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# Predictive Analytics and Artificial Intelligence in People Management

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## Introduction

Rewards and recognition program designers are at a crossroads. Only two decades ago practitioners mainly provided sales managers with trophies, merchandise, and travel rewards. Over the years, their focus shifted to the design of incentive reward and travel programs. Today, many practitioners have become true *professionals* with deep knowledge of motivational theory and leading practices in employee and customer motivation, engagement, retention, and performance (Incentive Roundtable, 2018).

This evolution comes at pivotal moment in economic history. Today's most celebrated and respected organizations put their people first, alongside customers. Their CEOs elevate the importance of people management to the level of finance, sales, and marketing (for example, Boudreau 2017; Charan, Barton, and Carey 2018; Johansen 2017; Mankins and Garton, 2017; Shoker 2018).

For reward program owners—those responsible for designing and implementing incentive, recognition, and reward programs—this represents both opportunity and risk. When leaders look to the practices in place at this era's most successful firms, including Google, Apple, Zappos, Tesla, and nearly every "unicorn,"[1] they see a paradigm emerging in which work itself is the new reward (for example, Bock 2015; Charan, Barton, and Carey, 2018; Doshi and McGregor 2015).

To thrive in today's environment, in which virtually no skilled worker is involuntarily without work, organizations must design work and work environments to offer the essentials of human motivation that everyone needs to perform at their best. These universal drivers include, but are not limited to, autonomy, purpose, learning, inclusion, and appreciation (Doshi and McGregor 2015). Organizations must also understand the *unique* motivators for each and every employee, if not customer. One-size-fits-all incentives no longer work well enough to attract, keep, and engage employees or customers.

So far, most organizations have yet to *fully* embrace the shift from twentieth-century command and control techniques and the pursuit of rational employee satisfaction, to this century's emphasis on employee autonomy and the goal of achieving employee engagement and emotional commitment. Thus, reward programs owners have an opportunity to claim at least some of the gap that human resources (HR), compensation, and others have yet to fill; this opportunity won't last long. Most organizations that fail to compete on talent will fail outright. Elsewhere, HR, compensation, and others will work to fill the void. If reward program owners are left on the sidelines, they might find themselves entirely automated and outsourced.

Reward program owners should look to firms like Google, WL Gore, Tesla, and dozens of others that now use big data, predictive analytics, and machine learning techniques to monitor and analyze their talent continuously. Such usage gives those firms the ability to make better decisions about how to recruit, onboard, retain, develop, and motivate their people. It also helps them make better decisions about strategic initiatives designed to motivate performance, including those

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[1] Publicly traded start-ups valued at over $1 billion are often labelled "unicorns" (see: https://en.wikipedia.org/wiki/Unicorn_(finance)

that incorporate rewards—and to deliver those rewards on a one-to-one basis.

We are entering a new era in which the possibilities presented by advanced data analytics are only constrained by our imaginations. A significant and rapidly expanding body of research attests to the varied uses and potential of artificial intelligence (AI) in business, workforce management, and, to a degree, rewards and recognition (Chui et al. 2018). As People Analytics author Ben Waber puts it, the *"power of analytics [provides] a nearly superhuman ability to understand and change the world around us"* (Waber 2018).

Based on an extensive literature review and interviews with subject matter experts, this paper explores the current and near-term potential uses of AI in people management generally, and incentives, rewards, and recognition specifically, including reflections on the potential of AI to dramatically change the way organizations motivate, recognize, and reward employees, partners, and customers. Though claims of AI's use and impact are often overblown today, both those who champion it and those who warn against it agree that its impact will eclipse that of computerization and the internet (Cava 2018; Daugherty and Wilson 2018).

Indeed, rapid advances in deep neural networks and self-learning algorithms,[2] perhaps integrated with augmented reality and serious gaming, portend the most impactful developments in the history of workforce technology—all likely within the next five years. Reward program owners who understand advanced analytics and AI will be poised to act now to position themselves and their firms for this future. The primary goal of this paper is to provoke thought about what that may mean in the next several years.

## Artificial Intelligence and People Management

The future of AI in incentives, rewards, and recognition (IRR) is bound, in part, to the future of AI in related fields. By exploring advances in disciplines such as HR and marketing, for example, reward program owners are likely to find inspiration for solutions in their own. It is worthwhile, therefore, to define "artificial intelligence" and then to briefly examine its history in a related field (where its use is slightly ahead), before discussing AI in rewards and recognition specifically.

