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Sales Performance Decomposition: Attribution Modeling & Predictive Sales Analytics

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ABSTRACT
To do well in sales we need to understand what drives them. This is important for making marketing plans and keeping sales up over time. We are trying to figure out how much each marketing method contributes to sales when customers take a path to buy something. We also want to make a system to predict future sales. We suggest using a combination of Multi-Touch Attribution and advanced Machine Learning to make predictions our method involves looking at three ways to give credit to marketing methods. Linear, Time-Decay and Position-Based. To break down past sales data into what each channel did. We then use the method to help make a customized system to predict sales using XGBoost and a Neural Network to make the predictions more accurate. We tested this using data from an e-commerce site with 50,000 customer journeys across eight marketing channels the results show that using the Position-Based method with our suggested system works best giving us an idea of how well we can predict sales. This helps us understand what marketing methods work and makes it easier to predict sales so we can make plans. This study shows that combining attribution science with intelligence is a good way to make a system that works well for businesses, with many sales channels.

Keywords: Sales Attribution Modeling, Predictive Sales Analytics, Multi-Touch Attribution, Ensemble Learning, XGBoost Marketing Mix Optimization, Machine Learning, Customer Journey Analytics, Revenue Forecasting.

I. Introduction

The way we do business has changed a lot because of technology. This change has made sales performance analysis complicated for sales teams. We used to look at how money the company made but now we have to think about marketing, how people behave and computers. Today people look at things before they decide to buy something from our company. They check media, emails, search engines and other websites to learn more about our products. This makes it hard to know what really works and what does not work for our sales performance that is why we need something called Multi-Touch Attribution. Multi-Touch Attribution helps us understand how all these different things people look at affect their decision to buy something from our company. We also use something called sales analytics to try to guess how money our company will make in the future. We look at what happened in the past what is going on in the world. What is happening inside our company to make these guesses about our sales performance. This helps us get ready for what might happen and use our resources wisely for our company.

There is a problem with the way we do things now. We usually only look at what happened after it happened. We do not use that information to help us make predictions about the future of our sales performance. This means we do not make the decisions we can to improve our sales performance now that we have a lot of data and computers are getting better we can do things differently for our company. This research is trying to create a way of doing things that combines the best of both worlds. We want to break down how well we are selling our products into parts so we can see what is really working for our company. We will use Multi-Touch Attribution to do this and use what we learn from Multi-Touch Attribution to help us make predictions about the future of our sales performance we will test our way of doing things to make sure it is better, than what we're doing now for our company we will create a system that can help us understand what happened in the past and what might happen in the future for our sales performance.

1.1 Motivation

The main reason for this research is that companies have a time figuring out how well their marketing is working when they use many different channels. Companies spend a lot of money on platforms. They have trouble measuring how well each one is doing because of a few big problems.

Customer Journey Complexity: When people buy something they usually do not follow a path. They interact with companies in ways and these interactions can affect each other in complicated ways that are hard to understand.

Data Siloing: The information that companies collect from marketing, sales and website analytics is often stored in systems, which makes it hard to get a complete picture of what customers are doing.

Heuristic Model Limitations: The old ways of figuring out which marketing channels are working like using rules are not flexible enough to handle changing data.

The Prediction-Interpretation Gap: While some models can make predictions they often do not help us understand why they are making those predictions about marketing.

By creating a system where we use what we learn from marketing to help make predictions about marketing this study creates a cycle where we can keep learning and improving our marketing. By looking at what happened in the past with our marketing we can get an understanding of what's going on with our marketing, which helps us make more accurate and understandable predictions about our marketing. These predictions, about our marketing can then help us plan and optimize how we spend our money on marketing in the future, which creates a system that can keep getting better on its own with our marketing.

2. Related Work

This section reviews research in marketing attribution and predictive sales analytics. It highlights a gap that this work aims to fill.

2.1. Evolution of Marketing Attribution Modeling

The way we assign credit for conversions has changed a lot. It used to be simple. Now its more complex. Early digital analytics used Last-Click Attribution, which gave much credit to the last touchpoint. They also used First-Click Attribution, which gave much credit to where the customer came from.

- ✓ These methods had problems so Multi-Touch Attribution (MTA) models were created.
- ✓ MTA models like Linear Time-Decay and Position-Based gave a view.
- ✓ However these models were still based on rules. Didn't adapt well to new data.

Then new methods were introduced.

- Shapley Value Attribution uses game theory to give credit to channels based on their contribution.
- Probabilistic models, like Markov chains show the customer journey as a process to estimate conversion chances.
- Machine learning techniques, like regression and survival analysis predict conversion chances.

Marketing Attribution models are used to explain results.

- They are not often used to predict performance.

The outputs of these models are rarely used as inputs for forecasting.

These models help us understand what happened. Not what will happen.

Marketing Attribution and predictive sales analytics are crucial, for businesses.

They help businesses make decisions.

2.2. Predictive Analytics in Sales Forecasting

Sales forecasting is a field that uses different mathematical methods. We have been using methods like ARIMA and Exponential Smoothing for a time. These methods are good at finding patterns in sales data over time. However they do not take into account things like marketing campaigns that happen outside of our sales data.

We can use methods like regression to include these marketing factors.. These methods have trouble dealing with complex relationships between many different factors.

Now we have machine learning which has changed the way we do sales forecasting. Methods like Random Forest and Gradient Boosting Machines are very good at handling sales data. These methods are widely used in the industry to forecast sales. We also have Deep Learning models like Long Short-Term Memory networks that're good at finding patterns in sales data over time.

