Intelligent Autonomous Systems based on Data Analytics and Machine Learning

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Intelligent Autonomous Systems

• According to Wes Bush, CEO of NGC, Autonomous Systems¹ should be
  – Able to perform complex tasks without the ongoing connection to humans.
  – Cognitive enough to act without a human’s judgment lapses or execution inadequacies.

• Intelligent Autonomous Systems (IAS) are highly Cognitive, Reflexive, Multitasking, and effective in Knowledge Discovery.

• Examples of IAS: NGC’s BAMS-D, BACN, BAT UAS, Andro’s UGV as well as V2V Communication Systems.

Research Focus

- **Cognitive Autonomy & Knowledge Discovery:**
  - Monitor as well as simulate system’s environment / interactions i.e. **Data Provenance**.
  - Discover new useful patterns and anomalies.
  - Make decisions based on predictions and discoveries.
  - Learn system’s own limitations and capabilities.

- **Reflexivity:**
  - Adapt to meet the mission objectives with limited or no human intervention and allow graceful degradations.

- **Trust:**
  - Provide consensus, verifiability, and integrity.
Problem Statement

1. Enhance the cognizance of IAS by applying machine learning analytics on provenance data to enable learning, understanding, and predictive capability of the system.

2. Apply advanced data analytics techniques on-the-fly on provenance data streams for knowledge discovery—new useful patterns and anomalies.

3. Investigate new integrated data analytics for discovering and analyzing hidden raw data to increase the value of the gathered data.

4. Facilitate learning from provenance data to improve the adaptability of IAS.
**Problem Statement**

5. Apply blockchain technology to provide verifiability and integrity i.e. trust to provenance data.

6. Advance data representation as well as reasoning based on probabilistic, ontological, semantic, and commonsense reasoning.

7. Advance science of autonomy through theory and practice.
Challenges

- Simon’s Law of bounded rationality\(^1\).

- Generating optimal mission plans with limited information.

- Live monitoring and selecting (or) allocating appropriate resources for mission success.

- Reacting to the dynamic, unknown, and uncertain environment to perform the best action and Learning.

- Scalability.

Research Approach

• Employ machine learning techniques on sensor and provenance data to learn and understand
  – the underlying patterns of interaction through probabilistic inference of Deep Neural Networks (DNN),
  – conduct forensics to detect anomalies through novel Density-based techniques,
  – provide assistance in decision making by on-the-fly semantic, ontological, and probabilistic reasoning (e.g. Game Theory).
Research Approach

• Apply customized advanced data analytical techniques to incomplete and hidden raw data to discover new knowledge:
  
  – **Correlation-based** and **Subspace-based** pattern recognition.
  
  – **Replicator Neural Networks** for outlier detection.
  
  – **Clustering** and **Sequential Pattern Mining** through **Hidden Markov Models (HMM)** to classify expressive data.
Research Approach

• Enhance the autonomous system’s
  – self-awareness and adaptation through **reinforcement learning** implemented through higher-order Markov Decision Processes (MDP),
  – self-healing through **replacement policies**, and
  – self-optimization with reliability estimates with **Bayesian Statistics**.

• Utilize blockchain technology for storing provenance data for providing trust, using the NGC-WaxedPrune system envisioned by Donald Steiner, Jason Kobes, and Leon Li, and demonstrated at TechFest in 2016.
Combination of Two Research Goals:

- **Advancing the Science of Autonomy**
  - Definitions
  - Theory
  - Quantification

- **Developing the Components of Autonomy**
  - Cognitive Autonomy
  - Knowledge Discovery
  - Reflexivity
  - Trust

**A Combined Approach To IAS**
Intelligent Autonomous System Architecture:

- Client Services
- Requests
- Trusted Response
- Actionable Intelligence
- Intelligent Autonomous System
- Reinforcement Learning & Adapt
- Blockchain Storage (Provenance Data)
- On-the-fly ML / Cognitive Processing
- Knowledge Discovery (Data analytics / Forensics)
- Discovered Knowledge
Graphical Illustration
Components of IAS

We propose a comprehensive approach to IAS by developing the components of autonomy in a smart system:

- **Cognitive Autonomy**: self-awareness / prediction
- **Knowledge Discovery**: new insights from raw data
- **Reflexivity**: adapt / self-heal / replace
- **Trust**: verifiability / consensus
Cognitive Autonomy – Definition

• A system has cognitive autonomy if it is able to act without the lapses of human judgment or execution inadequacies\(^1\).

