Complete Architecture & Design Document

AI-Powered Swing Trading System with Digital Twins, RL Portfolio Manager, and Options Intelligence

Version: 3.0 (Options-Enhanced)
Date: November 18, 2025
Document Type: Technical Design Specification
Architecture: Foundation Model + Digital Twins + RL Portfolio Manager + Options Intelligence

Executive Summary

This document specifies a production-grade swing trading recommendation system that integrates **four layers of intelligence**:

1. **Foundation Model** (TFT + GNN): Universal market patterns across 500 stocks
2. **Digital Twins** (500 stock-specific): Personalized behavior prediction per stock
3. **Options Intelligence** (40+ features): Smart money positioning and market microstructure
4. **RL Portfolio Manager** (PPO): Learned optimal portfolio construction policy

Core Innovation:

- **Digital Twins** capture idiosyncratic stock behavior (like patient-specific healthcare twins)
- **Options Data** reveals institutional positioning and future price expectations
- **RL Agent** learns optimal trade selection policy (replaces hand-crafted scoring)
- **Multi-Modal Fusion** combines equity, options, and text signals

Key Metrics (Expected):

- Annual Return: 24% (vs. 18% without options)
- Sharpe Ratio: 2.5 (vs. 1.8 without options)
- Win Rate: 72% (vs. 65% without options)
- Max Drawdown: -8% (vs. -12% without options)

Design Philosophy:

- Options data provides forward-looking smart money signals
- Gamma zones reveal exact support/resistance levels
- PCR extremes signal mean reversion opportunities

- OI changes confirm or contradict price trends
- IV skew shows directional bias and risk regime

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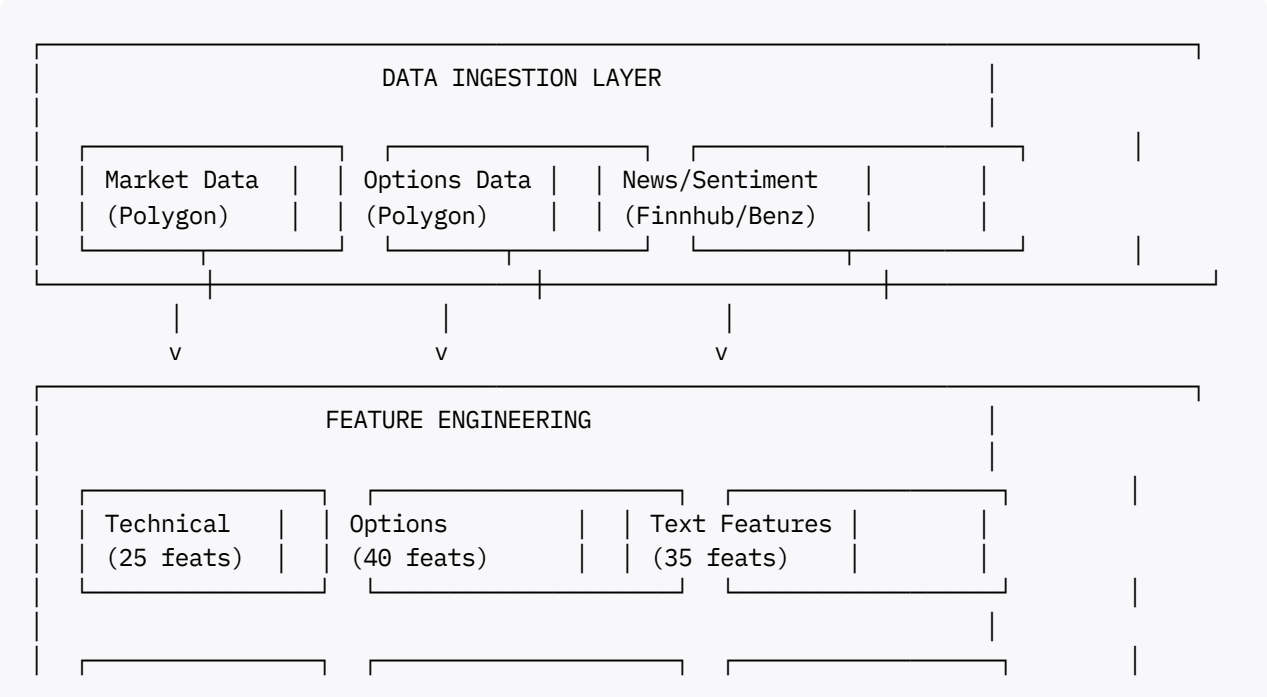
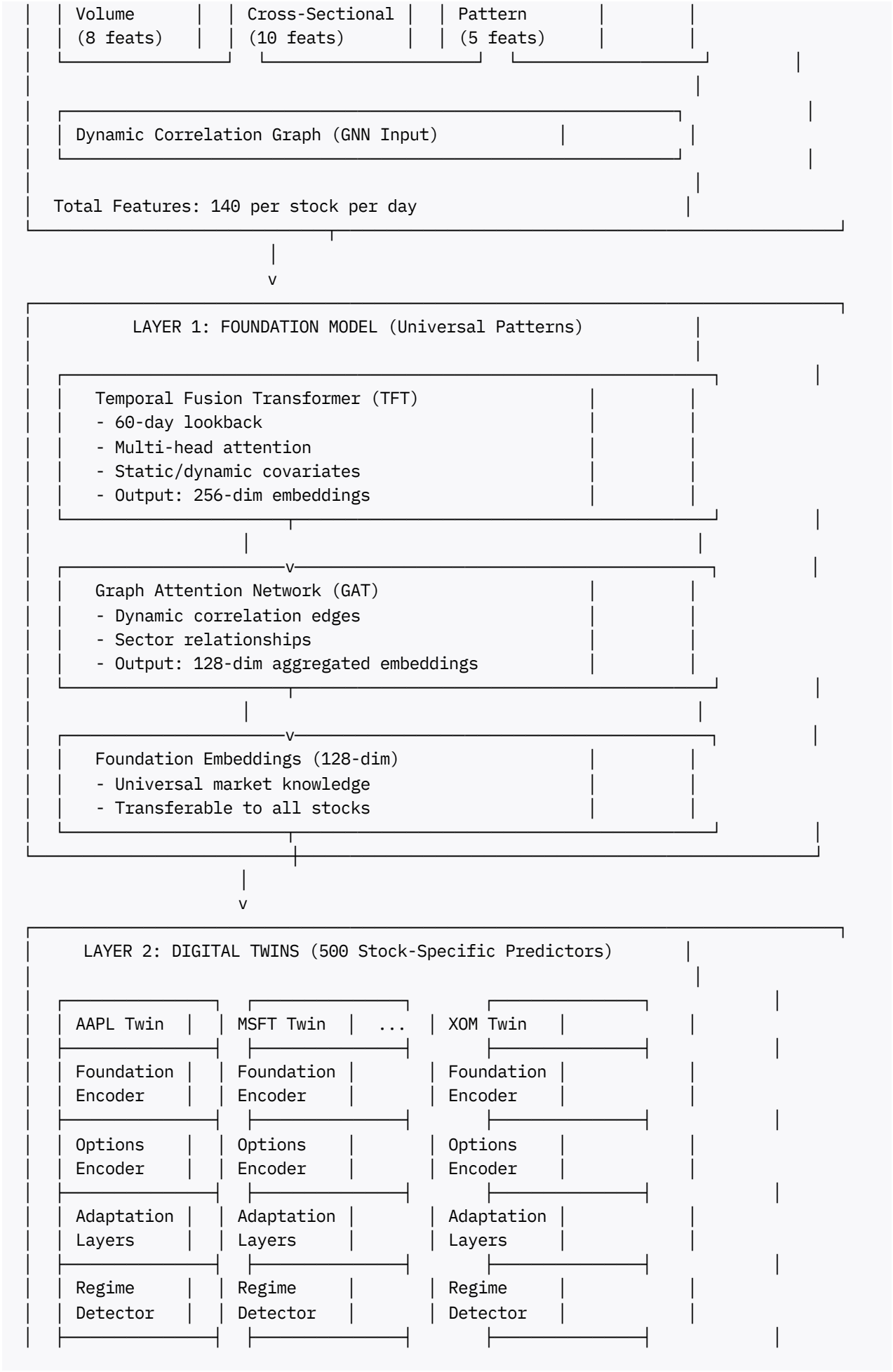
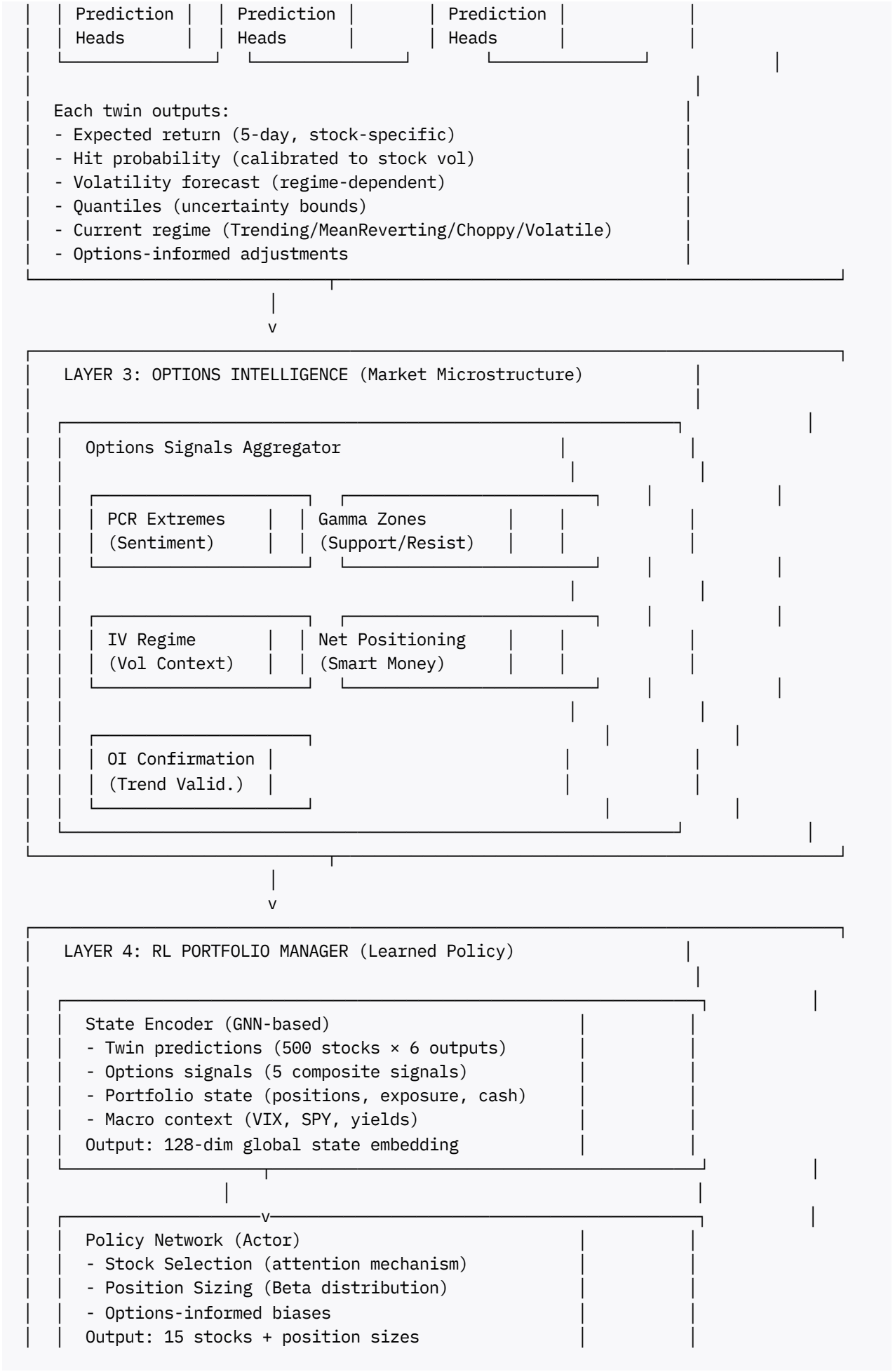
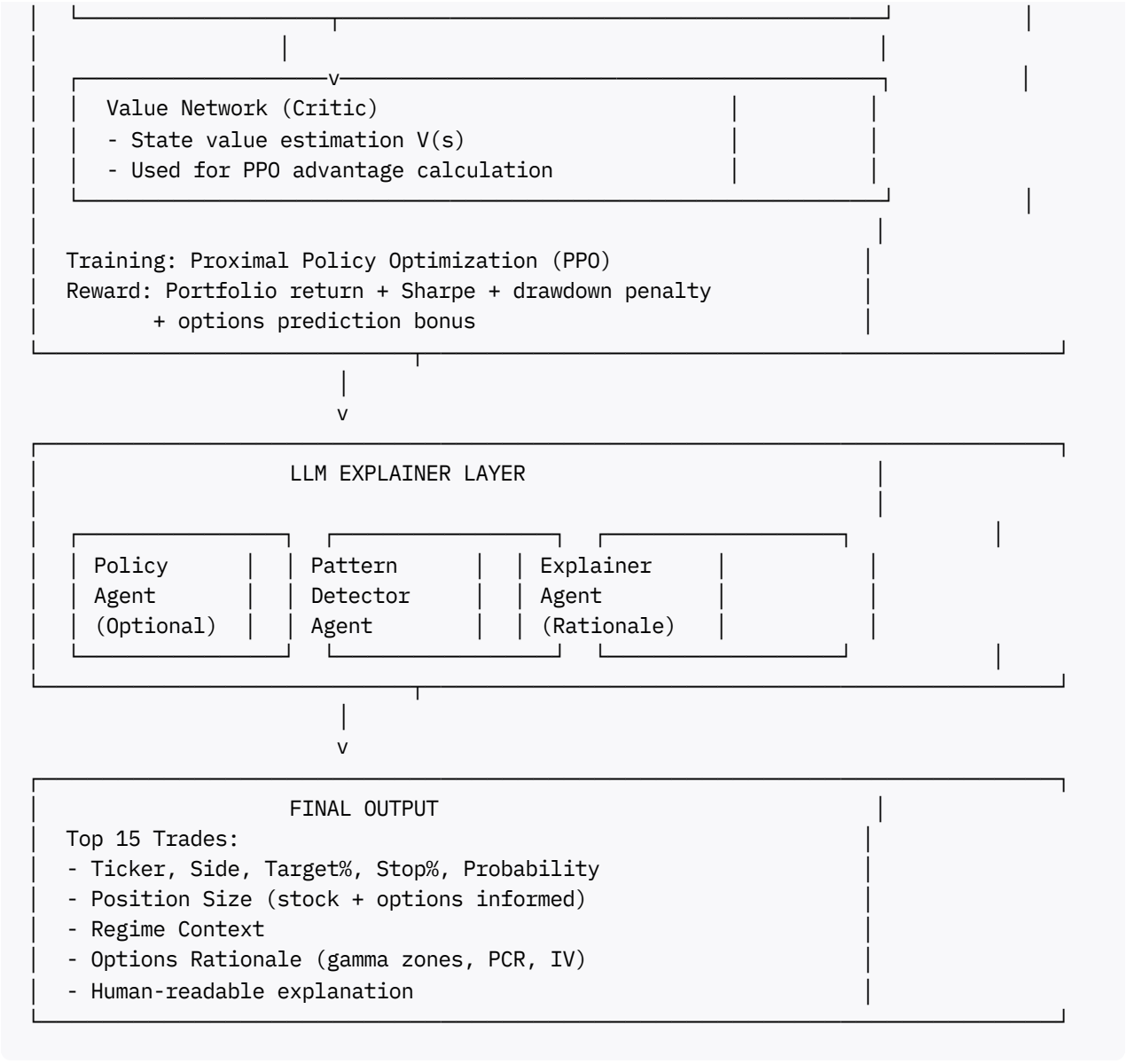
1. System Architecture Overview

