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SMART RPA – powered by Machine Learning

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ABSTRACT

Robotic Process Automation (RPA) is one of the smartest technology evolutions in recent years. It is, a software installed on a system. RPA can be implemented in a well-defined environment with defined procedures and clarity with reference to decision making. RPA's limitation is that it cannot be automated if it involves decision making supported by knowledge-based application. ML can come to aid here. ML can build a knowledge base based on historical data and use it for decision making and prediction. Combining RPA with ML can create powerful automation solution in medical device domain. Specialized skills are required in the nascent area of ML. RPA being designed for end user, the ROI for any organization can go up with the potent combination. This paper will touch the areas of RPA applicability in clinical domain, ML requirements and the possible impact of ML-RPA combination.

INTRODUCTION

Process transformation and automation have gained much of the attention in recent times. Companies are leveraging process automation technology to drive goals, efficiency, and digital transformation.

Gartner reported that organizations interest in process transformation is accelerating, demand for robotic process automation (RPA) software witnessing the growth of 63.1 percent in revenue to $846 million in 2018. The demand to push RPA software revenue to $1.3 billion in 2019 is also expected.

RPA is a technology that enables the automation of IT applications and highly manual, repetitive processes. Key benefits include faster processes, reduced risks and lower compliance costs. Machine learning meanwhile, is defined as "the field of study that gives computers the ability to learn by its own without being explicitly programmed." (Arthur Samuel, 1959)

SMART RPA or IPA (Intelligent Process Automation) or No-Code automation is the evolution of automation which would lead to bounty yields if implemented in automating silo process to begin with and all areas in clinical domain. This would cut drug's time to market from the lab and aid in saving more lives, faster.

AUTOMATION – THE HISTORY

1776 Adam Smith writes "Wealth of Nations" where he describes the concept of "division of labour"

1760–1840 Industrial revolution gathers steam as machines take over more manufacturing processes previously done by hand. In the two centuries since the industrial revolution, the world's average per capita income has increased over 10-fold, while the world's population has increased over 6-fold.

1911 Frederick Winslow Taylor publishes "The Principles of Scientific Management" for the American Society of Mechanical Engineers. The work advocates the "enforced standardization of methods, enforced adoption of the best implements and working conditions, and enforced cooperation" in order to improve efficiency. Although hugely unpopular with workers at the time and now considered largely obsolete, Taylor's work laid the foundation for modern industrial engineering.

1913 Henry Ford introduces moving assembly belts into plants producing "Model T" cars in order to increase efficiency. By 1916, the car cost less than half of what it cost in 1908.

1920's Walter A. Shewhart at Bell Laboratories pioneers the use of Statistical Process Control (SPC). SPC focused on detecting and preventing manufacturing issues before they became problems—an advantage over methods like inspection which meant throwing out defective products.

Advances in Quality Management & Early Computing

1940s-1970s Japanese engineers Taiichi Ohno, Shigeo Shingo and Eiji Toyoda are credited with developing the Toyota Production System—sometimes called "Just in Time Manufacturing"

1941 Conrad Zuse develops the Z3, often considered the world's first digital computer. Developments in computer technology advanced rapidly in the 40s and 50s. These computers took up an entire room and could only perform basic math calculations.

1950s Dr. W. Edwards Deming, an American statistician who had worked with Shewhart, trains hundreds of Japanese engineers and businessmen in SPC and concepts of quality. Joseph Juran, a Romanian born American engineer also influenced by Shewhart's work, moves to Japan to teach quality management methods. By the 1970s Japan was considered the world leader in quality.

Advent of the era of digital process management

1980's America has crisis of confidence as Japan's economy roars ahead and American-made products are largely seen as inferior in quality. American TV network NBC runs a documentary called If Japan Can, Why Can't We? seen as the moment where the works of Dr. W. Edwards Deming was popularized in the West.

1980's FileNet develops a digital workflow management system designed to route scanned documents through a predefined process. This early system—later acquired by IBM—is often cited as the precursor to modern BPM Software.

