Lecture 15
Evaluating Classification Models

Case Study: Credit Card Fraud

Data set of credit card transactions from Vesta.

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import pandas as pd

df_fraud = pd.read_csv("https://datasci112.stanford.edu/data/fraud.csv")
df_fraud
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c1-c14: dolandırıcılık ile ilgili oluşturulmuş istatistiksel veya davranışsal özellikler

sahte mi değil mi

	card4	card6	P_emaildomain	TransactionAmt	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	isFraud
0	visa	debit	gmail.com	62.950	139.0	110.0	0.0	0.0	135.0	93.0	0.0	0.0	93.0	0.0	93.0	0.0	637.0	114.0	0
1	visa	debit		35.950	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	3.0	1.0	0
2	visa	debit	yahoo.com	117.000	1.0	1.0	0.0	0.0	0.0	2.0	0.0	0.0	1.0	0.0	1.0	0.0	4.0	1.0	1
3	visa	debit	hotmail.com	54.500	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0
4	visa	debit	gmail.com	255.000	1.0	3.0	0.0	0.0	0.0	4.0	0.0	0.0	2.0	0.0	3.0	1.0	20.0	1.0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
59049	mastercard	debit	gmail.com	20.522	1.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	0
59050	mastercard	credit	yahoo.com	50.000	1.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	1.0	0
59051	mastercard	debit	icloud.com	97.950	2.0	2.0	0.0	0.0	1.0	2.0	0.0	0.0	1.0	0.0	2.0	0.0	15.0	2.0	0
59052	visa	debit	gmail.com	16.723	1.0	2.0	0.0	1.0	0.0	1.0	1.0	2.0	0.0	1.0	1.0	1.0	1.0	1.0	1
59053	mastercard	debit		107.950	24.0	21.0	0.0	0.0	14.0	13.0	0.0	0.0	17.0	0.0	18.0	0.0	84.0	17.0	0

59054 rows × 19 columns

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1	visa	debit		35.950	1.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	3.0	1.0	0
2	visa	debit	yahoo.com	117.000	1.0	1.0	0.0	0.0	0.0	2.0	0.0	0.0	1.0	0.0	1.0	0.0	4.0	1.0	1
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...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
59049	mastercard	debit	gmail.com	20.522	1.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	0
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59054 rows × 19 columns

Goal: Predict isFraud, where 1 indicates a fraudulent transaction.

1. Recap

2. Precision and Recall

Classification Model

We can use *k*-nearest neighbors for classification:

```
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer

pipeline = make_pipeline(
    make_column_transformer(
        (OneHotEncoder(handle_unknown="ignore", sparse_output=False),
         ["card4", "card6", "P_emaildomain"]),
        remainder="passthrough"),
    StandardScaler(),
    KNeighborsClassifier(n_neighbors=5))
```

“Kategorik sütunları one-hot encode et, tüm sayıları ölçekle(scale), sonra 5-komşulu KNN ile fraud / normal sınıflandır.”

dense matrix

Training a Classifier

```
X_train = df_fraud.drop("isFraud", axis="columns")
y_train = df_fraud["isFraud"]
```

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```
from sklearn.model_selection import cross_val_score