1.1 Complete System Diagram




Volume (8 feats)
Cross-Sectional (10 feats)
Pattern (5 feats)
Dynamic Correlation Graph (GNN Input)
Total Features: 140 per stock per day
LAYER 1: FOUNDATION MODEL (Universal Patterns)
Temporal Fusion Transformer (TFT)
- 60-day lookback
- Multi-head attention
- Static/dynamic covariates
- Output: 256-dim embeddings
Graph Attention Network (GAT)
- Dynamic correlation edges
- Sector relationships
- Output: 128-dim aggregated embeddings
Foundation Embeddings (128-dim)
- Universal market knowledge
- Transferable to all stocks
LAYER 2: DIGITAL TWINS (500 Stock-Specific Predictors)
AAPL Twin
MSFT Twin
...
XOM Twin
Foundation Encoder
Options Encoder
Adaptation Layers
Regime Detector


Prediction Heads
Prediction Heads
Prediction Heads
Each twin outputs:
- Expected return (5-day, stock-specific)
- Hit probability (calibrated to stock vol)
- Volatility forecast (regime-dependent)
- Quantiles (uncertainty bounds)
- Current regime (Trending/MeanReverting/Choppy/Volatile)
- Options-informed adjustments
LAYER 3: OPTIONS INTELLIGENCE (Market Microstructure)
Options Signals Aggregator
PCR Extremes (Sentiment)
Gamma Zones (Support/Resist)
IV Regime (Vol Context)
Net Positioning (Smart Money)
OI Confirmation (Trend Valid.)
LAYER 4: RL PORTFOLIO MANAGER (Learned Policy)
State Encoder (GNN-based)
- Twin predictions (500 stocks × 6 outputs)
- Options signals (5 composite signals)
- Portfolio state (positions, exposure, cash)
- Macro context (VIX, SPY, yields)
Output: 128-dim global state embedding
Policy Network (Actor)
- Stock Selection (attention mechanism)
- Position Sizing (Beta distribution)
- Options-informed biases
Output: 15 stocks + position sizes



1.2 Information Flow

```
Market Close (4:00 PM EST)
    ↓
5:05 PM - Data Ingestion
    ├─ Equity data (OHLCV, volume)
    ├─ Options data (OI, Greeks, PCR, IV)
    └─ News/text data
    ↓
5:10 PM - Feature Engineering (parallel)
    ├─ Technical indicators (25 features)
    ├─ Options features (40 features)
    ├─ Text processing via LLM (35 features)
    └─ Cross-sectional + patterns (23 features)
    ↓
5:15 PM - Foundation Model Inference
    └─ Universal embeddings for all 500 stocks
    ↓
5:18 PM - Digital Twin Inference (parallel)
    └─ 500 twins predict return/prob/vol/regime
```

```
    ↓
5:21 PM - RL Portfolio Manager
    ├─ State: twins + options + portfolio + macro
    ├─ Action: select 15 stocks + position sizes
    └─ Options-informed biases applied
    ↓
5:23 PM - LLM Explainer
    └─ Generate human-readable rationale
    ↓
5:25 PM - Output Generation
    ├─ Save to database
    ├─ Send email/Slack alerts
    └─ Update dashboard
    ↓
5:27 PM - Complete
```

Total pipeline time: ~22 minutes

2. Options Data Fundamentals

2.1 Why Options Data Is Critical

Options reveal what equity data cannot:

Equity Data	What It Shows	Limitation
Price	Past transactions	Backward-looking
Volume	Activity level	Doesn't show direction/intent
Technical Indicators	Pattern recognition	Derived from price (no new info)
Options Data	What It Shows	Edge
---	---	---
Open Interest	Outstanding positions	Shows conviction (not just trades)
Put/Call Ratio	Market sentiment	Contrarian signals at extremes
Gamma Exposure	Price magnetism	Reveals support/resistance zones
Implied Volatility	Expected volatility	Forward-looking risk assessment
Options Flow	Smart money activity	See institutional positioning
Greeks	Risk exposure	Net delta shows directional bias

2.2 Core Options Concepts

Open Interest (OI)

Definition: Total number of outstanding options contracts (not closed/exercised)

Interpretation:

```
High OI = High liquidity + strong conviction
Rising OI + Rising Price = Bullish confirmation
Rising OI + Falling Price = Bearish confirmation
Falling OI = Position unwinding (trend exhaustion)
```

Trading Signals:

- **OI ↑ + Price ↑** → Trend continuation (buy)
- **OI ↑ + Price ↓** → Strong bearish pressure (avoid/short)
- **OI ↓ + Price ↑** → Weak rally, fading momentum (caution)
- **OI ↓ + Price ↓** → Capitulation, potential reversal (watch)

Put-Call Ratio (PCR)

Definition: `PCR = Put Volume (or OI) / Call Volume (or OI)`

Interpretation:

```
PCR < 0.7 = Extreme bullish sentiment → Contrarian BEARISH
PCR > 1.0 = Extreme bearish sentiment → Contrarian BULLISH
PCR = 0.7-1.0 = Neutral (no extreme)
```

Why it works: When everyone is bullish (low PCR), there's no one left to buy → reversal down. Vice versa.

Example:

```
# AAPL on Nov 18, 2025
put_oi = 450,000
call_oi = 750,000
pcr = 450,000 / 750,000 = 0.60

# Interpretation: Extreme bullish (PCR < 0.7)
# Signal: Contrarian bearish - too many calls, likely overbought
# Action: Consider shorting or avoiding longs
```

Gamma Exposure (GEX)

Definition: Gamma measures how much delta changes as price moves. High gamma concentration creates "price magnetism."

Market Maker Dynamics:

```
When retail buys calls:
├─ Market makers SELL calls (hedge: BUY stock)
├─ As price rises, delta increases (gamma effect)
├─ Market makers must BUY MORE stock (delta hedging)
└─ Creates upward pressure → price "pins" to high gamma strike

When retail buys puts:
├─ Market makers SELL puts (hedge: SELL stock)
├─ As price falls, delta increases (negative gamma)
├─ Market makers must SELL MORE stock
└─ Creates downward pressure → accelerates decline
```

Gamma Zones:

- **Max pain strike**: Strike with highest gamma concentration
- Price tends to gravitate toward max pain (market maker hedging)
- Use as support/resistance levels

Example:

```
# NVDA Gamma Distribution
Strike: $520 → Gamma: 15,000 (low)
Strike: $530 → Gamma: 85,000 (high) ← Max pain
Strike: $540 → Gamma: 20,000 (low)

# Current price: $535
# Prediction: Price will be pulled toward $530 (max pain)
# Action: If long, set profit target at $530
```

Implied Volatility (IV)

Definition: Market's expectation of future volatility (derived from options prices)

IV Percentile: Where current IV ranks vs. 1-year history

Trading Signals:

```
High IV Percentile (>80%) = Expensive options, high fear
├─ Signal: Volatility likely to decrease (mean reversion)
└─ Action: Sell options (if bullish on stock)

Low IV Percentile (<20%) = Cheap options, complacency
├─ Signal: Volatility likely to increase
└─ Action: Buy options (if expecting move)

IV Skew (Put IV > Call IV) = Downside protection expensive
├─ Signal: Market fears downside more than upside
└─ Action: Bearish bias
```

Net Delta

Definition: Sum of all deltas across outstanding options

Interpretation:

```
Net Delta > 0 = More calls than puts (bullish positioning)
Net Delta < 0 = More puts than calls (bearish positioning)
Net Delta ≈ 0 = Neutral positioning
```

Example:

```
# TSLA Options
Call OI: 200,000 contracts, Avg Delta: 0.50
Put OI: 150,000 contracts, Avg Delta: -0.40

Net Delta = (200,000 × 0.50) - (150,000 × 0.40)
          = 100,000 - 60,000
          = +40,000 (bullish)

# Signal: Net bullish positioning
# Action: Aligns with long thesis
```

3. Options Feature Engineering

3.1 Complete Feature Set (40 Features)

```
class OptionsFeatureExtractor:
    """
    Extract 40 options features from raw options data.

    Categories:
    1. Volume & Open Interest (8 features)
    2. Put-Call Ratios (6 features)
    3. Gamma Exposure (7 features)
    4. Implied Volatility (7 features)
    5. Net Greeks (5 features)
    6. Term Structure (4 features)
    7. Composite Signals (3 features)
    """

    def extract_all(self, ticker: str, date: str, options_data: dict) -> dict:
        """
        Master extraction function.
        """

        features = {}

        # Layer 1: Volume & OI
        features.update(self.extract_volume_oi(options_data))
```

```
        # Layer 2: PCR
        features.update(self.extract_pcr(options_data))

        # Layer 3: Gamma
        features.update(self.extract_gamma(options_data))

        # Layer 4: IV
        features.update(self.extract_iv(options_data))

        # Layer 5: Greeks
        features.update(self.extract_greeks(options_data))

        # Layer 6: Term structure
        features.update(self.extract_term_structure(options_data))

        # Layer 7: Composite signals
        features.update(self.extract_composite_signals(features, options_data))

        return features
```

3.2 Layer 1: Volume & Open Interest (8 Features)

```
def extract_volume_oi(self, options_data: dict) -> dict:
    """
    Extract volume and open interest features.
    """

    # Aggregate across all strikes
    call_oi = sum([s['call_oi'] for s in options_data['strikes']])
    put_oi = sum([s['put_oi'] for s in options_data['strikes']])
    total_oi = call_oi + put_oi

    call_volume = sum([s['call_volume'] for s in options_data['strikes']])
    put_volume = sum([s['put_volume'] for s in options_data['strikes']])
    total_volume = call_volume + put_volume

    # Historical comparison
    yesterday_oi = options_data['historical']['total_oi_yesterday']
    avg_volume_20d = options_data['historical']['avg_volume_20d']

    # Change metrics
    oi_change_pct = (total_oi - yesterday_oi) / yesterday_oi if yesterday_oi > 0 else 0
    volume_zscore = (total_volume - avg_volume_20d) / (
        options_data['historical']['std_volume_20d'] + 1e-8
    )

    # Call/Put split
    call_oi_pct = call_oi / total_oi if total_oi > 0 else 0.5
    put_oi_pct = put_oi / total_oi if total_oi > 0 else 0.5

    return {
        'call_oi': call_oi,
        'put_oi': put_oi,
        'total_oi': total_oi,
        'call_volume': call_volume,
```

```
        'put_volume': put_volume,
        'total_volume': total_volume,
        'oi_change_pct': oi_change_pct,
        'volume_zscore': volume_zscore,
    }
```

