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Boosting Human Insight by Cooperative AI: Foundations of Shannon-Neumann Logic

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Abstract

We present the logical foundation of an artificial intelligence (AI) capable of dealing with complex dynamic challenges, that would be very hard to handled using traditional approaches (e.g. predicate logic and deep learning). The AI is based on a cooperative questioning game, to boost insight. Insight gains are measured by information, probability, uncertainty (Shannon), as well as utility (von Neumann). The framework is a two-person cooperative iterated QA game, in which both players (human, AI agent) benefit (positive-sum): the human player gains insight and the AI player learns to improve its suggestions. Generally speaking, valuable insight is typically gained by asking 'good' questions about the 'right' topic, at the 'appropriate' time and place: by posing insightful questions. In this study, we propose a logical and mathematical framework, for the meanings of 'good, right, appropriate', within clearly-defined classes of human intentions.

Index terms— artificial general intelligence, complexity, cooperative learning games, frame drift problem.

? In section 1, we discussed algorithmic vs human intelligence, and the purpose of SN-Logic.

? In section 2, we present the two-person (human H, AI agent A SN) cooperative Iterated Questioning (IQ) game's role, from both H's and A SN 's perspectives

? In section 2.3, we discuss the dynamic drift problem: coping with the changing human understanding of a given complex challenge, using a dynamic optimization process. It's impossible to clearly define a single problem, in complex challenges (e.g. war on drugs) so that they can last for decades

? In sections 3.1-3.2, we discuss SN-Logic's requirements to cope with insight (which involves causality, information, logic, probability, uncertainty and utility) and the spaces over which SN-Logic operates

? In sections 3.3-3.4, we introduce SN-Logic's grammar: semantics + syntax The syntax is used by question generators, to build millions of possible questions

? In section 3.5, we present SN-Logic predicates of two classes: problem difficulty minimizing, and solution quality-maximizing, used in all inferences

? In section 3.6, we discuss the complexity and scope of SN-Logic, and section 3.7 highlights the distinction between knowledge acquisition (symbolic AI) and cooperative (machine) learning, both present in our AI

? In section 3.8, we introduce the normal form for making SN-inferences, about a question's insightfulness

? In section 4, we introduce the Insight Gain Tensor μ (when, where, what, which) to select sound inferences, from the many valid normal-form inferences, and measures of insight gains associated to these questions

? In section 5, we illustrate the use of SN-Logic, and we perform a validation test, to show how SN-Logic/IQ-game helps finding a solution path, to a component of a hard real-world solved case (quantum field theory research topic)

The Iterated Questioning or IQ game, is described in paper I. During a game session, the AI-agent, A SN , poses the human player H, a question q ? Q , it thinks is most insightful, given H's current cognitive mindset $C(t)$. H then explores it, and reports if it was insightful. These are the game's cooperative policies, both players agree to adopt for each Q&A episode. The game serves several purposes which benefits both players (positive-sum game) [7,9] For the human player, H, the IQ-game has the following main roles:

? The IQ-game is a Q&A process that reduces uncertainty and increases information about a specific problem, via a sequence of Q&As. It provides an effective tool, to gain insight on the many aspects of a complex challenge.

? The IQ-game drives a sequential (mostly left-hemispheric) conscious reasoning for solving well-defined (narrow) tasks. This process is mirrored by algorithmic AI. For complex tasks, this process alone fails to deliver full solutions. Conceptual solutions to such problems require the next process: insight-gaining.

1 II. Two-Person Cooperative IQ-Game

a) IQ-game: Human player perspective insight-gains (see paper I [8]): built by combining information, probability, uncertainty [6] and utility [7]. This paper is structured as follows:

7. Von Neumann, J. and Morgenstern O. (1944) Theory of Games and Economic Behavior, Princeton University Press: Princeton, NJ.

2 Ref

? The IQ-game drives a parallel (mostly right-hemispheric) non-conscious process, for gaining insights leading to an 'aha' moment. Largely non-conscious processing can be used, where the first process proves too slow or impossible (task is too broad, ill-defined and complex).

? The IQ-game is driven by dual goals: minimizing obstacles and maximizing solution qualities. The minimizing questions guide H to eliminate or reduce difficulties in the problem, when possible. The maximizing questions guide H to boost specific solution qualities, when constraints allow it. It is a dynamic optimization (changes with H's understanding). We discuss this process in section 3.4.

