KITA KOD

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DOMAIN 2 QUANTITATIVE TRADING

UM HACKATHON 2025

2025

Our Team

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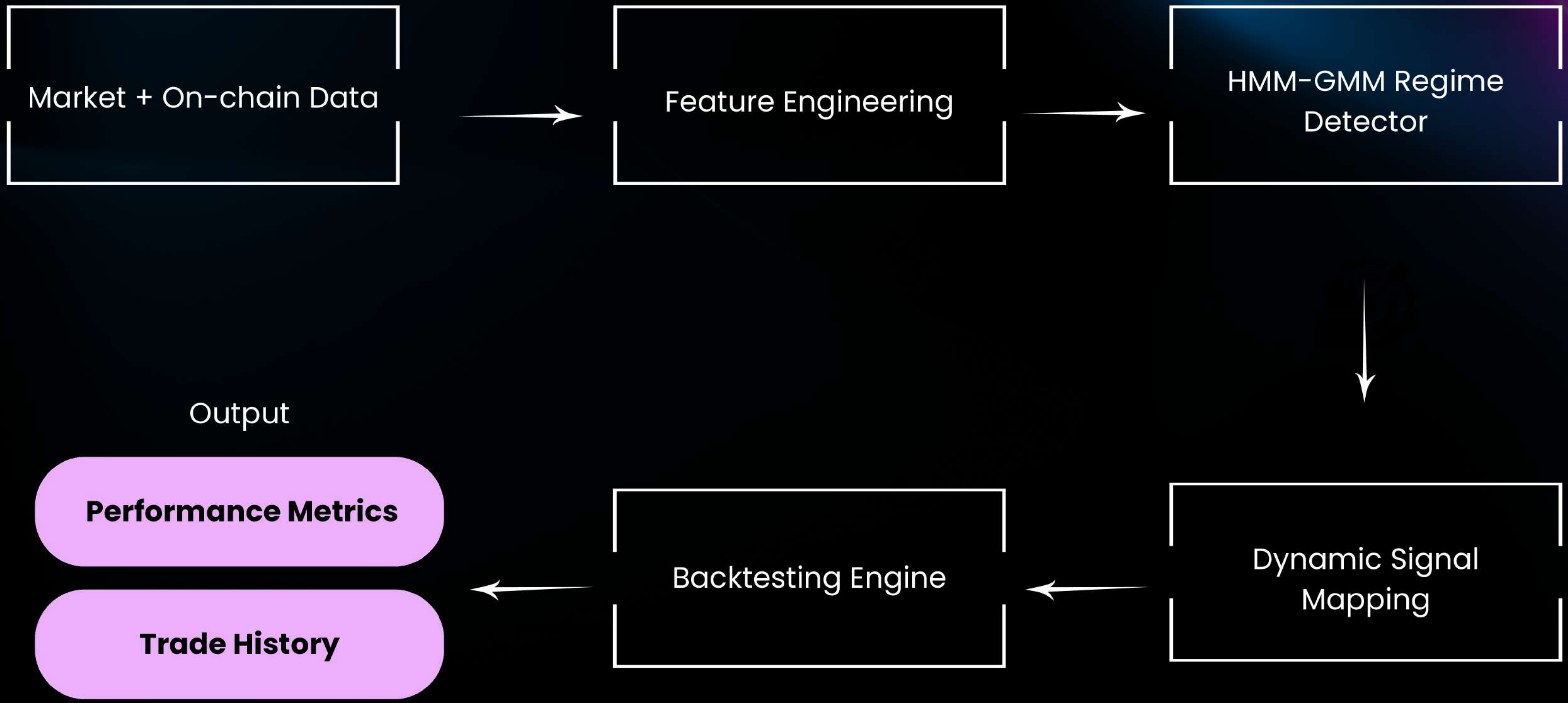
TEOH ZHI YEE

