Artificial Intelligence Use Cases and Best Practices for Marketing

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Introduction: This Report in Context

Data. It's the lifeblood of digital marketing — so it should come as no surprise that artificial intelligence (AI) and machine learning (ML) are an essential part of a modern marketer's toolkit. During the past few years, AI has made significant inroads in the digital ad ecosystem for audience and product development, creative testing and measurement, and is now expanding into the realm of creative planning, compliance and privacy, and even identity management in a post cookie world.

The reality is that AI is the only technology that can keep up with the petabytes and terabytes of data that are the hallmark of successful digital marketing playbooks today.

AI is uniquely able to help brands and marketers make decisions about what creative they need to serve, how it should be designed and how it should look and feel — in real time and at scale. Adjacent to these industry shifts is the increasing complexity of data, evolving expectations, and the necessity to invent new, scalable solutions that move at the speed of advertising while observing transparent and privacy-centric approaches.

As part of the IAB Programmatic+Data Center's mission to increase the industry's understanding of how data can transform businesses, IAB created the AI Working Group to bring together AI and ML thought leaders and expert practitioners to produce essential AI resources to inform tomorrow's market leaders. In December 2019, the AI Working Group released the first Artificial Intelligence in Marketing Report, designed to help brand marketers and their agencies identify the opportunities that artificial intelligence and machine learning present and the first guide of its kind to offer a full picture of the benefits of AI in marketing.

In 2020, the AI Standards Working Group, newly co-chaired by IBM Watson Advertising and Nielsen, has expanded its work to develop AI standards, best practices, use cases, and terminologies. This resource, *Artificial Intelligence* **Use Cases and Best Practices** *for Marketing*, seeks to help executive leaders, marketers, and technologists who are taking steps to incorporate intelligent solutions into their advertising and marketing operations to navigate AI and machine learning with adjacent industry understanding, best practices, and guidelines. This guide is for people already working with AI or looking to leverage it in their business. It's also designed to help executives, marketers, and technologists understand why AI is a key part of the advertising ecosystem and how it is being used to great effect.

In the near future, the AI Standards Working Group will follow this report with one on the algorithmic bias of AI and how we build towards better AI standards for the industry. These efforts seek to explain how AI is revolutionizing advertising, why it's important, and what issues the industry faces as a whole if stakeholders don't familiarize themselves with the power of AI.

Over the next decade, from audience and targeting to creative resonance and insights, AI will increasingly augment consumer marketing strategy and outcomes. Businesses and their marketing practices must embrace and understand these evolving possibilities to remain competitive in tomorrow's marketplace.

Personas

As the industry continues to transform to the demands of tomorrow, it is important to address the needs of the roles driving the models for change. We have identified three key roles in the overall decision-making and implementation processes across the marketing and advertising ecosystem and using a user-stories approach, we define example need states.

While your exact role might not be listed here, the intent is to showcase the relevance across varying levels of engagement from decision making and strategic planning to execution.

- **Agency C-Suite**
- **Marketer**
- **Technologist**

Agency C-Suite

Budget owners and decision makers, investment leaders, technology leaders, activation leaders, client relationship owners, operations leaders, and people leaders

What is your role?

“I lead my agency with creative passion and wake up each day wanting to make my employees’ and my clients’ lives better. I believe that technology enables us to be the best version of ourselves as humans and I work with my peers and executive team to approach our employee and client experiences through that lens. I’m excited by the exponential growth in technology, but I’m weary of separating the reality from the hype and implementing solutions cost effectively.”

How do you envision AI/ML enabling success within your functional role?

- Enabling people to focus on the tasks at which they excel as humans such as establishing and executing strategic vision
- Bringing a competitive advantage differentiator to my agency to attract both top tier clients and high potential employees
- Increasing profit margins by reallocating human effort against meaningful work and offloading business-critical yet high-volume, tedious tasks to machines
- Improving the agency employee experience and increasing talent retention

What apprehensions do you have about AI/ML?

- Alignment to business priorities and objectives
- Customer apprehensions about AI
- Cost and ease of implementation
- Ownership and maintenance post deployment given the evolution of technology
- How to ensure that my teams have the skills they need to use the technology effectively
- Navigating the various technology providers and selecting the best one for my firm’s needs
- Implementing solutions with a third-party implementation partner or leveraging existing internal resources
- Identifying internal stakeholders, program sponsors, and/or steering committee members (i.e., CIO/CTO, CFO, COO, Chief Automation Officer, etc.)

Marketers

Media planners, media buyers, creatives, and brand marketers

What is your role?

"I work at an agency that does media planning/buying for some of the world's largest brands. Prior to working within a large holding company, I worked at a bespoke agency that handled regional and some national brands."

"We offer branding and communications to help companies engage audiences via multiple media channels."

"We focus on all aspects of marketing."

How do you envision AI/ML enabling success within your functional role?

- Automatic ad creation for addressable and non-addressable programmatic media formats
- Automatic media mix modeling based on brand and performance metrics
- Audience optimization via addressable and non-addressable programmatic media formats
- Sourcing vendors that offer media efficiency through their AI/machine algorithms
- Natural language processing and sentiment analysis offer an excellent opportunity for creatives to gather information and provide a human touch
- As interaction and content consumption improves, optimization will continue to develop via owned media assets
- Supply chain optimization: Optimizing media mix and creative ad serving based on product supply overages and or low inventory levels
- Owned media optimization: Contextual owned media based on audience cohorts to drive more sales and personalization
- Fraud detection and brand safety

What apprehensions do you have about AI/ML?

- Bias: Is a media vendor using AI/MLto my clients' benefit or their benefit
- Adoption: Pitching a new AI and ML tactic to a traditional account
- Excessive AI/ML: Lack of human touch that results in issues at the account level
- Adoption: Will adopting AI/ML help our hurt career development
- Trend recognition: Will automatic trend recognition cause more "science" than "art"
- Cultural cues: Will we go too far with sentiment analysis
- Interactions: What is the ceiling for measuring interactions and how will consumers respond

Technologists

People responsible for AI implementation within the agency, brands, and platforms including solution architects, product leads, product developers, engineers, data scientists, and data teams

What is your role?

“I evaluate, select, implement, and optimize AI algorithms best suited for the business problems at hand.”

“I manage the procurement and quality of annotated data sets used to train supervised machine learning algorithms. I contribute to increasing the performance and decreasing the bias of the AI service by making sure training data is accurately labeled, representative of the problem space, of sufficient quantity, and that human annotators are culturally diverse.”

“I architect and build software platforms that facilitate training algorithms and run inference at the scale required for the business. I expose AI capabilities at an API level for internal and external consumption.”

“I use an assortment of data science tools and statistical techniques to monitor and adjust the performance of AI that is integral to our operations. I use various analytical techniques to assure our stakeholders that our systems are functioning efficiently and within the parameters set by the business and regulatory authorities.”

How do you envision AI/ML enabling success within your functional role?

- If the AI/ML performs well (e.g., high precision and recall), I am successful
- If the AI/ML use scales per business requirements, I am successful
- If the AI/ML is free of unintended biases, I am successful

What apprehensions do you have about AI/ML?

- The algorithm could be biased (e.g., it assumes certain behavior based only on race or gender)
- Staying on top of current trends in the space and ensuring that I have ample time dedicated to leveraging best practices in line with the technology as it evolves
- The AI-based system might not perform fast enough or scale to its intended use level
- Sufficient training data to build a performant algorithm might not be available or affordable
- Finding and attracting technical talent to build AI systems
- Accurately estimating effort required and amount of training data needed to deliver on performance goals

AI Best Practices

As we approach industry-wide adoption, expert-led best practices can help us to evaluate and adopt AI-supported methodologies for homegrown and partner-based solutions. We have gathered insights and guidance from some of the leading agencies, brands, and advertising technology providers to help you prepare and execute with an informed approach.

Understand the problem you are trying to solve and define a goal that results in a business outcome that addresses that problem. You can't just apply AI; it's meant to augment your understanding, decision making, and communications, not replace it.

- Evaluate your AI approach to ensure that it truly solves that problem.
- Clearly understand how to separate AI hype from reality.
- AI solutions should not be blindly trusted. Understand what data is being applied and how that data is affecting the result.
- Identify the right success metrics.
- It's easy to fall into the grand AI deception trap. Find the right partners and technology providers who will guide and support your team through the AI-adoption journey.
- Evaluate the key data that the model is using to learn more about your inputs and the quality or reliability of the data.
- Evaluate new data sets that could be used to improve modeling.
- Define a practice that puts product use/development, AI and data inclusion, and legal compliance in lockstep and include them in your process. Make sure your AI vendors are doing the same.
- Plan for training, and make sure to experiment with outcomes. Building a prototype, even with poor performance is critical. Make sure to test different ideas in parallel.
- Train, but also hire for, an AI future. AI expertise in your team is paramount to success in the next two years and even more so over the next ten.
- Formulate and communicate what hyperautomation means for your organization, partners, and ecosystem, and then act.
- Plan for the inevitable reality that customers' and business stakeholders' demands will yield a mandate that everything that can and "should" be automated will be automated.
- Prioritize automation and AI investments based on an iterative multi-year journey premised on multiple concurrent business-driven initiatives.
- Continue to evaluate the efficacy of an AI model over time, as the underlying data may change, or there may be product modifications that introduce new variables that drive performance.

AI Use Cases

AI is having a profound effect on how brands talk to consumers and helping savvy marketers deliver better, smarter, and more relevant conversations and experiences to consumers. But while AI is not new, there is still considerable confusion about what it can do and the best way to leverage it in marketing. Additionally, there are concerns around using it in privacy-forward, unbiased ways.

