mmm project-checkpoint

January 18, 2024

[ ]:
```
#https://www.kaggle.com/datasets/saicharansirangi/adanalyse
import jax.numpy as jnp
import numpyro
import pandas as pd
import numpy as np
from sklearn.metrics import mean_absolute_percentage_error
```

[ ]:
```
from lightweight_mmm import lightweight_mmm
from lightweight_mmm import optimize_media
from lightweight_mmm import plot
from lightweight_mmm import preprocessing
from lightweight_mmm import utils
```

```
WARNING:tensorflow:From C:\Users\jarvi\AppData\Local\Packages\PythonSoftwareFoun
dation.Python.3.11_qbz5n2kfra8p0\LocalCache\local-packages\Python311\site-
packages\keras\src\losses.py:2976: The name
tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

1 Preparing the Data

[ ]:
```
# Load the dataset from an Excel file
data = pd.read_excel("Sr Advertising Analyst Work Sample (1).xlsx")

# Group data by 'Date' and 'Ad group alias', and sum the values for␣
↪'Impressions', 'Spend', and 'Sales'
agg_data = data.groupby(["Date", "Ad group alias"])[["Impressions", "Spend",␣
↪"Sales"]].sum()

# Drop the 'Brand 1 Ad Group 12' from the data as it has zero cost in the␣
↪training dataset
agg_data = agg_data.drop(["Brand 1 Ad Group 12"], axis=0, level=1)

# Unstack 'Impressions' column: This reshapes the data from a multi-index␣
↪series to a dataframe
```

```python
# where each column represents an 'Ad group alias' and each row represents a␣
↪'Date'. Fill NaN values with 0.
media_data_raw = agg_data['Impressions'].unstack().fillna(0)

# Similarly, unstack 'Spend' and 'Sales' columns to align them with␣
↪'Impressions'
costs_raw = agg_data['Spend'].unstack()
sales_raw = agg_data['Sales'].reset_index().groupby("Date").sum()
data
```

[ ]:

```
            Date Brand Alias        Ad group alias ASIN/SKU Alias Marketplace  \
0     2021-10-17     Brand 1  Brand 1 Ad Group 10        ASIN414     Walmart
1     2021-10-17     Brand 1  Brand 1 Ad Group 11        ASIN385     Walmart
2     2021-10-17     Brand 1  Brand 1 Ad Group 11        ASIN389     Walmart
3     2021-10-17     Brand 1  Brand 1 Ad Group 13        ASIN377     Walmart
4     2021-10-17     Brand 1  Brand 1 Ad Group 13        ASIN399     Walmart
…          …           …                   …              …          …
9581  2022-01-11     Brand 2   Brand 2 Ad Group 2        ASIN508      Amazon
9582  2022-01-11     Brand 2   Brand 2 Ad Group 3        ASIN512      Amazon
9583  2022-01-11     Brand 2   Brand 2 Ad Group 3        ASIN516      Amazon
9584  2022-01-11     Brand 2   Brand 2 Ad Group 3        ASIN520      Amazon
9585  2022-01-11     Brand 2   Brand 2 Ad Group 5        ASIN619      Amazon

      Impressions  Clicks   Spend     Sales  Orders  Units  \
0              33       0   0.000    0.0000       0      0
1               0       0   0.000    0.0000       0      0
2               0       0   0.000    0.0000       0      0
3             380       8   2.340    0.0000       0      0
4            3805       7   6.684    0.0000       0      0
…             …      …     …       …      …     …
9581         4639      10   7.360    0.0000       0      0
9582        15336      49  33.790  638.7375       6      6
9583         4811       6   3.660    0.0000       0      0
9584        22838      36  19.570  294.9500       4      4
9585         1826       3   1.990  876.4250       3      6

      Advertised Units sold  Other SKU units sold  Advertised SKU Sales  \
0                         0                     0                  0.00
1                         0                     0                  0.00
2                         0                     0                  0.00
3                         0                     0                  0.00
4                         0                     0                  0.00
…                      …                    …                   …
9581                      0                     0                  0.00
9582                      1                     5                 55.99
9583                      0                     0                  0.00
9584                      3                     1                158.97
```

