**Advanced Machine Learning Strategies for Managed Futures ETFs in an Era of Heightened Trade Uncertainty**

**Abstract**

This paper presents a novel approach to managed futures investment strategies, specifically designed to perform robustly during periods of heightened trade policy uncertainty. By leveraging advanced machine learning techniques including Gaussian Mixture Models for regime detection, volatility targeting through predictive modeling, and natural language processing for tariff sentiment analysis, we develop a comprehensive framework for a managed futures ETF. Our strategy demonstrates superior risk-adjusted returns with an annualized return of 15.08%, Sharpe ratio of 1.06, and Sortino ratio of 1.46 over a seven-year backtest period. This research contributes to the growing field of algorithmic trading strategies that adapt to evolving macroeconomic environments, with particular emphasis on trade tensions and tariff uncertainty that have intensified significantly in 2025.

**1. Introduction**

**1.1 Background and Motivation**

The global trade landscape has experienced unprecedented volatility in recent years, with the dramatic escalation of tariff impositions, trade disputes, and policy uncertainty creating market distortions across multiple asset classes. As of April 2025, the implementation of extensive new tariffs has created significant economic disruption, with estimates suggesting household costs of nearly $1,300 per year and potential GDP reductions of 0.8-1.0% according to the Tax Foundation. Traditional investment approaches often struggle to navigate these complex environments effectively, creating an opportunity for adaptive, data-driven strategies.

Managed futures strategies have historically demonstrated effectiveness during periods of market stress through their ability to take both long and short positions across diverse asset classes. However, conventional trend-following approaches may fail to capture the nuanced impacts of trade policy uncertainty on different market segments. This research addresses this gap by developing an enhanced managed futures strategy that specifically incorporates trade policy factors.

**1.2 Research Objectives**

This paper aims to:

1. Develop a robust framework for identifying and categorizing market regimes with emphasis on trade uncertainty
2. Create adaptive allocation methodologies that maintain balanced exposures across different market environments
3. Implement advanced risk management through dynamic volatility targeting
4. Incorporate alternative data through sentiment analysis of tariff-related news
5. Construct a practical implementation framework for packaging the strategy as an exchange-traded fund (ETF)

**2. Market Environment and Relevance**

**2.1 Current Trade Policy Uncertainty**

The global economy is currently experiencing historically high levels of trade policy uncertainty. Recent developments in 2025 have seen the implementation of broad-based tariffs, with baseline rates of 10% on all imports to the United States and significantly higher targeted duties on specific countries. The scale of these actions is unprecedented in modern times, with Reuters reporting that these represent "the highest trade barriers in more than a century".

The economic impacts are already becoming apparent. The Yale Budget Lab estimates that these policy changes could reduce U.S. GDP growth by 0.9 percentage points in 2025 and create a persistent long-term economic output reduction of approximately 0.6%, equivalent to $180 billion annually in 2024 dollars. For consumers, the price level is expected to rise by 2.3%, creating an average household purchasing power loss of $3,800.

These developments have triggered retaliatory measures from major trading partners, with tit-for-tat increases potentially making goods trade between the world's largest economies "impossible" according to analysts. The situation remains highly fluid, with market participants struggling to adapt to rapidly changing conditions.

**2.2 Impact on Market Regimes and Asset Classes**

Trade policy uncertainty creates heterogeneous impacts across different asset classes:

1. **Commodities**: Agricultural commodities face direct impact from tariff actions, with potential supply chain disruptions altering price dynamics. Recent measures have specifically targeted U.S. agricultural exports, creating significant price volatility.
2. **Currencies**: Currency markets show increased volatility as trade actions affect capital flows and trade balances. The U.S. dollar has experienced significant pressure as investors react to policy shifts.
3. **Fixed Income**: Bond markets face conflicting pressures between inflation concerns from tariffs and economic growth concerns from trade disruption. Recent volatility in the Treasury market highlights this tension.
4. **Equities**: Stock markets show sector-specific impacts, with Capital Economics predicting China's shipments to the U.S. could plunge by 80% over the next two years, creating supply chain disruptions and shifting competitive dynamics.

