PART I: AN INTRODUCTION TO “CLASSICAL” MACHINE LEARNING

WHAT DOES MACHINE LEARNING DO?

<u>the machine is told what to look for</u>

<u>SUPERVISED</u>

<u>the machine is NOT told what to look for</u>

<u>UN-SUPERVISED</u>

TWO BIG TYPES OF MACHINE LEARNING ALGORITHMS

CAT

CAT

SUPERVISED LEARNING

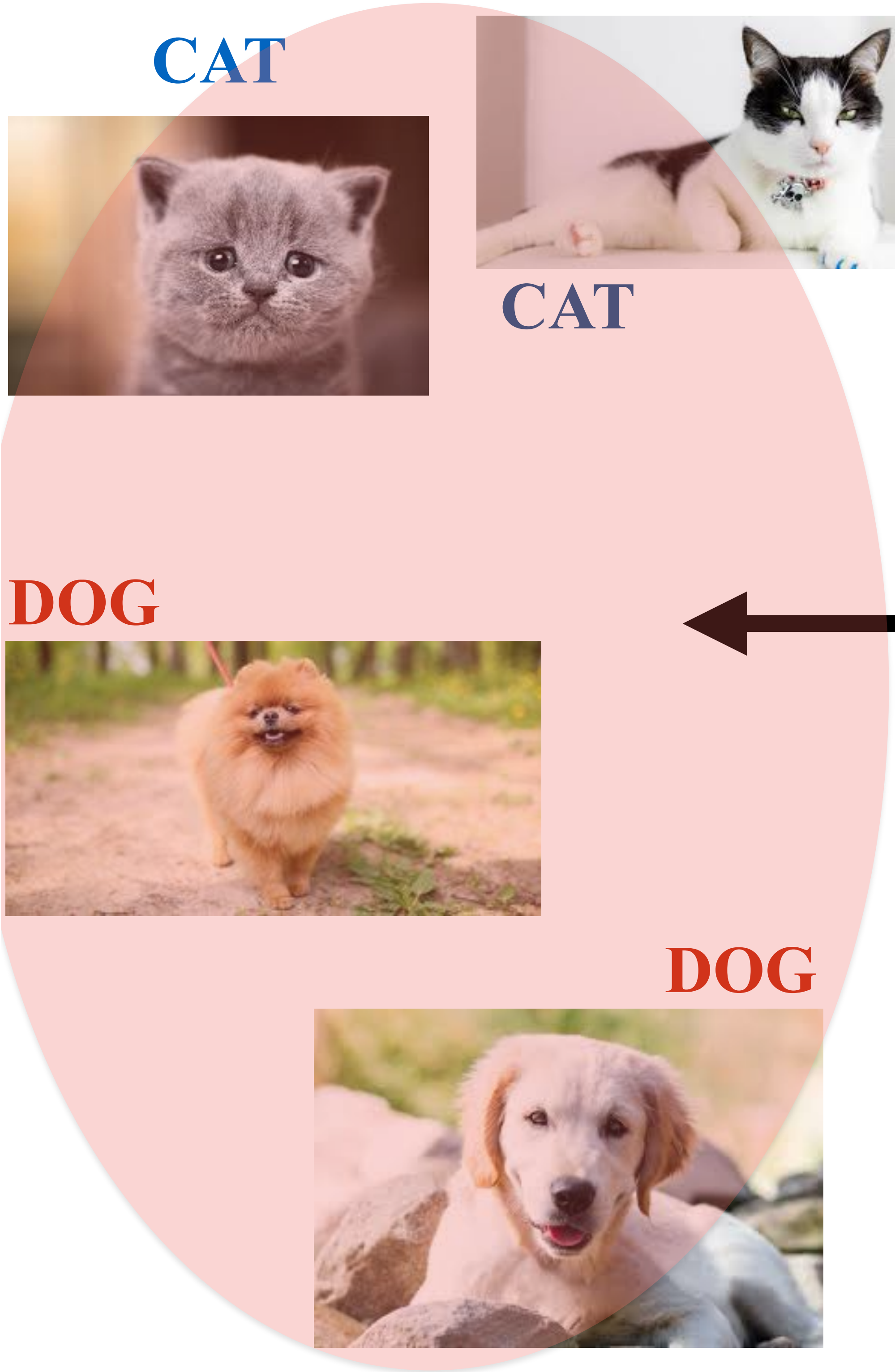
the machine is told what to look for

HUMAN LABELLING

DOG

DOG

SUPERVISED LEARNING

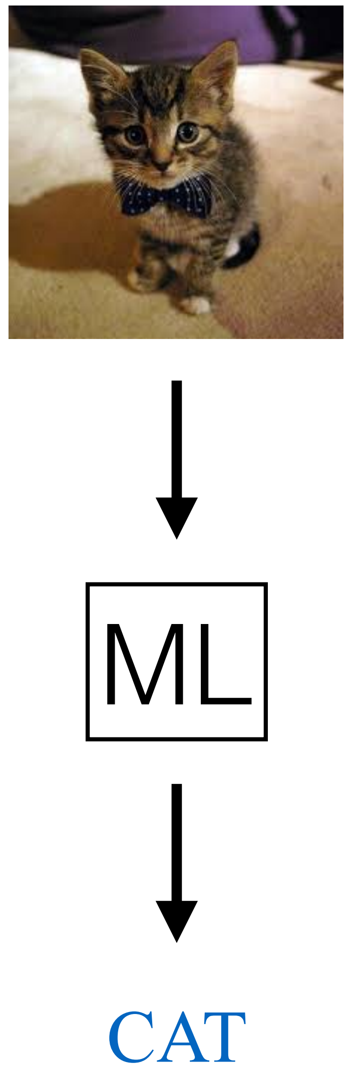


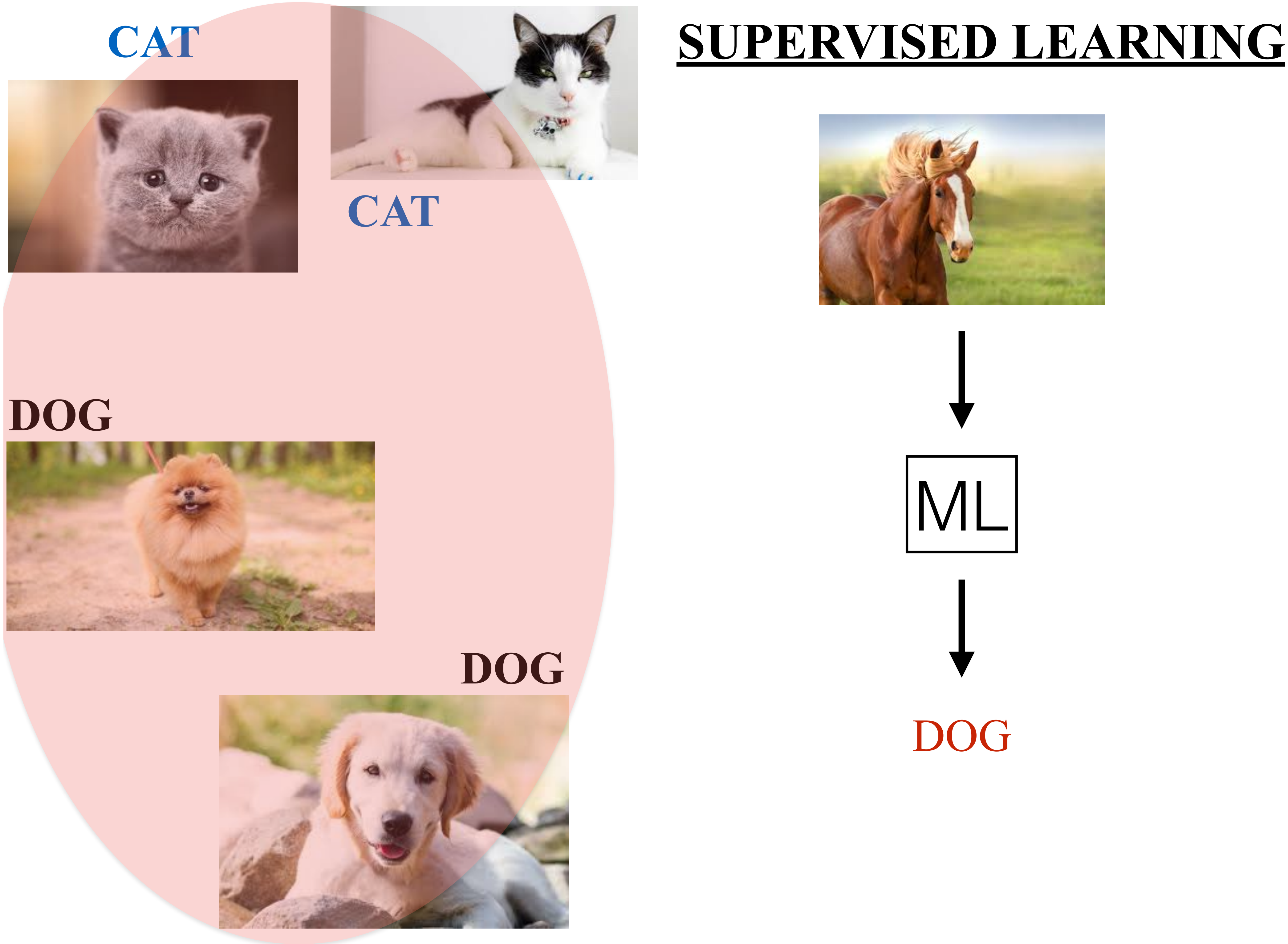
the machine is told what to look for

HUMAN LABELLING

TRAINING SET OF LABELED EXAMPLES

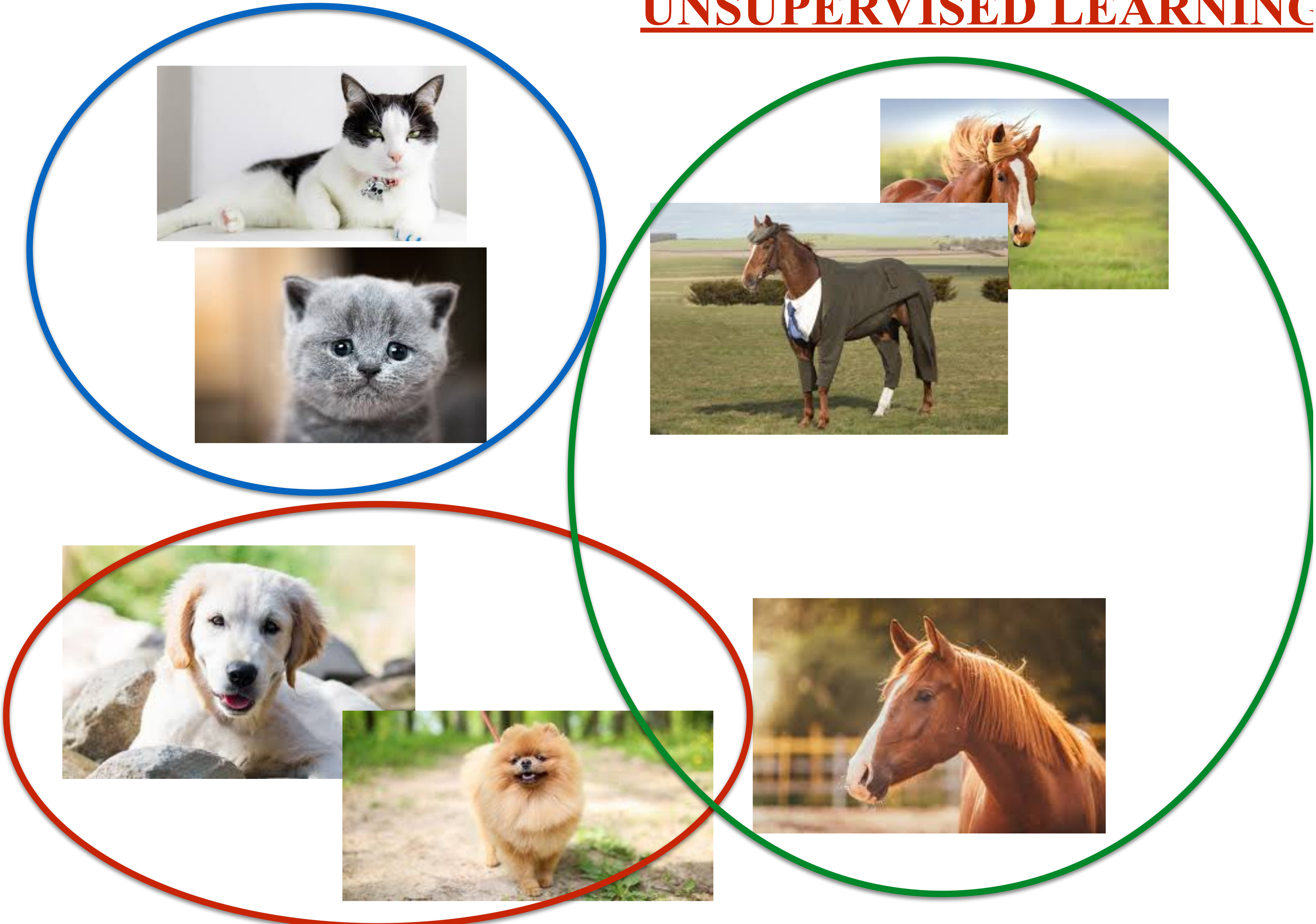
SUPERVISED LEARNING



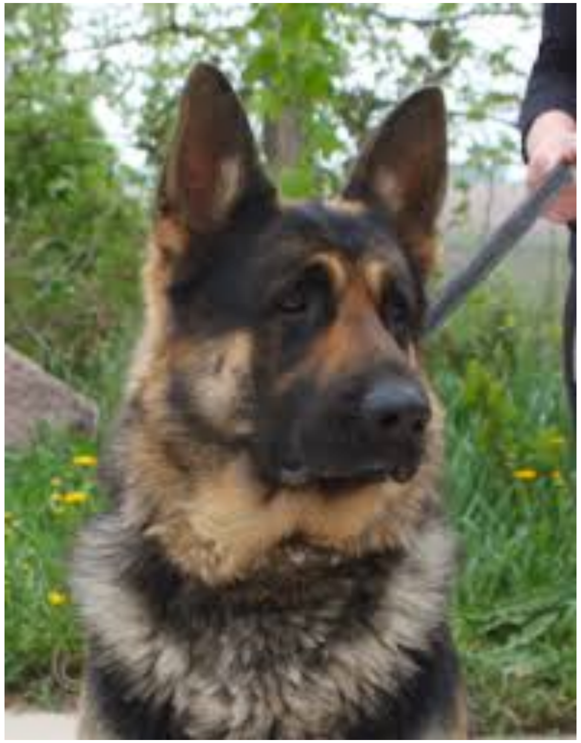

SUPERVISED LEARNING
CAT
CAT
DOG
DOG
ML
DOG

UNSUPERVISED LEARNING

UNSUPERVISED LEARNING



UNSUPERVISED LEARNING



THE DEFINITION OF CLASSES IS SOMETIMES NOT OBVIOUS

WHAT DOES MACHINE LEARNING DO?

the machine is told what to look for

SUPERVISED

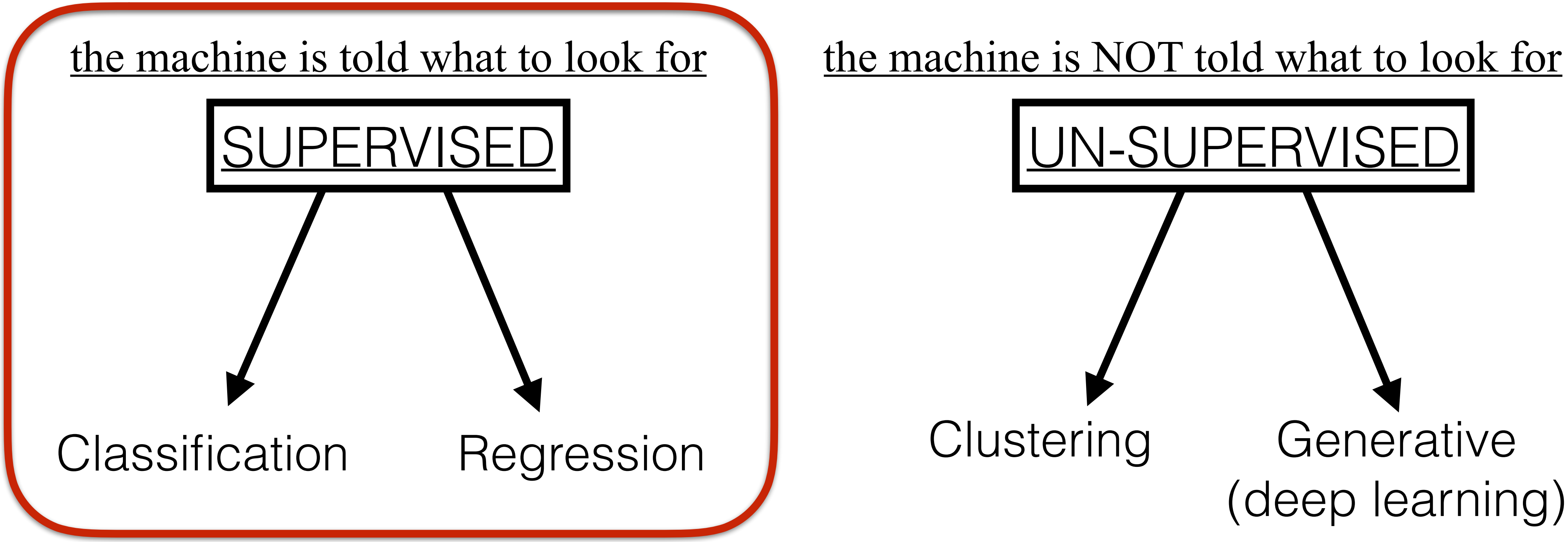
- Classification
- Regression

the machine is NOT told what to look for

UN-SUPERVISED

- Clustering
- Generative (deep learning)

WHAT DOES MACHINE LEARNING DO?



TODAY

WHAT DOES MACHINE LEARNING DO?

