An overview of Boosting

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Plan of talk

- Generative vs. non-generative modeling
- Boosting
- Alternating decision trees
- Boosting and over-fitting
- Applications

Toy Example

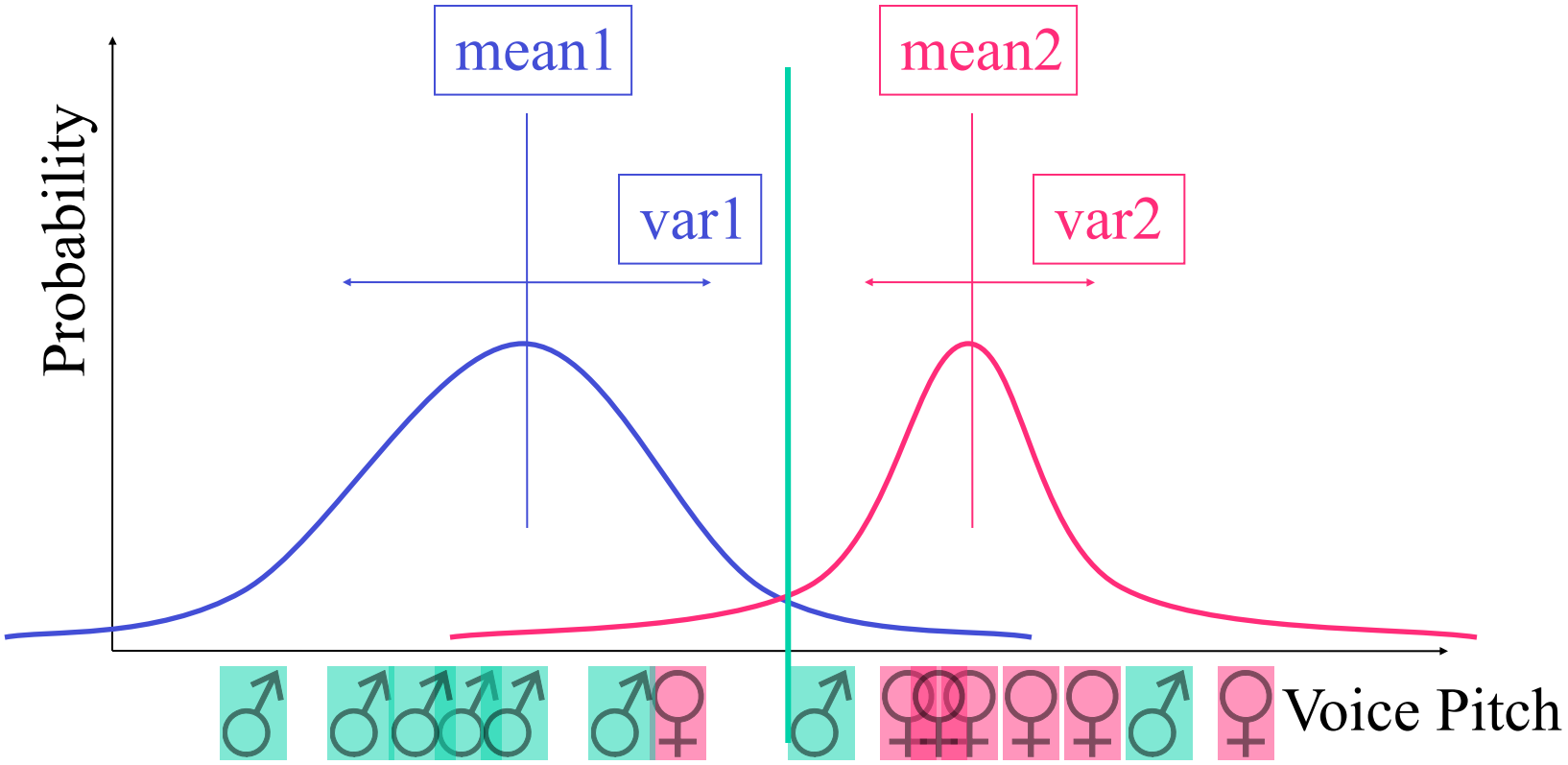
- Computer receives telephone call
- Measures Pitch of voice
- Decides gender of caller

Human Voice

Male

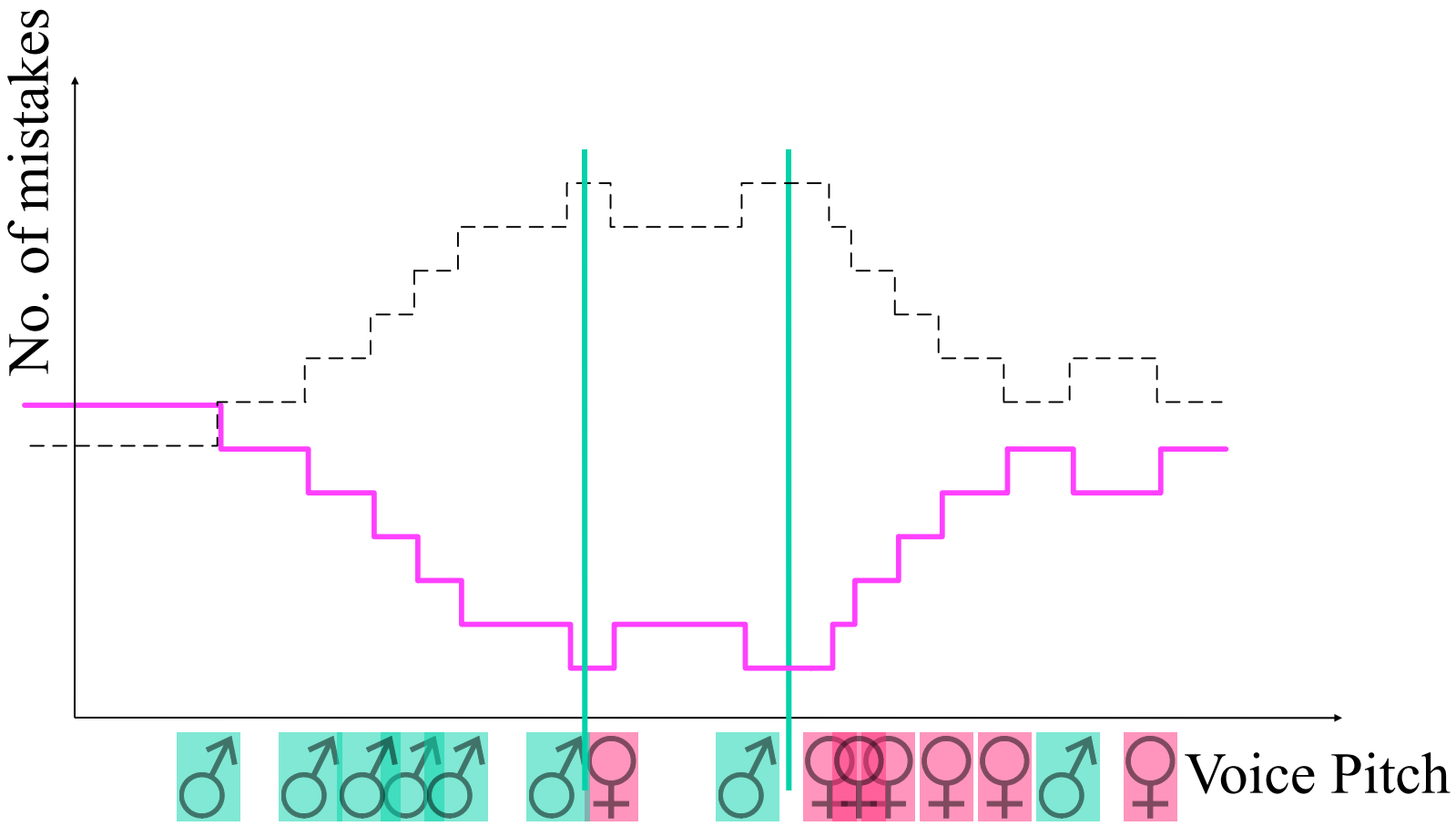
Female

Generative modeling

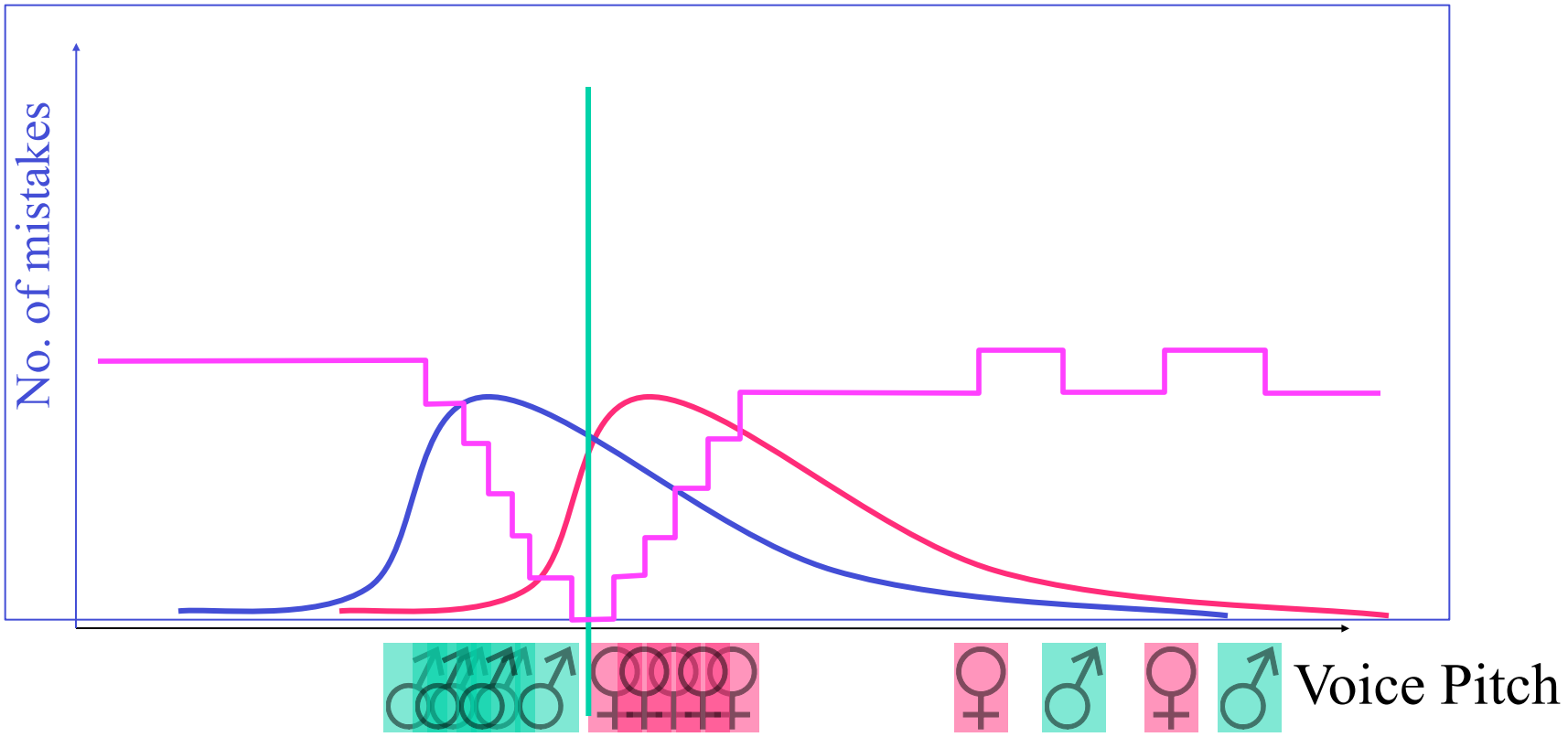


Discriminative approach

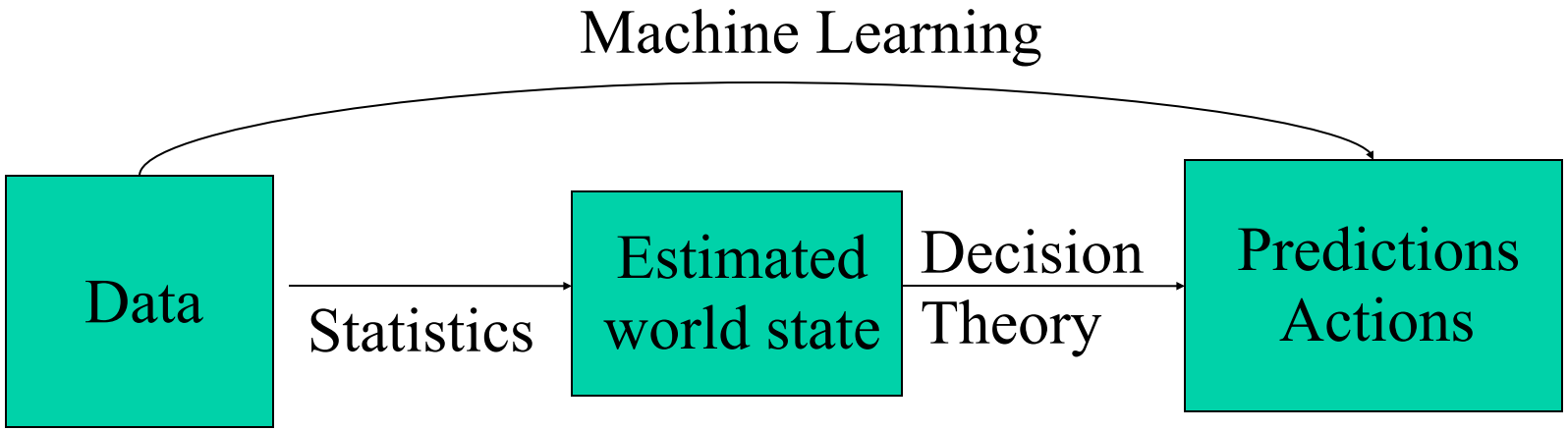
[Vapnik 85]



Ill-behaved data



Traditional Statistics vs. Machine Learning



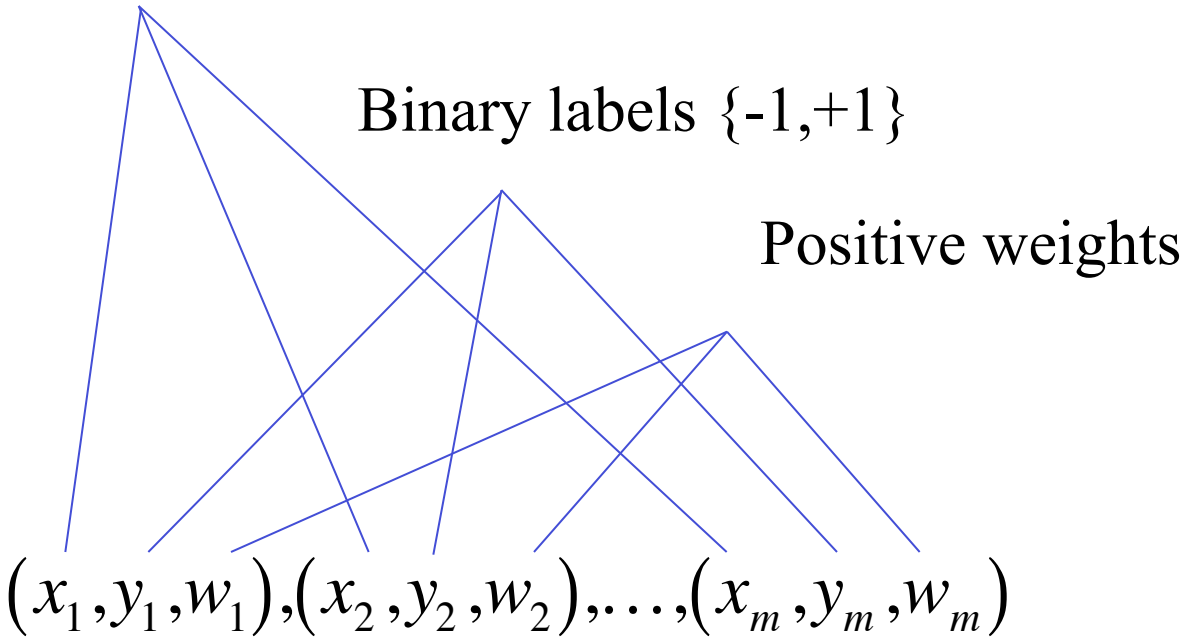
Comparison of methodologies

Model	Generative	Discriminative
Goal	Probability estimates	Classification rule
Performance measure	Likelihood	Misclassification rate
Mismatch problems	Outliers	Misclassifications

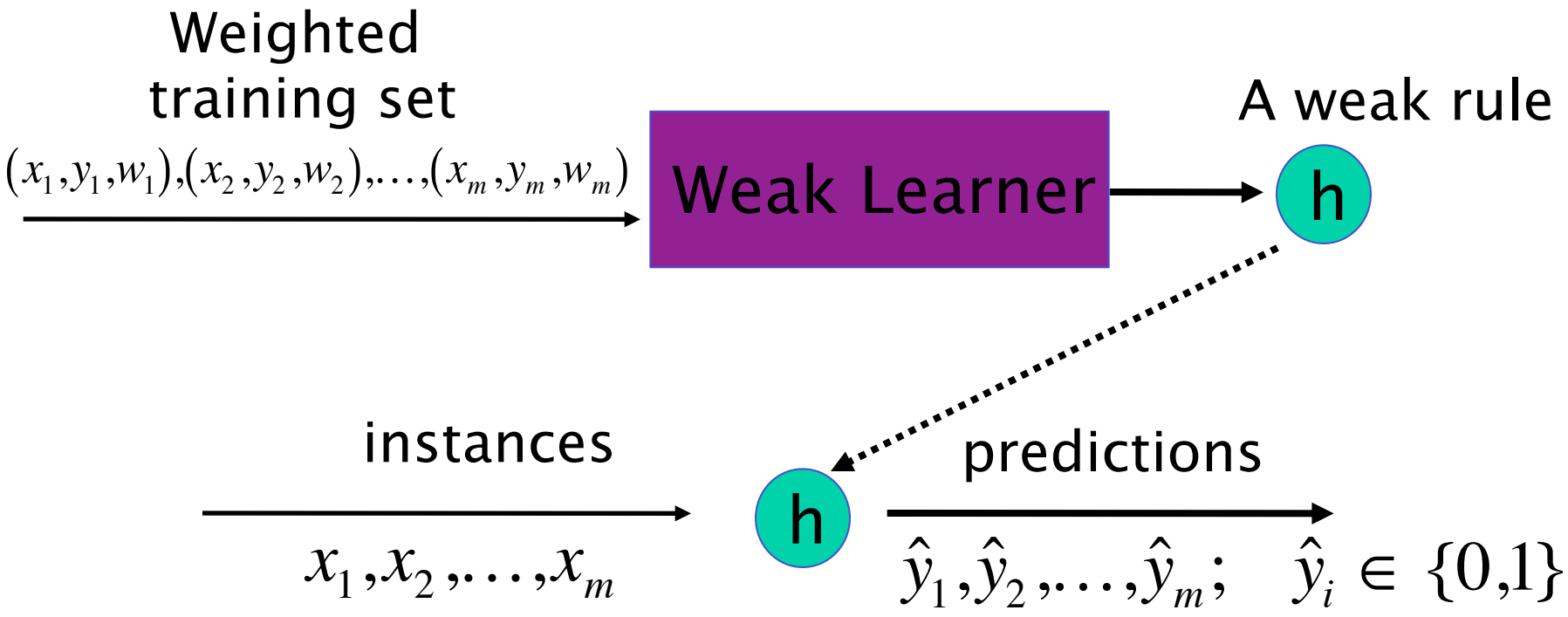
Boosting

A weighted training set

Feature vectors



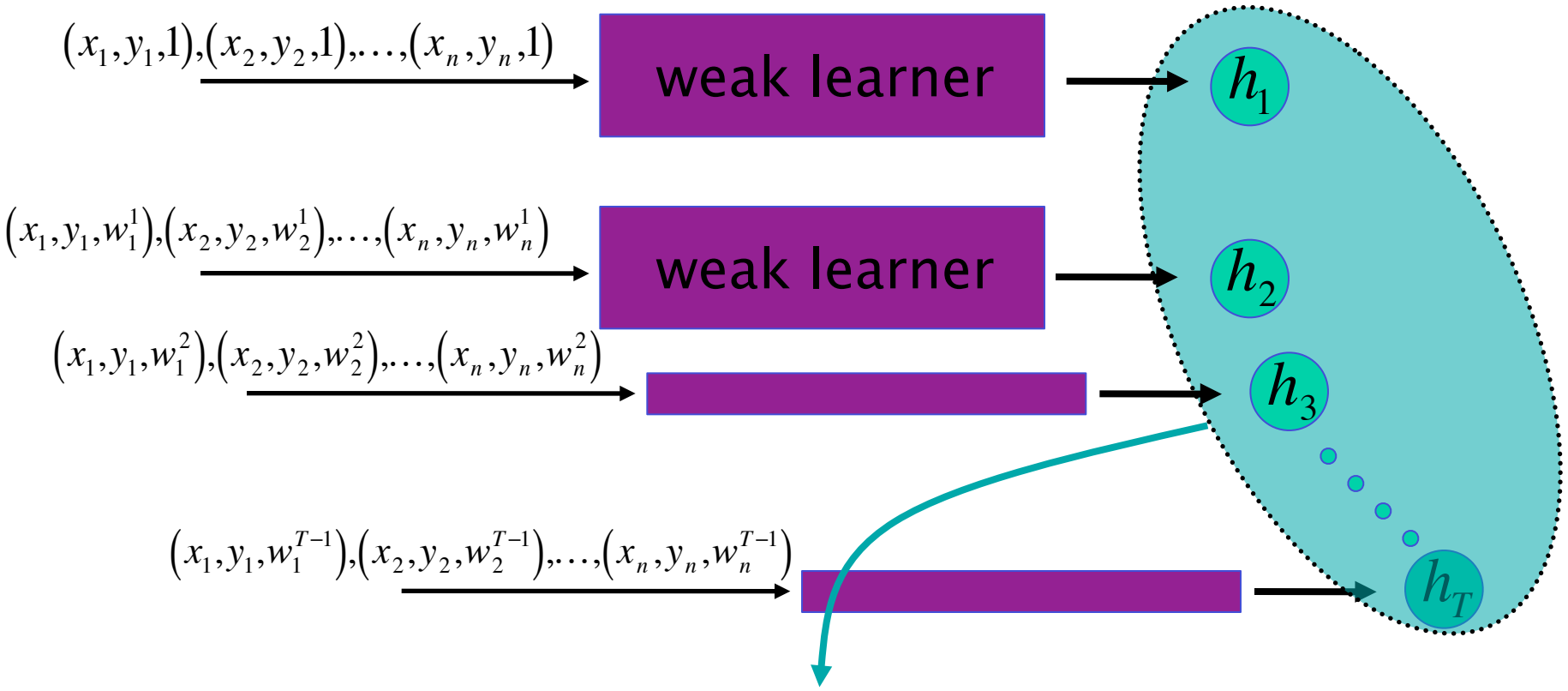
A weak learner



The weak requirement:

$$\left| \frac{\sum_{i=1}^{m} y_i \hat{y}_i w_i}{\sum_{i=1}^{m} w_i} \right| > \gamma > 0$$

The boosting process



$$F_T(x) = \alpha_1 h_1(x) + \alpha_2 h_2(x) + \ldots + \alpha_T h_T(x)$$

Adaboost

Freund, Schapire 1997

Weak Rule: $h_t : X \to \{0,1\}$

Label: $y \in \{-1,+1\}$

Training set: $\{(x_1, y_1, 1), (x_2, y_2, 1), \ldots, (x_n, y_n, 1)\}$

$$F_0(x) \equiv 0$$

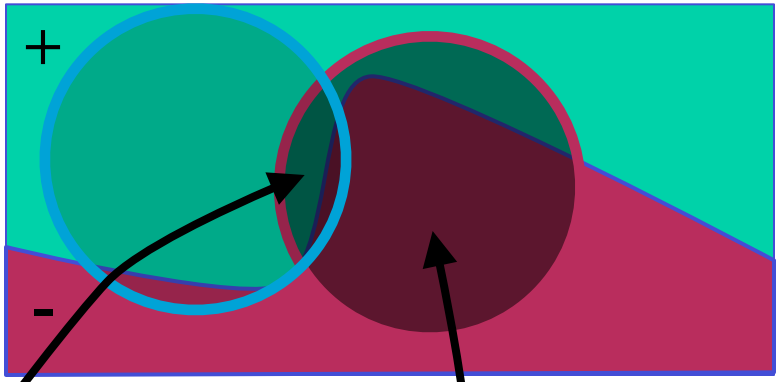
$$\text{for } t = 1..T$$

$$w_i^t = \exp(-y_i F_{t-1}(x_i))$$

$$\text{Get } h_t \text{ from } weak-learner$$

$$\alpha_t = \frac{1}{2}\ln\left(\epsilon + \sum_{i:h_t(x_i)=1, y_i=1} w_i^t\right) \Big/ \left(\epsilon + \sum_{i:h_t(x_i)=1, y_i=-1} w_i^t\right)$$

$$F_t = F_{t-1} + \alpha_t h_t$$



A Formal Description of Boosting

[Slides from Rob Schapire]

- given training set $(x_1, y_1), \ldots, (x_m, y_m)$
- $y_i \in \{-1, +1\}$ correct label of instance $x_i \in X$
- for $t = 1, \ldots, T$:
  - construct distribution D_t on $\{1, \ldots, m\}$
  - find weak classifier ("rule of thumb")

$$h_t : X \to \{-1, +1\}$$

with small error ϵ_t on D_t:

$$\epsilon_t = \Pr_{i \sim D_t}[h_t(x_i) \neq y_i]$$

- output final classifier H_{final}

AdaBoost

[Slides from Rob Schapire]

[with Freund]

- constructing D_t:
  - $D_1(i) = 1/m$
  - given D_t and h_t:

$$\begin{aligned} D_{t+1}(i) &= \frac{D_t(i)}{Z_t} \times \begin{cases} e^{-\alpha_t} & \text{if } y_i = h_t(x_i) \\ e^{\alpha_t} & \text{if } y_i \neq h_t(x_i) \end{cases} \\ &= \frac{D_t(i)}{Z_t} \exp(-\alpha_t \, y_i \, h_t(x_i)) \end{aligned}$$

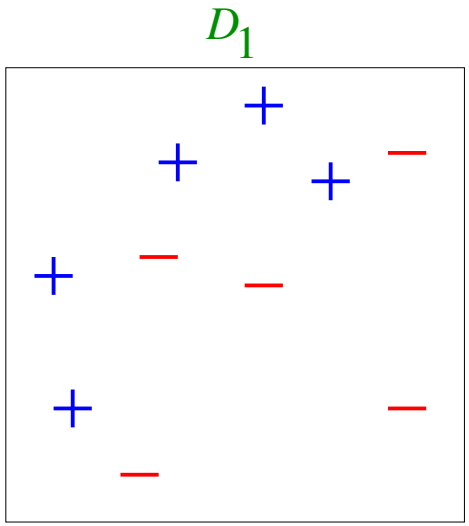
where $Z_t =$ normalization factor

$$\alpha_t = \tfrac{1}{2} \ln \left(\frac{1-\epsilon_t}{\epsilon_t} \right) > 0$$

- final classifier:
  - $H_{\text{final}}(x) = \text{sign} \left(\sum_t \alpha_t h_t(x) \right)$

Toy Example

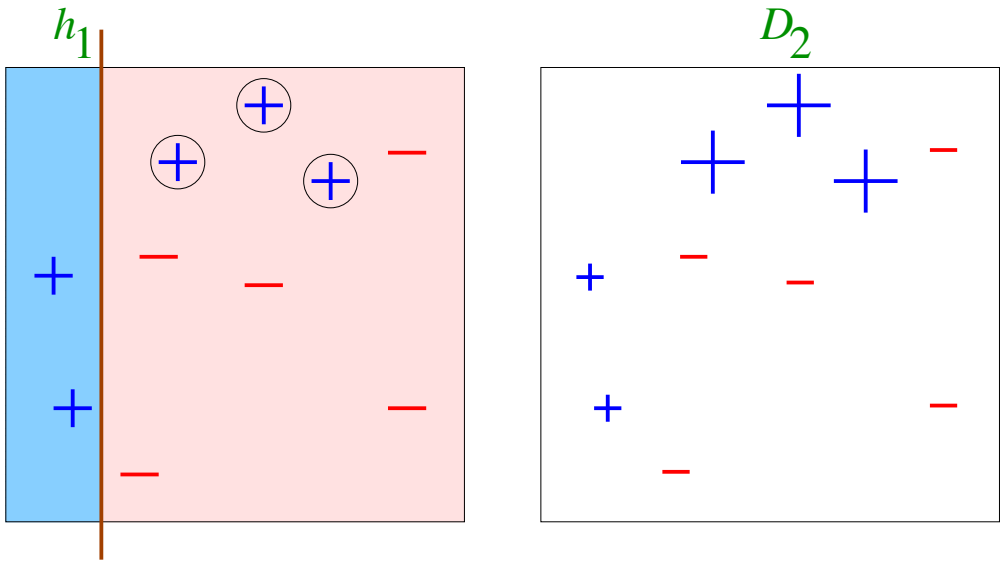
[Slides from Rob Schapire]



weak classifiers = vertical or horizontal half-planes

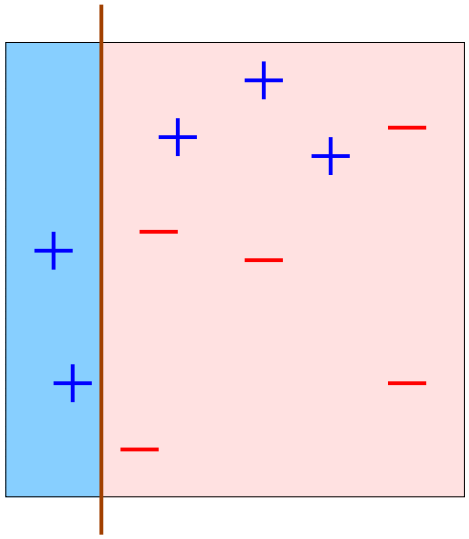
Round 1

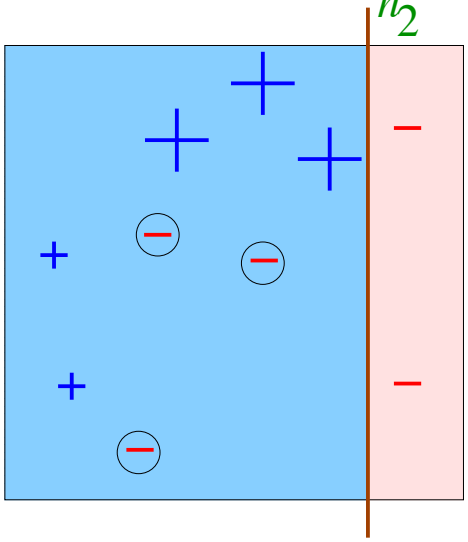
[Slides from Rob Schapire]

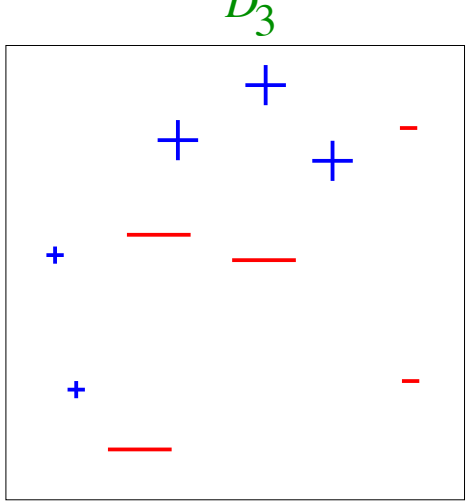


Round 2

[Slides from Rob Schapire]





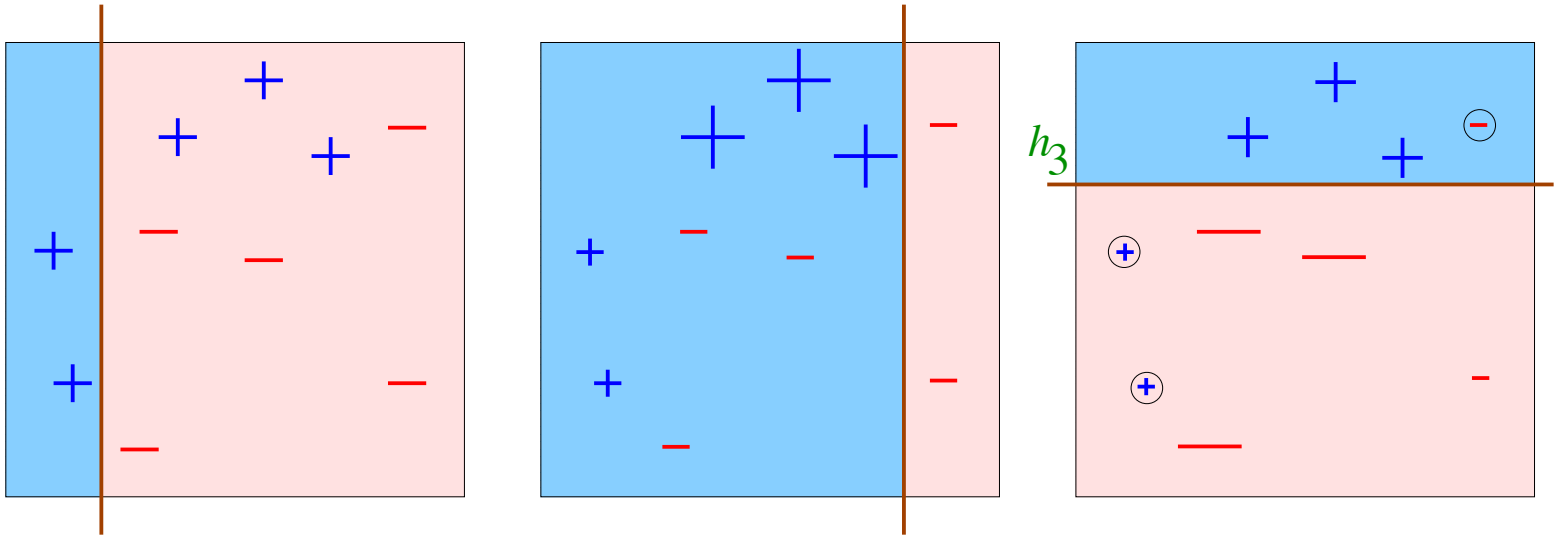


$\varepsilon_2 = 0.21$

$\alpha_2 = 0.65$

Round 3

[Slides from Rob Schapire]

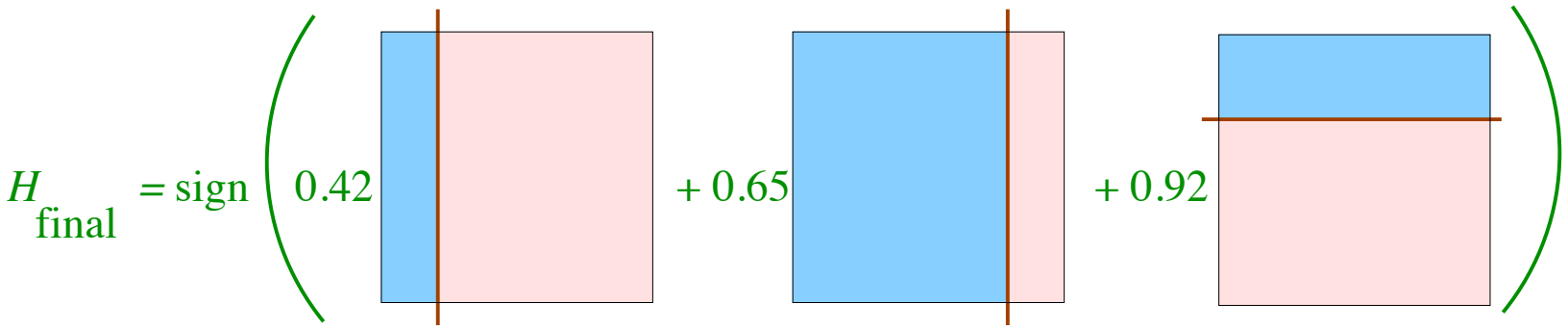


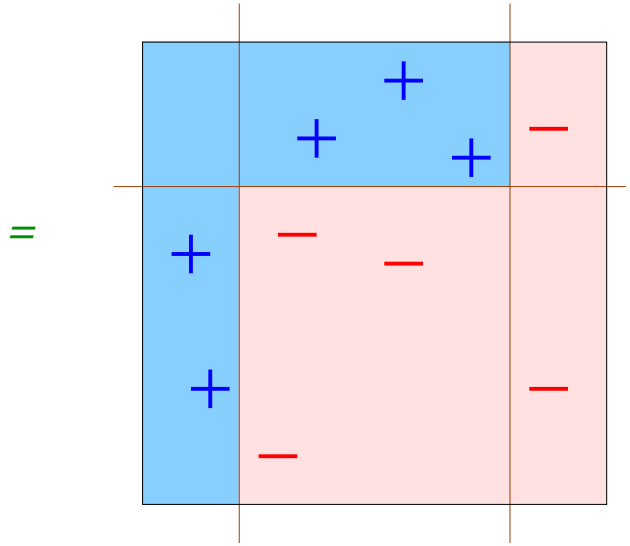
$\varepsilon_3 = 0.14$

$\alpha_3 = 0.92$

Final Classifier

[Slides from Rob Schapire]





Analyzing the Training Error

[Slides from Rob Schapire]

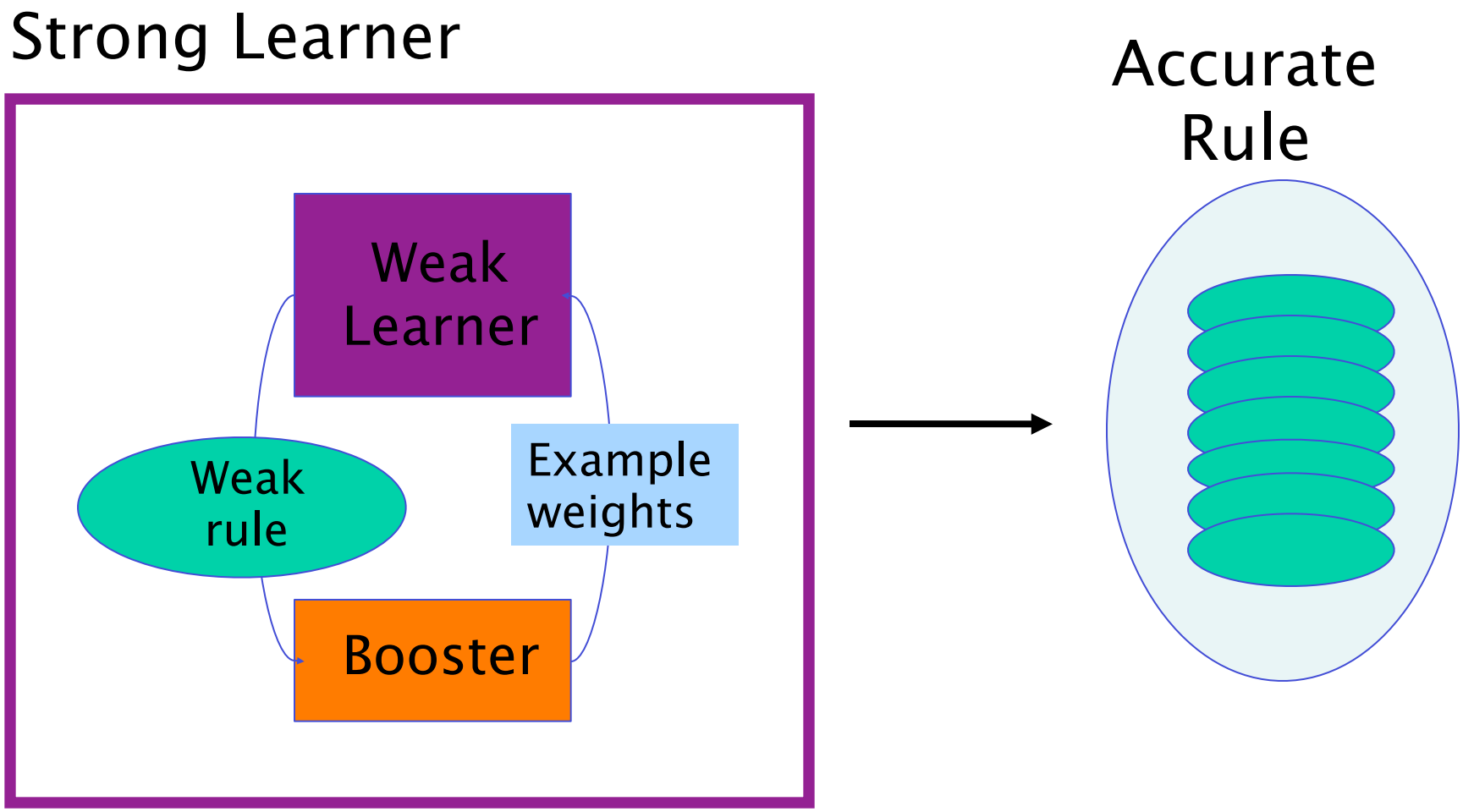
[with Freund]

- Theorem:
  - write ϵ_t as $\frac{1}{2} - \gamma_t$ [γ_t = "edge"]
  - then

$$\begin{aligned} \text{training error}(H_{\text{final}}) &\leq \prod_t \left[2\sqrt{\epsilon_t(1-\epsilon_t)} \right] \\ &= \prod_t \sqrt{1-4\gamma_t^2} \\ &\leq \exp\left(-2 \sum_t \gamma_t^2 \right) \end{aligned}$$

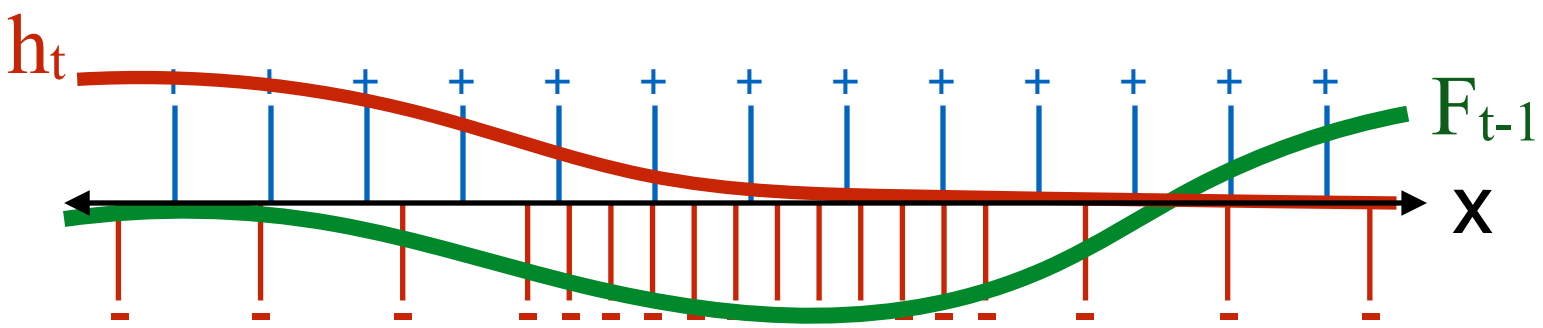
- so: if $\forall t : \ \gamma_t \geq \gamma > 0$
  then $\text{training error}(H_{\text{final}}) \leq e^{-2\gamma^2 T}$
- AdaBoost is adaptive:
  - does not need to know γ or T a priori
  - can exploit $\gamma_t \gg \gamma$

Boosting block diagram



AdaBoost as variational optimization.