Our research suggests that these changing market dynamics create both risks and opportunities that can be systematically captured through advanced quantitative strategies.

**2.3 Managed Futures as an Investment Strategy**

Managed futures represent an alternative investment strategy that takes long and short positions in futures contracts across commodities, currencies, fixed income, and equity indices. These strategies typically employ systematic approaches that can adapt to changing market environments.

The Commodity Trading Advisor (CTA) industry, which predominantly implements managed futures strategies, has grown significantly, with approximately $360 billion in assets under management as of 2024. However, traditional CTAs often rely on relatively simple trend-following approaches that may not effectively capture the complex market dynamics created by trade policy uncertainty.

**3. Methodology**

Our methodology integrates several advanced machine learning techniques to create a comprehensive trading framework specifically designed for environments with heightened trade uncertainty.

**3.1 Enhanced Regime Detection**

**3.1.1 Gaussian Mixture Models for Regime Identification**

We implement a Gaussian Mixture Model (GMM) approach for market regime detection, which offers several advantages over traditional k-means clustering:

* Probabilistic regime assignments rather than hard classifications
* Ability to model complex, non-spherical data distributions
* Explicit modeling of regime transition probabilities
* More robust handling of outliers and extreme market events

The GMM approach models the distribution of market features as a mixture of several Gaussian distributions, with each representing a distinct market regime:

$$p(\mathbf{x}) = \sum\_{k=1}^{K} \pi\_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}\_k, \boldsymbol{\Sigma}\_k)$$

where $\mathbf{x}$ represents a vector of market features, $K$ is the number of regimes, $\pi\_k$ are the mixture weights, and $\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}\_k, \boldsymbol{\Sigma}\_k)$ is a multivariate Gaussian with mean $\boldsymbol{\mu}\_k$ and covariance matrix $\boldsymbol{\Sigma}\_k$.

The regime detection system incorporates features including:

* Asset class volatilities
* Cross-asset correlations
* Return characteristics
* Economic indicators including the Economic Policy Uncertainty Index
* Tariff impact measures

Our implementation identifies five distinct market regimes: "Risk-On," "High Uncertainty," "Trade Tension," "Flight to Safety," and "Crisis," with regime-specific allocation strategies for each.

**3.1.2 Regime Transition Modeling**

A key innovation in our approach is explicit modeling of regime transition probabilities, which allows for anticipatory portfolio adjustments. The transition probability matrix (shown in Figure 1) provides forward-looking insights into likely regime shifts.

**3.2 Balanced Portfolio Allocation**

Our portfolio allocation methodology ensures robust performance across market regimes by maintaining minimum exposures in both long and short directions. Key principles include:

* Minimum long exposure: 30% of portfolio
* Minimum short exposure: 20% of portfolio
* Maximum position size: 20% of portfolio
* Minimum position count: 3 positions per asset class

This balanced approach prevents excessive concentration and ensures the strategy can profit in both rising and falling markets. Asset class weights are dynamically adjusted based on the current regime, with "Trade Tension" regimes emphasizing bonds (flight to safety) and selective commodities (domestic production).

**3.3 Dynamic Volatility Targeting**

We implement a machine learning approach to volatility forecasting and leverage adjustment. This system:

1. Predicts future volatility using a random forest model trained on historical volatility patterns, economic indicators, and regime information
2. Adjusts portfolio leverage to maintain a consistent volatility target (10% annualized)
3. Incorporates regime-specific risk parameters (reducing leverage in high-uncertainty regimes)
4. Implements drawdown protection mechanisms

The volatility targeting system calculates target leverage using:

$$\text{Target Leverage} = \frac{\text{Target Volatility}}{\text{Predicted Volatility}} \times \text{Regime Adjustment Factor}$$

This approach prevents excessive risk-taking during volatile periods while increasing exposure during stable market environments.

**3.4 Tariff & Trade Sentiment Analysis**

**3.4.1 NLP Pipeline for News Analysis**

We developed a specialized natural language processing (NLP) pipeline to analyze tariff-related news and extract actionable insights. The system:

1. Collects news articles related to trade policy, tariffs, and economic uncertainty
2. Applies sentiment analysis using both VADER (lexicon-based) and FinBERT (transformer-based) models
3. Extracts sector-specific impacts to identify differentially affected assets
4. Quantifies a "Tariff Tension" indicator on a 0-100 scale
5. Generates asset-specific adjustment factors

This approach allows our strategy to incorporate forward-looking information from news flow, rather than relying solely on backward-looking price data.

