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# Identification of Unique Trend Dynamics in An Integrated Investment Decision-Support Framework

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**Abstract:** In stock markets, the performance of traditional technology-based investment methods is limited because they only take into account single-dimensional event factors. The study shows how the integration of multi-dimensional stock market dynamics can improve performance and proposes a three-layer integrated investment decision-support framework. In the framework, we emphasize on one key dynamics that previous studies have neglected: unique trends of stocks-the patterns which only relate to individual stocks themselves. We adopted a Domain Knowledge-dependent AutoSplit method to study the dynamics and investigate its usage. Our experiments showed that this key dynamics plays an important role in investment decision making and it is an essential part of the framework. The integrated investment framework with incorporating this key dynamics is promising and our experimental results showed that it outperformed single-dimensional traditional methods and benchmark indices.

**Key words:** Unique trends, integrated investment framework

## INTRODUCTION

While there are a crowd of finance methods (such as fundamental analysis, technical analysis, contrarians' theory) in stock markets to help identify investment opportunities, they have different strengths and weakness[1-3]. There is an increasing need to integrate the different methods in stock markets and it is becoming more and more common for finance practitioners to adopt different methods simultaneously to get an optimized investment result[4]. However, some research problems have been observed in existing technology-based methods. Here are two problems that we shall consider throughout the study:

**Single-dimension vs integration of multi-dimensions:** Existing technology-based methods mainly focus on technical analysis, with a few which consider other dimensions. However, none of integration-related methods covers different dimensions of stock market structures as a whole to reflect the whole market situation, nor are different conventional methods integrated in a systematic way to incorporate their advantages. As a result, integration-based methods can not help investors to thoroughly and comprehensively understand the market and to identify all potential investment opportunities

**Lack of investigation into unique trends:** patterns identified by these methods are in a mixture and are not recognized on separate levels-general, group or individual level. Particularly they often ignore unique trends of stocks-patterns which relate only to individual stocks.

**Lack of domain knowledge-dependent feature:** These technology-based methods often neglect or misunderstand the importance of domain knowledge, thus their results are difficult to interpret, use and reuse for practitioners and academics.

Because of these problems, existing methods can not assist investors to identify investment opportunities very well and their performance is regarded as limited. In this paper, we address these problems and propose a novel three-layer integrated decision-support framework composed of Analysis, Synthesis and Investment Decision Support, in which we emphasize a key dynamics at first layer of the framework: identification of unique trends of stocks using Domain Knowledge-dependent Autosplit method.

## DESCRIPTION OF A THREE-LAYER INTEGRATED INVESTMENT DECISION-SUPPORT FRAMEWORK

In our previous studies[5], based on surveys on multi-dimensional stock market structure[6-8], we propose a novel

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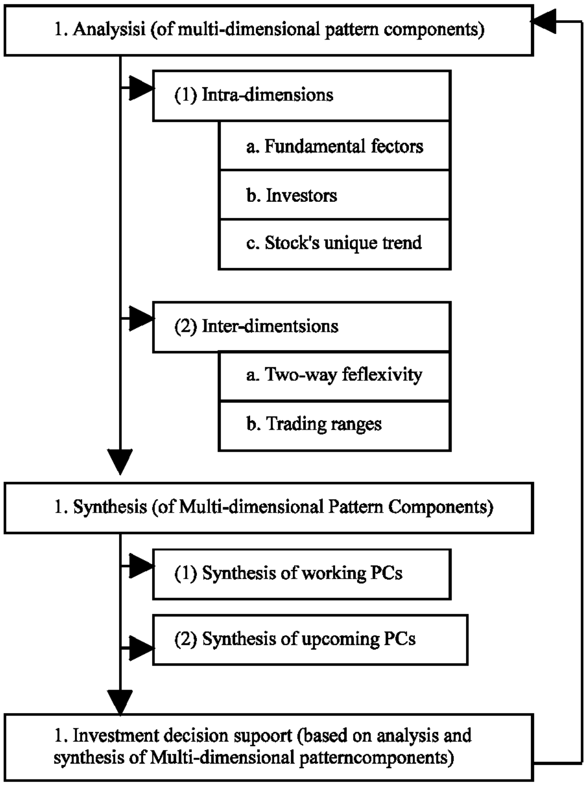



three-layer integrated frameworks analyzing and synthesizing multi-dimensional stock market dynamics and supporting investment decisions. This three-layer integrated investment decision support framework is shown in Fig. 1.

