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Tracking Challenges in Online Social Environment using Deep Learning Techniques

[1]Mrs. R. Ramya, [2]Dr. S. Kannan
[1]Assistant Professor, Department of CSE, A.V.C College of Engineering, Mayiladuthurai, Tamil Nadu, India
[2]Professor, Department of CSE, E.G.S Pillay Engineering College, Nagapattinam, Tamil Nadu, India

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ABSTRACT

Social network event prediction is much more important task in many of the applications like medical, security, etc. With fast-growing technology, People spent most of the time in Social Networks. They can express their views and opinions in social network community. The main reason behind this phenomenon happens to be the ability of online community. It can provide a platform for users to connect with their family, friends, and colleagues. The information shared in social network and media spreads very fast, which makes it attractive for attackers to gain information. However, event prediction is a more complex task because it is challenging to classify, contains temporally changing the concept of discussion and heavy topic drifts learning. In this research, we present to addresses the challenge of accurately representing relational features is observed from complex social communication network behavior for the event prediction task. In this, graph learning methodologies are more complex to implement. Here the concept gives, to learn the complex statistical patterns of relational state transitions between actors preceding an event and then, to evaluate these profile findings temporally. The event prediction model which leverages on the RFT framework discovers, identifies and adaptively ranks relational occurrence as most likelihood predictions of event in social network communities. Most extensive experiments on large-scale social datasets across important indicator tests for validation. It shows that the RFT framework performs comparably better by Hybrid Probabilistic Markovian (HPM) predictive method. Deep learning relational models appear to have considerable potential, especially in the fast growing area of social network communities. This study opens the door to precise prediction events in spatio-temporal phenomena, adding a new tool to the data science revolution. Also, Social network analysis software has many algorithms for graph features data has been collected.

Keywords : Event Prediction, Artificial Intelligence, Deep leaning, Fractal Neural Networks

I. INTRODUCTION

Now-a-days, Predicting the Event in social network communities is really difficult. It gives some combinations of multiple disciplines across world wide applications. Some of them include recommender systems, marketing and advertising, governance and rule etc. Some main examples of emerging event prediction applications include predicting disease in various medical applications and medical condition prevention, patient-drug matching pair diagnosis and administration, cyber security, data privacy in social network communities etc. The social pre-cursors of a large majority of real life events are often staged through popular online social media like facebook, twitter, google, etc. These social pre-cursors are mainly identified as activity through online social medium as information transactions. Although it may be identified to think of a similarity based approach on how an actor incites other members within a community through matching attributes, such a culmination of affective sentiments. Modeling rare events is challenging with analytical solution from first principle equations, even when known, are seldom tractable, and uncertainties from unresolved scales makes long-range models of the average dynamical behavior incompatible with reliable prediction of low frequency events.

II. CHALLENGES

Although number of approaches has been developed to address certain field of spatial-temporal event tracking and prediction, their methods have been very limited in applications to identify the events has been critically addressed. Furthermore, techniques to focuses on the application of batch processing learning methods which can only be used at static instances in time. These approaches are known to be unsalable to continuous data streams and changing environment contexts. In the same vein, many relational learning approaches used in trending studies, also lack depth and representative power. For example, some referenced methods developed to date which can primarily on learning how the spatial-temporal dependencies based on word-feature changes. These semantic patterns are used for precursors. They are modeled to predict eventful occurrences by using fractal net in a future timeframe. Furthermore, some of the critical key questions are difficult, that may still remain unanswered. Here, address the solution as to develop a Fractal framework for tracking rare events in the online social network environment within the discrete time.

III. SOME DATA MODELS

To address these issues, this Research paper adopts the Fractal Net (FN) model which was developed and extends its efficiency by adapting the dynamic growth of the fractal network into a robust adversarial framework. FNs, translates ground truths of the Relational Turbulence Theory (RTT) framework into the lowest evidence principle decompositions of our model. It is able to self-evolve from a meta-learning perspective in this regard we response to random “anytime-sequenced” data streams of fluctuating information sophistication. Then, define what relational turbulence is explained for our motivation.