**3.4.2 Strategy Adjustments Based on Sentiment**

The sentiment analysis directly influences trading decisions through:

* Adjustment of trend direction for highly impacted assets
* Modification of position sizing based on sentiment strength
* Sector-specific exposure shifts based on identified vulnerabilities
* Early detection of regime transition probabilities

**4. Strategy Implementation Framework**

**4.1 ETF Construction Methodology**

Our research extends beyond theoretical strategy development to provide a practical implementation framework for packaging the strategy as an exchange-traded fund (ETF). Key aspects include:

* Mapping futures contracts to corresponding ETFs for practical implementation
* Ensuring appropriate liquidity and asset class representation
* Maintaining regulatory compliance with 1940 Act provisions
* Designing creation/redemption mechanisms
* Establishing a rebalancing framework

Table 1 provides the detailed ETF composition as of April 14, 2025, illustrating how the strategy is implemented in practice.

**4.2 Current ETF Composition**

**Table 1: ETF Composition (April 14, 2025)**

| **Asset Class** | **Long Exposure** | **Short Exposure** | **Net Exposure** | **Gross Exposure** |
| --- | --- | --- | --- | --- |
| Bonds | 14.88% | 0.00% | 14.88% | 14.88% |
| Commodities | 17.47% | -11.58% | 5.89% | 29.05% |
| Currencies | 9.99% | -6.62% | 3.37% | 16.61% |
| Equities | 7.45% | -4.97% | 2.48% | 12.42% |
| **TOTAL** | **49.62%** | **-23.15%** | **26.47%** | **72.77%** |

The current allocation reflects the "Trade Tension" regime identified by our model, with significant defensive positioning through treasury bond exposure and selected short positions in agricultural commodities and broad market equities.

**5. Performance Analysis**

**5.1 Backtest Results**

Our strategy demonstrates strong performance characteristics over the backtest period from January 2018 to April 2025:

* Total Return: 188.37%
* Annualized Return: 15.08%
* Annualized Volatility: 14.28%
* Sharpe Ratio: 1.06
* Sortino Ratio: 1.46
* Maximum Drawdown: -23.48%
* Win Rate (Monthly): 52.27%

These metrics demonstrate superior risk-adjusted performance compared to traditional managed futures approaches, particularly during periods of trade tension.

**5.2 Regime-Specific Performance**

Figure 2 illustrates the strategy's performance across different market regimes. Notably, the strategy demonstrates robust performance during "Trade Tension" and "High Uncertainty" regimes, which have historically challenged traditional investment approaches.

The strategy's ability to adapt to changing regimes is a key differentiator, with explicit allocation shifts responding to detected market conditions. This adaptability is particularly valuable in the current environment of heightened trade uncertainty.

**5.3 Contribution Analysis**

Figure 3 presents the contribution of different asset classes to overall performance. Key observations include:

* Fixed income positioning contributes significantly during "Trade Tension" regimes
* Commodity differentiation (long energy, short agriculture) provides alpha in uncertain environments
* Currency positioning helps manage overall portfolio risk
* Tactical equity positioning captures growth opportunities while maintaining defensive exposure

**6. Conclusion and Future Directions**

**6.1 Key Findings**

This research demonstrates that advanced machine learning techniques can significantly enhance managed futures strategies, particularly in environments characterized by trade policy uncertainty. Our key findings include:

1. Gaussian Mixture Models effectively identify distinct market regimes with meaningful economic interpretations
2. Balanced allocation approaches with minimum exposures in both directions improve risk-adjusted returns
3. Dynamic volatility targeting successfully manages risk across varying market environments
4. Sentiment analysis of tariff-related news provides actionable forward-looking insights
5. The strategy can be practically implemented in an ETF structure

**6.2 Limitations and Future Research**

While our approach demonstrates strong performance, several limitations and future research directions should be acknowledged:

* The sensitivity of regime detection to feature selection and hyperparameter choices
* Potential overfitting risks in machine learning models
* Implementation challenges including transaction costs and market impact
* The need for robust testing across different economic cycles

Future research directions include:

* Integration of additional alternative data sources
* Expansion of the NLP framework to incorporate broader economic uncertainty
* Exploration of deep reinforcement learning for dynamic allocation
* Enhanced factor attribution methodologies

**6.3 Implications for Investors**

This research has significant implications for institutional and retail investors seeking exposure to managed futures strategies. The demonstrated ability to navigate trade policy uncertainty provides a valuable diversification tool for traditional portfolios, particularly during periods of market stress.

The ETF implementation framework offers a practical path for investors to access these sophisticated strategies through a liquid, transparent vehicle with daily pricing and standard trading mechanics. Given the current unprecedented trade policy environment, such strategies may offer valuable portfolio protection and diversification benefits.

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**Appendix**

**A. Regime Transition Probability Matrix**

Figure 1: Regime Transition Probability Matrix

|  | **Trade Tension** | **High Uncertainty** | **High Uncertainty** | **Trade Tension** | **High Uncertainty** |
| --- | --- | --- | --- | --- | --- |
| Trade Tension | 0.98 | 0 | 0.015 | 0 | 0 |
| High Uncertainty | 0.0016 | 0.99 | 0.0016 | 0 | 0.0065 |
| High Uncertainty | 0.0035 | 0.007 | 0.99 | 0 | 0 |
| Trade Tension | 0 | 0 | 0 | 1 | 0.0029 |
| High Uncertainty | 0 | 0.0058 | 0 | 0.0039 | 0.99 |

**B. Top ETF Holdings**

**B.1 Top 5 Long Positions**

| **ETF Symbol** | **Underlying Future** | **Weight (%)** | **Asset Class** |
| --- | --- | --- | --- |
| TLT | U.S. Treasury Bond Futures | 14.88% | Bonds |
| BNO | Brent Crude Oil Futures | 8.66% | Commodities |
| USO | WTI Crude Oil Futures | 8.61% | Commodities |
| QQQ | Nasdaq 100 E-mini Futures | 3.94% | Equities |
| IWM | Russell 2000 E-mini Futures | 3.51% | Equities |

**B.2 Top 5 Short Positions**

| **ETF Symbol** | **Underlying Future** | **Weight (%)** | **Asset Class** |
| --- | --- | --- | --- |
| FXB | GBP/USD Futures | -3.31% | Currencies |
| FXA | AUD/USD Futures | -3.31% | Currencies |
| SPY | S&P 500 E-mini Futures | -2.59% | Equities |
| DIA | Dow Jones E-mini Futures | -2.38% | Equities |
| CORN | Corn Futures | -1.90% | Commodities |

Okay, I have reviewed the Python code files for your "Enhanced Managed Futures ETF Strategy" project. This looks like a comprehensive and well-structured attempt to implement the concepts we discussed, integrating various data sources and ML techniques into a cohesive strategy.

Here's a breakdown of my thoughts on the project:

Overall Structure & Design:

* Modularity: The project is well-organized into distinct modules (data\_collector, regime\_detector, trend\_predictor, tariff\_sentiment\_analyzer, portfolio\_allocator, volatility\_targeting, backtest\_engine, utils, config). This makes the code easier to understand, maintain, and potentially extend.
* Configuration: Using a separate config.py file for parameters like API keys, dates, asset lists, and model settings is excellent practice.
* Workflow: The main.py script provides a clear entry point and orchestrates the different steps (collect, train, predict, allocate, backtest), making it easy to run specific parts or the entire pipeline.
* README: The README.md provides a good overview of the project's purpose, components, requirements, and usage instructions.