? The IQ-game provides a non-brittle reasoning framework, which continuously adapts to the human player H's cognitive intentions C. This mindset C evolves as H's understanding of the challenge progresses. The IQ-game copes with the framework drift problem (section 2.3).

For the AI-agent, A SN, the IQ-game has these roles:

? The IQ game produces game session episodes, from which the agent A SN can learn via cooperative learning.

? The IQ game ensures the agent remains human-aligned [10], because of the continuous human judgments. What is useful, informative, insightful for a human player H, does not necessarily mean the same for A SN, even if it starts that way. In the learning process, these values can drift apart, due to many factors. In the IQ game, human valuation is the ultimate arbiter, for the insight value of a question (since any AI short of a full AGI superintelligence, will fail miserably at this task), while SN-Logic estimates the insight values, given C(t).

? The IQ game taps into a most valuable human resource: our collective evidence-based knowledge, undeniably our greatest accomplishment (culture, science, technology).

Note that our collective belief-based human selections are often poor (e.g. who we put in power as our leader). The forces here are complex and evolutionary: desire for control, cognitive biases and herd mentality from the fear of social isolation (e.g. [11]).

These factors are absent in the IQ procedure, since decisions are individual, and based directly on one's own experience of a question's insight, within a very specific cognitive context C(t). It uses direct evidence-based judgment, where H's main incentive is to make life easier for herself. There are, of course individual variations in the experienced insightfulness of questions, but only stable patterns (across many individuals) are retained in cooperative learning (not presented in this paper). A complex challenge is typically time-evolving, multi-objective, multi-solution, multidiscipline, multi-level and open-ended, making it hard from the start, to clearly define a single problem, even when it is urgent (e.g. a crisis) or critical (e.g. sustainability), or both (e.g. a pandemic) Instead, there is a drift in the framing of problem and its solutions, as we accumulate new insights about a challenge: a framework drift problem. The drift cannot be handled with a static AI/ML system, focused on a given narrow problem.

The IQ-game, copes with the framework drift, by using an adaptive reasoning framework, and an adaptive cognitive intention $C = \{f \text{ framework, where, when, what}\}$ (section 3.3-3.4) which tracks the human player H's current understanding of the conceptual framework. It follows H's evolving understanding of the challenge, helping the SN-logic suggest the insightful questions, within each context C. The IQ-game doesn't define a problem from the start, but instead, let's H describe the Standard Logic Programming (predicate logic) is very effective when making strict deductions, but it cannot cope with the cooperative 2-person IQ-game. The purpose of SN-Logic is to provide an inference engine with the following requirements: it has to be ...

? precise (ambiguity-free) semantics axioms

? consistent (contradiction-free) framework within which, all SN-inferences can be made (normal-form inferencing)

? transparent (natural language, no hidden layers)

? explainable (no unjustifiable moves)

? human-aligned (no conflicts of with human cognitive intentions)

? non-brittle able to cope with fundamental concepts related to human-insight: causality (causes of insight), time-dependence (evolving understanding), information, probability, uncertainty (Shannon), utility (von Neumann), and insight (paper I). Brittleness is a common cause of AI failures.

To satisfy these requirements, we need a consistent set of SN-Logic definitions, axioms and rules, to which we now turn.

106 To reason using a predicate logic (such as SN-Logic), the variables x need spaces X , to scope the quantification:
107 $?x ? X, ?x ? X$. SN-Logic's concepts are partitioned in six compact concept spaces, over which we can perform
108 inferences (see appendices A-F):

109 Five vector spaces $\{T, S D, S C, S G, S S\}$, are used to describe the human player H 's changing cognitive
110 mindset $C(t)$, during the IQ-game. The AI agent, $A SN$, needs to know $C(t)$, because the insightfulness of
111 a question, depends on H 's increasing understanding of the challenge and its possible solutions, as insight is
112 accumulated.

113 The (tensor product) space $S A$, of possible conceptual actions (operation x object) provide the raw material
114 to build conceptual solutions.

115 3 Notes

116 ? Vector space T of exploration stages: vector variable [when ? T] describe the current stage when of the
117 exploration cycle. The vector [when] rotates in T over time (appendix A). SN-Logic's role, is to provide guidance
118 for insight-building via a Q&A process: suggesting when/where to pose which questions about what topic. To be
119 used in inferences, the meanings of the parts of speech (variables {when, where, what, which}), and the sentence
120 structure (questions which ? $q ? Q$), have to be both consistent and precise.

