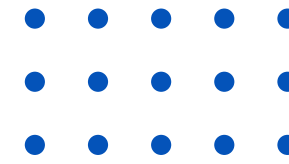




UMHackathon 2025



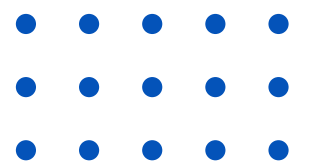
SolidTech

Alpha Strategies Using HMM or ML



Speaker
Shawn Garcia

Date
13 April 2025



Problem Statement

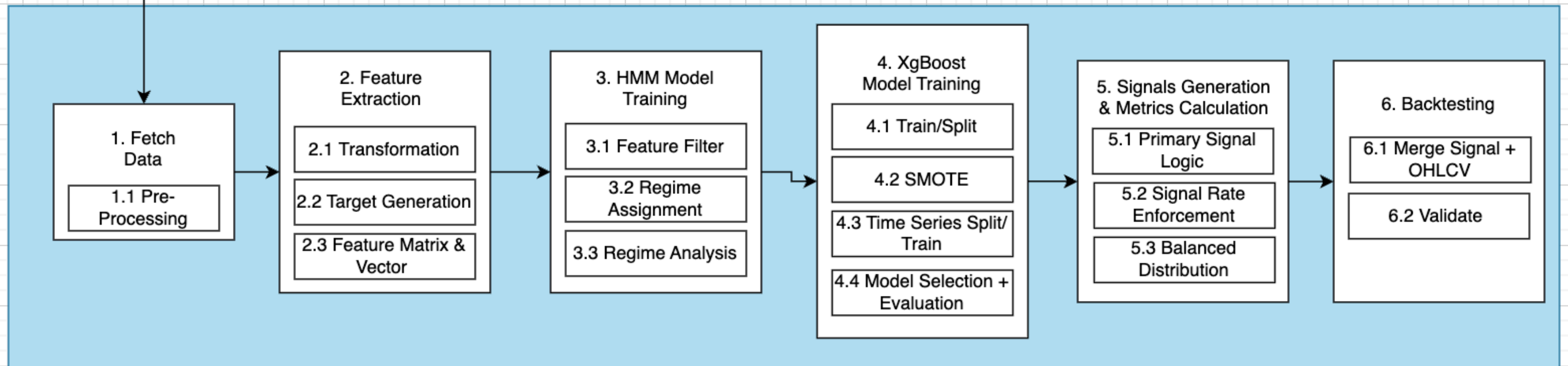
Develop a Machine Learning (ML) model that analyzes on-chain data from various sources (e.g., CryptoQuant, Glassnode, Coinglass) to generate an alpha trading strategy that maximizes profit.