This integrated framework consists of three layers

- Analysis of Stock Market Structures: Since stock price formation is the result of integrated enforcement of multiple event factors within market structures, it can be decomposed into multi-dimensional dynamics, in which we focus on a two-way reflexivity dynamics between investors' behaviors and market reactions. To model these multi-dimensional stock market dynamics, we proposed concepts of pattern components, which represent basic unit components that derive from each dimension of stock market structures, with features of being understandable, interpretable, usable and reusable for finance practitioners and academics
- Synthesis of Stock Market Structures: After individual pattern components being identified and modelled from historic data set at the first layer, working and upcoming pattern components can synthesize to reflect current and potential market situations
- Investment Decision Support based on Analysis and Synthesis: Once potential investment opportunities are identified and trading strategies are created based on the result of the second layer, they can be inputted to investors' knowledge base and then be used to help investors optimize their decision making.

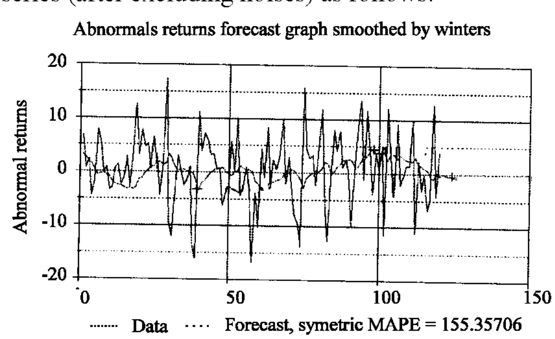
This three-layer integrated framework has a cyclic process: after the third layer, the results of investment decision-support can be used to adjust or optimize both the models of pattern components identified at the first layer and the models of integration at the second layer. In the cyclic process, parameters of pattern components and their synthesis can be optimized and so optimal investment decisions can be achieved.

## FIRST LAYER: UNIQUE TREND DYNAMICS OF STOCKS

In the first layer, we focus on identification of unique trends of stocks, through integrating domain knowledge-dependent features into Autosplit methods[7].

**Definitions of unique trends of stocks:** In stock markets, unique trends of a stock only belong to the stock itself and dramatically affect the unique changes of market situations of the stock. The unique trends derive from the unique characteristics of multi-dimensions of the stock structure, including its unique stock price and volume movement, its unique shareholder constitutions and its unique company-level fundamental factors. Although few relevant studies have been done, identification of unique trends is significant in research and trading practice. Unique trends of a stock can be defined and identified in following ways:

Firstly, unique trends of a stock is a clean data set by excluding general-level trend, group-level trend and noise from original data sets of the stock. Therefore, we can use comparative returns concepts to identify unique trends, which is the difference of real market price and predicted price using regression model of market and/or industry movement. In this way, the modeling excludes the 'contaminated' effects of market and/or industry and focuses on unique trends of the stock. In an experiment, we identified NAB's abnormal returns and their smoothed series (after excluding noises) as follows:



From these experimental results, we observed that smoothed unique trends fluctuate at smaller spans than original return series and some patterns can be derived using tools similar to conventional technical analysis, i.e. MA, MACD.etc.

Secondly, unique trends of a stock can be trends (or features) discovered which have most significant correlation to the stock itself. That is,

unique trend = {u| u in Trends and correlation (u, stock) is maximum}

Thirdly, unique trends of a stock can be a sum up of effects of individual-level pattern components of the stock. That is,

unique trend = ∑ individual-level pattern components

Based on above definitions and considering the need of integrating finance domain knowledge, we adopt a Domain Knowledge-dependent Auto-split method to identify unique trends of a stock.

**A domain knowledge-dependent auto-split method for identification of unique trends**

**Necessity of integrating domain knowledge-dependent feature into autosplit methods:** Traditionally, data mining methods (including AutoSplit[9] and ICA) and other technologies are used to identify independent hidden variables in stock markets, but few studies focus on unique trends of stocks. In our studies of identification of unique trends using these methods, we observe following problems: These methods generate a large number of patterns (hidden variables), many of which are uninteresting and difficult for finance domain experts (i.e., investors) to understand, or irrelevant to problems in trading practices. Moreover, discovered variables are in a mixture and they may be totally incompatible with known domain knowledge. The domain knowledge-dependent feature is important to solve the problems of the methods. However, few existing methods (i.e. AutoSplit) incorporate domain knowledge with their computation process and this makes their results difficult to interpret, use and reuse.

