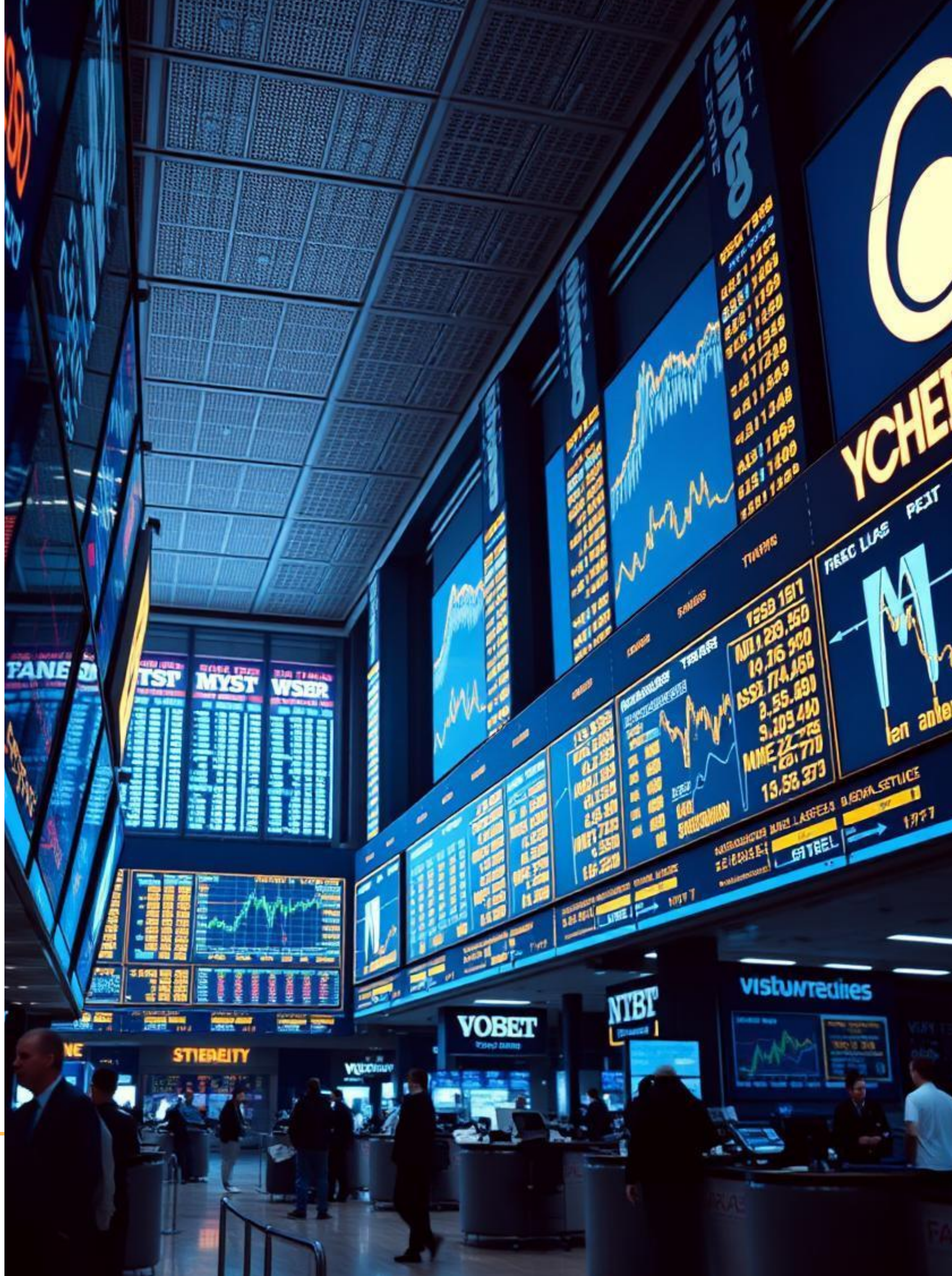

# OPTIVER – TRADING AT THE CLOSE

# TRADING AT THE CLOSE

## *MARKET MICROSTRUCTURE MODELING*

Institutional traders often execute large-volume orders near market close to minimize price impact and tracking error. This activity drives order book imbalances, increasing volatility and execution risk.

The resulting dislocations in order flow and price discovery present both risks and opportunities - making it essential to understand and model microstructure signals leading up to the close.



# Why predicting THE CLOSE matters?

### MARKET CONTEXT

The closing auction sets the official end-of-day price, marked by a surge in volume and sharp shifts in buy-sell imbalance.

### THE PROBLEM

Last-minute trading is chaotic and noisy - order flow is unpredictable, and each stock exhibits unique behavior.

### OUR GOAL

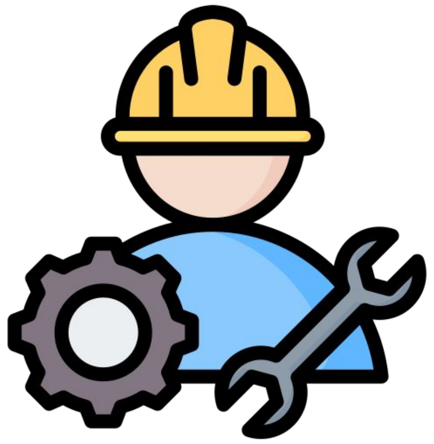
Develop a real-time model to predict auction imbalance in the final moments - giving traders a critical edge when it matters most.

# OUR APPROACH

## ANALYZE

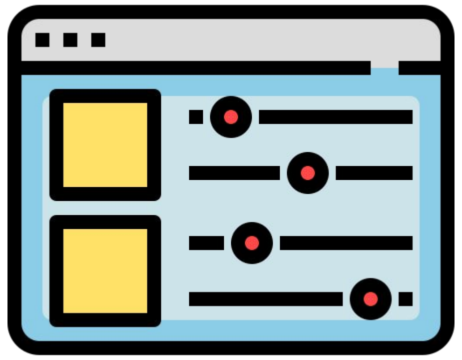
- Define **meaningful windows** for stock prediction
- **Identify features** to predict stock movements

## ENGINEER



- Same-Day Dynamics
- Intra & Inter-Window Deltas
- Rolling Stats

## PREDICT



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- Perform **window-specific** feature selection
- Blend outputs to generate final stock-level prediction

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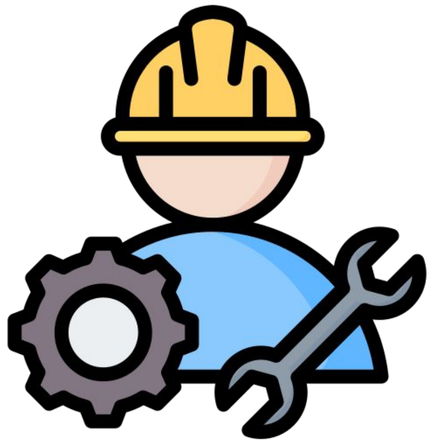