```
9585                      0                      6                    0.00

      Other SKU sales
0                0.00
1                0.00
2                0.00
3                0.00
4                0.00
…                …
9581             0.00
9582           455.00
9583             0.00
9584            76.99
9585           701.14

[9586 rows x 15 columns]
```

[ ]:
```
data.dtypes
```

[ ]:
```
Date                       datetime64[ns]
Brand Alias                        object
Ad group alias                     object
ASIN/SKU Alias                     object
Marketplace                        object
Impressions                         int64
Clicks                              int64
Spend                             float64
Sales                             float64
Orders                              int64
Units                               int64
Advertised Units sold               int64
Other SKU units sold                int64
Advertised SKU Sales              float64
Other SKU sales                   float64
dtype: object
```

[ ]:
```
data.columns
```

[ ]:
```
Index(['Date', 'Brand Alias', 'Ad group alias', 'ASIN/SKU Alias',
       'Marketplace', 'Impressions', 'Clicks', 'Spend', 'Sales', 'Orders',
       'Units', 'Advertised Units sold', 'Other SKU units sold',
       'Advertised SKU Sales', 'Other SKU sales'],
      dtype='object')
```

[ ]:
```
# Define the split point
split_point = pd.Timestamp("2021-12-15")
```

```
# Ensure the split point is within the dataset range
if split_point in media_data_raw.index:
    # Splitting media data into training and testing sets
    media_data_train = media_data_raw.loc[:split_point - pd.Timedelta(1, 'D')]
    media_data_test = media_data_raw.loc[split_point:]

    # Splitting target (sales) data into training and testing sets
    target_train = sales_raw.loc[:split_point - pd.Timedelta(1, 'D')]
    target_test = sales_raw.loc[split_point:]

    # Calculating costs for training period
    costs_train = costs_raw.loc[:split_point - pd.Timedelta(1, 'D')].
 ↪sum(axis=0).loc[media_data_train.columns]

    # Generating organic data
    np.random.seed(0)  # For reproducibility
    organic_raw = pd.DataFrame({'organic_search': 0, 'organic_social': 0},␣
 ↪index=media_data_raw.index)
    organic_sales_values = sales_raw['Sales'].astype(float).values  # Ensure␣
 ↪values are floats
    organic_raw['organic_search'] = organic_sales_values / 10 + np.random.
 ↪randint(10000, 100000, size=organic_raw.shape[0])
    organic_raw['organic_social'] = organic_sales_values / 10 + np.random.
 ↪randint(10000, 100000, size=organic_raw.shape[0])
else:
    print("Split point is not within the dataset range. Please check your dates.
 ↪")
```

[ ]:
```
# organic_search: Simulates organic traffic from search engines. This␣
 ↪represents the engagement or visits a website receives from unpaid search␣
 ↪results, typically influenced by search engine optimization (SEO) efforts.␣
 ↪It's calculated as a fraction of sales data plus a random component to␣
 ↪introduce variability.

# organic_social: Simulates organic engagement from social media platforms.␣
 ↪This column represents the traffic or engagement received through non-paid␣
 ↪means, like natural shares, likes, or posts on a company's social media␣
 ↪profiles. Similar to organic search, it's derived from a fraction of sales␣
 ↪data with an added random component for variability.

organic_raw
```

[ ]:
```
            organic_search  organic_social
Date
2021-10-17     81087.50575    102002.50575
2021-10-18     56116.07750     52682.07750
2021-10-19     56018.49375     68558.49375
```

```
2021-10-20     58911.44050     75776.44050
2021-10-21     34689.12050     95203.12050
…                      …             …
2022-01-07     92785.00400     41170.00400
2022-01-08     22075.41950     95450.41950
2022-01-09     93551.48625     28625.48625
2022-01-10     84182.07725     92834.07725
2022-01-11     63898.98900     65847.98900

