MASTER TABLE FOR LIBRARIES AND TOOLKITS THAT FOCUS ON DAS DATA

Library / Toolkit	Primary Purpose	Typical Capabilities
Obspy [1, 2]	Handling seismic waveforms	Reading DAS or seismic data, Filtering, Event detection Phase picking, and Spectrograms. Obspy
DASCore [3]	General-purpose core for DAS I/O & processing	Supports many vendor formats (TDMS, SEG-Y, HDF5, Zarr), implements lazy chunked workflows utilizing Dask, facilitates standard processing (detrending, filtering, decimation), and enables rapid visualization; serves as the cornerstone of the "DAS Data Analysis Ecosystem (DASDAE)." DASCore
DASPy [4, 5]	Lower the entry barrier for DAS signal processing	Consolidated object class for strain, phase, and strain rate; encapsulations for frequency-wavenumber filtering, FK beamforming, FK migration, and coherence analysis; extensions for TensorFlow-based denoising. DASPy
Xdas [6]	N-dimensional labelled data model	Treats DAS frames as xarray/dask objects; on-the-fly coordinate transforms, metadata propagation, interactive plotting, GPU-accelerated operations via CuPy when available. Xdas
Lightguide [7, 8]	Advanced filtering & modelling	High-order Butterworth, FK, curve-let, and wavelet denoising; forward modelling for gauge-length and cable-ground coupling; tight integration with Pyrocko for event workflows. Lightguide
Distpy [9]	Scalable prototyping & pipeline orchestration	Graph-based "branched network" engine for extensive parallel DAS workflows; delivers pre-constructed modules for calibration, noise reduction, and STA/LTA-type triggers. distpy
MLDAS [10, 11]	Machine-learning experimentation	Comprehensive PyTorch framework for large-scale DAS classification and segmentation; includes parallel HDF5 loaders, GPU batching, and hyper-parameter optimization; features instructive notebooks for event detection. MLDAS
iDAS-convert [12]	Vendor TDMS → seismology formats	Streams Silixa iDAS files to MiniSEED/SEG-Y with configurable down-sampling (about 200 MB s^{-1} on cluster) and concurrent I/O; ideal for field-to-archive workflows. IDAS
DAS4Whales [13]	Marine bioacoustics with DAS	Concise examples for importing raw TDMS strain-rate data from iDAS interrogators into numpy or MATLAB arrays; an effective foundation prior to transitioning to open-source solutions. DAS4Whales
DASstore/ NoisePy4DAS-SeaDAS [14]	Cloud-optimised storage back-end	Repackages DAS frames into segmented Zarr objects for efficient S3/Azure/local object storage; integrates with NoisePy workflows for ambient noise interferometry. NoisePy4DAS
ARRAYUDF [11, 15, 16]	To speed up and automate processing of huge seismic array datasets	Feature extraction, noise reduction, event identification, ambient noise correlation, etc. Executed utilizing parallel computing frameworks (such as Dask, Spark, or Python's multiprocessing); may also be tailored into seismic processing pipelines. ArrayUDF
GPyOpt [17-19]	Automatically tuning hyperparameters of machine learning models or any black-box function	Find best hyperparameters for deep learning models (e.g., learning rate, batch size). Optimize any expensive-to-evaluate function (e.g., model training, simulation). Efficient search where evaluations are slow or costly. GPyOpt

MASTER TABLE FOR DATA AVAILABILITY

Dataset & Paper Data Used	Dataset Description	Dataset Availability	Repository Link	Format	Size
[20]	Noise interferometry. Type of shared data: Preprocessed	Yes	River stage and precipitation data	-	Hundreds of TB
FORGE [21-27]	Enhanced geothermal system	Yes	Utah FORGE	TDMS/SEGY	16TB
Cook Inlet [28]	Earthquake data	Yes	Dasway	HDF5	502 GB
California Geological Survey [29]	Some waveform data, metadata, and the earthquake catalog in this study were accessed through the Northern California Earthquake Data Center	Yes	NCEDC Earthquake	-	>40 TB
Excavator [30]	Data collection in a suburban area near Vienna, Austria. Real-time system evaluations over 3 months.	Yes	Bublin, M.	EXCEL	-
SCALODEEP [31]	The detection of earthquake signals is a fundamental yet challenging task in observational seismology.	Yes	SCALODEEP	NPZ	4.85 GB
SAFOD DAS array [32]	Earthquake events available within period of 22 days	Yes	DASDetection, Dasmrrcoh_dataonly	NPY	1.3 GB
The SCEDC Earthquake Data AWS Public Dataset. [33]	The "ridgecrest_north" dataset is extracted from The SCEDC Earthquake Data AWS Public Dataset.	Yes	Quakeflow_das, scedc	H5	-
POROTOMO [34]	Geothermal, natural lab	Yes	Porotomo	HDF5/SEGY	<100TB
Antarctica [35]	Passive & Active seismic surveys	Yes	Antartica	MSEED	-
Garner Valley [36]	Natural tectonics	Yes	Garner	-	-
Stanford phase 1 [37]	Urban	No	-	-	-
Monterrey Bay Dark Fiber [38]	Plate tectonics	Yes	-	-	-

MASTER TABLE FOR SOURCE CODE AVAILABILITY

Paper Reference	Application Type	Code Type	Software/Programming Language	Repository Link
K. Gonzalez [39]	Microseismic Denoising	Preprocessing	Matlab/python	HOSVD
S. Lapins [40]	Denoising	Preprocessing	Python	DAS-N2N
X. Gu [41]	Denoising	Preprocessing	Python	CEGCurtin
Y. Chen [21]	Denoising	Preprocessing	Python	Sigrecover Sigrecover2
Y. Ni [28]	Lossy Compression, Wavefield Separation, and Edge Computing	Data Management	Python	DAS-reconstruction
D. Wamriew [22]	Microseismic Events	Preprocessing	Python	Das_Microseismics_Inversion
M. Bublin [30]	Pipeline monitoring	Event Detection	Python	Bublin, M.
M. Saad [31]	Earthquake Detection	Event Detection	Python	SCALODEEP
F. Huot [19]	Microseismic Events	Event Detection	Python	Microseismic_detection
D. Wamriew [23]	Microseismic Events	Event Detection	Python	DL4Reservoir
Y. Chen [32]	Earthquake events	Event Detection	Python	Dasmrrcoh
W. Zhu [33]	Earthquake events	arrival-time picking	Python	PhaseNet GaMMA EQNet
P. Yu [25]	Microseismic Events	Event Detection	Python	DASEventNet

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