Education:

The Quest for the Lost Wisdom in the Maze of Knowledge

Jubair Al-Jaafar, Khalid Al-Khateeb
International Islamic University
Malaysia
jubair@kict.iiu.edu.my khalid@iiu.edu.my
and
Adidah Lajis
University of Kuala Lumpur
Malaysia
adidahlajis@yahoo.co.uk

Abstract

A novel method to assess the complex **E**ducation process has been devised. The technique involves the quantification of **L**earning **O**utcome, which has hitherto been largely subjective and cumbersome despite the technological advance in learning and teaching aids. The new technique presents an objective assessment in a mathematical form. The approach is an innovated **M**etric **S**uit based on a measure of **E**ntropy related to learning outcome. The '**I**nformation' entropy is computed and used as a measure of **K**nowledge. Another learning outcome is the proper application of relevant knowledge termed '**W**isdom'. Wisdom can also be measured using entropy computations. In this sense, entropy is related to the factor of disorder. The various parameters are represented by random variables. Because the amount of the required computations is very large, only the most effective of variables will be considered. The results obtained so far are encouraging. However, more tests on the proposed Metric Suit from various areas of application will further ascertain its robustness. Comprehensive tests and thorough analyses will provide a strong basis for evaluation judgment. The model treats the education process as a communications channel. The transfer of information between the sender and the recipient depends on the amount of uncertainty presented by each of the components that constitute the system. The computations of **"Entropy"** involve all the programs that constitute a discipline at university level.

Key words: Education, Learning Outcome, Metric Suit, Entropy, Wisdom, Knowledge.

1. Introduction

Education is a complex process and its evaluation requires collective effort, especially at university level. The epistemology of learning described by (Scardamalia and Bereiter, 2002) as "knowledge building" is a motivation to assess the level of knowledge generated through a specific learning system. There are many factors involved in the evaluation process, most of which are random variables. Evaluation is currently based on human judgment and use manual techniques. It concentrates mainly on teaching and teaching related matters, as in the classical evaluation methods of school education. However, research is an integral part of the modern education process, which must be incorporated in the assessment of today's education. In the emerging knowledge based economy, knowledge is seen as the most important competitive resource (Drucker, 1993; Stewart TA Intellectual Capital, 1997, Alwis et. al, 2002). The evolution of Information Technology being one of the fastest advancing disciplines can play an important role in improving the education system itself, as well as the methodologies involved in the evaluation process of the education system. It can provide a basis in developing an objective methodology in determining suitable accreditation criteria. The approach suggested in this work is aimed at developing a non-biased methodology with minimum interference from human subjective parameters, but still relies on the valuable expertise of the human elements. This work is based on computations of **"Entropy"** for each program in a discipline at university level. The model assumes the education process as a communications channel. The transfer of information between the sender and the recipient depends on the amount of uncertainty presented by each of the components that constitute the system.

2. Entropy Based Learning Outcome Measurement

Entropy may be defined in different ways according to the specific context in which it is used, such as thermodynamics, information theory, software engineering, and knowledge processing. For the purpose of this work, it shall be related to information theory. The term Entropy in this context was introduced by Shannon in 1969, as a quantitative measure of uncertainty associated with random phenomena. Information theory on the other hand, according to Wikipedia (2006), is a discipline in applied mathematics involving the quantification of data that can be reliably stored in a medium and/or communicated over a channel, with the goal of enabling the system to handle as much correct data as possible. Therefore, it is a phenomenon concerned with uncertainty. The description of a random phenomenon by a mathematical model refers to a probability space. By considering a set of **n** events with a probability distribution $\{p_1, p_n\}$, the uncertainty can be quantified using entropy, **H**.

