

“Machine Learning and Artificial Intelligence (AI) for Effective Marketing”

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ABSTRACT:

Machine learning is a term thrown around in technology circles with an ever-increasing intensity. Major technology companies have attached themselves to this buzzword to receive capital investments, and every major technology company is pushing its even shinier parent artificial intelligence (AI).

While the topic of machine learning and AI has been exhaustively covered in the technology space, not enough documentation has been created in the marketing space on the topic, including how it affects marketers and their work. This space is so thick with technology-based terminology, but not every marketer is opting to explore the full potential of Machine learning with limited bandwidth available with them. With many products coming to market, it is important to prepare marketers to tackle the landscape armed with a solid foundation.

Machine learning touches an ever-increasing number of industries, we'll also touch on several different ways that machine learning is impacting people in many professions. Most data scientists use R and Python for machine learning, but we still see very few marketer these days that only lives and breathes data science.

Keywords: Machine Learning, Artificial Intelligence (AI), Product Management, Product Manager (PM),

RESEARCH METHODOLOGY:

This is a conceptual research with explorative methodology. The secondary data was collected from different authentic sources like various research papers, articles, newspapers, blogs and presentations on Machine Learning & Artificial Intelligence (AI) in product Management.

OBJECTIVE:

1. To study importance of Machine Learning/AI and how it is transforming today's product management
2. To understand different aspects of AI and different ways of

INTRODUCTION:

Machine learning is a term thrown around in technology circles with an ever-increasing intensity. Major technology companies have attached themselves to this buzzword to receive capital investments, and every major technology company is pushing its even shinier parent artificial intelligence (AI).

The reality is that Machine Learning as a concept is as old as computing itself. As early as 1950, Alan Turing was asking the question, “Can computers think?” In 1969, Arthur Samuel helped define machine learning specifically by stating, “[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed.” While the concept has been around for more than half a century, we have finally reached a point in technological advancement where hardware and software can actually help developers match their aspirations with tangible reality. This development has led to not only the rise of machine learning and AI advancements, but, more importantly, also advancements inexpensive enough for anyone to use.

The global market size of machine learning enabled solutions is expected to reach \$8.81 billion by 2022. That would constitute a whopping 44.1% compound annual growth rate (CAGR) between 2016 and 2022. Machine learning for marketing has extensively changed the landscape of digital marketing by focusing on personalization, behavioral targeting, micro-targeting and other marketing parameters. The implementation of ML algorithms in the marketing sector is producing phenomenal results for all sizes and domains of businesses globally

According to the QuanticMind survey, more than 97% of the industry experts believe that the future of the digital marketing will be fully influenced by machine learning techniques and AI based marketing automation. The major drivers of ML and AI-based marketing include the following:

- Chatbots for great user experience
- Personalization of marketing at scale
- Micro-moments or right information at the right time, in a real-time environment
- Increasing volume of dark social sharing
- The advent of modern AI and machine learning tools
- Predictive intelligence based content creation

The difference between AI and machine learning marketing based marketing and the traditional variety is quite clear. Traditional marketing is launched with very limited insight into the behaviors and purchasing patterns of the targeted audience. Meanwhile, AI-based projects for digital marketing are fully equipped with specific information about customer behavior, purchasing patterns and many other parameters. This added information helps in achieving better conversion rates and a substantial increase in the company sales. Numerous kinds of ML models are extensively used in present day digital marketing to unleash the power of AI in the modern businesses. A few very important machine learning based marketing models include the following:

- Effective risk prediction and interventions
- Efficient predictive data modeling
- Machine learning based pay per click campaigns
- ML insight based content campaigns
- Highly targeted email campaigns
- Real-time content help through chatbots and other tools