<u>the machine is told what to look for</u>

SUPERVISED

- Classification
- Regression

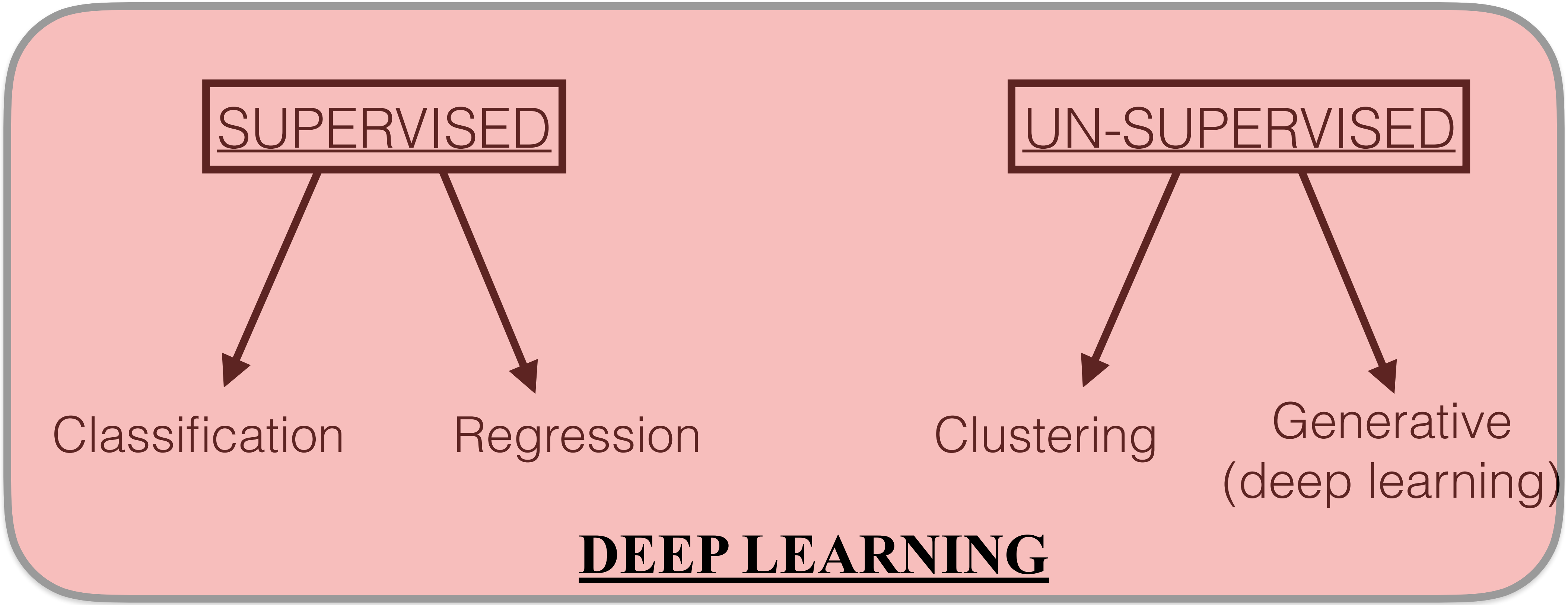
<u>the machine is NOT told what to look for</u>

UN-SUPERVISED

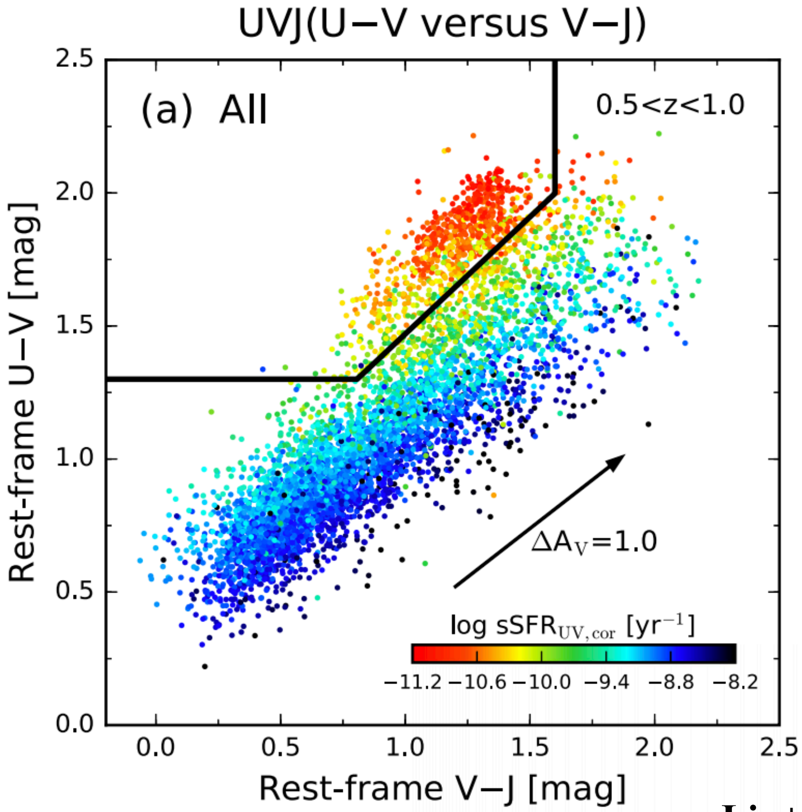
- Clustering
- Generative (deep learning)

TOMORROW

WHAT DOES MACHINE LEARNING DO?

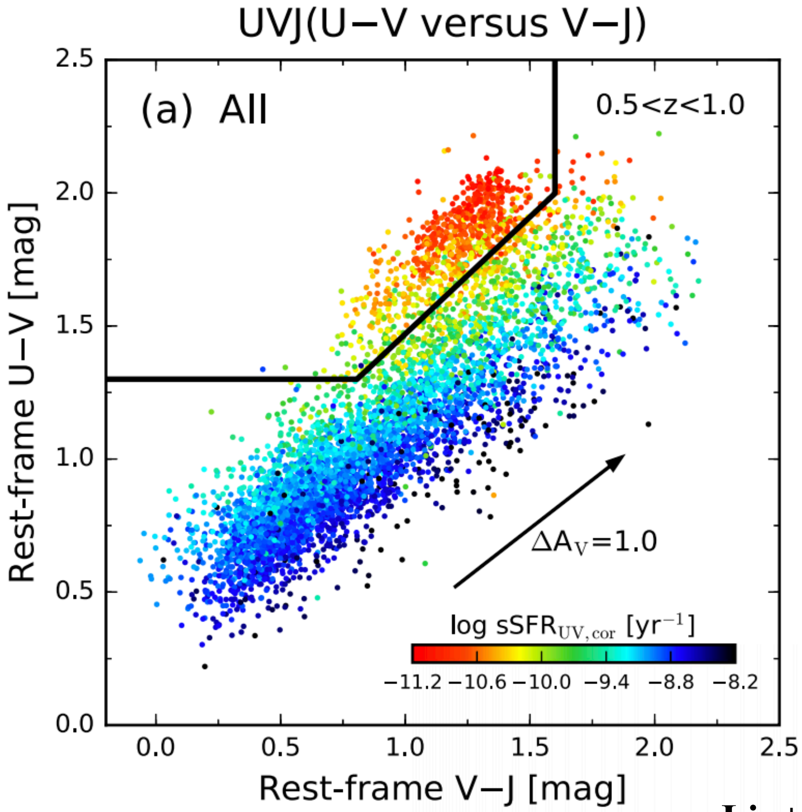


<u>**THRE IS NO MAGIC IN MACHINE LEARNING, AND IT IS ACTUALLY PRETTY SIMPLE**</u>



Liu+18

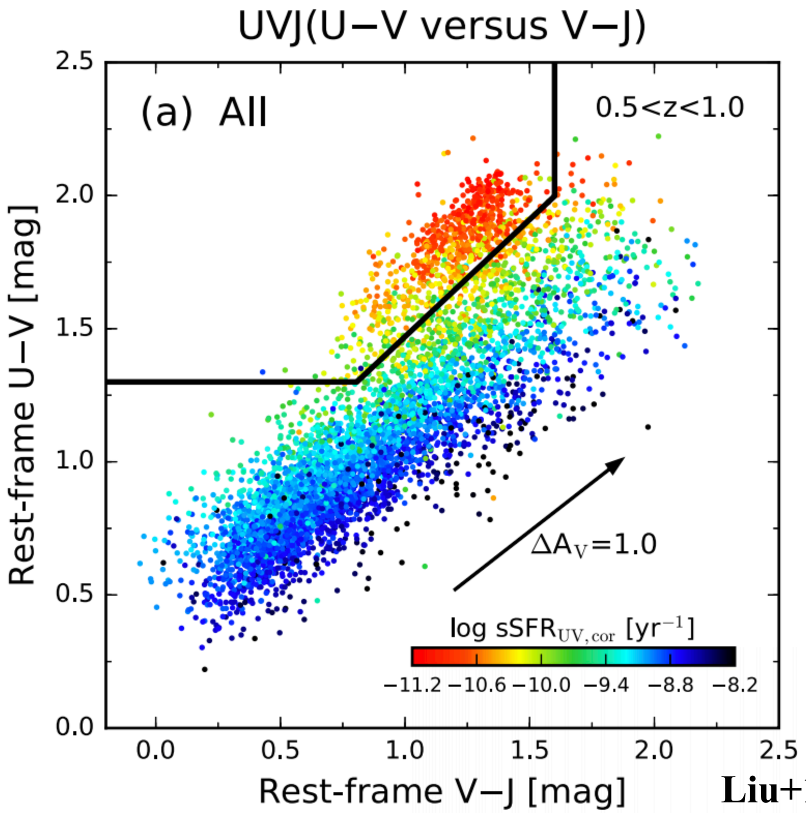
$$f_W(\vec{x}) = \vec{y}$$



Liu+18

$$f_W(\vec{x}) = \vec{y} \longrightarrow$$

LABEL
Q , SF

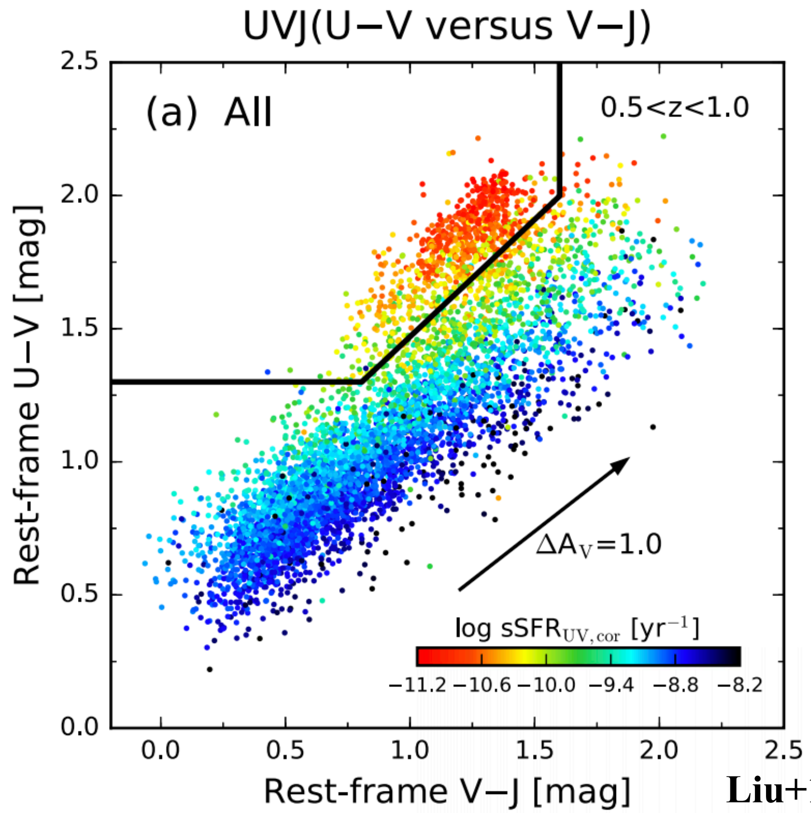


Liu+18

$$f_{\vec{W}}(\vec{x}) = \vec{y} \longrightarrow \text{LABEL: } Q(0), SF(1)$$

LABEL
Q(0) , SF(1)

(U-V, V-J) FEATURES



Liu+18

$$f_{\vec{W}}(\vec{x}) = \vec{y} \rightarrow$$

LABEL

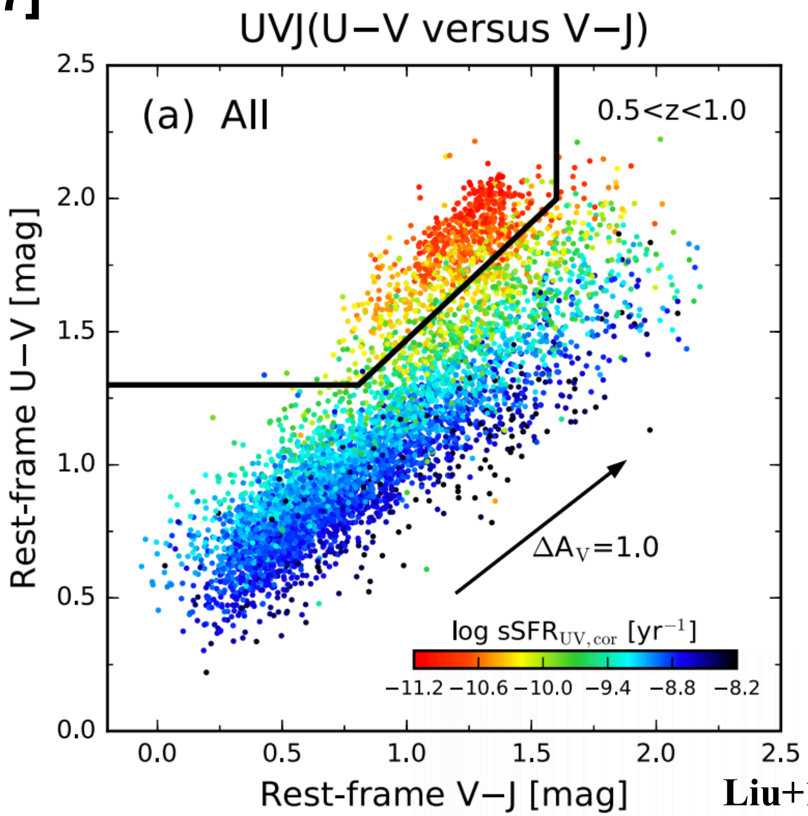
Q(0) , SF(1)

NETWORK FUNCTION

(U-V, V-J) FEATURES

sgn[(u-v)-0.8*(v-j)-0.7]

WEIGHTS



Liu+18

“CLASSICAL”
MACHINE LEARNING

$$f_{\vec{W}}(\vec{x}) = \vec{y} \longrightarrow \text{LABEL Q , SF}$$

sgn[(u-v)-W1*(v-j)-W2]

REPLACE THIS BY A GENERAL
NON LINEAR FUNCTION WITH SOME PARAMETERS W

SUPERVISED LEARNING

Given a dataset with <u>known labels</u> (measurements) - find a function that can assign (predict) measurements for an unlabeled dataset

<u>Training set</u>

$$(\vec{x_1}, \vec{x_2}, \vec{x_3}, ..., \vec{x_n})$$

<u>Measurements</u>
<u>(colors, fluxes, spectra indices…)</u>

$$(\vec{y_1}, \vec{y_2}, \vec{y_3}, ..., \vec{y_n})$$

<u>Label</u>
<u>(morphology, object type, redshift …)</u>

SUPERVISED LEARNING

Given a dataset with known labels (measurements) - find a function that can assign (predict) measurements for an unlabeled dataset

Training set

$$(\vec{x_1}, \vec{x_2}, \vec{x_3}, \ldots, \vec{x_n})$$

$$(\vec{y_1}, \vec{y_2}, \vec{y_3}, \ldots, \vec{y_n})$$

$$f_W(\vec{x}) = \vec{y}$$

?

SUPERVISED LEARNING

Unlabeled set

$$(\vec{x_1}', \vec{x_2}', \vec{x_3}', ..., \vec{x_n}')$$

$$(\vec{y_1}', \vec{y_2}', \vec{y_3}', ..., \vec{y_n}')$$

Training set

$$(\vec{x_1}, \vec{x_2}, \vec{x_3}, ..., \vec{x_n})$$

$$(\vec{y_1}, \vec{y_2}, \vec{y_3}, ..., \vec{y_n})$$

$$f_W(\vec{x}) = \vec{y}$$

?

$$(\vec{x_1}, \vec{x_2}, \vec{x_3}, ..., \vec{x_n}) \qquad \vec{x} \in \mathbb{R}^d$$

$$(\vec{y_1}, \vec{y_2}, \vec{y_3}, ..., \vec{y_n}) \qquad \vec{y} \in \mathbb{R} \qquad \vec{y} \in \mathbb{N}$$

