CSE419 – Artificial Intelligence and Machine Learning 2018

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https://github.com/FurkanGozukara/CSE419_2018

Lecture 8
Multiclass

Based on Asst. Prof. Dr. David Kauchak (Pomona College) Lecture Slides

Multiclass classification

examples

label

apple

orange

apple

banana

banana

pineapple

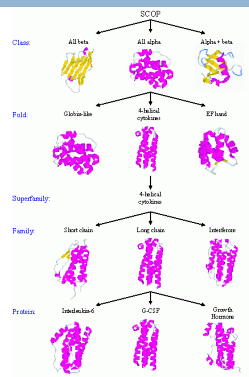
Same setup where we have a set of features for each example

Rather than just two labels, now have 3 or more

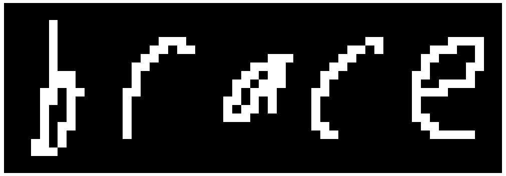
real-world examples?

Real world multiclass classification

document classification



protein classification

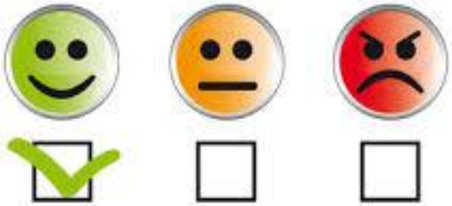


handwriting recognition

face recognition

most real-world applications
tend to be multiclass

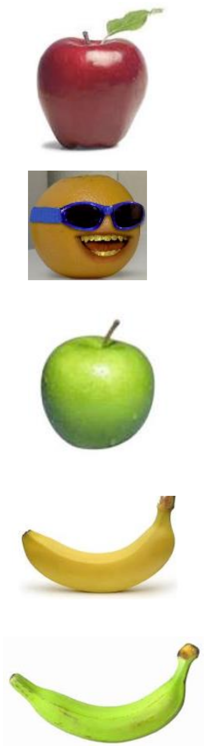
emotion recognition

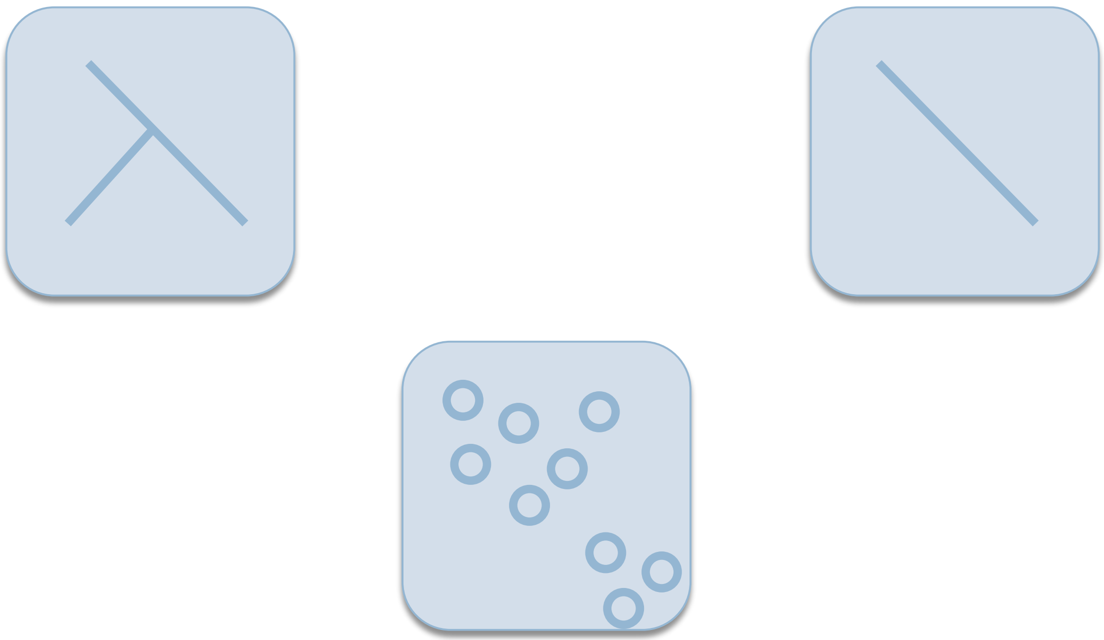


sentiment analysis

autonomous vehicles

Multiclass: current classifiers





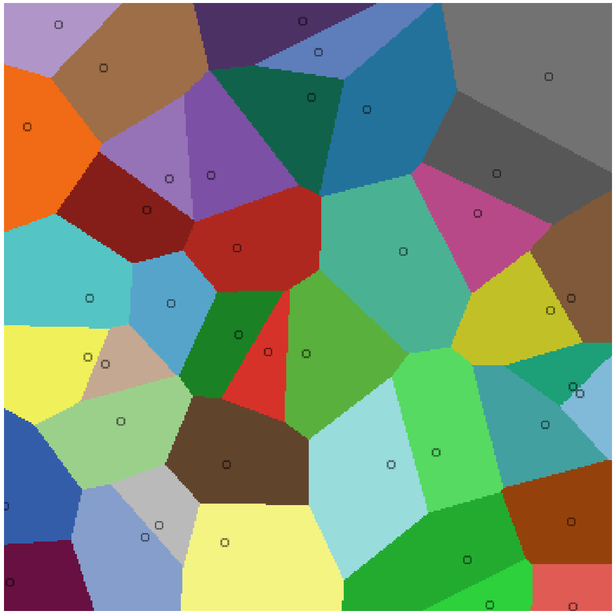
Any of these work out of the box?
With small modifications?

k-Nearest Neighbor (k-NN)

To classify an example ***d***:

- Find ***k*** nearest neighbors of ***d***
- Choose as the label the majority label within the ***k*** nearest neighbors

No algorithmic changes!



Decision Tree learning

Base cases:

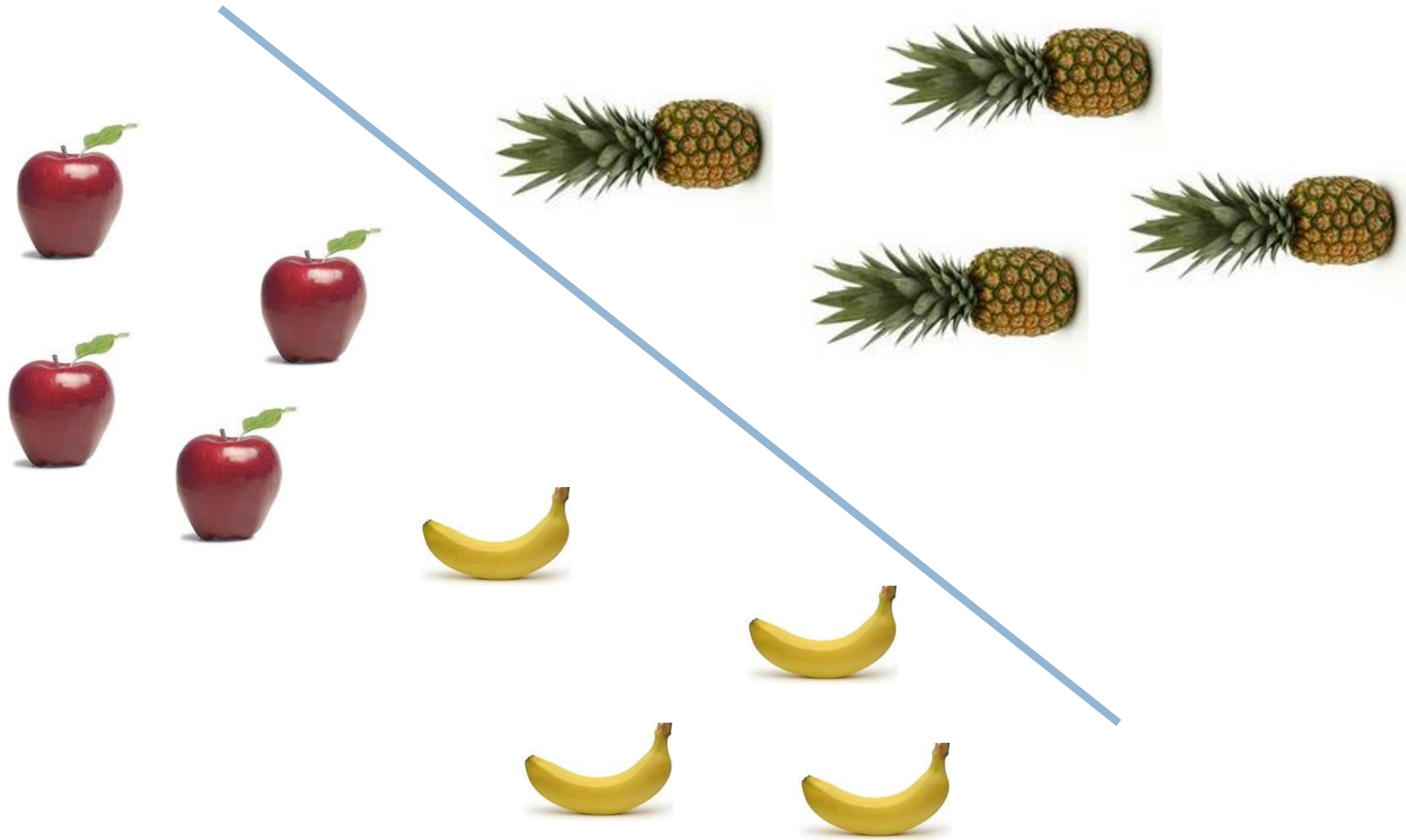
1. If all data belong to the same class, pick that label
2. If all the data have the same feature values, pick majority label
3. If we're out of features to examine, pick majority label
4. If the we don't have any data left, pick majority label of *parent*
5. *If some other stopping criteria* exists to avoid overfitting, pick majority label