[87 rows x 2 columns]
```

2 Scaling The Data

[ ]:
```
# Split organic data into training and testing sets based on the split point
organic_data_train = organic_raw.loc[:split_point - pd.Timedelta(1, 'D')]
organic_data_test = organic_raw.loc[split_point:]

# Initialize scalers for media, organic, target (sales), and costs data
# Using CustomScaler with mean as the divide operation for normalization
media_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
organic_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
target_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)
cost_scaler = preprocessing.CustomScaler(divide_operation=jnp.mean)

# Scale training data using the respective scalers
media_data_train_scaled = media_scaler.fit_transform(media_data_train.values)
organic_data_train_scaled = organic_scaler.fit_transform(organic_data_train.
 ↪values)
target_train_scaled = target_scaler.fit_transform(target_train['Sales'].
 ↪astype(float).values.squeeze())
costs_scaled = cost_scaler.fit_transform(costs_train.values)

# Scale testing data (only transform, as the model should not learn from␣
 ↪testing data)
media_data_test_scaled = media_scaler.transform(media_data_test.values)
organic_data_test_scaled = organic_scaler.transform(organic_data_test.values)

# Store the names of media channels for future reference
media_names = media_data_raw.columns
```

3 Hyperparameter Tuning

[ ]:
```
adstock_models = ["adstock", "hill_adstock", "carryover"]
degrees_season = [1,2,3]
```

```python
# Iterate over each model and degree of seasonality
for model_name in adstock_models:
    for degrees in degrees_season:
        # Initialize the LightweightMMM model with specified parameters
        mmm = lightweight_mmm.LightweightMMM(model_name=model_name)
        # Fit the model to the training data
        mmm.fit(
            media=media_data_train_scaled,
            media_prior=costs_scaled,
            target=target_train_scaled,
            extra_features=organic_data_train_scaled,
            number_warmup=1000,
            number_samples=1000,
            number_chains=1,
            degrees_seasonality=degrees,
            weekday_seasonality=True,
            seasonality_frequency=365,
            seed=1
        )

        # Predict using the model on test data
        prediction = mmm.predict(
            media=media_data_test_scaled,
            extra_features=organic_data_test_scaled,
            target_scaler=target_scaler
        )
        p = prediction.mean(axis=0)

        # Calculate the Mean Absolute Percentage Error (MAPE)
        mape = mean_absolute_percentage_error(target_test['Sales'].
 ↪astype(float).values, p)
        print(f"model_name={model_name} degrees={degrees} MAPE={mape}␣
 ↪samples={p[:3]}")
```

```
sample: 100%|      | 2000/2000 [00:35<00:00, 56.81it/s, 1023 steps of size
5.48e-03. acc. prob=0.80]

model_name=adstock degrees=1 MAPE=0.13815459576825026 samples=[30050.174
30058.537 29521.695]

sample: 100%|      | 2000/2000 [00:41<00:00, 48.48it/s, 1023 steps of size
3.57e-03. acc. prob=0.94]

model_name=adstock degrees=2 MAPE=0.3041605588534186 samples=[29475.06
29211.238 28458.979]

sample: 100%|      | 2000/2000 [00:35<00:00, 55.84it/s, 1023 steps of size
5.68e-03. acc. prob=0.80]

model_name=adstock degrees=3 MAPE=0.5756250713617705 samples=[28193.895
```

```
27556.273 26228.738]

sample: 100%|      | 2000/2000 [00:20<00:00, 95.97it/s, 511 steps of size
6.15e-03. acc. prob=0.92]

model_name=hill_adstock degrees=1 MAPE=0.1714074262903557 samples=[33889.223
33299.668 33069.496]

sample: 100%|      | 2000/2000 [00:21<00:00, 92.95it/s, 511 steps of size
7.99e-03. acc. prob=0.81]

model_name=hill_adstock degrees=2 MAPE=0.21885346262753802 samples=[32644.643
31559.6   30911.268]

sample: 100%|      | 2000/2000 [00:28<00:00, 70.92it/s, 1023 steps of size
5.33e-03. acc. prob=0.90]