The problem with machine learning models is that they are hard to understand. While we can get importance scores from methods like XGBoost we do not get a picture of which marketing channels are driving sales. This makes it hard to use the sales forecasts to make decisions about marketing budgets. Predictive Analytics in Sales Forecasting is still a field that needs to be improved. Sales forecasting models like these need to be able to provide detailed information about which marketing channels are working. This will help us to make decisions about where to spend our marketing money. Predictive Analytics, in Sales Forecasting is an area that we need to keep working on.

2.3. Toward An Integrated Approach

We need to connect the gap between figuring out why something happened and predicting what will happen next. Some early studies have tried using information from the part to help with the second part like using the order of things that happened and how long they took to help guess how much a customer will be worth to a company over time. Other people have suggested using two systems, one for each part but these systems do not always work well together.

This study tries to fix this problem by suggesting a system where everything works closely together. We think of figuring out why something happened as a part of the process not as a separate thing. By doing this we can make our predictions more accurate and easier to understand all within one system. The Customer Lifetime Value models will get better because we are using information from the part to make the predictions. This makes our system better, at predicting what will happen and easier for people to understand how it works.

3. Research Methodology

3.1. Problem Statement

The main issue this research is trying to solve is that people look at sales performance in pieces. They try to figure out how well their sales channels did in the past. They do this separately from trying to predict how much money they will make in the future. This causes three problems inefficient Resource Allocation: When people make marketing decisions based on models that only look at the last thing a customer did before buying they often do not use their money wisely. They do not invest enough in the things that help get customers interested in the place diminished Forecast. Interpretability: If predictive models do not take into account what was learned from looking at the past they are not as good. Are hard to understand. This means the predictions are not as accurate and are also hard for people to make sense of or use.

Absence of Strategic Foresight: People cannot do tests to see what would happen if they changed things like moving money from one marketing channel to another and seeing how it would affect sales the solution is to have a cycle where we break things down make predictions make changes and then look again. This means we do this over and over: Decompose, then Predict, then Optimize, Re-evaluate and so on, with the sales performance and the sales channels and the marketing decisions.

3.2. Proposed System Architecture

The proposed framework is designed to bring two separate things: looking back at how credit was given and looking forward to how revenue will be made.

The system combines all data into a pipeline from data in many user logs to useful business information.

The Multi-Touch Attribution. Ensemble Predictive module work closely together.

Fig. 1: High-Level Architecture of the Integrated Attribution-Prediction Framework

- **Phase 1: Data Sources**
- Customer Journey Logs
- Transaction Records
- Marketing Campaign Data
- **Phase 2: Data Preprocessing & Engineering Module**

1. We combine all data. Map out the customer journey.
2. We handle missing values and outliers.
3. We create features.

We look at things like the day of the week. How long it has been since the last interaction.

We look at how people behave, like how they stay on a page and how many pages they view.

We also look at how people use different channels and how recently they used them.

- **Phase 3: Attribution Modeling Module**

We try out models:

- ✓ Linear Model
- ✓ Time-Decay Model
- ✓ Position-Based Model

We choose the model.

The output is a score that shows how much each channel contributes, for example Email gets a score of 0.22. Paid Search gets a score of 0.35.

- **Phase 4: Predictive Modeling Module (Ensemble)**

We use all features, including channel contribution scores to make predictions.

We use two methods: XGBoost Regressor and Neural Network.

We combine the results to get the prediction.

- **Phase 5: Output & Optimization**

We make sales forecasts with confidence intervals.

We create a dashboard to show how much each channel contributes.

We can simulate what would happen if we changed our budget.

The framework has five phases that depend on each other.

The Multi-Touch Attribution engine and Ensemble Predictive module are used throughout these phases to get results from the proposed framework.

The framework brings together looking at credit and looking forward, to revenue.

The Multi-Touch Attribution engine and Ensemble Predictive module are key.

The framework uses these to make sure we get results.