1986 Engineers working at Motorola pioneer the use of Six Sigma, a new technique for process improvement. Six Sigma uses statistical methods to identify causes of and then reduce variation (seen as the cause of problems that can lead to defective products or services) in processes. Although similar to SPC, Six Sigma, was credited for moving quality management out of being just a bunch of statisticians in a backroom.

1990 James Womack, Daniel Roos and Daniel T. Jones publish The Machine That Changed the World about the Toyota Production System. The book looked at how the company's system of "Lean" production produced superior results to those of traditional mass manufacturing.

1993 Michael Hammer and James A. Champy publish Reengineering the Corporation: A manifesto for Business Revolution, which sparked off a fervour of Business Process Reengineering (BPR) initiatives in Fortune 500 companies. In contrast to TQM or Lean, BPR focused on radical transformation rather than iterative, continuous improvement of processes. By the late 90s BPR had largely fallen out of fashion.

1980s/1990s Advances in computer technology and processing speed means that Personal Computers (PCs) start to experience widespread adoption by both companies and individuals.

1986 Dr. W. Edwards Deming publishes "Out of the Crisis" (originally published as Quality, Productivity and Competitive Poison in 1982) where he proposes a management theory based on his famous 14 points.

1990 Analyst firm Gartner coins the acronym ERP—"Enterprise Resource Planning." By the mid-1990's ERP tools handled all sorts of back office processes and data including accounting, HR and maintenance as well as front office processes supported by CRM (Customer Relationship Management). Thus begins the digitization of enterprise data and processes.

1990's Many companies adopt Total Quality Management (TQM)—a method similar to Six Sigma but also incorporating aspects of the Japanese system of continuous improvement.

1995 Jack Welch, CEO of General Electric, makes Six Sigma a key part of managing the company. By the late 1990s, most Fortune 500 organizations had begun Six Sigma initiatives to reduce costs and improve quality.

Era of Business Process Management

2000s Analyst firm Gartner coins the term "Business Process Management Suite" to refer to a vast array of software applications that deal with processes (whether carried out by machines or people). The term "workflow" falls out of fashion in IT circles (although some argue it made a comeback in the late 00's).

2007 BusinessWeek runs an article entitled "Six Sigma: So Yesterday?" about how major companies like Home Depot, GE, and 3M, were either abandoning or reducing their Six Sigma programs.

2013 Where will the combination of process and technology take us next?

2000s Business Process Management software advances to handle a wide range of functionality from process modeling, management through to reporting and analytics.

2012 Gartner coins the term intelligent Business Process Management (iBPM) to refer to BPM Suites that include support for analytics and complex event processing. Forrester coins the term Smart Process Applications to refer to BPM software that supports collaborative processes and incorporates data, analytics, and content.

RPA hands individual tasks over to software robots to streamline, and BPA takes an entire business process and automates it from start to finish.

BPA VS RPA

BPA –

- BPA focuses on restructuring the actual core operations and workflows of a business to make day-to-day tasks more efficient
- BPA overhauls the processes with the capability to remove roadblocks and create smooth workflows. RPA, on the other hand is quicker and adaptable.

RPA –

- RPA uses software to augment the performance of existing processes
- Boosts productivity with minimal process change. As a result, the process in place is unchanged, eliminating data integration and analysis efforts. Brings an easy-to-calculate ROI. The cost of an RPA robot will range from $5,000 to $10,000 annually. In some use cases, there is a one-to-one relationship between a robot and a worker. In others, a single robot replaces three to five workers.
- Savings are easy to calculate.
- Is a fresh alternative to the “big spend” of typical BPM programs. Business process management (BPM) as a technology strategy too often drives a wedge between the business and the technology management organization. BPM has a legacy of long implementations and fuzzy business cases — the opposite of RPA.