We believe education through examples and best-practices are the only way our industry will be able to scale AI and get a full picture of consumers' online experience. What follows are a series of in-depth use cases written by IAB members meant to highlight successful implementations of AI in marketing and considerations for helping professionals across the advertising and marketing ecosystem bring it into their marketing practices.

This report highlights specific use cases across the advertising and marketing ecosystem intended to educate all three personas in this report about why and how AI is critical to their success. These use cases include:

Contextual - With advanced contextual AI advertisers can sort through billions of pieces of digital content and videos to find an ideal environment to place non-intrusive ads without infringing on personal data.

Conversations – Ad-based chatbots can provide a cookieless interactive AI solution that helps marketers have personalized conversations with consumers virtually anywhere online.

Creative - Predictive and regressive ML models are reshaping the prospect of dynamic creative assembly by empowering brands to predict which elements resonate best with every member of their audience.

Data Migration - Advances in automation technology have made repetitive and manual data migration work obsolete and addressable via robotic process automation (RPA).

Measurement - By using AI to integrate big data and traditional measurement methods, companies can leverage both the volume of third-party and census measurement data for richer and more actionable marketing metrics.

Predictive Audiences - AI reduces media waste by better segmenting prospective audiences based on their likelihood to act alike.

Process Discovery - As automation and AI capabilities evolve to cost effectively emulate humans, it's possible to combine technologies such as computer vision, pattern recognition, and ML to train an AI to create business analyst outputs.

Traffic Shaping - Traffic shaping relies on ML models that leverage historical trading data to predict the likelihood of future buying events.

Video - New tools can automate video management and distribution workflows to enhance the value of video experiences for audiences and marketers alike.

Use Case: Contextual

Author: Ken Weiner, Chief Technology Officer, GumGum
Primary Persona Stakeholders: Technologists
Secondary Persona Stakeholders: Agency C-Suite and Marketers

Contextual targeting has taken more of a backseat to behavioral targeting in recent years, however, contextual is making a comeback. This is largely due to two things: growing data privacy regulations and the introduction of sophisticated machine learning and AI.

Over the past few years, contextual advertising has slowly evolved to implement sophisticated machine learning and AI technology. Growing from simple keyword matching techniques to now being able to fully understand the context of a webpage or video like a human would. This progress has vastly changed how the advertising industry is approaching contextual AI.

With advanced contextual intelligence advertisers can sort through billions of pieces of digital content and videos to find an ideal environment to place non-intrusive ads without infringing on personal data.

Publishers are also benefiting from contextual intelligence using the tool to increase monetization by packaging content in real time that aligns to advertisers' brand suitability criteria.

Contextual intelligence will play a critical role for the advertising industry as we move forward in navigating how to build a world where brands can find the ideal environment to advertise while providing the best possible user experience for consumers without using any personal data.

How It Works

Machine learning models associate web pages, images, and videos with sets of contextual and brand safety segments as well as prominent keywords. These segments and keywords are leveraged by advertisers to contextually target (and avoid) campaigns. Data segments are made available via demand-side platform (DSP) prebid integrations as well as contextual private marketplaces (PMPs) within supply-side platforms (SSPs).

GumGum leverages deep learning to develop each model and assembles a large data set of annotated content. Annotations are provided by both in-house specialists and crowdsourcing partners. For example, to predict whether a web page contains violence, human annotators would be asked to look at many web pages, one at a time, and indicate each time whether or not the text or images on the page contain violence. Multiple annotators must agree on the page's classification before it is included in the resulting ground truth data set. The data set is then leveraged for training a neural network and measuring the performance of the resulting model. As violence is often used as an avoidance category, performance of the neural network is tuned to meet a recall threshold while maximizing precision.

Considerations

Keyword-only approaches to contextual targeting may mistakenly associate content containing a word like “shoot” with violence, when in fact it is really about basketball (shoot the ball), photography (photo shoot), or even botany (new plant shoots). Contextual solutions based on supervised machine learning often perform better than those that solely focus on the appearance of specific keywords present in the text, audio transcription, or metadata. The correct classification of a web page may depend on the tone of the text, what’s depicted in the pixels of the images, or a combination of both. For a video, it may depend on what is spoken in the audio transcription, as well as what shows up in each video frame. All of these inputs can be codified into feature vectors that support the sophistication of the neural network.

Sentiment is another tactic often used in combination with content categories to aid in building a brand suitability profile. This involves determining whether the tone of the content is positive, negative, or neutral. This would allow a brand, for example, to target positive coronavirus news articles like top movies to watch during the lockdown but avoid negative coronavirus articles dealing with suffering patients or a growing death rate.

As is the case with any AI solution, bias can creep into contextual algorithms and it takes vigilance to minimize it. Training data sets must be as diverse as possible, and so must be the humans that contribute and review annotations. For example, a set of training data focused on identifying violence might contain too many images of people of a certain race holding a gun. A model trained on this data may incorrectly learn to associate people of that race with violence regardless of whether or not a gun is present. Ask your AI partner what steps it is taking to minimize this kind of bias.

Use Case: Conversations

Author: Robert Redmond, Head of AI Ad Product Design, Design Principal, IBM Watson Advertising
Primary Persona Stakeholders: Marketers
Secondary Persona Stakeholders: Agency C-Suite and Technologists

Brands want to feel connected with consumers. They want to listen and understand. Consumers want to engage in valuable interactions rather than being flooded with static display ads that offer no unique or personalized value.

While most marketers would love to better understand their audience's desires and behaviors, a lack of time, privacy concerns, budget, and resources can hinder the ability to foster these types of connections. But what if you could streamline the process of talking with consumers, providing a more personal experience at the scale of advertising?

Ad-based chatbots can provide a cookie-less interactive solution that helps facilitate personalized conversations with consumers virtually anywhere online. Powered by natural language processing, speech recognition, and features like tone analysis, this turnkey solution is designed to deliver more engaging ads and experiences by using AI to understand the user's intent and provide answers, recommendations, or next steps.

This insight may help you ensure that every interaction is unique and effective.

How It Works

The IBM Conversation platform provides an advertiser with three varying approaches: Recommendation, Selector, and Dialog. During the planning stages, the intended KPI is determined with the client and helps prescribe the appropriate method. Clients provide materials (websites, PDFs, FAQs, call center transcripts, etc.). The activation team works with the client on the conversation design that aligns their content and novel content with their objectives.

A corpus is created to help train the Watson natural language processing (NLP) algorithms. This corpus consists of intents, the meaning of the statement a consumer might make, the responses, and the system's voice in response to a consumer statement.

Once training begins, the system uses natural language generation techniques to create variant utterances to help the system understand the many different ways a consumer might state an intent.

In many executions, it is essential to understand more than just the intent of the consumer. We might use additional natural language services to understand the tone of their interaction or combine a series of choices to understand their personality.

The conversation is trained within a 90 percent or above conversational accuracy across the entire corpus at launch.

Once consumers begin interacting, the conversation uses its trained corpus and a series of directional features to drive the consumer to the intended outcome. The conversation intelligently understands when issues arise, prompting the consumer to confirm their intent — learning and applying the learning for future interactions.

At campaign completion, marketers can glean a myriad of insights from the recommendations delivered, questions answered, and interactions with the consumer. The results can help inform future campaign strategies, customer service efficiencies, and even improve product experiences.

Use Case: Creative

Author: Robert Redmond, Head of AI Ad Product Design, Design Principal, IBM Watson Advertising
Primary Persona Stakeholders: Technologists
Secondary Persona Stakeholders: Agency C-Suite and Marketers

Current dynamic creative optimization (DCO) approaches require brands to pre-plan the right message for the appropriate consumer context and provide little room for learned adaptation as the campaign matures.

Predictive and regressive machine learning models are reshaping the prospect of dynamic creative assembly by empowering brands to predict which elements resonate best with every member of their audience.

How It Works

The predictive creative platform continuously consumes "last mile" consumer and contextual data signals to determine the optimal combination of creative and copy elements to help drive the highest engagement and (ultimately) conversion. The models focus on learning which consumer actions drive towards the optimal KPI across multiple variants. This learning is constantly employed throughout the campaign, working to move individuals closer to the intended outcome, say website conversion or purchase, by re-assembling the ads to which they are exposed.

When a campaign starts, unsupervised algorithms build clusters derived from consumer-driven features and then select the creative combinations that perform best for a particular cluster. After there is enough training impression volume, the supervised regression models are built for each creative combination and calibrated based on the probability of a conversion action. Across the course of a campaign, the models continue to learn and refine the approach, honing in on missed opportunities to be relevant to the overall audience, while defining rich campaign metrics that inform creative and strategic insights.

Considerations

Algorithms that react to the intangible way a consumer perceives a creative visual or message require a good amount of variation. In these types of scenarios, sticking too closely to brand standards or a finite set of rules for a campaign can hinder results. Consumers are very different and we need to feed the model fuel that allows it to decipher those differences. Creative variation is a must.

Use Case: Data Migration

Authors: Max Cheprasov, Chief Automation Officer, dentsu;
Brian Klochkoff, Director of Automation Solutions, dentsu
Primary Persona Stakeholders: Technologists
Secondary Persona Stakeholders: Agency C-Suite and Marketers

Accelerated digital transformation is top of mind right now for any business, including advertising and media agencies and as a result migrating data from legacy on-premise systems to newer cloud-based platforms is often a tricky and painstaking process. It's especially difficult when you're working on a deadline. If you don't have an application programming interface (API) to export that information in bulk, you're likely looking at tens of thousands, or even hundreds of thousands, of hours to get the job done.

