Domain Background

The LPPLS model provides a flexible framework to detect bubbles and predict regime changes of a financial asset (Sornette, 2013). A bubble is defined as a faster-than-exponential increase in asset price, that reflects positive feedback loop of higher return anticipations competing with negative feedback spirals of crash expectations. It models a bubble price as a power law with a finite-time singularity decorated by oscillations with a frequency increasing with time.

Here is the model and a description of its 7 parameters:

$$E[ln\, p(t)] = A + B(t_c - t)^m + C(t_c - t)^m cos(\omega ln(t_c - t) - \varphi)$$

where:

$E[ln\, p(t)]$	expected log price at the date of the termination of the bubble
t_c	critical time (date of termination of the bubble and transition in a new regime)
A	expected log price at the peak when the end of the bubble is reached at t_c
B	amplitude of the power law acceleration
C	amplitude of the log-periodic oscillations
m	degree of the super exponential growth
ω	scaling ratio of the temporal hierarchy of oscillations
φ	time scale of the oscillations

Problem Statement

I would like to explore whether or not the LPPLS model can be used to build a portfolio that outperforms a stock index, like the S&P 500. I've written a program that fits the model to a given dataset. It can be reviewed here: https://github.com/Boulder-Investment-Technologies/lppls. However, I've found a potentially faster implementation that builds upon my work, it can be found here:
https://medium.com/@ch9.ki7/lppl-or-arbitrary-curve-fitting-with-tensorflow-and-keras-9a8123f504f2. I would like to implement the keras and tensorflow fitting procedure in my pypi package

then run the new fitter on all stocks in the S&P 500. Then build a backtest where the portfolio is selected based on the values of the S&P 500

Datasets and Inputs

I will use the adjusted daily closing price for each stock in the S&P 500. The data was collected from the IEX https://iexcloud.io/. The data is updated daily but I will only use data from 2015-04-29 to 2020-02-11. The dataset is stored in amazon aws s3 bucket here: https://boulderinvestmenttech.s3.amazonaws.com/iex_etl/data/agg/master.csv

Solution Statement and Evaluation Metric

The LPPLS model fit to empirical data can be quantified as correct or not ex post facto by observing that the singularity occurs simultaneously with the known bubble in the empirical data. The fitting procedure minimizes the 7 parameters from the model. Based on the literature from Sornette et al (2015) a metric known as the LPPLS-Confidence-Indicator can be used to determine the reliability of a bubble diagnosis. The LPPLS-Confidence-Indicator is a fraction whereby many LPPLS fits are conducted on shrinking time windows. Then the number of fits that satisfy the filtering condition found in the table below are divided by the total number of fits to give the confidence value.

Parameter	Filter Condition 1 (Early Warning)	Filter Condition 2 (End Flag)	Description
m Power Law Exponent	[0.01, 1.2]	[0.01, 0.99]	-
ω Log-periodic Frequency	[2, 25]	[2, 25]	-
t_c Critical Time	$[t_2 - 0.05dt,$ $t_2 + 0.1dt]$	$[t_2 - 0.05dt,$ $t_2 + 0.1dt]$	-
O Number of Oscillations	$[2.5, +\infty)$	$[2.5, +\infty)$	$O = \frac{\omega}{2\pi} ln \frac{t_c - t_1}{t_c - t_2}$
D Damping	$[0.8, +\infty)$	$[1, +\infty)$	$D = \frac{m\|B\|}{\omega\|C\|}$

I will use the LPPLS-Confidence-Indicator as defined in Sornette et al (2015) to classify qualified bubbles.

Benchmark model

In the context of this project, it makes most sense to compare the portfolio constructed by the LPPLS indicators to a benchmark portfolio or a broad stock index. I will use the S&P 500 index

Project Design

The strategy that uses the LPPLS-Confidence-Indicator is largely adapted from the work presented by Mamageishvili (2018) and Pham (2019) in their master's theses. The idea is to use the bubble early warning and the bubble end flag to signal enter and exit times. When a positive (negative) bubble early warning sign is raised you buy (sell) the underlying asset and when the bubble end flag sign is raised you sell (buy) the underlying asset. Thresholds for the early warning and end flags are set to determine enter/exit timings.

First I will calculate the LPPLS-Confidence-Indicator for all equities in the S&P 500 from 2015-04-29 to 2020-02-11 (dataset referenced above). With these values, I will then execute a backtest from the same timeframe to determine if the indicator based portfolio outperforms the base index.

References

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