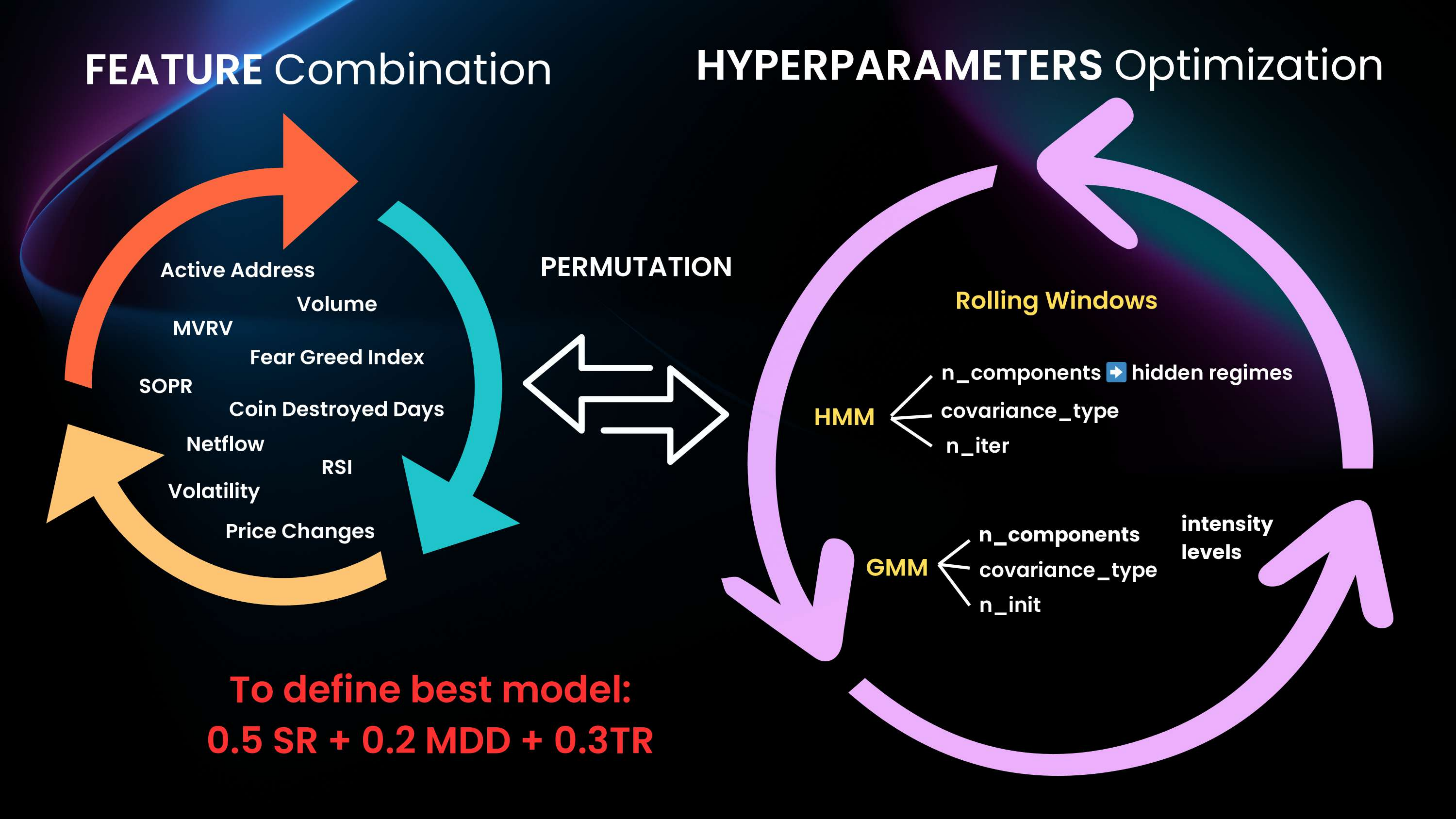
AutoQuant

"Automated. Regime-aware. Alpha-driven."

