Algo Professor
www.algoprofessor.weebly.com

Dr S Satyanarayana Ph.D.,FARSC

AlgoProfessor Objective

- Algo Professor Quantitative Research & Investment Management Company Trading in Indian financial markets, Dedicated to producing exceptional returns for its Investors by strictly adhering to Mathematical , Statistical , Artificial Intelligence and Machine Learning Methods.
-

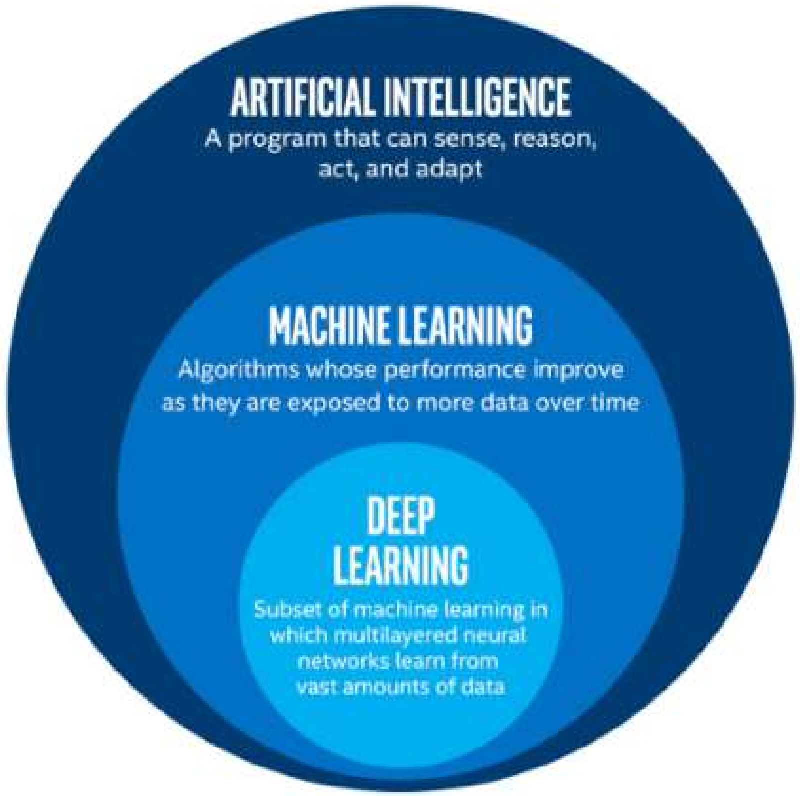
Dynamic
Deep Reinforcement Learning
Social
Algo Trading Strategies

Dr S.Satyanarayana
CEO & Chief Data Scientist
AlgoProfessor

Agenda

- Basic Terminology
- Domain Knowledge
- Deep Learning
- Reinforcement Learning
- Back Testing Results

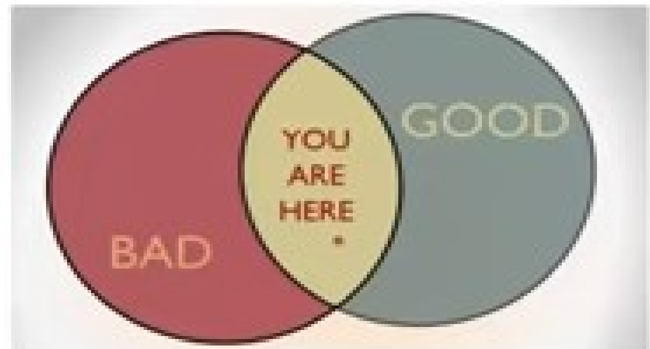
AI vs ML vs DL



AI. vs ML. vs DL.

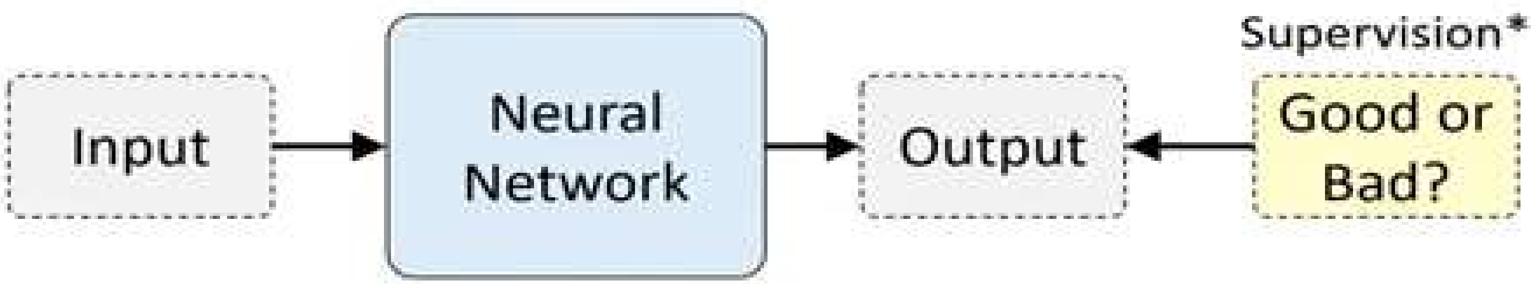
Types of Learning

- Supervised Learning
- Semi-Supervised Learning
- Unsupervised Learning
- Reinforcement Learning



It's all "supervised" by a loss function!

**Someone has to say what's good and what's bad (see Socrates, Epictetus, Kant, Nietzsche, etc.)*



Classes of Learning Problems

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn function to map
$$x \rightarrow y$$

Apple example:

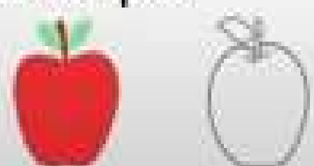
This thing is an apple.

Unsupervised Learning

Data: x
x is data, no labels!

Goal: Learn underlying structure

Apple example:



This thing is like the other thing.

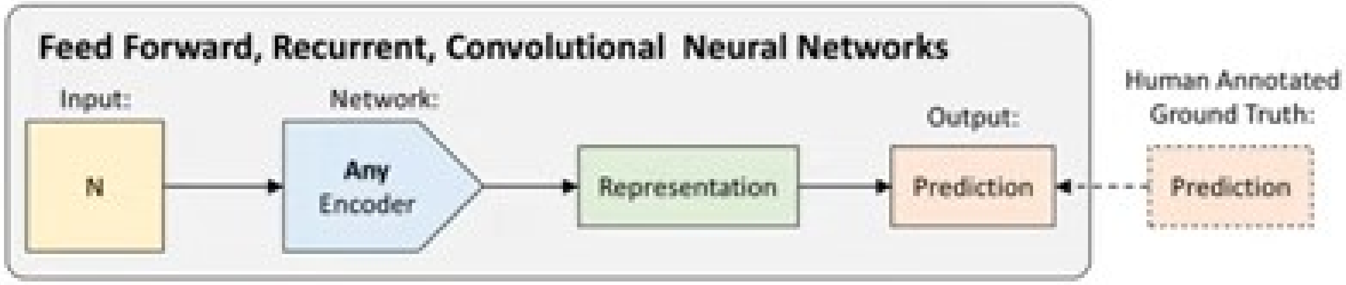
Reinforcement Learning

Data: state-action pairs

Goal: Maximize future rewards over many time steps

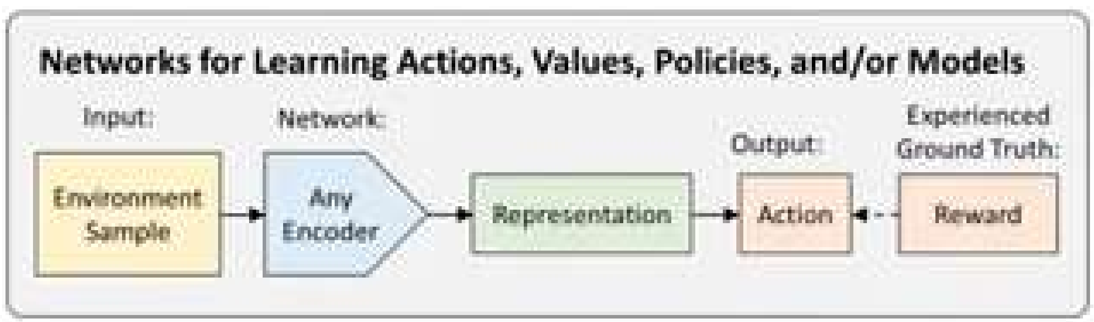
Apple example:

Eat this thing because it will keep you alive.

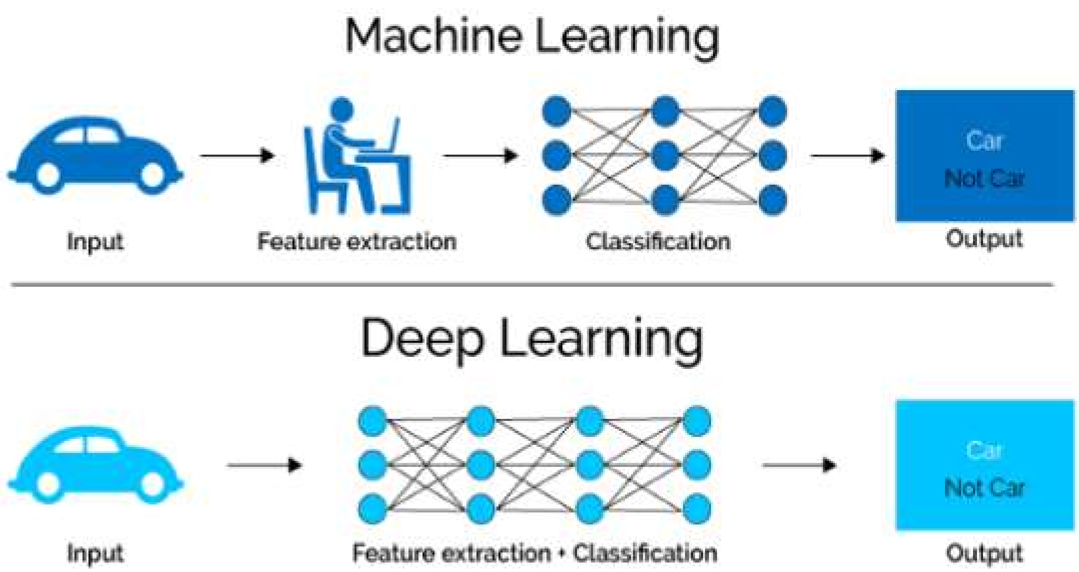


Supervised learning is “teach by **example**”:
Here’s some examples, now learn patterns in these example.

Reinforcement learning is “teach by **experience**”:
Here’s a world, now learn patterns by exploring it.



Machine Learning vs Deep Learning



Feature Extraction is only required for ML Algorithms.

Deep Learning

- Deep learning is a type of machine learning and artificial intelligence (AI) that imitates the way humans gain certain types of knowledge. While traditional machine learning algorithms are linear, deep learning algorithms are stacked in a hierarchy of increasing complexity and abstraction.

Reinforcement learning

- Reinforcement learning is a machine learning training method based on rewarding desired behaviors and/or punishing undesired ones. In general, a reinforcement learning agent is able to perceive and interpret its environment, take actions and learn through trial and error.

Social Trading

If you're new to the market, social trading is what you need. At its simplest it allows you to sift through hundreds of strategies, see key statistics and choose the ones you want to add to your portfolio. Since all the data is transparently available you can take into consideration additional factors, such as trading strategy past performance, backtesting results and asset-types.

Algo Trading

- Algorithmic trading (automated trading, black-box trading, or simply algo trading) is the process of using computers programmed to follow a defined set of instructions for placing a trade in order to generate profits at a speed and frequency that is impossible for a human trader.

Algo Trading Stratigies

The following are common trading strategies used in algo-trading:

- Trend-following Strategies.
- Arbitrage Opportunities.
- Index Fund Rebalancing.
- Mathematical Model-based Strategies.
- Trading Range (Mean Reversion)
- Volume-weighted Average Price (VWAP)
- Time Weighted Average Price (TWAP)
- Percentage of Volume (POV)

Algo Professor _Social Algo Trading Stategy

Super Bank Nifty Bot 400.0

★★★★★ 3 ratings

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ROI	Drawdown	Min Capital	Monthly Fee
83.92%	₹ 15.6 K (10%)	₹ 160,000	₹ 3,999 + 9%

Live Algo Professor Strategies

https://tradetron.tech/strategies?searchString=algo+professor&rating=&rank=on

6 ratings

Reinforcement Machine Learning Bank Nifty Bot

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NFO | News | Volatility | PivotPoint | SupportResistance | EarnTheta | HighFrequency | MarketNeutral | TrendFollowing | Breakout | Scalping | Swing | Bullish | Bearish | Directional

ROI	Drawdown	Min Capital	Monthly Fee
61.91%	₹ 12.6 K (13%)	₹ 100000	₹ 2999 + 10%

Super Bank Nifty Bot 400.0

3 ratings

Read More...

by: Algo Professor

NFO | Volatility | Bullish | Bearish | EarnTheta | IVSkew | EventBased | Momentum | HighFrequency | Intraday | Breakout

ROI	Drawdown	Min Capital	Monthly Fee
76.69%	₹ 15.3 K (10%)	₹ 160000	₹ 3999 + 9%

Deep Machine Learning Bank Nifty 5000 X Profit (Revised28-04-2021) Bot

★★★★★
5 ratings

Read More...

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NFO | Volatility | Bullish | Bearish | Arbitrage | EarnTheta | Directional | TrendFollowing | Momentum | HighFrequency | Scalping | Swing

ROI	Drawdown ⓘ	Min Capital	Monthly Fee ⓘ
42.60%	₹ 21.2 K (14%)	₹ 150000	₹ 3999 + 9%

Algo Professor Bank Nifty High Profit Bot (Start Date: 7-06-2021)

3 ratings

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ROI	Drawdown	Min Capital	Monthly Fee
58.66%	₹ 13.5 K (5%)	₹ 260000	₹ 4999 + 9%

Domain Knowledge

Nifty -50

Nifty 50 Index · 1M · NSE
O17531.90 H18604.45 L17452.90 C18114.90 +496.75 (+2.82%)
18114.90
0.00
18114.90
Vol
Vol
18114.90
5d 6h
INR
16000.00
14000.00
12000.00
10000.00
8000.00
6000.00
4000.00
2000.00
0.00
2001
2003
2005
2007
2009
2011
2013
2015
2017
2019
2021

Nifty Bank

NIFTY BANK · 1M · NSE
O37140.40 H40587.35 L36876.35 C40323.65 +2898.55 (+7.74%)
40323.65
0.00
40323.65
Vol
Vol
40323.65
5d 6h
36000.00
32000.00
28000.00
24000.00
20000.00
16000.00
12000.00
8000.00
4000.00
0.00
2001
2003
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2011
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2015
2017
2019
2021
1D 5D 1M 3M 6M YTD 1Y 5Y All
09:40:13 (UTC+5:30)
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Option

- An option is a contract giving the buyer the right, but not the obligation, to buy or sell an underlying asset (a stock or index) at a specific price on or before a certain date (listed options are all for 100 shares of the particular underlying asset).

Nifty & Nifty Bank Examples

NIFTY 50 INDEX	-0.35 %	18114.90
NIFTY BANK INDEX	0.73 %	40323.65
NIFTY OCT 18000 CE	-19.37 %	227.00
BANKNIFTY OCT 40000 CE	24.86 %	625.00
BANKNIFTY OCT 40300 CE	17.25 %	436.00
BANKNIFTY OCT 40300 PE	**-34.46 %**	**308.05**

Black-Scholes-Merton

- The Black-Scholes-Merton model, sometimes just called the Black-Scholes model, is a mathematical model of financial derivative markets from which the Black-Scholes formula can be derived. This formula estimates the prices of call and put options.

