Lecture 12

Dimensionality reduction

Information Systems
(Machine Learning)

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Lecture plan

- Dimensionality Reduction
- Feature Selection
- Feature Extraction
- More feature selection

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Dimensionality Reduction

What is dimensionality reduction?

- Collected many features?
- Maybe more than you need?
- Simplify the data in a rational and useful way?

Dimensionality Reduction

Why should we look at dimensionality reduction?

- Speed
- Space
- Quality
- Features nature

Dimensionality Reduction

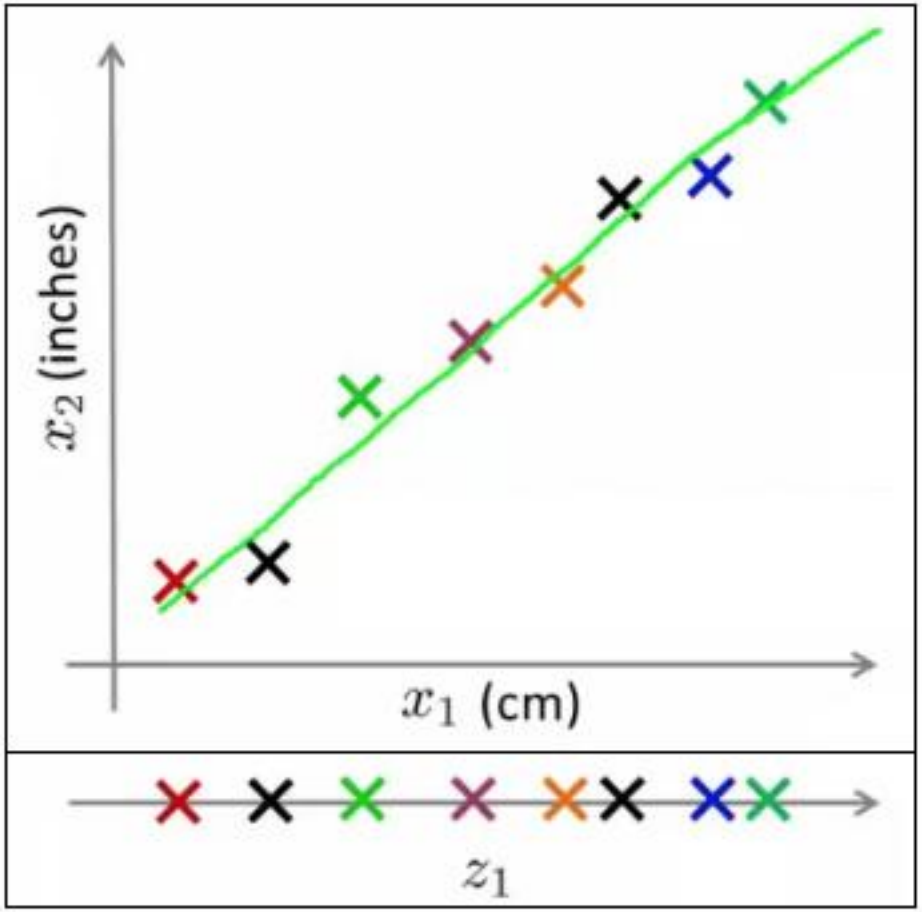
Curse of dimensionality:

- The dimensionality increases
- The volume of the space increases so fast
- That the available data become sparse

Dimensionality Reduction

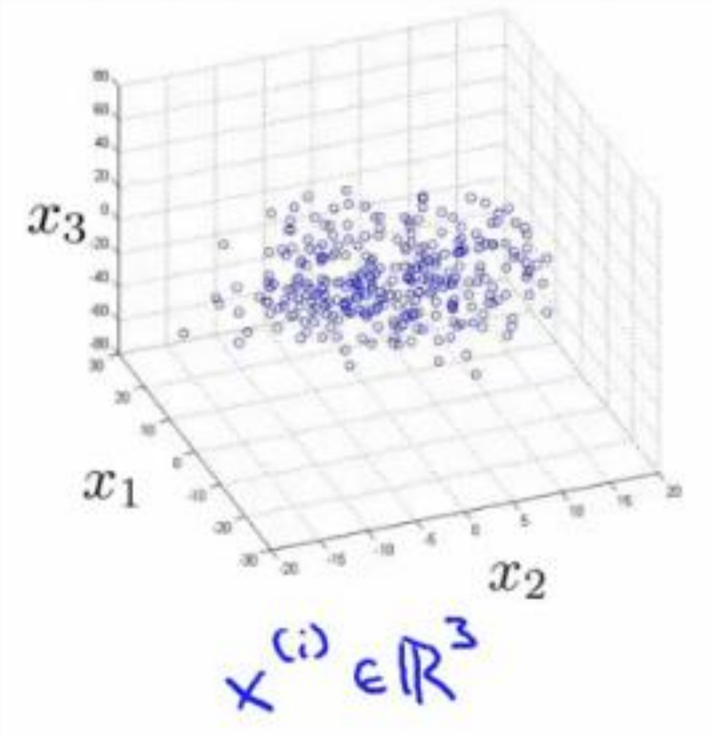
So what does dimensionality reduction mean?

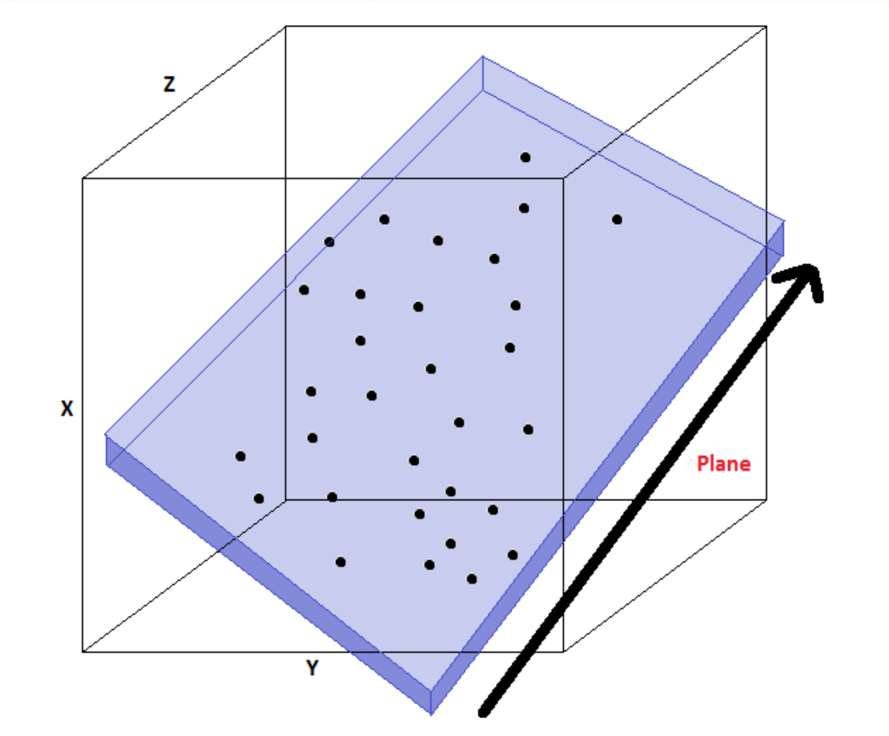
- Let plot a line
- Take exact example and record position on that line
- So we can present x^1 as 1D number



