

# Evaluating Boosting Algorithms to **lass** ar **lass**

## Comparison and Improvements

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## Contributions of this paper

- Algorithms are introduced
  - **AB**Boost
  - **AB**Boost
- **veral** **lass** boosting algorithms are compared **all**
  - **A**Boost
  - **CE**
  - **A**ost and variants

## What are **ar** **lass**

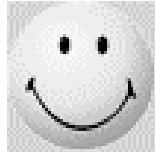
- **lass** that are *in* **ub**
- **lass** relative to their **lass**
- **am** **lass**
  - **lass** **lass** vs **lass**
  - **lass** **lass** vs **lass**
  - **lass** **lass** vs **lass**
  - **lass** **lass**

## Handling **ar** **lass**

- **lass** using an algorithm to **lass** a **lass** **lass** **lass** **lass**

	<b>lass</b> <b>lass</b> <b>C</b>	<b>lass</b> <b>lass</b> <b>C</b>
<b>lass</b> <b>lass</b> <b>C</b>	<b>lass</b> <b>lass</b> <b>C</b>	<b>lass</b> <b>lass</b> <b>C</b>
<b>lass</b> <b>lass</b> <b>C</b>	<b>lass</b> <b>lass</b> <b>C</b>	<b>lass</b> <b>lass</b> <b>C</b>

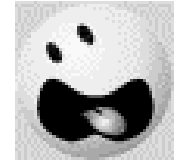
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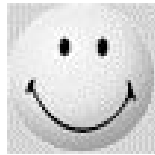
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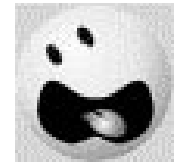
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## Boosting

- finding rare classes  $C$  from the rest of the data  $C$  is hard
- an improvement on the standard classification algorithm
- theoretical justification
- seems to work in practice
  - how boosting works has been shown on the training data

## Cost to Classify Classes

- accuracy is not a good metric for imbalanced classes
- simple  $\rightarrow$  all
  - can distinguish from
- simple  $\rightarrow$  decision
  - can distinguish from
- $\rightarrow$  all and  $\rightarrow$  decision usually don't

## Weak Classifier

- does not have a bias  $\rightarrow$  data is in  $C$  can't be in  $C$
- imbalanced classification as  $C$ 
  - accuracy is a bad measure
  - loss is all
- imbalanced classification as  $C$ 
  - loss is loss

## What is Boosting

- goal: high recall and high precision
- a machine learning technique to iteratively improve a classifier using weights
- iteratively change weights using training data
- $\rightarrow$  the model in each iteration is a weak classifier on the training data
- the final model is a strong classifier on the training data
- the model contributes to the final decision as a vote

# Boosting Algorithms

## Boosting Algorithms

- Boosting Algorithms that  $\text{minimize}$ 
  - variance
- Boosting Algorithms that  $\text{maximize}$ 
  - margin
- Robust Boosting Algorithms
  - resistant to outliers

## AdaBoost

- Boosting algorithm that  $\text{minimize}$ 
  - exponential loss
- Linear algorithm
- train on all data
- at each iteration the training model also returns something
- first train all data equally giving equal weight to all data points

## AdaBoost fails

- on training data  $\text{minimize}$ 
  - loss
- at iteration  $t$ 
  - train a model  $h_t$  using weights  $w_t$
  - compute the weight  $A_t$ 
    - $r_t = \sum_i w_{t-1} |h_{t-1}(x_i) - y_i|$
    - $A_t = \frac{1}{2} \ln \frac{1+r_t}{1-r_t}$
  - combine weights  $w_t$  for all  $h_t$ 
    - $w_t = \frac{A_t}{\sum_{i=1}^t A_i}$
    - final hypothesis  $H_t = \text{sign}(\sum_{i=1}^t A_i h_i)$

## AdaBoost

- improvement over AdaBoost
- similar to AdaBoost but  $\text{minimize}$ 
  - loss
- instability of all functions
- use  $A_t$  and  $A_t^n$  for positive and negative functions respectively

## arBoost fails

- can't model  $t$  using lights  $\square_t$
- a combinatorial light  $A_t^n$ 
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $A_t^n \square_{\mathcal{I}_t} \square_{\mathcal{I}_t}$
- a combinatorial light  $A_t^n$ 
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $A_t^n \square_{\mathcal{I}_t} \square_{\mathcal{I}_t}$

## arBoost fails

- a combinatorial light for positive relations
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
- a combinatorial light for negative relations
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
- a light  $\square_t$ 
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$
  - $\sum_{i \in \mathcal{I}_t} \square_i \square_{h_t}$

## arBoost

- a boosting algorithm that is not a standard arBoost
- if the current model is not good use a default model
- the default model is a naive classifier with good accuracy

## arBoost

- use a default model
- will model a function at iteration using lights  $\square_t$  and a default model