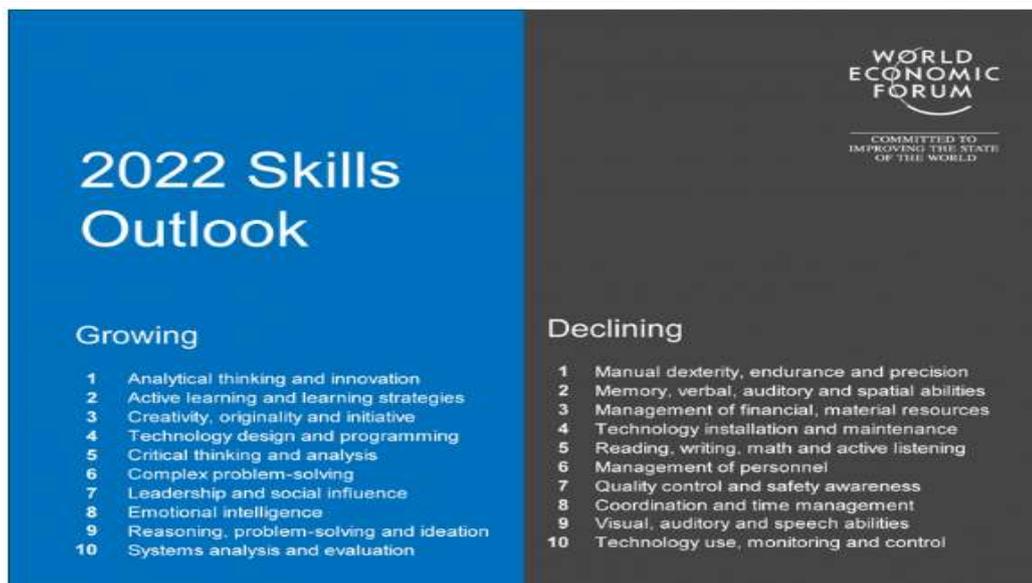
All of the above models powered by different types of algorithms help marketers to increase the targeted customer outreach, improve the relevance of their audience, trigger a response or action, and create a great user experience.

AI will transform product management

Sales, marketing, and customer service without AI is no longer effective or acceptable sales, marketing, or customer service. We are in the age of the connected stakeholder -- customers, business partners, employees, and communities. Every business, large and small, must transform to an AI-driven business. In the near term, companies and workers are less likely to be replaced by robots and more likely to be disrupted by companies and workers that are trained to use AI technologies to compete and win.

As artificial intelligence (AI) and machine learning (ML) capabilities are designed into new products and services, Product Managers need to enhance their skills in order to develop and provide functional requirements and AI-powered specifications to data engineering and data science teams.

According to the World Economic Forum's The Future of Jobs 2018 report, machines will overtake humans in terms of performing more tasks at the workplace by 2025 -- but there could still be 58 million net new jobs created in the next five years. The report notes that the growing skills for 2022 will include analytical thinking, creativity, critical thinking, complex problem solving, and systems analysis.



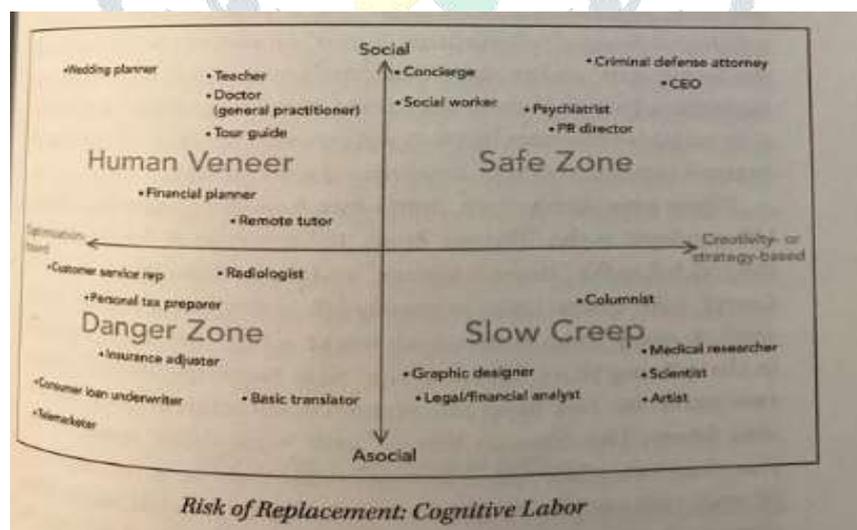
The *Future of Jobs Report 2018* also identified 10 emerging jobs in 2022, including data analysts and scientists, AI and machine learning specialists and general and operation managers as the top 3 jobs.

AI and advancements in automation may result in 75 million job displacements, but at the same time period another 133 million new roles will emerge where people and machines will co-exist, creating a net new 58 million jobs by 2022. The 2018 jobs report also forecasts that 42 percent of all current tasks in the workplace will be performed by machines in 2022, as compared to 29 percent in 2018.