Dimensionality Reduction

Another example 3D -> 2D





Lecture plan

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- More feature selection

Feature Selection

Goals of feature selection:

- Avoiding retraining and improving the quality of classification
- Best understanding of models
- Boosting of classifying models

Feature Selection

Type of elected attributes:

- Redundant attributes - do not carry any additional information
- Irrelevant attributes - are not generally informative

Feature Selection

Evaluation methods of feature selection:

- At various datasets
- With different classifiers (if possible)
- By adding to datasets noise and target vectors

Feature Selection

Feature selection types:

- Filter methods
    a. Univariate
    b. Multivariate
- Wrapper methods
    a. Deterministic
    b. Randomized
- Embedded methods

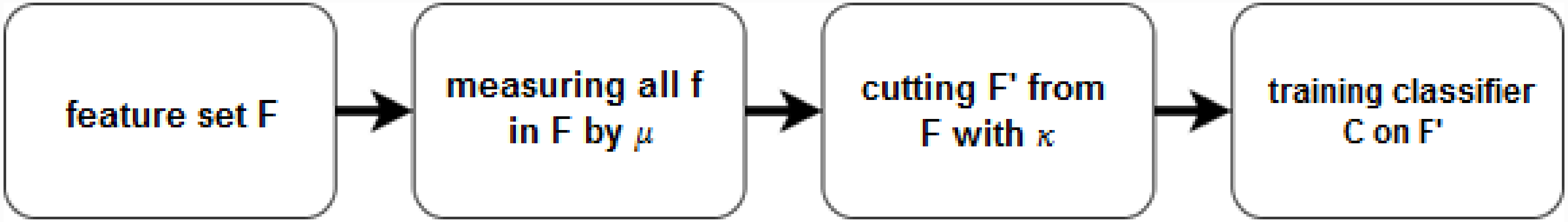
Feature Selection

Filter methods:

- Feature quality measure μ – relevance of the feature (or subset of features for multivariate) to the label
- Cutting rule κ – decides what features to leave based on the μ

Feature Selection

Filter methods:



Feature Selection

Filter methods:

Evaluate the quality of certain attributes and remove the worst of them.

+ Simple to compute, easy to scale

- Ignore the relationships between attributes or features used by classifier

Feature Selection

Examples of filter methods:

- Univariate:
  - Euclidian distance
  - Information gain
  - Spearman corellation coefficient
- Multivariate:
  - CFS
  - MBF

Feature Selection

Spearman corellation coefficient

$$\rho = \frac{\sum_{ij}(x_{ij}-\bar{x}_j)(y_i-\bar{y})}{\sqrt{\sum_{ij}(x_{ij}-\bar{x}_j)^2 \sum_i (y_i-\bar{y})^2}}$$

$$\rho \in [-1; 1]$$

$$\rho \to 0$$

Python SciPy:

`scipy.stats.pearsonr(x, y)`

Parameters:	**x** : *(N,) array_like* Input **y** : *(N,) array_like* Input
Returns:	*(Pearson's correlation coefficient,* 2-tailed p-value)

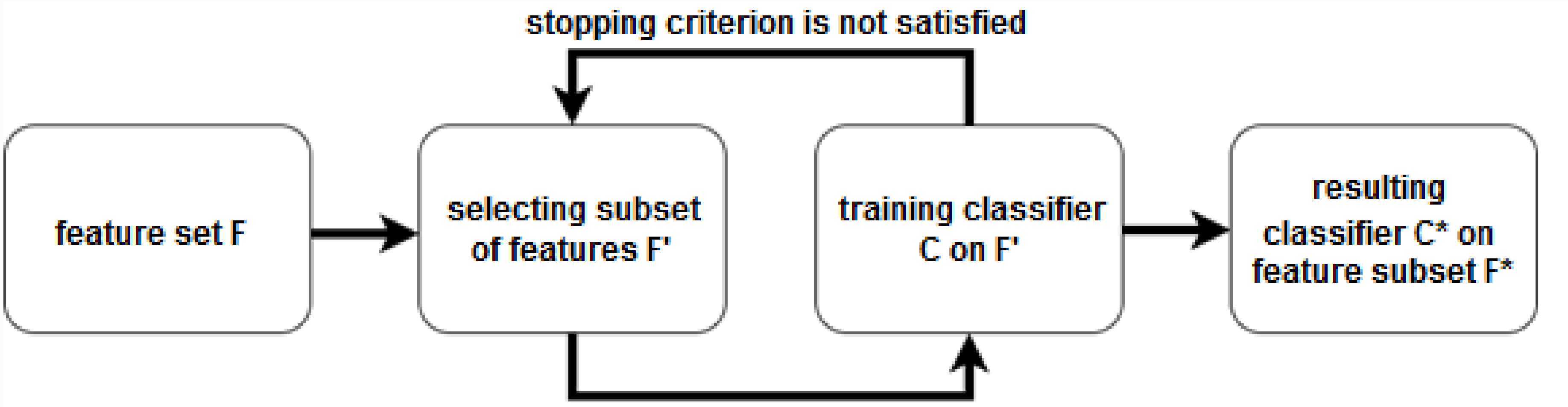
Feature Selection

Weka:

```
ASEvaluation evaluator = new CorrelationAttributeEval();
Ranker ranker = new Ranker();

// ranker.setThreshold(0.05); or ranker.setNumToSelect(10);

AttributeSelection selection = new AttributeSelection();

selection.setInputFormat(heavyInstances);

selection.setEvaluator(evaluator);
selection.setSearch(ranker);
Instances lightInstances = Filter.useFilter(heavyInstances, selection);
```

Feature Selection

Wrapper methods:



Feature Selection

Wrapper methods:

Get a subset of attributes of the source

+ Higher accuracy than Filtering

+ Consider the relationships between attributes

+ Direct interaction with the classifier

- Long computing time

- The probability of overfitting

Feature Selection

Examples of Wrapper methods:

- Deterministic:
  - SFS (sequential forward selection)
  - SBE (sequential backward elimination)
  - SVM-RFE
- Randomized:
  - Randomized Hill Climbing
  - Genetic Algorithms

Feature Selection

SVM-RFE

- Train SVM on training subset
- Rank features by received weights
- Throw out last features
- Repeat until the necessary amount of features will left

Feature Selection

SVM-RFE (Python example)

```
X = np.array([[1,2], [5,8], [1.5,1.8], [8,8],
[1,0.6], [9,11]])
y = [0,1,0,1,0,1]
```

Let use SVM:

```
clf = svm.SVC(kernel='linear', C = 1.0)
```

Let fit our model:

```
clf.fit(X,y)
```

Let predict predict something:

```
print(clf.predict([0.58,0.76]))
```

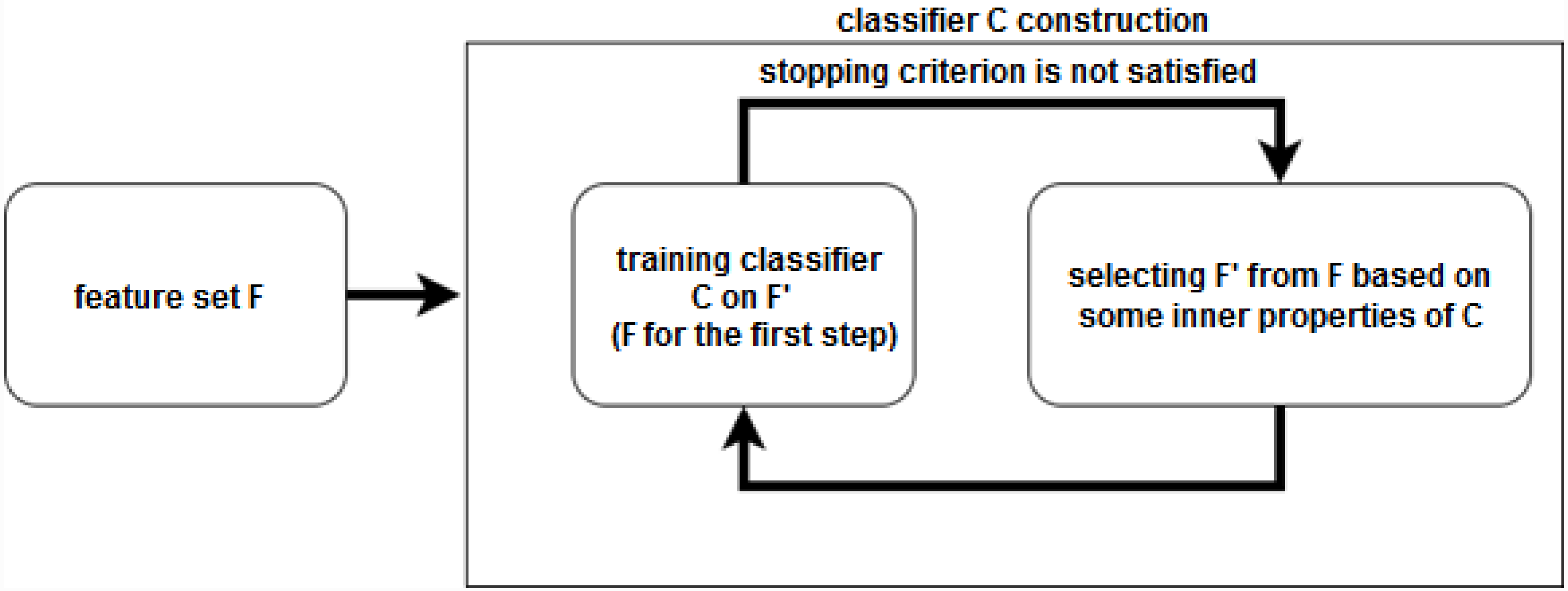
Feature Selection

Embedded

- Take into account the particular classifier
- Use individual method for each classifier

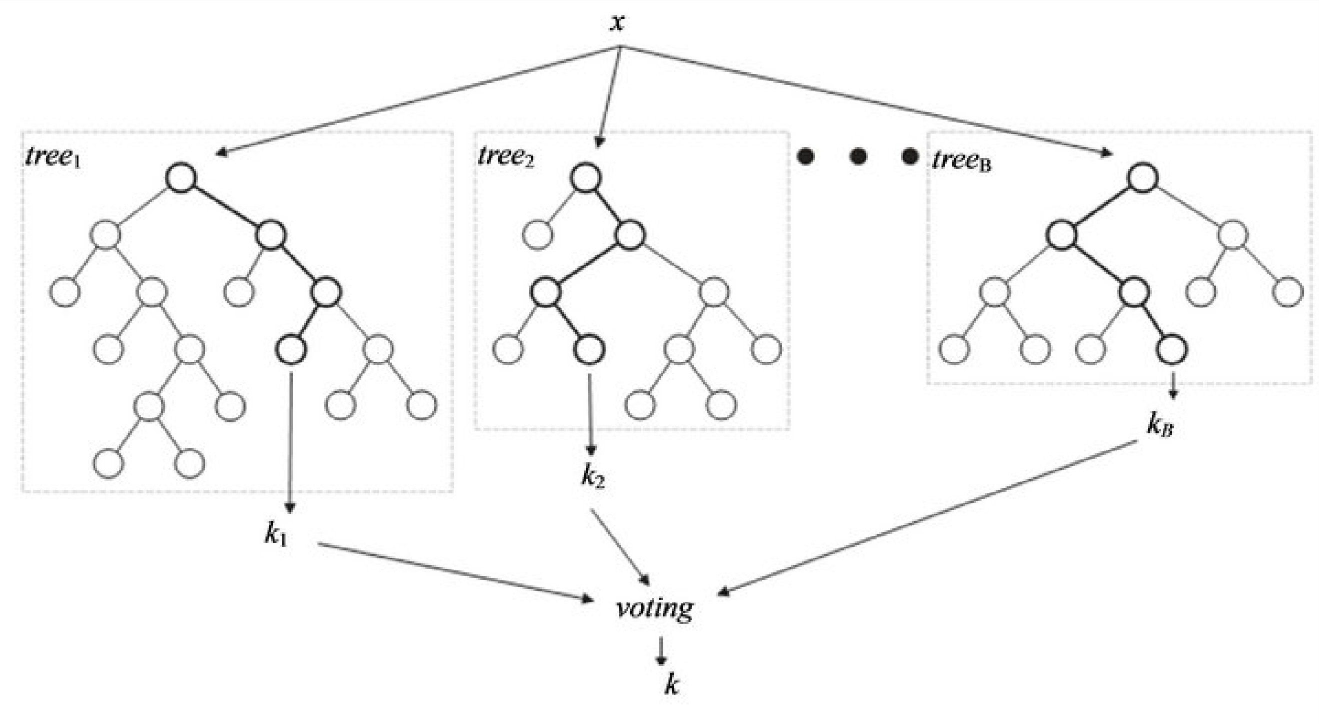
Feature Selection

Embedded



Feature Selection

Random Forest:



Feature Selection

Random Forest (Python example):

```
# Import the random forest package
from sklearn.ensemble import RandomForestClassifier
# Create the random forest object which will include all the parameters for the fit
forest = RandomForestClassifier(n_estimators = 100)
# Fit the training data to the Survived labels and create the decision trees
forest = forest.fir(train_data[0::, 1::], train_data[0::, 0])
# Take the same decision trees and run it on the test data
output = forest.predict(test_data)
```

Feature Selection

Random Forest (Weka):

```
int numFolds = 10;
br = new BufferedReader(new FileReader(“data.arff"));

	Instances trainData = new Instances(br);
	trainData.setClassIndex(trainData.numAttributes() - 1);

	RandomForest rf = new RandomForest();
	rf.setNumTrees(100);

	rf.buildClassifier(trainData);
	Evaluation evaluation = new Evaluation(trainData);
	evaluation.crossValidateModel(rf, trainData, numFolds, new Random(1));

	System.out.println("F-measure=  " + evaluation.fMeasure(0));
```

Lecture plan

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- More feature selection

Feature extraction

Motivation:

Collect a large data set (50 dimensions)

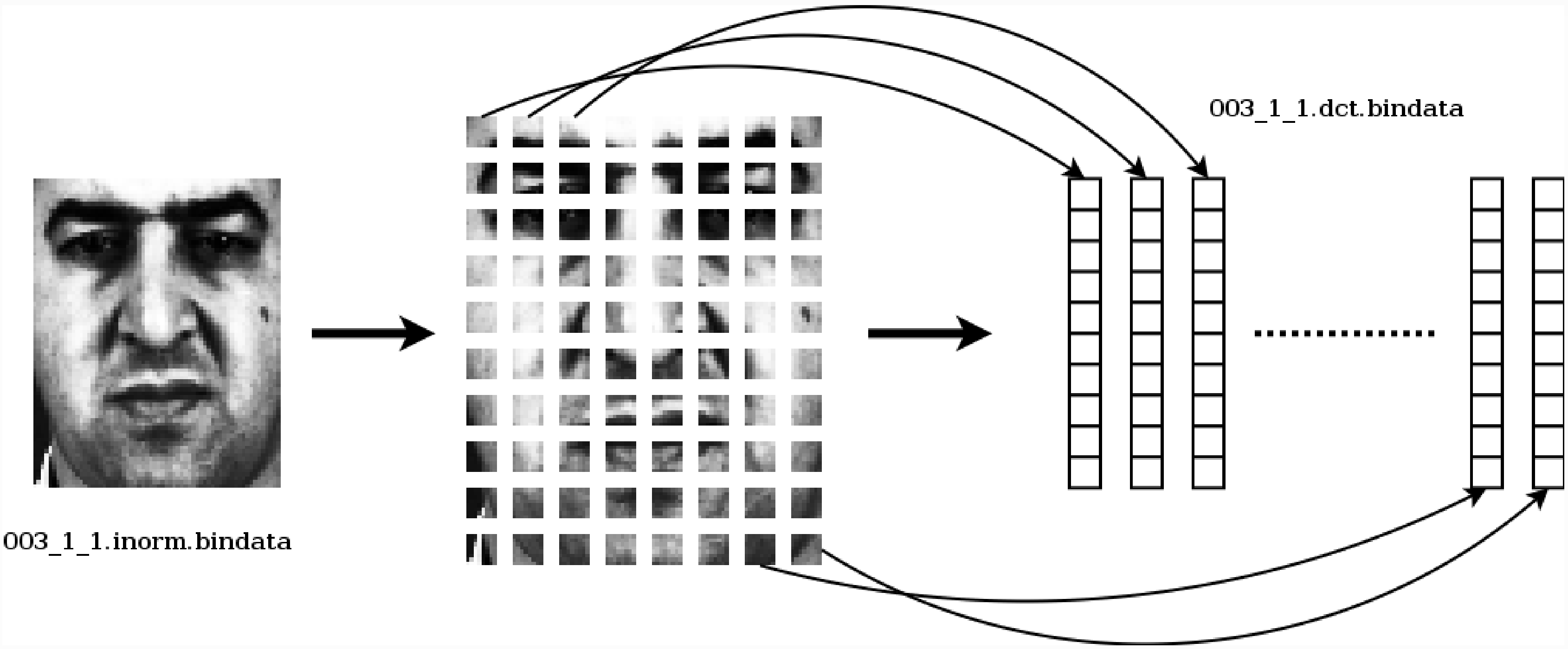
Country	GDP (trillions of US$)	Per capita GDP (thousands of intl. $)	Human Develop-ment Index	Life expectancy	Poverty Index (Gini as percentage)	Mean household income (thousands of US$)	...
Canada	1.577	39.17	0.908	80.7	32.6	67.293	...
China	5.878	7.54	0.687	73	46.9	10.22	...
India	1.632	3.41	0.547	64.7	36.8	0.735	...
Russia	1.48	19.84	0.755	65.5	39.9	0.72	...
Singapore	0.223	56.69	0.866	80	42.5	67.1	...
USA	14.527	46.86	0.91	78.3	40.8	84.3	...
...	...	...	...	...	...	...	

Feature extraction

Using feature extraction reduction come up with a different feature representation

Country	z_1	z_2
Canada	1.6	1.2
China	1.7	0.3
India	1.6	0.2
Russia	1.4	0.5
Singapore	0.5	1.7
USA	2	1.5
...	...	...

