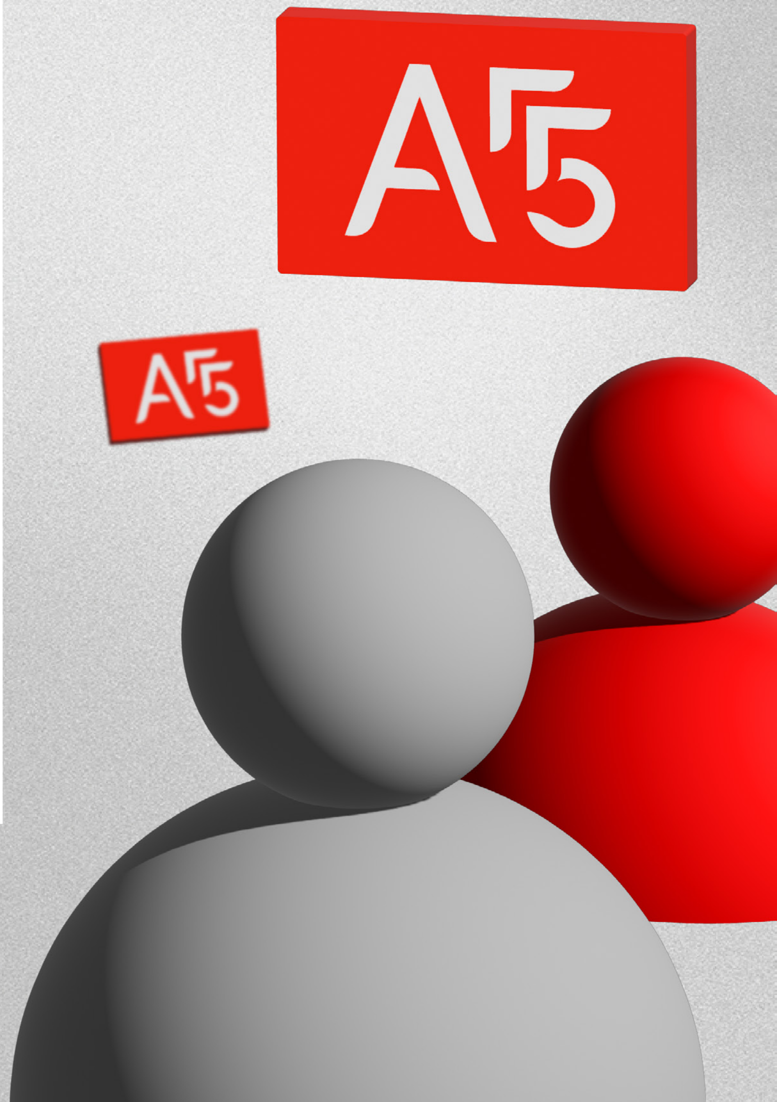
fifty-five

Agent55, fifty-five's Most Advanced MMM Solution



E-BOOK

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We help brands leverage data and technology to craft future-proof experiences

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fifty-five is a new kind of data company that helps brands leverage data to improve marketing, media, and customer experience through a combination of specialized consultancy and technology services. As the strategic data pillar of ***The Brandtech Group***, we offer services that combine strategy consulting, cloud services, media consulting and customer experience. ***fifty-five*** is made up of over 400 digital experts. **Digital consultants, tracking and media specialists, engineers and data scientists** all work in close collaboration to provide senior-level marketing consultancy and technical support to our clients, in every type of industry, all around the world.
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Strategy


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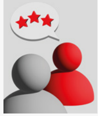

Customer experience

01.

Overview of the approach

Our advanced MMM solution, Agent55, relies on an Agent Based Model (ABM). Before deep diving into this solution, let us first present what ABMs are.

Introduction

An agent-based model (ABM) is a computational simulation that represents individual entities, known as agents, within a system. Each agent operates based on a set of rules and interacts with other agents as well as the environment. ABMs are used to explore the complex phenomena that emerge from these interactions, such as social behavior, economic systems, or ecological dynamics. By modeling individual actions and interactions, ABMs can provide insights into the collective behavior and emergent properties of a system as a whole.

ABMs have been used for many years in many different fields. A well-known example is Schelling's model of segregation (developed by economist Thomas Schelling), which proposes a simulation to explain how segregated societies could emerge. In his model, agents start with a certain geolocation, and at each step they must decide whether to stay or to move according to their current neighborhood. The more similar their neighborhoods are to them, the more likely they are to stay where they are. This model showed that even a mild level of similarity would lead to a segregated society.

ABMs are widely used in video games to make non-playable characters behave in a coherent way, or in healthcare to study the diffusion process of diseases (e.g., COVID-19) and simulate the consequences of certain actions (e.g., lockdowns)

Lastly, ABMs are also used in marketing to explore various strategies such as promotion, media, word of mouth, and others. At fifty-five, we strongly believe in the power of ABMs to fuel enlightened marketing decisions at a granular level.

Addressing marketing measurement challenges with ABM

In today's ever-changing marketing landscape, traditional marketing approaches often fall short when navigating the complexities of consumer behavior and rapidly shifting trends. Modern marketing decision-making faces challenges such as diverse consumer preferences, the influence of social media, and the continuous evolution of digital technologies. These factors contribute to an environment where market conditions can change swiftly and unpredictably, making advanced-decision support solutions essential. Advertisers require these solutions to replicate the complexities faced by decision-makers.

For over five years, fifty-five has been developing holistic models that faithfully represent the total reality in which brands operate. These models consistently integrate Paid, Owned, and Earned media, allow analysis at the consumer level, and facilitate multidimensional and conjoint analysis for operational, financial, and brand metrics.

Applications of ABM techniques, tried-and-tested in other fields and now made accessible by major advances in computing power and AI, appear particularly suited to current marketing challenges. The consumer-centric nature of ABM techniques leads to decisive gains in reliability, deeper and more granular insights, more actionable outcomes, and easier interpretation of findings. Based on AI, these computer models simulate the actions and interactions of independent agents - the consumers - and, through this, evaluate the impact generated by simple rules at an individual level within a more complex system - the market.

1 MMMs and ABMs

Traditional econometrics-based MMMs use statistical techniques, analyzing aggregated time series data to evaluate the impact of various marketing inputs on sales or other performance metrics. They leverage historical data, often at national or large-region levels, in a top-down approach. MMMs ignore past consumer behaviors and current perceptions of brands, simply finding correlated patterns in the past to extrapolate for the future.

By contrast, ABMs simulate the actions and interactions of consumers as virtual agents, creating a digital twin of the consumer population that fits all relevant behavioral and marketing data available at different levels of granularity. This bottom-up process offers a powerful framework for understanding and predicting complex market dynamics and consumer interactions, making it highly effective in particular for long-term strategic planning and scenario analysis.