For instance, by using original AutoSplit to analyze hidden variables among industry indices, we obtained following results of Base Vector Part:

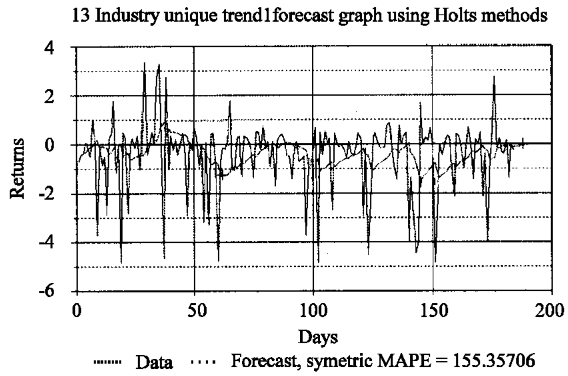
We also obtained following hidden Variables or patterns:

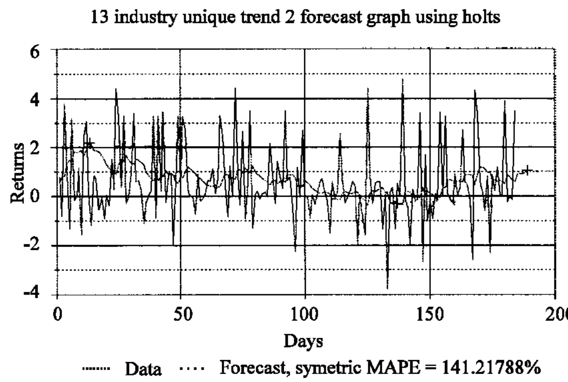
For this hidden variable H1, derived from base vector B, material index (AXMJ), healthcare index (AXHJ) and Consumer Staples (AXSJ) have strong positive contribution, but finance index (ASFJ) has a weak positive contribution. On the contrary, some industry indices (such as ASDJ-Consumer Discretionary, AXIJ-IT, AXTJ-telecommunication, AXUJ-utilities) have negative contributions. Considering each index's characteristics, it seems that H1 may represent most of Australian traditional industries (such as energy and healthcare) and does not represent new but weak industries such as IT and telecommunication. Therefore, H1 may represent trend of traditional strong industry of material and healthcare.

Similarly, for this hidden variable H2, derived from base vector B, healthcare index (AXHJ) and Consumer Discretionary (AXDJ) have strong positive contribution, but industrial index (ASIJ) has a weak positive contribution. On the contrary, some industry indices (such as Material index-AXMJ, AXIJ-IT, AXTJ-Telecommunication, AXUJ-Utilities) have negative contributions. Considering each index's characteristics, it seems that H1 may represent most of Australian traditional industries (such as energy and healthcare) and does not represent new but weak industries such as IT and telecommunication. Therefore, H1 may represent trend of traditional strong industries of *healthcare* and consumer discretionary. However, considering both H1 and H2, we found that their conclusions are vague and even meaningless (since both of hidden variables represent same industry-healthcare) and thus they are not solid and even useless. In order to be more solid and

