Xdas: a Python Framework for Distributed Acoustic Sensing

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Abstract

Xdas is a Python library designed to manipulate Distributed Acoustic Sensing (DAS) data. It provides a unified abstraction for reading any DAS file format into a standardized Python object, streamlining data handling across different acquisition systems. To address the challenge of massive, multi-file datasets, Xdas aggregates data chunks into virtually contiguous arrays organized by instrument and acquisition. This structure allows for efficient spatial and temporal slicing while minimizing overhead. To enable scalable offline processing of massive DAS datasets, Xdas process data in manageable chunks. To ensure processing continuity, Xdas uses a stateful pipes-and-filters architecture. Most Xdas operations are multithreaded by default to take full advantage of multicore systems. This approach also enables real-time data processing. Its built-in network streaming capabilities allow Xdas to be deployed on DAS instruments for custom, real-time workflows at the point of data generation. At its core, Xdas uses a labeled N-dimensional array structure that encapsulates both data values and coordinate metadata and can be used to handle any kind of dataset (not just time-space DAS records). This data model adheres to the established standards provided by the NetCDF4/HDF5 formats and the Climate and Forecast (CF) conventions. Designed to mirror the APIs of popular libraries such as NumPy, SciPy, and Xarray, Xdas minimizes the learning curve for new users. Its modular and extensible design means that adding support for a new file format or integrating a processing function typically requires less than ten lines of code.

Introduction

The advent of Distributed Acoustic Sensing (DAS) technology has firmly placed seismology into the realms of big data. While most DAS experiments last only several weeks, they produce data volumes comparable to what traditional seismological networks have accumulated over the span of years. Seismologists must now meticulously delineate data management plans and address the hardware necessities for storing and processing eventually hundreds of terabytes of data. DAS has introduced a novel observational paradigm by providing continuous sampling of the spatial dimension. In contrast to the previous practice of dealing with spatially sparse 1D time series, seismologists must now handle 2D time and space continuous representations of the wavefield. This necessitates the development of new standard analysis schemes, such as spatial filtering. It also requires the development of new tools that can effectively explore, process, and visualize the high volume of these higher dimensional datasets.

Even though DAS experiments have become commonplace in seismology, DAS remains a nascent technology. Each DAS interrogator model is unique, with each manufacturer utilizing their own set of parameterizations and file formats. While some standards are emerging (e.g., PRODML), at the time of writing this manuscript, the terminology, standard processing routines, and minimal set of metadata are still evolving.

As a result, working with DAS data is inherently challenging for several reasons: (i) High data volume. The issue of processing DAS data is often constrained by input/output (I/O) and memory limitations.

Reading and writing operations take an important part of the processing time, and datasets needs to be chunked to fit in memory (e.g., a 5 min of record for 10 000 channels at 100 Hz stored as float represents ~1 GB which is a typical manageable chunk size). (ii) Chunked file storage. Datasets are partitioned into a multitude of files of reasonable size, ranging from seconds to hours, depending on the manufacturer. This is a complication that can result in a slower temporal selection process compared to e.g. a single database. (iii) Absence of a widespread standard format. Each manufacturer usually supplies a set of scripts for opening their preferred (and sometimes proprietary) file format. The specific metadata content is dependent on the choices made by the manufacturers and sometimes depends on the acquisition technology.

Several software tools have recently been developed to facilitate the management and processing of DAS data. Most address specific challenges of the aforementioned one, either as plugins for existing frameworks (Isken et al., 2022) or as standalone sets of processing routines and/or I/O strategies (Nuwara, 2021; Hu & Li, 2024; Ni et al., 2024). Some are tailored to a particular field of research (Bouffaut, 2023). Recently, Chambers et al. (2024) proposed a multipurpose, end-to-end solution. This simultaneous exploration of multiple frameworks stems from the early stages of the development of DAS toolboxes and the still evolving usages and need of the community. However, as of the writing of this manuscript, no existing tool provides a first-class solution that completely abstracts away the logical complexities associated with the chunking of larger-than-memory datasets, nor provides high-performance online implementations of the common DAS processing routines that can be effectively applied both offline to massive DAS records and in real-time on instrument-generated or network-received streams.

In this paper, we present Xdas, a Python framework for DAS designed to bridge this gap. Xdas achieves these goals without compromising its generic, user-friendly design. To this end, the framework uses established coding conventions and syntax and is accompanied by comprehensive documentation and extensive tutorials. We present an overview of the software, introduce its native format, show a typical use case, benchmark its multithreading capabilities, illustrate the process of dealing with massive and real-time data, and explain how to add support for any file format or include custom processing functions. Finally, we introduce Xpick, a manual picking web application for DAS, which illustrates how Xdas can be used as the foundation for an ecosystem of DAS-related toolboxes.

Xdas overview

Xdas is designed to support users throughout the entire data workflow: from data preparation and exploration to deployment in production environments, whether for real-time or large-scale offline applications. Xdas foundations relies on several pillars: (i) Datasets virtualization and labeling: easy continuous data slicing in time and space, even when the underlying data are distributed over numerous smaller files. (ii) High-performance data processing: implementation of NumPy/SciPy functionalities with chunked-processing implementations for massive offline or real-time processing. (iii) Extensibility: great expressiveness and highly customizable routines that facilitate the development of external toolboxes.

