AI STRUGGLES TO BEAT FINANCIAL MARKETS, BUT COULD IT BEAT CRYPTOCURRENCY MARKETS?

Financial market data sets present complex challenges for AI and Deep Learning, so how could they possibly
In the spring of 2010, James Tyler, a doctor of mathematics from the University of Cambridge, was studying the behavior of some of his automated trading algorithms from a nondescript office on Wall Street, with increasing alarm.

Tyler had been running simulations of market events to judge the response time of his algorithmic trading programs and was starting to grow concerned that under certain market conditions, the algorithms could flag false signals leading to a feedback loop that would have unintended and catastrophic effects for the fund he worked at.

The high frequency trading (HFT) fund that Tyler worked at was one of a plethora of HFT funds clustered around the New York Stock Exchange (NYSE) in Wall Street, to gain nanosecond advantages by reducing the time required for trading orders to travel through high speed fiber-optic cables to the NYSE.

Tyler was his HFT fund's chief risk officer and it was his job to monitor the algorithms which fed off market data in order to execute high speed trades, scalping basis points on every trade to deliver profits to the fund's investors.
And because many of the algorithms which Tyler worked with relied on what traders refer to as “technical” indicators—objective market data such as price, volume and trade size—under certain market “triggers” many of the fund’s automated trading programs would simply execute sell orders in quick succession, which is what they were designed to do, to protect the fund’s portfolio.

In other words, if an algorithm “discovered” that a sell order was being made, it would then automatically place a “sell” order as well, but this consequent “sell” order would also trigger another algorithm to place another “sell” order and so on and so forth, until the programs imploded the market.

And despite HFT strategies assuring regulators that the odds of such an event ever occurring were close to zero, that is precisely what happened in the spring of 2010—the Flash Crash.
The U.S. had its second biggest intraday point drop (from opening) in its history, plunging almost 1,100 points (about 9%) within minutes before rebounding very rapidly to make up most of the losses.

While the actual cause of the Flash Crash is still debated and debatable to this very day, the U.S. Department of Justice (DOJ) pinned most of the blame on Navinder Singh Sarao, a 36-year-old small-time trader who worked from his parents’ modest stucco house in suburban west London.

According to the Commodity Futures Trading Commission (CFTC) investigation, Sarao “was at least significantly responsible for the order imbalances” in the derivatives market which affected stock markets and exacerbated the Flash Crash.

Sarao began his alleged market manipulation as far back as 2009 with commercially available trading software, modifying the code “so he could rapidly place and cancel orders automatically.”

According to the DOJ indictment, Sarao had placed orders amounting to some “US$200 million worth of bets that the market would fall,” replacing or modifying them some 19,000 times before they were ultimately cancelled.

Some of the practices which Sarao employed at the time were perfectly legal, including spoofing (entering and quickly canceling large buy or sell orders on an exchange to create false impressions of market conditions), layering (similar to spoofing, layering is a HFT strategy where a trader makes and then cancels orders that they never intended to have executed in the hopes of influencing price) and front running (dealing on advance, non-public information knowing that the information will affect the price of a security) – strategies which have since been banned.

But Sarao’s orders were by no means large.

In a market which trades trillions of dollars a day, US$200 million is barely enough to move the needle.

Some analysts suggest that the real reason for the Flash Crash was erroneous signals, picked up by algorithmic trading programs, which automatically scanned the market and then acted autonomously on such signals.

Which is why there was a flurry of sell orders, causing the market to crash, followed by signals that the market had been oversold, causing a flurry of buy orders to bring the market back to its original equilibrium.

And the lessons from the financial markets in 2010 (as well as a subsequent flash crash in 2015), may also provide some lessons for what happened with Bitcoin prices last week.

**Bitcoin Trading Is A Lot More Automated Than Anticipated**
Automated trading in the cryptocurrency markets quickly brought Bitcoin back down below US$4,000 about 24 hours later.

