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MARIF: A Multi-Agent Regime Intelligence Framework for Adaptive Options Strategy Selection in Indian Derivatives Markets

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Abstract
Retail participants in Indian index options markets typically apply a small set of habitual strategies regardless of the prevailing market environment, which increases the likelihood of mismatched risk exposure. This paper proposes the Multi-Agent Regime Intelligence Framework (MARIF), a conceptual, rule-based multi-agent architecture that classifies the prevailing market regime for NIFTY 50 and BANKNIFTY by combining five heterogeneous information sources: price-based technical indicators, India VIX volatility levels, NSE option-chain analytics (Open Interest and Put-Call Ratio), Market-Wide Position Limit (MWPL) institutional concentration data, and sentiment extracted from financial news headlines. Five specialised agents produce independent signals that a Coordinator Agent fuses through an explicit weighted-voting rule into a single regime label and an associated options-strategy recommendation, such as a Bull Call Spread, Bear Put Spread, Iron Condor, or Long Straddle. This paper presents the architecture, its grounding in established option-pricing theory, an explicit specification of the fusion rule, and a worked illustrative walk-through of how the framework processes a representative set of inputs. No live backtesting has yet been performed; the framework is presented at the design and specification stage, and a concrete empirical validation plan is proposed as immediate future work. The contribution is an interpretable, extensible architecture unifying signal domains that are normally treated separately in Indian derivatives literature, rather than a claim of validated trading performance.

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1. Introduction

A large share of retail option traders in India apply a fixed strategy — commonly, simply buying calls or puts — irrespective of the underlying market regime. This is inconsistent with basic financial engineering, under which the suitability of any option position depends jointly on at least four factors: the directional trend of the underlying, the prevailing implied-volatility regime, the depth and liquidity of the option chain, and the level of systemic or event risk implied by macroeconomic and news developments. Treating these dimensions independently, as most retail heuristics do, tends to produce mismatched risk exposure — for example, buying long-premium straddles in an already elevated-volatility environment, or running short-premium Iron Condors just ahead of a high-impact news event.

The Indian derivatives market is a natural setting in which to formalise this problem. NIFTY 50 and BANKNIFTY weekly options traded on the NSE constitute one of the largest exchange-traded options ecosystems in the world by contract volume, and the market provides several regime-relevant data feeds that are less commonly bundled together in existing research: India VIX as a domestic volatility gauge, real-time option-chain depth, MWPL as a public proxy for institutional concentration, and highly active FII/DII participation that leaves a visible imprint on open-interest structure.This paper proposes MARIF (Multi-Agent Regime Intelligence Framework), a conceptual architecture that assigns each of these information domains to a dedicated agent and fuses their outputs through an explicit, auditable Coordinator rule rather than an opaque model. The main contributions of this study are as follows:

- A multi-agent architecture that combines technical, volatility, option-chain, institutional-positioning (MWPL), and news-sentiment signals within a single, interpretable regime-classification pipeline for Indian index derivatives (Section 5).
- An explicit, auditable fusion rule for the Coordinator Agent — a weighted-voting formulation with stated weights — in place of an unspecified or opaque scoring function (Section 7).
- A worked illustrative walk-through showing how the fusion rule processes a representative set of inputs to reach a regime label and strategy recommendation (Section 10), together with a concrete, staged empirical-validation plan (Section 12).

The rest of the paper is organised as follows. Section 2 reviews related work. Section 3 analyses the specific research gap MARIF addresses. Section 4 grounds the design in financial engineering theory. Section 5 describes the proposed architecture and Section 6 the data sources it depends on. Section 7 gives the mathematical formulation of the fusion rule. Sections 8 and 9 detail agent responsibilities and the regime-to-strategy mapping. Section 10 presents an illustrative walk-through. Section 11 states the framework's limitations. Section 12 outlines future work, and Section 13 concludes.

2. Related Work

Hull's treatment of option pricing and the Greeks remains the standard theoretical basis for mapping volatility conditions to option-structure choice, and this paper's Section 4 builds directly on that mapping [1]. Chan emphasises that systematic strategy selection should be conditioned on the market regime rather than applied uniformly, which motivates MARIF's core design premise [2]. Lopez de Prado's Triple-Barrier labelling method and fractional-differentiation techniques are widely used to construct regime-aware machine-learning pipelines in quantitative finance [3]; MARIF's rule-based Coordinator is a simpler, more interpretable alternative to such learned labelling schemes, chosen deliberately for transparency at this design stage.

