Chance Discovery in a BDI Perspective of Planning: Anticipation, Participation and Correlation

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Abstract

Chance is a new event/situation with significant impact on an agent's decision making, that is, either an opportunity or a risk. In this paper, suggesting the modern scope of dynamic planning as a typical stage on which Chance Discovery and Management (CD&M) play a special role, we abstract 'chance' into three essentials, which provide not only its conceptual criteria but also methodological clarifications in a BDI (Belief-Desire-Intention Agent Theory [Georgeff et al., 1998]) viewpoint. By proposing a theory of Perception and its architecture integrated with IRMA, and a logical system for detecting motivational correlation, we suggest that a chance is an event/situation perceived or conceived outside an agent's previous anticipation, while inside (partially at least) control of her participation, and revealed by its correlation with her motivational attitudes as Desire and Intention.

1 Introduction

Facing an era of exceptions occupying the norm of challenges, we the agents are living in a changing world where uncertainty and chaos prevail, and chance problems erupt. Accordingly, more and more researchers start attending to various chances in numerous disciplines: AI, system theories, information theories, webs, nonlinear sciences, marketing theories, social analysis, ecology, etc.

A "chance" means a new event/situation that can be conceived either as an opportunity or as a risk. We abstract this concept into three essentials namely *knowledge incompleteness*, *motivation correlativeness* and *initiative openness*, which may suggest a methodological criterion.

Based on some philosophical claims that we propose and clarify in a planning view, and on some relevant contributions and deficiencies in previous planning approaches, we hereby design a hierarchy of Perception embedded in IRMA [Bratman et al., 1988] aiming at focusing agents' attention toward potentially influential events for both knowledge revision/extension, and plan management. In this architecture we also adopt AAR [Abe, 1997] theory integrated with ILP [Ad'e & Denecker, 1995] as an effective component generating new knowledge with creativity.

Chance Detection as a part of such Perception is to discover motivation-oriented impact. We demonstrate this function can be independent from agent's Belief. Therefore a computational inference of motivational correlation might be an ideal approach. Thus we applied our four-valued logic and a semantic system toward implementation of Chance Detection. With competence guaranteed by a descriptive theory [Chen, 2002], this system serves as a fitting filter that practically helps to focus agent's attention on such features that might affect the possible transformation of the agent's plan, which is obviously CD&M.

2 Three Essentials of Chance

Recently, common features of 'chance problems' in diverse range receive promising synthesis and analysis. The first step of this infant, Chance Discovery (CD), shows a remarkable coherence with other disciplines and an intuitive consensus on its definition. So, in conceptual sum, what is a 'chance event'? To this question we give three points as sine qua non:

1. it is so new to the agent that its pattern can hardly be deducted from her previous knowledge base;
2. it has impact on the achievement of her goals and desires, either positive or negative;
3. it is partially open to her control, or to her use of it for altering its impact, i.e. promoting its benefit or reducing and avoiding its threat.

We name such three points respectively *knowledge incompleteness*, *motivation correlativeness* and *Initiative Openness*.

2.1 Knowledge Incompleteness

CD is originated from the inevitable failure of foretelling events outside trend by conventional Knowledge Discovery (KD) methods based on tendency learning from historic data. Hence, in definitions of chance event, such adjectives as 'new', 'rare', 'novel' and 'exceptional' have been coincidently used to indicate its 'unlikeliness' as its first characteristic that distinguishes it from ordinary events.

From our methodological view, it is necessary to clarify that the reading of such 'unlikeliness' and those adjectives emphasizes on, in fact, NEITHER the tiny frequency NOR the poor probability of chance event per se, BUT the agent's own lack of knowledge about such event or its consequences, such as the incompleteness of her possible-outcome list, her ignorance of some rules and even her incorrect ideas, etc.

The low probability of chance event is merely the cause and explanation of agent's ignorance; statistical characteristic itself tells nothing about how to identify or deal with chance events, and CANNOT serve as criterion for discerning chance events. Just imagine how can an agent detect a chance by working out its probability according to a definitional criterion, while she even has no bit of its pattern! And who can tell HOW unlikely should it be as a chance?

We regard chance discovery as the discovery of its POSSIBILITY rather than that of its PROBABILITY. Hereby we advocate Abe's definition of two types of chance as an unknown event or a known event under unknown rules. [Abe, 2001] Chance is somewhat unexpected from deduction of knowledge base. When meeting an explicit chance event, the agent may feel it different or absent from her expectation and her decided plan; when turning a blind eye to an implicit chance event whose consequence will be out of her expectation, she does not know her fate is potentially changed. So one of the tasks of CD is to overcome such disregard by belief update, which generates creative explanations of her new observation and add them into her incomplete knowledge base.

2.2 Motivation Correlativeness

Chance events' increasing attraction in spite of difficult recognition is due to their high impact. However, what does 'impact' exactly mean and how to judge it?