WHAT AI CAN DO AND CAN'T DO: THE RISK-OF-REPLACEMENT GRAPH-

There is specific discussions going on types of cognitive labor that is like to be displaced by AI and advance automation. The displacement likelihood of jobs are cataloged in various zones. The 'Danger Zone' which includes jobs like language translators, telemarketers, radiologists and tax specialists and insurance adjuster. The 'Safe Zone' includes social workers, CEOs and PR directors.

What this means for job replacement this can be expressed simply thru two X-Y graphs – one for physical labor and another for Cognitive labor –



Risk of Displacement: Cognitive Labor / AI Superpowers - Dr. Kai Fu Lee

To better understand the impact of artificial intelligence (AI) on cognitive labor, one of the AI domain expert who is responsible for delivering AI-powered products and services at Salesforce Einstein, have provided his thoughts on the impact of AI on the future of product management function.

Following examples gives detailed insights on the future responsibilities of product management in the age of AI, and why product managers need to prepare differently as they bring to market AI-powered products and services:

On a massive stage in Cambridge, MA, in front of several hundred technology enthusiasts, ex-Stanford professor Andrew Ng scribbles away on a whiteboard. He was talking about how AI is changing the world, and how traditional job descriptions are breaking down. Ng gives an example of a chatbot. "Traditionally a Product Manager would provide product specifications through wire-frames. For a chatbot, wire-frames are completely useless to the engineers. They would like to know the logic inside," says Ng, who founded Coursera, an online education company, and who is now the CEO of AI consultancy Landing AI.

"It is for the more traditional product managers (PMs) to acquire the skills needed to be PMs in data-focused roles, like building products that leverage artificial intelligence,". Marco Casalaina, VP of Product at Salesforce Einstein, is working with a team on creating a course in Trailhead (Salesforce's online learning platform) to augment the skill sets of traditional PMs and to prepare them for the fourth industrial revolution of AI and machine learning. "We need to develop a smell test for our PMs, to give them the ability to quickly determine the feasibility of applying machine learning to solve a business problem," says Casalaina.

Engineering as a discipline has existed for thousands of years. Its roots can be traced back to the engineering of the pyramids of Egypt, to the building of military engines in the 1300s, to the inception of mechanical engineering with the rise of the steam engine in the 1800s. This makes it a mature and well-established discipline.

Product management is relatively new, less than 100 years old and thus still evolving. It was originally meant to be around managing brands (hence known as Brand Men) as it evolved into managing production systems in manufacturing. The birth of software technology heavily influenced its course and then came along agile methodologies. Today, as Artificial Intelligence eats software, it is quietly transforming the product management role once again.

There Is A Shift - The AI Product Managers Are Rising.

Imagine building a new recommendation system. Given a product bought by a user, this system should recommend similar products. Traditionally, a PM would work with a user experience designer and come up with the user interaction and experience (UI/UX) specification around the layout, when and where to display the recommendations, what is the behavior on interacting with them, etc. This can be extended to other recommendation engine use cases, like recommending friends in a social network, connections in a professional network, songs in a music app, or job candidates in a recruiting system.

However a modern recommendation system uses AI, and these kinds of product specifications are of no value to a machine learning engineer or a data scientist -- they need data. The systems they build are not coded; they're taught.

Let's say this recommendation system was destined to recommend job postings for job seekers, and vice versa. Here an AI product manager needs to provide particulars of the data that customers will have. What information do customers have about the jobs and the candidates? The PM needs to specify how the system functions in a "cold start," when there's a brand new customer who has not yet amassed enough data for the system to learn. And how do you evaluate that the recommendations are indeed good? This is a whole new breed of product specifications which did not exist until the recent dawn of AI.

In addition to working with their traditional cross-functional stakeholders (design, marketing, sales, engineering, dev ops), AI product managers now need to include data scientists and data engineers in the circle.

Here are the top areas on which an AI product manager needs to focus beyond those of a traditional PM:

Problem Mapping:

It is essential for the AI product manager to articulate the value proposition of an AI-powered feature and map the concrete user pain points. An AI product manager should do a careful analysis of the problem.

- Could it be solved by other means that are faster and easier to build than AI?

- Does businesses have long used rules engines and workflow systems to attempt to categorize cases correctly on the first try, and yet this problem persists.

Upon doing this analysis, an AI product manager might uncover an opportunity to use artificial intelligence to build a system to categorize the tickets by learning from prior successfully resolved tickets. This is a good example of an AI product manager mapping the high-level business problem to an AI solution.

