Time-series Sales Prediction Model

Business context can goals

- **Helps solve business problems and decision making:**
  - Demand planning: Plan inventory & stock, prepare resources to meet sudden spikes
  - Improve marketing strategies: Focus on which aspects to drive sales
- **What decisions will it support?**
  - Adjusting promotions,
  - Managing stock levels,
  - Planning resources,
  - Phasing ad spend, marketing activities,
  - ...

Features

```
['date', 'traffic', 'impressions', 'product_ad_spend', 'shop_ad_spend', 'product_page_bounce_count',
'traffic_from_search', 'run_product_ad', 'run_shop_ad', 'wm_yr_wk', 'wday', 'month', 'doubleday',
'near_dday', 'end_of_month', 'weekend', 'other_commercial_sale', 'day_offs', 'day_of_year',
'week_of_month', 'est_avg_price', 'avg_price', 'promotion_on', 'promotion_price', 'discount_rate',
'comment_received', 'product_rating', 'avg_category_comment', 'avg_category_rate', 'high_rating',
'high_comment', 'high_discount', 'wday_sin', 'wday_cos', 'month_sin', 'month_cos', 'wom_sin', 'wom_cos',
'day_of_year_sin', 'day_of_year_cos', 'payment_lag_3', 'payment_lag_28', 'product_ad_spend_lag_3',
'product_ad_spend_lag_28', 'shop_ad_spend_lag_3', 'shop_ad_spend_lag_28', 'traffic_rolling_7d_mean',
'impressions_rolling_7d_mean', 'payment_rolling_7d_mean', 'product_ad_spend_rolling_7d_mean',
'shop_ad_spend_rolling_7d_mean', 'traffic_rolling_28d_mean', 'impressions_rolling_28d_mean',
'payment_rolling_28d_mean', 'product_ad_spend_rolling_28d_mean', 'shop_ad_spend_rolling_28d_mean',
'cat_daily_avg_product_ad_spend', 'cat_daily_avg_traffic', 'cat_month_avg_product_ad_spend',
'cat_month_avg_traffic', 'cat_week_avg_product_ad_spend', 'cat_week_avg_traffic',
'continuous_zero_sales_days', 'zero_sales_rolling_mean_14d', 'zero_sales_rolling_max_14d',
'cat_rolling_avg_zero_sales_14d', 'cat_zero_sales_x_promotion', 'cat_rolling_avg_zero_sales_trend_14d',
'cat_rolling_avg_zero_sales_pct_change_14d', 'cat_rolling_avg_zero_sales_lag_7d',
'cat_rolling_avg_zero_sales_lag_14d', 'cat_rolling_avg_zero_sales_lag_28d', 'normalized_avg_price',
'normalized_promotion_price', 'ad_spend_during_promotion', 'weekend_ad_spend', 'CTR', 'product_category',
'brand', 'price_bin', 'product_id']
```

2 main base feature groups: Time

Group	Features
Present	• **Categorical features:** 'date', 'wday', 'month', 'day_of_year', 'week_of_month',etc. • **One-hot encoding:** 'doubleday', 'near_dday', etc.
Periodicity and cyclic patterns of time	'wday_sin', 'wday_cos', 'month_sin', 'month_cos', 'wom_sin', etc.
Past	• **Lagging features:** 'payment_lag_3', 'payment_lag_28', 'product_ad_spend_lag_3', 'product_ad_spend_lag_28', etc. • **Moving features:** 'traffic_rolling_7d_mean', 'impressions_rolling_7d_mean', 'payment_rolling_7d_mean', 'product_ad_spend_rolling_7d_mean', etc.

2 main base feature groups: Product

Group	Features
Product level	**Categorical features:** 'product_id' **Numeric features:** 'traffic', 'impressions','payment', 'avg_price', 'product_rating', 'comment_received', etc.
Product category level	**Categorical features:** 'product_category' **Numeric features:** 'cat_daily_avg_product_ad_spend', 'cat_daily_avg_traffic', 'cat_month_avg_product_ad_spend', 'cat_month_avg_traffic', etc.
Other dimensions	'brand'

Target

'payment'

Number of successfully processed payments.

