Dynamic Classifier Selection (DCS)
and
Dynamic Ensemble Selection (DES)

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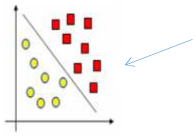
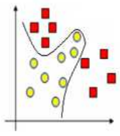
Introduction - Problem Definition

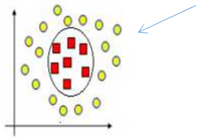
- Classification
  - The most important task in Machine Learning
  - Why?
    - Because, we do it frequently everyday.



- Find the frontier between the problem classes
- Sometimes, it is very easy !!
- A linear separable problem

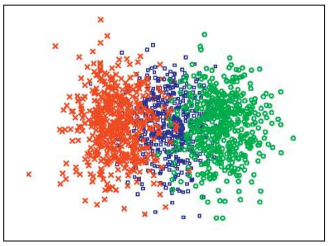
- But, sometimes, it is not so easy.
- Here, we have non linear separable problems





Introduction - Problem Definition

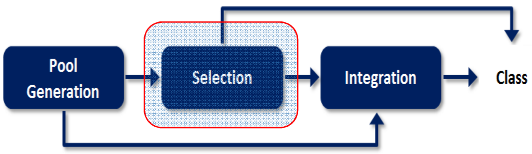
- Frequently,
  - Training a classifier to be capable of learning the wide variability found in a pattern recognition problem is a BIG challenging task.



- A monolithic classification system (based on a single classifier) sometimes is not able to cover well the whole feature space

Introduction - Problem Definition

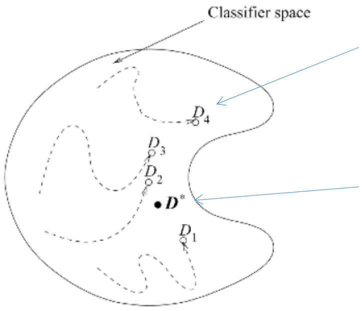
- Alternative
  - Multiple Classifier Systems (MCS)
    - Ensemble in which is expected the elements make different errors (diversity)
    - Diversity => different and sometimes complementary errors.
    - General overview of the MCS phases:



- Our focus today will be the selection model:
  - The use of dynamic selection strategy -> when the selection of classifiers is done during the testing phase.

Introduction – Problem Definition

- Why MCS is an interesting alternative?
  - Avoid the risk involved in the choice of one individual classifier



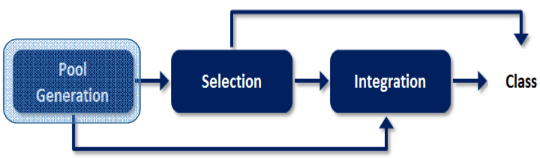
D_1, D_2, D_3 and D_4 are possible solutions (classifiers)

D* is the hypothetical optimal solution

Rationale behind:
by combining the classifiers we expect an "average" solution closer to the optimal solution.

Multiple Classifier Systems (ensembles)

- To select classifiers => we need a pool of them.
- What kind of pools can we generate?
- What is important to observe in a pool of classifiers?
- How can we create a pool of classifiers (or ensemble)?

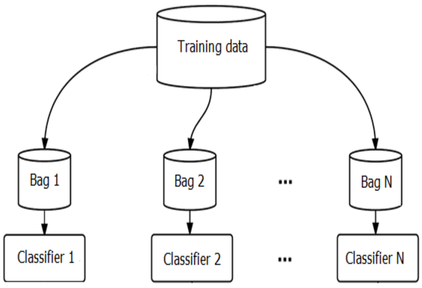


Pool Generation Stage

- Expected: a pool of diverse and accurate classifiers.
- Diversity?
  - Important to observe in a pool of classifiers.
  - Classifiers may compete each other making different and perhaps complementary errors.
- Kind of pools:
  - **Homogeneous**
    - Pool of classifiers based on the same base classifier (or learner)
    - Diversity is obtained by manipulating the training data
  - **Heterogeneous**
    - Pool of classifiers based on different base classifiers (learners)
    - Diversity is obtained by considering different learners (different concepts)

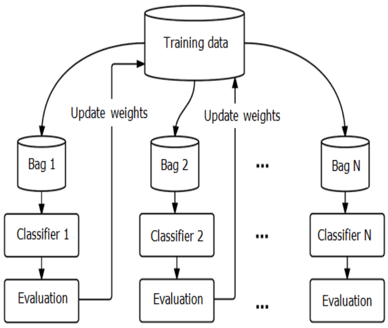
Homogeneous Pool (How to create?)