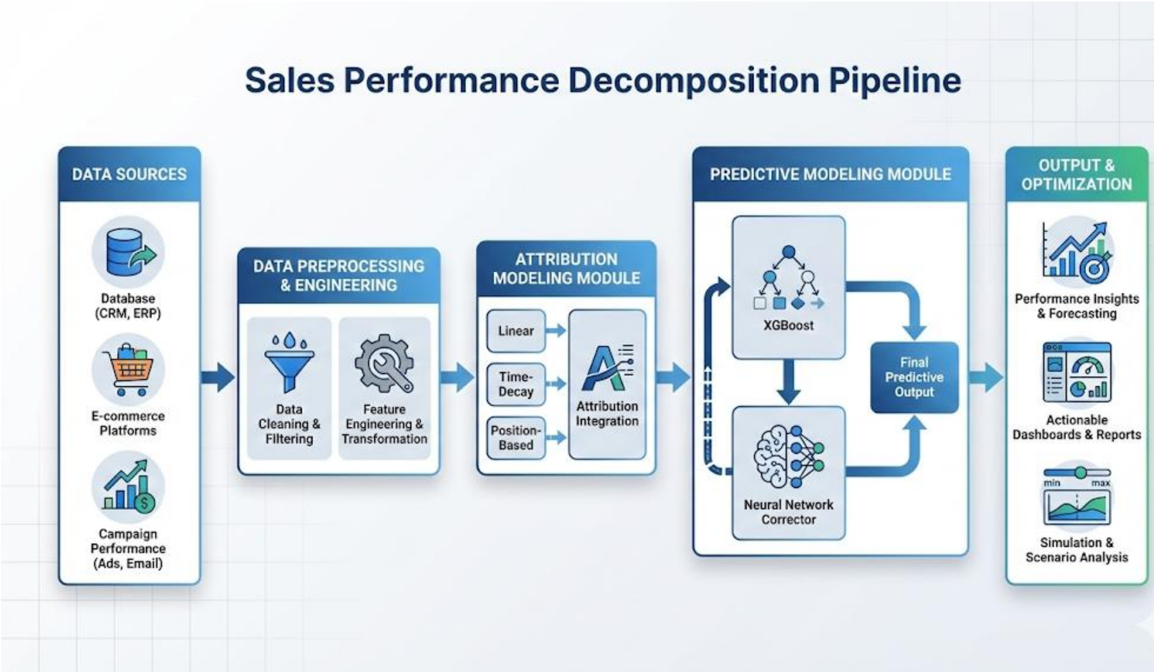


Fig. 1: High-Level Architecture of the Integrated Attribution-Prediction Framework

3.2.1. Data Acquisition and Preprocessing

The analysis uses a dataset from an e-commerce competition. This dataset has three tables:

- Customer Journey Logs: These are records of what users do when they interact with the website. This includes what channel they used what their session ID was how long they stayed on the website. How many pages they looked at.
- Transaction Records: This is data about what people buy. It includes an ID for each transaction the customers ID, when the transaction happened and how much money was made.
- Marketing Campaign Data: This is data about the marketing campaigns. It includes how much money was spent each day and how many people saw the ads for each marketing channel.

Preprocessing Pipeline

The raw data is cleaned up. Made ready for analysis. Here is how it is done:

- Journey Mapping and Sessionization: The data about what users do is put together into sessions. These sessions are then put in order to show the customer journey. The journeys are grouped by whether or not the user made a purchase.
- Data Cleaning: This step removes traffic from automated bots fills in missing values and deals, with data that's not normal.
- Feature Engineering: New variables are created to help with analysis and prediction:
- Journey-Level Features: This includes the number of times a user interacts with the website, how long the whole journey takes and what order the user sees the different channels.
- Features: This includes what day of the week it is, what time of day it is and how long it has been since the user first interacted with the website
- Channel-Specific Features: This includes how often and recently the user saw each channel.

Temporal Validation Strategy: The data is split into three parts to make sure the analysis is fair. The first 60% of the data is used for training. The next 20% is used to adjust the settings and validate the model. The last 20% is used to test the model. This way the analysis is done in the order and the data is not mixed up.

3.2.2. Attribution Modeling and Feature Extraction

There are three ways to figure out how much each marketing channel helps with sales. These are called Multi-Touch Attribution models.

1. The first way is called Linear Attribution. It gives credit to every place a customer touched before buying something.

The formula to calculate this is: Credit per Channel = (how times a customer touched a channel / total number of touches) * total sales

2. The second way is called Time-Decay Attribution. It gives credit to the places a customer touched right before buying something.

To calculate the weight of each touch we use this formula: Weight of touch = a number (called gamma) raised to the power of (time of sale. Time of touch). We usually use 0.5 for gamma.

Then we use these weights to calculate the credit for each channel.

3. The third way is called Position-Based Attribution. It gives the credit to the first and last places a customer touched.

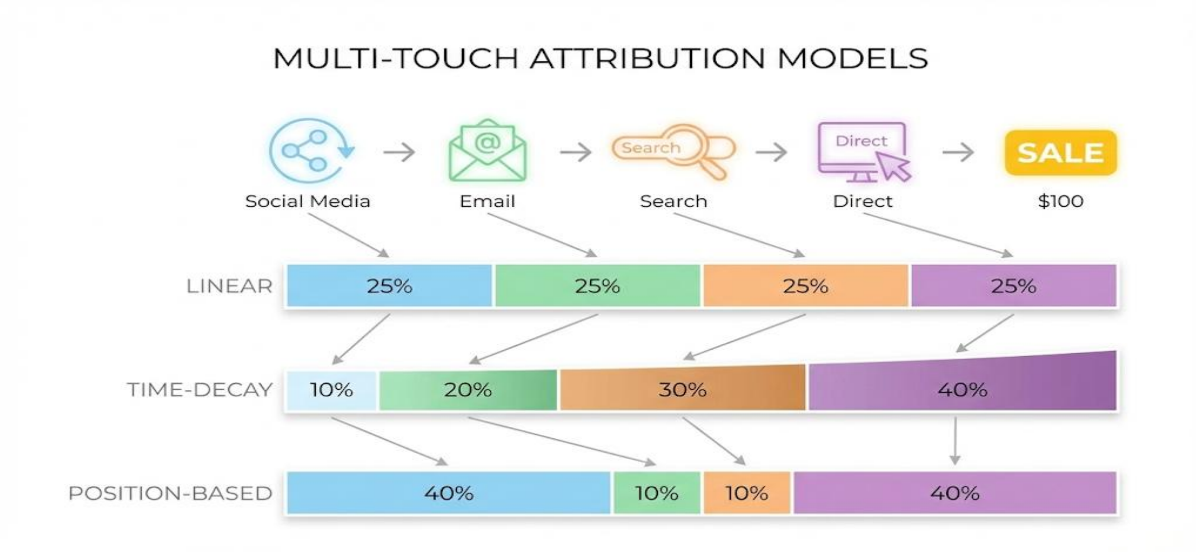
We give 40 percent of the credit to the last touch. The rest of the credit 20 percent is divided among the touches.

