



# Autonomous Trading with Options and Futures

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# Objective



We aim to leverage Autonomous Agents to create a risk-averse strategy that trades correlated options and futures together.



# Financial Background

# Options and Futures

## Options

- Enter position with less capital
- Delta lies in between -1 and 1
- Underlying assets are usually equities

## Futures

- Requires initial margin, involves taking on leverage
- Delta is always 1
- Underlying assets are usually commodities

# Correlation and Causation

**Correlated** options and futures bring about consistent movement between the two instruments which gives us the ability to trade them together.

The ETF 'XLE' (Energy Sector) is a weighted basket of energy equities.

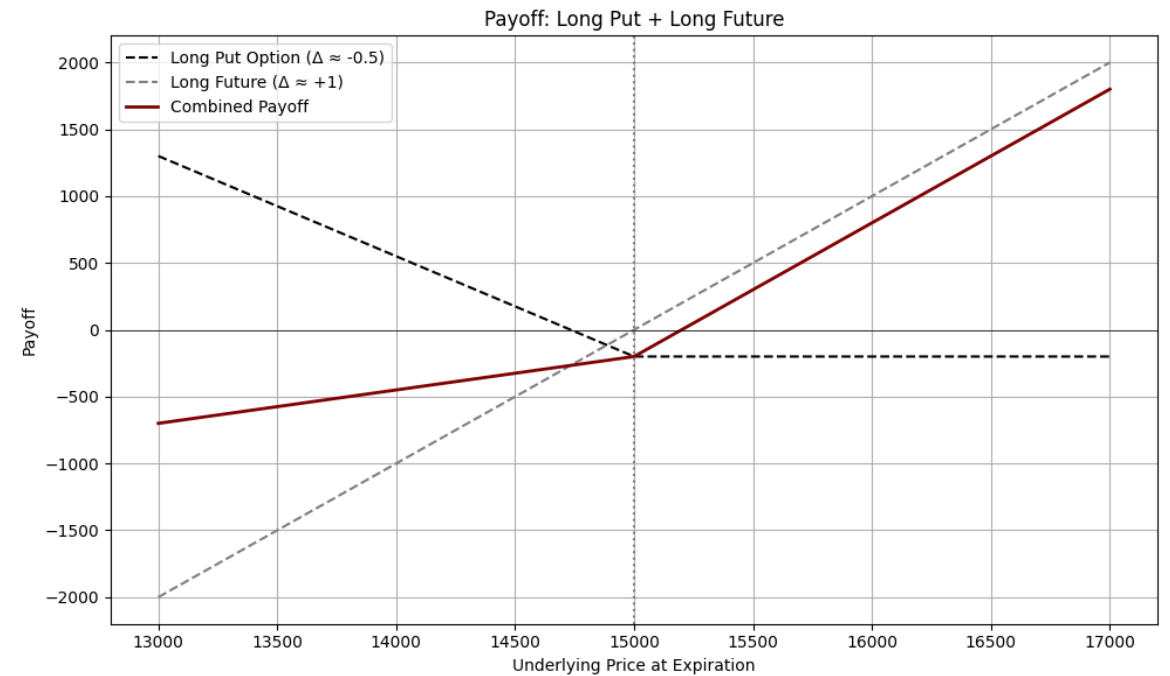
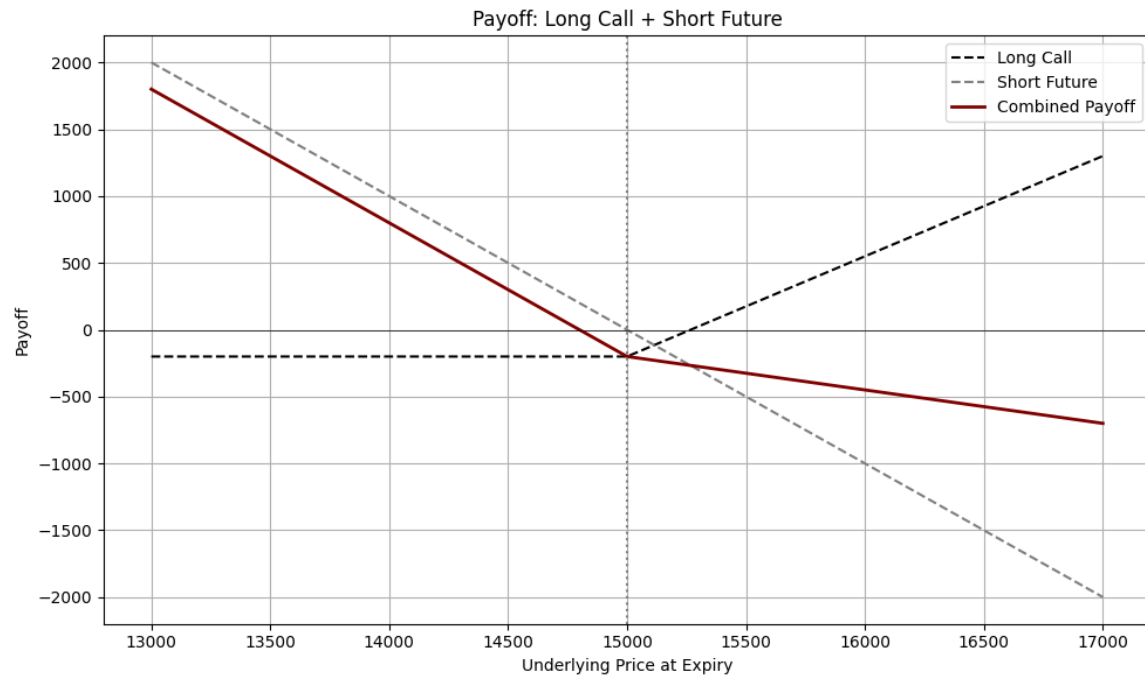
The future 'CL' (crude oil) tracks the commodity that drives the earnings of these energy equities.

