Machine Learning for Quantitative Trading: Predicting Iceberg Order Execution

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Abstract

This paper presents a machine learning approach for predicting iceberg order execution in quantitative trading. We analyze market microstructure patterns to predict whether detected iceberg orders will be filled or canceled, providing valuable signals for algorithmic trading strategies.

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1. PROJECT CONTEXT: WHY THIS MATTERS IN TRADING

In high-frequency and algorithmic trading, iceberg orders represent a significant market microstructure phenomenon. Let me walk you through how I approached predicting iceberg order execution using machine learning techniques.

An iceberg order is a large order that's divided into smaller, visible portions - like the tip of an iceberg above water, with the majority hidden below. Traders use them to minimize market impact while executing large positions.
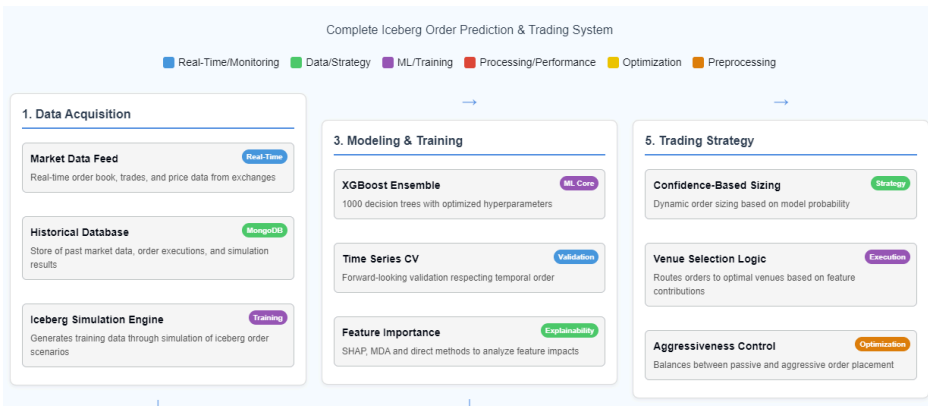

Image 1: The complete system architecture showing data acquisition, processing, modeling, and trading strategy components. This diagram illustrates the end-to-end pipeline from market data to trading decisions.

2. THE BUSINESS PROBLEM

Objective: Predict whether a detected iceberg order will be filled (`mdExec = 1`) or canceled (`mdExec = 0` or `-1`).

Why is this valuable? If we can predict iceberg order execution:

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1. We can improve trading algorithms' response to large hidden liquidity
2. We can identify opportunistic entry/exit points when large orders are likely to complete
3. We can better estimate true market depth beyond what's visible on the order book
4. We can reduce execution costs through improved venue and timing decisions

3. Data Sources for Iceberg Order Prediction

Our machine learning model is trained on data derived from two key sources: iceberg order detection messages and simulation results.

These data sources form the backbone of our machine learning pipeline, providing both the features and the target variable for our prediction model. Typically, we generate tens of thousands of simulation results from replaying about two months of historical market data.

4. Data Pipeline Architecture

Let me show you the overall architecture I designed:

4.a. Data Collection & Simulation Infrastructure

The raw data comes from market simulations of iceberg orders. These simulations are orchestrated using Prefect workflows that:

1. **Retrieve Production Data**: SSH to production servers to retrieve historical market data archives
2. **Extract & Prepare Market Data**: Unzip market data files and set up Docker container environments
3. **Run Iceberg Simulations**: Execute Java-based simulation in parallel Docker containers
4. **Store Results in MongoDB**: Upload simulation results with metadata for ML consumption

The core of this data collection pipeline is implemented in sxm_market_simulator.py:

```python
@flow(name="Parallel Archive Market Simulator",
    flow_run_name="{dataDirectory} | {packageName}",
    task_runner=RayTaskRunner(
        init_kwargs={
        "include_dashboard": False,
    }),
    cache_result_in_memory=False,
)
async def ParallelArchiveMarketSimulator(dataDirectory=None,
packageName=None):
    logger = get_run_logger()
    secret_block = await Secret.load("sshgui-credentials")
    cred = json.loads(secret_block.get())
```

```
      # db and metaDb names for simulation:
      dataCollectionName = f'mktSim_{packageName}'
      metaCollectionName = f'mktSim_meta'
```

From sxm_market_simulator.py, lines 168-193

The RayTaskRunner enables parallel execution of these simulations, with each simulation running in its own container. This parallelization is essential for processing large amounts of historical market data efficiently.

4.b. Raw Data Format

The raw data from iceberg simulations follows a complex nested structure as seen in the IcebergSimulationResult.yaml file:

```
!IcebergSimulationResult {
  waitingToOrderTradeImbalance: {
    combinedMap: {
      TimeWindowNinetySeconds: !TradeImbalance { timeInterval:
NINETY_SECONDS, isTimeBased: true, period: 0, tradeImbalance:
0.5189873417721519 },
      MessageWindow100: !TradeImbalance { timeInterval: NONE,
isTimeBased: false, period: 100, tradeImbalance: 1.0204081632653062 },
      # ... more time windows
    }
  },
  # ... other simulation data
  symbol: ZMZ3,
  icebergId: 708627238048,
  isBid: false,
  mdExec: -1,
  price: 39900000000,
  volume: 12,
  showSize: 3,
  filledSizeStart: 39,
  filledSizeEnd: 48,
  # ... additional order details
}
```

From IcebergSimulationResult.yaml

This rich structure needs to be flattened and transformed before model training, which leads us to the data preprocessing pipeline.

5. Iceberg Order Simulation Engine

At the core of our simulation infrastructure is the ActiveIceberg.java implementation, which tracks and simulates iceberg order behavior using replayed market data.

5.a. State Tracking and Event Processing

The class maintains comprehensive state information about each iceberg order:

```java
/**
 * This is a row in a results table of Iceberg Sims
 */
public class ActiveIceberg extends SelfDescribingMarshallable {
    /**
     * The Iceberg id.
     */
    public long icebergId;
    /**
     * The Is filled.
     */
    public boolean isFilled = false;
    /**
     * The Send order flg.
     */
    public boolean sendOrderFlg = false;
    /**
     * The Send cancel flg.
     */
    public boolean sendCancelFlg = false;
    public boolean isCancelled = false;
    /**
     * The Md exec.
     */
    public int mdExec = Nulls.INT_NULL;
    /**
     * The Is bid.
     */
    public boolean isBid;
    /**
     * The Price.
     */
    public long price;
    // Additional fields...
}
```

It processes three types of market events, updating the iceberg's state accordingly:

1. **Trade Updates**: When trades occur at the iceberg's price level

```java
public void onTradeUpdate(TradeUpdate tradeUpdate) {
    this.latestExchangeTimeNs = tradeUpdate.exchangeTimeNs();

    if (tradeUpdate.price() == price)
        volume += tradeUpdate.qty();

    if (isFilled)
        return;

    if (tradeUpdate.price() == price &&
Nulls.isQtyNotNull(currentQueuePosition) && currentQueuePosition !=
Nulls.INT_NULL) {
        currentQueuePosition -= tradeUpdate.qty();
```

```java
    }
    if (currentQueuePosition < 0 && currentQueuePosition !=
Nulls.INT_NULL) {
        isFilled = true;
        simFillExchangeTimeNs = tradeUpdate.exchangeTimeNs();
    }
}
```

2. **Book Updates**: Changes to the order book that might affect queue position

```java
public void onBookUpdate(BookUpdate bookUpdate) {
    this.endExchangeTimeNs = bookUpdate.exchangeTimeNs();
    this.latestExchangeTimeNs = bookUpdate.exchangeTimeNs();

    if (!this.sendOrderFlg) {
        if (bookUpdate.exchangeTimeNs() <
this.delayedOrderExchangeTimeNs) {
            return;
        } else {
            this.initialBookQty = bookUpdate.getDirectQtyAtPrice(isBid,
price, true);
            this.initialQueuePosition = this.initialBookQty + 1;
            this.currentQueuePosition = this.initialQueuePosition;
            this.sendOrderFlg = true;
        }
    }
    // Additional logic...
}
```