## Artificial Intelligence Defined

The terms big data, machine learning (ML), and artificial intelligence (AI) have grown so common in the mainstream and business media that, for many, they have lost meaning. Simply put and broadly defined, AI is anything man-made that learns from experience and mimics human intelligence (Digiday; Sysomos 2017; Hauptfleisch 2016; Marr 2016; Clauson 2018). Predictive analytics and machine learning are components of AI. Big data provides the fuel (vast, fast-flowing, and high-variety data) necessary for advanced predictive analytics and, increasingly, machine learning (Marr 2016).

Machine learning represents the latest technique in statistical analysis, pattern recognition, and predictive analytics (Theodoridis 2015). It uses algorithms to find patterns in data and to make predictions (Clauson 2018). Generally, machine learning falls into three categories: "supervised," in which analysts supply algorithms with enormous amounts of labeled data (i.e., examples) from which to learn; "unsupervised," in which algorithms learn on their own by finding patterns in unlabeled data; and "semi-supervised" which combines both techniques (Paskin 2018). Advanced

2        An algorithm is a set of rules that machines (computers) use to solve problems or achieve goals. It most commonly refers to tools used in solving mathematical or statistical problems but can also be likened to a recipe (a set of rules or procedures) for preparing a meal (see: https://www.merriam-webster.com/dictionary/algorithm)

machine learning involving "deep" neural networks (multi-layered machine learning patterned after the human brain) represents the current state of the art in predictive analytics *and* AI (Digiday; Sysomos 2017; Paskin 2018).

The latest AI accomplishment—whether fully autonomous cars, a bot that defeats the world's best players in the most complex games, one that predicts cancer, or one that personalizes incentives and rewards—very likely leverages leading-edge machine learning (Brynjolfsson and McAfee 2017). In the future, even the most advanced ML is likely to be eclipsed by emerging and entirely new forms of AI that can read, react to, and simulate human emotions or even become self-aware (Hintze 2016). At present, however, and at least for the next several years, ML will almost certainly represent leading-edge AI (Levy 2016; Manyika 2017). Therefore, this paper limits exploration of AI to the combination of big data, predictive analytics, and machine learning.

Though AI has seen previous hype cycles going back almost seven decades, this time is almost certainly different. Organizations today not only generate vast amounts of data, many can afford the means and tools to capture and store it. Second, computational power has grown almost inconceivably more powerful and less expensive than it was when the first experiments in AI were conducted in the 1950s. This increased power permits the analysis of huge amounts of fast-flowing structured and unstructured "big" data. Third, where algorithms used to require clear and voluminous coding to instruct computers in exactly what to do—an expensive, meticulous, and time-consuming process—today's advanced ML algorithms learn on their own, often with minimum instruction from humans (Brynjolfsson and McAfee 2017; Domingo 2015). Algorithms that learn from data entered into them, unlike hard-coded programs, can adapt to a changing world and grow exponentially more capable over time (Levy 2016; Henke 2016; Manyika 2017; Paskin 2018).

## AI in the Workplace

*"As reward intersects with a number of other key disciplines, including talent management, employee engagement and learning and development (L&D), it is well placed to demonstrate how HR data can be used strategically"* (Beagrie 2015).

In their 2018 book, *Talent Wins*, Ram Charan and Dominic Barton, two of the world's foremost advisors to CEOs, state: *"Good talent data that's expertly interpreted can be your most important competitive advantage."* They go on to argue that low cost and easy access makes financial capital a commodity, leaving human capital as the key differentiator in most organizations today (Charan, Barton, and Carey 2018).

Unfortunately, today's typical employee enters a stifling environment at work—far removed from the world of unlimited personal choice he or she takes for granted as a consumer—one in which uninspiring management practices and unfriendly technology erodes engagement and productivity. The new era of big data, predictive analytics, and machine learning promises to change this (Segal et al. 2014).

