Actualizing Progressive Learning - Discovering Resolute Paradigm In Social World

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ABSTRACT

Extended cognition is now a reality with rise of social web. Smart devices and emerging collective intelligence is aiding us to take part in tasks much bigger than we can naturally handle. In the age of digital natives, learning is the most affected process by this phenomenon, and has created a void in this space to rethink the model to suit the generation of web. Current educational model is not future proof as its creating more autonomous problem solvers, while future demands high caliber people to collaborate on interdisciplinary problems with potential global impact. Primary motto of this learning model is to develop critical thinking and continuous learning among individuals. Can such process be engineered in the first place? If ones goal is to attain the formal derivatives, what are the possible ways to realize it? Current paper discusses along with the generic web learning trends, a model based on Rhizomatic learning and contextual relations generated from similarity sets of social networks. This unique approach emphasizes more on distance among the similar sets to promote maximum diversity in the learning flows. Also leverages our earlier work, a feedback framework designed to judge diverse facets of a personality from interactions on the web.

Categories and Subject Descriptors

K.3.1 [**Computer Uses in Education**]: Collaborative learning

General Terms

Design, Human Factors, Experimentation

Keywords

Social learning, Context awareness, Homophily, Collaborative learning

1. INTRODUCTION

Inevitable effect of the connected world is the change in fundamental societal models, and learning is no exception. Being part of social web, smart devices are breathing with life, storing memories, capturing tacit knowledge and streaming them to network of choice in real time, thus extending the human cognition beyond the realms of natural possibilities. The definition of expert and learning is drifting too. Nobody is a custodian of knowledge like in the old times, rather everyone have access to vast amount of knowledge through web. Where exactly do the definitions of learner, expert /teacher fit into current educational context? One's ability to collaborate with others, agile learning, and dig inter disciplinary topics to spark interesting conversations is what makes them valuable among the crowd. Web facilitates to achieve all the above in some way or another.

Deleuze and Guattari introduced rhizome as a structural representation of evolving thought, which is heterogeneous in nature and only makes senses in multiplicity. Meaning rhizome has no particular beginning or end points, but comes into existence by capitalizing feedback from flexible experimentation by learners, as they map and adapt to new boundaries of knowledge. Individuals are naturally biased towards their similar set and tend to form connections more often. More interactions with the same person will erase this similarity boundary even further, due to the presence of social influence on one another, pushing the social system towards a uniform behavior [13]. Considering these facts building a learning model to maximize diversity of interactions can be quite daunting, but very essential to create new learning flows & develop desired qualities of critical thinking in an individual. This is applicable to all social systems, which is why a rhizomatic structure can map this evolving knowledge among learners easily. Also presents us a chance to observe the synchronicity of interactions in individual's learning curve. Same patterns can be used to redraw the boundaries by moving them to a new similar set that's more apt for the new boundary. Identifying the distance between these similar sets can show us a way to draw the boundary [2]. Topic shift matrix is derived from individual's interest graph to build a new similar set eventually.

This paper discusses diverse trends and practices of learning networks and how various social interactions on the web are influencing the learning flows. With a paradigm shift from e-learning to social, new learning networks are evolving every day. All ideas are derivative as research is, and build on top of something else. So how can we engineer the process of learning, with innovation as the primary output? This is where social web plays its role in formulating and assimilating core concepts into derivative learning streams. Section 2 discusses about the background of following learning models collaborative, rhizomatic and web-enhanced in detail. More on synchronicity effect, trends on consumer web and criticism are covered too. Section 3 presents detailed view of the proposed learning model, unifying similar sets and assessing distance between dissimilar sets, recording and reusing learning flow patterns. Section 4 presents a brief overall discussion and future direction and 5 lists out all the references helped for this paper.

2. BACKGROUND

The term homophily means "birds of a feather flock together". Monge and Contractor (2003) narrowed down to two hypotheses to prove the theory of existence of homophily, which include Turner's (1987) theory of self-categorization and Byrne's (1971) similarity attraction hypothesis [8]. Similarity attraction hypothesis tells that human beings are more likely to interact with whom they share their similarity graph [5]. Theory of self-categorization proposes that humans tend to group themselves in terms of relations and interests in order to make better sense of their pursuits.