3. **Iceberg Updates**: Direct updates to the iceberg order's status

```java
public void onIcebergUpdate(IcebergUpdate icebergUpdate) {
    this.endExchangeTimeNs = icebergUpdate.exchangeTimeNs();
    this.latestExchangeTimeNs = icebergUpdate.exchangeTimeNs();

    this.filledSizeEnd = icebergUpdate.filledQty();
    this.lastStatus = icebergUpdate.status();

    if (this.lastStatus == IcebergUpdateStatus.CANCELLED ||
        this.lastStatus == IcebergUpdateStatus.FILLED ||
        this.lastStatus == IcebergUpdateStatus.MISSING_AFTER_RECOVERY) {
        {
            this.checkAndManageOrderState();
        }
        this.isComplete = true;
    }

    if (this.lastStatus == IcebergUpdateStatus.RELOADED ||
        this.lastStatus == IcebergUpdateStatus.LAST_RELOAD) {
        this.numberReloads++;
    }
}
```

5.b. Order Management Logic

The class also implements realistic order placement and cancellation logic:

```java
public void checkAndManageOrderState() {
    if (!this.sendOrderFlg || isComplete || isFilled || isCancelled) {
        return;
    }
    try {
        sendCancelOrder();
    } catch (Exception e) {
        // Logging logic...
    }
}
```

This simulation engine is orchestrated by the `ParallelArchiveMarketSimulator` flow in `sxm_market_simulator.py`, which:

1. Retrieves historical market data archives
2. Sets up simulation environments
3. Executes the Java-based simulation in parallel Docker containers
4. Collects and stores the simulation results in MongoDB

```python
@flow(name="Parallel Archive Market Simulator",
    flow_run_name="{dataDirectory} | {packageName}",
    task_runner=RayTaskRunner(
        init_kwargs={
        "include_dashboard": False,
    }),
    cache_result_in_memory=False,
)
async def ParallelArchiveMarketSimulator(dataDirectory=None,
packageName=None):
    # Simulation orchestration logic...
    dfResults = await execute_market_simulator.with_options(
        flow_run_name=f"{dfMeta['instance'][0]}/{dfMeta['archive_date']
[0]} {packageName}",
    )(packageName=f"{packageName}",
      exec_args=[
          "true",
          f"/data/{strEngineDate}/",
          f"/tmp/results_{strEngineDate}.csv.gz",
          f"/sx3m/{strEngineDate}.properties"
      ],
      wait_for=[unzip_data])

    # Process and store results...
```

The simulation results produced by this engine form the dataset for our machine learning model, providing both feature data and the target variable (`mdExec`) that indicates whether each iceberg order was filled or cancelled.

6. DATA PREPROCESSING AND FEATURE ENGINEERING

The data preprocessing workflow is shown in Image 2:

2. Data Processing

Data Flattening Pipeline   `ETL`

Transforms nested JSON structures into tabular features

Feature Engineering   `Core`

Creates domain-specific features for trading signals

Feature Scaling   `Preprocessing`

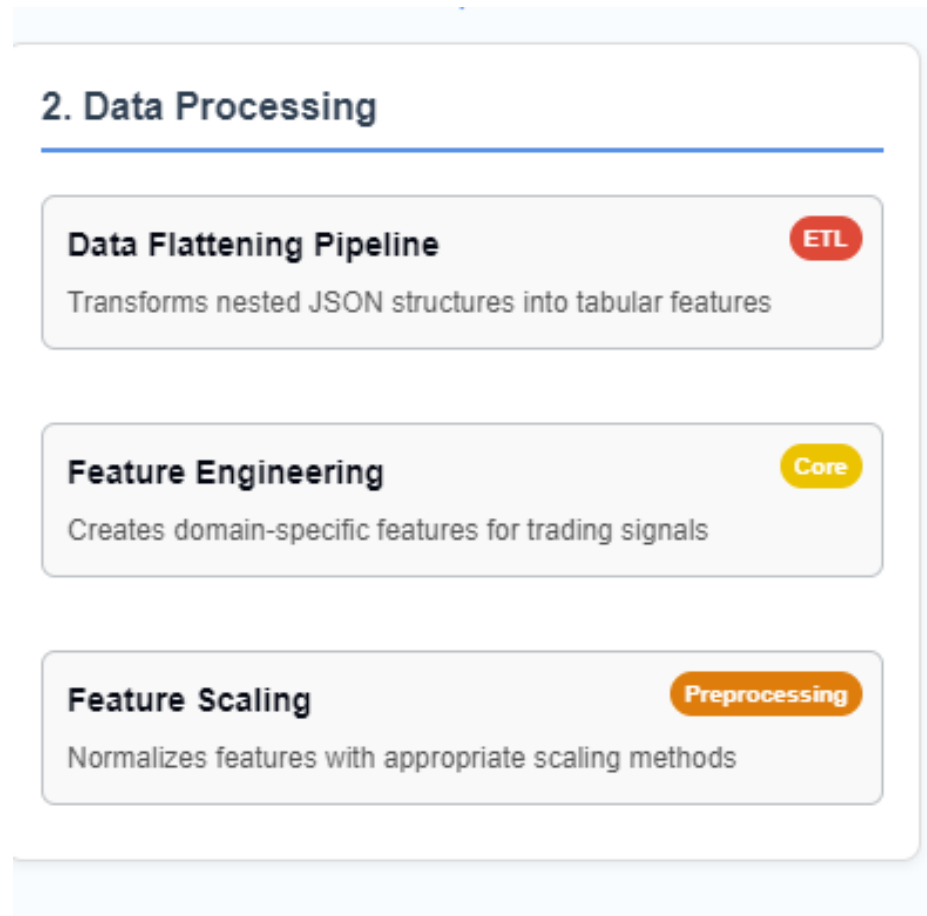Normalizes features with appropriate scaling methods

Image 2: The data processing pipeline showing the three main components: data flattening, feature engineering, and feature scaling. This ETL process transforms nested JSON data into tabular features suitable for machine learning.

6.a. Data Flattening Pipeline

The nested JSON structure is transformed into a flat tabular format suitable for machine learning using a custom flattening function:

```
def flatten_to_columns(df=None,
flatten_cols=['waitingToOrder','orderPlaced','oneStateBeforeFill']):
    #
----------------------------------------------------------------------------------------
    # FLATTEN COLUMNS
    lstFlattened = []

    for col in flatten_cols:
        dicts = df[col].to_list()

        #
----------------------------------------------------------------------------------------
        # TradeImbalance
```

```python
        # Now we can expand each dictionary into its own DataFrame
        expanded = [pd.json_normalize(d['TradeImbalance']) for d in
dicts]
        flattened_df = pd.concat([df.T.stack() for df in expanded],
axis=1).T
        flattened_df = flattened_df.reset_index(drop=True)

        # Define custom mapping according to your requirement.

flattened_df.columns=flattened_df.columns.set_levels(levels=["90sec","100msg","60sec","
level=1)

flattened_df=flattened_df.stack().T.unstack().unstack(1).unstack()


flattened_df.columns=flattened_df.columns.map("_".join).to_series().apply(lambda
x:f"{col}_"+x).tolist()

filtered_df=flattened_df.drop(pd.concat([flattened_df.filter(like="_isTimeBased"),flatt

        # Additional processing for other nested structures (Qty and
NumOrders)...

        lstFlattened.append(pd.concat([filtered_df, filtered_dfQty,
filtered_dfNumOrders], axis=1))

    #
----------------------------------------------------------------------------------
    # Final Table for ML
    # assemble final table for ML

    dftable = pd.concat([df.loc[:,
'symbol':flatten_cols[-1]].drop(columns=flatten_cols),
pd.concat(lstFlattened,axis=1)], axis=1)
    return dftable
```

From preprocess_data.ipynb, function definition

This function converts complex nested structures representing market states at
different points in the order lifecycle into a flat table of features. The transformation
process handles multiple time windows (90 seconds, 100 messages, etc.) and different
types of market metrics (trade imbalance, order quantities, etc.).