During the entire period, the volume of Bitcoin traded was relatively consistent—consisting primarily of market-making bots and other algorithmic trading programs that kept Bitcoin volumes more or less within a zone of equilibrium.

Things changed dramatically however towards the end of April.

Bitcoin trading volumes more than doubled across all cryptocurrency exchanges—this increased flurry of activity changed the trading band for Bitcoin, between US$4,000 and US$5,500—a level that stayed consistent until late April.

It was roughly around this time, when court documents dated April 24, 2019, revealed that the New York Attorney General was building a case against Bitfinex, for misusing funds belonging to Tether to cover over losses of some US$850 million at the cryptocurrency exchange.

The news of potential malfeasance at Bitfinex, far from putting a damper on Bitcoin prices actually put a shot in the arm of the world’s biggest cryptocurrency by market cap, pushing Bitcoin well beyond US$6,000 in the following weeks.

On the back of a significant increase in volume, automated trading programs went into action, feeding off market signals and pushing Bitcoin even higher.

The signals of increased trading volume from both automated trading programs as well as human traders led to more automated trading programs being activated and by mid-May, trading in Bitcoin was 8 times the amount it had been in January.

Because of the feedback loop created, automated trading programs, buoyed by human traders then proceeded to push Bitcoin even further, all the way up beyond US$7,000, a level not seen since the middle of 2018.

As Bitcoin started to test the US$8,000 level, that was sufficient signal for automated trading programs to start exiting their Bitcoin positions and almost overnight, Bitcoin plummeted back to the US$7,000 level on the back of heavy volume.
As volume started to stabilize, Bitcoin once again settled into a trading band, between US$8,000 towards the end of May.

But in the last few days of May, Bitcoin, having tested the US$8,000 barrier on several occasions in the previous weeks, powered through to push well beyond US$8,000, leading some to claim that the “crypto winter” was finally over.

But celebrating the spring thaw for Bitcoin may have been premature, as automated trading would once again keep Bitcoin within a band of between US$8,000 and US$9,000, never actually touching the US$9,000 level and never ever breaching it.

These signals were sufficient to rattle automated trading programs which then proceeded to sell-down Bitcoin collapsing it through the US$8,000 level towards the first week of June, a level where it continues to hover within a band of between US$7,500 and US$8,000.

**Automated Is As Automation Does**
Unlike financial markets, high-frequency trading (HFT) is not possible on any of the major cryptocurrency exchanges—with rates deliberately limited so as not to crash the exchange itself.

However, on decentralized exchanges (as well as some centralized exchanges), many of the behaviors prohibited in the financial markets are not only evident, but prevalent.

Behaviors like front running, spoofing and layering are all commonplace on cryptocurrency exchanges.

Such manipulation in cryptocurrency markets where the bulk of the trading is already so highly automated means that the quality of the data which automated trading programs consume and act in response to is extremely prone to feedback loops.

But unlike in the financial markets, these feedback loops take longer to manifest because of the lack of HFT.

So while cryptocurrency markets may not exhibit the flash crash susceptibility that regulated financial markets are at risk of experiencing, cryptocurrency markets are still susceptible to the erroneous, self-perpetuating feedback loops that define automated market behavior.

Trading bots detect increased volume which activate new trading programs which detect increased volume and so on and so forth.

**But What Were We Expecting?**

Because we've become so used to artificial intelligence or AI auto-populating search fields for us, recommending us books to buy or clothes to wear, reading our faces and (eventually) driving our cars, we've come to expect a lot from the technology.

But if there's one arena which AI has yet to conquer, it's the financial markets.

Thus far, a computerized stock picker or investment robot has yet to consistently outsmart the financial markets, but it's not for lack of trying.

In the mid-80s, a concerted push was made by some of the brightest technical minds, to scientifically model markets, as opposed to say, find a cure for cancer.
This is what happens when you leave your Roomba alone for too long. (Photo: Studio Canal | Carolco Pictures)

Many of these efforts to create the ultimate trading robot absorbed some of the top graduates in fields such as math, computer science and even rocket propulsion.

