LPPLS-Net: Advanced Neural Networks for Predicting Temporal Critical Points in Financial Systems

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SIAM Conference on Financial Mathematics and Engineering (FM25)

Motivation

Forecasting financial crashes is a critical yet challenging problem. The Log-Periodic Power Law Singularity (LPPLS) model captures bubble dynamics effectively, though parameter fitting is unstable. We develop a Deep Learning approach, trained on synthetic noisy datasets, to improve parameter fitting and achieve early and accurate detection of critical points.

Novel Contributions:

- Explored complex datasets using ARCH/GARCH noises, closely reflecting real market behavior.
- Designed a soft-penalty mechanism to guide boundary-aware non-linear parameters learning.
- Validated synthetic data using Topological Data Analysis (TDA), checking for early warning signals (spikes near the critical point).

Log-Periodic Power-Law Singularity

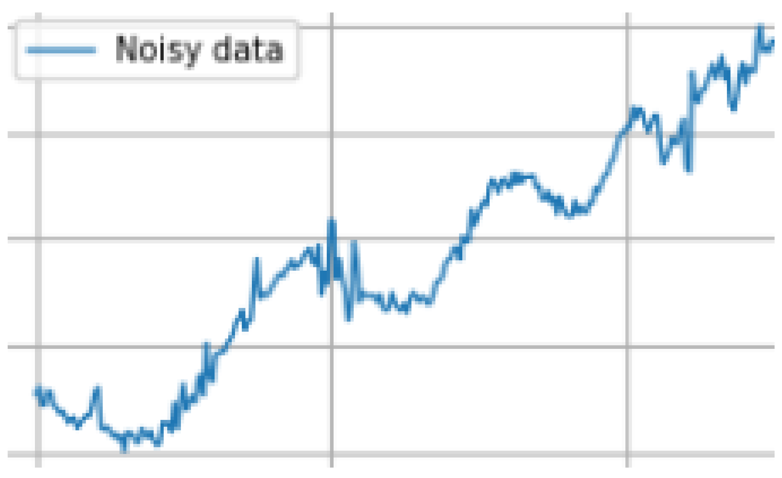
- LPPLS features accelerating growth and log-periodic oscillations nearing a critical point
- $\log(p(t)) = A + B(t_c - t)^m + C_1(t_c - t)^m \cos(\omega \log(t_c - t)) + C_2(t_c - t)^m \sin(\omega \log(t_c - t)) + \eta_t$
  where $p(t)$ =asset price, t_c = critical point, A, B, C_1, C_2, m, ω = trend parameters, η_t = noise
- The LPPLS model is applicable to a wide range of complex systems beyond financial markets.

LPPLS + AR(1) Noise

- Introduces correlated noise with memory.
- $\eta_t = \phi \cdot \eta_{t-1} + \epsilon_t$

