TOWARDS A CHANGE-BASED CHANCE DISCOVERY

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Abstract: This paper argues that chances (risks or opportunities) can be discovered from our daily observations and background knowledge. A person can easily identify chances in a news article. In doing so, the person combines the new information in the article with some background knowledge. Hence, we develop a deductive system to discover relative chances of particular chance seekers. This paper proposes a chance discovery system that uses a general purpose knowledge base and specialised reasoning algorithms.

1 INTRODUCTION

According to Ohsawa and McBurney (2003), a chance is a piece of information about an event or a situation with significant impact on decision-making of humans, agents, and robots. A 'chance' is also a suitable time or occasion to do something. A chance may be either positive –an opportunity or negative – a risk. For example, predicting a looming earthquake represents a "chance discovery".

Many approaches have been applied to chance discovery. Rare events may represent chances known to co-occur with important events, while the important events can be extracted using data mining techniques. KeyGraph, the application of this technique, was applied to various data, such as earthquake sequences, web pages, documents (Ohsawa et al., 1998; Ohsawa and Yachida, 1999; Ohsawa, 2003a; Ohsawa, 2003b). Tawfik (2004) proposes that chance discovery represents a dilemma for inductive reasoning. Induction assumes that current trends will carry into the future thus favoring temporal uniformity over change. However, current observations may lead to different possible futures in a branching time model. Finding a proper knowledge representation to represent all these possible futures is important. Otherwise some chances will be missed. Bayesian and game theoretic approaches are presented as viable chance discovery techniques. Abe (2003a, 2003b) considers chances as unknown hypotheses. Therefore, a combination of abductive and analogical reasoning can be applied to generate such knowledge and chances can be discovered as an extension of hypothetical reasoning. McBurney and Parson (2003) present an argumentation-based framework for chance discovery in domains that have multi agents. Each agent has a partial view of the problem and may have insufficient knowledge to prove particular hypotheses individually. By defining locutions and rules for dialogues, new information and chances can be discovered in the course of a conversation.

In this paper, we incorporate some new elements into the chance discovery process. These elements have implications to both the conception and discovery of chances and can be summarized as follows:

- Chances are not necessarily unknown hypotheses. Many chances result from known events and rules. For example, applying for the right job at the right time represents a chance for an employment seeker as well as the employer. In this case, the goal is clear. However, chance discovery means that the employment seeker applies at the proper time and for the employer, it means to correctly project which applicant will be better for the job.
- Inherently, chance discovery has a temporal reasoning component. New risks and opportunities are typically associated with change. An invention, a new legislation, or a change in weather patterns may result in many chances. Incorporating chance discovery in a belief update process is fundamental to this work. Chances are relative; someone's trash may be another's treasure. For example, finding a cure for a fatal disease represents more of a chance to an individual suffering from this condition or at risk to contact it.

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- To discover chances and take advantage of them, a system which can perform deductive reasoning is needed.

Therefore, we consider chance discovery as a process that tries to identify possibly important consequences of change with respect to a particular person or organization at a particular time. For this to happen, a logical reasoning system that continuously updates its knowledge base, including its private model of chance seekers (CS) is necessary. A chance discovery process may act as an advisor who asks relevant “what if” question in response to a change and present significant consequences much like seasoned parents advise their children. Such advice incorporates knowledge about the chance seekers, their capabilities, and preferences along with knowledge about the world and how it changes.

In a word, to discover chances, we need three things: First, a knowledgeable KB which can infer and understand commonsense knowledge and that can incorporate a model of the chance seeker. Second, we need a source for information about change in the world. Third, we need a temporal projection system that would combine information about change with the background knowledge and that would assess the magnitude of the change with respect to the knowledge seeker. Cyc knowledge base is supposed to become the world's largest and most complete general knowledge base and commonsense reasoning engine and therefore represents a good candidate as a source for background knowledge. Information about changes occurring in the world is usually documented in natural languages. For example, a newspaper can serve as a source for information about change. We need Nature Language Processing (NLP) tool to understand this newspaper. We assume that Cyc natural language module will be able to generate a working logic representation of new information in the newspaper. However, for the purpose of the present work, understanding news and converting it to Cyc representation has been done manually. This paper proposes an approach for assessing the implications of change to the chance seeker and bringing to the attention of the chance seeker significant risks or opportunities.