This type of work often acts as an obstacle for agencies to adopt newer, more flexible cloud-hosted SaaS solutions so they tend to remain on antiquated on-premise applications supported by clunky non-integratable mainframes. Typically, the data behind these older platforms is being transformed at the user interface layer which few people have access to or even understand. This means that it's easy to get meaningful data into these systems but pulling it out of the back end is a different story. Unfortunately, this can mean manually copy-pasting data into a tabular format. Describing this work as robotic would be an understatement.

Luckily, advances in automation technology make such manual work obsolete and addressable via robotic process automation (RPA). This is especially relevant in high pressure and aggressive timeline data migration projects where executive teams are rushing to give their people the modern marketing tools they need to do meaningful client work.

How It Works

Early adopters of RPA have used digital robots to execute the high volume, tedious actions that an entry-level worker might be stuck performing such as copying and pasting data from an old system to a spreadsheet for migrating data to a newer platform. To understand the technology, it's important to look at it through the lens of a real-world use case.

In one recent case study, a global advertising holding company leveraged 60 RPA bots to do the work of what would have taken 70 full-time employees a full year to do. The automated solution reduced processing time for each transaction by 90% from 3 minutes of manual effort per transcribed record to just 18 seconds of robotic effort. Not only did the RPA digital workforce cost a fraction of human labor, the work was performed with 100% accuracy requiring no re-work at all.

Anyone familiar with RPA has heard about its cost-saving benefits a hundred times before, but the real story here is the scale and speed of this project. Building 60 unattended robots in 30 days and completing a massive data migration initiative that involves millions of records should be impossible. But it's not, thanks to RPA.

Considerations

It is important to involve the business in such use cases since RPA technology is so tangible and accessible that it draws inspiration for future use cases from business users. It is not a technology that should be limited to the technology function and it is also not a technology that should be applied without a proper use case root cause analysis. It's easy for everything to look like a nail when you're holding a hammer, but when the use case is thoughtfully assessed and the solution is elegantly designed, RPA can be a very effective technology.

Use Case: Measurement

Authors: Nico Van de Bovenkamp, Lead Data Scientist, Nielsen; Rachel Worth, Lead Data Scientist, Nielsen
Primary Persona Stakeholders: Agency C-Suite
Secondary Persona Stakeholders: Marketers and Technologists

In the traditional linear ad/TV framework, measurement and attribution solutions were relatively straightforward and based on panels. With the growth in digital ad spaces, the now-fractured market and growth in potential data sources generates huge volumes of data, but with less rigorous control and depth of information than a classic panel approach. Measurement companies reporting ad views can be limited by what information is available about the impressions and viewers.

By using AI to integrate big data and traditional methods such as assigning viewership, creating coverage, and deduplicating across sources, measurement companies can leverage the volume of third-party and census measurement data. Combining big data with the statistical control and depth of information of panel measurement will increase the usefulness and depth of information they can make available to clients. Given the continued fracturing of the media landscape and expanded focus on privacy, AI will be a critical piece to the future of measurement solutions. The new Nielsen One cross-platform ad ratings product is an example.

How It Works

To properly measure and attribute ad and content impressions, companies rely on a combination of deterministic identifiers and supplemental data to assign the "who" to "what" was seen.

When deterministic identifiers such as login, email, device IDs, cookies, and other first- and third-party data are available, they can be used to help identify individuals when impressions are served. However, the story doesn't end there. These identifiers have gaps in coverage, erroneous attribution, and struggle to account properly for co-viewing and device sharing. Furthermore, first- and third-party data are often not available to attribute an impression to a viewer, and other known sources are required. Due to many coming changes in the industry, the limited availability of these deterministic identifiers, particularly cookies and mobile ad IDs (MAIDs), will both persist and expand.

In measurement systems, the provided first- and third-party data is often supplemented and corrected using other data sources including surveys and panel data. Probabilistically sampled survey and panel data are still the gold standard in rigorously assuring the "who" is correctly assigned to the "what" in content and advertising. In the past, this data was just used to provide weighting and statistical estimates. Today, they're used as truth labels to a vast ecosystem of AI to learn and understand consumer behaviors.

AI is trained to solve a specific task. While AI is not programmed to give a specific answer or way it'll solve that task, it's constructed to help solve a problem. The task of taking a campaign and finding out who saw it might seem straightforward, but there are many subproblems to consider. In most measurement systems, a combination of AI applications leverage the massive amount of data to connect impression events to deduplicated individuals for measurement.

It's no longer the case that all media comes through a single TV at home. Every household is now full of individuals with multiple devices, applications, and accounts that are shared, used independently, or all together. With comprehensive granular data, AI can be used to combine the vast mess of data points to parse out who is using the device, app, or account, correcting for biases due to co-viewing and device sharing.

Often, third-party measurements are not available at the individual level but are given in aggregate at various levels of granularity. These aggregates still require further correction because they are drawn from a subset of the population, and to be projected up to represent the full universe, must be accurately deduplicated. AI can learn the relationships between overlapping views to different segments of the ad ecosystem based on where the ad is seen and by whom.

In addition to compensating for incomplete data, there can also be inaccuracies in the measurements collected by third-party providers, which AI can help correct. By leveraging multiple data sources against one another, especially comparing panel data to third-party data for the cases where we have overlap, we can measure biases in coverage or users self-reporting incorrect information and apply corrections.

AI is critical in the journey to stitch together the fractured media ecosystem.

Considerations

Accuracy: Having a source of ground truth is key for accurate measurement. This is why it is important to make the most possible use of first-party, controlled panel data. It would be easy to generate modeled characteristics that look believable, but intuition can be misleading in such cases and it is necessary to have some ground truth from which to calculate objective measures of validity.

Stability: Because measurement provides a foundation on which ad markets buy and sell, the products must remain stable over time. This requires both the models themselves and their input data to be reliable and consistent. Stable relationships with third-party data providers are key. This means it is important to investigate the *longitudinal* accuracy of the models and their variance, especially under edge cases and non-linear events (e.g., a sudden release of new content).

Sample size: The goal in measurement and attribution is to provide a picture of everything going on in the market, from the high level down to granular details. This requires a diverse sample of data, to ensure representation is as fair as possible to all involved. The key question isn't always, "how many users" or "how many records" are used. While that often does mean a lot of data is required to capture the various devices, platforms, and array of content in the market, what's more important is that the data is representative of the population. Still, the increasing fragmentation of the market means many small slices to measure, and large data volumes are required to resolve small aspects. Small slices of the world cause models to "overfit" their data which can lead to many inconsistencies when they are applied in an app.

Sample type: Measurement can be based on partial census, full census, convenience panel, or probabilistically sampled panel data. Any measurement or attribution solution requires data to be collected. However, how and where that data is collected makes a big difference. Not all sample types are comprehensive enough to accurately capture a total market view.

Partial census is data collected that represents only a portion of the behavior of a consumer. For example, a website may be able to track all campaigns on the content it owns but has no visibility into the campaign placements on other sites or applications. While partial census data can be large, it's ultimately sure to be biased and lacks coverage of the market — even for the largest players.

A census measurement is one that covers essentially all activity in the relevant area. This is typically accomplished via a digital tag or a direct server-to-server connection. By measuring every ad seen, there would be no need to apply weighting or corrections. However, there is no complete census measurement for the entire ad market, and census alone doesn't provide a path to putting one market segment into context with the rest. Furthermore, simply having census measurement doesn't guarantee to account for viewability, fraudulent or invalid traffic, or attention. And, of course, having only census measurement answers the "what" but not the "who" of measurement.

Panels are often used to bridge this gap by measuring a sample of people or activity across all segments of a market. A first-order approximation that could cheaply add coverage would be a "convenience sample" where pools of individuals' data are collected directly from whoever signs. While this solution is cheap, fast, and will scalably answer the "who," it runs a large risk of not representing the population and introducing large biases into measurement. The gold standard of measurement solutions would be a probabilistically sampled panel in which individuals are selected and weighted to match the total population of real viewers. In the rapidly evolving ecosystem of content and advertising, no sample type perfectly captures measurement and attribution. Maintaining and recruiting a well-distributed sample provides comprehensive data but is expensive and difficult to maintain. Ultimately, the future of measurement and attribution will have to leverage a combination of probabilistic sampling and big data.

Use Case: Predictive Audiences

Author: Robert Redmond, Head of AI Ad Product Design, Design Principal, IBM Watson Advertising
Primary Persona Stakeholders: Marketers
Secondary Persona Stakeholders: Agency C-Suite

Traditionally marketers merely had demographics, which were seldom perfect and limited how many segments could be targeted. The emergence of look-alike audiences appeared valuable, but they don't tell the whole story. Look-alikes only identify people with similar simple attributions like demographic profiles. And the truth is people who look like each other don't always act like each other.

Predictive approaches can use AI to help reduce media waste by better segmenting prospective audiences based on their likelihood to act alike.

How It Works

A predictive audience works by layering multiple, continuous data signals with first-party CRM data and trusted third-party data to identify users that are most or least likely to take a desired action. This goes well beyond demographics using machine learning and predictive analytics to assemble behavioral segments from over thirteen thousand data points employing hundreds of models and thousands of variations, identifying the best fit on the fly.

It all starts by combining an advertiser's first-party audience seed data or acquired data via a seed pixel on brand properties to gather unique consumer insights. This seed data, consisting of things like content engagement, or type/count of interactions with the brand, is employed by machine learning algorithms and runs against thirteen thousand interest and action-based data points to analyze behavioral attributes across a wide range of consumer profiles. It then builds thousands of model variants, tests, and selects the best performing ones, while continuously learning from performance. This allows live training to guide training to rebuild segments regularly to achieve the highest performance.

