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Cognitive Automation in Industry – Design Principles and Case Study

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Abstract:
Automation, as we know is not a new phenomenon, automating the automation process that can learn, evolve, decide, and act as per context, just like a human is the new paradigm shift we all are experiencing of late with the advent of new technological enablers. The recent advances in computational capabilities, availability of historic data, low cost of sensors, and high-speed data transfer mechanisms are creating an opportunity to mimic a human brain and automate the process which matures along with the organization. Enterprises are now relying on software robotic systems which mimics the ways a repetitive task is handled by humans and preforms it in an analogous way, thereby eliminating the need of human intervention. But, these systems can neither take judgemental decisions nor can learn from previous actions and its results, thus restricting an automation process to simple repetitive process automations. This problem can be addressed by integrating cognitive features into software robotic systems, which will transform an enterprise into truly digital. In this paper we explored the evolution of cognitive systems, architecture, applications (case study) and challenges ahead in using cognitive models for industrial automations.

INTRODUCTION:

Cognition is defined as "The mental action or process of acquiring knowledge and understanding through thought, experience, and senses." Advances in artificial intelligence combined with computational power is giving us an opportunity to build a human like machine which can learn from experience and data available. It can be achieved by mimicking cognitive properties of human into a programmable machine using various mathematical models and machine learning techniques. These cognitive systems can infer, hypothesize, adapt and improve as they evolve, and its capabilities can be applied primarily in fields like healthcare, manufacturing, robotics, customer service (chatbots, smartphone assistance), finance, and general-purpose (phycology, neuroscience, medical research etc)

In industrial sector with Internet of things (IoT) huge volume of data is generated from multiple sources and this data when processed appropriately can help to generate meaningful insights and helps to track any of the enterprise processes. Automated processes built to automate repetitive tasks using RPA (Robotic Process Automation) often fail to adopt and evolve as they lack context based reasoning or self-learning abilities to act as per the changes in the data, processing requirements, or changes in the eco system For example, an RPA system that was built to handle invoice validations (for dollars), by mimicking the actions of a live agent, may fail to handle a new situation (processing rupees), unless it is trained and re-engineered to handle the same. In an intelligent processing world, this new change is expected to be absorbed as a natural progression, by detecting the change and applying suitable conversions without causing impact to the processing logic. To enable such intelligent processing, simple Automation is not enough, it needs smarter automation process that can understand the change based on context in a seamless fashion.

A cognitive RPA would be able to pick this change effectively and enable it. Thus, cognitive computing capabilities can be applied to solve few major problems of industrial automations.

COGNITIVE ARCHITECTURE:

Over last few decades, hundreds of cognitive architectures evolved and among them few architectures like ACT-R, Soar, CLARION, ICARUS, EPIC, LIDA are widely used/discussed. These cognitive architectures can be categorised based on various capabilities, properties and evaluation criteria's like recognition, decision making, perception, prediction, planning, acting, communication, learning, adaptability, generality, autonomy, problem solving and real-time operations. They leverage diverse technologies like machine learning, RPA, natural language processing, chatbots, image recognition, speech to text interpretation and so on.

Latest Evolving Architectures:

AI by Google (DeepMind) and Facebook AI Research (FAIR) are actively working on building cognitive capabilities to addresses many critical issues in AI. Natural language understanding, perceptual processing, general learning, and strategies for evaluating artificial intelligence are few key focus areas to improve fundamental characteristics of intelligence like learning and communication.

Google Deepmind launched AlphaGo in 2016, which was built using reinforced learning and neural network algorithms. It won a Chinese game GO, against world champion and finally ended the human domination on this game. Earlier programs built on Monto Carlo tree search failed to win over humans consistently. Unlike preprogramed cognitive abilities as seen in IBM Watson, Apple Siri or Google Now which serves specific purposes, AlphaGo is a general purpose and not pre-programmed. It learns by processing raw pixels as data input.

While developing AlphaGo, over million GO game pics played by humans are fed to the system to mimic a human player, further to improvise, it was made to play against itself for thirty million times. These advances in AI research is making intelligent automation possible in an industry.

We will now explore the process involved in designing a cognitive automation system for industrial automation and how various data elements such as Data mining, Data analytics are utilized to build enterprise data assets like Cognitive Automotive systems.

COGNITIVE DESIGN PRINCIPLES:

A cognitive system should be able to understand any kind of data and communicate with multiple data sources to process structured and unstructured data and generate meaningful insights or recommendations. Natural language processing, text to speech conversion, speech to text conversions are used widely in cognitive systems. The process involved in designing a cognitive system is iterative and should have 7 basic steps as shown in Figure 1. These are not sequential steps, and hence in the implementation process, we can go from one step to other depending on the results at each step.