# Adaboost fails

Given:  $T, M$ .  
 Initialize weight  $D_1(i) = 1/N$ .  
 for  $t = 1 \dots M$

- Learn weak model for  $y_i = +1$  (class C) examples,  $A_t^{C+} : x_i \rightarrow \{+1, 0\}$ , using  $D_t$ .
- Learn weak model for  $y_i = -1$  (class NC) examples,  $A_t^{C-} : x_i \rightarrow \{-1, 0\}$ , using  $D_t$ .
- Evaluate C's model and NC's model:
 
$$TP_t = \sum_{y_i > 0, A_t^{C+}(x_i) > 0} D_t(i)$$

$$FP_t = \sum_{y_i < 0, A_t^{C+}(x_i) > 0} D_t(i)$$

$$TN_t = \sum_{y_i < 0, A_t^{C-}(x_i) < 0} D_t(i)$$

$$FN_t = \sum_{y_i > 0, A_t^{C-}(x_i) < 0} D_t(i)$$
- Choose Model and Compute importance weight,  $\alpha_t$ :  
 If  $(1 - (TP_t - FP_t)^2) < (1 - (TN_t - FN_t)^2)$  then, Choose C's Model, by setting  $\lambda_t = A_t^{C+}$ :
 
$$\alpha_t = 0.5 \ln((TP_t / FP_t)) \quad (11)$$
 else Choose NC's Model by setting  $\lambda_t = A_t^{C-}$ :
 
$$\alpha_t = -0.5 \ln((TN_t / FN_t)) \quad (12)$$
- Update Weights:
 
$$D_{t+1}(i) = D_t(i) \exp(-\alpha_t |Z_t(A_t(x_i)) - y_i|) \quad (13)$$
 where  $Z_t$  is chosen such that  $\sum D_{t+1}(i) = 1$ .

Final Model:  

$$H(x) = \text{sign} \left( \sum_{1 \leq t \leq M} \alpha_t \right)$$

# Cost Sensitive Boosting Algorithms

- Adaboost same weight for true and false predictions
- Adaboost does not differentiate between positive and negative predictions
- Weights of false predictions are equal
- Algorithms Adaboost, B, B

# Cost Sensitive Algorithms

- Adaboost itself
  - as sensitive as an algorithm
- B and B
  - as sensitive as algorithms

# Boosting Applications

- B
  - $A_t$  for all  $t$
  - most are not rational voters
- B
  - $A_t$  computed using Adaboost
  - that is moral voters have greater importance
- Adaboost, B, B

## Light training is important

- how long training at each iteration is important to the boosting process
- sum of lights for all trees
- all algorithms try to increase light of each node through training light of each node in parallel as a result
- overfitting light of each node and too much information is lost

## Experiments

- the results are as follows
- all synthetic data
- each model's attributes have different correlations in each case
- data's attributes are different
- data's attributes are correlated

## Data sets

- test all the algorithms
  - AdaBoost and Boosting are used
  - AdaBoost and Boosting are used
- use the same parameters of each algorithm
- versions of each data set used
  - synthetic data
  - each gets progressively built and hard to distinguish from each other

## Data set results

DataSet		ABst	RB-1	SLIP	RB-2	CSB1	CSB2	ACst
snc1	R	77.04	77.04	81.13	74.93	77.04	77.04	77.04
	P	94.19	94.19	95.94	98.61	94.19	94.19	94.19
	F	84.76	84.76	87.92	85.16	84.76	84.76	84.76
snc2	R	76.78	76.78	69.39	76.78	76.78	76.78	77.31
	P	95.41	95.41	85.53	95.41	95.41	95.41	95.75
	F	85.09	85.09	76.62	85.09	85.09	85.09	85.55
snc3	R	41.03	41.16	35.09	49.21	43.14	43.14	79.02
	P	59.58	65.00	59.11	62.37	67.84	67.84	51.73
	F	48.39	51.10	44.04	55.01	52.74	52.74	62.33
snc4	R	54.75	58.71	47.63	56.99	52.64	38.13	69.53
	P	79.33	90.45	94.75	82.60	55.65	51.89	75.38
	F	64.79	71.20	63.39	67.45	54.10	43.95	72.79
snc5	R	47.23	51.58	43.14	53.96	56.46	55.67	63.19
	P	76.50	87.87	88.14	89.50	50.33	77.86	92.47
	F	58.40	65.00	57.93	67.33	53.33	64.92	75.08

## AdaBoost

- test all the algorithms
- AdaBoost attributes are correlated
- Weak classifiers used
  - In conditions of weak classifier using the training data
  - Good classifier means that in the training data the classifier is better than random classifier

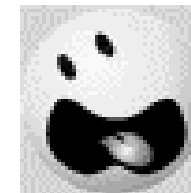
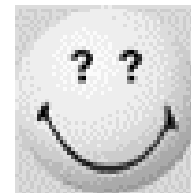
## AdaBoost results

Class		ABst	RB-1	SLIP	RB-2	CSB1	CSB2	ACst
2.9%	R	50.93	57.20	64.80	56.27	57.07	84.00	67.20
	P	71.27	81.25	57.51	82.10	60.03	44.74	68.39
	F	59.41	67.14	60.94	56.77	58.51	58.39	67.79
5.7%	R	63.20	68.67	63.60	73.20	67.07	84.13	76.00
	P	80.61	83.74	71.19	81.70	72.90	46.43	72.15
	F	70.85	75.45	67.18	77.22	69.86	59.84	74.03
13.1%	R	76.53	77.47	70.00	79.73	77.07	88.67	74.80
	P	80.62	83.35	78.59	86.04	72.70	58.18	85.55
	F	78.52	80.30	74.05	82.77	74.82	70.26	79.86
23.1%	R	78.27	84.40	80.80	80.80	86.13	96.13	85.07
	P	83.74	85.43	82.56	86.45	76.81	68.60	84.39
	F	80.91	84.91	81.67	83.55	81.21	80.07	84.73

## Summary

- Right classifier is important
  - recall vs precision
- AdaBoost
  - AdaBoost is better than AdaBoost
  - AdaBoost is better than other classifiers
  - AdaBoost is not overfitting in
  - AdaBoost is more sensitive than other algorithms like AdaBoost

## Handwritten questions



- smiley face from smiley font