RPA VS IPA

In layman’s term, IPA is RPA moving to the next level of evolution in digital labor, in terms of intelligence and sophistication as it means automation enabled by ‘context-aware’ robots. Context-aware is the key here as that’s what essentially differentiates IPA from RPA. IPA stands at the higher end of digital labor, wherein robots can learn from prior decisions and data patterns to make decisions by themselves.

As McKinsey puts it, IPA “takes the robot out of the human”. In its report ‘Intelligent process automation: The engine at the core of the next-generation’, McKinsey describes IPA as follows:

At its core, IPA is an emerging set of new technologies that combines fundamental process redesign with robotic process automation and machine learning. It is a suite of business-process improvements and next-generation tools that assists the knowledge worker by removing repetitive, replicable, and routine tasks. And it can radically improve customer journeys by simplifying interactions and speeding up processes. IPA mimics activities carried out by humans and, over time, learns to do them even better. Traditional levers of rule-based automation are augmented with decision-making capabilities thanks to advances in deep learning and cognitive technology.

According to McKinsey five core technologies come together to form IPA. These five technologies are RPA, Smart Workflow, Machine Learning/Advanced Analytics, Natural-Language Generation (NLG) and Cognitive agents.

- Robotic process automation (RPA): a software automation tool that automates routine tasks such as data extraction and cleaning through existing user interfaces. The robot has a user ID just like a person and can perform rules-based tasks such as accessing email and systems, performing calculations, creating documents and reports, and checking files. RPA helped one large insurance cooperative to reduce excess queue procedures affecting 2,500 high-risk accounts a day, freeing up 81 percent of FTEs to take on proactive account-management positions instead.
- Smart workflow: a process-management software tool that integrates tasks performed by groups of humans and machines (for instance, by sitting on top of RPA to help manage the process). This allows users to initiate and track the status of an end-to-end process in real time; the software will manage handoffs between different groups, including between robots and human users, and provide statistical data on bottlenecks.
- Machine learning/advanced analytics: algorithms that identify patterns in structured data, such as daily performance data, through “supervised” and “unsupervised” learning. Supervised algorithms learn from structured data sets of inputs and outputs before beginning to make predictions based on new inputs on their

own. Unsupervised algorithms observe structured data and begin to provide insights on recognized patterns. Machine learning and advanced analytics could be a game changer for insurers, for example, in the race to improve compliance, reduce cost structures, and gain a competitive advantage from new insights. Advanced analytics has already been implemented extensively in leading HR groups to determine and assess key attributes in leaders and managers to better predict behaviors, develop career paths, and plan leadership succession.

- Natural-language generation (NLG): software engines that create seamless interactions between humans and technology by following rules to translate observations from data into prose. Broadcasters have been using natural-language generation to draft stories about games in real time. Structured performance data can be piped into a natural-language engine to write internal and external management reports automatically. NLG has been used by a major financial institution to replicate its weekly management reports.
- Cognitive agents: technologies that combine machine learning and natural-language generation to build a completely virtual workforce (or "agent") that is capable of executing tasks, communicating, learning from data sets, and even making decisions based on "emotion detection." Cognitive agents can be used to support employees and customers over the phone or via chat, such as in employee service centers. A UK auto insurer that uses cognitive technology saw a 22 percent increase in conversion rates, a 40 percent reduction in validation errors, and a 330 percent overall return on investment.

Intelligent automation promises to improve efficiency, quality, customer experience, and more. It will have applications in all parts of the business, from IT to human resources, operations to finance.

Here's an example by McKinsey of how IPA can put these five core technologies into action in an insurance company. A human claims processor pulls data from 13 disparate systems to provide the service. With IPA, robots can replace manual clicks (RPA), interpret text-heavy communications (NLG), make rule-based decisions that don't have to be preprogrammed (Machine Learning), offer customers suggestions (cognitive agents), and provide real-time tracking of handoffs between systems and people (smart workflows).