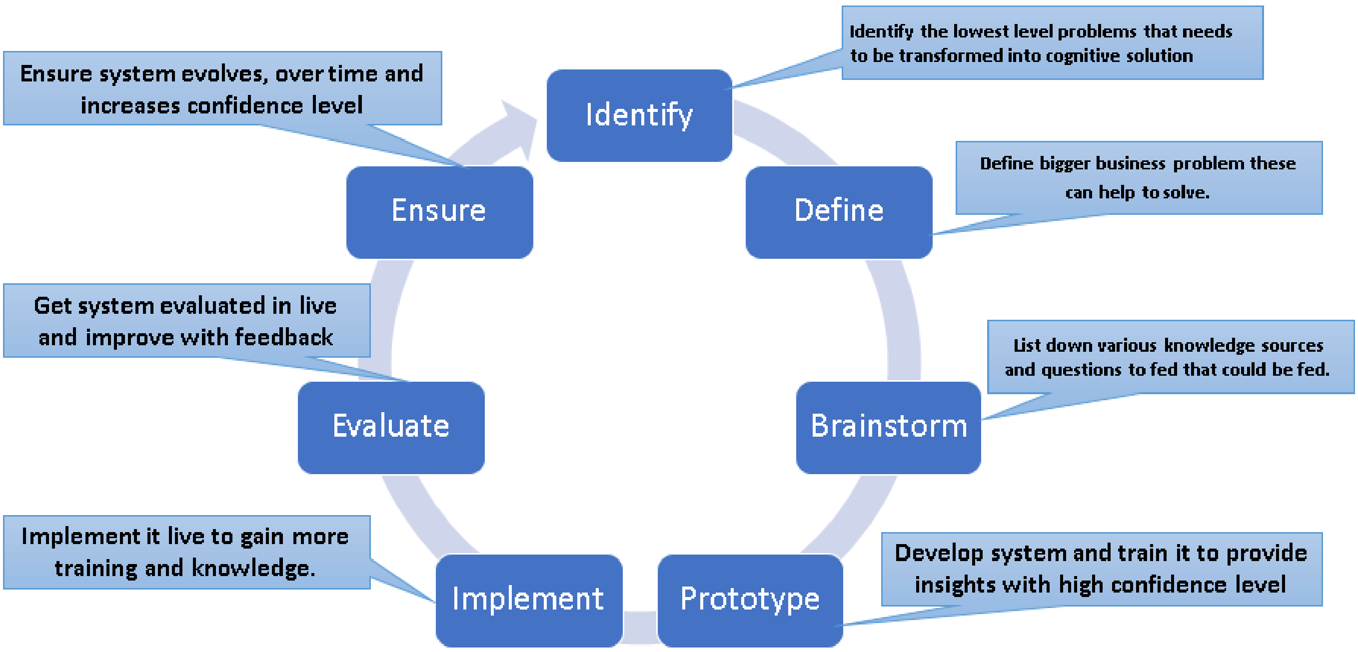

Figure 1: Cognitive design principles

The maturity of a cognitive model is measured by the confidence level of the recommendations or the actions taken by a cognitive process. Hence, improving the confidence level of a system plays a vital role in making the cognitive process successful. There are multiple factors which can influence the confidence level depending on the data it has access to. In a normal scenario, the confidence level can be improved based on the human actions taken to the recommendations suggested by the cognitive system. These are self-evolving and require human intervention for updating the context and improving the confidence level.

INDUSTRIAL COGNITIVE AUTOMATION:

Productivity improvement, accuracy, cost savings, scalability and flexibility are few major benefits of adopting automation in industries. However, even managing the automation tasks is becoming repetitive and having a human like automation system with decision making skills based on context would be vital differentiator for an industry.

In systems like RPA, we have used technology as a tool to automate most of the repetitive tasks, further cognitive system can help to make technology as a subordinate which can help to do most of the repetitive and pattern-based decision making work and evolve with time to become a master at work. It can be achieved by integrating and processing entire enterprise data and external relevant data.

Figure 2 shows typical setup of a cognitive system in an industry. The data generated from multiple source is pre-processed and fed to an analytics system. Operational real-time data is integrated with it to perform pattern discovery, anomaly detections and many other hidden values to give a meaning information and insights. Cognitive systems compare this data with external relevant source data and enterprise asset management data (EAM) to provide suggestions/recommendations and take appropriate action as programmed.