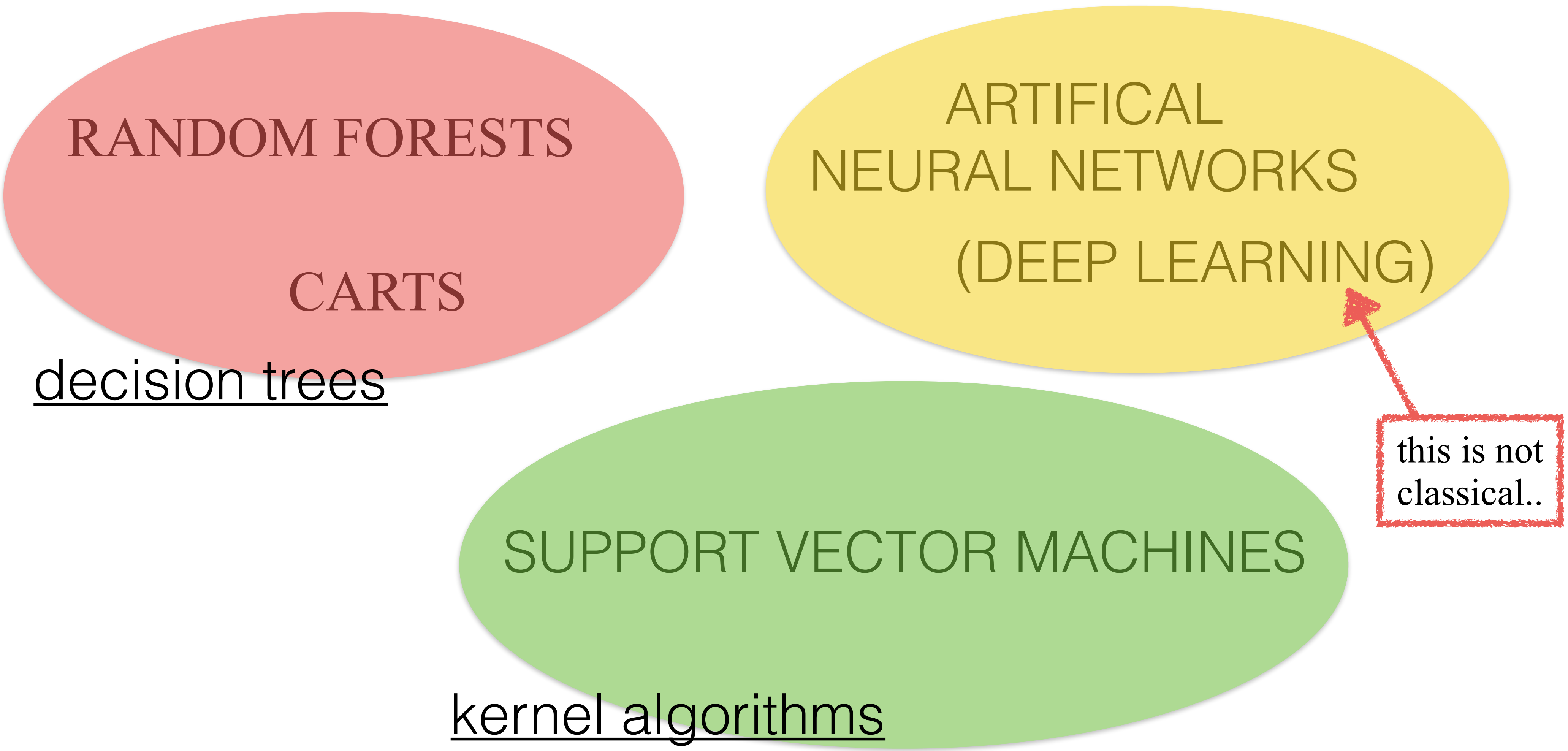
GENERAL GOAL: Find a (non-linear) function that outputs the correct class / measurement for a given input object:

$$f_W(\vec{x})$$

Number of parameters - can be large

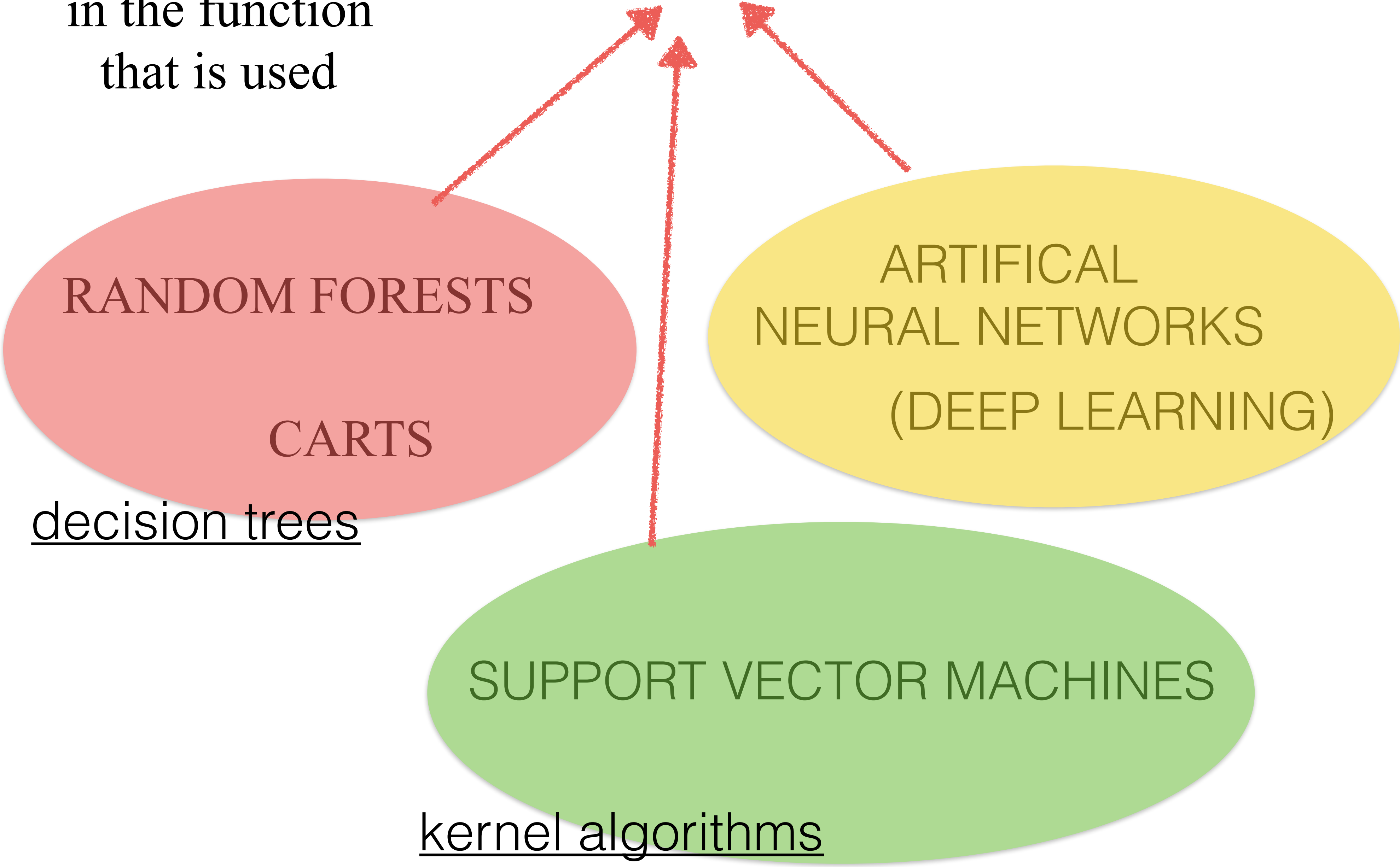
It is translated into a minimization problem : find W such as the prediction error is minimal <u>over all unseen vectors</u>

Different "classical" supervised machine learning methods



The differences are in the function that is used

$$f_W(\vec{x})$$



We need two key elements

1. A LOSS FUNCTION

2. A MINIMIZATION OR OPTIMIZATION ALGORITHM

WE NEED 2 KEY ELEMENTS:

1. A LOSS FUNCTION

2. A MINIMIZATION OR OPTIMIZATION ALGORITHM

THIS IS COMMON TO ALL MACHINE LEARNING ALGORITHMS

1. DEFINE A LOSS FUNCTION

$$loss(F_W(.), \vec{x_i}, \vec{y_i})$$

For example: $(F_W(\vec{x_i}) - \vec{y_i})^2$ (MSE LOSS FUNCTION)

2. MINIMIZE THE EMPIRICAL RISK WITH OPTIMIZATION

$$\Re_{empirical}(W) = \frac{1}{N}\sum_{i}^{N}[loss(W, \vec{x}, \vec{y})]$$

MINIMIZE THE RISK

1. DEFINE A LOSS FUNCTION

$$loss(F_W(.), \vec{x_i}, \vec{y_i})$$

For example: $(F_W(\vec{x_i}) - \vec{y_i})^2$ (MSE LOSS FUNCTION)

MORE DETAILS ABOUT LOSS FUNCTIONS IN THE ANN SECTION

2. MINIMIZE THE EMPIRICAL RISK WITH OPTIMIZATION

$$\Re_{empirical}(W) = \frac{1}{N}\sum_{i}^{N}[loss(W, \vec{x}, \vec{y})]$$

MINIMIZE THE RISK

EMPIRICAL RISK?

$$\Re_{empirical}(W) = \frac{1}{N}\sum_{i}^{N}[loss(W, \vec{x}, \vec{y})]$$

WE ARE MINIMIZING WITH RESPECT TO A FINITE NUMBER OF OBSERVED EXAMPLES

EMPIRICAL RISK?

$$\Re_{empirical}(W) = \frac{1}{N}\sum_{i}^{N}[loss(W, \vec{x}, \vec{y})]$$

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OBSERVED DATASET

EMPIRICAL RISK?

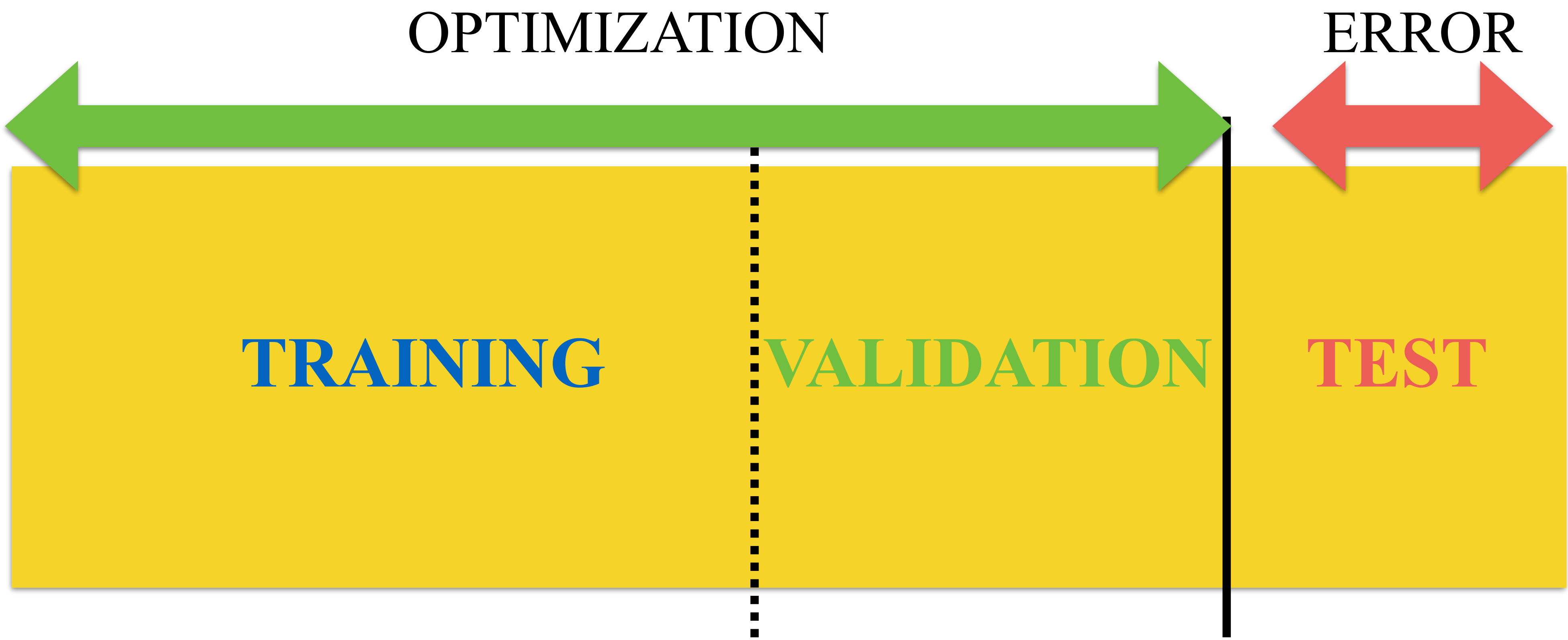
$$\Re_{empirical}(W) = \frac{1}{N}\sum_{i}^{N}[loss(W,\vec{x},\vec{y})]$$

WE ARE MINIMIZING WITH RESPECT TO A FINITE NUMBER OF OBSERVED EXAMPLES

ALL “GALAXIES IN THE UNIVERSE”

OBSERVED DATASET

In practice

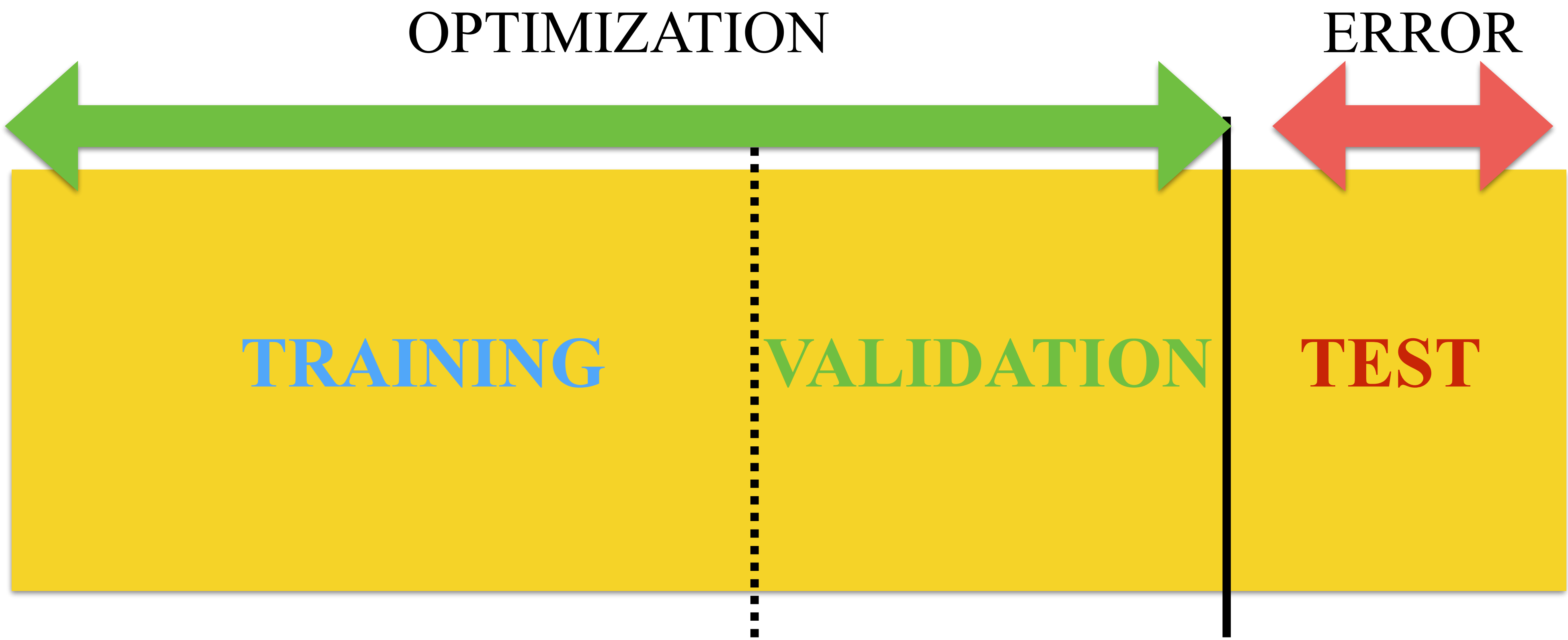


training set: use to train the classifier

validation set: use to monitor performance in real time - check for overfitting

test set: use to train the classifier

In practice



NO CHEATING! NEVER USE TRAINING TO VALIDATE YOUR ALGORITHM!

The algorithm used to minimize is called OPTIMIZATION

THERE ARE SEVERAL OPTIMIZATION TECHNIQUES

Optimization

THERE ARE SEVERAL OPTIMIZATION TECHNIQUES

THEY DEPEND ON THE MACHINE LEARNING ALGORITHM

Optimization

THERE ARE SEVERAL OPTIMIZATION TECHNIQUES

THEY DEPEND ON THE MACHINE LEARNING ALGORITHM

NEURAL NETWORKS USE THE GRADIENT DESCENT AS WE WILL SEE LATER

$$W_{t+1} = W_t - \lambda_h \bigtriangledown f(W_t)$$

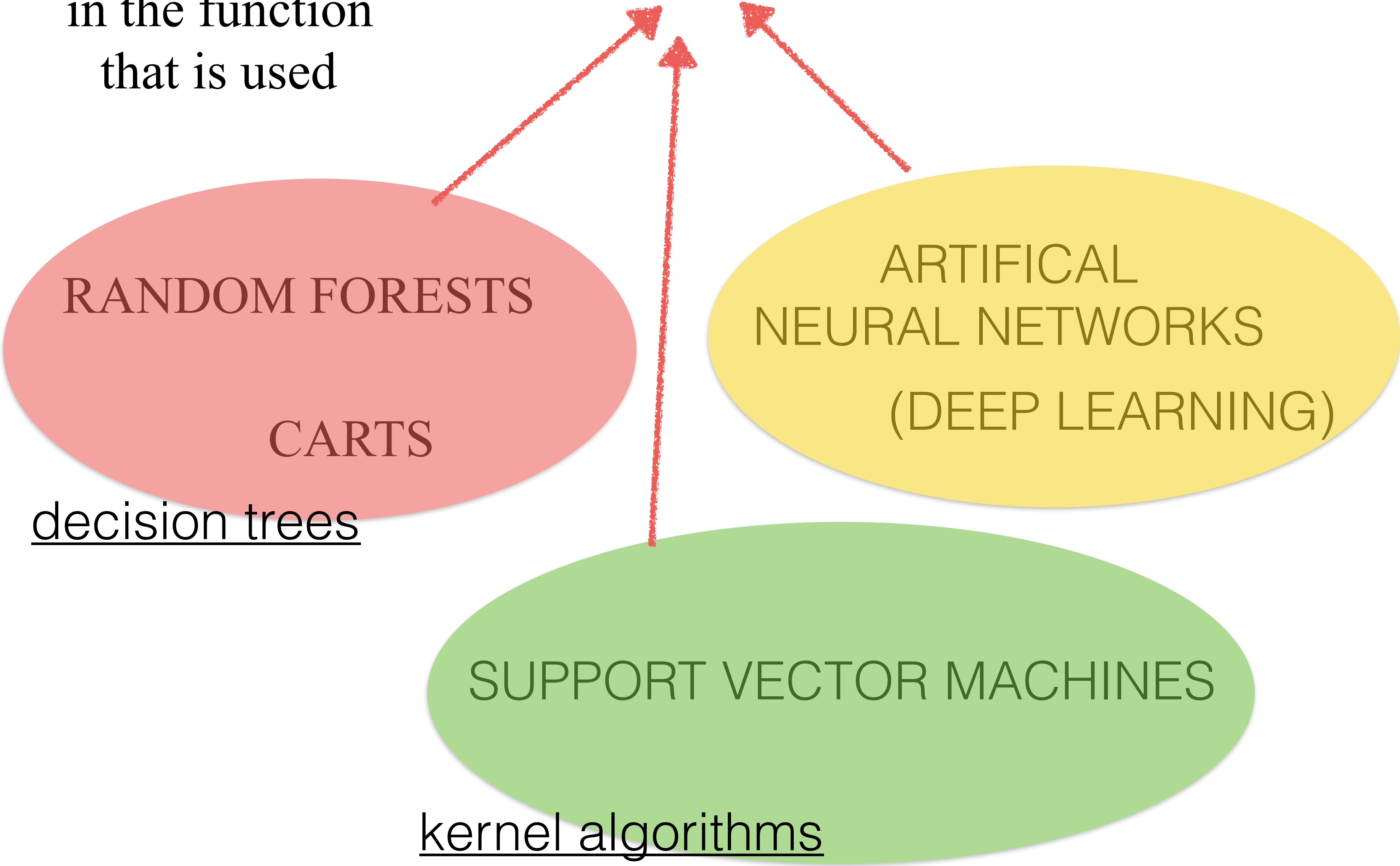
learning rate
(hyper parameter)