Otherwise:

- calculate the "score" for each feature if we used it to split the data
- pick the feature with the highest score, partition the data based on that data value and call recursively

No algorithmic changes!

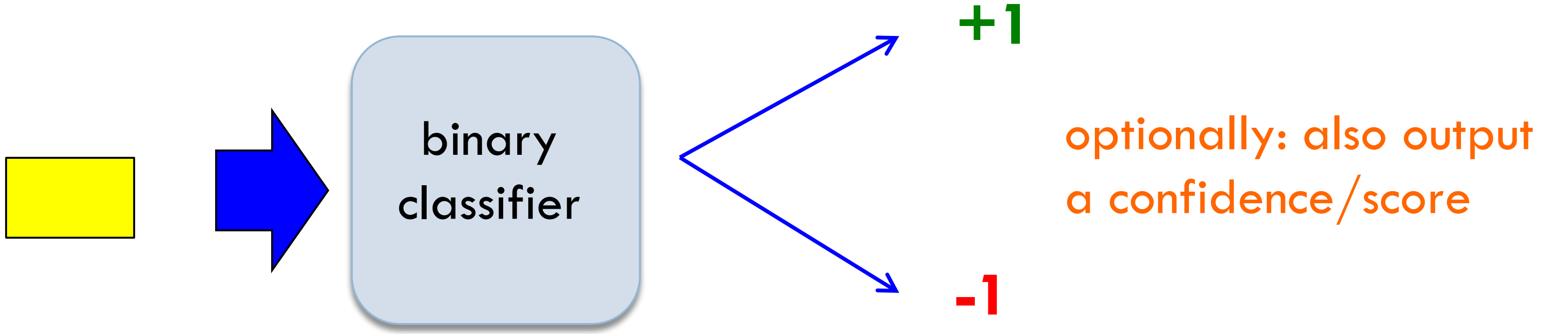
Perceptron learning



Hard to separate three classes with just one line ☹

Black box approach to multiclass

Abstraction: we have a generic binary classifier, how can we use it to solve our new problem



Can we solve our multiclass problem with this?

Multiclass classification

examples

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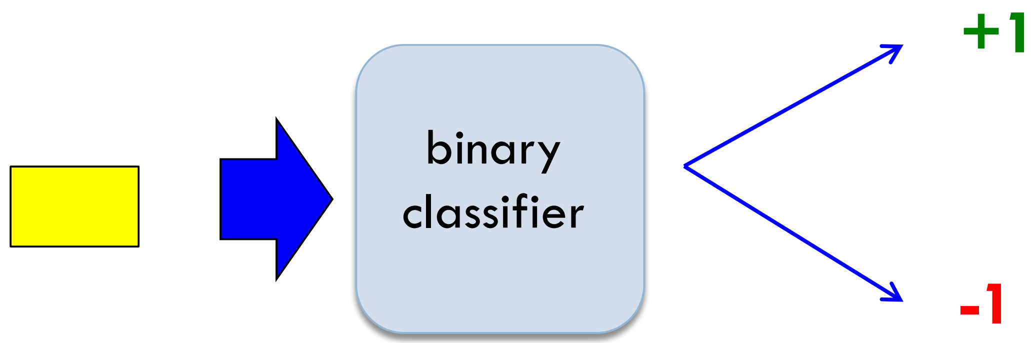


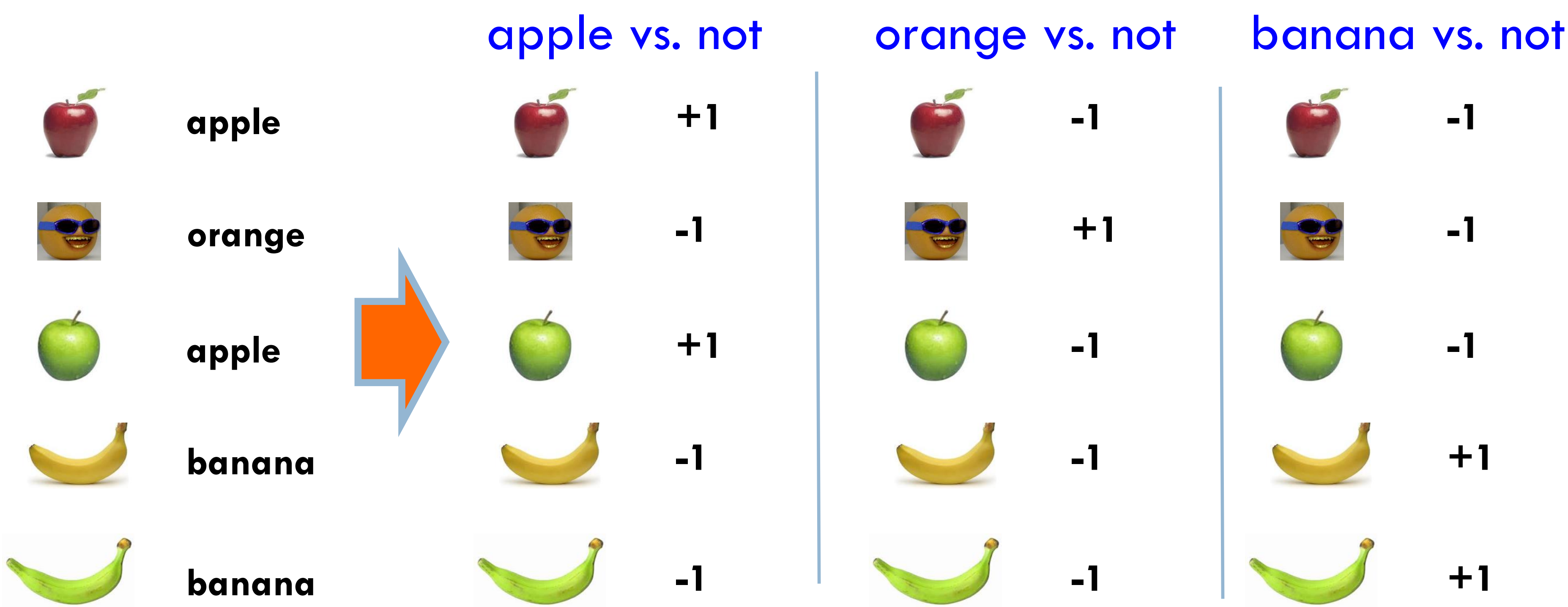
optionally: also output a confidence/score

Can we solve our multiclass problem with this?