2 Operational benefits compared to traditional MMM techniques

Despite the need for specialized skills that may not be readily available within most marketing teams, more intense data requirements, and computational demands, the consumer-centric core of ABMs offers significant advantages for marketing effectiveness measurement and optimization:

1. **Holistic View:** Simulating behaviors and responses at a consumer journey-level is by nature:
   - **Full Funnel:** ABMs capture different steps of the consumer journey - purchasing, as well as brand equity metrics such as perception and consideration or repeated purchases;
   - **Omnichannel:** BMs simulate all touchpoints a consumer is exposed to or interacts with, communication drivers, and non-media actions (e.g., pricing and promotions);
   - **Multi-brands/Multi-products:** Modeling consumer-level brand/product choices allows to address complex halo effects within an umbrella brand or take competitive impacts into account.
2. **Granularity:** The consumer-centric approach offers deeper insights at the finest operational levels, for instance:
   - **Consumer segments** (based upon demographics, psychographics, behaviors, consumption patterns, or loyalty program memberships);
   - **Point-of-Sales segments** (offline purchases and online commerce, clusters of shops according to their characteristics, offerings, or catchment areas);

- **Geographic segmentation;**
  - **Touchpoints and messaging** (beyond over-aggregated channels and to the level of ad formats and message attributes or types of creative);
  - **Time frames** (considering the impact of marketing actions over different time ranges)...

3. **Scenario testing and forecasting:** ABMs provide a robust framework for exploring the impact of different marketing strategies under various conditions. This is particularly useful in dynamic markets where the same events are not necessarily repeated, and for strategic decisions involving high levels of uncertainty, such as new product launches, evaluation of nascent media channels, or tactical actions on previously unaddressed consumer segments.

4. **Flexibility and adaptability:** ABMs have proven to be highly flexible, adaptable to change, and capable of simulating various scenarios and dynamic interactions among agents.

3 Complementary use of traditional MMM and ABM

There are profound differences in conception between econometrics-based models and ABMs, but this does not in any way mean that they are alternative approaches. On the contrary, they are complementary ways of modeling the same reality. The most suitable technique to choose depends on the goals to achieve or problems to be solved. Often, combining both methodologies yields excellent results.

Use cases

	Entry-level models*	Advanced regression-based models**	Agent55
1. Model development easiness	Simple	Medium	Medium
2. Media channel contribution and saturation	Yes	Yes	Yes
3. Media deep dive contribution and saturation	No	With additional effort	Yes
4. Media cross effect	With additional effort	With additional effort	Yes
5. Multiple KPIs	No	Yes	Yes
6. Campaign strategy modeling	No	No	Yes
7. Long term and short term	No	With additional effort	Yes
8. KPI or dimension crossing (e.g. by cluster x touchpoint)	No	No	Yes
9. Simulation of new external events	No	No	Yes
10. Consider channel specificities (e.g., push vs pull)	No	partially and with additional effort	Yes

**entry-level models refers to prepackaged libraries like Robyn or Meridian. Although those libraries are very good for some use cases, more advanced algorithms must be considered when lots of granularity and KPIs are required.*

***advanced regression-based models refer to more sophisticated techniques that leverage hierarchical structure and multi-task learning. We can cite UCM (Unobserved Components Models), for instance, or multi-task regression models.*

1 Ease of development per model

- **Entry-level models:** Several open source libraries exist to set up traditional MMM. We can cite for instance Meta's solution, Robyn, or Google's solution, Meridian. Thanks to these libraries, model development for such a solution is much easier than before, although media expertise is of course still mandatory to make the best out of them.
- **Advanced regression-based models:** Advanced regression-based models are solutions based on algorithms like Unobserved Components Models (UCM), nested models or other hierarchical and multi-task learning approaches already existing in machine learning solutions. No templatized versions of such solutions are publicly available, making it more difficult for new users to set up their own solution from scratch. Besides, most of these solutions can be very difficult to train and maintain in production in uncertain times like ours.
- **Agent55:** Although advanced agent-based solutions tailored to a precise use case are complex to implement, Agent55 templatized solution allows gains in effectiveness and modularity, making it easier to master for newly onboarded collaborators.

2 Media channel contribution and saturation

Media channel contribution and saturation curves are natively obtained in entry-level models and can be computed with low effort in advanced regression-based models. That information can also be obtained in Agent55.

3 Media deep dive contribution and saturation

- **Entry-level models:** Entry-level models can only provide contribution and saturation at one level of granularity: the model's own. That is, if the model is national, contribution and saturation can only be obtained at the national level.
- **Advanced regression-based models**: Advanced regression-based models can provide deeper analysis on contribution and saturation like geographic measurements. However, any desired level of granularity for those metrics must be defined prior to model development to ensure they are appropriately taken into account. Besides, the more granularity one wants, the more difficult it will be to keep all levels of insights coherent. In some models, having geographical contributions that add up coherently to the national value may be tricky.
- **Agent55:** By design, Agent55 is calibrated at the consumer level. Therefore, any measurement aggregate can be natively obtained simply by aggregating the result at the desired level; any sum will remain coherent with any other aggregation. We can thus aggregate results by population cluster with no effort, while the national-level result will always be coherent with the value of each cluster. For instance, we can compute media contributions for each population cluster by just looking at the appropriate agents. By design, the weighted average of cluster media contributions

(weight=cluster size) will be exactly the same as the national contributions.

Agent55 can also measure national media channels at a local level. For instance, even though TV budgets can only be set up at the national level, in Agent55, each individual agent that sees an ad can be geolocalized, which allows the model to measure TV impact at a geographical level without introducing any bias in local TV GRP.

4 Media cross-effect

As media channels performance does not work in silos, adjusting media channel investment as a whole is crucial to prevent bad decision-making.

- **Entry-level models:** Adding crossed variables (e.g., crossing social impressions with TV GRP) may be done in entry-level models. However, since each new variable increases model complexity, not all possible crossing may be added. For example, with 10 touchpoints, there are 45 two-by-two possible crossings, 120 three-by-three crossing, 210 four-by-four etc. All crossings will result in more than one thousand (there are exactly 2^10=1024 of them) additional variables, which cannot be fitted by an entry-level model.
- **Advanced regression-based models:** Here, cross-effects can be dealt with the exact same way as with entry-level models, leading to the same exact drawbacks and limitations.
- **Agent55:** In Agent55, all touchpoints work together in order to move the agents’

perception of the brand. Besides, unlike other models where saturation is computed touchpoint by touchpoint, in Agent55 saturation arises both at touchpoint level and at a global level, where all touchpoints are considered at the same time. As a consequence, cross-effects are managed at the agent level as in real-life, ensuring a global coherence for the marketing strategy. Media cross-effect is therefore a native consequence of the model. We can obtain the contribution of any group of touchpoints by just cutting said touchpoints from a simulation and comparing the result with a scenario where all are activated. Because of cross-effects, the contribution of the group as a whole will be different from the sum of each touchpoint's individual contribution when taken out one by one.

5 Multiple KPIs

- **Entry-level models:** Entry-level models can only deal with one KPI at a time. If multiple KPIs need to be investigated, multiple independent models must be developed. This could result in contradictory results between each model stemming from a lack of global coherence.
- **Advanced regression-based models**: Nested models and multi-task learning can be used to deal with multiple KPIs at once. However, the solution's complexity will increase linearly with each added KPI. It may become impossible to train the models if the expected output is too granular.
- **Agent55:** Each KPI represents one decision among all the decisions that the model's

agents must make. Thus, adding KPIs simply adds new decisions to agent behavior. Although doing so increases global model complexity as new actions must be set up, most of the model's structure will remain the same. In other words, the most difficult step is adding the first KPI, with any other coming at a marginal cost.

6 Campaign strategy modeling

We will use a specific example here, with campaign A doing 100k impressions and targeting consumers in the brand's catchment area, and campaign B doing 100k impressions and targeting consumers that showed affinity for sports.

