CSE419 – Artificial Intelligence and Machine Learning 2018

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https://github.com/FurkanGozukara/CSE419_2018

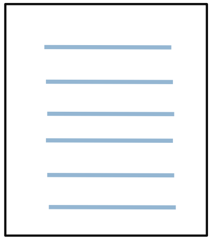
Lecture 9

Ranking

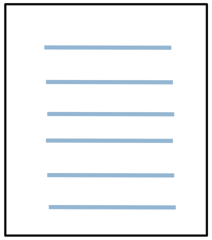
Based on Asst. Prof. Dr. David Kauchak (Pomona College) Lecture Slides

An aside: text classification

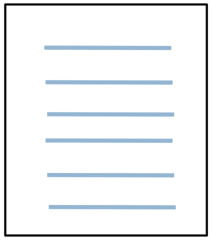
Raw data labels



Chardonnay

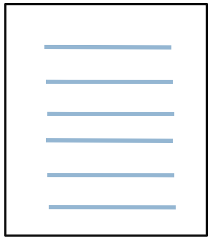
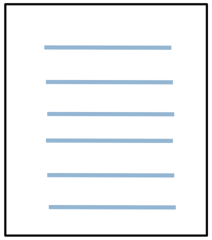
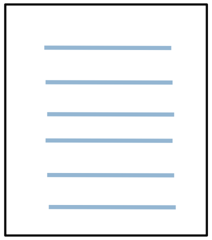


Pinot Grigio



Zinfandel

Text: raw data

Raw data	labels	Features?
	Chardonnay	
	Pinot Grigio	
	Zinfandel	

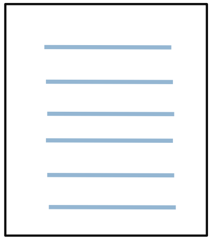
Feature examples

Raw data	labels	Features
	Chardonnay	Clinton said pinot repeatedly last week on tv, "pinot, pinot, pinot"
	Pinot Grigio	(1, 1, 1, 0, 0, 1, 0, 0, ...)
	Zinfandel	Occurrence of words

pinot clinton said california across tv wrong capital

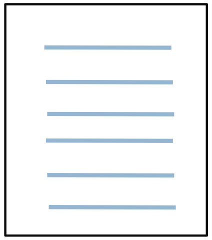
Feature examples

Raw data | labels | Features



Chardonnay

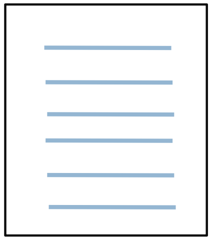
Clinton said pinot repeatedly last week on tv, “pinot, pinot, pinot”



Pinot Grigio

(4, 1, 1, 0, 0, 1, 0, 0, ...)

pinot clinton said california across tv wrong capital



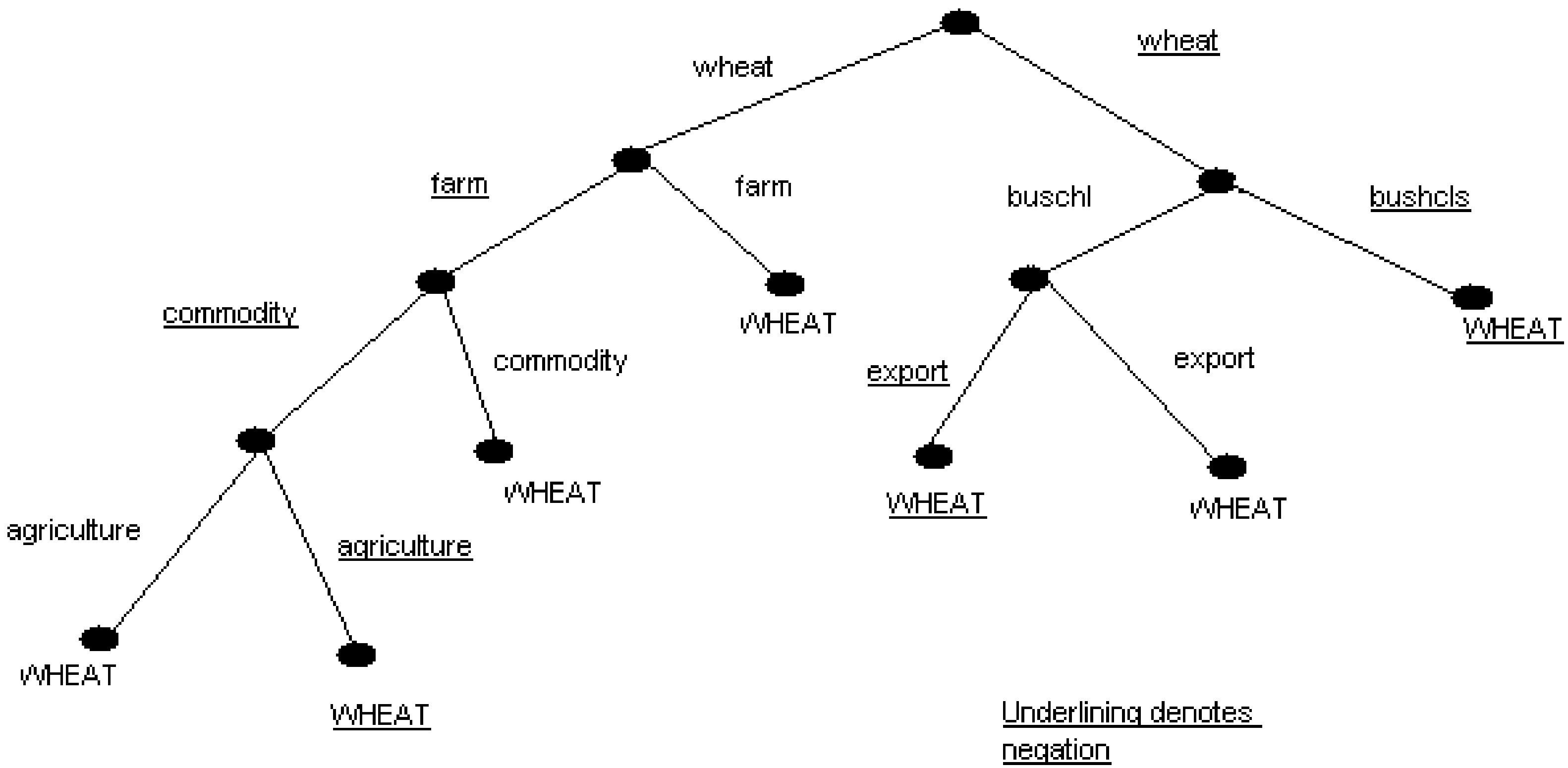
Zinfandel

Frequency of word occurrences

The most used weighting algorithm is TF*IDF (term frequency * inverse document frequency)