While less than one in ten HR organizations currently possesses a predictive analytics capability, let alone proficiency in advanced ML (Bersin 2017), most intend to soon. For example, a 2015 PricewaterhouseCoopers survey revealed that 86 percent of HR organizations plan to advance their people analytics capabilities in coming years (McGregor 2016) and, in a 2017 Harvard Business Review survey, more than 50 percent of 230 executives said they were planning to significantly

improve their HR analytics (Charan, Barton, and Carey 2018). According to the survey, heads of HR are now hiring analytics professionals and even data scientists, hoping to grow predictive analytics, ML, and AI capabilities like those in Figure One below. Mastery of these four levels of data analytics help organizations move from a guessing game to insights that can suggest to them what to do to dramatically improve their outcomes (Dearborn 2015).
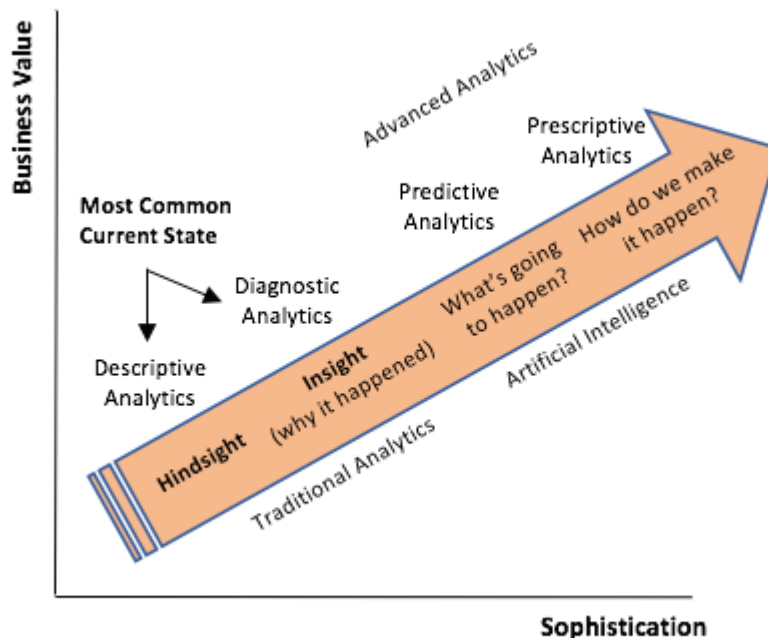


*See Appendix A for definitions of Descriptive, Diagnostic, Predictive and Prescriptive Analytics

## Figure One: The State of People Analytics

## The Potential for AI in People Management

As was reported in *The New York Times* in April 2013, "*Today, every e-mail, instant message, phone call, line of written code and mouse-click leaves a digital signal. These patterns can now be inexpensively collected and mined for insights into how people work and communicate*" (Lohr 2013).

Most large organizations today have the data and processing power needed for advanced people analytics (Bersin 2013). Large firms generate many petabytes (the equivalent of about 120 million digital photographs)[3] of data every day, much of it generated by the workforce. Employee surveys, performance reviews, polls, organizational network analysis (ONA)[4], activity on corporate social networks, peer recognition portals, learning management systems and self-service benefits portals, feed a constant stream of structured data. Add to this the enormous and high-velocity data from employees' "digital exhaust"[5] (Goldman 2018), including email, text, website visits, keystrokes, external social media activity, and even data from sensors in mobile phones and/or employee badges, and the sheer amount of workforce data that even small firms

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3    Terabytes, gigabytes, & petabytes: How big are they? See: https://www.lifewire.com/terabytes-gigabytes-amp-petabytes-how-big-are-they-4125169
4    See Appendix A for a definition of Organizational Network Analysis
5    See Appendix A for a definition of Digital Exhaust

generate grows significant (Pentland 2010). Combined with computer processing power readily available to most organizations, this data can be analyzed with other financial and business data to yield powerful insights (Peck 2013; Segal et al. 2014).

Given a glimpse of AI's potential, leaders are eager to break away from traditional, and backward-looking HR analysis (i.e., descriptive analytics). They are now exploring the means to attract and hire better talent, predict attrition, find hidden talent across the organization and deploy it expertly, deliver real-time feedback and recognition, assemble optimal teams for specific challenges, conduct real-time performance management, and provide insights to managers in how to better engage, inspire and coach their team-members (*HR Examiner* 2018). For this, they need advanced analytics (AI) capabilities. Of course, organizations also hope to use AI to provide optimized and individualized incentives and rewards (Charan, Barton, and Carey, 2018).

Most IRR programs lag behind people management in the exploration and adoption of advanced analytics and AI. Again, it is useful to briefly examine the state of the art in select elements of a closely related field like people management, before moving into a detailed exploration of the current and potential uses of AI in reward and recognition.

