Measuring Intelligence Quotients of Hyper-Intelligent Semantic Networks

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Abstract

Berners-Lee's initial concept of the Internet was one of a complex, highly connected web of semantic knowledge built from a global collective intelligence. The Internet instead has evolved and cycled through different epochs of scale-free socio-technical-economic subnets of competing information streams, reminiscent, in part, of the growth spurts of print, television and telephony. The meaning of an intelligent semantic web transcends these stages of development – transparent and ubiquitous mobility and utility of processes leading to the construction of modular abstract web units of computational intelligence and resulting composites of computational organs and regimes. Nonetheless, in order to know what is more useful or powerful computationally begs for clarity of a spectrum and measurement of universal intelligence. This paper investigates conceptual types of abstract IQ measurement with respect to human-machine hybrid organizations. This manifestation is presented in the fold of ideas of hyper-intelligent networks that further climb the ladder of cognition in conscious-like, reflective, and thinking computational units possible in globally formed subnets of a semantic-evolving Internet. These intelligences liberate and extend the spans of the collective of human intelligence, transpersonal development possible with the integration of machines, humans, and hybrid computational species, utilizing emergent physical computational concepts, thus resulting in über-networks. The social implications for these potential super-intelligent subnets within the Internet are the vast acceleration of service lifecycles, organization transparency, and new co-opetive scenarios.

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Introduction

The ultimate goal of Berners-Lee's initial concept of the Internet was to have a complex, highly connected web of semantic knowledge built from the collective intelligence of the ensuing network (Berners-Lee, Hendler, and Lassila, 2001). This grew from his concern of the façade of the early web as a social curiosity built on low level communication of knowledge slightly above that of television and telephony. However, the semantic web, as this vision has come to be known, only introduces piecewise ontological power affixed to the contagion effects of social networks (Barabási, Newman, and Watts, 2006). Two developments produce a perceived accelerated collective intelligence for networks: (1) the scale free power-law of dissipation, and (2) individual node decision logic computed on its environment. Social networks in general and social semantic networks, in particular, display notions of intelligence by introducing complexity through network multi-directional feedback and propagation in their respective structures. The true semantic web holds the promise of combining and exploiting social network and computational intelligences. The question remains, "what are these hybrid intelligences."

In this paper, the information web is modeled as a concurrent adaptive agent-based time Petri net. It is also posited that a clearer definition of a network human-machine intelligence metric can be applied to a semantic web by adding degrees of adaptability, concurrent, and non-standard logic complexity to its underlying structure modeled by properly modified time Petri nets. We then extend these definitions to quantum-gravity and general uncertainty networks as future versions of a super semantic web consisting of biologic-inorganic-cosmic agents and further generalize a notion of universal intelligence IQ for these entities.

Some Terms

Causaloid – a tentative probabilistic causal net framework for quantum gravity that connects spacetime regions (event horizons).

Gödel automata/machine – a computational machine or automata which is capable of self rewriting its logic in order to improve on a rewards-based optimization.

GTU – general theory of uncertainty, a notion that variants of all uncertainty models can be represented by a constrained variable, a relationship functional, along with the underlying general stochastic nature of distribution of the constraint. Statistical parameters are part of this representation in which quantum logic, fuzzy logic, probability, possibility, Dempster-Shafer, and other models of uncertainty are parameterized under this meta-model for uncertainty (Zadeh, 2006).

MIQ – machine intelligence quotient, adopted measurements of intelligence quotients which were later developed into standardized intelligence scores of humans applied to decision-processing of computational units and hybrid man-machines.

Social networks – network structures consisting of thinking, empathic nodes such as combinations of human, animal, and machine units that help define a collective influence on each other and in outputting results to inputs that mimic decision-making.

Semantic web – the notion of a semantically tied Internet via the introduction of ontologies, descriptive languages, collective information, and dissemination of such knowledge and data to give an effect of learning.

Petri-nets (PN) – bipartite directed graphs with two classes of nodes that help model network processes with concurrency in actions, conditions for events, states (conditions are met or not), and events. Specifically, a Petri net consists of a set of conditions and events. When certain conditions are met, certain events are triggered. An initial marking of the network is the set of initial conditions met. If a condition is met, a token (dot) is placed (inside) for that condition (usually represented as a circle). An alternative description of a Petri net is that of a mutually exclusive set of places (placeholders) P, and transitions, T, along with a set of directed arcs between the two, with an initial marking, M_0. A place, p, may be an input, output or both of a transition t depending on either an arc maps to or from a transition to a place. A marking is the set of states of each node of the net. Formal mathematical definitions are given in the appendix.

von Neumann automata/machine – a computational machine or automata that is capable of self-replication without self-referentialness.

Theoretical Framework

Intelligence quota (quotient) notions for computational units, including humans are based on psychometric measurements, repeatable statistical experiments in collecting the potential of general problem-solving. Intelligence quotients were initially achievement scores divided by chronological age. These were subsequently replaced by statistically standardized scores. Collective networks and computational units pose a different type of challenge to this definition of intelligence. Additionally, different, more diverse concepts of multiple human and social intelligences have given rise to new controversies about the traditional view of IQ (Gardner, 1983; Goreman, 2005). Combining these multiple intelligences with an attempt to define a hybrid computational IQ taking into account network collective emergence may manifest a more apt realization of general intelligence in networks of human-machine mixtures. Additionally, concepts from recently developed universal IQs for human-machine agent systems generalize both human and machine intelligence quotas (MIQs).

These metrics are more appropriate than Church-Turing-Deutsch or Searle Chinese Room intelligence tests which do not measure intelligence (Detterman, 2011; Dowe and Hernandez-Orallo, 2012). Rather, they measure similarity to human decision making or the equivalent notion that any physical or humanly logical manifestation is computable (Church, 1947; Turing, 1950; Searle, 1980; Deutsch, 1985). Information on the type, architecture, and programming characteristics of the creators of its software and hardware ethos of the machine are necessary in order to more efficiently and accurately measure a truer IQ of that machine. Machines are nonetheless extraordinarily diverse in their makeup. In a sense, the universe of possible machines crafted from anthropomorphic imaginations and intellect add, at least, another potential level of complexity to that of human circuitry. In this way, the notion of universal IQ tests for collectives and hybrids of machines, humans, and other subcombinations thereof is exceedingly difficult and imprecise.

To that end, the emergent properties of networks and evolutionary processes within those collections may shed light on producing more powerful notions of universal IQ tests. Combined with novel ideas from non-Newtonian cosmology and physics and non-classical logic systems, hybrid machine/human collectives may be constructed and elevated to higher self-reflective and thinking entities. These prototypical über-entities may then help define novel notions of IQ for emergence and hence for evolutionary universal IQ tests. In this study we examine some of these emergent physico-logico theories of collectives. We define a class of self-replicating and self-writing machines in the framework of emergent physical models such as quantum gravity and generalized uncertainty logics. We commence with self-replicating machines (Von Neumann machines) and universal and optimally efficient self-writing programs known as Gödel machines, which are combined to form evolutionary intelligence machines that can then form clusters or networks of intelligent agents in a generalized semantic network intelligence (von Neumann, 1966; Schmidhuber, 2006). The causal and physical structure of this networked machine may then be conceptualized as a quantum-gravity causal network computer utilizing a diverse representation of underlying uncertainty models and grammars (Lloyd, Mohseni, and Rebentrost, 2013; Hardy, 2007; Zadeh, 2006).

Semantics of this network are manifested through the use of Petri nets to model the dynamics of concurrent machine states. Time Petri nets are used to simulate concurrency in networks where time constraints are put on the triggering of events. Here, we utilize non-standard logic versions of time Petri nets (fuzzy and quantum) to model the intelligence of web dynamics through its human-machine nodes. Universal IQs are then applied to these Petri net models to generalize semantic networks to diverse web participants and their ensuing collective intelligence. The web may also be framed as an evolutionary machine, as described above.

Methodology

In this conceptualization, the author utilizes the design science methodology of information systems research in which new notions or paradigms are built (artifacts) from the synthesis of smaller scoped ideas applied to larger scoped ones (Hevner, March, Park, and Ram, 2004). Meta-models for constructing a computational approach to generalize IQ for hyper-intelligent semantic networks will be given based on recent generalization to IQ for human-machine agents and networks.

Hypothesis

Human-machine networks in general and social semantic networks, in particular, such as smarter notions of a semantic web, have measureable computational intelligence in the sense of optimal Bayesian reward seeking and parsimoniousness (Hawkins, 2004; Hernandez-Orallo and Dowe, 2010). Computational intelligence is measureable through predictability and risk assessment power. Concepts of cognitive improvement, reinforcement learning, and dynamic relationships can be conceived based upon these iterative, emergent, and evolutionary measurements. Empowered networks of self-predicting, self-writing, and self-replicating agents are then optimally intelligent and robust entities. In turn, semantic networks embodied with this agency structure are optimally efficient and robust in a Bayesian global sense. These structures can then be specialized to the web dynamic.

Scope and Limitations

This paper shall be a conceptual exercise in sculpturing novel ideas about defining IQs for networks of human-machine hybrid nodes and notions of general techno-socio-economic value for these hybrid networks. This study is a research-based exposition that does not collect data nor manifests traditional quantitative or qualitative experimentation. It is a concept paper on the possibilities for defining generalized intelligence for diverse networks of thinking entities.

Significance of the Study

This study attempts to present a novel idea for defining a generalized IQ for intelligent semantic networks, particularly, a version of an intelligent semantic web. As such, the implications for our technical society are theoretical in nature, but present with the potential of building a more powerful version of our current notion of a semantic web and the proceeding step to living in a hyper-intelligent web. This hyper-intelligent web is this paper's projection for the next technology to follow in web science.

Background

The web as the ubiquitous social network

Social networks have been described as highly dynamic and interconnected groups of social species producing interleaved communication and pseudo-learning not possible or made efficient by individual social nodes alone. However colloquial the notion of "wisdom of the crowds" may be and as evangelized in Surowiecki (2005), networks without critically disruptive filters may not be as intelligent as smaller groups or individuals (MacKay, 1980). Moreover, conventional wisdom, quaintness for the "follow the leader" contagion, so prominent in crowd mentality, may lead to a massive group neurosis of hyper self-confidence in predictability power. Black swans, as risk juggernauts, it seems, are not often respected by the most analytic among us (Taleb, 2007).

Notwithstanding the dangers of mass mob psychology, Barabási, Newman, and Watts (2006) and Strogatz (2001) describe the complexity and non-linear dynamics of such social network entities through the cascading effects caused by power-law, scale free structures, mixed chaotic behaviors, clustering, assortativity, reciprocity, dense sub-communities, and loose hierarchies, such as holarchies. These network dynamics coupled with the proliferation of species, cultures, and geographically separated subgroups has caused the intermingling of memes as much as progeny. The idea of the web as the largest reasoning social network was popularly put forth in Barabási (2003). However, simultaneous to this, the web has separated us further by the ubiquity of pan-networking without physicality (Kadushin, 2012). The web has morphed our social dimensions, shortening some while widening others.

