



# CIS 678 - Machine Learning

Predictive modeling: Classification Metrics and Imbalanced Data



# Classification Matrices

- Accuracy

$$\text{Accuracy} = \frac{\text{Nb of correct predictions}}{\text{Nb of (correct + incorrect) predictions}}$$



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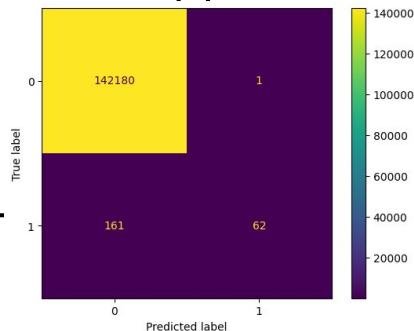
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- Not always
- Let's analyze the confusion matrix of our [credit card fraud detection notebook](#)
  - Accuracy metric can be catastrophic



```
[20] # Make predictions using the testing set
y_pred = clf.predict(X_test)
# The mean squared error
print("accuracy: %.5f" % accuracy_score(y_test, y_pred))
```

accuracy: 0.99886



# Classification Matrices

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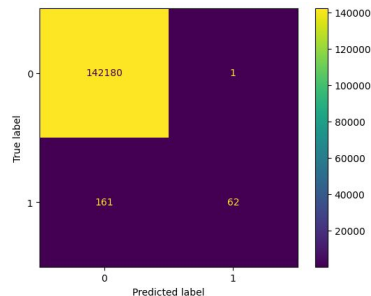
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- Is accuracy a good metric?
- Not always
- Let's analyze the confusion matrix of our [credit card fraud detection notebook](#)
  - Accuracy metric can be catastrophic
- What other metrics we may use?

# Classification Matrices

- Accuracy

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



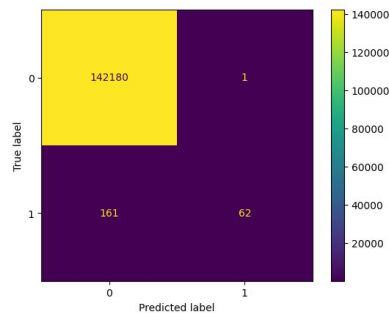
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True	N	P
	Predicted	
N	TN	FP
P	FN	TP





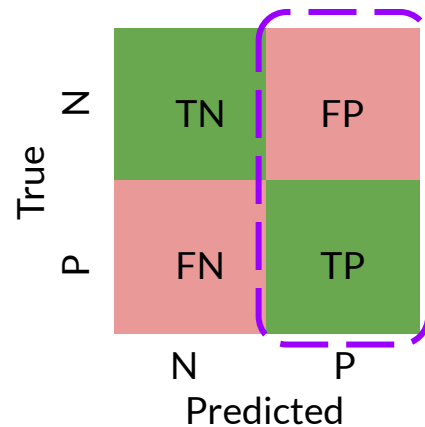
## Other important classification metrics

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

# Metrics

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

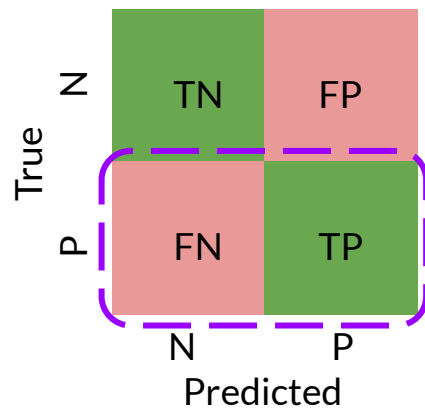
$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$



# Metrics

- Recall (also called **Sensitivity**)