Data Literacy:

One of the most significant aspects in the evolution of the AI product manager is the need for data literacy. An AI product manager needs to understand the right questions to ask about their customers' data if they are to succeed with an AI initiative. Is the relevant data readily available among customers? Is there enough data, and is it the kind of data from which AI can learn? Is the data clean or noisy? Does the use case require a real-time solution or would a batch solution suffice? Related to it, are there enough of prior examples or precedents which can be used to teach a machine learning system. That is typically known as a supervised problem. If there are no previous examples (also known as outcomes), the machine would have to learn without any supervision of precedents. This is known as an unsupervised problem. This brand new dimension of data literacy is entirely absent in traditional PM roles.

Acceptance Criteria in the world of AI:

Once an AI-powered feature is built, AI product managers need to define the criteria to determine whether it is ready to serve production customers. In traditional product management, this criteria might include feature completeness, the number of open bugs, and fit and finish; but in AI product management, the key metric is AI accuracy. Depending on the business objective, an AI product manager needs to make a judgment as to which machine learning metrics need to be optimized, and at what point the AI is performing sufficiently well to solve the customer's problem. This will then be mapped to the top line business metric such as case resolution time, or sales lead conversion lift.

For example, in the sales domain, sales executives are interested in increasing the number of incoming leads converting into sales. AI-based lead scoring can provide a prediction for every incoming lead as to whether it is likely to convert into a sale or not. This can help the salespeople focus their time on the right leads. The AI product manager thus needs to define a threshold of AI accuracy such that its use will reliably lift the conversion rate of customers' sales leads.

Explain-Ability, Ethics, and BIAS:

"Why did this AI just make the decision that it did?" is a common question among users consuming AI. AI differs from traditional software in the sense that the outcomes are not based on a set of hand-coded rules; as such the decisions it makes can sometimes defy ready explanation. Additionally, the behavior of AI changes over time as it continues to learn.

Being thoughtful about explain-ability and providing mechanisms to make AI-powered features more transparent is the key to unlocking adoption of such features. An AI product manager needs to specify how his or her products will explain themselves to their users. Sometimes this involves a trade-off: some AI algorithms are more explainable than others. For problems in domains where there is high regulation, like healthcare, explain-ability beats accuracy. It is incumbent upon the AI product manager to strike the right balance for the use case and industry they are serving.

AI product managers also need to evaluate bias and consider the ethical implications of AI-powered applications. Is the data gathered representative and diverse enough? Is there data in the data-set which can introduce unwanted and unethical biases, like race or gender? This is hardly a simple technical decision. Gender, for example, can be a crucial signal for AI in medical diagnosis applications, but it is probably irrelevant in predicting which job applicant is more likely to fit a job description. It falls to the AI product manager to make decisions on which data is ethically fit for a given application.

Scaling from Research to Production:

The attributes of a production AI application delivered at scale are very different than "data science projects" still in the research stage. Engineers who are taking AI applications to production need specifications around where the data is expected to be. Will it be online in a cloud environment? Or distributed across many mobile devices? They need to understand how quickly the AI needs to emit its output -- real-time AI output can be resource-intensive for both the engineers and the machines. There are numerous other considerations around how often and when machine learning models retrain, what metrics need to be computed to understand the system's continuing performance, what feature engineering is required, and much more.

If you are a PM reading this and have experience building web and mobile applications but have not wet your feet in AI and ML (machine learning) products, you might be wondering -- "I had never had to deal with any of these!" That is precisely the point.

Though AI recently caught a lot of tailwinds, AI was prevalent even two decades back in the domain of search and Ad targeting. Some of you who worked on those early products leveraging AI and ML might be smiling now. As AI and ML eat software, more and more PMs need to level up their skills to manage these products and provide requirements and specifications which will add value to the data engineering and data science teams. This will lead to actually solving customer pain points and not just building a cool technology feature.

Machine Learning For Product Managers: Defining the Business Problem:

Every company is overflowing with data. They look around and see innovation is happening in the industry. Executives hear from their customers about their AI strategy. Management sees competitors with AI solution and make critical moves that bite into their addressable market. With all this background noise, the immediate reaction for the management is to conclude that we got to do something with our data and let us go and hire some data scientists. You are assuming that Machine Learning is the solution and are looking for a problem it can solve.

What is the problem we are trying to solve?