- Bagging (Breiman, 1996)
  - Bootstrapped Aggregation
  - **Random sampling with replacement** from the original dataset
  - Any element has the same probability to appear in a new Bag
  - Each Bag_i corresponds to X% of the training samples



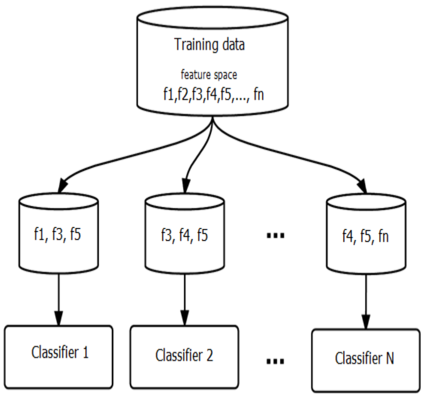
Homogeneous Pool (How to create?)

- Boosting (R.E. Schapire, et al., 1997)
  - **Random sampling with replacement** over weighted data
  - **Misclassified data have its weights increased** to emphasize the most difficult instances. Thus, subsequent classifiers will focus on them during their training.
  - Each Bag$_i$ corresponds to X% of the training samples



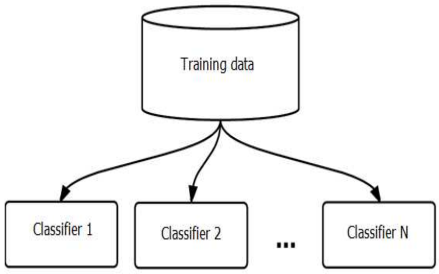
Homogeneous Pool (How to create?)

- Random Subspace (T.K. Ho, 1998)
  - Features ("attributes") are randomly sampled, with replacement, for each learner.



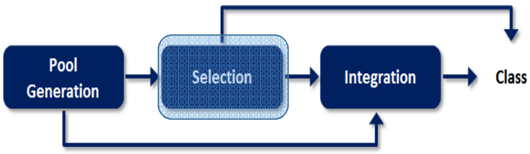
Heterogeneous Pool (How to create?)

- Classifiers trained using different learners
- Different inducers (KNN, Decision Trees, SVM, ...) mean different concepts



Multiple Classifier Systems (ensembles)

- With the pool created, we can combine all of them or perform some selection.
- What kind of selection is possible?



Selection Stage

- Types of selection (in terms of number of classifiers)
  - **Classifier selection** => selection of just one classifier from the pool
  - **Ensemble selection** => selection of a subset of classifiers
- Types of selection (in terms of when the selection is done)
  - **Static** => selection done during the training phase
    - The classifier(s) selected are used to classify the whole testing set
  - **Dynamic** => selection done during the testing phase
    - For each each testing sample is done a specific selection.
- Where to measure the competence of each classifier?
  - Feature space is divided in partitions (one or more **local regions)**
- How to measure the compentence?
  - The **most capable classifier(s)** for each local region is (are) determined.

Static Selection

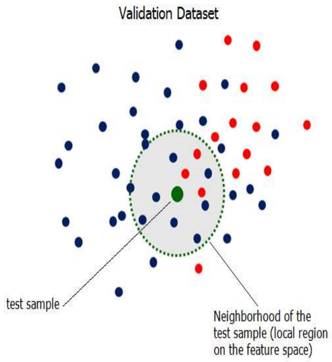
- The **partitioning** is usually based on clustering or evolutionary algorithms, and it is executed **during the training phase**.
- The competence of each classifier is determined during the training phase of the system
- Strategies: Exhaustive search or Optimization processes (GA or PSO, for instance).
- Strategies (Ruta and Gabrys, 2005)
  - Exhaustive Search
  - Forward Search
  - Backward Search
  - Optimization based approaches (GA and PSO based)

Dynamic Selection

- The **partitioning** scheme is usually based on the NN-rule during the **testing phase**.
- The neighborhood of the unknown pattern is defined to measure the classifiers competence.
- Thus, the competence of each classifier is defined on a local region on the entire feature space defined in a validation dataset (DSel).