J.
contribution

| Hi | AXOR | ^AXEJ | ^AXMJ | ^AXNJ | ^AXDJ | ^AXSJ | ^AXHJ | ^AXFJ | ^AXIJ | ^AXTJ | ^AXUJ | ^AXPJ | ^AXXJ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.1878 | -0.2435 | 0.8725 | 0.2732 | -0.6018 | 0.4702 | 0.5942 | 0.058 | -0.7813 | -0.6919 | -0.6121 | 0.1479 | -0.3767 |
| 2 | -0.2886 | -0.419 | -1.518 | 0.3473 | 0.7698 | -0.5848 | 0.8185 | 0.0433 | -1.0528 | -0.9738 | -0.8198 | -0.2398 | -0.506 |
| 3 | -0.2046 | -0.3589 | -1.4073 | 0.399 | 0.7648 | -0.4974 | 0.6815 | 0.0983 | -14.1198 | -1.1156 | -0.8516 | -0.2354 | -0.4268 |
| 4 | -0.1891 | -0.246 | -1.0222 | 0.3303 | 0.7649 | -0.5046 | 0.6896 | 0.0783 | -0.8633 | -0.7464 | -0.7758 | -0.1671 | -0.4705 |
| 5 | -0.1521 | -0.153 | -0.5211 | 0.1976 | 0.397 | -0.4393 | 0.4605 | 0.0815 | -0.4666 | -0.411 | -0.3274 | -0.0818 | -0.3111 |
| 6 | -0.2519 | -0.2721 | -1.1677 | 0.3302 | 0.8121 | -0.4871 | 0.7015 | 0.0619 | -1.0942 | -0.9018 | -0.8526 | -0.2027 | -0.4462 |
| 7 | -0.2562 | -0.2244 | -0.9867 | 0.4588 | 1.0468 | -0.5612 | 0.8623 | 0.0483 | -0.8117 | -0.7311 | -0.7347 | -0.1375 | -0.583 |
| 8 | -0.2414 | -0.3146 | -1.0531 | 0.3308 | 0.7572 | -0.518 | 0.7161 | 0.038 | -1.0227 | -0.8543 | -0.8168 | -0.1985 | -0.476 |
| 9 | -0.0278 | -0.0146 | -0.082 | 0.0603 | 0.0944 | -0.3127 | 0.2038 | 0.0012 | -0.0581 | -0.0515 | -0.0484 | -0.005 | -0.1218 |
| 10 | -0.1053 | -0.0145 | -0.4018 | 0.1602 | 0.3391 | -0.387 | 0.4124 | 0.0424 | -0.4119 | -0.3535 | -0.3292 | -0.0573 | -0.1815 |
| 11 | -0.1586 | -0.1374 | -0.9846 | 0.2407 | 0.5919 | -0.5058 | 0.7358 | 0.0144 | -0.9173 | -0.74 | -0.5813 | -0.1582 | -0.3765 |
| 12 | -0.0769 | -0.286 | -0.4021 | 0.1007 | 0.2597 | -0.1914 | 0.2393 | 0.0184 | -0.396 | -0.3078 | -0.2719 | -0.0679 | -0.1518 |
| 13 | -0.2504 | -0.12461 | -01.0525 | 0.3457 | 0.7755 | -0.5237 | 0.7369 | 0.0359 | -1.0192 | -0.8658 | -0.841 | -0.2047 | -0.4939 |




meaningful, it is necessary to integrate real domain knowledge into data mining processes.

**Introduction of a Domain Knowledge-Dependent AutoSplit Method:** To solve these problems, we propose a Domain Knowledge-dependent Quasi Auto-Split Method, which integrates finance domain knowledge (i.e. pattern components discovered) with AutoSplit Method in following ways:

Firstly, we can integrate known pattern components in Preprocessing: For instance, we can determine the dimension size (or number of variables) based on the number of identified pattern components plus reasonable extra unknown variables and this also can reduce the unpredictable span of data series by excluding the effects of known pattern components.

Secondly, we can integrate known pattern components during Processing: for instance, in the formula of Autosplit X = H*B, after discovering and modeling P known pattern components, we can obtain first P columns of H (hidden variable matrix) which represent each pattern component's effect models and their attributes B (base matrix) which represent each stock's contribution or strength to the effect of the pattern component. Then we need to Figure out attributes of each stock's hidden variables, which are the remaining columns of H after first P columns. To obtain these columns in H, since only individual stock contributes non-zero strength to the unique trend, we can set their related rows of B as (0, 0…1…0), where 1 indicates the individual stock's strength. Based on these known base vector B and stock series X, we can easily work out the unique trends in H, that is, H = XB-1.

Finally, we can integrate known pattern components after processing: after processing, we need to integrate domain knowledge to understand and interpret hidden variables identified. For example, we can identify which stocks (or other dimensional variables) contribute most or have highest correlation to hidden variables; or which known pattern components have same or most similar representation patterns to hidden variables.

**Experiments of using a domain knowledge-dependent autosplit method to identify unique trends of stocks:** In following experiments, this method is used to identify unique trends of stocks and results (hidden variables discovered, or unique trends of stocks) are interesting and interpretable for both trading practitioners and academics. In a one-month period (16/02/2005-15/03/2005), we obtain data source of returns for finance industry stocks, including AORD, AXFJ, AMP, NAB, CBA, ANZ, SGB

In the preprocessing phase, we recognized following pattern components in the data series:

- A general-level pattern component (Rise of interest rates) was identified: from Feb 18, interest rate rise was hinted by Australian Federal Bank and on March 2, it was formally announced by Australian Federal Bank.
- An Industry-level pattern component was identified: according to fundamental analysis of finance industry, its mid-term and long-term prospective (especially in this period) is compromising and its trend is booming.

