



Evolutionary Computation for Feature Selection and Feature Construction

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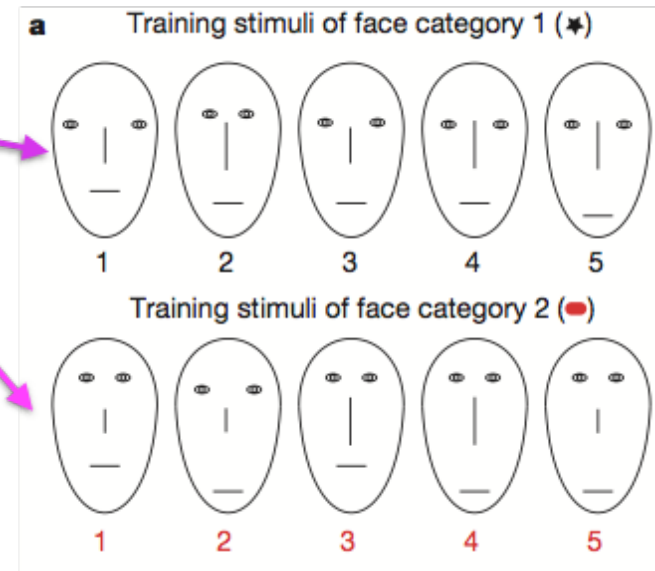
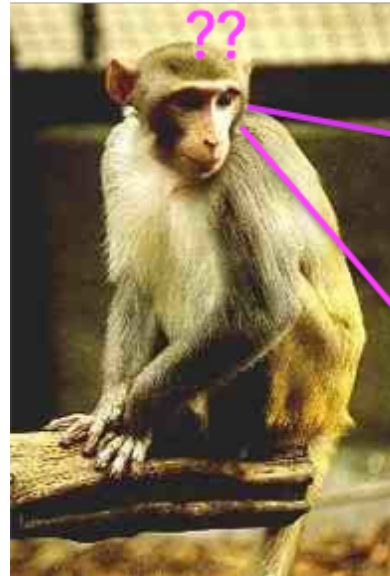
IEEE CIS Webinar Mon, Sep 25, 2017 2:00 PM - 3:00 PM NZDT

Outline

- Introduction
- Feature Selection and Feature Construction
- EC for Feature Selection and Construction: Strengths
- State-of-the-art in EC for Feature Selection and Construction
- Weakness and Issues
- Feature Selection Bias
- Future Directions

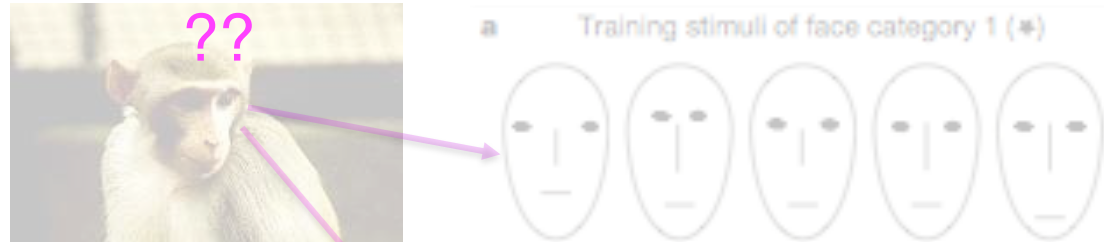
Feature Selection: Example from Biology

- Monkeys performing classification task:
 - Diagnostic features:
 - Eye separation
 - Eye height
 - Non-Diagnostic features:
 - Mouth height
 - Nose length



Feature Selection: Example from Biology

- Monkeys performing classification task
 - Diagnostic features:



“The data from the present study indicate that neuronal selectivity was shaped by **the most relevant subset of features** during the categorisation training.”

—*Nathasha Sigala, Nikos Logothetis*

(52/44) were selective to one or both of the diagnostic features (and not for the non-diagnostic features)



Dataset (Classification)

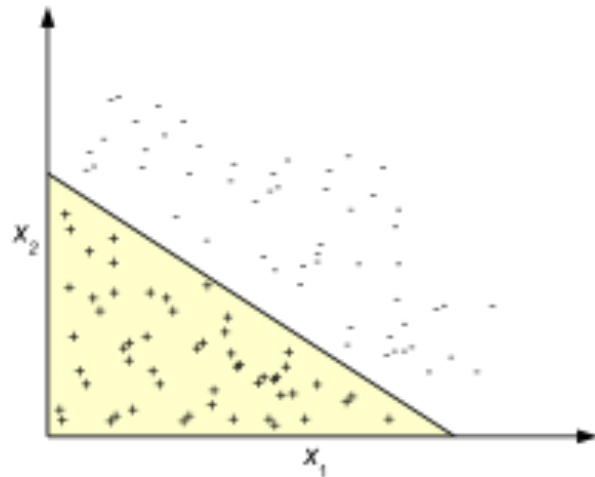
Credit card application:

- 7 applicants (examples/instances/observations)
- 2 classes: Approve, Reject
- 3 features/variables/attributes

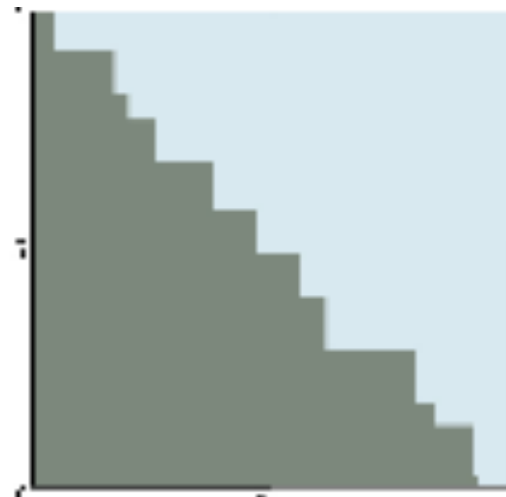
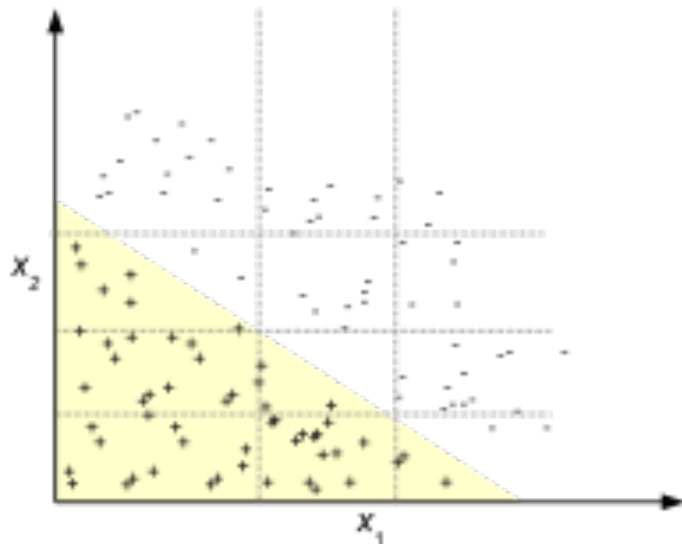
	Job	Saving	Family	Class
Applicant 1	true	high	single	Approve
Applicant 2	false	high	couple	Approve
Applicant 3	true	low	couple	Reject
Applicant 4	true	low	couple	Approve
Applicant 5	true	high	children	Reject
Applicant 6	false	low	single	Reject
Applicant 7	true	high	single	Approve

What is a Good feature?

- The measure of goodness is subjective with respect to the type of classifier.



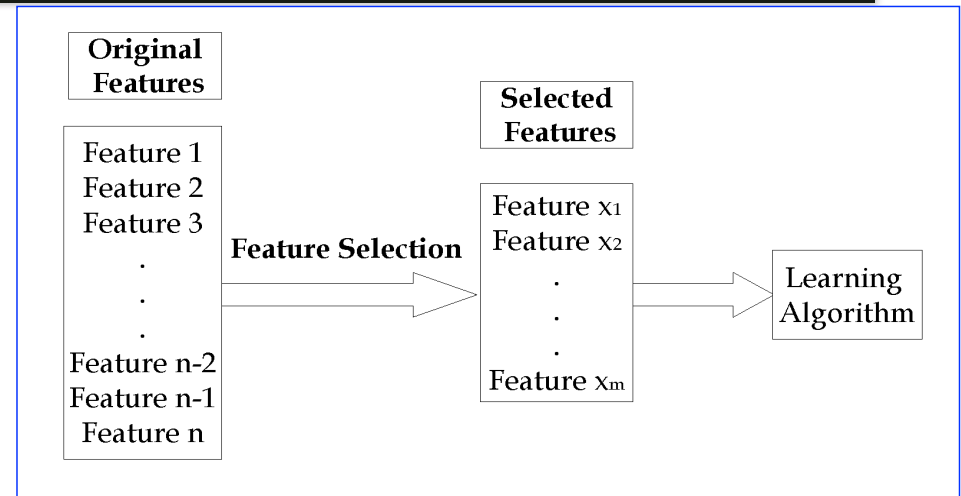
The features in this figure, x_1 and x_2 , are good for a linear classifier.



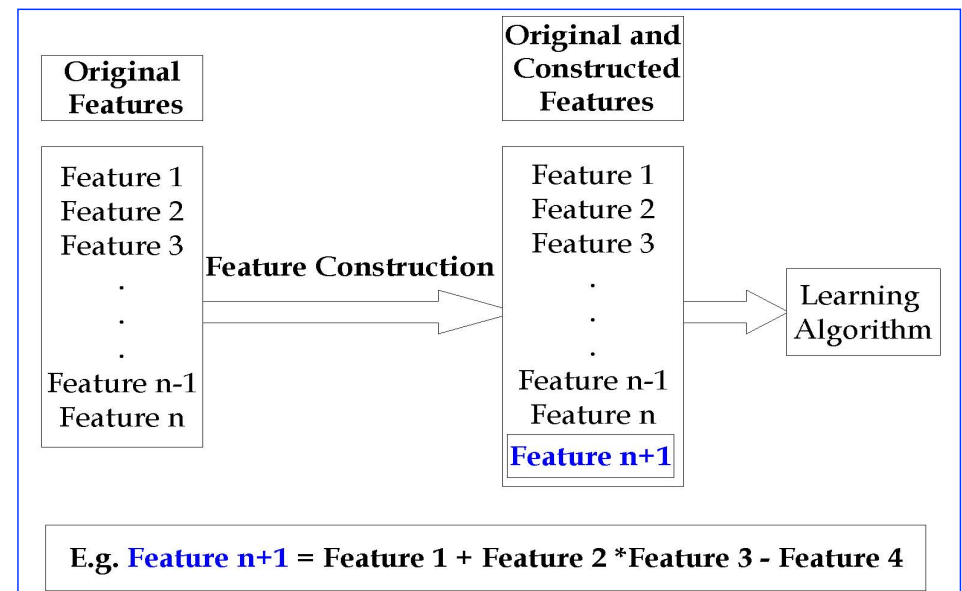
The same set of features are not good for a decision tree classifier that is not able to transform its input space.

Feature Selection and Feature Construction

- Feature selection aims to pick a subset of relevant features to achieve similar or better classification performance than using all features.



- Feature construction is to construct new high-level features using original features to improve the classification performance.



Why Feature Selection ?

- The **quality of input features** can drastically affect the learning performance.
- “**Curse of the dimensionality**”
 - Large number of features: 100s, 1000s, even millions
- **Not all** features are useful (relevant)
- Redundant or irrelevant features may reduce the performance (e.g. **classification accuracy**)
- **Costly**: time, memory, and money

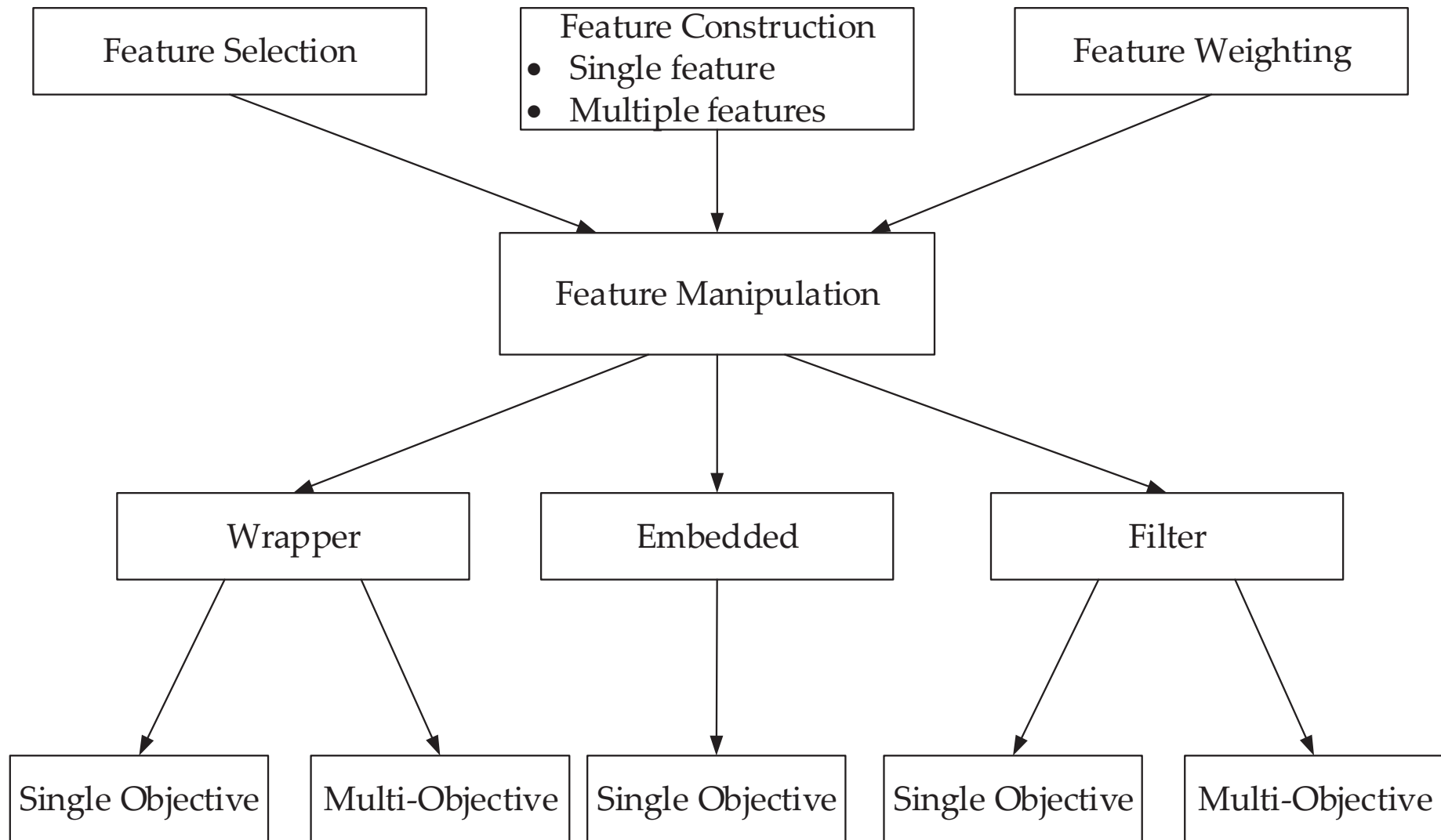
Why Feature Construction?

- Why Feature Selection?
- Even if the quality of the original features is good, transformations might be required to make them usable for **certain types of classifiers**.
- A large number of classification algorithms are unable of **transforming** their **input space**.
- Feature construction **does not add to the cost of extracting** (measuring) original features; it only carries computational cost.
- In some cases, feature construction can lead to **dimensionality reduction or implicit feature selection**.

What can FS/FC do ?