weights to be learned

epoch

$$f_W(\vec{x})$$

The differences are
in the function
that is used



DECISION TREES ALGORITHMS

DECISION TREES

CARTS

Classification Trees

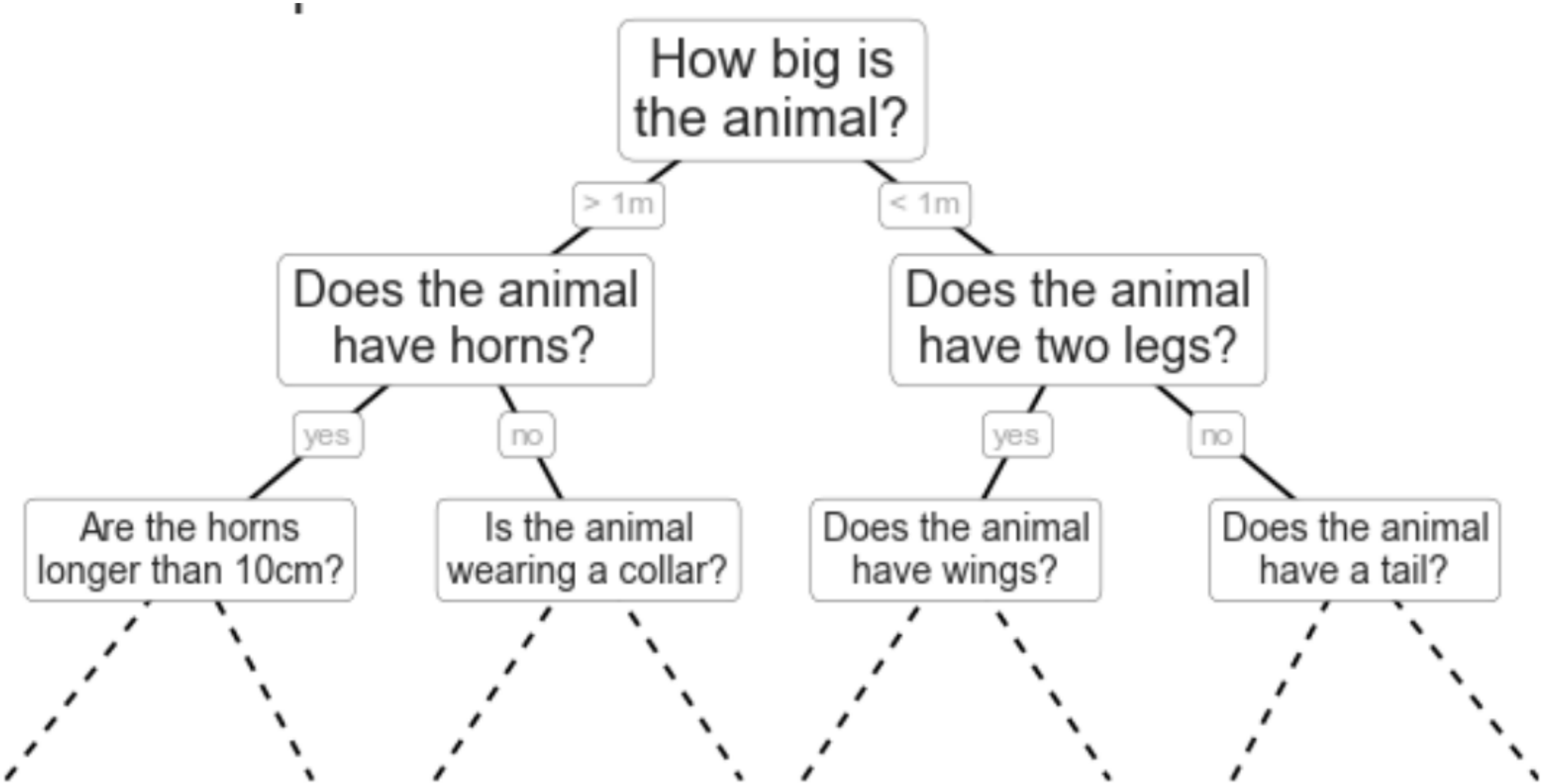
Regression Trees

BOOSTED TREES

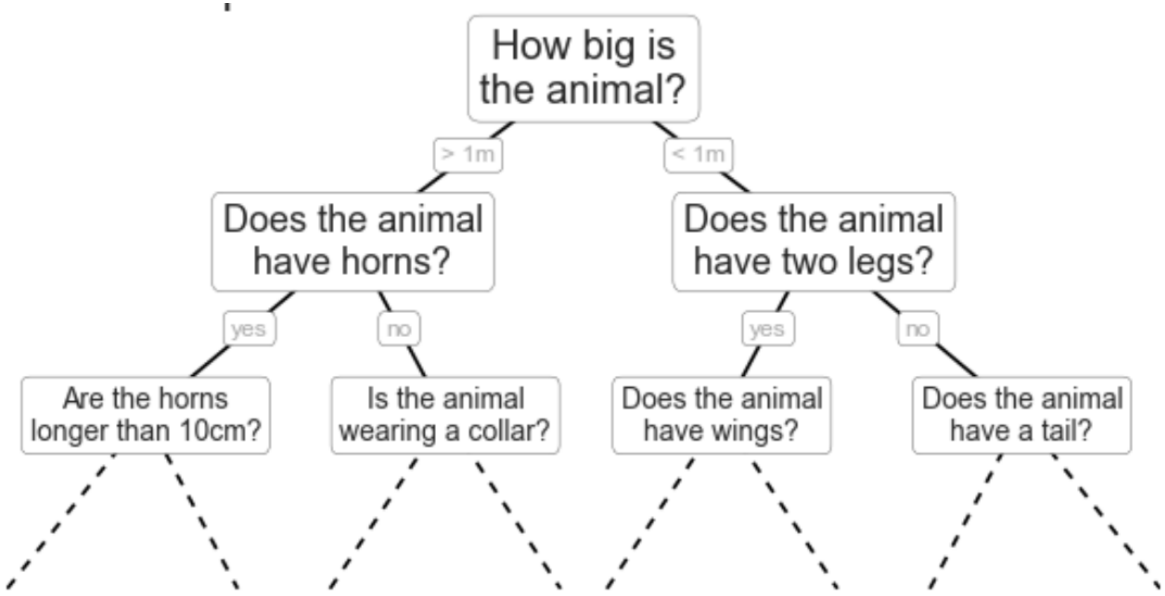
Random Forests

CLASSIFICATION AND REGRESSION TREES (CARTS)

THIS IS THE SIMPLEST AND MORE INTUITIVE MACHINE LEARNING ALGORITHM



DECISION TREES (CARTS)



IT IS BUILT IN AN ITERATIVE WAY

1. FROM THE INPUT PARAMETERS, FIRST FIND THE PROPERTY THAT BEST SPLITS INTO 2 GROUPS **[I.E. MINIMIZES SOME LOSS FUNCTION]**

2. REPEAT STEP 1 WITH ANOTHER PARAMETER

3. AT THE END THERE IS A TREE WHERE, AT EACH POINT, ONE OF TWO DECISIONS CAN BE MADE

DECISION TREES (CARTS)

TYPICAL METRICS USED:

[THE IDEA IS TO FIND THE SPLITTING VALUE THAT PUTS ALL OBJECTS OF A GIVEN CLASS IN ONE LEAF]

DECISION TREES (CARTS)

TYPICAL LOSS FUNCTION USED:

GINI IMPURITY

$$G = 1 - \sum_{j=1}^{c} p_j^2$$

DECISION TREES (CARTS)

TYPICAL LOSS FUNCTION USED:

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$$G = 1 - \sum_{j=1}^{c} p_j^2$$

fraction of
objects in each class given
a split value

Decision trees (CARTS)

TYPICAL LOSS FUNCTION USED:

GINI IMPURITY

$$G = 1 - \sum_{j=1}^{c} p_j^2$$

IF THERE IS ONLY ONE CLASS
THE GINI IMPURITY GOES TO 0

fraction of
objects in each class given
a split value

DECISION TREES (CARTS)

[b/a, color, size, SFR …]

$$\vec{x_i} = (p_1, p_2, ..., p_n)$$

(parameters)

TRAINING DATA

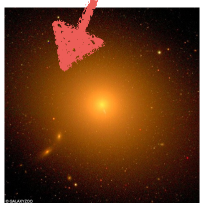
$(\vec{x_2}, \vec{y_2})$

$(\vec{x_1}, \vec{y_1})$

$(\vec{x_3}, \vec{y_3})$ $(\vec{x_4}, \vec{y_4})$

$$\vec{y_i} = (y_1, y_2, ..., y_n)$$

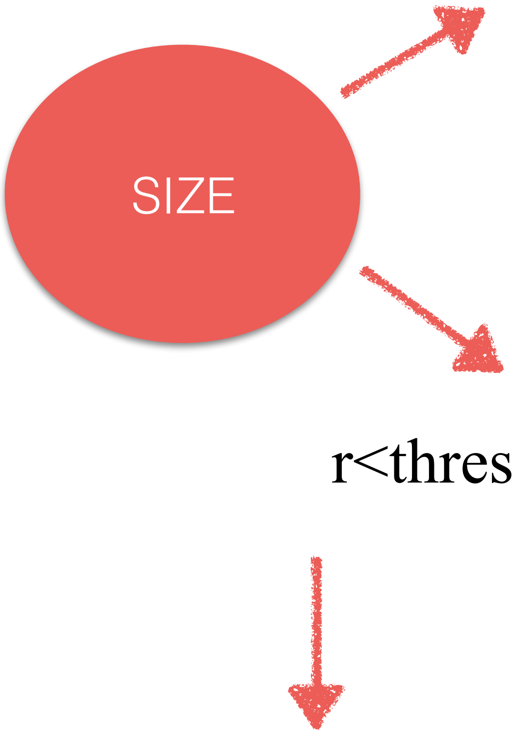
(classes)



[elliptical / spiral]

DECISION TREES (CARTS)

r>thres.

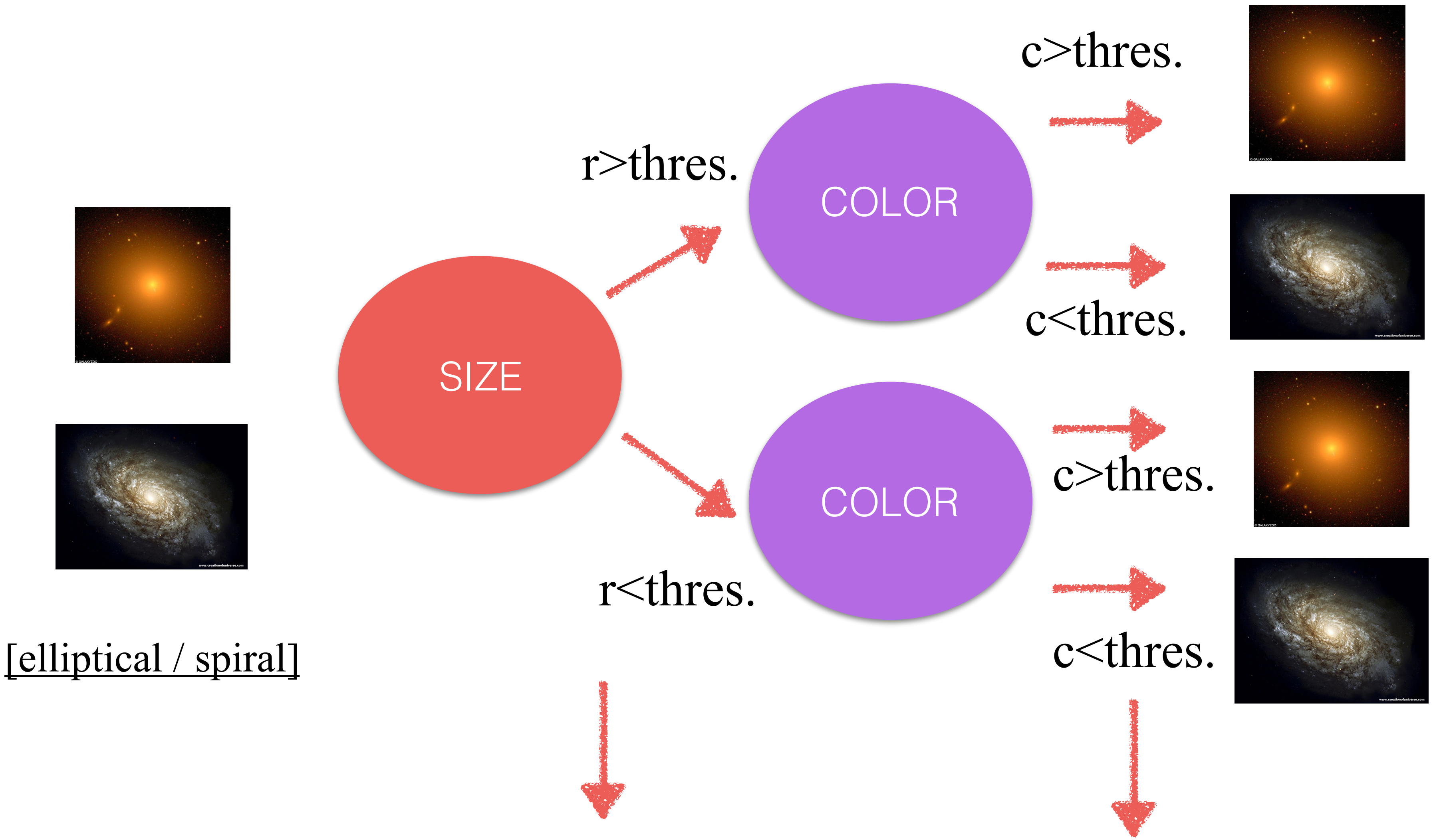


r<thres.

[elliptical / spiral]

LOOK FOR THRES. SO THAT
GINI IMPURITY IS MINIMAL

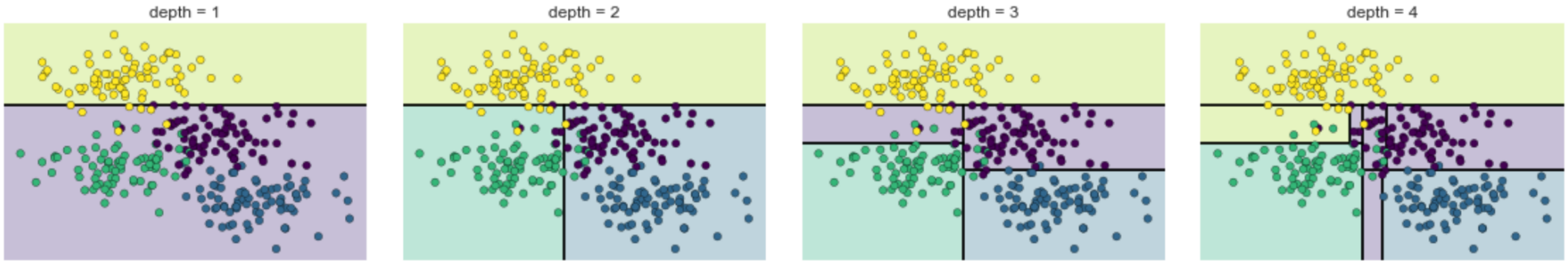
DECISION TREES (CARTS)



LOOK FOR THRES. SO THAT GINI IMPURITY IS MINIMAL

LOOK FOR 2nd THRES. SO THAT GINI IMPURITY IS MINIMAL

DECISION TREES (CARTS)



IT IS SIMPLY A PARTITION OF THE PARAMETER SPACE WITH CONSTANT BOUNDARIES - THE NUMBER OF BOUNDARIES DEPENDS ON THE DEPTH OF THE ALGORITHM (HYPER-PARAMETER)

RANDOM FORESTS

ONE PROBLEM WITH CLASSIFICATION TREES IS THAT THEY CAN EASILY OVERFIT

THE DECISIONS ARE VERY SPECIFIC TO THE TRAINING SET AND NOT REPRESENTATIVE OF THE FULL POPULATION

RANDOM FORESTS

RANDOM FORESTS TRY TO SOLVE THIS PROBLEM BY INTRODUCING SOME RANDOM INFORMATION IN THE TRAINING PROCESS

[b/a, color, size, SFR …]

TRAINING DATA

$$\vec{x_i} = (p_1, p_2, ..., p_n)$$

(parameters)

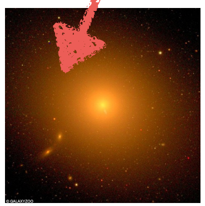
$(\vec{x_2}, \vec{y_2})$

$(\vec{x_1}, \vec{y_1})$

$(\vec{x_3}, \vec{y_3})$ $(\vec{x_4}, \vec{y_4})$

$$\vec{y_i} = (y_1, y_2, ..., y_n)$$

(classes)



[elliptical / spiral]

