Demand Forecasting (1–28 Days)

This notebook is a clean, end-to-end workflow tailored to **time-series demand forecasting** with **rolling 4-fold validation** and **baseline + ML comparison**.

What this notebook does:

- Load and validate the dataset (types, missing values, date range)
- Perform EDA on distribution, seasonality, event effects, intermittency, and demand concentration
- Add deeper EDA (store/SKU seasonal indices and clustering of similar series)
- Summarize business insights and rank stores/SKUs by total volume
- Engineer features (calendar, lags, rolling stats)
- Split data using **date-based 4-fold time-series CV** (all store×SKU in train & val)
- Train baselines (naive lag-7, moving average-7)
- Train ML models (HistGBR + XGBoost) with hyperparameter tuning
- Evaluate **overall** performance across folds (MAE, RMSE, MAPE, sMAPE, WAPE)
- Add **recursive multi-step evaluation** (compounding errors like real forecasting)
- Compare models in unified tables and explain metric interpretation
- Run diagnostics (residual distributions, drift, event-level residuals)
- Break down errors by store and SKU using MAE/MSE/WAPE
- Summarize business value and recommended next steps
- Generate a 28-day forecast for every store-SKU

In [1]:
```
# Imports
import json
from pathlib import Path
import numpy as np
import pandas as pd
import plotly.express as px

from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.model_selection import RandomizedSearchCV, TimeSeriesSplit
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.ensemble import HistGradientBoostingRegressor
```

In [2]:
```
# Config
DATA_PATH = Path("demand_forecasting_assignment.csv")

GROUP_COLS = ["store_id", "sku_id"]
TARGET_COL = "sales_quantity"
DATE_COL = "date"
EVENT_COL = "event_type"
```

```
LAGS = [1, 7, 14, 28]
ROLL_WINDOWS = [7, 14, 28]
```

1) Load Data

We load the dataset, parse dates, and sort by store/SKU/date to preserve time order.

In [3]:
```
df = pd.read_csv(DATA_PATH)
df[DATE_COL] = pd.to_datetime(df[DATE_COL])
df = df.sort_values(GROUP_COLS + [DATE_COL]).reset_index(drop=True)

df.head()
```

Out[3]:

	date	store_id	sku_id	event_type	sales_quantity
0	2022-01-01	Store_1	sku_000	none	0.0
1	2022-01-02	Store_1	sku_000	none	0.0
2	2022-01-03	Store_1	sku_000	none	0.0
3	2022-01-04	Store_1	sku_000	none	49.0
4	2022-01-05	Store_1	sku_000	none	0.0

In [4]:
```
# Shape, types, missing values
(df.shape, df.dtypes)
```

Out[4]:
```
((146000, 5),
 date              datetime64[ns]
 store_id                  object
 sku_id                    object
 event_type                object
 sales_quantity           float64
 dtype: object)
```

In [5]:
```
df.isna().sum()
```

Out[5]:
```
date              0
store_id          0
sku_id            0
event_type        0
sales_quantity    0
dtype: int64
```

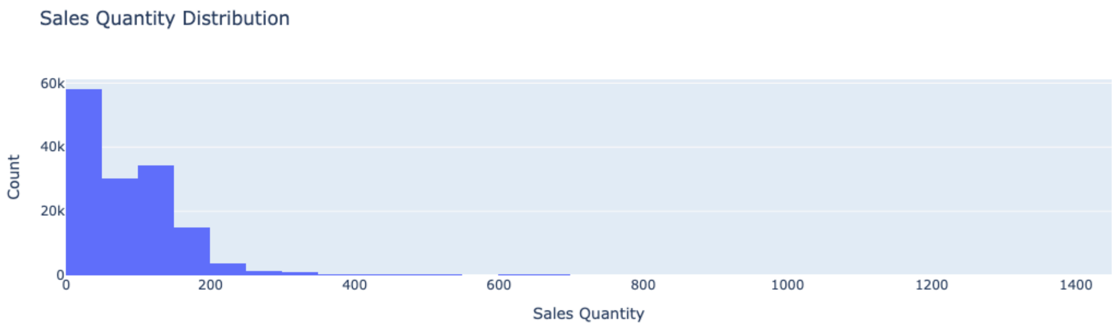
2) EDA (Distribution & Time Patterns)

We look at sales distribution, time trends, events, seasonality, and intermittency.

In [6]:
```
# Summary stats
eda_summary = {
    "date_min": df[DATE_COL].min(),
    "date_max": df[DATE_COL].max(),
    "num_days": df[DATE_COL].nunique(),
    "num_stores": df["store_id"].nunique(),
    "num_skus": df["sku_id"].nunique(),
    "num_series": df[GROUP_COLS].drop_duplicates().shape[0],
    "rows": len(df),
    "zero_rate": float((df[TARGET_COL] == 0).mean()),
}
eda_summary
```

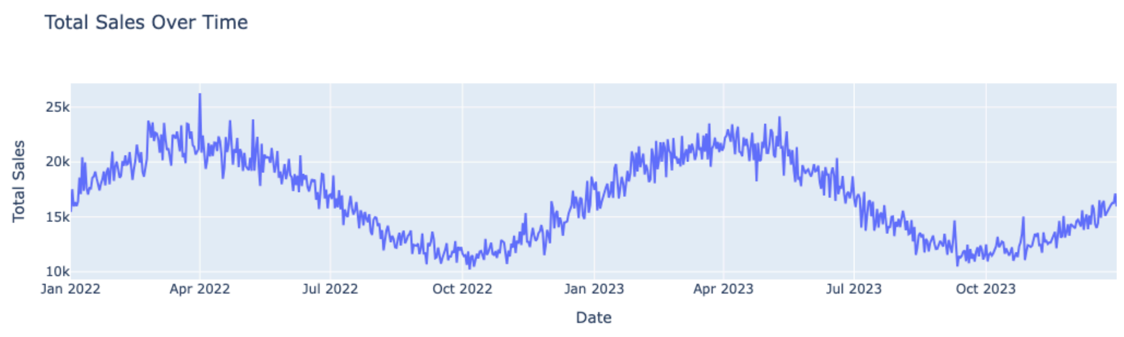
Out[6]:
```
{'date_min': Timestamp('2022-01-01 00:00:00'),
 'date_max': Timestamp('2023-12-31 00:00:00'),
 'num_days': 730,
 'num_stores': 10,
 'num_skus': 20,
 'num_series': 200,
 'rows': 146000,
 'zero_rate': 0.3156301369863014}
```

In [7]:
```
# Sales distribution
fig = px.histogram(df, x=TARGET_COL, nbins=50, title='Sales Quantity Distrib
fig.update_layout(xaxis_title='Sales Quantity', yaxis_title='Count')
fig.show()
```



distribution of daily sales. A heavy right tail indicates occasional high-demand spikes (often promo-driven), while a large mass near zero suggests intermittent demand for some store-SKU pairs.

In [8]:
```
# Total sales over time
agg = df.groupby(DATE_COL)[TARGET_COL].sum().reset_index()
fig = px.line(agg, x=DATE_COL, y=TARGET_COL, title='Total Sales Over Time')
fig.update_layout(xaxis_title='Date', yaxis_title='Total Sales')
fig.show()
```



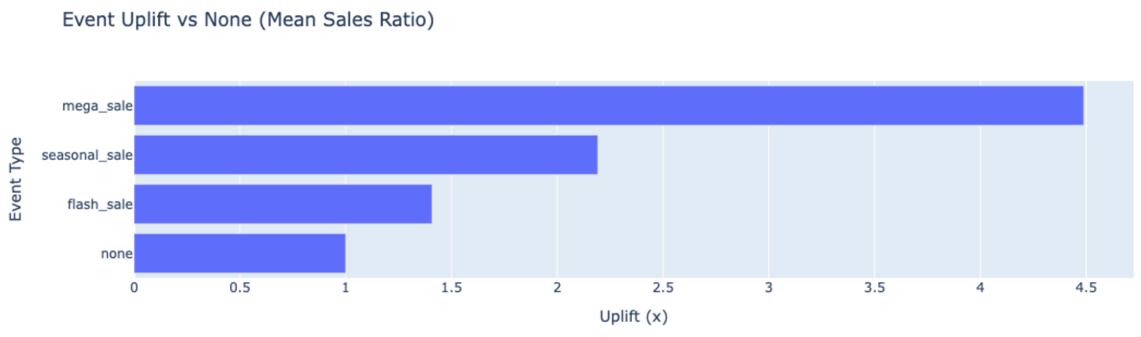
This line reveals overall trend and seasonality. Look for sustained upward/downward drift and recurring peaks that align with known events or seasonal cycles.