121 A SN needs a basic grammar (syntax, semantics, vocabulary) to communicate effectively with the human
122 player H , in a consistent and precise manner. SN-Logic is based on four consistent (contradiction-free) axioms,
123 to define its semantics precisely (ambiguity-free).

124 Let the human-player H 's cognitive mindset $C(f \text{ framework}, p)$ be defined by the current reasoning f framework
125 (next section), and three (intention) parameters: $p = \{\text{when} = p 1, \text{where} = p 2, \text{what} = p 3\}$, then:

126 (Sem 1) Shannon-informative questions: a question (which) $q(p, \text{action})$, that reduces uncertainty (Shannon
127 entropy) for H , who's mindset is $C(f \text{ framework}, p)$ (Sem 2) Neumann-useful questions: a question (which) $q(p,$
128 $\text{action})$, that has a human-aligned (via the 2-person IQ-game) utility, within a mindset $C(f \text{ framework}, p)$. It
129 helps H make progress towards a solution.

130 (Sem 3) SN-insightful questions: question (which) $q(p, \text{action})$ satisfying (Sem 1, Sem 2) is SN-insightful,
131 within a mindset $C(f \text{ framework}, p)$, otherwise it is SN-insightless.

132 4 Notes

133 These SN axioms of semantics, allow the AI to cope with core concepts of causality (causes of insight), dynamics
134 (changing reasoning frames) information, probability, uncertainty [6], utility [7] and insight (paper I). These are
135 necessary components of an insight-boosting AI. The axioms Sem1, Sem2 restrict the form of allowed questions.
136 This constraint is used by a Q-generator of questions $q ? Q$, to which we now turn.

137 The cooperative IQ-game is driven by dual-objectives: to minimize the problem's causes of difficulty, and to
138 maximize the solution's quality. The optimization must continuously adapt to H 's understanding of the challenge,
139 over an IQ-game session).

140 The SN-grammar has a simple syntax, specified for each question class Q . All questions $q ? Q$ will fall into two
141 classes $Q = \{Q \text{ min}, Q \text{ max}\}$, from two complementary (dual) perspectives: (a) causes of cognitive difficulty
142 (to minimize), (b) qualities of solution (to maximize). Each question class generates many of specific questions,
143 aimed at making insight-gains.

144 The purpose of SN-Logic is to incrementally boost our insight about solutions, by suggesting when/where to
145 pose which types of questions about what topic, while adapting to a moving target: our current understanding
146 the obstacles in a challenge

147 The question generator, or Q-gen, of difficulty-minimizing questions, uses a specific syntax for an evolving
148 cognitive mindset $C \text{ min} (f \text{ rame}, \text{topic}, p 1, p 2, p 3)$. There is a lot of freedom in which questions to
149 pose, even at a specific place and time, within a well-defined framework. We select a set of six commonly useful
150 problemsolving questions, to illustrate the procedure. Q-Gen Syntax: difficulty-minimizing questions $q(p, \text{action})$
151 ? $Q \text{ min } q \text{ min} 1$: at what exploration stage are we in now? (specifies when = $p 1 ? T$) $q \text{ min} 2$: what reasoning
152 frame are we operating in, now? (specifies [frame]) $q \text{ min} 3$: what topic in [frame] are we focusing on, now?
153 (specifies [topic]) $q \text{ min} 4$: where does the main difficulty reside? (specifies where = $p 2 ? S D$) $q \text{ min} 5$: what,
154 more specifically, causes this difficulty? (specifies what = $p 3 ? S C$) $q \text{ min} 6$: can you reduce the difficulty
155 (where) and avoid its causes (what), by using these actions? (specifies action ? $S A$ and which = $q \text{ min} 6 ? Q$
156 min)

157 5 The variable [action] (? S

158 $A ? O P \times O b$), is a product [verb operation] ($? O p$) \times [noun object] ($? O b$) (

159 6 appendices and section 5).

160 The [frame] variable, labels the reasoning framework currently being used (e.g. a discipline, a subject, a specialty,
161 a model, a system, a theory, a technology etc.). This framework can change from one exploration stage to the
162 next. It is a moving target, which mirrors our current understanding of a complex challenge.

163 The [topic] variable, labels a set of items we're focusing on, within [frame] (e.g. agents, assumptions, bounds,
 164 properties, qualities, relations, statements, strategies, tactics, techniques etc.). Typically, [topic] is a tool we use
 165 within [frame], to make progress. For a concrete example, see section 5.

