Applications of machine learning for volatility estimation and quantitative strategies

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Machine Learning for Quant Strategies

• Theoretical foundations of Machine/Statistical Learning:
  – Approximation vs Estimation error
  – Simplicity vs Complexity

• Why Alternative Risk Premia products failed

• Example of supervised learning for selecting volatility models

• Risk-profile of systematic investment strategies
Data Overfitting: many solutions to fit data points locally with different global behaviour
Example of perfect in-sample fit for an asset price path

5-degree polynomial trend-line with near perfect explanatory power $R^2=98\%$
Example of out-sample forecast for short vol ETN

- How to prevent ML algorithms from falling into this trap?
Credit derivatives crisis in October 2008

• Quant models for credit derivatives relied on multi-parameter models with linear fits: one parameter for market price of each instrument
• The models failed to calibrate and work in distressed markets during the Financial Crisis

S&P 500 Index Daily Movers

<table>
<thead>
<tr>
<th>Gainers %  ↓</th>
<th>Losers %  ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>WMT 0.30%</td>
<td>AIG -23.10%</td>
</tr>
<tr>
<td>MCD 0.23%</td>
<td>MER -19.56%</td>
</tr>
<tr>
<td>KO 0.11%</td>
<td>LEH -19.29%</td>
</tr>
<tr>
<td></td>
<td>GNW -18.64%</td>
</tr>
<tr>
<td></td>
<td>ACAS -18.17%</td>
</tr>
<tr>
<td></td>
<td>GE -17.97%</td>
</tr>
<tr>
<td></td>
<td>DDR -17.10%</td>
</tr>
<tr>
<td></td>
<td>HIG -16.86%</td>
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</table>
Alternative risk premia (ARP) crisis in October 2018

- ARP is marketed by major banks as market-neutral using overstated back-tests
- ARP products proliferated from 2015 with estimated AuM $500 bln at mid of 2018
- Performance of live ARP products from 2015 has been less spectacular than back-tests

<table>
<thead>
<tr>
<th>Gainers</th>
<th>YTD % ↓</th>
<th>Losers</th>
<th>YTD % ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rates Momentum Index</td>
<td>7%</td>
<td>Multi-Asset Value Index</td>
<td>-61%</td>
</tr>
<tr>
<td>Credit Multi-Style Index</td>
<td>5%</td>
<td>Multi-Asset Volatility Index</td>
<td>-34%</td>
</tr>
<tr>
<td>Rates Value Index</td>
<td>4%</td>
<td>Equity Volatility Index</td>
<td>-27%</td>
</tr>
<tr>
<td>Currency Volatility Index</td>
<td>4%</td>
<td>Equity Multi-Style Index</td>
<td>-26%</td>
</tr>
<tr>
<td>Credit Carry Index</td>
<td>1%</td>
<td>Credit Momentum Index</td>
<td>-22%</td>
</tr>
<tr>
<td>Multi-Asset Multi-Style Index</td>
<td></td>
<td>Multi-Asset Index</td>
<td>-21%</td>
</tr>
<tr>
<td>Equity Size Index</td>
<td></td>
<td>Equity Index</td>
<td>-20%</td>
</tr>
<tr>
<td>Multi-Asset Momentum Index</td>
<td></td>
<td>Equity Quality Index</td>
<td>-19%</td>
</tr>
<tr>
<td>Commodity Volatility Index</td>
<td></td>
<td>Commodity Volatility Index</td>
<td>-17%</td>
</tr>
<tr>
<td>Equity Carry Index</td>
<td></td>
<td>Equity Carry Index</td>
<td>-16%</td>
</tr>
<tr>
<td>Commodity Multi-Style Index</td>
<td></td>
<td>Commodity Multi-Style Index</td>
<td>-14%</td>
</tr>
<tr>
<td>Equity Value Index</td>
<td></td>
<td>Equity Value Index</td>
<td>-13%</td>
</tr>
<tr>
<td>Commodity Smart Beta Index</td>
<td></td>
<td>Commodity Smart Beta Index</td>
<td>-13%</td>
</tr>
<tr>
<td>Equity Momentum Index</td>
<td></td>
<td>Equity Momentum Index</td>
<td>-11%</td>
</tr>
<tr>
<td>Equity Smart Beta Index</td>
<td></td>
<td>Trend-Following Index</td>
<td>-11%</td>
</tr>
<tr>
<td>Trend-Following Index</td>
<td></td>
<td>Currency Carry Index</td>
<td>-10%</td>
</tr>
<tr>
<td>Currency Carry Index</td>
<td></td>
<td>Credit Index</td>
<td>-10%</td>
</tr>
<tr>
<td>Credit Index</td>
<td></td>
<td>-8%</td>
<td>-8%</td>
</tr>
</tbody>
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Rich class of decision rules may reduce the approximation error but increases the estimation error.

**Bayesian learning**: select the rule with the highest posterior probability but prior probabilities are needed(!)

**Probably Approximately Correct (PAC) learning**: if class D is PAC learnable there exists a finite sample size of for given level of approximation and estimation error.