Potential process automation benefits (Source: Deloitte Project report)

Process type	**Potential benefits of automation***
High-volume transactional processes (e.g., requisitions, purchase orders and invoices)	Can reduce the average time and associated costs to execute transactional processes by **60% to 80% on average** Helps enable process to be executed approximately **15 times faster** than a human and operates **24x7**, leading to high throughput
High–risk processes with multiple handoffs (e.g., non–conformance reports, CAPA documentations)	Can eliminate need for manual intervention, and reduces the number of employees needed to execute tasks by **20% to 60%** Helps increase compliance by reducing errors and time spent on rework and review by **70% to 99%**
Data validation processes (e.g., risk assessments)	Helps ensure data consistency and accuracy in reporting by eliminating manual errors by **80% to 99%** Helps improve ability to shift FTE focus from report generation to analysis by **30% to 60%**
Dependent or linked processes (e.g., change management)	Helps decrease processing time by **up to 300%** by enabling processes to be executed outside standard business hours (i.e., overnight and weekends) Helps enable organizations to build automated system connections/interfaces without investing in IT architecture by **20% to 50%**

BOTS

Here is an example of automation. Creation of BOTS – software robots – which would automate certain steps.
In the below example, the bot does the following utilizing automagical.io platform:

> **Open Excel and reads the search terms it must search for.**
> **Opens Chrome and surfs to Google.com and enters search term.**
> **Saves all the urls from the first page.**
> **Writes the urls to excel.**

Code:

```
from automagica import *
excel_path = "Enter Path to Excel Here" #example: C:\\Users\Charan\\Desktop\\RPA Test\\data.xlsx
# Read information from the excel in the second row, for columns 2 to 10
lookup_terms = []
for col in range(2,10):
    try:
        print(col)
        lookup_terms.append(ExcelReadCell(excel_path, 2, col))
    except:
        pass
# Open Chrome
browser = ChromeBrowser()
for j,item in enumerate(lookup_terms):
from automagica import *
# Put the disease names of the first column in a list.
names = ExcelPutColumnInList("C:\\Users\\Charan\\Downloads\\disease.xlsx", "A2","A45")
# Create for every disease a folder with this name and save a .txt file in that folder with this extra information.
for name in names:
    CreateFolder("C:\\Users\\Charan\\Documents\\Subject\\" + ID)
    row = names.index(name) + 2
    data = ExcelPutRowInList("C:\\Users\\Charan\\Downloads\\disease.xlsx", "B"+str(row), "H" + str(row))
    WriteListToFile(data, "C:\\Users\\Charan\\Documents\\disease\\" + name + "\\" + name + ".txt")
```

The outcome of this code is an example of how manual process can be eliminated and automated. In our domain, there are several areas which requires reading from files, structuring data from unstructured data etc. which can be automated using coding. SDTM Bots and ADaM Bots can play the role of reading and structuring, saving data.

MACHINE LEARNING – THE APPROACH

There are different types of learning methodologies in ML.

SUPERVISED

Supervised learning consists of a labelled dataset with features. This is then fed into the learning algorithm during the training process where it will work out the relationship between the selected features and the labels. The learning outcome will then be used to classify new unlabeled data.

UNSUPERVISED

With unsupervised learning we tend not to know what the correct answer will be therefore the dataset is unlabeled. Rather, it is expected to discover patterns that suggest natural groupings in the data by itself.

An example scenario for this type of learning could be a marketing team looking for buying patterns using historical transactional data. The answer isn't obvious. Moreover, there could be many combinations of the correct answer dependent on what variables are factored in.

SEMI SUPERVISED

Many real-world machine learning problems fall into this zone as it's generally too expensive and time consuming to label your whole dataset for a fully supervised learning approach. On the other hand, an unsupervised learning approach may be unnecessary. Combining the two learning methods, therefore, should in theory give you the best of both worlds. Furthermore, many machine learning researchers have found that using both labelled and unlabeled data can produce considerable improvement in the learning accuracy when compared to unsupervised learning alone.