166 Questions $q \in Q_{min}$ are SN-insightful, only if they are SN-informative (axiom Sem 1): they attempt to reduce
 167 a maximum possible amount of uncertainty (alternatives, ignorance, options, possibilities), within the context C_{min} .
 168

169 The generator of quality-maximizing questions, uses a specific syntax for an evolving cognitive mindset C_{max}
 170 (f rame, topic, p_1, p_2, p_3): © 2022 Global Journals

171 7 Ref q max1

172 : at what exploration stage are we in now? (specifies when = $p_1 \in T$) q_{max2} : what reasoning frame are
 173 we operating in, now? (specifies [frame]) q_{max3} : what topic in [frame] are we focusing on, now? (specifies
 174 [topic]) q_{max4} : where do you need a boost (goal)? (specifies where = $p_2 \in S, G$) q_{max5} : what solution
 175 aspect, do you want to focus on? (specifies what = $p_3 \in S, S$) q_{max6} : can you boost your goal (where) and
 176 the solution's quality (what), by using these actions? (specifies action $\in S, A$ and which = $q_{max6} \in Q_{max}$)
 177 Questions in Q_{max} are SN-insightful, only if they are SN-informative (axiom Sem 1): they attempt to reduce
 178 a maximum amount of uncertainty (alternatives, ignorance, options, possibilities), within the context C_{max}
 179 . They are specificityboosting questions which reduce uncertainty (Shannon entropy) to increase the solution's
 180 quality.

181 The SN concept of insight involves notions in information, logic, probability, uncertainty and utility (see paper
 182 I). To cope with these, we need a logic with quantifiers for scoping the variables x to specific spaces X . In standard
 183 predicate logic, a predicate is a function p of a variable x , which maps a variable $x \in X$, into the predicate's truth
 184 values $\{T, F\}$ [12]. $X \in \{T, F\}$ and $x \in X \Rightarrow p(x) = T$ or F

185 In SN-Logic, an SN-predicate is a function q of a variable x , which maps a variable $x \in X$, into the predicate's
 186 insight values $\{\text{insightful } I+, \text{insightless } I0\}$. $X \in \{I+, I0\}$ and $x \in X \Rightarrow q(x) = I+ \text{ or } I0$

187 In SN-Logic we define the two classes (minimizing, maximizing) of predicates $q(x)$, the mindset parameter p
 188 $\in P \in \{\text{when, where, what}\}$ and the predicate variable 'cognitive action':

189 ? SN-predicate questions $q(p, \text{action}) \in Q_{min}$, where $p \in P$, action $\in S, A$? SN-predicate questions $q(p,$
 190 action) $\in Q_{max}$, where $p \in P$, action $\in S, A$ The parameter $p \in P$ is in the space P of cognitive mindsets C_{min}
 191 (f ramework, p): the set of H's intentions, during the IQ-game. The AI needs to know this intent, to make
 192 useful cooperative suggestions. The mindset parameter p , encodes the type of insight, H wants to boost, at any
 193 given time. Thus, the number of distinct classes of challenges SN-Logic can cope with, is effectively infinite (N
 194 = $10^7!$), yet, based on a few small, compact concept spaces (cardinality $\approx 10^2$). In this sense, SN-Logic is
 195 economical (Occam's razor).

196 The computed complexity of SN-Logic is a theoretical upper bound, to determine the scope of SN-Logic. In
 197 practice the computational cost will be much lower, due to universal constraints (common to all challenge classes),
 198 because they are imposed by (mostly) challenge-independent forces:

199 ? causality: universal root causes of cognitive difficulties (e.g. confusion due to ambiguity, indecision due to
 200 missing information) and solution quality (e.g. accuracy, adaptability)

201 ? logic: valid inferences with sound semantics

202 ? planning: logically necessary chronology of solution steps

203 ? problem-solving: universal tactics to minimize obstacles (to avoid/reduce), and maximize solution quality
 204 (to target/increase/maximize) (e.g. divideand-conquer, minimize ambiguity, maximize order, simplify)

205 ? information: a question is only informative, if it reduces uncertainty by eliminating alternatives, options,
 206 outcomes, possibilities, within a cognitive mindset (intention) C , restricting the insightful questions to a
 207 manageable subset: $q \in Q^*(C) \in Q$, with $\text{Card}(Q^*(C)) \ll \text{Card}(Q)$

208 ? utility: a question is only useful, if it helps H, overcome obstacles, given a cognitive intention C , restricting
 209 the insightful questions to a manageable subset: $q \in Q^*(C) \in Q$, with $\text{Card}(Q^*(C)) \ll \text{Card}(Q)$

210 These rules impose a lot of structure on the SN-agent's insight grain tensor μ (f rame, topic, when, where,
 211 what, which), which is, in its fully general form, a high-dimensional rank-6 tensor, but is in practice, very sparse
 212 and decomposable into simpler tensors and convolution kernels.

