Habu Project 1: Optimal Marketing Mix and Budget Optimization

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Research Objectives

- ❖ Apply, fine tune and compare different marketing mix models to obtain one that is best suited for informing advertising strategies on Amazon.
- ❖ Find out the effectiveness of various digital marketing channels in driving sales.
- ❖ Devise the optimized budget allocation to maximize ROI given an advertising budget.

Data

- ❖ Analysis of aggregate data sourced from Amazon Marketing Cloud

  - ➢ Daily data from seven brands spanning a duration of 12.5 months
  - ➢ One dataset on sales and converted users for each brand
  - ➢ One dataset on spend and user reach of six media channels (i.e. display, sponsored products, sponsored brands, sponsored display, videos, OTT) for each brand

Methods

Data Preprocessing

1. Merge the two datasets provided by Habu into a dataframe in a format that can be used for further analysis

dates	brand	channel	users	cost
2022-09-01	Brand C	Display	1038	8.30046
2022-09-01	Brand C	OTT	4	0.0708
2022-09-01	Brand G	OTT	7	0.1218
2022-09-01	Brand G	sponsored_products	4	4.66
2022-09-01	Brand LO	Display	463	2.23867
2022-09-01	Brand LO	sponsored_products	14	44.36
2022-09-01	Brand M	sponsored_products	8	6.16
2022-09-01	Brand N	sponsored_products	10	4.86
2022-09-02	Brand C	Display	1005296	6215.74917
2022-09-02	Brand C	OTT	347938	16190.4053
2022-09-02	Brand C	Video	42781	550.65473
2022-09-02	Brand G	Display	1590557	8796.38452
2022-09-02	Brand G	OTT	128440	3256.1643
2022-09-02	Brand G	sponsored_products	2944	6656.23
2022-09-02	Brand LA	Display	513784	3250.60586
2022-09-02	Brand LA	Video	17612	173.85862
2022-09-02	Brand LO	Display	4411934	18592.00919
2022-09-02	Brand LO	sponsored_products	11060	20499.98

+

conversion_dates	brand	sales	converted_users
2022-09-02	Brand C	4509.52	1501
2022-09-02	Brand G	15706.65	1905
2022-09-02	Brand LA	607.42	248
2022-09-02	Brand LO	45236.85	5464
2022-09-02	Brand M	21105.52	4357
2022-09-02	Brand N	14971.92	2773
2022-09-02	Brand R	6275.3	603
2022-09-03	Brand C	10807.06	2883
2022-09-03	Brand G	28422.52	3697
2022-09-03	Brand LA	1391.17	471
2022-09-03	Brand LO	82588.86	10199
2022-09-03	Brand M	39089.71	8276
2022-09-03	Brand N	27726.88	5199
2022-09-03	Brand R	11870.99	1131
2022-09-04	Brand C	10789.8	3040

1	dates	brand	total_users_reached	total_cost	sponsored_products_s	sponsored_products_u	sponsored_brands_s	sponsored_brands_u	video_s	video_u	OTT_s	OTT_u	sponsored_display_s	sponsored_display_u	display_s	display_u	sales	converted_users
2	2/9/2022	Brand C	1396015	22956.809	0	0	0	0	550.6547	42781	16190.41	347938	0	0	6215.749	1005296	4509.52	1501
3	2/9/2022	Brand G	1721941	18708.779	6656.23	2944	0	0	0	0	3256.164	128440	0	0	8796.385	1590557	15706.65	1905
4	2/9/2022	Brand LA	531396	3424.4645	0	0	0	0	173.8586	17612	0	0	0	0	3250.606	513784	607.42	248
5	2/9/2022	Brand LO	4422994	39091.989	20499.98	11060	0	0	0	0	0	0	0	0	18592.01	4411934	45236.85	5464
6	2/9/2022	Brand M	1990735	27193.268	16769.3	13675	0	0	0	0	0	0	0	0	10423.97	1977060	21105.52	4357
7	2/9/2022	Brand N	644414	10554.244	7189.5	8737	0	0	0	0	0	0	21.56	12	3343.184	635665	14971.92	2773
8	2/9/2022	Brand R	431224	6106.2821	506.05	204	0	0	0	0	0	0	0	0	5600.232	431020	6275.3	603
9	3/9/2022	Brand C	1454998	22644.106	0	0	0	0	666.6711	44824	15288.63	343681	0	0	6688.801	1066493	10807.06	2883
10	3/9/2022	Brand G	1781354	18728.455	6802.26	3019	0	0	0	0	2958.31	116216	0	0	8967.885	1662119	28422.52	3697
11	3/9/2022	Brand LA	508124	3587.2486	0	0	0	0	186.1757	20380	0	0	0	0	3401.073	487744	1391.17	471
12	3/9/2022	Brand LO	4637217	42548.251	22772.2	12291	0	0	0	0	0	0	0	0	19776.05	4624926	82588.86	10199
13	3/9/2022	Brand M	2090696	28727.55	17516.64	15310	0	0	0	0	0	0	0	0	11210.91	2075386	39089.71	8276
14	3/9/2022	Brand N	662726	11659.439	8104.01	9795	0	0	0	0	0	0	25.09	16	3530.339	652915	27726.88	5199

Methods

Exploratory Data Analysis

2. Simple descriptive statistics and data visualizations
3. Calculate simple ROI for all brands combined and individual brands
4. Run multiple linear regression models

Marketing Mix Models

5. Build a Marketing Mix Model with Google's LightweightMMM for all brands combined and for individual brands
6. Build a Marketing Mix Model with Robyn (from Meta) for all brands combined and for individual brands

Methods

Comparison

7. Compare the performance and results of LightweightMMM and Robyn
   a. Use performance metrics (in-sample fit and out-sample prediction) to compare their predictive power
   b. Compare interpretability
   c. Identify any common/different conclusions on effectiveness of various channels and budget optimization
8. Summarize findings and insights and develop recommendations
9. Evaluate and propose areas for further research

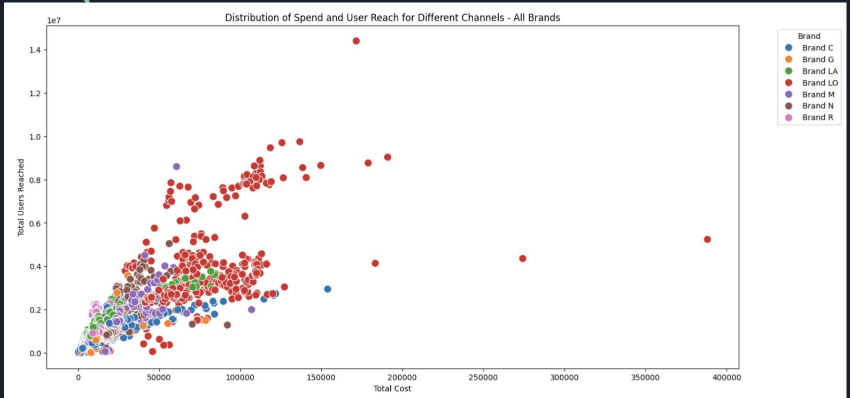
Findings & Insights - **Exploratory Data Analysis**

Two measures of media channels which can be used as inputs/independent variables: spend & user reach
Two key performance indicators can be used as dependent variable: sales & user conversion

From scatterplot, determine which one to include in our models. From the top diagram,

Spend vs User Reach

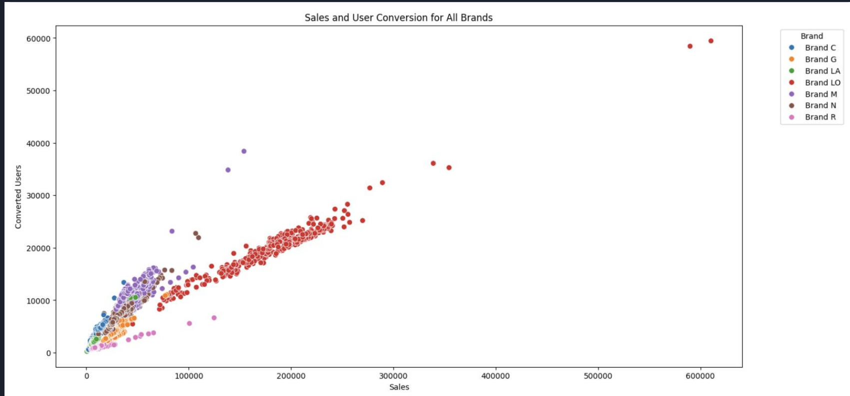
- No clear relationship and pattern varies across brands
- Depend on which media channels each brand spends on
- Choose to use spend in our models since it is more directly controlled by companies



the bottom diagram,

Sales vs User Conversion

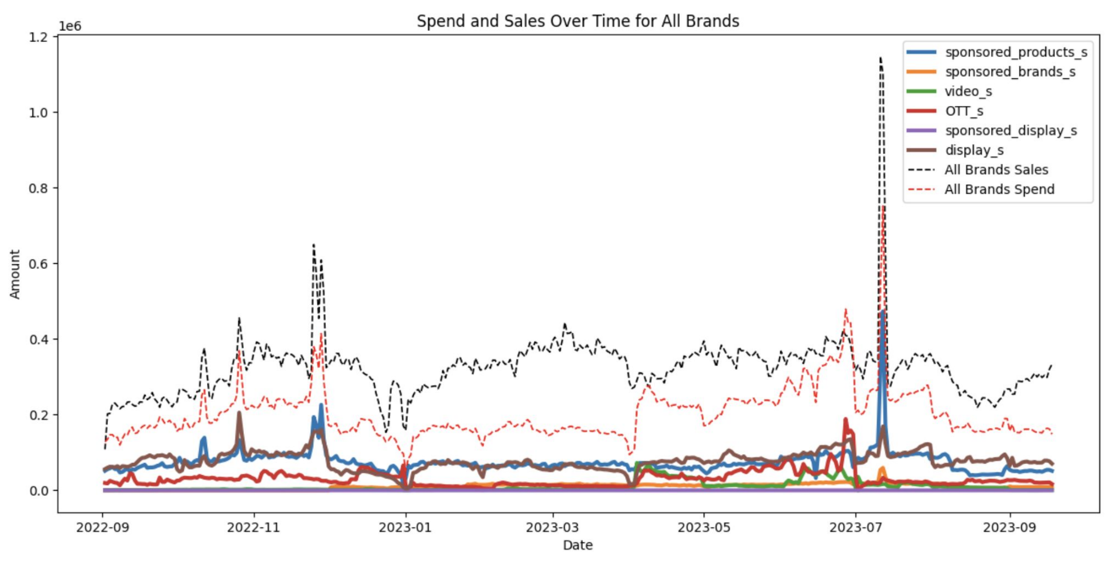
- Highly linear relationship
- Using either indicator would likely generate similar results
- Choose to use sales in our models as it is what most companies ultimately aim to maximize