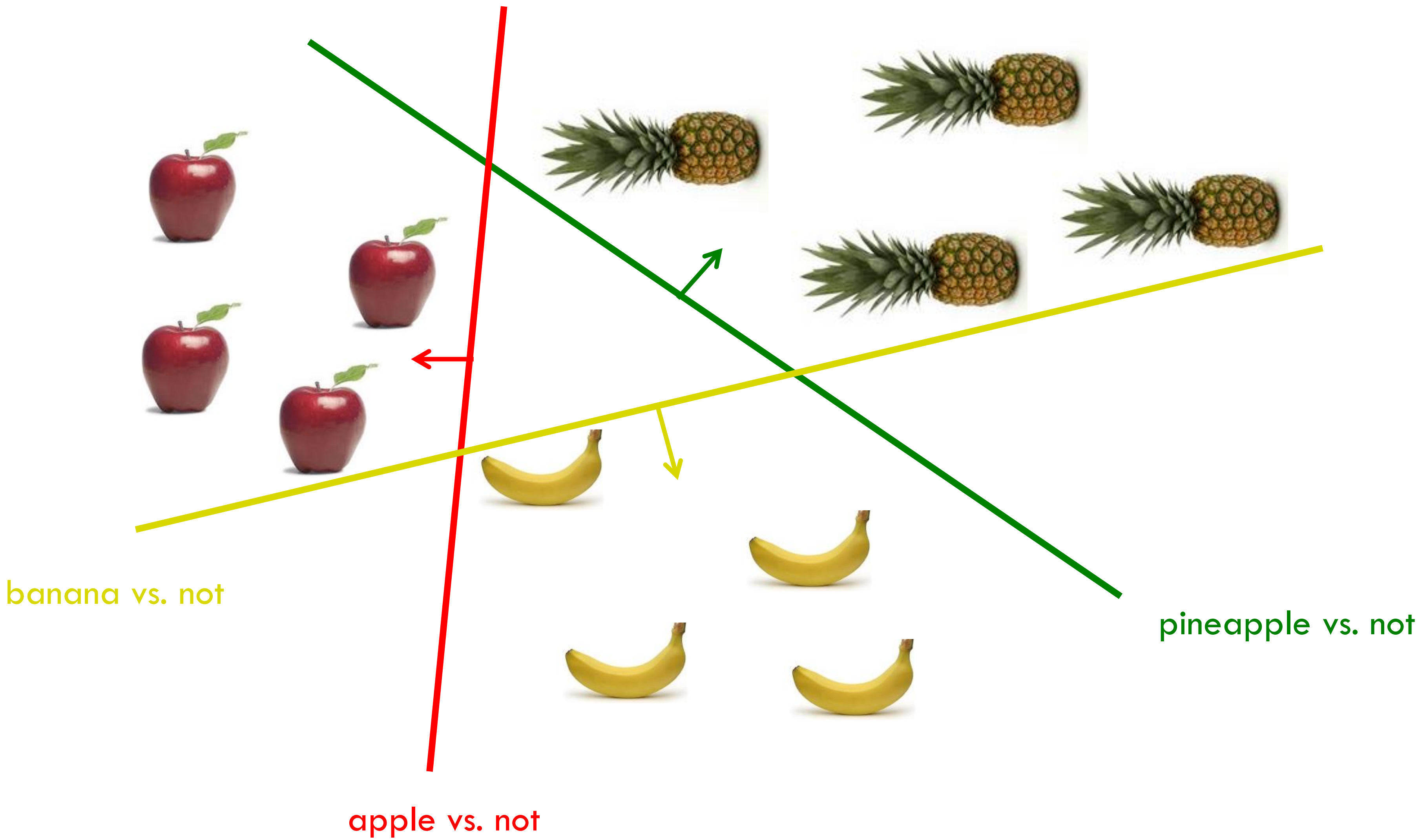
Approach 1: One vs. all (OVA)

Training: for each label *L*, pose as a binary problem

- all examples with label *L* are positive
- all other examples are negative



OVA: linear classifiers (e.g. perceptron)



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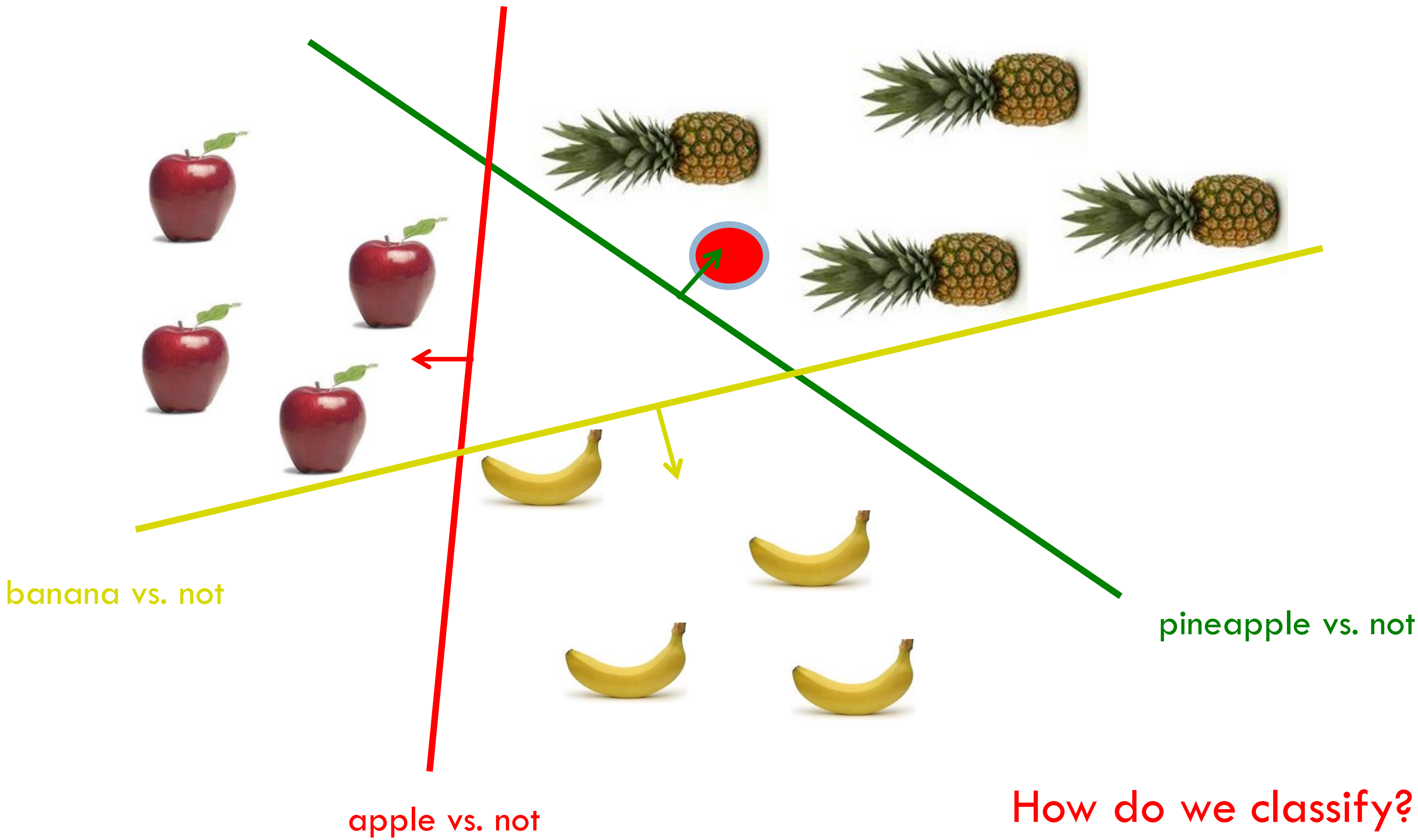
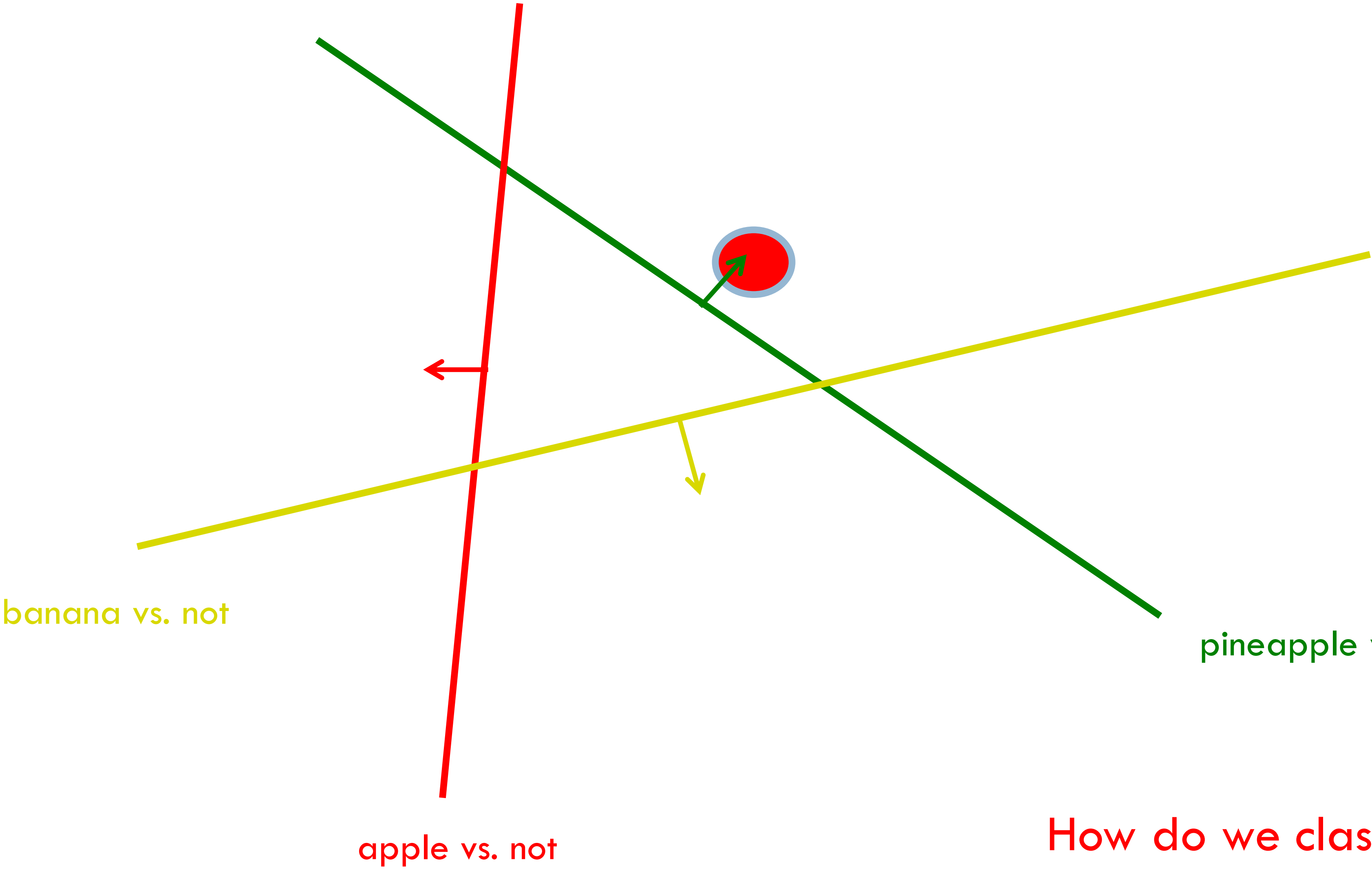