213 The structure imposed by the universal (challenge class-independent) constraints, is sufficient to construct
 214 factored ('vanilla') tensors μ^* of much lower dimensions and lower rank: knowledge acquisition. A 'flavor' is
 215 then learned to fine-tune the tensors to each class of challenge, via cooperative learning (not described in this
 216 paper). Given the complexity upper-bounds of SN-Logic, the fine-tuning possibilities are vast.

217 A SN's fundamental problem, is to use the IQ-game, to guide a human player H, in when and where, to pose
 218 which types of questions about what topic, to gain a maximum amount of insight into a complex challenge.

219 A standard normal form inferencing (analogous to conjunctive and disjunctive normal forms, in digital and
 220 predicate logic), is necessary for the AI to cope with the computational complexity of SN-Logic. The AI can
 221 efficiently search for predicate variables action $\in S, A$, used as building-blocks for conceptual solutions. Given
 222 an evolving inferencing framework (frame, topic), SN-normal forms are the following: These numbers already
 223 compare favorably to a typical human problem-solver H, working by herself. But the real power of SN-Logic (its

scope of applications), comes from the combinatorial possibilities: the possible combinations and permutations of insight-boosting questions, needed to solve each class of challenges:© 2022 Global Journals

8 g) Symbolic AI (knowledge acquisition) vs Learning h) SN-Logic Normal Form

Notes SN normal-form for minimizing inferences Given a minimizing mindset $C_{min}(f, \text{rame}, \text{topic}, p)$, where $p \in P = \{\text{when, where, what}\}$: if $q(p, \text{action}) \in Q_{min}(C_{min})$, such that $\mu_{min}(f, \text{rame}, \text{topic}, p, \text{action}) > \mu_{crit}$, then $q(p, \text{action}) \in Q_{min}$, and $q(p, \text{action})$ is SN-insightful, within C_{min}

9 SN normal-form for maximizing inferences

Given a maximizing mindset $C_{max}(f, \text{rame}, \text{topic}, p)$, where $p \in P = \{\text{when, where, what}\}$: if $q(p, \text{action}) \in Q_{max}(C_{max})$, such that $\mu_{max}(f, \text{rame}, \text{topic}, p, \text{action}) > \mu_{crit}$, then $q(p, \text{action}) \in Q_{max}$, and $q(p, \text{action})$ is SN-insightful, within C_{max}

The sets $Q^*(C)$, are maximum-insight subsets of Q_{min} or Q_{max} , and $\mu(f, \text{rame}, \text{topic}, p, \text{action})$ is an insight-gain tensor (discussed shortly) whose insight gains are above a minimum critical cutoff μ_{crit} . The purpose of an insight-gain cutoff scale is intuitive, but its mathematical justification is outside the scope of this paper, which focuses only on logical validity, and ignores scientific soundness. The cutoff is related to a scale-invariance due to a conformal symmetry, under the renormalization of probabilities (unitarity). Scale-separation is used in quantum field theories [13], but justified by the conformal symmetry [14] of a renormalization group [15].

To perform successful inferences autonomously, the AI agent needs to possess the means of deciding whether a predicate variable $q(p, \text{action}) \in Q^*(C)$, leads to insight gains above a minimum lower bound (that is, $q(p, \text{action}) \in Q^*(C)$). The insight-gain tensor provides the SN-agent, the ability to select sound inferences, from a vast number of merely, valid ones (that is, of SN normal-form).

