



# Introduction to **Audio Content Analysis**

module 6.0: evaluation and metrics

alexander lerch

# introduction

## overview

### corresponding textbook section

#### chapter 6

#### ■ lecture content

- evaluation methodology
- good practices
- metrics

#### ■ learning objectives

- design proper evaluation setups for machine learning algorithms
- list relevant metrics for different machine learning models



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# evaluation

## introduction

- without proper evaluation, there is no way to say whether a system works
- typical mistakes in evaluation
  - 1 non-representative test set
    - ① small, too homogeneous, ...
  - 2 tuning system parameters with the test set (explicitly or implicitly)
  - 3 using misleading evaluation procedures and metrics

# evaluation

## good practices 1/2

### ■ evaluation **method unrelated** to the specific implementation

- has to be task driven, not algorithm driven
- metrics should be unrelated to loss function

### ■ **expectations** clearly defined

- worst case performance (random)
- best case performance (oracle)
- realistic performance  $\Rightarrow$  baseline system
  - ▶ Zero-R classifier
  - ▶ standard approach

# evaluation

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# evaluation

## good practices 2/2

### ■ **comparability** to state-of-the-art

- use of established datasets and identical data splits
- running existing systems on your data

### ■ increase **reproducibility**

- automate evaluation
- publish source code

### ■ test for **statistical significance**

# evaluation

## good practices 2/2

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# evaluation

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- test for **statistical significance**

# classification metrics

## introduction

### ■ possible outcomes of two class problem (positive and negative):

- TP: Positives correctly identified as Positives,
- TN: Negatives correctly identified Negatives,
- FP: Negatives incorrectly identified Positives, and
- FN: Positives incorrectly identified Negatives.

### ■ visualization: confusion matrix

		Predicted		
		Positive	Negative	$\Sigma$
GT	Positive	TP True Positives	FN False Negatives	TP+FN # of GT Positives
	Negative	FP False Positives	TN True Negatives	FP+TN # of GT Negatives
		TP+FP # of Predicted Positives	TN+FN # of Predicted Negatives	TP+TN # of True Predictions
$\Sigma$				

# classification metrics

## accuracy and f-measure

- **accuracy**: how many predictions are accurate
- **macro accuracy**: averaged over classes (not observations)
- **precision**: how many predicted positives are correct
- **recall**: how many ground truth positives correctly predicted
- **f-measure**: combines precision and recall

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

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$$P = \frac{TP}{TP + FP}$$

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$$R = \frac{TP}{TP + FN}$$

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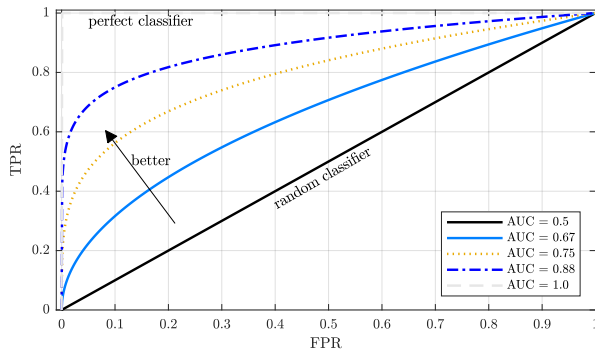
$$P = \frac{TP}{TP + FP}$$

$$R = \frac{TP}{TP + FN}$$

$$F = 2 \cdot \frac{P \cdot R}{P + R}$$

# classification metrics

## area under curve





# regression metrics

mae, mse,  $R^2$

goal: measure deviation

■ mean absolute error

■ mean squared error

■ coefficient of determination

$$MAE = \frac{1}{\mathcal{R}} \sum_{\forall r} |y(r) - \hat{y}(r)|$$

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$$R^2 = 1 - \frac{MSE(y - \hat{y})}{MSE(y - \mu_y)}$$

# summary

## lecture content

### ■ evaluation

- system development without evaluation is meaningless
- data and method need to be carefully selected
- metrics need to reflect the success of the system

### ■ classification metrics

- accuracy and macro accuracy
- precision, recall, and f-measure
- AUC

### ■ regression metrics

- MAE and MSE
- coefficient of determination