> *Most obviously, there are no opportunities or risks per se, they are only given with respect to certain values and goals of humans.* [Prendinger & Ishizuka, 2001]

In planning aspect, especially that of BDI architecture, such 'impact' can be nothing but influence on the achievement of an agent's Desire, Goal and Intention, either to facilitate it or impede it. So Desire/Goal and Intention should be the only key criteria for a chance's impact.

We suggest the determinant definition and evaluation of such 'impact' should be some correlation between the event/situation and the agent's motivational attitudes such as Desire/Goal. Though this impact may involve context and environmental factors (e.g. requiring references to the agent's current Belief), we should notice that an agent's knowledge about the context and environment are usually incompetent to aid discovery of correlations for chance problem, e.g. our current Belief is usually unavailable or unreliable in detection of a chance event. Thus, in order to assess whether an event/situation might be an opportunity, a risk or neither of them, we suggest an appropriate correlation that is computable and decidable with some function relatively independent from agent's Belief.

2.3 Initiative Openness

Thus discussed 'impact' brings importance on CD for another crucial reason that it is on human decision-making. Usually, having discovered an opportunity always means 'We still have an opportunity!' 'We can do something for it!' or to say the least, 'we used to have an opportunity and should have grasped it!' In contrast, even when a new event/situation has great causal impact on the agent's goal, if the agent can never do anything about it or its fated consequences, it cannot be considered as a chance. Chance makes sense merely in anticipation containing agent's plan rather than in fatal prediction that allows no initiative power. The so-called chance always leaves some freedom for the agent's own choice, and also some pending consequences that might be caused or prevented by the agent. So, in spite of the stressed distinction from each other, CD is essentially close to CM. That is why a CEO analyzing market should take into account his own decisions and intended plans since he himself is a participator of the game!

3 Chance Discovery in Dynamic Planning

We find planning the typical embodiment of 'predicting the future via inventing the future'. We also find planning with uncertainty in dynamic environment such a typical jungle that chance events lurk everywhere; nevertheless, during recent decade of development, nimrods contribute hunting techniques, though mostly indirectly, in which the three CD essentials listed above are all embodied in focus:

For knowledge incompleteness, much work has stressed on the resource-boundedness of an agent, and also on flexible structures and management of partial plans toward agent's making proper decisions even with limited knowledge during execution; For motivation correlativeness, there are two corresponding research trends: one is the renovation from task-oriented style toward goal/desire-oriented style, and the other is pervasive appeal to plan-rationale that is also goal-directed; For initiative openness, planning in its essence is a decision making process in which the agent is born to choose and invent the future, implying CM principles. Its commitment strategy and BDI interaction mechanisms remarkably integrate the agent's choice and decision with environmental causal link, especially under the stressed uncertainty.

However these approaches, significant though, have not directly abstracted a special chance problem as the target.

3.1 Plans embedded in agent's anticipation

- **Agent lives in her future sight:** 'We learn from yesterday and try for tomorrow', yes. 'Determined facts compose the past history, while uncertain possibilities create the future', yes. These basic thoughts from original verity deeply rooted in our mind can also turn into some obsessive bias, e.g. conceiving that knowledge is only about the past and the experience.

Who can deny the weather forecast is our episteme? Don't explain its inaccuracy by comparing it with recording yesterday's weather, since you would have felt that the last hour is even vaguer than tomorrow if you were suffering severe amnesia and ransacking the house for your weather record book.

Not only our hope lives in the future, but also our knowledge does. Agent's opening her mouth at an apple relies on her belief that there is not a worm in it; Her taking a step forward is based on her anticipation that no termitic fall of the front piece of floor will occur. We don't have proofs supporting these beliefs or foretelling today's similarity with yesterday. We live in the context where hypotheses prevail. Treating hypotheses more equally as experience is crucial for planning and to go beyond conditional KD.

To a planning agent, the only distinction between future and past is that to alter your knowledge about future you can both review and choose; but for the past history, you can only review. Anyway, why not change the first sentence of this paragraph into 'We learn about tomorrow and try out tomorrow'!

Time is a special one of state parameters: People usually say the world state is changing as time goes by. So-called 'state' can be represented by a tuple of parameters describing respective features of the world. We argue to regard time also as a parameter included in the tuple whose entity can be like {7:00, in dining room, eating, in pajamas,…}. Accordingly a *possible world* as a BDI term is a set of states indexed by time parameter, which presents a possible sequence temporally extended infinitely in both past and future. [Cohen & Levesque, 1990]