Separately, financial text-mining research — including the domain-specific sentiment dictionary developed by Loughran and McDonald for financial disclosures — has shown that structured sentiment scoring can extract usable directional signal from corporate filings and, by extension, financial news [4]. On the market-microstructure side, Put-Call Ratio and Open-Interest concentration are established practitioner indicators of institutional sentiment and potential inflection points [5], though they are typically studied in isolation rather than fused with volatility and sentiment signals. Jansen surveys machine-learning approaches to algorithmic trading broadly, including regime and feature-engineering techniques relevant to the Technical and Option Chain Agents described in Section 5 [6].

Table I positions MARIF against this prior work in terms of the signal domains combined and the transparency of the decision rule used, highlighting the relatively narrow set of approaches that combine institutional-positioning data with the other four domains inside a single interpretable pipeline.

Table 1: Comparison of Representative Strategy-Selection Approaches

Approach	Signal Domains Combined	Decision Rule
Technical-only systems	Price / indicators	Rule-based, single domain
Volatility-filter models [1]	IV / Greeks	Theory-based, single domain
ML regime labelling [3]	Price + engineered features	Learned, often opaque
Sentiment-only scoring [4]	News / text	Lexicon or model-based
PCR / OI studies [5]	Option-chain structure	Rule-based, single domain
Proposed MARIF	Technical + Volatility + Option-chain + MWPL + Sentiment	Rule-based, explicit, auditable

3. Research Gap Analysis

Existing algorithmic-trading research on Indian derivatives tends to treat price-direction prediction as a standalone objective, generally using one or two of the domains in Table I in isolation. Few frameworks in the published Indian-markets literature combine, within a single decision pipeline: (a) continuous volatility-regime monitoring via India VIX, (b) structural option-chain analysis (PCR, Max Pain, OI concentration), (c) institutional positioning via MWPL specifically, and (d) event-driven news sentiment. The absence of MWPL is notable, since it is specific to NSE's risk-management framework and rarely appears in academic strategy-selection research, despite being a readily available real-time signal of crowded institutional positioning. MARIF's contribution is architectural: a coherent, transparent way to combine these four dimensions, rather than a new indicator within any single dimension.

4. Financial Engineering Foundation

4.1. Implied Volatility

Implied Volatility (IV), extracted from the option-chain surface, reflects the market's consensus expectation of future realised volatility. Low-IV regimes generally favour credit strategies such as Iron Condors and Credit Spreads, since option premiums are cheap to buy and expensive to justify holding; high-IV regimes favour long-premium positions such as Straddles and Strangles, where a large realised move is more likely to offset the premium paid.

4.2. Option Greeks

Delta, Gamma, Vega and Theta jointly determine the risk profile of any constructed position. In MARIF, the Technical Agent's trend/momentum output and the Option Chain Agent's structural output are combined to approximate the directional and volatility exposure a recommended strategy should target, though MARIF does not currently compute Greeks numerically — identified as a specific extension in Section 12.

4.3. Strategy-Regime Mapping

Each regime detected by the Coordinator Agent is mapped to a canonical options strategy, formalised in Table IV (Section 9). This mapping follows standard options-theory prescriptions rather than being learned from data, keeping the recommendation auditable at this stage of development.

5. Proposed MARIF Architecture

MARIF comprises five specialised agents and one Coordinator agent that fuses their outputs, shown conceptually as a pipeline from raw market data to a final regime label and strategy recommendation. MARIF comprises five specialised agents and one Coordinator agent that fuses their outputs, shown conceptually as a pipeline from raw market data to a final regime label and strategy recommendation. Similar lightweight AI framework approaches have demonstrated the effectiveness of integrating heterogeneous data sources into structured analytical pipelines for intelligent decision support [7].

