

[WIP]

Time-series Sales Prediction Model

Business context can goals

- Helps solve business problems and decision making:
 - o Demand planning: Plan inventory & stock, prepare resources to meet sudden spikes
 - o Improve marketing strategies: Focus on which aspects to drive sales
- What decisions will it support?
 - Adjusting promotions,
 - Managing stock levels,
 - Planning resources,
 - o Phasing ad spend, marketing activities,
 - 0 .

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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'

2 main base feature groups: Product

Group	Features
Product level	<pre>Categorical features: 'product_id' Numeric features: 'traffic', 'impressions', 'payment', 'avg_price', 'product_rating', 'comment_received', etc.</pre>
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: Shopee Seller Center, Shopee Open Platform

Data range: Since 1st May, 2024

Caveats

- Small data size
- Only use internal data
- Still is a work in progress:
 - O Build multiple models to compare between models
 - Optimize feature engineering
 - Gathering more data
 - O Tailor to dataset's inherent natures: For example: Sporadic sales patterns of high-ticket products.
 - o ...

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.







