CIS 635 Knowledge Discovery & Data Mining

Predictive modeling: Classification Metrics and Imbalanced Data

Classification Matrices

- Accuray

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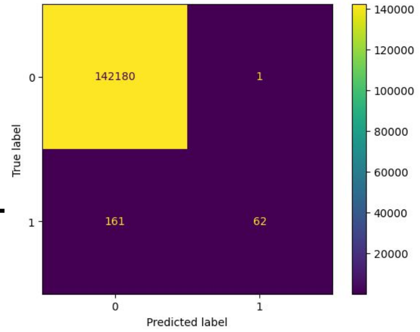
- Not always
- Let’s analyze the confusion matrix of our credit card fraud detection notebook
    - Accuray metric can be catastrophic

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     # The mean squared error
     print("accuracy: %.5f" % accuracy_score(y_test, y_pred))

     accuracy: 0.99886
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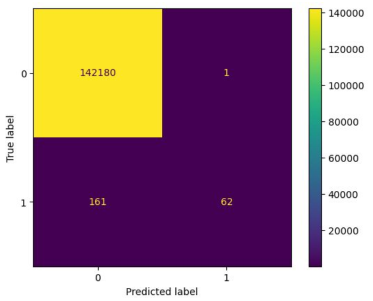
- Is accuracy a good metric?
- Not always
- Let's analyze the confusion matrix of our credit card fraud detection notebook
    - Accuray metric can be catastrophic
- What other metrics we may use?

Metrics

- Accuray

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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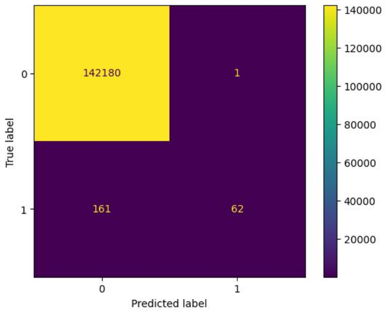
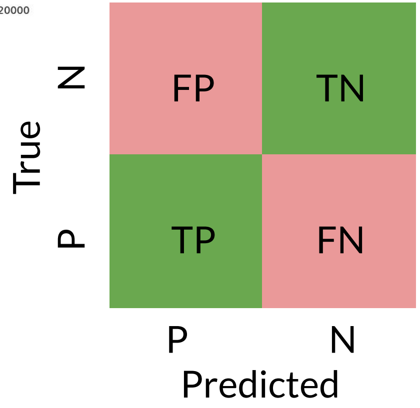




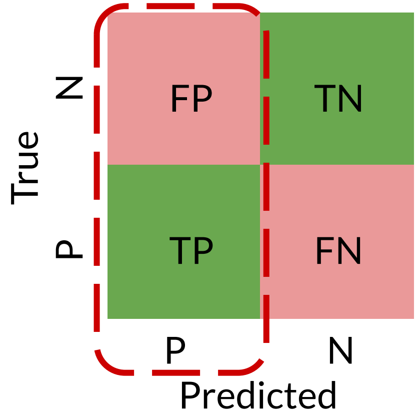
Other important classification metrics

- Precision (also called **Positive Predictive Value)**
- Recall (also called **Sensitivity)**
- F1 Score

Metrics

- Precision (also called **Positive Predictive Value**)

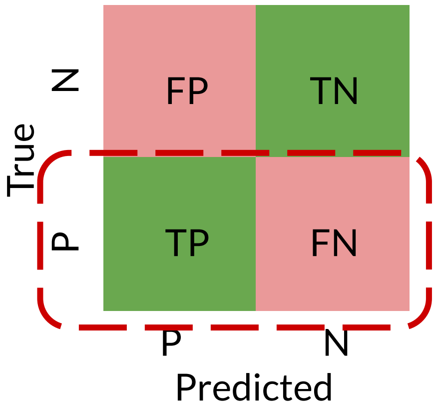
$$\text{Precision} = \frac{TP}{TP + FP}$$



Metrics

- Recall (also called **Sensitivity**)

