## Chapter 1 : Vector Autoregressive models VAR(p) models | STAT

*Model Estimation and Interpretation This section will be divided into 4 sub-sections: Sub-section examines the time series data by using the Augmented Dickey-Fuller () and Phillips and.*

Non-exhaustive cross-validation[ edit ] Non-exhaustive cross validation methods do not compute all ways of splitting the original sample. Those methods are approximations of leave-p-out cross-validation. The cross-validation process is then repeated k times, with each of the k subsamples used exactly once as the validation data. The k results can then be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling see below is that all observations are used for both training and validation, and each observation is used for validation exactly once. In 2-fold cross-validation, we randomly shuffle the dataset into two sets d0 and d1, so that both sets are equal size this is usually implemented by shuffling the data array and then splitting it in two. In stratified k-fold cross-validation, the folds are selected so that the mean response value is approximately equal in all the folds. In the case of binary classification, this means that each fold contains roughly the same proportions of the two types of class labels. Holdout method[ edit ] In the holdout method, we randomly assign data points to two sets d0 and d1, usually called the training set and the test set, respectively. The size of each of the sets is arbitrary although typically the test set is smaller than the training set. We then train build a model on d0 and test evaluate its performance on d1. In typical cross-validation, results of multiple runs of model-testing are averaged together; in contrast, the holdout method, in isolation, involves a single run. It should be used with caution because without such averaging of multiple runs, one may achieve highly misleading results. Similarly, indicators of the specific role played by various predictor variables e. While the holdout method can be framed as "the simplest kind of cross-validation", [10] many sources instead classify holdout as a type of simple validation, rather than a simple or degenerate form of cross-validation. For each such split, the model is fit to the training data, and predictive accuracy is assessed using the validation data. The results are then averaged over the splits. The disadvantage of this method is that some observations may never be selected in the validation subsample, whereas others may be selected more than once. In other words, validation subsets may overlap. This method also exhibits Monte Carlo variation, meaning that the results will vary if the analysis is repeated with different random splits. As the number of random splits approaches infinity, the result of repeated random sub-sampling validation tends towards that of leave-p-out cross-validation. In a stratified variant of this approach, the random samples are generated in such a way that the mean response value i. This is particularly useful if the responses are dichotomous with an unbalanced representation of the two response values in the data. Measures of fit[ edit ] The goal of cross-validation is to estimate the expected level of fit of a model to a data set that is independent of the data that were used to train the model. It can be used to estimate any quantitative measure of fit that is appropriate for the data and model. For example, for binary classification problems, each case in the validation set is either predicted correctly or incorrectly. In this situation the misclassification error rate can be used to summarize the fit, although other measures like positive predictive value could also be used. When the value being predicted is continuously distributed, the mean squared error , root mean squared error or median absolute deviation could be used to summarize the errors. The reason that it is slightly biased is that the training set in cross-validation is slightly smaller than the actual data set e. In nearly all situations, the effect of this bias will be conservative in that the estimated fit will be slightly biased in the direction suggesting a poorer fit. In practice, this bias is rarely a concern. Some progress has been made on constructing confidence intervals around cross-validation estimates, [14] but this is considered a difficult problem. Computational issues[ edit ] Most forms of cross-validation are straightforward to implement as long as an implementation of the prediction method being studied is available. In particular, the prediction method can be a "black box" â€" there is no need to have access to the internals of its implementation. If the prediction method is expensive to train, cross-validation can be very slow since the training must be carried out repeatedly. In some cases such as least squares and kernel regression , cross-validation can be sped up significantly by pre-computing certain values that are needed repeatedly in the training, or by using fast "updating rules" such as the Shermanâ€"Morrison formula. However one must be careful to preserve the "total blinding" of the validation set from the training procedure, otherwise bias may result. An extreme example of accelerating cross-validation occurs in linear regression , where the results of cross-validation have a closed-form expression known as the