

MACHINE LEARNING

Course Recap.

Last Update: 21st December 2022

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STRUCTURE

1. Overview.
2. ML Experience
3. Feature Extraction
4. Dimensionality Reduction
5. Training
6. Validation
7. Evaluation Metrics
8. Deep Learning
9. What's next?

OVERVIEW.

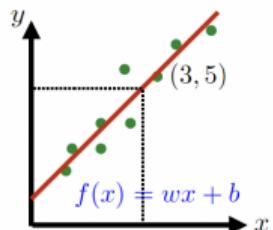
WHAT IS MACHINE LEARNING (ML)?

Definition (Tom Mitchell)

A computer program is said to **learn** from **experience** E with respect to some class of **tasks** T , and **performance measure** P , if its performance at tasks in T , as measured by P , **improves** with experience E .

$$x \rightarrow f(x) \rightarrow y$$

$$f(x) = \int_0^{\frac{\pi}{2}} \cos(x) e^{-2\gamma x} dx$$



Artificial Intelligence

Machine Learning

Supervised Learning

Linear Regression, SVM, Decision Tree, Random Forest

Semi-Supervised Learning

Deep Learning

Neural Networks (NN), Convolutional NN, Recurrent NN

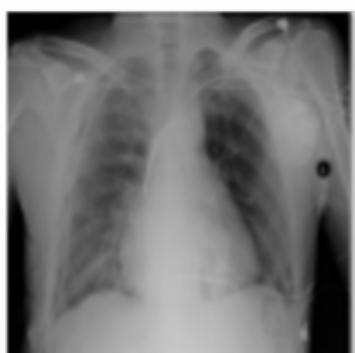
Unsupervised Learning

Stacked AutoEncoder (SAE), Variational Auto-Encoder (VAE)

Gaussian Mixture Models (GMM), Principle Component Analysis (PCA), K-Means, Spectral Clustering

TASKS - CLASSIFICATION

$$f(\text{X-ray image} ; \theta)$$



T_1 : Classification

$$y_q \in \{c_1, c_2, \dots, c_K\}$$

Tuberculosis Atelectasis

$$I_q \in \mathbb{R}^{m \times n}$$

TASKS - ANOMALY DETECTION

$$f(\quad ; \theta)$$



$$I_q \in \mathbb{R}^{m \times n}$$

T₂: Anomaly Detection

$$y_q \in \{c_N, c_A\}$$

Normal **Abnormal**

TASKS - REGRESSION

$$f(\text{[Image of a chest X-ray]} ; \theta)$$

T₃: Regression
 $y_q \in \mathbb{R}$
45 yrs

$$I_q \in \mathbb{R}^{m \times n}$$

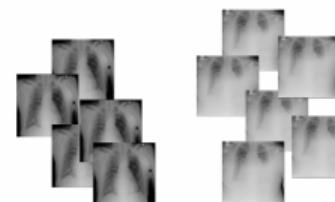
TASKS - RETRIEVAL

$$f(\quad ; \theta)$$



$$I_q \in \mathbb{R}^{m \times n}$$

T₄: Retrieval



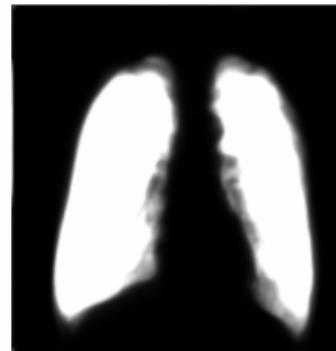
TASKS - SEGMENTATION

$$f(\quad ; \theta)$$



$$I_q \in \mathbb{R}^{m \times n}$$

T₅: Segmentation



$$y_q \in \mathbb{R}^{m \times n \times K}$$

ML EXPERIENCE

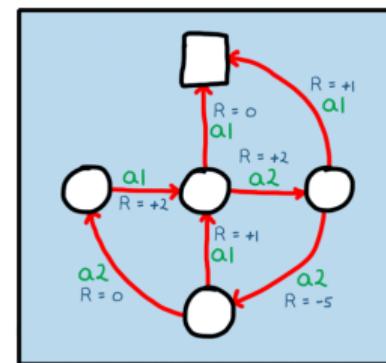
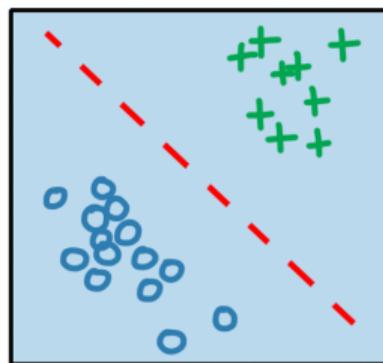
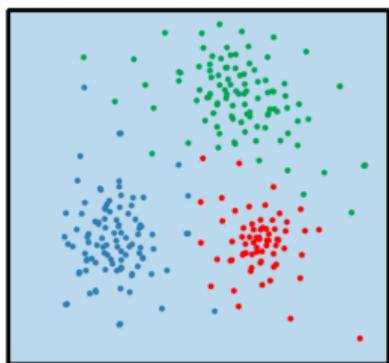
EXPERIENCE

machine learning

unsupervised
learning

supervised
learning

reinforcement
learning



Source: <https://www.mathworks.com/discovery/reinforcement-learning.html>



EXPERIENCE

EXPERIENCE

Pre-Processing

Feature Extraction

Dimensionality
Reduction

Training

Loss

Validation

Evaluation Metrics

Testing

FEATURE EXTRACTION

FEATURE EXTRACTION

Pre-Processing

Feature Extraction

Dimensionality Reduction

Training

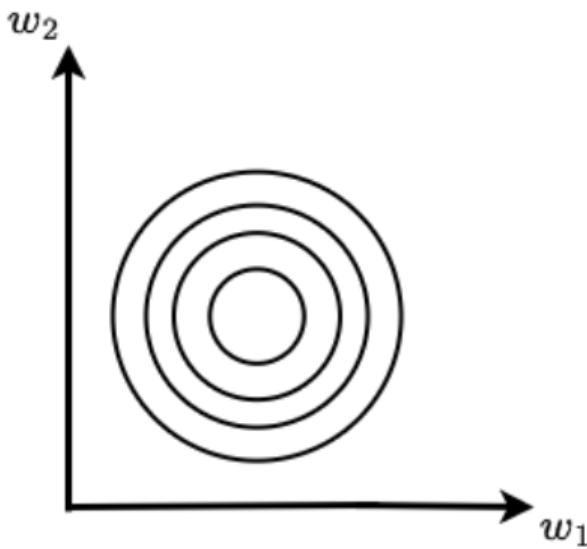
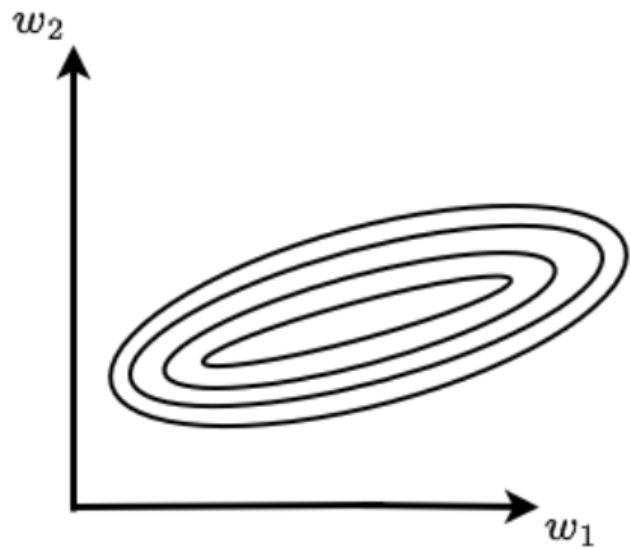
Loss