The AI performs SN normal-form inferences, to suggest insightful questions to explore, given human-targeted insight gains $C(p)$. These 'most insightful' questions, lie in a restricted subspace $Q^*(C) = \{Q_{min}(C_{min}), Q_{max}(C_{max})\}$, within a large space Q , of possible questions ($\text{Card}(Q) = 10^7$). Given a current mindset $C(p)$, A SN must find a subspace of questions $Q^*(C)$. This is where an insight-gain measure $\mu(p, \text{action})$ (convolution tensors and their kernels, used to restrict searches to optimal sub-spaces) are essential, to make sound inferences (real-world accurate), rather than merely valid ones (SN normal-form inferences). This will be presented elsewhere. For now, we simply discuss general constraints imposed by SN-Logic, on the tensor elements. The AI's capacity to generate SN-insightful I_+ questions, from a vast possibility of insightless I_0 ones (with actions $q(p, \text{action}) \in Q$), resides in the structure a highdimensional insight-gain tensor $\mu(\text{when, where, what, which}) \in \mu(p, \text{action})$, for each challenge class and reasoning frame. So the full rank-7 tensor is actually $\mu(\text{class, f, rame, topic, p}_1, p_2, p_3, \text{action})$. This function outputs the value g of insight gain associated to exploring a question which $q(p, \text{action}) \in Q$, where $p \in P$ encodes H's targeted insight gains. To be useful, the tensor μ is required to satisfy the following properties: $\mu: Cl \times Fr \times P \times SA \in [0, 1]$,

where Cl = set of challenge classes, Fr = set of reasoning frameworks (frame+topic), $P = T \times S_1 \times S_2$, $SA = O_p \times O_b$, $S_1 = SD$ or SG , and $S_2 = SC$ or SQ ? it is a measure of insight gain $\mu(\text{class, f, rame, topic, p, action}) = g \in [0, 1]$ (normalized)

? probability of all possible actions with a mindset p , must sum to one (unitarity)? $\mu_{crit} \in [0, 1]$ (minimum critical insight-gain value $\mu > \mu_{crit}$)

? $g = 0$ when $q(p, \text{action})$ is SN-insightless I_0 , given the mindset p

? $g = 1$ when $q(p, \text{action})$ is maximally SN-insightful I_+ , given the mindset p

? μ is initialized by satisfying heuristics from causality, information, logic, planning, problem solving and utility. These constraints provide the initial (challenge class-independent) approximation for μ

? μ gets optimized (fine-tuned) for specific classes of challenges, by cooperative learning, using the IQ-game's session episodes ©

10 Notes

We can now illustrate how SN-Logic is used, on a real challenge. In the IQ-game, both players (human: H, A SN) agree to use simple cooperative strategies, given H's current mindset C :

(1) A SN suggests its guess at a most insightful question ($q \in Q^*(C)$)

(2) H reports questions q she actually finds insightful The game's Q&A session, cycles over each obstacle, encountered within a challenge. Hundreds of such sub-problems may be encountered, to solve a challenge. Usually, the number and nature of these obstacles is unknown ahead of time, in real-world challenges.

For clarity, we use a single, static, not so complex, yet most difficult challenge. The scenario is: a young post-doctoral researcher, H, is trying to find a good quantum field topic, to spend her next ten years on. The first few moves (Q&As) of the two-person IQ-game, could proceed as follows: A by H: 'I want to identify the current obstacle'Q from A SN: 'Greetings! What2. Q from A SN: 'What is our current reasoning framework? (AI is using q_{min2} in Q-generator)

282 The framework is composed of a topic and a frame

283 11 Notes

284 The topic can be any useful tool we select, for overcoming the obstacle (select the closest match): The reasoning
 285 frame is the clearly-defined context, within which topic is being used ?? A by H: For my research direction, I
 286 want to identify a weakness in quantum field theory (QFT) (so here, [frame] ? theory, and [topic] ? qualities).
 287 A from H: 'I find some questions quite insightful, because (click on each insightful one, and note the reasons for
 288 your record):actions e.

289 12 Q from

290 I outlined the implications of QFT (e.g. including matrix unitarity), and QFT's experimental tests (e.g. including
 291 neutron decay experiments). I found reported incompatibilities (e.g. known violations of the CKM matrix's
 292 unitarity [16], in neutron decay experiments [17]). That seems like an interesting research area of quantum field
 293 theory, for me. This scenario shows how suggested questions from A SN , can replicate realworld solutions to
 294 obstacles, via a cooperative Q&A dialog. The researchers do something similar between themselves, early-on, to
 295 decide what to work on. But AI's complementary strength, is to cover many exploration paths, which are very
 296 often overlooked, yet may be key to quality solutions. This dynamic 'human-AI' interaction would be even more
 297 fruitful, in a group brainstorming session, where each member of the team, can select directions to explore and
 298 possible answers.

299 We mentioned (section 3.7), that insight-gain convolution tensors and kernels, form the bridge between the
 300 SN normal form inferencing (SN-validity), and measures of insight (SN-soundness); the bridge between logic
 301 (validity) and science (soundness). Initially, the tensors μ are the AI's 'vanilla' core, then, learned flavors are
 302 added to it, via machine learning to optimize the core AI, to distinct challenge classes.