We chose spend as independent variable and sales as dependent variable.

plot total sales and advertising spend over time, **sales follow closely with the spend on sponsored products, but less so with the spend on display or video**

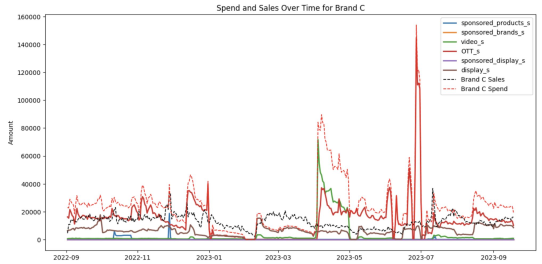
Findings & Insights - **Exploratory Data Analysis**

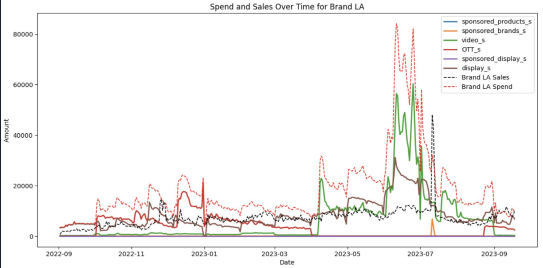


- Total sales and advertising spend generally exhibit similar trends over time
- Sales have a more similar pattern to spend on some media channels (e.g. sponsored products) than others (e.g. display or video)

Brands C and LA (negative ROI)

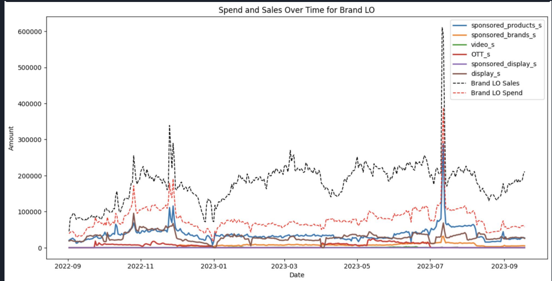
- Spends significantly exceed sales
- Spend mainly on video, OTT and display, which have no apparent relationship with sales





Brands LO (Highest ROI)

- Very healthy gap between sales and spends
- Spend mainly on sponsored products and display - former's pattern resembles that of sales



Findings & Insights - **Exploratory Data Analysis**

The main differences between brands with negative or close to zero ROIs and the other brands can be seen in their respective fractions of spend in sponsored products, sponsored brands, video and OTT.

	All Brands	Brand C	Brand G	Brand LA	Brand LO	Brand M	Brand N	Brand R
Sponsored products	36.84%	0.91%	50.17%	0.00%	47.53%	52.85%	25.01%	1.86%
Sponsored brands	5.1%	0.00%	6.87%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
video	4.93%	12.92%	0.00%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
OTT	14.85%	60.16%	6.96%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
Sponsored display	0.01%	0.00%	0.05%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
display	38.28%	26.01%	35.95%	45.82%	37.62%	40.69%	34.90%	60.55%
ROI	**60.67%**	**-45.19%**	**63.99%**	**-61.43%**	**130.44%**	**64.28%**	**51.36%**	**1.22%**

brands with **negative or close to zero ROIs (i.e. brands C, LA and R) spend negligible amounts on sponsored products and sponsored brands and instead spend mostly on video and OTT.** On the other hand, **brands with positive ROIs all spend considerable amounts on sponsored products and some amounts on sponsored brands.** They also tend to spend nothing on video and only small amounts on OTT. **Consistent with our findings in the previous slide, it is likely that sponsored products is the main media channel that has the greatest effect on sales.**