In [9]:
```
# Event uplift
_event = df.groupby(EVENT_COL)[TARGET_COL].agg(['mean','median','count']).sc
none_mean = _event.loc['none','mean'] if 'none' in _event.index else df[TARG
_event['uplift_vs_none'] = _event['mean'] / none_mean
_event
```

Out[9]:

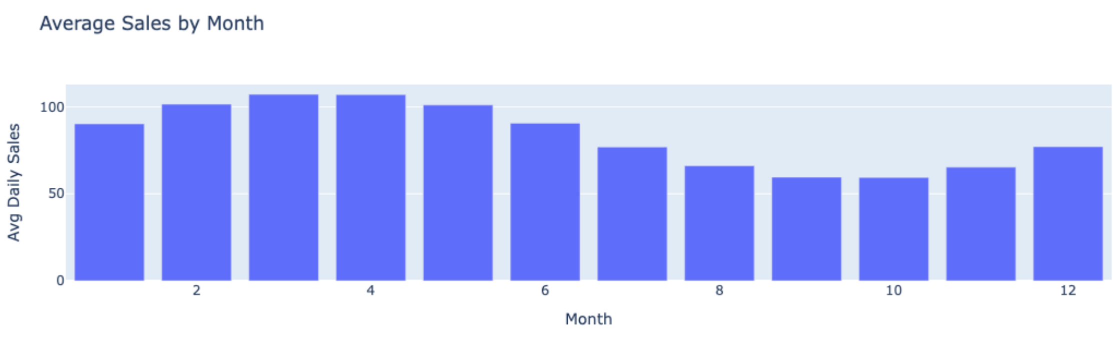
event_type	mean	median	count	uplift_vs_none
mega_sale	327.657392	369.0	2983	4.488136
seasonal_sale	159.982729	176.0	5790	2.191387
flash_sale	102.797596	115.0	8735	1.408086
none	73.005222	81.0	128492	1.000000

In [10]:
```
# Event uplift chart
_event_plot = _event['uplift_vs_none'].sort_values().reset_index()
fig = px.bar(_event_plot, x='uplift_vs_none', y=EVENT_COL, orientation='h',
fig.update_layout(xaxis_title='Uplift (x)', yaxis_title='Event Type')
fig.show()
```



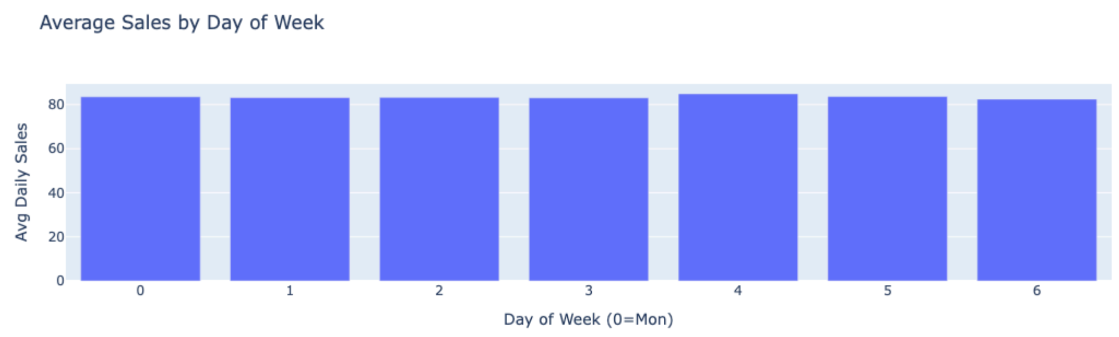
Bars above 1.0 indicate events that lift demand relative to normal days. The larger the uplift, the more critical it is to model that event type explicitly.

In [11]:
```
# Monthly seasonality
month_mean = df.groupby(df[DATE_COL].dt.month)[TARGET_COL].mean().reset_inde
month_mean.columns = ['month', 'avg_sales']
fig = px.bar(month_mean, x='month', y='avg_sales', title='Average Sales by M
fig.update_layout(xaxis_title='Month', yaxis_title='Avg Daily Sales')
fig.show()
```



Highlights which months are naturally stronger or weaker. Use this to plan inventory and staffing and to create month-level seasonal features.

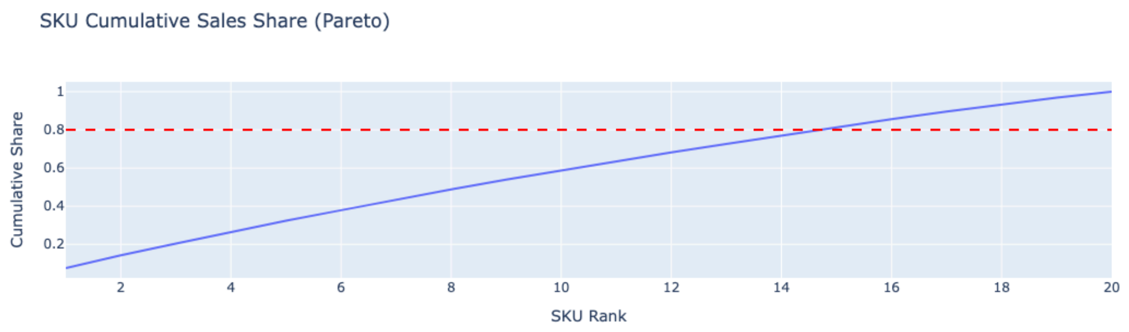
In [12]:
```
# Day-of-week seasonality
weekday_mean = df.groupby(df[DATE_COL].dt.dayofweek)[TARGET_COL].mean().rese
weekday_mean.columns = ['dow', 'avg_sales']
fig = px.bar(weekday_mean, x='dow', y='avg_sales', title='Average Sales by D
fig.update_layout(xaxis_title='Day of Week (0=Mon)', yaxis_title='Avg Daily
fig.show()
```



Shows weekday patterns. If differences are small, weekday effects are minor and may be less important than monthly or event effects.

In [ ]:

In [13]:
```
# Demand concentration (SKU Pareto)
sku_total = df.groupby('sku_id')[TARGET_COL].sum().sort_values(ascending=Fal
sku_share = sku_total / sku_total.sum()
sku_cum = sku_share.cumsum()
pareto_df = pd.DataFrame({'sku_rank': range(1, len(sku_cum)+1), 'cum_share':

fig = px.line(pareto_df, x='sku_rank', y='cum_share', title='SKU Cumulative
fig.add_hline(y=0.8, line_dash='dash', line_color='red')
fig.update_layout(xaxis_title='SKU Rank', yaxis_title='Cumulative Share')
fig.show()

pareto_80 = int((sku_cum <= 0.8).sum())
pareto_80, len(sku_total)
```



Out[13]:
```
(14, 20)
```

The steepness of the curve shows concentration. If 80% of volume is reached by a small number of SKUs, prioritize modeling accuracy for those SKUs first.