Dataset

Source: eCommerce data

Data range: 1st May - 31 Dec, 2024

Caveats

- **Small data size**
- **Only used available data within the platform**
- **Still is a work in progress:**
  - Build multiple models to compare between models
  - Optimize feature engineering
  - Gathering more data
  - Tailor to dataset's inherent natures: For example: Sporadic sales patterns of high-ticket products.
  - …

Evaluation metric

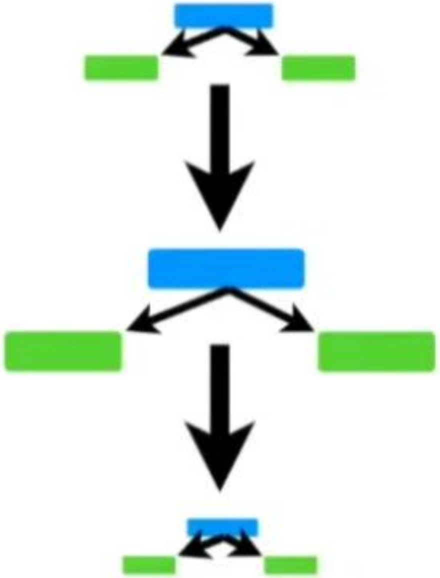
RMSE (Root Mean Squared Error):

- MSE calculates the average size of the errors (differences) between the predicted and actual sales, emphasizing larger errors because it squares the differences before averaging.
- Finally, it takes the square root, so the result is in the same unit as the target variable (e.g., number of payments).

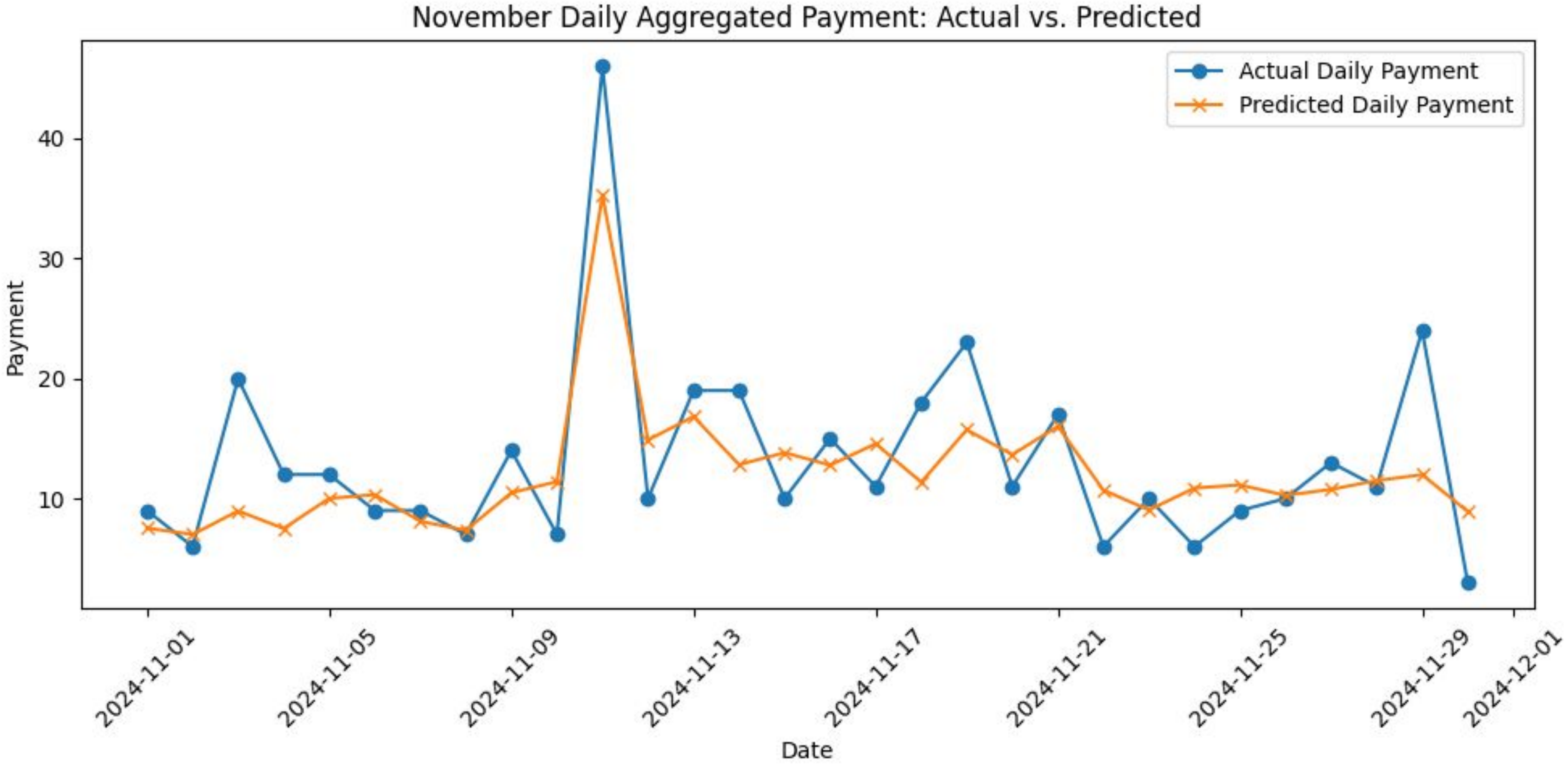
Modeling

XGBoost ("Extreme Gradient Boosting") is a powerful machine learning algorithm used for both regression and classification tasks.

