POLITECNICO
MILANO 1863

Analytics for Business Lab

Seminar:
Advertising campaign optimization

01.03.2025 I Marc-Antoine Fortin

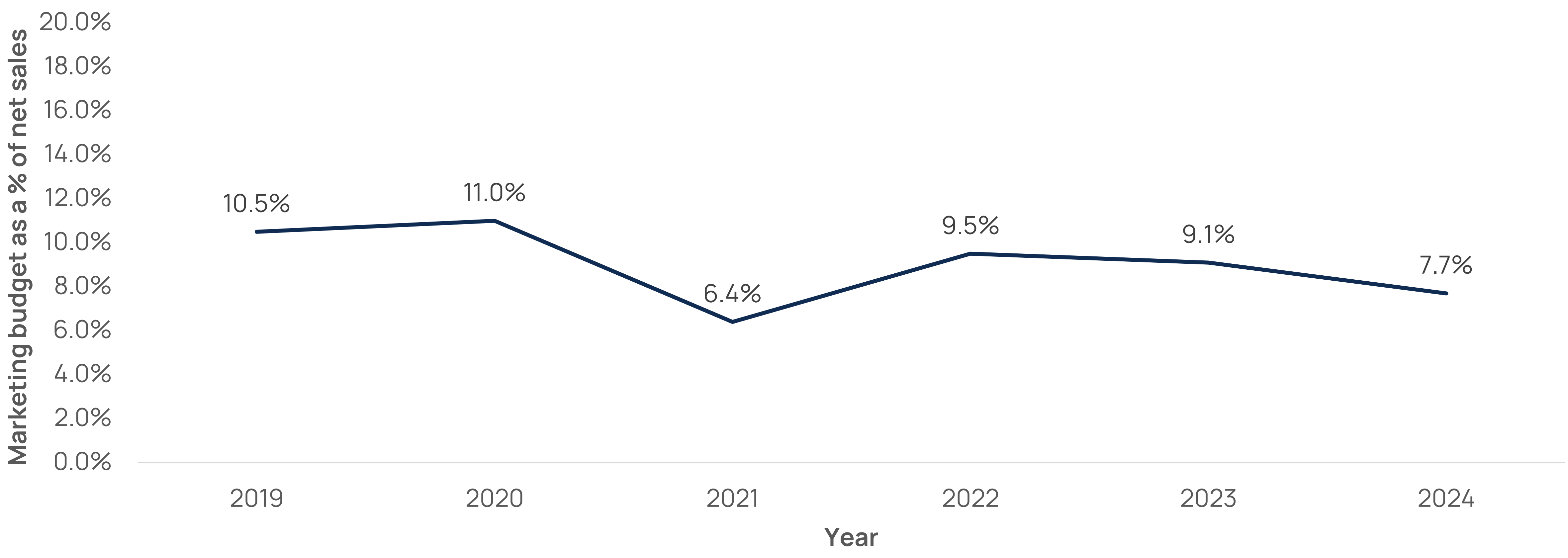
Agenda

Context of the advertising market

01

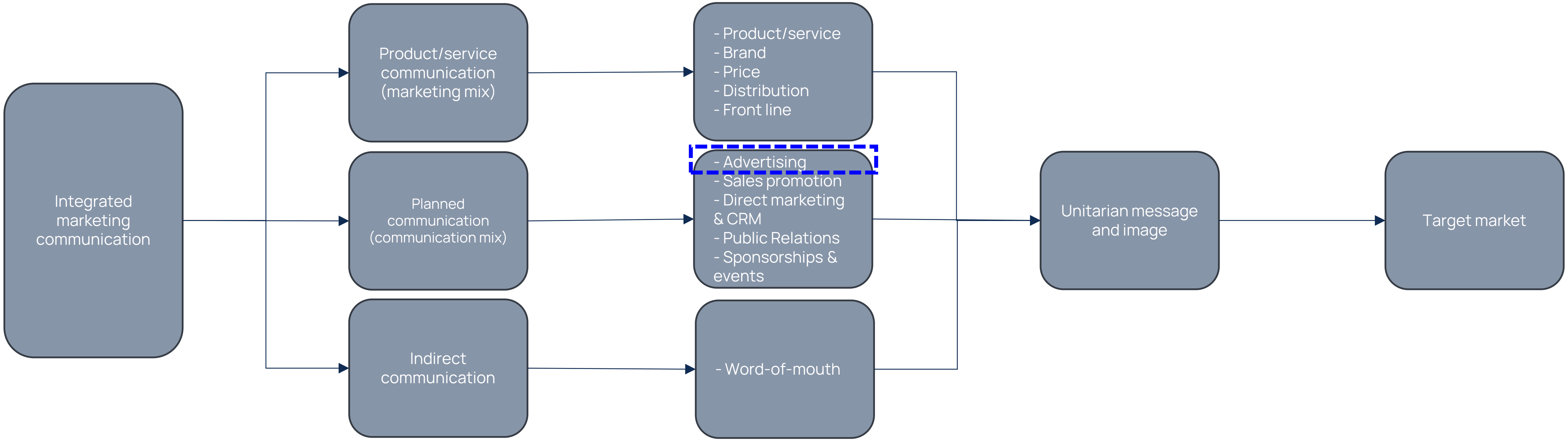
The company perspective

Firms' marketing budget represents on average 7.7% of net sales in 2024.



Source: 2024 Gartner CMO Spend Study

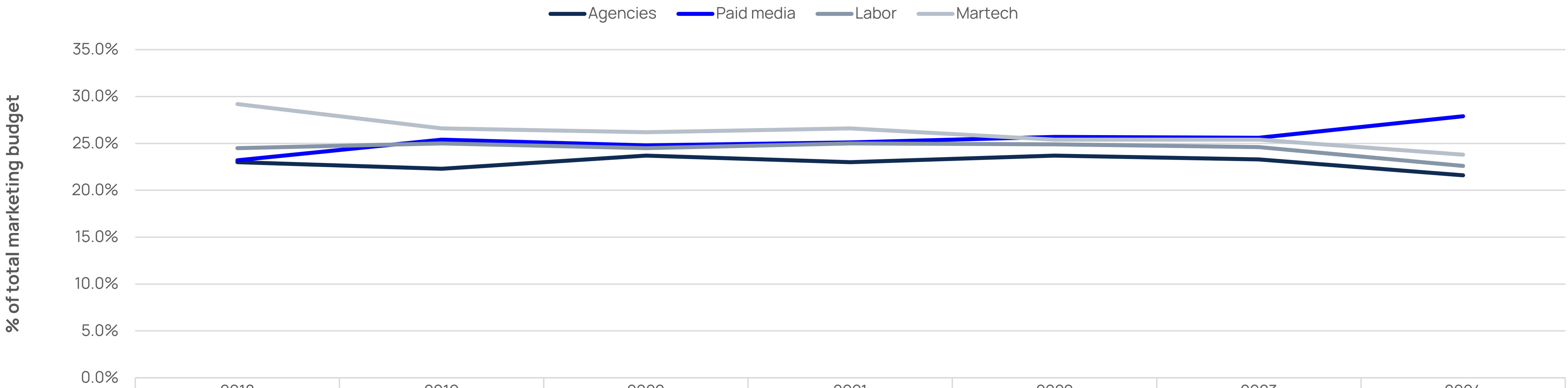
Advertising has to be considered in the wider Integrated Marketing Communication (IMC) process



The American Marketing Association defines **integrated marketing communication** (IMC) as "a planning process designed to assure that all brand contacts received by a customer or prospect for a product, service, or organization are relevant to that person and consistent over time."

Source: Kotler, P., & Keller, K. L. (2015). Marketing Management (15th edition). Pearson Education Limited.

27.9% of marketing budget is allocated to paid media.



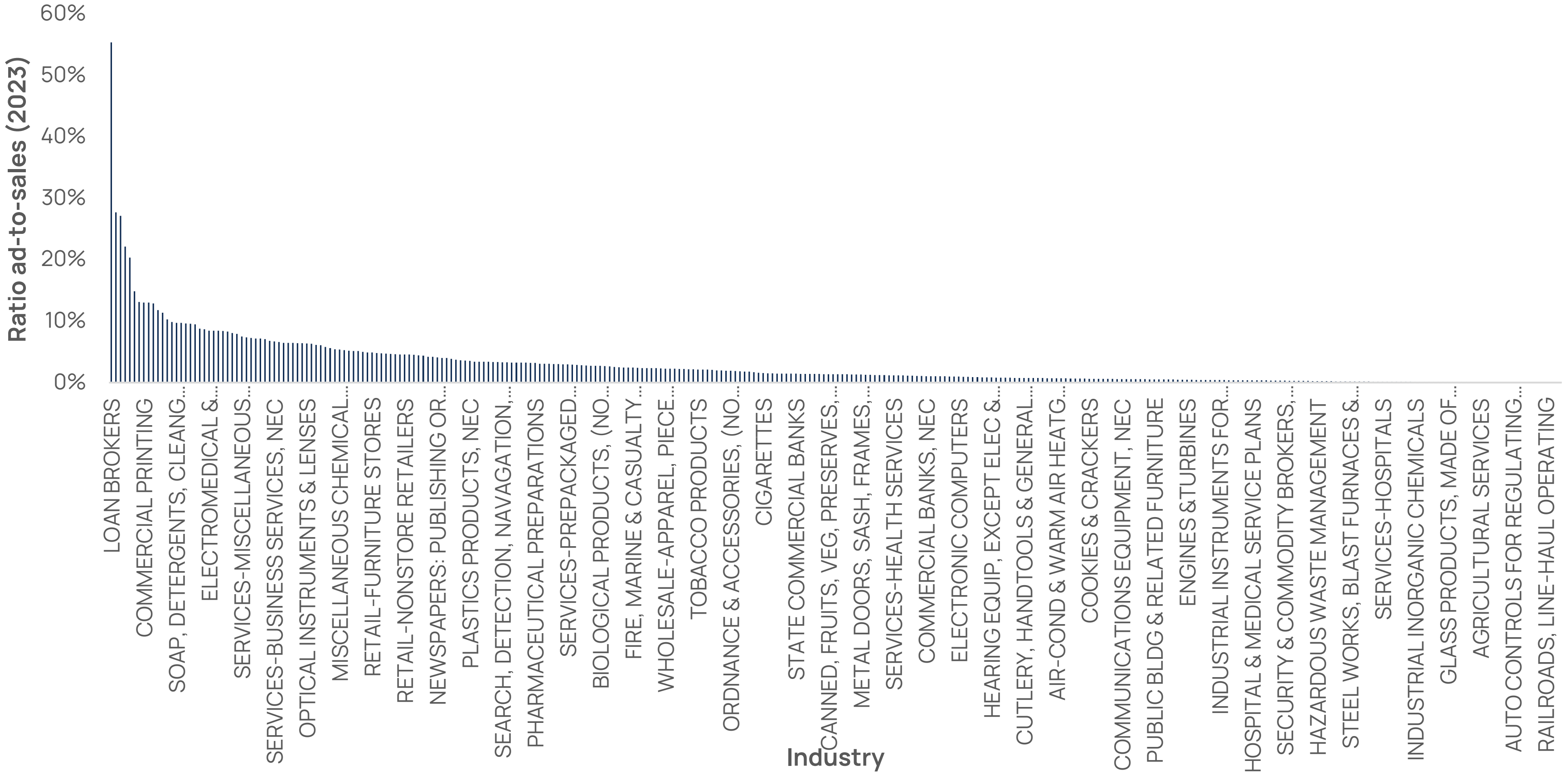
	2018	2019	2020	2021	2022	2023	2024
Agencies	23.0%	22.3%	23.7%	23.0%	23.7%	23.3%	21.6%
Paid media	23.2%	25.4%	24.8%	25.1%	25.7%	25.6%	27.9%
Labor	24.5%	25.0%	24.5%	25.0%	24.9%	24.6%	22.6%
Martech	29.2%	26.6%	26.2%	26.6%	25.4%	25.4%	23.8%

Year

Source: 2024 Gartner CMO Spend Study

Ad-to-sales ratio is highly variable depending on the industry.

Below example of the U.S. market



Top 10 ad-to-sales industries:

- LOAN BROKERS
- TRANSPORTATION SERVICES
- JEWELRY, SILVERWARE & PLATED WARE
- MORTGAGE BANKERS & LOAN CORRESPONDENTS
- SERVICES-SPECIALTY OUTPATIENT FACILITIES, NEC
- SERVICES-OFFICES & CLINICS OF DOCTORS OF MEDICINE
- PERFUMES, COSMETICS & OTHER TOILET PREPARATIONS
- COMMERCIAL PRINTING
- WATCHES, CLOCKS, CLOCKWORK OPERATED DEVICES/PARTS
- STEEL PIPE & TUBES

Source: Schonfeld and Associates, Inc. - Advertising Ratios and Budgets, 2024

Example of a company with annual revenues of €50M
Threshold between SME and large enterprise

€50M annual revenue

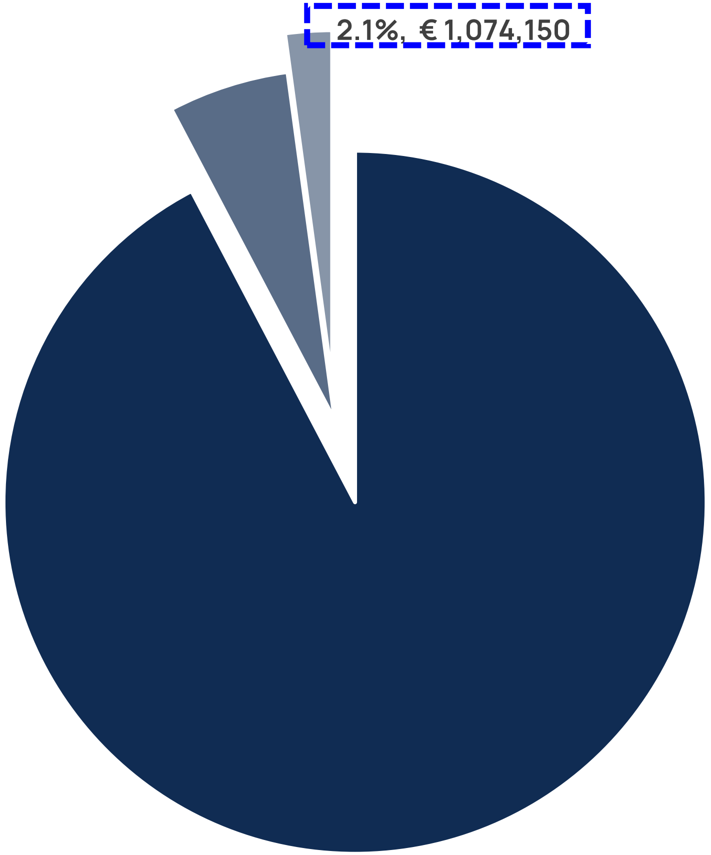
About 56% of Italian companies have revenues over €50M / year

€3.85M budget marketing

(7.7% of sales)

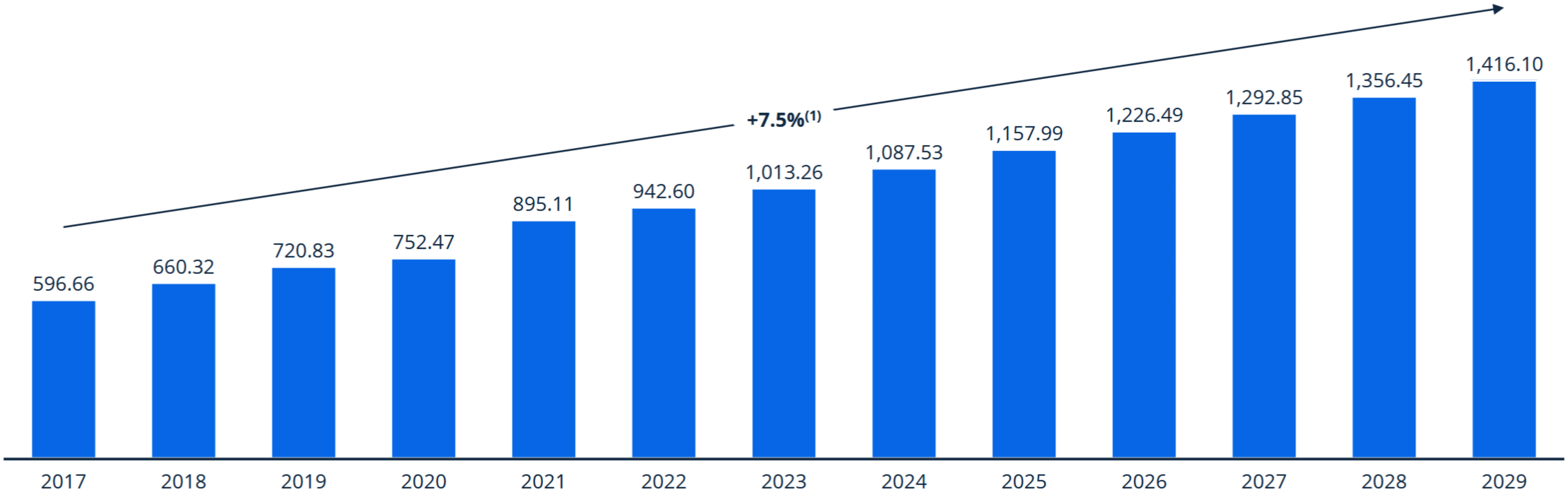
~ €1M budget paid media

(27.9% of marketing budget)



The market perspective

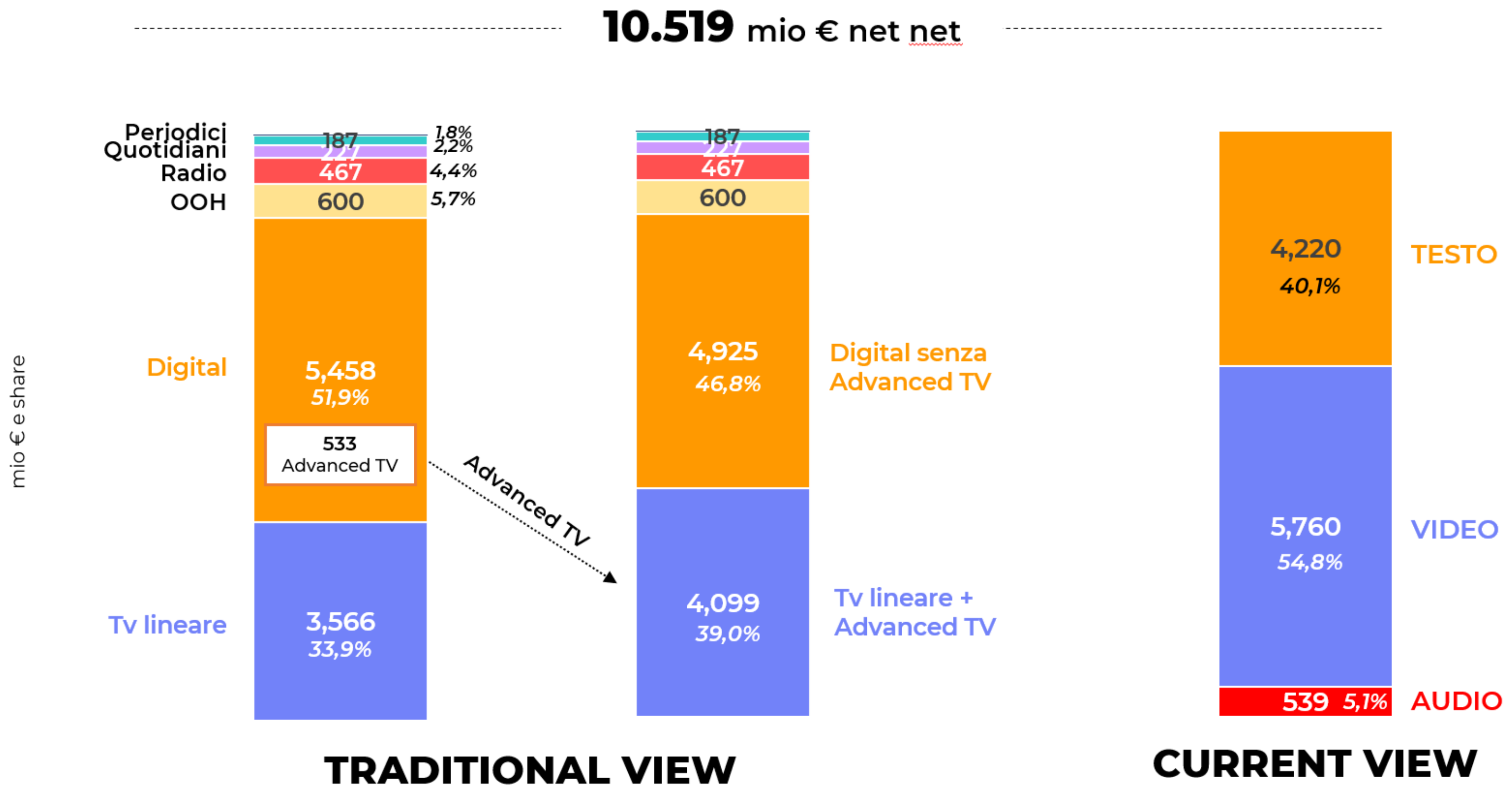
The advertising market shows average growth rates of around 7.5% per year



Advertising spending forecast, in billion US$

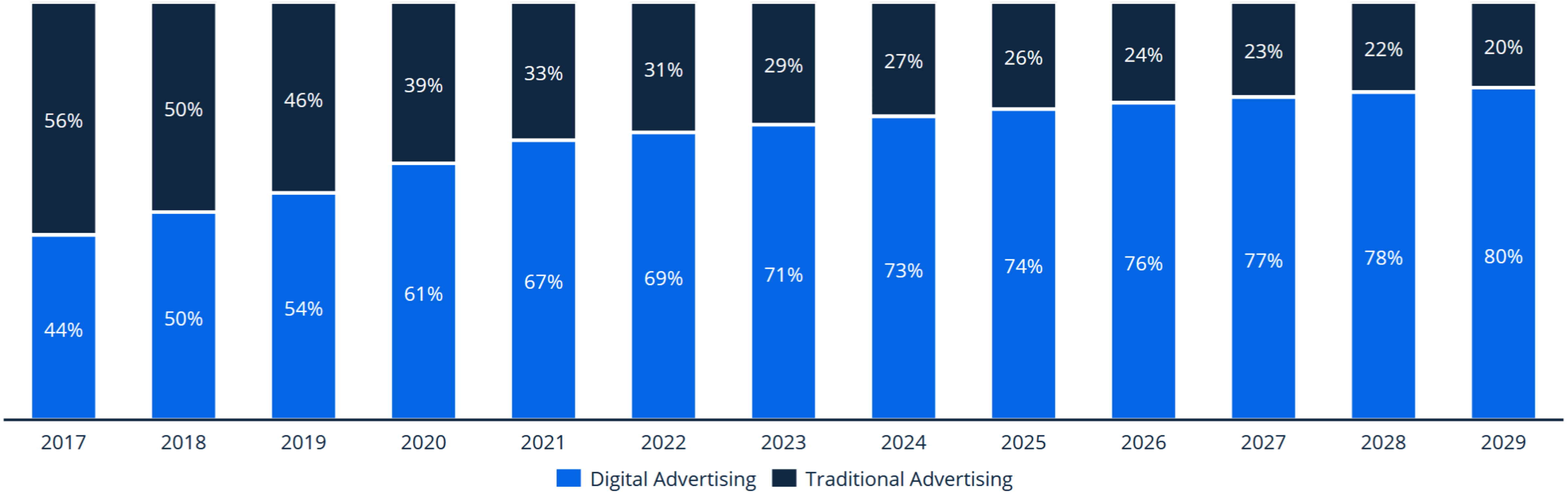
Source: Statista. (2024). *Advertising: Market data & analysis* (p. 309). https://www.statista.com/study/166789/advertising-market-data-and-analysis/

Advertising market in Italy broken down by media channels.