cross_val_score(
    pipeline,
    X=X_train, y=y_train,
    scoring="accuracy",
    cv=10
).mean()
```

cv=10
the most commonly used value (the standard in the literature).
10-fold cross-validation reduces overfitting while keeping the computational cost reasonable.
(Bir öğrenci sınav sorularının cevaplarını ezberler → O sınavda tam puan,ama yeni sorular gelince başarısız olur.
Modelde de aynısı olur: ezberleme = overfitting.)

Training a Classifier

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0.9681647131621484

How is the accuracy so high?

A Closer Look

Let’s take a closer look at the labels.

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y_train.value_counts()
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```
0      56935
1       2119
Name: isFraud, dtype: int64
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A Closer Look

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The vast majority of transactions are normal!

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Even though such predictions would be accurate *overall*, it is inaccurate for fraudulent transactions. A good model is "accurate for every class".

Precision and Recall

We need a score that measures “accuracy for class c”.

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  - **precision**: $P(\text{correct}|\text{predicted class } c)$
    - Among the observations that were predicted to be in class c, what proportion actually were? Pozitif dediğinin ne kadarının gerçekten pozitif olduğu.

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  - **precision**: $P(\text{correct}|\text{predicted class } c)$
    - Among the observations that were predicted to be in class c, what proportion actually were?
  - **recall**: $P(\text{correct}|\text{actual class } c)$.

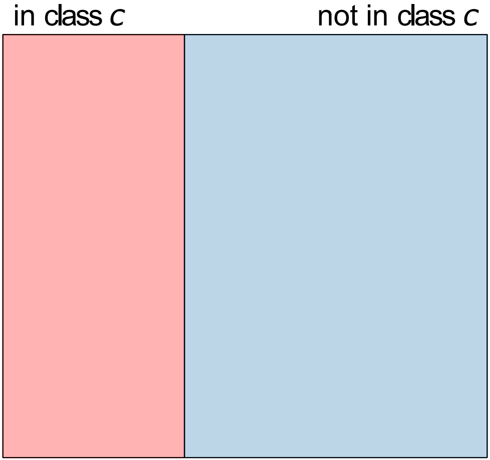
Precision and Recall

- We need a score that measures "accuracy for class *c*".

- There are at least two reasonable definitions:
  - **precision**: $P(\text{correct}|\text{predicted class } c)$