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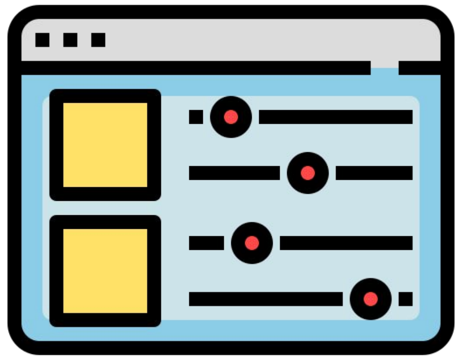

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# WINDOW LEVEL – STRATEGY

## WINDOW 1

*0 - 290 secs*

- Tight spreads as the book absorbs passive interest
- Only reference-price updates are available, driving early metrics
- Muted target moves establish baseline context for features

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## WINDOW 2

*300 - 470 secs*

- This time period sees the introduction of auction book features
- The near price and far price are used to reveal the auction dynamics.
- Key period for detecting price drift and imbalance buildup.

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## WINDOW 3

*480 - 540 secs*

- Imbalances surge as traders rush to close.
- WAP locks in on the closing price - strong predictive signal.
- Spreads and volatility peak, justifying a separate model.

# READING THE MARKET'S PULSE TO PREDICT

### Real-time Trading Behavior

- Reflect the current sentiment and liquidity in the market
- **Example signals:** Bid-ask spread, mid-price bias, buyer vs seller volume pressure

### Closing Price Pressure

- Auction mechanism that sets the official closing price
- **Example signals:** Auction imbalance size, reference price, buy/sell pressure flags

### Market Context

- Approximate the market's own behavior
- **Example signals:** Synthetic market WAP, stock vs. index price ratio

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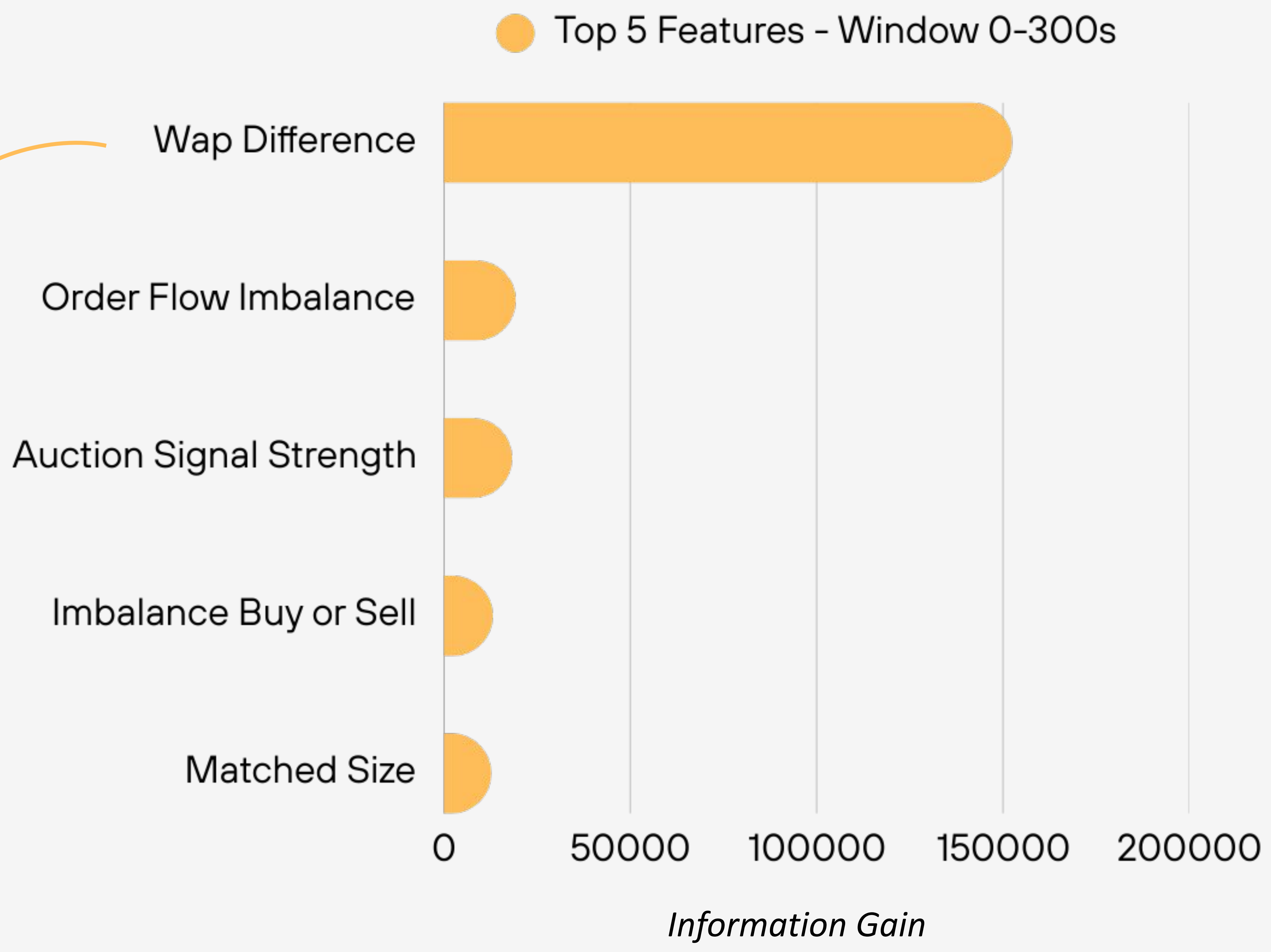
# EARLY SESSION DYNAMICS

DETECTS EARLY DIRECTIONAL BIAS
(BUYER VS SELLER)

*Early prediction hinges on price momentum (wap_diff), aggressive buyer/seller behavior, and auction sentiment setup.*



# EARLY SESSION DYNAMICS

QUANTIFIES EXCESS DEMAND OR SUPPLY (CAPTURES LIQUIDITY IMBALANCE)