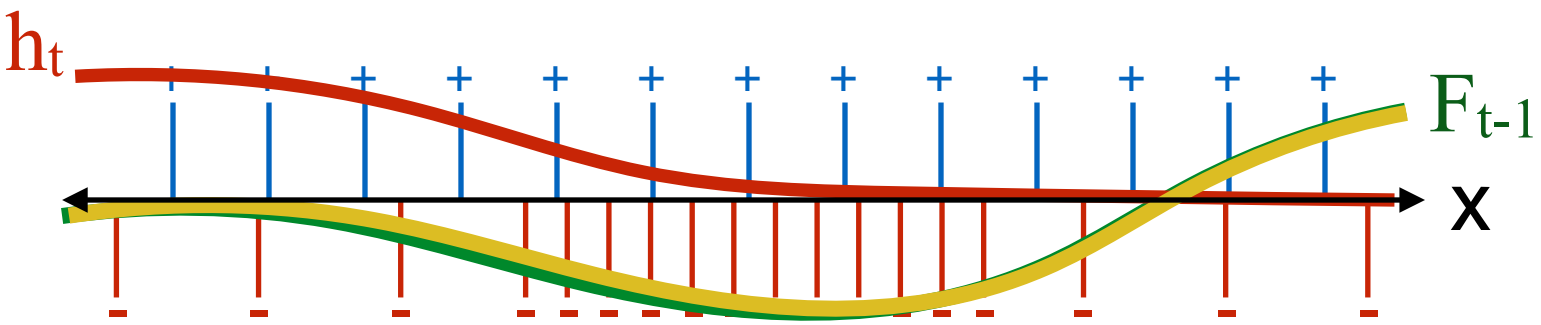
- x = input, a scalar,
- y = output, -1 or +1
- $(x_1,y_1),(x_2,y_2), \ldots ,(x_n,y_n)$ = training set
- F_{t-1} = Strong rule after t-1 boosting iterations.
- h_t = Weak rule produced at iteration t



AdaBoost as variational optimization.

- F_{t-1} = Strong rule after t-1 boosting iterations.
- h_t = Weak rule produced at iteration t

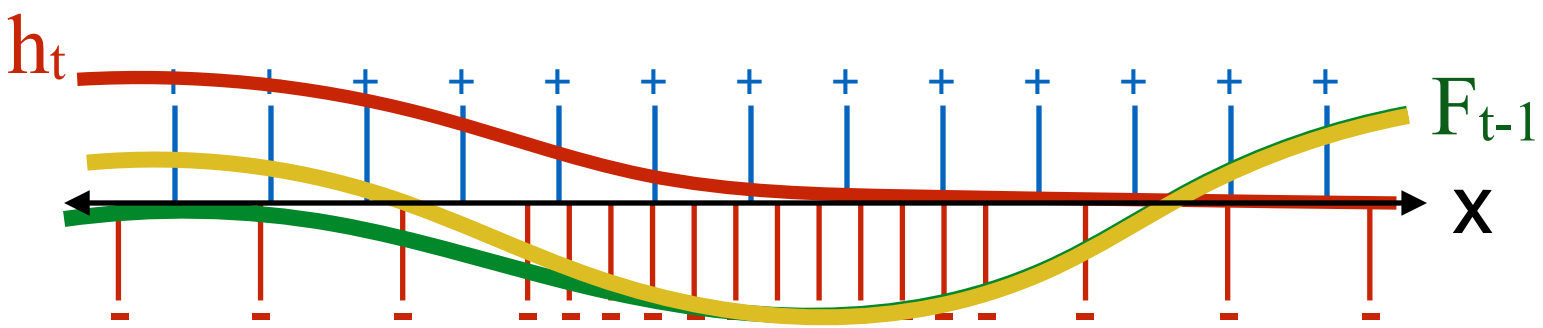
$$F_{t-1}(x) + 0 h_t(x)$$



AdaBoost as variational optimization.

- F_{t-1} = Strong rule after t-1 boosting iterations.
- h_t = Weak rule produced at iteration t

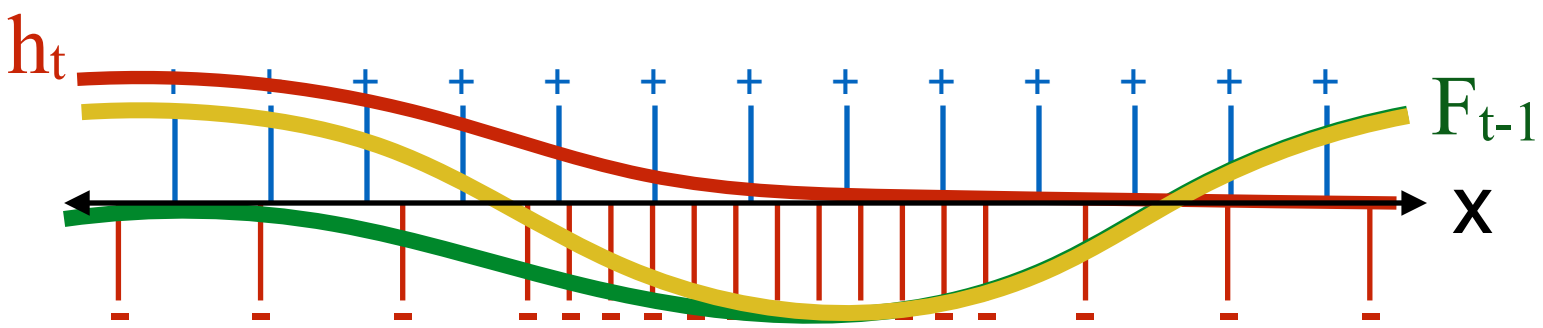
$$F_{t-1}(x) + 0.4 h_t(x)$$



AdaBoost as variational optimization.

- F_{t-1} = Strong rule after t-1 boosting iterations.
- h_t = Weak rule produced at iteration t

$$F_t(x) = F_{t-1}(x) + 0.8 h_t(x)$$



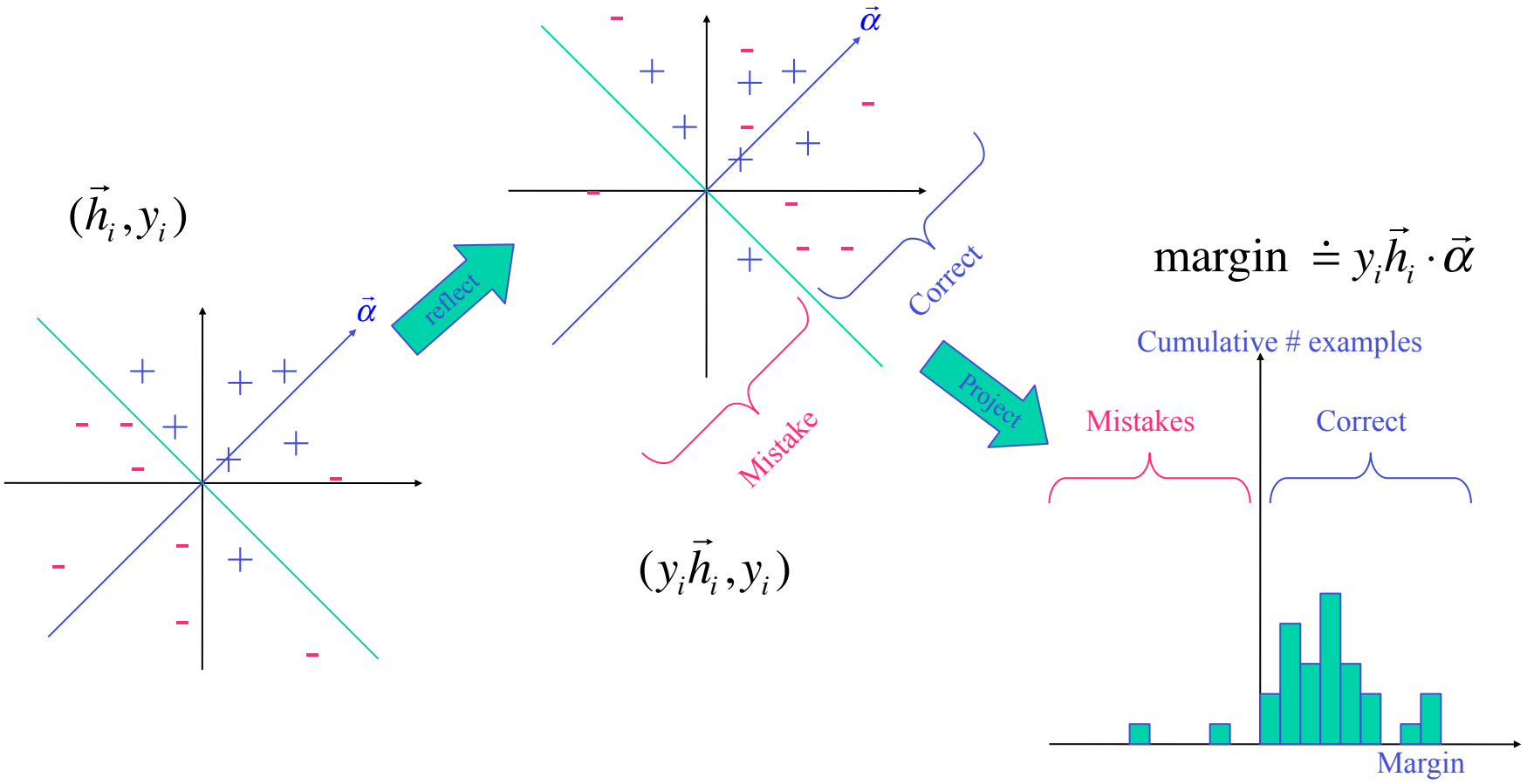
Margins

Fix a set of weak rules: $\vec{h}(x) = (h_1(x), h_2(x), \ldots, h_T(x))$

Represent the i'th example x_i with outputs of the weak rules: $\vec{h}_i$

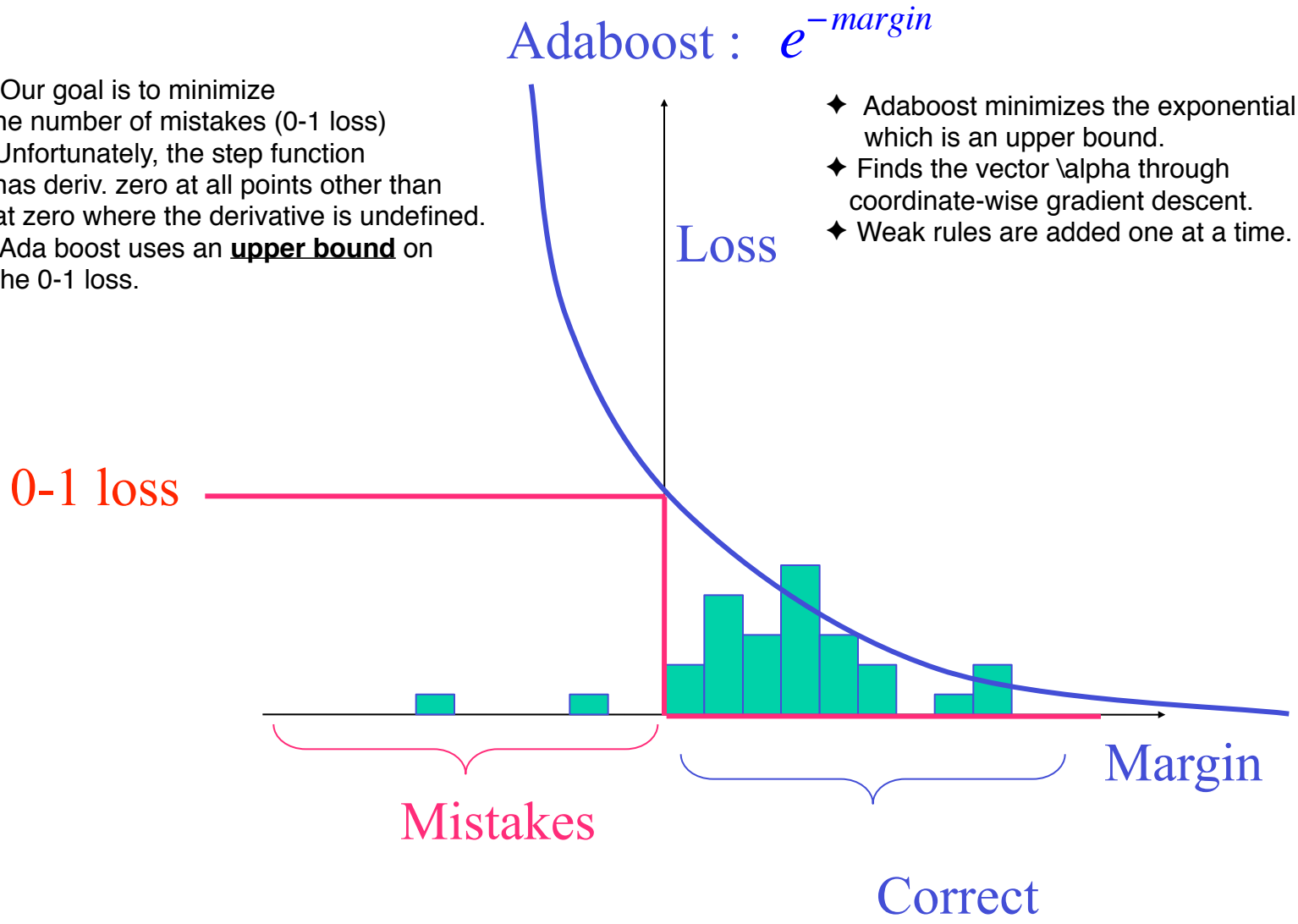
Labels: $y \in \{-1, +1\}$ Training set: $(\vec{h}_1, y_1), (\vec{h}_2, y_2), \ldots, (\vec{h}_n, y_n)$

Goal : Find a weight vector $\vec{\alpha} = (\alpha_1, \ldots, \alpha_T)$ that minimizes number of training mistakes



Boosting as gradient descent

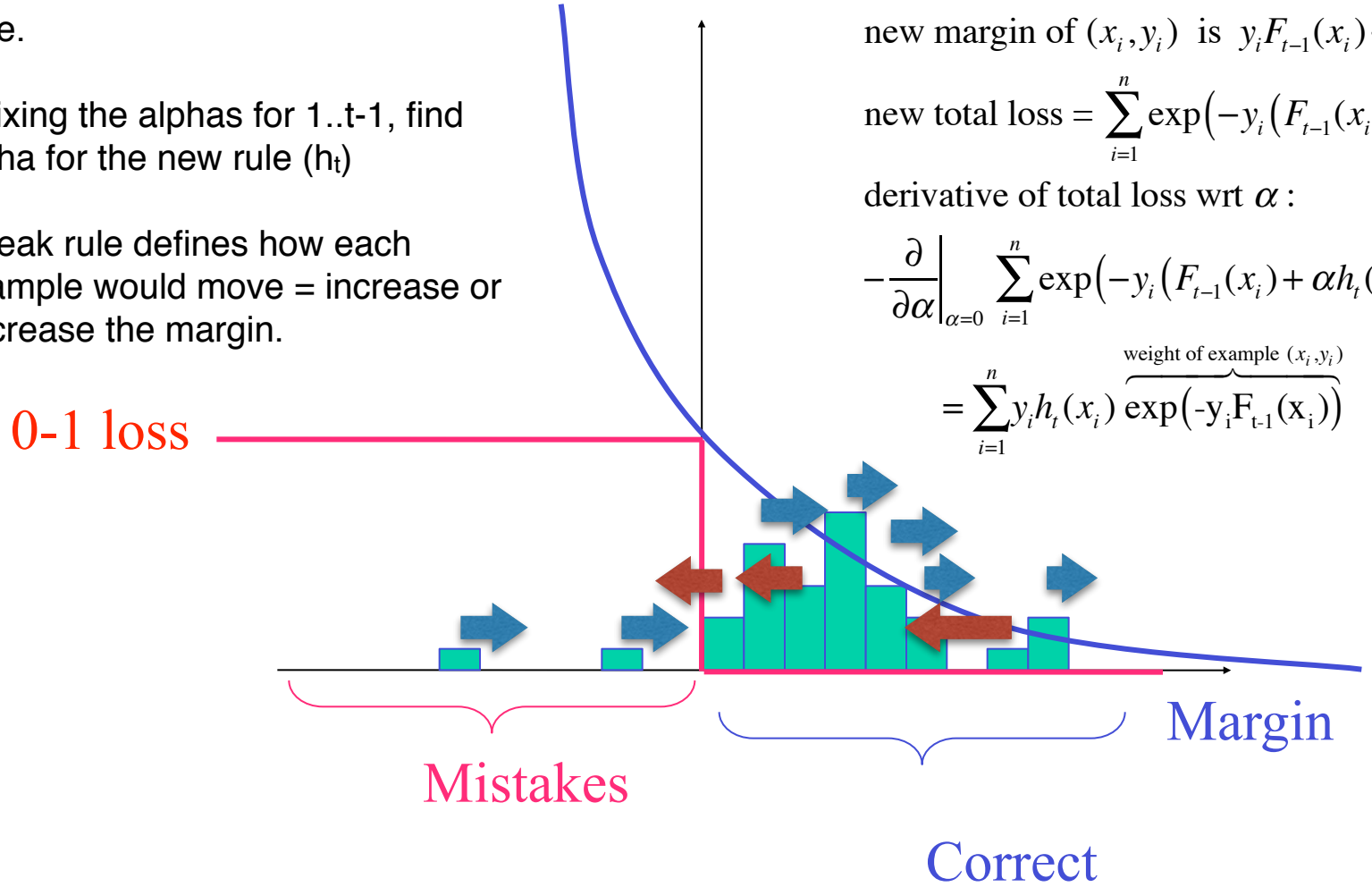
- Our goal is to minimize the number of mistakes (0-1 loss)
- Unfortunately, the step function has deriv. zero at all points other than at zero where the derivative is undefined.
- Ada boost uses an **upper bound** on the 0-1 loss.



- Adaboost minimizes the exponential loss which is an upper bound.
- Finds the vector \alpha through coordinate-wise gradient descent.
- Weak rules are added one at a time.

Adaboost as gradient descent

- Weak rules are added one at a time.
- Fixing the alphas for 1..t-1, find alpha for the new rule (h_t)
- Weak rule defines how each example would move = increase or decrease the margin.



new margin of (x_i, y_i) is $y_i F_{t-1}(x_i) + \alpha y_i h_t(x_i)$

new total loss $= \sum_{i=1}^{n} \exp\left(-y_i \left(F_{t-1}(x_i) + \alpha h_t(x_i)\right)\right)$

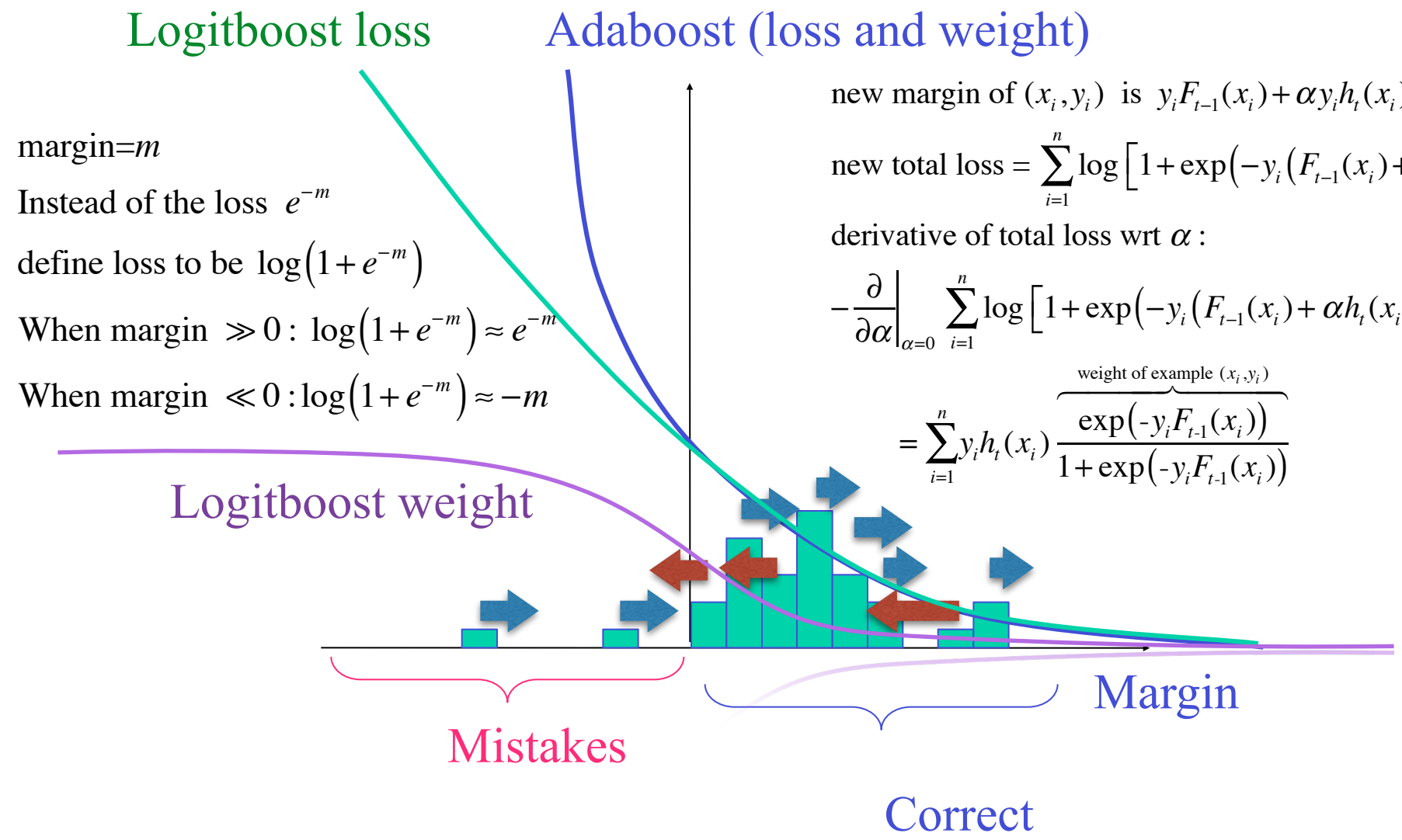
derivative of total loss wrt α :

$$-\frac{\partial}{\partial \alpha}\Big|_{\alpha=0} \sum_{i=1}^{n} \exp\left(-y_i \left(F_{t-1}(x_i) + \alpha h_t(x_i)\right)\right)$$

$$= \sum_{i=1}^{n} y_i h_t(x_i) \overbrace{\exp\left(-y_i F_{t-1}(x_i)\right)}^{\text{weight of example } (x_i, y_i)}$$

Logitboost as gradient descent

Also called Gentle-Boost and Logit Boost, Hastie, Freedman & Tibshirani



Noise resistance

- Adaboost:
  - perform well when a achievable error rate is close to zero (almost consistent case).
  - Errors = examples with negative margins, get very large weights, can overfit.
- Logitboost:
  - Inferior to adaboost when achievable error rate is close to zero.
  - Often better than Adaboost when achievable error rate is high.
  - Weight on any example never larger than 1.

Gradient-Boost / AnyBoost

- A general recipe for learning by incremental optimization
- Applies to any (differentiable) loss function.

labeled example is (x, y) (can be anything).

prediction is of the form: $F_t(x) = \sum_{i=1}^{t} \alpha_i h_i(x)$

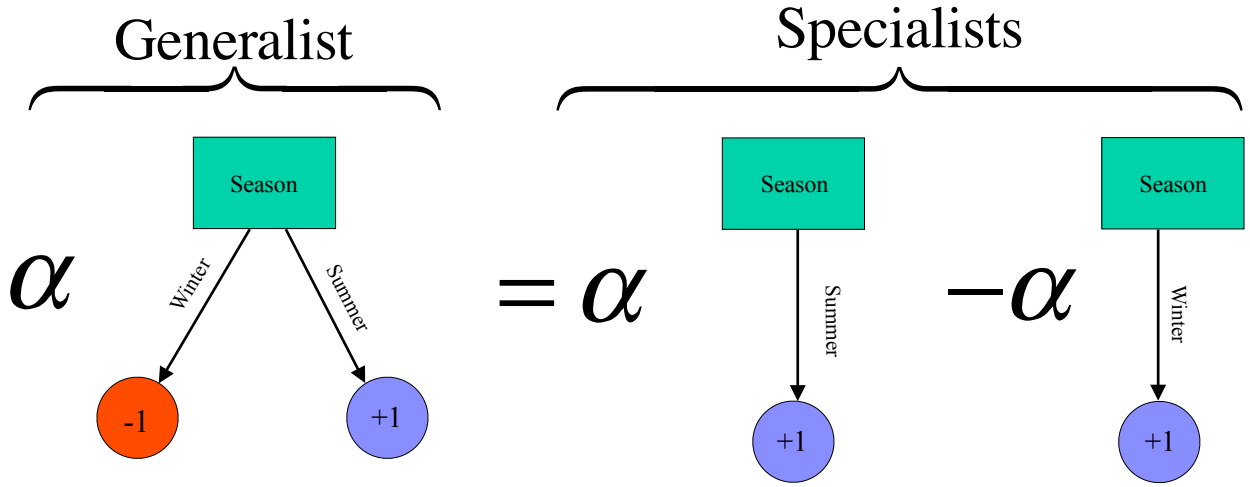
Loss: $L\left(F_t(x), y\right)$ Total Loss so far is: $\sum_{j=1}^{n} L\left(F_{t-1}(x_j), y_j\right)$

Weight of example (x, y): $\frac{\partial}{\partial z} L\left(F_{t-1}(x) + z, y\right)$

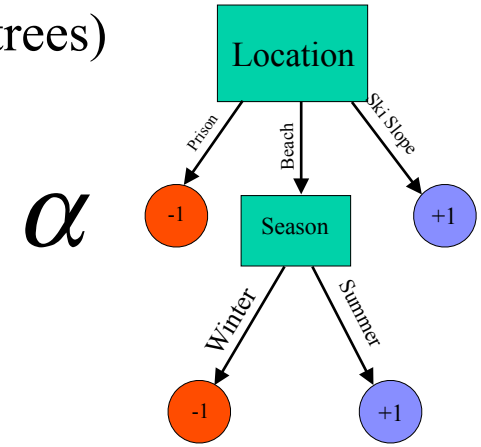
- At each iteration:
  - calc example weights
  - call weak learner with weighted example
  - Add generated weak rule to create new rule: $F_t = F_{t-1} + \alpha_t h_t$

Styles of weak learners

- Simple (stumps)



- Complex (fully grown trees)

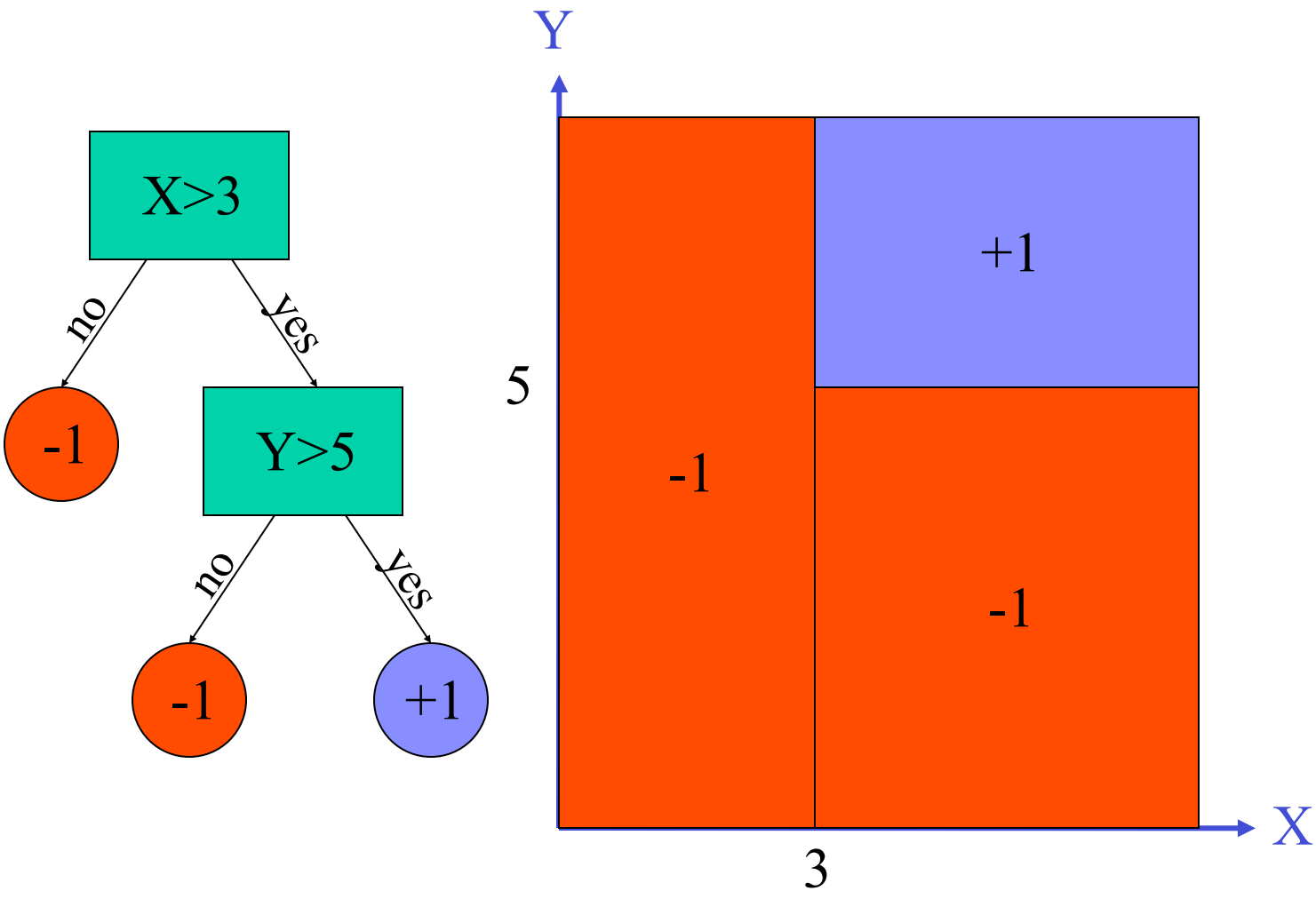


- Everything in between (neural networks, Nearest neighbors, Naive Bayes,…..)

Alternating Decision Trees

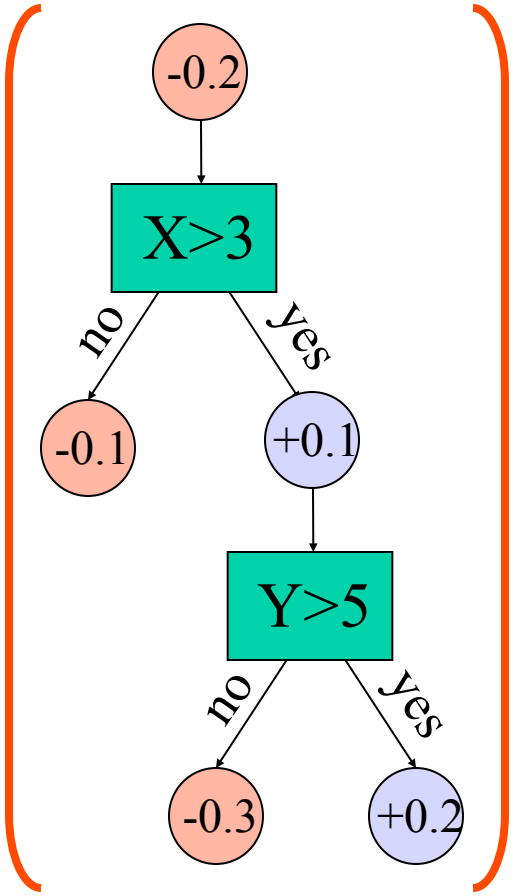
Joint work with Llew Mason

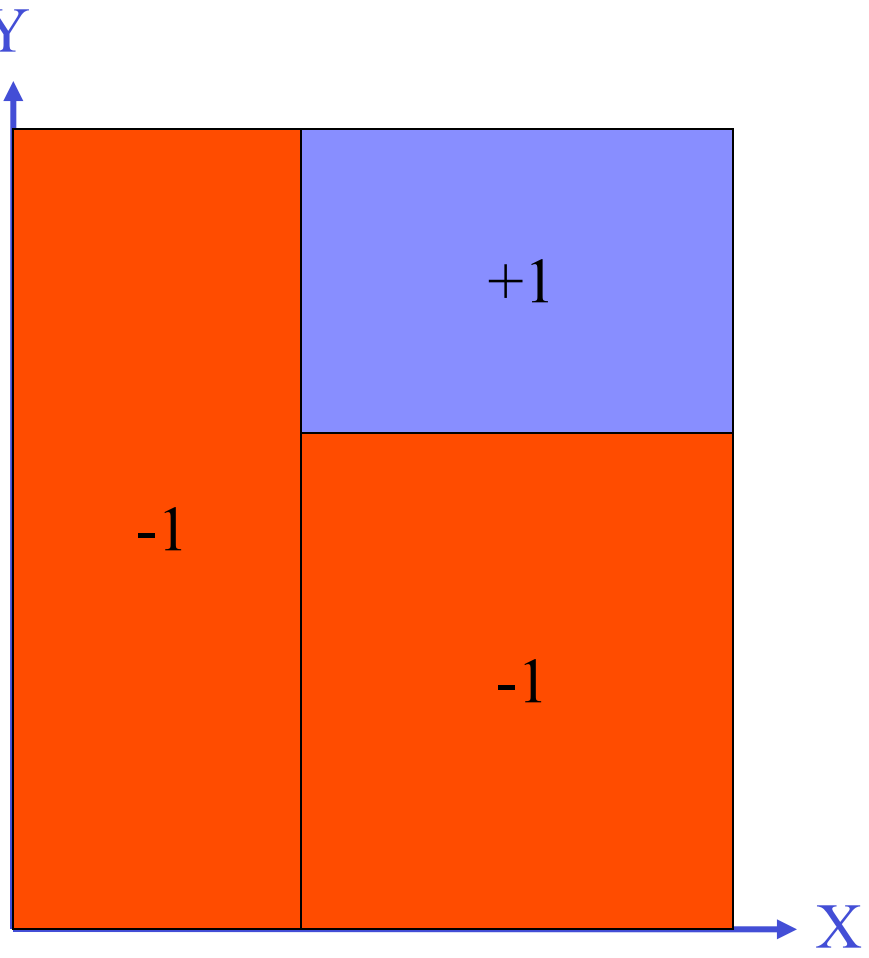
Decision Trees



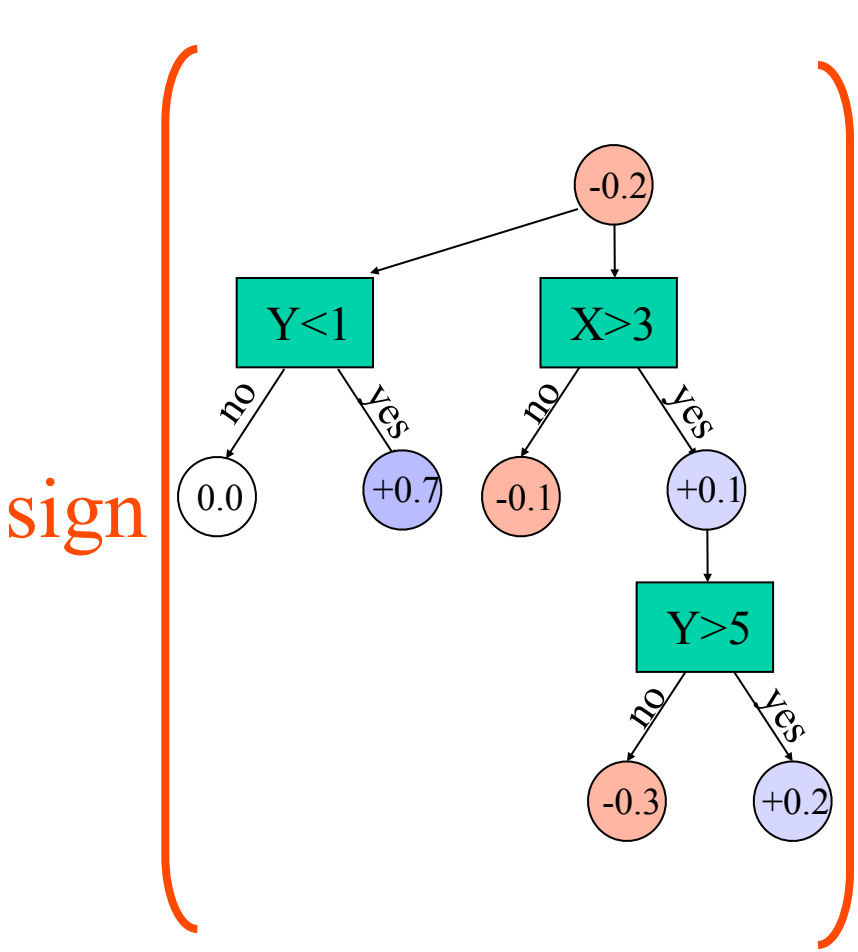
Decision tree as a sum

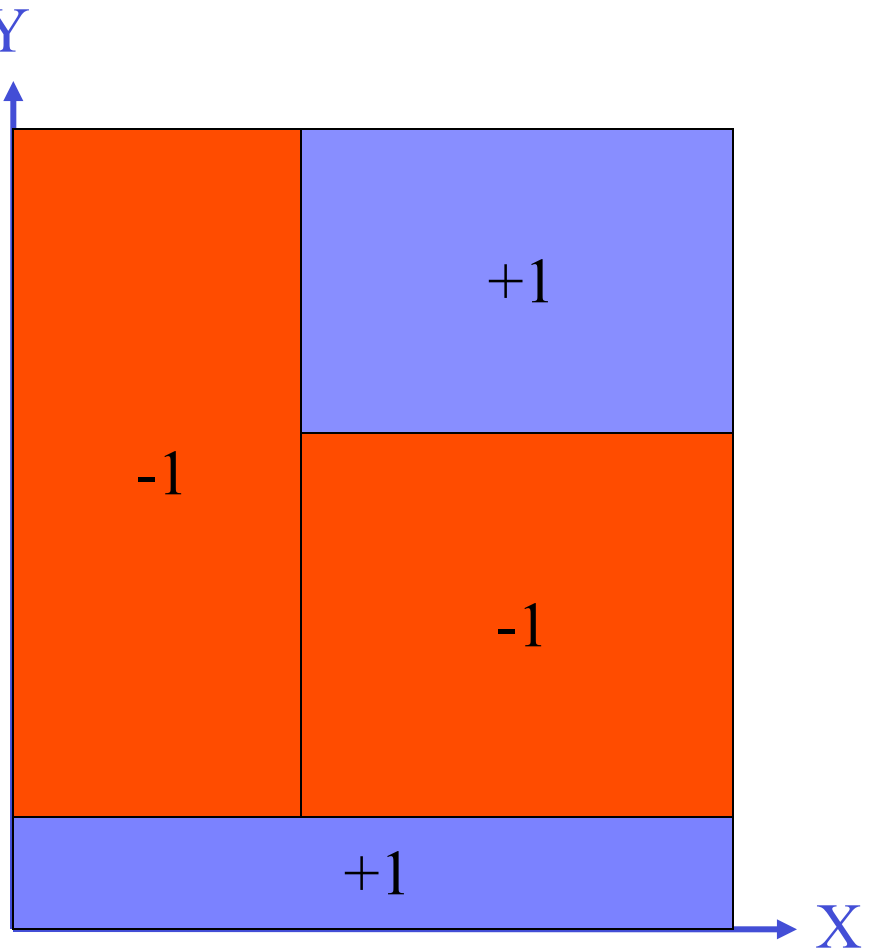
sign





An alternating decision tree

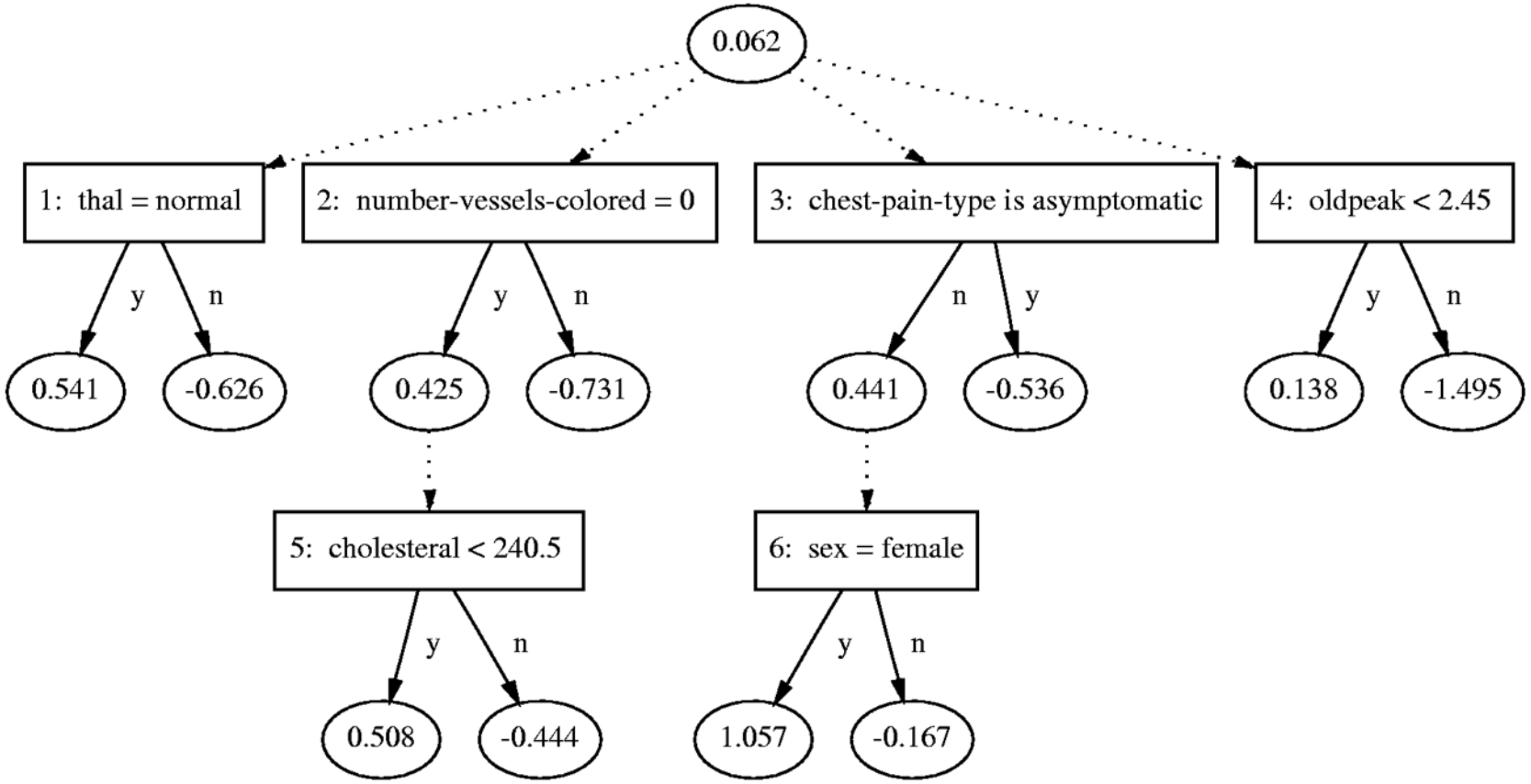




Example: Medical Diagnostics

- `Cleve` dataset from UC Irvine database.
- Heart disease diagnostics (+1=healthy,-1=sick)
- 13 features from tests (real valued and discrete).
- 303 instances.