model_name=hill_adstock degrees=3 MAPE=0.22601855742125002 samples=[32345.582
31027.676 30473.596]

sample: 100%|      | 2000/2000 [02:02<00:00, 16.26it/s, 255 steps of size
1.47e-02. acc. prob=0.88]

model_name=carryover degrees=1 MAPE=0.10048341215157608 samples=[30295.256
29732.867 29468.33 ]

sample: 100%|      | 2000/2000 [03:16<00:00, 10.15it/s, 511 steps of size
8.79e-03. acc. prob=0.93]

model_name=carryover degrees=2 MAPE=0.5290717765193821 samples=[28074.37
25816.383 25213.97 ]

sample: 100%|      | 2000/2000 [04:54<00:00,  6.78it/s, 1023 steps of size
3.80e-03. acc. prob=0.96]

model_name=carryover degrees=3 MAPE=0.788402733396885 samples=[27149.316
24041.635 22745.572]
```

4 Fitting the Model

[ ]:
```python
costs = costs_raw.sum(axis=0).loc[media_names]

media_scaler2 = preprocessing.CustomScaler(divide_operation=jnp.mean)
organic_scaler2 = preprocessing.CustomScaler(divide_operation=jnp.mean)
target_scaler2 = preprocessing.CustomScaler(
    divide_operation=jnp.mean)
cost_scaler2 = preprocessing.CustomScaler(divide_operation=jnp.mean)

media_data_scaled = media_scaler2.fit_transform(media_data_raw.values)
organic_data_scaled = organic_scaler2.fit_transform(organic_raw.values)
target_scaled = target_scaler2.fit_transform(sales_raw['Sales'].astype(float).
 ↪values)
costs_scaled2 = cost_scaler2.fit_transform(costs.values)
```

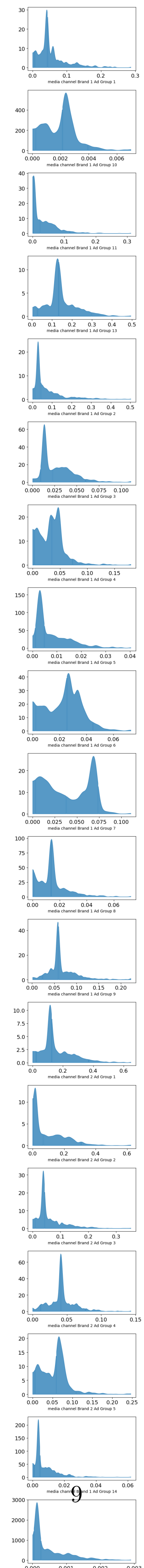
```
media_names = media_data_raw.columns

mmm = lightweight_mmm.LightweightMMM(model_name="carryover")
mmm.fit(media=media_data_scaled,
        media_prior=costs_scaled2,
        extra_features=organic_data_scaled,
        target=target_scaled,
        number_warmup=1000,
        number_samples=1000,
        number_chains=1,
        degrees_seasonality=1,
        weekday_seasonality=True,
        seasonality_frequency=365,
        seed=1)
```