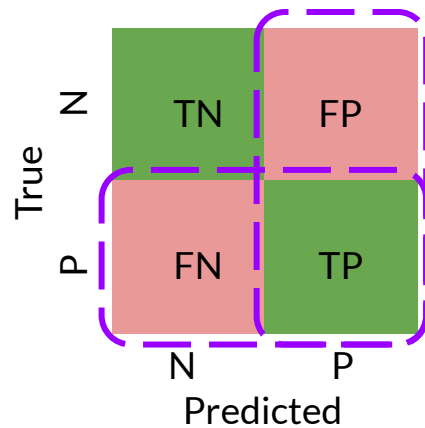
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$



# 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](#)

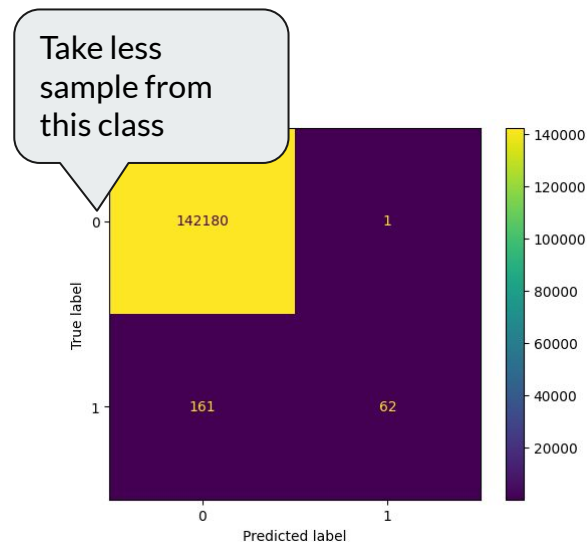


# Data Imbalance Problem

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

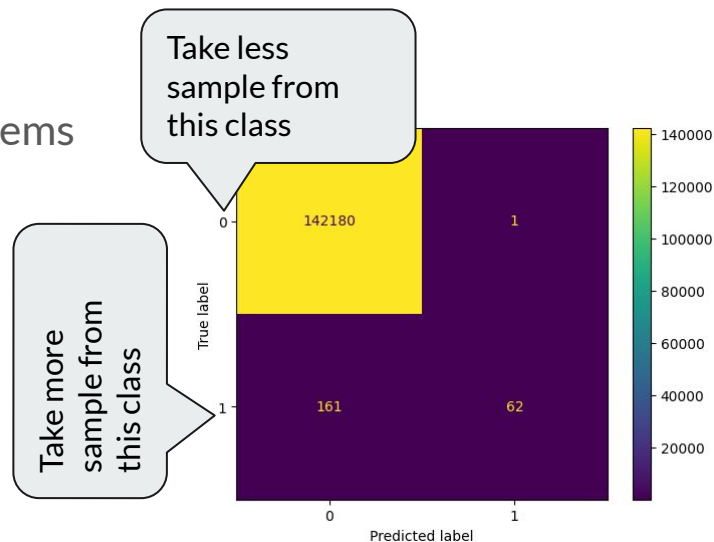
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- How to deal with Data Imbalance Problems
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    - Undersampling
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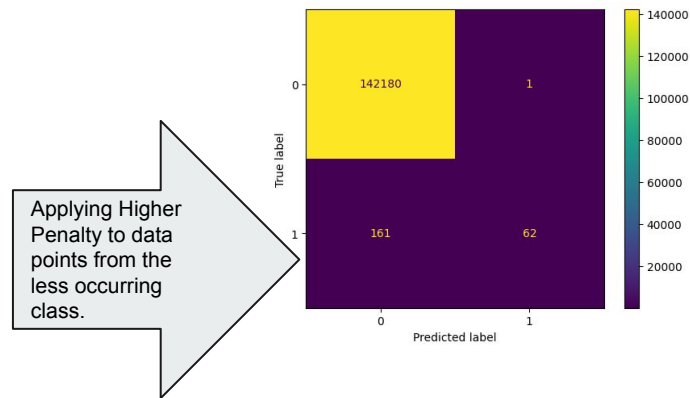


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  - Redefining model (loss function for an example)

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**QA**