Adtree for Cleveland heart-disease diagnostics problem



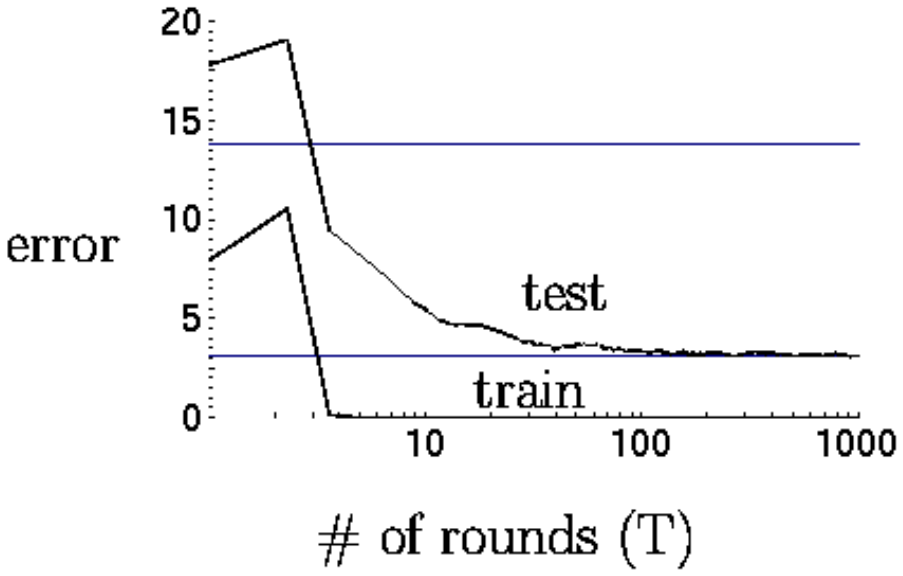
Cross-validated accuracy

Learning algorithm	Number of splits	Average test error	Test error variance
ADtree	6	17.0%	0.6%
C5.0	27	27.2%	0.5%
C5.0 + boosting	446	20.2%	0.5%
Boost Stumps	16	16.5%	0.8%

Boosting and over-fitting

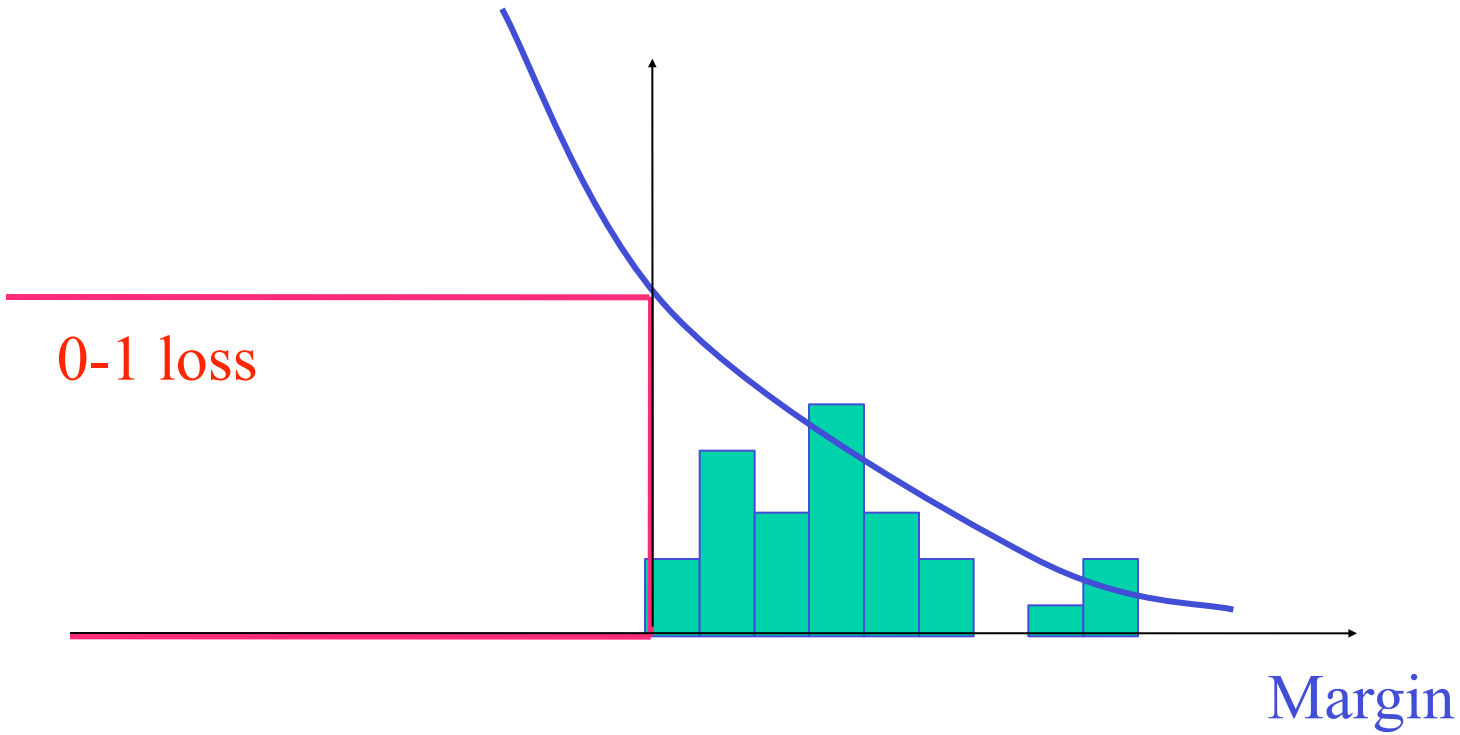
Curious phenomenon

Boosting decision trees

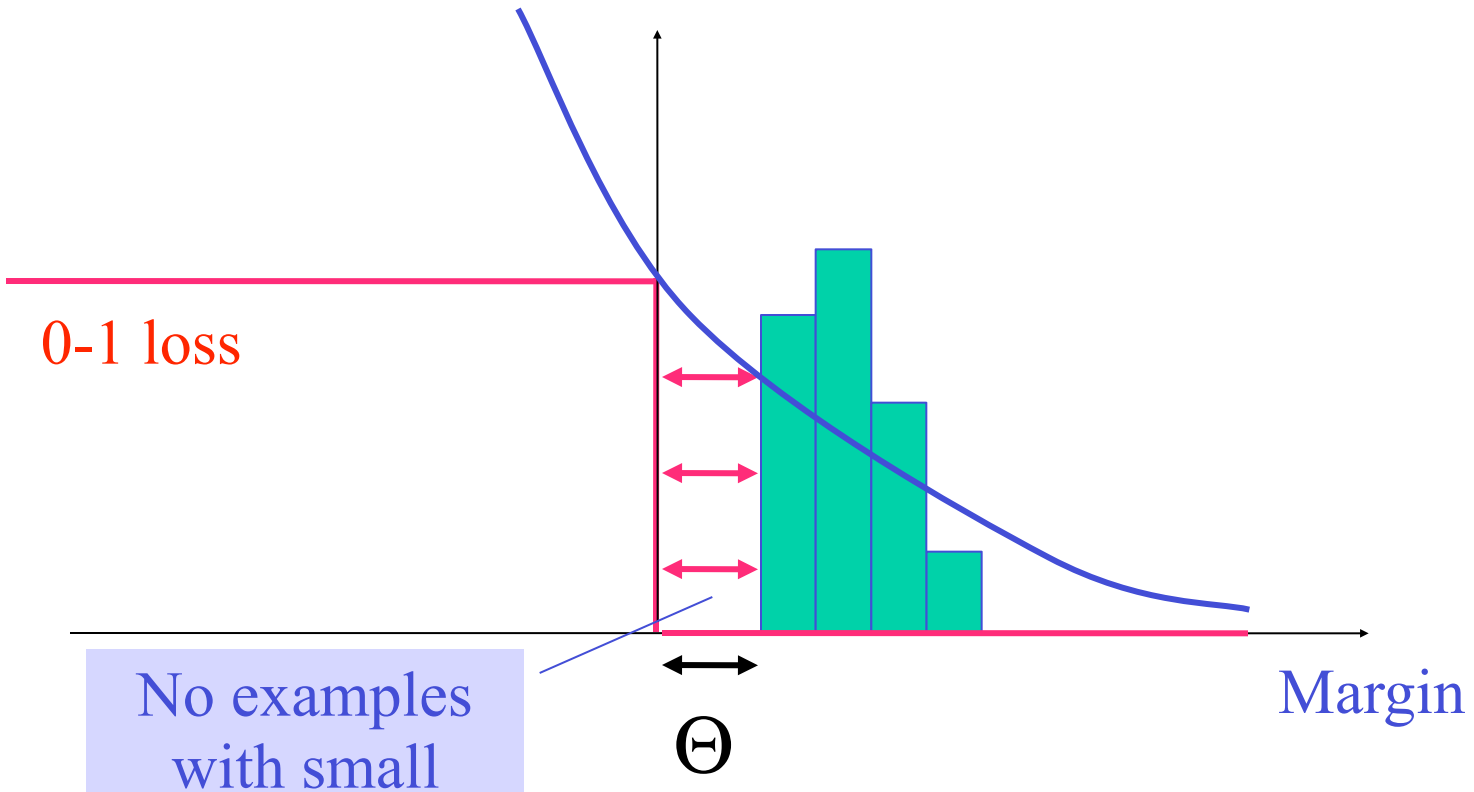


Using <10,000 training examples we fit >2,000,000 parameters

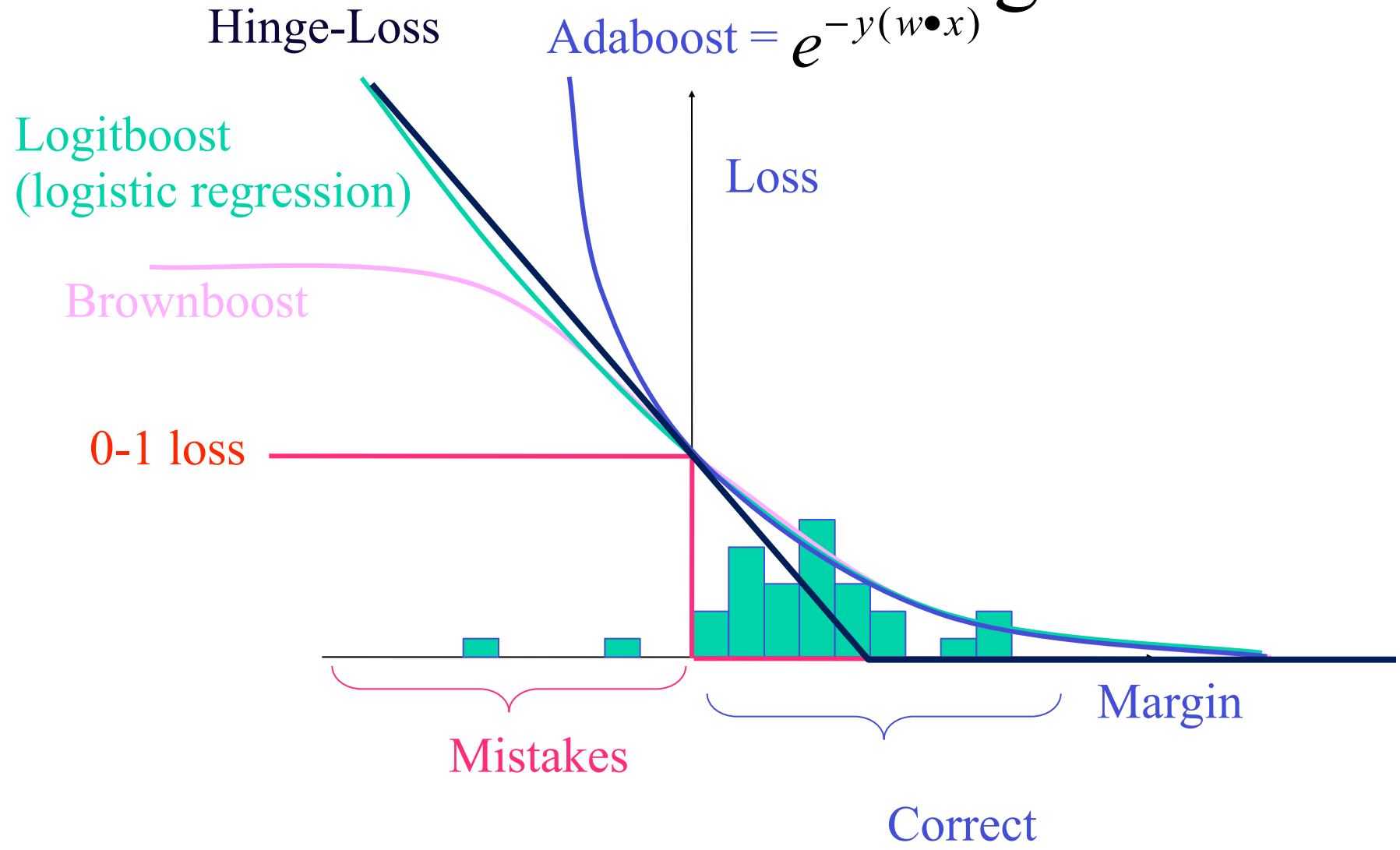
Explanation using margins



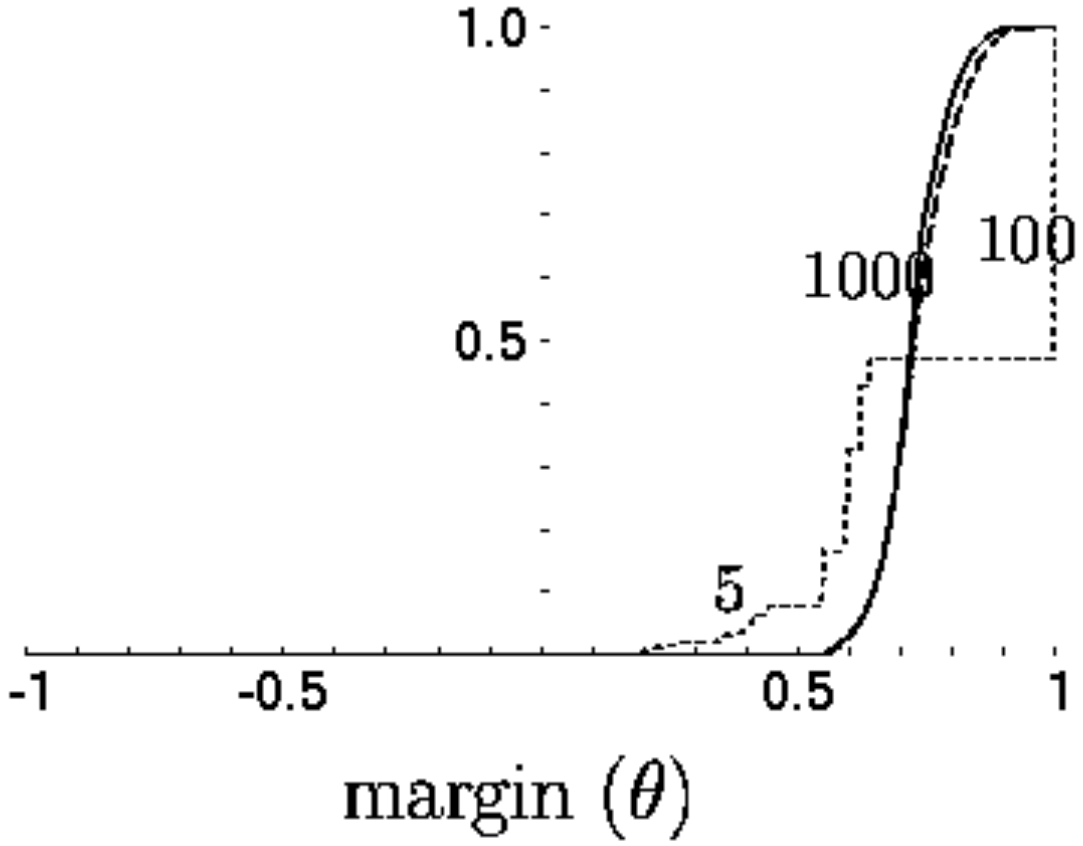
Explanation using margins



Minimizing error using loss functions on margin



Experimental Evidence



Theorem

Schapire, Freund, Bartlett & Lee
Annals of stat. 98

For any convex combination and any threshold $\forall f \in \mathcal{C}, \forall \theta > 0$:

Probability of mistake

Fraction of training example with small margin

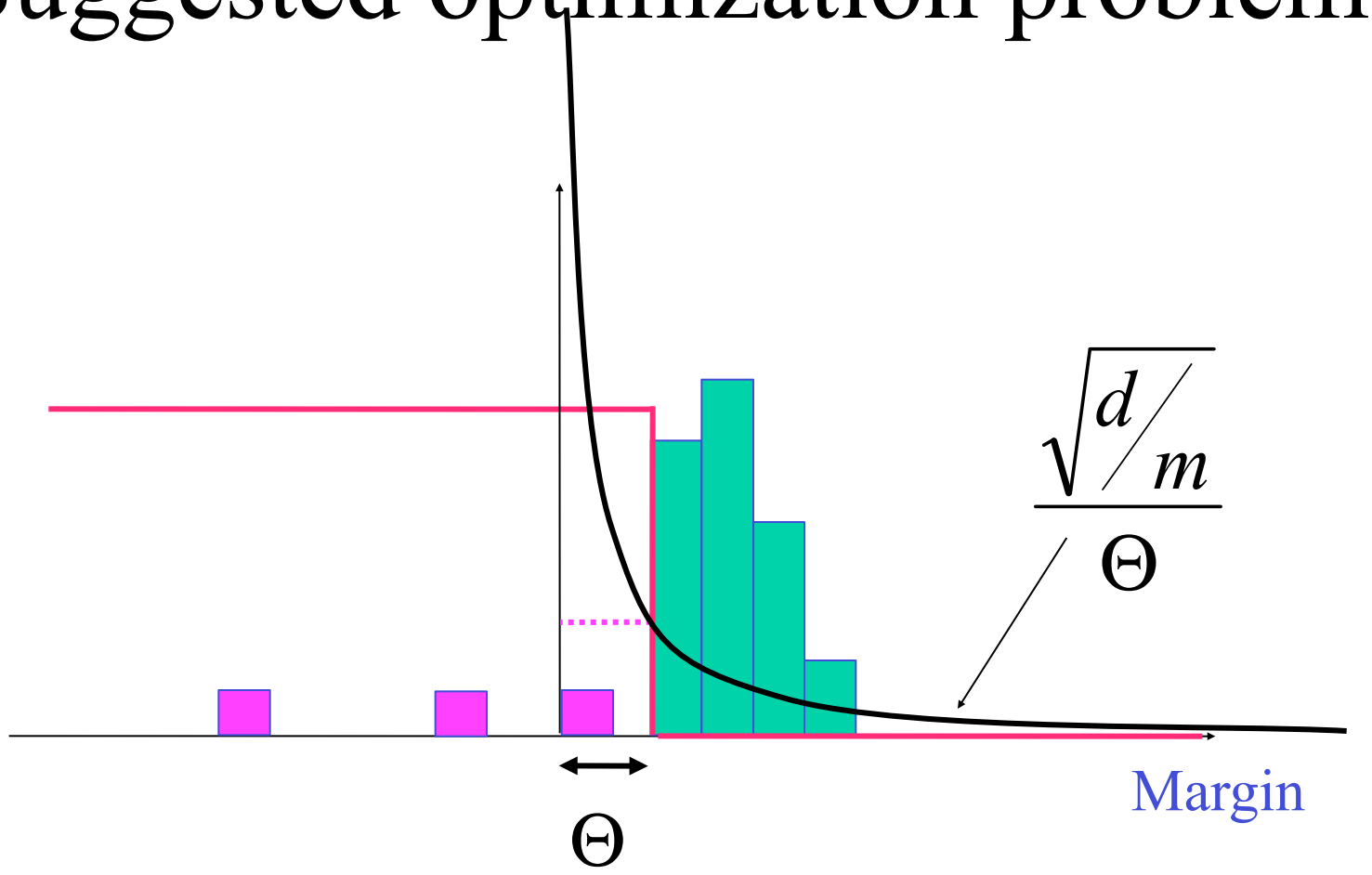
$$P_{(x,y)\sim D}\left[\text{sign}(f(x)) \neq y\right] \leq P_{(x,y)\sim S}\left[margin_f(x,y) \leq \theta\right] + \tilde{O}\left(\frac{\sqrt{d/m}}{\theta}\right)$$

Size of training sample

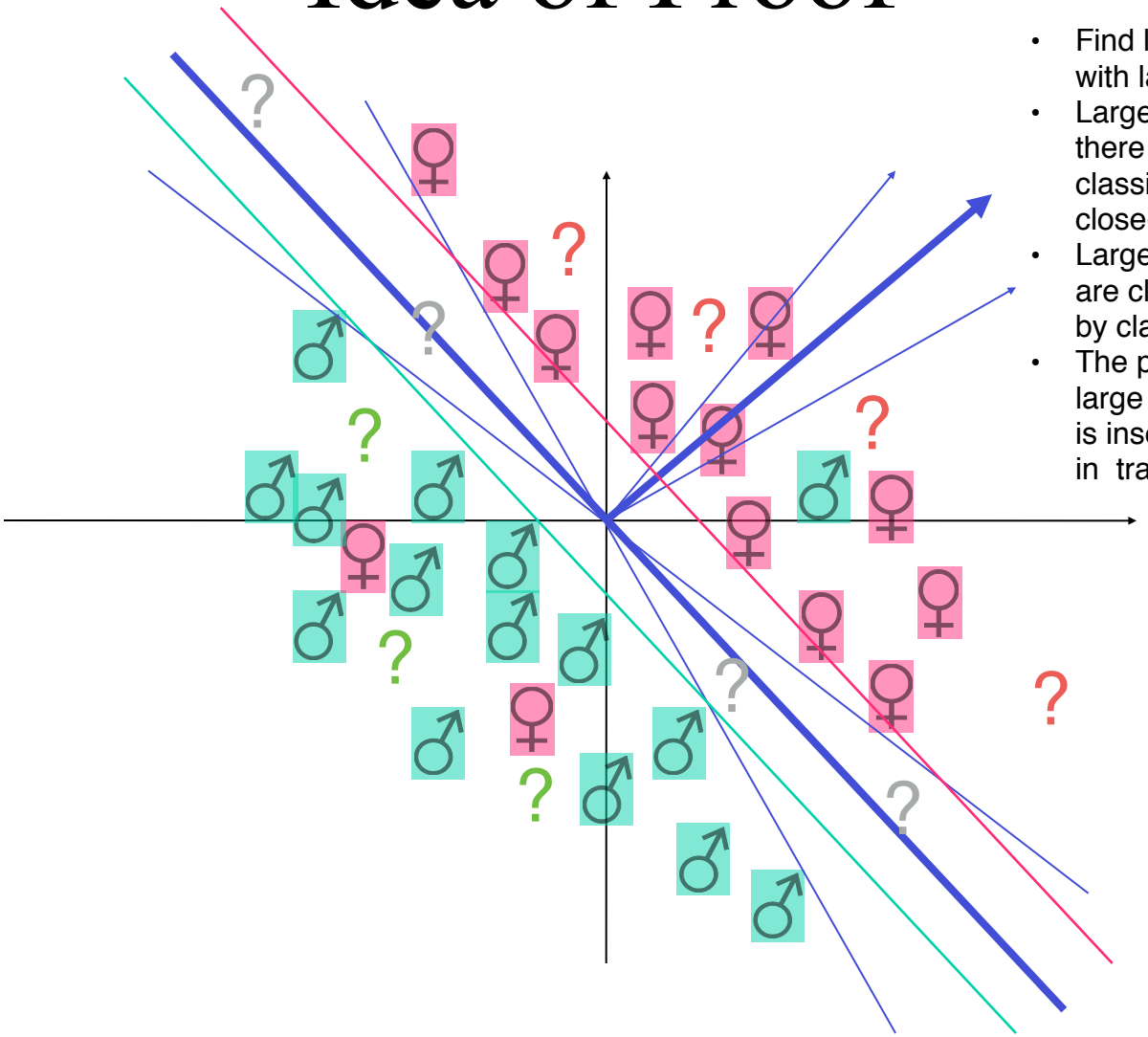
VC dimension of weak rules

No dependence on number of weak rules that are combined!!!

Suggested optimization problem



Idea of Proof



- Find linear classifier with large margin
- Large margin implies there is a **cone** of linear classifiers with close-to-minimal error.
- Large margin test examples are classified identically by classifiers in cone.
- The prediction on large margin test examples is insensitive to small changes in training set.

Why are large margins good?

- On examples with large margin, the prediction is stable.
- In other words, small changes in the training set will not cause the prediction to flip.
- We can predict with confidence.
- The confidence is different from when P(y|x) is close to 0 or to 1.
- It has to do with the stability of the classifier w.r.t. small changes in the training data.

The three sources of classification error

- **Bayes Error:** the minimal error rate achieved when the true distribution is known (exactly).
- **Model Bias:** error resulting from the inability of the model class to represent the true distribution.
- **Data Variation:** error resulting from the difference between the training set and the true distribution.

Example, Bayes Error

- X={1,2,3} dist. is uniform.(1/3,1/3,1/3)
- Y={-1,+1},
  - P(y=+1|x=1)=0.1
  - P(y=+1|x=2)=0.8
  - P(y=+1|x=3)=0.3
- Bayes optimal classifier: f(1)=-1,f(2)=+1,f(3)=?
  - f(3)=-1
- Bayes Error= (0.1+0.2+?)/3
  - (0.1+0.2+0.3)/3=0.6/3 = 0.2

Example, Model Bias

- Bayes optimal classifier: f(1)=-1,f(2)=+1,f(3)=-1

- Suppose our model only allows rules of the form $g_\theta(x) = \begin{cases} +1 & \text{if } x > \theta \\ -1 & \text{otherwise} \end{cases}$
- Cannot represent Bayes optimal classifier
- best threshold: $\theta = 1.1$ (or any number between 1 and 2)
- Error of best threshold
  - (0.1+0.2+0.7)/3=1/3=0.333
  - Compare with Bayes:(0.1+0.2+0.3)/3=0.2

Example, Data Variation (1)

- Consider a slightly different distribution:
- X={1,2,3} dist. is uniform.(1/3,1/3,1/3)
- Y={-1,+1},
  - P(y=+1|x=1)=0.1
  - P(y=+1|x=2)=0.8
  - P(y=+1|x=3)=0.6 (instead of 0.3)
- Bayes optimal classifier: f(1)=-1,f(2)=+1,f(3)=?
  - f(3)=+1
- Bayes Error= (0.1+0.2+?)/3
  - (0.1+0.2+0.4)/3=0.7/3 = 0.233…
- In this case the model **can** represent the Bayes optimal rule.

Example, Data Variation (2)

- In practice, we don't know the conditional probabilities, we estimate them from data:

$* x=1,\ 1\times(y=+1), 6\times(y=-1) \Rightarrow \hat{P}(y=+1\,|\,x=1)=1/7=0.14 \quad P(y=+1\,|\,x=1)=0.1$

$* x=2,\ 8\times(y=+1), 2\times(y=-1) \Rightarrow \hat{P}(y=+1\,|\,x=2)=0.8 \quad P(y=+1\,|\,x=2)=0.8$

$* x=3,\ 2\times(y=+1), 3\times(y=-1) \Rightarrow \hat{P}(y=+1\,|\,x=3)=0.4 \quad P(y=+1\,|\,x=3)=0.6$

- For x=3 estimate is below 0.5, truth is above 0.5
- Empirically optimal classifier : f(1)=-1, f(2)=+1, f(3)=-1
- This rule is NOT the Bayes optimal rule, it was misled by the empirical estimate for x=3. We say that the discrepancy is due to data variation.
- The best rule of the form $g_\theta(x)=\begin{cases} +1 & \text{if } x>\theta \\ -1 & \text{otherwise} \end{cases}$ IS equal to the Bayes optimal rule.
- **<u>Restricting the model class increases model bias while reducing data variation.</u>**

Methods for reducing data variation for classifiers

- **Model Selection:** Choosing the number of parameters in the model.
- **Weight Decay:** Decreasing the magnitude of the parameters
- **Margins:** increasing the classification margin. (Boosting, Support Vector Machines)
- **Bagging:** Taking the majority vote over randomize choice of training set.

Tradeoffs

- Weight decay, reducing the number of parameters decrease data variation, increase model bias.
- Bagging decreases data variation without significantly increasing model bias.
- Boosting reduces both variation and model bias.

The Bias/Variance tradeoff for **squared error**

- The squared error can always be decomposed into a bias term and a variance term.

$B(x) = E_{(x,y)}[y \mid x]$ The Bayes optimal regression function

$$E_{(x,y)}\left[\left(f(x)-y\right)^2\right] = \overbrace{E_x\left[\left(f(x)-B(x)\right)^2\right]}^{Bias} + \overbrace{E_{(x,y)}\left[\left(y-B(x)\right)^2\right]}^{Variance}$$

- For regression:
  - Increasing the number of features decreases bias and increases variance.
  - Reducing the size of the weights (Ridge regression, Lasso) Increases bias and decreases variance.

Applications of Boosting

Applications of Boosting

- Academic research
- Applied research
- Commercial deployment

Academic research

% test error rates

Database	Other	Boosting	Error reduction
Cleveland	27.2 (DT)	16.5	39%
Promoters	22.0 (DT)	11.8	46%
Letter	13.8 (DT)	3.5	74%
Reuters 4	5.8, 6.0, 9.8	2.95	~60%
Reuters 8	11.3, 12.1, 13.4	7.4	~40%

Schapire, Singer, Gorin 98

Applied research

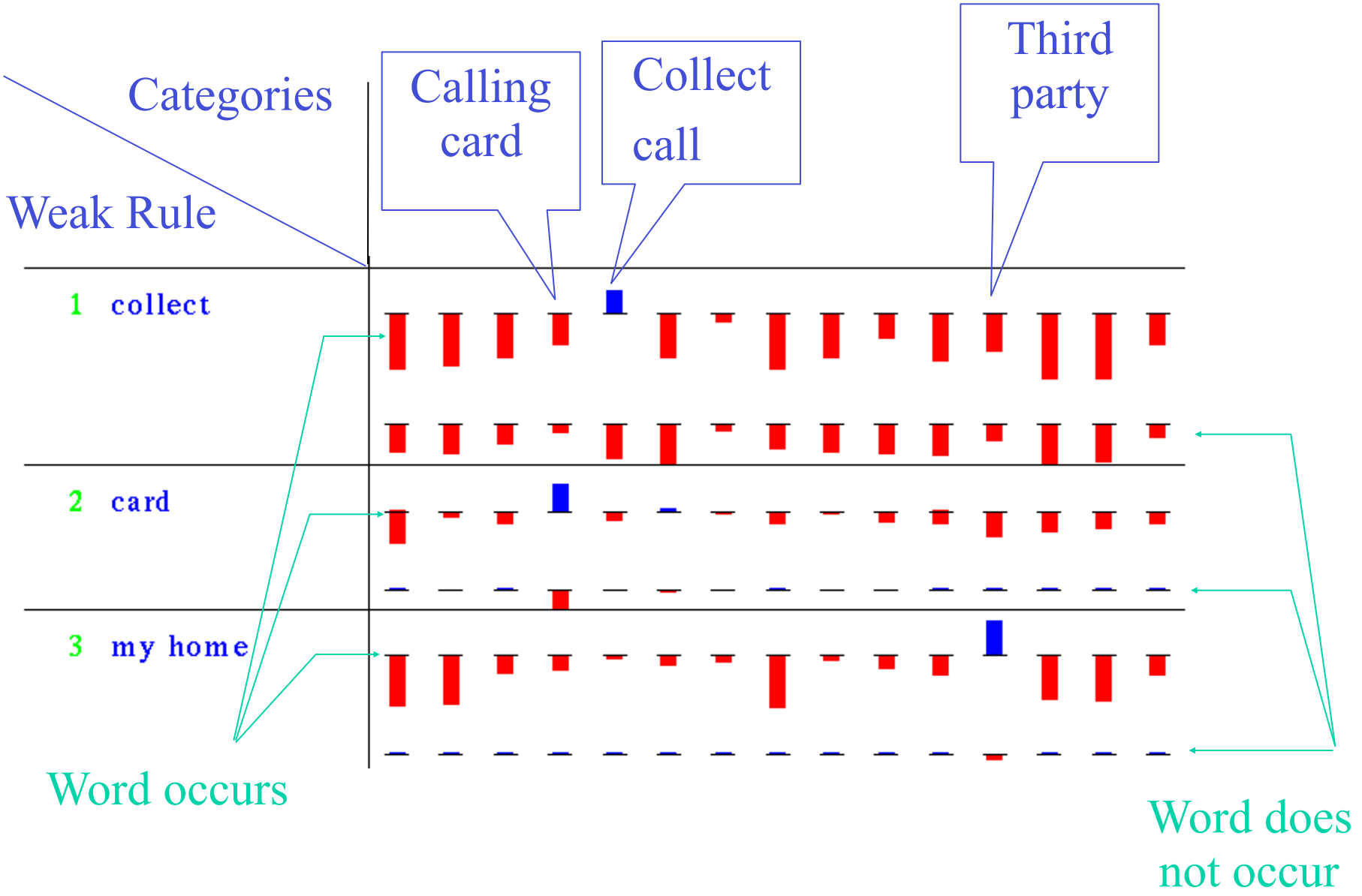
- *"AT&T, How may I help you?"*
  - Classify voice requests
  - Voice -> text -> category
  - Fourteen categories

– Area code,
– AT&T service,
– billing credit,
– calling card,
– collect,
– competitor
- competitor,
- dial assistance,
- directory,
- how to dial,
- person to person,
- rate,
- third party,
- time charge

Example transcribed sentences

- Yes I'd like to place a collect call long distance please ➢ collect
- Operator I need to make a call but I need to bill it to my office ➢ third party
- Yes I'd like to place a call on my master card please ➢ calling card
- I just called a number in Sioux city and I musta rang the wrong number because I got the wrong party and I would like to have that taken off my bill ➢ billing credit

Weak rules generated by “boostexter”



Results

- 7844 training examples
  - hand transcribed
- 1000 test examples
  - hand / machine transcribed
- Accuracy with 20% rejected
  - Machine transcribed: 75%
  - Hand transcribed: 90%

Freund, Mason, Rogers, Pregibon, Cortes 2000

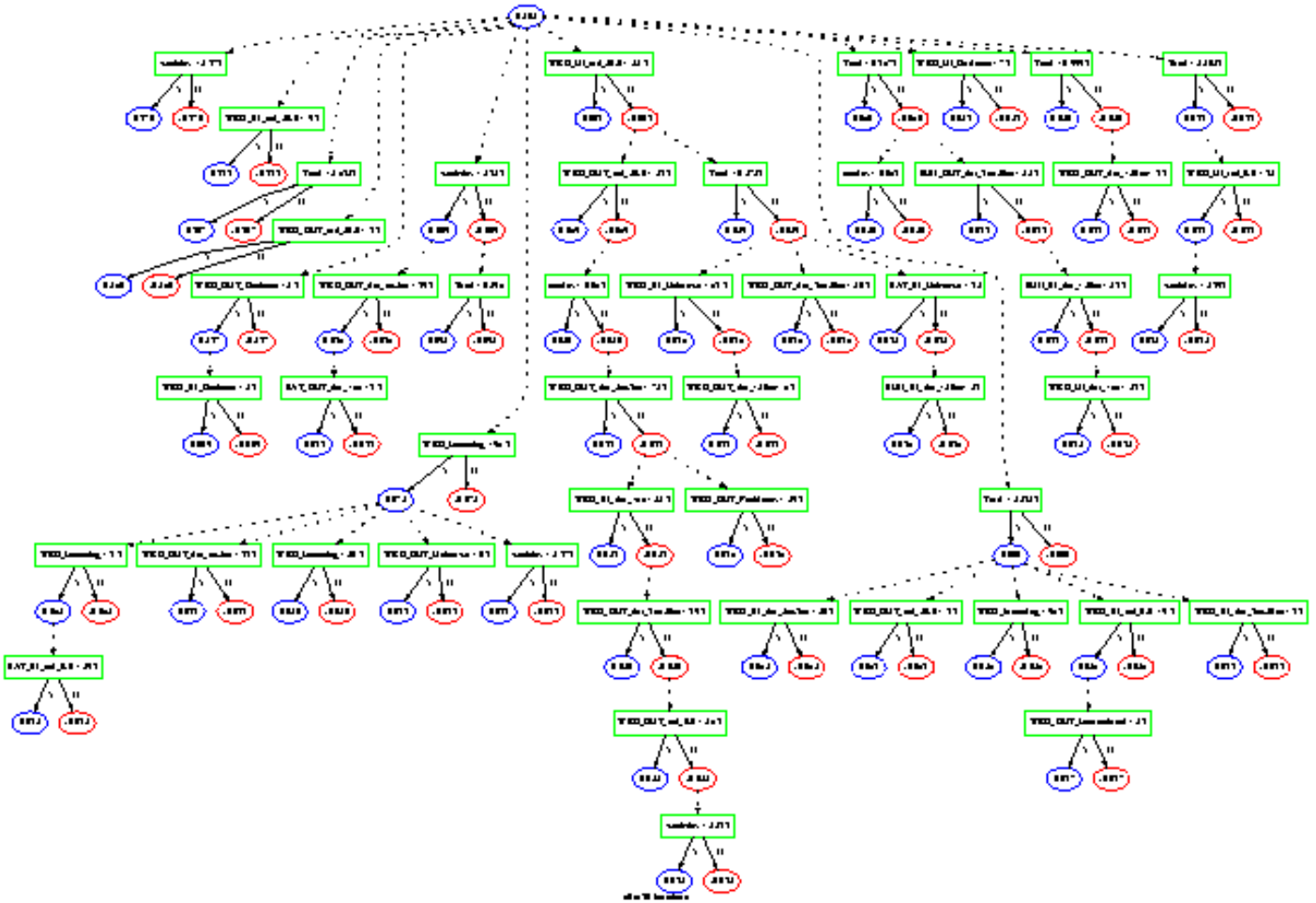
Commercial deployment

- Distinguish business/residence customers
- Using statistics from call-detail records
- Alternating decision trees
  - Combines very simple rules
  - Can over-fit, cross validation used to stop