$$H = -\sum_{i=1}^{n} pi \log_2 pi \quad (1)$$

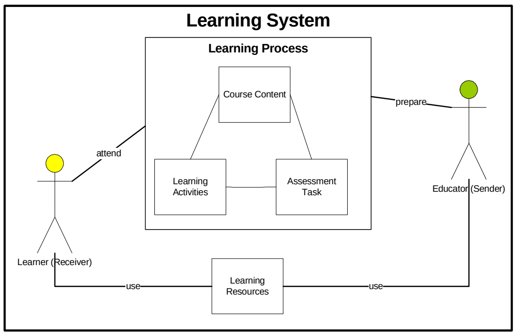
Hamming (1980) introduced entropy as a measure of the average information rate of a message or language (Peters and Pedrycz, 2000; Abran et. al, 2004). A message refers to a string of symbols drawn from an alphabet of symbols s_1, s_n. and Information provides a measure of the amount of the correct information contained in a message (Hamming, 1980; Abran et. al, 2004). Information, in this context is something that is not already known, i.e. when a symbol occurs where it is not expected, rather than if a symbol occurs where it is expected. Rate, in this context means the frequency of occurrence of each symbol (Hamming, 1980; Abran et. al, 2004). Thus, the amount of information conveyed by a single symbol in a message is related to its probability of occurrence (Alagar et al, 2000):

$$I_i = \log 2 \text{ pi} \ldots\ldots (2)$$

Information is additive (Hamming, 1980; Abram et. al, 2004); that is the amount of information conveyed by two symbols is the sum of their individual information content. It follows that an entire alphabet symbols s_1, s_q would on average provide the amount of information given by the entropy, calculated as a unit of information per symbol. It can be shown that the average amount of information conveyed by each symbol is $\log_2 q$. The minimum amount of information is conveyed by an alphabet in which one symbol occurs with a probability of one, and all others occur with a probability of zero. Such an alphabet is said to have language entropy of zero.

3. Knowledge Assessment Proposal

Information is any type of pattern that influences the formation or transformation of other patterns. System theory at times seems to refer information in this sense, assuming



information does not necessarily involve any conscious mind, and pattern

Fig. 1 Typical learning system scenario

Circulating (due to feedback) in the system can be called information. In other words, it can be said that information in this sense is something potentially perceived as representation, though not created or presented for that purpose (Wikipedia, 2006). Based on that, in this paper, we propose a new method for quantifying knowledge from an abstraction of the relationship among elements of a learning system.

There are two actors in the scenario; 1) a learner act as a receiver of a messages and 2) an educator act as a sender of a message. There is one important event attend by these actors, that is learning process which consists of learning content, learning activities and assessment tasks. There is also an important tools require during the learning process namely learning resources. There are 5 main random variables out of numbers of random variables in the learning system;

1) Educator (sender)
2) Learner (receiver)
3) Learning activities
4) Course Content
5) Learning resources.

4. The details of random variables:

4.1 Random variable 1: Educator (sender)

An educator is responsible in synchronizing teaching and learning elements that is teaching method, learning activities and assessment tasks with a course learning objectives. Educators' subject matter expertise and teaching methods applied are important factors for an effective teaching (Warren, 2005).

4.2 Random variable 2: Learner (recipient)

Learner prior knowledge is another important factor that enhancing the process of knowledge gains. An individual prior knowledge is known to be an important pre-requisite for individual knowledge construction and learning outcome. Many theoretical approaches stress the importance of learner's prior knowledge when acquiring knowledge from new learning material (Shapiro, 2004). Many empirical studies also highlight the influence of prior knowledge on individual learning outcomes (Dochy, 1992; Kalguya et al., 2001; O'Donnell & Dansereau, 2000). The elements of prior knowledge are education background and experiences.

4.3 Random variable 3: Learning Activities

Learning activities is defined as any activity or teaching method applied to deliver knowledge including the assessment task performed by the learner. Examples of learning activities are lecture, peer learning, tests / quizzes, case study and many others. Teaching method should support students in their learning activities. [APPENDIX B - Table 1] (Biggs, 1999) shows that the effectiveness of different sensory modalities and [APPENDIX B - Table 2] (Kenny and Milton, 2006) have listed a number of learning activities that suitable for certain teaching purposes. Both information is merged and a weight is assigned according to sensory effectiveness. A sensory effectiveness is normalized and later will be named as weight. [APPENDIX B - Table 3] shows each learning activities and its weight. The weight of learning activities will later be used in entropy measurement.