- **Entry-level models:** In an entry-level model, a touchpoint is usually described by a single variable. Thus, such a model would not be able to distinguish between the campaigns A and B used here. To do so, one would need to create two separate variables, with one for each strategy. This technique will evidently not scale too many campaign strategies and would not be able to deal with unforeseen strategies.
- **Advanced regression-based models**: Same technique and limits as entry-level models.
- **Agent55:** Each campaign strategy and audience is directly taken into account in the campaign broadcasting, and any new strategy is directly included. In Agent55, campaigns A and campaigns B will reach different agents who will behave differently. Each campaign's consequences will therefore be different.

7 Long term and short term

Media campaigns can have short term impacts as well as long term effects. Dealing with these long term effects is often a challenge with MMM.

- **Entry-level models:** The easiest way to deal with long term effects is to use multiplicative factors based on additional ad-hoc analysis. For example, we observed that, on average, the long term multiplicative factor of Radio is around 1.4 and TV's around 2.2. Thus, the obtained short term effect will be multiplied by the corresponding factor to calculate long term effects. This approach can be overly simplistic and miss many of each campaign strategy's specificities.
- **Advanced regression-based models:** Nested models deal with long term models by feeding a long term model's predictions into a short term model. While appealing, actually training such models require very complex mathematical tools that can be painful to implement and maintain in production.
- **Agent55:** In Agent55, marketing strategy will impact the agents' decision-making at different stages. For instance, performance campaigns will modify an agent likelihood to purchase, immediately resulting in a short term impact. Simultaneously, all campaigns will gradually modify the agents' perception of the brand, resulting in a long term effect. Long term and short term effects are then jointly and natively taken into account within the model.

8 KPI or dimension crossing (e.g., by cluster x touchpoint)

KPIs can involve different dimensions: media channel, customer segments, point of sales, product category, etc.

- **Entry-level models:** As with multiple KPIs, each dimension crossing in an entry-level model must be seen as a separate model to be measured. Additionally, granular results based on consumers' center of interest can not be measured because the data needed to train the model does not exist. Indeed, it is impossible to obtain TV GRP or touchpoints impressions on a subset of the population defined by their center of interest.
- **Advanced regression-based models:** Same as entry-level models.
- **Agent55:** Since Agent55 simulates the behavior of fictive consumers where each one has its own profile (socio demographic, center of interest, media consumption, ...), one can easily measure every dimension crossing of a KPI just by observing the right population. This white paper explains how we link marketing strategy to agent characteristics.

9 Simulating new external events

New external events can involve the arrival of a new competitor on the market, a disturbing external event such as a pandemic, a rise in prices and so on.

- **Entry-level models:** Entry-level models rely on classic machine learning techniques that, if properly trained, can be good estimators for new observations that are similar to past observations. However, they have poor generalizability power for distant new observations. Because of that, simulating new external events as previously described can result in unreliable results.

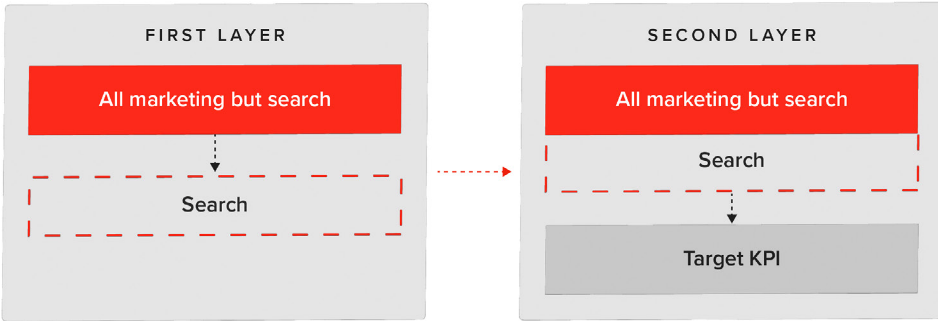
- **Advanced regression-based models:** Likewise.
- **Agent55:** As previously mentioned, Agent55 mimics consumer reactions according to stimulus. Thus, adding a new competitor with a given marketing pressure or a given price position is no issue. Agents' reactions based on marketing pressure and price sensitivity are well defined and can easily be generalized. Likewise, a rising price can be simulated in various scenarios where agents will focus their budget on basic needs. For events like a pandemic, we can simulate the behavior of agents that would be limited in their movements because of a lockdown, for instance. Of course, all of these simulations are subjected to hypothesizing agents' reactions to specific events, but those can still be helpful to anticipate scenarios and get knowledge on what marketing strategy would be the most robust and effective.

10 Considering channel specificities (e.g., push vs pull)

Not all channels behave the same. For instance, TV is a push channel with little targeting possibility, whereas Search is a pull channel (i.e., users come to you) and Social channels are push channels with many targeting possibilities.

Aside from this push/pull duality, each channel has its own specificities. Comparators and affiliation are more likely to reach promotion-sensitive people, and some channels and strategies might reach peopl close to a conversion while others will focus more on awareness.

- **Entry-level models:** Libraries are available as-is, without any channel specificities. All channels are treated the same and no particular method is applied on one or another.
- **Advanced regression-based models:** Hierarchical strategy can be developed to apply a special treatment to pull media. For instance, one can apply the first layer of a model to predict search performance metric (e.g., number of clicks) according to other marketing strategies and communications. The first prediction can then be passed on to a second layer to adjust for push media's impact on pull media.



Aside from this push -> pull mechanism, other channel specificities are harder or even impossible to take into account in traditional advanced MMM techniques.

- **Agent55:** For the push/pull mechanism, Agent55 integrates the same hierarchical structures as other traditional MMMs. On top of that, each media channel specificity is dissected in order to adjust campaign broadcasting, which allows to truly distinguish between channels and campaigns at a granular level.

ABM for MMM

In marketing mix modeling, the interactions between agents and environment we are interested in are, most of the time, between promotion, media (owned, paid, and earned), competition, seasonality, and other external factors. The model must thus determine a set of rules to define how the agents act according to those interactions, in a manner that mimics reality. Since the objective of such models is to model a specific brand's marketing strategy, we model the agents' interactions related to that brand's market. To set up an ABM for MMM, three main steps have to be designed.

1 1st step

The first step consists in creating an agent base (often between several thousand and one million fictive agents) that accurately represents a real population, as a survey would. Many data sources are available to create this base. Open data, paid surveys, various studies and more allow for the generation of synthetic data, recreating individuals with specific characteristics.

Agent ID	Age	Gender	City	...	Promophilia
123	27	M	Rennes		0.4
456	42	F	Bordeaux		0.6
789	54	F	Strasbourg		0.1

2 2nd step

The second step is to determine the actions performed by the environment. In our case, the environment is a specific business market composed of several brands. For MMM, brands can perform several actions: lead promotional campaigns, change prices, interact with consumers through different channels (Instagram, TV, Radio, ...).

