Dynamic Classifier Selection based on Complexity Analysis

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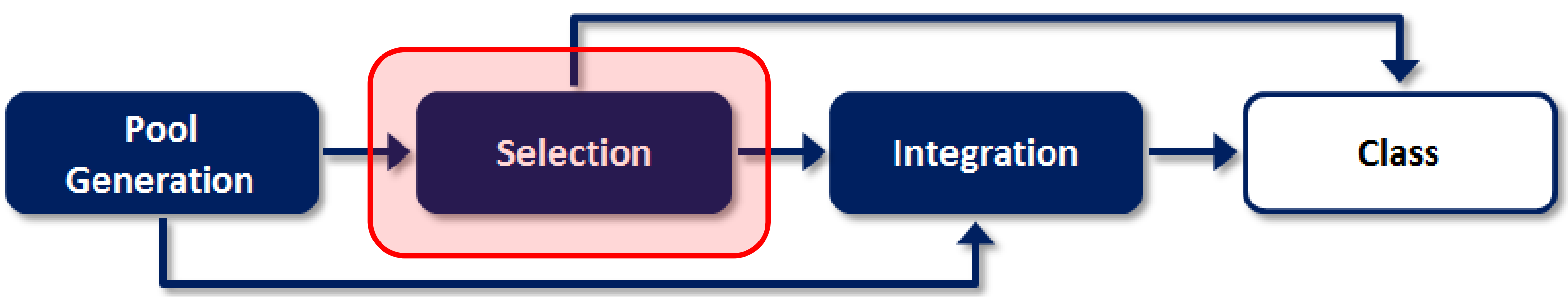
Introduction

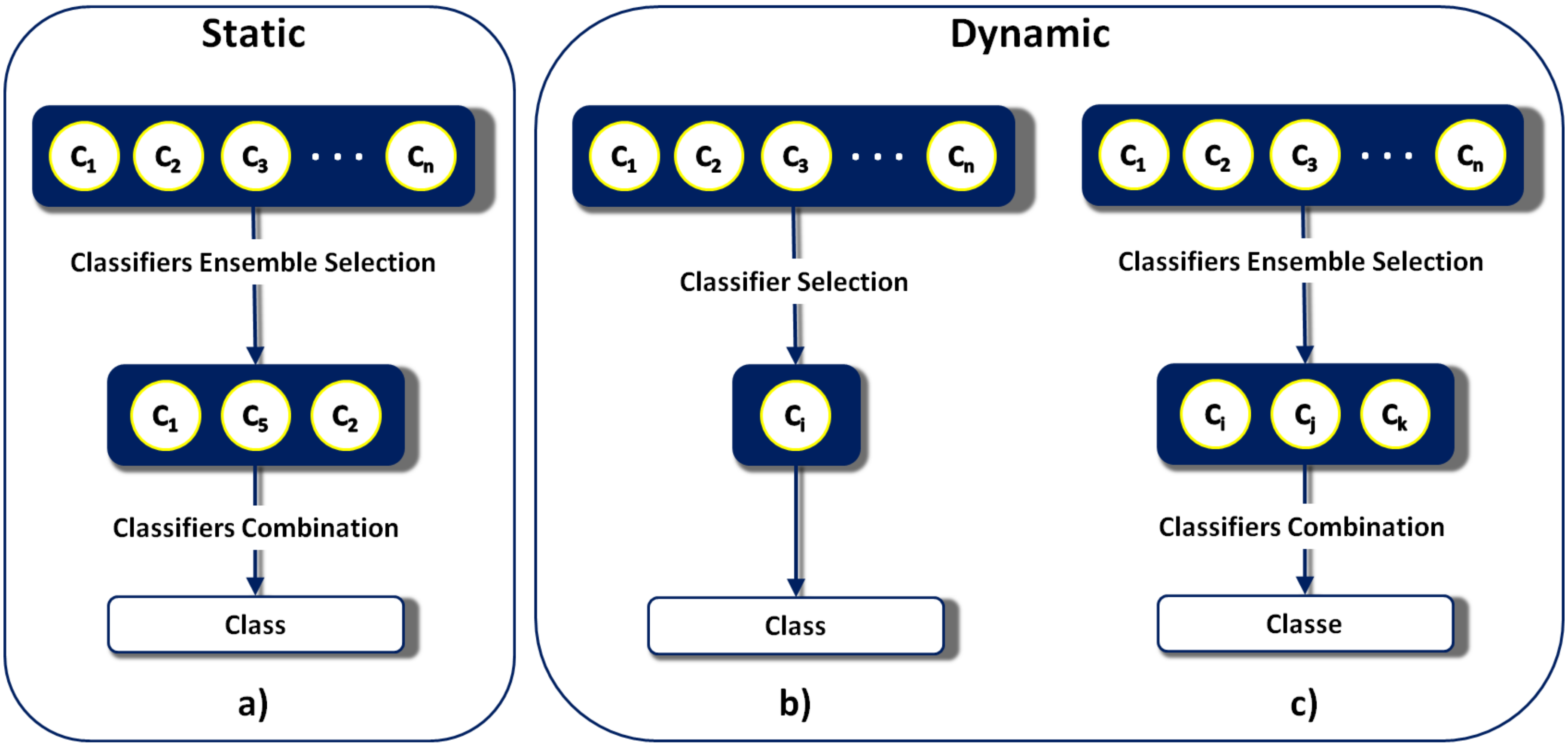
- Classification: most important task on pattern recognition
- Train a single classifier to be capable of learning the wide variability usually found in a pattern recognition is a challenging task (sometimes infeasible)

Introduction

- An interesting alternative is the use of Multiple Classifier Systems (MCSs)
  - Need to commit different erros
  - Diversity among the members



Introduction



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Introduction

- Selection Criteria
  - Local Accuracy
  - Diversity
  - Behavioral
  - Ambiguity
  - Ranking
  - ...

- Our hypothesis: use the problem complexity to evaluate the competence of each classifier in a pool