Data structures

As DAS metadata harmonization is still an ongoing process, Xdas currently focuses on a minimal subset of metadata that is applicable to all instruments. This subset consists of the correct labeling of the time and space dimensions. Only timestamps and the "optical" distance from the interrogator are parsed from instrument-generated files. Xdas then let users attach additional information, such as the cable's geographical coordinates. This latter requires careful and case-specific procedure as the "optical" distance often differs from the "geometrical" distance measured via geographic coordinates (e.g., due to cable slack, loops at junction boxes or fiber helicity). The framework also accommodates DAS-derived quantities, like frequency-wavenumber data.

To meet those requirements, Xdas employs the N-dimensional (N-D) labeled array data structure. Xdas reimplements a subset of the well-established Xarray package (Hoyer & Hamman, 2017) and extends it with features required for DAS data handling that could not be implemented as is with the current state of Xarray (see Interpolated coordinates and Virtual datasets sections). Those versed in Xarray will find Xdas a familiar environment, with the conversion of Python objects between one library to another being a straightforward process. Xdas is compatible with numerous DAS file formats from several manufacturers (AP Sensing, Alcatel Submarine Network, Febus, OptaSense, Silixa, Sintela, Terra15) and offers a custom NetCDF4 file structure for storing DAS data in accordance with the Climate and Forecast (CF) metadata convention. Xdas also supports seismological formats that can be read with Obspy (Beyreuther et al., 2010) enabling the join processing of DAS and traditional seismological data or even massive nodes datasets. The addition of support for an additional format can be accomplished with a few lines of code (see Extensibility section).

Data arrays

To ease time, space or any dimension selections, Xdas objects can be referenced by means of labels or coordinate values instead to the conventional practice of employing numerical indices. At is core Xdas implements the DataArray object (Fig. 1a) that extends the concept of a traditional N-D array by incorporating a set of coordinate objects attached to each dimension. It is composed of three main components: (i) a *data* attribute that contains an array of numerical values (e.g., a 2D array of strain-rate values), (ii) a *dims* attribute which maps each numerical axis to a (physical) dimension label (e.g., “time” for the first axis and “distance” for the second one), and (iii) a *coords* attribute which maps each dimension label to one dimensional and any number of optional non-dimensional Coordinate objects (e.g., one timestamp based coordinate object for the “time” dimension and a distance along the cable, longitude, latitude and depth coordinate objects for the “distance” dimension). Additionally, an *attrs* attribute can be used to store user-defined metadata as a key/values dictionary (note that Xdas does not process this information nor insure its survival through data manipulation).

Xdas allows the use of several kind of coordinates and data objects. To deal with massive datasets the strategy involves using lazy objects as a *data* attribute. Lazy objects provide a virtual representation of the target data and triggers the in-memory loading of only the queried subset when necessary. In contrast, metadata attributes (i.e., all except *data*) are fully loaded into memory for efficiency and must therefore be kept compact – particularly the coordinate attributes, which are essential for mapping numerical indices to physical values.

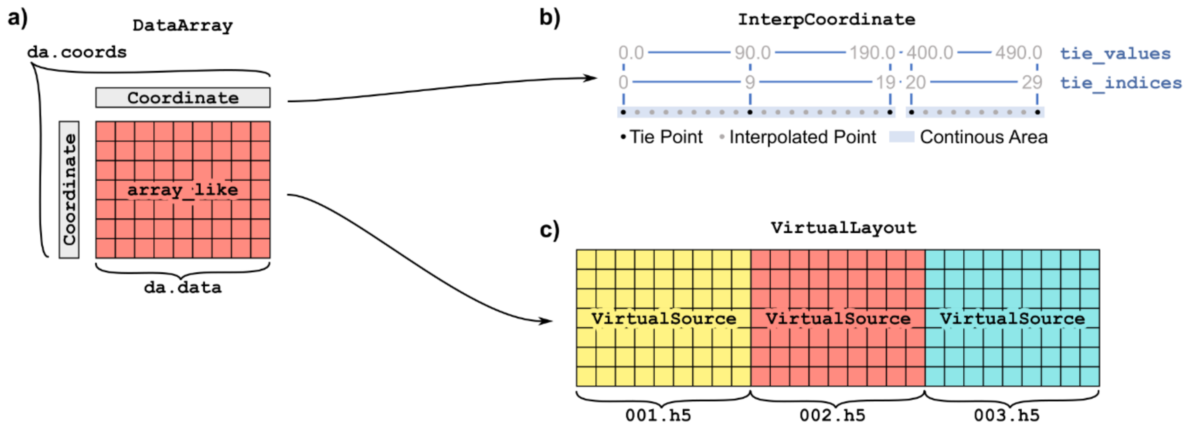


Figure 1. Overview of the data structure used in Xdas. (a) Xdas implements the N-D labeled array structure through a structure called data array. A data array can contain any array-like object and can attach to each of its dimensions one or more coordinate objects. In practice, the data array related to a typical DAS record is composed of a 2D array of strain-rate values with two attached “time” and “distance” coordinates. Several types of array-like objects and coordinates can be used but Xdas introduces two objects that are particularly useful for DAS data handling: (b) Interpolated coordinates as defined by the CF conventions. They are a compact way to represent quasi

evenly spaced coordinates with potential gaps/overlaps or tiny variations of the sampling rate. Tie points are stored for specific index/value pairs. To retrieve intermediate values linear interpolation is used. (c) Virtual datasets. Xdas provides a powerful way to virtually access any number of subfile through a master file with almost no overhead. Here an illustration of the consolidation of three files into a virtually contiguous layout is shown. In practice, files are typically virtually concatenated along the "time" dimension.

