Domain 2

QUANTITTIVE TRADING

Presented by: Ctrl+Defeat

ABOUT US

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KEY ASSUMPTION

VOLATILITY

THE VOLATILITY BETWEEN PRICE SHOW HOW THE MARKET FEELS, AND MIGHT HELP US GUESS WHAT HAPPENS NEXT AND DO A DECISION.

HOW THE VOLATILITY AFFECTS THE MARKET AND PEOPLE DECISION?

WE ASSUME THESE:

1. If a candle has a much bigger range than usual, it might mean a breakout or trend is starting.

2. If a market is moving a lot today, it will probably keep moving a lot tomorrow too.

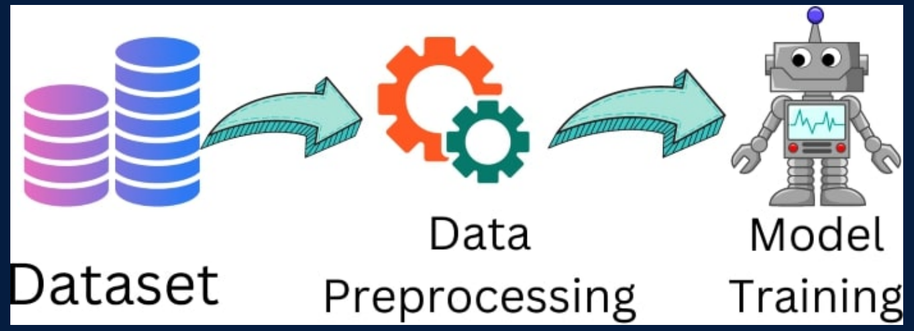
3. If the shadows are large compared to the full candle, it means the market is unsure – price was pushed away from the highs/lows. That could mean a potential reversal.

WE CAME OUT A CONCEPT

BACKTESTING FRAMEWORK

Our backtesting framework plays a critical role in validating the effectiveness of our HMM-based quant trading strategy. By leveraging historical multi-source candle data and volatility-driven features, we simulate realistic trading environments to assess performance before live deployment.

DATA PREPROCESSING



Aggregates and cleans high-frequency candle data (≤1-day intervals) from platforms like CryptoQuant, Glassnode, and Coinglass.

Feature Extraction & Signal Generation

Computes engineered volatility features (RangeVol, VolCluster, WickRatio).

Calculates a SignalScore, weighted by these features, and integrates HMM-predicted market regimes to generate Buy/Sell/Hold signals.

STRATEGY EXECUTION

Executes trades based on model outputs, accounting for a 0.06% transaction fee.

Ensures minimum 3% trade signal activity per data row to maintain trading frequency.

PERFORMANCE EVALUATION

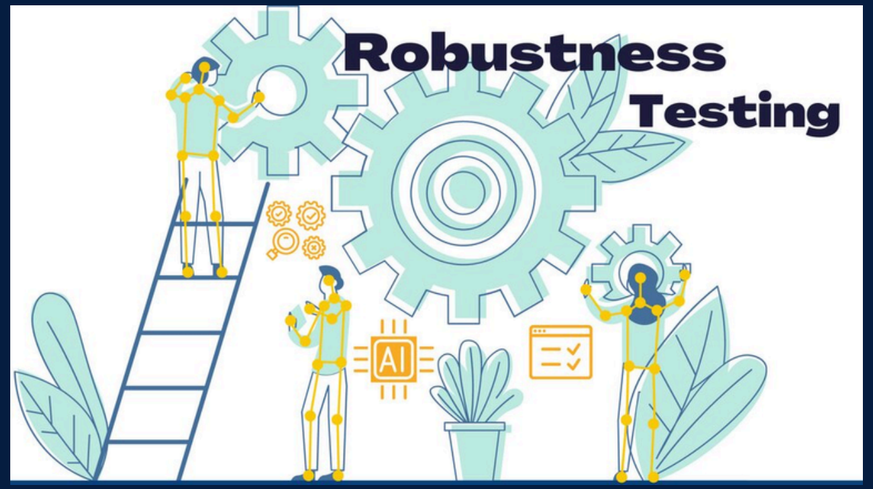
Assesses strategy via key metrics:

Sharpe Ratio ≥ 1.8 (risk-adjusted return)

Maximum Drawdown ≥ -40% (drawdown control)

Trade Frequency ≥ 3% (signal sufficiency)

ROBUST TESTING TIMELINE

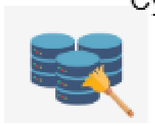


Covers multiple years of historical backtesting, followed by at least one year of forward testing on unseen data.

This end-to-end backtesting system ensures our quant strategy is not only theoretically sound but also practically robust, paving the way for confident real-world trading execution.