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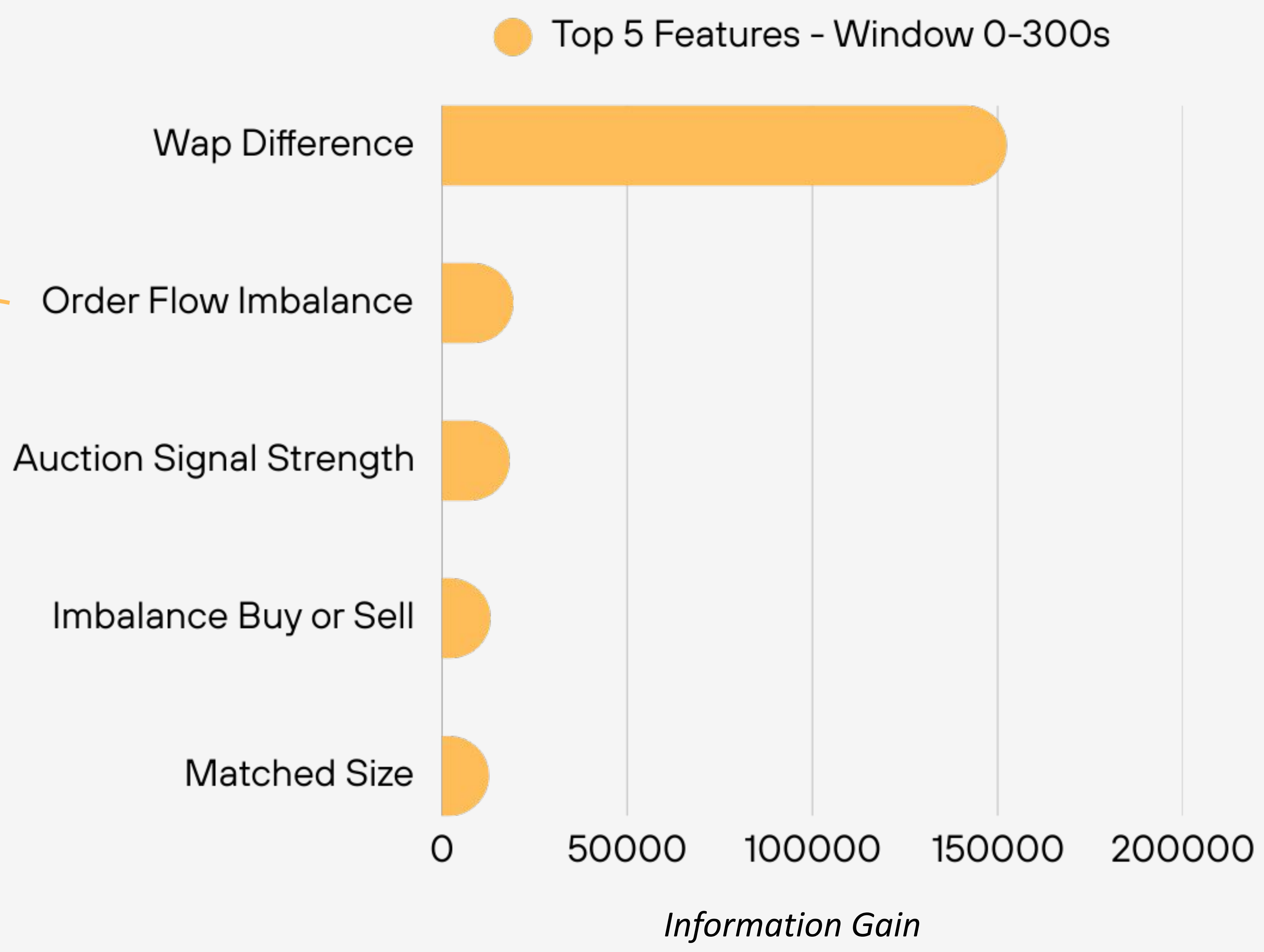
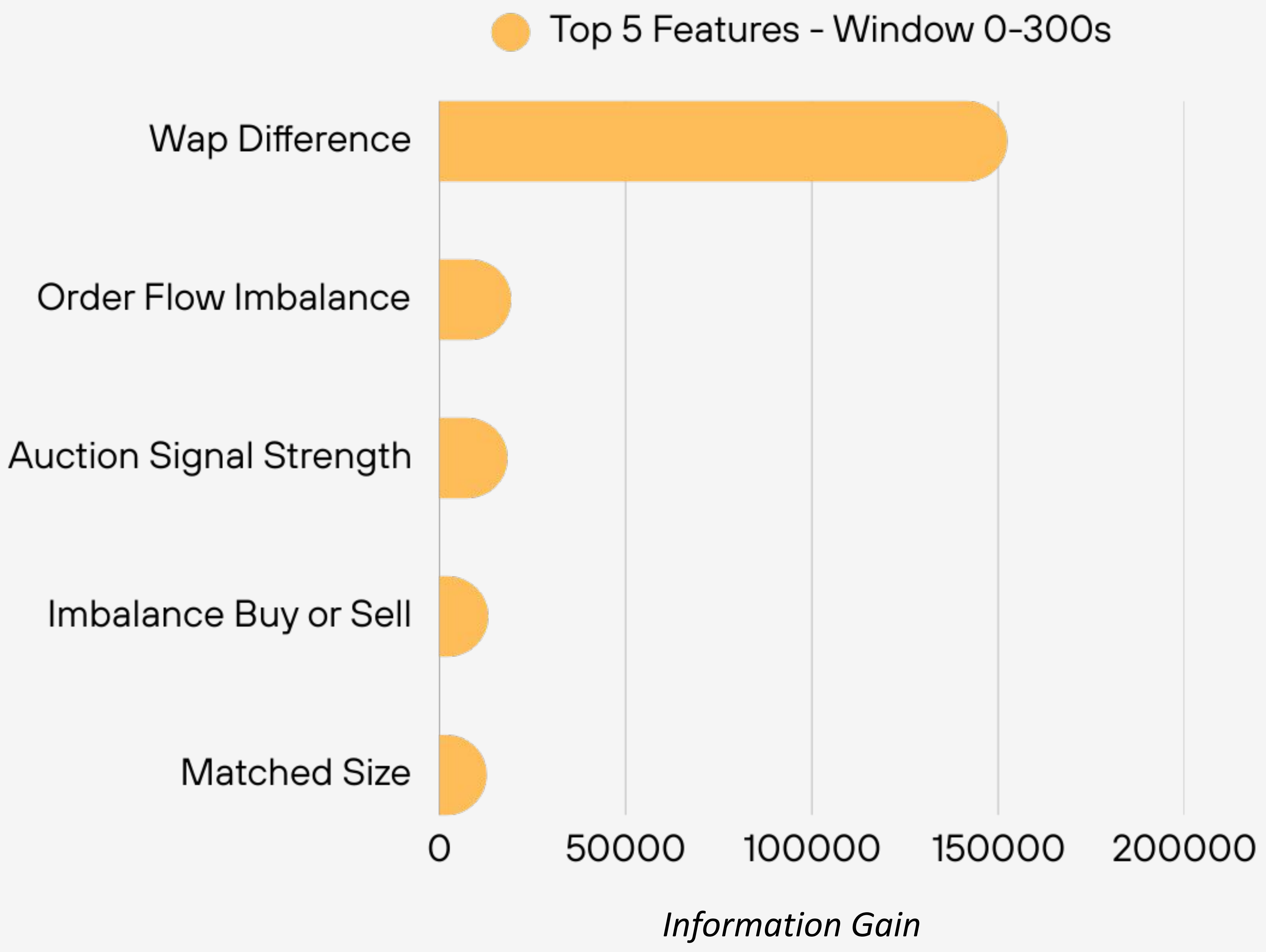