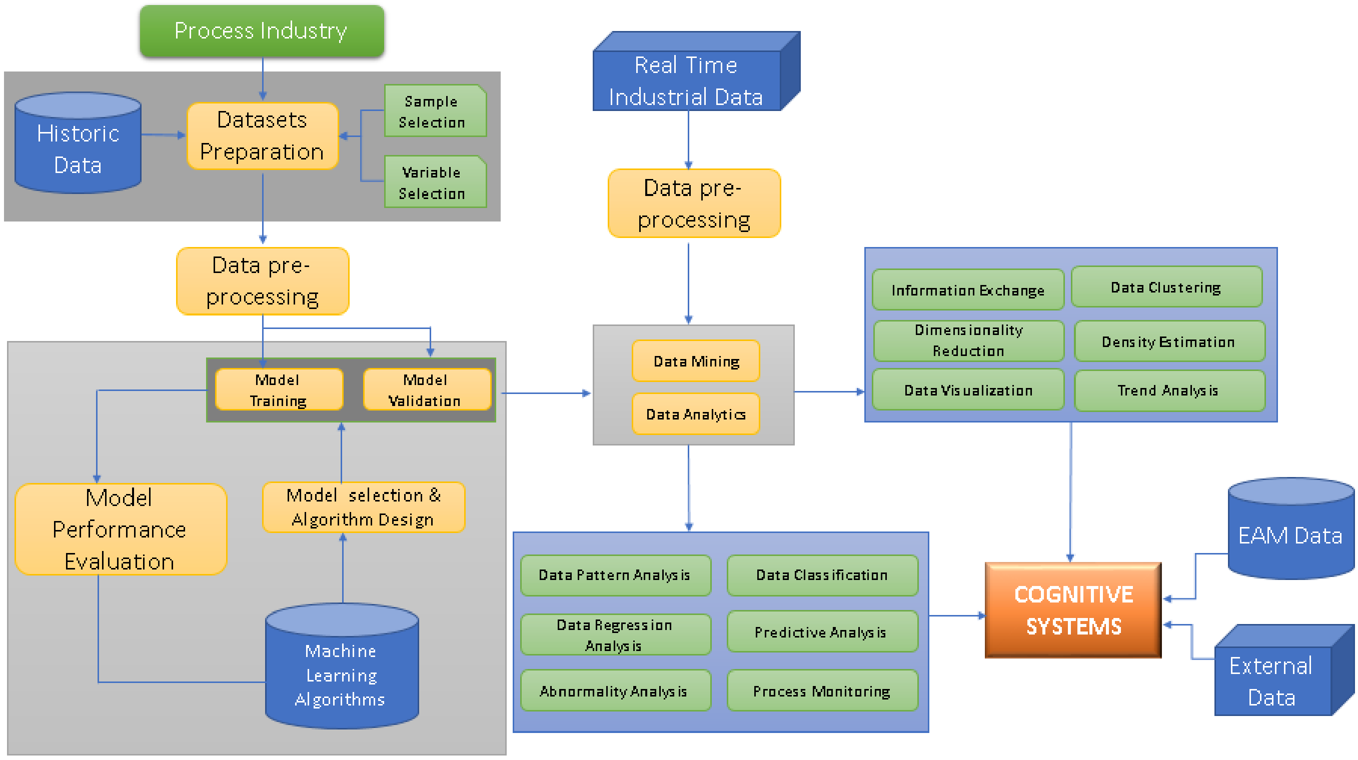

Figure 2: Typical Industrial Cognitive systems Architecture

Figure 3: Cognitive model maturity stages.

The systems design may vary based on the business and complexity involved. However, the integration of multiple enterprise level system is necessary for building a cognitive system.

INDUSTRIAL AUTOMATION PROCESS MATURITY:

Automation process in an industry evolves over time and it needs access to integrated industrial data, as a prerequisite. Once the data is integrated and organizational process are accessible, then building an effective cognitive automation model can be possible. To develop a simple self-learning model, a back-propagation algorithm is used by considering the no. of hidden layers as per business process. Hidden layers are no. of levels of classification an input should be filtered to recommend a possible action or result.

Any cognitive automation model offers minimal or no assistance to humans at the start, but captures all the actions performed. In this beginning state, human should take all the actions and cognitive model gets trained in parallel. In learning state, model suggests all possible actions that can be taken for a given set of conditions. In evolution state, model narrows down the possible outcomes and suggests only few recommendations based on the actions taken by humans while selecting a list of options suggested during learning state. In premature state, model can be designed in multiple ways based on criticality of process and business complexity. It can be set to provide specific amount of time to select the option from multiple suggestions or to act only when human approves. In either case, the difference in expected output and actual result would be tracked for model self-improvement. In maturity state, model would suggest one single option which is the best possible solution depending on the previous learnings. In post maturity model, there are multiple options in which a model can be designed, either to inform the human after executing the action or inform human only when asked, or inform human only if there is any deviation in expected result and actual result. The state beyond this is autonomous, where the model acts independently without any intervention of humans.

