Bet Sizing Algorithm For Intraday VIX Trading Strategies

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Introduction

- Trading strategies mostly bet on the side of the trade i.e., long/short, and labels the trades 1 or -1
- These strategies can be enhanced if we can optimally assign the size to each strategy bet (which also includes no bet at all)
- Like betting strategies used in poker, we need design an algorithm that can predict the size of bet/trade by way of using leverage
- Machine Learning models are prime candidates for betting algorithms as they will only be concerned with the size of the trade and not the side.
- To use machine learning models for sizing the bets, we first label each trade either 0 or 1, based on its return and a given threshold.
- For example, of a given long trade returned 0.50%, and our threshold for a good-sized trade is 0.10%, label “1”, is assigned to that trade, conversely if the trade returned less than 0.10%, label “0” is assigned to it
- Once we have a labelled dataset, we include a host of features that can drive the size of the trade, and train a machine learning classifier to predict the labels defined in the previous step
- The output of the machine learning classifier is a probability score in the range [0,1], which is used in ”Kelly betting criteria” to compute the optimal leverage for that trade
- The implementation details are presented in the next slide

Candidate Strategies: Description

- We use 4 intraday trading strategies (no overnight trades) on VXX ETF (Long Volatility ETF) as our candidate set.
- The strategies trade US market hours, and 3 out of the 4 strategies are based on price action/patterns
- The description of each strategy is as follows
  - **Multi Pivot Points Breakout (MULTI_PIVOT_BO):** This strategy calculates multiple high and low pivot points based on minimum price moves (in %) and analyzes the pattern of the pivot points. i.e., are the pivot points expanding or contracting (this is like range expansion and contraction). The strategy enters a trade buy/sell if range is expanding and price breaks the maximum/minimum of last ‘n’ (eg 3) pivot points.
  - **Opening Gap (BO_SLOPE) Breakout :** This strategy takes buy or sell trades based on range breakouts computed by previous n-days high-low ranges. It also has time of the day filter and opening gap filters to reduce false positive trades
  - **Range Breakout (IDXOG) :** This strategy is a little similar to range break out strategy, where it takes buy/sell signals if the opening gap is above/below a threshold and price breaks the current day high/low
  - **Volatility Carry (VOL_CARRY):** This is short volatility strategy designed to capture the carry in volatility products (since Imp Vols > realized Vols). The Volatility carry is captured by shorting VXX intraday short (enter) 9:45 AM and long (exit) 3:45PM. However, a host of filters and risk management signals (like contango/backwardation, VIX levels) are incorporated into this strategy to protect it against an adverse event. (this strategy is short VXX ETF on most days)
- Due to lack of availability of intraday data the strategies are backtested only till Aug-2020, the out-of-sample performance of strategy begins Jan-2019
- A brief description of the performance of each strategy is presented in the next slide

Candidate Strategies: Performance

Metrics	MULTI_PIVOT_BO	IDXOG	BO_SLOPE	VOL_CARRY
Avg Trade return	0.131%	0.82%	0.35%	0.246%
Total Trades	226	132	46	291
% Profitable	54%	50%	57%	51%
Total Returns	29.54%	11.21%	14.27%	71.6%
Annualized Returns	16.80%	6.59%	8.33%	38.26%
Standard Deviation	26.6%	15.7%	10.92%	24.1%
Sharpe	0.63	0.42	0.76	1.59

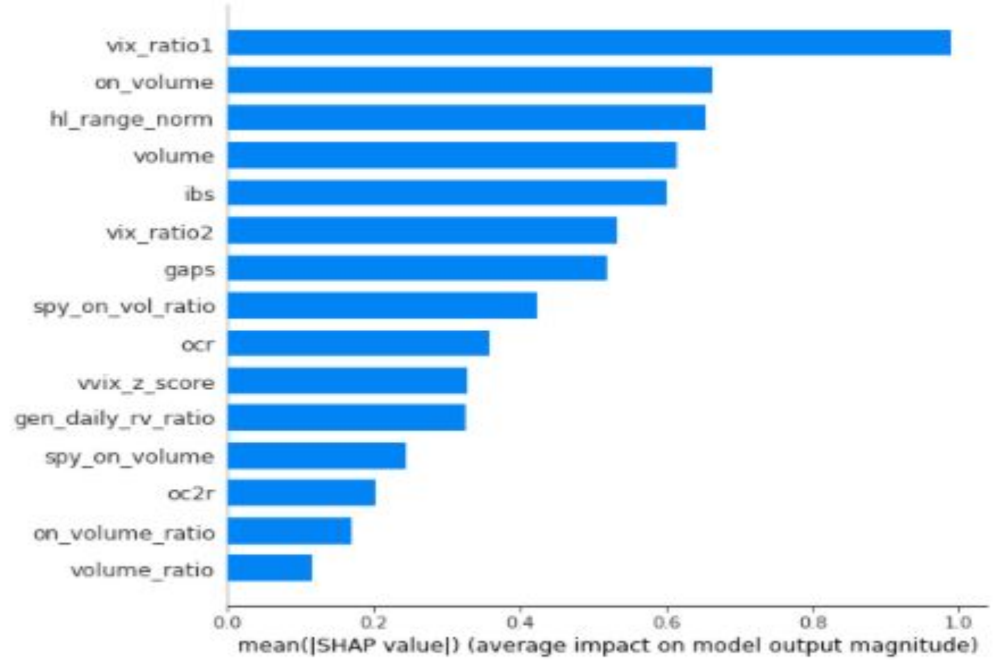
- The total slippage and transaction cost for each round-trip trade is assumed to be around 4 basis points, or 2 basis points for one way trade