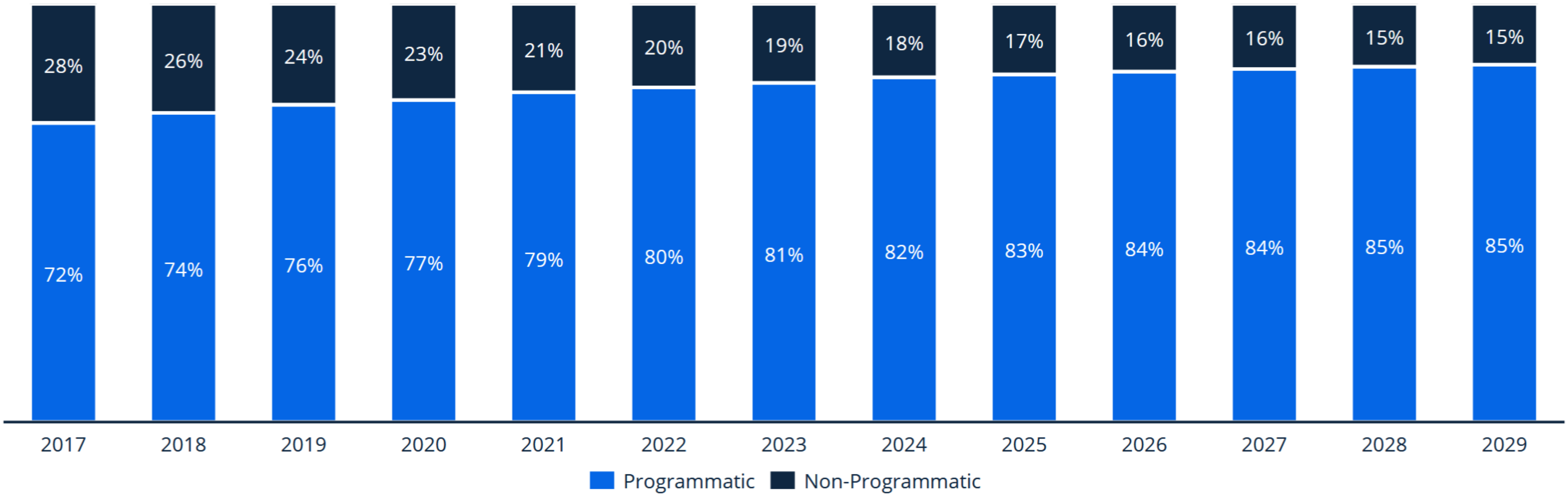
Source: UNA Media Hub. (2024) *CROSSROADS: Un mondo al bivio. Uno sguardo al mercato pubblicitario '24-'25: tra certezze e riserve.*

73% of the advertising market share in 2024 was attributed to digital ad spending



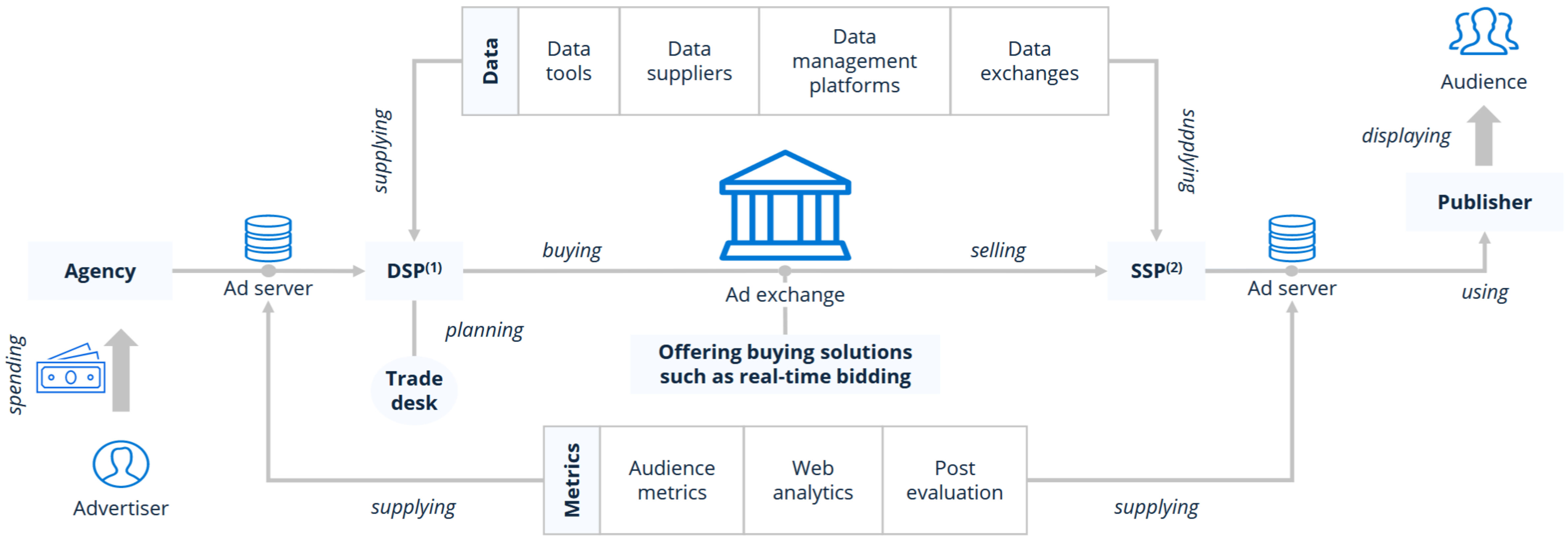
Source: Statista. (2024). *Advertising: Market data & analysis* (p. 309). https://www.statista.com/study/166789/advertising-market-data-and-analysis/

Programmatic advertising represented 82.0% of the digital advertising market in 2024



Source: Statista. (2024). *Advertising: Market data & analysis* (p. 309). https://www.statista.com/study/166789/advertising-market-data-and-analysis/

Process of programmatic advertising



Source: Statista. (2024). *Advertising: Market data & analysis* (p. 309). https://www.statista.com/study/166789/advertising-market-data-and-analysis/

A triangulation approach to advertising campaign optimization

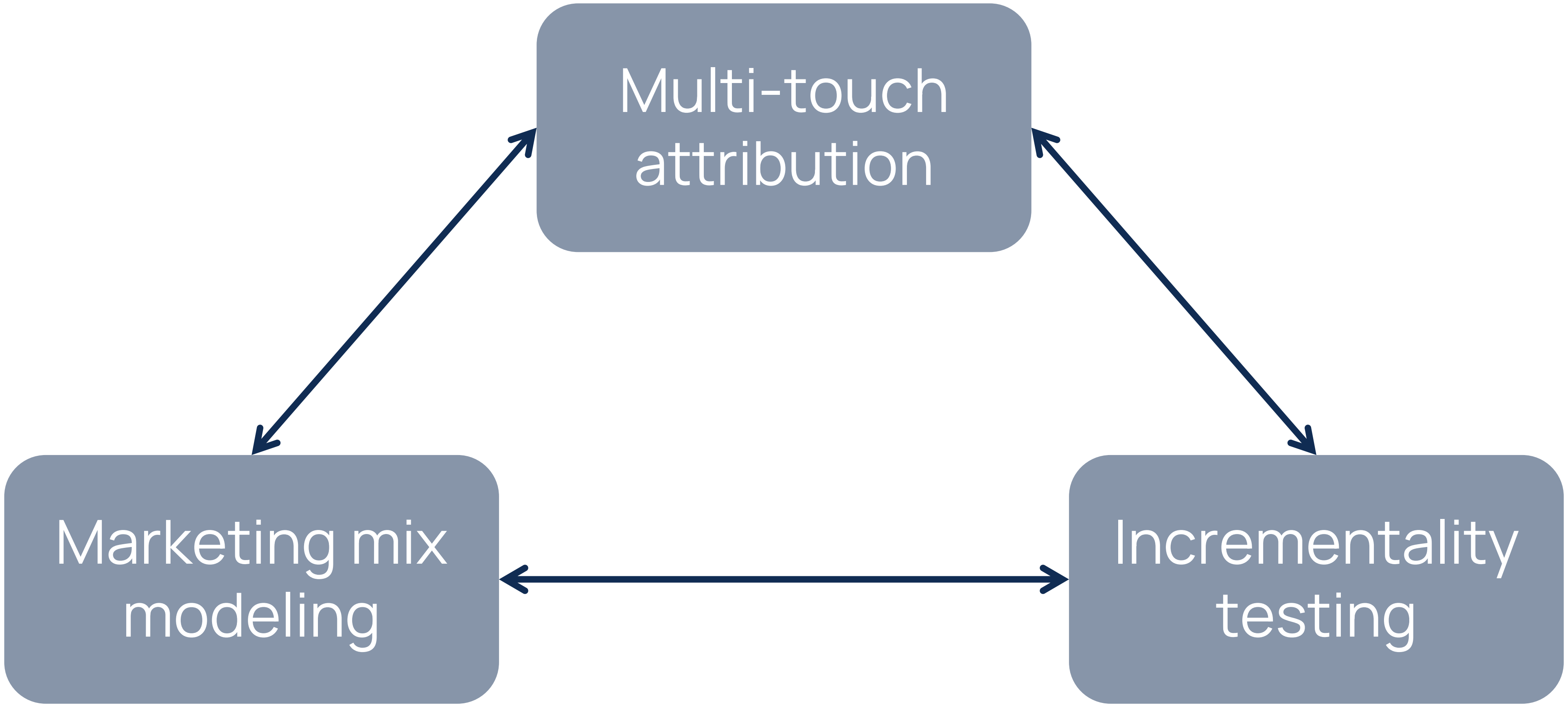
02

“Since all models are wrong the scientist must be alert to what is **importantly** wrong.

It is inappropriate to be concerned about mice when there are tigers abroad.”

Box, G. E. P. (1976). Science and Statistics. Journal of the American Statistical Association, 71(356), 791–799. https://doi.org/10.1080/01621459.1976.10480949

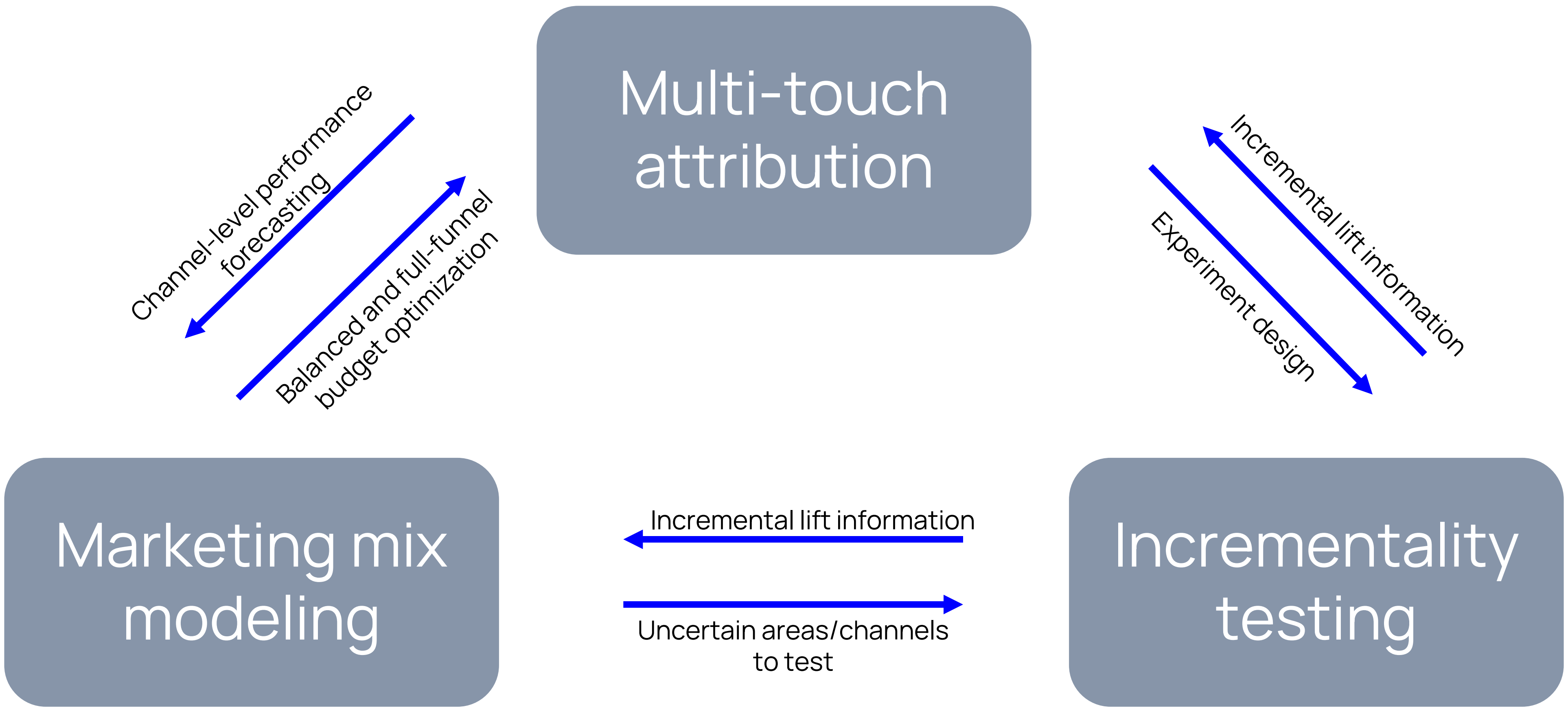
Triangulation in marketing measurement



Comparison of the three approaches

	Multi-touch attribution	Marketing mix modeling	Incrementality testing
Data	• Granular consumer's touchpoint data: Browser cookies, UTM codes, tracking pixels, and similar identifiers.	• Aggregated time-series data on marketing investment, costs, revenues, and contextual elements (e.g. competitors, general economy, etc.)	• Experimental data from geo-testing, holdout tests, and controlled studies.
Goal	• Measure and optimize marketing effectiveness in near real-time.	• Analyze and optimize long-term marketing investment across multiple channels.	• Empirically quantify the incremental impact of marketing efforts on sales.
Pros	• Provides granular insights for tactical campaign optimization. • Allows quick adaptation to market dynamics and trends. • Helps optimize budget allocation and creative performance.	• Integration of digital and traditional channels. • privacy-safe and does not use any cookie or user-level information. • Provides a holistic and strategic view of marketing effectiveness. • Accounts for offline and online marketing impacts. • Answers high-level budget allocation and return-on-investment (ROI) questions.	• Provides causal insights into marketing effectiveness. • Yields generalizable results that can inform future strategies. • Overcomes attribution limitations of other methods.
Cons	• Only track addressable channels, which lead to an over-evaluation vs. non-addressable channels. • Limited when used in isolation, lacks a holistic view of the full marketing funnel. • Dependent on cookies, making it less reliable with increasing privacy restrictions.	• Causality rests on strong assumptions • Requires large volumes of high-quality historical data. • Complexity increases with more variables, demanding advanced data science expertise. • Significant pre-processing and model tuning effort needed.	• Often ad-hoc and piecemeal approach. • Requires a rigorous experimental design with large, representative samples. • Needs sufficient test duration for reliable results.

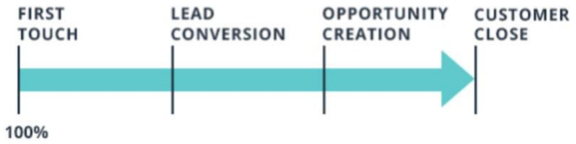
Approach to triangulation between the three methods.



Multi-touch attribution

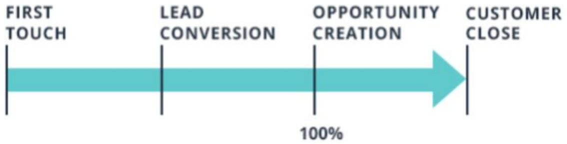
Attribution modeling – possible approaches

First touch

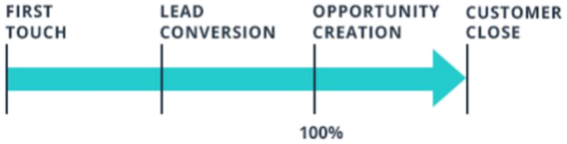


Lead conversion

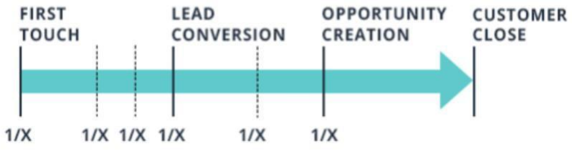
Opportunity creation (or last touch)



Customer close



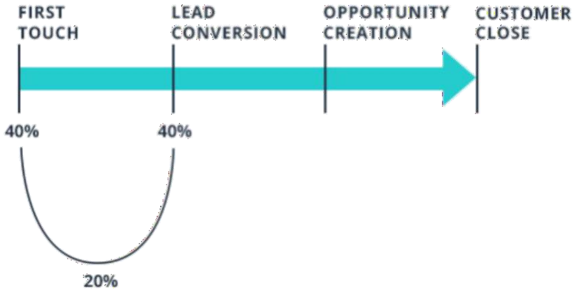
Linear model



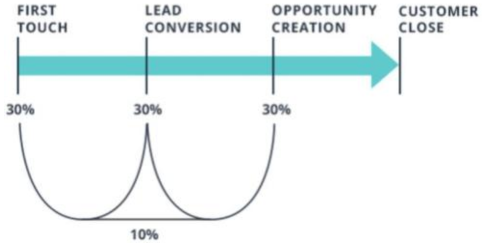
Where X equals the total number of touchpoints

Time decay model

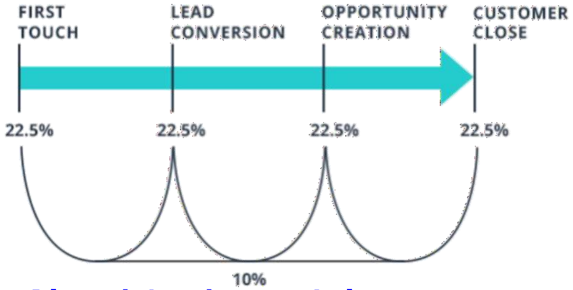
U-shaped model



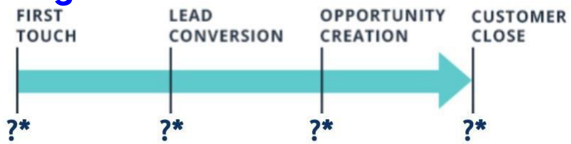
W-shaped model



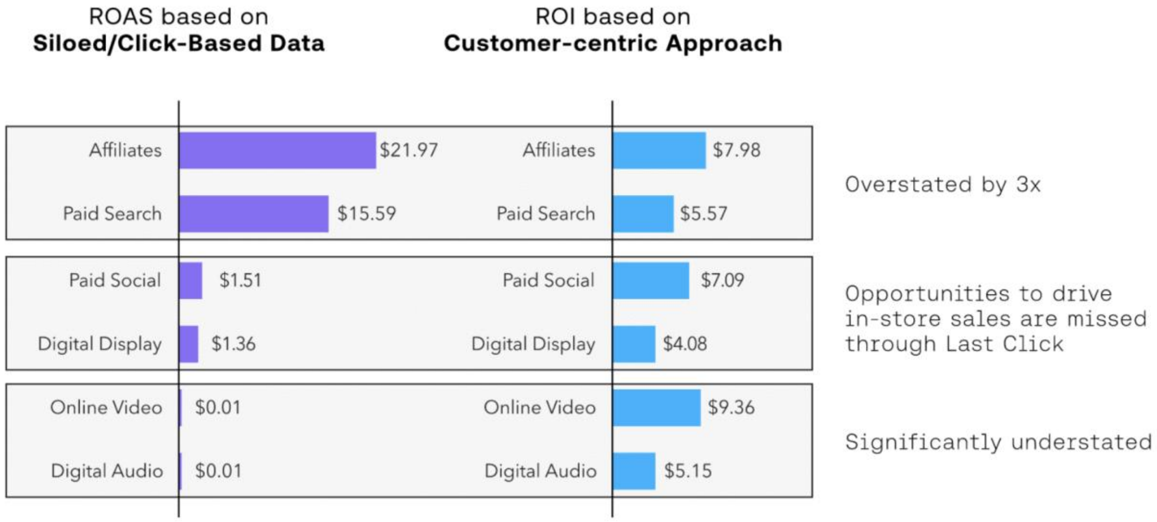
Z-shaped model

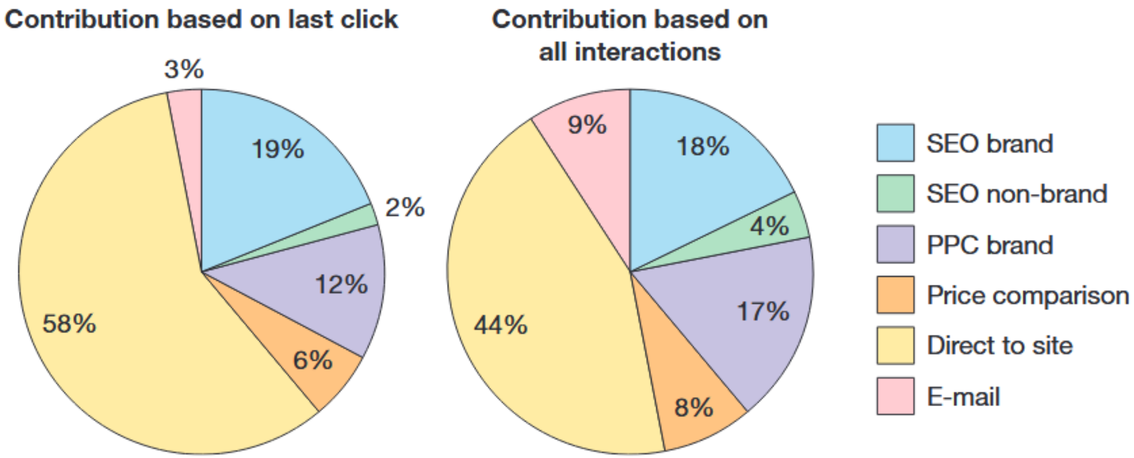


Algorithmic model



The attribution model have an important impact on the results.





