



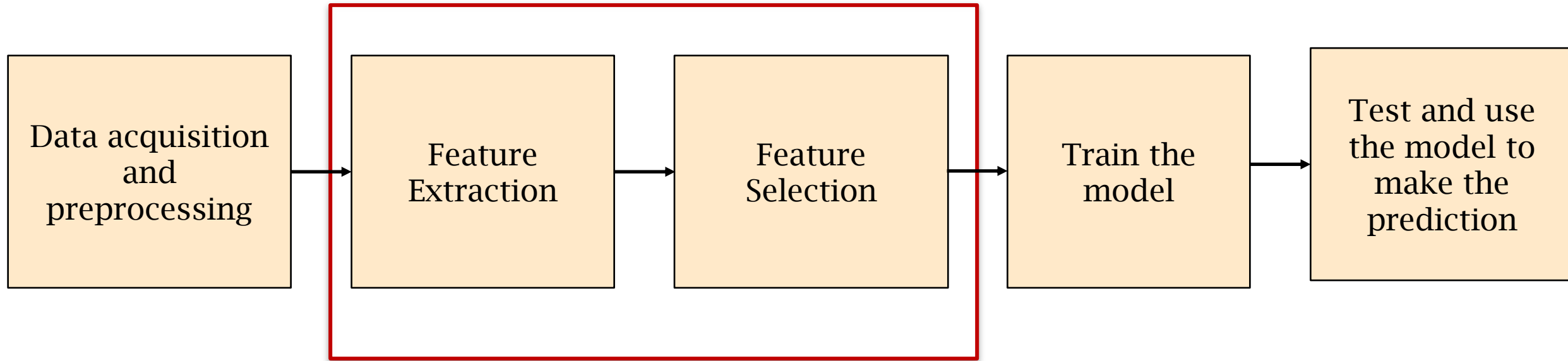
CS 522 – Selected Topics in CS

Lecture 03 – Feature Engineering

+ Topics to be covered

- What is Feature
- Feature Engineering
- Feature Extraction
- Feature Selection
- Feature Encoding

Feature Engineering



Sometimes feature extraction is a part of preprocessing.
Feature extraction also include feature encoding, standardization and normalization

+ What is Feature (Review)

- The *initial pick* of feature is always an *expression* of *prior knowledge*.
- *Images* → pixels, contours, textures, etc.
- *Signal* → samples, spectrograms, etc.
- *Time series* → ticks, trends, reversals, etc. العلامات - اتجاهات - انعكاسات
- *Biological data* → DNA, marker sequences, genes, etc.
- *Text data* → words, grammatical classes and relations, etc.

+ What is Feature Engineering ?

- Feature engineering is the *science* (and art) of *extracting* information from *raw data*.
- It is a process that *transform raw data* into *features* that *better* represent the *underlying problem to the predictive models*, resulting in *improved* model *accuracy* on *unseen* data.

Machine Learning Mastery:

Jason Brownlee

- Feature Engineering is a *Representation Problem*
 - Machine learning algorithms *learn a solution to a problem from sample data*.
 - In this context, feature engineering asks: *what is the best representation of the sample data to learn a solution to your problem?*

+ What is Feature Engineering ?

- *Some machine learning projects succeed and some fail.*
- *What makes the difference?*
- *Easily the most important factor is the features used.*

A few useful things to know about Machine Learning: Pedro Domingos

A feature is an *individual measurable property* or *characteristic* of a phenomenon being *observed*.

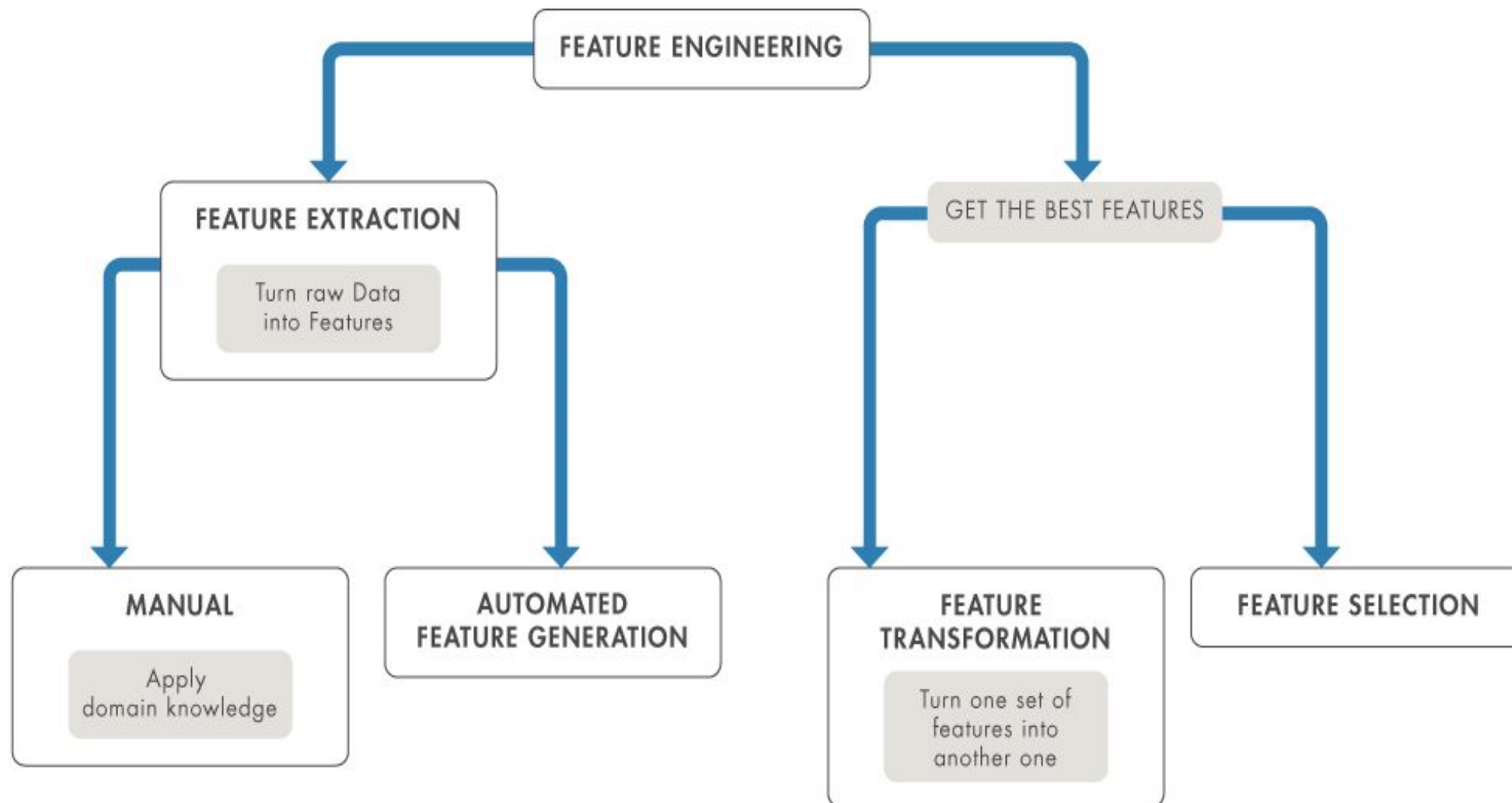
+ Goal of Feature Engineering

- *Convert unstructured* data into *input* to *learning* algorithm.
- *Expose* the *structure* of the *concept* to the *learning* algorithm.
- Work *well* with the *structure* of the model.
- Balance number of *features*, *complexity* of *concept*, *complexity* of *model*, and the *amount* of *data*.