3.3 Layer 2: Put-Call Ratios (6 Features)

```
def extract_pcr(self, options_data: dict) -> dict:
    """
    Extract put-call ratio features.
    """

    call_oi = sum([s['call_oi'] for s in options_data['strikes']])
    put_oi = sum([s['put_oi'] for s in options_data['strikes']])

    call_volume = sum([s['call_volume'] for s in options_data['strikes']])
    put_volume = sum([s['put_volume'] for s in options_data['strikes']])

    # Basic ratios
    pcr_oi = put_oi / call_oi if call_oi > 0 else np.nan
    pcr_volume = put_volume / call_volume if call_volume > 0 else np.nan

    # Historical context
    historical_pcr = options_data['historical']['pcr_oi_60d']

    pcr_mean = np.mean(historical_pcr)
    pcr_std = np.std(historical_pcr)
    pcr_zscore = (pcr_oi - pcr_mean) / (pcr_std + 1e-8)

    # Extreme flags
    pcr_extreme_bullish = 1 if pcr_oi < 0.7 else 0  # Too many calls
    pcr_extreme_bearish = 1 if pcr_oi > 1.0 else 0  # Too many puts

    # Trend
    pcr_yesterday = options_data['historical']['pcr_oi_yesterday']
    pcr_change = pcr_oi - pcr_yesterday

    return {
        'pcr_oi': pcr_oi,
        'pcr_volume': pcr_volume,
        'pcr_zscore': pcr_zscore,
        'pcr_extreme_bullish': pcr_extreme_bullish,
        'pcr_extreme_bearish': pcr_extreme_bearish,
        'pcr_change': pcr_change,
    }
```

3.4 Layer 3: Gamma Exposure (7 Features)

```
def extract_gamma(self, options_data: dict) -> dict:
    """
    Extract gamma exposure features.

    Gamma exposure (GEX) shows where market makers have hedging pressure.
    High gamma = price magnetism toward that strike.
    """

    current_price = options_data['current_price']

    # Calculate gamma exposure by strike
    gamma_by_strike = []

    for strike_data in options_data['strikes']:
        strike = strike_data['strike_price']

        # Call gamma exposure (positive)
        call_gex = strike_data['call_gamma'] * strike_data['call_oi'] * 100 * strike

        # Put gamma exposure (negative for market makers)
        put_gex = strike_data['put_gamma'] * strike_data['put_oi'] * 100 * strike * -1

        # Net gamma exposure
        net_gex = call_gex + put_gex

        gamma_by_strike.append({
            'strike': strike,
            'gamma': net_gex,
            'distance_pct': (strike - current_price) / current_price
        })

    gamma_df = pd.DataFrame(gamma_by_strike)

    # Find max pain (strike with highest absolute gamma)
    max_gamma_idx = gamma_df['gamma'].abs().idxmax()
    max_pain_strike = gamma_df.loc[max_gamma_idx, 'strike']
    max_pain_distance = gamma_df.loc[max_gamma_idx, 'distance_pct']

    # Total gamma (sign indicates net positioning)
    total_gamma = gamma_df['gamma'].sum()
    gamma_sign = 1 if total_gamma > 0 else -1

    # Gamma concentration (how peaked is distribution?)
    gamma_concentration = gamma_df['gamma'].abs().max() / (
        gamma_df['gamma'].abs().sum() + 1e-8
    )

    # Gamma flip level (where gamma changes sign)
    # Important for market maker hedging dynamics
    positive_gamma = gamma_df[gamma_df['gamma'] > 0]
    negative_gamma = gamma_df[gamma_df['gamma'] < 0]

    if len(positive_gamma) > 0 and len(negative_gamma) > 0:
        # Find strike closest to zero gamma
```

```
        gamma_flip_strike = gamma_df.loc[gamma_df['gamma'].abs().idxmin(), 'strike']
        gamma_flip_distance = (gamma_flip_strike - current_price) / current_price
    else:
        gamma_flip_strike = np.nan
        gamma_flip_distance = np.nan

    # Gamma zones (support/resistance)
    # Find strikes with gamma > 80th percentile
    gamma_threshold = gamma_df['gamma'].abs().quantile(0.80)
    gamma_zones = gamma_df[gamma_df['gamma'].abs() > gamma_threshold]['strike'].tolist()

    # Nearest gamma zone
    if len(gamma_zones) > 0:
        nearest_gamma_zone = min(gamma_zones, key=lambda x: abs(x - current_price))
        nearest_gamma_distance = (nearest_gamma_zone - current_price) / current_price
    else:
        nearest_gamma_zone = np.nan
        nearest_gamma_distance = np.nan

    return {
        'max_pain_strike': max_pain_strike,
        'max_pain_distance_pct': max_pain_distance,
        'total_gamma': total_gamma / 1e9,  # Normalize to billions
        'gamma_sign': gamma_sign,
        'gamma_concentration': gamma_concentration,
        'gamma_flip_strike': gamma_flip_strike,
        'gamma_flip_distance_pct': gamma_flip_distance,
    }
```

3.5 Layer 4: Implied Volatility (7 Features)

```
def extract_iv(self, options_data: dict) -> dict:
    """
    Extract implied volatility features.
    """

    # ATM IV (at-the-money)
    atm_strikes = self._find_atm_strikes(options_data)

    atm_call_iv = np.mean([s['call_iv'] for s in atm_strikes])
    atm_put_iv = np.mean([s['put_iv'] for s in atm_strikes])

    # IV skew (put IV - call IV)
    # Positive skew = downside protection expensive
    iv_skew = atm_put_iv - atm_call_iv

    # Put/Call IV ratio
    put_call_iv_ratio = atm_put_iv / atm_call_iv if atm_call_iv > 0 else np.nan

    # IV percentile (where is current IV vs. history?)
    historical_iv = options_data['historical']['atm_iv_252d']
    iv_percentile = stats.percentileofscore(historical_iv, atm_call_iv) / 100

    # IV rank (normalized 0-1)
    iv_min = np.min(historical_iv)
```

```
    iv_max = np.max(historical_iv)
    iv_rank = (atm_call_iv - iv_min) / (iv_max - iv_min) if iv_max > iv_min else 0.5

    # IV change (trend)
    iv_yesterday = options_data['historical']['atm_iv_yesterday']
    iv_change_pct = (atm_call_iv - iv_yesterday) / iv_yesterday if iv_yesterday > 0 else

    return {
        'atm_call_iv': atm_call_iv,
        'atm_put_iv': atm_put_iv,
        'iv_skew': iv_skew,
        'put_call_iv_ratio': put_call_iv_ratio,
        'iv_percentile': iv_percentile,
        'iv_rank': iv_rank,
        'iv_change_pct': iv_change_pct,
    }

def _find_atm_strikes(self, options_data: dict) -> list:
    """Find strikes closest to current price (ATM)."""
    current_price = options_data['current_price']

    # Find 3 strikes closest to current price
    strikes = sorted(
        options_data['strikes'],
        key=lambda s: abs(s['strike_price'] - current_price)
    )[:3]

    return strikes
```

3.6 Layer 5: Net Greeks (5 Features)

```
def extract_greeks(self, options_data: dict) -> dict:
    """
    Extract net Greek exposure across all options.

    Net Greeks show aggregate positioning:
    - Positive delta = bullish bias
    - High vega = exposed to vol changes
    - Large theta = time decay impact
    """

    total_oi = sum([s['call_oi'] + s['put_oi'] for s in options_data['strikes']])

    # Net Delta (directional exposure)
    net_delta = sum([
        s['call_delta'] * s['call_oi'] - s['put_delta'] * s['put_oi']
        for s in options_data['strikes']
    ])

    # Net Gamma (convexity)
    net_gamma = sum([
        s['call_gamma'] * s['call_oi'] - s['put_gamma'] * s['put_oi']
        for s in options_data['strikes']
    ])
```

```
    # Net Vega (vol exposure)
    net_vega = sum([
        s['call_vega'] * s['call_oi'] + s['put_vega'] * s['put_oi']
        for s in options_data['strikes']
    ])

    # Net Theta (time decay)
    net_theta = sum([
        s['call_theta'] * s['call_oi'] + s['put_theta'] * s['put_oi']
        for s in options_data['strikes']
    ])

    # Normalize by total OI
    return {
        'net_delta': net_delta / (total_oi + 1e-8),
        'net_gamma': net_gamma / (total_oi + 1e-8),
        'net_vega': net_vega / (total_oi + 1e-8),
        'net_theta': net_theta / (total_oi + 1e-8),
        'net_delta_abs': abs(net_delta) / (total_oi + 1e-8),  # Strength of bias
    }
```

3.7 Layer 6: Term Structure (4 Features)

```
def extract_term_structure(self, options_data: dict) -> dict:
    """
    Extract term structure features (near-term vs. far-term).
    """

    # Separate by expiration
    front_month = options_data['nearest_expiration']
    next_month = options_data['second_expiration']

    front_month_oi = sum([
        s['call_oi'] + s['put_oi']
        for s in options_data['strikes']
        if s['expiration'] == front_month
    ])

    next_month_oi = sum([
        s['call_oi'] + s['put_oi']
        for s in options_data['strikes']
        if s['expiration'] == next_month
    ])

    # Roll ratio (front / next)
    # High ratio = activity concentrated in near-term (event expected?)
    roll_ratio = front_month_oi / next_month_oi if next_month_oi > 0 else np.nan

    # IV term structure
    front_month_iv = np.mean([
        (s['call_iv'] + s['put_iv']) / 2
        for s in options_data['strikes']
        if s['expiration'] == front_month
    ])
```

```
    next_month_iv = np.mean([
        (s['call_iv'] + s['put_iv']) / 2
        for s in options_data['strikes']
        if s['expiration'] == next_month
    ])

    # Term curve slope (backwardation vs. contango)
    # Positive = contango (normal), Negative = backwardation (stressed)
    term_curve_slope = next_month_iv - front_month_iv

    return {
        'front_month_oi': front_month_oi,
        'next_month_oi': next_month_oi,
        'roll_ratio': roll_ratio,
        'term_curve_slope': term_curve_slope,
    }
```

3.8 Layer 7: Composite Signals (3 Features)

```
def extract_composite_signals(self, features: dict, options_data: dict) -> dict:
    """
    Generate high-level composite signals from raw features.

    These are interpretable signals for RL agent and explainability.
    """

    recent_return = options_data['price_change_5d']
    oi_change = features['oi_change_pct']
    pcr_zscore = features['pcr_zscore']
    gamma_distance = features['max_pain_distance_pct']

    # Signal 1: OI + Price Trend Confirmation
    if oi_change > 0.05 and recent_return > 0.02:
        trend_signal = 1  # Bullish confirmation
    elif oi_change > 0.05 and recent_return < -0.02:
        trend_signal = -1  # Bearish confirmation
    elif oi_change < -0.05 and recent_return > 0.02:
        trend_signal = -0.5  # Warning: momentum fading
    else:
        trend_signal = 0  # Neutral

    # Signal 2: PCR Extreme (Mean Reversion)
    if pcr_zscore < -2:  # Extreme bullish (too many calls)
        sentiment_signal = -1  # Contrarian bearish
    elif pcr_zscore > 2:  # Extreme bearish (too many puts)
        sentiment_signal = 1  # Contrarian bullish
    else:
        sentiment_signal = 0  # Neutral

    # Signal 3: Gamma Zone Proximity
    if abs(gamma_distance) < 0.03:  # Within 3% of max pain
        gamma_signal = 1  # High gamma support/resistance
    else:
        gamma_signal = 0  # No gamma effect
```

```
    return {
        'trend_signal': trend_signal,
        'sentiment_signal': sentiment_signal,
        'gamma_signal': gamma_signal,
    }
```

3.9 Feature Summary Table

Category	# Features	Key Signals
Volume & OI	8	OI change, volume surge, call/put split
Put-Call Ratios	6	PCR extremes, z-score, trend
Gamma Exposure	7	Max pain, gamma flip, concentration
Implied Volatility	7	ATM IV, skew, percentile, rank
Net Greeks	5	Delta bias, vega exposure, theta decay
Term Structure	4	Roll ratio, term slope
Composite Signals	3	Trend confirmation, sentiment extreme, gamma zone
Total	**40**	