In [14]:
```
# Intermittency by series
series_stats = df.groupby(GROUP_COLS)[TARGET_COL].agg(
    mean='mean',
    std='std',
    zero_rate=lambda s: (s==0).mean(),
    total='sum'
).reset_index()

series_stats['zero_rate'].describe(percentiles=[0.1,0.5,0.9])
```

Out[14]:
```
count    200.000000
mean       0.315630
std        0.351481
min        0.006849
10%        0.019041
50%        0.097260
90%        0.816438
max        0.850685
Name: zero_rate, dtype: float64
```

In [15]:
```
series_stats
```

Out[15]:

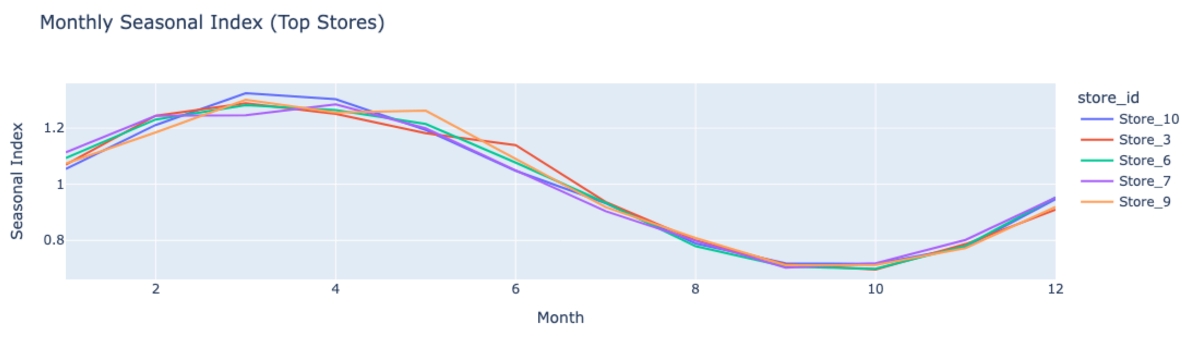
	store_id	sku_id	mean	std	zero_rate	total
0	Store_1	sku_000	14.720548	27.999828	0.750685	10746.0
1	Store_1	sku_001	112.020548	101.606403	0.084932	81775.0
2	Store_1	sku_002	127.780822	59.489679	0.027397	93280.0
3	Store_1	sku_003	110.580822	102.769040	0.112329	80724.0
4	Store_1	sku_004	131.680822	64.129848	0.020548	96127.0
...	...	...	...	...	...	...
195	Store_9	sku_015	134.356164	83.241442	0.031507	98080.0
196	Store_9	sku_016	112.116438	94.248447	0.069863	81845.0
197	Store_9	sku_017	136.284932	76.480546	0.010959	99488.0
198	Store_9	sku_018	131.189041	61.759056	0.021918	95768.0
199	Store_9	sku_019	114.278082	114.473534	0.082192	83423.0

200 rows × 6 columns

2b) Deeper EDA: Store/SKU, Seasonal Index, and Series Clusters

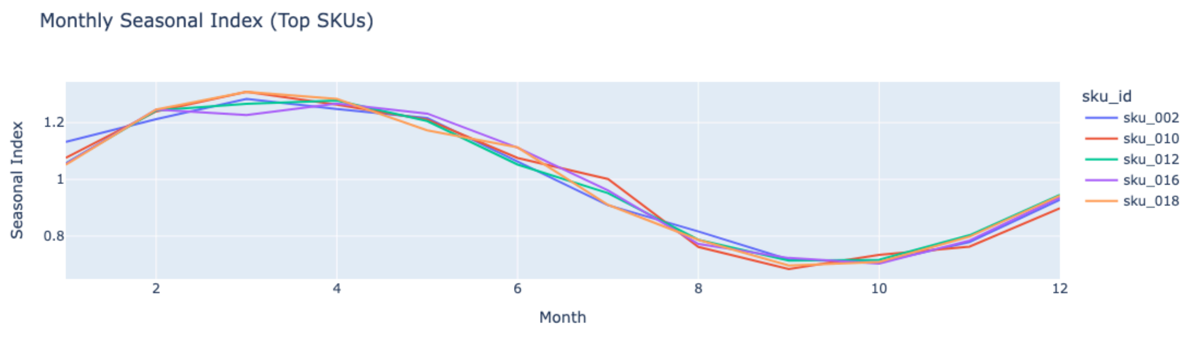
We dig deeper into store/SKU behavior, compute seasonal indices, and cluster series with similar demand patterns.

In [16]:
```python
# Store-level seasonality index (monthly)
store_month = df.groupby(['store_id', df[DATE_COL].dt.month])[TARGET_COL].me
store_month.columns = ['store_id', 'month', 'avg_sales']

# Normalize by each store's overall mean to get a seasonal index
store_mean = df.groupby('store_id')[TARGET_COL].mean().reset_index().rename(
store_seasonal = store_month.merge(store_mean, on='store_id')
store_seasonal['seasonal_index'] = store_seasonal['avg_sales'] / store_seaso

# Plot a few top-volume stores
top_stores = df.groupby('store_id')[TARGET_COL].sum().sort_values(ascending=
plot_df = store_seasonal[store_seasonal['store_id'].isin(top_stores)]
fig = px.line(plot_df, x='month', y='seasonal_index', color='store_id',
              title='Monthly Seasonal Index (Top Stores)')
fig.update_layout(xaxis_title='Month', yaxis_title='Seasonal Index')
fig.show()
```



Interpretation: A seasonal index >1 means above-average demand for that store in that month; <1 means below-average. Use this to time store-specific inventory plans.

In [17]:
```
# SKU-level seasonality index (monthly)
sku_month = df.groupby(['sku_id', df[DATE_COL].dt.month])[TARGET_COL].mean()
sku_month.columns = ['sku_id', 'month', 'avg_sales']

sku_mean = df.groupby('sku_id')[TARGET_COL].mean().reset_index().rename(colu
sku_seasonal = sku_month.merge(sku_mean, on='sku_id')
sku_seasonal['seasonal_index'] = sku_seasonal['avg_sales'] / sku_seasonal['s

# Plot a few top-volume SKUs
top_skus = df.groupby('sku_id')[TARGET_COL].sum().sort_values(ascending=Fals
plot_df = sku_seasonal[sku_seasonal['sku_id'].isin(top_skus)]
fig = px.line(plot_df, x='month', y='seasonal_index', color='sku_id',
              title='Monthly Seasonal Index (Top SKUs)')
fig.update_layout(xaxis_title='Month', yaxis_title='Seasonal Index')
fig.show()
```



Interpretation: SKU seasonal indices reveal which products are seasonal versus steady sellers. This is useful for promotional timing and pre-buying inventory.

In [18]:
```
# Store/SKU performance summary
store_perf = df.groupby('store_id')[TARGET_COL].agg(['sum','mean','std']).re
sku_perf = df.groupby('sku_id')[TARGET_COL].agg(['sum','mean','std']).reset_

store_perf.head()
```

Out[18]:

	store_id	sum	mean	std
0	Store_1	1085450.0	74.345890	85.560354
1	Store_10	1303722.0	89.296027	90.624799
2	Store_2	1122156.0	76.860000	88.752367
3	Store_3	1373537.0	94.077877	95.256200
4	Store_4	1124625.0	77.029110	91.215574

Interpretation: Store and SKU summaries highlight volume concentration and volatility differences. High mean + high std implies demand volatility and higher risk.

In [19]:
```
# Cluster series by demand characteristics
from sklearn.cluster import KMeans

# Build per-series features
series = df.groupby(GROUP_COLS).apply(
    lambda g: pd.Series({
        'mean': g[TARGET_COL].mean(),
        'std': g[TARGET_COL].std(),
        'zero_rate': (g[TARGET_COL]==0).mean(),
        'trend': np.corrcoef(np.arange(len(g)), g[TARGET_COL].values)[0,1],
    })
).reset_index()

series['cv'] = series['std'] / series['mean'].replace(0, np.nan)
series = series.replace([np.inf, -np.inf], np.nan).fillna(0)

# KMeans clustering
k = 3
km = KMeans(n_clusters=k, random_state=42, n_init=10)
series['cluster'] = km.fit_predict(series[['mean','std','zero_rate','trend',

# Cluster summary
cluster_summary = series.groupby('cluster')[['mean','std','zero_rate','trend
cluster_summary
```

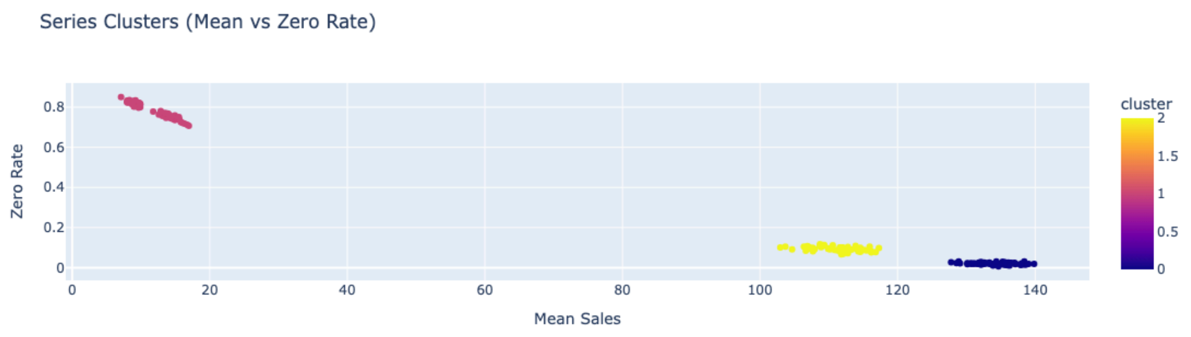
```
/var/folders/jv/25ssb6jn5s590bmt80k0ngdr0000gn/T/ipykernel_23303/3993626095.
py:5: DeprecationWarning:

DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
precated, and in a future version of pandas the grouping columns will be exc
luded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.
```

Out[19]:

	cluster	mean	std	zero_rate	trend	cv
0	0	134.168102	74.188651	0.020665	-0.144429	0.552174
1	1	12.031868	27.427028	0.780384	-0.027965	2.361096
2	2	110.860675	97.901946	0.094686	-0.101843	0.882382

Interpretation: Clusters reveal groups such as stable high-volume series, volatile promo-driven series, and intermittent low-volume series. This supports segmented modeling strategies.