Validation

Evaluation Metrics

Testing

PRE-PROCESSING -- MOTIVATION



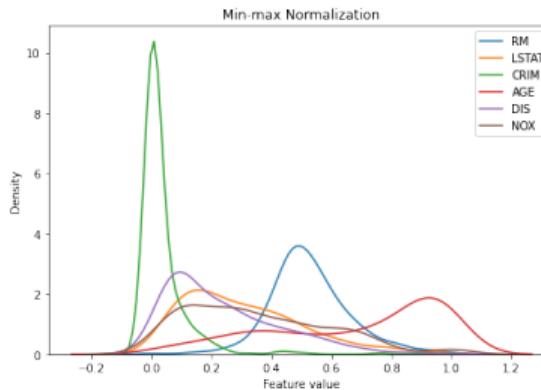
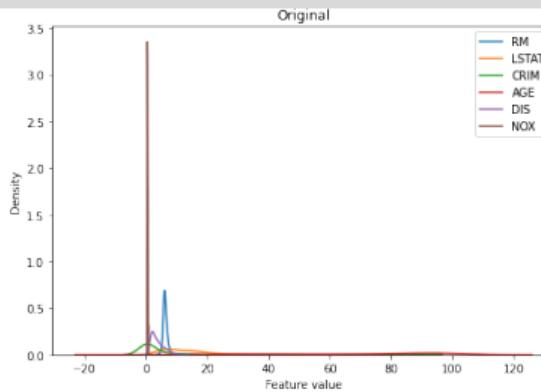
PRE-PROCESSING -- FEATURE SCALING

Normalization: It is the process of rescaling the values of all features to a range between 0 and 1.

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Image Source:

<https://mkang32.github.io/python/2020/12/27/feature-scaling.html>



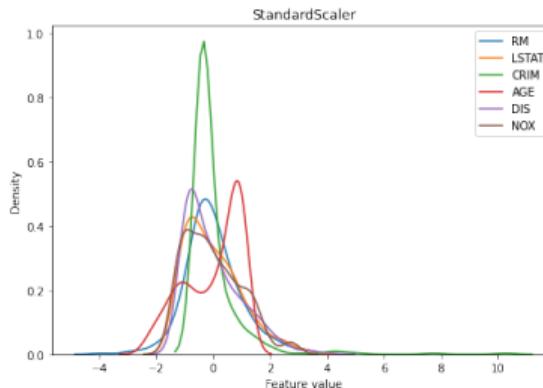
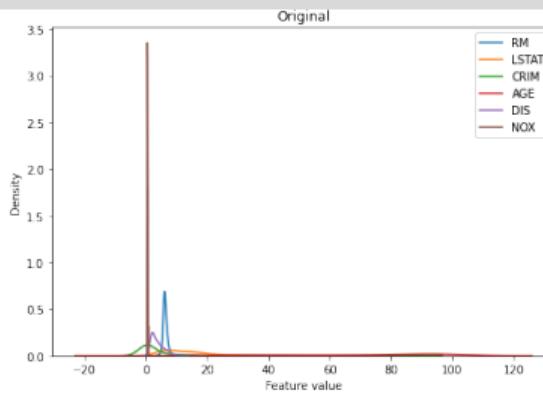
PRE-PROCESSING -- FEATURE SCALING

Standardization: It is the process of representing the data as a Normal distribution with a 0 mean and a unit (1) standard deviation.

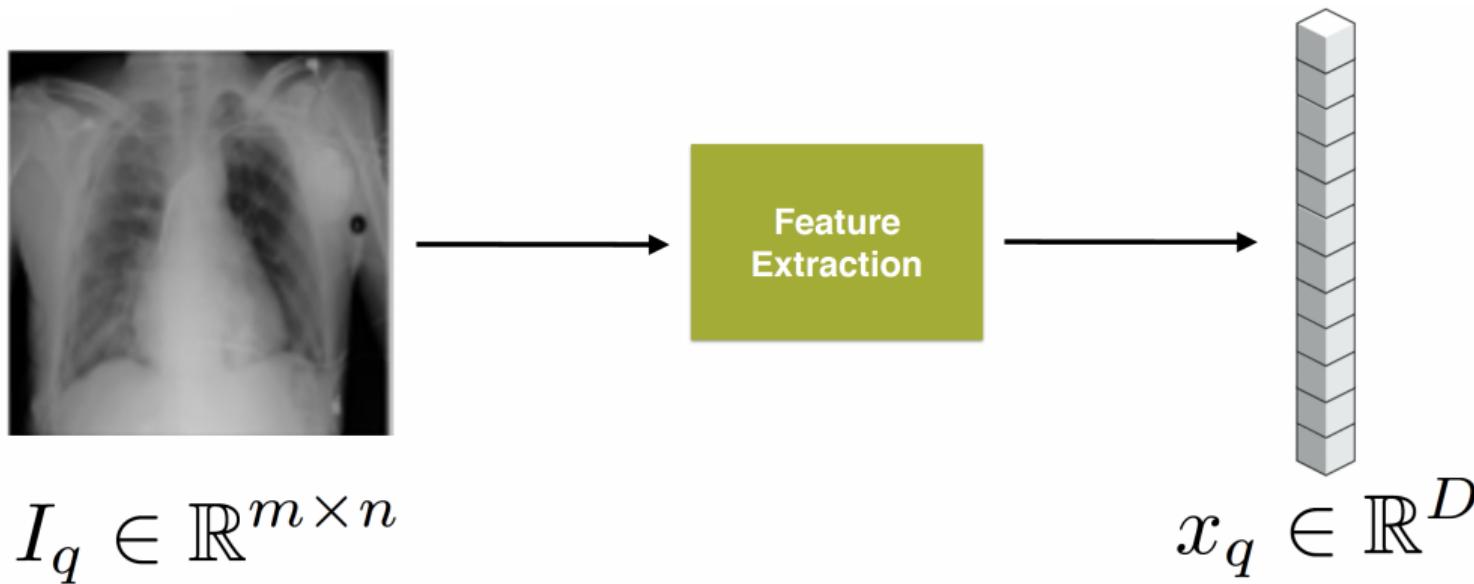
$$z_i = \frac{x_i - \mu_x}{\sigma_x}$$

Image Source:

<https://mkang32.github.io/python/2020/12/27/feature-scaling.html>



FEATURE EXTRACTION



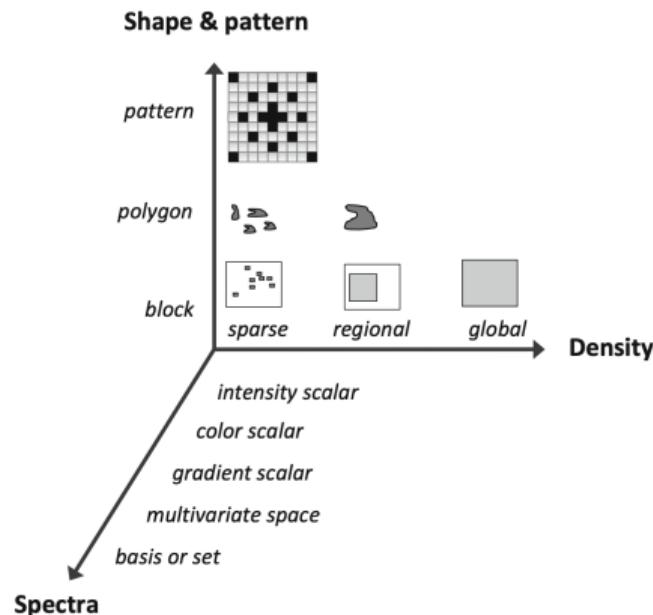
FEATURE EXTRACTION

Local Pixel Features (Binary, Spectra,
e.g., SIFT, SURF, HoG, ...etc.)

Global Pixel Features (Texture, SDM,
...etc.)

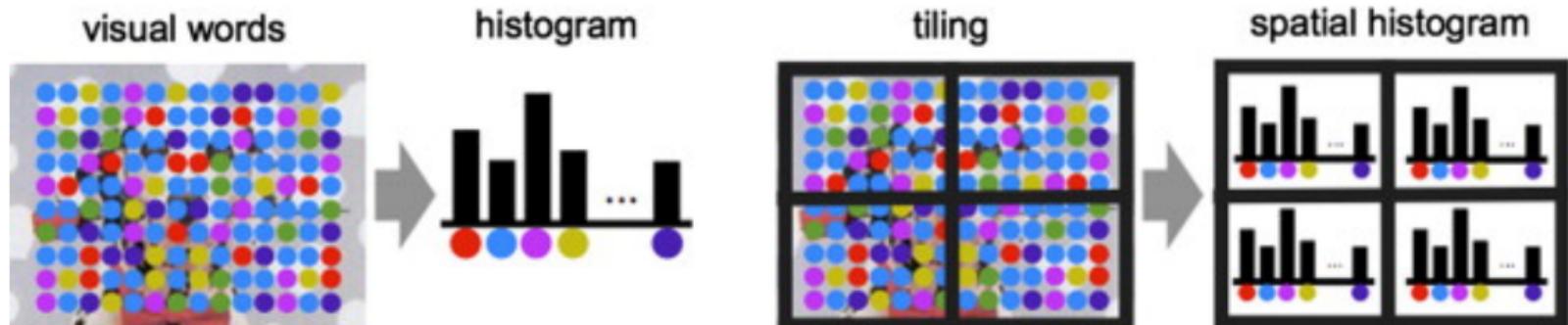
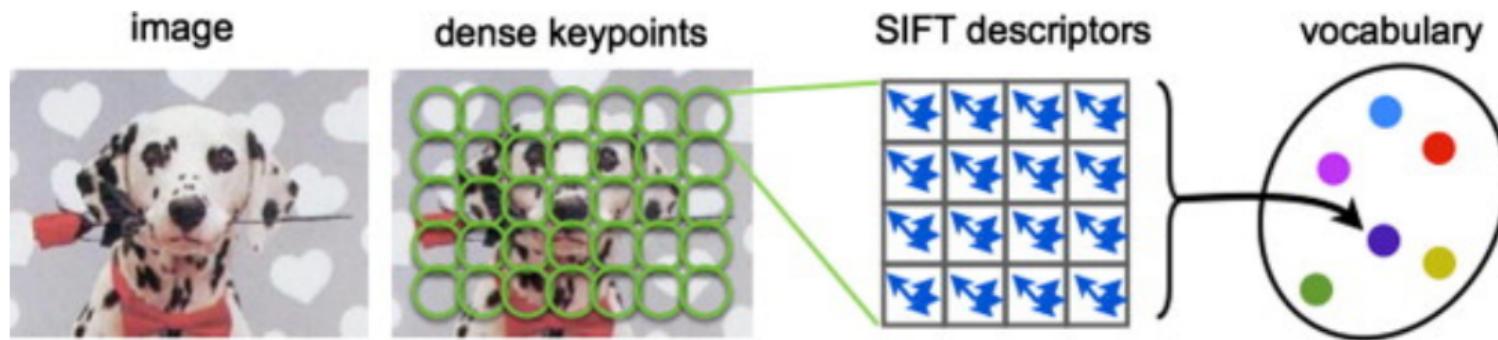
Shape of Pixel Regions (Area,
Perimeter, Centroids ...etc.)

Basis sets (Haarlike, Bag of words,
...etc.)



Adopted from Fig.5.1 in Krig, S., 2014. Computer vision metrics: Survey, taxonomy, and analysis (p. 508). Springer nature.

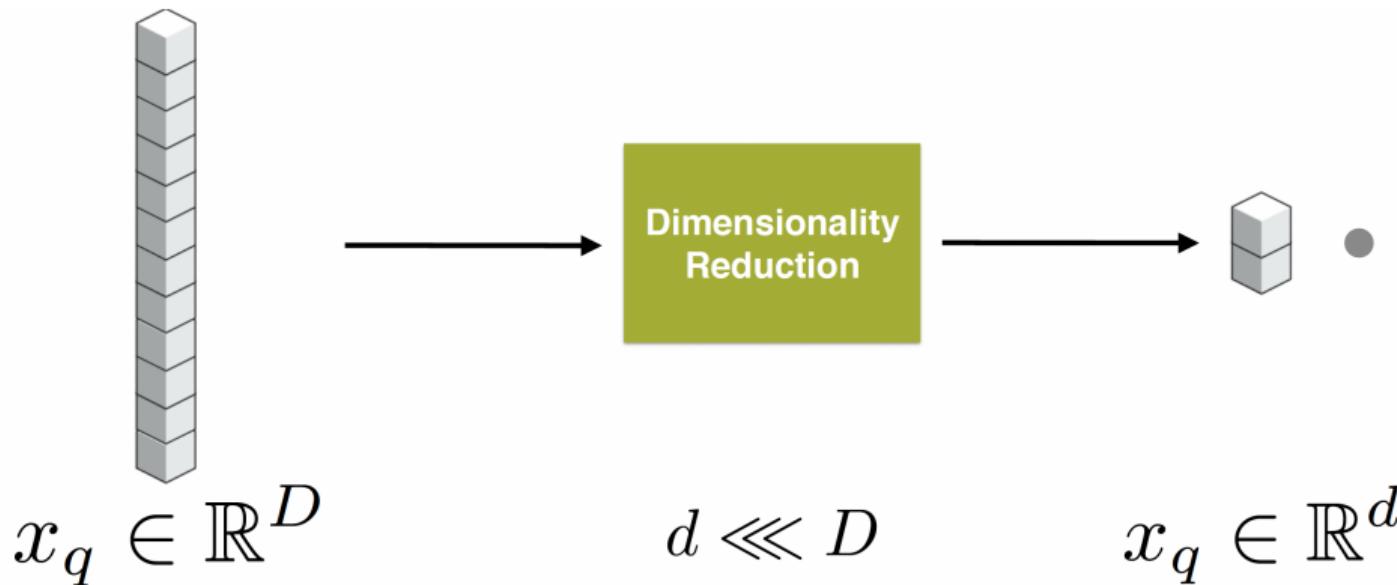
FEATURE EXTRACTION



Adopted from Fig.1 in El-Gayar, M. M., and H. Soliman. "A comparative study of image low level feature extraction algorithms." Egyptian Informatics Journal 14.2 (2013): 175-181.