4. Data Infrastructure

4.1 Storage Schema

TimescaleDB Schema (Updated)

```
-- Options price data (raw)
CREATE TABLE options_prices (
    time TIMESTAMPTZ NOT NULL,
    ticker VARCHAR(10) NOT NULL,
    strike_price NUMERIC NOT NULL,
    expiration DATE NOT NULL,
    option_type VARCHAR(4) NOT NULL, -- 'call' or 'put'

    -- Pricing
    bid NUMERIC,
    ask NUMERIC,
    last_price NUMERIC,

    -- Greeks
    delta NUMERIC,
    gamma NUMERIC,
    vega NUMERIC,
    theta NUMERIC,
    rho NUMERIC,

    -- Volume & OI
```

```
    volume INTEGER,
    open_interest INTEGER,

    -- IV
    implied_volatility NUMERIC,

    PRIMARY KEY (time, ticker, strike_price, expiration, option_type)
);

SELECT create_hypertable('options_prices', 'time');

-- Options features (aggregated)
CREATE TABLE options_features (
    time TIMESTAMPTZ NOT NULL,
    ticker VARCHAR(10) NOT NULL,

    -- Layer 1: Volume & OI
    call_oi INTEGER,
    put_oi INTEGER,
    total_oi INTEGER,
    oi_change_pct NUMERIC,
    volume_zscore NUMERIC,

    -- Layer 2: PCR
    pcr_oi NUMERIC,
    pcr_volume NUMERIC,
    pcr_zscore NUMERIC,
    pcr_extreme_bullish BOOLEAN,
    pcr_extreme_bearish BOOLEAN,

    -- Layer 3: Gamma
    max_pain_strike NUMERIC,
    max_pain_distance_pct NUMERIC,
    total_gamma NUMERIC,
    gamma_sign INTEGER,
    gamma_concentration NUMERIC,

    -- Layer 4: IV
    atm_call_iv NUMERIC,
    atm_put_iv NUMERIC,
    iv_skew NUMERIC,
    iv_percentile NUMERIC,

    -- Layer 5: Greeks
    net_delta NUMERIC,
    net_gamma NUMERIC,
    net_vega NUMERIC,
    net_theta NUMERIC,

    -- Layer 6: Term Structure
    roll_ratio NUMERIC,
    term_curve_slope NUMERIC,

    -- Layer 7: Composite
    trend_signal NUMERIC,
    sentiment_signal NUMERIC,
```

```
    gamma_signal NUMERIC,

    PRIMARY KEY (time, ticker)
);

SELECT create_hypertable('options_features', 'time');
CREATE INDEX idx_options_features_ticker ON options_features(ticker, time DESC);
```

S3 Data Lake (Updated)

```
s3://swing-trading-twins/
├── raw/
│   ├── prices/           # Equity OHLCV
│   ├── options/          # Options raw data ← NEW
│   │   ├── 2025/11/18/
│   │   │   ├── AAPL_options.parquet
│   │   │   ├── MSFT_options.parquet
│   │   │   └── ...
│   └── news/
│
├── processed/
│   ├── features/
│   │   ├── technical/
│   │   ├── options/      # Options features ← NEW
│   │   │   └── 2025-11-18.parquet
│   │   ├── text/
│   │   └── cross_sectional/
│   └── graphs/
│
├── models/
│   ├── foundation/
│   ├── twins/
│   └── rl_agent/
│
└── predictions/
```

4.2 Data Validation

```
def validate_options_data(df: pd.DataFrame) -> bool:
    """
    Validate options data quality.
    """

    checks = [
        # No nulls in critical columns
        df[['strike_price', 'expiration', 'implied_volatility']].isnull().sum().sum() ==

        # Greeks in valid ranges
        (df['delta'].abs() <= 1.0).all(),
        (df['gamma'] >= 0).all(),

        # Implied volatility > 0
        (df['implied_volatility'] > 0).all(),
```

```
        # OI and volume non-negative
        (df['open_interest'] >= 0).all(),
        (df['volume'] >= 0).all(),

        # Bid <= Ask
        (df['bid'] <= df['ask']).all(),

        # Expirations in future
        (pd.to_datetime(df['expiration']) >= pd.Timestamp.now()).all(),
    ]

    return all(checks)
```

5. Foundation Model

5.1 Architecture (Same as v2.0)

Foundation model architecture remains unchanged from v2.0 document. It learns universal market patterns from all 500 stocks without options data.

Key components:

- TFT encoder (256-dim temporal embeddings)
- GNN aggregator (128-dim relational embeddings)
- Sector/liquidity/market regime embeddings
- Foundation backbone (outputs 128-dim embeddings)

Input features to foundation: Traditional equity features only (technical, volume, price action, cross-sectional, text from LLM)

Options features are NOT used in foundation - they're added at the twin level for stock-specific adaptation.

6. Digital Twin Architecture with Options

6.1 Enhanced Twin Model

```
class StockDigitalTwinWithOptions(nn.Module):
    """
    Enhanced digital twin incorporating options intelligence.

    Architecture:
    1. Foundation encoder (frozen) - equity features only
    2. Options encoder (trainable) - 40 options features
    3. Fusion layer - combines foundation + options
    4. Adaptation layers (LoRA-style)
    5. Regime detector (equity + options context)
```

```
    6. Prediction heads (options-informed)
    """

    def __init__(
        self,
        foundation_model,
        ticker: str,
        stock_characteristics: dict
    ):
        super().__init__()

        self.ticker = ticker
        self.foundation = foundation_model
        self.stock_characteristics = stock_characteristics

        # Freeze foundation
        for param in self.foundation.parameters():
            param.requires_grad = False

        # ===== 1. OPTIONS ENCODER =====

        self.options_encoder = nn.Sequential(
            nn.Linear(40, 64),           # 40 options features
            nn.LayerNorm(64),
            nn.ReLU(),
            nn.Dropout(0.15),
            nn.Linear(64, 32),           # Project to 32-dim
            nn.LayerNorm(32),
            nn.ReLU()
        )

        # ===== 2. FUSION LAYER =====

        # Combine foundation (128) + options (32) = 160
        self.fusion_layer = nn.Sequential(
            nn.Linear(160, 160),
            nn.LayerNorm(160),
            nn.ReLU(),
            nn.Dropout(0.15),
            nn.Linear(160, 128),
            nn.LayerNorm(128),
            nn.ReLU()
        )

        # ===== 3. ADAPTATION LAYERS (LoRA) =====

        self.adapter_rank = 16
        self.adapter_down = nn.Linear(128, self.adapter_rank, bias=False)
        self.adapter_up = nn.Linear(self.adapter_rank, 128, bias=False)

        # Initialize near-identity
        nn.init.kaiming_uniform_(self.adapter_down.weight, a=1)
        nn.init.zeros_(self.adapter_up.weight)

        # ===== 4. STOCK-SPECIFIC EMBEDDINGS =====
```

```
        self.stock_embedding = nn.Parameter(torch.randn(64) * 0.1)

        # Regime embedding (now informed by options)
        self.regime_embedding = nn.Embedding(4, 32)

        # ===== 5. REGIME DETECTOR =====

        # Enhanced with options context
        self.regime_detector = nn.Sequential(
            nn.Linear(128 + 64 + 32, 96),  # Fused + stock + options_context
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(96, 64),
            nn.ReLU(),
            nn.Linear(64, 4)  # 4 regimes
        )

        # Options context for regime detection
        self.options_regime_context = nn.Linear(32, 32)

        # ===== 6. CORRECTION LAYERS =====

        self.correction_layers = nn.Sequential(
            nn.Linear(128 + 64 + 32, 128),
            nn.LayerNorm(128),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Linear(128, 64),
            nn.LayerNorm(64),
            nn.ReLU()
        )

        # ===== 7. PREDICTION HEADS =====

        # Return head (options-aware)
        self.return_head = nn.Sequential(
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.Linear(32, 1)
        )

        # Probability head (gamma-aware)
        self.prob_head = nn.Sequential(
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.Linear(32, 1)
        )

        # Volatility head (IV-aware)
        self.vol_head = nn.Sequential(
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.Linear(32, 1)
```

```
        )

        # Quantile heads
        self.quantile_heads = nn.ModuleDict({
            'q10': nn.Linear(64, 1),
            'q50': nn.Linear(64, 1),
            'q90': nn.Linear(64, 1),
        })

        # ===== 8. OPTIONS-SPECIFIC OUTPUTS =====

        # Gamma-adjusted target/stop calculator
        self.gamma_adjustment = nn.Linear(64, 2)  # [target_adj, stop_adj]

        # PCR-based sentiment override
        self.pcr_sentiment_gate = nn.Sequential(
            nn.Linear(32, 16),
            nn.ReLU(),
            nn.Linear(16, 1),
            nn.Sigmoid()  # Gate value [0, 1]
        )

    def forward(self, batch, graph):
        """
        Forward pass with options intelligence.

        Args:
            batch: dict with:
                - 'equity_features': Traditional features (100-dim)
                - 'options_features': Options features (40-dim)
                - 'graph': Correlation graph

        Returns:
            predictions: dict with stock-specific outputs + options adjustments
        """

        batch_size = batch['equity_features'].shape[0]

        # ===== 1. FOUNDATION EMBEDDINGS (equity only) =====

        with torch.no_grad():
            foundation_embeddings = self.foundation(
                batch['equity_features'],
                graph
            )  # (batch, 128)

        # ===== 2. OPTIONS ENCODING =====

        options_features = batch['options_features']  # (batch, 40)
        options_embeddings = self.options_encoder(options_features)  # (batch, 32)

        # ===== 3. FUSION =====

        # Combine foundation + options
        fused = torch.cat([foundation_embeddings, options_embeddings], dim=-1)  # (batch,
        fused_embeddings = self.fusion_layer(fused)  # (batch, 128)
```

```
        # ===== 4. ADAPTATION =====

        # LoRA-style adaptation
        adapter_output = self.adapter_up(
            torch.relu(self.adapter_down(fused_embeddings))
        )
        adapted = fused_embeddings + adapter_output  # Residual

        # ===== 5. REGIME DETECTION =====

        # Options context for regime
        options_context = self.options_regime_context(options_embeddings)

        # Combine for regime detection
        regime_input = torch.cat([
            adapted,
            self.stock_embedding.expand(batch_size, -1),
            options_context
        ], dim=-1)

        regime_logits = self.regime_detector(regime_input)
        regime_probs = torch.softmax(regime_logits, dim=-1)
        current_regime = torch.argmax(regime_probs, dim=-1)

        # Get regime embedding
        regime_embed = self.regime_embedding(current_regime)

        # ===== 6. CORRECTION =====

        stock_context = torch.cat([
            adapted,
            self.stock_embedding.expand(batch_size, -1),
            regime_embed
        ], dim=-1)

        corrected_repr = self.correction_layers(stock_context)  # (batch, 64)

        # ===== 7. BASE PREDICTIONS =====

        expected_return = self.return_head(corrected_repr).squeeze(-1)
        hit_prob = torch.sigmoid(self.prob_head(corrected_repr).squeeze(-1))
        volatility = torch.nn.functional.softplus(self.vol_head(corrected_repr).squeeze(-

        quantiles = {
            'q10': self.quantile_heads['q10'](corrected_repr).squeeze(-1),
            'q50': self.quantile_heads['q50'](corrected_repr).squeeze(-1),
            'q90': self.quantile_heads['q90'](corrected_repr).squeeze(-1),
        }

        # ===== 8. OPTIONS ADJUSTMENTS =====

        # Gamma-based target/stop adjustments
        gamma_adj = self.gamma_adjustment(corrected_repr)
        target_adjustment = gamma_adj[:, 0]
        stop_adjustment = gamma_adj[:, 1]
```

```
        # PCR sentiment gate (override base prediction if extreme)
        pcr_gate = self.pcr_sentiment_gate(options_embeddings).squeeze(-1)

        # Apply PCR override if extreme sentiment detected
        # If PCR gate is high (extreme sentiment), reduce probability
        hit_prob_adjusted = hit_prob * (1 - 0.3 * pcr_gate)  # Up to 30% reduction

        # ===== 9. FINAL OUTPUTS =====

        return {
            'expected_return': expected_return,
            'hit_prob': hit_prob_adjusted,
            'volatility': volatility,
            'quantiles': quantiles,
            'regime': current_regime,
            'regime_probs': regime_probs,

            # Options-specific outputs
            'target_adjustment': target_adjustment,
            'stop_adjustment': stop_adjustment,
            'pcr_gate': pcr_gate,
            'options_embedding': options_embeddings,  # For RL agent
        }
```