Social networks when interconnected as critical-thinking nodes of processing species, exhibit forms of emergent intelligence. Again, it is tantamount that intelligent social networks possess self-criticality and disruptive innovation of ideas. These are developmental intelligences as in individuals. So, while the paradigm of measuring the directional potentiality of intelligence of processing entities (anthropoids, organisms, and inorganic/organic-built machines) through gross intelligence quotients (standardized IQ scores and MIQs - machine IQs) subsists, intelligence of networks has received lesser attention, a paradoxical situation considering the now universal acceptance of forms of connectionism for human reasoning. Intelligent social agents as nodes in a social network promulgate collective intelligence in varying forms and spectra. Their processing dynamics should then be better dissected in order to construct metrics for measuring collective intelligence ala notions of universal IQ for human-machine agents (Hernandez and Dowe, 2010).

Semantic networks, Petri nets, and the web

Petri nets serve as excellent experimental mathematical constructs to model semantic networks-networks of entities that possess transformational relationships between nodes. The visionary work of Berners-Lee and others to foresee the prodigy of the initial DARPA net being a semantic network is known as the semantic web (Berners-Lee, Hendler, and Lasilla, 2001).

This rigor is sometimes lost in the domain-specific way in which the semantic web has been developed through the conventional RDFS/SPARQL/OWL technology trilogy and other related technologies as structured by W3C (2012) and described for the practitioner in Allemang and Hendler (2011). Petri nets, though, can model generalized transition systems that supersede the structure of the present web. Time Petri nets handle the case of when time constraints are put on network transactions. Furthermore, extensions to Petri nets that take into account the novel structure of non-standard logics such as fuzzy and quantum systems have been explored and can be applied to extend the power of the current web (Chen, Ke, and Chang, 1990; Li and Laro-Rosano, 2000; Ito, Ohta, and Tsuji, 2008; Huang and Xu, 2009).

Measurements of IQ in humans and machines

Approaches in psychometrics endeavor to more accurate measure and predict potential intelligence in humans. The original measurement was named a quotient because it calculated the ratio of a person's measured performance on a test against their chronological age. This eventually was replaced by broad spectrum statistically relevant standardized (Gaussian) scores within age groups. These tests are therefore relative to age intervals. Spearman (1927) devised a correlation analysis that chose the most positively correlated tests across different mental acuity measurements, globally forming an overall factor that measured positive effectiveness across all administered tests, the *g*-factor. Tests with high *g* factors were posited to have contributed the most to overall IQ and have been included in the batteries of conventional IQ tests. These scores and therefore, indirectly, the *g*-factor are nonetheless, based on normalized tables of scores that try to match a person's score with their expected chronologically appropriate score, the group distribution being set to $N(0,15)$, i.e., normal with mean 100 and standard deviation of 15. The quotient label and subsequent abbreviation, IQ remained, as unfortunate reminders. The g-factor was later separated into four constituent parts labeled, g_f, g_c, g_q and g_v, to depict central nervous system functionality for fluid intelligence, crystallized intelligence, quantitative reasoning, and visual-spatial reasoning respectively (Jensen, 1998; Deary, 2001; Horn and McArdle, 2007). Raven's visual IQ test, devised in 1938 remains a stalwart for today's battery of IQ tests. Continually revised standardized broad spectrum IQ tests, such as the Stanford-Binet and Wechsler scales are used in many current psychometric tests.

Because conventional IQ tests are age-time dependent, scores may change in an individual's lifetime. Additionally, administration of old category tests to more recent generations has shown that a rising movement in IQ occurs, the so-called Flynn Effect (Flynn, 1994). Higher g-factored tests have risen at greater rates than specifically administered educational content tests, specifically visual acuity tests which may have been influenced more from the technological boom of visual instruments and stimuli (Neisser, 1997). College entrance examinations tend to normalize somewhat for such time-related effects, but only as gross indicators of success in educational pursuits, not genuine intelligence. Rather than be conclusive about the diverse definition of intelligence, it seems that artificial tests have been assigned as the indicators of and de facto definition of a narrowly defined intelligence.

The theory of multiple intelligences has presented a diverse view of a human's spectrum of intellect. Gardner (1983) and others pursued the idea that a rainbow of categorically different intellectual accomplishments are plausible including the following list: (1) naturalist, (2) musical, (3) logical-mathematical, (4) existential, (5) interpersonal, (6) bodily-kinesthetic, (7) linguistic, (8) intra-personal, and (10) spatial. More recently in Goreman (2005), emotional intelligence in which a person's acuity to deal with their emotional status effectively was introduced as an additional practical measure. Risk intelligence has also been posited as a person's ability to predict (i.e., calculate probabilities), and hence, better assess risk (Apgar, 2006). There may indeed appear to be a continuous spectrum of meaningful and distinctive intelligence categories for humans as our collective ability to observe, patternize, and invent increase. More recently, in Hampshire, Highfield, Parkin, and Owen (2012), based on large scale studies, human intelligence has been shown to be highly diversified and of a fractionated nature. If we are to pursue a diverse definition of intelligence, human or otherwise, we must include not only different measurements, but a computationally sound methodology that addresses the need to accurate represent individual and ensemble traits.

Computational units process information and produce results and as such, present with the possibility to measure versions of general artificial intelligence (GAI). Indeed, this is a vibrant area of research within the GAI field which is itself quickly becoming the main emphasis of AI. The advantage of measuring a theoretical IQ for machines over human intelligences is that parameters of results can be readily quantified. Recent efforts to define a machine intelligence quotient (MIQ) have centered on the concept of rewards-based reinforcement learning and fuzzy variants thereof within the machine learning field (Repperger, 2001; Bien, Bang, Kim, and Han, 2002; Ulinwa, 2007; Legg and Hutter, 2007; Zarkadakis, 2011). Hernandez-Orallo and Dowe (2010) typify machine learning testing in a general system control-theoretic setting as follows: a machine, π is administered a test in an environment, μ through a sequence of actions, $a^{\pi,\mu} = \left(a_i^{\pi,\mu}\right)_{i=1,2,\ldots n}$, the normalized rewards, $\left(r_i^{\pi,\mu}\right)_{i=1,2,\ldots n}$ are given based on observations, $o^{\pi,\mu} = \left(o_i^{\pi,\mu}\right)_{i=1,2,\ldots n}$. The expected cumulative reward, $\hat{v}_\mu^\pi$ given to π during the test is posited to be a measure of machine intelligence, (i.e., the machine achieves reward levels as a means of learning),

$$\hat{v}_{\mu}^{\pi} = E_{a^{\pi,\mu}}\left(\sum_{i=1}^{\infty} r_i^{\pi,\mu}\right) \tag{1.1}$$

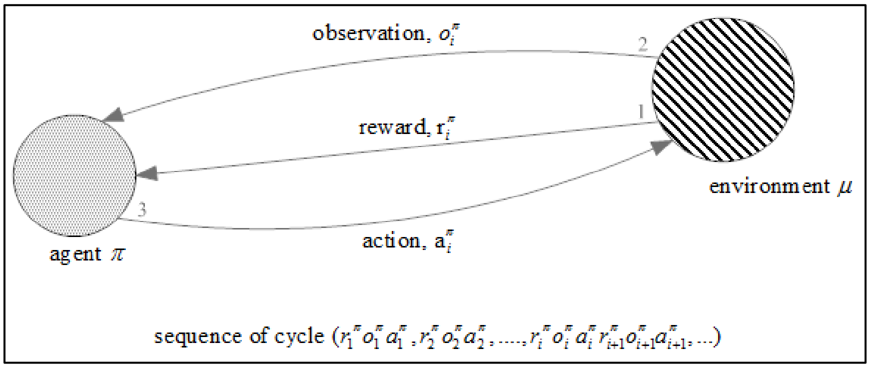

Figure 1 - Rewards-based agent-environment dynamic

The sequence of events follows as $r_1^{\pi,\mu} o_1^{\pi,\mu} a_1^{\pi,\mu} \ldots\ldots\ldots r_i^{\pi,\mu} o_i^{\pi,\mu} a_i^{\pi,\mu} r_{i+1}^{\pi,\mu} o_{i+1}^{\pi,\mu} a_{i+1}^{\pi,\mu} \ldots\ldots\ldots\ldots$, an initial reward, followed by an observation, and then a subsequent action from the testee. The pair $\left(r_i^{\pi,\mu}, o_i^{\pi,\mu}\right)$ represents a *perception* of step progression. In stochastic machines, one can assign conditional (or Bayesian) probability distributions to agents and environment as follows, $p_{\pi}(a_j \mid r_1^{\pi,\mu} o_1^{\pi,\mu} a_1^{\pi,\mu} \ldots\ldots\ldots r_i^{\pi,\mu} o_i^{\pi,\mu} a_i^{\pi,\mu})$ is the probability of the machine (agent) π executing the action, $a_j^{\pi,\mu}$ given that the sequence of events, $r_1^{\pi,\mu} o_1^{\pi,\mu} a_1^{\pi,\mu} \ldots\ldots\ldots r_{j-1}^{\pi,\mu} o_{j-1}^{\pi,\mu} a_{j-1}^{\pi,\mu}$ has transpired and $p_{\mu}((r_j^{\pi,\mu}, o_j^{\pi,\mu}) \mid r_1^{\pi,\mu} o_1^{\pi,\mu} a_1^{\pi,\mu} \ldots\ldots\ldots r_{j-1}^{\pi,\mu} o_{j-1}^{\pi,\mu} a_{j-1}^{\pi,\mu})$ is the probability of the environment outputting the perception, $\left(r_j^{\pi,\mu}, o_j^{\pi,\mu}\right)$ given that the sequence of events, $r_1^{\pi,\mu} o_1^{\pi,\mu} a_1^{\pi,\mu} \ldots\ldots\ldots r_{j-1}^{\pi,\mu} o_{j-1}^{\pi,\mu} a_{j-1}^{\pi,\mu}$ has transpired. The state of the machine test at cycle time interval *i* will then consist of the triplet $\left(r_i^{\pi,\mu}, o_i^{\pi,\mu}, a_i^{\pi,\mu}\right)$. Legg and Hutter (2007) quantify machine IQ by accumulating expected rewards over the set of all possible test environments Ω, for a machine agent π:

$$\Upsilon_U^\pi \equiv \sum_{\mu\in\Omega} p_U(\mu)\hat{v}_\mu^\pi = \sum_{\mu\in\Omega} p_U(\mu) E_{a^{\pi,\mu}}\left(\sum_{i=1}^{\infty} r_i^{\pi,\mu}\right) \tag{1.2}$$

where all environments, μ are codifiable on a universal machine U and are distributed as p_U. This is consistent with the notion that a human intelligence test should be diverse and practically measureable. The bounded-reward constraint condition, $\hat{v}_\mu^\pi \le 1$ is imposed on each environment μ in order that Υ_U^π converges. There are, however, several concerns about the computability of Υ_U^π, as addressed by Hernandez-Orallo and Dowe. Sums may be infinite, the dependence on a universal machine, and defining the distribution, p_U, entails using a variant of computational complexity, such as Kolmogorov complexity (K-complexity) which is incomputable. To get around these computational problems Hernandez-Orallo and Dowe invoke the use of the time-bounded version of Levin's *K*-complexity (*Kt*-complexity) given by:

$$Kt_U^{\max}(\mu,n) = \min_{p \ni U(p)=\mu}\left\{ l(p) + \log\left[\max_{{}^i a^{\pi,\mu} \le n}\left(t\left(U, p, {}^i a^{\pi,\mu}\right)\right)\right]\right\} \tag{1.3}$$

where μ is an environment, p is a program executing on a universal Turing machine U, *l(p)* denotes the length of *p*, *U(p)* denotes the results of *p* on U, and $t\left(U, p, {}^i a^{\pi,\mu}\right)$ denotes the time to execute *p* to print the perception $\left(r_{i+1}^{\pi,\mu}, o_{i+1}^{\pi,\mu}\right)$ after the sequence of actions ${}^i a^{\pi,\mu}$ in U. $Kt_U^{\max}(\mu,n)$ then depicts the optimal combination of length and execution time possible for an environment codifiable in U to produce a reward in U. In this paper we weigh each contribution to (de)emphasis time or length with convex weights, (w_l, w_t), $w_l + w_t = 1$, to obtain a weighted version of $Kt_U^{\max}(\mu,n)$ and make explicit an agent, $\pi \in \Pi$ from a multi-agent network, Π *:*

$$Kt_{U,w}^{\max}(\pi,\mu,n)=\min_{p\ \ni\ U(p)=\mu}\left\{w_l l(p)+w_t\log\left[\max_{{}^i a^{\pi,\mu}\le n}\left(t\left(U,p,{}^i a^{\pi,\mu}\right)\right)\right]\right\} \tag{1.4}$$