3 3rd step

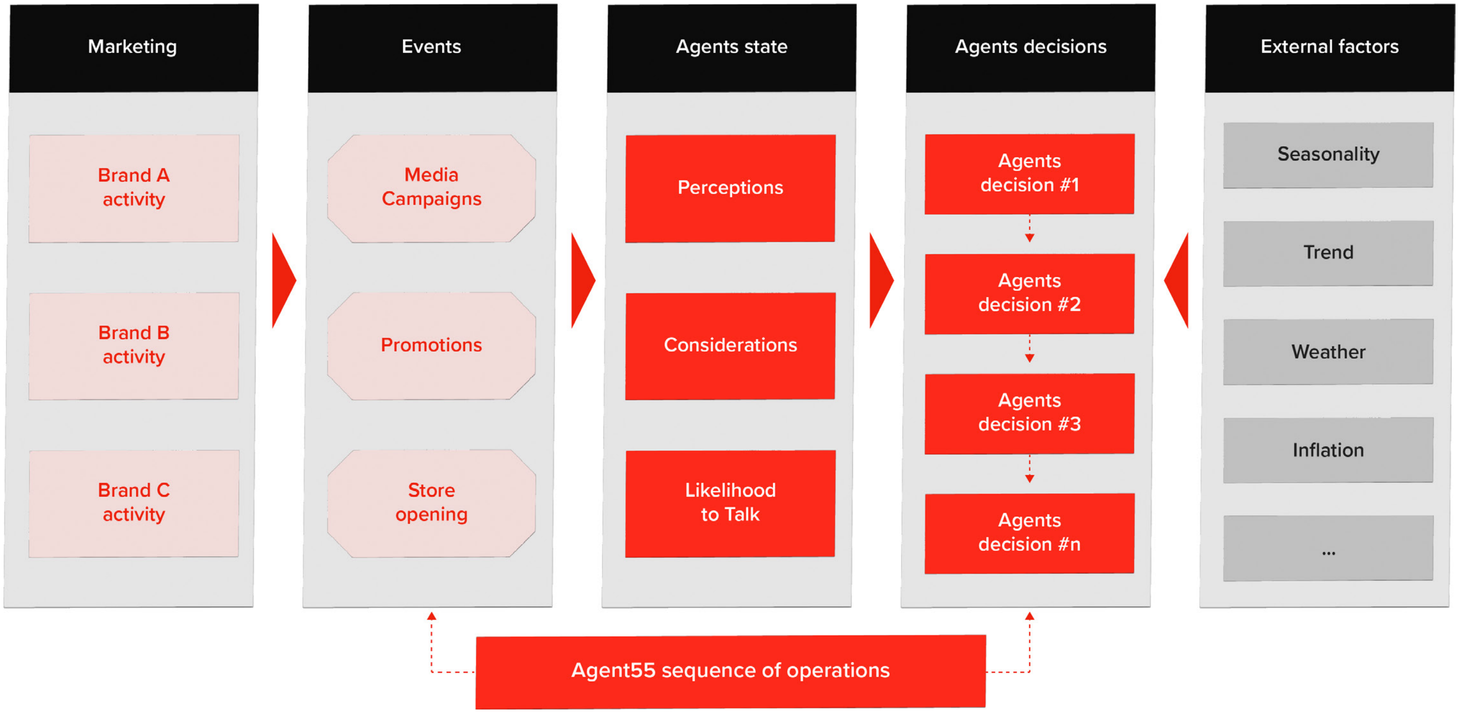
The third step requires defining interactions between the agents and the environment. At each step, usually once a week, each agent will make a series of decisions, e.g., whether or not to buy something, in which category to buy, how much to spend, in a physical store or online, for which brand, etc. All those actions will depend on that agent's own characteristics, defined by the agent base and the actions performed by the environment. For example, a promotional campaign will push users to buy something, and a TV campaign will increase user likelihood to buy the advertised brand.

Once the model is created and calibrated (see below for details on calibration), one can measure any metrics that are replicable by the model. For instance, to answer the question “what was the impact of last year’s promotional campaigns?”, we can remove the promotional campaign from the brand’s actions, observe how differently agents behave, and compare with the baseline scenario. The difference between the two will represent the promotional campaigns’ impact. With inherent granular modelisation, one can also observe said impact per gender, age group, and city, or by crossing these criteria through observed differences between specific groups of agents.

Note:

A granular metric is only relevant if the granularity plays a role within the model. For instance, if age is never used to link environmental actions to agents nor to define agent behavior, it would be fruitless to measure results by age as the output would not be affected by this metric.

02. Main components of the model



Overview

To model agent behavior on a desired market, Agent55's process is as follows:

1. Marketing: each brand defines its activity through marketing operations, which will be spread to agents through events.
2. Events: list all types of activities through events attributed at agent level. This can be, for instance, the broadcasting of a campaign on a particular touchpoint with a given strategy, a specific promotional campaign, or even a store opening.
3. Agent state: describe different attributes presented by agents and condition their decision journey. For instance, agents may only purchase from brands they are considering and be more likely to choose the one they hold in the highest esteem. Agents can also communicate between themselves and influence each other. Events will modify agent perception, esteem, and likelihood to "talk."
4. External factors: other factors can influence agent decisions, like seasonality, trend, or even weather.
5. Agent decision: eventually, agents will make a series of decisions according to their own states and the external factors they have been exposed to.

Marketing

All marketing strategies that one would want to account for in MMM can be incorporated as long as their integration is specified when creating the model (or integrated in upgrade). Most of those strategies are available at an aggregated level; the role of the model will be to spread a strategy at the agent level.

Marketing activity can integrate the following sources of information, among others:

1. budget, impressions, reach, frequency, clicks, campaign GRP on a media channel (a TV channel, a social network, OOH, etc.). Additionally, we can integrate extra campaign specificity depending on targeted audience, message type (e.g., brand awareness, notoriety, performance), and more;

2. promotional activity, which can be local or national, or other types of targeting;

3. other marketing decisions such as a store opening.

At this stage, the information is only available as raw figures and definitions. This data will be turned into agent level features at the next step.

Events

Events are the transformation of marketing activity into agent-level estimated features. For example, media campaign information is transformed into a list of numbers that will be distributed to agents. We call the process that transforms aggregated campaigns information into an agent-level vector the broadcasting of the campaign.

Example
Instagram campaign

Media Campaign

- Impressions volume = 120k
- Theoretical max frequency = 10
- Reach = 30%

Distribution of potential values

A mathematical function will distribute campaign values to values per individual, usally using a beta-binominal function

(0,2,5,3,0,0,0,5,0,0, ...,11,...7,0,1,1,0)

70% of values = 0
Max value = 10
Sum of values = 120k

Value per agent

Potentials values of a media campaign will ve assigned to specific agents according to their characteristic and media consumption habits

Agent 1244 *0*
Agent 7874 *10*
Agent 174 *1*
Agent 6767 *0*

Media impact per agent

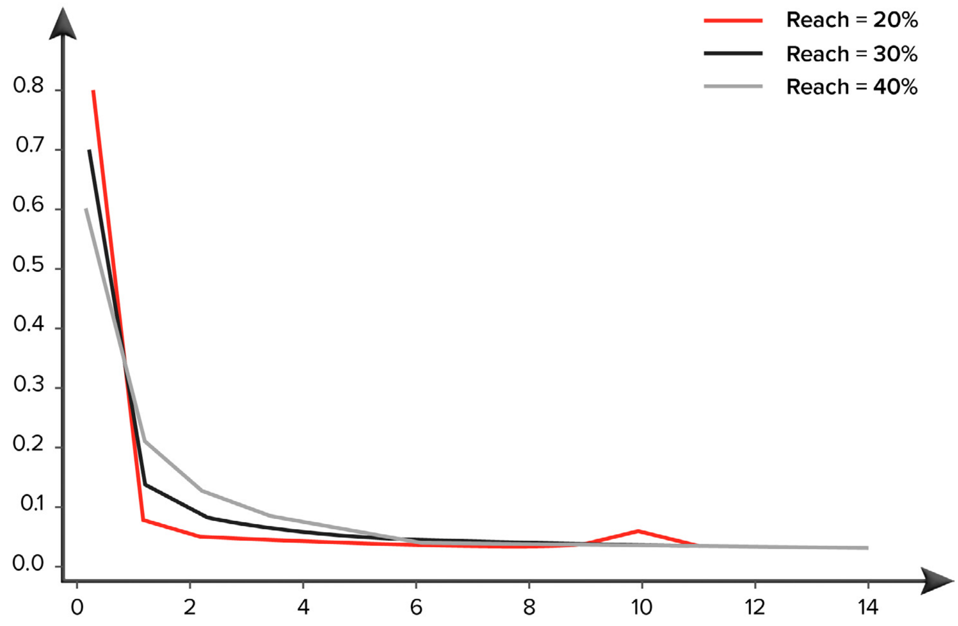
Adstock, saturations and touchpoint weight are then applied at the agent level to compute media impact over agent perception**

The beta binomial distribution is a good fit in this case. Beta binomial has three degrees of freedom which allows us to mimic three parameters – in our case, impressions, reach, and frequency.