Secretive hedge funds like Renaissance Technologies, D.E. Shaw and PDT Partners plied the trade, carving out extraordinary returns in the latter half of the 20th century.

And part of the reason that many of these “robo” hedge funds with their “black boxes” were able to deliver extraordinary returns was the state of computing technology at the time.

During a period when computers were relatively slow (by today’s standards) and information did not travel as quickly or as freely, the early algorithmic trading outfits were better able to find, preserve and exploit profitable trading strategies for longer periods than today.

But as computers evolved and with the advent of the internet, once profitable strategies which regularly delivered in excess of 30% annualized returns were no longer able to perform to their previous levels.

Top flight quant funds such as James Simon's Renaissance Technologies tweaked their algorithms and to be sure, Simon's trading strategies were never purely algorithmically driven anyway, with a fair measure of human oversight and discretion initiating and leading trades.
For the same reasons that self-driving cars have a tendency to end up in car crashes, AI-driven investing also has a tendency to result in flash crashes.

**Keep Still So I Can Shoot You**

There are simply too many variables and unknown unknowns as well as unknowable unknowns in the financial markets, for AI in its current state of development to deal with.

In quantspeak, data of the sort that AI has to deal with in the financial markets is “non-stationary.”

An example of stationary data might be the distance of say, your driveway from your door. Short of an earthquake or remodel, that distance is likely to remain constant and if a machine is fed hundreds of pictures of your driveway and your door, it will in all probability be able to identify your home.

But financial markets are charged with data that can change dramatically in unprecedented and unforeseeable ways—for instance when Russia defaulted on its sovereign debt in the 90s.

Not so with cryptocurrencies.

As an unconstrained asset, with limited correlation to other assets, the data sets that need to be considered when it comes to trading cryptocurrencies are far fewer—many of which are speculative and many of which are co-dependent, resulting in far more predictable patterns then say in the financial markets.
There's a divinity that shapes our ends, rough hew them how we will. (Image by Lorenzo Cafaro from Pixabay)

Stocks on the other hand move all the time and not always for any discernible reason, with most market moves what economists term “noise” trading.

Returning to the analogy of your door and your driveway, imagine if a computer was instead trying to identify your home based on pictures of your home taken both day and night and in varying lighting conditions.

Most of the data in those pictures would be “noise” and worse, the light in some of those pictures at least could lead to “false positives,” which could induce the computer to mistake someone else’s home for yours.

And as data sets go, historical stock price data is not particularly voluminous, meaning that what may appear to be a significant data point may actually be insignificant if a larger amount of data were available — sort of the way jagged peaks and troughs on a chart tend to smooth out with more data over a longer period of time.

To illustrate this difficulty, say you’re trying to predict how stocks will perform over a one-year horizon. Because there’s only reliable stock information from 1900 onward, there are only 118 non-overlapping one-year periods usable for examination purposes.

In contrast, Facebook, which has a virtually endless supply of data with which to work with, processes no fewer than 350 million pictures a day.
Limited Data & Limited Edges

Obvious signals, say buying stocks on the first day of every month, are of limited value and even if they worked in the past are probably more a product of coincidence, than reflective of any predictive skill.

And even if it wasn’t just luck that discovered these “obvious signals,” thanks to the relative transparency with which financial markets trade with, such advantages will be quickly discovered and any profits, traded away.

So instead of trying to find “obvious signals,” many analysts have turned to divining the subtle—ones that predict the future price with only 51% certainty.

While that may not sound like a lot of confidence, consider that in casinos, a 51% advantage is the average house advantage for most table (card) games such as Blackjack and Baccarat and more than sufficient to ensure that over the long run, the house always wins.

The same goes for hedge funds deploying such strategies.

By taking a large number of very small bets with a small advantage such as 51% and juicing those bets with leverage, managers can make outsize returns in relation to the actual size of the funds invested.