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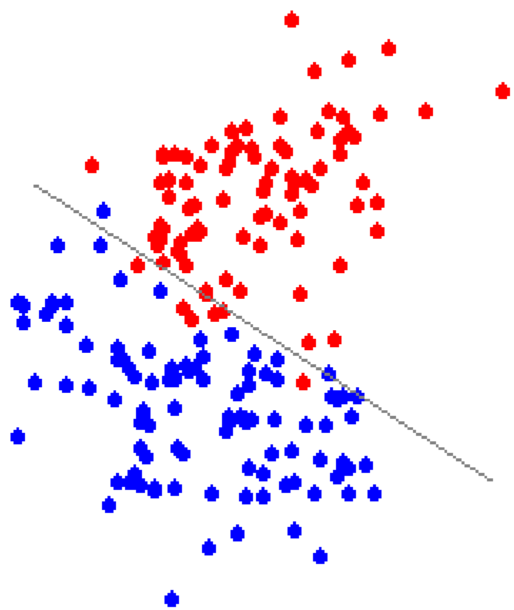
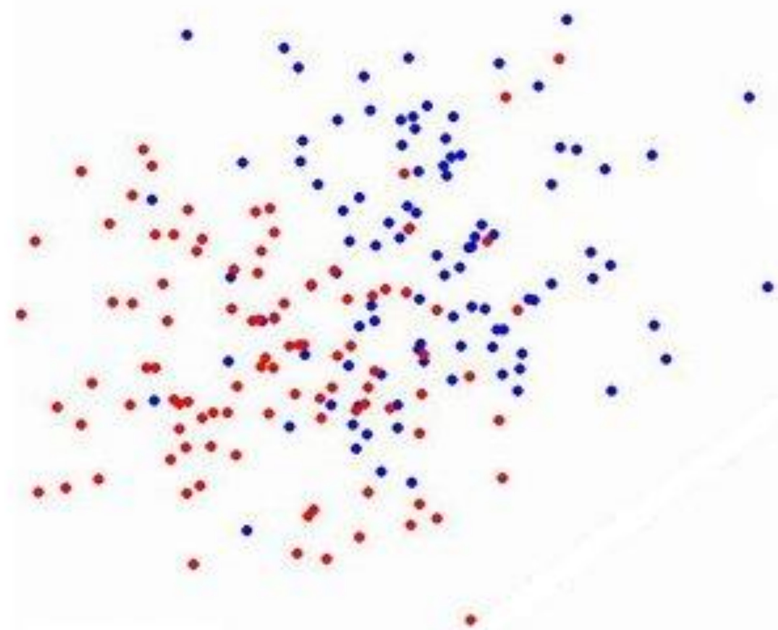
Complexity Measures

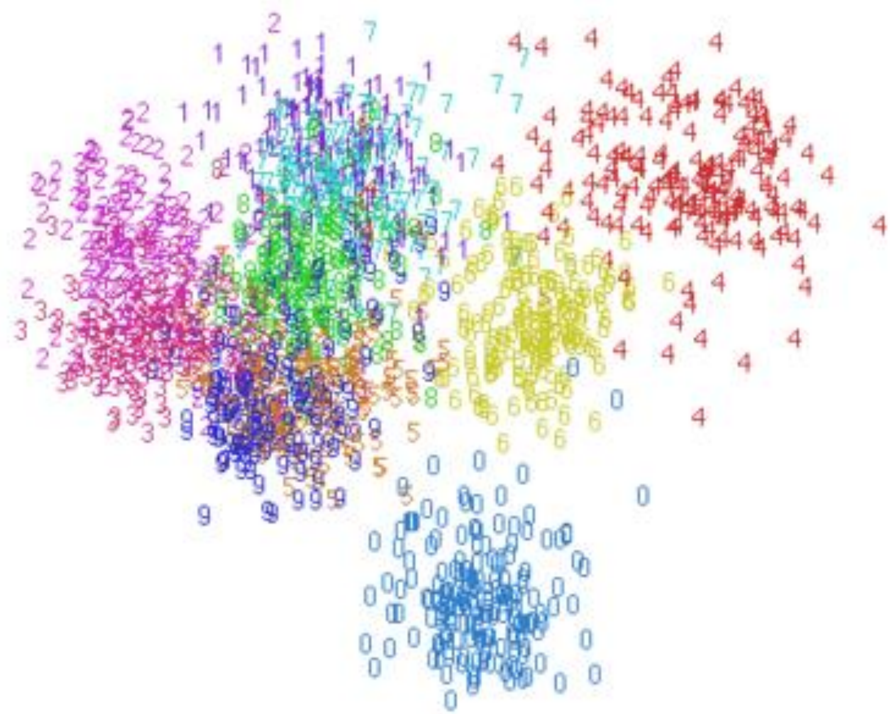
- Relationship between data characteristics and performance of classifiers





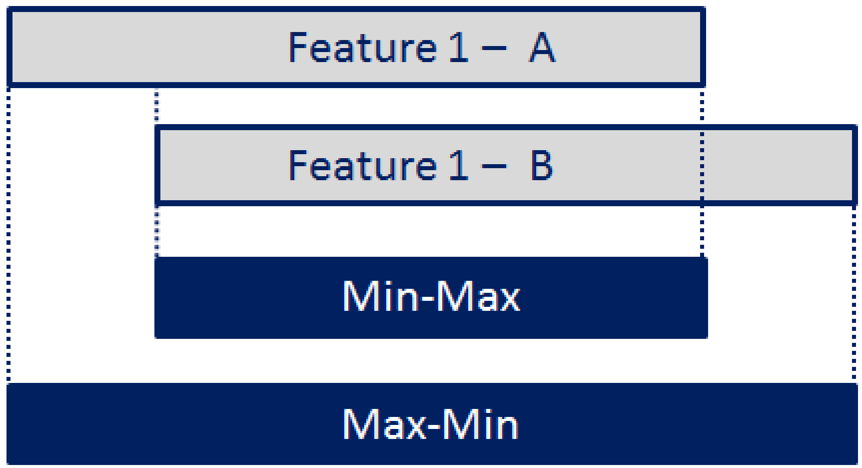
Complexity Measures

- Number of Classes, Instances, Features, etc...