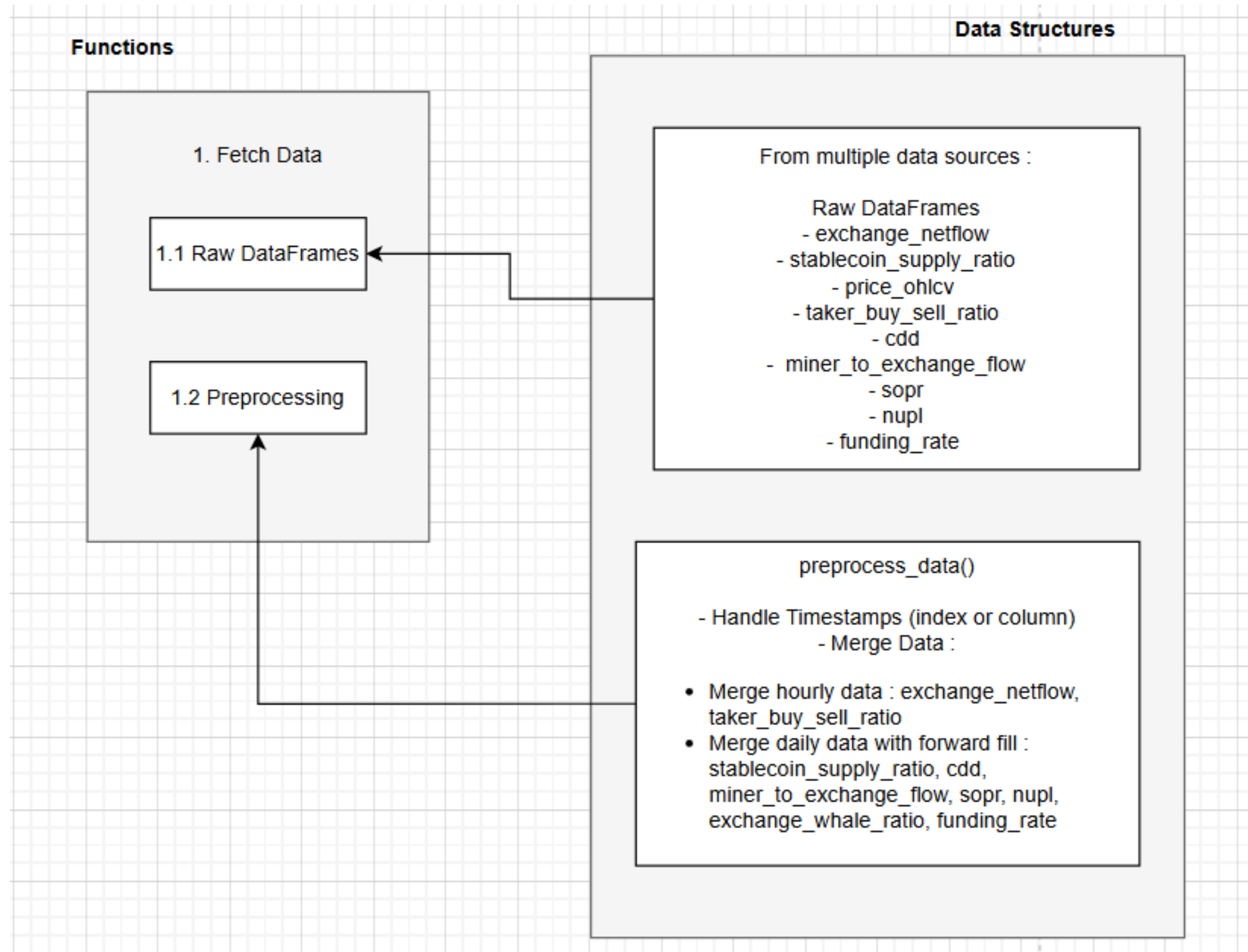
Architectural Overview of the ML-based Alpha Trading Strategy

Cybotrade Datasource - CryptoQuant Endpoints

Functions



Fetch Data & Pre Processing



Fetch Data & Pre Processing

Data Fetching

Data Sources Configuration:

- Defines data points with customizable parameters (time window, exchange type).
- Supports hourly or daily data fetching.

Fetching Mechanism:

- **Asynchronous Fetching:** Ensures multiple datasets are fetched in parallel for efficiency.

Data Output:

- Stored in a dictionary of Pandas DataFrames.
- **Filtering:** Some sources are excluded if incompatible (ex: mvrw for hourly data).

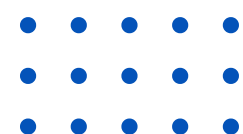
Pre Processing

Data Cleaning:

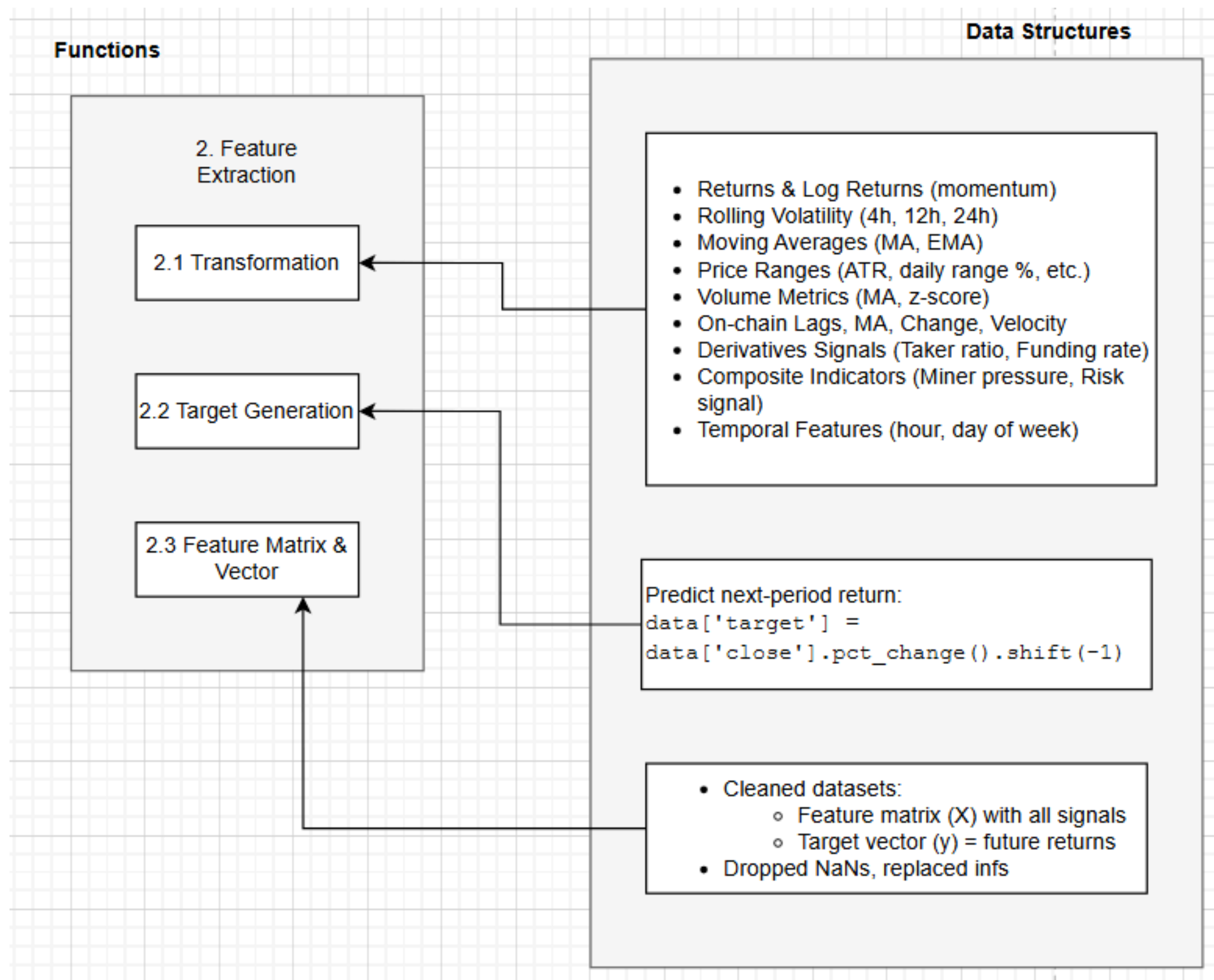
- Checks any data frames that are empty or none & skips them.
- Standardized timestamps.
- Rename the column to match the source name.

Data Merging:

- **Hourly data sources** (e.g., exchange_netflow, taker_buy_sell_ratio) are merged directly into the primary dataset (price_ohlcv).
- **Daily data sources** (e.g., stablecoin_supply_ratio, sopr): **Forward filling** is applied to carry the last known value across the rest of the day to ensure there are no missing data points for those intervals.



Features Engineering



Features Engineering

1

Price-Based Features

- **Returns:** $returns = close.pct_change()$
 - → Captures price momentum.
- **Log Returns:** $log_returns = log(close).diff()$
 - → Stabilizes variance for modeling.
- **Rolling Volatility:** $rolling(std\ of\ returns)$
 - → Measures recent price fluctuation over 4h, 12h, 24h.
- **Moving Averages (MA, EMA):** $rolling(mean\ of\ close)$ and *exponential moving average*
 - → Identifies short- and medium-term trends.
- **Price Range:** $ATR = high.max - low.min$, $range_pct = (high - low) / close$
 - → Detects volatility spikes and intraday dynamics.