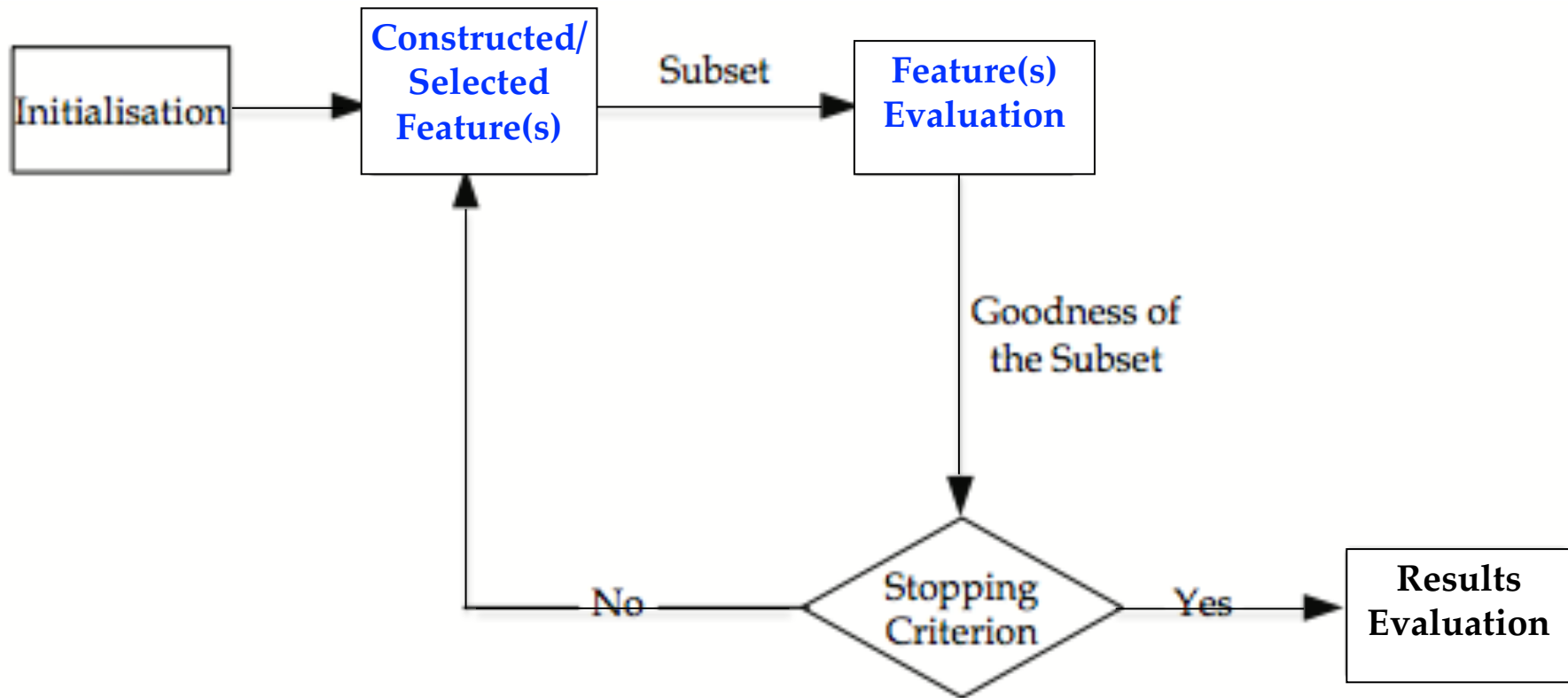
- Improve the (classification) performance
- Reduce the dimensionality (NO. of features)
- Simplify the learnt model
- Speed up the processing time
- Help visualisation and interpretation
- Reduce the cost, e.g. save memory
- and ?

Feature Manipulation (FS, FC and others)

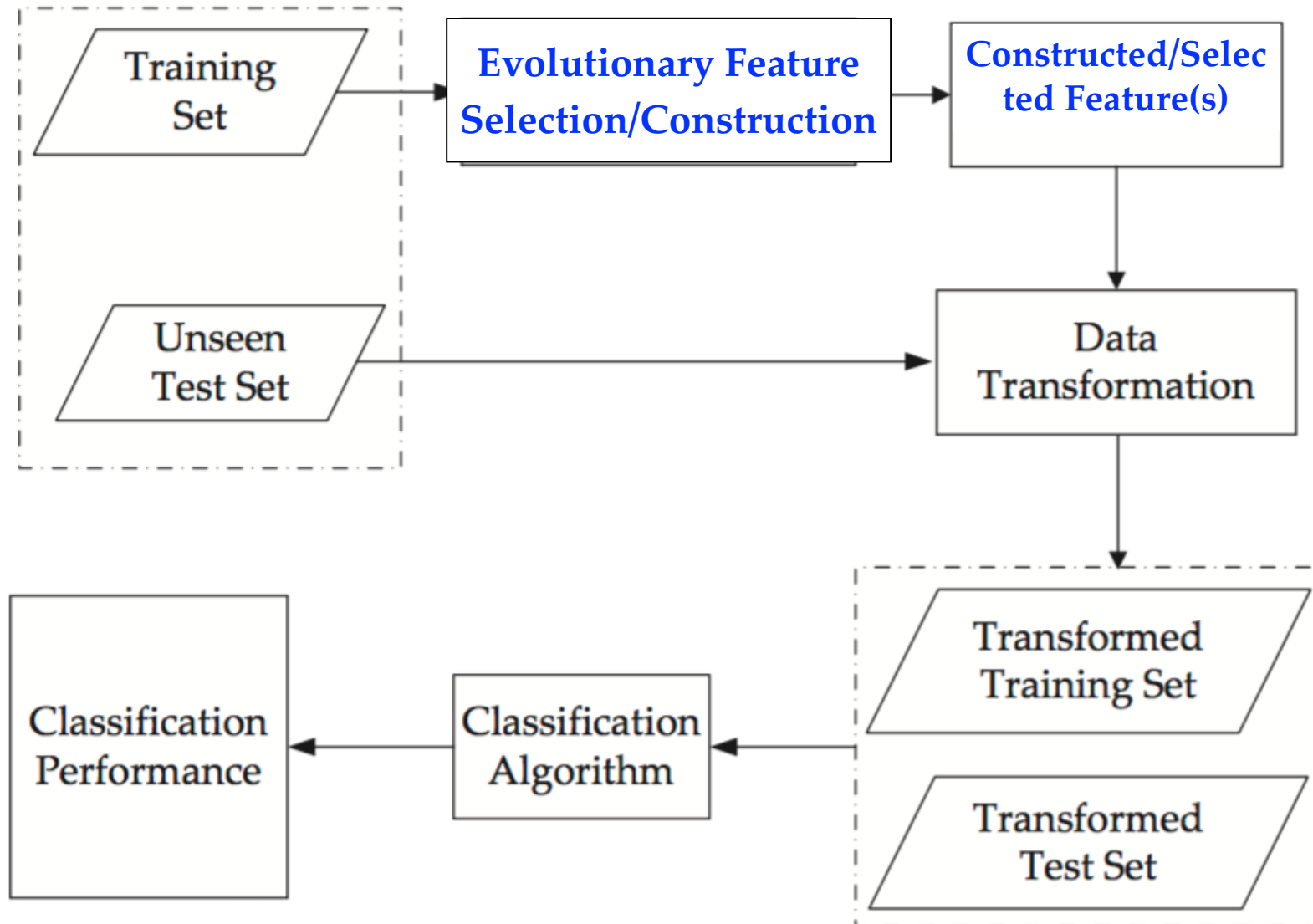


Feature FS/FC Process

- On training set:



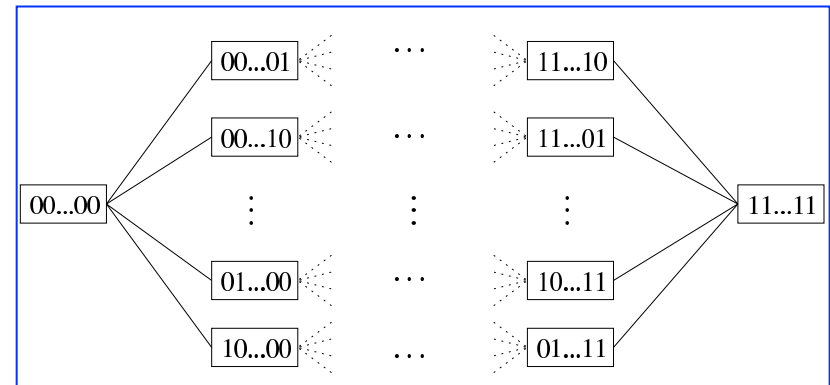
General FS/FC System



Challenges in FS and FC

- Large search space: 2^n possible feature subsets

- 1990: $n < 20$
- 1998: $n \leq 50$
- 2007: $n \approx 100s$
- Now: 1000s, 1 000 000s



- Feature interaction

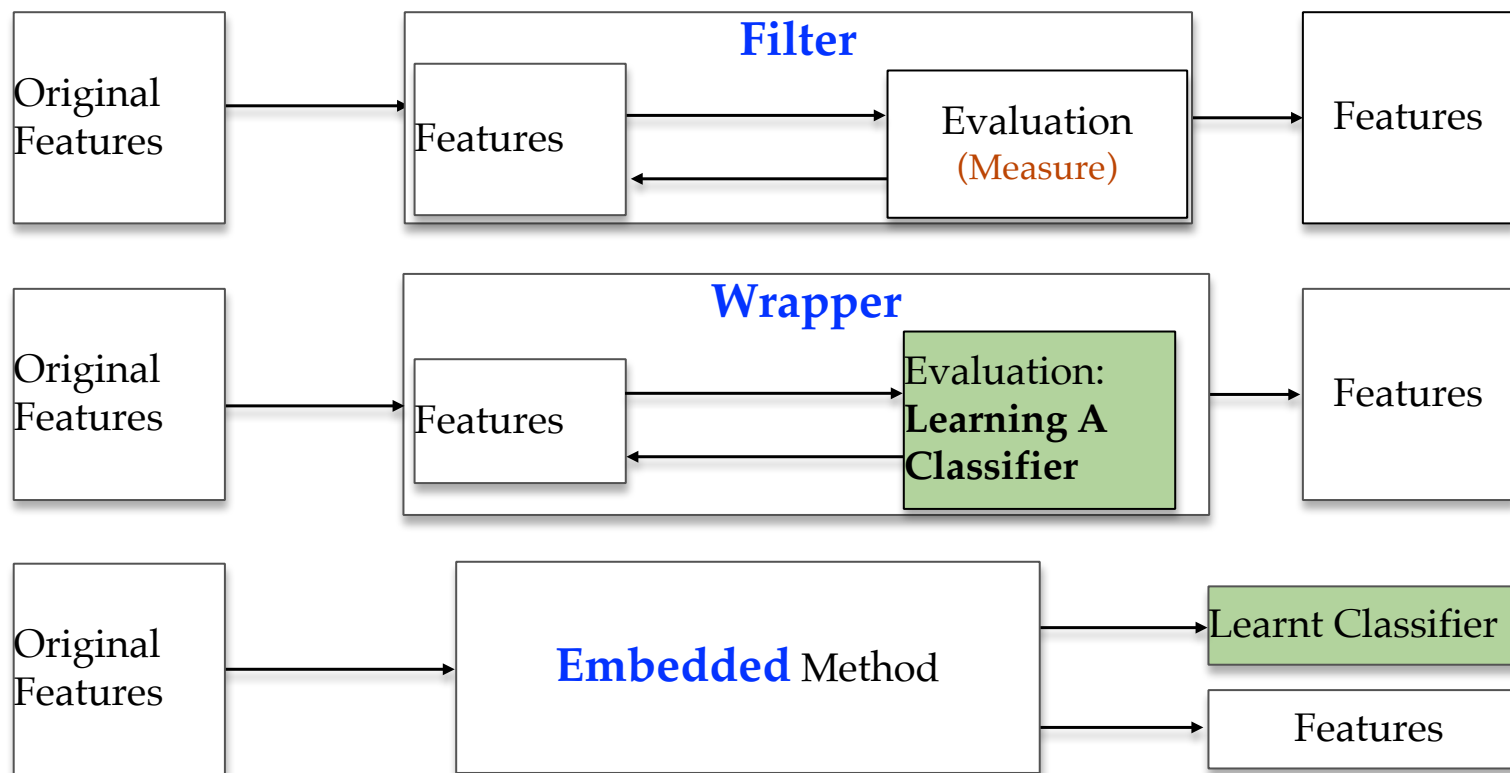
- Relevant features may become redundant
- Weakly relevant or irrelevant features may become highly useful

- Slow processing time, or even not possible

- **Multi-objective Problems — challenging**

Feature Manipulation Approaches

- Based on Evaluation ——— learning algorithm
 - Three categories: Filter, Wrapper, Embedded
 - Hybrid (Combined)



Feature Selection Approaches

- Generally:

	Classification Accuracy	Computational Cost	Generality (different classifiers)
Filter	Low	Low	High
Embedded	Medium	Medium	Medium
Wrapper	High	High	Low

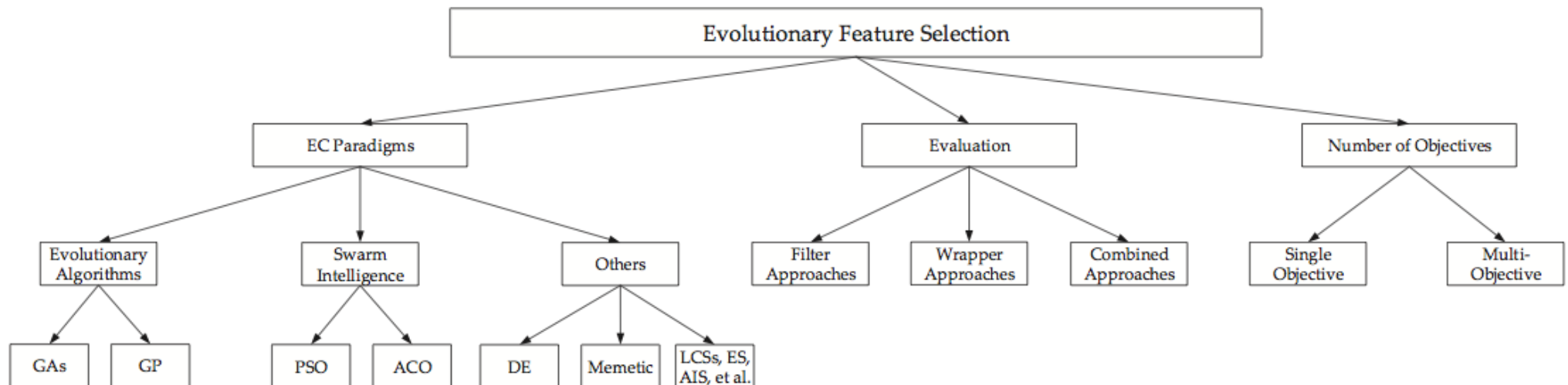
EC for FS/FC: Strengths

- Do not make any assumption
 - such as whether it is linearly or non-linearly separable, and differentiable
- Do not require domain knowledge
 - but flexible and can be easily incorporated within, or make use of, domain-specific methods or existing methods such as local search, which often leads to a better hybrid approach.
- EC can simultaneously build model structures and optimise parameters
 - Embedded approaches
- Easy to handle constraints
- EC algorithms maintain a population
 - produce multiple solutions in a single run, particularly suitable for multi-objective problems