Dynamic Selection

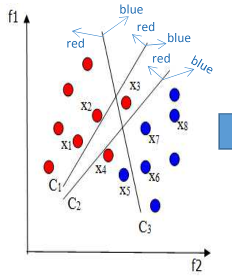
- Where to measure the competence of each classifier?
  - Local region in the feature space defined by the NN rule (K-Nearest Neighbors of the test sample)
- How to measure the competence of each classifier?
  - Different strategies in the literature.



Dynamic Selection

- Why dynamic selection is interesting?
- Given 3 classifiers (C1, C2 and C3)

difficult samples



	(1) - Correct classification / (0) - Misclassification							
Classifiers	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
C_1	1	1	0	0	1	1	1	1
C_2	1	1	1	0	1	1	1	1
C_3	1	1	0	1	0	1	1	1
Fusion (vote)	1	1	0	0	1	1	1	1

- only C_2 is able to correctly classify x_3
- only C_3 is able to correctly classify x_4
- C_1 or C_2 can correctly classify x_5

Fusion: 6/8 (75%)
Best classifier: C_2 => 7/8 (87,5%)
Oracle: 100% (pool upperlimite)
Research question:

How can we select the most promising classifier for each test sample?

Dynamic Selection (Strategies)

- Dynamic Selection Methods [Britto et al, 2014]
  - Competence estimated from each classifier:
    - Ranking scheme: [Sabourin, 1993]
    - Accuracy: OLA and LCA Methods [Woods et at, 1997]
    - Probability information: a Priori, a Posteriori methods [Didaci et al., 2005]
    - Oracle information: Knora method [Ko et al, 2008]
    - Classifier Behaviour: [Giacinto & Roli, 2011]
    - Meta classifier: [Cruz et. Al., 2014]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Dynamic selection of classifiers—A comprehensive review

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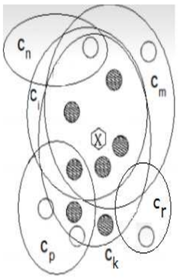
  - Competence estimated from the group
    - Diversity: [Santana et al., 2006]
    - Consensus: [Santos at al., 2007]
    - Other group-based measures: [Xiao et al, 2009]

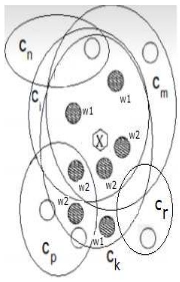
OLA Method (Classifier Selection)

- OLA - Overall Local Accuracy (Woods, 1997)
  - It selects a single classifier
  - Given:
    - pool with N classifiers (c_i, c_k, c_m, c_n, c_p, c_r)
    - test sample x (hexagon in the figure)
    - neighborhood size = 7 (grey circles)
  - Strategy: classifier with best accuracy in the neighborhood of x
  - Example:
    - c_i = 5/7 = 71.4%
    - c_k = 7/7 = 100% (c_k will be selected)
    - c_m = 5/7 = 71.4%
    - c_n = 0/7 = 0%
    - c_p = 2/7 = 28.5%%
    - c_r = 0/7 = 0%



LCA Method (Classifier Selection)

- LCA – Local Class Accuracy (Woods, 1997)
  - It selects a single classifier
  - Given:
    - pool with N classifiers (c_i, c_k, c_m, c_n, c_p, c_r)
    - validation dataset
    - test sample x (hexagon in the figure)
    - neighborhood size = 7 (grey circles)
  - Strategy: classifier with best accuracy considering the class predicted to the test sample (x)
  - Example:
    - c_i = 3/4 = 75% (predicted to x class w_2)
    - c_k = 4/4 = 100% (predicted to x class w_2) (c_k will be selected)
    - c_m = 2/3 = 66% (predicted to x class w_1)
    - c_n = 0/3 = 0% (predicted to x class w_1)
    - c_p = 2/4 = 50% (predicted to x class w_2)
    - c_r = 0/4 = 0% (predicted to x class w_2)



