Computational Communication Science 2 Week 6 - Lecture »Validation (in Supervised Machine Learning)«

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Today

Recap

Recap

Last week, we discussed:

- Supervised Machine Leaning (SML)
- The principles behind SML
- The steps of SML
- Some commonly used ML models

At home, you:

- Got some hands-on experience SML (week 6 exercises)

Recap

Today, we:

- Review your first SML experience
- Take a deep dive into validating SML-models

Recap

Last week, you practiced with code that:

- Read in some data (Q1)
- Split the data into a train and a test set (Q2)
- Set up a Count vectorizer (Q3)
- Trained a Naïve Bayes model with the count vectorizer (Q4)
- Requested some metrics for validation (Q5)

Recap Q1

```
import csv
from collections import Counter
import matplotlib.pyplot as plt

file = "hatespeech_text_label_vote_RESTRICTED_100K.csv"
tweets = []
labels = []

with open(file) as fi:
  data = csv.reader(fi, delimiter='\t')
  for row in data:
   tweets.append(row[0])
   labels.append(row[1])

print(len(tweets) == len(labels)) # there should be just as many tweets as there are labels

Counter(labels)
plt.bar(Counter(labels).keys(), Counter(labels).values())
```

Recap Q2

Split the dataset:

```
from sklearn.model_selection import train_test_split

tweets_train, tweets_test, y_train, y_test = train_test_split(tweets,
    labels, test_size=0.2, random_state=42)
```

Recap Q3

What happens here?

```
from sklearn.feature_extraction.text import (CountVectorizer)

countvectorizer = CountVectorizer(stop_words="english")
X_train = countvectorizer.fit_transform(tweets_train)
X_test = countvectorizer.transform(tweets_test)
```

Recap Q4

The actual SML part (yes, truly, it is three lines of code!):

```
nb = MultinomialNB()
nb.fit(X_train, y_train)
y_pred = nb.predict(X_test)
```

Recap Q5

You can check what was created:

```
nb = MultinomialNB()
nb.fit(X_train, y_train)
y_pred = nb.predict(X_test)

print(y_pred[:10])
```

```
['normal' 'normal' 'normal' 'normal' 'spam' 'normal' 'normal' 'normal' 'abusive' 'normal']
```

Recap Q5

Classification report:

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))
```

Up next

Classification report: validate your classifier.

More about this today!

Validating models

Validation

Validation: When we assess the "fit" between the theoretical concept that is studied and the obtained measures (Birkenmaier et al., 2023)

Or when we try to answer the question: "How well does the classifier work?"

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Validation

What criteria should we use to decide on this?

Entirely context specific!

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Validation

Compare different goals for using SML:

- To automatically decide what Instagram users should see an advertisement
- To automatically remove spam from Twitter feed

Would you use the same criterion in both cases to determine how well a classifier works? Why (not)?

Validation

There are various evaluation metrics available for machine learning.
In scikit-learn, they are presented by ways of a classification report!

Zooming out

So far, we:

- Reviewed the exercise and the basic steps of SML
- Talked about what validation is

Next, we will talk about:

- Some commonly used validation metrics
- Input for SML
- Finding the best classifier

Validation metrics

Precision

Precision quantifies the number of positive class predictions that actually belong to the positive cases.

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Recall

Recall quantifies the number of positive class prediction made out of all positive examples in the dataset.

OR: How many of the cases that we wanted to find did we actually find?

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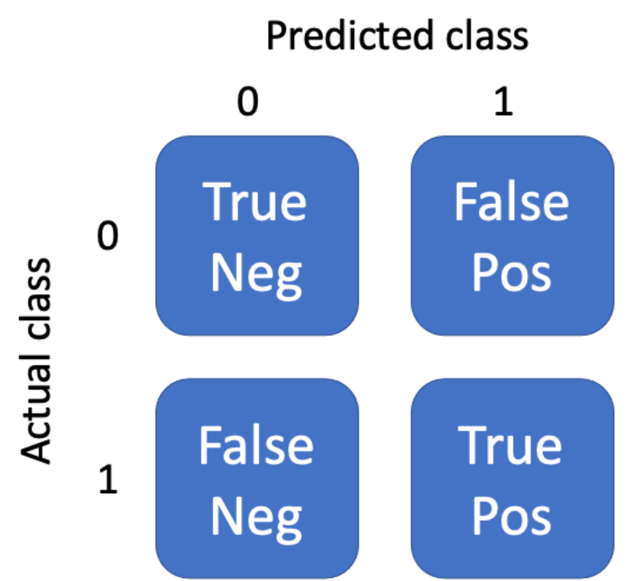
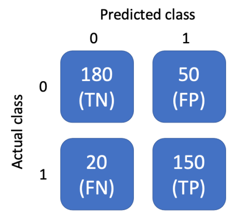
Precision and Recall



Precision and Recall



Precision is calculated as: $\frac{\text{TP}}{\text{TP+FP}}$

In this example $\frac{150}{150+50}$ which is 0.75

Recall is calculated as $\frac{\text{TP}}{\text{TP+FN}}$

In this example $\frac{150}{150+20}$ which is 0.88

What does this look like in code?

Let's ask for a confusion matrix:

```
from sklearn.metrics import confusion_matrix

y_test = [0, 1, 1, 1, 0]
y_pred = [0, 0, 1, 1, 1]

print(confusion_matrix(y_test, y_pred))
```

```
[[1  1 ]
[ 1  2]]
```

The classification report

Let's get some metrics for validation:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
abusive	0.81	0.88	0.85	5369
hateful	0.83	0.05	0.10	966
normal	0.78	0.93	0.85	10848
spam	0.67	0.30	0.41	2817
accuracy			0.78	20000
macro avg	0.77	0.54	0.55	20000
weighted avg	0.78	0.78	0.75	20000

F_1-score

But wait...

Compare different goals for using SML:

- To automatically decide what Instagram users should see an advertisement
- To automatically remove spam from Twitter feed

Such information was not available in the exercise for last week!

F_1-score

F_1-score: The harmonic mean of precision and recall. (Weighted average of precision and recall)

$F_1\text{-score} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$

Accuracy

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weighted avg	0.78	0.78	0.75	20000

Accuracy

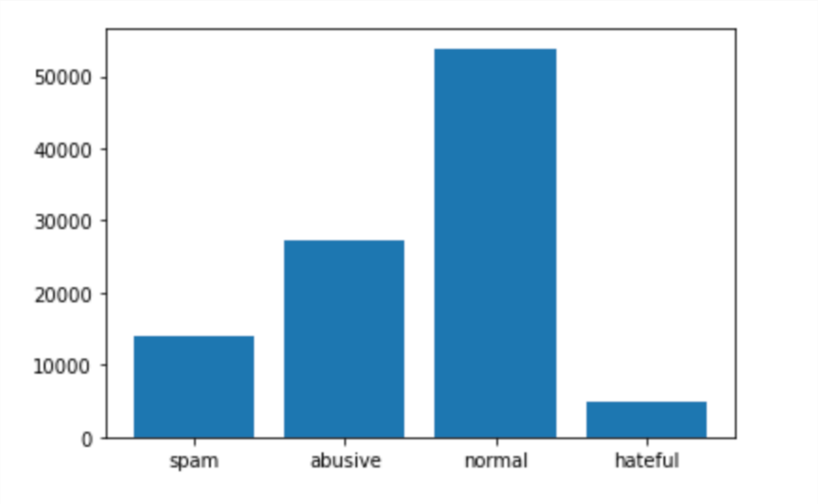
Accuracy: In which percentage of all cases was our classifier right?

Accuracy

Class distribution: The number of examples that belong to each class.

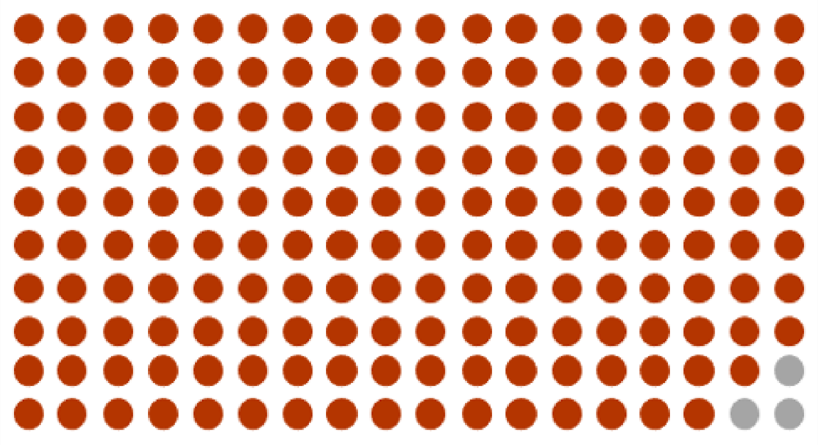
Imbalanced classification: A predictive modeling problem where the distribution of examples across the classes within a training dataset is not equal.

Accuracy



50000
40000
30000
20000
10000
0
spam
abusive
normal
hateful

Accuracy



Majority class (red dots) vs. minority class (grey dots)

Accuracy

Always check how your cases are distributed across the labels.

If your training data overrepresents certain cases, be aware of its potential consequences.

More about the consequences of bad input data next week!

Validation: Best practices

Back to this question:

How do you know what metric is most suitable to assess your model?

Validation: Best practices

Decide what metric is best to use beforehand.

Consider:

- What does a specific metric tell you? How does this relate to your question?
- Is class imbalance an issue?
- What will the classifier be used for? How much room is there for errors?

The latter can bring you back to the question: To SML or not to SML?

Validation: Best practices

SML suitability depends on:

- How hard/easy it is to translate the decision proces for classification into straight-forward rules