| Date | AORD | AXFJ | ANZ | SGB | NAB | CBA | | | |
|---|---|---|---|---|---|---|---|---|---|
| 16/02/05 | 0.681938 | 1.226327 | 4.173934 | 0.176006 | 0.747624 | -1.70982 | | | |
| 17/02/05 | 1.277061 | 0.611867 | -3.75473 | -2.82469 | -1.34665 | -4.79888 | | | |
| 16/02/05 | -0.3346 | -1.46993 | 0.418799 | 1.061413 | -0.90009 | 0.988719 | | | |
| 21/02/05 | 0.188246 | 0.525547 | -2.09805 | 3.519423 | -2.40941 | 6.858713 | | | |
| 22/02/05 | -1.59221 | -0.70087 | 8.950551 | -6.53352 | 2.108961 | 1.81891 | | | |
| 23/02/05 | -3.6992 | -6.05686 | -5.59853 | -7.35654 | -4.68369 | -3.15764 | | | |
| 24/02/05 | -1.76051 | -5.28669 | -3.98342 | 1.985969 | -9.05612 | -2.81256 | | | |
| 25/02/05 | 3.144812 | 3.933131 | 5.649779 | 3.76636 | 4.628404 | 6.695633 | 1 | 1 | 1 |
| 28/02/05 | 1.210215 | 2.853556 | -0.20795 | 3.202514 | -1.53733 | 3.369439 | 1 | 1 | 1 |
| 1/03/05 | 0.814224 | 0.389684 | -1.45841 | 3.003065 | 6.116925 | -2.16306 | 1 | 0 | 0 |
| 2/03/05 | 0.82311 | 0.884348 | 1.66636 | -3.35774 | 4.231156 | -0.36156 | 0 | 1 | 0 |
| 3/03/05 | 1.413355 | 1.97443 | 3.519927 | 4.588282 | -0.15041 | -0.24121 | 0 | 0 | 1 |
| 4/03/05 | 1.667239 | 2.245554 | 4.921237 | 2.974032 | -0.45153 | 5.15667 | 0 | 0 | 0 |
| 7/03/05 | 1.722636 | 0.830366 | --1.02067 | -0.69794 | -1.50849 | 2.614808 | | | |
| 8/03/05 | 0.483584 | 0.165883 | 0 | 2.61152 | 0 | 1.065173 | | | |
| 9/03/05 | -0.03085 | -2.98684 | 0.204326 | -5.06319 | -2.57652 | -5.23253 | | | |
| 10/03/05 | -2.45452 | -2.90133 | -4.10489 | 0.351087 | 0.303915 | -4.93317 | | | |
| 11/03/05 | -0.69349 | -0.88572 | -3.51993 | -1.758228 | -1.52171 | -4.74511 | | | |
| 14/03/05 | 2.695277 | 1.548825 | 1.867044 | 0.88003 | 2.432177 | 3.047693 | | | |
| 15/03/05 | -0.79342 | 0.873752 | 4.120472 | 5.069303 | -1.0624 | -2.68084 | | | |

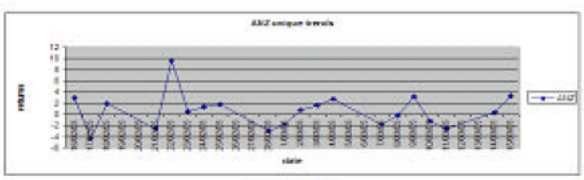
In the processing phase, above identified pattern components and their models are integrated into following Autosplit computation:

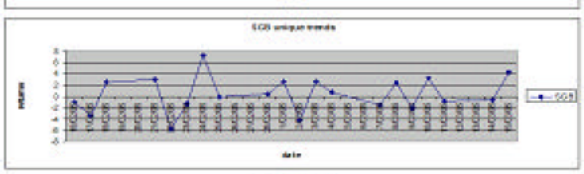
From above computing, we obtained following 4 individual stocks' hidden variables.