Oil price movement has a causal impact on XLE, so the option prices react to the price of the ETF.

Other option and future pairs we used were:  
XLC/NQ and XLK/NQ

# Hedging a future with option(s)

The instruments traded are option-future pairs in a straddle-like structure.





# Autonomous Trading



# Reinforcement Learning

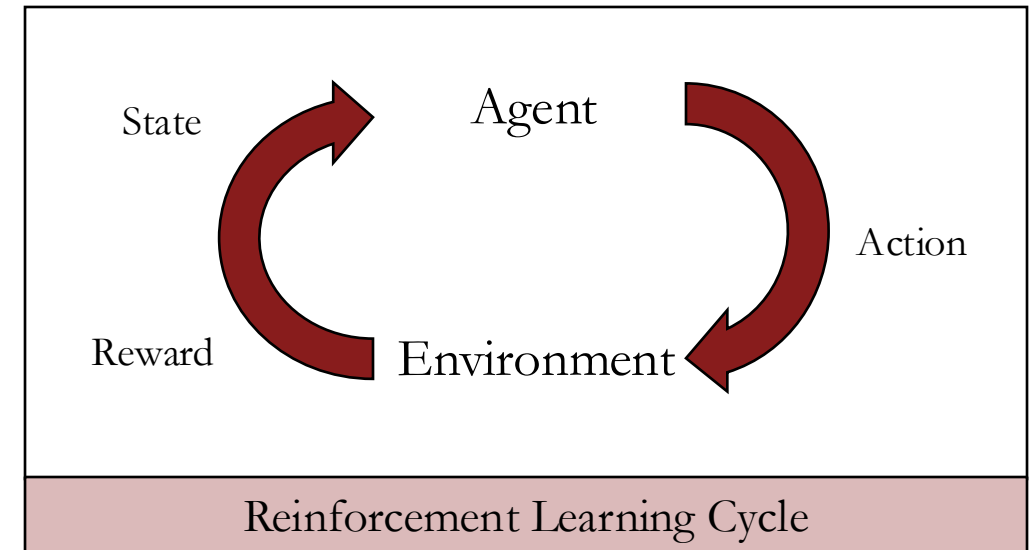
Reinforcement Learning (RL) is a field of Machine Learning that takes inspiration from behavioral psychology.

- RL models learn by taking actions in an environment and getting feedback in the form of a reward/penalty.

Over time, the model figures out the best action it can take given a particular environment state.

- ChatGPT: selecting the better answer
- DeepMind's AlphaGo

Reinforcement Learning originates from UMass Amherst and Professor Barto's work





# Financial Agents

- The markets are incredibly complex – no amount of data can ever capture their entirety due to limitations in compute.