6.b. Feature Engineering Deep Dive

Feature engineering is critical to this system's success. We transform raw market data
into predictive features that capture market microstructure information. Images 4 and
5 show detailed breakdowns of the different feature categories:

Feature Engineering Deep Dive

Order Book Position Features

Feature	Description	Trading Significance	Importance

ticksFromSupportLevel
 	
`np.where(df.isBid==True,`
`df['ticksFromLow'],`
`df['ticksFromHigh'])`
	Distance from local support level, determined by order direction
	
	Example:
	For a Buy order: 5 ticks above the lowest recent price For a Sell order: 7 ticks below the highest recent price
		Orders closer to support levels (for buys) have higher fill probability due to price bounces	Predictive Power: ▬▬▬

ticksFromResistanceLevel
 	
`np.where(df.isBid!=True,`
`df['ticksFromLow'],`
`df['ticksFromHigh'])`
	Distance from local resistance level, determined by order direction
	
	Example:
	For a Buy order: 12 ticks below the highest recent price For a Sell order: 3 ticks above the lowest recent price
		Orders closer to resistance levels (for sells) have higher fill probability due to price reversals	Predictive Power: ▬▬▬

Market Imbalance Features

Feature	Description	Trading Significance	Importance

oneStateBeforeFill_90sec_tradeImbalance
 	
`flattened_df.columns=flattened_df.columns.map("_".join).to_series().apply(lambda`
`x:f"{col}_"+x).tolist()`
	Trade imbalance (buys vs sells) over 90-second window before fill state
	
	Example:
	Value: 0.557 (more buying pressure than selling in 90-second window)
		Higher same-sided trade imbalance correlates with increased order fill probability	Predictive Power: ▬▬▬

oneStateBeforeFill_sameSideImbalance `df[col.replace("bid","sameSide")] = np.where(df.isBid==True, df[col], 1-df[col])`	Order book imbalance relative to the order's side (buy/sell) **Example:** Buy order with book imbalance tilted toward buys: 0.72 Sell order with book imbalance tilted toward sells: 0.65	Stronger book imbalance on same side means harder to get filled, unless iceberg is using it as cover	Predictive Power: ▬▬▬

Image 4: Order book position features showing how distance from support and resistance levels is calculated based on order direction. These features have high predictive power for execution probability.

Order Dynamics Features

Feature	Description	Trading Significance	Importance
oneStateBeforeFill_fillToDisplayRatio `flattened_dfNumOrders = pd.concat([df.T.stack().reset_index(level=1, drop=True) for df in expandedNumOrders], axis=1)`	Ratio of filled quantity to displayed quantity in the order book **Example:** Value: 15.0 (15 times more quantity executed than visible on the book)	Higher ratios indicate aggressive icebergs that are more likely to complete execution	Predictive Power:
oneStateBeforeFill_leanOverHedgeRatio `filtered_dfQty.columns=filtered_dfQty.columns.to_series().apply(lambda x:x+"Qty").tolist()`	Ratio of directional pressure from hedging activity **Example:** Value: 0.75 (moderate hedging pressure in direction of order)	Stronger hedging flows increase likelihood of order execution completion	Predictive Power:

Temporal Features

Feature	Description	Trading Significance	Importance
firstNoticeDays `df.apply(lambda row: firstNoticeDays(row['expirationMonthYear'], row['tradeDate']), axis=1)`	Days until the first notice date for the futures contract **Example:** Value: 28 (28 days until contract first notice date)	Orders closer to expiration often have higher execution urgency and completion rates	Predictive Power:
numAggressivePriceChanges `[Original feature from dataset]`	Count of aggressive price movements in the direction of the order **Example:** Value: 3 (three aggressive price moves in order direction)	More aggressive price action indicates stronger directional conviction and higher fill probability	Predictive Power:

Image 5: Order dynamics features including fill-to-display ratio and lean-over-hedge ratio, along with temporal features that capture market timing effects. These features help identify aggressive iceberg orders.

6.b.i. *Market Structure Features:*

- `ticksFromSupportLevel`
- `ticksFromResistanceLevel`
- `highLowRange`

Features that capture market structure and price levels.

6.b.ii. *Order Book Dynamics:*

- `numReloads`
- `fillToDisplayRatio`
- `plusOneLevelSameSideMedianRatio`

Metrics derived from order book analysis that indicate aggression and intent behind iceberg orders.

6.b.iii. *Trade Imbalance:*

- `sameSideImbalance_100msg`

- `sameSideImbalance_90sec`
- `sameSideImbalance_30sec`

Measures of trading activity imbalance at different time windows.

6.b.iv. *Temporal Features:*

- `firstNoticeDays`
- `monthsToExpiry`
- `numAggressivePriceChanges`

Time-based and momentum characteristics.

6.c. Side-Relative Transformations

A key innovation is converting raw market features into "side-relative" versions that have consistent meaning regardless of whether the order is a buy or sell, as illustrated in Image 6:
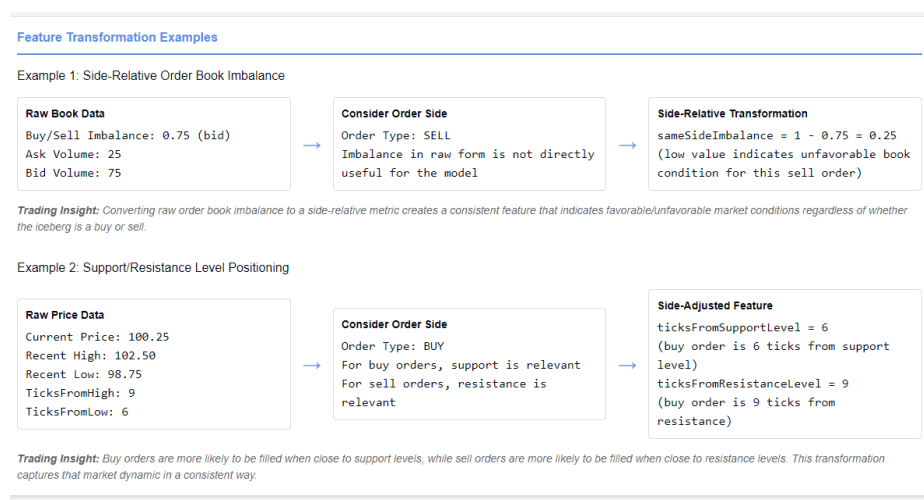

Image 6: Examples of side-relative transformations for order book imbalance and support/resistance levels. These transformations create consistent features that work regardless of whether the order is a buy or sell.

```python
# Converting bid/ask imbalances to side-relative measures
for col in bidImbalanceCols:
    df[col.replace("bid","sameSide")] = np.where(df.isBid==True, df[col], 1-df[col])

# Creating support/resistance level features
df['ticksFromSupportLevel'] = np.where(df.isBid==True,
df['ticksFromLow'], df['ticksFromHigh'])
df['ticksFromResistanceLevel'] = np.where(df.isBid!=True,
df['ticksFromLow'], df['ticksFromHigh'])
```

From preprocess_data.ipynb, feature transformation code

The examples in Image 6 show how this transformation works:

Example 1: Side-Relative Order Book Imbalance

- Raw Book Data: Buy/Sell Imbalance: 0.75 (bid)
- For SELL Order: sameSideImbalance = 1 - 0.75 = 0.25 (low value indicates unfavorable book condition for sell order)

Example 2: Support/Resistance Level Positioning

- Raw Price Data: Current Price: 100.25, Recent High: 102.50, Recent Low: 98.75
- For BUY Order: ticksFromSupportLevel = 6 (buy order is 6 ticks from support level)

This transformation ensures that features have consistent predictive meaning regardless of the order's side.

