

peaks: a Python package for analysis of angle-resolved photoemission and related spectroscopies

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Summary

The electronic band structure, describing the motion and interactions of electrons in materials, dictates the electrical, optical, and thermodynamic properties of solids. Angle-resolved photoemission spectroscopy (ARPES) provides a direct experimental probe of such electronic band structures, and so is widely employed in the study of functional, quantum, and 2D materials (Damascelli et al., 2003; King et al., 2021; Sobota et al., 2021). peaks (Python Electron spectroscopy Analysis by King group @ St Andrews) provides a Python package for advanced data analysis of ARPES and related spectroscopic data. It facilitates the fast visualisation and analysis of multi-dimensional datasets, allows for the complex data hierarchy typical to ARPES experiments, and supports lazy data loading and parallel processing, reflecting the ever-increasing data volumes used in ARPES. It is designed to be run in an interactive notebook environment, with extensive inline and pop-out GUI support for data visualisation.

Statement of need

Over recent years, significant technological improvements have developed ARPES into a truly multidimensional spectroscopy. Besides the traditional resolution of energy and up to three momentum directions, temperature, spin, spatial, and temporal-dependent ARPES measurements are becoming increasingly common (King et al., 2021; Sobota et al., 2021), typically requiring efficient handling and advanced analysis of 3-, 4-, and higher-dimensional datasets. Extensive use of international light sources for performing ARPES measurements, during intensive experiment campaigns running over several days, further motivates a collaborative approach to performing data analysis. There is also an ever-increasing push to incorporate machine learning (ML) methods into the analysis pipeline (Ágústsson et al., 2025; Iwasawa et al., 2022; Kim et al., 2021; Melton et al., 2020), while greater transparency and reproducibility in ARPES data analysis can be ensured by the development and utilisation of open-source packages, with clear and transparent metadata handling (Scheffler et al., 2022).

The above requirements all motivate the use of Python as a modern approach to ARPES data analysis. To this end, several packages have been developed. PyARPES (Stansbury & Lanzara, 2020) represents a pioneering development in this direction. It appears to no longer be actively maintained by the original author, although a maintained fork does exist (Arafune, 2025). Despite many excellent features, it makes several fundamental convention choices (regarding angular and energy scales and units, alignments, and sign conventions) which, in our view, complicates its use when employed with multiple experimental setups as is typical in the ARPES community, while approximations are used in the critical momentum-space conversions. pesto (Polley, 2025) is an excellent easy-to-use alternative, but is heavily oriented towards use with data collected from the Bloch beamline of the Max-IV synchrotron. We have recently discovered ERLabPy (Han, 2025) which provides similar functionality to peaks,

42 although with some differences in the approach to handling the data (e.g. co-ordinate systems).
43 The need to accommodate not only different data formats but also manage distinct angle and
44 sign convention choices for data acquired at multiple facilities can add significant complexity
45 for the user, in particular for on-the-fly processing: this is something that peaks attempts to
46 simplify for the end user, aiding quick and efficient on-the-fly analysis e.g. for sample alignment
47 during intense experimental runs. Other packages that we are aware of tend to focus on a
48 subset of the functions required, e.g. for ARPES data analysis (Das, 2025) or visualisation
49 (Kramer & Chang, 2021).

50 peaks

51 peaks attempts to provide a relatively comprehensive suite of tools for ARPES and related
52 spectroscopic data via a modular approach, supporting the experimenter from initial data
53 acquisition, visualisation, and sample alignment through data processing and more advanced
54 analysis. peaks builds heavily on the xarray package (Hoyer & Hamman, 2017), providing a
55 powerful data structure for the N-D labelled data arrays common to ARPES data. This also
56 supports the use of dask arrays (Dask Development Team, 2016) for lazy data loading and
57 processing, e.g. for datasets that are beyond the available memory, or to facilitate parallel
58 processing. peaks is intended to be run using interactive notebooks. Data is loaded into
59 xarray:DataArray's using location-specific data loaders to support multiple starting data
60 formats and conventions, reflecting the heterogeneity in existing ARPES setups. Extensive
61 metadata is included in the DataArray attributes, making use of pydantic (Colvin et al.,
62 2025) models to ensure a consistent metadata framework, while pint (Grecco, 2025) is used
63 for ensuring reliable handling of units in both the ARPES dataset and associated metadata.
64 Data can also be loaded into xarray:DataTree structures, allowing the user flexibility over
65 grouping data in configurations which reflect the data hierarchy of the underlying experiment,
66 and permitting batch processing or metadata configuration. General data loaders exist for
67 several of the core ARPES spectrometer manufacturers, as well as for the ARPES setups of
68 several central facilities commonly used in the community. A class-based approach for the data
69 loaders provides an efficient route to extending this to new setups in future. For data saved
70 using the standard data formats of one of the common ARPES spectrometer manufacturers,
71 implementing a new loader can be as simple as subclassing the relevant parent class and
72 defining a few sign and unit conventions, while complete loaders can also be developed starting
73 from bespoke data formats. peaks aims to maintain a record of processing steps that have
74 been applied to the data, building up a detailed analysis history which can be easily inspected
75 which – together with use in interactive notebooks – facilitates enhanced data provenance and
76 effective collaborative working on ARPES data analysis.