4.4 Random variable 4: Learning Resources

Learning resources is defined as any tool applied to enhance the process of knowledge transfer. For example, the use of Internet will foster the process of information gathering.
Learning resources include the reference books, software, Internet, laboratories and etc.

4.5 Random variable 5: Course content

Course content is one of the main sources in the learning process. The course content is divided into a series of topics each of which in most cases a prerequisite to the other.

Random variables will be mapped into an undirected complete graph consisting of nodes and edges. This graph will be known as learning system graph. A node is corresponds to an event of learning process and numbered alphabetically. An edge is corresponds to an interaction of one event with another event and numbered according to its time of occurrences. (Figure A Appendix A) shows an example of learning system graph.

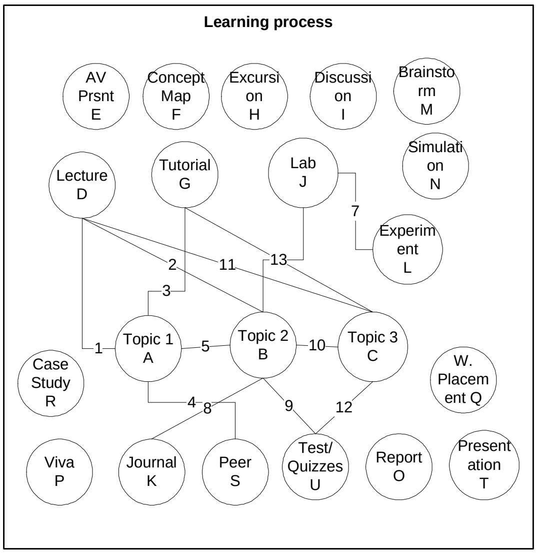


Fig. 2 Learning Process Graph, ***SP***

As shown in Figure 2, there are twenty-one events which three of the events are representing topics and eighteen of them are learning activities. And there is a total of thirteen interactions line in the graph. For example, event A that is representing Topic 1 is having five interactions line that is with event D (Lecture), event B (Topic 2), event S (Peer) and event G (Tutorial). Thus, each event has its own interaction pattern and this information is recorded in a table named pattern table. Each event will be check against all interaction line in the graph. In this example, each event will be check against thirteen interactions line. And thus will be generated ten events interaction pattern which each pattern lengths is thirteen digits. The event that is connected with an interaction line will be encoded with 1 else 0 and this process will be continued until all interaction line is checked. Interaction pattern for event A is 1011100000000 and is converted into a binary number and event A will have a value of 5888. Each event that represent learning activities is assigned a weight. All topics event is assign a weight of 1. [APPENDIX C - Table 4] is an example of pattern table for Learning Process Graph as shown in Figure 3. When a learning system graph ***S*** is formed, calculation of metric takes place. The probability of mass function ***p*** for each event is estimated by the number of occurrences of the row pattern divided by the number of events. There are numbers of pattern table will be generated, that is total of interacted event + 1. Pattern table that is generated for all events is called main pattern table while pattern table generated based on event and its interaction is called sub-pattern table. Figure 2 shows an example of learning system graph ***S*** consist of three different graphs; 1) educator graph, ***SE*** 2) learning process graph, ***SP*** and 3) learner graph, ***SL***.

5. Conditional Mutual Information of Learning System

Mutual information or transinformation is one of the most useful and important measures (Wikipedia, 2006). This is a measure of how much information can be obtained about one random variable by observing another. The mutual information of Learning Process relative to Educator (which represents conceptually the average amount of information about learning process can be gained by observing educator) is given by:

I **(*L*earning *P*rocess, *E*ducator)**

= ***I*** **(*LP* , *E*)**

= H (*LP*) – H (*LP* | *E)*

$$= -\sum_{lp \in LP} p(lp) \sum_{e \in E} p(lp,e) \log \frac{p(lp,e)}{p(lp)}$$

$$= -\sum p(e, lp) \log \frac{p(lp, e)}{p(lp)\, p(e)}$$

Thus, the mutual information of Learner relative to Learning process (which represents conceptually the average amount of information about learner process can be gained by observing learning process) is given by:

I **(*L*earner, *L*earning *P*rocess, *E*ducator)**

= ***I*** **(*L*, *LP* , *E*)**

= H (*L*, *LP*) – H (*L*, *LP* | *E)*

= H (*L*) + H (*LP*, *L*) – (H (*L*|*E*) – H (*LP*| *E*, *L*)

The entropy of the learner is given by:

H (*L*) = H (*L*earner | *R*esource)

= H (*L*| *R* = *r*)

$$= -\sum_{l \in L} p(l, r) \log\ p(l, r)$$

The entropy of an educator is given by:

H (*E*) = H (*E*ducator | *R*esource)

= H (*E*| *R* = *r*)

$$= -\sum_{e \in E} p(e, r) \log\ p(e, r)$$

The entropy of learning process is given by:

H (*LP*) = H (Learning ***A***ctivities, ***C***ourse Content)

= H (*A*) + H (*C*)

$$= -\sum_{a \in A} p(a, c) \log\ p(a, c)$$

Where the entropy of the distribution of ***n*** learning activities event is given by:

$$H = -\sum_{i=n}^{i=1} event\ weight \times p_i \times \log_2 p_i$$

5.1 Excess entropy and knowledge generation

Excess entropy is the difference between the sum of the entropies taken separately and the entropy of the predicates together (Gottipati, 2003; van Emden, 1970). It would be zero when there is no interaction between predicates and the system of all predicates is trivially simple. When excess-entropy is greater than zero, there is an interaction between components that can be regarded as evidence of knowledge generation. Knowledge generated by each graph is quantified in terms of the entropy amount of information based on an abstraction of the interaction among learning events in the learning system. The amount of knowledge delivered is based on the concept of excess-entropy. The amount of knowledge generated by graph of learning system, ***S*** is highly dependent on the knowledge generated by the graph of educator, ***SE*** and also the ability of learner to gain or to construct new knowledge also highly dependent on its own graph, ***SL*** and the knowledge generated by the learning system graph, ***S*** and educator graph, ***SE***.

[APPENDIX C - Table 4] is an example of learning process pattern table generated based on the given graph showed in Figure 2. [APPENDIX C - Table 5 and Table 6] is an example of sub-pattern tables each representing pattern table for event "A" and event "B". Sub-pattern table will be generated for all events and the total of entropy generated by each event is summed.

APPENDIX C - Table 7, summarizes the result of entropy amount generated by each event and the entropy of all events taken together (main pattern table as shown in APPENDIX C - Table 4).

5.2 Methodology

A case study approach is taken to illustrate the usefulness of the propose measurement in a real world setting. A graph can represent an abstraction of learning system interaction. The research project is consisting of 3 tasks:

- Developing research tools
- Collecting data from various resources
- Analysing data

6. Result and Analysis

The higher value of bits generated indicates that the higher amount of knowledge has been generated. As shown in Table 6, event E, F, H, I, M, N, O, P, Q and R have zero entropy meaning they have zero amount of knowledge generated. It is because event E (represents Audio-Vide-Presentation) does not interacts with any event in the process of learning and do the rest of zero entropy events. Event B (Topic 2) is having the higher amount of entropy and it has the higher interaction among others that is a total of 6 interactions. And event K (Journaling) is having the lowest amount of entropy and it only has one interaction only. Even though event S (Peer Learning) also having only one interaction but the amount of entropy is higher than Journaling because Peer Learning is having a higher weight compared to Journaling.

6.1 Comparison with other techniques

Many techniques were developed to assess the level of knowledge. The assessments were done thru knowledge representation, knowledge structure, a quantitative and qualitative measure and other techniques. Rugg and McGeorge (1997) describe a card sorting technique that is designed to elicit a subject's understanding of a field by categorizing a field-specific set of cards in systematic way. This technique is used to identify the ways in which a subject organizes field-specific knowledge, which is different from the approach taken by standardized test that examine knowledge application and replication. The assumption underlying the sorting technique is that a subject's ability to organize the cards in multiple meaningful ways in commensurate with the subject's knowledge acquisition field. This technique is used to measure the knowledge acquisition of a group of subjects and it produces a quantitative measure that can be used to determine the group's level of knowledge acquisition.