Sociology has a long history in explaining the effect of new social ties on personal learning and behavior. Sociologists identified two major phenomenon selection and social influence as a root cause of this effect. Both factors can be observed on social web with thriving new fluid connections between people. Notion is that people are naturally biased towards their similar set and often tend to form connections with them. Increase in interactions will blur this boundary even further, due to the presence of social influence on one another. It is the same factor that constantly pushes social systems towards uniform behavior which can be observed in social networks [6] [7]. Learning methods leveraging these factors can positively impact innovation at much larger scope. To understand innovation at larger scope, Jay and Tishman suggested mimicking it as *thinking disposition* comprising of individual's abilities, inclinations and sensitivities. Such heterogeneous characteristics and connections bind into the concept of rhizome. Synchronicity is yet another major social factor observed during the intersection of two events, which are totally unrelated and never meant to occur at the same time, but did in the incidence of meaningful collision of behavioral patterns. Though rhizome resists chronology attributing to its nature of being in the middle of things, its propagation can reveal the structure of synchronized events.

2.1 Collaborative learning

Collaborative learning model is too hard to define as it has a broad meaning in various contexts. Going by pier-re's theory (1999) on effects of collaboration on learning, interactions can be broadly classified into Synchronicity, interactivity and negotiability based on resulting feedback from the collaboration [1]. Best part of his approach is considering the influence of interactions on learner's cognitive process rather than just the frequency of its repetition. This serves as a strong parameter while observing the patterns among social connections. Often the most successful innovations are evolved from best analogies encountered by the subject with a similar correlation at a different place and time (Jean 1980). Better learning processes can be developed when scientists from machine learning or computer science in general collaborate with psychology, as the wide differences between multi agent systems and psychology can bring lot of unnoticed concepts to the fore. Some use cases to observe these patterns are, sharing course related material while working on assignments. Even though distributed cognition treats the group as a single entity cognitive system, they're multiple seeds in reality each with its own significance to take on the issue.

2.1.1 Web-enhanced learning

Web has diversified dimensions of learning and erased all the limitations of space and time. Notion of education expanded beyond the classroom and learning happens everywhere. Be it the social networks we're part of, or the smart gadgets we carry, bombards us all day with a fleet of new information. Decision to whether pursue this information or not, tunes our interest set with time. Individuals acquire knowledge through multiple learning networks they're part of, either to engage or collaborate or play. These daily interactions within global communities often lead to serendipitous discovery resulting in new thought threads. These leads will eventually carve their own path of learning subjected to individual interest.

Case: Swedish school 'Vittra' took the concept of learning to a whole new level by removing classrooms from the school. Learning happens in day-day life from all over and not just at a particular block of space. Having convinced that straight row desks and closed walls don't do much to foster student's creativity or develop collaboration skills, they embraced the system. Major shift lies with the teacher itself. Traditional role of a teacher is to transfer knowledge to a set of audience, in easily consumable manner over a period of time. Plain creative spaces like a house/ village are built to simulate collaborative atmosphere and students are taught in groups subject to their pace. Whole idea of Vittra's case is to maximize the diversity to foster innovation and collaboration among future generation. This case study is a real world interface with learning. How can we build a learning system on the web guided by similar principles? Social networks and interactions give enough data to realize such learning environment online.

Trends on Consumer Web Augmented Knowledge models in education can help individuals with rich contextual presence. Innovative applications have the power to engage a learner with multiple learning styles and can carve out a unique learning path in the real world. One of the greatest successes of leveraging the economics of web in education sector was achieved by a new startup called Udacity. When Sebastian Thrun, a Stanford robotics veteran opened his artificial intelligence course to the world in a unique learning format to benefit people with no formal background in the domain, it has attracted >160,000 from 173 countries[16] . Number of fruitful collaborations resulted from the course. Power of collective intelligence is clearly visible here. These are the kind of programs that push the boundaries of learning and reinvent teaching methodologies.