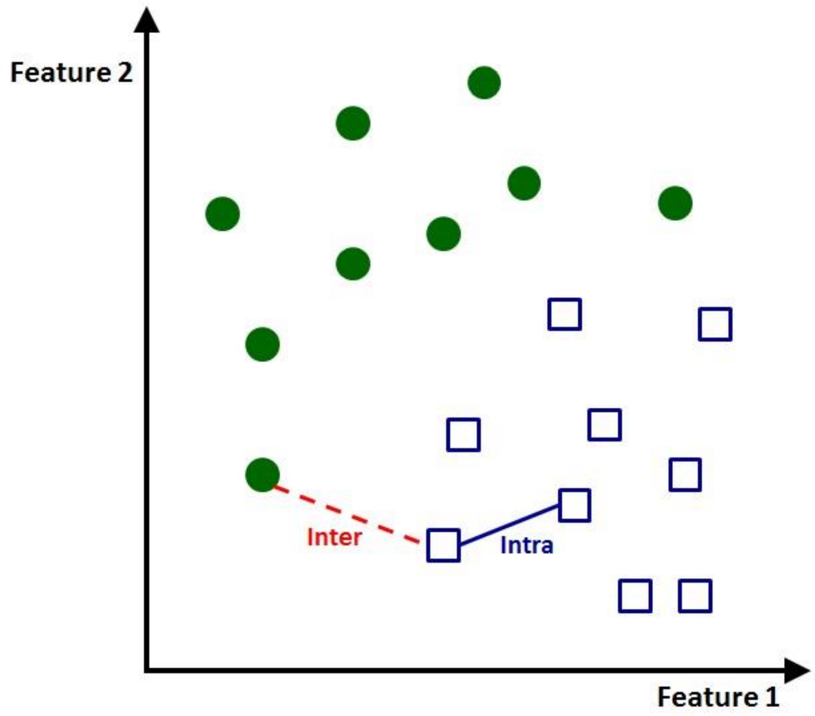
Complexity Measures

- Class Overlap
  - F1, F2, F3, F4



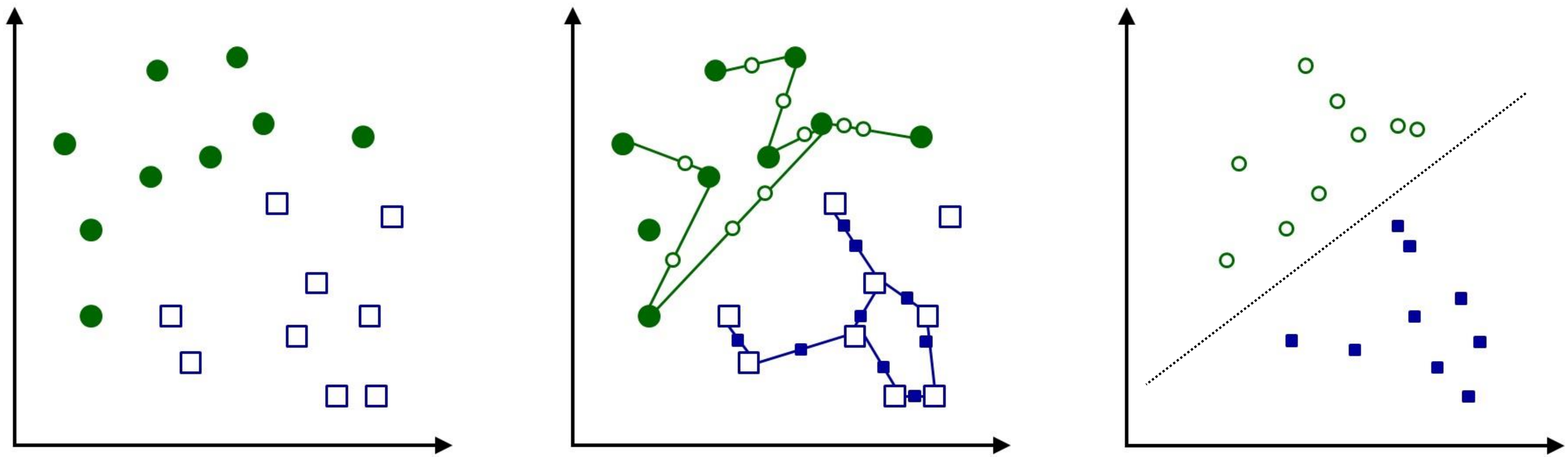
Complexity Measures

- Separability of classes
  - L1, L2, N1, N2, N3



Medidas de Complexidade

- Geometry, Topology and Density Measures
  - L3, N4, T1, T2, C1, D1, D2, D3



Proposed Method

- Idea: dynamically select the classifier(s) trained on data with similar complexity than that observed in the local region where the test pattern is located.

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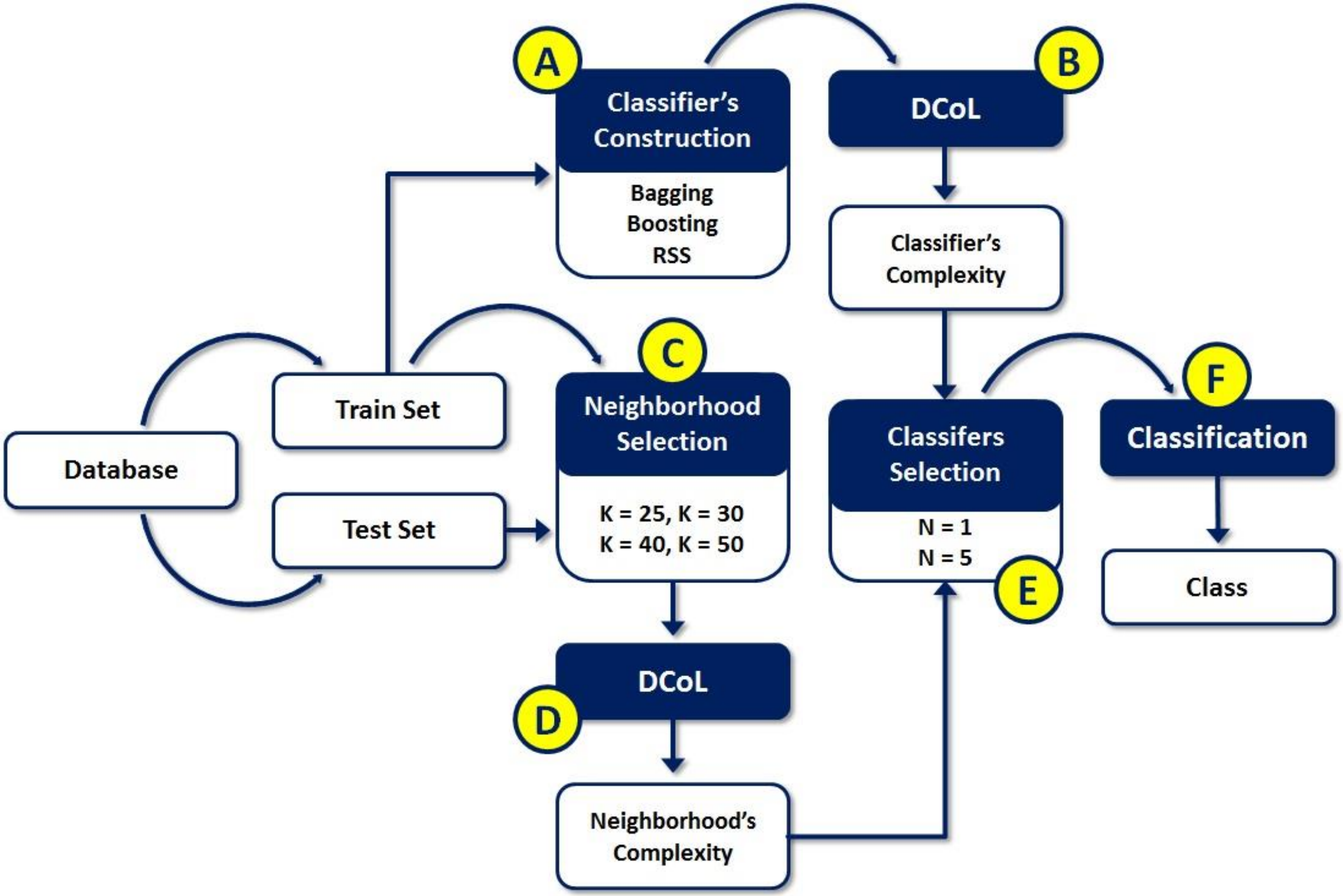
Proposed Method