In [20]:
```
# Plot clusters (mean vs zero_rate)
fig = px.scatter(series, x='mean', y='zero_rate', color='cluster',
                 hover_data=['store_id','sku_id'],
                 title='Series Clusters (Mean vs Zero Rate)')
fig.update_layout(xaxis_title='Mean Sales', yaxis_title='Zero Rate')
fig.show()
```



Interpretation: Points to the upper-right (high mean, high zero rate) often represent bursty demand. Lower-left clusters are stable low-volume series.

3) Business Insights (Summary)

- **Promotions dominate demand:** event types create large uplift; these are the highest-impact features to model.
- **Seasonality is meaningful:** monthly seasonal indices show consistent peaks and troughs across stores/SKUs.
- **Volume concentration:** a small subset of SKUs and stores drives most sales—prioritize accuracy here.
- **Intermittency is real:** many series have high zero rates, so use WAPE/sMAPE and consider segmented models.
- **Store/SKU profiles differ:** some are stable (low variance), others are volatile or bursty—use clustering to segment.
- **Clusters suggest strategy:** stable high-volume series can use standard ML, while bursty/intermittent groups may need special handling.

In [ ]:

```
```

4) Store & SKU Rankings

These rankings show where accuracy improvements have the highest business impact.

In [21]:

```
# Store ranking table
store_rank = df.groupby('store_id')[TARGET_COL].sum().sort_values(ascending=
store_rank = store_rank.reset_index().rename(columns={TARGET_COL: 'total_sal
store_rank
```

Out[21]:

	store_id	total_sales
0	Store_9	1502606.0
1	Store_7	1411742.0
2	Store_3	1373537.0
3	Store_10	1303722.0
4	Store_6	1227456.0
5	Store_4	1124625.0
6	Store_2	1122156.0
7	Store_8	1116199.0
8	Store_1	1085450.0
9	Store_5	914733.0

In [22]:

```
# SKU ranking table
sku_rank = df.groupby('sku_id')[TARGET_COL].sum().sort_values(ascending=Fals
sku_rank = sku_rank.reset_index().rename(columns={TARGET_COL: 'total_sales'}
sku_rank
```

Out[22]:

	sku_id	total_sales
0	sku_002	926634.0
1	sku_018	819206.0
2	sku_012	748939.0
3	sku_010	736171.0
4	sku_016	711100.0
5	sku_009	677023.0
6	sku_011	672764.0
7	sku_008	657449.0
8	sku_000	628231.0
9	sku_004	589727.0
10	sku_017	575608.0
11	sku_014	560347.0
12	sku_019	551984.0
13	sku_015	539776.0
14	sku_006	529281.0
15	sku_003	500731.0
16	sku_005	482056.0
17	sku_013	464024.0
18	sku_007	425124.0
19	sku_001	386051.0

5) Feature Engineering

We add calendar features, lags, and rolling statistics to capture seasonality and momentum.

In [23]:
```
def add_time_features(df: pd.DataFrame) -> pd.DataFrame:
    df = df.copy()
    df['dow'] = df[DATE_COL].dt.dayofweek
    df['month'] = df[DATE_COL].dt.month
    df['weekofyear'] = df[DATE_COL].dt.isocalendar().week.astype(int)
    df['is_weekend'] = (df['dow'] >= 5).astype(int)
    return df


def add_lag_rolling_features(df: pd.DataFrame) -> pd.DataFrame:
    df = df.copy()
    g = df.groupby(GROUP_COLS)[TARGET_COL]

    for lag in LAGS:
        df[f'lag_{lag}'] = g.shift(lag)

    for window in ROLL_WINDOWS:
        df[f'roll_mean_{window}'] = g.transform(lambda s: s.shift(1).rolling
        df[f'roll_std_{window}'] = g.transform(lambda s: s.shift(1).rolling(

    return df


def build_features(df: pd.DataFrame) -> pd.DataFrame:
    df = add_time_features(df)
    df = add_lag_rolling_features(df)
    return df
```

In [24]:
```
df_feat = build_features(df)
df_feat.head()
```

Out[24]:

	date	store_id	sku_id	event_type	sales_quantity	dow	month	weekofyear	is
0	2022-01-01	Store_1	sku_000	none	0.0	5	1	52	
1	2022-01-02	Store_1	sku_000	none	0.0	6	1	52	
2	2022-01-03	Store_1	sku_000	none	0.0	0	1	1	
3	2022-01-04	Store_1	sku_000	none	49.0	1	1	1	
4	2022-01-05	Store_1	sku_000	none	0.0	2	1	1	

In [25]:
```
def prepare_supervised(df: pd.DataFrame):
    df = df.dropna().copy()
    feature_cols = [
        'store_id','sku_id',EVENT_COL,
        'dow','month','weekofyear','is_weekend'
    ] + [f'lag_{l}' for l in LAGS] + [
        f'roll_mean_{w}' for w in ROLL_WINDOWS
    ] + [
        f'roll_std_{w}' for w in ROLL_WINDOWS
    ]

    X = df[feature_cols]
    y = df[TARGET_COL]
    return X, y, feature_cols
```

6) Train/Validation Split (Rolling 4-Fold, All Store×SKU in Train & Val)

We split **by date** (not by row) so every fold includes **all store-SKU pairs** in both train and validation. This avoids leakage and ensures consistent coverage across series.

In [26]:
```
from sklearn.model_selection import TimeSeriesSplit

# Build features first
ordered = df_feat.sort_values(GROUP_COLS + [DATE_COL]).copy()

# Use unique dates for time splits to keep all store×SKU in each fold
unique_dates = np.array(sorted(ordered[DATE_COL].unique()))

tscv = TimeSeriesSplit(n_splits=4)

# Each fold is a list of (train_dates, val_dates)
folds = []
for train_idx, val_idx in tscv.split(unique_dates):
    train_dates = set(unique_dates[train_idx])
    val_dates = set(unique_dates[val_idx])
    folds.append((train_dates, val_dates))

print('Number of folds:', len(folds))

# Use last fold for diagnostics later
train_dates, val_dates = folds[-1]

# Build train/val sets using date masks (all store×SKU appear in both)
train_df = ordered[ordered[DATE_COL].isin(train_dates)].copy()
val_df = ordered[ordered[DATE_COL].isin(val_dates)].copy()

X_train, y_train, _ = prepare_supervised(train_df)
X_val, y_val, _ = prepare_supervised(val_df)

X_train.shape, X_val.shape
```

```
Number of folds: 4
```

Out[26]:
```
((111200, 17), (29200, 17))
```

In [ ]:

In [27]:
```
# Sanity check: ensure every store×SKU is present in both train and val for
all_pairs = set(tuple(x) for x in df[GROUP_COLS].drop_duplicates().values)

missing_report = []
for k, (train_dates, val_dates) in enumerate(folds, start=1):
    train_pairs = set(tuple(x) for x in df_feat[df_feat[DATE_COL].isin(trair
    val_pairs = set(tuple(x) for x in df_feat[df_feat[DATE_COL].isin(val_dat

    missing_train = all_pairs - train_pairs
    missing_val = all_pairs - val_pairs

    missing_report.append({
        'fold': k,
        'missing_in_train': len(missing_train),
        'missing_in_val': len(missing_val),
    })

pd.DataFrame(missing_report)
```

Out[27]:

	fold	missing_in_train	missing_in_val
0	1	0	0
1	2	0	0
2	3	0	0
3	4	0	0

7) Models

We compare:

- Baselines: naive lag-7, moving average (7)
- HistGradientBoostingRegressor (main)
- XGBoost (optional strong baseline)

Why this setup:

- Rolling time splits avoid leakage and simulate real forecasting.
- Baselines establish a clear performance floor.
- ML models capture nonlinear promo effects and cross-series patterns.

