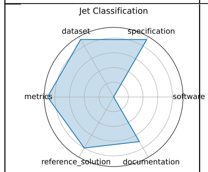
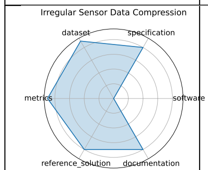
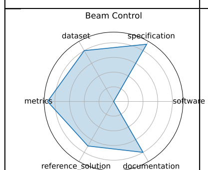
1 Benchmark Overview Table

Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	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	[1]⇒
	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	[2]⇒
	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)	[2], [3]⇒

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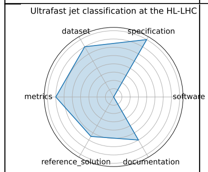
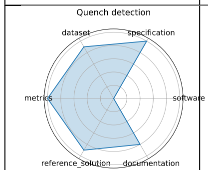
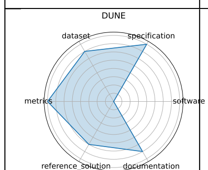
	Ultrafast jet classification at the HL-LHC	Particle Physics	FPGA-optimized real-time jet origin classification at the HL-LHC	jet classification, FPGA, quantization-aware training, Deep Sets, Interaction Networks	Classification	Real-time inference under FPGA constraints	Accuracy, Latency, Resource utilization	MLP, Deep Sets, Interaction Network	[4]⇒
	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)	
	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)	[5]⇒

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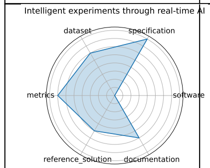
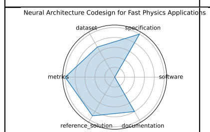
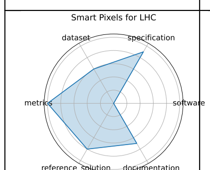
	Intelligent experiments through real-time AI	Instrumentation and Detectors; Nuclear Physics; Particle Physics	Real-time FPGA-based triggering and detector control for sPHENIX and future EIC	FPGA, Graph Neural Network, hls4ml, real-time inference, detector control	Trigger classification, Detector control, 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)	[6]⇒
	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)	[7]⇒
	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	[8]⇒

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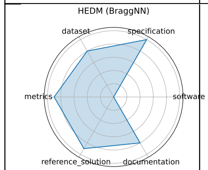
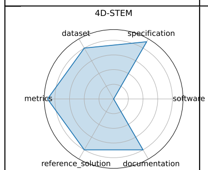
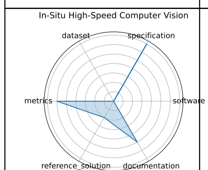
	HEDM (BraggNN)	Material Science	Fast Bragg peak analysis using deep learning in diffraction microscopy	BraggNN, diffraction, peak finding, HEDM	Peak detection	High-throughput peak localization	Localization accuracy, Inference time	BraggNN	[9]⇒
	4D-STEM	Material Science	Real-time ML for scanning transmission 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)	[10]⇒
	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	[11]⇒

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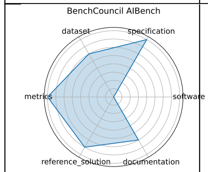
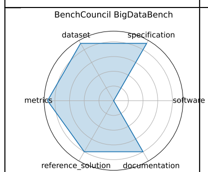
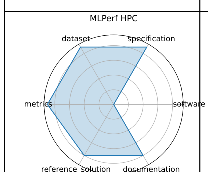
	BenchCouncil AIBench	General	End-to-end AI benchmarking across micro, component, and application levels	benchmarking, AI systems, application-level evaluation	Training, Inference, End-to-end AI workloads	System-level AI workload performance	Throughput, Latency, Accuracy	ResNet, BERT, GANs, Recommendation systems	[12]⇒
	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	[13]⇒
	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	[14]⇒

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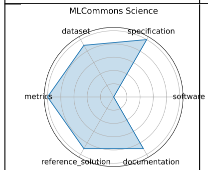
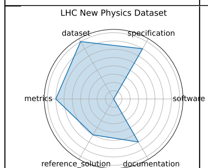
	MLCommons Science	Earthquake, Satellite Image, Drug Discovery, Electron Microscope, CFD	AI benchmarks for scientific applications including time-series, imaging, and simulation	science AI, benchmark, MLCommons, HPC	Time-series analysis, Image classification, Simulation surrogate modeling	Inference accuracy, simulation speed-up, generalization	MAE, Accuracy, Speedup vs simulation	CNN, GNN, Transformer	[15]⇒
	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	[16]⇒

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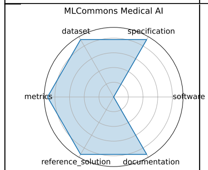
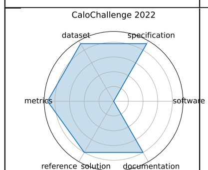
	MLCommons Medical AI	Healthcare; Medical AI	Federated benchmarking and evaluation of medical AI models across diverse real-world clinical data	medical AI, federated evaluation, privacy-preserving, fairness, healthcare benchmarks	Federated evaluation, Model validation	Clinical accuracy, fairness, generalizability, privacy compliance	ROC AUC, Accuracy, Fairness metrics	MedPerf-validated CNNs, GaNDLF workflows	[17]⇒
	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	[18]⇒