2

Volume & Activity-Based Features

Compute liquidity and interest signals:

- $volume_ma = volume.rolling(10).mean()$
- $volume_zscore = (volume - mean) / std$
 - → These indicate volume surges or anomalies.

3

On-Chain Metrics Transformation

For each on-chain metric (like netflow, sopr, nupl, etc.):

- **Lagged Values:** $feature_lagN = feature.shift(N)$
 - → Captures delayed reactions in investor behavior.
- **Moving Averages:** $feature_maN = feature.rolling(N).mean()$
 - → Smooths out noise in indicators.
- **Changes & Velocity:** $feature.diff(N)$ and $feature.diff / std$
 - → Measures how fast the signal is changing.



Features Engineering

4

Derivatives Market Signals

For *taker_buy_sell_ratio*, we compute:

- **Short-Term Sentiment Smoothing:** *rolling mean, z-score, and extreme condition flags*
 - → Helps detect aggressive buying or selling pressure.
- **Funding Rate:** *deviation from mean*
 - → Measures trader bias in perpetual futures.

5

Composite Features (Cross-Interacted Signals)

- $netflow_stablecoin_ratio = netflow / stablecoin_ratio$
- $miner_whale_pressure = miner_to_exchange_flow * exchange_whale_ratio$
- $risk_signal = (nupl \ \& \ sopr \ conditions)$
 - → These synthesize multiple signals into strategic alpha indicators.

6

Target Generation (Formulation for Supervised Learning)

- $data['target'] = data['close'].pct_change().shift(-1)$
 - → You predict the next-hour return, aligning features with future labels.



Assumption & Hypothesis

1

Buy Signal (📈🟢 Bullish Regime):

Hypothesis: If the **stablecoin ratio is decreasing** (💰↓), and technical indicators (like a rising RSI out of oversold levels or a bullish MACD crossover) confirm momentum, this suggests that **investors are moving away from safety toward growth**—potentially signaling an emerging **bull market**.

Action: Consider **buying**.

2

Sell Signal (📉🔴 Bearish Regime):

Hypothesis: As mentioned earlier, **if the stablecoin ratio is rising sharply** (💰↑) indicating higher "stablecoin velocity," investors might be **shifting to cash**. Combined with bearish technical signals (such as declining MACD or RSI in overbought territory), this could mean the market is **entering or already in a bear mode**.

Action: Consider **selling**.