One can then approximate the probability p_U, for environments codifiable in U, using this complexity definition for output reward strings, $p_U(\mu)=2^{-Kt_U^w(\mu)}$. Hernandez-Orallo and Dowe further restrain the class of environments for practical computational reasons (i.e., balanced environments which possess symmetric rewards where $-1\le r_i\le 1,\forall i$, in addition to the condition $\hat{v}_\mu^\pi=E_{a^{\pi,\mu}}\left(\sum_{i=1}^{\infty}r_i^{\pi,\mu}\right)=0$ for a random machine agent *π*, and whose system is *n*-action reward-sensitivity, the condition in which for every subsequence of actions ${}^k a^{\pi,\mu}=\left(a_i^{\pi,\mu}\right)_{i=1,2,\ldots k}$ of length *k*, $\exists$ integer $m>0,m\le n,\ni$ for two other sequences, ${}^m b^{\pi,\mu}=\left(b_i^{\pi,\mu}\right)_{i=1,2,\ldots m}$ and ${}^m c^{\pi,\mu}=\left(c_i^{\pi,\mu}\right)_{i=1,2,\ldots m}$, the sum of rewards given as a result of the sequence of actions, $\left({}^k a^{\pi,\mu},{}^m b^{\pi,\mu}\right)$, given by $r\left({}^k a^{\pi,\mu},{}^m b^{\pi,\mu}\right)$ is different than $r\left({}^k a^{\pi,\mu},{}^m c^{\pi,\mu}\right)$). They next address the issues of time-sensitive testing and average rewarding in their final definition of universal intelligence IQ (here we add a weighting scheme for program time and length):

Definition. Adjusted (de-emphasize long tests while emphasizing complex tests) reward-weighted timed universal intelligence for finite subsets of reward-sensitive and balanced sub-environments of Ω with finite interactions using $Kt_{U,w}^{\max}$:

$$\Upsilon_U^\pi(m,n)\equiv\frac{1}{mn}\left(\sum_{\mu\in S}W_\mu^\pi\right)=\frac{1}{mn}\left(\sum_{\mu\in S}v_\mu^\pi(n)\Phi\left(n,Kt_{U,w}^{\max}(\pi,\mu,n)\right)\right) \tag{1.5}$$

where Φ is a bi-function such that $\Phi(x, y) \to -\infty$ as $x \to \infty$ and $\Phi(x, y) \to \infty$ as $y \to \infty$, S is a finite subset of *m* environments being *n*-action reward sensitive and is distributed as

$p_U^t(\mu) = 2^{-Kt_{U,w}^{\max}(\mu,n)}$ in Ω.

Finally one can compute a time-interrupted version of Υ_U^π considering averages over a limited time period. Let τ denote the time up to measurement and n_τ^π the number of completed interactions made by agent π in μ by time μ, and t_{n_τ} is the total time elapsed until action a_i was actuated.

Definition. Physical time limited, adjusted (de-emphasize long tests while emphasizing complex tests) reward-weighted timed universal intelligence for finite subsets of reward-sensitive and balanced sub-environments of Ω with weighted length/time finite interactions using $Kt_{U,w}^{\max}$:

$$\Upsilon_U^\pi\left(m,n,\tau\right) \equiv \frac{1}{m\widehat{n}}\left(\sum_{k=1}^{\widehat{n}} W_\mu^\pi \mid_\tau\right) = \frac{1}{m\widehat{n}}\left(\sum_{k=1}^{\widehat{n}} r_k^{\pi,\mu}\Phi\left(\tau, Kt_{U,w}^{\max}\left(\pi,\mu,\widehat{n}\right)\right)\right) \tag{1.6}$$

where Φ is a bi-function such that $\Phi(x, y) \to -\infty$ as $x \to \infty$ and $\Phi(x, y) \to \infty$ as $y \to \infty$, S is a finite subset of *m* environments in Ω, being *n*-action reward sensitive and distributed as

$p_U^t(\mu) = 2^{-Kt_{U,w}^{\max}(\mu,n)}$, and $\widehat{n} = n_\tau\left(\dfrac{t_{n_\tau}}{\tau}\right)$.

We now consider the interaction of hybrid systems which consist of cooperative (co-opetive on a spectrum) human and machine agents. Many systems including manufacturing and control systems are physical manifestations for such models. More abstractly, the semantic web may also be considered a hybrid human-machine system because of intermediate web services, human controlled transactions, and the interplay between the two. In Anthony and Jannett (2007), interactions between human and machine intelligences and complexities are discussed in a simplified interplay model. Hybrid system intelligence is defined as:

$$M_{IQ} = C_{IQ} - H_{IQ} \tag{1.7}$$

where C_{IQ} is the IQ attributable to the control subsystem (the interface between and containing both human operators and machines) and H_{IQ} to purely humans in the system. We look more closely at the definitions of each component.

$$\begin{aligned} C_{IQ} &= \sum_{i=1}^{n} \left(\alpha_{M,i} + \alpha_{H,i} \right) c_i, \\ \mathrm{H}_{IQ} &= \sum_{i=1}^{n} \alpha_{H,i} c_i + k_{HM} \sum_i \sum_j \alpha_{M,i} \alpha_{H,j} f_{ij} + k_{MH} \sum_i \sum_j \alpha_{H,i} \alpha_{M,j} f_{ji} \end{aligned} \tag{1.8}$$

where for a task sequence $T = \left(T_i\right)_{i=1,\ldots,n}$, $\alpha_{M,i} = 1_{[T_i \text{ is a machine task}]}$, $\alpha_{M,i} = 1_{[T_i \text{ is a machine task}]}$,

$f_{ij} =$ quantity of data transfered from T_i to T_j, $c_i =$ task intelligence cost required to execute T_i,

$k_{MH} =$ complexity measure in transferring data from machine to human,

$k_{HM} =$ complexity measure in transferring data from human to machine, and n is the number of tasks.

Here we can equate tasks with intelligence tests. Various environments can then be set for the execution of each task in a test. The statistical mean of a rewards-based optimization, as in (1.6) of the ensemble of tests over each environment, can then be computed. The complexity measures, (k_{MH}, k_{HM}) can each be measured using the time-bounded Levin $Kt_U^{\max}(\mu, n)$ metric given a sequence of subtask steps and the triplet state for each step, $\left(r_i^{\pi,\mu}, o_i^{\pi,\mu}, a_i^{\pi,\mu}\right)$ for each human-machine agent involved in a task test executed under an environment. The task costs, c_i are viewed as single-task (test) IQ measures required to perform the task T_i for each human-machine agent involved in executing that task. These may then be modified and recalculated appropriately using the definition of timed IQ measure from $\Upsilon_U^{\pi}\left(m,n,\pi\right)$ in (1.6):

$$\begin{aligned}
&c_{U,M_i,H_j}^{i}\left(m_{i,M_k,H_j}, n_{i,M_k,H_j}, \tau_{i,M_k,H_j}\right) = \Upsilon_{U,M_i,H_j}^{\pi}\left(m_{i,M_k,H_j}, n_{i,M_k,H_j}, \tau_{i,M_k,H_j}\right) \\
&k_{M_iH_j}\left(m_{M_iH_j}, n_{M_iH_j}, \tau_{M_iH_j}\right) = \Upsilon_U^{M_iH_j}\left(m_{M_iH_j}, n_{M_iH_j}, \tau_{M_iH_j}\right) \\
&k_{H_jM_i}\left(m_{H_jM_i}, n_{H_jM_i}, \tau_{H_jM_i}\right) = \Upsilon_U^{M_iH_j}\left(m_{H_jM_i}, n_{H_jM_i}, \tau_{H_jM_i}\right)
\end{aligned} \tag{1.9}$$

where $\Pi\left(T_i\right)$ is the set of agents engaged in carrying out task T_i, τ_i is the limit time for task T_i, n_i is the number of steps in task T_i (assumed to be n_i-actions reward sensitive), m_i is the number of environments under which task T_i is to be tested., τ_{i,H_jM_k} is the limit time for transferring data from human agent H_j to machine agent M_k, n_{i,H_jM_l} is the number of steps performing the transfer of data from human agent H_j to machine agent M_k (assumed to be n_{HiMj}-actions reward sensitive), and $m_{H_iM_j}$ is the number of environments under which data transfer from human agent H_i to machine agent M_j will be tested. Each task may be considered as being performed under different environments and agents, agents in a hybrid networked system. Inherent in (1.9) are the sequence of triplet states:

$$\begin{aligned}
&\left(r_i^{\pi,\mu}, o_i^{\pi,\mu}, a_i^{\pi,\mu}\right), \pi \in \Pi\left(T_i\right), i = 1, 2, \ldots n \\
&\left(r_i^{H_k,\mu}, o_i^{H_k,\mu}, a_i^{H_k,\mu}\right), H_k \in H = \text{set of human agents} \\
&\left(r_i^{M_k,\mu}, o_i^{M_k,\mu}, a_i^{M_k,\mu}\right), M_k \in M = \text{set of machine agents}
\end{aligned} \tag{1.11}$$

The component IQs in (1.8) can then be expressed as:

$$\begin{aligned} C_{IQ} &= \sum_{i=1}^{n} \sum_{M_k \in \Pi(T_i)} \sum_{H_j \in \Pi(T_i)} \left(\alpha_{M_k,i} + \alpha_{H_j,i}\right) c^i_{U,M_i,H_j}\left(m_{i,M_k,H_j}, n_{i,M_k,H_j}, \tau_{i,M_k,H_j}\right), \\ \mathrm{H}_{IQ} &= \sum_{M_k \in \Pi(T_i)} \sum_{H_j \in \Pi(T_i)} \left[\sum_{i=1}^{n} \alpha_{H_j,i} c^i_U \left(m_{i,M_k,H_j}, n_{i,M_k,H_j}, \tau_{i,M_k,H_j}\right) + k_{H_j M_k} \sum_i \sum_l \alpha_{M_k,i} \alpha_{H_j,l} f_{il} + k_{M_i H_j} \sum_i \sum_l \alpha_{H_i,l} \alpha_{M_j,i} f_{li} \right] \end{aligned} \tag{1.12}$$