303 The AI's core will be initialized by heuristics from causality, information, logic, planning, problem-solving, and
 304 utility. These apply to all types of challenges. The tensors' added flavor, needs to be learned using cooperative
 305 learning via a renormalization procedure, from the IQ-game's episodes. The construction of the insightgain
 306 tensors and cooperative learning will be described in future work.

307 13 VI. Discussion

308 14 Ref

309 We presented the foundations of SN-Logic, designed to boost human insight, to help overcome challenges that are
 310 hard to deal with, using traditional AI (mainly, predicate logic and deep learning neural nets). This required a
 311 logic, capable of coping with the concepts necessary to measure insight-gains: causality (causes of insight gains),
 312 dynamics (adaptive reasoning frameworks), information, probability, uncertainty ??Shannon) and utility (von
 313 Neumann).

314 In this paper, we presented the following:

315 ? The two-person (H, A SN) cooperative IQ-game's role from both H's and A SN 's perspectives
 316 ? The frame drift problem: coping with the changing understanding of a challenge, using a (non-brittle) logic
 317 and optimization process, which continuously adapt to the current human understanding and intention

318 ? SN-Logic's requirements to compute insightfulness (which involves causality, information, logic, probability,
 319 uncertainty and utility) and the concept spaces over which SN-Logic operates (to scope the quantifiers)

320 ? SN-Logic's grammar: semantics + syntax for posing questions $q ? Q$ from a vast space of potential questions.
 321 The syntax is used by a dual question generator ($q ? Q_{min}$, $q ? Q_{max}$), from which all questions are built (N
 322 ques = $O(10^7)$)

323 ? SN-Logic predicates of two question classes: problem difficulty-minimizing, and solution quality-maximizing,
 324 used in all inferences

325 ? The complexity of SN-Logic, and show it's broad scope and capability of coping with a large number of
 326 distinct challenge classes.

327 ? The SN normal-form for making valid inferences, about a question's insightfulness, efficiently within a vast
 328 space of possibilities

329 15 b) Conclusion

330 Issue ersion I

331 V IV (F)

332 ? Insight Gain Tensors μ (when, where, what, which) are necessary to select sound inferences (real-world
 333 accurate), from a vast (effectively infinite) number of valid ones (those with SN normal-form). μ measures the
 334 human insight gains, associated to questions posed, within their cognitive mindsets (C_{min} , C_{max})

335 ? A validation test, to show that SN-Logic can replicate the solution steps, to a real-world solved case
 336 (discovery in quantum field theory)

337 This paper focused solely on logic and validity of SN-inferences. It has not dealt with the equally important
338 issue of scientific soundness and accuracy. We will present the construction of the insight-gain convolution tensors
339 and kernels, and the learned structure (cooperative learning), in future papers.

A: Vector Space of Exploration Steps T (sample)¹



4

Figure 1: (Sem 4)



Figure 2:



34

Figure 3: 3 ? 4 ?

340



Figure 4:



Figure 5:

? Vector space S_C of difficulty causes: vector variable [what ? S_C] describes what in the reasoning's framework, is causing H difficulty. The vector [what] rotates in S_C over time while exploring the challenge (appendix C).

? Vector space S_G of mental goals: vector variable [where ? S_G] describes the solution quality, H intends to improve. The vector [where] rotates in S_G over time while exploring the challenge (appendix D)

? Vector space S_S of solution elements: vector variable [what ? S_S] describe what aspect of the solution, H intends to improve. The vector [what] rotates in S_S over time while exploring the challenge (appendix E)

?

Figure 6: ?

To compose something To compute something To construct something To design something To discover something To govern something To invent something To manage something To optimize something To predict something To reconstruct something e.g. intelligence, inverse problems, sensing e.g. music, arts, literature, programming e.g. any domain e.g. any domain e.g. engineering, technology e.g. science, mathematics e.g. crisis mitigation, leadership e.g. engineering, science, technology e.g. corporate, government e.g. any domain e.g. any domain To solve something e.g. any domain A by H: Boosting Human Insight by Cooperative AI: Foundations of Shannon-Neumann Logic
 to specify a current obstacle
 to minimize the obstacle
 to explore solution ideas
 to question a solution idea
 to verify a solution idea
 V. Validation Test: Post-Doc Researcher's Dilemma