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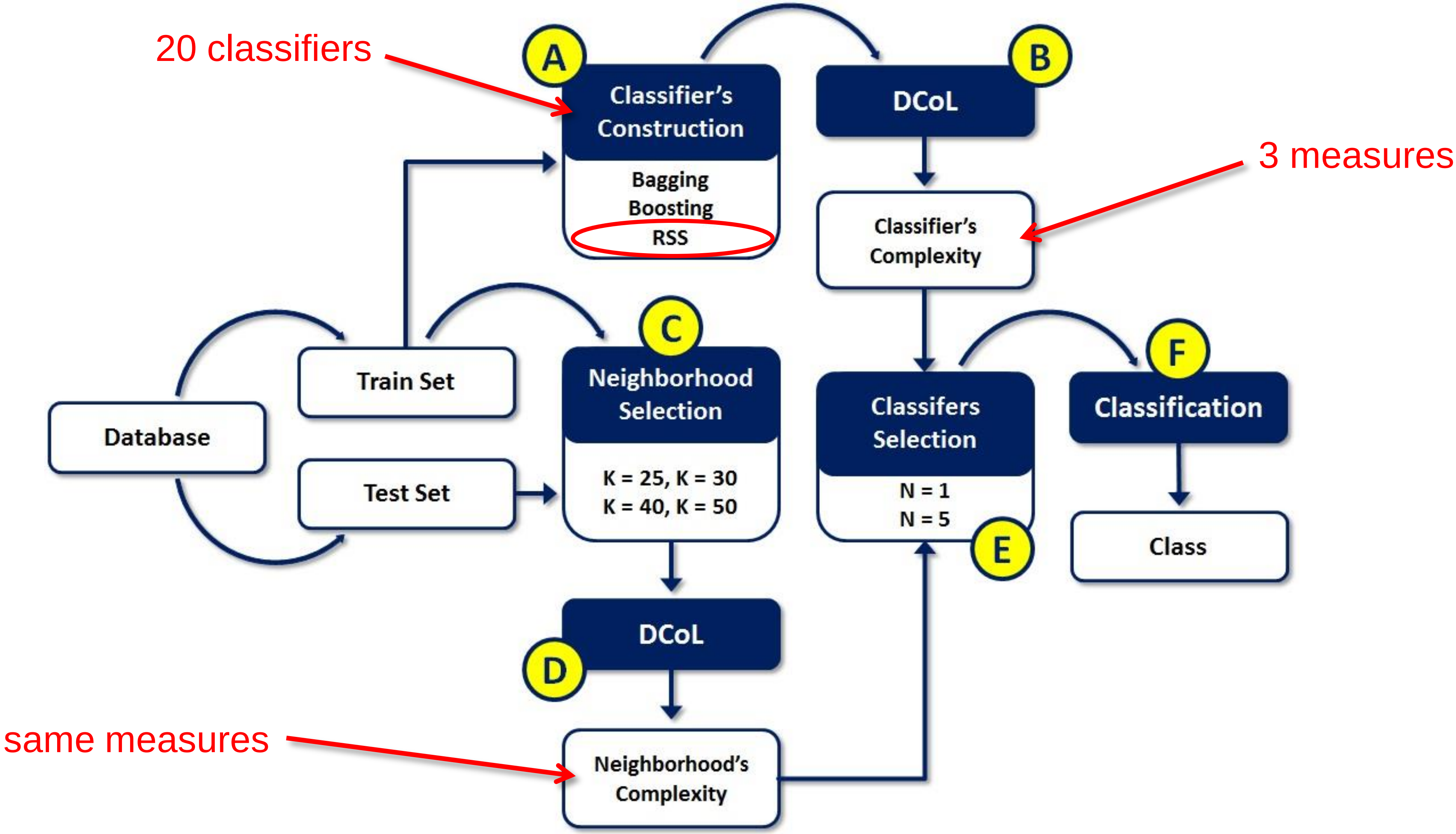
Proposed Method



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Proposed Method

- Characterization of Databases

Base	Classes	Tr	Ts	Features	RS-Card.	Bagging (%)	Boosting (%)
Blood	2	374	374	4	-	66	66
Diabetes	2	383	383	8	4	66	66
Haberman	2	154	152	3	-	66	66
Image	7	231	2079	19	4	66	66
Iris	3	75	75	4	-	66	66
Letter	26	10007	9993	16	12	66	66
Liver	2	172	173	6	3	66	66
Sonar	2	105	103	60	12	66	66
Vehicle	4	424	422	18	6	66	66
WBC	2	284	285	30	5	66	66
Wine	3	88	88	13	6	66	66
Yeast	10	745	739	8	5	66	66
Ionosphere	2	176	175	34	8	66	66

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Results

- Spacial representation (F1 x N2 x N4)
  - Bagging ◇
  - Boosting X
  - RSS O
  - Test □
  - Train △

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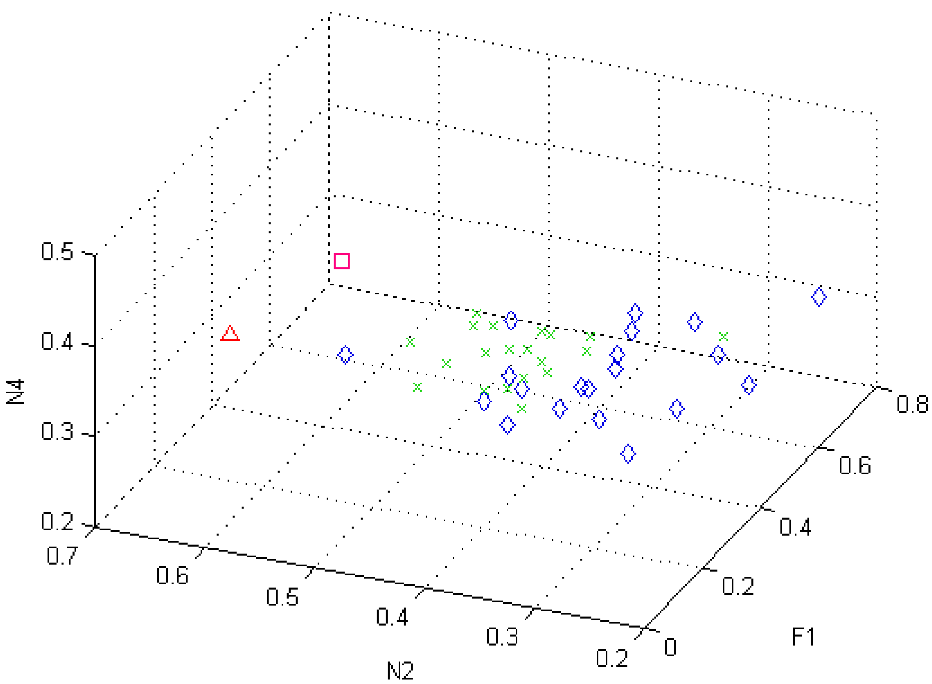
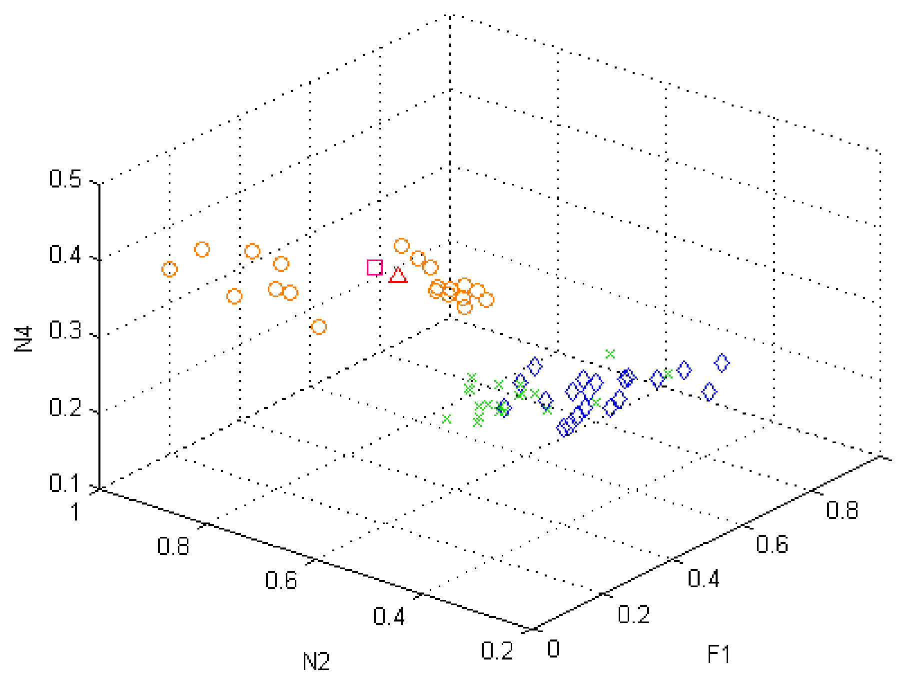
Results

