In practice, linear models are applied to regression and classification problems with the goals of inference and prediction. Numerous asset pricing models have been developed by academic and industry researchers that leverage linear regression. Applications include the identification of significant factors that drive asset returns for better risk and performance management, as well as the prediction of returns over various time horizons. Classification problems, on the other hand, include directional price forecasts.

The functional relationship produced by a supervised learning algorithm can be used for inference— that is, to gain insights into how the outcomes are generated. Alternatively, you can use it to predict outputs for unknown inputs.

In the case of algorithmic trading as an example, we can use inference to estimate the statistical association of the returns of an asset with a risk factor. This implies, for instance, assessing how likely this observation is due to noise, as opposed to an actual influence of the risk factor. Prediction, in turn, can be used to forecast the risk factor, which can help predict the asset return and price and be translated into a trading signal.

Hi Radhika,

In both cases you have input data (historical data), model, and output.

The matter is how do you handle the data;

if you have already analysed it and got your conclusion, it is obvious inference.

if you use the unknown/unfamiliar data to train the model to get a clue that is a prediction.

Hi Jim,

In most cases the prediction models are wrong or False, you should not have an expectation of only True.

In both cases you train models with data.

The only difference here if you can read and you are able to analyse the data, then you would come to some conclusions, that is inference.

If you are unable to analyse the data or working with unknown, you train the model to get a clue, that is prediction (wrong or right)

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