CONCEPTUAL DIAGRAM

Data Collection and Preprocessing



CyboTrade API (Live)

Collect

Glassnode, CryptoQuant, Coinglass

<= 1 days intervals

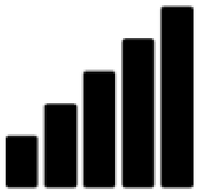
Data (Candle Model) Preprocessing:

Data Cleaning,
Data Formatting,
Extract Features

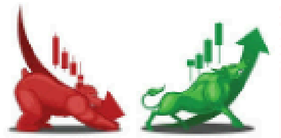
Volatility Feature Extraction

```
SignalScore =
        w1 * RangeVol
        +
        w2 * VolCluster
        -
        w3 * WickRatio

where;

    - RangeVol =
        High - Low
    - VolCluster =
        std(Close - N:t)
    - WickRatio =
        (High - max(open,close)
        + min(open,close) - low)
        / (high - low + e)
```

Calculate Signal Score



HMM modelling



- Regime Detection

(HMM predicted market)

- Match Pattern

Signal Generation

- Buy, Sell, Hold Signals
- Processing fees (0.06%)

Strategy Execution

Executes trades based on model outputs, accounting for a 0.06% transaction fee.

Ensure minimum 3% trade signal activity per data row to maintain trading frequency

Performance Evaluation - Key Metrics

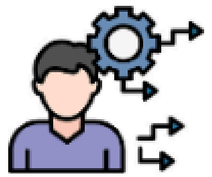
- ✅ **Sharpe Ratio ≥ 1.8** (risk-adjusted return)
- ✅ **Maximum Drawdown ≥ -40%** (drawdown control)
- ✅ **Trade Frequency ≥ 3%** (signal sufficiency)