For a meeting from 8:00 to 10:00 e.g., the participator's 'in meeting room at 8:00' and 'in meeting room at 11:00' make different sense. In the famous *Little Nell Problem*, the mere goal of the hero 'I must remove Nell from the tracks' itself makes no sense for saving Nell. What actually works is 'I must remove Nell from the tracks BEFORE the train reaches Nell's present location.' We can also solve Little Nell Problem radically by distinguish '*expected achievement*' and '*executed achievement*'. The former is for planning and the latter is for execution. Their relation should be clarified here. For example, sentence p = '$\underline{\text{now is 8:00}} \supset \underline{\text{I arrived meeting-room}}$' can be an agent's goal, she can have '$\underline{\text{now is 7:00}} \wedge p$' as *expected achievement* and '$\underline{\text{now is 8:00}} \wedge p$' as *executed achievement*. The BDI-expression B(p) should not lead to immediate drop of intention p, since such belief might be *expected achievement.*

Environmental Changes vs. Mental Changes: Alteration from previous situation vs. Deviation from previous anticipation

Though an agent keeps modifying her cognitive attitudes with the continuous environmental alteration into her perception, NOT every environmental change perceived leads to a mental change. In fact, what influence an agent's cognitive attitude are just those world states discovered incompatible with or absent from her previous belief. An agent merely need attend to such new events that might correct or elaborate her knowledge. Hence, the new values of environmental parameters sensed by agent should be compared with her corresponding previous forecast (either her previous observations or her inferential hypothesis) rather than with the parameter's previous state.

3.2 Resource-bounded Planning and Rationale-based Monitoring

Commitment strategy may be one of the earliest significant steps toward resource-bounded agents in dynamic environments. Bratman in his famous theory of Intention argues that agents should tend to focus their practical reasoning on commitments to future plans, i.e. intentions they have adopted, and thus bypass full-fledged deliberation of new options that conflict with their intentions, unless those options can be easily recognized as potentially special in some way. This idea has initiated IRMA (as depicted in Figure 1) [Bratman et al. 1988] and BDI modeling theory, and its filtering strategy has successfully limited the amount of computational resources it requires, and further more, suggests a way of screening options out of entrance into further process such as agent's attention or deliberation.

In fact an agent's intention should help to restrict not only the range of options she further deliberates but also that of options she attends to in the first place. Reviewing the Opportunity Analyzer part in Figure 1 providing new options proposed from environment, we feel this part still far from maturity. How are new options suggested with respect to environmental changes?

To focus also an agent's perception and make her just respond appropriately to relevant changes rather than all could possibly occur in the world, some work introduced *rationale-based monitors* that present the 'right' features of the world state that are included in the plan rationale, i.e., the reason for recent planning decisions. [Pollack & McCarthy, 1999] [Veloso et al., 1995] [Veloso et al., 1998] Such monitoring is a three-stage process involving *monitor generation*, *deliberation* and *plan transformation*. Each step is mainly based on the plan rationale. This is really a contributive complement that may solve great deal of problems. However it is still incompetent for discovering chance events, since their relationship with the plan rationale are seldom explicit for direct using. However the contributive idea of focusing attention on those features likely to affect plan suggests a lot to our CD approach toward a design of perception with ability of filtering different types of features to catch perceived chance.

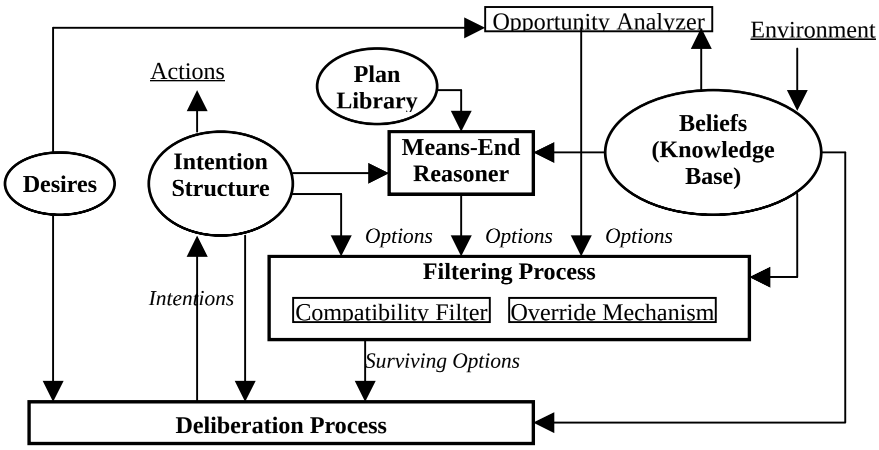

Figure 1. An Architecture for Resource-bounded Agent, from [Bratman et al.,1988]