1 Distribution fitting

With little effort, we can find the beta binomial's parameters that respect our desired constraints. For instance, the above figure shows three examples for campaigns that achieve 120k impressions on 100k agents with a maximal repetition of 10 and different reach values. The x-axis is the number of impressions

Example of beta binomial distribution for 120k impressions on 100k agents with a max repetition of 10.



that will be attributed to an agent and the y-axis is the percentage of agents that will receive this many impressions. We see that the value in “0 impression” corresponds to expected reach (an actual 100%-reach).

2 Impression attribution

Once fitted, we can sample from the beta binomial distribution. Distribution sampling means that we generate values that respect the distribution, like rolling a dice is a uniform distribution sampling. Let assume the campaign we are focusing on has 120k impressions, 30% reach, and 10 max frequency. If we have 100k agents, we sample 100k values from the previously fitted distribution. By definition, 70% of these values will be 0, the maximal value will be 10, and the sum of all values will be 120k. What is left is to attribute each value to a precise agent. This cannot be done at random, as we would lose all the interest presented by the agent-based model, and it would not make sense to compute metrics at different levels of granularity. Instead, we will leverage the agents’ characteristics that are present in the agent base.
When the agent base is created, each agent receives a certain level of affinity with each media channel (see below on how to integrate this information). If the campaign took place on Instagram, the higher the agent's affinity with Instagram is, the higher the value from the distribution they will get. But we can add many more constraints. For instance, if the campaign targeted agents that like football, we should have created an affinity score with football within the base and integrated it in the attribution process. If the campaign is geo-targeted or focuses on specific age groups, we can filter out agents that do not match those conditions so that they

receive exactly 0 impressions. We thus obtain a single value per agent that mimics what happened in real life as accurately as possible.

2 Adstock, saturation and impact

Once all of a given step's campaigns have been broadcasted, we know how much each agent has been exposed to each brand. These values will pass through several accumulation and saturation transformations (to account for memory and mental saturation) to produce a final, unique number per agent: the media activity impact.

Unlike traditional MMM, in Agent55, saturation is polymorph. It can come from three sources:

1. **Reach:** if there are no more new people to reach on the platform, there will be a saturation effect. Not everyone within a population is watching TV, listening to the radio, etc.

2. **Agent saturation by channel group:** even though we work at a more granular level for campaign definition, agent saturation occurs at a higher level, i.e., a group of channels. No matter which TV channel the agent has seen the ad on, it will accumulate in their mind. Agent mental saturation happens at this level of granularity first.

3. **Global agent saturation:** besides agent saturation at the group channel level, agents can be tired of hearing about a brand after a while. Thus a second layer of saturation arises, based on a global exposition accumulation.

Agent state

Unlike agent characteristics, which remain fixed all throughout the simulation, agent state changes over time according to events. Three mains agent states can be implemented in Agent55, but others can be integrated:

1. **(Mandatory) Perception:** each agent has its own perception for each brand, which will impact their choices.
2. **(Optional) consideration:** prior to making a decision, agents consider only a subset of brands. Events may change the list of brands which belong to this subset. If consideration is omitted, we assume that all brands are being considered
3. **(Optional) Likelihood to “talk”:** word of mouth can be taken into account within Agent55 in order to model a form of earned media. Agents may discuss brands with each other and influence others' perception and esteem. Events such as promotions may affect their likelihood to talk.
4. **(Bonus) Satisfaction:** user satisfaction can also be integrated into the model. When experiencing the purchased product, user satisfaction can evolve and impact future decision-making.

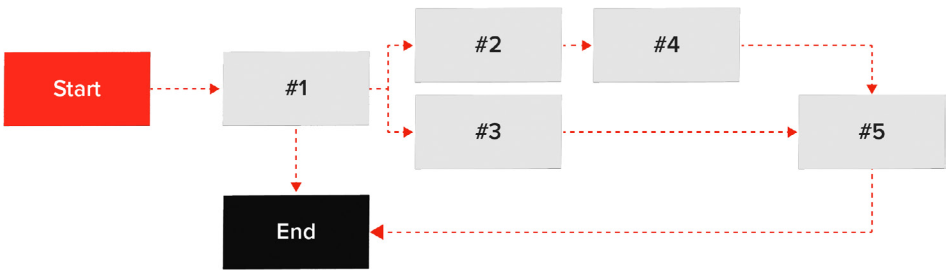
External factors

External factors such as seasonality, trend, weather, or inflation are events that touch all populations and are not the results of direct actions taken by brands. External factors can depend on an agent's geolocation, but as they constitute macroeconomic factors, they do not distinguish agents individually.

Agent decision

At each step/date, agents will go through a decision process. This means that each agent will individually make a series of decisions in which each choice may depend on the results of the previous one. For instance, the first decision can be whether or not to visit a website related to the brands modeled in Agent55. If the answer is “no”, the agent decides to go or not to a physical store (#3), and if it is “yes”, if can decide what product category to browse (#2) and then to add product to their cart (#4). Eventually, they can choose which brand(s) to add to their final purchase. This process is 100% customizable to mimic real life as precisely as possible and model each of the metrics one wants to follow.

Each agent decision will depend on the agent’s own characteristics but also their state, external factors, and specific events. For instance, a promotional campaign can encourage agents to make a purchase regardless of brand when they would not have done so otherwise. In this case, promotion does not directly affect the agent's state but will impact their decision process. Thus, besides defining the series of decision agents will go through, one must also specify what will play a role at each step among events, agent state, and external factors.



03.

Prerequisites

Data

In order to set up Agent55, several sources of data must be leveraged. Below, we list the most common sources.

1 Internal data

All the orders historically made, both offline and online, constitute the first source of data. It can be used to estimate purchase seasonality by product category and geography, or to compare between online and offline. Other metrics can be decomposed as well, such as "add to cart" rates, using online tracking data. All of this information will be essential to calibrate the model and simulate behavior realistically.

CRM data is also very useful for Agent55, as it allows more granularity in understanding agent behavior. With CRM data, we can get more information on the relationship between consumer characteristics and observed metrics. One does not need extensive identification for a machine learning model to learn how to link characteristics and metrics (see section 4 for more details), as a model can be trained with fewer observations.