The advertiser has full control over training parameters allowing them to determine which attributes hold value and which to leave out, which segments are being used, and the ability to allow for exclusions, ownership over the metrics that drive model performance, and gates to control outputs.

The result is prediction-based unique act-alike segments tailored to your individual campaign KPIs and scored into the following segments: Low – not likely to take desired action; Medium – somewhat likely to take desired action; High – very likely to take desired action. This leaves the brand the power to appropriately position powerful messaging that resonates with audiences who "do-alike."

Considerations

A depth of understanding about the current consumer is required to generate behavioral driven act-alike segments, either using an existing first-party data set, or data gathered via a seed pixel.

Use Case: Process Discovery

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Boring and repetitive tasks are a part of any company's vital tasks. Offloading this makework would make teams more efficient, productive, creative, and improve the employee experience overall. It would also give them time to engage in the more strategic and rewarding aspects of their roles, thus elevating every employee's potential and increasing client satisfaction in the process.

But identifying and automating this repetitive work often means hiring expensive business analysts to perform traditional and antiquated time and motion studies. The outputs from these exercises often result in anecdotal insight from subject matter experts and process owners whose day was interrupted to be interviewed by business analysts.

As automation and AI capabilities evolve to cost effectively emulate humans, it's possible to combine technologies such as computer vision, pattern recognition, and machine learning to train an AI to create business analyst outputs. Early adopters are experiencing massive benefits and competitive advantage at a fraction of the traditional consultancy fees associated with these process mapping and time/motion study exercises.

How It Works

This type of technology is referred to as process and task mining. It can be leveraged in various ways using different methodologies and sets of data to achieve similar outputs, but the predominant use has been to gain transparency into enterprise operations in an objective and non-invasive way which generates actionable outputs. This technology does not disrupt the day-to-day work of an employee being observed, the outputs are empirical, and operations teams use the AI-generated insights to optimize processes, identify opportunities for offshoring and automation, and even uncover behavioral patterns and nuances across client teams. Ultimately, those insights tend to be used to optimize and automate processes to increase productivity and allow more time for higher-value tasks, which would lead to better client experiences and improved business results.

Advanced and best-in-class providers leverage artificial neural networks (ANN), natural language processing (NLP), and machine learning (ML) models in combination with advanced optical character recognition (OCR) and computer vision to analyze low-resolution videos that have been recorded on as many machines as the software has been deployed to for the observation cycle. This approach allows the actual analysis to be swiftly done by AI on a massive scale using much deeper and more granular data.

In one notable case study, a global advertising holding company was able to uncover 2,200 processes in the first five months with a two-person process mining program which would have taken 30 business analysts to do manually in the same time. In another instance, an enterprise was able to observe over 100,000 hours of work done by 300 people creating a nine terabyte data ocean for analysis. Currently, solution architects are required to assess the outputs and recommend appropriate solution paths for the use cases identified; but as the technology evolves exponentially, it is safe to believe that this type of recommendation engine is imminent.

Inviting participants to willingly participate in the process mining exercise is critically important. The strategic imperative for such a program is to improve the day-to-day work so people in an industry as human centric as advertising can truly be elevated and tap into their full creative potential.

Considerations

To successfully automate repetitive tasks, it is key to understand the data privacy requirements at the geographic/regulatory level as well as the enterprise's cybersecurity policies. Also consider the technical capabilities of administrators for process mining programs given the early raw potential of the involved technologies. For example, a process data scientist with a good understanding of the technologies as well as the industry-specific business operations would make a strong leader for any process and task mining program.

Use Case: Traffic Shaping

Author: Isaac Schechtman, Sr. Director Product Strategy, IPONWEB
Primary Persona Stakeholders: Marketers
Secondary Persona Stakeholders: Agency C-Suite

Every day in programmatic advertising, several trillion ad impression opportunities (known as bid requests) get passed between trading platforms in the hopes that a buyer, sitting behind a demand-side platform (or DSP), will detect attributes about a singular impression opportunity that make him or her want to place a bid to win that specific ad placement.

The cost to process those trillions of bid requests, a high portion of which are duplicated across publishers and platforms, is exorbitantly high — so high that only a few technology platforms can shoulder it. All other buy-side platforms use a combination of tactics to ensure they can receive as much of the bidstream as they need (and the right profile of supply) to satisfy campaign buying requirements, without listening to so much that they incur unnecessary hardware processing costs. This practice is known as traffic shaping, and it is a key application of machine learning in programmatic advertising.

Traffic shaping relies on machine learning models that leverage historical trading data to predict the likelihood of future buying events. More specifically, unique algorithms sitting in a DSP assess the value of a given impression opportunity coming into the platform, based on all available data points attached to that bid request, against historical bidding patterns to decide if the impression opportunity is valuable to its buyers. If yes, the bid request has a greater chance of getting passed through from supplier to buyer. If not, it is more likely that the bid request will get discarded.

To maintain accuracy, the algorithm works based on reinforcement learning, applying both the current processed results in combination with the exploration of a control group of unfiltered traffic to constantly update and refine the algorithm. This is essential in adtech as campaigns and corresponding traffic requirements are in a constant state of flux.

The principle behind traffic shaping is for DSPs to only listen to supply that is likely to be considered valuable to buyers. For tech platforms facilitating this type of trading, the cost of listening to supply is only offset by fees taken when buyers bid on and win impressions. The more intelligent their traffic-shaping models, the more they can reduce costs while maintaining campaign delivery. But every buyer has different buying needs; programmatic supply is always changing, as are individual buying requirements; and all decisions in programmatic need to take place in less than a second, several billion times per hour. This is something only machines can do.

Effective traffic-shaping algorithms can reduce traffic by up to 90% while maintaining spend in the 95 to 110% range. In some cases, spend levels can even be elevated through traffic shaping, especially when buyers have very narrow targeting requirements. Additional benefits of traffic shaping can be seen in the reduction of server costs, processing speed overhead, logging/reporting costs, and speed reductions.

How It Works

A traffic-shaping algorithm is programmed to answer the following questions:

- How often is a particular request likely to be bid on?
- How likely is that request to generate an impression?
- What is the approximate price/value of the impression?

This is accomplished through reinforcement learning and is executed in real time to ensure relevance. This process adds approximately 10 to 40 milliseconds to the decision speed, depending on the volume of analysis and processing set-up.

To process this information, traffic is segmented into a combination of standard parameters to determine how valuable it is to a buy partner's bidding system (often an AI/ML-powered system focused on performance). This is done on a rolling schedule throughout the day to ensure freshness. Best practice is to do this every four hours or more, though more frequently than hourly is not required. In addition, long-term learning maps are aggregated to represent activity over the past 24 hours.

The traffic-shaping algorithm is used to determine the level of quality of the request to the respective buyer's bidding system, where it will determine if the traffic is likely to be bid on and bought, or not bid on, and thus shape the traffic accordingly. This will lead to significant variations on how traffic is distributed per trading pair partners and can account for the current bidding behavior as well as campaign setup. The algorithm will automatically optimize away from likely poor quality traffic as new buyers and suppliers are added.

Considerations

Speed

Using a regression model for the ML algorithm over an artificial neural network (ANN) is essential for real-time bidding (RTB) decision-making to be processed and executed at scale with minimal latency.

Balancing Predictions

A traffic-shaping algorithm must be able to account for external influences such as a weekend versus a weekday and other seasonality factors. This can be achieved by maintaining and storing separate historical aggregated data files based around historical bidding patterns which are used as a cross reference point to guide the algorithm during different periods.

Capturing Changing Inputs

A critical area for consideration is the changing nature and volume of both requests and bids. Although it is very important to capture historical data on bidding patterns, capturing new requirements in real time is equally important. This is applied using a reinforcement learning algorithm so past learnings can be applied to new, currently unidentified trading while maintaining the known data shaping and transitioning the new data to a known data set over time.

Learning

Capturing the changing nature of campaigns is a key component of accuracy. Having a fixed set of parameters such as a very detailed but static form works short term but would completely fail to take into consideration new campaigns activated post model shaping, or be too widespread to drive any efficiency benefits. To avoid this scenario, you need a statistically relevant amount of raw unfiltered traffic, which is constantly analyzed in combination with the live-shaped traffic. Results should be fed back in real time into the inputs for iterative processing.

Testing

There are a variety of ways to test the efficiency and accuracy of the output of the model:

- Live feedback
  - Campaign delivery
  - Deal delivery
- Analysis of historical data files
- Live pulsing/tracking against raw unfiltered requests
- Measurement against results

Algorithm Complexity

Building on initial models yields more accurate measurements. As layers of complexity are added, traffic is funneled more effectively, and in turn, leads to a better understanding of working with the model. Relative to the current example, a good practice would be not only to feed the outputs and results back into the model as a constant feedback mechanism but to also build separate time scale aggregates (i.e., over last 3 | 6 | 9 | 12 | 24 hours | 7 days, etc.) to maintain an accurate look back and capture the trading patterns across a wider set of fixed time (i.e., a day or a week).

Training

Before any algorithm can be used in a live setting it is important to train and test to ensure that the algorithm works as intended and does not skew the results. In the case of the reinforcement learning model, you can train it on the known data sets, but then test the results for its success/biases on both the known and unknown data.

Data Cleanliness

A key consideration (and potential issue) for building a traffic-shaping algorithm is the cleanliness of the data that is used within the model. Within open RTB, there will be many (slightly) different implementations of fields represented in each request/response which will have to be normalized and/or accounted for. With details varying significantly within individual requests, ensuring that there is a large amount of variance of the data needed to build the model leads to a more accurate outcome, but also requires more processing.