3

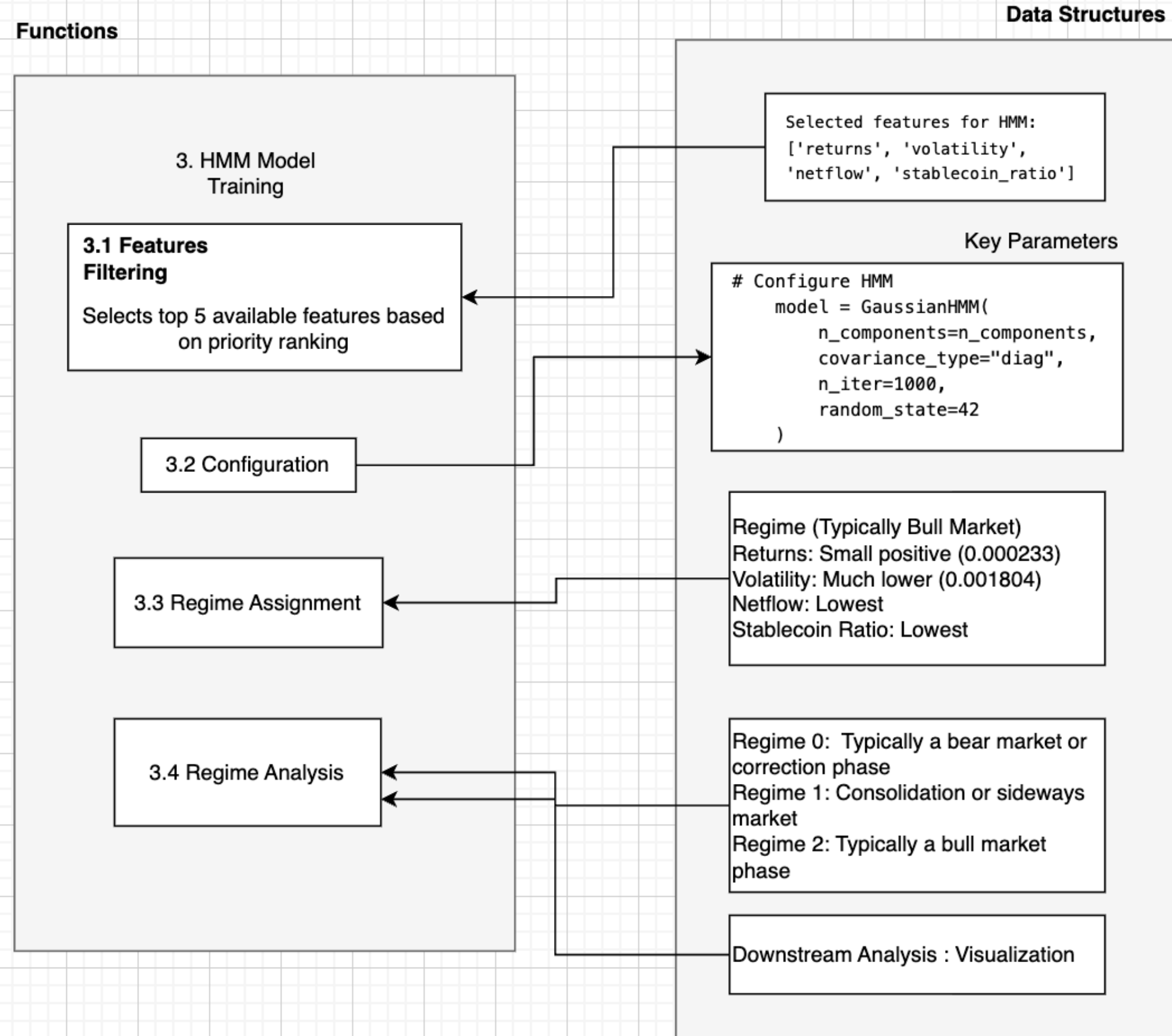
Hold Signal (😐🟡 Neutral Regime):

Hypothesis: When indicators are **mixed or neutral**—for example, if the stablecoin ratio is relatively stable and technical indicators show **no clear trend**—the market might **not be committing to a bullish or bearish regime**.

Action: **Hold** your position until **clearer signals** emerge.