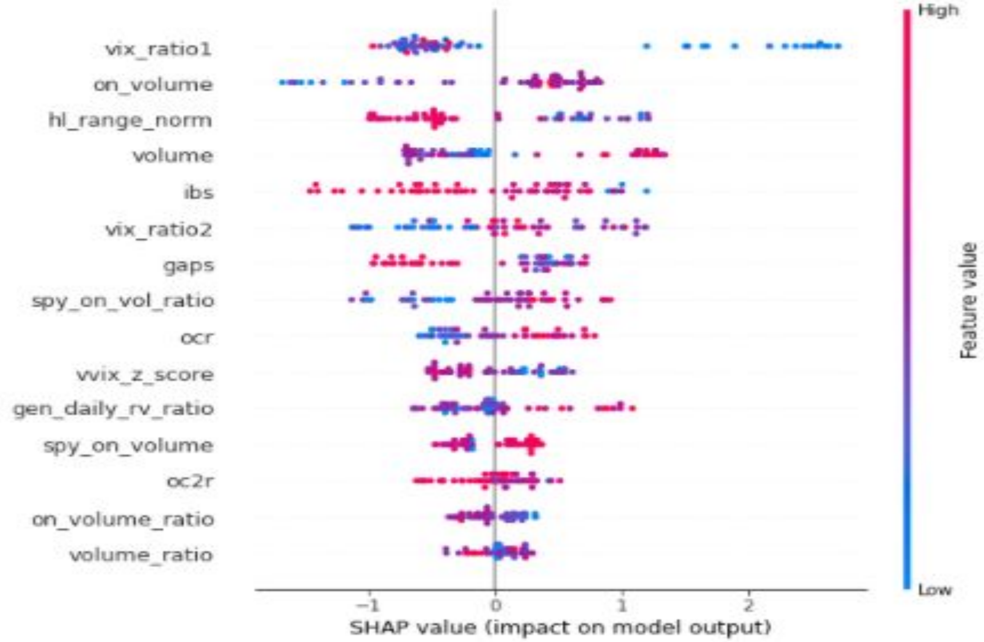
Bet-Sizing features

- To train a classifier to predict the size of the trade we use a host of features constructed from price and volume data of VXX and SPY ETF.
- The features are as follows
  - Overnight Volumes: Overnight volumes in SPY and VXX ETFs respectively
  - Opening Gaps: opening gap in VXX ETF
  - OCR and OC^2R: (close - open)/(high-low) and (close - open)^2/(high-low)
  - Volumes : Previous day volumes
  - Volume ratio : (avg of 5 day volume)/(avg of 20 day volume)
  - Overnight Volume ratio : (avg of 5 day overnight volume)/(avg of 20 day overnight volume) for SPY and VXX ETFs
  - Normalized high-low range
  - Z-score of VVIX (volatility of volatility index)
  - IBS (Internal Bar Strength) : (Close - Low)/(High-Low)
  - Contago/backwardation : VIX1m/VIX9day, VIX3m/VIX1m
  - Realized volatility (daily_rv) : Annualized standard deviation of last 20 day returns
- All features are computed on daily basis and the size of the bet i.e. leverage is decided before the start of the day.
- There is no look-ahead bias in the feature set, as the features (relevant) are lagged by 1 day
- The classifier used for this particular project is Bayesian Networks/Random Forest

