

purgedcv: Label-Aware Cross-Validation for Overlapping-Horizon Prediction in Python

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Abstract

Cross-validation is routinely used to estimate out-of-sample performance in statistical learning, but standard shuffled or blocked folds can be invalid when responses are measured over future intervals. A label such as the mean demand over the next twelve half-hours, the next-day rainfall amount, or the return over the next twenty bars overlaps the labels of nearby rows. If overlapping label intervals are split between training and test sets, the validation score partly measures information reuse rather than generalization. This article formalizes split-level conditions for leakage-aware validation in overlapping-label time-series and panel data, and presents **purgedcv**, a Python implementation that exposes purging, embargoing, walk-forward validation, group-purged folds, and combinatorial purged cross-validation through the **scikit-learn** splitter protocol, with diagnostic assertions for auditing train/test splits. A controlled experiment with an unpredictable target shows that shuffled k-fold can report a mean out-of-sample R^2 of 0.918 while admitting complete train/test label overlap. A full-population benchmark on Low Carbon London smart-meter data shows a more nuanced case: the temporal leakage gap is small but measurable, whereas the larger issue is household-level generalization. The software, notebooks, tests, and benchmark scripts are open source and make the validation choice auditable rather than implicit.

Keywords: cross-validation; data leakage; time series; panel data; model validation; reproducible software; Python; scikit-learn; purged cross-validation; embargo; combinatorial purged cross-validation

1 Introduction

Cross-validation is often treated as a neutral measurement device: choose a splitter, fit the same estimator on each training fold, and average the test scores. That view depends on an independence assumption that is not satisfied by many time-indexed prediction tasks. In a forecasting or backtesting problem, row i is usually not just an instantaneous observation. Its response may be defined by an evaluation interval that starts at the prediction time and ends after a future horizon. Nearby rows can therefore share part of the same future outcome window. Standard shuffled k-fold cross-validation can place one row in the test fold and another row whose label interval overlaps it in the training fold. The resulting score is then contaminated by information that would not be available when the model is used prospectively.

Data leakage is a well-known source of inflated performance estimates in machine learning [7]. It is especially damaging in scientific applications where a model is selected or reported after

many iterations, since the optimistic score becomes part of the published evidence rather than merely a development mistake [11]. In financial machine learning, López de Prado [10] proposed purging and embargoing as practical guards against leakage from overlapping labels and serial dependence, and Combinatorial Purged Cross-Validation (CPCV) as a way to obtain multiple out-of-sample backtest paths. Bailey and Lopez de Prado’s Probabilistic Sharpe Ratio and Deflated Sharpe Ratio then address the related problem of selection bias after trying multiple strategies [1, 2].

The same validation problem appears outside finance. Household electricity demand, equipment degradation, rainfall, clinical monitoring, and air-quality forecasting all contain future-horizon labels or repeated entities. What matters is whether any training-label window overlaps a test-label window, whether a post-test serial-dependence buffer has been respected, and whether the deployment target involves unseen entities rather than future observations from already-seen entities.

This article makes three contributions. First, it states a directly checkable interval condition for overlapping-label validation. Second, it presents `purgedcv`, an open Python implementation of purging, embargoing, walk-forward validation, group-purged k-fold, and CPCV path reconstruction through the `scikit-learn` cross-validation interface, together with leakage diagnostics for auditing splits [9, 14]. Third, it reports reproducible experiments that show both dramatic and undramatic outcomes: a synthetic task where leakage fabricates strong skill, and a real smart-meter benchmark where the larger issue is not temporal leakage but household-level generalization.