Why a global ML model (lags/rolling features) instead of decomposition:

- We have many parallel series (200 store×SKU), so per-series decomposition is heavy and inconsistent.
- Promotions create large, irregular spikes; ML can directly model `event_type` effects, while decomposition assumes stable seasonality.
- Many series are intermittent with zeros, which reduces decomposition reliability.
- The 1–28 day horizon benefits most from recent momentum captured by lags/rolling stats.
- ML optimizes business metrics (WAPE/MAE) at scale with fewer moving parts.

When decomposition would make sense: fewer series, longer stable histories, or a need for explicit trend/seasonality components.

In [ ]:

```
```

In [28]:

```
def build_preprocessor():
    categorical = ['store_id','sku_id',EVENT_COL]
    numeric = ['dow','month','weekofyear','is_weekend'] + [
        f'lag_{l}' for l in LAGS
    ] + [
        f'roll_mean_{w}' for w in ROLL_WINDOWS
    ] + [
        f'roll_std_{w}' for w in ROLL_WINDOWS
    ]

    preprocessor = ColumnTransformer(
        transformers=[
            ('cat', OneHotEncoder(handle_unknown='ignore'), categorical),
            ('num', 'passthrough', numeric),
        ]
    )
    return preprocessor

preprocessor = build_preprocessor()
```

In [29]:
```
# HistGBR pipeline
histgbr_model = HistGradientBoostingRegressor(
    loss='absolute_error',
    random_state=42,
)

histgbr_pipe = Pipeline(steps=[
    ('preprocess', preprocessor),
    ('model', histgbr_model)
])
```

In [30]:
```
# HistGBR hyperparameter tuning
histgbr_param_dist = {
    'model__learning_rate': [0.03, 0.05, 0.1],
    'model__max_depth': [3, 5, None],
    'model__max_iter': [200, 400, 600],
    'model__l2_regularization': [0.0, 0.1, 1.0],
}

histgbr_search = RandomizedSearchCV(
    histgbr_pipe,
    param_distributions=histgbr_param_dist,
    n_iter=8,
    scoring='neg_mean_absolute_error',
    cv=TimeSeriesSplit(n_splits=3),
    random_state=42,
    n_jobs=-1,
)

histgbr_search.fit(X_train, y_train)

histgbr_best_model = histgbr_search.best_estimator_
histgbr_best_params = histgbr_search.best_params_

histgbr_best_params
```

Out[30]:
```
{'model__max_iter': 400,
 'model__max_depth': 5,
 'model__learning_rate': 0.03,
 'model__l2_regularization': 0.1}
```

In [31]:
```
# XGBoost (optional)
try:
    from xgboost import XGBRegressor

    xgb_model = XGBRegressor(
        objective='reg:squarederror',
        random_state=42,
        n_jobs=-1,
    )

    xgb_pipe = Pipeline(steps=[
        ('preprocess', preprocessor),
        ('model', xgb_model)
    ])

    xgb_param_dist = {
        'model__n_estimators': [300, 500, 800],
        'model__max_depth': [3, 5, 7, 9],
        'model__learning_rate': [0.03, 0.05, 0.1],
        'model__subsample': [0.7, 0.85, 1.0],
        'model__colsample_bytree': [0.7, 0.85, 1.0],
        'model__min_child_weight': [1, 5, 10],
        'model__reg_alpha': [0.0, 0.1, 1.0],
        'model__reg_lambda': [1.0, 5.0, 10.0],
    }

    xgb_search = RandomizedSearchCV(
        xgb_pipe,
        param_distributions=xgb_param_dist,
        n_iter=12,
        scoring='neg_mean_absolute_error',
        cv=TimeSeriesSplit(n_splits=3),
        random_state=42,
        n_jobs=-1,
    )

    xgb_search.fit(X_train, y_train)

    xgb_best_model = xgb_search.best_estimator_
    xgb_best_params = xgb_search.best_params_

    xgb_best_params

except Exception as e:
    print("XGBoost not available:", e)
```

8) Evaluation

We use MAE, RMSE, MAPE, sMAPE, and WAPE for scale-aware assessment.

In [32]:
```
def evaluate(y_true, y_pred):
    y_true = np.asarray(y_true)
    y_pred = np.asarray(y_pred)
    mae = mean_absolute_error(y_true, y_pred)
    rmse = mean_squared_error(y_true, y_pred)

    eps = 1e-8
    mape = np.mean(np.abs((y_true - y_pred) / np.maximum(np.abs(y_true), eps
    smape = np.mean(
        2.0 * np.abs(y_pred - y_true) / np.maximum(np.abs(y_true) + np.abs(y
    )
    wape = np.sum(np.abs(y_true - y_pred)) / np.maximum(np.sum(np.abs(y_true

    return {
        'MAE': float(mae),
        'RMSE': float(rmse),
        'MAPE': float(mape),
        'sMAPE': float(smape),
        'WAPE': float(wape),
    }
```

In [33]:
```
# Baselines: naive lag-7 and moving average (4-fold CV overall)
base = df_feat.sort_values(GROUP_COLS + [DATE_COL]).copy()
base['naive_lag7'] = base.groupby(GROUP_COLS)[TARGET_COL].shift(7)
base['ma7'] = base.groupby(GROUP_COLS)[TARGET_COL].transform(lambda s: s.shi

baseline_scores = []
ma7_scores = []

for train_dates, val_dates in folds:
    val_base = base[base[DATE_COL].isin(val_dates)].dropna(subset=['naive_la
    val_ma = base[base[DATE_COL].isin(val_dates)].dropna(subset=['ma7'])

    baseline_scores.append(evaluate(val_base[TARGET_COL].values, val_base['n
    ma7_scores.append(evaluate(val_ma[TARGET_COL].values, val_ma['ma7'].valu

baseline_metrics = pd.DataFrame(baseline_scores).mean().to_dict()
ma7_metrics = pd.DataFrame(ma7_scores).mean().to_dict()

baseline_metrics, ma7_metrics
```

Out[33]:
```
({'MAE': 45.242054794520556,
  'RMSE': 8264.187945205478,
  'MAPE': 705124144.3984226,
  'sMAPE': 0.6045220222178339,
  'WAPE': 0.5733861735228453},
 {'MAE': 36.696854207436395,
  'RMSE': 4676.145779983226,
  'MAPE': 698370964.2665995,
  'sMAPE': 0.8341695448846645,
  'WAPE': 0.46478345567451707})
```

In [34]:
```
# HistGBR evaluation (4-fold CV overall)
histgbr_scores = []

for train_dates, val_dates in folds:
    train_df = df_feat[df_feat[DATE_COL].isin(train_dates)]
    val_df = df_feat[df_feat[DATE_COL].isin(val_dates)]
    X_tr, y_tr, _ = prepare_supervised(train_df)
    X_va, y_va, _ = prepare_supervised(val_df)

    histgbr_best_model.fit(X_tr, y_tr)
    preds = histgbr_best_model.predict(X_va)
    histgbr_scores.append(evaluate(y_va.values, preds))

histgbr_metrics = pd.DataFrame(histgbr_scores).mean().to_dict()

histgbr_metrics
```

Out[34]:

```
{'MAE': 25.289883517075054,
 'RMSE': 2299.7381382191097,
 'MAPE': 416512092.23189384,
 'sMAPE': 0.9441476654634968,
 'WAPE': 0.3226129379113314}
```