+ Benefits of Feature Engineering

- *Improving* the accuracy of ML model
- *Solving Overfitting* problem
- *Speed up* your *computation*
- *Understandability* for ML process

+ Feature Engineering



+ Feature Extraction

- Feature extraction refers to the process of *transforming raw data* into *numerical features* that can be *processed* while *preserving the information* in the *original data set*.
- It yields *better results* than *applying* machine learning *directly* to the raw data.
- Feature Extraction can be performed using *two way*
- *Manual Feature Extraction*
 - Manual feature extraction requires *identifying* and *describing* the *features* that are *relevant* for a *given problem* and *implementing* a way to *extract* those features.
 - In many situations, having a *good understanding* of the *background* or *domain* can *help* make *informed decisions* as to which features could be *useful*.
 - It is impractical for the huge datasets.

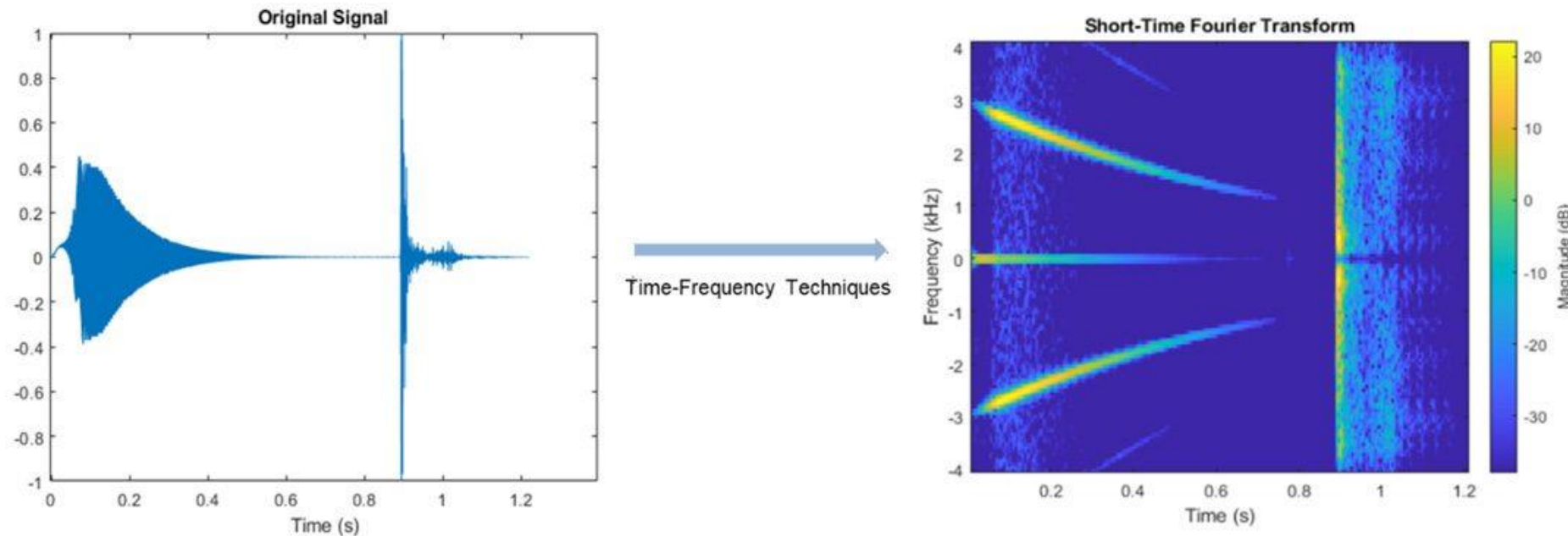
+ Feature Extraction

■ Automated Feature Extraction

- Automated feature extraction uses *specialized algorithms* or *deep networks* to extract features automatically from *signals* or *images* without the *need* for *human intervention*.
- This technique can be very *useful* when you want to move *quickly* from *raw data* to developing machine learning algorithms.