Black–Scholes formula [edit]

The Black–Scholes formula calculates the price of European put and call options. This price is consistent with the Black–Scholes equation as above; this follows since the formula can be obtained by solving the equation for the corresponding terminal and boundary conditions:

$$C(0,t) = 0 \text{ for all } t$$
$$C(S,t) \rightarrow S \text{ as } S \rightarrow \infty$$
$$C(S,T) = \max\{S-K, 0\}$$

The value of a call option for a non-dividend-paying underlying stock in terms of the Black–Scholes parameters is:

$$C(S_t, t) = N(d_1)S_t - N(d_2)Ke^{-r(T-t)}$$
$$d_1 = \frac{1}{\sigma\sqrt{T-t}}\left[\ln\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)\right]$$
$$d_2 = d_1 - \sigma\sqrt{T-t}$$

The price of a corresponding put option based on put–call parity with discount factor $e^{-r(T-t)}$ is:

$$P(S_t, t) = Ke^{-r(T-t)} - S_t + C(S_t, t)$$
$$= N(-d_2)Ke^{-r(T-t)} - N(-d_1)S_t$$

Alternative formulation [edit]

Introducing some auxiliary variables allows the formula to be simplified and reformulated in a form that is often more convenient (this is a special case of the Black '76 formula):

$$C(F,\tau) = D\left[N(d_+)F - N(d_-)K\right]$$

$$d_+ = \frac{1}{\sigma\sqrt{\tau}}\left[\ln\left(\frac{F}{K}\right) + \frac{1}{2}\sigma^2\tau\right]$$

$$d_- = d_+ - \sigma\sqrt{\tau}$$

The auxiliary variables are:

- $D = e^{-r\tau}$ is the discount factor
- $F = e^{r\tau}S = \frac{S}{D}$ is the forward price of the underlying asset, and $S = DF$

with $d_+ = d_1$ and $d_- = d_2$ to clarify notation.

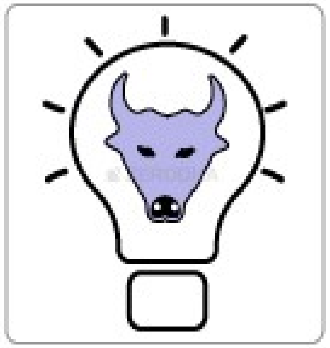
Given put–call parity, which is expressed in these terms as:

$$C - P = D(F - K) = S - DK$$

the price of a put option is:

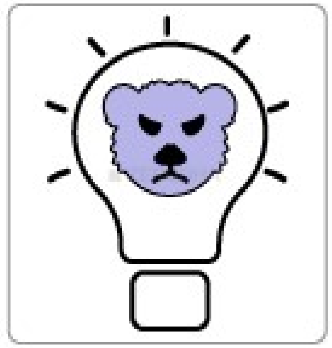
$$P(F,\tau) = D\left[N(-d_-)K - N(-d_+)F\right]$$

		Call	Put
Delta	$\frac{\partial V}{\partial S}$	$N(d_1)$	$-N(-d_1) = N(d_1) - 1$
Gamma	$\frac{\partial^2 V}{\partial S^2}$	$\frac{N'(d_1)}{S\sigma\sqrt{T-t}}$	
Vega	$\frac{\partial V}{\partial \sigma}$	$SN'(d_1)\sqrt{T-t}$	
Theta	$\frac{\partial V}{\partial t}$	$-\frac{SN'(d_1)\sigma}{2\sqrt{T-t}} - rKe^{-r(T-t)}N(d_2)$	$-\frac{SN'(d_1)\sigma}{2\sqrt{T-t}} + rKe^{-r(T-t)}N(-d_2)$
Rho	$\frac{\partial V}{\partial r}$	$K(T-t)e^{-r(T-t)}N(d_2)$	$-K(T-t)e^{-r(T-t)}N(-d_2)$



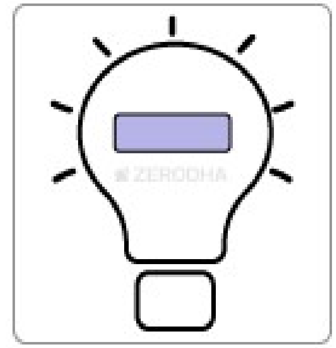
Bullish Strategies

1. Bull Call Spread
2. Bull Put Spread
3. Call Ratio Back Spread
4. Bear Call Ladder
5. Call Butterfly
6. Synthetic Call
7. Straps



Bearish Spreads

1. Bear Call Spread
2. Bear Put Spread
3. Bull Put Ladder
4. Put Ratio Back spread
5. Strip
6. Synthetic Put

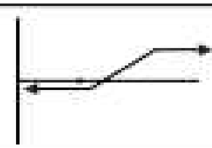
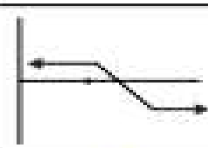
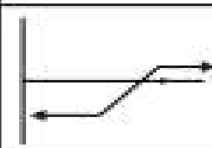
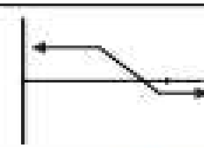


Neutral Strategies

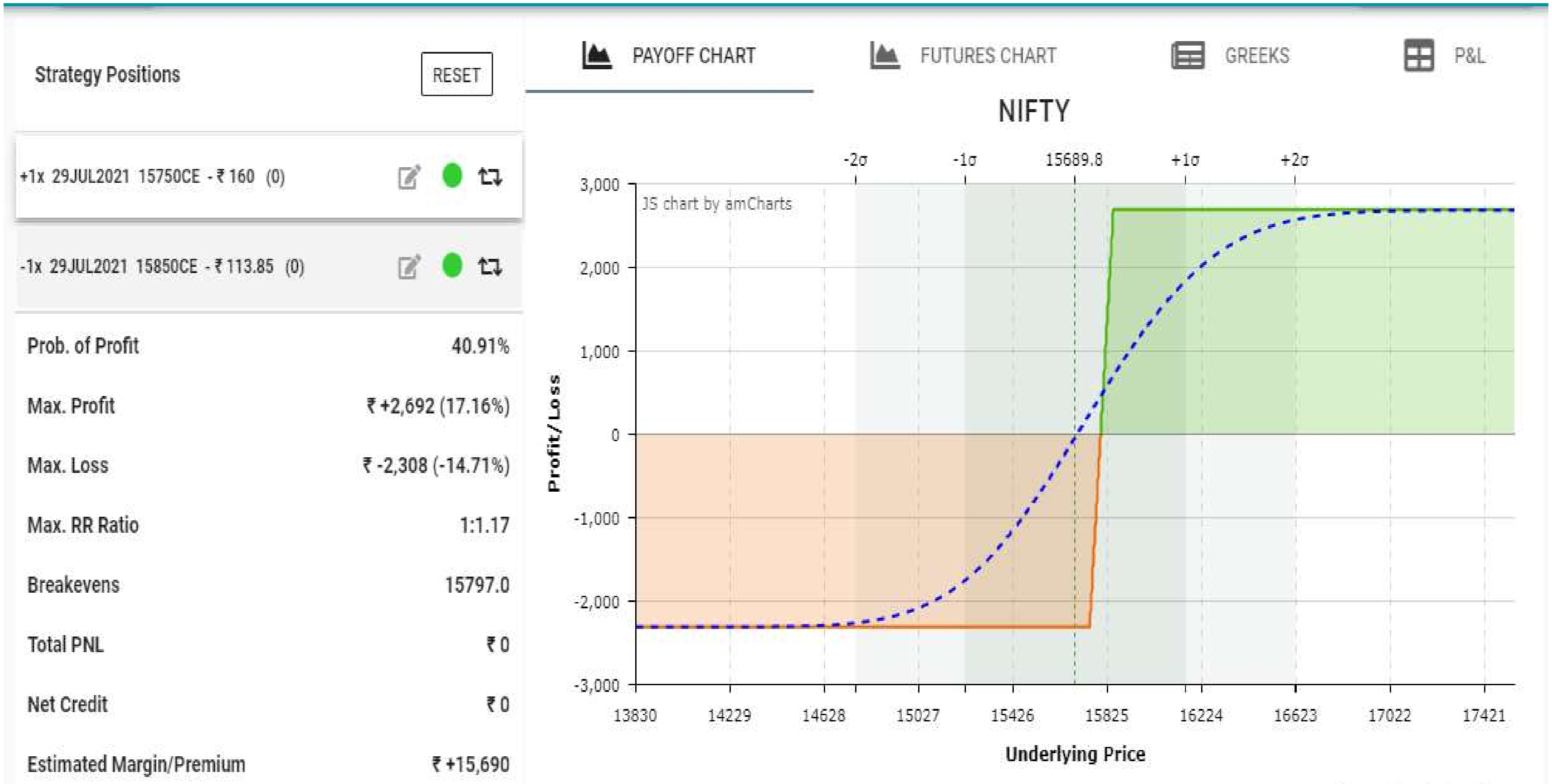
1. Long & Short Straddles
2. Long & Short Strangles
3. Long & Short Iron Condor
4. Long & Short Butterfly
5. Box

Live Code Using Tradetron/Python

Vertical Spread Cheat Sheet

	Long Call Vertical Spread	Short Call Vertical Spread	Long Put Vertical Spread	Short Put Vertical Spread
Description	Long call, short further OTM call	Short call, long further OTM call	Long put, short further OTM put	Short put, long further OTM put
Example	ATM = 100 Long 105 call Short 110 call	ATM = 100 Short 105 call Long 110 call	ATM = 100 Long 95 put Short 90 put	ATM = 100 Short 95 put Long 90 put
Pay or Collect Premium	Pay	Collect	Pay	Collect
Needed Directionality				
Passage of Time without Market Movement	– –	+ +	– –	+ +
Increase in Implied Volatility without Market Movement	+	–	+	–
Payoff Thumbnail Chart				
Maximum Risk	Cost of the spread	Width of the spread minus premium received	Cost of the spread	Width of the spread minus premium received
Maximum Profit	Width of the spread minus premium paid	Premium received	Width of the spread minus premium paid	Premium received
Breakeven Points	Long strike plus premium paid	Long strike plus premium paid	Long strike minus premium paid	Long strike minus premium paid

Nifty Long Call Vertical Spread



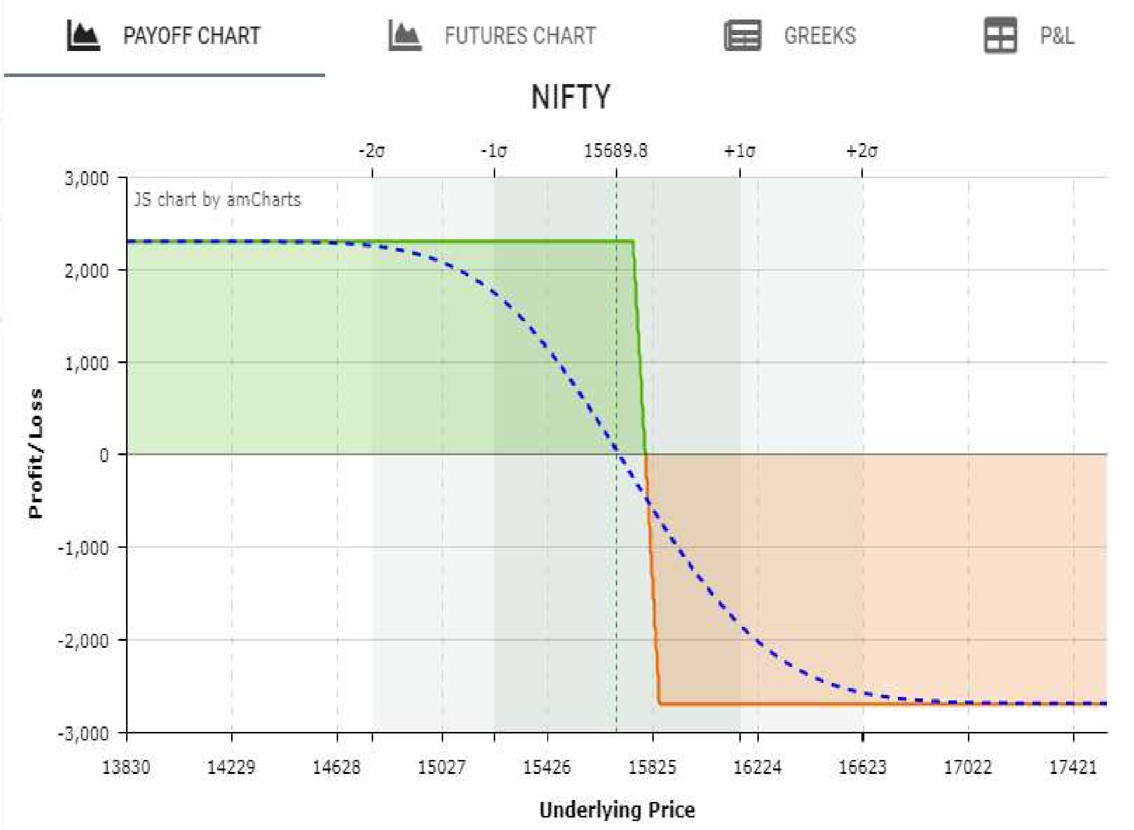
Nifty Short Call Vertical Spread

Strategy Positions RESET

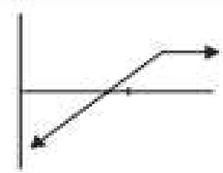
-1x 29JUL2021 15750CE - ₹ 160 (0)

+1x 29JUL2021 15850CE - ₹ 113.85 (0)

Prob. of Profit	59%
Max. Profit	₹ +2,308 (11.31%)
Max. Loss	₹ -2,692 (-13.19%)
Max. RR Ratio	1:0.86
Breakevens	0-15796.0
Total PNL	₹ 0
Net Credit	₹ +2,307.5
Estimated Margin/Premium	₹ +20,409



Covered Call Cheat Sheet

	Covered Call
Description	Long underlying stock, short call
Example	ATM = 100 Long 100 shares of stock Short one 105 strike call
Pay or Collect Premium	Collect
Needed Directionality	
Passage of Time without Market Movement	+ + +
Increase In Implied Volatility without Market Movement	– – –
Payoff Thumbnail Chart	
Maximum Risk	Price of the stock when the covered call is sold minus premium received (if stock drops to zero)
Maximum Profit	Regret point (call strike price plus premium received) minus price of the stock when the covered call is sold
Breakeven Points	Stock price when the covered call is sold minus premium received