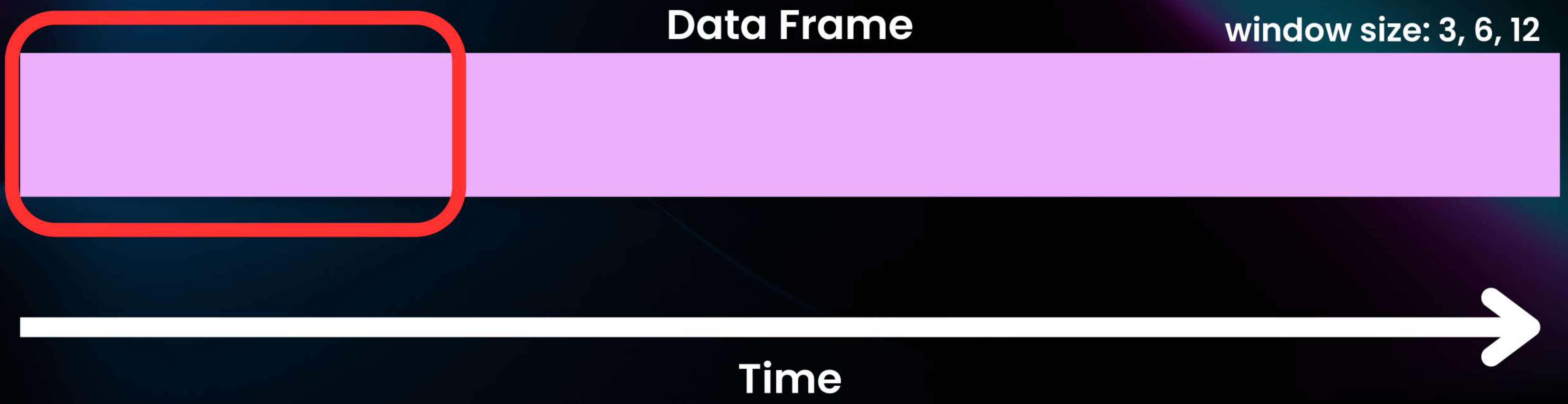
Automation & Modularity of the AutoQuant Pipeline



HMM-GMM Regime Detector & Signal Generator


FEATURE Combination
HYPERPARAMETERS Optimization
Active Address
Volume
MVRV
Fear Greed Index
SOPR
Coin Destroyed Days
Netflow
RSI
Volatility
Price Changes
PERMUTATION
Rolling Windows
HMM
n_components ➡️ hidden regimes
covariance_type
n_iter
GMM
n_components
covariance_type
n_init
intensity
levels
To define best model:
0.5 SR + 0.2 MDD + 0.3TR

Rolling Window (parameter)