+ Feature Extraction in different types of Data

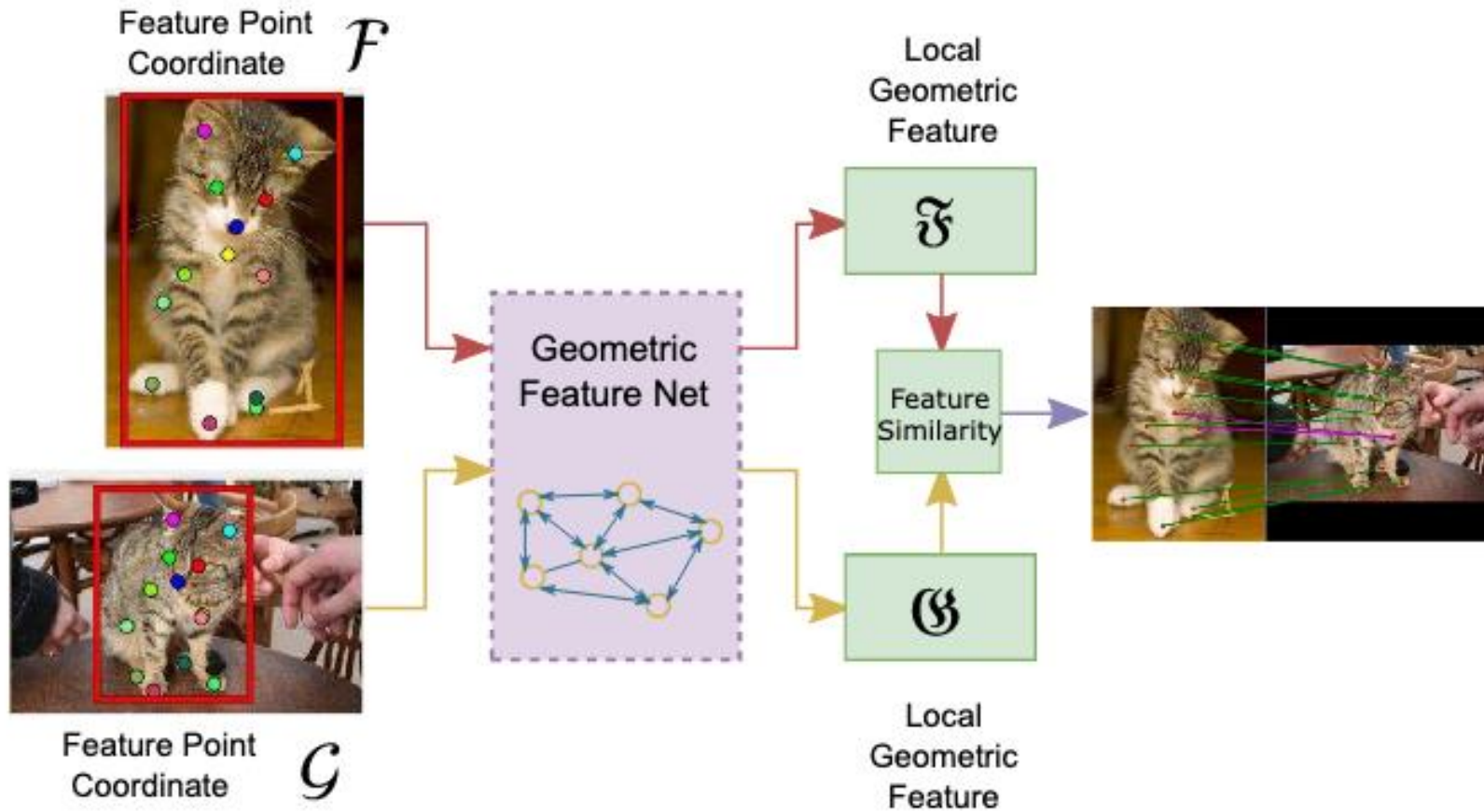
Time Series / Audio Data



Spectrogram of a *signal* using short-time *Fourier transform*.
Spectrogram shows variation of *frequency* content over time.

+ Feature Extraction in different types of Data

Image / Visual Data



Feature Extracted from *Images*

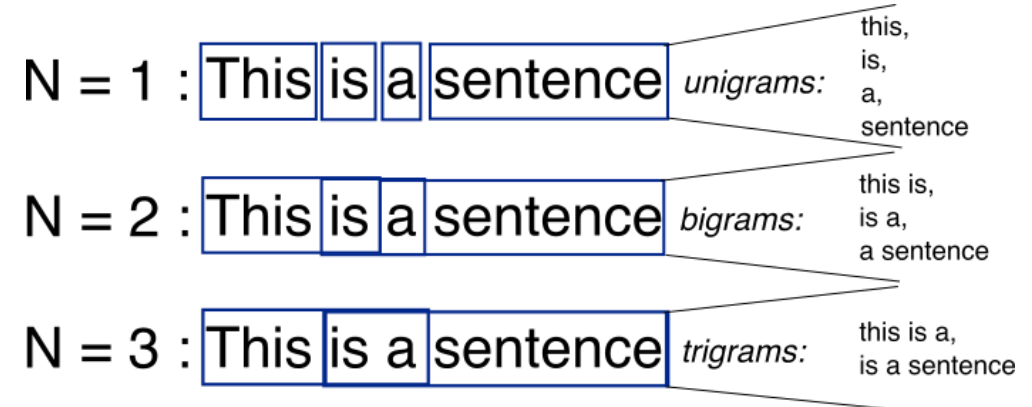
+ Feature Extraction in different types of Data

Textual Data

	1 This	2 movie	3 is	4 very	5 scary	6 and	7 long	8 not	9 slow	10 spooky	11 good	Length of the review(in words)	
Review 1	1	1	1	1	1	1	1	0	0	0	0	7	negative
Review 2	1	1	2	0	0	1	1	0	1	0	0	8	negative
Review 3	1	1	1	0	0	0	1	0	0	1	1	6	positive

- **Vector of Review 1:** $[1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0]$
- **Vector of Review 2:** $[1\ 1\ 2\ 0\ 0\ 1\ 1\ 0\ 1\ 0\ 0]$
- **Vector of Review 3:** $[1\ 1\ 1\ 0\ 0\ 0\ 1\ 0\ 0\ 1\ 1]$

Review 1: this movie is very scary and long
 Review 2: this movie is very long and is slow
 Review 3: this movie is long, spooky, good



Feature Extracted from text

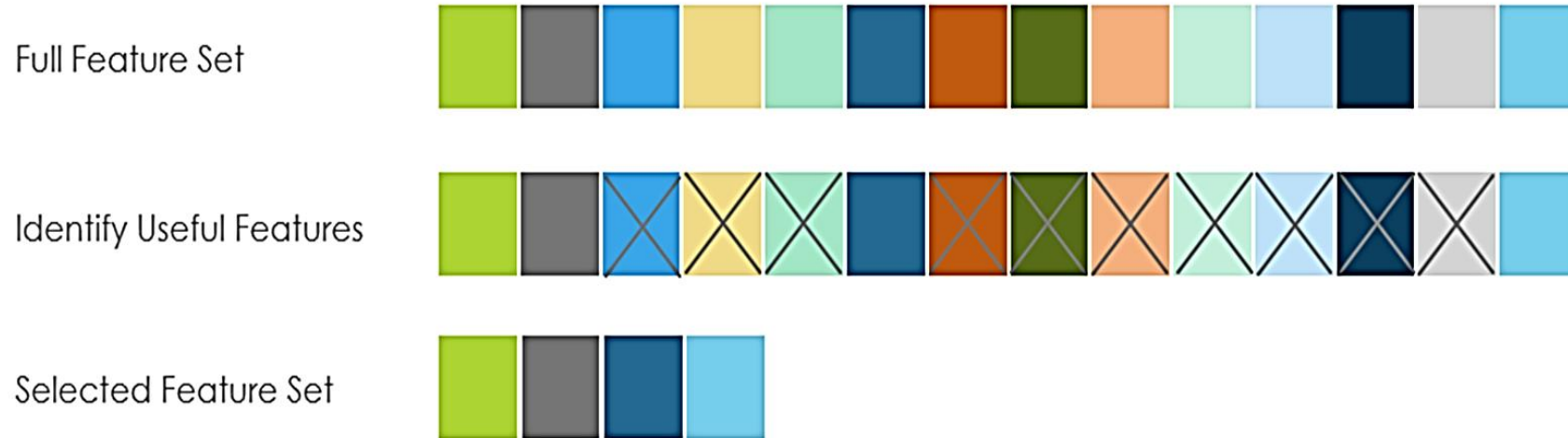
+ Feature Selection

- As a dimensionality reduction technique, feature selection aims to choose a small subset of the relevant features from the original features by removing *irrelevant, redundant, or noisy features*.
- Feature selection usually can lead to better *learning performance, higher learning accuracy, lower computational cost, and better model interpretability*.
- *The aim of feature selection is to maximize relevance and minimize redundancy.*



Feature Selection

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- **Given:** a set of predictors (“*features*”) V and a target variable T
- **Find:** *minimum set F* that achieves *maximum classification performance* of T (for a given set of classifiers and classification performance metrics)