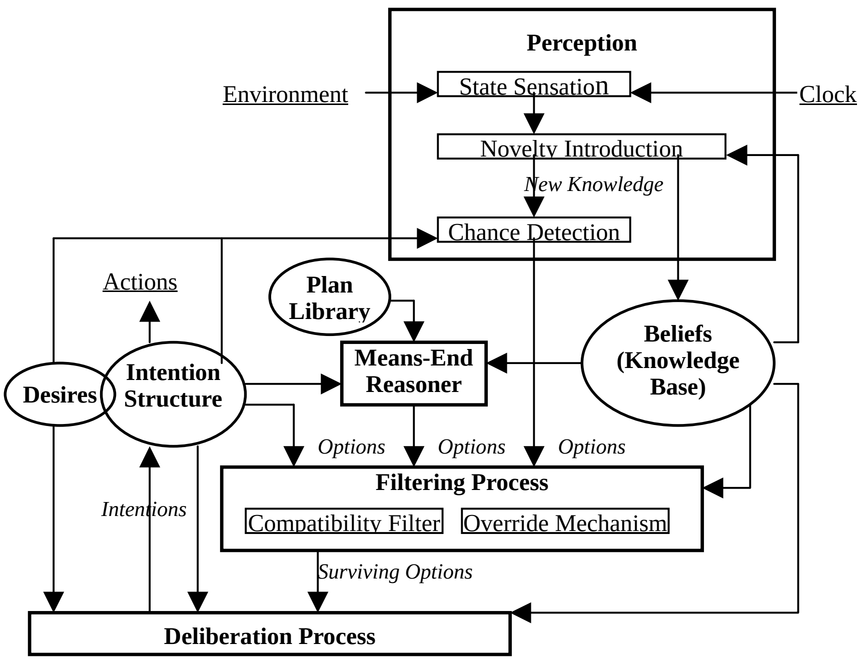

Figure 2. An Overall Architecture for Resource-bounded Agent with Hierarchical Perception

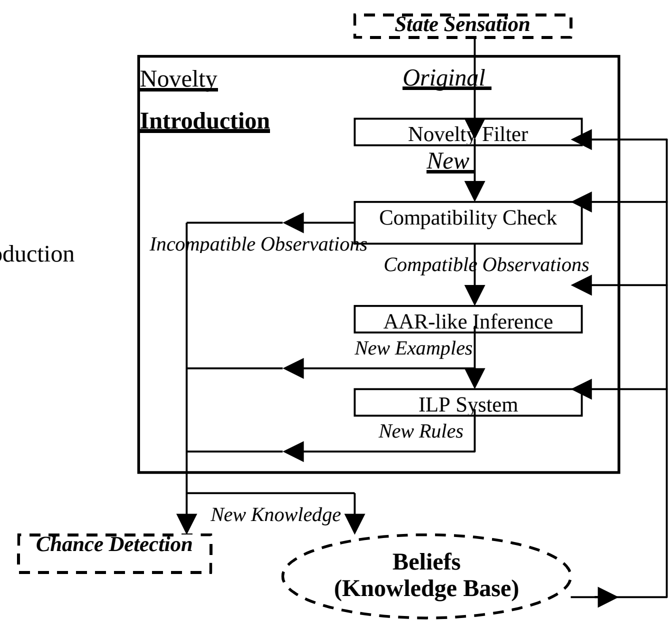

Figure 3. The Process of Novelty Introduction

3.3 Three Layers of Perception

The deductive and monotonic characteristics of the Knowledge Base inference reveal its born incompetence for CD. So of course there should be another mechanism for this duty. We suggest a hierarchy of agent's perception that consists of three layers namely *State Sensation*, *Novelty Introduction* and *Chance Detection*. (Figure 2) Its structure is for a process through which the perceived information flow can be finely filtered, classified and even inspected in a smooth and fast way. Such perception structure effectively focuses agents' attention toward those events worth noticing either for knowledge extension or for plan transformation. Principles of each part are as follows:

State Sensation: Although our overall effort is toward selective focusing of agent's perception, the real-time full-fledged physical sensation of all available world state parameters is nevertheless necessary. As the outmost (also lowest) layer of perception, it provides its successor in the flow with all the original data needed. A comparison can tell: our brain does not notice every detail and event in sight, but our conscientious eyes do receive all they can sense by light, and submit all these original information options to nerves.

A special reason for this layer's role has been discussed in 3.1 that executed achievements distinguished from expected ones should be monitored in real time. All environmental responses to the execution in parallel with planning should be conveyed. A clock tells time as a parameter integrated into the state, and State Sensation submits these states to comparison with anticipation in the next layer.

Novelty Introduction: The Novelty Introduction part in our agent's perception is a process to discover what is NEW among her observations and send it to both knowledge base and chance detection. It consists of four sub-processes. (Figure 3)

In the following, let B be Belief in form of a clause set representing Knowledge Base, and let O be an Observation as the original real-time information from State Sensation.

Novelty Filter checks whether the observed state can be deducted from Knowledge Base, i.e.

$$B \models O \;\; \textbf{?}$$

If NO it passes; and if YES it is discarded. Thus the states passed over into inner layer are only those new to the agent's anticipation that may change her mind, either by correcting or elaborating, as discussed in 3.1.