5.1. Technical Agent

Processes NIFTY 50 and BANKNIFTY OHLCV data and computes EMA-20, EMA-50, RSI, MACD and Average True Range (ATR) to determine trend direction and momentum strength. Output: a discrete trend label (Bullish, Bearish, or Sideways) with a strength score.

5.2. Volatility Agent

Monitors India VIX level and percentile rank, classifying the environment as Low (below 15), Moderate (15–20) or Elevated (above 20), which guides premium-buying versus premium-selling bias.

5.3. News Agent

Applies a lexicon- or model-based sentiment score to intraday financial news headlines, producing a polarity score in the range [−1, +1] that is bucketed into bearish, neutral, or bullish.

5.4. Option Chain Agent

Analyses NSE option-chain data — OI-weighted PCR, Max Pain level, and OI concentration and changes across strikes and expiries — to infer institutional hedging posture and likely support/resistance zones.

5.5. MWPL Agent

Tracks Market-Wide Position Limit utilisation as a proxy for aggregate institutional participation; elevated MWPL is treated as a signal of crowded positioning and therefore elevated systemic (squeeze/unwind) risk.

5.6. Coordinator Agent

Receives the five agent outputs, applies the explicit weighted fusion rule defined in Section 7, and emits the final regime classification together with the associated strategy recommendation from Table IV.

6. Data Sources

Table II summarises the data source each agent depends on. All sources are either free, publicly available NSE/exchange feeds or standard news APIs; no proprietary data is required to implement MARIF.

Table 2: Dataset Summary

Dataset	Purpose in MARIF
NIFTY 50 OHLCV	Trend and momentum detection (Technical Agent)
BANKNIFTY OHLCV	Sector confirmation signal (Technical Agent)
India VIX (daily)	Volatility regime classification (Volatility Agent)
NSE option-chain data	Market structure and PCR analysis (Option Chain Agent)
MWPL concentration data	Institutional participation proxy (MWPL Agent)
Financial news headlines	Sentiment scoring via NLP (News Agent)

7. Mathematical Formulation

Let the feature vector observed at time t be:

$$X_t = [\text{Technical}_t, \text{Volatility}_t, \text{Sentiment}_t, \text{OptionChain}_t, \text{MWPL}_t]$$

where each component is a discretised category emitted by the corresponding agent (e.g., $\text{Technical}_t \in$ {Bullish, Bearish, Sideways}, $\text{Volatility}_t \in$ {Low, Moderate, Elevated}). The Coordinator's fusion function is defined explicitly as a weighted-voting rule so that every recommendation is auditable:

$$R_t = \text{argmax over regime } r \text{ of } \Sigma\, (w_i \cdot \text{vote}_i(r))$$

Here $\text{vote}_i(r)$ equals 1 if agent i's discretised output is consistent with candidate regime r and 0 otherwise, and w_i is a fixed, hand-assigned weight reflecting that agent's reliability for regime detection: w_i = 0.30 (Technical), 0.25 (Volatility), 0.20 (Option Chain), 0.15 (MWPL) and 0.10 (News), reflecting the comparatively higher noise level of headline-based sentiment. R_t is the regime label with the highest total weighted vote, drawn from {BullTrend, BearTrend, Sideways, HighVol, LowVol}. The strategy S is then selected deterministically via Table IV:

$$S = StrategyMap(R_t)$$

A historical-analogy refinement — adjusting S when X_t closely resembles a stored prior regime vector via cosine similarity — is proposed as a future enhancement (Section 12) rather than part of the current rule-based Coordinator, since it requires a historical regime database that has not yet been constructed.

8. Agent Responsibilities

Table 3: Agent Input–Output Specification

Agent	Primary Input	Output Signal
Technical Agent	OHLCV + indicators	Trend direction and strength
Volatility Agent	India VIX time series	Volatility regime class
News Agent	Financial headlines (NLP)	Sentiment polarity score
Option Chain Agent	OI / PCR / Max Pain	Market structure signal
MWPL Agent	Client concentration data	Crowding risk score
Coordinator Agent	All 5 agent outputs	Final regime + strategy

9. Market Regime Classification and Strategy Mapping

Table 4: Regime-To-Strategy Mapping

Detected Regime	Recommended Option Strategy
Bull Trend (Low VIX)	Bull Call Spread
Bear Trend (Low VIX)	Bear Put Spread
Sideways / Rangebound	Iron Condor / Short Strangle
High Volatility Breakout	Long Straddle / Strangle
Low Volatility Compression	Credit Spread / Calendar Spread

10. Illustrative Walk-Through

To demonstrate how the Coordinator Agent's fusion rule operates in practice, this section works through a single representative, hand-constructed input scenario. This illustrates the framework's mechanics; it is not a backtested or empirically observed result and should not be read as evidence of trading performance.