+ Feature Selection

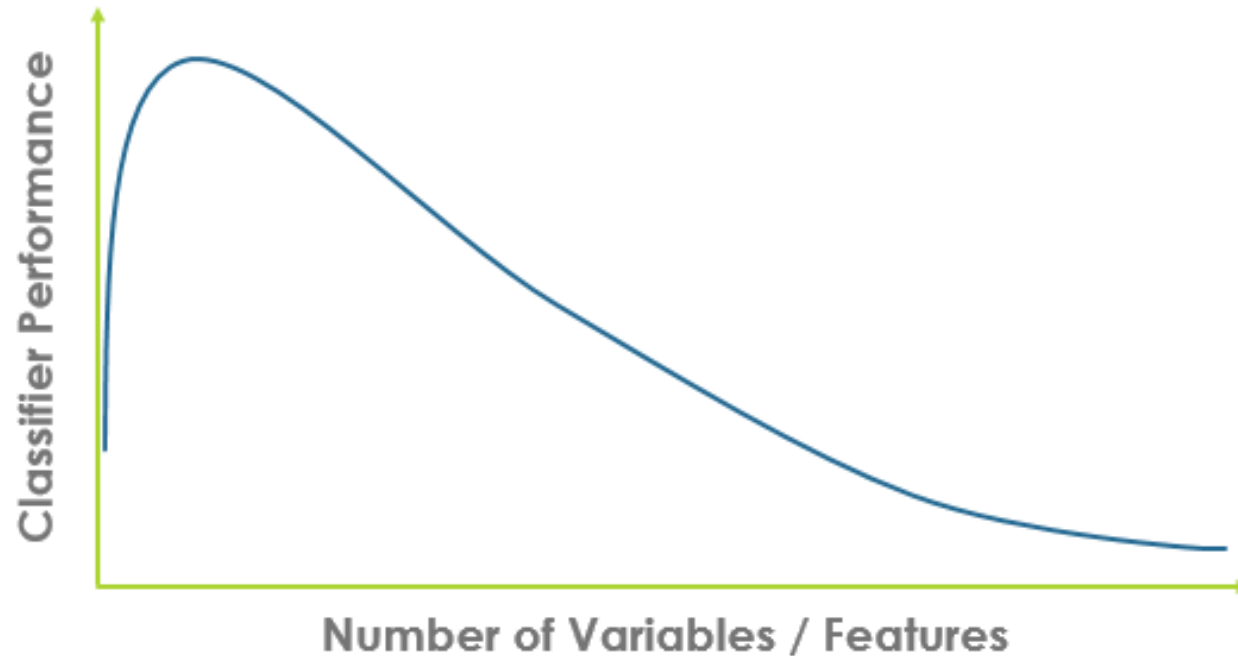
- Feature selection is also called *variable selection* or *attribute selection* or *dimensionality reduction*
- A process of *reducing* the number of features used to *build* the model with the *goal* of keeping only *informative, discriminative* and *non redundant* features.
 - It is the *automatic selection* of *attributes* in your *data* (such as columns in tabular data) that are *most relevant* to the *predictive modelling problem* you are working on.
- To keep *“relevant features only”*, we will remove the features that are
 - Non informative
 - Non discriminative غير مميز
 - Redundant

+ Feature Selection

- The *objective* of variable selection is three-fold:
 - *Improving* the *prediction performance* of the predictors,
 - Providing *faster* and more *cost-effective predictors*,
 - Providing a *better understanding* of the *underlying process* that generated the data.
- *Removing a redundant variable* helps to *improve accuracy*.
- *Inclusion of a relevant variable* has a *positive* effect on model *accuracy*.
- Too many variables might result to *overfitting* which means model is not able to *generalize* pattern
- Too many variables lead to *slow computation* which in turns requires *more memory and hardware*.
- It *reduces* the *complexity* of a model and makes it *easier* to interpret.

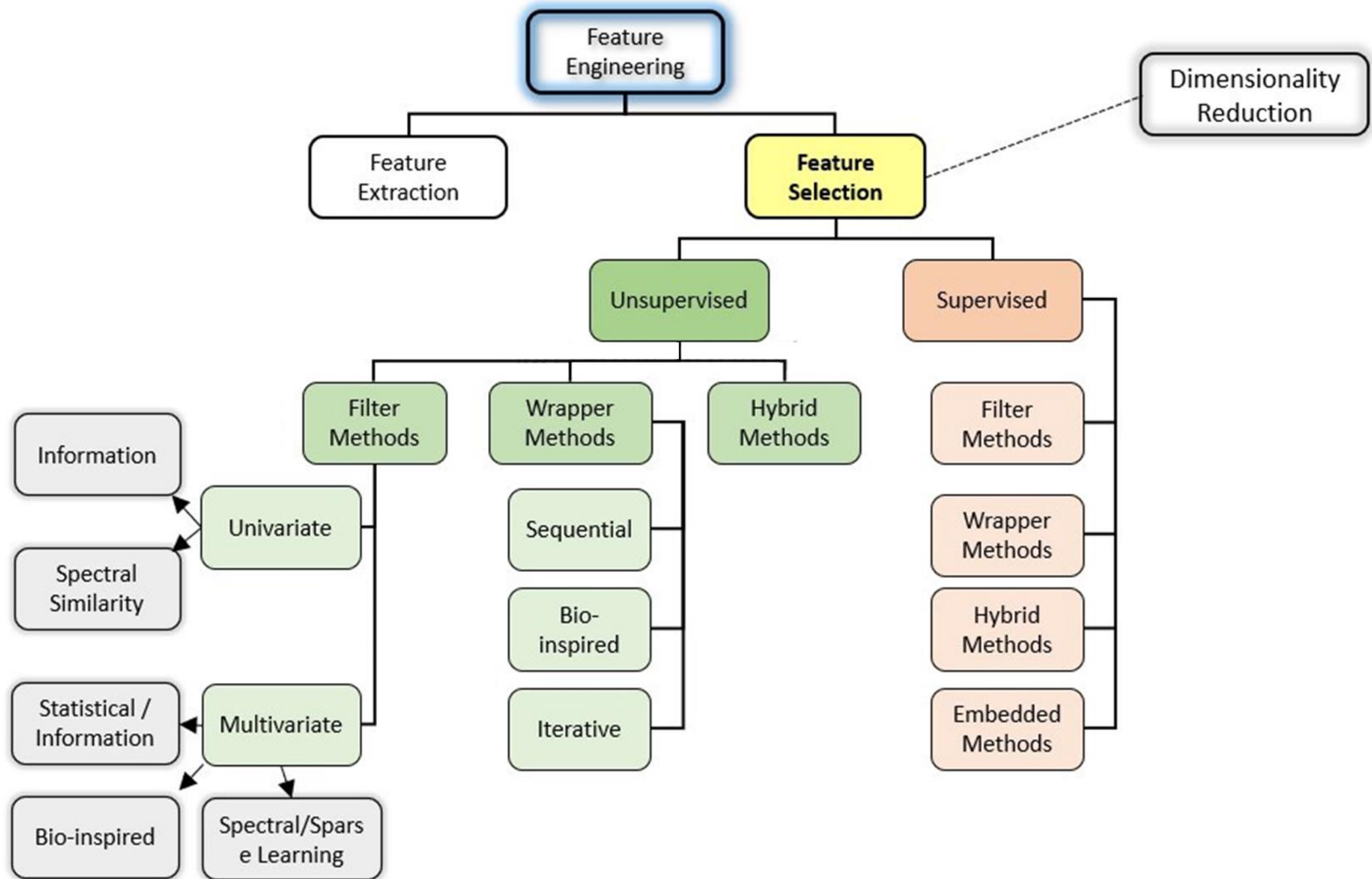
+ Curse of dimensionality

- The required number of samples (to achieve the same accuracy) grows *exponentially* with the *number of variables*!
- The *classifier's performance* usually will *degrade* for a large number of features!



