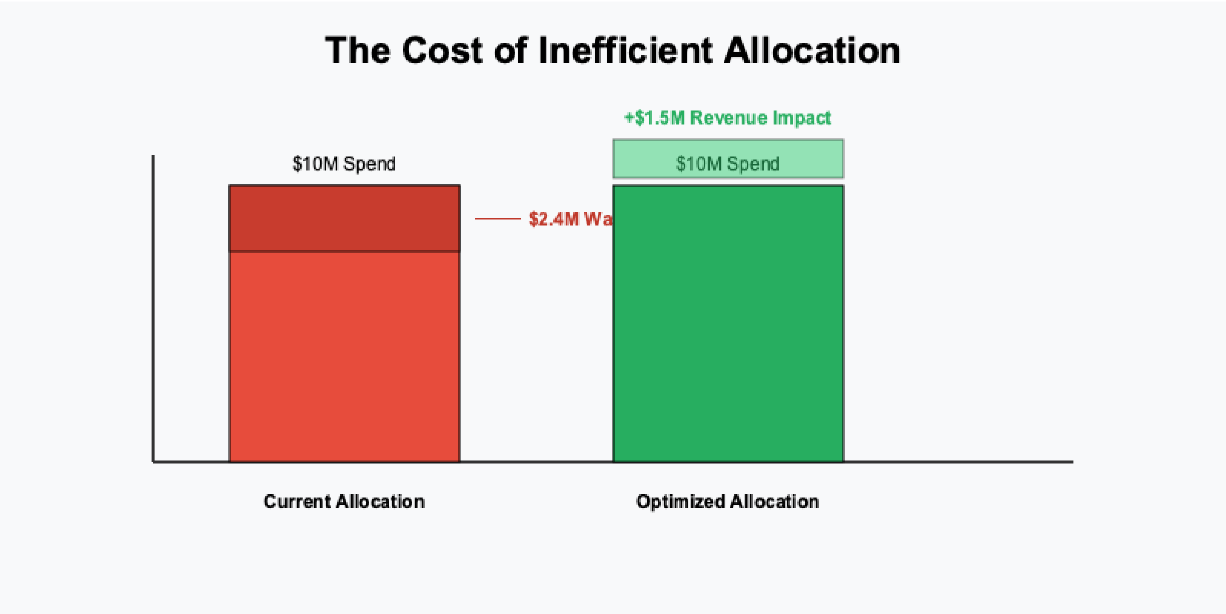
Global B2B Marketing Mix & ROI Engine: Optimize Spend with Snowflake

For global manufacturers, fragmented marketing data across regions and channels hides the true drivers of revenue.

The Cost of Inaction



Problem Impact

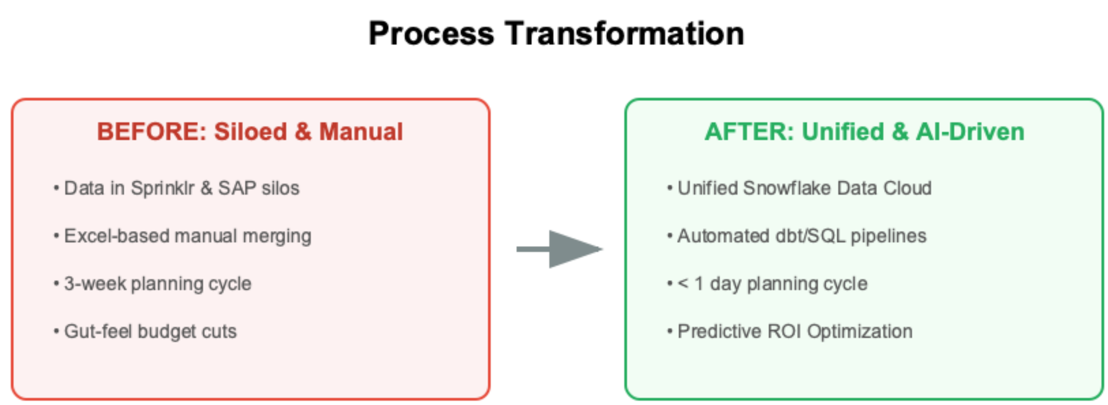
P&G's "Digital Media Transparency Crisis" (2017–2019) exposed how even sophisticated marketers waste billions when attribution data lives in silos. P&G cut $200M in digital ad spend and saw *zero* impact on sales growth—proving their existing measurement was blind to what actually drove revenue.

