BEYOND BINARY CLASSIFICATION

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CS 158 – Spring 2022

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Admin

Assignment 4

Assignment 2 graded

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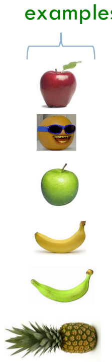
Multiclass classification

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?

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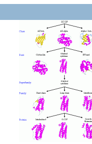
Real world multiclass classification

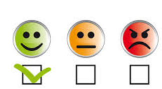

document classification


protein classification


handwriting recognition


face recognition

most real-world applications tend to be multiclass


sentiment analysis


autonomous vehicles


emotion recognition

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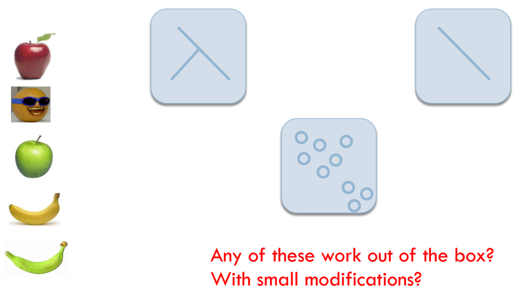
Multiclass: current classifiers



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

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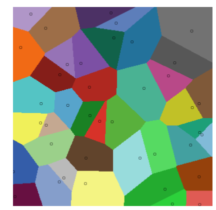
k-Nearest Neighbor (k-NN)

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!



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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!

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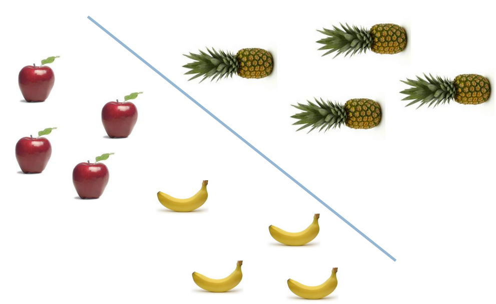
Perceptron learning



Hard to separate three classes with just one line ☹

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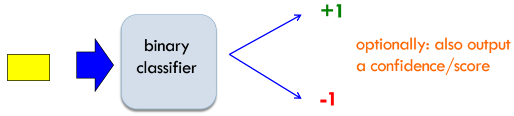
Black box approach to multiclass

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?

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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

	apple vs. not	orange vs. not	banana vs. not
apple	+1	-1	-1
orange	-1	+1	-1
apple	+1	-1	-1
banana	-1	-1	+1
banana	-1	-1	+1

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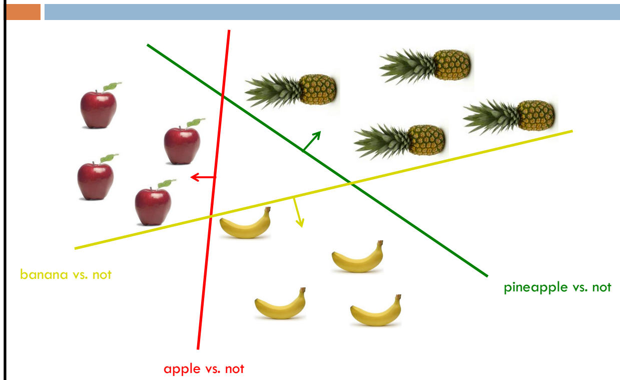
OVA: linear classifiers (e.g. perceptron)



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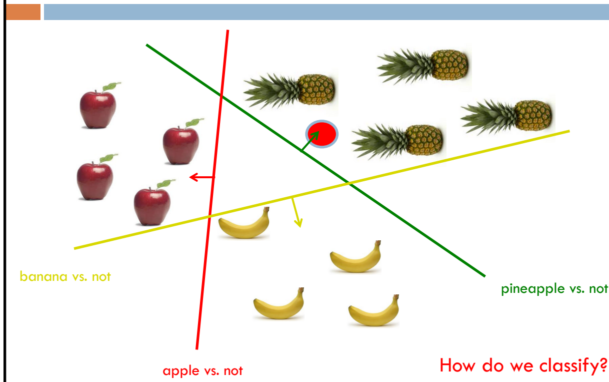
OVA: linear classifiers (e.g. perceptron)



How do we classify?