Findings & Insights - **Regression Results**

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  sales   R-squared:                       0.897
Model:                            OLS   Adj. R-squared:                  0.897
Method:                 Least Squares   F-statistic:                     3879.
Date:                Mon, 04 Dec 2023   Prob (F-statistic):               0.00
Time:                        01:50:35   Log-Likelihood:                -30205.
No. Observations:                2673   AIC:                         6.042e+04
Df Residuals:                    2666   BIC:                         6.047e+04
Df Model:                           6
Covariance Type:            nonrobust
========================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
const               -5838.9513    614.672     -9.499      0.000   -7044.234   -4633.669
sponsored_products_s    1.1227      0.050     22.524      0.000       1.025       1.220
sponsored_brands_s      9.1087      0.212     42.912      0.000       8.693       9.525
video_s                -0.6515      0.069     -9.378      0.000      -0.788      -0.515
OTT_s                   0.2588      0.048      5.373      0.000       0.164       0.353
sponsored_display_s   -18.8589     24.251     -0.778      0.437     -66.411      28.693
display_s               2.4183      0.058     41.450      0.000       2.304       2.533
==============================================================================
Omnibus:                      402.837   Durbin-Watson:                   1.743
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4742.462
Skew:                           0.301   Prob(JB):                         0.00
Kurtosis:                       9.498   Cond. No.                     3.74e+04
==============================================================================
```

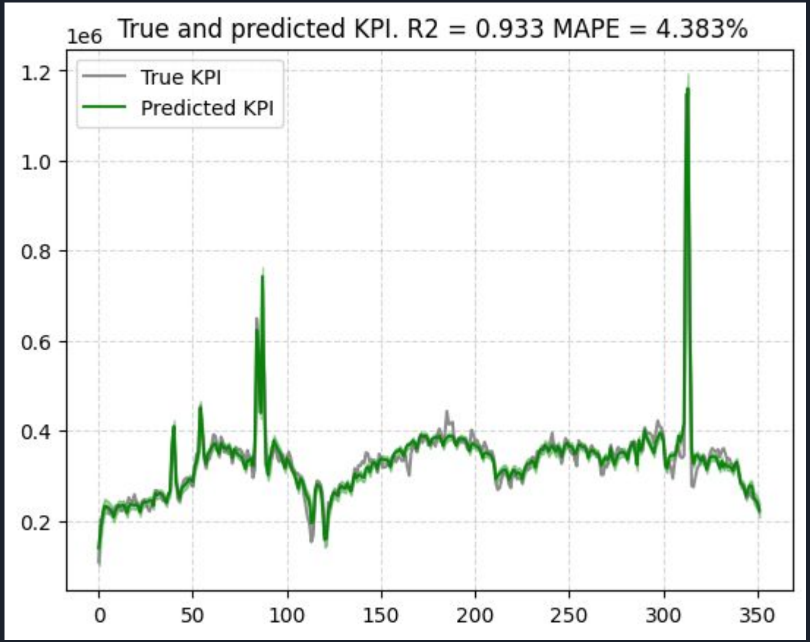
Overall, the **linear regression model** is statistically significant and has a pretty high R square value in explaining the variance in sales.

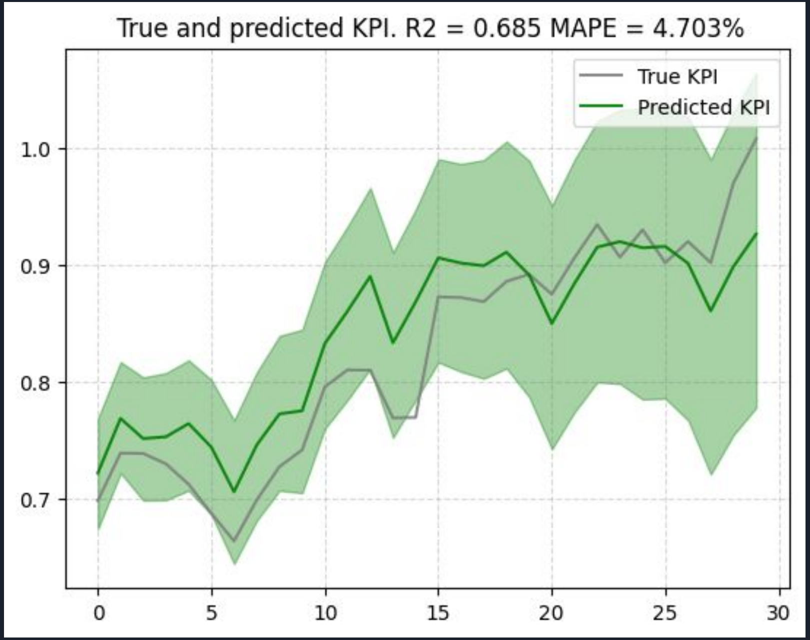
coefficients on the media channels, it can be seen that **sponsored brands have the largest positive effect on sales, followed by display and sponsored products. It is noted that video has a slight negative association with sales**, while the coefficient on sponsored display is insignificant.

apply the marketing mix models to better inform advertising strategies.

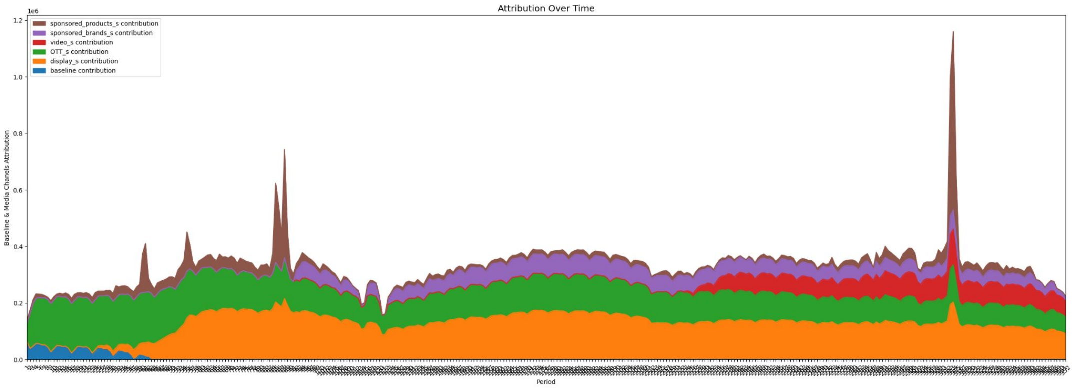
Findings & Insights -
LightweightMMM: Model Training

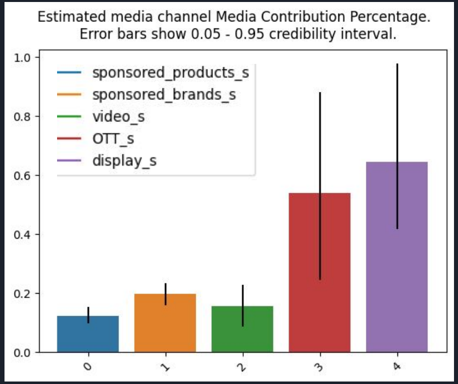
- ❖ Applying hill adstock transformation produces the best model fit
- ❖ Dropped sponsored display as an input channel

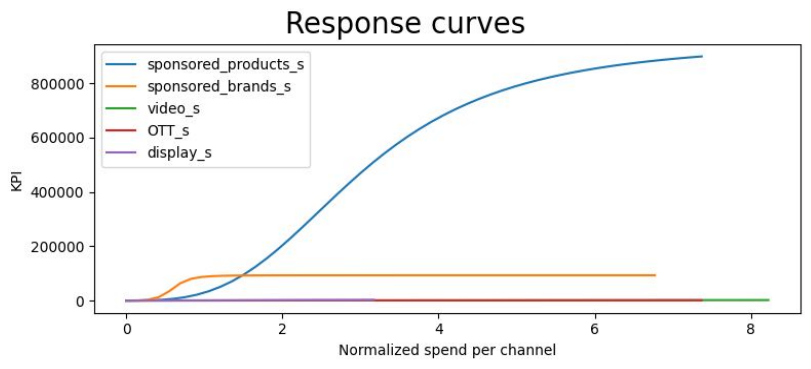


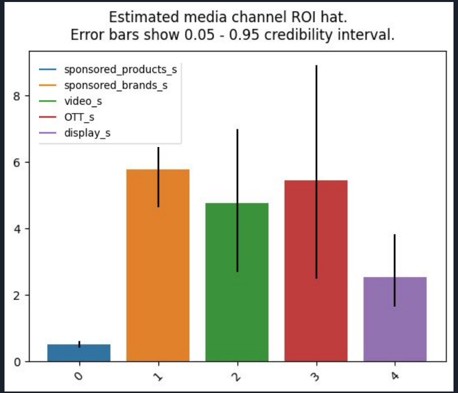


Findings & Insights - **LightweightMMM: Channel Effectiveness**







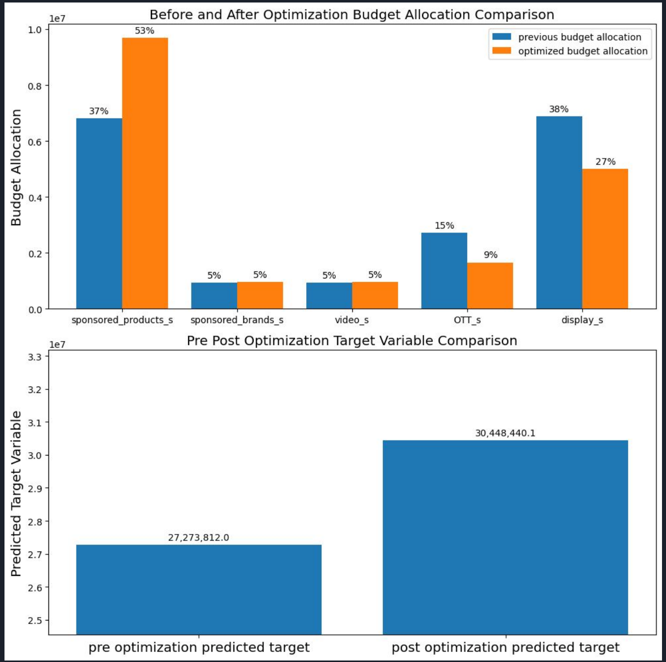


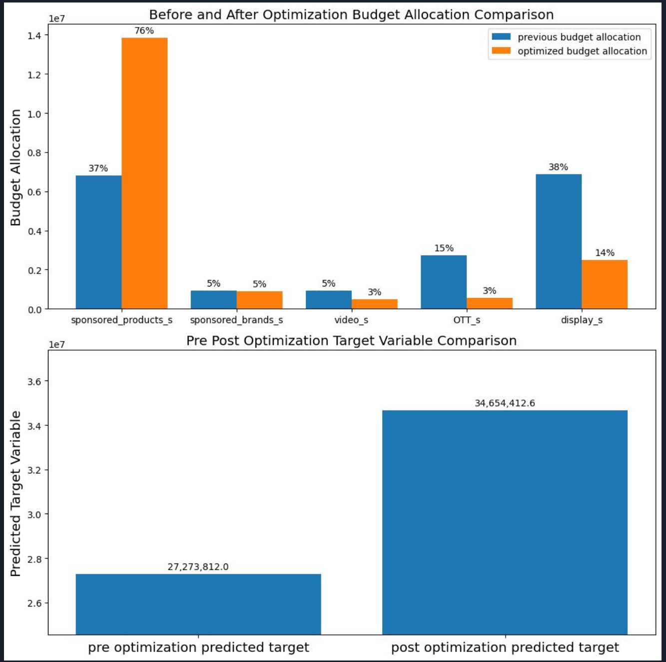
Findings & Insights -
LightweightMMM: Budget Optimization

Initial spending on each channel changed by
±40%

Sponsored products ↑↑
OTT ↓
Display ↓

Sales ↑ 11.6%





Initial spending on each channel changed by
±100%

Sponsored products ↑↑↑
OTT ↓↓
Display ↓↓
Video ↓

Sales ↑ 27.1%

If we allow initial budget allocation to change freely until it stabilizes, 92% should be spent on sponsored products, 5% on sponsored brands and 3% on OTT. This would generate a 41.3% increase in sales.

Findings & Insights - **Comparison with Robyn**

Robyn
R-square (test): 0.79

Initial spending on each channel changed by ±40%

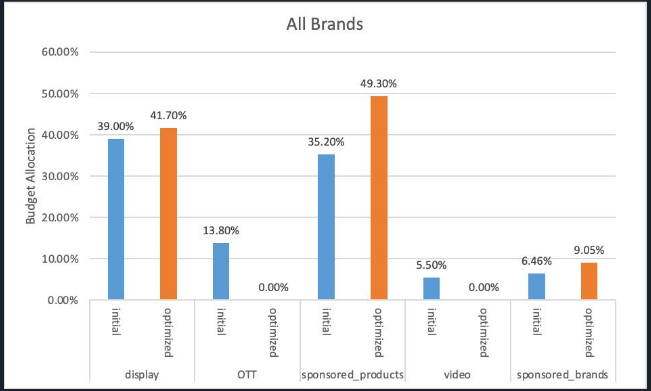
	display		OTT		sponsored_products		video		sponsored_brands	
	initial	optimized	initial	optimized	initial	optimized	initial	optimized	initial	optimized
Brand C	28.90%	40.50%	67.70%	54.80%	0.221%	0.133%	3.280%	4.590%		
Brand LA	44.90%	62.80%	4.38%	2.63%			50.80%	34.60%		
Brand M	55.10%	39.60%			38.70%	54.10%			6.22%	6.27%
Brand N	36.60%	51.20%			47.90%	39.10%	0.36%	0.22%	6.70%	9.38%
All Brands	39.00%	41.70%	13.80%	0.00%	35.20%	49.30%	5.50%	0.00%	6.46%	9.05%

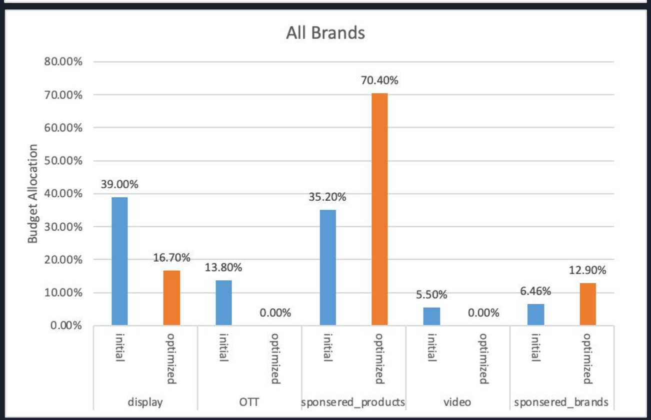
❖ Budget reallocation indicated by increases & decreases in spending on various media channels under Robyn's optimization (for all brands combined and four selected brands - C, LA, M, N)

Initial spending on each channel changed by ±100%

	display		OTT		sponsored_products		video		sponsored_brands	
	initial	optimized	initial	optimized	initial	optimized	initial	optimized	initial	optimized
Brand C	28.90%	57.90%	67.60%	35.60%	0.221%	0.000%	3.280%	6.550%		
Brand LA	44.90%	73.80%	4.38%	0.00%			50.80%	26.20%		