Massive datasets (for 1997)

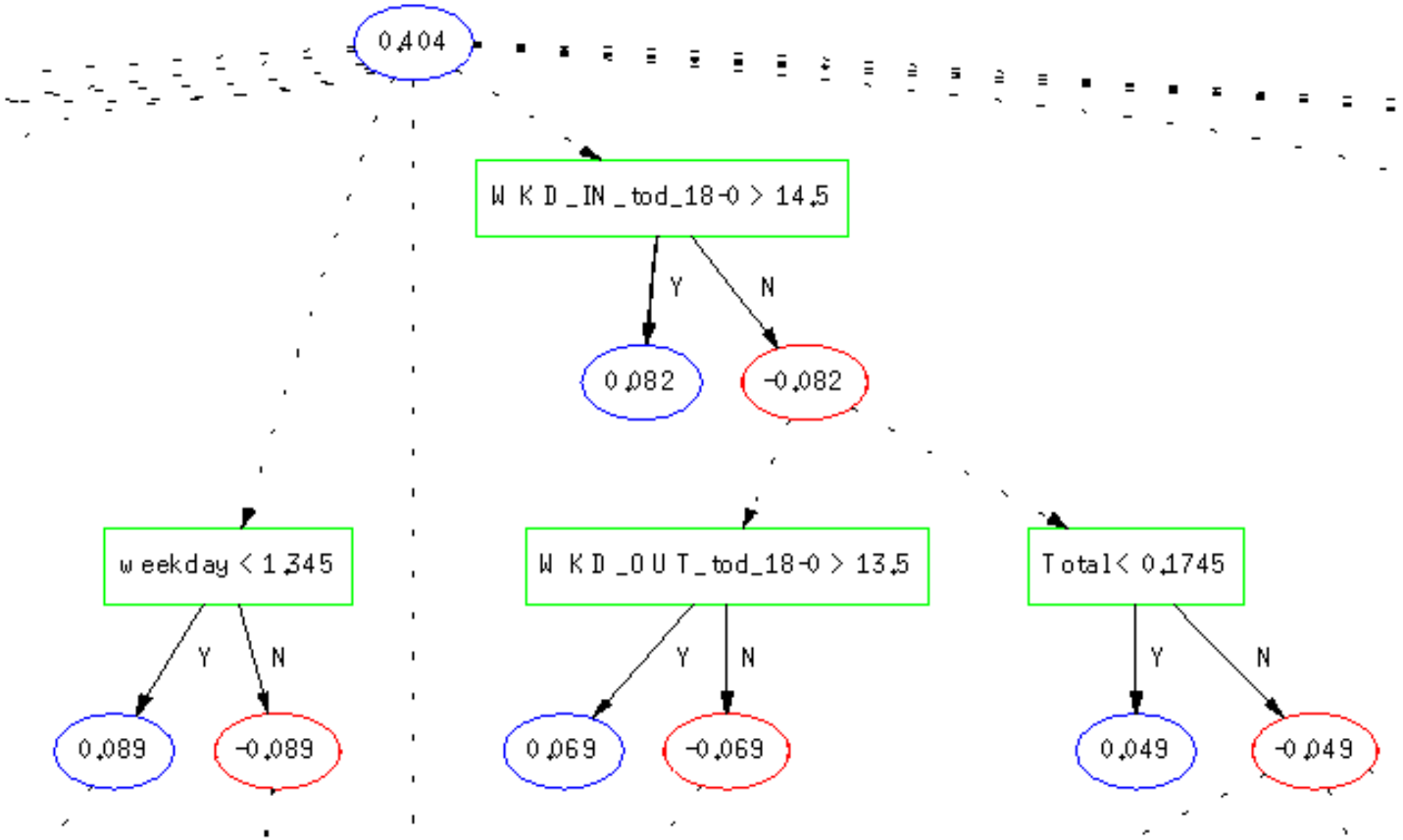
- 260M calls / day
- 230M telephone numbers
  - Label unknown for ~30%
- Hancock: software for computing statistical signatures.
- 100K randomly selected training examples,
- ~10K is enough
  - Training takes about 2 hours.
  - Generated classifier has to be both accurate and efficient

Alternating tree for “buizocity”

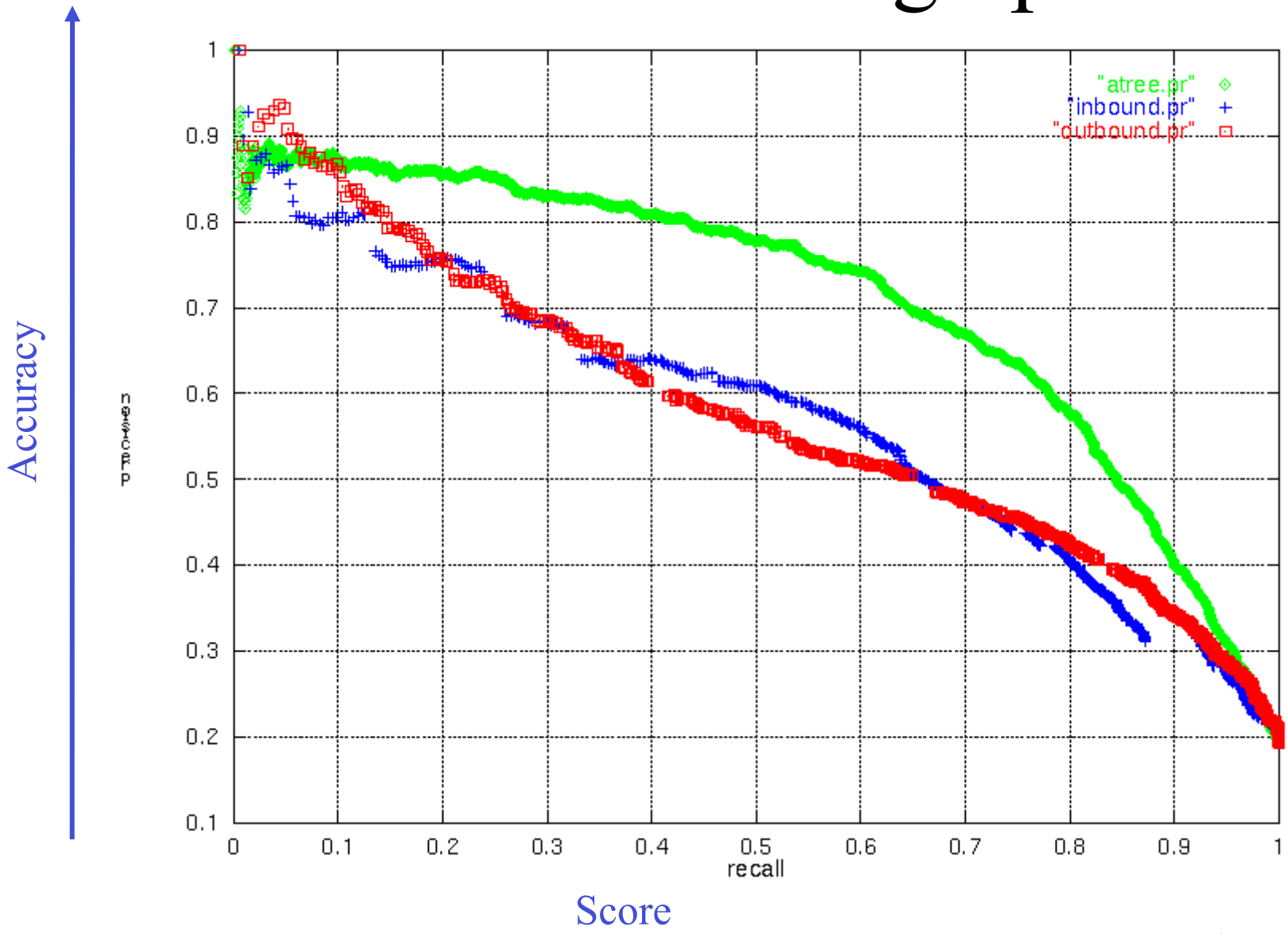


Alternating Tree (Detail)

Positive predictions ⇔ Residences
Negative predictions ⇔ Businesses



Precision/recall graphs



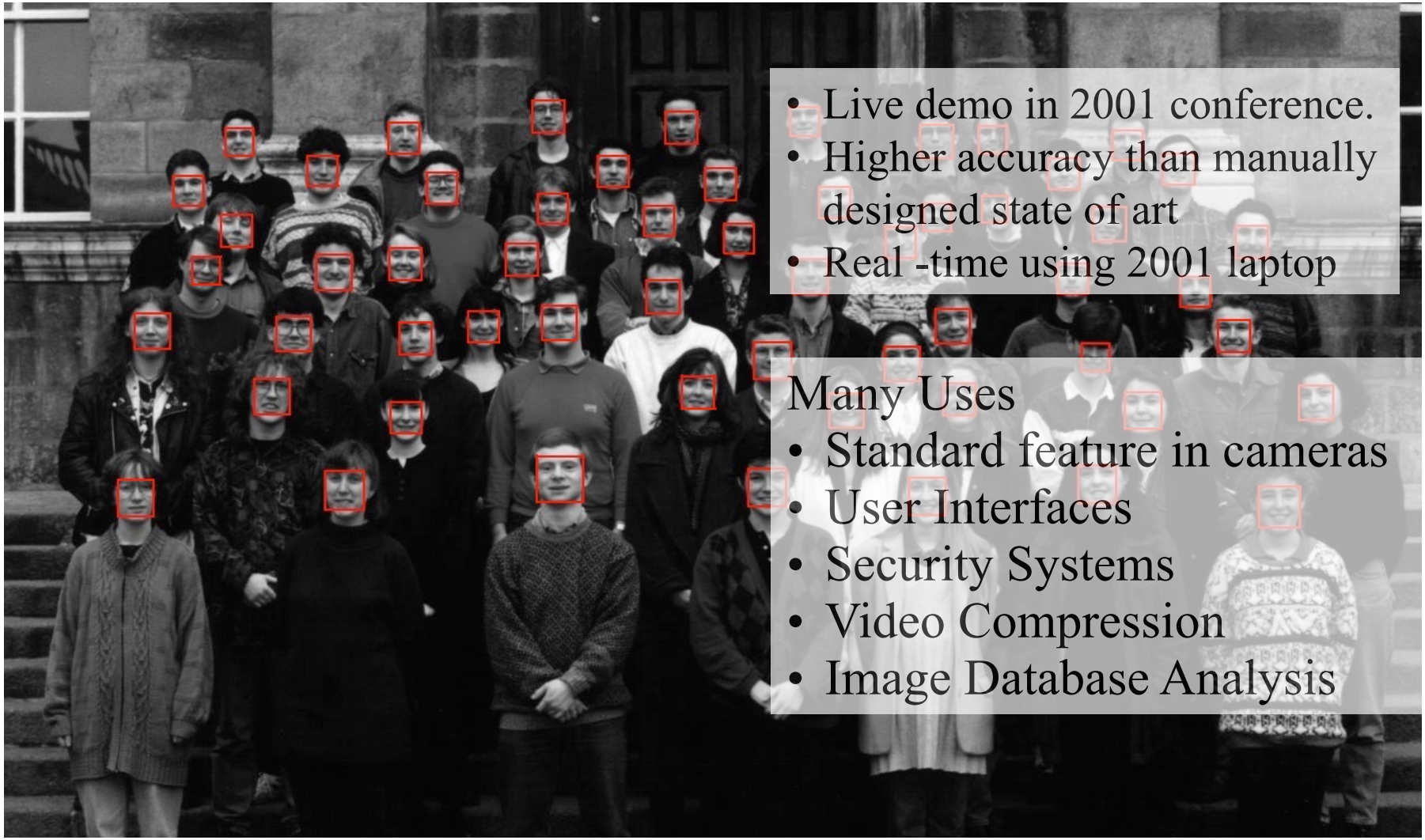
Business impact

- Increased coverage from 44% to 56% for Accuracy ~94%
- Saved AT&T 15M$ in the year 2000 in operations costs and missed opportunities.

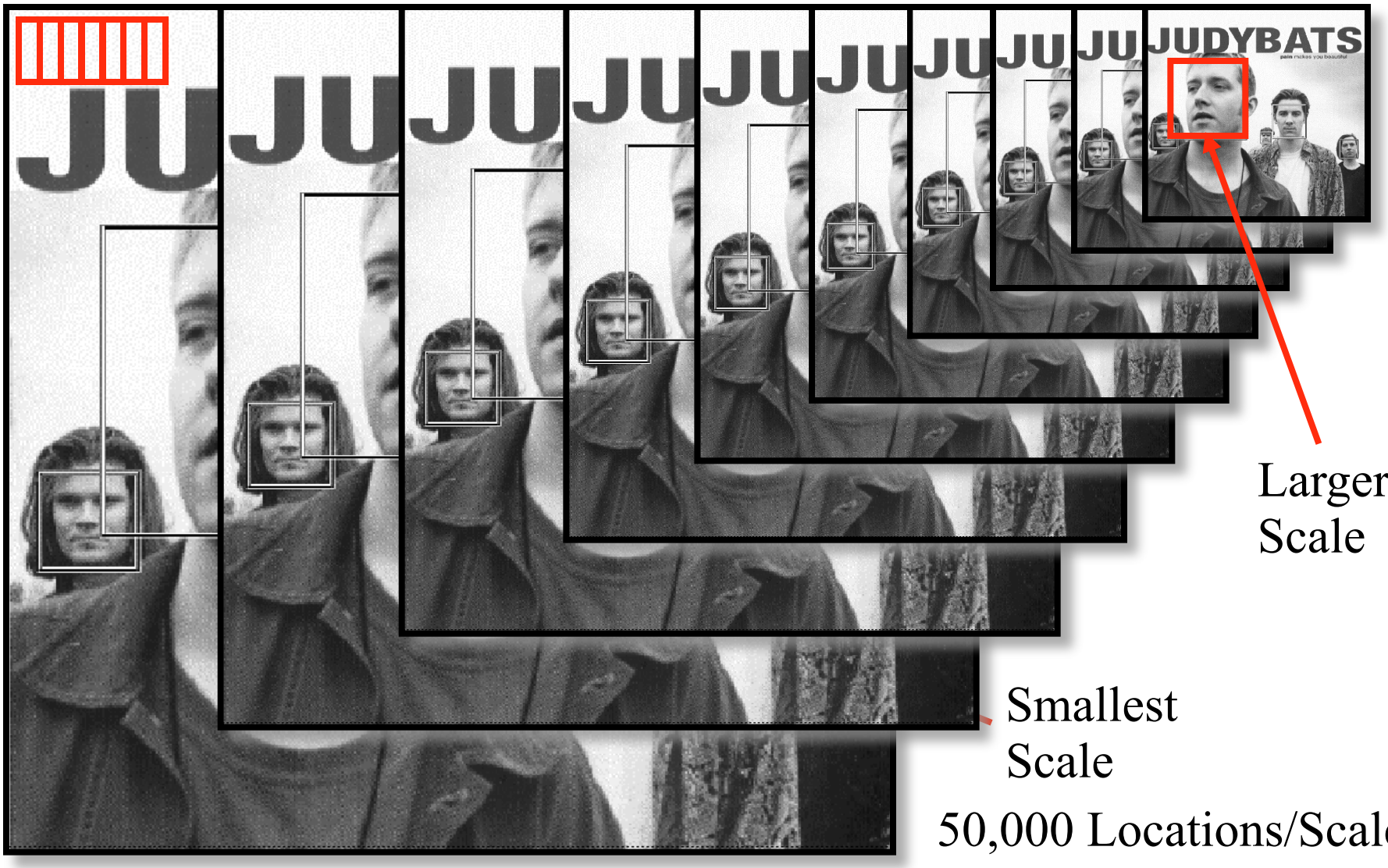
Face Detection

Viola and Jones / 2001

Face Detection / Viola and Jones



Face Detection as a Filtering process



Classifier is Learned from Labeled Data

- Example: 28x28 image patch
- Label: Face / Non face

- 5000 faces, 10^8 non faces
- Faces are normalized
  - Scale, translation
  - Rotation remains…

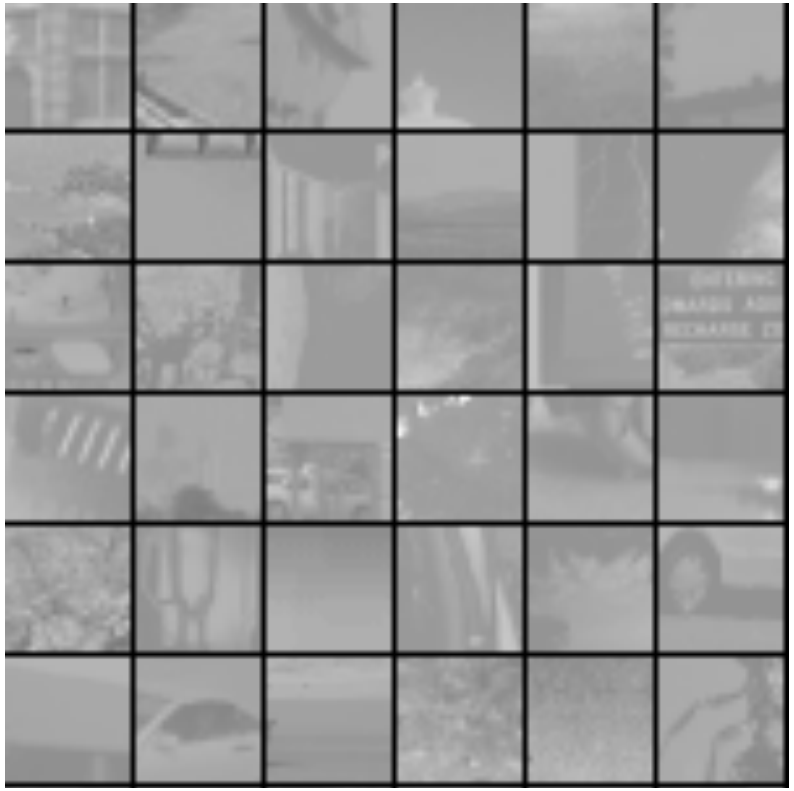
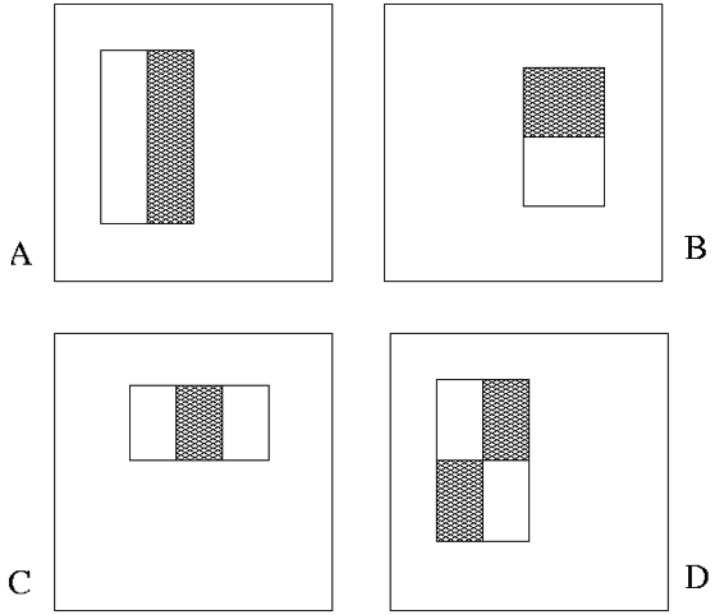


Image Features

"Rectangle filters"

Similar to Haar wavelets

Papageorgiou, et al.



$$h_t(x_i) = \begin{cases} 1 & \text{if } f_t(x_i) > \theta_t \\ 0 & \text{otherwise} \end{cases}$$

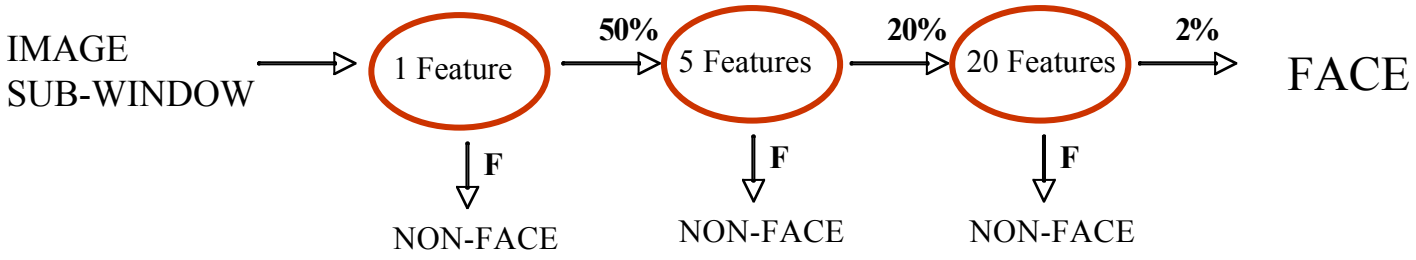
Very fast to compute using "integral image".

$60{,}000 \times 100 = 6{,}000{,}000$
Unique Binary Features

Combined using adaboost

Cascaded boosting

- Features combined using Adaboost
  - Find best weak rule by exhaustive search.
  - Ran for 2 days on a 250 node cluster
- For detection, features combined in a cascade:



  - Runs in real time, 15 FPS, on laptop

Paul Viola and Mike Jones

Summary

- Boosting is a computational method for learning accurate classifiers
  - Resistance to over-fit explained by margins
  - Boosting has been applied successfully to a variety of classification problems

Boosting under high noise.

Adaboost is sensitive to label noise

- Letter / Irvine Database
- Focus on a binary problem: {F,I,J} vs. other

Label Noise	Adaboost	Logitboost
0%	0.8% ±0.2%	0.8% ±0.1%
20%	33.3% ±0.7%	31.6% ±0.6%

- Boosting puts too much weight on outliers.
- Need to give up on outliers.

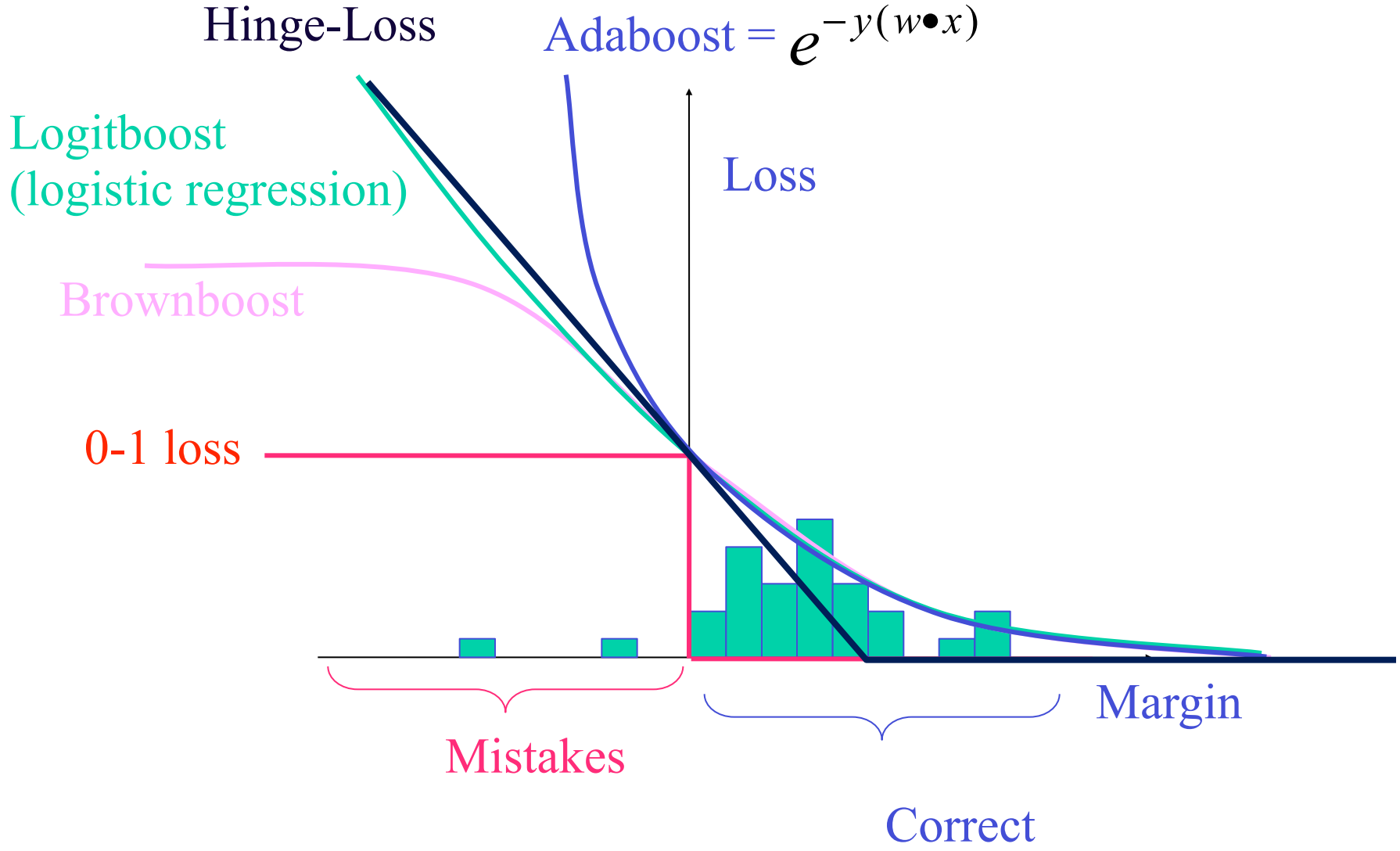
Robustboost - A new boosting algorithm

Label Noise	Adaboost	Logitboost	Robustboost
0%	0.8% ±0.2%	0.8% ±0.1%	2.9% ±0.2%
20%	33.3% ±0.7%	31.6% ±0.6%	22.2 ±0.8%

error with respect to original (noiseless) labels

20%	22.1% ±1.2%	19.4% ±1.3%	**3.7% ±0.4%**

Approximating mistake loss with convex functions

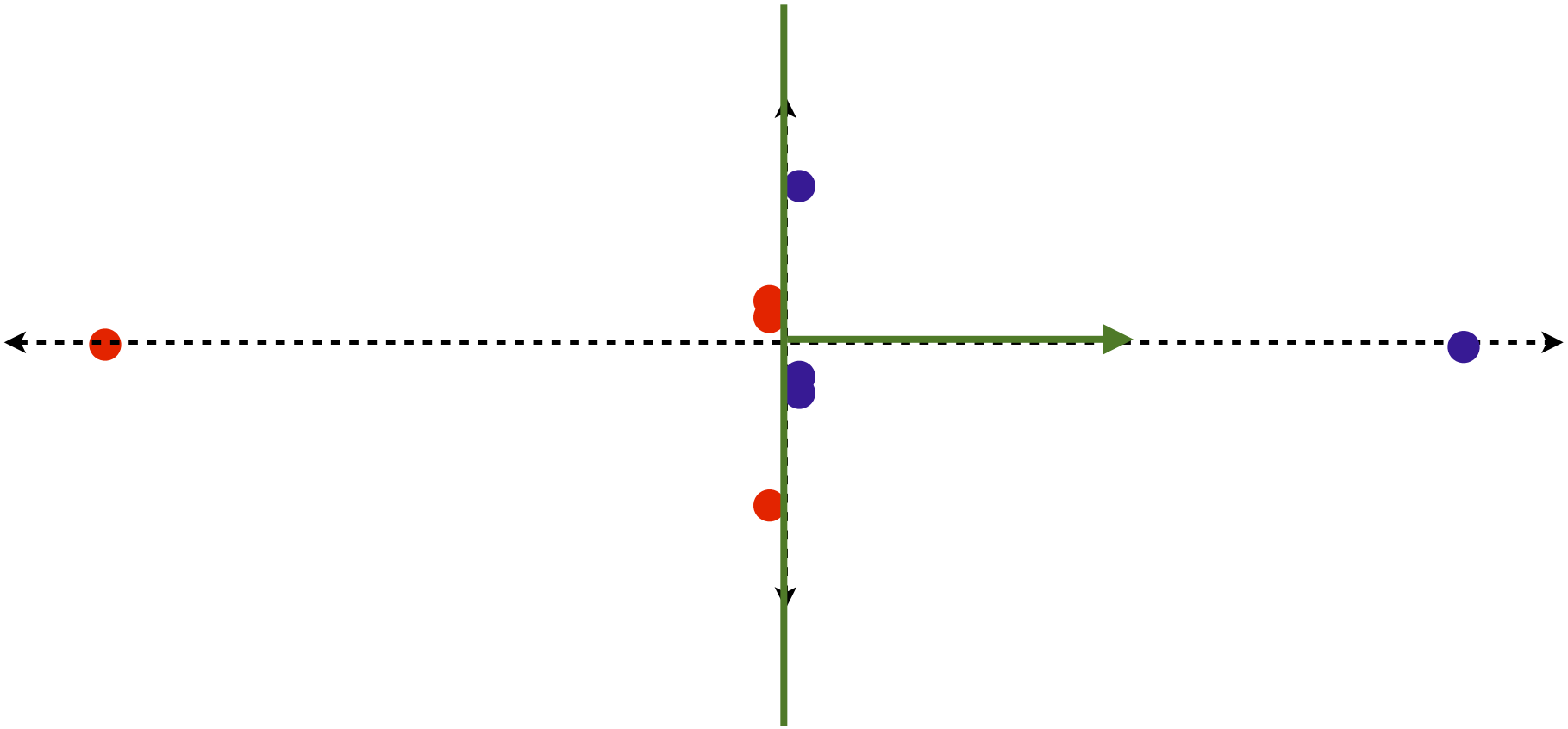


Label noise and convex loss functions

- Algorithms for learning a classifier based on minimizing a convex loss function: perceptron, Adaboost, Logitboost, Logistic regression, soft margins SVM.
- Work well when data is linearly separable.
- Can get into trouble when not linearly separable.
- Problem: Convex loss functions are a poor approximation for classification error.
- But: No known efficient algorithms for

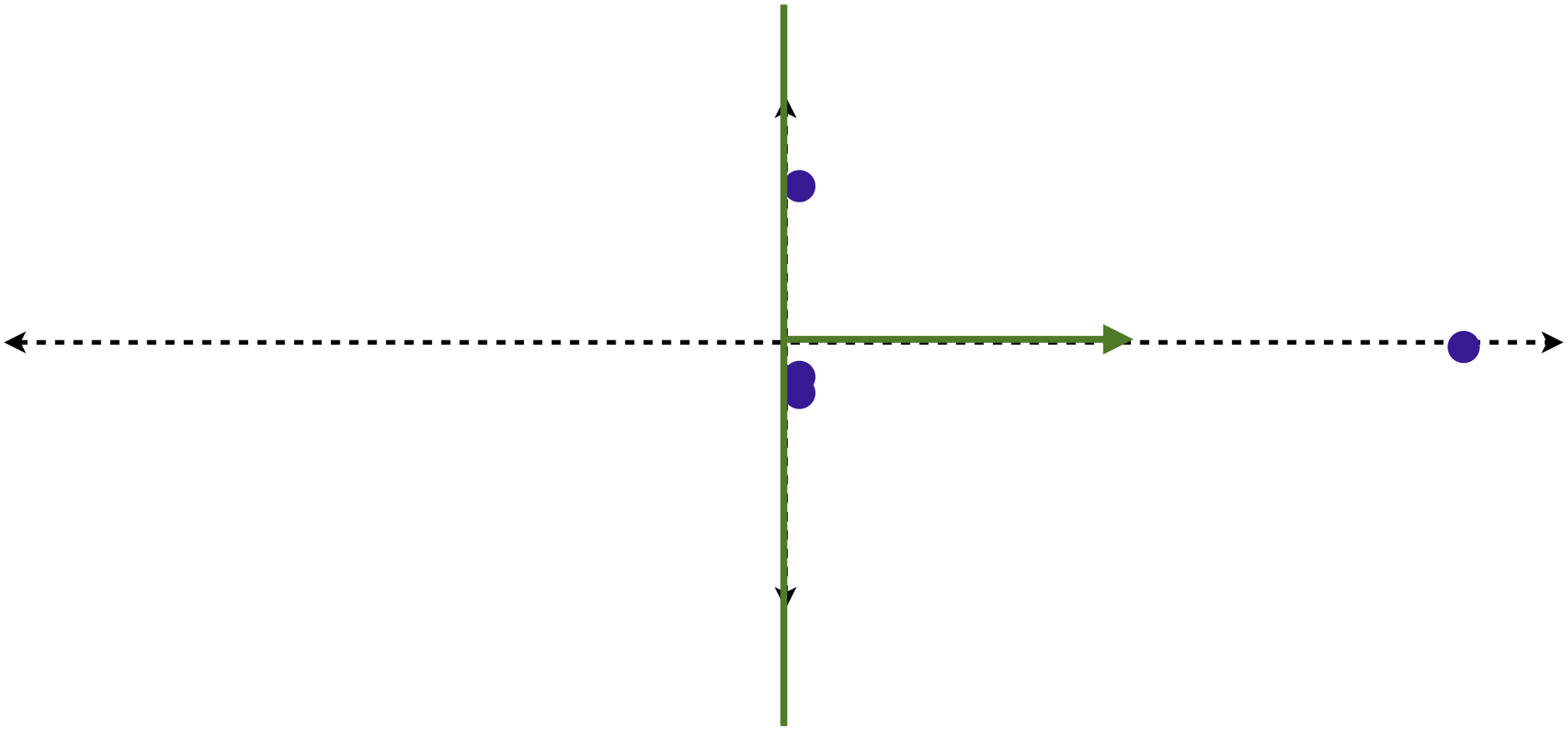
Random label noise defeats any convex loss function

[Servedio, Long 2010]



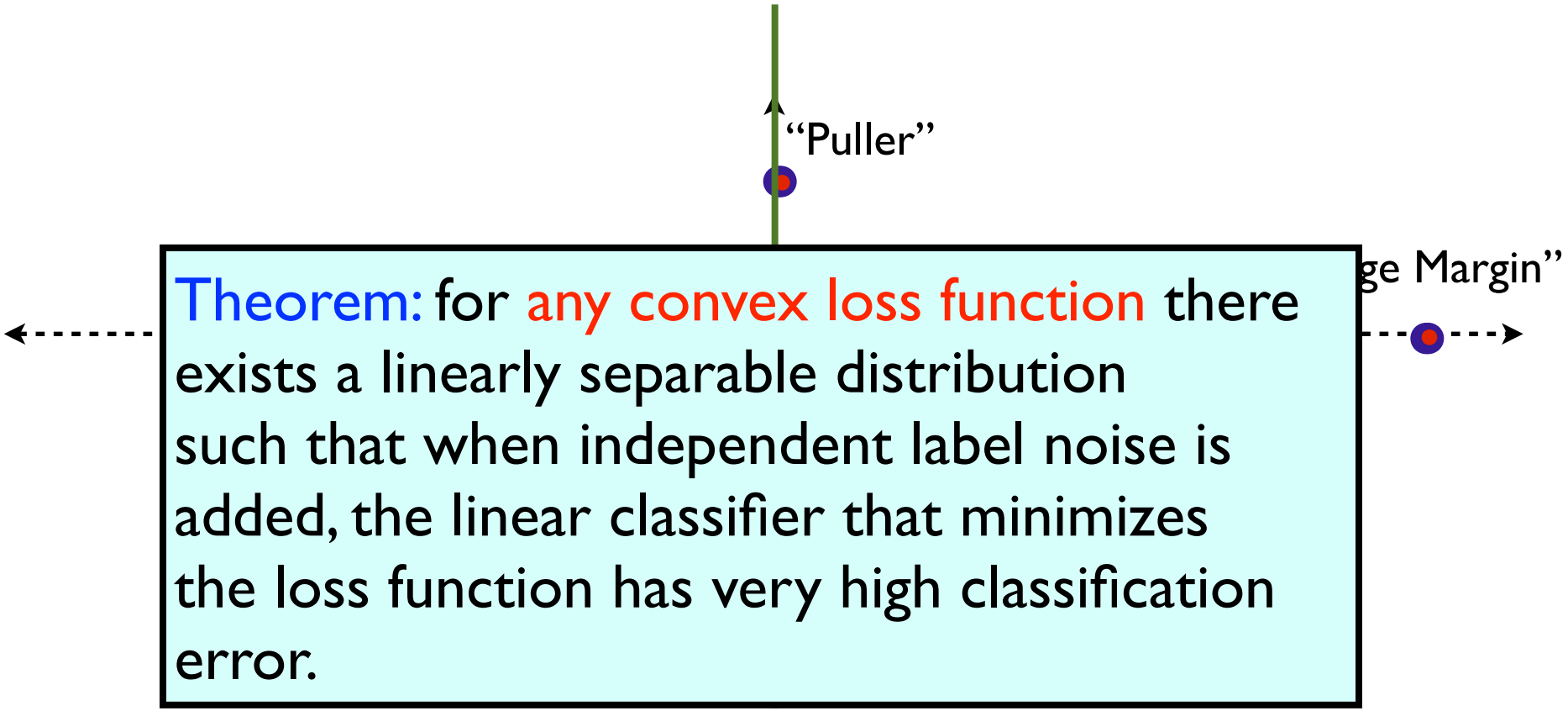
Considering one symmetric half

[Servedio, Long 2010]



Adding random label noise

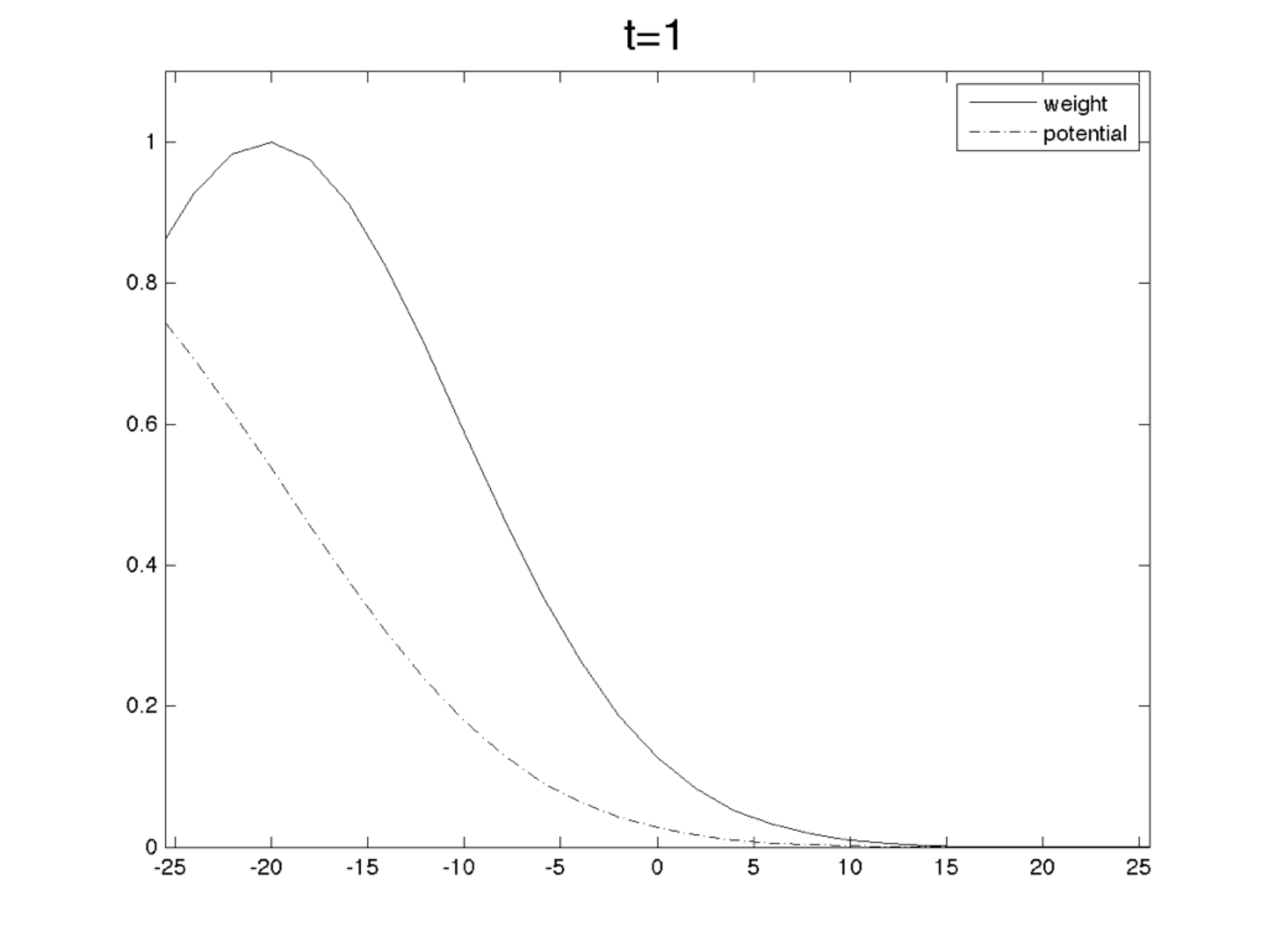
[Servedio, Long 2010]



Theorem: for any convex loss function there exists a linearly separable distribution such that when independent label noise is added, the linear classifier that minimizes the loss function has very high classification error.