HMMs are sensitive to noise — rolling averages make it easier to detect sustained patterns

```
for window in window_sizes:
    print(f"\n🔁 Processing window size: {window}")

    rolled_train_df = train_df.copy()
    rolled_test_df = test_df.copy()
    for feature in all_features + [target_col]:
        rolled_train_df[feature] = train_df[feature].rolling(window=window, min_periods=1).mean()
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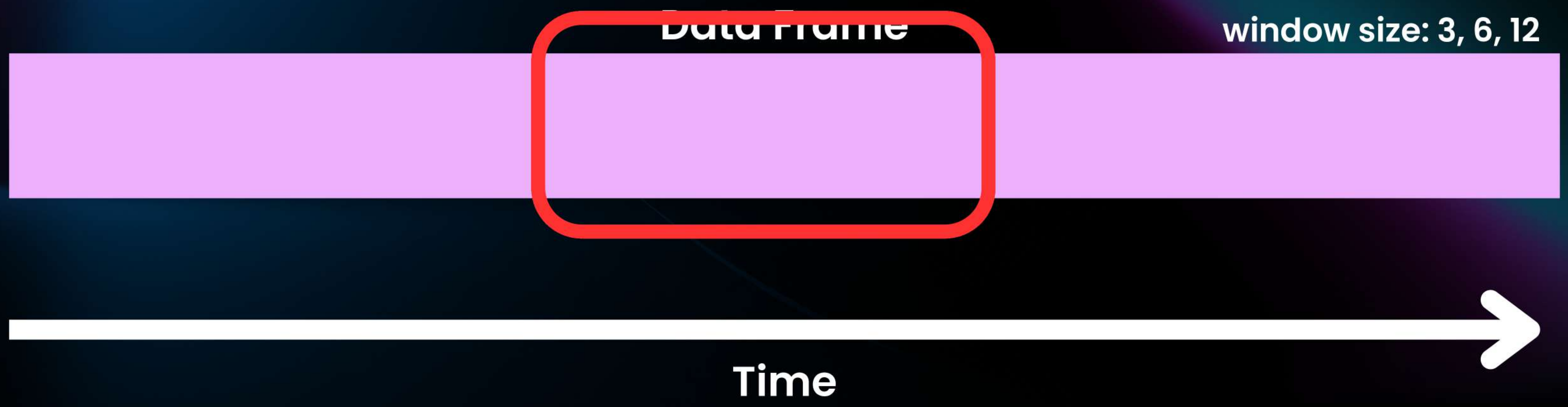

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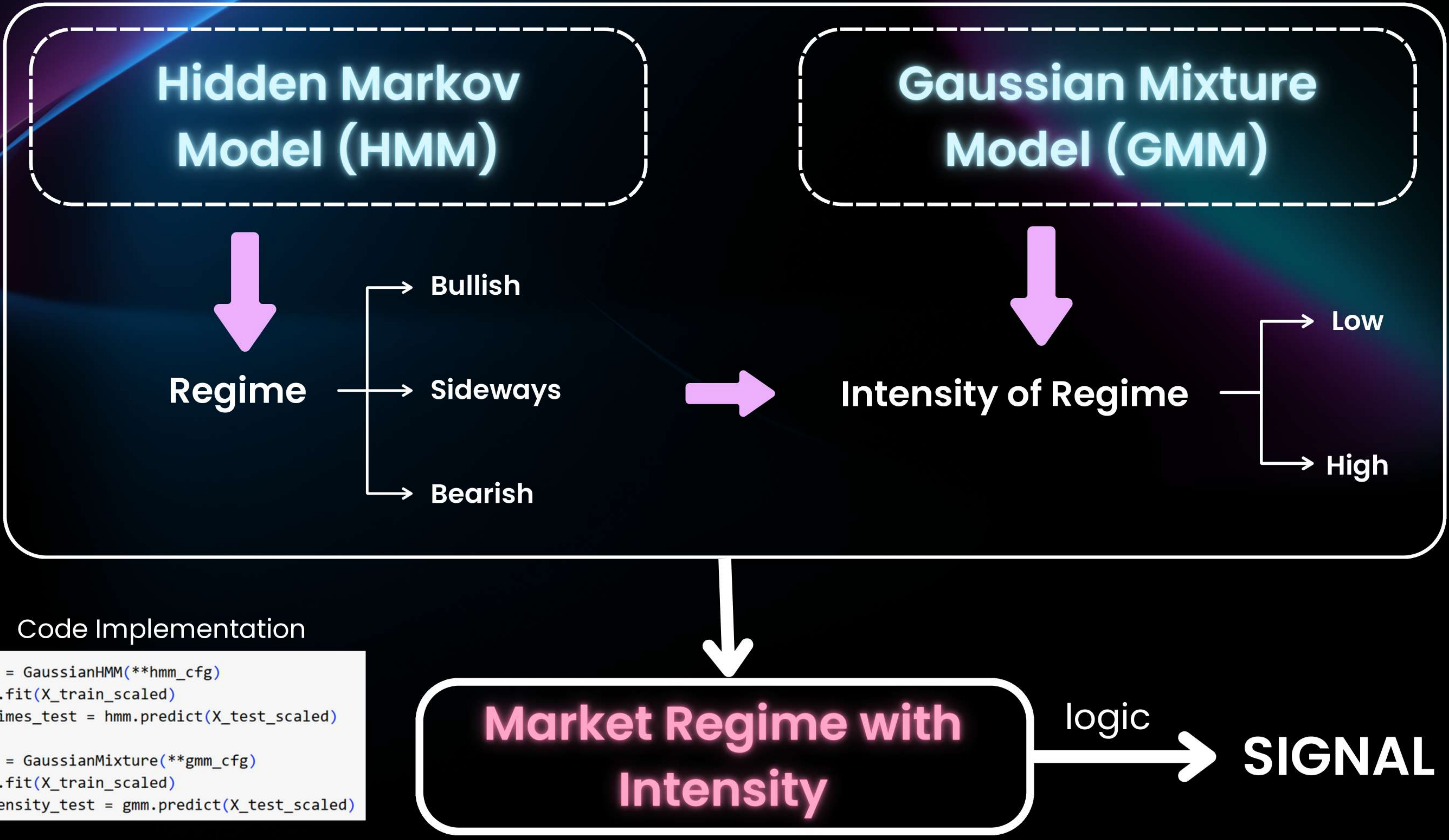
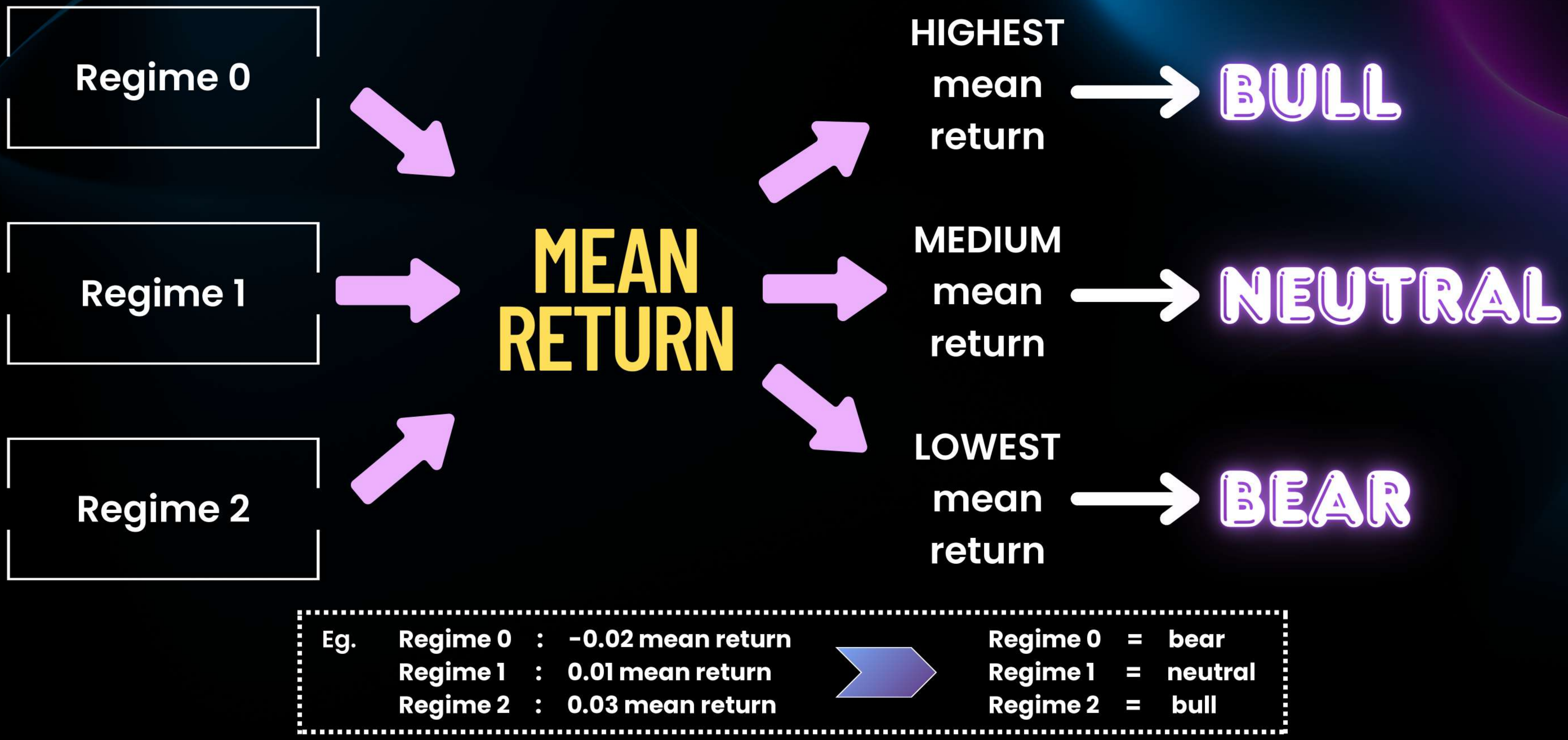


Code Implementation