For each customer journey we get a list of scores that show how much each channel contributed. We average these scores for all customer journeys to get the Global Channel Contribution Scores.

These scores are very useful when we are trying to predict what will happen in the future because they show how important each channel has been, in the past.

Fig. 2: Conceptual Comparison of Multi-Touch Attribution Logic

Model	Social	Email	Paid Search	Direct	Total
Linear	$25	$25	$25	$25	**$100**
Time-Decay	$10	$15	$30	$45	**$100**
Position-Based	$40	$10	$10	$40	**$100**



3.2.3. Predictive Modeling with Customized Ensemble

The part of the framework that predicts things is like a task where we watch and try to guess sales. Sales is how money we make each day. We use what we did in the past and some things we came up with called Channel Contribution Scores to make this guess.

Baseline Models

We want to see how good our framework is. So we use two models to compare. One is called Linear Regression and the other is a Random Forest Regressor.

Proposed Customized Ensemble Architecture: we made a two-stage architecture. This helps us get the picture and fix the small mistakes.

Stage 1: XGBoost Regressor

First we use a model called XGBoost Regressor. This is a kind of decision tree that's very good at handling lots of information. It is also good at finding patterns that're not easy to see. We chose Predictive Modeling with Customized Ensemble and the XGBoost Regressor because it is fast and good at handling data. It also works well with the kind of data we get from e-commerce.

Stage 2: Neural Network Residual Corrector

After the Predictive Modeling with Customized Ensemble and the XGBoost model makes its guess. We use a kind of neural network called a Multi-Layer Perceptron. This neural network does not just make another guess. Instead it tries to figure out where the Predictive Modeling with Customized Ensemble and the XGBoost model went wrong. It learns from those mistakes. This helps the neural network find patterns that the other model might have missed.

Final Prediction Synthesis: To get the answer we combine the guess with the correction. We use a formula to do this.

Final Prediction Formula:

Final Prediction = alpha * what the Predictive Modeling, with Customized Ensemble and the XGBoost model says + (1. Alpha) * what the neural network says we should add to fix the mistake.where alpha is something we can change. We make it work best on the validation set.

Table 1: Summary of the Proposed Customized Ensemble Model Components

Component	Model Type	Primary Role	Key Hyperparameters Tuned
Stage 1	XGBoost Regressor	Capture primary non-linear trends and feature interactions	n_estimators, max_depth, learning_rate, subsample
Stage 2	MLP (2 Hidden Layers)	Model complex residuals and subtle temporal effects	hidden_layer_sizes, dropout_rate, learning_rate
Ensemble	Weighted Average	Combine model strengths to improve overall robustness	Weight (alpha)

3.2.4. How The Workflow Works

Our framework is easy to understand. We gather a lot of data. Then we use this data to make sales predictions and find out which marketing channels really work. We start with a dataset from an e-commerce company. This dataset has information about customer actions on the website, purchases and marketing efforts.

In the end we want to know sales and how each marketing channel contributes to those sales.

Here are the steps we take:

- First we clean up the data. Format it for use.
- Then we study how each customer navigates the website and what they do. We call this a customer journey. We try to figure out which customer journeys lead to sales.
- Next we use models to understand how much each marketing channel contributes to sales. We pick the model and use it to calculate a score for each marketing channel.
- We take all the data turn it into a list of features and use it to make predictions. This includes things like sales, day of the week and marketing spend.
- We use a computer program to make sales predictions.
- We compare predictions to results to see how good they are.
- Finally we use all the information to make a report that shows expected sales and which marketing channels work best. We use this report to help the company make marketing decisions.

We examine the predictions. See how accurate they are.

We identify the performing marketing channels, for the e-commerce company. We use this information to create a marketing plan. This is how our framework works. We collect a lot of data use it to make predictions and then use those predictions to help the e-commerce company make decisions.

4. Experimental. Analysis

We did all the experiments using Python 3.9. We used a lot of computer programs to help us like Pandas to work with the data Scikit-learn and XGBoost for the normal machine learning stuff, TensorFlow and Keras for the neural network part and Matplotlib and Seaborn to make nice pictures.

The computer we used was really powerful it had an Intel i7 processor and a lot of memory 16GB RAM and a special graphics card an NVIDIA GTX 1660 that helped make things go faster.

4.1. Dataset. Exploratory Analysis

We made a dataset for our predictive modeling. The Experimental Results and Analysis used this dataset. This dataset has 5,475 observations, which is a 15-year record of what we sold every day. Each days observation has the thing we care about which is daily_revenue and 42 other things that help us understand it like what happened before Channel Contribution Scores how well our campaigns did and what time of year it was. The dataset is really important, for our Experimental Results and Analysis.