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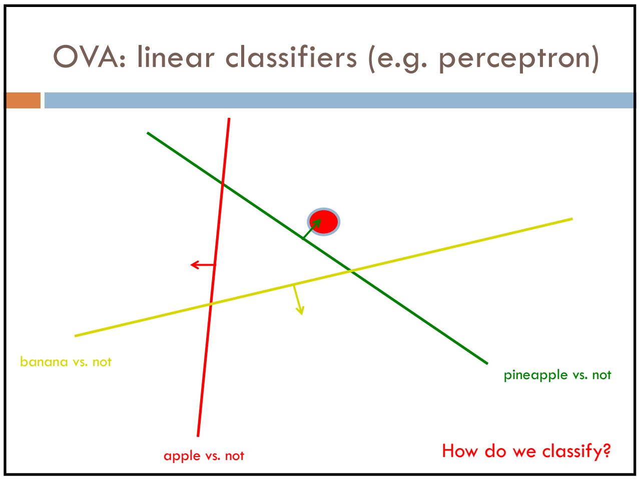
OVA: linear classifiers (e.g. perceptron)
banana vs. not
pineapple vs. not
apple vs. not
How do we classify?

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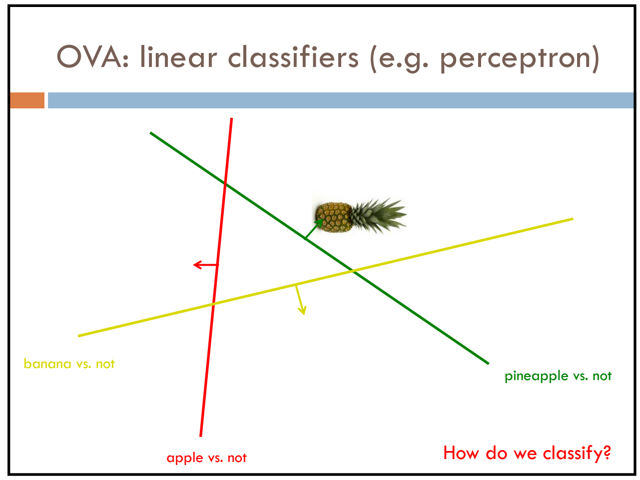
OVA: linear classifiers (e.g. perceptron)
banana vs. not
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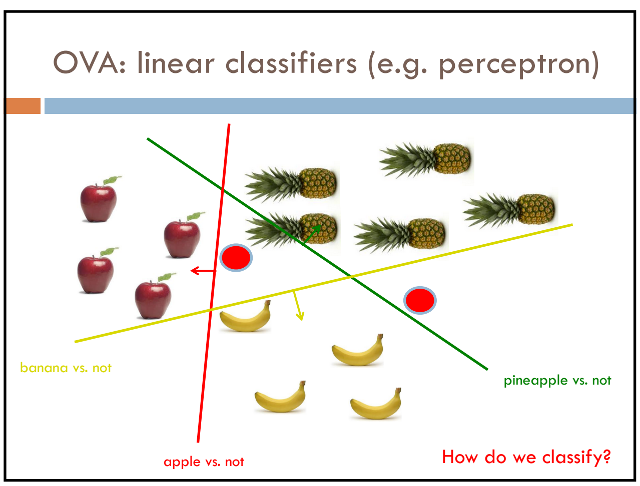
14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banana vs. not
pineapple vs. not
apple vs. not
How do we classify?

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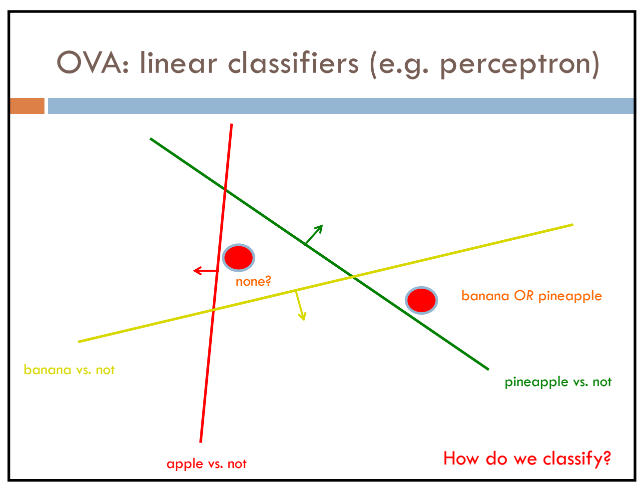
OVA: linear classifiers (e.g. perceptron)
none?
banana *OR* pineapple
banana vs. not
pineapple vs. not
apple vs. not
How do we classify?