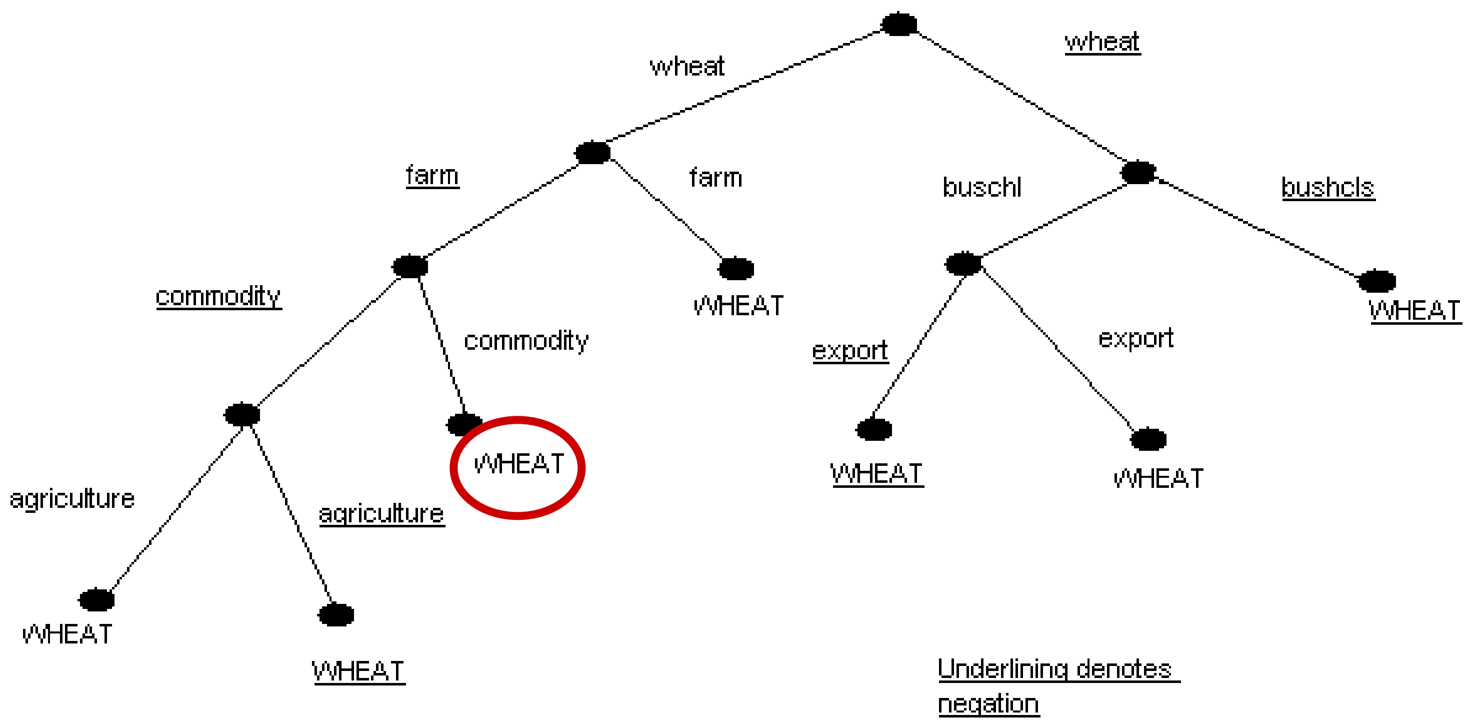
Decision trees for text

Each internal node represents whether or not the text has a particular word



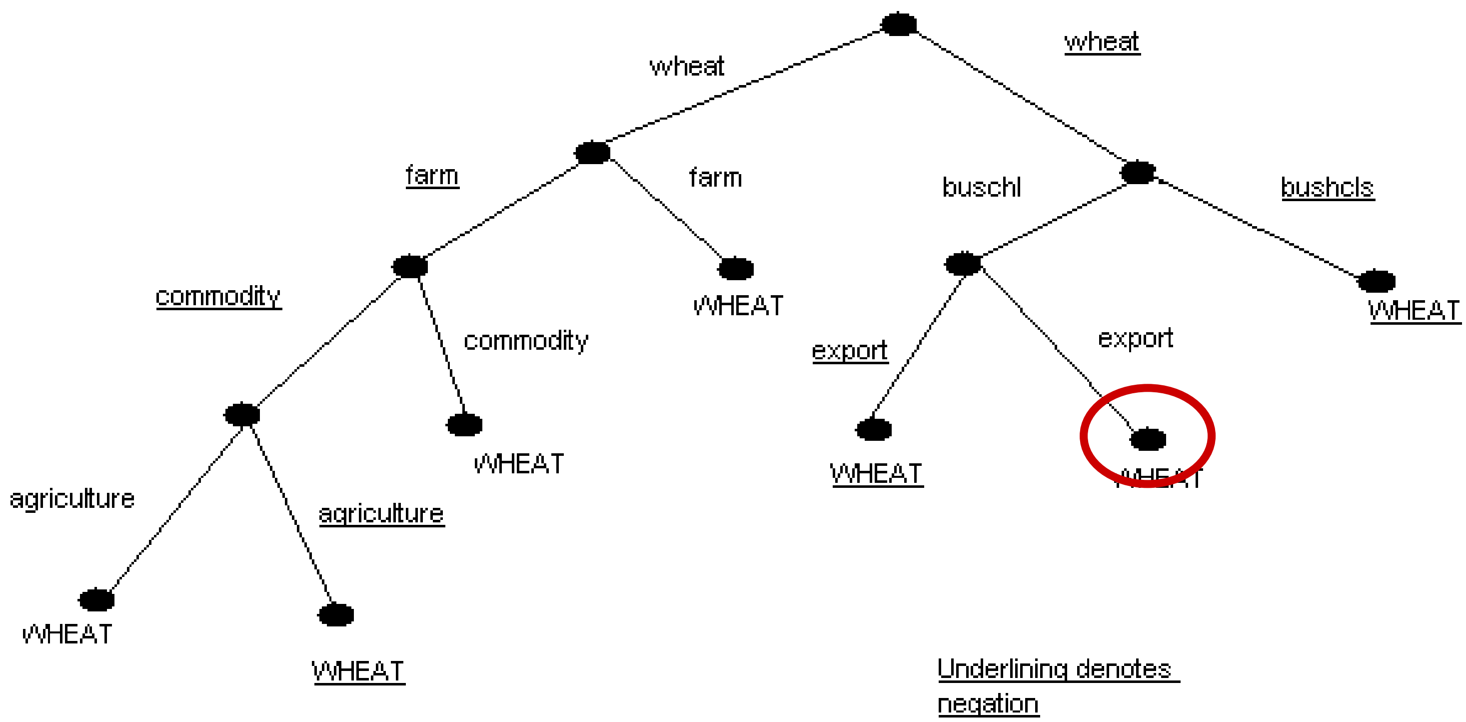
Decision trees for text

wheat is a commodity that can be found in states across the nation

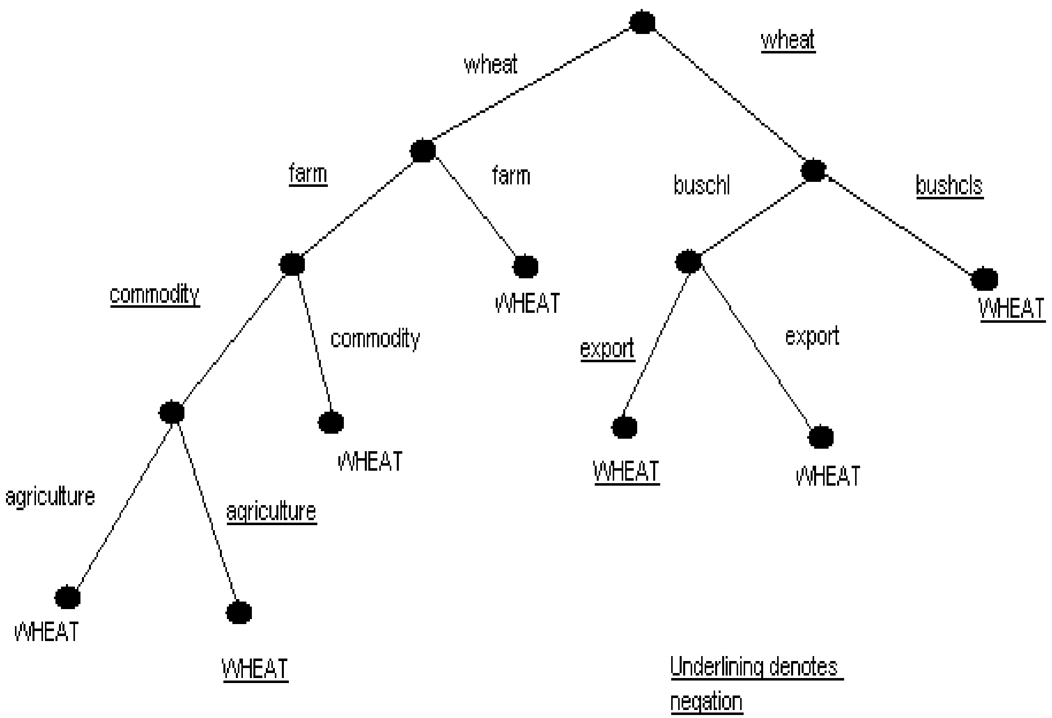


Decision trees for text

The US views technology as a commodity that it can export by the buschl.