Boost by majority, Brownboost,

- Target error set at start.
- Defines how many boosting iterations are needed
- The loss function depends on the time-to-finish.
- Close to end - give up on examples with large negative margins.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-15
-10
-5
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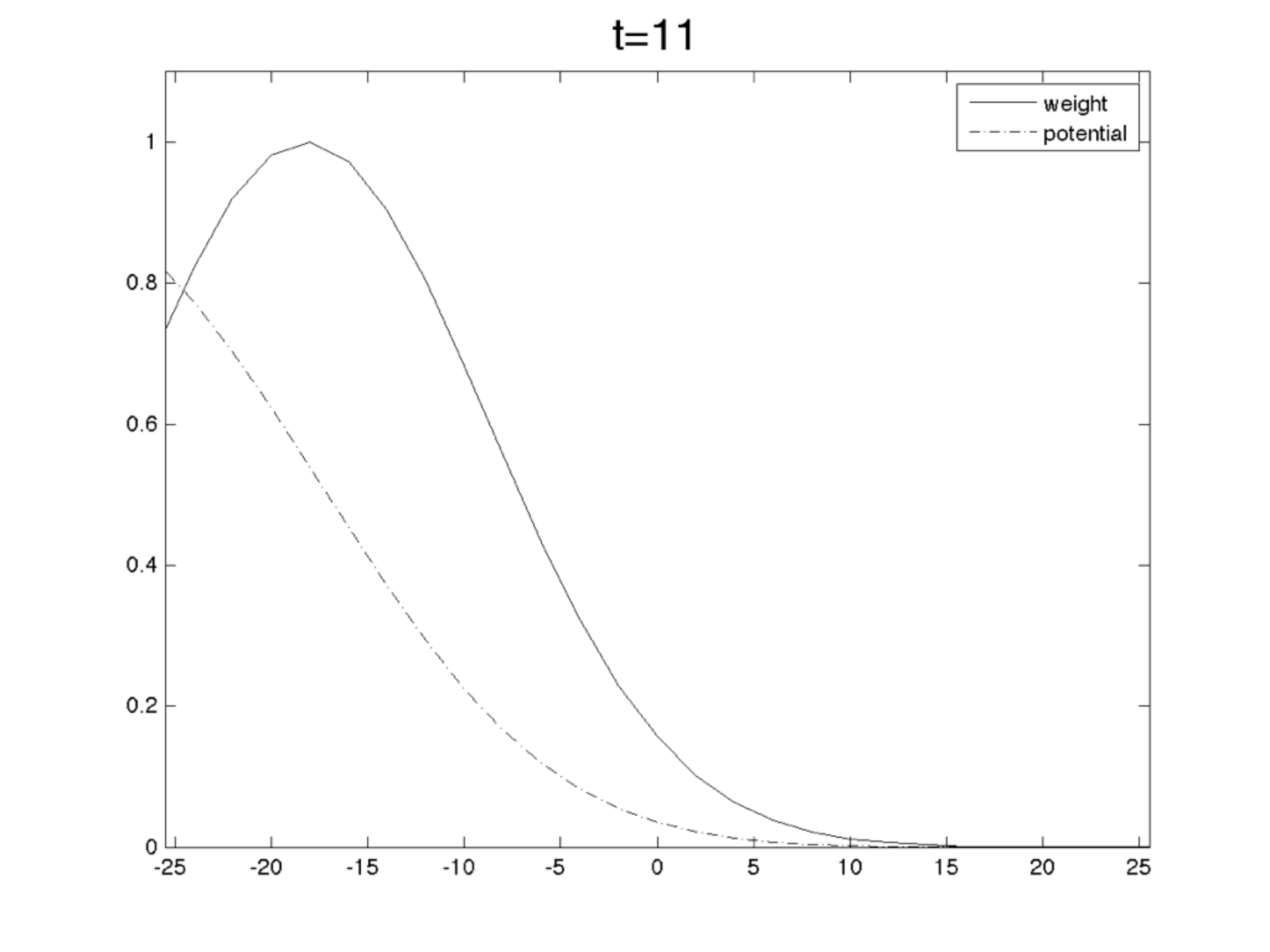
20
25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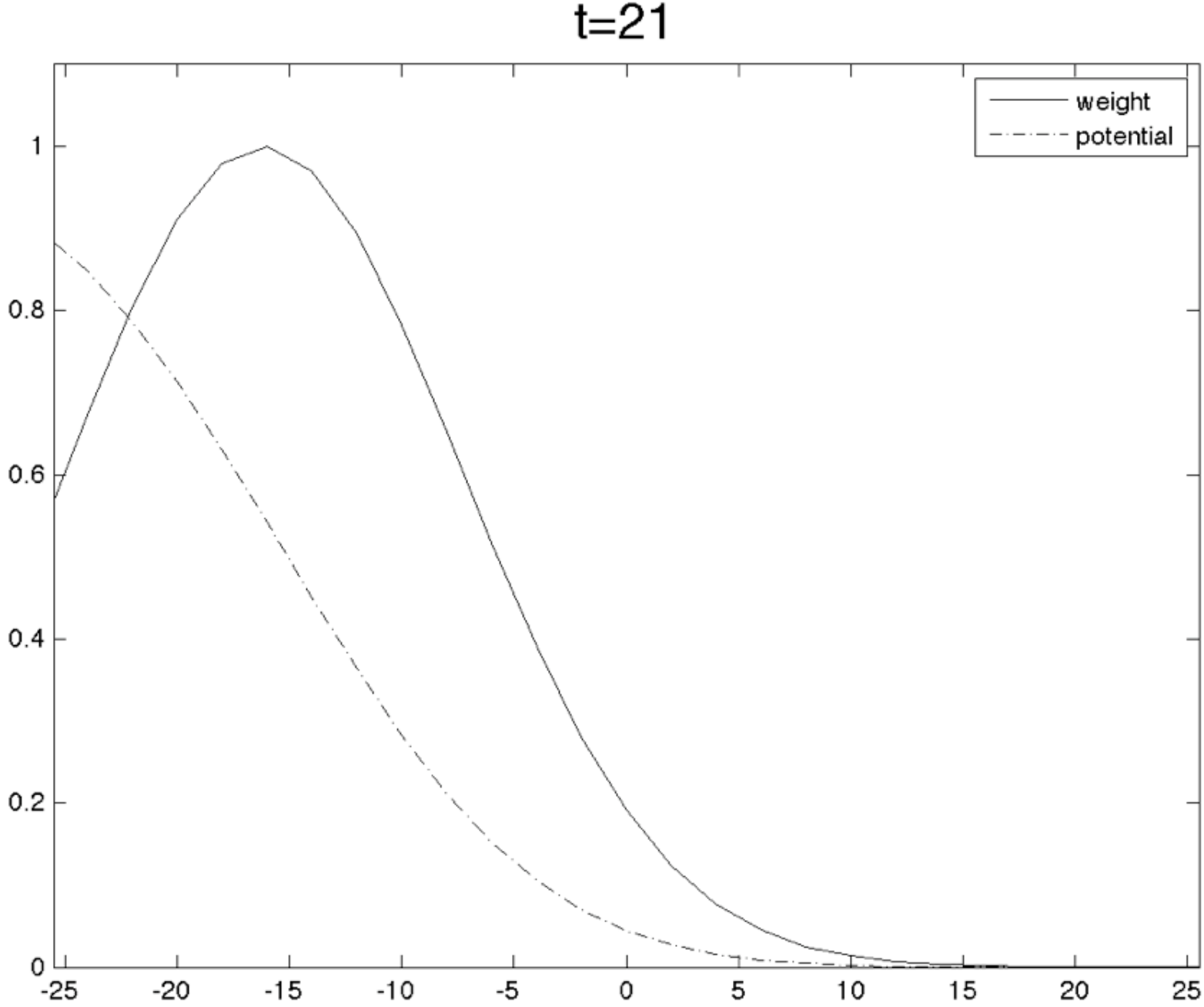
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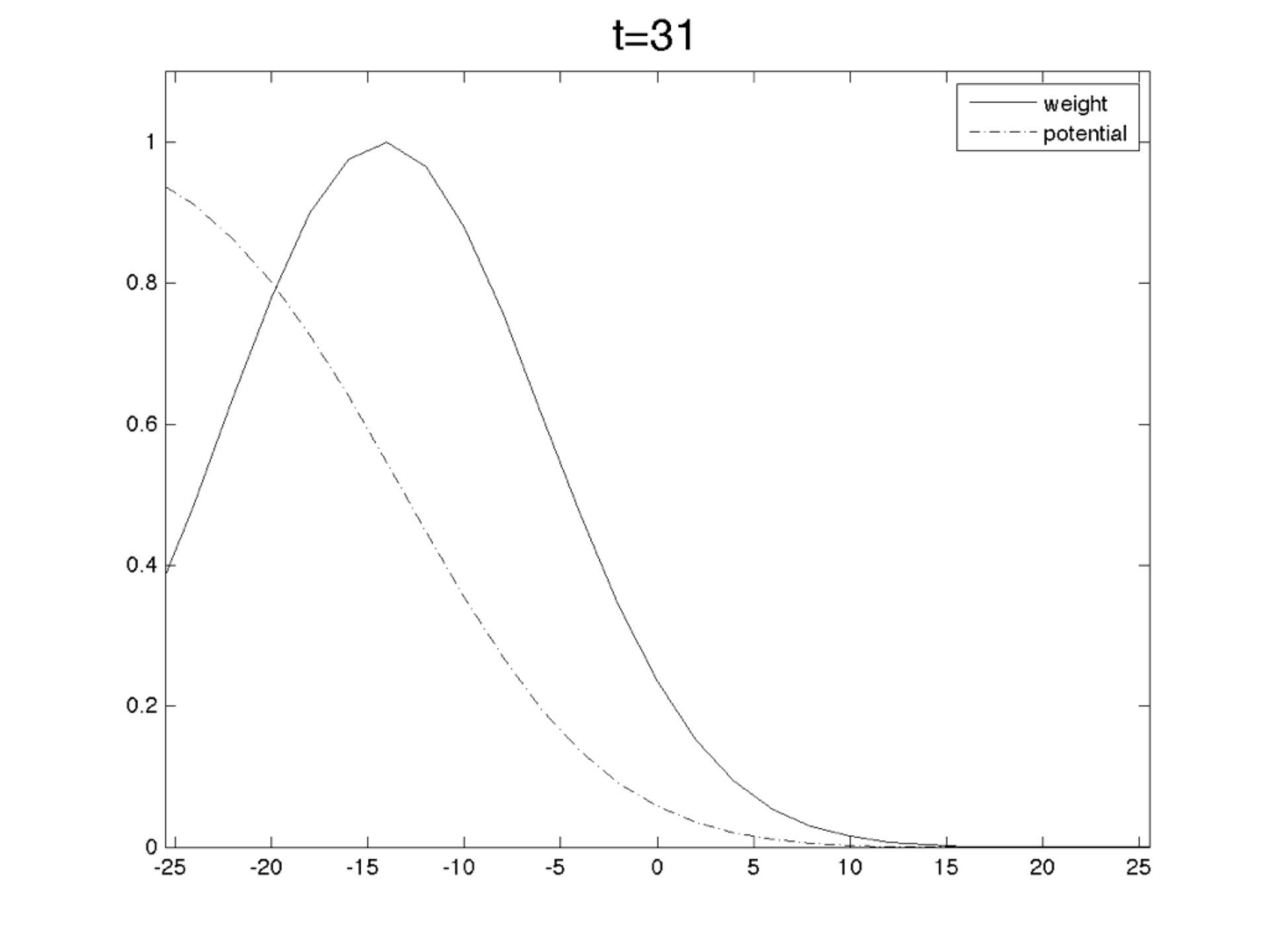
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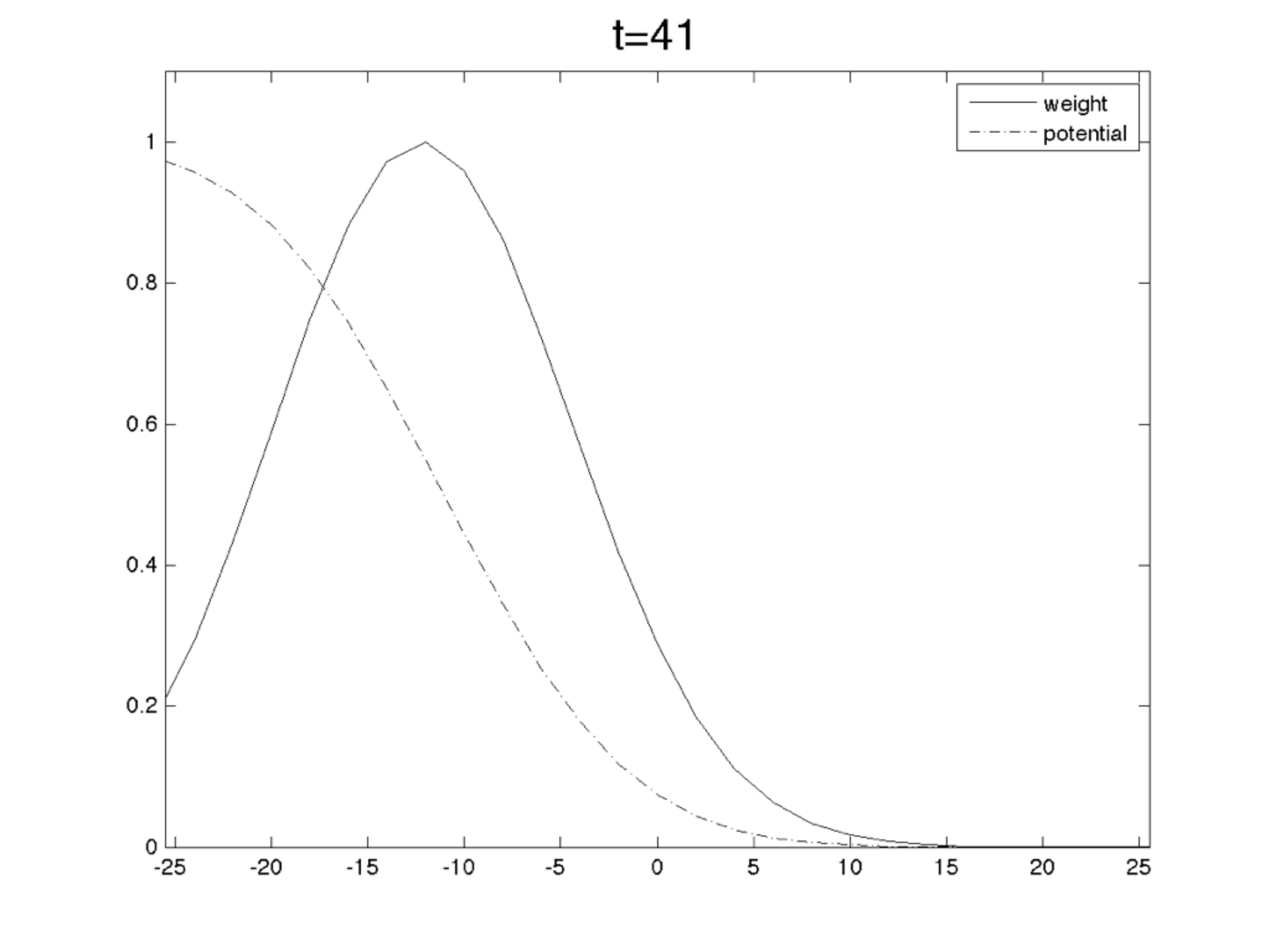
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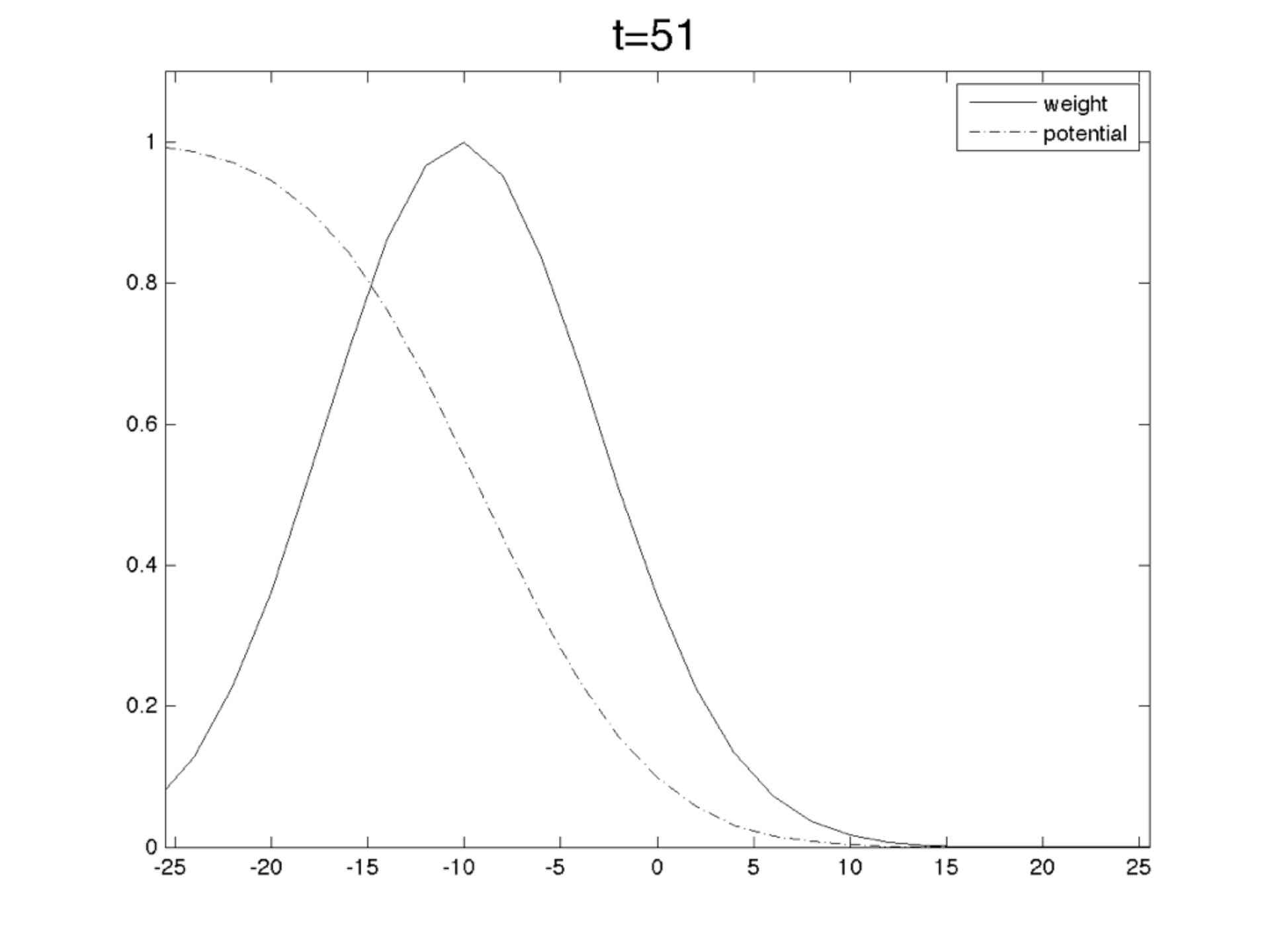
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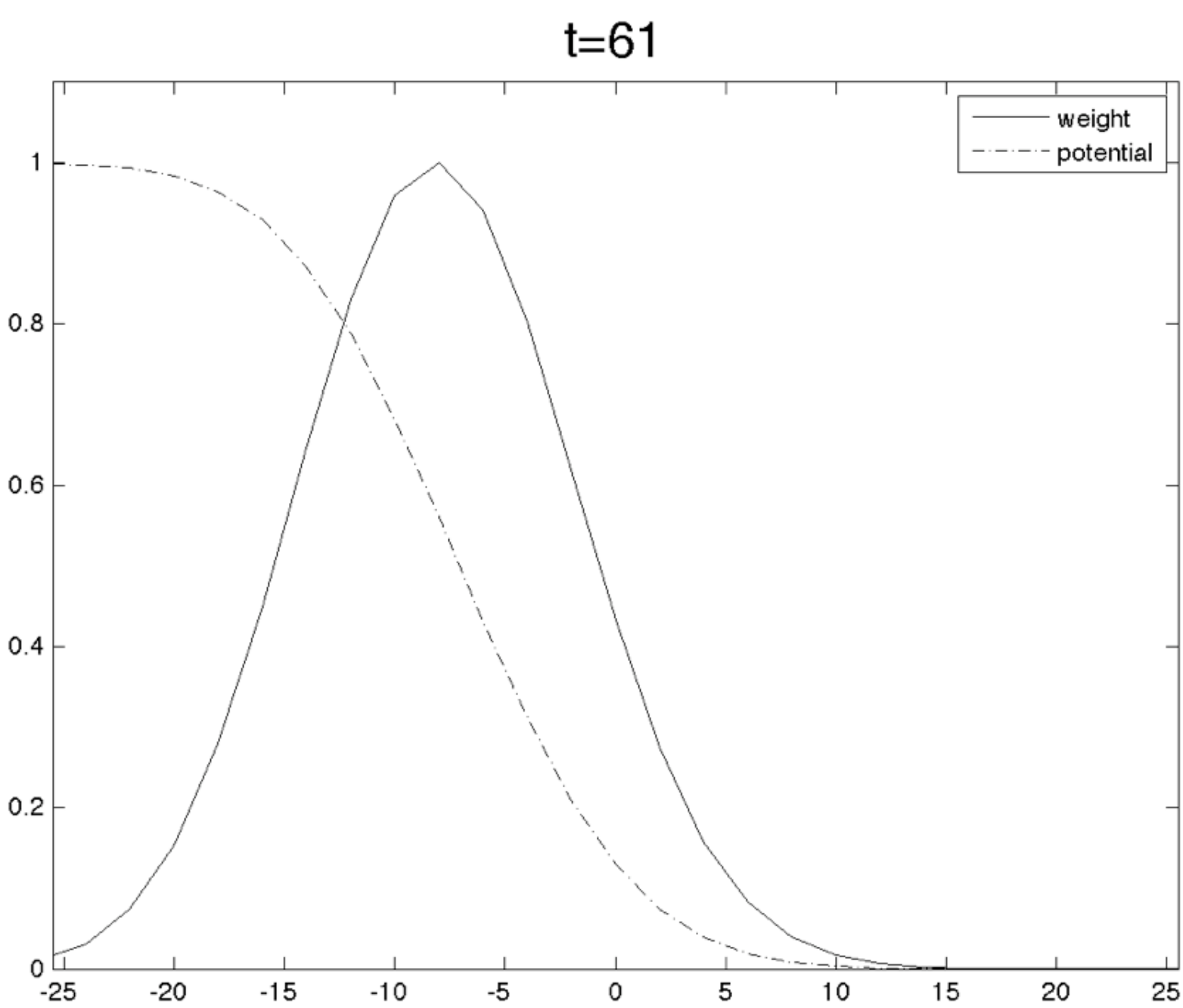
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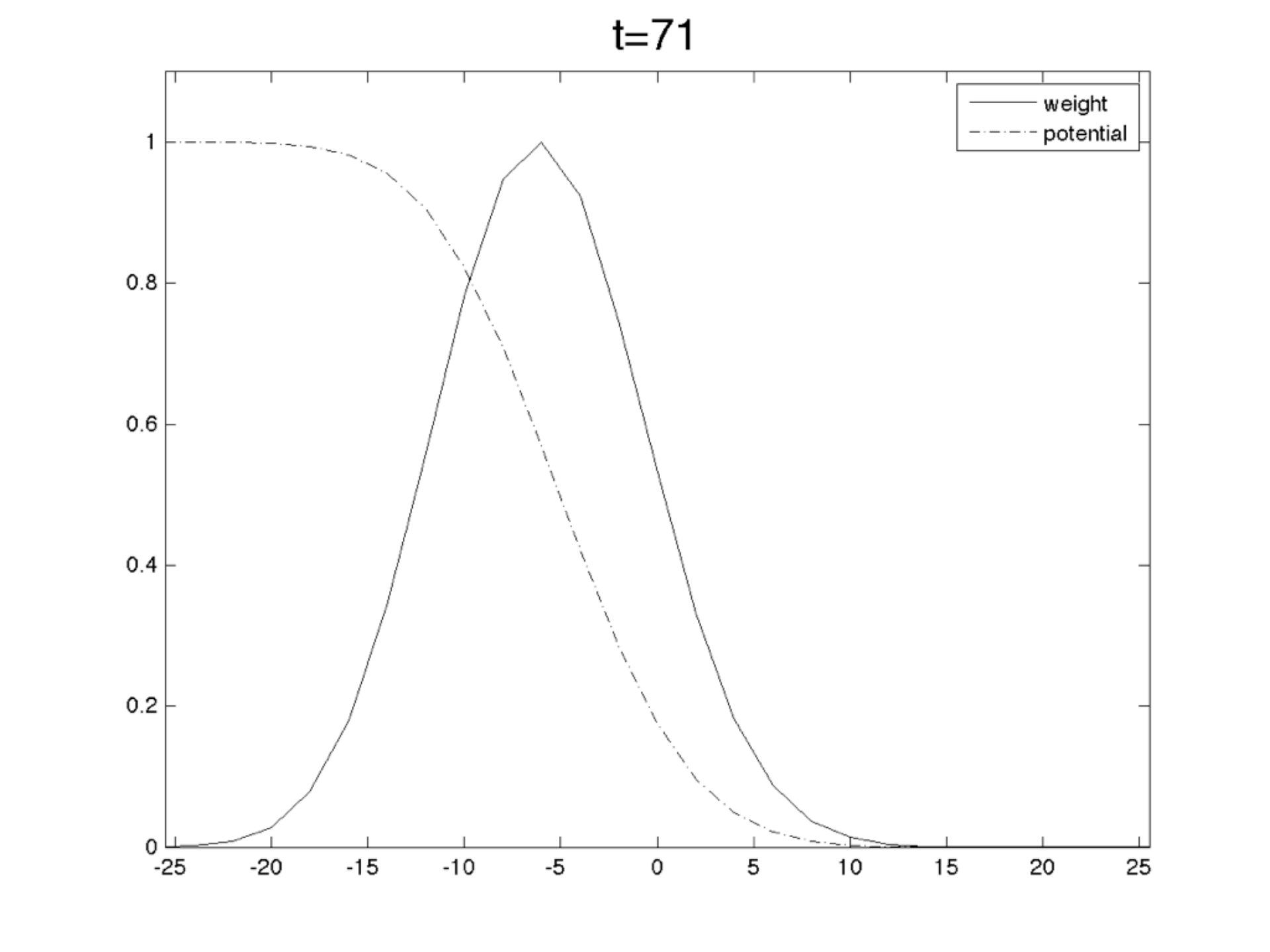
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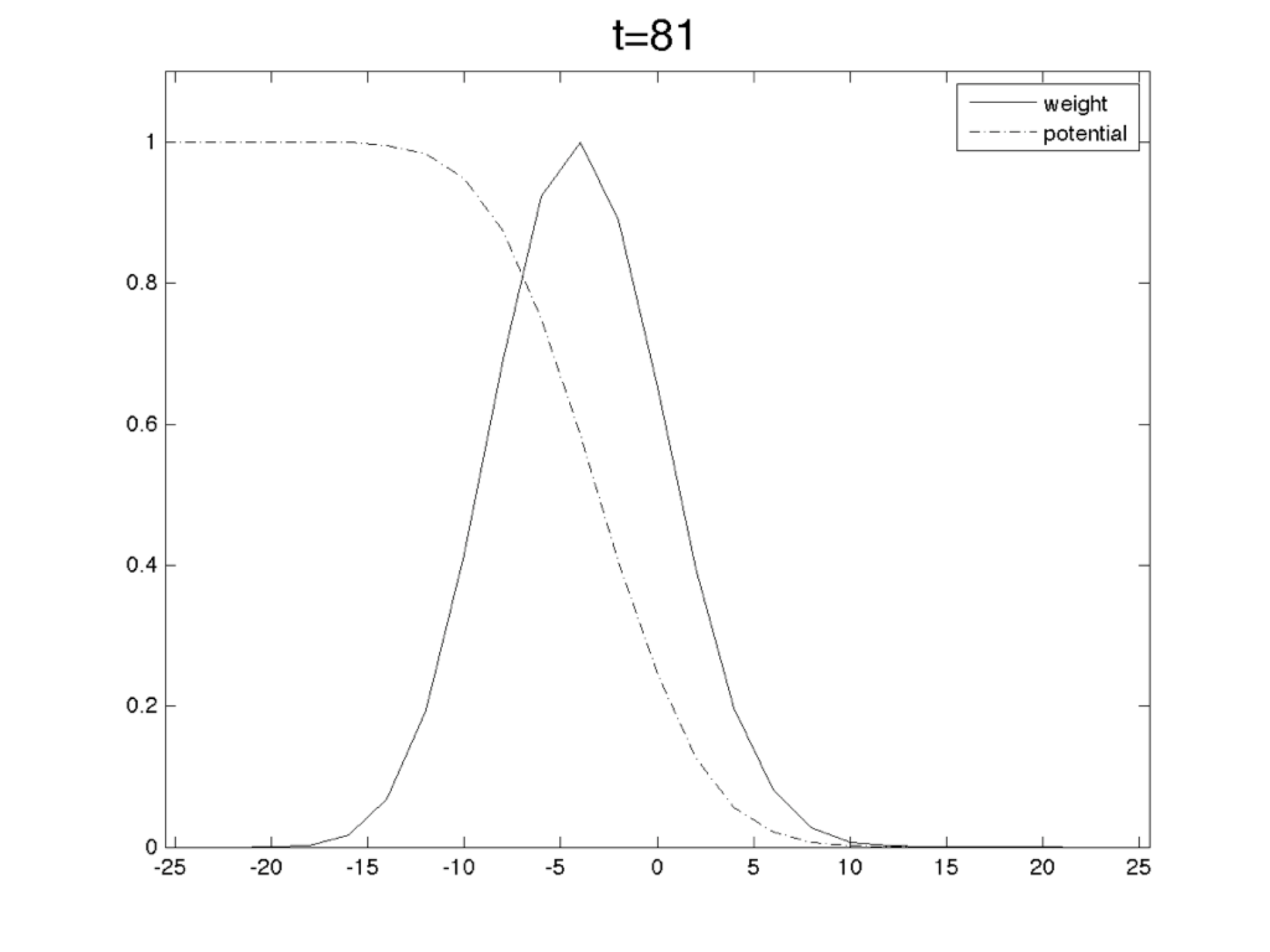
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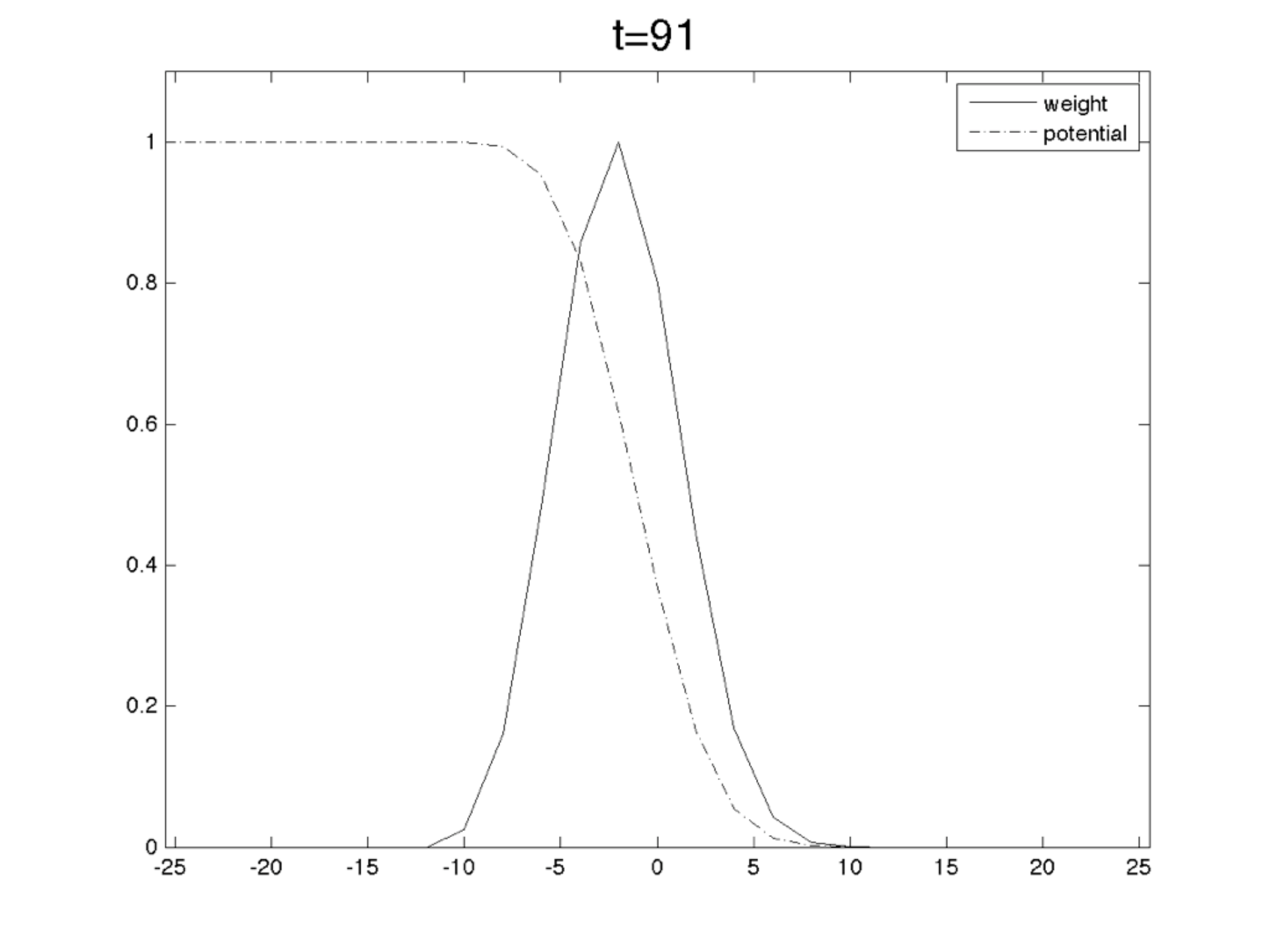
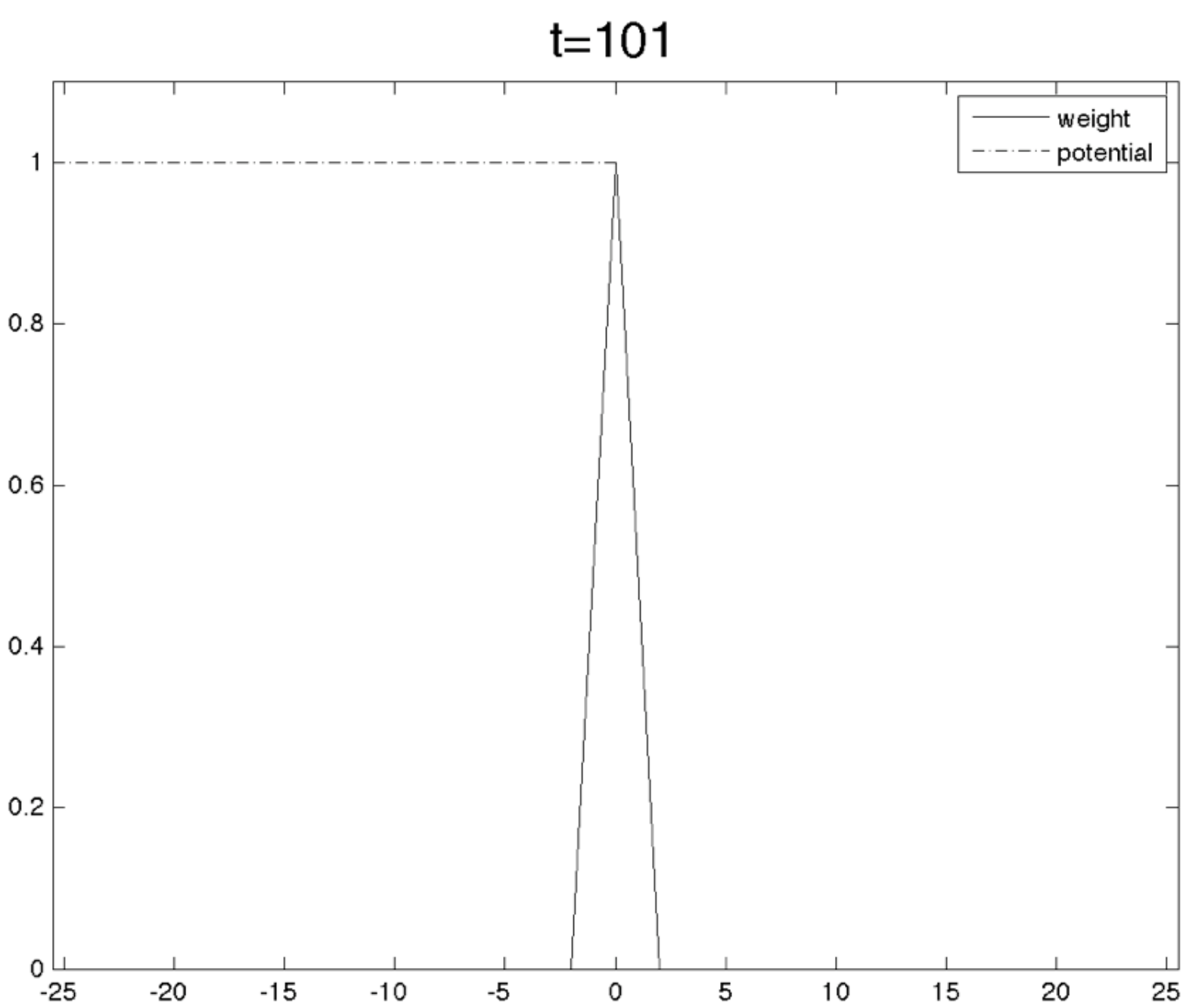
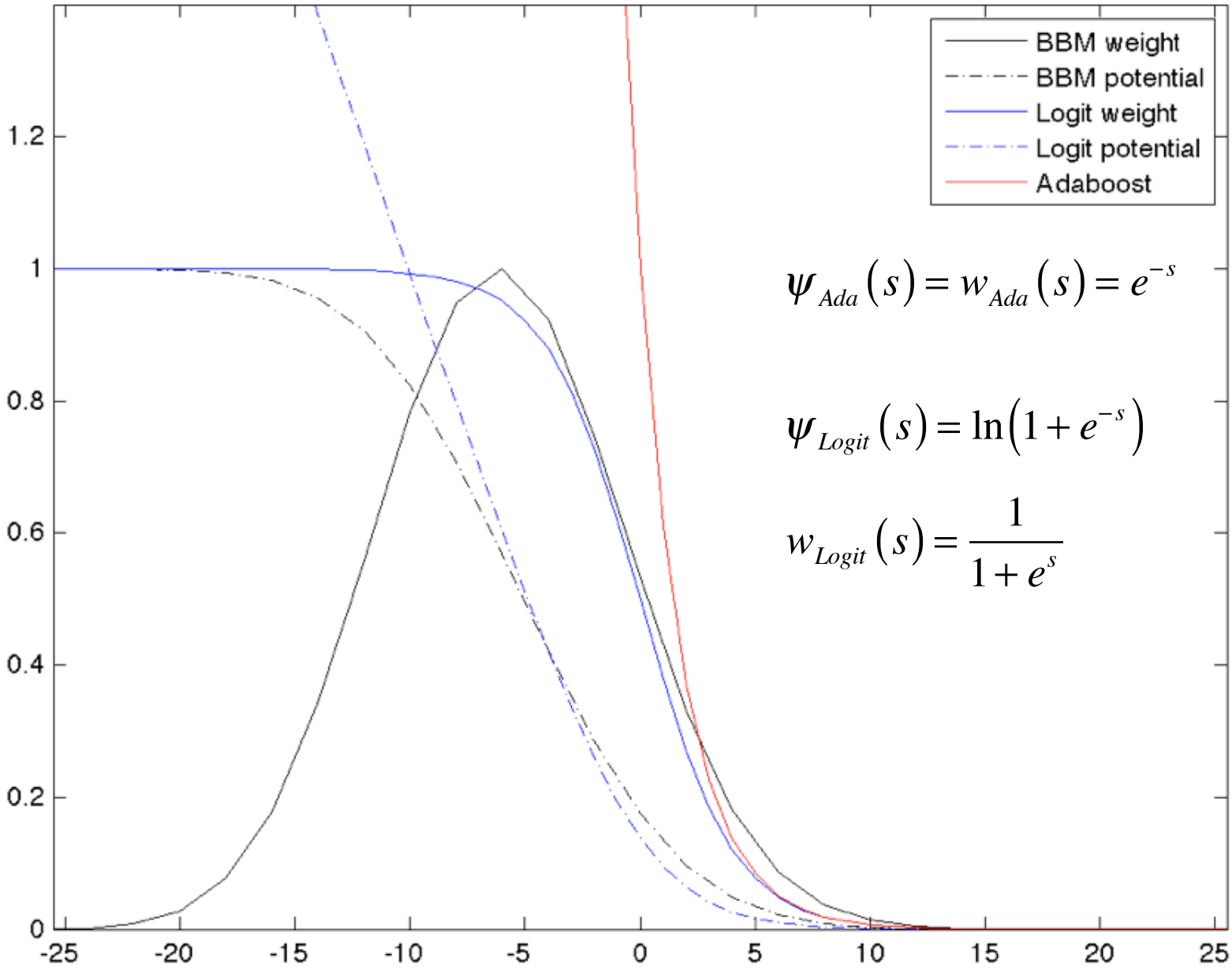
-10
-5
0
5
10
15
20
25