Approximation error: the class D may not have good rules

Estimation error: we are unable to identify the good rule for prediction from training data.
Vapnik-Chervonenkis (VS) dimension measures the richness of the class of decision rules

- VC dimension predicts the bounds of the sample size for PAC learning
- Example using single-parametric threshold classifier: buy if last return is higher than threshold, sell otherwise: the VC dimension is one
PAC learning using Hierarchy of Decision rules

• Restricting the richness of the class may improve PAC learning but may increase the approximation error

• Split the class $D$ of all decision rules into a sequence of classes $D_i$ which are PAC learnable

• VC dimension is a measure of the complexity of rules in class $D_i$

• Select a rule by minimizing:

$$\text{Approximation Error} + \text{Complexity}$$

$D_1 =$ the class with simplest decision rules

$D_2 = D_1 +$ the class with more complex rules

$D = D_1 + D_2 + ...$
PAC learning for the process of systematic trading includes at least three classes of decision rules:

- **Signal**
  - Look for predictors with highest scores
- **Portfolio**
  - Manage risk allocation and diversification
- **Execution**
  - Minimize trading costs and slippage

Examples of inconsistent trading processes:
1. Signal that works only on one asset: cannot diversify the portfolio
2. Signal that changes too frequently: execution costs can be too high
Example of designing strategy for volatility trading: learning hierarchy to reduce the dimensionality

<table>
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<th>Strategy design</th>
<th>Strategy Parameters</th>
</tr>
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<tbody>
<tr>
<td>Volatility Model Parameters</td>
<td>*Optimal 2-d set</td>
</tr>
</tbody>
</table>

Split 2-dimensional problem into two orthogonal 1-dimensional problems

**Volatility Model Parameters**

*Optimal 1-d set

**Strategy Parameters**

*Optimal 1-d set
Model forecast of realized volatility is applied to estimate the volatility risk-premium

- Relative value volatility trading: Sell/buy options with high/low expected spread and delta-hedge

![Volatility Risk-Premium Chart]

**Volatility Risk-Premium = VIX at MonthStart - S&P500 Realized Monthly Volatility**

- Average = 4%
- Minus Standard Deviation = -3%
- Plus Standard Deviation = 10%
Multiple classes of volatility models are applied for the forecast of realized volatility

| Sample space estimators                                      | • Close-to-close, Intraday estimators (Parkinson, etc...)  
|                                                              | • Assume random walk for the volatility                  |
| GARCH models                                                 | • Garch (1,1), Asymmetric Garch, etc                      
|                                                              | • Apply long-term history with mean-reversion             |
| Bayesian parametric models                                   | • Continuous type models with priors for vol forecast    
|                                                              | • Apply intraday high/low price data                     |
| Hidden Markov Chain Models (HMC)                            | • Discrete states of volatility                           
|                                                              | • Classification problem in unsupervised machine learning|
Selection of model with the best forecast power

Class of decision rules: all volatility models
Implementation: use 40 models from 4 model classes

Uniform metric for model selection
Implementation: distribution tests for the stability of the forecast

Select model with the highest score for the asset or asset class
Implementation: Regularly update the tests as new data is available
Distribution tests is applied for volatility normalized returns over forecast period

\[ Z(n) = \frac{\text{Realized Return (n)}}{\text{Volatility Forecast}(n)} \]

For a model with strong predicative power, sample distribution of \( Z(n) \) is symmetric with standard deviation of 1 (unbiased forecast)
Robust estimator provides tight bounds for volatility forecast with no “surprises”

- Robust application for strategies with volatility targeting and time series normalization
Top-3 models for High Yield Bonds ETF using the normality test annually

- Use past rolling window of 3 year for one step forecast evaluation
- Each model is numbered (1,2,...)
- Stable ranks for Markov chain (31-32) and GARCH models (21-30)
Top-3 models for the S&P 500 index using normality test in walk-forward analysis annually

- Markov Chain models (31,32) are frequently on the top
- Intraday estimators (1-10) are also reliable while being least complex
Quantitative Strategies have changing profile in different market regimes

- Apply the quantile regression of returns on the strategy vs returns on the benchmark
- Three regimes: bear, normal, and bull
- Example using CBOE Put index selling at-the-money put options on the S&P 500 index
Risk profile of HFR Bank Systematic Risk Premia Multi-Asset Index vs SG Trend-following CTAs

• Bank Risk Premia Index is short 3× leveraged put and long 5× leveraged call
• Trend-following CTAs replicate protection for bear regimes with overall positive performance
• The difference between amateur and professional applications of ML methods

[Graphs showing quarterly returns and linear equations for different market conditions]
Conclusions: Machine Learning for Quant Strategies

• Machine/Statistical learning models are as good as people behind them

• Nested approach for strategy design to balance between complexity and approximation & estimation errors

• Understanding of how the strategy behaves in different market regimes

• Models adaptation to different regimes: no free or fixed parameters
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