Interpolated coordinates

In Xdas, the mapping between indices and related physical values or labels can be encoded in two ways: (i) DenseCoordinate requires a dense vector with the same length as the size of the related dimension. This is the most generic labeling method (e.g., it can be used to name each DAS channel individually according to some user-defined convention) and is the only method supported by Xarray. However, this approach is limited when dealing with extended yearly time series, where the vector encoding the indices-to-times mapping may exceed the available memory capacity. For instance, one year's worth of timestamps sampled at 100 Hz and stored in double-precision format exceeds 20 GB. This hinders efficient inverse label-to-index mapping, as working from disk rather than from memory is significantly slower. (ii) InterpCoordinate implements a scheme adapted to quasi-evenly spaced samples (Fig. 1b). The strategy implemented in Xdas follows the conventions set by the CF conventions (Gregory, 2003) (see 8.3 Lossy Compression by Coordinate Subsampling – CF 1.11). In Xdas, the index-to-timestamp information is stored through a specified number of tie points. Each tie point associates to a given index a given timestamp. Timestamps corresponding to intermediate indices are calculated through linear interpolation. In accordance with the established convention, the presence of two tie points within the same index interval indicates the existence of a discontinuity. This approach enables the handling of gaps and overlaps, as well as the accommodation of internal clock drifting for instruments that are not synchronized by GNSS. Xdas provides methods for removing minor artificial gaps and overlaps within a specified tolerance.

Virtual datasets

DAS datasets consist of numerous files (e.g., OptoDAS instruments from Alcatel Submarine Network produce one file every 10 s). Making a temporal selection entails traversing the file tree to identify the relevant files, loading the correct portion of each file and performing the data and metadata concatenation. Xdas streamlines this process through its virtual dataset feature (Fig. 1c) using either a native, high-performance, low-level HDF5 implementation (Folk et al., 2011; Koziol et al., 2014) or a custom flexible Dask-based solution (Rocklin, 2015) for non-HDF5 files. A virtual dataset is built from one or more source files which data is virtually concatenated via references. This enables accessing the whole dataset through a unique entry point without rewriting or rearranging the original files. In practice, functions such as open_mfdataarray catalog and index the underlying files and return a unified data array comprising of a virtual array and consolidated coordinates. Note that the files to be consolidated must have the same acquisition parameterization to allow metadata aggregation and virtual array concatenation, otherwise Xdas will try to split them into different homogeneous datasets, considering the spatio-temporal sampling rate and the data format (float, integer, ...). As regular data arrays, "virtual" ones can then be stored to disk once for all (the difference laying in the fact that the data attributes only contain pointers rather than "true" data). This enables seamless subsequent access and navigation of the entire dataset with minimal latency. The user can query portions of the dataset based on a range of timestamps and distances, without having to consider the corresponding N-D array indices in each data file, midnight transitions, leap years, or small irregularities in the data size from one file to the next.

Data collections

The DataArray structure is optimized to handle data and metadata from a single acquisition. It allows for the potential inclusion of gaps and overlaps but cannot handle change in the acquisition parameters. A dataset with changes in the number of samples along the spatial dimension (e.g., due to a change in spatial resolution or in the length of sensed cable) cannot be encompassed into a unique DataArray which stores the data as a unique continuous array. Working with multiple acquisitions can happen when exploring different instrument parametrizations; or when multiple instruments are used simultaneously. To address such scenarios, Xdas introduces an additional layer of abstraction, referred to as DataCollection objects.

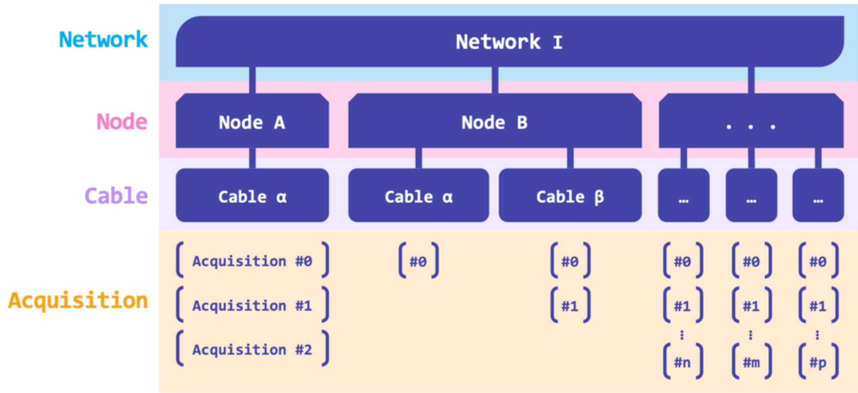


Figure 2. DataCollection structure. This flexible structure is a tree comprising nested dictionaries or lists where the leaves are DataArray objects (here illustrated by brackets). Here an example of a hierarchy with four levels (network, node, cable, acquisition). The first three levels are dictionary-like objects with labeled entries. The last level is a list-like object, containing a varying number of DataArray objects that correspond to different acquisition with potentially different parametrization.