- How much data there are to classify
- How much room there is for errors

Zooming out

So far, we:

- Reviewed the exercise and the basic steps of SML
- Talked about what validation is
- Discussed some commonly used validation metrics

Next, we will talk about:

- Additional validation methods

Additional validation methods

Birkenmaier et al., 2023

Comparison to human-annotations is one way to assess (external) validity.

More options are available, although used less frequently.

Birkenmaier et al., 2023

Additional approaches:

- Justification of pre-processing steps
- Inspecting descriptive statistics
- Qualitative (error) analysis
- Report on the rejection of poorly performing models

Yet, validation remains hard for scholars working with CTAM. Why?

Birkenmaier et al., 2023

Recommendations

- Justify concstructs and outline operationalizations
- Always validate CTAM
- Combine internet and external validation
- Always compare to human annotations
- Maximize transparency and reproducibility

Validation: Best practices

In last week's lecture, we saw that you can train many different classifiers.

Amongst other, classifiers can differ based on:

- The vectorizer that is used on the data (i.e., count vectorizer or tf-idf vectorizer)
- The underlying model (e.g., Naïve Bayes, Logistic Regression, Decision Trees, SVM, etc.)

Knowing about validation methods, you may wonder: How do you know what classifier is best beforehand?

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Knowing about validation methods, you may wonder: How do you know what classifier is best beforehand?

Selecting a classifier

You don't!

Typically, various classifiers are trained and their performance is compared.

The best performing classifier is then selected and used to annotate more/new data.

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Selecting a classifier

Heed Birkenmaier atl.'s (2023) advice and explicitely discuss and argue for your choices.

Zooming out

Today, we:

- Reviewed the exercise and the basic steps of SML
- Talked about what validation is
- Discussed some commonly used validation metrics
- Looked beyond the commonly used validation metrics

Zooming out

Tomorrow and this week, you will:

- Set up multiple different classifiers
- Validate those classifiers
- Select the best performing classifier

Work on the tutorial exercises for this week.