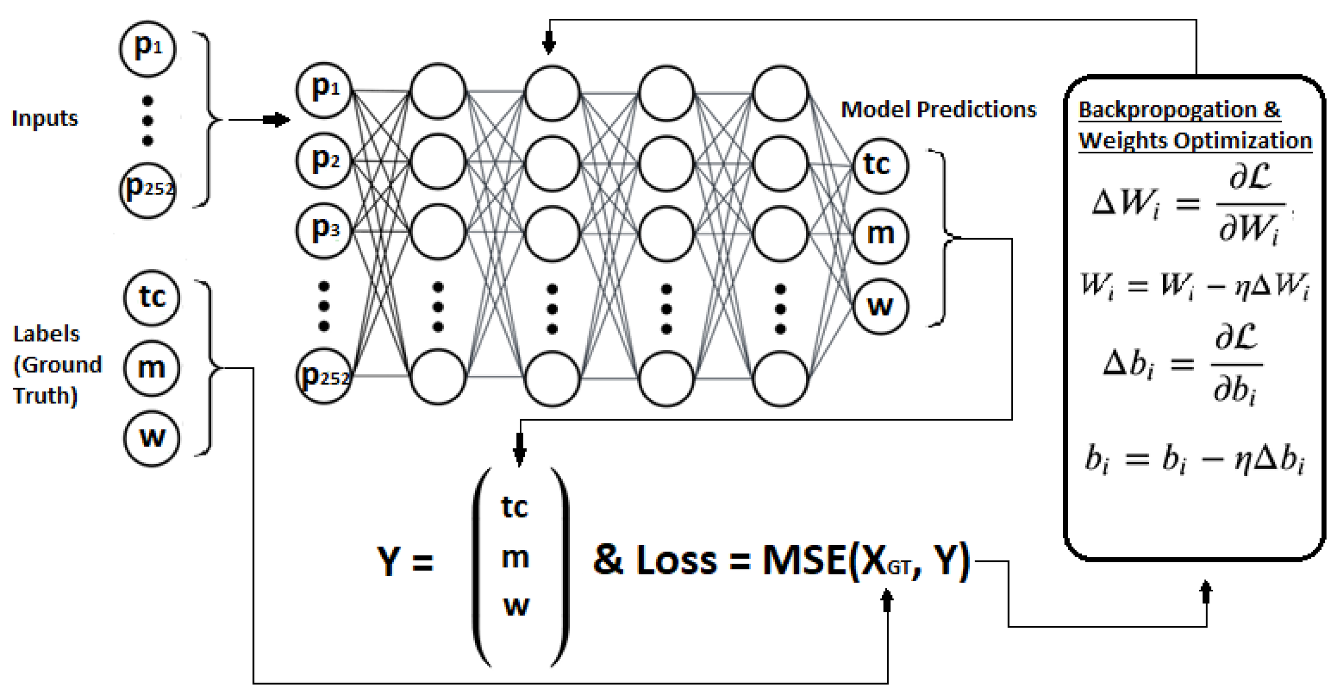
LPPLS + GARCH(1,1) Noise

- Captures clustered, time-varying volatility.
- $\eta_t = \sigma_t \cdot \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 \eta_{t-1}^2 + \beta_1 \sigma_{t-1}^2$



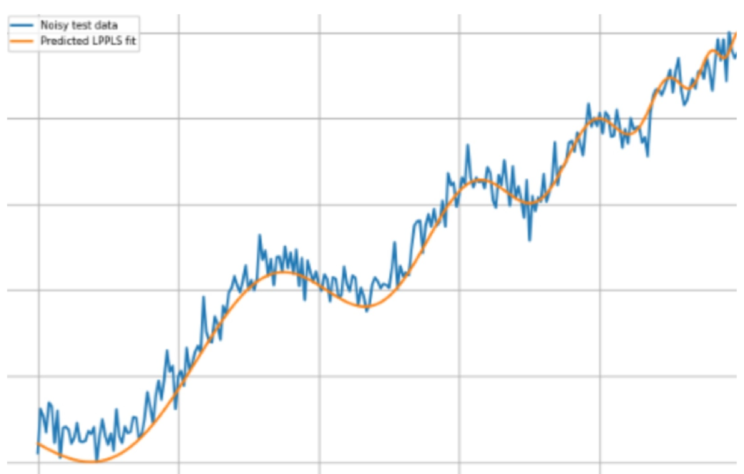
Supervised Training Methodology

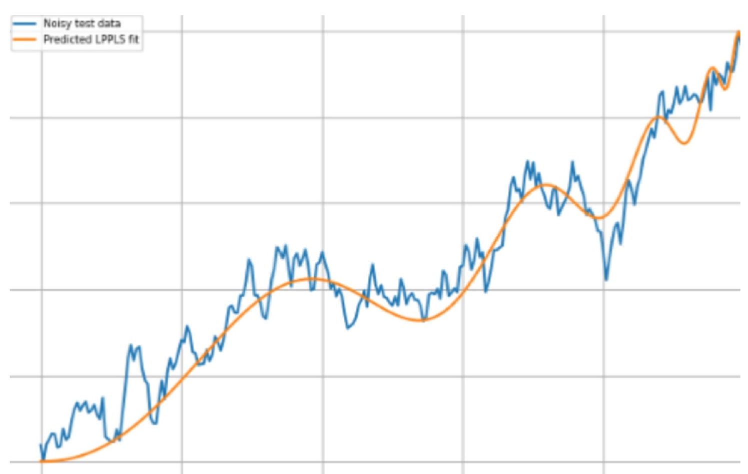
- Train on synthetic LPPLS series with white, AR(1) and GARCH(1,1) noise, resampled to 252 points.
- Use curriculum learning to stabilize training and weighted loss for balanced parameter estimation.
- Apply sigmoid-based transformations to enforce valid LPPLS parameter ranges during prediction.