Cognitive models can be widely used in many of the day to day activities of an enterprise and assists employee just like a co-worker.

INDUSTRY AUTOMATION - BUSINESS CASE:

A logistic management company operates from multiple locations in India. It collects the products from port and delivers them to a warehouse (inbound), picks items from warehouse and delivers them to distributors (outbound). They manage fleet (for transporting goods from port to warehouse and warehouse to delivery station), a conveyor belt (to get goods from port to goods handling area) and warehouse /inventory (where all the goods are placed for dispatch). Following are the key pain areas identified.

1. Goods handling cost is high - due to delay in transportation.
2. Conveyor belt breakdown during peak load time.
3. Time delay during shipment of goods. – which impacts the brand image

Suggested Solution: Effective fleet management, conveyor operations and Shipment management using cognitive abilities would solve this problem. An interconnected enterprise model is built to manage all these components, further a cognitive model to effectively manage the process without any human intervention is designed.

Stage 1: Enterprise level database is integrated with fleet and inventory management. With this, the system can understand the advance receivables and advance shipments and alert the user well in advance if it anticipates inventory over run on any day. (Cognitive predictive capability)

Stage 2: Temperature, pressure and vibration sensors are attached to conveyor belt to track the performance and identify the reasons of failing at peak times. (Predictive Analysis)

Stage 3: All transport vehicles are attached to a GPS tracker which can receive message and alert driver appropriately. (Intelligent systems)

Stage 4: At stores, where items are picked for delivery, an automated lighting system is placed. By scanning the advance shipment note, light is switched on at the rack from where the inventory items are to be picked. (Intelligent Systems)

Stage 5: All the above automations are fed to a cognitive model to ensure timely suggestions are provided to human and actions are taken. (Cognitive Automation)

Following are few improvements from above solution:

1. Conveyor belt performance optimization – by prescriptive analysis.

   Using the sensor data (Temperature, Pressure, Vibration) collected from a conveyor belt under multiple scenarios, system can predict the appropriate time by when an issue might come in the belt. Post maturity state, the system can be able to increase or decrease the speed of conveyor belt automatically depending on the fleet movement which can be tracked by GPS. The system ensures to operate the belt in optimum conditions.

2. Optimum utilization of fleet, by forecasting the demand on a given day (Reduced fleet cost)

   Cognitive intelligent systems automatically send SMS to selected fleet drivers to speed up or slowdown depending upon the goods received at bay from conveyor belt. It will also slow down the conveyor belt if there is any delay in fleet arrival. (Human like decisions, backed by data)

3. Effective and error free inventory management.

   Inventory received and delivered items (shipments) are tracked. Once an invoice no. is scanned or entered, system automatically switches on the light at appropriate rack from where the products in invoice are to be collected. – Ensures error free shipments.

4. Automation of PO, Inventory and Shipment creations – (Cross leveraging cognitive abilities for unspecified problem areas)

Tracking invoices and product movements helps us to build new capabilities to our cognitive model, with this, it can raise automatic purchase order to preferred vendor whenever goods in inventory reduces beyond a certain limit. Model predicts the days remaining for any item to become zero and automatically sends an alert. These calculations are done based on quantity movement patterns noticed by the cognitive model. The model validates the manual purchase orders raised by human and suggests alternatives. (In case any product is available in the store or at any other location, then system shows them as suggestions before submitting the purchase order). This would help to save huge upfront cost and inventory overrun.

Cognitive models have various complexity levels of applications and in our above solution we have used data science and predictive/prescriptive analysis to provide solutions to major problems faced by a logistic management company.

Cognitive process automation can be applied in automating majority of the repetitive tasks in accounting, claims processing, compliance audits, data entry, timesheet updating/approvals, payroll processing, onboarding and offboarding etc. Visual computing and autonomous robots or general-purpose robots are other complex cognitive model’s applications.

CONCLUSION:

Automation drives the Industry productivity, we have noticed notable change over last few decades using mechanical automations and script-based automations for few simple repetitive tasks. With Industrial 4.0, connected and self-driving enterprise has now become a reality. Cognitive intelligence would soon become a co-worker to assist humans in handling most of the day to day activities. However, lengthy process involved in incremental learning, ability of cognitive model to understand world semantics and the abilities to decide and act in an unexpected situation are few challenges which might delay replication of these for general purpose. But, very soon, our human minds would be assisted with a cognitive wearable device which will be upgraded along with us as we grow. Future is very exciting, and the contributions of AI would address most of the challenges.

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