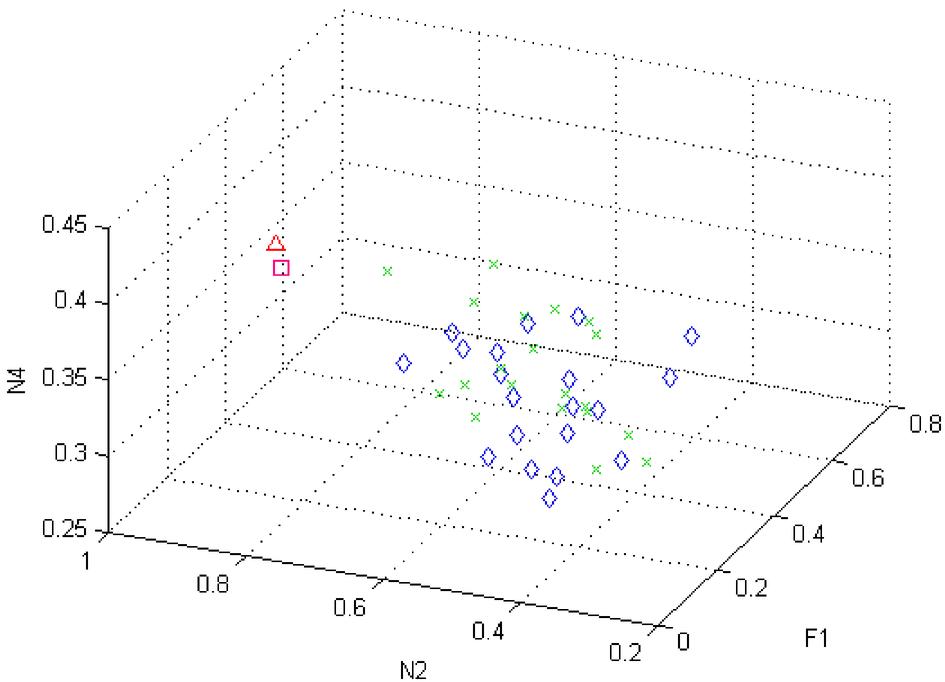


Blood

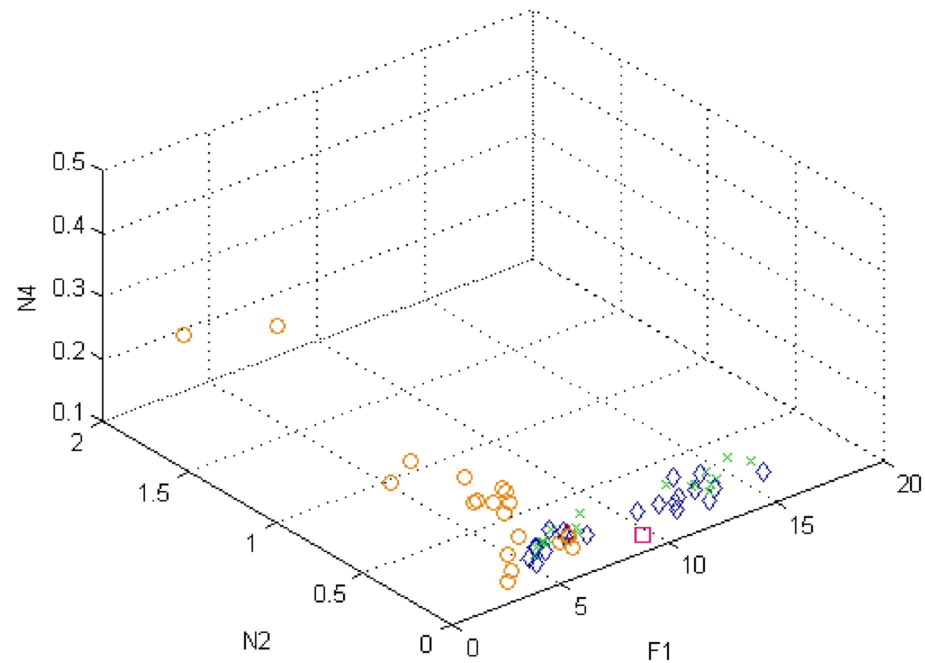


Diabetes

Results



Haberman



Image

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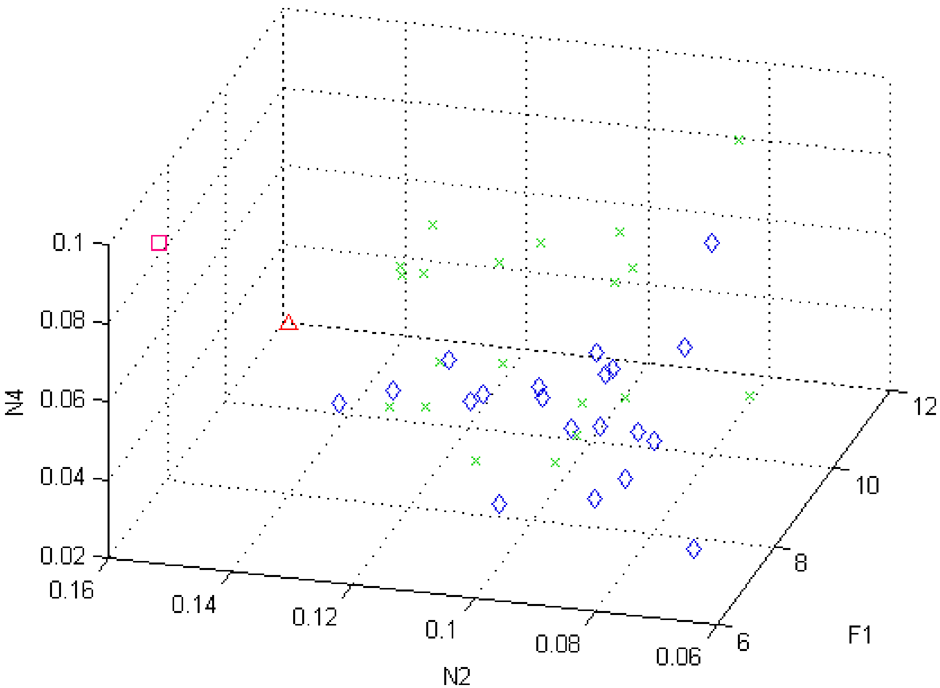
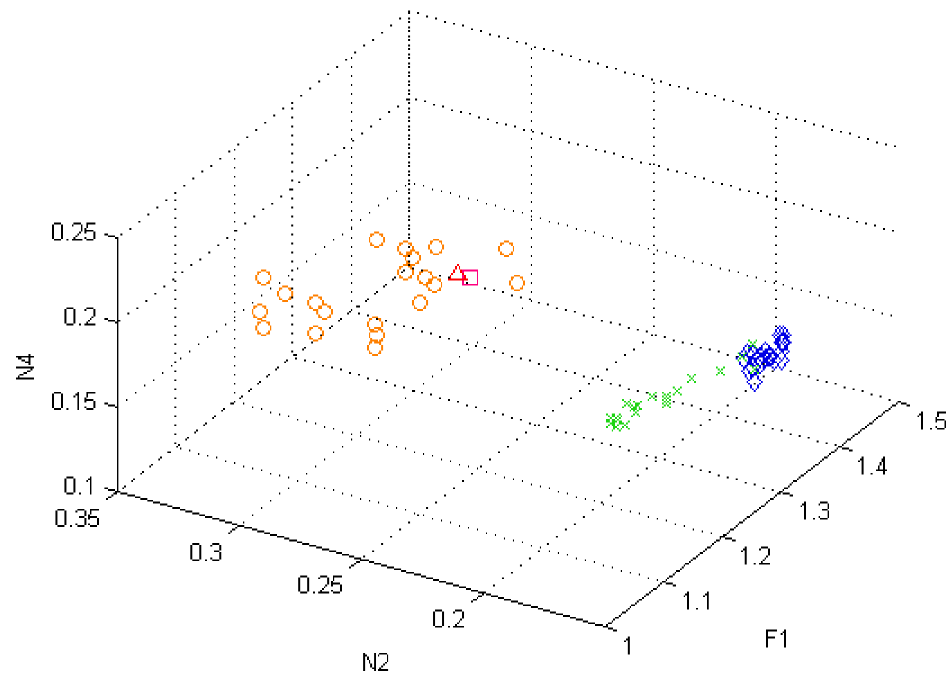
Results