Feature Selection

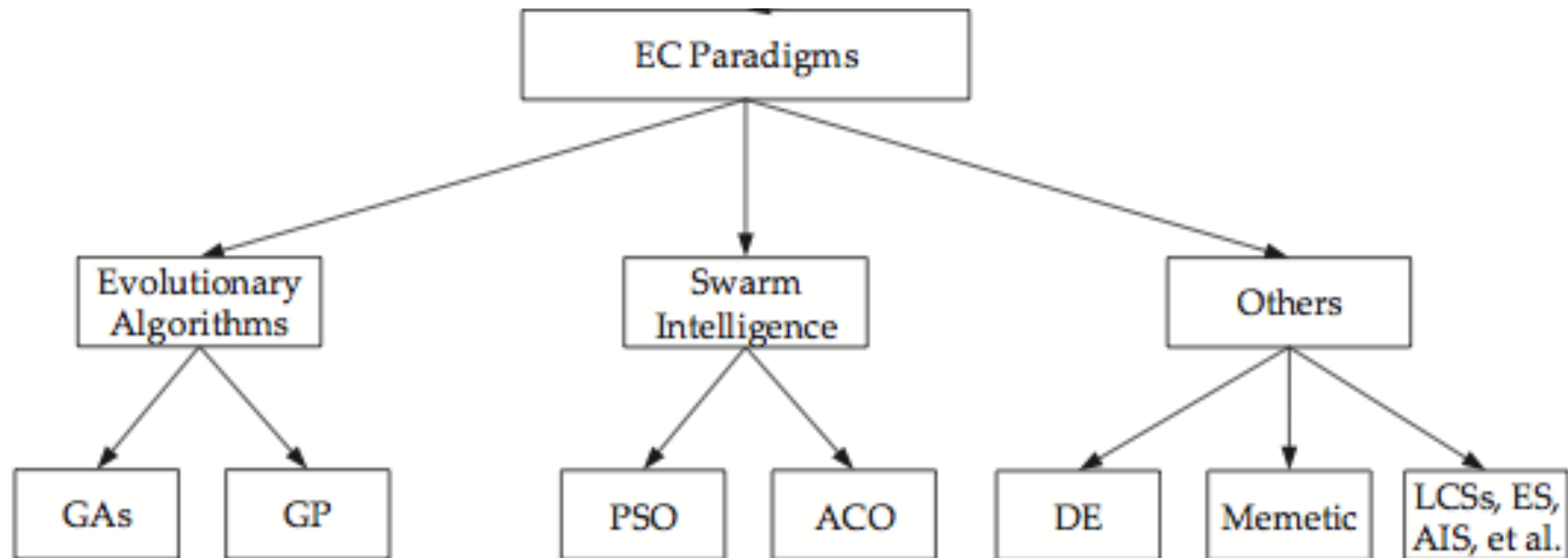
EC for Feature Selection

- EC Paradigms
- Evaluation
- Number of Objectives

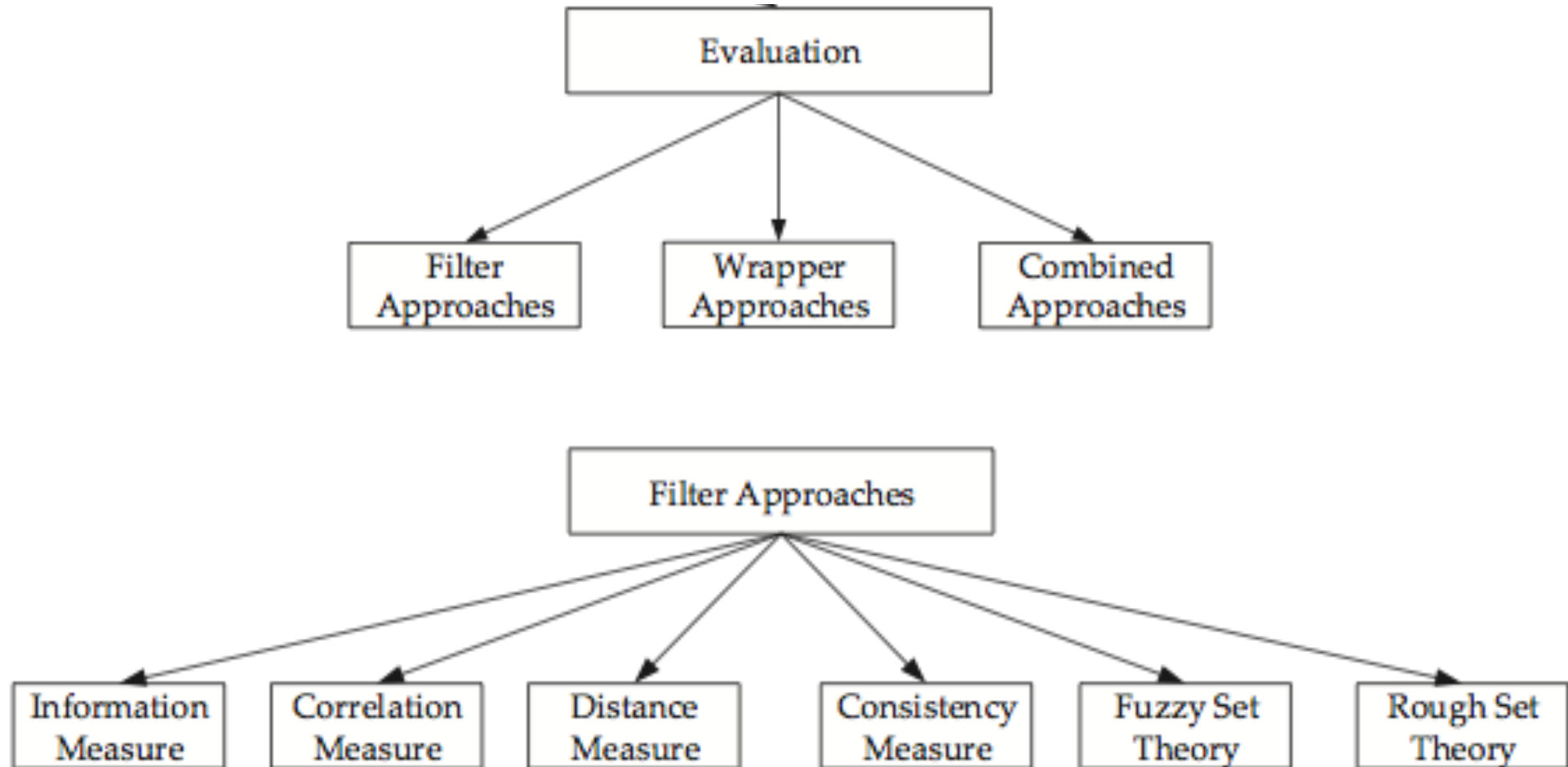


EC for Feature Selection

- Genetic algorithms (GAs), Genetic programming (GP)
- Particle swarm optimisation (PSO), ant colony optimisation(ACO)
- Differential evolution (DE), memetic algorithms, learning classifier systems (LCSs)



EC for Feature Selection



GAs for Feature Selection

- Over 25 years ago, first EC techniques
 - Filter, Wrapper, Single Objective, Multi-objective
- Representation
 - Binary string
- Search mechanisms
 - Genetic operators
- Multi-objective feature selection
- Scalability issue

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R. Leardi, R. Boggia, and M. Terrile, "Genetic algorithms as a strategy for feature selection," *Journal of Chemometrics*, vol. 6, no. 5, pp. 267–281, 1992.

Z. Zhu, Y.-S. Ong, and M. Dash, "Markov blanket-embedded genetic algorithm for gene selection," *Pattern Recognition*, vol. 40, no. 11, pp. 3236–3248, 2007.

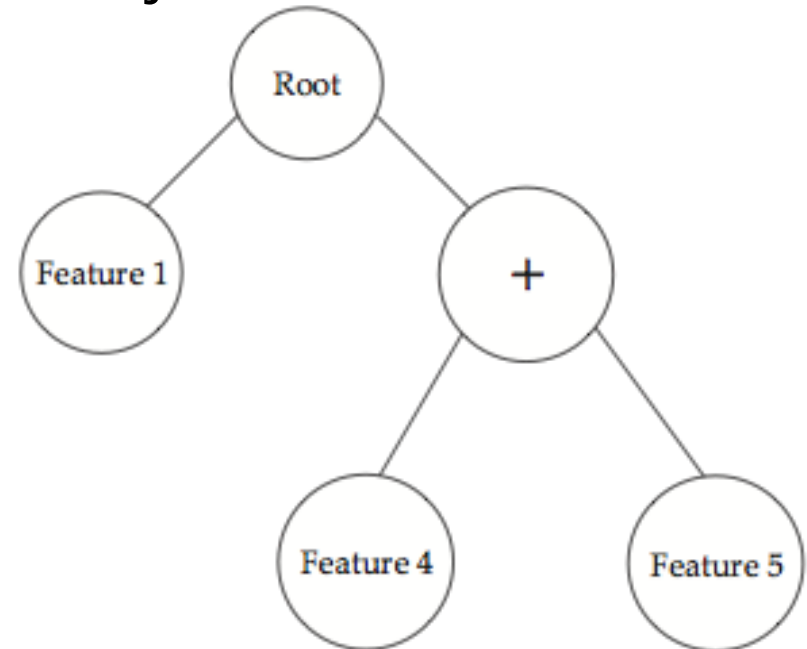
W. Sheng, X. Liu, and M. Fairhurst, "A niching memetic algorithm for simultaneous clustering and feature selection," *IEEE Transactions on Knowledge and Data Engineering*, vol. 20, no. 7, pp. 868–879, 2008.

Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", *IEEE Transaction on Evolutionary Computation*, vol. 20, no. 4, pp. 606-626, Aug. 2016.

GP for Feature Selection

- Implicit feature selection
 - Filter, Wrapper, Single Objective, Multi-objective
- Embedded feature selection
- Feature construction

- Computationally expensive



L. Jung-Yi, K. Hao-Ren, C. Been-Chian, and Y. Wei-Pang, "Classifier design with feature selection and feature extraction using layered genetic programming," *Expert Systems with Applications*, vol. 34, no. 2, pp. 1384–1393, 2008.

Purohit, N. Chaudhari, and A. Tiwari, "Construction of classifier with feature selection based on genetic programming," in *IEEE Congress on Evolutionary Computation (CEC)*, pp. 1–5, 2010.

M. G. Smith and L. Bull, "Genetic programming with a genetic algorithm for feature construction and selection," *Genetic Programming and Evolvable Machines*, vol. 6, no. 3, pp. 265–281, 2005.

Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", *IEEE Transaction on Evolutionary Computation*, vol. 20, no. 4, pp. 606-626, Aug. 2016.

PSO for Feature Selection

- Very popular in recent years
 - Filter, Wrapper, Single Objective, Multi-objective
- Representation, continuous PSO vs Binary PSO
- Search mechanism
- Fitness function

0.7	0.12	0.84	0.69	0.25	0.06	0.92	0.45	0.36	0.80	0.67	0.30	0.41
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- Scalability

E. K. Tang, P. Suganthan, and X. Yao, "Feature selection for microarray data using least squares SVM and particle swarm optimization," in IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB), pp. 1–8, 2005.

L. Y. Chuang, H. W. Chang, C. J. Tu, and C. H. Yang, "Improved binary PSO for feature selection using gene expression data," Computational Biology and Chemistry, vol. 32, no. 29, pp. 29–38, 2008.

C. L. Huang and J. F. Dun, "A distributed PSO-SVM hybrid system with feature selection and parameter optimization," Application on Soft Computing, vol. 8, pp. 1381–1391, 2008.

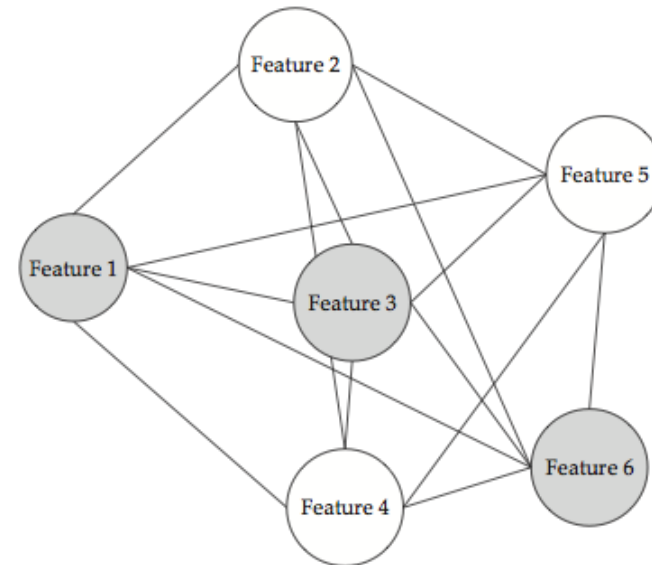
B. Xue, M. Zhang, and W. N. Browne, "Multi-objective particle swarm optimisation (PSO) for feature selection," in Proceeding of the 14th Annual Conference on Genetic and Evolutionary Computation Conference (GECCO), pp. 81–88, ACM, 2012.

Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", IEEE Transaction on Evolutionary Computation, vol. 20, no. 4, pp. 606-626, Aug. 2016.

ACO for Feature Selection

- Start from around 2003
 - Filter, Wrapper, Single Objective, Multi-objective
- Representation
- Search mechanism
- Filter approaches

- Scalability



- S. Kashef and H. Nezamabadi-pour, "An advanced ACO algorithm for feature subset selection," *Neurocomputing*, 2014.
- S. Vieira, J. Sousa, and T. Runkler, "Multi-criteria ant feature selection using fuzzy classifiers," in *Swarm Intelligence for Multi-objective Problems in Data Mining*, vol. 242 of *Studies in Computational Intelligence*, pp. 19–36, Heidelberg, 2009.
- C.-K. Zhang and H. Hu, "Feature selection using the hybrid of ant colony optimization and mutual information for the forecaster," in *International Conference on Machine Learning and Cybernetics*, vol. 3, pp. 1728–1732, 2005.
- R. Jensen, "Performing feature selection with aco," in *Swarm Intelligence in Data Mining*, vol. 34 of *Studies in Computational Intelligence*, pp. 45–73, / Heidelberg, 2006.
- L. Ke, Z. Feng, and Z. Ren, "An efficient ant colony optimization approach to attribute reduction in rough set theory," *Pattern Recognition Letters*, vol. 29, no. 9, pp. 1351–1357, 2008.
- Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", *IEEE Transaction on Evolutionary Computation*, doi: 10.1109/TEVC.2015.2504420, published online on 30 Nov 2015

DE, LCSs, and Memetic

- DE: since 2008
 - potential for large-scale
- LCSs:
 - implicit feature selection
 - embedded feature selection
- memetic:
 - population search + local search
 - Wrapper + filter

A. Al-Ani, A. Alsukker, and R. N. Khushaba, "Feature subset selection using differential evolution and a wheel based search strategy," *Swarm and Evolutionary Computation*, vol. 9, pp. 15–26, 2013.

Z. Li, Z. Shang, B. Qu, and J. Liang, "Feature selection based on manifold-learning with dynamic constraint handling differential evolution," in *IEEE Congress on Evolutionary Computation (CEC)*, pp. 332–337, 2014.

I.-S. Oh, J.-S. Lee, and B.-R. Moon, "Hybrid genetic algorithms for feature selection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 11, pp. 1424–1437, 2004.

S. Palanisamy and S. Kanmani, "Artificial bee colony approach for optimizing feature selection," *International Journal of Computer Science Issues (IJCSI)*, vol. 9, no. 3, pp. 432–438, 2012.

Z. Zhu, S. Jia, and Z. Ji, "Towards a memetic feature selection paradigm [application notes]," *IEEE Computational Intelligence Magazine*, vol. 5, no. 2, pp. 41–53, 2010.

Y. Wen and H. Xu, "A cooperative coevolution-based pittsburgh learning classifier system embedded with memetic feature selection," in *IEEE Congress on Evolutionary Computation*, pp. 2415–2422, 2011.

Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "A Survey on Evolutionary Computation Approaches to Feature Selection", *IEEE Transaction on Evolutionary Computation*, doi: 10.1109/TEVC.2015.2504420, online on 30 Nov 2015

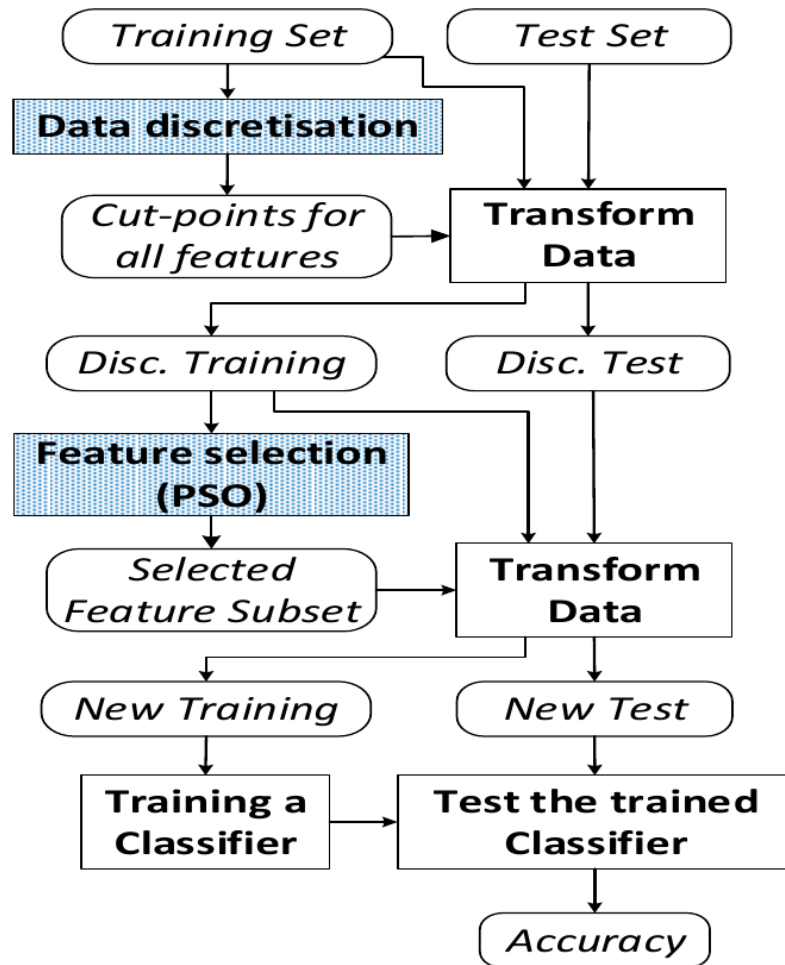
Related Areas (Applications)

- Biological and biomedical tasks
 - gene analysis, biomarker detection, cancer classification, and disease diagnosis
- Image and signal processing
 - image analysis, face recognition, human action recognition, EEG brain-computer-interface, speaker recognition, handwritten digit recognition, personal identification, and music instrument recognition.
- Network/web service
 - Web service composition and development, network security, and email spam detection.
- Business and financial problems
 - Financial crisis, credit card issuing in bank systems, and customer churn prediction.
- Others
 - power system optimisation, weed recognition in agriculture, melting point prediction in chemistry, and weather prediction.