The paper is organized as follows: Section 2 establishes the notion that chance and change are tied together. Section 3 introduces Cyc knowledge base and its technology. Section 4 presents the chance discovery system based on Cyc.

2 CHANCES IN CHANGES

Chances and changes exist everywhere in our daily life. In general, changes are partially observable by a small subset of agents. Therefore, it is more likely to learn about changes happening in the world through others. For example, information about change could be deduced from conversations in chat rooms, newspapers, e-mail, news on the WWW, TV programs, new books and magazines, etc. In another word, change causing events occur daily around the world. The amount and rate of those events is very large. However, a relatively small portion of these changes represent risks or opportunities to any particular chance seeker.

Initially, the system starts with a stable knowledge base KB. The knowledge base represents the set of widely held knowledge. As part of KB’s knowledge, each chance seeker maintains its own private knowledge that describes its current attributes. In addition to KB, each chance seeker also maintains its private goals and plans about how to achieve those goals. If chance seeker doesn’t maintain its goals, the system will use default goals that are widely accepted as common goals. For example, the system assumes that all people want to become more famous or richer, want their family members and relatives to be rich and healthy, etc. We assume that the chance seeker has already exploited the chances present in the current KB and that the current plans of chance seeker are the best according to current KB. However, current plans may only be able to achieve part of the goals. For example, the goal to own a house in Mars is unachieved by current knowledge.

A goal of chance seeker can be represented by a set of sentences describing a future status of chance seeker’s attributes. For example, if chance seeker set up the goal to be a famous scientist, the system can judge the achievement of the goal by measuring chance seeker’s current attributes, such as education, occupation, published papers, social class, etc. The system maintains an attribute framework of chance seeker in KB. The attribute framework can be able to change if necessary. A goal can be considered as a future projection of current framework. On the other hand, a future set of attributes could satisfy many goals of chance seeker. Current plans of chance seeker project current set of attributes to the most achievable set of attributes.

As new information B becomes available, an update operation is triggered. The update operation proceeds in two phases: a explanation phase and a projection phase. The explanation phase tries to revise current plans that may have been proven to be inaccurate by the occurrence of B. Similarly, the projection phase, revises current plans to take into account the occurrence of B. A risk is detected if the occurrence of B results in a threat to the causal support for one of the plans of the chance seeker. An opportunity is detected if B satisfies one of the followings: the occurrence of B enables another one of the goals of the chance seeker to become achievable, or better plans can come up after B. In some cases, a particular piece of new information will result in both risks and opportunities.

3 CYC KNOWLEDGE BASE FOR CHANCE DISCOVERY

The Cyc knowledge base (KB) (OpenCyc.org, 2002) is a formal system that represents of a vast quantity of fundamental human knowledge: facts, rules of thumb, and heuristics for reasoning about objects and events of everyday life. The medium of representation is the formal language known as CycL. CycL is essentially an augmentation of first-order predicate calculus (FOPC), with extensions to handle equality, default reasoning, skolemization, and some second-order features. For example:

```
(#$forAll ?PERSON1
(#$implies
(#$isa ?PERSON1 #$Person)
(#$thereExists ?PERSON2
(#$and
(#$isa ?PERSON2 #$Person)
(#$loves ?PERSON1 ?PERSON2))),
```

in English, means

```
"Everybody loves somebody."
```

In Cyc, a collection means a group or class. Collections have instances. Each instance represents an individual. For examples,

```
(#$isa #$AbrahamLincoln, #$Person).
(#$isa #$BillGates, #$Person).
```

Abraham Lincoln and Bill Gates are individuals. Person is a collection. A collection could be an instance of another collection. For example,

```
(#$genls #$Dog, #$Mammal),
```

means "Collection Dog is an instance collection of collection Mammal".

In other word, Dog is a specialization of Mammal. It can be said that every individual is an instance of Thing, which is the most general collection in Cyc KB. Some individuals could be part of other individuals. For example, Microsoft is an individual. Joe works for Microsoft. Joe is part of Microsoft.

Constants are the "vocabulary words" of the Cyc KB, standing for something or concept in the world that many people could know about. For example, #$isa, #$Person and #$BillGates are constants.

