Turning Point Induced Knowledge Forecasting under Uncertainties (TrIK)

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Abstract: *Time series forecasting is used in many applications like price prediction, stock trend analysis, etc., This forecasting is dependent on multiple variables, which have an impact on contextual uncertainties. The inability to handle contextual uncertainty, induces incorrect predictions, leading to crucial business decision-making failures. This further restricts the abilities of forecasting and decision-making in a dynamic and partially observable real-life environment. This paper proposes a Turning Points-based approach along with shoulder impact processing. This imparts uncertainties in learning and handles such scenarios more scientifically and gracefully. Turning points are predicted based on probable impending surprise. These turning points are forecasted based on uncertainties found in the variables contributing to sudden out-of-the-pattern changes in the next cycle of forecasting. The shoulder impact areas are classified based on trend changes to improve decisions. Multivariate analysis, fuzzy time series analysis, and contextual impact determination assist to identify such uncertainties and inter-dependencies for improved forecasting. These points support trend forecasting instead of forecasting at an instance. This helps in many applications including decision-making regarding pricing, storing, and distribution of short-span, medium-span, and long-term span perishable commodities. TrIK can be extended to multiple time series forecasting applications to reduce wastage and economic loss.*

Keywords: *Time series forecasting, shoulder area, turning point, knowledge discovery, surprise, uncertainty.*

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1. Introduction

There are many applications those deal with Time series data, forecasting, classification, and decision-making. Generally, time series [15] applications use continuous real-life data. This data is gathered from a partially observable and dynamic environment.

Real-life data is dynamic, continuous, and contains uncertainty at different levels. Traditional time series forecasting on such real-life data does not take into account uncertainty. Dennis Lindley defined uncertainty as “An inability to decide whether a logical statement is true or false” [22, 23]. Traditional algorithms are unable to utilize uncertainty in decision-making. The inclusion of uncertainty is experimented with by researchers differently. These approaches include the use of probabilistic theory, interpolation, and other mathematical operations. The uncertainty in the data is due to a lack of information. Is there a way to determine and utilize contextual information which reduces uncertainty in decision-making? For example, predicting a commodity or stock price for the next week has many uncertainties due to unknowns [38]. These unknowns are due to the availability of items, government policies, and other information. In such time series forecasting, many variables contribute to uncertainty like the availability of items, and environmental variables like government policies, weather, etc. There is some information missing that is not available in multivariate analysis. This implies that multiple variable analysis is not enough to find the correct trend used in forecasting [20].

For example, in Figure 1, April and December 2018 show a sudden trend change in the price of Amazon stocks. It is necessary to understand the impact of these changes while forecasting. The sudden unexpected change in behavior is typically defined as a turning point. The turning point though looks isolated, it always comes up with impact in the shoulder area. Thus, in the given example turning points and associated shoulder areas could be determined. These findings assist in decision-making. Turning points are derived from the context which includes associated news from relevant communities and behavioral changes in allied commodities. Inputs from news aid in understanding trends as well as environmental factors. Multivariant analysis with forecasting is a benchmark before finding turning points. This paper represents finding and associating turning points and shoulder areas for a better understanding of trend change. Turning points are points from forecasting that have shift change. The shoulder area is the area from forecasting that represent an impact due to turning points and trends. Shoulder areas are classified as plateau, sharp trend changes, etc.

Figure 1. Uncertainty time series of amazon stock price.

2. Literature Survey

Many researchers have been working on time series analysis. This analysis is to find and represent knowledge that is used in forecasting [13, 14]. The main stage of knowledge discovery from time-series data requires sequence analysis. The input sequences are modelized as time series sequence events even if they are in the form of text or multimedia. In general, numeric data provided in a sequence of series for medical and other domains is modeled as a stream with time stamping i.e. time series inputs. This could be a sequence of moves in the case of games or sports or a sequence of transactions in the case of financial data. Many researchers used an integrated approach to discover the knowledge. For this, collaborative and distributed approaches to computing are used [12, 32, 35]. Some of the researchers used social media datasets [30], review datasets [10], and pre-knowledge of Wikipedia to extract useful information [6, 19, 29] from data streams.

Once sequences are analyzed and compared, based on inferences, these are modeled in different knowledge models. M¨orchen *et al.* [27]. Created a framework that finds the muscle active information extraction mechanism. They have extracted time-series data from kinesiological EMG to find the pattern for multivariant input sequences [27, 28, 37]. To build knowledge there is a necessity of evidence of activities and their documentation. Here activities are modeled into events for time series input sequences. Thus, cases are mapped to each event to build knowledge in various forms, found in the form of relationships, graphs, or any other mathematical representation [26, 33]. Time series analysis is a part of data mining techniques where univariate or multiple variates are analyzed for understanding trends, prediction, or classification. Time series have different applications based on different methods like temporal classification, clustering, association, prediction, summarization, outlier detections, etc. These methods are applied for different purposes. These methods consider time-space like short-term, medium-term, long term time series [15].