Under the definitions of (1.12), M_{IQ} can be considered a measure of the hybrid IQ of a collective, (i.e., a collective intelligence quotient of a cooperative agent-based network). In a co-opetive agent-based network, the task intelligence costs increase based on the game strategies that are executed by the agents mainly as a result of the added computations needed to calculate effective equilibrium strategies, if they exist. This is considered a future research project for intelligence quotient of agent networks employing uncooperative and coalition-forming game strategies. Additionally, (1.12) may be generalized further to accommodate for various categories of agents, hybrids of organic-inorganic machines on a spectrum of processing type and computing media. The resulting sums would be over all categories of these co-opetive hybrid computational machines. If the index space, $\mathcal{M} = \left(\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_d\right)$ represents the hybrid machine category census (*d* distinct hybrid machine agent types), then (1.12) can be generalized to:

$$\begin{aligned} C_{IQ} &= \sum_{i=1}^{n} \sum_{M_k \in \mathcal{M}_k, k=1,2,\ldots,d} \sum \left(\sum_{k=1}^{d} \alpha_{M_k,i} \right) c^i_{U,M_1,\ldots,M_d}\left(m_{i,M_1,\ldots,M_d}, n_{i,M_1,\ldots,M_d}, \tau_{i,M_1,\ldots,M_d}\right), \\ \mathrm{H}_{IQ} &= \sum_{M_k \in \Pi(T_i) \cap \mathcal{M}_k, k=1,2,\ldots,d} \sum \left[\sum_{i=1}^{n} \alpha_{M_k,i} c^i_U \left(m_{i,M_1,\ldots,M_d}, n_{i,M_1,\ldots,M_d}, \tau_{i,M_1,\ldots,M_d}\right) + \sum_{q \in perm(M_1,\ldots,M_d)} k_q \sum_i \sum_l \alpha_{q,i} f_{il} \right] \end{aligned} \tag{1.13}$$

where q is a subset of a permutation of $\left(M_1, M_2, \ldots, M_d\right)$, $\alpha_{q,i} = 1_{[\text{all machines in } q \text{ partake in } T_i]}$, and $k_q = \sum_{\pi \in q \subseteq \Pi} Kt^{\max}_{U,w}\left(\pi, \mu, n\right)$, is the modified *Kt*-complexity associated with interfacing between all machines in the subnet $q \subseteq \Pi$, in testing in the environment, μ . Note that in the subnet, *q*, all agents execute per their natural parallelization/synchronization scheme. It is assumed that individual task (test) subprograms have been appropriated so that the subnet complexity, k_q is additive in the individual agent subprogram complexities, $Kt_{U,w}^{\max}(\pi, \mu, n)$.

We will now consider modeling an agent-based interaction network with transitions, with Petri nets. The web may be specifically considered as an instantiation of such an object. This will then be merged with our notions of calculating M_{IQ} for that network, so that the properties of its Petri net can be expressed and expanded upon in M_{IQ} . We use the initial Petri net model for agent-based interactive networks from Ezzedine and Kolski (2008) and Marzougui, Hassine, and Barkaoui (2010). Petri nets can be used to generalize service transition systems that display state through transition mappings, conditions for the execution of events or services, and placeholder resources (properties) of those entities in a directed bipartite graph structure. We model service interactive agents as a 6-tuple, $\pi = \left(S_\pi, A_\pi, E_\pi, C_{\pi,} R_\pi, P_\pi\right)$ where $S_\pi = \left(s_1^\pi, s_2^\pi, ..., s_{n_\pi}^\pi\right)$ is a set of services that they can render, $E_\pi = \left(e_1^\pi, s_2^\pi, ..., e_{n_\pi}^\pi\right)$ a set of events triggering these services, $C_\pi = \left(c_1^\pi, c_2^\pi, ..., c_{n_\pi}^\pi\right)$ a set of conditions (singular and compound) necessary to establish those services, $R_\pi = \left(r_1^\pi, r_2^\pi, ..., r_{n_\pi}^\pi\right)$ are the resources necessary for those services , and $P_\pi = \left(p_1^\pi, p_2^\pi, ..., p_{n_\pi}^\pi\right)$ are properties produced by those services. Additionally, each service, s_i^π is comprised of a set of actions, $a_i^\pi = \left(a_{i_1}^\pi, a_{i_2}^\pi, ..., a_{n_i}^\pi\right)$ some of which may be visible as in displayable or tangible or invisible as in an internal control. We denote the set of visible actions for agent π as $va_i^\pi = \left(va_{iv_1}^\pi, a_{iv_2}^\pi, ..., a_{nv_i}^\pi\right)$ and non-visible actions as $nva_i^\pi = \left(a_{inv_1}^\pi, a_{inv_2}^\pi, ..., a_{nnv_i}^\pi\right)$.

When an agent π is presented with a trigger event, e_i^π , it must then check for the presence of the pre-conditions, c_i^π and the availability of the resources, r_i^π before actuating the actions, a_i^π that produce the properties, p_i^π . The Petri net representation of this class of service agent network consists of the network state, (i.e., the state of each agent), housed in the places, while the transition consist of the compound transition given by trigger event-check pre-condition and pre-resources-actuate actions-produce properties. This transition will then lead to another network state and subsequent place. Denote the state *i* of the agent network by $\Pi^i(N) = \left\{ \pi^i = \left(e_1^{\pi^i}, s_2^{\pi^i}, ..., e_{n_\pi}^{\pi^i} \right) | \, \pi \in N \right\}$. Note that as state changes, event triggers, pre-conditions, resources, properties, and actions may also change for each agent member.

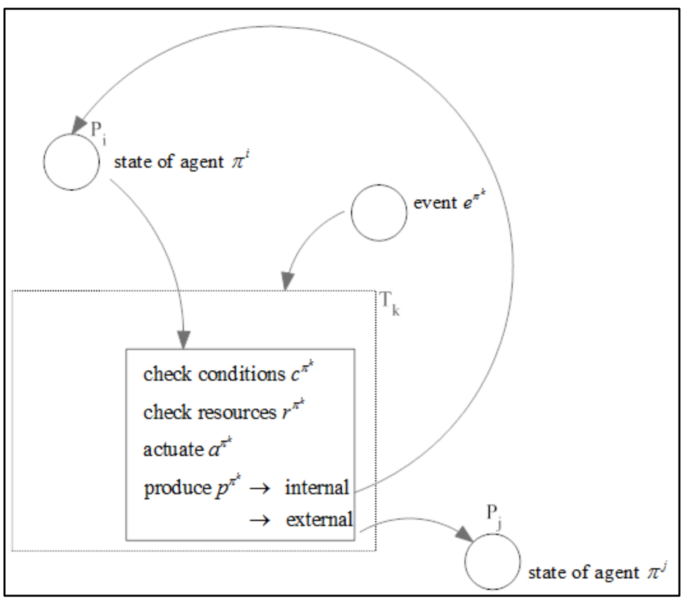

Figure 2- Petri net for service agent network

If one now imposes time constraints on the firings of transitions, (i.e., the trigger events and the ensuing checks, actuation, and production), given by lower and upper time bounds,

$\alpha^{\pi} = \left(\alpha_i^{\pi}\right), \beta^{\pi} = \left(\beta_i^{\pi}\right), 0 \le \alpha_i^{\pi} \le \beta_i^{\pi}$, a time service agent Petri net can be represented as the 8-tuple, $\pi = \left(S_{\pi}, A_{\pi}, E_{\pi}, C_{\pi}, R_{\pi}, P_{\pi}, \alpha^{\pi}, \beta^{\pi}\right)$.

We discuss how to frame the Petri net formalism of a time service agent network to the framework for the reward-based intelligence quotient metric of that agent network. Rewards can be viewed as the eventual products that are manifested by the actuation of agent services. Agents learn by reinforcement of reward optimization. If then products produced by way of certain actions are optimized, then a reward-based approach can be overlaid onto the Petri net as a dynamic. The rewards-based agent network is stochastic and so a rewards-based Petri net can be framed as a stochastic Petri net (SPN) (see Appendix for definition of a general stochastic Petri net, GSPN) which is then represented as the extended tuple $\pi = \left(S_{\pi}, A_{\pi}, E_{\pi}, C_{\pi}, R_{\pi}, P_{\pi}, \alpha^{\pi}, \beta^{\pi}, p^{\pi}, \mu^{\pi}\right)$, where $\left(p^{\pi}, \mu^{\pi}\right)$ are conditional probabilities respectively of the agent actions and environment feedbacks. The environment feedbacks for the service agent network are essentially the product portfolios of the agents, which would be the rewards, and the observations from the environment would be the events triggered to actuate the next actions from the agent network. The triplet state of the rewards-based network, $\left(r_i^{\pi,\mu}, o_i^{\pi,\mu}, a_i^{\pi,\mu}\right)$, would then be rewritten in the Petri net formalism as $\left(r_i^{\pi,\mu}, e_i^{\pi,\mu}, a_i^{\pi,\mu}\right)$ where its properties $p_i^{\pi,\mu}$ are derived from its resources $r_i^{\pi,\mu}$ under the environment μ. The time constraints in measuring M_{IQ} must satisfy the conditions $\alpha_i^{\pi} \le \tau_i^{\pi} \le \beta_i^{\pi}, i = 1, 2, \ldots n$. In (1.13), the M_{IQ} metric without regard to the nature of an agent, can then be framed through the time Petri net structure.

Emergent notions of machine intelligence

Considerable generalizations may be made to expand the Petri net formalism that involve emergent physical models, including quantum and evolutionary processes and the formalism of a general stochastic Pertri net just discussed earlier in this section. See the Appendix for functional definitions of quantum and evolutionary Petri nets in attempts to present versions of these extensions. Specifically, we look at quantum and quantum-gravity versions of Petri nets. In the Appendix, a quantum Petri net (QPN) is a quantum extension of a five-tuple extended complex-valued Petri net $\Gamma = \left(P, T, {}^{\bullet}(-), (-)^{\bullet}, M_0, w\right)$ such that the firing sequences transition using quantum firing rules (QFRs)) (i.e., at integer time instances for quantized time and without conflict). See the Appendix for definitions of the components of Γ. The weight function $w : \left(P \times T\right) \cup \left(T \times P\right) \to C$ is complex-valued and as such acts as the complex amplitude of quantum probabilities. The architecture of a QPN Γ, model quantum structures such as a qubit, quantum Turing machines (QTMs), and more generally, quantum state machines (QSMs) (Ito, Ohta, and Tsuji, 2008). Time service agent Petri nets π, discussed before can therefore be generalized to quantum versions using the complex weighing function *w* and QFRs.

We now look at a version of a quantum gravity causal net from Hardy (2007) as a prototype for a quantum-gravity automaton. This automaton may then be simulated by a corresponding version of a quantum-gravity Petri net. Hardy (2007) proposed using a notion of causaloids Λ. Denote by *S* the set of all possible computer gates. Let *N* be the number of agents in a quantum-gravity system. We restrict the number of gates to use to some subset, $S_N = \left(s_i\right)_{i \in I_N} \subset S$ where I_N is a labeling index set with *N* labels. Quantum-gravity computers (QGCs) can then be defined as pairs $\left(\Lambda, S_N\right)$. The class of QGCs generated by the causaloid Λ, that are restricted by an upper bound of *M* agents is given by $\Upsilon_M^\Lambda = \{(\Lambda, S_n) \mid \mathrm{n} \le M\}$.