B2B manufacturers face the same challenge at a different scale: **$2.4M in wasted annual spend** per business unit due to inefficient "peanut-butter" budget allocation. Marketing leaders struggle to correlate top-of-funnel digital spend with booked revenue that lags by 6–18 months in SAP.

The Problem in Context

- **Fragmented Attribution.** Ad spend (Sprinklr) and Revenue (SAP) live in silos, making ROI calculation manual and delayed.
- **Long Sales Cycles.** The 9-month lag between a LinkedIn impression and a Distributor Invoice obscures cause-and-effect.
- **Blind Budgeting.** Without data-driven curves, regional leads cut spend indiscriminately, risking future pipeline.
- **Lost Signals.** Validating the impact of "soft" metrics like Brand Sentiment (PMI/SOV) on hard revenue is practically impossible.

The Transformation



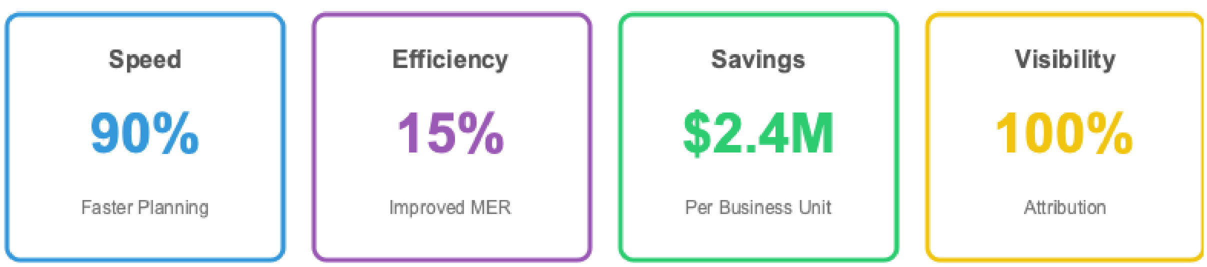
Before After

From spreadsheet-based lagging indicators to AI-driven predictive allocation. Regional marketers stop guessing and start optimizing with real-time model coefficients.

What We'll Achieve

- **15% Improvement in MER.** (Marketing Efficiency Ratio) by shifting budget to high-marginal-ROI channels.
- **90% Faster Planning.** Reduce quarterly planning cycles from weeks to days with automated data prep.
- **Unified Visibility.** A single view of ROI across Industrial, Healthcare, and Consumer business units.
- **Predictive Agility.** Simulate "What-If" scenarios to defend budget decisions to the CFO.

Business Value



ROI Value

Metric	Value	Impact
Speed	90%	Faster quarterly planning
Efficiency	15%	Improved MER
Savings	$2.4M	Annual savings per business unit
Visibility	100%	Cross-BU attribution coverage

Unlocking millions in incremental revenue by optimizing the marketing mix without increasing top-line budget.

Why Not Last-Click Attribution?

A skeptical reviewer might ask: *"Why build a statistical model when we can just track conversions?"*

Last-click attribution fails for B2B because:

Challenge	Reality	Why Last-Click Fails
6-18 month sales cycles	A LinkedIn impression in January may not convert until September	Last-click credits only the final touchpoint before close
Multi-stakeholder buying	6-10 people influence a B2B purchase	Each sees different channels; no single "converter"
Offline revenue recognition	SAP invoices lag deals by weeks/months	Digital tracking can't connect to ERP revenue
Brand effects	Display ads build awareness that Search captures	Last-click gives 100% credit to Search, 0% to Display

Marketing Mix Modeling (MMM) solves this by using *statistical regression* to estimate the causal effect of each channel on revenue—accounting for time delays, diminishing returns, and confounding factors.

