class LPPLIndicatorGenerator()

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1 LPPL analyses

The `LPPLIndicatorGenerator` computes indicators using two robustness analyses of the LPPLS model:

1. **Window-size variation:** The calibration window always ends at the current date, but its length is varied (e.g. from 1 month to 1 year). This tests how sensitive the fitted t_c and parameters are to the amount of historical data used.
2. **Calibration-date variation:** The window length is fixed, but its end date is shifted over a short neighbourhood before the current date. This evaluates temporal stability of the LPPLS fit through time.

Together, these two perturbations produce distributions of fitted parameters and critical times, from which the final LPPL indicators are derived.

2 Computed Indicators

2.1 Percentage of Qualified Fits (Window Shift)

For each target date, the LPPLS model is recalibrated over a range of window lengths. A fit is counted as *qualified* if it satisfies the internal Filimonov–Sornette structural bounds

$$0 < m < 1, \qquad 2 \leq \omega \leq 15, \qquad -60/365 < t_c - t_{\text{end}} < 252/365,$$

together with the acceptance thresholds

$$R^2 \geq R^2_{\min}, \qquad \text{RMSE} \leq \text{RMSE}_{\max}, \qquad |B| = \kappa \geq \kappa_{\min}, \qquad t_c \leq t_{\text{end}} + H_{t_c}.$$

The indicator is the fraction of all attempted window sizes that pass these conditions. A high percentage means the LPPLS structure is robust to changes in window length, whereas a low value signals sensitivity to the amount of historical data used.

2.2 Percentage of Qualified Fits (Date Shift)

Here the window length is fixed, and the calibration end date is shifted backward over a short neighbourhood before the target date. Each recalibration must satisfy the same structural constraints

$$0 < m < 1, \qquad 2 \leq \omega \leq 15, \qquad -60/365 < t_c - t_{\text{end}} < 252/365,$$

and the same quality thresholds

$$R^2 \geq R^2_{\min}, \qquad \text{RMSE} \leq \text{RMSE}_{\max}, \qquad \kappa \geq \kappa_{\min}, \qquad t_c \leq t_{\text{end}} + H_{t_c}.$$

The indicator reports the proportion of calibration dates yielding qualified fits. High values imply temporal stability of the LPPLS pattern, while low values indicate that the model is sensitive to the exact calibration end date.

2.3 Crash Probability via KDE (Window Shift)

From the distribution of predicted critical times t_c obtained by varying window sizes, we compute the probability of a crash occurring within a chosen horizon H (e.g. $H = 3$ months):

$$P_{\text{crash},w} = \int_0^H \text{KDE}_w(\Delta t_c)\, d\Delta t, \qquad \Delta t_c = t_c - t_{\text{current}}.$$

A high value indicates a concentration of predicted t_c inside the horizon.

2.4 Crash Probability via KDE (Date Shift)

Analogously, we compute

$$P_{\text{crash},d} = \int_0^H \text{KDE}_d(\Delta t_c)\, d\Delta t$$

based on calibrations using different end dates. Agreement between $P_{\text{crash},w}$ and $P_{\text{crash},d}$ strengthens the signal.

2.5 Trustworthiness Indicator

To measure whether the two independent perturbation methods (window shift and date shift) agree on the *timing* of a potential crash, we compute:

$$\text{trustworthiness} = P_{\text{conf}} \cdot \text{overlap}, \qquad P_{\text{conf}} = \min(P_{\text{crash},w}, P_{\text{crash},d}),$$

where

$$\text{overlap} = \int_0^H \min\big(f_w(t),\ f_d(t)\big)\, dt.$$

Interpretation:

- If one method predicts a crash and the other does not, the overlap is low.
- If both predict crashes but at different times, the overlap remains low.
- If both predict a crash *soon and at similar times*, the overlap is high, yielding a strong, trustworthy signal.

2.6 Bubble Sign

The bubble sign is computed from the sign of the LPPL parameter B (via $\kappa = -B$):

$$\text{bubble\_sign} = \begin{cases} +1, & B < 0 \quad \text{(positive bubble)}, \\ -1, & B > 0 \quad \text{(negative bubble)}. \end{cases}$$

It indicates whether the system is entering a speculative bubble (super-exponential growth) or a negative bubble (accelerated correction or rebound regime).

3 Input Parameters

Below is the example usage:

```
gen = LPPLIndicatorGenerator(
    price_series=data,
    qualified_fit_r2_min=0.9,
    qualified_fit_rmse_max=0.06,
    qualified_fit_kappa_min=0.05,
    qualified_fit_tc_horizon_years=0.5,
)

indicators = gen.build_indicator_table(
```

```
    years_for_calibration=1.5,
    diff_windows_indicator_min_window_years=1/12,
    diff_windows_indicator_max_window_years=1.0,
    diff_windows_indicator_step_window_years=20/365.25,
    diff_dates_indicator_neighborhood_years=1/12,
    diff_dates_indicator_step_years_dates=5/365.25,
    crash_HORIZON_years_for_indicator=0.25,
)
```

3.1 Explanation of Constructor Parameters

- **price_series**: Time series of asset close prices.
- **qualified_fit_r2_min**: Minimum R^2 required for a fit to be considered credible.
- **qualified_fit_rmse_max**: Maximum allowed RMSE for a qualified fit.
- **qualified_fit_kappa_min**: Minimum strength of the bubble parameter $\kappa = |B|$.
- **qualified_fit_tc_horizon_years**: Maximum allowable prediction horizon for t_c beyond the calibration window.

3.2 Explanation of build_indicator_table Parameters

- **years_for_calibration**: Minimum history length required before computing any indicator (e.g. 1.5 years).
- **diff_windows_indicator_min/max_window_years**: Range of rolling window sizes used for LPPL calibration.
- **diff_windows_indicator_step_window_years**: Increment between consecutive window sizes.
- **diff_dates_indicator_neighborhood_years**: Length of the date-shift neighborhood around the target date.
- **diff_dates_indicator_step_years_dates**: Step between successive calibration dates inside the neighborhood.
- **crash_HORIZON_years_for_indicator**: Time horizon H (in years) used when evaluating crash probability from KDEs.