Marketing Mix Modeling (MMM) in the Age of Privacy Concerns

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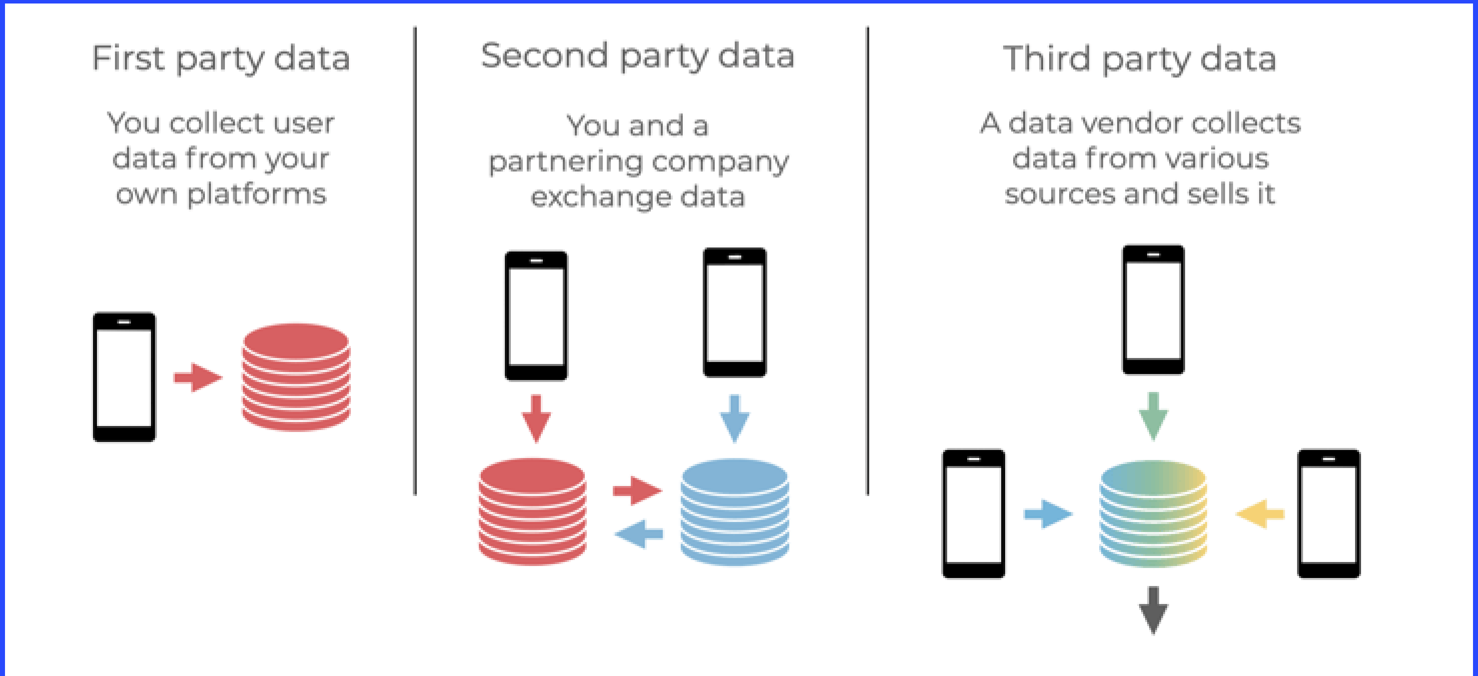
Marketing and Privacy Jokes

- What does the new Chips Ahoy Marketing Director do on her first day at work?
- Enable cookies
- What’s a social media marketer’s favorite snack?
- InstaGraham crackers
- Why am I unable to lose weight after visiting several fitness websites?
- Because I keep accepting their cookies

Introduction and Context

- Privacy regulations like GDPR and CCPA are reshaping marketing analytics
- Third-party cookies are being phased out, limiting digital attribution
- Marketing Mix Modeling (MMM) is making a comeback as a privacy-first solution



Demise of Third-Party Cookies

- Google Chrome is phasing out third-party cookies through Privacy Sandbox initiative, with full deprecation planned for 2025
- Apple’s Intelligent Tracking Protection (ITP) limits third-party cookie tracking lifespans
- Apple’s App Tracking Transparency (ATT) requires user opt-in for mobile ad IDs
- Many privacy laws now restrict cross-site tracking, reducing digital attribution accuracy