t=91
weight
potential
1
0.8
0.6
0.4
0.2
0
-25
-20
-15
-10
-5
0
5
10
15
20
25


t=101
weight
potential
1
0.8
0.6
0.4
0.2
0
-25
-20
-15
-10
-5
0
5
10
15
20
25

BBM/Logitboost/Adaboost



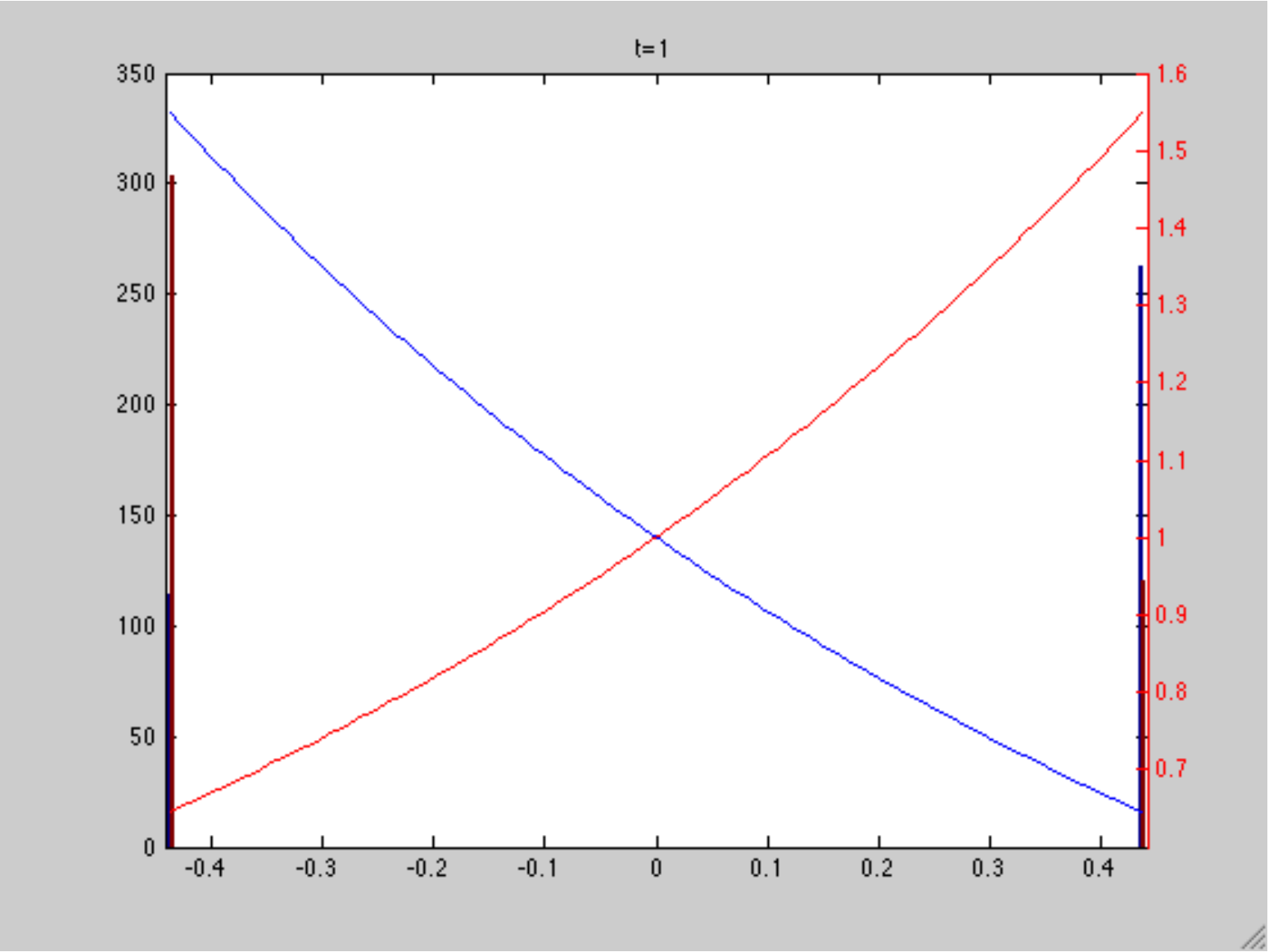
$$\psi_{Ada}(s) = w_{Ada}(s) = e^{-s}$$

$$\psi_{Logit}(s) = \ln\left(1 + e^{-s}\right)$$

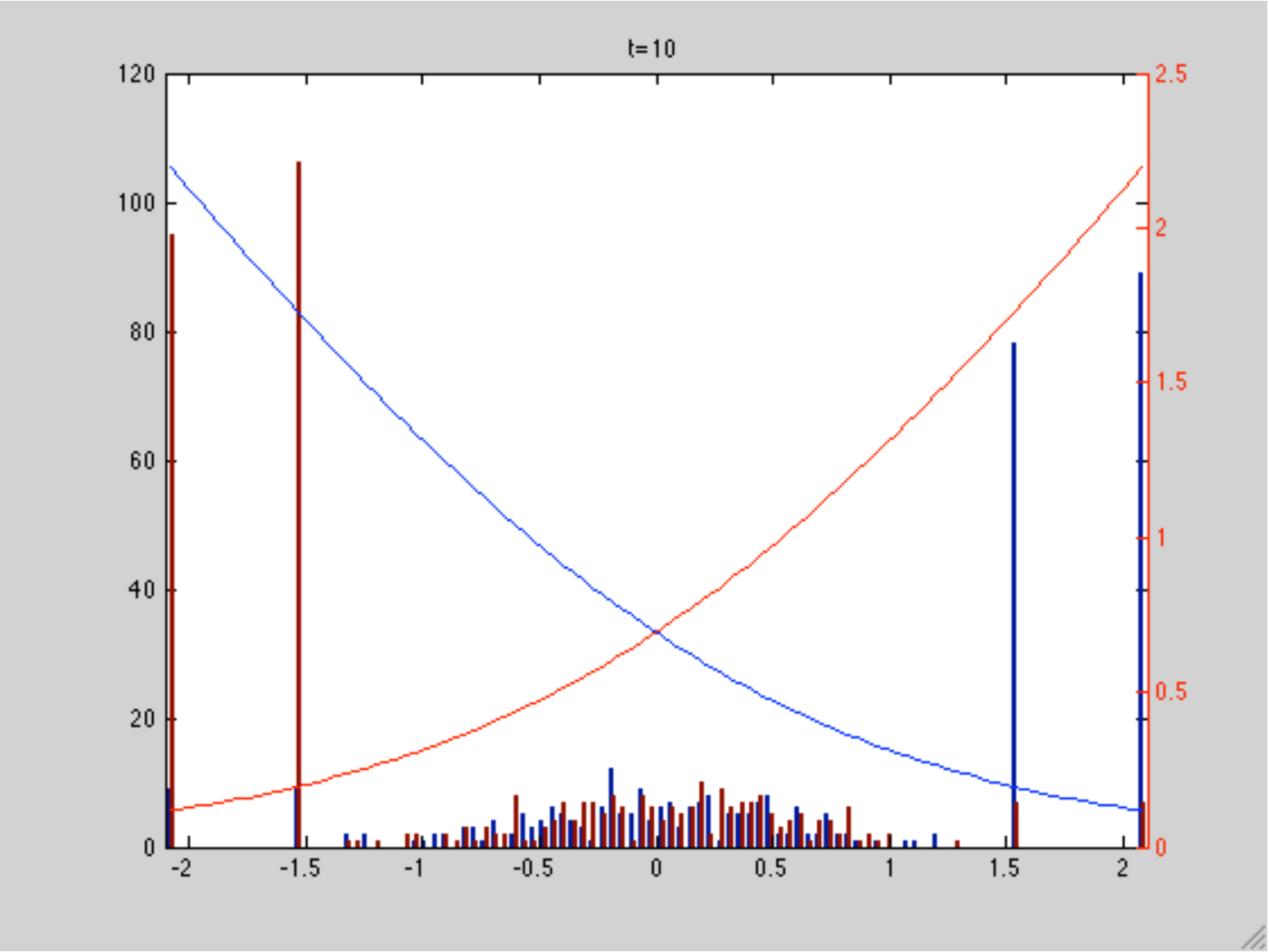
$$w_{Logit}(s) = \frac{1}{1 + e^{s}}$$

Experimental Results on Long/Servedio synthetic example

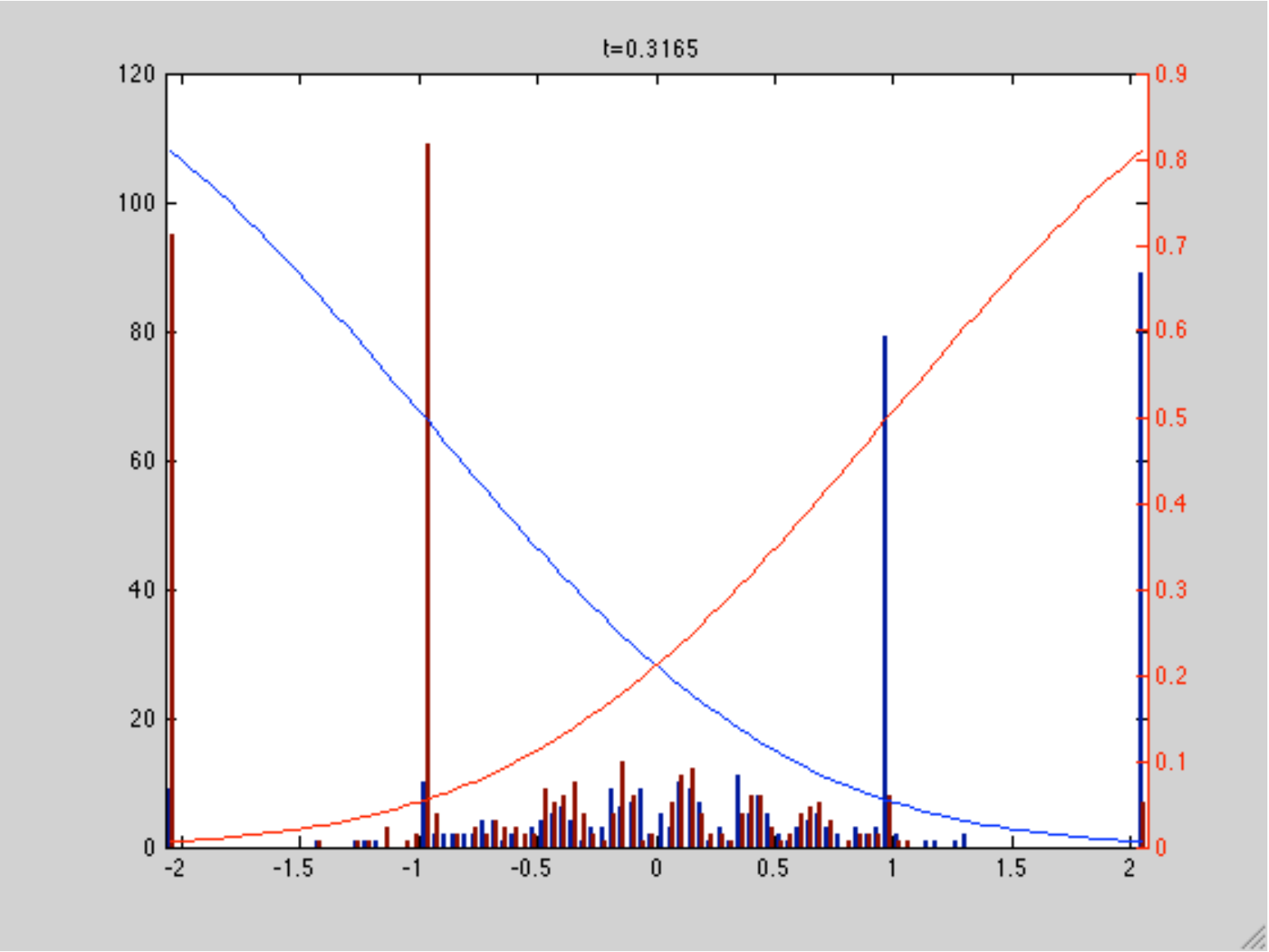
Adaboost on Long/Servedio



LogitBoost on Long/Servedio



Robustboost on Long/Servedio



Experimental Results on real-world data

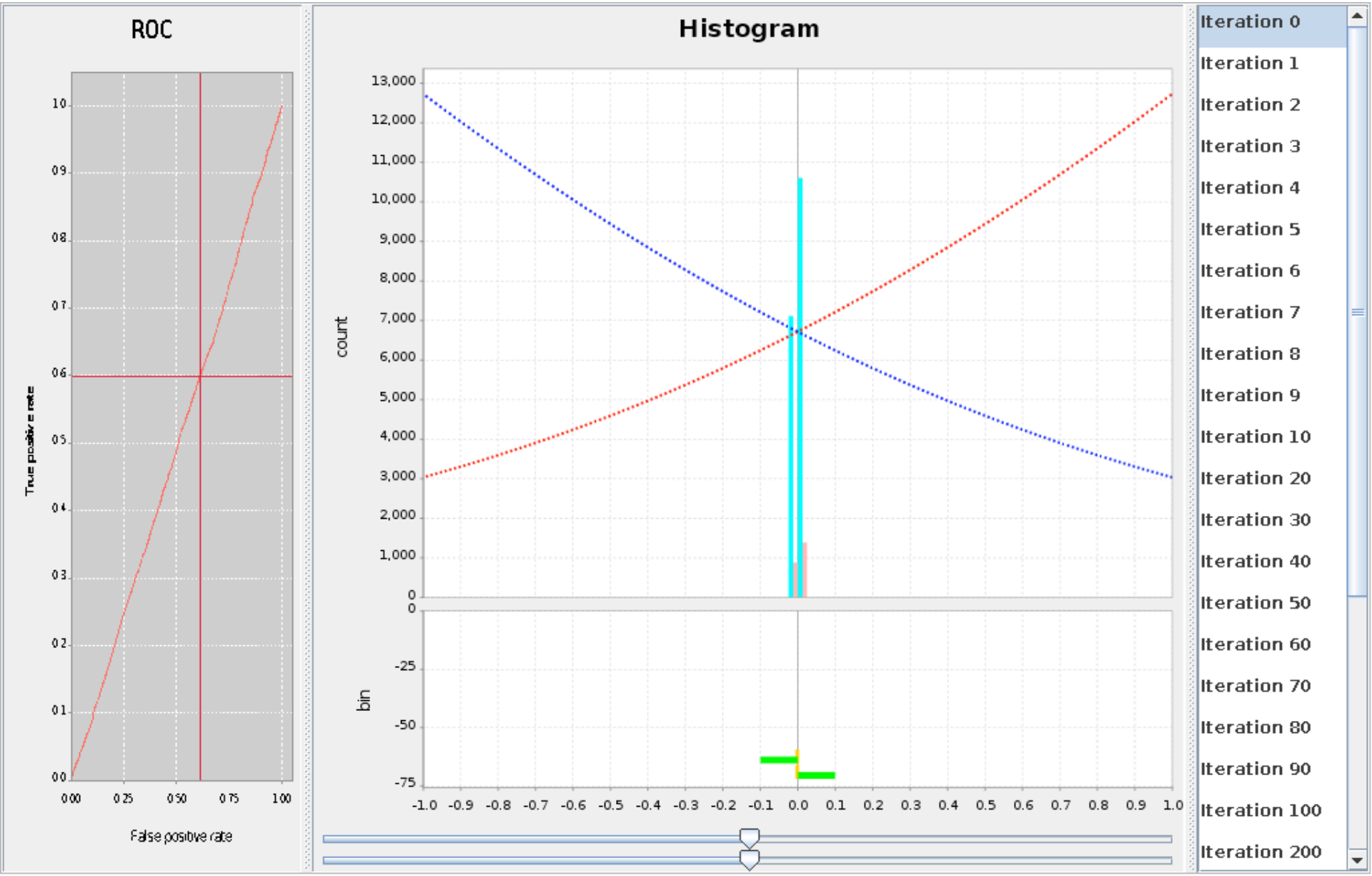
Robustboost - A new boosting algorithm

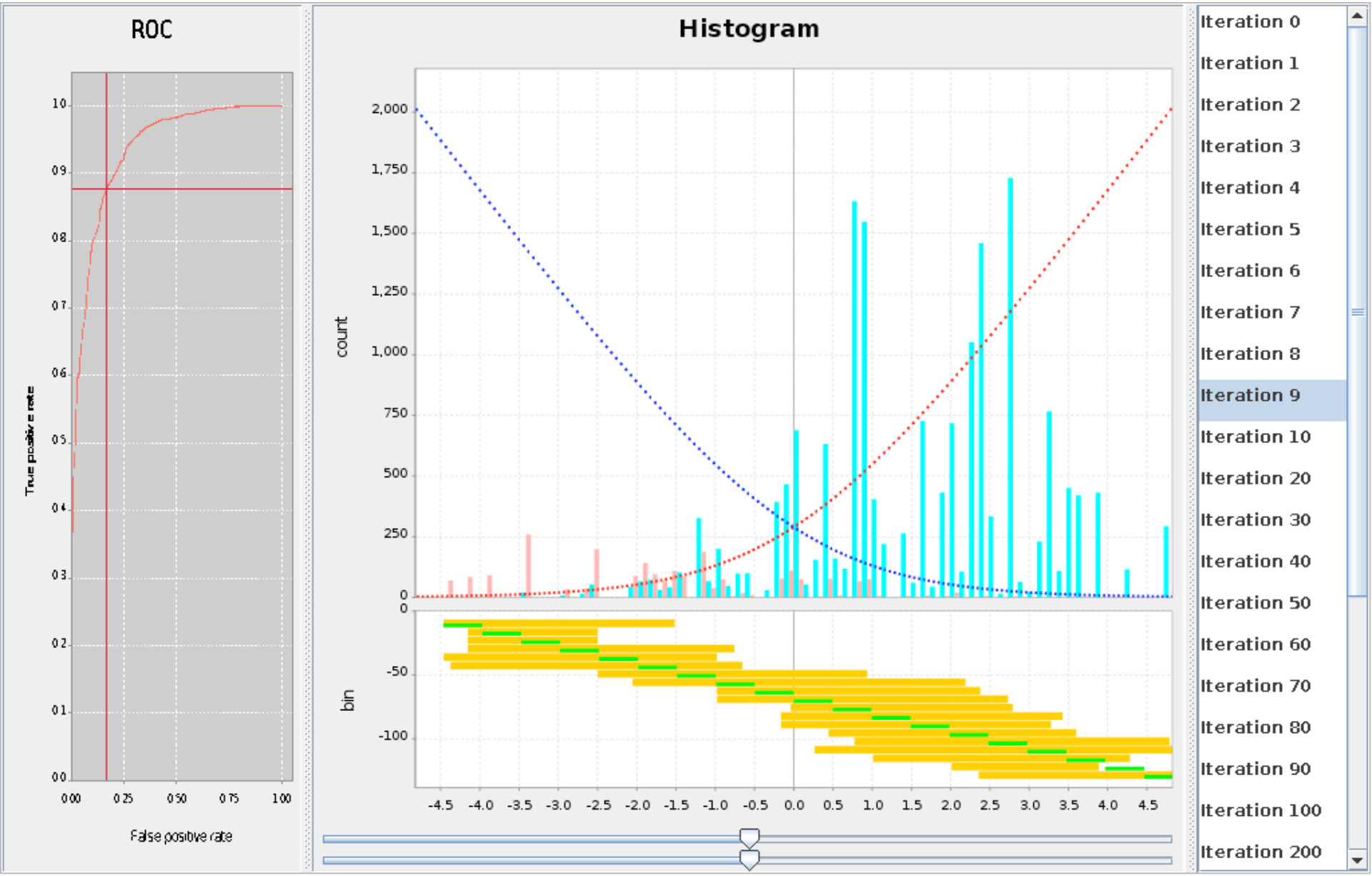
Label Noise	Adaboost	Logitboost	Robustboost
0%	0.8% ±0.2%	0.8% ±0.1%	2.9% ±0.2%
20%	33.3% ±0.7%	31.6% ±0.6%	22.2 ±0.8%

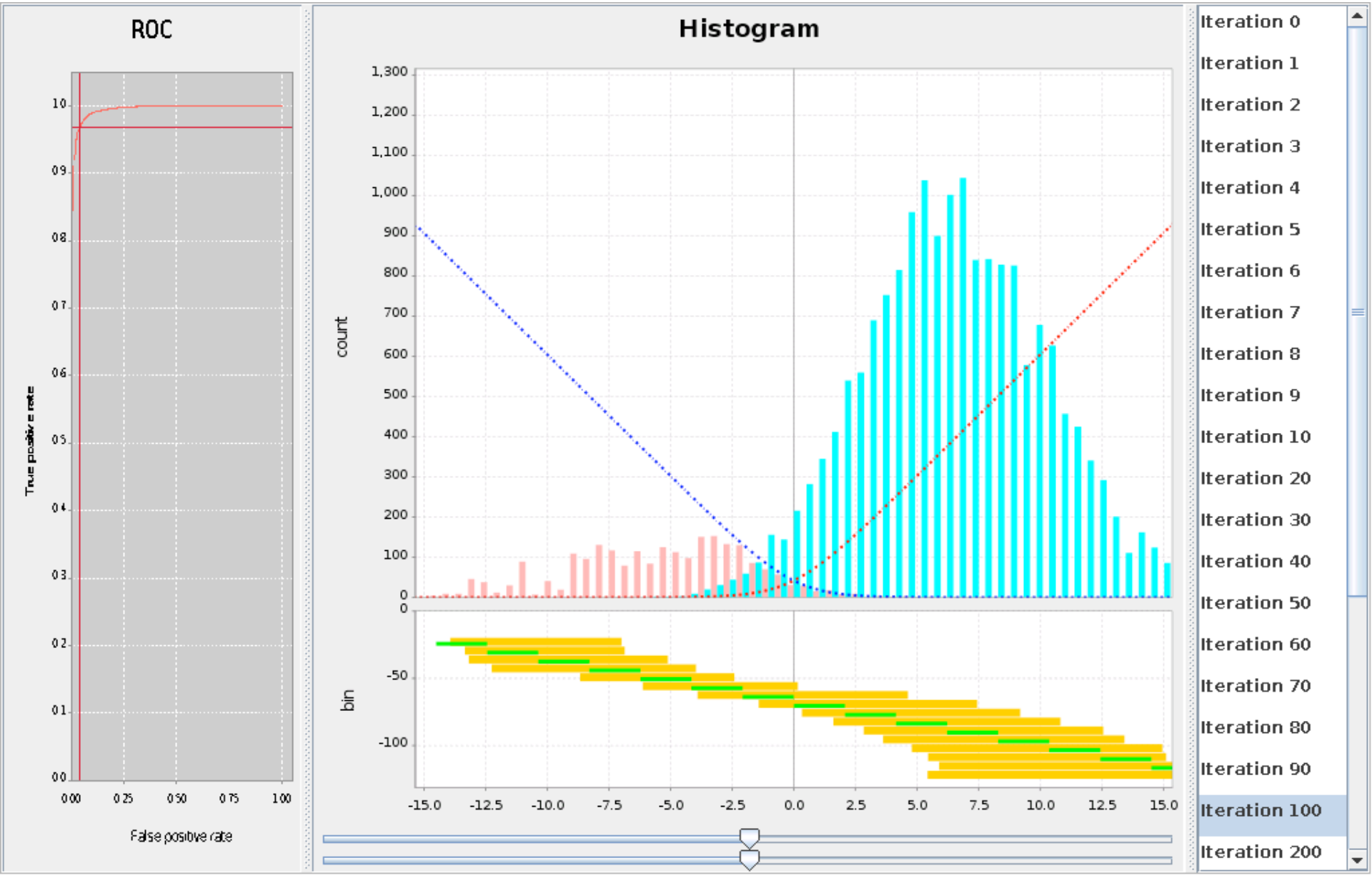
error with respect to original (noiseless) labels

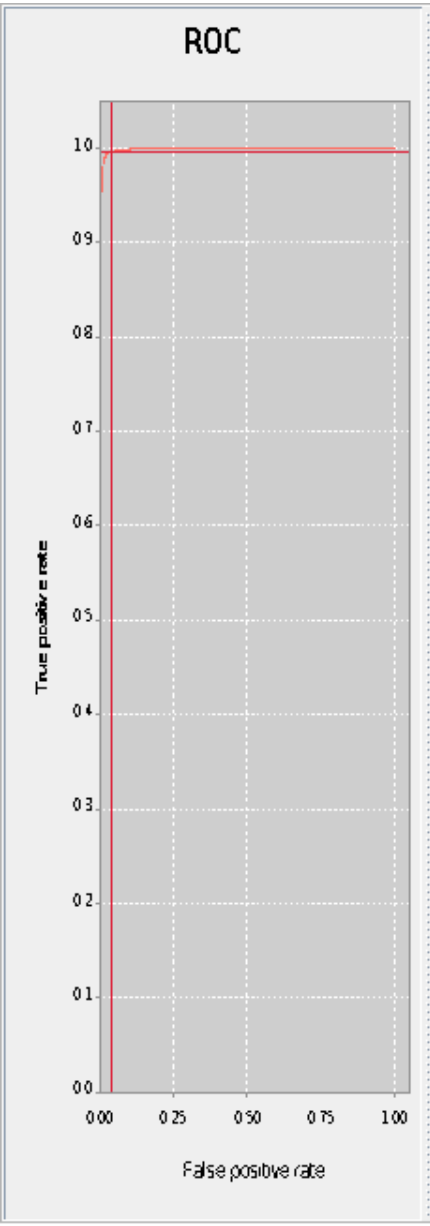
20%	22.1% ±1.2%	19.4% ±1.3%	**3.7% ±0.4%**

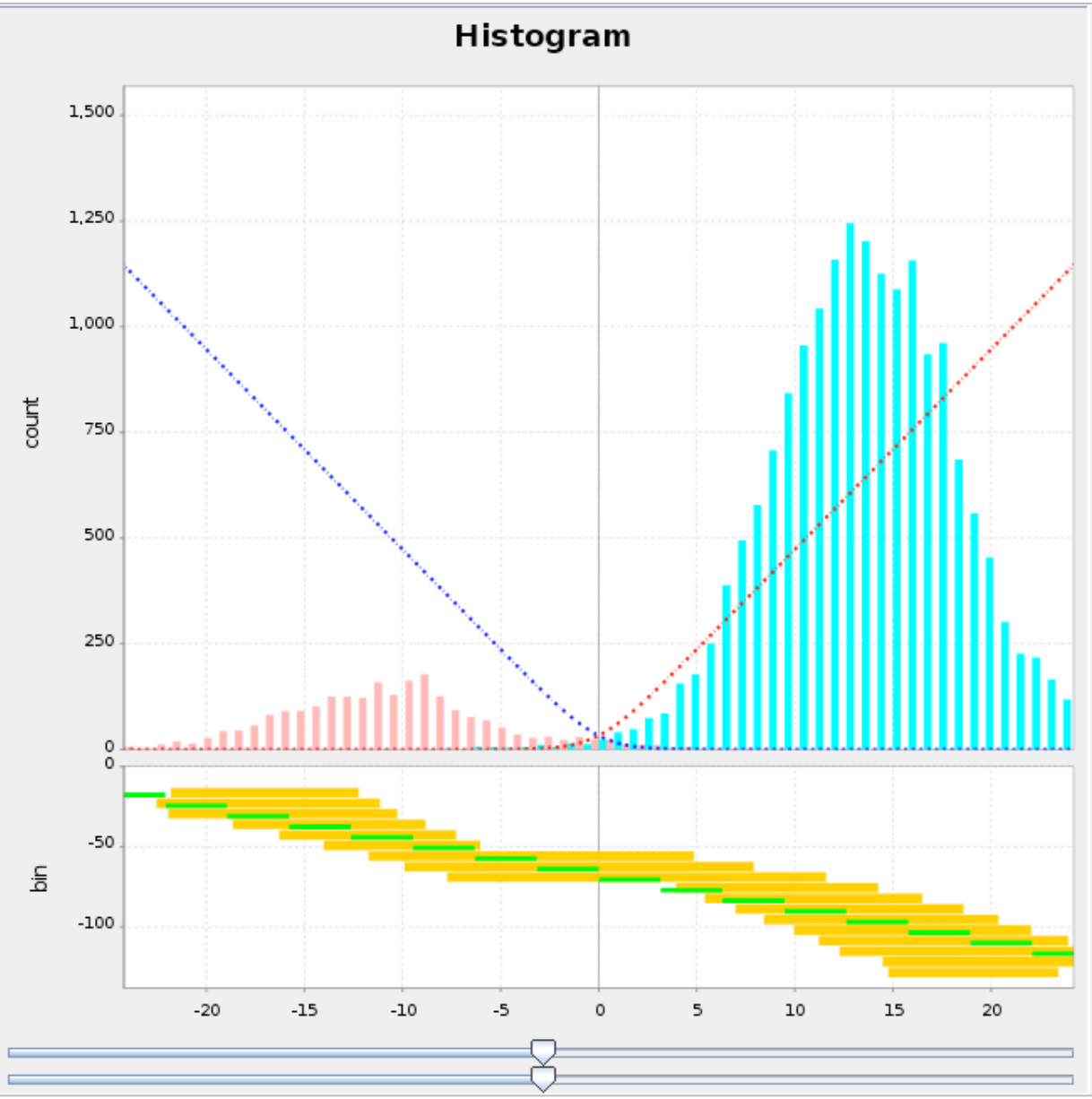
Logitboost
0% Noise


ROC
True positive rate
False positive rate
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.00
0.25
0.50
0.75
1.00
Histogram
count
bin
13,000
12,000
11,000
10,000
9,000
8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
-25
-50
-75
-1.0 -0.9 -0.8 -0.7 -0.6 -0.5 -0.4 -0.3 -0.2 -0.1 0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200


ROC
True positive rate
False positive rate
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.00
0.25
0.50
0.75
1.00
Histogram
count
2,000
1,750
1,500
1,250
1,000
750
500
250
0
bin
0
-50
-100
-4.5
-4.0
-3.5
-3.0
-2.5
-2.0
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200

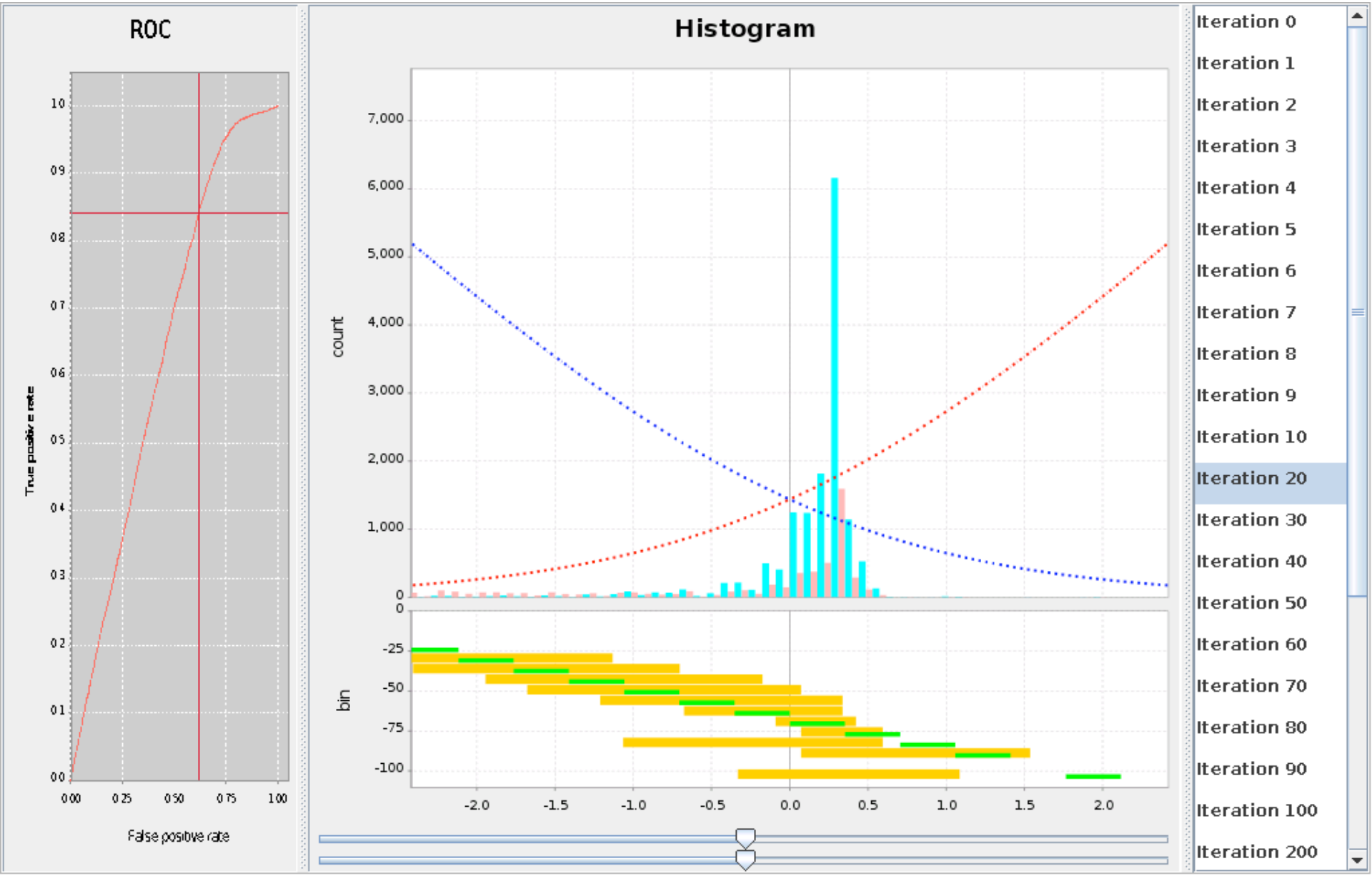

ROC
True positive rate
False positive rate
0.00
0.25
0.50
0.75
1.00
Histogram
count
bin
1,300
1,200
1,100
1,000
900
800
700
600
500
400
300
200
100
0
-50
-100
-15.0
-12.5
-10.0
-7.5
-5.0
-2.5
0.0
2.5
5.0
7.5
10.0
12.5
15.0
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200

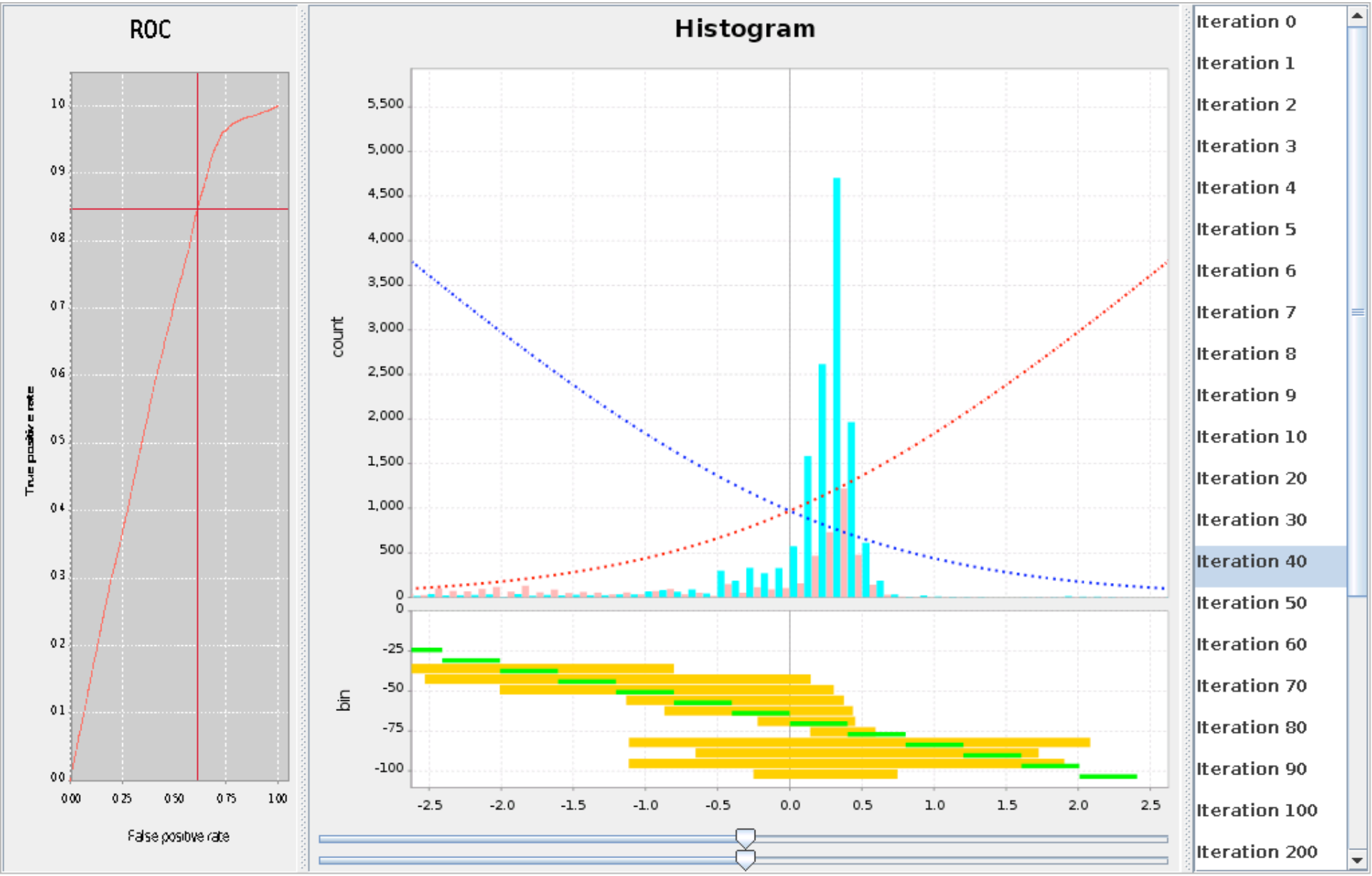


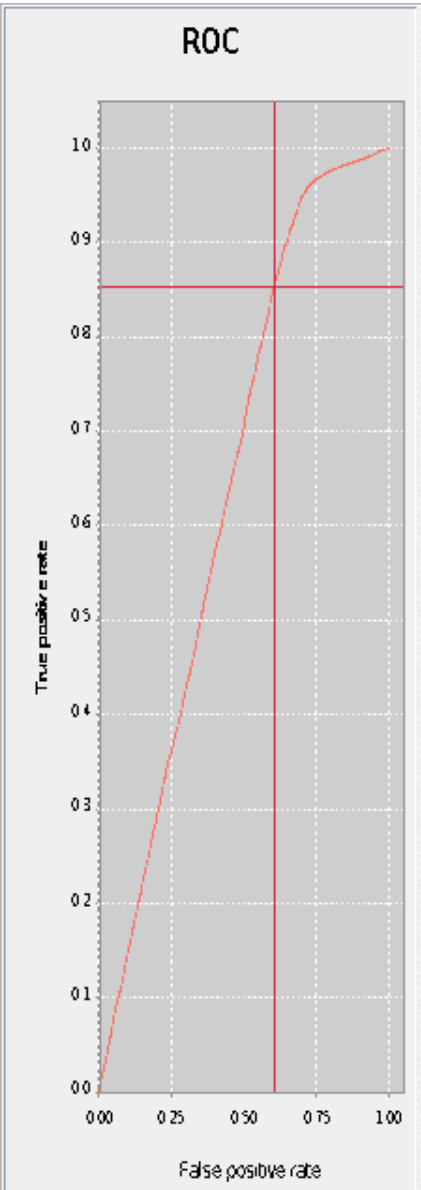


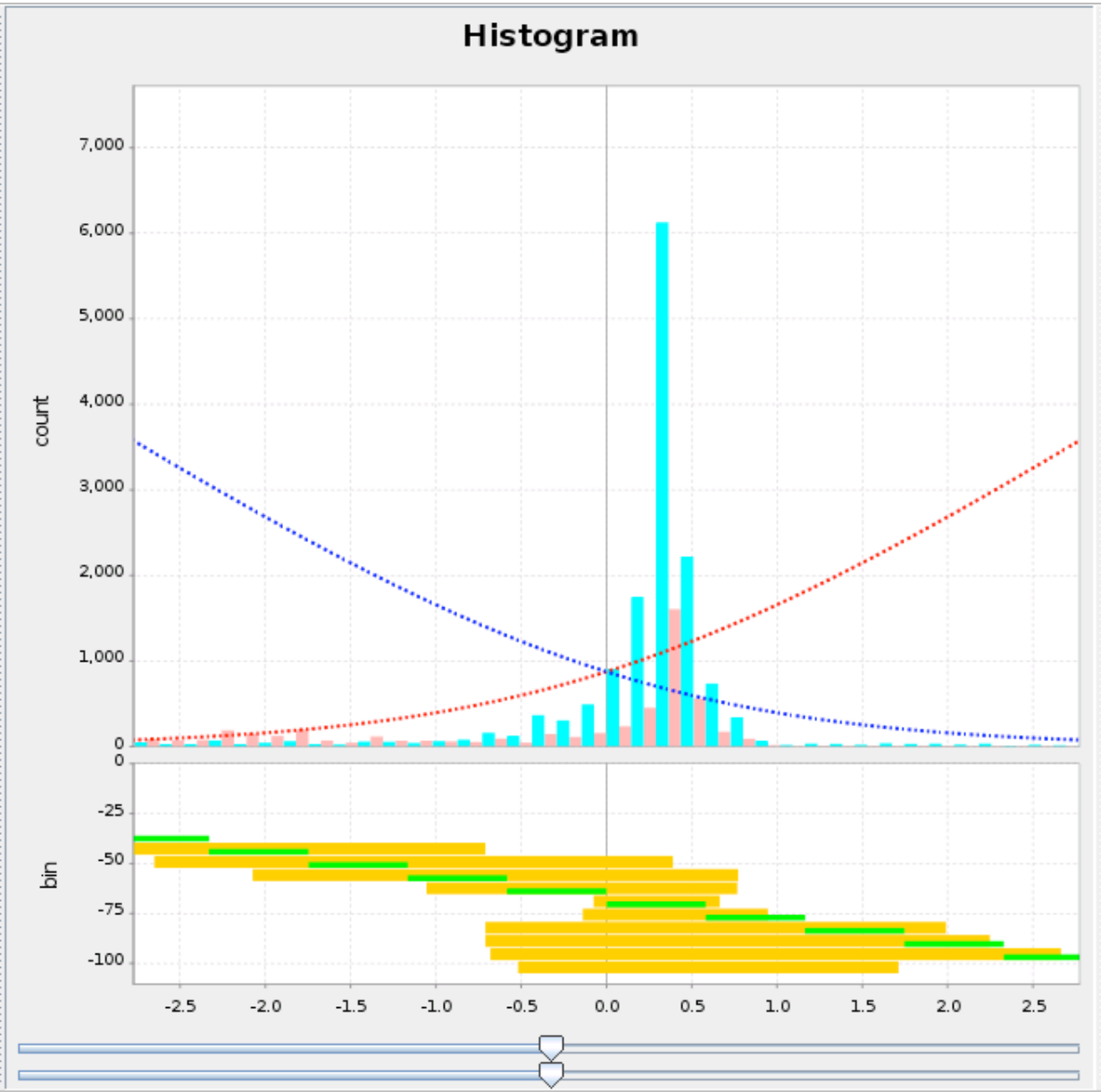
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200
Iteration 300
Iteration 400
Iteration 500
Iteration 600
Iteration 700
Iteration 800
Iteration 900
Iteration 1000
Iteration 2000