prediction residual error sum of squares PRESS. Limitations and misuse[ edit ] Cross-validation only yields meaningful results if the validation set and training set are drawn from the same population and only if human biases are controlled. In many applications of predictive modeling, the structure of the system being studied evolves over time i. Both of these can introduce systematic differences between the training and validation sets. For example, if a model for predicting stock values is trained on data for a certain five-year period, it is unrealistic to treat the subsequent five-year period as a draw from the same population. If the model is trained using data from a study involving only a specific population group e. New evidence is that cross-validation by itself is not very predictive of external validity, whereas a form of experimental validation known as swap sampling that does control for human bias can be much more predictive of external validity. Yet, models are also developed across these independent samples and by modelers who are blinded to one another. When there is a mismatch in these models developed across these swapped training and validation samples as happens quite frequently, MAQC-II shows that this will be much more predictive of poor external predictive validity than traditional cross-validation. The reason for the success of the swapped sampling is a built-in control for human biases in model building. In addition to placing too much faith in predictions that may vary across modelers and lead to poor external validity due to these confounding modeler effects, these are some other ways that cross-validation can be misused: By performing an initial analysis to identify the most informative features using the entire data set â€" if feature selection or model tuning is required by the modeling procedure, this must be repeated on every training set. Otherwise, predictions will certainly be upwardly biased. Note that to some extent twinning always takes place even in perfectly independent training and validation samples. This is because some of the training sample observations will have nearly identical values of predictors as validation sample observations. And some of these will correlate with a target at better than chance levels in the same direction in both training and validation when they are actually driven by confounded predictors with poor external validity. If such a cross-validated model is selected from a k-fold set, human confirmation bias will be at work and determine that such a model has been validated. This is why traditional cross-validation needs to be supplemented with controls for human bias and confounded model specification like swap sampling and prospective studies. Cross validation for time-series models[ edit ] Since the order of the data is important, cross-validation might be problematic for time-series models. A more appropriate approach might be to use forward chaining. Applications[ edit ] Cross-validation can be used to compare the performances of different predictive modeling procedures. For example, suppose we are interested in optical character recognition , and we are considering using either support vector machines SVM or k nearest neighbors KNN to predict the true character from an image of a handwritten character. Using cross-validation, we could objectively compare these two methods in terms of their respective fractions of misclassified characters. If we simply compared the methods based on their in-sample error rates, the KNN method would likely appear to perform better, since it is more flexible and hence more prone to overfitting [ citation needed ] compared to the SVM method. Cross-validation can also be used in variable selection. A practical goal would be to determine which subset of the 20 features should be used to produce the best predictive model. For most modeling procedures, if we compare feature subsets using the in-sample error rates, the best performance will occur when all 20 features are used. However under cross-validation, the model with the best fit will generally include only a subset of the features that are deemed truly informative. A recent development in medical statistics is its use in meta-analysis. It forms the basis of the validation statistic, Vn which is used to test the statistical validity of meta-analysis summary estimates.

## Chapter 2 : Estimation statistics - Wikipedia

*A model's purpose is to inform medical decisions and health care resource allocation. Modelers employ quantitative* *methods to structure the clinical, epidemiological, and economic evidence base and gain qualitative insight to assist decision makers in making better decisions.*

## Chapter 3 : Linear Regression Analysis - Predicting an Unknown Value

*Specification, Estimation, and Analysis of Macroeconometric Models Ray C. Fair Harvard University Press Cambridge, Massachusetts, and London, England*

## Chapter 4 : Project Estimation Techniques | Cost Engineering

*Model Estimation and Interpretation â€¢ For OLS models, both model estimation and interpretation are relatively easily, since the effects are linear.*

## Chapter 5 : Cross-validation (statistics) - Wikipedia

*Washington University in St. Louis CSEs Â© Raj Jain Overview! Analysis of Simulation Results! Model Verification Techniques! Model Validation Techniques.*