EMBEDDED VISION DESIGN 3

ML PERFORMANCE

HANDS ON

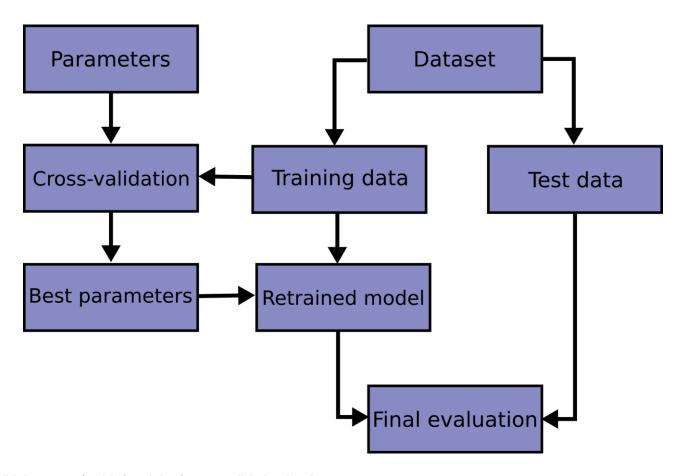
JEROEN VEEN



QUIZ TIME

- Individual, multiple-choice questions
- Online: http://www.socrative.com room 1PTGB6PY
- Open book quiz, so books and slides can be consulted
- HAN student number, so NOT your name, nickname or anything else.
- Quiz starts exactly at class hour and takes 10 minutes.
- Be on time and have your equipment prepared.

EVALUATING ESTIMATOR PERFORMANCE



Source: https://scikit-learn.org/stable/modules/cross_validation.html

CONFUSION MATRIX

ACTUAL

(Type I error)

True Positive (TP)

Reality: A wolf threatened. Shepherd said: "Wolf."

Outcome: Shepherd is a hero.

False Positive (FP)

Reality: No wolf threatened. Shepherd said: "Wolf."

Outcome: Villagers are angry at shepherd for waking them up.

False Negative (FN)

Reality: A wolf threatened. Shepherd said: "No wolf."

Outcome: The wolf ate all the sheep.

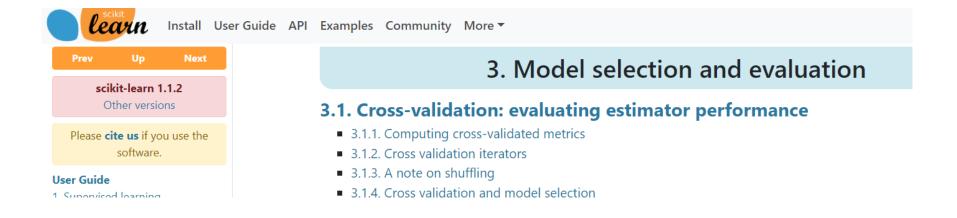
Type II error)

True Negative (TN)

Reality: No wolf threatened. Shepherd said: "No wolf." Outcome: Everyone is fine.

LOOK INTO THE SCKIT USER GUIDE

Find the descriptions of the model evaluation functionality



https://scikit-learn.org/



MULTICLASS AND MULTILABEL

- extending a binary metric to multiclass or multilabel problems, the data is treated as a collection of binary problems
- several ways to average binary metric calculations across the set of classes

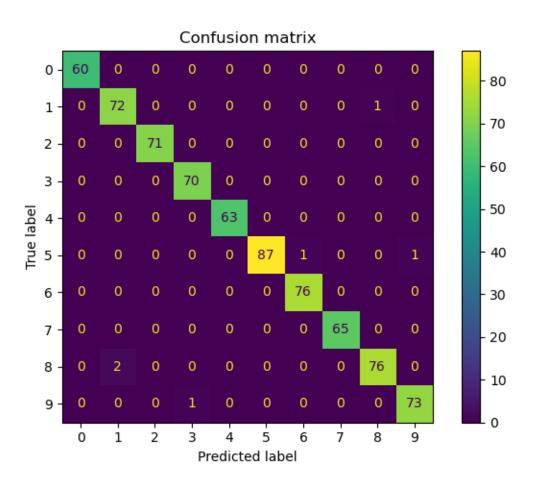
- "macro" simply calculates the mean of the binary metrics, giving equal weight to each class. In problems where infrequent classes are nonetheless important, macro-averaging may be a means of highlighting their performance. On the other hand, the assumption that all classes are equally important is often untrue, such that macro-averaging will over-emphasize the typically low performance on an infrequent class.
- "weighted" accounts for class imbalance by computing the average of binary metrics in which each class's score is weighted by its presence in the true data sample.