Table 5: Illustrative Scenario Inputs And Output

Market Component	Illustrative Input Signal
NIFTY 50 price action	Sideways-to-bullish recovery
BANKNIFTY price action	Bullish recovery, outperforming NIFTY
India VIX level	Low volatility (below 15)
News sentiment	Moderately positive (illustrative score: +0.62)
MWPL utilisation	Elevated institutional participation
Coordinator output (Section 7 rule)	Bullish Consolidation → Bull Call Spread

Under the weighting scheme in Section 7, the Technical and Volatility Agents' bullish, low-volatility signals dominate the weighted vote, and the resulting regime label maps to a Bull Call Spread via Table IV — consistent with standard financial-engineering prescription for a mildly bullish, low-volatility environment. This confirms the internal logical consistency of the fusion rule on a hand-constructed case; it does not establish that the recommendation would have been profitable, nor that the framework generalises across regimes.

11. Limitations

Several limitations should be noted. First, MARIF has not yet been backtested against historical NSE data; the illustrative walk-through in Section 10 demonstrates the fusion rule's logic on one hand-constructed case and does not establish predictive or trading performance. Second, the Coordinator's agent weights (Section 7) are currently hand-assigned based on domain reasoning rather than empirically estimated, and may not be optimal until calibrated against historical data. Third, the News Agent's sentiment scoring depends on the quality and coverage of the underlying headline feed, and lexicon-based sentiment models are known to struggle with sarcasm, negation, and domain-specific financial jargon — a risk only partially mitigated by giving the News Agent the lowest fusion weight. Fourth, MWPL disclosures are published with a reporting lag by NSE rather than in true real time, which may reduce the timeliness of the MWPL Agent's signal during fast-moving sessions. These limitations directly motivate the phased validation plan in Section 12.

12. Future Work

The following extensions are planned, in priority order, to move MARIF from a specified architecture to an empirically validated system:

- **Large-scale backtesting:** applying MARIF across at least 5 years of historical NSE data (NIFTY 50 and BANKNIFTY OHLCV, India VIX, historical option-chain snapshots, and MWPL disclosures) to compute regime-conditional P&L, Sharpe ratio, and maximum drawdown, benchmarked against a buy-and-hold baseline and a single-indicator (VIX-only) baseline.
- **Reinforcement learning integration:** replacing the fixed-weight Coordinator rule with a deep RL agent trained to maximise risk-adjusted returns, once sufficient backtested data exists to support training.
- **Historical regime similarity search:** constructing a historical regime database and implementing cosine-similarity matching of current feature vectors against it, to support the analogy-based refinement described in Section 7.
- **Live paper trading:** deploying MARIF in a simulated live environment using a broker API (e.g., Dhan API or Zerodha Kite Connect) for real-time data ingestion and simulated order management, prior to any live capital deployment.
- **Explainability layer:** integrating SHAP values once a learned (non-rule-based) Coordinator is introduced, to keep individual regime classifications interpretable for practitioner review.

13. Conclusion

This paper introduced MARIF, a Multi-Agent Regime Intelligence Framework that proposes to integrate technical analysis, India VIX volatility signals, NSE option-chain analytics, MWPL institutional positioning, and financial news sentiment within a single, interpretable, rule-based decision architecture for Indian derivatives markets. The paper specified the Coordinator Agent's fusion rule explicitly and worked through an illustrative example demonstrating the architecture's internal logical consistency. MARIF is presented as a conceptual, design-stage framework rather than a validated trading system; its central contribution is an interpretable structure for combining signal domains that Indian-markets literature has so far treated separately. The immediate priority for future work is the large-scale backtesting programme outlined in Section 12, without which no claim about trading performance can be made.

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