Bet-Sizing features Importance: SHAP

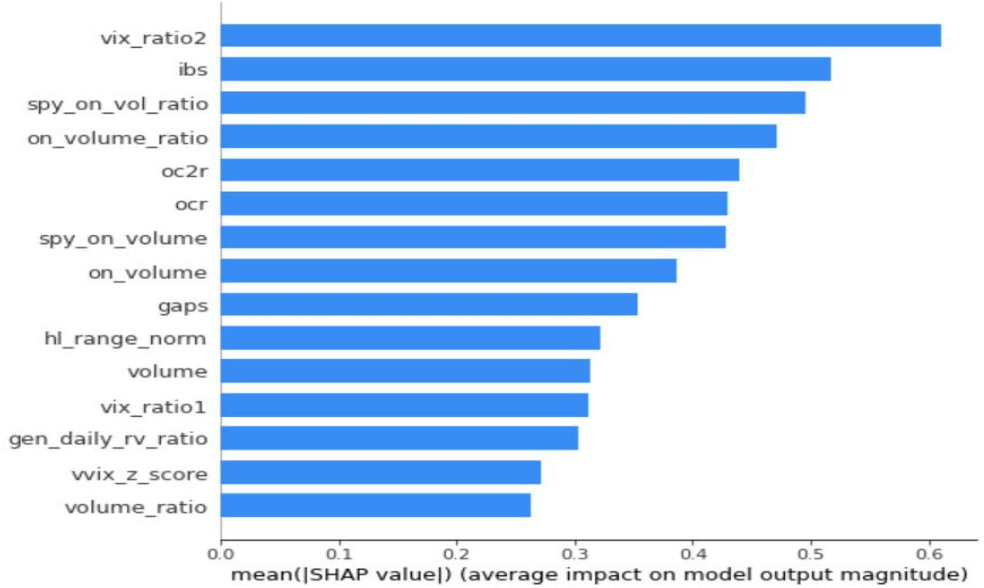
- We use SHapley Additive exPlanations (SHAP), a game-theoretic feature importance model to visualize the impact of bet-sizing features on a sample strategy i.e. BO_SLOPE
- Based on the mean shapley plot (left), we can see that vix_ratio_1 or Vix1m/Vix9d, VXX Overnight Volumes, and daily VXX high to low range impact the bet labels the highest
- From shapley impact plot, we can see that low vix_ratio_1 values which coincides with period of high near-term volatility, pushes the classifier labels towards 1, indicating this strategy performs well during periods of high volatility,
- similarly high overnight volumes pushes the classifier label towards 1, indicating high overnight volumes may be indicative of a big move in the market.
- Feature selection is performed on a rolling window basis to include top 80% of the features using SHAP model