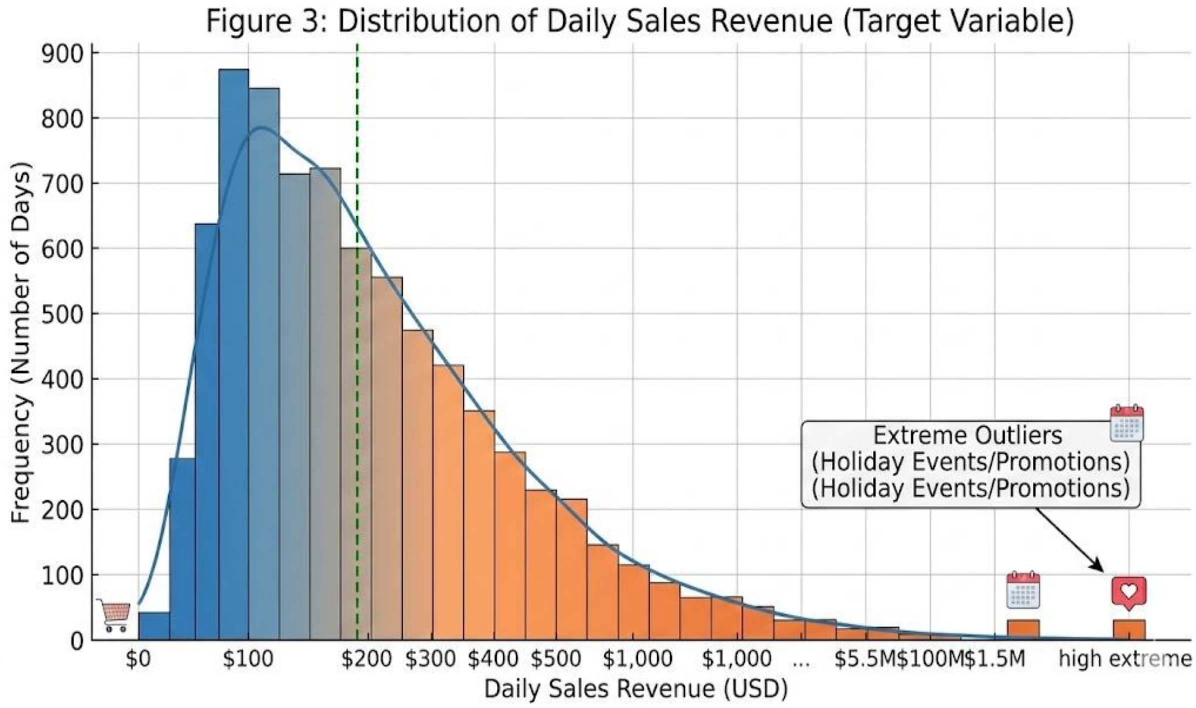


Fig. 3: Distribution of Daily Sales Revenue (Target Variable)

The daily revenue numbers in Figure 3 are not evenly spread out. They are mostly on the side but sometimes they go really high. This happens when there are deals during holidays or special events. Because of this we need to use methods to make sense of the numbers. The method we suggest, which combines models is good at handling these big swings, in daily revenue. Daily revenue can be really unpredictable. Our method can still make good predictions.