Feature Selection Through Data Discretisation

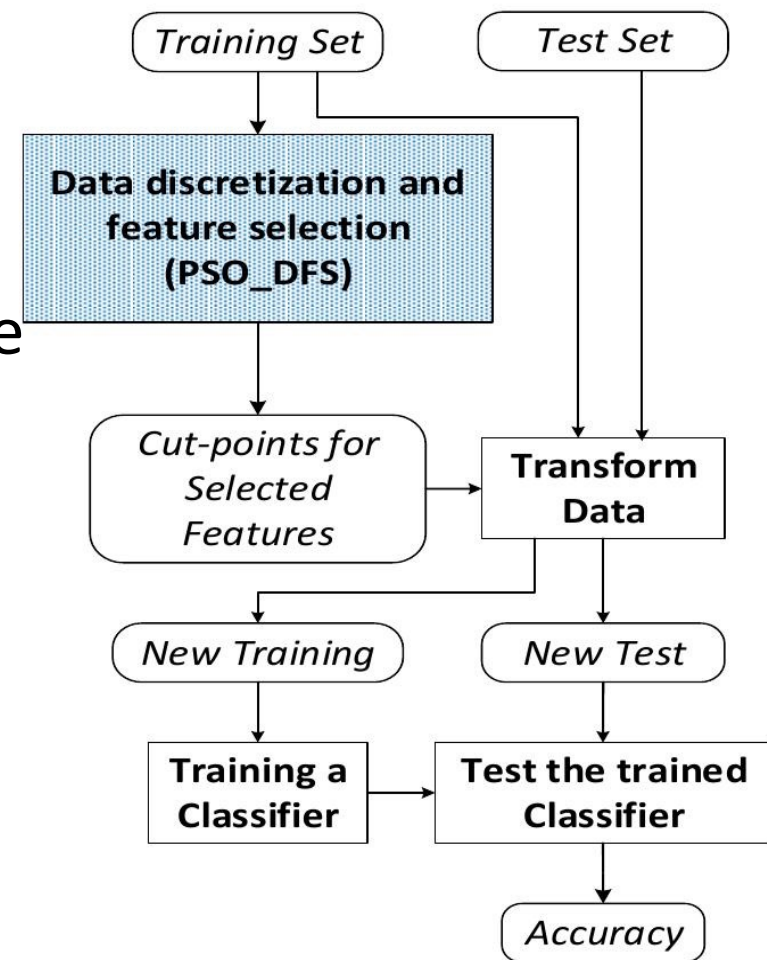
Bare-Bone Particle Swarm Optimisation

Two-stage (PSO-FS)

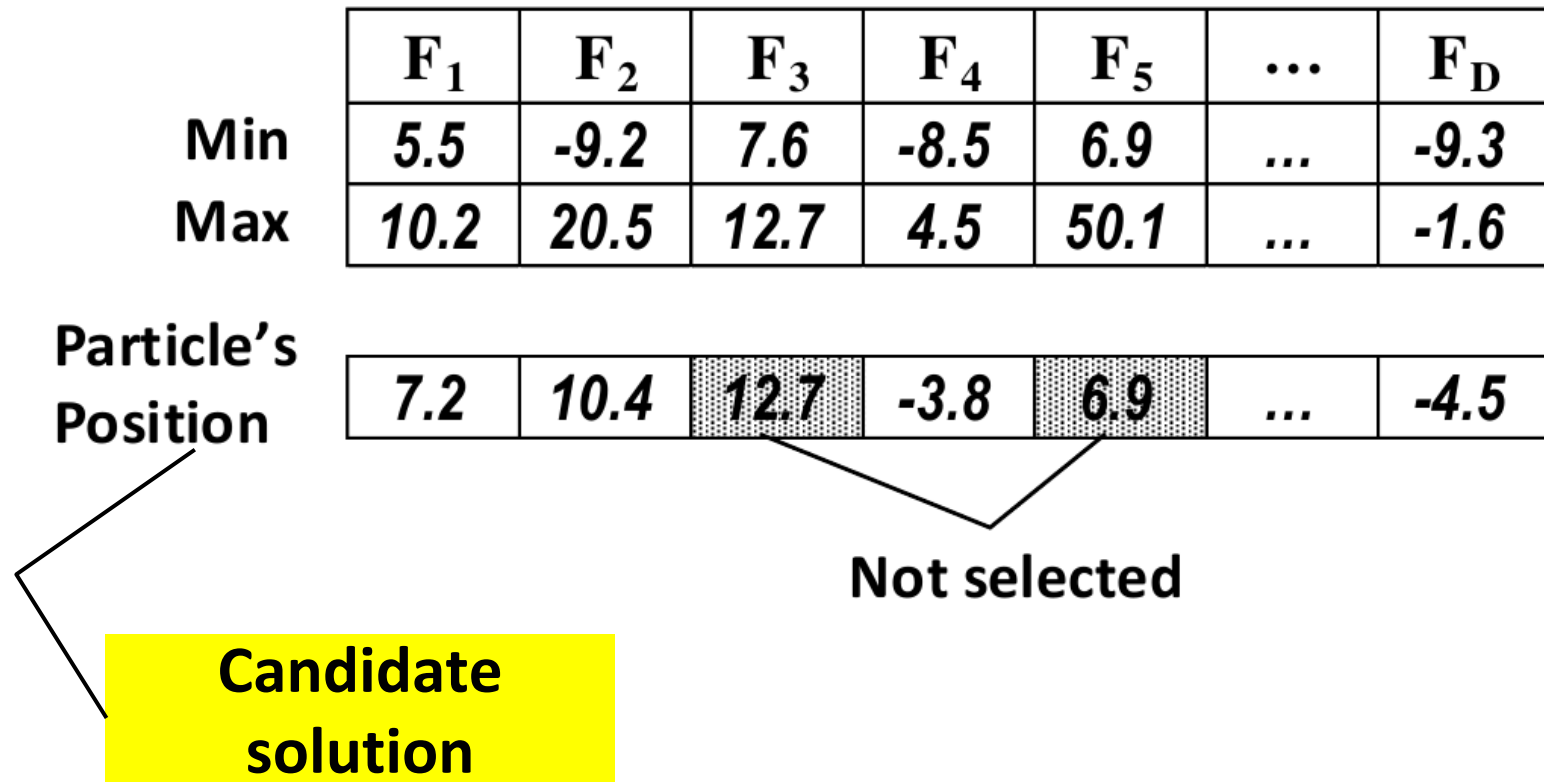


• One-stage (PSO-DFS)

Proposed



Feature Selection Through Data Discretisation



Confidence of a feature's decision

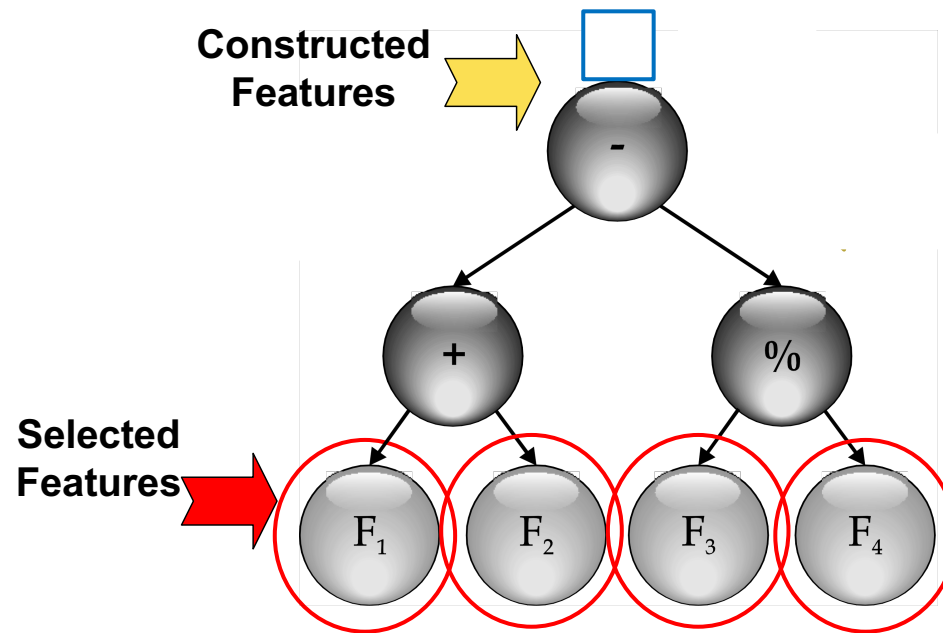
- Given a position $\mathbf{X} = (x_1, x_2, \dots, x_m)$ where x_j in $[0,1]$
- The position entry x_i not only indicates the decision on the corresponding features but also shows the confidence of that decision:
 - $x_1 = 0.8, x_2 = 0.9$: both 1st and 2nd features are selected but it is believed that the 2nd feature is more deserved to be selected since $x_2 > x_1 > \theta$.
 - $x_1 = 0.6, x_2 = 0.5$: both 1st and 2nd features are not selected but it is believed that the 2nd feature is more deserved to be removed since $x_2 < x_1 < \theta$.

The further the position entry from the threshold θ , the more confident the decision

Feature Construction

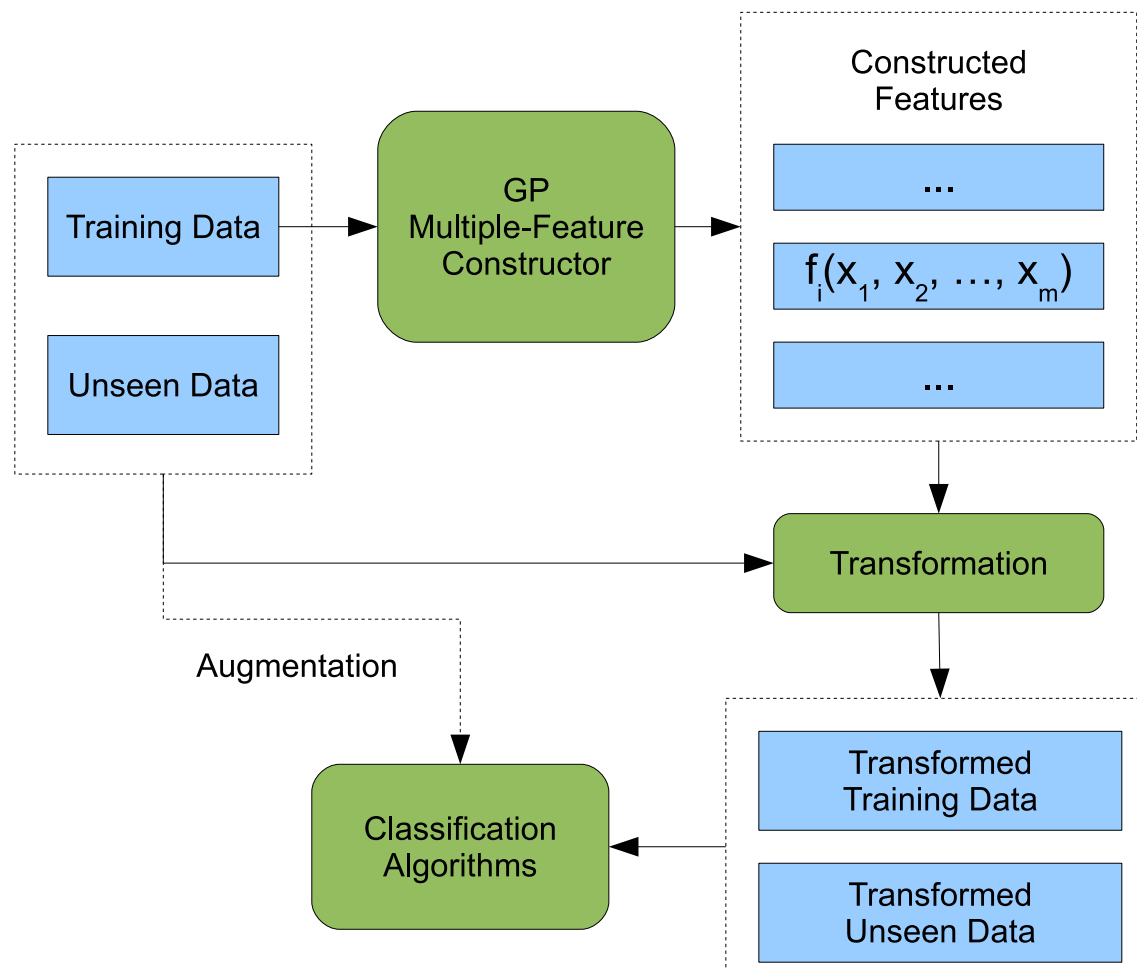
Why Use GP for Feature Construction?

- GP is **flexible** in making mathematical and logical functions
- There **isn't much structural (topological) information** in the search space of possible functions, so using a meta-heuristic approach (such as evolutionary computation) seems reasonable.



GP for FC: A System Diagram

- One constructed feature for one class



GP for FC Measure: Entropy of Class Intervals

Defining a measure of goodness for a single feature:

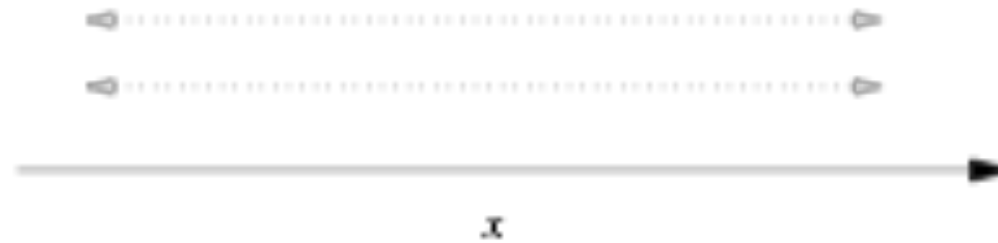
- The interval of a *class* along a feature is determined by the dispersion of the instances of that class along the feature axis. The dispersion of instances themselves is related to the distribution of data points in that class.
- An interval ***I*** is represented with a pair (*lower, upper*) which shows the lower and upper boundaries of the interval. ***I_c*** is used to indicate an interval for class ***c***.
- The interval of class ***c*** could be formulated as follows if the class distributions were normal.

$$I_c = [\mu_c - 3\sigma_c, \mu_c + 3\sigma_c]$$

- However, the normality assumption is not always satisfied.