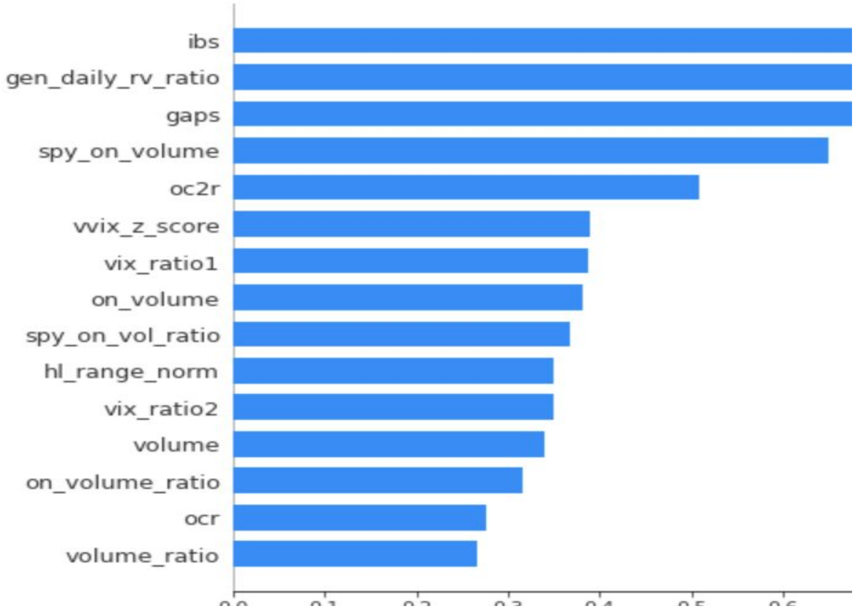


FEATURE IMPORTANCE PLOTS

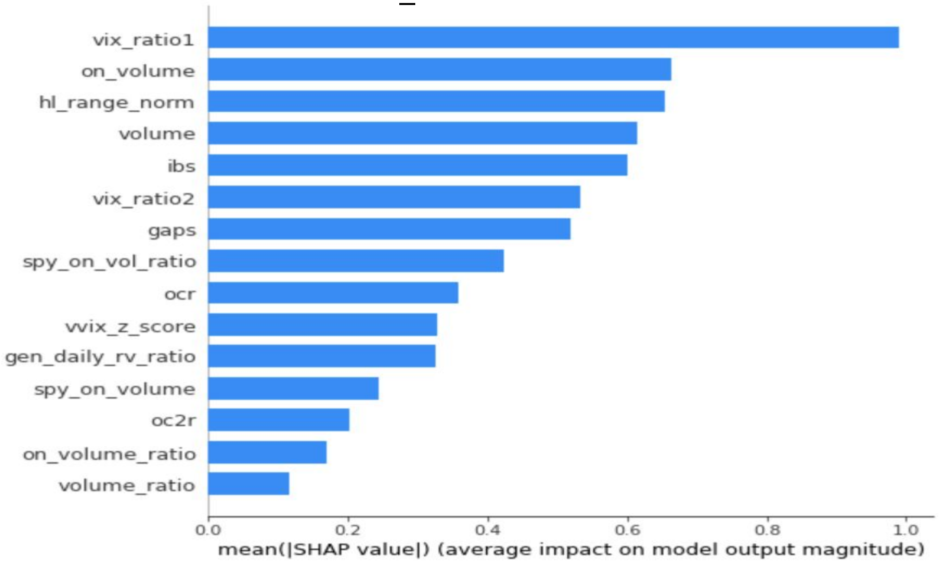
VOL CARRY



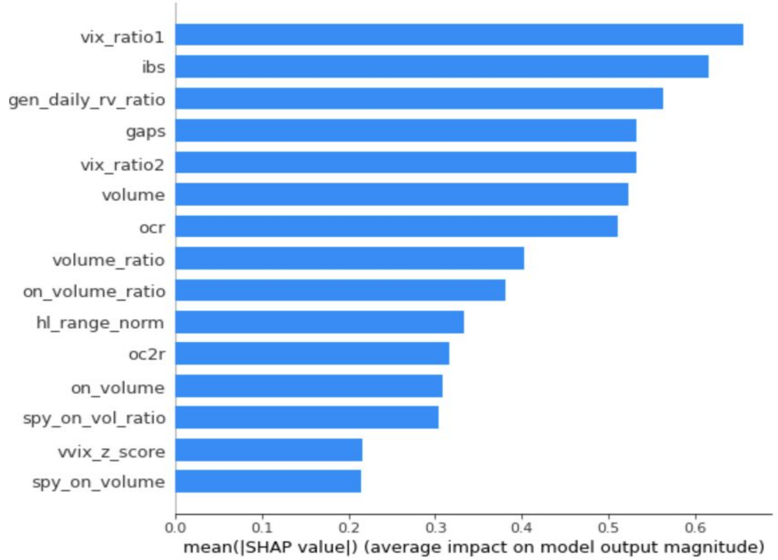
IDXOG



BO_SLOPE

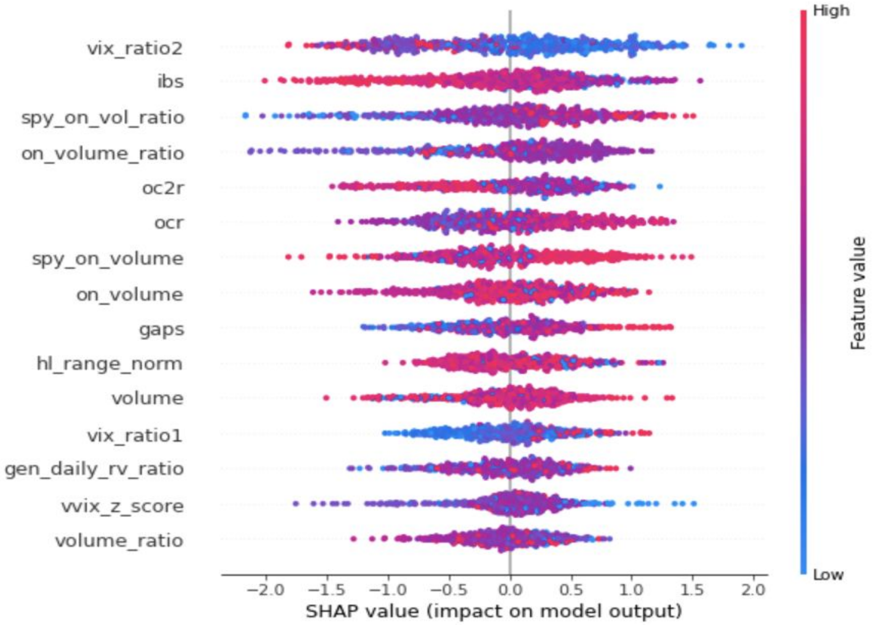


MULTI_PIVOT_BO

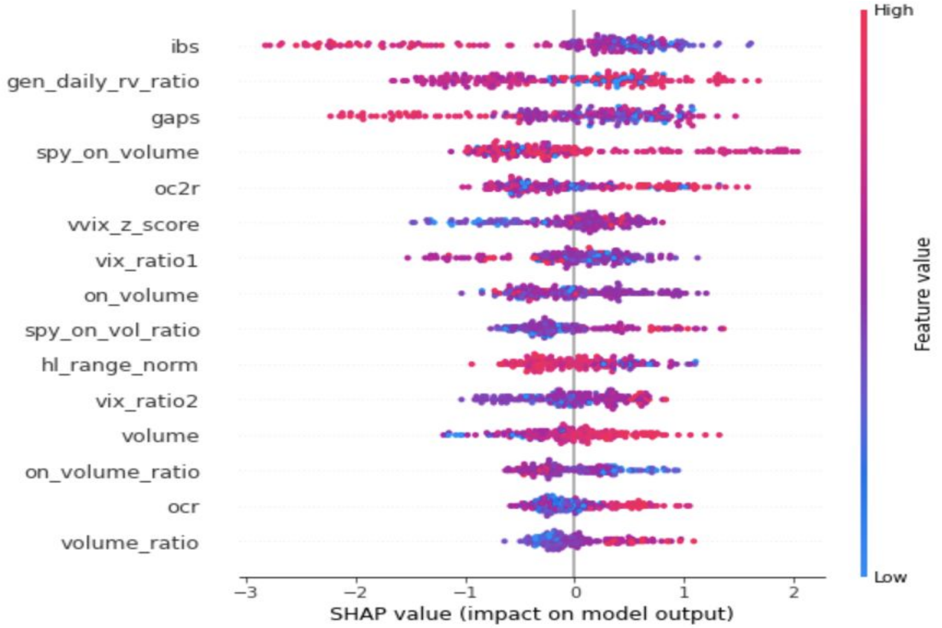


FEATURE IMPORTANCE SUMMARY PLOT

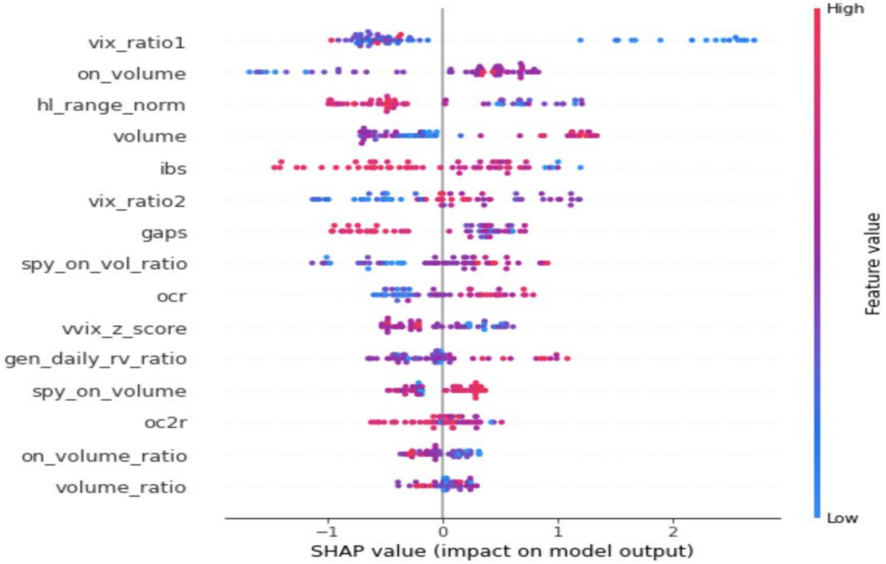
VOL CARRY



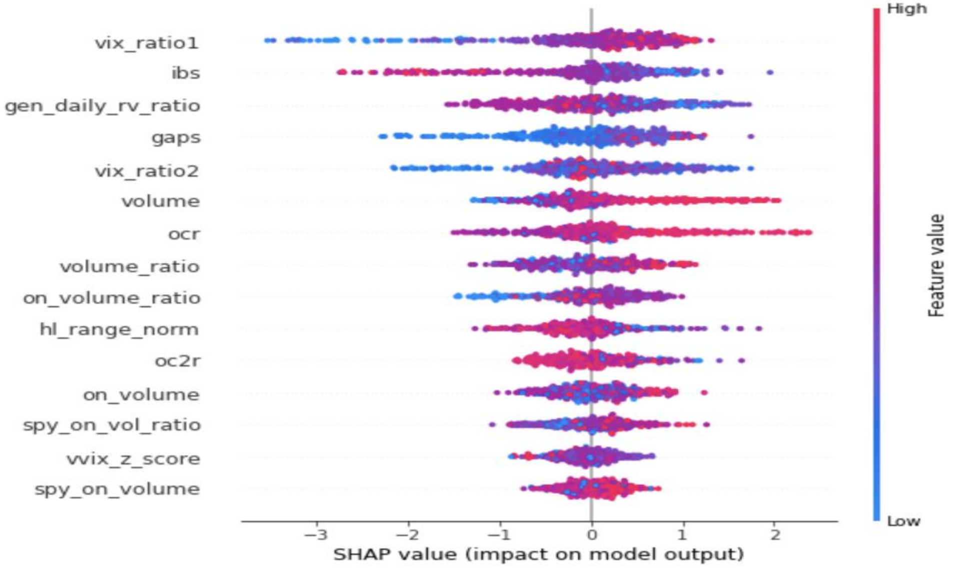
IDXOG



BO_SLOPE

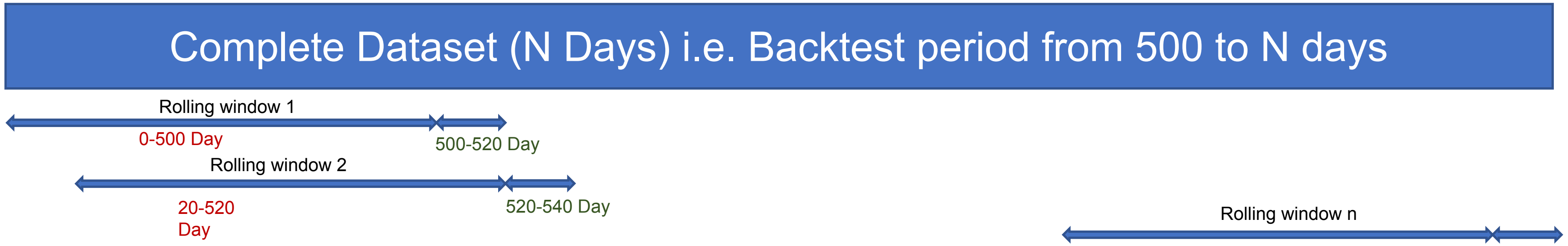


MULTI_PIVOT_BO



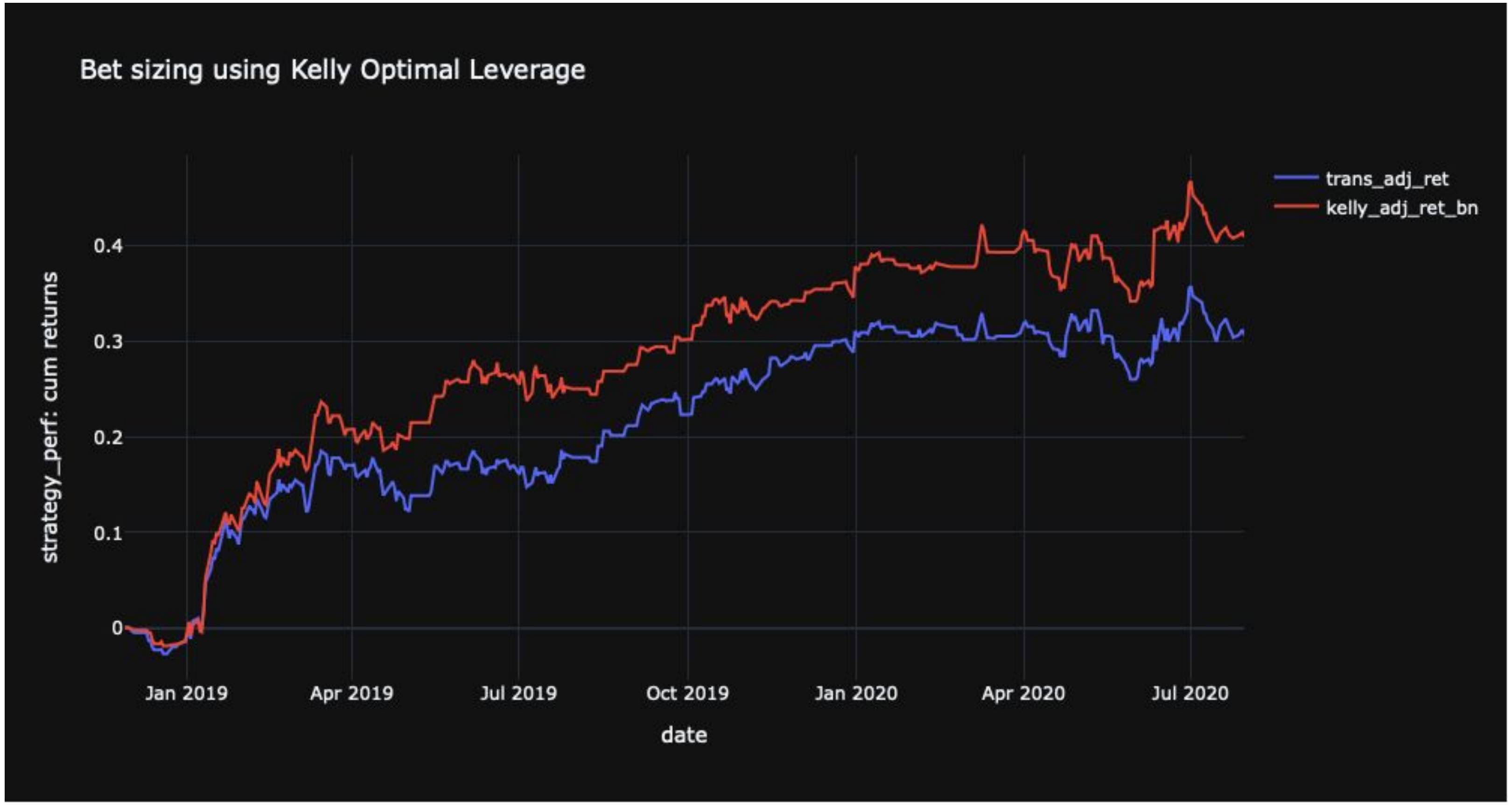
Kelly Betting Criteria and backtesting methodology

- The bet-sizing classifier outputs a probability score between [0,1], this output is used in a Kelly-betting criteria to compute the optimal leverage ratio for each strategy
- Kelly's betting criteria for a discreet game is given as
  - f*=$\frac{b*p-q}{b}$; where
  - B=odds i.e. (Profit Booking)/(Stop Loss) or (Avg return of Winning Trade)/(Avg return of Losing Trade)
  - p = probability of Success (output of the classifier)
  - q = 1-p = probability of failure
- We train a Bayesian network classifier for each strategy and use the above formula to compute optimal leverage ratio, and B or odds in our case is computed based on profit booking and stop loss levels which are 5% and 2% respectively
- Since optimal leverage can get really high, to protect the portfolio of strategies from an adverse event, we limit the optimal leverage in the range [0,2], using a min-max scalar
- To backtest the bet-sizing algorithm, we use a rolling window methodology, with a lookback of 500 days and rolling window of 20 days, as shown below
- Where lookback window is used for training and rolling window is used for testing