How do we classify?

OVA: linear classifiers (e.g. perceptron)



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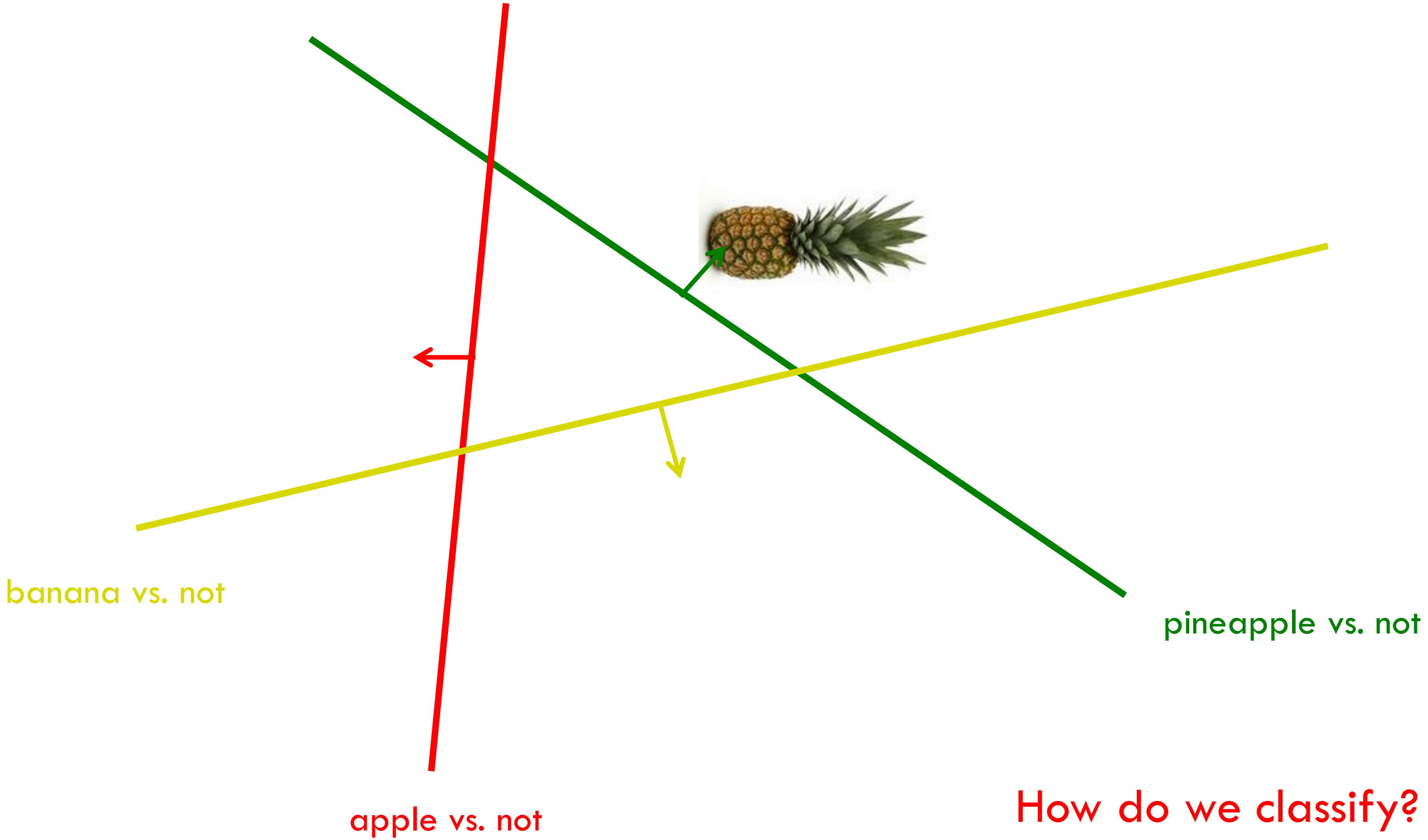
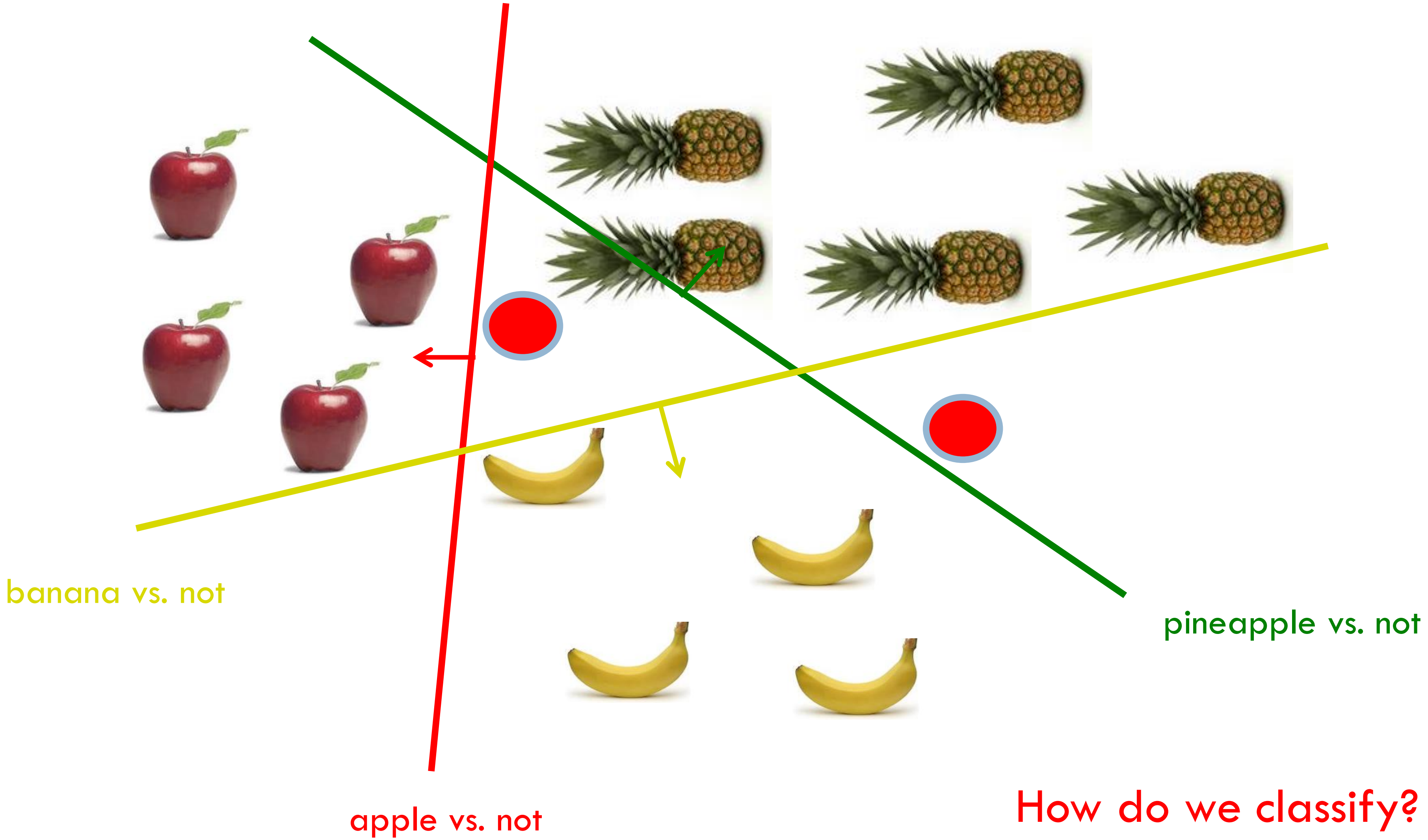
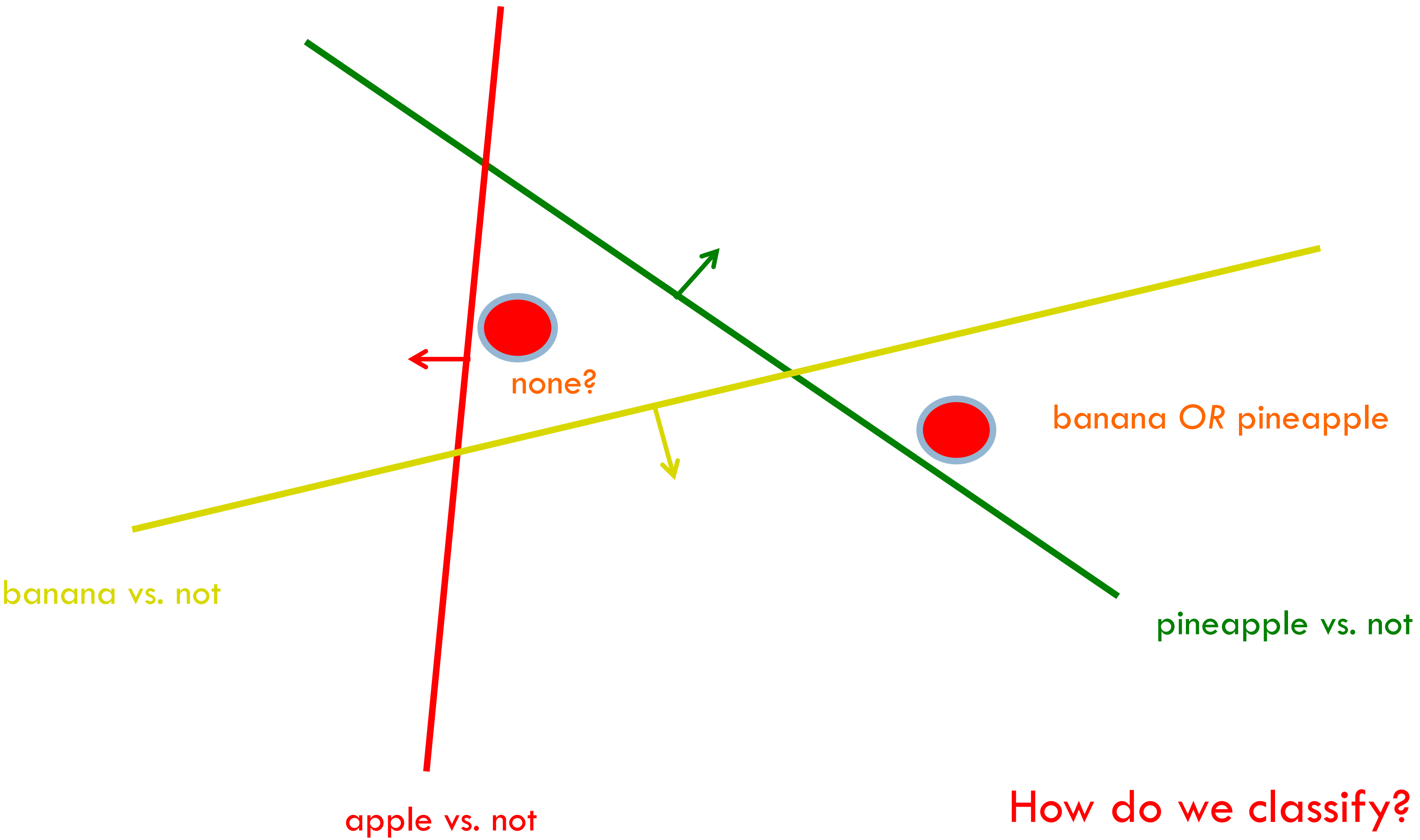


How do we classify?

OVA: linear classifiers (e.g. perceptron)