Compatibility Check checks whether the new knowledge is compatible with agent's previous knowledge, i.e.

$$B \models \neg O \, \textbf{?}$$

If NO, the new knowledge cannot be judged by Knowledge Base and is the typical input of next abduction; If YES, we have two alternatives in design: one is to ignore and discard such a conflict, and the other is to accept the new discovery into her Knowledge Base and negate her previous incompatible knowledge. We say the former is so self-confident that keeps to her previous belief; and the latter is self-questioning to correct her mistake in mind. We recommend the self-questioning design style for non-monotonic Belief update, since much of the agent's knowledge is hypotheses or deductions under incomplete rules, she had better believe in her eyes rather than her guess!

AAR-like Inference is totally adopted from Abe's Abductive Analogical Reasoning as the abductive inference integrated with the inductive ***ILP System***. The process generates hypotheses by analogical abduction under similar observations, and by induction from these abduced hypotheses it invents predicate rules. These new hypotheses and rules, together with original observations, are put into the Knowledge Base as new knowledge. [Abe, 1997] [Abe, 2001(www)][Abe, 2001])

On the whole of Novelty Introduction, its input is the original observation from State Sensation; and its output is the knowledge the agent didn't have before, including the original observations, new hypotheses, new explanations (abduced from AAR) and new rules (inducted from ILP).

Chance Detection: As we argued in 2.2 and 2.3, only events with desire-oriented compact on decision-making can be called Chance. Thus the Chance Detection takes the most essential role as finding influential relation between the new event/situation and the (sub)goals of agent's plan. If the new, novel knowledge provided by Novelty Introduction not only extends the agent's knowledge, but also influences her decision for her desire, e.g. causes the transformation of her plan as mentioned in 3.3, then the new knowledge itself or its original perceived event is no doubt a typical Chance!

So what mechanism or inferential method should Chance Detection use? What properties are required? Before giving our proposal, we have to make clear of another problem: In real world such impact is never isolate but always determined or influenced by context and environment. So, ***is it necessary for Knowledge Base to directly assist Chance Detection for discovering impact****?*

If it is necessary, Chance Detection gets data just from Intention Structure and Knowledge Base, all information about novel events can be indirectly but adequately fetched from updated Knowledge Base; If it is unnecessary, Novelty Introduction should send new knowledge directly to Chance Detection, and the Knowledge Base need not directly interfere with Chance Detection's work at all.

In our answer, it is ***unnecessary***, which can be simply demonstrated as follows:

The discovery of some irrationality of previously adopted plan via latest Belief update may fire the transformation or further elaboration of her plan. Here the so-called 'irrationality' is just used to mean the plan adopted is no more the best choice or adequately full consideration with current knowledge. Now assume plan P is rational for her goals G under Belief B (clause set), denoted as

$$B \models_m R(P,G),$$

Here '$\models_m$' represents deductive inference from Knowledge Base.

Then the agent perceives an event she cannot explain in her knowledge base B, which triggers her Novelty Introduction to generates new knowledge N (clause set). N is thus added into B and updated it to be B+N (here '+' represents asymmetric set union with which B is submitted to N's correction). If according to B+N, P is no more rational, then according to the born monotony of the deductive Belief inference presented by $\models_m$, P is also irrational according to mere N, denoted as:

$$(B+N \not\models_m R(P,G)) \Rightarrow (N \not\models_m R(P,G))$$

This means it doesn't matter if Chance Detection neither consults her present knowledge base nor waits to check her updated knowledge base, since the newly introduced knowledge N can tell ALL necessary information for a transformation. Whenever her updated knowledge B+N might warn an newly discovered irrationality and a necessary transformation, her newly introduced knowledge N also could NOT let it pass at all!

Hereby Novelty Introduction puts N into both Knowledge Base and Chance Detection directly at the same time, and the Chance Detection faces new knowledge in the first place as Knowledge Base does. The mere perception including Chance Detection is already sufficient to discover and pretreat it.

Hence, as impact analysis, it will be ideal and feasible for Chance Detection to adopt a mere computational inference between the (sub)goals in the plan and a perceived novel event. This inference should be fast, adequate and independently decidable without respect to Belief.

4 A Formal Theory of Motivational Correlation

Having come to the point that Chance Detection requires a decidable inference for correlation, we will suggest some formal definitions and present a practical tool.

4.1 Correlation: a Fitting Filter toward Plan Rationale

There are a variety of so-called 'correlations' in the world; here we suggest a logical correlation, which can properly reflect whether there exists between two clauses an interactional relevance or influence in not only the form but also the 'meaning' or 'content' at a propositional logic level.

We define these concepts in a classical logic (CL) just toward a formal theory used as a criterion for judgment and explanation of the characteristic and purpose of an effective semantic system, which will be introduced later. Such criterion accords with the most general intuition and role of correlation, especially that functioning in the relationship with such motivational attitudes as desires and goals.

In all following definitions, φ and ϕ represent clauses as propositional wff. Let Atom(φ), a subset of Atom, be the set of all φ's propositional variables; and let [φ] be the set of all φ's CL-valuations.