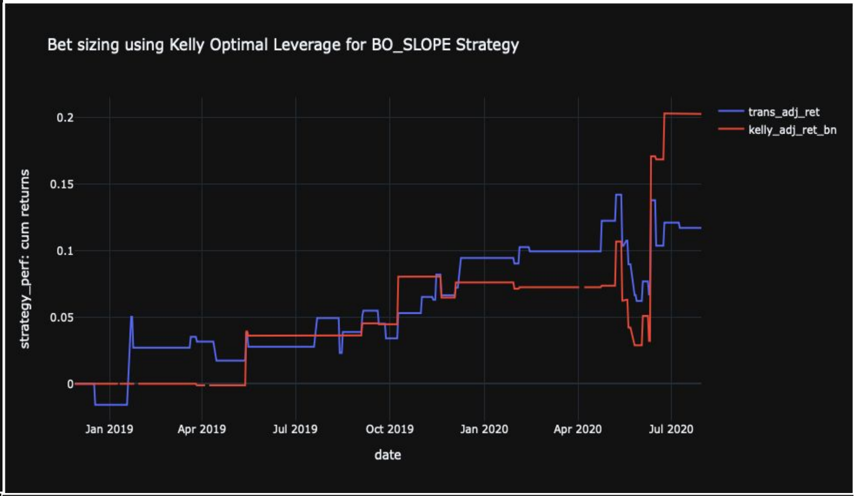
Performance Analysis

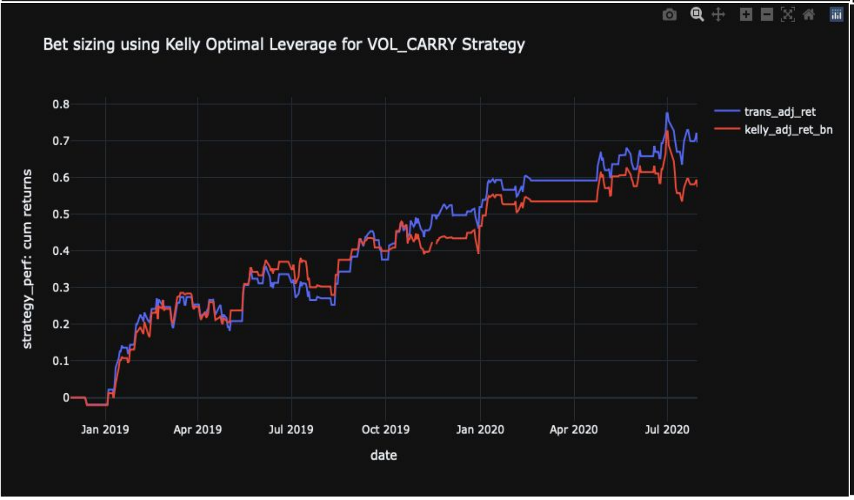
- To evaluate the performance of the bet sizing algorithm on a portfolio level basis, we compare the equi-weighted portfolio of strategies without leverage with the equi-weighted portfolio of strategies with Kelly leverage
- From the plot and the table below, we can see that bet-sizing using Kelly criteria, outperforms the un-leverage portfolio both on absolute and on risk adjusted basis

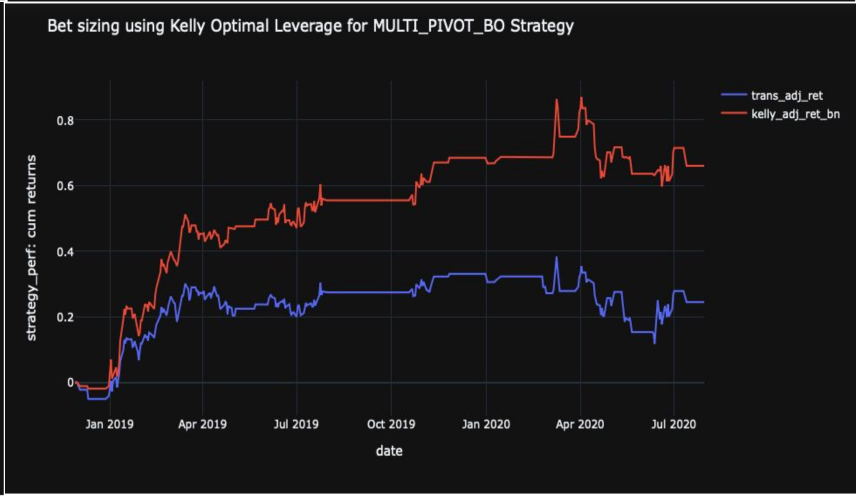


Metric	No Leverage	Kelly Leverage
Total returns	30.62%	40.92%
Ann returns	17.38%	22.85%
Stdev	12.85%	14.25%
Sharpe	1.35	1.60

