📊 Market Mix Modeling with XGBoost

> **A comprehensive Marketing Mix Model (MMM) leveraging Prophet for time-series decomposition and XGBoost for response modeling, with advanced adstock transformations and SHAP-based interpretability.**

Open in Colab | License MIT | python 3.8+

🎯 Project Overview

This project demonstrates an end-to-end **Marketing Mix Modeling** workflow that:

- 📈 **Quantifies** the impact of various marketing channels on sales revenue
- 🔄 **Models** carryover effects using geometric adstock transformations
- 📉 **Captures** saturation and diminishing returns through SHAP analysis
- 💰 **Optimizes** marketing budget allocation across channels
- 🎛️ **Tunes** hyperparameters using Optuna for both Prophet and XGBoost

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📁 Repository Structure

```
Market-Mix-Model_using_XgBoost-main/
│
├── 📓 MMM_using_XgBoost.ipynb    # Main Jupyter notebook (1,642 lines)
├── 📊 MMM_data.csv               # Weekly marketing & sales data (208 rows)
├── 📅 prophet_holidays_daily.csv # Holiday calendar (46,194 entries)
├── 📄 README.md                  # Original project readme
├── 📜 LICENSE                    # MIT License
├── 🚫 .gitignore                 # Python gitignore template
└── 📖 my_readme.md               # This comprehensive guide
```

📊 Dataset Description

Primary Dataset: `MMM_data.csv`

Column	Description	Type
`DATE`	Week ending date	datetime
`revenue`	Sales revenue ($K) — **Target Variable**	float
`tv_S`	Television advertising spend ($K)	float
`ooh_S`	Out-of-home advertising spend ($K)	float

Column	Description	Type
`print_S`	Print media advertising spend ($K)	float
`facebook_S`	Facebook paid advertising spend ($K)	float
`facebook_I`	Facebook influencer marketing spend ($K)	float
`search_S`	Search engine marketing spend ($K)	float
`search_clicks_P`	Pay-per-click campaign spend ($K)	float
`competitor_sales_B`	Competitor sales benchmark ($K)	float
`newsletter`	Email newsletter marketing spend ($K)	float
`events`	Promotional events (`event1` , `event2` , `na`)	categorical

📅 **Time Range:** November 2015 – November 2019 (≈208 weekly observations)

Holiday Dataset: `prophet_holidays_daily.csv`

- **46,194** daily holiday entries across multiple countries (1995–2023)
- Filtered to **US holidays** and aggregated to weekly frequency
- Used by Prophet to capture demand shocks (Black Friday, Independence Day, etc.)

🔬 Methodology

Phase 1: Time Series Decomposition with Prophet

```
┌─────────────────────────────────────────────────────────────┐
│                    RAW REVENUE DATA                         │
└─────────────────────────────────────────────────────────────┘
                             │
                             ▼
┌─────────────────────────────────────────────────────────────┐
│                    PROPHET MODEL                            │
│  • Yearly seasonality    • Holiday effects                  │
│  • Weekly seasonality    • Event regressors                 │
│  • Trend extraction      • Hyperparameter tuning (Optuna)   │
└─────────────────────────────────────────────────────────────┘
                             │
                             ▼
┌─────────────────────────────────────────────────────────────┐
│              EXTRACTED COMPONENTS                           │
│  📈 Trend  │  🔄 Seasonality  │  🎄 Holidays  │  🎉 Events  │
└─────────────────────────────────────────────────────────────┘
```

Prophet Hyperparameters Tuned:

- `seasonality_prior_scale` — Controls flexibility of seasonal patterns
- `changepoint_prior_scale` — Controls detection of trend changes
- `holidays_prior_scale` — Controls impact of holidays on forecast
- `seasonality_mode` — Additive vs multiplicative seasonality

Phase 2: Adstock Transformation

Marketing effects don't vanish instantly—they **carry over** across weeks. The geometric adstock transformation models this decay:

$$x_{t}^{adstock} = x_t + \alpha \cdot x_{t-1}^{adstock}$$

Where:

- x_t = Raw spend at time t
- α = Decay rate (0 to 1)
- Higher α = Longer carryover effect