Causaloids can be viewed as extensions of classical probabilistic causal nets Λ_C conditioned by relativistic spacetime regional causation (event horizons) that are linked by indefinite causal structures. The definition of an indefinite causal structure is given in more detail in Hardy (2007) and is the driving force behind the idea of physical causaloids. Essentially, indefinite causal structure is the ethos that causality is not dependent on a time structure, but on something more general, (i.e., a quantum-gravity induced unified spacetime). Hardy (2007) has shown that quantum-relativistic and classical mechanical structures can be simulated by classes of Υ_M^Λ for small *M*. Hardy further conjectures that a class of Υ_M^Λ may also simulate a QGC. In particular, by using limiting cases of this Υ_M^Λ, to classical and quantum computers, and utilizing a course-grained geometry, a universal computer (Λ, S_U) (with a particular gate subset S_U) within the class Υ_M^Λ can also be simulated. In any case, causaloid structures can be applied to QPNs to extend a Petri net to the realm of quantum-gravity structures. We expand the definition of a QPN to include a causaloid component, and thus define a causaloid induced quantum-gravity Petri net (CIQGPN) $\Gamma_\Lambda = \left(P, T, {}^\bullet(-), (-)^\bullet, M_0, w, \Lambda\right)$. In Γ_Λ all notions of transition and firing rules are dependent on the dynamics of Λ. In particular, we may expand time service agent Petri nets to CIQGPNs utilizing associated causaloid structures.

The concept of general uncertainty Petri nets generated by Zadeh's GTU constraint representations will be introduced later as a further generalization to CIQGPNs, since the structural dynamics of a causaloid is a type of uncertainty measure through regionally linked causal probabilities. Quantum and causaloid probabilities may be expressed through GTU constraints by the nature of the logical structure of its underlying precisiation natural language PNL) (Zadeh, 2006).

The idea of evolutionary processes begs the question, “can Petri nets endowed with rules for evolution make sense as a well-defined structure for evolutionary Petri nets and can they simulate evolutionary automata as Petri nets can for classical automata (and finite state machines)?” In the Appendix, the construction of such evolutionary processes from Burgin (2013) is given. Here we present a proposal for the structure of evolutionary Petri nets. These evolutionary Petri nets start with a sequence of general automata (all the automata types we have discussed in generality, including the GTU inspired automata in the next section may be substituted) $E = \{A_t\}_{t \in T}$. Following the rules for an evolutionary automata from Burgin (2013), one can reverse-engineer Petri nets that evolve to sequences of general Petri nets, $E = \{A_t\}_{t \in T}$, indexed by time. In the case of CIQGPNs, time is replaced by a causaloid induced spacetime index, *st*. Following the rules of Burgin (2013), a evolutionary Petri net is the a sequence of Petri nets $E = \{A_t\}_{t \in T}$ following the Burgin evolution rules outlined in the Appendix. Again, service agent Petri nets may be extended to forms of *E* with the concept of timed being replaced by possibly indefinite causal structures driven by causaloids Λ, and indefinite spacetime indices *st*. Measured information thermodynamic and entropy notions of time flow may also be approached as indexing surrogates for time under gravitational rules (Yi and Kim, 2013).

We now review a general theory of uncertainty (GTU), from Zadeh (2006), in which a meta-pattern for uncertainty metrics is developed. The motive will be to eventually develop GTU rewards-based Petri nets for the most general uncertainty setting to pursue IQ metrics.

In Zadeh(2006), a generalized theory of uncertainty (GTU) in which notions of uncertainty including: (a) probabilistic, (b) possibilistic, (c) veristic, (d) usuality (fuzzy probability), (e) random, (f) fuzzy graphic, (g) bimodal, and (h) group types of uncertainty are modeled through a generalized constraint model. A generalized constraint language (*GCL*) consists of generalized constraints coupled with rules for qualification, combination, and propagation. Generalized constraints (*GC*) are triplets of the form (X, r, R) where *X* is a constrained variable, *R* is a constraining relation, and *r* is an indexing variable which identifies the modality or type of constraint semantics. The index list consists of the following pneumonic: $r = blank$, possibilistic, $r = p$, probabilistic, $r = v$, veristic, $r = u$, usuality, $r = rs$, random set, $r = fg$, fuzzy graph, $r = bm$, bimodal, *qp*, quantum probabilistic, and $r = g$, group variable.

A formal uncertainty language such as a *GCL* calculates precisiations (the mapping of a vague measure into a precise number) more readily than formalized logics. Constrained variables, *R* take the form of: (a) a general *m*-vector, (b) a proposition, (c) a function, (d) a function of another variable, (e) a conditioned variable, (f) a structure, (g) a group variable, or (h) another generalized constraint. Bi-valent conjunction, projection, and propagation operators, $\otimes_c$, $\otimes_{proj}$, $\otimes_{prop}$ respectively act on two (possibly different) *GC* objects, $\left(X_{k_1} \text{ is } \_i_1 \ R_{j_1}\right)$ and $\left(X_{k_2} \text{ is } \_i_2 \ R_{j_2}\right)$ to generate a third (possibly different) GC object $(X_{k_3} \ is\_i_3 \ R_{j_3})$.

A *GC* object, $g = (X, r, R)$, is now associated with a test-score $ts_g(u)$ which associates an object *u* (which the constraint is applicable to), a degree to which *u* satisfies the constraint. The test score defines the semantics of the constraint that is associated with *g*. The value of $ts_g(u)$ may be a point in the unit interval, $[0,1]$, a vector, or other mathematical structure such as a member of a semi-ring, lattice, poset, or bimodal distribution. The relation, *R* from *g* is allowed to be non-bivalent, as in a fuzzy equivalence. In this way, a *GC* generalizes a fuzzy set and so, a *GCL* can lead to a generalized fuzzy system of generalized constraints as well as other paraconsistent systems and quantum logic.

Because the conditional probabilities and the complexity distribution associated with rewards-based agent networks can be replaced by appropriately designed GTU logics, all rewards-based Petri nets can be likewise generalized. With this generalization applied to the Petri net uncertainty model, reward-based agent networks can be based on a *GC* object and hence, the IQ metric of (1.16) can be applied with a *GC* as a parameter in the associated Petri net model of the rewards-based agent network. As in the formal definitions of quantum and fuzzy Petri nets (see Appendix), the firing rules for transitions can be reformulated using an associated GC.

Definition. GTU (general theory of uncertainty) Petri net (GTUPN): a GTUPN is a complex (extended) version of a generalized stochastic Petri net (GSPN) (see Appendix for definition of GSPN and EPN) replacing the firing delay pdfs with a GC objects, $gc = \left(x, is\_, R\right)_{x,is\_,R}$, with associated test score function $ts_g(u) \doteq R\left(E_g\left[u\right]\right)$, to define the firing rules (FR) of the marking process. This defines an 8-tuple, $\left(P, T, {}^{\bullet}(-), (-)^{\bullet}, M_0, w, H, gc\right)$ with the FR:

$$M_R(p) = ts_g\left[M(p)\right] = R\left(E_g\left[M(p)\right]\right) \tag{1.14}$$

We now construct the MIQ metric from the components of (1.13) for a general heterogeneous machine adaptive agent network with GTU logics as a structure for very general uncertainty-based communication (transition firings). We use the agent layout of (1.13) in a rewards-based multi environment testing schema with the GTUPN structural dynamics. Tokens in the GTUPN are represented as network agent states $\left(r_i^{\pi,\mu}, e_i^{\pi,\mu}, a_i^{\pi,\mu}\right)$ as before. The firing rules (FR) are given by (1.14). Transitions are given by the sequence of checks-event preconditions, resources available, actuate actions, and produce products. Rewards are issued and observations made by environmental controllers. In the GTUPN, the firings of the sequence are dictated by the uncertainty conditions in the gc object for the agent (place).

Two other concepts of generalized machine intelligence will be reviewed as examples of measuring IQ. The first concerns the Church-Turing-Deutsch (CTDT) hypothesis and subsequent definition of Gödel machines as self-writing, self-referential, and self-improving. The second reviews the notion of Von-Neumann machines as intelligent self-replicating (genetic) machines.

Gödel machines (*G*-machine) are based on dynamic, self-writing programs that learn from reinforcement towards the optimization of its future utility function value evaluated at a given time, *t*:

$$u(s, env) = E_{\mu}\left[\sum_{\tau=t}^{T} r(\tau) \middle| s, env\right] \tag{1.15}$$

where $env \in E$ (set of computational environments), $s \in S$ is the state of the agent machine, μ is a pdf for the distribution of reactions of the environment to the agent machine, and r is a real-valued reward input (Schmidhuber, 2006). This is a form of machine reinforcement learning that is equivalent to the setup of (1.1). The *G*-machine consists of self-modifying code, p which includes, (1) a problem solving subroutine that interacts with the environment, and (2) a general proof searcher subroutine that creates pairs, *(p_{switch}, proof)*, each of which is a substring of *s*, until a proof of a target theorem is found. This is equivalent to the proposition that the immediate rewrite of *p* using the current program, p_{switch} produces a higher utility than *p* on the given machine. If this is so, p_{switch} is executed, which may possibly completely rewrite *p*, including its proof searcher subroutine (self-writing). The key to the foundation of this program is that a target theorem can be proved. Godel's self-referential formula points to flawed or possible allowance of unprovable, but true propositions. *G*-machines need to reject those improvement programs that it cannot find a proof of a target theorem. Instructionally, the *G*-machine program is outlined in 6 steps:

(1) get-axiom (*n*)

(2) apply-rule(*k*,*m*,*n*)

(3) delete-theorem(*m*)

(4) set-switchprog(*m*,*n*)

(5) check-proof

(6) state2theorem(*m*,*n*)

See Schmidhuber (2006) for details on the substeps involved in each of these step routines and on how this program is globally optimal in self-changes (i.e., no local optimization). *G*-machines may be generalized to stochastic *G*-machines by utilizing probability distributions for the computations involved in every aspect of *p*. Schmidhuber (2006) points out that this strategy in building stochastic *G*-machines reflects more realism based on machine-media error-proneness and on the improved axiomatic consistency of probabilistic settings. Schmidhuber also enumerates various improvements to a *G*-machine through subroutine alterations meant to minimize the relatively most least important interactions between agent and environment.

We propose that Zadeh's GTU formalism be used to build very general uncertainty-based *G*-machines, superseding those of stochastic or deterministic *G*-machines and its subsequent GTUPN representation. A GTU *G*-machine, g would be based on a vector of *gc* objects, $gc = (gc_i)_{i=1,2,\ldots,N_g}$ where N_g is the number of distinct uncertainty type of calculations and agent-environment interactions performed in *g*. Schmidhuber (2006) finally showed that the *G*-machine formalism is *O()*-optimal at minimum, while being self-referential. It corrects itself while other notions of reinforcement learning, such as that of our first reviewed approach are hard-wired.