Brand M	55.10%	22.70%			38.70%	77.30%			6.22%	0.00%
Brand N	36.60%	0.00%			47.90%	86.60%	0.36%	0.00%	6.70%	13.40%
All Brands	39.00%	16.70%	13.80%	0.00%	35.20%	70.40%	5.50%	0.00%	6.46%	12.90%

❖ Focusing on the optimization result for all brands, Robyn recommends similar budget reallocation as LightWeightMMM: allocate majority of budget to sponsored products, followed by display and sponsored brands





Findings & Insights - **Comparison with Robyn**

Bounded: 100%

BRAND C

Google Lightweight	Robyn
R-square (test): 0.22 Revenue change: 1.5 (1M)	R-square (test): 0.64 Revenue change: 3.3 (190k)
Sponsored P: 1% Video: 17% OTT: 53% Display: 29%	Sponsored P: 0% Video: 6.6% OTT: 35.6% Display: 58%

No sponsored products spending on optimization period

BRAND LA

Google Lightweight	Robyn
R-square (test): 0.37 Revenue change: 1.8 (1.7M)	R-square (test): 0.36 Revenue change: 1.2(82k)
Video: 30% OTT: 15% Display: 55%	Video: 26% OTT: 0% Display: 74%

Findings & Insights - **Comparison with Robyn**

Bounded: 100%

BRAND N

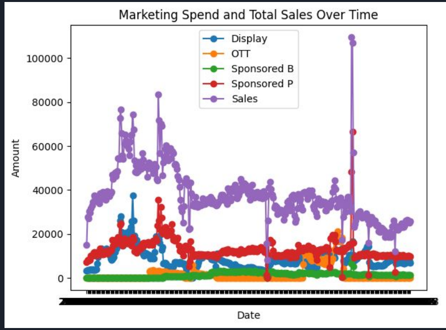
Google Lightweight	Robyn
R-square (test): 0.5 Revenue change: 1.07 (3M)	R-square (test): 0.34 Revenue change: 2.9 (800k)
Sponsored P: 95% Sponsored B: 5% Video: 0% OTT: 0% Sponsored D: 0% Display: 0%	Sponsored P: 87% Sponsored B: 13% Video: 0% OTT: 0% Sponsored D: 0% Display: 0%

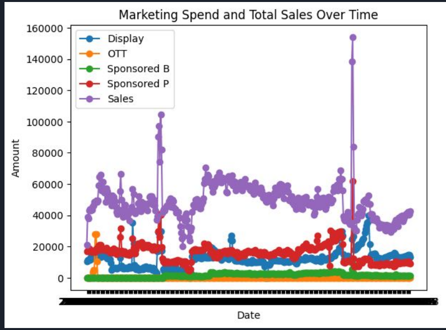
BRAND M

Google Lightweight	Robyn
R-square (test): 0.17 Revenue change: 1.2 (1.7M)	R-square (test): 0.85 Revenue change: 1.2 (1.1M)
Sponsored P: 18% Sponsored B: 1% Display: 80%	Sponsored P: 77% Sponsored B: 0% Display: 23%

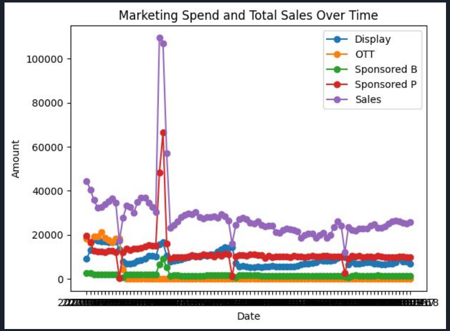
Findings & Insights - **Comparison with Robyn**

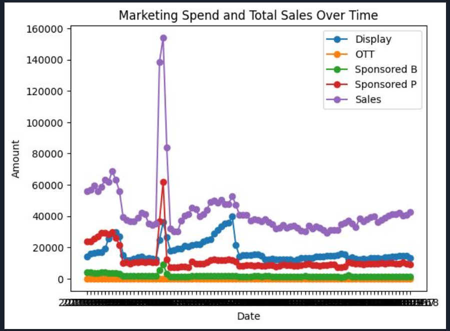
- **General trend for M & N:** sales follow closely sponsored products for the whole year
- **Last 90 days:** for brand M, Display mirrors sales more strongly
- Google Lightweight seems to be more susceptible to being biased by recent trends in the optimization stage *(weight this argument with managerial understanding)*





360 days





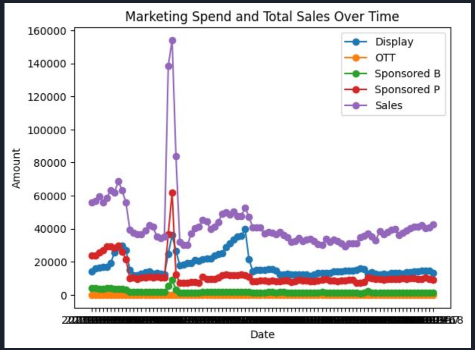
90 days

BRAND N

BRAND M

Recommendations - **General advertising strategy**

38%



Prioritize spending in platform specific channels

Use Display for specific purpose (i.e. new impactful creative)

Recommendations - **How to best use MMMs**

Beware of different types of marketing channels (results may behave differently)

Collinearity does not appear to impact the model significantly

Custom parameters is minor

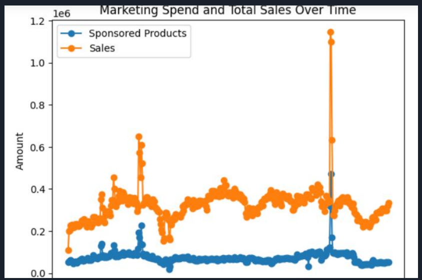
Choose optimization period containing max # of channels

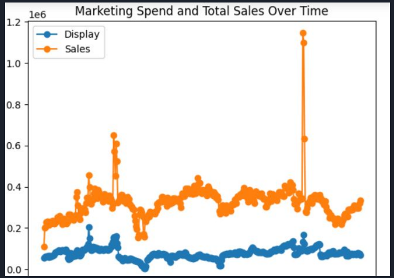
Use your managerial understanding

Understand your data (what type of transformation is appropriate)

Recommendations - **Understand your data**

	Remove Sponsored Product (37% of total spend)				Remove Display (38% of total spend)			
	In sample model fit		Out of sample prediction		In sample model fit		Out of sample prediction	
	R square	MAPE	R square	MAPE	R square	MAPE	R square	MAPE
adstock	0.762	9.4%	0.86	4.3%	0.845	7.7%	0.737	9.2%
hill_adstock	0.838	6.9%	0.17	12.9%	0.921	4.888%	0.889	6.3%





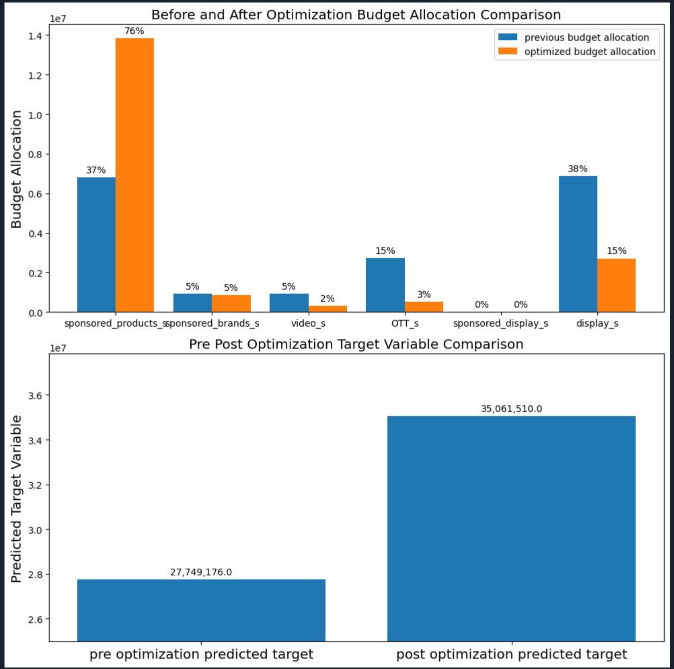
Keep channels consistent with promotion platform

Beware of channels' spending weights

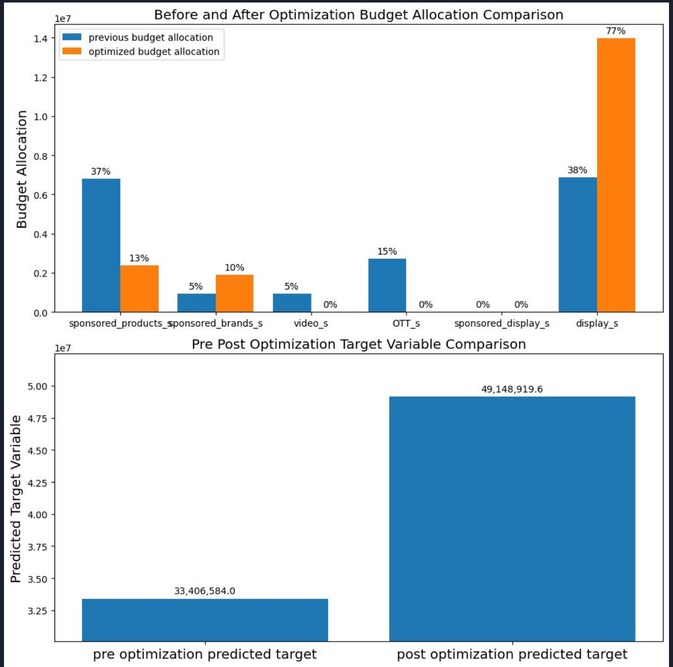
Applying appropriate transformations is crucial

Recommendations - **Understand your data**
Adstock vs. Hill Adstock

Misrepresentation of spend behavior



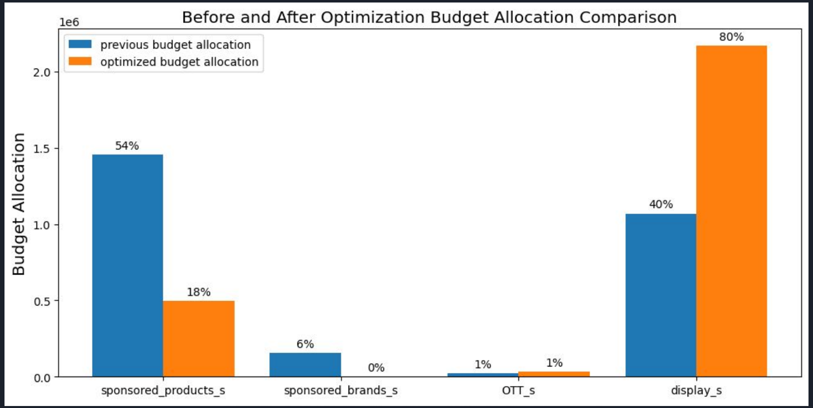
Hill_Adstock



Adstock

Recommendations - **Managerial understanding to best optimize results**

VS.



Brand M

- Make your analysis on both models
- Check for differences or similarities -> more insights will be derived from this and will allow managerial judgment to be used for interpretation
- **Use Google for best simplicity/effectiveness but beware of opti results when R square < 20%**

- Drastic changes in spend should be investigated
- Google Lightweight is biased by last 2 months of a Display advertising working well (use boundaries accordingly)

Limitations and Further Research

PROJECT

- Results are specific to advertising on Amazon
- Results depend on the type of products and brands
- Include more control variables, e.g. competitor sales, offline advertising, economic performance, etc.

MMM

- Apply different functions to different channels (varying behavior)
- Explore effect on different market segments
- Geo level granularity

Appendix

Google Lightweight: https://github.com/google/lightweight_mmm

Model Training