• Given a system in a distributed environment, how can it be cognitive of its three major operational layers:
  
  1. Current state of the system, operating software, and operational parameters.

  2. Learn and anticipate the future of its state and that of its neighboring systems.

  3. Client or third party services and their interactions with the system.

Cognitive Autonomy – Challenges

• The amount of training data necessary for cognitive computing through deep learning.

• Feature selection (FS) usually performed outside the boundaries of the model (often by humans).

• Reliability on large sample size by end-to-end reinforcement learning to enable cognition.

• Extracting low-dimensional representation relevant to learning a task from high-dimensional data.

• Exploring vast perception-action spaces in which the system operates.
Technique for Cognitive Autonomy

Autonomous Learning of Intermediate State Representation from Past Experiences:

• Employs deep autonomous encoders networks using deep neural networks.

• Uses decelerated interpretation of features to represent states:
  a) Uses Laplacian eigenmaps (LEM) for state representation using Auto Deep Encoder Networks
  b) Applies Slow Feature Selection (SFS) to high-dimensional data
Auto Deep Encoder Networks

• The Deep Encoder will be implemented through Deep Q-Networks (DQN), which uses DNN.

• DQN trains Convolutional Neural Network (CNN)\(^2\) to approximate the high non-linear Q-function with an online gradient decent.

• It reduces Bellman Error of function \(Q_\theta\) for all training samples, \(\{z^t, a_t, r_t\}_{t=1}^n\)

\[
\min_\theta \sum_{t=1}^{n-1} (r^t + \gamma \max(a) Q_\theta(z^{t+1}, a) - Q_\theta(z^t, a))^2
\]

\(^2\)Contributes to Adaptive Real-Time Detection and Examination Network (ARDEN) IRAD
Implementation of DQN

Slow Feature Selection (SFS)

- SFS will be implemented through reinforcement learning by *subspace invariant* features.

- Unlike Deep encoder, it does not depend on *reward* and it can *transfer* discovered knowledge from previous tasks.

- The spectral encoding of SFS through LEM depends on transition probability, not connectivity of the states.
Experiment

- **Objective:** Implement reinforcement learning through subspace invariant features.

- **Input:**
  - Synthetic data of operating parameters
  - Simulated provenance data in Active Bundle scheme of NGC/WaxedPrune system.

- **Output parameters:** Mean accumulated reward, Convergence of reinforcement learning algorithm.

- **Experimental setup:** Apply Reinforcement learning algorithm used in DQN to the features and simulate feedback loop with learning new features.
Cognitive Autonomy Technique

Autonomous Features Extraction and Classification:

- Goal directed selection of features.
- Establishes feedback loop between perceptual and cognitive engines.
- Uses Adaptive Control of Thought—Rational (ACT-R) classifier\(^3\) that simultaneously learns:
  - Connection between features and classes
  - Encoding which feature—which class

\(^3\)http://act-r.psy.cmu.edu/
ACT-R Components

 Imaginal Buffer

Encode feature given label

Utility

Infer label given observed features

Classify exemplar
ACT-R with Goal-directed FS

- Three components drive classification: Feature-encoding, Class inference, and Encoding.

- Feature-encoding places features in imaginal buffer, which provides class-inference associated with past features.

- Instance-based learning (IBL) in ACT-R performs similar to a \textit{k-Nearest Neighbors} classifier.

- Feedback loop is triggered once the class corrections are made, associating features and corrected classes.
Quantities of Associated Components

• Activation of feature retrieval process

\[ A_i = \sum_{n=1}^{N} W_n S_{ki} + \varepsilon \]

• Component’s Utility,

\[ C_i = \frac{u_i}{e^{\frac{\sqrt{2s}}{s}}} \]

\[ \frac{\sum_j e^{\frac{\sqrt{2s}}{s}}}{\sum_j e^{\frac{\sqrt{2s}}{s}}} \]

• Here, Utility

\[ U_i = U_i(n-1) + \alpha [R_i(n) - U_i(n-1)] \]
Experiment

- **Objective**: Test classification accuracy and feature selection model performance.