Machine Learning is not magic. Machine Learning is a solution. One has to define what the problem we are solving clearly is. Beware of the temptation to use the hot technology like Machine Learning to look for a problem it can solve. Or finding a problem without asking the question if that problem is big enough to tackle and invest resources. Machine Learning is like a drill bit. Which drill bit you use would be dependent on the problem you are trying to solve.

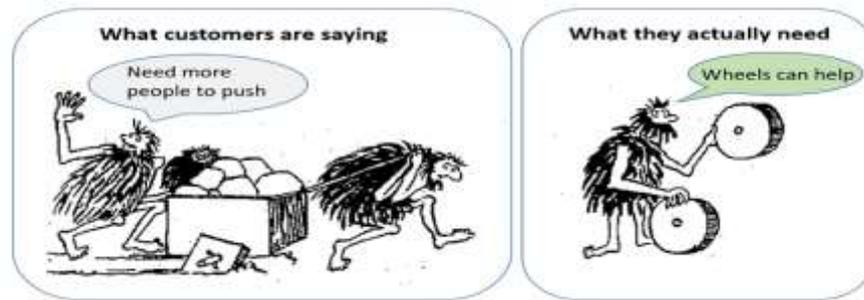
It's important to define the problem you are trying to solve, the business results you are looking forward to achieving and the benefit you are trying to find for your customer. Once the problem is clearly defined, then one can start thinking about the data we need, the model to create, the algorithm to use, the insights and action to take based on the predicted insight.

Product Manager Collaboration:

Defining what problem to solve is a question a Product Manager in coordination with the business stakeholders needs to establish. The Product Manager should perform initial customer interviews to understand their customer's key pain points to validate the problem they are solving.

Dig Deeper into customer's intentions:

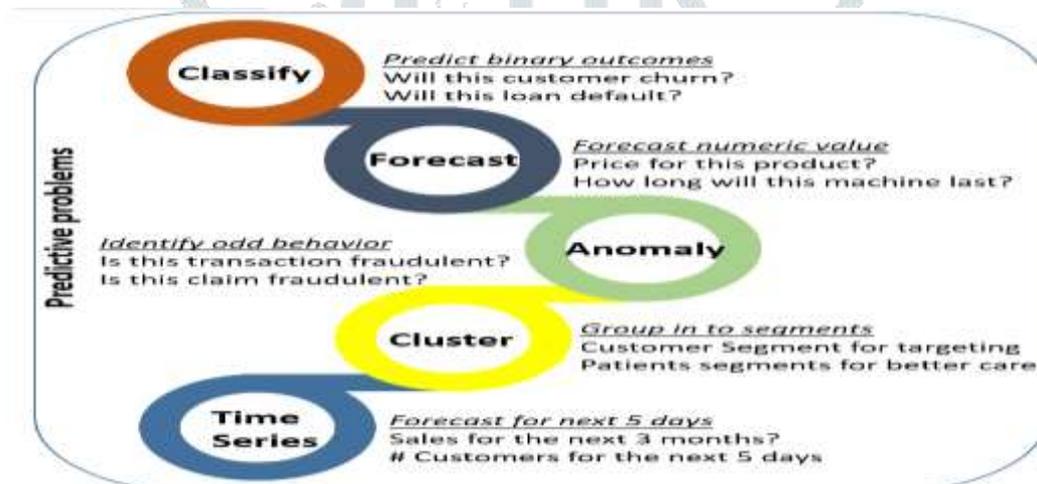
When getting customer feedback, it is essential to get to the root of the problem for the use case the customer has articulated.



For example, the customer may ask can I export this data (predictive insight) into a CSV file?. One can think we need a CSV data export feature. Or maybe we can dig deeper, and the reason they may be wanting to do that would be they want to load the predicted insight directly into their CRM application for them to take action. So the real feature is for the predictive insight to drive some actions with some deeper integration with the CRM system and not exporting data into CSV. It is the job of the product manager to dig deeper into that insight.

Predictive Framework: Examples of predictive business problems:

Framework for Product Managers to think about adding predictive insights by looking at some common/popular problems with good ROI. The example / framework below are not models to build. They are examples of popular problems we can solve.



Simple example application:

Say you have an existing product that you sell in the accounting space. Problems that you could solve that may differentiate your solution from the competitor would be problems like

- 1. Classification:**
 - Will this customer default on their payment?
 - Will this customer pay their invoice on time?
- 2. Forecasting:**
 - What would be the total billables next month?
- 3. Clustering:**
 - Segmenting customers based on customer demographics & purchase behavior to better engage with them
- 4. Anomaly:**
 - Does this invoice look odd?