DIMENSIONALITY REDUCTION

DIMENSIONALITY REDUCTION



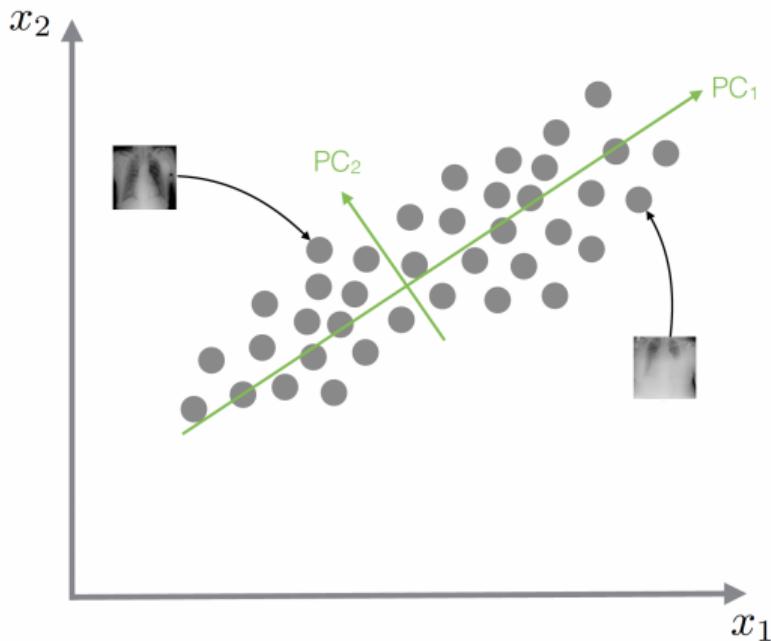
DIMENSIONALITY REDUCTION

Principal Component Analysis (PCA)

is a statistical technique for reducing the dimensionality of a dataset

linearly transform the data into a new coordinate system where (most of) the variation in the data can be described with fewer dimensions than the initial data

The new coordinate system components are called Principal Components (PCs)



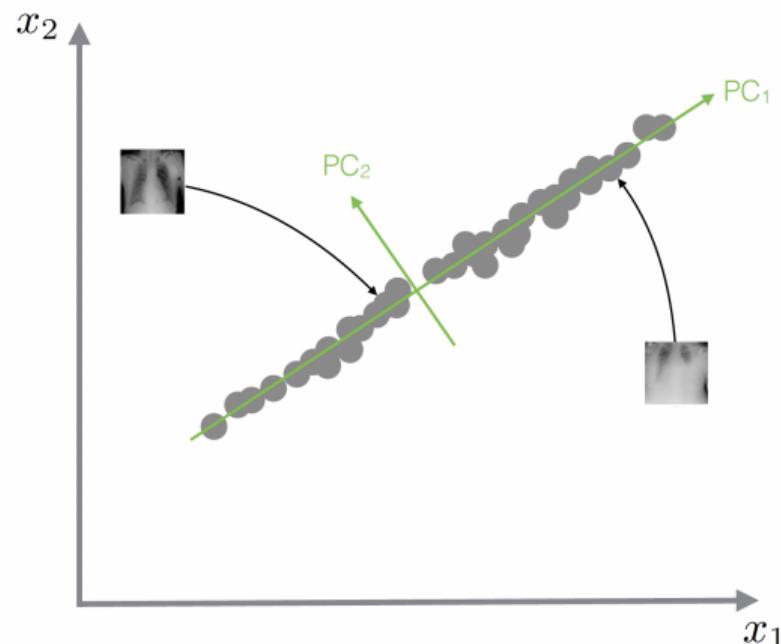
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Structure
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Overview.
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ML Experience
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Feature Extraction
oooooooooooo

Dimensionality Reduction
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Training
oooooooooooo

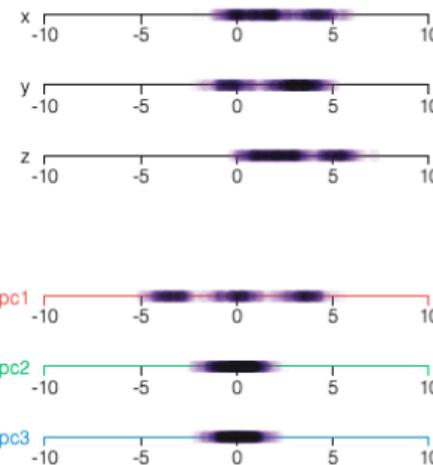
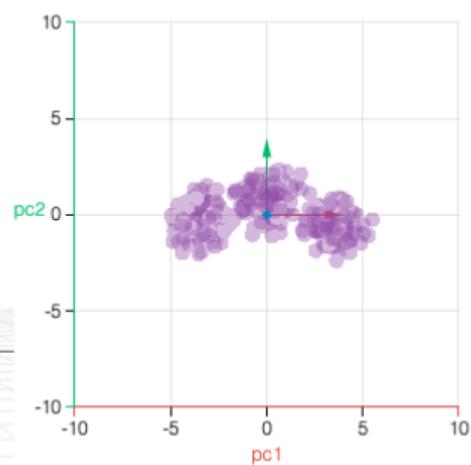
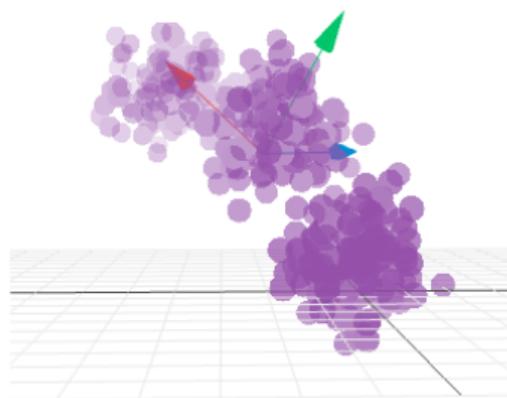
Validation
ooo

