

# Features Fusion

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Building blocks for the project:

- Features extractors: color and shape
- Classifier

How to combine multiple features extractors?

- 1 Late fusion
- 2 Early fusion
- 3 Implicit fusion

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# Late fusion

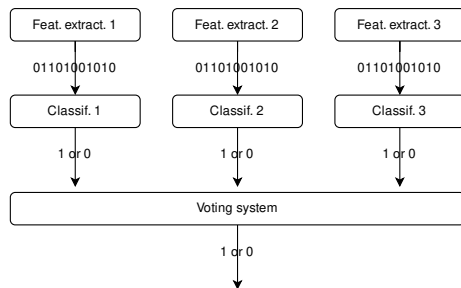
Simpler but less efficient

## Definition

In **late fusion**, a.k.a. **decision fusion**, we process each feature set before making any decision.

Common strategies:

**voting** (majority, consensus, average...)



# Late fusion

Simpler but less efficient

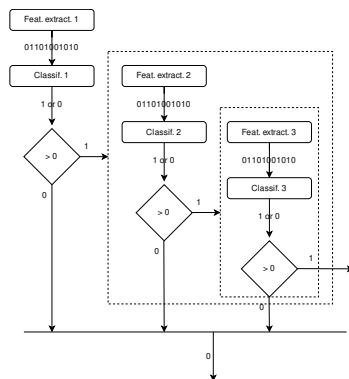
## Definition

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Common strategies:

**voting** (majority, consensus, average. . . )

**cascade** of classifiers (e.g. Haar cascade)  
*can speed things up*



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## Early fusion

Harder but more efficient

### Definition

In **early fusion**, a.k.a. **data fusion**, we merge all features before processing them.

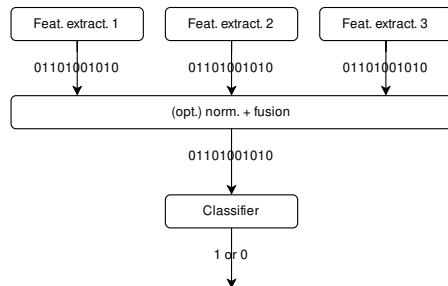
We must fuse all our features into 1 single representation space.

This leads to several problems:

- We may need to convert our features.

- We may need to normalized our features.

- We must aggregate our features.





Some examples:

Qualitative  $\rightarrow$  Quantitative

Int  $\rightarrow$  Float32

Some examples:

### 1) Min-max normalization

Scaling using minimum and maximum of each feature component  
Highly sensitive to outliers

**Min-max**

$$X_i' = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}$$

Some examples:

### 2) Z-score normalization

Scaling using arithmetic mean  $\mu$  and std deviation  $\sigma$  of each feature component

One of the most common normalization techniques

Also sensitive to outliers

$$\textbf{Z-score} \quad X_i' = \frac{X_i - \mu}{\sigma}$$

Some examples:

#### 3) Tanh normalization

Also computed using  $\mu$  and  $\sigma$

More robust and efficient normalization

$$\mathbf{Tanh} \quad X_i' = \frac{1}{2} \left\{ \tanh \left[ 0.01 \cdot \left( \frac{X_i - \mu}{\sigma} \right) \right] + 1 \right\}$$

Some examples:

### 4) MAD normalization

Computed using the median and median absolute deviation

Insensitive to outliers and the points in the extreme tails of the distributions

$$\mathbf{MAD} \quad X_i' = \frac{X_i - \text{median}(X_i)}{\text{median}(|X_i - \text{median}(X_i)|)}$$

Some examples:

- Concatenation (depth-wise, column-wise)

- Average, Median

- Maximum or Minimum

- ...

- 1 Late fusion
- 2 Early fusion
- 3 **Implicit fusion**

### Definition

In **explicit** fusion, as seen previously, the combination process is **manually** designed and tuned.  
In **implicit** fusion, on the opposite, the combination of the features is **learned automatically**.

**Both** explicit and implicit fusion are **early** fusion schemes.

The extent to which fusion can be learned automatically depends on the classifier used:

**Simple linear classifiers** require *explicit* feature fusion.

**Neural networks** fall in this category.

**Tree-based classifiers** can leverage *unscaled, heterogeneous* features natively.  
They can even mix *qualitative* and *quantitative* features!