The main motivation of this approach is to, characterize Relational Turbulence by probabilistic measures of Relational Intensity, Relational Interference and Relational Uncertainty is found. Then extending the concepts that use the principle of Relational Turbulence Theory (RTT) the framework can be established in theoretical processes. It can linked with some relational features learned over the past event occurrences. The main novelty of our model focuses firstly, consider the relational profile on discovering relational intelligence through three popular social Knowledge Graphs (KGs): Twitter, Google and Email datasets. Then, leveraging on this discovery to generalize the event occurrences for these three major social streaming platforms such as

Twitter, Google Feed and Live Journal. Instead of the number of layers of neurons, depth in FNs is reflected by average number of states in the inferred SSC models. Instead of assuming fixed memory less non-linear activation functions.

IV. RESEARCH OBJECTIVES

This Research addresses the following important research objectives for event prediction tasks:

- To determine the Proper identification and representations of complex online social communities with highly indexed correctness in social network for generalized the event prediction.
- To determine prediction, the Classification of relational profile attributes to dynamic social communication patterns.
- To find the dynamic Quantification of errors arising from social disruptions can be identified in event predictive representations.
- To demonstrate FN applicability in diverse spatial-temporal phenomena.

V. LITERATURE SURVEY

Relational Turbulence Model

Relational Turbulence was typically summarized as a resultant state in conflict of interests from competing goals between two or more actors in question. Although some of the conflicts does provide the basis of stimulation for communication within a network relationship that is centered in a flux, it also correlates to negative consequences in the form of detrimental event occurrences if left undetected and unchecked. An important discriminator of detecting conflict and hence the resulting turbulence in any relationship model between networks of actors is the observation and management of relational altering events. As reciprocated negative expectancy violations grow larger over time, instability in a cumulative relational flux of an Online Social Network increases . Excluding the relational expectation management, some detrimental relational altering events include: geographic displacements (or low proximity measures), conflict escalation (high frequencies of friction), environmental changes (expectation disparities), etc.. Relational Turbulence is defined as modifications which occur within a relationship that may cause friction between actors and their local online community. These modifications are mostly studied as a series of transitions between actor-environmental states that inadvertently influences relational characteristics by altering communication flux patterns of a given relationship in an Online Social Network. These shifting of data in relational characteristics during difficult state transitions which means altering events may lead to volatile consequences. The Relational Turbulence Model (RTM) defines an artificial building which enables very high intelligent predictions of communication behaviors during relationship transitions, in an environment of continuous online social disruptions. Turbulent relationship development shifts between continuous framework and affective communicative states of flux which are affected by the polarization of sentiments. The extent of such polarizations is characterized by actor interferences and relational uncertainty as state transition probabilities that can cause conflict. These two prime relational features in online social communities enable the effective detection and prediction of conflict and event occurrences in sentimental and affective computing

VI. EXISTING SYSTEM

While RTM explains and predicts relational conflicts through communicative behaviors between actors, Relational Turbulence Theory (RTT) correlates uncertainty and interference to specific behaviors, actions and sentiments (either hidden or expressed).