Evaluation on Test Datasets

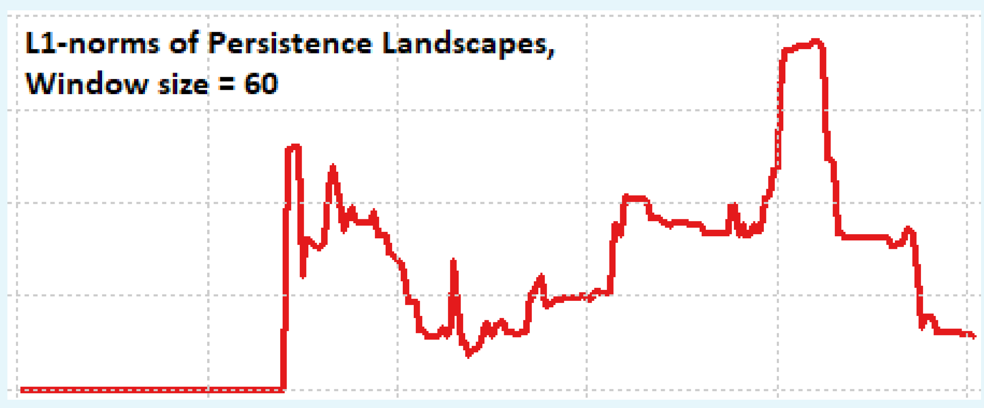
- LPPLS+GARCH achieved lower parameter error (<5%) than LPPLS+AR on 500 synthetic tests.
- Mean squared error was consistently lower with GARCH noise, indicating better fit to noisy data.





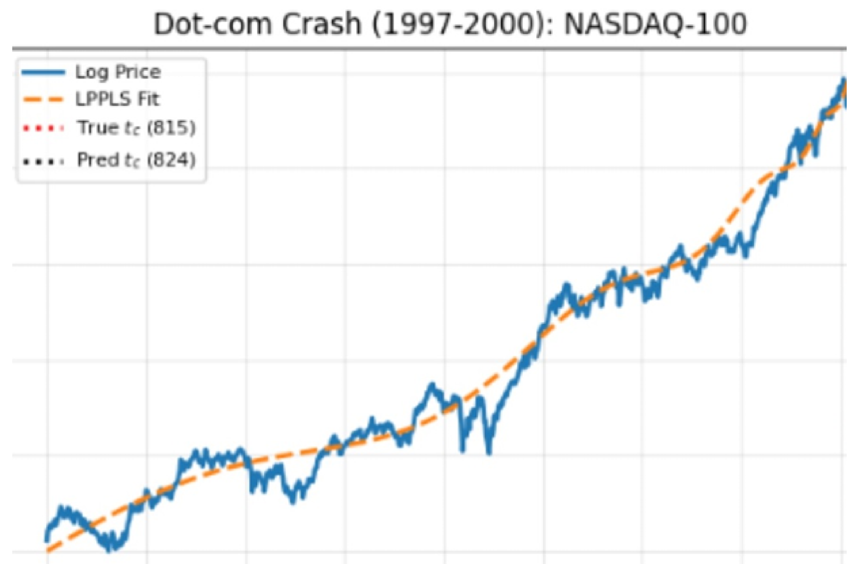
Validation of Synthetic Datasets using Topological Data Analysis (TDA)

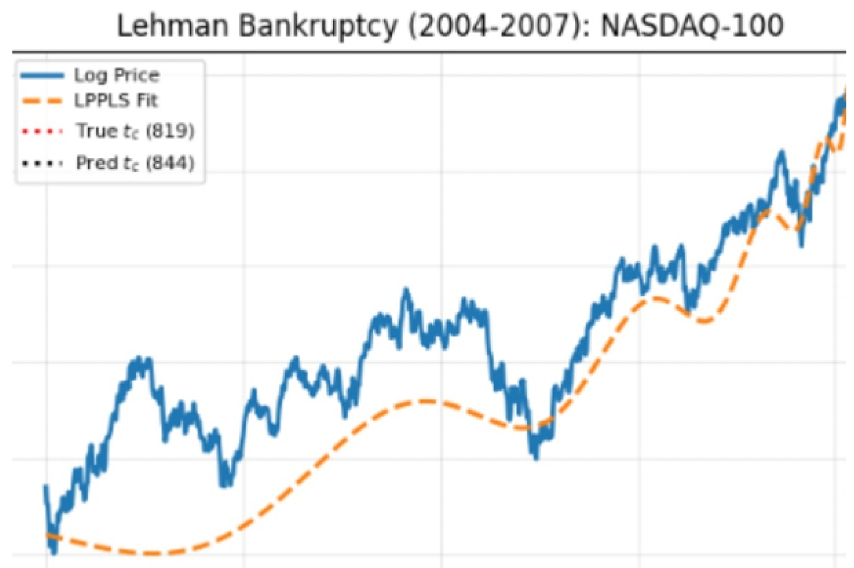
- Applied TDA (persistent homology) to synthetic series: computed L^1-norms of persistence landscapes over a sliding window
- Only TDA signals featuring early warning signals (spikes near the critical point) are kept for training data.