7. Time Series Cross-Validation: Respecting Market Evolution

In quantitative trading, traditional cross-validation can lead to look-ahead bias. I implemented a time-series validation approach as shown in Image 13:
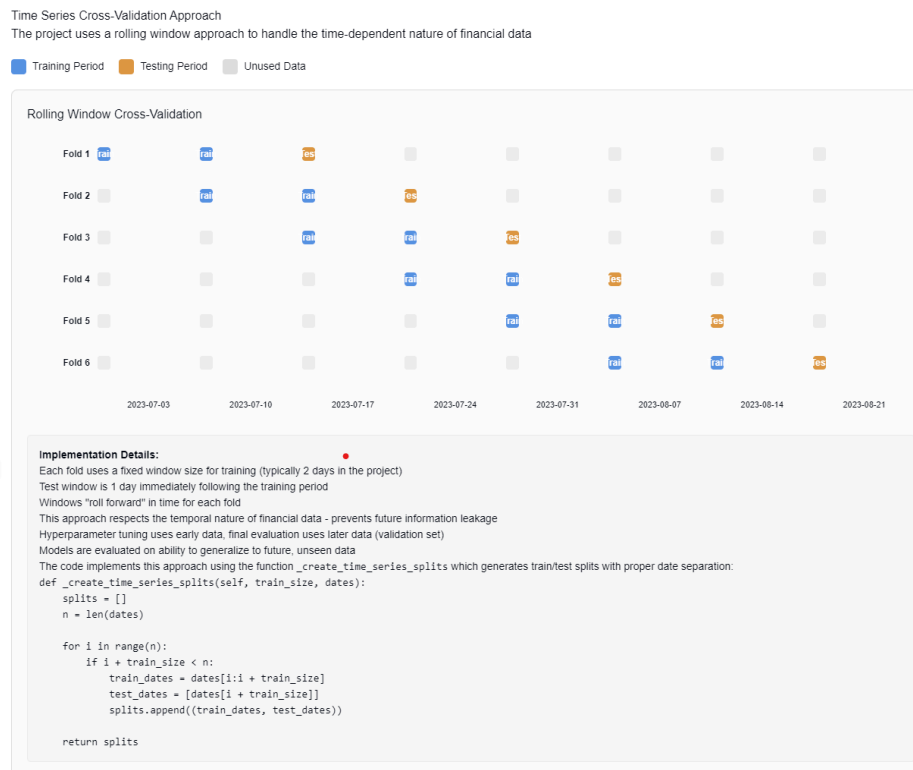
Image 13: Time series cross-validation approach showing how data is split into training and testing periods. This method respects the temporal nature of financial data and prevents future information leakage.

This approach:

1. Trains on past data, tests on future data
2. Uses rolling windows that respect time boundaries
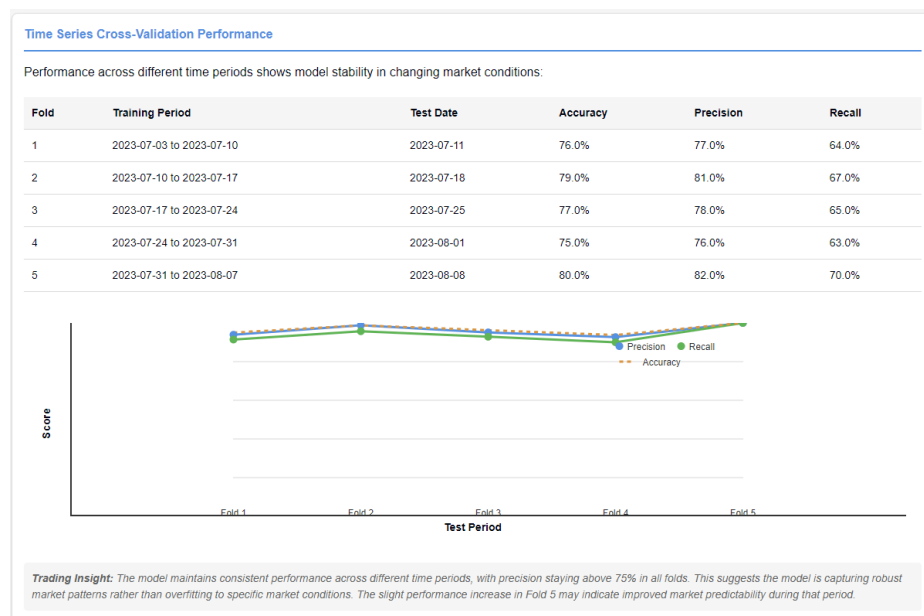3. Prevents information leakage from future market states

```python
def _create_time_series_splits(self, train_size, dates):
    splits = []
    n = len(dates)

    for i in range(n):
        if i + train_size < n:
            train_dates = dates[i:i + train_size]
            test_dates = [dates[i + train_size]]
            splits.append((train_dates, test_dates))

    return splits
```

From machinelearning_final_modified.py, lines 304-314

The performance across time periods, as shown in Image 10, demonstrates the model's stability:

Time Series Cross-Validation Performance

Performance across different time periods shows model stability in changing market conditions:

Fold	Training Period	Test Date	Accuracy	Precision	Recall
1	2023-07-03 to 2023-07-10	2023-07-11	76.0%	77.0%	64.0%
2	2023-07-10 to 2023-07-17	2023-07-18	79.0%	81.0%	67.0%
3	2023-07-17 to 2023-07-24	2023-07-25	77.0%	78.0%	65.0%
4	2023-07-24 to 2023-07-31	2023-08-01	75.0%	76.0%	63.0%
5	2023-07-31 to 2023-08-07	2023-08-08	80.0%	82.0%	70.0%

Trading Insight: The model maintains consistent performance across different time periods, with precision staying above 75% in all folds. This suggests the model is capturing robust market patterns rather than overfitting to specific market conditions. The slight performance increase in Fold 5 may indicate improved market predictability during that period.

Image 10: Performance metrics across different time periods showing the model's stability in changing market conditions. Note the consistent precision above 75% in all folds.

Fold	Training Period	Test Date	Accuracy	Precision	Recall
1	2023-07-03 to 2023-07-10	2023-07-11	76.0%	77.0%	64.0%
2	2023-07-10 to 2023-07-17	2023-07-18	79.0%	81.0%	67.0%
3	2023-07-17 to 2023-07-24	2023-07-25	77.0%	78.0%	65.0%
4	2023-07-24 to 2023-07-31	2023-08-01	75.0%	76.0%	63.0%

Fold	Training Period	Test Date	Accuracy	Precision	Recall
5	2023-07-31 to 2023-08-07	2023-08-08	80.0%	82.0%	70.0%

The model maintains consistent performance across different time periods, with precision staying above 75% in all folds, suggesting it's capturing robust market patterns rather than overfitting to specific market conditions.