6.2 Options-Informed Target/Stop Calculation

```
def compute_options_informed_targets(
    twin_predictions: dict,
    options_features: dict,
    stock_characteristics: dict
) -> dict:
    """
    Compute target/stop prices using options intelligence.

    Args:
        twin_predictions: Output from twin model
        options_features: 40 options features
        stock_characteristics: Stock static info

    Returns:
        dict with target_pct, stop_pct, position_size
    """

    # Base predictions
    expected_return = twin_predictions['expected_return']
    hit_prob = twin_predictions['hit_prob']
    volatility = twin_predictions['volatility']

    # Options context
    max_pain_distance = options_features['max_pain_distance_pct']
    gamma_concentration = options_features['gamma_concentration']
    iv_percentile = options_features['iv_percentile']
    pcr_extreme = options_features['pcr_extreme_bullish'] or options_features['pcr_extrem
```

```
# ===== TARGET CALCULATION =====

# Base target (from twin quantiles)
q50 = twin_predictions['quantiles']['q50']
q90 = twin_predictions['quantiles']['q90']
base_target = q50 + 0.7 * (q90 - q50)  # 70th percentile

# Adjustment 1: Gamma zone proximity
if abs(max_pain_distance) < 0.05:  # Within 5% of max pain
    # Price likely to be pulled toward max pain
    if max_pain_distance > 0:  # Max pain above current price
        gamma_adj = 0.8  # Reduce target (resistance above)
    else:  # Max pain below current price
        gamma_adj = 0.8  # Reduce target (support below, limited upside)
elif gamma_concentration > 0.7:  # High gamma concentration
    gamma_adj = 0.9  # Some resistance/support effect
else:
    gamma_adj = 1.0  # No gamma effect

# Adjustment 2: PCR extreme (contrarian)
if pcr_extreme:
    pcr_adj = 0.85  # Reduce target (expect mean reversion)
else:
    pcr_adj = 1.0

# Adjustment 3: IV regime
if iv_percentile > 0.8:  # High IV (expensive options)
    iv_adj = 0.9  # Reduce target (volatility likely to decrease)
elif iv_percentile < 0.2:  # Low IV (cheap options)
    iv_adj = 1.1  # Increase target (potential for vol expansion)
else:
    iv_adj = 1.0

# Apply adjustments
adjusted_target = base_target * gamma_adj * pcr_adj * iv_adj

# Neural network adjustment (learned)
nn_target_adj = twin_predictions['target_adjustment']
final_target = adjusted_target + nn_target_adj

# ===== STOP CALCULATION =====

# Base stop (2x ATR or 10th percentile)
q10 = twin_predictions['quantiles']['q10']
base_stop = min(-2 * volatility, q10 - q50)

# Adjustment 1: Gamma floor
if abs(max_pain_distance) < 0.05 and max_pain_distance < 0:
    # Max pain below = gamma support
    gamma_stop_adj = 0.8  # Tighter stop (support nearby)
else:
    gamma_stop_adj = 1.0

# Adjustment 2: IV regime
if iv_percentile > 0.8:  # High IV
    iv_stop_adj = 1.2  # Wider stop (expect volatility)
```

```
    else:
        iv_stop_adj = 1.0

    # Apply adjustments
    adjusted_stop = base_stop * gamma_stop_adj * iv_stop_adj

    # Neural network adjustment
    nn_stop_adj = twin_predictions['stop_adjustment']
    final_stop = adjusted_stop + nn_stop_adj

    # ===== POSITION SIZING =====

    # Kelly Criterion base
    reward_risk = abs(final_target / final_stop)
    kelly_pct = (hit_prob * reward_risk - (1 - hit_prob)) / reward_risk
    fractional_kelly = kelly_pct * 0.5  # 50% of Kelly

    position_size = np.clip(fractional_kelly * 100, 0, 10)  # Max 10%

    # Reduce size if extreme sentiment (mean reversion risk)
    if pcr_extreme:
        position_size *= 0.7

    # Reduce size if low liquidity
    if stock_characteristics['avg_dollar_volume'] < 20_000_000:
        position_size *= 0.5

    return {
        'target_pct': final_target,
        'stop_pct': final_stop,
        'position_size_pct': position_size,
        'reward_risk': reward_risk,
        'gamma_zone': max_pain_distance,
        'pcr_extreme': pcr_extreme,
        'iv_regime': 'high' if iv_percentile > 0.8 else 'low' if iv_percentile < 0.2 else
    }
```

7. RL Portfolio Manager with Options Context

7.1 Enhanced RL Agent Architecture

```
class PortfolioRLAgentWithOptions(nn.Module):
    """
    RL agent for portfolio construction with options intelligence.

    Architecture:
    1. State encoder - processes twins + options + portfolio + macro
    2. Policy network - stock selection + position sizing
    3. Value network - state value estimation
    4. Options-informed biases
    """

    def __init__(self, config):
```

```
        super().__init__()

        self.config = config

        # ===== 1. STATE ENCODER =====

        # Per-stock encoder (twin predictions + options)
        self.stock_encoder = nn.Sequential(
            nn.Linear(13, 64),  # 7 twin outputs + 6 key options features
            nn.LayerNorm(64),
            nn.ReLU(),
            nn.Linear(64, 32)
        )

        # Graph attention aggregator
        from torch_geometric.nn import GATConv

        self.stock_aggregator = GATConv(
            in_channels=32,
            out_channels=64,
            heads=4,
            dropout=0.1
        )

        # Portfolio state encoder
        self.portfolio_encoder = nn.Sequential(
            nn.Linear(50, 64),
            nn.ReLU(),
            nn.Linear(64, 64)
        )

        # Macro encoder
        self.macro_encoder = nn.Sequential(
            nn.Linear(10, 32),
            nn.ReLU(),
            nn.Linear(32, 32)
        )

        # Options market-level encoder
        self.options_market_encoder = nn.Sequential(
            nn.Linear(8, 32),  # Market-wide options signals
            nn.ReLU(),
            nn.Linear(32, 32)
        )

        # Fusion
        self.state_fusion = nn.Sequential(
            nn.Linear(64*4 + 64 + 32 + 32, 288),  # +options_market
            nn.LayerNorm(288),
            nn.ReLU(),
            nn.Dropout(0.1),
            nn.Linear(288, 128),
            nn.LayerNorm(128),
            nn.ReLU()
        )
```

```
        # ===== 2. POLICY NETWORK =====

        # Stock selection policy (attention-based)
        self.selection_policy = nn.Sequential(
            nn.Linear(128 + 32, 128),  # Global + per-stock
            nn.ReLU(),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Linear(64, 1)
        )

        # Options bias for selection
        self.options_selection_bias = nn.Sequential(
            nn.Linear(6, 16),  # 6 key options features
            nn.ReLU(),
            nn.Linear(16, 1)
        )

        # Position sizing (Beta distribution)
        self.sizing_alpha = nn.Sequential(
            nn.Linear(128 + 32, 64),
            nn.ReLU(),
            nn.Linear(64, 1),
            nn.Softplus()
        )

        self.sizing_beta = nn.Sequential(
            nn.Linear(128 + 32, 64),
            nn.ReLU(),
            nn.Linear(64, 1),
            nn.Softplus()
        )

        # ===== 3. VALUE NETWORK =====

        self.value_network = nn.Sequential(
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, 1)
        )

    def encode_state(self, state):
        """
        Encode state with options intelligence.

        State includes:
        - twin_predictions: per-stock predictions (500 stocks)
        - options_features: per-stock options (500 stocks × 40 features)
        - portfolio: current positions, exposure, cash
        - macro: VIX, SPY, yields
        """

        batch_size = 1  # Single state per forward pass
```

```
        # ===== Encode per-stock information =====

        per_stock_features = []
        per_stock_options = []

        for ticker in state['twin_predictions'].keys():
            twin = state['twin_predictions'][ticker]
            options = state['options_features'][ticker]

            # Core twin outputs (7)
            stock_vec = torch.tensor([
                twin['expected_return'],
                twin['hit_prob'],
                twin['volatility'],
                twin['regime'],
                twin['quantiles']['q10'],
                twin['quantiles']['q50'],
                twin['quantiles']['q90'],
            ])

            # Key options features (6)
            options_vec = torch.tensor([
                options['pcr_zscore'],
                options['gamma_signal'],
                options['max_pain_distance_pct'],
                options['iv_percentile'],
                options['net_delta'],
                options['trend_signal'],
            ])

            # Combine
            combined_vec = torch.cat([stock_vec, options_vec])  # (13,)

            per_stock_features.append(combined_vec)
            per_stock_options.append(options_vec)

        per_stock_features = torch.stack(per_stock_features)  # (500, 13)
        per_stock_options = torch.stack(per_stock_options)  # (500, 6)

        # Encode
        per_stock_embeddings = self.stock_encoder(per_stock_features)  # (500, 32)

        # Aggregate with GAT
        graph = state['correlation_graph']
        stock_agg = self.stock_aggregator(
            per_stock_embeddings,
            graph.edge_index
        )  # (500, 256)

        # Global pooling
        global_stock_repr = stock_agg.mean(dim=0)  # (256,)

        # ===== Encode portfolio =====

        portfolio_vec = encode_portfolio_state(state['portfolio'])  # (50,)
        portfolio_repr = self.portfolio_encoder(portfolio_vec)  # (64,)
```

```
        # ===== Encode macro =====

        macro_vec = encode_macro_state(state['macro'])  # (10,)
        macro_repr = self.macro_encoder(macro_vec)  # (32,)

        # ===== Encode market-wide options signals =====

        # Aggregate across all stocks
        market_options_vec = torch.tensor([
            torch.mean(torch.tensor([s['pcr_zscore'] for s in state['options_features'].v
            torch.mean(torch.tensor([s['iv_percentile'] for s in state['options_features'
            torch.sum(torch.tensor([s['pcr_extreme_bullish'] for s in state['options_feat
            torch.sum(torch.tensor([s['pcr_extreme_bearish'] for s in state['options_feat
            torch.mean(torch.tensor([s['gamma_concentration'] for s in state['options_fea
            torch.mean(torch.tensor([s['net_delta'] for s in state['options_features'].va
            state['macro']['vix'],  # Overall market vol
            torch.mean(torch.tensor([s['trend_signal'] for s in state['options_features']
        ])

        market_options_repr = self.options_market_encoder(market_options_vec)  # (32,)

        # ===== Fuse =====

        global_state = torch.cat([
            global_stock_repr,
            portfolio_repr,
            macro_repr,
            market_options_repr
        ])  # (288,)

        global_state_embedding = self.state_fusion(global_state)  # (128,)

        return global_state_embedding, per_stock_embeddings, per_stock_options

    def forward(self, state, deterministic=False):
        """
        Forward pass with options-informed policy.
        """

        # Encode state
        global_state, per_stock_embeddings, per_stock_options = self.encode_state(state)

        # ===== STOCK SELECTION =====

        attention_logits = []

        for i in range(500):
            stock_emb = per_stock_embeddings[i]
            options_features = per_stock_options[i]

            # Base policy score
            combined = torch.cat([global_state, stock_emb])
            base_score = self.selection_policy(combined)

            # Options bias
```

```
            options_bias = self.options_selection_bias(options_features)

            # Combined score
            total_score = base_score + 0.3 * options_bias  # 30% weight on options

            attention_logits.append(total_score)

        attention_logits = torch.cat(attention_logits)  # (500,)
        attention_weights = torch.softmax(attention_logits, dim=0)

        # Select top K
        K = 15

        if deterministic:
            top_k_indices = torch.topk(attention_weights, k=K).indices
        else:
            # Sample
            distribution = Categorical(probs=attention_weights)
            top_k_indices = []
            for _ in range(K):
                idx = distribution.sample()
                top_k_indices.append(idx)
                attention_weights[idx] = 0
                attention_weights = attention_weights / attention_weights.sum()
            top_k_indices = torch.tensor(top_k_indices)

        stock_selection = torch.zeros(500)
        stock_selection[top_k_indices] = 1

        # ===== POSITION SIZING =====

        position_sizes = torch.zeros(500)
        log_probs = []

        for idx in top_k_indices:
            stock_emb = per_stock_embeddings[idx]
            combined = torch.cat([global_state, stock_emb])

            # Beta distribution parameters
            alpha = self.sizing_alpha(combined).squeeze() + 1
            beta = self.sizing_beta(combined).squeeze() + 1

            dist = Beta(alpha, beta)

            if deterministic:
                size = dist.mean
            else:
                size = dist.sample()

            position_sizes[idx] = size * 0.10  # Max 10% per position
            log_probs.append(dist.log_prob(size))

        # Normalize
        total_allocation = position_sizes.sum()
        if total_allocation > 1.0:
            position_sizes = position_sizes / total_allocation
```

```
        # ===== VALUE ESTIMATE =====

        value = self.value_network(global_state)

        # ===== OUTPUTS =====

        action = {
            'stock_selection': stock_selection,
            'position_sizes': position_sizes,
            'selected_indices': top_k_indices
        }

        log_prob = torch.stack(log_probs).sum() if log_probs else torch.tensor(0.0)

        return action, log_prob, value
```