The assertion is the fundamental unit of knowledge in the Cyc KB. Every assertion consists of:

- an expression in CycL language that makes some declarative statement about the world
- a truth value which indicates the assertion's degree of truth. There are five possible truth values, including monotonically true, default true, unknown, default false and monotonically false.
- A microtheory of which the assertion is part of a theory. Section 3.1 gives a detailed explanation of microtheories.
- A direction which determines whether inferences involving the assertion are done at assert time or at ask time. There are three possible values for direction: forward (inferences done at assert time), backward (inferences done at ask time), and code (assertion not used in regular inference).
- A justification which is the argument or set of arguments supporting the assertion's having a particular truth value.

An assertion could be a rule or a Ground Atomic Formula (GAF). A rule is any CycL formula which begins with #$implies. A GAF is a CycL formula of the form, (predicate arg1 [arg2 ...argn]), where the arguments are not variables.

In Cyc, time is part of the upper ontology. It is a physical quantity. A temporal object such as an event, a process, or any physical object has a temporal extent. The time model is interval-based with suport for points. TimeInterval has dates, years, and so on, as its subcategories. An event is a set of assertions that describe a dynamic situation in which the state of the world changes. An event has non-empty space and time components. It may also have performer, beneficiaries, or victims. A script in CycL is a type of complex event with temporally-ordered sub-events. Applications can use script recognition – that allows them to identify a larger script from some stated events that are constituent parts of the script. Scripts can also be used for planning and for reading comprehension.

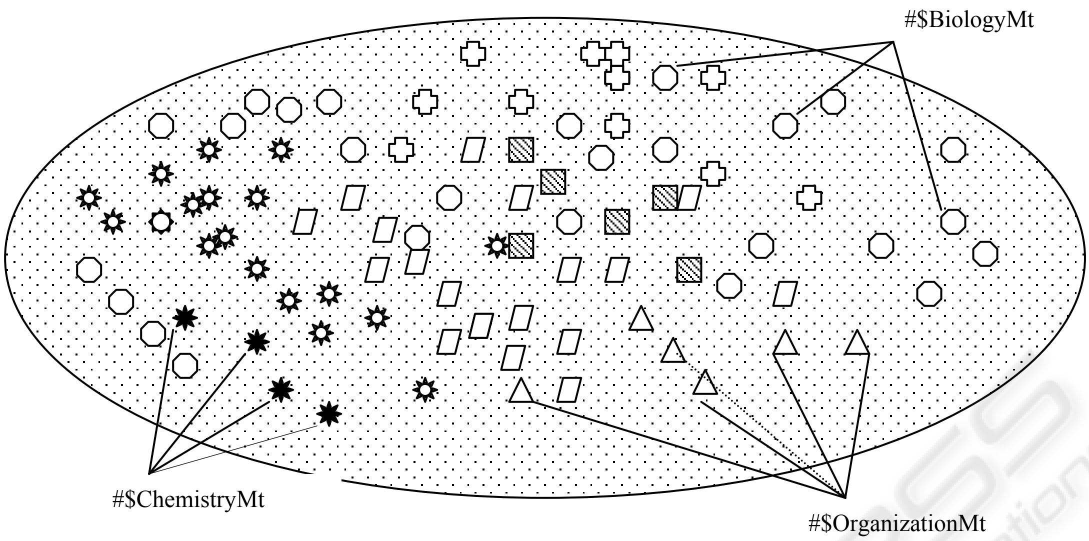

Figure 1: Cyc Knowledge Base as a sea of Assertions

3.1 Microtheories

A microtheory (Mt) is a bundle of assertions. The bundle of assertions may be grouped based on shared assumptions, common topic (geography, football, etc), or source (CIA world fact book 1997, USA today, etc). The assertions within a Mt must be mutually consistent. Assertions in different Mts may be inconsistent. For example,

```
MT1: Mandela is President of South
Africa
MT2: Mandela is a political prisoner
```

Microtheories are a good way to cope with global inconsistence in the KB, providing a natural way to represent things like different points of views, or the change of scientific theories over time. Mts are one way of indexing all the assertions in Cyc KB.

There are two special Mts, one is #$BaseKB (always visible to all other Mts), the other one is #$EverythingPSC (all other Mts are visible to this Mt). #$EverythingPSC is a microtheory which has no logically consistent meaning but has a practical utility just because it is able to see the assertions in every microtheory.