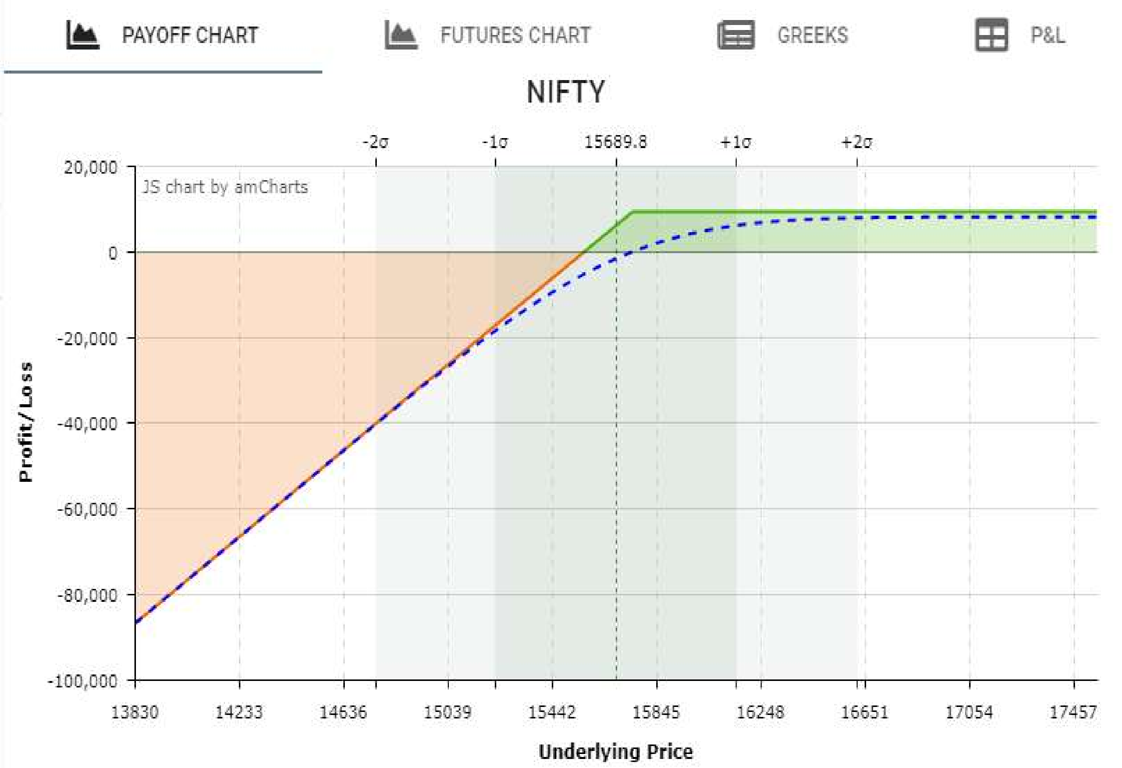
Nifty Covered Call

Strategy Positions RESET

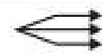
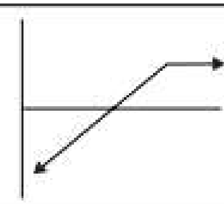
+1x 29JUL2021 FUTURES - ₹ 15721 (0)

-1x 29JUL2021 15750CE - ₹ 160 (0)

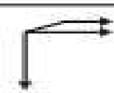
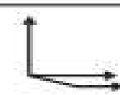
Prob. of Profit	60.96%
Max. Profit	₹ +9,450 (7.80%)
Max. Loss	₹ Undefined
Max. RR Ratio	NA
Breakevens	15561.0
Total PNL	₹ 0
Net Credit	₹ +8,000
Estimated Margin/Premium	₹ +121,215



Covered Put Cheat Sheet

	Covered Put
Description	Short put, long cash to buy stock at the strike price
Example	ATM = 100 Short one 95 strike put Long $9,500
Pay or Collect Premium	Collect
Needed Directionality	
Passage of Time without Market Movement	+ + +
Increase in Implied Volatility without Market Movement	– – –
Payoff Thumbnail Chart	
Maximum Risk	Strike price minus premium received (if stock drops to zero)
Maximum Profit	Premium received
Breakeven Points	Strike price minus premium received

Calendar Spread Cheat Sheet

	Long Call Calendar Spread	Short Call Calendar Spread	Long Put Calendar Spread	Short Put Calendar Spread
Description	Long longer-dated call, short shorter-dated call with same strike	Short longer-dated call, long shorter-dated call with same strike	Long longer-dated put, short shorter-dated put with same strike	Short longer-dated put, long shorter-dated put with same strike
Example	ATM = 100 Long 105 call expiring June Short 105 call expiring March	ATM = 100 Short 105 call expiring June Long 105 call expiring March	ATM = 100 Long 95 put expiring June Short 95 put expiring March	ATM = 100 Short 95 put expiring June Long 95 put expiring March
Pay or Collect Premium	Pay	Collect	Pay	Collect
Needed Directionality				
Passage of Time without Market Movement	+ +	– –	+ +	– –
Increase in Implied Volatility without Market Movement	+ +	– –	+ +	– –
Payoff Thumbnail Chart	Too many assumptions required	Too many assumptions required	Too many assumptions required	Too many assumptions required
Maximum Risk	Cost of the spread	Theoretically unlimited	Cost of the spread	Theoretically unlimited
Maximum Profit	Theoretically unlimited	Net premium received	Theoretically unlimited	Net premium received
Breakeven Points	Too many assumptions required	Too many assumptions required	Too many assumptions required	Too many assumptions required

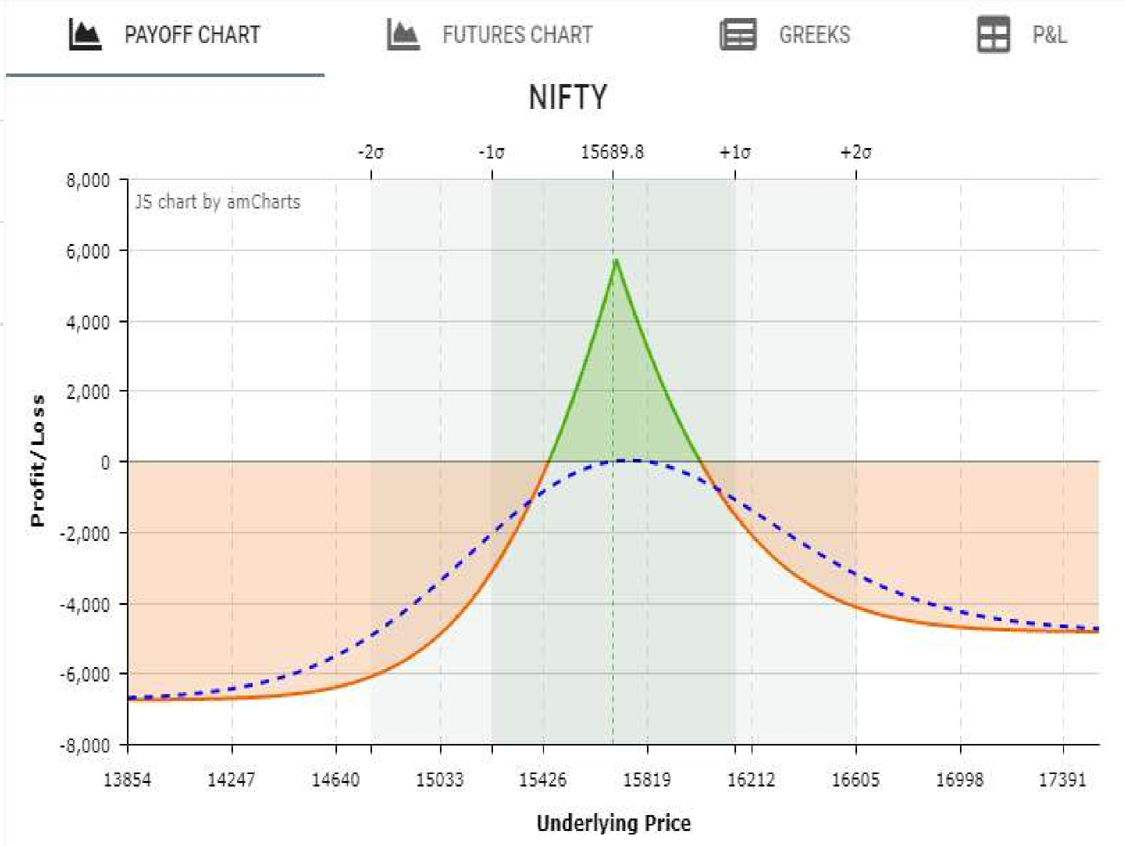
Nifty Long Calendar Spread

Strategy Positions RESET

+1x 26AUG2021 15700CE - ₹ 321.4 (0)

-1x 29JUL2021 15700CE - ₹ 186.75 (0)

Prob. of Profit	46.52%
Max. Profit	₹ +5,699 (30.64%)
Max. Loss	₹ -6,732 (-36.20%)
Max. RR Ratio	1:0.85
Breakevens	15443.0-16016.0
Total PNL	₹ 0
Net Credit	₹ 0
Estimated Margin/Premium	₹ +18,598



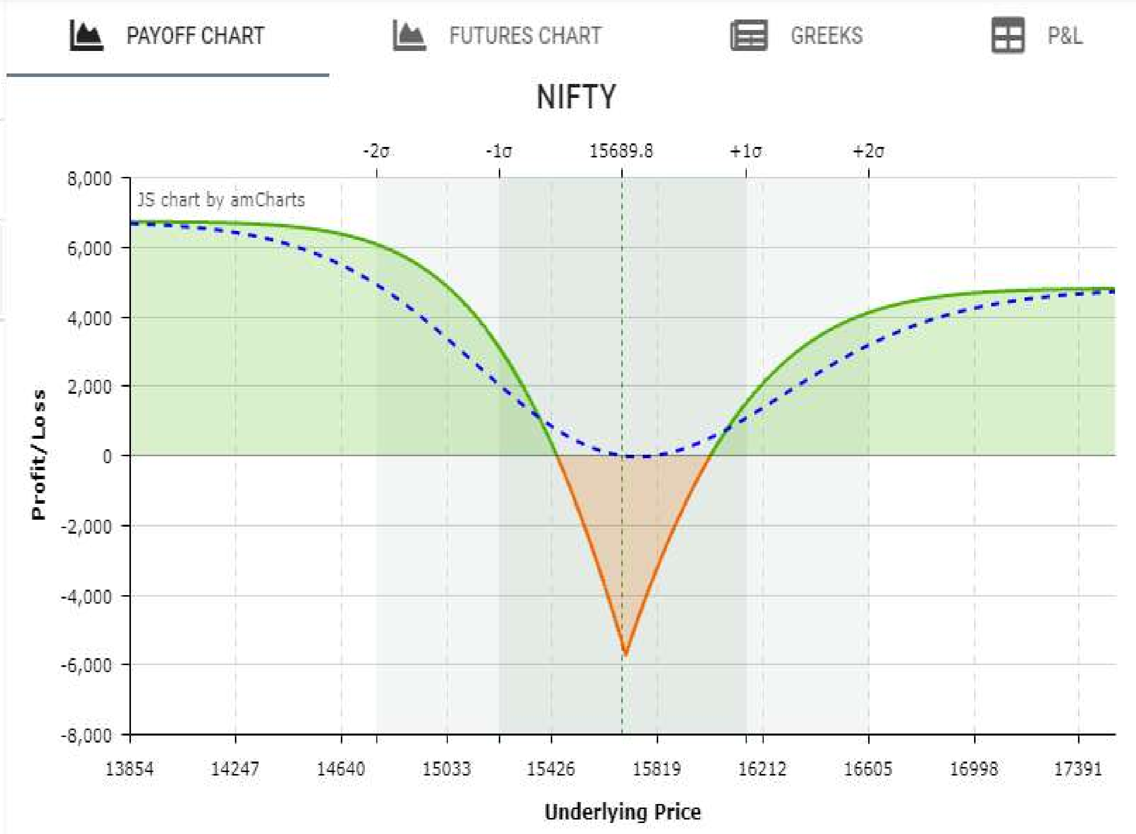
Nifty Short Calendar Spread

Strategy Positions RESET

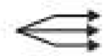
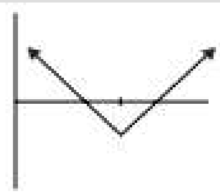
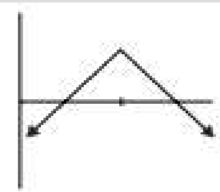
-1x 26AUG2021 15700CE - ₹ 321.4 (0)

+1x 29JUL2021 15700CE - ₹ 186.75 (0)

Prob. of Profit	53.48%
Max. Profit	₹ +6,732 (29.94%)
Max. Loss	₹ -5,699 (-25.35%)
Max. RR Ratio	1:1.18
Breakevens	15443.0-16016.0
Total PNL	₹ 0
Net Credit	₹ +6,732.5
Estimated Margin/Premium	₹ +22,482



Straddle Cheat Sheet

	Long Straddle	Short Straddle
Description	Long ATM call, long ATM put	Short ATM call, short ATM put
Example	ATM = 100 Long 100 Call Long 100 Put	ATM = 100 Short 100 Call Short 100 Put
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	– – – – –	+ + + + +
Increase in Implied Volatility without Market Movement	+ + + + +	– – – – –
Payoff Thumbnail Chart		
Maximum Risk	Cost of the straddle	Theoretically unlimited
Maximum Profit	Theoretically unlimited	Premium received
Breakeven Points	Strike price ± Cost of the straddle	Strike price ± Cost of the straddle

Nifty Long Straddle

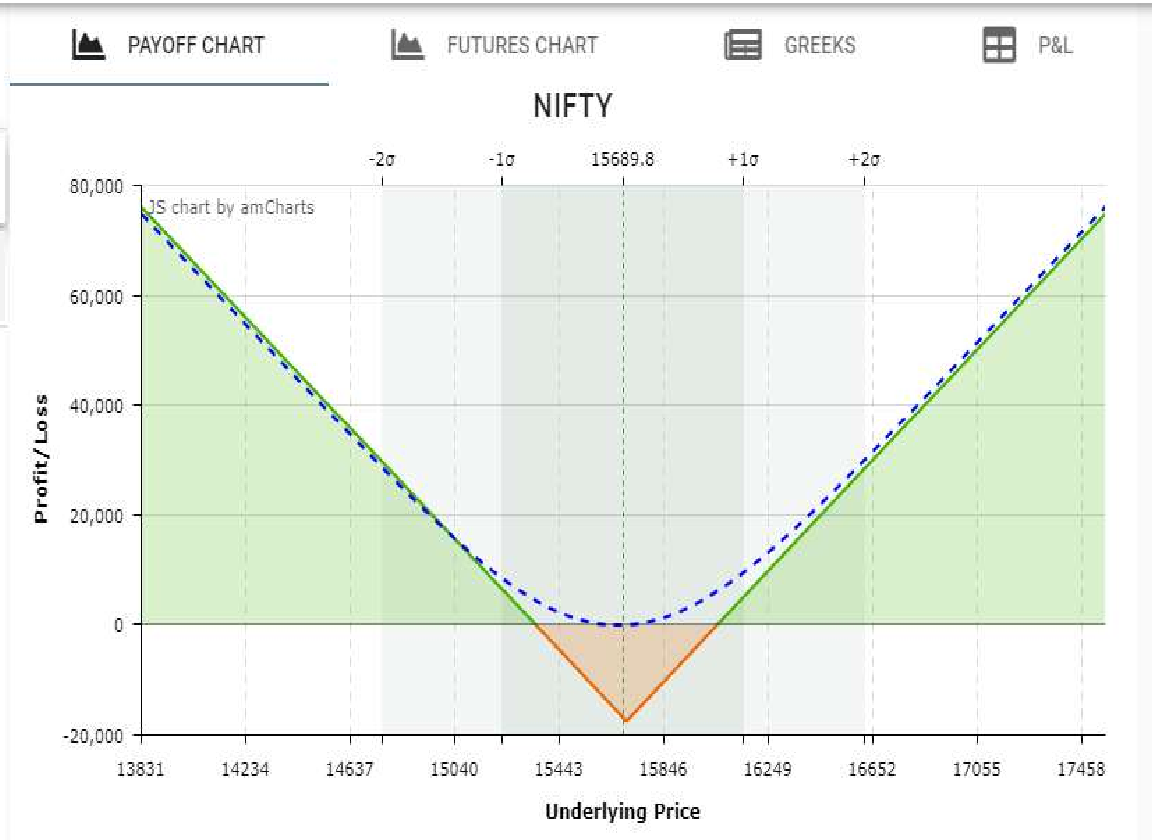
Strategy Positions

RESET

+1x 29JUL2021 15700CE - ₹ 186.75 (0)

+1x 29JUL2021 15700PE - ₹ 163 (0)

Prob. of Profit	45.3%
Max. Profit	₹ Undefined
Max. Loss	₹ -17,438 (-99.71%)
Max. RR Ratio	NA
Breakevens	15351.0-16049.0
Total PNL	₹ 0
Net Credit	₹ 0
Estimated Margin/Premium	₹ +17,488



Nifty Long Straddle

Strategy Positions

RESET

+1x 29JUL2021 15700CE - ₹ 186.75 (0)