Channel-Specific Adstock Ranges:

Channel	α Range	Interpretation
TV	0.3 – 0.8	Long memory (brand building)
OOH	0.1 – 0.4	Medium memory
Print	0.1 – 0.4	Medium memory
Facebook	0.0 – 0.4	Short-medium memory
Search	0.0 – 0.3	Short memory (immediate response)
Newsletter	0.1 – 0.4	Medium memory

Phase 3: XGBoost Response Modeling

```
Features = [
    # Prophet Components
    'trend', 'season', 'holiday', 'events',

    # Contextual
    'competitor_sales_B',

    # Media Channels (with adstock)
    'tv_S', 'ooh_S', 'print_S', 'facebook_S', 'search_S',

    # Organic
    'newsletter'
]
```

XGBoost Hyperparameters Tuned via Optuna:

- `n_estimators` (5–100)
- `max_depth` (4–7)
- `learning_rate` (0.001–0.1)
- `subsample` (0.5–1.0)
- `colsample_bytree` (0.5–1.0)
- `reg_alpha`, `reg_lambda`, `gamma` (regularization)

Phase 4: SHAP Interpretability

SHAP (SHapley Additive exPlanations) provides:

- **Feature Importance** — Which channels drive revenue most
- **Response Curves** — Spend vs. SHAP value reveals saturation
- **Effect Share** — Contribution % per channel

📈 Key Metrics

Metric	Formula	Purpose
RMSE	$\sqrt{\frac{1}{n}\sum(y - \hat{y})^2}$	Prediction accuracy
MAPE	$\frac{100}{n}\sum\lvert\frac{y - \hat{y}}{y}\rvert$	Percentage error
NRMSE	$\frac{RMSE}{y_{max} - y_{min}}$	Normalized accuracy
R^2	$1 - \frac{SS_{res}}{SS_{tot}}$	Variance explained
RSSD	$\sqrt{\sum(effect_share - spend_share)^2}$	Budget efficiency

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🚀 Quick Start

Option 1: Google Colab (Recommended)

Click the **Open in Colab** badge above and run all cells sequentially.

Option 2: Local Installation

```bash
# Clone repository
git clone https://github.com/Praveen76/Market-Mix-Model_using_XgBoost.git
cd Market-Mix-Model_using_XgBoost

# Create virtual environment
python -m venv mmm_env
source mmm_env/bin/activate  # Windows: mmm_env\Scripts\activate

# Install dependencies
pip install pandas numpy prophet optuna shap xgboost scikit-learn
pip install seaborn matplotlib plotnine plotly
```

```
# Launch notebook
jupyter notebook MMM_using_XgBoost.ipynb
```

Dependencies

```
pandas>=1.3.0
numpy>=1.21.0
prophet>=1.1.0
optuna>=3.0.0
shap>=0.41.0
xgboost>=1.6.0
scikit-learn>=1.0.0
seaborn>=0.11.0
matplotlib>=3.4.0
plotnine>=0.9.0
plotly>=5.0.0
```

📓 Notebook Workflow

```
graph TD
    A[📥 Load Data] --> B[🎄 Load Holidays]
    B --> C[🔧 Encode Events]
    C --> D[⚙️ Tune Prophet with Optuna]
    D --> E[📊 Extract Trend/Season/Holiday]
    E --> F[🔄 Apply Adstock Transformations]
    F --> G[⚙️ Tune XGBoost with Optuna]
    G --> H[📈 Train Final Model]
    H --> I[🔍 SHAP Analysis]
    I --> J[💰 Budget Optimization]
    J --> K[💾 Save Model]
```

Step	Description	Key Output
Step 0	Import libraries & load data	`df`, `holidays_weekly_us`
Step 1	Prophet hyperparameter tuning	`best_params` for Prophet
Step 1.a	Train Prophet & evaluate	MAPE, RMSE, R^2 on test set
Step 1.b	Extract decomposition components	`trend`, `season`, `holiday`, `events`
Step 2	Define adstock & helper functions	`AdstockGeometric` class
Step 3	XGBoost + Optuna optimization	`experiment.best_trial`