- **Input**:
  - Simulated provenance data and log files of transactions and interactions in NGC/WaxedPrune system.
  - Cohn-Kanade facial expression dataset.

- **Output parameters**: Classification accuracy, Dimension reduction accuracy, and feature selection model output.

- **Experimental setup**: Apply slow feature learning, ACT-R classification algorithm, and autonomous feature learning and classification to provenance data (uncategorized).
Cognitive Autonomy

Benefits of the Proposed Techniques:

• Goal-directed feature selection increases accuracy and context-sensitive semantic perception.

• Feedback loop improves autonomous perception between perceptual and cognitive systems.

• Reinforcement learning allows the classifiers to select features as function of their effectiveness.

• Slow Feature Analysis relies on few samples and previous intermediate states

These solutions contribute to

Smart Autonomy IRAD & Automated Mission Planning for Autonomous Systems IRAD
Cognitive Autonomy - Live Monitoring

• Enhanced live monitoring technique: We use Artificial Intelligence (AI) techniques to detect anomalies (failures or attacks) and determine when to trigger the virtual reincarnation process more efficiently reducing so performance overhead.
Cognitive Autonomy - Live Monitoring

Virtualized Environment

External Metrics
- Throughput
- Latency
- Reconfiguration Time

Internal Metrics

**Processor Level:**
- Processor Time
- Privilege Time
- Interrupt Time
- Queue Length
- Context Switches/Sec

**Memory Level:**
- Available Mbytes
- Page Reads/Sec
- Pages/Sec
- Cache Bytes
- Cache Faults/Sec

**Network Level:**
- Bytes Total/Sec
- Bytes Received/Sec
- Bytes Sent/Sec

...More
Cognitive Autonomy - Live Monitoring

**External Metrics**
- Throughput
- Latency
- Reconfiguration Time

**Virtualized Environment**

**Internal Metrics**

**Processor Level:**
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**Network Level:**
- Bytes Total/Sec
- Bytes Received/Sec
- Bytes Sent/Sec

...More

**Training Process?**

(1) Workload

(2) Record Metrics
Cognitive Autonomy - Live Monitoring

- Selection of non-redundant metrics
- Relationships between internal and external metrics
- Internal and/or external metrics efficiently trigger the Virtual Reincarnation process
Reflexivity – Definition

Given a smart system operating in a distributed computing environment, it should be able to:

1. Replace anomalous/underperforming modules
2. Reconfigure system parameters to respond to anomalous system behavior
3. Swiftly adapt to changes in context
4. Enforce proactive and reactive response policies
5. Achieve continuous availability even under attacks and failures

Reflexivity – Challenges

- Automatically replacing underperforming modules without restarting the mission
- Anticipating anomalous behaviors with limited knowledge discovery
- Automatically switching context without disrupting the ongoing mission
- Updating the policies that govern the behavior on-the-fly, efficiently dealing with conflicts
- Updating replacement replicas
Reflexivity Technique

Graceful Degradations (Replica or Self-healing) by Combinatorial Balanced-block Designs:

- Combinatorial Structure is a subset satisfying certain conditions
- Each block contains systems and their replicas that are mathematically distributed
- The systems and their replicas in the distributed blocks are strategically connected to receive updates
Combinatorial Balanced-block Design

- A balanced incomplete block design on a set of \( v \) elements is a collection of \( b \) \( k \)-subsets such that each element appears exactly in \( r \) subsets and each pair of elements appears exactly in \( \lambda \) subsets.

- Notation is \((b, v, r, k, \lambda)\)-configuration.

