MACHINE LEARNING FOR THE RETAIL INVESTOR

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Predictive Market Analysis

01
MARKET TREND
By running regressions on the largest 50 ETFs, you reveal a good view of market conditions by understanding the trends.

02
SENTIMENT ANALYSIS
Similarly, understanding how reporters see market is a good indication of volatility. This also indicates company performance.

03
PRICE PREDICTION
By running regressions on price data, a short-term expected price forecast can be generated by factoring in various market scenarios.

04
INTEREST RATES
Similar to price prediction, predicting interest rates gives investors the upper hand on Fed Funds Futures, valuations, credit risk.

05
QUANTIFY RISK
Using classification models, algorithms categorize risk and “tighten” their parameters for entering trades.

06
TREND DISCOVERY
With NLP, you can discover financial trends within social media (Reddit, Twitter). Also, finding correlations between companies reveals pairs trading ideas.

Algorithmic Trading and Tuning

Quantamental

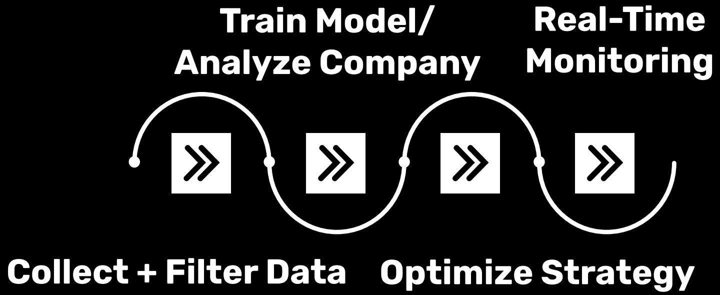
Using a combination of **fundamental analysis and quantitative strategies**, find as well as rule out any securities that do not meet a certain standard. Then, use the **company's future expected performance** as well as machine learning tactics to generate a forecast and potentially invest in the security.

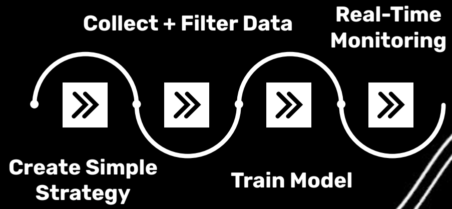
Model-Free

Find trends in market data to make direct predictions on **future price movement**. This can be done with a variety of **machine learning techniques**, such as regressions, classifications, clustering, and reinforcement learning. After, the model can **generate buy and sell** signals.

Model-Augmented

Develop a simple algorithmic trading strategy, and **then train a model** to tune the parameters of the strategy. Methods like hyperparameter tuning, reinforcement learning, and using ensemble models can lift a simple strategy into one that is well **optimized**.



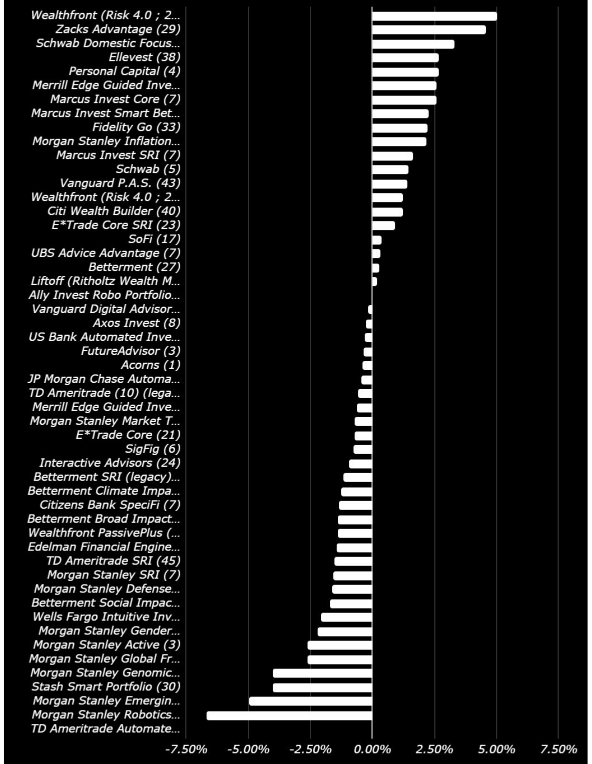


Robo Advisors

If you don't want to make it yourself, you don't have to.
Robo advisors are online investment services that allow algorithms to make the decisions that typically would be delegated to investment managers.

Why would you want it?
They can be personalized to your specific risk tolerance, strategy preference, and exposure preferences. They have a low barrier to entry (account minimums), and are offered by large and prominent brokers like Fidelity, Merrill, Vanguard, etc.

Robo Advisor Performance vs Benchmark Over 1 Year



See References for note.[1]

Pros and Cons of ML in Investing

Advantages of ML

FOR DIY-ERS

Fine tune your model based on your own investment philosophy.