Iris



Letter

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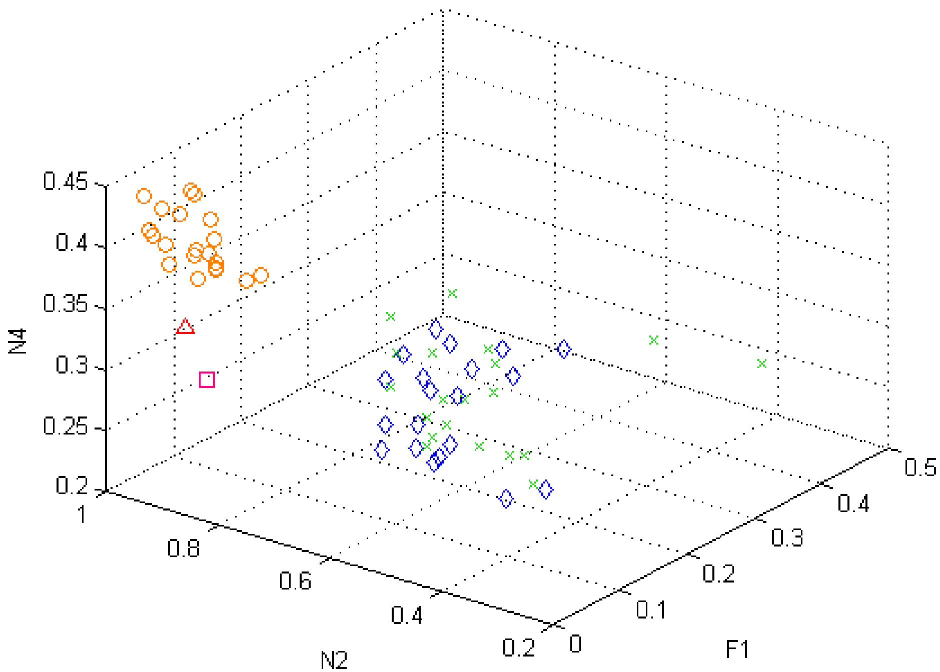
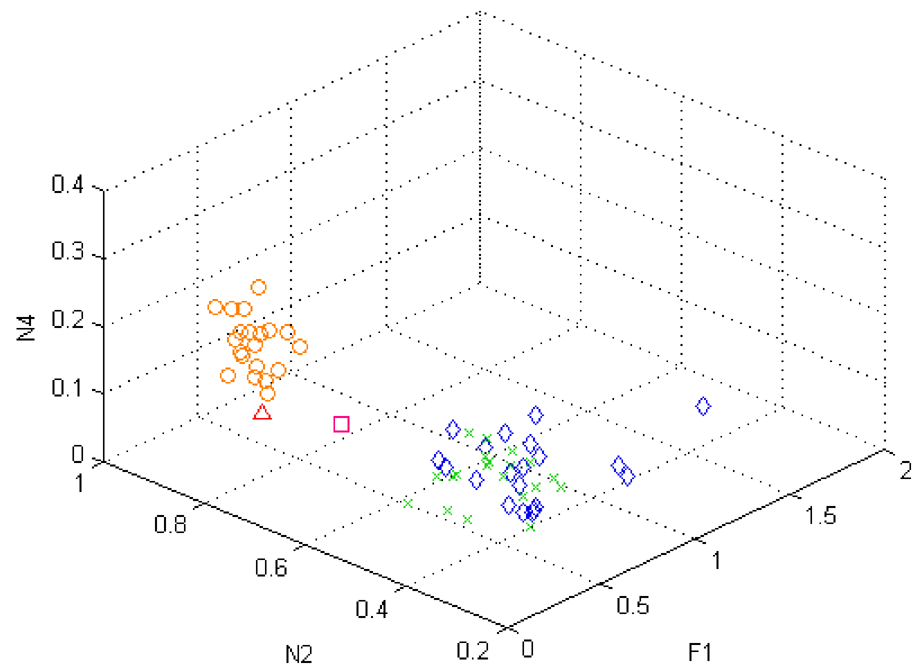
Results