# EARLY SESSION DYNAMICS

SIGNALS IF AUCTION PRICE IS AGGRESSIVELY ABOVE/BELOW WAP

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# EARLY SESSION DYNAMICS

CAPTURES DIRECTIONAL SIGNAL BEFORE MATCH

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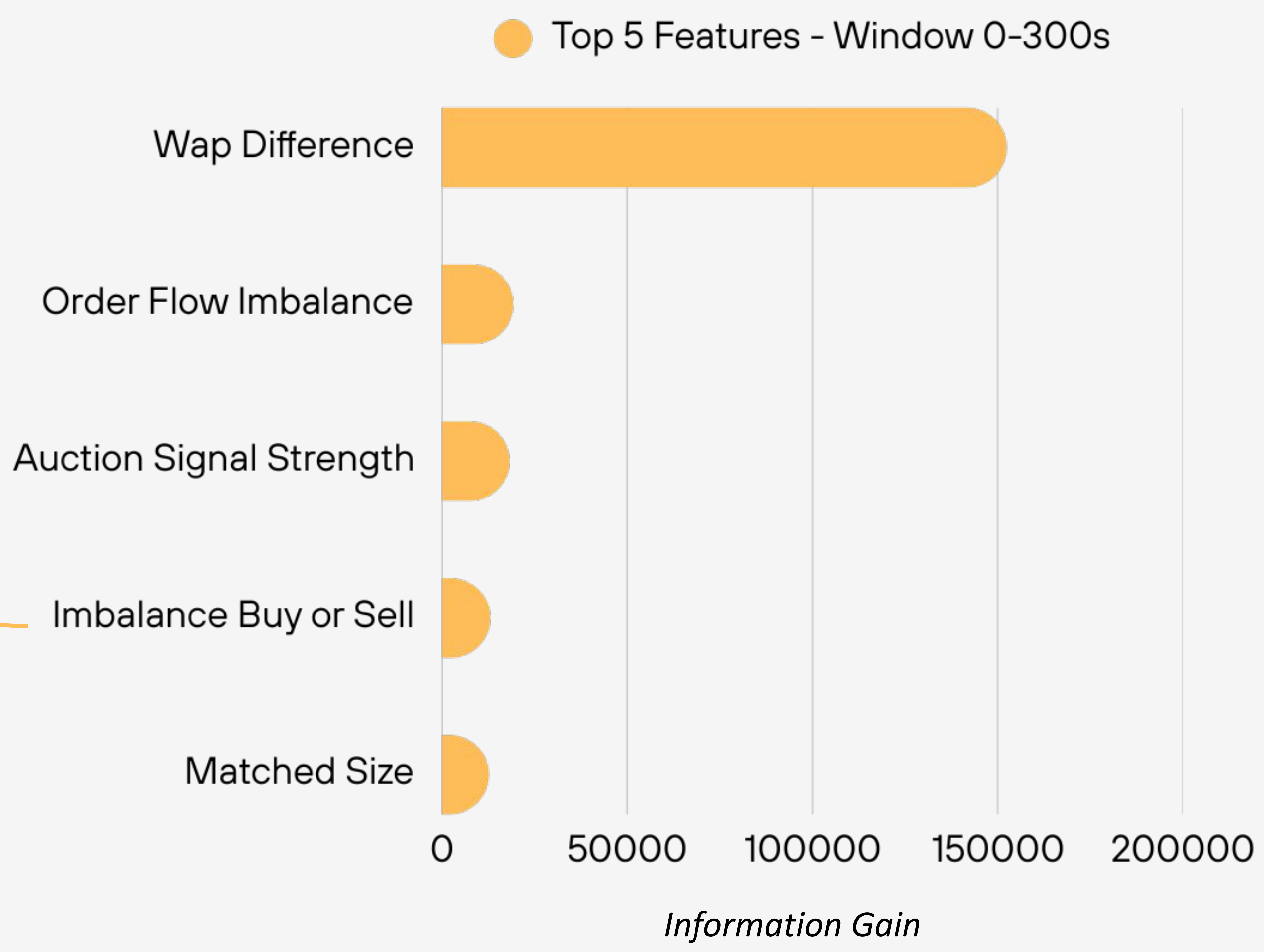