+ Categorization of Feature Selection Techniques

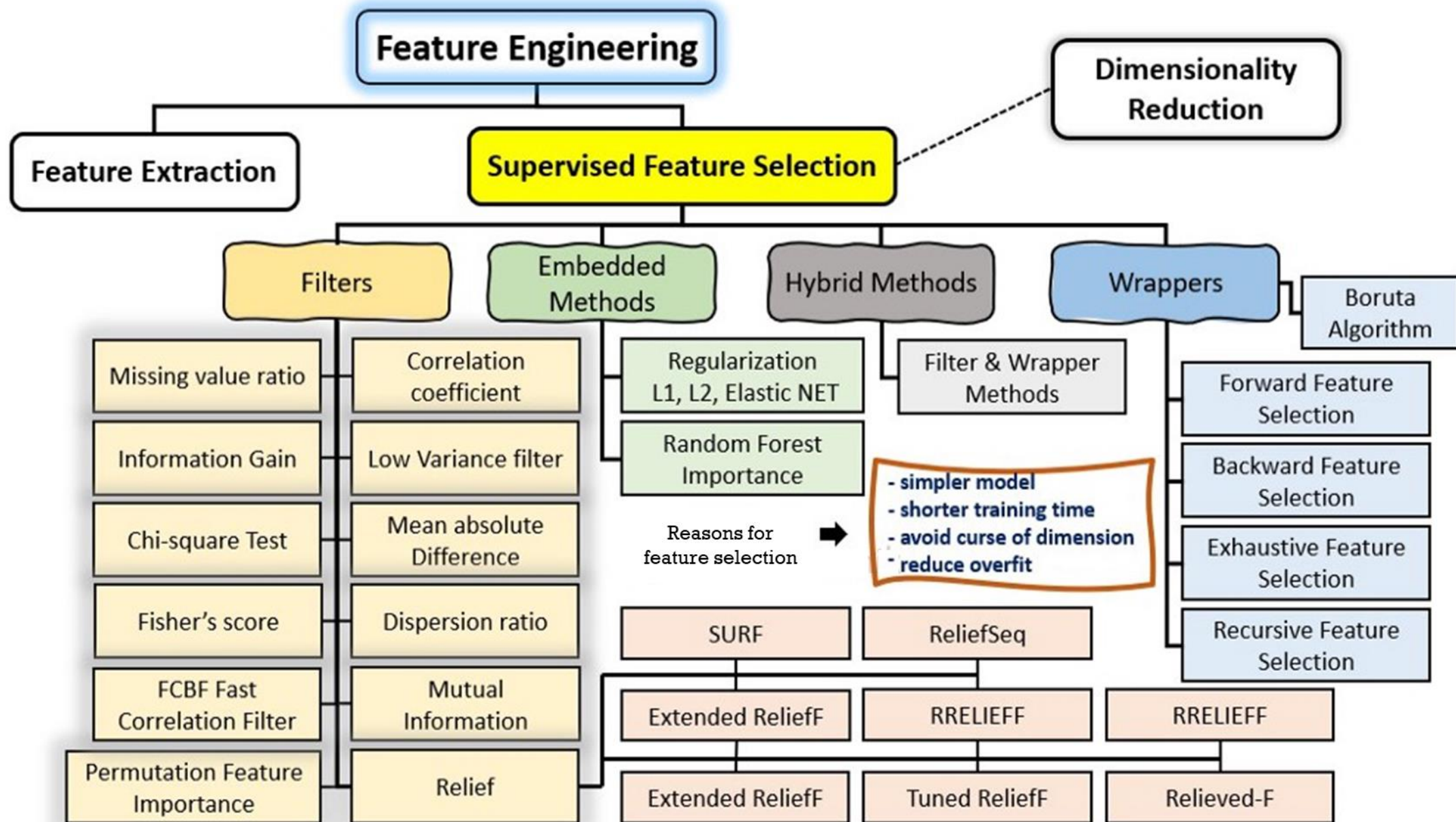
- *Unsupervised feature selection* techniques *ignore* the *target variable*, such as methods that *remove redundant* variables using *correlation*.
- *Supervised feature selection* techniques use the *target variable*, such as methods that *remove irrelevant variables*.



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Supervised Feature Selection

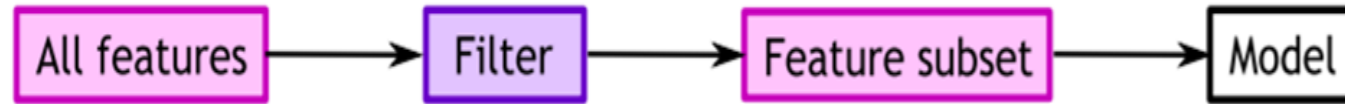
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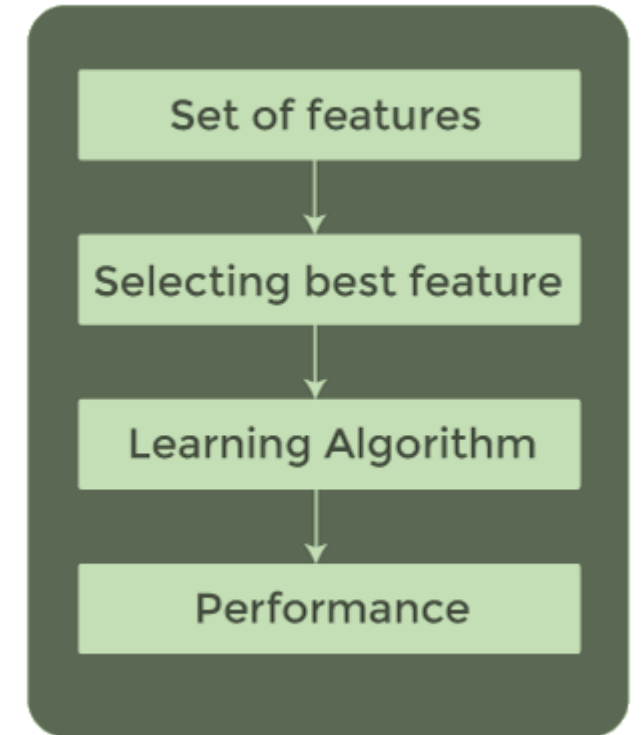
+ Supervised Feature Selection

- ***Four*** type of supervised Feature Selection
 - Filter
 - Wrapper
 - Embedded
 - Hybrid
- **Before training model**
 - ***Statistical method:*** Removing features with low variance
 - ***Filter method:*** Univariate feature selection
- **While training model**
 - ***Wrapper method:*** Recursive feature elimination
 - ***Embedded method:*** L1-based feature selection

+ 1. Filter Supervised Feature Selection



- In Filter Method, features are selected using *statistics measures*.
- This method *does not depend* on the *learning* algorithm and *chooses* the features as a *pre-processing step*.
- The filter method *filters* out the *irrelevant* feature and *redundant* columns from the model by using *different* metrics through *ranking*.
- The advantage of using filter methods is that it *needs low computational time* and *does not overfit the* data.