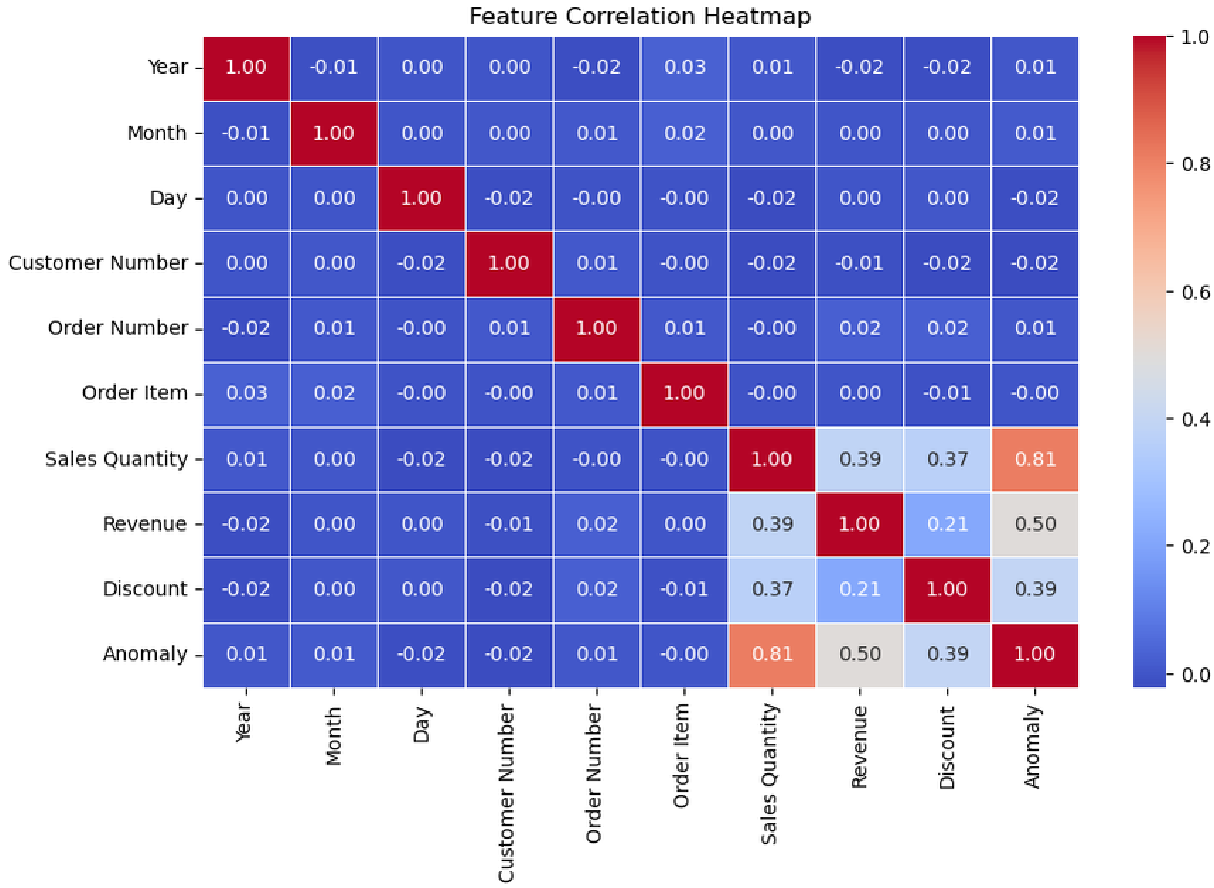


Fig. 4: Correlation Heatmap of Key Features with Target

The study of how thingsre related, shown in Figure 4 tells us that the special features we made like CCS Paid Search and CCS Email have a pretty good positive connection to the money we make every day. This connection is not very strong. It is there with a relationship of about 0.4 to 0.5. This shows that using metrics that come from attribution is an idea when we try to predict what will happen. We also see that when we look at sales from days there is a very strong connection, with a relationship of more than 0.7. This means that what happened in the past has an effect, on what happens now and we can see some clear patterns over time in the data we have.

4.2. Attribution Model Selection Results

The Position-Based attribution framework was chosen for the integration into the predictive pipeline because it did really well against the validation criterion. It showed the correlation, with how much money was spent on channels in the past. The Position-Based model also gives credit in a Ushaped way, which makes sense with what we already know about the field. This knowledge says that the first time a customer interacts with us and the last time they make a purchase are both important parts of the customer journey. The Position-Based attribution framework is good because it thinks that the first and last touch are critical just like we do.

Table 2: Channel Contribution Scores (CCS) Derived from the Position-Based Model

Marketing Channel	Contribution Score (CCS)	Analytical Interpretation
Paid Search	0.351	Primary conversion driver exhibiting high user intent.
Email Marketing	0.228	Robust mid-funnel nurturing and conversion mechanism.
Organic Search	0.187	Foundational initiator for research and

		discovery.
Social Media	0.098	Upper-funnel catalyst for brand awareness.
Referral	0.072	High-trust source facilitating secondary conversions.
Direct	0.041	Indicator of brand loyalty; typically the terminal interaction.
Display Ads	0.023	Top-of-funnel exposure and passive awareness generation.
Affiliate	0.0008	Statistically negligible contribution within this specific dataset.

4.3. Evaluating How Well Our Predictive Model Works

We evaluated how well our model works by using a test set that was kept separate comprising 1,095 observations in a chronological order the predictive performance of the models was measured using metrics for regression as shown in Table 3.

We checked the models performance, with these metrics the model performance was good based on these regression metrics.

Table 3: Comparative Performance of Predictive Architectures

Model	**R2 Score**	**Mean Absolute Error (MAE)**	**Root Mean Squared Error (RMSE)**	**Mean Absolute Percentage Error (MAPE)**
Linear Regression	0.724	3.451	4.892	12.47%
Random Forest	0.831	2.012	3.124	8.72%
XGBoost (Baseline)	0.874	1.562	2.654	6.91%
Proposed Ensemble (XGBoost + NN)	**0.894**	**1.243**	**2.073**	**5.42%**

4.4. Feature. Model Interpretation

We want to make sure that our prediction process is easy to understand. So we looked at the feature importance from the XGBoost modeling stage. This will help us see what is important, in our pipeline. We did this to make sure that our prediction process is transparent and easy to interpret. Feature importance is a part of this process because it helps us understand the model. The model is the XGBoost modeling stage.