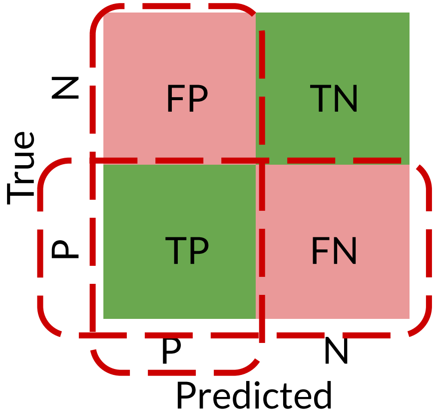
$$\text{Recall} = \frac{TP}{TP + FN}$$



Metrics

- F1 Score

$$\text{F1 Score} = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$



Data Imbalance Problem

- Demonstration through a practical example
  - CC fraud detection

Data Imbalance Problem

- How to deal with Data Imbalance Problems
    - Through Sampling Bias

Data Imbalance Problem

- How to deal with Data Imbalance Problems
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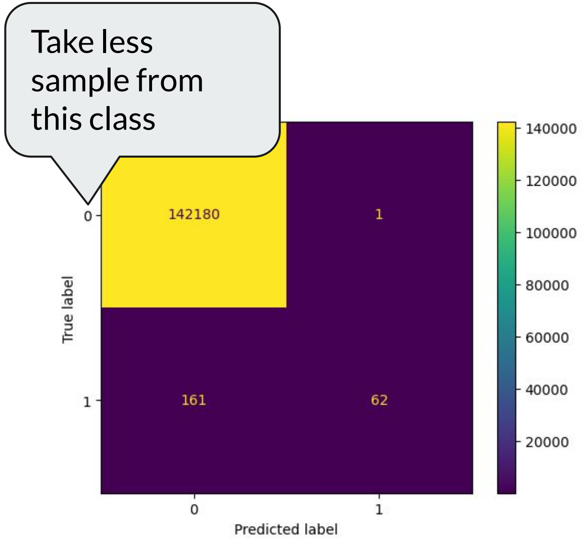
        - Undersampling
        - Oversampling



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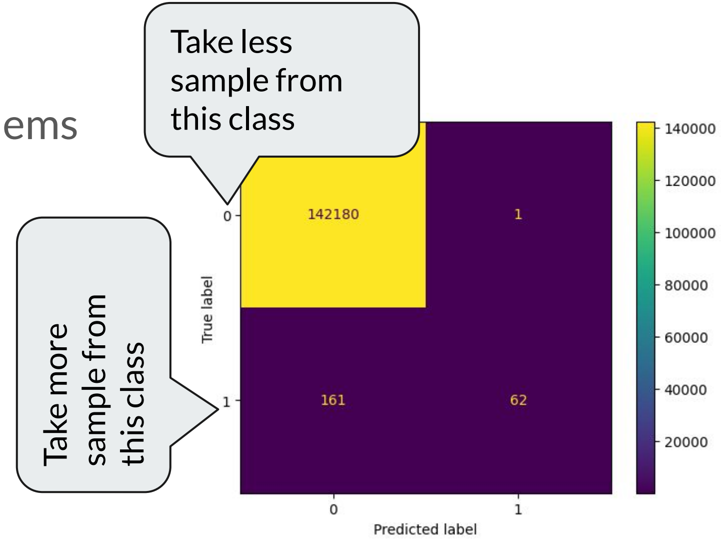

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  - Redefining model (loss function for an example)

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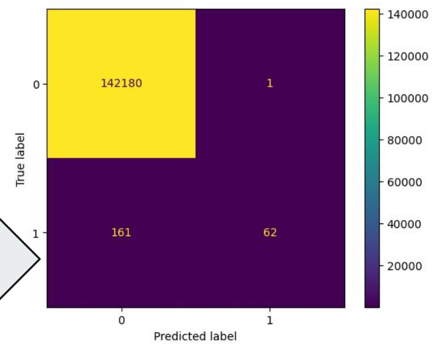
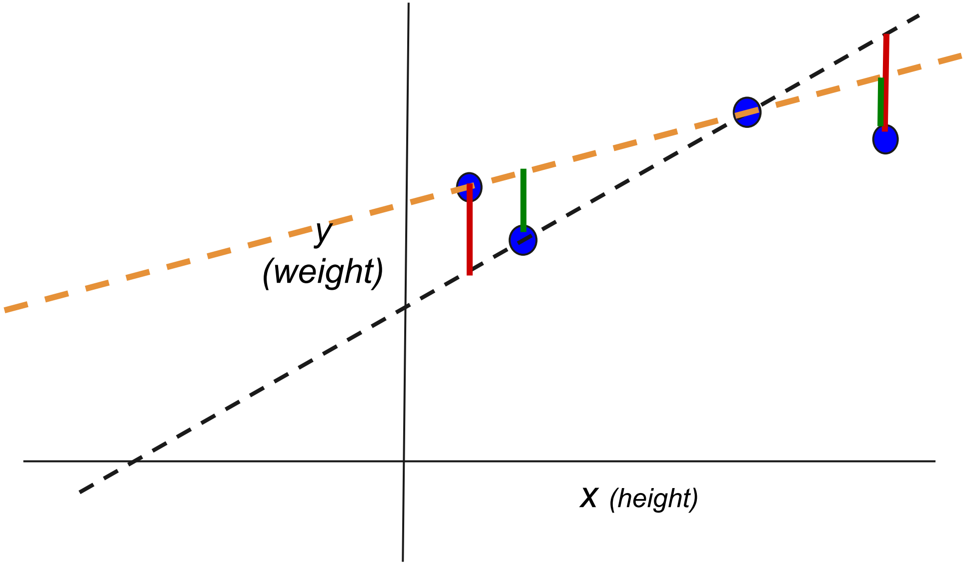
Applying Higher Penalty to data points from the less occurring class.



Fitting a linear function/model



Model

$$\hat{y} = \beta_0 + \beta_1 x$$

$$\Theta = \{\beta_0, \beta_1\}$$

Fitting Error

$$\epsilon = |\hat{y} - y|$$

Optimization function

$$E_\Theta = \frac{1}{2}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

$$\Theta^* = \mathrm{argmin}_\Theta\, E\{(x_i, y_i)\}_{i=1,\cdots,N}$$

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