GP for FC Measure: Examples of good and bad class intervals

- Overlapping intervals

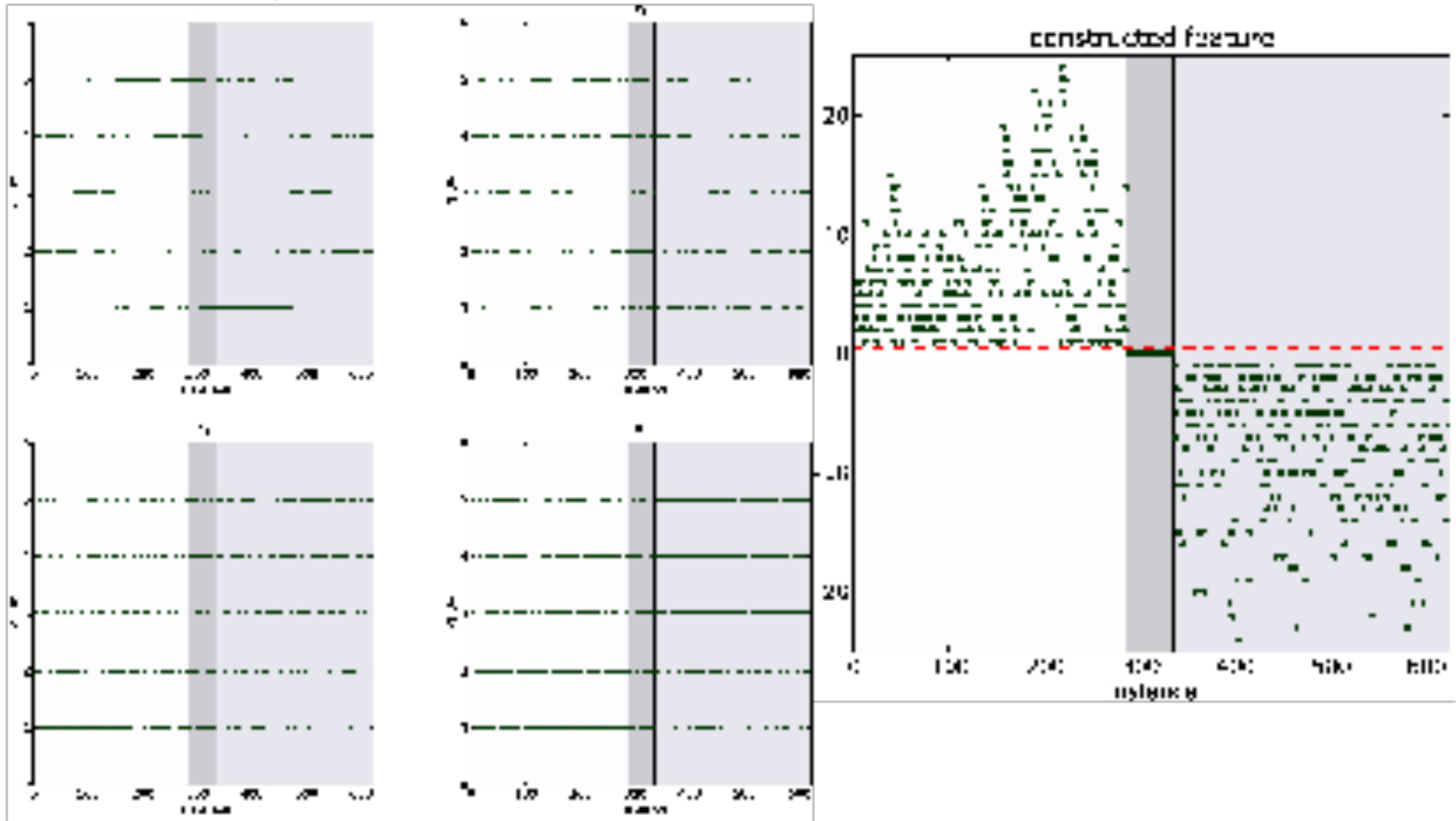


- Non-overlapping intervals



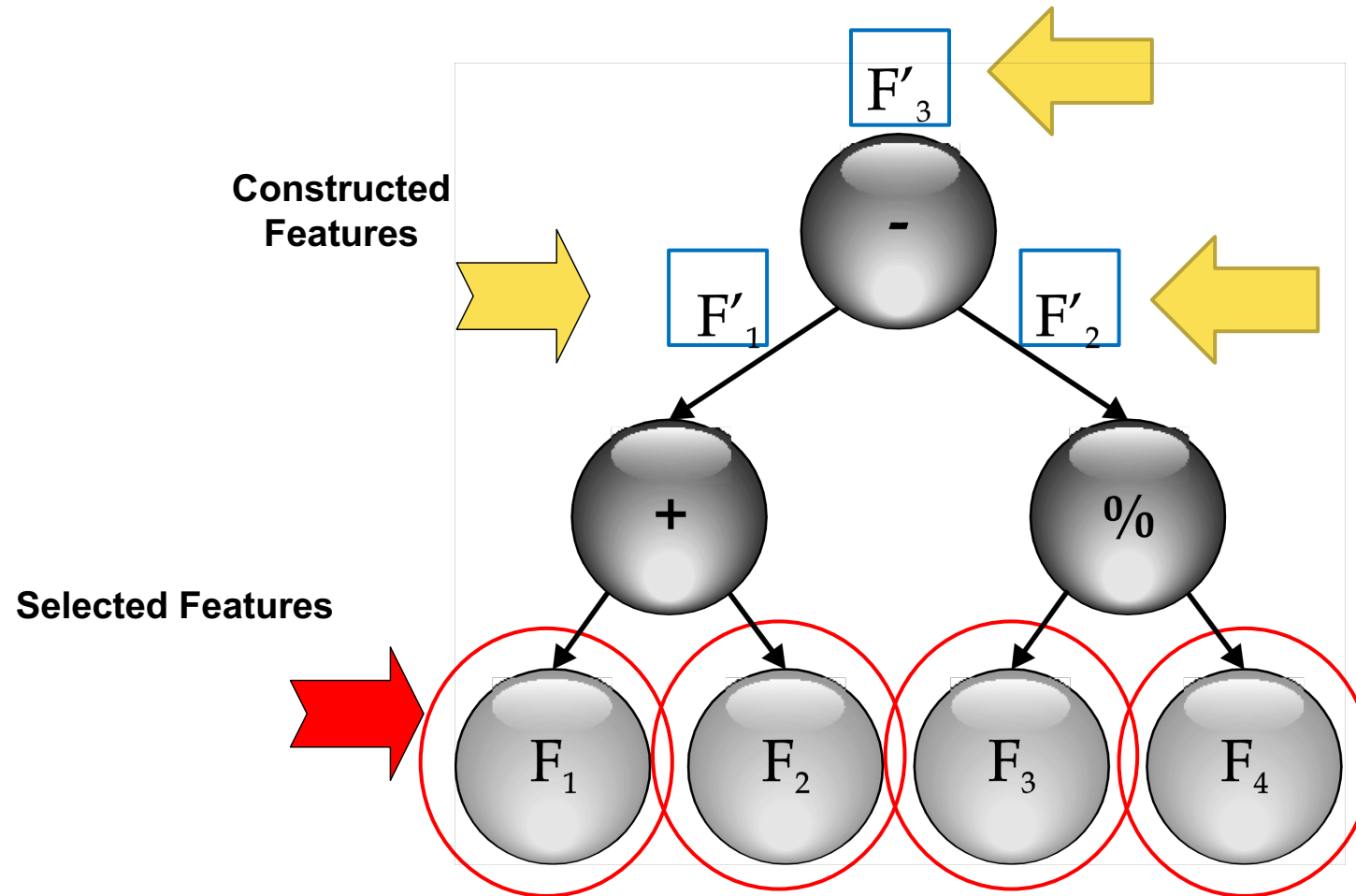
GP for FC Measure: Original VS Constructed

- 4 features, 3 classes



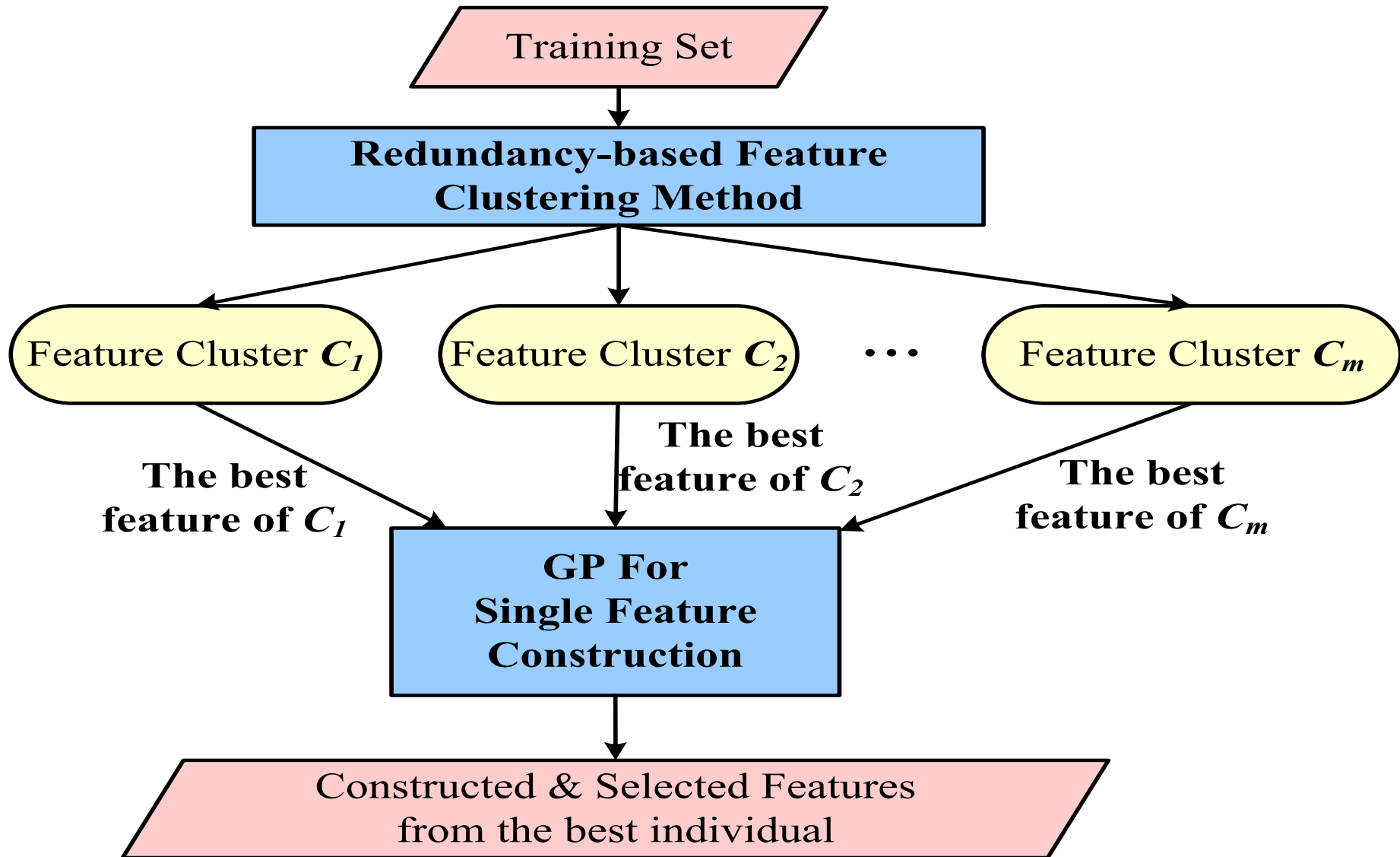
GP for FC Measure: Multiple feature construction

- Construct multiple features from a single tree

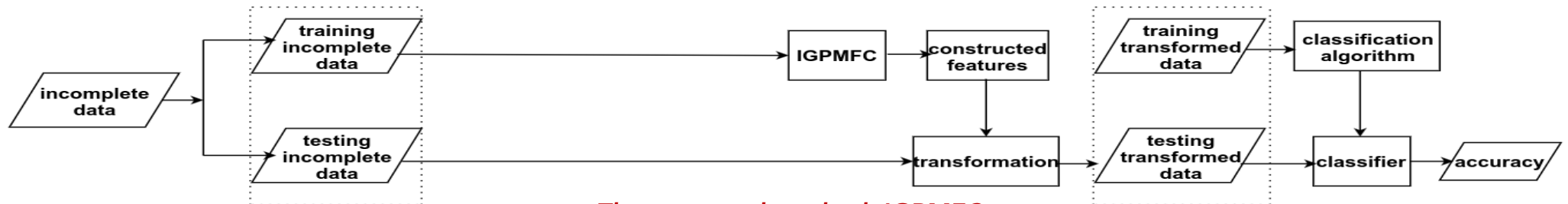


Soha Ahmed, Mengjie Zhang, Lifeng Peng and Bing Xue. "Multiple Feature Construction for Effective Biomarker Identification and Classification using Genetic Programming". Proceedings of 2014 Genetic and Evolutionary Computation Conference (GECCO 2014). ACM Press. Vancouver, BC, Canada. 12-16 July 2014. pp.249--256

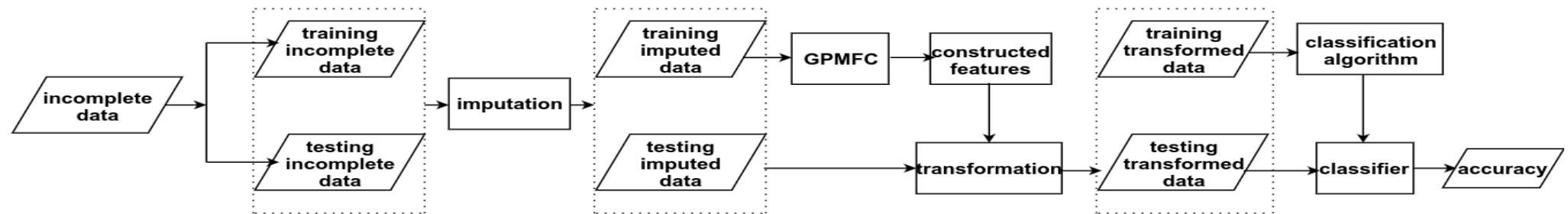
Feature Clustering for GP-Based FC



Classification with Incomplete data with GP-Based FC



The proposed method: IGPMFC

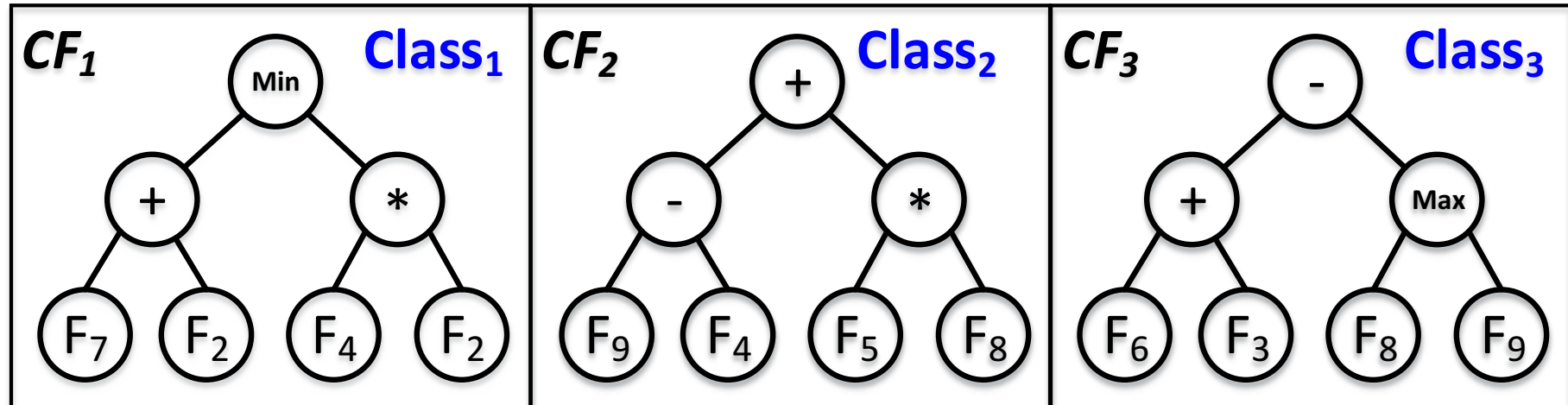


Imputation combined GPMFC



Baseline: Classifier able to directly classify incomplete data

Multiple feature construction using GP with multi-tree representation



1. Constructed feature set (CF): CF₁, CF₂, CF₃

- $CF_1 = \text{Min} ((F_7 + F_2), (F_4 * F_2))$
- $CF_2 = (F_9 - F_4) + (F_5 * F_8)$
- $CF_3 = (F_6 + F_3) - \text{Max} (F_8, F_9)$

2. Selected feature set (Ter): F₂, F₃, F₄, F₅, F₆, F₇, F₈, F₉

3. Combination set (CFTer): CF₁, CF₂, CF₃, F₂, F₃, F₄, F₅, F₆, F₇, F₈, F₉

Multiple feature construction using GP with multi-tree representation

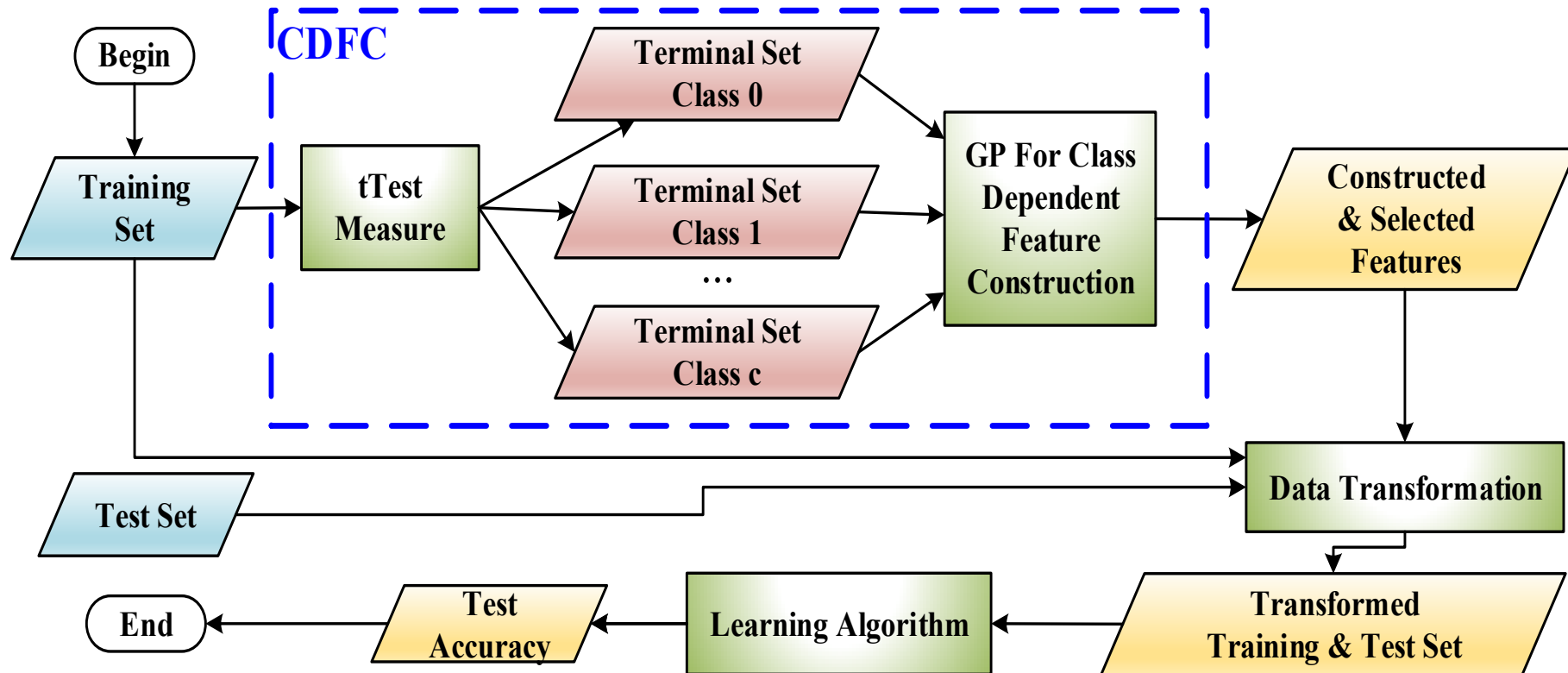
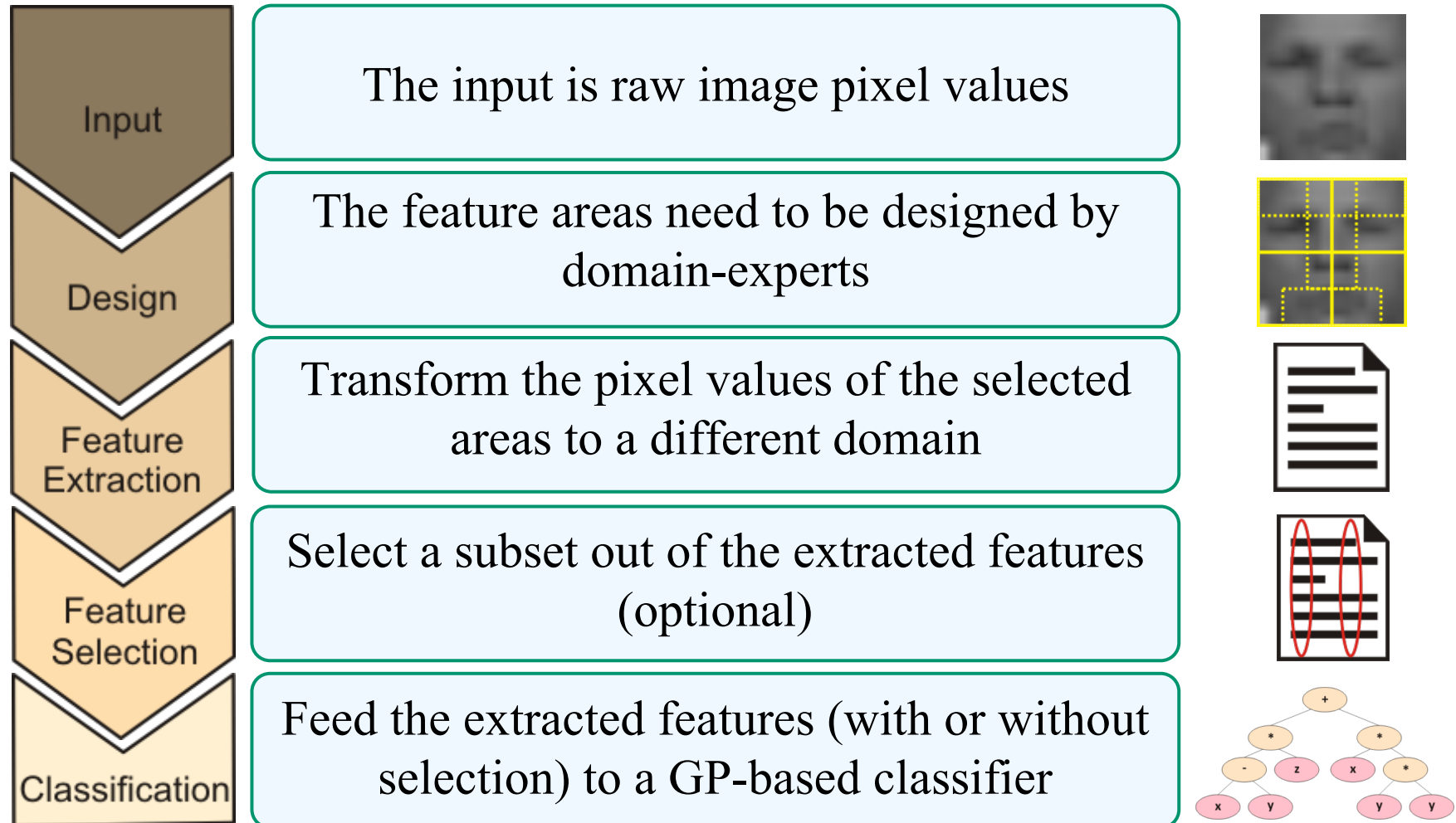