In cryptocurrency markets, a 51% advantage is not only possible, it’s relatively pedestrian.
“What you do speaks so loud, I can’t hear what you’re saying.” (Image by SeppH from Pixabay)

Because there are far fewer signals to monitor and because the “noise” is far easier to identify and isolate, trading advantages can be far larger than 51%.

And unlike financial markets where there are minimum order sizes and minimum brokerage fees regardless of the size of the trade, cryptocurrency markets generally work on a percentage of every trade, regardless of the size of the trade.

What this means is that even cryptocurrency traders who trade relatively small amounts can still yield alpha as if he or she were a large-sized hedge fund, availing themselves of trade fees of a few basis points regardless of the trade size.

Not so in the financial markets, which is why many managers look to improve returns by reducing transaction costs. Because, as mentioned, in financial markets each transaction regardless of size attracts a minimum cost.

The other way that managers can cut costs is to reduce slippage, which is the actual cost paid for buying a specific security, as opposed to the target price.

Say for instance the price of a share of General Motors is US$100, but only 100 shares are available at that price and if you wanted to buy 1,000 shares of GM, you’d need to bid up the price, which may result in the average cost of your shares being US$105 or even more—a 5% premium on your target price.
amount of illiquid stock, might make sellers think that they can fetch a better price for their stock or automated trading programs might immediately withdraw their sell orders, forcing the price to surge upwards, despite there being no significant reason for prices to rise other than the withdrawal of liquidity.

The Tricky Business of Liquidity

The same market behavior is observable in cryptocurrency markets.

Take Bitcoin for instance.

Depending on which cryptocurrency exchange you intend to buy your Bitcoin from and how much Bitcoin you buy, you could be the market for Bitcoin, with your moves affecting the overall price of Bitcoin.

Which is why when investor are seeking to acquire large amounts of Bitcoin, they tend to spread their purchases across a variety of cryptocurrency exchanges, with many also using over-the-counter or OTC transactions that are off-market and do not affect the price of Bitcoin in the open market.

And while many use CoinMarketCap (a website) to determine the price of Bitcoin, it is far from authoritative, using a closely guarded algorithm to determine the blended price of Bitcoin from various undisclosed sources—hardly the stuff of transparency.

But fortunately, computers can be taught to anticipate transaction costs and this helps traders in two ways.

First, if an algorithm can effectively predict the likely slippage based on the order size and historical liquidity, the edge required for a trading signal could come down from say 51% to 50.5%, meaning more trades can be made, yielding more opportunities for profit.

And more trades also means, according to the law of large numbers, better chances at achieving target odds.
The house always wins because it doesn't have to go home, you do. (Image by Linda72 from Pixabay)

The second way reducing slippage helps is that more profit can be squeezed from existing opportunities.

Say for instance a widely known model identifies Bitcoin as 1% undervalued.

Without understanding transaction costs, a trader might purchase only 100 Bitcoins, lest it risk too much slippage and push the price of Bitcoin above the 1% spread that it's looking to capture.

But another trader armed with an algorithm that can predict the transaction cost with perhaps an 80% probability might know that 500 Bitcoins could be purchased without pushing the price of Bitcoin beyond 1%.

The trader who is able to effectively predict and price transaction cost could boost their returns by 500% — a huge advantage in any market and significantly affecting long-run returns.

In order to squeeze transaction costs further, some quant managers build their own high-frequency trading operations, in which they can act as market makers, making profits by matching buyers and sellers.

In the cryptocurrency markets, market makers (of which my firm is but one of many) also employ market making algorithms that provide constant liquidity for cryptocurrency exchanges and match buyers and sellers.

Running these market making operations does not just contribute to bottom lines, it also provides deep insight into market behavior.
Looking for Alpha Between Sofa Cushions

Some quant managers who struggle with market data are finding other kinds of information to mine instead of just what the market tells them.