# EARLY SESSION DYNAMICS

HIGHER = MORE BUYER INTEREST
EARLY ON

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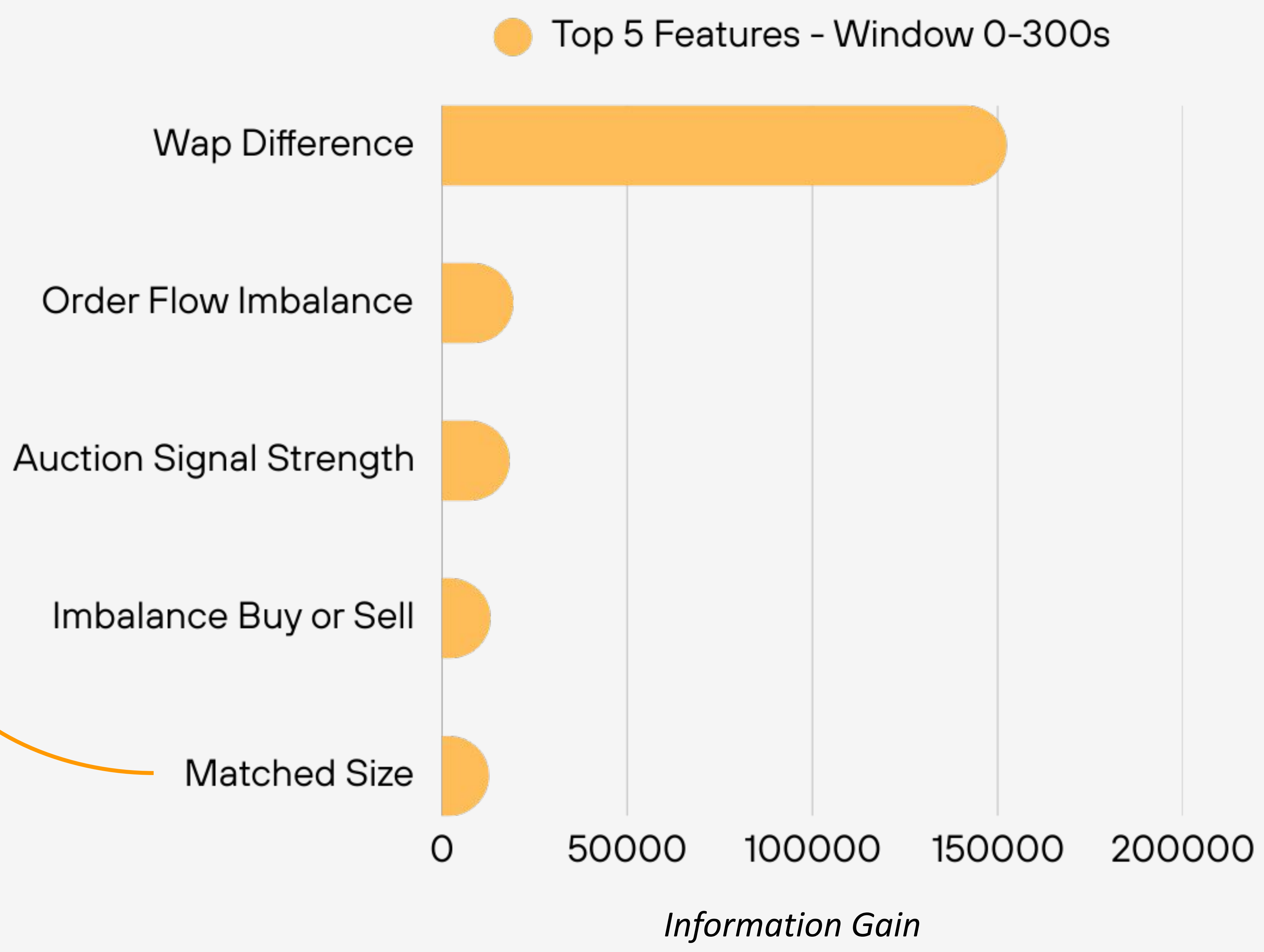
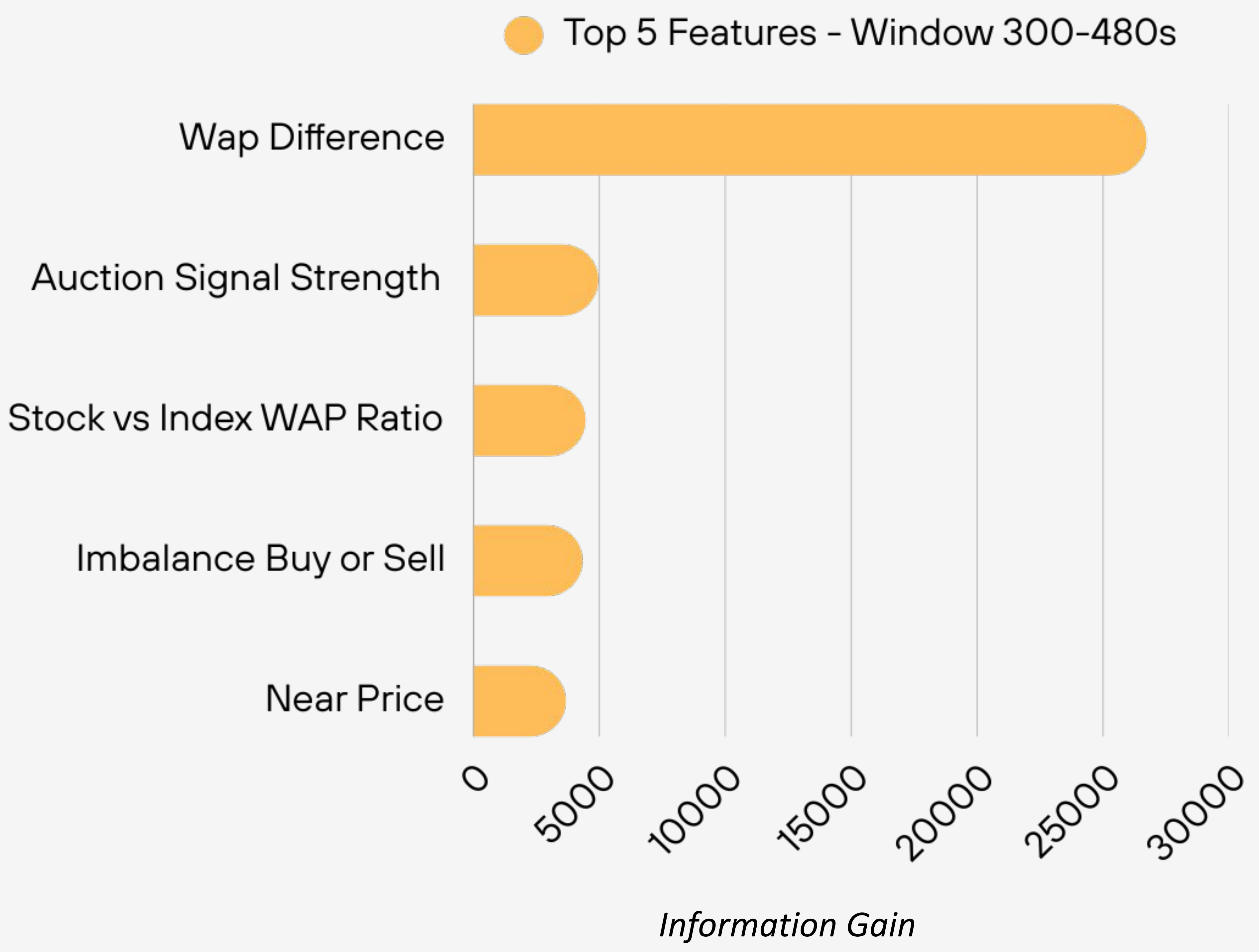