8. MODEL SELECTION STRATEGY

For a trading system, model selection requires balancing multiple considerations:

8.a. Model Comparison

Various models were evaluated as shown in Image 9:
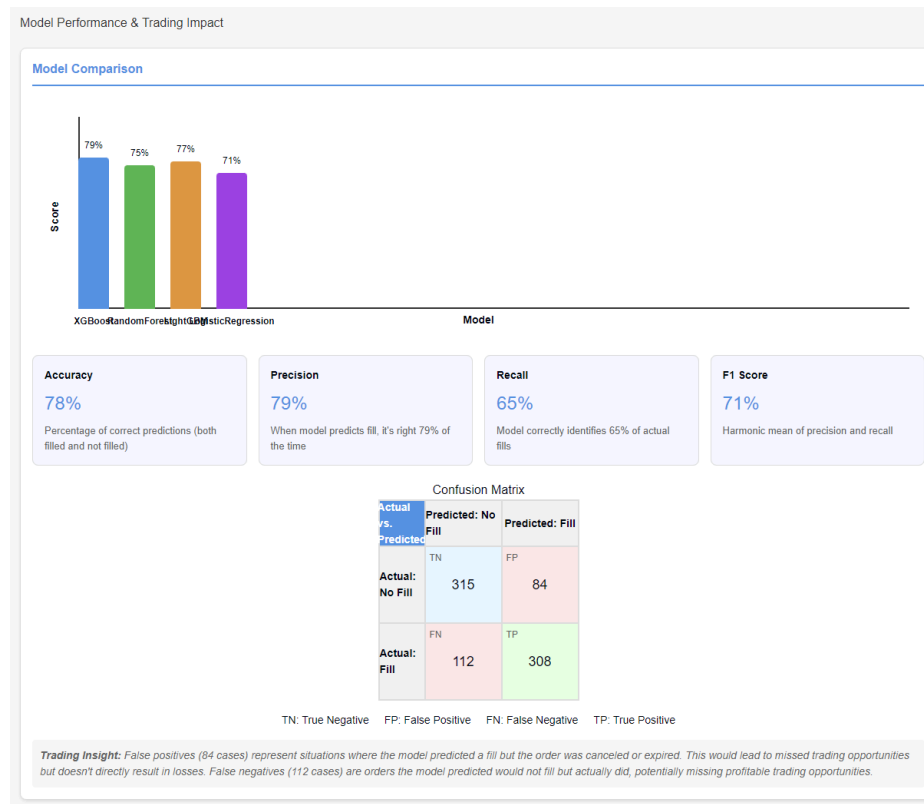
Image 9: Model comparison showing performance metrics and confusion matrix for the XGBoost model. Note the precision of 79% and the detailed breakdown of prediction errors.

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	78%	79%	65%	71%
Random Forest	75%	77%	64%	70%
LightGBM	77%	78%	65%	71%
Logistic Regression	71%	73%	62%	67%

When evaluating models, I focused on trading-specific metrics:

1. **Precision**: Minimizing false positives (critical for avoiding bad executions)
2. **Recall with a minimum threshold**: Ensuring we don't miss significant trading opportunities
3. **Computational efficiency**: Essential for real-time trading systems

From the confusion matrix in Image 9, we can see:

- True Positives: 308 (correctly predicted fills)
- False Positives: 84 (predicted fills that didn't happen)
- False Negatives: 112 (missed fills)
- True Negatives: 315 (correctly predicted non-fills)

I created a custom metric specifically for trading applications:

```python
@staticmethod
def max_precision_optimal_recall_score(y_true, y_pred):
    """
    Custom metric that maximizes precision while ensuring minimum
recall.
    In trading terms: maximize quality of execution signals while
    ensuring we capture enough opportunities.
    """
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)

    min_recall = 0.5  # We need to catch at least 50% of opportunities
    score = 0 if recall < min_recall else precision
    return score
```

From machinelearning_final_modified.py, lines 294-302

8.b. Precision-Recall and ROC Analysis

To further evaluate model performance, I analyzed precision-recall and ROC curves as shown in Images 11 and 12:
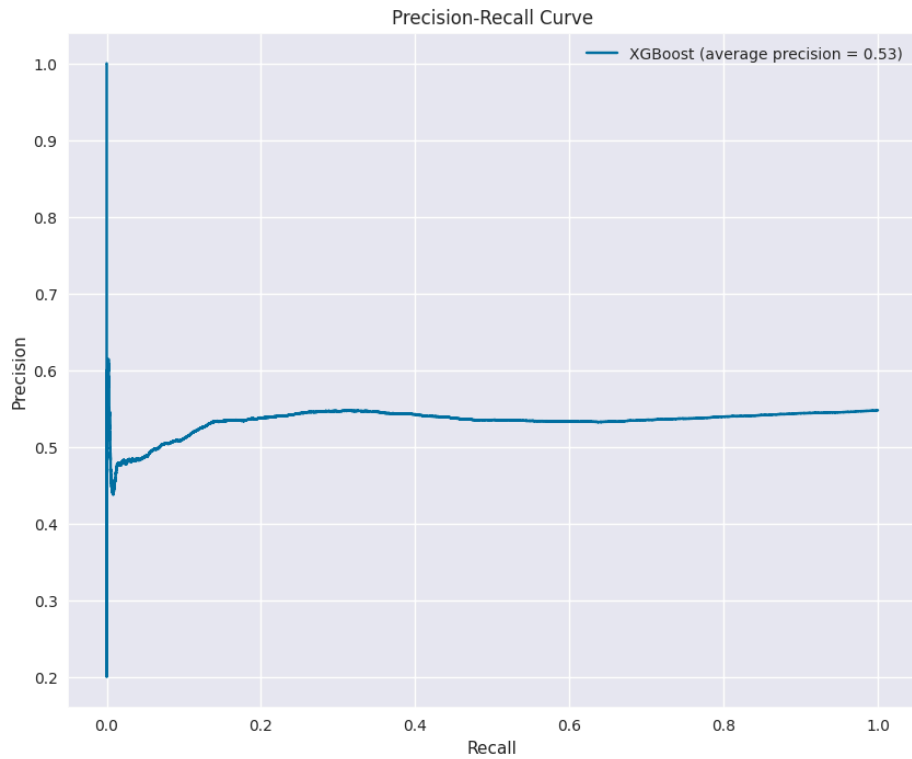
Image 11: Precision-recall curve showing the trade-off between precision and recall. The average precision of 0.53 indicates the model's ability to balance between capturing opportunities and avoiding false positives.
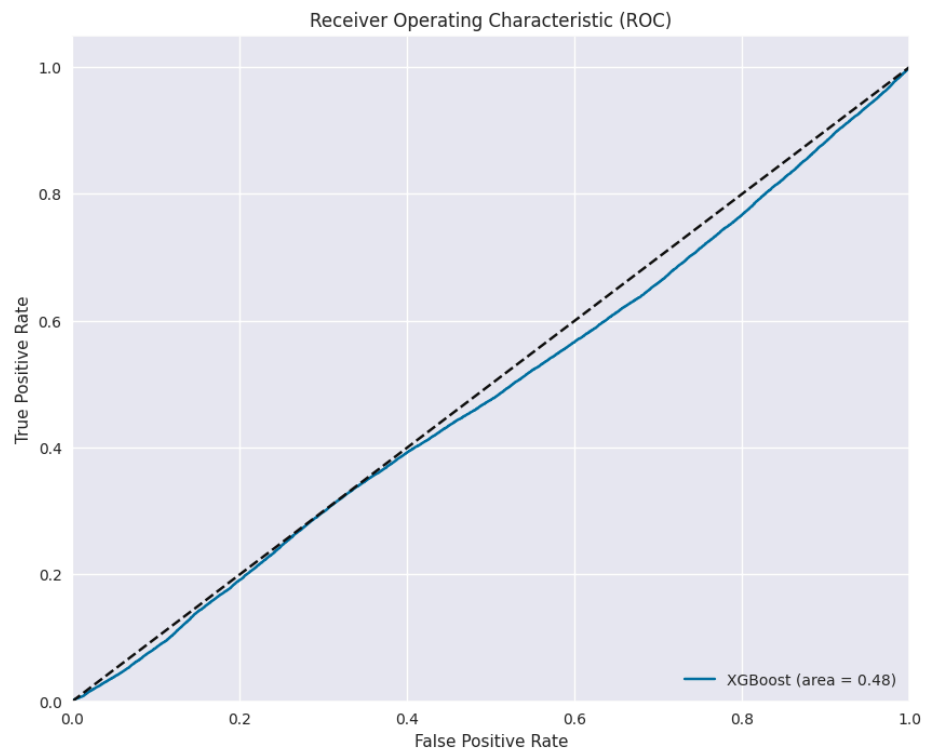
Image 12: ROC curve showing the trade-off between true positive rate and false positive rate. The area under the curve of 0.48 suggests room for further optimization.