```python
#initialize variables for model
media_data = all_brands[["sponsored_products_s", "sponsored_brands_s", "video_s", "OTT_s", "display_s"]].to_numpy()
target = all_brands["sales"].to_numpy()
costs = all_brands[["sponsored_products_s", "sponsored_brands_s", "video_s", "OTT_s", "display_s"]].sum().to_numpy()
#split data
data_size = media_data.shape[0]
split_point = data_size - 30
media_data_train = media_data[:split_point, ...]
media_data_test = media_data[split_point:, ...]
target_train = target[:split_point]
target_test = target[split_point:]
#scale data
media_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
target_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
cost_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
media_data_train = media_scaler.fit_transform(media_data_train)
target_train = target_scaler.fit_transform(target_train)
costs = cost_scaler.fit_transform(costs)
#train model
mmm = lightweight_mmm.LightweightMMM(model_name="hill_adstock")
mmm.fit(
    media=media_data_train,
    media_prior=costs,
    target=target_train,
    degrees_seasonality = 3,
    seasonality_frequency = 365,
    weekday_seasonality = True,
    media_names = ["sponsored_products_s", "sponsored_brands_s", "video_s", "OTT_s", "display_s"],
    number_warmup=number_warmup,
    number_samples=number_samples,
    seed=SEED)
#prediction
new_predictions = mmm.predict(media=media_scaler.transform(media_data_test),
                              seed=SEED)
#obtain channel contribution and effectiveness
media_contribution, roi_hat = mmm.get_posterior_metrics(target_scaler=target_scaler, cost_scaler=cost_scaler)
plot.plot_media_baseline_contribution_area_plot(media_mix_model=mmm,
                                                target_scaler=target_scaler,
                                                fig_size=(30,10))
plot.plot_bars_media_metrics(metric=media_contribution, metric_name="Media Contribution Percentage")
plot.plot_bars_media_metrics(metric=roi_hat, metric_name="ROI hat")
plot.plot_response_curves(media_mix_model=mmm, target_scaler=target_scaler, seed=SEED)
```

Budget Optimization