```
sample: 100%|      | 2000/2000 [01:48<00:00, 18.51it/s, 255 steps of size
1.21e-02. acc. prob=0.65]
```

5 Plotting

[ ]:
```
plot.plot_media_channel_posteriors(media_mix_model=mmm,␣
 ↪channel_names=media_names)
```

[ ]:

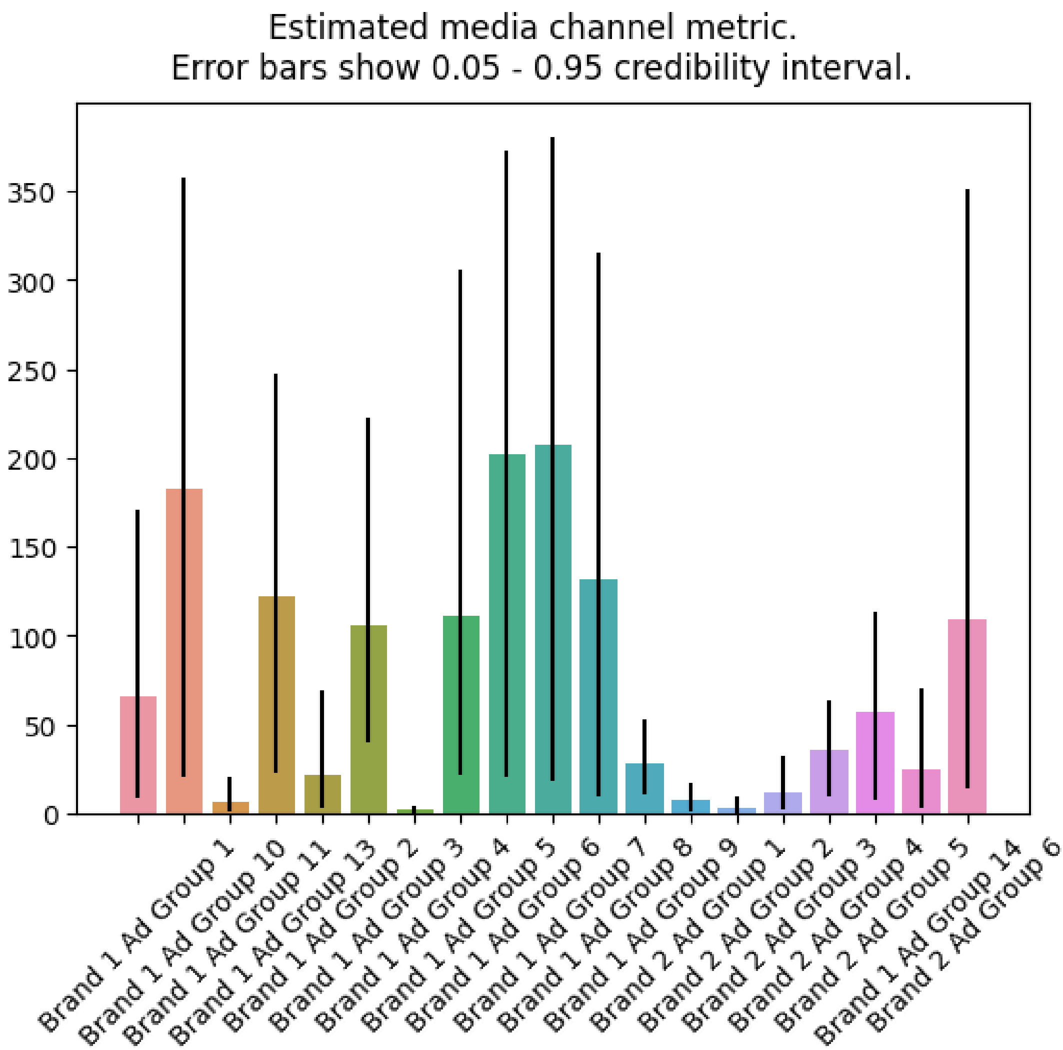


media channel Brand 1 Ad Group 1
media channel Brand 1 Ad Group 10
media channel Brand 1 Ad Group 11
media channel Brand 1 Ad Group 13
media channel Brand 1 Ad Group 2
media channel Brand 1 Ad Group 3
media channel Brand 1 Ad Group 4
media channel Brand 1 Ad Group 5
media channel Brand 1 Ad Group 6
media channel Brand 1 Ad Group 7
media channel Brand 1 Ad Group 8
media channel Brand 1 Ad Group 9
media channel Brand 2 Ad Group 1
media channel Brand 2 Ad Group 2
media channel Brand 2 Ad Group 3
media channel Brand 2 Ad Group 4
media channel Brand 2 Ad Group 5
media channel Brand 1 Ad Group 14
media channel Brand 2 Ad Group 6

[ ]:
```
media_contribution_pct, roi_hat = mmm.get_posterior_metrics(
    cost_scaler=cost_scaler2,
    target_scaler=target_scaler2
)
```

[ ]:
```
plot.plot_bars_media_metrics(metric=roi_hat, channel_names=media_names)
```

[ ]:



6 Optimize Media

[ ]:
```
prices = jnp.ones(mmm.n_media_channels)