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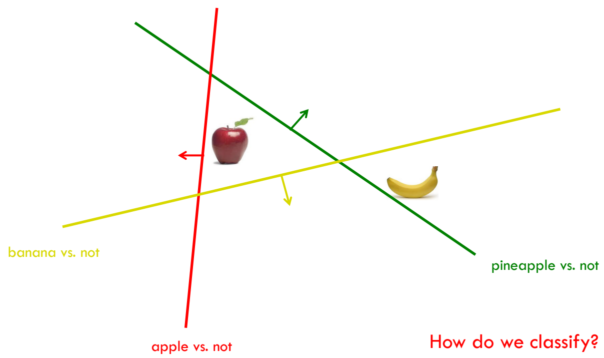
OVA: linear classifiers (e.g. perceptron)



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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

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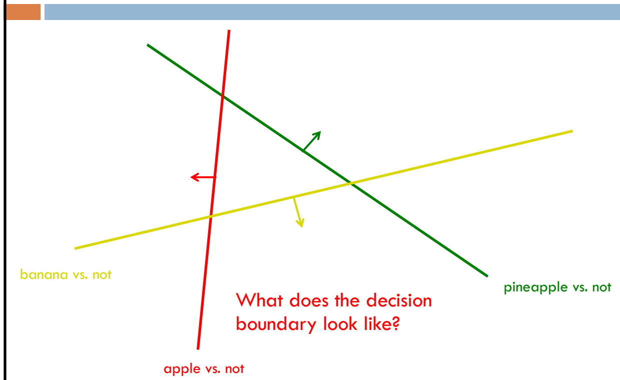
OVA: linear classifiers (e.g. perceptron)



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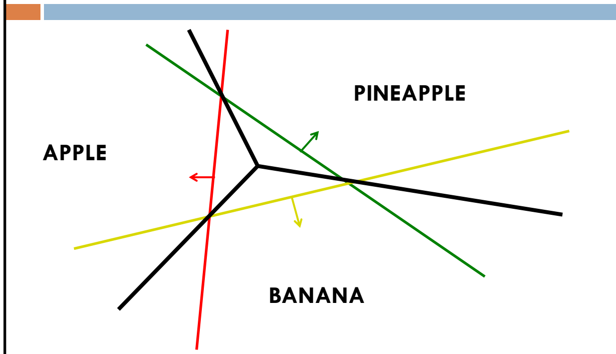
OVA: linear classifiers (e.g. perceptron)



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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?

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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

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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 $label_j$ and $label_k$:

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

      - train classifier on this subset of the data

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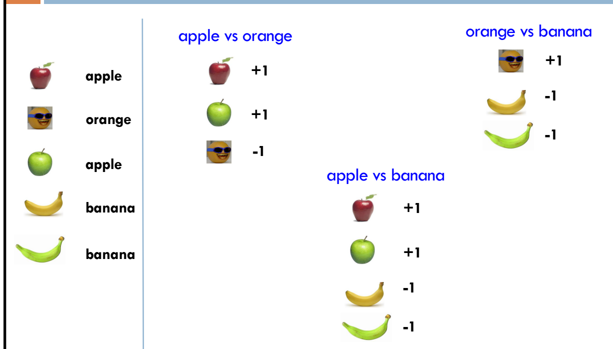
AVA training visualized



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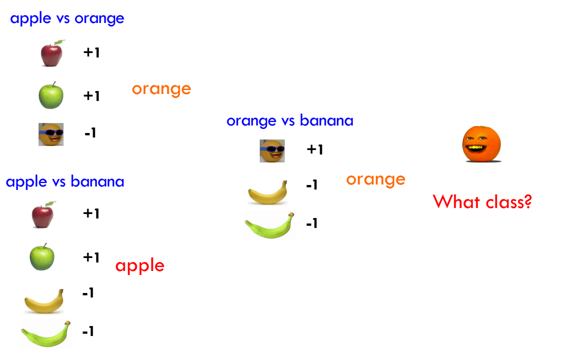
AVA classify



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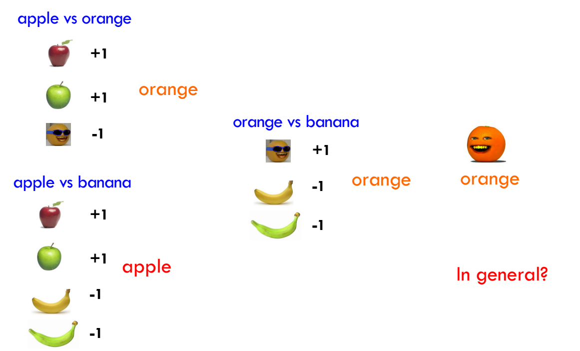
AVA classify



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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.*

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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

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OVA vs. AVA

Train/classify runtime?