```python
prices = jnp.ones(mmm.n_media_channels)
n_time_periods = 90
budget = jnp.sum(jnp.dot(prices, media_data.mean(axis=0)))* n_time_periods
solution, kpi_without_optim, previous_media_allocation = optimize_media.find_optimal_budgets(
    n_time_periods=n_time_periods,
    media_mix_model=mmm,
    budget=budget,
    prices=prices,
    media_scaler=media_scaler,
    target_scaler=target_scaler,
    bounds_lower_pct = 0.4,
    bounds_upper_pct = 0.4,
    seed=SEED)
optimal_buget_allocation = prices * solution.x
previous_budget_allocation = prices * previous_media_allocation
plot.plot_pre_post_budget_allocation_comparison(media_mix_model=mmm,
                                                kpi_with_optim=solution['fun'],
                                                kpi_without_optim=kpi_without_optim,
                                                optimal_buget_allocation=optimal_buget_allocation,
                                                previous_budget_allocation=previous_budget_allocation,
                                                figure_size=(10,10))
```

SAMPLE CODES

Appendix

Robyn: https://facebookexperimental.github.io/Robyn/

Model Training

```
#Initialize variables for model
InputCollect <- robyn_inputs(
  dt_input = media_sales_all,
  dt_holidays = dt_prophet_holidays,
  date_var = "dates",
  dep_var = "sales",
  dep_var_type = "revenue",
  prophet_vars = c("trend", "season", "holiday", "weekday"),
  prophet_country = "US",
  paid_media_spends = c("sponsored_products_s", "sponsored_brands_s", "video_s", "OTT_s", "sponsored_display_s", "display_s"),
  paid_media_vars = c("sponsored_products_u", "sponsored_brands_u", "video_u", "OTT_u", "sponsored_display_u", "display_u"),
  window_start = "2022-09-02",
  window_end = "2023-09-18",
  adstock = "geometric")
#Define and add hyperparameters
hyper_names(adstock = InputCollect$adstock, all_media = InputCollect$all_media)
hyper_limits()
hyperparameters <- list(
  display_s_alphas = c(0.5, 3),
  display_s_gammas = c(0.3, 1),