The assessment of knowledge thru knowledge representation were assessed by applying various techniques such as clustering model, set-theoretical model, semantic future-comparison, network model and neurocognitive model (Solso, 1995; Goldsmith et. al, 1991; Gonzalvo et al, 1994; Chen et. al, 2001). In 1998, Ye applied multidimensional scaling of dissimilarity data and analysis of angular variance to assess knowledge representation to assess the statistical significance and nature of knowledge representation differences between skill groups

6.2 Comparison with Chen et al

Chen et. al (2005) were applied the knowledge structure analysis process follow of the Structural approach by Goldsmith, Johnson and Acton (1991). The characteristic of concept map are also added in this method to generate a concept-map like representation in order to display the knowledge structure in a hierarchical way. The structural approach is used structural way to assess mental knowledge. A data mining techniques, single linkage (Chen et. al, 2001) clustering algorithm was adopted to distinguish user groups with similar knowledge. After clustering, a concept-map like representation with the characteristics of concept map is created to compare an individual's mental knowledge with another.

6.3 Comparison with Kokorich

Kokorich (2006) applied a quantitative measure to assess a quality of knowledge of remote training as an indicator of the quality of the training. She identified three elements which subject to an assessment, 1) the level of preparation of teaching material 2) availability and variety of means of interaction between participants of educational process and 3) the system of assessment student knowledge. At the same time the teacher's assessment concerning representation of a material and its understanding by student is brought in process of an assessment of quality of knowledge.

7. Conclusion

The interaction pattern exist in the learning system can be used to quantify the amount of knowledge generated. The amount of knowledge generated does not depend on its interaction alone but also a kind of event is being involves in the interaction. However, further research should be done to ensure the proposed techniques may be adapted to difference learning scenario that is general content and technical content learning objectives.