+ 1. Filter Supervised Feature Selection methodology

1. Creates *groups* of the *features* as per different criteria.
2. Creates a *benchmark* for each group.
3. Tests the *correlation of features* inside the *group*, compared to the predetermined *group benchmark*.
4. Keeps only the features that are *less correlated to each other* than to the group benchmark.

+ 1. Filter Supervised Feature Selection

- Common Filter Feature selection methods are
 - Information Gain
 - Chi-square Test
 - Fisher's Score
 - Missing Value Ratio
 - Correlation coefficient filter
 - High correlation filter
 - Low variance filter

+ 1. Filter Supervised Feature Selection

■ *Missing Value Ratio*

- *Remove* those features which have *high ratio* of *missing* values
- A *predefined threshold* may be defined. In case of *low missing* vales, the imputation technique may need to be applied.
- The variable is having *more* than the *threshold* value can be *dropped*.

■ *Information Gain*

- Information gain determines the *reduction in entropy* while *transforming* the dataset.
- It can be used as a *feature selection* technique by calculating the *information gain* of each variable with respect to the *target variable*.

■ *Chi-square Test*

- Chi-square test is a technique to determine the *relationship* between the *categorical* variables.
- The chi-square value is calculated between each *feature* and the *target* variable, and the desired number of features with the *best chi-square value* is selected.

+ 1. Filter Feature Selection

■ *Fisher's Score*

- Fisher's score is one of the popular *supervised technique* of features selection.
- It returns the *rank* of the *variable* on the *fisher's criteria* in *descending* order. Then we can select the variables with a *large fisher's score*.

■ *Correlation Coefficient*

- Features should be *correlated* with the *target* but should be *uncorrelated* among *themselves*.

■ *High Correlation Filter*

- *High Correlation* between *two features* means they have *similar trends* and are likely to *carry similar information*.
- If the correlation coefficient *crosses* a certain *threshold value*, we can *drop one of* the features.

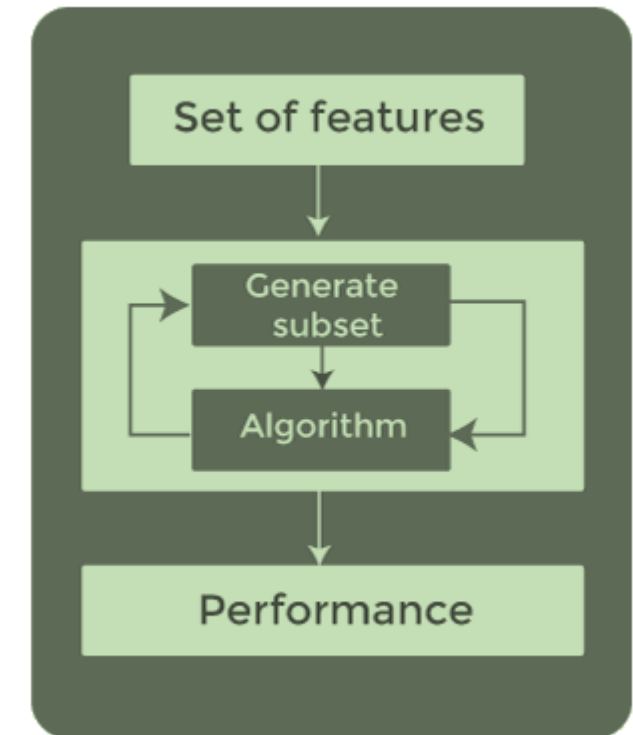
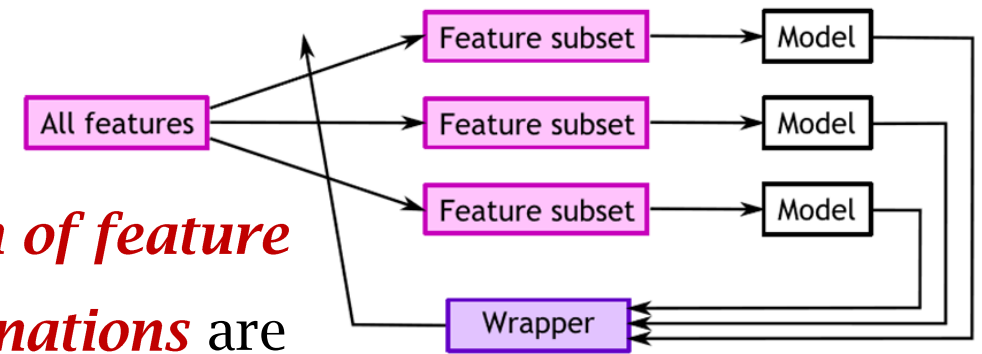
+ 1. Filter Feature Selection

- *Low variance Filter*

- Features in a dataset where *all the observations* have the *same* value, *e.g. 1*
- Such features have *0 variance* and may *not be significant*.
- The assumption is that features with *higher variance* may contain *more useful* information.

+ 2. Wrapper Supervised Feature Selection

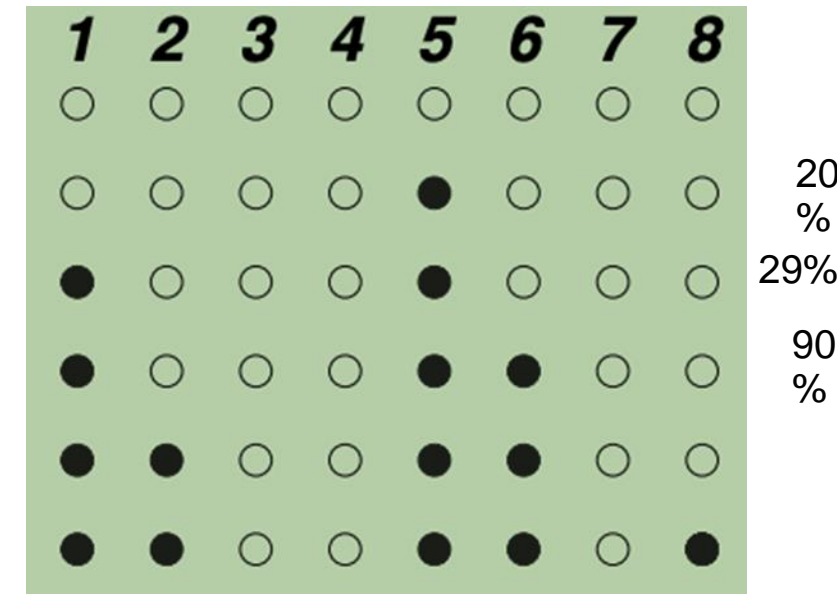
- The Wrapper methodology considers the *selection of feature sets* as a *search problem*, where *different combinations* are *prepared, evaluated, and compared* to other combinations.
- A *predictive model* is used to *evaluate* a *combination* of *features* and *assign* model *performance scores*.
- The *performance* of the Wrapper method *depends* on the *classifier*.
- The *best subset* of features is selected based on the *results* of the *classifier*.