  display_s_thetas = c(0, 0.3),
  OTT_s_alphas = c(0.5, 3),
  OTT_s_gammas = c(0.3, 1),
  OTT_s_thetas = c(0.3, 0.8),
  sponsored_brands_s_alphas = c(0.5, 3),
  sponsored_brands_s_gammas = c(0.3, 1),
  sponsored_brands_s_thetas = c(0, 0.3),
  sponsored_display_s_alphas = c(0.5, 3),
  sponsored_display_s_gammas = c(0.3, 1),
  sponsored_display_s_thetas = c(0, 0.3),
  sponsored_products_s_alphas = c(0.5, 3),
  sponsored_products_s_gammas = c(0.3, 1),
  sponsored_products_s_thetas = c(0, 0.3),
  video_s_alphas = c(0.5, 3),
  video_s_gammas = c(0.3, 1),
  video_s_thetas = c(0.3, 0.8),
  train_size = c(0.5, 0.8))
#Add hyperparameters into robyn_inputs()
InputCollect <- robyn_inputs(InputCollect = InputCollect, hyperparameters = hyperparameters)
#Build initial model
OutputModels <- robyn_run(
  InputCollect = InputCollect,
  cores = NULL,
  iterations = 2000,
  trials = 5,
  ts_validation = TRUE,
  add_penalty_factor = FALSE)
#Calculate Pareto fronts, cluster and export results and plots
OutputCollect <- robyn_outputs(
  InputCollect, OutputModels,
  pareto_fronts = "auto",
  csv_out = "pareto",
  clusters = TRUE,
  export = create_files,
  plot_folder = robyn_directory,
  plot_pareto = create_files)
print(OutputCollect)
#Select model
select_model <- "1_271_7"
myOnePager <- robyn_onepagers(InputCollect, OutputCollect, select_model, export = FALSE)
```

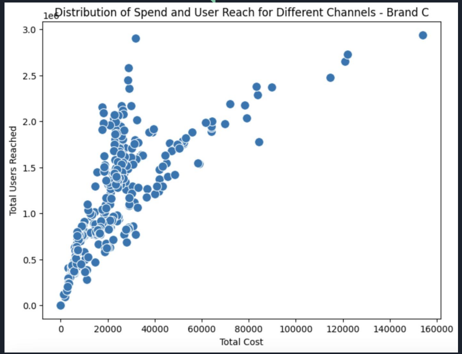
Budget Optimization

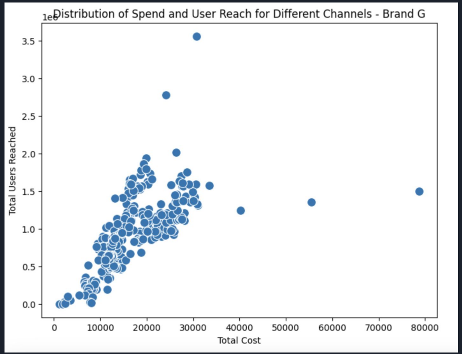
```
AllocatorCollect1 <- robyn_allocator(
  InputCollect = InputCollect,
  OutputCollect = OutputCollect,
  select_model = select_model,
  date_range = c("2022-09-02", "2023-09-18"),
  total_budget = NULL,
  channel_constr_low = c(0.7, 0.7, 0.7, 0.7, 0.7, 0.7),
  channel_constr_up = c(1.5, 1.5, 1.5, 1.5, 1.5, 1.5),
  channel_constr_multiplier = 3,
  scenario = "max_response",
  export = create_files
)
# Print & plot allocator's output
print(AllocatorCollect1)
plot(AllocatorCollect1)
```

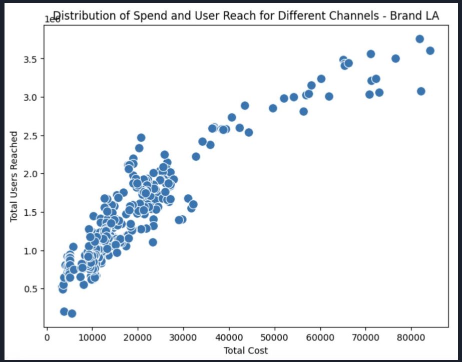