Backtesting & Forward Testing

Backtesting

Apply model to historical dataset

Observe how the strategy performs during both bull and bear market states

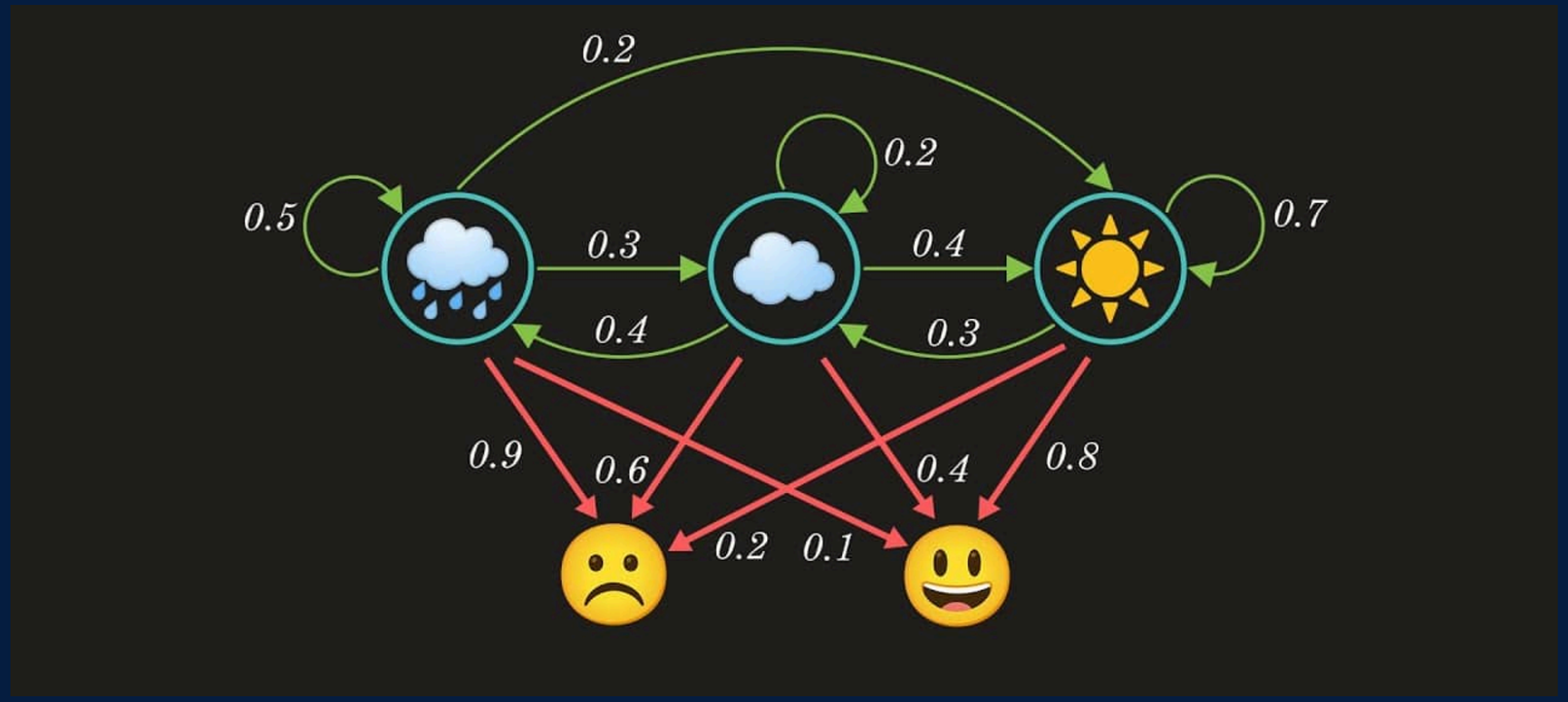


Forward Testing

Forwad-test on unseen data

Evaluate how it performs in real-time conditions

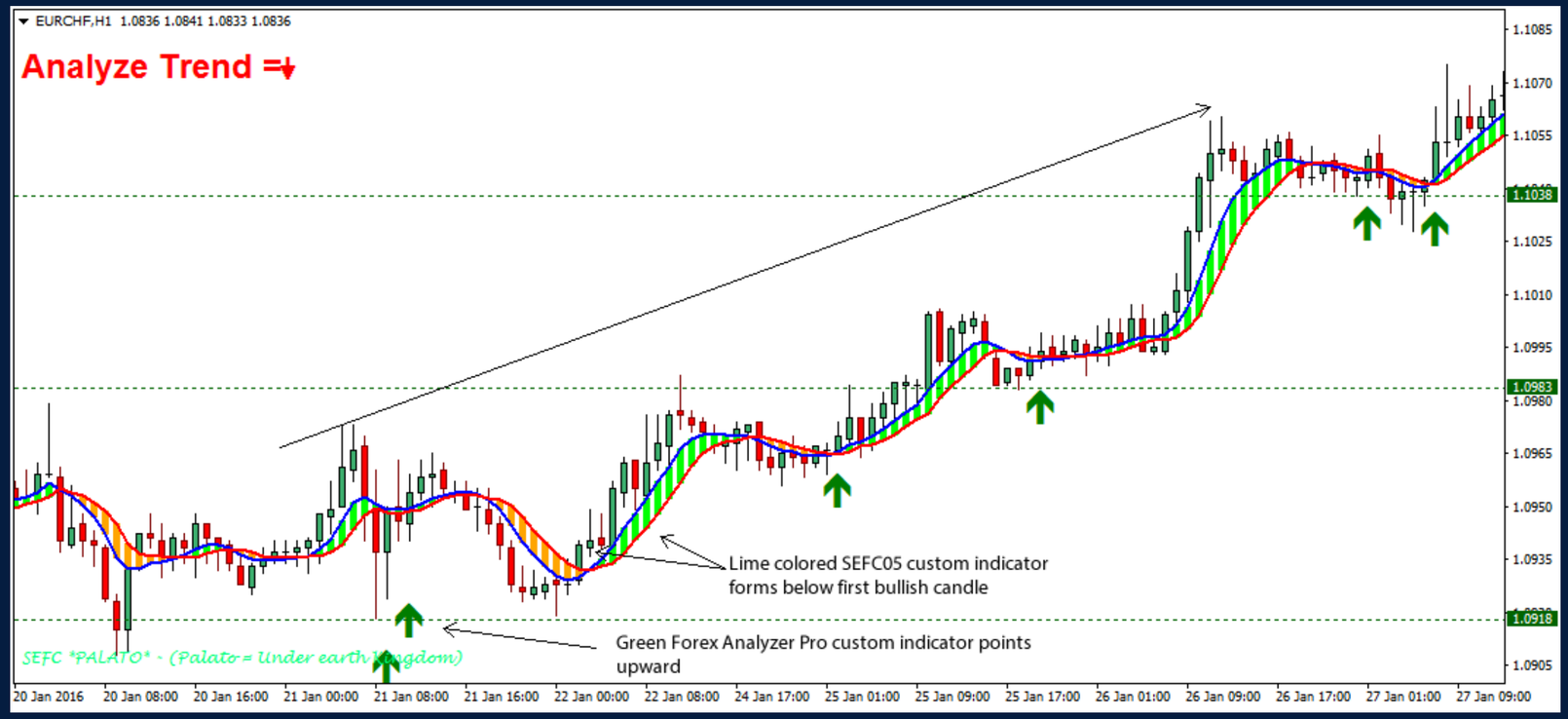
WHY WE USED HMM MODEL FOR OUR DATA MODELLING?