Another major example of this scale is 'Singularity University' which broke out from the traditional paradigm and brought in high potential individuals from all major disciplines to take on problems of potential global impact. Khan academy has pioneered online learning by developing a unique model of self-assessment for individuals, that let individuals learn things at their own pace to facilitate effective learning. Multiple institutions have been trying this platform in real classes to judge the effectiveness of the approach. Social networking sites like Google+ and Twitter are enhancing the learning experience with real-time streams and serendipitous content. In addition to this, a user interacts at many different levels through curation platforms, bulletin boards etc., and carving out his personal learning network. Field of research has been influenced the most with prominent Academic networks 'Mendley, Academia, Scholar' making research better and faster by collaboration. Note taking tools [clip notes, audio, and video] are helping people to extend their cognition into smart devices by storing what they see & hear in real time. Though they're not a physical extension to the brain in literal sense, they act like one in meaningful manner. Last but not the least, this list can't be finished without adding Wikipedia, the largest collection of human collaborative knowledge repository.

Downside Copyright & Censorship has turned out to be biggest downside of web in 21st century, blocking free flow of information. These issues are setting up blockades for people in certain parts of the world, ultimately affecting the spread of knowledge and learning. With about ⅔rd of the global population without an Internet connection, improper broadband penetration in the world is adding up to the problems list, in taking up online learning programs to masses.

Networked learning is built around learning communities and interactions, to extend the access of knowledge beyond the traditional limitations of local communities or domains (Salmon 2001) [10]. Learning methods are divulging towards social, so as to involve more people and to spark meaningful conversations between similar sets. Learning flows are observed from these sets to model the best collaborative learning approach.

2.1.2 Rhizomatic Learning

Mimicking the behavioral aspects of collaborative learning resembles endless map of a rhizome with no start or end points, but can only be understood in social co-existence and not in its entirety. This is a theory of learning built on the concept of dynamic networks. Rhizomatic learning is a unique model, where experts don't guide the curriculum with their inputs, rather discussed and build by the people involved in the learning process in real time. Same set of people constantly reshape the content, spontaneously reacting to the shift in engagement levels of the referred space (Cormier.D 2007). Rhizomatic learning can lead to build a flexible education model, one that can adapt to dynamic changes of knowledge map, and rewire in tune with the emerging relations on social web. Whenever a new piece of information is thrown into the community, each person validates it within the limits of their contextual abilities, to judge the value addition factor of it. If proven, it is generally accepted and added to the community sparking a new seed of knowledge in the network. Same people, who are part of other networks, plug this seed to much larger audience, spreading the knowledge. As new information pours in from diverse learning environments, people with interdisciplinary backgrounds are often the most benefited from Rhizomatic learning.

3. METHODOLOGY

This paper builds on further comprehension of our earlier work on interest graphs while integrating the approach to procure social learning. Current block presents a brief explanation on the main inputs and outputs to the system, and how exactly this information fits into the current scenario of social learning networks. Basic idea is to map users, their interests and activities together with other users in the platform. All the activities performed by a user are fed to the graph, to analyze the subjective nature of these interactions with respect to an individual. This graph is also supplemented with derived interests from the activities performed by them, to analyze inclination nature of these activities. With all the granular signals captured and mapped, it serves as a primary input for enabling social learning. Signals judge the subjective value added by interactions to user and ideally returns feedback on behavioral facets of the user [16]. Social objects can reveal variety of details about human behavior i.e., identifying skills, collaborative nature, ability to assimilate new concepts and inclination towards these concepts from the feedback data. Intention is to identify a unique pattern that defines the extent of inclination. This, in tune with learning patterns from the past, forms the topic-shift matrix.

