Conditional Correlation Modeling using Machine Learning and Multivariate GARCH

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Conditional variance-covariance modeling

We consider a k-dimensional log return series, $r_t = (r_{1,t}, \ldots, r_{k,t})'$ such that

$$r_t = H_t^{1/2} z_t,$$

where conditional variance-covariances of returns r_t is denoted by a $k \times k$ positive definite matrix H_t, with $H_t^{1/2}$ its Cholesky decomposition, and z_t denotes a $k \times 1$ vector of independent and identically distributed random variables with mean zero and unit variance. We consider a reparameterization of H_t, i.e. $H_t = D_t R_t D_t$, where D_t is a diagonal matrix with conditional volatility of each marginal return series on its diagonal and matrix R_t includes all pairwise correlations $\rho_{i,j,t}$, with $\rho_{i,j,t} = \rho_{j,i,t}$:

$$\begin{pmatrix} h_{1,1,t}^{1/2} & & 0 \\ & \ddots & \\ 0 & & h_{k,k,t}^{1/2} \end{pmatrix} \begin{pmatrix} 1 & \rho_{1,2,t} & \cdots & \rho_{1,k,t} \\ \rho_{2,1,t} & 1 & & \rho_{2,k,t} \\ \vdots & & \ddots & \vdots \\ \rho_{k,1,t} & \rho_{k,2,t} & \cdots & 1 \end{pmatrix} \begin{pmatrix} h_{1,1,t}^{1/2} & & 0 \\ & \ddots & \\ 0 & & h_{k,k,t}^{1/2} \end{pmatrix},$$

Diagonal elements of matrix D_t are modeled parametrically using GARCH(1,1) and GJR-GARCH(1,1) specifications, whereas the conditional correlation matrix R_t is estimated in a nonparametric manner using nonparametric machine learning algorithms k-nearest neighbor and random forest.

The system is a variant of the model considered in Tassiulas and Ephremides [1] where it is assumed that the number of flows stays fixed over time, and all flows have a continuous influx of traffic. It can be shown that in this case, so-called MaxWeight scheduling provides maximum stability, i.e. it achieves stability whenever feasible to do so at all. When using this scheduling rule, in each slot the server selects the flow as follows:

where R_i denotes the transmission rate, and Q_i denotes the backlog of flow i. This is different from MaxRate scheduling for example, where only the transmission rate is used to select the flow to be served. However, MaxWeight scheduling fails when applied to the dynamic setting under consideration. In contrast to the standard scenario with a fixed number of flows, the instability no longer manifests itself in the form of a few flows with large backlogs, but rather as an excessive number of flows with relatively small backlogs. Because the strategy takes backlog into account, it will give priority to newly arrived flows, so it does not benefit from the service rate variation - the phenomenon that allows the selection of the highest of multiple transmission rates - as it would have when treating all flows equally.

In contrast we consider a strategy close to MaxRate scheduling, and show that this does provide maximum stability. This is done through the Foster-Lyapunov criterion, using the following Lyapunov function:

where N_i is the number of flows with a backlog of i bits, B denotes the number of bits for each flow, and $R^{\max}$ the maximum feasible transmission rate.

The difference can also be seen in Figure 1, which shows the evolution of the system over time under both strategies.
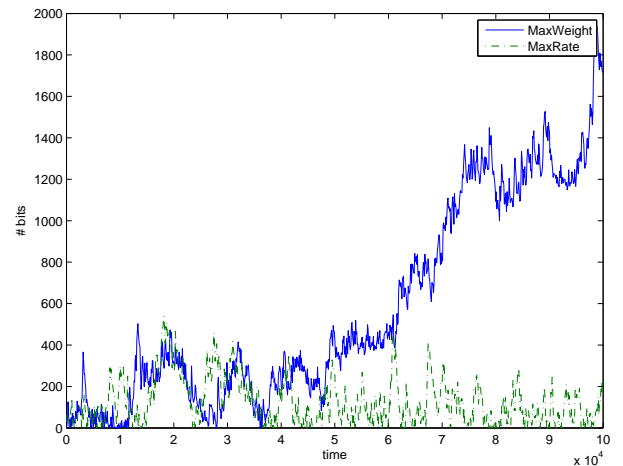

Figure 1: Number of bits in the system plotted against time for MaxWeight and MaxRate scheduling.

References

[1] L. Tassiulas, A. Ephremides (1993). Dynamic server allocation to parallel queues with randomly varying connectivity. IEEE Trans. Inf. Theory 30, 466–478.