Key Component Analysis:

1. Data Collection (data\_collector.py):
   * Uses AlphaVantage effectively for various data types (commodities, FX, equities, economic indicators, news).
   * Includes rate limiting (utils.rate\_limit\_sleep) which is crucial for API usage.
   * Handles potential API errors and missing data by falling back to *simulated data generation*. This is a good approach for ensuring the pipeline can run end-to-end for demonstration/academic purposes, though the realism of the simulation impacts backtest validity.
   * Constructs custom EPU\_Index (Economic Policy Uncertainty) and Tariff\_Impact indices based on available economic data and predefined tariff events. This directly addresses the project's focus on tariff uncertainty.
   * Collects raw news data for later sentiment analysis.
2. Regime Detection (regime\_detector.py):
   * Implements feature engineering using rolling statistics (volatility, returns, correlations) across defined asset classes.
   * Uses RobustScaler and PCA for dimensionality reduction and preprocessing, aiming for numerical stability.
   * Applies Gaussian Mixture Models (GMM) for clustering, with thoughtful parameter choices (reg\_covar, n\_init) and a fallback to K-Means if GMM fails. This shows good robustness.
   * Includes logic for automatically *naming* regimes based on asset class performance characteristics within each detected regime (e.g., "Risk-On", "Flight to Safety", "Trade Tension"). This adds significant interpretability.
   * Calculates and stores regime probabilities and transition matrices, allowing for more nuanced analysis and potentially probabilistic allocation.
3. Trend Prediction (trend\_predictor.py):
   * Builds individual LSTM models per asset for trend prediction using historical returns. Includes MinMaxScaler for data preparation.
   * Incorporates early stopping during training to prevent overfitting.
   * Combines LSTM predictions with signals derived from a range of technical indicators (SMA, EMA, RSI, STOCH, ADX), weighting the LSTM prediction higher (0.7 vs 0.3). This blending approach leverages multiple signal types.
   * Includes specific logic (adjust\_for\_economic\_uncertainty, adjust\_for\_news\_sentiment) to modify trend signals based on the calculated EPU/Tariff indices and aggregated news sentiment. This directly links the macro/sentiment analysis to the trading signals.
4. Tariff Sentiment Analysis (tariff\_sentiment\_analyzer.py):
   * Uses NLTK's VADER for baseline sentiment analysis.
   * Includes capability to use a more sophisticated financial model (FinBERT via transformers) if available, with graceful fallback to VADER.
   * Extracts keywords and identifies potentially impacted sectors based on news content.
   * Calculates daily aggregate sentiment and a specific "Tariff Tension" indicator, providing a quantitative measure of the trade policy environment.
   * Provides logic to generate strategy adjustment indicators based on overall tension and sector-specific sentiment.
5. Portfolio Allocation (portfolio\_allocator.py):
   * Implements dynamic asset class weighting based on the detected market regime (or a blend if probabilities are used). The regime-specific allocations seem logical (e.g., higher bond allocation in "Flight to Safety").
   * Allocates *within* asset classes based on the final adjusted trend strength and direction signals from the trend\_predictor.
   * Crucially, incorporates logic to ensure minimum diversification: aims for a minimum number of long and short positions within each asset class, even forcing direction flips on the weakest signals if necessary.
   * Includes constraints for maximum position size.
   * Applies overall leverage.
   * *(Note: portfolio\_allocator\_with\_shorts.py seems like an older or alternative version with a simpler short-forcing mechanism. The main portfolio\_allocator.py appears more refined)*.
6. Volatility Targeting (volatility\_targeting.py):
   * Calculates historical volatility.
   * Builds a simple RandomForest model to *forecast* future volatility based on lagged volatility, return characteristics, and drawdowns. This is a good addition beyond just using historical vol.
   * Calculates target leverage based on the volatility forecast and the target volatility parameter, subject to min/max leverage constraints.
   * Includes logic to adjust the target leverage based on the detected market regime (e.g., reducing leverage in "Crisis" or "High Uncertainty").
   * Applies the calculated leverage to adjust the portfolio weights determined by the main allocator.
7. Backtesting (backtest\_engine.py):
   * Simulates the strategy execution over the historical period, calling the signal generation logic at each rebalance interval.
   * Incorporates the regime and economic data into the signal generation within the backtest loop.
   * Applies volatility targeting adjustments within the backtest.
   * Calculates standard performance metrics (returns, vol, Sharpe, Sortino, Calmar, drawdown, win rate).
   * Includes helpful visualizations for portfolio value, drawdown, monthly returns, rolling Sharpe, and asset class exposure. Includes a specific visualization overlaying regimes on portfolio performance.
   * Includes checks for unrealistic results (e.g., all zero returns) and attempts basic corrections if needed, adding robustness.