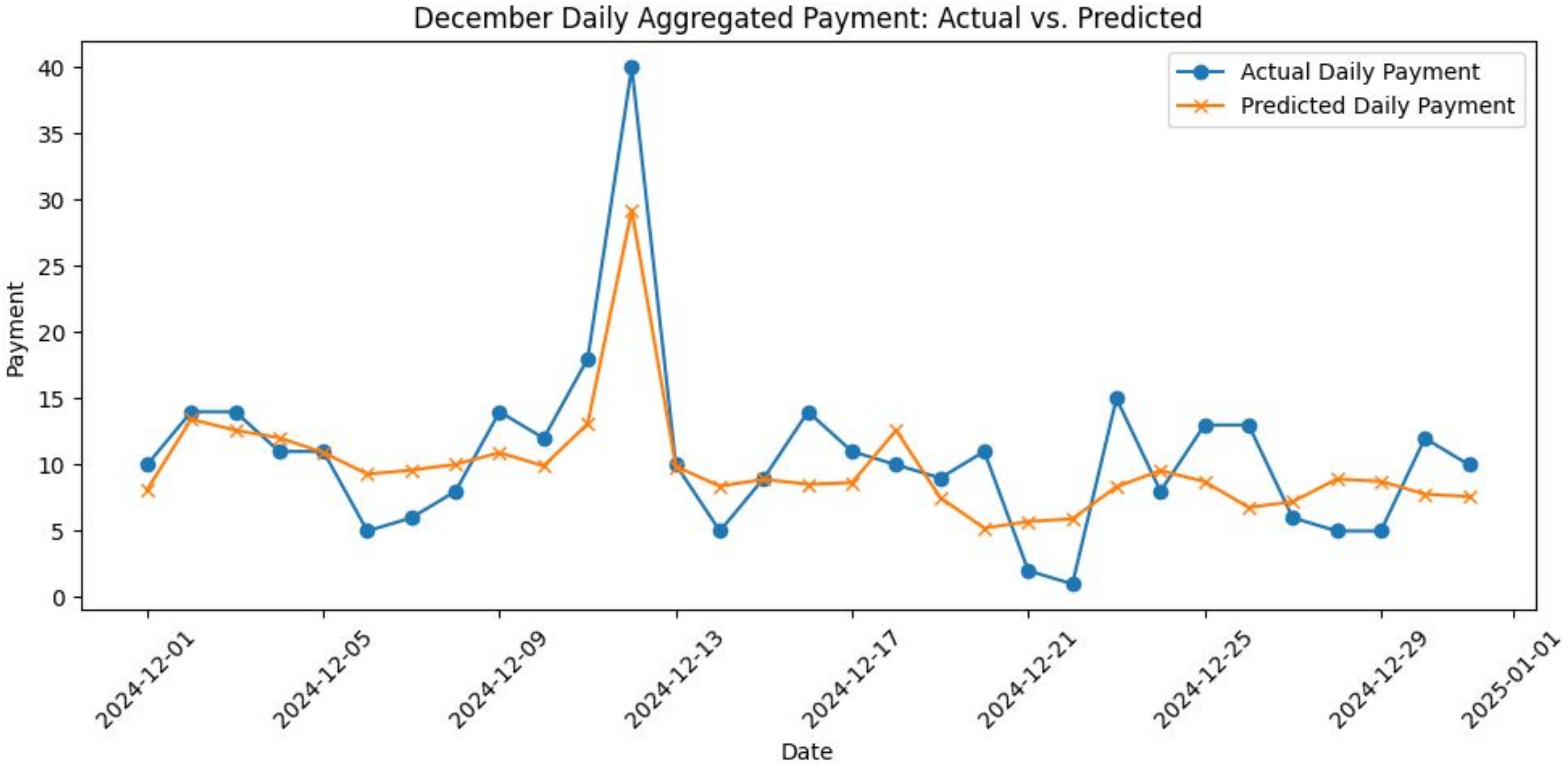
- Imagine you're guessing sales for tomorrow. You might start with a rough estimate.
- XGBoost creates a series of "decision trees" that refine this estimate step by step.
- Each tree learns from the mistakes of the previous trees, improving accuracy with every step.

