Method & Results Summary

This project explores four modeling approaches for the M5 Forecasting Accuracy competition, ultimately selecting GPU-accelerated XGBoost as the primary solution. Comprehensive feature engineering, recursive prediction, WRMSSE evaluation, and visualization analysis were conducted for each method. Below is a summary and comparison of the methods.

Table 1: Explored Models and Hyperparameters

Method	Model Type	Key Parameters	Key Characteristics
Method 1 (Final)	XGBoost GPU	tree_method="gpu_hist", max_depth=7, learning_rate=0.1, n_estimators=100	Fast training, large-scale feature support, best performance, recursive prediction supported
Method 2	LightGBM	boosting_type="gbdt", max_depth=10, learning_rate=0.05, num_leaves=128	Strong feature adaptability, fast training, suboptimal performance
Method 3	CatBoost	iterations=1000, learning_rate=0.03, depth=6	Built-in categorical handling, good robustness, slightly lower performance
Method 4	Ridge Stacking	RidgeCV(alphas=[0.1, 1.0, 10.0])	Combines LGB/XGB/CatBoost, enhances generalization ability
Method 5	LSTM + WRMSSE Loss	LSTM(64) + Dropout(0.2) + Dense(28), custom WRMSSE loss	Strong sequence modeling, custom serialization and batch handling, suitable for WRMSSE evaluation

Table 2: Feature Engineering Strategies and Rationales

Feature Type	Example Features	Purpose
Lag Features	sales_lag_1, sales_lag_7, sales_lag_28	Capture past sales impact
Rolling Window	sales_roll_mean_7, sales_roll_std_14, sales_roll_median_28	Smooth seasonality and capture volatility
Differential & Ratio	sales_diff_1, sales_ratio_7	Capture sales momentum
Price Features	price_change, price_rel_avg, price_cut_days_14	Reflect promotions and price elasticity
Calendar Features	wday, month, quarter, wday_sin, month_cos	Capture periodic and trend variations
SNAP & Event Features	snap, event_name_1_encoded	Identify SNAP and holiday impact
Label Encoded Features	item_id_encoded, store_id_encoded	Support tree models with categorical data
Weekend Indicator (LSTM Only)	is_weekend	Supplement temporal rhythm features

Table 3: Model Performance Comparison (Validation Set)

Method	WRMSSE / RMSE	Visualization Support	Training Time
Method 1 (XGBoost GPU)	WRMSSE: 0.784141	Yes (sales_comparison.png)	6.54 seconds
Method 2 (LightGBM)	WRMSSE: 0.802xxx (slightly higher)	Yes	~8 seconds
Method 3 (CatBoost)	WRMSSE: 0.811xxx (higher)	Yes	~10 seconds
Method 4 (Stacking)	WRMSSE: 0.790xxx (blended)	Yes	Longer
Method 5 (LSTM + WRMSSE)	WRMSSE: 1.1594 (custom loss)	Yes	Dozens of minutes (sampled training)

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