Feature Extraction



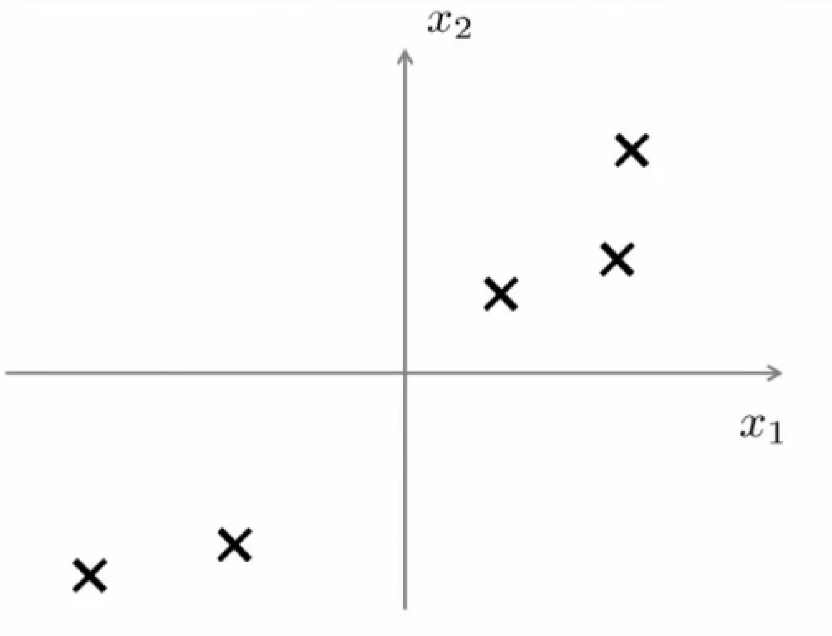
Feature Extraction

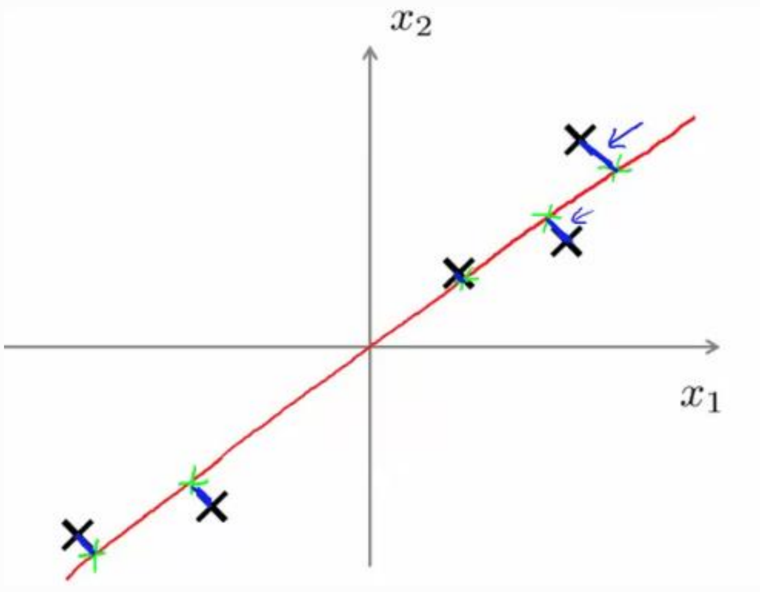
Feature Extraction

- Reducing the amount of resources required to describe a large set of data
- New features
- Linear and nonlinear

Feature Extraction

PCA tries to find the surface (a straight line in this case) which has
the minimum projection error





Feature Extraction

PCA (Python example)

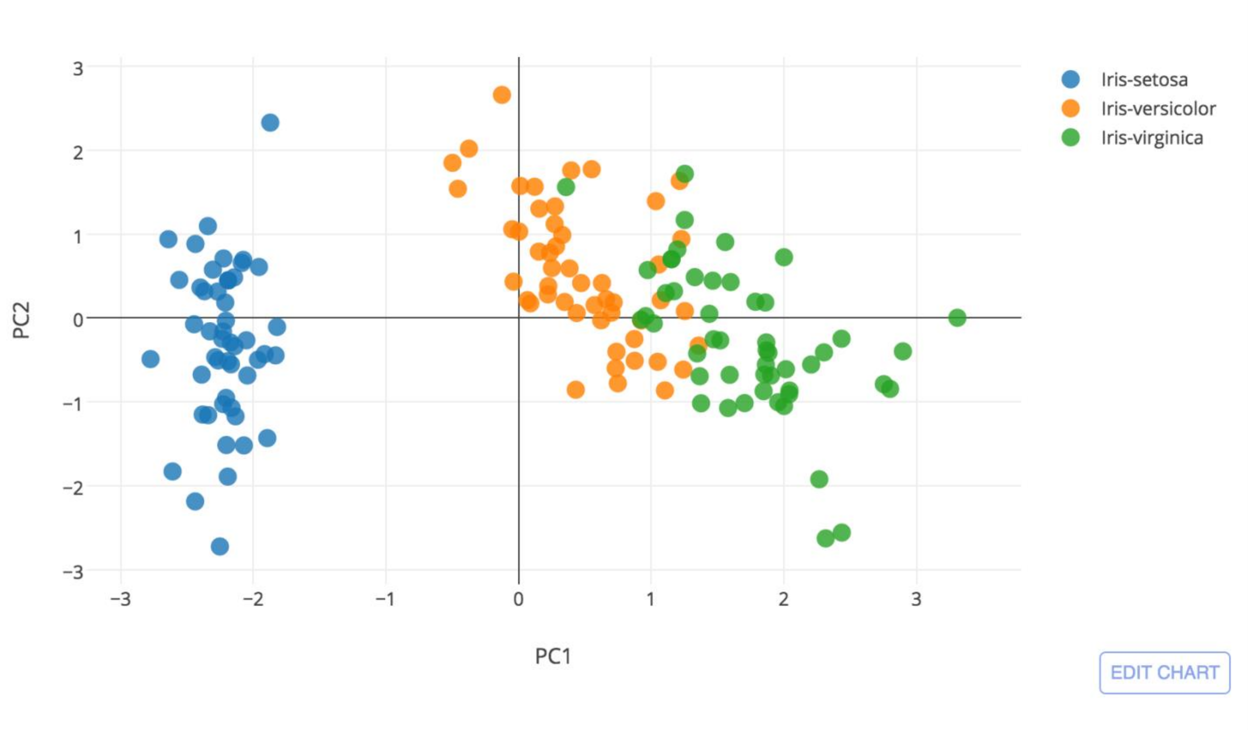
Let use Iris-data and import PCA

```
from sklearn.decomposition import PCA as sklearnPCA
sklearn_pca = sklearnPCA(n_components=2)
Y_sklearn = sklearn_pca.fit_transform(X_std)
```

Feature Extraction

PCA (Python example)

