EXPLORIUM

Marketers and Data Science:

Tapping Into The Data You Need to Build a Smarter Marketing Organization

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Not another buzzword

As marketers, we're pretty used to getting buzzwords thrown at us regularly: micro-influencers, gamification, omnichannel, microcopy, hyper-relevant, hyper-targeting, hyper-everything. It can be a lot.

With the expansion of artificial intelligence (AI) and big data in recent years, it seems like marketers now have even more buzzwords to understand and consider implementing into their workflow. The thing is, AI and machine learning (ML) can feel, for most of us, totally out of reach. We tend to think AI is limited to the more technical side of our organization or a part of a platform we use in our marketing tech-stack (how many tools do you currently use that *claim* to have AI?). But, it's not. In fact, marketing is actually a perfect place for data science and machine learning to make a business impact.

Marketing teams collect tons of data on every platform we use — and we use a lot of them. Not leveraging this data is a huge lost opportunity because the truth is, AI and machine learning aren't going anywhere.

In a landscape that's rapidly changing, marketers who start thinking data science-driven now will not only stay ahead of the pack, but also keep their organizations afloat.

We know what you're thinking:
"Obviously a data science company thinks I need to be leveraging data science."

You can't fool a marketer. But even if you're not ready to implement predictive models right this second, it's important that you're educated about what these "buzzwords" mean for you and the changing world of marketing. To be frank, you can't afford not to.

→ **22% of marketers currently are using AI-based applications with an additional 57% planning to use in the next two years.**

(Salesforce, State of Marketing Report)

Marketing science 101: terms you should know

Let's get some basic definitions out of the way before we go any further. A lot of terms surrounding data science and AI often get misused or confused for one another, so it's time to set the record straight:

1. **Data science as a service**

   Data science as a service (DSaaS) means outsourcing your data science production to a company who can handle all of it, end-to-end, for you. Marketing leaders may have the desire, but lack the internal resources, to do data science. That shouldn't stop them. For this reason, many marketing leaders look to outside vendors and experts to handle their data science needs for them.

2. **Data science**

   Data science is an interdisciplinary field that combines business knowledge with programming, statistics, and math in order to generate insights based on data. Data scientists build machine learning models for business leaders produce predictions to be used by various parts of the organization to optimize processes (like, marketing).

3. Data scientist/Data Analyst

"Data scientist" and "data analyst" are often used interchangeably by marketers but the truth is, they're not the same thing. A data analyst looks at internal and external datasets (see below) and produces reports and dashboards that focus on trend analysis and data monitoring. Data scientists, on the other hand, use internal and external data to predict things like customer behavior and then provide tactical insights for optimization. Data analysts are historians, data scientists are fortune tellers.

4. Internal/external datasets

In order for data scientists to do their job, they rely on data. This data can be internal, which is housed within your organization — like data from Google Analytics, your CRM, product usage, etc. — or, this data can be external, which your organization does not collect and own, but that can be purchased — like customer data platforms.

Acquiring external data is often labor- and resource-intensive, but is seen as a game-changer for data scientists who want to improve their models' performance (more on that later). In volatile economic times, and even in the best of conditions, external data gives context from the ever-changing world to your internal data — which is, quite frankly, no longer relevant today.

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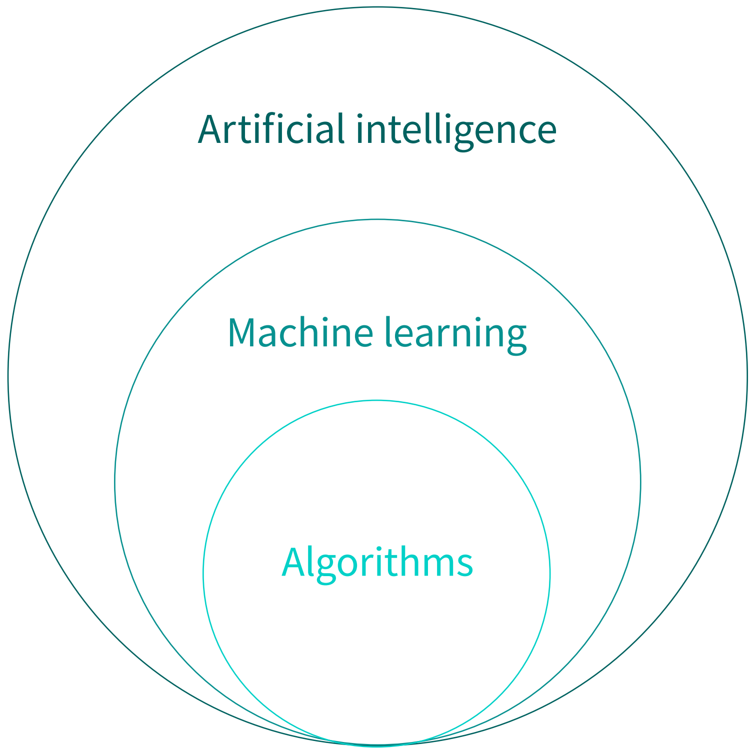
5. Predictive modeling

Predictive modeling is the process of using data and statistics to predict an outcome to a specific question. Predictive models can generate insights into future events like the likelihood a lead will convert into a customer, or what channels you should spend the most money on for advertising.