EXAMPLE

```
digits = datasets.load digits()
X train, X test, y train, y test = train test split(
    digits.data, digits.target, test size=0.4, random state=0)
clf = Pipeline([
    ("scaler", StandardScaler()),
    ("svm clf", SVC(kernel="poly", degree=3, coef0=1, C=5))
clf.fit(X train, y train)
print("mean accuracy on the given test data and labels: {}".format(clf.score(X test, y test)))
scoring metric = "precision macro"
nr of folds = 5
score = cross val score(clf, X train, y train, cv=nr of folds, scoring=scoring metric)
print("{}-fold cross validation metric {} : {}".format(nr of folds, scoring metric, score))
```

CONFUSION MATRIX

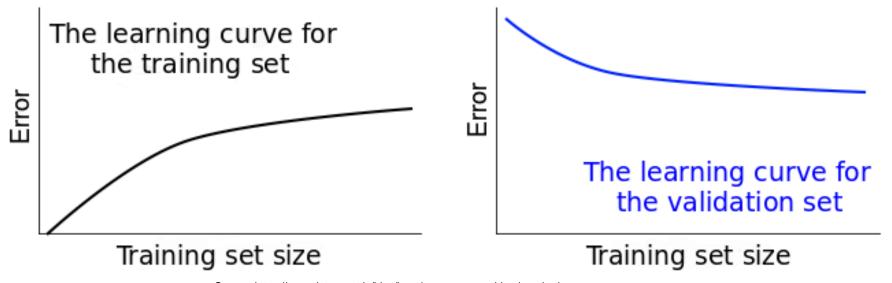


TRY IT FOR YOURSELF

performance_01.py performance_02.py

LEARNING CURVES

- Cost as a function of the training set size (or the training iteration)
- Examine evolution of train and validation learning curves



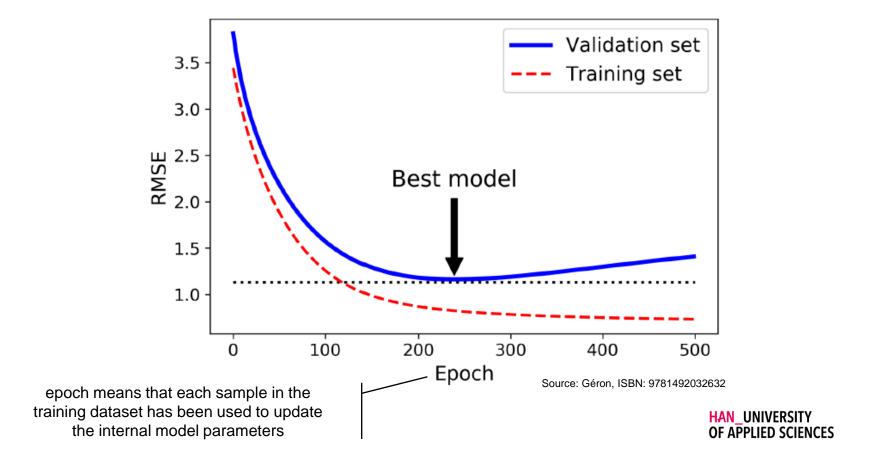
Source: https://www.dataquest.io/blog/learning-curves-machine-learning/

TRY IT FOR YOURSELF

• performance_03.py

EARLY STOPPING

Interpretation of learning curves



LEANING CURVES IN REGRESSION

- Exercise 02: Plot the learning curves for polynomial regression and experiment with various degrees
- Can you interpret the curves?
- Build on Regression_01.py and see Géron, page 130-134