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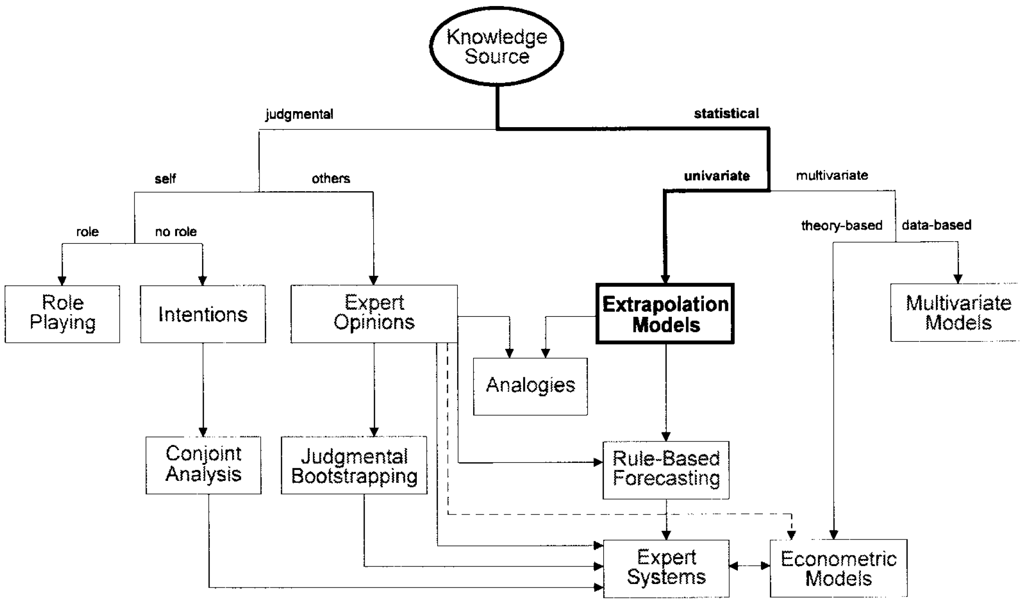
EXTRAPOLATION



Pure extrapolation of time series assumes that all we need to know is contained in the historical values of the series that is being forecasted. For cross-sectional extrapolations, it is assumed that evidence from one set of data can be generalized to another set.

Because past behavior is a good predictor of future behavior, extrapolation is appealing. It is also appealing in that it is objective, replicable, and inexpensive. This makes it a useful approach when you need many short-term forecasts.

The primary shortcoming of time-series extrapolation is the assumption that nothing is relevant other than the prior values of a series.

"Extrapolation of Time-Series and Cross-sectional Data" by J. Scott Armstrong describes principles for developing and using extrapolation methods. It includes such principles as "make seasonal adjustments only when seasonal effects are expected and only if there is good evidence by which to measure them."

In "Neural Networks for Time-Series Forecasting," Bill Remus from the University of Hawaii and Marcus O'Connor from the University of New South Wales describe how neural nets can contribute to extrapolation. Neural nets are feasible for long time series. Given the importance of neural nets to the research community and commercial claims about their success, this review is welcome. While validation research is in short supply, Remus and O'Connor summarize some promising research.

Using neural networks to make forecasts is controversial. One major limitation of neural nets is that you must rely on the data to lead you to the proper model. Also, neural nets are more complex than many of the older time-series methods. The method is similar to stepwise regression, an earlier method in which the analyst depends on the data to produce a model. To date, complex atheoretical approaches have had little success in forecasting.