2 Validation with overlapping labels

Let a supervised learning data set contain observations

$$z_i = (x_i, y_i, p_i, e_i, g_i), \quad i = 1, \dots, n,$$

where x_i is the feature vector, y_i is the response, p_i is the prediction time, e_i is the evaluation time at which the response is fully known, and g_i is an optional group identifier such as a household, patient, engine, or season. The label interval for row i is

$$I_i = [p_i, e_i).$$

The interval is half-open: a label window ending exactly where another begins is not counted as overlapping. This convention matches the implementation’s half-open interval diagnostics. For a train/test split (A, B) , label-overlap leakage is present when

$$\exists i \in A, \exists j \in B \quad \text{such that} \quad I_i \cap I_j \neq \emptyset.$$

A leakage-aware split must remove such training rows before fitting the estimator. In practice, a second guard is often needed after a test block. If the process remains serially correlated after the test interval, training immediately after the test block can still reuse information tied to that test period. An embargo removes training rows whose prediction time lies inside a post-test buffer of fixed duration or fixed fraction of the sample.

For panel data there is a separate deployment question. If the intended use is prediction on new entities, a chronological split that mixes the same entity across training and test sets may answer the wrong question even when no label intervals overlap. In that case the split must also satisfy

$$\{g_i : i \in A\} \cap \{g_j : j \in B\} = \emptyset.$$

Thus validation has at least three distinct requirements: interval disjointness, post-test embargo, and group disjointness. They are not interchangeable. A fixed integer gap may remove leakage

for a single constant horizon, but it does not express variable horizons, time-duration embargoes, CPCV test blocks, or entity-level generalization.

CPCV adds a second idea to purging. A time series is first divided into N ordered blocks, and each fold holds out k of those blocks, producing $\binom{N}{k}$ purged test combinations. Each combination supplies out-of-sample predictions for the dates in its held-out blocks. The fold predictions can then be recombined into several complete backtest paths, so a single modeling exercise yields a distribution of out-of-sample trajectories rather than one path. This is useful beyond trading: the same structure exposes how much a validation conclusion depends on the particular historical periods used as test blocks.

3 Software implementation

`purgedcv` implements the interval operations and splitters needed to make these requirements executable. The package is written in Python, is MIT licensed, and follows the `scikit-learn` splitter protocol, so the same objects can be passed to `cross_val_score`, `GridSearchCV`, and `Pipeline`. Runtime dependencies are intentionally small: `numpy`, `pandas`, `scikit-learn`, and `scipy` [5, 12, 14, 21]. Table 1 summarizes the public components exposed by the package.

Table 1: Main public API in `purgedcv`.

Component	Function or class	Purpose
Primitive	<code>purge</code>	Drop training rows whose label intervals overlap test labels
Primitive	<code>apply_embargo</code>	Drop post-test training rows inside an embargo buffer
Splitter	<code>WalkForwardSplit</code>	Expanding or rolling chronological validation
Splitter	<code>PurgedKFold</code>	Contiguous folds with label-aware purging and embargo
Splitter	<code>PurgedGroupKFold</code>	Purged folds with disjoint held-out groups
Splitter	<code>CombinatorialPurgedCV</code>	CPCV folds with multiple test-block combinations
Paths	<code>reconstruct_paths</code>	Assemble CPCV folds into backtest paths
Metrics	<code>probabilistic_sharpe_ratio</code>	Probability that skill exceeds a benchmark
Metrics	<code>deflated_sharpe_ratio</code>	Sharpe-ratio inference corrected for selection bias
Metrics	<code>min_track_record_length</code>	Minimum observations needed to establish a Sharpe ratio
Diagnostics	<code>assert_*</code> functions	Check temporal, embargo, and group-leakage invariants

The implementation separates interval arithmetic from splitter orchestration. For each fold, test label intervals are sorted and merged once, and candidate training intervals are tested against the merged set. This avoids duplicating boundary logic across splitters and is particularly important for CPCV, where the test set may contain several non-adjacent blocks. In such a fold, purging must apply to the union of test label intervals, not to the convex hull between the first and last test block.