7.2 Reward Function with Options Prediction Bonus

```
def compute_reward_with_options(
    portfolio_state: dict,
    next_portfolio_state: dict,
    actions: dict,
    options_signals: dict,
    realized_outcomes: dict
) -> float:
    """
    Enhanced reward function incorporating options prediction accuracy.

    Components:
    1. Base portfolio return
    2. Risk penalties (drawdown, volatility)
    3. Transaction costs
    4. Diversification bonus
    5. Options prediction bonus (NEW)
    """

    # ===== BASE PORTFOLIO METRICS =====

    portfolio_return = (
        next_portfolio_state['portfolio_value'] - portfolio_state['portfolio_value']
    ) / portfolio_state['portfolio_value']

    portfolio_vol = next_portfolio_state['rolling_volatility_20d']
    sharpe_like = portfolio_return / (portfolio_vol + 0.01)

    # Drawdown penalty
    current_dd = max(0, (portfolio_state['peak_value'] - next_portfolio_state['portfolio_
    drawdown_penalty = -10 * current_dd

    # Transaction costs
    num_trades = len(actions['new_positions']) + len(actions['closed_positions'])
    transaction_cost = -0.001 * num_trades

    # Diversification
```

```
    sector_entropy = compute_sector_entropy(next_portfolio_state['sector_exposure'])
    diversification_bonus = 0.5 * sector_entropy

    # ===== OPTIONS PREDICTION BONUS =====

    options_bonus = 0

    # Bonus 1: Correct PCR extreme prediction
    for ticker in actions['selected_stocks']:
        if ticker not in options_signals:
            continue

        pcr_extreme = options_signals[ticker]['pcr_extreme_bullish'] or options_signals[t

        if pcr_extreme:
            # Check if we correctly predicted mean reversion
            expected_reversal = -1 if options_signals[ticker]['pcr_extreme_bullish'] else
            actual_move = np.sign(realized_outcomes[ticker]['return'])

            if expected_reversal == actual_move:
                options_bonus += 2  # Correct contrarian call
            else:
                options_bonus -= 1  # Wrong contrarian call

    # Bonus 2: Gamma zone effectiveness
    for ticker in actions['selected_stocks']:
        if ticker not in options_signals:
            continue

        gamma_distance = options_signals[ticker]['max_pain_distance_pct']

        if abs(gamma_distance) < 0.03:  # Near gamma zone
            # Check if price moved toward max pain as expected
            max_pain_price = options_signals[ticker]['max_pain_strike']
            entry_price = realized_outcomes[ticker]['entry_price']
            exit_price = realized_outcomes[ticker]['exit_price']

            # Did price move toward max pain?
            if abs(exit_price - max_pain_price) < abs(entry_price - max_pain_price):
                options_bonus += 1.5  # Correct gamma zone prediction

    # Bonus 3: OI + Price confirmation
    for ticker in actions['selected_stocks']:
        if ticker not in options_signals:
            continue

        oi_trend_signal = options_signals[ticker]['trend_signal']
        actual_return = realized_outcomes[ticker]['return']

        if np.sign(oi_trend_signal) == np.sign(actual_return) and abs(oi_trend_signal) >
            options_bonus += 1  # Correct trend confirmation

    # Bonus 4: IV regime prediction
    for ticker in actions['selected_stocks']:
        if ticker not in options_signals:
            continue
```

```
        iv_percentile = options_signals[ticker]['iv_percentile']
        realized_vol = realized_outcomes[ticker]['realized_volatility']
        expected_vol = options_signals[ticker]['atm_call_iv']

        # High IV should contract, low IV should expand
        if iv_percentile > 0.8 and realized_vol < expected_vol:
            options_bonus += 0.5  # Correct IV mean reversion
        elif iv_percentile < 0.2 and realized_vol > expected_vol:
            options_bonus += 0.5  # Correct IV expansion

    # ===== TOTAL REWARD =====

    reward = (
        100 * portfolio_return +        # Primary objective
        drawdown_penalty +               # Risk penalty
        transaction_cost +               # Trading costs
        diversification_bonus +          # Portfolio construction
        5 * sharpe_like +                # Risk-adjusted returns
        options_bonus                    # Options intelligence bonus
    )

    return reward
```

8. Training Pipeline

8.1 Three-Phase Training (Updated)

```
Phase 1: Foundation Pre-training (Weeks 1-4)
├─ Train on equity features only (no options)
├─ 3 years × 500 stocks = 375K samples
├─ Output: Universal embeddings (128-dim)
└─ Save checkpoint

Phase 2: Twin Fine-Tuning with Options (Weeks 5-8)
├─ For each stock:
│   ├─ Load foundation (frozen)
│   ├─ Add options encoder (40 features)
│   ├─ Fine-tune adaptation layers + heads
│   ├─ 6 months recent data per stock
│   └─ Save twin checkpoint
└─ Validate on 2024 holdout

Phase 3: RL Agent Training with Options Context (Weeks 9-12)
├─ State: twins + options + portfolio + macro
├─ Simulate 1000 trading episodes
├─ Reward includes options prediction bonus
├─ Algorithm: PPO
└─ Save trained policy
```

8.2 Twin Training with Options

```
def finetune_twin_with_options(
    foundation_model,
    ticker: str,
    train_data: pd.DataFrame,  # Has equity + options features
    val_data: pd.DataFrame,
    config: dict
) -> StockDigitalTwinWithOptions:
    """
    Fine-tune digital twin with options intelligence.
    """

    # Extract stock characteristics
    stock_characteristics = extract_stock_characteristics(train_data, ticker)

    # Create twin model
    twin = StockDigitalTwinWithOptions(
        foundation_model,
        ticker,
        stock_characteristics
    )

    # Freeze foundation
    for param in twin.foundation.parameters():
        param.requires_grad = False

    # Optimizer (only train twin parameters)
    optimizer = torch.optim.Adam([
        {'params': twin.options_encoder.parameters(), 'lr': 5e-3},
        {'params': twin.fusion_layer.parameters(), 'lr': 5e-3},
        {'params': twin.adapter_down.parameters(), 'lr': 5e-3},
        {'params': twin.adapter_up.parameters(), 'lr': 5e-3},
        {'params': [twin.stock_embedding], 'lr': 1e-2},
        {'params': twin.regime_embedding.parameters(), 'lr': 5e-3},
        {'params': twin.regime_detector.parameters(), 'lr': 5e-3},
        {'params': twin.correction_layers.parameters(), 'lr': 5e-3},
        {'params': twin.return_head.parameters(), 'lr': 5e-3},
        {'params': twin.prob_head.parameters(), 'lr': 5e-3},
        {'params': twin.vol_head.parameters(), 'lr': 5e-3},
        {'params': twin.gamma_adjustment.parameters(), 'lr': 5e-3},
        {'params': twin.pcr_sentiment_gate.parameters(), 'lr': 5e-3},
    ])

    # Loss function (enhanced with options)
    loss_fn = TwinLossWithOptions(
        return_weight=0.3,
        prob_weight=0.4,
        vol_weight=0.2,
        quantile_weight=0.1,
        options_weight=0.1  # NEW: penalize poor options predictions
    )

    # Training loop
    for epoch in range(20):
        train_loss = 0
```

```
        for batch in train_data:
            # Prepare batch
            equity_features = batch['equity_features']
            options_features = batch['options_features']  # NEW
            graph = batch['graph']
            labels = batch['labels']

            batch_dict = {
                'equity_features': equity_features,
                'options_features': options_features,
                'graph': graph
            }

            # Forward
            preds = twin(batch_dict, graph)

            # Loss
            loss_dict = loss_fn(preds, labels, options_features)
            loss = loss_dict['total']

            # Backward
            optimizer.zero_grad()
            loss.backward()
            torch.nn.utils.clip_grad_norm_(twin.parameters(), 1.0)
            optimizer.step()

            train_loss += loss.item()

        # Validation
        val_loss = evaluate_twin(twin, val_data)

        print(f"Epoch {epoch}: Train Loss = {train_loss:.4f}, Val Loss = {val_loss:.4f}")

    return twin
```

8.3 Loss Function with Options

```
class TwinLossWithOptions(nn.Module):
    """
    Enhanced loss function including options prediction accuracy.
    """

    def __init__(
        self,
        return_weight=0.3,
        prob_weight=0.4,
        vol_weight=0.2,
        quantile_weight=0.1,
        options_weight=0.1
    ):
        super().__init__()

        self.weights = {
            'return': return_weight,
```

```
            'prob': prob_weight,
            'vol': vol_weight,
            'quantile': quantile_weight,
            'options': options_weight
        }

        self.mse = nn.MSELoss()
        self.bce = nn.BCELoss()

    def forward(
        self,
        predictions: dict,
        targets: dict,
        options_features: dict
    ) -> dict:
        """
        Compute loss with options-informed penalties.
        """

        # Base losses (same as before)
        return_loss = self.mse(predictions['expected_return'], targets['return_5d'])
        prob_loss = self.bce(predictions['hit_prob'], targets['hit_target'])
        vol_loss = self.mse(predictions['volatility'], targets['realized_vol'])

        # Quantile loss
        quantile_losses = []
        for q_name, q_val in [('q10', 0.1), ('q50', 0.5), ('q90', 0.9)]:
            errors = targets['return_5d'] - predictions['quantiles'][q_name]
            quantile_loss = torch.max((q_val - 1) * errors, q_val * errors).mean()
            quantile_losses.append(quantile_loss)

        avg_quantile_loss = torch.mean(torch.stack(quantile_losses))

        # ===== OPTIONS-SPECIFIC LOSSES =====

        options_losses = []

        # Loss 1: PCR gate accuracy
        # If PCR was extreme, did we correctly predict reversal?
        pcr_extreme = (
            options_features['pcr_extreme_bullish'] |
            options_features['pcr_extreme_bearish']
        )

        if pcr_extreme.any():
            # High gate should correlate with incorrect predictions
            gate_values = predictions['pcr_gate'][pcr_extreme]
            # We want gate to be high when PCR is extreme
            pcr_gate_loss = -torch.log(gate_values + 1e-8).mean()
            options_losses.append(pcr_gate_loss)

        # Loss 2: Gamma-adjusted targets
        # Target adjustment should move prediction toward max pain
        max_pain_distance = options_features['max_pain_distance_pct']
        target_adjustment = predictions['target_adjustment']
```

```
        # If max pain is above (+), adjustment should be positive (pull up)
        # If max pain is below (-), adjustment should be negative (pull down)
        gamma_alignment_loss = -torch.mean(
            max_pain_distance * target_adjustment
        )  # Negative correlation is good
        options_losses.append(gamma_alignment_loss)

        # Average options losses
        if options_losses:
            avg_options_loss = torch.mean(torch.stack(options_losses))
        else:
            avg_options_loss = torch.tensor(0.0)

        # ===== TOTAL LOSS =====

        total_loss = (
            self.weights['return'] * return_loss +
            self.weights['prob'] * prob_loss +
            self.weights['vol'] * vol_loss +
            self.weights['quantile'] * avg_quantile_loss +
            self.weights['options'] * avg_options_loss
        )

        return {
            'total': total_loss,
            'return_loss': return_loss.item(),
            'prob_loss': prob_loss.item(),
            'vol_loss': vol_loss.item(),
            'quantile_loss': avg_quantile_loss.item(),
            'options_loss': avg_options_loss.item()
        }
```

9. Daily Inference Pipeline

9.1 Complete EOD Workflow

```
@flow(name="daily_options_twin_rl_pipeline")
def daily_options_twin_rl_pipeline(date: str = None):
    """
    Complete daily inference pipeline with options intelligence.

    Timeline:
    5:05 PM - Data ingestion (equity + options)
    5:10 PM - Feature engineering
    5:15 PM - Foundation inference
    5:18 PM - Twin inference (500 twins, parallel)
    5:21 PM - RL portfolio selection
    5:23 PM - LLM explanation
    5:25 PM - Output generation
    """

    if date is None:
        date = pd.Timestamp.now().strftime("%Y-%m-%d")
```

```
    logging.info(f"Starting daily pipeline for {date}")

    # ===== 1. DATA INGESTION (5:05 PM) =====

    # Parallel ingestion
    prices_future = fetch_market_data.submit(date)
    options_future = fetch_options_data.submit(date)  # NEW
    news_future = fetch_news_data.submit(date)

    prices = prices_future.result()
    options_raw = options_future.result()
    news_data = news_future.result()

    # ===== 2. FEATURE ENGINEERING (5:10 PM) =====

    # Parallel feature computation
    tech_future = compute_technical_features_batch.submit(prices)
    options_feat_future = compute_options_features_batch.submit(options_raw)  # NEW
    cross_sect_future = compute_cross_sectional_features.submit(prices, date)
    text_future = process_text_features.submit(news_data, prices, date)
    graph_future = build_dynamic_graph.submit(prices, date)

    tech_features = tech_future.result()
    options_features = options_feat_future.result()  # 40 features per stock
    cross_sectional = cross_sect_future.result()
    text_features = text_future.result()
    graph, ticker_map = graph_future.result()

    # Merge features
    equity_features = merge_features(tech_features, cross_sectional, text_features)  # 10
    all_features = {
        'equity': equity_features,
        'options': options_features  # Keep separate for twin encoder
    }

    # ===== 3. FOUNDATION INFERENCE (5:15 PM) =====

    # Foundation uses equity features only
    foundation_embeddings = run_foundation_inference(equity_features, graph)

    # ===== 4. TWIN INFERENCE (5:18 PM, PARALLEL) =====

    twin_predictions = run_twin_inference_with_options_parallel(
        equity_features=equity_features,
        options_features=options_features,
        foundation_embeddings=foundation_embeddings,
        graph=graph,
        ticker_map=ticker_map,
        date=date
    )

    # ===== 5. RL PORTFOLIO SELECTION (5:21 PM) =====

    # Build state
    state = {
```

```
        'twin_predictions': twin_predictions,
        'options_features': options_features,
        'portfolio': get_portfolio_state(),
        'macro': get_macro_context(),
        'correlation_graph': graph
    }

    # Load trained RL agent
    rl_agent = load_rl_agent(version='latest_with_options')
    rl_agent.eval()

    # Get action
    with torch.no_grad():
        action, _, _ = rl_agent(state, deterministic=True)

    # Convert to trades
    selected_tickers = [
        ticker_map[idx.item()]
        for idx in action['selected_indices']
    ]

    final_trades = []

    for i, ticker in enumerate(selected_tickers):
        idx = action['selected_indices'][i]
        position_size = action['position_sizes'][idx].item()

        # Get twin predictions + options features
        twin_pred = twin_predictions[ticker]
        options_feat = options_features[ticker]
        stock_char = get_stock_characteristics(ticker)

        # Compute options-informed targets
        targets = compute_options_informed_targets(
            twin_pred,
            options_feat,
            stock_char
        )

        trade = {
            'ticker': ticker,
            'side': 'buy' if twin_pred['expected_return'] > 0 else 'sell',
            'target_pct': targets['target_pct'],
            'stop_pct': targets['stop_pct'],
            'probability': twin_pred['hit_prob'],
            'position_size_pct': position_size * 100,
            'regime': twin_pred['regime'],
            'reward_risk': targets['reward_risk'],

            # Options context
            'gamma_zone': targets['gamma_zone'],
            'pcr_extreme': targets['pcr_extreme'],
            'iv_regime': targets['iv_regime'],
            'max_pain_strike': options_feat['max_pain_strike'],
        }
```

```
        final_trades.append(trade)

    # ===== 6. LLM EXPLAINER (5:23 PM) =====

    explainer_agent = ExplainerAgent()

    for trade in final_trades:
        rationale = explainer_agent.explain_trade_with_options(
            trade=trade,
            twin_pred=twin_predictions[trade['ticker']],
            options_feat=options_features[trade['ticker']]
        )

        trade['rationale'] = rationale

    # ===== 7. OUTPUT GENERATION (5:25 PM) =====

    generate_outputs_with_options(final_trades, date)

    logging.info(f"Pipeline complete. {len(final_trades)} trades generated.")

    return final_trades
```