Liver



Sonar

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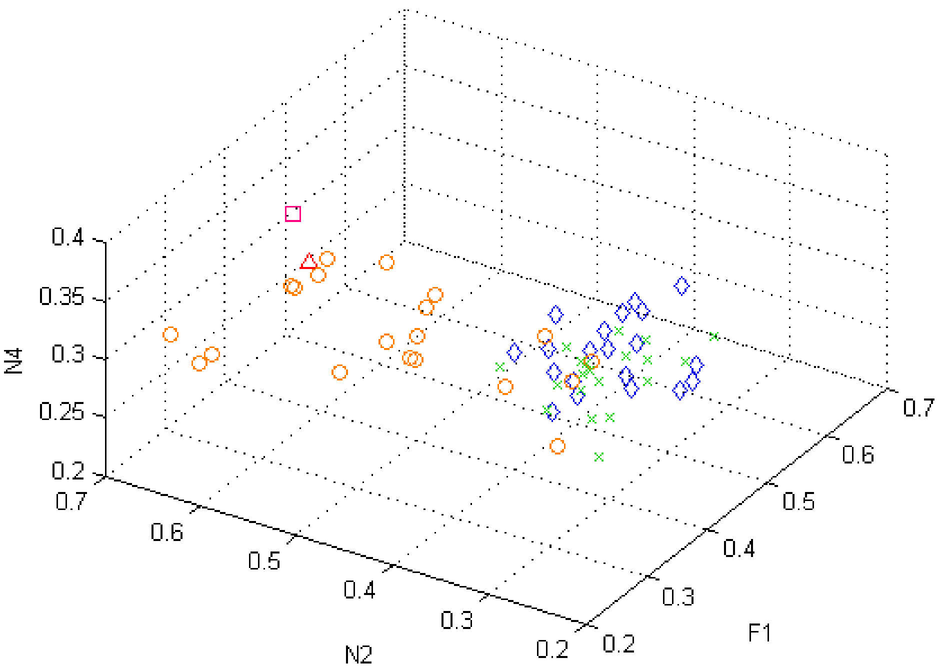
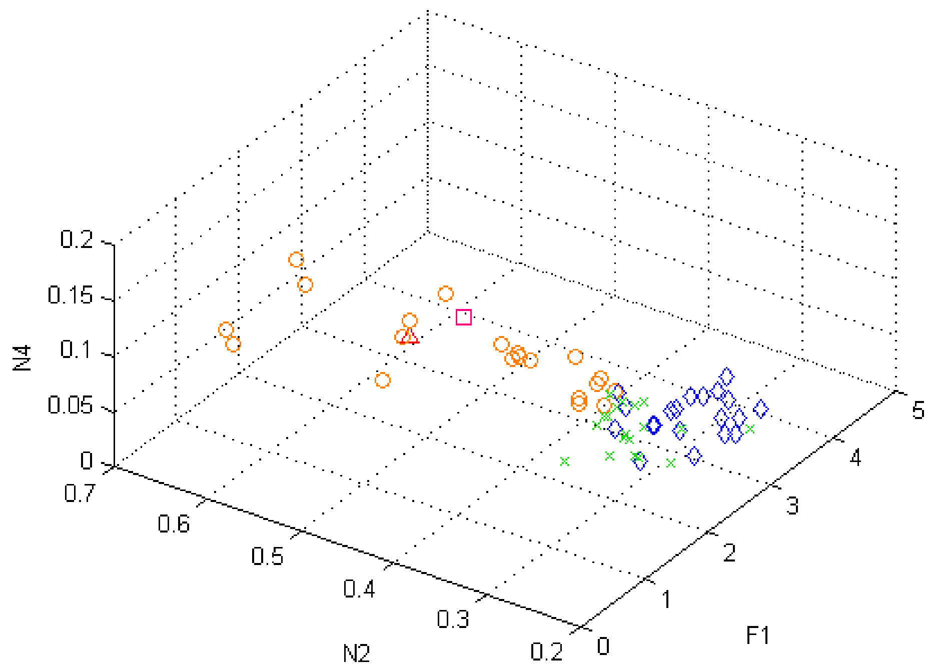
Results



Vehicle



WBC

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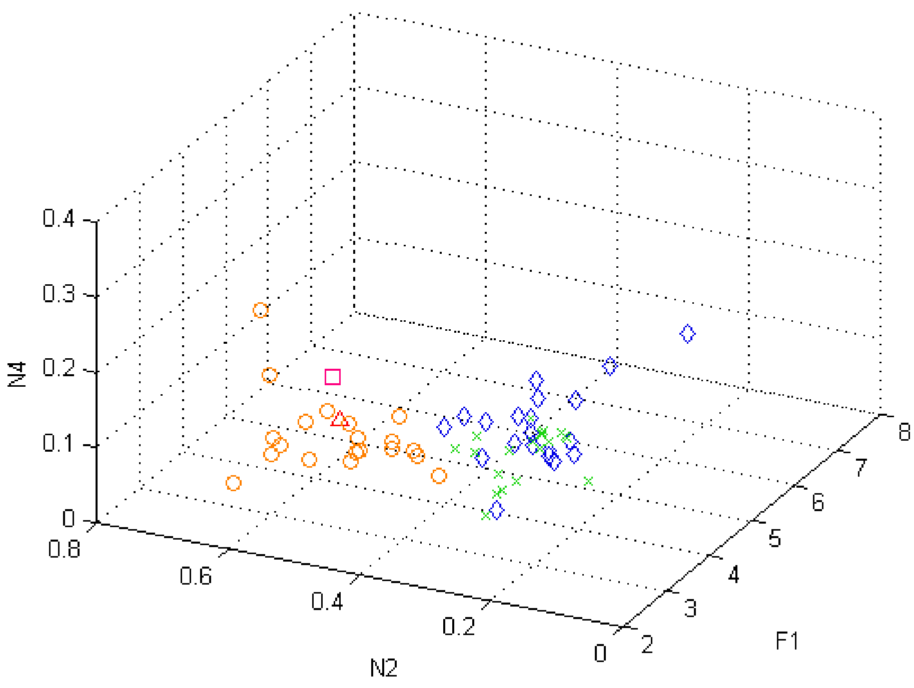
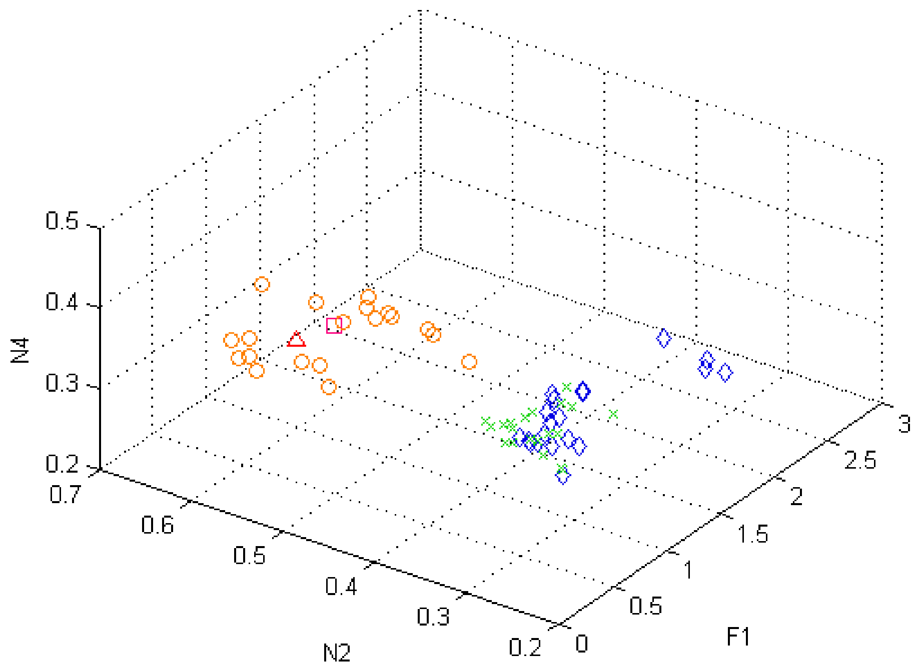
Results

