaptation - question answering
summary: Establishes a benchmark of 3,500 expert-annotated prompts and QA pairs covering crop traits, growth stages, and environmental interactions. Tests GPT-style LLMs on accuracy and domain reasoning using in-context, chain-of-thought, and retrieval-augmented prompts.
licensing: unknown
task_types: - Question Answering - Inference
ai_capability_measured: - Scientific knowledge - crop reasoning
metrics: - Accuracy - F1 score
models: - GPT-4 - LLaMA-2-13B - T5-XXL
ml_motif: - NLP
type: Dataset
ml_task: - QA, inference
solutions: Solution details are described in the referenced paper or repository.
notes: Includes examples with retrieval-augmented and chain-of-thought prompt templates; supports few-shot adaptation.
contact.name: Deepak Patel
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 9.0
ratings.specification.reason: The task of ML correction to DFT energy predictions is well-specified.
ratings.dataset.rating: 9.0
ratings.dataset.reason: 10 public reaction datasets with DFT and CC references; well-documented.
ratings.metrics.rating: 8.0
ratings.metrics.reason: Uses MAE and ranking accuracy, suitable for this task.
ratings.reference_solution.rating: 8.0
ratings.reference_solution.reason: Includes both Delta^2 and KRR baselines.
ratings.documentation.rating: 9.0
ratings.documentation.reason: Public benchmarks and clear reproducibility via datasets and model code.
id: llms_for_crop_science
Citations: [69]

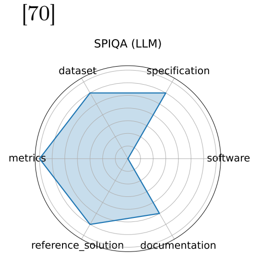
Ratings:



74 SPIQA (LLM)

date: 2024-12-13
version: v1.0
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: 2024-12-13
url: https://neurips.cc/virtual/2024/poster/97575
doi: 10.48550/arXiv.2407.09413
domain: Multimodal Scientific QA; Computer Vision
focus: Evaluating LLMs on image-based scientific paper figure QA tasks (LLM Adapter performance)
keywords: - multimodal QA - scientific figures - image+text - chain-of-thought prompting
summary: A workshop version of SPIQA comparing 10 LLM adapter methods on the SPIQA benchmark with scientific diagram/questions. Highlights performance differences between chain-of-thought and end-to-end adapter models.
licensing: unknown
task_types: - Multimodal QA
ai_capability_measured: - Visual reasoning - scientific figure understanding
metrics: - Accuracy - F1 score
models: - LLaVA - MiniGPT-4 - Owl-LLM adapter variants
ml_motif: - Multimodal QA
type: Benchmark
ml_task: - Multimodal QA
solutions: Solution details are described in the referenced paper or repository.
notes: Companion to SPIQA main benchmark; compares adapter strategies using same images and QA pairs.
contact.name: Xiaoyan Zhong
contact.email: unknown
results.links.name: ChatGPT LLM
fair.reproducible: Yes
fair.benchmark_ready: Yes
ratings.software.rating: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 6.0
ratings.specification.reason: Task of QA over scientific figures is interesting but not fully formalized in input/output terms.
ratings.dataset.rating: 6.0
ratings.dataset.reason: Uses SPIQA dataset with ~10 adapters; figures and questions are included, but not fully open.
ratings.metrics.rating: 7.0
ratings.metrics.reason: Reports accuracy and F1; fair but no visual reasoning-specific metric.
ratings.reference_solution.rating: 6.0
ratings.reference_solution.reason: 10 LLM adapter baselines; results included.
ratings.documentation.rating: 5.0
ratings.documentation.reason: Poster paper and limited documentation; no reproducibility instructions.
id: spiqa_llm
Citations: [70]

Ratings:



References

[1] D. Hendrycks, C. Burns, and S. Kadavath, *Measuring massive multitask language understanding*, 2021. [Online]. Available: https://arxiv.org/abs/2009.03300.