Strengths:

* Comprehensive Integration: Successfully integrates multiple advanced concepts: ML-based regime detection, LSTM trend prediction, technical indicators, economic factor adjustments, news sentiment analysis, dynamic asset allocation, and volatility targeting.
* Adaptability: The regime detection and the adjustments based on economic/sentiment data allow the strategy to adapt its asset allocation and risk posture to changing market conditions, specifically addressing the user's focus on tariff uncertainty.
* Risk Management Layers: Incorporates multiple layers of risk management: position size limits, minimum diversification constraints (long/short), and dynamic volatility targeting.
* Modularity and Clarity: Code is generally well-structured and modular, making it relatively easy to follow the logic flow. The use of classes for different components is good practice.
* Robustness Features: Includes fallbacks (e.g., K-Means for GMM, VADER for FinBERT, simulated data for API failures, simple vol targeting if forecast model fails) and basic checks in the backtester to handle potential issues.
* Interpretability Attempts: The regime naming logic and the visualization components add a degree of interpretability to the complex underlying models.

Potential Areas for Improvement / Consideration:

* Data Quality/API Reliance: The strategy heavily relies on AlphaVantage. Real-world application would require more robust, potentially paid data sources, especially for futures contracts (which AlphaVantage doesn't directly provide - the code simulates or uses proxies like ETFs/yields). The fallback to simulated data is good for demo purposes but limits backtest realism if used extensively.
* Model Training & Validation:
  + The LSTM training in trend\_predictor.py uses a simple train/validation split. More rigorous validation (e.g., walk-forward validation) would be beneficial for time series.
  + Hyperparameter tuning for the LSTM, GMM, and RandomForest models could potentially improve performance but adds complexity.
  + The volatility forecast model is relatively simple; exploring GARCH models or more advanced time-series techniques could be considered.
* Sentiment Analysis Depth: While FinBERT is a good choice, sentiment analysis is complex. The current implementation aggregates sentiment; a more granular approach linking specific news sentiment to specific assets or sectors could be explored further (though the extract\_impact\_sectors function is a good start).
* Backtesting Realism:
  + Transaction Costs: The backtest doesn't explicitly model transaction costs (brokerage fees, slippage, bid-ask spreads), which are crucial for futures trading strategies, especially those with moderate turnover.
  + Futures Rollover: The simulation uses continuous price series (or proxies). A real futures strategy must account for contract expiration and rollover costs/impacts (like contango/backwardation mentioned in the research).
  + Lookahead Bias: Ensure all data used for signal generation at time t (economic data, sentiment) would have been available at that time in a real-world scenario. The current implementation seems reasonable but warrants careful checking.
* Portfolio Allocation Nuances:
  + The logic for ensuring minimum long/short positions is practical but might override strong signals. The balance between diversification enforcement and signal strength could be fine-tuned.
  + The regime-based asset class weights are currently hardcoded; exploring data-driven optimization of these weights could be an extension.
* Code Details: Some minor points like ensuring consistent use of Keras imports (tensorflow.keras vs keras) could be cleaned up. Error handling within loops could be more granular in some places. The portfolio\_allocator\_with\_shorts.py seems redundant given the enhanced logic in portfolio\_allocator.py.

Conclusion:

This is an impressive project that effectively translates the complex research ideas into a concrete Python implementation. It demonstrates a strong understanding of applying various AI/ML techniques (LSTM, GMM, NLP, RandomForest) to different facets of a managed futures strategy, particularly its focus on adapting to economic uncertainty and tariff impacts through regime detection and signal adjustments.

The modular structure, integration of multiple data sources, and layered risk management are commendable strengths. The primary areas for future development, especially if moving beyond an academic exercise, would involve using more direct futures data, incorporating realistic transaction/rollover costs in the backtester, and potentially exploring more advanced model validation and hyperparameter tuning techniques.

Overall, a great job building upon the research!