Printing out decision trees



(wheat
  (buschl
    predict: not wheat
    (export
      predict: not wheat
      predict: wheat))
  (farm
    (commodity
      (agriculture
        predict: not
wheat
        predict: wheat)
      predict: wheat)
    predict: wheat))

Ranking problems

Suggest a simpler word for the word below:

vital

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

Suggest a simpler word

Suggest a simpler word for the word below:

acquired

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

Suggest a simpler word

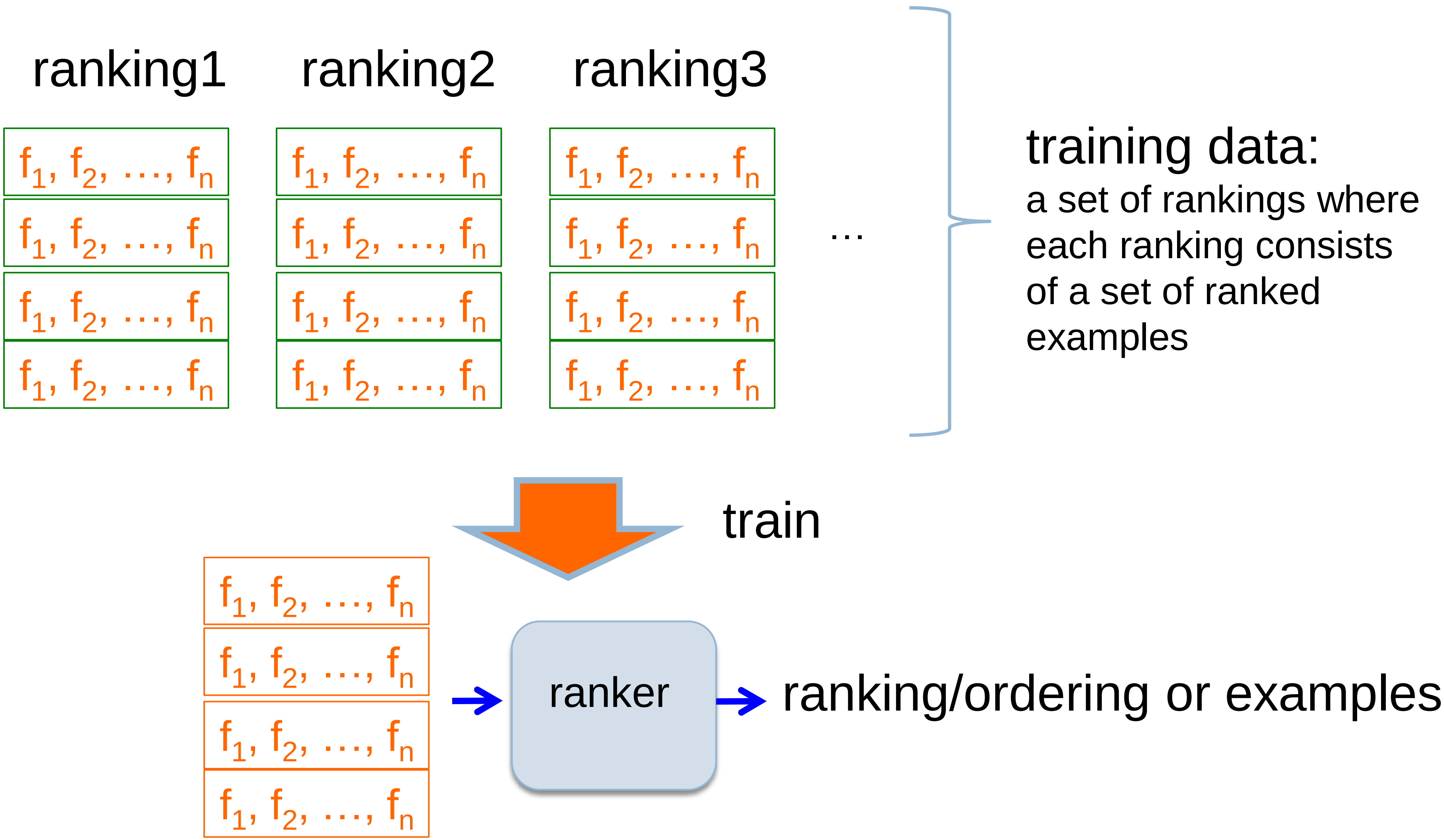
vital	acquired	
important	gotten	
necessary	received	
essential	gained	
needed	obtained	…
critical	got	
crucial	purchased	
mandatory	bought	
required	got hold of	
vital	acquired	