## AI in Talent Acquisition and Onboarding

AI in hiring currently eclipses that of any other component of people management (*HR Examiner* 2018). Using predictive tools such as programmatic recruitment advertising, algorithms both seek and attract qualified candidates. Once a person applies to a job advertisement, algorithms sort and screen them automatically using machine learning techniques. As Bledi Taska, chief economist at Burning Glass, says, *"Identifying people through the algorithms is faster, more precise, and fairer because there is less bias"* (Taska 2018).

At Unilever, job applicants that initial algorithms screen in are invited to play a series of online games constructed around principles of cognitive neuroscience. These "serious" but engaging games use ML to generate and analyze copious amounts of data from applicants' behaviors, attributes, and job-related traits. Successful applicants then participate in a fully automated, AI-powered online interview that assesses their emotions, truthfulness, and the content of their answers against the requirements of the job. Next, qualified candidates are assisted by an AI chatbot that answers their questions, informs them of the status of their candidacy, and schedules an in-person interview for them. Only after successfully passing through "the machines" does a candidate meet with a live interviewer. Unilever has reduced time to hire from more than four months to about four weeks, while reducing recruiter screening time by 75 percent (Daugherty and Wilson 2018).

Professor Charles Scherbaum of Baruch College in New York has helped develop similar tools to aid organizations in making better hires: *"We use algorithms to predict future job performance in hiring. For example, we assess college athletes going into professional drafts for certain sports. We provide information to teams, some of whom use them to make their draft picks. For the past five years, we've done very well at predicting who ends up being effective at the professional level. This is the same process for any employee selection that uses machine learning algorithms"* (Scherbaum 2018).

Finally, as candidates become hires and join organizations, effective onboarding is vital. On average, employees who don't receive it quit or are let go earlier in their tenure (Maurer 2015;

Wislow 2017). Algorithms that use the copious information and data collected during the hiring process begin predicting team fit and learning needs even before a new employee's first day on the job, allowing managers to craft tailored onboarding plans for each new hire (Sathe 2017; Wislow 2017).

## AI in Employee Retention

Predictive retention analysis is among the most mature, implemented, and simple solutions in the field of predictive workforce analytics (Westfall 2017). Algorithms (or even predictive models built in late versions of Excel) used now by thousands of organizations, predict which employees are at risk of leaving the organization. In some cases, the algorithms identify individuals even before employees have consciously formed an intent to leave (Beygelman 2018). In their everyday work and behaviors, employees give off many signals about their intentions, allowing organizations to build predictive statistical models that understand and forecast turnover. Using this information, managers (or the AI itself) can intervene to stop talent from leaving, including the use of tailored incentives, rewards and recognition (Grillo 2015).

For example, Joberate, a predictive analytics platform that uses machine learning, looks at employee social media activities on publicly accessible social media channels, like LinkedIn and Twitter, to assess job seeking behavior patterns. If, for example, an employee has a public profile and updates their education, employment history, or joins a professional group—and does these or other activities on multiple occasions over a certain period of time—Joberate's software will gradually increase the employee's "J-Score." The J-Score not only measures job seeking activities, it tracks other actions that correlate to job seeking activities. Once a person's J-Score reaches and then exceeds a certain number, the likelihood that the employee will leave at some point over the next 120 days increases if nothing is done to prevent it. So far, it has proven accurate in more than 90 percent of cases over more than a four-year time period (Beygelman 2018).

## AI in Learning

Worldwide, organizations spend more than $350 billion on workplace training each year (Brinson 2018; Statista 2018). Senior executives currently rank learning as their third most important corporate initiative (Zoomi, 2018). Despite learning's importance, however, traditional classroom training, technology-enhanced classroom learning, and eLearning have, at best, returned unexciting results for years. According to University of Michigan business professor Dave Ulrich, *"Perhaps 20 to 30 percent of ideas learned in leadership training [for example] turn into practice"* (Ulrich and Smallwood 2013).

The greatest opportunity for improvement in workplace learning most likely lies in creating highly engaging, hyper-personalized instruction. AI promises a realistic solution to the problem of one-size-fits-all education. AI-enabled intelligent tutoring systems (ITS), for example, date back to the 1980s at the college level and in the military (Anderson, Conrad, and Corbett 1989; Lesgold 1988). More than two decades ago, researchers found that intelligent agents[6] embedded with tools based on cognitive science, could dramatically improve learning outcomes in high school students studying algebra (Koedinger et al. 1997). Since then, a series of rigorous experiments have confirmed those findings applied to other subjects and levels (Aleven and Koedinger 2002; Pane, Griffin, and McCaffrey 2016; Ritter et al. 2007; Sales and Pane 2015).