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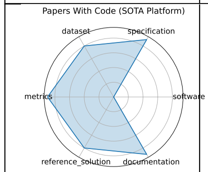
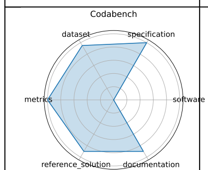
	Papers With Code (SOTA Platform)	General ML; All domains	Open platform tracking state-of-the-art results, benchmarks, and implementations across ML tasks and papers	leaderboard, benchmarking, reproducibility, open-source	Multiple (Classification, Detection, NLP, etc.)	Model performance across tasks (accuracy, F1, BLEU, etc.)	Task-specific (Accuracy, F1, BLEU, etc.)	All published models with code	[19]⇒
	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	[20]⇒

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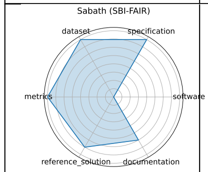
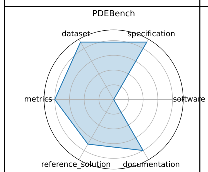
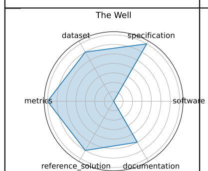
	Sabath (SBI-FAIR)	Systems; Metadata	FAIR metadata framework for ML-driven surrogate workflows in HPC systems	meta-benchmark, metadata, HPC, surrogate modeling	Systems benchmarking	Metadata tracking, reproducible HPC workflows	Metadata completeness, FAIR compliance	N/A	[21]⇒
	PDEBench	CFD; Weather Modeling	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	[22]⇒
	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	[23]⇒

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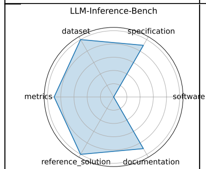
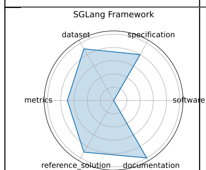
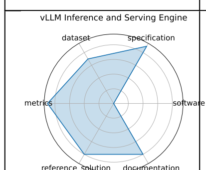
	LLM-Inference-Bench	LLM; HPC/inference	Hardware performance benchmarking of LLMs on AI accelerators	LLM, inference benchmarking, GPU, accelerator, throughput	Inference Benchmarking	Inference throughput, latency, hardware utilization	Token throughput (tok/s), Latency, Framework-hardware mix performance	LLaMA-2-7B, LLaMA-2-70B, Mistral-7B, Qwen-7B	[24]⇒
	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	[25]⇒
	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	[26]⇒

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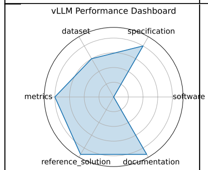
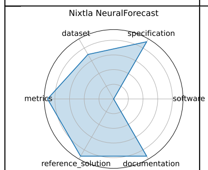
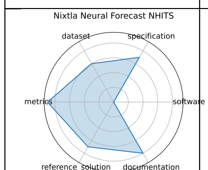
	vLLM Performance Dashboard	LLM; HPC/inference	Interactive dashboard showing inference performance of vLLM	Dashboard, Throughput visualization, Latency analysis, Metric tracking	Performance visualization	Throughput, latency, hardware utilization	Tokens/sec, TTFT, Memory usage	LLaMA-2, Mistral, Qwen	[27]⇒
	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	[28]⇒
	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	[29]⇒

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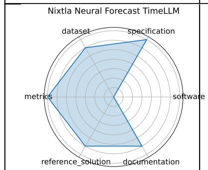
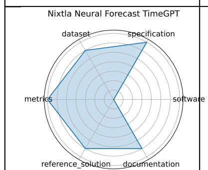
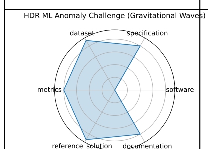
	Nixtla Neural Forecast TimeLLM	Time-series; General ML	Reprogramming LLMs for time series forecasting	Time-LLM, language model, time-series, reprogramming	Time-series forecasting	Model reuse via LLM, few-shot forecasting	RMSE, MAPE	Time-LLM	[30]⇒
	Nixtla Neural Forecast TimeGPT	Time-series; General ML	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	[31]⇒
	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	[32]⇒

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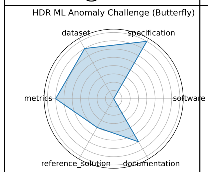
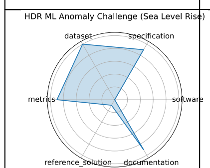
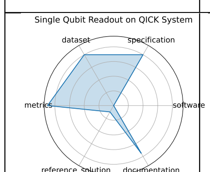
	HDR ML Anomaly Challenge (Butterfly)	Genomics; Image/CV	Detecting hybrid butterflies via image anomaly detection in genomic-informed dataset	anomaly detection, computer vision, genomics, butterfly hybrids	Anomaly detection	Hybrid detection in biological systems	Classification accuracy, F1 score	CNN-based detectors	[32]⇒
	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	[32]⇒
	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	[33]⇒

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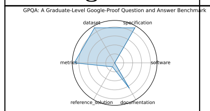
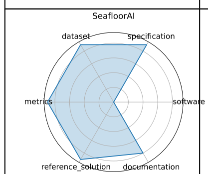
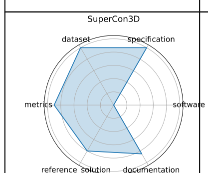
	GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark	Science (Biology, Physics, Chemistry)	Graduate-level, expert-validated multiple-choice questions hard even with web access	Google-proof, multiple-choice, expert reasoning, science QA	Multiple choice	Scientific reasoning, knowledge probing	Accuracy	GPT-4 baseline	[34]⇒
	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 multi-modal models	[35]⇒
	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	[36]⇒

