Using Markov Switching Models for a High-Frequency Forex Scalping Strategy

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Motivation and Research Question

Motivation:

- Intraday gold prices (XAU/USD) exhibit distinct regimes:
  - **Trend-following (Momentum)**
  - **Mean-reversion (Range-bound)**
- Traditional indicators lag real-time regime shifts.
- Adaptive statistical models (Markov switching) potentially improve scalping strategies by timely regime identification.

Research Question:

- *Can regime-based Markov switching models significantly enhance high-frequency scalping performance on XAU/USD?*

Significance:

- Adaptive to market changes.
- Quick response without traditional indicator lag.

Data Description

Data Source:

- High-frequency XAU/USD price and volume data of 2020 to 2025 (Tick, 1-minute and 5-minute intervals).

Data Preprocessing:

- Calculating log-returns:

$$r_t = \log(P_t) - \log(P_{t-1})$$

- Removing microstructure noise (bid-ask bounce, extreme spikes).
- Aggregating data at optimal intervals for robust signals.

Control Variables:

- Volatility measures (realized volatility).
- Recent price momentum indicators.
- Transaction costs (spread, slippage).

Markov Switching Model Structure

Trend-Following Regime (Autoregressive AR(1)):

$$r_t = \phi_1 r_{t-1} + \epsilon_t, \quad \phi_1 > 0$$

Mean-Reversion Regime (Ornstein-Uhlenbeck Process):

$$dp_t = -\kappa(p_{t-1} - m)dt + \sigma dW_t$$

Discrete-time Approximation (AR(1)):

$$r_t = \phi_2 r_{t-1} + \epsilon_t, \quad \phi_2 < 0$$

Variable Definitions:

- r_t: Log-return at time t.
- p_t: Price at time t.
- ϕ_1, ϕ_2: AR(1) coefficients (trend/momentum, mean-reversion).
- $\epsilon_t \sim N(0, \sigma^2)$: White-noise residual.
- κ: Mean-reversion speed.
- m: Long-term equilibrium level.
- σ: Volatility of returns.

Hidden Markov Model (HMM)

Why HMM?

- Statistical modeling of hidden regimes based solely on observable data.
- Flexible adaptation to regime changes.

Mathematical Formulation:

$$X_t | X_{t-1} \sim \text{Categorical}(P_{X_{t-1}}), \quad Y_t | X_t \sim N(\mu_{X_t}, \sigma^2_{X_t})$$

Definitions:

- X_t: Hidden state at time t (Trend or Mean-Reversion).
- Y_t: Observed return at time t.
- $P_{ij} = P(X_t = j | X_{t-1} = i)$: Probability transition between states.
- μ_{X_t}, $\sigma^2_{X_t}$: Mean and variance conditional on state X_t.

Estimation Technique:

- Baum-Welch Algorithm (EM).

Further Research Directions

Improving Regime Forecasting:

- **Integration of Order Flow Data:**
  - Incorporating real-time order book information (bid/ask imbalance, order aggressiveness) to predict regime transitions more effectively.
  - Capturing market participants' intent beyond price movements alone.
- **Utilizing US Dollar Index (DXY) Data:**
  - Analyzing DXY as a proxy for USD strength or weakness.
  - Enhancing predictive accuracy of regime shifts in XAU/USD by factoring external currency influences.

Expected Benefit:

- Higher accuracy and quicker detection of regime changes.
- Enhanced trading signals through multi-dimensional analysis.

Detailed Trading Logic by Regime

Trend-Following Regime:

- **Entry Criteria**: $P(\text{trend}) > 0.8$ with directional price confirmation.
- **Exit Criteria**: Quick profit or momentum reversal.
- **Position Sizing**: Inverse volatility scaling.

Mean-Reversion Regime:

- **Entry Criteria**: $P(\text{mean-revert}) > 0.8$ with price deviation beyond threshold.
- **Exit Criteria**: Price returns to equilibrium, or tight stop-loss triggered.
- **Position Sizing**: Volatility and recent price range considerations.

Ambiguous Regime:

- Stand aside when regime probabilities unclear (< 0.7).

Master Thesis Progress

1	**Theory and Literature Review**	Completed
2	**Data Collection and Preprocessing**	Completed
3	**Model Building and Hyperparameter Tuning**	Ongoing
4	**In-Sample Backtesting and Optimization**	Pending
5	**Out-of-Sample Testing**	Pending
6	**Paper Trading (Optional)**	Pending

Conclusion

- Markov switching models offer adaptive regime detection, improving scalping outcomes.
- Detailed statistical modeling of regimes surpasses traditional lagging indicators.
- Critical aspects:
  - Managing microstructure noise (bid-ask bounce, tick irregularities).
  - Robust validation through realistic simulations.
  - Thorough out-of-sample and stress testing.
- Potential for significant edge in high-frequency trading.

References

- Hamilton, J.D. (1989). "A new approach to the economic analysis of nonstationary time series and the business cycle." Econometrica. (Introduced Markov-switching autoregressive models; EM estimation approach)
- Christensen, H., Godsill, S., Turner, R. (2020). "Hidden Markov Models Applied To Intraday Momentum Trading With Side Information." arXiv:2006.08307
- Zakamulin, V. Giner, J. (2023). "Optimal Trend Following Rules in Two-State Regime-Switching Models."
- QuantConnect Research (2023). "Intraday Application of Hidden Markov Models." (Example of 3-state HMM for intraday regime detection)
- Hudson Thames (2021). "Pairs Trading with Markov Regime-Switching Model." (Illustrative strategy logic using regime probabilities and thresholds)