77 The use of xarray:DataArray accessors allow easy chaining of analysis methods together for
78 most functions. Extensive capabilities are included for data visualisation, including static plots
79 and interactive tools for 2-, 3-, and 4-D datasets (see, e.g. Figure 1). Tools are included for
80 aiding the experimenter in aligning samples for subsequent measurements, with care taken to
81 handle the different conventions used at different experimental facilities in a way that facilitates
82 both standardised data analysis and also the use of peaks for 'on-the-fly' analysis during
83 experiments. Additional core functionality includes tools for ARPES-specific data selection
84 (e.g. momentum (MDC) and energy (EDC) distribution curve extraction), merging, summation,
85 and symmetrisation, data processing (e.g. momentum conversion and Fermi level corrections,
86 data normalisation), and derivative-type methods to aid data visualisation. Capabilities for
87 data fitting (including parallel processing and fitting of lazily-loaded data - see e.g. Figure 2)
88 are included, building on the extensive lmfit (Newville et al., 2025) package. Core capabilities
89 for processing time-resolved ARPES data are included, while specific data selection and helper
90 methods are included for spatially-resolved ARPES. Initial functionality (principal component
91 analysis, clustering, and denoising) is included for related unsupervised machine learning
92 analysis of such spatially-resolved ARPES data, built around standard Scikit-learn framework
93 (Pedregosa et al., 2011).

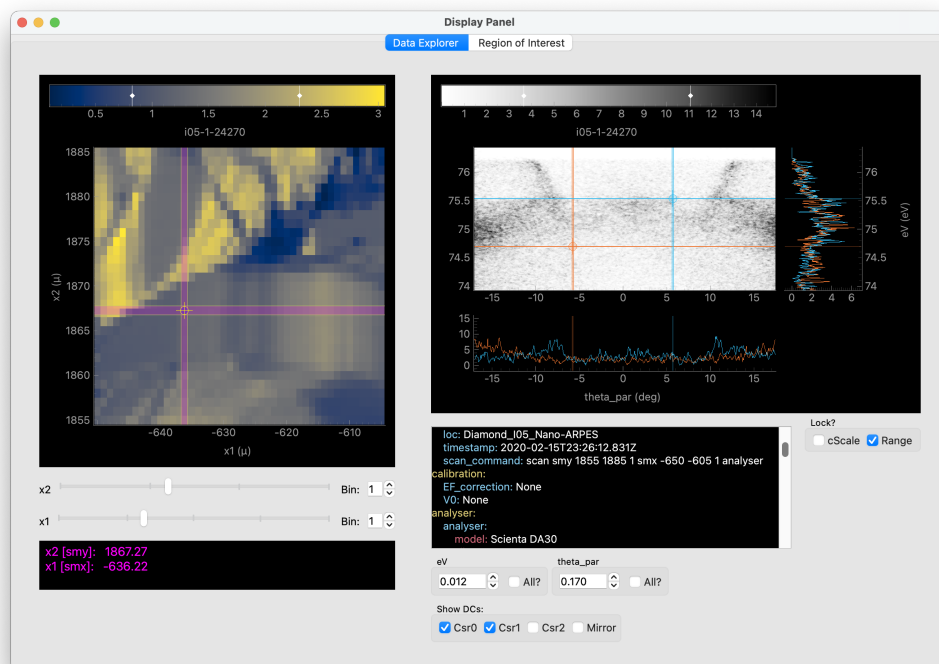


Figure 1: Example data visualisation tool for a 4D dataset (spatially-resolved ARPES). The tab shown allows interactive data exploration, while the secondary tab facilitates region of interest analysis.

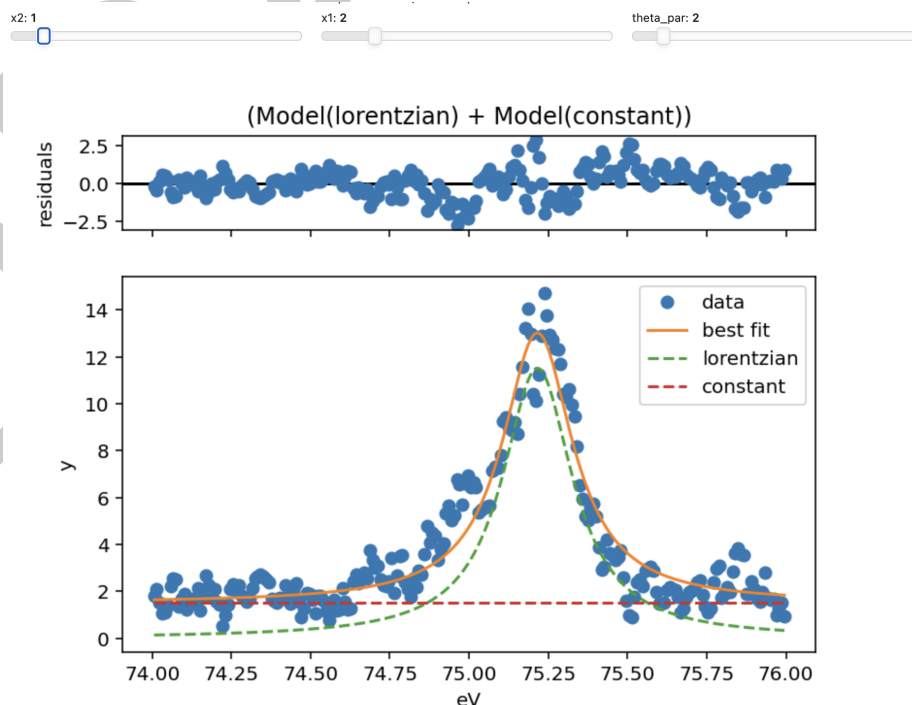


Figure 2: Example fitting of lazily-loaded data. The relevant individual EDC is loaded into memory and the fit performed only when selected by the sliders, facilitating fitting even of very large datasets. Similar approaches allow the parallel fitting of individual EDCs or MDCs from across a large, e.g. spatially-resolved, dataset.

In the future, peaks could be augmented with additional ML approaches tailored to ARPES data analysis, facilitated by the standard xarray-based data structures used. The incorporation of additional data structures and functionality for processing spin-resolved ARPES data is also planned.

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