A DataCollection object is a tree-like structure comprising a hierarchical nesting of either other DataCollections or, at the final leaves, DataArrays objects. Each node of the tree can either referenced by a label (e.g., the name of the instrument) or by position (e.g., the number of the acquisition). This flexible structure can represent any hierarchical organization, enabling the accommodation of a wide range of data structures. Fig. 2 depicts a structure that has been adapted for a pool of DAS instruments situated in multiple telecommunication nodes and connected to disparate cables. The interrogator configuration has undergone modifications over time, resulting in the presence of multiple acquisitions. It is anticipated that this flexible structure will be able to adapt to emerging metadata schemes, such as the DAS metadata standard that has been proposed by the DAS-RCN group (Lai et al., 2024).

A subset of the methods applicable to DataArray objects are likewise applicable to DataCollection objects. As a result, the tree is traversed, and the method is applied to every DataArray encountered within the DataCollection. This approach is beneficial when performing temporal selection over a complex multi-acquisition dataset.

Xdas native format

Xdas can write any DataArray and DataCollection object to disk as NetCDF4/HDF5 files, utilizing a specific format. The DataArray structure is written by simply reusing the proven NetCDF4 file structure in conjunction with the well-established CF conventions. If no changes have been made to the raw data other than slicing, both DataArray and DataCollection will be written without copying any data (unless the user requests it). The resulting file will rather include pointers to the original files. In any other case the data will be written to disk. Due to their nature, raw DAS data are large, and it may be beneficial to save the data of interest in a compressed form. With Xdas, users can choose to use all standard NetCDF4 and HDF5 compression filters with the h5netcdf and hdf5plugin libraries. In particular, Xdas includes the ZFP compression algorithm (Lindstrom, 2014), which is suited for conservative lossy compression of floating-point data (Issah & Martin, 2024) and can typically reach a compression factor of four without the introduction of any discernible errors. The DataCollection structure is saved by employing the group feature of NetCDF4 to write multiple DataArrays in a single file. The Xdas native format is a valuable tool for the storage and transfer of processed data, as well as for the compression of raw data for long-term storage.

Typical workflow

The utilization of Xdas for data analysis is analogous to that of Xarray, which is, in turn, is analogous to NumPy (Harris et al., 2020) and/or SciPy (Virtanen et al., 2020). In contrast to other software that provides only large, opaque processing systems, Xdas offers a set of small, modular components that allow users to customize their workflow while maintaining flexibility. To facilitate simplicity, Xdas attempts to adhere to the function signatures observed in Xarray, NumPy, and SciPy, employing two conventions: (i) Rather than providing the axis number, the dimension label must be provided; (ii) a parallel keyword argument may be passed to parametrize multithreading processing (see Performance).

To illustrate a typical workflow, we process an example event (Fig. 3). In the case that a master virtual file has not been created prior to this step, it must first be created (step b in Fig. 3). This process may take a few minutes to complete for datasets containing millions of files. In subsequent instances, the master file can be accessed with minimal delay, usually less than a second (step c). Subsequently, we query a time and space selection of the data (step d). At this stage, the data can be loaded into memory in a contiguous array (the array memory order and format – i.e., row or column major order, integers or floats – follow the layout of the original files). As an example, the FK representation can be plotted from scratch in a few lines of code (step e), applying a sequence of NumPy/SciPy-like operations to the data set. This example illustrates the versatility and expressiveness of Xdas and its ability to handle arbitrary coordinates, such as frequency and wavenumber in this case. Certain specific processing routines provided by Xdas can be applied, such as a conversion to velocity (Trabattoni et al., 2023) and time/space decimations (step g). The processed waveforms can then be plotted either as a 2D image or trace by trace in a single line of code (steps f, g, h), leveraging the encapsulated metadata to ensure accurate labeling of the axes. This style of processing and visualization is like that of ObsPy or Xarray and therefore be familiar to most users.