Whether it's commodities traders using satellite photos of feed lots or social media feeds, alternative data may provide some help especially where the classical data is either cumbersome or unreliable.

To that end, many cryptocurrency traders monitor Twitter, Medium, Telegram and Reddit to mine information about potential cryptocurrency movements to gain an edge in their trading.

But as such data becomes easier and easier to find, the advantage that such data provides typically suffers from a lack of longevity.

Rob Arnott of Research Affiliates and Campbell Harvey, a professor at the Fuqua School of Business, North Carolina—two of the best known experts in quant investing—have warned investor against using machine learning to derive investment strategies from data sets that lack sufficient depth.
Looking for alpha means you need to go where no one else is prepared to. (Image by skeeze from Pixabay)

Arnott and Harvey have even proposed a checklist for applying deep learning techniques, with a specific focus on the depth of specific data sets, because the alternative Arnott suggests, is akin to driving a Ferrari on a dirt track.

But even if specific catering for thin data sets is made, there are still considerable risks when applying alternative data sources towards deep learning.

Because even a minor bias in a data set has the potential to be picked up by a trading model, leading to extraordinary returns, future decisions made by such trading models may be based on a series of false positives or confirmation bias—the algorithms see more of what you’ve been trained to notice.

For example, if in your mind you’ve decided to buy a red Ferrari, you may suddenly find yourself seeing the car you want to buy everywhere you go, when in fact, the statistical likelihood is that the instances of the car appearing is exactly the same as it was before, you simply have started taking notice of it.

So the combination of new data and powerful data mining tools is a potentially dangerous mix—because deep learning tools can very easily and inadvertently be designed with existing biases—leading to conclusions or predictions based on patchy or misconstrued data.

Keep It Simple Stupid
“One tool that Renaissance uses is linear regression, which a high school student could understand.”

Granted not just any high school student would get linear regression—probably the ones doing AP Calc would—the technique is simply a way to find the relationship between two variables.

While linear regression may be difficult to determine between the dollar and say Bitcoin, it is interestingly enough, a lot easier to determine within cryptocurrencies themselves, in particular between Ethereum and Bitcoin.

But in the financial markets, linear regression gets more tricky.

Because of the non-stationary nature of data sets in financial markets, even where linear regression is “discovered,” it may be based on a set of false positives or quickly evolve into a different relationship.

Which is why AI still struggles with pattern determination and predictive models in financial markets—there are simply too many moving parts.

**Autonomous Alpha**

Although hedge funds continue to pour resources into creating the Skynet (a fictional artificial neural network-based conscious group mind and artificial general intelligence system from the *Terminator* movies) of trading, finding new market signals is still very much a human endeavor.

Some of the top quant funds still employ hundreds of Ph.D.s in subjects such as mathematics, computer science and even rocket propulsion.

The fundamental core of discerning patterns in a highly random universe is still very much akin to rocket science.

To build the Skynet of investing, one that perhaps won’t threaten to destroy the financial world in its wake, will require researchers to crack the code of causation.

Because correlation does not imply causation, such an autonomous investing system would for example, not only need to detect that a rise in a particular stock is accompanied by a rise in interest rates, it would also need to come up with a good reason for it.

For now at least, humans still have an advantage over machines at this sort of critical thinking and analysis, but AI is starting to make inroads.

Deep learning in particular has driven recent advances in AI such as image recognition and speech translation, two notoriously complex data sets.
T-800 was unimpressed at attempts to school it. (Photo: Warner Bros. via CNET/CBS Interactive.)

And though deep learning’s use in finance is limited, that hasn’t stopped researchers from trying to use it.

Zachary Lipton, a professor at Carnegie Mellon University, co-authored a paper with John Alberg of Euclidean Technologies, an investment management firm, attempting to demonstrate one possible approach to addressing the “noise” problem inherent in financial market data sets—track company fundamentals like revenue or profit margins that ultimately drive company returns instead of stock prices.

But even Lipton and Alberg’s approach has its limitations.