```
hmm = GaussianHMM(**hmm_cfg)
hmm.fit(X_train_scaled)
regimes_test = hmm.predict(X_test_scaled)

gmm = GaussianMixture(**gmm_cfg)
gmm.fit(X_train_scaled)
intensity_test = gmm.predict(X_test_scaled)
```

Dynamic Signal Mapping Logic



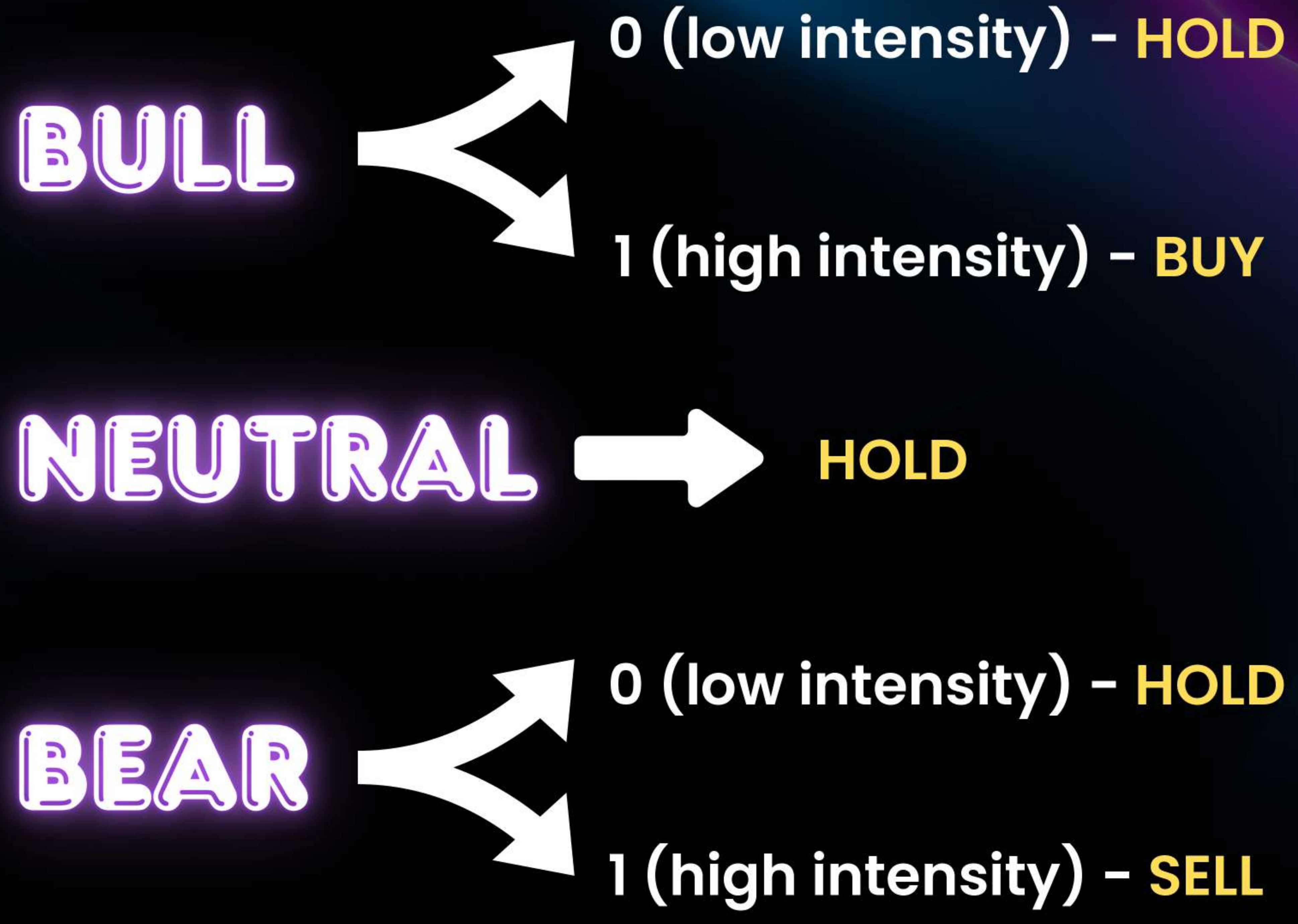
How We Know when to Buy, Sell or Hold

The Logic:

Only **BUY** when the regime has the **highest mean returns**, and intensity is high.

Only **SELL** when the regime has the **lowest mean returns**, and intensity is high.

Otherwise, just **HOLD**.



Regime label

"Signals are generated based on the underlying market regime, not arbitrary rules."

Actual average return of each regime to rank