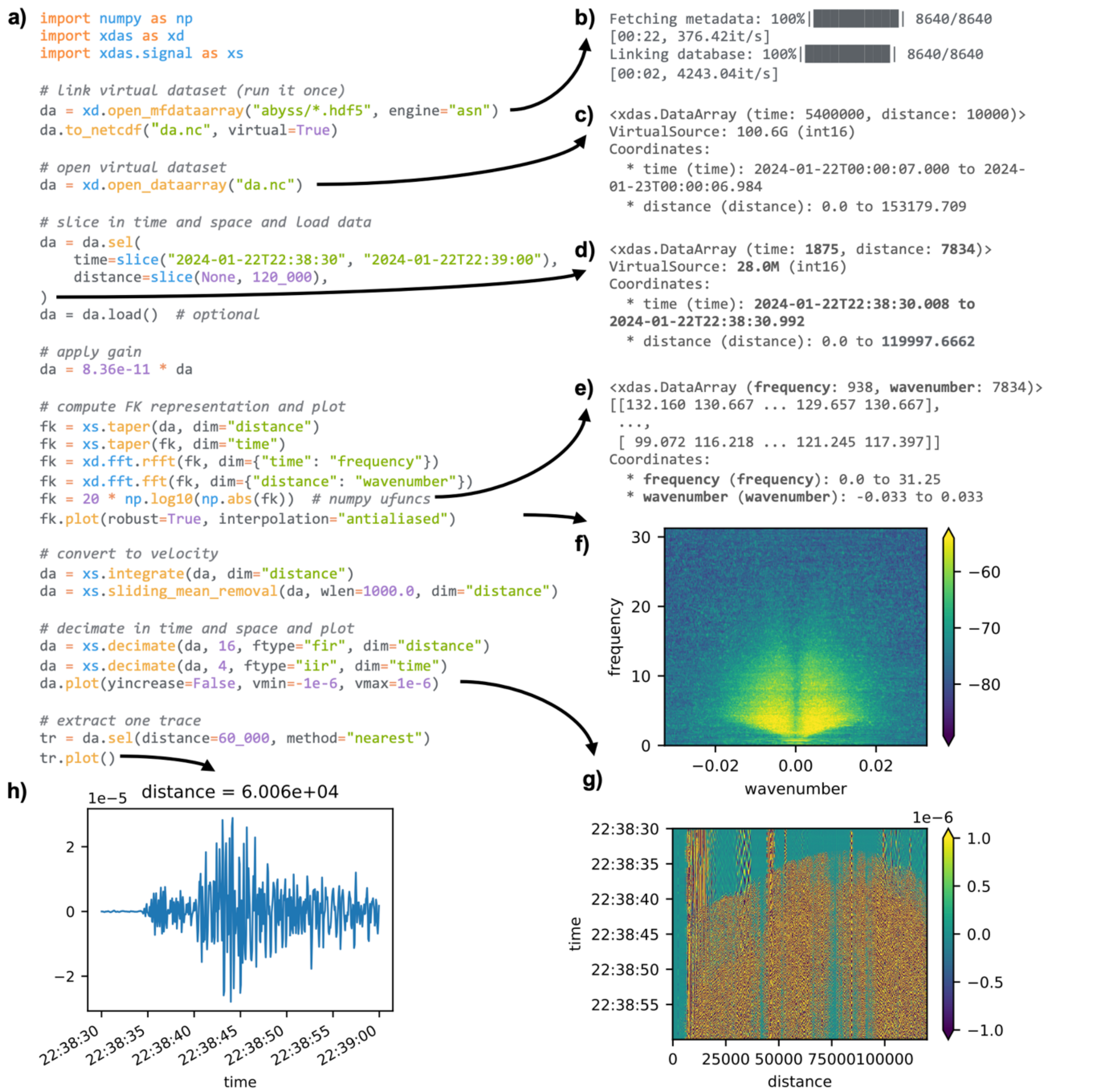


Figure 3. Typical workflow. (a) Example python scripts. (b) Liking of the virtual data array. Must be run only once. Here one day of ten-second files (i.e., 8640 files) are linked, which takes about 20 s (on a 24-core machine reading from a 36-hard-disk-drive RAID60 array). The DataArray.to_netcdf method write the virtual dataset to disk as a NetCDF4/HDF5 file. (c) Virtual data array once all files have been linked. Opening it take less than one second. (d) Data array after slicing. In bold, fields that have changed. Note that now the data array only contains 28MB (rather than 100 GB for the entire data set) and hence can be loaded in memory (note that Xdas will automatically load data when required). It is up to the user to apply any instrumental response, usually as a conversion factor. (e) The data array structure can be used with other coordinate systems than time-space dimensions. Here an FK result is stored. (f) The FK is plotted in a single line of code and metadata is used to produce a labeled plot. (g) Same but for the converted-to-velocity and decimated waveforms. (h) Xdas allows trace by trace analysis. Note that Xdas does not yet handle units which is why they are missing in the plot labels.

Performance

When working from cloud storage or Network-Attached Storage, the data reading, transfer, and writing is generally the limiting factor when processing DAS data, Multithreading acceleration is relevant when the data is locally available which is the considered scenario of this section.

Server-grade disk arrays allow data reading speeds of up to several gigabytes per second, and CPU core counts often exceed several dozen. In this context, the objective is to provide a computational pipeline that can optimally use the available compute resources to match the input/output (I/O) access speed.

Xdas achieves this by avoiding unnecessary overhead by processing the data N-D array as a whole (and not trace by trace) and by implementing a versatile multithreading solution. Under typical conditions, Xdas provides one order-of-magnitude speed gain compared to strategies that involve splitting the data into traces and then joining the processed traces (Fig. 4a) using standard tools such as ObsPy (Beyreuther et al., 2010). When multithreading is enabled, Xdas accelerates NumPy/Scipy operations, with performance scaling almost linearly with the number of threads, provided that the overall computational load justifies the small additional overhead of parallelism (Fig. 4b).

