Regime Detection in Financial Markets using Signature Methods

Update 02

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Review - Methods for the market regime detection

Paper Link: arXiv:2306.15835,
Repository: Link

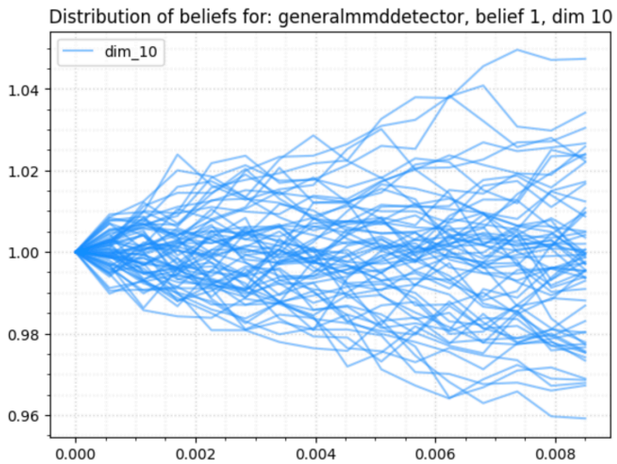
- **Parameteric method**:
  - Apply known stochastic models (e.g., GBM, Heston) as prior belief classes $\mathbb{P}_i = \left(\text{model}_i, \theta_i\right)$
  - Calculate signature MMD between observed and model-generated path sets $\alpha(\hat{s})_i = \frac{1}{n}\sum_{\ell=1}^{n} \mathscr{D}^r_{\text{sig}}\left(\hat{s}, x_i^\ell\right)$
  - Use bootstrapping to estimate the MMD Null distribution for each $\mathbb{P}_i = \left(\text{model}_i, \theta_i\right)$ and get thresholds c_i^α
  - If $\alpha(\hat{s})_i \leq c_i^\alpha$, accept the null (i.e., path is consistent with the model $\mathbb{P}_i$), otherwise, ; otherwise, detect a regime switch
- **Non-Parameteric method (auto-evaluator):**
  - Construct a current path group using a sliding window $\text{EvalWindow}(t) = \left\{s^{t-N+1}, \ldots, s^t\right\}$
  - For each lag l, compute signature-based MMD: $\text{score}_l(t) := \mathscr{D}^r_{\text{sig}}\left(\text{ EvalWindow }(t),\ \text{EvalWindow }(t-l)\right)$
  - Aggregate MMD scores over all lags: $\text{Score}(t) := \frac{1}{|L|}\sum_{l \in L} \text{score}_l(t)$
  - Fit historical scores to an empirical or Gamma distribution to derive threshold
  - If $\text{Score }(t) \geq c^\alpha,$ then a regime change is detected
  - Multi-lag averaging reduces noise, and stabilizes detection

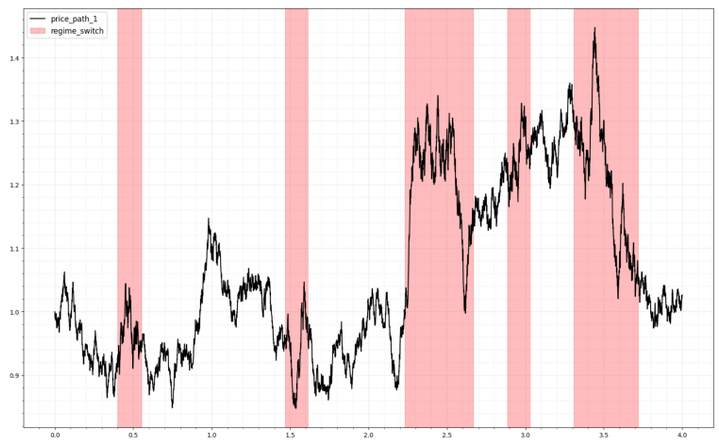
Parameteric Method

Assume we have a belief class following a GBM model with $\mu = 0$ and $\sigma = 0.2$, and a switching class that possibly follows a GBM model with $\mu = 0$ and $\sigma = 0.3$.