To mitigate the number of variances and account for the standardization of the requests, use key component fields. To accomplish this, the algorithm can take key data points in the request and use these to segment traffic based on focus areas. For example:

- Browser version
- Content
- Buyer
- User info
- Geo
- Domain
- Language
- AdSlot
- AdSize
- Datacenter

In addition to the fields and segments in the requests, to process the data and build up the machine learning algorithm, these fields need to be assessed against key fields and data from the responses. For example:

- Creative ID
- Campaign ids
- Bid price
- Bid volume
- Impression volume
- Click volume
- Time of day
- Newness of campaign

Preserving Privacy Standards

Running these algorithms without breaching strict new privacy guidelines and policies from various jurisdictions around the world will be a key future challenge as more of the aforementioned parameters in bid requests will be classified as protected, thus being unusable or requiring specific user consent. The goal is to ensure that the ML regression model can still do what it is intending to, while also not triggering legislative penalties.

Key considerations here would be to not use fields classified as PII such as IP addresses and specific user identifiers in the input fields and when processing user data. It will be important to stay up to date on changing privacy regulation and make sure the data set is updated and in compliance with new regulation. The best future-proof practice with regards to specific user ID is to develop off a user group instead. The other option would be to ensure user consent is in place and only process traffic where this is the case.

Data Inputs, Processing, and Outputs

In this particular model there are a variety of data inputs that are used for predictions. Initially, there are key static settings and parameters to guide the process for each buyer, key settings to direct at a high-level intent and key interests. Next for the real-time processing, there are other essential inputs similar to those listed above that will allow segmentation into significant streams of traffic, enabling each to be processed independently and capture the current bidding intent of the buyer's algorithm.

In addition to the key standard fields and inputs from the requests, key data and fields from the responses are also needed to be assessed and processed. Layered over the top of this are aggregated processed historical data files that capture the intent over a longer term to account for variable situations, such as day parting, when you schedule ads for certain times of day or certain days of the week, and to capture any new campaigns set up.

What the algorithm is working to ideally output is an exact match of the correct traffic for the individual buyers bidding patterns based on campaign set up/success. This is accomplished by looking at the combination of historical data, static filters, and real-time and raw data to assess the value of each request based on intent, the likelihood of a bid response, winning the bid, and overall winning price, balancing this against the cost of distribution, and then shape the traffic accordingly.

Explainability

Interestingly, one of the oddities of machine learning is that the more an algorithm can be explained, the less valuable and accurate the algorithm tends to be. Conversely, the more complex and unexplainable an algorithm is, the more likely it is to be accurate and yield better results.

Bias

One of the key things to remember in any AI/ML system is to avoid trying to bias the processing. As the machine learns and attempts to predict, unless specifically accounted for, human involvement or erroneous inputs often ends up amplifying bias.

Some potential areas of bias that should be considered and avoided when building a traffic-shaping regression ML model include:

- **Fairness** - The algorithm should be designed to provide the correct distribution of requests for each buyer based on her own historical and current bidding patterns, and should be designed to be fair to all parties irrespective of size and volume of a buyer's spend.
- **Impartiality bias** - By design, as previously described, the regression model ML is meant to be impartial, as the algorithm is learning individually for each buyer based on unique bidding patterns (i.e., the model will have different performance between SSP1 and DSP1 than SSP1 and DSP2).
- **Unconscious bias** - Often based on inaccurate or imperfect data used to train and process the algorithm, unconscious bias can occur during the processing of data to predict events based on the imperfect input data. An example of this occurring in traffic shaping would be when an event chain is broken and bidding algorithms can optimize towards increasing bidding on broken impression tracking where a lack of a feedback loop can cause imperfect inputs and processing.

To guard against bias, constant analysis of multiple data points from both processed and unfiltered data are required to ensure that the feedback loops are accurate. A similar situation can occur with auditing impressions and clicks on lower volumes, which should also be taken into account.

Use Case: Video

Author: Melissa Hart, Global VP Marketing, AnyClip
Primary Persona Stakeholders: Agency C-Suite, Marketers, and Technologists

In today's post-COVID world, our personal and professional lives have become increasingly virtual. As work, school, entertainment, and the latest news have all shifted online, we are consuming and producing more digital video content than ever before.

Demand for online video is skyrocketing, and content owners of all types are confronted with new challenges as they seek to meet shifting audience expectations. But with operating budgets and headcounts shrinking and new, potentially inexperienced video owners now finding themselves solving complex distribution challenges as the participants and workflows of this ecosystem have changed. Within this context, new needs have arisen:

- **Video management:** Automated tools to streamline the workflows of managing fast-growing video libraries and user-generated content collections at scale
- **Video distribution:** Access to streaming video tools that can reliably deliver meaningful content experiences to audiences in ways that are ideally cost-effective and easy for inexperienced or small/single-person video production teams to use
- **Value:** Enhancing experiences for viewers while delivering ROI for advertisers who seek to align their brands with video content in scalable and impactful ways

To meet these evolved standards, new tools are required to automate management and distribution workflows and to enhance the value of video experiences for audiences and marketers alike. Data and AI can make this advancement possible, but due to the complexities of analyzing video image and audio content in real time, traditional video technologies have been incapable of implementing automation and big-data thinking to video workflows.

Newer technologies, such as AnyClip's Luminous Platform, address this fundamental need by creating and organizing the data of video content. Deep content data flows through the Platform's tools and video players, automating workflows and enhancing precision, ultimately helping content owners to manage, distribute and maximize their video's value and achieve results in all the ways they need.

How It Works

AI for video can be applied across every stage of the video management, distribution, and consumption lifecycle. While the participants and benefits may vary from stage to stage, the one thing each has in common is a fundamental reliance on video content metadata.

AI technology facilitates the creation of this data and how it can be applied to provide both back-end (editorial) and front-end (viewer-facing) benefits.

Video Management

Video metadata has traditionally relied on manual content tagging practices to apply and associate specific data tags with video assets. Through this process, editors and content teams manually label files or key frames within their video libraries according to their basic attributes such as the topic, host, or theme of the content or where and when it might publish. This metadata then helps teams locate these files within their library so that they can be added into curated playlists or manually embedded into articles.

By integrating AI technologies into video management toolsets, metadata creation and tagging are automated, empowering sharper accuracy and streamlined video management workflows. By way of example, using AnyClip's Luminous Platform, core AI technology instantly analyzes every frame of every video ingested into the Platform's cloud-based repository. Operating more than ten times faster than real-time, Luminous analyzes the image and audio contents of each frame of video, automatically tagging detailed content attributes at the specific timestamps within the video when they're recognized. The criteria of this analysis include:

- **Key frame detection** - Detection of scene, subject matter, and other primary composition changes
- **Optical character recognition (OCR)** - Recognition of text, logos, and other characters
- **Facial recognition** - Identification of celebrities, public figures, or other significant individuals (e.g., executives, brand ambassadors, mascots)
- **Brand and product recognition** - Detection of specific products, brands, businesses, and/or organizations
- **Brand safety detection** - Recognition of keywords, images, behaviors, sentiments, or topics that may be perceived as negative or inappropriate for some viewers
- **Automatic speech recognition** (ASR) - Also known as "speech-to-text," ASR uses linguistic algorithms to transform audio signals into words in text which can be used for video subtitling, transcription, closed captioning, and more

After metadata has been created and tagged to the content, videos can then be further organized into categories. Some examples of organization methodologies may include:

- **IAB Tech Lab Content Taxonomy** - Aligning video collections according to current industry standards for content classification
- **Proprietary taxonomies** - Organizing videos according to a brand's existing product catalog or content matrix

Backed by meticulous content data and organization, large complex video libraries are then instantly rendered easy to manage. With robust content data, libraries can be searched to locate video assets according to any of their tagged features. Video assets themselves can be searched to identify key moments, people, and products. User-generated content can be automatically screened and validated for publication. Playlists can be built automatically, curating videos into collections aligned by the similarities of their data.

All of this data and automation ultimately matters for two reasons. First, automated user-friendly tools lower the barriers for usability, enabling a wider range of potentially less-experienced or less-technical individuals to accrue and properly manage video libraries. Video tools are democratized. Second, by streamlining content workflows with automation, it frees up human bandwidth on editorial teams, allowing professionals to focus on more strategic work.

Video Distribution

Once a content library has been analyzed and organized by its data, AI can also benefit the user-facing aspects of video distribution, attracting an audience at scale, and creating more meaningful and precise viewing experiences for audiences while sparing editorial teams valuable time and resources.

One way AI can be applied in video distribution is to improve the relevance of video content recommendations surfaced to viewers. While traditional video technologies have attempted automating content recommendations, these approaches traditionally involve matching manually-tagged metadata about a video asset with the cookie data of a user's previous browsing history. The trouble with this approach is two-fold: Manually-tagged content data is typically a shallow dataset, yielding fewer points of reference to inform alignments. Other issues stem from the use of browser cookie data to infer audience interests, a practice that can be inaccurate, stale, or blocked by browser security settings altogether.

AI content analysis, on the other hand, provides a richer dataset about each video asset, ultimately enabling more meaningful content recommendations in ways that respect user privacy. By applying this data to various aspects of the viewer experience, newer video distribution technologies are capable of achieving more accurate and relevant viewing experiences.

A few examples of this technology in use by AnyClip's Luminous Platform include:

- **Dynamic carousel curation:** Using content data to inform video recommendations, it can curate playlists adjacent to video players by aligning content assets by their data similarities. Unlike cookie-based or manually curated methods, recommendations curated by AI technology can be automatically updated in real time, as new assets are uploaded and instantly analyzed in the platform's back-end repository.
- **Page-matching:** By meshing content data with natural language processing (NLP) technology, AI can automatically crawl article page contents and surface the most relevant matching video from a back-end library instantaneously upon page load.
- **Video-on-demand (VOD):** Combining AI technology with VOD interfaces, content data, and automation can be used to curate programming recommendations based on underlying audience content consumption trends and/or build channels of content aligned by nuanced viewer interests.