Nonetheless, it remains that the measurement of an MIQ for a *G*-machine involves the optimization of (1.1) or the equivalent (1.15). However, proceeding as a *G*-machine, one can compare the performance of a general agent machine when calculating MIQ against that of a universal *G*-machine (one in which the underlying hardware is a universal Turing machine). The normalization of such scores would then serve as an alternative and possibly more computable version of MIQ and would be a version of a standardized MIQ, something not addressed by our previous discussion. Hence, for an agent, π , a new IQ metric, $GMIQ_\pi$ takes the form,

$$GMIQ_\pi = \frac{MIQ_\pi}{MIQ_G} \tag{1.16}$$

where MIQ_G is the MIQ metric from (1.6) for a universal *G*-machine. In a similar way, for multi-agent systems, (1.13) can be restated using this normalization for each agent, against the MIQ score, MIQ_G, of a universal distributed multi-agent *G*-machine network. A multi-agent version of a *G*-machine would be further parameterized by the level of interaction and uncertainty between agents and between environments and sub-coalitions of agents. Sub-coalitions form sub Petri nets as such and their representation can be investigated as coalesced sub-collective intelligences leading to the crystallization of the larger collective intelligence of the whole net.

Von Neumann (1966) established the computational rules for a machine to self-replicate based on copies of its computational DNA. It is based on three premises of self-replication, (1) logical universality – the ability to function as a general purpose computer, simulating a universal Turing machine, (2) construction capability – the ability to self-replicate from its own materials which would include program logic and physical components, and (3) constructional universality – the ability to manufacture any of the finite-sized machines from the requisite sub-components contained in the original creator machine. In the original kinematic version of a von Neumann machine, the self-replicator agent machine, *SR* would consist of four agent components: (1) a constructor, *A*, capable of building another copy of *SR* when given the program blueprints of *SR*, (2) a blueprint copier machine, *B*, (3) a controller machine, *C*, that properly synchronizes the control of the alternating actions of the constructor, A, and the copier, B, and (4) a set of blueprints, $\phi(A, B, C)$ that completely and explicitly describes how to build the triplet *(A,B,C)*. We denote a von Neumann machine by this designated quadruple, $SR = (\phi, A, B, C)$ (modified from Freitas and Merkle (2005)). One cycle of actions (the initial one), ζ from agent components is as follows:

(1) controller *C* actuates (triggers) copier *B*

(2) copier *B* copies ϕ, producing a second copy of the blueprints, ϕ_2

(3) controller C actuates A to construct a second copy of (A,B,C), (A_2,B_2,C_2) , using blueprint ϕ and then to tie them together with ϕ_2 , thus producing the full copy of SR,

$SR_2 = (\phi_2, A_2, B_2, C_2)$

No self-referentialness is needed as this is an iterative process. An equivalent cellular automaton was developed by von Neumann. Von Neumann had a full program to conceive of several types of self-replicators including, (i) kinetic machine, (ii) cellular machine, (ii) neuron machine, (iv) continuous (non-discrete) machine, and (v) probabilistic machine (Freitas and Merkle, 2005). This purely artificial construct predated the discovery of DNA and genomics and is an exact program for cellular reproduction.

If we denote by l_π , the lifecycle of agent machine π , t_ζ denote the cycle time of cycle ζ , $[n]_t =$ largest int $\ni \sum_{i=1}^{[n]_t} t_{\zeta_i} \le t$, and $SR(t)$ as the composite agent system of machines after time t of replication, then through the actions, $\zeta^{[n]_t} = \left(\zeta_1, \zeta_2, ..., \zeta_{[n]_t}\right)$, $SR(t) = \bigcup_{i=1}^{[n]_t} SR_i \delta\left(l_{SR_i} - t\right)$, where $\delta(x) = \begin{cases} 1 & x > 0, \\ 0 & x \le 0 \end{cases}$ is the usual delta function. The growing ($\zeta_i > l_{SR_i}$) agent network, $SR(t)$, may then be considered a hardwired program with the ability to replicate in order to increase its concurrency given that each subcomponent, A_i , that is alive at time t, (i.e., $\zeta_i > \sum_{j=i+1}^{[n]_t} l_{SR_j}$) is a version of a universal Turing machine capable of executing task processes separate from replication, i.e., a general purpose computation. Assuming that replication is perfect (mutations are not produced), then the network of agents, $SR(t)$ at time t, can be tested for intelligence as in (1.13). Now we introduce into the blueprint program ϕ , a subroutine that will instruct the machine copies to parallelize and synchronize according to a chosen concurrency scheme φ. The new blueprint (ϕ, φ) will then be copied in the von Neumann replicating cycle. Intelligence tests on the von Neumann network machine that last a sufficiently long time will then learn by concurrency speed, at least those task tests that are stable asymptotically parallelizable. At a certain time, t_p, the threshold for parallel speedup is reached, in which case, performance is stabilized.

The specter of improving a von Neumann network machine by replacing the component A by a suitable Gödel machine A_g seems to indicate the potential for unparalleled power. Consider the parallelizable Gödel-von Neumann machine, $SR_G = (\phi, \varphi, A_G, B, C)$. The most general version of SR_G would be the complete Gödelization, $SR_{CG} = (\phi_G, \varphi_G, A_G, B_G, C_G)$ in which each component is a G-machine version of an ancestor. Measuring MIQ_G of SR_{CG} would amount to comparing its MIQ to that of a suitably non-parallelized network of G-machines. Further generalization by introducing the notions of GTU as the parameters of uncertainty in computations gives us GTU-inspired universal machines. They would supersede the development of universal quantum computers as posited in Deutsch (1985) because quantum logic is represented as a special case of a *gc* object.

Semantic networks and web technologies

We conclude our discussion of MIQs by looking at the more practical prospect of the semantic web as a network of intelligent agents, framing it as a class of evolutionary adaptive agent-based Petri nets. This will lead to certain proposals to generalize the semantic web to GTU embedded semantics, which generalize quantum, quantum gravity, and evolutionary versions of

Petri nets, Gödel-von Neumann equivalent webs, and finally, the measurement of an MIQ for these variants.

In Hamadi and Benatallah (2003), a Petri net formalism (actually a Petri algebra)) was introduced for the web services architecture overlay. Zhang, Chung, Chung, and Kim (2003) proposed a similar construct that is used as a basis for the WS-Net proposal. In our discussion, we will assume that the web services architecture, while being the most practical and adopted on the web, remains the de facto structure of the web for our purposes. In that, a service Petri net was defined and embedded in a definition of a web service. The web Petri net is simply a labeled Petri net $SN = (P, T, W, i, o, l)$ where the first three components are as in our BPN modeling structure, $i \in P$, where $\bullet i = \{x \in P \cup T \mid (x,i) \in W\} = \varnothing$ (a place with no incoming arcs, emits information), $o \in P$, where $o\bullet = \{x \in P \cup T \mid (o,x) \in W\} = \varnothing$ (a place with no outgoing arcs, houses results of services), and $l : T \to \mathcal{A} \cup \{\upsilon\}$ where $\mathcal{A}$ is a set of operation names with $\upsilon \notin \mathcal{A}$, a silent (pass-thru) operation.

A web service is then defined as the tuple $WS = (S_{name}, D, L, URL, CS, SN)$ where S_{name} is the name of the service, *D* is the description of the service, *L* is the location of the service, *URL* is the invocation of the service, *CS* is the set of component services (single and composite), and *SN* is a service net that describes the dynamics of the service. In *SN*, *i* is the initial marking, noted as M_o before which means that place *i* has the only token. The execution of *WS* starts with a token in *i* and commences when that token reaches *o*. Hamadi and Benatallah develop the algebraic structure of SN which included the service operators: composition (comp), empty element (empty), XOR (xor), iteration (iter), selection (select), discrimination (disc), refinement (refine), parallelization (parallel), and selective sequential execution (alternate). Service operations are modeled as transitions in *T*, and states of services are modeled by places in *P*. The state space of services is given by the set {NotInstantiated, Ready, Running, Suspended, Completed}. The arcs in *W* depict the casual relationships between a state of a service and an operation on it. This introduces a rigor to the concept of a well-defined software process architecture for the Internet and made it possible to legitimize the end results of the work of the W3C on the semantic web architecture (W3C, 2012).

The semantics of Petri nets are built into the behavior of their respective triggers for transitions and of what tokens are moved from one place to another. Hence, a semantic Petri net is essentially a Petri net structure with the dynamics of the rules for triggers and the description of tokens moved succinctly defined as part of the Petri net formalism. Any Petri net structure can be made into a semantic net by virtue of an embedded set of firing rules (FR), the nature of the arcs, the token descriptions, and the network structure of the places and transitions.

Ontologies are used to describe patterns of behavior of web services and their interaction. This describes the order of web service execution as well as the capability to equate web services in terms of interchangeable classes. This is the behavioral semantic power introduced by ontologies and the OWL specifications. Ontologies through the OWL and OWL-S specifications can also be modeled with Petri nets as in Gasevic and Devdzic (2006) and Brogi, Corfini, and Iardella (2007) using a Petri net markup language PNML and OWL-S translation mappings. In Brogi, Corfini, and Iardella (2007), a formal Petri net is defined to model ontologies from OWL-S, the (consume-produce-read) CPR net. It is defined as the tuple, $N = (C_N, D_N, T_N, F_N, I_N)$ where C_N are control places, D_N are data places, T_N are transitions, F_N are the control flow relations, and I_N are the data flow relations. Here, $C_N \cap D_N = \varnothing$ (Bonchi, Brogi, Corfini, and Gadducci, 2007). Pre-, post-, read-, and produce-set sets are defined for each transition, *t*:

$$^{\Diamond}t = \{s \in C_N \mid (s,t) \in F_N\}$$ (pre-set)
$$t^{\Diamond} = \{s \in C_N \mid (t,s) \in F_N\}$$ (post-set)
$$^{\bullet}t = \{s \in D_N \mid (s,t) \in I_N\}$$ (read-set)
$$t^{\bullet} = \{s \in D_N \mid (t,s) \in I_N\}$$ (produce-set)

Markings in N consist of a set of places in $P_N = C_N \cup D_N$. In this Petri net, each place can have at most one token representing one service state. The transition, $t \in T$ is enabled by a marking M if $^{\Diamond}t \cup {}^{\bullet}t \subseteq M$ and $M \cap t^{\Diamond} = \varnothing$. Enabled transitions may actuate a firing which removes tokens from each $p \in {}^{\Diamond}t$ and adds a token to each $p \in \{t^{\Diamond} \cup t^{\bullet}\}$. More formally, we define a firing operator (step) for a transition t and a marking M for N as a triple $FS = M\left|t\right\rangle M'$ such that $^{\Diamond}t \cup {}^{\bullet}t \subseteq M$, $M \cap t^{\Diamond} \subseteq t^{\Diamond}$ and $M' = (M \setminus {}^{\Diamond}t) \cup t^{\Diamond} \cup t^{\bullet}$. Lastly, the equivalence relation $M\left|\;\right\rangle M'$ holds if there exists some t such that $M\left|t\right\rangle M'$. Service operators of (1) sequence (sequential execution), (2) if-then-else (conditional execution), (3) choice (non-deterministic execution), (4) split (parallel execution), (5) any-order (unordered sequential execution), (6) repeat-while, and (7) repeat-until (iterative execution) have been implemented in this Petri net formalism.