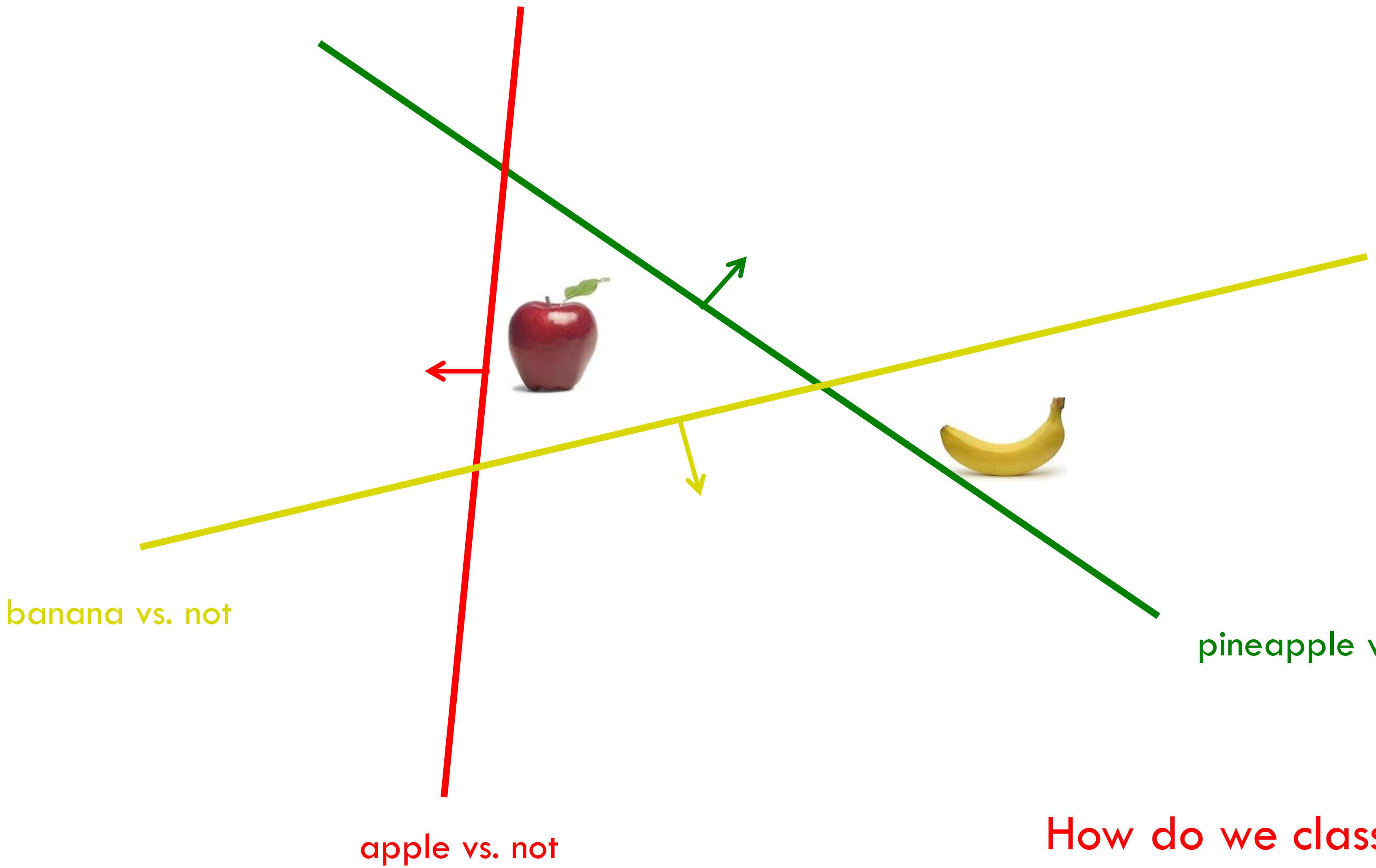


OVA: linear classifiers (e.g. perceptron)



How do we classify?

OVA: linear classifiers (e.g. perceptron)



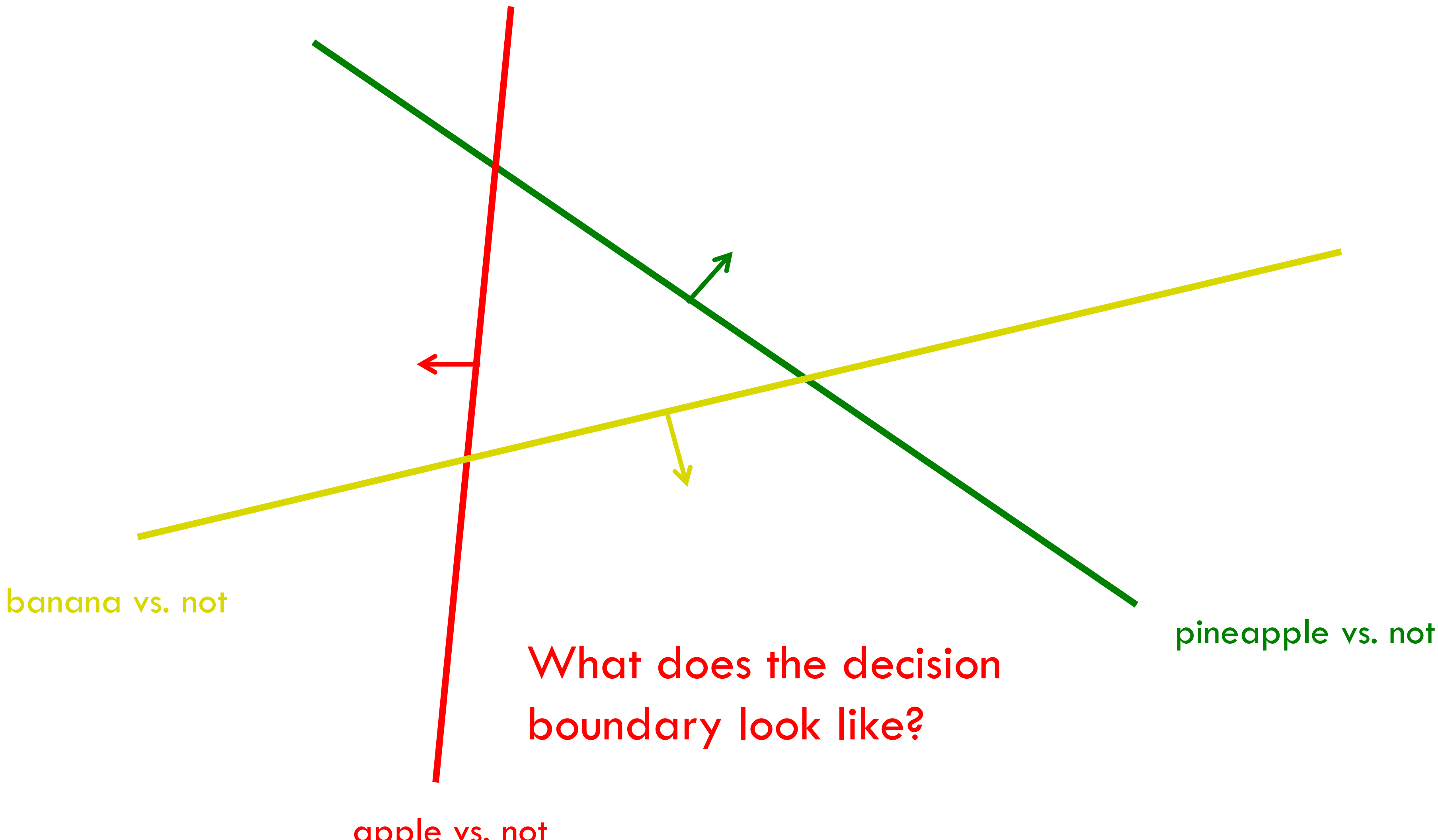
How do we classify?

OVA: classify

Classify:

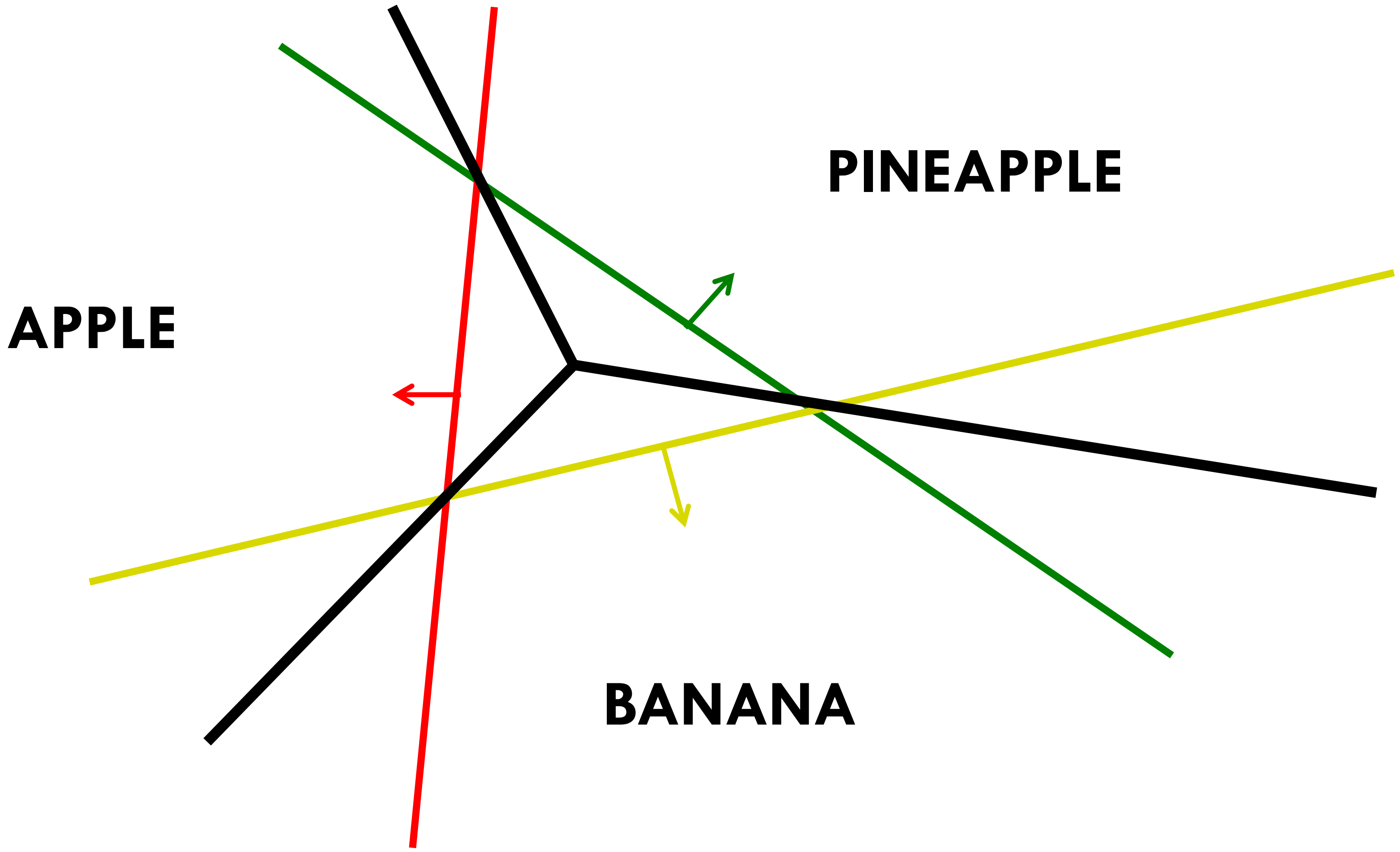
- If classifier doesn't provide confidence (this is rare) and there is ambiguity, pick one of the ones in conflict
- Otherwise:
  - pick the most confident positive
  - if none vote positive, pick *least* confident negative

OVA: linear classifiers (e.g. perceptron)



What does the decision boundary look like?