The system keeps track of user learning behavior and topic shift patterns. Matrix approach provides us with the holistic view of, how a particular topic shift pattern builds a learning behavior. Patterns from this matrix yields similar set of users connected via same or different social platforms. Quoting the general issue observed in current recommendation systems in social platforms, interest set is narrowed down to segregate and promote items with higher confidence ratio. This narrows down the interest set and shrinks it further, eventually minimizing the user's exposure set. This is not an ideal scenario for a learning network to evolve. In contrast, constant exposure to new things that broadly deviate from the key threshold of similarities, generates better analogies strengthening learning patterns. It creates an environment that trains the system to expand similarity set using topic-shifts across asymmetrical set of topics. While analyzing similarities between people one should always go by ratios, but never the plain quantitative approach, as an individual's browsing behavior might not capture entirety of his interest subset. Best approach is to normalize it with the relative least in subset to bring all the people in the set on to the same line. There will always be topics, yet unexplored and unmapped to his interest subset. Here mapping the interest along with the facet data from the interest graph, will group similar users based on resemblance in topic shift matrices. Similar users are grouped into matrix subjected to a confidence limit and shifted to a new matrix whenever a shift in the graph occurs[4], a due effect of following a learning flow pattern evolved from synchronicity matrix.

3.1 Topic Shift Matrix

Learning curve encounters a huge shift when a user stumbles across interesting information. Being in the middle of things is attributed most in Rhizomatic learning. This leads to exploration of the field adding a new node to the interest subset. Intensity of interest creates further nodes as they explore related topics. User remapping is performed, once the interest is established in the graph. All the topics, a user (*U1)* is associated with initially, are mapped and compared with existing users (U2..Un) in the platform. Users with the topic similarity over the system threshold will be mapped and these topics will form the new topic-shift matrix. If the user gets hooked to a topic for quite an amount of time crossing the threshold, sends the update signal to topic shift matrix. This will constantly keep the user in tune with his current interests and the users with the similar interests.

Unique threshold values are associated with different matrix as the shift in the matrix varies based on the contemporary composition of the matrix. Jaccard coefficient is proved to be an efficient way to identify these similarity and diversity between sets. A statistic variable coined by [15] (Jaccard.P 1901).
Jaccard similarity coefficient = Size of intersection/ Size of union

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}.$$

This value is calculated for all the pairs in the group to fill the matrix with similarity coefficient against interest groups. Jaccard distance gives us the desired output of dissimilarity between groups. It motivates the user towards new learning curves and diversifying the interest graph.

$$J_\delta(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}.$$

$$T(A,B) = \frac{A \cdot B}{\|A\|^2 + \|B\|^2 - A \cdot B}$$

Above set complement can't be applied in general when the subject becomes uni-dimensional vector with a value of 0 or 1.

Tanimato distance is pretty much similar to Jaccard distance, except that it handles bit vectors and not sets. The resultant of this will be a topic-shift matrix for every user in the platform reflecting the interests of the users with a very high profile similarity. This will be used to deduce the synchronicity matrix to suggest new topics which is tasteful to the current user's interest but yet unexplored.

3.2 Synchronicity Matrix

Synchronicity is the intersection of events that are unrelated and never meant to occur at the same time, but did in the event of meaningful collision of behavioral patterns (Carl Gustav Jung 1920). Very often users with diverse interest end up on the same page at the same time, following totally different paths. These paths are highly unpredictable, but can add valuable information to user's interest graph. Synchronicity matrix looks for such collisions to occur, and when they do it backtracks through the access patterns until the point when last topic shift had happened. Same process is repeated for all the users linked to the collision and partial topic shifts across the pathway are recorded too. Each matrix is a representation of events/topics that lead to this particular collision. This is based on multiple sources and needs a fuzzy calculation. Sorensen index works well in this scenario distributing the load to both the sets of users in comparison and identifying the distance range of the outcome. Its ability to ignore or least regard the weight of outliers without losing sensitivity for heterogeneous data makes Sorensen method a favorable one in the current scenario.

$$QS = \frac{2C}{A+B} = \frac{2n(A \cap B)}{n(A)+n(B)}$$

Qs is the similarity coefficient of topics A and B, and C is the common pattern shared by both topics along with their individual access patterns. Sorensen coefficient places the similarity in the range of [0,1]. Complement of the same expression can be used for distance calculation between topics. Predicting synchronicity provides the possible outliers, commonly ignored in the existing system. Combining these with the topic-shift matrix will frame the final set of relevant and undiscovered topics for a user.