The Science Behind the Model

This solution implements four core techniques from econometrics and marketing science. Each addresses a specific challenge that simpler approaches miss.

1. Geometric Adstock (Carryover Effect)

Problem: A $100k LinkedIn campaign in Week 1 doesn't just affect Week 1. In B2B, someone sees an ad, researches for weeks, then converts.

Solution: Spread each week's spend across future weeks with exponential decay:

```
Week 1: $100k spend → Effective: $100k
Week 2: $0 spend    → Effective: $70k  (70% carryover)
Week 3: $0 spend    → Effective: $49k  (70% × $70k)
Week 4: $0 spend    → Effective: $34k  ...and so on
```

The decay rate (θ) varies by channel:

- LinkedIn B2B: θ = 0.7–0.9 (long consideration cycle, effects persist 6-8 weeks)
- Paid Search: θ = 0.1–0.3 (immediate intent, fast decay)
- Display: θ = 0.4–0.6 (awareness building, medium decay)

The model *learns* the optimal θ for each channel—no manual configuration required.

2. Hill Saturation (Diminishing Returns)

Problem: Doubling spend doesn't double revenue. The 10th impression to the same person has near-zero value.

Solution: Apply an S-curve (Hill function from pharmacology) that flattens at high spend:

```
Response ■              ●●●●●●●●●●●●●  ← Saturation (flat)
   ▲     ■          ●●●●●
   ■     ■       ●●●                 ← Efficient zone
   ■     ■     ●●
   ■     ■   ●●
   ■     ■●●■■■■■■■■■■■■■■■■■■■■■■■■ Spend
           γ (half-saturation point)
```

Two learned parameters per channel:

- γ **(gamma):** Spend level where response = 50% of maximum. If γ = $50k, you're at half-effectiveness at $50k/week.
- α **(alpha):** Steepness of the curve. Higher α = sharper transition from efficient to saturated.

This enables **marginal ROI calculation**: "What's the *next* dollar worth?" rather than just average ROI.

3. Evolutionary Hyperparameter Optimization

Problem: With 20 channels × 3 parameters (θ, α, γ) = 60 parameters, grid search is impossible. Traditional gradient descent doesn't work because the objective isn't smooth.

Solution: Nevergrad's TwoPointsDE (Differential Evolution)—an evolutionary algorithm that:

1. Starts with a population of random parameter guesses
2. "Breeds" new guesses by combining good performers
3. Keeps the best, discards the worst
4. Repeats for 500 iterations

Why this matters: Unlike black-box AutoML, we optimize *interpretable* marketing parameters. The output isn't just "predicted revenue"—it's *why* each channel contributes with explainable decay rates and saturation points.

4. Ridge Regression with Positive Constraints

Problem: Marketing channels are correlated (LinkedIn and Display both spike in Q4). Standard regression produces unstable, uninterpretable coefficients.

Solution: Ridge Regression with L2 penalty:

- **Handles multicollinearity:** When channels move together, Ridge shrinks coefficients toward zero rather than producing wild estimates.

- **Interpretable:** Each coefficient represents "revenue per unit of saturated, adstocked spend."
- **Economically valid:** We penalize negative coefficients—marketing should never *hurt* revenue.

Why not Lasso? Lasso (L1) zeros out channels entirely. We want every channel's contribution estimated, even if small.

Why not Neural Networks? Interpretability. A CMO needs to explain *why* LinkedIn gets more budget, not just that the model said so.