The diagnostic functions are deliberately independent of the package’s own splitters. They accept training indices, test indices, prediction times, and evaluation times, and can audit a split produced by any library or by hand. This turns the validation contract into an assertion that can be placed in tests.

```
from purgedcv import PurgedKFold
from purgedcv.diagnostics import assert_no_temporal_leakage

cv = PurgedKFold(
```

```

    n_splits=5,
    prediction_times=prediction_times,
    evaluation_times=evaluation_times,
    purge_horizon="12h",
    embargo="2h",
)

for train_idx, test_idx in cv.split(X, y):
    assert_no_temporal_leakage(
        train_idx, test_idx, prediction_times, evaluation_times
    )

```

The package is maintained as a public open-source project with continuous integration, strict static typing, and an extensive test suite covering split invariants, numerical metrics, end-to-end reproducibility, notebook-derived fixtures, and packaging quality gates. The repository accepts issues and pull requests, and the core validation behavior is protected by tests rather than by example output alone.

4 Existing software and differentiators

Several packages overlap with part of this problem. `scikit-learn` provides `TimeSeriesSplit`; its `gap` argument is a fixed integer count rather than a label-aware interval, and it does not provide group-purged folds, CPCV paths, or split-level diagnostics. `tscv` provides fixed-gap splits, which are useful when the required buffer is known and constant, but it does not represent variable label horizons or grouped deployment targets. `timeseriescv` implements purged and combinatorial time-series cross-validation, but it does not unify variable-horizon label intervals, group-purged folds, post-test embargoes, CPCV path reconstruction, and independent diagnostic assertions in a typed `scikit-learn`-compatible package [18]. `mlfinlab` is the best-known implementation associated with the financial machine-learning literature, but it is distributed as a commercial product and therefore cannot serve as a permissive dependency for open scientific software [6]. The companion benchmark also records two non-tabulated open alternatives: `mlfinpy` did not run on the modern `pandas` stack used here, and `RiskLabAI` failed because a plotting dependency was unavailable. Those failures are recorded with exact exception messages rather than imputed scores.

`purgedcv` is therefore not differentiated by claiming new purging mathematics. Its contribution is integration and auditability. Unlike fixed-gap splitters or single-purpose CPCV implementations, `purgedcv` unifies (a) variable-horizon label intervals, (b) group-purged folds, (c) post-test embargoes, (d) CPCV path reconstruction, and (e) split-level diagnostics as assertions that can be run on third-party or hand-written splits. This combination is what lets the same validation contract be used in ordinary `scikit-learn` model selection, in notebook examples, and in automated tests.

5 Reproducible experiments

All experiments described here are included in the public repository as scripts or notebooks. The synthetic leakage proof is deterministic and requires no external data. The real-data notebooks download public data sets on first use and cache them locally. The full Low Carbon London benchmark is an offline script because the raw corpus is approximately 8 GB; the script writes both the per-subsample CSV and a Markdown summary.

5.1 Controlled leakage task

The controlled task is designed so that no feature has genuine predictive content. Let ϵ_t be independent noise and define the response at row t as the mean of the next H future noise values. The only feature is a monotone clock. A model cannot forecast the future noise, but shuffled k-fold can exploit overlap between adjacent future-horizon labels. Large positive R^2 is therefore evidence of validation leakage, not model skill.

Table 2 reports a Random Forest experiment with $n = 1500$, $H = 20$, five outer folds, and seed 0. The overlap column is the mean fraction of training rows whose label window overlaps any test label window, averaged across folds.

Table 2: Controlled leakage task. Positive R^2 is fabricated because the target is unpredictable by construction.