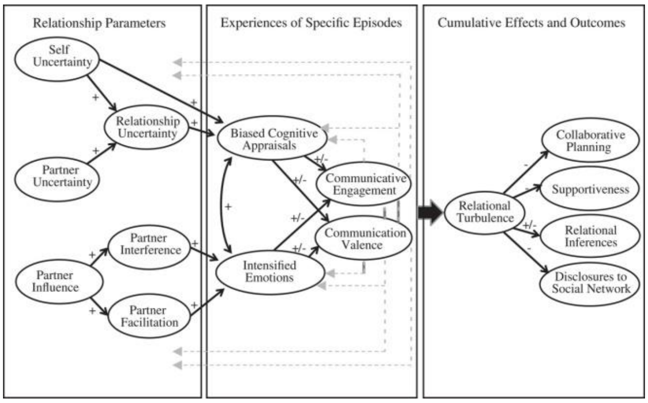

Table 1- Event Prediction in Online Social Networks

Study the related subjects; they include Features Relational Turbulence Theory, Disclosures to social Relational Interference, Collaborative Planning, Supportiveness, Intensity and Uncertainty, Expectancy Violation, Engagement, Valance. Expectancy Violation Sentiment polarity, triadic closure, Emotion Gradient, Relational State Aberrations. Relational Turbulence Model Relational disruptions, Relational state altering events, Uncertainty, Associative irritations, longitudinal analysis. Relational characteristics Reciprocity, Directed information transfer, latent semantics. Relational state transitions Relational disruptions, Gradient turning points. Relationship Parameter, Experiences of Specific Episodes and Cumulative effects and Intelligence Relational Turbulence profile, State transition. Relational Fractals Sentiment, Confidence and Mentions.

VII. EVENTS PREDICTION

As an in-depth overview, there are two categories of methods used for predicting events in social networking. The first category is the Markova sequenced model. Another name which is known as association rule-based prediction. In this category, future event occurrences are predicted based on past event association patterns. While this approach can be able to capture temporal features relative to key events, it assumes that events are correlated to each other in a fixed sequence. The second category is the stochastic word distribution model. It is also known as narrative generation. In this category, future event occurrences are predicted based on the topic-context word distributions surrounding key actors in question. For example, when the name suggested ”Donald Trump” and the topic-context may become ”President of the United States” is mentioned, there will be main focus events notified which are stochastically related (e.g. trade wars, tax tarrifs, mexico border, grade tax etc.). While this approach is able to represent a co-reference resolution between word-topic to events, it overlooks the temporal aspects of such occurrences.

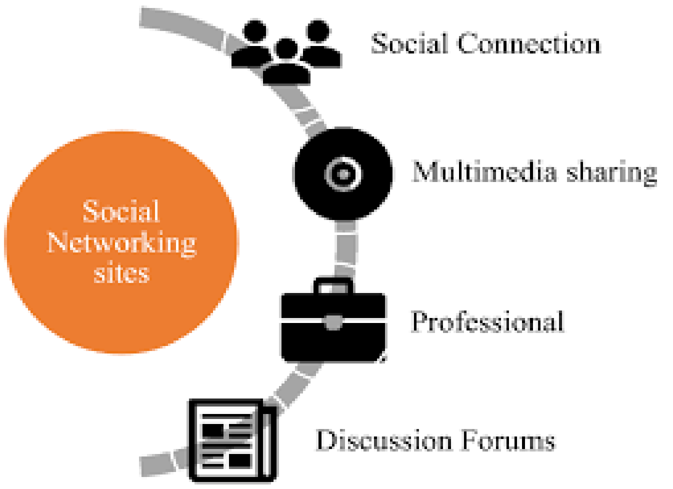

Fig. 1: Social Networking Community

Initially, this research can analyses some tweets for finding more complex topic detection, classification of Prediction and tracking the events. Existing methods such as bias events towards certain topics in question such as terrorist attacks, floods, etc. Secondly, this research introduces a new RTT framework as a structured theoretical process that quantifies the evolution of learned relational features over past casuals in the event prediction task. To the best of our knowledge, there are no existing approaches which have used a socially relational approach to address the problem of event prediction. Thirdly, this research introduces a new practical extended architecture that is capable of leveraging on the design developed in unsupervised event prediction in a continuous stream of social transactions. Regarding this, there is no one similar architecture developed in mainstream approaches which leverages on the efficient adaptive effects of fractal structures toward representing dynamic complexities of observed communicative relational behaviors in Online Social Networks for event prediction tasks.

