HackRush'24: Quantitative Finance Challenge

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What is G-Arch?

The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model is a statistical model commonly used in finance to forecast volatility, particularly in the context of asset returns. It is an extension of the ARCH (Autoregressive Conditional Heteroskedasticity)

Model Structure: The GARCH model captures the conditional heteroskedasticity, or time-varying volatility, in financial time series data. It assumes that the current volatility of an asset's returns is dependent on past squared observations of returns (autoregressive term) as well as past volatility (moving average term). The model is specified with two main components:

1. **Autoregressive (AR) term:** This component captures the dependence of current volatility on past squared observations of returns. It represents the persistence of volatility over time.

2. **Moving Average (MA) term:** This component captures the dependence of current volatility on past volatility. It represents the mean-reverting behaviour of volatility towards its long-term average.

Volatility Equation (Conditional Variance):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

- σ_t^2 is the conditional variance of the asset's returns at time t.
- ω is the constant term or intercept.
- α_i are the coefficients of the autoregressive (AR) terms, where $i = 1, 2, ..., p$.
- ε_{t-i}^2 are the squared residuals (squared error terms) from past observations of returns.
- β_j are the coefficients of the moving average (MA) terms, where $j = 1, 2, ..., q$.
- σ_{t-j}^2 are the past conditional variances, representing the moving average of past squared residuals.

Parameter Estimation: The parameters of the GARCH model (e.g., the coefficients of the AR and MA terms) are estimated using statistical methods such as maximum likelihood estimation (MLE). These parameters determine the dynamics of volatility in the model.

In the context of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, p and q are parameters that determine the autoregressive and moving average orders, respectively, of the model.

p: This parameter represents the autoregressive order, which refers to the number of lagged squared error terms (volatility shocks) included in the model.

q: his parameter represents the moving average order, which refers to the number of lagged conditional variances (volatility) included in the model. It captures the effect of past volatility on the current volatility.

Why G-ARCH?

1. Financial time series often exhibit volatility clustering, where periods of high volatility are followed by periods of high volatility and vice versa. GARCH models are well-suited for capturing this clustering phenomenon by allowing volatility to be dependent on past volatility shocks.
2. GARCH models explicitly model conditional heteroskedasticity, which refers to the phenomenon where the variance of a time series is not constant over time but varies depending on past information.
3. GARCH models explicitly model conditional heteroskedasticity, which refers to the phenomenon where the variance of a time series is not constant over time but varies depending on past information.
4. GARCH models have relatively simple and interpretable parameterisations, making it easier to understand the underlying dynamics of volatility.

Trading Strategy:

Our trading strategy is designed to capitalise on forecasted changes in volatility while aligning trading positions with prevailing market trends. The strategy consists of three main components: volatility forecasting, market trend identification, and position management.

1. **Volatility Forecasting:**
   - Utilise the Generalised AutoRegressive Conditional Heteroskedasticity (GARCH) model to forecast future volatility for selected stocks.
   - Implement the GARCH model on historical daily stock price data to predict volatility over a rational forecast horizon.
   - Validate the accuracy of volatility forecasts through backtesting and comparison with actual volatility.

2. **Market Trend Identification:**
   - Determine market trends based on price movements over a specified period.
   - Define a bullish market trend as continuous price increases over five consecutive days or minor price decreases (not exceeding 1%) on any given day within the period.
   - Identify a bearish market trend as continuous price decreases over five consecutive days or minor price increases (not exceeding 1%) on any given day within the period.

3. **Trading Signals and Position Management:**
   - Initiate trades when the forecasted volatility for the next data point exceeds the current volatility.

- Take long (buy) positions if the market trend is bullish, indicating potential opportunities for profit from increasing prices.
- Take short (sell) positions if the market trend is bearish, aiming to capitalise on downward price movements.
- Adjust position sizes based on the magnitude of the difference between actual and forecasted volatility, scaling up positions during periods of higher volatility.
- Implement strict stop-loss and risk management strategies to limit potential losses and protect capital.

By integrating these elements into our trading strategy, we aim to maximise returns while effectively managing risk in dynamic market conditions. The strategy leverages volatility forecasts and market trend analysis to make informed trading decisions, optimising performance and profitability over time.