The Cyc KB is the repository of Cyc's knowledge. It consists of constants and assertions involving those constants. It could be regarded as a sea of assertions, see figure 1. Form ontology point of view, the Cyc KB could also be thought of as

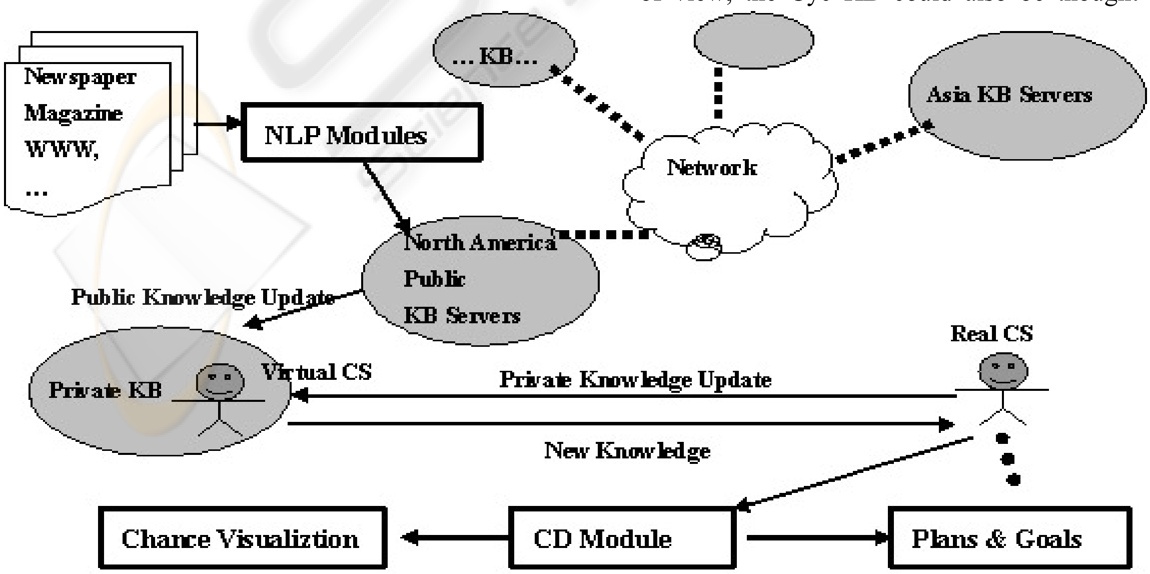

Figure 2: Chance Discovery System.

made up of layers ordered by degree of generality. Cyc uses two rules of inference in theorem proving, modus ponens and modus tollens.

Cyc-NL is the natural language processing system associated with the Cyc KB. It could translate natural language into CycL. Cyc-NL has three main components: a lexicon, a syntactic parser and a semantic interpreter. The lexicon along with a generative morphology component generates part-of-speech assignments for words in a sentence. The syntactic parser uses a grammar to generate all valid parses for the sentence. The semantic interpreter produces pure CycL equivalent for the input sentence.

4 CHANCE DISCOVERY SYSTEM

Figure 2 shows the framework of chance discovery system. Nature Language Processing (NLP) modules analyze daily news and generate new knowledge which is represented in logic. The new knowledge is then integrated into public Cyc KB servers. The private Cyc KB server owned by the chance seeker will connect to public KB servers and update its knowledge. On the other hand, the chance seeker updates its private attributes in the private Cyc KB. The knowledge about chance seeker can be regarded as a virtual chance seeker living in Cyc KB. A chance seeker sets up its goals or uses default goals in the Goals & Plans Module. New knowledge triggers the CD modules that measure the relevance of the new knowledge to the chance seeker. The new knowledge is considered to be a chance candidate if the relevance score is above a certain threshold. By trying to revise current plans using the new knowledge, the magnitude of this chance candidate can be measured using a utility evaluation process. When the magnitude of the utility is above a specified threshold, a chance is detected. Finally, the system visualizes the chances to chance seeker, and revises current plans for future chance detections.

4.1 The Relevance of New Knowledge

New knowledge is relevant to the chance seeker if it has an immediate impact on the seeker's attributes or on the achievability of the chance seeker's goals. For example, the new knowledge that shows that the chance seeker inherited a fortune is relevant as it changes the seeker's wealth attribute. The new information can affect the achievability of goals in three ways:

- making new goals achievable,
- making some previously achievable goals unattainable, or
- changing the cost or reward of achieving some goals.

A goal is considered achievable if the system finds a plan to the goal from the current state. To impact the achievability of a plan, the new knowledge could affect the causal support for actions in the plan or the likelihood of success.