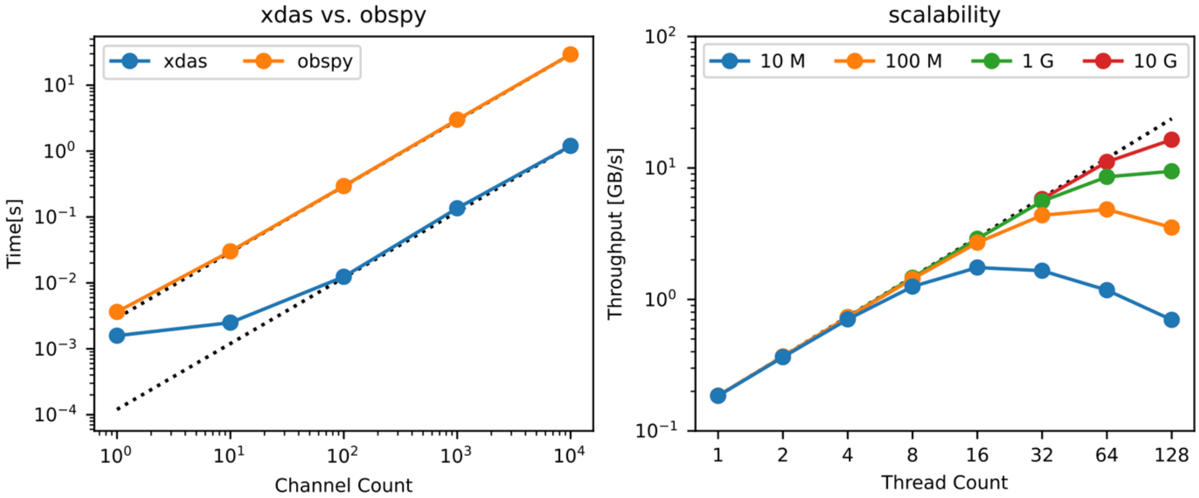


Figure 4. Benchmark of Xdas. Each measure consists in the smaller elapsed time over 7 runs. (a) Single-threaded temporal decimation using a 12 order IIR filter for a 10 000 samples long signal with varying number of channels. Obspy scales linearly (ideal linear scalability in black dotted lines), meaning it has a fixed extra overhead per channel whereas Xdas take advantage of processing every channel in a single run, reducing the overhead per channel. (b) Multi-threaded decimation with Xdas. A spatial decimation of a factor 16 is applied with FIR filtering. The single-threaded version uses the base SciPy function and can be used as reference. Depending on the chunk size (different solid-colored lines, legend gives the number of samples of the chunk which number of channels was fixed to 10 000 and number of time samples increased from 1 000 to 1 000 000) and number of threads, the overhead implied by multi-threading can limit the scalability (ideal scalability in black dotted lines). The throughput, measured as the amount of data bytes processed by second, reaches several GB/s when using several tens of cores. Those benchmarks have been run on a 128-core node of the DANTE/IPGP platform.

Massive and real-time processing

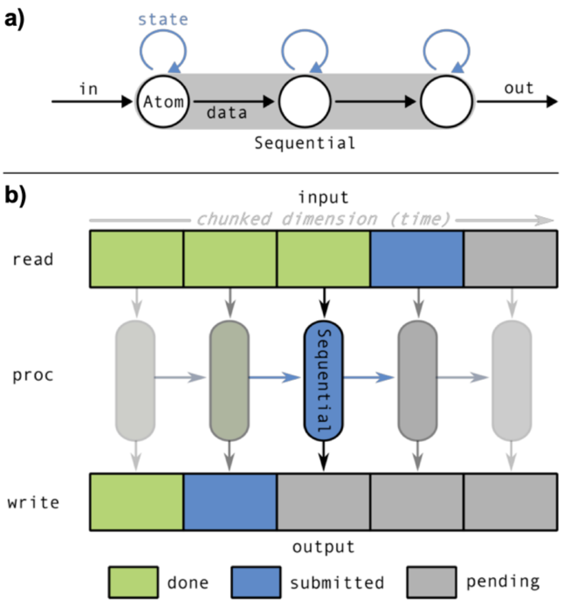
A major challenge with DAS data lies in the processing of extensive time periods. In most cases, only small subsets of the data (up to few minutes) can be loaded into memory at once. To perform a posteriori analysis of the entire dataset, continuous chunked-based processing is necessary. A comparable challenge is encountered in applications requiring quasi-real time processing. Xdas provides a solution for the online processing of data while simultaneously optimizing input/output operations.

The chunk processing architecture is based on an overall first-in-first-out (FIFO) strategy, which is particularly well-suited for real-time applications. Furthermore, it allows for the use of infinite impulse response (IIR) processing, where the outcome of the previous iteration is needed to compute the next iteration. This contrasts with finite impulse response (FIR) processing, where the data can be processed in any order, provided that sufficient overlap is loaded.

To ensure continuity of processing across chunks, Xdas introduces "atoms", which are elementary operations that can retain any final state of the previously processed chunk that is required as the initial state of the next iteration (Fig. 5a), provided there is no gap (otherwise the state is reset). Atoms are meant to be chained together and used as processing pipeline. To maximize throughput, each Atom is parallelized individually. In the case of straightforward filtering routines, this approach can achieve throughput of several gigabytes per seconds and to match the I/O bandwidth.

A common strategy to maximize processing bandwidth is to divide a pipeline into three concurrent operations: data reading (or awaiting new data in real-time), computation, and data writing. By staggering the output of each operation (as illustrated in Fig. 5), the latency associated with I/O operations can be circumvented (hence the common term "latency hiding"). The user is thus required to create three objects: a data loader (which can be a real-time data stream or a chunked view of offline archives), a signal processing chain (comprised of a sequence of Atoms), and a data writer (that can either write to disk or stream to another device).