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APPENDIX –A-

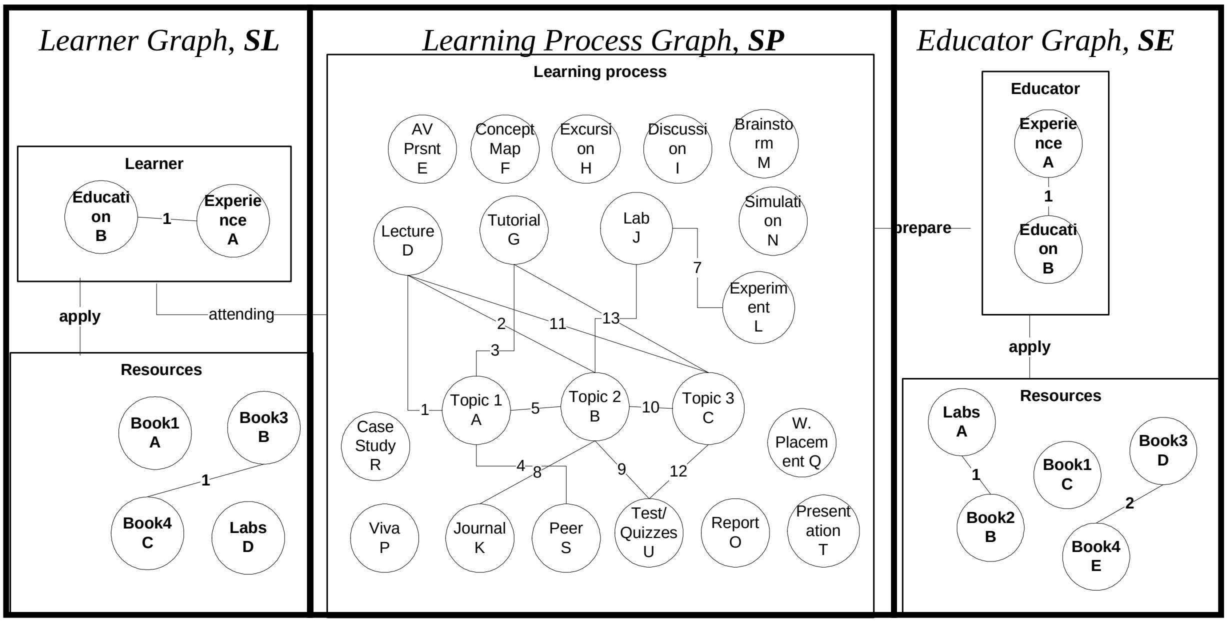

Fig. A Example of Learning System Graph***, S***

APPENDIX –B-

Table 1: Effectiveness of different sensory modalities

Most people learn:
10 % of what they read
20 % of what they hear
30 % of what they see
50 % of what they see and hear
70 % of what they talk over with others
80 % of what they use and do in real life
90 % of what they teach someone else

Table 2: Learning activities sensory effectiveness

Learning Objectives	Learning Activities	Description	Effectiveness
Introducing or summarizing new concepts	▪ Lecture	Conveying material verbally	10 %
	▪ Audio-visual presentation	Audio, video, CD multimedia presentation	30 %
	▪ Concept map	A graphical presentation of related information in which common or shared concepts are linked together	50 %
Developing understanding, exploring concepts, exploring different perspectives	▪ Tutorial	Secondary learning sessions, designed to help student learn material	20 %
	▪ Excursion	Organized visit to a place or website to see a particular process or ideas	50 %
	▪ Concept map	See above	50 %
	▪ Discussion	A formal or information conversation on a given topic. Also called dialogue.	70 %
	▪ Laboratory	Student practice techniques and processes doing pre-determined exercises in laboratory	50 %
	▪ Journaling	Learner keeps written records of their intellectual and emotional	10 %
	▪ Experiment	A study is designed so that the learner becomes the investigator and observes changes in outcomes	50 %
	▪ Brainstorm	A collaborative problem solving that involves generating possible solutions, establishing criteria to evaluate them, then applying the criteria to select the best solution	70 %
	▪ Test/Quizzes	An exercise to determine the level of student understanding	50 %
	▪ Research paper / Report	A written document that include a review of literature and provide one perspective of the subject. A research report includes multiple perspective	50 %
	▪ Interview / viva	Research conducted by questioning individuals in order to answer a question, highlight an issue, or develop a perspective	70 %
Relating theory to practice	▪ Work placement	Student placed in a real work place, under supervision for a set of time to gain work related experience.	80 %
	▪ Case study	A specific case that student analyze in detail to identify the underlying principles, practices or lesson it contains	80 %
	▪ Simulation	A replica or representation of a real-world phenomena that enables relationships, context and concepts to be studied	80 %
	▪ Presentation	Involves researching topics, taking a position or a role, and studying a school of taught on the topic	90 %
	▪ Peer learning	A form of cooperative learning that enhances the value of student-student interaction and results in various advantageous learning outcomes.	70 %

Table 3: Learning activities effectiveness

Learning Objectives	Learning Activities	Effectiveness (weight)
Introducing new concepts	▪ Lecture ▪ Audio visual presentation ▪ Concept map	10 30 50
Developing understanding and exploring concepts	▪ Tutorial ▪ Excursion ▪ Concept map ▪ Discussion ▪ Laboratory ▪ Journaling ▪ Experiment ▪ Brainstorm ▪ Test / Quizzes ▪ Research paper / report ▪ Interview / Viva	20 50 50 70 50 10 50 70 10 50 70
Relating theory to practice	▪ Work placement ▪ Case study ▪ Simulation ▪ Presentation ▪ Peer learning	80 80 80 90 70