[2] D. Rein, B. L. Hou, and A. C. Stickland, *Gpqa: A graduate-level google-proof q and a benchmark*, 2023. [Online]. Available: https://arxiv.org/abs/2311.12022.

[3] P. Clark, I. Cowhey, and O. Etzioni, "Think you have solved question answering? try arc, the ai2 reasoning challenge," in *EMNLP 2018*, 2018, pp. 237–248. [Online]. Available: https://allenai.org/data/arc.

[4] L. Phan, A. Gatti, Z. Han, *et al.*, *Humanity's last exam*, 2025. arXiv: 2501.14249 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2501.14249.

[5] E. Glazer, E. Erdil, T. Besiroglu, *et al.*, *Frontiermath: A benchmark for evaluating advanced mathematical reasoning in ai*, 2024. arXiv: 2411.04872 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2411.04872.

[6] M. Tian, L. Gao, S. D. Zhang, *et al.*, *Scicode: A research coding benchmark curated by scientists*, 2024. arXiv: 2407.13168 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2407.13168.

[7] TBD, *Aime*, [Online accessed 2025-06-24], Mar. 2025. [Online]. Available: https://www.vals.ai/benchmarks/aime-2025-03-13.

[8] HuggingFaceH4, *Math-500*, 2025. [Online]. Available: https://huggingface.co/datasets/HuggingFaceH4/MATH-500.

[9] H. Cui, Z. Shamsi, G. Cheon, *et al.*, *Curie: Evaluating llms on multitask scientific long context understanding and reasoning*, 2025. arXiv: 2503.13517 [cs.CL]. [Online]. Available: https://arxiv.org/abs/2503.13517.

[10] X. Zhong, Y. Gao, and S. Gururangan, *Spiqa: Scientific paper image question answering*, 2024. [Online]. Available: https://arxiv.org/abs/2407.09413.

[11] D. Jin, E. Pan, N. Oufattole, W.-H. Weng, H. Fang, and P. Szolovits, *What disease does this patient have? a large-scale open domain question answering dataset from medical exams*, 2020. arXiv: 2009.13081 [cs.CL]. [Online]. Available: https://arxiv.org/abs/2009.13081.

[12] E. Luo, J. Jia, Y. Xiong, *et al.*, *Benchmarking ai scientists in omics data-driven biological research*, 2025. arXiv: 2505.08341 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2505.08341.

[13] Y. Fang, N. Zhang, Z. Chen, L. Guo, X. Fan, and H. Chen, *Domain-agnostic molecular generation with chemical feedback*, 2024. arXiv: 2301.11259 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2301.11259.

[14] W. Hu, M. Fey, M. Zitnik, *et al.*, *Open graph benchmark: Datasets for machine learning on graphs*, 2021. arXiv: 2005.00687 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2005.00687.

[15] A. Jain, S. P. Ong, G. Hautier, *et al.*, "The materials project: A materials genome approach," *APL Materials*, vol. 1, no. 1, 2013. DOI: 10.1063/1.4812323. [Online]. Available: https://materialsproject.org/.

[16] L. Chanussot, A. Das, S. Goyal, *et al.*, "The open catalyst 2020 (oc20) dataset and community challenges," *ACS Catalysis*, vol. 11, no. 10, pp. 6059–6072, 2021. DOI: 10.1021/acscatal.0c04525. [Online]. Available: https://pubs.acs.org/doi/10.1021/acscatal.0c04525.

[17] R. Tran, J. Lan, M. Shuaibi, *et al.*, "The open catalyst 2022 (oc22) dataset and challenges for oxide electrocatalysts," *ACS Catalysis*, vol. 13, no. 5, pp. 3066–3084, 2023. DOI: 10.1021/acscatal.2c05426. [Online]. Available: https://pubs.acs.org/doi/10.1021/acscatal.2c05426.