Library	Splitter	Mean R^2	Mean overlap	Folds
scikit-learn	KFold(shuffle=True)	0.918	1.000	5
scikit-learn	KFold(shuffle=False)	-1.017	0.025	5
scikit-learn	TimeSeriesSplit	-2.506	0.035	5
scikit-learn	TimeSeriesSplit(gap=20)	-1.430	0.000	5
purgedcv	PurgedKFold	-0.870	0.000	5
purgedcv	WalkForwardSplit	-1.899	0.000	5
purgedcv	CombinatorialPurgedCV	-1.471	0.000	15
tscv	GapKFold(gap_before=20, gap_after=20)	-1.217	0.000	5
timeseriescv	CombPurgedKFoldCV	-0.894	0.004	15
timeseriescv	PurgedWalkForwardCV	-1.543	0.000	4

The shuffled k-fold score of 0.918 is not a small optimism effect. It is a complete failure of the validation design. The blocked and chronological baselines remove most of the effect but still admit small amounts of overlap unless a suitable gap is supplied. A fixed `TimeSeriesSplit` gap can solve this particular constant-horizon toy problem, but it does not provide label-aware intervals, variable horizons, group-purged folds, diagnostics, or CPCV paths. The `purgedcv` splitters remove the overlap by construction and return negative R^2 , which is the expected outcome for an unpredictable target evaluated out of sample.

5.2 Low Carbon London smart-meter benchmark

The second experiment uses the Low Carbon London smart-meter data set from UK Power Networks and the London Datastore [19]. The prediction task is half-hourly household electricity demand forecasting. Features include calendar and lagged-load information, and the target is a forward-horizon mean. The validation schemes compare pooled shuffled k-fold, blocked k-fold, walk-forward validation, and held-out-household validation.

The full-population benchmark scans 167,932,474 raw rows, identifies 4,284 eligible Standard-tariff households with at least one year of data, draws 20 seeded subsamples of 60 households, and evaluates each validation scheme with the same modeling harness. Table 3 reports mean WAPE and 95% t-intervals. WAPE is $\sum |\hat{y} - y| / \sum |y|$, reported in percent.

By design, the result is less dramatic than the synthetic example. The temporal leakage gap between shuffled k-fold and walk-forward validation is measurable but small: 0.68 WAPE points, or 1.60% relative to walk-forward WAPE. The larger effect is the household gap. Scoring on unseen households is 2.56 WAPE points worse than the pooled temporal estimate, or 6.03% relative. This is the more important conclusion for deployment: if the model will be used for customers not seen during training, a purely temporal split answers a different question.

Table 3: Low Carbon London benchmark over 20 seeded subsamples of 60 households. Lower WAPE is better.

Metric	Mean	95% CI low	95% CI high
Naive shuffled k-fold WAPE	41.68	40.37	42.99
Blocked k-fold WAPE	42.43	41.07	43.80
WalkForwardSplit WAPE	42.36	41.01	43.71
GroupKFold household WAPE	44.92	43.38	46.45
Temporal gap, WAPE points	0.68	0.53	0.83
Temporal gap, relative percent	1.60	1.27	1.94
Household gap, WAPE points	2.56	2.08	3.03
Household gap, relative percent	6.03	4.93	7.12

5.3 Cross-domain examples

The repository also contains notebooks that exercise the same validation logic on other public data sets. Table 4 summarizes the role of each example. Some are designed to expose a large leakage effect; others show that a leakage-aware split can correctly report a small or absent gap. The “0.83–0.91” range in the first row refers to the companion notebook’s two models, k-nearest neighbors and Random Forest, rather than to multiple random seeds; the Random Forest-only benchmark in Table 2 reports 0.918.

Table 4: Reproducible examples included with the package.

Example	Data source	Main validation lesson
Synthetic leakage proof	Generated	k-nearest neighbors and Random Forest report R^2 of 0.83–0.91 on noise
Air quality	UCI air-quality data	A clock feature plus overlapping labels fabricates R^2 near 0.99
Earthquakes	USGS catalogue	Magnitude history has no skill; purged splits reject the illusion
Smart meters	Low Carbon London	Household generalization dominates temporal leakage
Clinical mortality	PhysioNet Challenge 2012	Whole-patient group holds are needed for patient-level inference
Predictive maintenance	NASA C-MAPSS	Walk-forward validation matches run-to-failure deployment
Rainfall	NOAA GHCN-Daily	One-day-ahead labels need purge and embargo buffers
Electricity load	PJM hourly load	CPCV paths expose score dispersion across back-test paths
Model comparison	Binance public bars	DSR prevents selecting an apparent edge after multiple trials
Sports prediction	Premier League matches	Honest validation shows calibration drift rather than a headline gap