OVA: linear classifiers (e.g. perceptron)



OVA: classify, perceptron

Classify:

- If classifier doesn't provide confidence (this is rare) and there is ambiguity, pick majority in conflict
- Otherwise:
  - pick the most confident positive
  - if none vote positive, pick *least* confident negative

How do we calculate this for the perceptron?

OVA: classify, perceptron

Classify:

- If classifier doesn't provide confidence (this is rare) and there is ambiguity, pick majority in conflict
- Otherwise:
  - pick the most confident positive
  - if none vote positive, pick *least* confident negative

$$prediction = b + \sum_{i=1}^{n} w_i f_i$$

Distance from the hyperplane

Approach 2: All vs. all (AVA)

Training:

For each pair of labels, train a classifier to distinguish between them

for i = 1 to number of labels:

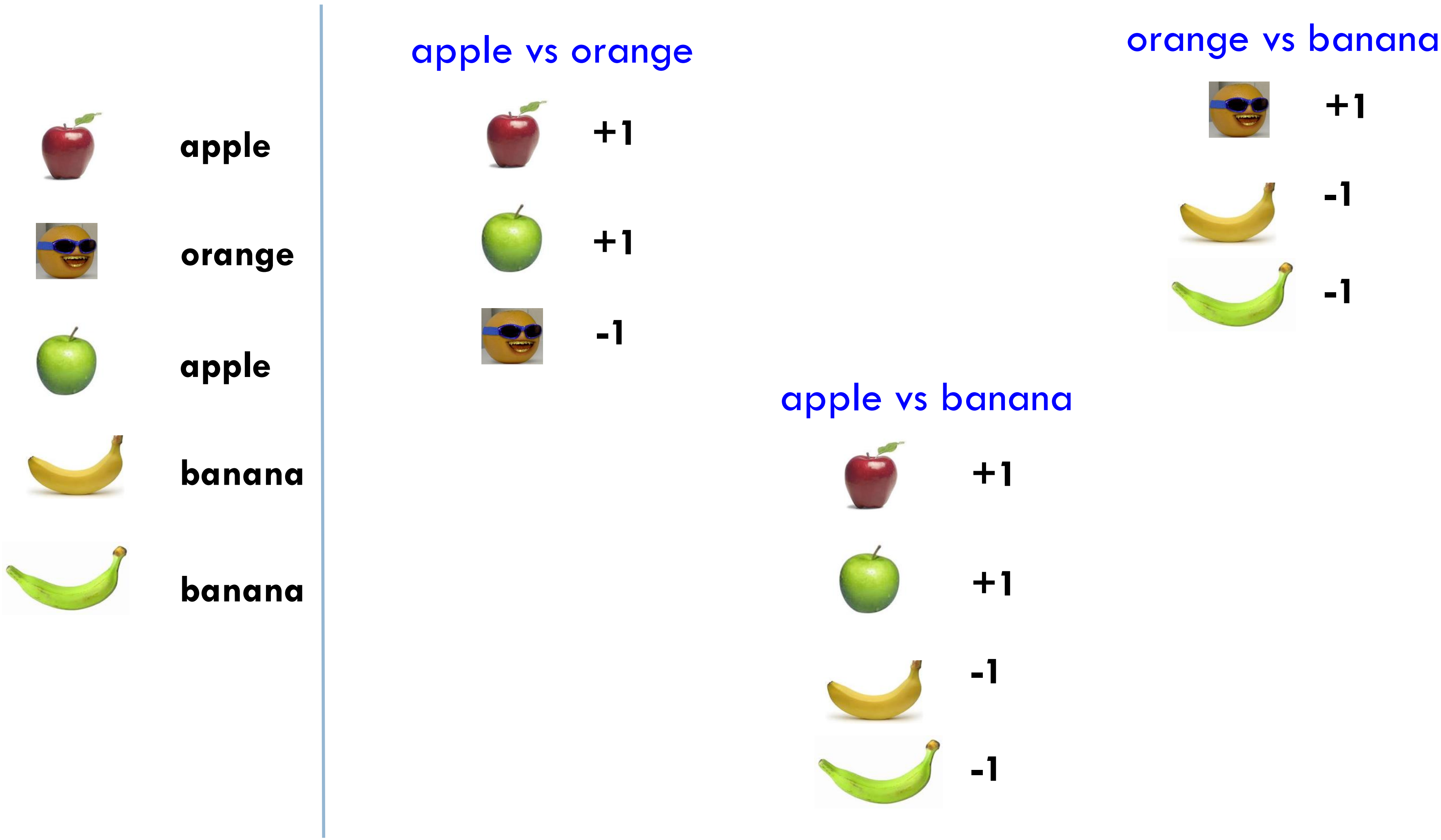
    for k = i+1 to number of labels:

        train a classifier to distinguish between $label_i$ and $label_k$:

            - create a dataset with all examples *with* $label_i$ labeled positive and all examples with $label_k$ labeled negative

            - train classifier on this subset of the data

AVA training visualized



AVA classify

apple vs orange

 +1

 +1

 -1

apple vs banana

 +1

 +1

 -1

 -1

orange vs banana

 +1

 -1

 -1

What class?

AVA classify

apple vs orange


+1


+1

orange


-1

apple vs banana


+1


+1

apple


-1


-1

orange vs banana


+1


-1

orange


-1

orange

In general?

AVA classify

To classify example e, classify with each classifier f_{jk}

We have a few options to choose the final class:

- Take a majority vote
- Take a weighted vote based on confidence
  - $y = f_{jk}(e)$
  - $score_j$ += y
  - $score_k$ -= y

How does this work?

*Here we're assuming that y encompasses both the prediction (+1,-1) and the confidence, i.e. y = prediction * confidence.*

AVA classify

Take a weighted vote based on confidence

- $y = f_{jk}(e)$
- $score_j += y$
- $score_k -= y$

If y is positive, classifier thought it was of type j:
- raise the score for j
- lower the score for k

if y is negative, classifier thought it was of type k:
- lower the score for j
- raise the score for k

OVA vs. AVA

Train/classify runtime?