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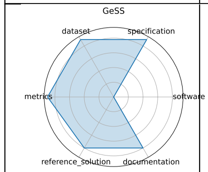
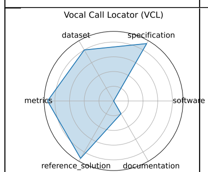
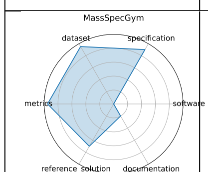
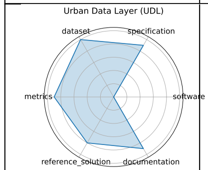
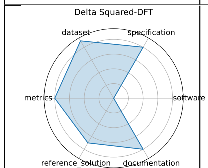
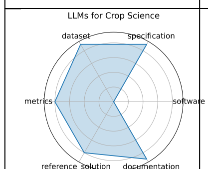
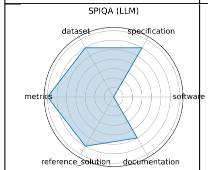
Ratings	Name	Domain	Focus	Keywords	Task Types	AI Capability	Metrics	Models	Citation
	GeSS	Scientific ML; Geometric Deep Learning	Benchmark suite evaluating geometric deep learning models under real-world distribution shifts	geometric deep learning, distribution shift, OOD robustness, scientific applications	Classification, Regression	OOD performance in scientific settings	Accuracy, RMSE, OOD robustness delta	GCN, EGNN, DimeNet++	[37]⇒
	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	[38]⇒
	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	[39]⇒

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	[40]⇒
	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	[41]⇒
	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	[42]⇒

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	[43]⇒

2 Radar Chart Table

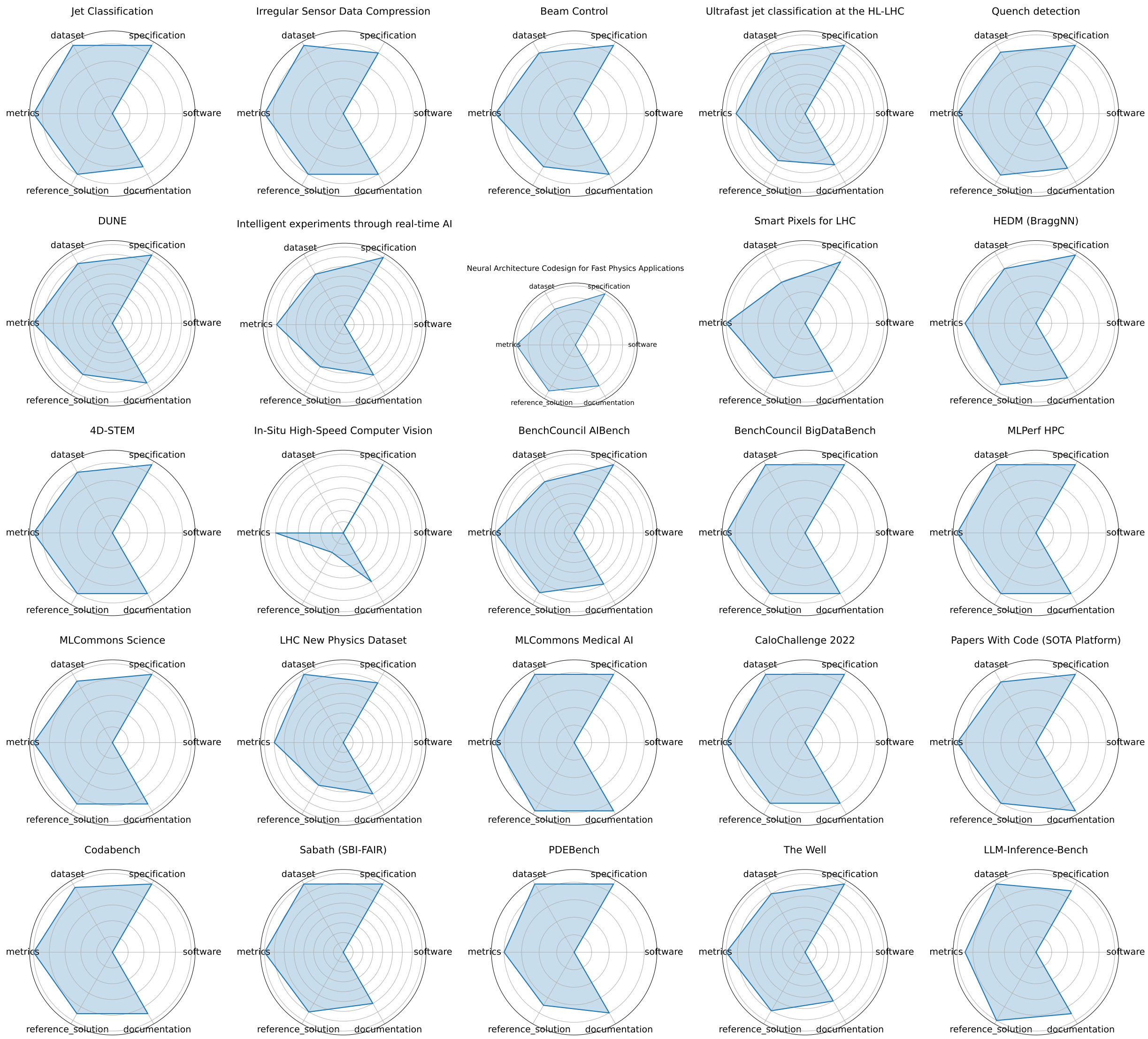


Figure 1: Radar chart overview (page 1)