[18] L. Chanussot, A. Das, S. Goyal, *et al.*, "Open catalyst 2020 (oc20) dataset and community challenges," *ACS Catalysis*, vol. 11, no. 10, pp. 6059–6072, 2021. DOI: 10.1021/acscatal.0c04525. eprint: https://doi.org/10.1021/acscatal.0c04525. [Online]. Available: https://doi.org/10.1021/acscatal.0c04525.

[19] R. Tran, J. Lan, M. Shuaibi, *et al.*, "The open catalyst 2022 (oc22) dataset and challenges for oxide electrocatalysts," *ACS Catalysis*, vol. 13, no. 5, pp. 3066–3084, Feb. 2023, ISSN: 2155-5435. DOI: 10.1021/acscatal.2c05426. [Online]. Available: http://dx.doi.org/10.1021/acscatal.2c05426.

[20] K. Choudhary, D. Wines, K. Li, *et al.*, "JARVIS-Leaderboard: A large scale benchmark of materials design methods," *npj Computational Materials*, vol. 10, no. 1, p. 93, 2024. DOI: 10.1038/s41524-024-01259-w. [Online]. Available: https://doi.org/10.1038/s41524-024-01259-w.

[21] F. J. Kiwit, M. Marso, P. Ross, C. A. Riofrío, J. Klepsch, and A. Luckow, "Application-oriented benchmarking of quantum generative learning using quark," in *2023 IEEE International Conference on Quantum Computing and Engineering (QCE)*, IEEE, Sep. 2023, pp. 475–484. DOI: 10.1109/qce57702.2023.00061. [Online]. Available: http://dx.doi.org/10.1109/QCE57702.2023.00061.

[22] Y. Luo, Y. Chen, and Z. Zhang, *Cfdbench: A large-scale benchmark for machine learning methods in fluid dynamics*, 2024. [Online]. Available: https://arxiv.org/abs/2310.05963.

[23] J. Roberts, K. Han, and S. Albanie, *Satin: A multi-task metadataset for classifying satellite imagery using vision-language models*, 2023. arXiv: 2304.11619 [cs.CV]. [Online]. Available: https://arxiv.org/abs/2304.11619.

[24] T. Nguyen, J. Jewik, H. Bansal, P. Sharma, and A. Grover, *Climatelearn: Benchmarking machine learning for weather and climate modeling*, 2023. arXiv: 2307.01909 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2307.01909.

[25] A. Srivastava, A. Rastogi, A. Rao, *et al.*, *Beyond the imitation game: Quantifying and extrapolating the capabilities of language models*, 2023. arXiv: 2206.04615 [cs.CL]. [Online]. Available: https://arxiv.org/abs/2206.04615.

[26] A. Talmor, J. Herzig, N. Lourie, and J. Berant, *Commonsenseqa: A question answering challenge targeting commonsense knowledge*, 2019. arXiv: 1811.00937 [cs.CL]. [Online]. Available: https://arxiv.org/abs/1811.00937.

[27] K. Sakaguchi, R. L. Bras, C. Bhagavatula, and Y. Choi, *Winogrande: An adversarial winograd schema challenge at scale*, 2019. arXiv: 1907.10641 [cs.CL]. [Online]. Available: https://arxiv.org/abs/1907.10641.

[28] J. Duarte, N. Tran, B. Hawks, *et al.*, *Fastml science benchmarks: Accelerating real-time scientific edge machine learning*, 2022. arXiv: 2207.07958 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2207.07958.

[29] J. Duarte, N. Tran, B. Hawks, *et al.*, *Fastml science benchmarks: Accelerating real-time scientific edge machine learning*, 2022. arXiv: 2207.07958 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2207.07958.

[30] D. Kafkes and J. S. John, *Boostr: A dataset for accelerator control systems*, 2021. arXiv: 2101.08359 [physics.acc-ph]. [Online]. Available: https://arxiv.org/abs/2101.08359.