Evaluation Metrics
oooooooooooo

Deep Learning
oo

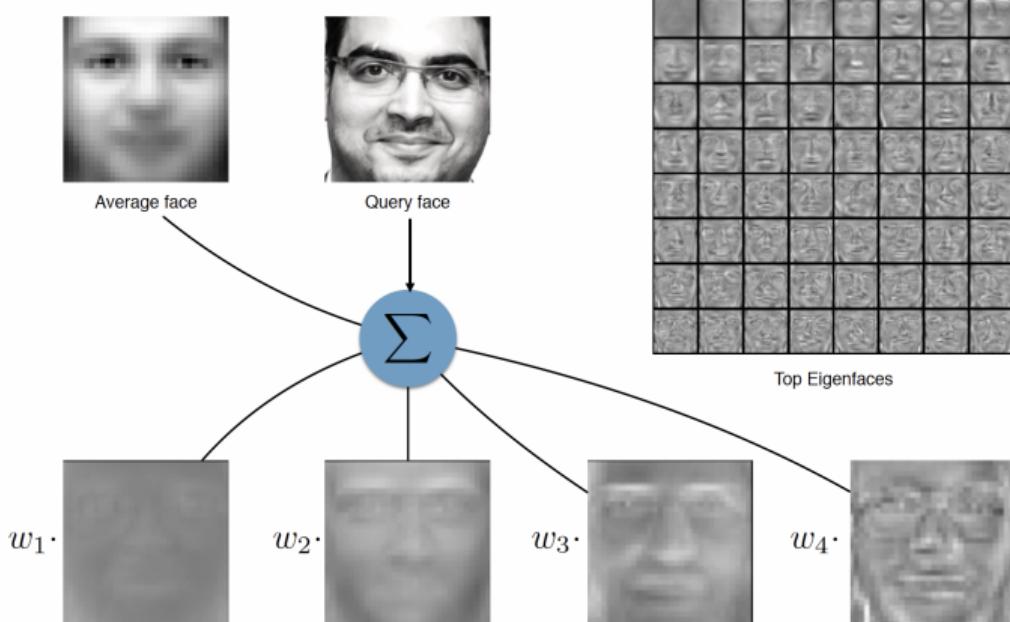
What's next?
ooo

DIMENSIONALITY REDUCTION



Source: <https://setosa.io/ev/principal-component-analysis/>

DIMENSIONALITY REDUCTION



TRAINING

TRAINING

Pre-Processing

Feature Extraction

Dimensionality
Reduction

Training

Loss

Validation

Evaluation Metrics

Testing

TRAINING

- **Supervised Learning**

- Derive general rules from labeled examples

- **Unsupervised Learning**

- Discover similarities within unlabelled data. Estimate their distribution

- **Semi-Supervised Learning**

- Make use of both labeled and unlabelled data

- **Reinforcement Learning**

- Make right decisions from the past experience

labeled examples:

$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\}$$

Input feature:

$$\mathbf{x} = (x_1, x_2, \dots, x_d) \in \mathbb{R}^d$$

Predicted output:

$$y \in \underbrace{\{c_1, c_2, \dots, c_K\}}_{\text{classification}} \quad \text{or} \quad y \in \underbrace{\mathbb{R}^k}_{\text{regression}}$$

Conditional distribution:

$$P(y|\mathbf{x}) \quad f(x) = \arg \max_x P(y|\mathbf{x})$$

Joint distribution:

$$P(\mathbf{x}, y) \quad P(y|\mathbf{x}) = \frac{P(\mathbf{x}, y)}{\sum_y P(\mathbf{x}, y)}$$

Complexity

TRAINING



$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_N, y_N)\}$$

$$y_q \in \{c_1, c_2, \dots, c_K\}$$

TRAINING

- **Supervised Learning**
 - Derive general rules from labeled examples
- **Unsupervised Learning**
 - Discover similarities within unlabelled data. Estimate their distribution
- Semi-Supervised Learning
 - Make use of both labeled and unlabelled data
- Reinforcement Learning
 - Make right decisions from the past experience

Unlabelled examples:

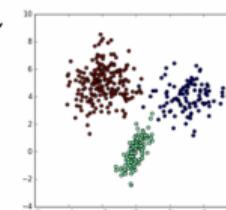
$$\mathcal{D} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$$

Input feature:

$$\mathbf{x} = (x_1, x_2, \dots, x_d) \in \mathbb{R}^d$$

Output (clusters):

$$\underbrace{\nabla}_{\text{clusters}} = \{C_1, C_2, \dots, C_K\}$$

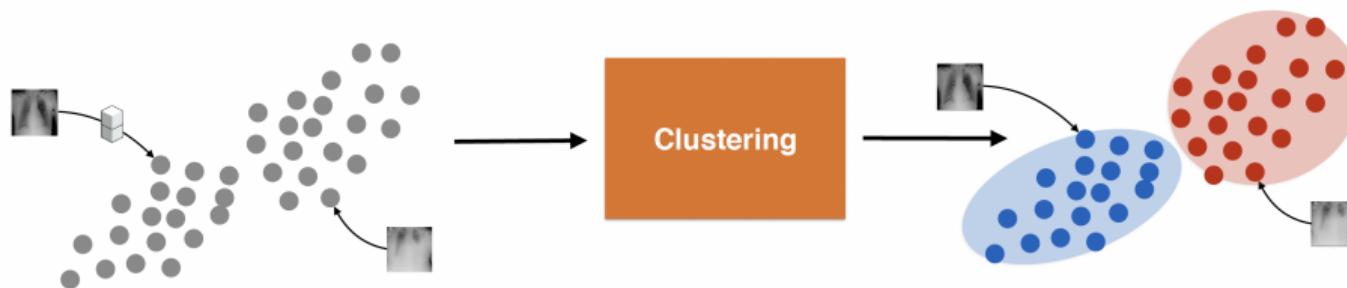


Mixture density:

$$f(\mathbf{x}) = \sum_{k=1}^K \pi_k f_k(\mathbf{x})$$

$$P(\theta|\mathbf{x}) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}; \mu_i, \Sigma_i)$$

TRAINING



$$x_q \in \mathbb{R}^d$$

$$y_q \in \{c_1, c_2, \dots, c_K\}$$

TRAINING

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Labeled & Unlabelled examples:

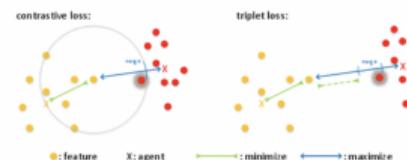
$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_L, y_L), \\ x_{L+1}, x_{L+2}, \dots, x_{L+U}\}$$