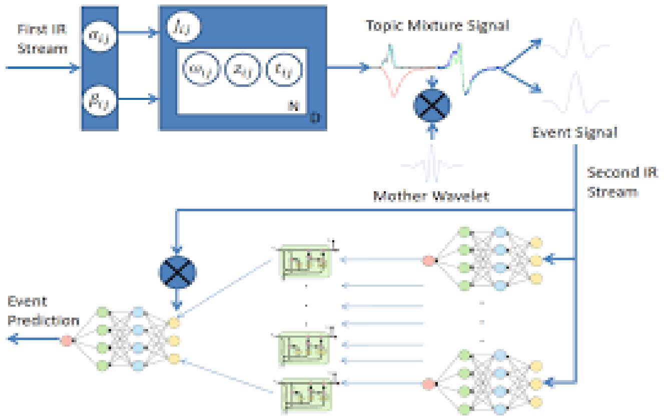

Fig 2: Sample event prediction Diagrammatic Representation

VIII. PROPOSED SYSTEM

Fractal Neural Network

At the main concept, it can be extended to RFT structural design, this study adopts the Fractal Neural Network (FNN) in [1]. This FNN is used in both discriminator and generator networks of our architecture to determine the accurate likelihoods of event predictions from ranked likelihoods of relational turbulence profiles. If we collect the sample paths are synchronizing the inputs. We show that this condition is equivalent to a finite set of causal states, which is the precise criterion for deep neural networks to model stochastic phenomena. Thus, it is now easy to construct counter examples where Neural Networks inference fails irrespective of the number of samples or the number and complexity of layers. Beyond predictive performance, FNs can provide insight into dynamical properties, which is generally difficult with NNs.

Neural Network Learning

Initially, implements a generative neural network (NN) architecture which is used to create false positives (posteriors) from a set of input training samples. This stage is processed in synchronization with calculations of actual truth values shared from the same set at the input. The second stage involves the use of a discriminative Neural Network design which will then estimate an actual output based on a risk / reward mechanism. The discriminative model estimates outputs based on concatenations of inputs which are derived from both generative and real-valued model outputs.

The Model Problem

From a real time point of view, wavelet signal structures of an event can be used to match information with real time exchanges in an active stream efficiently. However, when we used to predict events, it is highly inaccurate but we are going to correct with relevant details. Furthermore, a main key assumption we make in this paper is that the order of events are randomly distributed over the sentiments expressed in any given online social networks. This focus derives from the main fact that most real-life events are not strongly dependent on each other from any sequential occurrence events. Instead, they are highly correlated through key reciprocated relational sentiments to their common topic supersets of interest. Furthermore, the high costs of mainstream turing learning designs may used to generate the strong relations. Some examples makes training impractical on large scale problems like Twitter, GoogleFeed or LiveJournal.

Effective Solution

The overall model can be effectively identify the problem of topic drifts and over time it establishes soft event evidences. To achieve this, we may use the non-parametric mixture model. Additionally, we have adopted the Discrete Wavelet Transform (DWT) to overcome the problem of solving for an infinite number of coefficients - which is computationally intensive. In our architecture, an adapted hybrid FNN is used to drive predictable, accurate and strong estimations from continuous input data streams. Our approach achieves this objective without the associated heavy computational costs by a dynamic true depth scaling technique. This mechanism is used to build and collapse affixing structures in the FNN design.