❋ Belief class paramters:

1. T = 4 - Time to simulate regime-changed path until
2. dim = 10 - Dimensionality of simulated paths
3. n_steps = 16 - Regime path length
4. n_paths = 8 - Number of ensemble paths
5. belief_models = [‘gbm'] - Belief model type
6. model_pair_names = ['gbm', ‘gbm'] - Switching model types
7. path_bank_size = 100000 - Total paths used in belief class



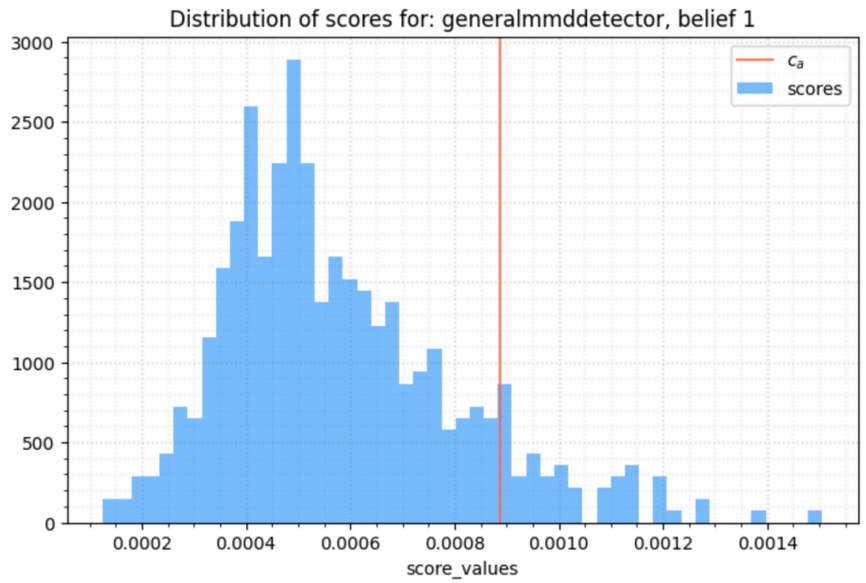


❋ Switching paramters:

1. n_regime_changes = 5 - Number of regime changes
2. r_on_args = ["poisson", 2]; r_off_args = ["poisson", 1/30]

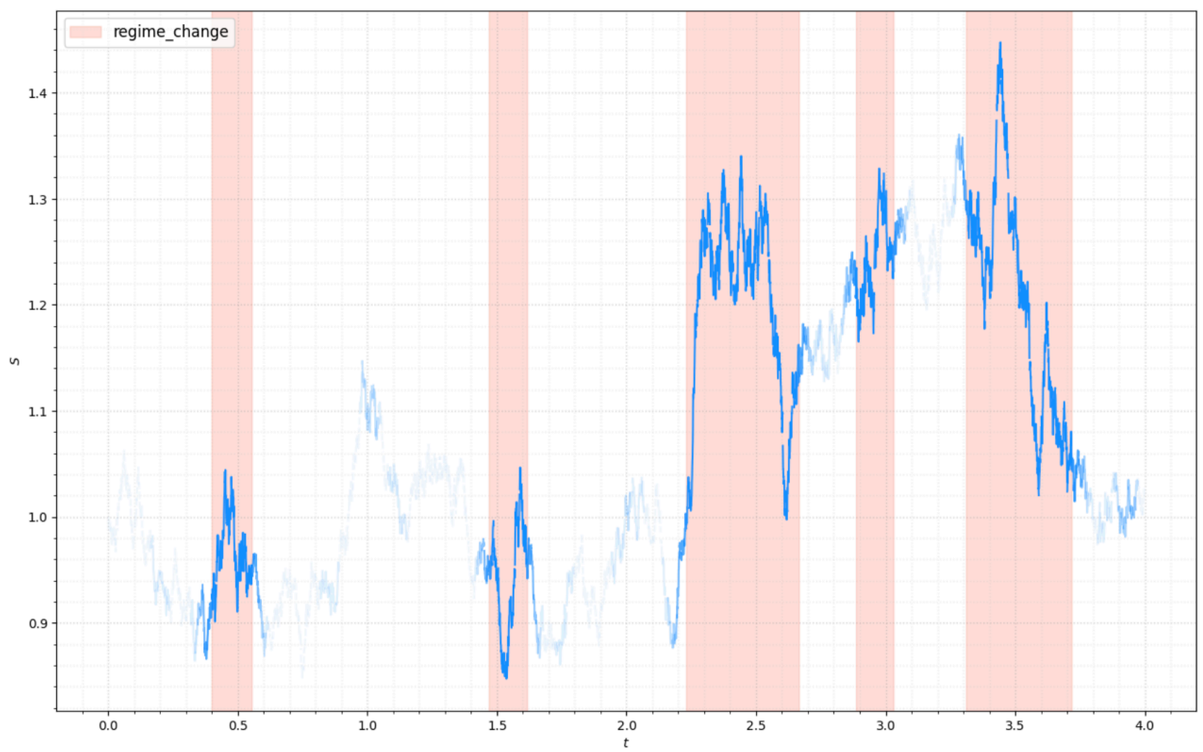
❋ MMDDetector paramters:

1. n_tests = 512, - Number of atoms in bootstrapped estimate
2. kernel_type = linear - Static kernel type
3. sigmas = 0.25 - Smoothing hyperparameters
4. Smoothing hyperparameters = 8 - Number of ensemble paths
5. dyadic_orders =2 - Dyadic orders of associated PDE solver
6. alpha_value = 0.9 - Confidence threshold