Input feature:

$$\mathbf{x} = (x_1, x_2, \dots, x_d) \in \mathbb{R}^d$$

Predicted Output:

$$y \in \{c_1, c_2, \dots, c_K\}$$



TRAINING

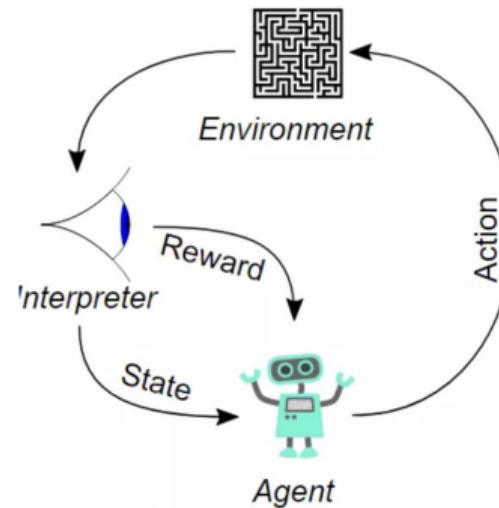


$$\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_L, y_L), \\ x_{L+1}, x_{L+2}, \dots, x_{L+U}\}$$

$$y_q \in \{c_1, c_2, \dots, c_K\}$$

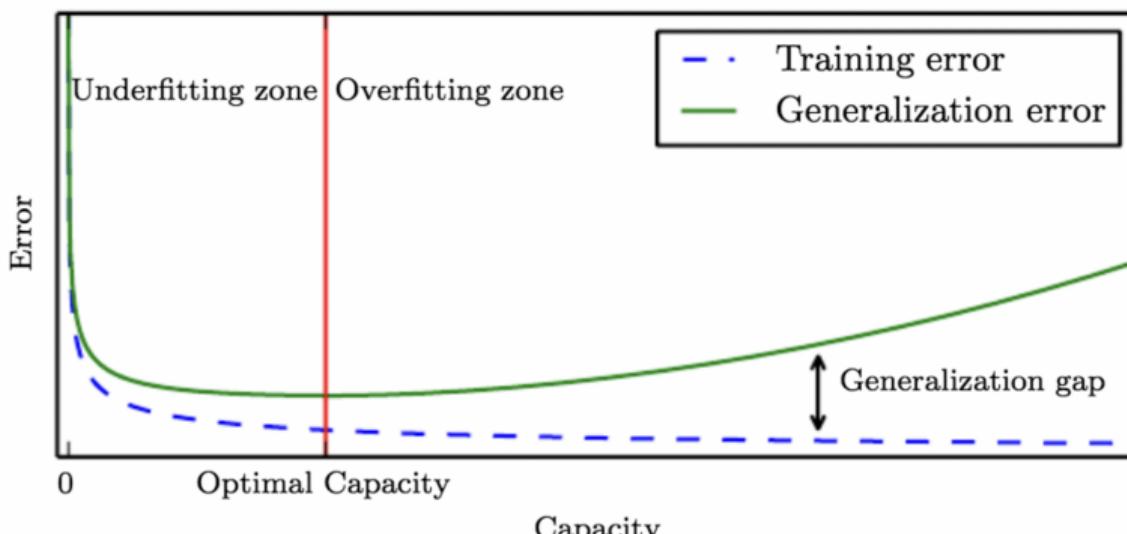
TRAINING

- **Supervised Learning**
 - Derive general rules from labeled examples
- **Unsupervised Learning**
 - Discover similarities within unlabelled data. Estimate their distribution
- **Semi-Supervised Learning**
 - Make use of both labeled and unlabelled data
- **Reinforcement Learning**
 - Make right decisions from the past experience



TRAINING

- **Bias**
 - Model Complexity
 - More data?
- **Variance**
 - Data variance
 - Weight decay
 - Dropout



Source: <http://www.deeplearningbook.org/contents/ml.html>

VALIDATION

Structure
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Overview. ML Experience
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Feature Extraction
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Dimensionality Reduction
oooooooooooo

Training
oooooooooooo
Validation
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Evaluation Metrics
oooooooooooo

Deep Learning
oo

What's next?
ooo

VALIDATION

Pre-Processing

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VALIDATION

Non-Exhaustive Cross Validation

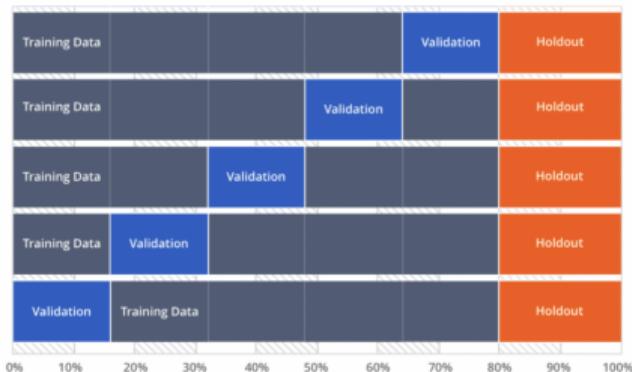
Holdout method

k-fold Cross Validation (k-fold CV)

Exhaustive Cross Validation

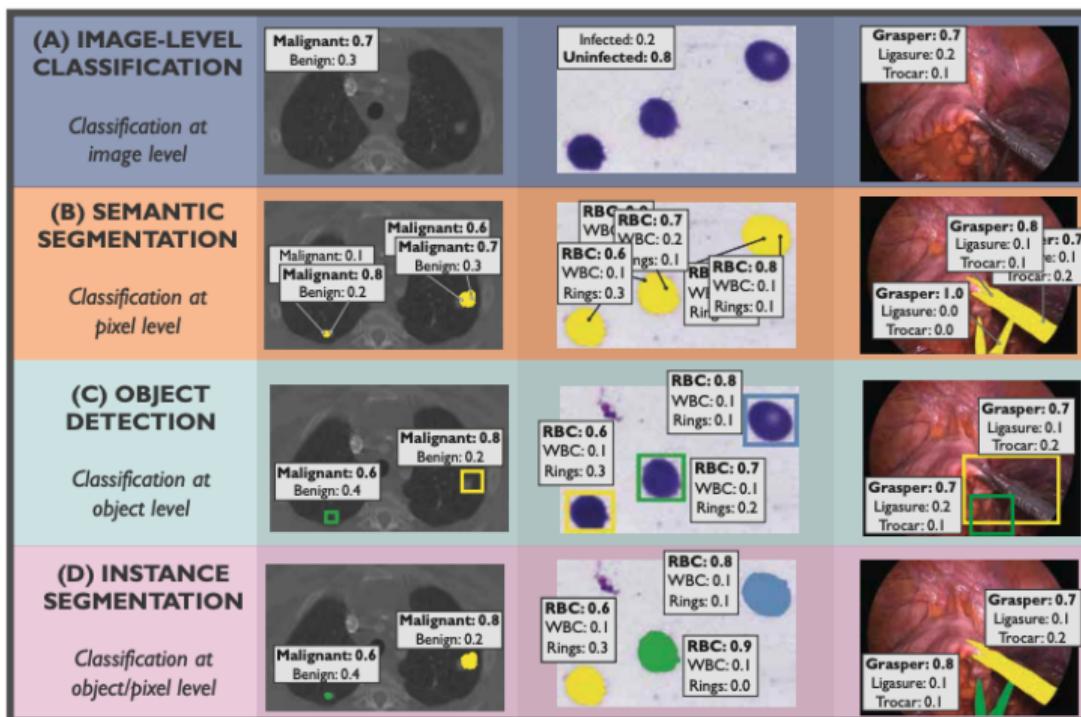
Leave-one-out Cross Validation (LOOCV)