Definition 1 (Correlation) φ is **correlative** with ϕ, if there exist such two CL-valuations v and v' that:

(1) $v(\varphi) \neq v'(\varphi)$;

(2) $v(\phi) \neq v'(\phi)$;

(3) $\forall x \in \text{Atom}: (x \notin \text{Atom}(\varphi) \cap \text{Atom}(\phi) \supset v(x) = v'(x))$

Intuitively, this definition means two logically correlative clauses must have at least one common atom whose change in truth-value can directly lead to both changes in respective truth-values of the two clauses. Thus defined 'common atom' takes an influential role as effective content in both clauses. Hereby in a logical level we have revealed the impacting or potentially impacting tie between two events/situations as their common influential content.

Examples: $x \wedge y$ is correlative with $y \wedge z$;

$x \wedge (x \vee y)$ is correlative with x, but NOT correlative with y;

x is NOT correlative with $\neg x \wedge x$.

φ and ϕ are correlative when they may influence each other in truth-value. Such influence is embodied in the change or valuation and the change of truth-values. This does accord with the monitor generation principles about how the world state changes fire plan transformations, suggested by the work of Rationale-based monitoring. Though this monitor generation per se has a little corrigible conflict with some of our views stated in 3.1, it really implies the embodiment of logical influence as 'value change'. [Veloso, 1998]

Definition 2 (Positive Correlation)

φ is **positively correlative** (**P-correlative** in short) with ϕ, if φ is correlative with ϕ, and

(1) If ϕ is an atomic formula, then:

there exist such two classical logic valuations v and v' that: v, v' $\in [\varphi] \cap [\phi]$, s.t.

$v(\varphi) = v(\phi)$, $v'(\varphi) = v'(\phi)$ and $v(\phi) = - v'(\phi)$;

(2) If $\phi \equiv \phi_1 \vee \phi_2$ or $\phi \equiv \phi_1 \wedge \phi_2$, then:

φ is P-correlative with ϕ_1, when φ is correlative with ϕ_1, or

φ is P-correlative with ϕ_2, when φ is correlative with ϕ_2;

(3) For else cases:

φ is P-correlative with the conjunctive/disjunctive normal form of ϕ.

Intuitively, φ and ϕ are correlative when they can influence each other in truth- value.

Examples: $x \wedge y$ is NOT P-correlative with $\neg y$, though they are correlative.

$\neg x$ is NOT P-correlative with x, though they are correlative.

Thus defined correlation seems neither too strong nor too weak as a filter ruling out perceived contents irrelevant with plan rationale, and even those irrelevant with the potential rationale. Having scrutinized various semantics, we find most logics with threat either of filtering out too much potentially relevant chance or that of letting pass into consideration two many features in a seeming literal relevance rather than meaning valid relevance, which will press too much into deliberation and depress the focusing effect of other established techniques for planning agents. In contrast, the following semantic system we introduce guarantees in logical aspect to prevent both disregarding influential consequences and letting in irrelevant trash.

4.2 A Logic for Motivational Attitudes

We have been attempting a computable logical framework toward formalization of motivational attitudes such as Intention and Goal structure since 1999 [Chen & Liu, 1999]. We used to present a similar system called L_{mp4c} that shows some notable properties for the formalization of agent's intention. A later representation called L_{m4c} for motivational consequences is equivalent to L_{mp4c} in logical aspect while it gains some simplifications in the technical aspect. [Chen et al., 2000] [Ji, 2000]

L_{m4c} is a four-valued semantic system based on the four-value "truth" set T = {t, f, 1, 0}, where t and f respectively read truth and falsehood, and 1 and 0 represent two cognitively-abstracted states called 'hypothetical truth' and 'hypothetical falsehood'.

Definition 3 (Cognitive Valuation) A **cognitive valuation** on propositional language L is a mapping $\pi : L \to T$ such that

(1) $\pi (x) \in T$, for all $x \in L$;

(2) $\pi (\neg\varphi) = -\pi (\varphi)$;

(3) $\pi (\varphi\wedge\phi) = \min (\pi (\varphi), \pi (\varphi))$; and

(4) $\pi (\varphi\vee\phi) = \max (\pi (\varphi), \pi (\varphi))$,

where – is a function on T defined as $-t = f$, $-f = t$, $-1 = 0$, $-0 = 1$, and the functions min and max are defined under the ordering $0 \prec f \prec t \prec 1$.

Intuitively, a cognitive valuation represents a possible cognitive state of an agent rather than a possible (physical) state of the world.

Definition 4 (Cognitive True/False Model)

π is a **cognitive true model** of φ, denoted by $\pi\in[\varphi]_t$, iff $\pi (\varphi) = t$;

π is a **cognitive false model** of φ, denoted by $\pi\in[\varphi]_f$, iff $\pi' (\varphi) = f$

Definition 5 (Cognitive Abstraction) π is a **cognitive abstraction** of π', denoted by $\pi\leqslant\pi'$,iff

$\forall x\in \text{Atom}: \pi (x)\in\{t,f\} \Rightarrow \pi'(x) = \pi (x)$.