APPENDIX –C-

Table 4: Main Pattern Table for Learning System Graph, SL

Event	Description	Interaction Pattern	Binary	Probability	Nodes Weight	Entropy (bits)
A	Topic	1011100000000	5888	1/21	1	0.145
B	Topic	0100110111000	2488	1/21	1	0.145
C	Topic	0000000001111	15	1/21	1	0.145
D	Lecture	1100000000100	6148	1/21	10	
E	AV Presentation	0000000000000	0	11/21	30	10.16
F	Concept Map	0000000000000	0	11/21	50	16.94
G	Tutorial	0010000000001	1025	1/21	20	2.9
H	Excursion	0000000000000	0	11/21	50	16.94
I	Discussion	0000000000000	0	11/21	70	23.71
J	Laboratory	0000001000001	65	1/21	80	11.6
K	Journal	0000000100000	32	1/21	10	1.45
L	Experiment	0000001000000	64	1/21	50	7.249
M	Brainstorm	0000000000000	0	11/21	70	23.71
N	Simulation	0000000000000	0	11/21	80	27.1
O	R Paper/Report	0000000000000	0	11/21	50	16.94
P	Viva/Interview	0000000000000	0	11/21	70	23.71
Q	Work Placement	0000000000000	0	11/21	80	27.1
R	Case Study	0000000000000	0	11/21	80	27.1
S	Peer Learning	0001000000000	512	1/21	70	10.15
T	Presentation	0000000000000	0	11/21	90	30.48
U	Tests/ Quizzes	0000000010010	18	1/21	50	7.249
	Entropy Amount					286.3

Table 5: Event Pattern Table ***(SP-A)***

Event	**Interaction Pattern**	**Binary**	**Probability**	**Nodes Weight**	**Entropy (bits)**
A	1111	15	1/21	1	0.145
B	0001	1	1/21	1	0.145
C	0000	0	16/21	1	0.2072
D	1000	8	1/21	10	1.45
E	0000	0	16/21	30	6.216
F	0000	0	16/21	50	10.36
G	0100	4	1/21	20	2.9
H	0000	0	16/21	50	10.36
I	0000	0	16/21	70	14.5
J	0000	0	16/21	80	16.58
K	0000	0	16/21	10	2.072
L	0000	0	16/21	50	10.36
M	0000	0	16/21	70	14.5
N	0000	0	16/21	80	16.58
O	0000	0	16/21	50	10.36
P	0000	0	16/21	70	14.5
Q	0000	0	16/21	80	16.58
R	0000	0	16/21	80	16.58
S	0010	2	1/21	70	10.15
T	0000	0	16/21	90	18.65
	Entropy Amount				203.5

Table 6: Event Pattern Table ***(SP-B)***

Event	**Interaction Pattern**	**Binary**	**Probability**	**Nodes Weight**	**Entropy (bits)**
A	010000	16	1/21	1	0.145
B	111111	63	1/21	1	0.145
C	000001	1	1/21	1	0.145
D	100000	32	1/21	10	1.45
E	000000	0	15/21	30	7.21
F	000000	0	15/21	50	12.02
G	000000	0	15/21	20	4.807
H	000000	0	15/21	50	12.02
I	000000	0	15/21	70	16.82
J	000000	0	15/21	80	19.23
K	000100	4	1/21	10	1.45
L	000000	0	15/21	50	12.02
M	000000	0	15/21	70	16.82
N	000000	0	15/21	80	19.23
O	000000	0	15/21	50	12.02
P	000000	0	15/21	70	16.82
Q	000000	0	15/21	80	19.23
R	000000	0	15/21	80	19.23
S	000000	0	15/21	70	16.82
T	000000	0	15/21	90	21.63
	Entropy Amount				236.5

Table 7: Summary of Event Entropies for SP

Event	**Event Entropy taken separately (bits)**	**Event entropy taken together (bits)**	**Total Knowledge Generated**
A	203.5		
B	236.5		
C	235.9		
D	172.9		
E	0		
F	0		
G	177		
H	0		
I	0		
J	171		
K	93.2		
L	109.1		
M	0		
N	0		
O	0		
P	0		
Q	0		
R	0		
S	101.2		
T	0		
U	134.5		
Total	1635 Bits	286 bits	1349 bits