Since the data is processed in discrete units, or "chunks", the optimal chunk size should be selected based on three key considerations: (i) Increasing the chunk size can lead to enhanced performance, while simultaneously reducing the overheads associated with the process of chunking. (ii) The size of the data chunk is constrained by the amount of available memory. Xdas maintains a maximum of three chunks in memory at any given time. However, the memory allocation required to store intermediate results must also be considered. (iii) In a real-time setup, an increase in the chunk size will result in a corresponding increase in delay.



c)

```
import scipy.signal as sp
import xdas as xd
import xdas.signal as xs
import xdas.processing as xp
import xdas.atoms as xa

# data loader (choose one option)
da = xd.open_dataarray("da.nc")
dl = xp.DataArrayLoader(da, chunks={"time": 10000})  # offline
dl = xp.ZMQSubscriber("tcp://localhost:3333")  # real-time
dl = xp.RealTimeLoader("directory/to/watch") # real-time

# atoms
sos = sp.iirfilter(8, 0.8 / 4, btype="low", output="sos")
atoms = xa.Sequential([
    xs.decimate(..., 16, ftype="fir", dim="distance"),
    xa.SOSFilter(sos, dim="time"), # with state passing
    xa.DownSample(4, dim="time"), # idem
])

# data writer (choose one option)
dw = xp.DataArrayWriter("chunks") # offline
dw = xp.ZMQPublisher("tcp://*:5555") # real-time

# process
xp.process(atoms, dl, dw)
```

d)

```
0%| | 125G/72.5T [02:30<24:48:28, 891MB/s, read=66.7%,
proc=33.3%, write=0.0%]
```

Figure 5. Xdas introduces the Atom object to enable chunk-based processing. (a) Each Atom takes one input and returns one output. To ensure continuity in a very generic way, Atom objects use state passing. The final state of the preceding iteration is used as the initial state of the next iteration. Atom objects can be concatenated in a processing chain through the Sequential Atom (in this example three atoms are shown). This latter also takes one input and returns one output hence is an Atom by definition. (b) Sequential graph of tasks. To perform continuous processing of DAS data, Xdas uses a chunk-based approach. Each input chunk (top rectangles) goes through a processing chain made of a sequence of Atom objects. Processed chunks are then written to disk or streamed over the network chunk by chunk (bottom rectangles). While the input is generally DAS data, the output can be of any type (e.g., phase picks). Xdas decouples the I/O tasks (read, write) from the processing tasks (proc). As soon as a chunk is available in memory, the processing chain is applied, and the result is put in a writing queue. (c) Related code for a conventional space and time decimation routine to reduce data volume. First a data loader must be defined either as a chunked view of a data array (the chunk size in sample must be provided) or by subscribing to a data stream (through the ZMQ protocol or watching at newly created files). The processing chain is composed of callable objects that takes and returns one chunk. Here: (i) a spatial decimation that is natively parallelized along time, (ii) a state aware filter (that uses cascaded second-order sections) used for antialiasing followed by an integer down sampling. Lastly, a data writer is defined, and the processing chain is applied. (d) Monitoring of the processing.

Extensibility and Interoperability

Xdas is designed to be extensible. Two common use cases include: (i) adding a user-defined processing routine and (ii) supporting an additional file format. In most cases, extending Xdas entails the writing of a few lines of code (Fig. 6). The process involves addressing the two primary aspects of a Xdas data array:

unpacking the data and coordinates objects, potentially performing operations on them, and then repacking them into a DataArray object. To add a new file format, the user is required to specify a function that must read one file and output a DataArray object. This function can then be passed as an engine keyword argument to all Xdas reading functions. The custom reading function must fetch and parse the data and coordinates information. To wrap a Python function meant to work on NumPy arrays, minimal work is generally required. If the processing is done along an axis, the dimension label must be converted into its numerical axis value. The function can be then applied to the data array values and, if necessary, the coordinates must be updated. Xdas provides Python decorators to parallelize function and make them behave as potential atoms.


```python
import h5py
import numpy as np
from xdas import DataArray
from xdas.virtual import VirtualSource

def read(fname):
    with h5py.File(fname, "r") as file:
        t0 = np.datetime64(round(1e9 * file["t0"][()]), "ns")
        dt = np.timedelta64(round(1e9 * file["dt"][()]), "ns")
        dx = file["dx"][()]
        data = VirtualSource(file["data"])
    nt, nd = data.shape
    t = {"tie_indices": [0, nt - 1], "tie_values": [t0, t0 + (nt - 1) * dt]}
    d = {"tie_indices": [0, nd - 1], "tie_values": [0.0, (nd - 1) * dx]}
    return DataArray(data, {"time": t, "distance": d})
```

```python
import scipy.signal as sp
from xdas.parallel import parallelize
from xdas.atoms import atomized

@atomized
def decimate(da, q, *args, dim="last", parallel=None, **kwargs):
    axis = da.get_axis_num(dim)
    across = int(axis == 0)
    func = parallelize(across, across, parallel)(sp.decimate)
    data = func(da.values, q, *args, **kwargs)
    return da[{dim: slice(None, None, q)}].copy(data=data)
```

Figure 6. Extensibility of Xdas. (a) Adding the support for a new file format generally consists into providing the path to the data array and parsing the start time and spatial and temporal spacing. Here a hypothetical simple file format is used as example. For real world application, the four lines into the with statement block must be adapted. (b) Wrapping a signal processing function that is applied along one axis require to convert the dimension name in its related axis number, processing the data (optionally in a parallelized manner), and handling coordinates changes if any. Here we reimplement the decimate function almost as it is implemented in Xdas.

Xdas is designed to enhance flexibility by interoperating with several seismological and DAS-related libraries. Its DataArray.to_stream and DataArray.from_stream methods facilitate seamless conversion to and from the Obspy Stream object, thereby leveraging standard seismological routines and I/O operations – such as writing SAC, MiniSEED, and SEGY files. Recently, the unidas library (https://github.com/DASDAE/unidas) has proposed a solution for interoperability among multiple DAS packages, including DASCore, DASPy, Lightguide, and Xdas. This approach simplifies the integration of alternative libraries to address gaps in missing routines or unsupported data formats.