Time series-based forecasting with uncertainty consideration mainly uses parametric uncertainty calculated using a probabilistic approach [22]. Also, time series and risk association are provided by measuring uncertainty using evidence theory [3]. Time series forecasting quite often produces results with errors due to unbounded uncertainty. Forecasting is categorized on uncertainty and risk associated [24] with them. There are multiple time series algorithms proposed for different applications. Time series analysis has three components: Trends, Seasons, and Residuals. The forecasting algorithms like Autoregressive Integrated Moving Average (ARIMA) [4], Probabilistic based prediction [2, 39], Support Vector Machine (SVM) [5, 18], Artificial Neural Networks (ANN), etc., were proposed [11, 16, 17, 31]. These algorithms try to find an association between input variables and forecasting variables. They usually analyze the trend, seasons with or without a moving window, etc., These algorithms are classified mainly into two classes; linear and non-linear modeling. In the case of linear modeling, regression is the primary method that has many algorithms, while non-linear modeling includes probabilistic, neural network-based forecasting methods.

2.1. Linear Modeling: Regression

The regression-based algorithms are usually used univariate or multivariate forecasting for the price of an item or time required to do a certain task etc, it has a relationship like:

$$y_t = \sum_t v_t a_t + e_t \tag{1}$$

VAR [1, 25, 32, 40] has a relationship like

$$y_{i,t} = \sum_{i,t} y_{i,t} a_i + e_t \tag{2}$$

where *y* is the forecasting variable, *v* is the vector for the variable, a is the regression coefficient, *e* is the error rate, and *t* is time. In non-linear forecasting, there are different models. These models typically learn from patterns, rules, and statistical associations. Relationships and associations are established using mathematical functions or combinational mathematics. These are of the following types:

- Forecasting based on Artificial Neural Network (ANN) [11, 16, 17, 31, 34].
- Forecasting based on Evolutionary Computing (EC) [8, 9].
- Forecasting based on Support Vector Machine (SVM) [5, 18].
- Forecasting based on nearest neighbour [11].
- Forecasting with fuzzy [21, 28, 36].
- Rule-based forecasting [1].

Time series analysis is provided by many researchers but, they generally focus on value prediction. There are very limited attempts focusing on trend change detection. To understand major business implications, one needs to identify unexpected or surprising changes.

In this paper, we have proposed TrIK forecasting. Dynamic scenarios contribute to uncertainty in forecasting. Turning points support incorporating uncertainty. Sudden changes associated with turning points are captured with trend indicators in the form of shoulder areas. The association between turning points with shoulder area is classified to analyze trend change. Here, a dynamic environment has limited information for forecasting. News is one type of input that adds information in detecting trend change due to uncertainties. This adds another type of context to inputs in forecasting.

3. Proposed System: TrIK Forecasting

Turning point forecasting assists in detecting uncertainty for trend changes [7]. The turning points are calculated by using news associated with commodities. Commodity news is used to find Turning News Index (TNI). Bayesian Network-based forecasting is applied before finding turning points. The shoulder area is the area nearby turning points that makes an impact on the trend. The shoulder area provides intuitive information about trend change. These areas are classified based on sharp changes, the plateau of sustainability, and other aspects. The area is classified into five classes described in the result section.

The proposed system is shown in Figure 2 which represents forecasting based on turning points and shoulder area. Preprocessing and filtering operations are performed before finding multivariate analysis. TNI is calculated from textual news data and mapped to this multivariate analysis as the feature which is used for the forecasting. Once time series forecasting is performed turning points and shoulder areas are predicted. Contextual Bayesian Network-based forecasting is used. News related to items is used to detect surprises that impact forecasting. The Bayesian Network-based approaches are used for uncertainty modeling and forecasting [2, 39]. To forecast surprises, we have used commodity news and a simple bag of words (BoW) or n-gram approach. The approach models are listed below with the description.

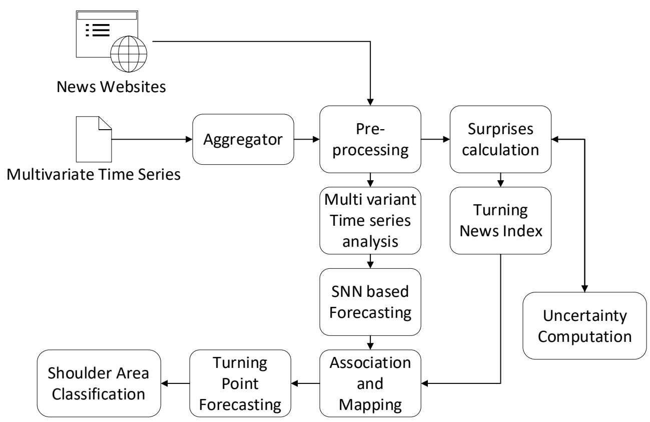

Figure 2. TrIK forecasting system under uncertainty.