Validation: Why You Should Trust This Model

Skeptical reviewers ask: *"How do I know this isn't just overfitting?"*

Time-Series Cross-Validation

Unlike standard k-fold CV (which randomly shuffles data), we **never let the model see future data**:

```
Fold 1: Train [Week 1-52]  → Test [Week 53-65]   (predict Q1 next year)
Fold 2: Train [Week 14-65] → Test [Week 66-78]  (predict Q2 next year)
Fold 3: Train [Week 27-78] → Test [Week 79-91]  (predict Q3 next year)
```

This mimics real-world use: *"Given everything up to today, how well can we predict next quarter?"*

Quality thresholds:

CV MAPE	Interpretation
< 10%	Excellent—model is highly predictive
10-20%	Good—suitable for budget optimization
20-30%	Acceptable—directional insights only
> 30%	Poor—investigate data quality

Bootstrap Confidence Intervals

We don't just report "LinkedIn ROI = 3.2x". We report:

> ***LinkedIn ROI = 3.2x [2.8, 3.6] at 90% confidence***

How it works:

1. Resample data 100 times with replacement
2. Re-fit the model each time
3. Collect distribution of ROI estimates
4. Report 5th and 95th percentiles

IS_SIGNIFICANT flag: When the entire confidence interval is above zero, we're confident the channel has positive ROI—not just statistical noise.

From Average ROI to Marginal ROI

A channel with 5x average ROI might already be saturated with 0.5x marginal ROI. **Budget decisions are about the *next* dollar, not past dollars.**

Response Curves with Efficiency Zones

```
Revenue ■            ●●●●●●●●●●●●●  ← SATURATED (mROI < 0.8)
Contrib ■        ●●●●●               Next dollar returns < $0.80
  ▲     ■      ●●●                 ← DIMINISHING (0.8 < mROI < 1.5)
  ■     ■    ●●                      Still positive but flattening
  ■     ■  ●●                      ← EFFICIENT (mROI > 1.5)
  ■     ■●●                          Every dollar returns > $1.50
  ■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■■ Spend
```

The model outputs response curves with:

- **Marginal ROI at each spend level**

- **Confidence bands** from bootstrap
- **Efficiency zone classification** (Efficient / Diminishing / Saturated)

Budget Optimizer

Given learned response curves, how should we reallocate spend?

Constrained Optimization Problem

```
MAXIMIZE: Total predicted revenue = Σ (saturated_response × coefficient)
SUBJECT TO:
  1. Total budget unchanged (budget neutral)
  2. Each channel can only change ±30% (realistic for CMO approval)
  3. All spend ≥ 0
```

Why constraints matter: Without them, the optimizer says "put 100% in LinkedIn." But:

- CMOs can't pivot all spend in one quarter
- Vendor contracts require minimum commitments
- Channel inventory is finite

Economic Principle: Equalize Marginal Returns

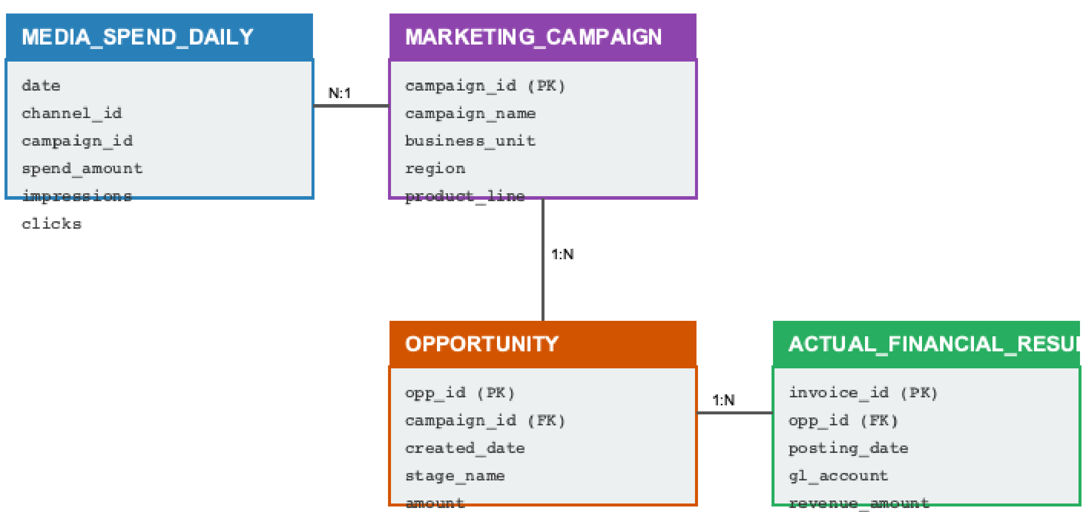
The optimal allocation **equalizes marginal ROI across channels**. If LinkedIn has mROI = 3.0 and Display has mROI = 1.5, shift budget until they converge (~2.0 each).