Parameteric Method

SIG-CON scores



SIG-CON Threshold

General_MMD_Detector scores:

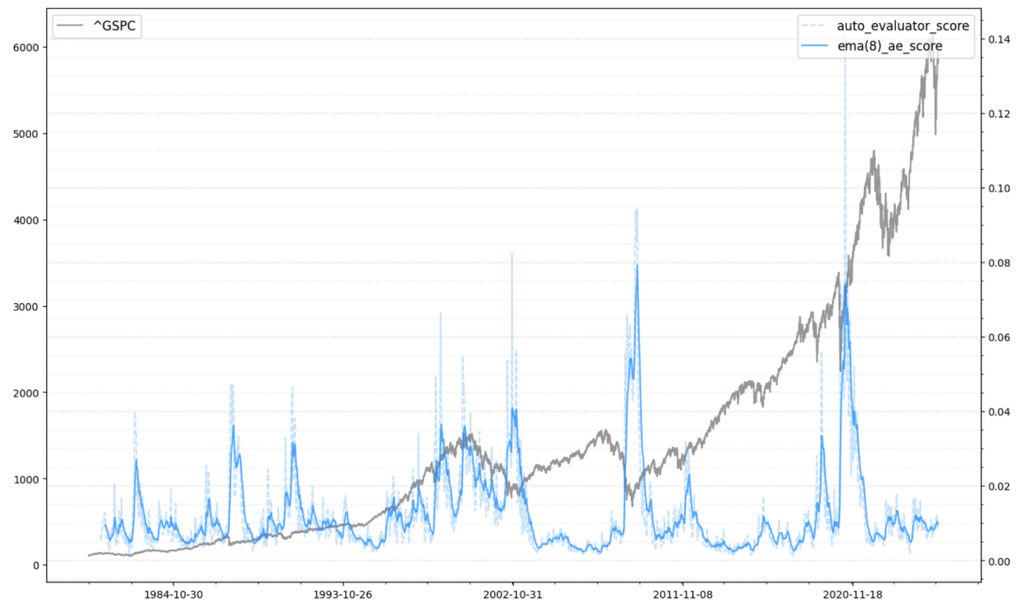
- regime_on: 99.5158%
- regime_off: 83.2931%
- total: 88.5168%

- **As shown in the plots, SIG-CON detects regime changes between high MMD scores and annotated regime regions.**
- The thresholded plot (right) highlights detected regimes (red bands), matching well with underlying structure.

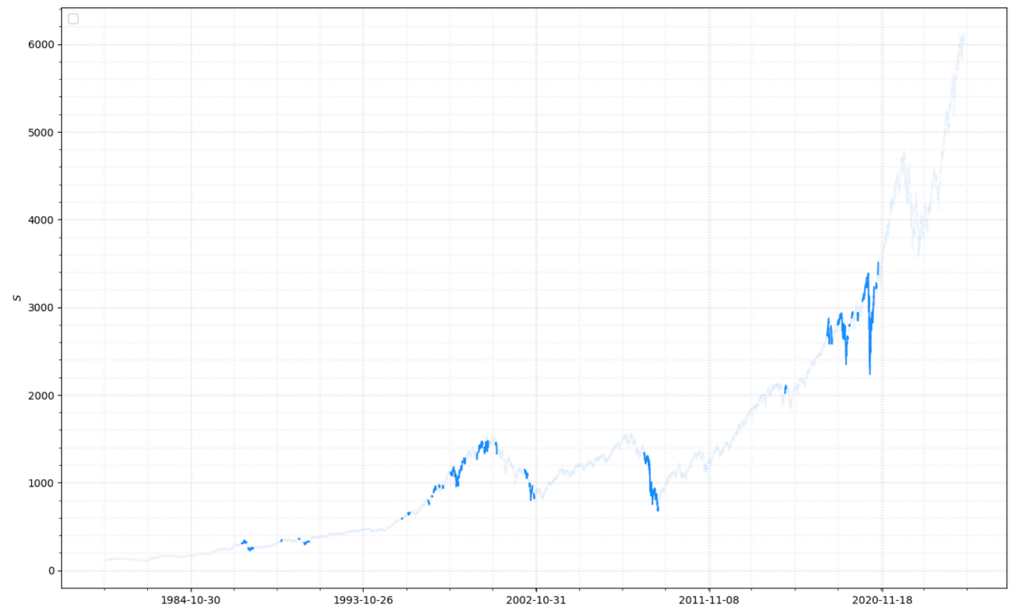
Non-parameteric method on real markets

- Daily historical prices (1980–2025 NYSE) of GSPC, KO, IBM, PG, JPM, XOM, and GE were analyzed using the auto-evaluator regime detection framework