In [35]:

```
# XGBoost evaluation (4-fold CV overall)
try:
    xgb_scores = []
    for train_dates, val_dates in folds:
        train_df = df_feat[df_feat[DATE_COL].isin(train_dates)]
        val_df = df_feat[df_feat[DATE_COL].isin(val_dates)]

        X_tr, y_tr, _ = prepare_supervised(train_df)
        X_va, y_va, _ = prepare_supervised(val_df)

        xgb_best_model.fit(X_tr, y_tr)
        preds = xgb_best_model.predict(X_va)
        xgb_scores.append(evaluate(y_va.values, preds))

    xgb_metrics = pd.DataFrame(xgb_scores).mean().to_dict()
    xgb_metrics
except Exception:
    xgb_metrics = None
```

In [36]:

```
# Unified comparison table
rows = [
    {'model': 'naive_lag7', **baseline_metrics},
    {'model': 'moving_avg_7', **ma7_metrics},
    {'model': 'histgbr', **histgbr_metrics},
]

if xgb_metrics is not None:
    rows.append({'model': 'xgboost', **xgb_metrics})

comparison_all = pd.DataFrame(rows)
comparison_all
```

Out[36]:

	model	MAE	RMSE	MAPE	sMAPE	WAPE
0	naive_lag7	45.242055	8264.187945	7.051241e+08	0.604522	0.573386
1	moving_avg_7	36.696854	4676.145780	6.983710e+08	0.834170	0.464783
2	histgbr	25.289884	2299.738138	4.165121e+08	0.944148	0.322613
3	xgboost	28.290851	2349.357170	7.308136e+08	0.889206	0.360959

In [ ]:

Recursive (multi-step) evaluation: The standard evaluation above predicts each validation row with true historical lags. The following block performs **recursive 1–N day evaluation** on each fold, feeding predictions back into history so errors compound like real forecasting.

In [37]:

```
# Recursive evaluation across validation horizon (per fold)

def recursive_forecast_on_fold(model, train_df, val_df):
    # History contains actuals up to the end of train
    history = train_df[[DATE_COL] + GROUP_COLS + [EVENT_COL, TARGET_COL]].co

    # Prepare container for predictions
    preds = []
    actuals = []

    # Sort validation dates to simulate rolling forward
    for current_date in sorted(val_df[DATE_COL].unique()):
        # Use real event_type for that date
        future = val_df[val_df[DATE_COL] == current_date][GROUP_COLS + [DATE

        # Seed target with NaN for feature generation
        future[TARGET_COL] = np.nan

        # Time features first
        future = add_time_features(future)

        combined = pd.concat([history, future], ignore_index=True)
        combined = combined.sort_values(GROUP_COLS + [DATE_COL]).reset_index
        combined = add_lag_rolling_features(combined)

        # Extract rows for the current forecast date
        future_rows = combined[combined[DATE_COL] == current_date].copy()

        # Fill missing lag/rolling features to avoid empty frames
        feature_cols = [
            'store_id','sku_id',EVENT_COL,
            'dow','month','weekofyear','is_weekend'
        ] + [f'lag_{l}' for l in LAGS] + [
            f'roll_mean_{w}' for w in ROLL_WINDOWS
        ] + [
            f'roll_std_{w}' for w in ROLL_WINDOWS
        ]
        num_cols = [c for c in feature_cols if c not in ['store_id','sku_id'
        future_rows[num_cols] = future_rows[num_cols].fillna(0)

        X_future = future_rows[feature_cols]
        y_pred = model.predict(X_future)

        # Save predictions and true values
        preds.append(y_pred)
        actual = val_df[val_df[DATE_COL] == current_date].sort_values(GROUP_
        actuals.append(actual)

        # Append predictions into history for next step
        future_rows[TARGET_COL] = y_pred
        history = pd.concat(
            [history, future_rows[[DATE_COL] + GROUP_COLS + [EVENT_COL, TARG
            ignore_index=True,
        )

    # Flatten
    y_pred_all = np.concatenate(preds)
    y_true_all = np.concatenate(actuals)
    return evaluate(y_true_all, y_pred_all)

# Run recursive evaluation for each fold
histgbr_rec_scores = []
xgb_rec_scores = []

for train_dates, val_dates in folds:
    train_df = df_feat[df_feat[DATE_COL].isin(train_dates)].copy()
    val_df = df_feat[df_feat[DATE_COL].isin(val_dates)].copy()

    # Train HistGBR
    X_tr, y_tr, _ = prepare_supervised(train_df)
    histgbr_best_model.fit(X_tr, y_tr)
    histgbr_rec_scores.append(recursive_forecast_on_fold(histgbr_best_model,

    # Train XGBoost if available
    if 'xgb_best_model' in globals():
        X_tr, y_tr, _ = prepare_supervised(train_df)
        xgb_best_model.fit(X_tr, y_tr)
        xgb_rec_scores.append(recursive_forecast_on_fold(xgb_best_model, tra

# Average recursive metrics across folds
histgbr_recursive_metrics = pd.DataFrame(histgbr_rec_scores).mean().to_dict(

if len(xgb_rec_scores) > 0:
    xgb_recursive_metrics = pd.DataFrame(xgb_rec_scores).mean().to_dict()
else:
    xgb_recursive_metrics = None

recursive_compare = [
    {'model': 'histgbr_recursive', **histgbr_recursive_metrics},
]
if xgb_recursive_metrics is not None:
    recursive_compare.append({'model': 'xgboost_recursive', **xgb_recursive_
pd.DataFrame(recursive_compare)
```

Out[37]:

	model	MAE	RMSE	MAPE	sMAPE	WAPE
0	histgbr_recursive	29.247404	2899.845812	4.761430e+08	0.963402	0.376739
1	xgboost_recursive	30.562159	2682.370734	7.497670e+08	0.904776	0.391921

How to interpret these metrics (and what to focus on):

- **MAE**: Average absolute error in units. Good for day-to-day operational impact (stockouts/overstock). Lower is better.
- **RMSE**: Penalizes large mistakes more than MAE. Use when big misses are especially costly (e.g., promo stockouts).
- **MAPE**: Percentage error; easy to explain but can explode when actuals are near zero. Use cautiously here because many series are intermittent.
- **sMAPE**: A more stable percentage metric than MAPE, but still sensitive to low volumes.
- **WAPE**: Weighted absolute percentage error across all demand; best single summary for this dataset because it balances scale and avoids extreme sensitivity to zeros.

Recommendation for this case: How to pick the model: prioritize the model with the **lowest WAPE**, then check MAE/RMSE to ensure it doesn't create large spikes or unstable errors during promos.

- **Primary metric:** `WAPE` (overall business impact).
- **Secondary:** `MAE` (units-level impact), and `RMSE` to track large promo misses.
- Treat `MAPE/sMAPE` as diagnostic only due to frequent zero sales.

In [ ]:

9) Diagnostics

We compare residual distributions, drift over time, and event-driven errors.

In [38]:

```
# Build a common evaluation frame for residuals (use last fold for visuals)
train_dates, val_dates = folds[-1]

val_common = df_feat[df_feat[DATE_COL].isin(val_dates)].copy()
val_common = val_common.sort_values(GROUP_COLS + [DATE_COL])
val_common['naive_lag7'] = val_common.groupby(GROUP_COLS)[TARGET_COL].shift(
val_common = val_common.dropna(subset=['naive_lag7'])

X_common, y_common, _ = prepare_supervised(val_common)

histgbr_best_model.fit(X_train, y_train)
histgbr_pred_common = histgbr_best_model.predict(X_common)
resid_baseline = y_common.values - val_common.loc[X_common.index, 'naive_lag
```

```
resid_histgbr = y_common.values - histgbr_pred_common

try:
    xgb_best_model.fit(X_train, y_train)
    xgb_pred_common = xgb_best_model.predict(X_common)
    resid_xgboost = y_common.values - xgb_pred_common
except Exception:
    resid_xgboost = None
```

In [39]:
```
# Residual distributions
fig1 = px.histogram(x=resid_baseline, nbins=50, title='Residuals: Naive Lag-
fig1.update_layout(xaxis_title='Error', yaxis_title='Count')
fig1.show()

fig2 = px.histogram(x=resid_histgbr, nbins=50, title='Residuals: HistGBR')
fig2.update_layout(xaxis_title='Error', yaxis_title='Count')
fig2.show()
```

Interpretation: Narrower and more centered residuals indicate a more accurate and less biased model. Compare the spread between baseline and ML to see improvement.