Let plot PCA-results



Feature Extraction

PCA (Weka)

```
PrincipalComponents pca = new PrincipalComponents();

pca.setInputFormat(trainingData);
pca.setMaximumAttributes(100);
newData = Filter.useFilter(newData, pca);
```

Feature Extraction

TSNE

- Nonlinear
- Used for visualization
- Tries to save the distance relationships between objects

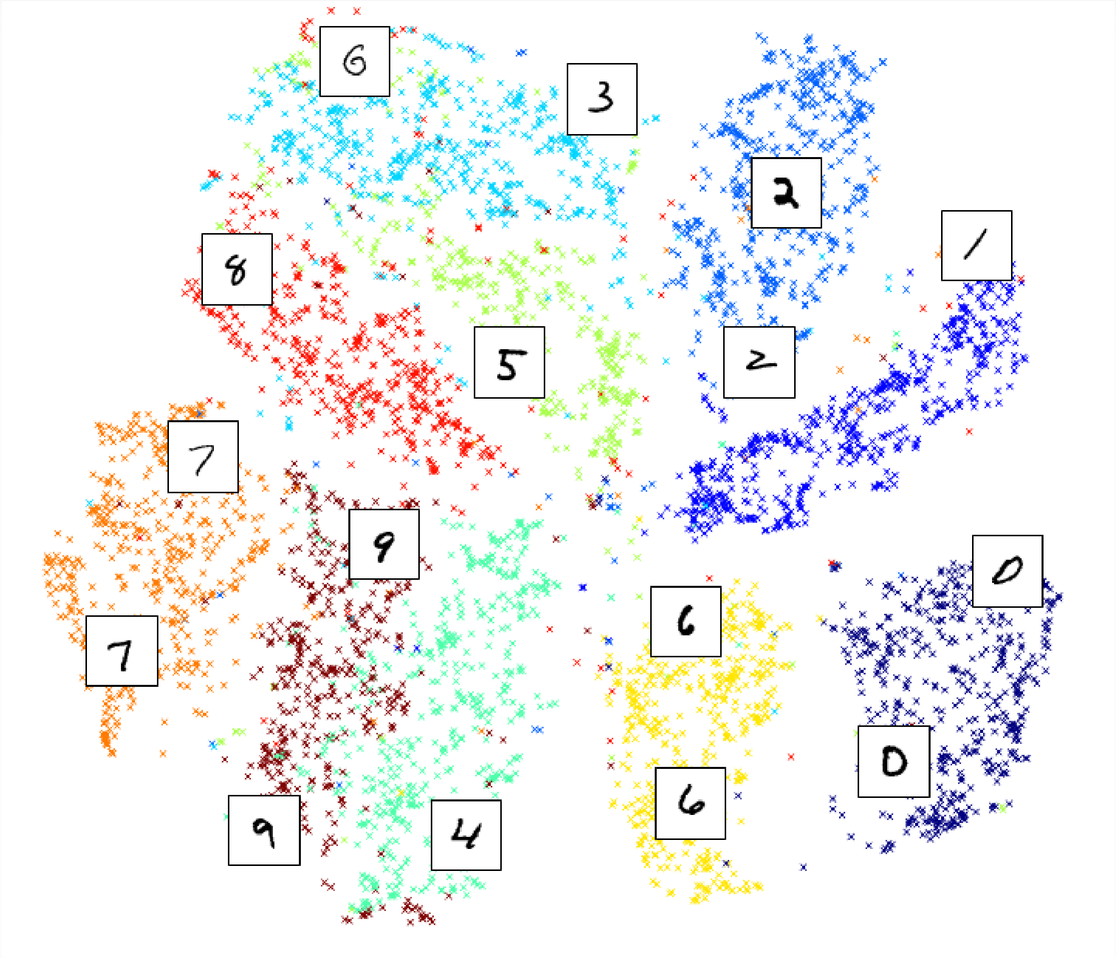
Feature Extraction

TSNE

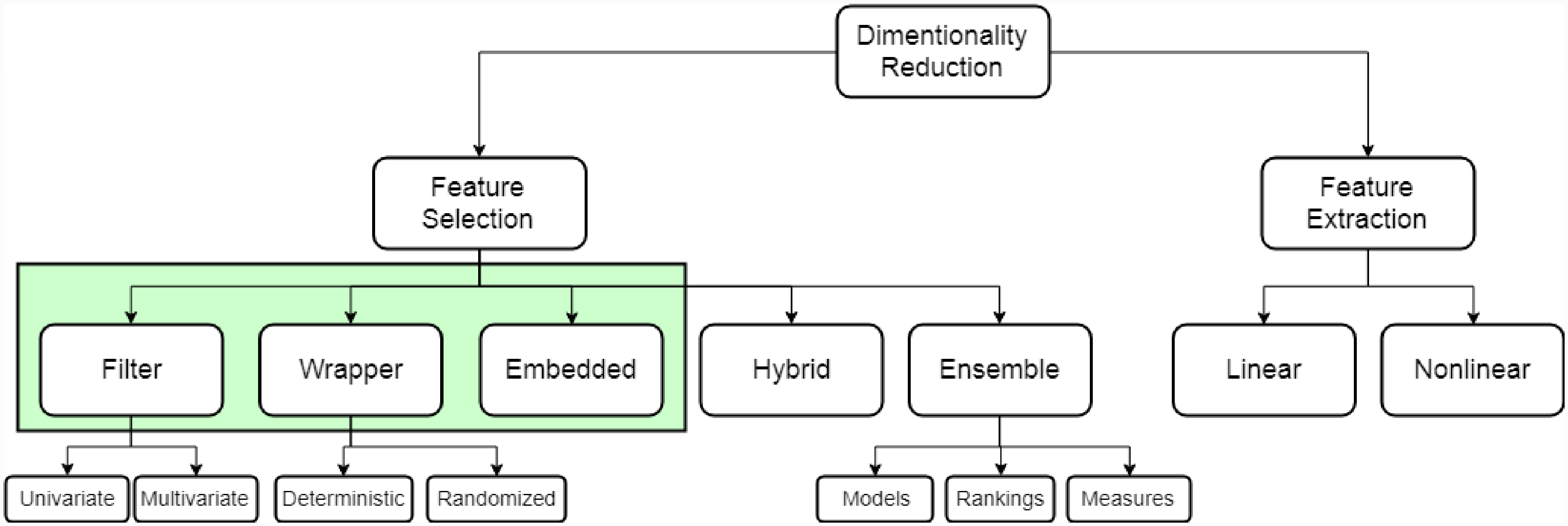
1. Builds a probability distribution over all pairs of objects: similar with high, dissimilar with low
2. Defines a probability distribution over all pairs of objects in 2d space
3. Minimizes the Kullback–Leibler divergence between the two distributions with respect to the locations of the points in the map