Image Recognition/Classification

Image Recognition/Classification

- The traditional way
- Domain-specific pre-extracted features approach (DS-GP)

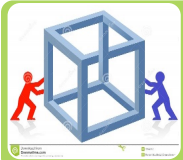


Images: GP-Surff

- Improve domain-independent object classification in images by using GP techniques.



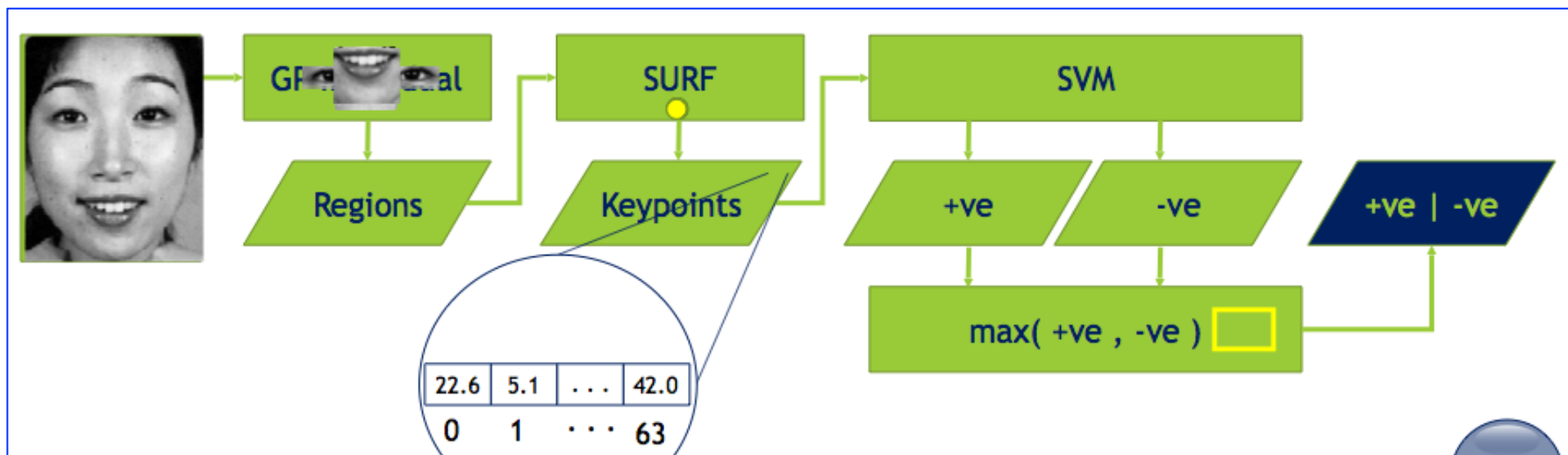
Designing a program representation that is capable of detecting sub-regions of the image that are rich in features;



Constructing a classification system to extract features from the selected regions and then use a SVM classifier and voting scheme to predict the class label; and

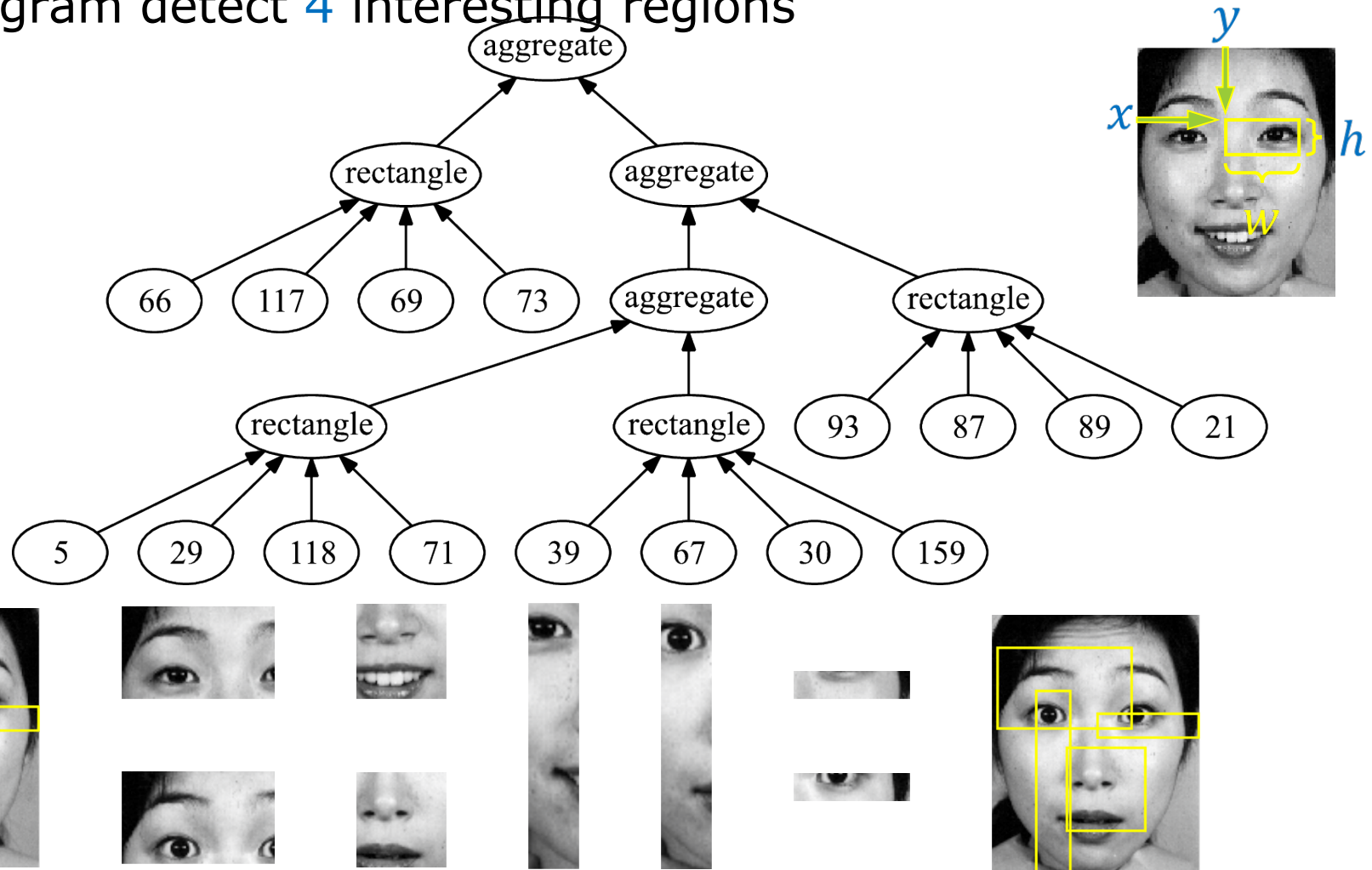


Investigating whether the regions detected by the new method are similar to those designed by domain experts.



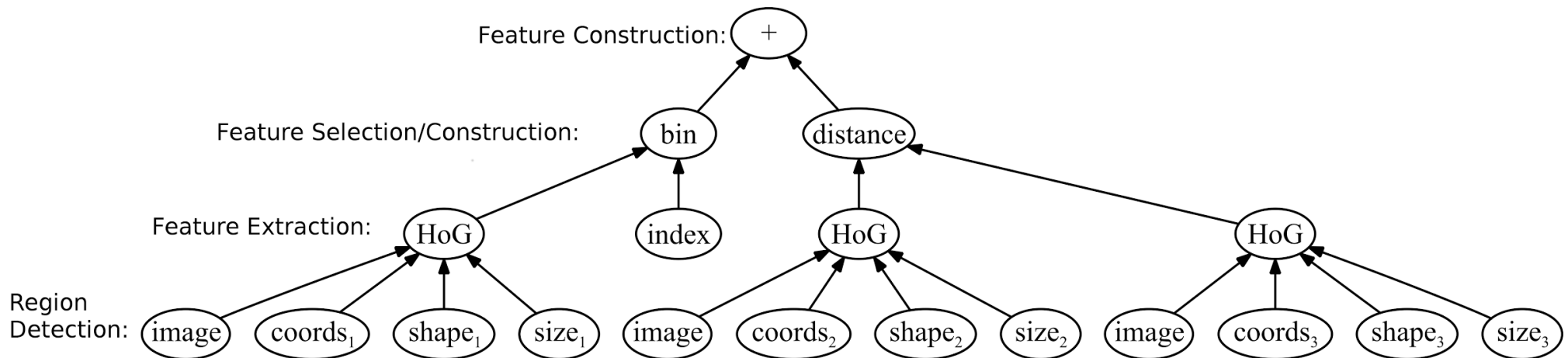
Images: GP-Surff

- A program evolved on **JAFFE**, average over **95%** test accuracy
- The program detect **4** interesting regions



Images: GP-HoG Method

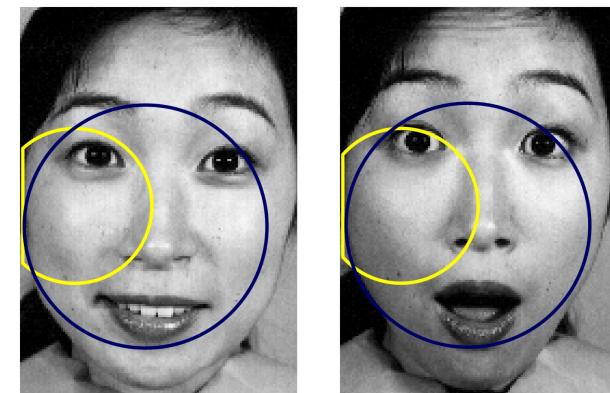
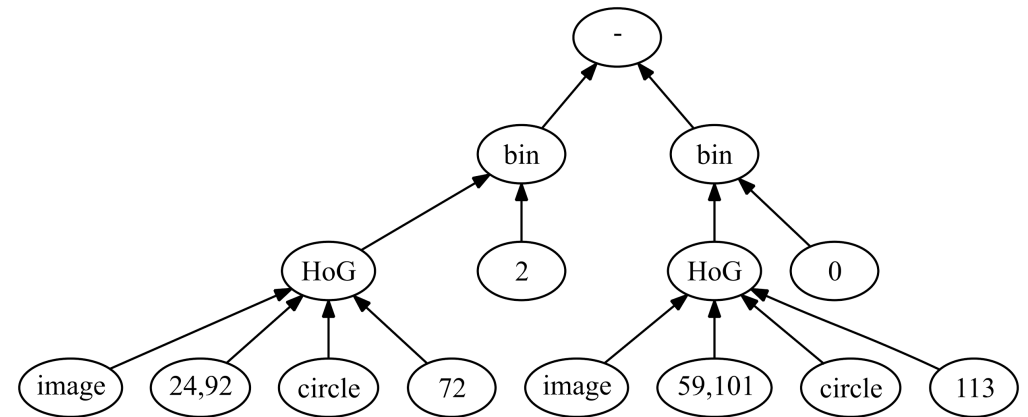
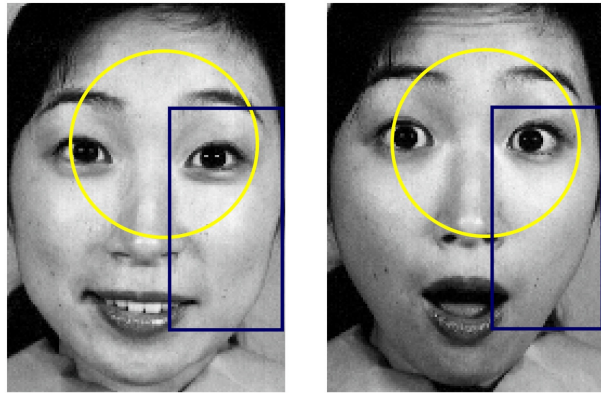
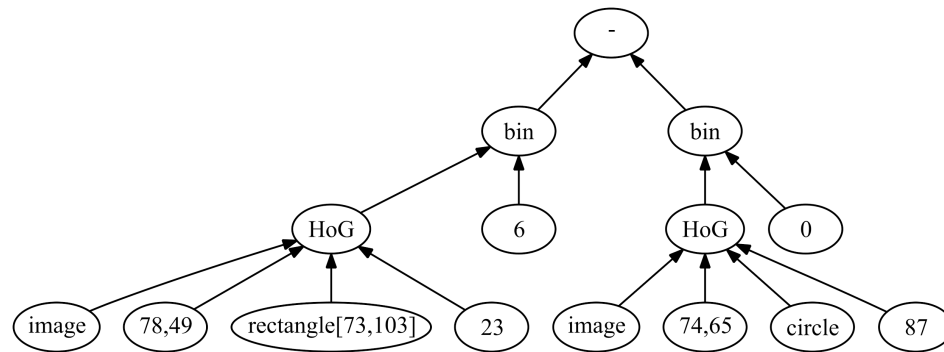
- GP-HoG uses strongly typed GP to perform three tasks in the same tree structure.
- All layers are trained simultaneously and coherently.
- Output of the tree is thresholded.



Andrew Lensen, Harith Al-Sahaf, Mengjie Zhang, Bing Xue. "Genetic Programming for Region Detection, Feature Extraction, Feature Construction and Classification in Image Data". Proceedings of the 19th European Conference on Genetic Programming (EuroGP 2016). Lecture Notes in Computer Science. Vol. 9594. Porto, Portugal, March 30 - April 1, 2016. pp. 51-67

Images: GP-HoG Method

- The below tree has 98% training and 95% test performance on the Jaffe dataset despite being very simple.
- The below tree has 95% training and 100% test performance on the Jaffe dataset.