6. Artificial intelligence

Artificial intelligence, not to be confused with machine learning, can generally be thought of as making machines think like humans. Whenever a machine completes a task based on a set of rules it has learned, it is considered AI.



7. Machine learning

Machine learning can be thought of as a subset of AI. It's basically a technique that gets machines to the point of AI by training them on how to make an accurate prediction using data. This is the "learned" thing we mentioned above.

8. Algorithms

An algorithm is a set of rules in a specific order that a machine learning model follows to generate a prediction. Say, for example, you're trying to get to a museum for the first time. The directions you would follow in order to get there would be your algorithm because you need to follow them in a specific order to reach your end goal.

Let's recap: **algorithms** are a set of rules used for **machine learning** to train **predictive models** to complete a task (therefore becoming **artificially intelligent**). All of this is based on **internal and external datasets** and falls under the domain of **data science**.

All of this can be done internally or as a **data science as a service** in order for business leaders to better address challenges.

Ta-da!

What's the deal with data?

Now that we've gotten some definitions out of the way, let's take a look at the thing that makes all of this possible: DATA.

→ **Why external data matters.**

Before Google, if you had a question, you were limited to the information either you (or the people in close proximity to you) had. You could probably get a decent answer to some of your questions this way, but if you had access to information outside of your small network you could certainly get a much better answer. The same is true for machine learning models.

Today, data comes from everywhere and everything. Every click and pageview online; every "like" on Instagram and Facebook; every credit card purchase; all of your smart TVs, watches, assistants; and so on. Your organization likely collects tons of data that can be used by data scientists for machine learning purposes. However, imagine all of the data that exists in the world that you're not collecting and that could make the predictions from these models better. That's where the external data we mentioned earlier comes in.

Think about it like this: Before Google, if you had a question, you were limited to the information either you (or the people in close proximity to you) had. You could probably get a decent answer to some of your questions this way, but if you had access to information outside of your small network you could certainly get a much better answer.

The same is true for machine learning models. If the data they have to work with is limited to only what your organization collects, you'll get a decent prediction. But, if external data is brought in to give your models more context to learn from, you'll get way better predictions.

We hate to sound alarmist, but external data is always a must-have for your organization. All it takes is one black swan event to turn your relevant data into a pile of irrelevant ones and zeros, your internal data will no longer do the job on its own. You need external data to steer your metaphorical ship through these rough waters. Without this extra context you're not doing your best to redirect your marketing efforts. It's really that simple.

Before your data team starts looking at external data, however, you should get acquainted with the data you're already collecting.

We're guessing that at the very least you're using a marketing automation tool (like Hubspot, Marketo, or MailChimp), a CRM (like Salesforce), and have a website. If that's the case, you're likely collecting a fair amount of data points, including:

- → First and last name
- → Email address
- → Industry/vertical
- → Phone number
- → Company size
- → Job title
- → Email opens and link clicks
- → Pages visited on your website
- → Referral source
- → Conversion forms completed

If you're running paid ads on social media or syndicating content with third-party websites then you're gathering even more data that you can harness for lead scoring, improving conversion rates, and more. The further advanced your marketing tech stack gets from there (video platforms, influencer marketing tools, SEO and site optimization tools, social listening platforms, etc.) the more data you'll have at your disposal.

This is where it can get tricky.

From data-driven to data science-driven

Depending on the size of your marketing organization and the tools you use, your maturity when it comes to using data to drive your efforts will be different. The ultimate goal for marketers should be to move from data-friendly to data-driven to data science-driven. However, this can often seem like a far off dream — especially if you're part of our data-friendly group.

Remember, if you don't have an internal data team (or even if you do), data science as a service is a cost-effective option to jump into the data science world. You can skip data-driven levels instantly and start making a real impact on your business instantly.

Where are you on the data scale?

Level one: data-friendly

Data-friendly marketers definitely know they should be using data to make decisions. Their process usually involves looking at the analytics or insights tab in the various platforms they use and trying to connect the dots manually. This could look like a huge export of data into spreadsheets (not fun unless you're an Excel wizard) or drawing conclusions based on domain knowledge you have in your brain. Either way, you likely end up creating a PowerPoint to explain the conclusions you've made to your peers.

These marketers may also run an A/B test on an email subject line here and there to optimize that specific send but are not necessarily looking at those results to improve future emails. They may also pop into Google Analytics every once in a while to see the number of blog sessions they have this quarter and how long users are staying on the page.