Feature Extraction

TSNE
MNIST



Dimensionality reduction



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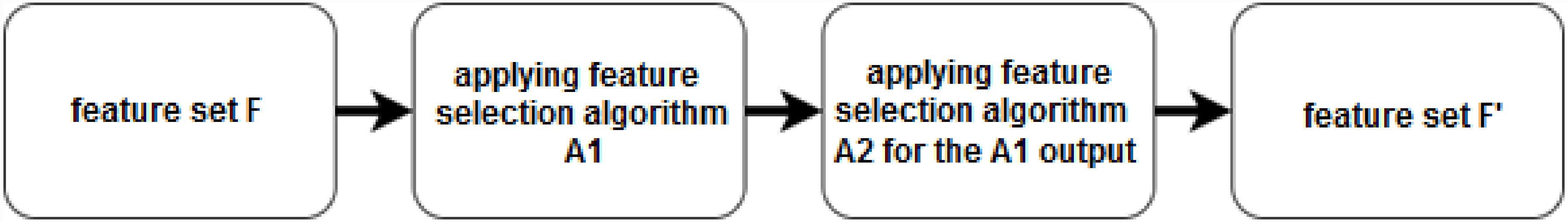
More feature selection

Hybrid



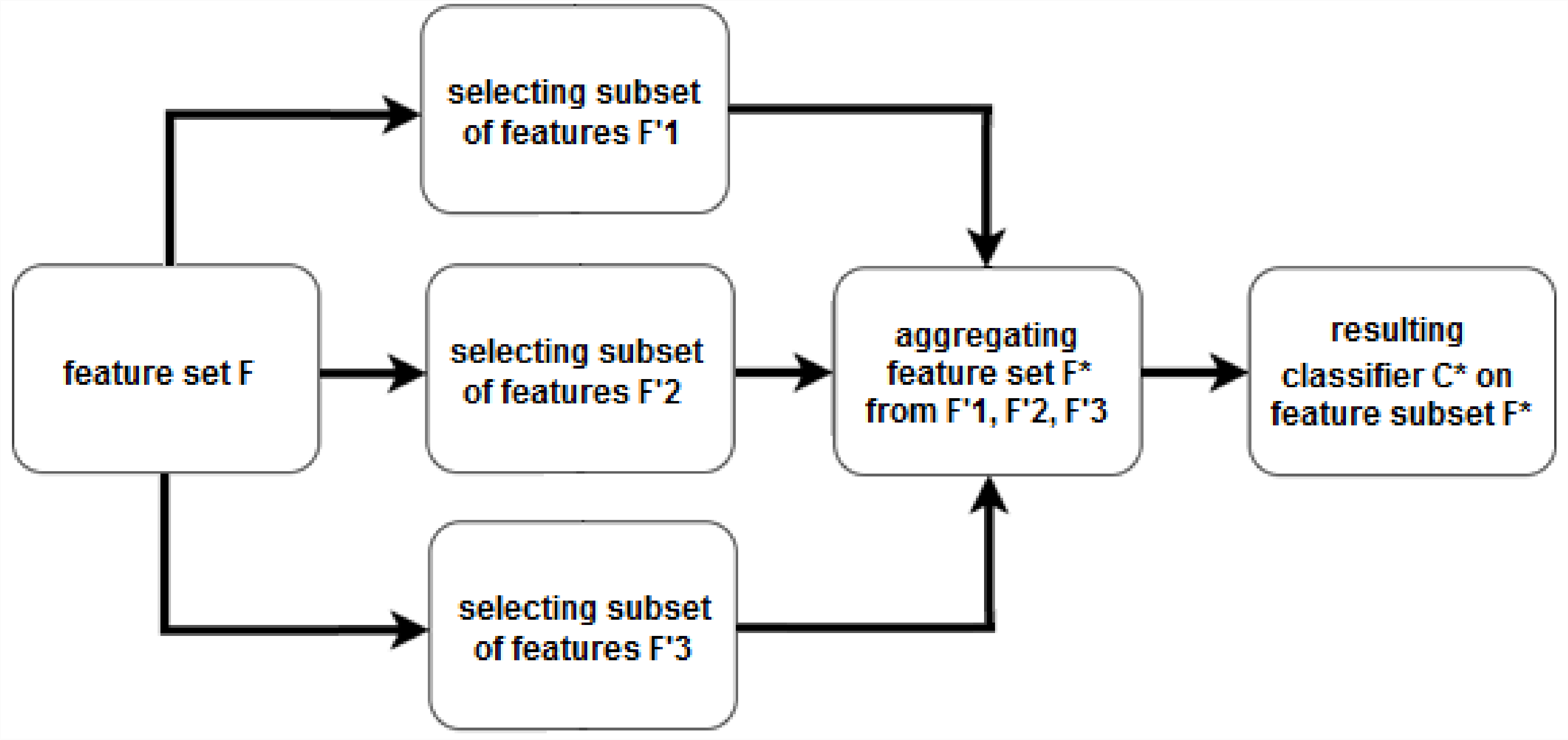
More feature selection

Hybrid

- Combines strengths of different approaches
- Most common case: filter (or set of filters) and then wrapper or embedded