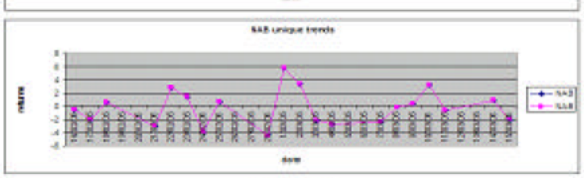
The results of unique trends can be further investigated as follows:

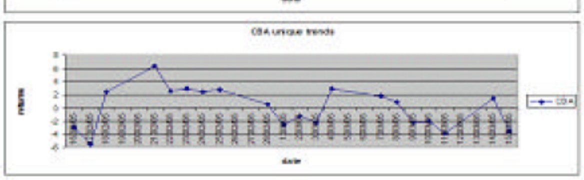
**Direct usage with original results:** we can treat above results as final unique trends of the stocks directly. In next step, we can identify patterns of these final unique trends and make appropriate predictions accordingly by incorporating the patterns into integration process (Third layer of the framework). The procedures can be illustrated as follows by using a few examples of patterns:

- Top/bottom patterns. In above ANZ example, we observed that top/bittern pattern has a cyclic period (average 5 days) with an average range of [-3, 3].
- Trends of movement. In above CBA example, range of returns decreased from [-6, 6] to [-4, 2]
- Indirect usage-cleaning data series first: A random walk exists if the next data point is equal to the last data point plus some random deviation. Many financial securities move in this manner. Under this condition, the best prediction for the next value in a series is simply the last value. Since above results of unique trends include noises (or random walk factors), they need to be cleaned by excluding such noises. We can adopt following multiple methods to clean the results and predict next data movement:









**Moving average:** This method works well if the data contains no trend or cyclic pattern.

**Simple Exponential Smoothing:** This method works well if the data contains no trend or cyclic pattern and the most recent data points are more significant than earlier points.

**Linear Exponential Smoothing (Holt's method):** This method works well if the data contains a trend but no cyclic pattern.

**Seasonal Exponential Smoothing (Winter's method):** This method works well if the data contains a trend and a cyclic pattern.

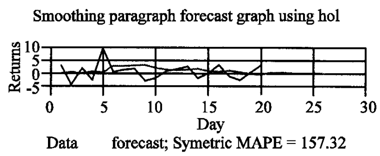
Table 1 and Figures illustrate some examples of using these methods to smooth original unique trends data series and make predictions accordingly, particularly ones derived from Holt's method.

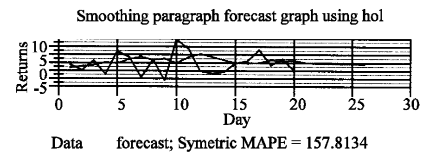
As I discussed above, different smoothing techniques work best in particular situations. In the experiments, I adopt DecisionPro package to choose the most suitable techniques for producing accurate predictions. By comparing the perditions derived from different methods with actual results (real market returns), I found that Linear Exponential Smoothing method (Holt's method) works best in identifying unique trends of stocks, as perditions and actual results have same movement directions (their returns are all positive or all negative) and their movement extents (or returns) have high correlations and have no significant difference. This is compatible with the conclusions of previous studies that Exponential Smoothing method (Holt's method) works well in the data contains a trend (unique trends in this case) but no cyclic pattern.

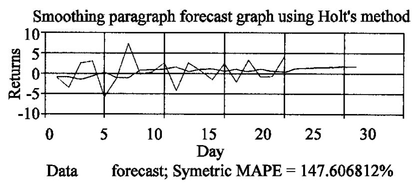
From these experiments, we observe that adopting domain knowledge-dependent Autosplit method has following significance. Firstly, in line with the known pattern components that are integrated in the AutoSplit computation, unique trends identified by integrating domain knowledge are more domain knowledge-relevant and so they are more interpretable and understandable for finance domain users than original Autosplit results, particularly their strength settings (only 1 for the stock and 0 for the rest) of unique trends made them really uniquely related to individual stocks themselves. Secondly, their processing is more time-efficient than original AutoSplit method, as known pattern components are integrated directly. Thirdly, unique trends are extremely useful in the situations when no significant general-level and group-level events occur in the period, where stock's own movement makes more sense. Finally,