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

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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, so often it is slower

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)

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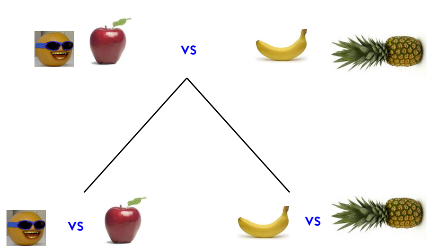
Approach 3: Divide and conquer



Pros/cons vs. AVA?

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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

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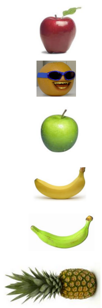
Multiclass evaluation



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

How should we evaluate?

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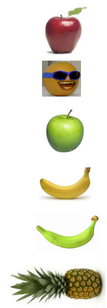
Multiclass evaluation



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

Accuracy: 4/6

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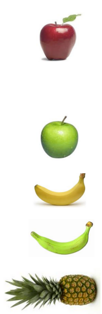
Multiclass evaluation imbalanced data



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

Any problems?

Data imbalance!

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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?

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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

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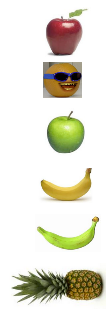
Macroaveraging vs. microaveraging



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

?

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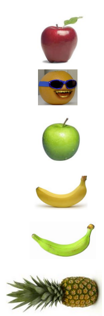
Macroaveraging vs. microaveraging



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

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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

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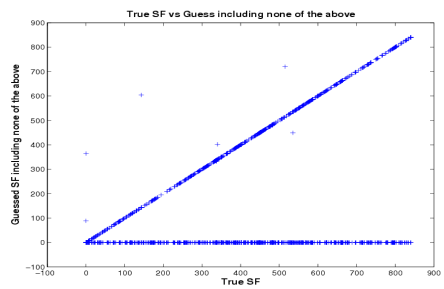
Confusion matrix



BLAST classification of proteins in 850 superfamilies

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Multilabel vs. multiclass classification

• Is it edible? • Is it sweet? • Is it a fruit? • Is it a banana?	Is it a banana? Is it an apple? Is it an orange? Is it a pineapple?	Is it a banana? Is it yellow? Is it sweet? Is it round?

Any difference in these labels/categories?

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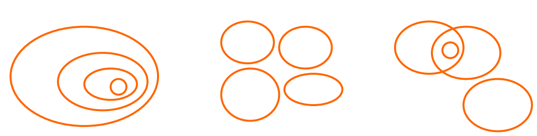
Multilabel vs. multiclass classification

• Is it edible? • Is it sweet? • Is it a fruit? • Is it a banana?	Is it a banana? Is it an apple? Is it an orange? Is it a pineapple?	Is it a banana? Is it yellow? Is it sweet? Is it round?

Different structures



Nested/ Hierarchical   Exclusive/ Multiclass   General/Structured

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Multiclass vs. multilabel

Multiclass: each example has one label and exactly one label

Multilabel: each example has ***zero or more*** labels. Also called annotation

Multilabel applications?

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Multilabel

Image annotation

Document topics

Labeling people in a picture

Medical diagnosis

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Ranking problems

Suggest a simpler word for the word below:

vital

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Suggest a simpler word

Suggest a simpler word for the word below:

vital

word	frequency
important	13
necessary	12
essential	11
needed	8
critical	3
crucial	2
mandatory	1
required	1
vital	1

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Suggest a simpler word

Suggest a simpler word for the word below:

acquired

48

Suggest a simpler word

Suggest a simpler word for the word below:

acquired

word	frequency
gotten	12
received	9
gained	8
obtained	5
got	3
purchased	2
bought	2
got hold of	1
acquired	1

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Suggest a simpler word

vital	acquired	
important	gotten	
necessary	received	
essential	gained	
needed	obtained	…
critical	got	
crucial	purchased	
mandatory	bought	
required	got hold of	
vital	acquired	

training data

train

list of synonyms → ranker → list ranked by simplicity

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Ranking problems in general

ranking1	ranking2	ranking3	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	…
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	

training data:
a set of rankings where each ranking consists of a set of ranked examples

train

$f_1, f_2, \ldots, f_n$
$f_1, f_2, \ldots, f_n$
$f_1, f_2, \ldots, f_n$
$f_1, f_2, \ldots, f_n$

→ ranker → ranking/ordering or examples

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Ranking problems in general

ranking1	ranking2	ranking3	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	…
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	

training data:
a set of rankings where each ranking consists of a set of ranked examples

Real-world ranking problems?