REINFORCEMENT

Reinforcement learning is a sophisticated style of learning inspired by game theory and behavioral psychology. This method of learning usually involves an agent, the machine that is making the action, and an interpreter. The agent will be exposed to an environment where it will execute an action and then the interpreter will either reward or punish the agent dependent on the success of that action. The goal for the agent is to find the best way to maximize the rewards by iteratively interacting with the environment in different ways. The only thing that the data scientist will provide in this type of learning is a method for the agent to quantify its performance.

PREDICTIVE ANALYTICS - ALGORITHMS

CLASSIFICATION

Classification algorithms are used to identify the class that an object from a dataset would belong to. These tasks usually fall into three different categories; binomial classification, multi-class classification and anomaly detection.

Binomial classification can be used for scenarios where the object will fall into one of the two classifications e.g. identifying whether an email is junk mail or flagging a fraudulent insurance claim. Whereas **multi-class classification** focuses on scenarios where there are many classifications, such as identifying the type of an animal; dog, cat, or horse, or figuring out what type of product a customer is likely to buy; a tablet, laptop, or desktop.

Anomaly detection is a type of single class classification algorithm where the only goal is to find outliers in your dataset or unusual objects that appear outside of the normal distribution. This can be used in events such as flagging fraudulent transactions, medical problems, or malfunctioning equipment.

REGRESSION

Regression algorithms involve continuous data, usually used in predicting a dependent variable based on the relationship between your independent variables. Some examples of regression models include financial forecasting, weather forecasting, or predicting product demand.

RANKING

Ranking algorithms determine the relative importance of objects in connection with other objects in the dataset. The page rank algorithm is probably the most well-known example as it's extensively used by Google on their search engine results page. Other scenarios include movie recommendations, based on viewing patterns, or hotel recommendations based on popularity.

CLUSTERING

Unlike classification or regression, some clustering algorithms are not used to predict a specific value. Rather, the algorithm is expected to explore the data and organize the objects into groups called clusters. Cluster analysis is mostly used in unsupervised learning techniques and deals with more complex scenarios such as where to place an emergency ward within a geography based on regions that are more accident-prone.

LEARNING MODELS

LINEAR REGRESSION

Linear Regression is a model very familiar to statisticians. This model has also been applied to machine learning, as a standard method for showcasing relationships between a dependent variable and independent variable when the independent variable changes.