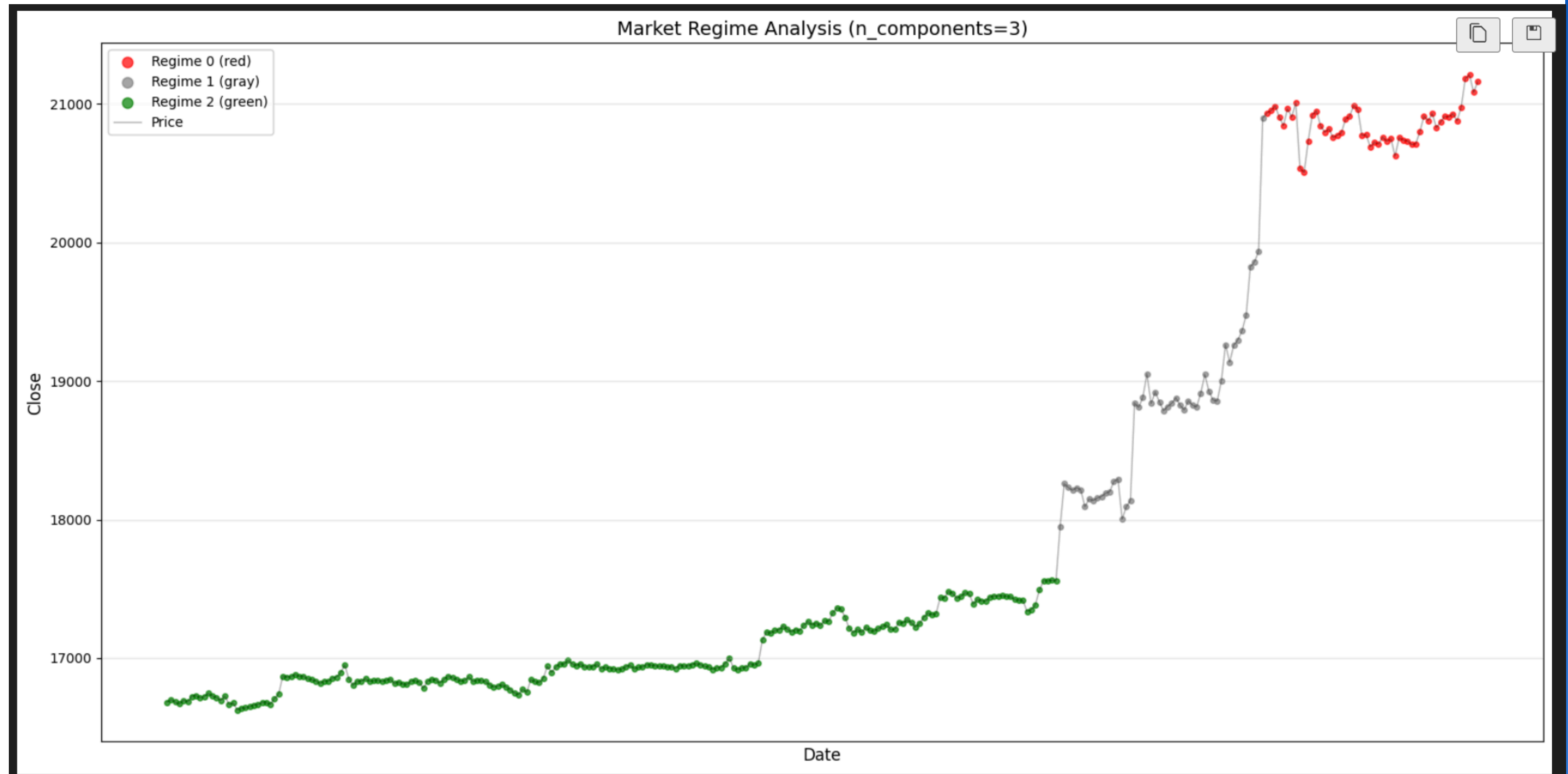


HMM Modelling - Identify Potential Market Regimes

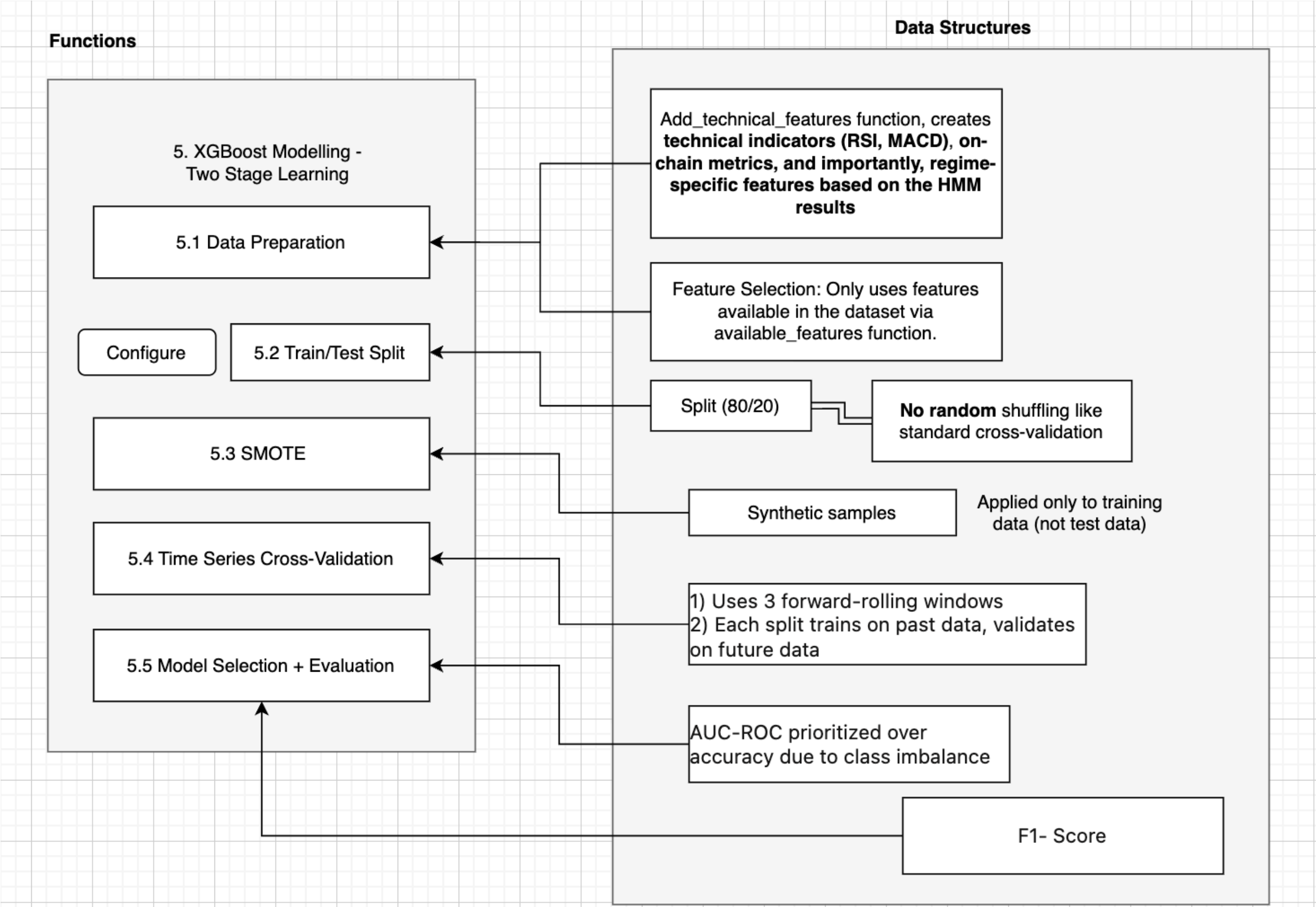


HMM Modelling - Identify Potential Market Regimes

Downstream Visualization



XGBoost - Predict Future Price Movement



=== Feature Engineering ===
Selected features: ['returns', 'volatility', 'rsi_14', 'macd', 'macd_hist', 'netflow_ma_ratio', 'stablecoin_velocity', 'regime', 'returns_regime_0', 'returns_regime_1', 'returns_regime_2']