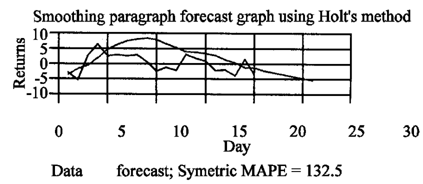
Table 1: Prediction and actual results of smoothing of unique trends

| Methods Stock | Moving average perdition | Simple exponential smoothing | Holt' smoothing prediction in following days | Winter's smoothing prediction in following days | Actual results in following days |
|---|---|---|---|---|---|
| ANZ | 0.29821 | 0.58074 | 0.2667; 0.21108; 0.15546; 0.09984; 0.04421; -0.01141 | 12.05628; -3.92072; -2.1207; 2.53753; 10.77193; 21.139495 | 0.2872; 0.3148; 0.0744; 0.1291; 0.0035; -0.1421 |
| SGB | 0.8411 | 0.39675 | 0.122343; 1.32805; 1.43266; 1.53727; 1.64188; 1.74649 | 4.72157; 1.16267; -3.69833; -5.45608; 9.04248; 5.1158 | 0.0274; 1.6741; 0.5122; 0.1277; 3.1341; 4.3124 |
| NAB | -0.16119 | -0.24374 | -0.05495; -0.12437; -0.19379; -0.26321; -0.33263; -0.40205 | -0.41515; -6.05046; -0.40059; 1.17264;-4.27743;-1.37768 | -0.2937; -1.5276; -4.2761; -0.8492;-1.0732;-2.0570 |
| CBA | -0.13069 | -2.40555 | -2.30873; -2.92551; -3.5423; -4.15909; -4.77587; -5.39266 | 2.76; -4.78395; -15.08688; -9.6089; -3.71632; 5.93238 | -4.5436; -7.0792; -1.6933; -0.8915; -5.1143; -9.7345 |




after further excluding known individual-level pattern components from the results of unique trends of the stocks, remaining part of unique trends of the stocks more closely indicate the patterns of stock movement itself.

**More experiments for justification:** In most cases, unique trends are used line with other pattern components. In other words, they are not used separately but integrally. Therefore, we only consider the final results of its integration with other pattern components in Second layer of the framework. As experimental results of layer 2 indicate, the integration is promising because the results are better than benchmarks and other conventional methods. For instance, we triggered trading signals (buy, sell or hold) at 80 important time points based on the integration results of pattern components, in ASX (Australia Stock Exchange) for the period of 01/01/2005-30/6/2005. It was observed that trading performance (with 48% aggregate returns) was much better than the performance of benchmark market indices (4.16%), top performing funds (20%) (Morningstar) and conventional methods (i.e. 14% for MACD method in our experiments).

As we discuss above, we can investigate the situations where no significant general-level and group-level events occur in the period and stock's own movement makes more sense. We did related experiments for top 33 stocks for the period 2005 to investigate such situations and found that results are promising. For instance, there is 75% accuracy rate between such unique trends and real market directions (positive or negative returns) and there is no significant difference between prediction and actual results based on Sample Paired Test. If we trade (buy, held or sell) based on the prediction in the training period, we got a promising accumulative returns of 53%.

## SECOND LAYER AND THIRD LAYER: SYNTHESIS AND DECISION SUPPORT

The price formation is the result of integral co-enforcement of multiple forces (or pattern components). We can treat each pattern component as an individual force with attributes of strength (its quantity side, or how much it is), direction (its quality side, or where it goes) and length (how long it lasts). Based on these attributes, integration can be achieved either by simple summing up strength of working and upcoming pattern components, or by using Hermite's interpolation of both strength and directions of working and upcoming pattern components, which include two-way reflexivity model of investors' decisions and market reactions we discussed in previous sections.

Individual pattern components and their synthesis are identified with their unique attributes. Their identifiable attributes include directions, strength, effect period, effect stages, etc. Based on the attributes of their synthesis results, trading strategies can be created and be used as an aid of investors' decision making. For instance, for the attribute Direction, it has value of UP, Down or Neutral. Accordingly, its related trading strategy is Buy at the beginning of UP, sell at the ending of Down, Hold at the period of Neutral.

The three-layer framework is implemented in a DSS prototype-ITFIDSS. Proposed prototype is a KB-DSS in essence and we adopted a KB-DSS methodology proposed by[10]. The initial prototype was implemented by mainly using C++. An industry partner, Tricom Australia Ltd, contributed expert domain knowledge and involved in the prototype implementation. More description of these layers of the framework and the design of the prototype can be found in our previous study[5].

Based on our experiments of the prototype, we obtained following evaluation results:

**Real transaction results:** 10 real investors were chosen to use the prototype to identify real important trading points in ASX market in evaluation period (01/07/2005-30/08/2005) and thus real transaction results were obtained. Similar experiments were executed in training period (01/01/2004-31/12/2004) and testing period (01/01/2005-30/06/2005). Table 2 shows performance of the prototype and its comparison with market baselines.