Turning Point News Index TNI (for calculating surprises from news text, TF-IDF Model is used from BoW)

$$TNI = \{BoW, n - gram\}; TNI \in (-1,1) \tag{3}$$

Joint probabilities used for fusion and association

$$P(A|B) = C^{-1} \prod_{j \in J} P(A(j)|P(j)\alpha(j)) \prod_{k \in A} L(k|B) \tag{4}$$

where joint probability is calculated with a product of probability with "*C*" as the normalizing constant and likelihood function "*L*"

Turning Points are predicted using Central Difference (CD)

$$\frac{dy}{dx} = \frac{d\ Price_{forecast}}{d\ Date} \tag{5}$$

$$\frac{d^2y}{dx^2} = \frac{d^2\ Price_{forecast}}{d\ Date^2} \tag{6}$$

$$Curvature = \left| \frac{dx * d^2y - dy * dx^2}{\sqrt{(dx)^2 + (dy)^2}} \right| \tag{7}$$

$$CD = \sum_{i=0}^{n} (-1)^i \sum_i^n f\left(x + \left(\frac{n}{2} - i\right) h\right) \tag{8}$$

Shoulder Area (SA) impact measurement and classification

$$SA = trend * forecast(i) + (1 - trend) * mean(forecast);\ TP \in SA \tag{9}$$

The Algorithm (1) represents TrIK system working.

Algorithm 1: Turning Point Induced Knowledge Forecasting(TrIK)

INPUTS
S[i]: ith variable
TN[j]: jth Turning News as one external input
TNI[j]: jth Turning News Index used to calculate surprises from news
Price[k]: kth price forecast
ts : Start of time series interval for forecasting
te : end of time series interval for forecasting
FM : Forecasting Model
BoW : Bag of Words Model to find surprises
CD : Central Difference Model
OUTPUT
TP: Turning Point
SA: Shoulder Area

```
for j to n do
    TNI[j] = BoW(TN[j])
for k=ts to te do
    Price[k] = FM(S[k])
for k=ts to te do
    if k-j==1 then
        Price[k] = Price*TNI[j]
for k=ts to te do
    TP = CD(S[k])
for k=ts to te do
    SA[k] = SA(Price([k]),TP)
```

4. Results and Discussion

The comparison of results of the proposed approach TrIK with standard Bayesian Network (BN) is shown in

Table 1. The results show improvement in accuracy in all the cases except for Apple price forecasting. The steady trend of Apple prices is the obvious reason behind it. The results show an average 1.03 RMSE improvement and marginal change in Bias. Table 2 represents sample results for TNI calculation for which commodity news was considered from different sources. These news are crawled and TNI is found for associated commodities. The classification of shoulder areas is performed. It is represented by color codes: red, orange, yellow, green, and blue. Wherein red represents an acute and vanishing trend, orange is sharp and persistent, yellow represents a persistent plateau trend. Also, green and blue represent a steady trend with spikes due to turning points. The forecasting results with turning points and shoulder area identification classified are also shown in Figure 3. Experimentation is performed using the dataset data.world (Data: https://data.world/raghu543/fruits-and-vegetables-prices-in-india).

The commodity prices considered from the dataset are Cucumber, Cabbage, and Apple. The results are forecasted with a 70-30 ratio of training and testing data. The association derived here between cucumber and cabbage commodities has a periodic change shift based on classified shoulder areas. This indicates commodities from the same domain follow the association rule. Such association is observed in cucumber and cabbage but not with apple data. The turning points shown in the figure indicate a phase shift in trend. For example, cabbage price forecasting without TNI has a trend shift at sample 132. After this turning point, the price is forecasted and actual prices are in a downward direction, it has a sharp impact on the trend hence shoulder area is in the red class, which is represented in figures from Table 2. This means a sharp trend change within the acute shoulder area. The new feature of the News index called TNI is introduced in this research for which LSTM results are also shown in Table 1.

Table 1. Commodity forecasting comparison.

	Bias				RMSE			
	A	B	C	D	A	B	C	D
F	0.17	0.05	0.6	0.48	11.99	10.15	10.5	9.3
G	0.39	0.38	0.82	0.77	13.75	11.84	11.8	10.9
H	-0.54	-1.18	-0.2	-1.3	8.61	9.3	6.4	7.2

(A = BN without TNI, B = BN with TNI, C = LSTM without TNI, D = LSTM with TNI, F = Cucumber, G = Cabbage, H = Apple)

Table 2. Sample TNI calculation on vegetable news.