- We will implement a \((7, 7, 3, 3, 1)\)-configuration. But there are other configurations such as \((13, 13, 4, 4, 1)\), \((21, 21, 5, 5, 1)\), \((26, 13, 6, 3, 1)\), \((35, 15, 9, 3, 1)\).
Consider a seven 3-system subsets of 7-system set $Z = \{S1, S2, S3, S4, S5, S6, S7\}$ and there are 7 subsets (blocks) are available each with three elements:

$$DB\ 1 = \{S1, S5, S7\},$$
$$DB\ 2 = \{S1, S2, S6\},$$
$$DB\ 3 = \{S2, S3, S7\},$$
$$DB\ 4 = \{S1, S3, S4\},$$
$$DB\ 5 = \{S2, S4, S5\},$$
$$DB\ 6 = \{S3, S5, S6\},$$
$$DB\ 7 = \{S4, S6, S7\}.$$
(7, 7, 3, 3, 1)-configuration

\[ DB_1 \quad DB_2 \quad DB_3 \quad DB_4 \quad DB_5 \quad DB_6 \quad DB_7 \]

\[
DB_1: S_1 \mid S_5 \mid S_7 \\
DB_2: S_1 \mid S_2 \mid S_6 \\
DB_3: S_2 \mid S_3 \mid S_7 \\
DB_4: S_1 \mid S_3 \mid S_4 \\
DB_5: S_2 \mid S_4 \mid S_5 \\
DB_6: S_3 \mid S_5 \mid S_6 \\
DB_7: S_4 \mid S_6 \mid S_7
\]

\[ CL_1 \quad CL_2 \quad CL_3 \quad CL_4 \quad CL_5 \quad CL_6 \quad CL_7 \]

\[ CL \quad DB \quad S \]

- **CL** – Communication Link
- **DB** – Distributed Block
- **S** – System
For example, consider:

- $S1$ and $S6$ are communicating.
- Both systems are in $DB2$.
- Update/processing can take place instantaneously.

- Corresponding distributed blocks are updated independently and simultaneously without interfering with others and progress in parallel.

- When any system in any DB acts in anomalous fashion, that system can be replaced immediately.
Experiment

- **Objective:** Test the combinatorial balanced block design with Virtual Machines and NGC/WaxedPrune system

- **Input:** Simulated anomalous scenarios in provenance data and performance parameters, and VM machines in (7,7,3,3,1)-configuration.

- **Output parameters:** Convergence of prediction algorithm, time of predication and replacement action, and mission interruption (delay) time.

- **Experimental setup:** Implement reinforcement learning with deep neural networks to learn about anomalies, and attack VMs with simulated scenarios.
Automated Policy Changes based on Advanced Distributed Data Analytics:

• Each system in a distributed cloud environment performs aggregated analytics (adhering to privacy & security constraints)

• Performs predictive analytics and changes policies accordingly

• Communicate the policy changes with other systems in the distributed framework
Autonomous Active Block

ENC (Classified Data)

Adaptive Policy Block

Data Analytics & Decision Engine

Policy Enforcement Engine
Autonomous Active Block Components

• Classified data:
  – One-way public key encrypted data

• Adaptive Policy Block (APB):
  – Describes Autonomous Active Block and its access control policies
  – Policies manage Autonomous Active Block interaction with services and hosts

• Data Analytics & Decision Engine:
  – Conducts aggregated analytics & influences policies

• Policy Enforcement Engine:
  – Enforces policies specified in APB
Analytics in Autonomous Active Block

• Each Autonomous Active Block (2AB) performs individual aggregated analytics such as Count, Average, etc. on qualified attributes.

• These aggregate analytics guarantee privacy of individual 2ABs. Consider an aggregation,

  – 2AB$_1$ wants to get the average age in the system

  – 2AB$_1$ sends its age attribute with perturbation: “Age (a)” + “Random Number (r)”

  – 2AB$_1$(a + r = a$_n$) + 2AB$_2$(a + a$_n$ = a$_{n1}$) + …

  – Final average = (a$_{nn}$ – r) / count(2AB)
Policy Updates by Analytics

• Based on the aggregation, policies of 2AB will be updated.
  – For example, authenticated user 1 accessed several 2ABs in a short time.
  – The average of access requests can be calculated, and if it exceeds the normal mean set by the admin, the user can be blocked.
  – Policy will be updated to reflect this change.

• The policy change will be communicated to the other 2ABs.
Experiment

- **Objective:** Test Automated Active Block (2AB) scheme and policy updates in NGC/WaxedPrune system.

- **Input:** 2AB set up and reference policies.

- **Output parameters:** Time taken for analytics, accuracy of aggregate analytics, and accuracy and realiability of policy changes.