Figure 7:

discipline	e.g. molecular biology
subject	e.g. protein folding
context	e.g. social revolution
environment e.g. location and time	
event	e.g. activity or pandemic crisis
model	e.g. just-in-time supply-chains
principle	e.g. quantum computing
method	e.g. optimization
network	e.g. communication or transport
theory	e.g. general relativity
specialty	e.g. programming
system	e.g. quantum communications
technology ...	e.g. fresh water extractor

Figure 8:

5. Q from A (explore any question you think is promising, or move-on)
 (AI is using q min6 in Q-generator + SN normal-form inferences + insight-gain
 Notations/kernels) by exploring: idealized cases of the theory (QFT)
 solved cases of the theory (QFT)
 simple cases of the theory (QFT)
 by outlining:
 consequences (causal) of the theory (QFT)
 implications (logical) of the theory (QFT)
 predictions (temporal) of the theory (QFT) tests (experimental) of the theory (QFT) by identifying:

inconsistent aspects of the theory (QFT)
 limitations of the theory (QFT) problematic aspects of the theory (QFT)
 inability to apply inability to compute inability to construct uncertain aspects of the theory (QFT) [topic]

inaccuracies (scientific, technical) A by H: I can't evaluate the weaknesses [topic = qualities] of quantum
 limitations (scope of applicability) unexplained items (no explanation) unjustified items (lack justification)
 missing direction in [topic]
 in/of [frame]

missing information about [topic] in/of [frame]
 missing intuition for [topic]
 in/of [frame]

missing knowledge of [topic]
 in/of [frame]

missing metric for [topic]
 in/of [frame]

missing ranking of [topic]
 in/of [frame]

missing standard for [topic]
 in/of [frame]

missing value of [topic]
 in/of [frame]

[Note: A by H: 'I lack an intuition for the weaknesses of QFT']

Figure 9:

7. Q from A
ersion I V
IV
Issue
Volume XXII
(F)
Frontier Research
of Science
Global Journal

Figure 10:

Notes
 clarity about the level of ambiguity of confidence in the level of complexity of construction of the level of dependencies in criticism of the level of flaws in exploitation of the level of fragmentation of imagination for the level of implicitness in intuition for the level of impracticality of understanding of the level of imprecision of etc.
 level of incompleteness of [item]
 level of inconsistency in VII. Appendices level of indecision about [item]
 level of indetermination in [item]
 level of inefficiency of [item]
 Global time basis vector: when ? p 1 ? T) to identify an obstacle [item] [frame]
 to minimize the obstacle to explore solution ideas to question [item] [frame]
 a solution idea to verify a solution idea inability to classify [item] [frame]
 inability to compute inability to connect inability to construct [item] [frame]
 Sci- inability to count inability to decide inability to design inability [item] [frame]
 ence to eliminate inability to evaluate inability to exploit inability [item] [frame]
 Front to extract inability to identify inability to interpret inability [item] [frame]
 tier to organize inability to perform inability to plan inability to [item] [frame]
 Re- predict inability to rank inability to relate inability to select [item] [frame]
 search inability to simplify level of insufficiency of level of uncertainty [item] [frame]
 Vol- in level of unpredictability of level of weakness of solution's [item] [frame]
 ume agents solution's cases solution's components solution's conse- [item] [frame]
 XXII quences etc. missing assumption about missing bounds on so- [item] [frame]
 Is- lution's constraints solution's dimensions missing capacity for [item] [frame]
 sue solution's economy missing classification of solution's efficiency [item] [frame]
 er- missing confidence in solution's effectiveness missing connec- [item] [frame]
 tion tions in solution's ethics missing constraints on solution's form [item] [frame]
 I missing evidence for missing explanation for missing freedom [item] [frame]
 V to solution's framework solution's information solution's justi- [item] [frame]
 IV fication missing information about solution's methods missing [item] [frame]
 (interpretation of solution's plan missing intuition for solution's [item] [frame]
 F properties missing justification for solution's qualities missing [item]
) motivation for solution's relationships missing organization of [item]
 solution's requirements missing representation of solution's [item]
 resources missing restriction on solution's restrictions miss- [item]
 ing scales in solution's space missing statements in solution's [item]
 statements missing tools for solution's sustainability missing
 verification of solution's utility solution's value etc. etc.
 inability to solve [frame]
 inability to transform [frame]
 inability to verify [frame]
 etc.

[Note: B:CNote]

Figure 11:

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