RANDOM FORESTS

$(\vec{x_2}, \vec{y_2})$

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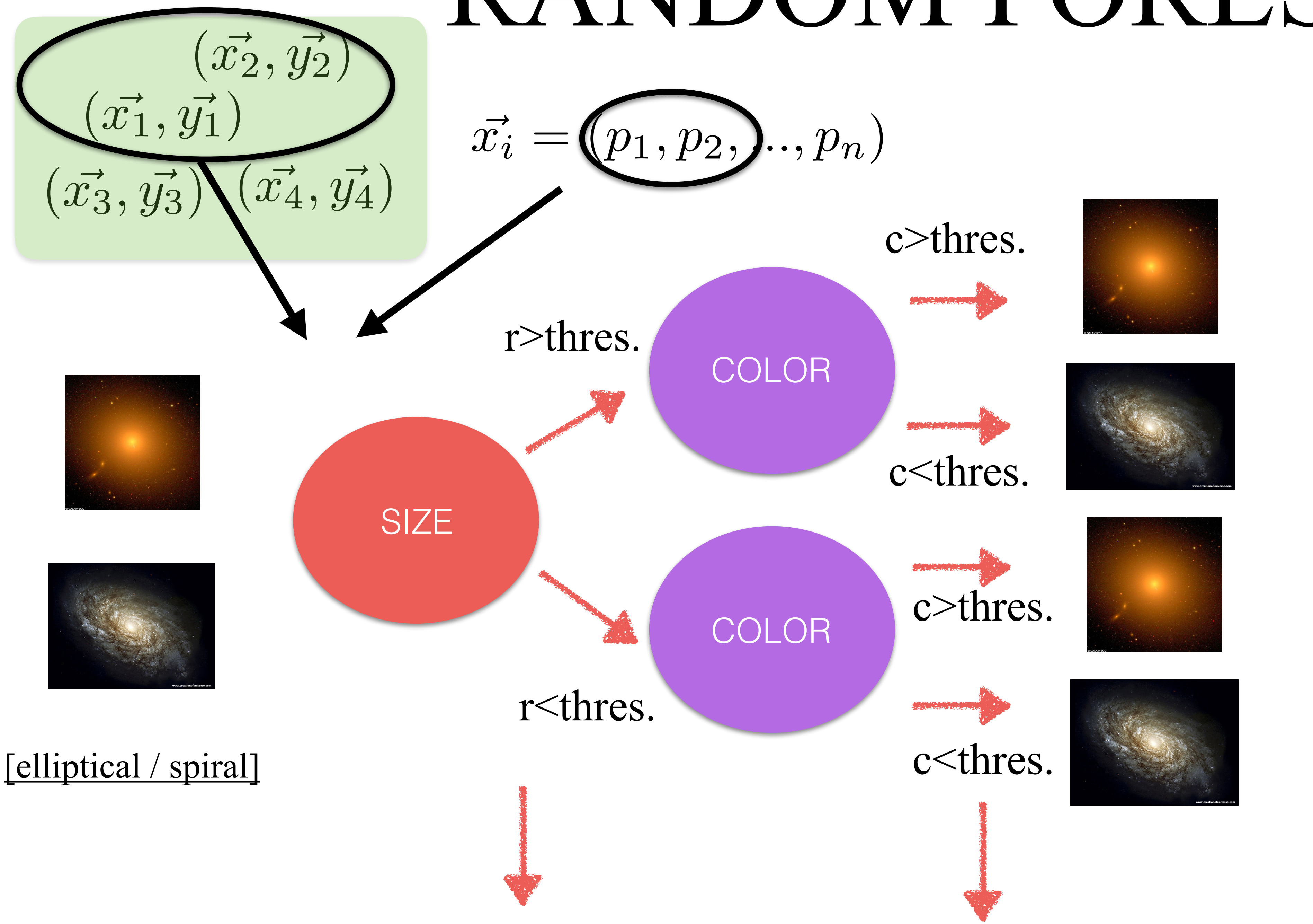
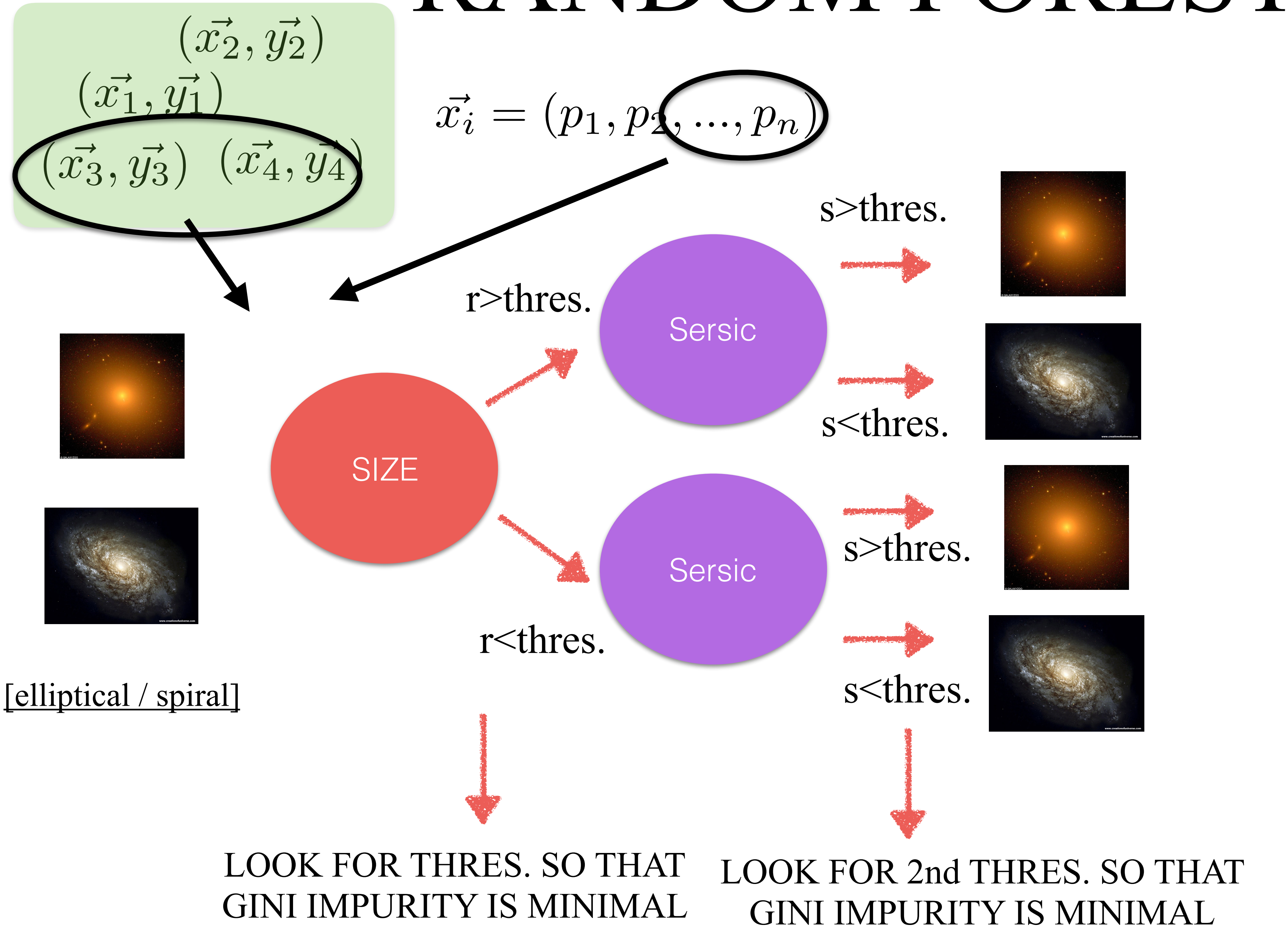
RANDOM FORESTS



LOOK FOR THRES. SO THAT GINI IMPURITY IS MINIMAL

LOOK FOR 2nd THRES. SO THAT GINI IMPURITY IS MINIMAL

RANDOM FORESTS



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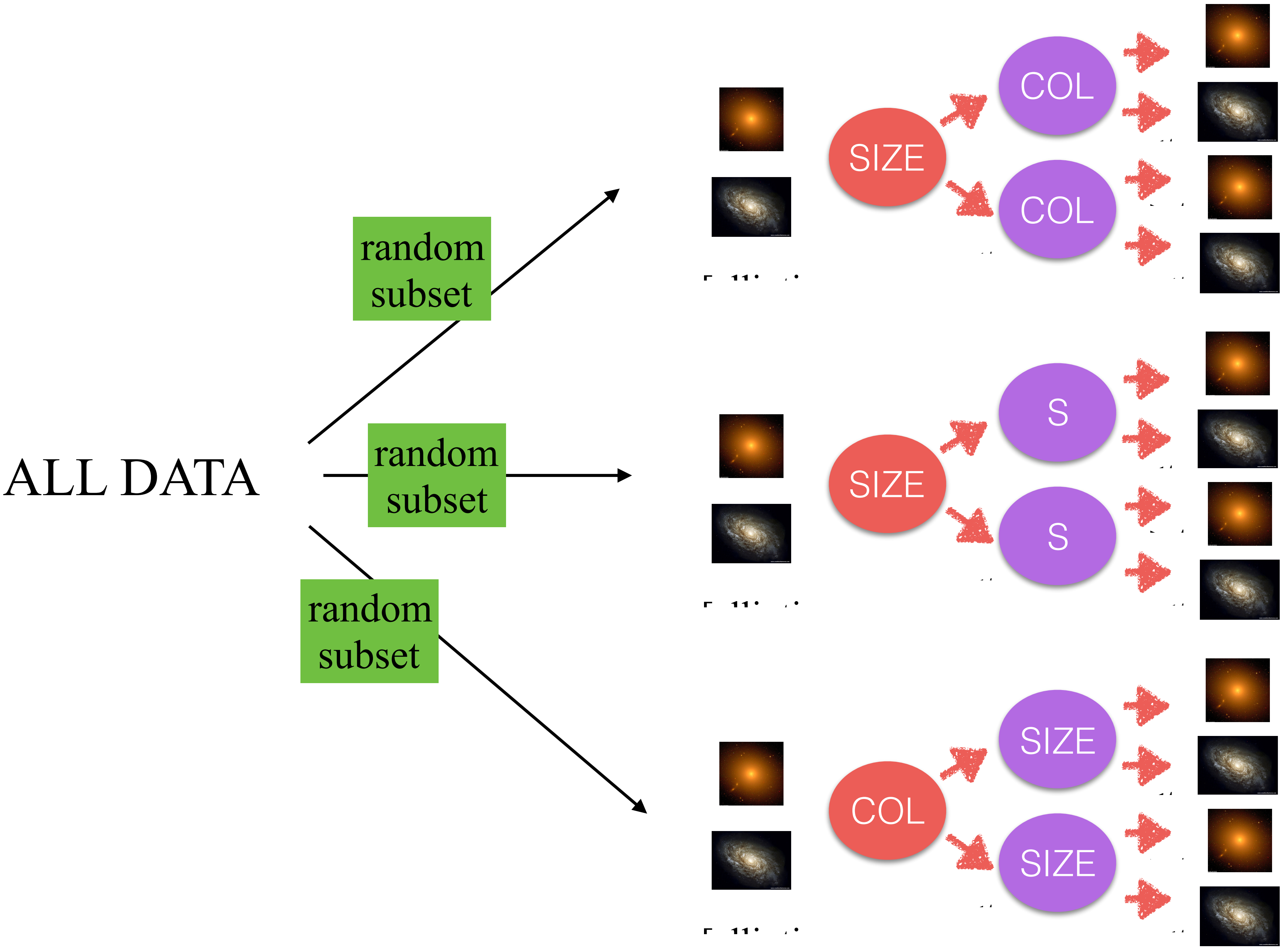

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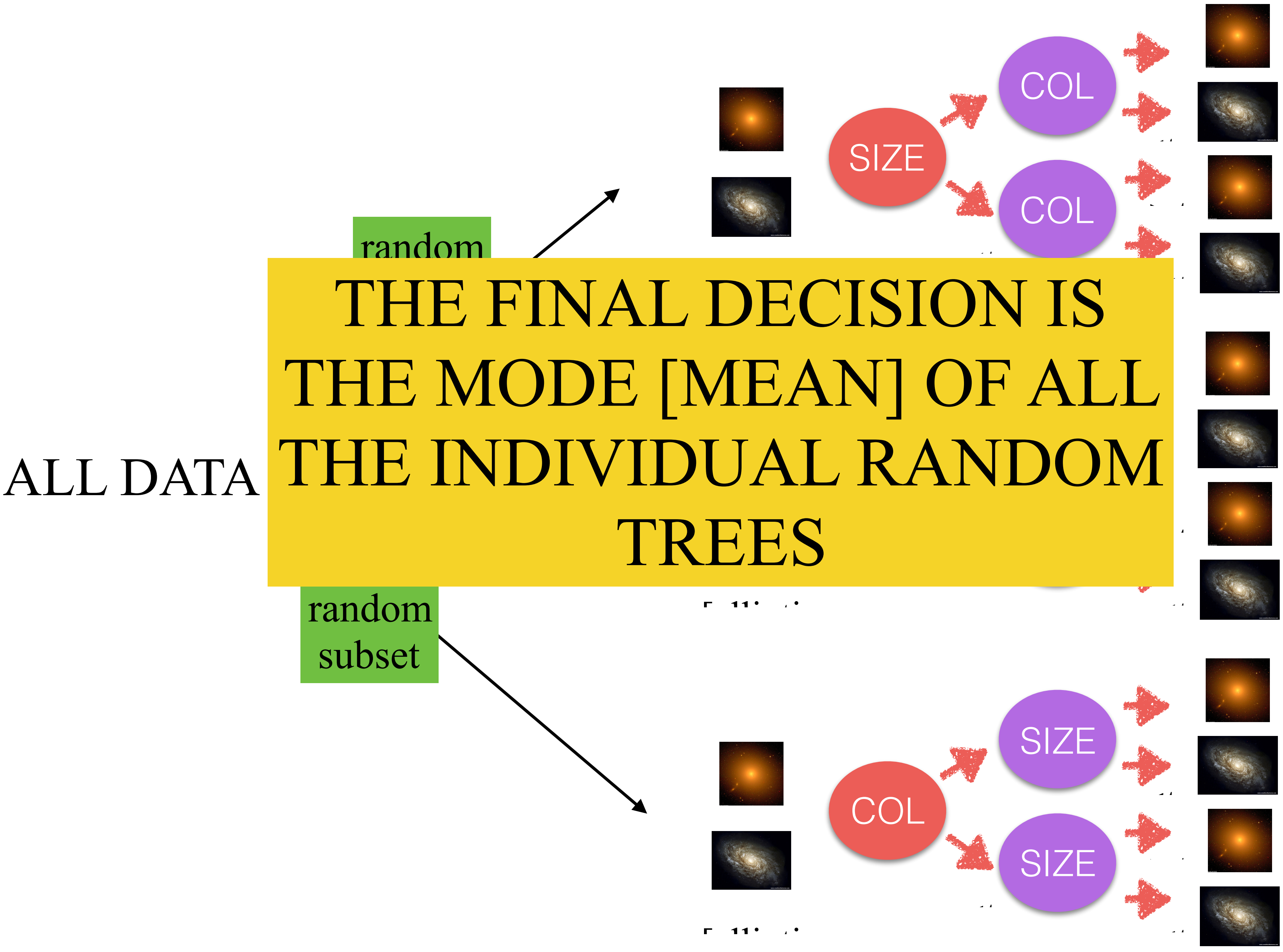

THE FINAL DECISION IS THE MODE [MEAN] OF ALL THE INDIVIDUAL RANDOM TREES

Random Forests

ONE KEY ADVANTAGE OF DECISION TREE ALGORITHMS IS THAT THEY ARE VERY EASY TO INTERPRET

ONE CAN EASILY DETERMINE THE MOST IMPORTANT FEATURES TO TAKE DECISIONS

RANDOM FORESTS

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Rank	Property	AUC	Success label[a]
	ALL	0.9074 ± 0.0106	Outstanding
1	CVD	0.8559 ± 0.0039	Excellent
2	$M_{\rm bulge}$	0.8335 ± 0.0060	Excellent
3	B/T	0.8267 ± 0.0028	Excellent
4	$M_{\rm halo}$	0.7983 ± 0.0045	Acceptable
5	M_*	0.7819 ± 0.0025	Acceptable
6	$M_{\rm disc}$	0.7124 ± 0.0016	Acceptable
7	δ_5	0.5894 ± 0.0015	Unacceptable
8	Re	0.5599 ± 0.0013	Unacceptable

IMPORTANCE OF PARAMETERS TO PREDICT IF A GALAXY IS QUENCHED

Teimiroonia+16

PRACTICAL NOTE: *Python scikit learn*

- All these different methods are standard and available in Python
- Very easy to use
- All info here

sklearn.ensemble.RandomForestClassifier

class `sklearn.ensemble.` **`RandomForestClassifier`**(*n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False, class_weight=None*) ¶ [source]

NUMBER OF RANDOM TREES

<u>EVERY ML ALGORITHM HAS A NUMBER OF HYPER PARAMETERS WHICH NEED TO BE TUNED</u>

<u>EXCEPT FOR VERY FEW CASES, THERE ARE NO PRE-DEFINED RULES</u>

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METRIC TO MINIMIZE

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MAXIMUM NUMBER OF SPLITS

EVERY ML ALGORITHM HAS A NUMBER OF HYPER PARAMETERS WHICH NEED TO BE TUNED

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MAXIMUM NUMBER OF SPLITS

```
>>> from sklearn.ensemble import RandomForestClassifier
>>> from sklearn.datasets import make_classification
>>>
>>> X, y = make_classification(n_samples=1000, n_features=4,
...                            n_informative=2, n_redundant=0,
...                            random_state=0, shuffle=False)
>>> clf = RandomForestClassifier(max_depth=2, random_state=0)
>>> clf.fit(X, y)
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=2, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=0, verbose=0, warm_start=False)
>>> print(clf.feature_importances_)
[ 0.17287856  0.80608704  0.01884792  0.00218648]
>>> print(clf.predict([[0, 0, 0, 0]]))
[1]
```

sklearn.ensemble.RandomForestClassifier

class sklearn.ensemble. **RandomForestClassifier** (*n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False, class_weight=None*) ¶ [source]

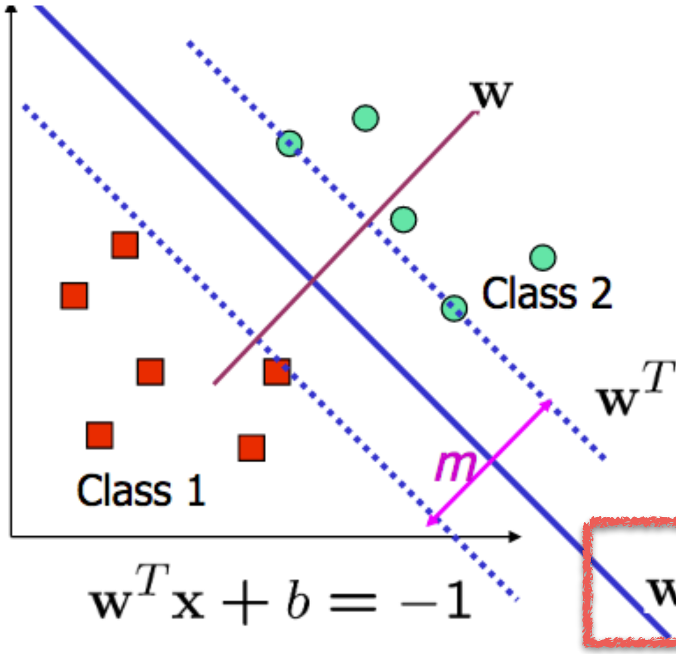
MAXIMUM NUMBER OF SPLITS

```
>>> from sklearn.ensemble import RandomForestClassifier
>>> from sklearn.datasets import make_classification
>>>
>>> X, y = make_classification(n_samples=1000, n_features=4,
...                            n_informative=2, n_redundant=0,
...                            random_state=0, shuffle=False)
>>> clf = RandomForestClassifier(max_depth=2, random_state=0)
>>> clf.fit(X, y)
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=2, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
```

DIFFERENT CLASSIFIERS ARE OBJECTS WITH METHODS TO FIT, PREDICT ETC..

```
>>> print(clf.predict([[0, 0, 0, 0]]))
[1]
```