MCB

- MCB – Multiple Classifier Behavior (Giacinto and Roli, 2001)
  - It selects a single classifier
  - Given:
    - pool with N classifiers (c_i, c_k, c_m, c_n, c_p, c_r)
    - Decision space on the validation dataset (output of the classifiers)
    - test sample x (hexagon in the figure)
    - neighborhood size = k (grey circles)
  - Strategy: OLA on neighbors for which the classifiers present similar behavior in terms of decision
  - Example:
    - Similar Behavior:
      - Neighbors 1, 3, 7
    - Final decision: OLA considering neighbors 1, 3 and 7
    - the selected classifier must be significantly better than the others, otherwise the pool is used.

Decision space	c_i	c_k	c_m	c_n	c_p	c_r
Neighbor 1	w_1	w_1	w_1	w_1	w_1	W_1
Neighbor 2	w_2	w_2	w_1	w_2	w_1	w_2
Neighbor 3	w_1	w_1	w_1	w_1	w_1	w_1
Neighbor 4	w_2	w_2	w_2	w_1	w_1	w_1
Neighbor 5	w_1	w_1	w_1	w_2	w_2	w_2
Neighbor 6	w_1	w_2	w_2	w_2	w_1	w_1
Neighbor 7	w_1	w_1	w_1	w_2	w_1	w_1
Test sample	w1	w1	w1	w2	w1	w1

Knora (K-Nearest Oracles)

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From dynamic classifier selection to dynamic ensemble selection

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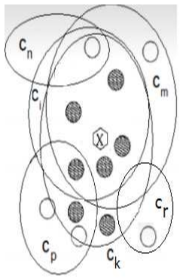
Knora-Eliminate

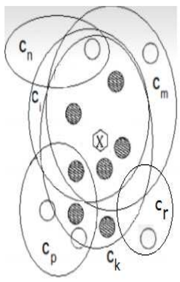
- KNE – Knora-Eliminate (Ko et. al, 2008)
  - It selects an ensemble
  - Given:
    - pool with N classifiers (c_i, c_k, c_m, c_n, c_p, c_r)
    - meta-space constructed using the validation dataset
    - test sample x (hexagon in the figure)
    - neighborhood size = k (grey circles)
  - Strategy: ensemble that correctly classify all neighbors of x
  - Example:
    - Ensemble: c_k



Meta Space	c_i	c_k	c_m	c_n	c_p	c_r
Neighbor 1	1	1	1	0	0	0
Neighbor 2	1	1	1	0	0	0
Neighbor 3	1	1	1	0	0	0
Neighbor 4	1	1	1	0	0	0
Neighbor 5	1	1	1	0	1	0
Neighbor 6	0	1	0	0	1	0
Neighbor 7	0	1	0	0	0	0

Knora-Union

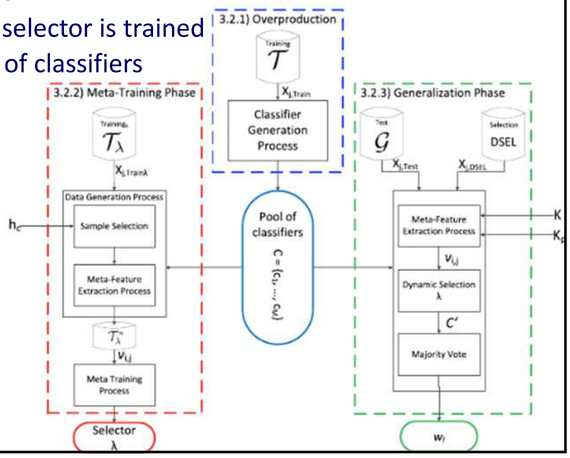
- KNU – Knora-Union (Ko et. al, 2008)
  - It selects an ensemble
  - Given:
    - pool with N classifiers (c_i, c_k, c_m, c_n, c_p, c_r)
    - meta-space constructed using the validation dataset
    - test sample x (hexagon in the figure)
    - neighborhood size = k (grey circles)
  - Strategy: ensemble that correctly classify at least one neighbor of x
  - Example:
    - Ensemble: c_i, c_k, c_m, c_p