Testing the relevance of new information to the chance seeker is desirable to filter out irrelevant information. Fully testing the relevance of new information with respect to its impact on the chance seeker's attributes and plans could be computationally expensive. Therefore, we gradually apply a series of relevance tests with increasing computational cost. These tests are:

- testing if the new information is subsumed by existing knowledge,
- testing for temporal relevance,
- testing for spatial relevance,
- testing for impact on the chance seeker's attributes, and
- testing for impact on the chance seeker's plans.

To verify that the new information is actually new, and is not subsumed by knowledge already in the KB, we test if it is entailed by existing knowledge. For example, if the KB contains assertions indicating that Paul Martin is the leader of the Liberal Party, that the Liberals won the largest number of seats in the parliament and that the leader of the party that wins the most seats becomes the Prime Minister. It becomes redundant to add an assertion indicating that Paul Martin became the Prime Minister. Similarly, if KB contains a generalization of the new information, this information will be redundant.

The relevance of information in a dynamic stochastic system degenerates gradually over time. The rate of degeneration of information relevance with respect to a rational decision maker depends on the probabilities of change as well as on the relative utilities (Tawfik and Khan, 2005). Cyc supports a notion of possibility akin to probability. However, it is unlikely that the probabilistic knowledge in the KB will be specified fully to construct dynamic belief networks. Therefore, we rely on the intersection of the temporal extents associated with temporal object in the KB to verify the mutual relevance of temporal objects. Similarly, most spatial effects also weaken with distance. Therefore, it is fair to filter out new knowledge whose spatial or temporal effects lie outside the scope of interest.

New knowledge could be divided into rules and events (facts). We consider that the chance seeker relies on a rule if chance seeker includes some actions that are causally supported by the consequences of the rule into its plan. The impact of the rule measures the role of the rule in reaching the goals. It could be regarded as the utility changes that are credited to the rule B. If S represents the state of chance seeker's attributes, then impact is given by:

$$impact_B=V(S_B)-V(S)$$

To assess $V(S_B)$, we consider two cases: In one case, $V(S_B)$ may already be stated clearly in the rule. For example, the time saving from taking a newly built high speed train to a certain destination will be clearly stated in the news. On the other hand, if $V(S_B)$ is unclear, we can deduce a reasonable hypothesis by combining the new rule and existing rules in background KB. This hypothesis will not go beyond the known knowledge. For example, if there is an assertion in KB stating that all the people in the same country speak the same language, then communicating with all Brazilians will be the utility of learning Portuguese for a chance seeker who wants to travel to Brazil. Note that this utility could be inaccurate since it is based on a hypothesis. In general, $impact_B$ may act as a greedy measure of progress towards the goals but does not guarantee reaching these goals. An exogenous rule may undermine actions in the other part of chance seeker.

When new knowledge is an event, to determine the value of an event, we have to take other factors into account. An event could be composed by a bundle of assertions describing its features, such as actions, locations, time, physical object involved, etc. The impact of an event according a particular chance seeker is based on the following features:

- Importance of the entities involved in the event. To evaluate an event, we take the importance of those objects into account. For example, 'Microsoft' may be considered to be a more important company than other small companies. However, a small company currently working with Microsoft may be important.
- The relationship between involved objects and chance seeker needs to be taken into account. For example, a company owned by family members may mean a lot to chance seeker though it's a small company. For example, the chance seeker may work for this small business. Generally, close relatives, friends, and acquaintances are more important that strangers.

According to the above:

$$impact_{Event}=\sum_i V_E(Size(Objects_i), relations(Object_i, CS))$$

Where V_E is a value function that takes into account the importance/size of objects, the attributes involved and the relationships between objects and the chance seeker including spatio-temporal relationships. V_E tries to guess the potential change in the chance seeker's attributes.

A negative impact indicates that the new knowledge is a potential threat. In the case of irrelevant new knowledge, the impact will be inside the range of [negative threshold, positive threshold]. The new knowledge will be integrated into KB for future reference. On the other hand, the new knowledge will be considered as a chance candidate if the impact is outside the range.

4.2 The Magnitude of Chances

Here, B is the set of new knowledge that passes the relevance tests, the system will try to revise current plans (CP) of the chance seeker using B. Partial Order Planning (POP) and SATplan algorithm (Russell and Norvig, 2002) can be used to generate new plans (NP_B) by taking B into account. In our system, SHOP (Nau et al. 1999) generates the plans for the chance seeker. SHOP is a domain-independent automated-planning system. It is based on ordered task decomposition, which is a type of Hierarchical Task Network (HTN) planning.

