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Unfolding Financial Markets

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Background: Imagine a small inquisitive child playing with his or her toys in the backyard or garden. This is a privileged child who has many new and old playthings. The old standbys are comfortable, but this child also likes to explore the new and most recent additions. An unexpected experience with a new toy leads the child back to the familiar ones and a startling sound, like a car backfiring, may cause the child to abandon the entire ensemble altogether and head for the house.

This picture has some correspondence to the behavior of a financial market. If we think of the market as an organism responding to pleasant and unpleasant experiences, and also if we think that the organism places value on each item it encounters, this will allow us to exploit a very useful behavioral model of utility called *unfolding*.

Unfolding has a fairly long history. The central idea was originally proposed by Clyde Coombs in the 1950s[1] when he considered how to model liking and preference at an individual level. According to the model, a person's hedonic response to an item (the degree of utility placed on it) depends on the similarity of the item to an individual's ideal. The basis for the similarity of interest may depend on several underlying drivers that are not identified in advance and are treated as latent variables. The word *unfolding* refers to the result of estimating the parameters associated with items' latent variables, or coordinates, in a multidimensional space. Coombs conceived the items and ideals as deterministic (fixed) points and this led to degeneracies, which despite sometimes fitting the data well, are uninterpretable solutions.

This problem was solved by assuming that the items are *probabilistic*[2] rather than deterministic. In 2001, The Institute for Perception introduced a novel method called Landscape Segmentation Analysis® (LSA) that solved the degeneracy problem[3]. LSA has been applied to numerous types of hedonic data in many product categories and has also been applied to complex sensory variables[4].

The purpose of this report is to consider an application of LSA to financial markets as a tool in behavioral economics and to add to its already extensive range of applications.

Scenario: As an individual investor in a number of financial markets, you take an interest in new and alternative analytic methods that help you to see the performance of financial instruments over time. You are also interested in how these instruments cluster and on what basis. From these insights you would like to make predictions about their performance in the future. You are already familiar with the application of LSA to product liking in a number of product categories and this has helped you to understand consumer markets and to predict product portfolios.

As an initial exploration, you take data from a period with a significant market downturn. November 13, 2014 through November 12, 2015 included a period when there was fear of a slowdown in China's economy. In this scenario the actual stock closing prices are used. Thinking of the closing prices as hedonic measures, you convert them to values relative to their 52-week highs so that each stock is scaled on the same 0-1 basis.

LSA Data and Model: Typically LSA is applied to data from individual responses to a common set of items. Here you consider each day to correspond to an individual, called the *market*, so that the ideal points will correspond to the daily location of the market's ideal stock. This is a hypothetical stock that would always be at its 52-week high. Stock prices depend on the proximity of the market to the stocks. The model also includes a parameter that usually refers to an individual's tendency to provide high or low ratings. In the context of a financial market, this parameter refers to the *market health* or the tendency to score all stocks high or low due to some exogenous influence. When market health drops quickly it means that some unexpected crisis has affected the market (equivalent to the child running for safety.) The stocks are modeled as points in an *n*-dimensional space based on the probabilistic similarity model.

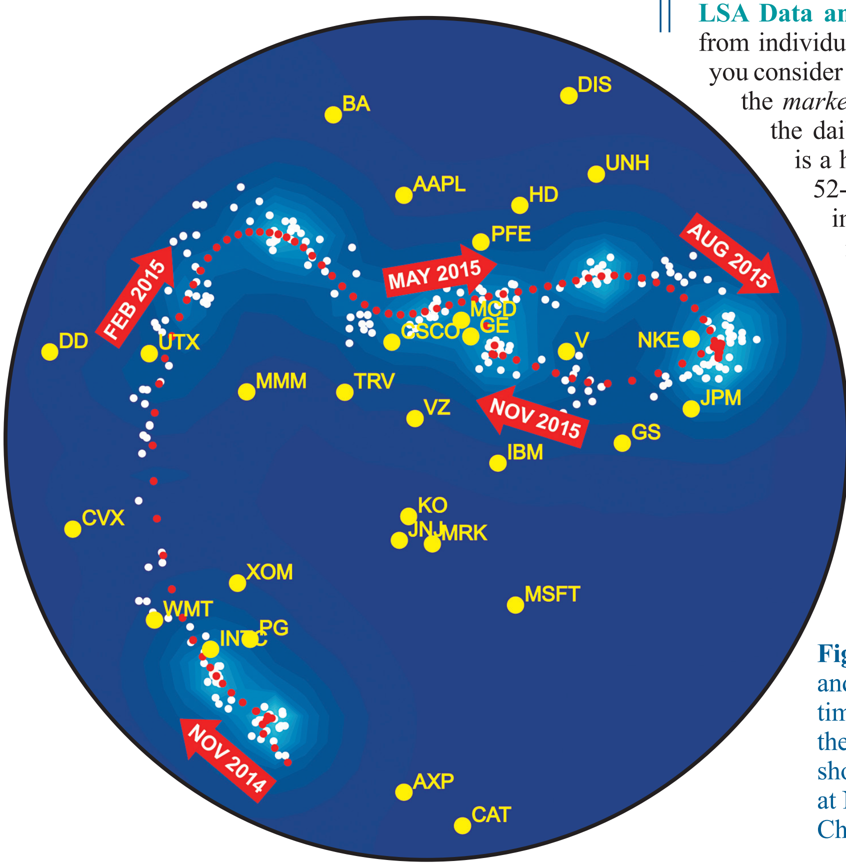

Figure 1. LSA map of 30 stocks (in yellow) and market values (white dots) over a one-year time period. A Bézier curve of red dots shows the fit through the market values with red arrows showing its direction and dates. The abrupt turn at NKE in August was caused by fears of a China slowdown.