Support Vector Machines



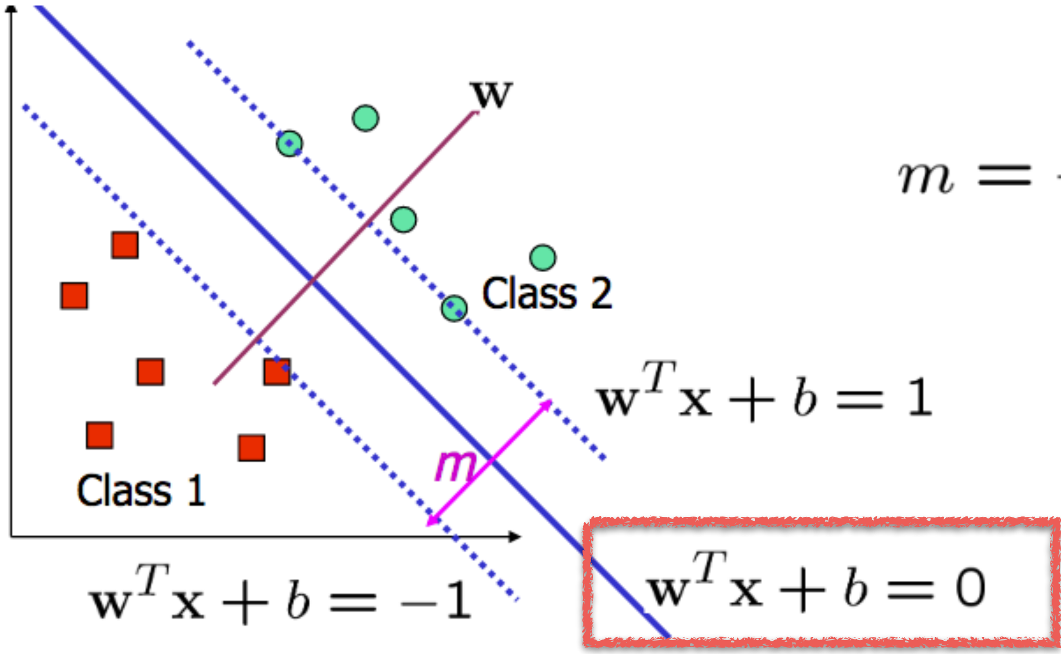
$$m = \frac{2}{||\mathbf{w}||}$$

$$\boxed{\mathbf{w}^T\mathbf{x} + b = 0}$$

<u>equation of the hyperplane</u>

[Credit: M. Law]

Support Vector Machines



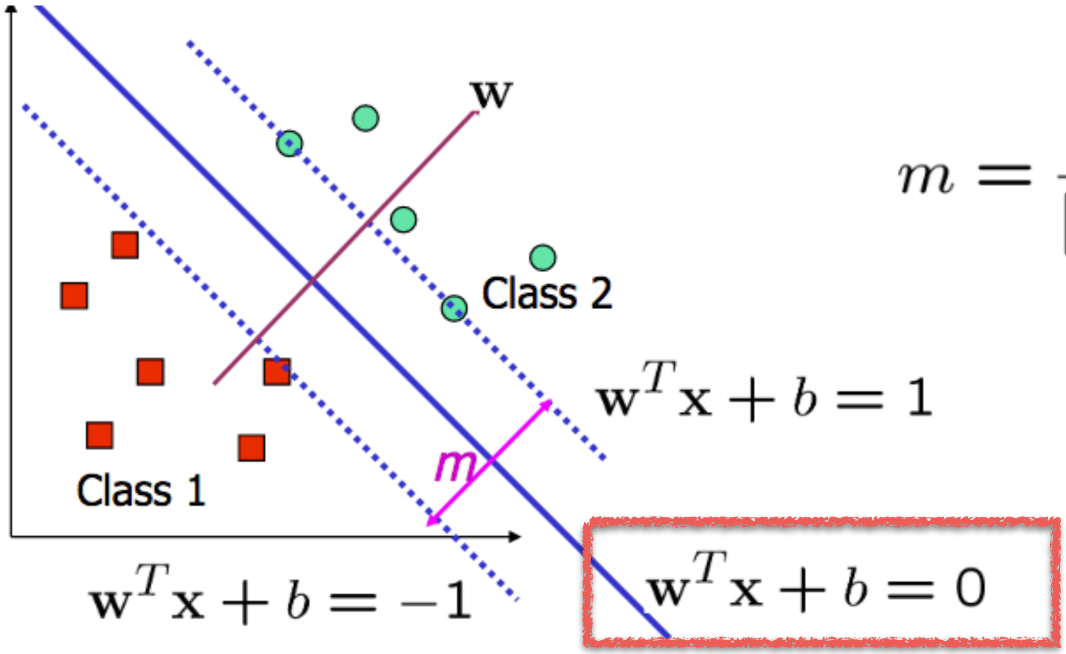
$$m = \frac{2}{||\mathbf{w}||}$$

<u>equation of the hyperplane</u>

THE GAME HERE IS TO FIND THE W THAT
MAXIMIZES THE MARGIN [MINIMIZE ||w||/2]

[Credit: M. Law]

Support Vector Machines



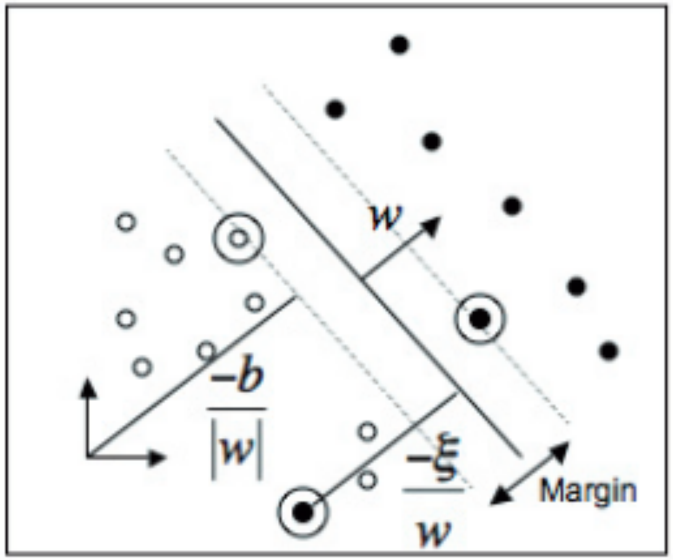
$$m = \frac{2}{||\mathbf{w}||}$$

equation of the hyperplane

IF THE PROBLEM IS LINEARLY SEPARABLE, THERE IS AN IDEAL SOLUTION [see figure]

[Credit: M. Law]

Support Vector Machines



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IN MOST CASES THE DATA ARE NON LINEARLY SEPARABLE

$$\mathbf{x_i}.\mathbf{w} + b \geq +1 - \epsilon_i$$

$$\mathbf{x_i}.\mathbf{w} + b \geq +1 + \epsilon_i$$

THE CONDITION IS RELAXED BY ADDING A POSITIVE STACK VARIABLE

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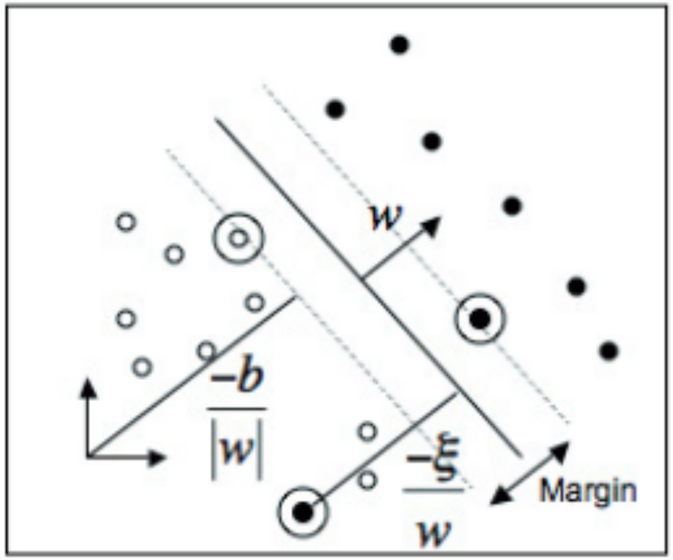
Support Vector Machines



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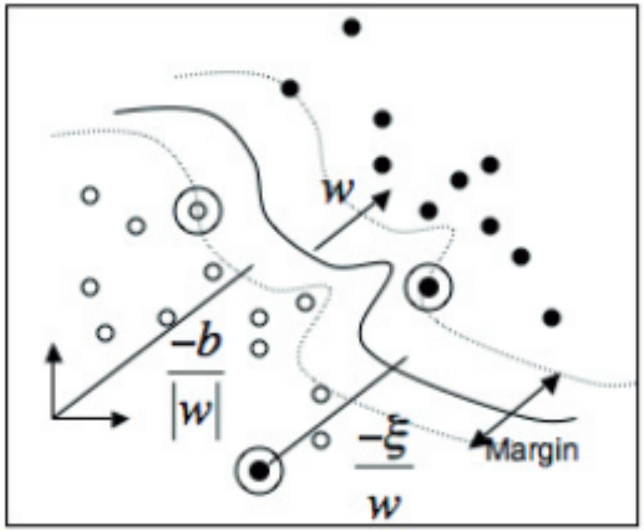
THE CONDITION IS RELAXED BY ADDING A POSITIVE STACK VARIABLE

THE FUNCTION TO MINIMIZE: $$\frac{||w^2||}{2} + T[\sum \epsilon_i]$$

THE LARGER T, THE MORE ERRORS ARE PENALIZED

Support Vector Machines



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THE FINAL TRICK IS TO FIND NON-LINEAR BOUNDARIES

WE MAP THE PLANE INTO A NEW EUCLIDIAN SPACE WHERE THE POINTS ARE SEPARABLE

$$\Phi : \mathbb{R} \to H$$

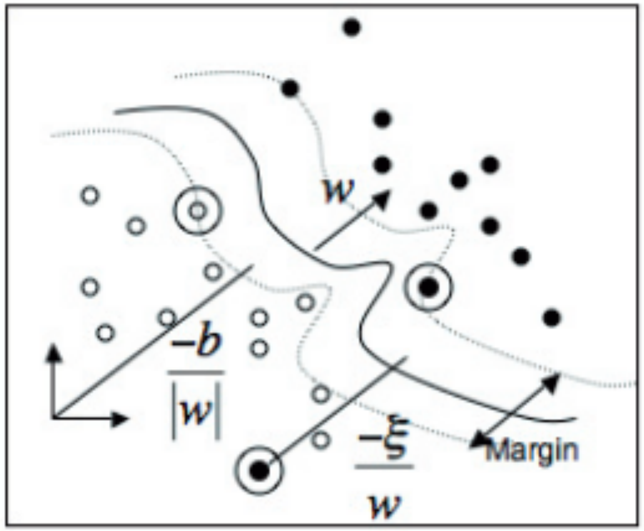
SINCE WE ONLY NEED TO COMPUTE INNER PRODUCTS IN THIS SPACE

$$x_i . x_j$$

THE TRAINING ALGORITHM WOULD ONLY DEPEND ON THE DATA THROUGH THE PRODUCTS IN H

$$\Phi(x_i).\Phi(x_j)$$

Support Vector Machines



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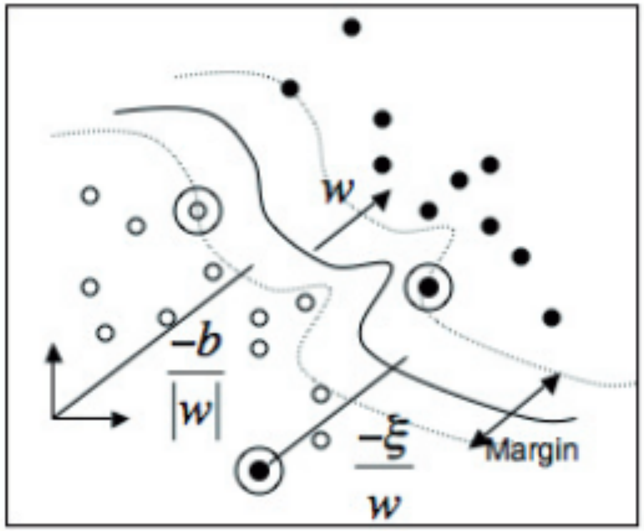
THE FINAL TRICK IS TO FIND NON-LINEAR BOUNDARIES

IF THERE IS A **KERNEL FUNCTION** SO THAT:

$$K(x_i, x_j) = \Phi(x_i).\Phi(x_j)$$

THEN THERE IS NO NEED TO EXPLICITLY KNOW Φ

Support Vector Machines



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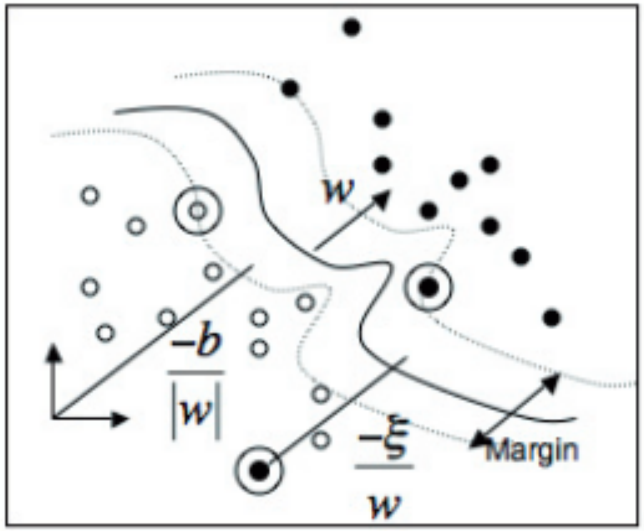
SVM IS CALLED **A KERNEL METHOD**

Support Vector Machines



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SVM IS CALLED **A KERNEL METHOD**

EXAMPLE OF KERNEL: $$K(x, y) = e^{-g||x-y||^2}$$

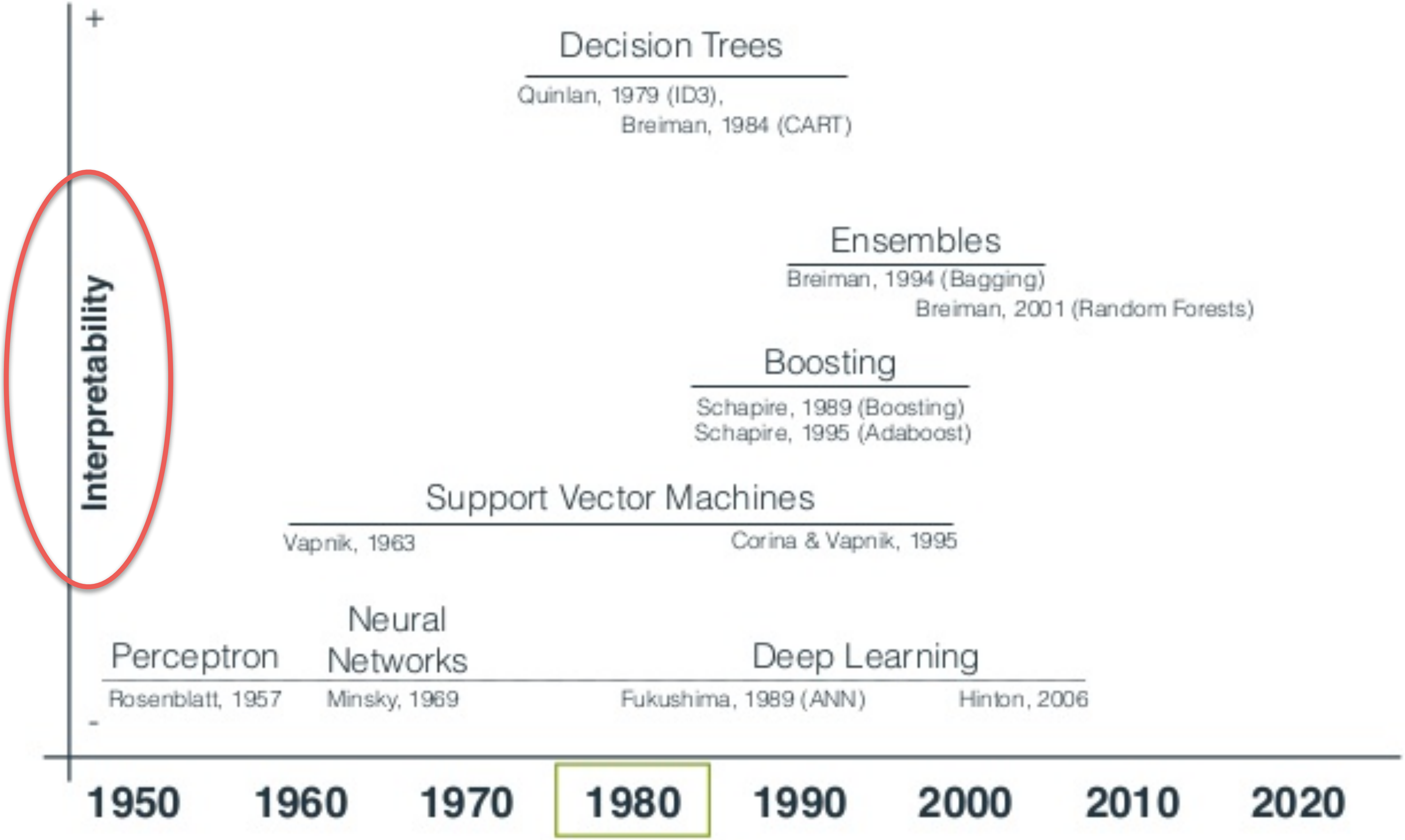
[GAUSSIAN RBF]

HOW TO CHOOSE YOUR CLASSICAL CLASSIFIER?