- Instead of trying to decide when to trade solely based on specific indicators, have the model/agent learn from its past successes and failures.

- Use the market as an environment, since we can never represent it with 100% accuracy or certainty.

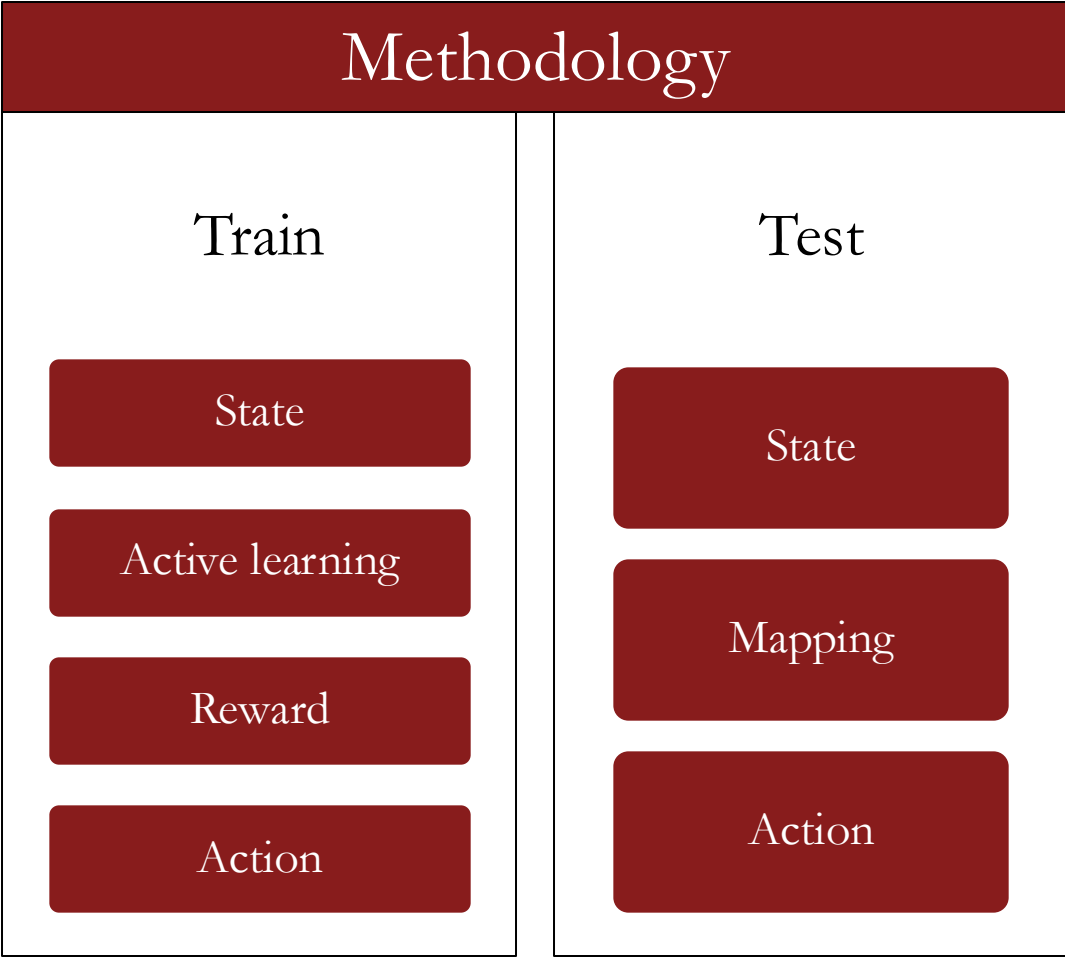
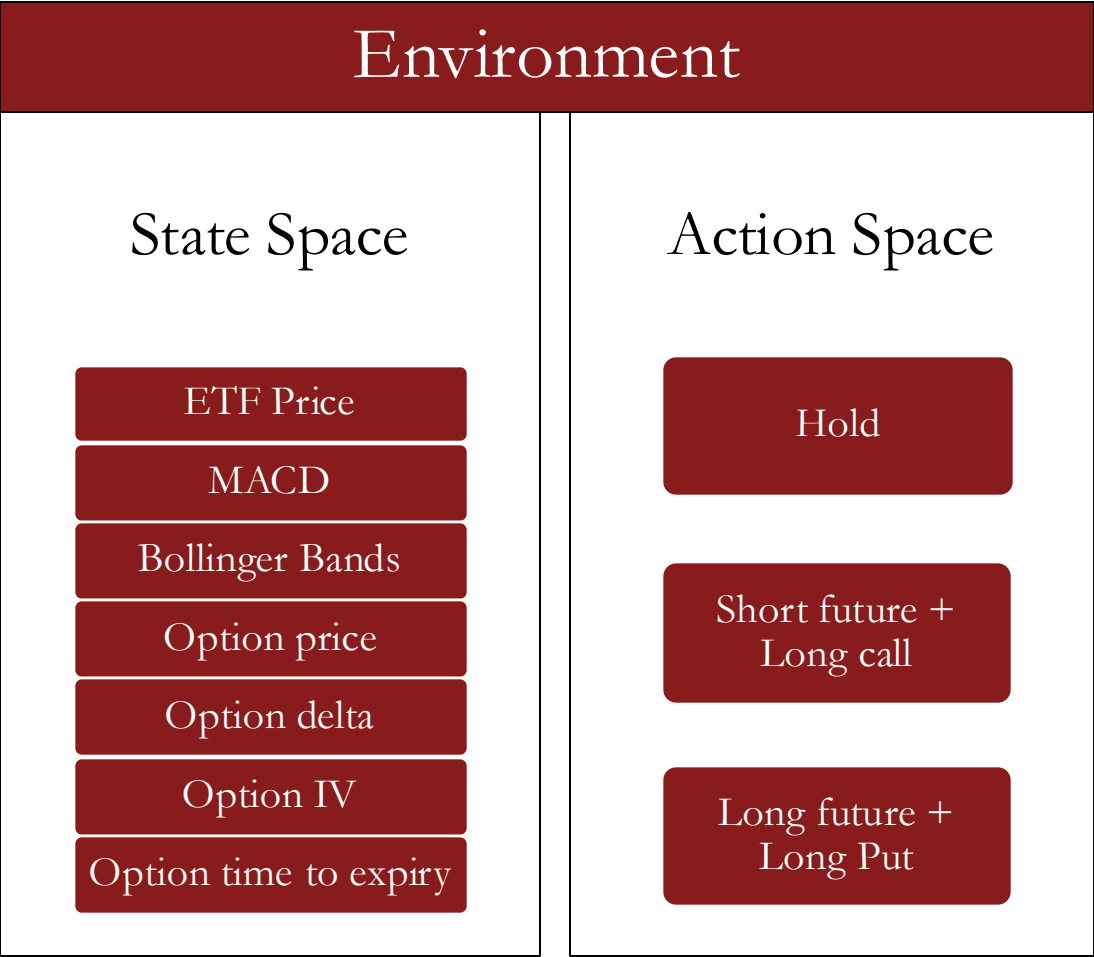
- Have the model learn when to enter positions or hold based on making trades (timing the market).