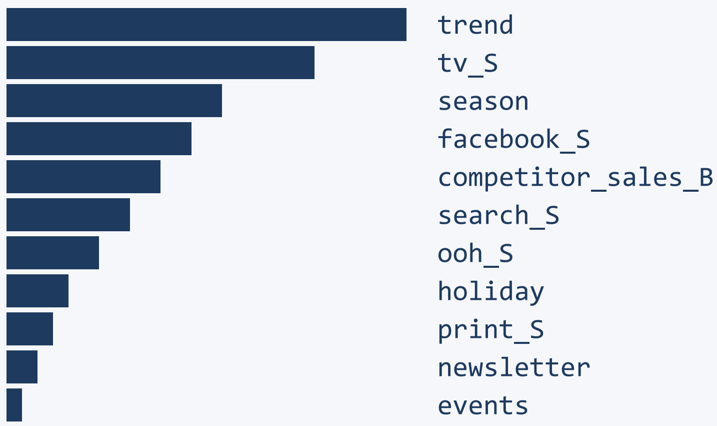
Step	Description	Key Output
Step 4	Model refit & SHAP analysis	Feature importance, effect shares
Step 5	Multi-objective optimization	Pareto front (MAPE vs RSSD)
Step 6	Save final model	`final_xgboost_model.json`

📊 Expected Outputs

1. Prophet Component Plots

- **Trend** — Long-term growth trajectory
- **Yearly Seasonality** — Annual demand patterns
- **Holiday Effects** — Spikes around major holidays
- **Event Impact** — Promotional campaign effects

2. Feature Importance (SHAP)



3. Spend vs Effect Share

Channel	Spend Share	Effect Share	Efficiency
TV	35%	42%	☑ Over-performing
Facebook	25%	28%	☑ Efficient
Search	20%	15%	⚠ Under-performing
OOH	12%	10%	⚠ Under-performing
Print	8%	5%	✖ Inefficient

4. Response Curves

Non-linear SHAP vs. Spend curves reveal **diminishing returns** — where additional spend yields minimal incremental revenue.

💡 Business Applications

Budget Reallocation

```
Current Allocation          Recommended Allocation
─────────────────           ─────────────────────
TV:         35% ─────────────► TV:         40% (+5%)
Facebook:   25% ─────────────► Facebook:   28% (+3%)
Search:     20% ─────────────► Search:     15% (-5%)
OOH:        12% ─────────────► OOH:        10% (-2%)
Print:       8% ─────────────► Print:       7% (-1%)
```

Scenario Simulation

- **What if** TV spend increases by 20%?
- **What if** we cut Print entirely?
- **What if** we double Search during Q4?

Apply adstock transformation → Pass through XGBoost → Project revenue impact.

⚠ Limitations & Assumptions

Assumption	Implication
Static pricing	Revenue changes attributed to marketing, not price
No macro shocks	External events (COVID, recession) not modeled
Linear adstock decay	May oversimplify complex carryover dynamics
Correlation ≠ Causation	SHAP measures association, not true causal effect
US holidays only	Results may differ for other geographies

🔧 Troubleshooting

Issue	Solution
Prophet installation fails	Use `pip install prophet==1.1.4` or conda-forge
Memory error during Optuna	Reduce `n_trials` or `n_estimators` range
MAPE returns NaN	Check for zero revenue values; use SMAPE instead
SHAP feature mismatch	Ensure train/test have identical columns
Plotly charts not rendering	Set `pio.renderers.default = 'notebook'`

📚 References

- Prophet Documentation
- XGBoost Documentation
- SHAP Documentation
- Optuna Documentation
- Robyn by Meta (MMM inspiration)

📜 License

This project is licensed under the **MIT License** — see LICENSE for details.

👤 Credits

Original Author: Praveen Kumar Anwla
Organization: TowardsMachineLearning.Org

🤝 Contributing

1. Fork the repository
2. Create a feature branch (`git checkout -b feature/improvement`)
3. Commit changes (`git commit -m 'Add improvement'`)
4. Push to branch (`git push origin feature/improvement`)
5. Open a Pull Request

⭐ Star this repo if you find it useful!

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