Output: **Predicted revenue lift** from reallocation (e.g., "+$2.4M without increasing total spend").

Why Snowflake

- **Unified data foundation.** Integrate Sprinklr, Salesforce, and SAP data in one governed place without ETL friction.
- **Performance that scales.** Train complex models on full historical data using Snowpark Python—no data movement.
- **Collaboration without compromise.** Share ROI models securely across regional teams without data copying. Row-level security ensures regions see only their data.
- **Built■in AI/ML and apps.** Democratize insights via Cortex Analyst (natural language) and Streamlit dashboards.

The Data



Data ERD

Source Tables

Table	Type	Records	Purpose
`MEDIA_SPEND_DAILY`	Fact	~100k	Daily ad spend, impressions, clicks by channel/campaign
`ACTUAL_FINANCIAL_RESULT`	Fact	~50k	Invoiced revenue from ERP (SAP) at line-item grain
`OPPORTUNITY`	Fact	~20k	CRM pipeline stages to track intermediate conversion
`MARKETING_CAMPAIGN`	Dim	~500	Metadata linking campaigns to Business Groups

Model Input View

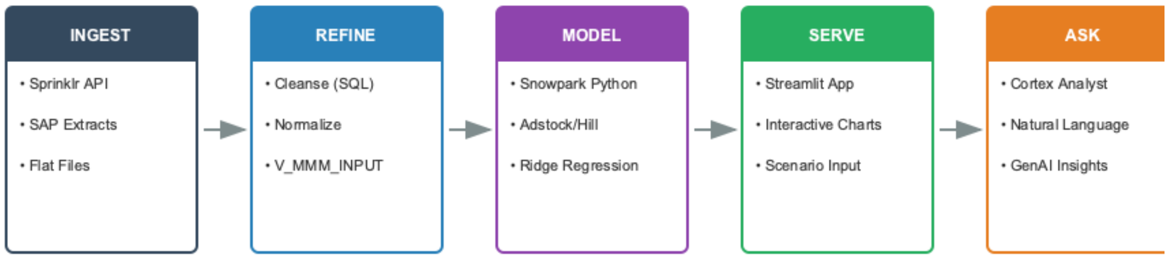
The `V_MMM_INPUT_WEEKLY` view aggregates to weekly grain with:

- Spend, impressions, clicks per Channel × Region × Product
- Revenue from SAP aligned to fiscal weeks
- Control variables: PMI, Competitor SOV, seasonality (Fourier terms)

Data Characteristics

- **Freshness:** Weekly batch updates to align with fiscal reporting cycles.
- **Trust:** Row-level access policies ensure Regional leads only see their Business Unit's data.
- **Relationships:** Campaigns link to Opportunities; Opportunities link to Financial Results.

Solution Architecture



Architecture

- **Ingest:** Raw data from Sprinklr/SAP lands in Snowflake `RAW` schema.
- **Refine:** SQL transforms data into the `ATOMIC` schema (normalized, governed).
- **Model:** Snowpark Python notebook trains MMM with Adstock + Hill + Ridge.
- **Serve:** Streamlit App consumes `MMM.MODEL_RESULTS` for visualization.
- **Ask:** Cortex Analyst enables natural language queries on the semantic model.