+1x 29JUL2021 15700PE - ₹ 163 (0)

Prob. of Profit	45.3%
Max. Profit	₹ Undefined
Max. Loss	₹ -17,438 (-99.71%)
Max. RR Ratio	NA
Breakevens	15351.0-16049.0
Total PNL	₹ 0
Net Credit	₹ 0
Estimated Margin/Premium	₹ +17,488

PAYOFF CHART FUTURES CHART GREEKS P&L

Position	IV	Delta	Theta	Gamma	Vega
+1x 29JUL2021 15700CE	12.58	52.46	-483.17	0.09	1397.63
+1x 29JUL2021 15700PE	12.38	-47.52	-475.47	0.09	1397.58
	Positional Greeks	4.94	-958.64	0.18	2795.21

Greeks in Decimals

Greeks in Rs

Nifty Short Straddle

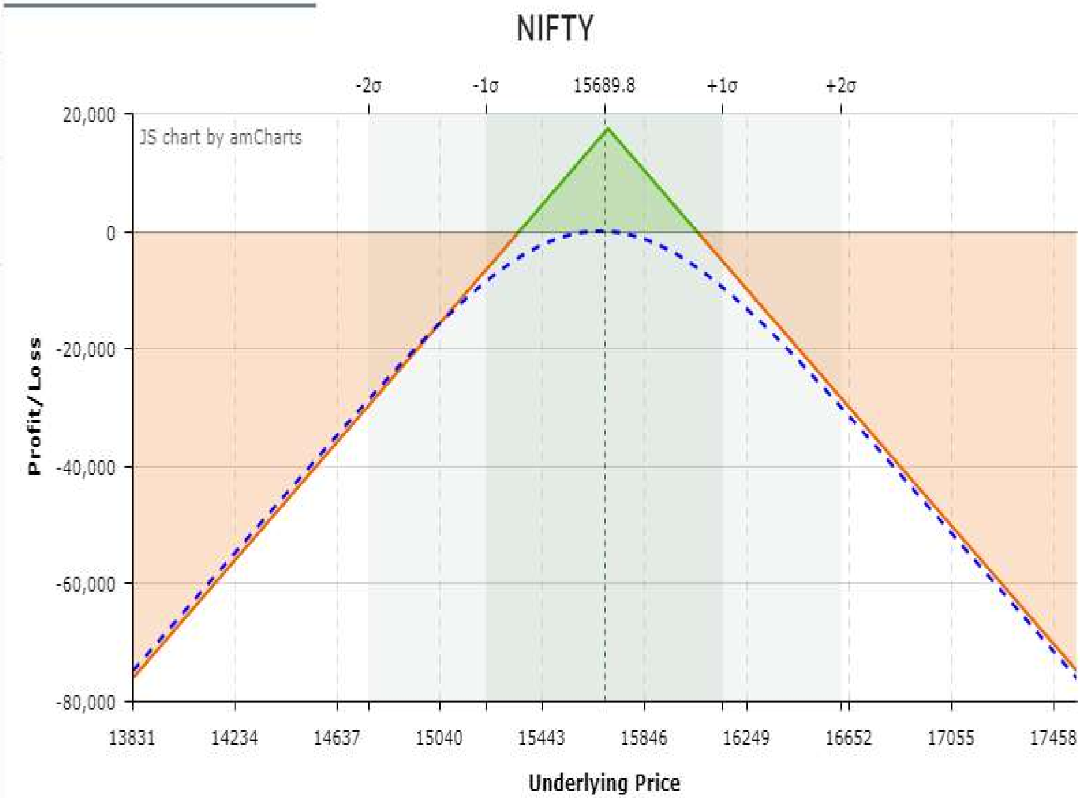
Strategy Positions RESET

-1x 29JUL2021 15700CE - ₹ 186.75 (0)

-1x 29JUL2021 15700PE - ₹ 163 (0)

Prob. of Profit	54.69%
Max. Profit	₹ +17,438 (15.12%)
Max. Loss	₹ Undefined
Max. RR Ratio	NA
Breakevens	15351.0-16049.0
Total PNL	₹ 0
Net Credit	₹ +17,487.5
Estimated Margin/Premium	₹ +115,314

PAYOFF CHART FUTURES CHART GREEKS P&L



Strategy Positions

RESET

-1x 29JUL2021 15700CE - ₹ 186.75 (0)

-1x 29JUL2021 15700PE - ₹ 163 (0)

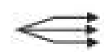
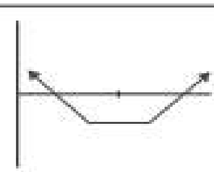
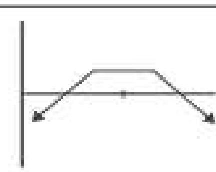
Prob. of Profit	54.69%
Max. Profit	₹ +17,438 (15.12%)
Max. Loss	₹ Undefined
Max. RR Ratio	NA
Breakevens	15351.0-16049.0
Total PNL	₹ 0
Net Credit	₹ +17,487.5
Estimated Margin/Premium	₹ +115,314

PAYOFF CHART FUTURES CHART GREEKS P&L

Position	IV	Delta	Theta	Gamma	Vega
-1x 29JUL2021 15700CE	12.58	-52.46	483.12	-0.09	-1397.75
-1x 29JUL2021 15700PE	12.38	47.52	475.43	-0.09	-1397.7
	Positional Greeks	-4.94	958.55	-0.18	-2795.45

☐ Greeks in Decimals ☐ Greeks in Rs

Strangle Cheat Sheet

	Long Strangle	Short Strangle
Description	Long OTM call, long OTM put	Short OTM call, short OTM put
Example	ATM = 100.00 Long 105 call Long 95 put	ATM = 100 Short 105 call Short 95 put
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	− − − −	+ + + +
Increase in Implied Volatility without Market Movement	+ + + +	− − − −
Payoff Thumbnail Chart		
Maximum Risk	Cost of the strangle	Theoretically unlimited
Maximum Profit	Theoretically unlimited	Premium received
Breakeven Points	Call strike price plus cost of the strangle Put strike price minus cost of the strangle	Call strike price plus cost of the strangle Put strike price minus cost of the strangle

Nifty Long Strangle

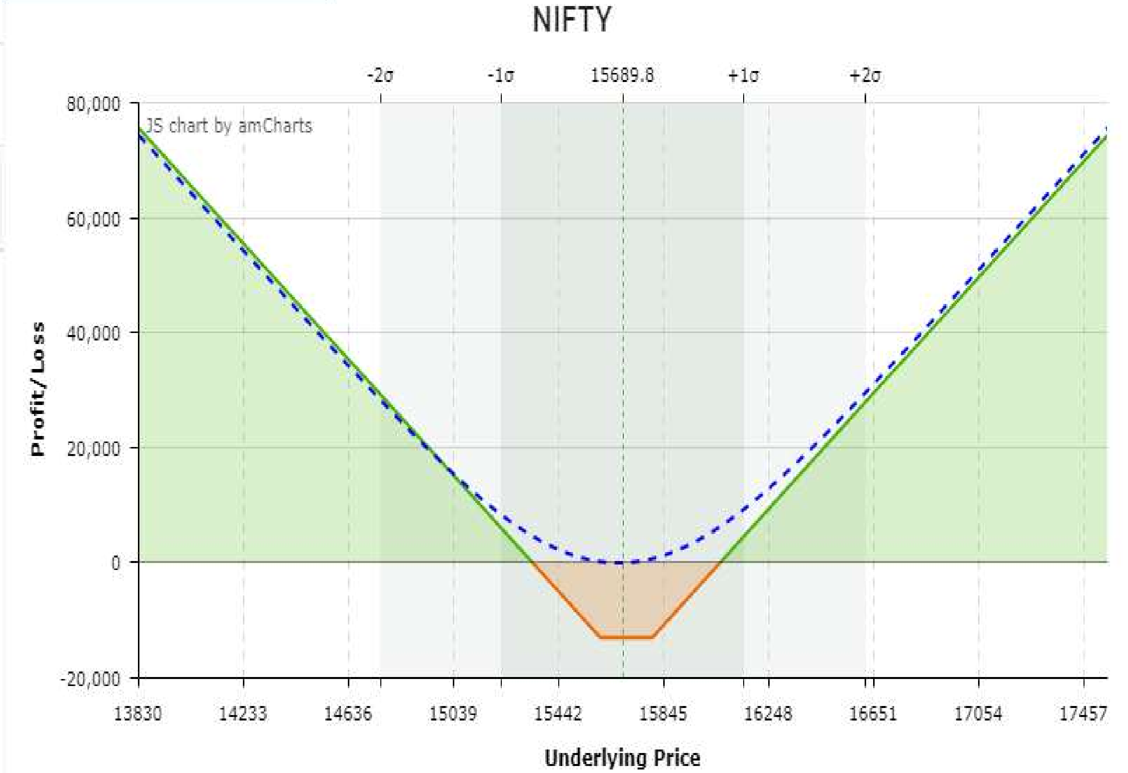
Strategy Positions RESET

+1x 29JUL2021 15800CE - ₹ 136 (0)

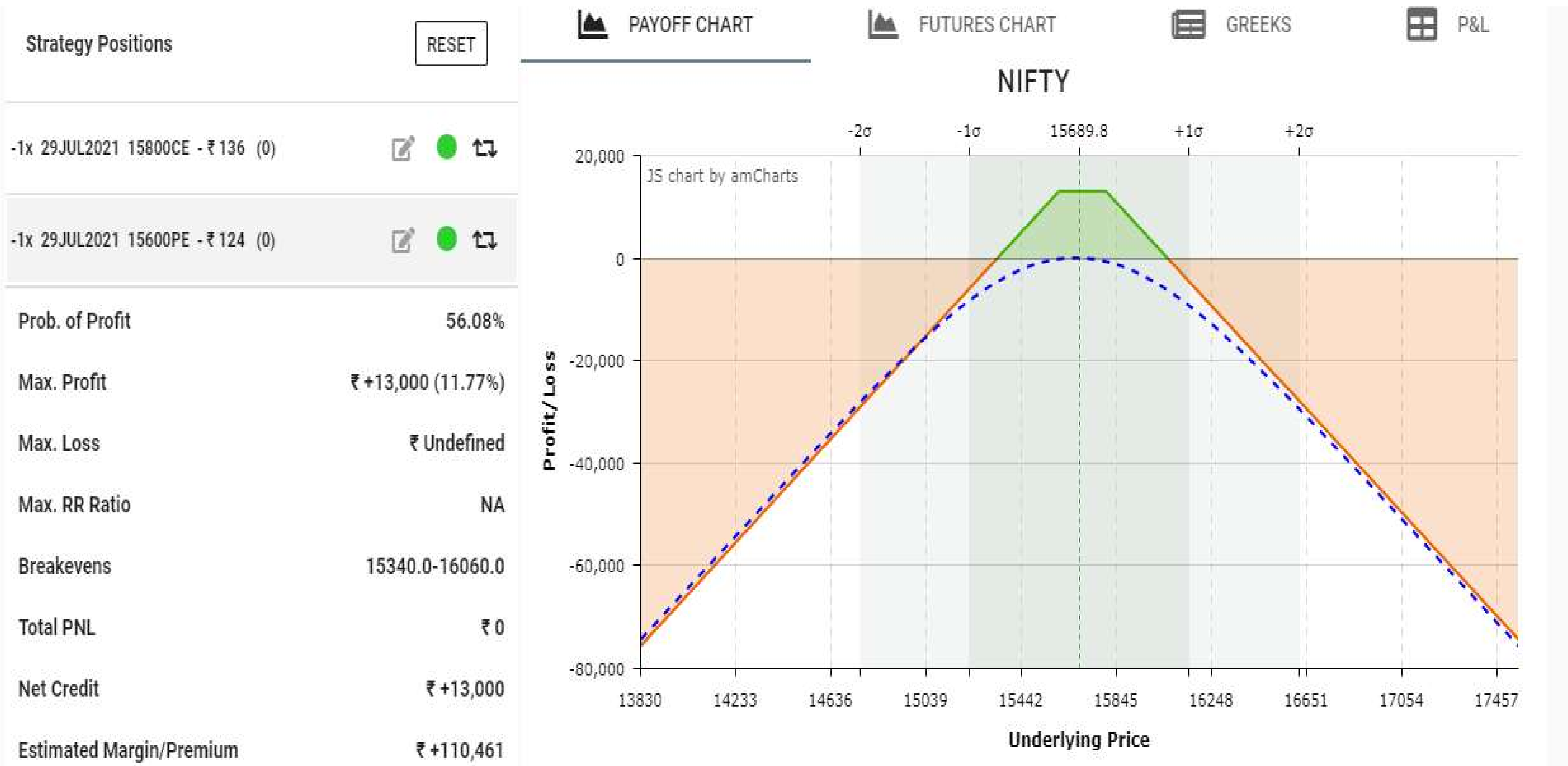
+1x 29JUL2021 15600PE - ₹ 124 (0)

Prob. of Profit	43.92%
Max. Profit	₹ Undefined
Max. Loss	₹ -13,000 (-100.00%)
Max. RR Ratio	NA
Breakevens	15340.0-16060.0
Total PNL	₹ 0
Net Credit	₹ 0
Estimated Margin/Premium	₹ +13,000

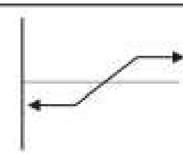
PAYOFF CHART FUTURES CHART GREEKS P&L



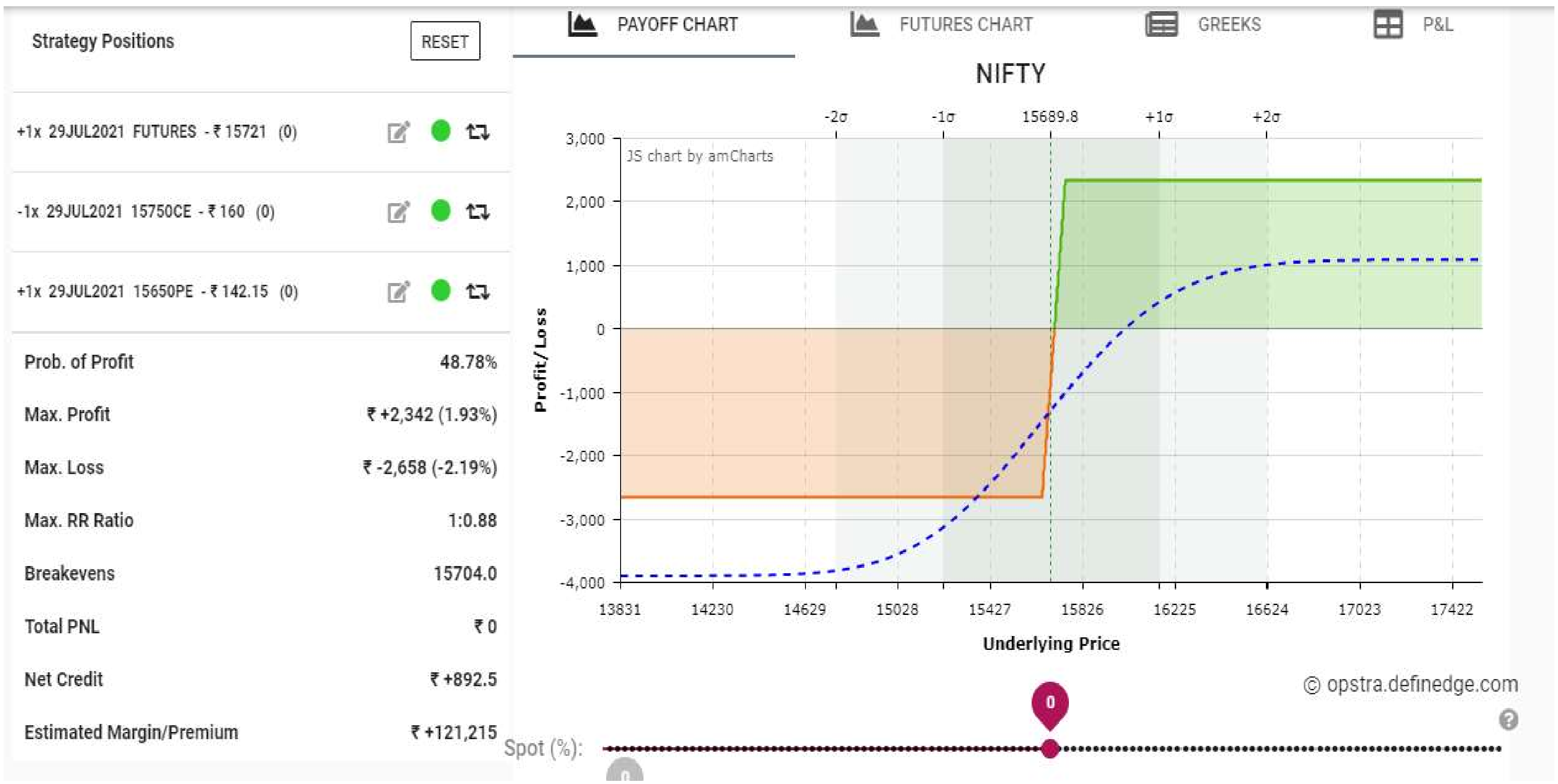
Nifty Short Strangle



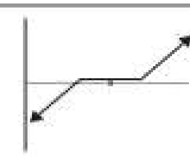
Collar Cheat Sheet

	Collar
Description	Long underlying stock, short OTM covered call, long OTM put
Example	ATM = 100 Long 100 shares of stock Short one 105 strike call Long one 95 strike put
Pay or Collect Premium	Pay or collect very small amount of net premium
Needed Directionality	
Passage of Time without Market Movement	Little or no net impact
Increase in Implied Volatility without Market Movement	Little or no net impact
Payoff Thumbnail Chart	
Maximum Risk	Price of the stock when the collar is executed minus put strike price plus any net premium paid or minus any net premium received
Maximum Profit	Call strike price minus price of the stock when the collar is executed minus any net premium paid or plus any net premium received
Breakeven Points	Current stock price