3.3 Learning Matrix

People are divulging more personal information on the web than ever before. Building rich profiles and accurate interest graphs was never this easy. The very same graph can reveal granular details about information cascades with others in social circles or beyond. Diffusion patterns of social interactions indirectly capture the interest subset outside the core network of individuals. This enlarges the scope of recognition and identifying people with similar flow patterns. Topic matrix with highest distance among the similar sets is identified with a degree of confidence to map user to a new set with a different threshold to act as a seed source for flow suggestions and serendipity.

New set of discovered users learning matrix is compared with that of shifted user. This comparison refines the users who followed a different flow pattern to cover the distance. Once the users are filtered with near close fuzzy value of synchronous, it is more likely for the individual to pursue the learning flow pattern generated from this similarity set. The similarity matrix is a function of the mutual interest of an individual with the others in the system, irrespective of their social connections. This interest is not complementary between users. A user may have a higher similarity ratio to another and may have a very low value in return based on the exploration pattern of both the users.

$$S_A = f\,|X_1, X_2 \ldots X_n|\; where, T_A \cap T_X \geqslant \theta . n(A), X \varepsilon (U - A)$$

$S_A : Similarity\ ratio\ user\ A$
$T_A : Topics\ explored\ by\ A$
$X : Users\ in\ the\ system\ excluding\ A$
$T_X : Topics\ explored\ by\ x$
$\theta : Confidence\ variable$

Considering an initial user A, The Similarity score S(A) is calculated with all the users, to find the topics that are explored by the users with a similarity score with higher confidence. The sample matrix after traversing the entire user base should look like the below matrix.

U	U_1	U_2	...	....	U_n
U_1	1	.86	.23	.42	.76
U_2	.41	1	.85	.91	.14
...	..92	.24	1	.65	.83
...	.65	.76	.73	1	.43
U_n	.90	.54	.96	.79	1

Individuals with relatively common interest, shares the same learning matrix at some point in the flow. They are given a common weightage throughout the events, wherever their interest graph is correlated. Shortlisted individuals who are already a part of user's social graph are weighted, as synchronicity factor is naturally close. Topic gets weighted, when shared learning matrix users pursue it.

User's current associated topics when removed from the established topic-shift matrix, generates a list of recommended topics. Sorting this by weightage and merging the resultant with the synchronicity matrix provides learning matrix for the user. Individual topics are selected and their accumulated weights are derived by the summation of the weights from all the users in the similarity filtered List. This new list when sorted by the weights of the topic provides the best topic user might want to check out, which would be easy to learn given the background and his learning matrix. Observing the result of this new pattern can guide us to arrive at best learning flow, which expands the learning subset instead of narrowing it down. Final list with the weightage for recommendation is the topic shift matrix's initial input.

Having reverse engineered the synchronicity matrix, above two events judge the success of new learning flow patterns, Learner eventually shifts to a new subset when he meets his current goal. Now, once the suggestion is made and if the user chooses to purse it, it leads to a chain of events that change his interest graph, learning matrix, and the entire calculation of the similarity sets are redone by eliminating the users who have fallen in the lines of interest graph and who fall below the learning matrix threshold. This is largely an elastic representation of generating flow patterns for progressive learning.

4. DISCUSSIONS & CONCLUSION

Proposed model finds the most sought out learning flow pattern for a particular topic by mapping the synchronicity of events with interest graph in similarity sets. For streamlined and agile learning progress, there is still a need to improve the final set of suggestions and finding the alternate path to reach a final topic. These sets will be more like embedded graphs with unique weights and optimized paths in alignment with the learning goals of the user.

There is still work to be done in interest mapping and level of knowledge in respective fields to design better profile classifiers. These estimations will lead to the creation of a healthier system with higher probability of compliance with the user learning pattern and thus, resulting in stronger flow patterns. Synchronicity matrix should be trained with field browsing data in real-time. This might open new problems such as anonymizing the usage data collection leaving no traits. In the context of current scenario, this can help us immensely to progress further. Calculation of distance and similarity in learning matrix can be improved with a better indexing method. Aside from the technical issues, human factor plays a major role in judging the effectiveness of learning model. Outcomes of testing such model in a closed network audience and similar effects in a hybrid network with partial public presence will be the next task. Learning as a process itself is slow in nature and evolves over time.

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