NO RULE OF THUMB - REALLY DEPENDS ON APPLICATION

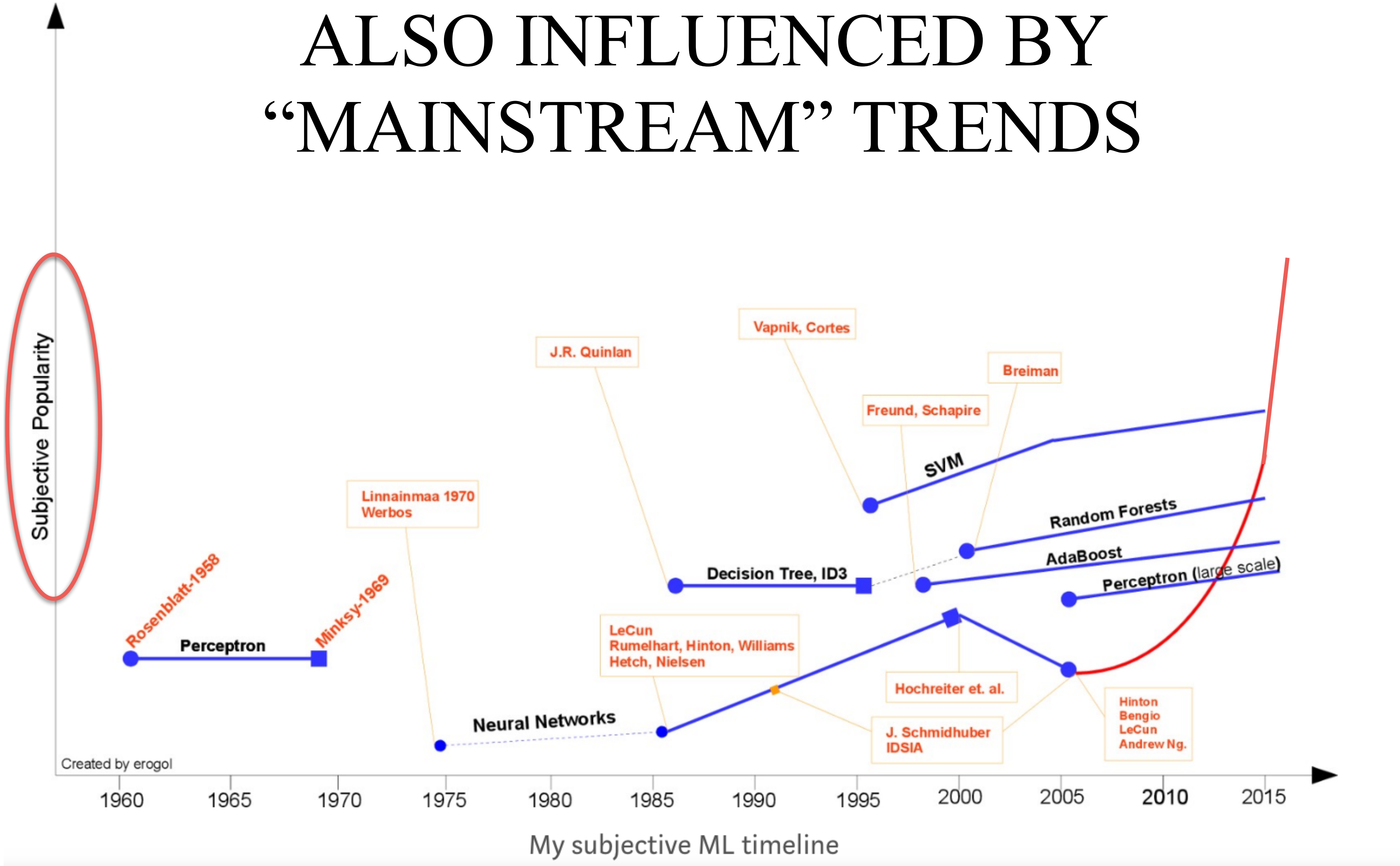
ML METHOD	++	—	Python
CARTS / RANDOM FOREST	Easy to interpret ("White box") Litte data preparation Both numerical + categorical	Over-complex trees Unstable Biased tress if some classes dominate	sklearn.ensemble.RandomForestClassifier sklearn.ensemble.RandomForestRegressor
SVM	Easy to interpret + Fast Kernel trick allows no linear problems	not very well suited to multi-class problems	sklearn.svm sklearn.svc
NN	seed of deep-learning very efficient with large amount of data as we will see	more difficult to interpret computing intensive	sklearn.neural_network.MLP_CLassifier sklearn.neural_network.MLP_Regressor

CAN DEPEND ON YOUR MAIN INTEREST



credit

ALSO INFLUENCED BY "MAINSTREAM" TRENDS

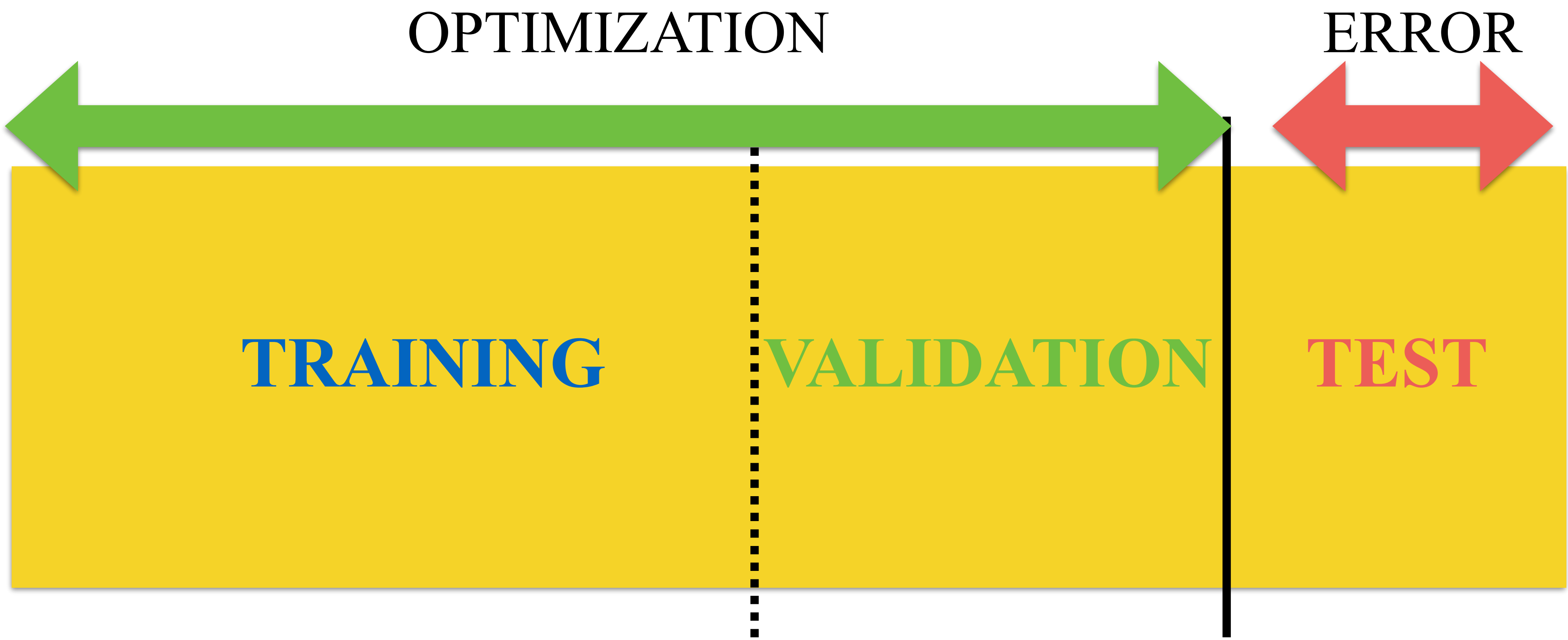


Source

HOW DO I KNOW THAT MY MACHINE LEARNING ALGORITHM IS WORKING?

- The way results are evaluated depends strongly on the type of problem
  - Binary Classification: ACC, ROC, P-C
  - Multi-Class: Confusion Matrix
  - Regression: RMSE, Bias, Scatter etc..

REMEMBER



training set: use to train the classifier

validation set: use to monitor performance in real time - check for overfitting

test set: use to train the classifier

Evaluation of results [binary class.]

THE MOST STRAIGHTFORWARD WAY IS TO EVALUATE THE TOTAL ACCURACY

true positives

true negatives

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

MEASURES HOW MANY OBJECTS ARE CORRECTLY CLASSIFIED

Evaluation of results [binary class.]

THE MOST STRAIGHTFORWARD WAY IS TO EVALUATE THE TOTAL ACCURACY

true po… …ue negatives

$$ACC = \frac{\ldots}{TP + TN + FP + FN}$$

NOT VERY INFORMATIVE IF UNBALANCED CLASSES

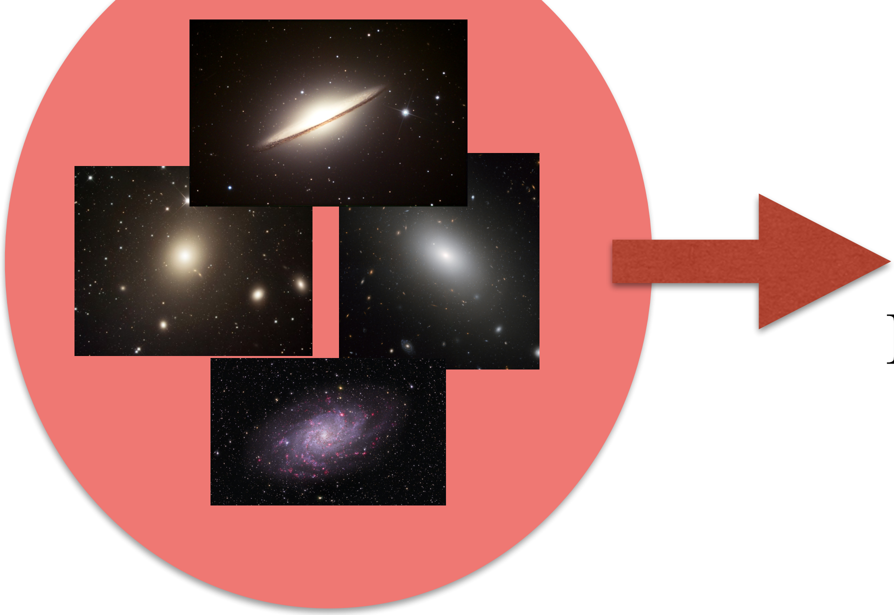
MEASURES HOW MANY OBJECTS ARE CORRECTLY CLASSIFIED

IMAGINE AN EXTREME CASE WITH VERY UNBALANCED DATA…

[90% E, 10% S]

IMAGINE AN EXTREME CASE WITH VERY UNBALANCED DATA…

[90% E, 10% S]



IF I SAY THAT ALL GALAXIES IN THE UNIVERSE ARE ELLIPTICALS I WILL BE RIGHT 90% OF THE TIMES

Evaluation of results [binary class.]

THE ROC CURVE (Receiver Operating Characteristic)

IT IS BASED ON TWO VERY SIMPLE PARAMETERS

1. $$\boxed{TPR = \frac{TP}{TP + FN} \quad \text{[Also called Sensitivity, Completeness]}}$$

"Fraction of positive examples classified correctly"

Evaluation of results [binary class.]

THE ROC CURVE (Receiver Operating Characteristic)

IT IS BASED ON TWO VERY SIMPLE PARAMETERS

1. $$TPR = \frac{TP}{TP + FN}$$

TRUE POSITIVE RATE

[Also called Sensitivity, Completeness]

"Fraction of positive examples classified correctly"

2. $$FPR = \frac{FP}{FP + TN}$$

FALSE POSITIVE RATE

[Also called Specificity, Contamination]

"Fraction of negative examples classified as positive"

Evaluation of results [binary class.]

YOU WANT THIS TO BE AS BIG AS POSSIBLE

ver Operating Characteristic)

IT IS BASED ON TWO VERY SIMPLE PARAMETERS

1. $TPR = \frac{TP}{TP + \ldots}$

TRUE POSITIVE RATE

ompleteness]

YOU WANT THIS TO BE AS SMALL AS POSSIBLE

"Fraction of positive examples classified correctly"

2. $$FPR = \frac{FP}{FP + TN}$$

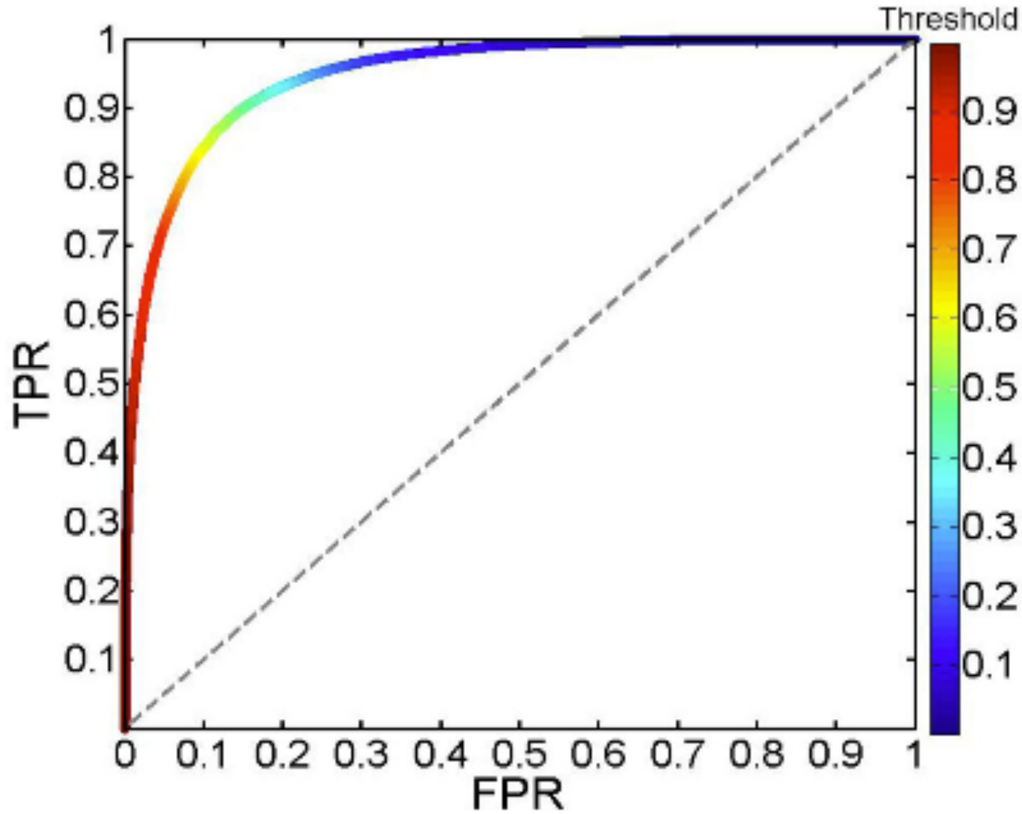
FALSE POSITIVE RATE

[Also called Specificity, Contamination]

"Fraction of negative examples classified as positive"

IF YOUR CLASSIFIER OUTPUTS A SORT OF PROBABILITY, TPR AND FPR CAN BE PLOTTED ONE AGAINST THE OTHER

<u>ROC CURVE</u>



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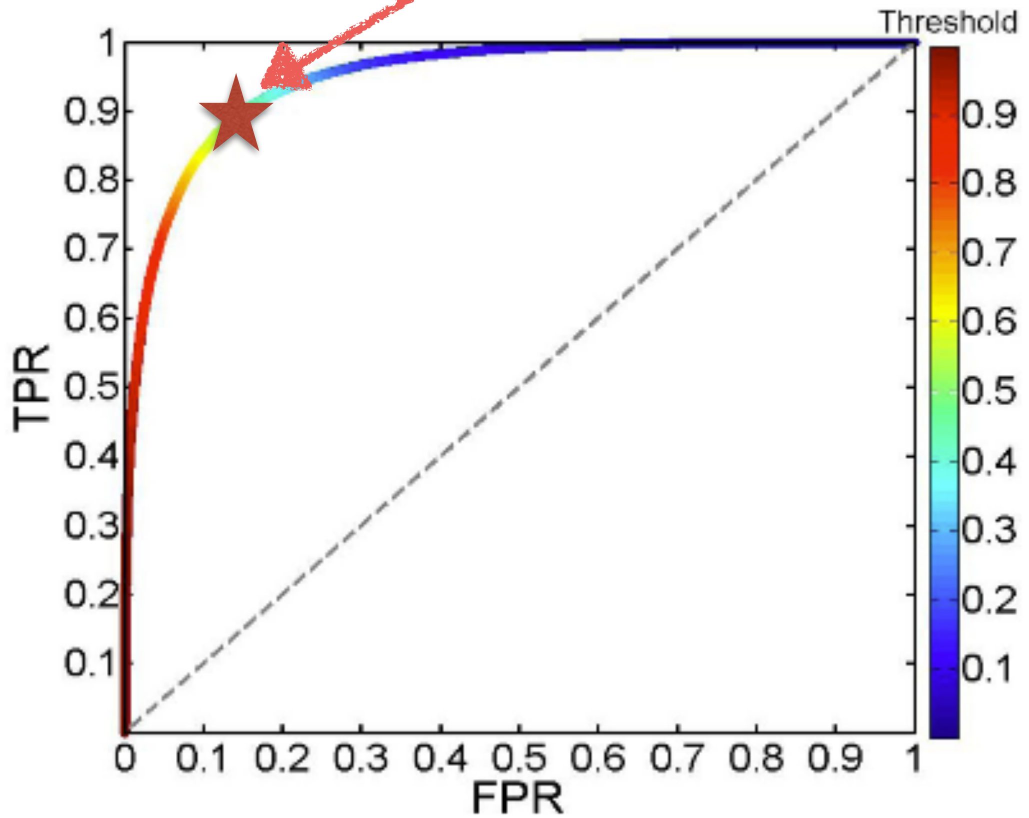
IF YOUR CLASSIFIER OUTPUTS A SORT OF PROBABILITY, TPR AND FPR CAN BE PLOTTED ONE AGAINST THE OTHER