# MID-SESSION LIQUIDITY SHIFT

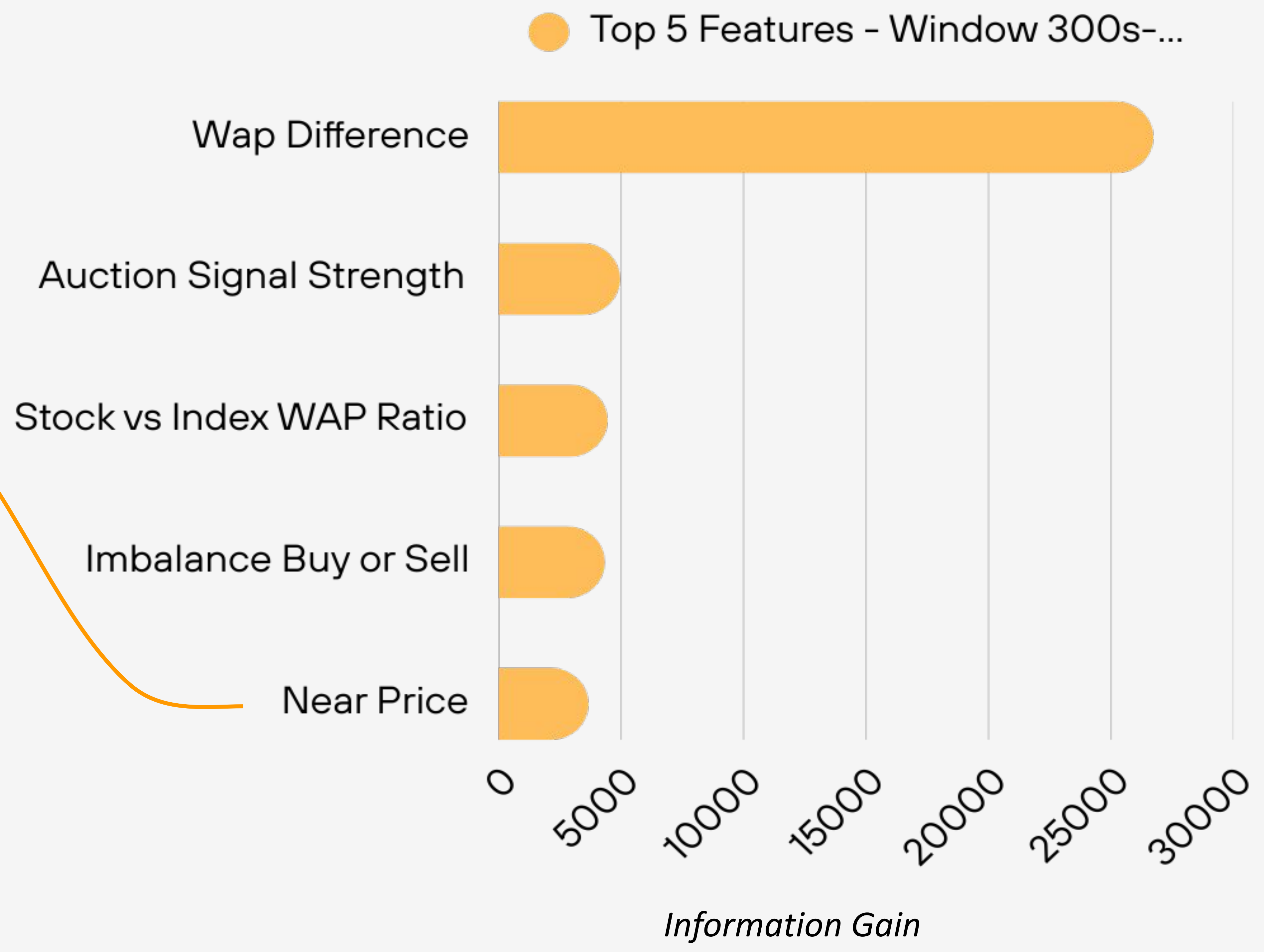
DEVIATION FROM SYNTHETIC INDEX TRACKS STOCK-SPECIFIC MOVES

*Mid-session reveals whether momentum persists or fades, while auction pressure and peer deviation (vs index) gain importance.*



# MID-SESSION LIQUIDITY SHIFT

REFERENCE PRICE ANCHORS WAP — KEY FOR VOLATILITY SIGNALS

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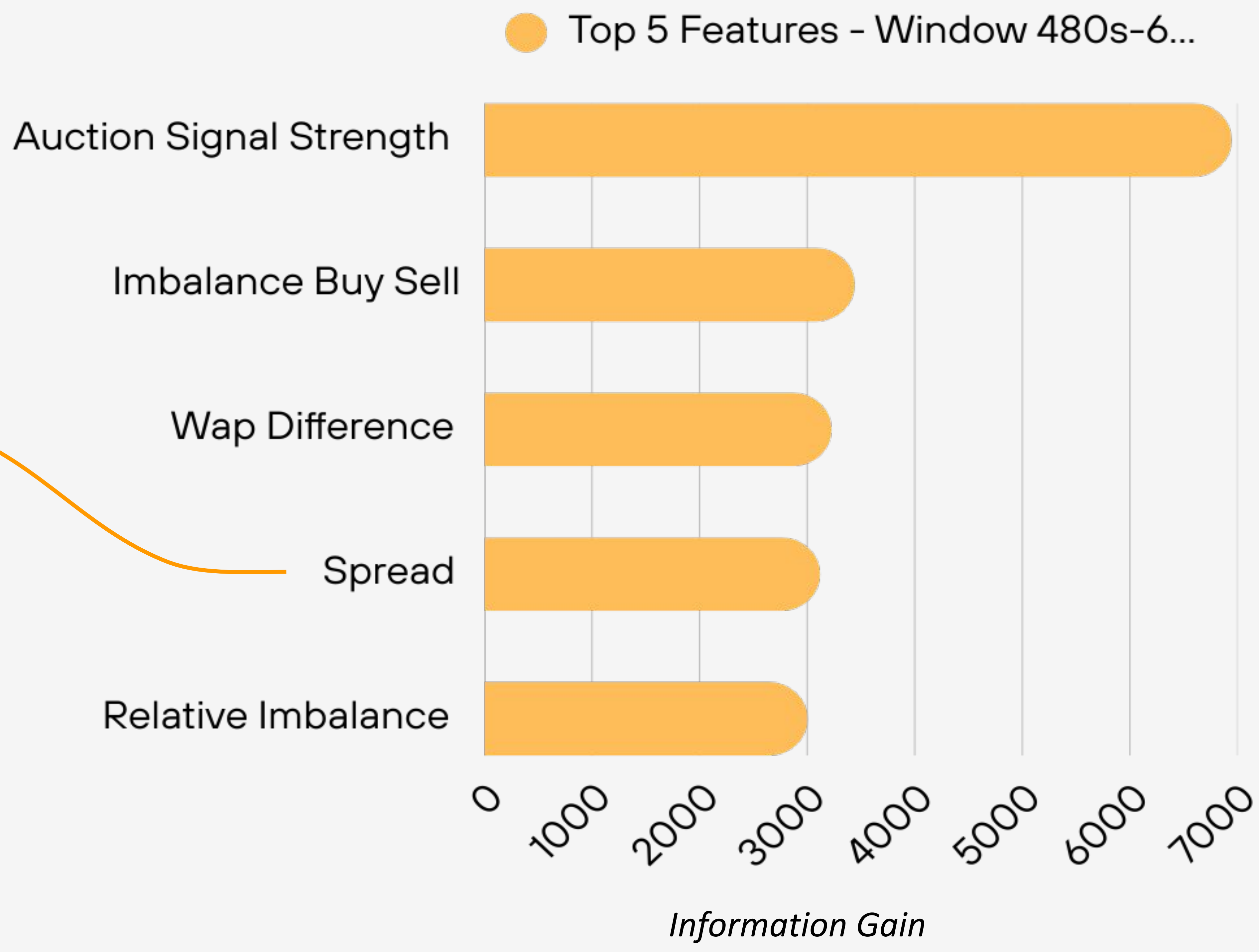
# FINAL AUCTION PRESSURE INDICATORS