```
regime_df = pd.DataFrame({'regime': regime_seq, 'return': price_changes_test})
regime_mean = regime_df.groupby('regime')['return'].mean().sort_values()
regime_rank = {reg: idx for idx, reg in enumerate(regime_mean.index)}
```

Regimes are not manually defined

Signal Execution

"Signals are only triggered when the regime classification has high intensity."

Avoids overtrading and only commits when the model is sure.

```python
signals = []
for r, i in zip(regime_seq, intensity_seq):
    r_rank = regime_rank[r]
    if r_rank == 0 and i == 1:
        signals.append(-1)  # SELL
    elif r_rank == len(regime_mean) - 1 and i == 1:
        signals.append(1)   # BUY
    else:
        signals.append(0)   # HOLD
return signals
```

If intensity is low no action is taken noise is filtered out

Performance Output
(Forward Test)

Sharpe Ratio (SR)	Maximum Drawdown (MDD)	Trade Frequency
2.7846	- 22.28%	19.54%
≥1.8	≥-40%	≥3%

Equity vs Price

Buy / Sell Signals on Price

Alternative Solution 1: Reinforcement Learning

Reinforcement Learning for Adaptive Crypto Trading with Regime Awareness

What we have?

1. **RL Agent -** Deep Q-Learning
2. **Progressive Backtester**
3. **Reward Function**

Why it's smart?

1. **Regime-aware**
2. **Dynamic reward shaping**
3. **Plug-and-play backtester**

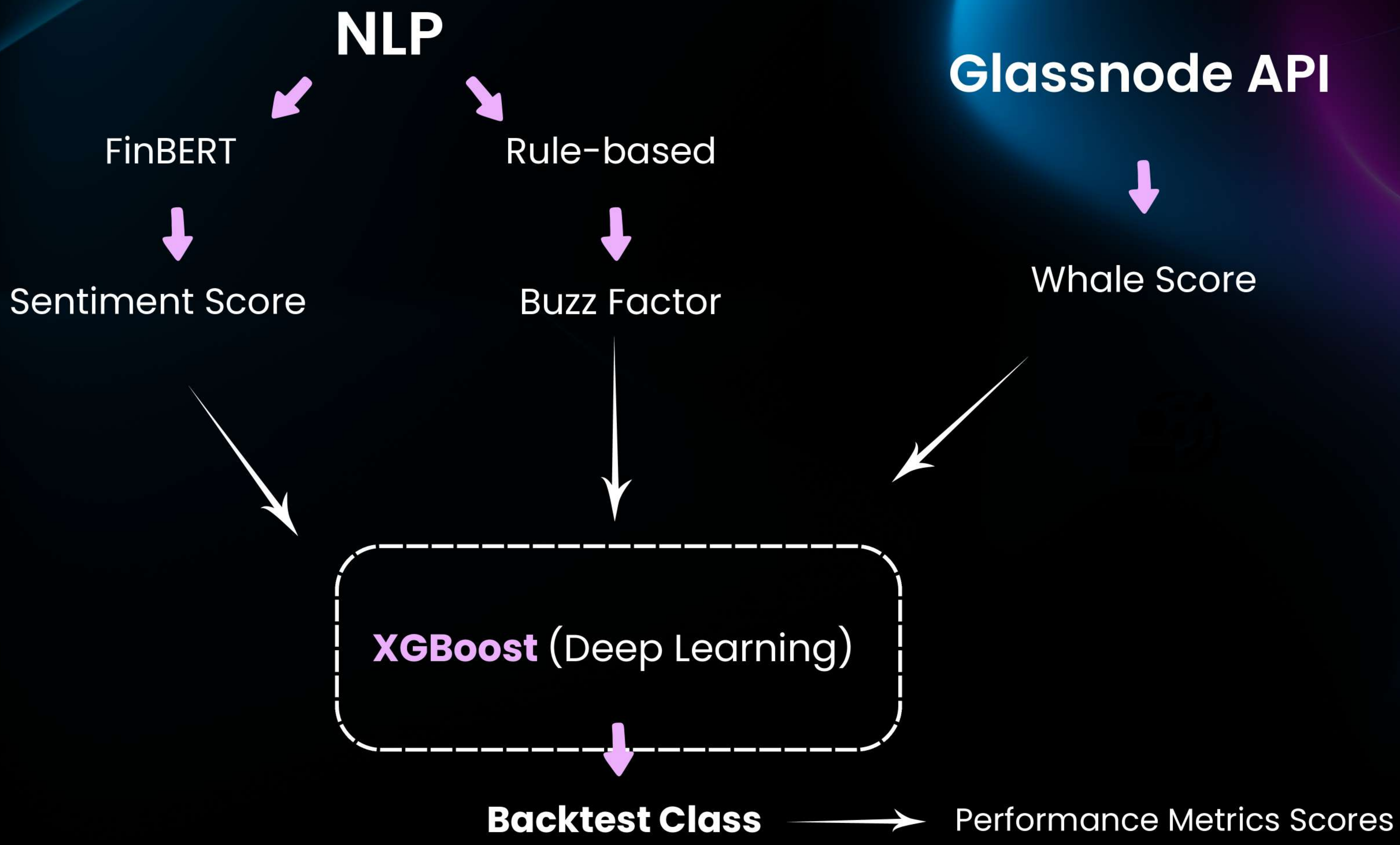