Readjust your risk and portfolio dynamically based on market conditions.

Faster and more accurate/informed than the typical retail investor.

FOR OUTSOURCING

Quant funds use these types of methodologies to discover alpha, and sometimes, they yield higher returns.[4]

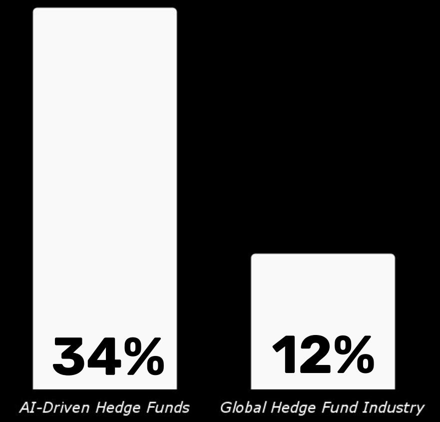
Saves time, effort, and potentially money that would have been spent researching.

56%
of hedge funds

report using AI to inform investment decisions.[2]

3x
increase

from 2017 to 2018. Now, it is most likely higher.[2]



cumulative returns for 3 years through May, 2020 for AI-driven hedge funds vs. the global hedge fund industry.[3]

Disadvantages of ML

The elephant in the room

It is challenging due to the large learning curve for people on both sides of the business-computer science spectrum with lots of technicalities.

Yes, adding ML to your algos could help boost returns, but if not robust enough, it also could really hurt, especially if you make it yourself.

Model overfitting is always an issue and tends to be quite common. Therefore, backtests are not always an indication of future returns.[5]

A black box

When implementing on your own, adding machine learning to your strategies make debugging complex and requires significant efforts to determine the correctness of your logic.

This also applies to robo advisors or AI-driven hedge funds.

Brokerage fees with trading frequency, deployment costs, and data costs add up.

Base Strategy

STACKED EMAS

Using exponential moving averages, we derive the general movement of the market.

TTM SQUEEZE

Adding the TTM Squeeze to find entry points creates a simple strategy to build from.

```
def getEMAs(df, freqs=MA_PERIODS):
  for freq in freqs:
    df[f"{freq} EMA"] = talib.EMA(df["Close"], timeperiod=freq)
  return df

SPY_df = getEMAs(SPY_df)

def ttm_squeeze(df, window=21, multiplier=1.5):
    upper_band, _, lower_band = talib.BBANDS(df["Close"], window, multiplier)
    df["Upper Bollinger Band"] = upper_band
    df["Lower Bollinger Band"] = lower_band

    atr = talib.ATR(df["High"], df["Low"], df["Close"], timeperiod=window)
    df["ATR"] = atr
    ema = talib.EMA(df["Close"], window)
    keltner_upper = ema + multiplier * atr
    keltner_lower = ema - multiplier * atr
    df["Lower Keltner Channel"] = keltner_lower
    df["Upper Keltner Channel"] = keltner_upper
    df["TTM Squeeze"] = (lower_band > keltner_lower) & (upper_band < keltner_upper)

    return df

SPY_df = ttm_squeeze(SPY_df)
```

```
def getSignalsFromConditional(series):
  signals = (series).astype(int).astype(float).diff().fillna(0)
  entries = (signals == 1)
  exits = (signals == -1)
  return [entries, exits]
```

```
[long_entries, long_exits] = getSignalsFromConditional(((SPY_df_head["8 EMA"] > SPY_df_head["Close"])
         & (SPY_df_head["13 EMA"] > SPY_df_head["8 EMA"]) &
         (SPY_df_head["21 EMA"] > SPY_df_head["13 EMA"]) & SPY_df_head["TTM Squeeze"]))

[short_entries, short_exits] = getSignalsFromConditional(((SPY_df_head["8 EMA"] < SPY_df_head["Close"])
         & (SPY_df_head["13 EMA"] < SPY_df_head["8 EMA"]) &
         (SPY_df_head["21 EMA"] < SPY_df_head["13 EMA"]) & SPY_df_head["TTM Squeeze"]))
```

Idea for ML in Finance

How Can We Use ML to Make it Better?

Sentiment Analysis

Get more accurate signals by incorporating sentiment analysis from the news or even social media (linear, logistic, or random forest regressions).

Hyperparameter Tuning

Build the strategy's robustness (using the model-augmented approach) by learning which patterns result in (un)profitable trades.

Feature Engineering

Add new features that put each trade in context of the broader market. E.g. Set penalty for shorting when top 50 ETFs are in bull market.

References and Notes

1.
https://www.theroboreport.com/data/total-portfolio-returns/
Total Portfolio Returns vs. Normalized Benchmark ~60/40 (Stock market/Bond market) Allocations (Last Updated: 12/31/2022).

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