training data

train

list of synonyms → ranker → list ranked by simplicity

Ranking problems in general



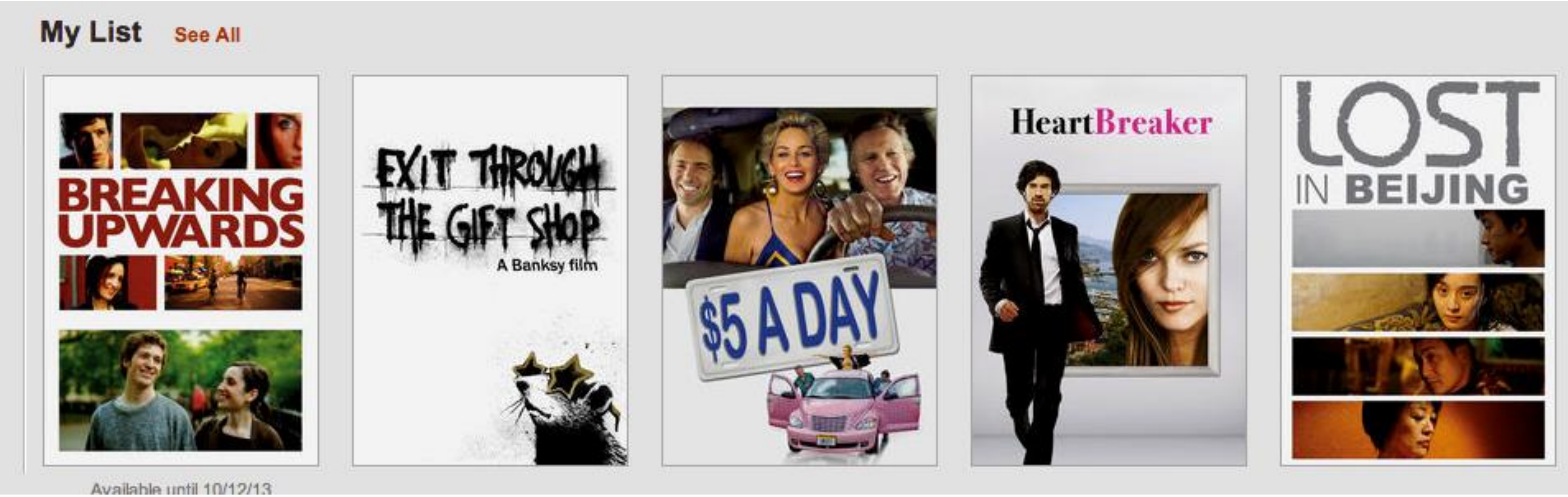
Ranking problems in general

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

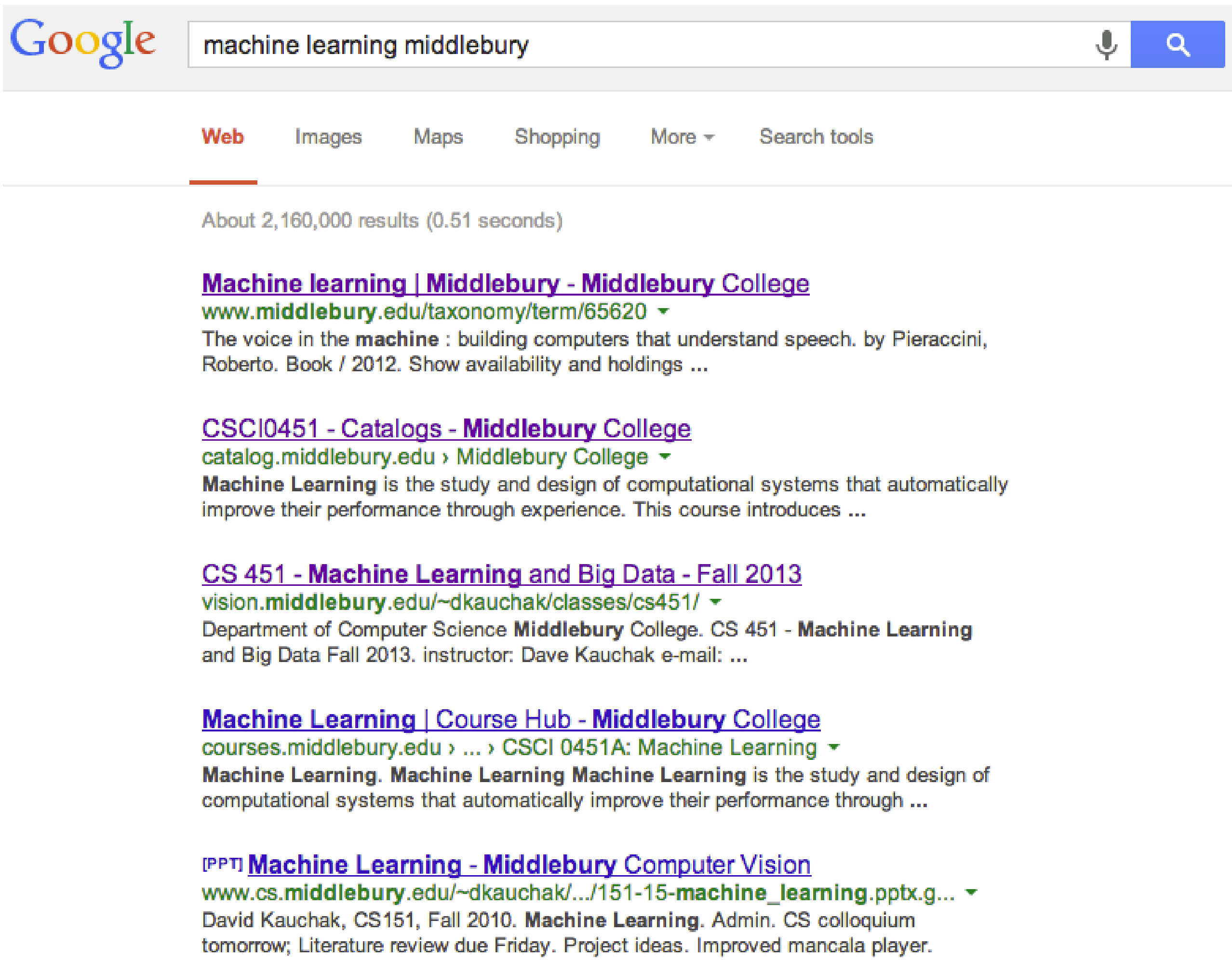
training data:
a set of rankings where each ranking consists of a set of ranked examples

Real-world ranking problems?

Netflix My List



Search


Google
machine learning middlebury
Web
Images
Maps
Shopping
More
Search tools
About 2,160,000 results (0.51 seconds)
Machine learning | Middlebury - Middlebury College
www.middlebury.edu/taxonomy/term/65620
The voice in the machine : building computers that understand speech. by Pieraccini, Roberto. Book / 2012. Show availability and holdings ...
CSCI0451 - Catalogs - Middlebury College
catalog.middlebury.edu › Middlebury College
Machine Learning is the study and design of computational systems that automatically improve their performance through experience. This course introduces ...
CS 451 - Machine Learning and Big Data - Fall 2013
vision.middlebury.edu/~dkauchak/classes/cs451/
Department of Computer Science Middlebury College. CS 451 - Machine Learning and Big Data Fall 2013. instructor: Dave Kauchak e-mail: ...
Machine Learning | Course Hub - Middlebury College
courses.middlebury.edu › ... › CSCI 0451A: Machine Learning
Machine Learning. Machine Learning Machine Learning is the study and design of computational systems that automatically improve their performance through ...
[PPT] Machine Learning - Middlebury Computer Vision
www.cs.middlebury.edu/~dkauchak/.../151-15-machine_learning.pptx.g...
David Kauchak, CS151, Fall 2010. Machine Learning. Admin. CS colloquium tomorrow; Literature review due Friday. Project ideas. Improved mancala player.

Ranking Applications

reranking N-best output lists

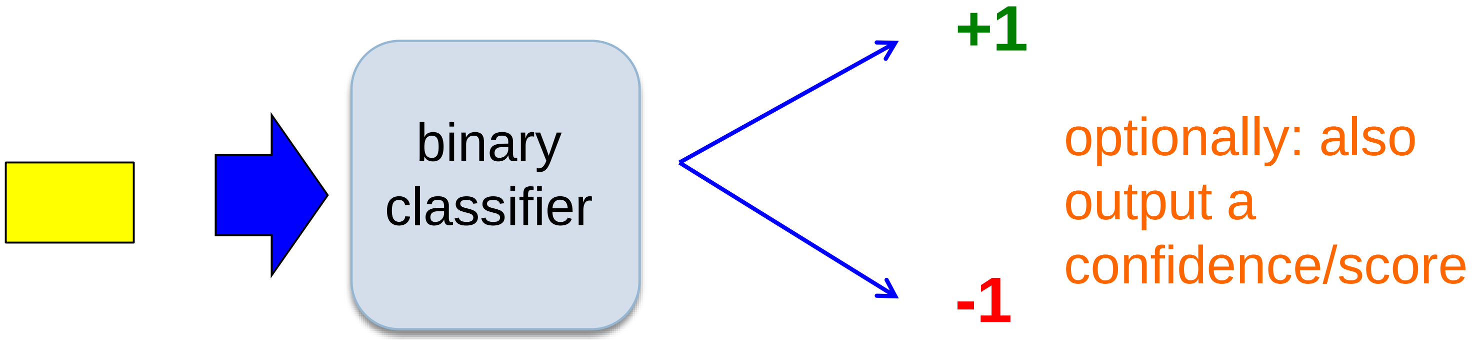
- machine translation
- computational biology
- parsing
- …

flight search

…

Black box approach to ranking

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



Can we solve our ranking problem with this?