→ Data science-driven marketing also means using data that you don't have within your marketing tech stack. With such a robust picture, you'll be able to predict with confidence and target your efforts better than ever.

This is a great start. All of these actions are habits that should continue to happen regularly. However, in order to optimize your efforts, you'll need to move to the next level.

Level two: data-driven

Data-driven marketers have already realized the problem with looking at siloed datasets and have moved to combine all (or most) of their data into one platform. Modern business intelligence (BI) and analytics tools can be self-service enough for some non-technical marketers to create dashboards that give a picture of what's happening in one place.

The dashboards you create should allow you to drill down and see whatever you want on a granular level. You should have a more holistic view of what has happened in the past, which you can then use to try and connect the dots and make decisions to improve moving forward.

This is where BI and analytics fall short. When you use BI tools, you're only able to report on data of events that have happened in the past. This means you can't actually look in the future and are stuck guessing what you think might happen next.

Level three: data science-driven

Data science-driven marketers can look into their crystal ball and see the future thanks to predictive models. These models go the next step beyond business intelligence by understanding what has happened in the past and telling you what will likely happen in the future.

When you use predictive models to improve your marketing you can ask a specific question you want answered (like, “Who should I send direct mail to?” or “How do I know what leads will convert?”) and get a specific answer so that you can optimize your work for the best possible results.

Data science-driven marketing also means using data that you don’t have within your marketing tech stack. Data scientists can bring in data from across the other parts of your organization that you don’t have access to or external data from outside your organization. With such a robust picture, you’ll be able to predict with confidence and target your efforts better than ever.

Real-world examples to get your mind working

Okay, all this talk is nice, but you're probably wondering how this is actually possible in the real world and what exactly you can do with a data science marketing state of mind. No problem. Let's get into it.

Ad tech

If you're running ads on AdWords, for example, then you already have a whole load of data points that can help you predict customer lifetime value based on a person's first click. How? Well, when a person clicks on an ad, your Google AdWords collects data around what that person searched for to see your ad, cost per click, IP address (which can determine their location), and more. If you create a model from this information and combine it with data such as interests, hobbies, and social media data, you can pretty easily determine lifetime value. All based on a single click.

Direct mail

Unlike the direct mail of the past, today's direct mail can be made much more effective with a little help from data. If you have a direct mail model that uses historical data from your CRM and takes into account buying trends and spending capacity, it can be combined with the geographic data of your leads, giving a pretty clear picture where to spend money on direct mail.

→ Although 82% of marketing leaders said customer experience is the main reason they're adopting AI, it's arguably more important for marketing in a world where everything we thought we knew is suddenly irrelevant.

(Statista, 2018)

Customized experiences

Marketers need to convert leads and that can be pretty damn hard. Offering people who land on your website a customized experience that shows them products and services your model predicts they'll want to purchase, can move the needle for your conversion rate.

One of our customers, GlassesUSA.com, uses audience segmentation models fueled by demographic and geospatial data to provide a different experience for each audience and offer smarter shopping experiences in terms of what products, services, and upgrades a particular person will see. This has increased both conversion rate and order value leading to a 15-20% increase in the per-session value for the affected segment.

Advanced Combining models

Let’s say you’re an online lending company and the risk department is using a risk model to determine if a loan applicant is likely to pay back their loan or not. At the same time, your marketing team is working on a direct mail model to predict where to send direct mail to get the most bang for your buck. Once both models are working, you can now tie them together to send direct mail to people who you predict are likely to pay back their loans.

Or, pretend for a minute that your organization has a churn prediction model to figure out when and if customers will leave. At the same time, your marketing team has a model to predict leads with the highest customer lifetime value. The outcome of the churn prediction model can be a great data point to feed into your lifetime value model because if, for example, a customer is going to churn quickly, their lifetime value will be less.

Of course, this point isn't sufficient on its own. Knowing that a customer isn't going to churn doesn't also mean that they will be worth millions of dollars. However, combined with other signals and data points from other models, it can make your lifetime value model stronger.