Source: analytic partners. (2023, December 11). *Data Doesn't Lie, but Your ROI Metrics May Mislead*. Analytic Partners. https://analyticpartners.com/blog/data-doesnt-lie-but-your-roi-metrics-may-mislead/

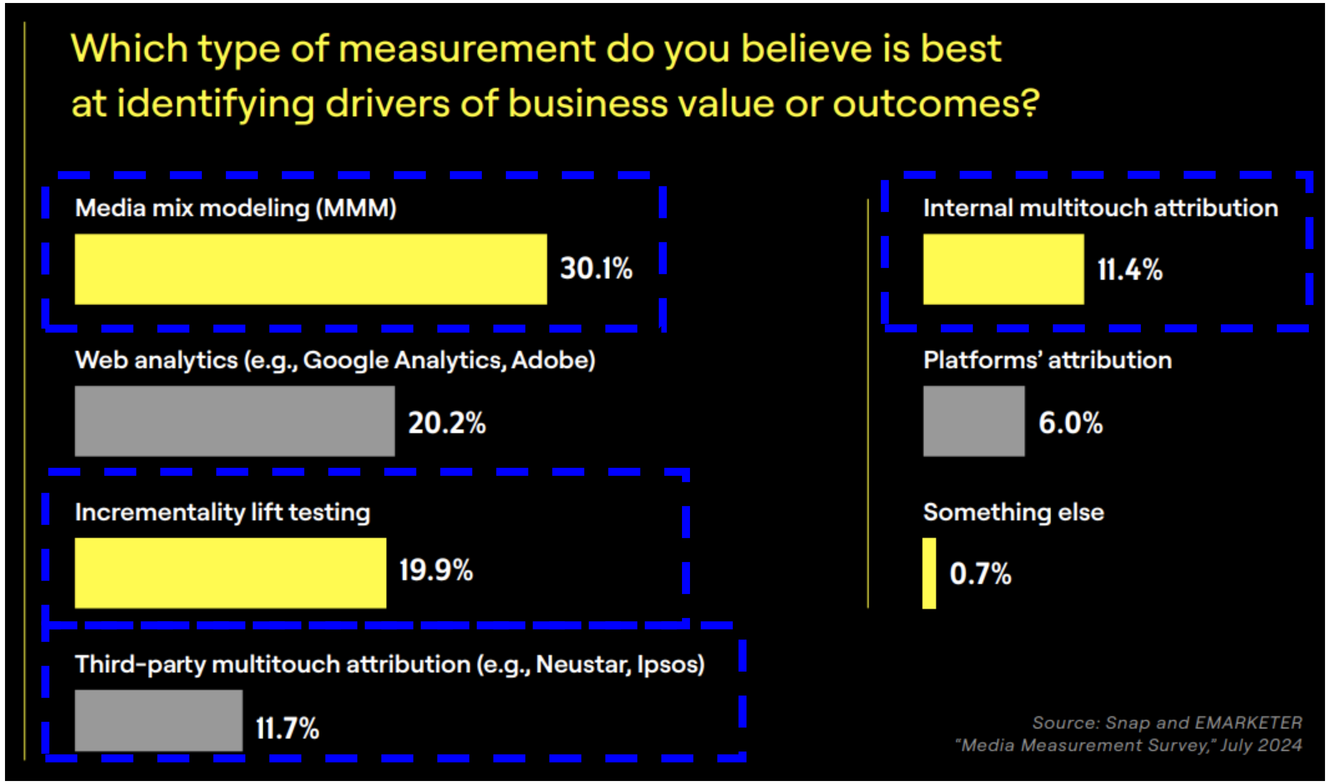
Shift toward complementary approaches.

78.4% of marketers use last-click attribution.

63.5% of marketers don't think last-click is aligned with how people actually shop

69.9% of marketers believe last-click has gaps in tracking on most platforms

74.5% are planning to move away from last-click measurement.



Source: eMarketer. (2024). *The Last Days of Last-Click? How expanding attribution away from last-click will unlock growth.*

Incrementality testing

Overview of incrementality testing

Incrementality testing helps determine whether a marketing action (e.g., ads, promotions) actually drives results or if conversions would have happened anyway. It isolates true causal impact by comparing exposed vs. unexposed groups.

Why It Matters

- Measures real impact – Aims to distinguish correlation from causation.
- Optimizes budget allocation – Avoids overspending on ineffective tactics.
- Improves decision-making – Helps marketers invest in what truly works.
- Filters out noise – Accounts for external factors like seasonality and organic sales.

How It Works

- Randomized control groups – Compare users exposed to an ad versus those who weren't.
- Holdout tests – Keep a portion of the audience unexposed to see the baseline.
- Geo-testing & Ghost Ads – More advanced methods for measuring lift in digital ads.

In this lecture, we will focus on A/B/n testing, a powerful method for controlled experiments in marketing.

The anatomy of the advertising budget decision: a balance between heuristics and analytics

Four components of advertising budget decision:

Heuristics (rules of thumb)
- Advertising-to-sales ratio
- Competitive parity

Analytics (data-driven models)
- Baseline spending
- Adaptive experimentation

Dual control theory

Balancing the objectives:

Optimal profit-maximizing allocation

Experimentation

Empirical evidence that brands from categories with high uncertainty in advertising effectiveness can benefit from double-digit revenue lifts by placing higher emphasis on adaptive experimentation.

Source: Kolsarici, C., Vakratsas, D., & Naik, P. A. (2020). The Anatomy of the Advertising Budget Decision: How Analytics and Heuristics Drive Sales Performance. *Journal of Marketing Research*, *57*(3), 468–488. https://doi.org/10.1177/0022243720907578

A/B/n testing

A/B testing

C1

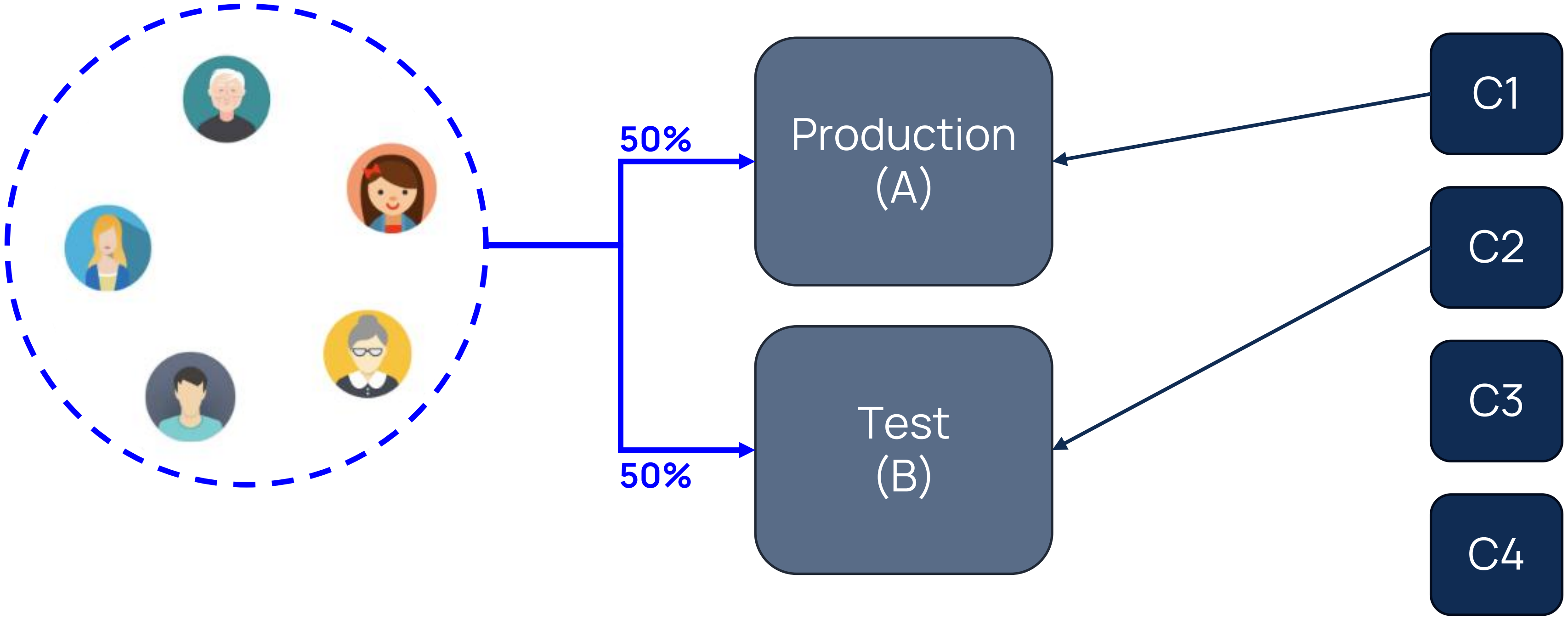
C2

C3

C4

A/B testing

(Sequential) A/B testing



Several definitions of reward

Profit maximisation

- Demand is to estimate (for every price we have a truncated Gaussian distribution), then multiplied by marginal profit
- Conversion rate is to estimate (for every price we have a binomial distribution), then multiplied by marginal profit
- (Less frequently) Marginal cost is to estimate (for every price we have a truncated Gaussian distribution)

Several definitions of reward

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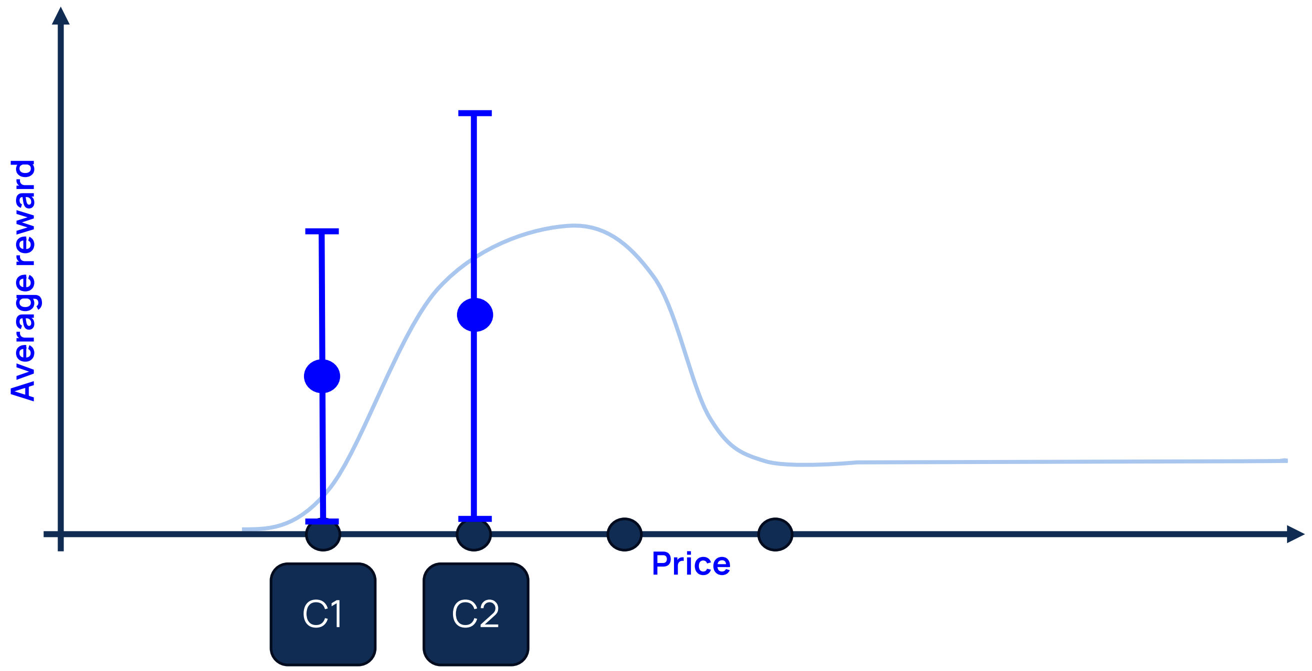
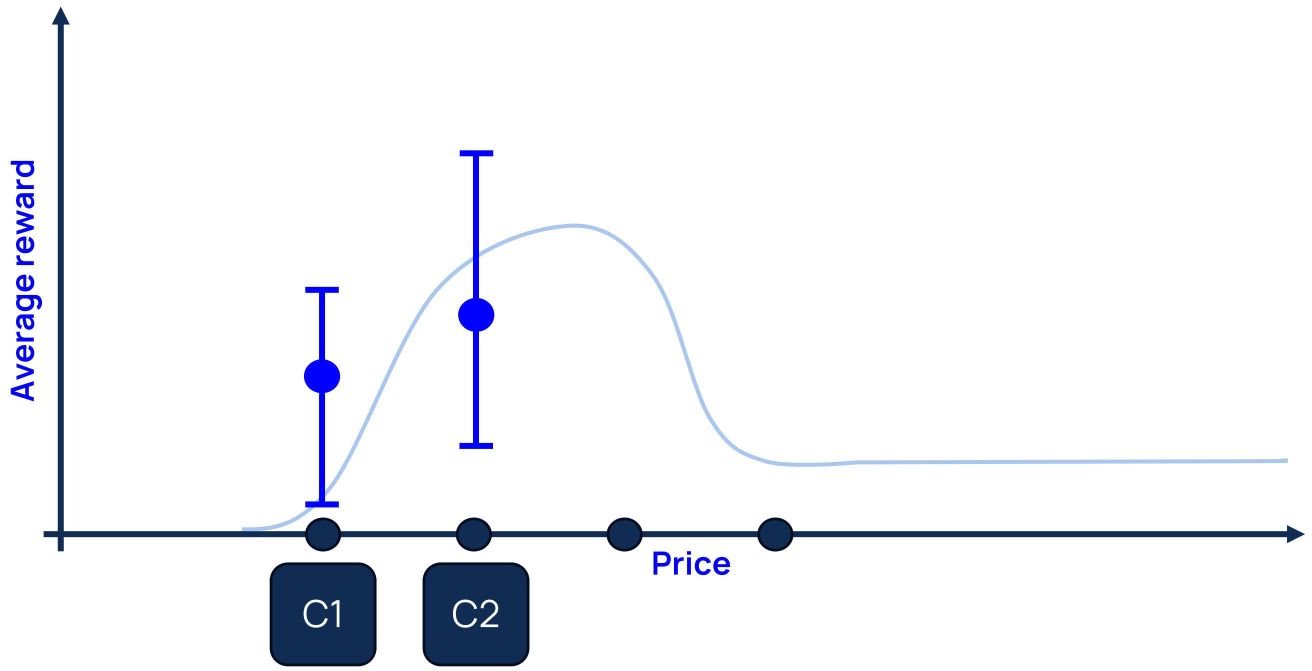
Volumes maximisation (market invasion)

- Demand is to estimate (for every price we have a truncated Gaussian distribution)
- Conversion rate is to estimate (for every price we have a binomial distribution)

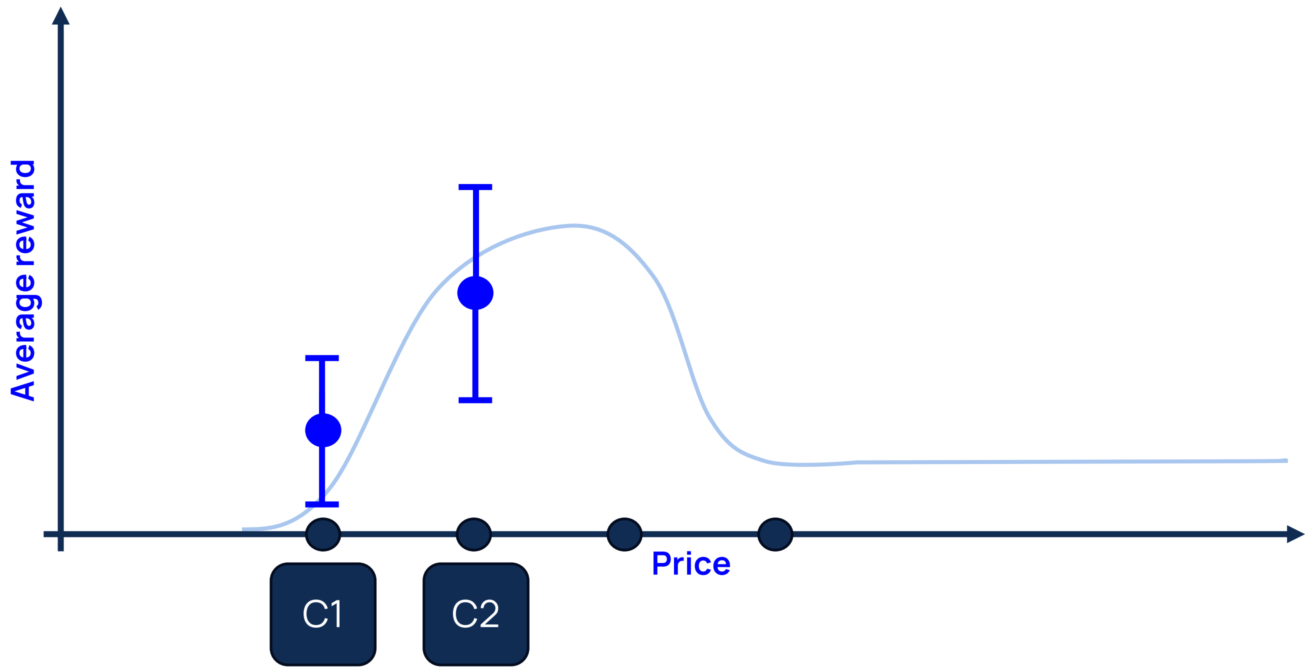
Data collection results in a certain confidence interval.



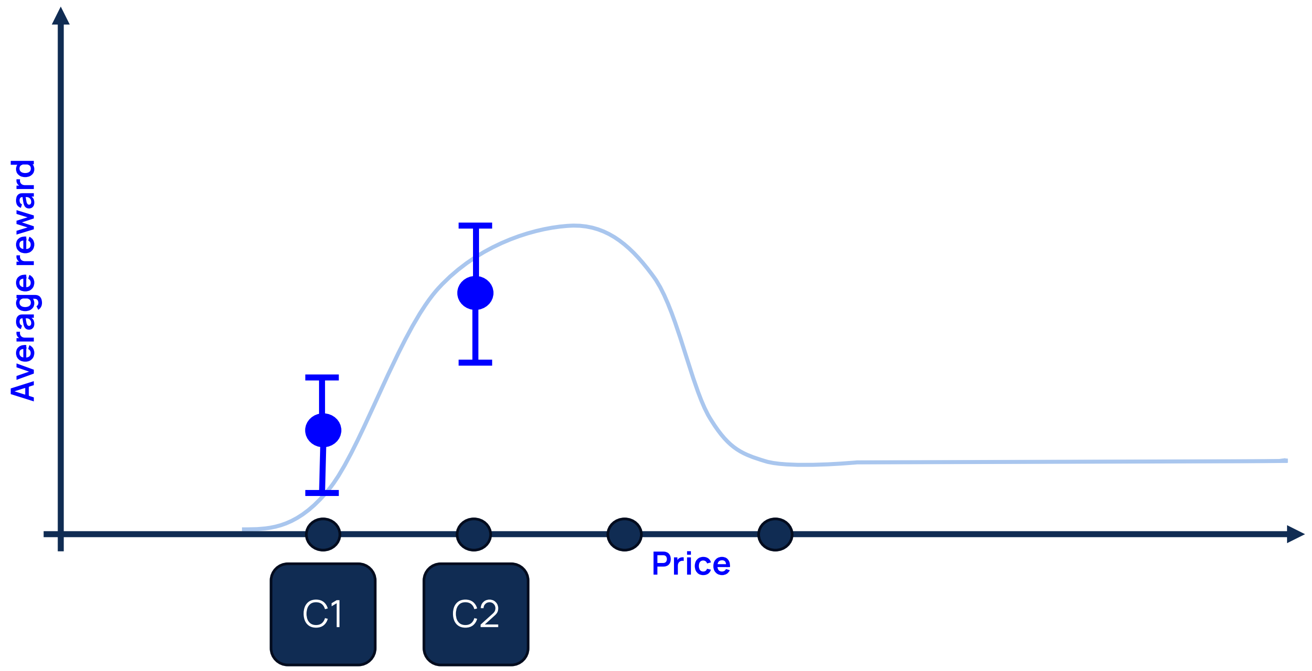
We can have more accurate confidence intervals as we collect more data.



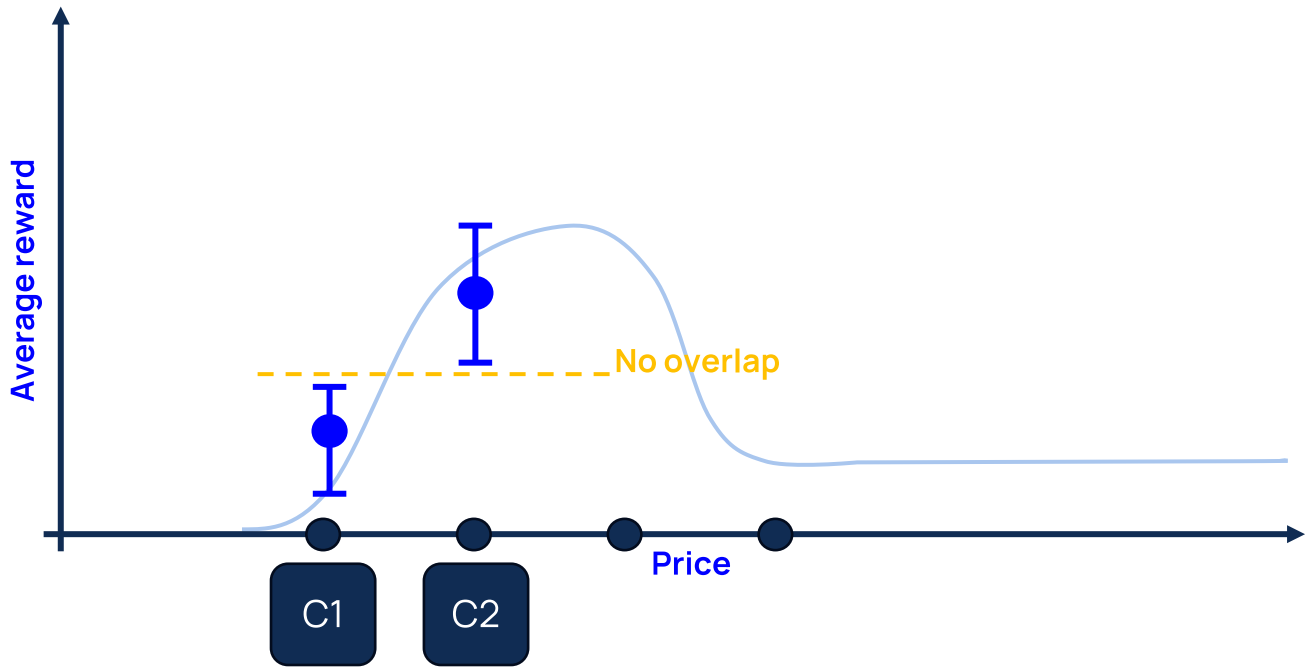
… more and more accurate.