By adopting NP_B instead of CP, the chance seeker may be able to achieve a different set of goals, or save less time and/or money while achieving the same goals. All these features can be reflected by a utility function mapping. The magnitude of B denoted by M_B is represented as the utility difference between NP_B and CP.

There could be a gap between the goals of NP_B and the goals of CS. As describing in section 2, a set of goals can be represented by a future status of attributes important to the chance seeker. If we use a utility function (V) to map those attributes into real values and add them together, we can represent a notion of preference. The change in the utilities could be represented as:

$$M_B=V_{NP_B}-V_{CP}$$

M_B represents the difference between new plans and current plans. If M_B in the range of [negative threshold, positive threshold], it means that NP_B and CP are roughly the same. The magnitude of B is low. Whether B is a chance or not, there are the following possible cases:

- ***Short-term setback***: When B has negative effect on chance seeker's attribute and no threat to the current plans, B will be ignored.
- ***Potential risk***: When B has negative effect on chance seeker, and threatens some of the current plans. However, repair plans can be found such that the new plans including the repair plans can achieve the same goal as before. This is considered a potential risk even though it is possible to repair the plans because if the

chance seeker proceeds with the original plans the goals may not be reached.

- ***Risk:*** Repair plans cannot be found, NP_B achieve fewer goals than before. M_B is out of range. The system will consider B is a risk.
- ***Short-term prosperity***: When B has positive effect on chance seeker's attribute, and no effect on the current plans.
- ***Exploitable efficiency***: NP_B can achieve the same goals as *CP* but in significantly shorter time or costs less. B is considered as a chance.
- ***Improved reliability:*** NP_B can achieve the same goals as before for approximately the same cost but offer an alternative for some plan elements.
- ***Inefficient alternative***: Exploiting B, NP_B can achieve fewer goals than before or the same goals at a higher cost without threatning CP. B is ignored.
- ***Opportunity:*** NP_B can achieve more goals than before. M_B is significant and positive and B is considered a chance.
- ***Short-term gain long-term risk:*** When B has positive effect on chance seeker, threatens some of the current plans and the plans cannot be repaired.
- ***Short-term loss long-term gain***: B results in an immediate loss but enables longer term plans.

Finally, if a chance is detected, NP_B will be set as CP.

4.3 Visualizing Chances

When a chance is detected, visualizing chances is important as the last step of chance discovery. Sometimes chance seeker may not understand why chances returned by chance discovery system are chances. Visualization of chances could emphasize on the explanation and help chance seeker to realize chances.

A detail visualization explanation including display of the future status of attributes of chance seeker, display of chance seeker's current plans, etc, may be necessary. Kundu et al. (2002) present a 3-D visualization technique for hierarchical task network plans. Such visualizations will be useful for the chance seeker to understand the interactions between various elements in the plan.

5 DISCUSSION & EVALUATIONS

The evaluation of chance discovery (CD) systems could be based on precision, efficiency and chance management. As discussed in Section 1, many previous CD approaches regard chances as unknown hypothesises, focusing on techniques to derive common chances, i.e. chances for all people. Our approach focuses on knowledge management, finding chances in known knowledge (news, WWW, etc) for a particular chance seeker by the support of a large and rich knowledge base. In the 2005 tsunami tragedy, scientists correctly detected the occurrence of the tsunami, but failed to warn the relevant people in South Asia in time to evacuate. Hence, chances are relative.

KeyGraph, as introduced in Section 1, is a widely used technique in CD research. Matsumura and Ohsawa (2003) present a method to detect emerging topic (web page as chance) by applying KeyGraph on web pages. A "Human Genome project" example was presented. Its benefits include finding cures to conquer fatal illness. Two sets of web pages (C_A and C_B), each containing 500 web pages, were obtained by searching "human genome" in Google. C_A was obtained on Nov 26, 2000. C_B was on Mar 11, 2001. In the output of KeyGraph, Celera (www.celera.com), a growing HG research website, was detected as a chance in C_B because Celera co-occurred with the most important (foundation) websites in C_B. The set of foundation websites of C_A and C_B, such as NCBI (the National Centre for Biotechnology Information), etc, is almost the same. The following events about Celera were reported in the meantime:

1. The Human Genome Project team and Celera announced the completion of the draft sequence of the human genome in June, 2000.
2. Craig Venter, President and Chief Scientific Officer of Celera and Francis Collins, Director of the Human Genome Project, met President Bill Clinton and British Prime Minister Tony Blair for the progress of the human genome analysis.
3. Papers about the completion were published in Nature and Science in 2001.