- **Auto Evaluator Parameters**:
  - n_steps =8, n_paths = 8
  - kernel_type = “rbf"
  - sigmas = [1]
  - dyadic_orders = [2]
  - n_scores = 200
  - lags = [-4, -8, -12]
  - threshold_method = “bootstrap"
  - alpha_value = 0.90



- **Top plot**:
  - Blue line shows MMD-based score tracking market regime
- **Bottom plot**:
  - Regime change regions identified via thresholding (high α-scores)

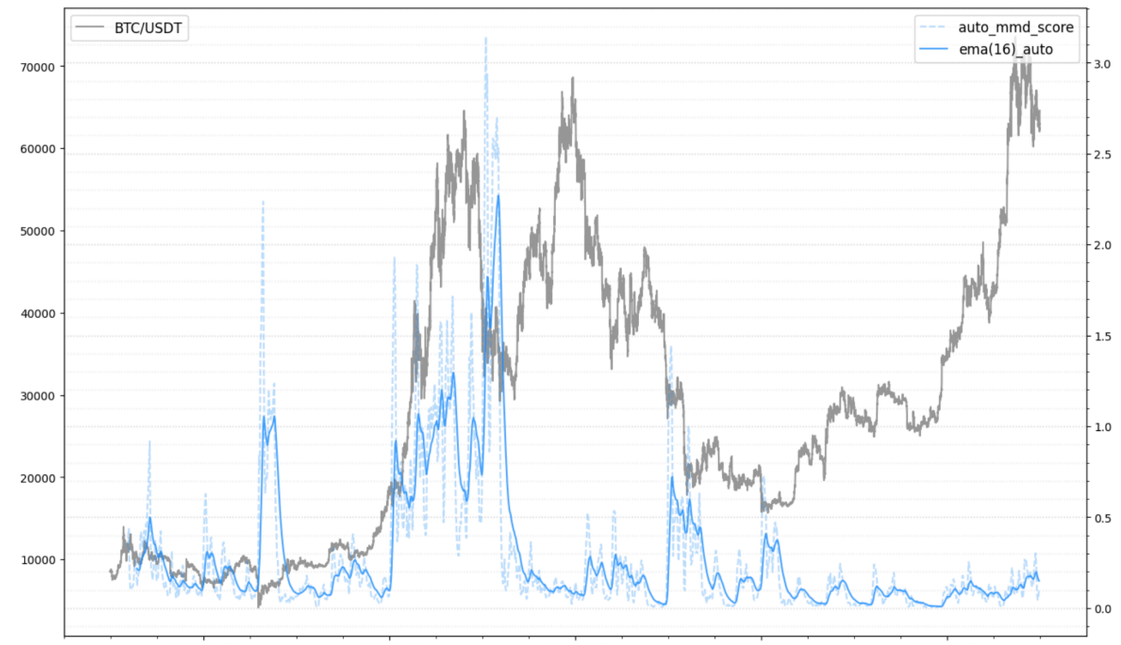


The Auto-Evaluator can effectively detect regime shifts

Non-parameteric method on real markets

Hourly data (2019-06-01 to 2024-04-30) for BTC/USDT, ADA/USDT, ETH/USDT, XRP/USDT, BNB/USDT, and MATIC/USDT was used for analysis.

- **Auto Evaluator Parameters**:
  - n_steps =32, n_paths = 8
  - kernel_type = “rbf"
  - sigmas = [1]
  - dyadic_orders = [3]
  - n_scores = 250
  - lags = [-8, -16]
  - threshold_method = “bootstrap"
  - alpha_value = 0.90



- **Top plot**:
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Auto-Evaluator successfully captures some regime transitions in crypto markets, **but the score elevation becomes less apparent after 2022, despite evident regime changes.**

Summary and Next Steps

- Reviewed **arXiv:2306.15835** — Chapter 3/4 and part of Chapter 7 (Slide 2)
- Re-ran the toy example using the **parametric method**; confirmed that MMD-based approaches can effectively identify regime switches under the given model (Slide 3-4)
- Re-ran the **non-parametric method (Auto-Evaluator)** on NYSE equities; observed that certain regime shifts were effectively detected (Slide 5)
- Re-ran the **Auto-Evaluator on crypto markets**; while some regime changes were detected, **score elevation flattened over time**, indicating reduced sensitivity in later periods (Slide 6)

Next Steps:

- Review and rerun **clustering real equities** in the paper to identify regimes directly from historical data
- Review and rerun **Non-ensemble regime evaluation in the paper**: test model sensitivity on single paths
- Consider the **full detection pipeline**: from raw data → transform → score → signal
- Test/Optimise the parameters like n_steps/n_paths to check differences.