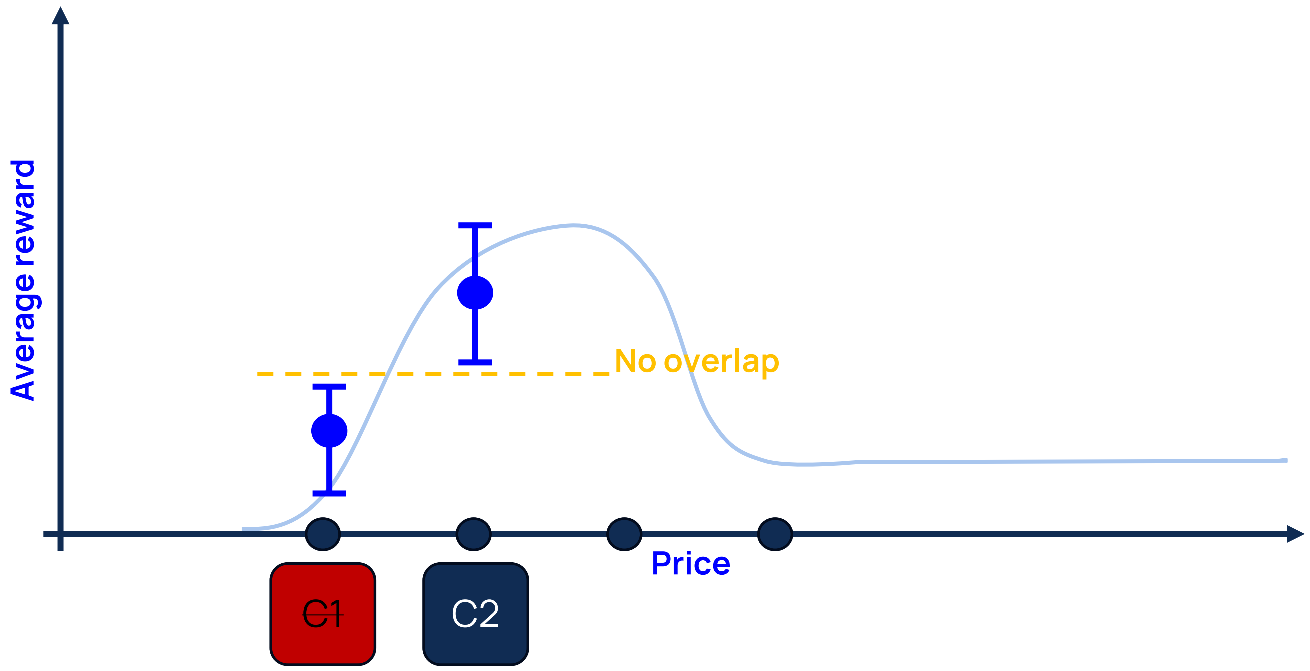
… evermore accurate!



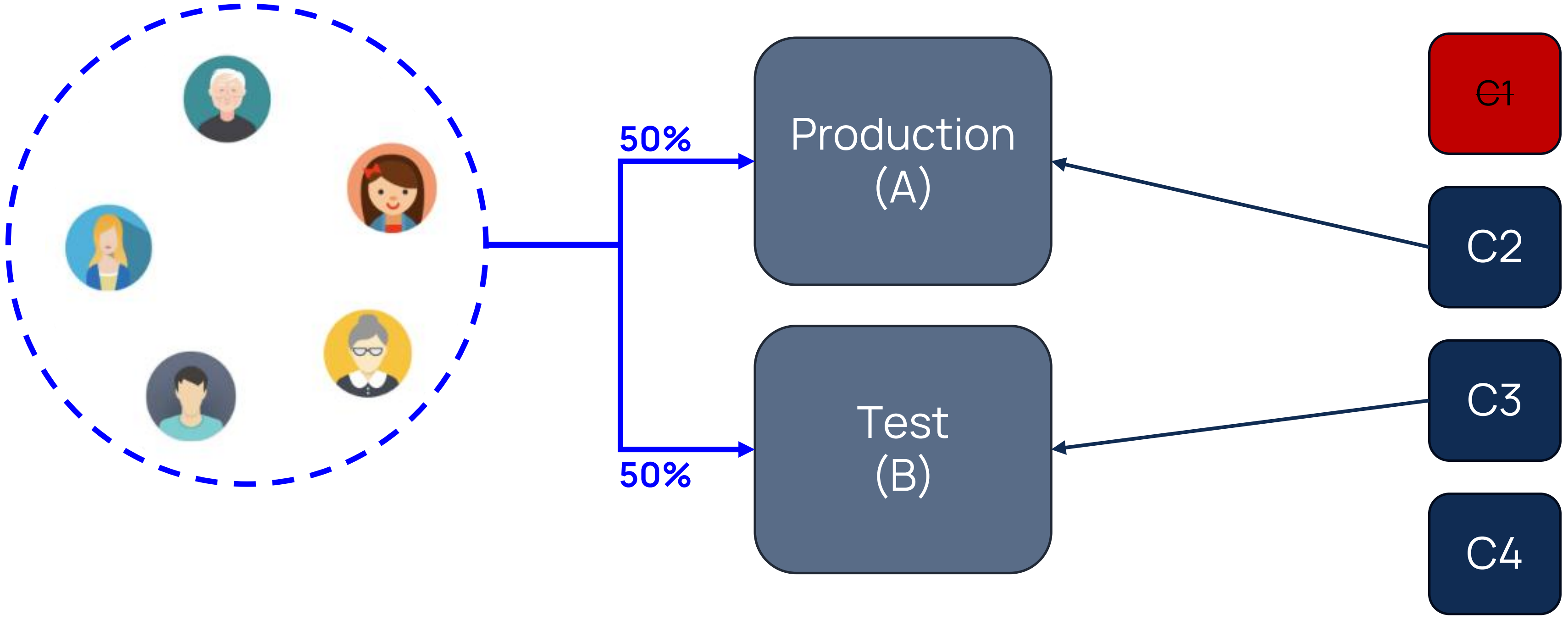
… until we reach the point in which confidence intervals do not overlap.



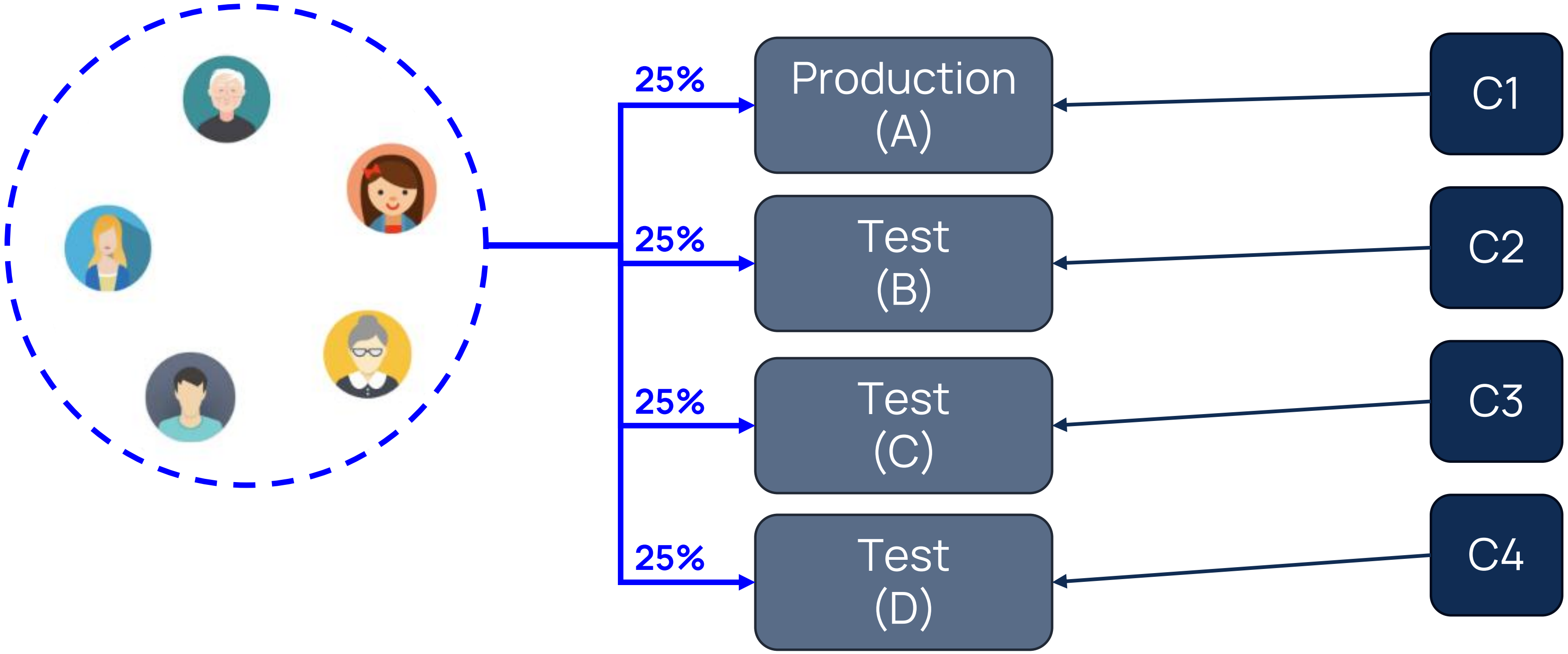
In this case, we can conclude that C2 is better than C1.



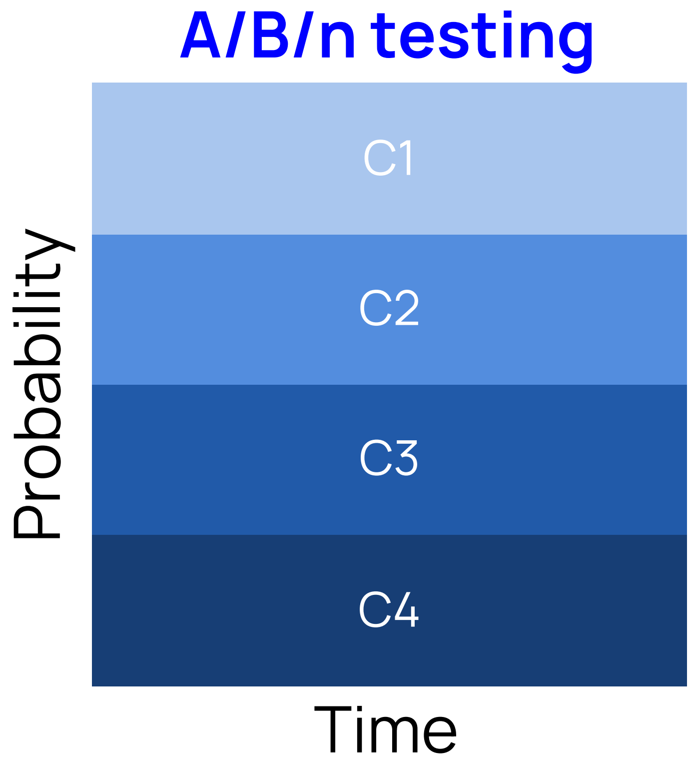
(Sequential) A/B testing with C2 and C3



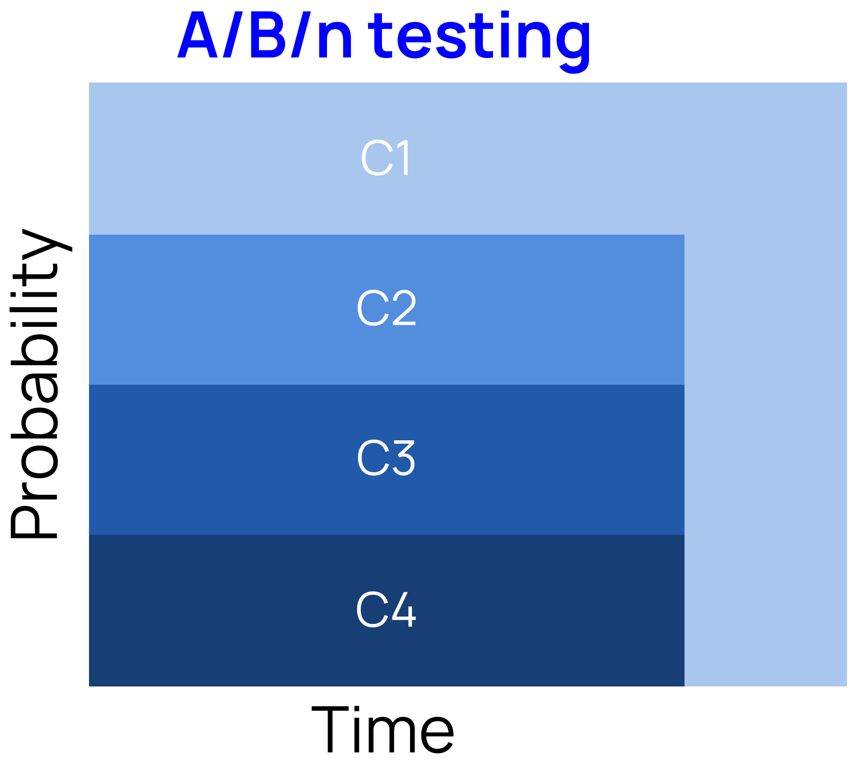
A/B/n testing



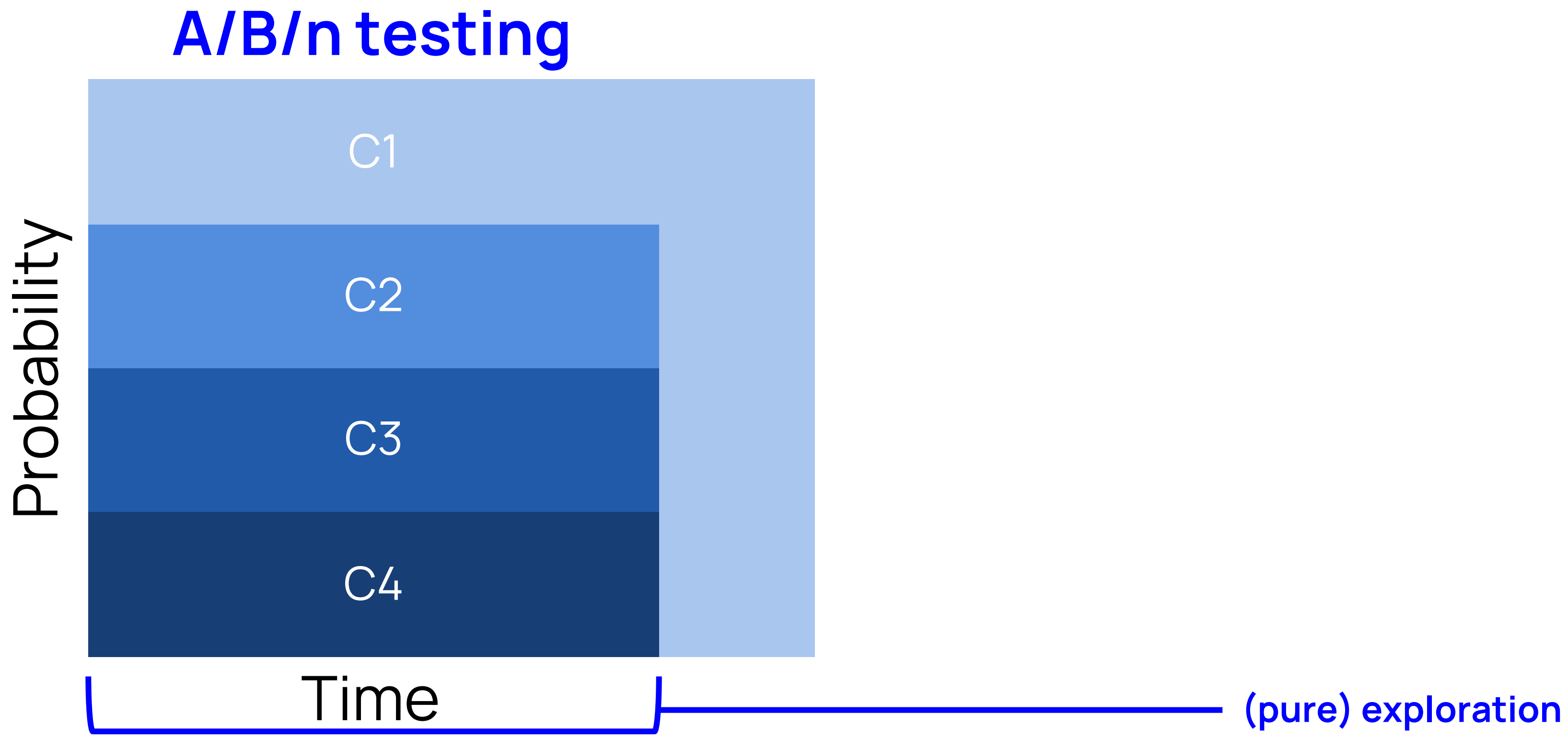
A/B/n testing during time



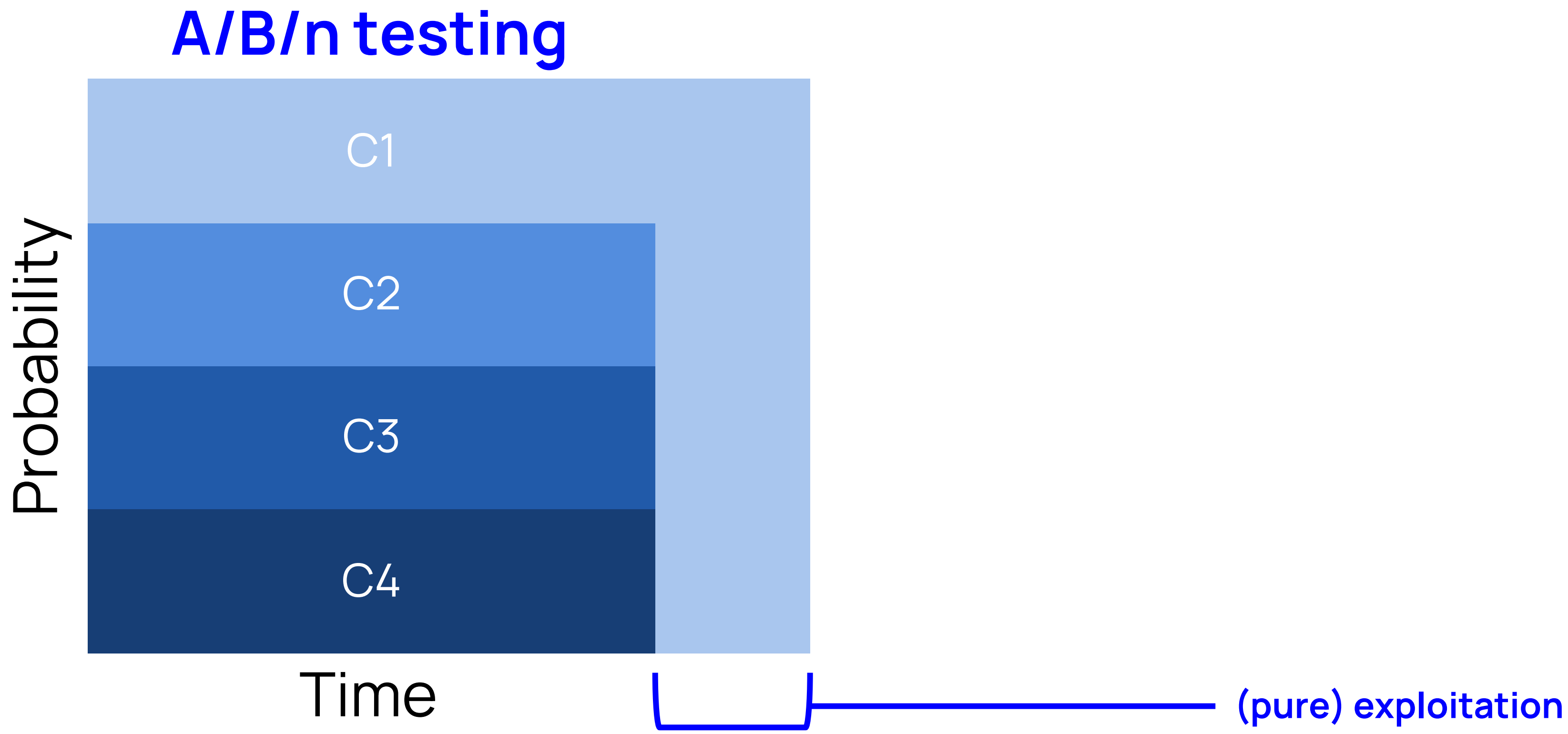
A/B/n testing during time



A/B/n testing during time - Exploration phase



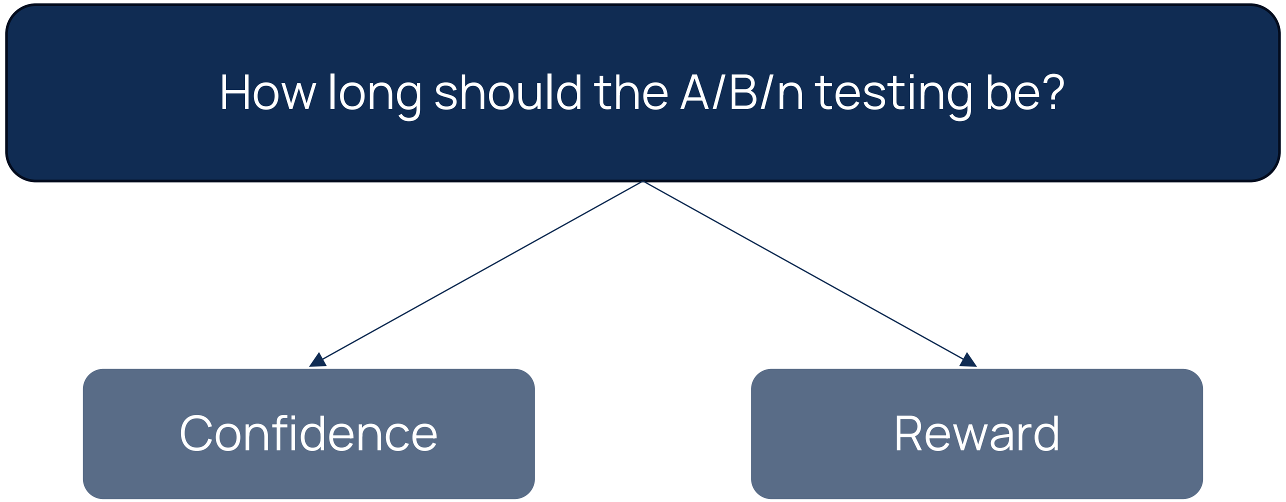
A/B/n testing during time - Exploitation phase



Constant low reward during the exploration phase that we expect would increase in the exploitation phase.

