Machine Learning

Classification

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Objectives

Objectives:

- Understand classification tasks
- Identify classification problems
- Review common classification algorithms
- Determine effectiveness of classification models
- Train models using classification algorithms
- Select best models

What is classification?

Definition

- Binary classifier
- Multi-class
- One vs all (OVA) or One-vs-rest
- One vs one

Example Task

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- Given medical and demographic information of a patient, predict their probability of a heart attack in the next 24 months.

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Example Data

Common Algorithms

List

- Decision Tree
- Logistic Regression (Yes, it's a classifier)
- Stochastic Gradient Descent
- Nearest Neighbors
- Support Vector Classification
- Random Forest
- Gradient Boosting

Metrics

Sample Numbers

There are 60,000 samples for a binary classification task.

5,421 of the samples are the positive case.

54,579 of the samples are the negative case.

A certain binary classifier predicts 3,530 of the positive samples correctly, and 53,892 of the negative samples correctly.

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Sounds pretty good.

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Actual Negative	True-Negative	False-Positive
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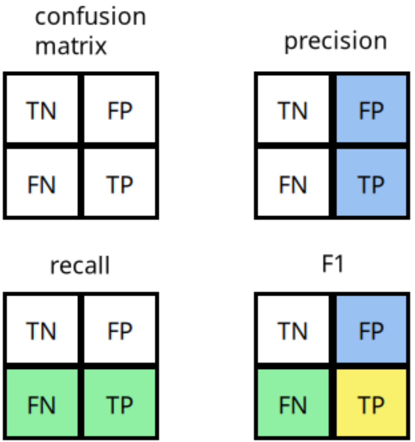
Do we still feel good about the quality?

Confusion Matrix - Metrics

- TN, FP, FN, TP
- precision $= \frac{TP}{TP+FP}$
- recall $= \frac{TP}{TP+FN}$
- $F_1 = \frac{2}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$
- $F_1 = \frac{TP}{TP + \frac{FP+FN}{2}}$



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Now how do we feel about the quality?

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Summary

- Accuracy
- Confusion Matrix
- Precision
- Recall
- F_1

Implementation

Summary

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