+ 2. Wrapper Supervised Feature Selection

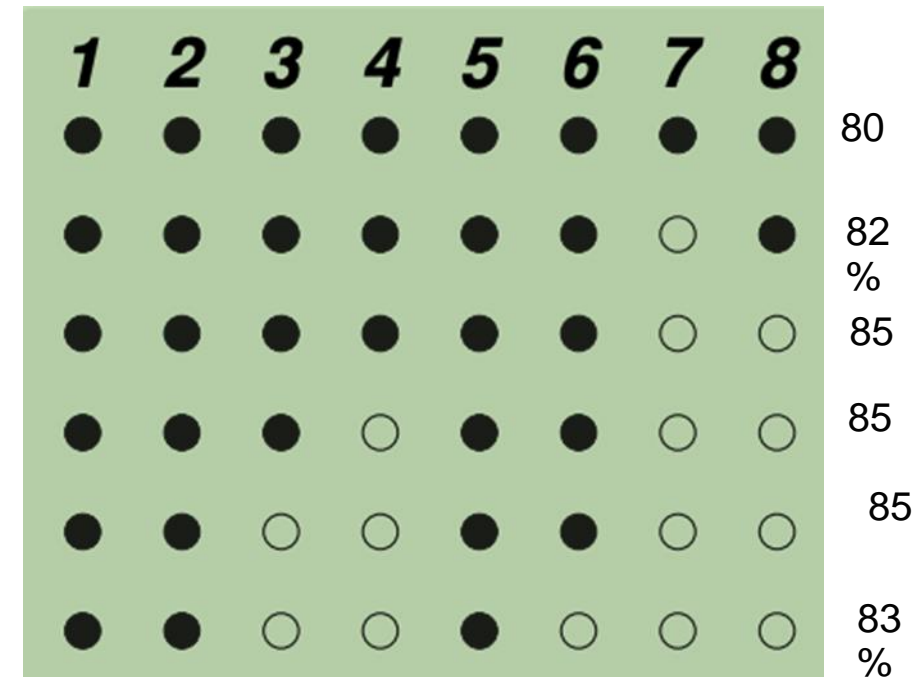
■ *Forward selection*

- Forward selection is an *iterative process*, which begins with an *empty* set of features.
- After each *iteration*, it keeps *adding on* a feature and *evaluates* the *performance* to check whether it is *improving* the performance or *not*.
- The process continues until the *addition* of a new variable/feature *does not improve* the performance of the model.



+ 2. Wrapper Supervised Feature Selection

- *Backward elimination*
- *Backward* elimination is also an *iterative* approach, but it is the *opposite* of forward selection.
- This technique begins the process by *considering all* the *features* and *removes* the *least significant feature*.
- This elimination process *continues* until *removing* the features *does not* improve the performance of the model.



+ 2. Wrapper Supervised Feature Selection

■ *Exhaustive Feature Selection*

- Exhaustive feature selection is one of the *best feature selection methods*, which evaluates each *feature set as brute-force*.
- It means this method *tries & make* each *possible combination* of features and *return* the best performing feature set.

■ *Recursive Feature Elimination*

- Recursive feature elimination is a recursive *greedy optimization* approach, where features are selected by *recursively* taking a *smaller and smaller* subset of features.
- Now, an *estimator* is trained with *each set of features*, and the *importance* of each feature is determined using *coef_attribute* or through a *feature_importances_attribute*.
- This process repeats recursively on *pruned set until* the desired num of *features reached*

+ 2. Wrapper Method

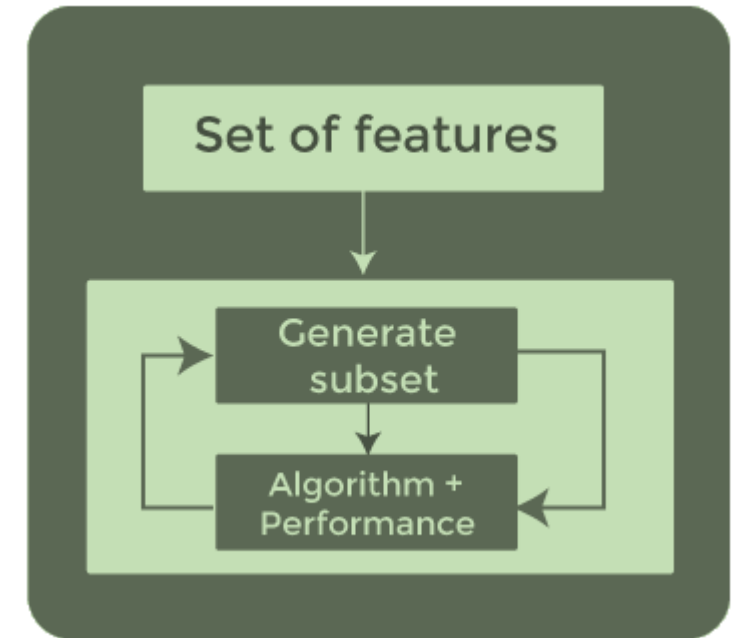
- *Computationally expensive* than filter method
- Perform *better* than filter method
- Not recommended on *high number of features*.
- Before applying the wrapper feature selection, we must specify:
 - *What model type and which learning algorithm shall be used?*
 - *How to evaluate the model accuracy?*
 - Based on testing data, or using k-fold cross-validation?

+ Filter Vs. Wrapper

- Wrapper methods are *computationally more expensive* than filter methods, *due* to the *repeated learning* steps and *cross-validation*.
- However, these methods are more *accurate* than the *filter* method

+ Embedded Feature Selection

- In the Embedded method, there are *ensemble learning* and *hybrid learning* methods for feature selection.
- Since it has a *collective decision*, its performance is *better* than the other *two models*.
- It is *computationally less intensive* than *wrapper* methods. However, this method has a *drawback specific to a learning model*.
- *Random forest is one such example of wrapper and embedded feature selection.*
- *Example*: : LASSO Regularization L1, Random Forest.