    - Among the observations that were predicted to be in class *c*, what proportion actually were? Pozitif dediğinin ne kadarının gerçekten pozitif olduğu.
  - **recall**: $P(\text{correct}|\text{actual class } c)$.
    - Among the observations that were actually in class *c*, what proportion were predicted to be? Gerçek pozitiflerin ne kadarını yakalayabildin?

A Geometric Look at Precision and Recall

A Geometric Look at Precision and Recall



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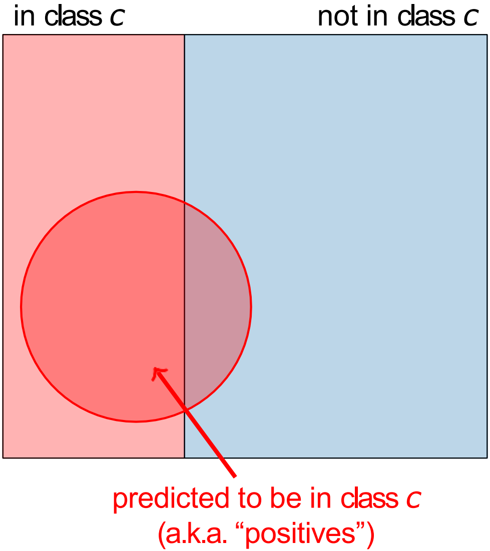

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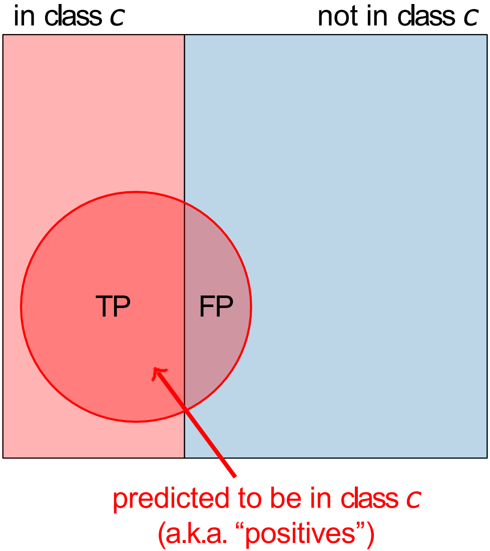

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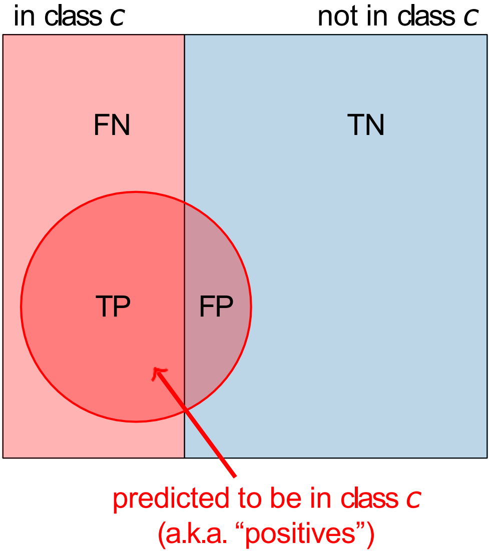

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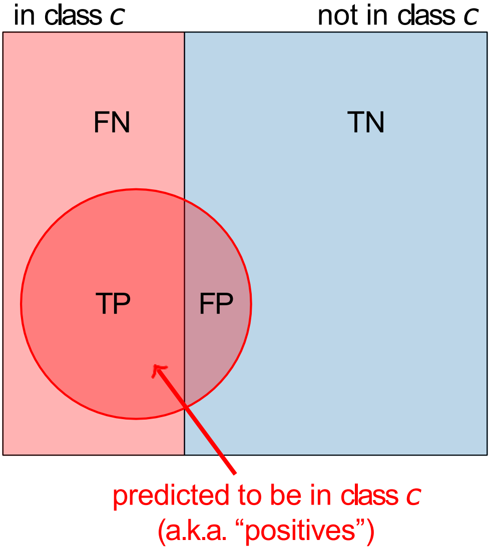
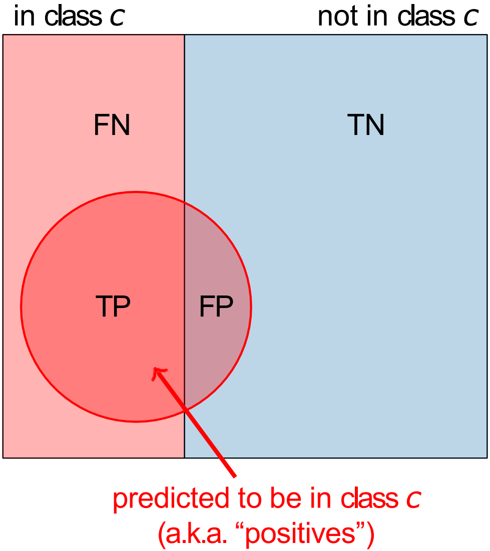


precision = ______

A Geometric Look at Precision and Recall



$$\textbf{precision} = \frac{}{\text{TP} + \text{FP}}$$

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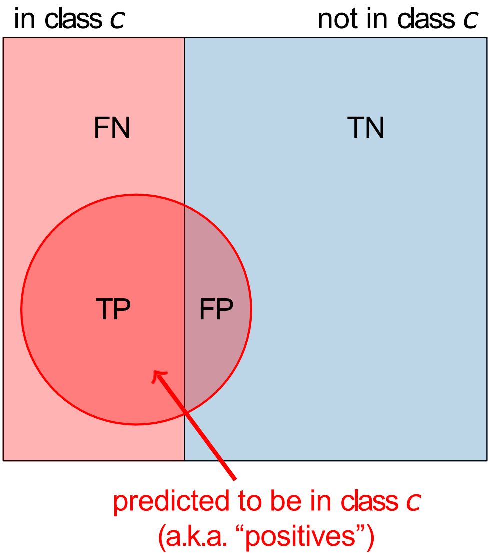
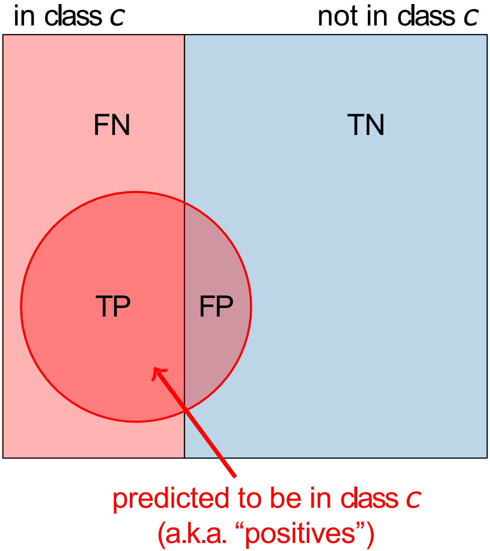


$$\textbf{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

A Geometric Look at Precision and Recall



$$\textbf{precision} = \frac{TP}{TP + FP} \qquad \textbf{recall} = \frac{\qquad}{\qquad}$$

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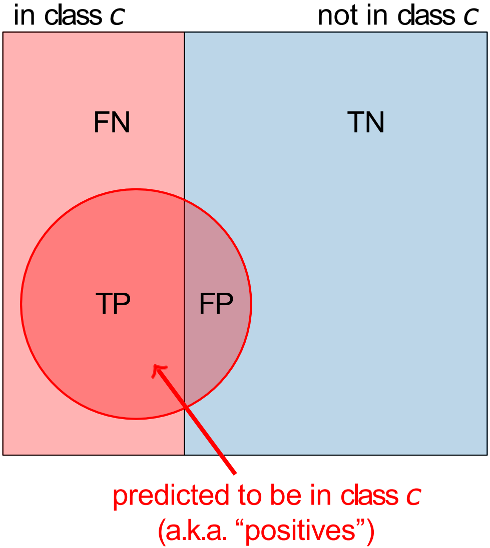
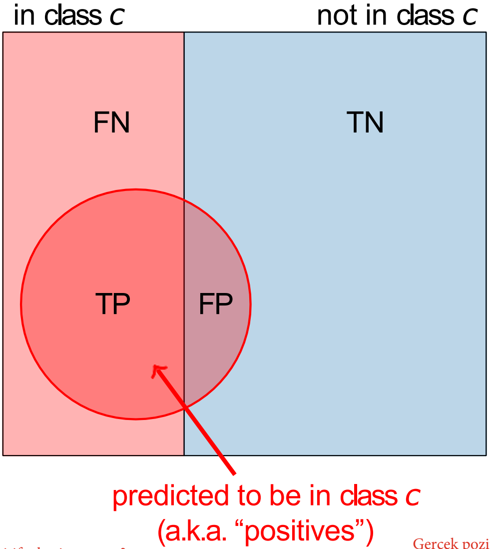


$$\textbf{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \textbf{recall} = \frac{}{\text{TP} + \text{FN}}$$

A Geometric Look at Precision and Recall



Ne kadar isabetli pozitif tahmin yaptım?

$$\textbf{precision} = \frac{TP}{TP + FP}$$

Gerçek pozitiflerin ne kadarını yakalayabildin?

$$\textbf{recall} = \frac{TP}{TP + FN}$$

Precision and Recall by Hand

To check our understanding of these definitions, let's calculate a few precisions and recalls by hand.

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```
array([[56817,   118],
       [ 1524,   595]])
```