If you look at the above, we are not talking about what models to build or what algorithm to use or what data we need. We are identifying what problems to solve and which of these will be of value to your customers and will help drive your business.

Validate with your customers if the above questions add value to them. Validate if these help your business results. Once you got some good feedback, you can move on to the next step of putting a simple POC to validate the ideas for a product-market fit.

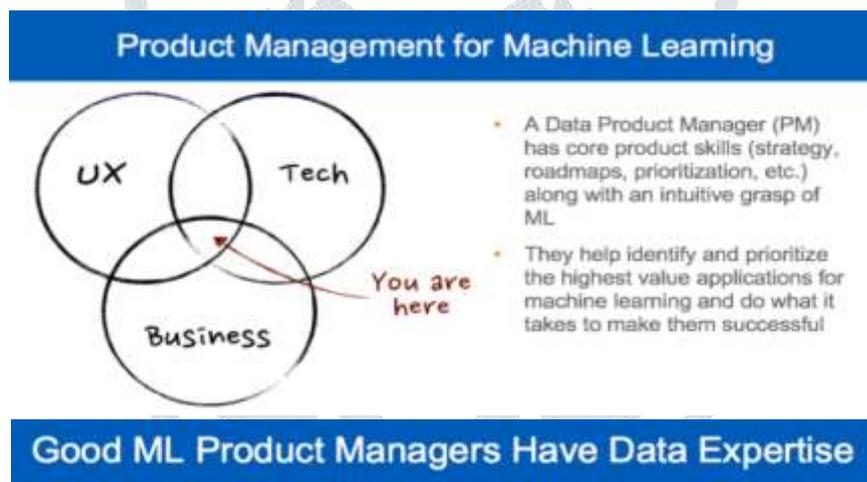
Machine Learning Product Management: Lessons Learned -

Over the years, we have listened to data scientists and machine learning (ML) researchers relay various pain points and challenges that impede their work. Unfortunately, a common challenge that many industry people face includes battling “the model myth,” or the perception that because their work includes code and data, their work “should” be treated like software engineering.

In an early iteration of Pete Skomoroch’s ML product management presentation in November 2018 at the O’Reilly Radar Conference. Pete indicated that one of the reasons why ML projects are hard is because “machine learning shifts engineering from a deterministic process to a probabilistic one.” Pete Skomoroch, O’Reilly Radar Conference, San Francisco, November 2018.

Product Management for Machine Learning:

ML requires a more experimental approach than traditional software engineering. It is more experimental because it is “an approach that involves learning from data instead of programmatically following a set of human rules.” Because the nature and approach of ML projects is more experimental, industry people and their companies won’t know what will happen until they try it (i.e., more probabilistic rather than deterministic). This may present challenges for product management as many product managers (PM) have been trained on shipping projects with a deterministic approach.



- Know the difference between easy, hard, and impossible machine learning problems
- Even if something is feasible from a machine learning perspective, the level of effort may not justify building the feature
- Know your company’s data inside and out including quality issues, limitations, biases, and gaps that need to be addressed
- Develop an intuitive understanding of your company’s data and how it can be used to solve customer problems

To help address these challenges, PM needs to acquire some additional skills including developing intuition about how ML works, understanding what is feasible from a ML perspective, and “know[ing] the difference between easy, hard, and impossible machine learning problems.”

PMs can leverage that intuition to calibrate the tradeoffs of various approaches given their company’s data “and how it can be used to solve customer problems.” It is recommended by experts to bring in ML experts and data scientists early in the process as well as “creating a chart of impact and ease, then ranking projects by ROI” when iterating on which features or projects to prioritize. The combination of a deep understanding of the company’s data, how the data can solve customer problems, ML intuition, and domain expertise, helps

PMs ensure that they are working on the right problems that matter to the business. Following 5 steps for shipping most ML projects and notes that steps 2-4 take up the majority of the time. These steps also reflect the experimental nature of ML product management.