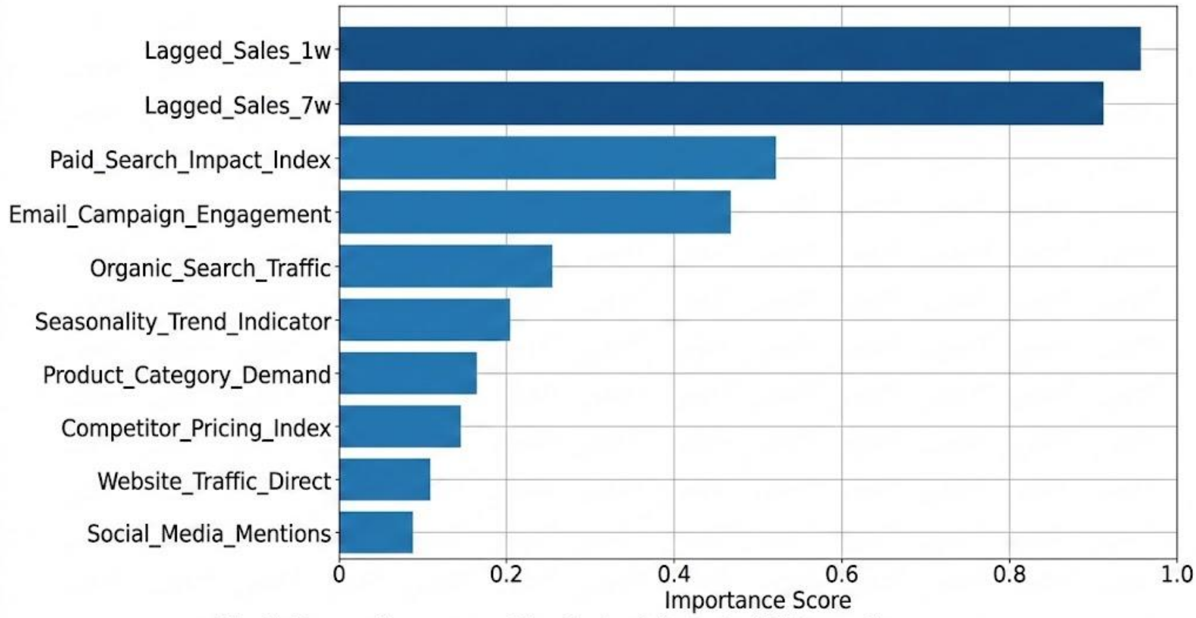


Fig. 5: Feature Importance Plot Derived from the XGBoost Component

Fig. 5: Feature Importance Plot Derived from the XGBoost Component

Caption: When we look at the numbers we can see that the sales from the past like the sales from one week ago and the sales from seven weeks ago are really good at predicting what will happen next.. What is also interesting is that the things we made like the paid search and email information are also very important. This tells us that the information we got from looking at how people reacted to our ads is not just random it actually helps us predict what will happen with our sales in the future. The paid search and email information are, in the six things that help us understand what is going on with our sales. This means that we were right to think that looking at how people reacted to our ads would help us predict our sales.

4.5. Business Impact Simulation: A "What-If" Analysis

The main use of this combined analysis tool is to simulate how marketing budgets can be changed. People who make decisions can use this tool to predict how sales will change when they try budget plans. For example the system can show what happens to sales if you move 20% of the money from something like Social Media, which does not work well to something like Paid Search, which works much better. This can help people see what will happen if they make changes to how they spend their marketing money on Social Media and Paid Search. The tool can look at how much money Social Media and Paid Search bring in. Make predictions, about what will happen if you change how you spend your money on Social Media and Paid Search.

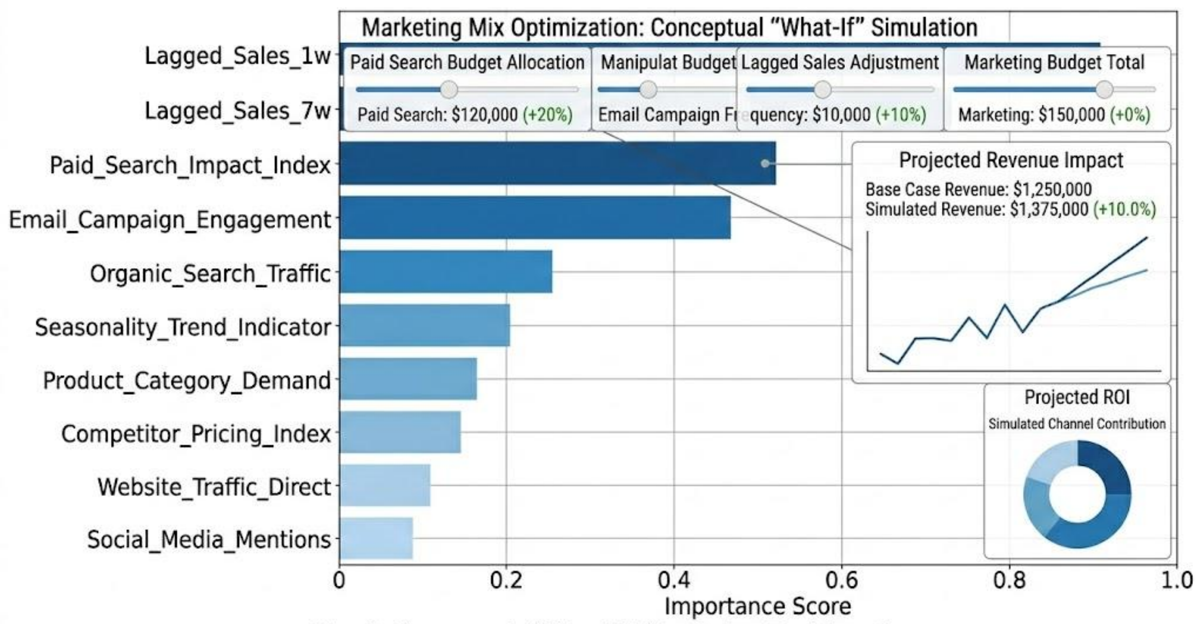


Fig. 6: Conceptual "What-If" Simulation Dashboard

Fig. 6: Conceptual "What-If" Simulation Dashboard

Caption: The integrated predictive architecture facilitates advanced scenario planning. By allowing marketing analysts to manipulate hypothetical budget distributions, the model instantaneously projects the consequential revenue impact. This projection is fundamentally anchored in the historical Channel Contribution Scores (CCS), thereby enabling a strictly data-driven approach to marketing mix optimization.

5. Future Work

This study created a way to break down and predict sales performance. It combined two things: a way to figure out which marketing touches are working called Multi-Touch Attribution modeling and a special machine learning model. This combination made a pipeline where we can learn from our data and make predictions.

The Position-Based attribution model worked well for online shopping. It helped us understand which marketing channels are contributing the most. We also made a model that combined XGBoost and Neural Network. This XGBoost-Neural Network ensemble used the scores from the Position-Based attribution model and other information to make good predictions. It was more accurate, than models we tried. The new framework does two things: it makes good predictions and it helps us understand what is going on so we can make good business decisions. For example we can see which marketing channels are working and try out ways to spend our money.