Meta Space	c_i	c_k	c_m	c_n	c_p	c_r
Neighbor 1	1	1	1	0	0	0
Neighbor 2	1	1	1	0	0	0
Neighbor 3	1	1	1	0	0	0
Neighbor 4	1	1	1	0	0	0
Neighbor 5	1	1	1	0	1	0
Neighbor 6	0	1	0	0	1	0
Neighbor 7	0	1	0	0	0	0

META-DES

- Meta-DES – Meta Learning based Dynamic Ensemble Selection (Cruz, et al. 2014)
- It selects an ensemble
- Composed of three Phases
  - Meta-Training: a classifier selector is trained
  - Pool Generation: the pool of classifiers is generated
  - Generalization: the operational phase of the system.

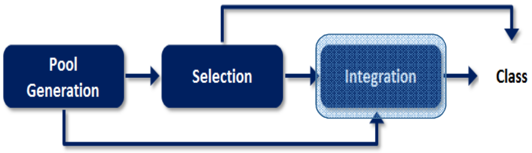


Library for Dynamic Selection

- DesLib
  - https://arxiv.org/pdf/1802.04967.pdf
  - https://github.com/scikit-learn-contrib/DESlib
  - https://pypi.org/project/DESlib/

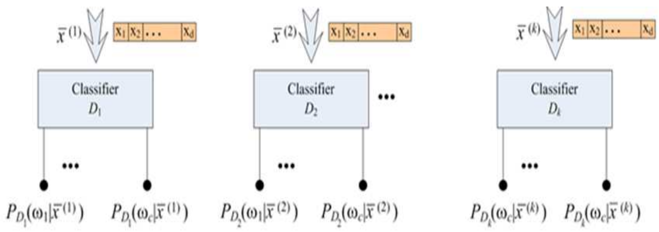
Multiple Classifier Systems (ensembles)

- How can we combine classifiers?



Fusion of Classifiers

- Different strategies in the literature, but:
  - It depends on the classifier output
    - only the class label (few alternatives)
    - a confidence value on its decision (many alternatives)
  - The classifier output can be a probability for each class: $P_{Di}(w_j|x^{(i)})$ is the output probability of the classifier *Di* for class w_j given the test sample $x^{(i)}$.



Fusion of Classifiers

- Majority vote rule (MVR)
  - Possible to use when the classifier output is the class label only.

$$\hat{\omega} = \max_{i \in [1,k]} count\left[\arg\max_{\omega \in \Omega} P_{D_i}(\omega \mid x) \right]$$

Fusion of Classifiers

- Maximum (Max)

$$\hat{\omega} = \arg\max_{\substack{i \in [1,k] \\ \omega \in \Omega}} P_{D_i}(\omega \mid x)$$

- It is usually combined with other rules (final decision).

Fusion of Classifiers

- Sum

$$\hat{\omega} = \arg\max_{\omega \in \Omega} \sum_{i=1}^{k} P_{D_i}(\omega \mid x)$$

- Weighted Sum

$$\hat{\omega} = \arg\max_{\omega \in \Omega} \sum_{i=1}^{k} w_i P_{D_i}(\omega \mid x)$$

the weigth w_i can be learned from the training set.

Fusion of Classifiers

- Product

$$\hat{\omega} = \arg\max_{\omega \in \Omega} \prod_{i=1}^{k} P_{D_i}(\omega \mid x)$$

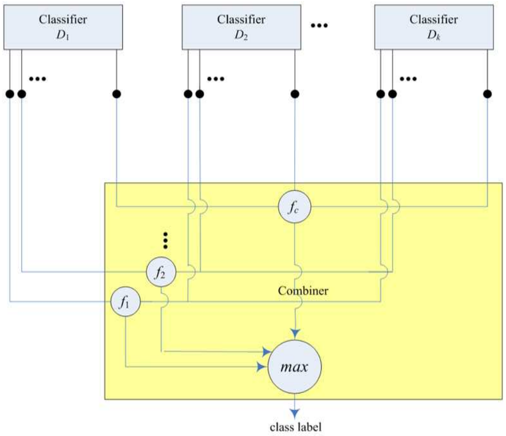
- Weighted product

$$\hat{\omega} = \arg\max_{\omega \in \Omega} \prod_{i=1}^{k} \left[P_{D_i}(\omega \mid x)\right]^{w_i}$$

the weigth w_i can be learned from the training set.