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6    In this context, an intelligent agent searches, retrieves, and presents information from external sources, tailored to the learner's needs (based on their activity in the course).

Today's state of the art in AI for learning might be represented by Zoomi, a learning solutions provider that embeds AI in eLearning. Zoomi offers the first off-the-shelf toolset that enables learning and development professionals to implement authentic AI in eLearning. Zoomi's platform offers personalization, adaptive learning, content curation, and automated, real-time assessment. Its algorithms examine various types of learning content (e.g., video, PowerPoint, paper-based, etc.), then break the content down and classify each word, phrase, and concept. As a learner goes through the material, every key stroke, every pause, every break, etc., is analyzed in real time by algorithms that assess and predict the learner's progress (Zoomi 2018).

The Zoomi system creates new learning content from scratch, adapting the course content to each learner's level and needs. Moreover, Zoomi parses content on internal social networks to find the same words, phrases, and concepts as in the learning content. It reports on the frequency of use and who is struggling versus who is helping others learn on internal collaboration platforms such as Slack. Some of Zoomi's clients have dropped quizzes and assessments from their online courses entirely because the tool assesses learners more accurately and in real time, without interrupting the flow of their learning or work (Brinson 2018).

## AI in Employee Engagement and Performance Management

Though still rare, mannequins in clothing stores use AI to augment the performance of salespeople. Internet-enabled and equipped with sensors, the mannequins use facial recognition algorithms to identify shoppers and interpret their emotional states. The AI then checks their shopping history and recent social media activity, all in a second or two. Next, it passes this knowledge and its recommendations to a human sales person. This is just one way leading-edge AI is already enhancing human performance. More commonly, in-house sales people use tools like "6Sense" that help them craft and send emails at precisely the right time. With intentional trigger words and phrases, the AI predicts what messaging will increase the likelihood of response from customers and prospects (Daugherty and Wilson 2018).

AI can also be used to learn about salespeople themselves, including their selling patterns, styles, and how long they've been with company. It can estimate the amount of repeat business they're likely to close, and can predict what a person will sell in any given year. When it combines that information with correlations and patterns from learning management systems correlated to sales and performance data, for example, it can predict what more a person might sell if they take various actions—e.g., by collaborating with certain colleagues, taking particular courses, or prioritizing calls and prospects differently. And, of course, AI can also suggest to a sales manager the optimal way to incentivize and reward each of the people on their team (Wolfersberger 2018).

Michael Housman, chief data science officer at Rapportboost.AI, uses algorithms to analyze the live chats his clients' representatives have with their customers. *"We focus on human interactions by working in the background on live chats. Our algorithms know what makes a successful live chat and a poor one, based on hundreds of variables we test. A few examples include formality, reassuring words, small talk, empathy, and responsiveness. When we determine that, our platform provides guidance to chat managers around how to coach the agents. Chat coaches can log in and see how their agents are performing against the most important success factors. Jenny Craig, one of our clients, saw their conversion rates increase 40% after using our machine augmented conversational platform"* (Housman 2018).

Klick Health, a large Canadian healthcare consulting firm, has developed a passive data collection system and ML tool it calls "Genome." Genome calculates the average time it takes to complete a variety of tasks and alerts leaders when projects appear to be going off track. It also reminds project leaders of the outstanding and urgent things they need to do. Project managers know they're being monitored and are thought to perform better as a result (Goldman 2018). Klick Health recognizes that productivity is a state of mind, so to speak. It looks for ways to measure employees' "flow time" (moments of peak performance) and uses a data tool called "RescueTime" that can help track the activities of employees to flag and reduce distractions that may impact flow and productivity (Segal et al. 2014).

Of course, AI has many uses in motivating people as well. Of note are recommendation engines that help employees choose career paths that lead to high performance, satisfaction, and retention. For example, if a person with an engineering degree wants to run the division someday, algorithms can scour the data looking for patterns and suggest the optimal mix of additional education, work experience, and soft skills they should obtain—and even the order in which to obtain them (Wellers, Elliott, and Noga 2017).