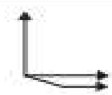
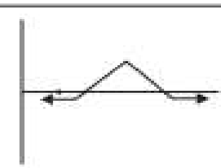
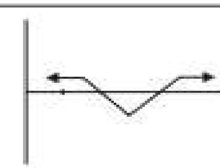
Nifty Collar



Risk Reversal Cheat Sheet

	Risk Reversal
Description	Long OTM covered call, short OTM put, long cash to buy stock at the strike price
Example	ATM = 100 Long one 105 strike call Short one 95 strike put Long $9,500
Pay or Collect Premium	Pay or collect very small amount of net premium
Needed Directionality	↑
Passage of Time without Market Movement	Little or no net impact
Increase in Implied Volatility without Market Movement	Little or no net impact
Payoff Thumbnail Chart	
Maximum Risk	Strike price of the put minus any net premium received (if stock drops to zero)
Maximum Profit	Theoretically unlimited
Breakeven Points	Call strike price ± Any net premium received Put strike price ± Any net premium received

Call Butterfly Cheat Sheet

	Long Call Butterfly	Short Call Butterfly
Description	Long one OTM call Short two further OTM calls Long one even further OTM call	Short one OTM call Long two further OTM calls Short one even further OTM call
Example	ATM = 100 Long one 105 call Short two 110 calls Long one 115 call	ATM = 100 Short one 105 call Long two 110 calls Short one 115 call
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	− −	+ +
Increase in Implied Volatility without Market Movement	+	−
Payoff Thumbnail Chart		
Maximum Risk	Cost of the butterfly	Difference between wing strike and body strike minus net premium received
Maximum Profit	Difference between wing strike and body strike minus net premium paid	Premium received
Breakeven Points	Lowest strike + Net premium paid Highest strike − Net premium paid	Lowest strike + Net premium paid Highest strike − Net premium paid

Nifty Long Call Butterfly

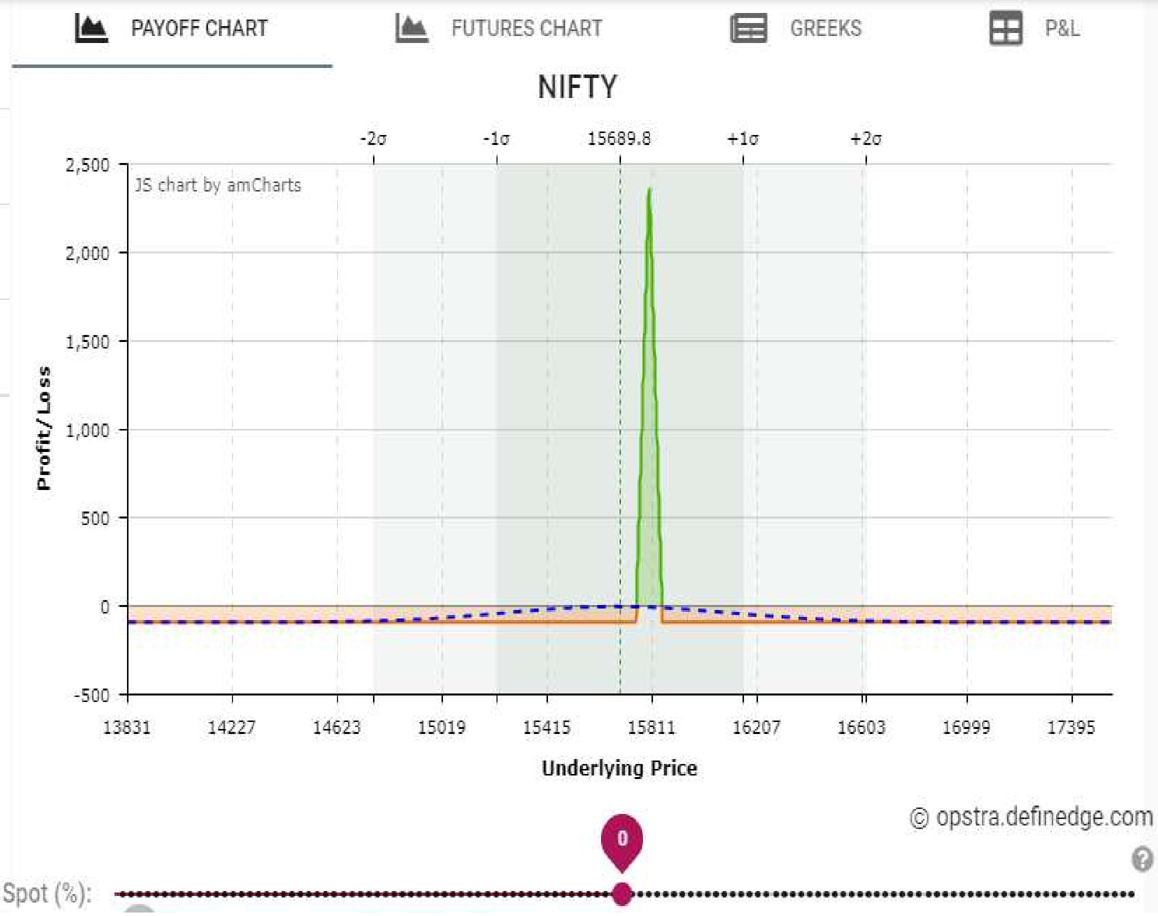
Strategy Positions RESET

+1x 29JUL2021 15750CE - ₹ 160 (0)

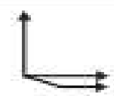
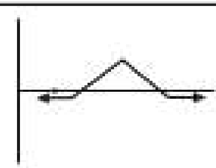
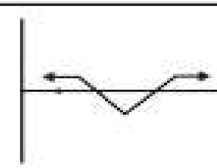
-2x 29JUL2021 15800CE - ₹ 136 (0)

+1x 29JUL2021 15850CE - ₹ 113.85 (0)

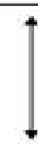
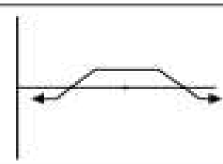
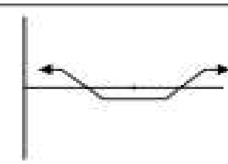
Prob. of Profit	7.94%
Max. Profit	₹ +2,358 (7.51%)
Max. Loss	₹ -92 (-0.29%)
Max. RR Ratio	1:25.63
Breakevens	15752.0-15848.0
Total PNL	₹ 0
Net Credit	₹ 0
Estimated Margin/Premium	₹ +31,415



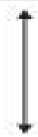
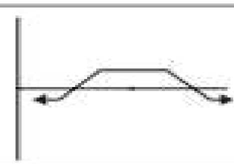
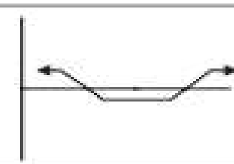
Put Butterfly Cheat Sheet

	Long Put Butterfly	Short Put Butterfly
Description	Long one put Short two further OTM puts Long one even further OTM put	Short one put Long two further OTM puts Short one even further OTM put
Example	ATM = 100 Long one 95 put Short two 90 puts Long one 85 put	ATM = 100 Short one 95 put Long two 90 puts Short one 85 put
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	− −	+ +
Increase in Implied Volatility without Market Movement	+	−
Payoff Thumbnail Chart		
Maximum Risk	Cost of the butterfly	Difference between wing strike and body strike minus net premium received
Maximum Profit	Difference between wing strike and body strike minus net premium paid	Premium received
Breakeven Points	Lowest strike + Net premium paid Highest strike − Net premium paid	Lowest strike + Net premium paid Highest strike − Net premium paid

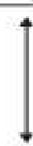
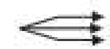
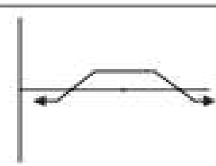
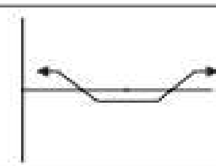
Call Condor Cheat Sheet

	Long Call Condor	Short Call Condor
Description	Long ITM call vertical spread Short OTM call vertical spread	Short ITM call vertical spread Long OTM call vertical spread
Example	Long One 90 strike call Short One 95 strike call Short One 105 strike call Long One 110 strike call	Short one 90 strike call Long one 95 strike call Long one 105 strike call Short one 110 strike call
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	+ +	– –
Increase in Implied Volatility without Market Movement	+	–
Payoff Thumbnail Chart		
Maximum Risk	Net premium paid	Width of ITM spread – Premium received for selling ITM spread + Premium paid for OTM spread
Maximum Profit	Width of ITM spread – Cost of ITM spread + Premium received for OTM spread	Net premium received
Breakeven Points	Second lowest strike – Max profit Second highest strike + Max profit	Second lowest strike – Net premium received, second highest strike + Net premium received

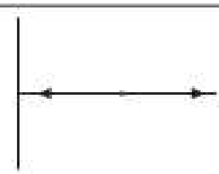
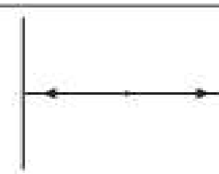
Put Condor Cheat Sheet

	Long Put Condor	Short Put Condor
Description	Long ITM put vertical spread Short OTM put vertical spread	Short ITM call vertical spread Long OTM call vertical spread
Example	Long one 110 strike put Short one 105 strike put Short one 95 strike put Long one 90 strike put	Short one 110 strike put Long one 105 strike put Long one 95 strike put Short one 90 strike put
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	+ +	− −
Increase in Implied Volatility without Market Movement	+	−
Payoff Thumbnail Chart		
Maximum Risk	Net premium paid	Width of ITM spread − Premium received for selling ITM spread + Premium paid for OTM spread
Maximum Profit	Width of ITM spread − Cost of ITM spread + Premium received for OTM spread	Net premium received
Breakeven Points	Second highest strike − Max profit Second lowest strike + Max profit	Second highest strike − Net premium received, second lowest strike plus net premium received

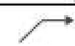
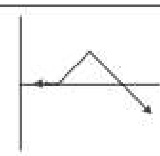
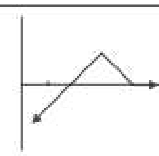
Iron Condor Cheat Sheet

	Long Iron Condor	Short Iron Condor
Description	Long OTM call vertical spread Long OTM put vertical spread	Short OTM call vertical spread Short OTM put vertical spread
Example	Long one 105 strike call Short one 110 strike call Long one 95 strike put Short one 90 strike put	Short one 105 strike call Long one 110 strike call Short one 95 strike put Long one 90 strike put
Pay or Collect Premium	Pay	Collect
Needed Directionality		
Passage of Time without Market Movement	– –	+ +
Increase in Implied Volatility without Market Movement	+	–
Payoff Thumbnail Chart		
Maximum Risk	Net premium paid	Width of one spread minus net premium received
Maximum Profit	Width of one spread minus net premium paid	Net premium received
Breakeven Points	Lower call strike plus net premium paid, higher put strike plus net premium paid	Lower call strike plus net premium received, higher put strike plus net premium received

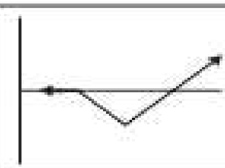
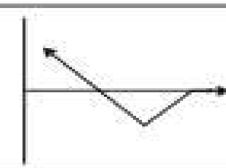
Conversion and Reversal Cheat Sheet

	Conversion	Reversal
Description	Long shares Short shares synthetically	Short shares Long shares synthetically
Example	Long 100 shares Short one 100 strike call Long one 100 strike put	Short 100 shares Long one 100 strike call Short one 100 strike put
Pay or Collect Premium	Pay if strike price is above share price, collect if strike price is below share price	Pay if strike price is below share price, collect if strike price is above share price
Needed Directionality	Does not matter, no movement will generate a profit or loss	Does not matter, no movement will generate a profit or loss
Passage of Time without Market Movement	No impact	No impact
Increase in Implied Volatility without Market Movement	No impact	No impact
Payoff Thumbnail Chart		
Maximum Risk	Pin risk is the only risk inherent in a conversion	Pin risk is the only risk inherent in a reversal
Maximum Profit	Should be zero	Should be zero
Breakeven Points	A conversion should break even at every price for underlying at expiration	A reversal should break even at every price for underlying at expiration

Ratio Spread Cheat Sheet

	Call Ratio Spread	Put Ratio Spread
Description	Long one OTM call Short two further OTM calls	Long one OTM put Short two further OTM puts
Example	ATM = 100 Long one 105 call Short two 110 calls	ATM = 100 Long one 95 put Short two 90 puts
Pay or Collect Premium	Either is possible, net premium should be very small	Either is possible, net premium should be very small
Needed Directionality		
Passage of Time without Market Movement	+	+
Increase in Implied Volatility without Market Movement	-	-
Payoff Thumbnail Chart		
Maximum Risk	Unlimited	Limited only because the underlying stock can not fall below zero
Maximum Profit	Higher strike price minus lower strike price minus (plus) any net premium paid (received)	Higher strike price minus lower strike price minus (plus) any net premium paid (received)
Breakeven Points	Higher strike price plus width of the ratio spread plus (minus) net premium received (paid)	Lower strike price minus width of the ratio spread plus (minus) net premium paid (received)

Back Spread Cheat Sheet

	Call Back Spread	Put Back Spread
Description	Short one OTM call Long two further OTM calls	Short one OTM put Long two further OTM puts
Example	ATM = 100 Short one 105 call Long two 110 calls	ATM = 100 Short one 95 put Long two 90 puts
Pay or Collect Premium	Either is possible, net premium should be very small	Either is possible, net premium should be very small
Needed Directionality	↑	↓
Passage of Time without Market Movement	-	-
Increase in Implied Volatility without Market Movement	+	+
Payoff Thumbnail Chart		
Maximum Risk	Lower strike price minus higher strike price plus (minus) any net premium paid (received)	Higher strike price minus lower strike price plus (minus) any net premium paid (received)
Maximum Profit	Theoretically unlimited	Limited only because the price of the underlying stock can't drop below zero
Breakeven Points	Higher strike price plus width of the back spread plus (minus) net premium paid (received)	Lower strike price plus width of the back spread minus (plus) net premium paid (received)

Algo Trading Strategies

Playing Atari with Deep Reinforcement Learning

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Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

DRML Research Paper

LETTER

doi:10.1038/nature14236

Human-level control through deep reinforcement learning

Volodymyr Mnih[1*], Koray Kavukcuoglu[1*], David Silver[1*], Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

The theory of reinforcement learning provides a normative account[1], deeply rooted in psychological[2] and neuroscientific[3] perspectives on animal behaviour, of how agents may optimize their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the environment from high-dimensional sensory inputs, and use these to generalize past experience to new situations. Remarkably, humans and other animals seem to solve this problem through a harmonious combination of reinforcement learning and hierarchical sensory processing systems[4,5], the former evidenced by a wealth of neural data revealing notable parallels between the phasic signals emitted by dopaminergic neurons and temporal difference reinforcement learning algorithms[3]. While reinforcement learning agents have achieved some successes in a variety of domains[6-8], their applicability has previously been limited to domains in which useful features can be handcrafted, or to domains with fully observed, low-dimensional state spaces. Here we use recent advances in training deep neural networks[9-11] to develop a novel artificial agent, termed a deep Q-network, that can learn successful policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning. We tested this agent on the challenging domain of classic Atari 2600 games[12]. We demonstrate that the deep Q-network agent, receiving only the pixels and the game score as inputs, was able to surpass the performance of all previous algorithms and achieve a level comparable to that of a professional human games tester across a set of 49 games, using the same algorithm, network architecture and hyperparameters. This work bridges the divide between high-dimensional sensory inputs and actions, resulting in the first artificial agent that is capable of learning to excel at a diverse array of challenging tasks.