2 Consumer media market study

Many consumer media market studies are available. For France, we can cite Kantar TGI, and AIMC Marcas for Spain. Such studie provide very insightful data on the entire market to be linked to agent characteristics. Indeed, those studies are often split by cluster, with clusters defined by age, gender, SPC, revenue, or type of residence. Hundreds of answered questions allow us to understand consumer habits such as the number of stores they've visited, the number of purchases they made last year, their visit fré-quency, or even their levels of awareness and consideration.

Offline competition media activity can also be obtained through various data providers and will be useful to estimate marketing pressure on competitors.

Another type of information avai-lable in such studies that is abso-lutely crucial for Agent55 is media channel consumption. Estimation by socio-demographic criterion and geography can be obtained through these studies, which can then be used to generate indi-vidual media channel affinity using simple models. Eventually, each agent receives an affinity score per media channel, such as TV or Radio main channels or social media platforms. This value will be used during the “impressions attri-bution” described previously.

3 Open data

Many other sources of data can be used to gain more knowledge about consumers' habits or market information. We can for instance obtain information about market share and competitors' physical stores locations or use specific keywords Google trends to be used as proxies.

Competitors' online campaigns can also be gathered using open source APIs like the ones from Google, Meta and TikTok, thanks to ads transparency politics.

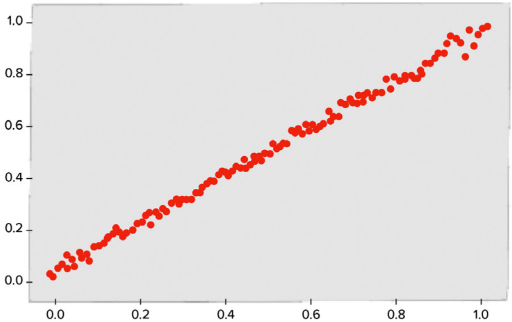
Agent Base

Now that we have gathered our data sources to create Agent55, let's focus a bit more on the agent base creation process.

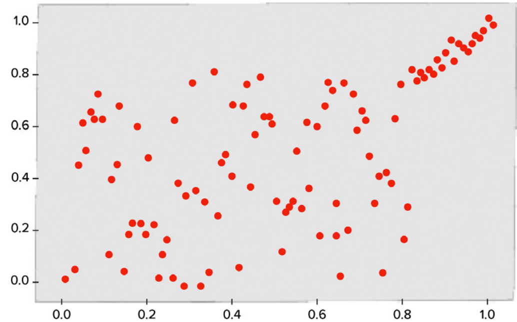
The previously mentioned data sources are very useful to learn the distribution of each characteristic, one at a time. For instance, if we know that for cluster 1, the distribution of ages slices [20-30], [30-40], [40-50], [50-60]n and [60+] are respectively 15%, 30%, 26%, 18% and 11%, we can easily sample ages from this repartition. We can do the same for SPC, gender, revenue, residence type, etc. However, we need to correlate characteristics between themselves in order to obtain meaningful agents. For instance, as revenue and age are correlated, we cannot sample one independently from another.

To obtain such correlation insight, several solutions are possible. Sometimes cross-table distribution is available, i.e., we know the repartition for two characteristics at the same time. Otherwise, open data or online studies can be found to obtain correlation insights. Mathematically speaking, we then use copula to correlate two or more characteristics into a final distribution that respects correlation constraints, copulas allowing for multiple correlations. For instance, we can have linear correlation (the higher the value of x, the higher the value of y), correlation at extreme values (e.g., only high x values are correlated with high y values) or U-shaped correlation (high x values are correlated with high and low y values). The global correlation process is a tree graph, processed by our code to generate the best possible agent base.

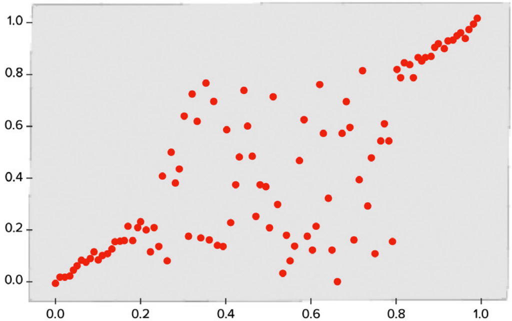
Illustration of different correlations. Examples are purely illustrative



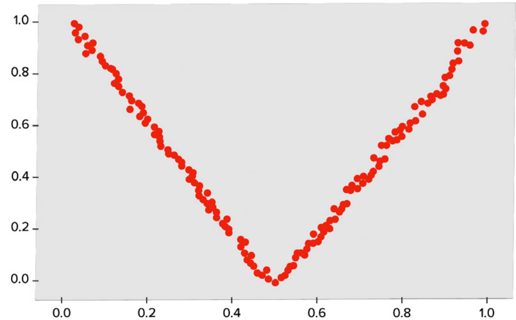
Linear correlation (e.g. promophilia and inverse revenue)



Correlation at extreme - one sided (e.g. age and print comsumption)



Correlation et extreme - one sided (e.g. residence type and age - young and old people are more likely to live in an apartment whereas less correlation is observed in the rest of the population



U-shaped correlation (e.g. age and inverse revenue - young and old people are more likely to have a low revenue)

04.

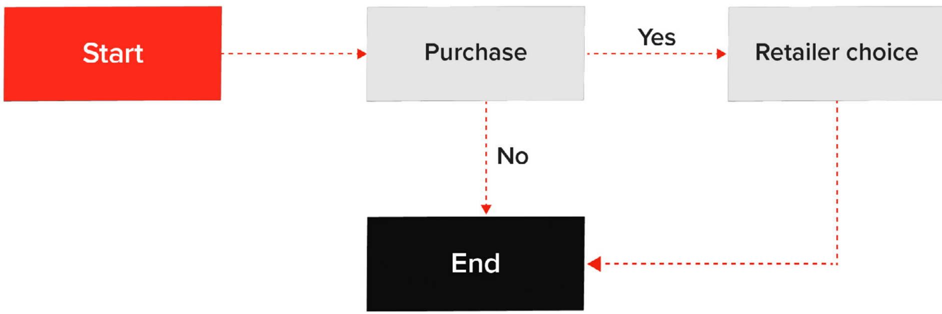
A deep dive into the main steps of the agent decision process

Agent Base

As previously mentioned, the agent decision process is depicted as a Directed Acyclic Graph (DAG). For the sake of clarity, let's consider this very simple DAG.

(see figure to the right)

Every week, each agent will decide whether or not to purchase something on the market. If the answer is "yes", the agent will move to the second step, that is, to decide which brand to choose for this purchase. Otherwise, the process ends for this agent. Of course, the DAG could be much more complicated since this one only models the number of conversions. We could add steps to adjust for product categories, distinguishing between online and offline conversions, and take into account the amount spent.



Purchase [math] [confidential]

Using identified users' orders history and global figures for target brand sales and competitors, we can estimate the purchase probability of each agent, identified or not.

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Brand choice [math] [confidential]

Agents purchasing during this step must then decide which brand to buy from. This choice will be modeled as a softmax function. Each agent will personally score each brand and the final probability will be the softmax of those scores.

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1 Inertia

Consumers have a tendency to default to their usual choice without comparing different options. This is modeled through inertia, which represents the probability that an agent will choose the same brand that they are used to no matter the score they would have attributed to each brand.