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

$f_1, f_2, \ldots, f_n$

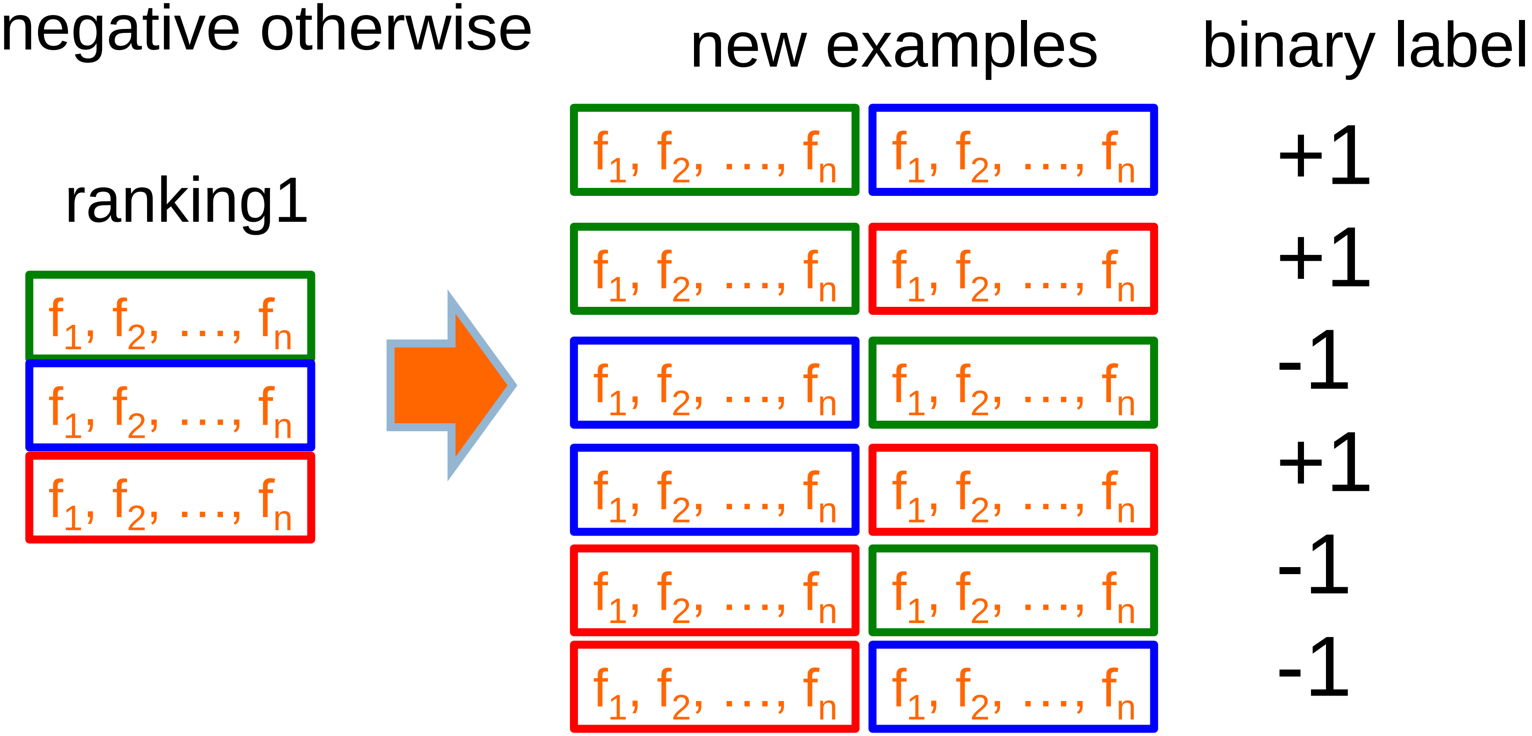
$f_1, f_2, \ldots, f_n$

$f_1, f_2, \ldots, f_n$

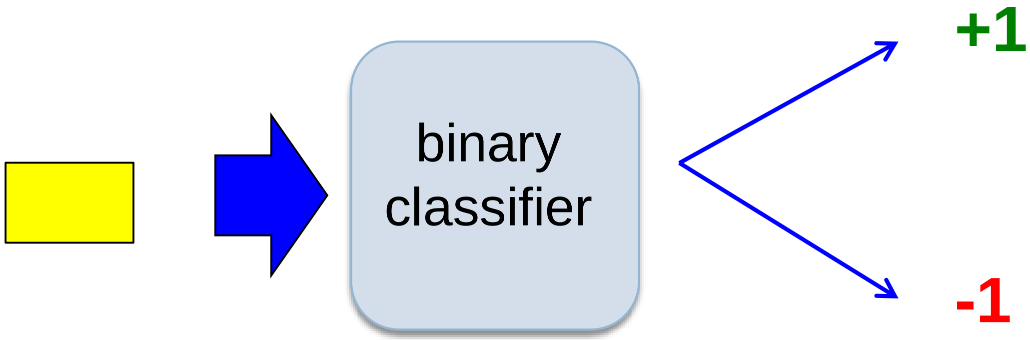
Predict better vs. worse

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

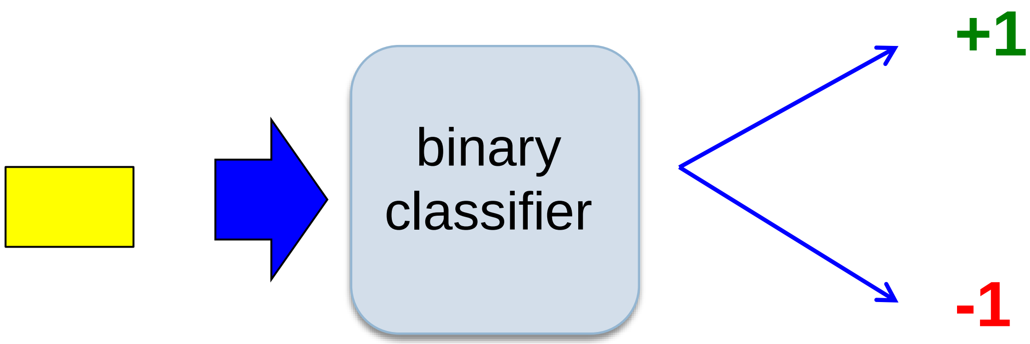


Predict better vs. worse

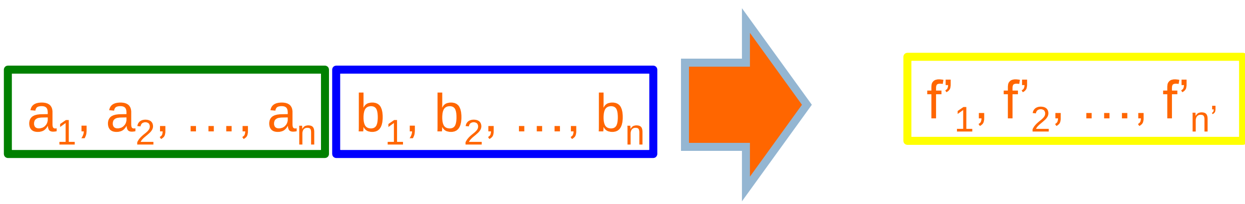


Our binary classifier only takes one example as input

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.

Combined feature vector

Many approaches! Will depend on domain and classifier

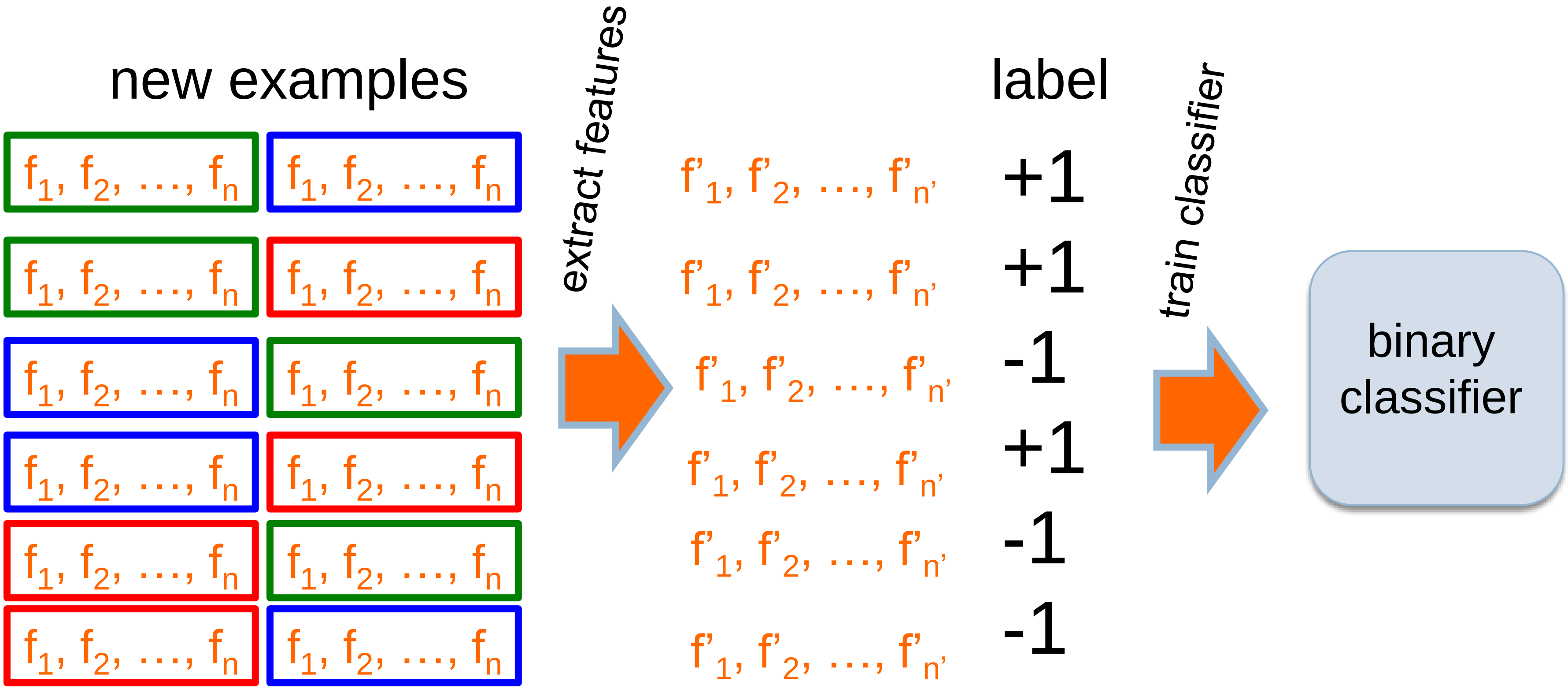
Two common approaches:

1. difference: $f'_i = a_i - b_i$

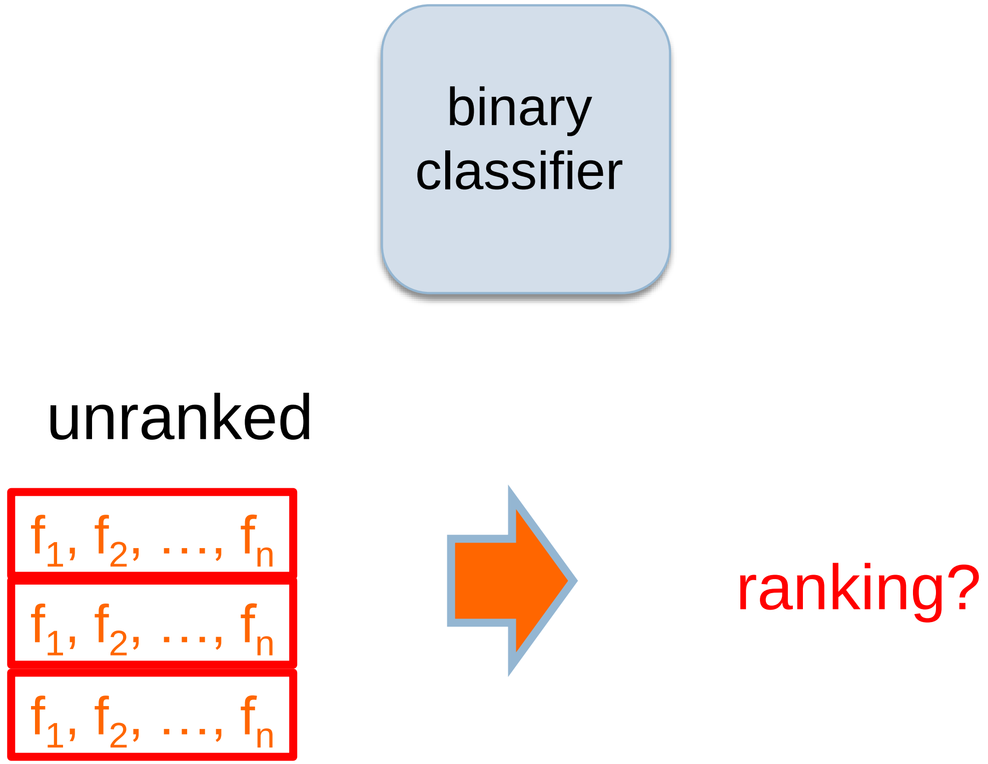
2. greater than/less than:

$$f'_i = \begin{cases} 1 & if\ a_i > b_i \\ 0 & otherwise \end{cases}$$

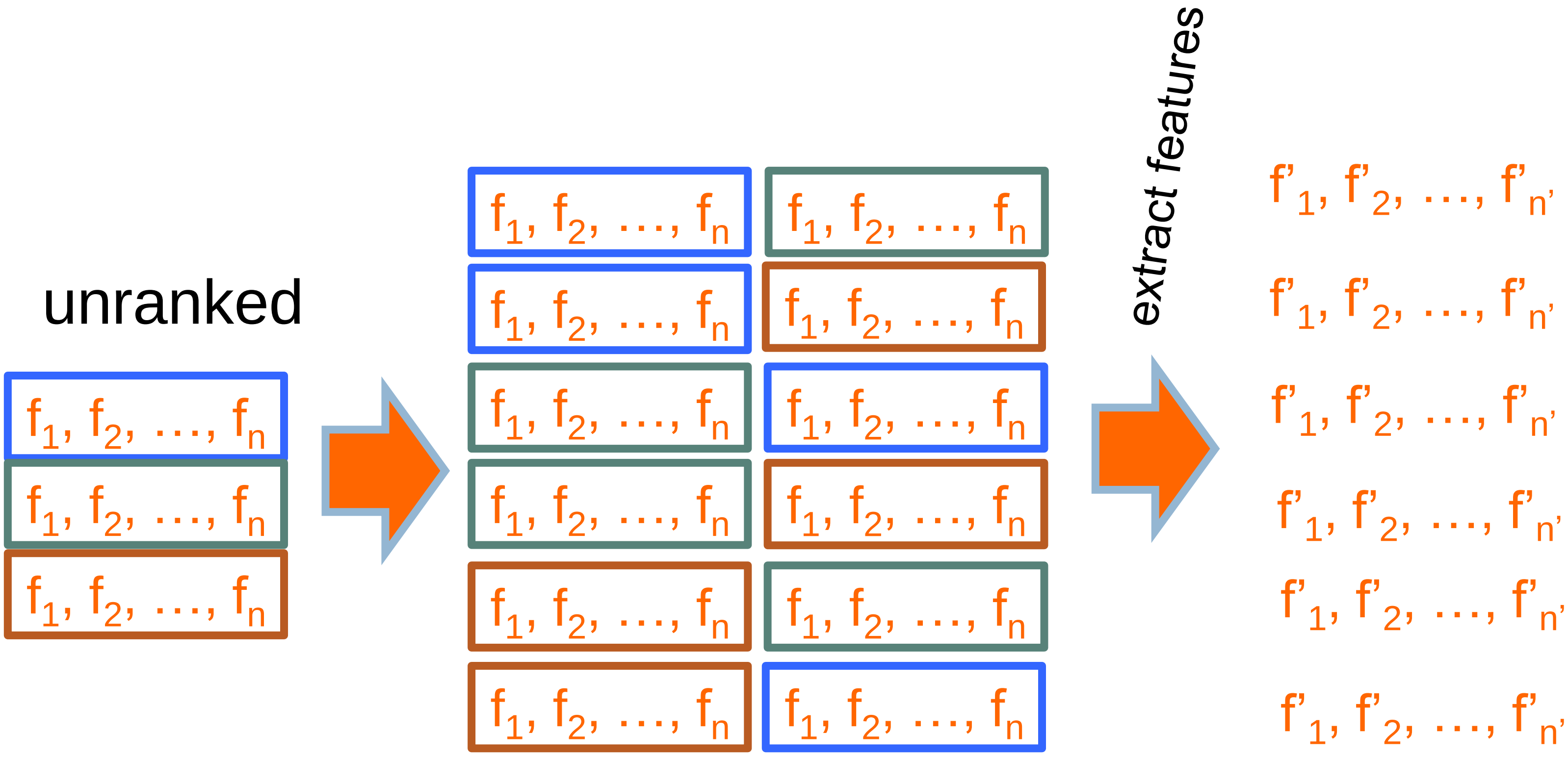
Training


new examples
f1, f2, …, fn
extract features
f'1, f'2, …, f'n'
label
+1
+1
-1
+1
-1
-1
train classifier
binary classifier