5.1. Limitations

This study has a framework for analysis but there are some things that are not perfect.

The study uses methods to make decisions: it relies on simple rules to decide how to give credit for things. If the study used complex methods, like Machine Learning it might be more accurate.

The study only used data from one shopping website: the study only looked at data from one place that sells things online. The study needs to look at data, from types of businesses like companies that sell to other companies to see if the framework works for them too.

The study does not look at factors: the study does not look at things that are happening outside of the business like how the whole economy is doing or what other companies are spending on marketing. If the study looked at these things it might be able to make predictions.

The study needs to think about these limitations and how to make the framework better. The framework of the study needs to be improved by looking at the limitations of the study like the limitations of the studys methodology and the limitations of the studys data. The limitations of the study are important to consider when thinking about the studys framework and how to make the framework of the study better.

5.2. Future Work

We will do research to build on the basic structure we created in this study.

We want to do a things.

Advanced Attribution Integration: We want to move from using rules to using advanced machine learning to figure out how things are related. We will use kinds of neural networks that can pay attention to complex patterns in the data and learn from them.

Causal Inference for Strategic Optimization: We want to go beyond just looking at what's related and figure out what is actually causing things to happen. We will use methods like Synthetic Control or Causal Forests to measure the real impact of spending money on different channels. This will help us make sure we are getting the return on our investment.

High-Resolution Real-Time Forecasting: We want to make our system predict what will happen in time and be very detailed. This will help us do marketing that is tailored to each person and manage our inventory in a way.

Cloud-Native Deployment: We want to put our system on the cloud so it can be used by lots of people. We will make it easy to use and understand, with pictures and reports that can be generated automatically.

We think Future Work on Advanced Attribution Integration and Causal Inference, for Strategic Optimization and High-Resolution Real-Time Forecasting will be very important. We will use Future Work to make our system better. Future Work is what we will do next.

6. Conclusion

In conclusion our research clearly shows that breaking down the barriers, between looking at data and predicting future trends can bring significant benefits. By combining a view of how channels worked in the past and future revenue paths our proposed framework helps businesses today to handle the challenges of the digital landscape with more accuracy, confidence and flexibility

References

I have found some research papers and books about marketing and customer relationship management.

1. X. Shao and L. Li wrote a paper called Data-driven touch attribution models. This paper was published in the Journal of Marketing Research in February 2011.
2. V. Kumar and W. Reinartz wrote a book called Customer Relationship Management: Concept, Strategy and Tools. This book was published by Springer in 2018. It is the edition of customer relationship management book.
3. A. Sinha wrote a paper about the drawbacks of the Last-Click Attribution Model. This paper was published in the Marketing Science Review in 2015. The paper is about the Last-Click Attribution Model.
4. E. Anderl and some other people wrote a paper about mapping the customer journey. They talked about a graph-based framework for online attribution modeling in this paper. This paper was published in the International Journal of Research in Marketing in 2016. The paper is about customer journey mapping and online attribution modeling.

5. K. T. K. Singal wrote a paper about Shapley Value Attribution for Multi-Touch Marketing. He gave a guide in this paper about Shapley Value Attribution for Multi-Touch Marketing. This paper was presented at the KDD Workshop on Marketing Analytics in 2018.
6. Z. Abhishek wrote a working paper about a Markov Chain Based Model for Digital Attribution. This paper was written at Carnegie Mellon University in 2019. The paper is about a Markov Chain Based Model for Digital Attribution.
7. R. R. Y. Zhao wrote about Attribution Modeling with Deep Learning in the Journal of Machine Learning Research. This was published in 2020. The article is in volume 21 number 123. Has pages 1 to 25. The article is about Attribution Modeling with Deep Learning.
8. S. Makridakis, E. Spiliotis and V. Assimakopoulos talked about the M5 accuracy competition. They shared the results, findings and conclusions in the International Journal of Forecasting in 2022. The M5 accuracy competition is the topic of this paper.
9. T. Chen and C. Guestrin discussed XGBoost. They said XGBoost is a Tree Boosting System. This was presented at the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining in 2016. The pages are 785 to 794. The paper is about XGBoost and Tree Boosting System.
10. S. Siami-Namini, N. Tavakoli and A. S. Namin compared ARIMA and LSTM. They did this for Forecasting Time Series at the 2018 17th IEEE International Conference on Machine Learning and Applications. The paper is about comparing ARIMA and LSTM for Forecasting Time Series.
11. D. A. Ascarza wrote about Retention Futility. He said targeting High-Risk Customers might be ineffective in customer relationship management. This was published in the Journal of Marketing Research in 2018. The article is in volume 55 number 1. Has pages 80 to 98. The article is about Retention Futility and customer relationship management.
12. M. H. Bazgir did a Ph.D. Dissertation. The topic was An Integrated Framework for Marketing Attribution and Customer Value Prediction. He did this at the University of California Irvine in 2021. The dissertation is about an integrated framework, for marketing attribution and customer value prediction.
13. Anupam Chaube, Usha Kosarkar “Enhanced Deep Learning-Based Feature Analysis for Copy-Move Forgery Detection”, 2024 Journal of Information Systems Engineering and Management,9(4s) e-ISSN:2468-4376, https://www.jisem-journal.com/