● 0  
Hold

● 1  
Trade a  
**Short  
Future +  
Long Call**

● 2  
Trade a  
**Long  
Future +  
Long  
Put**

# Our Model



# Reward Function

If no trades have been made yet (no data):

Randomly **choose** between short future + long call and long future + long put and assign a reward of **1**

Otherwise:

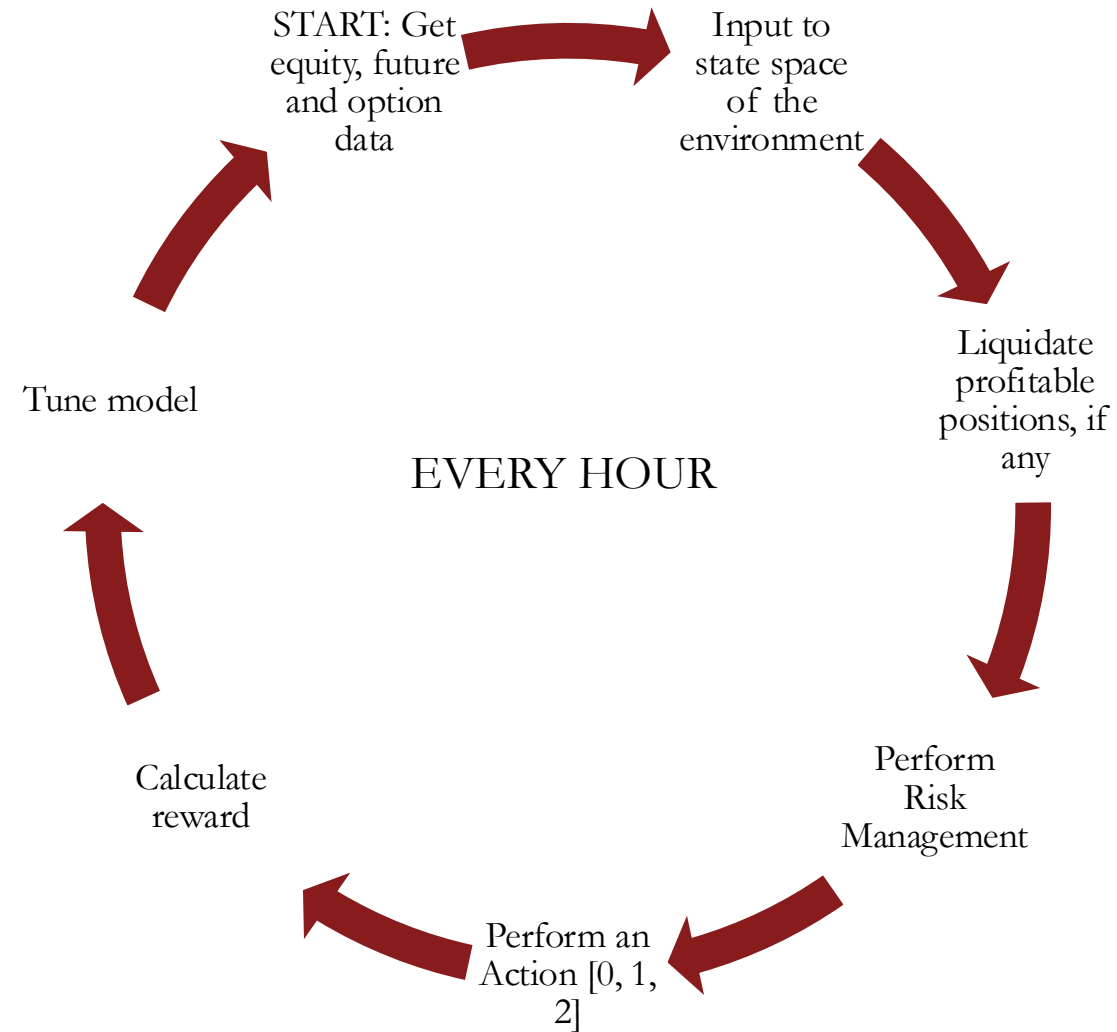
1. Calculate the **change in the portfolio value** from the last hour of trading (i.e. between the last time new data was received and the current state) and assign the reward that value
2. Scaling the reward to match model criteria.
3. Calculate a **simplified Sharpe ratio term** (Mean/Std. Deviation) over the last 30 hours and add it to the reward.
4. Encourage trading by penalizing holding - when the reward is non-positive, **subtract 1** from the reward.

$$Reward = \Delta(Portfolio Value) * scale\_factor + \frac{mean}{std.deviation}$$