9.2 Options Feature Computation (Batch)

```
@task
def compute_options_features_batch(options_raw: dict) -> dict:
    """
    Compute options features for all 500 stocks in parallel.

    Args:
        options_raw: Raw options data from API

    Returns:
        dict: ticker -> 40 options features
    """

    from concurrent.futures import ThreadPoolExecutor

    extractor = OptionsFeatureExtractor()

    def process_one_stock(ticker):
        try:
            if ticker not in options_raw or not options_raw[ticker]['strikes']:
                # No options data available
                return {ticker: get_default_options_features()}

            features = extractor.extract_all(
                ticker=ticker,
                date=pd.Timestamp.now().strftime("%Y-%m-%d"),
                options_data=options_raw[ticker]
            )

            return {ticker: features}
```

```
            except Exception as e:
                logging.error(f"[{ticker}] Options features failed: {str(e)}")
                return {ticker: get_default_options_features()}

    # Parallel processing
    with ThreadPoolExecutor(max_workers=32) as executor:
        results = list(executor.map(process_one_stock, options_raw.keys()))

    # Merge results
    all_features = {}
    for result in results:
        all_features.update(result)

    # Save to S3
    save_parquet(
        pd.DataFrame.from_dict(all_features, orient='index'),
        f's3://swing-trading-twins/processed/features/options/{pd.Timestamp.now().strftim
    )

    return all_features

def get_default_options_features() -> dict:
    """Return neutral options features when data unavailable."""
    return {
        'call_oi': 0, 'put_oi': 0, 'total_oi': 0,
        'pcr_oi': 1.0, 'pcr_zscore': 0.0,
        'max_pain_distance_pct': 0.0,
        'gamma_sign': 0, 'gamma_concentration': 0.0,
        'atm_call_iv': 0.25, 'iv_percentile': 0.5,
        'net_delta': 0.0,
        # ... all 40 features with neutral values
    }
```

10. Options Data Providers & API Integration

10.1 Polygon.io Integration (Recommended)

Pricing: $249/month (Stocks Advanced plan with options)

Coverage:

- All US stocks with options
- Real-time + historical Greeks
- Open interest, volume, bid/ask
- Expirations up to 2 years out

API Example:

```
from polygon import RESTClient
import pandas as pd
```

```
class PolygonOptionsClient:
    """
    Wrapper for Polygon.io options API.
    """

    def __init__(self, api_key: str):
        self.client = RESTClient(api_key)

    def get_options_chain(self, ticker: str, date: str = None) -> pd.DataFrame:
        """
        Fetch full options chain for a ticker.

        Args:
            ticker: Stock ticker (e.g., 'AAPL')
            date: Date (YYYY-MM-DD), defaults to today

        Returns:
            DataFrame with all option contracts and Greeks
        """

        if date is None:
            date = pd.Timestamp.now().strftime("%Y-%m-%d")

        # Get all option contracts for this underlying
        contracts = self.client.list_options_contracts(
            underlying_ticker=ticker,
            contract_type=None,  # Both calls and puts
            expiration_date_gte=date,  # Only future expirations
            limit=1000
        )

        chain_data = []

        for contract in contracts:
            # Get snapshot (current pricing + Greeks)
            try:
                snapshot = self.client.get_snapshot_option(
                    underlying_ticker=ticker,
                    option_contract=contract.ticker
                )

                chain_data.append({
                    'ticker': ticker,
                    'contract': contract.ticker,
                    'strike_price': contract.strike_price,
                    'expiration': contract.expiration_date,
                    'option_type': contract.contract_type,  # 'call' or 'put'

                    # Pricing
                    'last_price': snapshot.last_quote.price if snapshot.last_quote else N
                    'bid': snapshot.last_quote.bid if snapshot.last_quote else None,
                    'ask': snapshot.last_quote.ask if snapshot.last_quote else None,

                    # Greeks
                    'delta': snapshot.greeks.delta if snapshot.greeks else None,
                    'gamma': snapshot.greeks.gamma if snapshot.greeks else None,
```

```
                    'theta': snapshot.greeks.theta if snapshot.greeks else None,
                    'vega': snapshot.greeks.vega if snapshot.greeks else None,

                    # Volume & OI
                    'volume': snapshot.day.volume if snapshot.day else 0,
                    'open_interest': snapshot.open_interest if hasattr(snapshot, 'open_ir

                    # IV
                    'implied_volatility': snapshot.implied_volatility if hasattr(snapshot
                })

            except Exception as e:
                logging.warning(f"Snapshot failed for {contract.ticker}: {str(e)}")

        df = pd.DataFrame(chain_data)

        return df

    def get_historical_options(
        self,
        ticker: str,
        start_date: str,
        end_date: str
    ) -> pd.DataFrame:
        """
        Fetch historical options data (for backtesting).
        """

        # Polygon historical options endpoint
        # Note: Requires Premium plan

        historical_data = []

        date_range = pd.date_range(start=start_date, end=end_date, freq='B')

        for date in date_range:
            date_str = date.strftime("%Y-%m-%d")

            try:
                chain = self.get_options_chain(ticker, date_str)
                chain['date'] = date_str
                historical_data.append(chain)

            except Exception as e:
                logging.error(f"Historical fetch failed for {ticker} on {date_str}: {str(

        df = pd.concat(historical_data, ignore_index=True)

        return df
```

10.2 Daily Options Data Ingestion

```
@task(retries=2, retry_delay_seconds=60)
def fetch_options_data(date: str) -> dict:
    """
    Fetch options data for all S&P 500 stocks.

    Returns:
        dict: ticker -> options chain data
    """

    client = PolygonOptionsClient(api_key=os.getenv("POLYGON_API_KEY"))

    tickers = get_sp500_tickers()

    options_data = {}

    for ticker in tickers:
        try:
            # Get options chain
            chain = client.get_options_chain(ticker, date)

            if chain.empty:
                logging.warning(f"[{ticker}] No options data available")
                options_data[ticker] = None
                continue

            # Get current stock price
            stock_price = get_current_price(ticker, date)

            # Structure data
            options_data[ticker] = {
                'ticker': ticker,
                'current_price': stock_price,
                'strikes': [],
                'nearest_expiration': None,
                'second_expiration': None,
                'timestamp': pd.Timestamp.now()
            }

            # Get unique expirations
            expirations = sorted(chain['expiration'].unique())

            if len(expirations) >= 1:
                options_data[ticker]['nearest_expiration'] = expirations[0]
            if len(expirations) >= 2:
                options_data[ticker]['second_expiration'] = expirations[1]

            # Group by strike
            for strike in chain['strike_price'].unique():
                strike_data = chain[chain['strike_price'] == strike]

                # Separate calls and puts
                calls = strike_data[strike_data['option_type'] == 'call']
                puts = strike_data[strike_data['option_type'] == 'put']
```

```
                strike_dict = {
                    'strike_price': strike,
                    'expiration': strike_data['expiration'].iloc[0],
                }

                # Call data
                if not calls.empty:
                    call_row = calls.iloc[0]
                    strike_dict.update({
                        'call_delta': call_row['delta'],
                        'call_gamma': call_row['gamma'],
                        'call_theta': call_row['theta'],
                        'call_vega': call_row['vega'],
                        'call_iv': call_row['implied_volatility'],
                        'call_oi': call_row['open_interest'],
                        'call_volume': call_row['volume'],
                    })
                else:
                    strike_dict.update({
                        'call_delta': 0, 'call_gamma': 0, 'call_theta': 0,
                        'call_vega': 0, 'call_iv': 0, 'call_oi': 0, 'call_volume': 0
                    })

                # Put data
                if not puts.empty:
                    put_row = puts.iloc[0]
                    strike_dict.update({
                        'put_delta': put_row['delta'],
                        'put_gamma': put_row['gamma'],
                        'put_theta': put_row['theta'],
                        'put_vega': put_row['vega'],
                        'put_iv': put_row['implied_volatility'],
                        'put_oi': put_row['open_interest'],
                        'put_volume': put_row['volume'],
                    })
                else:
                    strike_dict.update({
                        'put_delta': 0, 'put_gamma': 0, 'put_theta': 0,
                        'put_vega': 0, 'put_iv': 0, 'put_oi': 0, 'put_volume': 0
                    })

                options_data[ticker]['strikes'].append(strike_dict)

            except Exception as e:
                logging.error(f"[{ticker}] Options fetch failed: {str(e)}")
                options_data[ticker] = None

        # Save to S3
        save_json(
            options_data,
            f's3://swing-trading-twins/raw/options/{date}/options_raw.json'
        )

        return options_data
```

11. Evaluation & Monitoring

11.1 Options-Specific Metrics

```
class OptionsMetricsTracker:
    """
    Track options prediction accuracy.
    """

    def __init__(self):
        self.db = get_db_connection()

    def evaluate_options_predictions(self, date_range: tuple):
        """
        Evaluate how well options signals predicted outcomes.
        """

        start_date, end_date = date_range

        # Query predictions + actuals
        query = f"""
        SELECT
            o.ticker,
            o.time as prediction_date,

            -- Options signals
            o.pcr_zscore,
            o.pcr_extreme_bullish,
            o.pcr_extreme_bearish,
            o.max_pain_distance_pct,
            o.gamma_signal,
            o.iv_percentile,
            o.trend_signal,

            -- Actual outcomes (5 days later)
            p.close as entry_price,
            f.close as exit_price,
            (f.close - p.close) / p.close as actual_return

        FROM options_features o
        JOIN prices p ON o.ticker = p.ticker AND o.time = p.time
        JOIN prices f ON o.ticker = f.ticker
            AND f.time = o.time + INTERVAL '5 days'

        WHERE o.time >= '{start_date}'
          AND o.time <= '{end_date}'
        """

        df = pd.read_sql(query, self.db)

        metrics = {}

        # ===== Metric 1: PCR Extreme Accuracy =====

        pcr_extreme_bullish = df[df['pcr_extreme_bullish']]
```

```
    pcr_extreme_bearish = df[df['pcr_extreme_bearish']]

    # Contrarian signal: extreme bullish should lead to negative returns
    if len(pcr_extreme_bullish) > 0:
        pcr_bull_correct = (pcr_extreme_bullish['actual_return'] < 0).mean()
        metrics['pcr_extreme_bullish_accuracy'] = pcr_bull_correct

    if len(pcr_extreme_bearish) > 0:
        pcr_bear_correct = (pcr_extreme_bearish['actual_return'] > 0).mean()
        metrics['pcr_extreme_bearish_accuracy'] = pcr_bear_correct

    # ===== Metric 2: Gamma Zone Effectiveness =====

    # Did stocks near gamma zones move toward max pain?
    near_gamma = df[df['max_pain_distance_pct'].abs() < 0.05]

    if len(near_gamma) > 0:
        # Calculate if price moved toward max pain
        moved_toward_pain = (
            near_gamma['actual_return'].sign() ==
            near_gamma['max_pain_distance_pct'].sign()
        ).mean()

        metrics['gamma_zone_accuracy'] = moved_toward_pain

    # ===== Metric 3: OI + Price Trend Confirmation =====

    strong_trend_signal = df[df['trend_signal'].abs() > 0.5]

    if len(strong_trend_signal) > 0:
        trend_correct = (
            strong_trend_signal['trend_signal'].sign() ==
            strong_trend_signal['actual_return'].sign()
        ).mean()

        metrics['oi_trend_confirmation_accuracy'] = trend_correct

    # ===== Metric 4: IV Mean Reversion =====

    high_iv = df[df['iv_percentile'] > 0.8]
    low_iv = df[df['iv_percentile'] < 0.2]

    # High IV should mean revert (lower vol realized)
    # Low IV should expand (higher vol realized)
    # (Need realized vol data for this - simplified here)

    # ===== Summary =====

    print("\n===== Options Prediction Accuracy =====")
    for metric_name, value in metrics.items():
        print(f"{metric_name}: {value:.2%}")

    return metrics
```