# Convert Pandas Series to a numpy array
average_spend_per_channel = np.array(media_data_raw.mean(axis=0))

# Ensure prices is a numpy array as well
prices = np.array(prices)

# Calculate budget using numpy operations and then cast to jnp array if needed
budget = jnp.array(np.sum(prices * average_spend_per_channel) * 10)

# Run optimization with the specified parameters.
solution, kpi_without_optim, previous_media_allocation = optimize_media.
 ↪find_optimal_budgets(
    n_time_periods=10,  # Define the number of time periods you want to␣
 ↪optimize for
    media_mix_model=mmm,  # Your trained LightweightMMM model
    extra_features=organic_data_scaled[-10:, :],  # Use the last 10 rows of␣
 ↪your scaled organic data
    budget=budget,  # The total budget you have set for the media
    prices=prices,  # The prices array as calculated earlier
    media_scaler=media_scaler,  # The scaler used for media data
    target_scaler=target_scaler,  # The scaler used for target variable
    seed=1  # Set a seed for reproducibility
)
```

```
Optimization terminated successfully    (Exit mode 0)
            Current function value: -334833.5567096917
            Iterations: 146
            Function evaluations: 5655
            Gradient evaluations: 145
```

[ ]:
```
# Obtain the optimal weekly allocation.
optimal_buget_allocation = prices * solution.x
optimal_buget_allocation
```

[ ]:
```
array([4.43621719e+04, 3.19525421e+02, 8.65542375e+05, 2.35178875e+05,
       3.07092406e+05, 3.79362744e+03, 3.59021500e+06, 4.65559357e+02,
       5.36847461e+03, 7.44366162e+03, 6.32196729e+03, 1.07695938e+05,
       4.19150600e+06, 4.76517741e+06, 1.28371575e+06, 3.09438312e+05,
       2.30177906e+05, 1.10530984e+05, 1.80508521e+03])
```

[ ]:
```