Beyond content recommendation, AI and content data can also be used to enhance video playback experiences, allowing for a more interactive and personalized content experience. This can include:

- **Interactivity** - Using AI and content data to power call-to-action buttons within the player UI, to promote featured products, people, or keywords seen inside video, in real-time
- **Search within content** - Empowering viewers to search within videos to find specific moments, people, brands, products, or other information within the content

AI Effects on Value

AI can provide many benefits for publishers seeking to monetize their video audience — and for the advertisers seeking to reach and engage these viewers. By threading content data and automation throughout standard adops/campaign management workflows, publishers can leverage AI to create new inventory through enhanced engagement, lift the market value of existing ad experiences, and enhance the range of solutions available for marketers. A few examples of this technology at work within AnyClip's Luminous Video Platform include:

- **Contextual targeting** - Using video content data to deliver ad campaigns adjacent to editorial video content featuring a specific brand, product, person, keyword, theme, or category to lift relevance and impact
- **Brand safety** - Anti-targeting ad campaign delivery to not appear adjacent to editorial video content known to feature sensitive, negative, or competitive content
- **Call to action buttons** - Leveraging AI-powered call-to-action buttons for performance marketing or ecommerce purposes
- **Analytics** - Dynamic visualization of revenue and content performance, using content data to reveal the brands, hosts, keywords, and other criteria providing the most value

Considerations

Analysis and Data Creation

Factors affecting quality and accuracy of AI content analysis and tagging:

- **Video quality** - Video should be of good quality to be properly analyzed; low-quality videos are likely to provide lower quality analysis
- **Live action vs. animation** - Animated videos are likely to provide lower quality results compared to live-action content
- **Audio track** - A cleaner audio track provides significantly better accuracy compared to a noisy audio track (e.g., audio with substantial background interference or white noise)
- **Analysis speed** - File size optimization and manual prioritization of content analysis queue is recommended for prompt analysis and availability of content for distribution in those use cases where content publishing is time sensitive

Content Matching

Factors affecting quality and accuracy of page matching:

- **Page caching** - To ensure accuracy of content recommendations, especially in the context of a live news environment, article pages should be crawled frequently to identify updates and ensure that the most recent videos are aligned with the latest information contained in an article
- **Paywall barriers** - Page analysis technologies either need to be permissioned in behind paywalls or optimized to circumvent paywalls to retrieve the article content data necessary for video match to occur

Standard Terminology and Definitions

As AI and machine learning become increasingly prevalent in advertising operations, it is important to have a solid foundational understanding of the differences between supervised and unsupervised learning or natural language processing and natural language understanding. Below is an introduction to several of the major concepts across the AI and machine learning ecosystem.

Learn these terms and then continue to explore the suggested related terms to deepen your knowledge of the technologies that are transforming advertising and marketing.

- Algorithm
- Artificial Intelligence
- Artificial Neural Networks
- Chatbot Assistants
- Machine Learning
- Natural Language Processing
- Reinforcement Learning
- Robotic Process Automation
- Supervised Learning
- Text-to-Speech/ Speech-to-Text
- Unsupervised Learning

Algorithm

An algorithm is a sequence of well-defined computer instructions that solve a problem or perform a computation such as calculations, data processing, or automated reasoning.

Also known as: computer algorithm, algorithmic rule

In Depth

In computer systems, an algorithm is an instance of finite logic written in code by developers to effectively solve a class of problems or complex calculations, producing an output with or without input. Algorithms are formulated within a finite amount of space and time, written in a well-defined formal language (i.e., Javascript, Python, PHP).

An algorithm alone does not solve a problem. Rather, the algorithm is the result or means to attempting to solve the problem. A proper algorithmic approach takes planning and understanding of the data, the problem, and the intended outcomes.

Relevant applications: real-time bidding, ad tech solutions, creative optimization

Why It's Important

Agency C-Suite	Marketers	Technologists
An algorithm is the foundation to any effort to solve a problem for the organization, the core instruction. Understanding your core business problems will help you advocate for the use of the "right" algorithms.	Like the consumer journey, an algorithm helps step an input through understanding to logical action.	Using algorithms is part of the daily effort, seeking out ways to employ data and solve problems through the application of computer-assisted logic.

Artificial Intelligence

Artificial intelligence or AI is the empowerment of machines to use reason and understanding to complete tasks, unlike natural intelligence, which humans and animals employ and involve conscious reasoning and understanding.

Also known as: *augmented intelligence and typically associated with machine learning*

In Depth

In computer science, AI research is defined as the study of intelligent agents: any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. Colloquially, the term artificial intelligence is applied when a machine mimics cognitive functions that humans associate with other human minds, such as learning and problem-solving.

Intelligence is demonstrated by machines that mimic cognitive functions that humans associate with other human minds, such as learning and problem-solving.

Artificial intelligence is understood to come in two possible forms: general and narrow.

General AIs (aka strong AIs) do not exist outside of science fiction. In theory, a general AI possesses the computational flexibility to adapt itself to solve many problems, or perform many tasks, given sufficient data.

Narrow AIs (aka weak AIs) have existed since the dawn of modern computing. Narrow AIs perform a single or limited number of specified tasks, where they rely on a specific set of inputs and generate a predictable output. Narrow AIs can further divide into two subtypes: classical AI and machine learning.

Relevant applications: *natural language processing, machine learning, computer vision, deep learning, cognitive science*

Why It's Important

Agency C-Suite	Marketers	Technologists
From audience and targeting to creative resonance and insights, AI augments business strategy and outcomes. Executives must embrace and understand these evolving possibilities to remain competitive.	AI is uniquely able to help marketers make decisions about what creative they need to serve, how it should be designed, and how it should look and feel — in real time and at scale. Adjacent to these industry shifts is the increasing complexity of data, evolving expectations, and the necessity to invent new, scalable solutions that move at the speed of advertising while observing transparent and privacy-centric approaches.	Technologists are responsible for assessing which AI tools and features are worth building and implementing to accelerate the business.

Artificial Neural Networks

Artificial neural networks (ANN) combine algorithms and computational power to process problems by mimicking biological neural networks' form and function like our brains.

Also known as: *neural networks, neural nets*

In Depth

The artificial neural network, or simply a neural network (NN), is a computing system based on a collection of connected nodes referred to as neurons. Neurons transmit signals (data) to other neurons, similar to how the human brain works.

As a neuron receives input, it processes it and can decide to pass the signal to nearby neurons. The deciding computations performed within the neuron are typically nonlinear functions deriving the sum of the inputs. Between these neurons are connections referred to as edges. Neurons and edges are usually weighted, either positively or negatively, based on the signal's strength. This weight adjusts as the neural network continues to learn.

The standard approach is to break neurons into layers. These layers will perform different transformations on their inputs. The signals that pass through the network from the first layer (input) to the last layer (output) possibly traversing all layers multiple times. Most often, neural networks learn by processing example data and learn to perform a task without being programmed to follow specific rules.

Relevant applications: *image classification, natural language processing (NLP), automated gaming*

Why It's Important:

Agency C-Suite	Marketers	Technologists
ANNs learn from experience so simple computational operations can be used to solve complex, non-linear problems — ideal for scaling a part of the business.	Neural networks allow marketers to make predictions about consumer behavior. Campaign outcomes, marketing automation, content creation, and sales forecasting are the most common practices.	ANNs can be used for modeling non-linear problems and to predict the output for a given input based on training values. You will most likely want to use an ANN when you are dealing with a massive amount of data and require very accurate outcomes. It is worth noting that you will give up some of the explainability for the accuracy.

Chatbot Assistants

A chatbot uses natural language processing, natural language understanding, and sometimes tone or sentiment analysis to power a conversation using speech-to-text, text-to-speech, or other input and output methods.

Also known as: *digital assistant, agent*

In Depth

Chatbots and digital assistants are dialog-based systems that can help a human navigate through the exploration of information, complete tasks, or obtain a recommendation based on their specific requirements through conversation.

The most advanced chatbots are trained across a corpus of information, allowing them to respond to a user's natural language inputs. They use a variety of techniques to understand the tone of the inputs a consumer makes and use that as part of the intelligent response.

Relevant applications: *product discovery/recommendations, customer service, task management*

Why It's Important

Agency C-Suite	Marketers	Technologists
Businesses are facing challenges in rapidly shifting customer/consumer attitudes and loyalties, and need to simplify interaction experience, ensure consumer satisfaction, and derive key feedback and actionable insights to retain and deepen those relationships. These solutions provide quick and accurate points of engagement that lower bounce-rates, reduce frustrations in call-centers, and ensure the customer feels heard. Additionally, these automated dialog-based systems can relieve businesses of repetitive tasks such as frequently asked questions and account queries as well as providing personalized recommendations at scale, increasing business efficiency without sacrificing customer relationships.	Marketers can use dialog-based systems through various consumer touchpoints. By applying well-trained natural language practices, chatbots can provide more empathic and personalized 1:1 relationships and can differentiate the brand. The insights derived from the consumer inputs and conversation path can reveal important insights, such as what messages resonate and how to apply them in more broad engagement tactics, where there may be unforeseen blind spots that need to be clarified, and the ability to extract product/brand/experience feedback at scale.	In the development of chatbots, engineers can continue to refine semantic relationships among concepts, phrases, and key terms that enrich a computer's ability to better process language. A refined system provides the critical foundation for computer-human interactions and the ability to design more empathic, sensitive, and nuanced conversations.