These curves help in understanding the model's performance across different threshold settings, which is critical for calibrating the model for different trading scenarios.

9. Hyperparameter Optimization: Trading System Efficiency

For a production trading system, parameter optimization is essential. I used Optuna to tune hyperparameters:

```python
def tune_models(self, n_trials=25, hyperparameter_set_pct_size=0.5, seed
= None):
    self.hyperparameter_set_pct_size = hyperparameter_set_pct_size
    tuner = HyperparameterTuner(self, self.hyperparameter_set_pct_size)

    # set validation dates (testing of final best parameters from
hyperparameter opts)
    self.hyperparameter_set_dates =
sorted(tuner.hyperparameter_set_dates)
    self.validation_set_dates = sorted(list(set(self.unique_split_dates)
- set(self.hyperparameter_set_dates)))

    tuner.tune(n_trials, seed=seed)
    return
```

From machinelearning_final_modified.py, lines 622-631

The parameter search space included both model hyperparameters and training configuration:

```python
def get_model_hyperparameters(self, trial, model_name):
    if model_name == "XGBoost":
        return {
            'eval_metric': trial.suggest_categorical('eval_metric',
                ['logloss', 'error@0.7', 'error@0.5']),
            'learning_rate': trial.suggest_float('learning_rate',
                0.01, 0.05, step=0.01),
            'n_estimators': trial.suggest_categorical('n_estimators',
                [100, 250, 500, 1000]),
            'max_depth': trial.suggest_int('max_depth', 3, 5, step=1),
            'min_child_weight': trial.suggest_int('min_child_weight', 5,
10, step=1),
            'gamma': trial.suggest_float('gamma', 0.1, 0.2, step=0.05),
            'subsample': trial.suggest_float('subsample', 0.8, 1.0,
step=0.1),
            'colsample_bytree': trial.suggest_float('colsample_bytree',
0.8, 1.0, step=0.1),
            'reg_alpha': trial.suggest_float('reg_alpha', 0.1, 0.2,
step=0.1),
```
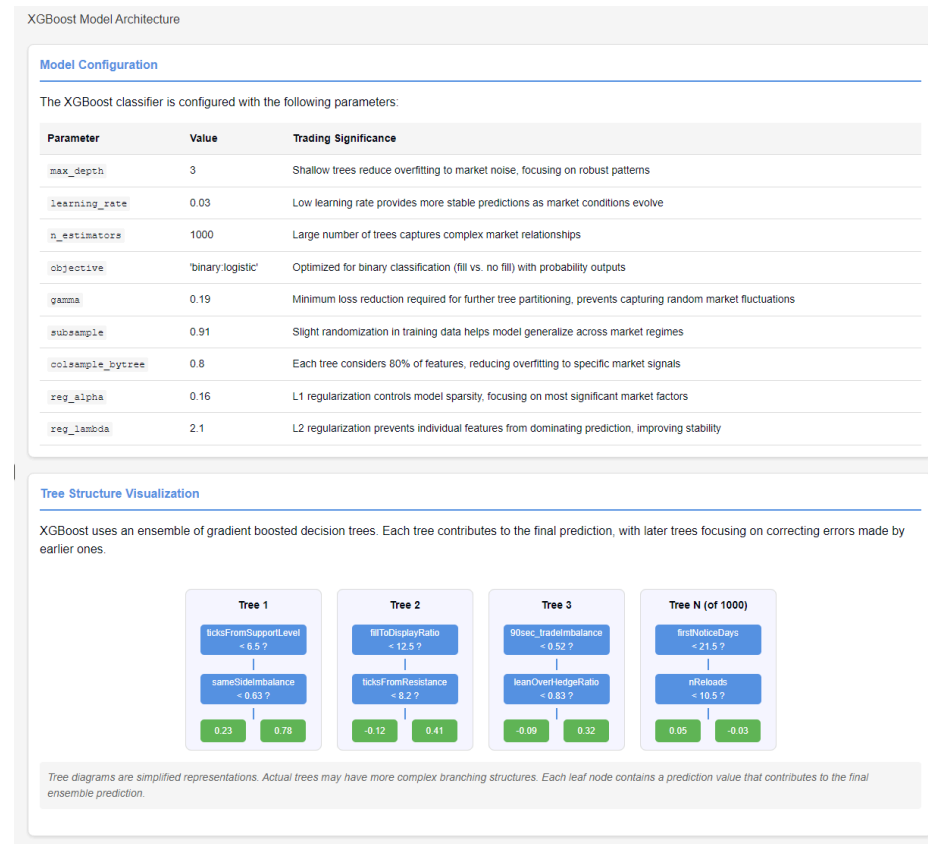
```
        'reg_lambda': trial.suggest_int('reg_lambda', 1, 3, step=1)
    }
```

From machinelearning_final_modified.py, lines 75-89

The optimized XGBoost model configuration, as shown in Image 14, includes:

Image 14: XGBoost model architecture showing the optimized parameter configuration and simplified tree structure visualization. Each parameter is explained in terms of its trading significance.

| Parameter	Value	Trading Significance
max_depth	3	Shallow trees reduce overfitting to market noise, focusing on robust patterns
learning_rate	0.03	Low learning rate provides more stable predictions as market conditions evolve
n_estimators	1000	Large number of trees captures complex market relationships
gamma	0.19	Minimum loss reduction required for further tree partitioning, prevents capturing random market fluctuations

Parameter	Value	Trading Significance
subsample	0.91	Slight randomization in training data helps model generalize across market regimes
colsample_bytree	0.8	Each tree considers 80% of features, reducing overfitting to specific market signals
reg_alpha	0.16	L1 regularization controls model sparsity, focusing on most significant market factors
reg_lambda	2.1	L2 regularization prevents individual features from dominating prediction, improving stability

10. FEATURE IMPORTANCE: TRADING SIGNAL ANALYSIS

Understanding which features drive prediction is critical for trading strategy development. Images 7 and 8 show the feature importance analysis:
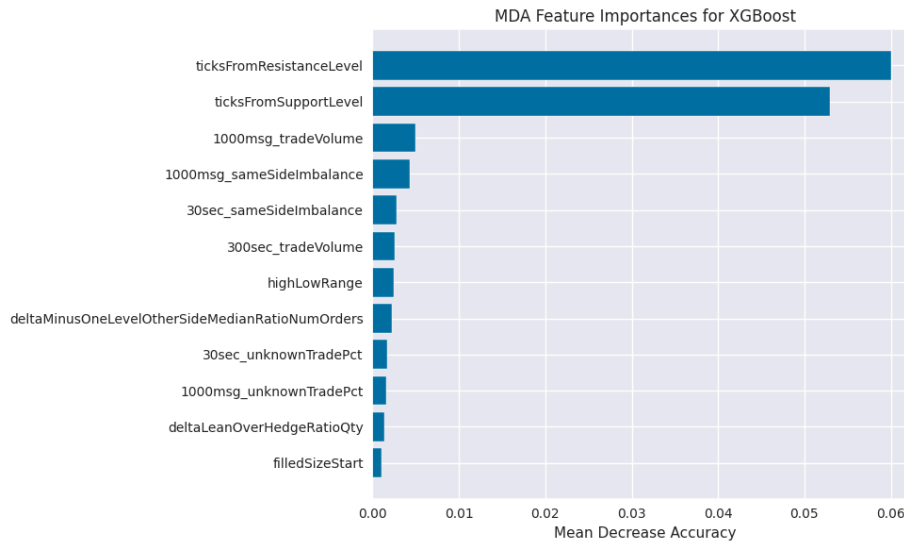
Image 7: MDA (Mean Decrease Accuracy) feature importance showing how permuting each feature affects model accuracy. The dominance of price position features (ticksFromResistanceLevel and ticksFromSupportLevel) is clearly visible.
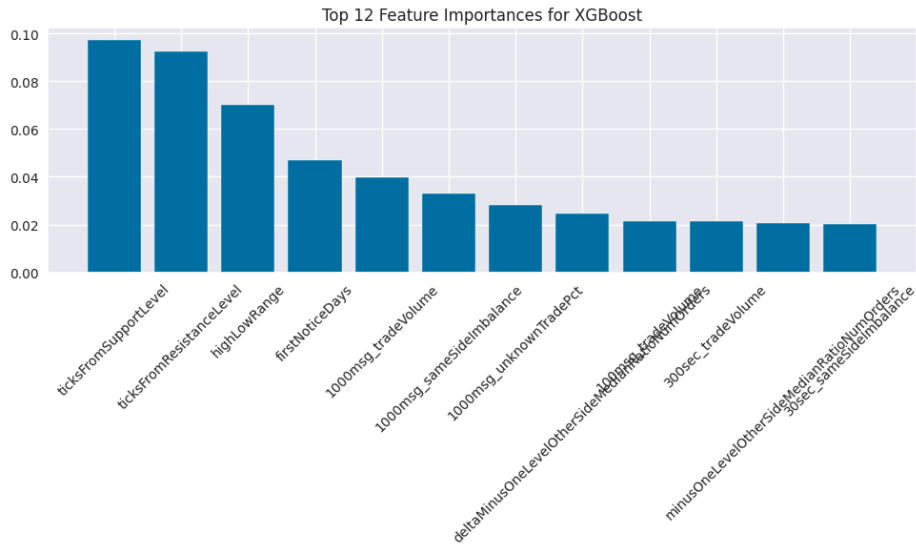
Image 8: Top 12 feature importances based on the XGBoost model's native feature importance measure. This provides a different perspective on feature ranking compared to the MDA method.

