



## **PERFORMANCE METRICS Part-4**

**LECTURE 19** 

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- Open RStudio
- Asymmetric Misclassification Costs
  - When misclassification error for a class of interest is more costly than for the other class
  - Example, misclassifying a customer as false positive who is actually likely to respond to the promotional offering
    - Opportunity cost of foregone sale vs. costs of making an offer (profit of ₹20 for a ₹ 100 item vs. ₹1 scenario)
  - Misclassification rate is not appropriate metric in this case



- Asymmetric Misclassification Costs
  - Other considerations
    - Costs of analyzing data
    - Actual net value impact per record
    - New Goal: minimization of costs or maximization of profits
- Open Excel
- How to improve actual classifications by incorporating asymmetric misclassification costs?
  - Change the rules of classification e.g. cutoff value



Performance Metrics based on asymmetric misclassification costs

average misclassification cost = 
$$\frac{c_0 n_{0.1} + c_1 n_{1.0}}{n}$$

- Measures average cost of misclassification per observation
- Where c<sub>i</sub> is cost of misclassifying a class i observation

- Ratio of costs  $(c_0/c_1)$
- Future misclassification costs
  - Prior Probabilities  $(p_0/p_1)$
  - $(p_0/p_1)^* (c_0/c_1)$
- Lift curve incorporating costs
- Open RStudio
- Lift vs.
  - No. of records or cutoff value?



- Asymmetric misclassification costs for m classes (m>2)
  - Classification matrix will be 'm×m'
  - m prior probabilities
  - m(m-1) misclassification costs
  - Matrix for misclassification costs becomes complicated
  - Lift chart not usable for multiclass scenario



- Oversampling of rare class members
  - Simple random sampling vs. stratified sampling
- Oversampling approach
  - 1. Sample more rare class observations (equivalent of oversampling without replacement)
    - Lack of adequate no. of rare class observations
    - Ratio of costs is difficult to determine
  - 2. Replicate existing rare class observations (equivalent of oversampling with replacement)



- Typical solution adopted by analysts
  - Sample equal no. of members from both the classes
- Oversampling adjustment for performance evaluation
  - Score
    - 1. Validation partition without oversampling
    - 2. Oversampled validation partition and then remove the oversampling effects by adjusting weights



- Typical steps in rare class scenario
  - 1. Build the candidate models on training partition with 50% class 1 observations and 50% class 0 observations
  - 2. Validate the models with the validation partition drawn using simple random sample taken from original dataset
- Detailed steps
  - 1. Separate the class 1 and class 0 observations into two strata (distinct sets)
  - 2. Half the records from class 1 stratum are randomly selected into training partition



- Detailed steps
  - 3. Remaining class 1 records are reserved for validation partition
  - Randomly select class 0 records for training partition equal to no. of class 1 records in step 2
  - Randomly select class 0 records to maintain the original ratio of class
    0 to class 1 records for validation partition
  - 6. For test partition, a random sample can be taken from validation partition

## Key References

- Data Science and Big Data Analytics: Discovering, Analyzing, Visualizing and Presenting Data by EMC Education Services (2015)
- Data Mining for Business Intelligence: Concepts, Techniques, and Applications in Microsoft Office Excel with XLMiner by Shmueli, G., Patel, N. R., & Bruce, P. C. (2010)

# Thanks...