Increasingly, organizations are also using algorithms to monitor employee morale. Social analytics and continuous "social listening" tap into what people are talking about on internal and external social media to conduct "sentiment analysis."[7] Some organizations now combine qualitative information from polls and surveys with quantitative data from sentiment analysis to analyze positive or negative data and gain insight into employee morale across the enterprise. This is a practice B.near Global President Chris Broderick utilized in leading AI engagement initiatives at IBM. In one case, IBM's decision to disallow use of ride-sharing services provoked a strong and immediate response on its employee collaboration platform. Social listening tools alerted Broderick's team, who advised senior management. The decision was reversed the same day (Bort 2015; Broderick 2018). Broderick now does the same analyses for other clients. *"We use annual surveys and weekly polling with a real-time social listening platform/engine. Through a combination of these channels of data we're able to understand what's important to employees—what is and isn't working—and can leverage this knowledge into interventions"* (Broderick, 2018).

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7        Social listening and sentiment analysis involve monitoring social media and other sites to assess online sentiment about a topic, a brand, etc. (see: https://trackmaven.com/marketing-dictionary/social-listening/)

## Acknowledgements:

## Appendix: Glossary of Terms Not Defined

**Aggregate Analysis:** Imagine you run a wedding business. An aggregate analysis tells you that most of your customers live in Oregon and are women in their early 30s. These insights let you narrow in on advertising vehicles that reach that audience most efficiently.

**Correlation**: Correlations demonstrate the link between two variables. For example, in your business, which of the advertising vehicles you use produce the most leads? A correlation analysis using Excel can reveal the links between lead generation and advertising vehicles very quickly, allowing you to eliminate some and invest more heavily in others.

**Trends Analysis:** The continued tracking of correlations over time.

**Sizing and Estimation:** Educated guesses about the potential of a market, for example, using knowledge, experience, and the data at hand—a common and sometimes valuable practice.

**Segmentation**: When you divide your customers or employees into groups, you may do so to study their specific characteristics and behaviors so that you can tailor your offerings. You might also segment products to determine which ones sell well and identify their various levels of profitability, or rewards to see which resonate best and drive the desired behaviors.

**Customer/Employee Life Cycle (CLC) Analysis**: Studying customer or employee behavior at various stages, to determine things such as how long it takes a customer to upgrade from a free to a paid subscription on a website or for an employee to lose some of the initial enthusiasm/ engagement they brought to the organization when they joined.

**Ambient or Passive Data (aka "Data Exhaust)**: "There are two types of data: self-reported and ambient. Self-reported data involves filling out time sheets, surveys, performance evaluations, and expense reports—all examples of this type of data. Ambient data is information about a behavior that is automatically collected without the user's having to actively enter each data point. Swiping into work with an active RFID badge, sending emails, making calls, and even adding events to an electronic calendar are all examples of ambient data" (Segal et al. 2014).

**Datafication, or Digitization**: Refers to taking information about all things under the sun— including elements we never used to think of as information at all, such as a person's location, the vibrations of an engine, or the stress on a bridge—and transforming it into a data format to make it quantified. This allows us to use the information in new ways, such as predictive analytics: detecting that an engine is prone to a breakdown based on the heat or vibrations that it produces. As a result, we can unlock the implicit, latent value of the information.

**Descriptive Analytics**: The first and easiest type of analytics; the one most organizations perform, looks back at what happened in the past. These descriptive analytics uncover trends and typically display them in charts or on dashboards. The information can alert leaders to future problems or opportunities. Good descriptive analysis results from asking questions about the variables and how they might affect one another. Many questions might lead to one or a few valuable insights, but those insights can have tremendous impact. For example, you might learn that sales revenue is more a function of opportunities raised, combination of products pitched, and attendance at a particular course, than tenure of sales rep, size of territory, and past performance. Analysts must take caution not to influence the results by seeking data that fits their hypotheses. Go beyond

descriptive analytics to better understand why variables impact each other and to avoid relying on imperfect conclusions from what is the least rigorous of the four levels of analysis.

**Diagnostic Analytics**: At this stage, you ask why something happened. Here you'll use more advanced statistical techniques to uncover the connections between data. For example, by using techniques to isolate dozens of variables against just one, you can often determine which causes the effect. Diagnostic analyses helps you determine, for example, what makes some of your sales reps highly effective while others languish. With this information, you can design better training, coach reps in the precise areas they require help, and hire new reps in a more targeted fashion.