To an intuitive sense, if $\pi\leqslant\pi'$, then π' contains no less "intention judgments" than π. Hereafter $\pi\approx\pi'$ denotes that $\pi\leqslant\pi'$ & $\pi'\leqslant\pi$; and $\pi<\pi'$ denotes that $\pi\leqslant\pi'$ & $\pi\approx\pi'$. (Note that $\approx$ is different from =.)

Definition 6 (Minimal Cognitive True/False Model)

π is a **minimal cognitive true model** of φ, denoted by $\pi\in〖\varphi〗_t$, iff

$\neg\exists\pi'\in[\varphi]_t: \pi'<\pi \;\&\; \pi'(\varphi) = \pi (\varphi)$;

π is a **minimal cognitive false model** of φ, denoted by $\pi\in〖\varphi〗_f$, iff

$\neg\exists\pi'\in[\varphi]_f: \pi'<\pi \;\&\; \pi'(\varphi) = \pi (\varphi)$.

We use '$\to$' to represent a special implication as defined below.

Definition 7 (Reducing Implication) φ **reducingly implicates** ϕ,

denoted by $\models_{Lm4c} \varphi\to\phi$, iff

$\forall\pi\in〖\phi〗_t, \exists\pi'\in〖\varphi〗_t : \pi\leqslant\pi' \;\&\; \pi'(\varphi) = \pi (\phi)$; and

$\forall\pi\in〖\phi〗_f, \exists\pi'\in〖\varphi〗_f : \pi\leqslant\pi' \;\&\; \pi'(\varphi) = \pi (\phi)$.

Theorem 1 (Consequential Correlation) $\models_{Lm4c} \varphi\to\phi$ iff φ is P-correlative with ϕ.

This theorem indicates a logical equivalence between the descriptive interpretation of correlation and the reasoning tool as its implementation.

This reasoning tool has many significant properties such as *reflexivity*, *transitivity*, *decidability*, *and classical equivalence in normal forms* etc., which offers great convenience and general feasibility for computation. Hence it is very practical for implementation. There is already a very fast algorithm for this semantic system. [Zhou, 2001]

Theorem 2 (Reflexivity, Transitivity)

(1) $\forall\varphi\in L$: $\models_{Lm4c} \varphi\to\varphi$;

(2) $\forall\varphi, \phi, \psi\in L$: ($\models_{Lm4c} \varphi\to\phi$ & $\models_{Lm4c} \phi\to\psi$) $\Rightarrow$ $\models_{Lm4c} \varphi\to\psi$

Theorem 3 (Normal Forms)

Let $\models_{Lm4c} \varphi\leftrightarrow\phi$ represent that $\models_{Lm4c} \varphi\to\phi$ & $\models_{Lm4c} \phi\to\varphi$. We have:

$\models_{Lm4c}\ \varphi_1\wedge(\varphi_2\wedge\varphi_3) \leftrightarrow (\varphi_1\wedge\varphi_2)\wedge\varphi_3$

$\models_{Lm4c}\ \varphi_1\vee(\varphi_2\vee\varphi_3) \leftrightarrow (\varphi_1\vee\varphi_2)\vee\varphi_3$

$\models_{Lm4c}\ \varphi_1\wedge\varphi_2 \leftrightarrow \varphi_2\wedge\varphi_1$

$\models_{Lm4c}\ \varphi_1\vee\varphi_2 \leftrightarrow \varphi_2\vee\varphi_1$

$\models_{Lm4c}\ \varphi_1\wedge(\varphi_2\vee\varphi_3) \leftrightarrow (\varphi_1\wedge\varphi_2)\vee(\varphi_1\wedge\varphi_3)$

$\models_{Lm4c}\ \varphi_1\vee(\varphi_2\wedge\varphi_3) \leftrightarrow (\varphi_1\vee\varphi_2)\wedge(\varphi_1\vee\varphi_3)$

$\models_{Lm4c}\ \neg(\varphi_1\wedge\varphi_2) \leftrightarrow \neg(\neg\varphi_1\vee\neg\varphi_2)$

$\models_{Lm4c}\ \neg(\varphi_1\vee\varphi_2) \leftrightarrow \neg(\neg\varphi_1\wedge\neg\varphi_2)$

$\models_{Lm4c}\ \neg\neg\varphi \leftrightarrow \varphi$

$\models_{Lm4c}\ \varphi \leftrightarrow \varphi\wedge\varphi$

$\models_{Lm4c}\ \varphi \leftrightarrow \varphi\vee\varphi$

Theorem 3 indicates that almost all the transformation rules for normal forms in classical propositional calculus are perfectly preserved in L_{m4c}. Such rules are necessary not only for effective reasoning, but also for the support to consequential correlation that every clause has its corresponding conjunctive or disjunctive normal form in L_{m4c} equivalence. Besides, normal forms as consequences never introduce irrelevant new atoms.