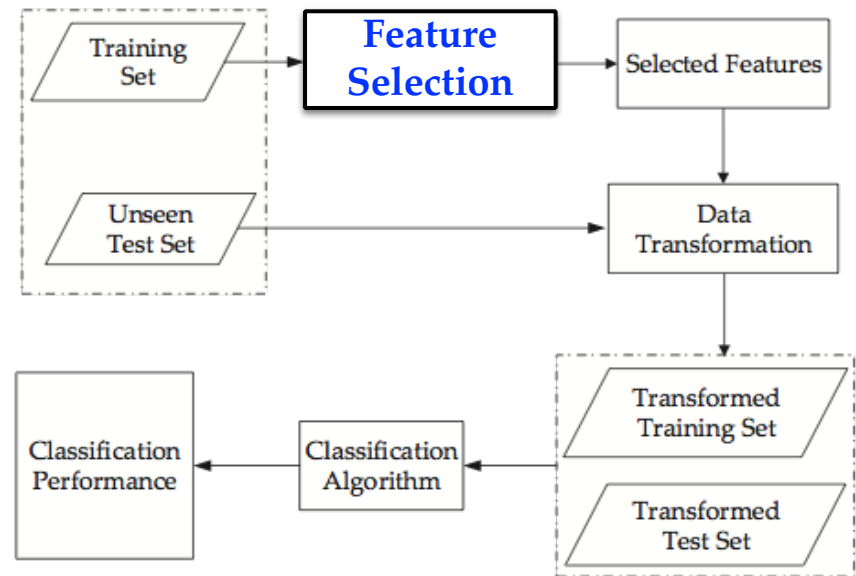
Weakness and Issues

Weakness and Issues

- Search space:
 - Large search space: bit-string/vector with a length equal to the total number of features
 - Classification accuracy or existing filter measures in the fitness function, which often cannot lead to a smooth fitness landscape or with low locality
- Long computational time
 - A large number of evaluations
 - Wrapper: each evaluation involves a learning process of a machine learning or data mining algorithm
 - Filters are computationally cheaper than wrappers
- Poor scalability
 - the dimensionality of the search space often equals to the total number of features, thousands, or even millions
 - the number of instances is large

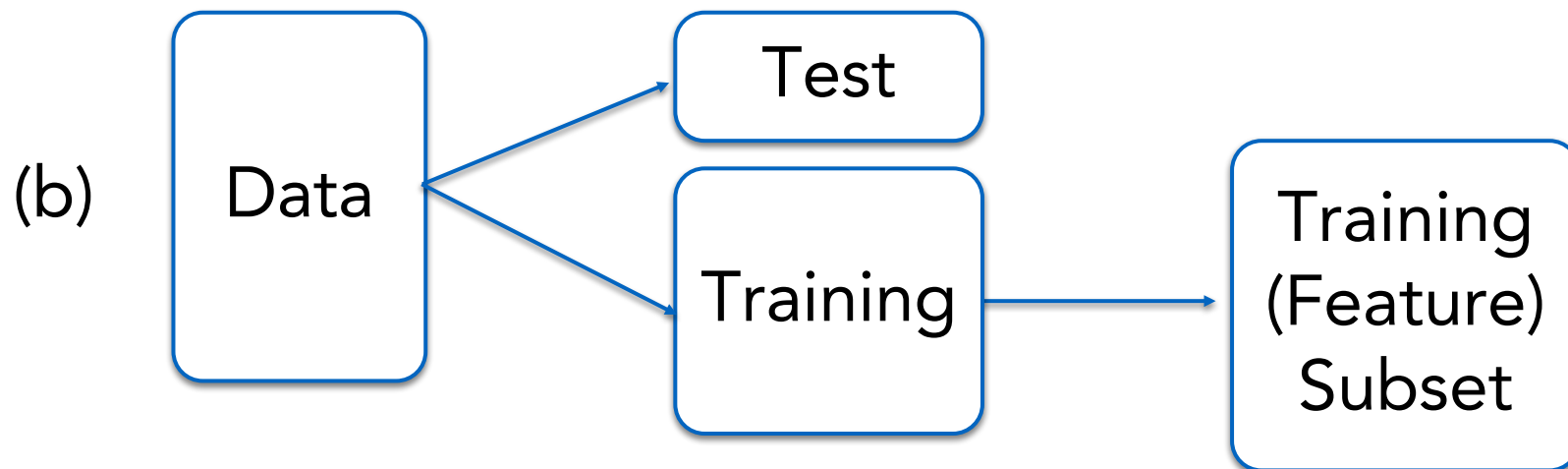
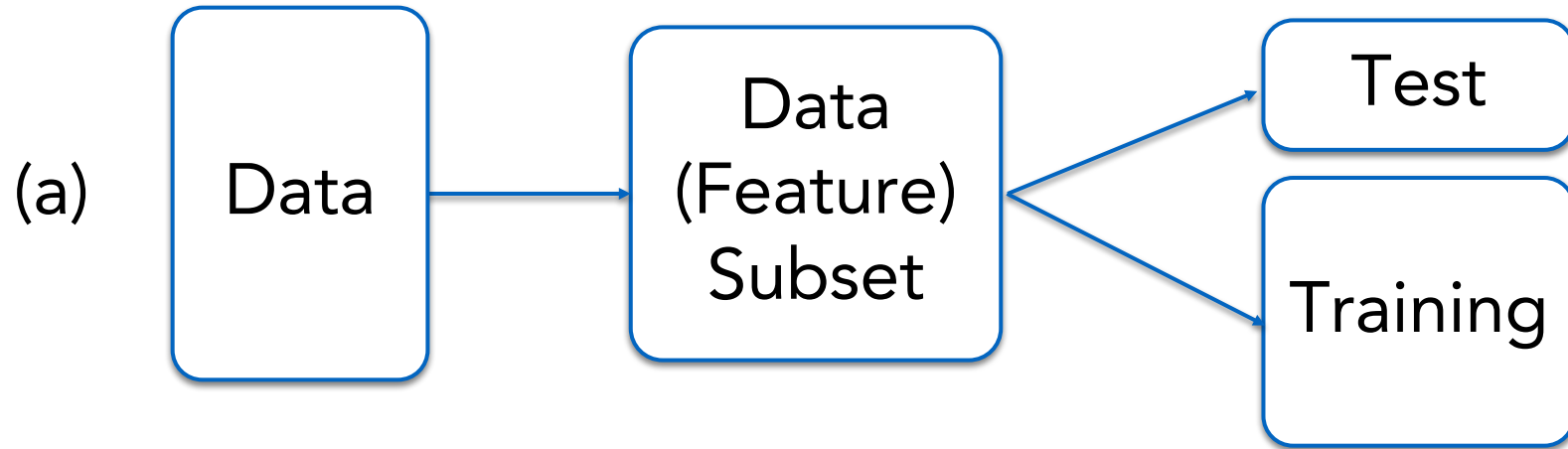
Weakness and Issues

- Feature selection or construction bias issue
 - If the **whole dataset** is used during FS/FC process, the experiments have **FS/FC Bias**
 - **Wrapper**: each evaluation involves a classification training and testing process: **sub-training and sub-test sets**

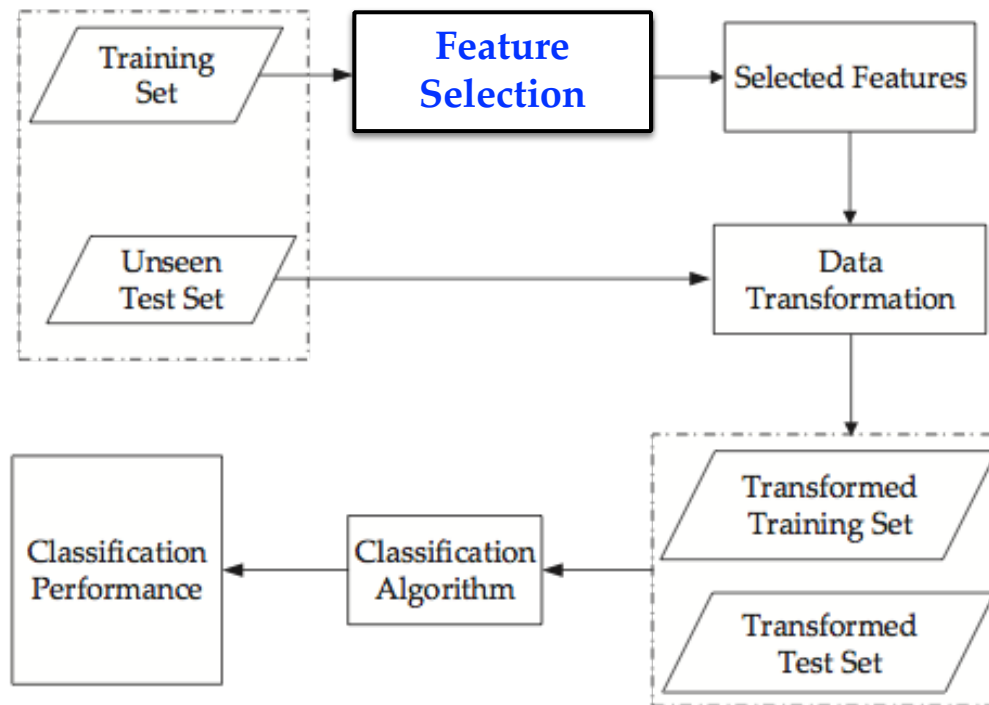


- Generalisation issue
 - especially wrappers: selected or constructed features can easily overfit the wrapped learning algorithm and the training data, leading to poor performance on unseen test data
 - Feature construction

Any problem ?



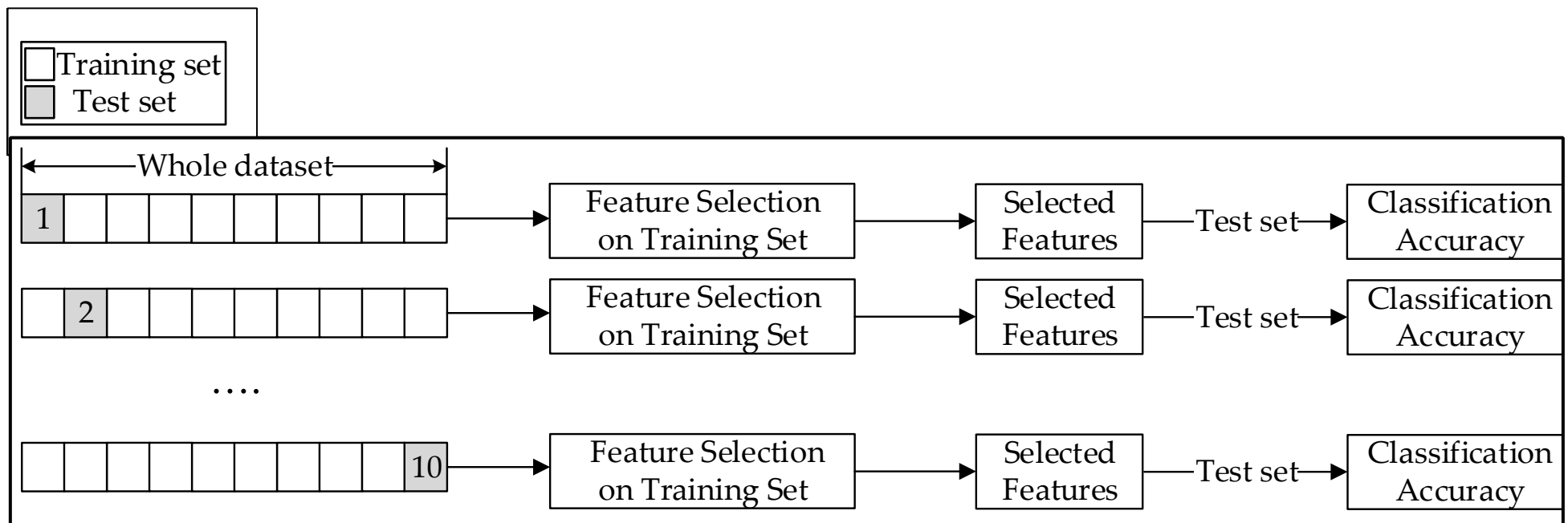
Feature Selection/Construction Bias



- If the **whole dataset** is used during FS/FC process, the experiments(or evaluation) have **FS/FC Bias**
- What if only a small number of instances available ?
 - In classification, use **k-fold cross** validation
 - How to use **k-fold cross validation in FS/FC** to evaluate a FS/FC system ?

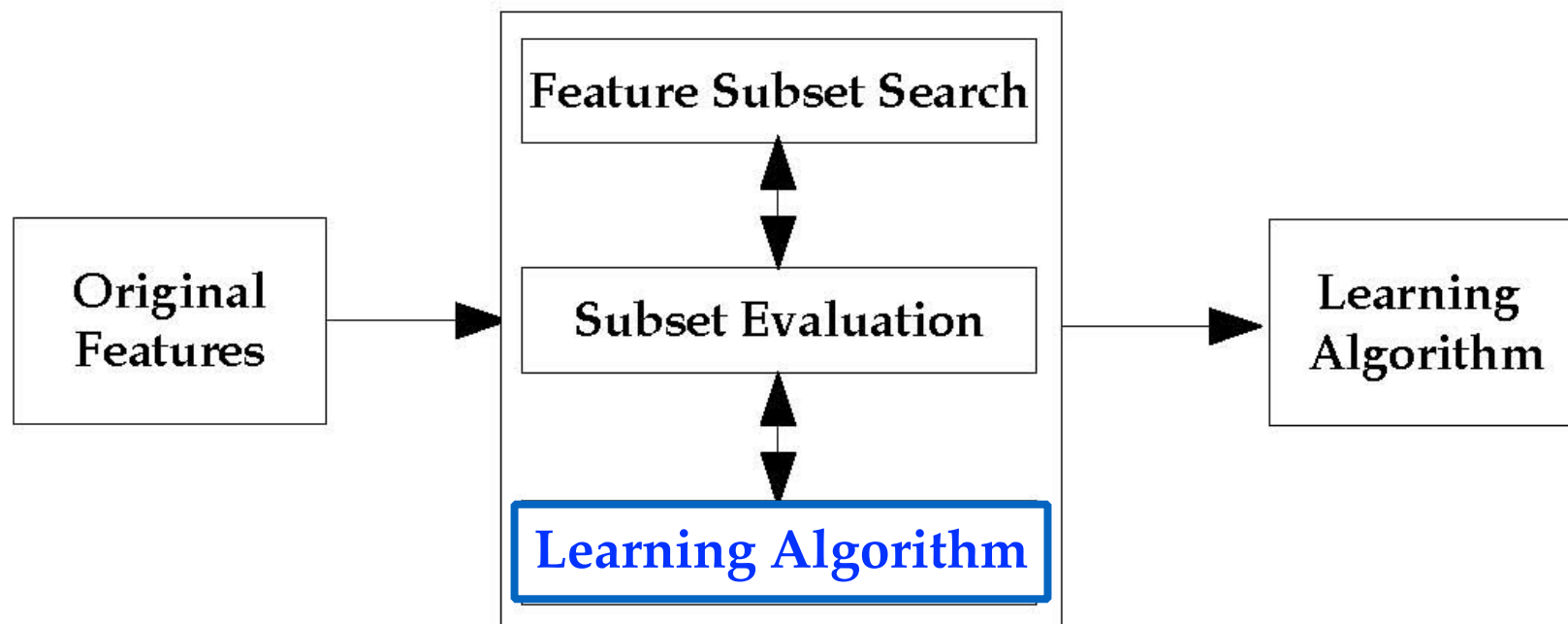
K-CV for FS/FC without Bias — Outer Loop

- k-fold cross validation (K-CV) in FS/FC to evaluate a FS/FC system *without bias*
- Use 10-CV for FS as an example
 - repeat FS 10 times
 - the average accuracy as the final performance



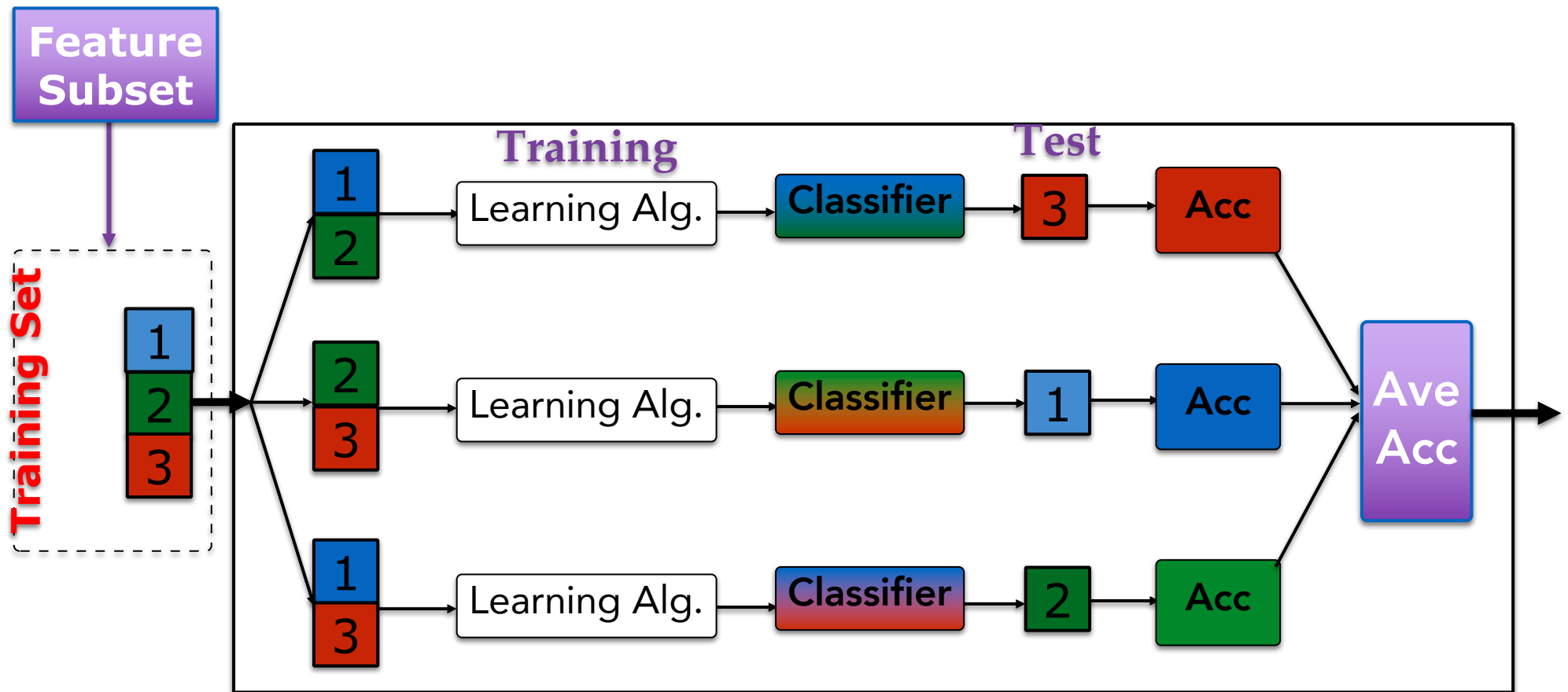
K-CV for *Wrapper* FS/FC without Bias

- **Wrapper**: each evaluation involves a classification training and testing process: sub-training and sub-test sets
- How to use K-CV to evaluate a wrapper FS/FC system ?
- **Outer** loop and **inner** loop