In Li and Xiong (2012) a Petri net formalism is developed for web services in which mediation-aided composition is developed. An implemented prototype tool of this performance measurement Petri net formalism is given in Xiong, Pu, Zhu, and Griffith (2013). This Petri net formalism endeavors to mediate incompatibilities of web services on the fly by automatically generating the BPEL (Business Process Execution Language) specification code of a composition in order to carry out the new web service (Tan, Rao, Fan, and Zhu, 2007). Workflow nets (oWFNs) model the web services and are composed using mediation type transactions. Next, a mechanism for calculating the reachability of these compositions is used, the modular reachability graph (MRG). An event-condition-action rule-base is then employed to automatically generate the BPEL specification code of the composed web service. In these approaches using BPEL, the BPEL specification is transformed into a service workflow net (a special kind of color Petri net). BPEL possesses formal Petri net semantics (Hinz, Schmidt, and Stahl, 2005, Stahl, 2005).The service flows are then analyzed to see if their mediation-aided composition does not violate the constraints that are pre-conditioned from either side of the server and the requester.

In our previous discussions about generalizing Petri nets for quantum, quantum-gravity causal nets and GTU constraint, and of the more powerful evolutionary Gödel-von Neumann machines, we posited through the sequential building of more general constructs, that any original Turing machine agent, π can be viewed as a special case of a GTUPN (GTU Petri net) and then developed into a single Gödel-von Neumann machine, $SR_{CG}(\pi)$ based on the original agent being Gödelized, π_G and with Gödel copier, *B* and Gödel controller, *C* helper agent machines and a Gödelized blueprint, (ϕ_G, φ_G). The machine $SR_{CG}(\pi)$ may be extended to be evolutionary as well in the form of a sequence of machines $\left\{SR^i_{CG}(\pi)\right\}_{i\in I}$ following Burgin's evolutionary rules. The semantics of operation of each computation are further generalized based on a *gc* object to get a GTU-based computation space for $SR_{CG}(\pi)$. One can then attempt the same morphogenesis with the web services algebra, *S*. Practically, web services in *WS* or *N* can be viewed as agents. Their generalization to $SR_{CG}(\pi)$ means that these agents grow to produce a super-network version of $SR_{CG}(\pi)$ since the seed is already an exceedingly large number of agents.

The algebraic structure of such a super-network, labeled here as $SR_{CG}(SN)$ are presumed to be preserved because composition and identities are preserved in the GTU-Gödel-von

Neumann transmogrification of a Turing machine agent. This is certainly an area for further rigor and research. The implications for the current portfolio of web semantic technologies, including the trilogy of RDFS/SPARQL/OW, Allemang and Hendler (2011), and the surface collective intelligence of social network programming, Segaran (2007), point to more powerful renditions of algorithms embedded in data and ontologies, and of ontology generators as powerful machines onto their own, (i.e., ontologies are to be built using $SR_{CG}(\pi)$ machines). Certainly, the physical portion of self-replicating in a von-Neumann architecture is limited, but the ability to self-replicate soft simulators using global idle processors or at least, sub-optimally used processors, is a prospect for artificial network growth, (i.e., crystallization of web service processors and processes). Utilizing the MIQ variants in this discussion, we have formalized a method to measure a diverse IQ for networks of interacting agents. These agents are heterogeneous and the methodology is completely applicable to the web where agents are mixtures of human operators, web service agents, specialized processors, and hybrids through social network processes. This is accomplished using the web service network, *WS* or *N*, as a Petri net and subsequently applying a variant of MIQ submitted in this paper, as framed for very general Petri net formalisms, and specified to the *WS* or *N* Petri net architectures.

Burgin (2013) has introduced the notion of a universal general evolutionary automata (See Appendix for details on Burgin's evolutionary automata). We previously defined a version of an evolutionary Petri net. We now formally define a semantic network framework using both evolution and GTU -inspired automata. An apriori defined sequence of automata components, A_t is gathered, $E = \{A_t\}_{t \in T}$ for each stage of reproduction *t*. The *E* automata are referred to as general evolutionary *K* machines (*K-GEMs*), where *K* is a class of automata with one input and two output units. An automata U is then universal for *H*, a class of evolutionary automata, if *U* obtains the same results as does any members $A \in H$ or no results when A gives no results. See the appendix for formal definitions. We may further generalize this notion of evolutionary automata by injecting general uncertainty into the selection of a class of fitness functions as each stage using a Zadeh GTU structure, $g = (X, r, R, ts)$. We define g_t to be the GTU operator that selects the class of functions F_E to be considered for an optima at stage t from a universe of fitness function classes, $\mathcal{F}$ for the evolutionary automata E. Denote a GTU universal evolutionary Turing machine (GUETM) by $\Upsilon = (E, \mathcal{F}, g_t)$ where E is a universal evolutionary Turing machine, $\mathcal{F}$ a superclass of classes of fitness functions, and g_t a GTU object. Now instead of the sequence of component automata defining an evolutionary automata, $E = \{A_t\}_{t \in T}$, apriori, we instigate the notion of Gödel-von Neumann machines/automata for a seed machine/automata. The new evolutionary automata is governed by the dynamics of optimized code and reproduction within the $SR_{CG}(\pi)$ network framework plus the GTU structure of fitness optima. Different types of GTU non-determinism will dictate the construction of fitness choice (variation and selection) of evolutionary automata and of Gödel-von Neumann construction of potential progeny. This überclass of networks, notated as $ESR_{CG}(\pi)$, may then be investigated as a potential proliferator of an evolutional hyper-intelligent network structure for a hypersemantics with highly evolvable measured IQ.

Conclusions and Future Work

In this paper, generalizations to Petri net formalisms and heterogeneous machine IQ were presented. By framing multi-agent based systems as Petri nets and then applying general notions of computational machines, it was posited that more powerful machines can be used to measure truer, more diverse versions of intelligence in networks of agent machines. This formalism was conceptualized to be applied to the current formalism of the web service architecture of the web.

The measurement of intelligence of heterogeneous networks of machines (we have dropped the term human-machine since our notion of agent has expanded beyond this spectrum during the discussion) has vast implications for our new global techno-socio-economic framework. Cooperative (co-opetive) systems can be viewed as whole intelligent beings with holistic properties through a more diverse definition of intelligence. These metrics endeavor to capture aspects of intelligence through the abilities of agents to reason, predict, generalize, and actuate in familiar and unfamiliar environments. In a sense, intelligence is about optimal adaptability through Bayesian reasoning. They also capture intelligence measurement through their ability to optimally prune through information, computing optima for non-greedy self-preservation and service. Many view the semantic web as the ultimate social tool for generations to come. However, the limitations of the web are those of networks. Measuring how networks think through iterative intelligence metrics can provide an answer to some of these sub-optima.

There were many areas of further research and rigor left as gaps that were presented in this paper. While serving mainly as a guide of propositions for more powerful intelligence metrics and nuanced super-networks for the web, it opened up more questions than answers. This was an expository into them. One area of inquisition is the notion of experimental SR_{CG} networks. Can an environment be built where starting from an agent seed, π, one can test for the controlled viability of a $SR_{CG}(\pi)$ network? Indeed, can an individual $SR_{CG}(\pi)$ machine be built in isolation if at all with current computational media/circuitry? What would a probabilistic semantic web be, (i.e., a GTU-based Petri algebra) and is it already one (error-prone transactions and communications, ulterior motives, etc.)? Finally, in the area of adapting human intelligence metrics, the MIQ developed in this paper may be expanded upon using some of the recent notions of cognitive flexibility, the so-called cadre of *g*-factor variants in Jensen (1998), and of the multiple intelligence theories of Gardner (1983), and developed versions thereof in Goreman (2005). Indeed, emotional intelligence may be viewed as the ability to optimize emotional spaces and this is essentially a measure of how sub-optimal computations that have been taking up resources otherwise suited to constructive and fulfilling goals, are adapted, inhibited, or damped. Each sentient intelligence is then given a threshold of sub-optimality and a threshold of contribution to the overall predictability and generalization power of the agent. The Petri net formalism defined for the web service ontology net N may be structured as a Petri algebra (as WS has) so that it can have an even richer mathematical structure than a Petri net alone. Limited by the scope of the paper, the rewards-based functional is somewhat simplistic in the sense that parsimony is better served by more powerful divergence measures such as information criteria (IC) statistics that simultaneously measure predictability and generalizability in statistically optimal fashions (Burnham and Anderson, 1998; Nakamura and Judd, 2006). In a follow up paper, we will utilize some generalizations to IC that account for our very general approach to uncertainty using the GTU and other weighting schemes in our redefinition of a reinforcement functional (Sepulveda, 2013).

An analysis of the semantic network framework here may be extended to interaction models between semantic network agents that are emergent in nature, such as quantum entanglement and coherence among qubits (*e*-bits and *co*-bits respectively) (Bennett, Devetak, Harrow, Shor, and Winter, 2012).

Finally, further to the more general mathematical descriptions of semantic networks, the higher order representations possible from the application of category and topos theories may be utilized. In this vein, Abramsky (2008) has promoted the utilization of category-theoretic notions of causal Petri nets in terms of discrete physics using symmetric monoidal categories initially developed in Mesequer and Montanari (1990). Recall, briefly that a category C has both objects or types given by a set $A=\{A_i\}_{i\in I}$ and for each pair $A_i, A_j \in A$, a set of morphisms $C(A_i, A_j)$ which are mapping $f : A_i \to A_j$, along with identities $\mathrm{id}_A : A \to A$ and compositions $f_j \circ f_i$ as $A_i \xrightarrow{f_i} A_j \xrightarrow{f_j} A_k$. Symmetric monoidal categories have in addition, an associative operation $\otimes$ acting on both the objects and morphisms of C as a bifunctor, $A_i \otimes A_j$, acting as a tensor product (natural isomorphisms) such that $f_i \otimes f_j : A_i \otimes A_j \to A_{i_k} \otimes A_{j_k}$, $ass_{A,B,C} : A\otimes(B\otimes C)\to(A\otimes B)\otimes C$, $r_A : A\otimes I \to A$, $l_A : I \otimes A \to A$, with well behaved symmetry operators (braiding) $\sigma_{A_i,A_j} : A_i \otimes A_j \to A_j \otimes A_i$. These operators satisfy two coherence axioms (Schmitt, 2008). This category is directly related to the category Rel of sets (objects) and relations (morphisms) used in theoretical computer science. Mesequer and Montanari defined Petri net categories using these symmetric monoidal categories, and added the processes of sequential and parallel composition. Applying the appropriate extensions to such categories, in order to describe the more general approach to Petri nets, leading to a framework for the semantic networks given in this paper, presents with some intriguing possibilities for Petri and semantic net classes and processes. These new mathematical categories may then lead to tools for representing more powerful formalisms and structure for our central theme of hyperintelligent semantic networks.

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Appendix

In this appendix, we give definitions for successive expansions and generalizations of the Petri net formalism to be referred to in the body of the paper. The conventional definition of Petri nets for computational modeling is given initially as a background for the ensuing definitions of emergent versions thereof.