[31] P. Odagiu, Z. Que, J. Duarte, *et al.*, *Ultrafast jet classification on fpgas for the hl-lhc*, 2024. DOI: https://doi.org/10.1088/2632-2153/ad5f10. arXiv: 2402.01876 [hep-ex]. [Online]. Available: https://arxiv.org/abs/2402.01876.

[32] M. Khan, S. Krave, V. Marinozzi, J. Ngadiuba, S. Stoynev, and N. Tran, "Benchmarking and interpreting real time quench detection algorithms," in *Fast Machine Learning for Science Conference 2024*, Purdue University, IN: indico.cern.ch, Oct. 2024. [Online]. Available: https://indico.cern.ch/event/1387540/contributions/6153618/attachments/2948441/5182077/fast_ml_magnets_2024_final.pdf.

[33] A. A. Abud, B. Abi, R. Acciarri, *et al.*, *Deep underground neutrino experiment (dune) near detector conceptual design report*, 2021. arXiv: 2103.13910 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2103.13910.

[34] J. Kvapil, G. Borca-Tasciuc, H. Bossi, *et al.*, *Intelligent experiments through real-time ai: Fast data processing and autonomous detector control for sphenix and future eic detectors*, 2025. arXiv: 2501.04845 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2501.04845.

[35] J. Weitz, D. Demler, L. McDermott, N. Tran, and J. Duarte, *Neural architecture codesign for fast physics applications*, 2025. arXiv: 2501.05515 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2501.05515.

[36] B. Parpillon, C. Syal, J. Yoo, *et al.*, *Smart pixels: In-pixel ai for on-sensor data filtering*, 2024. arXiv: 2406.14860 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2406.14860.

[37] Z. Liu, H. Sharma, J.-S. Park, *et al.*, *Braggnn: Fast x-ray bragg peak analysis using deep learning*, 2021. arXiv: 2008.08198 [eess.IV]. [Online]. Available: https://arxiv.org/abs/2008.08198.

[38] S. Qin, J. Agar, and N. Tran, "Extremely noisy 4d-tem strain mapping using cycle consistent spatial transforming autoencoders," in *AI for Accelerated Materials Design - NeurIPS 2023 Workshop*, 2023. [Online]. Available: https://openreview.net/forum?id=7yt3N0o0W9.

[39] Y. Wei, R. F. Forelli, C. Hansen, *et al.*, *Low latency optical-based mode tracking with machine learning deployed on fpgas on a tokamak*, 2024. DOI: https://doi.org/10.1063/5.0190354. arXiv: 2312.00128 [physics.plasm-ph]. [Online]. Available: https://arxiv.org/abs/2312.00128.

[40] W. Gao, F. Tang, L. Wang, *et al.*, *Aibench: An industry standard internet service ai benchmark suite*, 2019. arXiv: 1908.08998 [cs.CV]. [Online]. Available: https://arxiv.org/abs/1908.08998.

[41] W. Gao, J. Zhan, L. Wang, *et al.*, *Bigdatabench: A scalable and unified big data and ai benchmark suite*, 2018. arXiv: 1802.08254 [cs.DC]. [Online]. Available: https://arxiv.org/abs/1802.08254.

[42] S. Farrell, M. Emani, J. Balma, *et al.*, *Mlperf hpc: A holistic benchmark suite for scientific machine learning on hpc systems*, 2021. arXiv: 2110.11466 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2110.11466.

[43] J. Thiyagalingam, G. von Laszewski, J. Yin, *et al.*, "Ai benchmarking for science: Efforts from the mlcommons science working group," in *High Performance Computing. ISC High Performance 2022 International Workshops*, H. Anzt, A. Bienz, P. Luszczek, and M. Baboulin, Eds., Cham: Springer International Publishing, 2022, pp. 47–64, ISBN: 978-3-031-23220-6.

[44] T. Aarrestad, E. Govorkova, J. Ngadiuba, E. Puljak, M. Pierini, and K. A. Wozniak, *Unsupervised new physics detection at 40 mhz: Training dataset*, 2021. DOI: 10.5281/ZENODO.5046389. [Online]. Available: https://zenodo.org/record/5046389.