First, it assumes that the quality of the data is impeccable. Given the variety and complexity of valuation models and accounting standards, the quality of inputs in financial markets varies greatly.

Second, because financial markets are constantly adaptive and data sets are generally not deep nor long enough, enduring trends are barely discernible if they exist at all.

Speaking to the Financial Times, Andrew Lapthorne, head of quantitative equity research at Société Générale, an investment bank, cautions,
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computing and self-driving cars—these are predictions that AI generally struggles with as they require absorbing a large amount of highly generalized data to divine trends—in other words, critical, "out-of-the-box" thinking.

One of the reasons why AI and deep learning struggle so much in the financial markets is because two of the most unpredictable human emotions of greed and fear are made manifest in this highly competitive arena.

And financial markets determine so much of what it means to be human—everything we do is directly or indirectly dictated by the financial markets—that the factors which influence market prices are as varied as the humans that are influenced by them.

The amount we pay on our mortgages, how much our food costs, whether we drive to work or walk, everything routes back to the financial markets, making predictive models that much more difficult when left purely to automatons.

But because cryptocurrency markets (for now) have limited influence in actual daily life, the factors involved are far fewer and more determinate.

Because most of cryptocurrency trading is autonomously and algorithmically driven, patterns are more easily discernible and human trading behavior often sticks out in stark contrast to established market behavior.

This means that if relatively small advantages, in the region of 51% to 55% are sought out in the cryptocurrency markets, they can almost be guaranteed.

The issue of course is not the opportunity to profit—it’s the magnitude of such profits.

Currently, cryptocurrencies simply do not have the volume and liquidity necessary for autonomous trading strategies to be deployed in large quantums.

Percentage returns for algorithmic cryptocurrency trading may be significant, but beyond certain volumes, especially when assets under management start approaching the hundreds of millions of dollars, traders need to get far more creative and circumspect in deploying funds as the opportunities are far fewer at larger order sizes.

For now at least, AI and machine learning are still some ways away from consistently beating the financial markets, but with a bit of tweaking they may be a lot closer to beating the cryptocurrency markets.

And while the prospect of searching for phantom signals that eventually disappear could dissuade some people from working in finance or cryptocurrency trading—the lure of solving tough problems coupled with the potential to make some serious money means that there will always be more than enough people who will try.
Mark Holland

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Jose Lazo

This shows the limitations and the level of sophistication AI can achieve.

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While the sources, and consequently the volume of big data continue to multiply due to the emergence of technologies like IoT, the need for making better use of the data that is gathered is also becoming more apparent. To fulfill this need, adaptive intelligence, which adds to the capabilities of traditional analytics can enable businesses to further automate their business intelligence tools.

Considering their increasing adoption and propagation across nearly every industry, the eventual confluence and the growing interdependence of big data and AI is hardly surprising. While big data has been around for a while now, applications of the technology, until recently, failed to make the impact they were expected to upon their emergence. In fact, it was estimated that 85% of big data initiatives had failed to deliver their expected results. While the reasons for the underwhelming impact of big data initiatives are numerous, not having the right tools and people to clean, analyze, and proactively seek and solve problems has been a major part of the problem. In recent years, the use of AI to clean -- and solve problems using -- the enormous body of data collected is making applications of data analytics more effective. However, when it comes to making decisions, there is still a large dependence on humans. Among the numerous ways that AI is enabling the effective utilization of big data by minimizing the role of humans, one way is through the recently emerged concept of adaptive intelligence.

Adaptive intelligence is a subset of artificial intelligence that goes beyond just converting inputs into insights to enable action. It helps in delivering the most contextually relevant output whenever required, by training. While there is little doubt regarding the superiority of analytics and artificial intelligence in term of computational capability, there is still a lot left to be desired in terms of making artificial intelligence actually "intelligent". Thus adaptive intelligence, while eliminating all the limitations that come with human-driven decision-making, incorporate certain cardinal elements that can only be achieved by virtue of human involvement. Read on to know how critical business analytics is to the modern-day enterprise, and how adaptive intelligence takes it to the next level.
use of business analytics to drive problem-solving and growth has become the standard across different industries, from agriculture and healthcare to entertainment and tourism. Businesses are increasingly becoming reliant on data analysis to drive both their operational and strategic decisions.