We set out to create a single algorithm that would be able to develop a wide range of competencies on a varied range of challenging tasks—a central goal of general artificial intelligence[13] that has eluded previous efforts[8,14,15]. To achieve this, we developed a novel agent, a deep Q-network (DQN), which is able to combine reinforcement learning with a class of artificial neural network[16] known as deep neural networks. Notably, recent advances in deep neural networks[9-11], in which several layers of nodes are used to build up progressively more abstract representations of the data, have made it possible for artificial neural networks to learn concepts such as object categories directly from raw sensory data. We use one particularly successful architecture, the deep convolutional network[17], which uses hierarchical layers of tiled convolutional filters to mimic the effects of receptive fields—inspired by Hubel and Wiesel's seminal work on feedforward processing in early visual cortex[18]—thereby exploiting the local spatial correlations present in images, and building in robustness to natural transformations such as changes of viewpoint or scale.

We consider tasks in which the agent interacts with an environment through a sequence of observations, actions and rewards. The goal of the agent is to select actions in a fashion that maximizes cumulative future reward. More formally, we use a deep convolutional neural network to approximate the optimal action-value function

$$Q^*(s,a) = \max_\pi \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \mid s_t = s, a_t = a, \pi\right],$$

which is the maximum sum of rewards r_t discounted by γ at each time-step t, achievable by a behaviour policy $\pi = P(a|s)$, after making an observation (s) and taking an action (a) (see Methods)[19].

Reinforcement learning is known to be unstable or even to diverge when a nonlinear function approximator such as a neural network is used to represent the action-value (also known as Q) function[20]. This instability has several causes: the correlations present in the sequence of observations, the fact that small updates to Q may significantly change the policy and therefore change the data distribution, and the correlations between the action-values (Q) and the target values $r + \gamma \max_{a'} Q(s', a')$. We address these instabilities with a novel variant of Q-learning, which uses two key ideas. First, we used a biologically inspired mechanism termed experience replay[21-23] that randomizes over the data, thereby removing correlations in the observation sequence and smoothing over changes in the data distribution (see below for details). Second, we used an iterative update that adjusts the action-values (Q) towards target values that are only periodically updated, thereby reducing correlations with the target.

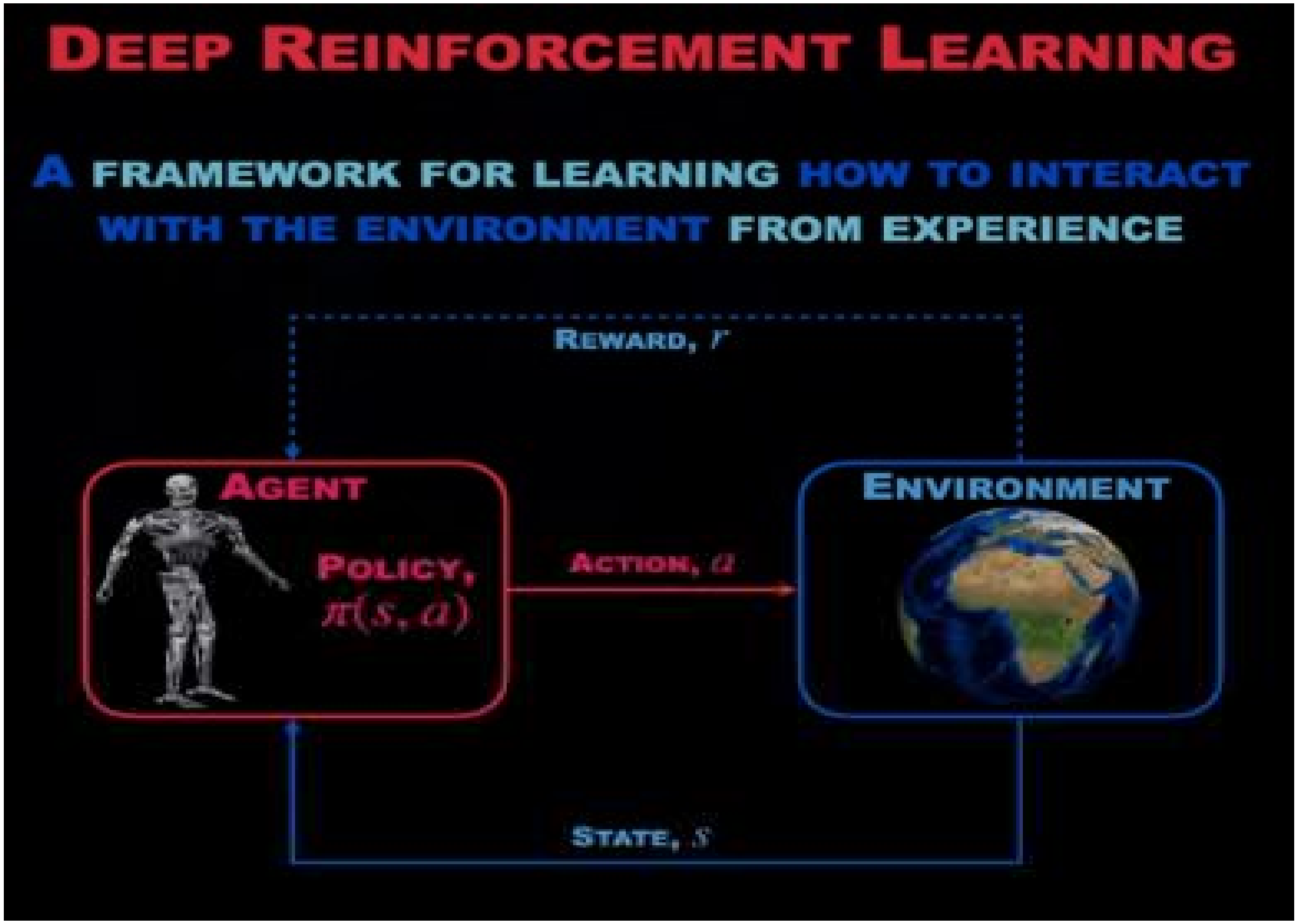
While other stable methods exist for training neural networks in the reinforcement learning setting, such as neural fitted Q-iteration[24], these methods involve the repeated training of networks *de novo* on hundreds of iterations. Consequently, these methods, unlike our algorithm, are too inefficient to be used successfully with large neural networks. We parameterize an approximate value function $Q(s,a;\theta_i)$ using the deep convolutional neural network shown in Fig. 1, in which θ_i are the parameters (that is, weights) of the Q-network at iteration i. To perform experience replay we store the agent's experiences $e_t = (s_t,a_t,r_t,s_{t+1})$ at each time-step t in a data set $D_t = \{e_1,\ldots,e_t\}$. During learning, we apply Q-learning updates, on samples (or minibatches) of experience $(s,a,r,s') \sim U(D)$, drawn uniformly at random from the pool of stored samples. The Q-learning update at iteration i uses the following loss function:

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s') \sim U(D)}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta_i^-) - Q(s,a;\theta_i)\right)^2\right]$$

in which γ is the discount factor determining the agent's horizon, θ_i are the parameters of the Q-network at iteration i and θ_i^- are the network parameters used to compute the target at iteration i. The target network parameters θ_i^- are only updated with the Q-network parameters (θ_i) every C steps and are held fixed between individual updates (see Methods).

To evaluate our DQN agent, we took advantage of the Atari 2600 platform, which offers a diverse array of tasks ($n = 49$) designed to be

[1]Google DeepMind, 5 New Street Square, London EC4A 3TW, UK.


DEEP REINFORCEMENT LEARNING
A FRAMEWORK FOR LEARNING HOW TO INTERACT WITH THE ENVIRONMENT FROM EXPERIENCE
REWARD, r
AGENT
POLICY, $\pi(s,a)$
ACTION, a
ENVIRONMENT
STATE, s

Reinforcement Learning in Stock Trading

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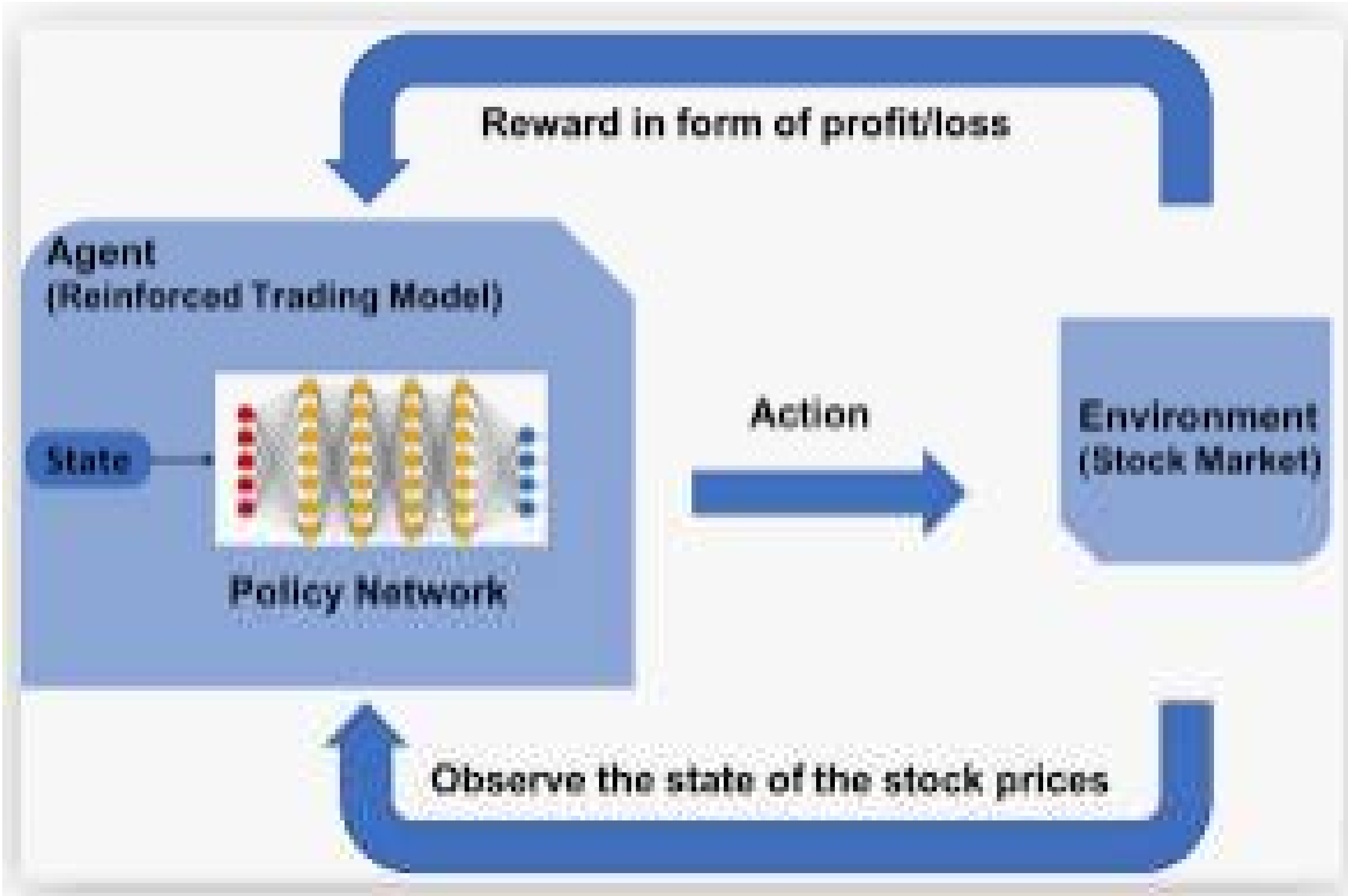
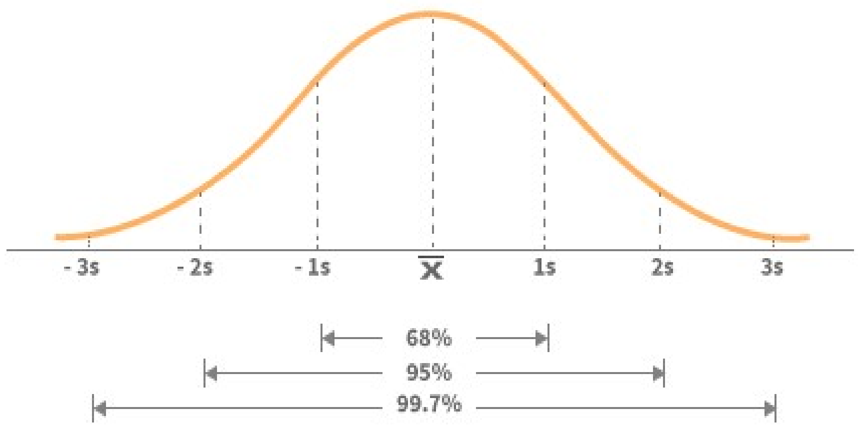
Abstract. Using machine learning techniques in financial markets, particularly in stock trading, attracts a lot of attention from both academia and practitioners in recent years. Researchers have studied different supervised and unsupervised learning techniques to either predict stock price movement or make decisions in the market.
In this paper we study the usage of reinforcement learning techniques in stock trading. We evaluate the approach on real-world stock dataset. We compare the deep reinforcement learning approach with state-of-the-art supervised deep learning prediction in real-world data. Given the nature of the market where the true parameters will never be revealed, we believe that the reinforcement learning has a lot of potential in decision-making for stock trading.

Keywords: Reinforcement Learning · Machine learning · Stock Trading.