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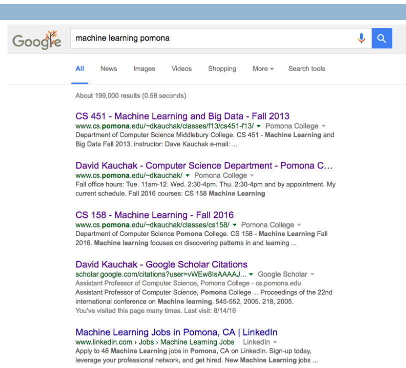
Search



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Ranking Applications

reranking N-best output lists
- machine translation
- computational biology
- parsing
- …

flight search

…

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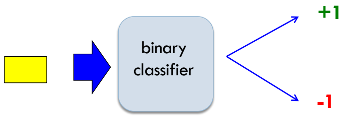
Black box approach to ranking

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



optionally: also output a confidence/score

Can we solve our ranking problem with this?

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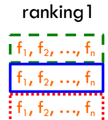
Predict better vs. worse

Train a classifier to decide if the first input is better than second:
- Consider all possible pairings of the examples in a ranking
- Label as positive if the first example is higher ranked, negative otherwise

ranking1



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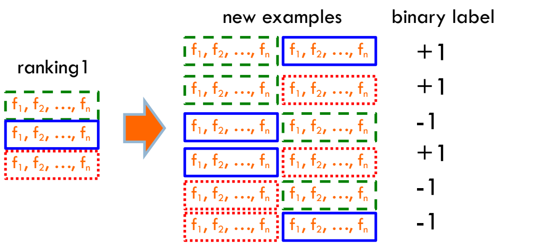
Predict better vs. worse

Train a classifier to decide if the first input is better than second:
- Consider all possible pairings of the examples in a ranking
- Label as positive if the first example is higher ranked, negative otherwise



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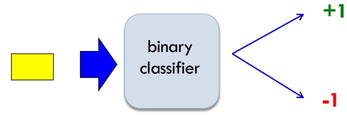
Predict better vs. worse



Our binary classifier only takes one example as input

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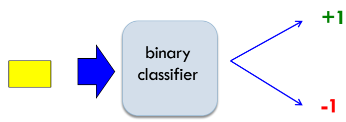
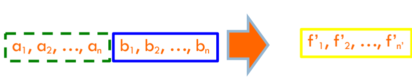
Predict better vs. worse



Our binary classifier only takes one example as input



How can we do this?
We want features that compare the two examples.

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Combined feature vector

Many approaches! Will depend on domain and classifier

Two common approaches:

1. difference:
$$f'_i = a_i - b_i$$
2. greater than/less than:
$$f'_i = \begin{cases} 1 & \text{if } a_i > b_i \\ 0 & \text{otherwise} \end{cases}$$

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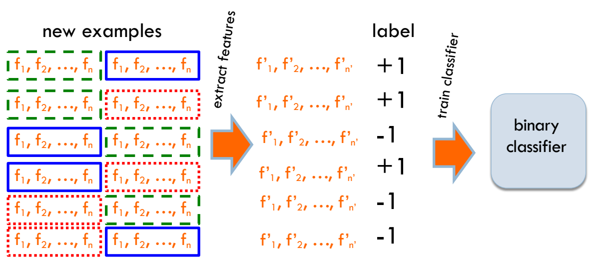
Training



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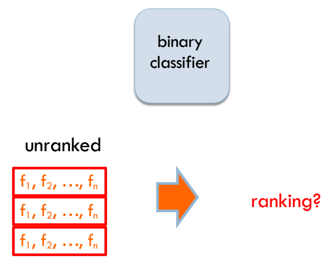
Testing



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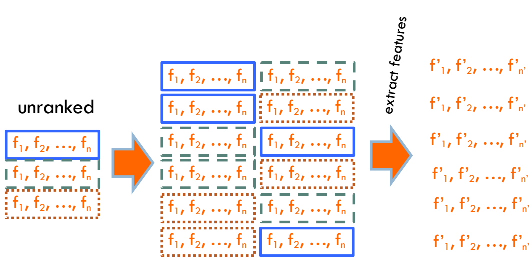
Testing



