Fine classing meaning

Before reading, be prepared here to take a look at other posts in this series: Explains how to convert data to a scorecard model, assuming that the scorecard development, data preparation, and initial variable selection process (filtering) is complete, and that a filtered training dataset can be used for modeling. The development process consists of four main parts: variable transformations, model training using logistic regression, model validation and scaling. Figure 1: The standard scorecard development process variable conversions you will admit something, tortured enough data. (Ronald Coase, Economist) A standard scorecard model based on logistic regression is a additive model. Therefore, custom variable transformations are required. Widely adopted transformations - fine classification, rough classification, and either fake coding or evidence weight (WOE) conversion - create a see orderly process that provides both an easy model result to implement and explain business. Additionally, these transformations help transform nonlinear relationships between arguments and dependent variables into a linear relationship: customer behavior, which is typically requested by the business. Review Classification Fine classification is applied to all continuous variables and separate variables with high cardinality. This is usually the first binning process between 20 and 50 fine-grained boxes. Rough Classification Rough classification is where a binning process is applied to fine-grained boxes to combine those at similar risk and usually create up to fewer boxes. The goal is to achieve simpliability and minimize loss of information by creating fewer boxes, each with markedly different risk factors. However, to create a robust model that is resistant to excessive suitability, each bin box must contain a sufficient number of observations from the total account (5% is the minimum recommended by the most practitioners). These opposing objectives can be achieved through optimal binning optimization, which maximizes the prediction power of a variable during the rough classification process. Optimal binning uses statistical measures used during variable selection, such as information value, Gini, and ki-square statistics. The most popular measure, again, is the value of information, although the combination of two or more measures is usually useful. If the missing values contain predictive information, they must be a separate class or combined with a bin with similar risk factors. The binary (dummy) variable designation process for all rough classes except the Dummy Encoding Reference class. This approach can present problems because extra variables require more memory and processing resources, and because of excessive compliance due to reduced degrees of freeness from time to time. Evidence Weight (WOE) Conversion This is an alternative (and more preferred) approach to puppet coding all over the class with a risk value, and in turn, narrows the risk values into a single numeric variable. A numeric variable explains the relationship between an argument and a dependent variable. Both are suitable for logistical regression modeling in the WOE framework as a result of daily rate calculation. In addition, woe conversion standardizes all arguments, so subsequent logistical regression parameters can be directly compared. The main drawback of this approach is to consider only the relial risk of each repossess, without considering the proportion of accounts in each warehouse. It can be used to evaluate the relial contribution of each repossess instead of the information value. Both dummy encoding and WOE conversion give similar results. Which to use depends mainly on the preferences of data scientists. But be warned: optimal binning, puppet coding, and evidence conversion weight, time-consuming manual processes. A software package for binning, optimization and WOE conversion is therefore extremely useful and highly recommended. Figure 2: World Programming software is a widely used technique of automatic optimal binning with Model Training and Scaling Logistics regression and credit scoring to solve WOE conversion binary classification problems. Before model assembly, another itering of variable selection is valuable for checking whether new WOE converted variables are still good model candidates. Preferred candidate variables are variables that have a linear relationship with the dependent variable, have good coverage in all categories, have a normal distribution, contain a significant overall contribution, and have a higher knowledge value (usually between 0.1 and 0.5) that is work-related. Many analytics vendors often include a logistic regression model in their software products in a wide range of statistical and graphical functions. For example, implementing SAS language PROC LOGISTIC in WPS provides a comprehensive set of options for automatic variable selection, restriction of model parameters, weighted variables, obtaining separate analyses for different segments, scoring in a different dataset, creating automatic distribution code. Once the model is aligned, the next step is to set the model as a scale requested by the business. This is known as scaling. Scaling is a measurement tool that ensures the consistency and standardization of scores across different scorecards. Minimum and maximum score values and score range in risk interpretation assist and should be notified to the business. Most of the time, the business requirement is to use the same score range for multiple scorecards so that they all have the same risk interpretation. A popular scoring method creates logaracatic discerning scores, where the rate doubles in a predetermined number of points. This requires specifying three Base scores, such as 600 points, base rates (for example, 50:1), and scores to double rates (for example, 20). Points points correspond to each box of model variables, while the model is translated into breakpoints. The score table allocation and scaling output represent the actual scorecard model. Figure 3: Scorecard scaling Model Performance Model evaluation is the final step in the modeling process. It consists of three different stages: evaluation, verification and acceptance. Did I get the Accuracy Assessment Model right? is the first question he must ask to test the model. The key metrics evaluated are statistical measures, including model accuracy, complexity, error rate, model fabrication statistics, variable statistics, severity values, and ratio ratios. Verification for robustness Did I make the right model? the next question to ask when acting on classification accuracy and statistical evaluation for ranking ability and job evaluation. The selection of validation metrics depends on the type of model classifier. The most common metrics for binary classification problems are gain charts, lifting charts, ROC curves, and Kolmogorov-Smirnov charts. The ROC curve is the most common tool for visualizing model performance. It is a multipurpose tool used for champion-challenger methodology to choose the best performing model. Test model performances on invisible data and compare them with training data. Optimal threshold selection that maximizes the actual positive rate and minimizes the false positive ratio. The ROC curve is created by drawing sensitivity to the possibility of false alarm (false positive rate) at different thresholds. Evaluation of performance measurements at different thresholds is a desirable feature of the ROC curve. Different types of business issues will have different thresholds based on a business strategy. The field under the ROC curve (AUC) is a useful measure that indicates the predictor's ability to predict. At credit risk, an AUC of 0.75 or higher is a prerequisite for standard and model acceptance adopted by the industry. Figure 4: Model performance metrics Will the acceptance model be accepted for usefulness? is the last question to ask to test whether the model is business-valuable. This is the critical stage at which the data scientist must play the model result into operation and defend its models. The main evaluation criterion is the business benefit of the model; therefore, benefit analysis is central part when presenting results. Data scientists should make every effort to track and understand the results and findings so that they can present the results in a short way. Failure to do so may result in model rejection and, as a result, project failure. What does this mean in the context of this article? With rough segmentation, the author means a segmentation that does not have much detail. Good on the other hand, detail means a high level of segmentation. But more importantly what does [this] mean in the context of the overall computer vision? The most common use on a CV is to explain how general or specific a classification a class is. A rough class is a very large one, while a thin class is a very special one. Intended use What the author mentions in the expression is the level of detail of the segmentation obtained. A rough segmentation means that we have large stains covering each class without much detail. On the other hand, even a subtle segmentation would be at a much higher level of detail that you can go down to the pixel level (i.e. the correct segmentation of pixels). In the following two examples, this is to make a clear view. When moving from left to right, segmentation maps go from rough to thin: Keep in mind that in the images on the far right, there are not many details of those on the left, while in the most accurate images there is an almost pixel perfect (i.e. fine details) segmentation map. Alternative use Since this is not a built-in terminology, it can sometimes resort to the nature of classes in a rough and thin classification role. Take, for example, the picture at the top; The label for the rough classification task can be a tree. For a nice classification task there would be labels such as oak tree, pine tree, etc. The most obvious example of this is the cifar dataset, which has two versions: a rough one with a class of 10 and a thin one with 100 classes, which are all subclasses of rough classes. For example, if you have a rough class of fish, thin ones goldfish, mourning fish, ray, shark, trout, etc. an example for Semantic segmentation can be the following: I want to make a street segmentation model. This means that a rough segmentation simply divides the image into paths, vehicles, etc. On the other hand, a subtle segmentation can also detect the type of vehicle, such as trucks, cars, etc.

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