Machine Learning Product Development

1. Verify you are solving the right problem
2. Theory + model design (in parallel with UI design)
3. Data collection, labelling, and cleaning
4. Feature engineering, model training, offline validation
5. Model deployment, monitoring & large scale training
 - Iterate: repeat process, refine live model & improve
 - 80% of effort and gains come from iterations after shipping v 1.0
 - Use derived data from the system to build new products

Pete relays that one of the most significant value adds to improve model accuracy is feature engineering, which is discovering the creative signals you find in the raw data, extracting them from the raw data, and then transforming them into suitable formats (or better inputs) for your machine learning model. It is recommended in getting the first version of the algorithm out quickly to users so that iterative improvements can be made to support business impact. PMs to keep in mind that approximately 80% of the work happens after the first version ships. This work includes model improvements as well as adding new signals and features into the model. It also recommended that PMs refrain from “endless UI changes” on ML projects before the product is put before users because “seemingly small UI changes may result in significant back end ML engineering work” that may put the overall project at risk. The last step for a PM is to “use derived data from the system to build new products” as this provides another way to ensure ROI across the business.

Addressing the Uncertainty that ML Adds to Product Roadmaps:

As ML projects are more experimental and probabilistic in nature, they have the potential to “add uncertainty to product roadmaps.” Here, are common challenges and key questions for PMs to consider.

ML Adds Uncertainty to Product Roadmaps

- PMs are often uncomfortable with expensive ideas that have an uncertain probability of success
- Many organizations will struggle to justify the expense of projects that require significant research investment upfront
- Some ML products may need to be split into time boxed projects that get to market in a shorter time frame
- What can you productize now vs. much later on?
- Keep track of dependencies on other teams and have a “Plan B”

Then, he recommends that PMs Collect data using appropriate user input forms that will collect the right data they need to “model the underlying phenomena you want to predict and that PMs will need to balance the desire for exhaustive data collection with user experience carefully.”

Data Quality & Standardization

- Guide user input when you can
- Use auto suggest fields
- Validate user inputs, emails
- Collect user tags, votes, ratings
- Track impressions, queries, clicks
- Sessionize logs
- Disambiguate and annotate entities (company names, locations, etc.)

“

Every single company I've worked at and talked to has the same problem without a single exception so far — poor data quality, especially tracking data

—
Ruslan Belkin
VP of Engineering, Salesforce.com

It is also recommended that PMs to reconsider their approach to testing given that ML systems run on underlying input data that often changes over time in unpredictable ways. Experts advocates use by real users as “sunlight is the best disinfectant”. This also reinforces his earlier recommendation of shipping version 1.0 quickly.

Testing Machine Learning Products

- Algorithm work that drags on without integration in the product where it can be seen and tested by real users is risky
- Ship a complete MVP in production ASAP, benchmark, and iterate
- Beware unintended consequences from seemingly small product changes
- Remember the prototype is not the product - see what happens when you use a more realistic data set or scale up your inputs
- Real world data changes over time, ensure your model tests and benchmarks keep up with changes in underlying data
- Machine learning systems tend to fail in unexpected ways

According to Statista, digital advertising spending will exceed \$335 billion globally and \$117.53 billion in the USA alone by 2020. This is a clear indication that the companies are spending extravagantly in the domain of digital marketing. There are great examples of big companies that are using AI and ML marketing for their businesses. A few very important examples of are given below:

- Amazon uses AI and ML for its online store
- Netflix uses the predictive analysis tool for better content curation
- Google, for website ranking
- Yelp, for image processing
- Pinterest uses them for its recommendation algorithms and content detection for better user experience
- IBM Watson’s extensive use in the better recommendation for cancer treatments in many healthcare organizations in the USA and abroad
- Salesforce uses its Einstein Machine Learning Technology for scoring and lead prediction purposes in digital marketing • Virgin Mobile uses Amperlo AI-based marketing platform for customer life value maximization and optimization of customer interactions
- Walmart uses machine learning based software for anticipating customer needs and providing suitable solutions for them Other than the above mentioned, there are numerous companies that use the commercial machine learning platforms for their marketing needs in the marketplace

CONCLUSION:

Based on the evidence presented in this article, it can be concluded that the traditional methods of Product Management cannot offer the sustainable solution and every PM should enhance their skill sets to understand use of Machine Learning/Artificial intelligence. These skill sets would help their organizations plan the product introductions/sustenance with effective ROI for their efforts. The triumvirate of skillful people, artificial intelligence and machine learning-based smart automation is going to be the future of digital marketing.

The future of digital marketing is closely associated with artificial intelligence and machine learning based marketing. A huge number of big corporations are already benefiting. Now, many small and medium-sized organizations are extensively pursuing this path to get the most of its great power in the domain of digital marketing.

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