[45] A. Karargyris, R. Umeton, M. J. Sheller, *et al.*, "Federated benchmarking of medical artificial intelligence with medperf," *Nature Machine Intelligence*, vol. 5, no. 7, pp. 799–810, Jul. 2023. DOI: 10.1038/s42256-023-00652-2. [Online]. Available: https://doi.org/10.1038/s42256-023-00652-2.

[46] C. Krause, M. F. Giannelli, G. Kasieczka, *et al.*, *Calochallenge 2022: A community challenge for fast calorimeter simulation*, 2024. arXiv: 2410.21611 [physics.ins-det]. [Online]. Available: https://arxiv.org/abs/2410.21611.

[47] A. Blum and M. Hardt, "The ladder: A reliable leaderboard for machine learning competitions," in *Proceedings of the 32nd International Conference on Machine Learning*, F. Bach and D. Blei, Eds., ser. Proceedings of Machine Learning Research, vol. 37, Lille, France: PMLR, Jul. 2015, pp. 1006–1014. [Online]. Available: https://proceedings.mlr.press/v37/blum15.html.

[48] Z. Xu, S. Escalera, A. Pavão, *et al.*, "Codabench: Flexible, easy-to-use, and reproducible meta-benchmark platform," *Patterns*, vol. 3, no. 7, p. 100 543, Jul. 2022, ISSN: 2666-3899. DOI: 10.1016/j.patter.2022.100543. [Online]. Available: http://dx.doi.org/10.1016/j.patter.2022.100543.

[49] P. Luszczek, "Sabath: Fair metadata technology for surrogate benchmarks," University of Tennessee, Tech. Rep., 2021. [Online]. Available: https://github.com/icl-utk-edu/slip/tree/sabath.

[50] M. Takamoto, T. Praditia, R. Leiteritz, *et al.*, *Pdebench: An extensive benchmark for scientific machine learning*, 2024. arXiv: 2210.07182 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2210.07182.

[51] R. Ohana, M. McCabe, L. Meyer, *et al.*, "The well: A large-scale collection of diverse physics simulations for machine learning," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 44 989–45 037. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/4f9a5acd91ac76569f2fe291b1f4772b-Paper-Datasets_and_Benchmarks_Track.pdf.

[52] K. T. Chitty-Venkata, S. Raskar, B. Kale, *et al.*, "Llm-inference-bench: Inference benchmarking of large language models on ai accelerators," in *SC24-W: Workshops of the International Conference for High Performance Computing, Networking, Storage and Analysis*, 2024, pp. 1362–1379. DOI: 10.1109/SCW63240.2024.00178.

[53] L. Zheng, L. Yin, Z. Xie, *et al.*, *Sglang: Efficient execution of structured language model programs*, 2024. arXiv: 2312.07104 [cs.AI]. [Online]. Available: https://arxiv.org/abs/2312.07104.

[54] W. Kwon, Z. Li, S. Zhuang, *et al.*, "Efficient memory management for large language model serving with pagedattention," in *Proceedings of the 29th Symposium on Operating Systems Principles*, ser. SOSP '23, Koblenz, Germany: Association for Computing Machinery, 2023, pp. 611–626. DOI: 10.1145/3600006.3613165. [Online]. Available: https://doi.org/10.1145/3600006.3613165.

[55] S. Mo, *Vllm performance dashboard*, 2024. [Online]. Available: https://simon-mo-workspace.observablehq.cloud/vllm-dashboard-v0/.

[56] K. G. Olivares, C. Challú, F. Garza, M. M. Canseco, and A. Dubrawski, *Neuralforecast: User friendly state-of-the-art neural forecasting models.* PyCon Salt Lake City, Utah, US 2022, 2022. [Online]. Available: https://github.com/Nixtla/neuralforecast.