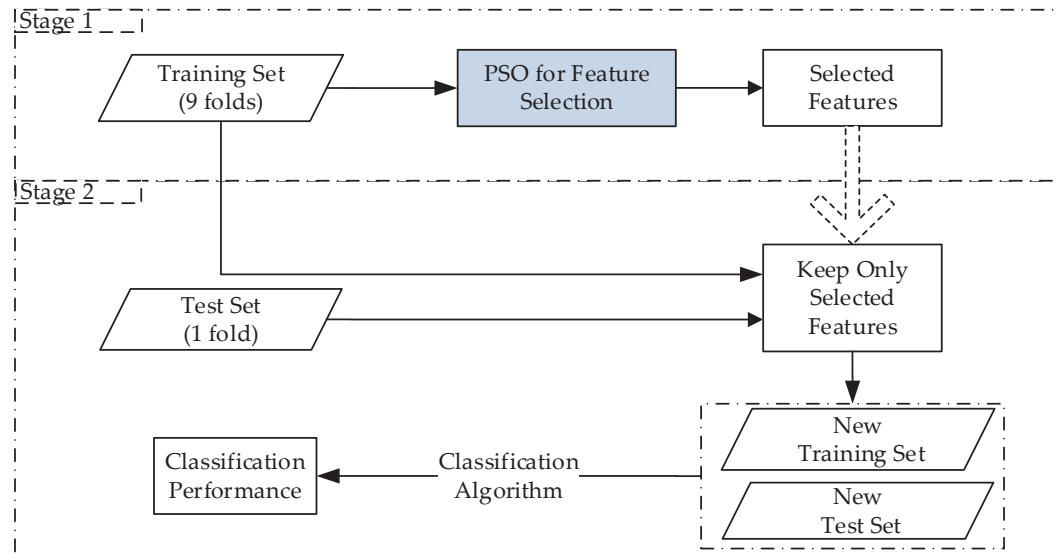
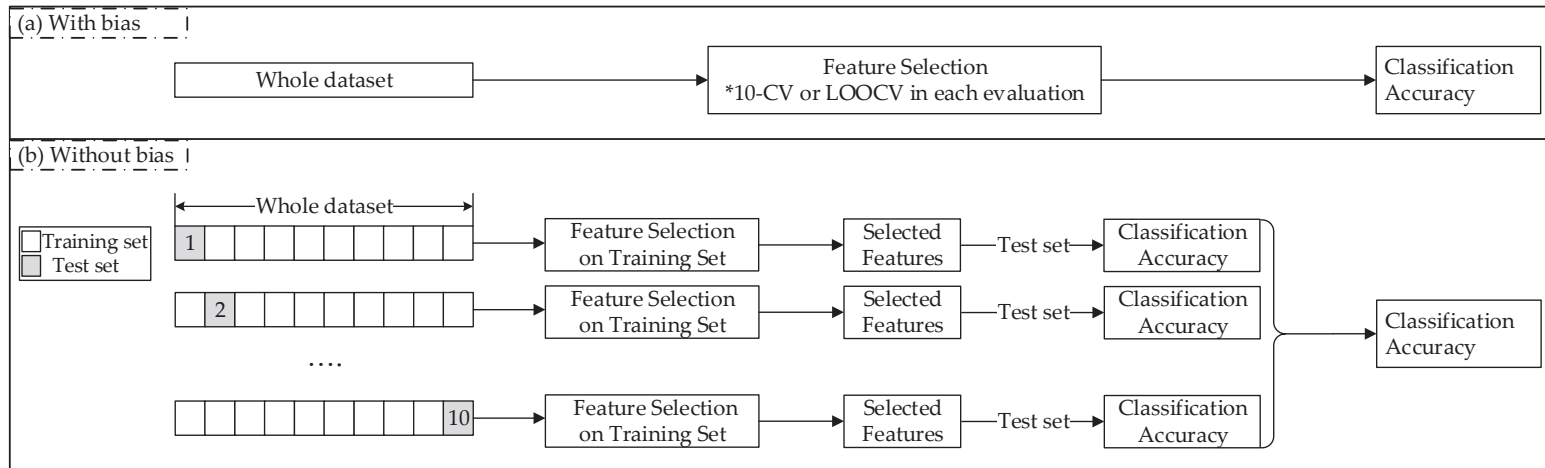
K-CV in Each Evaluation — Inner Loop

- 3-CV as an *inner loop* to *evaluate* a feature subset
- In **each** evaluation:



Ron Kohavi, George H. John, Wrappers for feature subset selection, In Artificial Intelligence, Volume 97, Issues 1–2, 1997, Pages 273-324,

An Example



- Run 30 times of PSO for feature selection in each of the 10 folds
- $30 * 10 = 300$ PSO runs

Feature Selection/Construction Bias

- Ron Kohavi, George H. John, Wrappers for feature subset selection, In *Artificial Intelligence*, Volume 97, Issues 1–2, 1997, Pages 273-324
- Christophe Ambroise and Geoffrey J. McLachlan, Selection bias in gene extraction on the basis of microarray gene-expression data, *Proc. Nat. Acad. Sci. USA*, 2002, vol. 99 (pg. 6562-6566)
- Z. Zhu, Y. S. Ong and M. Dash, "Wrapper-Filter Feature Selection Algorithm Using a Memetic Framework," in *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 37, no. 1, pp. 70-76, Feb. 2007.
- Jerzy Krawczuk and Tomasz Łukaszuk. 2016. The feature selection bias problem in relation to high-dimensional gene data. *Artif. Intell. Med.* 66, C (January 2016), 63-71. DOI=<http://dx.doi.org/10.1016/j.artmed.2015.11.001>
- Binh Tran, Bing Xue and Mengjie Zhang. "Investigation on Particle Swarm Optimisation for Feature Selection on High-dimensional Data: Local Search and Selection Bias", *Connection Science*, vol. 28, no. 3, pp. 270-294, 2016.

Future Directions

- Efficient and effective filter measure for the fitness function:
 - reduce the computational cost,
 - smooth the landscape of the search space,
 - improve the learning and generalisation performance, and
 - increase the interpretability/understandability of the obtained feature set
- Representation
 - Reduce the search space
 - Incorporate more information of about the features, e.g. relative importance of features, feature interactions or feature similarity
 - Embedded feature selection or construction

Future Directions

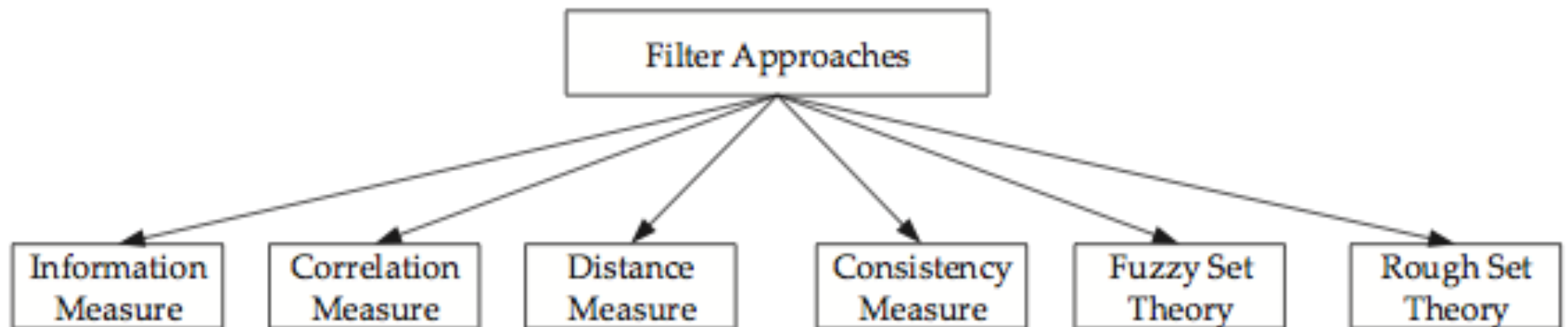
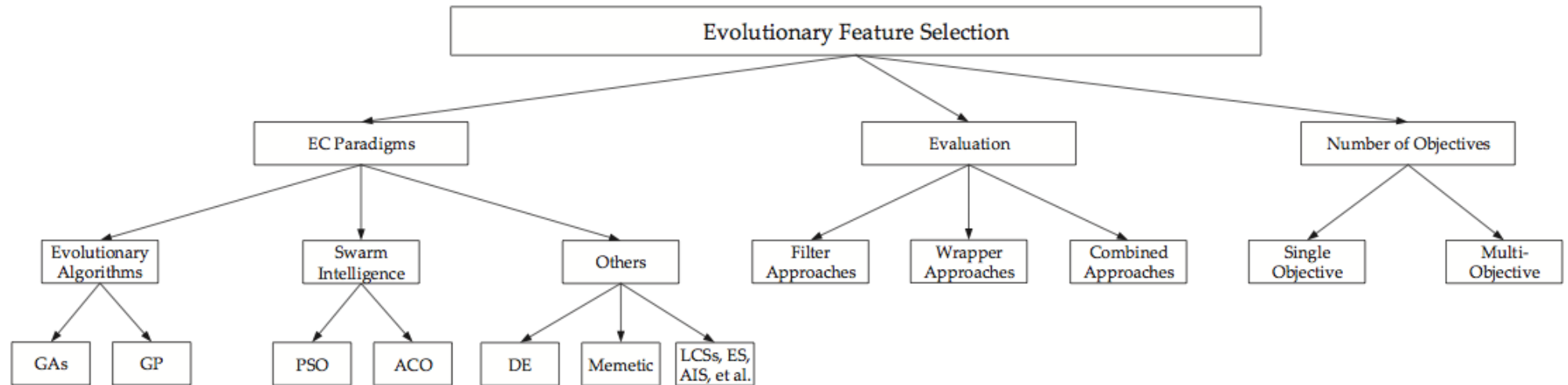
- Search mechanism
 - Evolutionary multi-objective optimisation
 - Combinatorial optimisation
 - Memetic computing
 - Large-scale optimisation
 - Surrogate models
 - Adaptive parameter control techniques
- Feature construction
 - both feature selection and feature construction
- Instance selection and construction
- Combining EC with machine learning *approaches*
- Feature selection and feature construction for other machine learning tasks: clustering and symbolic regression

If you are interested,

- Bing Xue, Mengjie Zhang, Will Browne, Xin Yao. "[A Survey on Evolutionary Computation Approaches to Feature Selection](#)", IEEE Transaction on Evolutionary Computation, vol. 20, no. 4, pp. 606-626, Aug. 2016. doi: 10.1109/TEVC.2015.2504420
- [Tutorial in GECCO 2016](#): Bing Xue and Mengjie Zhang. "Evolutionary Computation for Feature Selection and Feature Construction". Proceedings of 2016 Genetic and Evolutionary Computation Conference (GECCO 2016) Companion, ACM Press. Dever, Colorado, USA. 20-24 July 2016.pp. 861-881
- More: <http://homepages.ecs.vuw.ac.nz/~xuebing/index.html>

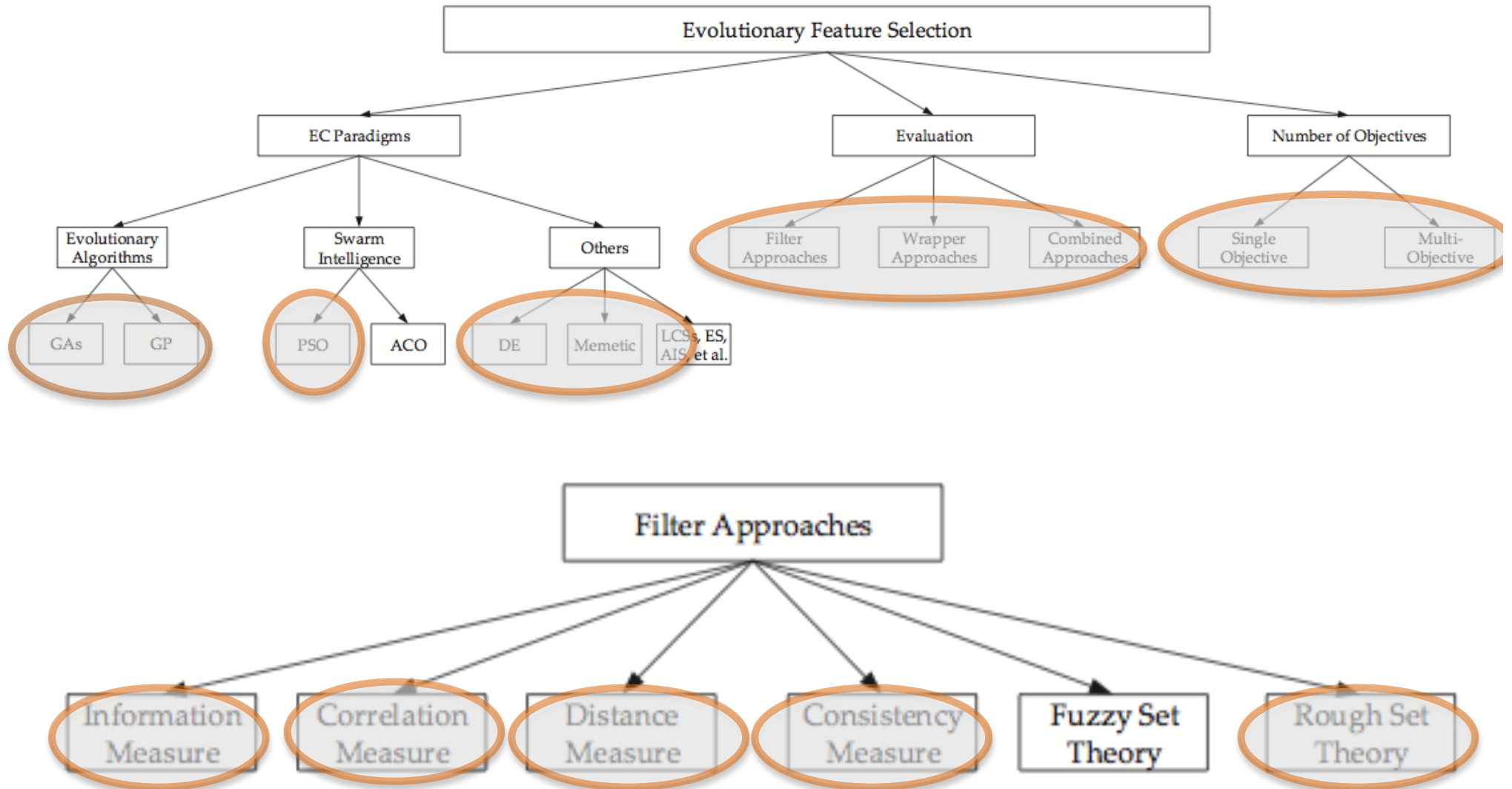
Work from ECRG

- More: <http://homepages.ecs.vuw.ac.nz/~xuebing/index.html>



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- More: <http://homepages.ecs.vuw.ac.nz/~xuebing/index.html>



Acknowledgement

- Thanks everyone in the Evolutionary Computation Research Group at Victoria University of Wellington, New Zealand



Activities in 2018

- Task Force on Evolutionary Computation for Feature Selection and Construction, IEEE CIS
- Proposed Special session on Evolutionary Feature Selection and Construction in IEEE WCCI/CEC2018
- Proposed Special session on Transfer Learning in Evolutionary Computation in IEEE IEEE IEEE WCCI/CEC2018
- IEEE Symposium on Computational Intelligence in Feature Analysis, Selection, and Learning in Image and Pattern Recognition (FASLIP) in IEEE SSCI 2018

2019 IEEE Congress on Evolutionary Computation

June 2019, Wellington, New Zealand





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- Combinatorial optimisation: scheduling, routing, web services
- Computer vision and image analysis
- Multi- and many- criteria optimisation
- Transfer learning

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- Evolutionary Computation Research Group, Victoria University of Wellington, New Zealand
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 - Evolutionary Image Analysis
 - Classification and Clustering
 - Transfer Learning
- Huawei NZ and NZ Marsden Funded Project
- Contact: Mengjie.Zhang@ecs.vuw.ac.nz or Bing.Xue@ecs.vuw.ac.nz