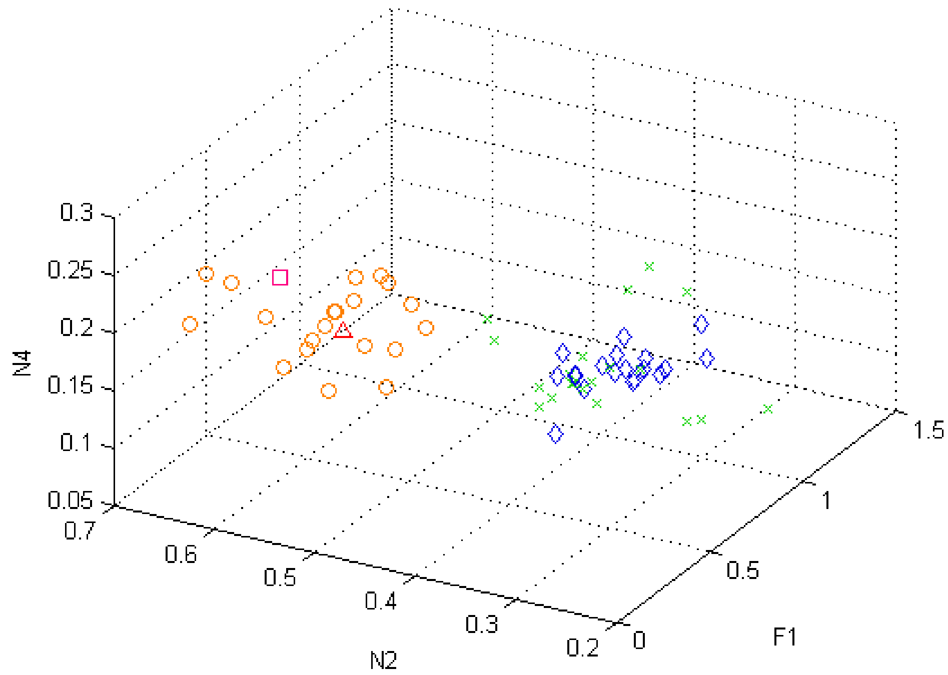


Wine



Yeast

Results



Ionosphere

Results

- Analysis of average dispersion
  - relative to classifiers centroid
  - relative to test set

  - From the 12 tested bases:
    - Yeast, Image, Iris, Vehicle e Ionosphere shown best accuracy for the most disperse pools
    - Blood, Haberman, Sonar e Wine presented best performance for the most compact pools

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Results

- From the 12 tested bases:
  - To Haberman, Iris and Wine bases, the best pool was the farther to the test set
  - WBC, Yeast, Blood, Vehicle, Ionosphere and Liver performed best for the closest sets of test

Results

- Bagging

Base	SB	CMB	KU	KE	OLA	LCA	APR	APO	ORA	Short1	Short5
Blood	74,87	75,94	**76,20**	**76,20**	73,26	72,19	71,66	71,66	95,99	75,40	75,40
Diabetes	71,02	67,10	70,24	67,36	67,62	69,45	66,84	67,62	93,21	68,93	**71,80**
Haberman	71,05	69,08	71,71	70,4	70,4	68,41	70,4	70,4	97,37	**75,66**	**75,66**
Image	83,55	**85,28**	84,37	84,8	83,41	78,79	83,41	83,46	97,40	80,57	83,36
Iris	**96**	94,67	94,67	94,67	**96**	93,33	92	92	98,67	90,67	93,33
Liver	67,05	63,58	**67,63**	63,01	64,16	65,9	53,76	60,69	99,42	55,49	64,16
Sonar	**76,7**	**76,7**	**76,7**	72,82	**76,7**	67,96	67,96	67,96	95,15	66,02	73,79
Vehicle	61,61	59,01	60,66	60,19	57,82	54,27	56,4	56,4	92,89	57,11	**66,66**
WBC	**92,63**	91,93	91,58	91,579	90,89	88,77	90,88	90,88	98,95	90,53	91,23
Wine	75,56	72,22	70	70	73,33	72,22	68,89	68,89	93,33	**78,89**	72,22
Yeast	51,69	52,23	52,77	52,50	49,12	48,17	49,12	49,12	85,93	51,15	**55,35**
Ionosphere	85,71	81,14	84	83,43	83,43	**91,43**	83,44	83,43	92	84,57	84

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Results

- Boosting

Base	SB	CMB	KU	KE	OLA	LCA	APR	APO	ORA	Short1	Short5
Blood	76,41	78,08	**76,74**	76,20	76,48	72,73	71,64	75,67	95,46	73	76,20
Diabetes	68,67	68,41	69,19	67,89	67,89	69,71	67,89	67,89	95,04	67,36	**69,97**
Haberman	**75**	70,4	75	73,68	69,74	73,68	69,08	70,4	96,05	74,34	74,34
Image	82,64	**86,39**	86	86,53	82,4	76,67	81,48	81,48	96,54	81,53	84,75
Iris	**96**	**96**	**96**	**96**	**96**	**96**	**96**	**96**	98,67	90,67	**96**
Liver	61,27	58,38	63,01	62,43	61,27	**67,05**	59,54	59,54	99,42	60,12	63,01
Sonar	78,64	77,67	**80,58**	78,64	75,73	72,82	67,96	72,82	98,06	74,76	77,67
Vehicle	61,14	61,37	62,79	**63,03**	59,01	54,03	55,45	55,45	92,18	60,9	61,85
WBC	**92,98**	89,47	90,88	90,88	90,88	87,02	90,88	90,88	98,6	91,58	90,88
Wine	**77,78**	71,11	71,11	71,11	75,56	70	61,11	61,11	97,78	73,33	75,56
Yeast	49,53	52,64	51,96	52,23	49,26	45,74	49,26	49,26	87,15	51,56	**54,13**
Ionosphere	83,43	80	82,86	82,86	82,86	**88,57**	82,86	82,86	89,14	84	81,14

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Results

- RSS

Base	SB	CMB	KU	KE	OLA	LCA	APR	APO	ORA	Short1	Short5
Diabetes	70,76	71,54	**72,32**	**72,32**	61,88	65,8	67,89	61,88	99,74	67,36	70,24
Image	**87,78**	82,68	82,49	82,49	64,84	49,26	69,61	64,84	98,9	74,99	81,29
Liver	67,05	63,58	67,63	67,63	67,63	**68,21**	61,85	67,63	100	56,64	60,69
Sonar	80,58	77,67	80,58	80,58	76,7	77,67	76,7	76,7	100	75,73	**81,55**
Vehicle	**70,14**	67,3	68,01	68,01	54,27	50,24	61,85	54,27	98,58	60,66	67,77
WBC	92,28	92,63	**94,04**	**94,04**	89,12	59,3	88,87	89,12	100	85,61	90,52
Wine	**93,33**	80	76,67	76,67	67,78	58,89	90	67,78	100	87,78	90
Yeast	48,04	**55,21**	53,32	53,32	43,03	36,13	35,59	40,87	94,86	45,60	51,56
Ionosphere	88,57	89,14	**89,72**	89,14	84,57	85,71	85,14	85,14	98,29	84	89,71

Conclusions

- Proposed DSOC method has shown to be an interesting strategy for classifier/ensemble selection
- Experimental results were similar to that of related works available in the literature.
- Ensenble selection was superior to classifier selection
- Further work
  - Better understand the complexity analysis
  - Generate pools of classifiers based on complexity
  - To consider combining class accuracy and data complexity

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