Performance Analysis: Component Wise







Strategy	Type	Total Return	Annual ret	Stdev	Sharpe
IDXOG	No leverage	16.79%	9.76%	15.78%	0.62
	Kelly Leverage	15.43%	9.00%	17.52%	0.51
BO_SLOPE	No leverage	11.70%	6.86%	10.84%	0.63
	Kelly Leverage	20.26%	11.70%	13.10%	0.89
VOL Carry	No leverage	69.52%%	37.26%	23.57%	1.58
	Kelly Leverage	57.35%	31.26%	23.92%	1.31
MULTI PIVOT BO	No leverage	24.48%	14.04%	26.44%	0.53
	Kelly Leverage	66.03%	35.55%	33.21%	1.07

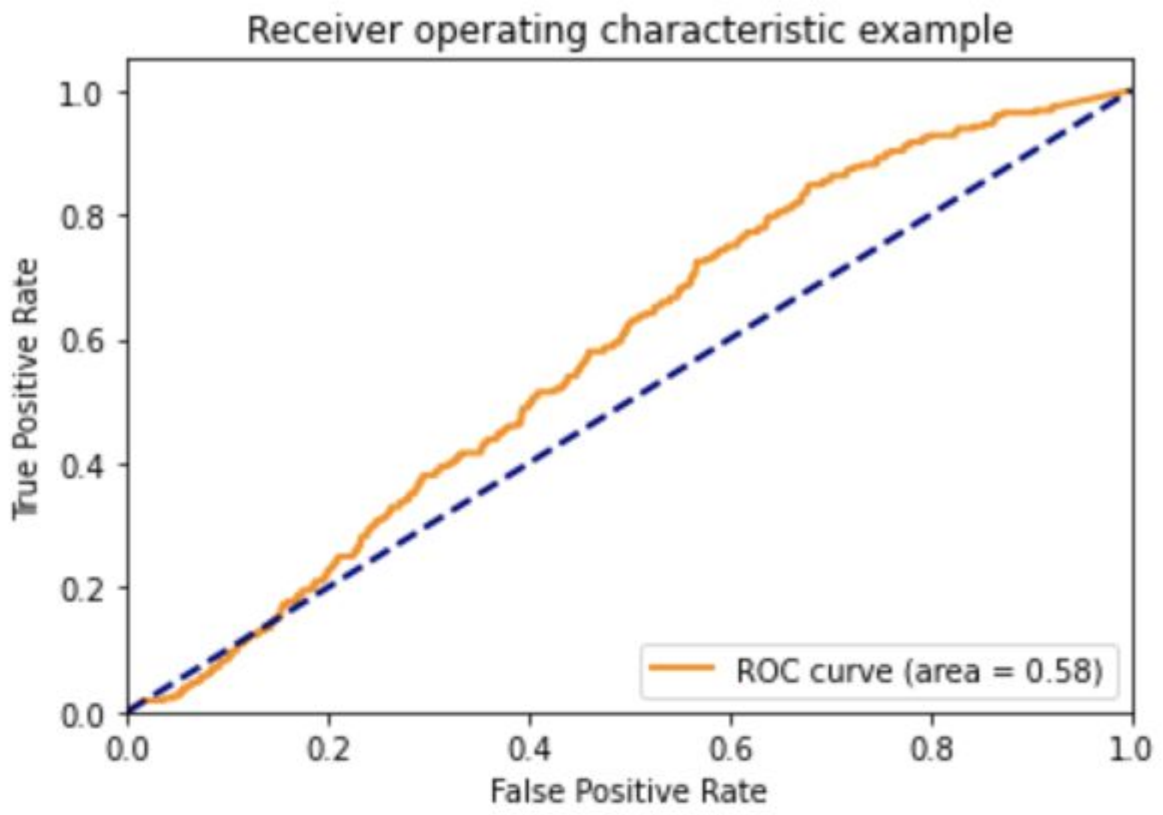
- Based on the plots and tables we can see that bet-sizing mostly worked for price based strategies
- The worst performance was observed in the volatility carry strategy
- This could be down to the fact that volatility carry strategy used some feature which are similar to bet-sizing features
- Using a different set of features that are appropriate for a volatility carry strategies may improve the performance of the bet sizing algorithm

Classification Metrics

Classification Report

	precision	recall	f1-score	support
0	0.86	0.58	0.69	1404
1	0.19	0.51	0.28	276
accuracy			0.57	1680
macro avg	0.53	0.55	0.49	1680
weighted avg	0.75	0.57	0.63	1680

ROC and Area Under Curve



Conclusion and future scope

- In this exercise we observed machine learning algorithms can be used to learn the size of the trade using a host of price and volume features
- The output of the classifier was used in a Kelly betting criterion to compute the optimal leverage of each trading strategy
- The bet-sizing algorithm outperformed the no-leverage portfolio significantly

- For future scope:
    - Test a richer feature set not just limited to price and volume data, like features on order book and options market activities
    - Using a heavier machine learning models, (I could not test it using random forest due to time constraints)
    - Using intraday features, that can adjust the size of the bet on an intraday basis, current features only use EOD features
    - Use a strategy allocation model to improve the performance of portfolio on an overall basis (it’s part of another project), strategy allocation can be done on weekly/monthly basis