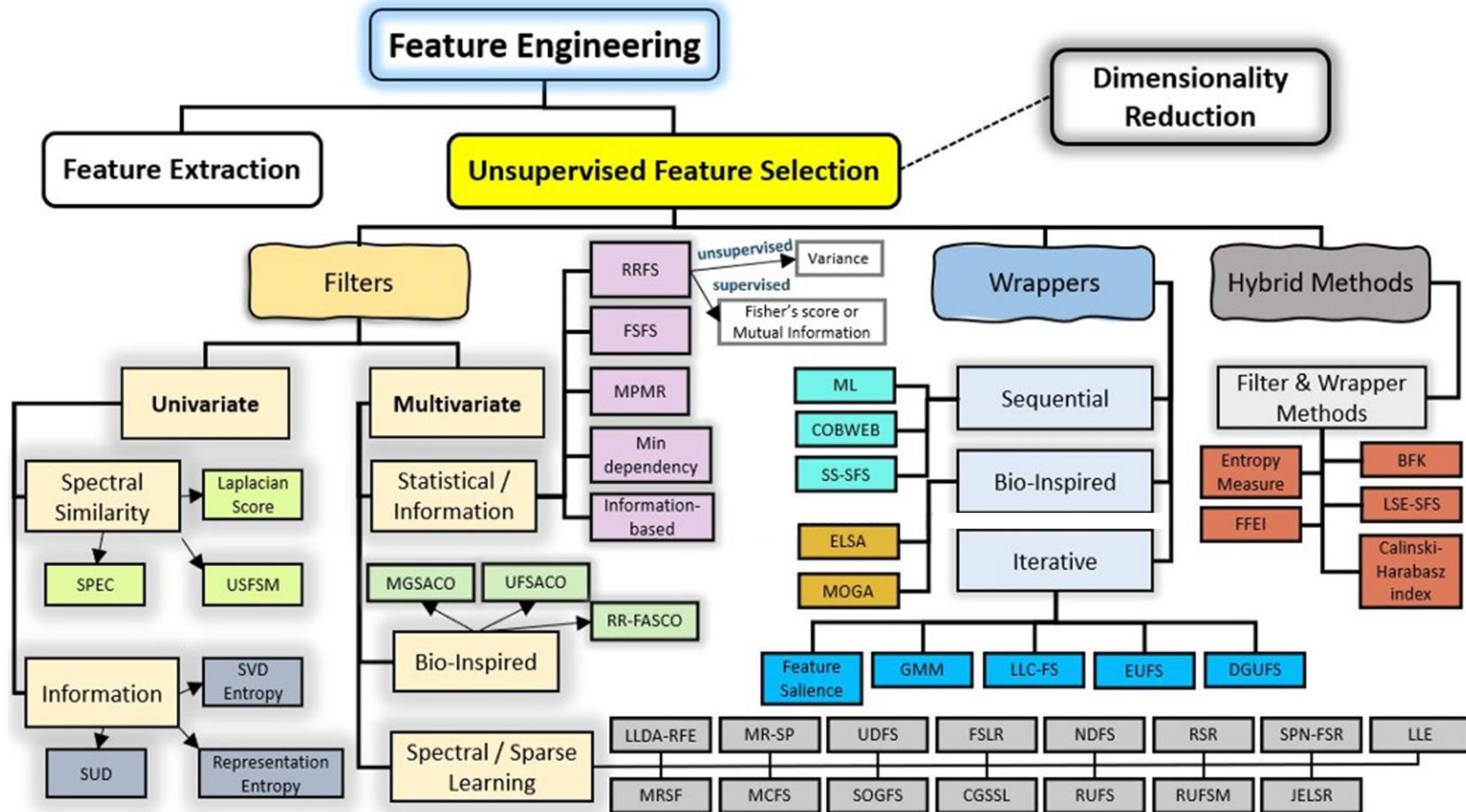


+ Hybrid Feature Selection

- The process of creating *hybrid feature selection methods* depends on *what you choose to combine*.
- The main priority is to *select the methods* you're going to use, then *follow* their *processes*.
- The idea here is to use these *ranking methods* to *generate* a *feature ranking* list in the *first step*, then use the *top k features* from this list to perform *wrapper methods*.
- With that, we can *reduce the feature space* of our dataset using these *filter-based* rangers to improve the *time complexity* of the wrapper methods.

+ Unsupervised Feature Selection

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+ Review

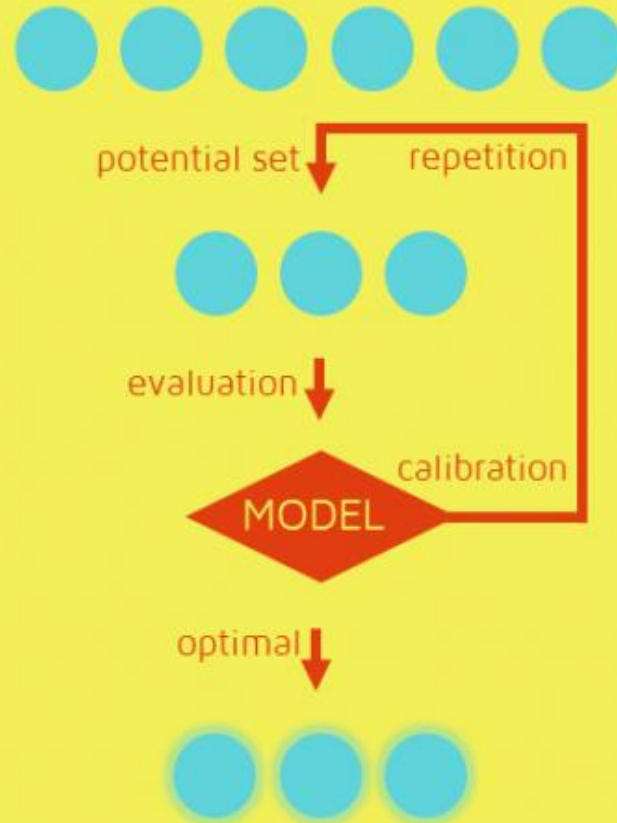
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feature selection

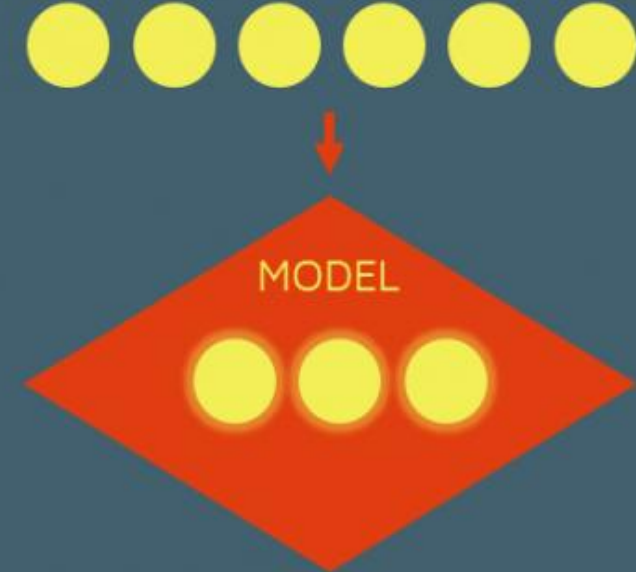
filter



wrapper



embedded





End of Lecture – 03