=== Model Training ===

=== Model Performance ===
Best Validation AUC: 0.5962
Test AUC: 0.5562

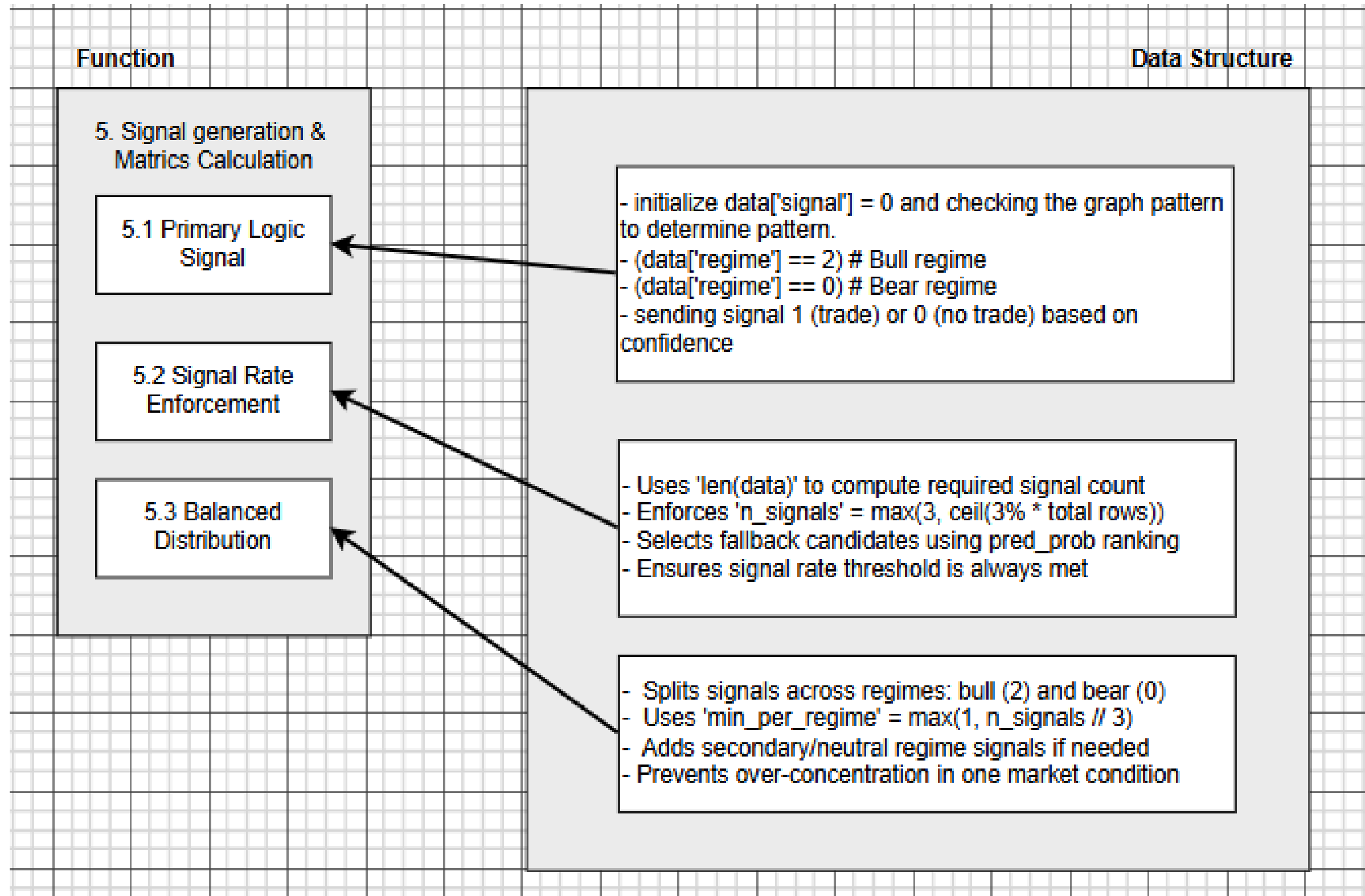
Classification Report:

	precision	recall	f1-score	support
0	0.43	0.87	0.57	23
1	0.75	0.25	0.38	36
accuracy			0.49	59
macro avg	0.59	0.56	0.47	59
weighted avg	0.62	0.49	0.45	59

Feature Importance:

	Feature	Importance
3	macd	0.181372
1	volatility	0.172746
...		
7	regime	0.000000
8	returns_regime_0	0.000000

Metrics & Signal Generation



Backtesting

Functions

6. Backtesting

6.1 Merge signals +
OHLCV

6.2 Validate

Data Structures

1. Try Exact Merge :

```
merged = pd.merge(  
    dfs['price_ohlcv'],  
    signals,  
    on='timestamp',  
    how='left'  
)
```

2. Nearest Merge ($\pm 1h$) if no signal match
(merge_asof)

3. Fallback : Generate signal from pred_prob (if
still missing)

- Fill missing as 0
- Ensure signal are ints
- Exports to CSV

Backtesting

1

Data Synchronization

- Convert and standardize timestamps for both signal data and price data.
- Ensure alignment across datasets — even if the timestamps don't match exactly.

2

Signal Matching Logic

- **Step 1:** Try an exact timestamp match for each signal.
- **Step 2 (fallback):** If no match, use *merge_asof* to find the nearest price data within ± 1 hour.
- **Step 3 (last resort):** If still no signals are matched, generate signals directly from prediction probabilities (e.g., $pred_prob \geq 0.5$).

3

Save Backtest-Ready Dataset

- **Format includes:**
 - *timestamp, open, high, low, close, signal, regime, pred_prob*
- Export to CSV for analysis or use in evaluation tools like backtesting engines.





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Thank You

For your attention to this presentation.