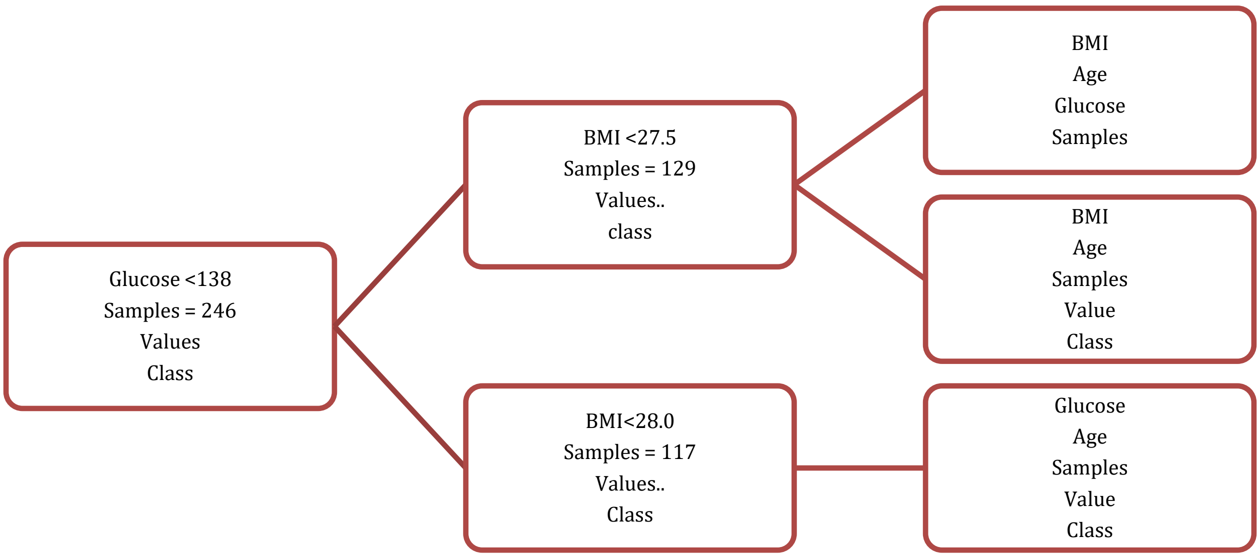
DECISION TREES

This type of algorithm has high interpretability and handles outliers and missing observations well. It is possible to have multiple decision trees working together to create a model known as *ensemble trees*; *random forest* and *gradient boosting* are examples of this type of model. Ensemble trees can increase prediction and accuracy whilst decreasing overfitting to some extent.

Here is an example of decision tree for PIMA Diabetes patients using SCIKIT Learn library from Python

Code:

```
# load dataset
pima = pd.read_csv("pima-indians-diabetes.csv", header=None, names=col_names)
#split dataset in features and target variable
feature_cols = ['pregnant', 'insulin', 'bmi', 'age','glucose','bp','pedigree']
X = pima[feature_cols] # Features
y = pima.label # Target variable
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
# 70% training and 30% test
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()
# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)
#Predict the response for test dataset
y_pred = clf.predict(X_test)
from sklearn.tree import export_graphviz
from sklearn.externals.six import StringIO
from IPython.display import Image
import pydotplus
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
filled=True, rounded=True,
special_characters=True,feature_names = feature_cols,class_names=['0','1'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('diabetes.png')
Image(graph.create_png())
```



Graphical representation: outcome of decision tree coding shows the graphical representation of a decision tree

SUPPORT VECTOR MACHINES

A typical algorithm that is used for classification, but can also be turned into a regression algorithm, is Support Vector Machines (SVM). SVM can bring greater accuracy when it comes to classification problems by finding the optimal hyperplane, a division between the different data classes. To find the optimal hyperplane, the algorithm will draw multiple hyperplanes between the classes. Then, the algorithm will calculate the distance from the hyperplane to the closest vector points, commonly referred to as the margins. It'll then choose to use the hyperplane which produces the greatest margin; the optimal hyperplane. Finally, it'll utilize the optimal hyperplane in the classification process.

K-MEANS CLUSTERING

K-Means clustering is used for finding similarities between data points and categorizing them into several different groups, K being the number of groups.

HIERARCHICAL CLUSTERING

Hierarchical clustering creates a known number of overlapping clusters of different sizes along a hierarchical tree to form a classification system. This type of clustering can be achieved through various methods with the most common methods being agglomerative and divisive.
The agglomerative approach is a bottom-up method which consists of all objects starting within their own respective clusters. These clusters of objects are then joined together by taking the two most similar clusters and merging them. Conversely, divisive clustering takes a top-down approach where all the objects start in the same cluster and are then divided into two separate clusters through an algorithmic process like K-Means. The splitting process is repeated until the desired number of clusters is achieved.

NEURAL NETWORKS

Neural networks are highly associated with robotics and neuroscience which naturally makes it the most exciting algorithm to explore. Neural networks, specifically artificial neural networks, consists of three layers; an input layer, an output layer and one or many hidden layers which are used to detect patterns in the data. It does this by assigning a weight to a neuron inside the hidden layer each time it processes a set of data.