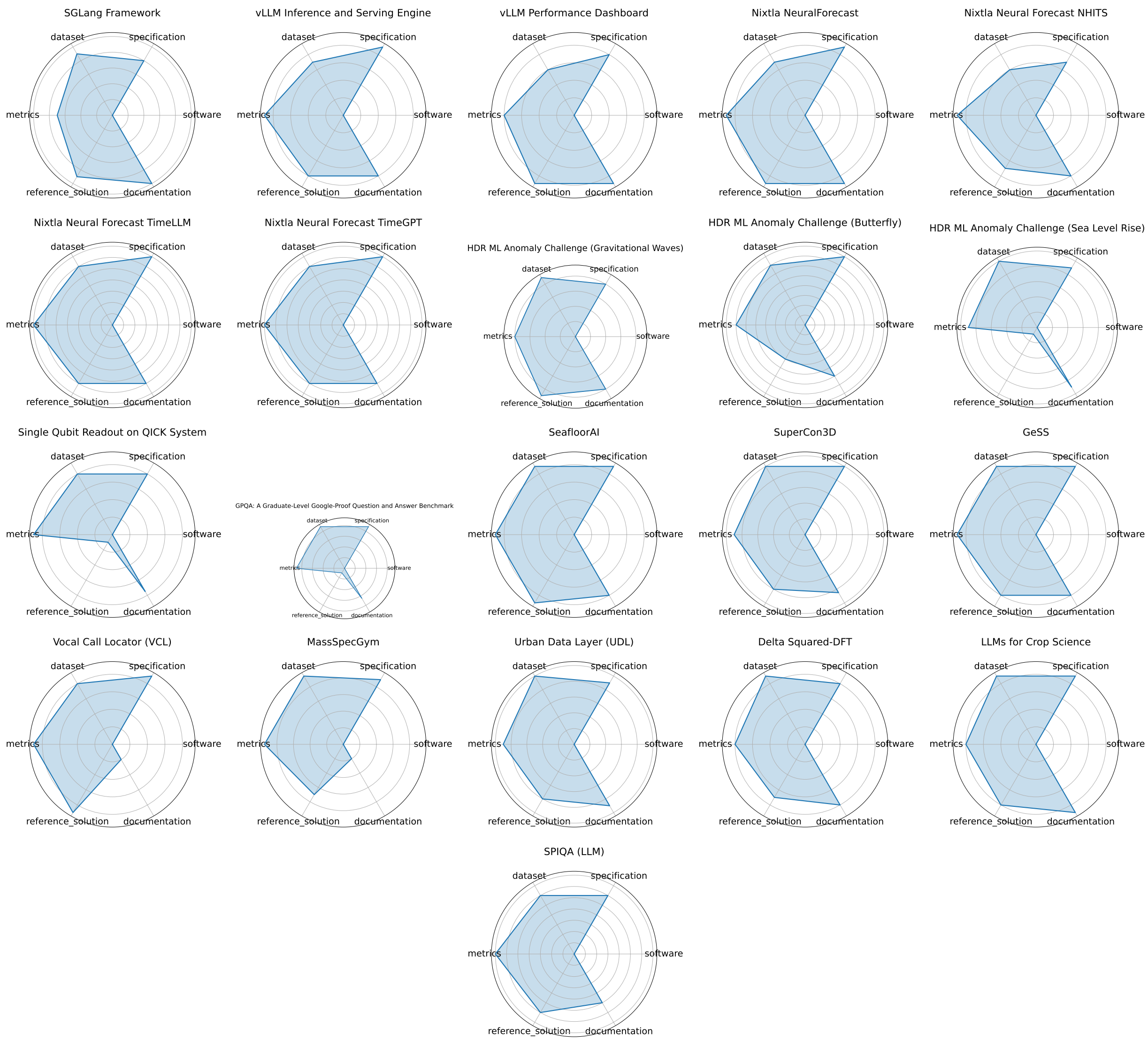


Figure 2: Radar chart overview (page 2)

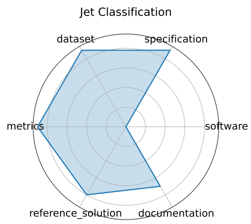
3 Benchmark Details

4 Jet Classification

date: 2024-05-01
version: TODO
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/fastmachinelearning/fastml-science/tree/main/jet-classify
doi: TODO
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: TODO
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: TODO
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: [1]

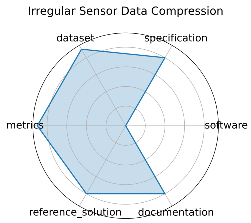
Ratings:



5 Irregular Sensor Data Compression

date: 2024-05-01
version: TODO
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/fastmachinelearning/fastml-science/tree/main/sensor-data-compression
doi: TODO
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: TODO
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: TODO
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: [2]

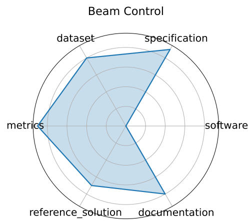
Ratings:


Irregular Sensor Data Compression
dataset
specification
metrics
software
reference_solution
documentation

6 Beam Control

date: 2024-05-01
version: TODO
last_updated: 2024-05
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/fastmachinelearning/fastml-science/tree/main/beam-control
doi: TODO
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: TODO
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: TODO
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 pre-trained weights would improve usability.
id: beam_control
Citations: [2], [3]

Ratings:

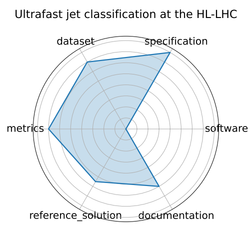


Beam Control
dataset
specification
metrics
software
reference_solution
documentation