Model Outputs

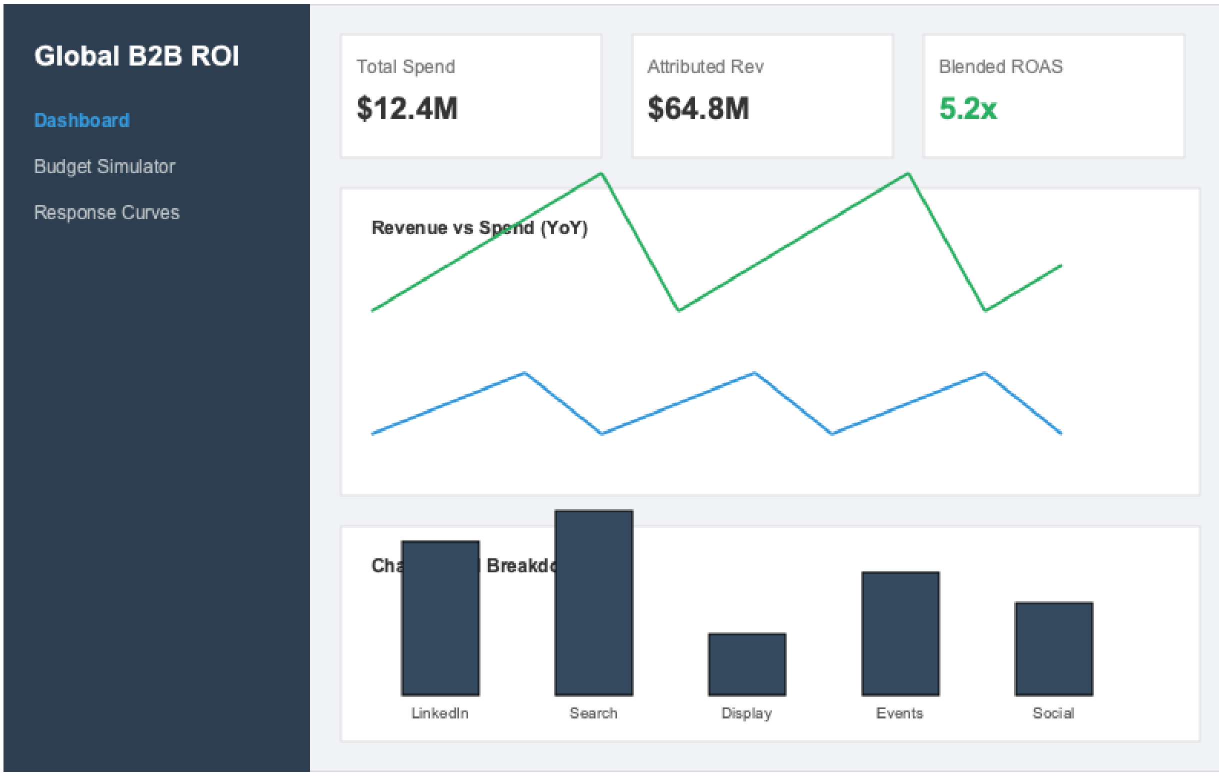
Table	Purpose
`MMM.MODEL_RESULTS`	Channel-level ROI with confidence intervals, marginal ROI, learned parameters
`MMM.RESPONSE_CURVES`	100-point curves per channel with CI bands and efficiency zones
`MMM.MODEL_METADATA`	Model version, quality metrics (R^2, CV MAPE), hyperparameter settings

How It Comes Together

1. **Ingest & Normalize.** Load and join spend/revenue data. → `sql/03_load_data.sql`
2. **Train MMM Model.** Optimize Adstock/Saturation params, fit Ridge Regression. → `notebooks/01_mmm_training.ipynb`
3. **Validate.** Time-series CV (MAPE < 15%) + Bootstrap CI (90%). → [Notebook Cell 6-9]
4. **Deploy App.** Launch Interactive ROI Dashboard. → `streamlit/mmm_roi_app.py`
5. **Simulate Spend.** Adjust sliders to see marginal ROI impact. → [Streamlit Page 2]
6. **Ask Questions.** "Show me ROAS by Channel for EMEA." → [Cortex Analyst]