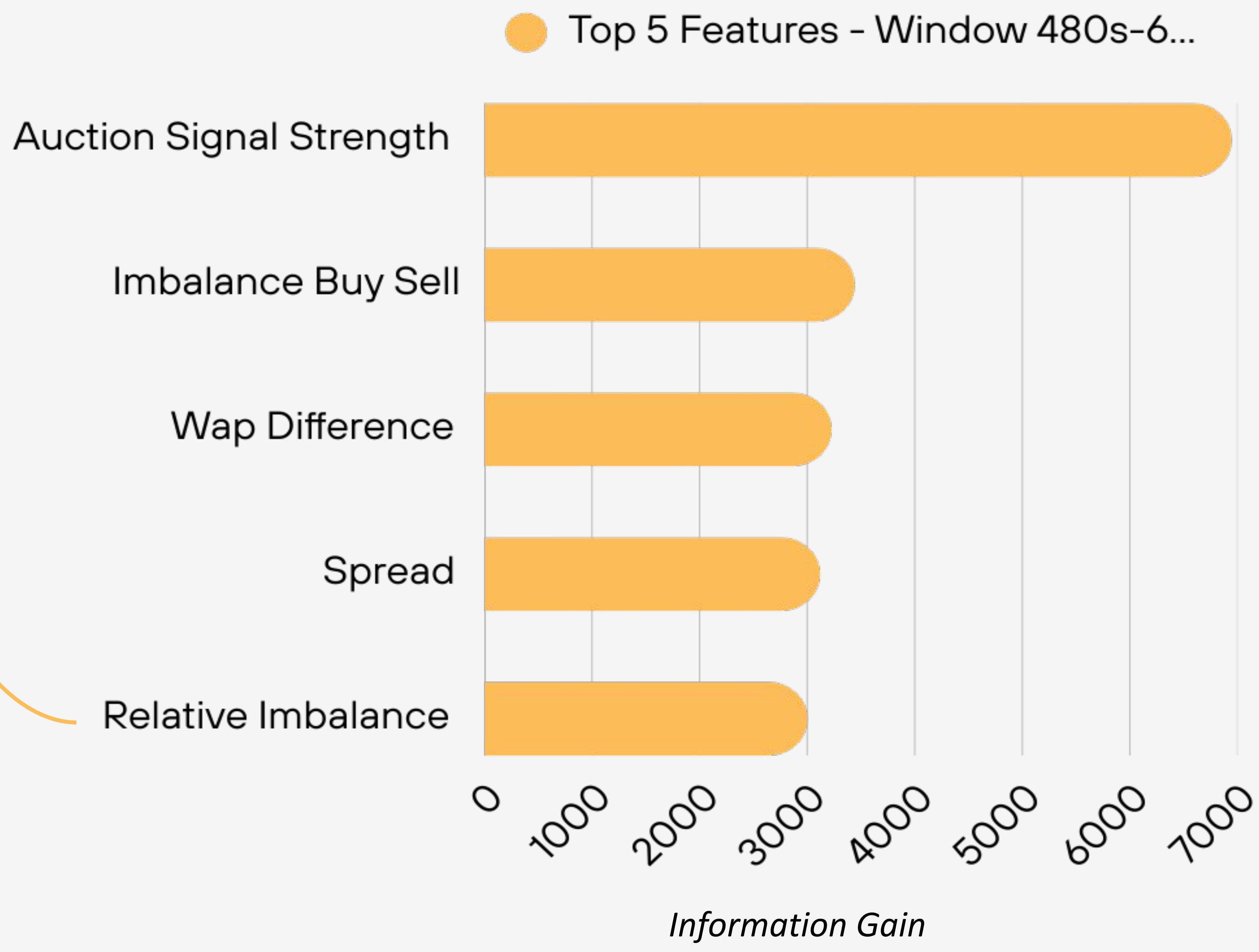
TIGHTER SPREAD = MORE LIQUIDITY, TIGHTER MATCH




*Final predictions rely on the auction setup tension and residual imbalance that drives last-minute price changes.*

# FINAL AUCTION PRESSURE INDICATORS

**UNFILLED IMBALANCE BEFORE AUCTION DRIVES PRESSURE**

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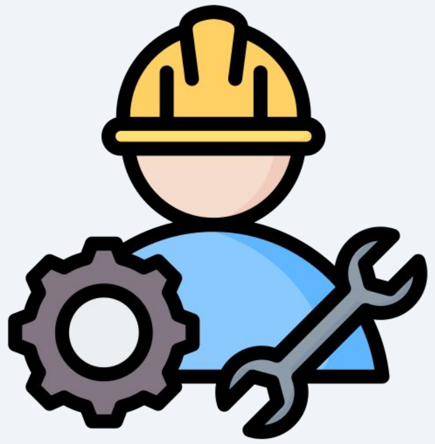

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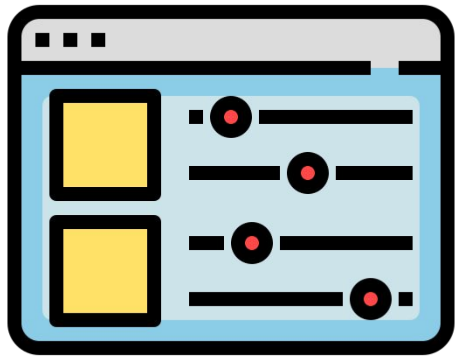

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# HOW WE DESIGNED FEATURES TO CAPTURE MARKET DYNAMICS

Feature Engineering Framework Driven by
Top Predictive Signals across time windows

### SAME-DAY HISTORICAL

- Captures real-time market microstructure
- Reflects current session's liquidity and volatility

### INTRA-WINDOW HISTORICAL

- Detects short-term momentum shifts
- Tracks price or order flow acceleration over seconds

### INTER-WINDOW HISTORICAL

- Compares early and late auction window behaviors
- Helps model auction pressure buildup