Logitboost
20% Noise

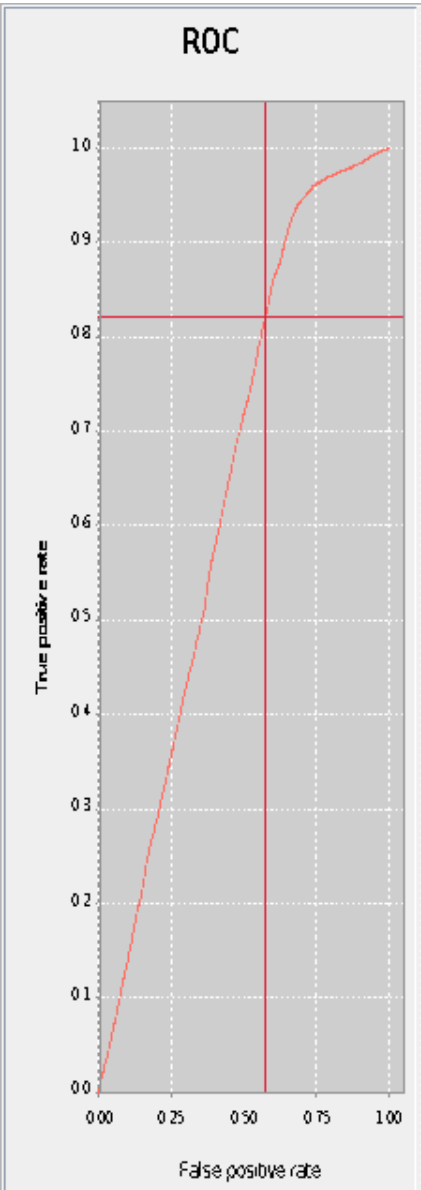

ROC
True positive rate
False positive rate
Histogram
count
bin
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200

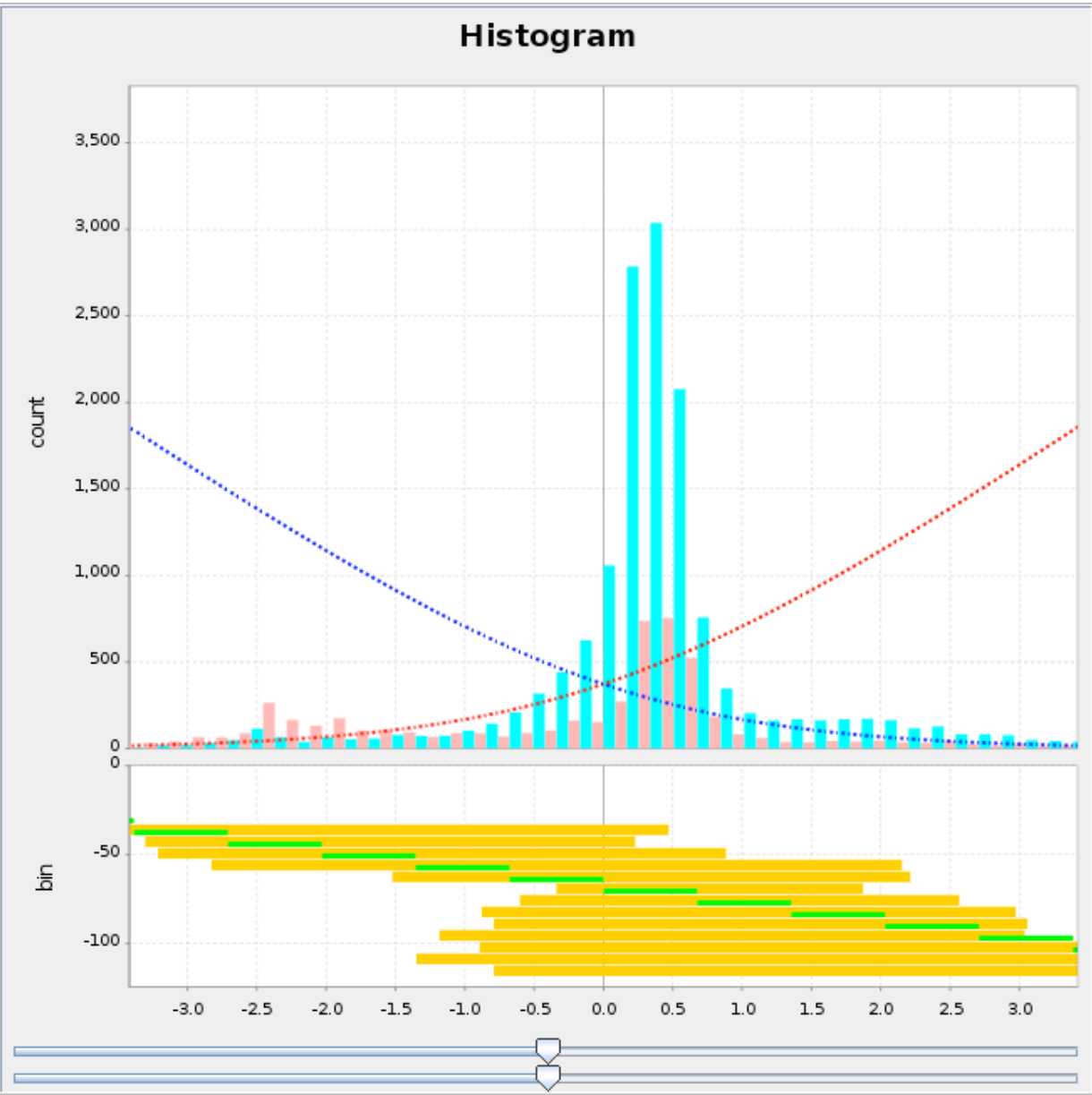

ROC
True positive rate
False positive rate
Histogram
count
bin
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200



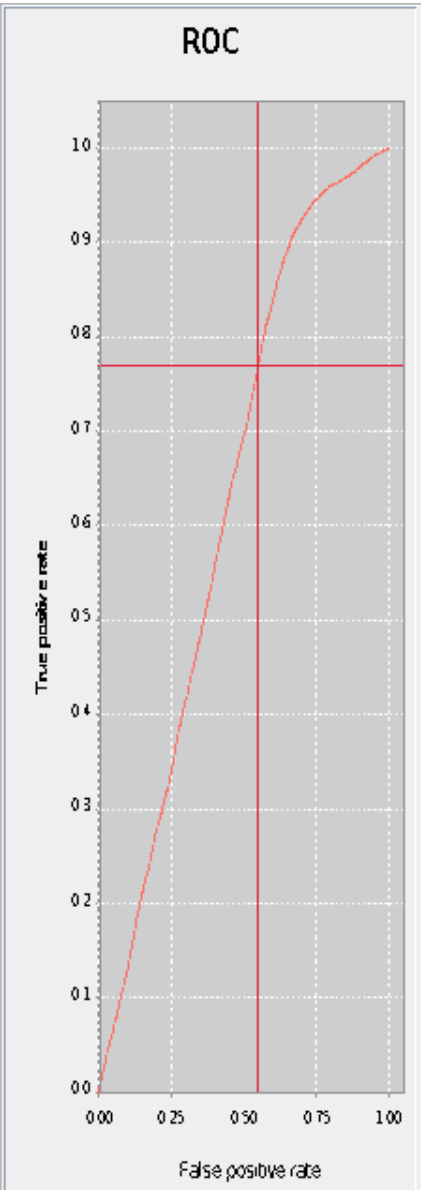


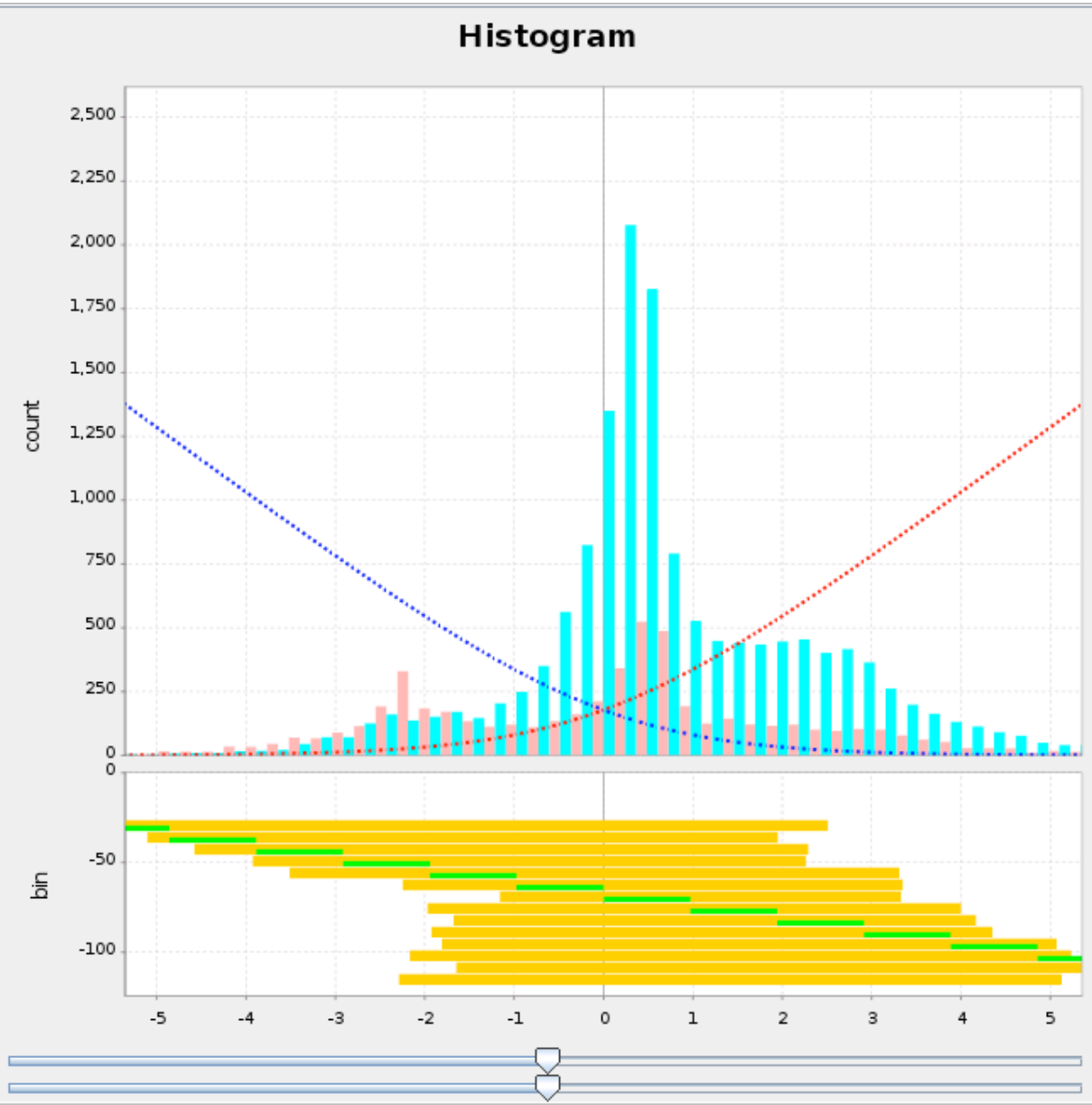
Iteration 0
Iteration 1
Iteration 2
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200

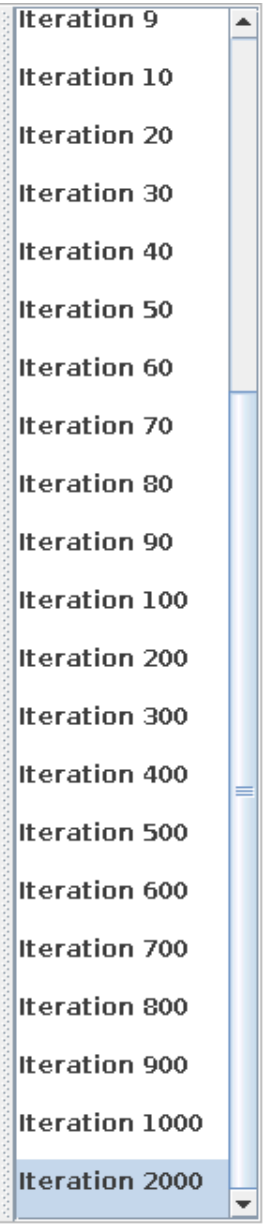




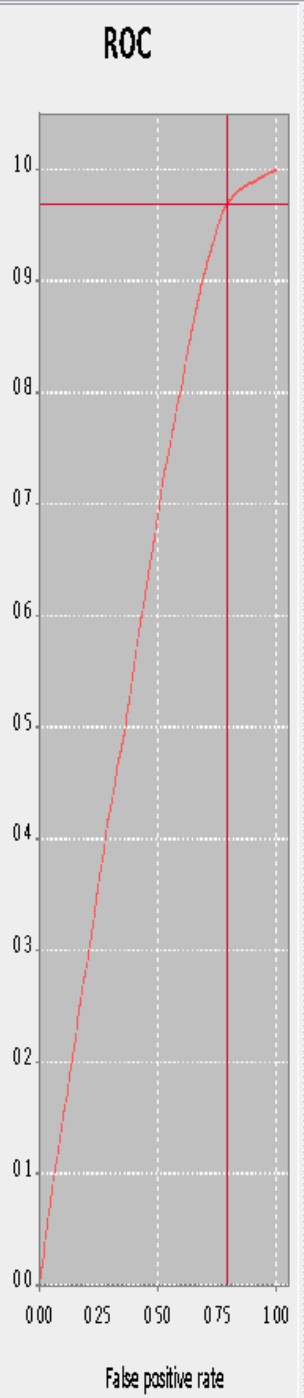
Iteration 3
Iteration 4
Iteration 5
Iteration 6
Iteration 7
Iteration 8
Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200
Iteration 300
Iteration 400
Iteration 500

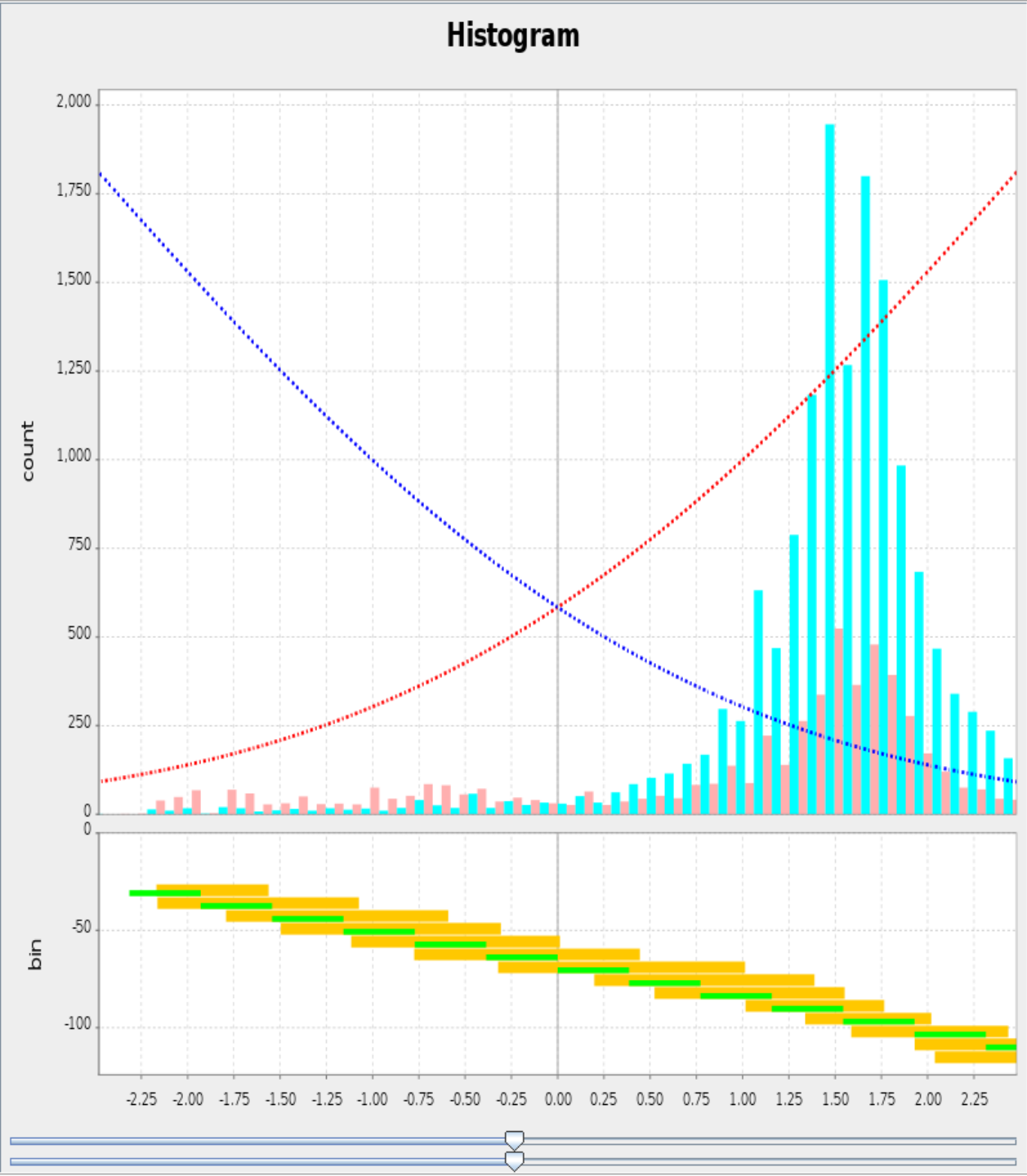

ROC
True positive rate
False positive rate
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.00
0.25
0.50
0.75
1.00


Histogram
count
bin
2,500
2,250
2,000
1,750
1,500
1,250
1,000
750
500
250
0
-50
-100
-5
-4
-3
-2
-1
0
1
2
3
4
5

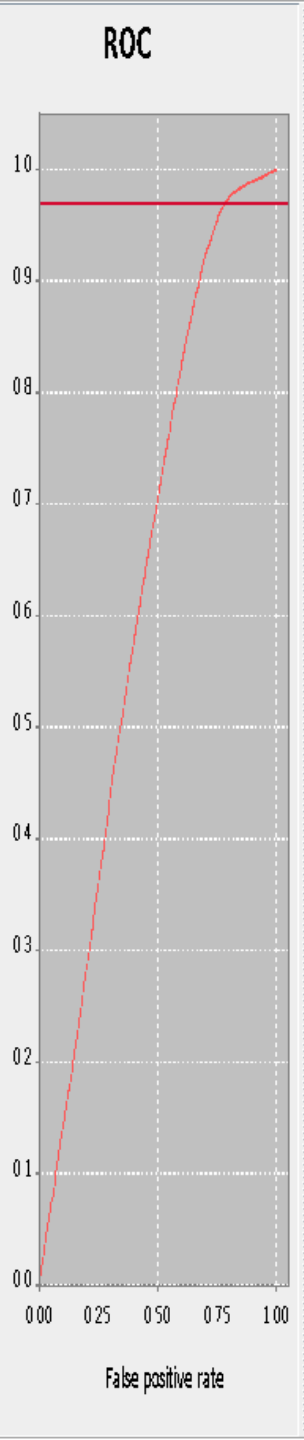

Iteration 9
Iteration 10
Iteration 20
Iteration 30
Iteration 40
Iteration 50
Iteration 60
Iteration 70
Iteration 80
Iteration 90
Iteration 100
Iteration 200
Iteration 300
Iteration 400
Iteration 500
Iteration 600
Iteration 700
Iteration 800
Iteration 900
Iteration 1000
Iteration 2000

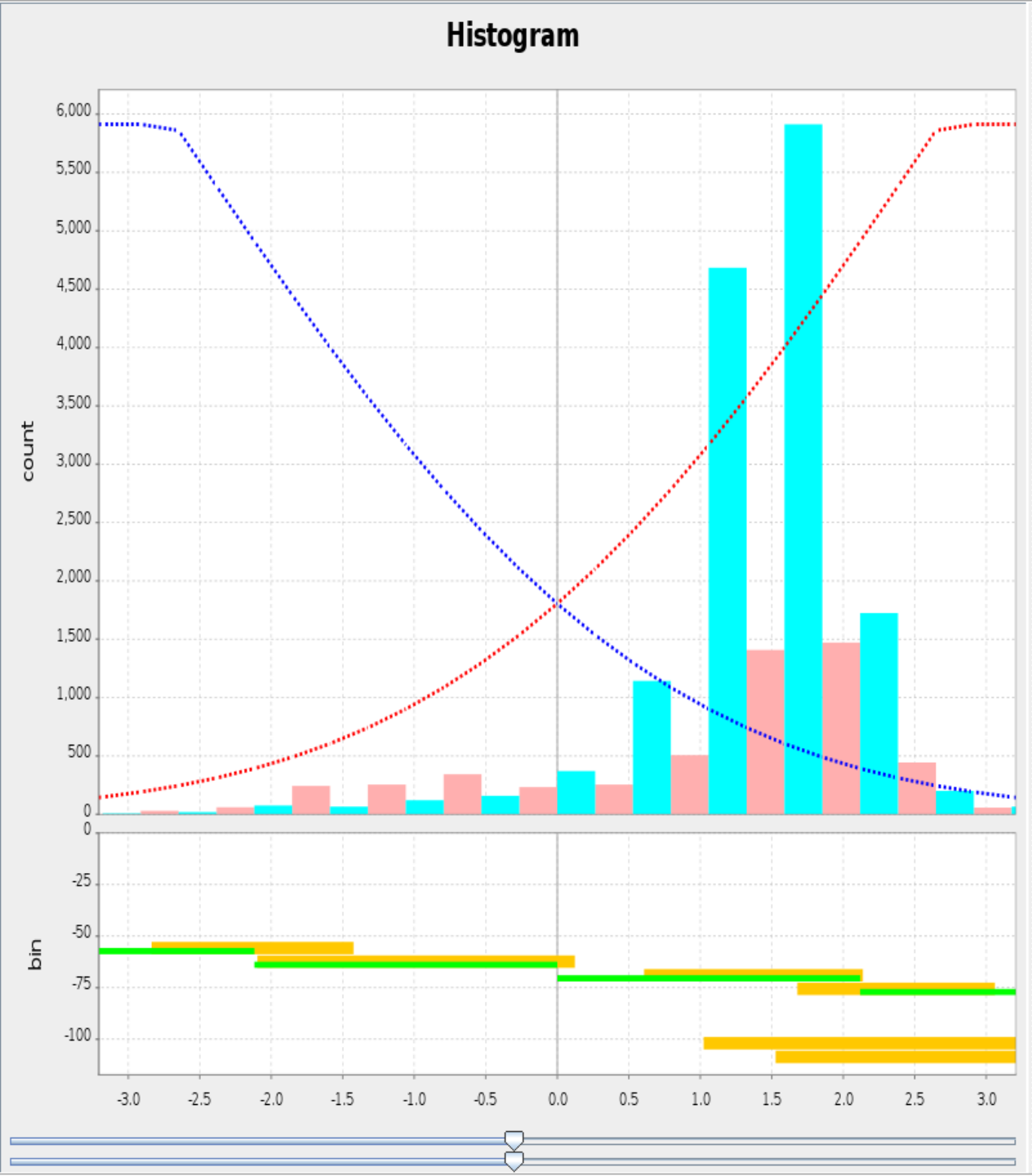
Robustboost
20% Noise



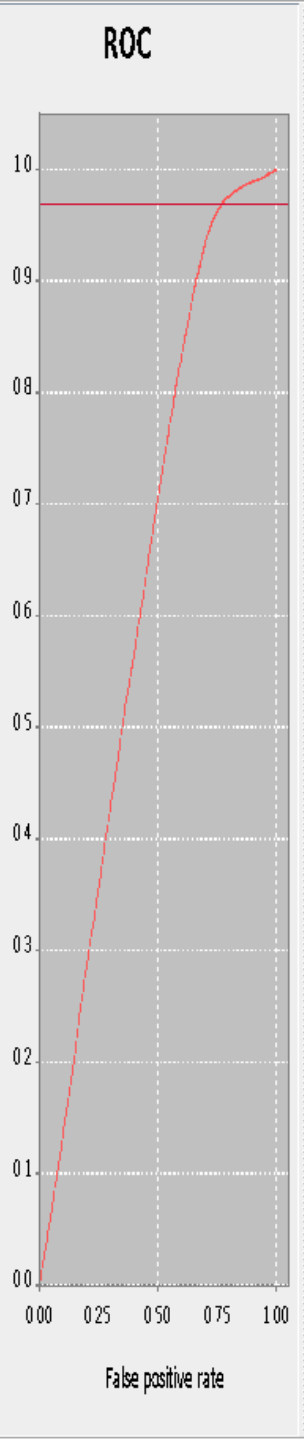


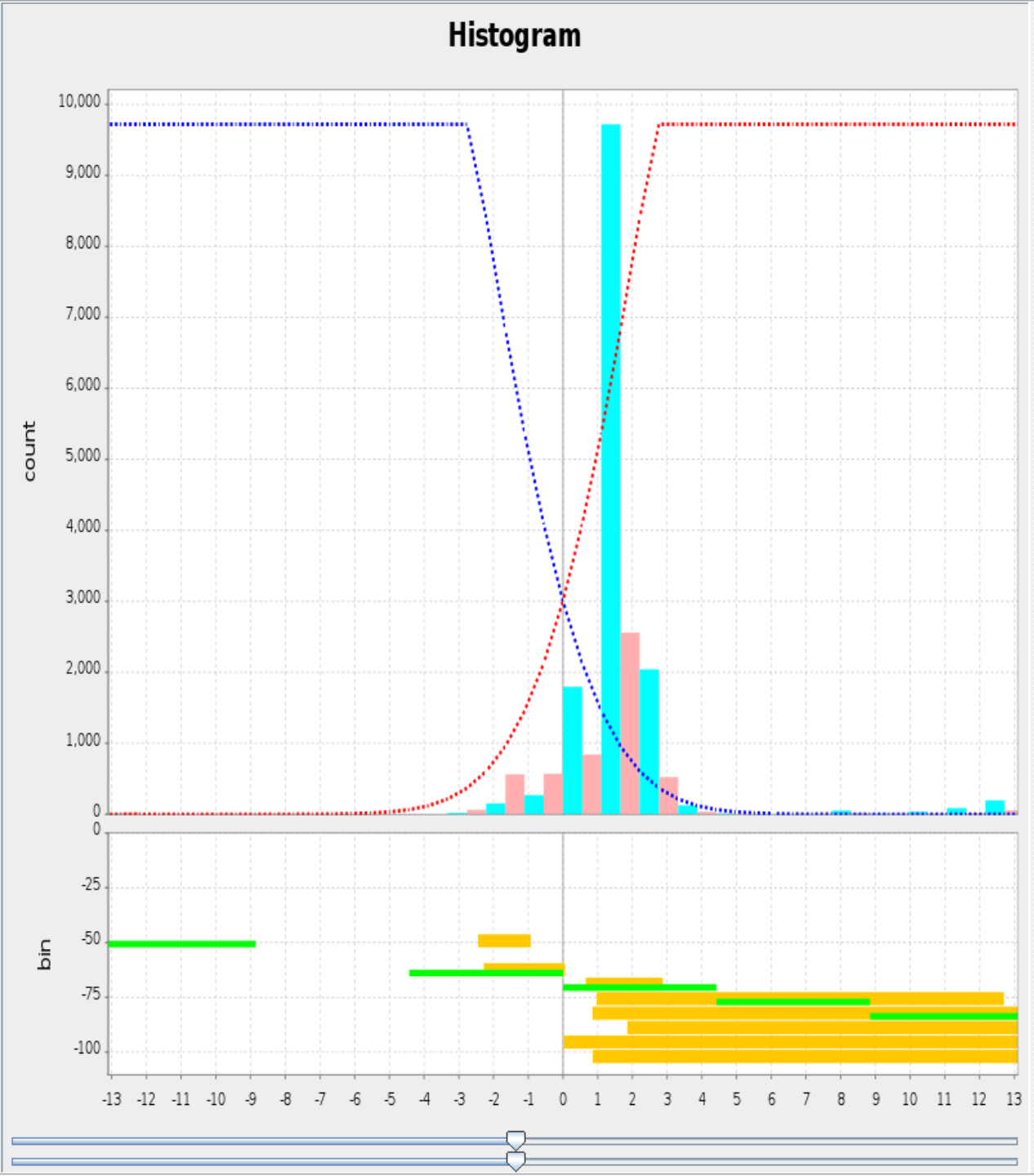
Iteration 0 [T=0.003+/-0.000]
Iteration 1 [T=0.003+/-0.000]
Iteration 2 [T=0.004+/-0.000]
Iteration 3 [T=0.004+/-0.000]
Iteration 4 [T=0.004+/-0.000]
Iteration 5 [T=0.004+/-0.000]
Iteration 6 [T=0.004+/-0.000]
Iteration 7 [T=0.004+/-0.000]
Iteration 8 [T=0.004+/-0.000]
Iteration 9 [T=0.004+/-0.000]
Iteration 10 [T=0.004+/-0.000]
Iteration 11 [T=0.004+/-0.000]
Iteration 12 [T=0.004+/-0.000]
Iteration 13 [T=0.004+/-0.000]
Iteration 14 [T=0.004+/-0.000]
Iteration 15 [T=0.004+/-0.000]
Iteration 16 [T=0.004+/-0.000]
Iteration 17 [T=0.004+/-0.000]
Iteration 18 [T=0.004+/-0.000]
Iteration 19 [T=0.004+/-0.000]
Iteration 20 [T=0.004+/-0.000]
Iteration 21 [T=0.004+/-0.000]
Iteration 22 [T=0.004+/-0.000]
Iteration 23 [T=0.004+/-0.000]
Iteration 24 [T=0.004+/-0.000]
Iteration 25 [T=0.004+/-0.000]
Iteration 26 [T=0.004+/-0.000]
Iteration 27 [T=0.004+/-0.000]
Iteration 28 [T=0.004+/-0.000]



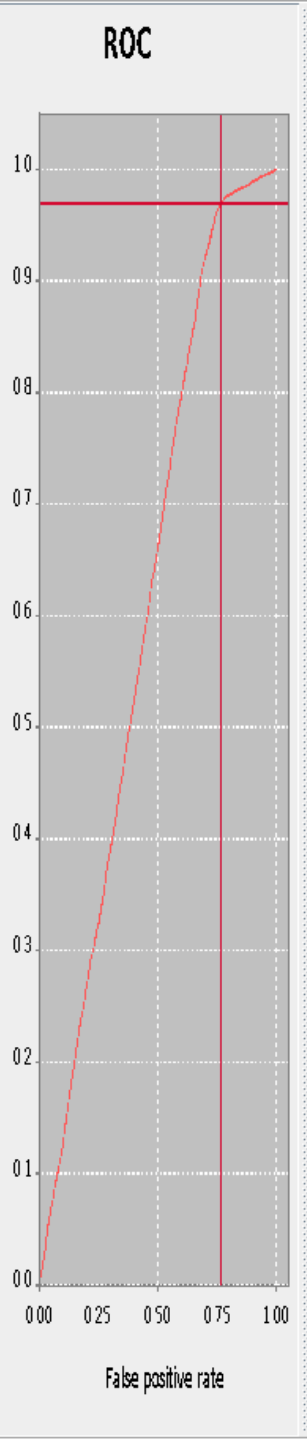


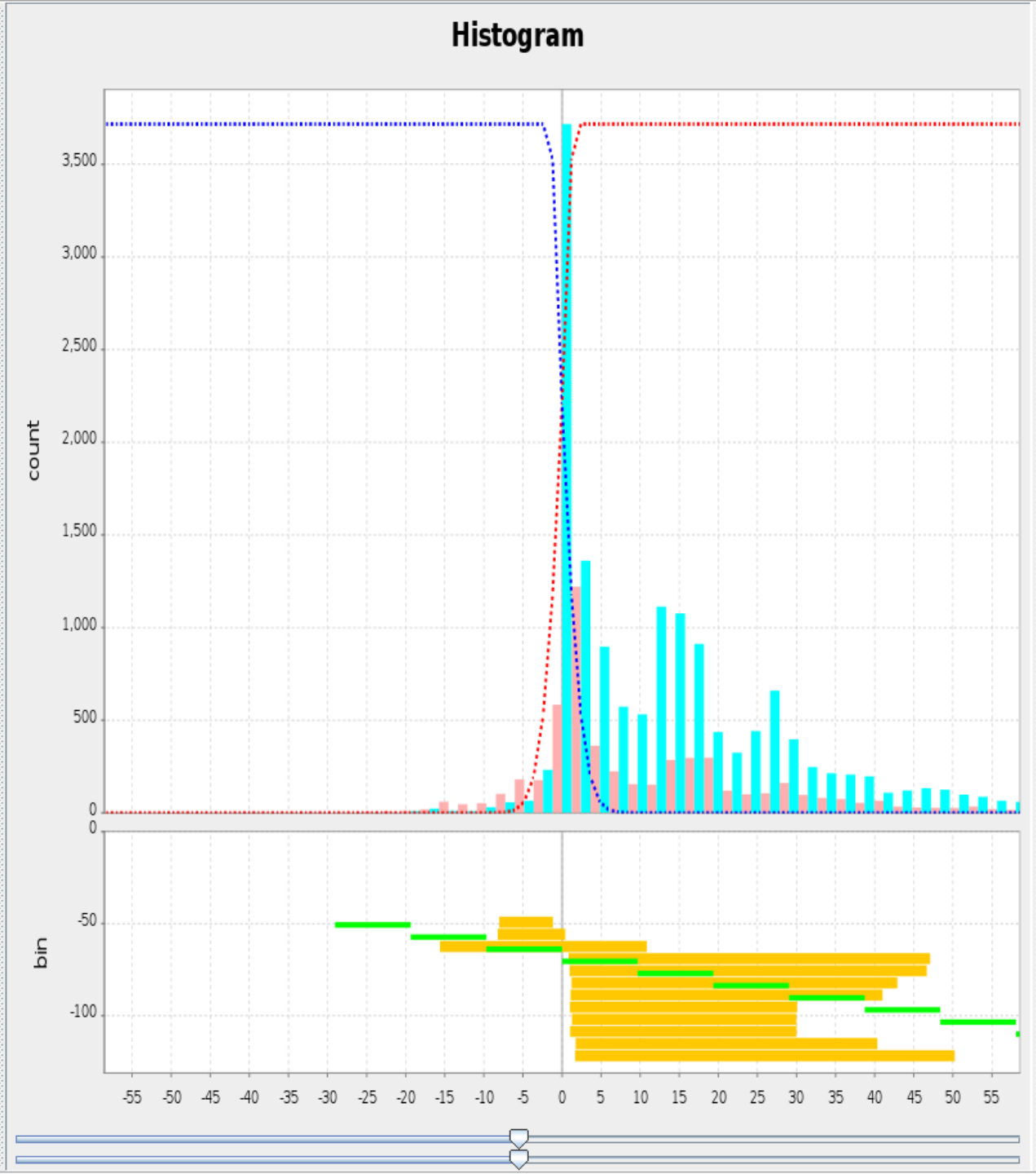
Iteration 21 [T=0.004+/-0.000]
Iteration 22 [T=0.004+/-0.000]
Iteration 23 [T=0.004+/-0.000]
Iteration 24 [T=0.004+/-0.000]
Iteration 25 [T=0.004+/-0.000]
Iteration 26 [T=0.004+/-0.000]
Iteration 27 [T=0.004+/-0.000]
Iteration 28 [T=0.004+/-0.000]
Iteration 29 [T=0.004+/-0.000]
Iteration 30 [T=0.004+/-0.000]
Iteration 31 [T=0.004+/-0.000]
Iteration 32 [T=0.004+/-0.000]
Iteration 33 [T=0.004+/-0.000]
Iteration 34 [T=0.004+/-0.000]
Iteration 35 [T=0.004+/-0.000]
Iteration 36 [T=0.004+/-0.000]
Iteration 37 [T=0.004+/-0.000]
Iteration 38 [T=0.004+/-0.000]
Iteration 39 [T=0.004+/-0.000]
Iteration 40 [T=0.004+/-0.000]
Iteration 41 [T=0.004+/-0.000]
Iteration 42 [T=0.004+/-0.000]
Iteration 43 [T=0.004+/-0.000]
Iteration 44 [T=0.004+/-0.000]
Iteration 45 [T=0.004+/-0.000]
Iteration 46 [T=0.004+/-0.000]
Iteration 47 [T=0.004+/-0.000]
Iteration 48 [T=0.004+/-0.000]
Iteration 49 [T=0.004+/-0.000]



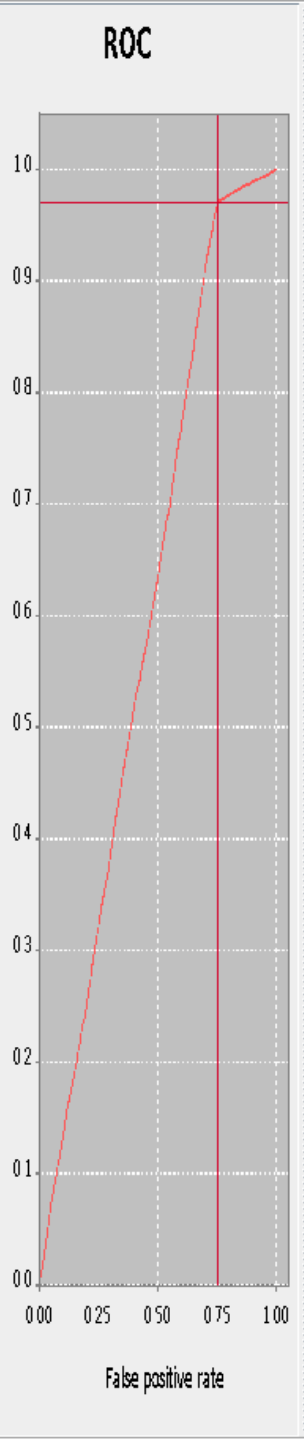


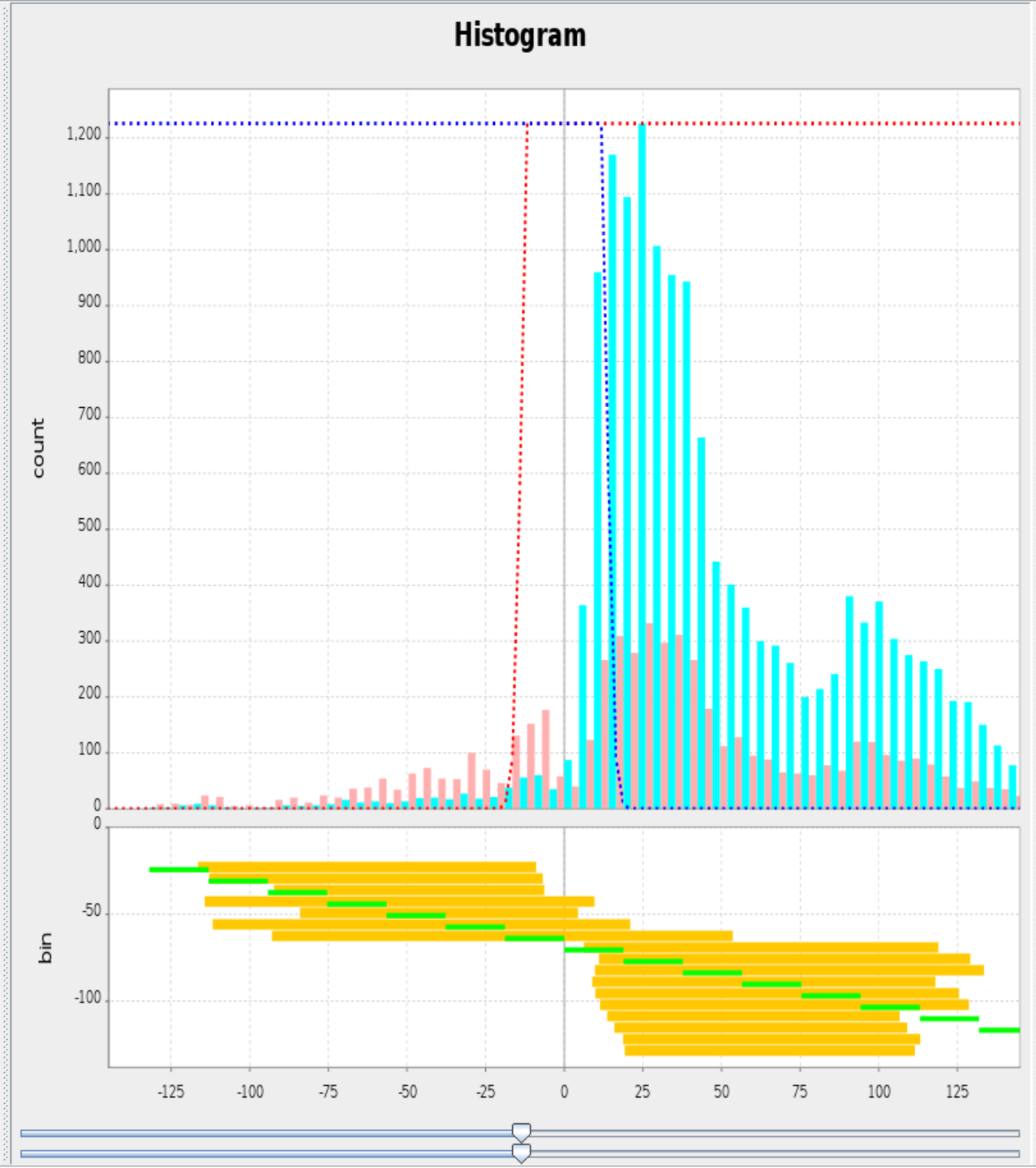
Iteration 72 [T=0.005+/-0.000]
Iteration 73 [T=0.005+/-0.000]
Iteration 74 [T=0.005+/-0.000]
Iteration 75 [T=0.005+/-0.000]
Iteration 76 [T=0.005+/-0.000]
Iteration 77 [T=0.005+/-0.000]
Iteration 78 [T=0.005+/-0.000]
Iteration 79 [T=0.005+/-0.000]
Iteration 80 [T=0.005+/-0.000]
Iteration 81 [T=0.005+/-0.000]
Iteration 82 [T=0.005+/-0.000]
Iteration 83 [T=0.005+/-0.000]
Iteration 84 [T=0.005+/-0.000]
Iteration 85 [T=0.005+/-0.000]
Iteration 86 [T=0.005+/-0.000]
Iteration 87 [T=0.005+/-0.000]
Iteration 88 [T=0.005+/-0.000]
Iteration 89 [T=0.005+/-0.000]
Iteration 90 [T=0.005+/-0.000]
Iteration 91 [T=0.005+/-0.000]
Iteration 92 [T=0.005+/-0.000]
Iteration 93 [T=0.005+/-0.000]
Iteration 94 [T=0.005+/-0.000]
Iteration 95 [T=0.005+/-0.000]
Iteration 96 [T=0.005+/-0.000]
Iteration 97 [T=0.005+/-0.000]
Iteration 98 [T=0.005+/-0.000]
Iteration 99 [T=0.005+/-0.000]
Iteration 100 [T=0.005+/-0.000