Impact on Marketing Analytics

- User-level tracking (multi-touch attribution) is becoming obsolete
- Companies must shift to privacy-friendly models like MMM
- Marketing analytics must adapt to new regulations and limitations

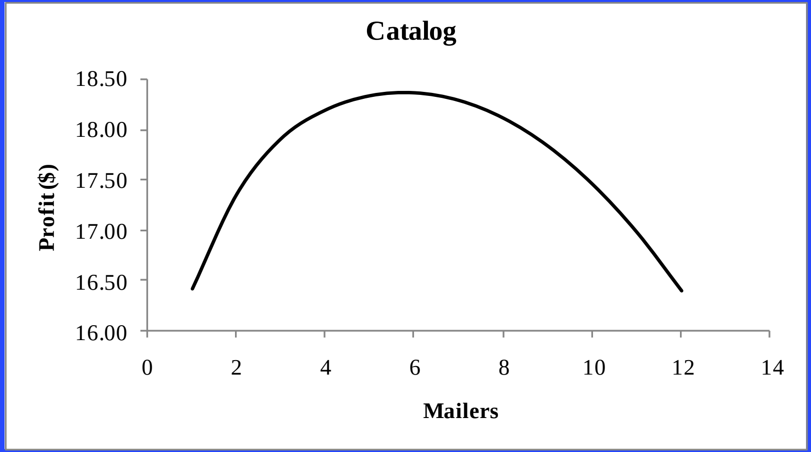
What is Marketing Mix Modeling (MMM)?

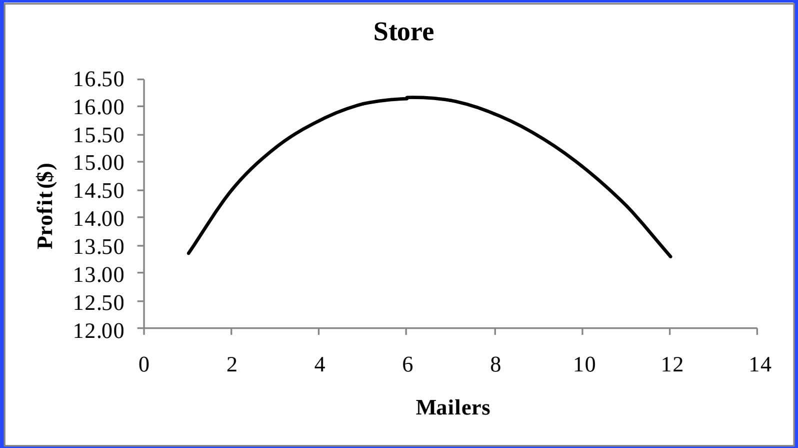
- A statistical/econometric/machine learning/optimization-based approach to measure marketing effectiveness across multiple channels
- Uses aggregate, historical data (not user-level)
- Estimates ROI on marketing spend without violating privacy laws

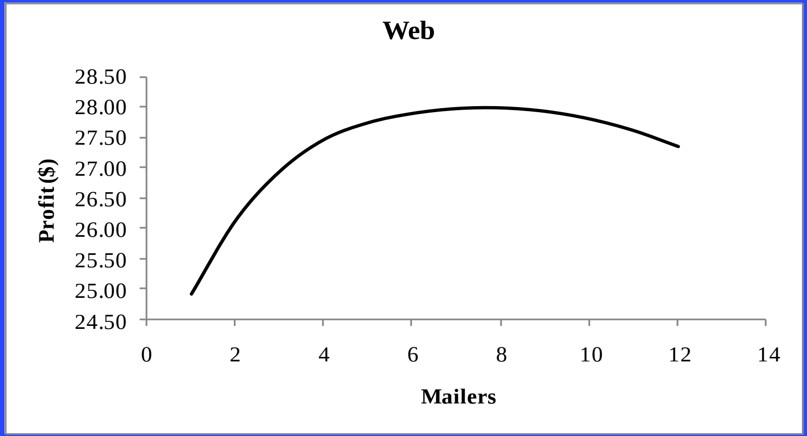
MMM1.0: Rules of Marketing Mix Allocation