7 Ultrafast jet classification at the HL-LHC

date: 2024-07-08
version: TODO
last_updated: 2024-07
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/pdf/2402.01876
doi: TODO
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: TODO
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: TODO
notes: Uses quantization-aware training; hardware synthesis evaluated via hls4ml
contact.name: Patrick Odagiu
contact.email: unknown
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: [4]

Ratings:



Ultrafast jet classification at the HL-LHC
dataset
specification
metrics
software
reference_solution
documentation

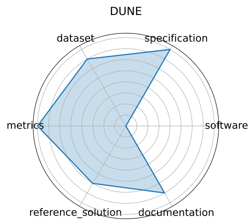
8 Quench detection

date: 2024-10-15
version: TODO
last_updated: 2024-10
expired: unknown
valid: yes
valid_date: TODO
url: https://indico.cern.ch/event/1387540/contributions/6153618/attachments/2948441/5182077/fast_ml_magnets_2024_final.pdf
doi: TODO
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. :contentReference[oaicite:2]{index=2}
licensing: TODO
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: TODO
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: 0
ratings.software.reason: Not analyzed.
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

9 DUNE

date: 2024-10-15
version: TODO
last_updated: 2024-10
expired: unknown
valid: yes
valid_date: TODO
url: https://indico.fnal.gov/event/66520/contributions/301423/attachments/182439/250508/fast_ml_dunedaq_sonic_10_15_24.pdf
doi: TODO
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: TODO
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: TODO
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: [5]

Ratings:

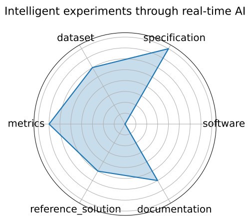


DUNE
specification
dataset
metrics
software
reference_solution
documentation

10 Intelligent experiments through real-time AI

date: 2025-01-08
version: TODO
last_updated: 2025-01
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/pdf/2501.04845
doi: TODO
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: Resaerch 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: TODO
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: TODO
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 (lanl.gov)
contact.email: unknown
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: [6]

Ratings:


Intelligent experiments through real-time AI
dataset
specification
metrics
software
reference_solution
documentation

11 Neural Architecture Codesign for Fast Physics Applications

date: 2025-01-09

version: TODO

last_updated: 2025-01

expired: unknown

valid: yes

valid_date: TODO

url: https://arxiv.org/abs/2501.05515

doi: TODO

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: TODO

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: TODO

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.

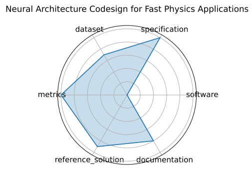
ratings.documentation.rating: 8.0

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: [7]

Ratings:



Neural Architecture Codesign for Fast Physics Applications
dataset
specification
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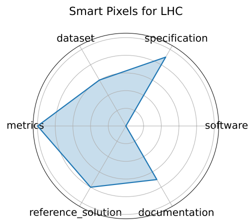
12 Smart Pixels for LHC

date: 2024-06-24
version: TODO
last_updated: 2024-06
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/abs/2406.14860
doi: TODO
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: TODO
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: TODO
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: [8]

Ratings: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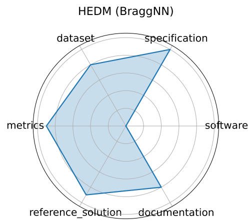
13 HEDM (BraggNN)

date: 2023-10-03
version: TODO
last_updated: 2023-10
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/abs/2008.08198
doi: TODO
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: TODO
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: TODO
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: [9]

Ratings:


HEDM (BraggNN)
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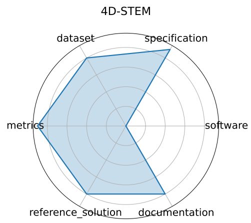
14 4D-STEM

date: 2023-12-03
version: TODO
last_updated: 2023-12
expired: unknown
valid: yes
valid_date: TODO
url: https://openreview.net/pdf?id=7yt3N0o0W9
doi: TODO
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: TODO
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: TODO
notes: In-progress; model design under development.
contact.name: unknown
contact.email: unknown
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: [10]

Ratings:



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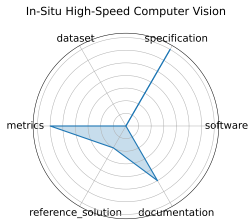
15 In-Situ High-Speed Computer Vision

date: 2023-12-05
version: TODO
last_updated: 2023-12
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/abs/2312.00128
doi: TODO
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: TODO
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: TODO
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: [11]

Ratings:


In-Situ High-Speed Computer Vision
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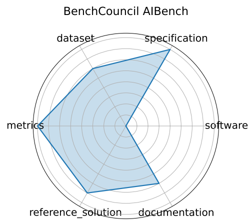
16 BenchCouncil AIBench

date: 2020-01-01
version: TODO
last_updated: 2020-01
expired: unknown
valid: yes
valid_date: TODO
url: https://www.benchcouncil.org/AIBench/
doi: TODO
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: TODO
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: TODO
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: [12]

Ratings:


BenchCouncil AIBench
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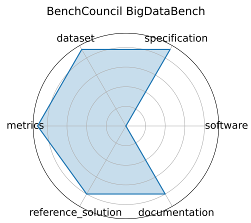
17 BenchCouncil BigDataBench

date: 2020-01-01
version: TODO
last_updated: 2020-01
expired: unknown
valid: yes
valid_date: TODO
url: https://www.benchcouncil.org/BigDataBench/
doi: TODO
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: TODO
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: TODO
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: [13]

Ratings:


BenchCouncil BigDataBench
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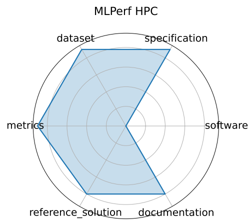
18 MLPerf HPC

date: 2021-10-20
version: TODO
last_updated: 2021-10
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/mlcommons/hpc
doi: TODO
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: TODO
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: TODO
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: [14]

Ratings: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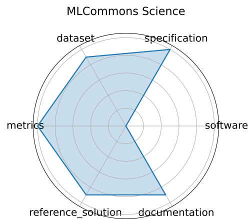
19 MLCommons Science

date: 2023-06-01
version: TODO
last_updated: 2023-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/mlcommons/science
doi: TODO
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: TODO
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: TODO
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: [15]

Ratings: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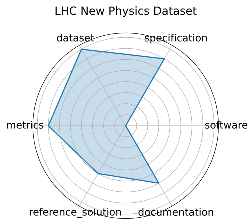
20 LHC New Physics Dataset

date: 2021-07-05
version: TODO
last_updated: 2021-07
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/pdf/2107.02157
doi: TODO
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: TODO
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: TODO
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: [16]

Ratings:


LHC New Physics Dataset
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specification
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21 MLCommons Medical AI

date: 2023-07-17

version: TODO

last_updated: 2023-07

expired: unknown

valid: yes

valid_date: TODO

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

doi: TODO

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: TODO

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: TODO

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.

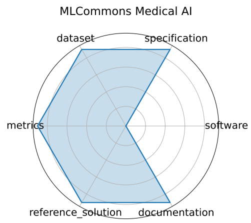
ratings.documentation.rating: 9.0

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

id: mlcommons_medical_ai

Citations: [17]

Ratings:


MLCommons Medical AI
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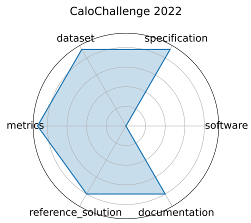
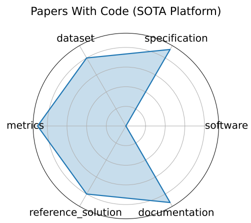
22 CaloChallenge 2022

date: 2024-10-28
version: TODO
last_updated: 2024-10
expired: unknown
valid: yes
valid_date: TODO
url: http://arxiv.org/abs/2410.21611
doi: TODO
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: TODO
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: TODO
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: [18]

Ratings: 
CaloChallenge 2022
dataset
specification
metrics
software
reference_solution
documentation

23 Papers With Code (SOTA Platform)

date: ongoing
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://paperswithcode.com/sota
doi: TODO
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: TODO
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: TODO
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: [19]

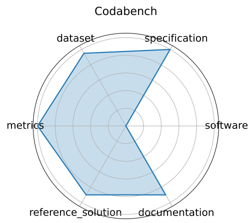

Papers With Code (SOTA Platform)
dataset
specification
metrics
software
reference_solution
documentation

Ratings:

24 Codabench

date: 2022-01-01
version: TODO
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: TODO
url: https://www.codabench.org/
doi: TODO
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: TODO
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: TODO
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: 0
ratings.software.reason: Not analyzed.
ratings.specification.rating: 10.0
ratings.specification.reason: Simulation task (generative calorimeter showers) is clearly stated with multiple datasets, fidelity requirements, and performance constraints.
ratings.dataset.rating: 9.5
ratings.dataset.reason: Public datasets available in multiple sizes and formats; well-documented; not versioned
ratings.metrics.rating: 10.0
ratings.metrics.reason: Histogram similarity, classifier AUC, and generation latency are clearly defined and benchmarked across all submissions.
ratings.reference_solution.rating: 9.0
ratings.reference_solution.reason: 31 model implementations submitted; some made public and reproducible, though others remain undocumented or private.
ratings.documentation.rating: 9.0
ratings.documentation.reason: Paper, leaderboard, and Gemini doc are comprehensive; unified repo or launchable baseline kit would push this to a 10.
id: codabench
Citations: [20]

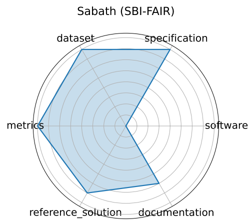
Ratings:


Codabench
dataset
specification
metrics
software
reference_solution
documentation

25 Sabath (SBI-FAIR)

date: 2021-09-27
version: TODO
last_updated: 2023-07
expired: unknown
valid: yes
valid_date: TODO
url: https://sbi-fair.github.io/docs/software/sabath/
doi: TODO
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: TODO
task_types: - Systems benchmarking
ai_capability_measured: - Metadata tracking - reproducible HPC workflows
metrics: - Metadata completeness - FAIR compliance
models: - N/A
ml_motif: - Systems
type: Platform
ml_task: - NA
solutions: TODO
notes: Developed by PI Piotr Luszczek at UTK; integrates with MiniWeatherML, AutoPhaseNN, Cosmoflow, etc. :contentReference[oaicite:4]{index=4}
contact.name: Piotr Luszczek (luszczek@utk.edu)
contact.email: unknown
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: [21]

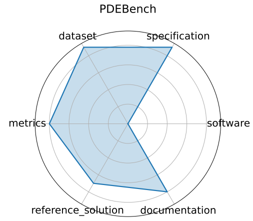
Ratings:


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

26 PDEBench

date: 2022-10-13
version: TODO
last_updated: 2025-05
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/pdebench/PDEBench
doi: TODO
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: TODO
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: TODO
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: [22]

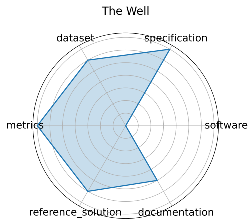
Ratings:



27 The Well

date: 2024-12-03
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://polymathic-ai.org/the_well/
doi: TODO
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: TODO
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: TODO
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: Wes Brewer
contact.email: unknown
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: [23]

Ratings:


The Well
dataset
specification
metrics
software
reference_solution
documentation

28 LLM-Inference-Bench

date: 2024-10-31

version: TODO

last_updated: 2024-11

expired: unknown

valid: yes

valid_date: TODO

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

doi: TODO

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: TODO

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: TODO

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.