- HELPS DETECT HIDDEN MARKET REGIMES (LIKE BULLISH OR BEARISH) BASED ON OBSERVED PRICE AND VOLATILITY PATTERNS

- ALLOWING US TO MAKE BETTER TRADING DECISIONS FROM NOISY MARKET DATA

WHAT ARE THE BACKTEST STRATEGIES THAT WE USED FOR?



Trend Following Strategy

Trends often form when volatility expands after a regime change.

High RangeVol or VolCluster indicates a breakout or sustained trend.

HMM detects trend regime → strategy rides the trend.

📈 Higher volatility reflects stronger sentiment = stronger trend confirmation.

🚨 Breakout Strategy

This strategy depends on volatility spikes to detect breakouts.

Sudden increase in RangeVol or VolCluster can signal a pre-breakout phase.

Your SignalScore, which combines volatility factors, becomes critical to predict breakout opportunities.

Momentum Strategy

Momentum thrives in volatile, trending markets — which is exactly where your volatility indicators (e.g., large RangeVol, increasing VolCluster) can detect strong moves.

🔧 SignalScore helps confirm whether the trend strength is high enough to enter a position.

📊 HMM captures the market regime (bullish/bearish), while volatility confirms momentum strength.

FIRST STAGE OF MODELLING

Define feature:

```
[8]
    global_df['Volatility'] = global_df['high'] - global_df['low']
    X = global_df[['Volatility']].values
    print(global_df['Volatility'])
```

```
0        80.6
1       106.6
2        49.7
3       151.1
4       102.6
        ...
9995     24.4
9996     45.4
9997     48.1
9998     32.1
9999     45.1
Name: Volatility, Length: 10000, dtype: float64
```

FIRST STAGE OF MODELLING

Train /test split

```
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
```

Define and Train HMM

```
model = GaussianHMM(n_components=3, covariance_type='full', n_iter=100, random_state=42)
model.fit(X_train)
```

GaussianHMM

```
GaussianHMM(covariance_type='full', n_components=3, n_iter=100, random_state=42)
```

Predict on training and test set

```
train_states = model.predict(X_train)
test_states = model.predict(X_test)

global_df['State'] = np.concatenate([train_states, test_states])
```

FIRST STAGE OF MODELLING

Define features

```
# Calculate the range volatility (difference between high and low prices)
global_df['RangeVol'] = global_df['high'] - global_df['low']

# Calculate rolling standard deviation (volatility) over the last 10 periods
global_df['VolCluster'] = global_df['close'].rolling(window=10).std()

# Calculate the upper wick (distance from the close or open to the high)
epsilon = 1e-6  # Small constant to avoid division by zero
global_df['upper_wick'] = global_df['high'] - global_df[['open', 'close']].max(axis=1)

# Calculate the lower wick (distance from the close or open to the low)
global_df['lower_wick'] = global_df[['open', 'close']].min(axis=1) - global_df['low']

# Calculate the wick ratio (relative size of the wicks)
global_df['wick_ratio'] = (global_df['upper_wick'] + global_df['lower_wick']) / (global_df['high'] - global_df['low'] + epsilon)
```

✓ 0.0s

Handle missing data

```
global_df = global_df.dropna(subset=['VolCluster']).reset_index(drop=True)
```

✓ 0.0s

Standardize features

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
global_df[['RangeVol', 'VolCluster', 'wick_ratio']] = scaler.fit_transform(
    global_df[['RangeVol', 'VolCluster', 'wick_ratio']]
)
```

✓ 0.1s

FIRST STAGE OF MODELLING

Evaluate Performance metric

```
sharpe = global_df['strategy_return_net'].mean() / global_df['strategy_return_net'].std() * np.sqrt(252)

cumulative_return = cumulative.iloc[-1] - 1

drawdown = cumulative / cumulative.cummax() - 1
max_dd = drawdown.min()

trade_freq = (global_df['signal'].diff() != 0).sum() / len(global_df)

print(f"Sharpe Ratio: {sharpe:.2f}")
print(f"Total Return: {cumulative_return:.2%}")
print(f"Max Drawdown: {max_dd:.2%}")
print(f"Trade Frequency: {trade_freq:.2%}")
```

✓ 0.0s

```
Sharpe Ratio: -0.11
Total Return: -5.74%
Max Drawdown: -7.84%
Trade Frequency: 2.23%
```

FIRST STAGE OF MODELLING


```
Sharpe Ratio: -0.17
Total Return: -9.03%
Max Drawdown: -10.98%
Trade Frequency: 2.95%
```

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That’s all from us.
Thanks