# The Algorithm

# Control Flow



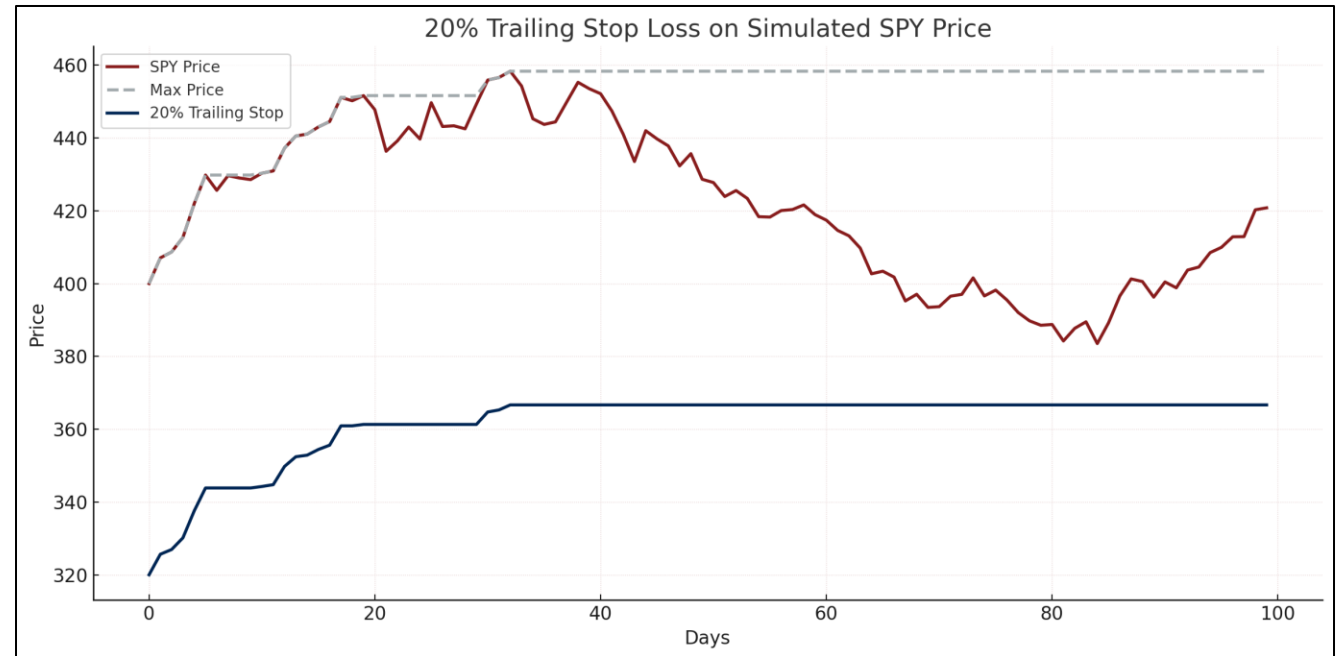
# Risk Management

## 15-20% Trailing Stop Loss

- Checked every hour
- Allows the model to explore and learn from mistakes
- 5% and 10% stop-loss fared worse, as our model incurred more losses gradually

## Position Liquidation Timing

- Positions are liquidated when:
  - An option contract is 2 days from expiry.
  - The contract holds unrealized profit





# Results



# Evaluation

All algorithm parameters remaining constant, different backtesting results can occur.

Model "re-starts" every backtest (model persistence)

5-month training phase: Oct 7th, 2024 – Feb 27th, 2025

2-month testing phase: Feb 27th, 2025 – April 30th, 2025

Each backtest only trades one future-option pair – ensures causality between actions and rewards

We only need one backtest that learned timing signals to demonstrate efficacy, as that model can be used in testing mode beyond the scope of the backtest

Large number of trades and win rate expresses the statistical confidence in model decisions, drawdown indicates the exploratory nature of RL

# XLE – CL Backtest



**Returns: 30.27%**

**Net Profit: \$151,335.00**

**Number of Trades: 5710**

**Win Rate: 77%**

**Sharpe Ratio: 1.11**

**Alpha: 0.43**

**Drawdown: 18.1%**

**SPY Returns: -2.34%**

# XLC – NQ Backtest



**Returns: 60.18 %**

**Net Profit: \$300,878.80**

**Number of Trades: 5673**

**Win Rate: 84%**

**Sharpe Ratio: 1.688**

**Alpha: 1.192**

**Drawdown: 39.8%**

**SPY Returns: -2.34%**

# XLK – NQ Backtest



**Returns:** 118.15 %

**Net Profit:** \$590,725.65

**Number of Trades:** 5688

**Win Rate:** 90%

**Sharpe Ratio:** 3.183

**Alpha:** 2.129

**Drawdown:** 35.3%

**SPY Returns:** -2.34%

# Summary



- 1 The model trades contracts itself - it's not just an indicator, but an agent.
- 2 The model trades **call options with short futures** and **put options with long futures** to make profit in either direction of the underlying.
- 3 Works well in high volatility market conditions and outperforms the S&P by a great margin.
- 4 Future Work : Multiple Pairs, MARL, Stabilizing Testing Methods.



# Questions?