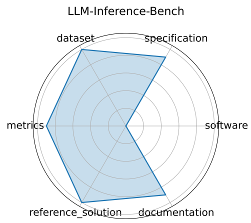
ratings.documentation.rating: 9.0

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

id: llm-inference-bench

Citations: [24]

Ratings:



LLM-Inference-Bench
dataset
specification
metrics
software
reference_solution
documentation

29 SGLang Framework

date: 2023-12-12

version: TODO

last_updated: 2025-06

expired: unknown

valid: yes

valid_date: TODO

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

doi: TODO

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: TODO

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: TODO

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.

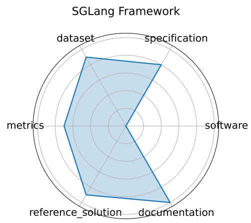
ratings.documentation.rating: 10.0

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: [25]

Ratings:

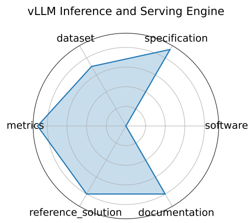


SGLang Framework
dataset
specification
metrics
software
reference_solution
documentation

30 vLLM Inference and Serving Engine

date: 2023-09-12
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/vllm-project/vllm/tree/main/benchmarks
doi: TODO
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: TODO
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: TODO
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: [26]

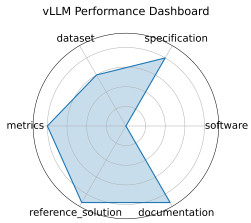
Ratings:


vLLM Inference and Serving Engine
dataset
specification
metrics
software
reference_solution
documentation

31 vLLM Performance Dashboard

date: 2022-06-22
version: TODO
last_updated: 2025-01
expired: unknown
valid: yes
valid_date: TODO
url: https://simon-mo-workspace.observablehq.cloud/vllm-dashboard-v0/
doi: TODO
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: TODO
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: TODO
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: [27]

Ratings:

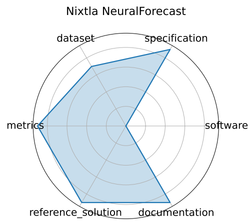


vLLM Performance Dashboard
dataset
specification
metrics
software
reference_solution
documentation

32 Nixtla NeuralForecast

date: 2022-04-01
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/Nixtla/neuralforecast
doi: TODO
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: TODO
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: TODO
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: [28]

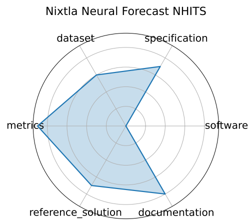
Ratings:


Nixtla NeuralForecast
dataset
specification
metrics
software
reference_solution
documentation

33 Nixtla Neural Forecast NHITS

date: 2023-06-01
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/Nixtla/neuralforecast
doi: TODO
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: TODO
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: TODO
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: [29]

Ratings:

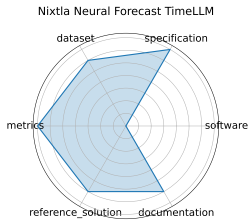


Nixtla Neural Forecast NHITS
dataset
specification
metrics
software
reference_solution
documentation

34 Nixtla Neural Forecast TimeLLM

date: 2023-10-03
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/Nixtla/neuralforecast
doi: TODO
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: TODO
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: TODO
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: [30]

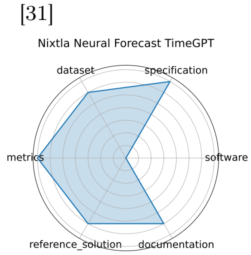
Ratings:



Nixtla Neural Forecast TimeLLM
dataset
specification
metrics
software
reference_solution
documentation

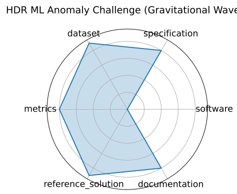
35 Nixtla Neural Forecast TimeGPT

date: 2023-10-05
version: TODO
last_updated: 2025-06
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/Nixtla/neuralforecast
doi: TODO
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: TODO
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: TODO
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: [31]

Ratings: 

36 HDR ML Anomaly Challenge (Gravitational Waves)

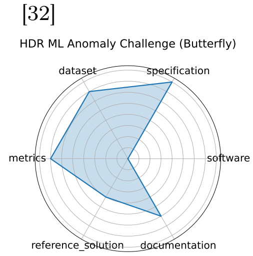
date: 2025-03-03
version: TODO
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: TODO
url: https://www.codabench.org/competitions/2626/
doi: TODO
domain: Astrophysics; Time-series
focus: Detecting anomalous gravitational-wave signals from LIGO/Virgo datasets
keywords: - anomaly detection - 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: TODO
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: TODO
notes: NSF HDR A3D3 sponsored; prize pool and starter kit provided on Codabench. :contentReference[oaicite:2]{index=2}
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: [32]