Testing

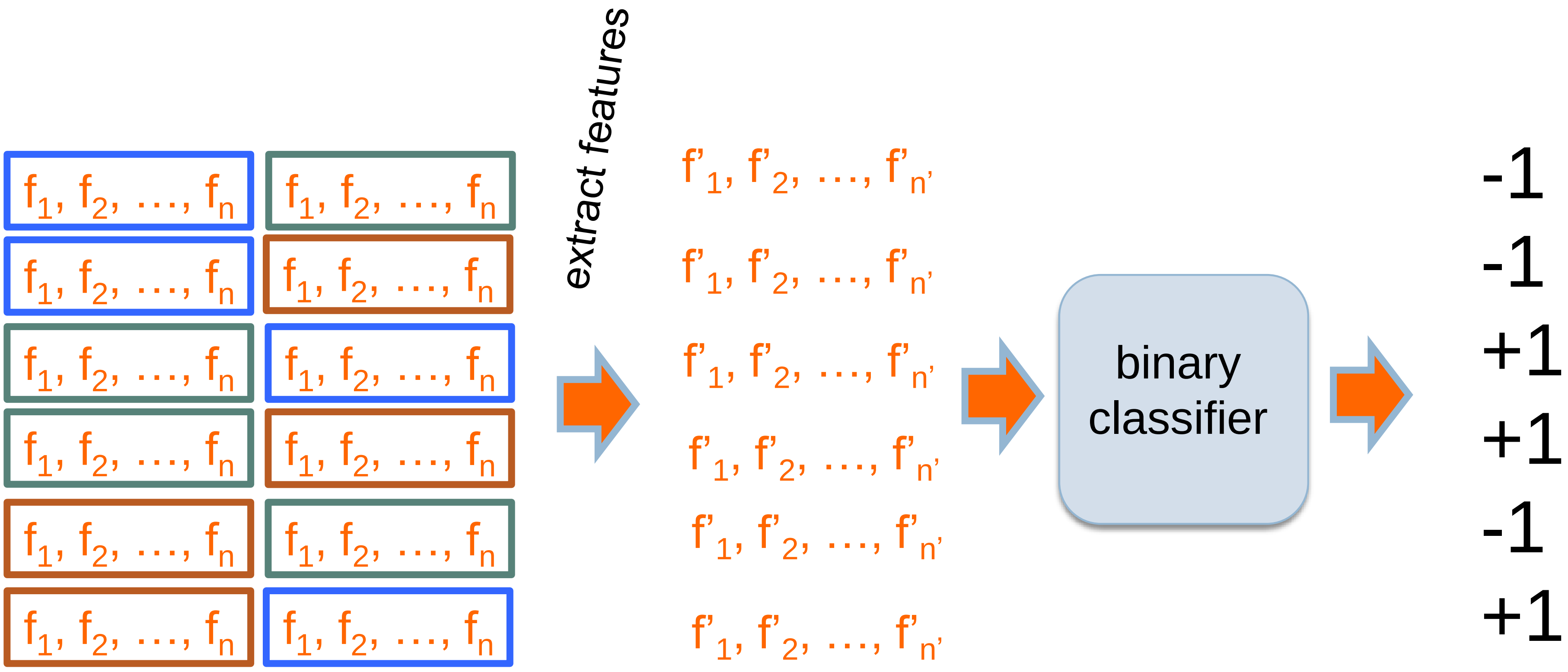


Testing



unranked
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
f1, f2, …, fn
extract features
f'1, f'2, …, f'n'
f'1, f'2, …, f'n'
f'1, f'2, …, f'n'
f'1, f'2, …, f'n'
f'1, f'2, …, f'n'
f'1, f'2, …, f'n'

Testing



Testing

$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	-1
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	-1
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	+1
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	+1
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	-1
$f_1, f_2, \ldots, f_n$	$f_1, f_2, \ldots, f_n$	+1

What is the ranking?

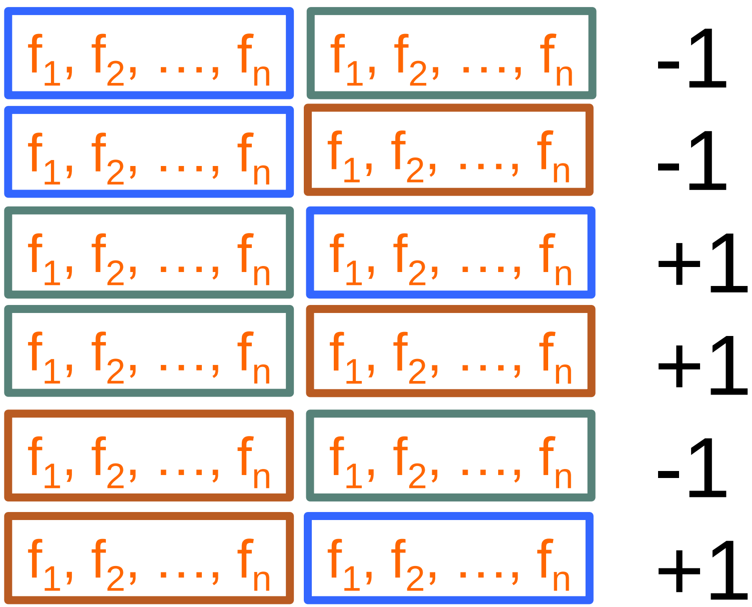
Algorithm?

Testing

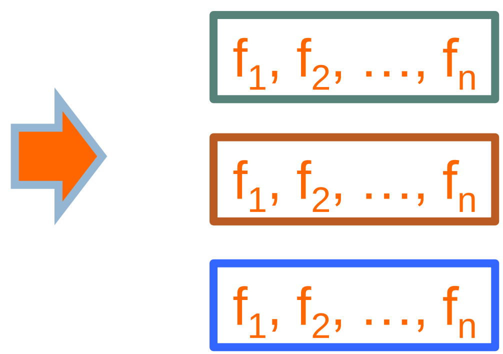
for each binary example e_{jk}:

  label[j] += $f_{jk}(e_{jk})$

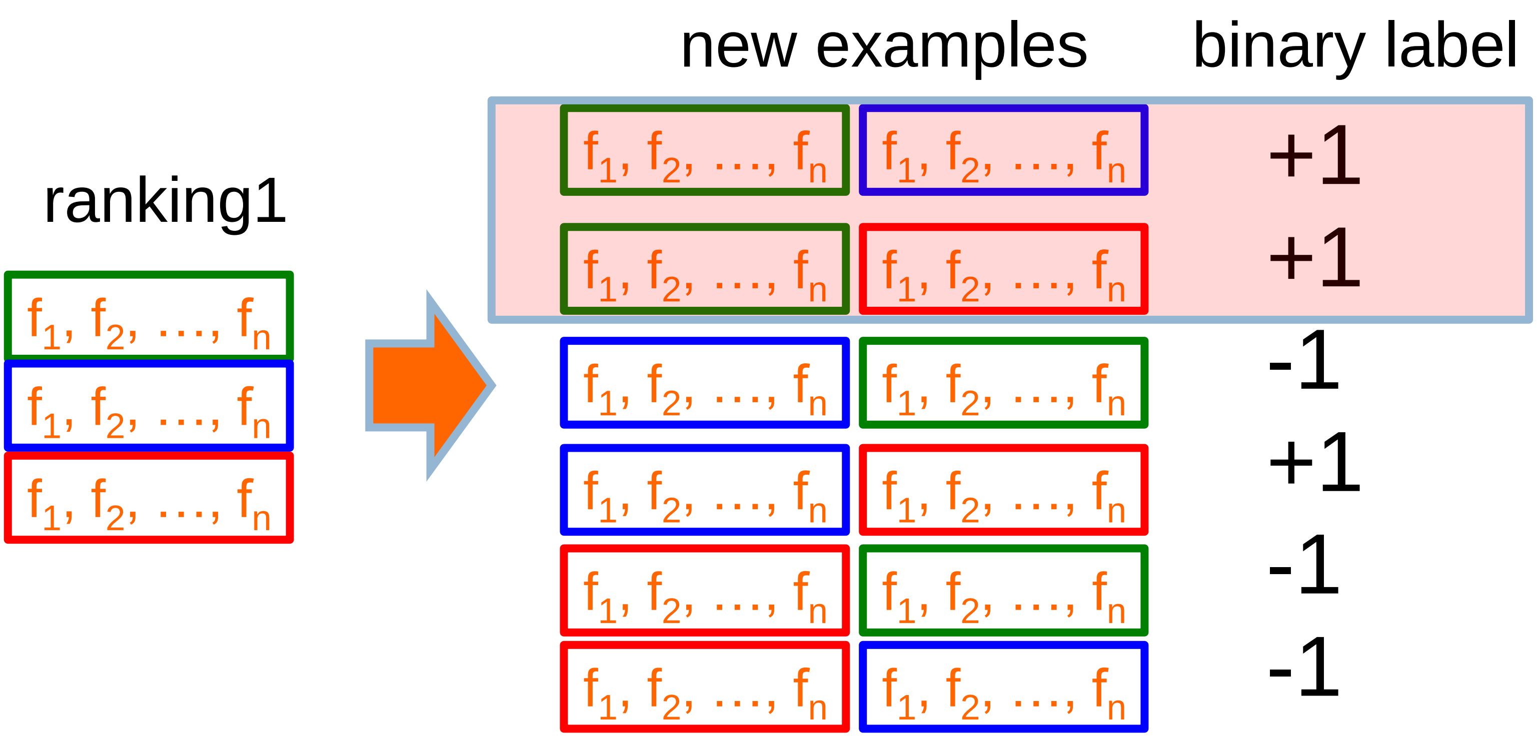
  label[k] -= $f_{jk}(e_{jk})$



rank according to label scores

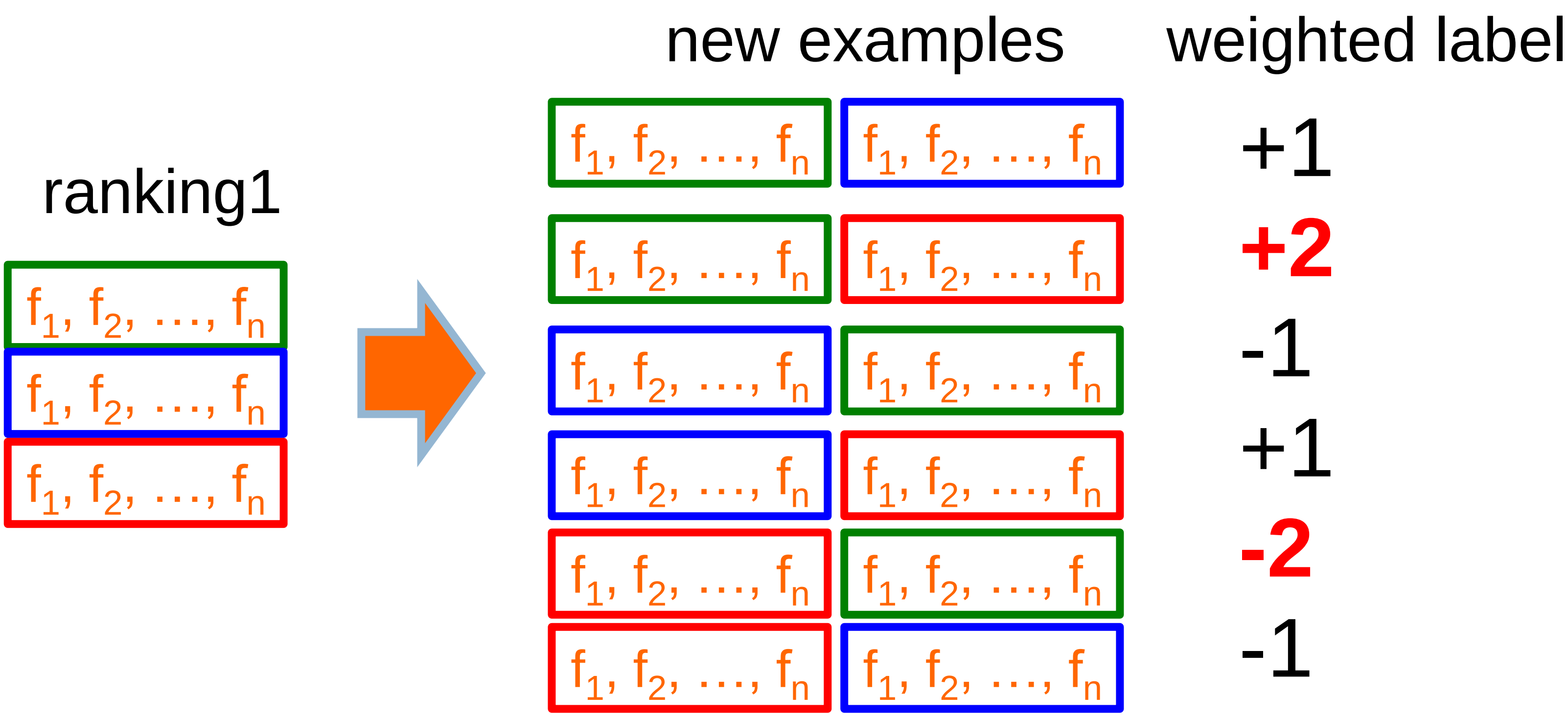


An improvement?



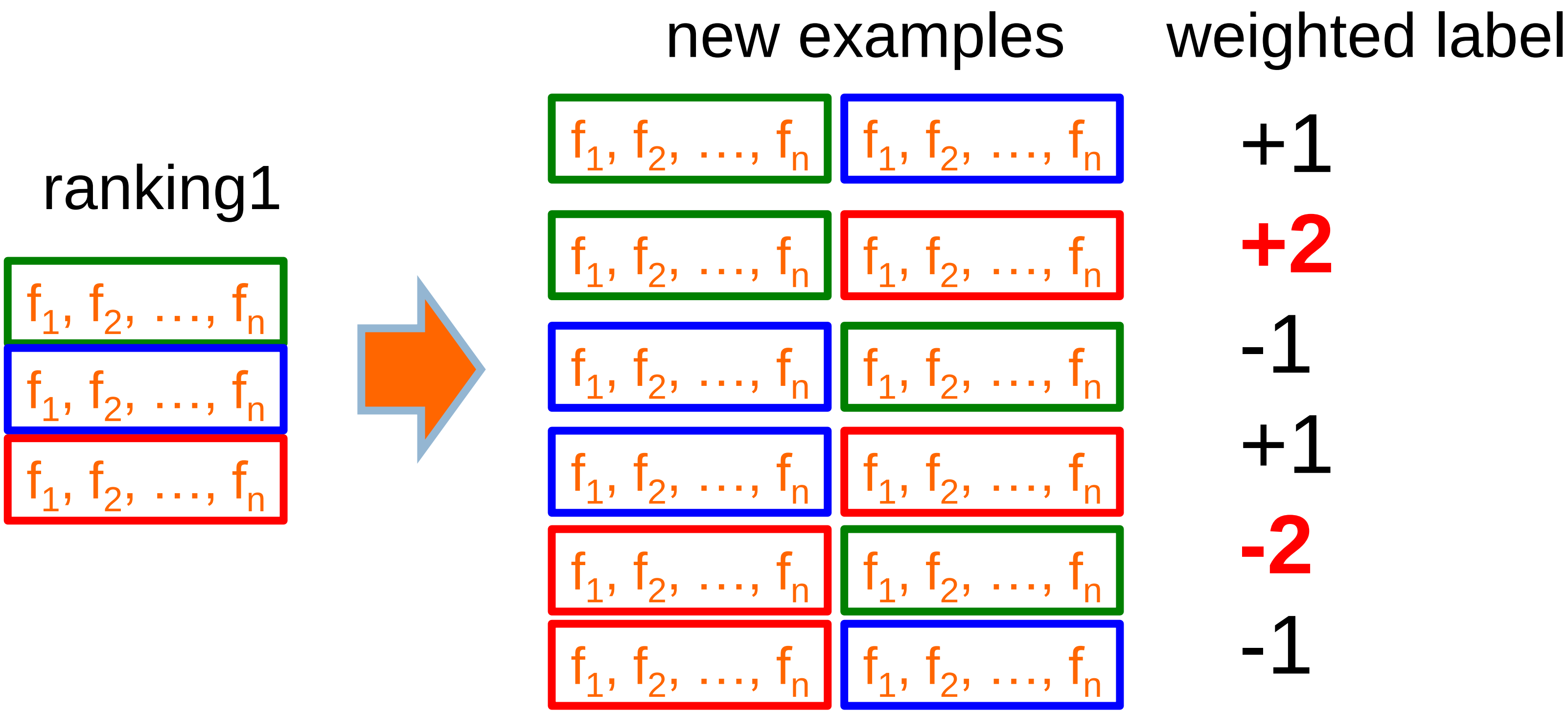
Are these two examples the same?

Weighted binary classification



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

Weighted binary classification



In general can weight with any consistent distance metric

Can we solve this problem?

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?

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!

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?

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?

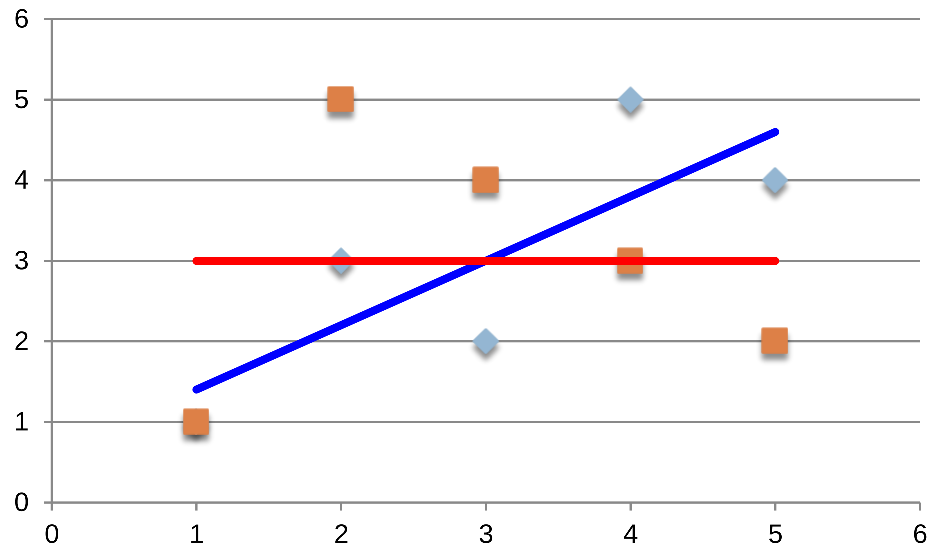
Doesn’t capture “near” correct

	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

$1/5 = 0.2$

Idea 2: correlation

ranking	prediction	prediction
1	1	1
2	3	5
3	2	4
4	5	3
5	4	2



Look at the correlation between the ranking and the prediction