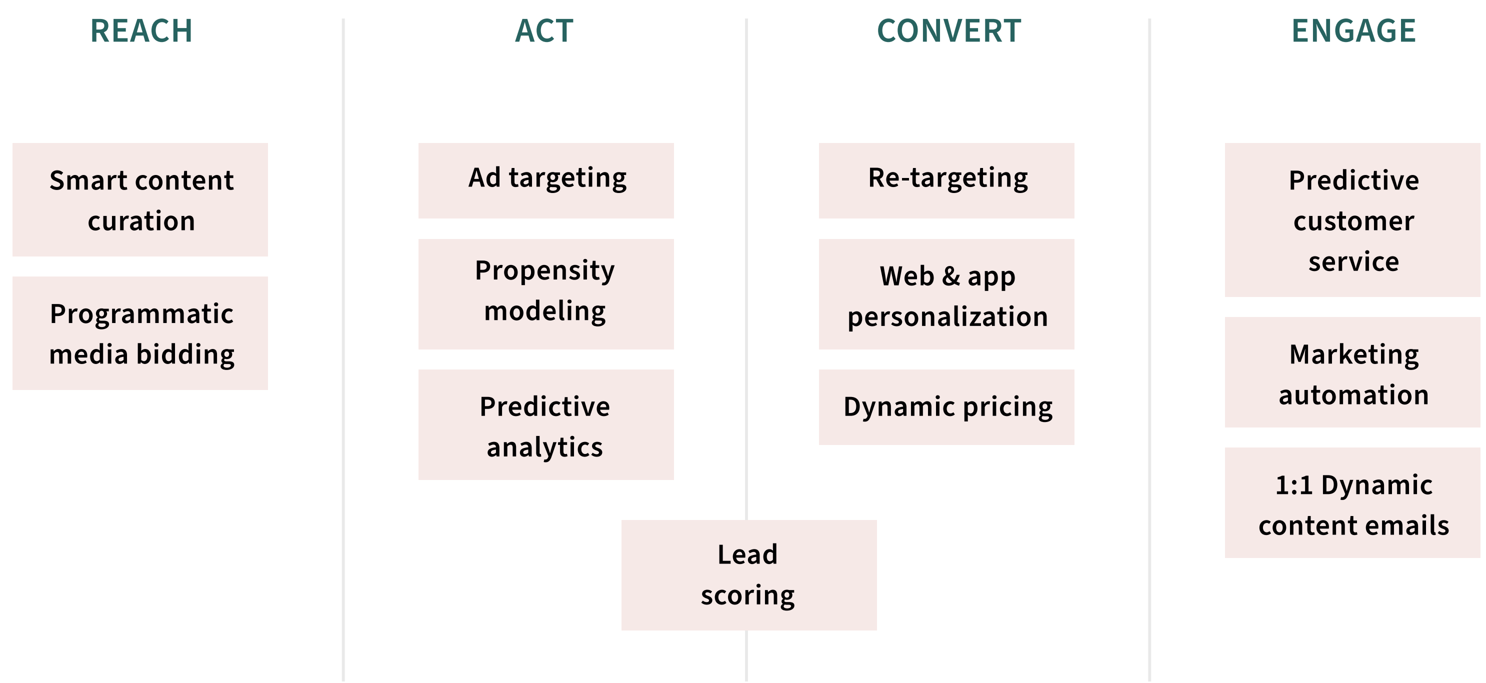
Imagine how over time, and with some cross-department knowledge sharing, you can create an amazing machine that connects predictions from one part of your organization to models in your department (and vice versa). *Mind blown.*

Checklist to start your marketing science project

Okay, you're ready to get started but where to do you even begin? If you have an internal data team, this checklist will walk you through what you'll need to do to get moving. If you're going the data science as a service route, these steps are still relevant but will be done alongside your vendor in a simple onboarding process.

1. **Take a look at your marketing and sales funnel.**
   Think about the points in the funnel where you'd want to implement machine learning. To get started we've put together a chart with some ideas and suggestions. Check it out on the next page.

2. **Think about the data you're already collecting.**
   This means going into all of your tools and platforms, and making a list that you can share with your data team. After all, they will be the ones who will need to extract that data and use it. Presenting it to them in a clear way not only shows you've done your due diligence but also gives them a place to start.



3. **Write a list of questions and pain points you want to predict.**

   You'll also need to go to your data team with questions and hypotheses you have. Although your data team should have business and domain knowledge, it's important to remember that you're not talking to other marketers here so you'll need to make them as specific and clear as possible.

4. **Speak to your data team or DSaaS vendor.**

   Understand what is and isn't possible given the data you have (and don't have). Answer all of the questions they have as specifically as possible. Again, the more specific you can be, the better.

5. Iterate and keep communication open.

The model your data team creates might not be perfect at first. Be open to testing different things to find the best fit. Remember to keep communication open with your data team, as well. If you bring on new tools or platforms you might also start collecting data that can help make the model better. It's important everyone is up to date on what new data is being collected.

Now get moving, you've got marketing to do! Good luck!

→ No data team? No problem. Explorium can manage this entire process for you as an end-to-end service. In this rapidly changing world, you can't afford to wait. So don't.

EXPLORIUM

About Explorium

Our automated data discovery and feature generation platform automatically connects a company's data to thousands of relevant premium, partner, and open data sources to extract an optimal feature set based on model impact. We’re creating a new category as the first company to empower and service business leaders and data scientists with end-to-end automation of data discovery and feature generation —

fueling superior decision-making and driving real business impact.