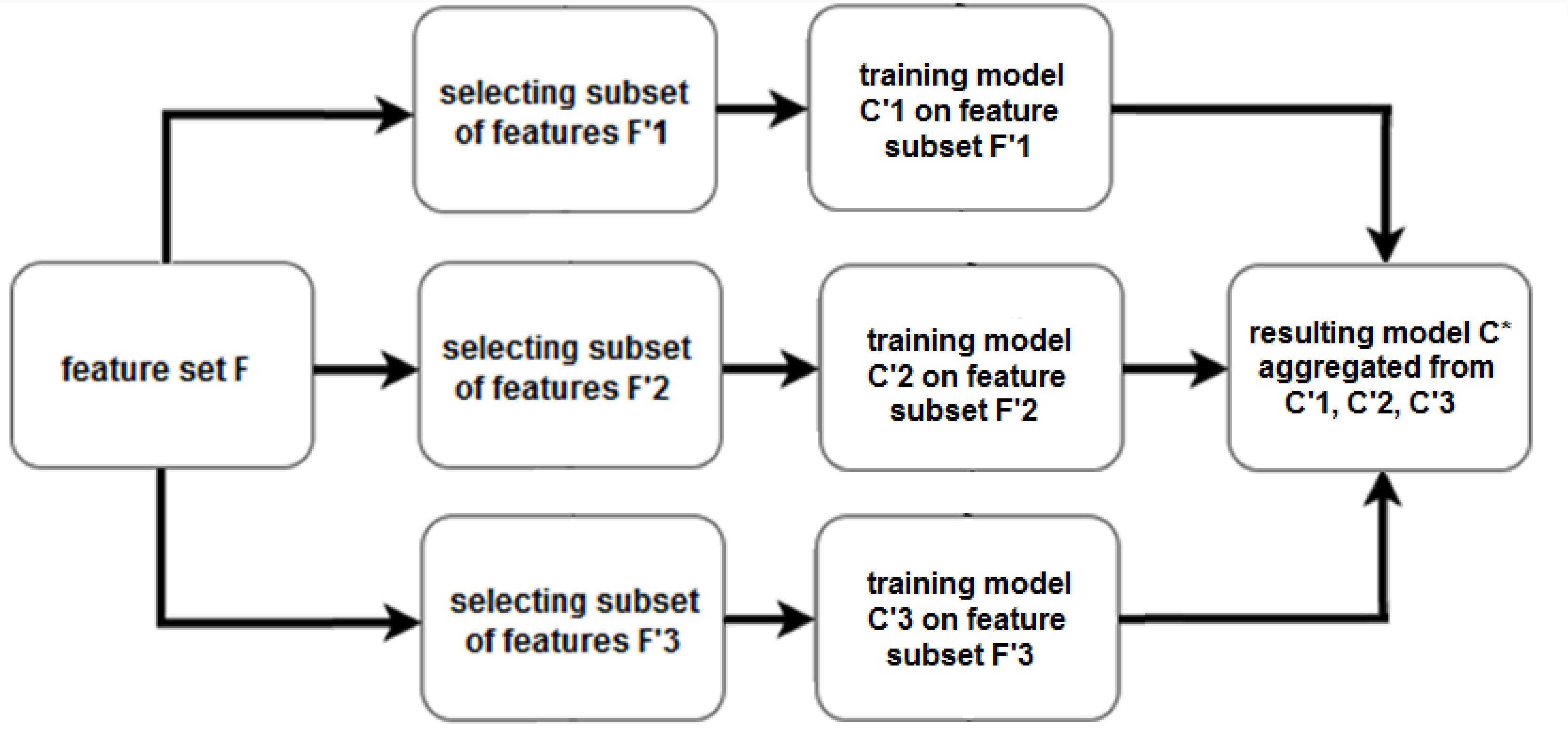
More feature selection

Ensemble (general)



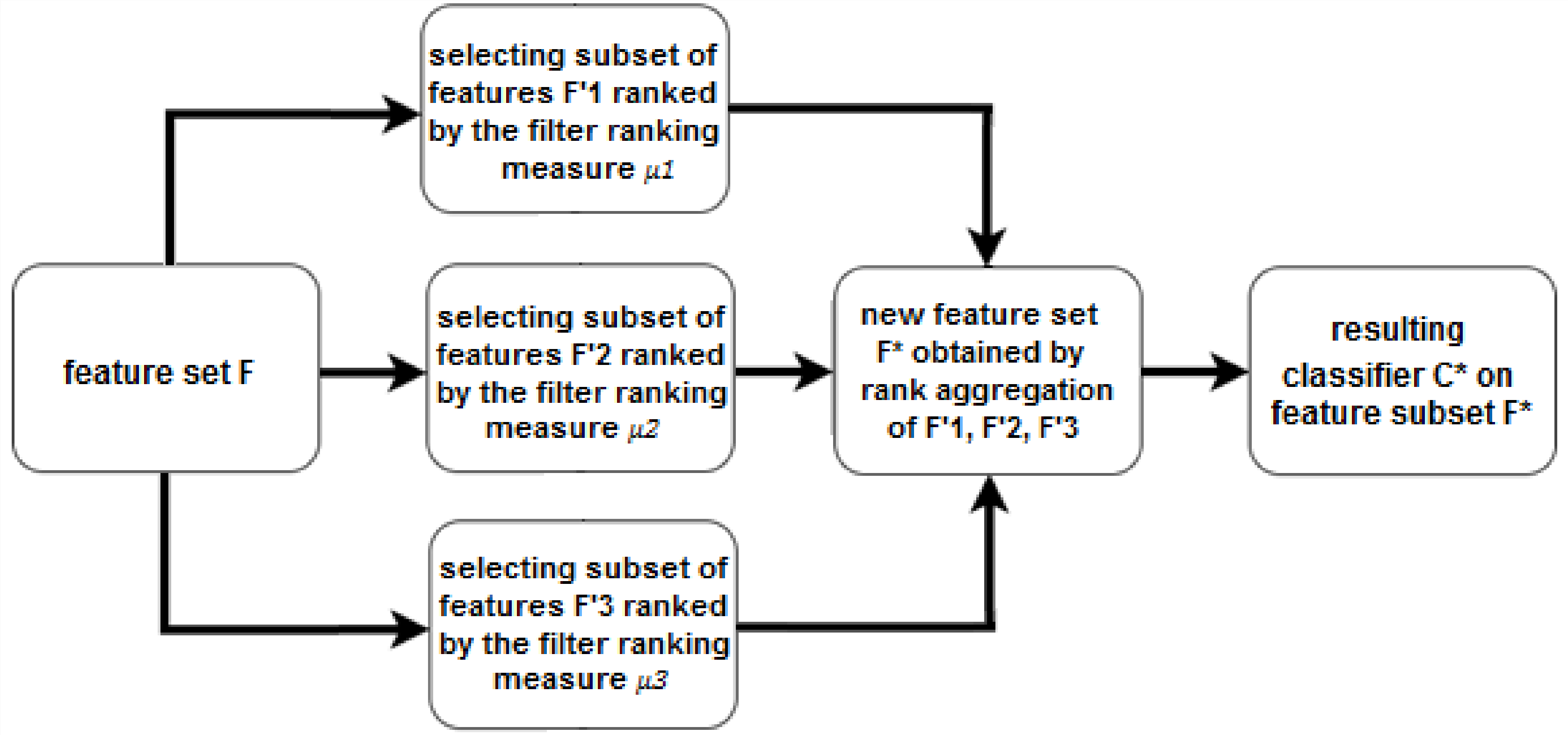
More feature selection

Ensemble (models)



More feature selection

Ensemble (rankings)



More feature selection

Ensemble (measures)