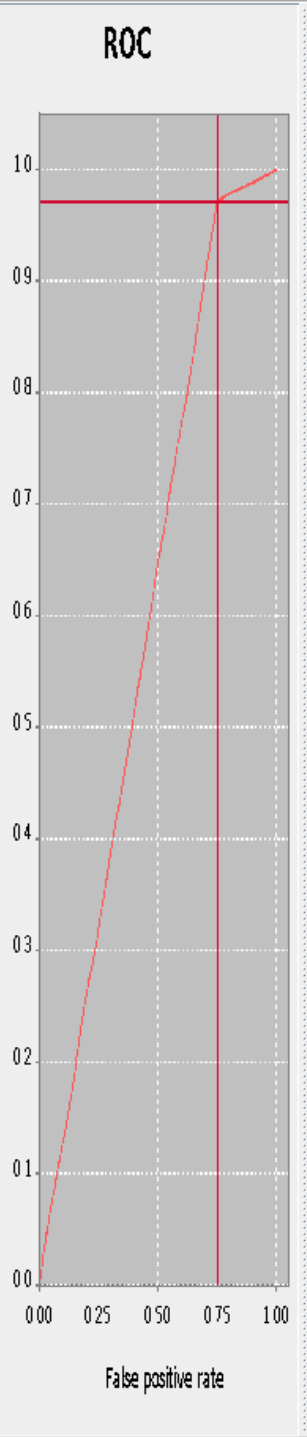


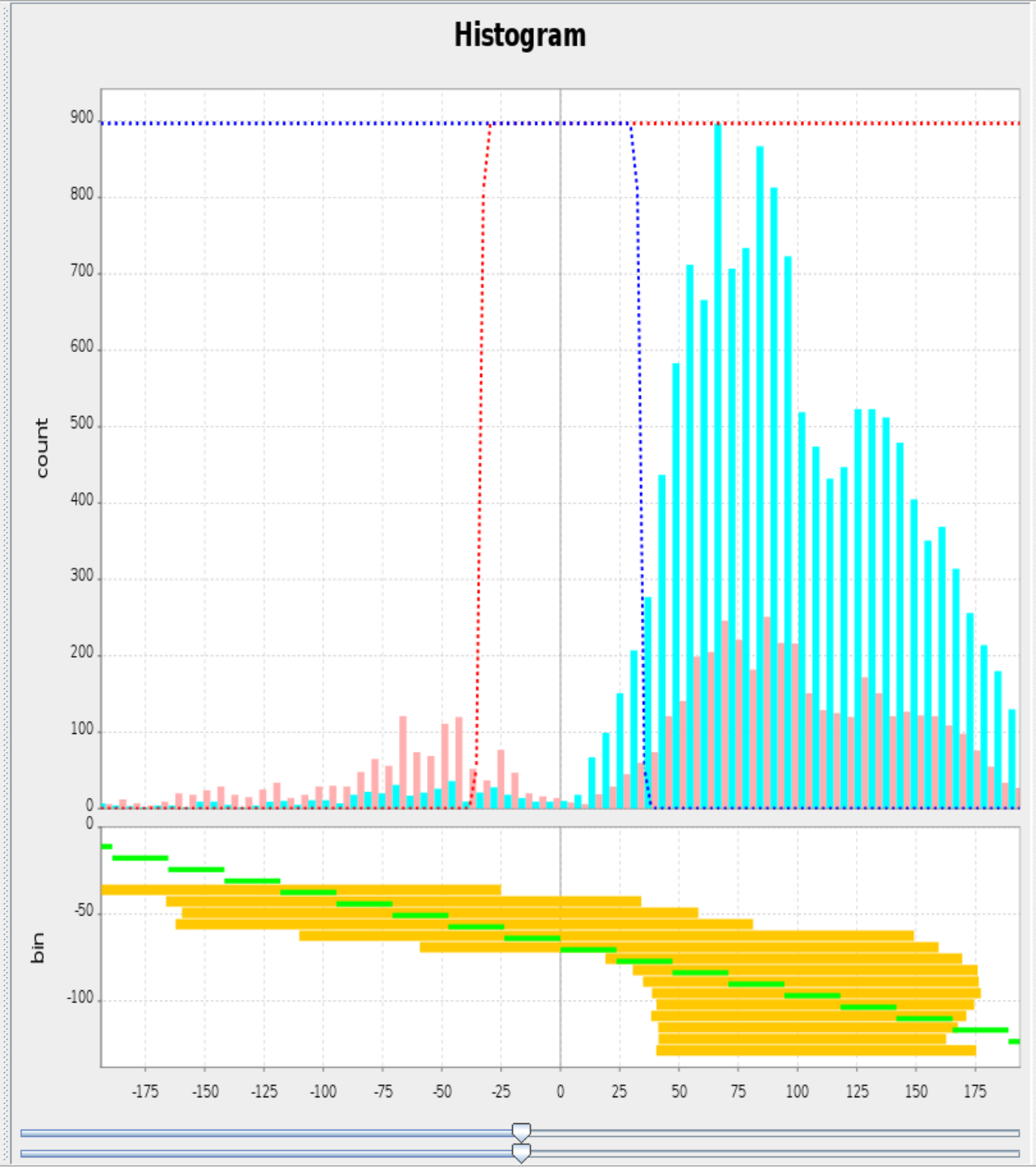
Iteration 172 [T=0.006+/-0.002
Iteration 173 [T=0.006+/-0.002
Iteration 174 [T=0.006+/-0.003
Iteration 175 [T=0.007+/-0.003
Iteration 176 [T=0.007+/-0.003
Iteration 177 [T=0.007+/-0.003
Iteration 178 [T=0.007+/-0.004
Iteration 179 [T=0.007+/-0.004
Iteration 180 [T=0.007+/-0.004
Iteration 181 [T=0.008+/-0.004
Iteration 182 [T=0.008+/-0.004
Iteration 183 [T=0.008+/-0.004
Iteration 184 [T=0.008+/-0.005
Iteration 185 [T=0.008+/-0.005
Iteration 186 [T=0.009+/-0.005
Iteration 187 [T=0.009+/-0.005
Iteration 188 [T=0.009+/-0.006
Iteration 189 [T=0.010+/-0.007
Iteration 190 [T=0.011+/-0.008
Iteration 191 [T=0.011+/-0.009
Iteration 192 [T=0.012+/-0.010
Iteration 193 [T=0.012+/-0.011
Iteration 194 [T=0.012+/-0.012
Iteration 195 [T=0.013+/-0.012
Iteration 196 [T=0.014+/-0.014
Iteration 197 [T=0.015+/-0.015
Iteration 198 [T=0.016+/-0.016
Iteration 199 [T=0.016+/-0.017
Iteration 200 [T=0.017+/-0.018



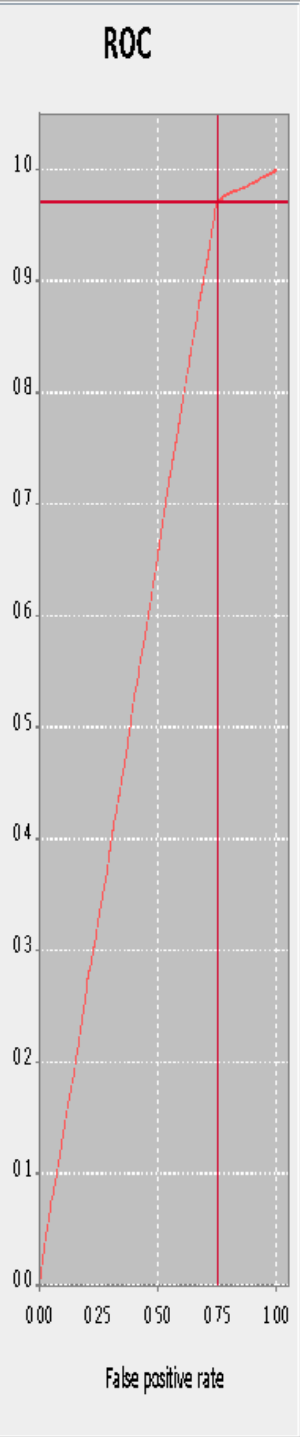


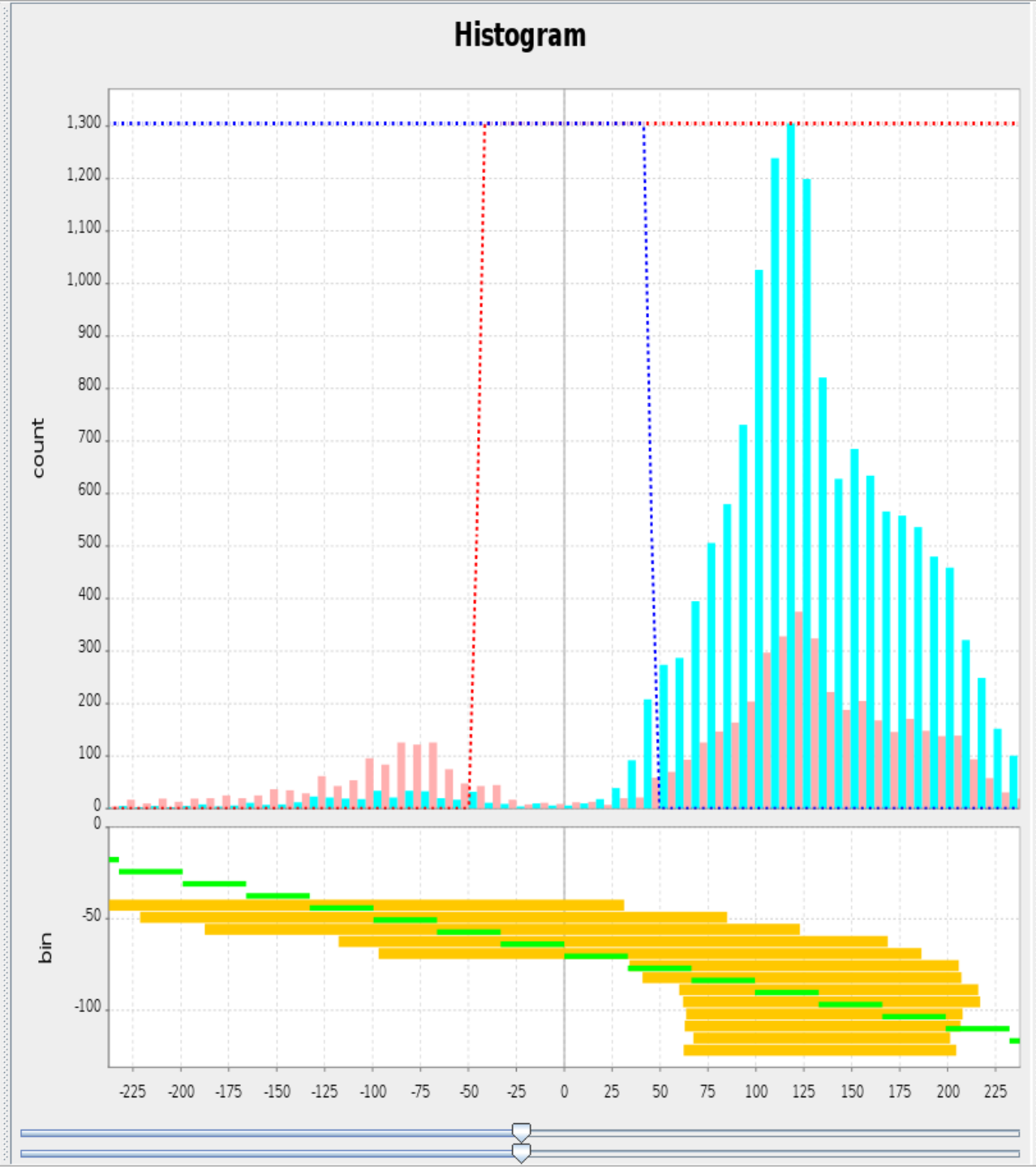
Iteration 222 [T=0.060+/-0.082]
Iteration 223 [T=0.062+/-0.083]
Iteration 224 [T=0.066+/-0.088]
Iteration 225 [T=0.067+/-0.090]
Iteration 226 [T=0.070+/-0.092]
Iteration 227 [T=0.073+/-0.096]
Iteration 228 [T=0.078+/-0.098]
Iteration 229 [T=0.080+/-0.099]
Iteration 230 [T=0.082+/-0.100]
Iteration 231 [T=0.086+/-0.102]
Iteration 232 [T=0.089+/-0.103]
Iteration 233 [T=0.092+/-0.105]
Iteration 234 [T=0.096+/-0.106]
Iteration 235 [T=0.098+/-0.107]
Iteration 236 [T=0.100+/-0.108]
Iteration 237 [T=0.103+/-0.109]
Iteration 238 [T=0.106+/-0.112]
Iteration 239 [T=0.109+/-0.112]
Iteration 240 [T=0.114+/-0.113]
Iteration 241 [T=0.117+/-0.115]
Iteration 242 [T=0.124+/-0.117]
Iteration 243 [T=0.128+/-0.119]
Iteration 244 [T=0.132+/-0.123]
Iteration 245 [T=0.139+/-0.126]
Iteration 246 [T=0.143+/-0.128]
Iteration 247 [T=0.147+/-0.130]
Iteration 248 [T=0.152+/-0.131]
Iteration 249 [T=0.157+/-0.134]
Iteration 250 [T=0.160+/-0.135]



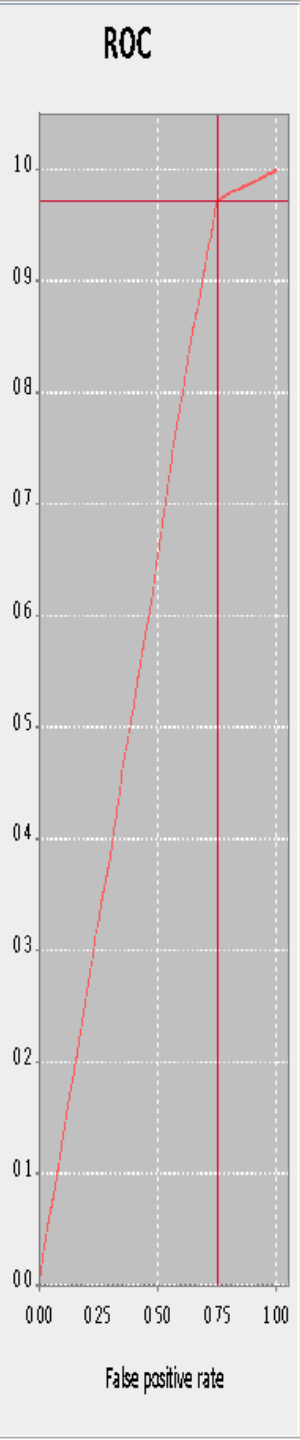


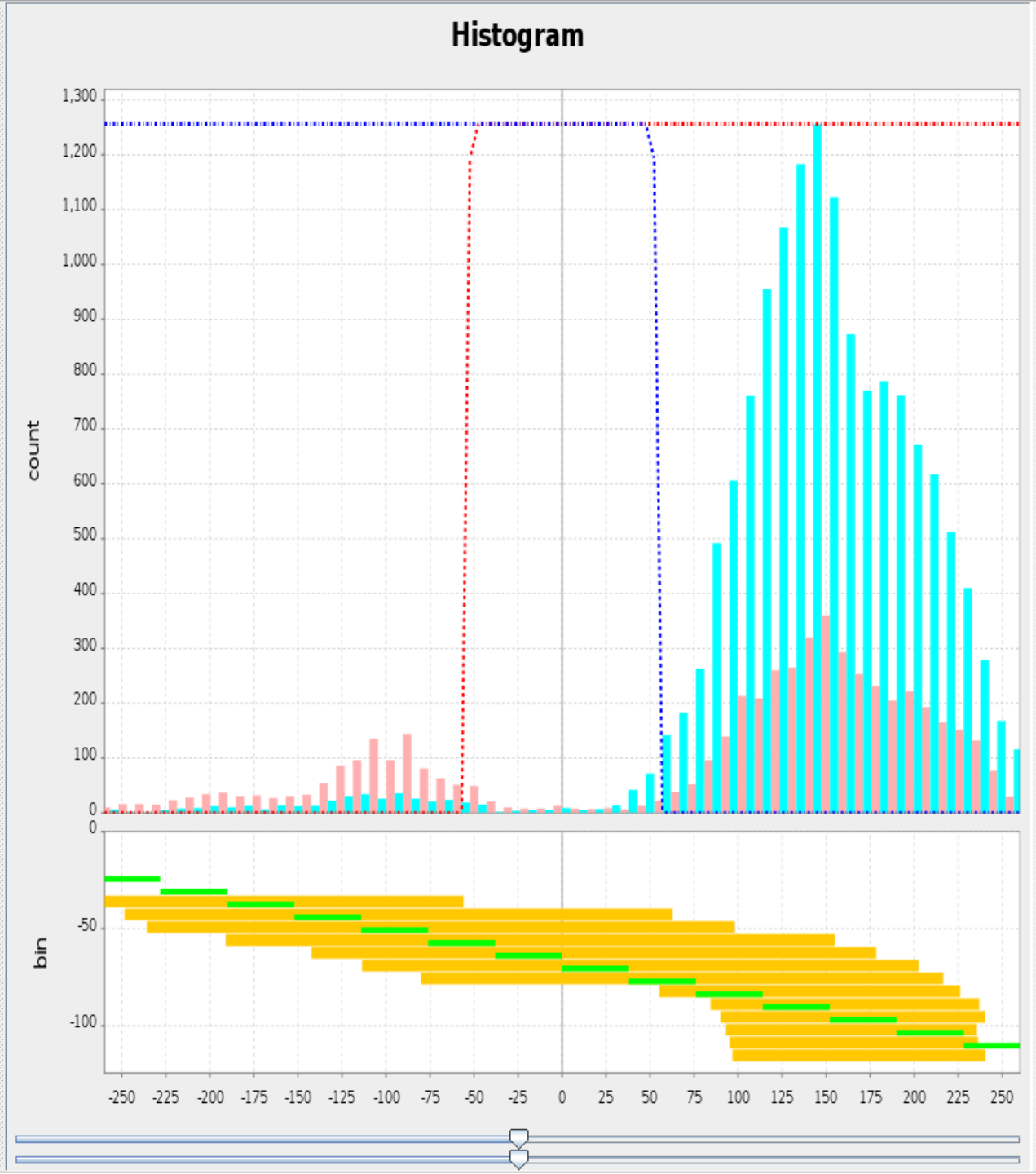
Iteration 272 [T=0.272+/-0.159
Iteration 273 [T=0.275+/-0.157
Iteration 274 [T=0.282+/-0.161
Iteration 275 [T=0.286+/-0.161
Iteration 276 [T=0.291+/-0.162
Iteration 277 [T=0.294+/-0.163
Iteration 278 [T=0.300+/-0.163
Iteration 279 [T=0.305+/-0.164
Iteration 280 [T=0.311+/-0.165
Iteration 281 [T=0.318+/-0.165
Iteration 282 [T=0.324+/-0.165
Iteration 283 [T=0.328+/-0.166
Iteration 284 [T=0.333+/-0.166
Iteration 285 [T=0.340+/-0.164
Iteration 286 [T=0.344+/-0.165
Iteration 287 [T=0.347+/-0.166
Iteration 288 [T=0.353+/-0.163
Iteration 289 [T=0.359+/-0.165
Iteration 290 [T=0.363+/-0.164
Iteration 291 [T=0.367+/-0.164
Iteration 292 [T=0.371+/-0.165
Iteration 293 [T=0.375+/-0.165
Iteration 294 [T=0.379+/-0.164
Iteration 295 [T=0.382+/-0.165
Iteration 296 [T=0.385+/-0.165
Iteration 297 [T=0.390+/-0.165
Iteration 298 [T=0.396+/-0.165
Iteration 299 [T=0.400+/-0.165
Iteration 300 [T=0.406+/-0.164



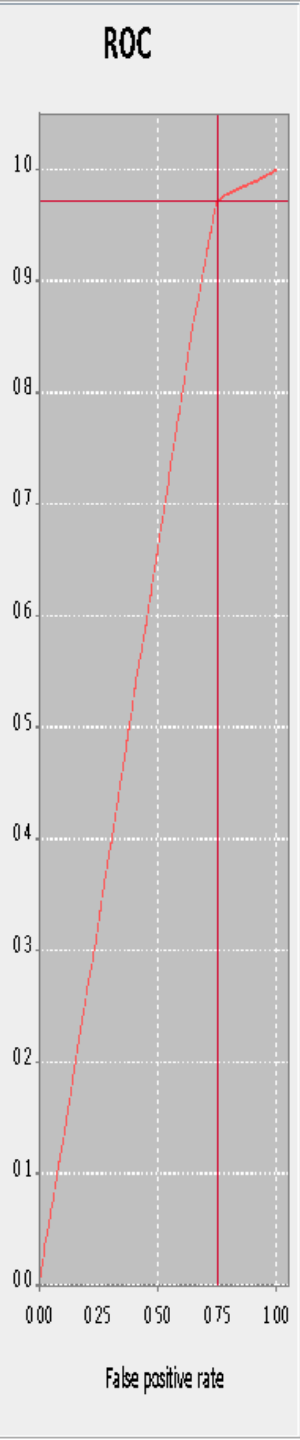


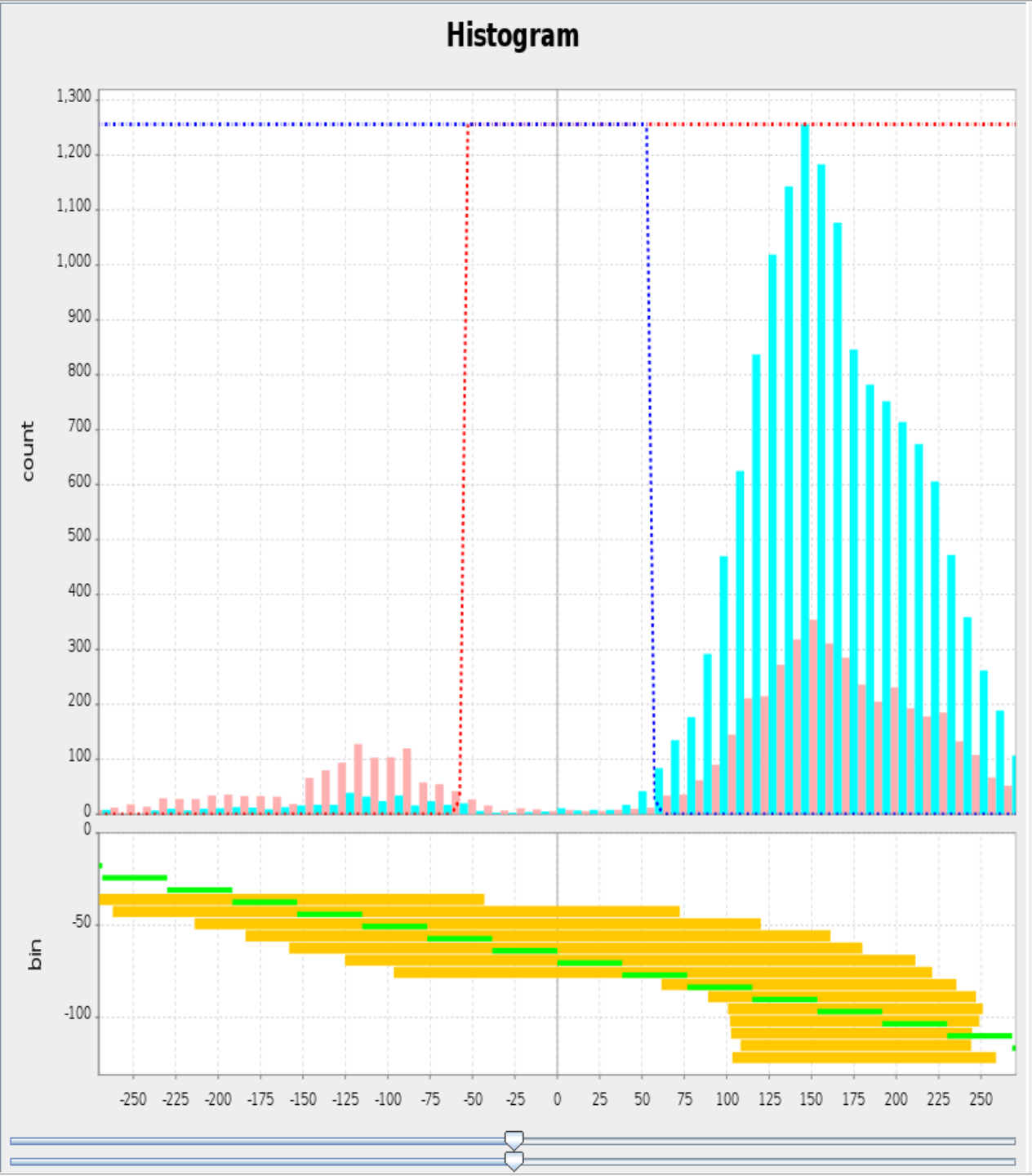
Iteration 322 [T=0.499+/-0.166]
Iteration 323 [T=0.502+/-0.166]
Iteration 324 [T=0.505+/-0.166]
Iteration 325 [T=0.508+/-0.166]
Iteration 326 [T=0.513+/-0.168]
Iteration 327 [T=0.518+/-0.169]
Iteration 328 [T=0.520+/-0.169]
Iteration 329 [T=0.525+/-0.169]
Iteration 330 [T=0.527+/-0.169]
Iteration 331 [T=0.531+/-0.169]
Iteration 332 [T=0.535+/-0.172]
Iteration 333 [T=0.538+/-0.171]
Iteration 334 [T=0.540+/-0.172]
Iteration 335 [T=0.542+/-0.173]
Iteration 336 [T=0.545+/-0.173]
Iteration 337 [T=0.550+/-0.173]
Iteration 338 [T=0.553+/-0.173]
Iteration 339 [T=0.557+/-0.174]
Iteration 340 [T=0.561+/-0.175]
Iteration 341 [T=0.563+/-0.175]
Iteration 342 [T=0.567+/-0.177]
Iteration 343 [T=0.571+/-0.178]
Iteration 344 [T=0.575+/-0.179]
Iteration 345 [T=0.579+/-0.180]
Iteration 346 [T=0.582+/-0.181]
Iteration 347 [T=0.586+/-0.181]
Iteration 348 [T=0.589+/-0.181]
Iteration 349 [T=0.592+/-0.181]
Iteration 350 [T=0.596+/-0.182]





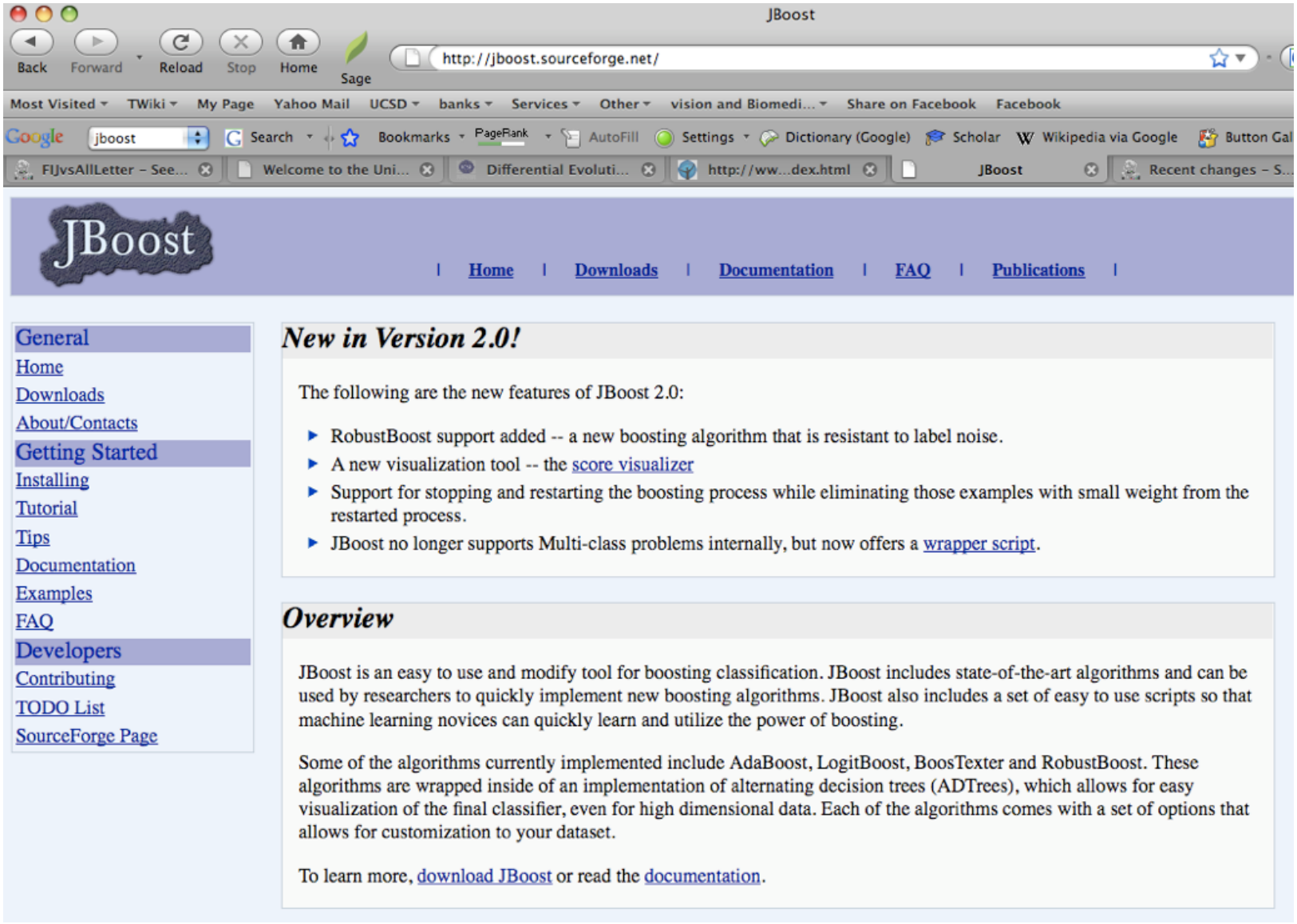
Iteration 372 [T=0.670+/-0.185
Iteration 373 [T=0.672+/-0.185
Iteration 374 [T=0.674+/-0.185
Iteration 375 [T=0.678+/-0.184
Iteration 376 [T=0.680+/-0.184
Iteration 377 [T=0.682+/-0.184
Iteration 378 [T=0.684+/-0.184
Iteration 379 [T=0.687+/-0.183
Iteration 380 [T=0.689+/-0.184
Iteration 381 [T=0.692+/-0.184
Iteration 382 [T=0.694+/-0.184
Iteration 383 [T=0.696+/-0.184
Iteration 384 [T=0.699+/-0.185
Iteration 385 [T=0.701+/-0.185
Iteration 386 [T=0.704+/-0.185
Iteration 387 [T=0.706+/-0.185
Iteration 388 [T=0.710+/-0.183
Iteration 389 [T=0.712+/-0.184
Iteration 390 [T=0.714+/-0.184
Iteration 391 [T=0.717+/-0.183
Iteration 392 [T=0.719+/-0.183
Iteration 393 [T=0.721+/-0.184
Iteration 394 [T=0.723+/-0.184
Iteration 395 [T=0.726+/-0.185
Iteration 396 [T=0.727+/-0.185
Iteration 397 [T=0.730+/-0.184
Iteration 398 [T=0.733+/-0.186
Iteration 399 [T=0.735+/-0.186
Iteration 400 [T=0.736+/-0.186





Iteration 403 [T=0.742+/-0.187
Iteration 404 [T=0.744+/-0.188
Iteration 405 [T=0.745+/-0.188
Iteration 406 [T=0.747+/-0.188
Iteration 407 [T=0.749+/-0.188
Iteration 408 [T=0.751+/-0.188
Iteration 409 [T=0.754+/-0.187
Iteration 410 [T=0.755+/-0.187
Iteration 411 [T=0.757+/-0.187
Iteration 412 [T=0.759+/-0.186
Iteration 413 [T=0.760+/-0.186
Iteration 414 [T=0.762+/-0.186
Iteration 415 [T=0.764+/-0.186
Iteration 416 [T=0.767+/-0.186
Iteration 417 [T=0.768+/-0.187
Iteration 418 [T=0.770+/-0.187
Iteration 419 [T=0.773+/-0.187
Iteration 420 [T=0.775+/-0.186
Iteration 421 [T=0.777+/-0.186
Iteration 422 [T=0.779+/-0.186
Iteration 423 [T=0.782+/-0.186
Iteration 424 [T=0.784+/-0.186
Iteration 425 [T=0.786+/-0.185
Iteration 426 [T=0.787+/-0.185
Iteration 427 [T=0.789+/-0.185
Iteration 428 [T=0.791+/-0.186
Iteration 429 [T=0.794+/-0.185
Iteration 430 [T=0.796+/-0.185
Iteration 431 [T=0.797+/-0.185

JBoost V2.0


JBoost
Back
Forward
Reload
Stop
Home
Sage
http://jboost.sourceforge.net/
Most Visited
TWiki
My Page
Yahoo Mail
UCSD
banks
Services
Other
vision and Biomedi...
Share on Facebook
Facebook
Google
jboost
Search
Bookmarks
PageRank
AutoFill
Settings
Dictionary (Google)
Scholar
Wikipedia via Google
Button Gal
FIJvsAllLetter – See...
Welcome to the Uni...
Differential Evoluti...
http://ww...dex.html
JBoost
Recent changes – S...
JBoost
Home
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Documentation
FAQ
Publications
General
Home
Downloads
About/Contacts
Getting Started
Installing
Tutorial
Tips
Documentation
Examples
FAQ
Developers
Contributing
TODO List
SourceForge Page
New in Version 2.0!
The following are the new features of JBoost 2.0:
RobustBoost support added -- a new boosting algorithm that is resistant to label noise.
A new visualization tool -- the score visualizer
Support for stopping and restarting the boosting process while eliminating those examples with small weight from the restarted process.
JBoost no longer supports Multi-class problems internally, but now offers a wrapper script.
Overview
JBoost is an easy to use and modify tool for boosting classification. JBoost includes state-of-the-art algorithms and can be used by researchers to quickly implement new boosting algorithms. JBoost also includes a set of easy to use scripts so that machine learning novices can quickly learn and utilize the power of boosting.
Some of the algorithms currently implemented include AdaBoost, LogitBoost, BoosTexter and RobustBoost. These algorithms are wrapped inside of an implementation of alternating decision trees (ADTrees), which allows for easy visualization of the final classifier, even for high dimensional data. Each of the algorithms comes with a set of options that allows for customization to your dataset.
To learn more, download JBoost or read the documentation.

Parallelizing Boosting

- Map-reduce not good because stateless
- Split features among slaves. Data stays in memory between iterations.
  - Each slave finds his best weak rule
  - Master chooses overall best weak rule.
- When weights get very skewed, flush memory and collect examples filtering them by weight.
  - Concentrates on the hard examples
- Can be combined with Co-training / Active learning.

Co-training


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MIDSPAN
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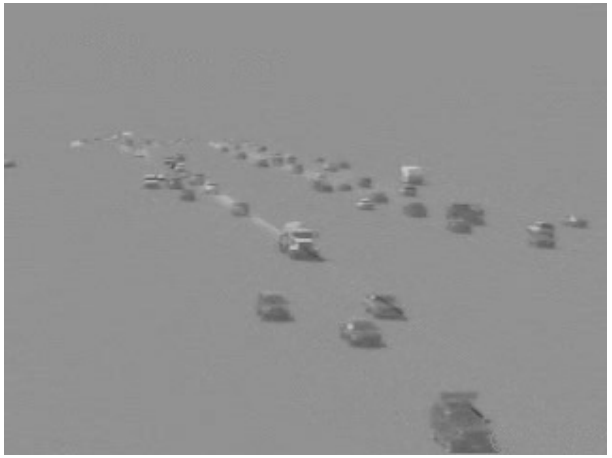

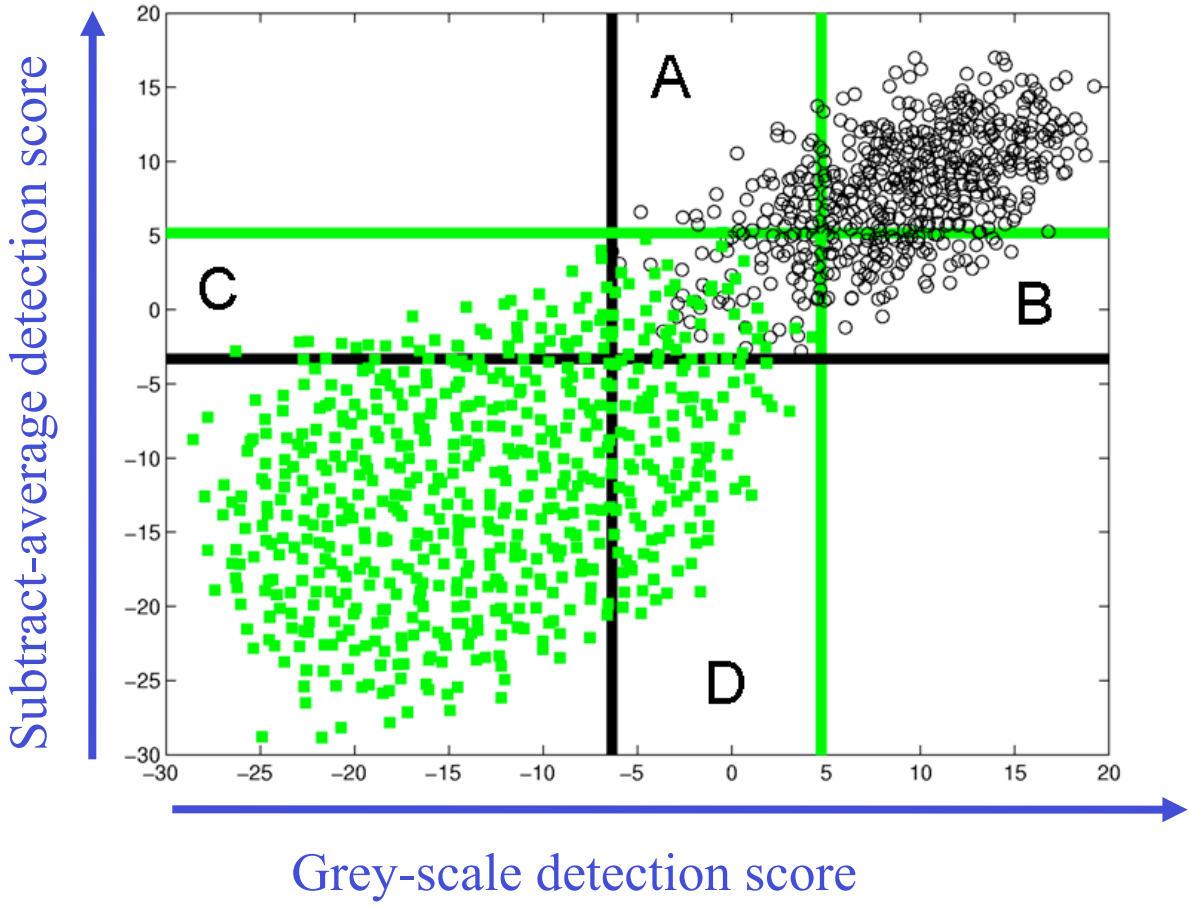
Subtract-average detection score
Grey-scale detection score
A
B
C
D
20
15
10
5
0
−5
−10
−15
−20
−25
−30
−30
−25
−20
−15
−10
−5
0
5
10
15
20

Summary

- **Boosting** is a method for learning an accurate classifiers by combining many weak classifiers.
- Boosting is **resistant to over-fitting**.
- **Margins** quantify prediction confidence.
- **High noise** is a serious problem for learning classifiers- can't be solved by minimizing convex functions.
- **Robustboost** can solve some high noise problems. Exact characterization still unclear.
- **Jboost** - an implementation of ADTrees and various boosting algorithms in java.
- **Book** on boosting coming this spring.
- Thank you, questions?