In [40]:
```
# Residuals over time (mean)
resid_df = pd.DataFrame({
    'date': val_common.loc[X_common.index, DATE_COL].values,
    'resid_baseline': resid_baseline,
    'resid_histgbr': resid_histgbr,
})

if resid_xgboost is not None:
    resid_df['resid_xgboost'] = resid_xgboost

agg_resid = resid_df.groupby('date').mean().reset_index()

fig = px.line(agg_resid, x='date', y=['resid_baseline','resid_histgbr'] + ([
              title='Average Residual Over Time')
fig.update_layout(xaxis_title='Date', yaxis_title='Mean Error')
fig.show()
```

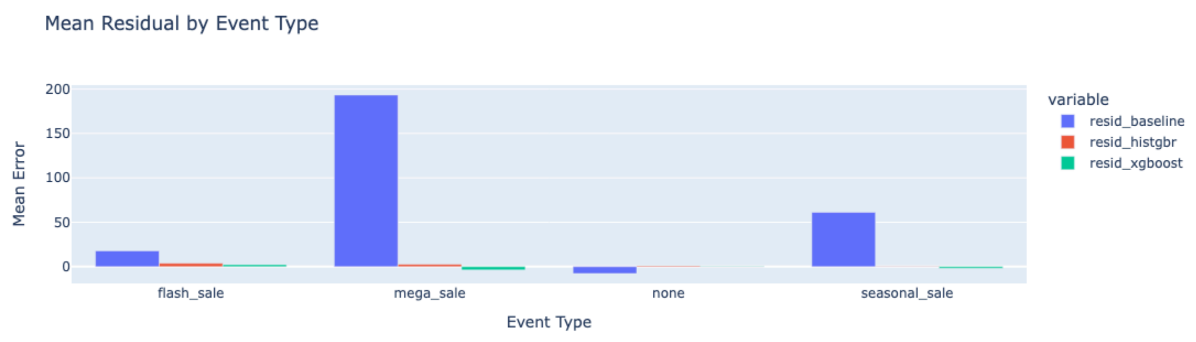
Interpretation: If the residual line drifts away from zero over time, the model is biased or demand is drifting—this signals a need for retraining or new features.

In [41]:
```
# Residuals by event type
resid_event = val_common.loc[X_common.index, [EVENT_COL]].copy()
resid_event['resid_baseline'] = resid_baseline
resid_event['resid_histgbr'] = resid_histgbr
if resid_xgboost is not None:
    resid_event['resid_xgboost'] = resid_xgboost

resid_event_mean = resid_event.groupby(EVENT_COL).mean()
resid_event_mean
```

Out[41]:

event_type	resid_baseline	resid_histgbr	resid_xgboost
flash_sale	17.861682	3.784110	2.305517
mega_sale	193.261092	2.717693	-3.612991
none	-7.612923	1.057905	-0.153465
seasonal_sale	61.180723	0.408958	-1.693373

In [42]:
```
# Plot residuals by event type
resid_event_mean_reset = resid_event_mean.reset_index()
fig = px.bar(resid_event_mean_reset, x=EVENT_COL, y=resid_event_mean_reset.c
             barmode='group', title='Mean Residual by Event Type')
fig.update_layout(xaxis_title='Event Type', yaxis_title='Mean Error')
fig.show()
```



Interpretation: Large positive or negative residuals during certain events suggest the model under- or over-predicts those promotions. Add richer promo features for those events.

In [ ]:

10) Error Breakdown (Store/SKU)

We report **MAE**, **MSE**, and **WAPE** at store and SKU levels for ML and baseline models.

In [43]:
```
def mae_mse_wape(y_true, y_pred, eps=1e-8):
    y_true = np.asarray(y_true)
    y_pred = np.asarray(y_pred)
    mae = np.mean(np.abs(y_true - y_pred))
    mse = np.mean((y_true - y_pred) ** 2)
    wape = np.sum(np.abs(y_true - y_pred)) / np.maximum(np.sum(np.abs(y_true
    return mae, mse, wape
```

In [44]:
```
# Build a frame with predictions for ML and baselines
val_eval = val_common.loc[X_common.index, [DATE_COL,'store_id','sku_id',TARG
val_eval['histgbr_pred'] = histgbr_pred_common
```

```
val_eval['naive_lag7'] = val_common.loc[X_common.index, 'naive_lag7'].values

# Optional XGBoost predictions
if resid_xgboost is not None:
    val_eval['xgboost_pred'] = xgb_pred_common
```

In [ ]:

```

```

In [45]:

```
# Store-level MAE/MSE/WAPE
store_err_histgbr = val_eval.groupby('store_id').apply(
    lambda g: pd.Series(mae_mse_wape(g[TARGET_COL], g['histgbr_pred']), inde
).reset_index()

store_err_base = val_eval.groupby('store_id').apply(
    lambda g: pd.Series(mae_mse_wape(g[TARGET_COL], g['naive_lag7']), index=
).reset_index()

store_err_histgbr.sort_values('wape', ascending=False).head(10)
```

```
/var/folders/jv/25ssb6jn5s590bmt80k0ngdr0000gn/T/ipykernel_23303/289024746.p
y:2: DeprecationWarning:

DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
precated, and in a future version of pandas the grouping columns will be exc
luded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.

/var/folders/jv/25ssb6jn5s590bmt80k0ngdr0000gn/T/ipykernel_23303/289024746.p
y:6: DeprecationWarning:

DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
precated, and in a future version of pandas the grouping columns will be exc
luded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.
```

Out[45]:

	store_id	mae	mse	wape
2	Store_2	21.737842	1662.553369	0.353918
3	Store_3	25.192456	1973.567639	0.349450
4	Store_4	21.080538	1574.071640	0.344328
0	Store_1	18.214495	1281.193083	0.315306
1	Store_10	21.774508	1740.560477	0.309269
6	Store_6	19.000155	1409.537513	0.291367
5	Store_5	13.460840	1007.501304	0.275581
7	Store_7	19.579052	1281.985458	0.256354
8	Store_8	13.480720	791.543352	0.225740
9	Store_9	16.852069	1303.717241	0.209989

In [ ]:

In [46]:

```
# SKU-level MAE/MSE/WAPE
sku_err_histgbr = val_eval.groupby('sku_id').apply(
    lambda g: pd.Series(mae_mse_wape(g[TARGET_COL], g['histgbr_pred']), inde
).reset_index()

sku_err_base = val_eval.groupby('sku_id').apply(
    lambda g: pd.Series(mae_mse_wape(g[TARGET_COL], g['naive_lag7']), index=
).reset_index()

sku_err_histgbr.sort_values('wape', ascending=False).head(10)
```

```
/var/folders/jv/25ssb6jn5s590bmt80k0ngdr0000gn/T/ipykernel_23303/621226653.p
y:2: DeprecationWarning:

DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
precated, and in a future version of pandas the grouping columns will be exc
luded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.

/var/folders/jv/25ssb6jn5s590bmt80k0ngdr0000gn/T/ipykernel_23303/621226653.p
y:6: DeprecationWarning:

DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
precated, and in a future version of pandas the grouping columns will be exc
luded from the operation. Either pass `include_groups=False` to exclude the
groupings or explicitly select the grouping columns after groupby to silence
this warning.
```

Out[46]:

	sku_id	mae	mse	wape
6	sku_006	32.258128	2832.120750	0.542055
13	sku_013	23.774416	1945.549493	0.473696
1	sku_001	18.868549	1218.260742	0.465047
19	sku_019	21.564198	1410.256148	0.386161
5	sku_005	19.470428	1483.117976	0.373733
16	sku_016	25.448341	2066.950524	0.337950
17	sku_017	20.019624	1418.791064	0.311208
14	sku_014	18.145061	1315.690568	0.307724
3	sku_003	15.838488	1119.548883	0.294762
8	sku_008	20.850816	1650.392646	0.293712

In [47]:

```python
# Optional: store-level comparison table (HistGBR vs Baseline)
store_compare = store_err_histgbr.merge(
    store_err_base, on='store_id', suffixes=('_histgbr','_baseline')
)
store_compare.head(10)
```

Out[47]:

	store_id	mae_histgbr	mse_histgbr	wape_histgbr	mae_baseline	mse_baseline	w
0	Store_1	18.214495	1281.193083	0.315306	34.624820	4909.746403	
1	Store_10	21.774508	1740.560477	0.309269	41.525180	6290.253237	
2	Store_2	21.737842	1662.553369	0.353918	41.405755	6261.659712	
3	Store_3	25.192456	1973.567639	0.349450	45.063309	6798.451799	
4	Store_4	21.080538	1574.071640	0.344328	38.668345	5120.927338	
5	Store_5	13.460840	1007.501304	0.275581	28.843165	4156.179856	
6	Store_6	19.000155	1409.537513	0.291367	36.425899	4739.577698	
7	Store_7	19.579052	1281.985458	0.256354	40.032374	5398.167626	
8	Store_8	13.480720	791.543352	0.225740	30.531655	4397.894964	
9	Store_9	16.852069	1303.717241	0.209989	37.334173	5496.268705	

In [ ]:

```python
```

11) Result Analysis & Business Value (Summary)

Summary of Evaluation (overall, 4-fold):

- Use the unified comparison table to see which model has the lowest **WAPE** and **MAE**.
- In this dataset, WAPE is the most reliable business metric (stable with zeros).