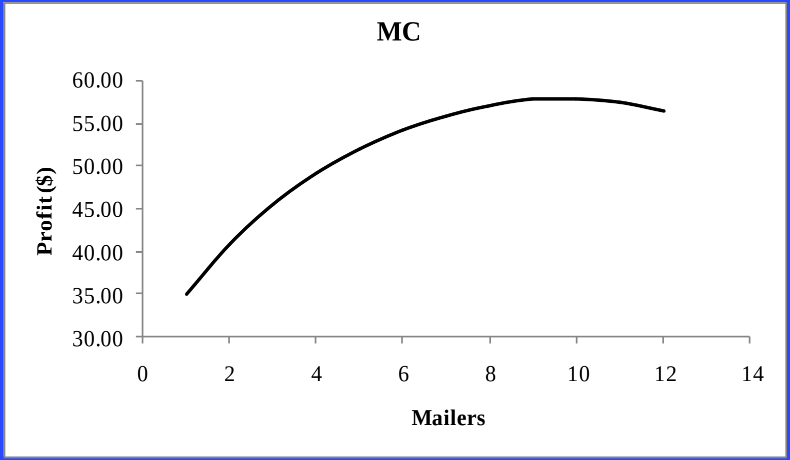
- Advertising and Sales Force
  - Allocate according to the ratio of elasticities (Gatignon and Hanssens 1987)
  - Allocate according to relative competitive ratio of elasticities (Shankar 1997)
- Advertising and Sales Promotion
  - Relative allocation (Sethuraman and Tellis 1991)
    - CPG: Promotional/Ad elasticity = 20
    - Durables: Promotional/Ad elasticity = 5
  - When there is interaction between advertising and sales promotion, increase budget and spend a bit more on the lower elasticity variable (Naik and Raman 2003)
  - Large brands underadvertise and overpromote; smaller brands underadvertise and underpromote (Naik, Raman, and Winer 2005)
  - Are firms myopic in overallocating to sales promotion? (Dekimpe and Hanssens 1999)
- New Channels
  - Complicated

Marketing Allocation by Channel









Why MMM Matters in the Privacy Era

- Compliant with GDPR, CCPA, and global privacy regulations
- Works with aggregated data—doesn’t rely on personal identifiers
- Provides a big-picture view, measuring both online and offline media impact

Modern Enhancements to MMM

- Machine Learning (ML): Captures complex patterns (non-linear relationships) beyond traditional regression models and process high volumes
- Bayesian Models: Provide uncertainty quantification and better accuracy
- Causal Inference: Ensures true incremental impact, avoiding misleading correlations

Machine Learning MMM

- ML enables high-dimensional modeling and complex interactions
- Algorithms such as XGBoost and Random Forests improve predictive power
- Allows modeling of structured and unstructured (NLP) data
- CNN, RNN, and deep learning models offer enhanced predictions
- Transformer models and LLMs present the latest frontiers in scalable, real time prediction models
- Attribution/Importance can be captured through SHAP (SHapley Additive exPlanation) values
- Caution: ML models may overfit noise and reflect biases. They must be interpretable to avoid 'black-box' problems. Regularizations (e.g., Ridge/Lasso) and constraints with business logic can help

Bayesian MMM

- Bayesian statistics improve MMM by incorporating prior knowledge (e.g., prior known elasticity)
- Provides credible intervals instead of single-point estimates
- Used in open-source tools like Facebook's Robyn and Google's LightweightMMM
- Moved from one-off static models to always-on models powered by cloud computing
- Google's Meridian (Enhanced LightweightMMM with time-varying coefficients & model calibration through lift testing)

Causal Inference in MMM

- MMM 2.0 moving from correlation to causation
- Incremental impact of marketing spend (e.g., return on extra $ spend on a channel)
- Geo-experiments and A/B tests help validate model predictions
- Leading firms integrate experimentation data into MMM to improve accuracy

Challenges in MMM

- Data Sparsity: Limited historical data can affect model reliability
- High Dimensionality: More marketing channels mean more complexity
- Media Saturation Effects: Understanding diminishing returns is crucial
- Integration with other Measurement Frameworks: MMM must work with attribution models and experiments

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Privacy-Preserving Technologies for MMM