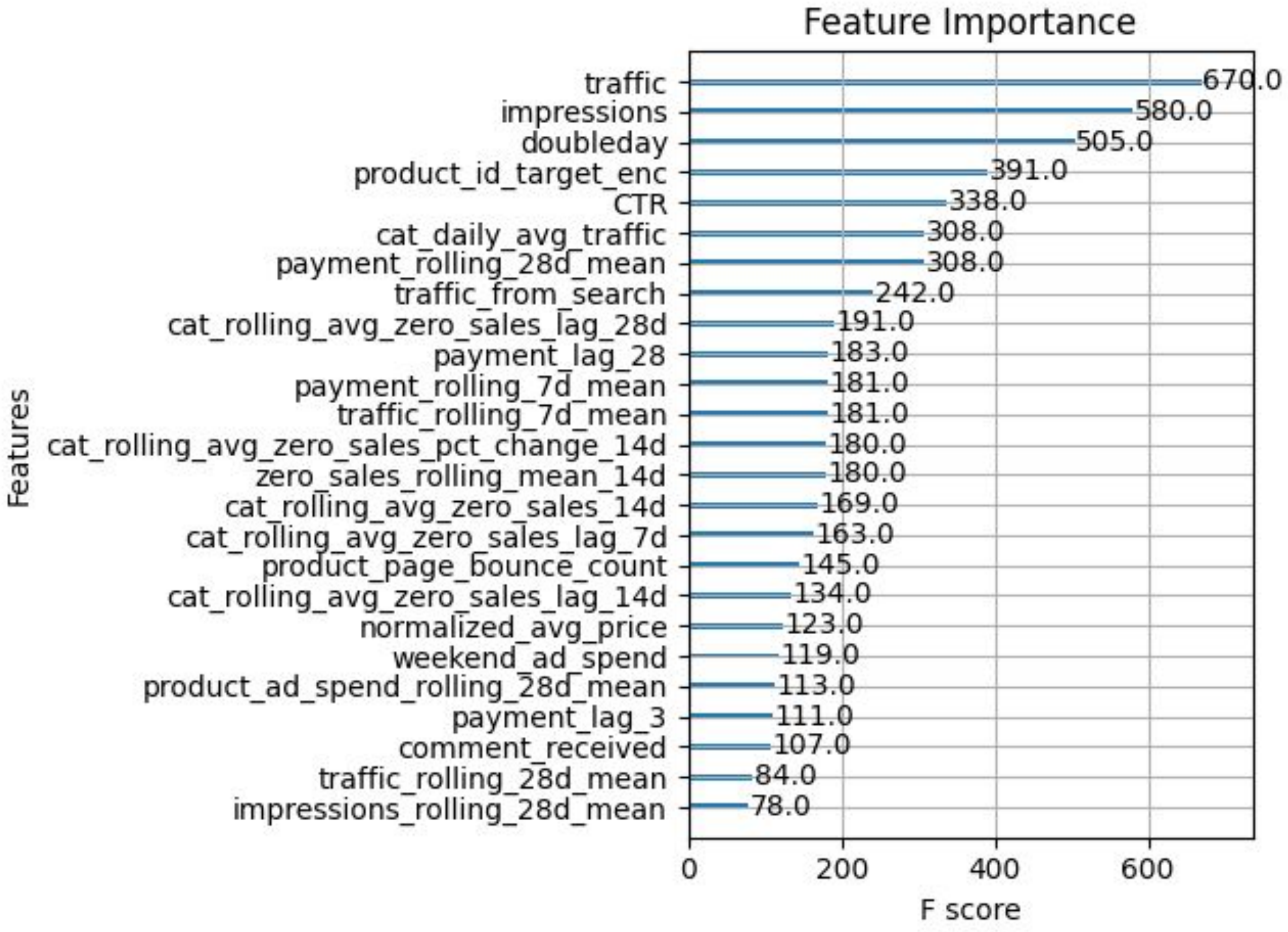


2024-11 RMSE: **0.538**



2024-12 RMSE: **0.645**





Average RMSE: **0.569**

Dec 2024 RMSE: **0.645**

Feature importance

In the case of the XGBoost model, feature importance is based on how often and how effectively each feature is used to split data in the decision trees:

1. **Frequency of Use (F Score):**
   - How many times a feature is used in the trees. Higher frequency means higher importance.
2. **Impact of Splits:**
   - Features that lead to larger improvements in prediction accuracy when used for splitting data are considered more important.