A manufacturing supply chain, for instance, generates terabytes-worth of data or business intelligence through its operations. The data includes external information such as that regarding the product demand, the supply of materials, regulations, competition, customers, and economic policies among others. It also includes internally generated data such as that related to the manufacturing activities and equipment, product design and development, inventory, vendors, and employees. Both the internally and externally generated data, if leveraged appropriately, can enable the manufacturer to make decisions that can improve their offerings, make their processes more efficient, maintain and grow their customer base, respond to changes quickly and effectively, and maximize profits.

For example, the data generated by the manufacturer’s main production facility can point to a flaw in process planning that leads to significant avoidable expenses. They can use the data to make better process planning decisions and maximize process efficiency. Business analytics is also becoming a staple in the service sector, where every industry, such as entertainment, finance, and healthcare is using analytics in innovative ways. Service sector organizations use business analytics to improve customer experience, boost customer satisfaction levels and ensure the retention and growth of their customer base.

**Adaptive Intelligence: Making Analytics Smarter**

![How Adaptive Intelligence Makes Analytics Smarter](image-url)
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data quality achieved through data cleansing, normalization, elimination of biases, and better data gathering practices, along with the decision-making that is done by humans based on data analysis.

The existing tools used for business analytics offer high-speed, high-volume data processing and computational abilities to turn data into usable insight which human employees, owners, and other decision-makers draw upon to carry out business activities. Thus, the effective use of business analytics requires a mix of machine and human capabilities. Adaptive intelligence combines these capabilities to offer businesses the ability to make the use of business analytics smarter and easier to use.

Adaptive intelligence not only analyzes large volumes of data to deliver valuable insights whenever requested by organizational personnel but also adapts the information based on specific situations. It ensures that the right information, in the right form, is delivered to the right people at the right time.

Adaptive intelligence, just like business analytics, helps businesses make better decisions. But, it makes the process of decision-making faster, more adapted to individual cases, and with minimal effort from the decision-maker. While business analytics focuses on data analysis and delivery of insights, adaptive intelligence adds the focus on context and relevance. This makes every instance of data analysis and decision-making faster and simpler for the stakeholders which culminates in the enterprise benefiting massively in terms of productivity, effective responsiveness, and, consequently, financial profitability.

While business analytics gives actionable insights when requested, adaptive intelligence proactively and autonomously provides insights when needed. It makes the process of determining the actions to be taken easier by simplifying the decision-making process. And like other AI systems, adaptive intelligence learns to perform analysis, make decisions, and prompt actions in better ways.

**End-to-End Automation: Applying Adaptive Intelligence**

The concept of adaptive intelligence is already gaining traction among business and tech leaders as an upgrade on business analytics. It can be used by businesses to make the process of sharing information across the enterprise easier. Thus regardless of where information is needed in an organization, be it in the accounting department or the customer service vertical, adaptive intelligence can deliver the requisite insights proactively by sensing the context. The penetration of adaptive intelligence will only increase with time as AI becomes smarter and technologies like the Internet of Things (IoT) become widely within organizations and across industries. Using IoT’s sensory and actuating end-points, adaptive intelligence can become more responsive through greater accuracy in data analysis and greater control over outcomes.

Industries like healthcare can greatly benefit from adaptive intelligence as information sharing, accurate data analysis, and prompt response to situations as they emerge are vital to its operations. Adaptive intelligence-based health technology is already being developed and tested to the benefit of all stakeholders in the healthcare industry. Eventually, adaptive intelligence may completely eclipse and replace business analytics applications in all industries. It would be hardly surprising, given its obvious benefits over traditional analytics.