Some other characteristic properties of L_{m4c} such as *motivational preservativity* and *side-effect exclusion* further guarantee the good effect to use reducing implication for correlation testing. Here we list only part of them under a title of irrelevance exclusion; and for full-scale details and proofs please see References [Chen et al., 2000] [Chen, 2002] [Ji, 2000].

Theorem 4 (Irrelevance Exclusion)

When clauses φ_1 and φ_2 are NOT correlative. We have in L_{m4c} the following NON-satisfactions as an exclusion of improper consequences:

$$\nvDash_{Lm4c} \quad \varphi_1 \rightarrow (\varphi_1 \vee \varphi_2)$$
$$\nvDash_{Lm4c} \quad \varphi_1 \rightarrow (\varphi_1 \wedge \varphi_2)$$
$$\nvDash_{Lm4c} \quad \varphi_1 \rightarrow (\varphi_1 \vee (\varphi_2 \wedge \neg\varphi_2))$$
$$\nvDash_{Lm4c} \quad \varphi_1 \rightarrow (\varphi_1 \wedge (\varphi_2 \vee \neg\varphi_2))$$
$$\nvDash_{Lm4c} \quad \varphi_1 \rightarrow (\varphi_1 \vee \neg\varphi_1)$$
$$\nvDash_{Lm4c} \quad (\varphi_1 \wedge \neg\varphi_1) \rightarrow \varphi_1$$
$$\nvDash_{Lm4c} \quad (\varphi_1 \wedge (\varphi_1 \vee \varphi_2)) \rightarrow (\varphi_1 \vee \varphi_2)$$
$$\nvDash_{Lm4c} \quad (\varphi_1 \vee (\varphi_1 \wedge \varphi_2)) \rightarrow (\varphi_1 \wedge \varphi_2)$$
$$\nvDash_{Lm4c} \quad (\neg\varphi_1 \wedge (\varphi_1 \vee \varphi_2)) \rightarrow (\varphi_1 \vee \varphi_2)$$

Different from 'correlation', our definition of 'P-correlation' is asymmetric, that is we have in L_{m4c} both $\vDash_{Lm4c} (\varphi_1 \vee \varphi_2) \rightarrow \varphi_1$ and $\nvDash_{Lm4c} \varphi_1 \rightarrow (\varphi_1 \vee \varphi_2)$, which guarantees involving no irrelevant content in consequences. For example, assuming that proposition x_1 is the only precondition of an agent's sub-plan P_1 while x_2 has nothing to do with P_1, and the agent used to believe in $x_1 \wedge x_2$ as her previous anticipation, which had supported her rationale for choice on P_1. When she newly perceived or conceived that $x_1 \wedge \neg x_2$, such an anticipation alteration about x_2 leads to belief update, but NOT at all triggers reconsideration on P_1's precondition, since, according to the first formula of Theorem 4, $x_1 \wedge x_2$ cannot be implicated from precondition x_1 and its confliction with the new knowledge $x_1 \wedge \neg x_2$ is irrelevant.

As another notable property, this logic is *non-monotonic*. Assume $x_1 \vee x_2$ as previous desire e.g., we have

$$\vDash_{Lm4c} \quad (x_1 \vee x_2) \rightarrow (x_1 \vee x_2);$$

however when $\neg x_1$ is newly added, still

$$\vDash_{Lm4c} \quad (\neg x_1 \wedge (x_1 \vee x_2)) \rightarrow x_2, \quad \text{but}$$
$$\nvDash_{Lm4c} \quad (\neg x_1 \wedge (x_1 \vee x_2)) \rightarrow (x_1 \vee x_2),$$

indicating that only x_1 but NOT $x_1 \vee x_2$ is still relevant.

All these guarantee the competence of Lm4c system as an appropriate filtering mechanism of Chance Detection in the perception architecture.

4 Conclusion

Through this paper, the three philosophical points we have made about Chance in Section 2, namely knowledge incompleteness, motivation correlativeness and initiative openness, are adequately embodied in our methodological view and an architecture for resource-bounded planning agent with a hierarchical perception and a formal reasoning tool for motivational correlation detection, which avails discovering chance event and exerting positively relevant influences in her planning procedure interleaved with her learning and executing. Thus for Chance, we come to conclusion in one sentence:

A chance is an event/situation perceived or conceived outside an agent's previous ***anticipation****, while inside (at least partially inside) control of her* ***participation****, and revealed by its* ***correlation*** *with her motivational attitudes as Desire and Intention.*

Acknowledgement

Thanks to colleagues in SIG on AI Logics at Multi-agent Systems Lab for their valuable discussions.

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