Error? Assume each binary classifier makes an error with probability ε

OVA vs. AVA

Train time:

AVA learns more classifiers, however, they're trained on much smaller data this tends to make it faster if the labels are equally balanced

Test time:

AVA has more classifiers

Error (see the book for more justification):

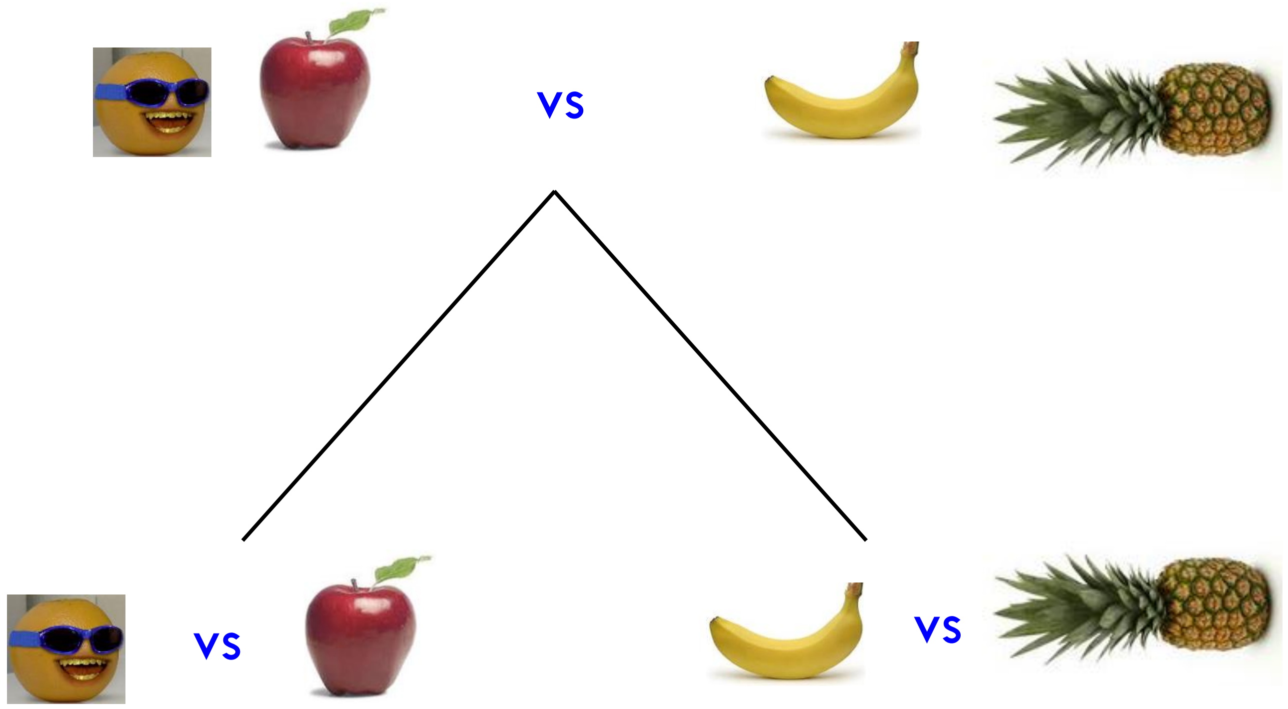
- AVA trains on more balanced data sets
- AVA tests with more classifiers and therefore has more chances for errors

- Theoretically:

-- OVA: ε (number of labels -1)

-- AVA: 2 ε (number of labels -1)

Approach 3: Divide and conquer



Pros/cons vs. AVA?

Multiclass summary

If using a binary classifier, the most common thing to do is OVA

Otherwise, use a classifier that allows for multiple labels:

- DT and k-NN work reasonably well
- We'll see a few more in the coming weeks that will often work better

Multiclass evaluation

	label	prediction
	apple	orange
	orange	orange
	apple	apple
	banana	pineapple
	banana	banana
	pineapple	pineapple

How should we evaluate?

Multiclass evaluation

	label	prediction
	apple	orange
	orange	orange
	apple	apple
	banana	pineapple
	banana	banana
	pineapple	pineapple

Accuracy: 4/6

Multiclass evaluation imbalanced data

	label	prediction
	apple	orange
	…	
	apple	apple
	banana	pineapple
	banana	banana
	pineapple	pineapple

Any problems?

Data imbalance!

Macroaveraging vs. microaveraging

microaveraging: average over examples (this is the "normal" way of calculating)

macroaveraging: calculate evaluation score (e.g. accuracy) for each label, then average over labels

What effect does this have?
Why include it?

Macroaveraging vs. microaveraging

microaveraging: average over examples (this is the "normal" way of calculating)

macroaveraging: calculate evaluation score (e.g. accuracy) for each label, then average over labels

- Puts more weight/emphasis on rarer labels
- Allows another dimension of analysis

Macroaveraging vs. microaveraging

	label	prediction
	apple	orange
	orange	orange
	apple	apple
	banana	pineapple
	banana	banana
	pineapple	pineapple

microaveraging: average over examples

macroaveraging: calculate evaluation score (e.g. accuracy) for each label, then average over labels

Macroaveraging vs. microaveraging

	label	prediction
	apple	orange
	orange	orange
	apple	apple
	banana	pineapple
	banana	banana
	pineapple	pineapple

microaveraging: 4/6

macroaveraging:

apple = 1/2

orange = 1/1

banana = 1/2

pineapple = 1/1

total = (1/2 + 1 + 1/2 + 1)/4

= 3/4

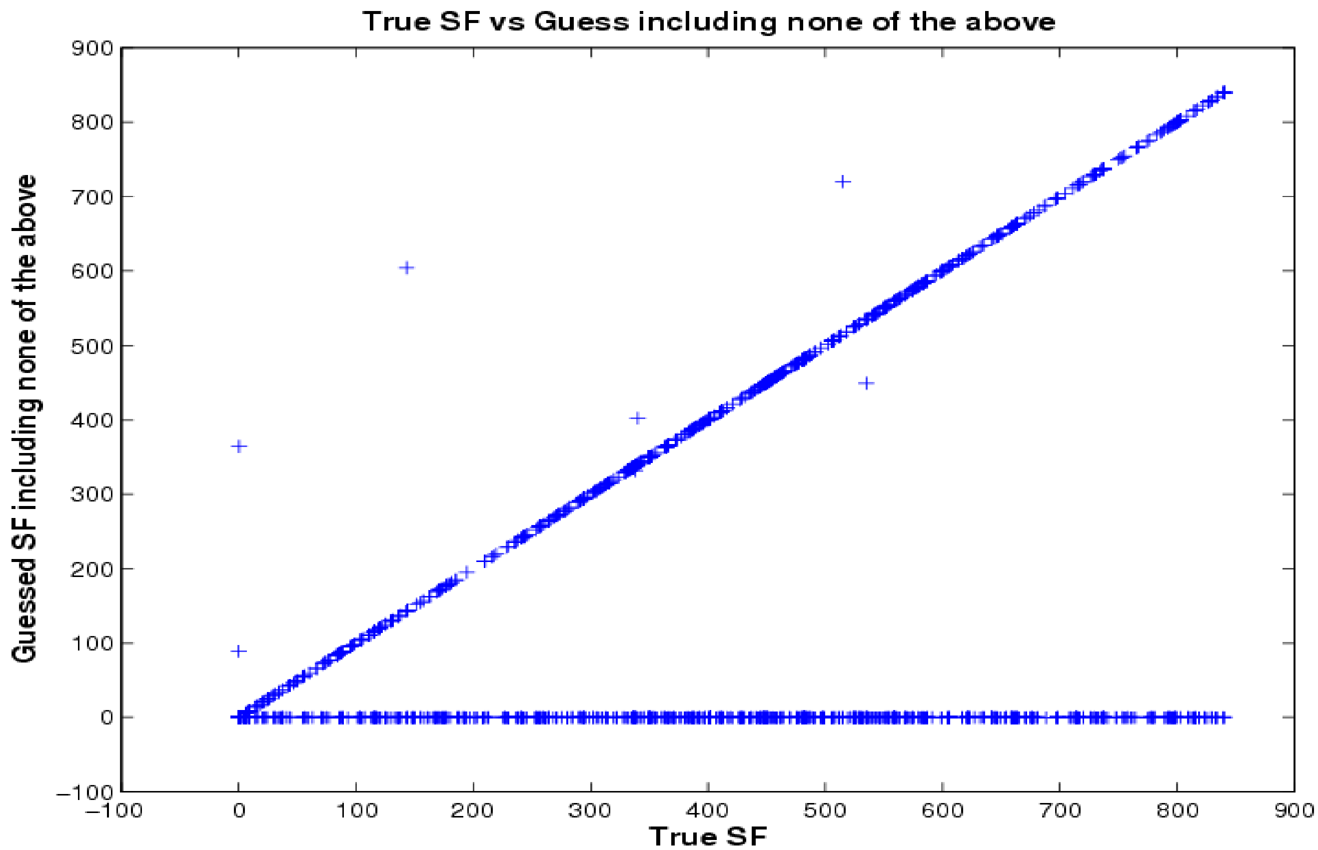
Confusion matrix

entry *(i, j)* represents the number of examples with label *i* that were predicted to have label *j*

another way to understand both the data and the classifier

	Classic	Country	Disco	Hiphop	Jazz	Rock
Classic	86	2	0	4	18	1
Country	1	57	5	1	12	13
Disco	0	6	55	4	0	5
Hiphop	0	15	28	90	4	18
Jazz	7	1	0	0	37	12
Rock	6	19	11	0	27	48

Confusion matrix



BLAST classification of proteins in 850 superfamilies