Key Visualizations

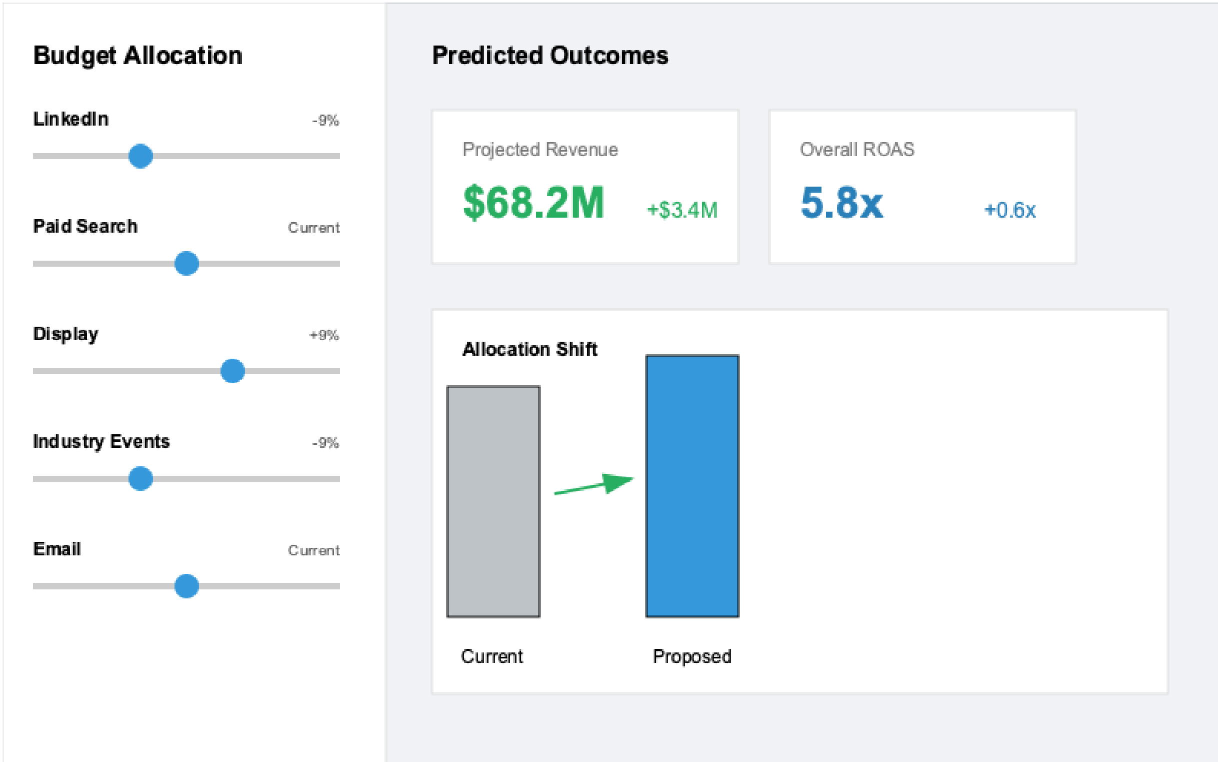
ROI Dashboard



Dashboard

Exec-level view of Total Spend, Attributed Revenue, and Blended ROAS. The dashboard surfaces channel performance across all regions and business units in a single pane.