Leave-p-out Cross Validation (L_pOCV)



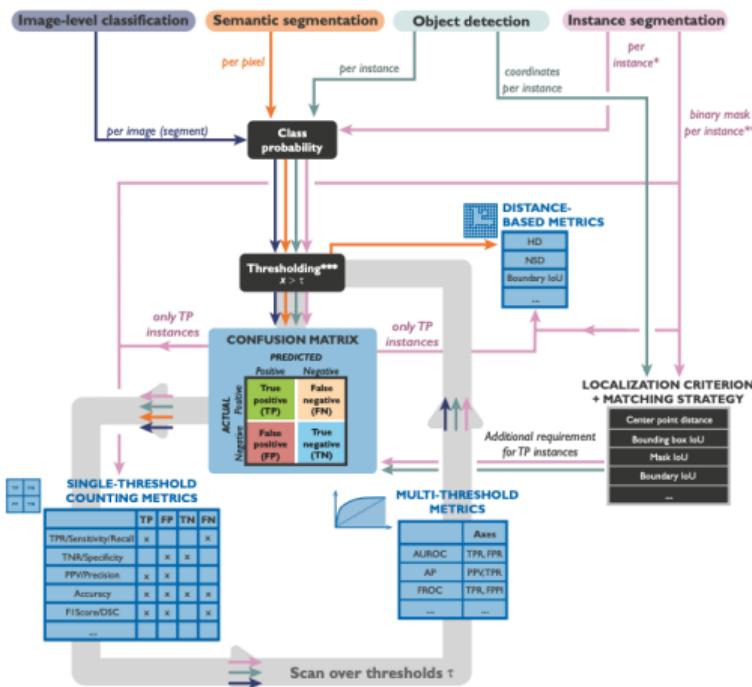
EVALUATION METRICS

EVALUATION METRICS



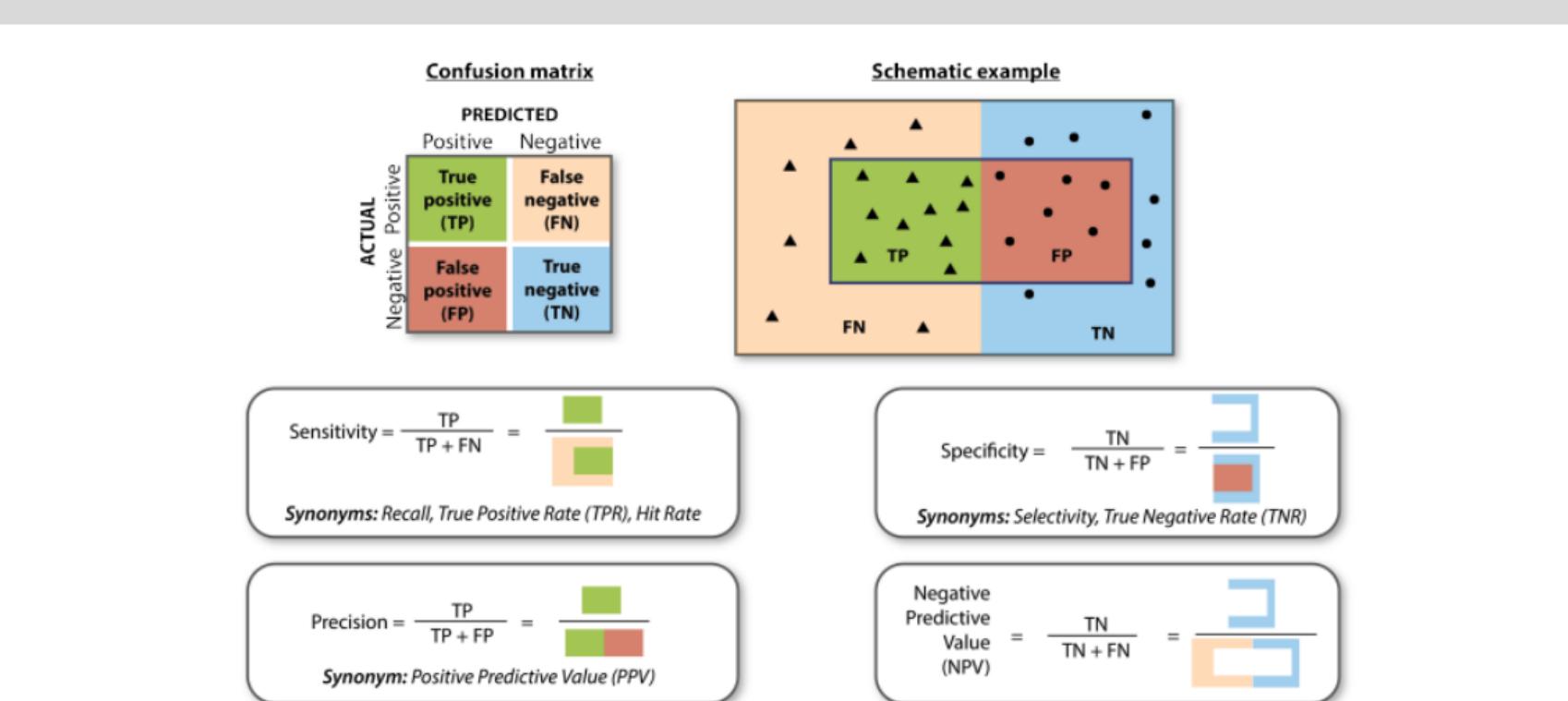
Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

EVALUATION METRICS



Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

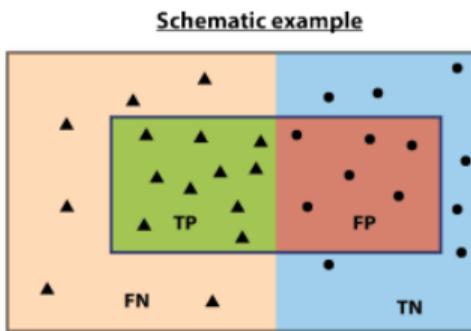
EVALUATION METRICS -- SINGLE THRESHOLD



Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

EVALUATION METRICS -- SINGLE THRESHOLD

		PREDICTED	
		Positive	Negative
ACTUAL	Positive	True positive (TP)	False negative (FN)
	Negative	False positive (FP)	True negative (TN)