- Synthetic Data: Generates artificial yet statistically accurate data for modeling
- Federated Learning: Trains models without centralizing sensitive data
- Data Clean Rooms: Secure environments for multi-source data collaboration

Synthetic Data

- AI-generated datasets mimic real data without privacy risks
- Enables MMM when actual customer data is restricted
- Used by major companies for scenario planning and modeling
- Artificially generated data mimicking real data's statistical properties
- Created using ML techniques like GANs and VAEs
- Used to train marketing models while complying with privacy regulations
- Real-World Examples:
  - Meta's Synthetic Data Research for ad effectiveness
  - Hazy AI enables financial and retail businesses to analyze consumer behavior privately

Federated Learning

- Decentralized model training allows MMM without exposing raw data.
- Used by companies like Google and Meta to ensure privacy-first analytics.
- Models train across devices without sharing raw data.
- Only model updates (not raw data) are shared with a central server.
- Reduces risk of data breaches and ensures compliance.
- Real-World Examples:
  - Google's Federated Learning for Ads (personalization without exposing user data).
  - NVIDIA's Clara Federated Learning for privacy-preserving AI in healthcare.

Data Clean Rooms

- Secure cloud-based solutions for analyzing marketing data across partners
- Used by Amazon, Google, and Facebook for privacy-first measurement
- Secure environments where companies pool data for joint analysis
- Access is restricted, and results are aggregated for privacy
- Real-World Examples:
  - Google Ads Data Hub (ADH) enables advertisers to analyze ad performance securely
  - Amazon Marketing Cloud (AMC) provides aggregated ad insights

Comparison and Suitability for MMM

- Synthetic Data: Good for privacy-compliant modeling and testing but may miss real-world nuances
- Federated Learning: Best for collaborative modeling where data sharing is restricted. Allows decentralized learning but requires high computing power
- Clean Rooms: Ideal for cross-platform advertising and marketing analysis but limited in analytical flexibility

MMM in Action: CPG

- Colgate-Palmolive uses MMM to optimize digital and retail media spend
- Key learning: TV advertising has a stronger impact on retail sales than digital alone
- MMM identified optimal budget allocations, leading to better ROI

Colgate World of Care

MMM in Action: Tech and Digital

- HelloFresh uses MMM to balance digital and offline marketing
- Found that podcasts and direct mail have long-term customer retention benefits
- Shifts budget dynamically based on MMM insights

MMM in Action: Financial Services

- Nationwide Insurance: Uses MMM to measure ROI of branding vs. direct response ads
- Found that TV + search ads together increased customer acquisition by 20%
- Now integrates MMM with experimental validation methods

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MMM in Action: Retail and E-Commerce

- Major fashion retailer: Used MMM to measure online-to-store 'halo effect'
- Found that search ads drove in-store visits beyond online conversions
- Adjusted attribution models based on MMM insights

Challenges to MMM

- Separating short-term and long-term effects
- Interaction and synergistic effects
- Data and measurement problems. Differing granularity and decision time frame across channels
- Understanding how different marketing channels work
- Most MMM focus on sales lifts, incremental effects, and attribution—not optimal allocation of efforts across marketing mix elements

Emerging Trends in MMM

- Causal structure discovery in shopping journey (e.g., causal graphs)
- ML and causal inference integration in MMM
- Long-term brand equity measurement using MMM
- Triangulation of ML, causal inference, and optimization (e.g., BCG 2019)
- **More Automated and AI-Driven MMM**: AI-powered MMM models improve speed and accuracy
- **Hybrid Models**: Combining MMM with digital attribution for a more holistic view
- **Real-Time & Cloud-Based MMM**: Faster decision-making with serverless architectures

Future of MMM

- MMM is critical in the privacy-first marketing era
- Advances in ML, Bayesian models, and causal inference improve its effectiveness
- Companies will integrate MMM with privacy-preserving technologies and experimentation

Key Takeaways

- Privacy laws require new measurement approaches
- MMM 2.0 is a scalable, privacy-friendly alternative to digital attribution.
- Effective MMM 2.0 involves a judicious combination of ML, Bayesian models, Causal inference, and Optimization methodologies
- Synthetic data, federated learning, and clean rooms are shaping the future of MMM
- Companies succeeding with MMM use a unified approach: MMM + experiments + privacy-first technology

Thank You!
Questions?

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