News	**TNI**
According to inflation data, there has been a marked decline in inflation across various food categories.	-0.33
Prices of most vegetables have risen by 20-30 percentage over the last two days, traders said.	0.5

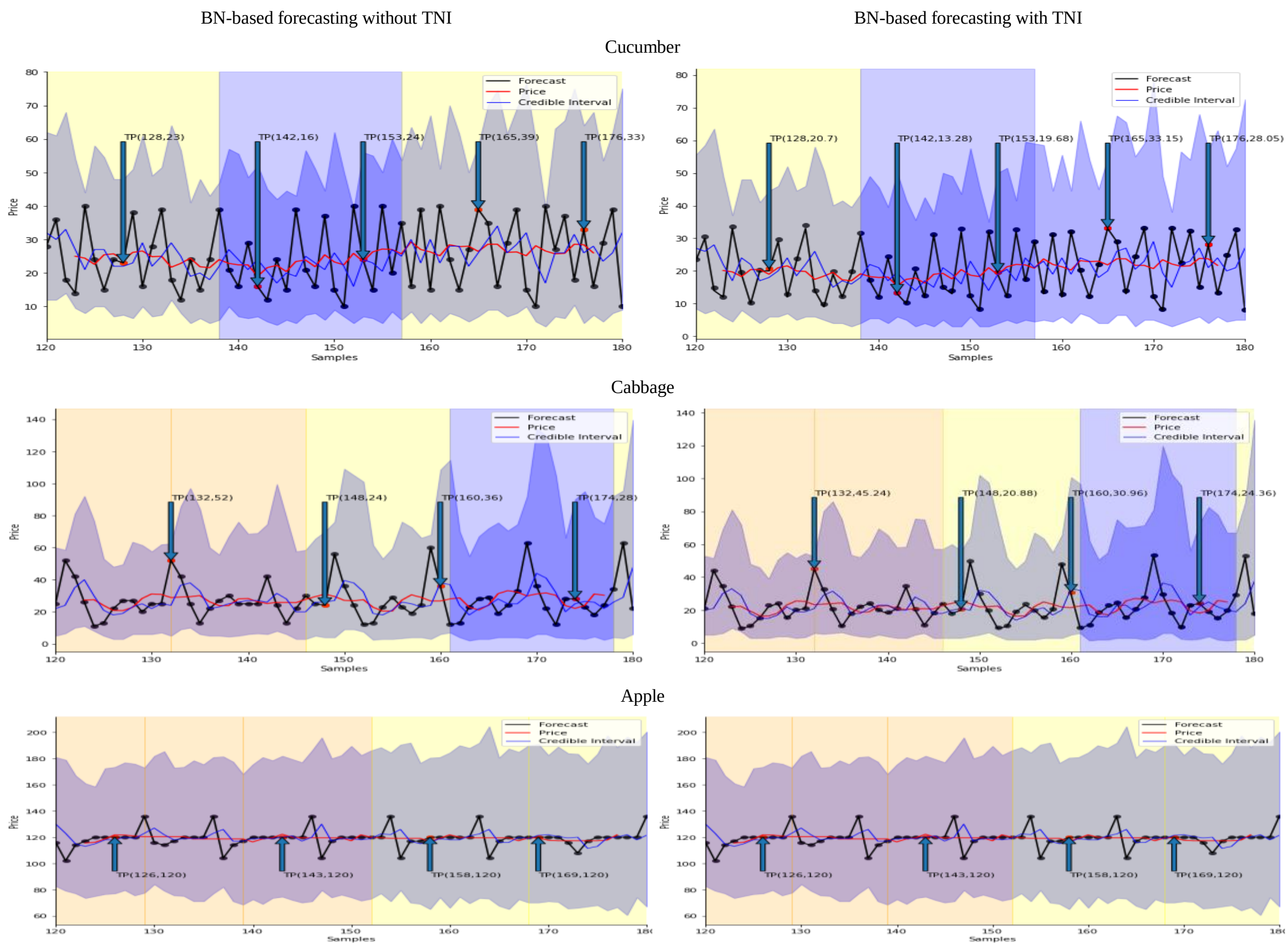

Figure 3. Commodity forecasting with TNI, TP, and SA.

5. Conclusions

The TrIK can deal with uncertainty where more surprises impact forecasting. The observations are enlisted. TrIK system has enhanced accuracy. It also assists in reducing training data-driven bias. Shoulder area calculation provides sharp trend changes, duration of trend change, and impact of the trend change. The turning points find the phase shift in forecasting. The association of shoulder areas from different commodities assists in decision-making, TrIK can be extended to other commodities like the stock market for forecasting.

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