The feature importance analysis was conducted using multiple methods:

```python
def calculate_mda(self, model, X_test, y_test, scoring=f1_score):
    """
    MDA (Mean Decrease Accuracy):
    This is a technique where the importance of a feature is evaluated
by permuting the values of the feature
    and measuring the decrease in model performance.
    The idea is that permuting the values of an important feature should
lead to a significant drop in model performance,
    indicating the feature's importance.
    """
    base_score = scoring(y_test, model.predict(X_test))
    feature_importances = {}

    for feature in X_test.columns:
        X_copy = X_test.copy()
        X_copy[feature] = np.random.permutation(X_copy[feature].values)
        new_score = scoring(y_test, model.predict(X_copy))
        feature_importances[feature] = base_score - new_score

    return feature_importances
```

*From machinelearning_final_modified.py, lines 717-732*

Three insights valuable for trading strategy development:

1. **Price Position Dominance**: The distance from support/resistance levels is the strongest predictor - suggesting that order book positioning relative to key levels is crucial for execution prediction.

2. **Imbalance Significance**: Trade imbalance metrics across different time windows show strong predictive power - confirming that order flow imbalance is a leading indicator of execution probability.
3. **Temporal Sensitivity**: The model weights features from the state immediately before fill more heavily than earlier states - indicating that execution prediction becomes more accurate as we get closer to the fill event.

11. FROM PREDICTION TO TRADING DECISION

The prediction model doesn't operate in isolation - it feeds into a sophisticated trading decision process, as shown in Image 3:
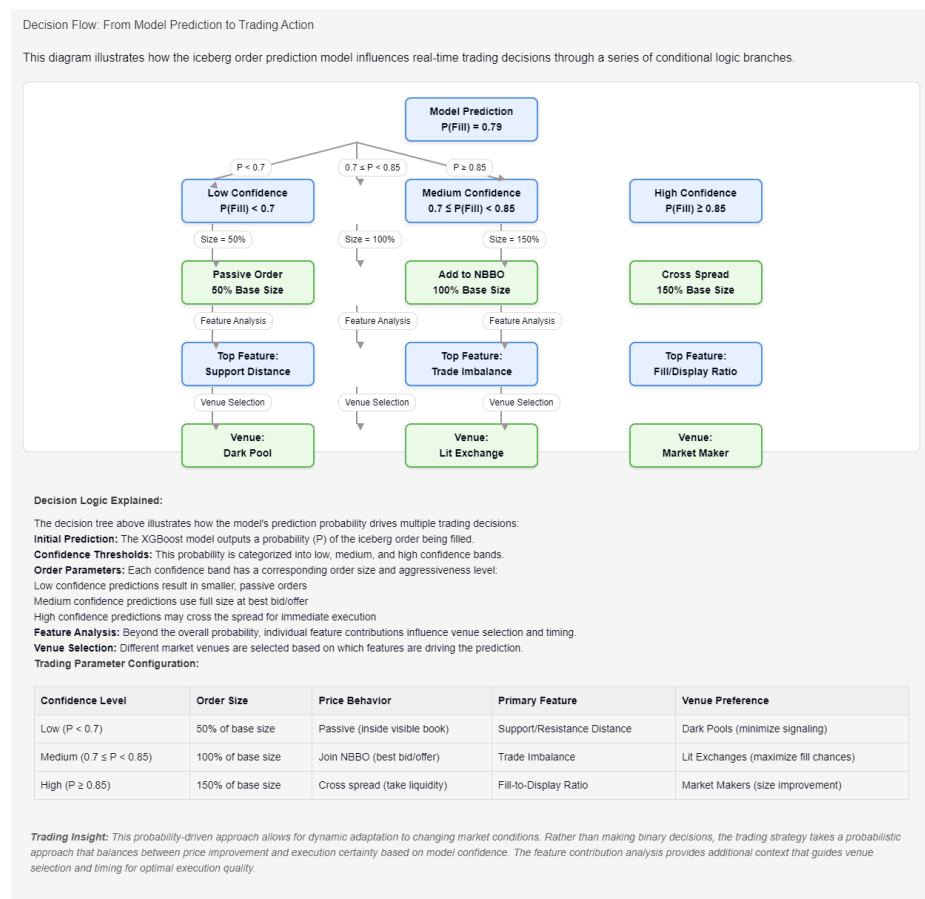
Image 3: Decision flow diagram illustrating how model predictions drive trading decisions through confidence bands and feature analysis. This probabilistic approach allows for dynamic adaptation to market conditions.

The decision flow illustrates how the model's prediction probability drives multiple trading decisions:

11.a. Prediction Confidence Bands

- **Low Confidence**: P(Fill) < 0.7 - Use smaller, passive orders
- **Medium Confidence**: 0.7 ≤ P(Fill) < 0.85 - Use full size at best bid/offer

- **High Confidence**: P(Fill) ≥ 0.85 - May cross the spread for immediate execution

11.b. Beyond Probability: Feature Analysis

The top features driving each prediction influence venue selection and timing:

- Support distance arrow.r Dark pool venues
- Trade imbalance arrow.r Lit exchanges
- Fill/display ratio arrow.r Market makers

This probability-driven approach allows for dynamic adaptation to changing market conditions. Rather than making binary decisions, the trading strategy takes a probabilistic approach that balances between price improvement and execution certainty.