Definition 1.1. Petri net (basic PN for modeling). A Petri net is a 5-tuple, $(C, E, {}^{\bullet}(-), (-)^{\bullet}, M_0)$ where C is a set of conditions, E is a set of events, ${}^{\bullet}(-): E \to 2^C$ is the precondition map (backward incidence), $(-)^{\bullet}: E \to 2^C$ is the post condition map (forward incidence), and M_0 is the initial marking of the network, a mapping $M_0 : T \to [0,1]$. $C \cap E = \varnothing$ (Hayman, 2010). The condition maps dictate what events can be triggered by what set of conditions and what set of conditions an event will create. The initial marking gives the initial state (represented continuously in [0,1]) of each transition. Alternatively, a pure Petri net formalism can be given as a bipartite directed graph consisting of the 5-tuple (P, T, F, w, M_0) where P is a set of places (which could be conditions C) and T is a set of transitions (which could be events E), $F \subseteq \{P \times T\} \cup \{T \times P\} \equiv {}^{\bullet}(-) \cup (-)^{\bullet}$ are the set of arc flows between places and transitions,

$w = \left(w^{i}_{^\bullet(-)}, w^{i}_{(-)^\bullet}\right) W : F \to \{1,2,\ldots\}$ are weight functions on arc flows such that $w^{i}_{^\bullet(-)} : {}^\bullet(-) \to \{1,2,\ldots\}, w^{i}_{(-)^\bullet} : (-)^\bullet \to \{1,2,\ldots\}$ and $M_0 : P \to \{0,1,2,\ldots\}$ is an initial marking which assigns to each place an integer depicting the number of tokens in it. Lastly, $P \cap T = \varnothing, P \cup T \neq \varnothing$ (modified from Best, Devillers, and Koutny (2001)). If the number of tokens in a place (transition) meets or exceeds the arc weight to a transition (place), then that place (transition) *enables* that transition (place). This is an equivalent notion to the development of precondition mappings of the basic PN.

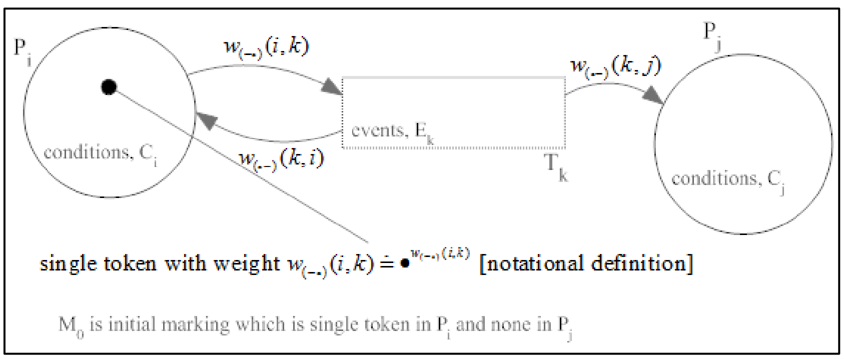

Figure 3 - Basic Petri net graph components

Definition 1.2. Time Petri net (TPN). A Time Petri net is a 5-tuple, $\left(C, E, {}^\bullet(-), (-)^\bullet, M_0\left(\alpha, \beta\right)\right)$ where C is a set of conditions, E is a set of events, ${}^\bullet(-) : E \to 2^C$ is the precondition map, $(-)^\bullet : E \to 2^C$ is the post condition map, and $M_0(\alpha, \beta)$ is the initial marking, $\alpha \in (\mathbb{Q}_{\geq 0})^T$, $\alpha \in \left(\mathbb{Q}_{\geq 0} \cup \{\infty\}\right)^T$, $M_0(\alpha, \beta) : T \to [0,1]$, are time constrained mappings on the firings of transitions, and $\mathbb{Q}_{\geq 0}$ are the positive rationals, $C \cap E = \varnothing$ (Cassez and Roux, 2004).

Definition 1.3. Generalized Stochastic Petri net (GSPN). A GSPN is an 8-tuple, $\left(C, E, {}^{\bullet}(-), (-)^{\bullet}, M_0\left(\alpha, \beta\right), \mathbb{P}, H, w\right)$ where $\left(C, E, {}^{\bullet}(-), (-)^{\bullet}, M_0\left(\alpha, \beta\right)\right)$ is a TPN (as above), H is a set of inhibitor arcs, $H \subset C \times E$, $\mathbb{P} : T \rightarrow \mathbb{R}^{+}$ is an assignment of priorities to transitions which associates lowest priority (0) with timed transitions and higher priorities (≥ 1) with immediate transitions, and $w = \left(w_1, w_2, ..., w_n\right)$ are stochastic parameters for the pdfs of the transition firing delay if t_i is a timed transition and is a weight of the firing probabilities of immediate transitions if t_i is an immediate transition (Haas, 2002).

Definition 1.4. Fuzzy Petri net (FPN). A Fuzzy Petri net is an 8-tuple, $\left(C, E, P_F, {}^{\bullet}(-), (-)^{\bullet}, M_0, \alpha_F, \beta_F\right)$ where C is a set of conditions, E is a set of events, ${}^{\bullet}(-) : E \rightarrow 2^C$ is the precondition map, $(-)^{\bullet} : E \rightarrow 2^C$ is the post condition map, and M_0 is the initial marking, $M_0 : T \rightarrow [0,1]$, P_F is a set of propositions, $\alpha : P \rightarrow [0,1]$ is a membership mapping, and $\beta : P \rightarrow P_F$, is a bijective mapping, $C \cap E \cap P_F = \varnothing$ (Aziz, Bohez, Parnichkun, and Saha, 2010).

Definition 1.5. Adaptive Fuzzy Petri net (AFPN). An Adaptive Fuzzy Petri net is a 9-tuple, $\left(C, E, P_F, {}^{\bullet}(-), (-)^{\bullet}, M_0, \alpha_F, \beta_F, w\right)$ where all components are as in Def. 1.3 above and where $w = \left(w^i_{{}^{\bullet}(-)}, w^i_{(-)^{\bullet}}\right)$ is a weighing scheme such that $w^i_{{}^{\bullet}(-)} : {}^{\bullet}(-) \rightarrow [-1,1], w^i_{(-)^{\bullet}} : (-)^{\bullet} \rightarrow [-1,1]$ are input and output weights respectively, assigned to all arcs of the Petri net. (Li and Laro-Rosano, 2000).

Definition 1.6. Extended (complex-valued) Petri net (EPN). An Extended Petri net is a 6-tuple, $\left(P, T, {}^{\bullet}(-), (-)^{\bullet}, M_0, w\right)$ where all components are as in Def. 1.1 above (modeling version) and where $w = \left(w^i_{\bullet(-)}, w^i_{(-)^\bullet}\right)$ is a weighing scheme such that $w_{\bullet(-)} : {}^{\bullet}(-) \to \mathbb{C}, w_{(-)^\bullet} : (-)^{\bullet} \to \mathbb{C}$ are input and output weights respectively, assigned to all arcs of the Petri net and $M_0 : T \to \mathbb{C}$.

Token classes are represented as complex numbers $w \in \mathcal{C}$. Symbolically, $\bullet^w$ denotes a token class with forward arc weight $w \in \mathcal{C}$ and ${}^w\bullet$ denotes a token class with backward arc weight $w \in \mathcal{C}$. For $v \in \mathcal{Z}, y \in \mathcal{C}$, if $w = v \cdot y \Rightarrow \bullet^w \equiv v \cdot \bullet^y$ (scaled token class). Transitions are categorized as either *choice firing*, denoted by ⍓, or as *free firing*, denoted by ■. Free firing transitions fire when they are enabled. Choice firing transitions are fired by a willful decision from an agent or coalition. The firing rule *(FR)* is as follows: the firing of an enabled transition *t* at a marking *M* actuates the movement of tokens, resulting in a new marking, $M_R \geq 0$ defined as:

$$M_R(p) = \begin{cases} M(p) + \alpha \cdot w_{(-)^\bullet}(t, p) & p \in {}^t\bullet \wedge p = \min({}^t\bullet, p) \notin \bullet^t, \\ M(p) - \alpha \cdot w_{\bullet(-)}(p, t) & p \in \bullet^t \wedge p = \min(\bullet^t, p) \notin {}^t\bullet, \\ M(p) & \text{otherwise} \end{cases}$$

where $\alpha = \min_{p \in \bullet t} |M(p)|$ and $\alpha \cdot w \Rightarrow$ the weight, *u* of each moved token was changed to $u \cdot w$ (modified from Tsuji (2000)).

Definition 1.7. Quantum Petri net (QPN). A Quantum Petri net is an EPN in which the following conditions hold: (1) all enabled transitions (those with existing preconditions satisfied) $t_k \in T$, are triggered only at integer time instances, $n\tau, n = 1, 2, \ldots$, which are called *enable times*, (2) at enable times, enabled transitions not in conflict with one another (transitions are in conflict when they have to share resources during their attempted execution and this does not guarantee a successful execution for either) fire simultaneously, (3) when enabled transitions fire, the changing of marking follows the firing rule *FR*, (4) at least one transition, *t* is chosen from a set of output transitions of a place *p* where $M(p) \neq 0$ and each *t* must fire at the time it has been enabled, (5) simultaneously available transition sets (SCT), *st*, are subsets of T whose transactions are not in conflict with one another, satisfying: $\forall t, t' \in st,\ \bullet^{t} \cap \bullet^{t'} = \varnothing$, and (6) a set of SCTs, *ST* exists and satisfies: $\forall st \in ST,\ \bullet^{st} = P$, at enable times, a SCT, $st \in ST$ is chosen and all enabled transitions in *st* fire. (Ito, Ohta, and Tsuji, 2008).

Definition 1.8. A *K-GEM* is a sequence $E = \{A_t\}_{t \in T}$ of automata from *K* that operates on population generations, $\{X_i\}_{i \in I}$ which are coded as words in the alphabet of *K*. The objective of the *K-GEM* is to conceive of a population *Z* that satisfies:

1. A_t (level automaton) of *E* represents a one-level evolutionary algorithm operating on the input generation X_i, applying recursive variation and selection operators, μ and ρ respectively.
2. X_0 is the initial generation and is operated on by A_1 consequently generating subsequent generations, X_1 (transfer output) that inputs to A_2.
3. A_t receives input from either A_{t+1} or A_{t-1}, then applies the operators μ and ρ to X_i producing X_{i+1} as its transfer output and when necessary (non-terminating node) sends it to either A_{t-1} or A_{t-1}.

4. The optimal search condition to select a population agent x_{i*} from X_i is

$x_{i*} = \arg\max_{x_i \in X_i} f\left(x_i\right)$ for some fitness performance measure *f* (Burgin, 2013).

Burgin (1984; 2013) signifies that a *K-GEM* is inductive of order *n* if each of its members is at most inductive of order *n*. Burgin further defines universal evolutionary automata (U) in much the same way that universal TMs are via codification.

Def. Let *H* be a class of evolutionary automata. An evolutionary automaton/algorithm/machine *U* is *universal for H* if given a coding $c\left(A\right)$ of automaton/algorithm *A* from *H* and input data *x*, *U* obtains the same result as *A* for input *x* or gives no result when *A* gives no result. An evolutionary automaton/algorithm/machine *U* is *universal in H* if it is universal for *H* and $U \in H$ (Burgin, 2013).