**Predictive Analytics**: The four levels of analysis don't necessarily work only in sequence. Normally, however, you'll graduate from descriptive to diagnostic to predictive, because after you know what and why, you'll want to leverage the data into even more valuable insights. By running your data through thousands, even millions of possible connections and correlations, algorithms can make startlingly accurate projections about the future. In sales, this might include predictions about which prospects will buy what products, and even why. To achieve this level of insight, use large datasets to "train" your predictive models. You might have a year's worth of data about particular KPIs concerning your sales reps, for example. Suppose you want to test how accurately performance against those KPIs predicts actual sales. To do so, take the first six months of KPIs for half your sales reps (first half) and add the full year of actual sales data concerning those reps. Process the data to determine the strength of the connection between the KPIs and sales, this becomes your predictive model. If your predictive model is strong enough, you'll want to use it to make decisions. But you need to test it first. To do so, take the KPI data for the other (second) half of your reps and run that against the same model. Separately, run your second half reps' KPI data against their own full year sales results data. The smaller the difference in outcomes between the two, the more valid your predictive model.

**Prescriptive Analytics**: Knowing what happened, why it happened and what might happen next leads to the logical question, what should we do about it? Prescriptive analytics uses highly sophisticated algorithms to build on predictive data to suggest optimal decisions and their consequences. The results from prescriptive analytics can give individual sales reps personalized action plans, for example, detailing exactly what they should do to make more sales. For example, which products to bundle for which customers, what training classes to attend and when and which prospects to prioritize based on probability models that forecast likelihood of closing.

**Social Listening**: "Many brands now employ artificial intelligence to monitor social media platforms, a practice known as social listening. With a sophisticated understanding of human language, AI can analyze social media trends to detect changes in conversations, alerting human operatives to changes in conversations about the brand or gathering information about the feelings of their customers." (Digiday; sysomos, 2017)

**Organizational Network Analysis (AKA Social Network Analysis)**: For at least the past two decades, organizations have been able to gain deep insight into the way information and knowledge flows in their organizations through ONA (Cross and Parker, The Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations, 2004). A typical ONA might collect data from email records and/or an employee survey, possibly even wearable sensors to build a map of the real networks at play inside organizations, including who talks to who, where people are isolated, etc. (see Figure Two, on following page)

**Branch 1**    **Branch 2**    **Branch 3**
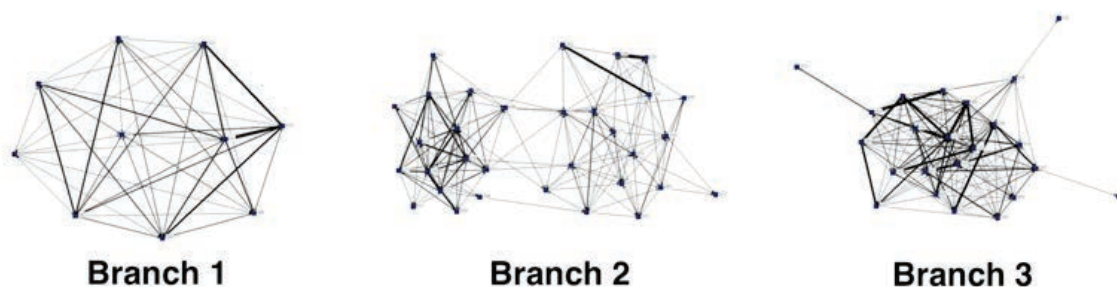
*Figure Two: ONA Maps for Three Bank Branches*

To illustrate the usefulness of ONA, Figure Two depicts three bank branches that do the same work in locations across a region. Branch 1outperforms Branch 2 by about 250% and Branch 3 by a little bit less. The ONA gives us clues. In Branch 1 managers had implemented an informal reward program, a target for the whole branch that if hit, earned everyone a bonus. The rewards incentivized employees to share information and they did. That is visible in the ONA map for Branch 1 where there are many connections and no outliers.

Managers in Branches A and B used individual incentives based on more traditional and quantifiable performance outcomes, such as loans underwritten. Where group incentives caused people to share in Branch 1, individual incentives have the opposite effect in the other Branches. Branch A outperformed Branches 2 and 3 significantly based on the same direct, quantifiable measures the other branches tried to incentivize.

From this, the bank surmised that group incentives, at least in this case, work better than individual ones. All of the bank's branches now use the same team-based incentives as Branch A. Sales have increased across the bank by more than one billion euros each year since (Waber, President & CEO, Humanyze, visiting scientist MIT Labs, 2018).

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