IX.MODEL AND METHODS

In our mechanim, data can be streamed from online social platform sources like Facebook, Twitter, GoogleFeed and LiveJournal. In an effective streaming, the data is sequentially triggered from various server sources through a data hash key using their correponding Aplications (for Google, Twitter and LiveJournal). Incoming streams are filtered according to queries of interest and decoded at the pre-processing stage of our model. This procedure extracts key confidence ρ_{ij} , salience ξ_{ij} and sentiment λ_{ij} scores in a social transaction using Googles NLP APIe . Firstly, all Information Retrieval (IR) in the first active stream before pre-processing are fed into the first phase of our model. our research provides new insights into event prediction from a relational intelligence perspective that results in more accurate predictions over time. Our results show that the FNN model is capable of learning adaptively to the complexity of information received in real-time. Our study uncovers three pivotal long-term objectives from a relational perspective. Firstly, relational features can be used to strengthen medical, cyber security and social applications where the constant challenges between detection, recommendation, prediction, data utility and privacy are being continually addressed. Secondly, in fintech applications, relational predicates (e.g. turbulence) are determinants to market movements - closely modeled after a system of constant shocks. Finally, in artificial intelligence applications like computer cognition, robotics and neuromorphs, learning relational features between social actors enables machines to recognize and evolve

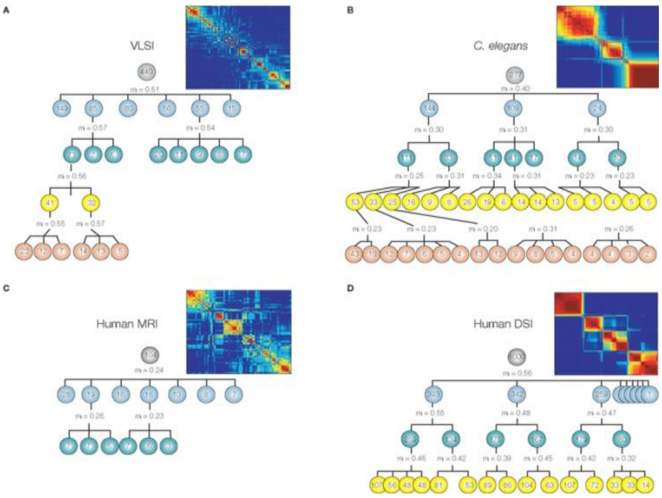

Fig 2 : Predicting the Events

X. RESULTS AND DISCUSSION

Analysis Based on Algorithm Time Complexity, Input File Formats and Graph Features IGraph and Networkx have algorithms for maximum number of features. Based on algorithms complexity we can say that IGraph is more useful software compare to other softwares. IGraph provide efficient algorithms for page rank, all types of centrality, density, MST and shortest path.

Table 1 : Comparison Based on Algorithm Time Complexity, Input File Formats and Graph Features

FEATURES	NETWORKX	IGRAPH	GEPHI	PAJEK
ISOMORPHISM	O(n2)	EXP	NA	NA
CORE m=no. of lines	O(M)	O(M)	O(M)	O(M)
CLIQUES	O(|V|/(log)2)	O(3|V|/3)		O(N)
SHORTEST PATH	O(|V|.|E|)	O(|V|+|E|)	O(|V|+|E|)	O(|V|+|E|)
CLUSTRING	O(V)	NA	O(V)	NA
ALL SIMPLE PATH	O(|V|+|E|)	O(|V|+|E|)	NA	NA
CLOSENESS CENTRALITY	O(n.|E|)	O(n.|E|)	NA	NA
DENSITY	O(n3)	O(1)	NA	NA
MST	NA	O(|V|+|E|)	NA	NA

The above, Libraries (Networkx or IGraph) are more useful for tasks involving millions of nodes and for operations such as the union and the difference between sets of nodes or for the clustering. Stand alone software are easy to use and easy to learn so for beginner Pajek and Gephi is suitable software. For complex dataset and research purpose we can use Networkx and IGraph software.

XI. CONCLUSION

A key limitation of FNs is the need for categorical data in self-similar compression. In systems with continuous valued observations, we can set a magnitude threshold effectively defining the events of interest. However more complex event definitions might be warranted elsewhere. Future research will investigate these issues, and attempt to address event frequencies significantly lower to what have been demonstrated here. Thus, in this study we have laid the groundwork to broaden the applicability of data driven analytics to rare event modeling in complex systems. We hope that this technology, integrated with existing tools, will push the boundaries on our current limits of predictive mitigation of natural disasters and catastrophic societal events.

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