- **Experimental setup:**
  - Implement 2AB architecture and aggregate analytics over 2ABs with known and new policy references.
  - Update policies to reflect predictions.
Benefits of the Proposed Techniques:

- Combinatorial scheme provides intrinsic reliability with automatic fault-tolerant.
- Increased availability of the systems with the convenient control of concurrent updates.
- Replicas can be used for other tasks concurrently when the original system is functioning properly.
- Knowledge Discovery for triggering replicas can help in new patterns of attacks.

These solutions directly contribute to MINT Enterprise Analytics IRAD and Collaboration in Autonomous Teams and Societies (CATS) IRAD.
Knowledge Discovery – Definition

Given a system in a distributed computing environment, it should be able to:

2. Perform advanced data analytics on-the-fly.
3. Classify unknown raw data.
4. Discover new insights and rich patterns.
Knowledge Discovery – Model

Data sampling from data input → Cleaning / Preprocessing → Transformation / Reduction

Knowledge

Patterns & Models → Evaluation Criteria

Data Mining

Visualization
Knowledge Discovery – Challenges

• Defining cross-platform formats for representing the data and working with sparse representation of data

• Large data sets collected from diverse sources are often “dirty” with duplicates, erroneous, perturbed, or tampered data.

• Data cleaning requires domain-specific software that can be time consuming and costly to develop

• High latency in real-time processing due to high volume, diversity, and velocity of the data.
Knowledge Discovery Technique

Sampling-based Query Processing (SQP) technique:

- Extract samples and then clean them

- Use the result of cleaning process to reduce the impact of dirty data on query answers

- Error biases can be addressed using confidence interval as function of sample size
SQP Implementation
SQP Implementation

• Extract random samples from the dirty data

• Apply data-cleaning techniques to clean the sampled data

• Run the aggregate queries and return the result with confidence interval

• To reduce the variance, normalized the data and run the aggregate queries again
Helicoidal Pattern in On-the-fly Computations:

The key idea behind the parallel processing is to host distributed data processing units (DDPU) that can (a) read (R) to load the data, (b) Analyze (A) to process and classify the data, and (c) toggle (T) to shift to/from read or analyze. For example,

DDPU 1 : R item 1 \(\rightarrow\) R item 2 \(\rightarrow\) A item 2

DDPU 2 : A item 1 \(\rightarrow\) R item 3 \(\rightarrow\) A item 4

DDPU 3 : R item 4 \(\rightarrow\) ...

Cycle 1 \hspace{2cm} Cycle 2 \hspace{2cm} Cycle 3
Experiment

- **Objective:** Test the accuracy of data cleaning and sampling using SQP technique.

- **Input:** Using synthetic and publicly available real datasets.

- **Output parameters:** Comparison between confidence interval and performance

- **Experimental setup:**
  - Test SQP and run the experiments on: Raw samples and normalized Samples
  - Compare the results of confidence interval and performance
  - Measure the performances of various regression and classification techniques on the Big Data streams
Knowledge Discovery

Benefits of the Proposed Techniques:

• SQP technique only requires small subset of samples to be cleaned.

• Value errors, condition errors, and duplication errors can be rectified through normalized sampling and cleaning with considerably less computing complexity.

• On-the-fly classification can accelerate the decision-making process

• With distributed processing based on priority-and-availability, latency can be significantly reduced.

These solutions directly contribute to Distributed Data Processing IRAD & Information Analytics IRAD
Trust

• We propose *data provenance* with *blockchain-based* mechanisms to build trustworthiness of the data and ensure identities of network participants.

• Integrity of data will be guaranteed by blockchain technology. Data can be used for threat detection.

• Optimized access for transaction validation procedure allows to reduce number of blocks in the blockchain.

• There is one Merkle tree per Active Bundle and it gets updated with the hash of the data each time a transaction occurs.
Challenges of Blockchain Technology Deployment:

• *Performance*: Blockchain is replicated to all the network participants and this imposes a performance overhead. This was discussed with Peter Meloy of NGC-UK.

• *Access Control (Read)*: Revoked access to data on a blockchain can be bypassed in the following ways:
  
  – By replaying old blocks against an empty blockchain and stopping before the revocation block is appended.
  