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array([[56817,   118],      ← actually in class 0
       [ 1524,   595]])
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array([[56817,   118],     ← actually in class 0
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array([[56817,    118],      ← actually in class 0
       [ 1524,    595]])     ← actually in class 1
          ↑
      predicted
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```

← actually in class 0

← actually in class 1

↑ predicted to be in class 0

↑ predicted to be in class 1

	Predicted 0	Predicted 1
Actual 0	56817	118
Actual 1	1524	595

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	Predicted 0	Predicted 1
Actual 0	TN=56817	FP=118
Actual 1	FN=1524	TP=595

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array([[56817,   118],
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← actually in class 0
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- What is the (training) accuracy?

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array([[56817,   118],
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← actually in class 0
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- What is the (training) accuracy? 97.2%

correct predictions/all

Accuracy = (TP + TN) / Total samples
TN = 56,817
TP = 595
Total samples = 56,817 + 1,524 + 118 + 595 = 59,054

Accuracy = (56,817 + 595) / 59,054≈ 0.972 = 97.2%

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array([[56817,   118],
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```

← actually in class 0
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- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions?

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array([[56817,   118],
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← actually in class 0
← actually in class 1

- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%

TN=56817
FN=1524

Precision =56817/ (56817 +1524)
Precision=56817/ 58341
= 0,973877≈0.974 (97.4%)

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- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%
- What's the recall for normal transactions?

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- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%
- What's the recall for normal transactions? 99.8%

TN=56817
FP=118
Recall_0 =56817/ (56817+118)
≈0.9979(99.8%)

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- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%
- What's the recall for normal transactions? 99.8%
- What's the precision for fraudulent transactions?

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- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%
- What's the recall for normal transactions? 99.8%
- What's the precision for fraudulent transactions? 83.5%

Precision = 595/(595+118)
(actual1 and predicted1/ predicted1)

Precision and Recall by Hand

To check our understanding of these definitions, let's calculate a few precisions and recalls by hand.

First, summarize the results by the **confusion matrix**.

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from sklearn.metrics import confusion_matrix
pipeline.fit(X_train, y_train)
y_train_ = pipeline.predict(X_train)
confusion_matrix(y_train, y_train_)
```

	Predicted 0	Predicted 1
Actual 0	TN=56817	FP=118
Actual 1	FN=1524	TP=595

```
array([[56817,   118],
       [ 1524,   595]])
```

← actually in class 0
← actually in class 1

- What is the (training) accuracy? 97.2%
- What's the precision for normal transactions? 97.4%
- What's the recall for normal transactions? 99.8%
- What's the precision for fraudulent transactions? 83.5%
- What's the recall for fraudulent transactions?

actual1 and predicted1/actual1

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recall =595/(595+1524)

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Note: Each class has its own precision and recall!

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To achieve a high F1 score, both precision and recall have to be high. If either is low, then the harmonic mean will be low.

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Kısaca:
Tek bir skor lazım → tüm sınıfların skorlarını ortalıyoruz (macro). Böylece GridSearchCV veya cross-validation gibi yöntemlerde kullanabiliriz.

Example:

```
cross_val_score(
    pipeline,
    X=X_train,  y=y_train,
    scoring="f1_macro",
    cv=10
).mean()
```

0.6475574801118277

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What if we instead used a threshold t other than 0.5?

Depending on which t we pick, we'll get a different precision and recall. We can graph this tradeoff.

Precision-Recall Curve

Let’s graph the precision-recall curve in a Colab.