CHALLENGES IN ML MODELS:

MISSING DATA AND IMPUTATION

UNUSED REPEATED COLUMNS

DATA TYPE CHANGES AND TIMESTAMP INFORMATION

NON- ALPHANUMERIC CHARACTERS

CATEGORICAL TO NUMERIC CONVERSION

APPLICATION IN OUR DOMAIN

CLINICAL DEVELOPMENT

Clinical-stage studies (phases I—III) cost an average of $1.1 billion over 7 years. The clinical development stage is thus one of the most expensive and extremely critical in the life sciences value chain. Added to this is the risk of non-compliance and data mismanagement. RPA's use can automate repetitive processes and bring in consistency in data entry, quality control and audit readiness in several areas including regulatory, clinical, safety operations. Few probable use cases:

Processing pharmacovigilance (PV) cases processing: Pharmacovigilance (PV) is a key area that could benefit from smart RPA. On an average, a large pharma company process approximately 700,000 adverse event (AE) cases annually. With pressure to be leaner and more efficient, companies need to be able to process this increased case load while maintaining their current cost base. Fifty percent of PV resources are currently spent on managing cases that require integration of data that varies in quality, structure and format. automating such manual steps the typical top biopharma can reduce time spent on PV by 45%, with potential multimillion-dollar annual savings (Source: EY).

Managing trial master process: sponsors can record and integrate all the activities related to a clinical trial, including from multiple trial sites, in a master data repository called a trial master file (TMF). (Since most of these master files are electronic in format, the "eTMF" designation is frequently used.) Although the TMF structure improves audit readiness, sponsors have yet to realize their full value because documents and data are still entered manually at present. Sponsors that use multiple CROs also must contend with multiple eTMFs that are not fully integrated. This limits insight into the trial master fi le content and process. In addition, staff must be trained and user accounts maintained and validated for each system. Automation reduces the manual effort associated with data entry and document uploading into the eTMF. EY estimates that RPA could reduce the time spent on data entry by 90%, potentially saving several million dollars a year per clinical trial (Source EY).

Supporting regulatory submission process: the regulatory submission process is time-intensive, requiring biopharma companies to carry out activities that include tracking the status of documents and compiling records to create a dossier. EY estimates that RPA could reduce process time by 65% and, thus, reduce the time to market (Source: EY).

Statistical Programming world: In the statistical programming world, we can look at the possibility of automating double programming concept; data conversion steps, data transformation steps; aggregating documents and files into final package.

SALES FORCE AUTOMATION

Bots can quickly aggregate key data to enable sales to focus on customer engagement. Bots can now manage routine (though still complex) data entry tasks, such as setting up meetings with physician groups, sending intelligent reminders for follow-up emails to prospects and customers, or providing call suggestions. Bots can help in assembling different data from the sales force, including past order history and contact information. This can help prepare sales reps for in-person meetings with providers, proactively flag opportunities and send follow-up notification reminders.

PRECISION MARKETING

Use case: A pharmaceutical company launched the first chatbot on Facebook Messenger for physicians in Italy and globally. The chatbot enables delivery of content tailored to each physician's specialization and answers complex questions by accessing data from a health database. In the future, the company plans to integrate the bot with Siri and other voice-recognition systems to improve the interactive experience.

A leading biopharma introduced a disease chatbot (Hives), which allows patients to have tricky conversations with a simulated dermatologist. This helps patients to explore issues on a private forum and collect the information they need to take next steps in managing their condition.

Providing real-time tailored knowledge to customers: chatbots could help enhance the physician experience — for instance, a physician can order a bot to bring up a drug's information related to a patient's specific diagnosis. Tailored communications to patients will be key to brand and therapy success in the future.

Acting as a virtual medical companion to patients: chatbots can act as virtual companions, checking when medications are taken, recording the latest biometric readings, inquiring about symptoms or making ingredient substitution suggestions to recipes found on the internet.

CONCLUSION - INVESTMENT IN EMERGING SCIENCES

Technology is growing at a pace unimagined before. Movement from a coded life to codeless life is the new journey. And its ML, DL concepts which are playing a great role in transforming the way life will look like in the future.

Clinical domain must open its arms cautiously to embrace the applications of the technology in all its processes. The journey of a chemical entity from lab to market could be made much easier, accurate, efficient and faster thus saving more suffering and holding on to the smiles on faces for a longer time bettering the current scenario.

As David Goleman puts it – The human brain being plastic, it is malleable. So should be artificial intelligence if it must match human intelligence and the journey has just begun.

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