The opportunity cost is directly dependent on the duration of the exploration phase.

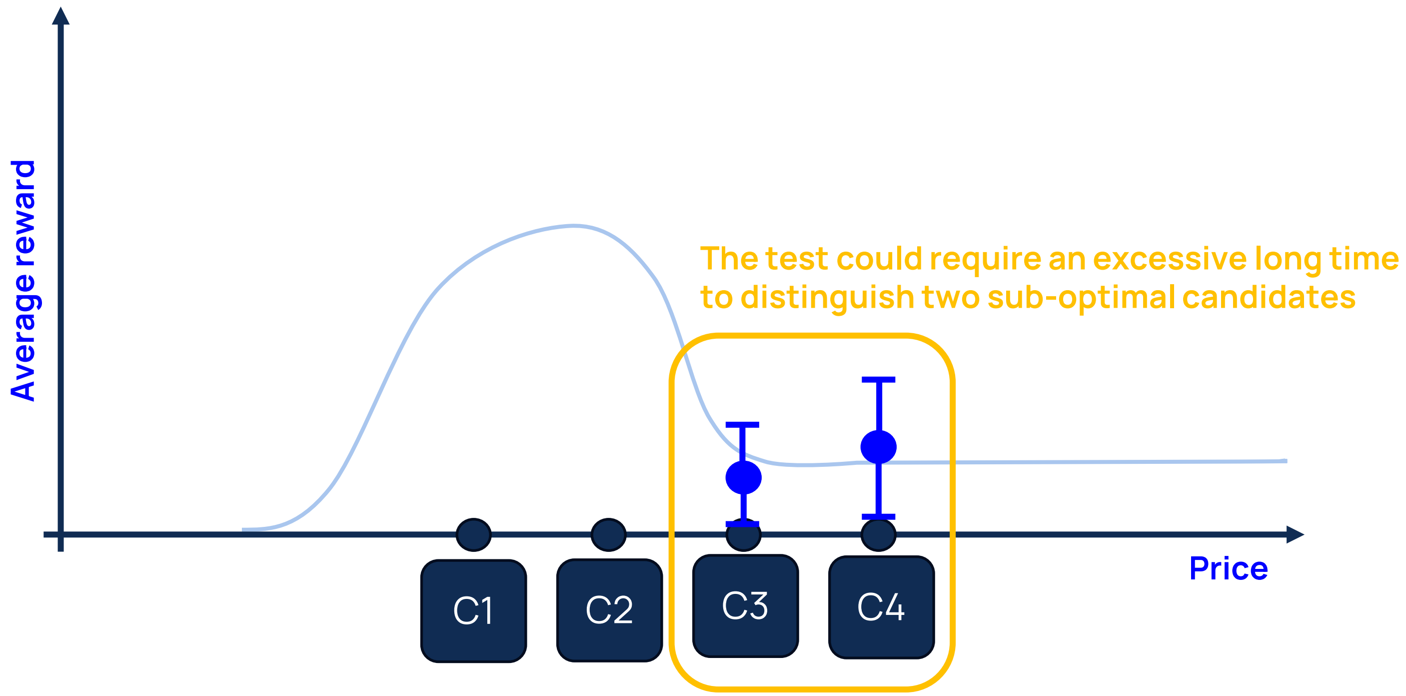
Derive the length of the exploration phase by balancing confidence and reward.



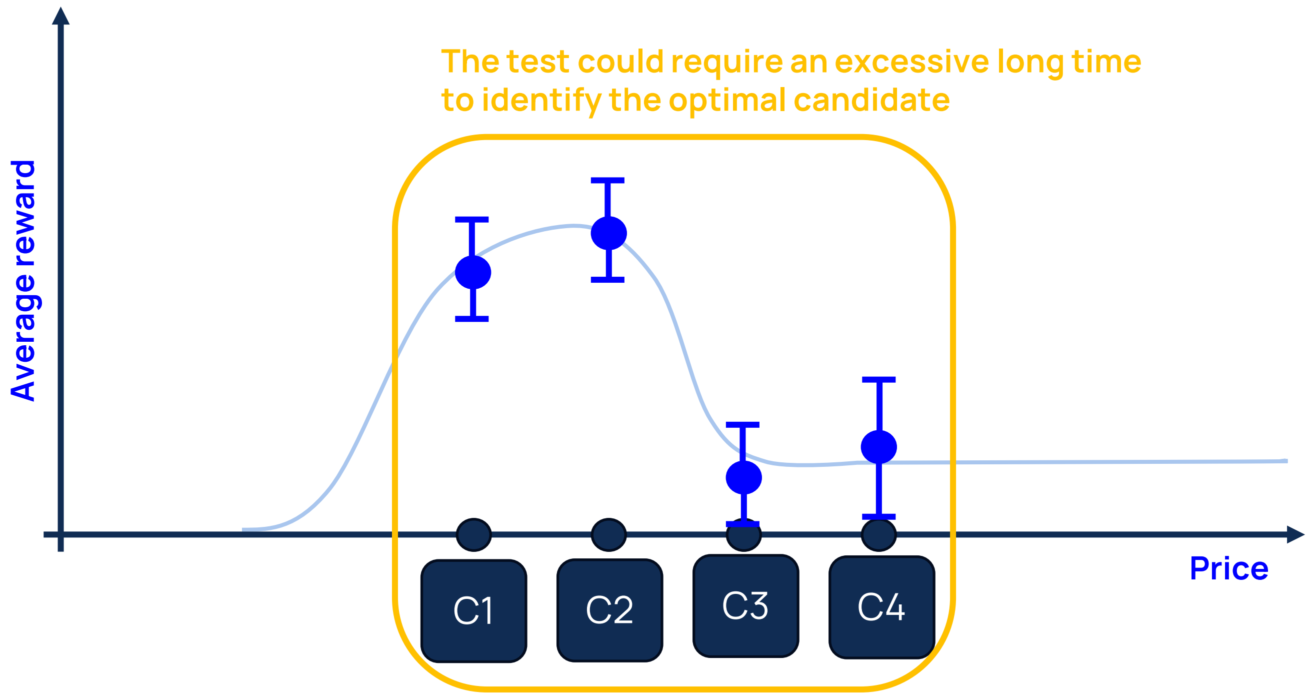
A/B/n weaknesses

- Assumption of stationary process
- Long time to identify the optimal candidate
- Discarding a potentially optimal candidate

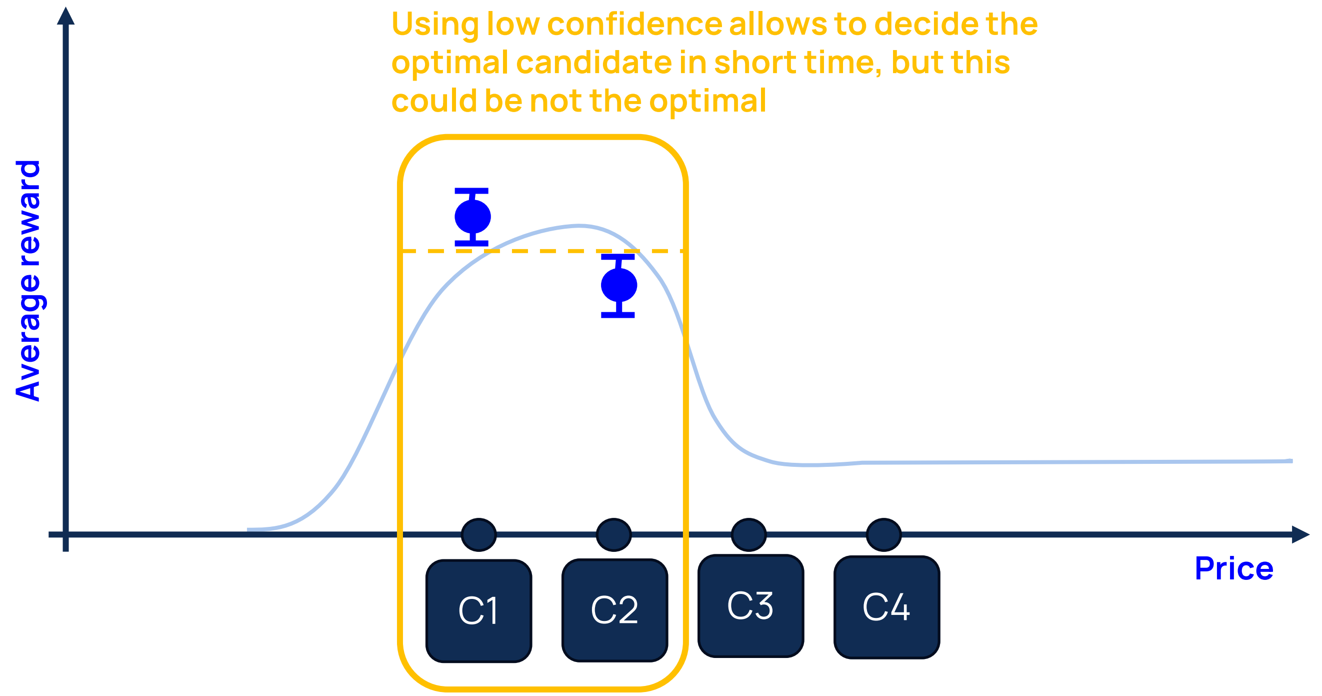
Example: sequential A/B testing



Example: A/B/n testing (length issue)

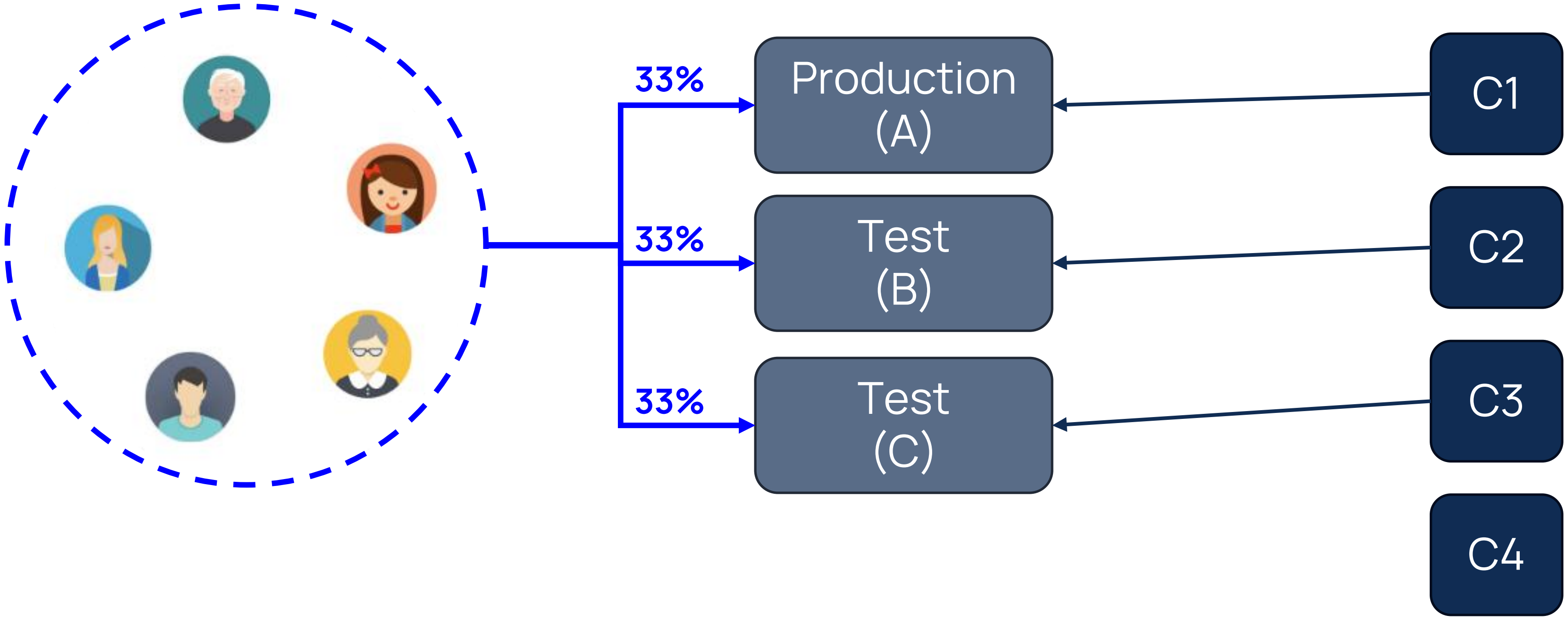


Example: A/B/n testing (low confidence issue)