2 Rationality

In ABM definitions, agents are characterized as boundedly rational. Bounded rationality is a cognitive bias that characterizes the fact that individuals do not necessarily choose the option that is optimal for them. Based on the definition of scores presented in the "brand choice" section, purely rational agents would choose the brand that has the maximal score. However, with the introduced formula, if we considers two brands with a score of 1 and 2, the probability to choose brand with score 2 is only:

$\frac{exp(2)}{exp(2)+exp(1)}$ = 73%, so 37% of

the time, the agent will choose a suboptimal brand from their point of view. To adjust for rationality, we add the hyperparameter R so that the brand choice formula is:

$$P(b|a,t) = \frac{exp(score(a,b,t))^R}{\sum_{c=1}^{B} exp(score(a,c,t))^R}$$

Following the previous example with two brands of score 1 and 2, and a rationality R=2, this new formula defines the probability to choose a brand with a score of 2:

as $\frac{exp(2)^2}{exp(2)^2+exp(1)^2}$ = 88%

A rationality R=3, would result in a probability of 95%. In practice, we choose a rationality between 1 and 3.

3 Decision

The final agent decision is therefore a two steps process:

1. Inertia? If yes, default to previous choice, else go to 2.
2. Brand choice according to the rationality-updated formula.

05.

Explaining the mathematical formulas

Notation (omitting the brand index for simplicity)

- a agent
- c a campaign
- $P_a(t)$ perception of agent a at time t
- E_c effectiveness of campaign c. Scaled so that the average worth 1
- tp touchpoint (TV, Radio, Social, ...)
- $views_a(t)$ vector containing the views of the agent on each touchpoint for one touchpoint
- $touchpoints_{force} = [tp_{force}]$ vector containing the impact of each touchpoint. Each tp_{force} is between 0.8 and 1.2 showing how bad/good is this touchpoint compared to the market
- $mediaForce$ the global media force parameter
- $att(a, tp)$ attention of agent a on touchpoint tp, is a market average value
- $att(a, tp) \times tp_{force}$ is the attention of agent a on touchpoint tp, is a brand specific value

Vocabulary

Media channels are more granular than touchpoints, the latter being a set of media channels. Campaign broadcasting takes media channels specificities into account thanks to the agent's media channel exposure level. Below is a list of touchpoints with media channels examples:

- TV: TF1, M6, France télévisions, ...
- Radio: NRJ, France Inter, RTL, ...
- Social: Facebook, TikTok, Instagram, ...
- OOH: billboards, DOOH, bus shelters, ...

- Print: list of magazines
- Comparator
- Affiliation
- Video: Youtube, Dailymotion, …

Weighted views [confidential]

The weighted views adjust the number of views the agent has been exposed to by two multiplicative factors:

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Touchpoint saturation [confidential]

From an agent's point of view, this saturation comes from the mental saturation brought on by exposure to a given brand on a particular touchpoint. This mental saturation increases with views volume, agent attention, the touchpoint's force, and campaign effectiveness. Indeed, an agent with very low attention will not really see the ads and thus will not saturate.

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View accumulation [confidential]

View accumulation accounts for the total exposition of an agent through their history with a given brand.

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Global saturation [confidential]

Keeping the agent's point of view in mind, individuals will mentally saturate based on a global exposure to a brand. We call this stage global saturation because it is based on all exposition and not touchpoint by touchpoint.

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Media impact on perception

The final media impact weight for a given step/date is the sum of doubly saturated views per touchpoint multiplied by a hyperparameter M:

$$V_{impact}(t|a) = M \times \sum_{tp} V_{satsat}(t|a, tp)$$

It follows that:

$$P_a(t + 1/2) = P_a(t) + V_{impact}(t|a)$$

Time effect on perception [confidential]

Each step/date, consumers forget a little about the brand. This continuous decrease must be countered by marketing activity. Time effect is a constant factor noted TE, so that:

$$P_a(t + 1) = P_a(t + 1/2) - TE$$

Or,

$$P_a(t + 1) = P_a(t) + V_{impact}(t|a) - TE$$

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What about touchpoint adstock?

The Agent-Based Model forces the developer to understand the underlying mechanism of an observed phenomenon. In practice, we often observe a delay between a campaign's broadcasting and its result on sales. It is also commonly accepted that repetition is the key.

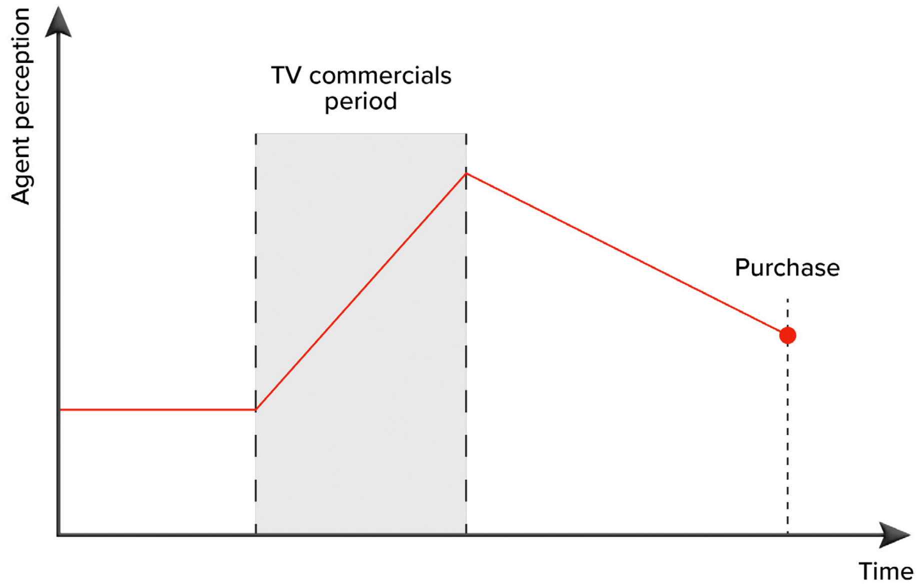
In traditional MMM, those two phenomena are modeled by a carryover function. See for instance equations 1, 2 and 3 of Google Bayesian MMM's paper. Some delay can be arbitrarily applied to the signal, which is combined with a geometric decay to weigh the signal's value appropriately. Such a formula works fine in practice but is just a mathematical trick to replicate the observed phenomenon.

From an agent's point of view, these "tricks" do not make sense. We cannot say that the agent sees an ad at step t, waits 3 weeks to process the information, and suddenly updates their perception. The impact on perception is immediate. The saturation, on the other hand, depends on an accumulation of views. So why do we observe delayed impact and how to account for this in ABM? To answer this question, let's use an example to understand the underlying effect:

1. TV commercials are known to have a big impact on user memory thanks to the nature of videos and the attention users give to the TV. They are also known to have a delayed impact on sales. This can be explained by the fact that TV commercials are not targeted at engaged users, so most of the people reached are not considering buying something right now, but maybe will in the future:

the impact is thus delayed. In Agent55, this is modeled by a high agent attention on the TV touchpoint, with 1 view on TV being worth more than 1 view on Display, and no correlation between campaign broadcasting and an agent likelihood to purchase. Consequently, the impact of a TV commercial will be high enough that an agent's perception will still be higher at the moment they decide to purchase than its initial value.

Evolution of perception before, during, and after a TV commercial. The red point is the moment the agent decides to purchase



2. Social media ads are known to have a short term impact, with a higher impact on online sales than on offline ones. In Agent55, this is dealt by correlating the views distribution sample with agent likelihood to purchase. Indeed, online media usually targets people that showed recent interest in similar products, and agent likelihood to purchase is a proxy of this information. Besides, while creating the agent base, the social media affinity of an agent is correlated with agent online affinity using previously introduced copula. As a consequence, the commercials will be targeted to users that are more likely to buy online and thus have a higher impact on online sales. However, if a social media campaign had a different targeting strategy like targeting users based on catchment area, this campaign will be processed differently during the broadcasting phase.