The examples deliberately include negative results. In the model-comparison notebook, several models are tried on the same public price data. Once the Deflated Sharpe Ratio corrects for the number of trials, no model clears a DSR threshold of 0.95. In the PJM electricity-load notebook, CPCV produces five paths whose DSR values range from 0.0011 to 0.7761 after correction for 20 trials. These are not failures of the software. They are the point of an honest validation pipeline: the method should make it easy to report that no reliable edge survived.

6 Discussion

The experiments show that leakage-aware validation is not a single recipe. In the controlled task, randomization is catastrophic because every test label has overlapping training labels. In the smart-meter benchmark, the temporal effect is small but statistically visible, while the larger operational issue is whether the model is expected to generalize to new households. In other domains, the required split can be driven by patients, engines, seasons, stations, or market regimes. The validation object should encode that deployment question rather than being chosen only for convenience.

`purgedcv` therefore treats diagnostics as first-class objects. A user can construct a split with this package, with another package, or by hand, and then check the interval and group invariants directly. This matters for reproducibility. A reported model score is only as meaningful as the split that created it, and the split should be auditable from code rather than described informally in prose.

There are limitations. Purging and embargoing remove a specific class of validation leakage; they do not solve all forms of leakage. Feature engineering can still use future data, target transformations can still be computed globally, preprocessing can still be fit outside the training fold, and entity leakage can still occur if the wrong group identifier is supplied. The package does not claim that every chronological split is optimal. In highly non-stationary settings, any historical validation estimate can be unstable. The role of the package is narrower: when labels are interval-valued, it makes the no-overlap condition explicit and executable.

Another limitation is maturity. The package is new, even though the underlying methods are established. The open repository contains tests, type checks, documentation, notebooks, and a reproducible benchmark, but wider external use will be needed to discover edge cases in unfamiliar data layouts. For this reason the software should be treated as validation infrastructure whose outputs remain the analyst’s responsibility, not as an automatic guarantee of scientific validity.

7 Conclusion

Overlapping-label prediction problems require more than a chronological split. The validation design must remove training labels that overlap test labels, respect any post-test dependence buffer, and match the entity structure of the deployment target. `purgedcv` provides these operations as small, auditable, `scikit-learn`-compatible components. The empirical examples show both extremes: validation leakage can fabricate strong performance on an unpredictable target, but in a real smart-meter task the larger gap can be between seen and unseen households. Making these distinctions explicit is the practical contribution: the package does not make models better, but it makes their validation harder to fool.

Availability and Zenodo record

The manuscript has reserved Zenodo DOI [10.5281/zenodo.20323362](https://doi.org/10.5281/zenodo.20323362). The software is available from the project repository at <https://github.com/eslazarev/purged-cross-validation> and distributed on PyPI as `purgedcv`: <https://pypi.org/project/purgedcv/>. The software archive is available on Zenodo under software concept DOI [10.5281/zenodo.20312695](https://doi.org/10.5281/zenodo.20312695). The source distribution contains the examples and benchmark tools; the wheel contains the importable `purgedcv` package.

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Computational details

The benchmark tables reported here were produced with `purgedcv` 0.0.6, Python 3.12.7, `numpy` 2.4.5, `pandas` 3.0.3, `scikit-learn` 1.8.0, and `scipy` 1.17.1 on macOS 26.3.1 (arm64). The package supports Python 3.10 and later; runtime dependency lower bounds are `numpy` 1.24, `pandas` 2.0, `scikit-learn` 1.3, and `scipy` 1.10.