# similar renormalization to get previous budget allocation
previous_budget_allocation = prices * previous_media_allocation
previous_budget_allocation
```

[ ]: Array([3.5958742e+04, 2.5899844e+02, 7.0158462e+05, 1.9062947e+05,
       2.4892059e+05, 3.0750090e+03, 4.3651935e+06, 3.7736951e+02,
       4.3515371e+03, 6.0336260e+03, 5.1244111e+03, 8.7295336e+04,
       3.3975185e+06, 5.4508305e+06, 1.0405443e+06, 2.5082211e+05,
       1.8657583e+05, 8.9593352e+04, 1.4631520e+03], dtype=float32)

[ ]:
```
# Both these values should be very close in order to compare KPI
budget, optimal_buget_allocation.sum()
```

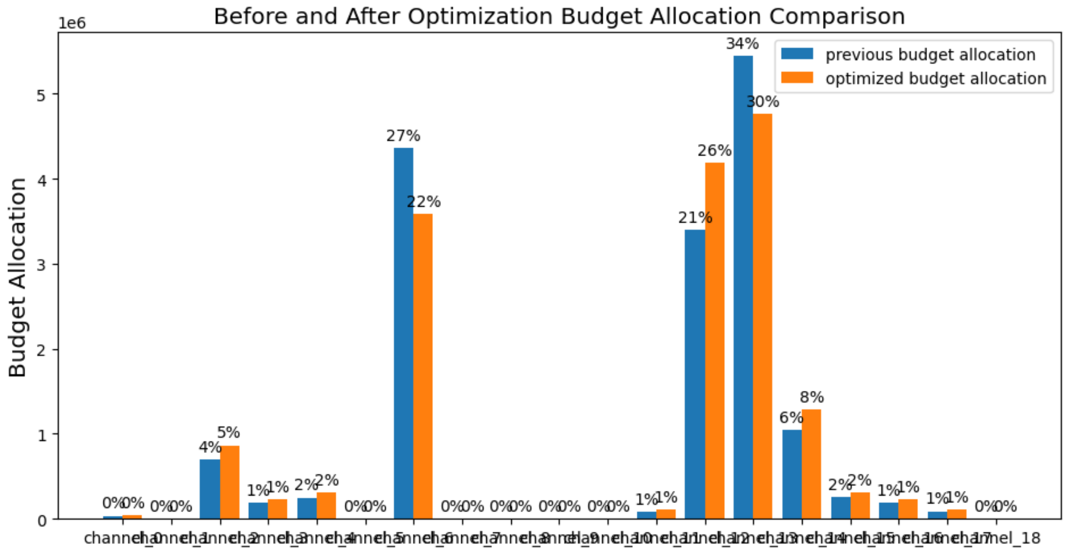
[ ]: (Array(16066151.03448276, dtype=float64), 16066151.034482755)

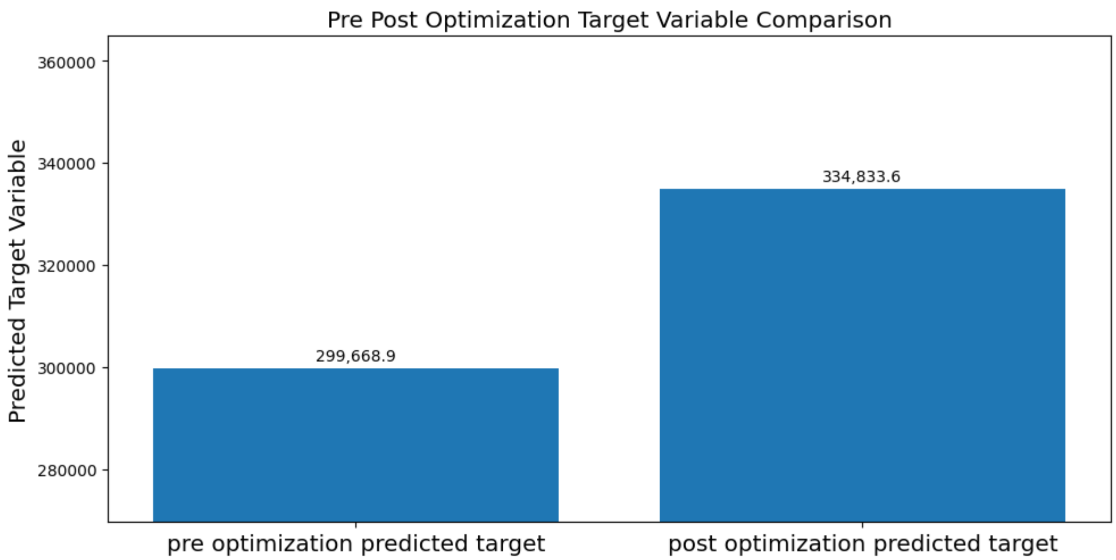
[ ]:
```
# Both numbers should be almost equal
budget, jnp.sum(solution.x * prices)
```

[ ]: (Array(16066151.03448276, dtype=float64), Array(16066150., dtype=float32))

[ ]:
```
# Plot out pre post optimization budget allocation and predicted target␣
 ↪variable comparison.
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))
```

[ ]:


Before and After Optimization Budget Allocation Comparison
1e6
Budget Allocation
previous budget allocation
optimized budget allocation
0
1
2
3
4
5
0% 0% 0% 0% 4% 5% 1% 1% 2% 2% 0% 0% 27% 22% 0% 0% 0% 0% 0% 0% 0% 0% 1% 1% 21% 26% 34% 30% 6% 8% 2% 2% 1% 1% 1% 1% 0% 0%
channel_0 channel_1 channel_2 channel_3 channel_4 channel_5 channel_6 channel_7 channel_8 channel_9 channel_10 channel_11 channel_12 channel_13 channel_14 channel_15 channel_16 channel_17 channel_18


Pre Post Optimization Target Variable Comparison
Predicted Target Variable
280000
300000
320000
340000
360000
299,668.9
334,833.6
pre optimization predicted target
post optimization predicted target