For a researcher in medicine whose goals include finding a cure for genetic diseases, our CD system would report a chance after evaluating events 1&2 and would propose new plans. The system may draw the researcher's attention to the draft sequence as early as on Jun 27, 2000 because Clinton and Blair are very important individuals. The degree of relevance will be high. The magnitude of "the draft sequence" will be high since it makes the researcher's unattainable goals achievable. Therefore, our approach could discover chances fast.

6 CONCLUSION

This paper describes a chance discovery system based on Cyc Knowledge base. The knowledge base works as a virtual reality. Cyc KB simulates the development of real society by continuously updating its knowledge. The new knowledge comes from newspaper, magazine, and WWW, etc. The chance discovery system searches chances in KB for on behalf of the virtual chance seekers. By assessing the relevance of new knowledge, the irrelevant knowledge to a chance seeker is ignored. Then chance in relevant knowledge is detected by considering its impact on the current plans and the possibility of new plans that are built based on the new knowledge.

REFERENCES

Abe, A., 2003a.. Abduction and analogy in chance discovery. *In Ohsawa, Y. and McBurney, P., editors, Chance Discovery, pages 231–247.* Springer-Verlag Berlin Heidelberg.

Abe, A., 2003b. The role of abduction in chance discovery. *New Gen. Comput.*, 21(1):61–71.

Kundu, K., Sessions, C.,,desJardins, M. and Rheingans, P. 2002. Three-dimensional visualization of hierarchical task network plans, *Proceedings of the Third International NASA Workshop on Planning and Scheduling for Space*, Houston, Texas.

McBurney, P. and Parsons, S., 2003. Agent communications for chance discovery. *In Ohsawa, Y. and McBurney, P., editors, Chance Discovery, pages 133–146.* Springer-Verlag Berlin Heidelberg.

Nau, D. Cao, Y., Lotem, A. and Muñoz-Avila, H. 1999. SHOP: Simple Hierarchical Ordered Planner. In *Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI-99),* pp. 968-973.

Ohsawa, Y., 2003a. Keygraph: Visualized structure among event clusters. *In Ohsawa, Y. and McBurney, P., editors, Chance Discovery, pages 262–275.* Springer-Verlag Berlin Heidelberg.

Ohsawa, Y., 2003b. Modeling the process of chance discovery. *In Ohsawa, Y. and McBurney, P., editors, Chance Discovery, pages 2–15.* Springer-Verlag Berlin Heidelberg.

Ohsawa, Y., Benson, N. E., and Yachida, M. ,1998. Keygraph: Automatic indexing by co-occurrence graph based on building construction metaphor. *Proceedings of the Advances in Digital Libraries Conference, pages 12–18.* IEEE Computer Society.

Ohsawa, Y. and McBurney, P., 2003. Preface. *In* Ohsawa,Y. and McBurney, P., editors, *Chance Discovery.* Springer-Verlag Berlin Heidelberg.

Ohsawa, Y. and Yachida, M., 1999. Discover risky active faults by indexing an earthquake sequence. *Proceedings of the Second International Conference on Discovery Science*, pages 208–219. Springer-Verlag.

OpenCyc.org,2002. OpenCyc documentation. http://www.openCyc.org/doc/.

Parsons, S. and McBurney, P., 2003. Logics of argumentation for chance discovery. In Ohsawa, Y. and McBurney, P., editors, *Chance Discovery*, pages 150–165. Springer-Verlag Berlin Heidelberg.

Russell, S. and Norvig, P., 2002. *Artificial Intelligence: A Modern Approach.* Prentice Hall Series in Artificial Intelligence, 2nd edition.

Tawfik, A. Y. 2004. Inductive reasoning and chance discovery. *Minds and Machines*, Volume 14 (Issue 4):441– 451.

Tawfik, A. Y. and Khan, S., 2005. The Degeneration of Relevance in Dynamic Decision Networks with Sparse Evidence, *Applied Intelligence*, to appear.