A split-generation microbenchmark is tracked as `tools/microbench.py`. It uses 1,000,000 timestamped rows, five folds, one feature, a constant 20-second label horizon, and no estimator fitting. In the recorded local run, `PurgedKFold` generated the five folds in 1.898 seconds best-of-three (mean 1.911 seconds), and wrote the environment details to `paper/microbench_summary.md`. The full Low Carbon London benchmark scanned 167,932,474 raw rows and ran 20 seeded 60-household subsamples in 53.8 minutes on the author’s local machine.

The main local reproduction commands are:

```
pip install -e "[dev,examples]"
pip install tscv timeseriescv
pytest -q
python tools/microbench.py
python tools/competitor_benchmark.py --out-dir examples/data
python tools/lcl_full_benchmark.py --k 20 --n 60 --seed 0
```

The competitor command above reproduces the reported Table 2 rows when `tscv` and `timeseriescv` are installed; unavailable competitors are recorded as `NOT RUN` with exact exception messages. For a fast core-only smoke check, use `-core-only`. The last command expects the raw Low Carbon London CSV files to be present locally. For faster checks, the repository includes end-to-end tests with synthetic fixtures that exercise the same parser, feature builder, and benchmark output format.

Generative AI disclosure

Generative AI tools, including OpenAI Codex/ChatGPT from the GPT-5 family, were used for code review, documentation drafting, and copy-editing. All design decisions, AI-assisted changes, and outputs were reviewed and validated by the author through unit, property, doctest, end-to-end, type-checking, and benchmark tests.

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References

- [1] David H. Bailey and Marcos López de Prado. The sharpe ratio efficient frontier. *Journal of Risk*, 15(2):3–44, 2012.

- [2] David H. Bailey and Marcos López de Prado. The deflated sharpe ratio: Correcting for selection bias, backtest overfitting, and non-normality. *Journal of Portfolio Management*, 40(5):94–107, 2014.
- [3] S. De Vito, E. Massera, M. Piga, L. Martinotto, and G. Di Francia. On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario. *Sensors and Actuators B: Chemical*, 129(2):750–757, 2008. 10.1016/j.snb.2007.09.060.
- [4] Ary L. Goldberger, Luis A. N. Amaral, Leon Glass, Jeffrey M. Hausdorff, Plamen Ch. Ivanov, Roger G. Mark, Joseph E. Mietus, George B. Moody, Chung-Kang Peng, and H. Eugene Stanley. Physiobank, physiobank, and physionet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):e215–e220, 2000. 10.1161/01.CIR.101.23.e215.
- [5] Charles R. Harris, K. Jarrod Millman, Stéfan J. van der Walt, Ralf Gommers, Pauli Virtanen, David Cournapeau, Eric Wieser, Julian Taylor, Sebastian Berg, Nathaniel J. Smith, Robert Kern, Matti Picus, Stephan Hoyer, Marten H. van Kerkwijk, Matthew Brett, Allan Haldane, Jaime Fernández Del Río, Mark Wiebe, Pearu Peterson, Pierre Gérard-Marchant, Kevin Sheppard, Tyler Reddy, Warren Weckesser, Hameer Abbasi, Christoph Gohlke, and Travis E. Oliphant. Array programming with NumPy. *Nature*, 585(7825):357–362, 2020. 10.1038/s41586-020-2649-2.
- [6] Hudson and Thames. mlfinlab: Financial machine learning package. Software product, <https://hudsonthames.org/mlfinlab/>, 2026. Accessed 2026-05-21.
- [7] Shachar Kaufman, Saharon Rosset, Claudia Perlich, and Ori Stitelman. Leakage in data mining: Formulation, detection, and avoidance. *ACM Transactions on Knowledge Discovery from Data*, 6(4):1–21, 2012. 10.1145/2382577.2382579.
- [8] Evgenii Lazarev. pricehub: Unified ohlc market-data fetcher. Python package, <https://pypi.org/project/pricehub/>, 2026. Binance public spot market data; subject to the exchange API terms.
- [9] Evgenii Lazarev. purgedcv: scikit-learn-compatible purged and combinatorial cross-validation for time-series and panel machine learning. Python package, <https://github.com/eslazarev/purged-cross-validation>, 2026. Software concept DOI; MIT license.
- [10] Marcos López de Prado. *Advances in Financial Machine Learning*. Wiley, Hoboken, NJ, 2018. ISBN 9781119482086. Purging and embargoing: chapter 7. Combinatorial Purged Cross-Validation: chapter 12.
- [11] Matthew B. A. McDermott, Shirly Wang, Nikki Marinsek, Rajesh Ranganath, Luca Foschini, and Marzyeh Ghassemi. Reproducibility in machine learning for health research: Still a ways to go. *Science Translational Medicine*, 13(586), 2021. 10.1126/scitranslmed.abb1655.
- [12] Wes McKinney. Data structures for statistical computing in Python. In *Proceedings of the 9th Python in Science Conference*, pages 56–61, 2010. 10.25080/Majora-92bf1922-00a.
- [13] Matthew J. Menne, Imke Durre, Russell S. Vose, Byron E. Gleason, and Tamara G. Houston. An overview of the global historical climatology network-daily database. *Journal of Atmospheric and Oceanic Technology*, 29(7):897–910, 2012. 10.1175/JTECH-D-11-00103.1.
- [14] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, Jake Vanderplas, Alexandre Passos, David Cournapeau, Matthieu Brucher, Matthieu Perrot, and Édouard Duchesnay. Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