EACH POINT HERE SHOWS THE VALUES OF TPR AND FOR FOR A GIVEN THRESHOLD

<u>ROC CURVE</u>



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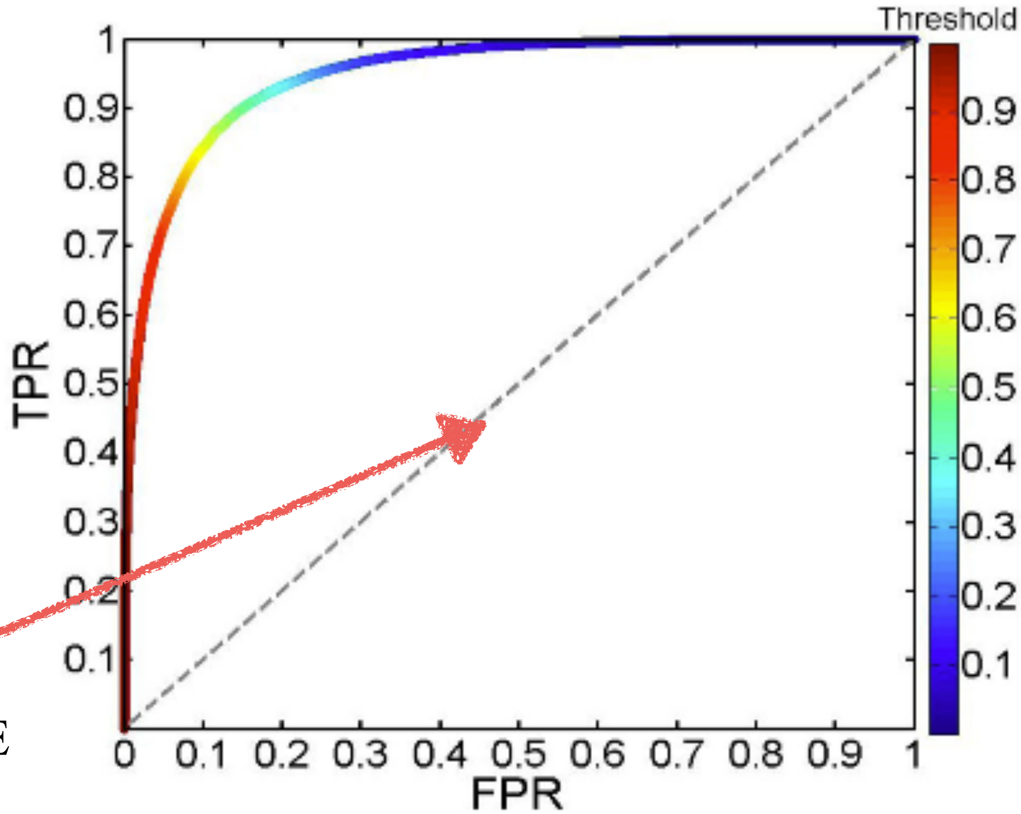
ROC CURVE



THE ONE-TO-ONE LINE IS A RANDOM CLASSIFICATION

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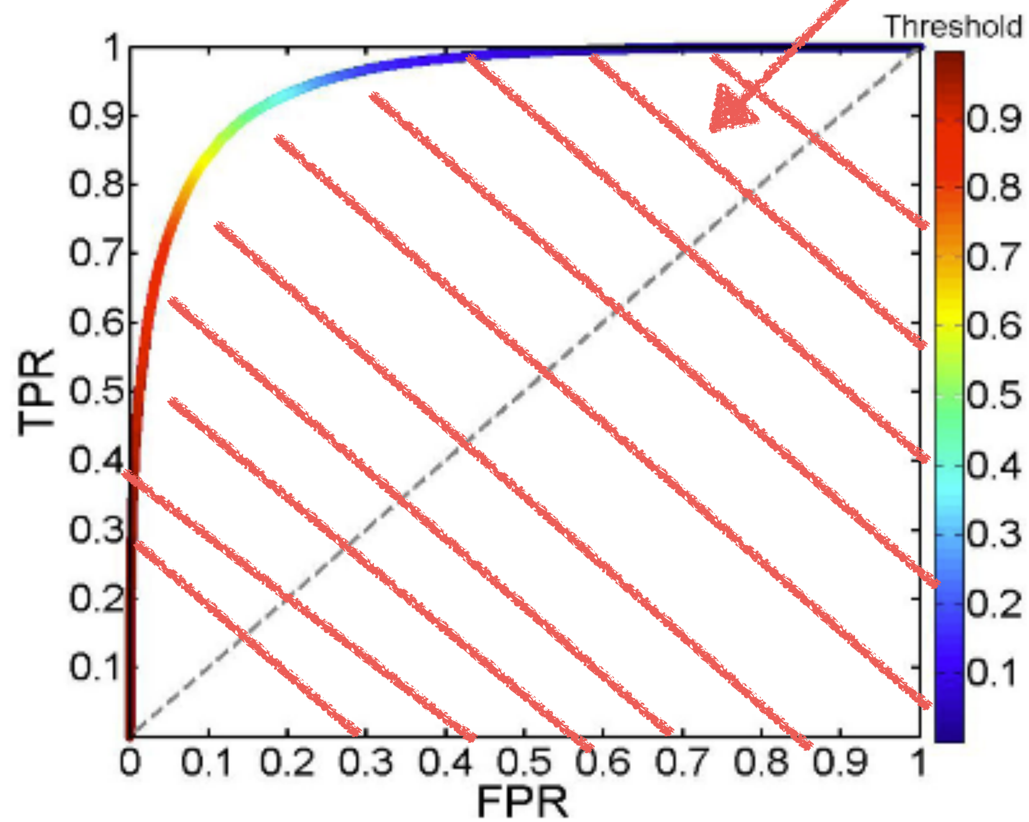
IF YOUR CLASSIFIER OUTPUTS A SORT OF PROBABILITY, TPR AND FPR CAN BE PLOTTED ONE AGAINST THE OTHER

THE AREA UNDER THE CURVE **[AUC]** ALSO MEASURES THE GLOBAL ACCURACY

ROC CURVE



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Evaluation of results

THE P-R CURVE (Precision - Recall)

$$Recall = \frac{TP}{TP + FN} = TPR \qquad \text{[completeness]}$$

$$Precision = \frac{TP}{TP + FP} \qquad \text{[purity]}$$

Evaluation of results

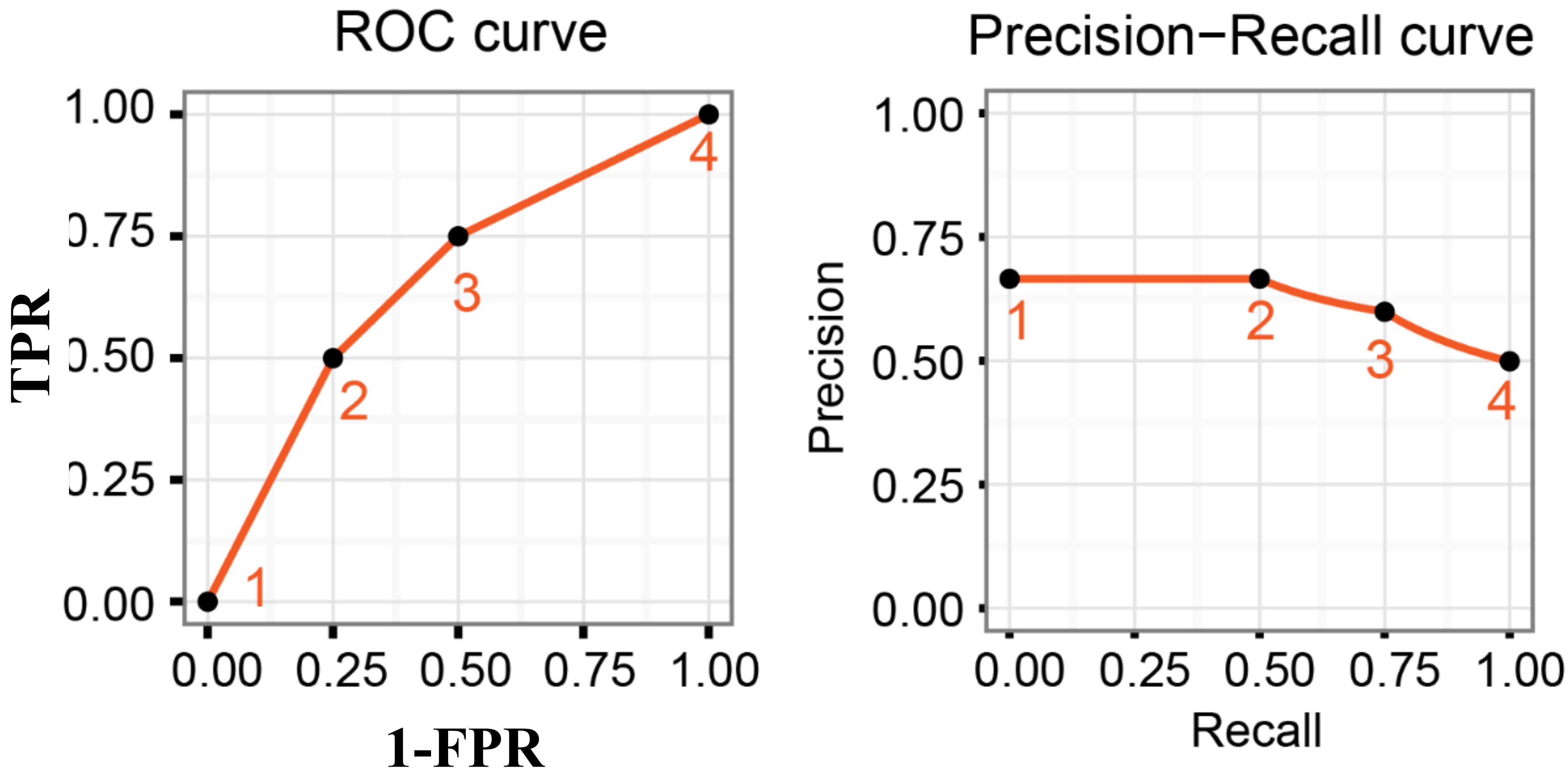
THE P-R CURVE (Precision - Recall)

$$Recall = \frac{TP}{TP + FN} = TPR \qquad \text{[completeness]}$$

$$Precision = \frac{TP}{TP + FP} \qquad \text{[purity]}$$

FOR BALANCED DATA: $Precision \sim 1 - FPR$

Evaluation of results



SUMMARY OF DIFFERENT ACCURACY TRACERS

		True condition				
	Total population	Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
Predicted condition	Predicted condition positive	**True positive**, Power	**False positive**, Type I error	Positive predictive value (PPV), Precision = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	Predicted condition negative	**False negative**, Type II error	**True negative**	False omission rate (FOR) = $\frac{\Sigma \text{ False negative}}{\Sigma \text{ Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$	
		True positive rate (TPR), Recall, Sensitivity, probability of detection = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{TPR}{FPR}$	Diagnostic odds ratio (DOR) = $\frac{LR+}{LR-}$	F_1 score = $\frac{2}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$
		False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	True negative rate (TNR), Specificity (SPC) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Negative likelihood ratio (LR−) = $\frac{FNR}{TNR}$		

SOURCE

SUMMARY OF DIFFERENT ACCURACY TRACERS

		True condition				
	Total population	Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
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THE F1 SCORE
COMBINES BOTH INFORMATIONS IN ONE VALUE

SOURCE

ALL THESE ARE INCLUDED IN SKLEARN

AND ARE VERY EASY TO USE. NO NEED OF CODING THEM AGAIN!

`sklearn.metrics.` **`precision_recall_curve`** (*y_true*, *probas_pred*, *pos_label=None*, *sample_weight=None*) ¶
[source]

Compute precision-recall pairs for different probability thresholds

Note: this implementation is restricted to the binary classification task.

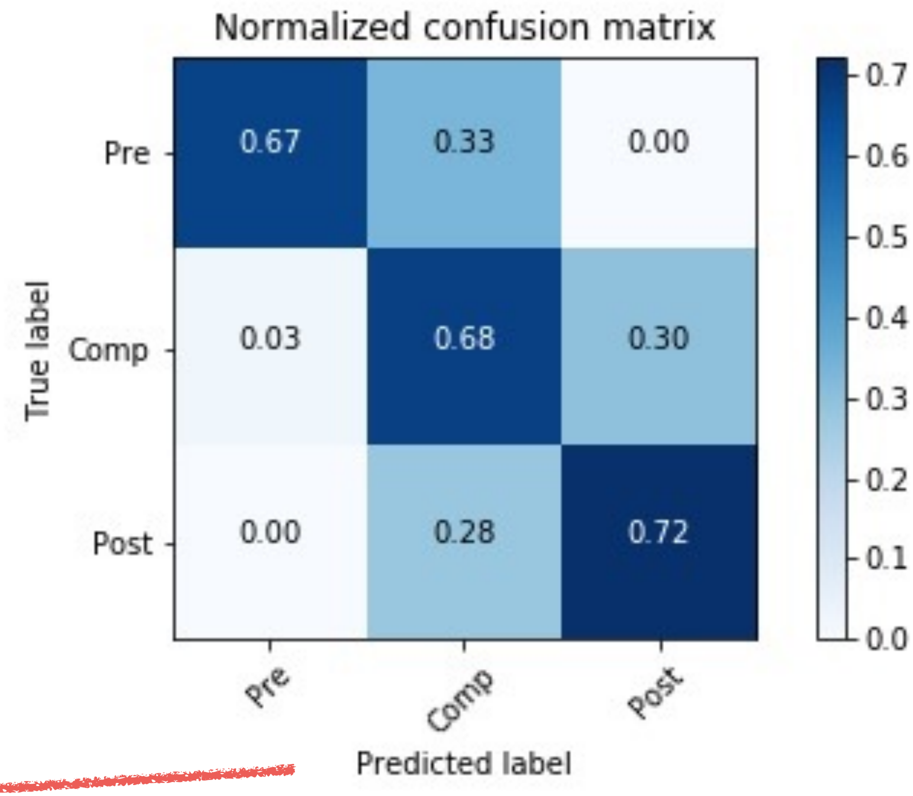
The precision is the ratio `tp / (tp + fp)` where `tp` is the number of true positives and `fp` the number of false positives. The precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

The recall is the ratio `tp / (tp + fn)` where `tp` is the number of true positives and `fn` the number of false negatives. The recall is intuitively the ability of the classifier to find all the positive samples.

The last precision and recall values are 1. and 0. respectively and do not have a corresponding threshold. This ensures that the graph starts on the x axis.

Evaluation of results [multi-class]

<u>CONFUSION MATRIX</u>



CORRESPONDENCE BETWEEN THE PREDICTED AND TRUE LABEL

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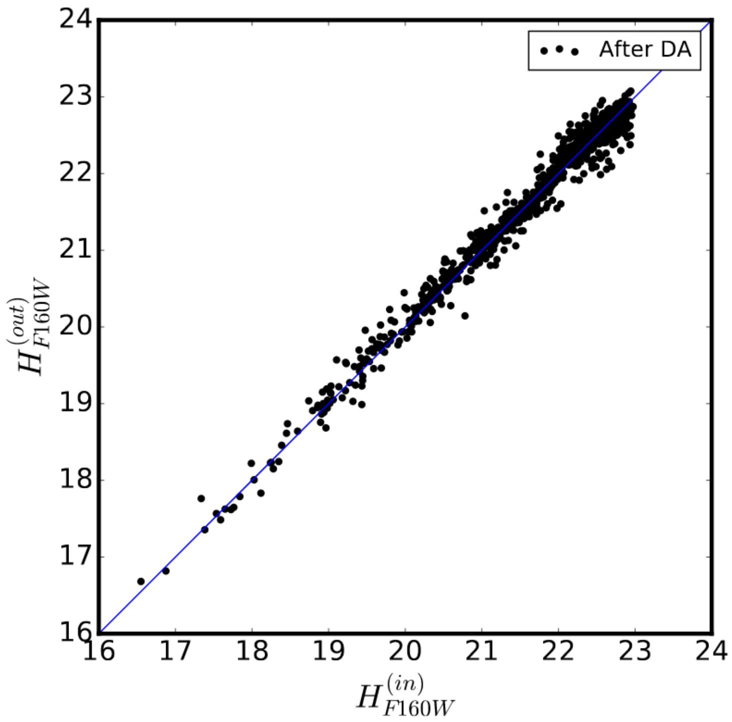
Evaluation of results [regression]



FOR REGRESSIONS, SIMPLY USE
“STANDARD ACCURACY MEASUREMENTS

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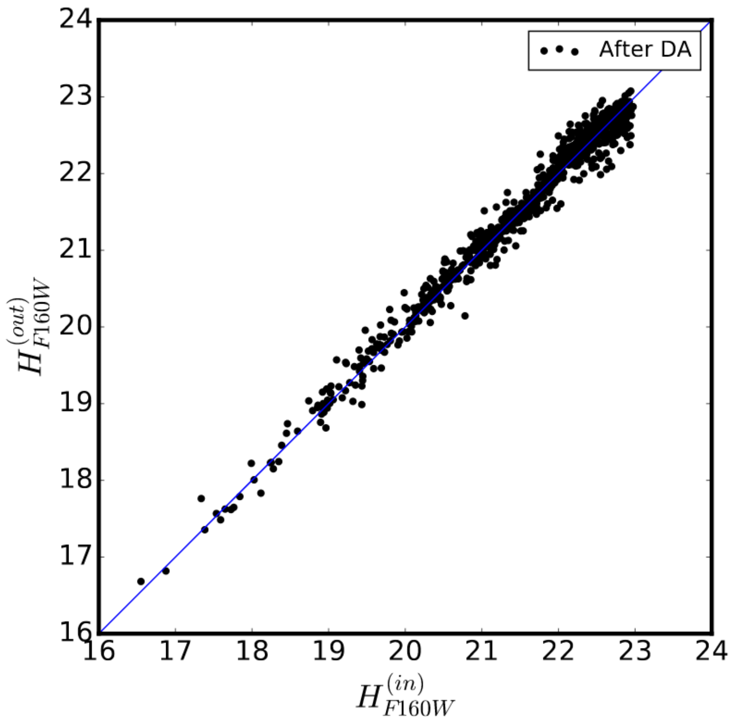
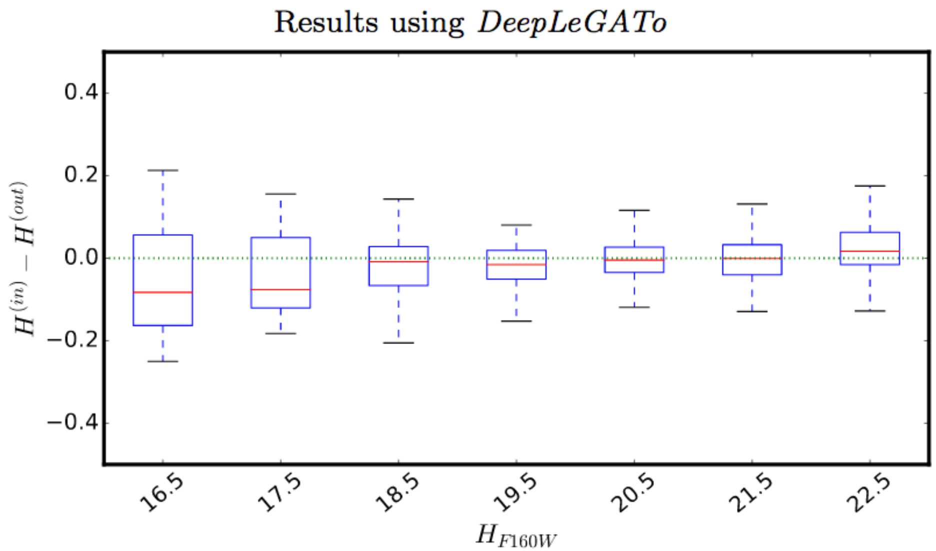
Evaluation of results [regression]



FOR REGRESSIONS, SIMPLY USE
“STANDARD ACCURACY MEASUREMENTS

BIAS, SCATTER …YOU KNOW!



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