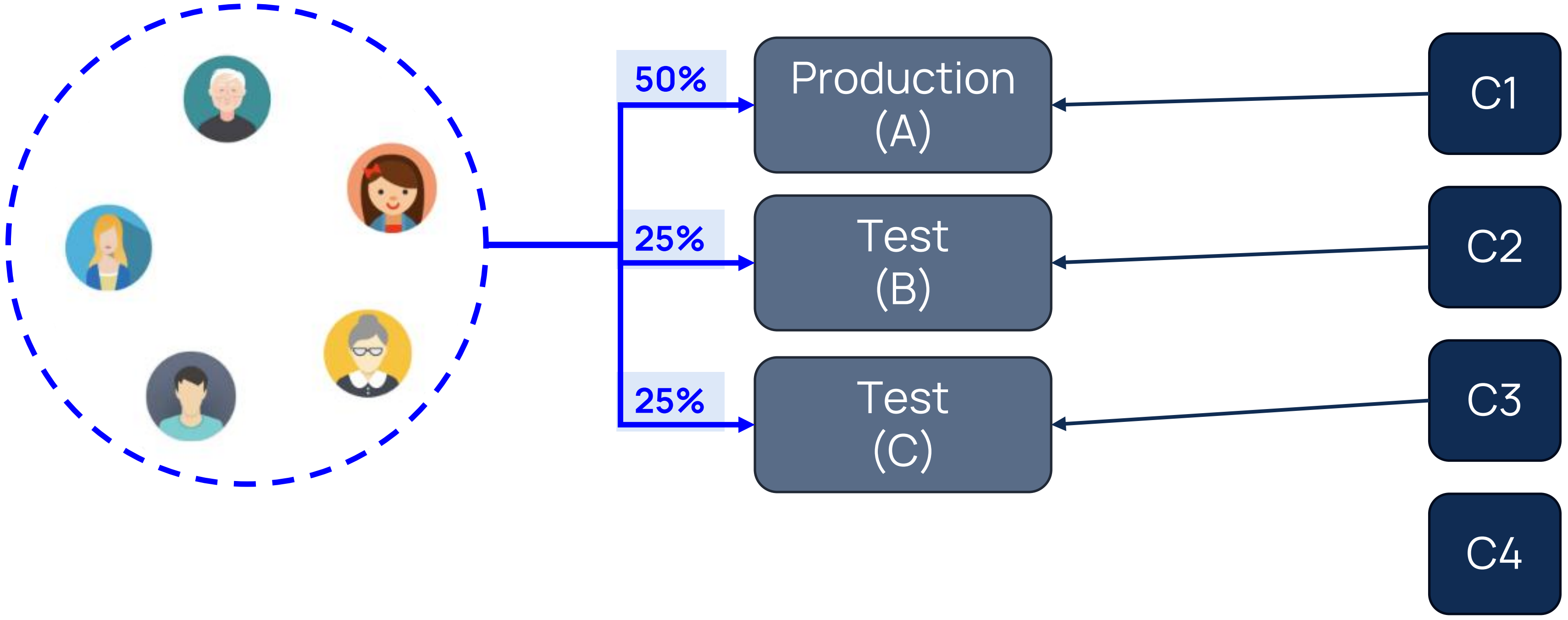


From A/B/n testing to Bandit algorithms

From A/B/n testing to bandit algorithms

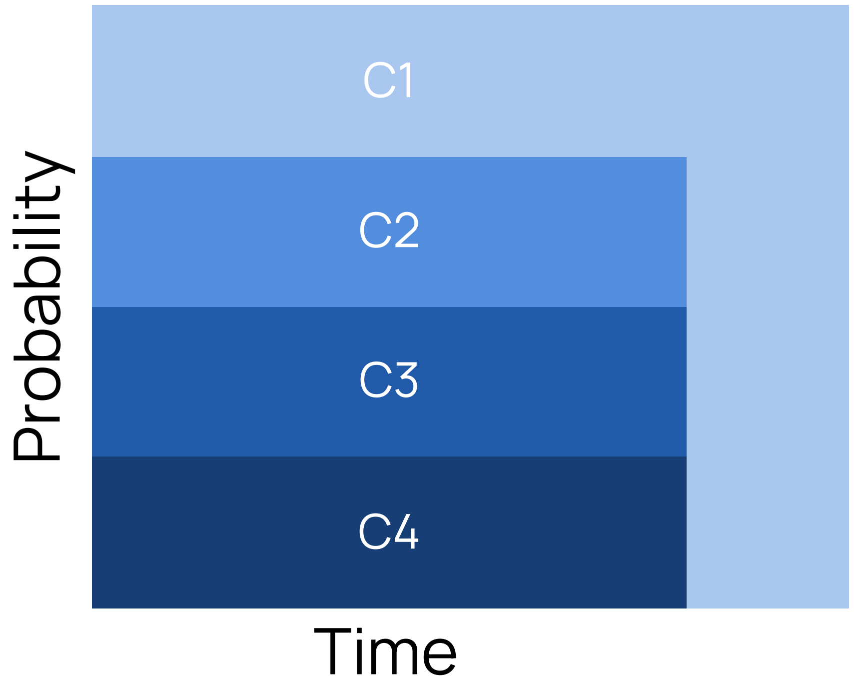


From A/B/n testing to bandit algorithms

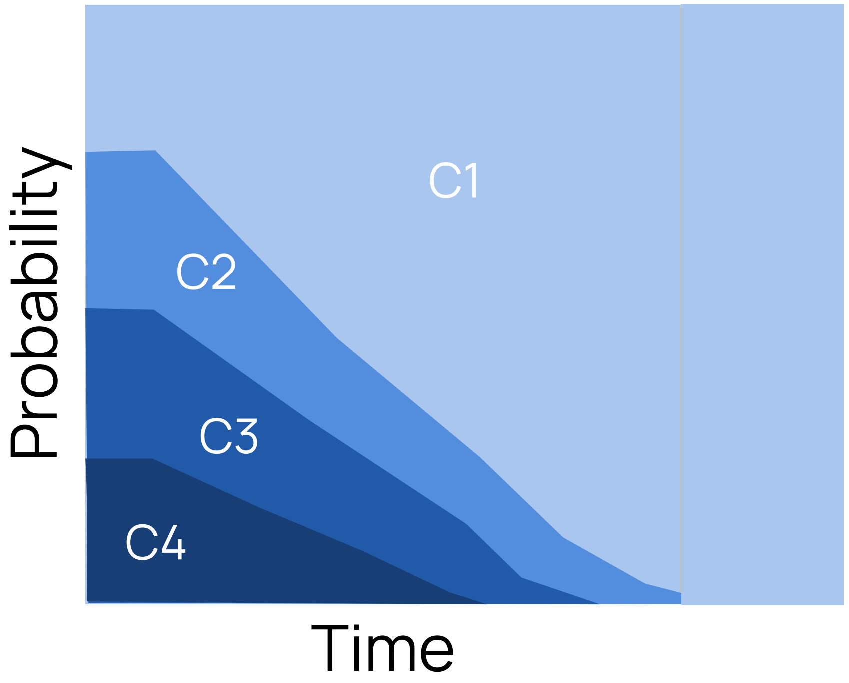


From A/B/n testing to bandit algorithms

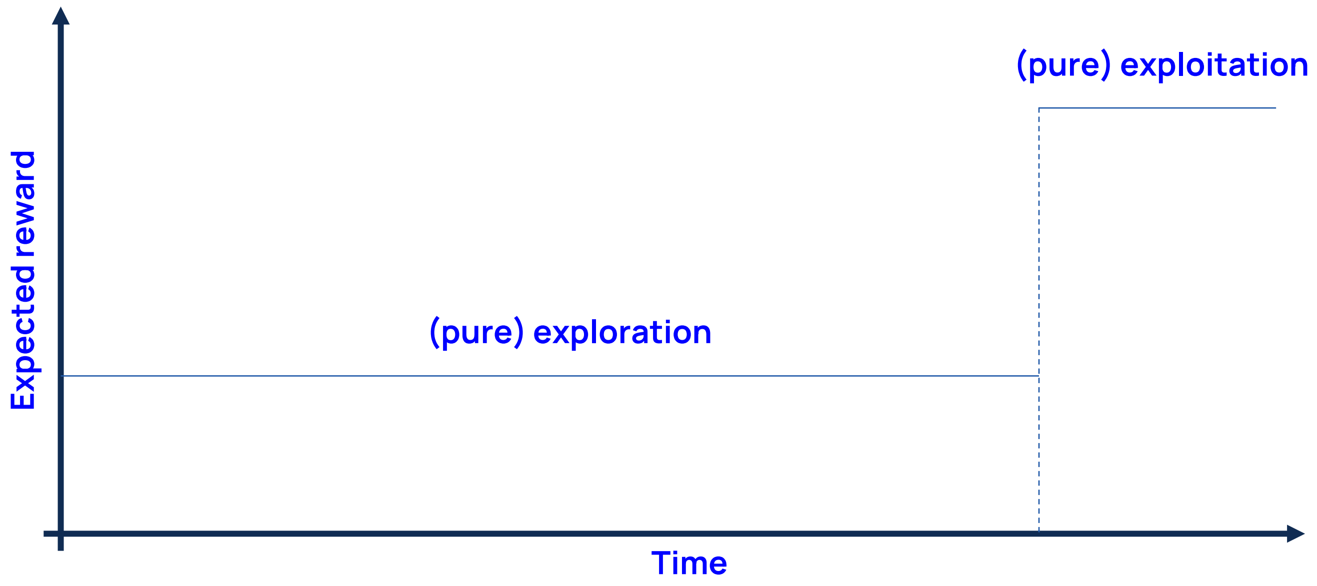
A/B/n testing



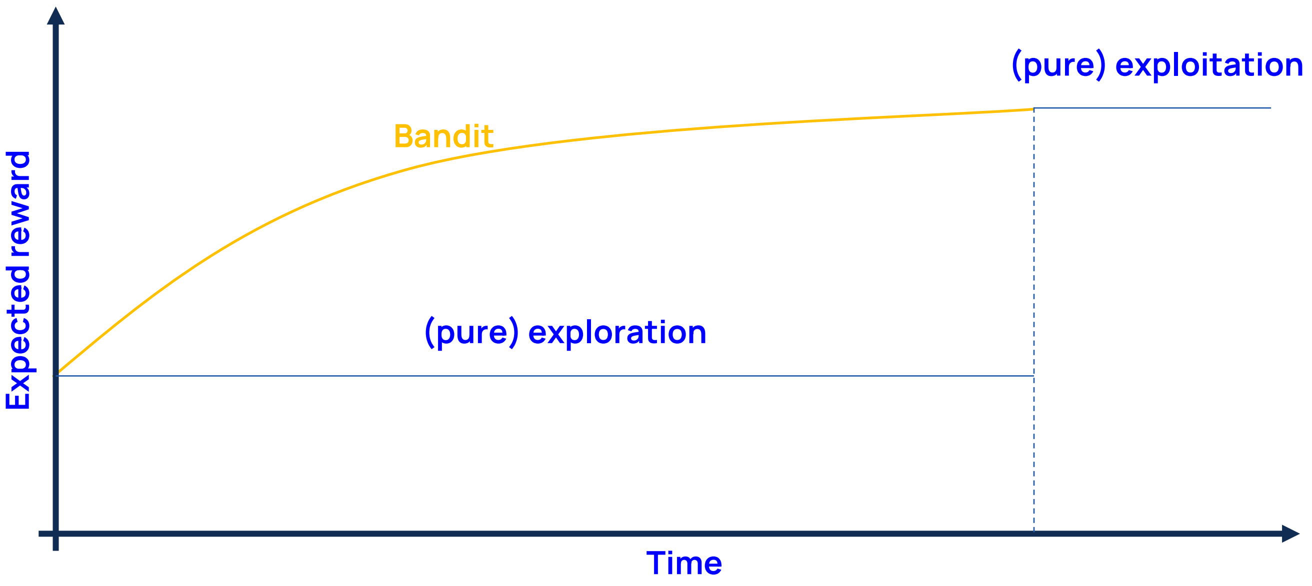
Bandit algorithms



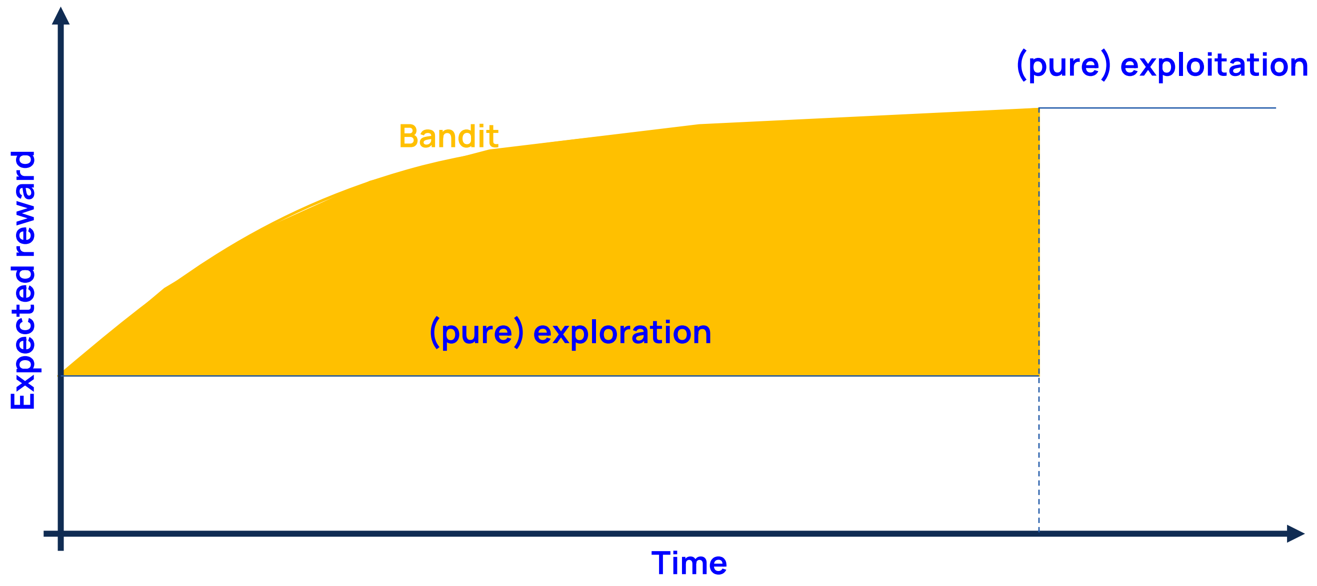
Performance comparison



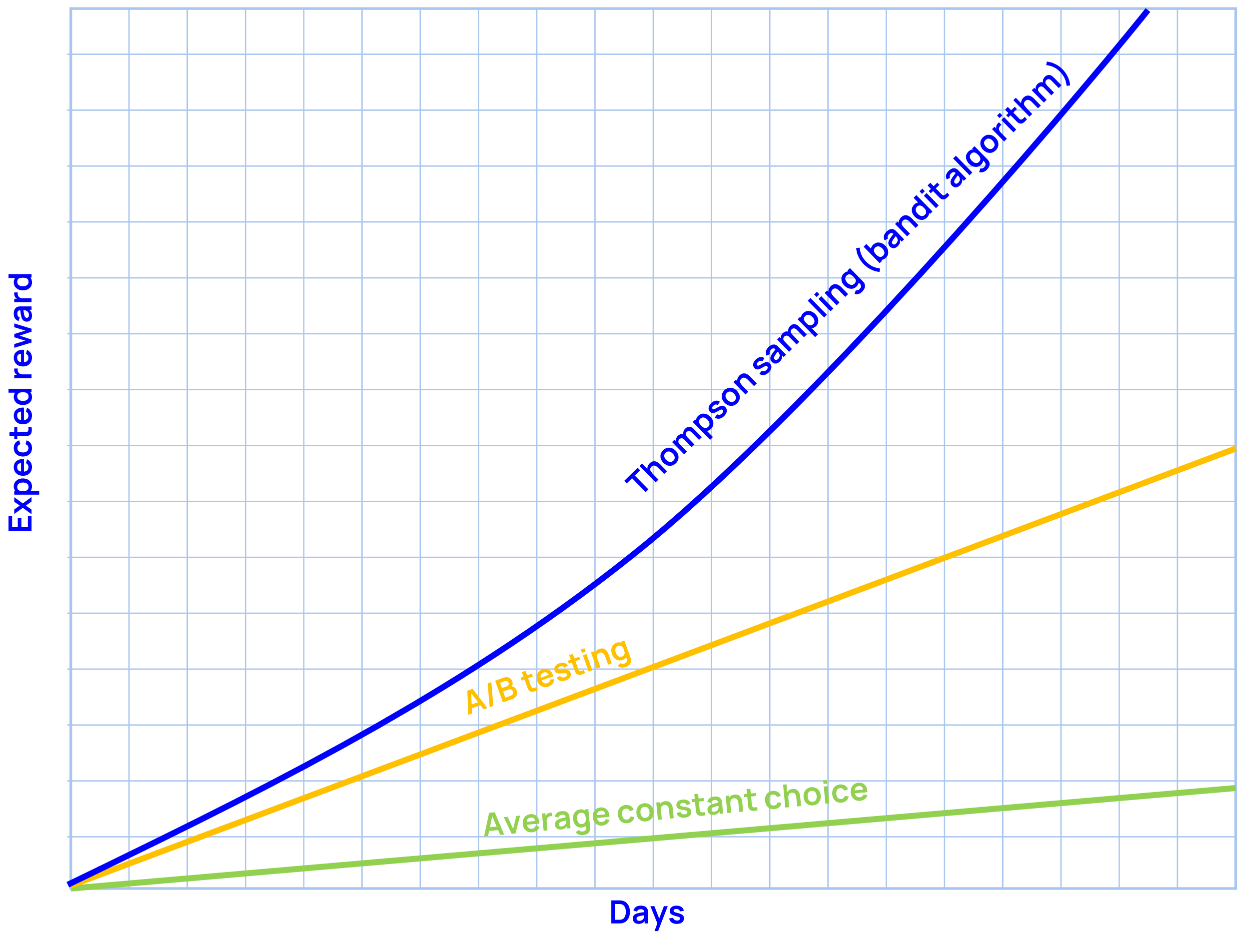
Performance comparison



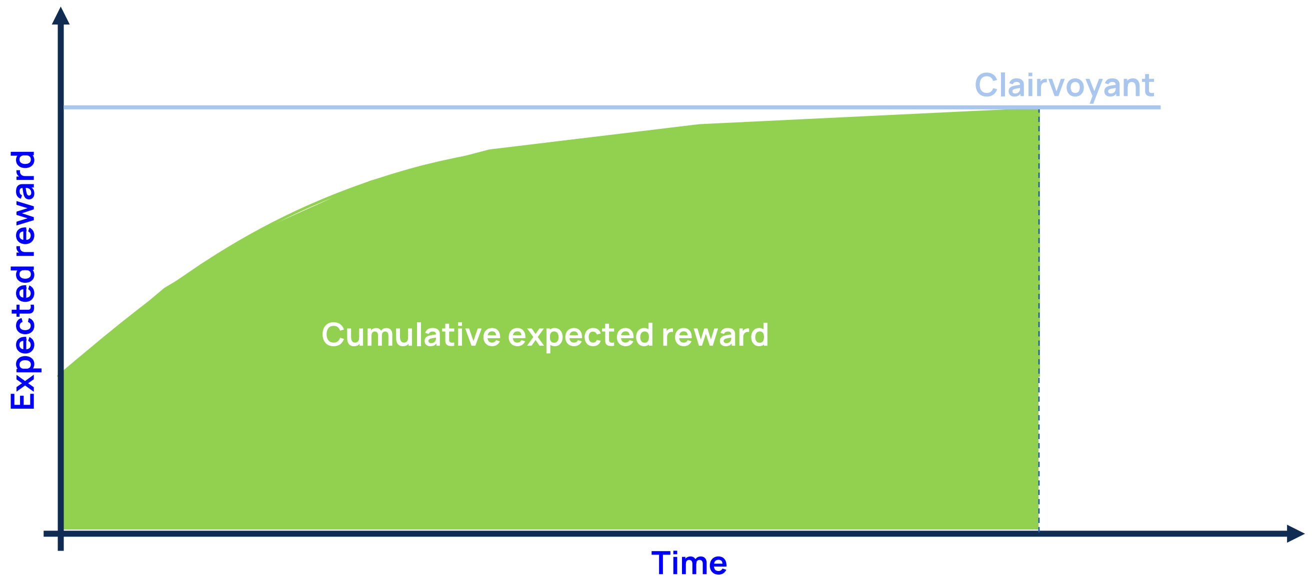
Performance comparison



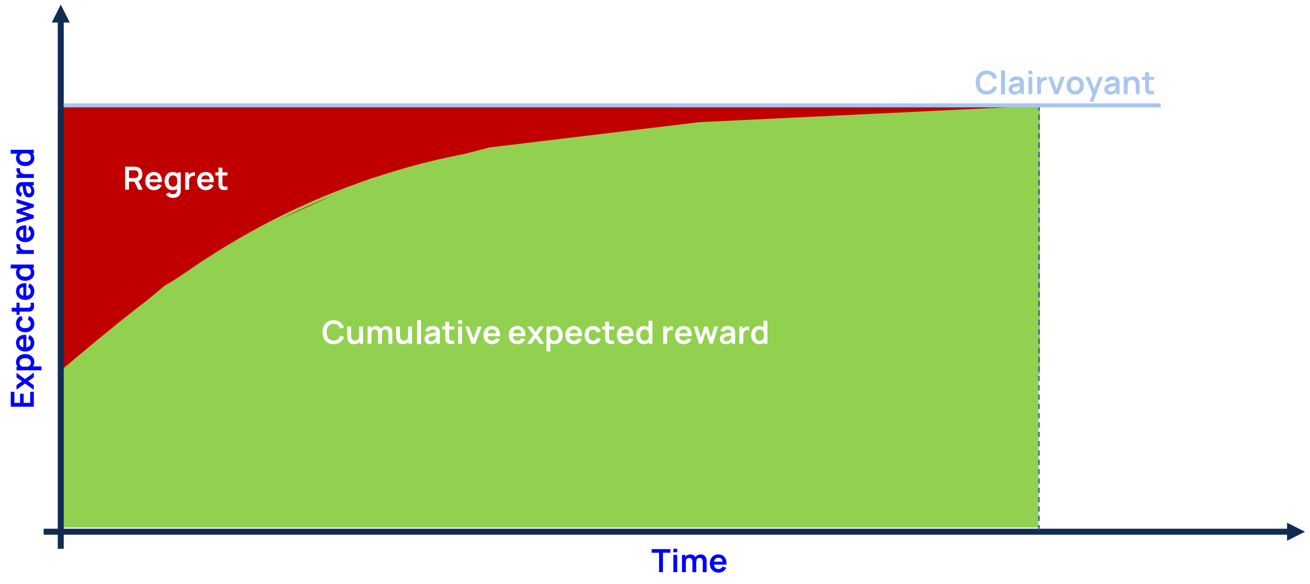
Scenarios: pricing for ecommerce



Scientific goal: regret minimization



Scientific goal: regret minimization



Offline vs. online learning

A/B/n testing (class of offline learning techniques)

- Collect a huge amount of data and then decide which candidate to play

Bandit (class of online learning techniques)

- At every given observed data decide the candidate to play

Some bandit algorithms

- UCB1
- UCB2
- UCBV
- KL-UCB
- Bayes-UCB
- Thompson Sampling

Some bandit algorithms

- All these algorithms are guaranteed to minimize the regret.

UCB1	UCB2
UCBV	KL-UCB
Bayes-UCB	Thompson Sampling

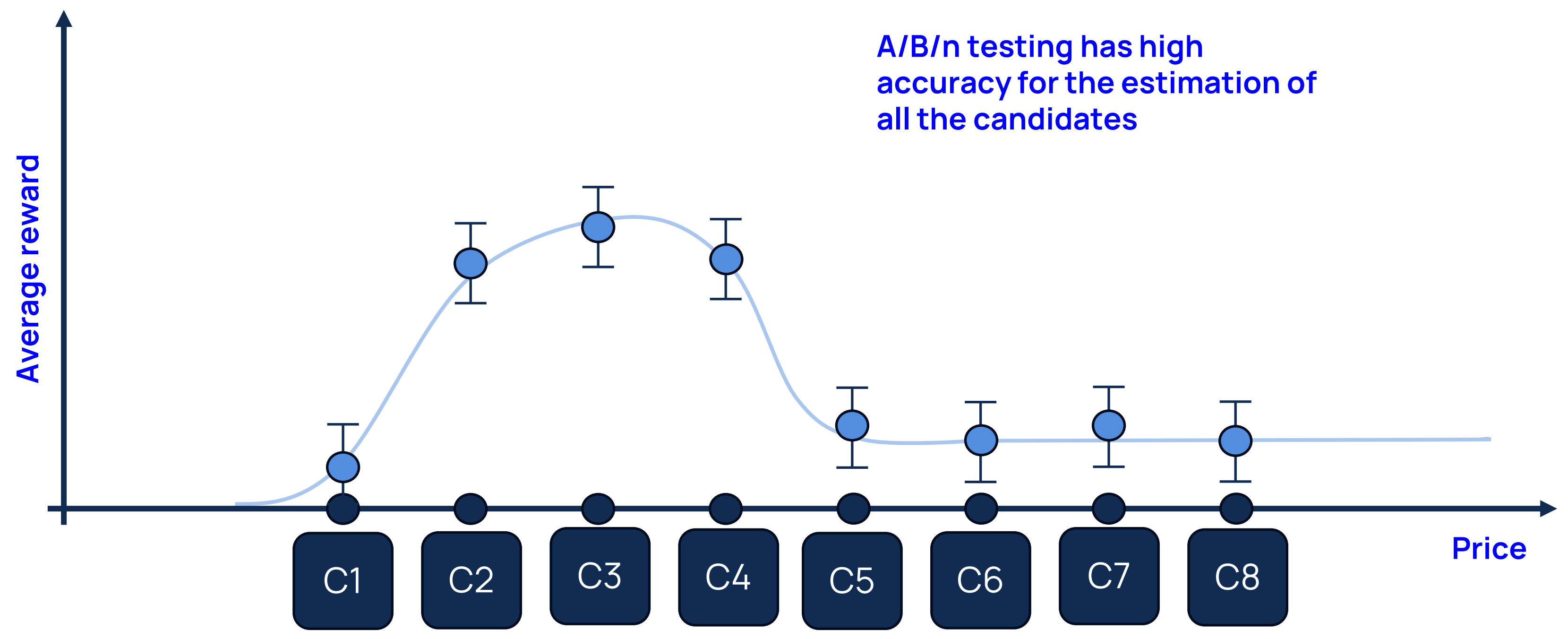
Some bandit algorithms

- All these algorithms are guaranteed to minimize the regret.
- These algorithms differ for empirical performance.

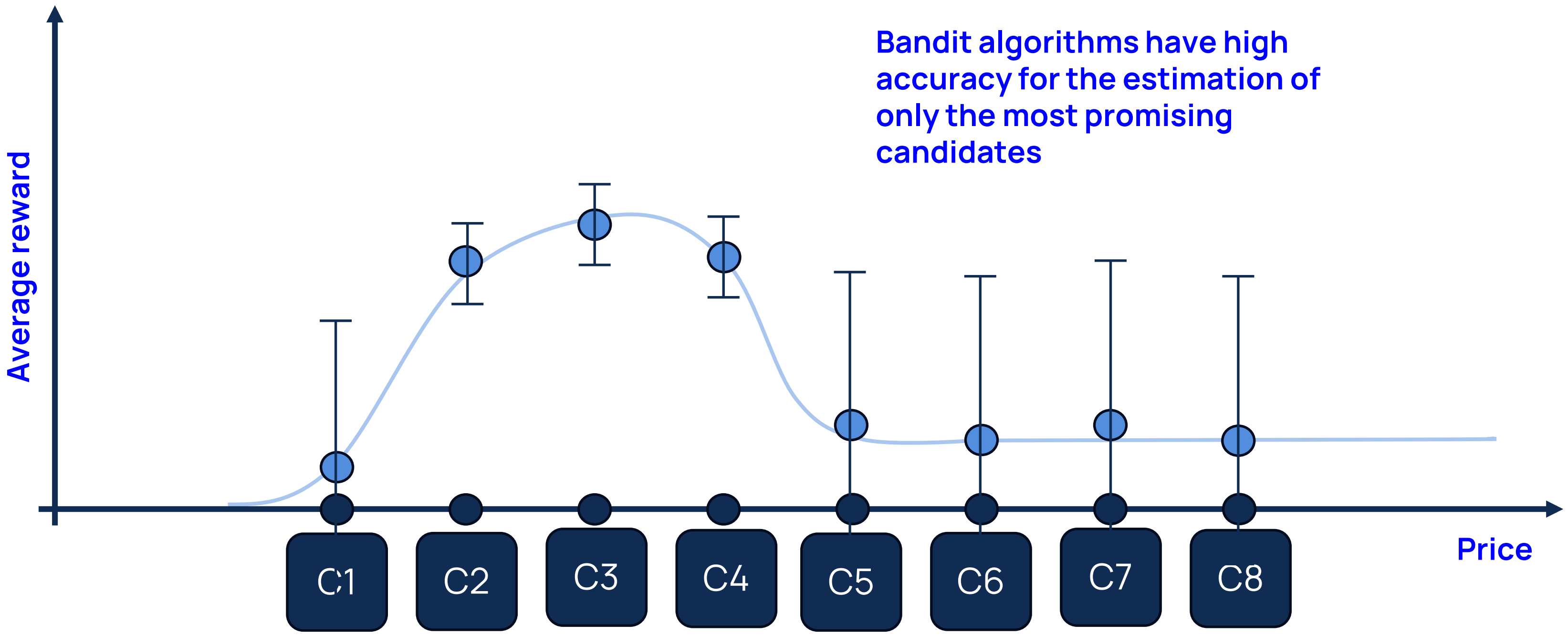
UCB1	UCB2
UCBV	KL-UCB
Bayes-UCB	Thompson Sampling

Why bandit?

A/B/n testing vs. bandit algorithms



A/B/n testing vs. bandit algorithms



Marketing mix modeling

… and food for thoughts on multichannel complementarity and cross effects

Complementarity and cross-effects in multichannel campaign: a new study

Source: Bell, J. J., Thomaz, F., & Stephen, A. T. (2024). EXPRESS: Beyond the Pair: Media Archetypes and Complex Channel Synergies in Advertising. Journal of Marketing. https://doi.org/10.1177/00222429241302808

Based on a large dataset from Kantar:

- 1083 advertising campaigns from 2008 to 2019
- From 557 global brands across 23 industries in 51 countries
- 11 media channels analized: TV, Outdoor, Online Display, Facebook, YouTube, Radio, Cinema, Magazines, Newspapers, Online Video, and Point of Sale.
- Average media-only spend of the U.S. campaigns in the dataset: US$ 12M
- Outcomes measured:
    - Motivation (purchase intent)
    - Association
    - Aided and Unaided Awareness

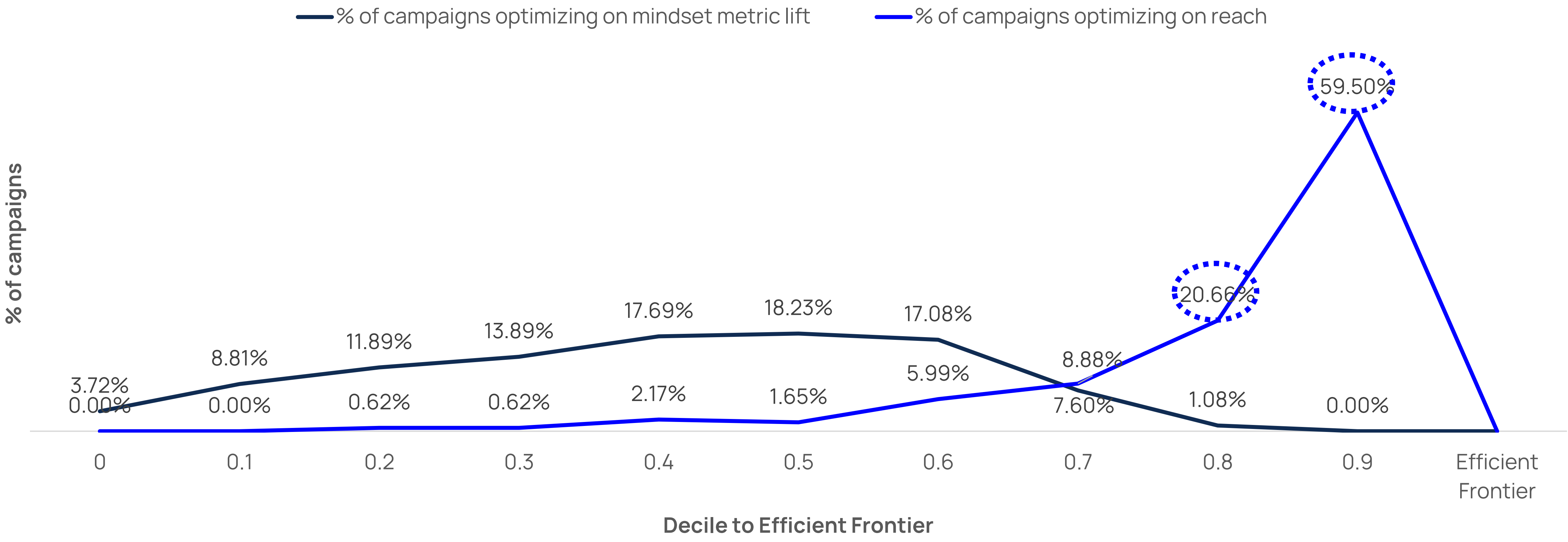
Beyond the Pair: Media Archetypes and Complex Channel Synergies in Advertising

Abstract

Prior research on advertising media mixes has mostly focused on single channels (e.g., television), pairwise cross-elasticities, or budget optimization within single campaigns. This is starkly detached from advertising practice where (i) there is an increasingly large number of media channels available to marketers, (ii) media plans employ complex combinations of channels, and (iii) marketers manage complementarities among many (i.e., more than pairs) channels. This research empirically learns complex channel complementaries using Latent Class analysis. Latent classes have three useful properties: (i) they account for non-random selection of channels into campaigns, (ii) they capture pairwise and higher-order interactions between channels, and (iii) they allow for meaningful interpretation. We empirically describe the most common media channel archetypes and estimate their relationship to the effectiveness of a set advertising campaigns on a set of common brand-related performance metrics. We use a dataset of 1,083 advertising campaigns from around the world run between 2008 and 2019. We find that there is not a systematically "best" media mix that correlates to dominant performance across all metrics, but clear patterns emerge given specific metrics. We find that traditional channels (TV, outdoor) are commonly paired with digital channels (Facebook, YouTube) in high-performing campaigns. We also find that current marketing practice appears far from optimal, and simple strategies have the potential to increase brand mindset metric lifts by 50% or more.