Xpick: a toolbox for manual picks edition

In the long term, rather than developing a large and complex monolithic library, we propose the creation of a constellation of toolboxes. This approach will facilitate the development of an ecosystem of tools for addressing diverse advanced aspects of data analysis in a more flexible and community-oriented manner. By offering a comprehensive solution for DAS data management and processing, Xdas serves as the foundation for the development of other DAS toolboxes.

One illustrative example of such a toolbox is Xpick (Fig. 7). Xpick is a web-based application designed for the editing of manual picks on DAS data. The software is designed to perform free-hand delineations of seismic phase arrivals on two-dimensional data, enabling the manual identification of any phase along thousands of DAS traces. Xpick can be operated on a remote machine and accessed via a local browser, which makes it suitable for deployment as a web service by any observatory.

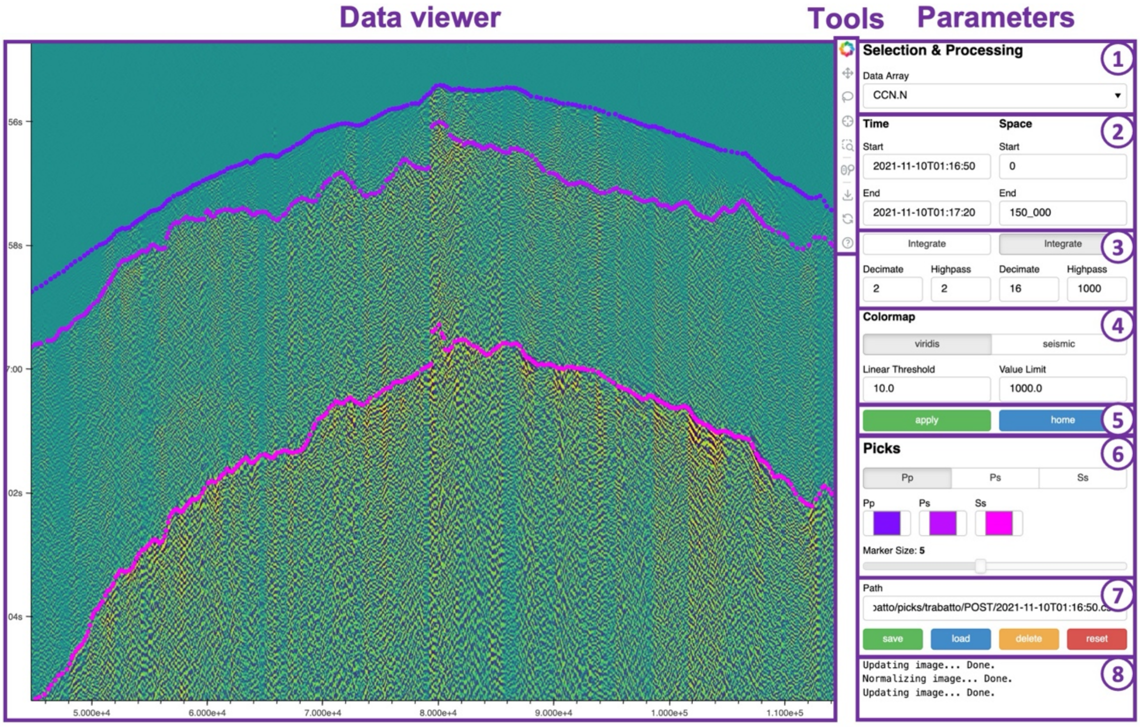


Figure 7. Xpick, the Xdas toolbox for editing manual picks on DAS data. Users explore any dataset both in time and in space and draw freely on the 2D plot of the waveform to delineate arrivals. This toolbox is an example of external tools that will be included in the Xdas ecosystem.

Conclusion and Perspectives

Xdas is an open-source Python framework that provides the fundamental functionalities for DAS data management and processing. The software is capable of handling large multi-file datasets of any format. It provides its own data format based on existing conventions and implements a state-of-the-art compression algorithm. It facilitates the time-based querying across multiple data files, provides multithreaded common processing routines, enables online processing for massive or real-time data analysis, and allows for straightforward extension. Xdas is intended to serve as the basis for other Python toolboxes that focus on advanced DAS data analysis and processing.

Looking ahead, Xdas could be enhanced by expanded metadata support, including unit management and instrumental response handling, although this will likely depend on reaching a community consensus on DAS metadata standards. Additionally, while Xdas currently implements a per-node multithreading strategy, it does not yet support distributing workloads across a multi-node cluster—a capability that will become increasingly important as yearly DAS datasets emerge, and retrospective analyses impose heavier computational demands. Consequently, computing infrastructures will also need to adapt, particularly in terms of I/O storage bandwidth. We encourage anyone interested to contribute to the improvement of Xdas' main functionalities or to develop their own Xdas-based toolboxes within the GitHub xdas-dev organization (https://github.com/xdas-dev).

Data and Resources

Xdas is available at https://github.com/xdas-dev/xdas (version 0.2 at the time of writing this manuscript). A complete documentation can be accessed at https://xdas.readthedocs.io. Tutorials are provided at: https://github.com/xdas-dev/tutorials. Xdas can easily be installed via pip (https://pypi.org/project/xdas). The scripts used to produce the figures of this study can be found at (https://github.com/atrabattoni/xdas_framework).

Declaration of Competing Interests

The authors acknowledge there are no conflicts of interest recorded.

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