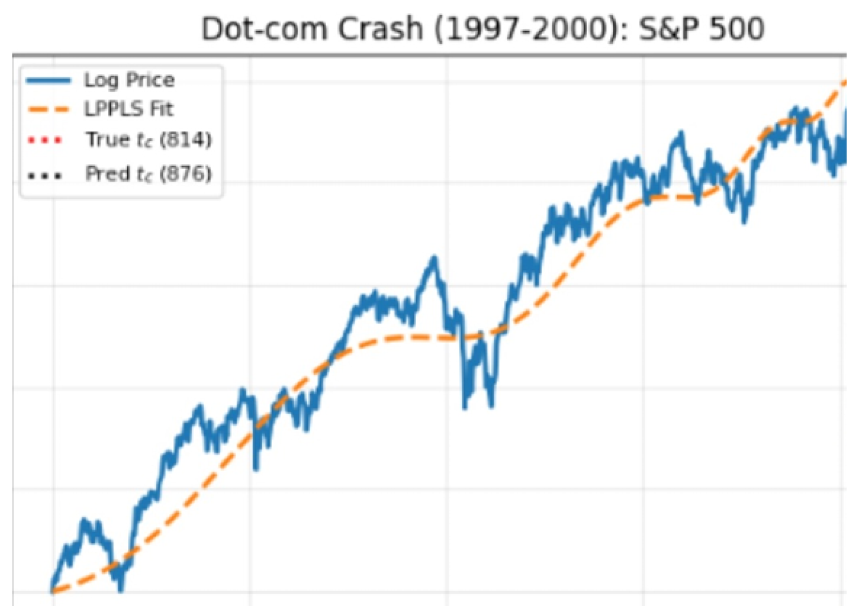


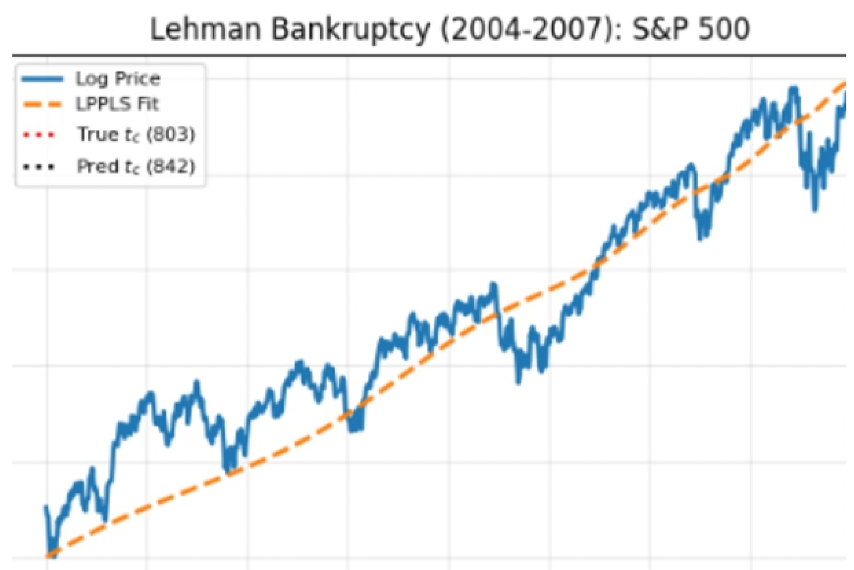
Application to Financial Markets

Tested on NASDAQ-100 & S&P 500 data during the dot-com bubble and Lehman Brothers crash.









Future Work

- Extend synthetic models with other noises.
- Adapt LPPLS-Net to handle variable-length time series using recurrent or transformer-based architectures.

Connect with Us

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Github

A digital version of this presentation can be found here: `https://github.com/VarunBiyyala/LPPLS-Net`.

References

[1] Marian Gidea and Yuri Katz. Topological data analysis of financial time series. Physica A, 491, 2018.

[2] Anders Johansen and Didier Sornette. Critical crashes. arXiv:cond-mat/9901035, 1999.

[3] Joshua Nielsen et al. Deep LPPLS: Forecasting of Temporal Critical Points in Natural, Engineering and Financial Systems. arXiv:2405.12803, 2024.