Reward in form of profit/loss
Agent
(Reinforced Trading Model)
State
Policy Network
Action
Environment
(Stock Market)
Observe the state of the stock prices

Normal Distribution and stock returns

To begin with, here is the distribution of Nifty's daily returns is –

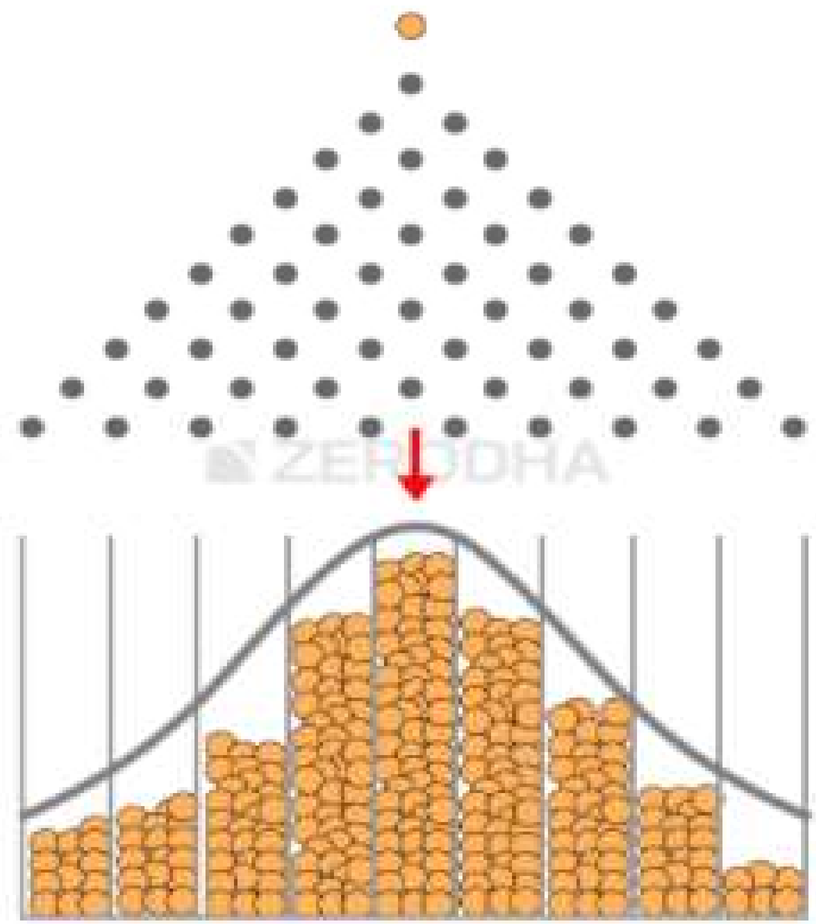


The bell curve above suggests that with reference to the mean (average) value –

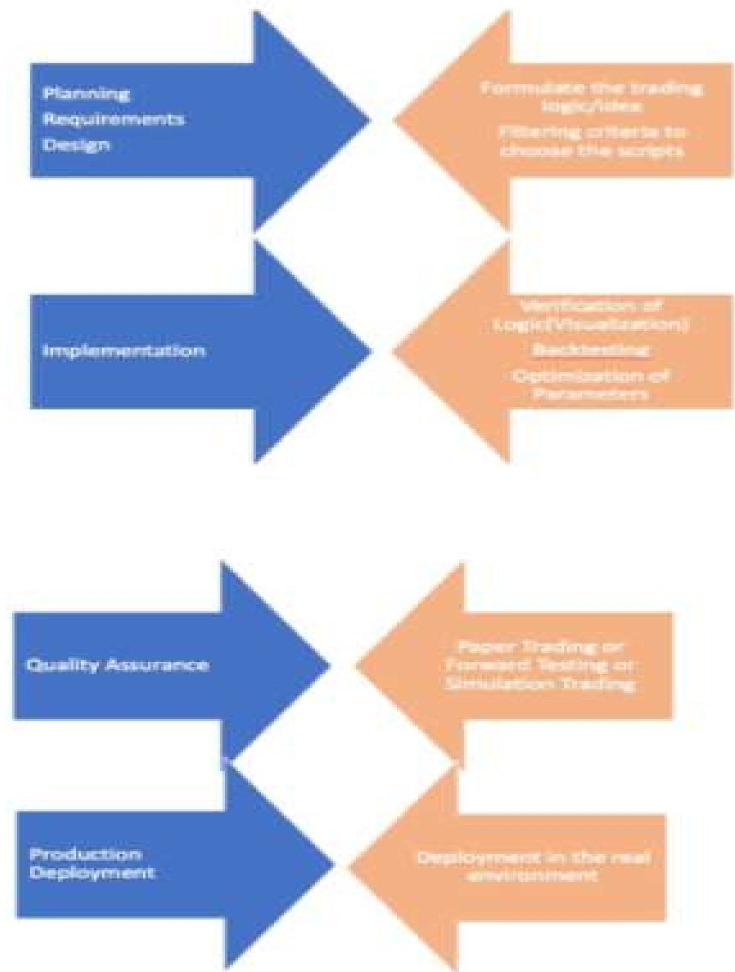
1. 68% of the data is clustered around mean within the 1st SD, in other words there is a 68% chance that the data lies within the 1st SD
2. 95% of the data is clustered around mean within the 2nd SD, in other words there is a 95% chance that the data lies within the 2nd SD
3. 99.7% of the data is clustered around mean within the 3rd SD, in other words there is a 99.7% chance that the data lies within the 3rd SD

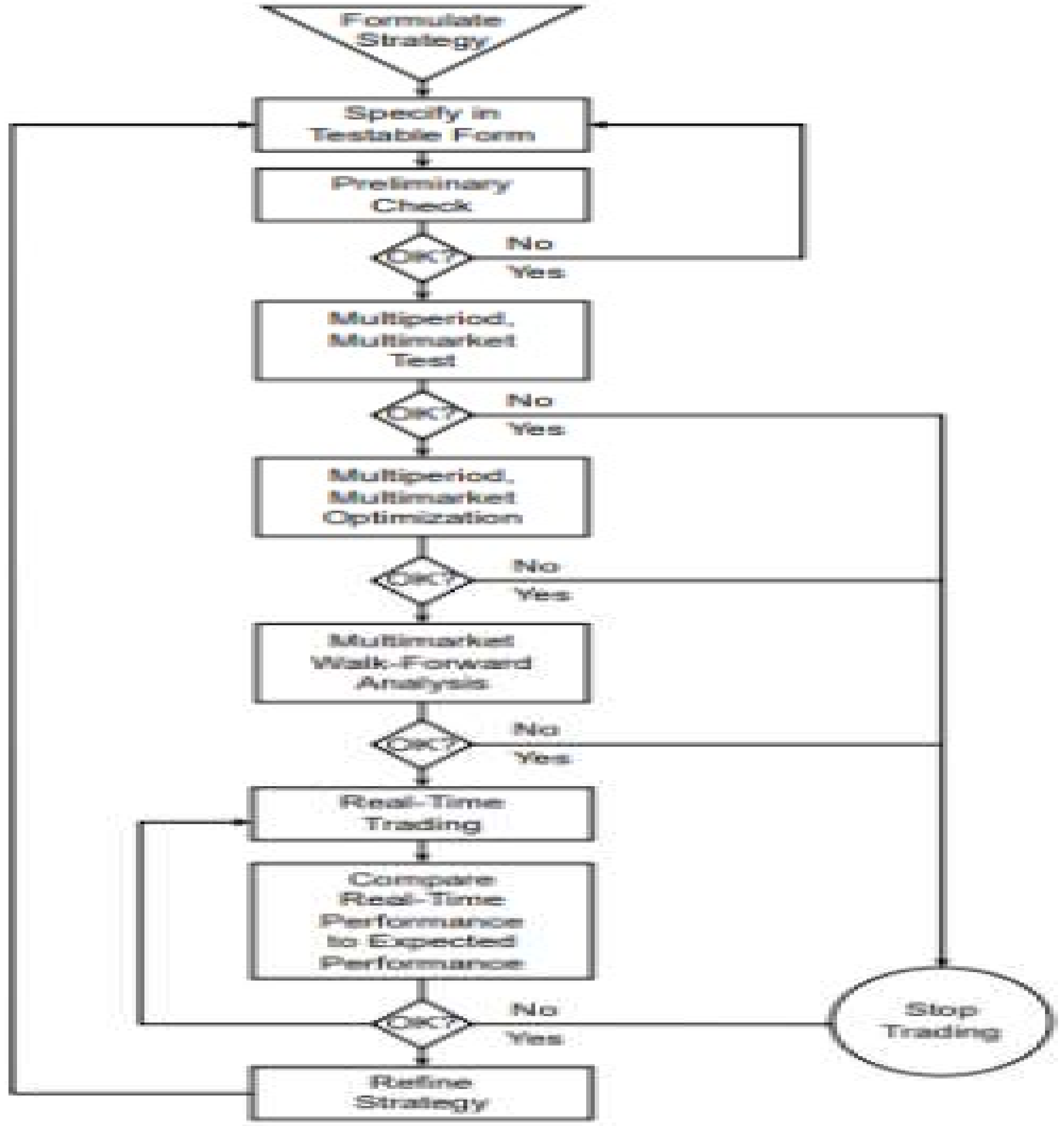
Since we know that Nifty's daily returns are normally distributed, the above set of properties is applicable to Nifty. So what does it mean?

Normal Distribution



Architecture




Formulate Strategy
Specify in Testable Form
Preliminary Check
OK?
No
Yes
Multiperiod, Multimarket Test
OK?
No
Yes
Multiperiod, Multimarket Optimization
OK?
No
Yes
Multimarket Walk-Forward Analysis
OK?
No
Yes
Real-Time Trading
Compare Real-Time Performance to Expected Performance
OK?
No
Yes
Stop Trading
Refine Strategy

AlgoProfessor Strategies 30 Different Parameters

- 1)Time Series Analysis
- 2)India Vix
- 3)Global Vix
- 4)52 Week High or Low
- 5)Every 500 Points Up or Down
- 6) News Events Like RBI, GDP, Budget Days
- 7)Earning Dates

AlgoProfessor Strategies 30 Different Parameters

- 8)option Greeks
- 9)Weekly Expiry Days Performance
- 10)Month Expiry Days Performance
- 11)Nifty vs. Gold vs. Crude oil
- 12)Any pandemic Days
- 13)Election Result Days
- 14)Initial Risk management
- 15)Different stop Loss Mechanism

AlgoProfessor Strategies 30 Different Parameters

- 16) Counter Idea
- 17)Gap up Day or Gap down Day
- 18)Entry Time ,stop Loss , Exit
- 19)ROI
- 20)Sharp Ratio
- 21)Mathematical formula
- 22)Normal Distribution Curve
- 23)Optimization

AlgoProfessor Strategies 30 Different Parameters

- 24)Latest Machine Methods
- 25)Equity Curve
- 26)Cumulative Profit
- 27)Option size
- 28)strikes Identification
- 29)Non Correlation of Different pattern
- 30)Winning ROI 20 % to 80 % Per Annum

Sharp ratio

$$S_a = \frac{E[R_a - R_b]}{\sigma_a}$$

S_a = Sharpe ratio

E = expected value

R_a = asset return

R_b = risk free return

σ_a = standard deviation of the asset excess return

Risk Free Sharp Ratio

Usually, any **Sharpe ratio** greater than 1.0 is considered acceptable to **good** by investors. A **ratio** higher than 2.0 is rated as very **good**. A **ratio** of 3.0 or higher is considered excellent. A **ratio** under 1.0 is considered sub-optimal. 16-Oct-2020

1. Annualized profit
2. Number of trades per year
3. Percentage of winning trades
4. Largest win
5. Length of largest win
6. Average win
7. Length of average win
8. Largest loss
9. Length of time in largest loss
10. Average loss
11. Length of time in average loss
12. Average winning run
13. Length of time in average winning run
14. Largest winning run
15. Length of time in largest winning run
16. Average losing run

17. Length of average losing run
18. Largest losing run
19. Length of largest losing run
20. Maximum equity drawdown
21. Length of maximum drawdown
22. Start and end data maximum drawdown
23. Maximum equity run-up
24. Length of maximum run-up
25. Start and end data maximum run-up

Back Test Results Focus Points

Capital
ROI %
ROI % Per Annum
Max DD
Max Single Day Profit
Max Single Day loss
Max Contunious Loss Days
Green Days %
Red Days %
Green Weeks %
Red Weeks %
Green Months %
Red Months %
Green Quarters %
Red Quarters %
Green Years %
Red years %
Shrap Ratio
Calmar Ratio

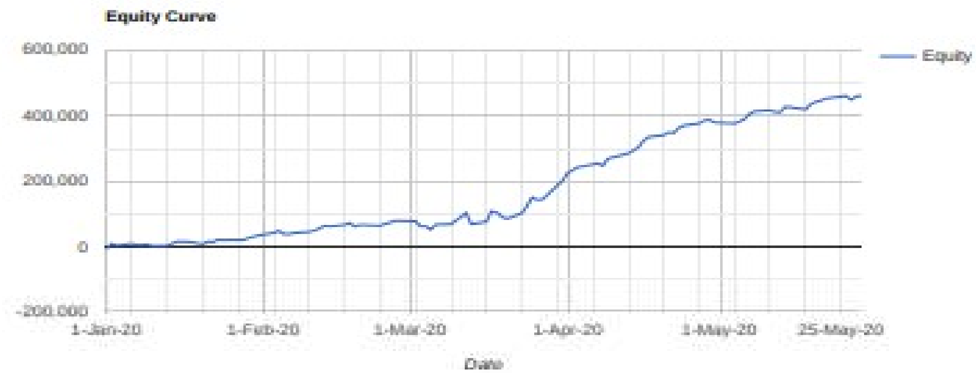
Backtest Report

Deep Reinforce Machine Learning Bank Nifty AlgoProfessor High Profit

Period: January 01, 2020 to May 31, 2020

Created: September 14, 2021

Strategy Link: http://tradetron.tech/strategy/1171872



Totals			
Capital	Rs. 300 K		
PNL	Rs. 459.5 K		
Drawdown	8.18%		
Std Deviation	0.56%		
Sharpe Ratio	6.79		

Month	Capital	PNL	PNL %
Jan, 20	-	Rs. 34.2 K	11.40
Feb, 20	-	Rs. 44.4 K	14.79
Mar, 20	-	Rs. 121.7 K	40.57
Apr, 20	-	Rs. 177.5 K	59.18
May, 20	-	Rs. 81.7 K	27.24

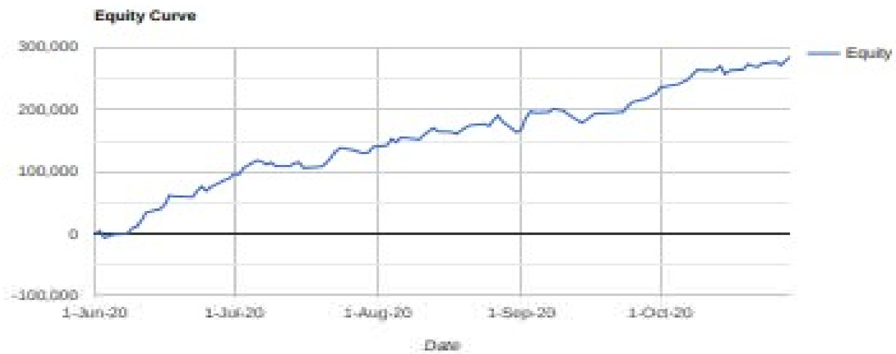
Backtest Report

Deep Reinforce Machine Learning Bank Nifty AlgoProfessor High Profit

Period: June 01, 2020 to October 31, 2020

Created: September 14, 2021

Strategy Link: http://tradetron.tech/strategy/1171872



Totals			
Capital	Rs. 300 K		
PNL	Rs. 284.2 K		
Drawdown	5.48%		
Std Deviation	0.33%		
Sharpe Ratio	6.61		

Month	Capital	PNL	PNL %
Jun, 20	-	Rs. 88.6 K	29.53
Jul, 20	-	Rs. 50.6 K	16.88
Aug, 20	-	Rs. 23.6 K	7.87
Sep, 20	-	Rs. 62 K	20.66
Oct, 20	-	Rs. 59.4 K	19.80

