BayesReconPy: A Python package for forecast reconciliation

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Summary

`BayesReconpy` implements methods for probabilistic forecast reconciliation in Python. It reconciles hierarchies containing real-valued time series, discrete time series and a mixture of real-valued and discrete time series (mixed hierarchies). The package is released under the LGPL (3) license and available on GitHub.

Statement of Need

Forecast reconciliation ensures coherence across hierarchical time series, where aggregate forecasts must equal the sum of their components. In practice, base forecasts—generated independently for each series—often violate these constraints.

Initial approaches addressed point forecasts using projection methods like OLS and MinT (Rob J. Hyndman et al., 2011; Wickramasuriya et al., 2019). More recently, probabilistic reconciliation methods have been introduced, providing richer uncertainty quantification (Jeon et al., 2019; Panagiotelis et al., 2023).

However, most existing tools are limited to Gaussian or continuous inputs, lack support for discrete or mixed-type forecasts, or are implemented only in R. Some, like ProbReco and DiscreteRecon, are no longer actively maintained, whereas pyhts does only point forecast reconciliation. A python-package covering both projection and a Bayesian method was prepared in reconcile (Dirmeier, 2025), but it's not complete and mentions the reconciliation functions to "loosely follow…but is not the same method".

`bayesReconPy` addresses these gaps. It provides a unified Python interface for probabilistic reconciliation using both conditioning and projection-based methods. It supports:

- Gaussian forecasts (Corani et al., 2021)
- Continuous non-Gaussian forecasts (Zambon, Azzimonti, & Corani, 2024)
- Discrete forecasts (Corani et al., 2024)
- Mixed discrete-continuous hierarchies (Zambon, Azzimonti, Rubattu, et al., 2024)

As a Python-native extension of the R package `bayesRecon`, `bayesReconPy` is the only actively maintained tool of its kind. It includes extensive documentation and example notebooks replicating key results from the literature. (Corani et al., 2021, 2024; Zambon, Azzimonti, & Corani, 2024).

Table 1: Probabilistic reconciliation methods comparison

Library	Cross-temp	Gauss-ian	Continuous (non-Gaussian)	Dis-crete	Mixed
bayesReconPy (Ours)	X	V	V	V	V
fable / fabletools (O'Hara-Wild et al., 2024)	V	V	V	X	X
FoReco (Girolimetto & Fonzo, 2024)	V	V	V	X	X
gluonts (Alexandrov et al., 2020)	X	V	V	X	X
hierarchicalforecast (Olivares et al., 2022)	X	V	V	X	X
thief (Rob J. Hyndman & Kourentzes, 2018)	X	V	X	X	X
scikit-hts (Ross, 2019)	X	V	V	X	X
reconcile (Dirmeier, 2025)	X	V	V	X	X

Note: V = Supported, X = Not supported

Usage

A hierarchy can contain Gaussian, continuous non-Gaussian, or discrete forecast distributions at different levels (see **Figure 1**). Base forecasts can be provided as parameters, samples, or probability mass functions (PMFs), depending on whether they are continuous or discrete.