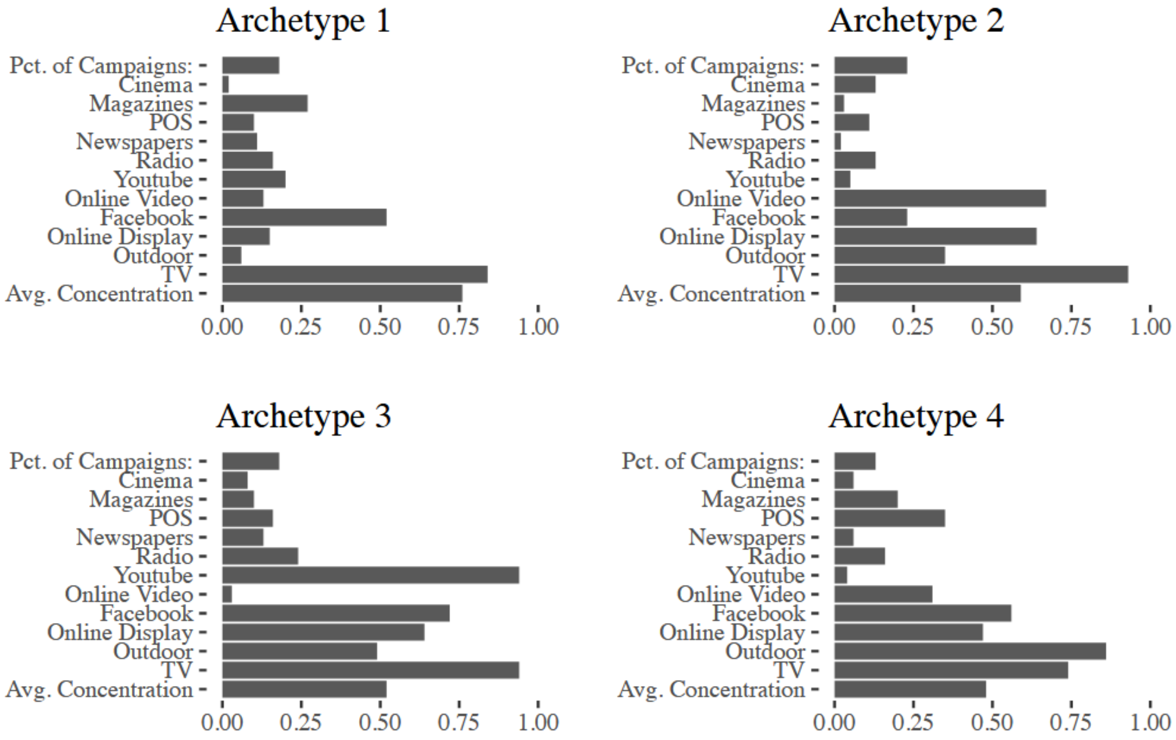
Keywords:
advertising, media planning, media complementarity, budget allocation, leading indicators

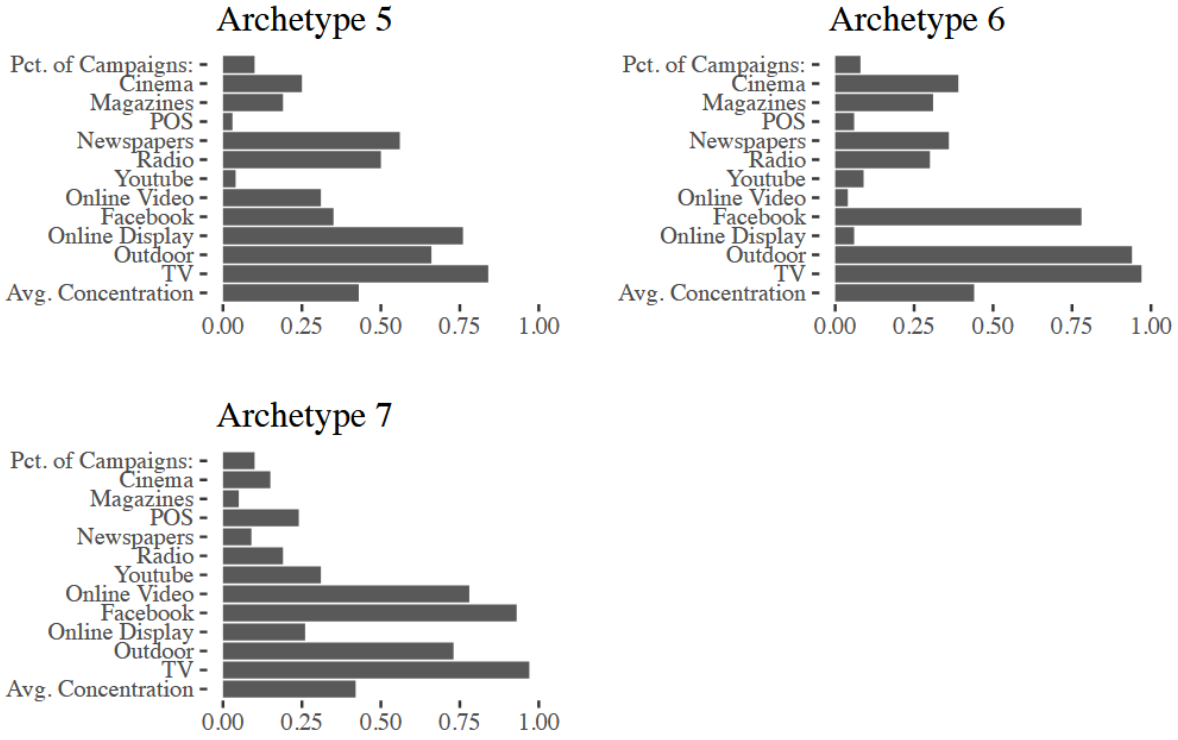
Campaigns are most often optimized on reach instead of other mindset metrics (purchase intent, association, recall)



Source: Bell, J. J., Thomaz, F., & Stephen, A. T. (2024). EXPRESS: Beyond the Pair: Media Archetypes and Complex Channel Synergies in Advertising. *Journal of Marketing*. https://doi.org/10.1177/00222429241302808

Archetypes of campaigns

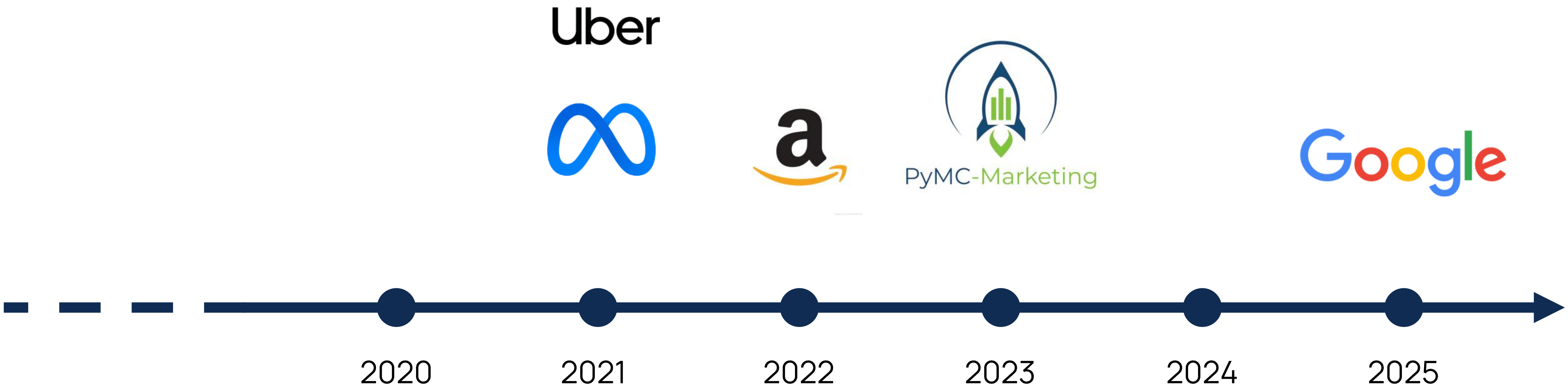




Google Meridian Demo

03

Trending in marketing-land: open-source marketing mix models



How did the marketing channels drive my revenue?

What was my marketing ROI?

How do I optimize my marketing budget allocation for the future?

Meridian model’s key features

- Based on **Bayesian causal inference**.
- Hierarchical **geo-level modeling** giving you more information compared to national-level data.
- Integration of **prior knowledge** about media performance using ROI priors. Can be derived from past experiments, past MMM results, domain knowledge (expertise), or industry benchmark.
    - You can control the degree to which priors influence the posterior distribution.
- Accounting for **media saturation and lagged effects**, which are hard to capture with linear regression.
    - Saturation is modelled using a Hill function, which captures diminishing marginal returns.
    - Lagged effects are modelled using an Adstock function with geometric decay.
- Optional use of **reach and frequency** to better predict how each media channel might perform with a change in spending.
- **Modeling lower funnel channels** such as paid search using Google Query Volume as a control variable.
- Optional inclusion of **non-media treatment variables** such as changes to price and promotions to estimate the effectiveness of non-media marketing actions.

Rule-of-thumb data requirements

At least 50 geo-level subdivisions

2-3 years of weekly data

Multiple channels

Meridian’s Bayesian Regression Model

Bayesian modeling is not necessary for causal inference. It is applied in Meridian for the following reasons:

- Bayesian priors provide a structured way to guide parameter estimation based on prior knowledge and the chosen level of regularization. Regularization is essential in MMM due to the high number of variables, strong correlations, and the complexity of media effects like adstock and diminishing returns.

- Meridian allows regression models to be **reparameterized in terms of ROI**, enabling the use of custom ROI priors. Any available insights, such as experimental data, can inform priors, ensuring results align with known expectations at a chosen confidence level.

- Since **media transformations are nonlinear** (e.g., adstock, diminishing returns) and cannot be estimated with linear mixed models, Meridian leverages advanced MCMC sampling to accurately estimate these effects.

Bayesian Modeling & MCMC

- Bayes' Theorem: Combines prior knowledge with data-driven insights to estimate media effects and quantify uncertainty.
  - **Prior** – What we believe before seeing the data.
  - **Likelihood** – How well the data supports different beliefs.
  - **Posterior** – Our updated belief after seeing the data.
- Priors and likelihood: The model uses hierarchical regression likelihoods and customizable priors to reflect beliefs about marketing channel effects.
- Markov Chain Monte Carlo (MCMC) convergence: Uses No U-Turn Sampler (NUTS) to generate posterior distributions; convergence is assessed via R-hat values.

Input data

mandatory

By geo

By week

KPI	Paid media	Organic media	Non-media treatments	Controls	Population
Preferably revenue	Impression Spend [reach] [frequency]	Impression [reach] [frequency]	Non-media treatments	Confounding variables or strong predictors of the KPI	Population size of each geo

Model specifications

You can change some aspects of the model specification:

- Media saturation and lagging
- Reach and frequency
- Paid search (with control variable SQV)
- ROI and default priors

Documentation: https://developers.google.com/meridian/docs/basics/model-spec

$$
\begin{aligned}
y_{g,t} = \mu_t + \tau_g &+ \sum_{i=1}^{N_C} \gamma_{g,i}^{[C]} z_{g,t,i} \\
&+ \sum_{i=1}^{N_N} \gamma_{g,i}^{[N]} x_{g,t,i}^{[N]} \\
&+ \sum_{i=1}^{N_M} \beta_{g,i}^{[M]} \boxed{HillAdstock}\left(\left\{ x_{g,t-s,i}^{[M]} \right\}_{s=0}^{L} ;\ \alpha_i^{[M]}, ec_i^{[M]},\ slope_i^{[M]} \right) \\
&+ \sum_{i=1}^{N_{OM}} \beta_{g,i}^{[OM]} \boxed{HillAdstock}\left(\left\{ x_{g,t-s,i}^{[OM]} \right\}_{s=0}^{L} ;\ \alpha_i^{[OM]}, ec_i^{[OM]},\ slope_i^{[OM]} \right) \\
&+ \sum_{i=1}^{N_{RF}} \beta_{g,i}^{[RF]} \boxed{Adstock}\left(\left\{ r_{g,t-s,i}^{[RF]} \cdot Hill\left(f_{g,t-s,i}^{[RF]};\ ec_i^{[RF]},\ slope_i^{[RF]} \right) \right\}_{s=0}^{L} ;\ \alpha_i^{[RF]} \right) \\
&+ \sum_{i=1}^{N_{ORF}} \beta_{g,i}^{[ORF]} \boxed{Adstock}\left(\left\{ r_{g,t-s,i}^{[ORF]} \cdot Hill\left(f_{g,t-s,i}^{[ORF]};\ ec_i^{[ORF]},\ slope_i^{[ORF]} \right) \right\}_{s=0}^{L} ;\ \alpha_i^{[ORF]} \right) \\
&+ \epsilon_{g,t}
\end{aligned}
$$

Time-varying intercepts that contribute a trend and seasonality component

Hill() and Adstock() functions for media saturation and lagging.

Main steps

0. Install
1. Load the data
2. Configure the model
3. Run model diagnostics
4. Generate model results
5. Run budget optimization
6. Save the model object

Demo: https://developers.google.com/meridian/notebook/meridian-getting-started (select Run in Google Colab)

0. Install

- Make sure you are using one of the available GPU Colab runtimes which is required to run Meridian. You can change your notebook's runtime in Runtime > Change runtime type in the menu.
- All users can use the T4 GPU runtime which is sufficient to run the demo colab, free of charge. Users who have purchased one of Colab's paid plans have access to premium GPUs (such as V100, A100 or L4 Nvidia GPU).
- Prerequisites and system recommendations:
  - Python 3.11 or 3.12 is required to use Meridian.
  - Using a minimum of 1 GPU (recommended).

```
# Install meridian: from PyPI @ latest release
pip install --upgrade google-meridian[colab,and-cuda]

# Install meridian: from PyPI @ specific version
# !pip install google-meridian[colab,and-cuda]==1.0.3

# Install meridian: from GitHub @HEAD
# !pip install --upgrade "google-meridian[colab,and-cuda] @
git+https://github.com/google/meridian.git"
```

0. Install

- Install the latest version of Meridian, and verify that GPU is available.
- Uses the TensorFlow Probability experimental MCMC package.

```
import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow_probability as tfp
import arviz as az

import IPython

from meridian import constants
from meridian.data import load
from meridian.data import test_utils
from meridian.model import model
from meridian.model import spec
from meridian.model import prior_distribution
from meridian.analysis import optimizer
from meridian.analysis import analyzer
from meridian.analysis import visualizer
from meridian.analysis import summarizer
from meridian.analysis import formatter

# check if GPU is available
from psutil import virtual_memory
ram_gb = virtual_memory().total / 1e9
print('Your runtime has {:.1f} gigabytes of available RAM\n'.format(ram_gb))
print("Num GPUs Available: ",
len(tf.config.experimental.list_physical_devices('GPU')))
print("Num CPUs Available: ",
len(tf.config.experimental.list_physical_devices('CPU')))
```

1. Load the data

Supported data types and formats

Geo-level data without reach and frequency

Geo-level data with reach and frequency

Geo-level data with organic media and non-media treatments

National data

1. Load the data
Differences between the types of input variables

Input variable	Cost	Adstock/Hill	Intervenable	Effect (% Contribution)
Media	x	x	x	x
Non-media			x	x
Organic media		x	x	x
Controls				

1. Load the data

Collect and organize your data – example of geo-level without reach or frequency

Data type	Description
Media data	Contains the exposure metric by channel, geo, and time period. This can be impressions, clicks, or any other unit similar unit. Media values must not contain negative values.
Media spend	Containing the media spending per channel, geo and time period. The media data and media spend must have the same dimensions.
Control variables	Contains the confounders that have a causal effect on both the target KPI and the media metric (such as Google query volume (GQV)). The selection of control variables is important for estimating the causal effect from an MMM.
KPI	The target KPI for the model to predict. For example, revenue amount or number of application installations. This is also the response variable of the MMM.
Revenue per KPI	Only required if your KPI is not revenue. Contains the average revenue for a KPI unit. In the absence of accurate revenue per KPI, it is recommended to approximate a rational value. If such information is unavailable, see Value of the KPI is unknown.
Geo population	Contains the population for each geo. Geo population (such as Nielsen DMA TV household population) is used to scale the media metric to put all geos on a comparable scale, see Input data for more details about media scaling.

2. Configure the model
Initialize the Meridian class

- Meridian uses Bayesian framework and Markov Chain Monte Carlo (MCMC) algorithms to sample from the posterior distribution.
- Initialize the Meridian class by passing the loaded data and the customized model specification. One advantage of Meridian lies in its capacity to calibrate the model directly through ROI priors
  - In this particular example, the ROI priors for all media channels are identical, with each being represented as Lognormal(0.2, 0.9).

```
roi_mu = 0.2     # Mu for ROI prior for each media channel.
roi_sigma = 0.9  # Sigma for ROI prior for each media channel.
prior = prior_distribution.PriorDistribution(
    roi_m=tfp.distributions.LogNormal(roi_mu, roi_sigma, name=constants.ROI_M)
)
model_spec = spec.ModelSpec(prior=prior)

mmm = model.Meridian(input_data=data, model_spec=model_spec)
```

1. Load the data
A look at the demo dataset

		Media data					Media spend					control variables		KPI	Revenue per KPI	Geo population		
geo	time	Channel0_	Channel1_	Channel2_	Channel3_	Channel4_	Channel0_	Channel1_	Channel2_	Channel3_	Channel4_	Competitor_Sales	GQV	conversior	revenue_per_conversion	population	Organic_cl	Promo
Geo0	25/01/2021	280668	0	0	470611	108010	2058.061	0	0	3667.397	841.6044	-1.3387649	0.11558147	1954577	0.020054754	136670.94	97320	0
Geo0	01/02/2021	366206	182108	19825	527702	252506	2685.287	1755.745	147.3181	4112.297	1967.504	0.8936449	0.9442244	2064250	0.02010317	136670.94	201441	0
Geo0	08/02/2021	197565	230170	0	393618	184061	1448.69	2219.122	0	3067.402	1434.187	-0.28454947	-1.290579	2086383	0.019928792	136670.94	0	0.683819
Geo0	15/02/2021	140990	66643	0	326034	201729	1033.841	642.5206	0	2540.731	1571.855	-1.0347397	-1.0845139	2826432	0.019987345	136670.94	0	1.289055
Geo0	22/02/2021	399116	164991	0	381982	153973	2926.607	1590.716	0	2976.725	1199.744	-0.3192759	-0.017502785	3551929	0.02000035	136670.94	0	0.227739
Geo0	01/03/2021	219462	149254	0	417941	41573	1609.254	1438.992	0	3256.948	323.9332	-0.65269506	-0.30211386	2241229	0.02014213	136670.94	0	0
Geo0	08/03/2021	39715	52062	273250	662155	381411	291.2191	501.9418	2030.5	5160.068	2971.921	1.4276155	-0.23733935	2553928	0.020031057	136670.94	0	0
Geo0	15/03/2021	114458	230897	122797	423700	229769	839.2888	2226.132	912.4952	3301.826	1790.34	0.45791247	0.8655758	2218997	0.020035092	136670.94	88088	0
Geo0	22/03/2021	235989	256233	0	413992	359812	1730.442	2470.402	0	3226.174	2803.623	0.89351004	-0.80686784	2322240	0.020043833	136670.94	334506	1.465963
Geo0	29/03/2021	428627	0	280553	501091	341979	3143.003	0	2084.768	3904.922	2664.67	0.520105	-0.24917367	2363708	0.019865984	136670.94	0	0.973131
Geo0	05/04/2021	221340	143848	0	397356	33530	1623.025	1386.872	0	3096.532	261.2628	-0.8563197	0.050081678	2229579	0.019946404	136670.94	46898	0
Geo0	12/04/2021	391678	50750	0	722273	171367	2872.066	489.2925	0	5628.559	1335.277	-1.4528581	1.5585525	3524765	0.019867629	136670.94	228913	1.627971
Geo0	19/04/2021	244001	0	0	329811	207582	1789.192	0	0	2570.165	1617.461	-1.9642203	-0.59979314	3347290	0.019929865	136670.94	140779	0.66907
Geo0	26/04/2021	205575	38204	0	397778	0	1507.425	368.3336	0	3099.821	0	-0.6964144	-1.240535	2779414	0.019973803	136670.94	0	0.55688
Geo0	03/05/2021	90953	0	0	78105	447455	666.9332	0	0	608.6598	3486.53	-1.5696856	-2.3092334	2335400	0.020143956	136670.94	0	1.265783
Geo0	10/05/2021	155015	289612	0	475510	254598	1136.682	2792.216	0	3705.574	1983.805	1.1948755	-1.364184	2429740	0.02005313	136670.94	0	0
Geo0	17/05/2021	139836	184700	0	277029	74744	1025.379	1780.736	0	2158.843	582.3986	-0.12523502	-0.71586806	4339777	0.020103911	136670.94	10126	0
Geo0	24/05/2021	388037	147001	0	92359	121726	2845.368	1417.271	0	719.739	948.4783	-0.4660951	-0.9799271	3068357	0.019971617	136670.94	0	0
Geo0	31/05/2021	0	491676	160928	801735	331396	0	4740.362	1195.844	6247.793	2582.208	0.1384334	1.8121941	2179793	0.019968163	136670.94	117413	0
Geo0	07/06/2021	221746	58085	0	628365	134211	1626.002	560.0109	0	4896.748	1045.76	0.36252737	0.016913712	1972933	0.020036265	136670.94	172884	0.234715
Geo0	14/06/2021	522698	53047	10339	800459	393926	3832.8	511.4384	76.82833	6237.85	3069.437	1.5063099	1.1276338	1048367	0.019912552	136670.94	330830	0
Geo0	21/06/2021	31481	111302	0	0	20292	230.8415	1073.088	0	0	158.1135	-1.636292	-0.27724043	3893564	0.019935414	136670.94	0	0
Geo0	28/06/2021	124951	98741	0	426485	344246	916.2311	951.9848	0	3323.53	2682.335	1.9607203	-1.8176672	1130191	0.020028308	136670.94	113464	0.158661
Geo0	05/07/2021	0	28473	0	416725	356255	0	274.5148	0	3247.471	2775.908	0.76883364	-1.5893306	1630339	0.020078905	136670.94	172538	0.843826
Geo0	12/07/2021	202855	208509	0	343028	111658	1487.48	2010.283	0	2673.163	870.0292	-0.20756881	0.14665473	1636970	0.019916069	136670.94	0	0
Geo0	19/07/2021	0	0	0	194185	0	0	0	0	1513.253	0	-2.278555	-0.76092386	2052384	0.02014443	136670.94	0	0.229254
Geo0	26/07/2021	0	188866	188847	551956	457125	0	1820.901	1403.308	4301.305	3561.877	1.6827729	-0.33497372	1971319	0.019972587	136670.94	476514	0
Geo0	02/08/2021	82595	246895	111412	144402	239598	605.6462	2380.372	827.8941	1125.302	1866.926	-0.6259522	-0.23797643	2183971	0.019968498	136670.94	34179	1.41145