Hyperautomation

Hyperautomation is the practical application of advanced technologies like robotic process automation, artificial intelligence, machine learning, and process mining to augment workers and automate processes in ways that are significantly more impactful and cover more cognitive-based tasks than traditional automation capabilities such as macros or isolated custom scripts.

Also known as: *robotic process automation (RPA), intelligent process automation (IPA), cognitive orchestration, AI fabric*

In Depth

Automation refers to the use of technology to facilitate or perform tasks that originally required some form of human judgment or action. The term "tasks" refers not only to tasks and activities in the execution, working or operational environment, but it also encompasses tasks in thinking, discovering, and designing these automations themselves. This suite of technologies and applied methodology is critical for the modernization of business operations as enterprises seek the multitude of benefits found at the intersection of operational excellence and technical potential.

Business-driven hyperautomation refers to an approach in which organizations rapidly identify, vet, and automate as many approved business processes as possible through a disciplined approach. Hyperautomation involves the orchestrated use of multiple technologies, tools, or platforms (inclusive of, but not limited to, AI, machine learning, event-driven software architecture, RPA, iPaaS, packaged software, and other types of decision, process, and task automation tools).

While few occupations are fully automatable, according to a recent McKinsey study 60 percent of all occupations have at least 30 percent technically automatable activities by adapting currently demonstrated technologies. By 2024, organizations will lower operational costs by 30% by combining hyperautomation technologies with redesigned operational processes. And, by 2025, companies that have adopted AI will be 10 times more efficient and have twice the market share of companies that have not.

Relevant applications: *software robots and virtual assistants, business process and workflow automation, process mining, data migration, citizen development, emulating low-value/high- cost tasks*

Why It's Important

Agency C-Suite	Marketers	Technologists
Hyperautomation has been a top technology trend over the past few years as enterprises move to integrate automation technologies and AI into holistic business operations. Enterprises have entered a race with their competition to increase margins and retain talent. Hyperautomation acts as an essential catalyst for digital transformation efforts to lower costs while empowering people to create more value for clients.	Marketers must be aware of the hyperautomation trend so that they can identify use cases that could be reallocated to automation technology and then push for those tasks to be picked up by an automation center or citizen developers. This will enable operations teams and technology teams to solve for real problems with modern technology while also empowering themselves to handle such use cases when they have access to low-code and no-code development studios.	Technologists should be aware of hyperautomation as a suite of technologies that can deliver high-impact business value as it sits at the intersection of operational excellence and technological advance. Hyperautomation's focus on solving business problems at the operational level with ease of use and low cost of implementation makes it a force to be reckoned with when seeking quick and high ROI. Early technical adopters of hyperautomation technologies will forge new career paths as early tech evolves and becomes part of the enterprise's DNA.

Machine Learning

The practice of machine learning (ML) focuses on the development of computer programs that can access data and use it to learn for themselves.

Also known as: *predictive analytics, expert system, natural language processing, knowledge engineering*

In Depth

Machine learning is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data," to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks. Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory, and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

Relevant applications: *bid optimization, image recognition, content, understanding campaign performance*

Why It's Important

Agency C-Suite	Marketers	Technologists
Machine learning can help a company look deeply at their data and consumers to discover patterns and relationships, predict and forecast outcomes, and augment complex processes. It can also improve customer segmentation and targeting, inform more performant media strategies, and deliver data-understanding for strategic insights.	Machine learning can help marketers better understand consumers and marketplace conditions, providing efficiency, automation, and better decisions at scale. Whether processing first-party data, predicting the right creative messaging or optimizing programmatic bidding — machine learning is a critical element of the modern marketer's strategy.	Machine learning provides engineers the ability to create systems that learn and improve with experience. These systems might use a supervised, unsupervised, or reinforcement learning method and employ several algorithmic approaches. With these tools, an engineer can craft programs that process large amounts of data and extract useful information, patterns, or predictions, and allow for human-free or augmented decisions.

Natural Language Processing

Natural language processing (NLP) is a branch of AI that focuses on empowering a computer to understand large amounts of natural language data in verbal or written form and the contextual nuances of the language within them.

Also known as: *artificial intelligence*

In Depth

NLP is a subfield of linguistics, computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages, particularly how to program computers to process and analyze language in many forms to derive meaning and understanding.

NLP is trained to understand the language, process the utterance's intent, extract entities to understand the subject and decipher the appropriate meaning to words. For example, "ball" might mean an object that can be thrown or rolled, and it could mean an event that one might attend in a gown or tuxedo. NLP is trained on sample utterances or content to understand the human variances in how we might say or write something.

Challenges in natural language processing frequently involve speech recognition, natural language understanding, and natural-language generation data.

Relevant applications: *brand safety targeting, contextual AI, sentiment analysis, chatbots, text prediction*

Why It's Important

Agency C-Suite	Marketers	Technologists
Many enterprises are using NLP to automate the customer experience via chatbots and can measure the sentiment of customers towards their businesses by analyzing social media posts that tag the company. NLP can also target the right customers by classifying content at scale in a programmatic environment.	In recent history, marketers have been using NLP mostly to ensure that their ads are not running in brand unsafe environments. With the upcoming deprecation of third-party cookies, markers are turning more towards the advanced capabilities of contextual AI, targeting customized page categories and optimizing campaigns based on content classification and sentiment analysis. Marketers can also test the sentiment of their ad copy and how different sentiment values perform in campaigns.	NLP programs are measured and tuned based on KPIs such as precision versus recall. Also, when working within the context of a programmatic advertising environment, technologists implement systems that improve coverage of the number of content pages that can be classified.

Reinforcement Learning

Reinforcement learning (RL) is a machine learning technique that empowers the system to understand a typical behavior within a particular context, maximizing its performance.

Also known as: *Q learning, deep RL*

In-Depth

Reinforcement learning (RL) is a range of machine learning where machine/software agents learn when and where to take actions in an environment to maximize the knowledge of cumulative reward.

Reinforcement learning is one of three fundamental machine learning paradigms, alongside supervised learning and unsupervised learning. Reinforcement learning differs from supervised learning in not needing labeled input/output pairs to be presented and not requiring sub-optimal actions to be explicitly corrected. Instead, reinforcement learning strives for a balance between exploration of undiscovered areas and exploitation of current understanding.

Relevant applications: *advanced A/B testing, automated gaming*

Why It's Important

Agency C-Suite	Marketers	Technologists
Reinforcement learning is all about decisions in the absence of data. Organizations are driven by decisions and can sometimes be limited by their ability to scale good decision making to serve or hyper serve their customers. RL as a tool allows decision automation at scale but comes with risks that need to be understood. However, the potential to scale, automate, and hyper serve is really powerful.	Understanding RL allows marketers to deploy tools and techniques that can help accelerate and hyper serve buyers. As RL models continuously improve, having these nurtured over time or adopting technology that can accelerate that nurturing can be a source of competitive advantage and significantly increase the efficacy of markets. From solutions like dynamic creative, chatbot or conversational deployments, or RL-based targeting and content personalization, marketers can drive meaningful conversations between customers and brand.	RL models take time to learn and become effective. Understanding this lifecycle is essential to ensuring the models have enough runway to learn while mitigating the cost and quality of using them with live customers/users. Aligning expectations is particularly important to ensure these can be nurtured successfully. Bias is particularly important here where perfectly well-meaning models deployed by very smart people learned to do things they were not intended to do and at times, cause brand damage.

Robotic Process Automation

Robotic process automation (RPA) is the technology that allows anyone today to configure computer software, or a “robot” to emulate and integrate the actions of a human interacting within digital systems to execute a business process.

Also known as: *software robots, macros on steroids, RPA bots*

In Depth

RPA is a form of business process automation technology based on metaphorical software robots or artificial intelligence/digital workers. It is sometimes referred to as software robotics. In traditional workflow automation tools, a software developer produces a list of actions to automate a task and interface to the back-end system using internal application programming interfaces (APIs) or dedicated scripting language. In contrast, RPA systems develop the action list by watching the user perform that task in the application’s graphical user interface (GUI) and then perform the automation by repeating those tasks directly in the GUI. This can lower the barrier to use of automation in products that might not otherwise feature APIs for this purpose.

In contrast to other traditional IT solutions, RPA allows organizations to automate at a fraction of the cost and time previously encountered. RPA is non-intrusive and leverages the existing infrastructure without disrupting underlying systems which would be difficult and costly to replace. With RPA, cost efficiency and compliance are no longer an operating cost but a byproduct of automation.

RPA robots are capable of mimicking many — if not all — human user actions. They log into applications, move files and folders, copy and paste data, fill in forms, extract structured and semi-structured data from documents, scrape browsers, and more.

RPA is a component of the hyperautomated enterprise’s automation capabilities. It is important to consider the team supporting and governing RPA capabilities through the form of an automation COE whether it be centralized, federated, or a hybrid.

It is also important to consider how this type of technology has the stigma of displacing workers, but it also acts as a powerful tool for these same workers through the form of citizen development training programs. Imagine a virtual assistant at the fingertips of each worker and the impact such accessible technology would have. This requires a broader governance model, change management program, and communications.