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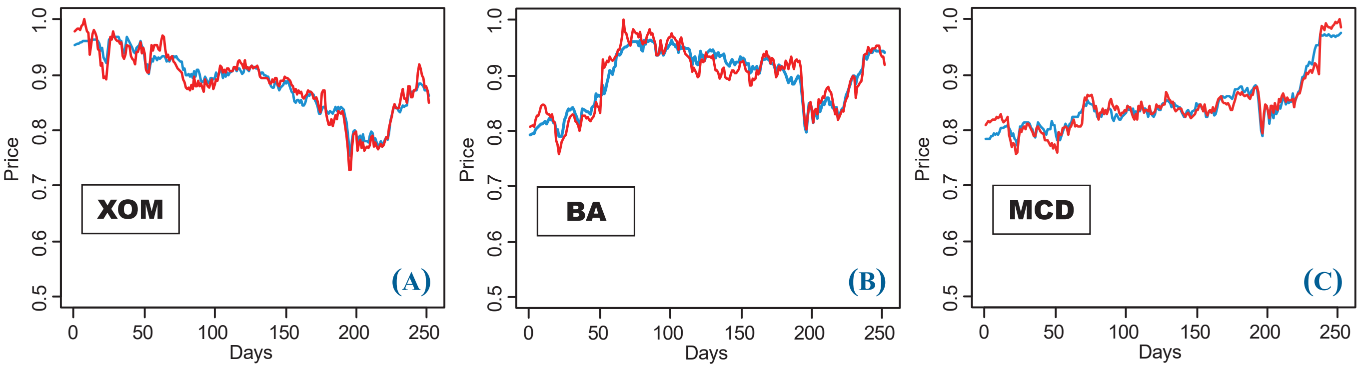
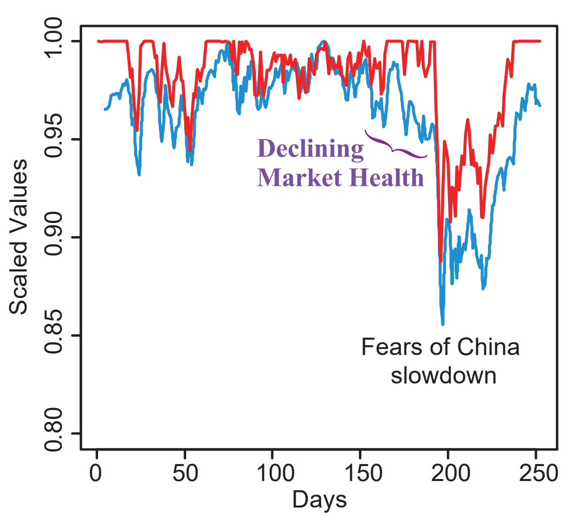


Figures 2 A-C. Actual (red line) and predicted (blue line) stock prices.

Application to the Stock Dataset: The goal of the LSA analysis is to fit the scaled daily stock closing prices for the ~250 trading days and 30 stocks in a two or three dimensional space. There are ~7500 data points. In two dimensions, about 11% of the number of data points are estimated as parameters and in three dimensions about 15% are used. This means that there are many more data points than parameters. These parameters include stock and daily market coordinates, stock variances, and market health for each day. The market health values apply to all the stocks on a given day.

Figure 1 shows the financial market landscape for the 30 Dow stocks with their symbols in yellow and daily market locations as white dots. What is remarkable about this plot is that the daily market locations are not a scatter plot and follow a time-dependent trend without the input of a time variable. The location of these points is based solely on the stock prices on each day without knowing the sequence of the prices. Arrows with dates are placed corresponding to the direction of the market over the ~250 days.

Figures 2A-C show the actual and fitted values for three selected stocks over the ~250 trading days. These stocks were chosen to represent three different regions of the market landscape in Figure 1 with different price patterns over time. Other stocks gave similar fits. Each predicted value depends on the location of the stock, it's variance, the location of the market, and market health.



An example of a relationship between Figure 1 and Figure 2 is the change in price of XOM and the market movement in Figure 1. Based on the path taken by the market, we would expect XOM to decline and then show a slight increase as the market moves south to CSCO. It should then decline as it moves away from XOM towards NKE. An abrupt turn moves it back in the direction of XOM which leads to an increase. These trends are observed in the standardized prices paid for XOM as shown in Figure 2A. The trends shown for BA and MCD in Figures 2B and 2C can be traced similarly in Figure 1.

Figure 3 shows the market health values plotted relative to the Dow Jones Industrial Average (DJIA). The DJIA generally follows market health although it appears to be more conservative. A major downturn occurred on August 24th (the 200th day in this dataset) due to fears of a China slowdown. Market health dropped dramatically on this day, but it was preceded by weakness in this parameter for several weeks beforehand. This was not evident in the DJIA. Figure 1 shows that after the major market downturn in August, the trend in market locations abruptly turned in the direction of CSCO, MCD, GE, V, and GS and away from NKE.

Predicting Future Directions: From these analyses, you see the value of LSA in representing stock prices over time, in following trends, and in assessing market health. Data from shorter periods using the same parameters may be needed to predict short term future directions.

Conclusion: Unfolding, as implemented in LSA, may be a very useful tool to study financial markets because it provides a way to visualize and quantify changes in item prices over time based on a very reasonable behavioral process model. It may be useful to study market drivers, to learn about financial instrument clusters, and possibly to predict short and long term trends.

References

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