In a nutshell, we do not need additional transformation to account for delayed effect and adstock. They are naturally integrated in the model with an appropriate campaign broadcasting that reflects the actual strategy of the brand.

>>>

Agent55 models the causes, the simulation outputs the consequences. We do not model the consequences as it would border on explicitly coding what we want to observe, which would result in a model that is incapable of generalizing. In a way, it would be like overfitting in classic machine learning. In truth, this is what ABMs are made for: display patterns observed in real life without explicitly coding them, just like Schelling's model of segregation explains segregation without forcing agents to behave a certain way.

06.

Calibration

Overview

Calibration consists in estimating the ABM's hyperparameters. Unlike usual machine learning where a simple loss can be computed and on which we can compute gradients to optimize parameters, such a procedure is not possible in ABM as there is no analytic formula to compute the results. ABM calibration is a moving research study where several solutions have been applied among grid search, genetic algorithm, or surrogate models. Most people tend to agree that, in ABM, there is not a single best solution for calibration: one must instead apply a specific procedure.

Thus, for Agent55, we set up our own procedure that relies on two pillars:

1. **Many different metrics at different scales to calibrate on**
2. **An onion-like structure**

1 Unlike a traditional MMM that optimizes the loss between the target KPI (for instance sales) and the predicted KPIs, by design, Agent55 allows for the computation of hundreds of KPIs. Although not all true KPI values are available in the data, the list of existing values is long. Here are some examples:

- national sales per week for the brand of interest,
- national sales per week and per product category for the brand of interest,
- geolocalized sales per week for the brand of interest,
- geolocalized sales per week and per product for the brand

of interest,

- yearly national sales for all brands
- average basket per brand
- average purchase frequency per brand
- average basket on identified users for the brand of interest
- average purchase frequency on identified users for the brand of interest
- order of magnitude of marketing impacts according to an entry-level MMM
- ranking of touchpoints in term of contribution according to an entry-level MMM
- unique buyers per year for the brand of interest
- unique buyers per year for all brands

The more metrics we can calibrate on, the easier the calibration will be.

2 State-of-the-art ABMs contain around 3 to 5 hyperparameters. A full Agent55 with an average size DAG contains around 20 hyperparameters. As classic calibration techniques would fail in such a scenario, we developed an “onion” strategy: Agent55 can run in specific cases where only a sample of hyperparameters play a role. For instance, we can stop the DAG at step 1 and calibrate only macro economics figures.

The onion calibration strategy is applied several times in a loop, like an alternating gradient descent. We start with a set of well-chosen hyperparameters using pre-analysis to find the hyperparameters' orders of magnitude (like $0.05 \leq s_1 \leq 10.4$ or $1 \leq R \leq 4$ as explained in the previous section) and applied onion calibration on all possible variations of the model. Once done, we start over with the first layer of the onion to account for side effects.

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Calibration layer examples [confidential]

[confidential]

Final calibration [confidential]

[confidential]

07.

Scenario simulation

Now that the model is calibrated, it can be used to simulate various scenarios. Some scenarios are designed to gather various metrics for reporting, others are more strategic and decision-oriented. Below are some examples.

Contribution

The contribution of touchpoints, media channels, or campaigns can have different meanings. One can compute the contribution of a campaign that takes place between date A and date B on sales that took place during the same period of time or on a longer period of time. In any case, to measure a contribution, we will simulate the behavior of agents with and without this campaign/media channel/touchpoint and compare results between the two scenarios on the desired periods. For simulation efficiency, the scenario where everything is run as usual will be done just once and serve as a reference scenario for all contributions.

With this technique, we can compute the contribution of any campaign or media channel or touchpoint at any level of granularity, whether national, by geographic areas, or by cluster of population. It can also be done on any metric defined in the agents' decision process. But keep in mind that, in order to measure the contribution at a given level of granularity, this granularity must be appropriately defined in the agent base and decision process.

Saturation

Like contribution, saturation may take several forms. In traditional MMM, the saturation curve shows the previous strategy's saturation, e.g., if the brand was targeting a given subpopulation and the model indicates that the touchpoint is saturated, it means that the subpopulation is saturated, but not necessarily the touchpoint itself. Targeting another subpopulation may give good results. This is the reason why granular modeling is important: it prevents false conclusions.

The first saturation provided with Agent55 is the saturation curve at iso strategy (i.e., replicating the same historical spending strategy). To do so, touchpoint by touchpoint, or channel by channel, we run the model with x% of the historical budget, campaign by campaign. We test x from 0 to 200 with a step of 10, and observe the target KPI's evolution.

We can then provide other saturations by playing on various volumetry levers. It could be, for instance, the number of targeted user clusters, geography, or communication waves.

All those simulations will provide a much better understanding of each touchpoint's situation compared to classic saturation curves.

Base forecasts

MMMs are often required to simulate future revenue based on a given marketing strategy. Agent55 does so by simulating agent behavior for the upcoming months. External trends are captured within each step of the agent's DAG decision process and the marketing strategy is input by the brand. Variations around this base strategy are also simulated by testing budget variations one touchpoint at a time within a given range or all touchpoints together proportionality. For instance, we will test 80% of the TV budget, 85%, 90%, 115%, 120%... or 80% of each touchpoint budget (i.e., 80% of the global budget), 85%, etc. Two by two, or three by three are also doable when required. For all these scenarios, we assume the same seasonality in budget investments is used. It means that if 20% of last year's TV budget was spent in January, the forecast will assign 20% of the new budget to January of the coming year. We call this scenario "base forecast at iso strategy."

More advanced scenarios

Many more different scenarios can be simulated using Agent55 since, as previously stated, Agent55 models the causes while the simulation outputs the consequences, meaning that any strategy can be fed to the model to estimate its consequences.

Such scenarios can be marketing

choices, such as changes in pricing, promotions, media investments or media strategies (number of waves, communication duration, time of communication prior to targeted event, ...).

Additionally, Agent55 can also estimate the consequences of events that are out of the advertiser's hand. For instance, we can simulate the arrival of a new competitor that is really aggressive in terms of pricing and communication pressure, and test various strategies to cope with this situation.

In a nutshell, any consumer characteristic, media targeting strategy or competitor strategy can be simulated in Agent55, as long as the considered scenario's specificities play a role in the model, run either on agent-decision process or on marketing strategy diffusion.

Conclusion

Agent55 is a highly effective implementation of an Agent-Based Model algorithm specifically designed for marketing applications. This advanced model has been constructed with modular steps, referred to as "meaningful bricks." These bricks represent key components or stages of the algorithm that can easily be adjusted and customized. This flexibility enables the model to be tailored to different specific use cases, ensuring its ability to address the unique requirements and characteristics of various business scenarios.

The extensive research and development efforts invested in creating Agent55 have resulted in a tool that can generate actionable insights. These insights are crucial for making informed marketing decisions for the future. By simulating the behavior of individual agents, the model provides a detailed understanding of potential market dynamics and outcomes. This allows businesses to anticipate changes, optimize strategies, and ultimately improve their marketing effectiveness.

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www.fifty-five.com · www.teahouse.tech · contact@fifty-five.com