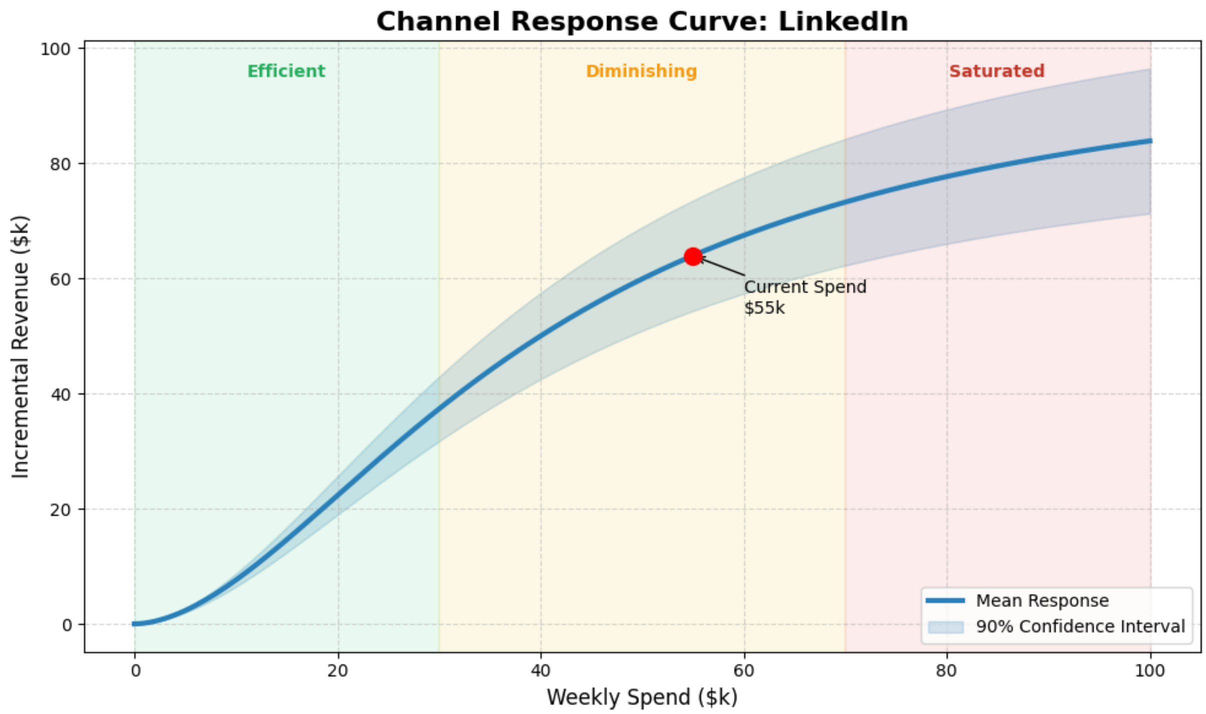
Budget Simulator



Budget Simulator

Interactive "Flight Simulator" allowing users to adjust channel spend (±30%) and see real-time predicted revenue impact based on marginal ROI curves.

Response Curves



Response Curves

Visualize the spend → revenue relationship for each channel with:

- Shaded confidence bands (90% bootstrap CI)
- Efficiency zone markers (Efficient / Diminishing / Saturated)
- Current spend position with marginal ROI annotation

Application Features

The application provides:

- Executive-level KPI cards with spend, revenue, and ROAS metrics
- Interactive channel-level ROI breakdowns with drill-down capability
- What-if scenario modeling with instant marginal ROI predictions
- Natural language queries via Cortex Analyst integration
- Learned parameter inspection (decay rates, saturation points)

Alternatives Considered

Approach	Why Not
Last-click attribution	Doesn't work for 6-18 month B2B sales cycles
Multi-touch attribution (MTA)	Requires user-level tracking; breaks with privacy regulations
Robyn (Meta)	Bayesian approach is 10x slower; requires MCMC tuning expertise
LightweightMMM (Google)	JAX-based; less compatible with Snowflake Python environment
Neural networks	Black box; CMO can't explain *why* a channel gets more budget

This solution uses **interpretable, production-ready techniques** that run natively in Snowflake with clear explanations for every coefficient.

Call to Action

Run the Demo

```
# 1. Deploy Infrastructure & Data
./deploy.sh

# 2. Train the Model
./run.sh main

# 3. Launch the App
./run.sh streamlit
```

Customize for Your Data

- Adjust `geo_level` in notebook config to model at GLOBAL, SUPER_REGION, or COUNTRY granularity.
- Modify adstock decay priors if you have domain knowledge about channel effects.
- Add macro indicators (PMI, inflation) to control for economic conditions.
- Extend the semantic model in `cortex/mmm_semantic_model.yaml` for custom metrics.

From peanut-butter spreading to precision-guided growth—with interpretable, validated models running natively in Snowflake.