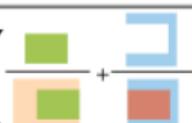
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} = \frac{\text{TP}}{\text{TP} + \text{FN}} + \frac{\text{TN}}{\text{TN} + \text{FP}}$$



$$F_1 \text{ Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

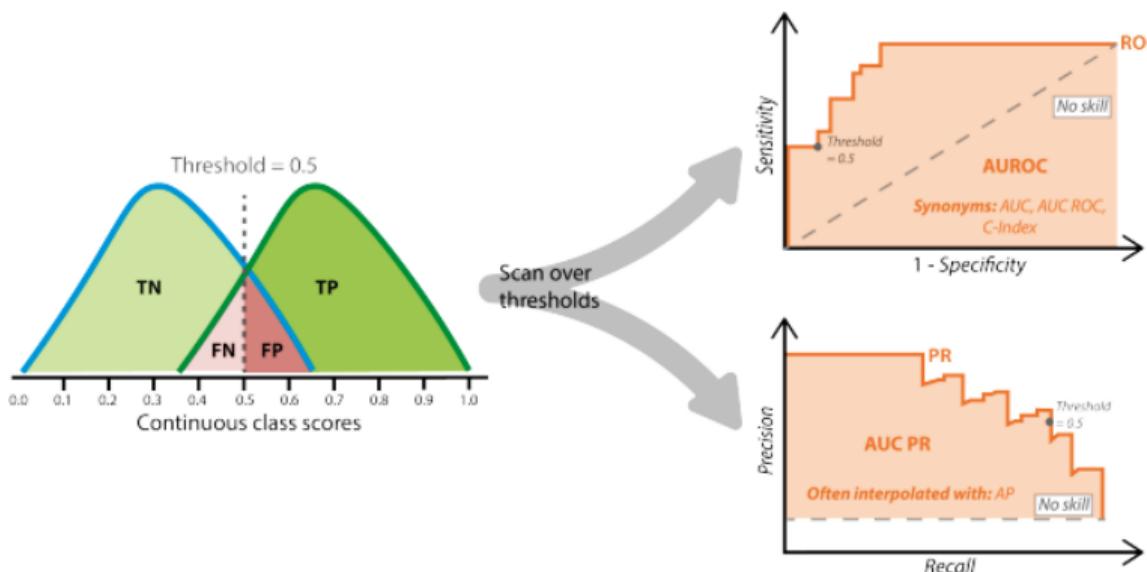
Synonym: Dice Similarity Coefficient (DSC)

$$\text{Balanced Accuracy} = \frac{1}{2} (\text{Sensitivity} + \text{Specificity}) = \frac{1}{2} \left(\frac{\text{TP}}{\text{TP} + \text{FN}} + \frac{\text{TN}}{\text{TN} + \text{FP}} \right) = \frac{1}{2} \left(\frac{\text{TP}}{\text{TP} + \text{FN}} + \frac{\text{TN}}{\text{TN} + \text{FP}} \right)$$



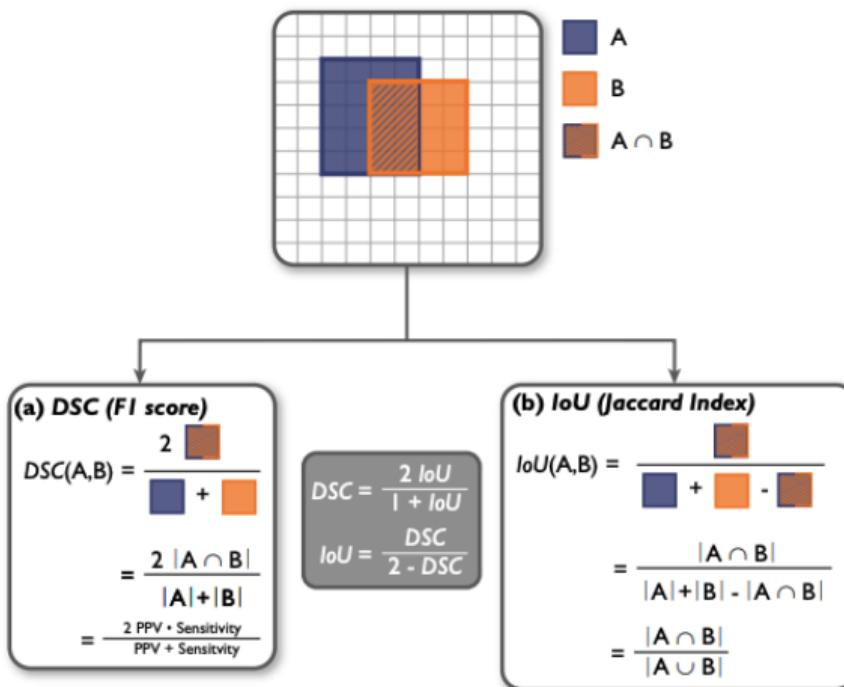
Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

EVALUATION METRICS -- MULTI-THRESHOLDS



Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

EVALUATION METRICS -- SEGMENTATION



Source: Reinke, Annika, et al. "Common limitations of image processing metrics: A picture story." arXiv preprint arXiv:2104.05642 (2021).

EVALUATION METRICS -- OTHER METRICS

- **Classification**

- Accuracy (ACC)
- Error Rate (top 1%, top 5%)
- Precision
- Recall
- F-Score
- Area Under ROC Curve
- Area Under PR Curve

- **Segmentation**

- Dice Coefficient (DICE)
- Jaccard index

- **Regression**

- Mean Absolute Error (MAE)
- Mean Square Error (MSE)
- Normalized Cross Correlation (NCC)

- **Synthesis/Denoising**

- Mean Square Error (MSE)
- Peake Signal to Noise Ratio (PSNR)
- Structural Similarity Image Measure (SSIM)
- Contrast to Noise Ratio (CNR)

- **Clustering**

- Davies-Bouldin index
- Purity
- Normalized Mutual Information (NMI)

DEEP LEARNING

DEEP LEARNING

Pre-Processing

Feature Extraction

Dimensionality Reduction

Training

Loss

Validation

Evaluation Metrics

Testing

WHAT'S NEXT?

NEXT COURSE?

Machine Learning II

Neural Networks for Sequences (Ch15)

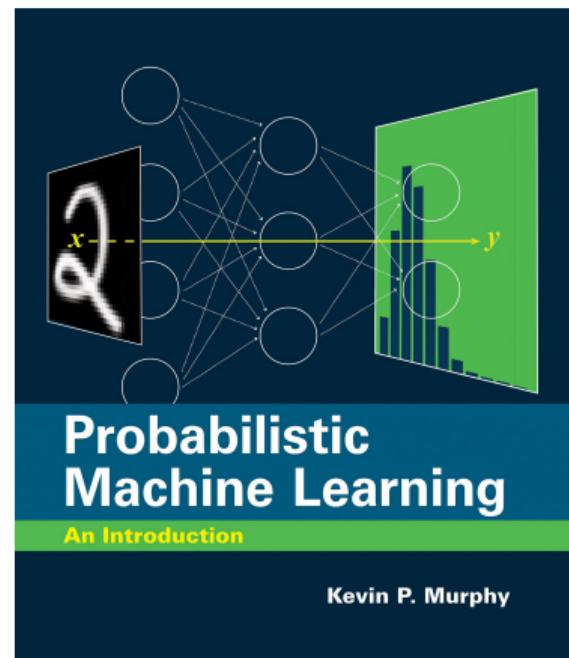
Kernel Methods – Support Vector Machine (Ch 17)

Trees, Forests, Bagging, and Boosting – Boosting
(Ch 18)

Beyond Supervised Learning – Learning with Fewer
Labeled Examples (Ch 19)

Beyond Supervised Learning – Recommender
Systems

Beyond Supervised Learning – Graph Embeddings



Questions