Why

How should we compare two classifiers?

Definition

Let $u_1, \ldots, u_n$ in $\mathcal{U}$ be a dataset of inputs and $v_1, \ldots, u_n$ in $\mathcal{V}$ be a dataset of labels. Let $G : \mathcal{U} \to \mathcal{V}$ be a classifier.

For each $i = 1, \ldots, n$, the classifier associates a prediction $G(u_i)$ with input u_i. The prediction $G(u_i)$ is *correct* if $G(u_i) = b_i$ and *incorrect* (*wrong*, an *error*) if $G(a_i) \neq b_i$. The *error rate* is the proportion of the dataset for which the classifier's prediction is an incorrect. In other words, the error rate is $(1/n)\,|\{i \mid G(a_i) \neq b_i\}|$.

Given two classifiers, it is natural to prefer the one with the lower error rate. If these two classifiers are the results of different inductors applied to the same dataset, we can use a separate dataset to *validate* these.

Boolean case

In the case that $B = \{-1, 1\}$, we call the class -1 *negative* and the class $+1$ *positive*. Similarly, we call an example (u_i, v_i) a *negative example* if $b_i = -1$ and a *positive example* if $b_i = 1$.

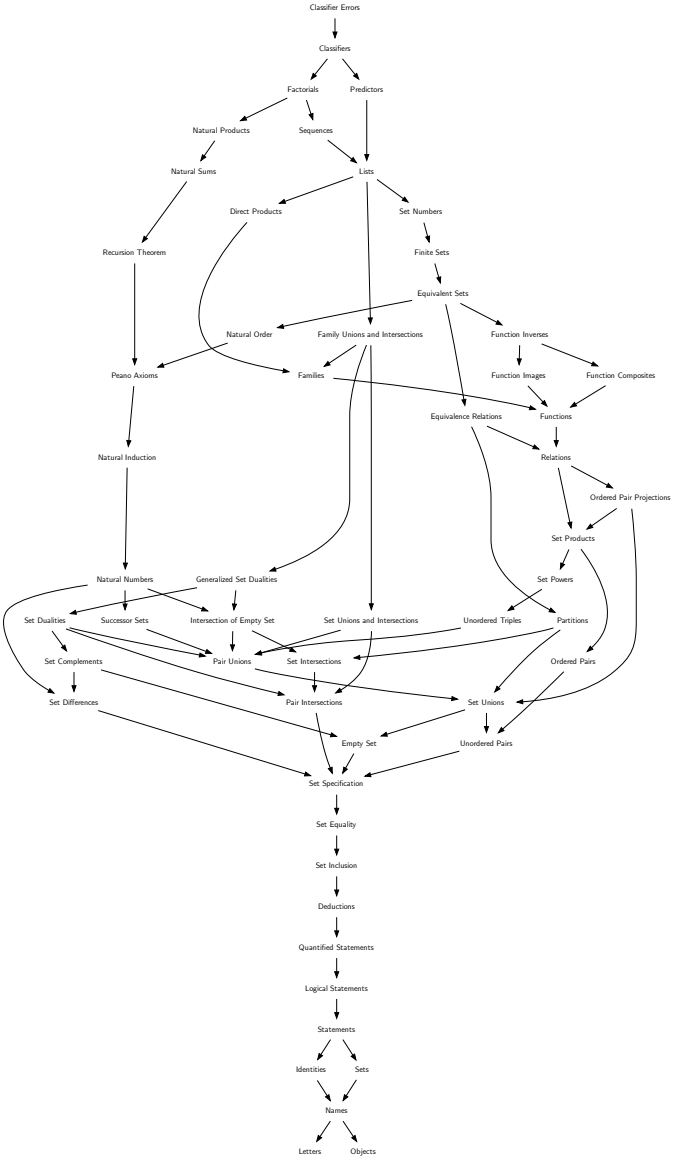
We call the result of u_i under classifier G a *true positive* if $v_i = 1$ and $G(u_i) = 1$, a *true negative* if $v_i = -1$ and $G(v_i) = -1$. In these two cases, the classifier has predicted the label correctly.

We call the result of u_i under classifier G a *false positive* (or *type I error*, read "type one error") if $v_i = -1$ and $G(u_i) = 1$ and a *false negative* (or *type II error*, read "type two error") if $v_i = 1$ and $G(u_i) = -1$. In these two cases the classifier has predicted the label incorrectly. Notice that the words positive and negative reference the classifier's prediction, not the true label.

The *false positive rate* (*false negative rate*) of a classifier on a dataset

is the proportion of dataset elements for which it predicts a *false positive* (*false negative*). The *true positive rate* (or *sensitivity*, *recall*) of G on a dataset is the proportion of positive examples which G labels positive.

The *precision* (or *positive predictive value*) of G is the proportion of all examples which the classifier labels *positive* whose label is positive. The *true negative rate* (or *specificity*, *selectivity*) is the proportion of negative examples which G labels negative. The *false alarm rate* is the proportion of negative examples which G *incorrectly* labels positive.


Classifier Errors
Classifiers
Factorials
Predictors
Natural Products
Sequences
Natural Sums
Lists
Direct Products
Set Numbers
Recursion Theorem
Finite Sets
Equivalent Sets
Natural Order
Family Unions and Intersections
Function Inverses
Peano Axioms
Families
Function Images
Function Composites
Equivalence Relations
Functions
Natural Induction
Relations
Ordered Pair Projections
Set Products
Natural Numbers
Generalized Set Dualities
Set Powers
Set Dualities
Successor Sets
Intersection of Empty Set
Set Unions and Intersections
Unordered Triples
Partitions
Set Complements
Pair Unions
Set Intersections
Ordered Pairs
Set Differences
Pair Intersections
Set Unions
Empty Set
Unordered Pairs
Set Specification
Set Equality
Set Inclusion
Deductions
Quantified Statements
Logical Statements
Statements
Identities
Sets
Names
Letters
Objects