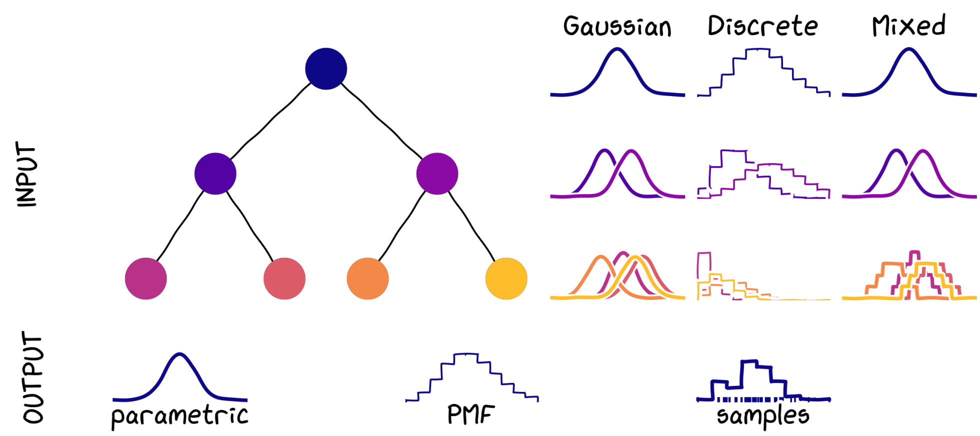

Figure 1: Types of reconciliation and output forms.

Below, we describe the suitable reconciliation algorithms for each case:

1. **All Gaussian forecasts**
   Use `reconc_gaussian` for analytical reconciliation (MinT) *(Corani et al., 2021; Wickramasuriya et al., 2019)*
2. **All continuous or all discrete forecasts**
   Use `reconc_buis` for sample-based reconciliation *(Zambon, Azzimonti, & Corani, 2024)*
3. **Mixed types (discrete bottom, Gaussian upper)**
   Use `reconc_mix_cond` or `reconc_td_cond` *(Zambon, Azzimonti, Rubattu, et al., 2024)*

Output formats by method:

- **Parametric** → `reconc_gaussian`
- **Samples** → `reconc_buis`
- **PMF** → `reconc_mix_cond`, `reconc_td_cond`

Note that in the case of MinT or OLS reconciliation, the inputs and outputs are expected as NumPy arrays. Documentation for the expected shape of these arrays is provided in the function descriptions.

Examples

Reconciliation of Negative Binomial Forecasts

We illustrate the use of `bayesReconPy` on a hierarchy of count-valued time series representing extreme market events across five economic sectors from 2005 to 2018. These predictive distributions are modeled using negative binomial distributions, and the hierarchy includes five bottom-level and one top-level series.

The dataset `extr_mkt_events`, included in the package, provides both the observed series and corresponding base forecasts. This dataset was used in the experiments reported in (Zambon, Agosto, et al., 2024).

A related Python notebook demonstrating this example is available:
Properties of the Reconciled Distribution via Conditioning

The code example shows how to apply the `reconc_buis` function using the summing matrix `A`, base forecast parameters, and the desired number of samples. Reconciliation is completed within seconds.

```
# Reconcile via importance sampling
buis = reconc_buis(A, base_fc_j,
        "params", "nbinom",
        num_samples=N_samples, seed=42)
samples_y = buis['reconciled_samples']
# Computational time for 3508 reconciliations: 20.13 seconds
```

Reconciliation of a Large Mixed Hierarchy

The M5 dataset (Makridakis et al., 2022) contains daily sales time series for 10 stores, each with 3049 bottom-level and 11 upper-level series. Existing reconciliation methods struggled with the hierarchy's scale and the requirement for non-negative forecasts.

`bayesReconPy` successfully reconciles 1-step-ahead forecasts for store `"CA_1"`, producing non-negative, probabilistic outputs. The base forecasts, generated using the ADAM method (Svetunkov & Boylan, 2023) via the `smooth` R package (Svetunkov, 2024), are included in the package.

A Python notebook illustrating this use case is available:
Reconciliation of M5 hierarchy with mixed-type forecasts

The example below demonstrates reconciliation using `reconc_td_cond`, where bottom-level forecasts are discrete and upper-level forecasts are continuous. Reconciliation completes in seconds.

```
N_samples_TD = int(1e4)

# TDCond reconciliation
start = time.time()
td = reconc_td_cond(
```

```python
        A,
        fc_bottom_4rec,
        fc_upper_4rec,
        bottom_in_type="pmf",
        num_samples=N_samples_TD,
        return_type="pmf",
        seed=seed
)
stop = time.time()

# Reconciliation time: 10.11 s
```

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