[57] C. Challu, K. G. Olivares, B. N. Oreshkin, F. G. Ramirez, M. M. Canseco, and A. Dubrawski, "Nhits: Neural hierarchical interpolation for time series forecasting," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 37, 2023, pp. 6989–6997.

[58] M. Jin, S. Wang, L. Ma, *et al.*, *Time-llm: Time series forecasting by reprogramming large language models*, 2024. arXiv: 2310.01728 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2310.01728.

[59] A. Garza, C. Challu, and M. Mergenthaler-Canseco, *Timegpt-1*, 2024. arXiv: 2310.03589 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2310.03589.

[60] E. G. Campolongo, Y.-T. Chou, E. Govorkova, *et al.*, *Building machine learning challenges for anomaly detection in science*, 2025. arXiv: 2503.02112 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2503.02112.

[61] G. D. Guglielmo, B. Du, J. Campos, *et al.*, *End-to-end workflow for machine learning-based qubit readout with qick and hls4ml*, 2025. arXiv: 2501.14663 [quant-ph]. [Online]. Available: https://arxiv.org/abs/2501.14663.

[62] K. X. Nguyen, F. Qiao, A. Trembanis, and X. Peng, *Seafloorai: A large-scale vision-language dataset for seafloor geological survey*, 2024. arXiv: 2411.00172 [cs.CV]. [Online]. Available: https://arxiv.org/abs/2411.00172.

[63] P. Chen, L. Peng, R. Jiao, *et al.*, "Learning superconductivity from ordered and disordered material structures," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 108 902–108 928. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c4e3b55ed4ac9ba52d7df11f8bddbbf4-Paper-Datasets_and_Benchmarks_Track.pdf.

[64] D. Zou, S. Liu, S. Miao, V. Fung, S. Chang, and P. Li, "Gess: Benchmarking geometric deep learning under scientific applications with distribution shifts," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 92 499–92 528. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/a8063075b00168dc39bc81683619f1a8-Paper-Datasets_and_Benchmarks_Track.pdf.

[65] R. E. Peterson, A. Tanelus, C. Ick, *et al.*, "Vocal call locator benchmark (vcl) for localizing rodent vocalizations from multi-channel audio," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 106 370–106 382. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c00d37d6b04d73b870b963a4d70051c1-Paper-Datasets_and_Benchmarks_Track.pdf.

[66] R. Bushuiev, A. Bushuiev, N. F. de Jonge, *et al.*, "Massspecgym: A benchmark for the discovery and identification of molecules," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 110 010–110 027. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/c6c31413d5c53b7d1c343c1498734b0f-Paper-Datasets_and_Benchmarks_Track.pdf.

[67] Y. Wang, T. Wang, Y. Zhang, *et al.*, "Urbandatalayer: A unified data pipeline for urban science," in *Advances in Neural Information Processing Systems*, A. Globerson, L. Mackey, D. Belgrave, *et al.*, Eds., vol. 37, Curran Associates, Inc., 2024, pp. 7296–7310. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2024/file/0db7f135f6991e8cec5e516ecc66bfba-Paper-Datasets_and_Benchmarks_Track.pdf.

[68] K. Khrabrov, A. Ber, A. Tsypin, *et al.*, *∇^2Dft: A universal quantum chemistry dataset of drug-like molecules and a benchmark for neural network potentials*, 2024. arXiv: 2406.14347 [physics.chem-ph]. [Online]. Available: https://arxiv.org/abs/2406.14347.

[69] T. Shen, H. Wang, J. Zhang, *et al.*, *Exploring user retrieval integration towards large language models for cross-domain sequential recommendation*, 2024. arXiv: 2406.03085 [cs.LG]. [Online]. Available: https://arxiv.org/abs/2406.03085.

[70] S. Pramanick, R. Chellappa, and S. Venugopalan, *Spiqa: A dataset for multimodal question answering on scientific papers*, 2025. arXiv: 2407.09413 [cs.CL]. [Online]. Available: https://arxiv.org/abs/2407.09413.