Relevant applications: *knowledge worker augmentation, data migration, integration via UI*

Why It's Important

Agency C-Suite	Marketers	Technologists
RRPA enables a wide range of applications that can lead to labor cost reductions and bottom-line improvements but 92% of C-Suite executives around the world use RPA to help their companies provide better service to customers and increase customer satisfaction. As RPA can play a pivotal role in improving workflows in any business function across the enterprise, it is a new lever sought by the C-Suite to creating a new competitive advantage over industry rivals.	RPA is driving innovation conversations across marketing organizations. While RPA is frequently prioritized in back-office operations (i.e., finance, HR, legal, IT), it is increasingly gaining ground in the front office. Not just in obvious areas such as contact centers, but also sales and marketing. CMOs today want to be more involved directly in customer engagement. Marketing wants to use all sources of data to improve the accuracy of the targeting efforts and the relevance of the content used. RPA can enhance the customer experience with software robots working behind-the-scenes. For example, an RPA bot can perform continuous competitive research, streamline and optimize digital ad placements, and respond to insights across multiple touchpoints and channels, inside and outside your company.	RPA is a software program that runs on an end user's machine (attended bots) or on a server (unattended bots) and performs a sequence of activities based on a defined set of rules and inputs from other systems or end users. The main goal of RPA is to transfer routine and repetitive tasks performed by humans to a virtual assistant or bot. The bots interact with software applications, websites, and other humans to complete work. They can even make predictions or decisions within more complex AI- and ML-driven use cases. For example, RPA is capable of setting up processes for different vendors and clients, establishing credit and payment approval workflows, processing payments and receipts, routing orders, sending late payment notifications, and more.

Supervised Learning

Supervised learning is a branch of machine learning that centers on finding patterns and making predictions based on learned input and output data.

Also known as: *machine concept learning*

In Depth

In supervised learning, a model is built around training data that is used to inform the desired understanding. In human psychology, this is often referred to as concept learning. A supervised algorithm analyzes the training data and generates a presupposed function that is mapped to new or production data examples.

There are many supervised learning algorithms available, each with its strengths and weaknesses. None of them are the single best for any given problem. Some of the most widely used algorithms include support vector machines, linear regression, logistic regression, naive Bayes, decision trees, k-nearest neighbor, and similarity learning.

There are four areas where issues can arise in supervised learning including bias-variance tradeoff, function complexity to training amount, dimension of the input space, and noise in the data inputs.

Other complexities can arise from the quality of the data, potential misdirection from redundant data, and type of data to algorithm choice. For example, when complex interactions exist between features, decision tree algorithms tend to perform better.

Relevant applications: *predictive outcomes, predictive audiences, creative performance prediction*

Why It's Important

Agency C-Suite	Marketers	Technologists
Supervised learning augments business strategy and outcomes. Executives must embrace and understand these evolving possibilities to remain competitive in tomorrow's marketplace.	Supervised learning can help marketers make better decisions faster and at scale. Image recognition, predictive analytics, customer sentiment, and pattern recognition are the most common supervised learning use cases for marketers.	Supervised learning models require certain levels of expertise to structure accurately. Datasets can have a higher likelihood of human error, resulting in algorithms learning incorrectly.

Text-to-Speech/Speech-to-Text

Speech-to-text and text-to-speech provide methodologies that enable the recognition and translation of spoken language into text and the transformation of text into spoken language.

Also known as: *automatic speech recognition (ASR), computer speech recognition, speech synthesizer, speech computer*

In Depth

In speech-to-text, the system analyzes a person's voice and converts the spoken language into text that can be understood and manipulated by a computer. Some systems require training where an individual speaker will speak text into the system and the system fine-tunes recognition to that individual's speech patterns. Systems that do not require training are referred to as speaker independent and work less accurately, but for a wider array of applications.

Text-to-speech is the practice of speech synthesis where a computer converts normal language text into speech. Historically this process has sounded robotic and has not delivered a wide enough range of pronunciations to sound realistic. More recently, the recording of human voices and the use of neural networks to map those sounds and full-word enunciations has provided a clearer path. A synthesizer can incorporate a model of the vocal tract and other human voice characteristics to create a completely synthetic voice output.

Relevant applications: *digital assistants, chatbots, conversational advertising*

Why It's Important

Agency C-Suite	Marketers	Technologists
With speech-to-text and text-to-speech, the business can listen with intent to what consumers are saying and employing speech synthesis to help transform the dialog with consumers.	Speech-to-text can enable marketers to better understand consumer intent, tone, and sentiment in areas like requests, complaints, and emergencies, detecting when the tone turns stressful. Likewise, they can use text-to-speech to enhance the frequency and quality of conversation with the consumer, showing understanding and providing clear instructions, for example in customer service scenarios.	Speech-to-text and text-to-speech tools can work together and be deployed at scale across a variety of applications from chatbots, and voice assistant skills to highly performant customer service systems. In addition, evolving capabilities like synthetic voice output can create various personas and expand audio experiences in partnership with customer service.

Unsupervised Learning

Unsupervised learning (UL) seeks to find undetected patterns in a data set with no pre-existing labels and minimal human supervision.

Also known as: *probabilistic methods, neural network methods*

In Depth

Unsupervised learning seeks to learn and define patterns with data that a human does not tag. The algorithm manifests self-organization capturing these patterns as neuronal predilections or probability densities.

The two most common approaches in unsupervised learning are principal component and cluster analysis. Cluster analysis provides a grouping mechanism to non-labeled data based on the appearance or nonappearance of commonalities. Principal components seek to most commonly reduce the dimensionality of vast data sets, modifying a set of variables into smaller ones that still include most of the information from the originating collection.

There are numerous approaches to unsupervised learning, including hierarchical clustering, k-means, mixture models, anomaly detection, local outliers, isolation forest, method of moments, and singular value decomposition.

Relevant applications: *audience discovery, attribution*

Why It's Important

Agency C-Suite	Marketers	Technologists
Often businesses build assumptions around their customers, users, and employees - and might use research or data to validate those assumptions. Unsupervised learning approaches allow personas to be grouped according to commonalities that appear in data and use those commonalities to better understand and take action on customers, users, and employees.	Marketers can use unsupervised learning to develop buyer personas based on their behaviors, then understand the journey of these personas and how they are based on the things they do. Looking at who those personas tend to be, allows marketers to target more effectively.	Unsupervised modeling methods are important and highly valuable but can also be computationally heavy. Engineering these models to work for their intended purpose can be simple but can also be heavy so understanding production needs and scale are particularly important.

Conclusion and Next Steps

AI is not just for data scientists and engineers anymore. It's an essential part of any marketing and business toolkit. Business leaders, marketers, agencies, product developers, data teams — and anyone in business can tap into the power of AI. A recent McKinsey survey estimates that 50% of companies report that their companies have adopted AI in at least one business function.

To keep pace, executives and marketers need to understand the applications of AI and how it can be used or is being used to improve performance and business value.

AI is essential for businesses and marketers looking to:

- Automate data-driven decisions
- Drive efficiencies
- Optimize marketing outcomes
- Propel measurement solutions
- Be relevant and remain competitive

But to use AI effectively, companies need to implement AI best practices and hire accordingly. AI is subject to the same fallacies as human judgment and can result in biased outcomes against certain groups. Also, in a world where privacy regulations are likely to be more prominent, AI should be implemented with user privacy in mind.

Marketers, agencies, and technologists that are tapping into the power of AI are uniquely positioned to succeed in today's market. Those that aren't risk of falling behind.

The AI Standards Working Group will follow this report with one on the algorithmic bias of AI and how we build towards better AI standards for the industry. Collectively these efforts seek to explain how AI is revolutionizing advertising and the entire digital marketing ecosystem.

Additional Resources

You'll find additional guidance on how to plan for an AI-driven strategy and guidance on how to evaluate solutions in:

Artificial Intelligence in Marketing Report
December 2019

AI Readiness in Digital Marketing
January 2018

Additional advertising resources that may be of interest:

Understanding Brand Safety and Brand Suitability in a Contemporary Media Landscape
December 2020

2021 Marketplace Outlook
December 2020

Brand Disruption 2021: The IAB Annual Report on the Evolving Consumer Ecosystem
November 2020

About IAB and the IAB Programmatic+Data Center

IAB empowers the media and marketing industries to thrive in the digital economy. Its membership comprises more than 650 leading media and technology companies that are responsible for selling, delivering, and optimizing digital advertising or marketing campaigns. The trade group fields critical research on interactive advertising, while also educating brands, agencies, and the wider business community on the importance of digital marketing. In affiliation with the IAB Tech Lab, it develops technical standards and best practices. Founded in 1996, IAB is headquartered in New York.

PROGRAMMATIC+
DATA CENTER

The IAB Programmatic+Data Center is a unit within IAB, founded to enhance existing IAB resources, and to drive the data agenda for the digital media, marketing, and advertising industry. The Programmatic+Data Center's mission is to expand the programmatic universe, increase the understanding of how data drives business, and make them easily accessible to all.

IAB Programmatic+Data Center is focused on:

- Gathering industry thought leaders to drive and set the data agenda
- Funding industry research to provide benchmarks and actionable insights on data management across platforms including programmatic, mobile, and the internet of things
- Developing industry best practices, guidelines, and standards for privacy, data security, measurement, and consumer data protection
- Creating educational materials including certification, infographics, videos, webinars, and seminars to demystify data for marketers and advertisers
- Hosting data-focused events that feature industry luminaries discussing data related topics

About the IAB AI Standards Working Group

Artificial Intelligence and Machine Learning business activities are used in a multitude of new and exciting ways impacting data-driven decision making. IAB's Programmatic+Data Center of Excellence has formed a working group to develop industry standards, guidelines, and best practices to ensure proper application of these techniques. The Working Group will define digital media industry approaches to business use cases and an advocacy plan to continually evolve and help guide future implementations of AI and ML.

The IAB AI Standards Working Group is open to IAB members. If you are interested in participating, please email committees@iab.com to join the working group.

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