  – An attacker holding a copy of a blockchain could use a modified client to just ignore the revocation block.

We discussed and learnt many blockchain ideas from Steve Seaberg (NGC)
Distinctive Attributes and Advantages

• **Cognitive Autonomy with Advanced Data Analytics:** Cognitive processing will be employed using activity pattern identification models to learn the operational parameters of the system.

• **Reflexive Systems:** We will design and implement the reflexive machine learning model to make decisions and trigger corresponding actions for adaptations, while proactively monitoring (being cognitive) the system.

• **Blockchain-based Provenance for Trust:** We will use blockchain technology to store provenance data and conduct analytics over blockchain.
Tangible Assets from Project

• **Stream Data Analytics Engine**: Processes data streams on-the-fly and in parallel.

• **Knowledge Discovery Engine**: This module will be implemented as a suite of advanced data analytics.

• **Cognitive Computing Engine**: This module will utilize data from the stream processor and the knowledge discovery modules to build a cognitive model of the system.

• **Data Provenance Ledger**: This will be implemented as a private ledger keeping immutable records of provenance data, based on the blockchain technology.
Integration with NGCRC & NGC IRAD Projects

- We have collaborated with Dr. Donald Steiner and Jason Kobes on Waxedprune.
- We are communicating with NG researchers:
  - Smart Autonomy (with Donald Steiner, Will Chambers, and Miguel Ochoa)
  - Rapid Autonomy prototype
  - Multi-intelligence (MINT) Enterprise Analytics (with Brock Bose).
  - Reliability Analysis Data System (RADS)
- We have discussed research questions and plan to collaborate with Peter Meloy in NG-UK. And Steve Seaberg.
1. **Smart Autonomy IRAD** (with Donald Steiner & Peter Meloy)
   - *Predictive Analytics for Responsive Forward Assessment, Investigation, and Targeting (PARFAIT) IRAD*
   - *Reliability Analysis Data System IRAD*

**Research Methodologies:**

- Simulating **Provenance** and **movement of data** from systems to client services in cloud platform.

- Employing **advanced machine learning analytics** across that data to detect abnormal behaviors from the users and the systems.

- Applying **Automated Predictive Analytics** to anticipate events and update system policies, automatically.

- Employing **Bayesian Statistics** to estimate the reliability of the system given the level of autonomy.
Collaboration with NGC IRADs

2. Automated Mission Planning for AS IRAD

- Collaboration in Autonomous Teams & Societies (CATS) IRAD
- Rapid Autonomy Prototype Implementation and Demonstration (RAPID) IRAD

Research Methodologies:

• Employing Reinforcement Learning and Deep Neural Networks (DNN) to identify plans and courses of actions to optimize mission performance.

• Enabling Cognitive Autonomy by automating the Observe, Orient, Decide, & Act (OODA) loop across all domains.

• Solving distributed partially observed Markov Decision Processes (POMDP) search and adversarial search problems.
Collaboration with NGC IRADs

3. **Information Analytics IRAD**

- *Analytic Flow Forge IRAD*
- *Distributed Data Processing IRAD*

**Research Methodologies:**

- Employing novel **Classification methods** and **Clustering algorithms** to manage voluminous amounts of diverse data.

- Discovering new knowledge from raw data to assist in decision-making and automating **Knowledge Discovery Process**.

- Employing novel distributed processing techniques to process **Big Data streams**.
Collaboration with NGC IRADs

4. **MINT Enterprise Analytics IRAD**
   - *Enterprise Information Management & Analytics IRAD*

Research Methodologies:

- Combining traditional **Ontologies** with **Semantic Vector Spaces** to extend ontology-like reasoning over diverse data.

- Discovering new knowledge from raw data to assist in decision-making and automating Knowledge Discovery Process.

- Employing novel distributed processing techniques to process **Big Data**
Plan for April 2018 Meeting

- Prototype and demonstration of the workflow of the property of autonomy with Cognitive Autonomy, Reflexivity, Knowledge Discovery, and Trust components.

- Collaboration and Integration with NGC Projects

- Presenting the work in conferences and workshops:
  - This work will be presented in CONSec 2017 held at MST in Rolla MO, on Oct. 28, 2017.