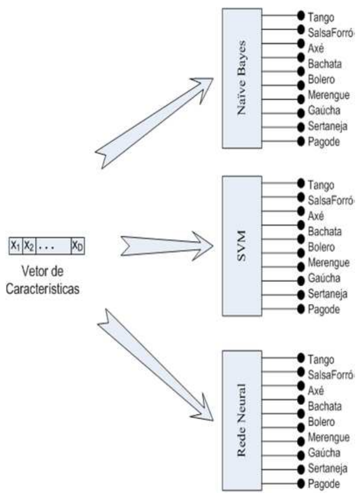
Fusion of Classifiers

- $f_1, \ldots, f_c$: fusion schema at class level
- Max is used to provide the final decision

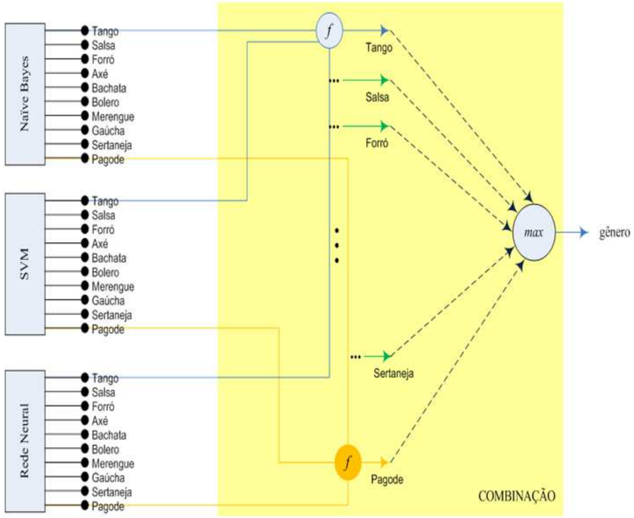


Fusion of Classifers

- Example

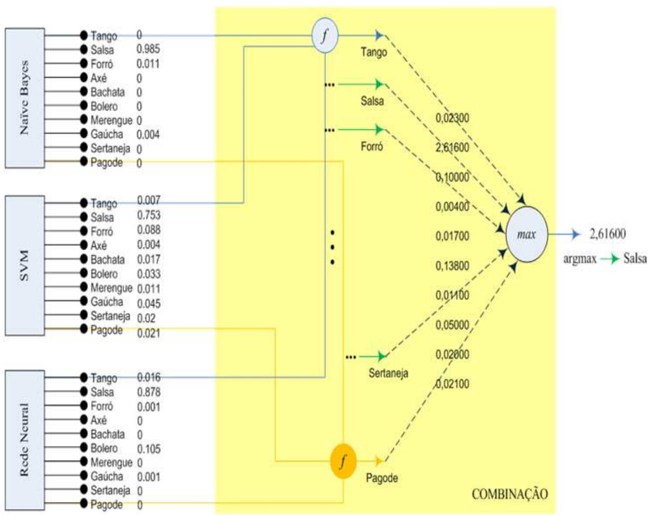


- Fusion of each class first

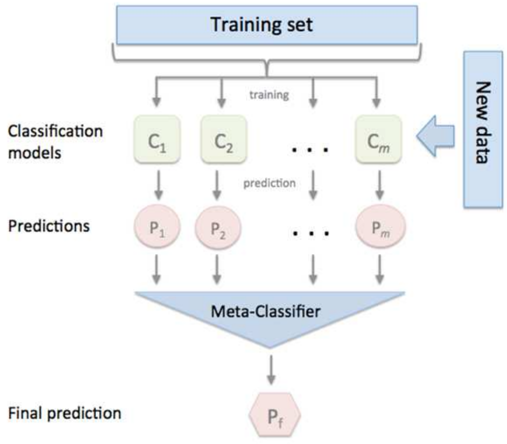


Fusion of Classifiers

- Final Decision



Fusion based on Stacking



- Source: http://rasbt.github.io/mlxtend/user_guide/classifier/StackingClassifier/

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