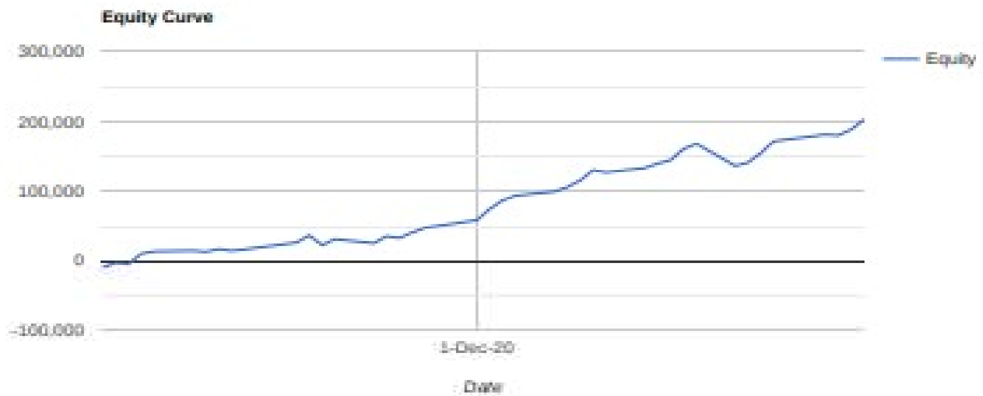
Backtest Report

Deep Reinforce Machine Learning Bank Nifty AlgoProfessor High Profit

Period: November 01, 2020 to December 31, 2020

Created: September 14, 2021

Strategy Link: http://tradetron.tech/strategy/1171872

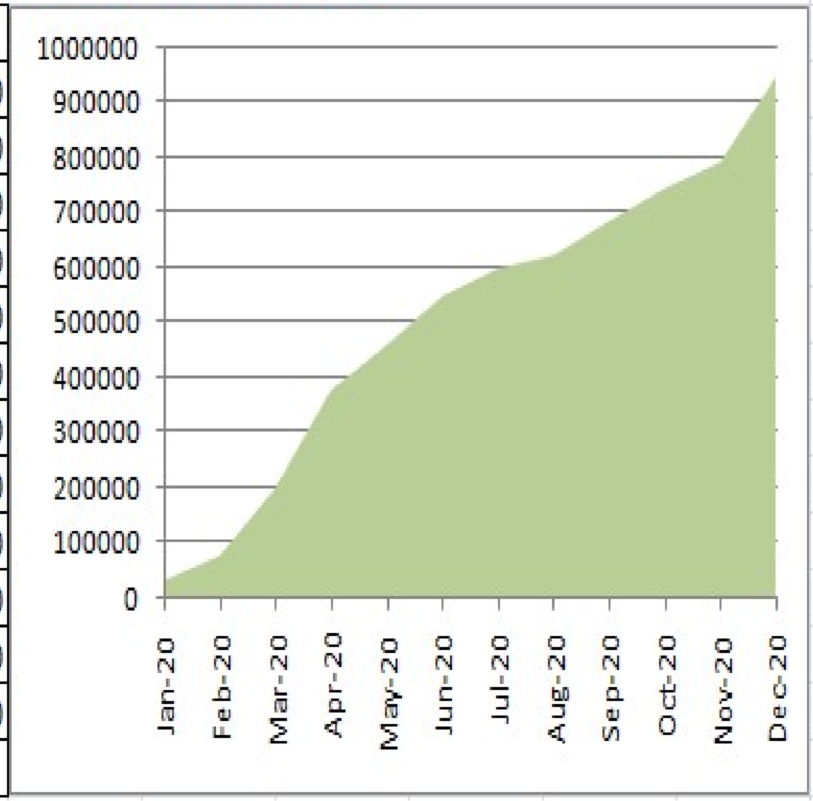


Totals			
Capital	Rs. 300 K		
PNL	Rs. 202.3 K		
Drawdown	6.72%		
Std Deviation	0.48%		
Sharpe Ratio	8.49		

Month	Capital	PNL	PNL %
Nov, 20	-	Rs. 47.7 K	15.90
Dec, 20	-	Rs. 154.6 K	51.55

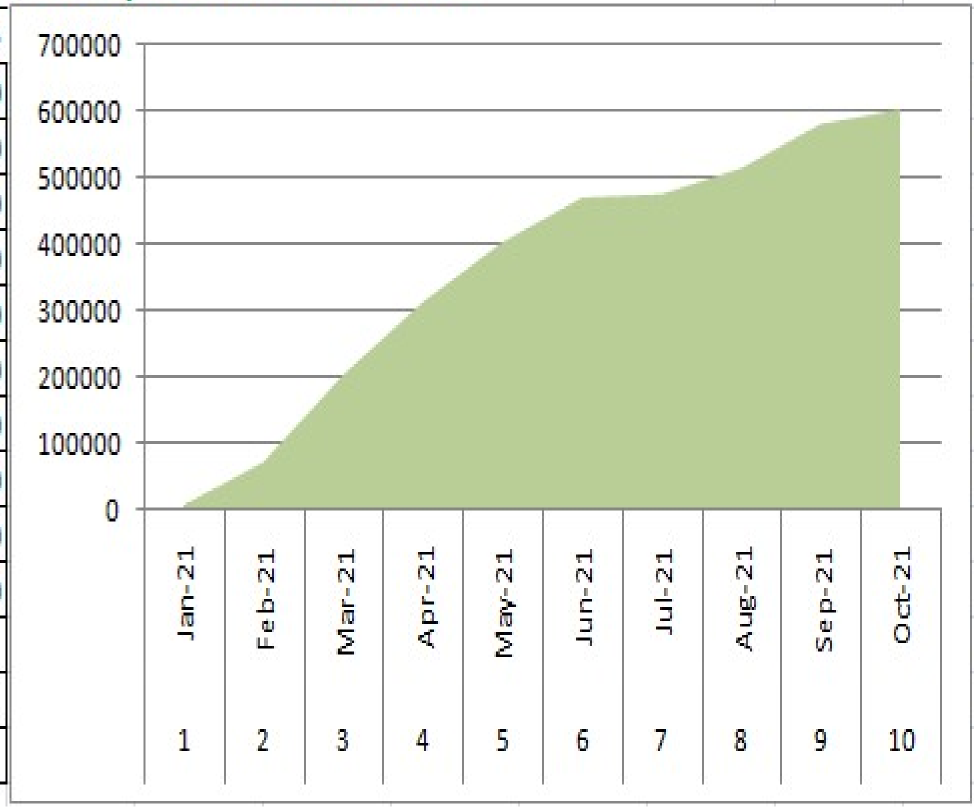
Deep RML Bank Nifty Performance 2020

S.no	Date	Profit	Cumulative
1	Jan-20	34200	34200
2	Feb-20	44400	78600
3	Mar-20	121700	200300
4	Apr-20	177500	377800
5	May-20	81700	459500
6	Jun-20	88600	548100
7	Jul-20	50600	598700
8	Aug-20	23600	622300
9	Sep-20	62000	684300
10	Oct-20	59400	743700
11	Nov-20	47700	791400
12	Dec-20	154600	946000
	Total	**946000**	



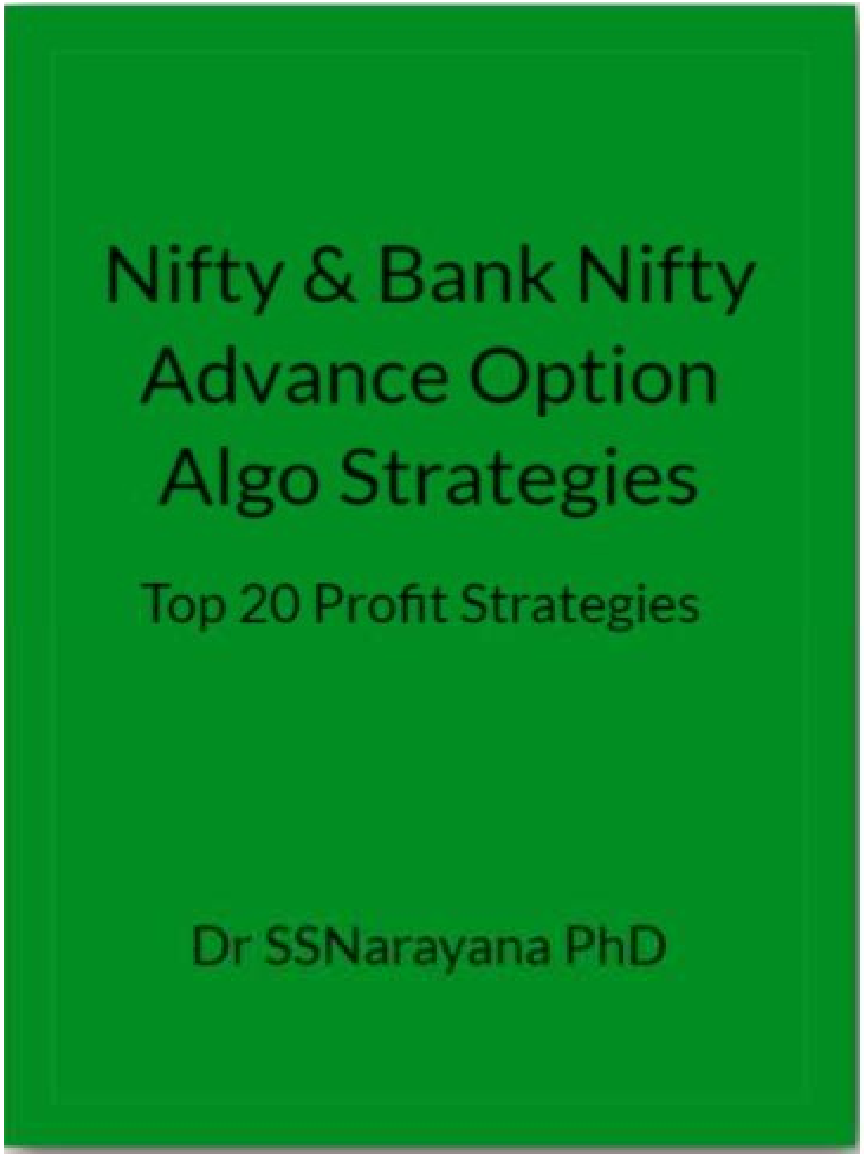
Deep RML Bank Nifty Performance 2021

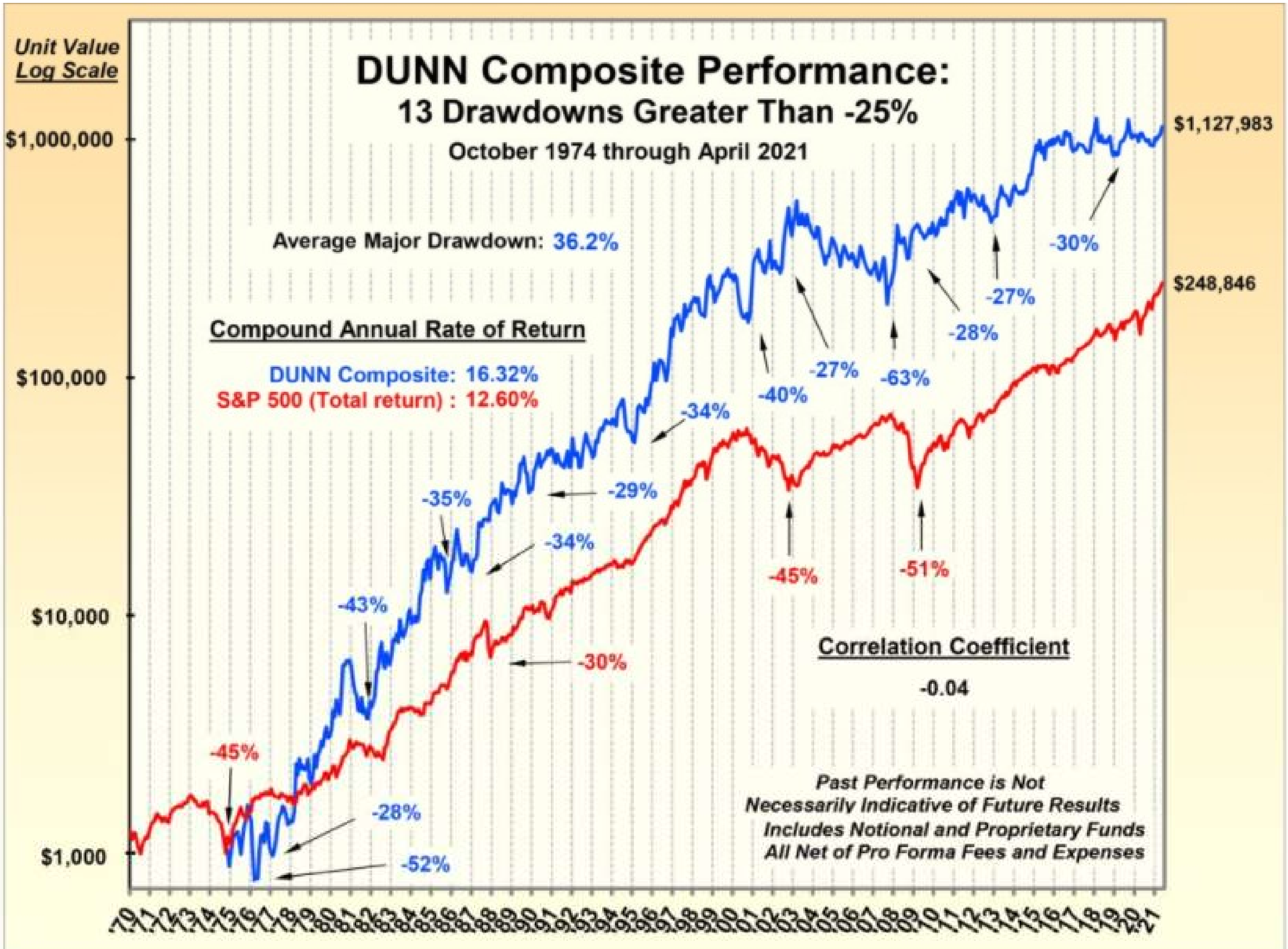
S.no	Date	Profit	Cumulative
1	Jan-21	7800	7800
2	Feb-21	65700	73500
3	Mar-21	130900	204400
4	Apr-21	108800	313200
5	May-21	89700	402900
6	Jun-21	66600	469500
7	Jul-21	5300	474800
8	Aug-21	38500	513300
9	Sep-21	66400	579700
10	Oct-21	22000	601700



Key Takeaways for Real-World Impact

- Deep Learning:
  - **Fun part**: Good algorithms that learn from data.
  - **Hard part:** Good questions, huge amounts of representative data.
- Deep Reinforcement Learning:
  - **Fun part:** Good algorithms that learn from data.
  - **Hard part:** Defining a useful state space, action space, and reward.
  - **Hardest part:** Getting meaningful data for the above formalization.


Nifty & Bank Nifty
Advance Option
Algo Strategies
Top 20 Profit Strategies
Dr SSNarayana PhD



Unit Value
Log Scale
DUNN Composite Performance:
13 Drawdowns Greater Than -25%
October 1974 through April 2021
$1,000,000
$100,000
$10,000
$1,000
$1,127,983
$248,846
Average Major Drawdown: 36.2%
Compound Annual Rate of Return
DUNN Composite: 16.32%
S&P 500 (Total return) : 12.60%
Correlation Coefficient
-0.04
Past Performance is Not
Necessarily Indicative of Future Results
Includes Notional and Proprietary Funds
All Net of Pro Forma Fees and Expenses
-45%
-28%
-52%
-43%
-35%
-34%
-30%
-29%
-34%
-40%
-27%
-63%
-28%
-27%
-30%
-45%
-51%


Thank you