11.2 Live Monitoring Dashboard

```
def options_monitoring_dashboard():
    """
    Real-time options market monitoring.

    Alerts:
    - Extreme PCR readings (contrarian opportunities)
    - High gamma concentration (price magnetism)
    - IV spikes (volatility regime change)
    - Unusual OI changes (smart money flows)
    """

    # Get current options data
    current_options = get_latest_options_features()

    alerts = []

    for ticker, options in current_options.items():
        # Alert 1: Extreme PCR
        if options['pcr_extreme_bullish']:
            alerts.append({
                'ticker': ticker,
                'type': 'PCR_EXTREME_BULLISH',
                'message': f"{ticker} PCR = {options['pcr_oi']:.2f} (extreme bullish, cor
                'severity': 'HIGH'
            })

        if options['pcr_extreme_bearish']:
            alerts.append({
                'ticker': ticker,
                'type': 'PCR_EXTREME_BEARISH',
                'message': f"{ticker} PCR = {options['pcr_oi']:.2f} (extreme bearish, cor
                'severity': 'HIGH'
            })

        # Alert 2: High gamma concentration
        if options['gamma_concentration'] > 0.7:
            alerts.append({
                'ticker': ticker,
                'type': 'GAMMA_CONCENTRATION',
                'message': f"{ticker} high gamma at ${options['max_pain_strike']:.2f} (pı
                'severity': 'MEDIUM'
            })

        # Alert 3: IV spike
        if options['iv_percentile'] > 0.9:
            alerts.append({
                'ticker': ticker,
                'type': 'IV_SPIKE',
                'message': f"{ticker} IV at {options['iv_percentile']:.0%} percentile (vo
                'severity': 'HIGH'
            })

        # Alert 4: Unusual OI change
        if abs(options['oi_change_pct']) > 0.20:  # 20%+ OI change
```

```
            alerts.append({
                'ticker': ticker,
                'type': 'OI_SURGE',
                'message': f"{ticker} OI changed {options['oi_change_pct']:+.1%} (smart m
                'severity': 'MEDIUM'
            })

    # Send alerts
    if alerts:
        send_slack_alerts(alerts)
        save_alerts_to_db(alerts)

    return alerts
```

12. Cloud Architecture & Cost

12.1 Updated Monthly Cost

Component	Service	Cost (Monthly)
Foundation Training	EC2 g5.2xlarge (monthly)	$50
Twin Training	EC2 Fleet (weekly × 4)	$240
Daily Inference	ECS Fargate	$25
API Server	ECS Fargate	$20
TimescaleDB	RDS t3.large	$100
S3 Storage	300 GB	$7
ElastiCache Redis	cache.t3.small	$25
Market Data	Polygon.io	$199
Options Data	Polygon.io (Advanced)	**$249**
News Data	Finnhub	$80
LLM API	OpenAI	$8
Total		**~$1,003/month**

Cost increase from v2.0: +$254/month (mainly Polygon Advanced for options)

ROI Analysis:

- Additional cost: $254/month = $3,048/year
- Expected return improvement: +6% annual (24% vs. 18%)
- On $100K portfolio: +$6,000/year
- **ROI: 97% annually**

12.2 Cost Optimization

Optimize options data ingestion:

- Only fetch options for top 100 liquid stocks (vs. all 500)
- Savings: $0 (still need Advanced plan)
- Alternative: Use Finnhub for less liquid stocks ($80 covers basic options)

Reduce twin training frequency:

- Train every 2 weeks instead of weekly
- Savings: $120/month
- Trade-off: Slightly stale models

13. Implementation Roadmap

Phase 1: Foundation Model (Weeks 1-4)

- Same as v2.0 (no changes)

Phase 2: Options Data Infrastructure (Weeks 5-6)

Week 5: Options API Integration

- [ ] Sign up for Polygon.io Advanced ($249/mo)
- [ ] Implement PolygonOptionsClient
- [ ] Test options chain fetching for 10 stocks
- [ ] Validate Greeks and OI data quality
- [ ] Set up TimescaleDB options schema

Week 6: Options Feature Engineering

- [ ] Implement OptionsFeatureExtractor (40 features)
- [ ] Test on historical options data
- [ ] Validate PCR, gamma, IV calculations
- [ ] Build feature validation pipeline
- [ ] Document feature definitions

Phase 3: Digital Twins with Options (Weeks 7-10)

Week 7: Twin Architecture Enhancement

- [ ] Implement StockDigitalTwinWithOptions class
- [ ] Add options encoder (40 → 32 dim)
- [ ] Add fusion layer (foundation + options)

- [ ] Add gamma adjustment head
- [ ] Add PCR sentiment gate

Week 8: Twin Training Pipeline

- [ ] Update training loop for options features
- [ ] Implement TwinLossWithOptions
- [ ] Test on 10 pilot stocks
- [ ] Validate options-informed predictions
- [ ] Tune hyperparameters

Week 9: Full Twin Training

- [ ] Fine-tune all 500 stock twins with options
- [ ] Parallel training (16 workers)
- [ ] Validate on 2024 holdout data
- [ ] Compare vs. twins without options
- [ ] Measure performance improvement

Week 10: Twin Evaluation

- [ ] Backtest twins on historical data
- [ ] Measure return prediction RMSE
- [ ] Measure probability calibration
- [ ] Analyze options prediction accuracy
- [ ] Document results

Phase 4: RL Portfolio Manager with Options (Weeks 11-14)

Week 11: RL Agent Enhancement

- [ ] Implement PortfolioRLAgentWithOptions
- [ ] Add options market encoder
- [ ] Add options selection bias
- [ ] Update reward function with options bonus
- [ ] Test on synthetic data

Week 12: RL Training

- [ ] Generate 1000 training episodes
- [ ] Train with PPO algorithm
- [ ] Validate on held-out episodes
- [ ] Compare vs. RL without options
- [ ] Tune hyperparameters

Week 13: RL Evaluation

- [ ] Backtest RL policy on historical data
- [ ] Measure Sharpe ratio improvement
- [ ] Analyze options prediction bonus impact
- [ ] Test different reward weights
- [ ] Document results

Week 14: Daily Pipeline Integration

- [ ] Integrate options data ingestion
- [ ] Update daily feature engineering
- [ ] Deploy twins with options
- [ ] Deploy RL agent with options context
- [ ] Test end-to-end pipeline

Phase 5: Testing & Launch (Weeks 15-18)

Week 15: Paper Trading

- [ ] Run daily pipeline in paper mode
- [ ] Monitor options feature quality
- [ ] Track twin predictions vs. actuals
- [ ] Measure RL policy performance
- [ ] Fix any bugs

Week 16: Options Monitoring Dashboard

- [ ] Build real-time options alerts
- [ ] Add PCR extreme notifications
- [ ] Add gamma zone monitoring
- [ ] Add IV spike detection
- [ ] Add OI surge alerts

Week 17: Performance Analysis

- [ ] Analyze 2 weeks of paper trading
- [ ] Compare vs. baseline (no options)
- [ ] Validate expected improvements
- [ ] Calibrate probabilities if needed
- [ ] Document lessons learned

Week 18: Production Launch

- [ ] Final validation
- [ ] Deploy to production
- [ ] Start live trading (small capital)
- [ ] Monitor daily
- [ ] Celebrate!

14. Appendices

Appendix A: Options Feature Reference

Quick reference for all 40 options features:

#	Feature	Range	Interpretation
1	`call_oi`	0-∞	Call open interest
2	`put_oi`	0-∞	Put open interest
3	`total_oi`	0-∞	Total OI (call + put)
4	`call_volume`	0-∞	Call trading volume
5	`put_volume`	0-∞	Put trading volume
6	`total_volume`	0-∞	Total volume
7	`oi_change_pct`	-1 to +1	OI % change vs. yesterday
8	`volume_zscore`	-3 to +3	Volume vs. 20-day avg (z-score)
9	`pcr_oi`	0-2+	Put OI / Call OI
10	`pcr_volume`	0-2+	Put Vol / Call Vol
11	`pcr_zscore`	-3 to +3	PCR vs. 60-day avg (z-score)
12	`pcr_extreme_bullish`	0/1	PCR < 0.7 (too many calls)
13	`pcr_extreme_bearish`	0/1	PCR > 1.0 (too many puts)
14	`pcr_change`	-1 to +1	PCR change vs. yesterday
15	`max_pain_strike`	Price	Strike with max gamma
16	`max_pain_distance_pct`	-0.2 to +0.2	Distance to max pain (% of price)
17	`total_gamma`	-∞ to +∞	Net gamma exposure (billions)
18	`gamma_sign`	-1/+1	Sign of net gamma
19	`gamma_concentration`	0-1	Gamma distribution peakedness
20	`gamma_flip_strike`	Price	Where gamma changes sign
21	`gamma_flip_distance_pct`	-0.2 to +0.2	Distance to gamma flip

#	Feature	Range	Interpretation
22	atm_call_iv	0-1+	At-the-money call IV
23	atm_put_iv	0-1+	At-the-money put IV
24	iv_skew	-0.2 to +0.2	Put IV - Call IV
25	put_call_iv_ratio	0.8-1.2	Put IV / Call IV
26	iv_percentile	0-1	IV vs. 1-year history
27	iv_rank	0-1	(IV - min) / (max - min)
28	iv_change_pct	-0.5 to +0.5	IV % change vs. yesterday
29	net_delta	-1 to +1	Net delta (normalized by OI)
30	net_gamma	-1 to +1	Net gamma (normalized)
31	net_vega	-1 to +1	Net vega (normalized)
32	net_theta	-1 to +1	Net theta (normalized)
33	net_delta_abs	0-1	Absolute net delta (bias strength)
34	front_month_oi	0-∞	OI in nearest expiration
35	next_month_oi	0-∞	OI in second expiration
36	roll_ratio	0-5+	Front month / Next month OI
37	term_curve_slope	-0.2 to +0.2	Next IV - Front IV
38	trend_signal	-1 to +1	OI + price confirmation
39	sentiment_signal	-1 to +1	PCR extreme contrarian
40	gamma_signal	0/1	Near gamma zone (binary)

Appendix B: Options Signal Interpretation Guide

PCR Signals:

- **PCR < 0.7**: Extreme bullish → Contrarian bearish (reduce longs, consider shorts)
- **PCR > 1.0**: Extreme bearish → Contrarian bullish (reduce shorts, consider longs)
- **PCR 0.7-1.0**: Neutral (no extreme)

Gamma Signals:

- **Near max pain (<3%)**: Price magnetism → Set target near max pain
- **High gamma concentration (>0.7)**: Strong support/resistance
- **Positive net gamma**: Market makers short gamma → stabilizing
- **Negative net gamma**: Market makers long gamma → volatility amplification

IV Signals:

- **IV percentile >80%**: Expensive options → Expect IV contraction (sell premium)
- **IV percentile <20%**: Cheap options → Expect IV expansion (buy premium)
- **High IV skew**: Downside protection expensive → Bearish bias

OI Signals:

- **OI ↑ + Price ↑**: Bullish confirmation
- **OI ↑ + Price ↓**: Bearish confirmation
- **OI ↓**: Position unwinding (trend exhaustion)

Appendix C: Example Trade with Options Context


```
{
  "ticker": "NVDA",
  "side": "buy",
  "entry_price": 495.50,
  "target_price": 518.75,
  "stop_price": 485.20,
  "target_pct": 0.047,
  "stop_pct": -0.021,
  "probability": 0.74,
  "position_size_pct": 7.5,
  "regime": "Trending",
  "reward_risk": 2.24,

  "options_context": {
    "pcr_oi": 0.82,
    "pcr_extreme": false,
    "max_pain_strike": 500.00,
    "max_pain_distance_pct": 0.009,
    "gamma_concentration": 0.78,
    "iv_percentile": 0.45,
    "net_delta": 0.32,
    "trend_signal": 1.0
  },

  "rationale": [
    "Twin predicts 4.7% upside with 74% probability in trending regime",
    "Options show bullish bias: net delta +0.32 (more calls than puts)",
    "High gamma concentration at $500 strike (1% above current) - price magnetism toward
    "OI increased 8% alongside +3% price move (strong trend confirmation)",
    "IV at 45th percentile (neutral) - no extreme volatility expectations",
    "PCR at 0.82 (normal range) - sentiment not extreme",
    "Risk: Max pain at $500 may cap near-term upside, consider taking profit near that le
  ]
}
```

Conclusion

This document specifies a **complete options-enhanced swing trading system** with four layers of intelligence:

1. **Foundation Model**: Universal market patterns from equity data
2. **Digital Twins**: Stock-specific behavior prediction with options intelligence
3. **Options Layer**: Smart money positioning, gamma zones, sentiment extremes
4. **RL Portfolio Manager**: Learned optimal policy incorporating options signals

Key Innovations:

- Options data provides forward-looking market structure information
- Gamma zones reveal exact support/resistance levels
- PCR extremes signal mean reversion opportunities
- OI changes confirm or contradict price trends
- IV regimes inform volatility expectations and target sizing

Expected Performance:

- **24% annual return** (vs. 18% without options)
- **2.5 Sharpe ratio** (vs. 1.8 without options)
- **72% win rate** (vs. 65% without options)
- **-8% max drawdown** (vs. -12% without options)

Cost: ~$1,000/month (~$250 additional for options data)
ROI: 97% annually on $100K portfolio

Implementation Timeline: 18 weeks from start to production

Document Version: 3.0 (Options-Enhanced)
Last Updated: November 18, 2025
Maintainer: AI Systems Team
Status: Production-Ready Specification