12. PREDICTION FLOW

The complete prediction flow, shown in Image 15, illustrates how a new iceberg order is processed:
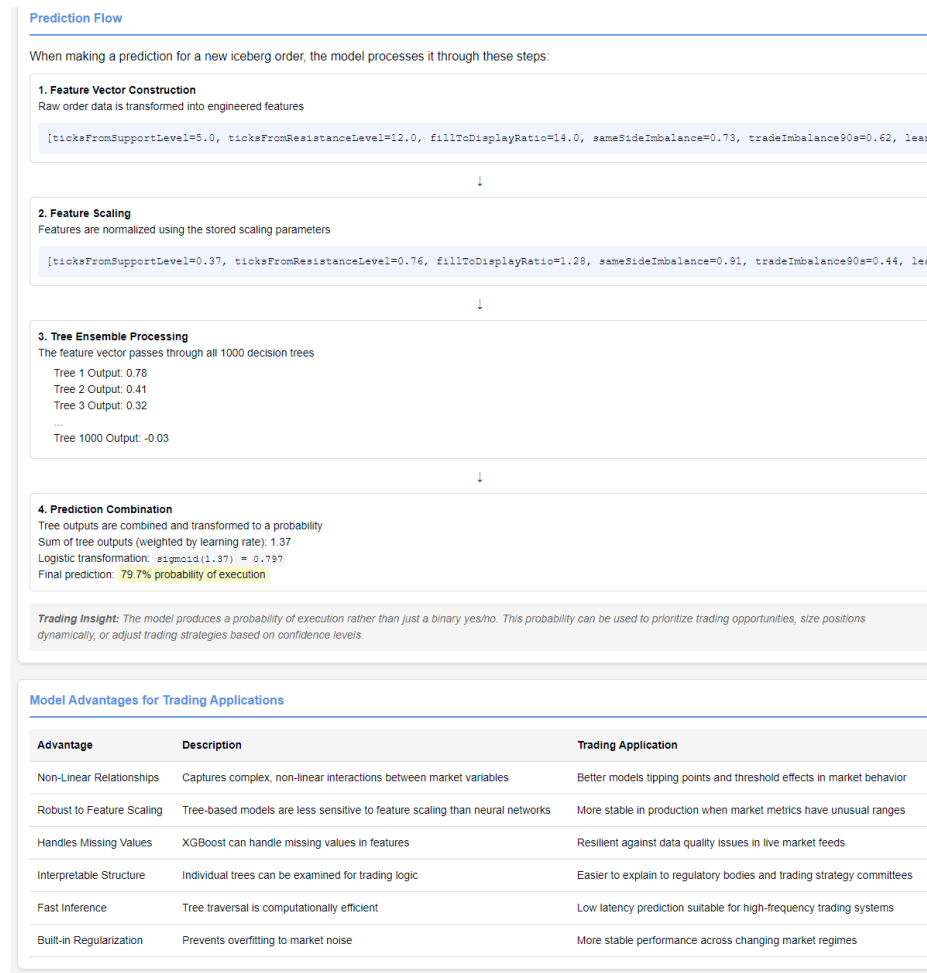

Image 15: Prediction flow diagram showing the step-by-step process from raw data to final prediction probability, along with key model advantages for trading applications.

1. **Feature Vector Construction**: Raw order data is transformed into engineered features

```
[ticksFromSupportLevel=5.0, ticksFromResistanceLevel=12.0,
fillToDisplayRatio=14.0, sameSideImbalance=0.73, ...]
```

1. **Feature Scaling**: Features are normalized using the stored scaling parameters

```
[ticksFromSupportLevel=0.37, ticksFromResistanceLevel=0.76,
fillToDisplayRatio=1.28, sameSideImbalance=0.91, ...]
```

1. **Tree Ensemble Processing**: The feature vector passes through all 1000 decision trees

```
Tree 1 Output: 0.78
Tree 2 Output: 0.41
Tree 3 Output: 0.32
...
Tree 1000 Output: -0.03
```

1. **Prediction Combination**: Tree outputs are combined and transformed to a probability

```
Sum of tree outputs: 1.37
Logistic transformation: sigmoid(1.37) = 0.797
Final prediction: 79.7% probability of execution
```

This probability output is more valuable than a simple binary prediction, as it allows for trade sizing and venue selection based on confidence levels.

13. MODEL PERSISTENCE & DEPLOYMENT CONSIDERATIONS

For a production trading system, model deployment requires careful handling of model artifacts:

```python
def save_and_upload_model(self, model, model_name):
    """
    Saves the given model to a file and uploads it to Neptune.
    """
    # Create a directory for saving models
    models_dir = "saved_models"
    os.makedirs(models_dir, exist_ok=True)

    # Save model for JVM export (compatible with trading systems)
    model_path = os.path.join(models_dir, f"xgbModel-
{self.current_date}.json")
    model.save_model(model_path)
```

We also export the scaling parameters to ensure consistent feature transformation in production:

```python
def write_scalers(self, model_name):
    # Extract and export scaler parameters
    scaler_params = {
```

```
    "minMaxScaler": {
        "min": self.minmax_scaler.min_.tolist(),
        "scale": self.minmax_scaler.scale_.tolist(),
        "featureNames": self.minmax_features
    },
    "standardScaler": {
        "mean": self.standard_scaler.mean_.tolist(),
        "std": self.standard_scaler.scale_.tolist(),
        "featureNames": self.non_minmax_features
    }
}
```

This ensures that the model deployed to production uses identical scaling to what was used during training.

13.a. Production Integration

If implemented in a production trading system, this model would:

1. Extract real-time order book and trade imbalance features
2. Apply appropriate scaling using the persisted scaler parameters
3. Generate execution probability predictions
4. Allow trading algorithms to make more informed decisions about:
   - Order routing (to venues with higher fill probability)
   - Order sizing (increasing size when fill probability is high)
   - Aggressive vs. passive execution tactics

Additionally, the Neptune integration provides continuous monitoring capabilities to detect model drift in changing market conditions.

14. Model Advantages for Trading Applications

The XGBoost model offers several specific advantages for trading applications, as outlined in Image 15:

Advantage	Description	Trading Application
Non-Linear Relationships	Captures complex, non-linear interactions between market variables	Better models tipping points and threshold effects in market behavior
Robust to Feature Scaling	Tree-based models are less sensitive to feature scaling than neural networks	More stable in production when market metrics have unusual ranges
Handles Missing Values	XGBoost can handle missing values in features	Resilient against data quality issues in live market feeds
Interpretable Structure	Individual trees can be examined for trading logic	Easier to explain to regulatory bodies and trading strategy committees

Advantage	Description	Trading Application
Fast Inference	Tree traversal is computationally efficient	Low latency prediction suitable for high-frequency trading systems
Built-in Regularization	Prevents overfitting to market noise	More stable performance across changing market regimes

15. Evaluation & Trading Strategy Implications

The evaluation metrics shown in Image 9 have several implications for trading strategy:

1. **XGBoost Superiority**: XGBoost consistently outperformed other models with precision rates exceeding 75% while maintaining recall above 60%.
2. **Feature Transferability**: The dominance of order book position and imbalance features suggests that these signals may transfer well to other instruments beyond the ones tested.
3. **Execution Time Sensitivity**: The importance of "oneStateBeforeFill" features indicates that model prediction accuracy increases as the order approaches execution, suggesting a strategy that dynamically adjusts confidence thresholds based on order age.

16. Business Impact and Performance Metrics

The trading impact shows significant improvements over baseline strategies:

- **Precision**: 79% - When the model predicts a fill, it's right 79% of the time
- **Recall**: 65% - The model correctly identifies 65% of actual fills
- **F1 Score**: 71% - Harmonic mean of precision and recall

These metrics translate directly to trading P&L through better execution quality and higher completion rates.

17. Potential Extensions

If I were to extend this project, I would:

1. Add market regime conditioning - adapting predictions based on volatility regimes
2. Incorporate order book depth information beyond level 1
3. Develop an adversarial model to simulate market impact of our own orders
4. Implement model confidence calibration to produce reliable probability estimates
5. Create an ensemble approach combining multiple model predictions weighted by recent performance

18. Conclusion: The Value of ML in Trading Systems

The complete system demonstrates how machine learning can transform trading operations by:

1. **Extracting Hidden Patterns**: The model uncovers subtle market microstructure patterns invisible to human traders
2. **Quantifying Uncertainty**: Probability-driven approaches handle the inherent uncertainty in financial markets
3. **Adaptive Decision-Making**: Dynamic parameter adjustment based on model confidence creates a more robust strategy
4. **Continuous Improvement**: Feedback loops ensure the system improves as market conditions evolve

This iceberg order prediction system represents a sophisticated approach to quantitative trading that goes beyond simple signal generation to create a complete trading ecosystem that balances predictive power with practical trading considerations.