Table 2: The Performance Evaluation of the Prototype ITFIDSS and its Comparison with Baselines

| Measurement (1): Success rate of prediction of stock movement direction | Success rate (in the evaluation period | Success rate (in the training period | Success rate (in the testing period |
|---|---|---|---|
| ITFIDSS prototype | 92% | 87% | 90% |
| Conventional method (MACD) | 16% | 57% | 62% |
| Excess Success rate | 76% | 30% | 28% |
| Measurement (2): Mean Prediction error variance (of returns) | In the evaluation period | In the training period | In the testing period |
| ITFIDSS prototype | 0.11 | 0.09 | 0.12 |
| Conventional method (MACD) | 2.33 | 3.21 | 2.86 |
| Excess mean prediction error variance | -2.22 | -3.12 | -2.74 |
| Measurement (3): Aggregate Returns | In the evaluation period | In the training period | In the testing period |
| ITFIDSS prototype | 55% | 62% | 48% |
| Compared with following baselines: | | | |
| S and P/ASX 200 Accumulation | 4.33% | 22.57% | 4.16% |
| Excess Returns (1) | 50.67% | 39.43% | 43.84% |
| Median returns of fund management | 7.1% | 13.1% | 4% |
| Excess Returns (2) | 47.9% | 48.9% | 44% |
| Australian hedge funds | 11% | 12.2% | 5.7% |
| Excess Returns (3) | 44% | 49.8% | 42.3% |
| Top 5 performing funds | 17.6% | 45% | 20% |
| Excess Returns (4) | 37.4% | 17% | 28% |
| Conventional methods (MACD) | 12% | 29% | 14% |
| Excess Returns (5) | 43% | 33% | 34% |

Table 3: Users' Perception Measures of prototype of ITFIDSS

| Users' perception measures | Results |
|---|---|
| (1) Scoring of usefulness: | 8.9 |
| -p value | 0.003 |
| (2) Scoring Of ease of use | 7.7 |
| -p value | 0.012 |
| (3) Scoring of Conviction that decisions are correct | 8.4 |
| -p value | 0.049 |
| (4) Scoring of control of the decision process | 7.7 |
| -p value | 0.038 |

As Table 2 shows, the prototype of the integrated framework is promising and outperforms both market baselines (e.g. performance of Australian market index ASX and fund managers) and conventional investment methods (such as MACD) in ASX markets.

**Perception measures:** In the experiments, users of the prototype (ten real investors and fund managers, including a broker from my industry partner Tricom.com) used and interacted with the prototype and evaluated it using perception measures. In the analysis, I tested the response average against the mid-point of the scale 5 which is noted as Sometimes useful (or Sometimes ease of use, or Sometimes convicted that decisions are correct, or Sometimes the decision process is under control). All proportional differences were tested by using the two-tailed Fisher's Exact Test. The users gave positive feedbacks on these aspects in both experiment and real trading practice and this is illustrated in following table, where and the usefulness scores can simply be presented along with their statistical significance as indicated by the two-tailed p-value.

More importantly, the users indicated that the ITFIDSS could help them gain a competitive edge, because it provided a systematic framework to integrate their work with different investment methods and helped them understand stock market comprehensively and thoroughly by disclosing a new key dynamics-Unique trends of stocks.

## CONCLUSION

In this study, we proposed a novel three-layer integrated framework of stock markets, composed of Analysis, Synthesis and Investment Decision Support. This integrated framework incorporates multi-dimensional stock market dynamics. In the framework, we emphasized on a key dynamics that previous studies neglected: unique trends of stocks-patterns which only relate to individual stocks themselves. We studied the dynamics and investigated their usage by proposing a Domain Knowledge-dependent Autosplit method, which can make identified trends interpretable and usable. Our studies showed that this key aspect plays an important role in investment decision making. The framework incorporating this key aspect is promising, because our experimental results showed that it outperformed single-dimensional traditional methods and benchmark indices.

Our future work includes adopting more methods to model the analysis and synthesis of multi-dimensions and multi-levels of stock market dynamics and to further investigate their attributes and optimize related parameters. In particular, we will focus on further optimization and usage of the unique trend dynamics and the Domain Knowledge-dependent Autosplit method (including parameter optimization) in the integrated framework.

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