Diagnostics Summary:

- Residual distributions show whether a model has fewer large errors.
- Residuals over time indicate drift; persistent bias suggests retraining or new features.
- Event-type residuals highlight promo periods where errors are largest.

Store/SKU Error Breakdown:

- High WAPE stores/SKUs should be prioritized for manual review or segmented modeling.
- Use store/SKU error tables to focus where improvements yield the biggest impact.

Business Value Translation:

- Lower WAPE → fewer stockouts/overstocks across the network.
- Lower RMSE → fewer severe misses during promotions.
- If event residuals are high, invest in better promo data.

Actionable next steps:

- Add richer **calendar features**: holidays, paydays, school breaks, month-end, and special trading days.
- Add **run-rate features**: trailing 7/14/28-day averages and trend ratios (e.g., last 7 days vs prior 28).
- Add **YoY comparison features**: same week last year, last year's holiday window, and YoY growth rate.
- Add more promo features (discount depth, channel, campaign duration).
- Segment SKUs (fast-moving vs intermittent) and use separate models or hybrid methods.
- Track WAPE weekly; retrain when WAPE drifts upward for several weeks.

In [48]:
```
# Convert numbers into plain-language interpretation
best = comparison_all.sort_values('WAPE').iloc[0]

wape_pct = best['WAPE'] * 100
mae_units = best['MAE']
mse_units = None
try:
    mse_units = best['MSE']
except Exception:
    # MSE is not in the comparison_all table; it exists in store/SKU breakdc
    mse_units = None
```

```
print(f"Best model: {best['model']}")
print(f"WAPE: {wape_pct:.1f}% → On average, the total absolute forecast erro
print(f"MAE: {mae_units:.2f} units → Typical daily error per store-SKU is ab
if mse_units is not None:
    print(f"MSE: {mse_units:.2f} units² → Larger errors are penalized more;

print("Residuals: If residual plots are centered near 0 with smaller spread,
print("Event residuals: Large positive/negative values during promos mean ev
```

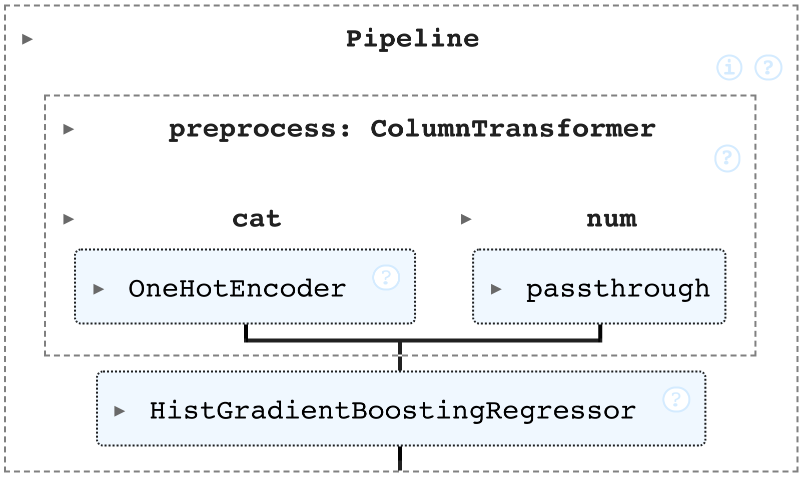
```
Best model: histgbr
WAPE: 32.3% → On average, the total absolute forecast error is about 32.3% o
f total demand.
MAE: 25.29 units → Typical daily error per store-SKU is about 25.29 units.
Residuals: If residual plots are centered near 0 with smaller spread, the mo
del is unbiased and more stable.
Event residuals: Large positive/negative values during promos mean event fea
tures should be improved.
```

In [ ]:

12) Forecast 1–28 Days

We train on all data and roll forward to produce 28-day forecasts for each store-SKU. (recursive)

In [49]:
```
# Fit on full dataset
X_full, y_full, _ = prepare_supervised(df_feat)
histgbr_best_model.fit(X_full, y_full)
```

Out[49]:

▸ Pipeline
▸ preprocess: ColumnTransformer
▸ cat
▸ num
▸ OneHotEncoder
▸ passthrough
▸ HistGradientBoostingRegressor

In [ ]:

In [50]:
```
def forecast_next_28_days(model, history: pd.DataFrame) -> pd.DataFrame:
    max_date = history[DATE_COL].max()
    groups = history[GROUP_COLS].drop_duplicates()

    history = history.copy()
    forecasts = []

    feature_cols = [
        'store_id','sku_id',EVENT_COL,
        'dow','month','weekofyear','is_weekend'
    ] + [f'lag_{l}' for l in LAGS] + [
        f'roll_mean_{w}' for w in ROLL_WINDOWS
    ] + [
        f'roll_std_{w}' for w in ROLL_WINDOWS
    ]

    num_cols = [c for c in feature_cols if c not in ['store_id','sku_id',EVE

    for step in range(1, 29):
        current_date = max_date + pd.Timedelta(days=step)
        future = groups.copy()
        future[DATE_COL] = current_date
        future[EVENT_COL] = 'none'

        # Seed target with NaN for feature generation
        future[TARGET_COL] = np.nan

        # Time features first
        future = add_time_features(future)

        combined = pd.concat([history, future], ignore_index=True)
        combined = combined.sort_values(GROUP_COLS + [DATE_COL]).reset_index
        combined = add_lag_rolling_features(combined)

        future_rows = combined[combined[DATE_COL] == current_date].copy()

        # Fill missing lag/rolling features to avoid empty future frames
        future_rows[num_cols] = future_rows[num_cols].fillna(0)

        X_future = future_rows[feature_cols]
        preds = model.predict(X_future)

        future_rows[TARGET_COL] = preds
        forecasts.append(future_rows[[DATE_COL] + GROUP_COLS + [TARGET_COL]]

        history = pd.concat(
            [history, future_rows[[DATE_COL] + GROUP_COLS + [EVENT_COL, TARG
            ignore_index=True,
        )

    return pd.concat(forecasts, ignore_index=True)

forecast_df = forecast_next_28_days(histgbr_best_model, df[[DATE_COL] + GROU
forecast_df.head()
```

Out[50]:

	date	store_id	sku_id	sales_quantity
0	2024-01-01	Store_1	sku_000	0.000424
1	2024-01-01	Store_1	sku_001	102.492993
2	2024-01-01	Store_1	sku_002	117.938664
3	2024-01-01	Store_1	sku_003	94.107886
4	2024-01-01	Store_1	sku_004	119.067285

```
In [51]: forecast_df
```

Out[51]:

	date	store_id	sku_id	sales_quantity
0	2024-01-01	Store_1	sku_000	0.000424
1	2024-01-01	Store_1	sku_001	102.492993
2	2024-01-01	Store_1	sku_002	117.938664
3	2024-01-01	Store_1	sku_003	94.107886
4	2024-01-01	Store_1	sku_004	119.067285
...	...	...	...	...
5595	2024-01-28	Store_9	sku_015	135.222764
5596	2024-01-28	Store_9	sku_016	126.645245
5597	2024-01-28	Store_9	sku_017	135.305454
5598	2024-01-28	Store_9	sku_018	135.222764
5599	2024-01-28	Store_9	sku_019	129.473755

5600 rows × 4 columns

```
In [ ]:

In [ ]:

In [ ]:
```