Accuracy metrics in classification problem

Logloss –

Log-loss measures the accuracy of a classifier. It is used when the model outputs a probability for each class, rather than just the most likely class.

Log-loss is a “soft” measurement of accuracy that incorporates the idea of **probabilistic confidence**. It is intimately tied to information theory: log-loss is the cross entropy between the distribution of the true labels and the predictions. Intuitively speaking, entropy measures the unpredictability of something. Cross entropy incorporates the entropy of the true distribution, plus the extra unpredictability when one assumes a different distribution than the true distribution. So log-loss is an information-theoretic measure to gauge the “extra noise” that comes from using a predictor as opposed to the true labels. By minimizing the cross entropy, one maximizes the accuracy of the classifier.

Log-loss is a metric that many times makes a lot of sense in a business context because it provides higher punishment for cases where you predict with high confidence but you’re wrong. In a business context that translates into trying to avoid making errors that might result in large missed financial opportunities (my model is very confident a person will not be hospitalized but he actually is) or reputation mishaps (my model is very confident someone has cancer but he actually doesn’t).

Also, more and more Kaggle competitions are multi-class in nature and there aren’t as many metrics for multi-class as there are for binary. Log-loss extends from binary to multi-class easily.