Performance Output

```
Trade Frequency: 0.12998375203099613
Sharpe Ratio: 0.11602660942899881
Max Drawdown: -0.5300151821793874
Trade Frequency: 0.12845547582637337
Sharpe Ratio: 0.11227756011930386
Max Drawdown: -0.5300151821793874
Trade Frequency: 0.12696067288020005
Sharpe: 0.1123, MDD: -0.5300, Trade Freq: 0.1270
Sharpe Ratio: -0.4951080411384241
Max Drawdown: -0.22133490659054356
Trade Frequency: 0.08727272727272728

Test Results:
Sharpe: -0.4951
Max Drawdown: -0.2213
Trade Frequency: 0.0873
Training and testing completed.
```

```
Sharpe Ratio: -1.1885150663626685
Max Drawdown: -6.301956593727259
Trade Frequency: 0.8882700613775858
Sharpe: -1.1885, MDD: -6.3020, Trade Freq: 0.8883
Epoch 2/30
Sharpe Ratio: -0.06503528166771765
Max Drawdown: -0.26626376194347134
Trade Frequency: 0.8962075848303394
Sharpe Ratio: -0.5468472848982199
Max Drawdown: -0.3401327903934693
Trade Frequency: 0.8891108891108891
```

Alternative Solution 2: Deep Learning


NLP
FinBERT
Rule-based
Sentiment Score
Buzz Factor
Glassnode API
Whale Score
XGBoost (Deep Learning)
Backtest Class
Performance Metrics Scores

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DEMO SESSION

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THANK YOU

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QnA

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