- [15] PJM Interconnection. Hourly metered load data. Public historical load data, 2026. Mirror used by the example; public domain dedication (CC0); accessed 2026-05-21.
- [16] Abhinav Saxena, Kai Goebel, Don Simon, and Neil Eklund. Damage propagation modeling for aircraft engine run-to-failure simulation. In *International Conference on Prognostics and Health Management*, 2008. 10.1109/PHM.2008.4711414.
- [17] Ikaro Silva, George Moody, Daniel J. Scott, Leo A. Celi, and Roger G. Mark. Predicting in-hospital mortality of icu patients: The physionet/computing in cardiology challenge 2012. In *Computing in Cardiology*, volume 39, pages 245–248, 2012.
- [18] timeseriescv contributors. timeseriescv: scikit-learn style cross-validation for time series. Python package, <https://pypi.org/project/timeseriescv/>, 2018. Version 0.2.
- [19] UK Power Networks. Smartmeter energy consumption data in london households (low carbon london). London Datastore, 2014. Dataset `smartmeter-energy-use-data-in-london-households`; open terms.
- [20] U.S. Geological Survey. Earthquake catalog. USGS FDSN event web service, 2026. Public domain. <https://earthquake.usgs.gov/fdsnws/event/1/>; accessed 2026-05-21.
- [21] Pauli Virtanen, Ralf Gommers, Travis E. Oliphant, Matt Haberland, Tyler Reddy, David Cournapeau, Evgeni Burovski, Pearu Peterson, Warren Weckesser, Jonathan Bright, Stéfan J. van der Walt, Matthew Brett, Joshua Wilson, K. Jarrod Millman, Nikolay Mayorov, Andrew R. J. Nelson, Eric Jones, Robert Kern, Eric Larson, C. J. Carey, İlhan Polat, Yu Feng, Eric W. Moore, Jake VanderPlas, Denis Laxalde, Josef Perktold, Robert Cimrman, Ian Henriksen, E. A. Quintero, Charles R. Harris, Anne M. Archibald, Antônio H. Ribeiro, Fabian Pedregosa, and Paul van Mulbregt. SciPy 1.0: Fundamental algorithms for scientific computing in Python. *Nature Methods*, 17:261–272, 2020. 10.1038/s41592-019-0686-2.