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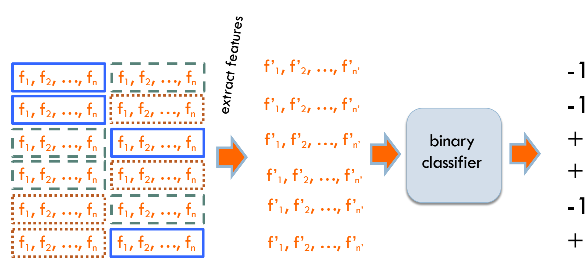
Testing



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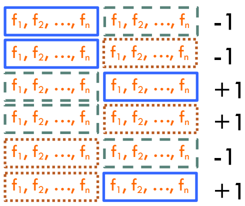
Testing



What is the ranking?
Algorithm?

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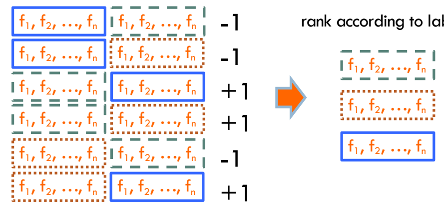
Testing

for each binary example e_{jk}:
label[j] += $f_{jk}(e_{jk})$
label[k] -= $f_{jk}(e_{jk})$

rank according to label scores



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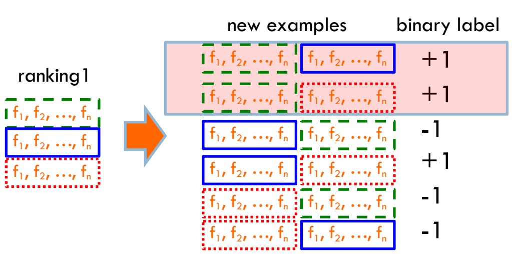
An improvement?



Are these two examples the same?

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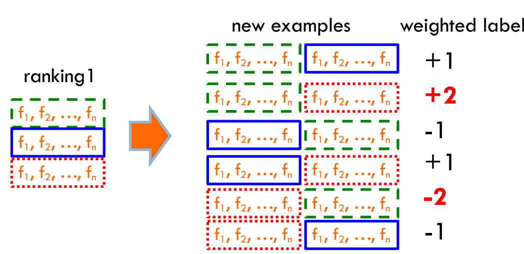
Weighted binary classification



Weight based on ***distance*** in ranking

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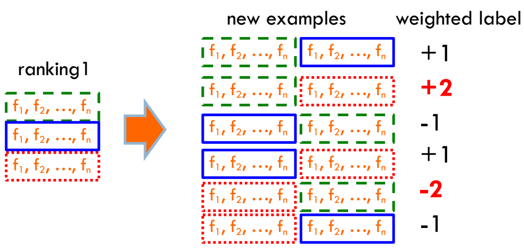
Weighted binary classification



In general can weight with any consistent distance metric

Can we solve this problem?

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Testing

If the classifier outputs a confidence, then we've learned a *distance* measure between examples

During testing we want to rank the examples based on the learned distance measure

Ideas?

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Testing

If the classifier outputs a confidence, then we've learned a *distance* measure between examples

During testing we want to rank the examples based on the learned distance measure

Sort the examples and use the output of the binary classifier as the similarity between examples!

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Ranking evaluation

	ranking	prediction
$f_1, f_2, \ldots, f_n$	1	1
$f_1, f_2, \ldots, f_n$	2	3
$f_1, f_2, \ldots, f_n$	3	2
$f_1, f_2, \ldots, f_n$	4	5
$f_1, f_2, \ldots, f_n$	5	4

Ideas?

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Idea 1: accuracy

	ranking	prediction
$f_1, f_2, \ldots, f_n$	1	1
$f_1, f_2, \ldots, f_n$	2	3
$f_1, f_2, \ldots, f_n$	3	2
$f_1, f_2, \ldots, f_n$	4	5
$f_1, f_2, \ldots, f_n$	5	4

1/5 = 0.2

Any problems with this?

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Doesn't capture "near" correct

	ranking	prediction	prediction
$f_1, f_2, \ldots, f_n$	1	1	1
$f_1, f_2, \ldots, f_n$	2	3	5
$f_1, f_2, \ldots, f_n$	3	2	4
$f_1, f_2, \ldots, f_n$	4	5	3
$f_1, f_2, \ldots, f_n$	5	4	2

1/5 = 0.2

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