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

37 HDR ML Anomaly Challenge (Butterfly)

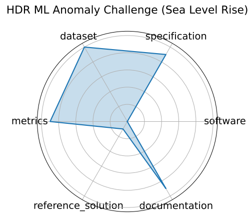
date: 2025-03-03
version: TODO
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: TODO
url: https://www.codabench.org/competitions/3764/
doi: TODO
domain: Genomics; Image/CV
focus: Detecting hybrid butterflies via image anomaly detection in genomic-informed dataset
keywords: - anomaly detection - 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: TODO
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: TODO
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: [32]

Ratings:



38 HDR ML Anomaly Challenge (Sea Level Rise)

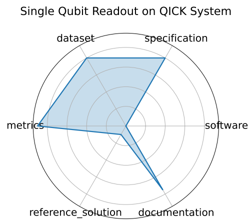
date: 2025-03-03
version: TODO
last_updated: 2025-03
expired: unknown
valid: yes
valid_date: TODO
url: https://www.codabench.org/competitions/3223/
doi: TODO
domain: Climate Science; Time-series, Image/CV
focus: Detecting anomalous sea-level rise and flooding events via time-series and satellite imagery
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: TODO
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: TODO
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: [32]

Ratings: 

39 Single Qubit Readout on QICK System

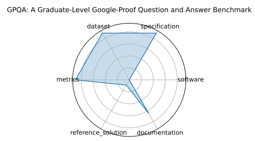
date: 2025-01-24
version: TODO
last_updated: 2025-02
expired: unknown
valid: yes
valid_date: TODO
url: https://github.com/fastmachinelearning/ml-quantum-readout
doi: TODO
domain: Quantum Computing
focus: Real-time single-qubit state classification using FPGA firmware
keywords: - qubit readout - hls4ml - 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: TODO
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: TODO
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: [33]

Ratings:


Single Qubit Readout on QICK System
dataset
specification
metrics
software
reference_solution
documentation

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

date: 2023-11-20
version: TODO
last_updated: 2023-11
expired: unknown
valid: yes
valid_date: TODO
url: https://arxiv.org/abs/2311.12022
doi: TODO
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: TODO
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: TODO
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: [34]

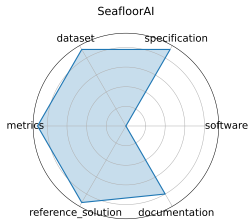

GPQA: A Graduate-Level Google-Proof Question and Answer Benchmark
dataset
specification
metrics
software
reference_solution
documentation

Ratings:

41 SeafloorAI

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97432
doi: TODO
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: TODO
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: TODO
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: ~15 TB
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: 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: [35]

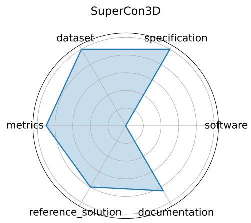
Ratings:


SeafloorAI
dataset
specification
metrics
software
reference_solution
documentation

42 SuperCon3D

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97553
doi: TODO
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: TODO
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: TODO
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: [36]

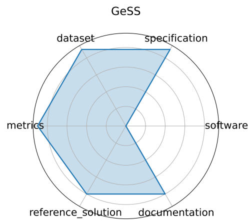
Ratings:


SuperCon3D
dataset
specification
metrics
software
reference_solution
documentation

43 GeSS

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97816
doi: TODO
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: TODO
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: TODO
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: [37]

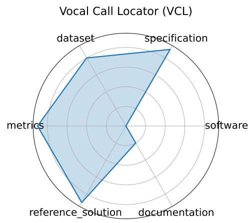
Ratings:


GeSS
dataset
specification
metrics
software
reference_solution
documentation

44 Vocal Call Locator (VCL)

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97470
doi: TODO
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: TODO
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: TODO
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: [38]

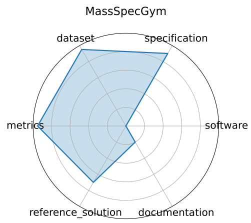
Ratings:


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

45 MassSpecGym

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97823
doi: TODO
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: TODO
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: TODO
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: [39]

Ratings:

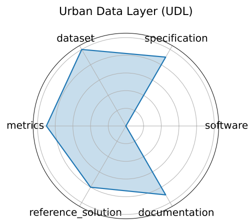


MassSpecGym
dataset
specification
metrics
software
reference_solution
documentation

46 Urban Data Layer (UDL)

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97837
doi: TODO
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: TODO
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: TODO
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: [40]

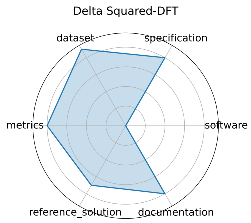
Ratings:


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

47 Delta Squared-DFT

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97788
doi: TODO
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: TODO
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: TODO
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: [41]

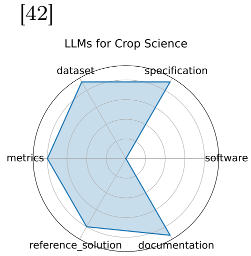
Ratings:



Delta Squared-DFT
dataset
specification
metrics
software
reference_solution
documentation

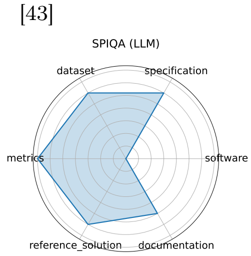
48 LLMs for Crop Science

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97570
doi: TODO
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: TODO
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: TODO
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: [42]

Ratings: 

49 SPIQA (LLM)

date: 2024-12-13
version: TODO
last_updated: 2024-12
expired: unknown
valid: yes
valid_date: TODO
url: https://neurips.cc/virtual/2024/poster/97575
doi: TODO
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: TODO
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: TODO
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: [43]

Ratings: 

References

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