SAMPLE CODES

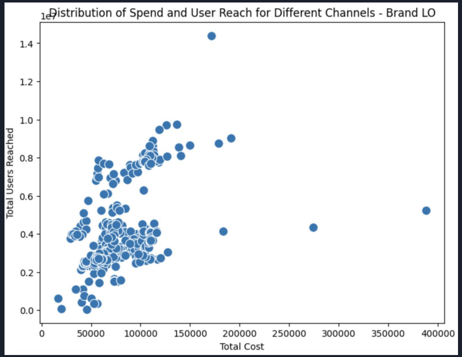
Appendix

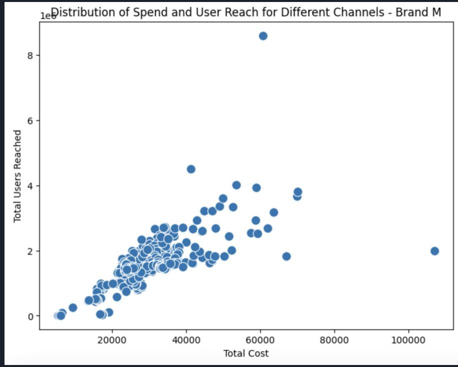
Additional Data Visualization - Distribution of Spend and User Reach by brands

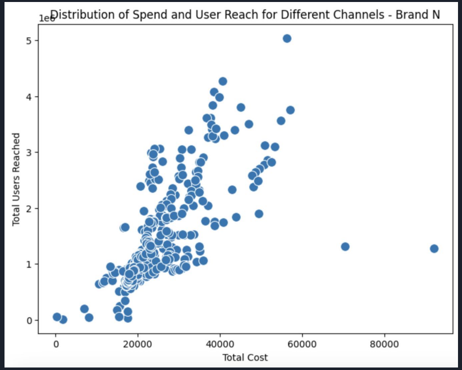


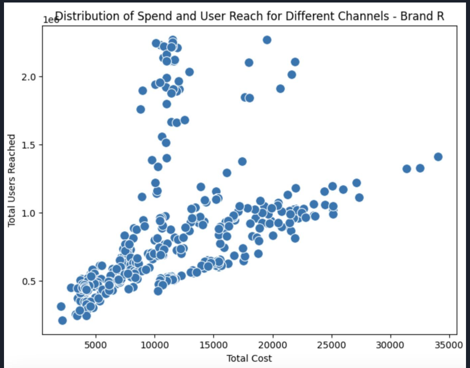






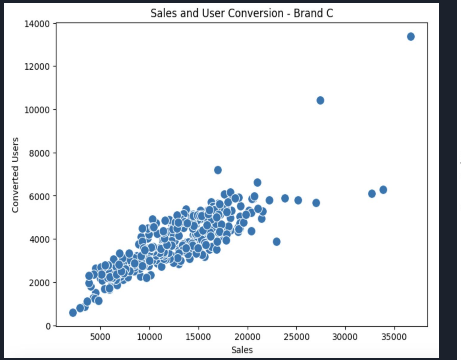


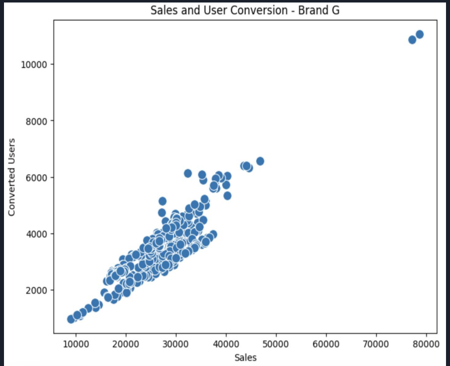


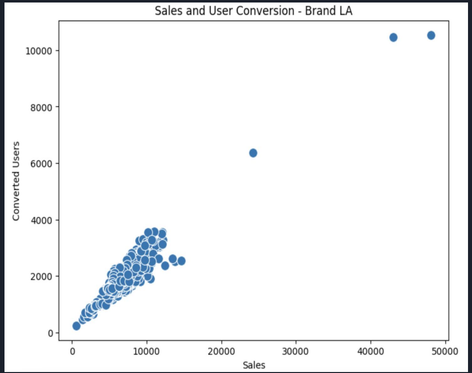


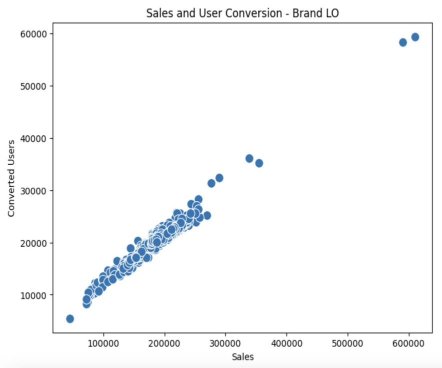
Appendix

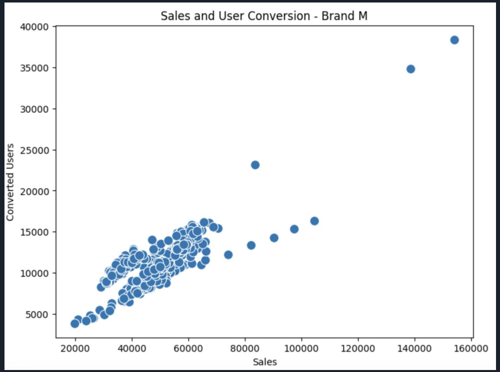
Additional Data Visualization - Distribution of Sales and User Conversion by brands

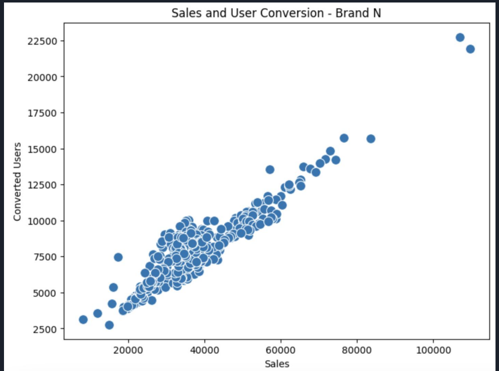


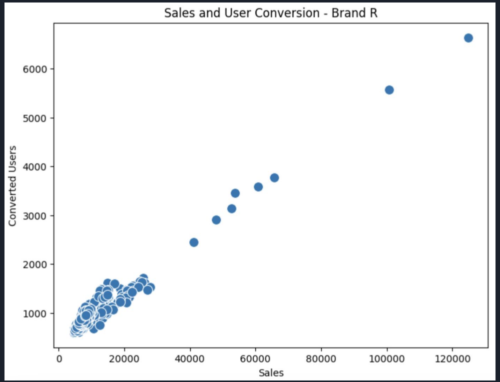






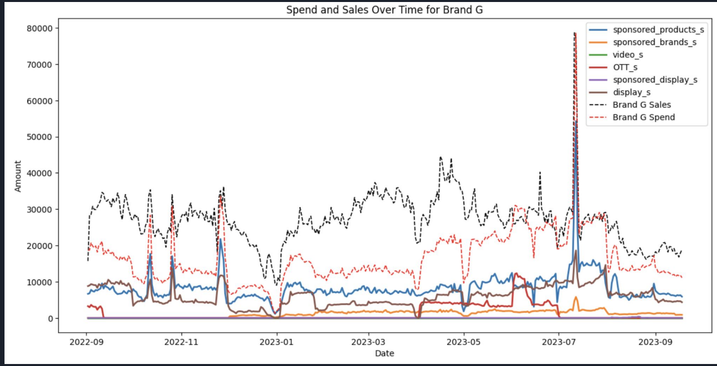


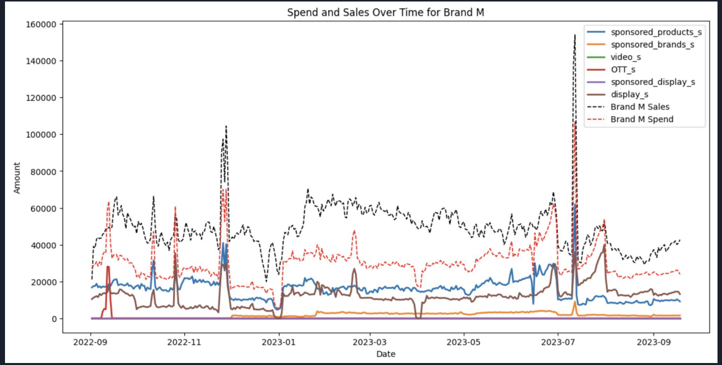


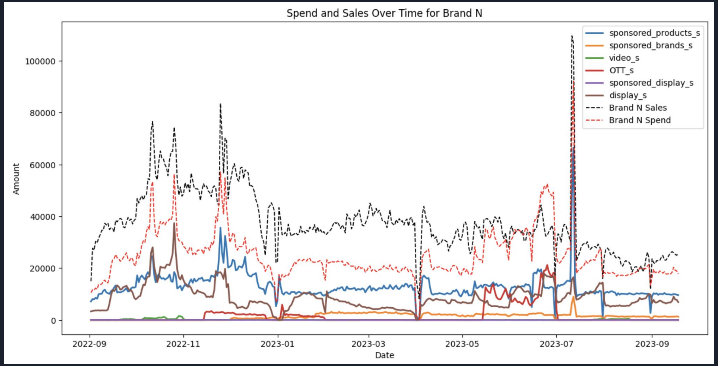


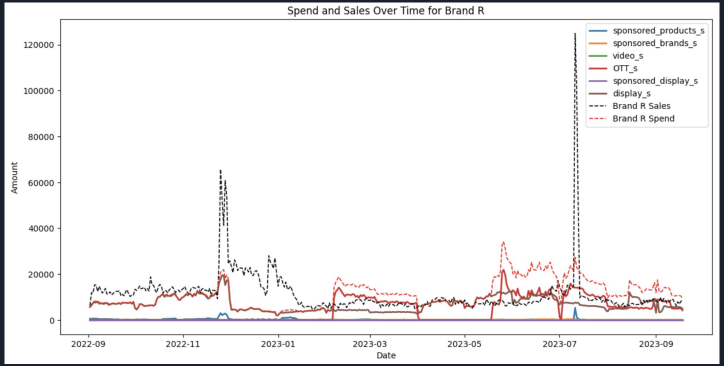
Appendix

Additional Data Visualization - Sales and Spends over time by brands







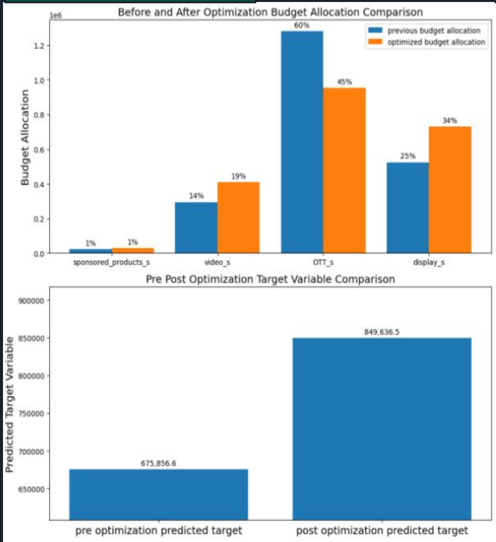


Appendix

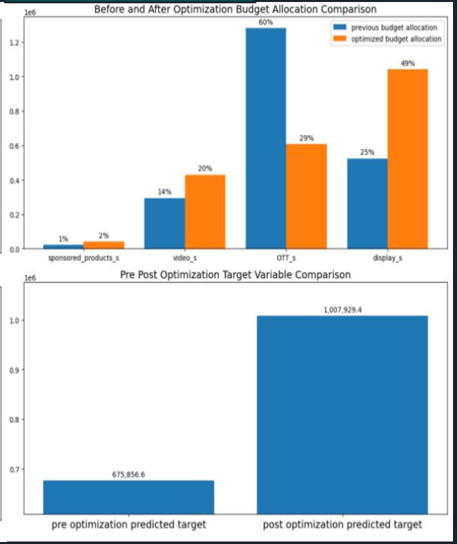
Google LightweightMMM Optimization Outputs

Brand C

±40%

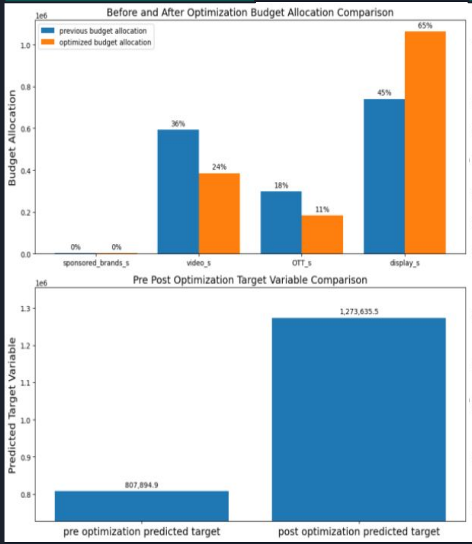


±100%

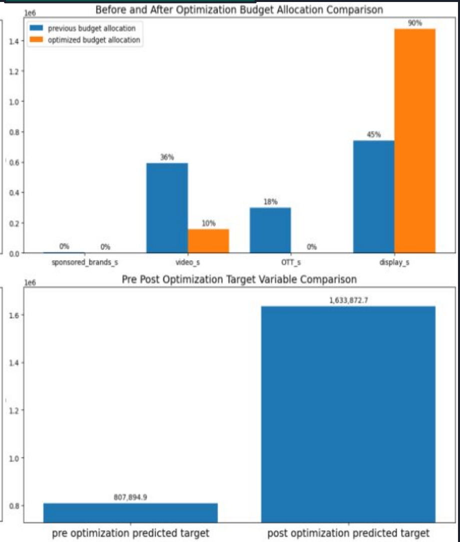


Brand LA

±40%



±100%

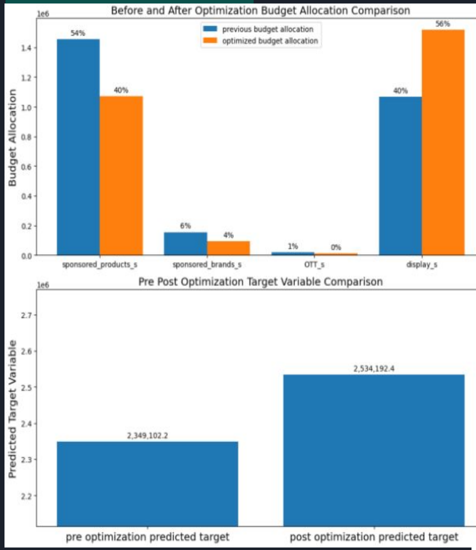


Appendix

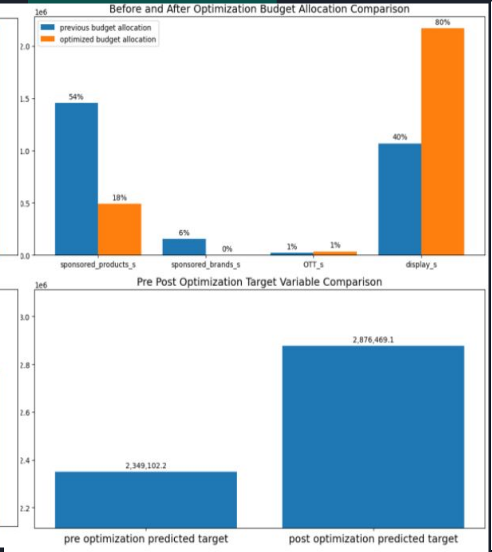
Google LightweightMMM Optimization Outputs

Brand M

±40%

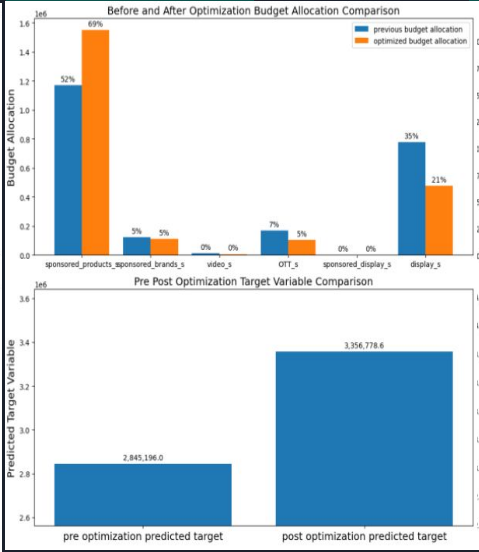


±100%

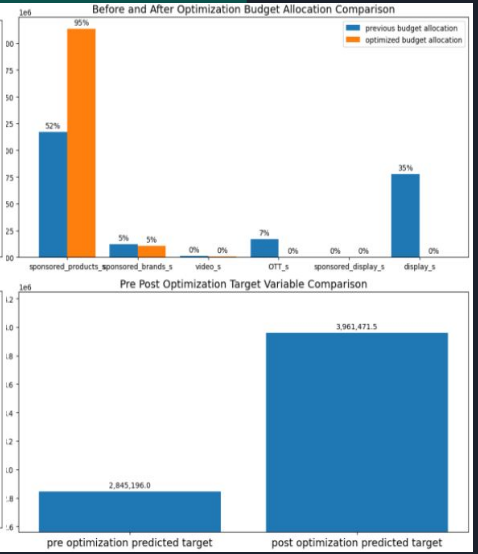


Brand N

±40%



±100%

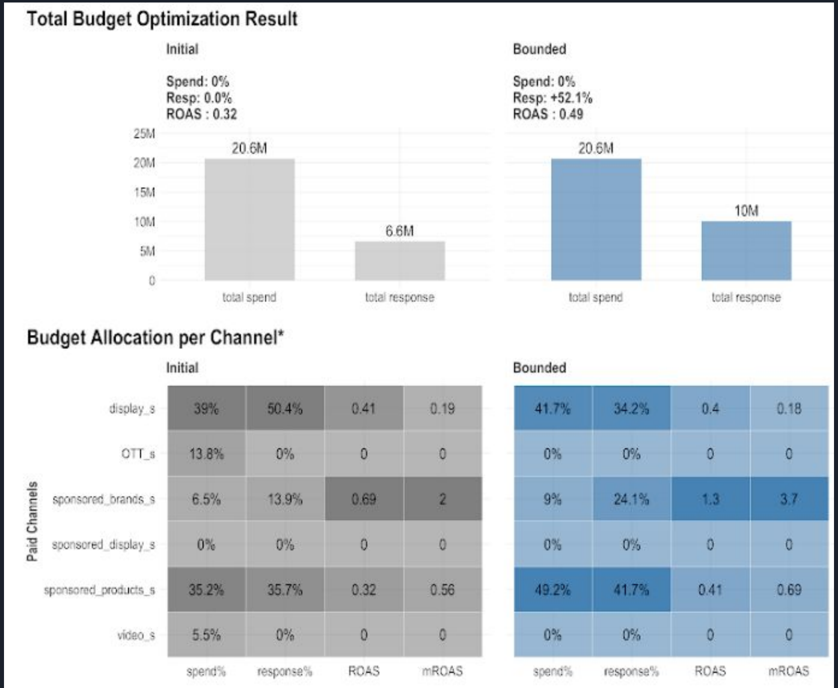


Appendix

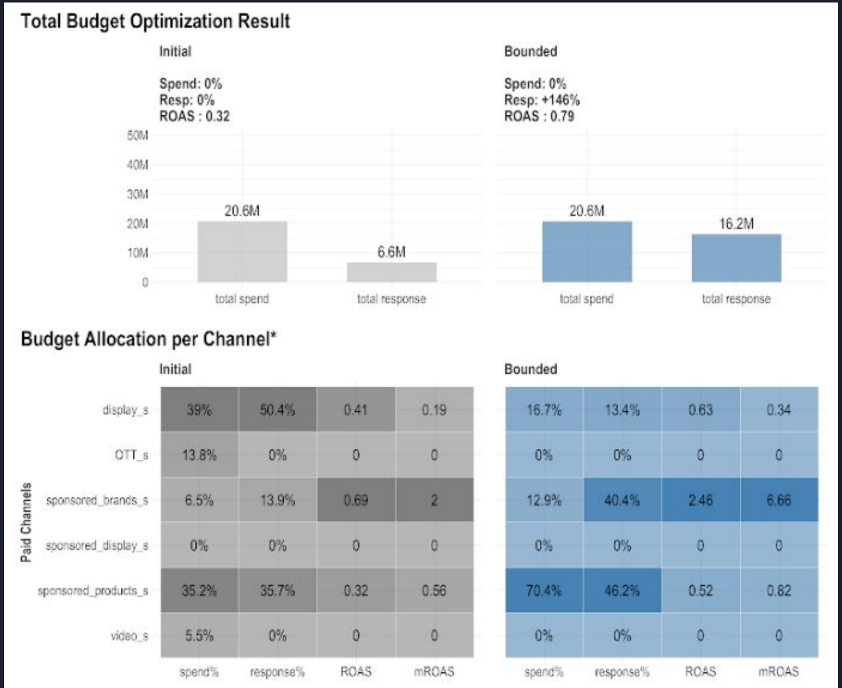
Robyn Outputs

All Brands

±40%



±100%



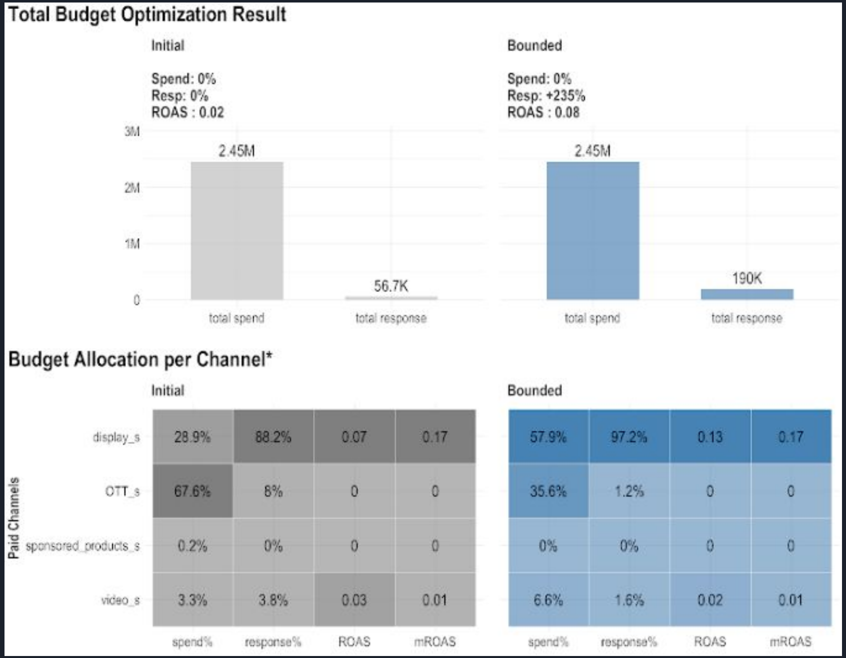
Appendix

Robyn Outputs

Brand C

±40%

±100%

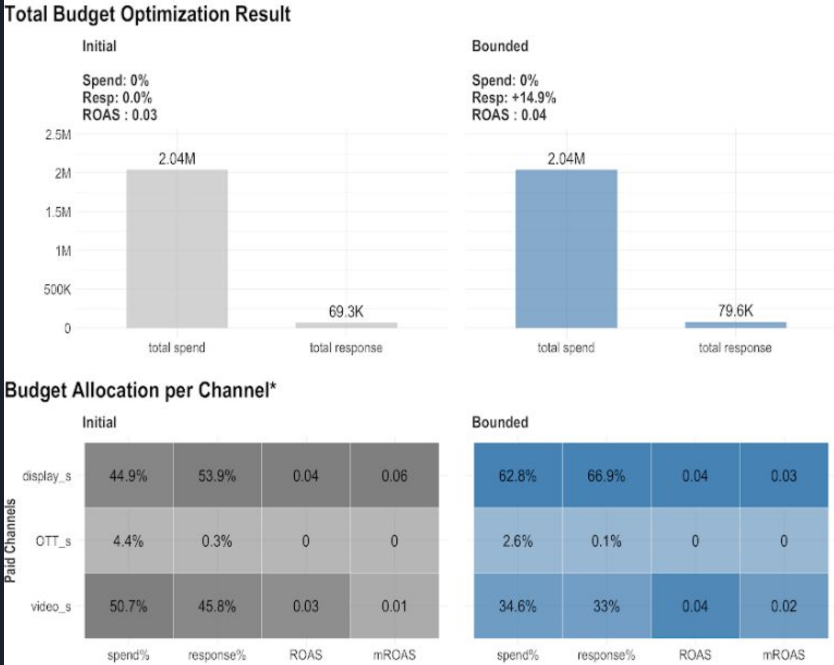


Appendix

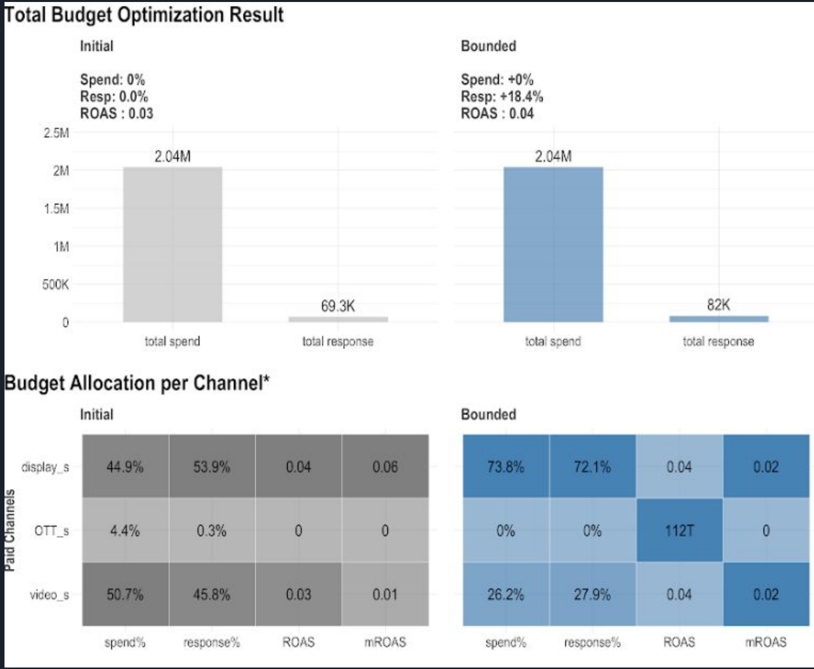
Robyn Outputs

Brand LA

±40%



±100%



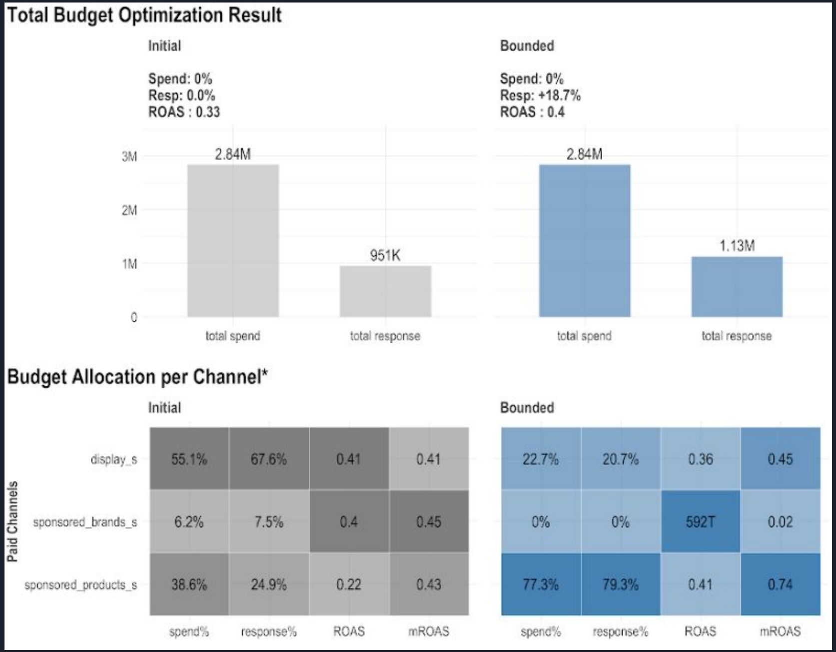
Appendix

Robyn Outputs

Brand M

±40%

±100%

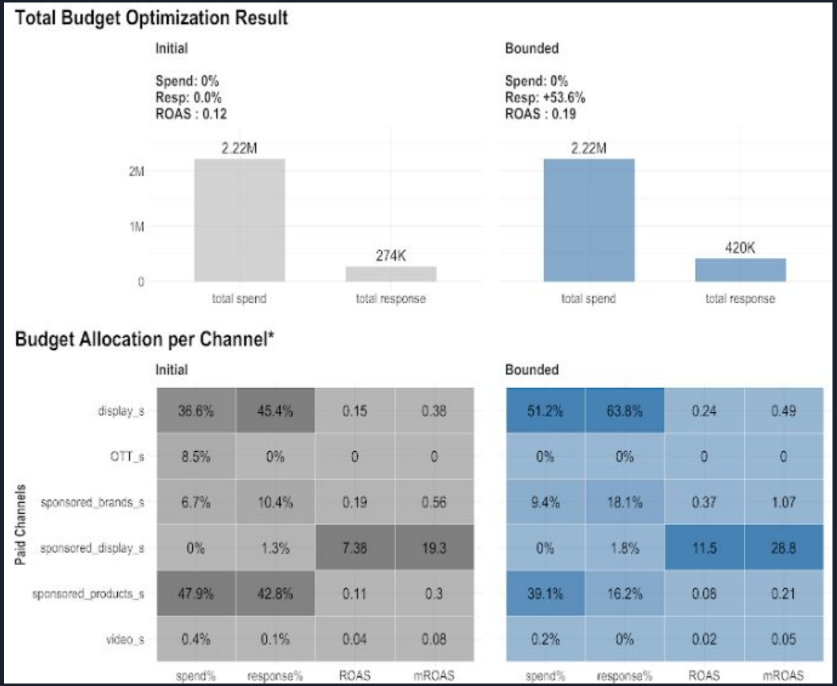


Appendix

Robyn Outputs

Brand N

±40%



±100%