1. Load the data

Mapping the column names with the corresponding variable types

- For example, the column names 'GQV' and 'Competitor_Sales' are mapped to controls.
- The required variable types are ‘time’, ‘controls’, ‘population’, ‘kpi’, ‘revenue_per_kpi’, ‘media’ and ‘spend’.
- If your data includes organic media or non-media treatments, you can add them using ‘organic_media’ and ‘non_media_treatments’ arguments.

```
coord_to_columns = load.CoordToColumns(
    time='time',
    geo='geo',
    controls=['GQV', 'Competitor_Sales'],
    population='population',
    kpi='conversions',
    revenue_per_kpi='revenue_per_conversion',
    media=[
        'Channel0_impression',
        'Channel1_impression',
        'Channel2_impression',
        'Channel3_impression',
        'Channel4_impression',
    ],
    media_spend=[
        'Channel0_spend',
        'Channel1_spend',
        'Channel2_spend',
        'Channel3_spend',
        'Channel4_spend',
    ],
    organic_media=['Organic_channel0_impression'],
    non_media_treatments=['Promo'],
)
```

1. Load the data
Mapping the channel names

- Map the media variables and the media spends to the designated channel names intended for display in the two-page HTML output.
    - In the following example, 'Channel0_impression' and 'Channel0_spend' are connected to the same channel, 'Channel0'.

```
correct_media_to_channel = {
    'Channel0_impression': 'Channel_0',
    'Channel1_impression': 'Channel_1',
    'Channel2_impression': 'Channel_2',
    'Channel3_impression': 'Channel_3',
    'Channel4_impression': 'Channel_4',
}
correct_media_spend_to_channel = {
    'Channel0_spend': 'Channel_0',
    'Channel1_spend': 'Channel_1',
    'Channel2_spend': 'Channel_2',
    'Channel3_spend': 'Channel_3',
    'Channel4_spend': 'Channel_4',
}
```

1. Load the data
Load the CSV file

- Load the CSV data using CsvDataLoader. Note that csv_path is the path to the data file location.
    - In this case, the file used is geo_all_channels.csv
- Note that the simulated data here does not contain reach and frequency. It is recommended to include reach and frequency data whenever they are available.

```
loader = load.CsvDataLoader(

 csv_path="https://raw.githubusercontent.com/google/meridian/refs/heads/main/meridian/data/simulated_data/csv/geo_all_channels.csv",
    kpi_type='non_revenue',
    coord_to_columns=coord_to_columns,
    media_to_channel=correct_media_to_channel,
    media_spend_to_channel=correct_media_spend_to_channel,
)
data = loader.load()
```

2. Configure the model

Initialize the Meridian class

- Use the sample_prior() and sample_posterior() methods to obtain samples from the prior and posterior distributions of model parameters.
  - If you are using the T4 GPU runtime this step may take about 10 minutes for the provided data set.

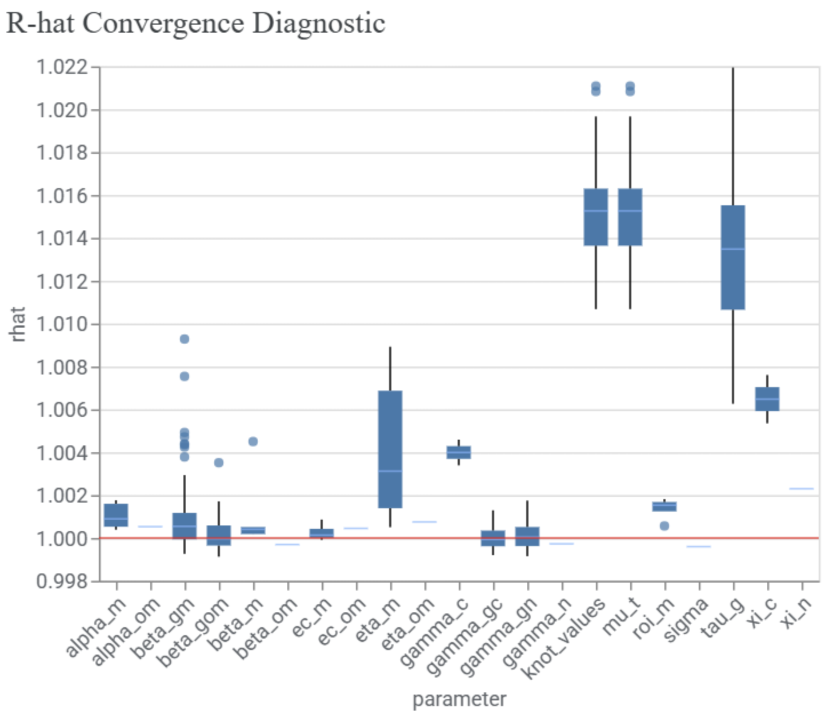
- The Meridian model uses a holistic MCMC samplic approach called No U Turn Sampler (NUTS).
  - Mathematical details and derivations can be found in Hoffman & Gelman, 2011 and Betancourt, 2018.

```
%%time
mmm.sample_prior(500)
mmm.sample_posterior(n_chains=7, n_adapt=500, n_burnin=500, n_keep=1000)
```

Step 3: Run model diagnostics
Assess convergence

- You assess the model convergence to help ensure the integrity of your model.
- Run the following code to generate r-hat statistics. R-hat close to 1.0 indicate convergence. R-hat < 1.2 indicates approximate convergence and is a reasonable threshold for many problems.
  - Refer to Gelman & Rubin, 1992 for more details.

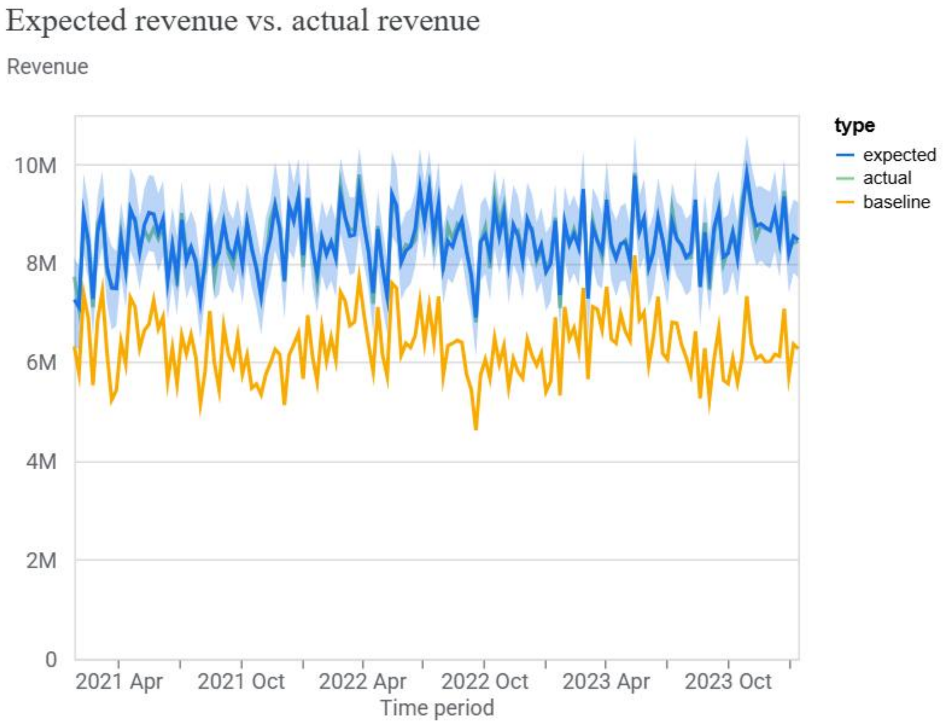
```
model_diagnostics = visualizer.ModelDiagnostics(mmm)
model_diagnostics.plot_rhat_boxplot()
```



Step 3: Run model diagnostics
Assess the model's fit

- Assess the model's fit by comparing the expected sales against the actual sales.

```
model_fit = visualizer.ModelFit(mmm)
model_fit.plot_model_fit()
```



4. Generate model results

Summary file has four components

- Model fit
- Channel contribution
- Return on investment
- Response curves

summary_output.html

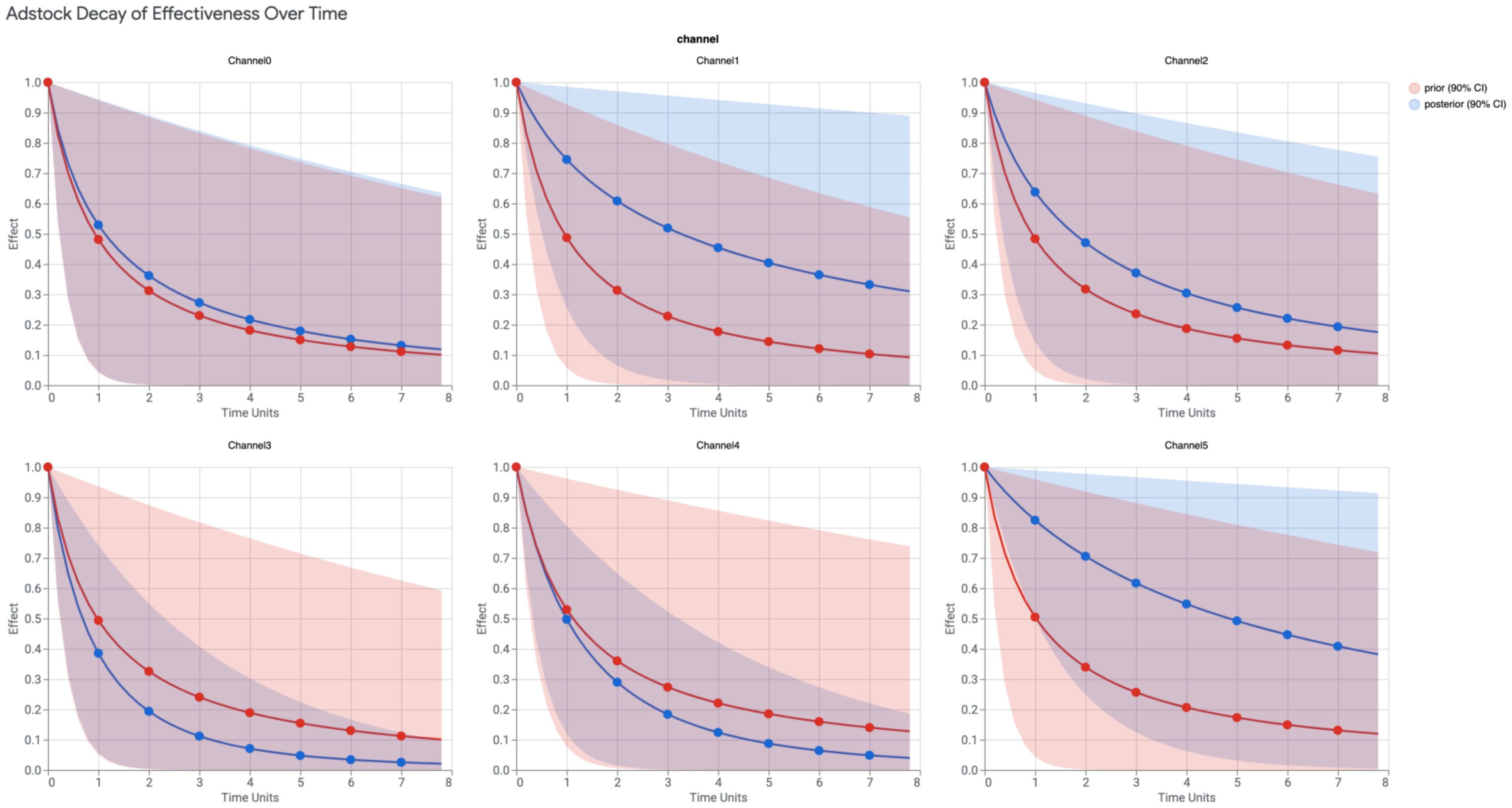
```
mmm_summarizer = summarizer.Summarizer(mmm)
```

```
from google.colab import drive
drive.mount('/content/drive')
```

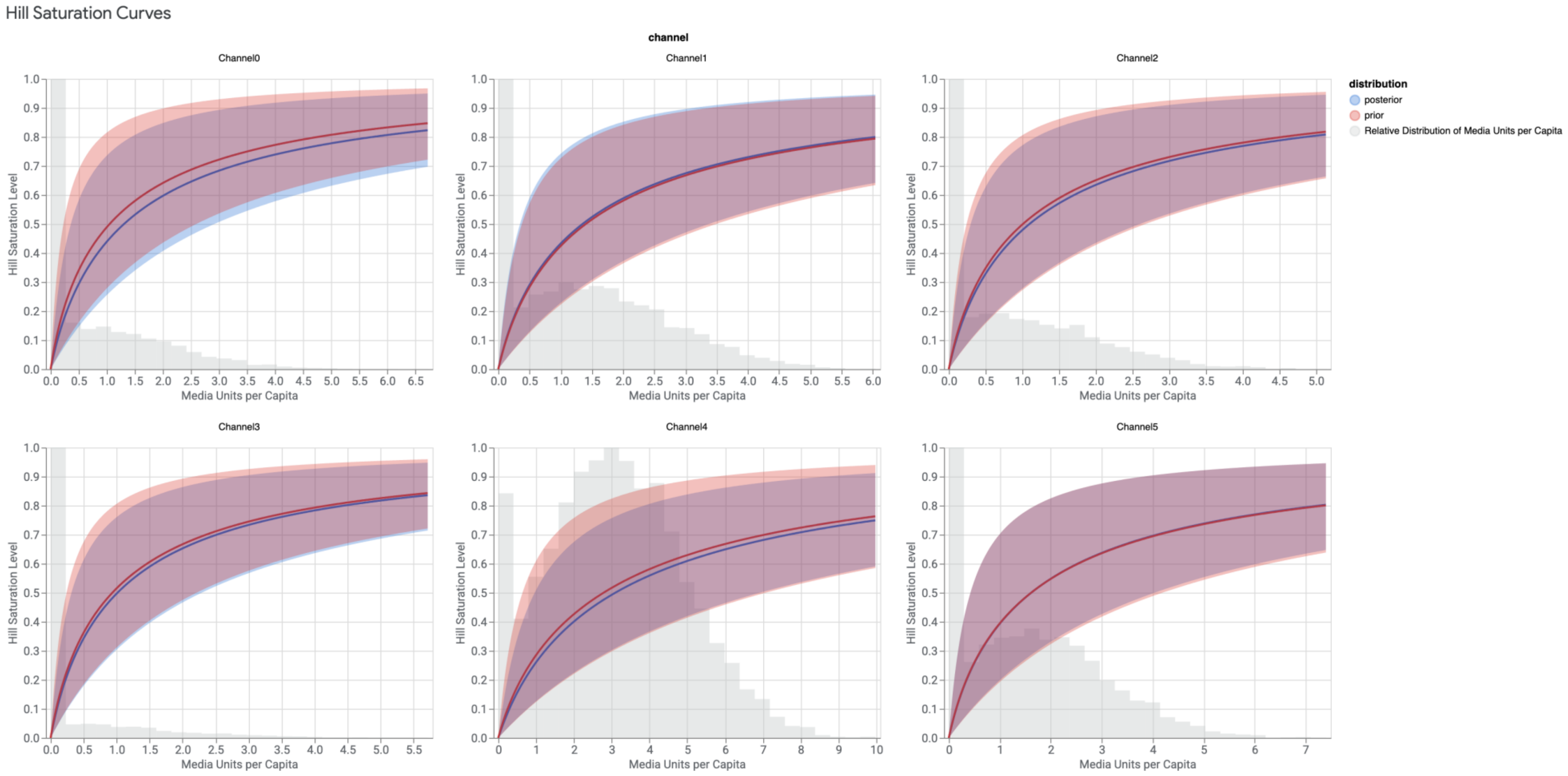
```
filepath = '/content/drive/MyDrive'
start_date = '2021-01-25'
end_date = '2024-01-15'
mmm_summarizer.output_model_results_summary('summary_output.html', filepath,
start_date, end_date)
```

```
IPython.display.HTML(filename='/content/drive/MyDrive/summary_output.html')
```

Adstock decay curves



Hill saturation curves



5. Run budget optimization

You can choose what scenario to run for the budget allocation. In default scenario, you find the optimal allocation across channels for a given budget to maximize the return on investment (ROI).

```
%%time
budget_optimizer = optimizer.BudgetOptimizer(mmm)
optimization_results = budget_optimizer.optimize()
```

Instantiate the BudgetOptimizer class and run the optimize() method without any customization, to run the default library's Fixed Budget Scenario to maximize ROI.

```
filepath = '/content/drive/MyDrive'
optimization_results.output_optimization_summary('optimization_output.html',
filepath)
```

Optimization file has three elements:

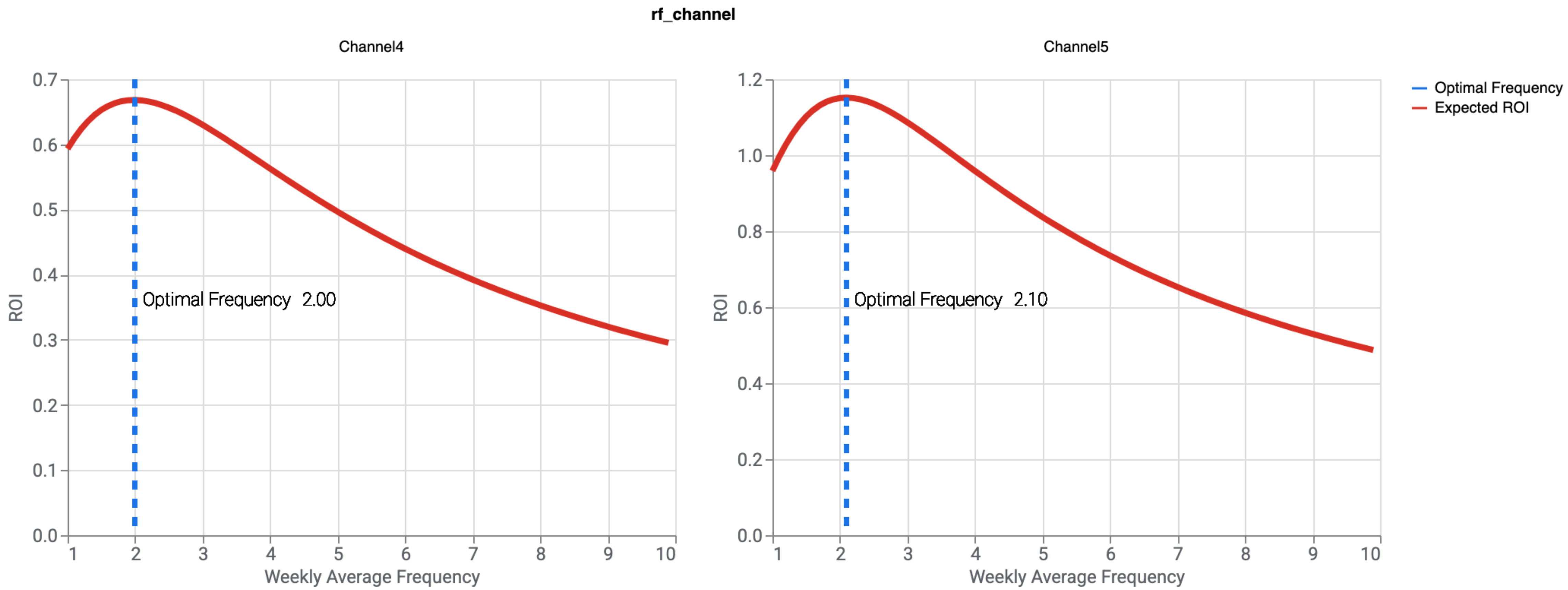
- Optimization scenario
- Recommended budget allocation
- Response curves with optimized spend

```
IPython.display.HTML(filename='/content/drive/MyDrive/optimization_output.html
')
```

optimization_output.html

Optimal frequency

Return on investment by weekly average frequency



6. Save the model object

- We recommend that you save the model object for future use. This helps you to avoid repetitive model runs and saves time and computational resources. After the model object is saved, you can load it at a later stage to continue the analysis or visualizations without having to re-run the model.

- Run the first snippet to save the model object.

- Run the second snippet to load the saved model.

```
file_path='/content/drive/MyDrive/saved_mmm.pkl'
model.save_mmm(mmm, file_path)
```

```
mmm = model.load_mmm(file_path)
```

Exercise: your turn to try the MMM demo

04

Compare different open-source MMM

- In groups of 4-5
- Retrieve the dataset used in the demo and start with some basic Exploratory Data Analysis (EDA).
- Run the Meridian demo in Google Colab
    - Try also the version with reach and frequency
- Read the documentation, in particular these sections:
    - Rationale-for-causal-inference-and-bayesian-modeling
    - ROI and mROI parameterization
    - Media saturation and lagging
    - Holdout observations
    - Causal estimands and estimation
- Identify the assumptions that must be met for causality
- Try alternative open-source models

References

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Thank you for your attention.