### PREVIOUS 'X' DAYS HISTORICAL

- Adds temporal memory for auction behavior
- Useful to capture persistent auction behaviors

In total we created 220 new features encompassing the above framework

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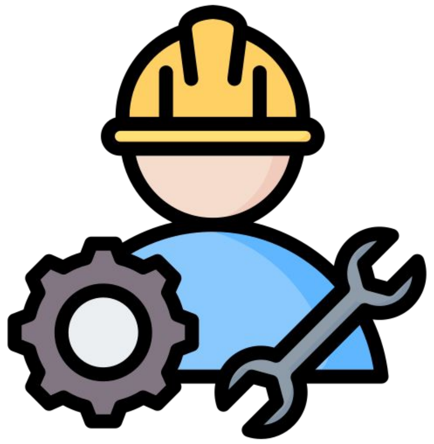

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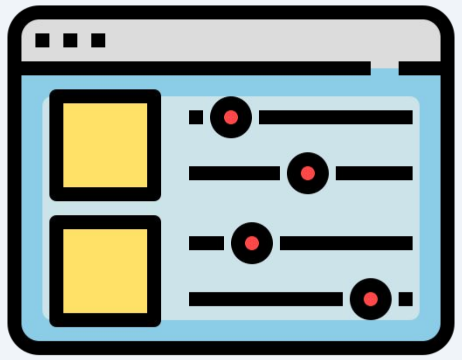

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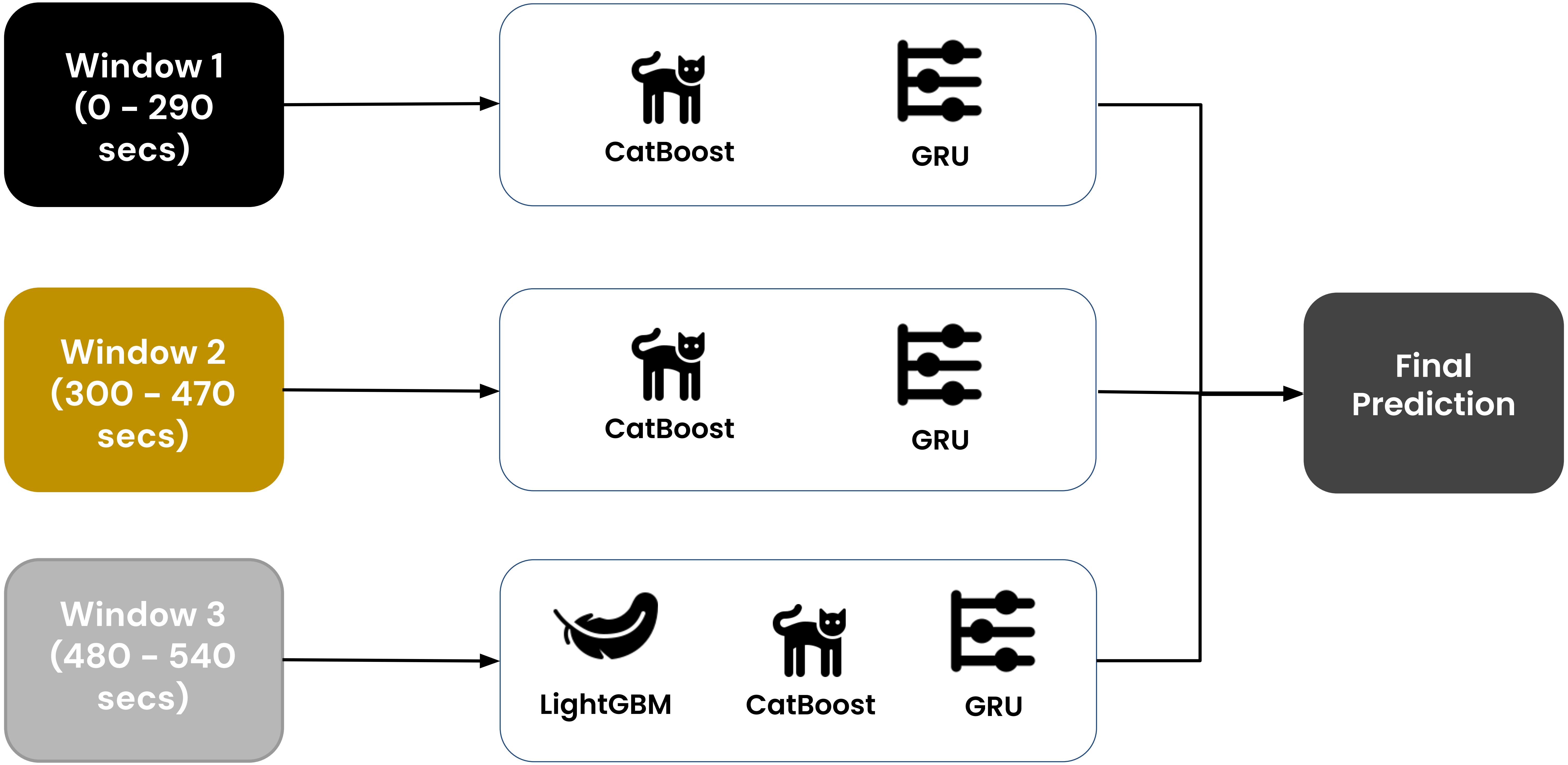


Models tested

# MODEL PERFORMANCE

| Window | Model Name | MAE | Runtime |
|---|---|---|---|
| 1 | Catboost | 6.11 | 2 hrs |
| | GRU | 6.32 | 3.5 hrs |
| 2 | Catboost | 5.22 | 1.5 hrs |
| | GRU | 5.23 | 2.5 hrs |
| 3 | Catboost | 4.98 | 1 hrs |
| | GRU | 4.99 | 2 hrs |
| | LightGBM | 5.00 | 1 hrs |

- GRU needed **4 layers** to handle early volatility
- CatBoost slightly better (**6.11 vs 6.32 MAE**)

- GRU performed best with **2 layers**
- Accuracy was on par (**5.22 vs 5.23 : MAE**)

- GRU did well with just **1 layer**
- CatBoost led slightly (**4.98 vs 4.99 MAE**)

# DEPLOYMENT AND RESULTS

- Final **CatBoost model pickled** and inference-ready across all 3 auction windows
- Achieved combined **MAE of 5.44** (on sample submission test), outperforming GRU and LGBM in both speed and stability
- Feature set is optimized and compact, ensuring minimal memory footprint
- Ready for integration in low-latency production pipelines

**FAST INFERENCE**

**HIGH ACCURACY (LOW MAE)**

**ROBUST TO FEATURE DRIFT**